

Wellcome trust advanced course  
“Molecular Evolution”

## **Markovian Models for Molecular Phylogenetics**

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# Markovian models of DNA sequence evolution

The evolution of a sequence site is modelled as follows:  
there are substitution rates  $i \rightarrow j$ , per time unit, that apply at any time during the evolutionary process.

Matrix  $M$  of instantaneous substitution rates:

$M =$

$\swarrow$	A	T	C	G
A	$-\lambda_A$	$m_{TA}$	$m_{CA}$	$m_{GA}$
T	$m_{AT}$	$-\lambda_T$	$m_{CT}$	$m_{GT}$
C	$m_{AC}$	$m_{TC}$	$-\lambda_C$	$m_{GC}$
G	$m_{AG}$	$m_{TG}$	$m_{CG}$	$-\lambda_G$

$m_{ij}$  = rate of  $i \rightarrow j$  substitution per time unit.

$\lambda_i$  are such that column sums = 0  
( $\lambda_i$  = total mutation rate of  $i$ )

Here,  $M$  follows the convention  $m_{\text{column}, \text{row}}$ . The other convention  $m_{\text{row}, \text{column}}$  is often used in the literature.

This most general model contains 12 free parameters.

# Markovian models of DNA sequence evolution (*continued*)

Any matrix  $M$  of instantaneous substitution rates possesses two major properties:

1) If  $F(t)$  is the vector of base frequencies at time  $t$

$$\frac{dF(t)}{dt} = MF(t)$$

2) If  $P(t)$  is the matrix of conditional substitution probabilities after  $t$  time units of evolution,  $P(t) = e^{Mt}$ .

ancestor:  $i$   $\xrightarrow{t \text{ time units}}$   $j$  : descendant

$$P_{ij}(t) = \text{proba } j \text{ at } t \text{ when } i \text{ at } 0$$

## Equilibrium frequencies of a Markovian model

Any realistic Markovian model possesses its own set of equilibrium frequencies  $F_{eq}$ :

$$\text{such that } \frac{dF_{eq}(t)}{dt} = 0 \quad \text{or} \quad MF_{eq} = 0$$

[  $F_{eq}$  is the eigenvector associated to the eigenvalue 0 of M ]

If any sequence evolves with constant substitution rates, it will reach a fixed composition, its equilibrium composition

$$F_{eq} = (\pi_A, \pi_T, \pi_C, \pi_G)$$

that will then remain unchanged.

# Reversibility of Markovian evolutionary models

Mathematical definition :

$$\forall i,j \pi_j m_{ji} = \pi_i m_{ij} \quad \Leftrightarrow \quad \forall i,j,t \pi_j P_{ji}(t) = \pi_i P_{ij}(t)$$

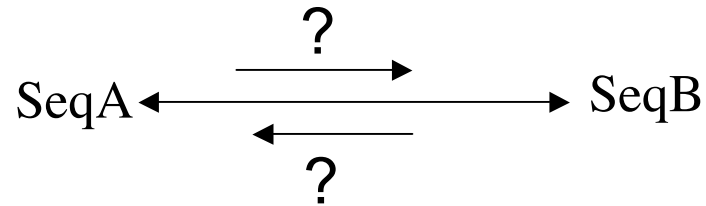
(at base equilibrium frequencies)

Conceptual definition :

for any pair of nucleotides  $(i,j)$ ,  $i \rightarrow j$  flux =  $j \rightarrow i$  flux

Consequences :

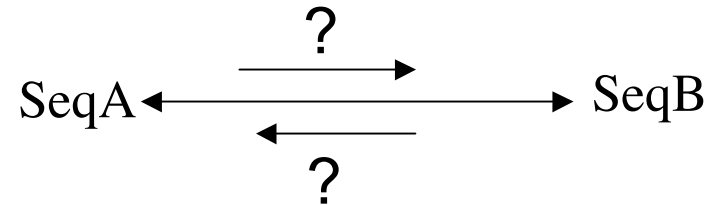
- The observation of two sequences at the extremities of a branch (during which evolution followed a constant Markovian model) contains no information about the direction of evolution.



- Computations can be done as though the tree is unrooted.

But there is no biological justification for believing that the molecular evolutionary process is reversible.

## Reversibility of Markovian evolutionary models (*continued*)



Only constraint: reversibility

General Time Reversible (9 parameters)

$$M = \begin{array}{c|ccccc} \begin{array}{c} \swarrow \\ A \\ T \\ C \\ G \end{array} & \begin{array}{c} A \\ T \\ C \\ G \end{array} & \begin{array}{c} T \\ C \\ G \end{array} & \begin{array}{c} C \\ G \end{array} & \begin{array}{c} G \end{array} \\ \hline A & -\lambda_A & a\pi_A & b\pi_A & c\pi_A \\ \hline T & a\pi_T & -\lambda_T & d\pi_T & e\pi_T \\ \hline C & b\pi_C & d\pi_C & -\lambda_C & f\pi_C \\ \hline G & c\pi_G & e\pi_G & f\pi_G & -\lambda_G \end{array}$$

Eq.  $(\pi_A, \pi_T, \pi_C, \pi_G)$

10 symbols but 9 parameters because  $\pi_A + \pi_T + \pi_C + \pi_G = 1$

## Tamura & Nei 93 (6 parameters)

$$M =$$

↙	A	T	C	G
A	$-\lambda_A$	$\beta\pi_A$	$\beta\pi_A$	$\alpha_R \frac{\pi_A}{\pi_R} + \beta\pi_A$
T	$\beta\pi_T$	$-\lambda_T$	$\alpha_Y \frac{\pi_T}{\pi_Y} + \beta\pi_T$	$\beta\pi_T$
C	$\beta\pi_C$	$\alpha_Y \frac{\pi_C}{\pi_Y} + \beta\pi_C$	$-\lambda_C$	$\beta\pi_C$
G	$\alpha_R \frac{\pi_G}{\pi_R} + \beta\pi_G$	$\beta\pi_G$	$\beta\pi_G$	$-\lambda_G$

Eq.  $(\pi_A, \pi_T, \pi_C, \pi_G)$

This is the most parameter-rich reversible model for which one can compute analytically the matrix  $P(t) = e^{Mt}$  of conditional substitutions.

Jukes & Cantor (1 parameter)

$$M = \begin{array}{c|ccccc} & \swarrow & A & T & C & G \\ \hline A & & -\lambda_A & r & r & r \\ T & & r & -\lambda_T & r & r \\ C & & r & r & -\lambda_C & r \\ G & & r & r & r & -\lambda_G \end{array}$$

Eq. (1/4, 1/4, 1/4, 1/4)

Kimura (2 parameters)

$$M = \begin{array}{c|ccccc} & \swarrow & A & T & C & G \\ \hline A & & -\lambda_A & r & r & \alpha r \\ T & & r & -\lambda_T & \alpha r & r \\ C & & r & \alpha r & -\lambda_C & r \\ G & & \alpha r & r & r & -\lambda_G \end{array}$$

Eq. (1/4, 1/4, 1/4, 1/4)

The Jukes & Cantor model has been historically the first one to be introduced.

Justification: simplicity.

Kimura's 2-parameter model aims at reflecting the fact that transitions are more frequent than transversions.



Felsenstein 81 (4 parameters)

$$M = \begin{array}{|c|c|c|c|c|} \hline \swarrow & A & T & C & G \\ \hline A & -\lambda_A & r\pi_A & r\pi_A & r\pi_A \\ \hline T & r\pi_T & -\lambda_T & r\pi_T & r\pi_T \\ \hline C & r\pi_C & r\pi_C & -\lambda_C & r\pi_C \\ \hline G & r\pi_G & r\pi_G & r\pi_G & -\lambda_G \\ \hline \end{array}$$

Eq.  $(\pi_A, \pi_T, \pi_C, \pi_G)$

Felsenstein's 1981 model allows for any arbitrary set of equilibrium frequencies.

Felsenstein 84 (5 parameters)

$$M = \begin{array}{|c|c|c|c|c|} \hline \swarrow & A & T & C & G \\ \hline A & -\lambda_A & \beta\pi_A & \beta\pi_A & \alpha \frac{\pi_A}{\pi_R} + \beta\pi_A \\ \hline T & \beta\pi_T & -\lambda_T & \alpha \frac{\pi_T}{\pi_Y} + \beta\pi_T & \beta\pi_T \\ \hline C & \beta\pi_C & \alpha \frac{\pi_C}{\pi_Y} + \beta\pi_C & -\lambda_C & \beta\pi_C \\ \hline G & \alpha \frac{\pi_G}{\pi_R} + \beta\pi_G & \beta\pi_G & \beta\pi_G & -\lambda_G \\ \hline \end{array}$$

Eq.  $(\pi_A, \pi_T, \pi_C, \pi_G)$

$\pi_R = \pi_{A+} \pi_G \quad \pi_Y = \pi_{C+} \pi_T$

Felsenstein's 1984 model was a pioneering attempt to incorporate both transition/transversion bias and an arbitrary set of equilibrium frequencies.

HKY-Hasegawa, Kishino, Yano: 5 params

$$M = \begin{array}{|c|c|c|c|c|} \hline \swarrow & \text{A} & \text{T} & \text{C} & \text{G} \\ \hline \text{A} & -\lambda_A & \pi_A b & \pi_A b & \pi_A a \\ \hline \text{T} & \pi_T b & -\lambda_T & \pi_T a & \pi_T b \\ \hline \text{C} & \pi_C b & \pi_C a & -\lambda_C & \pi_C b \\ \hline \text{G} & \pi_G a & \pi_G b & \pi_G b & -\lambda_G \\ \hline \end{array}$$

Eq.  $(\pi_A, \pi_T, \pi_C, \pi_G)$

Tamura 92 (3 parameters)

$$M = \begin{array}{|c|c|c|c|c|} \hline \swarrow & \text{A} & \text{T} & \text{C} & \text{G} \\ \hline \text{A} & -\lambda_A & \frac{1-\theta}{2} r & \frac{1-\theta}{2} r & \alpha \frac{1-\theta}{2} r \\ \hline \text{T} & \frac{1-\theta}{2} r & -\lambda_T & \alpha \frac{1-\theta}{2} r & \frac{1-\theta}{2} r \\ \hline \text{C} & \frac{\theta}{2} r & \alpha \frac{\theta}{2} r & -\lambda_C & \frac{\theta}{2} r \\ \hline \text{G} & \alpha \frac{\theta}{2} r & \frac{\theta}{2} r & \frac{\theta}{2} r & -\lambda_G \\ \hline \end{array}$$

Eq.  $((1-\theta)/2, (1-\theta)/2, \theta/2, \theta/2)$

The HKY model is another way to incorporate both transition/transversion bias and an arbitrary set of equilibrium frequencies.

HKY and F84 are very similar models.

This model aims at representing two phenomena :

- sequence G+C content
- transition/transversion bias

# Model hierarchy

GTR : 9 parameters

$\pi_A, \pi_T, \pi_C, a, b, c, d, e, f$

$a = b = e = f$

Tamura & Nei 93 : 6 parameters

$\pi_A, \pi_T, \pi_C, \beta, \alpha_R, \alpha_Y$

$\alpha_R / \pi_R = \alpha_Y / \pi_Y$

$\alpha_R = \alpha_Y$

HKY : 5 parameters

$\pi_A, \pi_T, \pi_C, a, b$

$\pi_A = \pi_T$

$\pi_C = \pi_G$

$\pi_A = \pi_T$

$\pi_C = \pi_G$

Felsenstein 84 : 5 parameters

$\pi_A, \pi_T, \pi_C, \beta, \alpha$

$\alpha = 0$

Tamura 92 : 3 parameters

$\theta, \alpha, r$

$\theta = 1/2$

Kimura : 2 parameters

$\alpha, r$

$\alpha = 1$

$\pi_A = \pi_T = \pi_C = 1/4$

Felsenstein 81 : 4 parameters

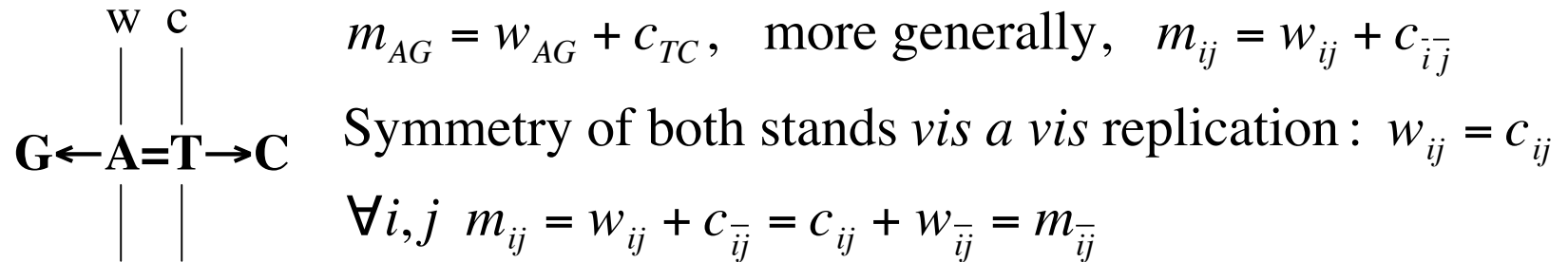
$\pi_A, \pi_T, \pi_C, r$

Jukes & Cantor: 1 parameter

$r$

# A biologically-motivated non-reversible Markovian model

Assumption: both DNA strands are replicated under the same conditions.



Lobry & Sueoka 95 (6 param.)

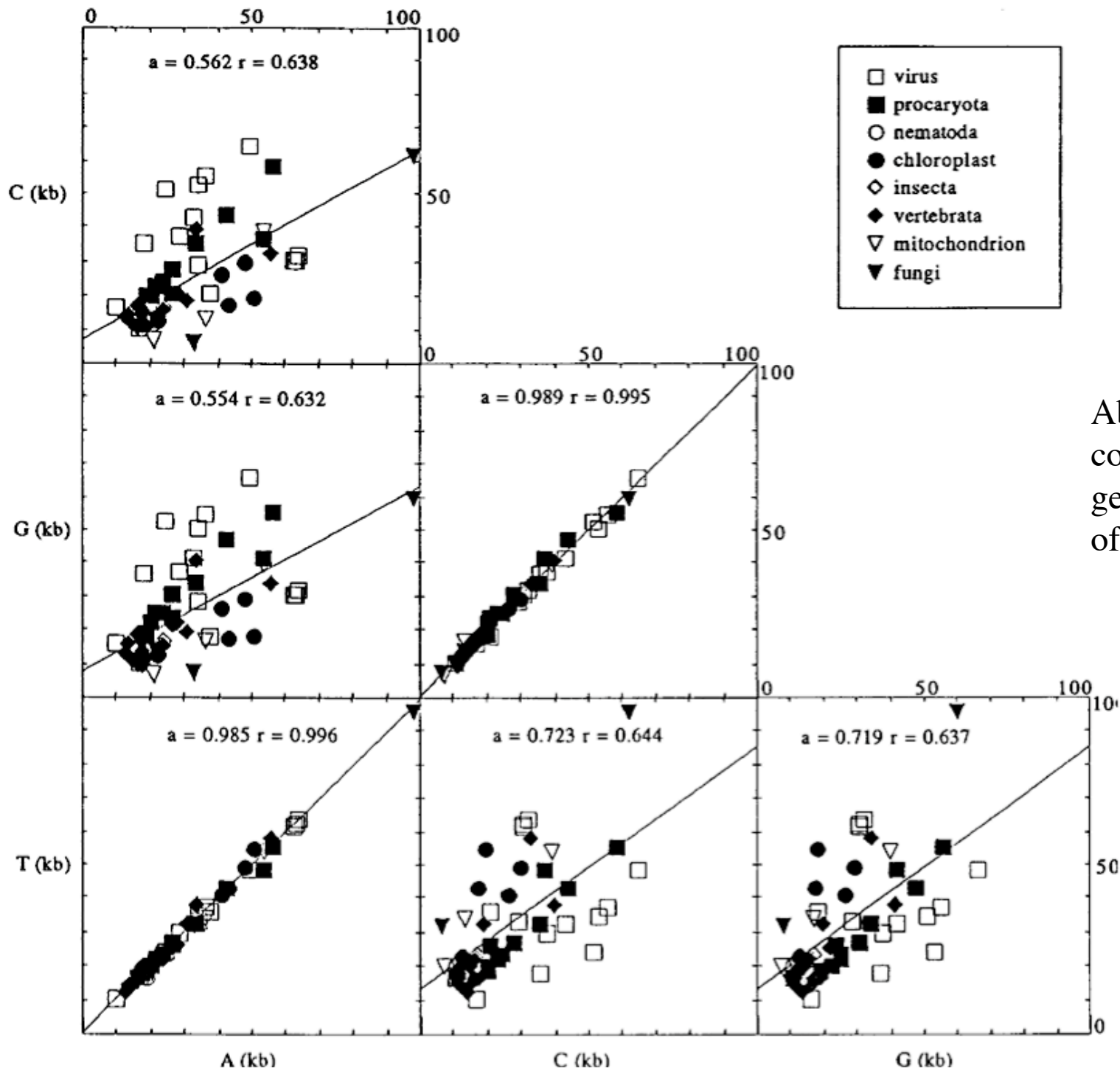
$$\mathbf{M} = \begin{array}{|c|c|c|c|c|}
 \hline
 \swarrow & \text{A} & \text{T} & \text{C} & \text{G} \\
 \hline
 \text{A} & -\lambda_A & a & d & b \\
 \hline
 \text{T} & a & -\lambda_T & b & d \\
 \hline
 \text{C} & e & c & -\lambda_C & f \\
 \hline
 \text{G} & c & e & f & -\lambda_G \\
 \hline
 \end{array}$$

Eq.  $(u/2v, u/2v, (v-u)/2v, (v-u)/2v)$

$$u = b+d; v = b+c+d+e$$

Non-reversible :  $\pi_A m_{AC} \neq \pi_C m_{CA}$

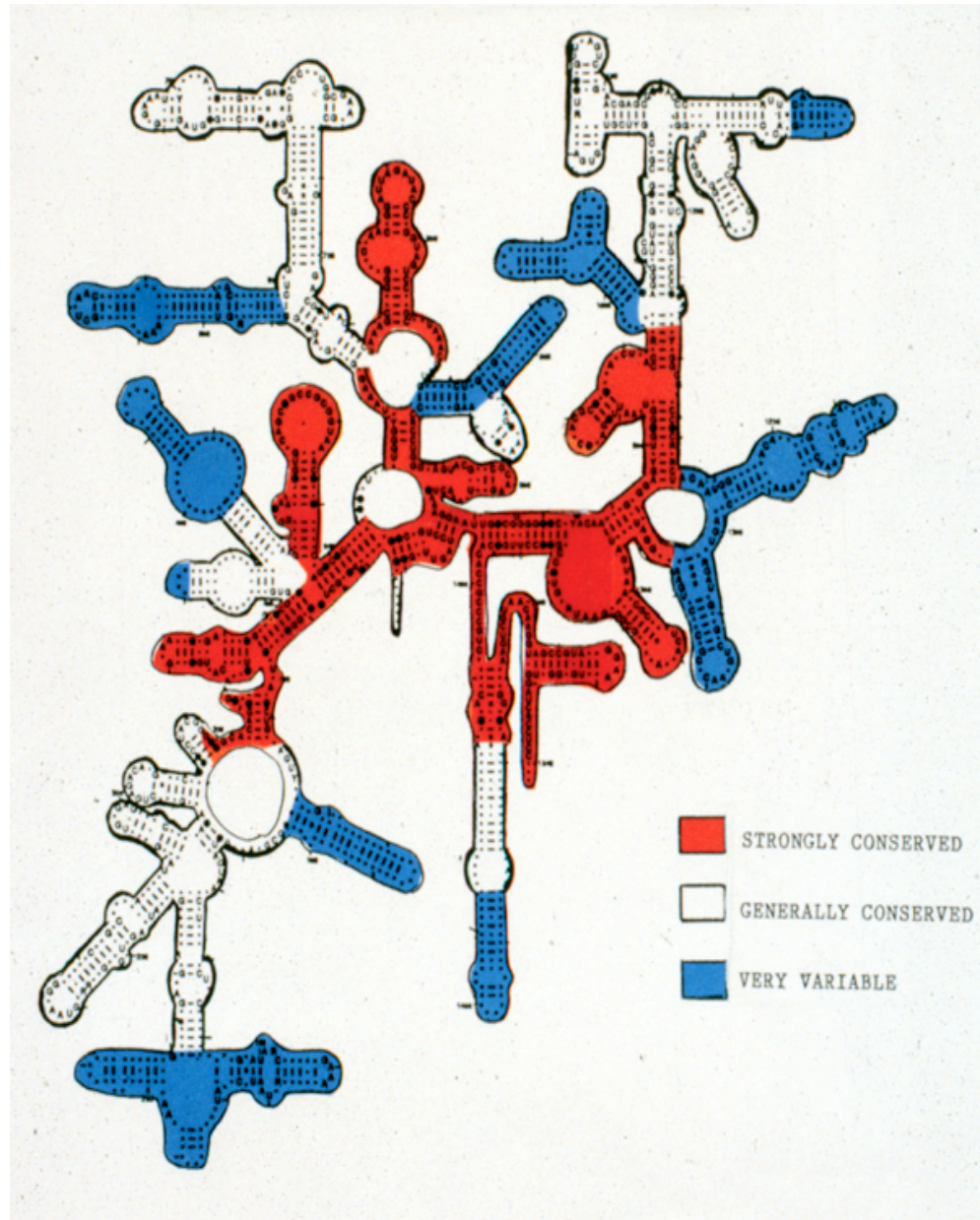
at equilibrium :  $[A]=[T]$  et  $[C]=[G]$



Absolute base compositions of genomic fragments of length  $\geq 50$  kb.

Lobry 1995  
 J Mol Evol 40:326

# Across sites evolutionary rate variation



**Small subunit  
ribosomal RNA  
(18S or 16S)**

# Modelling across sites evolutionary rate variation

Density  $f(r)$  of the gamma distribution :

$$f(r) = \frac{1}{\Gamma(\alpha)\beta^\alpha} r^{\alpha-1} e^{-r/\beta}$$

$\alpha$ : shape parameter

$\beta$ : scale parameter

mean:  $\alpha\beta$

variance:  $\alpha\beta^2$

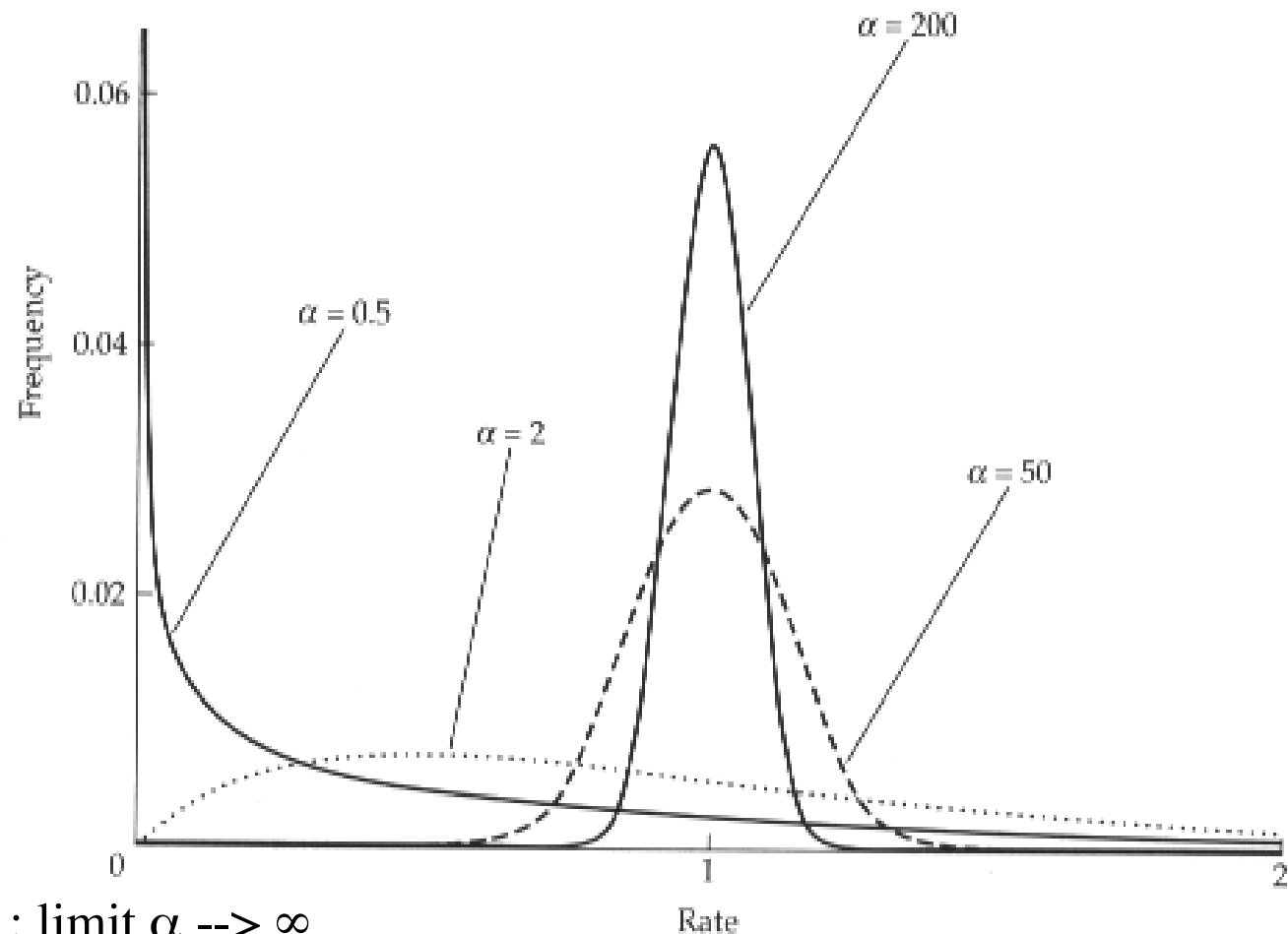
Taking  $\beta=1/\alpha$ ,

mean = 1

variance =  $1/\alpha$

This allows to model the distribution of evolutionary rates around the mean rate.

*The gamma distribution has no biological justification, it was chosen for its convenience.*

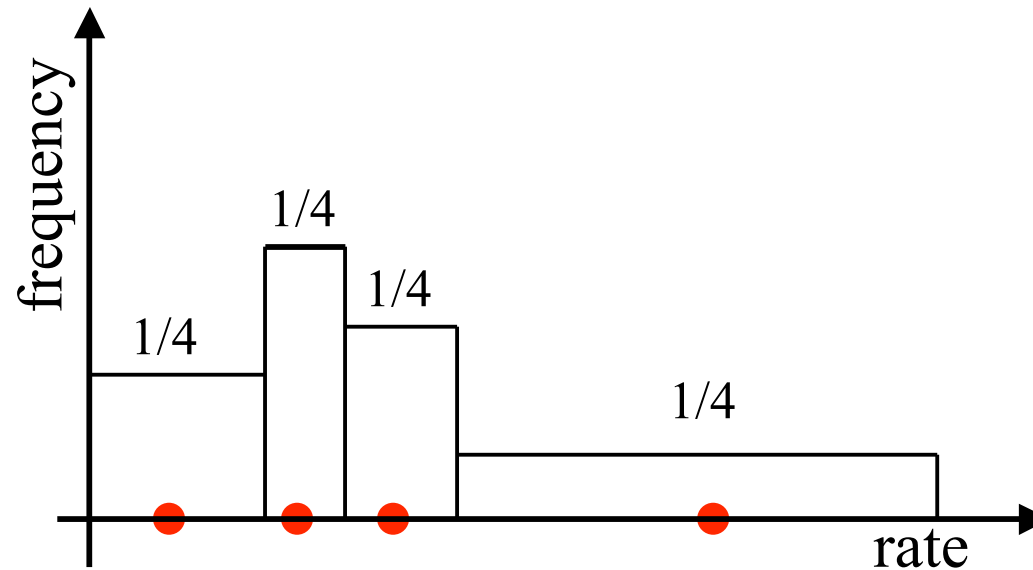


No variation across sites : limit  $\alpha \rightarrow \infty$

## Modelling across sites evolutionary rate variation (*continued*)

In many contexts, the gamma distribution is simplified by discretization to allow easy computations.

Example of discretization in 4 classes of equal weight:

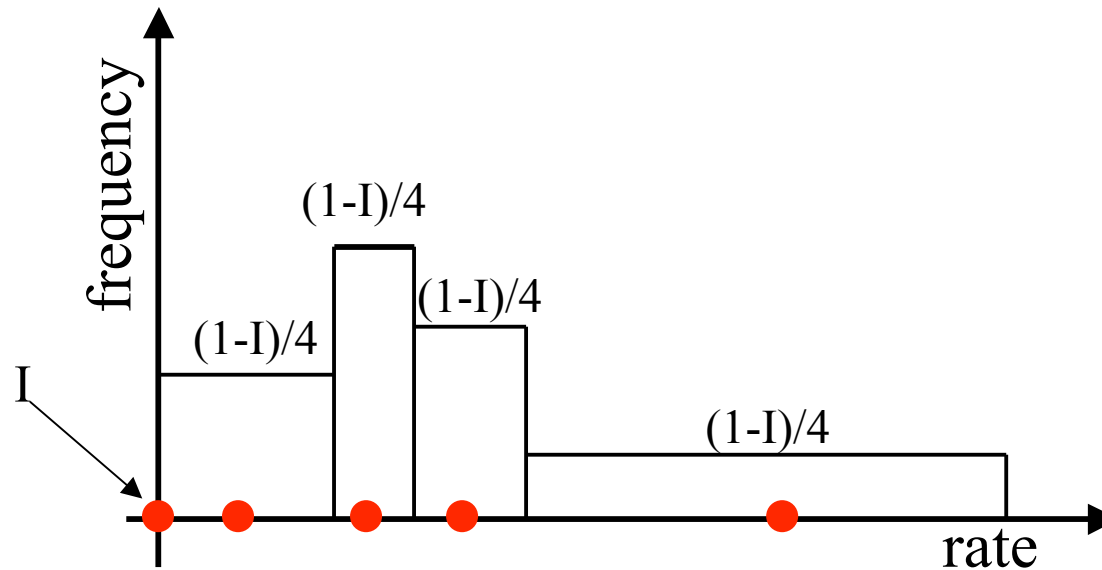




## Modelling across sites evolutionary rate variation (*continued*)

Frequently, an additional class of sites is allowed : invariable sites.  
This is the G + I model.

The fraction I of invariable sites needs to be estimated from the data.



# Markovian models of protein sequence evolution

The evolutionary process is modelled by a matrix  $Q$  of the rates  $q_{i,j}$  of amino acid replacements per unit time :

$$Q = (q_{i,j})_{i=1,\dots,20, j=1,\dots,20}$$

As with nucleotide evolutionary models, there are equilibrium amino acid frequencies:

$$(\pi_i)_{i=1,\dots,20}$$

# Reversible Markovian models of protein sequence evolution

General Time Reversible for DNA

↙	A	T	C	G
A	—	$a\pi_A$	$b\pi_A$	$c\pi_A$
T	$a\pi_T$	—	$d\pi_T$	$e\pi_T$
C	$b\pi_C$	$d\pi_C$	—	$f\pi_C$
G	$c\pi_G$	$e\pi_G$	$f\pi_G$	—

Eq.  $(\pi_A, \pi_T, \pi_C, \pi_G)$

More generally, for a reversible Markovian substitution process :

$$q_{ij} = s_{ij} \cdot \pi_j, \quad s_{ij} = s_{ji}, \quad \text{for } i \neq j$$

Thus  $q_{ij}$  can be decomposed in two components :

$s_{ij}$  represents the exchangeability of amino acids  $i$  and  $j$   
and  $\pi_i$ , the equilibrium frequency of amino acid  $i$ .

There are 190 free parameters in such a model.

## Empirical models of protein sequence evolution

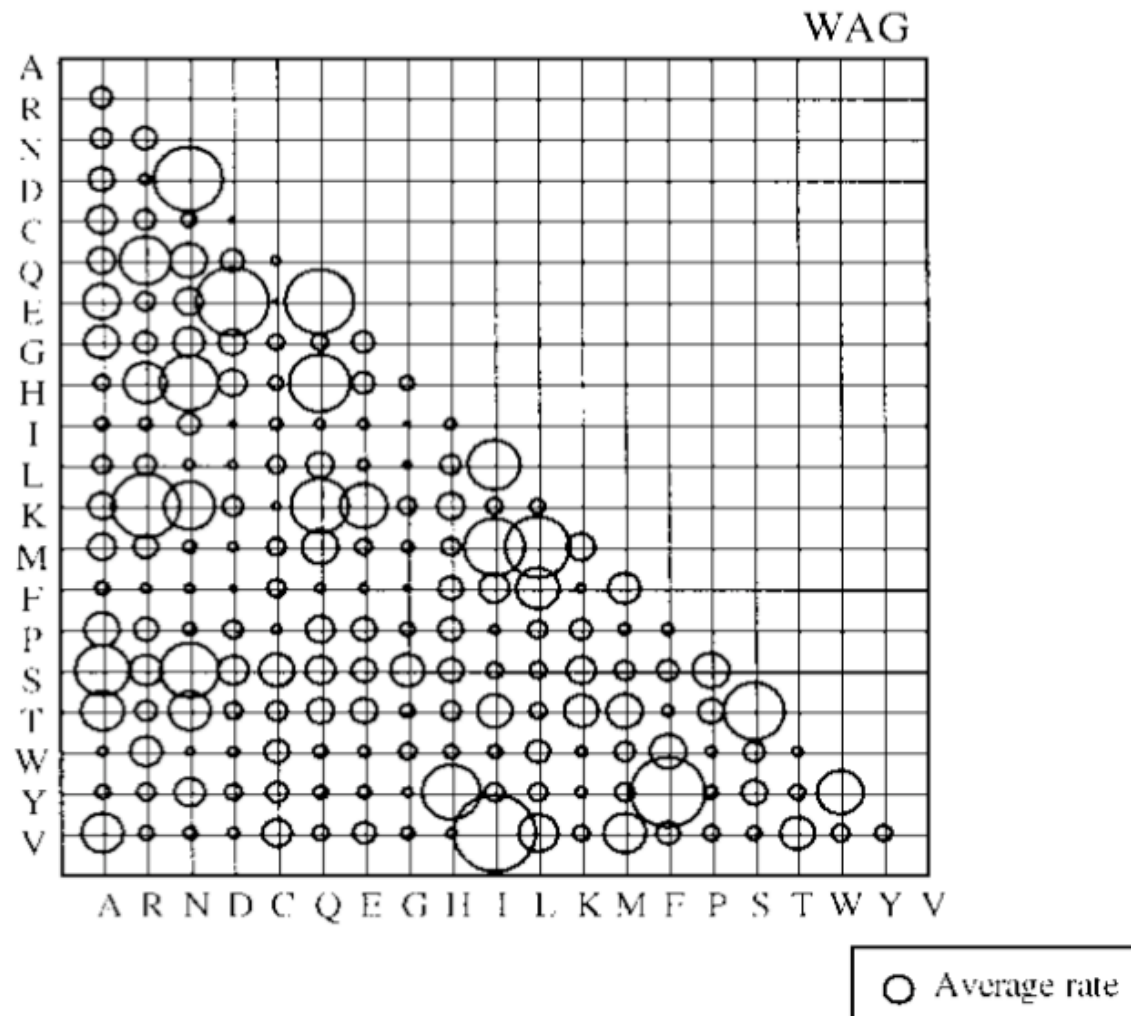
190 free parameters are too many for them to be estimated from a single protein sequence alignment.

Thus, empirically-derived values of exchangeabilities ( $s_{ij}$ ) are used.

These have been computed from very large sets of homologous proteins :

- The PAM model (Dayhoff, 1978) was built from 1,300 highly similar sequences ( $\geq 85$  % identity) belonging to 71 families.
- The JTT model (Jones et al., 1992) was built from 16,300 sequences ( $\geq 85$  % identity).
- The WAG model (Whelan & Goldman, 2001) was built from 3,905 proteins belonging to 182 families using a procedure that allowed for multiple replacements on a single branch at a single site.
- The LG model (Le & Gascuel, 2008) was built from 49,637 proteins of 3,912 families and improved by accounting for across-sites evolutionary rate variation.

# Schematic representation of the WAG amino acid replacement matrix



The area of each bubble represents the amino acid exchangeability parameter ( $s_{ij}$ ) for the replacement of amino acid  $i$  by amino acid  $j$  or vice versa. 21

Jargon :

Model JTT means  $s_{ij}$  are those from Jones *et al.* and  $\pi_i$  were as in proteins compiled by Jones *et al.*

Applying WAG + F to a protein data set means that Whelan and Goldman's empirical exchangeability values ( $s_{ij}$ ) were used and that equilibrium frequencies  $\pi_i$  were set to average amino acid frequencies of the data set.