introduction to (de novo) assembly

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The central dogma of molecular biology



Gene Expression



From DNA to RNA to proteins in eucaryotes

From DNA to proteins in eucarvotes

RNA-splicing in eucaryotes





Alternative splicing (AS) in RNA

DNA



Why sequencing?

Perfect Word



AACGGTAACTGAAC GTACGTACTACGTA CGTACCATGAACGG TAACTGAACGTACG TACTACGTACGTAC CATGAACGGTAACT GAACGTACGTACTA CGTACGTACCATG

Reality

- Cannot sequence full length DNA
- But we can sequence short fragments of it

DNA sequencing



DNA sequencing





DNA sequencing







Billions of short reads



AACGGTAACTGAACGTACGTACGTACGTACGTACCATG AACGGTAACTGAACGTACGTACGTACGTACGTACCATG AACGGTAACTGAACGTACGTACGTACGTACGTACCATG

Billions of short reads



AACGGTAACTGAACGTACGTACGTACGTACGTACCATG..... AACGGTAACTGAACGTACGTACGTACGTACGTACCATG..... AACGGTAACTGAACGTACGTACGTACGTACGTACCATG.....



AACGGTAACTGAACGTACGTACGTACGTACCATG

?

Next Generation Sequencing



Advantages:

 Construction of a sequencing library → clonal amplification to generate sequencing features

No in vivo cloning, transformation, colony picking...

- Array-based sequencing

Higher degree of parallelism
than capillary-based sequencing

RNA-seq



Why RNA-sequencing?

- Which region of the genome is transcribed
- Variability (AS events) of the mRNAs of the same gene
- Expression level of the mRNAs

coverage

- All genome positions are **covered** many times.
- The coverage is the number of reads covering a fixed position.



Some terminology

- read a 100-250 long word that comes out of a NGS machine
- coverage the average number of reads (or inserts) that cover a position in the target DNA piece
- shotgun sequencing the process of obtaining many reads from random locations in DNA, to detect overlaps and assemble
- **mate pair** a pair of reads from two ends of the same insert fragment (we know approx. distance)
- contig a contiguous sequence formed by several overlapping reads with no gaps
- consensus sequence sequence derived from the multiple alignment of reads in a contig

de novo assembly vs referenced-based mapping



de novo assembly

Methods

Different approaches

Basic idea

- greedy assembly
- Overlap-layout-consensus
- de bruijn graphs
- strings graphs

- Find all overlaps between reads
- Build a graph
- Simplify the graph (sequencing errors)
- Traverse a graph to produce a consensus.

Modelling and assembling NGS data (I)

• Given a set of strings $\mathcal{R} \subset \Sigma^* = \{A, C, T, G\}^*$ each $r \in \mathcal{R}$

is part of an unknown string $S \in \Sigma^*$ reconstruct the original

string $S \in \Sigma^*$

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- Shortest superstring problem (SSP)
 - Given a set of strings $r \in \mathcal{R}$ find a minimum length string $S \in \Sigma^*$ such that every $r \in \mathcal{R}$ is a substring of S

Shortest Superstring Problem

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Exercise 1

• SSP is NP-hard. (Garey and Johnson 1979)

Algorithm

- **Overlap** ov(s; t) of two strings s, t is the longest string y such, that s = xy and t = yz for some non-empty x, z.
- **Prefix** *pr(s; t)* of *s* w.r.t. *t* be the string *x* in the previous definition.
- s = pr(s; t)ov(s; t). Notice that pr(s; t)t is the shortest string containing s and t in that order. This string is usually called a merge of s and t.
- **Greedy approach:** We pick two strings *s_i s_j* with largest overlap from *R* (breaking ties arbitrarily) and replace them with their merge. Stop when there is only one string left.

Algorithm

- Greedy approach: We pick two strings s_i s_j with largest overlap from R (breaking ties arbitrarily) and replace them with their merge. Stop when there is only one string left.
 - How good is this algorithm? Can it have an approximation factor better than two?

Approximation algorithm

- A minimization problem is a problem where we want to find a solution with minimum value.
 - An algorithm for a minimization problem is called a ρ-approximation algorithm, for some ρ > 1, if the algorithm produces for any input I a solution whose value is at most ρ·opt(I).
- A maximization problem is a problem where we want to find a solution with maximum value.
 - An algorithm for a maximization problem is called a ρ-approximation algorithm, for some ρ < 1, if the algorithm produces for any input I a solution whose value isat least ρ · opt(I). The factor ρ is called the approximation factor (or the approximation ratio) of the algorithm.

Algorithm

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$$\{ab^k, b^kc, b^{k+1}\}$$

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The Greedy Conjecture [Blum et al. 1991]: The Greedy Algorithm has approximation factor 2.

Algorithm

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Exercise 2

 What is the best approximation value that you can prove for the greedy algorithm?

SSP: Problems (III)

• **Minimality :** requiring the superstring to be of minimal length, although motivated by parsimony, is in the best case questionable due to *repeats*.



• Local choices : in the true solution, the genome from which the reads were generated, several suffix-prefix read overlaps are not locally optimal.

Modelling and assembling NGS data (II) Overlap-Layout-Consensus



- **Overlap :** Build the overlap graph (find potentially overlapping reads)
- **Layout :** merge reads into contigs and simplify the graph.
- **Consensus :** Derive the DNA sequence and correct read errors

Building the overlap graph

Definition (Overlap Graph)

- Given a set of reads $\mathcal{R} \subset \Sigma^* = \{A, C, T, G\}^*$ the overlap graph is a complete weighted directed graph such that:
- $V = \mathcal{R}$ and $E = \mathcal{R}^2$;
- w(u, v) = length of the maximal suffix of *u* that is equal to a prefix of *v*

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In a more general definition a small number of mismatches is allowed for the suffix-prefix overlap. (Use DP to find the optimal overlap alignment)

Finding the optimal overlap alignment

- Overlap: suffix of X matches a prefix of Y
- We want to allow mismatches between X and Y.

 $\begin{array}{l} D[i,j]=min \ \{ \\ D[i-1,j]+score(X[i-1],-), \\ D[i, j-1]+score(-,Y[j-1]), \\ D[i-1, j-1]+score(X[i-1],Y[j-1]) \end{array}$

score(a,b)

	-	А	С	Т	G
-	8	8	8	8	8
А	8	0	4	4	2
С	8	4	0	2	4
Т	8	4	2	0	4
G	8	2	4	4	0

- X : CTCGGCCCTGG -
- Y: --CGACCCTAGTT

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Layout

- Graph simplification
 - remove all arcs that have weights below a given threshold.
 - remove from the graph all the edges that are transitively inferable. (**String graph**)

Consensus

- Find a *constrained* walk of minimum length in the graph
 - We define a *selection* function *s* that classifies the arcs:
 - optional : no constraint
 - *required* : present at leat once
 - *exact* : present exactly once
 - Selection function is defined using A-statistics (Meyers et al. 2000)

Overlap-Layout-Consensus and Hamiltonian Path

• Given a selection function s, a string graph G find an s-walk.

Finding a minimum s-walk is NP-hard from a reduction from Hamiltonian path (Medvedev et.al. 2007)

 Many assemblers use heuristics however for shorter reads and much deeper coverages, the overlap computation step is a computational bottleneck.

Finding overlaps

- For **N reads of length L** we need:
 - O(N²) comparisons
 - each comparison **O(L²)** alignment



Modelling and assembling NGS data (III) de Bruijn graph

De Bruijn graph

Given a set of reads *R* and an integer *k* we define the de Bruijn graph *B(R,k)*

- Vertices are substrings of length **k** (k-mers)
- Arcs are *k*-1 suffix-prefix overlaps that appear as a substring in *R*.

Example

R={ACTGAT,TCTGAG}, k=3



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de Bruijn graph vs overlap graph

- If all the reads of *R* have length exactly k + 1, the line graph of $G_k(R)$ is exactly the overlap graph of *R* with the arcs of weight zero removed.
- In a de Bruijn graph there is a loss of information with regard to the overlap graph: in de Bruijn graphs we do not have the information that two k-mers came from the same read.
 - As a consequence there are walks in the de Bruijn graph that are not read coherent (not entirely covered by reads).

Problem: Find an Eulerian path (visit each arc of the graph once).

- Finding an Eulerian path is polynomial but it may be not "read coherent".
- A graph may have an exponential number of Eulerian paths.

Computing a de Bruijn graph

- Given a read set *R*, we can build a de Bruijn graph $G_k(R)$ using a hash table to store all (k +1)-mers present in *R*.
- As each insertion and membership query in the hash table takes O(1) (expected) time, the de Bruijn graph can be built in time linear in the size of R, i.e. $O(\sum_{r \in \mathcal{R}} |r|)$.

We can compute a de Bruijn graph for a set of reads in linear time in the size of the reads.

de Bruijn graph : Theory

• Sparse Graph: out and in degree ≤ 4

de Bruijn graph : Theory

• Sparse Graph: out and in degree ≤ 4

de Bruijn graph : Reality



de Bruijn graph : Theory

• Sparse Graph: out and in degree ≤ 4

de Bruijn graph : Reality



What creates the complexity?

repeats challenge in assembly

Aa Assembly graph

Ab Correct assembly







Bb Correct assembly



Bc Misassembly



Ca Assembly graph



Cb Correct assembly



Cc Misassembly



