

Package ‘tulpa’

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Title Template Unified Latent Process Architecture for Bayesian Hierarchical Models

Version 0.2.0

Description A general-purpose engine for fitting Bayesian hierarchical models with spatial fields, temporal effects, spatially varying coefficients, and multiple inference backends. Scalable spatial structure includes Hilbert space approximate Gaussian processes (HSGP; Riutort-Mayol et al. 2023 <doi:10.1007/s11222-022-10167-2>), nearest-neighbor Gaussian processes (NNGP; Datta et al. 2016 <doi:10.1080/01621459.2015.1044091>), intrinsic conditional autoregressive models (ICAR; Besag, York, and Mollie 1991 <doi:10.1007/BF00116466>), the reparameterized Besag-York-Mollie model (BYM2; Riebler et al. 2016 <doi:10.1177/0962280216660421>), and stochastic partial differential equation fields (SPDE; Lindgren, Rue, and Lindstrom 2011 <doi:10.1111/j.1467-9868.2011.00777.x>). Temporal structure covers random walks, autoregressive processes, and Gaussian processes. Inference is tiered by correctness guarantee: exact Hamiltonian Monte Carlo with the No-U-Turn sampler, Laplace and nested Laplace approximations with hyperparameter integration (Rue, Martino, and Chopin 2009 <doi:10.1111/j.1467-9868.2008.00700.x>), and variational inference. Model-specific packages plug observation likelihoods into the engine through a templated C++ callback interface.

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Author Gilles Colling [aut, cre, cph] (ORCID:
[<https://orcid.org/0000-0003-3070-6066>](https://orcid.org/0000-0003-3070-6066)),
 Frances Y. Kuo [ctb, cph] (Sobol direction numbers in
 src/sobol_direction_numbers.h, BSD-3-clause),
 Stephen Joe [ctb, cph] (Sobol direction numbers in
 src/sobol_direction_numbers.h, BSD-3-clause)

Maintainer Gilles Colling <gilles.colling051@gmail.com>

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adjacency	<i>Construct a spatial adjacency graph for areal models</i>
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Description

Build the symmetric adjacency matrix that `spatial()` and `spatial_car()` consume, from a common spatial layout, instead of hand-coding it. The model still receives an explicit graph (`spatial(graph = g$adjacency, ...)`), so the graph stays inspectable before fitting – the engine never guesses connectivity from coordinates silently.

`adjacency()` is a single front-door verb that dispatches on the kind of input:

- a data.frame** cell centroids on a regular grid – queen (edge or corner) or rook (edge only) contiguity over the lattice. This covers both plain coordinate grids and rasterised cells passed as a table of centres.
- an sf object** polygon contiguity from shared boundaries (queen = share a point or edge; rook = share an edge). Requires **sf**.
- a SpatRaster (terra) or stars object** raster cells – the lattice of (non-NA) cell centres, queen or rook. Requires **terra** or **stars** respectively.

The result is a `tulpa_adjacency` object holding the matrix plus the cell identifier for each node, so a model can pass `g$adjacency` while the observation data is remapped to 1-based node indices with `node_index()`.

Usage

```
adjacency(x, ...)  
  
## Default S3 method:  
adjacency(x, ...)  
  
## S3 method for class 'data.frame'  
adjacency(  
  x,  
  type = c("queen", "rook"),  
  x_coord = "x",  
  y_coord = "y",  
  id = NULL,  
  order = 1L,  
  tolerance = 1.5,  
  offsets = NULL,  
  ...  
)  
  
## S3 method for class 'sf'  
adjacency(x, type = c("queen", "rook", "touches"), id = NULL, ...)  
  
## S3 method for class 'SpatRaster'  
adjacency(  
  x,  
  type = c("queen", "rook"),  
  order = 1L,  
  tolerance = 1.5,  
  offsets = NULL,  
  na_rm = TRUE,  
  ...  
)  
  
## S3 method for class 'stars'  
adjacency(  
  x,  
  type = c("queen", "rook"),  
  order = 1L,  
  tolerance = 1.5,  
  offsets = NULL,  
  na_rm = TRUE,  
  ...  
)
```

Arguments

x	The spatial layout: a <code>data.frame</code> of centroids, an <code>sf</code> polygon layer, or a raster (<code>SpatRaster</code> / <code>stars</code>).
---	---

...	Passed to methods.
type	Contiguity rule: "queen" (default; neighbours share an edge or a corner) or "rook" (neighbours share an edge only). For polygons, "touches" is an alias of "queen".
x_coord, y_coord	For the <code>data.frame</code> method, the names of the coordinate columns holding the cell centres (default "x" and "y").
id	For the <code>data.frame</code> and <code>sf</code> methods, an optional column naming each cell's identifier. Node <i>i</i> of the graph corresponds to <i>id</i> 's value in row <i>i</i> ; pass this column to <code>node_index()</code> to translate the observation data's cell column into node indices. Default NULL uses the row position (1:n) as the identifier.
order	For grid / raster layouts, the neighbourhood order (ring count): <code>order = 1</code> (default) is first-order contiguity (queen = 8 neighbours, rook = 4); <code>order = k</code> extends the stencil to the <i>k</i> -th ring, so queen keeps every cell within Chebyshev distance $k((2k + 1)^2 - 1)$ neighbours: 8, 24, 48, ... for $k = 1, 2, 3$ and rook every cell within Manhattan distance $k(2k + 1)$ neighbours: 4, 12, 24, ...). Any positive integer is allowed, so the neighbourhood is fully settable. Ignored by the <code>sf</code> (polygon) method, which is first-order contiguity only.
tolerance	For grid / raster layouts, the per-offset neighbour distance cut-off as a multiple of the inferred cell size: a candidate at a lattice offset is kept when its true centre distance is at most <code>tolerance</code> times that offset's expected distance. The default 1.5 admits a snapped neighbour while rejecting one much farther than its lattice slot implies; raise it only for irregularly spaced centroids. Neighbourhood extent is set by <code>order</code> , not by <code>tolerance</code> .
offsets	Advanced, grid / raster layouts only: a custom neighbour stencil as a two-column integer matrix or a list of length-2 <code>c(dx, dy)</code> lattice offsets (cell-step units, origin excluded). Supplying it overrides <code>type</code> and <code>order</code> and builds exactly that stencil, so any neighbourhood is expressible (anisotropic, ring-only, off-axis). An ICAR / CAR field is <i>undirected</i> , so the graph must be symmetric: an asymmetric stencil (e.g. <code>list(c(0, 1), c(-1, 0), c(1, 0))</code>) = up / left / right but not down) is symmetrized to an undirected graph, with a message, since a directed neighbourhood cannot be represented by an undirected field. Default NULL uses the <code>type / order</code> stencil.
na_rm	For raster layouts, drop cells whose value is NA before building the graph (default TRUE), so the nodes are the cells that carry data.

Value

A `tulpa_adjacency` object: a list with

`adjacency` the $[n \times n]$ symmetric sparse adjacency matrix (`dgCMatrix`, 0/1, zero diagonal) to pass as graph / adjacency.

`ids` the cell identifier for each node, in node order (length *n*).

`n` the number of nodes.

`cellsize` the inferred cell size `c(x, y)` for grid / raster layouts, or NA for polygons.

`type` the contiguity rule used.

See Also

[node_index\(\)](#) to map cell identifiers to node indices, [check_adjacency\(\)](#) to validate a hand-built matrix, [spatial\(\)](#) and [spatial_car\(\)](#) which consume the graph.

Examples

```
# A 3 x 3 regular grid of cell centres
grid <- expand.grid(x = 1:3, y = 1:3)
grid$cell <- paste0("c", seq_len(nrow(grid)))

g <- adjacency(grid, x_coord = "x", y_coord = "y", id = "cell",
               type = "queen")

g
g$adjacency

# Second-order (24-neighbour) queen contiguity: any order is settable
g2 <- adjacency(grid, id = "cell", order = 2)

# Advanced: a custom stencil (symmetrized for the undirected field)
g3 <- adjacency(grid, id = "cell", offsets = list(c(1, 0), c(0, 1)))

# Use it in a model: graph stays explicit and inspectable
spatial(graph = g$adjacency, formula = ~ 1 || cell_idx)

# Remap observation data (original cell ids -> 1:n node indices) by key
obs <- data.frame(cell = c("c5", "c1", "c5", "c9"))
obs$cell_idx <- node_index(g, obs$cell)
obs
```

agq_fit

*Adaptive Gauss-Hermite quadrature for one-RE GLMMs***Description**

Marginal-likelihood approximation for a generalised linear mixed model with one cluster-level intercept random effect. Adaptive Gauss-Hermite quadrature (AGQ) generalises Laplace by replacing the single-point Gaussian integral around the cluster's posterior mode with `n_quad`-point quadrature. AGQ at `n_quad = 1` recovers the Laplace approximation; higher `n_quad` reduces approximation error, especially for clusters with few observations or non-Gaussian likelihoods.

This is an engine block, not a front door: its tuning knobs (`max_iter`, `tol`, `n_quad`) sit in the signature rather than in a control list.

Scoped to the `lme4::glmer(..., nAGQ = N)` use case: one intercept-only RE term, families `binomial`, `poisson`, or `gaussian`. For multi-RE or random-slope models, use [tulpa_laplace\(\)](#) (Laplace at the joint mode) or HMC.

Usage

```
agq_fit(
  y,
  X,
  group,
  n_groups = max(group),
  family = c("binomial", "poisson", "gaussian"),
  n_trials = NULL,
  sigma_eps = 1,
  n_quad = 7L,
  beta_init = NULL,
  sigma_init = 1,
  max_iter = 200L,
  tol = 1e-06,
  verbose = FALSE
)
```

Arguments

y	Response vector.
X	Fixed-effects design matrix (n_obs x p).
group	Integer cluster labels (1-based, length n_obs).
n_groups	Number of clusters (default max(group)).
family	One of "binomial", "poisson", "gaussian".
n_trials	Trial sizes (binomial only; default rep(1, n_obs)).
sigma_eps	Residual SD (gaussian only; default 1). Held fixed at this value – it is not profiled or estimated, so for a gaussian response set it to a known / pre-estimated residual SD rather than the default.
n_quad	Number of Gauss-Hermite quadrature nodes per cluster. 1 recovers Laplace; common choices are 5 or 7. Default 7.
beta_init	Initial fixed-effects (default zeros).
sigma_init	Initial RE SD (default 1).
max_iter	Optimiser iteration cap (default 200).
tol	Convergence tolerance (default 1e-6).
verbose	Print optimiser summary (default FALSE).

Value

A list with class `tulpa_fit` carrying:

- means: named vector `c(beta, log_sigma_re)`.
- mode: same as means (Gaussian fit at the optimum).
- cov: covariance matrix of `(beta, log_sigma_re)` from inverse observed information.
- sigma_re: estimated RE SD.

- log_marginal: AGQ-approximated log marginal likelihood at the fitted values.
- n_quad: quadrature order used.
- n_iter, converged: optimiser diagnostics.
- inference_mode: "structured".
- inference_tier: 2L.
- backend: "agq".

An optimum at which the AGHQ objective is undefined (some group's solve fails there, so its value is the failure sentinel rather than a marginal likelihood) is an error naming the groups, not a returned fit.

Tier

Tier 2 (Structured). AGQ is exact in the limit $n_quad \rightarrow \infty$ but at finite n_quad it is a controlled approximation – same epistemic class as Laplace.

References

Pinheiro, J. C., & Bates, D. M. (1995). Approximations to the log-likelihood function in the non-linear mixed-effects model. *Journal of Computational and Graphical Statistics*, 4(1), 12-35.

See Also

[tulpa_laplace\(\)](#) for the joint-mode Laplace path (handles multi-RE and spatial structure).

Examples

```
set.seed(1)
n_g <- 20; n_per <- 5; n <- n_g * n_per
group <- rep(seq_len(n_g), each = n_per)
x <- rnorm(n)
X <- cbind(1, x)
u <- rnorm(n_g, 0, 0.8)
eta <- 0.3 + 0.7 * x + u[group]
y <- rbinom(n, 1, plogis(eta))

# Compare Laplace (n_quad = 1) and AGQ-7.
fit_lap <- agq_fit(y, X, group, family = "binomial", n_quad = 1)
fit_agq <- agq_fit(y, X, group, family = "binomial", n_quad = 7)
c(fit_lap$log_marginal, fit_agq$log_marginal)
```

as_draws

*Posterior draws in the posterior package's format***Description**

Convert a fit's posterior draws to a posterior draws object. `as_draws()` returns the `draws_array` shape; `as_draws_array()`, `as_draws_matrix()`, `as_draws_df()` and `as_draws_rvars()` return theirs. When the posterior package is installed these are also registered against its generics, so `posterior::as_draws(fit)` works.

Usage

```
as_draws(x, ...)

## S3 method for class 'tulpa_fit'
as_draws(x, n_draws = NULL, seed = NULL, ...)

as_draws_array(x, ...)

## S3 method for class 'tulpa_fit'
as_draws_array(x, n_draws = NULL, seed = NULL, ...)

as_draws_matrix(x, ...)

## S3 method for class 'tulpa_fit'
as_draws_matrix(x, n_draws = NULL, seed = NULL, ...)

as_draws_df(x, ...)

## S3 method for class 'tulpa_fit'
as_draws_df(x, n_draws = NULL, seed = NULL, ...)

as_draws_rvars(x, ...)

## S3 method for class 'tulpa_fit'
as_draws_rvars(x, n_draws = NULL, seed = NULL, ...)
```

Arguments

<code>x</code>	A <code>tulpa_fit</code> object.
<code>...</code>	Passed to the corresponding posterior converter.
<code>n_draws</code>	Number of draws to synthesize from the Gaussian approximation for a fit that carries none. <code>NULL</code> (default) errors on such a fit rather than silently approximating. Ignored, with a warning, when the fit already carries draws.
<code>seed</code>	Optional integer seed for the synthesis. The RNG state is restored afterwards.

Details

Fits differ in whether they carry draws at all. Sampler and nested-Laplace fits do, and convert directly. A Gaussian-approximation fit (`mode = "laplace"`, `mode = "eb"`) carries a mode and a precision instead, and converting it means *drawing from the approximation* – which is a modelling decision, not a format change, because every downstream posterior summary would then treat a normal approximation as a posterior sample. So it is opt-in: pass `n_draws` to synthesize that many draws from $N(\text{coef}(\text{object}), \text{vcov}(\text{object}))$, or get an error naming the alternative. Synthesized draws form a single chain and cover the fixed effects only.

Value

A posterior draws object of the requested shape.

See Also

`tulpa_draws_array()` for the base R array without the dependency, `posterior_sample()` for the raw matrix.

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(80))
df$y <- rpois(80, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson")
if (requireNamespace("posterior", quietly = TRUE)) {
  posterior::summarise_draws(as_draws(fit))
}
```

auto_grid

Mark an outer-grid setting as a default rather than a pin

Description

Declares that a setting shaping the outer hyperparameter grid carries a *default* the caller computed, not a choice the user made. The auto-recenter pass (`outer_grid_placement`) leaves a user-pinned setting exactly as given, and re-centres (or, for a prior, engages its own regularizer over) a marked one when the fit rails against its ceiling.

Three kinds of setting take the mark:

- a grid axis on a nested-Laplace prior block (`sigma_grid`, `tau_grid`, ...) – a numeric vector of nodes, or the $[n_cells \times k]$ matrix of pre-paired coordinates the families whose axis is a matrix take (`mcar` / `miid`'s `logchol_grid`, `tgmrf`'s `theta_grid_built`);
- a scalar grid-construction knob in `control`, for a driver that builds its axes rather than taking them (`fit_st_nested()`'s `n_grid_spatial`, `tau_upper`, ...);
- a `prior_sigma` hyperprior specification – a list, e.g. `list("pc.prec", c(U = 3, alpha = 0.01))`.

Wrapper packages are the intended caller: one that builds a default of its own – because it derives a second axis from it, hands the same vector to several blocks, or exposes its own argument with a default – would otherwise be indistinguishable from a user who pinned that setting deliberately. Mark it and the rescue stays live. A setting whose value is exactly the engine’s own default is recognised without a mark; anything else needs one.

The mark is an attribute, so it is dropped by `sort()`, `[], c()` and `as.numeric()`: build the value first, mark it last.

Usage

```
auto_grid(x)
```

Arguments

`x` Numeric vector or matrix of grid nodes, a numeric scalar knob, or a prior-specification list.

Value

`x` carrying the marker attribute. Numeric input is coerced to double IN PLACE, so everything else it carries – `dim()` and `dimnames()` above all – survives the mark; a list is returned unchanged apart from the attribute.

See Also

[is_auto_grid\(\)](#), [tulpa_nested_laplace_joint\(\)](#), [fit_st_nested\(\)](#)

Examples

```
prior <- list(type = "icar", sigma_grid = auto_grid(c(0.1, 0.5, 1, 2, 3)))
is_auto_grid(prior$sigma_grid)
is_auto_grid(auto_grid(list("pc.prec", c(U = 3, alpha = 0.01))))
```

bayes_R2

Bayesian R-squared

Description

Per posterior draw s , $R2_s = \text{Var}_i(\mu_si) / (\text{Var}_i(\mu_si) + \text{Var_res_s})$, where μ_si are the response-scale fitted means and Var_res_s is the family’s residual variance averaged over observations (Gelman et al. 2019). The linear predictor is rebuilt per draw exactly as in [posterior_predict\(\)](#) (fixed effects + random effects + offset at the training data).

Usage

```
bayes_R2(object, ...)

## S3 method for class 'tulpa_fit'
bayes_R2(
  object,
  ndraws = NULL,
  summary = TRUE,
  probs = c(0.025, 0.975),
  seed = NULL,
  ...
)
```

Arguments

<code>object</code>	A <code>tulpa_fit</code> object from <code>tulpa()</code> .
<code>...</code>	Passed to methods.
<code>ndraws</code>	Number of posterior draws to use. Defaults to all stored draws, or 400 on the draw-free Laplace tier.
<code>summary</code>	Summarize the per-draw values (default TRUE).
<code>probs</code>	Quantiles reported by the summary (default 2.5% / 97.5%).
<code>seed</code>	Optional integer seed (RNG state is restored on exit), used by the Gaussian fixed-effect sampling on draw-free fits.

Value

With `summary = TRUE` (default) a one-row data frame with `estimate` (posterior median), `std.error`, and the `probs` quantiles; with `summary = FALSE` the vector of per-draw R^2 values.

References

Gelman, Goodrich, Gabry & Vehtari (2019). R-squared for Bayesian regression models. *The American Statistician* 73(3):307-309.

Examples

```
set.seed(1)
d <- data.frame(x = rnorm(200))
d$y <- rnorm(200, 2 * d$x, 1)
fit <- tulpa(y ~ x, data = d, family = "gaussian", mode = "laplace", phi = 1)
bayes_R2(fit)
```

bridge_sampling	<i>Bridge sampling for marginal likelihood</i>
-----------------	--

Description

Estimate the log marginal likelihood $\log Z = \log p(y)$ from posterior draws via the Meng-Wong / Gronau bridge-sampling identity. Useful for Bayes factors, model comparison, and as a sanity check on Laplace-approximated marginal likelihoods.

The classical iterative scheme (Meng & Wong 1996; Gronau et al. 2017) is used with a multivariate-normal proposal fit to half of the posterior draws – the other half is used for the bridge ratio so the proposal is independent of the samples that score it. All computations are done in log-space via `logsumexp` for numerical stability.

Usage

```
bridge_sampling(
  draws,
  log_posterior,
  n_proposal = nrow(draws),
  max_iter = 1000L,
  tol = 1e-10,
  split = TRUE,
  verbose = FALSE
)
```

Arguments

<code>draws</code>	Numeric matrix of posterior draws, one parameter per column. Typically <code>fit\$draws</code> from a tulpa Tier-1 fit.
<code>log_posterior</code>	Function <code>function(theta) -> numeric</code> returning the <i>unnormalized</i> log posterior density $\log p(\theta, y)$ at a single parameter vector. Must accept a numeric vector of length <code>ncol(draws)</code> and return a finite scalar.
<code>n_proposal</code>	Number of proposal draws. Default <code>nrow(draws)</code> .
<code>max_iter</code>	Maximum bridge iterations (default 1000).
<code>tol</code>	Convergence tolerance on $ \log r_{t+1} - \log r_t $ (default <code>1e-10</code>).
<code>split</code>	Logical: split the posterior draws in half so the proposal is fit on one half and scored on the other (default <code>TRUE</code> , recommended). Set <code>FALSE</code> only for diagnostic comparison.
<code>verbose</code>	Print iteration history (default <code>FALSE</code>).

Value

A list with:

- `log_marginal`: the bridge-sampling estimate of $\log Z$.

- `n_iter`: bridge iterations to convergence.
- `converged`: logical.
- `re_sd`: relative MSE estimate (Fruehwirth-Schnatter 2004); a rough quality check, smaller is better.
- `proposal`: the fitted proposal `list(mean, cov)`.

Tier

Bridge sampling is a *post-hoc* marginal-likelihood estimator, not a sampling backend, so it does not appear in the [INFERENCE_TIERS](#) registry. It operates on draws from any Tier-1 (Exact) backend.

References

Meng, X.-L., & Wong, W. H. (1996). Simulating ratios of normalizing constants via a simple identity: a theoretical exploration. *Statistica Sinica*, 6, 831-860.

Gronau, Q. F., Sarafoglou, A., Matzke, D., Ly, A., Boehm, U., Marsman, M., ... & Steingroever, H. (2017). A tutorial on bridge sampling. *Journal of Mathematical Psychology*, 81, 80-97.

Examples

```
# Toy: marginal likelihood of N(theta | 0, 1) under Y = theta + eps,
# eps ~ N(0, 1), prior theta ~ N(0, 10). Closed-form available.
y <- 1.5
log_post <- function(theta) {
  dnorm(y, theta, 1, log = TRUE) + dnorm(theta, 0, 10, log = TRUE)
}
draws <- matrix(rnorm(2000, mean = y * 100 / 101, sd = sqrt(100 / 101)),
               ncol = 1)
bs <- bridge_sampling(draws, log_post)
bs$log_marginal # should match dnorm(y, 0, sqrt(101), log = TRUE)
```

check_adjacency

Validate a spatial adjacency matrix

Description

Check that a hand-built adjacency matrix is a well-formed spatial graph before passing it to [spatial\(\)](#) / [spatial_car\(\)](#): square, symmetric, zero on the diagonal, 0/1 valued, and free of isolated nodes. [adjacency\(\)](#) runs the same checks on the graphs it constructs.

Usage

```
check_adjacency(adjacency, ids = NULL)
```

Arguments

adjacency	A matrix (dense or sparse Matrix).
ids	Optional cell identifiers; if supplied, their length must match nrow(adjacency) and they must be unique.

Value

Invisibly, a tulpa_adjacency_check list with the per-check results (square, symmetric, zero_diag, binary, isolated-node indices, edge count) and an overall ok flag. Issues are reported via warning() and printed; the function does not stop, so every problem surfaces in one pass.

See Also

[adjacency\(\)](#) to construct a graph, [node_index\(\)](#).

Examples

```
adj <- matrix(0, 4, 4)
for (i in 1:3) adj[i, i + 1] <- adj[i + 1, i] <- 1
check_adjacency(adj)
```

check_diagnostics	<i>Quick convergence check</i>
-------------------	--------------------------------

Description

Runs the core convergence diagnostics on a fit and reports whether Rhat, bulk-ESS, and divergence thresholds are all met. A terse companion to [diagnostic_summary\(\)](#) for use in scripts and tests.

Usage

```
check_diagnostics(
  fit,
  rhat_threshold = 1.01,
  ess_threshold = 400,
  quiet = FALSE
)
```

Arguments

fit	A tulpa_fit object.
rhat_threshold	Maximum acceptable Rhat (default 1.01).
ess_threshold	Minimum acceptable bulk-ESS (default 400).
quiet	Logical; if TRUE, suppress messages (default FALSE).

Value

Invisibly, TRUE if all checks pass, FALSE if any fail, or NA for a non-chain (approximation) fit where Rhat/ESS do not apply.

See Also

[diagnostic_summary\(\)](#), [diagnostics\(\)](#), [n_divergent\(\)](#)

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))
check_diagnostics(fit)
```

check_model

Diagnostic panel plot

Description

Produces a 2x2 or 1x3 panel of diagnostic plots:

1. QQ plot of PIT residuals vs Uniform (with KS p-value)
2. Residuals vs fitted (with lowess smoother)
3. Dispersion histogram (observed variance vs simulated)
4. Spatial correlogram via Moran's I (if coords provided)

Usage

```
check_model(object, ...)
```

```
## Default S3 method:
```

```
check_model(object, coords = NULL, nsim = 250L, seed = 123L, ...)
```

Arguments

object	A fitted model with <code>simulate()</code> , <code>fitted()</code> , <code>residuals()</code>
...	Passed to methods.
coords	Optional N x 2 coordinate matrix for spatial panel
nsim	Number of simulations (default 250)
seed	Random seed (default 123)

Value

Invisible list with `ks_p`, `disp_ratio`, `moran` (if spatial)

<code>coef.tulpa_fit</code>	<i>Fixed-effect coefficients</i>
-----------------------------	----------------------------------

Description

Fixed-effect coefficients

Usage

```
## S3 method for class 'tulpa_fit'
coef(object, ...)
```

Arguments

<code>object</code>	A <code>tulpa_fit</code> object.
<code>...</code>	Ignored.

Value

Named numeric vector of fixed-effect posterior means (the Laplace mode for the Laplace tier). Random effects come from `ranef()`.

<code>compare_models</code>	<i>Compare models by information criteria</i>
-----------------------------	---

Description

Rank fitted models best-first by an information criterion. "waic" and "loo" use the native pointwise log-likelihood layer (`tulpa_criteria()` / `tulpa_psis()`) – WAIC and PSIS-LOO respectively, computed from each fit's `[n_draws x n_obs]` pointwise log-likelihood (`fit$draws$log_lik`), with no `loo` package dependency. "loglik" returns the (integrated) joint log-likelihood with the parameter count. A fit carrying no pointwise log-likelihood (a deterministic / point approximation) yields NA criterion columns rather than an error, so the table always has one row per model.

Usage

```
compare_models(..., criterion = c("waic", "loo", "loglik"))
```

Arguments

<code>...</code>	Named <code>tulpa_fit</code> objects.
<code>criterion</code>	"waic" (default), "loo", or "loglik".

Value

A data frame. For "loglik": model, n_params, logLik. For "waic" / "loo" (ranked best-first): model, elpd, se_elpd, p_eff, ic ($-2 * \text{elpd}$), delta (elpd gap to the best model), se_diff (SE of that pointwise elpd difference), and weight (the Akaike-style weight on the criterion).

See Also

[model_average\(\)](#) for model-averaged predictions, [tulpa_criteria\(\)](#) and [tulpa_psis\(\)](#) for the native criteria layer.

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(120))
df$y <- rpois(120, exp(0.4 + 0.5 * df$x))
f1 <- tulpa(y ~ x, data = df, family = "poisson")
f2 <- tulpa(y ~ 1, data = df, family = "poisson")
compare_models(full = f1, null = f2, criterion = "waic")
```

confint.tulpa_fit	<i>Credible intervals for the fixed effects</i>
-------------------	---

Description

Credible intervals for the fixed effects

Usage

```
## S3 method for class 'tulpa_fit'
confint(object, parm = NULL, level = 0.95, ...)
```

Arguments

object	A tulpa_fit object.
parm	Parameter names or indices (default: all fixed effects).
level	Interval level (default 0.95).
...	Ignored.

Value

Matrix with lower and upper columns. A nested-Laplace fit carries interval_source / interval_declined (which read produced the bounds – by default the grid's Gaussian-mixture CDF), retained_mass (the share of the grid weight the bounds are conditional on), and skew_applied, one logical per reported coefficient saying whether its bounds are the inner-Laplace skew-corrected quantiles or not. See [summary.tulpa_fit\(\)](#).

Description

Generic front doors onto the two criteria `tulpa_criteria()` computes that the **loo** package owns no generic for. WAIC and PSIS-LOO have theirs (`loo::waic()`, `loo::loo()`), so a model package registers methods on those rather than on new names that would mask them.

Usage

```
dic(object, ...)

## Default S3 method:
dic(object, loglik_at_mean = NULL, ...)

cpo(object, ...)

## Default S3 method:
cpo(object, ...)
```

Arguments

<code>object</code>	A pointwise log-likelihood matrix (draws x observations), or a fitted model object a method is registered for.
<code>...</code>	Passed to <code>tulpa_criteria()</code> (e.g. <code>group</code> , <code>chunk_size</code>).
<code>loglik_at_mean</code>	Length- <code>n_obs</code> vector of pointwise log-likelihoods at the posterior mean of the parameters. Required for DIC's plug-in deviance; without it the DIC fields are NA.

Details

The default methods take a draws x observations pointwise log-likelihood matrix, the same input `tulpa_criteria()` takes. A model package registers a method taking its own fit object, builds the matrix from the posterior, and delegates here.

Value

A `tulpa_criteria` object.

See Also

`tulpa_criteria()` for every criterion at once and for what the LOO unit means.

Examples

```
set.seed(1)
y <- rnorm(40)
mu <- matrix(rnorm(200 * 40, sd = 0.2), 200, 40)
ll <- dnorm(matrix(y, 200, 40, byrow = TRUE), mean = mu, log = TRUE)
cpo(ll)
```

diagnostics

Posterior diagnostics for a fitted model

Description

The diagnostic front door for any tulpa fit. What a fit's posterior draws can be asked depends on how they were produced, so this reads the draws provenance and returns the diagnostic that applies:

MCMC chain draws improved Rhat (the maximum of rank-normalized split-Rhat and folded split-Rhat), bulk / tail / mean / sd / quantile effective sample size, and Monte Carlo standard errors, following Vehtari et al. (2021). Split-Rhat is defined for a single chain, so a result is produced for any number of chains.

i.i.d. approximation draws the approximation-reliability table – the PSIS tail-shape pareto_k scored against the exact inner-Laplace marginal and the outer-grid quadrature effective sample size (the OUTER hyperparameter-grid integration layer), the inner-Laplace skewness diagnostic gamma_3 when computed (the INNER Gaussian approximation to the latent field, a separate layer pareto_k does not cover), a combined whole-fit verdict naming which layer degrades when one does, and a per-parameter posterior summary. See [laplace_diagnostics\(\)](#) for the full description of this table and its attributes.

point summaries no sample to diagnose; returns NULL with a message naming the backend.

Provenance is read from \$draws_kind (stamped by tulpa_dispatch), falling back to the backend registry's emits property and then to an inner \$joint_fit. A fit that predates the tag is treated as a chain, so an older fit is never silently refused.

Usage

```
diagnostics(fit, ...)

## Default S3 method:
diagnostics(
  fit,
  pars = NULL,
  measures = c("rhat", "ess_bulk", "ess_tail"),
  probs = c(0.05, 0.95),
  sbc = NULL,
  ...
)

## S3 method for class 'sbc'
diagnostics(fit, ...)
```

Arguments

<code>fit</code>	A <code>tulpa_fit</code> (or subclass) carrying posterior <code>\$draws</code> . Multiple chains are recognised from a 3D <code>[iter, chain, param]</code> draws array, a <code>\$chain_id</code> row map, or an <code>\$n_chains</code> count over chain-major rows.
<code>...</code>	Passed to the method.
<code>pars</code>	Optional character vector of parameter names to restrict to.
<code>measures</code>	Character vector selecting which diagnostics to compute, in output-column order. Available: <code>"rhat"</code> , <code>"rhat_bulk"</code> , <code>"rhat_fold"</code> , <code>"ess_bulk"</code> , <code>"ess_tail"</code> , <code>"ess_mean"</code> , <code>"ess_sd"</code> , <code>"mcse_mean"</code> , <code>"mcse_sd"</code> , <code>"ess_quantile"</code> , <code>"mcse_quantile"</code> . Defaults to the core set <code>c("rhat", "ess_bulk", "ess_tail")</code> . Applies to chain fits; the approximation-reliability table has a fixed set of columns.
<code>probs</code>	Numeric probabilities for the quantile-based measures (<code>"ess_quantile"</code> , <code>"mcse_quantile"</code>); each expands to one column named e.g. <code>ess_q5</code> , <code>ess_q95</code> . Default <code>c(0.05, 0.95)</code> . Chain fits only.
<code>sbc</code>	Optional <code>sbc()</code> result for the same model, whose calibration verdict is attached to the returned table.

Value

For a chain fit, a data frame with a parameter column followed by one column per requested measure; entries are NA for parameters that are constant or have too few draws. For an i.i.d. approximation fit, the `laplace_diagnostics` table (see that function for its attributes). For a point fit, NULL.

Extending

`diagnostics()` is an S3 generic so a model package can answer for its own fit class (`diagnostics.ratiod_fit()`, say) rather than shadowing this export with a same-named function. The default method does the provenance routing described above and is what a method should delegate to once it has assembled a draws array.

Calibration alongside reliability

The tables above score ONE fit's own internal reliability. Whether the backend's posterior is CALIBRATED is a different question, answered over many simulated data sets by `sbc()`, and the two disagree in both directions – a fit whose reliability band is clean on both layers can still fail calibration, and one whose outer $\hat{k}$ is well past the escalation threshold can pass. So the band is a screen, not a verdict. Pass an `sbc` result as `sbc =` and the calibration verdict is attached to the table and printed underneath it; `diagnostics()` called on the `sbc` result itself returns its report table.

References

Vehtari, Gelman, Simpson, Carpenter & Burkner (2021). Rank-normalization, folding, and localization: an improved Rhat for assessing convergence of MCMC. *Bayesian Analysis* 16(2):667-718.

Vehtari, Simpson, Gelman, Yao & Gabry (2024). Pareto smoothed importance sampling. *JMLR* 25(72):1-58.

See Also

[sbc\(\)](#) for calibration, [laplace_diagnostics\(\)](#) for the approximation-reliability table in full, [tulpa_draws_array\(\)](#), [plot_rhat\(\)](#), [plot_ess\(\)](#), [diagnostic_summary\(\)](#), [check_diagnostics\(\)](#)

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))

# chain fit -> Rhat / ESS
hmc <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
             control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                           seed = 1L))

diagnostics(hmc)

# deterministic fit -> PSIS approximation reliability
smc <- tulpa(y ~ x, data = df, family = "poisson", mode = "smc")
diagnostics(smc)
```

diagnostic_summary *Comprehensive Diagnostic Summary*

Description

Provides a comprehensive diagnostic report for a tulpa model, combining convergence metrics, divergence information, and actionable recommendations.

Usage

```
diagnostic_summary(fit, quiet = FALSE)
```

Arguments

fit A tulpa_fit object.

quiet Logical; if TRUE, suppress printed output (default: FALSE).

Value

A list with class tulpa_diagnostic_summary containing:

status Overall status: "PASS", "WARN", or "FAIL"

n_divergent Number of divergent transitions

divergent_pct Percentage of divergent transitions

worst_rhat Data frame of parameters with worst Rhat

worst_ess Data frame of parameters with worst ESS

e_bfmi E-BFMI value (HMC only)

pareto_k, quad_ess approximation fits only: the outer PSIS k-hat, or the grid quadrature ESS when no k-hat was produced

pareto_k_declined approximation fits only, and only when there is no k-hat: WHY – "not_requested" and "unguessable_axis: <axis>" are benign or permanent, "degenerate_proposal" and "grid_too_small" are signals about the fit, and "internal_inconsistency" is an engine bug and raises the status to "WARN"

inner_skew_max, inner_skew_declined approximation fits only: the largest scored inner-Laplace $|\gamma_3|$, or why nothing was scored ("coupled_arm" marks arms the inner layer could score neither per observation nor through the cell tensor)

axis_fields_dropped data frame of grid axes the fit's own resolved path could not read and dropped as engine defaults: one row per field, with the block, family, path and the axis that path integrated instead. Absent whenever every supplied axis was used

recommendations Character vector of recommendations

See Also

[check_diagnostics\(\)](#), [diagnostics\(\)](#), [plot_diagnostics\(\)](#)

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))
ds <- diagnostic_summary(fit)
print(ds)
```

`durbin_watson`

Durbin-Watson test for temporal autocorrelation

Description

Tests first-order autocorrelation in temporally-ordered residuals.

Usage

```
durbin_watson(object, alternative = c("two.sided", "greater", "less"))
```

Arguments

<code>object</code>	A numeric vector of temporally-ordered residuals
<code>alternative</code>	"two.sided", "greater" (positive autocorr), or "less"

Value

An htest object with DW statistic, lag-1 r, and p-value

fitted.tulpa_fit	<i>Fitted values (population level)</i>
------------------	---

Description

In-sample mean response from the fixed effects and the observation offset ($E[y] = g^{-1}(X\beta + \text{offset})$, trial-scaled for binomial). Random effects are held at their prior mean of zero; group-level effects are in `ranef()`. `y - fitted(object)` equals `residuals(object, type = "response")`.

Usage

```
## S3 method for class 'tulpa_fit'
fitted(object, ...)
```

Arguments

object	A tulpa_fit object (must carry \$model_matrix).
...	Ignored.

Value

Numeric vector of fitted mean responses, length nobs.

fit_spde	<i>Fit a Spatial Model using SPDE Laplace Approximation</i>
----------	---

Description

Fits a GLM with a Matern spatial field via the SPDE approach. Uses CHOLMOD sparse solver with optional nested Laplace for hyperparameter integration.

Usage

```
fit_spde(
  y,
  X,
  spatial,
  family = "binomial",
  n_trials = NULL,
  range = NULL,
  sigma = NULL,
  nested_laplace = is.null(range) || is.null(sigma),
```

```

    phi = 1,
    offset = NULL,
    re_idx = NULL,
    n_re_groups = 0L,
    sigma_re = 1,
    mode = c("laplace", "nuts"),
    control = list()
  )

```

Arguments

<code>y</code>	Integer response vector.
<code>X</code>	Design matrix.
<code>spatial</code>	A <code>tulpa_spatial</code> object from <code>spatial_spde()</code> or <code>spatial_spde_custom()</code> .
<code>family</code>	Distribution family: "binomial", "poisson", "neg_binomial_2", or "gaussian" (continuous-field geostatistics, with <code>phi</code> the observation-noise standard deviation).
<code>n_trials</code>	Integer vector of trial sizes (binomial only).
<code>range</code>	Spatial range parameter. If <code>NULL</code> , uses nested Laplace to integrate over range and sigma.
<code>sigma</code>	Marginal standard deviation. If <code>NULL</code> , uses nested Laplace.
<code>nested_laplace</code>	Logical. If <code>TRUE</code> (default when <code>range/sigma</code> are <code>NULL</code>), use nested Laplace approximation over hyperparameters.
<code>phi</code>	Dispersion parameter (negbin only).
<code>offset</code>	Optional fixed additive term on the linear predictor ($\eta = \text{offset} + X\beta + A w$), length <code>length(y)</code> ; <code>NULL</code> -> no offset.
<code>re_idx, n_re_groups, sigma_re</code>	Optional single iid random-intercept ($1 g$) term alongside the Matern field: <code>re_idx</code> is a length- <code>length(y)</code> 1-based group index, <code>n_re_groups</code> the number of groups, and <code>sigma_re</code> the (conditioned) random-effect SD. The field and the RE block are Laplace- marginalised jointly. <code>n_re_groups = 0</code> (default) is no RE term. Not supported for a fractional-nu field.
<code>mode</code>	Inference method (the method is an argument, not a parallel verb): "laplace" (default) is the nested-Laplace integration over (<code>range</code> , <code>sigma</code>) documented here; "nuts" delegates to <code>tulpa_nuts_spde()</code> for exact HMC over the field (and, unless both <code>range</code> and <code>sigma</code> are fixed, the Matern hyperparameters). <code>mode = "nuts"</code> does not support an offset or a random-effect term, and its sampler knobs pass via <code>control</code> (see <code>tulpa_nuts_spde()</code>); it returns that sampler's draws object.
<code>control</code>	A named list of numerical / tuning knobs (statistical arguments stay in the signature above). Recognized entries: • <code>method</code>: hyperparameter integration backend when nested Laplace is active. "ccd" (default) uses a central composite design centered on the joint posterior mode of (<code>range</code>, <code>sigma</code>), oriented by the local Hessian (9 design points instead of <code>n_grid^2</code>), folding the PC priors from <code>spatial\$prior_range</code>

/ spatial\$prior_sigma into the integrated marginal and falling back to "grid" if the surface is too flat for a Hessian-based design. "grid" uses a rectangular grid in $\log(\text{range}) \times \log(\text{sigma})$ around the prior modes.

- `n_grid`: grid points per hyperparameter dimension for `method = "grid"` (ignored under "ccd"). Default 5.
- `diagnose_k`: if TRUE (default), compute the outer Pareto- $\hat{k}$ accuracy diagnostic (`$pareto_k`) by importance sampling the joint `(range, sigma)` posterior on the log scale against the Gaussian proposal that orients the integration. See [tulpa_psis\(\)](#).
- `k_samples`: importance draws for `diagnose_k`. Default 200, each one extra batched SPDE marginal evaluation.
- `mode_find`: tuning for the outer `(range, sigma)` mode-find under `method = "ccd"`, as `list(factr =, ndeps =, maxit =)`; supply any subset. `ndeps` is the central-difference step for `optim()`'s numerical gradient on the log scale (default $1e-2$): it must clear the inner solver's convergence tolerance, and a step wide enough that its truncation error exceeds the reduction the line search chases near a flat optimum leaves L-BFGS-B aborting at the mode it just reached, in which case the CCD design declines to the rectangular grid. `factr` is the relative-reduction stop in units of `.Machine$double.eps` (default $1e5$); `maxit` the iteration cap (default 300).
- `max_iter`: maximum Newton iterations. Default 100.
- `tol`: Newton convergence tolerance. Default $1e-6$.
- `n_threads`: OpenMP threads. Default 1.
- `checkpoint`: grid-cell checkpoint/resume spec `list(path =, resume =)`. Each solved `(range, sigma)` cell is appended to `path`; a `resume = TRUE` run loads the finished cells and re-solves only the rest, so a killed or re-booted fit resumes instead of restarting. `resume = FALSE` starts a fresh file. Default NULL (off).

Value

A list with:

- `mode`: mode of the latent field (beta + mesh node effects)
- `log_marginal`: log marginal likelihood
- `converged`: convergence flag
- `spatial`: the spatial specification (for prediction)
- `pareto_k`, `pareto_k_is_ess`: outer Pareto- $\hat{k}$ and its importance-sampling ESS (NA when `diagnose_k = FALSE`)
- `nested`: nested Laplace results (if used)

References

Lindgren, Rue & Lindstrom (2011). An explicit link between Gaussian fields and Gaussian Markov random fields: the stochastic partial differential equation approach. *JRSS-B* 73(4):423-498. Rue, Martino & Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *JRSS-B* 71(2):319-392.

Examples

```
if (requireNamespace("fmesher", quietly = TRUE)) {
  set.seed(1)
  n <- 200L
  coords <- cbind(runif(n), runif(n))
  mesh <- fmesher::fm_mesh_2d(loc = coords, max.edge = c(0.15, 0.4), cutoff = 0.05)
  fem <- fmesher::fm_fem(mesh)
  A <- as(fmesher::fm_basis(mesh, loc = coords), "CsparseMatrix")
  spec <- spatial_spde_custom(C = fem$c0, G = fem$g1, A = A, nu = 1,
                             prior_range = c(0.3, 0.5), prior_sigma = c(0.6, 0.05))
  w <- as.numeric(rnorm(spec$n_mesh, 0, 0.6)); w <- w - mean(w)
  x <- rnorm(n)
  y <- rpois(n, exp(2.0 + 0.5 * x + as.numeric(spec$A %*% w)))
  fit <- fit_spde(y = y, X = cbind(1, x), spatial = spec, family = "poisson")
  fit$nested$range_mean
}
```

fit_st_nested

Fit an additive spatiotemporal GLM by nested Laplace

Description

Fits $y \sim X\beta + u_{\text{spatial}}[s] + v_{\text{temporal}}[t]$ with an areal spatial field (icar / bym2 / car_proper) and a temporal field (rw1 / rw2 / ar1), integrating the spatial precision, temporal precision, and (for ar1) the temporal autocorrelation over a hyperparameter grid via the `cpp_nested_laplace_st_*` kernels. The fixed-effect posterior is the grid-marginalised mixture; the spatial and temporal field posterior means are the grid-weighted latent modes.

Usage

```
fit_st_nested(
  y,
  X,
  spatial_idx,
  adjacency,
  temporal_idx,
  n_times,
  spatial_type = c("icar", "bym2", "car_proper"),
  temporal_type = c("ar1", "rw1", "rw2"),
  family = "binomial",
  n_trials = NULL,
  phi = 1,
  cyclic = FALSE,
  re_idx = NULL,
  n_re_groups = 0L,
  sigma_re = 1,
  control = list()
)
```

Arguments

y	Response vector.
X	Fixed-effects design matrix (nrow(X) == length(y)).
spatial_idx	Integer per-observation spatial-unit index (1-based).
adjacency	Spatial adjacency (a symmetric 0/1 matrix or sparseMatrix).
temporal_idx	Integer per-observation time index (1-based).
n_times	Number of distinct time points.
spatial_type	"icar" (default), "bym2", or "car_proper".
temporal_type	"ar1" (default), "rw1", or "rw2".
family	Response family (see family_names()).
n_trials	Binomial denominators, or NULL (= 1).
phi	Dispersion passed to the family.
cyclic	Logical; wrap the temporal field (seasonal). Default FALSE.
re_idx, n_re_groups, sigma_re	Optional single iid random-intercept term alongside the fields (conditioned on sigma_re); n_re_groups = 0 (default) is no RE term.
control	A list of numerical / grid knobs: n_grid_spatial, n_grid_temporal (default 4 each), n_grid_rho (ar1 only, default 3), tau_lower / tau_upper (precision grid bounds, default 0.25 / 16), rho_lower / rho_upper (ar1 grid, default 0.1 / 0.9), max_iter, tol, n_threads, auto_recenter (default TRUE; FALSE holds the grid exactly as specified – the per-axis policy names tulpa_nested_laplace() takes are refused here with an error, since this driver recentres on the grid's collapsed-edge regime rather than on a per-axis rail). The (tau_lower, tau_upper) span (and, for ar1, (rho_lower, rho_upper)) is a starting axis, not a hard ceiling: when the fitted precision (or, for ar1, autocorrelation) posterior mode rails a boundary node (pareto_k_regime = "collapsed_edge", see below), the driver fits a mode-Hessian via a derivative-free optim() over the collapsed grid and refits a grid re-centred on it (one attempt). A grid knob PINS the axes it shapes, and a pin always wins – but pinning is decided by value, not by presence: a knob set to the engine's own default, or marked with auto_grid(), expresses no preference and leaves its axes free. That is what lets a wrapper package thread its own n_grid-style argument through control without silently disabling the recenter for every fit it makes. Pinning is also per axis: tau_lower / tau_upper hold the two precision axes, n_grid_spatial / n_grid_temporal one each, and n_grid_rho / rho_lower / rho_upper the ar1 autocorrelation axis, so pinning one axis leaves the others free to be recentred. A pinned axis keeps its nodes exactly and is named in outer_grid_pinned_axes; with EVERY axis pinned the recenter declines outright and outer_grid_recenter_declined records which reason applied.

Value

A tulpa_fit (subclass tulpa_nested_laplace) carrying the fixed-effect posterior (draws via the grid mixture), spatial_effects, temporal_effects, log_marginal, weights, and theta_grid

over (tau_spatial, tau_temporal, rho). Also carries `pareto_k_regime` ("spread" / "collapsed_interior" / "collapsed_edge", see `tulpa_nested_laplace_joint()`'s return docs for the definition) and `outer_grid_placement` ("fixed" or "auto_recentered") plus, on a "fixed" placement, `outer_grid_recenter_declined` ("grid_knobs_overridden" / "grid_not_collapsed" / "no_usable_curvature" / "refit_failed" / "sd_ceiling_unresolved" / "sd_floor_unresolved"). A recentred fit also carries `outer_grid_pinned_axes`, the axes whose knobs were pinned and whose nodes were therefore kept, and `outer_grid_recenter_sd_clamp` / `_sd_raw` / `_sd_used` – per moved axis, which mode-SD bound the placement hit, the SD the stencil measured, and the SD the axis was laid from. A bound-decline is PER AXIS here: the axes the mode-find did resolve are still re-placed, and `outer_grid_recenter_sd_declined` names the ones that kept their incoming nodes and on which bound, so a partially re-placed grid is not read as a fully re-placed one. With every free axis declined the pass reports the grid as the fixed one it still is.

See Also

`tulpa()` (front door), `tulpa_nested_laplace()` (single field).

Examples

```
set.seed(1)
n_s <- 16L; n_t <- 8L; N <- 400L
adj <- matrix(0, n_s, n_s)
for (i in 1:(n_s - 1)) adj[i, i + 1] <- adj[i + 1, i] <- 1
s <- sample(n_s, N, TRUE); tt <- sample(n_t, N, TRUE)
us <- as.numeric(scale(cumsum(rnorm(n_s)))); vt <- as.numeric(scale(cumsum(rnorm(n_t))))
x <- rnorm(N)
y <- rbinom(N, 1, plogis(0.2 + 0.5 * x + 0.7 * us[s] + 0.6 * vt[tt]))
fit <- fit_st_nested(y, cbind(1, x), s, adj, tt, n_t, family = "binomial")
```

fixef

Fixed-effect coefficients (lme4-compatible)

Description

The fixed-effect point estimates, equivalent to `coef()` on a `tulpa_fit`. Provided under the `fixef` name for code written against the `lme4` / `nlme` interface: `lme4::fixef(fit)` and `nlme::fixef(fit)` dispatch here too when either package is installed, so a `tulpa_fit` can be dropped into an `lme4`-shaped workflow.

Usage

```
fixef(object, ...)

## S3 method for class 'tulpa_fit'
fixef(object, ...)
```


Arguments

object	A tulpa_fit object.
...	Ignored.

Details

Note the deliberate difference from `lme4::coef.merMod`, which returns per-group sums of the fixed and random effects. On a `tulpa_fit`, `coef()` returns the fixed effects alone and `fixef()` is its synonym; the random effects are `ranef()`.

Value

Named numeric vector of fixed-effect estimates.

See Also

`coef.tulpa_fit()`, `ranef()`

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(80))
df$y <- rpois(80, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson")
fixef(fit)
```

geweke_test

Geweke Convergence Test

Description

Performs Geweke's convergence diagnostic, comparing the mean of the first portion of a chain to the last portion. Useful for single-chain diagnostics.

Usage

```
geweke_test(fit, frac1 = 0.1, frac2 = 0.5, pars = NULL)
```

Arguments

fit	A tulpa_fit object.
frac1	Fraction of chain for first window (default: 0.1).
frac2	Fraction of chain for second window (default: 0.5).
pars	Character vector of parameter names (default: all main params).

Details

The Geweke test computes a z-score comparing the means of early and late portions of a chain. Large z-scores ($|z| > 2$) indicate the chain has not converged.

Value

A data frame with columns: parameter, z_score, p_value.

See Also

`diagnostics()`, `check_diagnostics()`

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))
geweke_test(fit)
```

glance.tulpa_fit

Model-level summary statistics (broom-compatible)

Description

Model-level summary statistics (broom-compatible)

Usage

```
## S3 method for class 'tulpa_fit'
glance(x, ...)
```

Arguments

`x` A tulpa_fit object.

`...` Ignored.

Value

Single-row data frame.

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(100))
df$y <- rpois(100, exp(0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson")
glance(fit)
```

imh_laplace

Independence Metropolis-Hastings with Laplace proposal

Description

Sample from a posterior using independence Metropolis-Hastings with a multivariate-normal proposal centred at the Laplace mode and scaled by the inverse Hessian. For posteriors that are well-approximated by a Gaussian near the mode this is dramatically cheaper than HMC: each iteration is one log-posterior evaluation plus one accept/reject step. Embarrassingly parallel across chains.

Use cases:

- Quick draws when Laplace is "almost right" but you want asymptotically-correct samples.
- Cross-validation, simulation studies, or other repeated-fit workflows where HMC startup cost dominates.
- Sanity check on the Laplace approximation: low IMH acceptance means the posterior is far from Gaussian and Laplace is biased.

Usage

```
imh_laplace(
  log_posterior,
  mode,
  hessian,
  n_iter = 2000L,
  warmup = n_iter%%2L,
  scale = 1,
  init = NULL,
  thin = 1L,
  verbose = FALSE
)
```

Arguments

log_posterior	Function function(theta) -> numeric returning the <i>unnormalized</i> log posterior at a single parameter vector.
mode	Numeric vector of length d: the Laplace mode (i.e., tulpa_laplace(...)\$mode[seq_len(d)] for the fixed-effects block, or any other mode you trust).

<code>hessian</code>	Symmetric positive-definite $d \times d$ matrix: the negative Hessian of <code>log_posterior</code> at mode (or <code>H_beta</code> from <code>tulpa_laplace</code>).
<code>n_iter</code>	Total iterations including warmup (default 2000).
<code>warmup</code>	Warmup iterations to discard (default <code>n_iter / 2</code>).
<code>scale</code>	Optional inflation factor on the proposal covariance (default 1.0). Values slightly > 1 (e.g., 1.5) give heavier-tailed proposals that improve mixing when Laplace underestimates posterior spread.
<code>init</code>	Optional starting parameter vector (default = mode).
<code>thin</code>	Keep every thin-th post-warmup sample (default 1).
<code>verbose</code>	Print acceptance rate at end (default FALSE).

Value

A list with class `tulpa_fit` carrying:

- `draws`: $(n_iter - warmup) / thin \times d$ matrix of draws.
- `means`: posterior means.
- `accept_prob`: per-iteration acceptance indicators.
- `mean_accept`: overall post-warmup acceptance rate.
- `log_prob`: per-draw log posterior values.
- `inference_mode`: "exact".
- `inference_tier`: 1L.
- `backend`: "imh_laplace".

Tier

Tier 1 (Exact). The MH accept/reject step makes the chain asymptotically correct under the standard MH conditions. Tier status does not depend on Laplace's quality – only its quality affects efficiency.

See Also

[`tulpa\_laplace\(\)`](#) for the mode + Hessian, [`bridge\_sampling\(\)`](#) for marginal-likelihood estimation on the resulting draws.

Examples

```
# Toy: Bernoulli logistic with one covariate.
set.seed(1)
n <- 100
x <- rnorm(n)
eta <- 0.3 + 1.2 * x
y <- rbinom(n, 1, plogis(eta))
X <- cbind(1, x)

lap <- tulpa_laplace(y, n_trials = rep(1L, n), X = X,
                    family = "binomial")
```

```
log_post <- function(beta) {
  eta <- as.numeric(X %*% beta)
  sum(y * eta - log1p(exp(eta))) +
  sum(dnorm(beta, 0, 10, log = TRUE))
}

fit <- imh_laplace(log_post, mode = lap$mode[1:2],
                  hessian = lap$H_beta, n_iter = 1000)
fit$mean_accept
colMeans(fit$draws)
```

inference_mode_info	<i>Print inference mode information</i>
---------------------	---

Description

Displays information about the inference modes available in tulpa, including their tiers, guarantees, and appropriate use cases.

Usage

```
inference_mode_info()
```

Value

NULL, invisibly. Called for the side effect of printing the available inference modes, their tiers, guarantees, and use cases to the console.

is_auto_grid	<i>Is an outer-grid setting marked as a default?</i>
--------------	--

Description

Is an outer-grid setting marked as a default?

Usage

```
is_auto_grid(x)
```

Arguments

x Any object.

Value

TRUE when x carries the `auto_grid()` marker.

See Also[auto_grid\(\)](#)**Examples**

```
is_auto_grid(auto_grid(c(0.5, 1, 2)))
is_auto_grid(c(0.5, 1, 2))
```

laplace_diagnostics	<i>Approximation-reliability diagnostics for a deterministic nested-Laplace fit</i>
---------------------	---

Description**[Deprecated]**

Use [diagnostics\(\)](#), which returns this table for any fit whose draws are an i.i.d. approximation sample. The sections below document that table; they remain the reference for its columns and attributes.

Per-parameter reliability diagnostics for a fit whose posterior draws are i.i.d. samples from a deterministic approximation (the nested-Laplace grid-mixture posterior $\sum_k w_k N(\text{mode}_k, V_k)$), where the between-chain Gelman-Rubin Rhat that [diagnostics\(\)](#) reports for a chain fit does not apply. This is the accessor that plays Rhat's role for the deterministic engine: it answers "did the approximation work", not "did the chains mix".

The headline is a Pareto-smoothed importance-sampling (PSIS) reliability diagnostic for the OUTER hyperparameter-grid integration. The nested integrator scores its hyperparameter grid against the exact inner-Laplace marginal posterior with a generalized-Pareto fit to the upper tail of the importance ratios $\log p_{\text{target}}(\theta) - \log q_{\text{proposal}}(\theta)$ (see [tulpa_psis\(\)](#)); the resulting tail-shape `pareto_k` is the "did the outer integration work" number – $\hat{k} < 0.5$ good, $0.5\text{--}0.7$ usable, ≥ 0.7 unreliable (Vehtari et al. 2024; Yao et al. 2018). It is computed at fit time and read back here; a fit that did not run the diagnostic, or whose grid proposal degenerated, reports it as NA and is assessed on the grid quadrature reliability instead.

`pareto_k` scores the outer integration only. A high `pareto_k` on a fit whose grid quadrature is healthy (`ess_grid` well above 1, largest cell weight modest) flags outer-integration (CI-width) calibration in the right-skewed hyperparameter tail and does not by itself invalidate the point estimates, which the grid quadrature governs.

`outer_regime` qualifies what a high `pareto_k` means, and is the reason a bare threshold on `pareto_k` is not a reliability verdict. A sharp hyperparameter posterior collapses the grid onto ~ 1 cell (`ess_grid` near 1); the outer integration has then degenerated to a point evaluation at the modal hyperparameter, so `pareto_k` is scoring how well a Gaussian at that mode stands in for the hyperparameter marginal, not how well a grid integrated it. Where the dominant cell is INTERIOR to the grid the collapse is benign – the grid bracketed the mode, the estimate is empirical Bayes there, and only integrated hyperparameter uncertainty is missing. Where it sits at a grid BOUNDARY the grid may simply be too narrow: `grid_edge_axes / grid_edge_sides` name the axes to widen. On a fit whose `pareto_k` cleared the good band, the outer diagnostic also fits a skew-normal proposal and reports the marginal's estimated skewness as `outer_skew_max`, so an inflated $\hat{k}$ that was purely

the symmetric proposal's mismatch with a skewed variance-component marginal is both corrected and explained. A skew-normal has Gaussian tails, so this can never mask a genuinely heavy-tailed target.

The grid quadrature reliability – the effective sample size $\text{ess_grid} = 1 / \sum(w_k^2)$ of the outer integration weights and the largest single cell weight – is always computed from the stored grid: a grid that collapses onto one cell (ess_grid near 1) integrates no hyperparameter uncertainty, while a spread grid does.

A SEPARATE layer – the inner Gaussian Laplace approximation to the latent-field conditional posterior $\pi(x \mid \theta, y)$, which `pareto_k` does not cover – is scored by `inner_skew`: the leading-order Edgeworth skewness estimate `gamma_3` (Rue, Martino & Chopin 2009 Sec 3.2.3) at the fitted MAP grid cell, computed when `control$diagnose_skew = TRUE` (the default) on the fitting call. Reading a high `pareto_k` alone as "the fit is broken" conflates the two layers: an `occu_cover` batch flagged 42/78 species "unreliable" on outer k -hat alone when their point estimates, governed by the healthy inner layer, were fine – the `reliability` attribute is the combined verdict that names which layer degrades, if either does.

Each parameter row also carries the rank-normalized split-Rhat and bulk / tail effective sample size of the draws (Vehtari et al. 2021). On i.i.d. draws these sit at ~ 1.00 and $\sim n_{\text{draws}}$ by construction; they are reported, clearly as i.i.d.-draw Monte-Carlo diagnostics and not chain mixing, to document that the reported posterior summaries are not Monte-Carlo-limited.

A posterior sample is what those per-parameter rows are computed from, and nothing else here needs one: every reliability quantity above is read off the fit. So a fit that carries no draws – a default single-block nested-Laplace fit, whose posterior is the retained outer-grid mixture rather than a sample – reports the full band with an empty per-parameter body and `n_draws = NA`, and records why in the `param_table_declined` attribute. `tulpa_posterior_draws()` samples that mixture where the rows are wanted. The one case that still returns `NULL` is a fit with neither draws nor any reliability quantity, such as a plain Laplace fit with no outer grid to score.

Usage

```
laplace_diagnostics(fit, pars = NULL)
```

Arguments

<code>fit</code>	A <code>tulpa_fit</code> (or subclass, e.g. a <code>tobs_fit</code>) whose draws are an i.i.d. approximation sample (<code>\$draws_kind == "iid"</code>).
<code>pars</code>	Optional character vector of parameter names to restrict to.

Value

A data frame with one row per parameter – `parameter`, `mean`, `sd`, `ess_bulk`, `ess_tail`, `rhat` – carrying attributes:

`pareto_k` the outer PSIS reliability k -hat (NA if not computed).

`pareto_k_band` "good" / "ok" / "unreliable" / NA.

`pareto_k_declined`, `pareto_k_declined_note` when `pareto_k` is NA, WHY: "not_requested", "not_applicable", "unguessable_axis" (naming the axis – a permanent limitation of that family, so read `ess_grid` instead), "draws_too_few", "grid_too_small", "no_varying_axis",

"degenerate_proposal", or "internal_inconsistency" (an engine bug worth reporting), plus a one-line reading of it.

pareto_k_is_ess importance-sampling ESS on the smoothed weights.

ess_grid, n_grid, rel_ess_grid, max_weight grid quadrature reliability.

outer_regime "spread" / "collapsed_interior" / "collapsed_edge" – whether the outer grid integrated hyperparameter uncertainty at all, and if not whether its dominant cell is interior (empirical Bayes at the mode: point estimates sound, hyperparameter uncertainty not integrated) or against a grid boundary (widen it).

grid_edge_axes, grid_edge_sides for an edge collapse, the axes the dominant cell sits against and on which side.

outer_skew_max largest estimated |skewness| of the hyperparameter marginal, computed only when the k-hat triggered the skew-normal proposal rescue (NA means the Gaussian proposal already fit, not "symmetric and unchecked").

outer_regime_note a one-line reading of a collapsed regime, or absent on a spread grid.

grid_railed_axes outer axes whose OWN marginal is maximal at one of their own endpoints, as axis:side – the span does not contain that axis's posterior mode, so its marginal is a truncated tail at any spacing. Reported whether or not the engine was allowed to, able to, or built to move the axis.

grid_placement, grid_recentred_axes, grid_placement_declined, grid_placement_note whether the outer grid was re-centred, on which axes, and – when it was not – why.

scope the outer diagnostic's scope string.

inner_skew_max the largest |gamma_3| among the scored latent indices (NA if control\$diagnose_skew = FALSE or nothing scored).

inner_skew_band "good" / "ok" / "unreliable" / NA, banded on inner_skew_max by the general skewness-magnitude convention (Bulmer 1979) – not a Rue-Martino-Chopin-specific cutoff.

inner_skew_scored, inner_skew_probed how many of the probed latent indices returned a finite gamma_3 vs how many were probed.

inner_skew_declined, inner_skew_arms_declined, inner_skew_declined_note when nothing was scored, WHY: "coupled_arm" (STRUCTURAL – the coupled arms have neither a per-observation sum nor a cell third-derivative tensor to read, so the outer k-hat is the only reliability number this fit has), "curvature3_unavailable", "no_finite_contribution", "no_probe_indices", "not_requested", "backend_unsupported", "solve_failed", or "not_converged" (the probe re-solve stopped short of a mode, so neither inner score has a point to read); the arms (1-based) a joint fit had no oracle for, which is also set on a PARTIALLY scored fit; and a one-line reading.

inner_pareto_k, inner_pareto_k_band the inner-Laplace importance k-hat over the probed subspace, and its band on the same convention as the outer k-hat. Available wherever a mode was found, including a fit gamma_3 cannot score.

inner_pareto_k_rel_ess, inner_pareto_k_is_ess the smallest realized importance efficiency and effective sample size across the probed indices – how much correcting the inner Gaussian actually needs, which is what makes the scale-free shape above readable.

inner_pareto_k_uniform TRUE when no probed index carried a material correction, i.e. the inner Gaussian reproduces the conditional posterior over the sampled region.

`inner_pareto_k_scored`, `inner_pareto_k_probed` how many probed indices returned a finite k -hat vs how many were probed.

`inner_pareto_k_declined`, `inner_pareto_k_declined_note` when it is NA, WHY, from the same closed vocabulary the outer k -hat uses.

`reliability` the combined whole-fit verdict: "reliable" only when both layers are good; otherwise names which layer is scoped or flags both as unreliable. The inner layer enters through the worse of its two scores, so a fit whose cubic term declined is still assessed.

and a trailing summary attribute (a one-row data frame of the headline numbers) for printing.

Scope

The PSIS `pareto_k` diagnoses the OUTER (hyperparameter) integration: whether the Gaussian-proposal-over-grid approximation of the marginal hyperparameter posterior $p(\theta \mid \text{data})$ can be importance-corrected to the exact inner marginal. This is the dominant approximation in nested Laplace and the one with an exactly evaluable target. A full latent-space PSIS against the exact joint posterior $\pi(x)$ is not computed: the latent prior marginal $p(x) = \int p(x \mid \theta) p(\theta) d\theta$ has no closed form, and for the marginalized-occupancy / cover-hurdle likelihoods the exact joint density is evaluable only inside the C++ kernel, so a stored fit cannot reconstruct it. The grid quadrature reliability is the complementary stored-fit number.

The inner layer carries a SECOND score, `inner_pareto_k`, which needs no likelihood derivative at all and therefore answers where `inner_skew` declines. The inner Gaussian at the fitted hyperparameter is an importance proposal for the exact conditional posterior, and the joint density is the target, so PSIS on that ratio scores the inner approximation directly. It is computed on the same probed indices along the same conditional-mean curve, one dimension per index, since importance sampling degrades with dimension and a k -hat over the whole latent field would report n_x rather than the approximation. A Pareto shape index is scale-free, so it is banded only on indices whose realized importance efficiency shows a correction worth describing; `inner_pareto_k_uniform` records that none did, which is what a well-approximated inner layer looks like.

`inner_skew` diagnoses the INNER (latent-field) Laplace: whether the Gaussian approximation to $\pi(x_i \mid \theta, y)$ is itself a good fit, at each scored latent index i . `gamma_3` is exact for a gaussian-family coefficient (the log-likelihood is exactly quadratic in η) and declines to NA – never a silently-wrong 0 ("perfectly Gaussian") – whenever no per-observation third-derivative oracle is available: a coupled multi-process likelihood (e.g. `tulpaObs`'s `occu_cover`, whose arms combine non-separably through a `CellCouplingSpec`) or a family with no registered third derivative. Only the requested latent indices are scored (every arm's fixed-effects coefficients by default – see `control$skew_idx`), since each index costs one extra linear solve; the full latent field is not scored by default on a large spatial field.

References

- Vehtari, Simpson, Gelman, Yao & Gabry (2024). Pareto smoothed importance sampling. *JMLR* 25(72):1-58.
- Yao, Vehtari, Simpson & Gelman (2018). Yes, but did it work?: Evaluating variational inference. *ICML*, PMLR 80:5581-5590.
- Vehtari, Gelman, Simpson, Carpenter & Burkner (2021). Rank-normalization, folding, and localization: an improved Rhat for assessing convergence of MCMC. *Bayesian Analysis* 16(2):667-718.

Rue, Martino & Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *JRSS-B* 71(2):319-392.

See Also

`diagnostics()` (the front door, which returns this table for i.i.d. fits), `tulpa_psis()`.

Examples

```
set.seed(1)
n <- 200L; x <- rnorm(n)
y <- rbinom(n, 1, plogis(-0.2 + 0.6 * x))
# `mode = "laplace"` returns a mode + covariance and carries no draws; a
# sampled deterministic backend is what this table describes.
fit <- tulpa(y ~ x, data.frame(y = y, x = x), family = "binomial",
             mode = "smc")
diagnostics(fit)
```

latent

Mark an expression as a latent block in a tulpa formula

Description

Wraps a user-defined latent block (currently a `tgmrfrf()` object) so the formula parser can recognise and route it to the inference layer. The call is structural – it is never executed at fit time. The parser evaluates the inner expression in the formula’s environment, removes the `latent(...)` term from the fixed-effects formula, and attaches the resulting object to `parsed$latent_blocks`.

Usage

```
latent(block)
```

Arguments

`block` A `tgmrfrf` (or, in the future, `tgeneric`) object.

Value

Returns `block` invisibly. Outside a formula context the call is a no-op pass-through.

latent_factor	Create a latent factor specification
---------------	--------------------------------------

Description

Define latent factors for capturing unmeasured shared structure between all processes. Factors are observation-level random effects that enter both linear predictors when `shared = TRUE` (default).

Usage

```
latent_factor(
  n_factors = 1L,
  prior = NULL,
  shared = TRUE,
  constraint = c("sum_to_zero", "first_zero"),
  scale = TRUE
)
```

Arguments

<code>n_factors</code>	Integer; number of latent factors. Default is 1. More factors capture more complex unmeasured structure but increase computational cost and risk overfitting.
<code>prior</code>	Prior for factor standard deviations. Default is a PC prior with $P(\sigma > 1) = 0.01$, which shrinks toward simpler models.
<code>shared</code>	Logical; if <code>TRUE</code> (default), latent factors enter both all process linear predictors identically. If <code>FALSE</code> , factors only affect the first process.
<code>constraint</code>	Identifiability constraint for factors: "sum_to_zero" (default): Factors sum to zero across observations "first_zero": First observation's factor is fixed to zero
<code>scale</code>	Logical; if <code>TRUE</code> (default), factor loadings are standardized to have unit variance before applying sigma.

Details

Why Use Latent Factors?:

When modeling multiple processes, they often share unmeasured confounders. For example, in relative abundance data, both the focal species count and total count might be affected by:

- Observer skill (unmeasured)
- Local microhabitat conditions (unmeasured)
- Weather on sampling day (unmeasured)

Without accounting for these shared drivers, estimates can be biased. Latent factors capture this shared structure without requiring the confounders to be measured.

Mathematical Model:

For observation i with K latent factors, on each of two model arms (processes 1 and 2):

$$\eta_i^{(1)} = X_i^{(1)}\beta^{(1)} + \sum_{k=1}^K f_{ik}\sigma_k + \dots$$

$$\eta_i^{(2)} = X_i^{(2)}\beta^{(2)} + \sum_{k=1}^K f_{ik}\sigma_k + \dots$$

where:

- $f_{ik} \sim N(0, 1)$ are standardized factor scores
- σ_k are factor standard deviations with PC prior
- Identifiability: $\sum_i f_{ik} = 0$ for each k

Because factors enter both linear predictors identically (when shared), they cancel in derived quantities (e.g., ratios, differences):

$$\eta_i^{(1)} - \eta_i^{(2)}$$

This means factors capture shared effects that would otherwise bias derived quantities.

Choosing n_factors:

- Start with `n_factors = 1` for simple unmeasured confounding
- Use `n_factors = 2-3` if you suspect multiple independent confounders
- More than 3 factors is rarely needed and risks overfitting
- The PC prior provides regularization, shrinking unneeded factors toward zero

Relationship to Random Effects:

Latent factors differ from random effects in several ways:

- Random effects are grouped (e.g., site-level), factors are observation-level
- Random effects require grouping structure, factors don't
- Factors capture residual correlation not explained by observed predictors

You can use both together: random effects for known grouping, factors for residual unmeasured confounding.

Value

A `tulpa_latent` object consumed by ratio / multi-arm model packages built on tulpa (e.g. `tulpaRatio`); not read by the single-response `tulpa()` front door (use `latent(tgmrf(...))` for a single-response latent Gaussian block).

See Also

`prior_pc()` for prior specification; `latent()` / `tgmrf()` for a single-response in-formula latent Gaussian block

Examples

```
# Basic latent factor (single shared factor)
latent_factor()

# Two latent factors
latent_factor(n_factors = 2)

# Custom prior (more regularization)
latent_factor(n_factors = 1, prior = prior_pc(U = 0.5, alpha = 0.01))

# Numerator-only factor (not shared)
latent_factor(n_factors = 1, shared = FALSE)

# The spec is consumed by a ratio / multi-arm model package (tulpaRatio owns
# the two-arm `species | total ~ ...` formula and the negbin/negbin ratio
# family); it is that package's fitter, not the single-response tulpa() front
# door, that reads the `latent_factor()` object.
```

latent_factors	<i>Extract latent factor posteriors from fit</i>
----------------	--

Description

Extract latent factor posteriors from fit

Usage

```
latent_factors(fit, summary = TRUE, probs = c(0.025, 0.5, 0.975))
```

Arguments

fit	A tulpa_fit object
summary	Logical; if TRUE, return summary statistics. If FALSE, return full posterior draws.
probs	Quantiles for summary. Default is c(0.025, 0.5, 0.975).

Value

If summary = TRUE, a data frame with columns for observation, factor, and summary statistics. If summary = FALSE, a matrix of posterior draws.

Examples

```
## Not run:
# `fit` is a ratio / multi-arm model fitted with latent factors by a consumer
# package (tulpaRatio owns the two-arm formula and the negbin/negbin ratio
# family and reads the latent_factor() spec):
```

```
# Get summary
factors <- latent_factors(fit)
head(factors)

# Get full posterior draws
factor_draws <- latent_factors(fit, summary = FALSE)

## End(Not run)
```

logLik.tulpa_fit	<i>Log-likelihood at the posterior mean</i>
------------------	---

Description

Log-likelihood at the posterior mean

Usage

```
## S3 method for class 'tulpa_fit'
logLik(object, ...)
```

Arguments

object	A tulpa_fit object.
...	Ignored.

Value

A logLik object.

mala	<i>Metropolis-Adjusted Langevin Algorithm (MALA)</i>
------	--

Description

Sample from a posterior using MALA: a Langevin proposal driven by the gradient of the log posterior, corrected by a Metropolis- Hastings accept/reject step. Each iteration is one log-posterior + one gradient evaluation. The natural stepping stone between random-walk MH and HMC: cheaper per iteration than HMC (no leapfrog integration), better-mixing than RWMH because the drift term moves toward higher density.

Step size epsilon is adapted via dual averaging during warmup to target an acceptance rate of 0.574 (Roberts & Rosenthal 1998 optimal for high-dimensional Gaussians).

Usage

```
mala(
  log_posterior,
  grad_log_posterior,
  init,
  n_iter = 2000L,
  warmup = n_iter%%2L,
  epsilon = 0.1,
  target_accept = 0.574,
  mass_diag = NULL,
  thin = 1L,
  verbose = FALSE
)
```

Arguments

log_posterior	Function function(theta) -> numeric returning the <i>unnormalized</i> log posterior.
grad_log_posterior	Function function(theta) -> numeric vector returning the gradient at theta.
init	Numeric vector: initial state (must give finite log_posterior).
n_iter	Total iterations including warmup (default 2000).
warmup	Warmup iterations (step-size adaptation + discarded; default n_iter / 2).
epsilon	Initial step size (default 0.1). Adapted during warmup.
target_accept	Target acceptance during warmup adaptation (default 0.574, the Roberts & Rosenthal 1998 optimum).
mass_diag	Optional preconditioner: a length-d vector of per-dimension variances , used as the diagonal inverse-mass M^{-1} . The proposal is $N(\theta + (\epsilon^2/2) * M^{-1} * \text{grad}, \epsilon^2 * M^{-1})$, so entry j scales the proposal variance along dimension j and the noise standard deviation is $\epsilon * \sqrt{\text{mass_diag}[j]}$. Default $\text{rep}(1, d)$. For posteriors with very different scales across dimensions, set this to (an estimate of) the posterior variances, i.e. the squared posterior SDs.
thin	Keep every thin-th post-warmup sample (default 1).
verbose	Print acceptance + step-size summary at end (default FALSE).

Value

A list with class `tulpa_fit` carrying:

- `draws`: post-warmup draws.
- `means`, `n_params`, `n_samples`, `log_prob`.
- `accept_prob`: per-iteration accepted indicators (post-warmup).
- `mean_accept`: post-warmup acceptance rate.
- `epsilon`: final adapted step size.

- inference_mode: "exact".
- inference_tier: 1L.
- backend: "mala".

Tier

Tier 1 (Exact). The MH step makes the chain asymptotically correct. Mixing depends on whether the gradient gives useful local geometry – poor for posteriors with very different scales across dimensions (use a preconditioner or HMC instead).

References

- Roberts, G. O., & Tweedie, R. L. (1996). Exponential convergence of Langevin distributions and their discrete approximations. *Bernoulli*, 2(4), 341-363.
- Roberts, G. O., & Rosenthal, J. S. (1998). Optimal scaling of discrete approximations to Langevin diffusions. *JRSS B*, 60(1), 255-268.

Examples

```
log_post <- function(t) -0.5 * sum((t - c(1, 2))^2)
grad <- function(t) -(t - c(1, 2))
fit <- mala(log_post, grad, init = c(0, 0), n_iter = 1000)
colMeans(fit$draws) # near c(1, 2)
fit$mean_accept     # should adapt toward 0.574
```

mcmc_draws

MCMC chain draws from a fit

Description

Returns a fit's posterior draws only when they form a genuine MCMC chain (`$draws_kind == "chain"`, or an untagged legacy fit); for an i.i.d. / approximation fit (nested Laplace, VI, SMC, ...) it returns NULL, because chain diagnostics do not apply. This is the accessor `diagnostics()` gates on. For the provenance-agnostic posterior sample used by summaries, see `posterior_sample()`.

Usage

```
mcmc_draws(fit)
```

Arguments

`fit` A `tulpa_fit` (or subclass) carrying posterior `$draws`.

Value

The chain draws matrix/array, or NULL for a non-chain fit.

See Also

[posterior_sample\(\)](#), [diagnostics\(\)](#)

model_average	<i>Model-averaged predictions</i>
---------------	-----------------------------------

Description

Combine fitted values from several models using native model weights computed from the point-wise PSIS-LOO (or WAIC) elpd via [tulpa_psis\(\)](#) – no loo package dependency. "loo" / "waic" give stacking weights (the simplex-optimal predictive combination); "pbma" / "pbma+" give pseudo-BMA(+) weights. Every model must carry an [n_draws x n_obs] pointwise log-likelihood (fit\$draws\$log_lik) over the same observations.

Usage

```
model_average(
  ...,
  weights = c("loo", "waic", "pbma", "pbma+"),
  fitted_fn = fitted
)
```

Arguments

...	Named tulpa_fit objects fitted to the same observations.
weights	"loo" (stacking, default), "waic", "pbma", or "pbma+".
fitted_fn	Function extracting a length-n_obs fitted vector from a fit (default fitted()).

Value

A list with averaged (the weighted fitted vector), weights (the named model weights), and comparison (the [compare_models\(\)](#) table).

References

Yao, Vehtari, Simpson & Gelman (2018). Using stacking to average Bayesian predictive distributions. *Bayesian Analysis* 13(3):917-1007.

See Also

[compare_models\(\)](#).

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(120))
df$y <- rpois(120, exp(0.4 + 0.5 * df$x))
f1 <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, seed = 1L))
f2 <- tulpa(y ~ 1, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, seed = 1L))
ma <- model_average(full = f1, null = f2, weights = "waic")
ma$weights
```

moran_i

Moran's I test for spatial autocorrelation in residuals

Description

Tests whether residuals exhibit spatial structure after model fitting. Supports inverse-distance and k-nearest-neighbour weight matrices. No external dependencies (uses normal approximation for inference).

Usage

```
moran_i(
  object,
  coords,
  weights = c("inverse", "knn"),
  k = 10L,
  resid_type = "pearson",
  alternative = c("two.sided", "greater", "less")
)
```

Arguments

object	A fitted model, or a numeric vector of residuals
coords	N x 2 coordinate matrix (required)
weights	Weight scheme: "inverse" or "knn"
k	Number of neighbours for knn (default 10)
resid_type	Residual type if extracting from model (default "pearson")
alternative	"two.sided", "greater", or "less"

Value

An htest object with Moran's I, expected I, and p-value

Examples

```
set.seed(1)
coords <- cbind(runif(50), runif(50))
resid <- rnorm(50)
moran_i(resid, coords)
```

nobs.tulpa_fit	<i>Number of observations in a tulpa fit</i>
----------------	--

Description

Number of observations in a tulpa fit

Usage

```
## S3 method for class 'tulpa_fit'
nobs(object, ...)
```

Arguments

object	A tulpa_fit object.
...	Ignored.

Value

Integer observation count.

node_index	<i>Map cell identifiers to graph node indices</i>
------------	---

Description

Translate a vector of original cell identifiers into the 1-based node indices of a tulpa_adjacency graph, by key (not by row order). Use it to add the node-index column the model's spatial grouping bar needs to the observation data, which typically has many rows per cell and a different row order than the graph.

Usage

```
node_index(graph, ids)
```

Arguments

graph	A tulpa_adjacency object from adjacency() .
ids	A vector of cell identifiers to look up (matched against graph\$ids).

Value

An integer vector the same length as `ids`, giving each one's node index in graph (NA for identifiers absent from the graph).

See Also

[adjacency\(\)](#).

Examples

```
grid <- expand.grid(x = 1:3, y = 1:3)
grid$cell <- paste0("c", seq_len(nrow(grid)))
g <- adjacency(grid, id = "cell")

obs <- data.frame(cell = c("c5", "c1", "c9"))
obs$cell_idx <- node_index(g, obs$cell)
obs
```

n_divergent

Number of divergent transitions

Description

Counts divergent transitions recorded by an HMC/NUTS fit, reading whichever field the backend populated (`$diagnostics$n_divergent`, `$diagnostics$divergent_idx`, `$diagnostics$divergent`, or the top-level `$n_divergent / $divergent`).

Usage

```
n_divergent(fit)
```

Arguments

`fit` A `tulpa_fit` object.

Value

Integer count of divergent transitions (0 if none are recorded).

See Also

[plot_divergences\(\)](#), [check_diagnostics\(\)](#)

pathfinder

Pathfinder: variational warm-start via L-BFGS + ELBO scoring

Description

Single-path Pathfinder (Zhang, Carpenter, Gelman, Vehtari 2022): run L-BFGS toward the posterior mode, fit a Gaussian at the optimum using the inverse-Hessian estimate, and report draws plus the ELBO. Cheap, derivative-only, embarrassingly parallel – meant as an HMC warm-start, an initialiser for `imh_laplace()`, or a quick sanity check on the Laplace approximation.

This implementation is **single-path only**. The full multi-path Pathfinder (K parallel L-BFGS runs + mixture proposal + Pareto- smoothed importance reweighting) is a follow-on. The single-path version is what most users want as a Laplace-equivalent diagnostic.

Usage

```
pathfinder(
  log_posterior,
  init,
  grad_log_posterior = NULL,
  n_draws = 1000L,
  max_iter = 100L,
  tol = 1e-06,
  verbose = FALSE
)
```

Arguments

<code>log_posterior</code>	Function <code>function(theta) -> numeric</code> returning the <i>unnormalized</i> log posterior at <code>theta</code> .
<code>init</code>	Numeric vector: initial point for L-BFGS. Should be in the support of the posterior (finite <code>log_posterior</code>).
<code>grad_log_posterior</code>	Optional function returning the gradient of <code>log_posterior</code> at <code>theta</code> . If <code>NULL</code> , gradients are computed numerically via <code>stats::optim</code> 's built-in finite differences.
<code>n_draws</code>	Number of draws from the fitted Gaussian (default 1000).
<code>max_iter</code>	L-BFGS iteration cap (default 100).
<code>tol</code>	Gradient-norm tolerance for L-BFGS convergence (default 1e-6).
<code>verbose</code>	Print L-BFGS / ELBO summary at end (default <code>FALSE</code>).

Value

A list with class `tulpa_fit` carrying:

- `draws`: `n_draws` × `d` matrix of Gaussian draws at the mode.
- `means`: posterior means (= mode for a Gaussian fit).

- mode: the L-BFGS mode.
- cov: the proposal covariance (solve(-hessian)).
- elbo: Monte-Carlo estimate of $E_q[\log p - \log q]$.
- n_iter: L-BFGS iterations.
- converged: logical.
- inference_mode: "structured".
- inference_tier: 2L.
- backend: "pathfinder".

Tier

Tier 2 (Structured). The output is a Gaussian approximation, not samples from the exact posterior – same epistemic class as `tulpa_laplace()`. Pair with `imh_laplace()` for an exact-tier upgrade.

References

Zhang, L., Carpenter, B., Gelman, A., & Vehtari, A. (2022). Pathfinder: parallel quasi-Newton variational inference. *Journal of Machine Learning Research*, 23(306), 1-49.

See Also

`imh_laplace()` for an exact-tier MH using the Pathfinder Gaussian as proposal; `bridge_sampling()` for marginal-likelihood estimation on the resulting draws.

Examples

```
# Toy: 2-D conjugate normal.
y <- c(0.5, -0.7)
log_post <- function(t) {
  sum(dnorm(y, t, 1, log = TRUE)) +
  sum(dnorm(t, 0, sqrt(10), log = TRUE))
}
pf <- pathfinder(log_post, init = c(0, 0), n_draws = 2000)
pf$mode      # near c(0.45, -0.64)
pf$elbo
```

pit_residuals

PIT (Probability Integral Transform) residuals

Description

For each observation, computes the quantile of the observed value within the posterior predictive distribution. If the model is correct, PIT residuals follow Uniform(0, 1).

Usage

```
pit_residuals(object, ...)

## Default S3 method:
pit_residuals(object, observed = NULL, nsim = 250L, seed = 123L, ...)
```

Arguments

object	A fitted model with a simulate() method, or a matrix of simulated values (n_obs x nsim)
...	Passed to methods.
observed	Observed response vector (required if object is a matrix)
nsim	Number of simulations (default 250)
seed	Random seed (default 123)

Details

For integer-valued responses, a randomisation step avoids discrete artefacts: the residual is drawn uniformly between $P(\text{sim} < \text{obs})$ and $P(\text{sim} \leq \text{obs})$.

Value

Numeric vector of length n_obs with values in $[0, 1]$

plot.tulpa_fit	<i>Plot fixed-effect posteriors</i>
----------------	-------------------------------------

Description

Plot fixed-effect posteriors

Usage

```
## S3 method for class 'tulpa_fit'
plot(x, type = c("density", "trace", "pairs", "smooth"), term = NULL, ...)
```

Arguments

x	A tulpa_fit object.
type	One of "density", "trace", "pairs", "smooth". The Laplace tier has no draws, so it always shows the Gaussian densities of the fixed effects. "smooth" draws the fitted curve of each $s(\dots)$ term and requires a fit carrying one.
term	For type = "smooth", which smoother to draw: index or covariate name. NULL (default) draws every one. Ignored by the other types.
...	Passed to plotting functions.

Value

The input `x`, returned invisibly. Called for the side effect of producing base-graphics plots of the fixed-effect posteriors.

```
plot.tulpa_prior_predict
```

Plot method for tulpa_prior_predict

Description

Density overlay of prior predictive draws. Requires bayesplot; falls back to base graphics `matplot` of a subset of draws otherwise.

Usage

```
## S3 method for class 'tulpa_prior_predict'
plot(x, process = 1L, max_draws = 50L, ...)
```

Arguments

<code>x</code>	A <code>tulpa_prior_predict</code> object
<code>process</code>	Process index or name (multi-process families)
<code>max_draws</code>	Maximum draws to overlay. Default 50.
<code>...</code>	Passed through.

Value

A `ggplot` object (via `bayesplot`) when `bayesplot` is installed; otherwise `NULL` invisibly, after drawing a base-graphics overlay. Called for the density overlay of the prior predictive draws.

```
plot.tulpa_st_summary
```

Plot method for spatiotemporal effects

Description

Plot method for spatiotemporal effects

Usage

```
## S3 method for class 'tulpa_st_summary'
plot(x, type = "heatmap", ...)
```


Arguments

x	Spatiotemporal effects object
type	Plot type: "heatmap" (default), "time_series", or "spatial_map"
...	Additional arguments passed to plotting functions

Value

A ggplot object when ggplot2 is installed; otherwise NULL invisibly, after drawing a base-graphics plot. Called for the side effect of visualizing the spatiotemporal interaction effects.

plot.tulpa_svc_posterior

Plot method for tulpa_svc_posterior

Description

Plot method for tulpa_svc_posterior

Usage

```
## S3 method for class 'tulpa_svc_posterior'
plot(x, term = 1, type = "mean", ...)
```

Arguments

x	A tulpa_svc_posterior object
term	Which term to plot (name or index). Default: first term.
type	Plot type: "mean" (default), "sd", or quantile (e.g., "q50")
...	Additional arguments passed to plotting functions

Value

A ggplot object when ggplot2 is installed; otherwise NULL invisibly, after drawing a base-graphics map. Called for the side effect of mapping the selected spatially-varying coefficient.

```
plot.tulpa_temporal_posterior
```

Plot method for tulpa_temporal_posterior

Description

Plot method for tulpa_temporal_posterior

Usage

```
## S3 method for class 'tulpa_temporal_posterior'
plot(x, component = NULL, type = "ribbon", ...)
```

Arguments

x	A tulpa_temporal_posterior object
component	Which component to plot (for multi-scale). Default: first.
type	Plot type: "ribbon" (default) or "line"
...	Additional arguments passed to plotting functions

Value

A ggplot object when ggplot2 is installed; otherwise NULL invisibly, after drawing a base-graphics plot. Called for the side effect of plotting the temporal-effect posterior.

```
plot.tulpa_tvc_posterior
```

Plot method for tulpa_tvc_posterior

Description

Plot method for tulpa_tvc_posterior

Usage

```
## S3 method for class 'tulpa_tvc_posterior'
plot(x, term = 1, type = "ribbon", ...)
```

Arguments

x	A tulpa_tvc_posterior object
term	Which term to plot (name or index). Default: first term.
type	Plot type: "ribbon" (default) or "line"
...	Additional arguments passed to plotting functions

Value

A ggplot object when ggplot2 is installed; otherwise NULL invisibly, after drawing a base-graphics plot. Called for the side effect of plotting the selected temporally-varying coefficient.

plot_acf	<i>Plot Autocorrelation Functions</i>
----------	---------------------------------------

Description

Creates autocorrelation function (ACF) plots for selected parameters. High autocorrelation indicates slow mixing and low effective sample size.

Usage

```
plot_acf(fit, pars = NULL, lags = 25, n_pars = 6)
```

Arguments

fit	A tulpa_fit object.
pars	Character vector of parameter names. If NULL, selects worst-mixing parameters based on ESS.
lags	Maximum number of lags to compute (default: 25).
n_pars	Maximum number of parameters to plot (default: 6).

Details

Ideal ACF plots show rapid decay to zero. Slow decay indicates high autocorrelation, which reduces effective sample size and may indicate poor mixing.

Value

A ggplot object (if ggplot2 available) or base R plot (invisible).

See Also

[plot_ess\(\)](#), [diagnostics\(\)](#)

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))

plot_acf(fit)
plot_acf(fit, lags = 10)
```

plot_divergences	<i>Plot Divergent Transitions</i>
------------------	-----------------------------------

Description

Creates visualizations to investigate divergent transitions. Parallel coordinates and scatter plots highlight where in parameter space divergences occur.

Usage

```
plot_divergences(fit, pars = NULL, type = c("parcoord", "scatter"))
```

Arguments

fit	A tulpa_fit object (HMC backend).
pars	Character vector of parameter names. If NULL, uses variance parameters.
type	Plot type: "parcoord" (parallel coordinates) or "scatter".

Details

Divergent transitions indicate regions of high posterior curvature that the sampler cannot efficiently explore. Common causes:

- Very narrow funnels (hierarchical models)
- Strong correlations
- Multi-modality

Value

A ggplot object or base R plot (invisible).

See Also

[plot_pairs\(\)](#), [n_divergent\(\)](#)

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))

plot_divergences(fit)
plot_divergences(fit, type = "scatter")
```

plot_energy	<i>Plot Energy Diagnostic (E-BFMI)</i>
-------------	--

Description

Creates overlaid histograms of marginal energy and energy transition, along with the E-BFMI statistic. Low E-BFMI indicates poor exploration of the posterior.

Usage

```
plot_energy(fit)
```

Arguments

`fit` A `tulpa_fit` object (HMC backend).

Details

E-BFMI (Energy Bayesian Fraction of Missing Information) compares the distribution of energy levels to energy transitions. Values below 0.3 indicate the sampler may not be exploring the full posterior.

Value

A ggplot object (if ggplot2 available) or base R plot.

See Also

[diagnostic_summary\(\)](#), [check_diagnostics\(\)](#)

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))
plot_energy(fit)
```

plot_ess

*Plot Effective Sample Size Diagnostic***Description**

Creates a visual display of effective sample size (ESS) for all parameters, expressed as a ratio of ESS to total samples. Low ESS indicates high autocorrelation.

Usage

```
plot_ess(fit, type = c("bulk", "tail"), threshold = 400, pars = NULL)
```

Arguments

fit	A tulpa_fit object.
type	Type of ESS: "bulk" (default) or "tail".
threshold	Minimum acceptable ESS (default: 400).
pars	Character vector of parameter names to include.

Details

ESS/iter ratio interpretation:

- Green: ESS $\geq$ threshold
- Yellow: threshold/2 $\leq$ ESS < threshold
- Red: ESS < threshold/2

Value

A ggplot object (if ggplot2 available) or base R plot (invisible).

See Also

[plot_rhat\(\)](#), [diagnostic_summary\(\)](#), [diagnostics\(\)](#)

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))

plot_ess(fit)
plot_ess(fit, type = "tail")
```

plot_map

*Plot spatial predictions as a map***Description**

Create publication-ready maps from a tulpa spatial fit: the fitted response surface or the prediction uncertainty (credible-interval width), on the response scale.

Usage

```
plot_map(
  x,
  coords = NULL,
  what = c("fitted", "uncertainty"),
  summary = c("median", "mean", "q2.5", "q97.5", "sd"),
  newdata = NULL,
  title = NULL,
  palette = "viridis",
  points = FALSE,
  point_color = "grey30",
  point_size = 0.5,
  na_color = "transparent",
  crs = NULL,
  legend_title = NULL,
  ...
)
```

Arguments

x	A tulpa_fit object with spatial structure, or a data frame containing predictions with coordinate columns.
coords	A data frame or matrix with spatial coordinates (columns named 'x'/'y', 'X'/'Y', 'lon'/'lat', 'longitude'/'latitude', or 'Easting'/'Northing'). Required if x is a data frame.
what	What to plot: "fitted" (default, the response-scale point prediction) or "uncertainty" (the 95% credible-interval width).
summary	Which summary statistic for what = "fitted": "median" (default) / "mean" (both the point prediction), "q2.5" / "q97.5" (the credible bounds), or "sd" (the link-scale standard error).
newdata	Optional data frame with prediction locations and covariates. If NULL and x is a tulpa_fit, uses fitted values at observed locations.
title	Plot title. If NULL, auto-generated based on what.
palette	Color palette: "viridis" (default), "magma", "plasma", "inferno", "cividis", "mako", "rocket", or a custom vector of colors.
points	Logical; if TRUE, overlay observation points. Default FALSE.

<code>point_color</code>	Color for observation points. Default "grey30".
<code>point_size</code>	Size for observation points. Default 0.5.
<code>na_color</code>	Color for NA values. Default "transparent".
<code>crs</code>	Coordinate reference system (proj4 string or EPSG code). If NULL, uses planar coordinates.
<code>legend_title</code>	Title for the color legend. If NULL, auto-generated.
<code>...</code>	Additional arguments passed to ggplot2 theme functions.

Details

This function provides a streamlined workflow for visualizing spatial predictions from tulpa models. It handles:

- Extracting predictions from `tulpa_fit` objects
- Converting to appropriate spatial format (stars/sf)
- Creating publication-quality maps with sensible defaults
- Uncertainty visualization via credible interval width

For custom maps or more control, extract predictions using `predict()` and use ggplot2 directly with `geom_stars()` or `geom_sf()`.

Value

A ggplot2 object that can be further customized.

Required packages

This function requires ggplot2. For raster-style maps, stars and sf are also needed. Install with:

```
install.packages(c("ggplot2", "stars", "sf"))
```

See Also

`predict.tulpa_fit()` for predictions at new locations

Examples

```
if (requireNamespace("ggplot2", quietly = TRUE)) {
  set.seed(123)
  n_sites <- 20
  df <- data.frame(
    y = rbinom(n_sites, 20, 0.4),
    elevation = rnorm(n_sites),
    site = factor(seq_len(n_sites)),
    lon = runif(n_sites),
    lat = runif(n_sites)
  )
  adj <- matrix(0, n_sites, n_sites)
  for (i in 1:(n_sites - 1)) adj[i, i + 1] <- adj[i + 1, i] <- 1
}
```



```

fit <- tulpa(
  y ~ elevation + spatial(site),
  data = df,
  family = "binomial",
  n_trials = rep(20L, n_sites),
  spatial = spatial_car(adj, group_var = "site"),
  mode = "laplace"
)
# Areal (CAR/ICAR) fits carry no point coordinates, so pass `coords`:
cc <- df[, c("lon", "lat")]
plot_map(fit, coords = cc)           # fitted response surface
plot_map(fit, what = "uncertainty", coords = cc)
plot_map_panel(fit, coords = cc)    # both side by side
}

```

plot_map_panel	<i>Plot multiple maps in a grid</i>
----------------	-------------------------------------

Description

Create a multi-panel figure with the fitted-value map and the prediction-uncertainty map side by side.

Usage

```
plot_map_panel(x, newdata = NULL, ncol = 2, ...)
```

Arguments

<code>x</code>	A <code>tulpa_fit</code> object with spatial structure.
<code>newdata</code>	Optional data frame with prediction locations.
<code>ncol</code>	Number of columns in the grid. Default 2.
<code>...</code>	Additional arguments passed to <code>plot_map()</code> .

Value

A patchwork object (if patchwork is installed) or a list of ggplots.

Examples

```

if (requireNamespace("ggplot2", quietly = TRUE)) {
  set.seed(123)
  n_sites <- 20
  df <- data.frame(
    y = rbinom(n_sites, 20, 0.4),
    elevation = rnorm(n_sites),

```

```

    site = factor(seq_len(n_sites)),
    lon = runif(n_sites),
    lat = runif(n_sites)
  )
  adj <- matrix(0, n_sites, n_sites)
  for (i in 1:(n_sites - 1)) adj[i, i + 1] <- adj[i + 1, i] <- 1
  fit <- tulpa(
    y ~ elevation + spatial(site),
    data = df,
    family = "binomial",
    n_trials = rep(20L, n_sites),
    spatial = spatial_car(adj, group_var = "site"),
    mode = "laplace"
  )
  cc <- df[, c("lon", "lat")]
  plot_map_panel(fit, coords = cc)
  plot_map_panel(fit, coords = cc, ncol = 1)
}

```

plot_pairs

Plot Bivariate Parameter Posteriors (Pairs Plot)

Description

Creates a pairs plot showing bivariate relationships between parameters. Divergent transitions (if present) are highlighted to help identify problematic posterior regions.

Usage

```

plot_pairs(
  fit,
  pars = NULL,
  highlight_divergent = TRUE,
  n_pars = 5,
  alpha = 0.3
)

```

Arguments

fit	A tulpa_fit object.
pars	Character vector of parameter names. If NULL, selects main variance parameters.
highlight_divergent	Logical; highlight divergent transitions in red (default: TRUE).
n_pars	Maximum number of parameters (default: 5).
alpha	Point transparency (default: 0.3).

Details

Pairs plots help identify:

- Strong correlations between parameters (potential non-identifiability)
- Multimodality
- Regions where divergences cluster (indicating problematic geometry)

Value

A ggplot object (if ggplot2/GGally available) or base R plot.

See Also

`plot_divergences()`, `diagnostics()`

Examples

```
set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))

plot_pairs(fit)
plot_pairs(fit, n_pars = 2)
```

plot_rhat

Plot Rhat Convergence Diagnostic

Description

Creates a visual display of Rhat values for all parameters, with color-coding to highlight convergence issues. Rhat values > 1.01 indicate potential convergence problems.

Usage

```
plot_rhat(fit, threshold = 1.01, pars = NULL)
```

Arguments

<code>fit</code>	A <code>tulpa_fit</code> object.
<code>threshold</code>	Rhat threshold for warnings (default: 1.01).
<code>pars</code>	Character vector of parameter names to include. If <code>NULL</code> (default), includes all main parameters (excludes high-dimensional RE/spatial).

Details

Color coding:

- Green: $R_{\text{hat}} < 1.01$ (converged)
- Yellow: $1.01 \leq R_{\text{hat}} < 1.05$ (borderline)
- Red: $R_{\text{hat}} \geq 1.05$ (not converged)

Value

A ggplot object (if ggplot2 available) or base R plot (invisible).

See Also

`plot_ess()`, `diagnostic_summary()`, `diagnostics()`

Examples

```
# Diagnostic plots require a fitted tulpa model
# See tulpa() examples for fitting models

set.seed(123)
df <- data.frame(x = rnorm(60))
df$y <- rpois(60, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson", mode = "hmc",
            control = list(n_iter = 500L, warmup = 250L, n_chains = 2L,
                          seed = 1L))

plot_rhat(fit)
```

posterior_predict	<i>Posterior predictive replicates</i>
-------------------	--

Description

Draw replicated responses from the posterior predictive distribution: the linear predictor is rebuilt per posterior draw (fixed effects, formula random effects, offset, and a posterior-mean SPDE field when present) and pushed through the family's sampling distribution.

Fits carrying posterior draws use them directly (fixed and random effects jointly per draw). The Laplace tier samples the fixed effects from the Gaussian approximation $N(\text{coef}(\text{fit}), \text{vcov}(\text{fit}))$ and holds the random effects at their posterior mode, so its replicates understate the RE posterior uncertainty. At newdata the prediction is population level (random effects at zero), matching `predict.tulpa_fit()`.

Usage

```
posterior_predict(object, ...)

## S3 method for class 'tulpa_fit'
posterior_predict(
  object,
  newdata = NULL,
  ndraws = NULL,
  n_trials = NULL,
  seed = NULL,
  ...
)
```

Arguments

<code>object</code>	A <code>tulpa_fit</code> object from <code>tulpa()</code> .
<code>...</code>	Passed to methods.
<code>newdata</code>	Optional data frame of covariates to predict at. Population level (fixed effects only); <code>NULL</code> (default) replicates at the training data with random effects and off-set included.
<code>ndraws</code>	Number of posterior draws to use. Defaults to all stored draws, or 400 on the draw-free Laplace tier.
<code>n_trials</code>	Binomial / beta-binomial trial counts for the replicates. Defaults to the training trials when <code>newdata</code> is <code>NULL</code> , else 1.
<code>seed</code>	Optional integer seed (RNG state is restored on exit).

Value

A `ndraws` x `n_obs` numeric matrix of replicated responses.

See Also

`pp_check()`, which uses these replicates; `simulate.tulpa_fit()`.

Examples

```
set.seed(1)
d <- data.frame(y = rpois(100, 4), x = rnorm(100))
fit <- tulpa(y ~ x, data = d, family = "poisson", mode = "laplace")
yrep <- posterior_predict(fit, ndraws = 100)
dim(yrep) # 100 x 100
```

posterior_sample	<i>Posterior parameter sample from a fit</i>
------------------	--

Description

Returns a fit's posterior draws for summary purposes (quantiles, derived quantities, density plots), regardless of how they were produced – an MCMC chain, a nested-Laplace node mixture, or a variational sample all answer here. For the chain-only view used by convergence diagnostics, see [mcmc_draws\(\)](#).

Usage

```
posterior_sample(fit)
```

Arguments

fit	A <code>tulpa_fit</code> (or subclass) carrying posterior <code>\$draws</code> .
-----	--

Details

A fit that carries no draws returns `NULL` with a message naming its backend, the posterior representation it carries instead, and the accessor that turns that representation into draws where one exists – an absent draws matrix is a property of the backend, not a failure of the accessor, and saying which is the difference between a diagnosable answer and a bare `NULL`.

Value

The posterior draws matrix/array, or `NULL` if the fit carries none.

See Also

[mcmc_draws\(\)](#), [tulpa_posterior_draws\(\)](#), [diagnostics\(\)](#)

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(80))
df$y <- rpois(80, exp(0.5 + 0.3 * df$x))
fit <- tulpa(y ~ x, data = df, family = "poisson")
dim(posterior_sample(fit))
```

post_hoc_lm

*Fit a post-hoc linear model on estimated parameters***Description**

Useful for exploring drivers of occupancy/detection/abundance variation after model fitting. Fits a weighted linear model and optionally generates bootstrap confidence intervals.

Usage

```
post_hoc_lm(
  formula,
  data,
  weights = NULL,
  n_boot = 1000L,
  probs = c(0.025, 0.975)
)
```

Arguments

formula	Model formula (e.g., <code>psi_hat ~ trait1 + trait2</code>).
data	A <code>data.frame</code> with response and predictors.
weights	Optional weights (e.g., inverse of standard errors).
n_boot	Number of bootstrap replicates for CI (default 1000, 0 to skip).
probs	Quantile probabilities for bootstrap CI (default 0.025, 0.975).

Value

A list of class "post_hoc_lm" with:

summary `data.frame` of coefficient estimates and CIs

lm_fit the underlying `lm` object

boot_coefs matrix of bootstrap coefficient samples (if `n_boot > 0`)

R2 R-squared from the fitted model

Examples

```
# Explore drivers of per-site estimates after fitting a model.
site <- data.frame(
  psi_hat = c(0.2, 0.5, 0.8, 0.4, 0.6, 0.3),
  se       = c(0.05, 0.04, 0.06, 0.05, 0.03, 0.05),
  trait    = c(1.0, 2.5, 3.8, 1.9, 3.1, 1.2)
)
fit <- post_hoc_lm(psi_hat ~ trait, data = site,
  weights = 1 / site$se^2, n_boot = 200L)
fit
```

pp_check	<i>Posterior predictive check</i>
----------	-----------------------------------

Description

Generate posterior predictive checks for a fitted tulpa model. Compares observed data to replicated data from the posterior predictive distribution.

Usage

```
pp_check(object, ...)

## S3 method for class 'tulpa_fit'
pp_check(
  object,
  type = c("dens_overlay", "scatter", "intervals", "stat"),
  component = NULL,
  stat = mean,
  ndraws = 50,
  ...
)
```

Arguments

object	A tulpa_fit object
...	Additional arguments passed to bayesplot functions
type	Type of check: "dens_overlay", "scatter", "intervals", "stat"
component	Which component: "numerator", "denominator", or "both"
stat	Function for "stat" type (default: mean)
ndraws	Number of posterior draws to use (default: 50 for plots)

Value

A ggplot object

Examples

```
# pp_check is a generic; model packages (e.g. tulpaObs, tulpaRatio) provide
# the posterior-predictive method for their fits.

set.seed(123)
n <- 200L
df <- data.frame(y = rpois(n, 5), x = rnorm(n),
                 site = factor(rep(1:10, each = 20)))
fit <- tulpa(y ~ x + (1 | site), data = df, family = "poisson",
            mode = "hmc", control = list(n_iter = 500, warmup = 250))
# Density overlay (dispatches to the model package's pp_check method).
```



```

if (requireNamespace("bayesplot", quietly = TRUE)) {
  pp_check(fit, type = "dens_overlay")
}

```

predict.tulpa_fit	<i>Predict at new covariate values (population level)</i>
-------------------	---

Description

Prediction of the linear predictor at newdata, on the link or response scale. The fixed-effect part is X beta with credible bounds from the fixed-effect covariance (`vcov()`). For a fit carrying a continuous spatial field, the posterior-mean field is interpolated (kriged) to the newdata coordinates and added to the linear predictor by default, so `predict()` gives the conditional (location-specific) prediction. Three continuous field families are supported: an SPDE Matern field (`spatial_spde()`), projected through the mesh; a Hilbert-space GP field (`spatial_gp(approx = "hsgp")`), where the Laplacian basis is re-evaluated at the new coordinates (with the training centring / boundary); and a GP / NNGP field (`spatial_gp()`), interpolated by the NNGP conditional mean at each new location's nearest training locations. The HSGP and GP/NNGP fields are marginalised over the hyperparameter grid (not plugged in at the posterior mean). Ordinary random effects are held at zero (population level); add group effects from `ranef()` when needed.

Usage

```

## S3 method for class 'tulpa_fit'
predict(
  object,
  newdata = NULL,
  type = c("link", "response"),
  se.fit = FALSE,
  level = 0.95,
  include_field = TRUE,
  ...
)

```

Arguments

object	A tulpa_fit object.
newdata	Data frame of covariates (and, for an SPDE fit, the coordinate columns named in the spec's coordinate formula). If NULL, predicts at the training design (requires <code>\$model_matrix</code>).
type	"link" (linear predictor) or "response" (mean scale). For a binomial fit the "response" scale here is the per-trial success probability $g^{-1}(\eta)$ (there is no <code>n_trials</code> at newdata); this differs from <code>fitted()</code> , which returns the trial-scaled expected count at the training design.

<code>se.fit</code>	If TRUE, also return the link-scale standard error and credible bounds. With an included SPDE field the SE propagates the joint (fixed-effect, field) posterior precision at the fitted hyperparameters – including the cross term – conditional on (<code>range</code> , <code>sigma</code>) (a nested fit's hyperparameter-grid spread is not propagated, so the bound is mildly optimistic when that posterior is wide). Integer-nu, no-RE SPDE fits only; other layouts decline with an explanation.
<code>level</code>	Credible-interval level (default 0.95).
<code>include_field</code>	For a continuous-spatial fit (SPDE, HSGP, or GP/NNGP), add the kriged field to the prediction (default TRUE). FALSE gives the fixed-effect (population) prediction. Ignored for fits with no continuous field. For an HSGP or GP/NNGP fit the field is added to the point prediction but its uncertainty is not yet propagated into <code>se.fit</code> (the interval reflects the fixed-effect covariance only).
<code>...</code>	Ignored.

Value

If `se.fit` = FALSE, a numeric vector. If `se.fit` = TRUE, a data frame with `fit`, `se.fit` (link scale), `lower`, `upper` on the requested scale.

```
print.tulpa_diagnostic_summary
```

Print method for diagnostic summary

Description

Print method for diagnostic summary

Usage

```
## S3 method for class 'tulpa_diagnostic_summary'
print(x, ...)
```

Arguments

<code>x</code>	A <code>tulpa_diagnostic_summary</code> object.
<code>...</code>	Ignored.

Value

The input `x`, returned invisibly. Called for the side effect of printing the diagnostic summary to the console.

print.tulpa_geweke	<i>Print method for Geweke test</i>
--------------------	-------------------------------------

Description

Print method for Geweke test

Usage

```
## S3 method for class 'tulpa_geweke'  
print(x, ...)
```

Arguments

x	A tulpa_geweke object.
...	Ignored.

Value

The input x, returned invisibly. Called for the side effect of printing the Geweke convergence diagnostic to the console.

print.tulpa_gp	<i>Print method for tulpa_gp</i>
----------------	----------------------------------

Description

Print method for tulpa_gp

Usage

```
## S3 method for class 'tulpa_gp'  
print(x, ...)
```

Arguments

x	A tulpa_gp object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the Gaussian-process spatial specification to the console.

print.tulpa_hsgp	<i>Print method for tulpa_hsgp</i>
------------------	------------------------------------

Description

Print method for tulpa_hsgp

Usage

```
## S3 method for class 'tulpa_hsgp'
print(x, ...)
```

Arguments

x	A tulpa_hsgp object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the Hilbert-space GP spatial specification to the console.

print.tulpa_latent	<i>Print method for tulpa_latent</i>
--------------------	--------------------------------------

Description

Print method for tulpa_latent

Usage

```
## S3 method for class 'tulpa_latent'
print(x, ...)
```

Arguments

x	A tulpa_latent object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the latent factor specification to the console.

```
print.tulpa_multiscale
```

Print method for tulpa_multiscale

Description

Print method for tulpa_multiscale

Usage

```
## S3 method for class 'tulpa_multiscale'
print(x, ...)
```

Arguments

x	A tulpa_multiscale object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the multi-scale spatial specification to the console.

```
print.tulpa_nested_laplace
```

Print method for nested-Laplace fits

Description

Compact one-screen summary of a [tulpa_nested_laplace\(\)](#) or [tulpa_nested_laplace_joint\(\)](#) fit: the hyperparameters integrated over, the outer-grid size, the outer Pareto- $\hat{k}$ accuracy diagnostic when present, and the wall-clock timing line ("fit in 5h 25m (grid 2h 09m)") when `fit$timing` is attached. Inherited by the single-block joint and multi-block joint subclasses.

Usage

```
## S3 method for class 'tulpa_nested_laplace'
print(x, ...)
```

Arguments

x	A tulpa_nested_laplace fit (or a joint subclass).
...	Ignored.

Value

x, invisibly.

print.tulpa_prior	<i>Print method for tulpa_prior</i>
-------------------	-------------------------------------

Description

Print method for tulpa_prior

Usage

```
## S3 method for class 'tulpa_prior'  
print(x, ...)
```

Arguments

x	A tulpa_prior object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the prior specification to the console.

print.tulpa_priors	<i>Print method for tulpa_priors</i>
--------------------	--------------------------------------

Description

Print method for tulpa_priors

Usage

```
## S3 method for class 'tulpa_priors'  
print(x, ...)
```

Arguments

x	A tulpa_priors object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the full prior specification to the console.

```
print.tulpa_prior_predict
```

Print method for tulpa_prior_predict

Description

Print method for tulpa_prior_predict

Usage

```
## S3 method for class 'tulpa_prior_predict'  
print(x, ...)
```

Arguments

x	A tulpa_prior_predict object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing a summary of the prior predictive draws to the console.

```
print.tulpa_rsr
```

Print method for tulpa_rsr

Description

Print method for tulpa_rsr

Usage

```
## S3 method for class 'tulpa_rsr'  
print(x, ...)
```

Arguments

x	A tulpa_rsr object
...	Passed to underlying print method

Value

The input x, returned invisibly. Called for the side effect of printing the spatial specification and its restricted-spatial-regression modifier to the console.

```
print.tulpa_simulate
```

Print method for tulpa_simulate

Description

Print method for tulpa_simulate

Usage

```
## S3 method for class 'tulpa_simulate'
print(x, ...)
```

Arguments

x	A tulpa_simulate object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing a summary of the simulated datasets to the console.

```
print.tulpa_spatial
```

Print method for tulpa_spatial

Description

Print method for tulpa_spatial

Usage

```
## S3 method for class 'tulpa_spatial'
print(x, ...)
```

Arguments

x	A tulpa_spatial object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the spatial specification to the console.

print.tulpa_svc	<i>Print method for tulpa_svc</i>
-----------------	-----------------------------------

Description

Print method for tulpa_svc

Usage

```
## S3 method for class 'tulpa_svc'  
print(x, ...)
```

Arguments

x	A tulpa_svc object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the spatially-varying-coefficient specification to the console.

print.tulpa_svc_posterior	<i>Print method for tulpa_svc_posterior</i>
---------------------------	---

Description

Print method for tulpa_svc_posterior

Usage

```
## S3 method for class 'tulpa_svc_posterior'  
print(x, ...)
```

Arguments

x	A tulpa_svc_posterior object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing a summary of the spatially-varying-coefficient posterior to the console.

```
print.tulpa_temporal
```

Print method for tulpa_temporal

Description

Print method for tulpa_temporal

Usage

```
## S3 method for class 'tulpa_temporal'
print(x, ...)
```

Arguments

x	A tulpa_temporal object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the temporal specification to the console.

```
print.tulpa_temporal_gp
```

Print method for tulpa_temporal_gp

Description

Print method for tulpa_temporal_gp

Usage

```
## S3 method for class 'tulpa_temporal_gp'
print(x, ...)
```

Arguments

x	A tulpa_temporal_gp object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the Gaussian-process temporal specification to the console.

```
print.tulpa_temporal_multiscale
    Print method for tulpa_temporal_multiscale
```

Description

Print method for tulpa_temporal_multiscale

Usage

```
## S3 method for class 'tulpa_temporal_multiscale'
print(x, ...)
```

Arguments

x	A tulpa_temporal_multiscale object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the multi-scale temporal specification to the console.

```
print.tulpa_temporal_posterior
    Print method for tulpa_temporal_posterior
```

Description

Print method for tulpa_temporal_posterior

Usage

```
## S3 method for class 'tulpa_temporal_posterior'
print(x, ...)
```

Arguments

x	A tulpa_temporal_posterior object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing a summary of the temporal-effect posterior to the console.

print.tulpa_tvc	<i>Print method for tulpa_tvc</i>
-----------------	-----------------------------------

Description

Print method for tulpa_tvc

Usage

```
## S3 method for class 'tulpa_tvc'
print(x, ...)
```

Arguments

x	A tulpa_tvc object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing the temporally-varying-coefficient specification to the console.

print.tulpa_tvc_posterior	<i>Print method for tulpa_tvc_posterior</i>
---------------------------	---

Description

Print method for tulpa_tvc_posterior

Usage

```
## S3 method for class 'tulpa_tvc_posterior'
print(x, ...)
```

Arguments

x	A tulpa_tvc_posterior object
...	Ignored

Value

The input x, returned invisibly. Called for the side effect of printing a summary of the temporally-varying-coefficient posterior to the console.

priors_default	Show default priors for a tulpa family
----------------	--

Description

Display the default prior specifications used for each model family. Useful for understanding what priors are applied before fitting and as a starting point for customization.

Usage

```
priors_default(family = NULL, spatial = FALSE, temporal = FALSE)
```

Arguments

family	A tulpa family object (e.g. a ratio family constructor from a model package such as tulpaRatio). If NULL (default), shows defaults for all families.
spatial	Logical; if TRUE, include spatial priors. Default FALSE.
temporal	Logical; if TRUE, include temporal priors. Default FALSE.

Details

Default priors in tulpa follow these principles:

- **Fixed effects (beta):** Normal(0, 2.5) - weakly informative, allows coefficients roughly in [-5, 5] on the link scale.
- **Random effect SD (sigma):** PC prior with $P(\text{sigma} > 1) = 0.01$ - favors simpler models with smaller variance components.
- **Overdispersion (phi):** PC prior with $P(\text{phi} > 10) = 0.01$ on the NB2 size phi (larger phi is less overdispersion; phi $\rightarrow$ Inf is the Poisson limit). The default keeps phi finite, allowing overdispersion while penalising extreme values.
- **Temporal correlation (rho):** Beta(2, 2) - symmetric prior centered at 0.5, appropriate for AR(1) correlation.
- **Spatial mixing (rho_spatial):** Beta(1, 1) = Uniform(0, 1) - no prior preference for structured vs. unstructured spatial variation.

Value

Invisibly returns a tulpa_priors object with the defaults. Primarily called for its side effect of printing.

See Also

[tulpa_priors\(\)](#) for creating custom priors

Examples

```
# Defaults for all families (no family argument)
priors_default()

# Family-specific defaults take a tulpa_family object. Model packages
# (e.g. tulpaRatio) register rich families; a minimal one is enough here.
fam <- tulpa_family(
  name = "poisson_gamma",
  simulate_fn = function(eta, params, n_obs, ...) rpois(n_obs, exp(eta[[1]]))
)
priors_default(fam)

# Including spatial parameters
priors_default(fam, spatial = TRUE)

# Use as a starting point for customization
my_priors <- priors_default(fam)
my_priors$beta <- prior_normal(0, 1) # Tighter prior on fixed effects
```

prior_beta

*Beta prior***Description**

Specify a beta prior for a parameter bounded in (0, 1).

Usage

```
prior_beta(alpha = 1, beta = 1)
```

Arguments

alpha	First shape parameter. Must be positive.
beta	Second shape parameter. Must be positive.

Details

- alpha = beta = 1: Uniform(0, 1)
- alpha = beta = 2: Symmetric, peaked at 0.5
- alpha > beta: Skewed toward 1
- alpha < beta: Skewed toward 0

Value

A tulpa_prior object

Examples

```
prior_beta(1, 1)  # Uniform
prior_beta(2, 2)  # Symmetric, centered at 0.5
prior_beta(5, 2)  # Skewed toward 1 (for high autocorrelation)
```

prior_exponential	<i>Exponential prior</i>
-------------------	--------------------------

Description

Specify an exponential prior for a positive parameter.

Usage

```
prior_exponential(rate = 1)
```

Arguments

rate Rate parameter (lambda). Must be positive.

Value

A tulpa_prior object

Examples

```
prior_exponential(1)
```

prior_from_spec	<i>Build a prior list for tulpa_nested_laplace() from a tulpa spec object</i>
-----------------	---

Description

Validates a tulpa_temporal or tulpa_spatial specification against data, then converts it to the prior list shape consumed by [tulpa_nested_laplace\(\)](#). Mainly an internal helper for callers that already have a fitted spec; users typically pass spec + data directly to tulpa_nested_laplace() instead.

Supported spec types:

- tulpa_temporal with type in {"rw1", "rw2", "ar1"}

- tulpa_spatial, areal type in {"car", "icar", "car_proper", "bym2"}. An areal spec returns the graph fields only – type, spatial_idx, n_spatial_units, adj_row_ptr, adj_col_idx, n_neighbors – plus scale_factor for bym2 and the eigenvalue-derived rho_bounds for proper CAR. No grid field is returned for any areal type: the outer axes are built later by the family’s registry defaults() closure, and proper CAR’s (tau, rho) grid is built there from those bounds.
- tulpa_gp / tulpa_hsgp, continuous type in {"gp", "nngp", "hsgp"}: validated against data and routed to the nngp / hsgp nested kernel through the shared converter.

SPDE is the one continuous field not built here – it carries its own (range, sigma) FEM integrator; call `fit_spde()` with the `spatial_spde()` spec.

Usage

```
prior_from_spec(spec, data)
```

Arguments

- spec A tulpa_temporal or tulpa_spatial object.
- data Data frame the spec resolves time/group/site indices against.

Value

A prior list ready for `tulpa_nested_laplace()`.

prior_gamma	<i>Gamma prior</i>
-------------	--------------------

Description

Specify a gamma prior for a positive parameter.

Usage

```
prior_gamma(shape = 2, rate = 0.1)
```

Arguments

- shape Shape parameter (alpha). Must be positive.
- rate Rate parameter (beta). Must be positive.

Details

Mean = shape/rate, Variance = shape/rate^2.

Value

A tulpa_prior object

Examples

```
prior_gamma(2, 0.1) # Mean = 20, weakly informative
prior_gamma(1, 1)   # Exponential(1)
```

prior_half_cauchy	<i>Half-Cauchy prior</i>
-------------------	--------------------------

Description

Specify a half-Cauchy prior for a positive parameter. Has heavier tails than half-normal, often used for variance parameters.

Usage

```
prior_half_cauchy(scale = 2.5)
```

Arguments

scale	Scale parameter. Must be positive.
-------	------------------------------------

Value

A tulpa_prior object

Examples

```
prior_half_cauchy(2.5)
```

prior_half_normal	<i>Half-normal prior</i>
-------------------	--------------------------

Description

Specify a half-normal (truncated at 0) prior for a positive parameter.

Usage

```
prior_half_normal(sd = 1)
```

Arguments

sd	Scale parameter. Must be positive.
----	------------------------------------

Value

A tulpa_prior object

Examples

```
prior_half_normal(1)
```

prior_normal	<i>Normal prior</i>
--------------	---------------------

Description

Specify a normal prior for a parameter.

Usage

```
prior_normal(mean = 0, sd = 2.5)
```

Arguments

- mean Prior mean. Default 0.
- sd Prior standard deviation. Must be positive.

Value

A tulpa_prior object

Examples

```
prior_normal(0, 2.5)
prior_normal(0, 1)
```

prior_pc	<i>Penalized complexity (PC) prior</i>
----------	--

Description

Specify a PC prior for a positive parameter (typically a standard deviation). PC priors shrink toward simpler models by penalizing deviation from a base model.

Usage

```
prior_pc(U = 1, alpha = 0.01)
```

Arguments

U	Upper bound. $P(x > U) = \alpha$.
alpha	Tail probability. Default 0.01.

Details

The PC prior is specified via: $P(\sigma > U) = \alpha$

- U is the upper bound you consider "large"
- alpha is the probability of exceeding it

This implies an exponential prior with rate $= -\log(\alpha) / U$.

Value

A tulpa_prior object

References

Simpson, D., Rue, H., Riebler, A., Martins, T. G., & Sørbye, S. H. (2017). Penalising model component complexity: A principled, practical approach to constructing priors. *Statistical Science*, 32(1), 1-28.

Examples

```
prior_pc(U = 1, alpha = 0.01)    # P(sigma > 1) = 0.01
prior_pc(U = 0.5, alpha = 0.05)  # Tighter, P(sigma > 0.5) = 0.05
```

prior_predict	<i>Prior predictive simulation</i>
---------------	------------------------------------

Description

Draw datasets from the prior predictive distribution: parameters are sampled from their priors (no data conditioning) and pushed through the model's linear predictor and the family's simulator.

Useful for checking whether priors imply plausible data ranges before fitting.

Usage

```
prior_predict(
  formula,
  family,
  data,
  priors = NULL,
  n_draws = 100,
  seed = NULL,
  ...
)
```

Arguments

formula	A model formula (e.g., $y \sim x + (1 \mid g)$). For multi-process families, a list of formulas keyed by process name.
family	A <code>tulpa_family</code> object exposing a <code>simulate_fn</code> (see <code>tulpa_family()</code>). Model packages (<code>tulpaRatio</code> , <code>tulpaObs</code>) provide families; tests can build a minimal one with <code>tulpa_family()</code> .
data	Data frame containing covariates and grouping factors. Used for dimensions and design matrices; the response column may be absent or NA.
priors	Prior specification (<code>tulpa_priors()</code>). If NULL, uses defaults.
n_draws	Number of prior parameter draws. Default 100.
seed	Optional integer seed for reproducibility.
...	Passed to <code>family\$simulate_fn</code> .

Value

A `tulpa_prior_predict` object: a list with

- `y`: list of length `n_draws`, each element the simulated response for that draw (matching whatever shape `family$simulate_fn` returns).
- `theta`: list of length `n_draws` of parameter draws (beta, sigma, RE coefficients `u`, family-specific extras).
- `linpred`: list of length `n_draws`, each a list of linear predictor vectors per process.
- `family`: the family used.
- `n_draws`, `n_obs`.

Examples

```
# Toy Gaussian family for illustration
fam <- tulpa_family(
  name = "gaussian",
  simulate_fn = function(eta, params, n_obs, ...) {
    rnorm(n_obs, eta[[1]], params$sigma_y)
  },
  extra_params = list(sigma_y = prior_half_normal(1))
)
df <- data.frame(y = rep(0, 20), x = rnorm(20))
pp <- prior_predict(y ~ x, fam, df, n_draws = 50, seed = 1)
length(pp$y) # 50
```

ranef	<i>Random-effect summaries</i>
-------	--------------------------------

Description

Random-effect summaries

Usage

```
ranef(object, ...)

## S3 method for class 'tulpa_fit'
ranef(object, ...)
```

Arguments

object	A tulpa_fit object.
...	Ignored.

Details

What each backend reports for a group effect follows what it computes:

- Sampler tier and the RE-covariance Gibbs debias ([tulpa_re_cov_gibbs\(\)](#), reached by `tulpa(..., control = list(re_cov = "gibbs"))`) draw the random effects jointly with everything else, so estimate / sd / bounds are the empirical posterior summaries.
- The RE-covariance integrator ([tulpa_re_cov_nested\(\)](#)) carries a Gaussian per-group posterior at each Sigma node; the reported summaries are the exact moments and quantiles of the weighted mixture of those, so they carry both the within-node curvature and the Sigma uncertainty. A group effect the subspace debias selected (`control$subspace_debias`) is moved by the Metropolis sampler at every node instead, and is reported from those draws.
- The Laplace tier reports the conditional mode with no spread (sd and the bounds are NA), which is the only per-group quantity it forms.

The source column says per row which of these produced it: "sampled" for a posterior draw summary, "mixture" for the node mixture, "mode" for a conditional mode. A fit whose backend never forms a per-group posterior at all (the adaptive Gauss-Hermite inner marginal integrates each group out by quadrature) errors with that reason rather than returning an empty table, which would be indistinguishable from a model with no random effects. A model that genuinely has none returns a zero-row data frame.

Value

Data frame with one row per random-effect coefficient: term (the group level, and the coefficient for a random slope), estimate, sd, the 2.5% / 97.5% bounds `conf.low` / `conf.high`, and source (which construction the row came from). sd and the bounds are NA on a backend that reports a point per group (see Details).

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(100), g = factor(rep(1:10, 10)))
df$y <- rpois(100, exp(0.3 * df$x))
fit <- tulpa(y ~ x + (1 | g), data = df, family = "poisson")
ranef(fit)
```

residuals.tulpa_fit	<i>Residuals from a tulpa fit</i>
---------------------	-----------------------------------

Description

Population-level residuals from the fixed-effect fitted mean: "response" is $y - E[y \mid \eta]$ on the response scale (trial-scaled for binomial, offset included); "pearson" additionally scales by the family standard deviation $\sqrt{\text{Var}(y \mid \eta)}$ at the fitted linear predictor. Random effects are held at zero, matching `fitted()`.

Usage

```
## S3 method for class 'tulpa_fit'
residuals(object, type = c("pearson", "response"), ...)
```

Arguments

object	A tulpa_fit object carrying \$y and \$model_matrix.
type	"pearson" (default) or "response".
...	Ignored.

Value

Numeric vector of length `nobs(object)`.

re_cov_pc_lkj_prior	<i>PC + LKJ hyperprior for a random-effect covariance</i>
---------------------	---

Description

Construct the default weakly-informative hyperprior used by `tulpa_re_cov_nested()` for one covariance block: independent Penalized-Complexity (PC) priors on the marginal standard deviations σ_i together with an LKJ prior on the correlation matrix R (correlated block) or no correlation (diagonal block), returned as a `log_prior_theta` function in the block's integration coordinates.

Usage

```
re_cov_pc_lkj_prior(
  n_coefs,
  prior_sigma = c(3, 0.05),
  eta = 2,
  correlated = TRUE
)
```

Arguments

<code>n_coefs</code>	Number of coefficients <code>c</code> in the RE block.
<code>prior_sigma</code>	$c(U, \alpha)$ giving $P(\sigma_i > U) = \alpha$ (default $c(3, 0.05)$), applied independently to every marginal SD.
<code>eta</code>	LKJ shape (default 2). $\eta = 1$ is uniform on correlation matrices; larger values favour weaker correlations. Ignored for a diagonal block.
<code>correlated</code>	TRUE (default) for a full covariance block (log-Cholesky coordinates, LKJ prior); FALSE for a diagonal / uncorrelated block (log-SD coordinates, no correlation). For <code>n_coefs = 1</code> the two coincide.

Details

For a correlated block the prior is specified on the natural scale, $p(\sigma, R) = \text{LKJ}(R \mid \eta) * \prod_i \text{PC}(\sigma_i)$, then pushed to the log-Cholesky coordinates θ of $\Sigma = L L'$ by the exact change-of-variables Jacobian. For a diagonal (uncorrelated) block the LKJ factor drops and $\theta_i = \log \sigma_i$ with Jacobian $\sum_i \theta_i$.

PC prior (Simpson et al. 2017) on each marginal SD: exponential with rate $\lambda = -\log(\alpha) / U$, so $P(\sigma_i > U) = \alpha$ – the `prior_sigma = c(U, alpha)` convention also used by the SPDE prior in `tulpa`.

LKJ prior (Lewandowski et al. 2009) on the correlation matrix: $p(R)$ proportional to $\det(R)^{(\eta - 1)}$. $\eta = 1$ is uniform over correlation matrices; $\eta > 1$ concentrates toward the identity. The normalizing constant is dropped (constant across the grid, so it cancels when the integration weights are renormalized).

Jacobian (correlated block): with θ packing $\log L_{ii}$ on the diagonal and the raw strict-lower entries of L , the change of variables from (σ, R) to θ adds $\sum_i (c + 2 - i) * \log L_{ii} - c * \sum_i \log \sigma_i$ to $\log p(\sigma, R)$. (Composition of the log-diagonal map, the standard Cholesky-to-covariance Jacobian $2^c \prod_i L_{ii}^{(c+1-i)}$, and the covariance-to- (σ, R) Jacobian; verified against numerical differentiation in `test-re-cov-prior.R`.)

Value

A function(θ) returning the scalar log prior density in the block's integration coordinates, suitable for one block of the `log_prior_theta` argument of `tulpa_re_cov_nested()`.

See Also

[tulpa_re_cov_nested\(\)](#)

 rubins_pool

Pool multiple imputation draws via Rubin's rules

Description

Pools per-imputation block fits via Rubin's rules. When every draw also carries a per-coefficient skewness vector `$gamma`, the third cumulant is pooled by the law of total cumulants

$$\kappa_3 = E[\kappa_3(X|k)] + 3 \text{Cov}(\mu_k, \sigma_k^2) + \kappa_3(\mu_k),$$

giving a pooled skewness `$gamma` alongside the usual `$mean` / `$se`. If any draw is missing `$gamma`, the third-cumulant path is skipped.

Usage

```
rubins_pool(draws)
```

Arguments

<code>draws</code>	List of K draws. Each draw is a named list of submodel results, each with <code>beta</code> (numeric vector), <code>se</code> (numeric vector), and optionally <code>gamma</code> (numeric vector, same length as <code>beta</code>).
--------------------	--

Value

A named list of pooled submodel summaries, each with `mean`, `se`, `V_within`, `V_between`, `V_total`, `K` (number of draws that contributed), and when applicable `gamma` (pooled skewness) and `kappa3` (pooled third cumulant).

 sbc

Simulation-based calibration

Description

Scores whether an inference algorithm's posterior is CALIBRATED, by reading the whole marginal CDF rather than one or two nominal levels. Draw a truth from the distribution the fit updates, simulate a data set at that truth, fit, and take the probability integral transform (PIT) of the truth under the reported posterior. Under exact inference those PIT values are exactly Uniform(0, 1), so the entire ECDF is the measurement (Talts et al. 2018).

Usage

```

sbc(object, ...)

## Default S3 method:
sbc(object, ...)

## S3 method for class 'character'
sbc(
  object = c("prior_predictive", "posterior"),
  simulator = NULL,
  fitter = NULL,
  model = NULL,
  n_sim = 100L,
  quantities = NULL,
  flat_prior = character(),
  level = 0.95,
  seed = 0L,
  n_ref = NULL,
  control = list(),
  ...
)

## S3 method for class 'sbc'
summary(object, baseline = NULL, ...)

## S3 method for class 'sbc'
plot(x, arm = NULL, quantity = NULL, folded = FALSE, ...)

```

Arguments

<code>object</code>	An sbc result.
<code>...</code>	Ignored.
<code>simulator, fitter</code>	The prior-predictive callbacks; see the contract above. Required for experiment = "prior_predictive".
<code>model</code>	The list of posterior-SBC callbacks. Required for experiment = "posterior".
<code>n_sim</code>	Number of simulations.
<code>quantities</code>	Optional character vector restricting which quantities are scored. Default scores every quantity every arm reports.
<code>flat_prior</code>	Character vector of scored quantities held FIXED under a flat prior, admitted by a structural argument the caller is asserting. Prior-predictive only.
<code>level</code>	Simultaneous band level.
<code>seed</code>	Offset added to the simulation index, so simulation <code>s</code> runs the callbacks at <code>seed + s</code> .
<code>n_ref</code>	Optional; when supplied it is passed to <code>fitter</code> (or to <code>model\$arms</code>) as <code>n_ref</code> , the number of reference values a rank predictive is formed against. The callback must accept it.

control	List of knobs: progress (default FALSE) and rand_seed, the pinned stream the within-atom randomizing uniforms come from (default the driver's own, so a result is reproducible and the fits are not perturbed by asking for the diagnostic).
baseline	Optional arm name. When given, the summary also carries the PAIRED CRPS differences of every other arm against it, seed by seed. A negative delta is the arm scoring better. This is refused on an experiment where the CRPS is not a proper posterior score.
x	An sbc result.
arm, quantity	Optional character vectors selecting which panels to draw. Default draws every (arm, quantity).
folded	Plot the folded PIT instead of the raw one.

Value

An object of class sbc:

pit one row per (simulation, arm, quantity): the truth, the raw and folded PIT, the CRPS and the predictive kind.

report one row per (arm, quantity): the KS distance, whether the ECDF stayed inside the simultaneous band, the exact uniformity p-value, the same three folded, and the mean CRPS with its standard error.

bands the calibrated simultaneous band, by sample size.

premises what each guard concluded.

crps_role the role the CRPS column has under this experiment.

The two experiments

"prior_predictive" ordinary SBC. $\theta \sim p(\theta)$, $y \sim p(y | \theta)$, fit, PIT. It reports self-consistency AVERAGED over the whole generative distribution.

"posterior" calibration CONDITIONAL on an observed data set (Sailynoja et al. 2026, Algorithm 2). $\theta' \sim \pi(\theta | y_{\text{obs}})$, $y \sim \pi(y | \theta')$, and the PIT is taken under the AUGMENTED posterior $\pi(\theta | y, y_{\text{obs}})$. That is ordinary SBC with $\pi(\theta | y_{\text{obs}})$ in the role of the prior, so the same band, the same folded read and the same proper score all carry over – and it needs no proper prior.

A fixed-truth sweep is not an SBC experiment and is not offered here: its PIT is not uniform under correct inference and its CRPS is a descriptive loss, not a proper posterior score.

What is reported

Three reads of the same PIT sample, per (arm, quantity):

raw the PIT ECDF against an exact SIMULTANEOUS band. A pointwise binomial band is not simultaneous – at $n = 100$, holding each order statistic at 95 percent holds all of them together at 0.4471 – so the band here is calibrated by bisection against the exact crossing probability of the uniform order statistics.

folded $2 |u - 1/2|$, also uniform, and where a symmetric over- or under-dispersion shows after cancelling in the raw ECDF.

CRPS the strictly proper score, closed form for the nested tier’s own Gaussian mixture, paired seed by seed through `summary(x, baseline = )`.

Every discrete PIT (a rank, a grid axis, a draw set) is randomized within its atom, $u = F(\theta^*) + V P(\theta)$, so one uniform reference and one band serve every quantity. Reading rank / n_ref against a continuous uniform is the classic silent SBC bug.

The callback contract

For experiment = "prior_predictive":

`simulator(seed)` returns a list carrying `theta`, a named numeric vector of the true values of the scored quantities, plus whatever the fitter needs. It must be a pure function of its seed.

`fitter(d)` returns a named list of ARMS, each a named list over quantities, each entry a predictive built by `sbc_mixture()` and its siblings. Several arms read off one solve per seed, so an arm-to-arm difference carries no fit-to-fit noise.

For experiment = "posterior", `model` is a list of six callbacks – `data_obs`, `fit(data)`, `draw_theta(fit, seed)`, `simulate(theta, seed)`, `pool(data_obs, replicate)`, `arms(fit, data)` – plus an optional `group_ids(data)` used to verify the fresh-groups premise below. The driver hands `draw_theta` and `simulate` DIFFERENT seeds, so `set.seed(seed)` at the top of each is the correct fixture; sharing one makes the replicate’s noise a function of the truth, which is not $p(y \mid \theta)$.

Two guards

The prior-predictive experiment draws the truth from the prior, so an IMPROPER prior cannot be used – and the nested-Laplace door puts no prior on the fixed effects. A scored quantity whose truth does not move across simulations was not drawn from a proper prior, and `sbc()` errors on it before spending the fits, pointing at experiment = "posterior". A location parameter whose flat prior leaves the PIT uniform by a structural argument is admitted through `flat_prior`, which is itself checked and travels on the result.

The posterior experiment rests on two premises, each of which silently invalidates the result when broken. The augmented posterior must condition on BOTH data sets, so a `pool()` returning no more than the replicate (or no more than the observed data) is refused. And the replicate must be conditionally independent of the observed data given `theta`, which for a hierarchical model whose group effects are integrated out means FRESH groups. Supply `group_ids` and the observable half of that is verified – the group LABELS are disjoint – and omit it and the result records the premise as unverified rather than assumed. The other half, that the simulator drew those groups’ effects from the prior rather than conditionally on the observed data, is not visible from outside the callback and is not claimed.

References

- Talts, Betancourt, Simpson, Vehtari & Gelman (2018). Validating Bayesian inference algorithms with simulation-based calibration. arXiv:1804.06788.
- Sailynoja, Schmitt, Buerkner & Vehtari (2026). Posterior SBC: simulation-based calibration checking conditional on data. *Statistics and Computing* 36:78. doi:10.1007/s11222026108259
- Grimt, Gneiting, Berrocal & Johnson (2006). The continuous ranked probability score for circular variables and its application to mesoscale forecast ensemble verification. *QJRM* 132(621C):2925-2942.

See Also

`sbc_mixture()` for the predictive shapes a fitter reports, `diagnostics()` for the single-fit reliability band that screens what this measures, `pit_residuals()` for single-fit posterior-predictive PIT residuals (a different quantity).

Examples

```
# A conjugate normal-normal model, whose posterior is exact, so its PIT must
# be uniform: the harness scoring itself.
sim <- function(seed) {
  set.seed(seed)
  mu <- rnorm(1)
  list(y = rnorm(10L, mu, 1), theta = c(mu = mu))
}
fitter <- function(d) {
  v <- 1 / (1 + length(d$y))
  list(exact = list(mu = sbc_normal(v * sum(d$y), sqrt(v))),
        narrow = list(mu = sbc_normal(v * sum(d$y), sqrt(v) / 2)))
}
res <- sbc("prior_predictive", simulator = sim, fitter = fitter, n_sim = 60L)
res
summary(res, baseline = "exact")
```

sbc_predictive

Predictive shapes an SBC fitter reports

Description

The tagged representations `sbc()` reads. A fitter (or a posterior-SBC arms) callback returns a named list of ARMS, each a named list over quantities, and each entry is one of these – the shape the backend actually reports for that quantity. Everything downstream (the PIT, the CRPS, drawing from a predictive) dispatches on the kind tag, so a new backend shape is one entry in three switches rather than a parallel scorer.

Usage

```
sbc_mixture(mu, var, w = NULL)
```

```
sbc_normal(mean, sd)
```

```
sbc_discrete(support, probs)
```

```
sbc_rank(rank, n_ref)
```

```
sbc_draws(x)
```

Arguments

<code>mu, var, w</code>	Component means, variances and weights. <code>w</code> defaults to equal weights and is normalized.
<code>mean, sd</code>	Mean and standard deviation of a single Gaussian.
<code>support, probs</code>	Finite support and its probabilities, normalized.
<code>rank, n_ref</code>	The rank in $0:n_ref$ of the truth among <code>n_ref</code> reference values, and that reference count.
<code>x</code>	Posterior draws.

Details

These are the extension point, not alternative front doors: `sbc()` is the verb, and these are the argument type it consumes.

`sbc_mixture()` is what an outer hyperparameter grid defines for a fixed effect – component `k` is $N(\mu_k, \text{var}_k)$ with weight `w_k`, which is exactly the mixture a nested-Laplace fit reports. `sbc_normal()` is the one-component case, with its own constructor so a collapsed-moment read says what it is. `sbc_discrete()` is a distribution on a finite support, which is what a discrete hyperparameter grid defines for its own axis. `sbc_rank()` is a rank of the truth among `n_ref` reference values, which is what a joint log-likelihood comparison against posterior draws produces – it needs no entry in the simulator’s `theta`, since the comparison against the truth already happened when the rank was formed. `sbc_draws()` is for a backend reporting no analytic marginal.

The last three have ATOMS, so their PIT is randomized within the atom by `sbc()`; reading a rank against a continuous uniform is the classic silent SBC bug.

Value

A list carrying a kind tag and that shape’s parameters.

See Also

[sbc\(\)](#)

Examples

```
sbc_normal(0.3, 0.1)
sbc_mixture(mu = c(0, 1), var = c(1, 4), w = c(0.7, 0.3))
sbc_discrete(support = c(0.5, 1, 2), probs = c(0.2, 0.5, 0.3))
```

<code>select_main_params</code>	<i>Select the "main" model parameters for diagnostic display</i>
---------------------------------	--

Description

Drops per-element latent-field entries (names ending in a bracketed index, e.g. `u[12]`, `w[3]`) so plots and summaries focus on scalar coefficients and hyperparameters rather than thousands of latent values.

Usage

```
select_main_params(param_names)
```

Arguments

param_names Character vector of parameter names.

Value

The subset of param_names that are not bracketed-index entries (or the full vector if that would be empty).

simulate.tulpa_fit	<i>Simulate responses from a fitted tulpa model</i>
--------------------	---

Description

Base-R alias for [posterior_predict\(\)](#): each simulation is one posterior predictive replicate at the training data.

Usage

```
## S3 method for class 'tulpa_fit'  
simulate(object, nsim = 1, seed = NULL, ...)
```

Arguments

object	A tulpa_fit object.
nsim	Number of simulated datasets (default 1).
seed	Optional integer seed (RNG state is restored on exit).
...	Ignored.

Value

A data frame with nsim columns (sim_1, ...), one row per observation, following the [stats::simulate\(\)](#) convention.

smooth_effects	<i>Extract fitted covariate smooths</i>
----------------	---

Description

The grid-marginalized posterior mean of each $s(x)$ term's latent values, one estimate per node (bin midpoint or unique covariate value). The latent block values are read from the fit's per-grid modes, weighted by the hyperparameter grid weights.

Usage

```
smooth_effects(object, term = 1L)
```

Arguments

object	A <code>tulpa_fit</code> from <code>tulpa()</code> with <code>s(...)</code> term(s) in the formula.
term	Which smoother: index or covariate name. Default 1.

Value

A data frame with columns `x` (node location) and `estimate` (the posterior-mean smooth at that node), with the covariate name as an attribute `"var"`.

Examples

```
set.seed(1)
d <- data.frame(x = runif(300, -2, 2))
d$y <- rpois(300, exp(0.3 + sin(2 * d$x)))
fit <- tulpa(y ~ s(x), data = d, family = "poisson")
sm <- smooth_effects(fit)
plot(sm$x, sm$estimate, type = "l")
```

spatial	<i>Areal spatially varying coefficient field</i>
---------	--

Description

Declare one or more areal (CAR / Besag) fields over a graph from an **lme4**-style bar formula. The bar's left-hand side lists the coefficients that vary smoothly over the graph; the right-hand side names the graph-node index. Each coefficient becomes an independent CAR field, entering the linear predictor scaled by that coefficient's per-observation design value:

$$\eta_i = \dots + \sum_c X_{ic} z_{g_i}^{(c)},$$

where g_i is the graph node of observation i , $z^{(c)}$ is the CAR field for design column c , and X_{ic} is that column's value at observation i . The intercept column is all ones, so $\sim 1 \parallel \text{cell}$ is the ordinary spatial intercept field; a covariate column (e.g. `time`) gives a spatially varying slope on that covariate (a per-region trend).

Use it inline in a `tulpa()` model formula, the same way a random-effect bar is written:

```
y ~ time + spatial(graph = adj, formula = ~ 1 + time || cell) + (1 | site)
```

Usage

```
spatial(graph, formula, proper = FALSE, shared = NULL, by = NULL)
```

Arguments

<code>graph</code>	Symmetric adjacency matrix of the spatial graph ($[n_node \times n_node]$, dense or sparse). One CAR field is defined over its nodes per coefficient.
<code>formula</code>	One-sided formula carrying a grouping bar, e.g. <code>~ 1 + time cell</code> . The left-hand side is expanded with <code>stats::model.matrix()</code> into one CAR field per column (1 = intercept field; a covariate = spatially varying slope on it; $\emptyset$ + drops the intercept). The right-hand side must be a single bare column naming the graph node. The double bar <code> </code> builds independent fields (each its own precision); a single bar <code> </code> builds correlated fields – a separable multivariate CAR where the per-cell coefficient vector shares a cross-covariance Σ (covariance $\Sigma(x) Q^{-1}$), so the intercept-slope correlation ρ is shared across the graph.
<code>proper</code>	Logical; FALSE (default) builds intrinsic CAR (ICAR / Besag) fields with the sum-to-zero constraint (ρ fixed at 1). TRUE builds proper CAR fields, each with its own precision $Q = D - \rho_{car} W$ and the spatial autocorrelation ρ_{car} estimated from the data (one (σ, ρ_{car}) pair per field). <code>summary()</code> and <code>print()</code> report the per-field ρ_{car} . Independent (<code> </code>) only; correlated proper CAR (a single <code> </code> with <code>proper = TRUE</code>) is a separate model.
<code>shared</code>	Optional shared-effect handle, passed through to the field blocks (see the model docs). Default NULL (shared).
<code>by</code>	Optional replicated-CAR factor: a bare column name (or a string) naming a factor in the model data. With L levels it builds one independent copy of the whole field per level – the field over the block-diagonal Kronecker graph $I_L(x) Q$ (L disjoint copies of the graph) – with the hyperparameters shared across levels (one Σ for <code> </code> ; one $(\sigma[, \rho_{car}])$ for <code> </code>). This is INLA's <code>replicate = /mgcv's s(cell, by = ...)</code> generalised to the varying-coefficient bar, and is orthogonal to the bar character: <code> / </code> sets the covariance among the coefficient columns within a field, while <code>by</code> sets how many independent replicates of the whole field exist. Default NULL (one field). Correlated proper CAR (<code> </code> with <code>proper = TRUE</code>) stays out of scope with or without <code>by</code> .

Details

Each field is independent (its own precision), matching INLA's two separate `f(cell, model = "besag")` and `f(cell.slope, time, model = "besag")` fields. Nesting (`a / b`), interaction, or ex-

pression grouping is rejected: the grouping must be a single graph node. Add ordinary nested random effects, e.g. (1 | site), as separate terms.

Value

A `tulpa_spatial_field` object describing the field(s). It is expanded into one CAR block per design column at fit time, when the data is available.

See Also

[spatial_car\(\)](#) for a single areal field passed via the `spatial =` argument, [spatial_svc\(\)](#) for the coordinate-based (Gaussian-process) spatially varying coefficient.

Examples

```
# Chain graph over 10 cells
adj <- matrix(0, 10, 10)
for (i in 1:9) adj[i, i + 1] <- adj[i + 1, i] <- 1

# Spatial intercept plus a spatially varying time slope
f <- spatial(graph = adj, formula = ~ 1 + time || cell)
print(f)
```

spatial_bym2

BYM2 spatial structure

Description

Specify a Besag-York-Mollie 2 (BYM2) spatial random effect. BYM2 decomposes the spatial effect into a structured (ICAR) component and an unstructured (IID) component, with a mixing parameter controlling the proportion of variance attributable to spatial structure.

BYM2 is preferred over plain CAR when you want to:

- Distinguish structured vs unstructured spatial variation
- Have an interpretable spatial fraction parameter
- Use the scaling from Riebler et al. (2016)

Usage

```
spatial_bym2(
  adjacency,
  level = c("group", "obs"),
  group_var = NULL,
  shared = NULL,
  scale_factor = NULL,
  parameterization = c("standard", "collapsed")
)
```

Arguments

adjacency	Symmetric adjacency matrix ([n_units x n_units]).
level	Either "group" (one effect per level of group_var) or "obs" (one effect per row of the data; nrow(data) must equal nrow(adjacency)).
group_var	Name of the grouping variable in the data; required when level = "group".
shared	Optional shared-effect handle (see model docs).
scale_factor	Scaling factor for the ICAR component. If NULL (default), computed from the adjacency matrix following Riebler et al.
parameterization	"standard" (default) or "collapsed" (deprecated).

Value

A tulpa_spatial object

References

Riebler, A., Sorbye, S. H., Simpson, D., & Rue, H. (2016). An intuitive Bayesian spatial model for disease mapping that accounts for scaling. *Statistical Methods in Medical Research*, 25(4), 1145-1165.

Examples

```
# Create adjacency matrix for 10 regions (chain structure)
adj <- matrix(0, 10, 10)
for (i in 1:9) {
  adj[i, i+1] <- adj[i+1, i] <- 1
}

# Create BYM2 spatial structure
bym2 <- spatial_bym2(adj, level = "group", group_var = "region")
print(bym2)

# Disease mapping with BYM2 spatial smoothing
set.seed(456)
n_regions <- 10
epi_data <- data.frame(
  region = factor(rep(1:n_regions, each = 4)),
  age = rnorm(n_regions * 4, 50, 10)
)
epi_data$cases <- rbinom(nrow(epi_data), size = 100, prob = 0.15)

fit <- tulpa(
  cases ~ age + spatial(region),
  spatial = spatial_bym2(adj, level = "group", group_var = "region"),
  data = epi_data,
  family = "binomial",
  n_trials = rep(100L, nrow(epi_data)),
```

```

    mode = "laplace"
  )
summary(fit)

```

spatial_car	<i>CAR / ICAR spatial structure</i>
-------------	-------------------------------------

Description

Constructs a conditional autoregressive spatial random effect from an adjacency matrix. With `proper = FALSE` (the default) this is the improper CAR / ICAR (type = "car"); with `proper = TRUE` it returns the same object as [spatial_car_proper\(\)](#).

Usage

```

spatial_car(
  adjacency,
  level = c("group", "obs"),
  group_var = NULL,
  proper = FALSE,
  shared = NULL,
  parameterization = c("standard", "collapsed")
)

```

Arguments

<code>adjacency</code>	Symmetric adjacency matrix ([n_units x n_units]).
<code>level</code>	Either "group" (one effect per level of <code>group_var</code>) or "obs" (one effect per row of the data; <code>nrow(data)</code> must equal <code>nrow(adjacency)</code>).
<code>group_var</code>	Name of the grouping variable in the data; required when <code>level = "group"</code> .
<code>proper</code>	If TRUE, use proper CAR (type = "car_proper"); else ICAR (type = "car").
<code>shared</code>	Optional shared-effect handle (see model docs).
<code>parameterization</code>	"standard" (default) or "collapsed" (deprecated).

Value

A `tulpa_spatial` object with type = "car" (or "car_proper" when `proper = TRUE`).

See Also

[spatial_car_proper\(\)](#), [spatial_bym2\(\)](#).

spatial_car_proper *Proper CAR spatial structure*

Description

Convenience wrapper for `spatial_car(..., proper = TRUE)`. Creates a proper conditional autoregressive (CAR) spatial random effect with the autocorrelation parameter ρ estimated from the data.

Use this when you want spatial autocorrelation to be a parameter of the model rather than fixed at 1 (as in ICAR). $\rho \approx 0$ collapses to IID, $\rho \approx 1$ approaches ICAR.

Usage

```
spatial_car_proper(
  adjacency,
  level = c("group", "obs"),
  group_var = NULL,
  shared = NULL
)
```

Arguments

<code>adjacency</code>	Symmetric adjacency matrix (<code>[n_units x n_units]</code>).
<code>level</code>	Either "group" (one effect per level of <code>group_var</code>) or "obs" (one effect per row of the data; <code>nrow(data)</code> must equal <code>nrow(adjacency)</code>).
<code>group_var</code>	Name of the grouping variable in the data; required when <code>level = "group"</code> .
<code>shared</code>	Optional shared-effect handle (see model docs).

Value

A `tulpa_spatial` object with type = "car_proper".

See Also

[spatial_car\(\)](#) for ICAR (ρ fixed at 1), [spatial_bym2\(\)](#) for the BYM2 decomposition.

Examples

```
adj <- matrix(0, 10, 10)
for (i in 1:9) adj[i, i+1] <- adj[i+1, i] <- 1
spec <- spatial_car_proper(adj, level = "group", group_var = "site")
print(spec)
```

spatial_gp

*Gaussian process spatial structure (NNGP)***Description**

Specify a Gaussian-process spatial random effect, approximated with a nearest-neighbour GP (NNGP) for scalability. Captures smooth spatial variation from point-referenced coordinates.

Usage

```
spatial_gp(
  coords,
  approx = c("nngp", "hsgp"),
  cov = c("exponential", "matern"),
  nu = 1.5,
  nn = 15,
  m = 6,
  c = 1.5,
  sigma_prior_U = 1,
  sigma_prior_alpha = 0.01,
  shared = NULL,
  scale_coords = TRUE,
  parameterization = c("noncentered", "centered", "collapsed")
)
```

Arguments

coords	A formula ($\sim \text{lon} + \text{lat}$) or character vector naming the coordinate variables in the data. With <code>approx = "nngp"</code> the coordinate DIMENSION is however many are named: two for a map, one for a transect or a depth profile, three for a depth-resolved domain. The neighbour graph and the neighbour covariance both read every column. <code>approx = "hsgp"</code> takes exactly two, and so does any sampler mode, because both store coordinates at a fixed 2-D stride.
approx	GP approximation: <code>"nngp"</code> (default, a nearest-neighbour GP with the <code>cov</code> / <code>nu</code> / <code>nn</code> arguments) or <code>"hsgp"</code> (a Hilbert-space basis GP with <code>m</code> functions per dimension and boundary factor <code>c</code>).
cov	Covariance function (NNGP only). One of <code>"exponential"</code> or <code>"matern"</code> .
nu	Matern smoothness parameter, one of 1.5 or 2.5. Used only when <code>cov = "matern"</code> (<code>nu = 0.5</code> is <code>cov = "exponential"</code>).
nn	Number of nearest neighbours used in the NNGP approximation.
m	Number of HSGP basis functions per dimension (<code>approx = "hsgp"</code>).
c	HSGP boundary factor, ≥ 1 (<code>approx = "hsgp"</code>).
sigma_prior_U, sigma_prior_alpha	Penalized-complexity prior on the field's marginal standard deviation (<code>approx = "hsgp"</code>), calibrated so that $P(\text{sigma} > \text{sigma_prior_U}) = \text{sigma_prior_alpha}$.

	Defaults to $P(\sigma > 1) = 0.01$. <code>sigma_prior_U</code> must be positive and <code>sigma_prior_alpha</code> must lie in $(0, 1)$.
<code>shared</code>	Whether the spatial effect is shared across processes in a multi-process model. NULL (default) shares the effect; FALSE fits process-specific effects and emits a warning.
<code>scale_coords</code>	Logical. Standardize coordinates before fitting (default TRUE).
<code>parameterization</code>	Latent parameterization for the exact-NUTS field. One of "noncentered" (default; samples $z \sim N(0, I)$ and reconstructs the field as $w = f(z, \sigma^2, \phi)$, avoiding the field/hyperparameter funnel), "centered" (places the NNGP density on the field directly), or "collapsed" (deprecated).

Value

A `tulpa_gp` object (also of class `tulpa_spatial`).

See Also

[spatial_car\(\)](#), [spatial_bym2\(\)](#) for areal spatial effects.

Examples

```
# GP spatial specification from coordinate columns
spatial_gp(~ lon + lat)
spatial_gp(~ lon + lat, cov = "matern", nu = 1.5)
```

<code>spatial_multiscale</code>	<i>Multi-Scale Gaussian Process spatial structure</i>
---------------------------------	---

Description

Specify a multi-scale spatial random effect that decomposes spatial variation into local (fine-scale) and regional (broad-scale) components. Each scale has its own range and variance parameters.

This is particularly useful for large datasets (>100k observations) where spatial patterns exist at multiple scales.

Usage

```
spatial_multiscale(
  coords,
  scales = c("local", "regional"),
  approx = c("nngp", "hsgp"),
  m = 6L,
  c_boundary = 1.5,
  range_local = c(0.01, 1),
  range_regional = c(1, 10),
```

```

cov = c("exponential", "matern"),
nu = 1.5,
nn_local = 10,
nn_regional = 30,
shared = NULL,
scale_coords = TRUE,
sampler = c("auto", "noncentered", "centered", "interweaved")
)

```

Arguments

coords	A one-sided formula specifying coordinate columns (e.g., $\sim \text{lon} + \text{lat}$), or a character vector of length 2 with column names.
scales	Character vector specifying scale names. Default: <code>c("local", "regional")</code> .
approx	Approximation method: "nngp" (default) for Nearest Neighbor GP; "hsgp" for Hilbert Space GP (faster for smooth fields).
m	Number of HSGP basis functions per dimension (default 6). Only used when <code>approx = "hsgp"</code> . Total basis functions will be m^2 .
c_boundary	Boundary factor for HSGP domain extension (default 1.5). Only used when <code>approx = "hsgp"</code> .
range_local	Plausible range interval for the local scale as <code>c(lower, upper)</code> in coordinate units. Default: <code>c(0.01, 1)</code> (after scaling). Under exact NUTS this is not a hard box: lower anchors a PC prior on that scale's range ($P(\text{range} < \text{lower}) = 0.05$, the same prior <code>spatial_gp()</code> uses), and the pair places the sampler's starting range at their geometric mean. The range itself is free on $(0, \text{Inf})$.
range_regional	Plausible range interval for the regional scale, read the same way. Default: <code>c(1, 10)</code> (after scaling). Keeping the two intervals separated is what identifies the scales against each other.
cov	Covariance function: "exponential" (default) or "matern".
nu	Smoothness parameter for Matern covariance, one of 1.5 or 2.5.
nn_local	Number of nearest neighbors for local scale. Default 10.
nn_regional	Number of nearest neighbors for regional scale. Default 30.
shared	Logical; if TRUE (default), spatial effects enter both all processes.
scale_coords	Logical; if TRUE (default), coordinates are scaled to unit variance before computing distances.
sampler	Latent parameterization for the exact-NUTS field. "auto" (default) and "noncentered" sample $z \sim N(0, I)$ per scale and reconstruct each field as $w = f(z, \sigma^2, \phi)$, avoiding the field/hyperparameter funnel; "centered" places the NNGP density on each field directly. "interweaved" alternates between parameterizations and is not implemented on the exact-NUTS path.

Details

The multi-scale model decomposes spatial variation additively:

$$\eta(s) = X\beta + w_{local}(s) + w_{regional}(s)$$

where each component follows an independent Gaussian process:

$$w_{local}(s) \sim GP(0, \sigma_{local}^2 C(\phi_{local}))$$

$$w_{regional}(s) \sim GP(0, \sigma_{regional}^2 C(\phi_{regional}))$$

Identifiability: With sufficient data (>500 locations), the two scales are typically well-identified when prior ranges are non-overlapping. PC priors on variance components help prevent overfitting.

Computational cost: Approximately 1.5-2x the cost of single-scale GP, as two NNGP likelihoods must be evaluated.

Value

A `tulpa_multiscale` object

See Also

[spatial_gp\(\)](#) for single-scale GP, [temporal_multiscale\(\)](#) for multi-scale temporal effects

Examples

```
# Create multi-scale spatial structure
ms <- spatial_multiscale(
  ~ lon + lat,
  range_local = c(0.1, 0.5),
  range_regional = c(1, 5)
)
print(ms)

set.seed(101)
n <- 25
df <- data.frame(
  lon = runif(n, 0, 10),
  lat = runif(n, 0, 10),
  depth = rnorm(n),
  temp = rnorm(n)
)
df$count <- rpois(n, exp(1 + 0.2 * df$depth))

# Both scales are sampled by exact NUTS (mode = "exact"); the field is
# returned as gp_local[i] / gp_regional[i] draws.
fit <- tulpa(
  count ~ depth + temp,
  data = df,
  family = "poisson",
  spatial = spatial_multiscale(
    ~ lon + lat,
    range_local = c(0.1, 0.5),
```



```

    range_regional = c(1, 5),
    nn_local = 5L,
    nn_regional = 8L
  ),
  mode = "exact",
  control = list(n_iter = 60L, n_warmup = 30L, seed = 1L)
)
summary(fit)

```

spatial_range

Extract spatial range and variance from a fitted spatial model

Description

Summarises the posterior of spatial hyperparameters. For sampler-tier fits this reads the raw hyperparameter draws; for a nested-Laplace spatial fit it summarises the outer hyperparameter grid. Works with ICAR, BYM2, GP (NNGP), CAR, SPDE, and SVC spatial types.

Usage

```
spatial_range(object, probs = c(0.025, 0.975))
```

Arguments

object	A <code>tulpa_fit</code> object fitted with a spatial component.
probs	Quantile probabilities for the summary (default 0.025, 0.975).

Value

A `data.frame` with rows for each spatial hyperparameter and columns mean, sd, and one quantile column per entry of `probs` (named from the probability, e.g. `q2.5`, `q97.5` for the defaults).

spatial_rsr

Restricted Spatial Regression (RSR)

Description

Apply Restricted Spatial Regression to mitigate spatial confounding. RSR orthogonalizes the spatial effect to the covariate space, preventing the spatial random effect from absorbing covariate information.

This is important when covariates are spatially smooth (e.g., climate variables, elevation) because the spatial random effect can "steal" variance from these covariates, leading to biased coefficient estimates.

Usage

```
spatial_rsr(spatial, restrict_to)
```

Arguments

spatial	A spatial specification (spatial_gp, spatial_car, etc.)
restrict_to	Formula specifying which covariates to orthogonalize against (e.g., ~ depth + temp). The spatial effect will be constrained to be orthogonal to the column space of these covariates.

Details

The RSR approach (Reich et al., 2006; Hodges & Reich, 2010) modifies the spatial random effect to be orthogonal to the fixed effect design matrix:

$$w_{RSR} = (I - P_X)w$$

where $P_X = X(X'X)^{-1}X'$ is the projection matrix onto the column space of X.

When to use RSR:

- Covariates are spatially smooth (environmental gradients)
- Interested in causal interpretation of covariate effects
- Coefficients appear attenuated toward zero

When NOT to use RSR:

- Covariates are spatially uncorrelated
- Spatial effect is the primary quantity of interest
- Prediction is the main goal (not causal inference)

Value

A modified spatial specification with RSR enabled

References

Reich, B. J., Hodges, J. S., & Zadnik, V. (2006). Effects of residual smoothing on the posterior of the fixed effects in disease-mapping models. *Biometrics*, 62(4), 1197-1206.

Hodges, J. S., & Reich, B. J. (2010). Adding spatially-correlated errors can mess up the fixed effect you love. *The American Statistician*, 64(4), 325-334.

See Also

[spatial_gp\(\)](#), [spatial_car\(\)](#)

Examples

```
# Create RSR spatial structure
rsr <- spatial_rsr(
  spatial_gp(~ lon + lat),
  restrict_to = ~ depth + temp
)
print(rsr)

# Areal binomial data on a chain of regions, covariate spatially confounded
set.seed(404)
n_regions <- 12
W <- matrix(0, n_regions, n_regions)
for (i in 1:(n_regions - 1)) W[i, i + 1] <- W[i + 1, i] <- 1
df <- data.frame(region = factor(rep(1:n_regions, each = 5)))
df$x <- as.integer(df$region) / 4 + rnorm(nrow(df), 0, 0.5)
df$y <- rbinom(nrow(df), 20, plogis(-0.5 + 0.6 * df$x))

# RSR orthogonalises the spatial field to x, protecting its coefficient
fit <- tulpa(
  y ~ x + spatial(region),
  data = df,
  family = "binomial",
  n_trials = rep(20L, nrow(df)),
  spatial = spatial_rsr(spatial_car(W, level = "obs"), restrict_to = ~ x),
  mode = "auto",
  control = list(n_iter = 500L, warmup = 250L)
)
summary(fit)
```

spatial_spde

*SPDE Spatial Field (Matern via Triangular Mesh)***Description**

Specify a continuous Matern spatial field using the SPDE approach (Lindgren, Rue & Lindstrom 2011). Builds a triangular mesh from observation coordinates, computes FEM matrices, and passes them to tulpa's SPDE Laplace engine with CHOLMOD sparse solver.

Usage

```
spatial_spde(
  coords,
  data = NULL,
  mesh = NULL,
  boundary = NULL,
  max_edge = NULL,
```

```

  cutoff = 0,
  nu = 1,
  prior_range = c(0.5, 0.5),
  prior_sigma = c(1, 0.5)
)

```

Arguments

coords	A formula $\sim x + y$ or a two-column matrix of coordinates.
data	Optional data.frame for formula evaluation.
mesh	A pre-built tulpa_mesh object. If NULL (default), a mesh is built automatically from coords.
boundary	Optional boundary: a two-column matrix of polygon vertices, an sf polygon, or NULL for convex hull with extension.
max_edge	Maximum edge length for mesh refinement. A single value or c(inner, outer).
cutoff	Minimum distance between mesh vertices. Default 0.
nu	Matern smoothness parameter. A positive number. Integer nu (1, 2, 3, ...) gives an exact FEM construction (operator order $\alpha = \text{nu} + 1$). Fractional nu (e.g. 0.5, 1.5) uses the operator-based rational SPDE approximation with BRASIL best-rational coefficients (Bolin & Kirchner 2020; Hofreither 2021); supported by the Laplace fitter fit_spde() (single-point and nested over range/sigma). NUTS and analytic marginal SEs remain integer-only. Default 1.
prior_range	Prior for the spatial range. A numeric vector c(U, alpha) where $P(\text{range} < U) = \alpha$. Default c(0.5, 0.5).
prior_sigma	Prior for the marginal standard deviation. A numeric vector c(U, alpha) where $P(\text{sigma} > U) = \alpha$. Default c(1, 0.5).

Value

A tulpa_spatial object with type "spde".

Examples

```

set.seed(42)
coords <- cbind(runif(50), runif(50))
spec <- spatial_spde(coords)
print(spec)

```

spatial_spde_custom	<i>SPDE Spatial Field from Custom Matrices</i>
---------------------	--

Description

Specify a continuous Matern spatial field using externally-provided FEM matrices. Use this with meshes from fmesh, rSPDE, or any other source.

Usage

```
spatial_spde_custom(
  C,
  G,
  A,
  nu = 1,
  prior_range = c(0.5, 0.5),
  prior_sigma = c(1, 0.5)
)
```

Arguments

C	Mass matrix (n_mesh x n_mesh sparse matrix, e.g. from <code>fmesher::fm_fem()</code> \$c0).
G	Stiffness matrix (n_mesh x n_mesh sparse matrix, e.g. from <code>fmesher::fm_fem()</code> \$g1).
A	Projection matrix (n_obs x n_mesh sparse matrix, e.g. from <code>fmesher::fm_basis()</code>).
nu	Matern smoothness parameter. A positive number; integer values give the exact FEM construction, fractional values the BRASIL rational SPDE approximation (supported by <code>fit_spde()</code>). Default 1.
prior_range	Prior for the spatial range. Default <code>c(0.5, 0.5)</code> .
prior_sigma	Prior for the marginal standard deviation. Default <code>c(1, 0.5)</code> .

Value

A `tulpa_spatial` object with type "spde".

spatial_svc	<i>Spatially varying coefficient structure</i>
-------------	--

Description

Specify a spatially varying coefficient (SVC): one or more fixed-effect coefficients are allowed to vary smoothly over space, with the variation governed by a Gaussian process (NNGP or HSGP approximation).

Usage

```
spatial_svc(
  coords,
  terms = 1,
  cov = c("exponential", "matern"),
  nn = 15,
  shared = NULL,
  scale_coords = TRUE,
  approx = c("nngp", "hsgp"),
  m = 6,
```

```

    c_boundary = 1.5,
    parameterization = c("noncentered", "centered")
)

```

Arguments

<code>coords</code>	A formula ($\sim \text{lon} + \text{lat}$) or character vector of length 2 naming the two coordinate variables in the data.
<code>terms</code>	Which coefficients vary over space. A formula, an integer vector of design-matrix column indices, or a character vector of term names. Default 1 (the intercept).
<code>cov</code>	Covariance function. One of "exponential" or "matern".
<code>nn</code>	Number of nearest neighbours used in the NNGP approximation (approx = "nngp").
<code>shared</code>	Whether the effect is shared across processes in a multi-process model. NULL (default) shares it; FALSE fits process-specific effects and emits a warning.
<code>scale_coords</code>	Logical. Standardize coordinates before fitting (default TRUE).
<code>approx</code>	Spatial approximation. "nngp" (nearest-neighbour GP) or "hsgp" (Hilbert-space GP).
<code>m</code>	Number of basis functions per dimension for the HSGP approximation (approx = "hsgp").
<code>c_boundary</code> <code>parameterization</code>	Boundary-extension factor for the HSGP domain (approx = "hsgp"). Latent parameterization for the exact-NUTS field (approx = "nngp" only; HSGP is already non-centered by construction). "noncentered" (default) samples $z_j \sim N(\emptyset, I)$ per term and reconstructs each field as $w_j = f(z_j, \sigma_{2j}, \phi_j)$, removing the field/hyperparameter funnel that otherwise attenuates the field's amplitude when it is weakly identified. "centered" places the NNGP density on each term's field directly; it is marginally cheaper on a well-identified response, but on a weakly identified one it recovers only about a third of the field's spread.

Value

A `tulpa_svc` object (also of class `tulpa_spatial`).

See Also

[spatial_gp\(\)](#) for a spatial random effect (rather than a varying coefficient).

Examples

```

# Intercept that varies smoothly over space
spatial_svc(~ lon + lat)

```

spatiotemporal

*Spatiotemporal interaction specifications for tulpa***Description**

Functions to specify spatiotemporal interaction effects for tulpa models. These capture dependencies that arise when spatial patterns vary over time, or when temporal trends differ across space.

Specify a spatiotemporal interaction effect for tulpa models. The interaction captures structured or unstructured deviation from the additive spatial + temporal model.

No tulpa backend fits an interaction term, so this constructor errors. The additive space-time model is fitted by `tulpa(spatial = , temporal = )` and by `fit_st_nested()`.

Usage

```
spatiotemporal(
  spatial,
  temporal,
  type = c("I", "II", "III", "IV", "iid", "separable"),
  shared = NULL
)
```

Arguments

<code>spatial</code>	A spatial specification from <code>spatial_car()</code> , <code>spatial_bym2()</code> , or <code>spatial_gp()</code> .
<code>temporal</code>	A temporal specification from <code>temporal_rw1()</code> , <code>temporal_rw2()</code> , <code>temporal_ar1()</code> , or <code>temporal_gp()</code> .
<code>type</code>	Interaction type: • "I" or "iid": Unstructured interaction (IID) • "II": Structured time at each location • "III": Structured space at each time point • "IV": Fully structured (Kronecker product of spatial and temporal) • "separable": Separable covariance (Kronecker product)
<code>shared</code>	Logical; if TRUE (default), spatiotemporal effect enters both all processes. Set to FALSE for process-specific effects (triggers warning about potential confounding).

Details

Spatiotemporal interactions extend the basic additive model:

$$\eta_{st} = X\beta + f_s(space) + f_t(time)$$

to include interactions:

$$\eta_{st} = X\beta + f_s(space) + f_t(time) + \delta_{st}$$

where δ_{st} captures space-time interactions.

Interaction Types (following Knorr-Held, 2000):

- **Type I:** Unstructured interaction - IID $\delta_{st} \sim N(0, \sigma^2)$
- **Type II:** Structured time, unstructured space - temporal structure at each location
- **Type III:** Structured space, unstructured time - spatial structure at each time
- **Type IV:** Structured space AND time - full Kronecker interaction

Separable Models:

- **Separable:** Covariance is Kronecker product $C_{st} = C_s \otimes C_t$
- **Non-separable:** GP with joint space-time metric

Type I (IID)

Independent random effect for each space-time combination:

$$\delta_{st} \stackrel{iid}{\sim} N(0, \sigma_\delta^2)$$

This is the simplest form, requiring S*T parameters but capturing no structured interaction.

Type II (Temporal structure per location)

Each location has its own temporal random effect:

$$\delta_{.t}^{(s)} \sim RW(\sigma^2)$$

This captures location-specific temporal trends but assumes independence across locations.

Type III (Spatial structure per time point)

Each time point has its own spatial random effect:

$$\delta_{s.}^{(t)} \sim ICAR(\tau)$$

This captures time-specific spatial patterns but assumes independence across time points.

Type IV (Full structure)

Kronecker product of spatial and temporal precision matrices:

$$Q_\delta = Q_s \otimes Q_t$$

This is the most constrained model, assuming the interaction has the same structure as the marginal effects.

Separable

For GP-based effects, assumes separable covariance:

$$C(\mathbf{s}_1, t_1; \mathbf{s}_2, t_2) = C_s(\mathbf{s}_1, \mathbf{s}_2) \cdot C_t(t_1, t_2)$$

Value

Nothing: the call always signals an error.

References

Knorr-Held, L. (2000). Bayesian modelling of inseparable space-time variation in disease risk. *Statistics in Medicine*, 19(17-18), 2555-2567.

See Also

[spatial_car\(\)](#), [spatial_gp\(\)](#), [temporal_rw1\(\)](#), [temporal_ar1\(\)](#)

spatiotemporal_effects

Extract spatiotemporal effects from fitted model

Description

Extract posterior distributions of spatiotemporal interaction effects from a fitted tulpa model.

Usage

```
spatiotemporal_effects(
  object,
  format = c("array", "long", "summary"),
  probs = c(0.025, 0.5, 0.975),
  ...
)

## S3 method for class 'tulpa_fit'
spatiotemporal_effects(
  object,
  format = c("array", "long", "summary"),
  probs = c(0.025, 0.5, 0.975),
  ...
)
```

Arguments

object	A tulpa_fit object fitted with spatiotemporal argument
format	Output format: "array" (default, S x T x draws), "long" (data frame with s, t, draw, value columns), or "summary" (posterior summaries).
probs	Quantiles to compute if format = "summary".
...	Ignored

Value

Spatiotemporal effects in requested format

Examples

```
## Not run:
# `fit` carries a Knorr-Held interaction block, which no tulpa backend
# fits: the spec comes from a model package that configures the
# interaction itself (see spatiotemporal() for what the engine does fit).
st_effects <- spatiotemporal_effects(fit, format = "summary")
head(st_effects)

## End(Not run)
```

spatiotemporal_gp	<i>Non-separable spatiotemporal GP</i>
-------------------	--

Description

Specify a non-separable Gaussian Process for spatiotemporal effects. Unlike separable models where the covariance factors as $C_s \otimes C_t$, non-separable models allow for direct space-time interaction in the covariance.

No tulpa backend fits a joint space-time covariance, so this constructor errors. A spatial GP alongside a temporal field is fitted by `tulpa(spatial = spatial_gp(...), temporal = ...)`.

Usage

```
spatiotemporal_gp(
  coords,
  time_var,
  cov_space = c("exponential", "matern", "gaussian", "spherical"),
  cov_time = c("exponential", "matern", "gaussian"),
  nonsep_type = c("product", "sum", "gneiting", "cressie_huang"),
  nn = 15,
  shared = NULL
)
```

Arguments

<code>coords</code>	A one-sided formula specifying coordinate columns (e.g., <code>~ lon + lat</code>), or a character vector of length 2.
<code>time_var</code>	Name of the time variable in data.
<code>cov_space</code>	Spatial covariance: "exponential" (default), "matern", "gaussian", or "spherical".
<code>cov_time</code>	Temporal covariance: "exponential" (default), "matern", or "gaussian".
<code>nonsep_type</code>	Non-separability type: "product": $C_{st} = C_s \cdot C_t$ (separable, for reference) "sum": $C_{st} = C_s + C_t$ "gneiting": Gneiting (2002) non-separable class

	• "cressie_huang": Cressie-Huang (1999) non-separable class
nn	Number of nearest neighbors for NNGP approximation. Default 15.
shared	Logical; if TRUE (default), effect enters both processes.

Details

The non-separable covariance functions allow for more flexible space-time dependence:

Gneiting class:

$$C(h,u) = \frac{\sigma^2}{(a|u|^{2\alpha} + 1)^\tau} \exp\left(-\frac{c\|h\|^{2\gamma}}{(a|u|^{2\alpha} + 1)^{\beta\gamma}}\right)$$

where h is spatial lag, u is temporal lag, and parameters control the space-time interaction.

Cressie-Huang class: Constructed via Fourier transform methods to ensure positive definiteness.

Value

Nothing: the call always signals an error.

References

Gneiting, T. (2002). Nonseparable, stationary covariance functions for space-time data. *Journal of the American Statistical Association*, 97(458), 590-600.

Cressie, N., & Huang, H. C. (1999). Classes of nonseparable, spatio-temporal stationary covariance functions. *Journal of the American Statistical Association*, 94(448), 1330-1340.

summary.tulpa_fit	<i>Posterior summary of the fixed effects</i>
-------------------	---

Description

Posterior summary of the fixed effects

Usage

```
## S3 method for class 'tulpa_fit'
summary(object, level = 0.95, ...)
```

Arguments

object	A tulpa_fit object.
level	Credible-interval level (default 0.95).
...	Ignored.

Value

Data frame: estimate, std.error, and lower/upper credible bounds, one row per fixed effect. Sampler tiers report empirical quantiles; the Laplace tier reports the Gaussian approximation.

On a nested-Laplace fit the estimate and standard error are the hyperparameter-grid-marginalized moments, and the bounds invert the Gaussian mixture $\sum_k w_k N(\mu_{kj}, V_{kjj})$ that grid defines, rather than reading $\mu \pm z \sigma$ off the single Gaussian matching those moments. An `interval_source` attribute records which read produced them ("`mixture_cdf`", "`gaussian_moment`", "`skew_map_cell`", or "`skew_map_cell/mixture_cdf`" when the two are in play on different coefficients) and `interval_declined` says why, whenever the mixture read did not run. A `retained_mass` attribute gives the share of the grid weight whose cells retained a fixed-effect block: 1 on a complete grid, and below 1 on one that dropped a positive-weight cell, whose report is then the posterior conditional on the cells that remain.

Where no per-cell block was retained the estimate falls back to the grid-weighted average of the per-cell modes, restricted to the cells whose inner solve reached a mode. A fit where none did reports NA with `interval_declined = "not_converged"`, rather than the vector its Newton started from as an estimate.

With `control$skew_correct = TRUE` a coefficient whose inner-Laplace `gamma_3` is in the band it is valid on reports Cornish-Fisher quantiles instead, and a `skew_applied` attribute names which coefficients took the correction. That correction is measured at the MAP cell, so it is reported on its own and is not composed with the mixture read; a coefficient it declines keeps the mixture read rather than falling back further.

An `axis_fields_dropped` attribute carries the grid axes the fit's own resolved path could not read, one row per dropped field (block, type, field, path, integrates, reason). It is NULL whenever every supplied axis was used, which is the ordinary case; `diagnostic_summary()` reads the same record in sentences.

A `beta_prior` attribute carries the Gaussian fixed-effect prior the fit ran under, as `list(mean, sd)`. It is the engine default, `prior_normal(0, 2.5)`, whenever the caller supplied none, and NULL on the paths that express no Gaussian prior on the fixed effects.

```
summary.tulpa_svc_posterior
```

Summary method for tulpa_svc_posterior

Description

Summary method for tulpa_svc_posterior

Usage

```
## S3 method for class 'tulpa_svc_posterior'
summary(object, probs = c(0.025, 0.5, 0.975), ...)
```

Arguments

object	A tulpa_svc_posterior object
probs	Quantiles to compute
...	Ignored

Value

A tulpa_svc_summary data frame with one row per location and term, holding the observation index, term name, coordinates, and the posterior mean, SD, and requested quantiles of each spatially-varying coefficient.

```
summary.tulpa_temporal_posterior
```

Summary method for tulpa_temporal_posterior

Description

Summary method for tulpa_temporal_posterior

Usage

```
## S3 method for class 'tulpa_temporal_posterior'  
summary(object, probs = c(0.025, 0.5, 0.975), ...)
```

Arguments

object	A tulpa_temporal_posterior object
probs	Quantiles to compute
...	Ignored

Value

A tulpa_temporal_summary data frame with one row per time point (per component for multi-scale fits), holding the posterior mean, SD, and requested quantiles of the temporal effect.

```
summary.tulpa_tvc_posterior
```

Summary method for tulpa_tvc_posterior

Description

Summary method for tulpa_tvc_posterior

Usage

```
## S3 method for class 'tulpa_tvc_posterior'
summary(object, probs = c(0.025, 0.5, 0.975), ...)
```

Arguments

object	A tulpa_tvc_posterior object
probs	Quantiles to compute
...	Ignored

Value

A tulpa_tvc_summary data frame with one row per time point and term, holding the posterior mean, SD, and requested quantiles of each temporally-varying coefficient.

```
svc
```

Extract spatially-varying coefficients from a fitted model

Description

Extract posterior distributions of spatially-varying coefficients (SVCs) from a fitted tulpa model with SVC specification.

Usage

```
svc(object, terms = NULL, summary = FALSE, probs = c(0.025, 0.5, 0.975), ...)
```

```
## S3 method for class 'tulpa_fit'
svc(object, terms = NULL, summary = FALSE, probs = c(0.025, 0.5, 0.975), ...)
```

Arguments

object	A tulpa_fit object fitted with svc argument
terms	Which SVC terms to extract. If NULL (default), extracts all.
summary	Logical; if TRUE, return summary statistics instead of full posterior draws.
probs	Quantiles to compute if summary = TRUE.
...	Ignored

Value

A `tulpa_svc_posterior` object containing:

- `draws`: Array of posterior draws (draws x locations x terms)
- `coords`: Coordinate matrix
- `term_names`: Names of SVC terms

See Also

[spatial_svc\(\)](#), [plot.tulpa_svc_posterior\(\)](#)

Examples

```
set.seed(303)
n <- 25L
df <- data.frame(lon = runif(n), lat = runif(n), x = rnorm(n))
bsurf <- 0.9 * sin(2.8 * df$lon) + 0.7 * cos(2.2 * df$lat)
df$count <- rpois(n, exp(0.2 + (0.8 + bsurf) * df$x))

# The varying slope on `x` is a spatial field; SVC is exact-mode only.
fit <- tulpa(
  count ~ x,
  data = df,
  family = "poisson",
  spatial = spatial_svc(~ lon + lat, terms = ~ x - 1, nn = 5L),
  mode = "exact",
  control = list(n_iter = 80L, n_warmup = 40L, seed = 1L)
)

svc_post <- svc(fit)
summary(svc_post)
```

temporal

Extract temporal effects from a fitted model

Description

Extract posterior distributions of temporal effects from a fitted tulpa model with temporal specification.

Usage

```
temporal(
  object,
  component = "all",
  summary = FALSE,
```

```

    probs = c(0.025, 0.5, 0.975),
    ...
)

## S3 method for class 'tulpa_fit'
temporal(
  object,
  component = "all",
  summary = FALSE,
  probs = c(0.025, 0.5, 0.975),
  ...
)

```

Arguments

<code>object</code>	A <code>tulpa_fit</code> object fitted with <code>temporal</code> argument
<code>component</code>	Which component to extract for multi-scale models: "all" (default), "trend", "seasonal", or "short_term".
<code>summary</code>	Logical; if TRUE, return summary statistics instead of full posterior draws.
<code>probs</code>	Quantiles to compute if <code>summary = TRUE</code> .
<code>...</code>	Ignored

Details

`temporal()` is overloaded. Given a fitted model it is the accessor described here. Given a one-sided formula (or a named `formula = / structure =` argument) it is instead the inline varying-coefficient field constructor used in a `tulpa()` model formula, the temporal mirror of `spatial()`: `temporal(formula = ~ 1 + x || time, structure = "rw1")` declares a smooth temporal level (the intercept column) plus a temporally varying slope on each covariate column. `structure` is one of "rw1" (default), "rw2", or "ar1"; only the double bar `||` (independent fields) is supported.

Value

A `tulpa_temporal_posterior` object

See Also

[temporal_multiscale\(\)](#), [temporal_rw1\(\)](#)

Examples

```

set.seed(131)
df <- data.frame(year = 1:40, x = rnorm(40))
df$count <- rpois(40, exp(1 + 0.2 * df$x))

fit <- tulpa(
  count ~ x,
  data = df,
  family = "poisson",

```



```

temporal = temporal_multiscale("year", trend = "rw2", seasonal = 12),
mode = "exact",
control = list(n_iter = 200L, n_warmup = 100L, seed = 1L)
)

# Extract all temporal effects
temp_post <- temporal(fit)
summary(temp_post)

```

temporal_ar	<i>AR(p) temporal latent field (general-order autoregressive)</i>
-------------	---

Description

A stationary autoregressive process of order p , $w_t = \sum_{j=1}^p \phi_j w_{t-j} + \varepsilon_t$, as a user-defined GMRF latent block for a model formula via `latent(temporal_ar(...))` – the general-order extension of `temporal_ar2()`, sharing the same construction: the precision is the exact stationary AR(p) GMRF (the banded inverse of the Yule-Walker Toeplitz autocovariance), and stationarity is enforced by the partial-autocorrelation parameterization (Levinson-Durbin map of p unconstrained `atanh_psi` hyperparameters), so the hyperparameter integration never leaves the stationary region.

The block's hyperparameters are `log_tau` (log innovation precision) and `atanh_psi1..atanh_psi<p>`; the AR coefficients are recovered through `psi_j = tanh(atanh_psi_j)` and the Levinson-Durbin recursion. Note the outer integration cost grows with the hyperparameter count $p + 1$; orders beyond 3-4 are better served by a sampler tier.

Usage

```

temporal_ar(
  time_idx,
  p = 2L,
  n_times = NULL,
  prior_tau_sd = 2,
  prior_psi_sd = 1.5,
  name = NULL
)

```

Arguments

<code>time_idx</code>	Integer vector (1-based) of the time point for each observation.
<code>p</code>	Autoregressive order (≥ 1).
<code>n_times</code>	Number of distinct time points; defaults to <code>max(time_idx)</code> .
<code>prior_tau_sd, prior_psi_sd</code>	Prior SDs for <code>log_tau</code> and the <code>atanh_psi</code> hyperparameters (weakly-informative Gaussian). Defaults 2 / 1.5.
<code>name</code>	Optional block label (default <code>ar<p></code>).

Value

A `tgmrf` / `tulpa_latent_block` object.

See Also

`temporal_ar2()` (the $p = 2$ shorthand), `temporal_ar1()` for the first-order formula-integrated process, `tgmrf()` for the general user-defined GMRF interface.

Examples

```
set.seed(1)
Tt <- 150L
w <- numeric(Tt); w[1:3] <- rnorm(3)
for (t in 4:Tt) w[t] <- 0.4 * w[t-1] + 0.2 * w[t-2] - 0.2 * w[t-3] + rnorm(1, 0, 0.4)
d <- data.frame(t = seq_len(Tt), y = w + rnorm(Tt, 0, 0.3))
fit <- tulpa(y ~ latent(temporal_ar(d$t, p = 3)), data = d,
             family = "gaussian", mode = "nested_laplace")
```

<code>temporal_ar1</code>	<i>AR1 temporal structure (First-order Autoregressive)</i>
---------------------------	--

Description

Specify a first-order autoregressive temporal random effect. AR1 models temporal correlation where each time point depends on the previous one: $\phi[t] = \rho * \phi[t-1] + \epsilon[t]$.

Unlike RW1/RW2, AR1 is a proper (stationary) model with an estimated autocorrelation parameter ρ .

Usage

```
temporal_ar1(time_var, group_var = NULL, shared = NULL, rho_prior = NULL)
```

Arguments

<code>time_var</code>	A formula ($\sim$ time) or single character string naming the time variable in the data.
<code>group_var</code>	Optional formula ($\sim$ g) or character string naming a grouping variable. When supplied, a separate random walk is fit per group; NULL (default) fits a single walk shared across all observations.
<code>shared</code>	Whether the temporal effect is shared across processes in a multi-process model. NULL (default) shares the effect; FALSE fits process-specific effects and emits a warning about unshared confounding.
<code>rho_prior</code>	Prior for the AR(1) autocorrelation. Default NULL is a Uniform(-1, 1) prior. Supply a <code>prior_beta(alpha, beta)</code> to place a Beta(alpha, beta) prior on $u = (\rho + 1)/2$ for a more informative prior (e.g. <code>prior_beta(5, 2)</code> favours positive autocorrelation). Honoured on both the exact-sampler and nested-Laplace paths.

Details

The AR1 process has marginal variance $\sigma^2 / (1 - \rho^2)$ and correlation between time points t and s of $\rho^{|t-s|}$.

The precision matrix is tridiagonal and full rank, so no constraints are needed.

Value

A tulpa_temporal object

Examples

```
# Create temporal AR1 specification
temporal_ar1("year")
temporal_ar1("year", group = "site")

# AR1 temporal correlation
set.seed(127)
df <- data.frame(
  year = rep(1:20, each = 3),
  x = rnorm(60)
)
f <- as.numeric(arima.sim(list(ar = 0.7), 20, sd = 0.4))
df$count <- rpois(60, exp(1 + 0.3 * df$x + f[df$year]))

fit <- tulpa(
  count ~ x,
  data = df,
  family = "poisson",
  temporal = temporal_ar1("year"),
  mode = "auto"
)
summary(fit)
```

temporal_ar2

AR(2) temporal latent field (second-order autoregressive)

Description

A stationary second-order autoregressive process $w_t = \phi_1 w_{t-1} + \phi_2 w_{t-2} + \varepsilon_t$ as a user-defined GMRF latent block, for use in a model formula via `latent(temporal_ar2(...))`. It reuses tulpa's nested-Laplace / NUTS machinery (no dedicated C++ kernel). The precision is the exact stationary AR(2) GMRF; stationarity is enforced by the PACF parameterization, so the hyperparameter grid never leaves the stationarity region.

The block's hyperparameters are `log_tau` (log innovation precision) and `atanh_psi1`, `atanh_psi2` (unconstrained partial autocorrelations); the AR coefficients are recovered as `phi2 = tanh(atanh_psi2)`, `phi1 = tanh(atanh_psi1) (1 - phi2)`.

Usage

```
temporal_ar2(
  time_idx,
  n_times = NULL,
  prior_tau_sd = 2,
  prior_psi_sd = 1.5,
  name = "ar2"
)
```

Arguments

<code>time_idx</code>	Integer vector (1-based) of the time point for each observation.
<code>n_times</code>	Number of distinct time points; defaults to <code>max(time_idx)</code> .
<code>prior_tau_sd, prior_psi_sd</code>	Prior SDs for <code>log_tau</code> and the two <code>atanh_psi</code> hyperparameters (weakly-informative Gaussian). Defaults 2 / 1.5.
<code>name</code>	Optional block label.

Value

A `tgmrf` / `tulpa_latent_block` object.

See Also

[temporal_ar1\(\)](#) for the first-order (formula-integrated) process; [tgmrf\(\)](#) for the general user-defined GMRF interface.

Examples

```
set.seed(1)
Tt <- 120L
w <- numeric(Tt); w[1:2] <- rnorm(2)
for (t in 3:Tt) w[t] <- 0.5 * w[t-1] + 0.3 * w[t-2] + rnorm(1, 0, 0.4)
d <- data.frame(t = seq_len(Tt), y = w + rnorm(Tt, 0, 0.3))
fit <- tulpa(y ~ latent(temporal_ar2(d$t)), data = d, family = "gaussian",
             mode = "nested_laplace")
```

temporal_corr

Extract temporal correlation parameters from a fitted model

Description

Returns posterior summary for temporal hyperparameters (`tau`, `rho` for AR1, `sigma`/lengthscale for temporal GP).

Usage

```
temporal_corr(object, probs = c(0.025, 0.975))
```

Arguments

object	A tulpa_fit object fitted with a temporal component.
probs	Quantile probabilities (default 0.025, 0.975).

Value

A data.frame with rows for each temporal hyperparameter.

temporal_gp	<i>Gaussian Process temporal structure</i>
-------------	--

Description

Specify a Gaussian Process (GP) temporal random effect for irregularly-spaced or continuous time points. Unlike RW1/RW2/AR1 which assume equally-spaced observations, GP temporal effects model correlation as a function of time distance.

This is particularly useful for:

- Irregularly-spaced time series
- Continuous time (e.g., exact timestamps)
- Smooth temporal trends with uncertainty

Usage

```
temporal_gp(
  time_var,
  cov = c("exponential", "matern", "gaussian", "periodic"),
  nu = 1.5,
  period = NULL,
  group_var = NULL,
  shared = NULL,
  scale_coords = TRUE,
  parameterization = c("noncentered", "centered")
)
```

Arguments

time_var	Name of the time variable in data. Can be a formula (e.g., ~ year) or a character string (e.g., "year"). Should be numeric (continuous time) or convertible to numeric.
cov	Covariance function: "exponential" (default, rough), "matern" (tunable smoothness), "gaussian" (very smooth), or "periodic" (for seasonal patterns).

nu	Smoothness parameter for Matern covariance, one of: • 0.5: equivalent to exponential (rough) • 1.5: once differentiable (moderate smoothness) • 2.5: twice differentiable (smooth) These are the smoothnesses with a closed form; anything between them needs a Bessel function of the second kind and is rejected. Ignored for non-Matern covariance functions.
period	Period for periodic covariance (e.g., 12 for monthly, 365 for daily data with annual cycle). Only used when cov = "periodic".
group_var	Optional name of grouping variable for panel data. If provided, separate GPs are estimated for each group.
shared	Logical; if TRUE (default), temporal effect enters both all processes.
scale_coords	Logical; if TRUE (default), time values are scaled to unit variance before computing distances.
parameterization	Parameterization for GP effects: "noncentered" (default) stores $z \sim N(0,1)$ and scales by covariance (better for weakly-informed effects); "centered" stores effects directly (better for strongly-informed effects).

Details

The GP temporal model adds a time-correlated random effect:

$$\eta(t) = X\beta + f(t)$$

where $f(t)$ follows a Gaussian process:

$$f(t) \sim GP(0, \sigma^2 C(|t - t'|; \phi))$$

The correlation function $C(d; \phi)$ depends on time distance d :

- **Exponential:** $C(d) = \exp(-d/\phi)$ - continuous but not differentiable
- **Matern:** Smooth with tunable roughness via ν
- **Gaussian:** $C(d) = \exp(-(d/\phi)^2)$ - infinitely differentiable
- **Periodic:** $C(d) = \exp(-2 \sin^2(\pi d/p)/\phi^2)$ - for seasonal data

Implementation: the exponential kernel (equivalently Matern with $\nu = 0.5$) is an Ornstein-Uhlenbeck process, so its joint density factorizes into a first-order Markov chain and evaluates in $O(T)$ with no matrix. The other kernels have no finite-dimensional state-space form and are evaluated from a dense $T \times T$ Cholesky, where T is the number of distinct time points.

The field is fit on the sampler path: its two hyperparameters (`log_sigma2_temporal_gp`, `logit_phi_temporal_gp`) are sampled jointly with the field and the fixed effects, so pass a sampler mode such as `mode = "hmc"`. There is no nested-Laplace kernel for it.

Value

A `tulpa_temporal_gp` object

See Also

[temporal_rw1\(\)](#), [temporal_ar1\(\)](#) for equally-spaced temporal effects, [spatial_gp\(\)](#) for spatial GP effects

Examples

```
# Create GP temporal specification
temporal_gp("timestamp")
temporal_gp("day", cov = "matern", nu = 1.5)
temporal_gp("month", cov = "periodic", period = 12)

# Irregularly-spaced time series
set.seed(140)
times <- sort(runif(40, 0, 10))
df <- data.frame(
  time = times,
  x = rnorm(40),
  y = rbinom(40, 1, 0.5)
)

fit <- tulpa(
  y ~ x,
  data = df,
  family = "binomial",
  temporal = temporal_gp("time"),
  mode = "hmc",
  control = list(n_iter = 200, warmup = 100, n_chains = 1)
)
```

temporal_multiscale *Multi-scale temporal structure*

Description

Specify a temporal random effect that decomposes variation into separate scales: a smooth trend, an optional seasonal cycle, and a short-term component. Each scale uses its own prior, letting slow and fast dynamics be modelled jointly.

Usage

```
temporal_multiscale(
  time_var,
  trend = c("rw2", "rw1", "none"),
  seasonal = NULL,
  short_term = c("ar1", "iid", "none"),
  group_var = NULL,
```

```
    shared = NULL
  )
```

Arguments

time_var	Single character string naming the time variable in the data.
trend	Prior for the smooth long-term trend. One of "rw2", "rw1", or "none".
seasonal	Optional integer period (≥ 2) of a seasonal cycle, e.g. 12 for monthly data with an annual cycle. NULL (default) omits the seasonal component.
short_term	Prior for the short-term component. One of "ar1", "iid", or "none".
group_var	Optional character string naming a grouping variable for group-specific temporal effects.
shared	Whether the effect is shared across processes in a multi-process model. NULL (default) shares it; FALSE fits process-specific effects and emits a warning.

Details

At least one of trend, seasonal, or short_term must be active.

Value

A tulpa_temporal_multiscale object.

See Also

[temporal_rw1\(\)](#), [temporal_rw2\(\)](#), [temporal_ar1\(\)](#) for single-scale temporal priors.

Examples

```
# Trend + annual seasonal cycle + AR1 short-term component on monthly data
temporal_multiscale("month", trend = "rw2", seasonal = 12, short_term = "ar1")
```

temporal_rtr	<i>Restricted temporal regression (RTR)</i>
--------------	---

Description

The temporal analogue of [spatial_rsr\(\)](#): constrain a temporal random effect to be orthogonal to a set of covariates, so a temporally smooth covariate does not have its fixed-effect coefficient attenuated by a confounded temporal field, $u_{RTR} = (I - P_X)u$.

No tulpa backend applies that projection to a temporal field, so this constructor errors rather than returning a specification that would fit as the unrestricted temporal model. [spatial_rsr\(\)](#) is the wired spatial analogue.

Usage

```
temporal_rtr(temporal, restrict_to)
```

Arguments

`temporal` A tulpa_temporal specification (e.g. [temporal_rw1\(\)](#), [temporal_ar1\(\)](#)).
`restrict_to` A one-sided formula giving the covariate space the temporal effect is made orthogonal to, e.g. $\sim x$.

Value

Nothing: the call always signals an error.

See Also

[spatial_rsr\(\)](#), [temporal_rw1\(\)](#), [temporal_ar1\(\)](#)

temporal_rw1	<i>RW1 temporal structure (First-order Random Walk)</i>
--------------	---

Description

Specify a first-order random walk temporal random effect. RW1 penalizes first differences, so adjacent time points are smoothed toward each other: $\phi[t] - \phi[t-1] \sim N(0, \sigma^2)$.

Usage

```
temporal_rw1(time_var, group_var = NULL, cyclic = FALSE, shared = NULL)
```

Arguments

`time_var` A formula ($\sim \text{time}$) or single character string naming the time variable in the data.
`group_var` Optional formula ($\sim g$) or character string naming a grouping variable. When supplied, a separate random walk is fit per group; NULL (default) fits a single walk shared across all observations.
`cyclic` Logical. If TRUE, the random walk wraps around so the last time point is a neighbour of the first (cyclic boundary, e.g. month of year). Default FALSE.
`shared` Whether the temporal effect is shared across processes in a multi-process model. NULL (default) shares the effect; FALSE fits process-specific effects and emits a warning about unshared confounding.

Details

The precision matrix is rank $T - 1$ (one constraint needed). RW1 is the least smooth of the random-walk priors; for smoother trends see [temporal_rw2\(\)](#), and for a stationary alternative see [temporal_ar1\(\)](#).

Value

A tulpa_temporal object.

See Also

[temporal_rw2\(\)](#), [temporal_ar1\(\)](#) for other temporal priors.

Examples

```
# Create temporal RW1 specification
temporal_rw1("year")
temporal_rw1("month", cyclic = TRUE)
```

temporal_rw2	<i>RW2 temporal structure (Second-order Random Walk)</i>
--------------	--

Description

Specify a second-order random walk temporal random effect. RW2 penalizes deviations from linearity, resulting in smoother trends than RW1: $\phi[t] - 2\phi[t-1] + \phi[t-2] \sim N(0, \sigma^2)$.

Usage

```
temporal_rw2(time_var, group_var = NULL, cyclic = FALSE, shared = NULL)
```

Arguments

time_var	A formula (~ time) or single character string naming the time variable in the data.
group_var	Optional formula (~ g) or character string naming a grouping variable. When supplied, a separate random walk is fit per group; NULL (default) fits a single walk shared across all observations.
cyclic	Logical. If TRUE, the random walk wraps around so the last time point is a neighbour of the first (cyclic boundary, e.g. month of year). Default FALSE.
shared	Whether the temporal effect is shared across processes in a multi-process model. NULL (default) shares the effect; FALSE fits process-specific effects and emits a warning about unshared confounding.

Details

RW2 produces smoother curves than RW1 because it penalizes the second derivative (curvature) rather than the first derivative (slope). It requires at least 3 time points.
The precision matrix is rank T-2 (two constraints needed).

Value

A tulpa_temporal object

Examples

```
# Create temporal RW2 specification
temporal_rw2("year")

# Smooth temporal trend
set.seed(126)
df <- data.frame(
  year = rep(1:20, each = 4),
  x = rnorm(80)
)
trend <- sin(seq(0, 2, length.out = 20))
df$count <- rpois(80, exp(1 + 0.3 * df$x + trend[df$year]))

fit <- tulpa(
  count ~ x,
  data = df,
  family = "poisson",
  temporal = temporal_rw2("year"),
  mode = "auto"
)
summary(fit)
```

temporal_tvc

Time-varying coefficient structure

Description

Specify a time-varying coefficient (TVC): one or more fixed-effect coefficients are allowed to evolve over time, with the evolution governed by a temporal prior (rw1, rw2, ar1, or a GP).

Usage

```
temporal_tvc(
  time_var,
  terms = 1,
  structure = c("rw1", "rw2", "ar1", "gp"),
  group_var = NULL,
  shared = NULL,
  sigma_prior_U = 1,
  sigma_prior_alpha = 0.01
)
```

Arguments

time_var	Single character string naming the time variable in the data.
terms	Which coefficients vary over time. A formula, an integer vector of design-matrix column indices, or a character vector of term names. Default 1 (the intercept).
structure	Temporal prior governing how the coefficients evolve. One of "rw1", "rw2", "ar1", or "gp".
group_var	Optional character string naming a grouping variable for group-specific time-varying coefficients.
shared	Whether the effect is shared across processes in a multi-process model. NULL (default) shares it; FALSE fits process-specific effects and emits a warning.
sigma_prior_U, sigma_prior_alpha	Penalized-complexity prior on each varying coefficient's marginal standard deviation, calibrated so that $P(\text{sigma} > \text{sigma_prior_U}) = \text{sigma_prior_alpha}$. Defaults to $P(\text{sigma} > 1) = 0.01$. sigma_prior_U must be positive and sigma_prior_alpha must lie in $(0, 1)$.

Value

A tulpa_tvc object.

See Also

[temporal_rw1\(\)](#), [temporal_rw2\(\)](#), [temporal_ar1\(\)](#) for the underlying temporal priors.

Examples

```
# Intercept that drifts as a first-order random walk over year
temporal_tvc("year", structure = "rw1")
```

test_dispersion	<i>Test for over- or underdispersion</i>
-----------------	--

Description

Compares the variance of observed data to the variance expected under the fitted model (via simulation). Ratio > 1 = overdispersion; < 1 = underdispersion. Equivalent to DHARMA::testDispersion().

Usage

```
test_dispersion(object, ...)
```

```
## Default S3 method:
test_dispersion(
  object,
  observed = NULL,
```

```

    nsim = 250L,
    seed = 123L,
    alternative = c("two.sided", "greater", "less"),
    ...
  )

```

Arguments

object	A fitted model with simulate() method
...	Passed to methods.
observed	Observed response vector (optional – extracted from fit)
nsim	Number of simulations (default 250)
seed	Random seed (default 123)
alternative	"two.sided", "greater", or "less"

Value

An htest object with dispersion ratio and p-value

test_outliers	<i>Test for outliers (simulation envelope)</i>
---------------	--

Description

Counts how many observations fall outside the min-to-max range of all simulations. Under a correct model, the expected number is approximately $2 * N / (nsim + 1)$. Equivalent to DHARMA::testOutliers().

Usage

```

test_outliers(object, ...)

## Default S3 method:
test_outliers(object, observed = NULL, nsim = 250L, seed = 123L, ...)

```

Arguments

object	A fitted model with simulate() method
...	Passed to methods.
observed	Observed response vector (optional)
nsim	Number of simulations (default 250)
seed	Random seed (default 123)

Value

An htest object (binomial test)

test_uniformity	<i>Test uniformity of PIT residuals</i>
-----------------	---

Description

If the model is correct, PIT residuals should follow Uniform(0, 1). Applies a Kolmogorov-Smirnov test against that null. Equivalent to `DHARMA::testUniformity()`.

Usage

```
test_uniformity(
  object,
  observed = NULL,
  nsim = 250L,
  seed = 123L,
  plot = FALSE
)
```

Arguments

object	A fitted model, a numeric vector of PIT residuals, or a matrix of simulations
observed	Observed data (if object is simulations matrix)
nsim	Number of simulations (default 250)
seed	Random seed (default 123)
plot	If TRUE, draws a QQ plot

Value

An `htest` object (KS test result)

test_zero_inflation	<i>Test for zero inflation</i>
---------------------	--------------------------------

Description

Compares the number of zeros in observed data to the distribution expected under the fitted model. Equivalent to `DHARMA::testZeroInflation()`.

Usage

```
test_zero_inflation(object, ...)

## Default S3 method:
test_zero_inflation(object, observed = NULL, nsim = 250L, seed = 123L, ...)
```

Arguments

object	A fitted model with <code>simulate()</code> method
...	Passed to methods.
observed	Observed response vector (optional)
nsim	Number of simulations (default 250)
seed	Random seed (default 123)

Value

An `htest` object with zero-inflation ratio and p-value

tgmrf	<i>User-defined GMRF latent block</i>
-------	---------------------------------------

Description

`tgmrf()` lets a user define a Gaussian Markov random field as a latent block in a tulpa model by supplying two R closures: a precision-matrix factory `Q(theta)` and a log-prior on `theta` `prior(theta)`. The resulting object plugs into a formula via `latent(tgmrf(...))` and is consumed by every tulpa inference tier (Laplace, EM+Laplace, VI, nested_laplace+CCD, NUTS, IMH-Laplace).

This is the latent-side dual of `LikelihoodSpec`. `LikelihoodSpec` lets a model package own the observation model; `tgmrf()` lets a script own a single latent block.

Usage

```
tgmrf(
  Q,
  prior,
  init,
  mu = NULL,
  graph = NULL,
  bounds = NULL,
  obs_idx = NULL,
  name = NULL
)
```

Arguments

Q	A function <code>function(theta)</code> returning a sparse precision matrix of class <code>Matrix::sparseMatrix</code> (typically <code>dgCMatrix</code>). The matrix must be square and symmetric. Called once at registration with <code>theta = init</code> to infer <code>n_latent</code> and capture the sparsity pattern.
prior	A function <code>function(theta)</code> returning a finite numeric scalar – the log-prior density at <code>theta</code> .

<code>init</code>	Numeric vector of starting values for <code>theta</code> . Names, if present, become the canonical <code>theta</code> names.
<code>mu</code>	Optional function <code>function(theta)</code> returning a numeric vector of length <code>n_latent</code> . Default <code>NULL</code> is equivalent to a zero mean.
<code>graph</code>	Optional sparse matrix specifying the upper bound on <code>Q</code> 's sparsity pattern. If supplied, the registration check verifies that the nonzero pattern of <code>Q(init)</code> is a subset.
<code>bounds</code>	Optional list with components <code>lower</code> and <code>upper</code> , each a numeric vector of length <code>length(init)</code> . Used by <code>nested_laplace + CCD</code> to build the outer grid; unused by <code>NUTS / VI</code> .
<code>obs_idx</code>	Optional integer vector mapping each observation to a latent slot in <code>[1, n_latent]</code> . If <code>NULL</code> (default), the fit-time driver assumes <code>N == n_latent</code> and uses <code>seq_len(N)</code> – i.e. one observation per latent slot, in row order.
<code>name</code>	Optional character; cosmetic label used by <code>print()</code> / <code>summary()</code> .

Details

For a Gaussian latent block $z \sim N(\mu(\theta), Q(\theta)^{-1})$:

$$\log p(z \mid \theta) = \frac{1}{2} \log \det Q(\theta) - \frac{1}{2} (z - \mu(\theta))^T Q(\theta) (z - \mu(\theta)) + \text{const}$$

the gradient $-Q(z - \mu)$ and Hessian $-Q$ wrt z are closed form, so the user never writes gradient code. The Laplace inner step needs only `Q(theta)` and `mu(theta)` at numeric `theta`. `NUTS` and `VI` additionally use a forward finite-difference gradient on `theta`, costing `dim(theta)` extra `Q` calls per outer step – cheap for the typical `dim(theta) <= 5`.

Value

An object of class `c("tgmrf", "tulpa_latent_block")` with components:

- `Q`, `prior`, `mu` – the user closures (or `NULL` for `mu`).
- `init`, `theta_names`, `theta_dim` – hyperparameter metadata.
- `n_latent` – inferred from `Q(init)`.
- `pattern` – captured sparsity pattern as a `dgCMatrix` of `1`s.
- `graph` – user-supplied pattern, validated against `pattern` if given.
- `bounds`, `name` – passed through.

See Also

[latent\(\)](#) for the formula slot that consumes a `tgmrf` block.

Examples

```
# Periodic AR(1) block, wrap-around tridiagonal precision.
periodic_ar1 <- function(n) {
  tgmrfr(
    Q = function(theta) {
      sigma <- exp(theta[1]); rho <- tanh(theta[2])
      d <- rep((1 + rho^2) / sigma^2, n)
      o <- rep(-rho / sigma^2, n)
      M <- Matrix::bandSparse(
        n, k = c(-1, 0, 1), diagonals = list(o, d, o)
      )
      M[1, n] <- M[n, 1] <- -rho / sigma^2
      methods::as(M, "CsparseMatrix")
    },
    prior = function(theta) {
      stats::dnorm(theta[1], 0, 1, log = TRUE) +
      stats::dnorm(theta[2], 0, 1, log = TRUE)
    },
    init = c(log_sigma = 0, atanh_rho = 0),
    name = "periodic_ar1"
  )
}

blk <- periodic_ar1(20)
print(blk)
```

tgmrf_cpp

User-defined GMRF latent block, compiled C++ backend

Description

`tgmrf_cpp()` is the compiled-C++ analogue of `tgmrf()`. Where `tgmrf()` takes R closures `Q(theta)` / `prior(theta)`, `tgmrf_cpp()` takes a user-written `.cpp` file that defines the same kernels as templated C++ (so the same source compiles against every AD type tulpa uses). The returned object has the same S3 class as `tgmrf()` – `c("tgmrf", "tulpa_latent_block")` – so every downstream consumer (formula parser, inference layers, S3 methods) treats the two paths identically. Only the dispatch on `Q(theta)` differs: registry-stored function pointer (`tgmrf_cpp()`) vs `Rcpp::Function` callback (`tgmrf()`).

The user `.cpp` file must include `<tulpa/tgmrf.h>` and call the `TULPA_REGISTER_TGMRF(id, Q_fn, mu_fn, log_prior_fn)` macro once. See `inst/examples/tgmrf_periodic_ar1.cpp` for a worked example.

Usage

```
tgmrf_cpp(
  cpp_file,
  id,
```

```

    init,
    mu = NULL,
    graph = NULL,
    bounds = NULL,
    obs_idx = NULL,
    name = NULL,
    cache_dir = tulpa_cache_dir(),
    rebuild = FALSE
  )

```

Arguments

cpp_file	Absolute path to the user's .cpp file. The file is compiled via <code>Rcpp::sourceCpp()</code> with caching keyed on <code>digest::sha256(file_contents) + TULPA_ABI_VERSION</code> so repeated calls with an unchanged source skip the rebuild.
id	Character: the stable id used as the registry key. Must match the first argument of <code>TULPA_REGISTER_TGMRF</code> in the user's .cpp.
init, mu, graph, bounds, obs_idx, name	Same arguments as <code>tgmrf()</code> . <code>init</code> is required and supplies the canonical theta names. <code>mu</code> is currently ignored on the C++ path – the <code>mu</code> kernel registered by <code>TULPA_REGISTER_TGMRF</code> is the source of truth; pass the argument here only to keep call sites symmetric with <code>tgmrf()</code> .
cache_dir	Directory for <code>Rcpp</code> 's <code>sourceCpp</code> cache. Defaults to a per-user location under <code>tools::R_user_dir("tulpa", "cache")</code> .
rebuild	Force a recompile even if the cached DLL is up to date. Default <code>FALSE</code> .

Value

An object of class `c("tgmrf", "tulpa_latent_block")` with the same fields as `tgmrf()` plus `backend = "cpp"` and `cpp_id = id`. The `Q / prior` fields are R wrapper closures around the registered C++ kernels, so callers (e.g. NUTS-over-theta) that hold the object can still call `block$Q(theta)` directly.

See Also

`tgmrf()` for the R-closure path; `latent()` for the formula slot that consumes a `tgmrf` block.

Examples

```

## Not run:
# Compile a user latent block against tulpa's AD types; see
# inst/examples/tgmrf_periodic_ar1.cpp for a complete block.
blk <- tgmr_cpp("my_block.cpp", id = "ar1", init = c(0, 0), graph = my_graph)

## End(Not run)

```

tidy.tulpa_fit	<i>Tidy fixed-effect table (broom-compatible)</i>
----------------	---

Description

Tidy fixed-effect table (broom-compatible)

Usage

```
## S3 method for class 'tulpa_fit'
tidy(x, conf.level = 0.95, ...)
```

Arguments

x	A tulpa_fit object.
conf.level	Interval level (default 0.95).
...	Ignored.

Value

Data frame: term, estimate, std.error, conf.low, conf.high.

Examples

```
set.seed(1)
df <- data.frame(x = rnorm(100), g = factor(rep(1:10, 10)))
df$y <- rpois(100, exp(0.3 * df$x))
fit <- tulpa(y ~ x + (1 | g), data = df, family = "poisson")
tidy(fit)
```

tulpa	<i>Fit a tulpa model</i>
-------	--------------------------

Description

Single entry point for fitting a Bayesian hierarchical model. `tulpa()` parses the formula, builds the model matrices, selects an inference backend through the tier/mode system (see [inference_mode_info\(\)](#)), assembles the arguments that backend needs, and dispatches.

The fit conditions on the random-effect standard deviations `sigma_re` (and, for non-Gaussian dispersion, `phi`): both the Laplace (Tier 2) and the sampler (Tier 1) paths target the posterior given these. Integrating over the hyperparameters is the role of the nested-Laplace / EM layer.

Usage

```

tulpa(
  formula,
  data,
  family = "gaussian",
  mode = "auto",
  sigma_re = NULL,
  n_trials = NULL,
  weights = NULL,
  phi = 1,
  estimate_phi = FALSE,
  phi2 = NULL,
  beta_prior = NULL,
  re_prior = NULL,
  ziformula = NULL,
  zi_prior = NULL,
  warm_start = NULL,
  spatial = NULL,
  temporal = NULL,
  control = list(),
  ...
)

```

Arguments

formula	A model formula. Fixed effects, $(1 \mid g)$ / $(1 + x \mid g)$ random effects, and <code>offset(...)</code> terms are recognised.
data	A data frame.
family	Character family name: one of <code>family_names()</code> ("binomial", "poisson", "neg_binomial_2", "gaussian", "beta", ...), or a categorical response family – "multinomial" (baseline-category logit via <code>tulpa_multinomial()</code>), "ordinal" (cumulative logit via <code>tulpa_ordinal()</code>), or "ordinal_probit" (cumulative probit). Categorical families take fixed-effect models only.
mode	Inference mode or backend. "auto" (default) picks the most reliable Tier 1/Tier 2 method expected to finish; a tier ("exact", "structured") or a backend name ("laplace", "mala", ...) forces it. "eb" estimates the random-effect covariance(s) by empirical Bayes instead of conditioning on <code>sigma_re</code> (see <code>tulpa_eb()</code>); it is opt-in by name, because its intervals are conditional on that estimate rather than marginal over it.
sigma_re	Random-effect SDs to condition on: length 1 (recycled) or one per RE term. Defaults to 1 per term with a message. Ignored by the backends that determine the covariance themselves ("eb", <code>re_cov_nested</code> , <code>re_cov_gibbs</code> , <code>gibbs</code> , <code>agq</code>), which warn if it is supplied anyway.
n_trials	Binomial denominators (<code>length nrow(data)</code>), or NULL.
weights	Optional observation weights (non-negative numeric vector, length <code>nrow(data)</code>): each observation's log-likelihood contribution is scaled by its weight (prior /

	frequency weights, e.g. survey weights or aggregated-data counts – a weight of 2 is equivalent to duplicating the row). Supported on the non-spatial Laplace path (mode = "laplace") and the log-posterior samplers (mala, imh_laplace, pathfinder); other backends reject weights loudly.
phi	Dispersion/precision passed to the family (residual variance for gaussian and lognormal, size for neg_binomial_2, precision for beta, scale for t). The variance convention holds across every backend; the SD-parameterized compiled kernels receive $\sqrt{\text{phi}}$ at the boundary.
estimate_phi	Estimate the dispersion from the data instead of conditioning on phi, which then supplies the starting value. $\log(\text{phi})$ joins the empirical-Bayes maximization as one further coordinate carrying the exact derivative of the Laplace log-marginal, so the estimate is ML-II: the hyperprior covers the random-effect covariances only and the dispersion enters unpenalized. <code>fit\$phi</code> is the estimate and <code>fit\$phi_estimated</code> distinguishes it from a conditioned value. Available under mode = "eb", and for the families whose dispersion derivative is registered (see tulpa_eb()). Any other mode errors rather than fitting at the starting value under a name that says otherwise.
phi2	Optional second dispersion: the Student-t degrees of freedom (family = "t"; default 4 when NULL) or the Tweedie variance power (family = "tweedie", required – a defaulted power would be a statistical decision the caller never made). Supported on the non-spatial Laplace path, the random-effect covariance paths (mode = "eb" and the nested Sigma integrator, which thread it into their inner Laplace solve), the log-posterior samplers, and the ModelData samplers. Backends without a phi2 channel refuse it rather than fit at the family's default. <code>estimate_phi</code> covers phi alone; phi2 is always conditioned on.
beta_prior	Optional <code>list(mean, sd)</code> Gaussian prior on the fixed effects. NULL takes the engine default, <code>prior_normal(0, 2.5)</code> , on every backend that carries a fixed-effect prior – the prior is a modelling statement, so the backend mode = "auto" selects does not change it. The nested-Laplace and SPDE paths hold their own field-conditional prior and reject a supplied <code>beta_prior</code> . The resolved prior is reported on the fit as <code>\$beta_prior</code> .
re_prior	Optional <code>list()</code> of random-effect / variance-component hyperpriors (statistical, so they live in the signature rather than in control). Recognised entries, each consumed by the backend that needs it: <code>hyperprior</code> ("flat" default or "pc_lkj", mode = "laplace" random slopes and mode = "eb" – see tulpa_re_cov_nested()), <code>prior_sigma</code> (PC-prior anchor <code>c(U, alpha)</code> on a free RE covariance SD, used when <code>hyperprior = "pc_lkj"</code>), <code>eta</code> (LKJ concentration for a correlated RE covariance, same condition), <code>prior_df / prior_scale</code> (inverse-Wishart on the RE covariance, <code>control\$re_cov = "gibbs"</code>), <code>prior_sigma_scale</code> (half-Cauchy scale on the RE SD for mode = "gibbs"), and <code>sigma_re_scale</code> (half-Cauchy scale on the RE / BYM2 SD for the ModelData samplers).
ziformula	Optional one-sided formula for the zero-inflation probability, e.g. ~ 1 for a constant structural-zero rate or $\sim x$ to model it. The response becomes a mixture: with probability <code>plogis(X_zi beta_zi)</code> the observation is a structural zero, otherwise it is drawn from family. Available for the count families with a compiled zero-inflated kernel; paired with <code>truncated_poisson</code> or <code>truncated_neg_binomial_2</code>

it is the hurdle model, since the base $P(Y = 0)$ is then 0 and the mixture degenerates to the two-part likelihood. Backends that do not carry the mixture refuse it rather than fit the model without it.

zi_prior	Optional list(sd) Gaussian prior on the zero-inflation coefficients, $\text{beta_zi} \sim N(0, \text{sd}^2)$; NULL (default) uses 2.5. One scalar SD applies to the whole block, and the mean is fixed at 0, because that is what the compiled kernels carry. The prior is what identifies the logit where a level contributes no zeros – there the likelihood is monotone in that coefficient and alone would send it to $-\text{Inf}$. $\text{sd} = \text{Inf}$ removes the penalty. Ignored without <code>ziformula</code> .
warm_start	Optional starting point for the NUTS sampler, from a cheaper fit of the same model: "eb" or "laplace" fits one first, or pass an existing fit from either mode. The sampler then starts at that mode with an inverse mass read off its curvature, instead of at the origin with a structural one. Chains after the first are dispersed around the mode at the fit's own scale, so between-chain spread – which <code>rhat()</code> compares against – is not collapsed by the shared starting point. Only the NUTS/HMC backends take one; the rest error rather than ignore it. Not available under a spatial, temporal or GP field, whose hyperparameters neither source fit estimates. The variance-component slots take an adapting mass by default, because a plug-in fit estimates no curvature for them. Passing a fit from <code>tulpa_eb()</code> with <code>marginal = TRUE</code> supplies one: its <code>theta_cov</code> gives each <code>log_sigma_re</code> slot a posterior variance to start from. This applies to uncorrelated terms, whose hyperparameter coordinates are the log standard deviations the sampler holds; a correlated term stays adapting, since its log-Cholesky coordinates are not the sampler's.
spatial	Optional spatial-field spec. How it is addressed depends on the field family: • Areal ("icar", "car", "bym2", "car_proper"): a list with type and adjacency, paired with a <code>spatial(col)</code> term in formula naming the per-observation unit column. Term and spec must be supplied together. • Continuous (<code>spatial_gp(~lon + lat)</code> for an NNGP field, <code>spatial_gp(~lon + lat, approx = 'hsgp')</code> for a Hilbert-space GP, <code>spatial_spde(~lon + lat, data)</code> for a Matern SPDE field): the spec object carries the coordinate columns (the SPDE spec also carries the mesh + FEM matrices), so no <code>spatial(col)</code> term is used – observations are mapped to locations from their coordinates. The mode selects how the spatial hyperparameter is handled: • <code>mode = "nested_laplace"</code>, <code>"structured"</code>, and <code>"auto"</code> (when not the binomial Gibbs case below) integrate the hyperparameter – the designed Tier 2 path, mirroring <code>latent(...)</code> blocks. Areal <code>icar/car/bym2/car_proper</code> and continuous <code>gp/nngp/hsgp</code> go through <code>tulpa_nested_laplace()</code>; SPDE is redirected to <code>fit_spde()</code>, which integrates (<code>range</code>, <code>sigma</code>) with its own CCD / grid design. • <code>mode = "laplace"</code> conditions on a fixed hyperparameter via <code>tulpa_laplace()</code> (the cheap explicit fit). • <code>mode = "gibbs"</code> routes the areal <code>icar/bym2</code> cases through the binomial Polya-Gamma samplers (Tier 1 exact); <code>mode = "auto"</code> picks this for a binomial <code>icar/bym2</code> field.

temporal	Optional temporal field spec (<code>temporal_rw1()</code> , <code>temporal_rw2()</code> , or <code>temporal_ar1()</code>), integrated by nested Laplace. A plain field routes the single-block temporal kernel; a <code>group_var</code> panel spec fits a separate walk per group sharing one hyperparameter; combined with an areal spatial field it forms an additive space-time joint prior.
control	Optional list of backend tuning arguments (e.g. <code>n_iter</code> , <code>warmup</code> , <code>epsilon</code> for mala; <code>n_draws</code> for pathfinder).
...	Reserved for future statistical arguments. Nothing is read from it today, so any entry errors: a stray name here is a misspelled argument or a tuning knob that belongs in <code>control</code> .

Value

A `tulpa_fit` object carrying the backend's output plus `inference_mode`, `inference_tier`, `backend`, `selection_reason`, `formula`, and `family`. Two field-name conventions to know when reaching into the object directly (the generic accessors handle both): on nested-Laplace fits `$weights` is the hyperparameter GRID weights; user observation weights are stored as `$obs_weights`. `$draws` is a draws matrix on engine fits, while model-package fits may carry a list (`$y_rep`, `$log_lik`) under the same name.

Coverage

- **No random effects and random intercepts** ($(1 | g)$) are supported on the design path (`mode = "laplace"`) and the sampler path (`mode = "mala"`, `"pathfinder"`, `"imh_laplace"`, and the ModelData kernels `"hmc"` / `"sghmc"` / `"sgld"` / `"mclmc"` / `"smc"` / `"vi"` / `"ess"`).
- **Random slopes** are supported on the Laplace (Tier 2) path: there is no scalar `sigma_re` to condition on, so the RE covariance Sigma is integrated rather than fixed. This covers correlated terms ($(1 + x | g)$, a full Sigma), uncorrelated terms ($(1 + x || g)$, a diagonal Sigma), and several terms together ($(1 + x | g) + (1 | h)$) – each term becomes a covariance block, and any accompanying $(1 | g)$ term is integrated as a 1x1 block (nothing is silently conditioned at `sigma_re = 1`). `mode = "laplace"` routes to the nested-Laplace Sigma integrator (`tulpa_re_cov_nested()`, CCD design, flat-in-log hyperprior by default – see `re_prior$hyperprior`); `control$re_cov = "gibbs"` switches to the exact Metropolis-within-Gibbs debias (`tulpa_re_cov_gibbs()`), and `control$re_cov = "aghq"` keeps the nested integrator but replaces the inner joint-Laplace marginal with adaptive Gauss-Hermite quadrature (`control$n_quad`, default 9 there; see `n_quad` in `tulpa_re_cov_nested()`). Both also run on the sampler path (`mode = "mala" / "pathfinder"`).
- `mode = "gibbs"` (Polya-Gamma) fits a single random-intercept model for `family = "binomial"` or `"neg_binomial_2"`, and **samples** the RE sd rather than conditioning on `sigma_re`; tune it via `re_prior$prior_sigma_scale` and a mean-zero `beta_prior`.
- **Latent prior blocks** (`latent(tgmrf(...))`) route to the nested-Laplace path (Tier 2), which integrates over the block hyperparameters. `mode = "auto"` and `"structured"` select it automatically when latent blocks are present; `mode = "nested_laplace"` forces it. At most one random-intercept $(1 | g)$ term may accompany the blocks (model richer grouping as an iid block). Joint multi-arm nested models cannot be expressed by a single-response formula – call `tulpa_nested_laplace_joint()` directly.

- The ModelData sampler kernels ("hmc", "ess", "sghmc", "sgld", "mclmc", "smc", "vi") thread the full latent vector – fixed effects, random effects (all forms), areal spatial (icar / bym2), and temporal (rw1 / rw2 / ar1) – through one ModelData builder and sample the variance components jointly with the field. `ess` carries random effects but declines a structured spatial / temporal block (its isotropic Gaussian-prior block cannot represent the graph precision); continuous-coordinate fields (gp / nngp / hsgp / spde), `car_proper`, and exotic latent blocks stay on the dedicated nested-Laplace / SPDE / Polya-Gamma paths.

References

Rue, Martino & Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *JRSS-B* 71(2):319-392. Hoffman & Gelman (2014). The No-U-Turn Sampler: adaptively setting path lengths in Hamiltonian Monte Carlo. *JMLR* 15(47):1593-1623.

See Also

[inference_mode_info\(\)](#), [tulpa_laplace\(\)](#), [mala\(\)](#), [pathfinder\(\)](#)

Examples

```
set.seed(1)
n <- 200L
g <- sample(letters[1:12], n, replace = TRUE)
d <- data.frame(
  y = rbinom(n, 1, plogis(-0.3 + 0.6 * rnorm(n))),
  x = rnorm(n),
  g = g
)
# Random-intercept logistic GLMM, Laplace tier.
fit <- tulpa(y ~ x + (1 | g), data = d, family = "binomial", mode = "laplace")
coef(fit)
summary(fit)
```

`tulpa_bar_field_replicate`

Replicate an areal graph across the levels of a factor (replicated CAR)

Description

Build the block-diagonal Kronecker graph $I_L \otimes Q$ and the level-offset node index for a replicated areal field: one independent copy of the graph per level of a by factor, all sharing one precision. This is the graph-side counterpart to [tulpa_bar_field_specs\(\)](#) – that helper expands the coefficient columns and is graph-agnostic, while replication needs the graph, so it is a sibling rather than a new argument. A downstream package composes the two (column expansion x replication) from the one implementation rather than re-deriving the Kronecker remap.

Usage

```
tulpa_bar_field_replicate(adjacency, node, by)
```

Arguments

adjacency	Symmetric adjacency matrix of the base graph ($[n_node \times n_node]$, dense or sparse).
node	Integer vector of 1-based graph-node indices, one per observation (the resolved bar right-hand side).
by	A vector of the same length as node giving each observation's replication level; coerced to a factor. With L distinct levels the field is replicated L times.

Value

A list:

adjacency the $[L \times n_node \times L \times n_node]$ block-diagonal Kronecker adjacency $I_L(x) \otimes Q$ (the base graph for $L == 1$).

index integer vector, one per observation: the node index offset into its level's copy ($node + (level - 1) * n_node$).

n_levels the number of replication levels L .

n_nodes the base graph node count n_node .

levels the factor levels of by, in replicate order.

See Also

[tulpa_bar_field_specs\(\)](#) for the coefficient-column expansion, [spatial\(\)](#) for the inline areal field constructor whose `by` = argument this powers.

Examples

```
adj <- matrix(0, 4, 4)
for (i in 1:3) adj[i, i + 1] <- adj[i + 1, i] <- 1
node <- rep(1:4, times = 2)
lev <- rep(c("a", "b"), each = 4)
rep_info <- tulpa_bar_field_replicate(adj, node, lev)
dim(rep_info$adjacency) # 8 x 8 (I_2(x) Q)
rep_info$index          # level b nodes offset by 4
```

`tulpa_bar_field_specs` *Expand a varying-coefficient bar into per-column field specs*

Description

Expand the left-hand side of an **lme4**-style varying-coefficient bar ($\sim 1 + w \mid \mid$ node) against a data frame into one descriptor per design matrix column. This is the same expansion `spatial()` and the inline `temporal()` field constructor use internally to turn a bar into one CAR / temporal field per design column, exposed so a downstream package can reuse the one implementation rather than re-parsing the bar grammar.

The bar's right-hand side names the node index (the graph node for a spatial field, the time index for a temporal field); it is not expanded but is returned as the node attribute. The left-hand side is expanded with `stats::model.matrix()`: the intercept column (1) is the unweighted (all-ones) field, and each covariate column is a varying coefficient whose per-observation weight is that column's design value (0 + drops the intercept).

Usage

```
tulpa_bar_field_specs(formula, data)
```

Arguments

<code>formula</code>	A one-sided formula carrying a single grouping bar, e.g. $\sim 1 + w \mid \mid$ cell. Use <code>tulpa_is_spatial_bar()</code> to test first. The right-hand side must be a single bare column naming the node index; nesting (a / b), interaction ($a:b$), or expression grouping is rejected.
<code>data</code>	A data frame whose columns the bar left-hand side and the node index refer to. The per-column weight vectors are evaluated against it, so they have <code>nrow(data)</code> entries.

Value

A list with one element per design-matrix column, each a list:

`column_name` character; "Intercept" for the intercept column, otherwise the `model.matrix()` column name (e.g. "w").

`weight` a numeric vector of length `nrow(data)` for a covariate column (the per-observation design value scaling that field), or NULL for the intercept column (which is the all-ones, unweighted field).

`is_intercept` logical; TRUE for the intercept column.

The list carries two attributes: `node` (character, the node-index column named by the bar right-hand side) and `correlated` (logical, TRUE for a single $|$, FALSE for a double $||$).

See Also

`tulpa_is_spatial_bar()` for the recognizer, `spatial()` for the inline areal field constructor that consumes this expansion.

Examples

```
d <- data.frame(cell = rep(1:5, each = 4), w = rnorm(20))

# Intercept plus a varying slope on w
specs <- tulpa_bar_field_specs(~ 1 + w || cell, d)
length(specs)           # 2
specs[[1]]$column_name  # "Intercept"
is.null(specs[[1]]$weight) # TRUE (unweighted field)
specs[[2]]$column_name  # "w"
identical(specs[[2]]$weight, d$w) # TRUE
attr(specs, "node")     # "cell"
```

tulpa_cache_clear	<i>Remove compiled blocks from the <code>tgmrfs_cpp()</code> cache</i>
-------------------	--

Description

Deletes cached compilation output under `tulpa_cache_dir()`. The cache holds build artefacts only – a removed entry is rebuilt by the next `tgmrfs_cpp()` call on the same source – so it can be emptied at any time.

Usage

```
tulpa_cache_clear(older_than = 0)
```

Arguments

<code>older_than</code>	Remove only entries whose last modification is more than this many days ago. 0 (the default) removes every entry.
-------------------------	--

Value

The number of entries removed, invisibly.

See Also

`tulpa_cache_dir()` for the location.

Examples

```
## Not run:
# Deletes the caller's own cached builds, so it is not run on check.
tulpa_cache_clear()           # empty the cache
tulpa_cache_clear(older_than = 30) # keep the last 30 days

## End(Not run)
```

tulpa_cache_dir	<i>Default cache directory for tgmrf_cpp()-compiled DLLs</i>
-----------------	--

Description

Reports the per-user directory under `tools::R_user_dir("tulpa", "cache")` where `tgmrf_cpp()` keeps the objects it compiles. Reporting the path does not create it: the directory appears the first time a compile needs it, and `tulpa_cache_clear()` removes what it holds.

Usage

```
tulpa_cache_dir(create = FALSE)
```

Arguments

`create` Create the directory if it is missing. FALSE (the default) only reports the path.

Value

Absolute path (character) to the cache directory.

See Also

`tulpa_cache_clear()` to remove cached objects.

Examples

```
# Where compiled tgmrf_cpp() blocks are cached. Reporting creates nothing.
tulpa_cache_dir()
```

tulpa_check_control	<i>Validate a control = list() surface against its canonical key set</i>
---------------------	--

Description

Front-door fitters across the tulpa* ecosystem carry their perf / numerical / tuning knobs in a single control list (design principle 6). Without a name check a misspelled knob is a silent no-op – `control$adaptive_grid` fits the default and reports nothing. This validates the names a caller supplied against the whitelist of what the target fitter actually reads, and errors listing the allowed set.

Usage

```
tulpa_check_control(control, allowed, where)
```

Arguments

control	The control list to validate. NULL and empty lists pass.
allowed	Character vector of accepted knob names.
where	Name of the calling fitter, used in the error message.

Details

Consumer packages (tulpaRatio, tulpaObs) call this with their own key registry rather than reimplementing the check.

Value

invisible(NULL), called for the side effect of erroring on an unknown or unnamed knob.

Examples

```
tulpa_check_control(list(max_iter = 50), c("max_iter", "tol"), "my_fit")
try(tulpa_check_control(list(max_itr = 50), c("max_iter", "tol"), "my_fit"))
```

tulpa_criteria	<i>Model criteria from a pointwise log-likelihood</i>
----------------	---

Description

Turn an [n_draws x n_obs] pointwise log-likelihood into the standard Bayesian goodness-of-fit currency: WAIC, DIC, conditional predictive ordinates (CPO) and their sum LPML, PSIS-LOO, all from one matrix. PSIS-LOO reuses the native [tulpa_psis\(\)](#) smoothing, so the CPO and LOO numbers are the same computation (CPO_i = exp(elpd_loo_i), LPML = elpd_loo). The input may be a matrix or a streaming [tulpa_loglik\(\)](#) so EVA-scale fits are processed in observation blocks.

Usage

```
tulpa_criteria(
  log_lik,
  criteria = c("waic", "loo", "cpo", "lpml", "dic"),
  loglik_at_mean = NULL,
  group = NULL,
  chunk_size = NULL,
  pointwise = FALSE
)
```

Arguments

log_lik	An [n_draws x n_obs] numeric matrix of pointwise log-likelihoods, or a <code>tulpa_loglik()</code> streaming wrapper.
criteria	Which criteria to compute. Any of "waic", "loo", "cpo", "lpml", "dic". "loo", "cpo", and "lpml" share the single PSIS pass; "dic" additionally needs <code>loglik_at_mean</code> .
loglik_at_mean	Optional length-n_obs vector of pointwise log-likelihoods evaluated at the posterior mean of the parameters, supplied by the caller (the model package knows the parameterization). Required for DIC's plug-in deviance; without it the DIC fields are NA.
group	Optional length-n_obs grouping (an integer / factor / character vector). The LOO unit is one column of <code>log_lik</code> : with <code>group = NULL</code> (the default) every column is its own fold (leave-one-row-out, e.g. per plot / per visit) and the result is byte-identical to the ungrouped call. When supplied, the per-draw pointwise log-likelihoods are summed within group to a [n_draws x n_groups] matrix before PSIS, so each fold is a whole group (leave-one-group-out cross-validation, LOGO-CV). Use it to switch the estimand from per-row to per-group LOO – e.g. on a cell-compressed hierarchical fit, leave out a whole cell rather than one of its rows. WAIC's variance term, <code>lppd</code> , <code>elpd_loo</code> , <code>cpo</code> and <code>pareto_k</code> are all computed on the grouped matrix. DIC is a plug-in deviance over all observations and is unaffected by group.
chunk_size	Number of observation columns to process per block. The default streams the whole matrix at once when materialized, else picks a block sized to a few million entries.
pointwise	If TRUE, also return the per-observation vectors (<code>elpd_waic</code> , <code>p_waic</code> , <code>elpd_loo</code> , <code>pareto_k</code> , <code>cpo</code>) for plotting / stacking.

Details

`p_waic` is the well-known positively-biased variance estimator at low draw counts; the result records `n_draws` and the count of observations with `p_waic_i > 0.4` (the `loo` heuristic for an unreliable WAIC), and the PSIS-LOO `elpd_loo` is the more stable figure to report when that count is non-trivial.

The LOO unit is whatever **one column of** `log_lik` holds. If the consumer built the matrix with one column per row (plot / visit), the default is per-row LOO; if a column already carries a whole group's compressed likelihood, leaving it out drops that group and `pareto_k` can blow up by construction. The `group` argument makes the unit explicit: supply it to aggregate columns into folds and report leave-one-group-out CV (LOGO-CV) instead, a different and deliberate estimand.

Value

A `tulpa_criteria` object: a list with the requested scalar scores (each estimate paired with its standard error where defined), `n_draws / n_obs`, the PSIS `pareto_k` summary, and – when `pointwise = TRUE` – a pointwise data frame.

References

Vehtari, Gelman & Gabry (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing* 27(5):1413-1432. Watanabe (2010). Spiegelhalter et al. (2002). Geisser & Eddy (1979).

See Also

[tulpa_psis\(\)](#) for the smoothing core, [tulpa_pit\(\)](#) for the probability-integral-transform companion, [compare_models\(\)](#) for model comparison.

Examples

```
# A draws x observations log-likelihood matrix (here built directly;
# in practice extracted from a fitted model's posterior draws).
set.seed(1)
y <- rnorm(40)
mu <- matrix(rnorm(200 * 40, sd = 0.2), 200, 40)
ll <- dnorm(matrix(y, 200, 40, byrow = TRUE), mean = mu, log = TRUE)
tulpa_criteria(ll)
tulpa_criteria(ll, criteria = "waic", pointwise = TRUE)$pointwise[1:3, ]
```

tulpa_diagnostics	<i>Simulation-Based Diagnostics for tulpa Models</i>
-------------------	--

Description

Model-checking tools based on posterior predictive simulation. These are native R implementations equivalent to DHARMA's test suite, with no external dependencies. They work with any model that provides `simulate()`, `fitted()`, and `residuals()` methods.

Value

The diagnostic functions documented in this family return their individual results (a test-statistic object, a data frame of residuals, or a `check_model` summary); see each function's own help page.

tulpa_draws_array	<i>Posterior draws as a 3D array</i>
-------------------	--------------------------------------

Description

Assembles a fitted model's posterior draws into an `[iteration, chain, parameter]` array – the layout expected by `bayesplot` and analogous to `posterior::as_draws_array()`. Multiple chains are recognised from a 3D draws array, a `$chain_id` row map, or an `$n_chains` count over chain-major rows; a single pooled chain yields a one-chain array.

Usage

```
tulpa_draws_array(fit)
```

Arguments

`fit` A `tulpa_fit` (or subclass) carrying posterior `$draws`.

Details

As with `posterior_sample()`, a fit that carries no draws returns `NULL` with a message naming its backend and the representation it carries instead.

Value

A numeric array with dimensions `[n_iter, n_chain, n_param]` and the parameter names on the third dimension, or `NULL` if the fit carries no draws. Chains of unequal length are truncated to the shortest.

See Also

`posterior_sample()`, `tulpa_posterior_draws()`, `diagnostics()`

tulpa_eb

Empirical-Bayes random-effect covariances

Description

Estimate one or more random-effect covariances Σ by maximizing the Laplace marginal likelihood over them (plus the hyperprior), then report the fixed effects conditional on the maximizer. This is the plug-in ("ML-II" / empirical-Bayes) counterpart of `tulpa_re_cov_nested()`, which integrates over Σ instead of fixing it at the maximizer.

Usage

```
tulpa_eb(
  y,
  n_trials = NULL,
  X,
  re_terms,
  family = "binomial",
  phi = 1,
  phi2 = NULL,
  prior_sigma = c(3, 0.05),
  eta = 2,
  hyperprior = c("flat", "pc_lkj"),
  log_prior_theta = NULL,
  beta_prior = NULL,
```



```

    offset = NULL,
    n_quad = 1L,
    marginal = FALSE,
    estimate_phi = FALSE,
    X_zi = NULL,
    zi_prior_sd = 2.5,
    control = list()
)

```

Arguments

<code>y, n_trials, X, family, phi</code>	Passed to tulpa_laplace() for the inner solve. <code>n_trials = NULL</code> defaults to 1 (binary / single-trial).
<code>re_terms</code>	Either a single random-effect term or a list of them; see tulpa_re_cov_nested() for the per-term fields.
<code>phi2</code>	Optional second dispersion, threaded into every inner tulpa_laplace() solve: the Student-t degrees of freedom (<code>family = "t"</code> , default 4 when NULL) or the Tweedie variance power (<code>family = "tweedie"</code> , required – a defaulted power would be a statistical decision the caller never made). A <code>phi2</code> supplied for any other family errors rather than being ignored. It is conditioned on, never estimated: <code>estimate_phi</code> covers <code>phi</code> alone.
<code>prior_sigma, eta</code>	Hyperparameters of the PC + LKJ prior used when <code>hyperprior = "pc_lkj"</code> (see re_cov_pc_lkj_prior()). Ignored when <code>hyperprior = "flat"</code> or <code>log_prior_theta</code> is supplied. When active, the prior is part of the maximized objective, so it regularizes the estimate: with few groups it is what keeps a block off the $\sigma = 0$ boundary.
<code>hyperprior</code>	"flat" (default) or "pc_lkj". "flat" maximizes with <code>log_prior_theta</code> the zero function – an unpenalized maximum-marginal-likelihood estimate, which can reach the $\sigma = 0$ boundary on small designs (see the "lower end of the search bracket" warning). "pc_lkj" builds the PC + LKJ prior from <code>prior_sigma / eta</code> , regularizing the estimate away from that boundary. Ignored when <code>log_prior_theta</code> is supplied. Must match <code>hyperprior</code> on the paired tulpa_re_cov_nested() call for the two to share <code>theta_hat</code> .
<code>log_prior_theta</code>	Optional function(<code>theta</code>) returning a scalar log prior density on the full stacked parameter vector, overriding <code>hyperprior</code> entirely. Default NULL, which defers to <code>hyperprior</code> .
<code>beta_prior</code>	Optional Gaussian prior on the fixed effects, threaded into every inner tulpa_laplace() solve (<code>list(mean, sd)</code>).
<code>offset</code>	Optional observation-level offset on the linear predictor (<code>length length(y)</code>), e.g. <code>log(exposure)</code> for a rate model. Not supported with <code>n_quad > 1</code> , which errors rather than dropping it.
<code>n_quad</code>	Quadrature order for the inner marginal. 1 (default) uses the joint-field Laplace inner solve. > 1 refines it with <code>n_quad</code> -point adaptive Gauss-Hermite quadrature, which requires a single shared grouping factor; see tulpa_re_cov_nested() .

marginal	Report fixed-effect intervals that carry the hyperparameter uncertainty, instead of the intervals conditional on <code>theta_hat</code> . The posterior for <code>theta</code> is taken as Gaussian around the maximizer with covariance <code>solve(H_theta)</code> , the inner mode is linearized in <code>theta</code> , and the law of total variance adds $J \text{ solve}(H_{\theta}) J'$ to the conditional covariance, where $J = d \text{ mode} / d \theta$. Both <code>H_theta</code> and <code>J</code> come from one central-difference stencil over the outer objective, costing $1 + 2k^2$ further inner solves for k hyperparameter coordinates (k is 1 for a scalar (<code>1 g</code>) block and 3 for a correlated (<code>1 + x g</code>) one). Default FALSE. Widens intervals; never narrows them. When the variance components themselves are the target, or the correction's two approximations look strained (a strongly skewed variance-component marginal), integrate with <code>tulpa_re_cov_nested()</code> instead.
estimate_phi	Estimate the family's dispersion alongside the random-effect covariances, instead of conditioning on <code>phi</code>. When TRUE the supplied <code>phi</code> is the starting value and <code>fit\$phi</code> is the estimate, with <code>fit\$phi_estimated</code> distinguishing the two cases. <code>log(phi)</code> joins the maximization as one further coordinate, carrying the exact derivative of the Laplace log-marginal with respect to it, so the cost is one more coordinate for BFGS and not a second optimization. The dispersion enters unpenalized – the hyperprior covers the covariance coordinates only – so this is the ML-II estimate of <code>phi</code>, not a MAP under an undeclared prior. Available for every family carrying a dispersion, which is every front-door family except <code>poisson</code>, <code>binomial</code> and <code>truncated_poisson</code> – those have no free dispersion at all, so estimating one is a category error rather than a missing feature, and it is refused. Needs <code>n_quad = 1</code>. Alongside <code>X_zi</code> both mixture kinds are covered. A hurdle (a zero-truncated base) has zero branch <code>log(pi)</code>, which carries no dispersion, so the base family's registered derivative is already the mixture's. Genuine zero inflation has zero branch <code>log(pi + (1 - pi) P(Y = 0))</code>, which depends on <code>phi</code> through <code>P(Y = 0)</code> and couples it to both linear predictors; that branch is supplied for <code>neg_binomial_2</code>, the only untruncated mixture family here with a free dispersion. Other untruncated bases are refused rather than handed the base derivative under a model it does not describe.
X_zi	Optional zero-inflation design matrix (<code>length(y)</code> rows), making the model a two-process mixture: each observation is a structural zero with probability <code>plogis(X_zi beta_zi)</code> and otherwise follows family. Paired with a zero-truncated family it is the hurdle model. The random effects enter the count predictor only, and the maximization is over the same covariance coordinates – the mixture changes the inner solve, not the outer objective's parameters. The ZI coefficients are reported alongside the count ones in <code>coef()</code> / <code>vcov()</code> , so the fixed block is <code>ncol(X) + ncol(X_zi)</code> wide. Needs <code>n_quad = 1</code> : the adaptive Gauss-Hermite inner marginal runs through a single-predictor oracle.
zi_prior_sd	Prior SD on <code>beta_zi</code> , keeping the logit identified where a level carries no zeros (the likelihood alone would send it to <code>-Inf</code>). Ignored when <code>X_zi</code> is NULL.
control	A named list of numerical knobs: <code>max_iter</code> , <code>tol</code> , <code>n_threads</code> (inner-solve controls, see <code>tulpa_laplace()</code>), and <code>outer_maxit</code> (iteration budget for the maximization over <code>Sigma</code> , default 500; applies to the Nelder-Mead simplex used

from two parameters up, since the one-parameter case is bracketed by Brent). Exhausting the budget warns. `outer_reltol` sets that maximization's convergence tolerance (default $1e-10$ for the gradient-driven methods, $1e-8$ for the simplex, which cannot resolve as finely); it is converted to L-BFGS-B's `factr` on the bounded path, so one request means the same thing whichever method runs. `sigma_init` supplies the starting random-effect SD – a scalar, or one per coefficient across all blocks – replacing the method-of-moments guess taken from a pilot fit at $\text{Sigma} = \text{I}$. Worth setting when the true scale is far from 1, where that pilot starts the search on a flat stretch, and when a run should be reproducible from its inputs rather than from a pilot fit. It is diagonal: it sets each coefficient's scale and leaves any correlation to be fitted. Two further knobs tune `marginal = TRUE` and are inert without it: `marginal_step` (the stencil step in theta space, default $1e-3$) and `marginal_richardson` (default FALSE; evaluate the stencil at `step` and `step / 2` and extrapolate, turning the $O(\text{step}^2)$ truncation error into $O(\text{step}^4)$ at twice the solves – worth it only when the inner solver's own noise sits well below the truncation error, i.e. a tight `tol`).

Details

Blocks, coordinates and the default hyperprior are exactly those of `tulpa_re_cov_nested()` – a correlated $(1 + x | g)$ term is a full $\text{Sigma} = L L'$ in log-Cholesky coordinates, an uncorrelated $(1 + x || g)$ term is diagonal in log-SD coordinates, and a scalar $(1 | g)$ term is the degenerate one-coefficient block. Both functions call the same outer objective and the same optimizer, so `tulpa_eb()`'s `theta_hat` and `tulpa_re_cov_nested()`'s `theta_hat` are the same estimate on the same data – which requires hyperprior to default the same way on both: "flat", the zero function, matching the nested-Laplace convention on every other scale axis in the engine (`icar / rw1 / rw2 / ar1`'s `tau` / iid all lack a hyperprior on their scale too; see `vignette("priors")`). Set `hyperprior = "pc_lkj"` for the weakly-informative PC + LKJ prior instead (see `re_cov_pc_lkj_prior()`) – the regularizer that, at small `G`, keeps a block off the $\text{sigma} = 0$ boundary this maximizer would otherwise reach.

The reported fixed-effect covariance is the conditional one at `theta_hat` (`solve(H_beta)`). It does not include the hyperparameter uncertainty that `tulpa_re_cov_nested()` integrates over, so EB intervals are narrower – increasingly so as the number of groups falls. Use the nested integrator when the variance components themselves, or calibrated fixed-effect intervals, are the target; use EB when the point estimate is, or as a fast starting fit.

Value

A `tulpa_fit` with:

- `mode`, `H_beta`: the fixed-effect (and, on the `n_quad = 1` path, random- effect) mode and the fixed-effect precision at `theta_hat`, driving `coef/confint/vcov/summary`.
- `map`: the $\text{Sigma} / \text{sigma} / \text{rho}$ summary at `theta_hat` (a single list for one block, a named list of them for several).
- `Sigma`: the estimated covariance (a matrix for one block, a named list of matrices for several).
- `theta_hat`, `log_marginal`, `layout`, `n_blocks`, `n_coefs`.
- `converged`: whether the inner Newton solve at `theta_hat` converged.

- `outer_convergence`: optim's code for the maximization over Sigma ($\emptyset$ on success). A non-zero value also warns.
- With `marginal = TRUE` and a correction that formed: `cov_marginal` (the widened fixed-effect covariance, which `vcov / summary / confint` then report), `cov_conditional` (the `solve(H_beta)` they would otherwise have reported, kept so the two are comparable on one fit), `H_theta` and `theta_cov` (the outer Hessian at `theta_hat` and its inverse, named by `theta_names`), and the `marginal_step / marginal_richardson` actually used. All absent when the correction was not requested or could not be formed, so `is.null(fit$cov_marginal)` tests whether the reported intervals are marginal. A requested correction that fails warns and leaves the conditional covariance in place.

References

Casella (1985). An introduction to empirical Bayes data analysis. *The American Statistician* 39(2):83-87. Rue, Martino & Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *JRSS-B* 71(2):319-392.

See Also

[tulpa_re_cov_nested\(\)](#) to integrate over Sigma rather than fix it; [tulpa_laplace\(\)](#) for the inner solve.

Examples

```
set.seed(1)
G <- 30L; per <- 10L; n <- G * per
grp <- rep(seq_len(G), each = per); x <- rnorm(n)
b <- rnorm(G, 0, 0.8)
y <- rpois(n, exp(0.3 + 0.5 * x + b[grp]))
re_term <- list(idx = grp, n_groups = G, n_coefs = 1L)
fit <- tulpa_eb(y, NULL, cbind(1, x), re_term, family = "poisson")
fit$map$sigma          # empirical-Bayes RE standard deviation
```

tulpa_em_laplace

Fit a latent-variable model via EM + Laplace approximation

Description

Generic EM engine. Model packages provide callbacks for the E-step (latent variable posterior) and the M-step encoding (how to assemble submodel data from weights). Each M-step submodel block is fit independently via [tulpa_laplace\(\)](#); the engine reads `family` and `offset` per block so heterogeneous-family mixtures (e.g. a binomial zero submodel + poisson positive submodel for a hurdle model) work without engine changes.

Usage

```

tulpa_em_laplace(
  e_step,
  m_step_encode,
  spatial = NULL,
  re_list = list(),
  max_iter = 50L,
  tol = 1e-04,
  damping = 0.3,
  correction = c("auto", "mi", "gibbs", "none"),
  n_imputations = 20L,
  n_gibbs = 10L,
  draw_z = NULL,
  m_step_extra = NULL,
  beta_prior = NULL,
  verbose = TRUE,
  ...
)

```

Arguments

- | | |
|------------------|---|
| e_step | Callback: function(fits, ...) -> list(weights = numeric, ...). Called once per EM iteration with the current per-submodel tulpa_laplace() fits. Must return a list whose weights element is the latent-variable posterior used by the next M-step. |
| m_step_encode | <p>Callback: function(weights, ...) -> list of blocks. Each block is itself a list with the following fields:</p> <ul style="list-style-type: none"> • y (numeric, required) – response. • X (matrix, required) – fixed-effects design with nrow(X) == length(y). • family (character scalar, required) – one of "binomial", "poisson", "gaussian", "negbin" / "neg_binomial_2", "gamma", "beta". Forwarded to tulpa_laplace() for that block. • n_trials (numeric or NULL, optional; absent or NULL defaults to 1) – binomial trial counts. • offset (numeric or NULL, optional) – observation-level offset, length-matched to y when non-NULL. • phi (numeric scalar, optional) – dispersion forwarded to tulpa_laplace() (used by negbin, gamma). • weights (numeric, optional; length length(y)) – per-observation likelihood weight, scaling that row's log-density, score and Fisher information. This is the channel a soft (fractional) latent label travels on; see the section below. • re_list, spatial (optional) – forwarded as-is. |
| spatial, re_list | Not consumed at the driver level – latent structure is per-submodel, set as a spatial / re_list field on each block m_step_encode() returns. Supplying either here is an error (rather than a silent no-op). |

max_iter	Maximum EM iterations.
tol	Convergence tolerance on max relative parameter change.
damping	EM damping factor in $[0, 1)$. With damping = d, the E-step weights are smoothed between iterations as $(1 - d) * \text{new} + d * \text{prev}$ (d = 0 is no damping); the M-step then refits on the smoothed weights, so the parameter update is damped indirectly through the weights rather than by mixing successive parameter vectors.
correction	Post-EM correction. "none" returns the EM point estimate only. "mi" draws $n_{\text{imputations}}$ independent hard z from the converged posterior weights $P(z y, \theta_{\text{hat}})$, refits each block on the hard z, and pools via <code>rubins_pool()</code> . "gibbs" runs a warm-started $z \theta_{\text{hat}} \rightarrow \theta_{\text{hat}} z$ Markov chain of length n_{gibbs} starting from the EM fits, also pooled via <code>rubins_pool()</code> . "auto" resolves to "none".
n_imputations	Number of MI draws (default 20L). Used when correction = "mi".
n_gibbs	Length of the Gibbs chain (default 10L). Used when correction = "gibbs".
draw_z	Optional function function(weights) -> hard_z that turns the E-step's continuous weights into a hard latent draw. Used only by correction %in% c("mi", "gibbs"). The default treats weights as a numeric vector of Bernoulli probabilities and draws per-observation. Multi-class / matrix-valued latent structures must supply their own callback.
m_step_extra	Optional function(fits, weights, ...) -> fits. Fired once per M-step in every phase (EM iterations, MI draws, Gibbs steps). Receives the freshly assembled list of <code>tulpa_laplace()</code> results (fits), the continuous E-step weights $P(z y, \theta_{\text{hat}})$ (NOT the hard z draw used by MI/Gibbs to encode the block), and any extra arguments forwarded through ... Returns a list with the same length and names as the input, possibly with mutated dispersion / shape / precision fields (e.g. fits[[k]]\$phi). Use this to update non-eta parameters that fall out of the Laplace M-step (NB overdispersion, Gamma shape, Beta precision, Gaussian sigma). When NULL (default), behavior is unchanged.
beta_prior	Optional Gaussian prior on the fixed effects, applied to every block fit via <code>tulpa_laplace()</code> (i.e. blocks without a prior field). NULL (default) keeps the weak built-in prior. Otherwise a list with sd (required) and optional mean; see <code>tulpa_laplace()</code> . The same prior flows into the MI / Gibbs correction refits, so penalized corrections come for free. A block may override the default by setting its own beta_prior field in <code>m_step_encode</code> (e.g. different priors for the occupancy and detection submodels). Use scalar mean / sd here when blocks differ in width; per-coefficient vectors belong on the block.
verbose	Print per-iteration progress.
...	Forwarded to <code>e_step</code> , <code>m_step_encode</code> , and <code>m_step_extra</code> .

Details

This is an engine block, not a front door: model packages call it programmatically, so its tuning knobs (max_iter, tol, damping) sit in the signature rather than in a control list.

Value

A list with:

- `fits` – named list of `tulpa_laplace()` results, one per block.
- `weights` – final E-step weights.
- `n_iter` – number of EM iterations actually run.
- `converged` – logical.
- `history` – `data.frame(iter, delta)` of max relative parameter change per iteration.
- `correction` – the resolved correction mode ("none", "mi", or "gibbs").
- `pooled` – present when `correction %in% c("mi", "gibbs")`. Named list of pooled per-submodel summaries from `rubins_pool()`.
- `draws` – present when `correction %in% c("mi", "gibbs")`. List of per-draw fits with beta / se attached.

Soft latent labels go in weights, not in y

The M-step maximizes the expected complete-data log-likelihood. For a Bernoulli latent z_i carrying E-step posterior weight w_i that is

$$Q = \sum_i [w_i \log p_i + (1 - w_i) \log(1 - p_i)],$$

a **weighted Bernoulli** log-likelihood, which carries no binomial coefficient. Encode it as two rows per unit – $y = 1$ at weight w_i and $y = 0$ at weight $1 - w_i$:

```
list(y      = rep(c(1, 0), each = n),
     X      = rbind(X, X),
     weights = c(w, 1 - w),
     family = "binomial")
```

A fractional y on a binomial block is refused, and is not the same objective: it asks for the exact binomial density at a non-integer response, whose normalizer `lchoose(n, y)` is not zero there and depends on w . On the weighted encoding the block's `log_marginal` is the Laplace marginal of Q , an EM objective that increases across iterations.

Examples

```
# Zero-inflated Poisson via EM: the E-step scores the posterior probability
# that each zero is non-structural. Those are soft labels, so the occupancy
# arm is the weighted Bernoulli above -- two rows per unit -- and the
# abundance arm weights each count by the same w.
set.seed(1)
n <- 200
z <- rbinom(n, 1, 0.7)
y <- rpois(n, 4) * z
X <- cbind(1, rnorm(n))

e_step <- function(fits, ...) {
```

```

    if (!length(fits)) return(list(weights = pmax(as.numeric(y > 0), 0.5)))
    psi <- plogis(drop(X %>% fits$occ$mode))
    lam <- exp(drop(X %>% fits$abund$mode))
    w <- ifelse(y > 0, 1, psi * exp(-lam) / (psi * exp(-lam) + (1 - psi)))
    list(weights = w)
  }
  m_step_encode <- function(weights, ...) {
    list(
      occ = list(y = rep(c(1, 0), each = n), X = rbind(X, X),
                  weights = c(weights, 1 - weights), family = "binomial"),
      abund = list(y = y, X = X, family = "poisson", weights = weights)
    )
  }
}

res <- tulpa_em_laplace(e_step, m_step_encode, verbose = FALSE)
res$converged
plogis(res$fits$occ$mode[1]) # P(non-structural), truth 0.7
exp(res$fits$abund$mode[1]) # abundance mean, truth 4

```

tulpa_em_mc

Generic Monte-Carlo EM driver

Description

Same M-step plumbing as [tulpa_em_laplace\(\)](#): every iteration calls `m_step_encode(weights, ...)` to assemble per-submodel blocks and fits each block via [tulpa_laplace\(\)](#). The difference is the E-step: instead of computing closed-form weights, an `e_step_sample` callback returns `n_mc` weight draws per iteration. Each draw is run through the M-step independently and the resulting parameter estimates are pooled via [rubins_pool\(\)](#).

Convergence criterion is the max relative change in *pooled* M-step parameter estimates between iterations. To increase Monte-Carlo accuracy as iterations progress (Booth-Hobert ascent-based MCEM), set `n_mc_growth > 1`.

This is an engine block, not a front door: model packages call it programmatically, so its tuning knobs (`max_iter`, `tol`, `n_mc`) sit in the signature rather than in a control list.

Usage

```

tulpa_em_mc(
  e_step_sample,
  m_step_encode,
  n_mc = 10L,
  n_mc_growth = 1,
  n_mc_max = 200L,
  max_iter = 30L,
  tol = 0.001,
  verbose = TRUE,
  ...
)

```


Arguments

e_step_sample	Function function(fits, n_mc, ...) -> list. Must return a list of length n_mc, each element a weights object of the same shape m_step_encode consumes (typically a numeric vector of length n_obs, or a matrix n_obs x K for K-class latent variables). On the first iteration fits is list() – the callback should return draws from the prior.
m_step_encode	Function function(weights, ...) -> list of blocks. Identical to the contract used by tulpa_em_laplace(): each block is a list with required fields y, X, family, and optional n_trials, offset, phi, re_list, spatial, weights. See ?tulpa_em_laplace for the full spec.
n_mc	Initial number of Monte-Carlo draws per iteration (default 10L).
n_mc_growth	Multiplicative growth of n_mc per iteration (default 1.0 = constant). Set > 1 for ascent-based MCEM that ramps up MC accuracy near convergence.
n_mc_max	Cap on n_mc (default 200L).
max_iter	Maximum EM iterations (default 30L).
tol	Convergence tolerance on max relative change in pooled parameter estimates (default 1e-3). Looser than tulpa_em_laplace default because Monte-Carlo noise floors the achievable precision.
verbose	Print per-iteration progress (default TRUE).
...	Forwarded to e_step_sample and m_step_encode.

Value

A list with:

- pooled – named list of pooled per-submodel summaries (mean, se, V_within, V_between, V_total); see rubins_pool().
- fits – list of per-MC-draw fit lists from the *final* iteration, each indexed by submodel name.
- n_iter – iterations actually run.
- n_mc_final – n_mc value used in the last iteration.
- converged – logical.
- history – data.frame(iter, n_mc, delta).

Tier

Inherits the tier of the inner M-step (Laplace => Tier 2). The Monte-Carlo E-step *itself* is exact in the limit $n_{mc} \rightarrow \infty$, so as a *full pipeline* MCEM is asymptotically Tier 1 if e_step_sample is exact.

References

- Wei, G. C. G., & Tanner, M. A. (1990). A Monte Carlo implementation of the EM algorithm and the poor man's data augmentation algorithms. *Journal of the American Statistical Association*, 85(411), 699-704.
- Booth, J. G., & Hobert, J. P. (1999). Maximizing generalized linear mixed model likelihoods with an automated Monte Carlo EM algorithm. *JRSS B*, 61(1), 265-285.

See Also

[tulpa_em_laplace\(\)](#) for the closed-form-weights variant, [rubins_pool\(\)](#) for the pooling rule.

Examples

```
## Not run:
# Monte-Carlo EM from two callbacks: e_step_sample() draws the latent
# variables and m_step_encode() encodes the complete-data design for the inner
# Laplace M-step (model packages such as tulpaObs supply these). See
# ?tulpa_em_laplace for the deterministic-E-step analogue.
fit <- tulpa_em_mc(e_step_sample, m_step_encode)

## End(Not run)
```

tulpa_ep

*Expectation-Propagation fit for a GLM***Description**

Fits a generalized linear model with a Gaussian coefficient prior by Expectation Propagation: the posterior is approximated by a Gaussian whose per-observation sites match the moments of the tilted distribution (via Gauss-Hermite quadrature). EP is exact for a Gaussian likelihood and typically more accurate than Laplace on skewed likelihoods, since it matches marginal moments rather than the mode curvature.

Usage

```
tulpa_ep(
  formula,
  data,
  family = "binomial",
  phi = 1,
  phi2 = NULL,
  n_trials = NULL,
  beta_prior = .tulpa_default_beta_prior("ep"),
  control = list()
)
```

Arguments

formula	Model formula.
data	A data frame.
family	Character family name (see family_names()).
phi	Dispersion / precision passed to the family (held fixed).
phi2	Optional second dispersion (Student-t degrees of freedom for family = "t"; default 4 when NULL).

n_trials	Binomial denominators (length nrow(data)), or NULL (= 1).
beta_prior	Fixed-effect prior as list(mean, sd): a mean-zero (mean = 0) Gaussian on every coefficient with SD sd (default the engine default, prior_normal(0, 2.5)). EP's site parameterisation assumes a mean-zero coefficient prior, so a non-zero mean errors – use a sampler (mode = "mala") for a shifted prior.
control	List: max_sweeps (default 50), tol (default 1e-6), damping (default 0.8), n_quad (Gauss-Hermite nodes, default 20), n_draws (default 2000), seed.

Value

A tulpa_fit (subclass tulpa_ep) with coefficients (posterior mean), vcov, draws, log_marginal (the EP approximation), converged.

References

Minka (2001). Expectation Propagation for approximate Bayesian inference. UAI. Rasmussen & Williams (2006). Gaussian Processes for Machine Learning, Algorithm 3.5.

See Also

[tulpa\(\)](#) (Laplace / sampler tiers), [pathfinder\(\)](#) (VI).

Examples

```
set.seed(1)
d <- data.frame(x = rnorm(200))
d$y <- rbinom(200, 1, plogis(-0.3 + 0.8 * d$x))
fit <- tulpa_ep(y ~ x, data = d, family = "binomial")
coef(fit)
```

tulpa_family

Construct a minimal tulpa_family for simulation

Description

Lightweight constructor for a tulpa_family object that exposes the contract required by [prior_predict\(\)](#) and [tulpa_simulate\(\)](#). Model packages (tulpaRatio, tulpaObs) register richer families that also link to C++ likelihoods; this helper is for tests and simple custom families that only need simulation.

Usage

```
tulpa_family(
  name,
  simulate_fn,
  process_names = "y",
  extra_params = list(),
  link_inv = NULL
)
```

Arguments

name	Family name (character, length 1).
simulate_fn	function(eta, params, n_obs, ...) returning a numeric vector of length n_obs (single-process) or a list of such vectors keyed by process_names (multi-process). eta is a list of linear predictors, one per process.
process_names	Character vector. Defaults to "y" (single-process).
extra_params	Named list of tulpa_prior objects for likelihood- specific scalar parameters (e.g., dispersion phi). Drawn at each prior-predictive iteration. Defaults to empty.
link_inv	List of inverse-link functions per process; defaults to identity for every process. tulpa passes the raw linear predictor to simulate_fn, so most families implement the link inside simulate_fn (e.g., $\mu = \exp(\eta)$ for Poisson). The link_inv slot exists for families that prefer to keep the inverse-link separate.

Value

A tulpa_family object.

Examples

```
fam <- tulpa_family(
  name = "poisson",
  simulate_fn = function(eta, params, n_obs, ...) {
    rpois(n_obs, exp(eta[[1]]))
  }
)
```

tulpa_formula

Formula parsing for tulpa models

Description

Parses mixed-model formulas by walking the formula's abstract syntax tree. R formulas are already parse trees – we do structural recursion to find random effect terms (| nodes) and separate them from fixed effects.

Value

The formula helpers documented in this family return parsed-formula structures (lists describing the fixed effects, random-effect terms, and latent blocks); see each function's own help page.

tulpa_gaussian	<i>Fit a Gaussian linear model via tulpa's generic engine</i>
----------------	---

Description

Proof-of-concept function demonstrating the tulpa generic interface. Fits $y \sim \text{Normal}(X * \text{beta}, \text{sigma})$ with HMC sampling.

Usage

```
tulpa_gaussian(  
  formula,  
  data,  
  beta_prior = .tulpa_default_beta_prior("gaussian"),  
  control = list()  
)
```

Arguments

formula	A formula (e.g., $y \sim x1 + x2$)
data	A data frame
beta_prior	Fixed-effect prior as <code>list(mean, sd)</code> : a mean-zero ($\text{mean} = 0$) Gaussian on every coefficient with SD <code>sd</code> (default the engine default, <code>prior_normal(0, 2.5)</code>).
control	List of numerical / sampler knobs: <code>iter</code> (total iterations, default 2000), <code>warmup</code> (default 1000), <code>step_size</code> (HMC step size, default 0.05), <code>n_leapfrog</code> (default 10), <code>seed</code> (NULL draws from the session RNG).

Value

A list with draws matrix, posterior means, and metadata

tulpa_gibbs	<i>Fit via Polya-Gamma Gibbs sampler</i>
-------------	--

Description

Public API for PG Gibbs sampling. Used by model packages for binomial and negative binomial GLMMs.

Usage

```

tulpa_gibbs(
  y,
  n_trials,
  X,
  group,
  n_groups,
  family = "binomial",
  beta_prior = .tulpa_default_beta_prior("gibbs"),
  prior_sigma_scale = 2.5,
  spatial = NULL,
  temporal = NULL,
  control = list()
)

```

Arguments

y	Response vector
n_trials	Trial sizes (binomial)
X	Design matrix
group	Integer vector of group indices (1-based)
n_groups	Number of groups
family	Character: "binomial" or "neg_binomial_2"
beta_prior	Fixed-effect prior as <code>list(mean, sd)</code> : a mean-zero ($\text{mean} = 0$) Gaussian on every coefficient with SD <code>sd</code> (default the engine default, <code>prior_normal(0, 2.5)</code>). The Polya-Gamma sampler uses a mean-zero prior, so a non-zero mean errors.
prior_sigma_scale	Prior scale for RE sigma (statistical; default 2.5).
spatial	Optional spatial spec. When supplied the fit routes to the matching spatial Polya-Gamma Gibbs sampler via <code>dispatch_gibbs_spatial()</code> ; <code>group/n_groups</code> are the iid random-effect block carried alongside the field. The full areal + continuous family is available for <code>family = "binomial"</code> ; <code>family = "neg_binomial_2"</code> is backed by the areal ICAR negbin sampler only. Supported types: • areal – "icar", "bym2", "rsr": a list with <code>type</code>, <code>adjacency</code> and a 1-based <code>spatial_idx</code> per observation (e.g. <code>list(type = "icar", adjacency = W, spatial_idx = unit)</code>). "rsr" reuses <code>spatial\$rsr_projection</code> if present, else builds the unit-level projector from the design. • continuous – "gp"/"nngp" (a validated <code>spatial_gp()</code> spec) and "multiscale_gp" (a validated <code>spatial_multiscale()</code> spec). These samplers carry no observation->location map, so they require one observation per unique location in coordinate order.
temporal	Optional temporal spec: a validated <code>temporal_multiscale()</code> object. Routes to the multiscale temporal Polya-Gamma sampler via <code>dispatch_gibbs_temporal()</code> (binomial only; RW1 trend + cyclic seasonal + AR1/IID short-term). Cannot be combined with <code>spatial</code> .

control A named list of numerical / tuning knobs (statistical arguments stay in the signature above): `n_iter` (default 2000), `warmup` (default 1000), `thin` (default 1, applied on every route including the spatial and temporal ones; the run keeps $\text{ceiling}((n_iter - \text{warmup}) / \text{thin})$ draws), `seed` (NULL draws from the session RNG; the Polya-Gamma kernels use R's RNG, so a seed makes the fit reproducible), `verbose` (default FALSE), `n_threads` (default 1).

Details

For `family = "neg_binomial_2"` the Polya-Gamma weights are drawn at the exact real shape $\text{PG}(y + r, \text{eta})$ and the dispersion r is updated by a random-walk Metropolis-Hastings step on $\log(r)$ whose stationary support is bounded to r in $[0.1, 500]$; data favouring a dispersion outside that range pile up at the boundary.

Every sampler that centres a latent effect – the negative-binomial kernels, and the binomial kernels carrying a spatial or temporal field – adds the removed level to the first coefficient, which leaves `eta` unchanged only when the first column of `X` is an all-ones intercept. Those routes error on a design without one.

Value

List with beta draws, RE draws, `sigma_re` draws (plus the spatial field draws when `spatial` is supplied)

Examples

```
set.seed(1)
G <- 20L; npg <- 15L; n <- G * npg
grp <- rep(seq_len(G), each = npg)
X <- cbind(1, rnorm(n))
b <- rnorm(G, 0, 0.6)
y <- rbinom(n, 1, plogis(X %*% c(-0.2, 0.5) + b[grp]))

fit <- tulpa_gibbs(y, rep(1L, n), X, grp, G, family = "binomial",
  control = list(n_iter = 500L, warmup = 250L))
colMeans(fit$beta)
```

tulpa_hyper_grid

Outer hyperparameter-grid integration with a user-supplied inner fit

Description

Generic driver for nested-Laplace-style outer integration over a small hyperparameter block. The user supplies per-axis specs (values + optional log-prior + log-scale / bounds / refinable metadata) and an `inner_fit` callback that, at every hyperparameter cell, returns the inner log marginal and optionally the fixed-effect posterior mode + marginal covariance. The driver builds the Cartesian outer grid, normalises the log-marginals to integration weights, reports per-axis posterior moments

and weighted quantiles, and (when the inner fit supplies them) law-of-total-covariance fixed-effect posterior + mixture draws.

This factors the per-family outer-grid plumbing in `tulpa_nested_laplace()` / `tulpa_nested_laplace_joint()` / `tulpa_re_cov_nested()` into one callback-driven entry point: downstream consumers (occupancy / N-mixture / cover hurdle families in `tulpaObs`, custom user families) drop in their own per-cell inner fit and get the outer integration for free.

Usage

```
tulpa_hyper_grid(
  hyper_specs,
  inner_fit,
  combine = c("law_of_total_cov", "weighted_mean_only", "none"),
  n_draws = 2000L,
  seed = NULL,
  beta_names = NULL,
  control = list()
)
```

Arguments

- | | |
|-------------|---|
| hyper_specs | A list of axis specs. Each spec is either a <code>hyper_axis_spec()</code> object or a plain list with the same fields (the driver auto-wraps); see hyper_axis_spec() . The outer grid is the Cartesian product of the per-axis grids; the joint log-prior is the sum of per-axis <code>log_prior</code> contributions (axes with <code>log_prior = NULL</code> are flat / improper). |
| inner_fit | <p>function(hypers) returning a list with:</p> <ul style="list-style-type: none"> • <code>log_marginal</code> – scalar; the inner-solve log marginal at this cell. Non-finite values are mapped to <code>-Inf</code> (the cell gets zero weight). • <code>beta_mean</code> – numeric vector of fixed-effect posterior mean at the cell. Required when <code>combine != "none"</code>. • <code>beta_cov</code> – $p \times p$ numeric matrix of fixed-effect marginal covariance at the cell. Required when <code>combine = "law_of_total_cov"</code>. <code>hypers</code> is a named numeric vector with the current cell's axis values (names match <code>vapply(hyper_specs, [[, character(1), "name"])</code>). Errors thrown by <code>inner_fit</code> are caught and treated as a failed cell (<code>log_marginal = -Inf</code>, no beta contribution). |
| combine | <p>How to pool per-cell fixed-effect posteriors into a single posterior over the betas. One of:</p> <ul style="list-style-type: none"> • <code>"law_of_total_cov"</code> (default) – compute $E[\text{Cov}(\beta \mid \theta)] + \text{Cov}(E[\beta \mid \theta])$ from the per-cell (<code>beta_mean</code>, <code>beta_cov</code>); synthesise <code>n_draws</code> posterior draws by mixture sampling. Requires <code>beta_mean</code> and <code>beta_cov</code> per cell. • <code>"weighted_mean_only"</code> – pool only the per-cell <code>beta_mean</code> into the weighted posterior mean. <code>beta_cov</code> is ignored; no draws. • <code>"none"</code> – do not assemble a fixed-effect posterior. Only the hyperparameter posterior is returned. <code>beta_mean</code> / <code>beta_cov</code> from <code>inner_fit</code> are ignored if supplied. |

n_draws	Number of posterior draws of the fixed effects to synthesise from the cell mixture (default 2000). Used only when combine = "law_of_total_cov". 0 disables draw synthesis (the law-of-total-cov mean and covariance are still returned).
seed	Optional integer seed for the draw synthesis.
beta_names	Optional character vector naming the fixed-effect coordinates. When NULL (default) the names are taken from the first successful cell's beta_mean (or beta1, beta2, ... if it is unnamed).
control	Optional list of refinement / tuning knobs: • adaptive_grid (FALSE) – run the boundary / interior refinement pass on every axis whose spec has refinable = TRUE. New cells are appended along the refining axis paired with the boundary modal cell's other-axis values, carrying a marginal-scale calibration so they contribute on the right scale. • adaptive_grid_edge_thresh (0.02) – per-axis trigger threshold. • adaptive_grid_max_passes (1L) – cap on refinement passes. • var_of_means_consistency (FALSE) – run a post-integration consistency pass: for refinable axes whose joint-grid var-of-means undershoots the Laplace-at-mode SD by more than tolerance, append Laplace-guided slice points at theta_mean +/- {0.7, 1.5} * theta_sd pinned at the modal cell. One kernel call per axis. • var_of_means_tolerance (0.7) – consistency-pass trigger ratio.

Value

A list of class c("tulpa_hyper_grid", "tulpa_fit", "list") with:

- theta_grid – numeric matrix [n_cells x n_axes] of outer-grid hyperparameter values; columns named after the axes.
- theta_names – character vector of axis names.
- log_marginal – numeric [n_cells]; per-cell log integrand inner\$log_marginal + log_prior(theta_cell). Non-finite / failed cells are -Inf.
- log_prior – numeric [n_cells]; per-cell log-prior contribution (the sum across axes of axis\$log_prior(theta_cell[axis])). 0 when all axes have log_prior = NULL.
- weights – numeric [n_cells] summing to 1 (or all NA with a warning when no cell carries finite mass).
- theta_mean, theta_sd – named numeric vectors; weighted posterior mean and SD per axis. SDs refit via the 3-point Laplace-at-mode parabola where possible.
- theta_median, theta_ci_lo, theta_ci_hi – named numeric vectors; weighted-quantile median and 2.5 / 97.5 (the recommended summary for right-skewed scale-like axes).
- beta, beta_cov, draws – fixed-effect posterior, present per combine:
 - combine = "law_of_total_cov": weighted mean, total covariance ($E[V] + V[E]$), [n_draws x p] mixture draws.
 - combine = "weighted_mean_only": weighted mean only; beta_cov and draws are NULL.
 - combine = "none": all three are NULL.

- means, param_names, process_info, n_samples, n_params, N – the tulpa_fit accessor surface, populated when a fixed-effect posterior is assembled.
- hyper_specs – echoed list of hyper_axis_spec objects (the normalised form).
- combine, n_failed, n_grid, refining_axis – diagnostic fields.
- adaptive_grid_info, var_of_means_consistency_info – present when the corresponding refinement pass fired.

See Also

[hyper_axis_spec\(\)](#) for the axis-spec constructor; [tulpa_nested_laplace_joint\(\)](#) for the family-specific outer-grid driver that this helper generalises.

Examples

```
## Not run:
# Integrate an inner fit over a hyperparameter grid: inner_fit(theta) returns
# a per-cell fit and hyper_specs names the axes. tulpa_nested_laplace() is the
# packaged driver built on this.
res <- tulpa_hyper_grid(hyper_specs, inner_fit)

## End(Not run)
```

tulpa_integrator	<i>Select the symplectic integrator for HMC and NUTS</i>
------------------	--

Description

Get or set the symplectic splitting integrator that the exact-MCMC tier (HMC / NUTS) uses to build its trajectory proposals. The integrator is backed by the SIMP library, which supplies leapfrog and the higher-order Yoshida members from one triple-jump composition.

Usage

```
tulpa_integrator(name, mts_substeps = 4L)
```

Arguments

name	Integrator name: "leapfrog" (default), "minerror2", "adaptive2", "adaptive3", "mts", "yoshida4", "yoshida6", or "yoshida8". Omit to query the current selection without changing it.
mts_substeps	Number of inner prior-force substeps per trajectory step for the "mts" integrator (default 4). Ignored by the other integrators.

Details

The default, "leapfrog", reproduces tulpa's historical trajectory step exactly.

"minerror2" is a two-stage order-two scheme whose coefficient is tuned to cancel the leading energy error on a Gaussian target. Since mass adaptation drives a posterior toward an isotropic Gaussian, it conserves energy well near the adapted optimum and adapts to larger step sizes, at two gradient evaluations per step. It is the recommended choice when leapfrog's step size is limited by energy error on a near-Gaussian posterior.

"yoshida4" is an order-4 scheme that also samples reliably (three gradient evaluations per step). "yoshida6" and "yoshida8" are available but experimental for NUTS: high-order composition integrators have a sharp step-size stability threshold that the dual-averaging adaptation pushes against, so "yoshida6" needs a high `adapt_delta` (0.95 or more) and "yoshida8" often fails to adapt. For sampling, prefer "leapfrog", "minerror2", or "yoshida4".

"adaptive2" and "adaptive3" are step-adapted versions of the two- and three-stage schemes. Rather than fixing the coefficient in advance, each NUTS chain resolves it at the end of warmup for its own operating point: the coefficient that minimizes the worst-case energy error over the band of dimensionless steps the chain actually takes, read off from the adapted mass matrix and the local posterior curvature. Where "minerror2" is optimal only in the small-step limit, "adaptive2" tracks the chain's realised step band; "adaptive3" spends a third gradient per step to hold a small error over a wider band. Both run a fixed placeholder of the same stage family during warmup, so the dual-averaged step size carries over. Step-adaptation applies to NUTS (the default sampler); the fixed-trajectory HMC path uses the placeholder.

"mts" is a multiple-time-stepping (RESPA) integrator. It splits the force into a stiff but cheap prior part – the Gaussian latent structure – and a smooth but expensive likelihood part. Each NUTS trajectory step takes `mts_substeps` inner leapfrog substeps against the prior force while evaluating the likelihood gradient only once, so the outer step can be larger without the stiff prior forcing it small. It pays one full gradient per step (as leapfrog does) plus `mts_substeps` cheap prior gradients, and helps most when the latent field is stiff relative to a comparatively flat likelihood. Like the other schemes it applies to NUTS.

The choice is process-global (like the gradient mode): set it once before fitting. It is read on the main thread at the start of sampling. Because it is process-global, a caller that changes it owns restoring it – and an error between the two calls would leave the process on the other integrator. `with_tulpa_integrator()` does both, restoring on error as well as on success.

Value

If name is omitted, the current integrator name. If name is given, the previous name is returned invisibly.

Examples

```
tulpa_integrator()           # current integrator
old <- tulpa_integrator("yoshida4")
tulpa_integrator(old)       # restore
```

tulpa_is_spatial_bar	<i>Recognize an inline varying-coefficient bar</i>
----------------------	--

Description

Test whether a one-sided formula carries a single varying-coefficient grouping bar of the form $\sim 1 + w \mid \mid$ node (independent fields, $\mid \mid$) or $\sim 1 + w \mid$ node (correlated fields, $\mid$). This is the same grammar `spatial()` and the inline `temporal()` field constructor accept, and the grammar `tulpa_bar_field_specs()` expands. A downstream package can use it to branch on "is this term a spatial / temporal varying-coefficient bar?" before calling `tulpa_bar_field_specs()`.

Usage

```
tulpa_is_spatial_bar(x)
```

Arguments

x	A one-sided formula (e.g. $\sim 1 + w \mid \mid$ node) or the bar language object itself (<code>quote(1 + w \mid \mid node)</code>).
---	--

Value

A single logical: TRUE when x is (or wraps) a $\mid \mid$ bar, FALSE otherwise (a plain formula such as $\sim 1 + w$, a non-bar term, or a non-formula / non-language input).

See Also

`tulpa_bar_field_specs()` for expanding the bar into per-column field specs.

Examples

```
tulpa_is_spatial_bar(~ 1 + w \mid \mid cell) # TRUE
tulpa_is_spatial_bar(~ 1 + w \mid cell)    # TRUE (correlated)
tulpa_is_spatial_bar(~ 1 + w)              # FALSE (no bar)
```

tulpa_kfold	<i>K-fold cross-validation for a tulpa fit</i>
-------------	--

Description

Splits the data into K folds, refits the model on each K - 1 training partition (via the fit's stored `tulpa()` call), and accumulates the held-out fold's pointwise log predictive density $\log \frac{1}{S} \sum_s p(y_i | \eta_i^{(s)})$ over the training posterior draws. The summed `elpd_kfold` is directly comparable to the `elpd_loo` from `tulpa_criteria()` – the exact refit counterpart to the PSIS-LOO approximation, for when the Pareto k-hat gate flags LOO as unreliable.

Fixed-effect / GLMM fits only: subsetting the observations breaks a spatial or temporal field, so those fits are rejected (use PSIS-LOO via `tulpa_criteria()`). Held-out random-effect groups contribute at their prior mean (population-level held-out prediction), matching `predict()`.

Usage

```
tulpa_kfold(object, data, K = 10L, folds = NULL, n_trials = NULL, seed = NULL)
```

Arguments

<code>object</code>	A <code>tulpa_fit</code> fitted through <code>tulpa()</code> (must carry <code>\$call</code>).
<code>data</code>	The data frame the model was fit to.
<code>K</code>	Number of folds (default 10).
<code>folds</code>	Optional integer vector of fold ids, length <code>nrow(data)</code> ; a random balanced partition is drawn when <code>NULL</code> .
<code>n_trials</code>	Optional binomial denominators (length <code>nrow(data)</code>); defaults to the trials stored on the fit, else 1 (Bernoulli). Each fold's refit receives the training rows' trials, and the held-out density is scored at the test rows' trials.
<code>seed</code>	Optional seed for the random partition.

Value

A list with `elpd_kfold` (summed held-out elpd), `se_elpd_kfold` (its standard error), pointwise (per-observation held-out elpd), `folds`, and `K`.

See Also

`tulpa_criteria()` for PSIS-LOO / WAIC on a single fit.

Examples

```
set.seed(1)
d <- data.frame(x = rnorm(120))
d$y <- rpois(120, exp(0.4 + 0.6 * d$x))
fit <- tulpa(y ~ x, data = d, family = "poisson", mode = "laplace")
cv <- tulpa_kfold(fit, data = d, K = 5, seed = 1)
cv$elpd_kfold
```

tulpa_laplace

*Fit a model via Laplace approximation***Description**

General-purpose Laplace approximation for latent Gaussian models. Finds the mode of the latent field (beta + random effects) and returns the Laplace-approximated marginal likelihood.

This is the public API for model packages (tulpaGlm, tulpaObs, etc.) to call tulpa's Laplace engine. As the low-level engine entry point (not a front-door fitter), it keeps its numerical controls (max_iter, tol, n_threads, return_hessian) inline in the signature rather than in a control list, so callers assembling many solves pass them positionally.

Usage

```
tulpa_laplace(
  y,
  n_trials,
  X,
  re_list = list(),
  family = "binomial",
  phi = 1,
  phi2 = NULL,
  spatial = NULL,
  weights = NULL,
  offset = NULL,
  max_iter = 100L,
  tol = 1e-06,
  n_threads = 1L,
  return_hessian = TRUE,
  beta_prior = NULL,
  return_re_cov = FALSE,
  X_zi = NULL,
  zi_prior_sd = 2.5,
  return_joint_hessian = FALSE,
  compute_skew = FALSE,
  skew_idx = NULL,
  debias = NULL
)
```

Arguments

y	Response vector (integer for binomial/poisson/negbin, numeric for gaussian)
n_trials	Trial sizes (integer vector, used for binomial only)
X	Fixed-effects design matrix
re_list	List of RE specifications. Each element is a list with:

	• <code>idx</code>: integer vector of group indices (1-based) • <code>n_groups</code>: number of groups • <code>n_coefs</code>: coefficients per group (1 = intercept-only, >1 = random slopes) • <code>sigma</code>: per-coefficient RE standard deviation(s), a diagonal covariance (uncorrelated, lme4 (<code>x g</code>)). A scalar is recycled to <code>n_coefs</code>. • <code>Z</code>: slope design matrix (<code>n_obs x n_coefs</code>) when <code>n_coefs > 1</code>; NULL means intercept-only. • <code>L / cov</code>: optional <code>n_coefs x n_coefs</code> covariance for a <i>correlated</i> term (lme4 (<code>1 + x g</code>)) – supply either a lower-triangular Cholesky factor <code>L</code> (covariance = <code>L L'</code>) or the covariance matrix <code>cov</code>. When present these take precedence over <code>sigma</code>; the off-diagonal enters both the joint Hessian (mode finding) and the marginal fixed-effect SE.
<code>family</code>	Character: "binomial", "poisson", "neg_binomial_2", "gaussian"
<code>phi</code>	Dispersion parameter. For gaussian / lognormal this is the residual VARIANCE (matching the R-side family registry and <code>tulpa()</code>); the SD-parameterized compiled kernels receive <code>sqrt(phi)</code> internally. For <code>neg_binomial_2</code> the size, beta the precision, t the scale.
<code>phi2</code>	Optional second dispersion: the Student-t degrees of freedom (<code>family = "t"</code> ; default 4 when NULL). Non-spatial path only.
<code>spatial</code>	Optional spatial specification (<code>tulpa_spatial</code> object)
<code>weights</code>	Optional observation weights (numeric vector, length <code>length(y)</code>). Scales each observation's log-density, score and Fisher curvature by the same <code>w_i</code> , on the spatial route as well as the non-spatial one, so the mode and the marginal precision <code>H_beta</code> describe one weighted model. NULL (default) uses 1.
<code>offset</code>	Optional observation-level offset on the linear predictor (numeric vector, length <code>length(y)</code>). NULL (default) uses 0.
<code>max_iter</code>	Maximum Newton iterations (default 100)
<code>tol</code>	Convergence tolerance (default 1e-6)
<code>n_threads</code>	Number of threads (default 1)
<code>return_hessian</code>	Logical: return the fixed-effect Hessian block? (default TRUE)
<code>beta_prior</code>	Optional Gaussian prior on the fixed effects. NULL (default) keeps the weak built-in prior $\beta \sim N(0, 100^2)$. Otherwise a list with element <code>sd</code> (prior standard deviation, required) and optional <code>mean</code> (prior mean, default 0). Each may be a scalar (applied to every coefficient) or a <code>length-ncol(X)</code> vector. Adds $\text{sum}((\beta - \text{mean})^2 / (2 * \text{sd}^2))$ to the negative log-posterior, so the mode is the penalized (MAP) estimate. A coefficient's sd may be <code>+Inf</code> , which sets its precision to 0 (no penalty on that coefficient). Not supported on the spatial path.
<code>return_re_cov</code>	If TRUE, additionally return per-group marginal posterior covariance blocks <code>Cov(u_g y, Sigma)</code> – one <code>n_coefs x n_coefs</code> matrix per (RE term, group), with the fixed effects and other groups marginalized out (each block is a diagonal block of the full inverse Hessian, not the inverse of a diagonal block). Used by the EM M-step for a full random-effect covariance. Non-spatial multi-RE path only.
<code>X_zi</code>	Optional zero-inflation design matrix (<code>length(y)</code> rows). When supplied the latent fixed-effect block becomes <code>[beta_count beta_zi]</code> and the family's compiled zero-inflated kernel is used. Non-spatial path only.

zi_prior_sd	Prior SD on the zero-inflation coefficients, $\text{beta_zi} \sim N(0, \text{zi_prior_sd}^2)$ (default 2.5, matching the samplers' <code>ModelData::zi_prior_sd</code>). It is what keeps the logit identified when a level contributes no zeros, where the likelihood alone drives beta_zi to $-\text{Inf}$. $+\text{Inf}$ removes the penalty. Ignored when X_{zi} is NULL.
return_joint_hessian	If TRUE, additionally return <code>H_joint</code> : the full joint posterior precision of the latent field [<code>beta</code> random effects] at the mode, as a symmetric sparse matrix. This is the matrix the Laplace approximation takes the determinant of, so it is what an exact derivative of the log-marginal has to differentiate through; <code>H_beta</code> is only its fixed-effect Schur complement. Costs one extra copy of the Hessian, so it is off by default. Non-spatial multi-RE path only.
compute_skew	If TRUE, additionally return the inner-Laplace reliability material at <code>skew_idx</code> : <code>inner_skew</code> (<code>gamma_3</code> , Rue Martino & Chopin 2009's cubic term), and the importance curve <code>inner_is_z / inner_is_log_joint</code> the inner Pareto-k-hat is fitted from. Costs one linear solve plus a fixed batch of objective evaluations per probed index. Non-spatial path only.
skew_idx	1-based latent indices to probe (in the [<code>beta</code> random effects] layout of mode). NULL with <code>compute_skew = TRUE</code> probes every latent index.
debias	Subspace debias: a list with <code>idx</code> (1-based latent indices to correct by Metropolis along the Gaussian-conditional-mean surface through the mode) and optional <code>n_iter / warmup / thin</code> . The result then carries <code>debias_draws</code> (<code>n_kept</code> x <code>length(idx)</code>), the sampled $x_S - \text{mode}_S$, <code>debias_sigma_ss</code> (the inner Laplace's own marginal covariance of x_S), <code>debias_accept</code> and <code>debias_idx</code> . NULL (default) or an empty <code>idx</code> leaves the solve bit-for-bit as it was and consumes no random number. Non-spatial path only.

Value

A list with:

- `mode`: full mode vector (`beta`, then RE values per term)
- `log_marginal`: Laplace-approximated log-marginal likelihood
- `n_iter`: number of Newton iterations
- `converged`: logical, whether the stopping rule was met
- `score_max`: largest absolute component of the joint penalized score at the returned mode – the residual the solve actually achieved, which is a different question from `converged` and the one anything differentiating through the mode depends on
- `log_det_Q`: log-determinant of the Hessian
- `H_beta`: fixed-effect block of the Hessian (if `return_hessian = TRUE`)
- `cov_blocks`: list of per-group posterior covariance matrices, one per (RE term, group) in term-major then group order (if `return_re_cov = TRUE`)

Examples

```

set.seed(1)
n <- 200L
X <- cbind(1, rnorm(n))
eta <- X %*% c(-0.3, 0.8)
y <- rbinom(n, 1, plogis(eta))
fit <- tulpa_laplace(y, rep(1L, n), X, family = "binomial")
fit$mode          # posterior mode of the fixed effects

```

tulpa_laplace_beta	<i>Fit a beta-regression model via Laplace, estimating the precision</i>
--------------------	--

Description

Thin wrapper around `tulpa_laplace()` for family = "beta". The Laplace engine treats ϕ as fixed per fit (same contract as `gamma` and `neg_binomial_2`); this wrapper does an outer 1-D optimisation of the Laplace-approximated log-marginal over ϕ , then refits at the optimum to return betas and Hessian.

The mean-precision parameterisation is $y \sim \text{Beta}(\mu * \phi, (1 - \mu) * \phi)$ with default logit link; y must be strictly in $(0, 1)$.

Usage

```

tulpa_laplace_beta(
  y,
  X,
  re_list = list(),
  spatial = NULL,
  weights = NULL,
  offset = NULL,
  max_iter = 100L,
  tol = 1e-06,
  n_threads = 1L,
  beta_prior = NULL,
  phi_init = NULL,
  phi_bounds = c(0.1, 10000),
  outer_tol = 1e-04,
  mode = c("laplace", "nuts"),
  control = list()
)

```

Arguments

<code>y</code>	Response in $(0, 1)$.
<code>X</code>	Fixed-effects design matrix.

re_list, spatial, weights, offset, max_iter, tol, n_threads, beta_prior	Passed to tulpa_laplace() verbatim. beta_prior places a Gaussian penalty on the fixed effects (a list with sd, optional mean; see tulpa_laplace()). It is included in the Laplace log-marginal that the precision phi is optimised against, so the penalised model is fit consistently across the outer phi search. Not supported with spatial (the spatial solver carries its own prior).
phi_init	Optional starting value for the precision. If NULL, a method-of-moments warm start is used.
phi_bounds	Numeric length-2 vector with lower/upper bounds on phi for the outer optimisation. Default <code>c(0.1, 1e4)</code> .
outer_tol	Tolerance for the outer optimisation. Default <code>1e-4</code> .
mode	Inference method (the method is an argument, not a parallel verb): "laplace" (default) is the Laplace + Brent-over-phi point fit documented here; "nuts" delegates to tulpa_nuts_beta() , which samples phi jointly with the coefficients via NUTS. In "nuts" mode the Laplace-only arguments (re_list, spatial, weights, offset, phi_init, phi_bounds, outer_tol) are not used, and NUTS knobs are passed via control (see tulpa_nuts_beta()).
control	Passed to tulpa_nuts_beta() when mode = "nuts" (ignored for mode = "laplace").

Value

For mode = "laplace", the list returned by [tulpa_laplace\(\)](#) at the optimum, augmented with phi (the optimised precision) and phi_log_marginal (the optimisation trace). For mode = "nuts", the draws object returned by [tulpa_nuts_beta\(\)](#).

Examples

```
set.seed(1)
n <- 200L
X <- cbind(1, rnorm(n))
mu <- plogis(X %*% c(0.2, 0.7)); phi <- 8
y <- rbeta(n, mu * phi, (1 - mu) * phi)
fit <- tulpa_laplace_beta(y, X)
fit$mode
```

tulpa_latent

Latent Factor Specification for Unmeasured Confounders

Description

Specify latent factors to capture shared unmeasured confounders between model processes. Latent factors are particularly useful when you suspect that both processes are driven by common unmeasured variables.

Value

The constructor documented in this family ([latent_factor\(\)](#)) returns a `tulpa_latent` specification object consumed by ratio / multi-arm model packages built on tulpa (e.g. `tulpaRatio`), where the shared factor enters two or more linear predictors and cancels in the derived ratio. It is a multi-arm construct: the single-response [tulpa\(\)](#) front door does not read it (for an in-formula latent Gaussian block on a single response, use `latent(tgmrf(...))`).

<code>tulpa_loglik</code>	<i>Streaming pointwise log-likelihood</i>
---------------------------	---

Description

Wrap a pointwise log-likelihood for [tulpa_criteria\(\)](#) without materializing the whole $[n_draws \times n_obs]$ matrix. A plain matrix is wrapped directly; a block generator (a function of an integer column vector returning the $[n_draws \times \text{length}(cols)]$ submatrix) lets the criteria accumulators stream over observation blocks, so an EVA-scale $[200 \times 1.16M]$ log-likelihood is consumed a few thousand columns at a time.

Usage

```
tulpa_loglik(x, n_obs = NULL, n_draws = NULL)
```

Arguments

- | | |
|-----------------------------|---|
| <code>x</code> | Either a numeric $[n_draws \times n_obs]$ matrix, an existing <code>tulpa_loglik</code> , or a function <code>f(cols)</code> returning the $[n_draws \times \text{length}(cols)]$ submatrix for the integer column indices <code>cols</code> . |
| <code>n_obs, n_draws</code> | Required when <code>x</code> is a generator function; the column and row counts of the implied matrix. |

Value

A `tulpa_loglik` object: a list with `get(cols)`, `n_obs`, `n_draws`, and `materialized`.

See Also

[tulpa_criteria\(\)](#)

tulpa_multinomial	<i>Multinomial (nominal K-class) logistic regression via Laplace</i>
-------------------	--

Description

Fits a baseline-category multinomial logit model: for a K-level unordered response, classes 1 . . K-1 each get their own linear predictor and class K is the baseline. The coupled multinomial likelihood is solved by a Newton step to the penalized mode (a Gaussian ridge prior on the coefficients) and summarized by a Laplace approximation, reusing the native multinomial kernel.

Usage

```
tulpa_multinomial(
  formula,
  data,
  beta_prior = .tulpa_default_beta_prior("multinomial"),
  control = list()
)
```

Arguments

formula	Model formula; the response must be a factor (or coercible to one) with ≥ 3 levels. The baseline is the last level.
data	A data frame.
beta_prior	Fixed-effect prior as <code>list(mean, sd)</code> : a mean-zero ($\text{mean} = 0$) Gaussian ridge on every coefficient with scalar SD <code>sd</code> (default the engine default, <code>prior_normal(0, 2.5)</code>). A finite SD keeps the mode finite under separation.
control	List of numerical knobs: <code>max_iter</code> (default 100), <code>tol</code> (default $1e-8$), <code>n_draws</code> (posterior draws, default 2000), <code>seed</code> .

Value

A `tulpa_fit` (subclass `tulpa_multinomial`) with `coef` (named `class:term`), `vcov`, `draws`, `log_marginal`, `classes`, `baseline`, and the standard generic-method support.

See Also

[tulpa\(\)](#) for single-process GLMMs.

Examples

```
set.seed(1)
n <- 300L; x <- rnorm(n)
eta <- cbind(0.5 + 1.0 * x, -0.3 - 0.8 * x)      # classes 1, 2 vs baseline 3
P <- cbind(exp(eta), 1); P <- P / rowSums(P)
y <- factor(apply(P, 1, function(pr) sample.int(3L, 1L, prob = pr)))
fit <- tulpa_multinomial(y ~ x, data = data.frame(y = y, x = x))
```

```
coef(fit)
```

tulpa_nested_laplace *Nested Laplace approximation for latent Gaussian models*

Description

Generic outer-grid nested Laplace driver. Builds a grid over the hyperparameters of a single latent prior block (spatial or temporal), runs an inner Laplace at each grid point with warm-starting, and integrates over the grid to give proper hyperparameter marginals.

Supported priors:

- Spatial (areal): "icar" (1D grid on tau), "bym2" (2D on (sigma, rho)), "car_proper" (2D on (tau, rho); rho lives in the eigenvalue interval $(1/\lambda_{\min}, 1/\lambda_{\max})$ of $D^{-1} W$).
- Spatial (continuous): "nngp" (2D on (sigma2, phi_gp)), "hsqp" (2D on (sigma2, length-scale)).
- Temporal: "rw1", "rw2" (1D grid on tau), "ar1" (2D on (tau, rho))
- SPDE continuous spatial: see `cpp_nested_laplace_spde()` (separate entry, rebuilds Q via SPDE Q-builder).

Usage

```
tulpa_nested_laplace(
  y,
  n_trials,
  X,
  prior = NULL,
  spec = NULL,
  data = NULL,
  re_idx = NULL,
  n_re_groups = 0L,
  sigma_re = 1,
  family = "binomial",
  phi = 1,
  likelihood = NULL,
  control = list()
)
```

Arguments

y	Response vector.
n_trials	Trial sizes (binomial). Pass 1L-vector otherwise.
X	Fixed-effects design matrix.
prior	A list describing the latent prior block. Required field type one of {"icar", "bym2", "car_proper", "rw1", "rw2", "ar1"}. Type-specific fields:

- `icar`: `spatial_idx`, `n_spatial_units`, `adj_row_ptr`, `adj_col_idx`, `n_neighbors` (CSR adjacency, 0-based); optional `tau_grid`.

Any block accepts an optional `svc_weight`, one weight per observation, which makes it a varying coefficient: observation `i` contributes `svc_weight[i] * f_i` instead of `f_i`, where `f_i` is the block's field at that row (`z[spatial_idx[i]]` for an areal block, `(A u)_i` for an SPDE one). Absent, the field enters un-weighted.

- `bym2`: same adjacency; `scale_factor`; optional `sigma_grid`, `rho_grid`.
- `car_proper`: same adjacency; optional `tau_grid`, `rho_grid`, `rho_bounds = c(lower, upper)` (defaults to `(0, 1)`).
- `rw1/rw2`: `temporal_idx` (1-based), `n_times`; optional `tau_grid`, `cyclic` (default `FALSE`).
- `ar1`: `temporal_idx`, `n_times`; optional `tau_grid`, `rho_grid`.

A default grid axis is a starting axis, not a hard ceiling: for `icar` (`tau_grid`) and `bym2` (`sigma_grid`) a posterior mode that rails a boundary node (`pareto_k_regime = "collapsed_edge"`) triggers one mode-Hessian recenter-and-refit, reported through `outer_grid_placement / outer_grid_recenter_declined` – see [tulpa_nested_laplace_jo](#) return docs. An axis the caller pinned is never moved; mark a grid your own code defaulted with `auto_grid()` to keep the recenter live on it.

<code>spec</code>	Optional <code>tulpa_temporal</code> or <code>tulpa_spatial</code> spec object (output of <code>temporal_rw1()</code> , <code>temporal_rw2()</code> , <code>temporal_ar1()</code> , <code>spatial_car()</code> , <code>spatial_bym2()</code> , etc.). When supplied alongside data, the prior list is built automatically via <code>prior_from_spec()</code> – pass either prior or spec, not both.
<code>data</code>	Data frame used to validate spec and resolve time/group/site indices. Required when spec is supplied.
<code>re_idx</code>	Optional 1-based RE group index per obs (defaults to no RE).
<code>n_re_groups</code>	RE group count (default 0).
<code>sigma_re</code>	RE standard deviation (default 1).
<code>family</code>	"binomial", "poisson", "neg_binomial_2", etc.
<code>phi</code>	Dispersion (negbin/gamma).
<code>likelihood</code>	Optional model-supplied likelihood, replacing the built-in family. Pass an external pointer to a <code>tulpa::NestedLikelihood</code> (built in a model package's own C++ from a <code>LikelihoodSpec</code>); the inner Laplace solve then reads the per-observation score, Fisher weight, and log-likelihood from that spec instead of family, so family/phi are ignored. Used by model packages to fit a custom response without adding a family to tulpa – for example <code>tulpaObs</code> threads its marginalized single-season occupancy likelihood (a scaled Bernoulli, with the latent occupancy state integrated out) through this. Multi-block prior only. Default <code>NULL</code> (use family).
<code>control</code>	Optional list of perf/numerical tuning knobs (statistical arguments stay top-level), following the control convention of <code>tulpa()</code> . Recognised elements (defaults in parentheses): • <code>max_iter</code> (50L), <code>tol</code> (1e-6) – inner Newton iteration budget and tolerance. • <code>n_threads</code> (1L) – inner-loop OpenMP threads.

- `x_init` (NULL) – warm-start for the first grid point’s inner solve.
- `keep_grid_hessians` (FALSE) – when TRUE, retain per-grid-point fixed-effects marginal Hessian H_{β} and mode $\hat{\beta}$ on the return list as `$grid_hessians` (list of dense $p \times p$ matrices) and `$grid_modes` (list of length- p vectors). Used downstream by simplified-Laplace (SLA) callers to assemble skew-aware marginals – see the cumulant pooling in [rubins_pool\(\)](#).
- `diagnose_k` (TRUE), `k_samples` (200L) – compute the outer Pareto- $\hat{k}$ accuracy diagnostic (`$pareto_k`) by importance sampling the hyperparameter posterior against the Gaussian proposal fitted to the grid, drawing `k_samples` extra inner-marginal evaluations. Computed for a single-block, single positive-scale-axis grid; left NA (with the grid’s quadrature ESS as the fallback diagnostic) for multi-block, multi-axis, or bounded-parameter grids. See [tulpa_psis\(\)](#).
- `diagnose_skew` (TRUE), `skew_idx` (NULL) – compute the inner-Laplace skewness diagnostic (`$inner_skew`, gamma_3, Rue Martino & Chopin 2009 Sec 3.2.3) at the fitted MAP grid cell: one extra Newton solve, scoring the p fixed-effects latent indices by default (pass `skew_idx`, 1-based latent indices, to score additional ones, e.g. specific spatial units – the full latent field is not scored by default since it costs one linear solve per index). This is the complementary layer to `diagnose_k`: the outer diagnostic scores the hyperparameter-grid integration around a FIXED inner Laplace, this scores whether that inner Gaussian approximation is itself a good fit to the latent-field conditional posterior. See [diagnostics\(\)](#) for the combined whole-fit verdict.
- `within_cell` ("box_uniform") – the WITHIN-CELL construction the reported per-axis hyperparameter intervals are read with. The outer grid’s weights say how much mass each cell holds; they do not say how it is spread inside the cell, and a quantile needs both. "box_uniform" puts the cumulative FULL mass at each cell EDGE and interpolates between edges; "chord" puts the cumulative MID-mass at each cell coordinate and interpolates between coordinates – the same masses over the same boxes with the knots moved half a cell, which measures as a whole order of convergence (2.00 against 1.04 on a fixture with a closed-form posterior). THE DEFAULT IS "box_uniform" since 0.0.188, decided on FIXED-TRUTH coverage at the placement the engine ships, with `auto_recenter = "resolve"` as the default. Summed |coverage - nominal| over nominal 0.95 / 0.80 / 0.50, chord against box-uniform: 0.2900 / 0.1233 on the pre-registered fixed-truth instrument, 0.2004 / 0.0361 over 4680 truth-swept fits of the same fixture, and 0.2467 / 0.1572 over nine (config, axis) rows spanning seven families, at 0.69 to 1.08x the width. The conditional-coverage swing that held the default back reads 0.110 at the shipped placement against 0.415 on the coarse pinned grid it was measured on, and at nominal 0.50 it is the same on both reads. `outer_grid_h_over_sd` is how wide a cell is on each axis (with `outer_grid_resolution_declined` naming why an axis carries no ratio, and `outer_grid_railed_axes` naming any axis whose nodes do not contain its own posterior mode), and `theta_within_cell` is what each axis was actually read with. Only a "density" support admits it – a CCD design, a locally refined grid and a posterior sample are not cell

partitions that tile – and an axis it declines on reports "chord" with a reason rather than erroring. Nothing else moves: point estimates, moments, draws and weights are untouched, and "chord" restores the previous report exactly.

- `skew_correct` (TRUE) – consume the inner-Laplace expansion instead of only grading it: report Cornish-Fisher marginal quantiles at each coefficient's own γ_3 , about the centre $\gamma_1 + \gamma_3 / 2$ that Rue, Martino & Chopin (2009) eq. (22) implies, from `summary()` / `confint()` wherever the combined inner band says the leading-order expansion is in its regime, and the Gaussian quantiles everywhere else. It is post-processing on the reported quantiles: draws, modes and weights are untouched, so a fit run with it off is bit for bit the fit it was before. A coefficient whose location term could not be formed declines rather than reading it as zero. The band that bounded the relocation itself (`centre_unreliable`) is off (Inf): scored over seven fixtures with an exact reference, every finite cutoff declines the coefficients the correction helps most, because a large centre carrying a small γ_3 is uniformly weak correlation rather than an expansion out of its regime. `$skew_correction` records the per-coefficient γ_3 , γ_1 and the centre they form, the band, the inner importance k -hat, the combined band, the eligibility and the reason behind it; the `skew_applied` attribute on `summary()` / `confint()` records what was actually used at the requested level. RMC fit a skew normal here instead; the series correction is the same-order alternative, and unlike a skew normal its skewness does not saturate inside the band it is applied on.

MEASURED. Against exact quadrature quantiles of rare-event binomial-logit posteriors it cuts total absolute endpoint error 69.2%, improving both endpoints in every case. Scored over the WHOLE marginal – paired CRPS against the exact posterior in a 400-replicate prior-predictive experiment – it reads -0.01643 against the uncorrected Laplace at $t = -1.89$, essentially all of the -0.01662 the exact posterior itself achieves, and its PIT re-enters the simultaneous SBC band. Applied about the Laplace mode instead of about $\gamma_1 + \gamma_3 / 2$ the same reshaping scored +0.00775 at $t = +3.54$, a net loss; the location term is what supplies that centre.

IT IS ON BY DEFAULT, so `summary()` / `confint()` on a nested-Laplace fit report the corrected quantiles wherever the combined inner band admits the coefficient; `skew_correct = FALSE` restores the uncorrected report exactly. Scored against the mixture read a correction-off fit gives, the flip is $t = -1.895$ on the rare-event intercept and $-3.765 / -3.201$ on the small-group Bernoulli design. Across twelve model classes read off one solve per seed, pooled 95% coverage moves 0.9510 $\rightarrow$ 0.9542 at a standard error of 0.0070, with every class inside the acceptance the shipped gates use. A fit the correction cannot help – a coupled one, whose location term is unreachable – reports what it reported before, to the bit.

- `subspace_debias` (FALSE) – correct only the latent directions the inner-layer diagnostics flagged, by exact Metropolis, and leave the rest at their Gaussian conditional. TRUE takes every default; a list overrides band (the inner-reliability floor a coordinate is selected at, default "ok"), `idx` (pin the corrected set explicitly, skipping the selector), `closure` / `closure_max`

(grow the set by strongly coupled precision-graph neighbours – declined on this backend, which retains no joint precision), the sampler budget `n_iter / warmup / thin`, and `n_draws`. The selector reads the per-index bands `diagnose_skew` already attached, so it costs no extra solve; the correction itself re-runs the settled grid once with the sampler on, and the fit then reports `$draws` – the per-cell Metropolis sample for the selected coordinates, the rest from the Gaussian conditional given them – instead of the Gaussian-mixture moments. An EMPTY selection leaves the fit bit-for-bit identical to the plain path. `$subspace_debias` records what was selected, the bands it was read from, and the per-cell acceptance rate. Requesting it turns `keep_grid_hessians` on, since the recombination reads exactly those per-cell pieces.

- `cila` (FALSE) – corrected integrated Laplace, the second inner-layer debias (after Lai, Margossian and Sheldon, arXiv:2605.20345). Where `subspace_debias` selects coordinates and runs exact Metropolis on them, this selects nothing: at every outer cell it draws `n_points` points from the whole inner Gaussian, weights each by the exact joint density it came from, and reports the weighted particles. TRUE takes the defaults; a list overrides `n_points` (1024L), variant ("qmc", a Sobol net; "is" for iid draws, "rqmc" for the net under `n_shift` random shifts), `n_shift` (8L), `n_draws` and seed. Below 512 points a cell's particle set is too coarse to be a marginal at all and the request is refused. The corrected per-cell masses become the fit's own weights / `log_marginal` and `weights_source` reports "cila"; the pre-correction pair is kept as `$cila$laplace`. A cell whose inner solve factorized sparsely draws through the CHOLMOD factor's own triangular and permutation solves; an LDL' factor has no square root to draw with and is declined with "sparse_factor_not_ll".
- `auto_recenter` (TRUE) – outer-grid placement policy. TRUE re-centres the movable default axes on the posterior mode and refits when the grid either RAILS (an axis's own marginal is maximal at one of its own endpoints) or does not RESOLVE its posterior (an axis's node spacing exceeds 2 posterior SDs in its own coordinate). Both tests read the weights the fit already stored, so a grid that brackets and resolves its mode costs nothing beyond them; when the pass does fire it is a second full grid solve plus a finite-difference mode/Hessian stencil. A recentred axis is mode ± 2.5 sd over 5 nodes, a cell width of 1.25 posterior SDs by construction, against a census median of 3.9 on the fixed spans.
Measured over 200 fixed-truth seeds on each of six configurations (icar chain / icar lattice / rw1 / bym2 / iid / nngp), the default moves mean lcov-erage - nominall from 0.043 to 0.030 at the 95% level, 0.171 to 0.084 at 80% and 0.243 to 0.129 at 50% against the rail-only policy, at 0.63 times the 95% interval width and 0.76 times the median bias, for 1.71 times the wall clock.
Three other values. "rail" is the rail test alone, which is what TRUE meant before the sizing measurement settled the default. FALSE integrates over the grid exactly as given, whatever it is, and records `outer_grid_recenter_declined` = "auto_recenter_disabled". "always" re-centres every movable default axis whatever the fit did, at 2.04 times the wall clock; it agrees with

the default seed for seed on five of the six measured configurations and differs on the one whose default axes already resolve their posterior, where it takes 50% coverage to 0.135 against a nominal 0.5.

Which families carry movable axes is `.NL_REGISTRY_AXIS_FIELD`: `icar`, `rw1`, `rw2`, `iid`, `bym2`, `nngp`, `hsgp` and `spde`. `car_proper`, `ar1` and `hsgp_mo` each carry a correlation axis with no guessable coordinate, and `mcar` / `miid` / `tgmrf` hold their axes in one matrix field; a fit of any of them records which through `outer_grid_recenter_declined` rather than passing in silence. The per-axis policy names are the standalone registry path only – `tulpa_nested_laplace_joint()` and `fit_st_nested()` refuse them rather than accept them and ignore them.

- `max_grid_cells` (2048L) – cell-count ceiling on a multi-block outer grid, refused with an error above it. Each cell is one inner Newton solve, so the default catches a per-block grid that multiplied out to a run nobody asked for; a deliberate converged tensor reference grid (4 axes at 7 levels is 2401 cells) raises it here.

Value

A list with:

- `theta_grid`: matrix or vector of grid hyperparameter values.
- `log_marginal`: $\log p(y, \text{mode} \mid \theta_k)$ at each grid point.
- `weights`: integration weights normalising to sum 1.
- `theta_mean`, `theta_sd`: posterior moments per hyperparameter.
- `n_iter`: inner Newton iterations per grid point.
- `modes`: matrix [`n_grid` x `n_x`] of inner modes, when stored.
- `pareto_k`, `pareto_k_is_ess`: outer Pareto- $\hat{k}$ and its importance-sampling ESS (NA when not computed for the grid; see `control$diagnose_k`).
- `inner_skew`, `inner_skew_idx`, `inner_skew_dropped`: the inner-Laplace skewness diagnostic (`gamma_3`) at each scored latent index and its 1-based index, plus a count of (index, observation) contributions dropped for a non-finite third derivative (see `control$diagnose_skew`).
- `timing`: named numeric of wall-clock seconds (`total`, `setup`, `grid`, `postproc`, `diagnostics`); the `grid` phase is the inner Laplace pass that scales with grid size. Surfaced one-line in `print`.
- `prior`: echoed input.

References

Rue, Martino & Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *JRSS-B* 71(2):319-392.

Examples

```
set.seed(1)
S <- 30L                                     # spatial units arranged in a chain
nb <- lapply(seq_len(S), function(s) setdiff(c(s - 1L, s + 1L), c(0L, S + 1L)))
nn <- lengths(nb)
```

```

field <- as.numeric(scale(cumsum(rnorm(S, 0, 0.4)))) # smooth spatial field
idx <- rep(seq_len(S), each = 6L); n <- length(idx); x <- rnorm(n)
y <- rbinom(n, 1L, plogis(-0.2 + 0.6 * x + field[idx]))
prior <- list(type = "icar", n_spatial_units = S, spatial_idx = idx,
              adj_row_ptr = c(0L, cumsum(nn)), adj_col_idx = unlist(nb) - 1L,
              n_neighbors = nn, tau_grid = c(0.5, 1, 2, 4, 8))
fit <- tulpa_nested_laplace(y, rep(1L, n), cbind(1, x), prior = prior,
                           family = "binomial")
fit$theta_mean           # marginalized ICAR precision

```

tulpa_nested_laplace_joint

Joint multi-likelihood nested Laplace approximation

Description

Outer-grid nested Laplace driver for *joint* models – multiple response arms sharing one latent prior block, parameterized as a per-arm field amplitude (sigma) on a unit-precision latent.

Supported priors:

- "bym2" – outer grid over (sigma, rho [, alpha]). Latent: phi (n_s) | theta (n_s) with unit-precision ICAR + iid components.
- "icar" – outer grid over (sigma [, alpha]). Latent: phi (n_s) with unit-precision ICAR.
- "car_proper" – outer grid over (sigma, rho_car [, alpha]). Latent: phi (n_s) with $Q = D - \text{rho_car} * W$.

Other backends (NNGP, HSGP, RW1/2, AR1) follow the same interface and land under Phase 3.

Usage

```

tulpa_nested_laplace_joint(
  responses,
  prior,
  copy = NULL,
  phi_grid = NULL,
  prior_sigma = NULL,
  prior_alpha = NULL,
  prior_phi = NULL,
  cell_coupling = "separable",
  control = list()
)

```

Arguments

- responses** A named list of arm specs (length ≥ 1). Each arm:
- **y** – numeric [N_arm] response.
 - **n_trials** – integer [N_arm] (use `rep(1L, N_arm)` for non-binomial).
 - **X** – numeric matrix [N_arm x p_arm] fixed-effects design.
 - **spatial_idx** – integer [N_arm], 1-based map obs $\rightarrow$ spatial unit.
 - **re_idx** – optional numeric [N_arm] 1-based RE group index; defaults to `rep(0, N_arm)` (no RE).
 - **n_re_groups** – optional integer (default 0L).
 - **sigma_re** – optional numeric (default 1); ignored when `n_re_groups == 0`.
 - **family** – one of "binomial", "gaussian", "poisson", "neg_binomial_2", "beta", "lognormal", "gamma", "inverse_gaussian". For "lognormal", y is on the natural scale and the linear predictor $\eta = E[\log y]$ (identity link on the log scale); the $-\log(y)$ Jacobian is included in the kernel's `log_lik`.
 - **phi** – numeric dispersion (gaussian/lognormal residual SD, negbin size, beta precision); default 1.
 - **field_coef** – optional per-arm field coefficient controlling this arm's multiplier on the shared latent field's amplitude. One of: * numeric scalar (default 1) – constant multiplier. 0 means the arm carries NO field at all (the per-row scatter $\eta + \text{field_coef} * \sigma * z$ is skipped for that arm). * character of length 1 – names an outer-grid hyperparam axis (currently "alpha"); the coefficient varies across the grid. * `list(name = , grid = )` – embedded axis declaration, equivalent to declaring the axis and naming it on this arm. At most one arm may declare a hyperparam-driven axis (the cover hurdle and `occu_cover` both need only one). Shared axes across multiple arms are deferred. A single-block copy coefficient is declared here, on the arm – not through a separate copy argument.
- prior** A list describing the shared latent prior block. Required field type. Backend-specific fields:
- **bym2**: `n_spatial_units`, `adj_row_ptr`, `adj_col_idx`, `n_neighbors`, `scale_factor` (default 1); optional `sigma_grid` (donor-arm field amplitude, default 5 log-spaced values in $[0.1, 3]$), `rho_grid` (default `c(0.2, 0.5, 0.8, 0.95, 0.99, 0.999)`).
 - **icar**: `n_spatial_units`, `adj_row_ptr`, `adj_col_idx`, `n_neighbors`; optional `sigma_grid` (default 5 log-spaced values in $[0.1, 3]$).
 - **car_proper**: same as `icar` plus `rho_car_grid` (default `c(0.5, 0.8, 0.95, 0.99)`).

`sigma_grid`'s default is a starting axis, not a hard ceiling: when the fitted field-SD posterior mode rails the top node (`pareto_k_regime = "collapsed_edge"`, see below), the driver re-centres the axis on a mode-Hessian and refits (up to two attempts, the second adding a light default PC(U=3, $\alpha=0.01$) prior on sigma unless `prior_sigma` was pinned – see there), so a sparse or strongly-identified species is not silently truncated at 3.0. This engages whether or not

`control$diagnose_k` computed the full outer Pareto-k diagnostic: the mode-Hessian is reused from the diagnostic when it ran, or computed on its own (one extra batched finite-difference solve, only when the grid actually collapsed) when it did not – so `diagnose_k = FALSE`, the default, does not leave a railed axis stuck. A `sigma_grid` the caller PINNED always wins: `auto-recenter` engages when the field is left NULL, when it is marked with `auto_grid()` (how a wrapper package declares an axis it defaulted rather than one the user chose), or when its nodes are exactly the engine’s own default axis. Declines gracefully (keeps the fixed-grid fit) when another axis in the same grid has unguessable support (`car_proper`’s `rho_car`); whichever way it declines, `outer_grid_recenter_declined` says which (see below).

copy Multi-block copy specification (multi-block prior only). For a single-block fit there is no copy argument: declare the copy coefficient on the arm via `responses[[X]]$field_coef = list(name = "alpha", grid = G)`. On the multi-block path copy is an unnamed list of specs – `list(list(arm, block, alpha_grid), ...)` – coupling N distinct shared latent fields, each onto its own arm with its own α axis, integrated over the product outer grid. Each spec must name a distinct block. The copy block may be any of `icar` / `bym2` / `car_proper` / `rw1` / `rw2` / `ar1` / `iid`; blocks with their own per-arm scaling (`lf`, `hsgp_mo`) or a precomputed precision (`tgmrf`) do not take a copy. A copy block’s own `sigma_grid` (the donor field amplitude, same default ceiling as the single-block prior’s `sigma_grid` above) auto-recenters on `collapsed_edge` the same way, one block per attempt.

phi_grid Optional list specifying per-arm dispersion axes on the outer grid. Accepts either a named list (keys = arm names) or a positional list of length `n_arms`. Each entry is one of:

- NULL or scalar – no axis for that arm; the kernel uses the parse-time scalar `responses[[k]]$phi`.
- numeric vector of length > 1 – adds a new outer-grid axis `phi_<arm>` taking those values; the kernel rewrites `arms[k].phi` at each grid point before the inner Newton solve.

Family-specific interpretation of `arm$phi` (the parse-time scalar and the grid values):

- `gaussian` – residual SD (variance is ϕ^2). Use `phi_grid` to estimate the residual SD as a hyperparameter instead of pinning it pre-fit.
- `lognormal` – residual SD on the log scale; identical kernel parameterization as `gaussian` plus the $-\log(y)$ Jacobian.
- `neg_binomial_2` – dispersion (variance is $\mu + \mu^2/\phi$).
- `beta` – precision (variance is $\mu(1-\mu)/(1+\phi)$).
- `gamma`, `inverse_gaussian` – shape / dispersion.
- `binomial`, `poisson` – ignored.

Each `phi_<arm>` axis is appended to the Cartesian product and varies slowest (within-spatial warm starts hold). The axis appears as a regular hyperparameter in `theta_grid`, `theta_mean`, and `theta_sd`, and participates in adaptive-grid refinement.

prior_sigma, prior_alpha

Optional regularizing hyperpriors on the donor field amplitude σ and on the copy coefficient α . Each is NULL (flat, default) or a list of the form `list(family, params)`:

- `list("pc.prec", c(U, alpha))` – Penalized Complexity prior, calibrated by $P(\theta > U) = \alpha$. Closed-form density $\lambda \exp(-\lambda \theta)$ with $\lambda = -\log(\alpha)/U$. Drop-in for the weakly-identified small-`n_pos` regime. Pick `U` at the upper end of plausible values so the prior shrinks the tail without biasing the modal cell when the data identifies it: default-friendly choice on σ is `c(U = 1.0, alpha = 0.01)` (donor amplitude); on the dimensionless copy coefficient α the recommended choice is `c(U = 8.0, alpha = 0.01)`. Too small a `U` over-shrinks the copy coefficient past the modal cell and, through the $\alpha * \sigma$ copy axis, inflates the coupled donor amplitude σ – e.g. on a fixture with truth $\alpha = 1$, `c(U = 2.0, alpha = 0.01)` pulls the α posterior below 1 and lifts σ above its truth.
- `list("half_normal", scale)` – half-normal with scale `scale > 0`. Sharper tail decay than PC; use when stronger regularization is desired and the truth is well inside the prior. The contribution is added to `log_marginal` cell-by-cell at the kernel-call boundary, so refinement passes (adaptive grid, var-of-means consistency) see the regularized posterior. When the data identifies the parameter (e.g. `n_pos >= ~200`) the prior is essentially harmless – the lever is tail-shrinkage at small `n_pos`. `prior_alpha` only applies when copy is active; `prior_sigma` applies on any `sigma`-named axis.

`prior_sigma` also interacts with the auto-recenter above: its second attempt engages the engine’s own weakly-informative `PC(U = 3, alpha = 0.01)` prior, and a `prior_sigma` the caller PINNED suppresses that (the caller’s prior stands). Pinning is decided by provenance, not presence: a spec marked with `auto_grid()`, or one equal by value to the engine’s own default, is a default and does not suppress the escalation. When it does, the fit carries `outer_grid_prior_declined = "prior_pinned"`, so a second attempt that changed only the grid geometry is legible rather than looking like the full escalation.

prior_phi

Optional regularizing hyperprior on the per-arm dispersion axes declared through `phi_grid` (e.g. a Beta precision on a cover arm, a negbin dispersion, a Gaussian residual SD). Same families as `prior_sigma` – NULL (flat over the `phi` grid, default), `list("pc.prec", c(U, alpha))`, or `list("half_normal", scale)`. A single spec re-weights every `phi_<arm>` axis on the grid, the way `prior_sigma` re-weights any `sigma`-named axis; with no `phi_grid` it is a no-op. Without it the `phi` grid carries an implicit flat prior over its bounds. The PC scale is the dispersion’s own units (a precision for beta, a size for `neg_binomial_2`), so pick `U` at the upper end of plausible values.

cell_coupling

Character scalar naming a per-cell coupled likelihood registered against tulpa’s process-global registry (see `src/cell_coupling_registry.h`). Defaults to `"separable"`, the arm- separable per-obs sum every existing joint fit uses. Consumer packages (e.g. `tulpaObs`) compile a `tulpa::CellCouplingSpec` subclass in their own `src/` and register it from `R_init_<pkg>` via the `tulpa_register_cell_coupling` C callable; the R driver validates the name against the registry and the inner

Newton routes the per-cell contribution through `evaluate_cell()` when the spec couples at least one arm.

control

Optional list of perf/numerical tuning knobs (statistical arguments stay top-level), following the control convention of `tulpa()`. Recognised elements (defaults in parentheses):

- `max_iter` (50L), `tol` (1e-6) – inner Newton iteration budget and tolerance.
- `n_threads` (1L) – inner-loop OpenMP threads (per-observation scatter, compute_eta, log-likelihood reduction). For typical joint workloads (N in the hundreds to a few thousand) inner parallelism is overhead-dominated; prefer `n_threads_outer`, which stacks better on many-core hardware. Capped at the physical performance-core count by default (see `n_threads_scatter`), as the inner per-observation loops oversubscribe a hybrid CPU's efficiency cores past that point. A fit is reproducible bit for bit at a GIVEN `n_threads`: the per-observation sum cuts its range into that many contiguous chunks and adds the chunk sums in chunk order, so nothing about the answer is left to the OpenMP runtime. Chunking imposes its own association, so two different `n_threads` agree only to floating-point tolerance (measured at 6e-14 on `log_marginal` over four families).
- `n_threads_scatter` (performance-core count) – cap on the inner per-observation threads. Overrides the default performance-core cap on `n_threads`; raise it to use all logical cores or lower it to leave headroom. No effect where the core topology cannot be resolved (off Windows), where `n_threads` is used as requested.
- `n_threads_outer` (1L) – outer-grid OpenMP threads. When > 1 , a pilot Laplace at the centre cell warm-starts the remaining cells, each dispatched across `n_threads_outer` threads with its own CHOLMOD solver and NewtonScratch (inner OpenMP auto-disabled). 1L is serial, chained warm-starts – bitwise identical to the pre-speedup driver. Recommended on multi-core workstations: `parallel::detectCores() - 1L`.
- `tile_warm` (TRUE) – when `n_threads_outer` > 1 and a copy block is present, group outer cells into tiles sharing every axis except the copy coefficient alpha, solve one warm Tier-2 per tile from the centre pilot, and warm-start the rest from their tile pilot. Falls back to the single-tier path when no copy block / single tile / `n_threads_outer` $\leq 1L$. FALSE recovers the pre-tiling behaviour (e.g. regression testing).
- `prune` (FALSE), `prune_tol` (1e-3) – opt-in cheap-pass screening. When `prune = TRUE`, the driver sweeps the outer lattice running a short inner Newton per cell, each warm-started from the previous screened cell's quasi-mode (lattice-adjacent), computes a screening Laplace log-marginal, softmax-normalises, and skips the full inner Newton on cells whose normalised weight is $< \text{prune_tol}$. The neighbour-warm-start sweep keeps every cheap mode near its cell's true mode, so the cheap ranking is faithful to the full-solve ranking even when the inner latent mode moves substantially across the grid. Pruned cells get `log_marginal = -Inf`, `n_iter = 0`, and inherit the pilot mode; the pilot cell is never pruned. A safety gate falls back to the full grid (with a warning) if the cheap-screen argmax disagrees with the full-solve argmax or the kept posterior collapses onto a cell the

screen badly mis-estimated, so a silently-wrong pruned posterior is impossible. Stacks with `n_threads_outer`. `prune_tol` must be in $[0, 1)$. Keep it conservative ($\leq 1e-3$); pruning helps most when the grid has many low-mass tail cells. Default FALSE (the full grid is correct).

- `x_init` (NULL) – warm-start for the first grid point’s inner solve.
- `verbose` (FALSE) – when TRUE, announce the engaged outer integrator for a multi-block prior in one line at selection time (see `integration`), and report each CCD decline reason.
- `store_Q` (FALSE) – also return the per-grid joint precision Q (lower triangle, CSC) as `Q_csc_p_per_grid`, `Q_csc_i_per_grid`, `Q_csc_x_per_grid`, `Q_csc_n`, letting callers compute INLA-style total-variance posterior moments (Var-of-means + Mean-of-Var) on inner latent coordinates such as fixed-effect betas.
- `keep_grid_hessians` (TRUE) – retain the per-grid-point fixed-effect mode and marginal precision as `$grid_modes / $grid_hessians`, which is what lets `summary.tulpa_fit()`, `confint.tulpa_fit()` and `vcov.tulpa_fit()` report the grid-marginalized fixed-effect covariance instead of NA. Memory is $O(n_{\text{fixed}}^2)$ per cell. When the retention is not available the reason is recorded on `$grid_fixed_declined`.
- `adaptive_grid` (FALSE), `adaptive_grid_edge_thresh` (0.02), `adaptive_grid_max_passes` (1L) – when `adaptive_grid` = TRUE, a mode-tracked 1D refinement pass triggers on any axis whose marginal boundary weight exceeds `adaptive_grid_edge_thresh`. New points are appended on that axis (interior densification + outward log-spaced extension) paired with the boundary cell’s modal other-axis values, each carrying a calibration term so it contributes on the marginal scale – $O(n_{\text{new_points}})$ kernel solves, not the full cartesian product. The edge score is $\max(\text{marginal_weight_at_boundary}, \exp(\max_log_marginal_at_boundary - \max_log_marginal_at_boundary))$ catching both boundary pile-up and integrand truncation; 0.02 is ~ 4 log units of decay. `adaptive_grid_max_passes` caps the passes (one usually suffices). Fixes posterior CI under-coverage when truth sits near a grid edge.
- `var_of_means_consistency` (TRUE) – run a post-integration consistency pass on the variance of the per-arm posterior means and attach `var_of_means_consistency_info`.
- `inner_factorization` ("auto") – which factorization the dense inner Newton applies to the Hessian it assembled: "auto" by the latent dimension, "sparse" for CHOLMOD, "dense" for the dense Cholesky. Independent of `force_sparse`, which selects the assembly path.
- `force_sparse` (FALSE) – linear-algebra backend for the inner joint solve. TRUE / FALSE select the sparse or dense path outright, regardless of the dense/sparse heuristic. "auto" selects by the latent dimension the fit will actually build, taking the sparse path above $n_x > 1000$ and the dense one at or below it, where the sparse symbolic-analysis and indirection overhead outweighs the fill-in saving. A model whose latent dimension cannot be determined resolves to dense.
- `integration` ("auto") – outer-grid node layout for a multi-block prior. A central composite design (CCD) integrates the hyperparameter posterior on $1 + 2d + 2^d$ nodes oriented by the Cholesky of the posterior covariance at the joint hyperparameter mode – far fewer inner solves than

the d-dimensional tensor product (25 vs 81 at $d = 4$). "auto" (the default) uses the CCD only at ≥ 4 transformable axes, where the tensor product's k^d blow-up bites hardest, and keeps the cheaper, more ridge-robust tensor grid at ≤ 3 axes; "ccd" lowers the CCD threshold to ≥ 3 axes; "grid" always forces the full tensor product. "grid_adaptive" is the low-dimensional companion to the CCD: it seeds a coarse subsample of the SAME tensor lattice (latent block axes and phi axes together), floods outward from the posterior mode on the fine lattice, and evaluates only the cells within a log-density cutoff of the peak – a strict, uniform-weight subset of the dense tensor, so its posterior matches the dense grid to that cutoff at fewer inner solves when the hyperparameter posterior concentrates (a sharply-identified field SD / precision). It declines back to the dense tensor on a diffuse posterior (kept region would rival the tensor) or a degenerate lattice, so it never costs accuracy; tune it with `adaptive_grid_cutoff / adaptive_grid_stride / adaptive_grid_max_frac`. The CCD auto-falls back to the tensor grid for an axis whose support is not safely transformable (a CAR_proper rho_car or a non-BYM2 rho), or a flat / ridged / degenerate outer mode-find or Hessian; an active phi_grid rides as a tensor axis crossed on top of the CCD. Single-block joint priors always use the tensor grid. The CCD mode-find runs cheap warm-started inner solves and does not write to the checkpoint file. Under `verbose = TRUE` the engaged integrator is announced in one line at selection time (e.g. outer integration: CCD (4 latent axes or tensor grid (72 cells), or CCD declined -> tensor grid), so the auto switch to the CCD at ≥ 4 axes is never silent. The resolved integrator is also returned on the joint result as `$integration`, alongside `$integration_requested` and `$integration_declined` (see Value), so a fallback is on the fit itself and not only in a verbose message.

- `local_ccd` (NULL) – local CCD refinement of a multi-block tensor grid. TRUE (defaults) or a list(`max_cells =`, `f0 =`, `skew_max =`) refines a few high-weight, mutually non-adjacent interior cells, replacing each with a small curvature-aware CCD node cloud so a coarse base grid resolves the sharply-peaked directions without the k^d tensor blow-up. The local curvature is a diagonal finite difference of the outer log-marginal over the cell's own grid neighbours (no mode-find; only the off-centre nodes are new solves), warm-started from the cell's inner mode; each refined cell's sub-nodes carry partition-of-unity design weights so the total integration weight is conserved (no double-count). `max_cells` (8L) caps the refined cells; `f0` (1.1) is the CCD radius. The design scale is shrunk per cell so the cloud fits the cell's Voronoi box (the local-Gaussian mass beyond it belongs to the neighbouring cells). A cell keeps its cloud only while the nodes' own log-marginals stay within `skew_max` (the `gamma3_ok` band, 0.5) of the quadratic the cloud was placed from, measured as a standardized cubic magnitude; above it the cell is put back as its own mass atom, which on a skewed outer target is measurably closer than the design. Engages only on the tensor path (the curvature stencil needs axis neighbours), at ≥ 4 transformable latent axes, with no active phi_grid; otherwise it is a no-op. The applied refinement is summarised on the result as `$local_ccd_info`. Also driven automatically by `k_refine = "ccd"`.

- `adaptive_grid_cutoff` (10), `adaptive_grid_stride` (2L), `adaptive_grid_max_frac` (0.75), `adaptive_grid_min_cells` (48) – tuning for integration = "grid_adaptive". `adaptive_grid_cutoff` is the log-density keep / expand radius from the peak (larger keeps more cells, closer to the dense tensor); `adaptive_grid_stride` the coarse-seed subsample stride per axis; `adaptive_grid_max_frac` the kept-fraction ceiling past which the builder declines back to the dense tensor; `adaptive_grid_min_cells` the smallest dense tensor worth the adaptive machinery – below it the builder declines BEFORE any inner solve (on a small tensor the coarse seed is already most of the grid, so there is no tail to skip). Ignored by the other integrators. The kept-cell / dense / solve counts are returned as `$adaptive_grid_info`.
- `inner_refresh` (1L) – inner-Newton Cholesky factor reuse interval (Shaman-skii / chord method). For a non-quadratic positive arm (e.g. a beta cover arm) the latent Hessian changes every inner iteration, so the default re-factorizes the sparse Cholesky on each step – the dominant per-grid-cell cost. `inner_refresh = m > 1` re-factorizes only every `m`-th inner step and reuses the cached factor in between (refreshing early whenever a reused solve fails). The gradient is exact on every step and each step is line-search safeguarded, so the converged mode is unchanged and the final mode-pass Hessian (`log_det`, SEs) is always fresh; only the path to the mode uses a stale curvature, which may cost a few extra inner iterations. Applies to the sparse joint path with the default `control$hessian = "lm"` curvature; the dense small-`n_x` path re-factorizes a cheap Hessian and ignores it. 2L-4L is a good range for a slow beta arm.
- `k_quality` ("report") – the reliability intent for the outer Pareto- $\hat{k}$, a single statement of how reliable the fit should be. "report" (default) computes the diagnostic and reports the achieved band. "ok" / "good" additionally name a TARGET band (the $\hat{k}$ confidently usable, resp. good) and raise the default `k_samples` (to 800L / 2000L, unless you set it) so the bootstrap CI can resolve it. "none" disables the diagnostic. The fit carries an honest verdict – `k_quality_requested`, `k_quality_reached`, `k_quality_best`, `k_quality_reason`, `k_quality_rounds` – and never silently downgrades: if the requested band is not confidently met it reports the band actually reached and why. For "ok" / "good", when the first fit does not reach the band the engine escalates by REFINING THE INTEGRATION GRID, driven by the bad $\hat{k}$ (see `k_refine`): each round widens / densifies the grid where the posterior mass escapes its current bounds and re-diagnoses, up to `k_max_rounds` times. This is the actual fix for a grid-width deficiency; `k_samples` is the separate knob that sharpens the $\hat{k}$ ESTIMATE and is not escalated here.
- `k_refine` ("grid") – the integration-refinement rung for `k_quality` "ok" / "good". "grid" (default) re-fits with adaptive grid refinement (`adaptive_grid`) each escalation round, driven by the bad $\hat{k}$, so a too-coarse / too-narrow grid is widened / densified where the importance weight concentrates until the band is reached or the budget is spent. "ccd" instead refines a few high-weight, mutually non-adjacent interior cells with local curvature-aware CCD node clouds (see `local_ccd`), the right rung when the grid is too coarse to resolve a sharply-peaked direction rather than too narrow; it

forces a tensor base grid (the curvature stencil needs axis neighbours) and engages only on the multi-block path at ≥ 4 transformable latent axes. "none" disables refinement: the band is reported but not chased.

- `k_max_rounds` (2L) – the grid-refinement round budget for `k_quality` "ok" / "good": the maximum number of refine-and-re-fit rounds after the first fit. Each round allows one more refinement pass than the last. 0L disables escalation (single-shot, the band is reported but not chased).
- `diagnose_k` (TRUE), `k_samples` (500L) – compute the outer Pareto- $\hat{k}$ accuracy diagnostic by importance-sampling the joint hyperparameter posterior against the proposal the integrator fits (mixed per-axis transforms: log for positive scales, logit for the BYM2 mixing weight, identity for the copy coefficient α). `k_samples` is the number of importance draws, each one an extra inner joint solve, and is the diagnostic's precision knob: a tighter `k-hat` needs MORE actual tail ratios, so increase `k_samples` (not `k_bootstrap`). The draws are RNG-restored so the fit's modes / draws are unchanged. A fit carrying an axis whose support is not safely known (CAR_proper's `rho_car`) declines to the quadrature-ESS fallback (`pareto_k` = NA). FALSE skips the diagnostic. "by_arm" additionally computes a `k-hat` restricted to each arm's hyperparameter axes (the other arms held at their posterior mean), reported in `pareto_k_by_arm`, to localise which arm drives a tail-heavy joint `k`; the joint `k` itself is unchanged. Per-arm `k` is defined for the multi-block layout with two or more arms and declines for the single-block shared-field layout. The legacy `k_samples` name is accepted as an alias for `k_samples`.
- `k_threads` (NULL) – outer-thread width for the diagnostic's importance batch. The `k_samples` re-solves are independent and run after the grid (every core free), each solved single-threaded once the batch saturates the pool, so widening it is a bit-identical wall-clock speedup (the `k-hat` is unchanged). NULL follows the fit's own thread grant – the larger of `n_threads_outer` and the inner `n_threads` – so a serial fit keeps a serial diagnostic while a threaded fit gets a free parallel one. "auto" uses the physical performance-core count (capped at 2 under R CMD check); an integer pins the width (1L forces serial). Always capped at `k_samples`.
- `k_bootstrap` (1000L) – bootstrap replicates for the outer Pareto- $\hat{k}$ uncertainty. The `k-hat` is a single fixed number for a fit + proposal; its sampling uncertainty GIVEN the proposal is estimated by resampling the diagnostic's raw importance log-ratios with replacement and re-fitting the GPD tail `k_bootstrap` times (no new inner solves). Reports `pareto_k_se_boot` (bootstrap SE), `pareto_k_ci_low` / `pareto_k_ci_high` (the 2.5\ closed-form GPD-shape MLE asymptotic SE $(1 + k)/\sqrt{M}$, a cross-check), and `pareto_k_band_confident` (TRUE iff the bootstrap CI lies within one reliability band). The bootstrap measures how UNSTABLE the current tail estimate is; it cannot create tail information. Increase `k_samples`, not `k_bootstrap`, to obtain more tail information. 0L skips it (point `k-hat` only). The per-arm `k` carries the same fields.
- `k_tail_points` (NULL) – number of upper-tail order statistics for the GPD fit. NULL uses the automatic PSIS rule $\lceil \min(0.2N, 3\sqrt{N}) \rceil$. An explicit value is an EXPERT tail-threshold control, capped at the 20\ so the fit stays

an extreme tail; it is NOT a precision knob (a request that drags body ratios into the tail lowers variance but biases the k -hat). The used and requested counts are reported in `pareto_k_tail_points/pareto_k_tail_points_requested`.

- `k_conf_bands` (NULL) – the reliability-band boundaries the bootstrap CI is tested against for `pareto_k_band_confident`. NULL (default) uses the sample-size-dependent boundaries $c(0.5, \min(1 - 1/\log_{10} S, 0.7))$ at the realised draw count S (Vehtari et al. 2024): the good cut is 0.5 and the usable cut tightens below 0.7 for small S (about 0.565 at $S = 200$, reaching 0.7 only past $S \approx 2154$). Supply a strictly-increasing numeric vector to fix the boundaries instead, e.g. $c(0.5, 0.7)$ for the size-independent good / ok / unreliable split.
- `diagnose_skew` (TRUE), `skew_idx` (NULL) – compute the inner-Laplace skewness diagnostic (`$inner_skew`, gamma_3, Rue Martino & Chopin 2009 Sec 3.2.3) at the fitted MAP grid cell: one extra Newton solve via the same `kernel_fn` the outer diagnostic reuses, scoring every arm’s fixed-effects coefficients by default (pass `skew_idx`, 1-based indices in the joint `[arm1_beta | arm1_re | arm2_beta | ... | blocks]` latent layout – see `$arm_layout` – to probe additional indices). This is the complementary layer to `diagnose_k`: that scores the outer hyperparameter-grid integration around a FIXED inner Laplace, this scores whether that inner Gaussian approximation is itself a good fit. A genuinely coupled arm (`cell_coupling != "separable"` on that arm, e.g. `tulpaObs`’s `occu_cover`) has no per-obs likelihood for the separable formula to score; it is scored instead by the contraction of the cell third-derivative tensor, which differences the cross-arm Hessian the coupling spec already returns. A fit that can carry neither reports NaN, not a silently wrong 0, and `$inner_skew_declined` says WHY – “coupled_arm” marks arms the inner layer could not score at all, distinct from a diagnostic that was simply switched off – while `$inner_skew_arms_declined` names the arms with no oracle, including on a partially scored fit. See [diagnostics\(\)](#) for the combined verdict. Wired for both the single-block backends (`icar/bym2/car_proper`) and the multi-block path (a per-group RE, a trend field, or an arm-specific field block).
- `within_cell` (“box_uniform”) – the WITHIN-CELL construction the reported per-axis hyperparameter intervals are read with. The outer grid’s weights say how much mass each cell holds; they do not say how it is spread inside the cell, and a quantile needs both. “box_uniform” puts the cumulative FULL mass at each cell EDGE and interpolates between edges; “chord” puts the cumulative MID-mass at each cell coordinate and interpolates between coordinates – the same masses over the same boxes with the knots moved half a cell, which measures as a whole order of convergence (2.00 against 1.04 on a fixture with a closed-form posterior). THE DEFAULT IS “box_uniform” since 0.0.188, decided on FIXED-TRUTH coverage at the placement the engine ships, with `auto_recenter = “resolve”` as the default. Summed `lcoverage - nominal` over nominal 0.95 / 0.80 / 0.50, chord against box-uniform: 0.2900 / 0.1233 on the pre-registered fixed-truth instrument, 0.2004 / 0.0361 over 4680 truth-swept fits of the same fixture, and 0.2467 / 0.1572 over nine (config, axis) rows spanning seven families, at 0.69 to 1.08x the width. The conditional-coverage swing that

held the default back reads 0.110 at the shipped placement against 0.415 on the coarse pinned grid it was measured on, and at nominal 0.50 it is the same on both reads. `outer_grid_h_over_sd` is how wide a cell is on each axis, and `theta_within_cell` is what each axis was actually read with. Only a "density" support admits it – a CCD design, a locally refined grid and a posterior sample are not cell partitions that tile – and an axis it declines on reports "chord" with a reason rather than erroring. Nothing else moves: point estimates, moments, draws and weights are untouched, and "chord" restores the previous report exactly.

- `skew_correct` (TRUE) – consume the inner-Laplace expansion instead of only grading it: report Cornish-Fisher marginal quantiles at each coefficient's own `gamma_3`, about the centre $\gamma_1 + \gamma_3 / 2$, from `summary()` / `confint()` wherever the combined inner band (`gamma_3` and the inner importance `k-hat`) says the leading-order expansion is in its regime, and the Gaussian quantiles everywhere else. It is post-processing on the reported quantiles: draws, modes and weights are untouched, so a fit run with it off is bit for bit the fit it was before. The band that bounded the relocation itself (`centre_unreliable`) is off (Inf): every finite cutoff was measured to decline the coefficients the correction helps most. `$skew_correction` records the per-coefficient `gamma_3`, `gamma_1` and the centre they form, the band, the `k-hat`, the combined band, the eligibility and the reason behind it; the `skew_applied` attribute on `summary()` / `confint()` records what was actually used at the requested level. A FULLY COUPLED fit declines it: the location term's contraction against a covariance block is not reachable from the cell third-derivative oracle, and an absent `gamma_1` is never read as zero. Such a fit therefore reports what it reported before the default moved, to the bit – a declined coefficient keeps the grid-mixture read. See [tulpa_nested_laplace\(\)](#) for the measurement behind the default.
- `subspace_debias` (FALSE) – correct only the latent directions the inner-layer diagnostics flagged, by exact Metropolis along the Gaussian-conditional-mean surface through each cell's mode, and leave the rest at their Gaussian conditional. Settings and semantics are the ones documented on [tulpa_nested_laplace\(\)](#). On a fully coupled fit `gamma_3` is NaN for every arm, so the selector rests on the derivative-free inner Pareto-`k-hat`; where that also bands the coordinate reliable, `idx` pins the set explicitly. An EMPTY selection leaves the fit bit-for-bit identical to the plain path. A fit whose inner solve took the `s2z` rank-1 or the PSD eigen-clamp path carries no usable factor to build the surface from and is left uncorrected, the same two paths `diagnose_skew` declines on.
- `cila` (FALSE) – corrected integrated Laplace, the second inner-layer debias (after Lai, Margossian and Sheldon, arXiv:2605.20345). Where `subspace_debias` selects coordinates and runs exact Metropolis on them, this selects nothing: at every outer cell it draws `n_points` points from the whole inner Gaussian, weights each by the exact joint density it came from, and reports the weighted particles. The cell marginals and the latent posterior both converge to the exact ones as the effort grows, so `n_points` is the only dial. TRUE takes the defaults; a list overrides `n_points` (1024L), variant ("qmc", a Sobol net; "is" for iid draws, "rqmc" for the net under `n_shift`

random shifts), `n_shift` (8L), `n_draws` (the reported draw count) and `seed` (the auxiliary stream, engine-owned so requesting the correction leaves every other posterior draw unchanged). Below 512 points a cell's particle set is too coarse to be a marginal at all and the request is refused. The correction reports DRAWS, so every coefficient-facing method reads them instead of the grid's Gaussian mixture, and the corrected per-cell masses become the fit's own weights / `log_marginal` with `weights_source` reporting "cila"; the pre-correction pair is kept as `$cila$laplace` and `$cila$retained_mass` is the original share of the cells that produced a usable particle set. `$cila` also carries the variant actually run and the PSIS grade (`pareto_k`, `rel_ess`) of the correction's own weights. A cell whose inner solve factorized SPARSELY draws through the CHOLMOD factor's own triangular and permutation solves; an LDL' factor carries no square root to draw with and is declined with "sparse_factor_not_ll".

- `auto_recenter` (TRUE) – re-centre a default outer grid axis on its posterior mode and refit when the fit rails against a boundary node. FALSE integrates over the grid exactly as given, whatever it is, and records `outer_grid_recenter_declined` = "auto_recenter_disabled". The joint rescues trigger on the whole grid's collapsed-edge regime rather than on a per-axis rail, so the per-axis policy names `tulpa_nested_laplace()` takes ("rail", "resolve", "always") are refused here with an error rather than accepted and ignored.
- `max_grid_cells` (2048L) – cell-count ceiling on a multi-block tensor outer grid, refused with an error above it. Each cell is one inner Newton solve, so the default catches per-block grids that multiplied out to a run nobody asked for; a deliberate converged tensor reference grid (4 axes at 7 levels is 2401 cells) raises it here, which `integration = "ccd"` cannot serve since a CCD is a different integration design.
- `checkpoint` (NULL) – grid-cell checkpoint/resume. Set `list(path = "fit.ckpt", resume = TRUE)` to make a killed or interrupted fit resumable: each completed outer-grid cell is appended to path, and a later call with the same responses + grid + control loads the finished cells and solves only the rest. EVA-scale joint fits run for hours, so a wrapper teardown, reboot, or OOM near the end otherwise loses the whole run. `resume = TRUE` (the default when a path is given) continues from an existing file; `resume = FALSE` removes it first and starts over. Adaptive-grid refinement cells are checkpointed under their own coordinate keys, so resume covers them too. A file written for different data or solver settings is rejected (fingerprint mismatch) rather than resumed onto a stale result.

Value

A list of class `c("tulpa_nested_laplace_joint", "tulpa_nested_laplace", "list")` with:

- `theta_grid`, `theta_names` – outer-grid hyperparameter values (includes the alpha axis when copy is set).
- `log_marginal`, `weights` – per-grid-point log-marginal and integration weights (sum to 1).
- `theta_mean`, `theta_sd` – posterior moments per hyperparameter, including alpha when copy is set.

- `theta_median`, `theta_ci_lo`, `theta_ci_hi` – weighted-quantile median and 2.5/97.5 empirical CI per hyperparameter axis (same names as `theta_mean`). Recommended summary for right-skewed scale-like axes (alpha at small `n_pos`, sigma/range/phi near a boundary), where the posterior mean is pulled by the right tail away from the bulk and mean ± 1.96 sd mis-states the uncertainty.
- `modes` – [`n_grid` x `n_x`] matrix of inner modes.
- `n_iter` – inner Newton iterations per grid point.
- `arm_layout` – list with per-arm `beta_start`, `re_start`, spatial offset(s) and `n_x` for decoding modes.
- `prior`, `responses`, `copy` – echoed inputs.
- `timing` – named numeric of wall-clock seconds: total plus the setup (validation / encoding / grid construction), `grid` (inner Laplace solves, including adaptive-refinement and consistency passes), `postproc` (weight / moment / marginal assembly) and diagnostics (outer Pareto- $\hat{k}$) phases. The grid phase is the one that scales with grid size and core count. Surfaced one-line in print.
- `pareto_k`, `pareto_k_is_ess`, `pareto_k_scope` – outer Pareto- $\hat{k}$ accuracy diagnostic and its importance-sampling ESS (both NA when `control$diagnose_k` = FALSE or the fit declines; see the `diagnose_k` control knob). `pareto_k` < 0.7 indicates the nested integration is reliable; ≥ 0.7 that the (skewed / heavy-tailed) hyperparameter posterior is misfit by the Gaussian grid and the fit should escalate to an exact debias.
- `pareto_k_declined` – when `pareto_k` is NA, WHY: "not_requested" (`control$diagnose_k` = FALSE; nothing is wrong), "unguessable_axis: <axis>" (a support the engine will not guess, e.g. `car_proper`'s `rho_car` – a PERMANENT limitation of that family, so read the quadrature ESS instead), "draws_too_few", "grid_too_small", "no_varying_axis", "degenerate_proposal" (the outer mode curvature came back non-finite – a signal about the fit), "not_applicable", or "internal_inconsistency" (an engine bug worth reporting). NA on a fit whose $\hat{k}$ WAS computed.
- `pareto_k_proposal_source` – how the outer importance proposal the $\hat{k}$ scores was built: "mode_hessian" from the Laplace curvature at the hyperparameter mode (the CCD design's, or a finite-difference Hessian when a sharp posterior collapses the grid), "grid_moment" from the grid-weighted covariance, "moment_matched" when the moment-matching refinement improved on either, "grid_mixture" when the faithful mixture-over-grid-cells proposal won, or "skew_normal" when the skew-normal rescue did. NA when the diagnostic is off or declines. The mode-Hessian source keeps the $\hat{k}$ meaningful when the grid concentrates on ~1 cell.
- `pareto_k_regime` – whether the outer grid actually integrated hyperparameter uncertainty: "spread", or "collapsed_interior" / "collapsed_edge" when the quadrature effective sample size falls below two cells so the integration has degenerated to a point evaluation at the modal hyperparameter. An interior collapse is benign (the grid bracketed the mode; the fit is empirical Bayes at that mode and only the integrated hyperparameter uncertainty is missing); an edge collapse means the mode sits at an extreme node, so the grid may be too narrow. Attached from the stored weights, so it is present even with `control$diagnose_k` = FALSE.
- `pareto_k_grid_edge_axes`, `pareto_k_grid_edge_sides` – for an edge collapse, which axes the dominant cell sits against and on which side ("lower" / "upper"); widen those axes and refit to confirm the mode is bracketed. Axes the grid pins to one value are excluded (pinned, not at a boundary).

- `outer_grid_placement` – "fixed" (the default `sigma_grid` axis was used as-is) or "auto_recentered" when a collapsed_edge on `sigma` triggered the mode-Hessian recenter-and-refit (see the prior argument above). `outer_grid_recenter_attempts` (integer) and `outer_grid_prior_added` (logical: whether the light default PC(U=3, alpha=0.01) `sigma` prior was applied) are set alongside it, plus `outer_grid_prior_declined` = "prior_pinned" when a second attempt ran but the caller's pinned `prior_sigma` held that prior back.
- `outer_grid_recenter_declined` – on a "fixed" placement, why the recenter did not run: "grid_not_collapsed" (the grid already brackets the mode – the common case, no refit needed), "axis_pinned" (the caller pinned `sigma_grid`; mark it with `auto_grid()` if it is a default rather than a choice), or "no_usable_curvature" (the mode-Hessian the recenter needs was unavailable or degenerate, e.g. a car_proper grid whose `rho_car` axis has unguessable support). Absent when the fit WAS recentered.
- `outer_grid_recenter_sd_clamp`, `outer_grid_recenter_sd_raw`, `outer_grid_recenter_sd_used` – on a recentered fit, one entry per moved axis: which mode-SD bound the placement hit ("none" / "floor" / "ceiling"), the SD the finite-difference stencil MEASURED, and the SD the axis was actually laid from. A clamped axis was laid from a substituted spread rather than a measured one, and the reported interval is read off that span; the two used to be indistinguishable on the fit.
- `pareto_k_outer_skew` – per-axis skewness of the hyperparameter marginal in the proposal's whitened coordinate, present only when a $\hat{k}$ above the good band triggered the skew-normal rescue pass. It is the EXPLANATION for an inflated $\hat{k}$: a symmetric Gaussian proposal against a right-skewed variance-component marginal has a heavy importance-ratio tail whatever the integration's quality. NULL when the Gaussian proposal already fit.
- `pareto_k_se_boot`, `pareto_k_ci_low`, `pareto_k_ci_high`, `pareto_k_se_formula`, `pareto_k_tail_points`, `pareto_k_tail_points_requested`, `pareto_k_band_confident` – the outer Pareto- $\hat{k}$ uncertainty, present whenever the diagnostic ran. `pareto_k_se_boot` is the bootstrap SE of the $\hat{k}$ and `pareto_k_ci_low` / `pareto_k_ci_high` its 2.5\ quantiles – the estimator's sampling spread GIVEN the proposal, not a posterior credible interval; `pareto_k_se_formula` is the closed-form GPD-shape MLE asymptotic SE cross-check. `pareto_k_tail_points` is the GPD tail size used and `pareto_k_tail_points_requested` the $\hat{k}_{tail_points}$ request (NA when automatic). `pareto_k_band_confident` is TRUE iff the bootstrap CI lies within one reliability band, NA when the bootstrap was off or could not fit. `diagnose_draws` and `diagnose_cost_ratio` (the diagnostic's draw budget and its wall-clock cost relative to the fit) are attached at the top level.
- `pareto_k_by_arm`, `pareto_k_by_arm_is_ess`, `pareto_k_by_arm_scope` – present only with `control$diagnose_k = "by_arm"`. Named (by arm) outer Pareto- $\hat{k}$ restricted to each arm's hyperparameter axes, the other arms held at their posterior mean, so a tail-heavy joint $\hat{k}$ can be localised to one arm. A per-arm entry is NA when that arm carries no varying axis. Each arm carries its own bootstrap uncertainty: `pareto_k_by_arm_se_boot`, `pareto_k_by_arm_ci_low` / `pareto_k_by_arm_ci_high`, `pareto_k_by_arm_se_formula`, `pareto_k_by_arm_tail_points` and `pareto_k_by_arm_band_confident`.
- `k_quality_requested`, `k_quality_reached`, `k_quality_best`, `k_quality_reason`, `k_quality_rounds` – the reliability verdict for the `control$k_quality` intent. `k_quality_requested` echoes the intent; `k_quality_best` is the band actually achieved ("good" / "ok" / "unreliable", or "uncertain" when the bootstrap CI crosses a boundary); `k_quality_reached` is TRUE/FALSE for an "ok" / "good" target (NA for "report" / "none"), never silently downgraded; `k_quality_reason`

records why it stopped; and `k_quality_rounds` is the number of escalation re-fits performed (0 when the first fit sufficed or escalation was off).

- `adaptive_grid_info` – when `adaptive_grid = TRUE`, a list with `triggered_axes` (character) and `n_points_added` (integer) describing the refinement passes. NULL otherwise.
- `local_ccd_info` – when `local_ccd` engaged (or `k_refine = "ccd"`), a list with `n_cells_refined`, `n_nodes_added`, the refined cells, the `n_cells_before / n_cells_after` grid sizes, `n_design_nodes` (the cells that carry an in-cell design weight rather than their own mass), `design_mass` (the share of the integration weight sitting on them) and `cell_share` (the share each refined cell held on the BASE grid, before any node was placed). The two shares differ: the replacement nodes sit nearer the peak than the cell's own coordinate did, so refining raises the share the refined region holds, and reading both separates how concentrated the base grid already was from how much the refinement concentrated it. Three per-cell readings come with it, on three orthogonal axes, none of them gating anything. Shape: `misfit` (the standardized cubic magnitude of the part of the cell the design cannot represent, the one reading `skew_max` gates on, with `misfit_declined / cells_declined` for the cells put back as their own mass atoms). Centring: `offset` (the norm of the whitened gradient, i.e. how far the cell's own peak sat from the cell's coordinate in units of its marginal spread) and `mode_gain` (the same displacement in the cell's own curvature units, $0.5 * g'(-H)^{-1} g$ in nats, read off the same fit's quadratic coefficients and comparable across cells whose curvature differs; NA where $-H$ is not positive definite, a cell with no interior peak to be displaced from). Mass: `log_mass_ratio` (the cell's refined mass over the coarse atom it replaced, `log_mass_refined - log_mass_coarse`, both carried on the log scale with the cell's outer design weight in them) and `max_node_weight` (the share the single largest node takes of its own cell's refined mass). Each carries a `_declined` twin for the cells the gate put back, whose nodes were evaluated before the score was read. `misfit` certifies that the design can represent the cell's shape and nothing more: a cell can be exactly quadratic and still be read at a point that is not representative of it (`offset / mode_gain`), and refining it can still move how much mass it competes for against its unrefined neighbours (`log_mass_ratio`, the embedded-rule local error indicator of adaptive cubature). NULL when local CCD was off or declined (single-block, < 4 axes, an active `phi_grid`, or no peaked interior cell).
- `integration_requested`, `integration_declined` – what integration asked for, and why the CCD did not run. `$integration` names the integrator that RAN, and `.nl_node_support()` keys the interval construction off it, so a caller who asked for a moment rule and received a density grid reads the reason here rather than inferring it. `integration_declined` is NA_character_ when nothing was declined, and otherwise one of "axis_count" (fewer transformable latent axes than the requested mode's threshold), "unguessable_axis" (a CAR_proper rho_car or a non-BYM2 rho), "degenerate_axis" (a single-valued axis), "modefind_ridge" / "modefind_boundary" / "modefind_degenerate" / "modefind_failed", "hessian_singular" or "hessian_not_pd". Multi-block fits only.
- `weight_kind` – one entry per outer-grid cell, "mass" or "design". A tensor cell holds the mass of its own cell and a CCD node holds a design weight, so a fit integrated by one rule reports one value throughout; a locally refined grid carries both, and this says which per cell instead of leaving it to be read off integration.
- `theta_interval_read`, `theta_interval_design_mass` – what the reported per-axis `theta_median / theta_ci_lo / theta_ci_hi` were read off, and how much of the integration weight sits on nodes whose cumulative sum is not a CDF. "density" is a weighted quantile over cells that discretize the posterior (`design_mass 0`), "moment_rule" an interval from the moments a

central-composite design delivers (design_mass 1), and "mixed" the locally CCD-refined grid, which carries both kinds at once. A mixed support still reports the weighted quantile, which measured best against a converged reference in both design_mass regimes; the share is the regime variable, since on that part of the support the quantile is bounded by the refined cells' own grid neighbourhoods rather than by the posterior. Every nested path stamps the pair, not only the multi-block driver.

- `within_cell_requested`, `theta_within_cell`, `theta_within_cell_declined` – the WITHIN-CELL construction the same intervals were read with. The kind above says what the integrator left; this says how each cell's mass was spread inside its own box when the grid was read back. "box_uniform" is the default and puts the cumulative full mass at each cell edge; "chord" (`control$within_cell`) puts the cumulative mid-mass at each cell coordinate, the same masses over the same boxes with the knots moved half a cell. The construction is recorded per axis, and an axis whose cell partition could not be built falls back to "chord" on its own with the reason in `theta_within_cell_declined` ("support_<kind>", "single_node", "boxes_do_not_tile", "no_usable_node").
- `theta_cell_edge_coord`, `theta_cell_edge_declined` – per axis, the COORDINATE that axis's outer cell edges were mirrored in, and why the support the axis declares did not produce them. A declared support is authoritative: its mirrored edge is used when finite and inside it, and otherwise the axis reports its extreme grid coordinate – which the containment test has already placed inside the support – rather than falling through to a coordinate guessed from the node values, which is what put a lower bound of 0 on a positive axis and a bound above 1 on a unit one. An axis that declares no support at all keeps the guess by design, but its mirrored edge is checked for being a representable double that brackets the coordinates, and falls back to the extreme grid coordinate with "mirrored_edge_not_representable" when it is not. `theta_cell_edge_declined` is NA where nothing was declined.
- `outer_grid_cell_width`, `outer_grid_axis_sd`, `outer_grid_h_over_sd` – per axis, the cell width and the posterior SD in that axis's own coordinate, and their ratio. A within-cell reconstruction resolves an interval endpoint to within one cell, so how much of the reported width and of its realized coverage is a property of where the grid fell rather than of the posterior is governed by this ratio; below `.nl_diag("grid_resolved")` the cells are narrower than the posterior they discretize and the two constructions converge to each other. NA on an axis whose own marginal is maximal at an endpoint, which is the placement question `outer_grid_railed_axes` reports.
- `outer_grid_resolution_declined` – per axis, why that axis carries no ratio, from the closed vocabulary `too_few_nodes`, `mode_at_edge`, `coord_not_finite`, `spacing_not_finite`, `stencil_degenerate`, `curvature_not_negative`; NA on an axis that scored. The reasons are not interchangeable: `mode_at_edge` says the grid does not contain that axis's own posterior mode, which is a stronger statement about the fit than any ratio, and the whole-grid resolved verdict is withheld while one is present rather than being read off the axes that did score.
- `prune_cheap_log_marginal`, `prune_mask`, `prune_n_pruned`, `prune_tol` – present only when `prune = TRUE` and the safety gate did not fall back. Cheap-pass log-marginals at every cell, a logical mask of pruned cells, the pruned-cell count, and the threshold actually applied. Pruned cells have `log_marginal = -Inf` so they get zero weight under `.nl_normalise_weights_safe`.
- `prune_fallback_triggered`, `prune_fallback_reason` – present only when the safety gate fell back to the full grid. The returned fit is the full-grid (unpruned) result; the reason string records which gate condition tripped.

(sigma, alpha) parameterization

Each arm's linear predictor reads

$$\eta_{arm} = X_{arm}\beta_{arm} + \sigma_{arm} \cdot z_s,$$

where z_s is a unit-precision latent (ICAR($\tau=1$) for ICAR/BYM2, or the BYM2 mix; CAR_proper uses the structure of $D - \rho_{car}W$). All arms share the donor amplitude σ from the outer-grid sigma_grid axis. The copy arm's amplitude is $\sigma_{arm} = \alpha \cdot \sigma$, where α is a direct outer-grid axis taken from copy\$alpha_grid. The Cartesian product is over (sigma, [rho/rho_car,] alpha[, phi]). Direct α as an outer-grid axis (rather than a post-hoc ratio $\alpha = \sigma_{pos}/\sigma_{occ}$) avoids plug-in bias on the weakly-identified ratio at small n_pos and lets a regularizing hyperprior land on α directly.

References

Rue, Martino & Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *JRSS-B* 71(2):319-392.

See Also

[tulpa_nested_laplace\(\)](#) for the single-arm engine.

Examples

```
set.seed(1)
S <- 25L                                     # shared spatial units (chain graph)
nb <- lapply(seq_len(S), function(s) setdiff(c(s - 1L, s + 1L), c(0L, S + 1L)))
nn <- lengths(nb)
field <- as.numeric(scale(cumsum(rnorm(S, 0, 0.4))))
mk_arm <- function(m, fam) {
  si <- sample(S, m, replace = TRUE); x <- rnorm(m)
  lin <- 0.2 + 0.5 * x + 0.8 * field[si]
  y <- if (fam == "binomial") rbinom(m, 1L, plogis(lin)) else lin + rnorm(m, 0, 0.5)
  list(y = as.numeric(y), n_trials = rep(1L, m), X = cbind(1, x),
       spatial_idx = si, family = fam, phi = if (fam == "gaussian") 0.5 else 1)
}
prior <- list(type = "icar", n_spatial_units = S,
             adj_row_ptr = c(0L, cumsum(nn)), adj_col_idx = unlist(nb) - 1L,
             n_neighbors = nn, sigma_grid = c(0.3, 0.7, 1.4))
fit <- tulpa_nested_laplace_joint(
  responses = list(occ = mk_arm(200L, "binomial"), pos = mk_arm(200L, "gaussian")),
  prior = prior)
fit$theta_mean      # shared field amplitude, integrated across both arms
```

tulpa_nuts_beta	<i>Fit a beta-regression model via NUTS (joint sampling of beta + log_phi)</i>
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Description

Bayesian counterpart to `tulpa_laplace_beta()`. Routes the Beta GLM through tulpa's full NUTS backend via the generic LikelihoodSpec interface, sampling the precision ϕ jointly with the regression coefficients on the log scale. NUTS performs exact marginalisation over ϕ , replacing the Brent outer-opt in `tulpa_laplace_beta()` and the deterministic nested-Laplace grid that would otherwise integrate over the Beta dispersion.

Mean-precision parameterisation, default logit link: $y_i \sim \text{Beta}(\mu_i * \phi, (1 - \mu_i) * \phi)$ with $\mu_i = 1 / (1 + \exp(-\eta_i))$ and $\eta_i = X_i \% \% \text{beta}$.

Usage

```
tulpa_nuts_beta(
  y,
  X,
  beta_prior = .tulpa_default_beta_prior("beta_nuts"),
  log_phi_prior_sd = 3,
  log_phi_init = 0,
  control = list()
)
```

Arguments

<code>y</code>	Response vector, strictly in $(0, 1)$.
<code>X</code>	Fixed-effects design matrix.
<code>beta_prior</code>	Fixed-effect prior as <code>list(mean, sd)</code> : a mean-zero ($\text{mean} = 0$) Gaussian on each coefficient with SD <code>sd</code> (default the engine default, <code>prior_normal(0, 2.5)</code>).
<code>log_phi_prior_sd</code>	Prior SD on $\log(\phi)$ ($\log_\phi \sim N(0, \log_\phi_prior_sd)$). Default 3 (very weak; covers ϕ from ~ 0.001 to ~ 1000 within ± 2 SD).
<code>log_phi_init</code>	Starting value for $\log(\phi)$. Default 0 (i.e. $\phi = 1$); a method-of-moments warm start can speed warmup in highly concentrated regimes.
<code>control</code>	A named list of numerical / sampler knobs (statistical arguments stay in the signature): <code>n_iter</code> (default 2000), <code>n_warmup</code> (default 1000), <code>max_treedepth</code> (default 10), <code>adapt_delta</code> (default 0.8), <code>seed</code> (NULL draws from the session RNG), <code>verbose</code> (default FALSE).

Value

A list with:

- `draws` – `n_samples` $\times$ $(p + 1)$ matrix of post-warmup draws, columns `beta[1] ... beta[p]`, `log_phi`.
- `means` – posterior means.
- `phi_summary` – posterior mean / median / quantiles of $\phi = \exp(\log_\phi)$.
- `accept_prob`, `divergent`, `treedepth`, `epsilon` – NUTS diagnostics from the underlying chain.

See Also

[tulpa_laplace_beta\(\)](#) for the Laplace + Brent point estimate; [tulpa_laplace\(\)](#) for the underlying Laplace engine.

Examples

```
set.seed(1)
n <- 150L
X <- cbind(1, rnorm(n))
mu <- plogis(X %*% c(0.2, 0.7)); phi <- 8
y <- rbeta(n, mu * phi, (1 - mu) * phi)

fit <- tulpa_nuts_beta(y, X, control = list(n_iter = 500L, n_warmup = 250L))
colMeans(fit$draws)
```

tulpa_nuts_spde	<i>Sample an SPDE GLM via NUTS, optionally jointly over Matern hypers</i>
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Description

Bayesian counterpart to [fit_spde\(\)](#) / [laplace_spde_at\(\)](#). Routes the SPDE-augmented GLM through tulpa's full NUTS backend via the generic LikelihoodSpec interface. Two modes:

- **Legacy / fixed-hyper** (`joint = FALSE`, the default): conditions on the supplied (`range`, `sigma`). Samples the latent block (`beta`, `w_mesh`, `log_phi`) jointly. Useful as the inner step of an outer CCD / nested-Laplace integration over hypers.
- **Joint hypers** (`joint = TRUE`): samples (`beta`, `z_mesh`, `log_kappa`, `log_tau`, `log_phi`) jointly via the non-centered transform $w = L(\theta)^{-T} z$. A PC prior (Fuglstad et al. 2019 JASA) on (`range`, `sigma`) is taken from `prior_range`, `prior_sigma`. Returns additional `w_draws`, `range_draws`, `sigma_draws`, `kappa_draws`, `tau_draws` columns/vectors on top of the raw parameter draws.

Usage

```
tulpa_nuts_spde(
  y,
  X,
  spatial,
  family = c("gaussian", "poisson", "binomial", "gamma", "neg_binomial_2", "beta"),
  n_trials = NULL,
  joint = FALSE,
  range = NULL,
  sigma = NULL,
  prior_range = NULL,
  prior_sigma = NULL,
```

```

log_kappa_init = NULL,
log_tau_init = NULL,
beta_prior = .tulpa_default_beta_prior("spde_nuts"),
log_phi_prior_sd = 3,
log_phi_init = 0,
control = list()
)

```

Arguments

y	Response vector. Family-specific: • gaussian: any real • poisson, neg_binomial_2: non-negative integers • binomial: non-negative integers in $[0, n_trials]$ • gamma: strictly positive reals • beta: strictly in $(0, 1)$
X	Fixed-effects design matrix.
spatial	A <code>tulpa_spatial</code> object from <code>spatial_spde()</code> / <code>spatial_spde_custom()</code> – supplies the FEM matrices (C0, G1) and projection (A) plus the smoothness ν .
family	One of "gaussian", "poisson", "binomial", "gamma", "neg_binomial_2", "beta".
n_trials	Integer vector for family = "binomial" (else ignored).
joint	Logical. FALSE (default) conditions on fixed (range, sigma). TRUE activates joint sampling of (log_kappa, log_tau) with the PC prior from prior_range, prior_sigma.
range, sigma	Fixed-hyper mode only. Matern range and marginal SD on the field. Default to the SPDE prior medians (<code>spatial\$prior_range[1]</code> , <code>spatial\$prior_sigma[1]</code>).
prior_range, prior_sigma	Joint mode only. PC prior anchors as <code>c(value, alpha)</code> pairs: • <code>prior_range = c(r0, a_r)</code> encodes $P(\text{range} < r0) = a_r$ • <code>prior_sigma = c(s0, a_s)</code> encodes $P(\text{sigma} > s0) = a_s$ Default to the spec's anchors (<code>spatial\$prior_range</code>, <code>spatial\$prior_sigma</code>) when those are length-2 PC anchors.
log_kappa_init, log_tau_init	Joint mode only. Initial values for the hyper slots. Default to the value implied by the PC anchor's ($r0$, $s0$) pair via $\text{kappa} = \sqrt{8 \nu} / r0$, $\text{tau} = 1 / (\sqrt{4 \pi}) * \text{kappa} * s0$.
beta_prior	Fixed-effect prior as <code>list(mean, sd)</code> : a mean-zero ($\text{mean} = 0$) Gaussian on each coefficient with SD sd (default the engine default, <code>prior_normal(0, 2.5)</code>).
log_phi_prior_sd	Prior SD on $\log(\phi)$. Role of ϕ is family-specific: • gaussian: ϕ is the residual SD (sampled jointly) • gamma: ϕ is the Gamma shape (sampled jointly) • neg_binomial_2: ϕ is the NB size r (sampled jointly)

	• beta: phi is the Beta precision (sampled jointly) • poisson, binomial: log_phi is held tight and ignored downstream.
log_phi_init	Starting value for log(phi).
control	A named list of numerical / sampler knobs (statistical arguments stay in the signature): n_iter (default 2000), n_warmup (default 1000), max_treedepth (default 10), adapt_delta (default 0.8), seed (NULL draws from the session RNG), verbose (default FALSE), noncenter (fixed-hyper only, default TRUE: sample the mesh field in a non-centered $v = L^{-T}$ z parameterisation – the same target density, a priori isotropised; ignored when joint = TRUE), and mass_matrix (NUTS metric: "auto" (default) picks a dense metric at ≤ 200 parameters and diagonal above, capturing the fixed-effect / field cross-curvature that corrects the intercept marginal; "diag", "dense", "block_diag" force the choice).

Value

A list with draws (matrix n_samples x n_params), means, phi_summary (where applicable), accept_prob, divergent, treedepth, epsilon, joint_hypers, plus the supplied spatial spec. In joint = TRUE mode additionally: w_draws (transformed $z \rightarrow w$ per draw), range_draws, sigma_draws, kappa_draws, tau_draws, and range_summary, sigma_summary (mean/median/5%/95% quantiles).

See Also

[fit_spde\(\)](#) for the Laplace counterpart and the nested-Laplace path over (range, sigma).

Examples

```
## Not run:
# SPDE-field NUTS. `spatial` is an SPDE spec built from a mesh, e.g.
# spatial_spde(~ x + y, df). See fit_spde() for the Laplace analogue.
fit <- tulpa_nuts_spde(y, X, spatial = spatial_spde(~ x + y, df))

## End(Not run)
```

tulpa_ordinal

Ordinal (ordered K-class) cumulative-logit regression via Laplace

Description

Fits a proportional-odds cumulative-logit model for an ordered factor response: $P(y \leq j \mid x) = \text{plogis}(c_j - x'\beta)$ with ordered cutpoints $c_1 < \dots < c_{\{K-1\}}$. The penalized mode (a ridge prior on the coefficients and cutpoints) is found by L-BFGS and summarized by a Laplace approximation. There is no separate intercept – the cutpoints carry the baseline levels.

Usage

```
tulpa_ordinal(
  formula,
  data,
  link = c("logit", "probit"),
  beta_prior = .tulpa_default_beta_prior("ordinal"),
  cut_prior_sd = 10,
  control = list()
)
```

Arguments

formula	Model formula; the response must be an ordered (or coercible) factor with ≥ 3 levels. An intercept in formula is dropped.
data	A data frame.
link	Cumulative link: "logit" (proportional odds, default) or "probit".
beta_prior	Fixed-effect prior as <code>list(mean, sd)</code> : a mean-zero (mean = 0) Gaussian ridge on every coefficient with scalar SD <code>sd</code> (default the engine default, <code>prior_normal(0, 2.5)</code>).
cut_prior_sd	SD of the mean-zero Gaussian ridge prior on the cutpoint parameters (default 10).
control	List of numerical knobs: <code>max_iter</code> (default 200), <code>n_draws</code> (default 2000), <code>seed</code> .

Value

A `tulpa_fit` (subclass `tulpa_ordinal`) with `coef` (covariate effects), `cutpoints`, `vcov`, `draws`, `log_marginal`, `levels`.

See Also

[tulpa_multinomial\(\)](#) for the nominal (unordered) case.

Examples

```
set.seed(1)
n <- 400L; x <- rnorm(n)
cuts <- c(-1, 0.5, 2); eta <- 0.8 * x
Fm <- plogis(outer(-eta, cuts, "+")); P <- cbind(Fm, 1) - cbind(0, Fm)
y <- ordered(apply(P, 1, function(pr) sample.int(4L, 1L, prob = pr)))
fit <- tulpa_ordinal(y ~ x, data = data.frame(y = y, x = x))
fit$coefficients; fit$cutpoints
```

tulpa_parse_formula	<i>Parse a mixed-model formula</i>
---------------------	------------------------------------

Description

Decomposes a formula into fixed effects and random effects by walking the formula's abstract syntax tree. This is structural recursion with pattern matching on bar terms – no string manipulation.

Usage

```
tulpa_parse_formula(formula)
```

Arguments

formula	A formula object (e.g., $y \sim x + (1 \mid \text{group})$)
---------	--

Value

A list with:

- response: character, the response variable label (NULL if none)
- response_expr: language object, the LHS of $\sim$ (NULL if none)
- fixed_formula: formula, the fixed-effects-only formula
- random_effects: list of parsed RE specifications
- n_re_terms: integer, number of RE terms
- latent_blocks: list of evaluated user-defined latent block objects (typically `tgmr` S3 objects), one per `latent(...)` term in the original formula. Empty list when no `latent(...)` terms are present.
- n_latent_blocks: integer, number of `latent(...)` terms
- original: the original formula

Examples

```
pf <- tulpa_parse_formula(y ~ x1 + x2 + (1 | group) + (x1 || site))
pf$response           # "y"
pf$fixed_formula      # y ~ x1 + x2
```

tulpa_pit

*Probability integral transform from a predictive CDF***Description**

The generic, family-agnostic half of a PIT residual check: the model package supplies the posterior-predictive CDF evaluated at each observation (a $[n_draws \times n_obs]$ matrix, or a draw-averaged $[n_obs]$ vector), and this returns the PIT value per observation. For a discrete or mixed response (a hurdle has a point mass at zero) supply the left limit `cdf_lower` ($P(Y < y)$); the randomized PIT then draws one uniform per observation and interpolates $F(y^-) + U(F(y) - F(y^-))$, which is uniform under a correct model. With `cdf_lower = NULL` the response is treated as continuous and the PIT is the draw-averaged CDF.

Usage

```
tulpa_pit(cdf, cdf_lower = NULL, jitter = TRUE)
```

Arguments

<code>cdf</code>	Posterior-predictive CDF at the observed value, $P(Y \leq y)$. A $[n_draws \times n_obs]$ matrix (averaged over draws here) or an $[n_obs]$ vector.
<code>cdf_lower</code>	Optional left-limit CDF $P(Y < y)$, same shape as <code>cdf</code> , for the randomized PIT of a discrete / mixed response.
<code>jitter</code>	If TRUE (default) and <code>cdf_lower</code> is NULL, add a tiny uniform jitter to break ties from a discretized CDF; ignored when <code>cdf_lower</code> is supplied (the interpolation already randomizes).

Value

Numeric vector of length `n_obs` of PIT values in $[0, 1]$.

See Also

[tulpa_criteria\(\)](#)

tulpa_posterior_draws

*Posterior draws from a nested-Laplace fit***Description**

Draw from the outer-grid mixture posterior of a nested-Laplace fit – the engine analogue of `inla.posterior.sample()`. Each draw picks an outer-grid cell $k \sim \text{Categorical}(\text{weights})$ and then samples that cell's inner Gaussian, so the draws are i.i.d. samples from $\text{sum}_k w_k N(m_k, V_k)$.

Sampling the mixture is the faithful primitive for marginalizing nonlinear derived quantities (e.g. `plogis(eta_2) - plogis(eta_1)`, expected-cover products $p * \mu$): compute the derived quantity per draw, then summarize. Collapsing the grid to a single moment-matched Gaussian biases skewed or multimodal-over-grid posteriors.

Usage

```
tulpa_posterior_draws(fit, idx = NULL, n = 1000, ...)
```

Arguments

<code>fit</code>	A nested-Laplace fit (tulpa_nested_laplace() or tulpa_nested_laplace_joint()).
<code>idx</code>	Optional integer vector of 1-based indices into whatever a draw covers for this backend (see above); <code>NULL</code> (default) returns all of them.
<code>n</code>	Number of posterior draws (default 1000).
<code>...</code>	Unused; for S3 compatibility.

Value

A numeric matrix [`n` x `length(idx)`], one row per draw. Carries `attr(, "draws_kind") = "iid"` (consistent with the draws-provenance gate), `attr(, "cells")` – the outer-grid cell index each row was drawn from – and `attr(, "scope")`, which of the two representations above the columns are.

What a draw covers

It depends on which representation the backend retained, and the returned matrix says so in its `scope` attribute.

`tulpa_nested_laplace_joint` the FULL latent vector – per-arm fixed effects, per-arm random effects, then the latent field(s) – because the joint fit retains each cell’s sparse precision over that vector (`control$store_Q = TRUE`). `scope` is `"latent"`.

`tulpa_nested_laplace (single-block)` the FIXED-EFFECT block. This backend inverts each cell’s precision into the marginal fixed-effect block and releases the precision itself, so the latent field is not part of the retained per-cell Gaussian and cannot be sampled from the fit. `scope` is `"fixed"`.

See Also

[tulpa_nested_laplace\(\)](#), [tulpa_nested_laplace_joint\(\)](#), [posterior_sample\(\)](#)

```
tulpa_posterior_draws.tulpa_nested_laplace_joint
```

Posterior draws from a joint nested-Laplace fit

Description

The [tulpa_posterior_draws\(\)](#) method for a joint nested-Laplace fit ([tulpa_nested_laplace_joint\(\)](#)). Each draw picks an outer-grid cell $k \sim \text{Categorical}(\text{weights})$ and then samples the inner latent vector from the constrained Gaussian $N(m_k, V_k)$ at that cell, where m_k is the cell’s inner mode and V_k is the inner-Laplace covariance with the ICAR / BYM2 sum-to-zero field constraint imposed (conditioning by kriging). The draws are i.i.d. samples from $\text{sum}_k \text{ weights}_k * N(m_k, V_k)$.

Usage

```
## S3 method for class 'tulpa_nested_laplace_joint'
tulpa_posterior_draws(fit, idx = NULL, n = 1000, ...)
```

Arguments

<code>fit</code>	A <code>tulpa_nested_laplace_joint</code> fit (single-block or multi-block). The fit must have been produced with <code>control\$store_Q = TRUE</code> so the per-grid sparse precision <code>Q_csc*_per_grid</code> is available.
<code>idx</code>	Optional integer vector of 1-based latent indices to return. <code>NULL</code> (default) returns the full latent vector. The latent vector stacks per-arm fixed effects, per-arm random effects, then the latent field(s); use <code>fit\$arm_layout</code> (<code>beta_start</code> , <code>re_start</code> , <code>phi_start</code> / <code>theta_start</code> / <code>field_starts</code> , all 0-based) to map a sub-block to indices.
<code>n</code>	Number of posterior draws (default 1000).
<code>...</code>	Unused; for S3 compatibility.

Details

The constrained draw at cell k uses the sparse Cholesky of the stored precision Q_k and the conditioning-by-kriging correction

$$z_c = z - Q_k^{-1} A^\top (A Q_k^{-1} A^\top)^{-1} A z,$$

where $z \sim N(\emptyset, Q_k^{-1})$ and A stacks the field sum-to-zero rows (one for an ICAR / CAR field; two – structured and unstructured – for a BYM2 field; one per spatial block in a multi-block fit). The returned draw is $m_k + z_c$, restricted to `idx`. Because m_k already satisfies the constraint (the inner solve centres the field), the mean is left unchanged and only the covariance is constrained, so the per-cell marginal matches the inner-Laplace constrained covariance exactly.

Cells with zero outer-grid weight (e.g. pruned cells) or no stored Q are dropped and the remaining weights renormalized. A degenerate single-cell grid (quadrature ESS 1) returns draws from that cell's $N(m_1, V_1)$.

Value

A numeric matrix [$n \times \text{length}(\text{idx})$] of latent draws, one row per draw, columns named $x<\text{idx}>$. Carries `attr(, "draws_kind") = "iid"` (consistent with the draws-provenance gate), `attr(, "cells")` – the outer-grid cell index each row was drawn from – and `attr(, "scope") = "latent"`.

See Also

[tulpa_posterior_draws\(\)](#), [tulpa_nested_laplace_joint\(\)](#), [posterior_sample\(\)](#)

tulpa_powerscale_sensitivity

Power-scaling prior / likelihood sensitivity

Description

Local power-scaling sensitivity (Kallioinen et al. 2024): how much each fixed-effect posterior moves when the prior or the likelihood is raised to a power α near 1. The existing draws are importance-reweighted by $\exp((\alpha - 1) * \log_component)$ (PSIS-smoothed via `tulpa_psis()`; no refits), and the sensitivity is the gradient of the cumulative Jensen-Shannon distance between the base and power-scaled posteriors with respect to $\log_2(\alpha)$.

Values above threshold flag sensitivity. High on **both** the prior and likelihood components indicates potential prior-data conflict; high prior with low likelihood indicates a strong prior / weak likelihood.

When the fit recorded per-draw hyperparameter log-prior values at draw-synthesis time (`$hyper_log_prior_draws`, stored by the nested-Laplace mixture paths such as `tulpa_re_cov_nested()` and the `tulpa()` random-slope redirect), a hyperparameter column reports the power-scaling sensitivity of the hyperparameter prior by the same reweighting; NA otherwise.

Usage

```
tulpa_powerscale_sensitivity(
  fit,
  data,
  prior = NULL,
  lower_alpha = 0.99,
  upper_alpha = 1.01,
  threshold = 0.05
)
```

Arguments

<code>fit</code>	A <code>tulpa_fit</code> fitted through <code>tulpa()</code> (fixed-effect / GLMM; spatial / temporal-field fits are rejected).
<code>data</code>	The data frame the model was fit to.
<code>prior</code>	The Gaussian fixed-effect prior the fit used, as <code>list(mean =, sd =)</code> (scalars recycled). Required for the prior component; omit to compute the likelihood component only.
<code>lower_alpha, upper_alpha</code>	Power-scaling grid endpoints for the gradient (defaults 0.99 / 1.01, as in priorsense).
<code>threshold</code>	Sensitivity flag threshold (default 0.05).

Value

A data frame with one row per fixed-effect parameter and columns variable, prior, hyperparameter, likelihood, diagnosis.

References

Kallioinen, Paananen, Buerkner & Vehtari (2024). Detecting and diagnosing prior and likelihood sensitivity with power-scaling. *Statistics and Computing* 34:57. Nguyen & Vreeken (2015). Non-parametric Jensen-Shannon divergence. ECML PKDD.

See Also

`tulpa_psis()`, `tulpa_criteria()`.

Examples

```
set.seed(1)
d <- data.frame(x = rnorm(150))
d$y <- rpois(150, exp(0.5 + 0.7 * d$x))
fit <- tulpa(y ~ x, data = d, family = "poisson", mode = "laplace",
            beta_prior = list(mean = 0, sd = 5))
tulpa_powerscale_sensitivity(fit, data = d, prior = list(mean = 0, sd = 5))
```

tulpa_priors	<i>Prior specification for tulpa models</i>
--------------	---

Description

Specify priors for model parameters. Supports both PC (penalized complexity) priors for variance components and standard distributions for other parameters.

Usage

```
tulpa_priors(
  beta = NULL,
  sigma = NULL,
  phi = NULL,
  rho_temporal = NULL,
  rho_spatial = NULL
)
```

Arguments

beta	Prior for fixed effects. Default: <code>prior_normal(0, 2.5)</code> .
sigma	Prior for random effect SDs. Default: PC prior with $P(\text{sigma} > 1) = 0.01$.
phi	Prior for overdispersion parameter. Default: PC prior with $P(\text{phi} > 10) = 0.01$.
rho_temporal	Prior for temporal autocorrelation. Default: <code>prior_beta(2, 2)</code> centered at 0.5.
rho_spatial	Prior for spatial proportion (BYM2). Default: <code>prior_beta(1, 1)</code> (uniform).

Details

PC priors (Simpson et al., 2017) provide principled regularization that:

- Favors simpler models (smaller variance components)
- Has interpretable parameters (tail probabilities)
- Prevents overfitting with sparse data

For other parameters, standard distributions are available via helper functions: `prior_normal()`, `prior_half_normal()`, `prior_half_cauchy()`, `prior_gamma()`, `prior_beta()`, `prior_exponential()`.

Value

A `tulpa_priors` object

References

Simpson, D., Rue, H., Riebler, A., Martins, T. G., & Sørbye, S. H. (2017). Penalising model component complexity: A principled, practical approach to constructing priors. *Statistical Science*, 32(1), 1-28.

Examples

```
# Default priors
tulpa_priors()

# Custom fixed effect prior
tulpa_priors(beta = prior_normal(0, 1))

# Tighter random effect prior
tulpa_priors(sigma = prior_pc(U = 0.5, alpha = 0.01))

# Half-Cauchy for random effect SD
tulpa_priors(sigma = prior_half_cauchy(2.5))

# Informative prior for temporal correlation
tulpa_priors(rho_temporal = prior_beta(5, 2)) # Prior mode at ~0.8
```

tulpa_profile

Profile the inner Laplace solve by phase

Description

Times the sparse joint Laplace solver one phase at a time – scatter (the Hessian and gradient assembly), factorize (numeric Cholesky), eta, line search, and the rest – and returns the breakdown as a data frame. The accumulator aggregates across the parallel outer-grid worker threads, so the reported times cover the whole fit rather than only the calling thread.

Usage

```
tulpa_profile(expr, sort = TRUE)
```

Arguments

expr	An expression that runs a fit (for example a call to <code>tulpa_nested_laplace_joint()</code>). Evaluated once, after the profile counters are reset.
sort	Logical; order rows by descending time. Default TRUE.

Details

Use it to settle where a per-cell solve spends its time, e.g. whether a slow joint `occu_cover()` fit is bound by the assembly scatter or the Cholesky factorize:

```
p <- tulpa_profile(
  tulpa_nested_laplace_joint(..., control = list(integration = "ccd"))
)
print(p)           # rows ordered by time; scatter vs factorize at top
fit <- attr(p, "value")
```

Value

A data frame with one row per phase and columns phase, seconds, calls, ms_per_call (mean wall time per phase call), and share (fraction of total timed seconds). The fit result is attached as the "value" attribute.

Examples

```
set.seed(1)
n <- 200L; X <- cbind(1, rnorm(n))
y <- rbinom(n, 1, plogis(X %*% c(0, 0.5)))
tulpa_profile(tulpa_laplace(y, rep(1L, n), X, family = "binomial"))
```

tulpa_psis

Pareto-smoothed importance sampling

Description

Smooths a set of importance ratios by replacing the largest weights with the order statistics of a generalized-Pareto fit to their upper tail, and returns the Pareto shape diagnostic `pareto_k` together with the smoothed (normalized) log weights and their importance-sampling effective sample size. `pareto_k` estimates the number of finite moments of the raw weight distribution: < 0.5 is good (finite variance). The usable upper boundary is sample-size dependent, $\min(1 - 1/\log_{10}(S), 0.7)$ for S draws (Vehtari et al. 2024): about 0.565 at $S = 200$, reaching the 0.7 cap only past $S \sim 2154$. Above it the proposal cannot be reliably corrected to the target.

Usage

```
tulpa_psis(log_ratios, tail_points = NULL)
```

Arguments

<code>log_ratios</code>	Numeric vector of (unnormalized) log importance ratios $\log p_{\text{target}}(x) - \log q_{\text{proposal}}(x)$ evaluated at draws $x \sim q$.
<code>tail_points</code>	Number of upper-tail order statistics for the generalized-Pareto fit, or <code>NULL</code> (default) for the automatic PSIS rule <code>ceil(min(0.2 * S, 3 * sqrt(S)))</code> . An explicit value is an expert tail-threshold control, capped at <code>floor(0.2 * S)</code> so the fit stays an extreme tail; it is NOT a precision knob (raise the draw count for a tighter shape estimate).

Value

A list with `pareto_k` (the tail shape, NA if the sample is too small to fit), `is_ess` (importance-sampling effective sample size, $1 / \sum(w^2)$ on the normalized smoothed weights), `log_weights` (the normalized smoothed log weights), `tail_len` (the tail size used), and `tail_smoothed` (FALSE when the tail kept its raw log ratios because the generalized-Pareto fit was not attempted or returned a shape / scale the quantile function is undefined at; `pareto_k` then reports the attempted fit and does not describe the returned weights).

References

Vehtari, Simpson, Gelman, Yao & Gabry (2024). Pareto smoothed importance sampling. *JMLR* 25(72):1-58.

See Also

[diagnostics\(\)](#) for the fit-level diagnostic front door.

Examples

```
set.seed(1)
# Well-behaved importance ratios: k-hat is small.
ps <- tulpa_psis(rnorm(2000))
ps$pareto_k
ps$is_ess
```

Description

PSIS-LOO with exact refits where the importance sampling is unreliable: observations whose Pareto k -hat exceeds `k_threshold` are re-scored by refitting the model without that observation (through the fit's stored `tulpa()` call, as in `tulpa_kfold()`) and evaluating the exact held-out log predictive density. All other observations keep their PSIS-LOO value, so the cost is one refit per flagged observation rather than per fold.

The same restrictions as `tulpa_kfold()` apply: fixed-effect / GLMM fits only (subsetting breaks a spatial / temporal field), and held-out random-effect groups contribute at their prior mean.

Usage

```
tulpa_reloo(
  object,
  data,
  k_threshold = .nl_diag("k_usable"),
  n_trials = NULL,
  ndraws = NULL
)
```

Arguments

<code>object</code>	A <code>tulpa_fit</code> fitted through <code>tulpa()</code> (must carry <code>\$call</code>).
<code>data</code>	The data frame the model was fit to.
<code>k_threshold</code>	Pareto k -hat above which an observation is refit (default 0.7, the standard PSIS reliability gate).
<code>n_trials</code>	Optional binomial denominators (<code>length nrow(data)</code>); defaults to the trials stored on the fit, else 1.
<code>ndraws</code>	Number of posterior draws used for the PSIS-LOO baseline (defaults to all stored draws, or 400 on the draw-free Laplace tier).

Value

A list with `elpd_loo` (corrected), `se_elpd_loo`, `looic`, `pointwise` (per-observation `elpd`, exact at the refit observations), `reloo_idx` (indices refit), `pareto_k` (the original k -hat values), and `k_threshold`.

See Also

`tulpa_kfold()` for the full refit-CV; `tulpa_criteria()` for PSIS-LOO / WAIC without refits.

Examples

```
set.seed(1)
d <- data.frame(x = rnorm(120))
d$y <- rpois(120, exp(0.4 + 0.6 * d$x))
fit <- tulpa(y ~ x, data = d, family = "poisson", mode = "laplace")
r1 <- tulpa_reloo(fit, data = d)
r1$elpd_loo
```

tulpa_re_aghq

*Adaptive Gauss-Hermite refinement of a grouped random-effect covariance***Description**

Refines a generalized linear mixed model's fixed effects and random-effect covariance by replacing the per-group Laplace integral with `n_quad`-point adaptive Gauss-Hermite quadrature (AGHQ). At `n_quad = 1` this is the joint Laplace (glmer `nAGQ = 1`); higher `n_quad` reduces the small-cluster attenuation of the variance components for binary / count data. Unlike `agq_fit()` (intercept-only RE, built-in binomial/poisson/gaussian likelihoods), this engine is **callback-driven**: the caller supplies the per-group conditional likelihood, so a custom marginal (e.g. a latent-state-integrated occupancy / detection likelihood, or the latent-abundance-integrated N-mixture marginal) refines through the same quadrature.

This is an engine block, not a front door: model packages call it programmatically, so its tuning knobs (`max_iter`, `n_quad`, `keep`) sit in the signature rather than in a control list.

The engine is **structure-agnostic**. It integrates the per-group marginal

$$M_g = \int \exp\{\ell_g(b_g)\} N(b_g; 0, \Sigma) db_g,$$

where b_g is the group's random-effect vector (dimension $\sum_m c_m$ over the RE terms) and $\ell_g(b_g)$ is the group's conditional log-likelihood when its linear predictors are perturbed by b_g . How b_g enters the likelihood – through one linear predictor, or through several coupled arms at different observation granularities (e.g. a per-site abundance arm and a per-visit detection arm sharing a species grouping) – lives entirely in the callback. The engine only needs, per group, the value / gradient / Hessian of ℓ_g in b_g (for the mode) and ℓ_g at the quadrature nodes (for the sum). The fixed parameters `theta` and the log-Cholesky coordinates of Σ are optimized jointly on $\sum_g \log M_g$; standard errors come from the exact-marginal Hessian.

Two callback forms select the structure (supply exactly one):

- `make_site` – the common **single-arm, per-row-separable** case ($\ell_g(b_g) = \sum_{i \in g} \log f_i(\eta_i + Z_i b_g)$ for one linear predictor η). The engine builds the oracle from the per-row marginal and the RE design `Z` itself.
- `make_group` – the **general / multi-arm** case. The caller supplies the per-group b-space oracle directly, so non-separable units (e.g. the visits of an N-mixture site coupled through the shared latent count) and random effects on several arms at once are handled with no engine change.

Scope: one shared grouping factor across all RE terms (the per-group integral factorizes). The total RE dimension per group should be small (the quadrature grid is `n_quad^dim`).

Usage

```
tulpa_re_aghq(
  theta0,
  re_terms,
  Sigma0,
```

```

make_site = NULL,
make_group = NULL,
oracle = NULL,
n_obs = NULL,
keep = NULL,
n_quad = 9L,
lkj_eta = 1,
theta_prior_sd = Inf,
sigma_prior = NULL,
gradient = c("fd", "analytic"),
max_iter = 200L
)

```

Arguments

theta0	Initial fixed-parameter vector. The engine optimizes these jointly with the RE covariance; the callback interprets them.
re_terms	A list of RE term specs (or one spec), each defining a covariance block: n_coefs (block dimension c_m), optional correlated (default TRUE for $c_m > 1$; FALSE gives a diagonal block), and n_groups (shared across terms). For the make_site path each term also carries idx (1-based group index, length n_obs) and, for a slope block, Z (the n_obs x n_coefs design). For the make_group path the per-observation idx / Z are optional – the callback owns them – and the term needs only n_coefs / correlated / n_groups.
Sigma0	List of initial per-term covariance matrices (the EM estimate).
make_site	function(theta) for the single-arm separable case, returning a list with: eta_re (length n_obs, the RE-arm fixed predictor), deriv = function(rows, eta) returning list(logL, d1, d2) (per-row marginal log-likelihood and its first/second derivatives w.r.t. the RE-arm predictor eta, used for the per-group mode), and lmat = function(rows, ETA) returning a length(rows) x ncol(ETA) matrix of per-observation log-likelihoods over the quadrature node columns. Supply this or make_group, not both.
make_group	function(theta) for the general / multi-arm case, returning a list with two per-group closures (let $d = \text{sum}(n_coefs)$ be the group RE dimension): - grad_hess(g, b) – for group g at RE value b (length d), the list list(logL, grad, negH): the group conditional log-likelihood $\ell_g(b)$, its gradient $\partial \ell_g / \partial b$ (length d), and the data-only observed information $-\partial^2 \ell_g / \partial b^2$ (d x d; the engine adds the Σ^{-1} prior curvature). - node_ll(g, B) – for group g, a numeric vector of length nrow(B) giving ℓ_g at each quadrature node (rows of the nrow x d matrix B are candidate b vectors). The callback owns all arm / design / clamping bookkeeping. Supply this or make_site, not both.
oracle	Optional prebuilt native (compiled) oracle, an external pointer to a REGroupOracle (constructed in a consumer package's src/ via LinkingTo: tulpa against <tulpa/aghq_oracle.h>). When supplied the engine drives it directly, with no per-group / per-node round trip into R, and neither make_site nor make_group is needed; re_terms, theta0 and Sigma0 must still describe the same layout the oracle exposes. The integration core is identical to the R-closure path.

n_obs	Number of observations (length of each term's idx). Required for the make_site path; ignored for make_group.
keep	Optional logical/integer mask of observations to include (default all; make_site path only). Rows outside keep are dropped from every group.
n_quad	Quadrature nodes per RE dimension. Either a single integer (default 9; 1 = Laplace) broadcast to every covariance block, or an integer vector of length length(re_terms) giving a per-block node count. The tensor grid then uses n_quad[b] nodes along every dimension of block b, for prod_b n_quad[b]^(dim_b) total nodes; a scalar reproduces the uniform grid exactly. Per-block orders let a heterogeneous stack spend fewer nodes on cheap scalar nuisance blocks than on the correlated coefficient blocks (e.g. c(3, 3, 2, 2) on blocks of dimension 2, 2, 1, 1 gives $3^2 * 3^2 * 2 * 2 = 324$ nodes rather than $3^6 = 729$).
lkj_eta	LKJ shape for an optional correlation penalty on each <i>correlated</i> block (log-density $(\eta - 1) \log \det R$, maximized at independence). 1 disables it; > 1 regularizes a weakly-identified correlation off the boundary without touching the marginal SDs. The marginal SDs are otherwise unpenalized (pure ML), so the refinement debiases them rather than shrinking them.
theta_prior_sd	Optional Gaussian ridge SD on the fixed parameters theta (a mean-zero $N(0, \text{theta_prior_sd}^2)$ prior, added to the optimized objective and hence the marginal Hessian). Inf (default) is pure ML on theta; a large finite value (e.g. 100) is a weak ridge that stabilizes a weakly-identified fixed effect without materially shifting the estimate.
sigma_prior	Optional Penalized-Complexity prior on the marginal standard deviations of one or more RE covariance blocks, added to the objective (and hence the marginal Hessian). NULL (default) is pure ML on the covariances – the refinement debiases the SDs rather than shrinking them. Otherwise a c(U, alpha) pair ($P(\text{sigma}_i > U) = \alpha$, the same convention as <code>re_cov_pc_lkj_prior()</code>) applied to every block, or a list list(blocks = <integer indices>, prior_sigma = c(U, alpha)) applied to the named blocks only. Reuses the exact PC log-prior + Jacobian of <code>re_cov_pc_lkj_prior()</code> . A weakly-identified variance component (e.g. a scalar dispersion / zero-inflation random effect at few groups) can drift to the boundary and flatten the marginal Hessian; a weak PC prior adds curvature there (the + log sigma Jacobian repels sigma -> 0, the - lambda sigma term caps inflation), keeping the joint optimum non-singular without materially shifting an identified fit.
gradient	How stats::optim gets the gradient of the AGHQ objective. "fd" (default) lets optim finite-difference the objective – correct at every n_quad and the only option for the R-closure (make_site / make_group) paths. "analytic" supplies the Fisher-identity gradient (posterior-weighted theta-score plus the Sigma moment-matching residual), which avoids the per-coordinate objective re-solve and so is far cheaper for the quadrature debias. It requires a prebuilt native oracle (the only one exposing the theta-score) and n_quad > 1: being the gradient of the true marginal it omits the node-placement terms (0 of the AGHQ truncation), so it agrees with the objective only as n_quad grows.
max_iter	Optimizer iteration cap (default 200).

Value

A list with: `theta` (refined fixed parameters), `Sigma_list` (refined per-term covariance), `blup` / `blup_var` (per-term `n_groups` x `n_coefs` posterior mean / variance of the RE), `group_ok` (logical, length `n_groups`: FALSE where that group's mode search or precision factorization failed, which is what the NA rows of `blup`, `blup_var`, `blup_cov_g` and `blup_cross_g` mean – a caller conditions its per-group reads on this rather than on trapping the accompanying warning), `blup_cross` (per-term `n_groups` x `n_theta` x `n_coefs` array: the mode/theta cross-Hessian block B_f , $-d^2 \ell_g / d\theta$ at each group's mode, in the same negative-Hessian sign convention as the posterior precision underlying `blup_var` – so a joint draw of `theta` and a group's RE `b_g` uses $b_g | \theta \sim N(b_g - C_{inv_g} \%*\% t(B_f_g) \%*\% (\theta_{draw} - \theta), C_{inv_g})$ with `C_{inv_g}` the group's `n_coefs` x `n_coefs` posterior covariance block. NA throughout when `blup_cross_available` is FALSE: the cross-Hessian needs the oracle's analytic `theta_score`, which the R-closure bridge (`make_site` / `make_group`) does not supply – only a prebuilt native oracle carries it), `blup_cov_g` / `blup_cross_g` (per-group lists, length `n_groups`, of the FULL joint posterior covariance (`d` x `d`, `d` = every RE term's width combined) and mode/theta cross-Hessian (`n_theta` x `d`) across ALL RE terms sharing that group – the superset `blup_var` / `blup_cross` reduce to a per-term diagonal block of when a group carries more than one term, since a group's terms are found jointly and can carry real posterior covariance BETWEEN terms (e.g. an abundance-arm and a detection-arm term sharing one grouping factor); same NA-when-unavailable rule as `blup_cross`), `theta_cov` / `theta_se` (fixed-parameter covariance / SE from the marginal Hessian), `re_par` / `re_par_cov` / `re_par_se` (the RE-covariance coordinates the optimizer carried – log-Cholesky for a full block, log-SD for a diagonal one – with their block of the same inverse Hessian, so $SE(\log \sigma)$ is available for a boundary test on a weakly-identified variance component), `re_par_layout` (per block: label, nc, full, the index range into `re_par` and the coord names, so a caller does not reconstruct the packing), `joint_cov` (the whole (`n_theta` + `n_chol`) inverse Hessian), `log_marginal` (the AGHQ marginal log-likelihood at the optimum, excluding any ridge), `n_quad`, `lkj_eta`, `converged`, and counts (`stats::optim`'s own function / gradient evaluation counts, so a caller reporting how much work the fit took has a number to report rather than NA). RE terms that do not share one grouping factor are an input error and stop. Three conditions warn and return NULL (caller keeps its prior fit): a singular / non-finite optimum, an objective that is already undefined at the starting parameters (some group's solve fails there, so there is nothing to descend), and an optimum whose objective is the failure sentinel rather than an attained marginal likelihood – the last two report which groups failed.

References

Pinheiro & Bates (1995). Approximations to the log-likelihood function in the nonlinear mixed-effects model. *Journal of Computational and Graphical Statistics* 4(1):12-35. Lewandowski, Kurowicka & Joe (2009). Generating random correlation matrices based on vines and extended onion method. *Journal of Multivariate Analysis* 100(9):1989-2001.

Examples

```
# A per-row-separable binomial GLMM marginal supplied through `make_site`.
llpe <- function(x) ifelse(x > 0, x + log1p(exp(-x)), log1p(exp(x)))
make_binom_site <- function(X, y, nt) function(theta) {
  eta_fixed <- as.numeric(X %% theta)
  list(eta_re = eta_fixed,
       deriv = function(rows, eta) {
         p <- plogis(eta)
```

```

      list(logL = y[rows] * eta - nt[rows] * l1pe(eta),
           d1 = y[rows] - nt[rows] * p, d2 = -nt[rows] * p * (1 - p))
    },
    lmat = function(rows, ETA) y[rows] * ETA - nt[rows] * l1pe(ETA))
  }
  set.seed(1)
  ng <- 30L; npg <- 8L; n <- ng * npg
  g <- rep(seq_len(ng), each = npg); x <- rnorm(n)
  X <- cbind(1, x); nt <- rep(3L, n); u <- rnorm(ng, 0, 0.9)
  y <- rbinom(n, nt, plogis(0.3 + 0.7 * x + u[g]))
  fit <- tulpa_re_aghq(theta0 = c(0, 0),
                      re_terms = list(list(idx = g, n_groups = ng, n_coefs = 1L)),
                      Sigma0 = list(matrix(0.25, 1, 1)),
                      make_site = make_binom_site(X, y, nt), n_obs = n, n_quad = 5L)
  sqrt(fit$Sigma_list[[1]][1, 1]) # adaptive-GHQ RE standard deviation

```

tulpa_re_cov_gibbs	<i>Gibbs estimation of random-effect covariances (exact-target debias)</i>
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Description

For one or more random-effects terms (e.g. $(1 + x | g)$, $(1 + x || g)$, or several terms together), estimate the random-effect covariances Σ by sampling the exact joint posterior $p(\beta, \{\Sigma\} | y)$ rather than fixing each Σ at the Laplace mode. This removes the Laplace / PQL "approximation" bias that shrinks variance components low for binary and low-count responses with small groups.

Usage

```

tulpa_re_cov_gibbs(
  y,
  n_trials = NULL,
  X,
  re_terms,
  family = "binomial",
  phi = 1,
  prior_df = NULL,
  prior_scale = NULL,
  beta_prior = .tulpa_default_beta_prior("re_cov_gibbs"),
  control = list()
)

```

Arguments

`y`, `n_trials`, `X`, `family`, `phi`

Passed to the likelihood and to `tulpa_laplace()` for the pilot solve. `n_trials = NULL` defaults to 1.

re_terms	Either a single random-effect term or a list of them. Each term is a list with <code>idx</code> (1-based group index per observation), <code>n_groups</code> , <code>n_coefs</code> (<code>c</code>), <code>Z</code> (the <code>n_obs</code> x <code>c</code> RE design; only required when <code>c > 1</code>), and <code>correlated</code> (TRUE for a full Sigma, FALSE for a diagonal one; defaults to TRUE). An optional <code>label / group_var</code> names the block. Any supplied <code>L / cov / sigma</code> is ignored – Sigma is what this function samples.
prior_df	Inverse-Wishart prior degrees of freedom. Applied to every correlated block (default <code>n_coefs + 1</code> , the minimal proper choice) and as the scalar inverse-gamma shape for every diagonal block (default 2). Must leave each block's prior proper – unlike <code>tulpa_re_cov_nested()</code> / <code>tulpa_eb()</code> (hyperprior = "flat" by default), the <code>Sigma_m b_m</code> conjugate draw here needs a proper Inverse-Wishart to sample from, so an improper flat prior is not an option; the minimal-df default is the closest analogue this sampler can offer.
prior_scale	Inverse-Wishart prior scale matrix. Used for a block when its dimension matches (default <code>diag(n_coefs)</code>); otherwise the per-block default is used.
beta_prior	Gaussian fixed-effect prior as <code>list(mean, sd)</code> (default the engine default, <code>prior_normal(0, 2.5)</code>). Scalar mean / sd are recycled to <code>ncol(X)</code> ; a <code>length-ncol(X)</code> vector sets a per-coefficient prior.
control	A named list of numerical / tuning knobs (statistical arguments stay in the signature above). Recognized entries: • <code>n_iter</code>: recorded post-warmup sweeps (default 2000). • <code>warmup</code>: warmup (burn-in) sweeps, used for proposal-scale adaptation (default 1000). • <code>thin</code>: keep every thin-th recorded sweep (default 1). • <code>seed</code>: optional integer seed for reproducibility. • <code>max_iter</code>, <code>tol</code>, <code>n_threads</code>: pilot-solve controls (see <code>tulpa_laplace()</code>).

Details

Metropolis-within-Gibbs targeting $p(\beta, \{b_m\}, \{\Sigma_m\} | y)$:

- $b_{\{m,g\}} | \beta, \Sigma, y$ – random-walk Metropolis per (term, group) (groups are conditionally independent given β and the covariances). The proposal *shape* is the Laplace per-group posterior covariance block (`return_re_cov` from `tulpa_laplace()`); the Metropolis acceptance is computed against the exact group log-likelihood plus the Gaussian RE log-prior, which corrects the non-Gaussianity the Laplace approximation misses. The linear predictor holds every other term's contribution fixed.
- $\beta | b, \Sigma, y$ – random-walk Metropolis, proposal shape from the Laplace fixed-effect Hessian block `H_beta`.
- $\Sigma_m | b_m$ – exact conjugate draw. A correlated block draws the full matrix from $IW(\text{prior_df} + G_m, \text{prior_scale})$; an uncorrelated (diagonal) block draws each variance from its scalar conjugate (inverse-gamma). No linearization enters this step.

A single Laplace solve provides the starting values (β , b) and the proposal shapes; the random-walk scales for the β block and the per-term b blocks are adapted toward their target acceptance during burn-in (Robbins-Monro), then held fixed for the recorded sweeps. The covariance summary marginalizes the derived scale / correlation parameters over the posterior draws via the same machinery as `tulpa_re_cov_nested()`.

For family = "gaussian" the response is already conditionally Gaussian, so there is no Laplace bias to remove; phi (the residual variance) is treated as known. The sampler still runs and is useful as a reference / for Sigma uncertainty.

Value

A list with:

- posterior: data frame with one row per parameter (sigma_i, rho_ij, Sigma_ij; prefixed by block label when there are several terms; diagonal blocks report no rho) and columns mean, sd, median, ci_lo, ci_hi.
- Sigma_mean: the posterior mean of Sigma (a matrix for one block, a named list of matrices for several).
- Sigma_draws: list of recorded draws; each element is the per-block list of Sigma matrices for that sweep.
- beta_draws / draws: matrix of recorded beta draws; draws (with means, param_names, process_info) drives the generic tulpa_fit methods.
- re: matrix of recorded random-effect draws, n_kept rows by one column per (block, group, coefficient) in that order – the exact per-group posterior the sweep samples. Row-aligned with beta_draws, so a draw is a joint (beta, b) state. This is what [ranef\(\)](#) summarizes and what [posterior_predict\(\)](#) adds to the linear predictor.
- accept: list with beta and b acceptance rates over recorded sweeps.
- n_kept, n_coefs (vector of per-block c), prior: bookkeeping.

References

Lewandowski, Kurowicka & Joe (2009). Generating random correlation matrices based on vines and extended onion method. *Journal of Multivariate Analysis* 100(9):1989-2001.

See Also

[tulpa_re_cov_nested\(\)](#) for the grid-integration (summary-bias) fix; [tulpa_laplace\(\)](#) for the pilot solve and per-group covariance blocks.

Examples

```
set.seed(1)
G <- 20L; per <- 12L; n <- G * per
grp <- rep(seq_len(G), each = per); x <- rnorm(n)
b <- cbind(rnorm(G, 0, 0.7), rnorm(G, 0, 0.5)) # random intercept + slope
eta <- -0.2 + 0.5 * x + b[grp, 1] + b[grp, 2] * x
y <- rbinom(n, 1L, plogis(eta))
re_term <- list(idx = grp, n_groups = G, n_coefs = 2L, Z = cbind(1, x),
               correlated = TRUE)
fit <- tulpa_re_cov_gibbs(y, rep(1L, n), cbind(1, x), re_term,
                        family = "binomial",
                        control = list(n_iter = 300L, warmup = 150L))
fit$Sigma_mean # exact-debias RE covariance posterior mean
```

tulpa_re_cov_nested *Nested-Laplace integration over random-effect covariances*

Description

For one or more random-effects terms (e.g. $(1 + x \mid g)$, $(1 + x \parallel g)$, or several terms together), integrate the Laplace marginal likelihood over the random-effect covariances Σ instead of fixing them at point estimates. Reports weighted posterior summaries (mean, SD, median, 2.5\ Sigma and its derived scale (sigma_i) and correlation (rho_ij) parameters, marginalizing the joint posterior over a Sigma-grid.

This corrects the plug-in-MAP ("summary") bias: the mode of a skewed variance-component marginal is biased low relative to its median, so the headline summary should be the marginalized median, not the mode.

Usage

```
tulpa_re_cov_nested(
  y,
  n_trials = NULL,
  X,
  re_terms,
  family = "binomial",
  phi = 1,
  phi2 = NULL,
  prior_sigma = c(3, 0.05),
  eta = 2,
  hyperprior = c("flat", "pc_lkj"),
  log_prior_theta = NULL,
  beta_prior = NULL,
  offset = NULL,
  n_quad = 1L,
  X_zi = NULL,
  zi_prior_sd = 2.5,
  control = list()
)
```

Arguments

y, n_trials, X, family, phi	Passed to <code>tulpa_laplace()</code> for the inner solve. <code>n_trials = NULL</code> defaults to 1 (binary / single-trial).
re_terms	Either a single random-effect term or a list of them. Each term is a list with <code>idx</code> (1-based group index per observation), <code>n_groups</code> , <code>n_coefs</code> (c), <code>Z</code> (the <code>n_obs</code> x <code>c</code> RE design, e.g. <code>cbind(1, x)</code> for $(1 + x \mid g)$; only required when <code>c > 1</code>), and <code>correlated</code> (TRUE for a full Σ , FALSE for a diagonal one; defaults to TRUE). An optional <code>label / group_var</code> names the block in the output. Any <code>L / cov / sigma</code> field is ignored – Σ is what this function integrates over.

phi2	Optional second dispersion, threaded into every inner <code>tulpa_laplace()</code> solve: the Student-t degrees of freedom (family = "t", default 4 when NULL) or the Tweedie variance power (family = "tweedie", required – a defaulted power would be a statistical decision the caller never made). A phi2 supplied for any other family errors rather than being ignored. It is conditioned on: the integration is over the random-effect covariances, not over phi2.
prior_sigma, eta	Hyperparameters of the PC + LKJ prior used when hyperprior = "pc_lkj" (see <code>re_cov_pc_lkj_prior()</code>): prior_sigma = c(U, alpha) with $P(\text{sigma}_i > U) = \alpha$ (default c(3, 0.05)) and LKJ shape eta (default 2). Ignored when hyperprior = "flat" or log_prior_theta is supplied.
hyperprior	"flat" (default) or "pc_lkj". "flat" integrates with log_prior_theta the zero function (flat in log(theta)), matching the nested-Laplace convention on every other scale axis in the engine. "pc_lkj" builds the PC + LKJ prior from prior_sigma / eta (the regularizer that keeps a variance component off the sigma = 0 boundary at small G). Ignored when log_prior_theta is supplied.
log_prior_theta	Optional function(theta) returning a scalar log prior density on the full stacked parameter vector, overriding hyperprior entirely. Default NULL, which defers to hyperprior.
beta_prior	Optional Gaussian prior on the fixed effects, threaded into every inner <code>tulpa_laplace()</code> solve (list(mean, sd)). NULL (default) keeps the weak built-in prior.
offset	Optional observation-level offset on the linear predictor (length length(y)), e.g. log(exposure) for a rate model. Not supported with n_quad > 1, which errors rather than dropping it.
n_quad	Quadrature order for the inner marginal. 1 (default) uses the joint-field Laplace inner solve (<code>tulpa_laplace()</code>). > 1 refines the inner marginal with n_quad-point adaptive Gauss-Hermite quadrature (the <code>tulpa_re_aghq()</code> debias applied inside the Sigma integration), reducing the small-cluster variance attenuation for binary / low-count data. AGHQ requires a single shared grouping factor (the per-group integral must factorize); with crossed RE terms n_quad > 1 errors. When AGHQ is used the fixed effects are integrated, so the reported fixed-effect posterior is the marginal (ML-II) one rather than the joint-mode (PQL) estimate.
X_zi	Optional zero-inflation design matrix (length(y) rows), making the model a two-process mixture: each observation is a structural zero with probability <code>plogis(X_zi beta_zi)</code> and otherwise follows family. Paired with a zero-truncated family it is the hurdle model. The random effects enter the count predictor only, and the integration runs over the same covariance coordinates – the mixture changes the inner solve, not the parameters being integrated over. The ZI coefficients are reported alongside the count ones in <code>coef()</code> / <code>vcov()</code> , so the fixed block is <code>ncol(X) + ncol(X_zi)</code> wide. Needs n_quad = 1: the adaptive Gauss-Hermite inner marginal runs through a single-predictor oracle.
zi_prior_sd	Prior SD on beta_zi, keeping the logit identified where a level carries no zeros (the likelihood alone would send it to -Inf). Ignored when X_zi is NULL.
control	A named list of numerical / tuning knobs (statistical arguments stay in the signature above). Recognized entries:

- `integration`: node layout, "ccd" (default, central-composite design, scales to larger total parameter count) or "grid" (full tensor product).
- `n_per_axis`: points per parameter axis in the tensor grid (default 5); used only when `integration = "grid"`.
- `span`: half-width of the tensor grid in posterior standard deviations per whitened axis (default 3); grid only.
- `n_draws`: posterior draws of the fixed effects synthesized from the node mixture (default 2000), exposed as draws for the generic `tulpa_fit` methods. The Sigma posterior is summarized directly from the integration nodes in posterior, independent of `n_draws`.
- `seed`: optional integer seed for the fixed-effect draw synthesis.
- `diagnose_k`: if TRUE (default), compute the outer Pareto k-hat accuracy diagnostic for the Gaussian proposal over the hyperparameters, returned as `pareto_k`.
- `k_samples`: importance draws for the `diagnose_k` estimate (default 200).
- `max_iter`, `tol`, `n_threads`: inner-solve controls (see `tulpa_laplace()`).
- `outer_maxit`: iteration budget for the mode-finding step that centres the integration grid (default 500). Applies to the Nelder-Mead simplex used from two parameters up; the one-parameter case is bracketed by Brent. Exhausting the budget warns, since the nodes are then centred on wherever the optimizer stopped.
- `checkpoint`: node checkpoint/resume spec `list(path = , resume = )`. Each completed CCD / grid node (one inner Laplace solve) is cached to `path`; a `resume = TRUE` run loads the finished nodes and re-solves only the rest. `resume = FALSE` starts fresh. A file written for different data, layout, or grid is rejected (fingerprint mismatch). Default NULL (off).
- `subspace_debias`: subspace debias, FALSE by default. TRUE takes every default; a list overrides `band` (the inner-reliability floor a coordinate is selected at, default "ok"), `idx` (pin the corrected set explicitly, skipping the selector), `probe` (the latent indices scored, default the fixed effects), `closure` (FALSE, TRUE, or a partial-correlation threshold: grow the set by the precision-graph neighbours it is strongly coupled to), `closure_max`, and the sampler budget `n_iter / warmup / thin`. When the selected set is non-empty, each integration node reports the selected fixed-effect coordinates from a Metropolis sample of the exact conditional along the Gaussian-conditional-mean surface, and the rest from the Gaussian conditional given them; an EMPTY set leaves the fit bit-for-bit identical to the plain path. What was selected is recorded in `subspace_debias` on the returned fit.

Details

Each term is one covariance **block**. A correlated block $((1 + x | g))$ is a full $\Sigma = L L'$ parameterized by its lower Cholesky factor in log-Cholesky coordinates (the log-diagonal and the strictly-lower entries of L , $c(c+1)/2$ values for a c -coefficient block), which keeps Σ positive definite for every coordinate. An uncorrelated block $((1 + x || g))$ is a diagonal Σ parameterized by its c log standard deviations. A scalar $(1 | g)$ term is the degenerate $c = 1$ block. Several blocks stack their parameters into one integration vector; a single-term model is the length-1 case.

Integration nodes live in the whitened stacked-parameter space, centred at the joint marginal-likelihood mode and rotated/scaled by the Cholesky of the mode's posterior covariance (`solve(Hessian)`), so points track the posterior ridge. Two node layouts are available via integration:

- "ccd" (default): a central-composite design (`ccd_grid()`) of $1 + 2k + 2^{(k-q)}$ points for the total $k = \text{sum_blocks}$ parameters, with the corrected R-INLA design weights (`ccd_weights()`). Scales polynomially in k , where the tensor grid is exponential.
- "grid": the full $n_{\text{per_axis}}^k$ tensor product with uniform cell weights – denser and more robust to a non-Gaussian whitened posterior, but only tractable for small k .

Each node k contributes integration weight proportional to $\Delta_k \cdot \exp(\log_{\text{marginal}}(\Sigma_k) + \log_{\text{prior_theta}}(\theta_k))$, following the INLA convention $\text{int} \sim \sum_k \Delta_k \pi(\theta_k)$.

The two layouts also decide how the reported median and 2.5% of each derived quantity are read off the nodes. A tensor grid's uniform cells discretize the posterior density, so the cumulative node weights are a CDF and the summary is the weighted quantile. A CCD is a moment rule: its nodes sit where they reproduce the integrand's first two moments and carry no probability mass of their own, so the summary is moment-matched instead – the first two weighted moments on each quantity's own coordinate (log for a scale or a variance, `atanh` for a correlation, the identity for a covariance) define a Gaussian there whose quantiles are mapped back. Scale intervals are therefore positive and asymmetric, and correlation intervals stay inside $(-1, 1)$. The mean and sd columns are the weighted moments under either layout.

By default (`hyperprior = "flat"`) `log_prior_theta` is the zero function: flat in $\log(\theta)$, the same convention the nested-Laplace spatial / temporal / RE-scale axes use (`icar / rw1 / rw2 / ar1`'s `tau / iid`, none of which carry a hyperprior on their scale either – see `vignette("priors")`). Set `hyperprior = "pc_lkj"` to use the weakly-informative PC + LKJ hyperprior instead, built per block by `re_cov_pc_lkj_prior()` and summed over blocks (PC prior on each marginal SD via `prior_sigma`, LKJ prior on each correlated block's correlation matrix via `eta`), expressed in the same parameterization with the exact change-of-variables Jacobian. Supply a custom `log_prior_theta` function to override either default (then `prior_sigma / eta / hyperprior` are ignored); it must act on the full stacked parameter vector. `tulpa_eb()` shares this same objective and the same default, so `tulpa_eb()$theta_hat` and `tulpa_re_cov_nested()$theta_hat` stay the same estimate on the same data under either setting.

Value

A list with:

- `posterior`: data frame with one row per parameter and columns mean, sd, median, `ci_lo`, `ci_hi`. Parameter names are `sigma_i`, `rho_ij`, `Sigma_ij` for a single block, prefixed by the block label (g. `sigma_1`, ...) when there are several blocks. Diagonal blocks report no rho.
- `map`: the plug-in-mode summary at `theta_hat` (a single list(`Sigma`, `sigma`, `rho`) for one block, or a named list of them).
- `Sigma_mean`: the weighted posterior mean of `Sigma` (a matrix for one block, or a named list of matrices).
- `beta`, `draws`, `means`, `param_names`, `process_info`: the fixed-effect posterior from the node mixture (drives `coef/confint/vcov/summary`).

- `re_nodes`, `re_var_nodes`: the per-group random-effect posterior at each integration node – conditional mean and marginal variance of every (block, group, coefficient), one row per node. `ranef()` reports the weights-mixture of them. NULL at `n_quad > 1`, whose inner marginal integrates each group out instead of conditioning on it; that fit carries `ranef_unavailable` (the reason) in their place.
- `re_debias_draws`, `re_debias_idx`: present when the subspace debias selected a random-effect coordinate. The sampled draws of those coordinates on the node mixture the fixed-effect draws use, and their positions within the random-effect block. `ranef()` reports those rows empirically and the rest from the Gaussian mixture, recording which in its source column.
- `theta_hat`, `theta_grid`, `weights`, `log_marginal`, `n_grid`, `layout`, `n_blocks`, `n_coefs` (vector of per-block c).
- `subspace_debias`: present only when `control$subspace_debias` was set. `idx` are the corrected latent coordinates, `bands` the per-probed-index reliability table they were read from, `closure_added` what the coupling closure added, and `accept` the per-node Metropolis acceptance rate.

References

Rue, Martino & Chopin (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *JRSS-B* 71(2):319-392. Lewandowski, Kurowicka & Joe (2009). Generating random correlation matrices based on vines and extended onion method. *Journal of Multivariate Analysis* 100(9):1989-2001.

See Also

`tulpa_laplace()` for the inner solve; `tulpa_nested_laplace()` for the analogous outer integration over spatial / temporal prior hyperparameters.

Examples

```
set.seed(1)
G <- 20L; per <- 12L; n <- G * per
grp <- rep(seq_len(G), each = per); x <- rnorm(n)
b <- cbind(rnorm(G, 0, 0.7), rnorm(G, 0, 0.5)) # random intercept + slope
eta <- -0.2 + 0.5 * x + b[grp, 1] + b[grp, 2] * x
y <- rbinom(n, 1L, plogis(eta))
re_term <- list(idx = grp, n_groups = G, n_coefs = 2L, Z = cbind(1, x),
               correlated = TRUE)
fit <- tulpa_re_cov_nested(y, rep(1L, n), cbind(1, x), re_term,
                        family = "binomial")
fit$Sigma_mean # marginalized RE covariance
```

tulpa_simulate	<i>Simulate data from a tulpa model</i>
----------------	---

Description

Generic simulator that dispatches through a `tulpa_family`'s `simulate_fn`. Given a model spec (formula + family + data) and a parameter vector or a fitted model, generate one or more synthetic response datasets.

Used internally by `prior_predict()` and exposed for posterior predictive checks, simulation-based calibration, and what-if analyses with fixed parameters.

Usage

```
tulpa_simulate(
  formula,
  family,
  data,
  theta = NULL,
  n_sims = 1L,
  priors = NULL,
  seed = NULL,
  ...
)
```

Arguments

<code>formula</code>	A model formula, or list of formulas keyed by process name.
<code>family</code>	A <code>tulpa_family</code> object (see <code>tulpa_family()</code>).
<code>data</code>	Data frame with covariates and grouping factors.
<code>theta</code>	One of: • A named list with <code>beta</code> (numeric or list per process), <code>u</code> (list of RE coefficient vectors, one per RE term per process), <code>extras</code> (named list of family-specific extras like <code>phi</code>, <code>sigma_y</code>). • A <code>tulpa_fit</code> object: posterior draws are sampled from <code>\$draws</code>. • <code>NULL</code>: equivalent to a single prior draw (shortcut).
<code>n_sims</code>	Number of simulated datasets. When <code>theta</code> is a fit, draws are subsampled (or recycled) to <code>n_sims</code> . Default 1.
<code>priors</code>	Used only if <code>theta = NULL</code> ; default <code>tulpa_priors()</code> .
<code>seed</code>	Optional integer seed.
<code>...</code>	Passed to <code>family\$simulate_fn</code> .

Value

A `tulpa_simulate` object: list with `y` (length-`n_sims` list of simulated responses), `theta` (parameters used per sim), `linpred`, `family`, `n_sims`, `n_obs`.

Examples

```
fam <- tulpa_family(  
  name = "gaussian",  
  simulate_fn = function(eta, params, n_obs, ...) {  
    rnorm(n_obs, eta[[1]], params$sigma_y)  
  },  
  extra_params = list(sigma_y = prior_half_normal(1))  
)  
df <- data.frame(y = rep(0, 20), x = rnorm(20))  
theta <- list(  
  beta = list(y = c(0.5, 1.0)),  
  u = list(y = list()),  
  extras = list(sigma_y = 0.5)  
)  
sim <- tulpa_simulate(y ~ x, fam, df, theta = theta, n_sims = 3, seed = 1)  
length(sim$y) # 3
```

tulpa_spatial	<i>Spatial structure specifications for tulpa</i>
---------------	---

Description

Functions to specify spatial random effects for tulpa models. Spatial effects are shared between processes by default, which helps prevent bias from spatially-structured unmeasured confounders.

Value

The spatial constructors documented in this family ([spatial_car\(\)](#), [spatial_bym2\(\)](#), [spatial_gp\(\)](#), and the others) each return a `tulpa_spatial` (or related) specification object to pass to the `spatial` argument of [tulpa\(\)](#).

tulpa_temporal	<i>Temporal structure specifications for tulpa</i>
----------------	--

Description

Functions to specify temporal random effects for tulpa models. Temporal effects are shared between processes by default, which helps prevent bias from temporally-structured unmeasured confounders.

Value

The temporal constructors documented in this family ([temporal_rw1\(\)](#), [temporal_rw2\(\)](#), [temporal_ar1\(\)](#), and the others) each return a `tulpa_temporal` specification object to pass to the `temporal` argument of [tulpa\(\)](#).

tulpa_tgmrf

Fit a custom tgmrf latent block

Description

One front door for inference over a user-defined `tgmrf()` latent block's hyperparameter vector `theta`. `mode` selects the inference engine, all of which share the same Laplace body for $(\beta, z) \mid \theta$:

- "imh" (default) – Tier-1 exact MCMC: the Laplace body plus an independence-Metropolis bias correction over θ (the "Laplace + MH debias" composition).
- "nuts" – Tier-1 exact MCMC: NUTS over the marginal θ posterior.
- "vi" – Tier-2 structured: a single-path Pathfinder Gaussian fit of the θ posterior (no bias correction).
- "nuts_joint" – Tier-1 exact MCMC sampling the FULL joint (β, z, θ) rather than the Laplace-marginalized θ (requires a C++-backend block, see `tgmrf_cpp()`).

The inference method is an argument, not a parallel verb.

Usage

```
tulpa_tgmrf(
  y,
  n_trials,
  X,
  block,
  family = "binomial",
  phi = 1,
  re_idx = NULL,
  n_re_groups = 0L,
  sigma_re = 1,
  mode = c("imh", "nuts", "vi", "nuts_joint"),
  control = list(),
  ...
)
```

Arguments

<code>y, n_trials, X</code>	Response, binomial trial counts (or NULL), and the fixed-effect design matrix.
<code>block</code>	A <code>tgmrf()</code> latent block.
<code>family, phi</code>	Observation family and its dispersion.
<code>re_idx, n_re_groups, sigma_re</code>	Optional scalar random-intercept structure.
<code>mode</code>	Inference engine: "imh", "nuts", "vi", or "nuts_joint".

`control` A list of numerical / tuning knobs for the chosen mode (e.g. `n_iter`, `warmup`, `thin`, `scale` for "imh"; `epsilon`, `max_depth`, `target_accept` for the NUTS modes; `n_draws`, `max_lbfgs`, `lbfgs_tol` for "vi"; plus the shared `pilot_axis_points`, `max_iter`, `tol`, `n_threads`, `verbose`). An unknown knob for the chosen mode errors rather than being silently ignored.

`...` Individual control knobs may also be passed directly by name; they are merged into `control` (a named argument here wins over the same name inside `control`).

Value

A `tulpa_tgmrf` / `tulpa_fit` object; `$backend` and `$mode` record the engine used.

See Also

`tgmrf()` for the block, `tgmrf_cpp()` for the compiled-block form.

Examples

```
## Not run:
# `block` is a tgmrf latent block (from tgmrf() / tgmrf_cpp()); the inference
# method is an argument, not a parallel verb. See vignette("tgmrf").
fit <- tulpa_tgmrf(y, rep(1L, length(y)), X, block = blk, mode = "imh")

## End(Not run)
```

`tulpa_validate`

Posterior predictive checks for tulpa models

Description

Visual and numerical checks comparing observed data to posterior predictive distributions. Essential for assessing model fit.

Value

The functions documented in this family return a `ggplot` object (`pp_check()`) or a `tulpa_prior_predict` object (`prior_predict()`); see each function's own help page.

tulpa_variogram	<i>Empirical semivariogram of residuals</i>
-----------------	---

Description

Computes the empirical semivariogram in distance bins for visual assessment of remaining spatial structure in residuals.

Usage

```
tulpa_variogram(
  object,
  coords,
  n_bins = 15L,
  max_dist = NULL,
  resid_type = "pearson"
)
```

Arguments

object	A fitted model, or a numeric vector of residuals
coords	N x 2 coordinate matrix (required)
n_bins	Number of distance bins (default 15)
max_dist	Maximum distance (default: half the maximum pairwise distance)
resid_type	Residual type if extracting from model (default "pearson")

Value

A tulpa_variogram data.frame with columns dist, gamma, n_pairs

tvc	<i>Extract temporally-varying coefficients from a fitted model</i>
-----	--

Description

Extract posterior distributions of temporally-varying coefficients (TVCs) from a fitted tulpa model with TVC specification.

Usage

```
tvc(object, terms = NULL, summary = FALSE, probs = c(0.025, 0.5, 0.975), ...)

## S3 method for class 'tulpa_fit'
tvc(object, terms = NULL, summary = FALSE, probs = c(0.025, 0.5, 0.975), ...)
```

Arguments

<code>object</code>	A <code>tulpa_fit</code> object fitted with <code>tvc</code> argument
<code>terms</code>	Which TVC terms to extract. If <code>NULL</code> (default), extracts all.
<code>summary</code>	Logical; if <code>TRUE</code> , return summary statistics instead of full posterior draws.
<code>probs</code>	Quantiles to compute if <code>summary = TRUE</code> .
<code>...</code>	Ignored

Value

A `tulpa_tvc_posterior` object containing:

- `draws`: Array of posterior draws (draws x times x terms)
- `time_levels`: Time point labels
- `term_names`: Names of TVC terms

See Also

[temporal_tvc\(\)](#), [plot.tulpa_tvc_posterior\(\)](#)

Examples

```
set.seed(160)
n_t <- 10L; reps <- 5L
walk <- cumsum(rnorm(n_t, 0, 0.35)); walk <- walk - mean(walk)
year <- rep(seq_len(n_t), each = reps)
df <- data.frame(year = year, x = rnorm(length(year)))
df$count <- rpois(nrow(df), exp(0.3 + (0.5 + walk[year]) * df$x))

# The slope on `x` walks in time; TVC is exact-mode only.
fit <- tulpa(
  count ~ x,
  data = df,
  family = "poisson",
  temporal = temporal_tvc("year", terms = ~ x - 1, structure = "rw1"),
  mode = "exact",
  control = list(n_iter = 200L, n_warmup = 100L, seed = 1L)
)

tvc_post <- tvc(fit)
summary(tvc_post)
plot(tvc_post, "x")
```

validate_mode	<i>Validate that a fit used the expected mode</i>
---------------	---

Description

Ensures the fit object was created with the expected inference mode. Useful for enforcing mode requirements in downstream analysis.

Usage

```
validate_mode(fit, expected_mode, error = TRUE)
```

Arguments

fit	A tulpa_fit object
expected_mode	Mode that should have been used
error	If TRUE (default), error on mismatch. If FALSE, return logical.

Value

If error = FALSE, returns TRUE/FALSE. Otherwise errors on mismatch.

VarCorr	<i>Random-effect variances and correlations</i>
---------	---

Description

Summarize the random-effect covariance of a fit: the standard deviation of each random-effect coefficient, the correlations between them within a term, and the covariance matrix itself.

Whether the covariance was estimated, sampled, or merely conditioned on is reported alongside it, because the three are different claims. A fit from mode = "laplace" conditions on sigma_re, so its values are the ones supplied; mode = "eb" estimates them; a sampler tier integrates them.

Usage

```
VarCorr(x, sigma = 1, ...)
```

```
## S3 method for class 'tulpa_fit'
VarCorr(x, sigma = 1, ...)
```

Arguments

x	A tulpa_fit.
sigma	Ignored, for compatibility with the VarCorr generic.
...	Ignored.

Value

A data frame with one row per random-effect coefficient: term, coef, sd, and source (one of "estimated", "sampled", "conditioned"). Correlated terms additionally carry the covariance matrices in the "cov" attribute, one per term, each with a "correlation" attribute. Returns an empty data frame when the fit has no random effects.

See Also

[ranef\(\)](#) for the per-level deviations, [tulpa_eb\(\)](#) to estimate the covariance rather than condition on it.

Examples

```
set.seed(1)
G <- 30L; per <- 10L; n <- G * per
grp <- rep(seq_len(G), each = per); x <- rnorm(n)
b <- rnorm(G, 0, 0.8)
d <- data.frame(y = rpois(n, exp(0.3 + 0.5 * x + b[grp])), x = x,
               g = factor(grp))
fit <- tulpa(y ~ x + (1 | g), data = d, family = "poisson", mode = "eb")
VarCorr(fit)
```

vcov.tulpa_fit	Variance-covariance matrix of the fixed effects
----------------	---

Description

Variance-covariance matrix of the fixed effects

Usage

```
## S3 method for class 'tulpa_fit'
vcov(object, ...)
```

Arguments

object	A tulpa_fit object.
...	Ignored.

Value

Fixed-effect variance-covariance matrix (empirical for sampler tiers, H_{β}^{-1} for the Laplace tier).

with_tulpa_integrator *Run an expression under a chosen symplectic integrator*

Description

Evaluate `expr` with the integrator set to `name`, then restore whatever was selected before – on an error as well as on success. The integrator selection is process-global, so a bare `tulpa_integrator()` call leaves every later fit in the session on the new scheme, and an error between setting and restoring leaves it there permanently.

Usage

```
with_tulpa_integrator(name, expr, mts_substeps = 4L)
```

Arguments

<code>name</code>	Integrator name, as for <code>tulpa_integrator()</code> .
<code>expr</code>	Expression to evaluate. Evaluated in the caller's environment.
<code>mts_substeps</code>	Inner prior-force substeps for "mts" (default 4).

Value

The value of `expr`.

See Also

`tulpa_integrator()`

Examples

```
with_tulpa_integrator("yoshida4", tulpa_integrator())
tulpa_integrator()    # unchanged
```

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