EECS730: Introduction to Bioinformatics

Lecture 05: Index-based alignment algorithms



Slides adapted from Dr. Shaojie Zhang (University of Central Florida)

Real applications of alignment

- Database search
- Assume we have a gene g and a genome G, and we want to find the homolog of g in G
- Smith-Waterman algorithm (local alignment) would take O(g*G) time.
- Even more ambitious, if you want to search g against all homologs from a collection of genomes...
- As of 2014, there are 157,943,793,171nt (~160 billion) being registered in the database NCBI NT (non-redundant nucleotide).

Naïve Smith-Waterman

- Given a newly discovered gene,
 - Does it occur in other species?
 - How fast does it evolve?



Let's try a shorter one...

>gi|57013850|sp|P69905.2|HBA_HUMAN RecName: Full=Hemoglobin subunit alpha; AltName: Full=Alpha-globin; AltName: Full=Hemoglobin alpha chain MVLSPADKTNVKAAWGKVGAHAGEYGAEALERMFLSFPTTKTYFPHFDLSHGSAQVKGHGKK VADALTNA VAHVDDMPNALSALSDLHAHKLRVDPVNFKLLSHCLLVTLAAHLPAEFTPAVHASLDKFLASV STVLTSK YR

Different flavors of BLAST

- BLASTN: nucleotide to nucleotide
- BLASTP: protein to protein
- BLASTX: nucleotide to protein; finding protein that is encoded by the query
- TBLASTX: nucleotide to nucleotide; finding nucleotide sequences that code for the same/similar protein
- TBLASTN: protein to nucleotide; finding nucleotides that code for the query

Index-based searches

(BLAST- Basic Local Alignment Search Tool)

Main idea:

- 1. Construct a dictionary of all the **words** in the query
- 2. Initiate a local alignment for each word match between query and DB

Running Time: O(MN)

However, orders of magnitude faster than Smith-Waterman



Words

- A k-long sequence fragment
- It is also called k-mer
- Intuition: if we require a k-mer to initialize the alignment, we can expect to speedup the alignment by a^k times (a is the size of the alphabet, 4 for DNA and 20 for protein), given that the distribution of different k-mers are uniform

The indexing scheme

Dictionary:

All words of length k (11-13, tunable)

Alignment initiated between *k*-mer matches

Alignment:

Ungapped extensions until score below statistical threshold Gapped extension until score below statistical threshold

Output:

All local alignments with score > statistical threshold



Example:

k = 4

The matching word GGTC initiates an alignment

Extension to the left and right with no gaps until alignment falls < T below best so far

Output:

GTAAGGTCC

GTTAGGTCC



Gapped extensions

- Extensions with gaps in a band around anchor
- Terminates after significant score drop-off

Output:

GTAAGGTCC-AGT

GTTAGGTCCTAGT



long words
(k = 15)short words
(k = 7)Sensitivity \checkmark Speed \checkmark

Sensitivity/Speed tradeoff

Та	ble 3.	Sensitivity and Specificity of Single Perfect Nucleotide K-mer Matches as a Search Criterion									
		7	8	9	10	11	12	13	14		
A.	81%	0.974	0.915	0.833	0.726	0.607	0.486	0.373	0.314		
	83%	0.988	0.953	0.897	0.815	0.711	0.595	0.478	0.415		
	85%	0.996	0.978	0.945	0.888	0.808	0.707	0.594	0.532		
	87%	0.999	0.992	0.975	0.942	0.888	0.811	0.714	0.659		
	89%	1.000	0.998	0.991	0.976	0.946	0.897	0.824	0.782		
	91%	1.000	1.000	0.998	0.993	0.981	0.956	0.912	0.886		
	93%	1.000	1.000	1.000	0.999	0.995	0.987	0.968	0.957		
	95%	1.000	1.000	1.000	1.000	0.999	0.998	0.994	0.991		
	97%	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999		
B.	K F	7 1.3e+07	8 2.9e+06	9 635783	10 143051	11 32512	12 7451	13 1719	14 399		

(A) Columns are for K sizes of 7–14. Rows represent various percentage identities between the homologous sequences. The table entries show the fraction of homologies detected as calculated from equation 3 assuming a homologous region of 100 bases. The larger the value of K, the fewer homologies are detected.

(B) K represents the size of the perfect match. F shows how many perfect matches of this size expected to occur by chance according to equation 4 in a genome of 3 billion bases using a query of 500 bases. Kent WJ, Genome Research 2002

Using gapped seeds

• To allow variations in between



The BLAST configuration



Gapped seeds

Table 7.	Sensitivity a	and Specific	ity of Multip	e (2 and 3) I	Perfect Nucle	otide K-mer	Matches as	a Search Cri	terion	
	2,8	2,9	2,10	2,11	2,12	3,8	3,9	3,10	3,11	3,12
A. 81%	0.681	0.508	0.348	0.220	0.129	0.389	0.221	0.112	0.051	0.021
83%	0.790	0.638	0.475	0.326	0.208	0.529	0.339	0.193	0.099	0.045
85%	0.879	0.762	0.615	0.460	0.318	0.676	0.487	0.313	0.180	0.093
87%	0.942	0.866	0.752	0.611	0.461	0.809	0.649	0.470	0.305	0.177
89%	0.978	0.940	0.868	0.761	0.625	0.910	0.801	0.648	0.476	0.314
91%	0.994	0.980	0.947	0.884	0.787	0.969	0.914	0.815	0.673	0.505
93%	0.999	0.996	0.986	0.962	0.912	0.993	0.976	0.933	0.851	0.722
95%	1.000	1.000	0.998	0.993	0.979	0.999	0.997	0.987	0.961	0.902
97%	1.000	1.000	1.000	1.000	0.999	1.000	1.000	0.999	0.997	0.987
B. N,K	2,8	2,9	2,10	2,11	2,12	3,8	3,9	3,10	3,11	3,12
F	524	27	1.4	0.1	0.0	0.1	0.0	0.0	0.0	0.0

(A) Columns are for N sizes of 2 and 3 and K sizes of 8–12. Rows represent various percentage identities between the homologous sequences. The table entries show the fraction of homologies detected as calculated by equation 10. (B) N and K represent the number and size of the near-perfect matches, respectively. F shows how many perfect clustered matches expected to occur by chance according to equation 14 in a translated genome of 3 billion bases using a query of 167 amino acids. Kent WJ, Genome Research 2002

Inexact matches

- Pre-building high-scoring *k*-mer pairs allowing mismatches
- Rescue homologs without long stretches of perfect matches
- More being used in protein alignment



Inexact matches

Table 5. Sensitivity and Specificity of Single Near-Perfect (One Mismatch Allowed) Nucleotide K-mer Matches as a Search Criterion

		12	13	14	15	16	17	18	19	20	21	22
A. 8	31%	0.945	0.880	0.831	0.721	0.657	0.526	0.465	0.408	0.356	0.255	0.218
8	3%	0.975	0.936	0.904	0.820	0.770	0.649	0.591	0.535	0.480	0.361	0.318
8	5%	0.991	0.971	0.954	0.900	0.865	0.767	0.719	0.669	0.619	0.490	0.445
8	7%	0.997	0.990	0.983	0.954	0.935	0.867	0.833	0.796	0.757	0.634	0.591
8	9%	1.000	0.997	0.995	0.984	0.976	0.939	0.920	0.897	0.872	0.775	0.741
9	1%	1.000	1.000	0.999	0.996	0.994	0.979	0.971	0.962	0.950	0.890	0.869
9	3%	1.000	1.000	1.000	0.999	0.999	0.996	0.994	0.991	0.988	0.963	0.954
9	5%	1.000	1.000	1.000	1.000	1.000	1.000	0.999	0.999	0.999	0.994	0.992
9	7%	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
В. К	, k	12	13	14	15	16	17	18	19	20	21	22
F		275671	68775	17163	4284	1070	267	67	17	4.2	1.0	0.3

(A) Columns are for K sizes of 12–22. Rows represent various percentage identities between the homologous sequences. The table entries show the fraction of homologies detected as calculated by equation 6 assuming a homologous region of 100 bases. (B) K represents the size of the near-perfect match. F shows how many perfect matches of this size expected to occur by chance according to equation 7 in a genome of 3 billion bases using a query of 500 bases. Kent WJ, Genome Research 2002

Reduced alphabet

(A) (C) (G) (H) (P)(K, R) (S, T) (F, Y, W)(E, D, N, Q) (I, L, V, M)



Table 1 A	list of	reduced	amino	acid	alphabets
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Alphabet	Size of the alphabet	Amino acid groups
all.20	20	P G E K R Q D S N T H C I V W Y F A L M
dssp.5	5	[AEHKQR] [FILMVWY] [CST] [DN] [GP]
dssp.10	10	[EKQR] [IV] [LY] F [AM] W [HT] C [DNS] [GP]
gbmr.4	4	g [Adeknqrst] [Cfhilmvwy] p
gbmr.10	10	g d n [Aefiklmqrvw] y h c t s p
hsdm.5	5	[LIVFMY] W C [DNTSKEQRAGP] H
sdm.6	6	[YFLIVM] C W [DNTSQKERAG] H P
murphy.5	5	[LVIMC] [ASGTP] [FYW] [EDNQ] [KRH]
murphy.10	10	A [KR] [EDNQ] C G H [ILVM] [FYW] P [ST]
td.5	5	[PG] [EKRQ] [DSNTHC] [IVWYF] [ALM]
td.10	10	P g [EKRQ] [DSN] T [HC] [IV] [WYF] A [LM]

The alphabets were downloaded from http://www.rpgroup.caltech.edu/publications/supplements/alphabets/HP/Welcome.html.

Longest exact match (using 20 amino acids) = 5 Longest "exact" match (using the reduced alphabet) = 10

Ye et al. BMC Bioinformatics, 2011

Choice of reduced alphabet in seeding



Ye et al. BMC Bioinformatics, 2011

Patterns

- Non-consecutive words
- Increase the probability of at least one hit while reduce the number of hits



Patterns

Note that using patterns less seeds will be generated, so it is also faster!!!



Variants of BLAST

- NCBI BLAST: search the universe http://www.ncbi.nlm.nih.gov/BLAST/
- MEGABLAST:
 - Optimized to align very similar sequences
 - Works best when $k = 4i \ge 16$
 - Linear gap penalty
- WU-BLAST: (Wash U BLAST)
 - Very good optimizations
 - Good set of features & command line arguments
- BLAT
 - Faster, less sensitive than BLAST
 - Good for aligning huge numbers of queries
- CHAOS
 - Uses inexact k-mers, sensitive
- PatternHunter
 - Uses patterns instead of k-mers
- BlastZ
 - Uses patterns, good for finding genes

BLAST statistics

- Score matrices used to seek local alignments of variable length should have a negative expected score. Otherwise the alignment will span over the entire sequence (good alignment score even for random sequences).
- $\sum p_{i*}p_{j*}S_{i,j} < 0$; p_i is the frequency of character *i*; p_j is the frequency of character *j*; and $S_{i,j}$ is the score for substituting character *i* with *j*.

Log odds score

- Let S_{i,j} be the scaled (to integers to facilitate score computation) logodds likelihood for substituting *i* with *j*.
- $S_{i,j} = \ln(q_{i,j} / p_{i*}p_j) / \lambda$; $q_{i,j}$ is the frequency of substituting *i* with *j*; λ is a scaling parameter that converts the score back to the "probability" space.
- Find the appropriate value for $\boldsymbol{\lambda}$

Finding λ

- We know that the sum of all $q_{i,i}$ should be 1.
- Recall that $S_{i,j} = \ln(q_{i,j} / p_{i*}p_j) / \lambda$

•
$$q_{i,j} = p_{i*}p_{j*}e^{(\lambda * S_{i,j})}$$
; and $f(\lambda) = \sum p_{i*}p_{j*}e^{(\lambda * S_{i,j})} = 1$.

- We know that λ is always a solution, i.e. f(0) = 1
- $f'(0) = \sum p_{i*}p_{j*}S_{i,j} < 0$ (the negative expected score assumption)

•
$$f''(\lambda) = \sum p_{i^*} p_{j^*} (S_{i,j})^2 e^{\lambda} (\lambda * S_{i,j}) > 0$$

Sketching the function



The *E*-value

- Given a particular scoring system, how many distinct local alignments with score $\geq S$ can one expect to find by chance from the comparison of two random sequence of lengths *m* and *n*? The answer, E(S,m,n), should depend upon *S*, and the lengths of the sequences compared.
- If we double the size of m, we will get twice more local alignments; if we double the size of n, we will also get twice more local alignments.
- *E*(*S*,*m*,*n*) is proportional to *m***n*

Frequency of observing a stretch of alignment

• $1/\Pi (q_{i,j} / p_{i*}p_j) = e^{(-\log(\Pi (q_{i,j} / p_{i*}p_j)))} = e^{(-\sum \log(q_{i,j} / p_{i*}p_j))}$

•
$$e^{(-\sum \log(q_{i,j}/p_i*p_j))} = e^{(-\sum \lambda *S_{i,j})} = e^{(-\lambda * \sum S_{i,j})} = e^{(-\lambda * S_i)}$$

• E(S,m,n) is proportional to $e^{(-\lambda * S)}$

The *E*-value

- *E*(*S*,*m*,*n*) is proportional to *m***n*
- E(S,m,n) is proportional to $e^{(-\lambda * S)}$
- $E(S,m,n) = K * m * n * e^{(-\lambda * S)}$
- *K* can be determined through simulation

With gaps

- The theory is provably valid only for local alignments without gaps.
- However, although no formal proof is available, random simulation suggests the theory remains valid when gaps are allowed, with sufficiently large gap costs.
- In this case, no analytic formulas for the statistical parameters λ and K are available, but these parameters may be estimated by random simulation.



https://wwwold.cs.umd.edu/class/fall2011/cmsc858s/Local_Alignment_Statistics.pdf