Chapter 3: Pairwise Sequence Alignment

Learning objectives

- Upon completion of this material, you should be able to:
- define homology as well as orthologs and paralogs;
- explain how PAM (accepted point mutation) matrices are derived;
- contrast the utility of PAM and BLOSUM scoring matrices;
- define dynamic programming and explain how global (Needleman–Wunsch) and local (Smith–Waterman) pairwise alignments are performed; and
- perform pairwise alignment of protein or DNA sequences at the NCBI website.

Outline

Introduction

Protein alignment: often more informative than DNA alignment

Definitions: homology, similarity, identity

Gaps

Pairwise alignment, homology, and evolution of life

Scorlng matrices

Dayhoff model: 7 steps

Pairwise alignment and limits of detection: the "twilight zone"

Allgnment algorithms: global and local

Global sequence alignment: algorithm of Needleman and

Wunsch

Local sequence alignment: Smith and Waterman algorithm

Rapid, heuristic versions of Smith-Waterman: FASTA and BLAST

Basic Local Alignment Search Tool (BLAST)

Pairwise alignment with dotplots

The statistical significance of pairwise alignments

Statistical significance of global alignments

Percent identity and relative entropy

Perspective

Pairwise sequence alignment is the most fundamental operation of bioinformatics

- It is used to decide if two proteins (or genes) are related structurally or functionally
- It is used to identify domains or motifs that are shared between proteins
- It is the basis of BLAST searching
- It is used in the analysis of genomes

Sequence alignment: protein sequences can be more informative than DNA

- protein is more informative (20 vs 4 characters); many amino acids share related biophysical properties
- codons are degenerate: changes in the third position often do not alter the amino acid that is specified
- protein sequences offer a longer "look-back" time

Example:

- --searching for plant globins using human beta globin DNA yields no matches;
- --searching for plant globins using human beta globin protein yields many matches

Pairwise alignment: DNA sequences can be more informative than protein

Many times, DNA alignments are appropriate

- --to study noncoding regions of DNA (e.g. introns or intergenic regions)
- --to study DNA polymorphisms
- --genome sequencing relies on DNA analysis

Definition: pairwise alignment

Pairwise alignment

The process of lining up two sequences to achieve maximal levels of identity (and conservation, in the case of amino acid sequences) for the purpose of assessing the degree of similarity and the possibility of homology.

Definitions: identity, similarity, conservation

$_{\circ}$ Homology

Similarity attributed to descent from a common ancestor.

Identity

The extent to which two (nucleotide or amino acid) sequences are invariant.

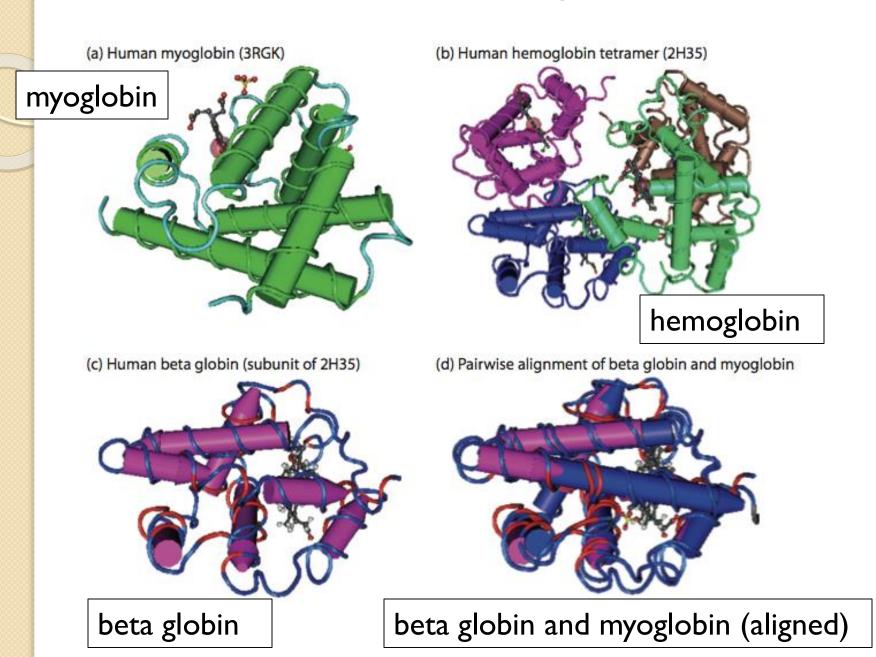
Similarity

The extent to which nucleotide or protein sequences are related. It is based upon identity plus conservation.

Conservation

Changes at a specific position of an amino acid or (less commonly, DNA) sequence that preserve the physicochemical properties of the original residue.

Globin homologs



Outline

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Definitions: two types of homology

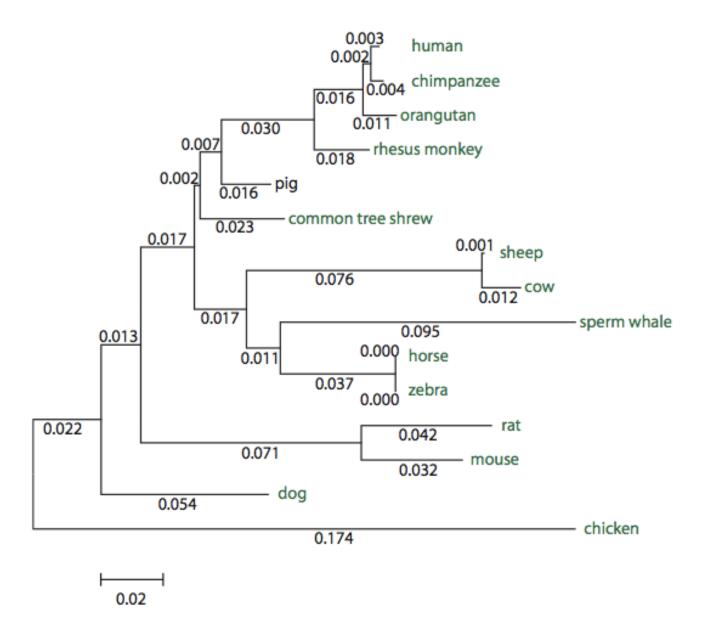
Orthologs

Homologous sequences in different species that arose from a common ancestral gene during speciation; may or may not be responsible for a similar function.

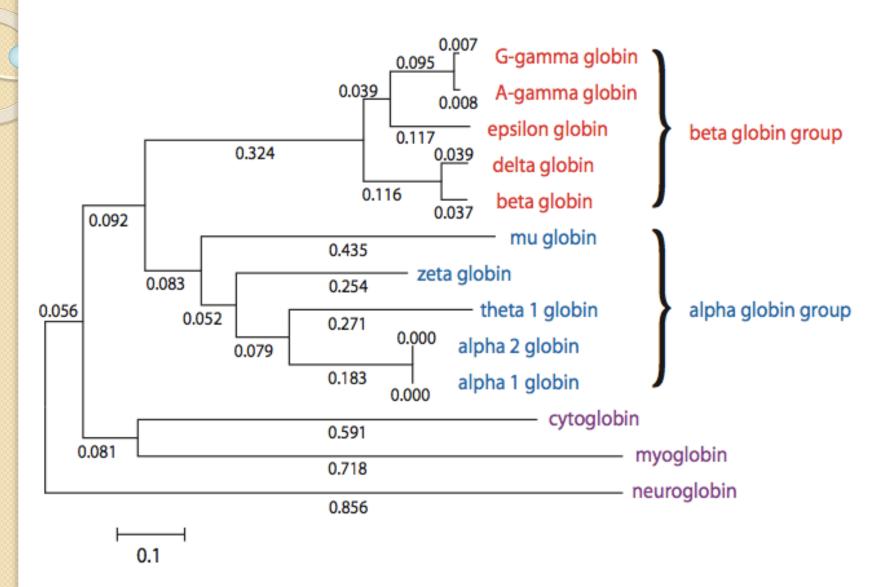
Paralogs

Homologous sequences within a single species that arose by gene duplication.

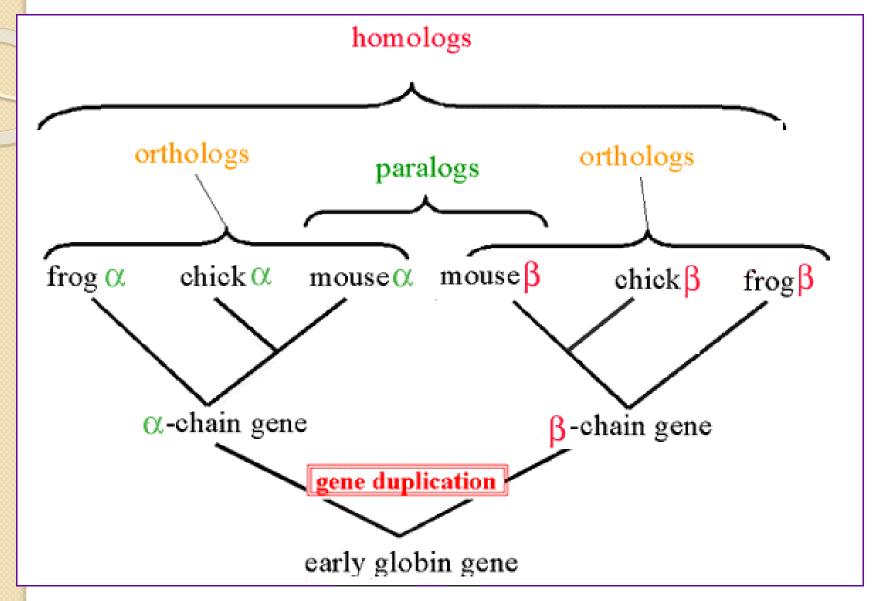
Myoglobin proteins: examples of orthologs



Paralogs: members of a gene (protein) family within a species. This tree shows human globin paralogs.



Orthologs and paralogs are often viewed in a single tree



Source: NCBI

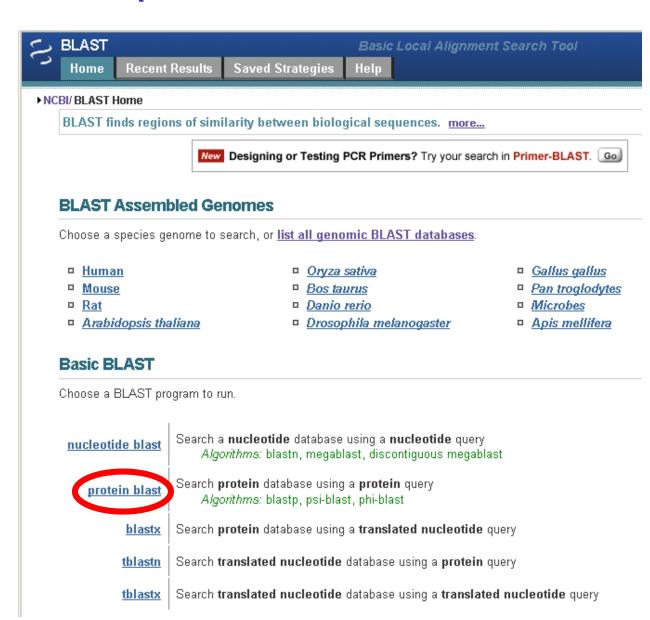
General approach to pairwise alignment

- Choose two sequences
- Select an algorithm that generates a score
- Allow gaps (insertions, deletions)
- Score reflects degree of similarity
- Alignments can be global or local
- Estimate probability that the alignment occurred by chance

Popular Resources

- PubMed
- PubMed Central
- Bookshelf
- BLAST
- бене
- Nucleotide
- Protein
- GEO.
- Conserved Domain

Find BLAST from the home page of NCBI and select protein BLAST...





Choose align two or more sequences...

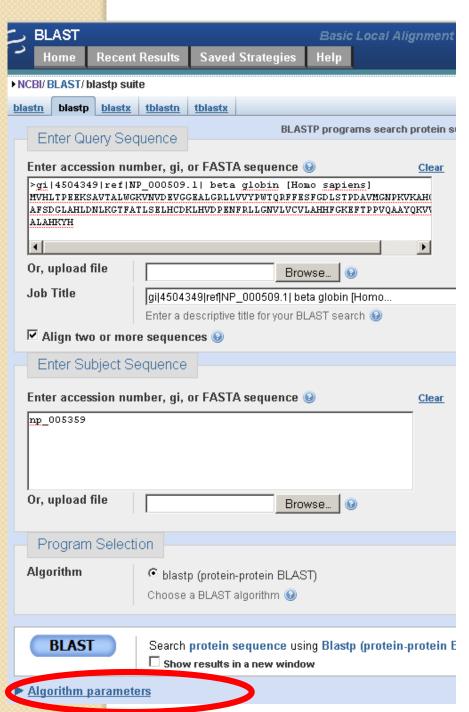
https://www.ncbi.nlm. nih.gov/protein/NP_00 0509.1

hemoglobin subunit beta [Homo sapiens]

And

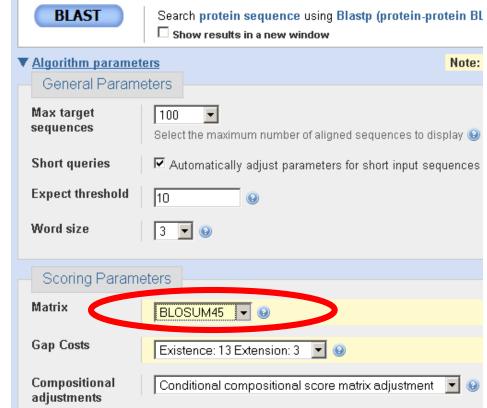
https://www.ncbi.nlm. nih.gov/protein/np_00 5359

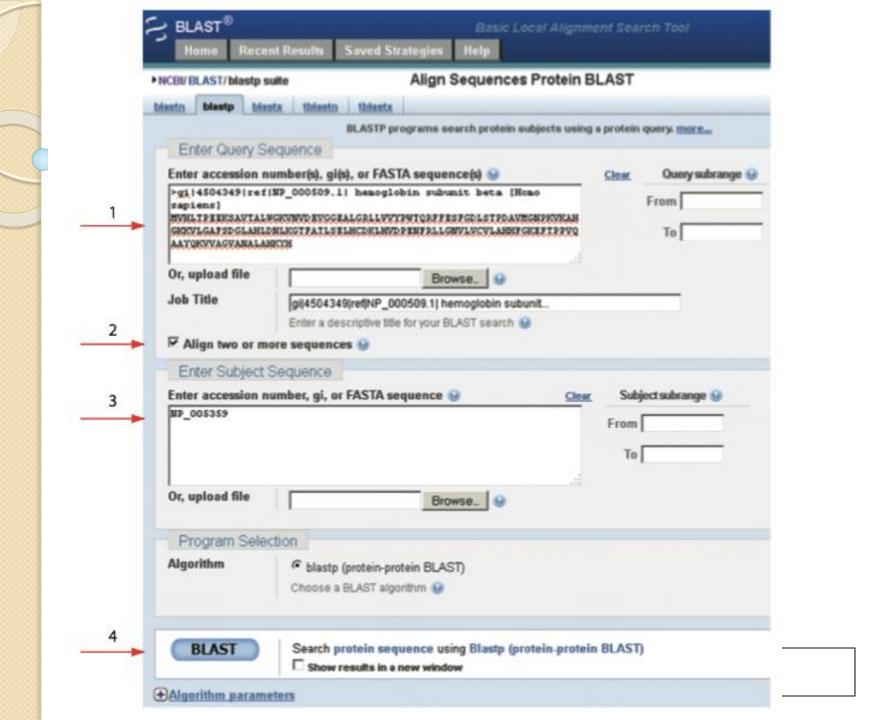
myoglobin [Homo sapiens]



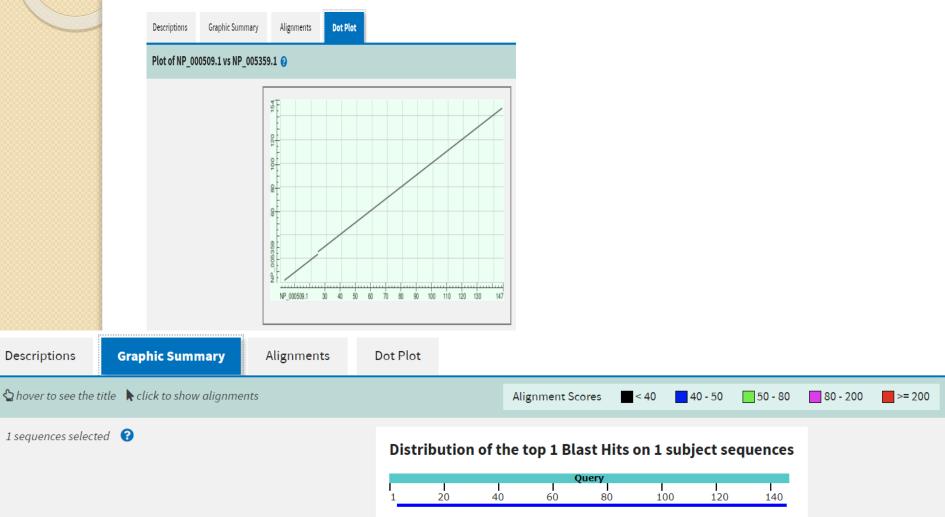
Enter the two sequences (as accession numbers or in the fasta format) and click BLAST.

Optionally select "Algorithm parameters" and note the matrix option.





BLAST output



Pairwise alignment of human beta globin (the "query") and myoglobin (the "subject")

```
Score = 43.9 bits (102), Expect = 1e-09, Method: Composition-based stats.
 Identities = 37/145 (25%), Positives = 57/145 (39%), Gaps = 2/145 (1%)
Query 4 LTPEEKSAVTALWGKVNVD--EVGGEALGRLLVVYPWTQRFFESFGDLSTPDAVMGNPKV
                     +WGKV D
                                GELRL
                                        +P T F+ F L + D +
Sbjct 3 LSDGEWQLVLNVWGKVEADIPGHGQEVLIRLFKGHPETLEKFDKFKHLKSEDEMKASEDL
                                                                    62
           KAHGKKVLGAFSDGLAHLDNLKGTFATLSELHCDKLHVDPENFRLLGNVLVCVLAHHFGK
                                                                    121
Query 62

KHG VLA L + +
                                    L++ H K + +
Sbjct 63
           KKHGATVLTALGGILKKKGHHEAEIKPLAQSHATKHKIPVKYLEFISECIIQVLQSKHPG 122
Query 122 EFTPPVQAAYQKVVAGVANALAHKY
                O A K +
                             +A Y
Sbjct 123 DFGADAQGAMNKALELFRKDMASNY
```

How raw scores are calculated: an example

```
Score = 18.1 bits (35), Expect = 0.015, Method: Composition-based stats.
 Identities = 11/24 (45%), Positives = 12/24 (50%), Gaps = 2/24 (8%)
Query 12 VTALWGKVNVD--EVGGEALGRLL
            +WGKV D
                       GELRL
Sbjct 11 VLNVWGKVEADIPGHGQEVLIRLF
                                 34
match 4 11 5 6 6 5 4 5
                                 sum of matches: +60 (round up to +61)
mismatch -1 1 0 -2 -2 -4 0 sum of mismatches: -13
         -2 0 -3 0
                  -11
                                 sum of gap penalties: -13
gap open
                  -2
gap extend
                                 total raw score: 61 - 13 - 13 = 35
```

For a set of aligned residues we assign scores based on matches, mismatches, gap open penalties, and gap extension penalties. These scores add up to the total raw score.

Second	letter
OCCOLIG	ICILCI

					1
W. C.	U	С	Α	G	
U	UUU } Phe UUA } Leu	UCU UCC UCA UCG	UAU Tyr UAC Stop UAG Stop	UGU Cys UGC Stop UGG Trp	DOAG
С	CUU CUC Leu	CCU CCC CCA CCG	CAU His CAC Gln	CGU CGC CGA CGG	UCAG
A	AUU } Ile AUA } AUG Met	ACU ACC ACA ACG	AAU Asn AAA Lys	AGU Ser AGC AGA Arg	UCAG
	GUU 1	GCU 1	GAU1	GGU1	U

Where do scores come from? We'll examine scoring matrices. These are related to the properties of the 20 common amino acids.

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Gaps

- Positions at which a letter is paired with a null are called gaps.
- Gap scores are typically negative.
- Since a single mutational event may cause the insertion or deletion of more than one residue, the presence of a gap is ascribed more significance than the length of the gap. Thus there are separate penalties for gap creation and gap extension.
- In BLAST, it is rarely necessary to change gap values from the default.

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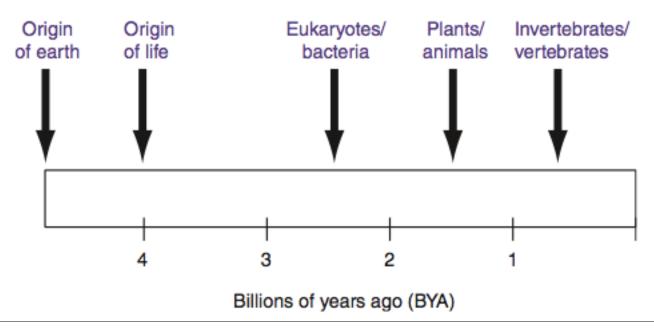
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Pairwise alignment and the evolution of life



When two proteins (or DNA sequences) are homologous they share a common ancestor. We can infer the sequence of that ancestor. When we align globins from human and a plant we can imagine their common ancestor, a single celled organism that lived 1.5 billion years ago, and we can infer that ancient globin sequence. Through pairwise alignment we can look back in time at sequence evolution.

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Step I: Accepted point mutations (PAMs) in protein families

PROTEIN	PAMS PER 100 MILLION YEARS
Immunoglobulin (Ig) kappa chain C region	37
Kappa casein	33
Epidermal growth factor	26
Serum albumin	19
Hemoglobin alpha chain	12
Myoglobin	8.9
Nerve growth factor	8.5
Trypsin	5.9
Insulin	4.4
Cytochrome c	2.2
Glutamate dehydrogenase	0.9
Histone H3	0.14
Histone H4	0.10

Margaret Dayhoff and colleagues developed scoring matrices in the 1960s and 1970s. They defined PAMs as "accepted point mutations." Some protein families evolve very slowly (e.g. histones change little over 100 million years); others (such as kappa casein) change very rapidly.

Protein

PAMs per 100 million years

Ig kappa chain	37
Kappa casein	33
luteinizing hormone b	30
lactalbumin	27
complement component 3	27
epidermal growth factor	26
proopiomelanocortin	21
pancreatic ribonuclease	21
haptoglobin alpha	20
serum albumin	19
phospholipase A2, group IB	19
prolactin	17
carbonic anhydrase C	16
Hemoglobin a	12
Hemoglobin b	12

Protein

PAMs per 100 million years

Ig kappa chain	37
Kappa casein	33
luteinizing hormone b	30
lactalbumin	27
complement component 3	27
epidermal growth factor	26
proopiomelanocortin	21
pancreatic ribonuclease	21
haptoglobin alpha	20
ı <u> </u>	

human (NP_005203) versus mouse (NP_031812) kappa casein

```
Score = 57.8 bits (138), Expect = 3e-07
Identities = 39/118 (33%), Positives = 61/118 (51%), Gaps = 2/118 (1%)

Query 1 MKSFLLVVNALALTLPFLAVEVQNQKQPACHENDERPFYQKTAPYVPMYYVPNSYPYYGT 60
M++F++V+N LALTLPFLA E+QN E ++ + + Y P+ V N + Y

Sbjct 2 MRNFIVVMNILALTLPFLAAEIQNPDSNCRGEKNDIVYDEQRVLYTPVRSVLN-FNQYEP 60

Query 61 NLYQRRPAI-AINNPYVPRTYYANPAVVRPHAQIPQRQYLPNSHPPTVVRLPNLHPSF 117
N Y RP++ A +PY+ ++R A I + Q +PN V +PSF

Sbjct 61 NYYHYRPSLPATASPYMYYPLVVRLLLLRSPAPISKWQSMPNFPQSAGVPYAIPNPSF 118
```

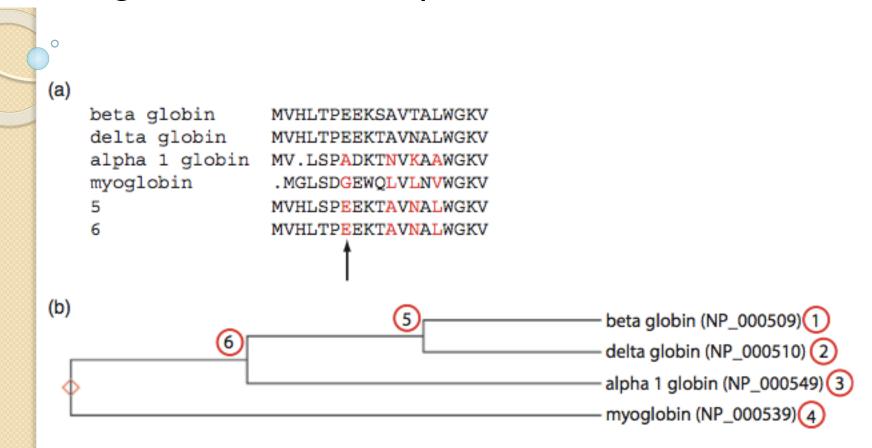
Protein

PAMs per 100 million years

apolipoprotein A-II	10
lysozyme	9.8
gastrin	9.8
myoglobin	8.9
nerve growth factor	8.5
myelin basic protein	7.4
thyroid stimulating hormone b	7.4
parathyroid hormone	7.3
parvalbumin	7.0
trypsin	5.9
insulin	4.4
calcitonin	4.3
arginine vasopressin	3.6
adenylate kinase I	3.2
-	

<u>Protein</u>	PAMs per 100 mi	llion years
triosephosphate isor		2.8
vasoactive intestinal	peptide	2.6
glyceraldehyde phosi	ph. dehydrogease	2.2
cytochrome c	,	2.2
collagen		1.7
troponin C, skeletal	muscle	1.5
alpha crystallin B cha	in	1.5
glucagon		1.2
glutamate dehydroge	enase	0.9
histone H2B, membe		0.9
ubiquitin		0

Step I: accepted point mutations are defined not by the pairwise alignment but with respect to the common ancestor



Dayhoff et al. evaluated amino acid changes. They applied an evolutionary model to compare changes such as 1 versus 2 not to each other but to an inferred common ancestor at position 5.

Dayhoff model step 2 (of 7): Frequency of amino

TABLE 3.1 Normalized frequencies of amino acid. These values sum to 1. If the 20 amino acids were equally represented in proteins, these values would all be 0.05 (i.e., 5%); instead, amino acids vary in their frequency of occurrence.

Gly	0.089	Arg	0.041
Ala	0.087	Asn	0.040
Leu	0.085	Phe	0.040
Lys	0.081	Gln	0.038
Ser	0.070	lle	0.037
Val	0.065	His	0.034
Thr	0.058	Cys	0.033
Pro	0.051	Tyr	0.030
Glu	0.050	Met	0.015
Asp	0.047	Тгр	0.010

If 20 amino acids occurred in nature at equal frequencies, each would be observed 5% of the time. However some are more common (G,A, L, K) and some rare (C,Y,M,W). https://molbiol-tools.ca/Amino acid abbreviations.htm

Normalized frequencies of amino acids:

Gly	8.9%	Arg	4.1%
Ala	8.7%	Asn	4.0%
Leu	8.5%	Phe	4.0%
Lys	8.1%	Gln	3.8%
Ser	7.0%	lle	3.7%
Val	6.5%	His	3.4%
Thr	5.8%	Cys	3.3%
Pro	5.1%	Tyr	3.0%
Glu	5.0%	Met	1.5%
Asp	4.7%	Trp	1.0%

Dayhoff model step 3: amino acid substitutions

	Α	R	N	D	С	Q	Е	G	Н	I	L	K	M	F	P	S	Т	W	Y	V
	Ala	Arg	Asn	Asp	Cys	Gln	Glu	Gly	His	Ile	Leu	Lys	Met	Phe	Pro	Ser	Thr	Trp	Tyr	Val
Α				•	_							•							_	
R	30																			
N	109	17																		
D	154	0	532																	
С	33	10	0	0																
Q	93	120	50	76	0															
E	266	0	94	831	0	422														
G	579	10	156	162	10	30	112													
Н	21	103	226	43	10	243	23	10												
I	66	30	36	13	17	8	35	0	3											
L	95	17	37	0	У	75	15	17	40	253										
K	57	477	322	85	0	147	104	60	23	43	39									
M	29	17	0	0	0	20	7	7	0	57	207	90								
F	20	7	7	0	0	0	0	17	20	90	167	0	17							
P	345	67	27	10	10	93	40	49	50	7	43	43	4	7						
S	772	137	432	98	117	47	86	450	26	20	32	168	20	40	269					
T	590	20	169	57	10	37	31	50	14	129	52	200	28	10	73	696				
W	0	27	3	0	0	0	0	0	3	0	13	0	0	10	0	17	0			
Y	20	3	36	0	30	0	10	0	40	13	23	10	0	260	0	22	23	6		
V	365	20	13	17	33	27	37	97	30	661	303	17	77	10	50	43	186	0	17	
	Α	R	N	D	С	Q	Е	G	Н	I	L	K	M	F	P	S	T	W	Y	V
	Ala	Arg	Asn	Asp	Cys	Gln	Glu	Gly	His	Ile	Leu	Lys	Met	Phe	Pro	Ser	Thr	Trp	Tyr	Val

From a survey of 1572 observed substitutions, the original amino acid (columns) are compared to the changes (rows).

Dayhoff model step 3: amino acid substitutions

	Α	R	N	D	С	Q	E	G
	Ala	Arg	Asn	Asp	Cys	Gln	Glu	Gly
Α								
R	30							
N	109	17						
D	154	0	532					
С	33	10	0	0				
Q	93	120	50	76	0			
Е	266	0	94	831	0	422		
G	579	10	156	162	10	30	112	
Н	21	103	226	43	10	243	23	10

Zooming in on the previous table, note that substitutions are very common (e.g. $D \rightarrow E, A \rightarrow G$) while others are rare (e.g. $C \rightarrow Q, C \rightarrow E$). The scoring system we use for pairwise alignments should reflect these trends.



Dayhoff step 4 (of 7): Mutation probability matrix for the evolutionary distance of I PAM

		Original amino acid																			
		A	R	N	D	С	Q	E	G	H	I	L	K	M	F	P	S	T	W	Y	V
		Ala	Arg	Asn	Asp	Cys	Gln	Glu	Gly	His	lle	Leu	Lys	Met	Phe	Pro	Ser	Thr	Trp	Tyr	Val
	A	98.7	0.0	0.1	0.1	0.0	0.1	0.2	0.2	0.0	0.1	0.0	0.0	0.1	0.0	0.2	0.4	0.3	0.0	0.0	0.2
	R	0.0	99.1	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.2	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0
	N	0.0	0.0	98.2	0.4	0.0	0.0	0.1	0.1	0.2	0.0	0.0	0.1	0.0	0.0	0.0	0.2	0.1	0.0	0.0	0.0
	D	0.1	0.0	0.4	98.6	0.0	0.1	0.5	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0
	С	0.0	0.0	0.0	0.0	99.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0
	Q	0.0	0.1	0.0	0.1	0.0	98.8	0.3	0.0	0.2	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
	E	0.1	0.0	0.1	0.6	0.0	0.4	98.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
acid	G	0.2	0.0	0.1	0.1	0.0	0.0	0.1	99.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.1
amino	H	0.0	0.1	0.2	0.0	0.0	0.2	0.0	0.0	99.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	I	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	98.7	0.1	0.0	0.2	0.1	0.0	0.0	0.1	0.0	0.0	0.3
Had Had	L	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.2	99.5	0.0	0.5	0.1	0.0	0.0	0.0	0.0	0.0	0.2
li de	K	0.0	0.4	0.3	0.1	0.0	0.1	0.1	0.0	0.0	0.0	0.0	99.3	0.2	0.0	0.0	0.1	0.1	0.0	0.0	0.0
Repli	M	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	98.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	F	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	99.5	0.0	0.0	0.0	0.0	0.3	0.0
	P	0.1	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	99.3	0.1	0.0	0.0	0.0	0.0
	S	0.3	0.1	0.3	0.1	0.1	0.0	0.1	0.2	0.0	0.0	0.0	0.1	0.0	0.0	0.2	98.4	0.4	0.1	0.0	0.0
	T	0.2	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.1	0.3	98.7	0.0	0.0	0.1
	W	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.8	0.0	0.0
	Y	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	99.5	0.0
	V	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.1	0.0	0.2	0.0	0.0	0.0	0.1	0.0	0.0	99.0

This mutation probability matrix includes original amino acids (columns) and replacements (rows). The diagonals show that at a distance of I PAM most residues remain the same about 99% of the time (see shaded entries). Note how cysteine (C) and tryptophan (W) undergo few substitutions, and asparagine (N) many.

Substitution Matrix

A substitution matrix contains values proportional to the probability that amino acid *i* mutates into amino acid *j* for all pairs of amino acids.

Substitution matrices are constructed by assembling a large and diverse sample of verified pairwise alignments (or multiple sequence alignments) of amino acids.

Substitution matrices should reflect the true probabilities of mutations occurring through a period of evolution.

The two major types of substitution matrices are PAM and BLOSUM.

PAM matrices: Point-accepted mutations

PAM matrices are based on global alignments of closely related proteins.

The PAMI is the matrix calculated from comparisons of sequences with no more than 1% divergence. At an evolutionary interval of PAMI, one change has occurred over a length of 100 amino acids.

Other PAM matrices are extrapolated from PAM1. For PAM250, 250 changes have occurred for two proteins over a length of 100 amino acids.

All the PAM data come from closely related proteins (>85% amino acid identity).



Dayhoff step 4 (of 7): Mutation probability matrix for the evolutionary distance of I PAM

			A	R	N	D	С	Q	E	G	H
			Ala	Arg	Asn	Asp	Cys	Gln	Glu	Gly	His
		A	98.7	0.0	0.1	0.1	0.0	0.1	0.2	0.2	0.0
		R	0.0	99.1	0.0	0.0	0.0	0.1	0.0	0.0	0.1
		N	0.0	0.0	98.2	0.4	0.0	0.0	0.1	0.1	0.2
		D	0.1	0.0	0.4	98.6	0.0	0.1	0.5	0.1	0.0
		C	0.0	0.0	0.0	0.0	99.7	0.0	0.0	0.0	0.0
		Q	0.0	0.1	0.0	0.1	0.0	98.8	0.3	0.0	0.2
	_	Е	0.1	0.0	0.1	0.6	0.0	0.4	98.7	0.0	0.0
	nino acid	G	0.2	0.0	0.1	0.1	0.0	0.0	0.1	99.4	0.0
	in	Н	0.0	0.1	0.2	0.0	0.0	0.2	0.0	0.0	99.1
- 1											

At this evolutionary distance of I PAM, I% of the amino acids have diverged between each pair of sequences. The columns are percentages that sum to 100%.

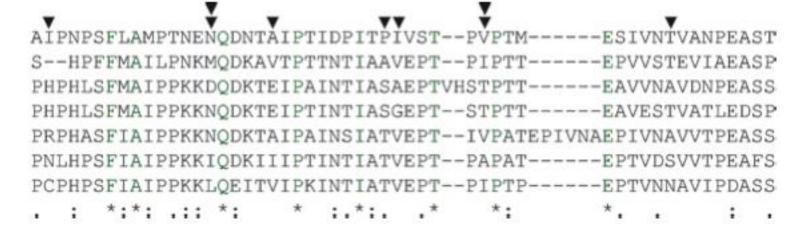
Dayhoff step 5 (of 7): PAM250 and other PAM matrices

164	IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGALQNII	207
164	IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGALQNII	207
162	IHDHFGIVEGLMTTVHAITATQKTVDGPSGKMWRDGRGAAQNII	205
168	IHDNFGIMEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII	211
162	IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII	205
161	INDNFEIVEGLMTTVHATTATQKTVDGPSGKLWRDGRGAAQNII	204
161	INDNFGILEGLMTTVHATTATQKTVDGPSGKLWRDGRGAAQNII	204
170	INDNFGIIEGLMTTVHAVTATQKTVDGPSGKLWRDGRGAGQNII	213
164	INDTFGIEEGLMTTVHATTATQKTVDGPSKKDWRGGRGASANII	207
162	INDAFGIEEGLMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII	205
161	INDEFGIDEALMTTVHSITATQKTVDGPSHKDWRGGRTASGNII	204
166	IHDNFGIIEGLMTTVHAITATQKTVDGPSSKDWRGGRAASFNII	209
	164 162 168 162 162 162 162 161 170 164 162 161	164 IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGALQNII 162 IHDHFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 168 IHDNFGIWEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 162 IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 162 IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 162 IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 162 IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 162 IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 163 IHDNFGIVEGLMTTVHAITATQKTVDGPSGKLWRDGRGAAQNII 164 INDNFGIVEGLMTTVHATTATQKTVDGPSGKLWRDGRGAAQNII 165 INDNFGIVEGLMTTVHATTATQKTVDGPSGKLWRDGRGAAQNII 170 INDNFGIVEGLMTTVHATTATQKTVDGPSGKLWRDGRGAAQNII 170 INDNFGIVEGLMTTVHATTATQKTVDGPSGKLWRDGRGAAQNII 171 INDNFGIVEGLMTTVHATTATQKTVDGPSKKDWRGGRGASANII 172 INDAFGIEEGLMTTVHATTATQKTVDGPSKKDWRGGRGASANII 173 INDAFGIEEGLMTTVHATTATQKTVDGPSKKDWRGGRGASANII 174 INDAFGIEEGLMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII 175 INDAFGIEEGLMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII 176 INDEFGIDEALMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII 177 INDEFGIDEALMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII 178 INDEFGIDEALMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII 179 INDEFGIDEALMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII 170 INDEFGIDEALMTTVHSLTATQKTVDGPSHKDWRGGRTASGNII

Consider a multiple alignment of glyceraldehyde 3phosphate protein sequences. Some substitutions are observed in columns (arrowheads). These give us insight into changes tolerated by natural selection.

Dayhoff step 5 (of 7): PAM250 and other PAM matrices

mouse rabbit sheep cattle pig human horse



Now consider the alignment of distantly related kappa caseins. There are few conserved column positions, and many some columns (double arrowheads) have five different residues among the 7 proteins. We want to design a scoring system that is tolerant of distantly related proteins: if the scoring system is too strict then the divergent sequences may be penalized so heavily that authentic homologs are not identified or aligned.

Dayhoff step 5 (of 7): PAM250 and other PAM matrices

original amino acid

PAM0	Α	R	N	D	С	Q	Е	G
Α	100	0	0	0	0	0	0	0
R	0	100	0	0	0	0	0	0
N	0	0	100	0	0	0	0	0
D	0	0	0	100	0	0	0	0
С	0	0	0	0	100	0	0	0
Q	0	0	0	0	0	100	0	0
E	0	0	0	0	0	0	100	0
G	0	0	0	0	0	0	0	100

original amino acid

PAM∞	Α	R	N	D	С	Q	Е	G
Α	8.7	8.7	8.7	8.7	8.7	8.7	8.7	8.7
R	4.1	4.1	4.1	4.1	4.1	4.1	4.1	4.1
N	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
D	4.7	4.7	4.7	4.7	4.7	4.7	4.7	4.7
С	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3
Q	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8
E	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
G	8.9	8.9	8.9	8.9	8.9	8.9	8.9	8.9

At the extreme of perfectly conserved proteins (PAM0) there are no amino acid replacements. At the extreme of completely diverged proteins (PAM ∞) the matrix converges on the background frequencies of the amino acids.

PAM250 matrix: for proteins that share ~20% identity

			Original amino acid																		
		Α	R	N	D	С	Q	Е	G	H	I	L	K	M	F	P	S	T	W	Y	V
	Α	13	6	9	9	5	8	9	12	6	8	6	7	7	4	11	11	11	2	4	9
	R	3	17	4	3	2	5	3	2	6	3	2	9	4	1	4	4	3	7	2	2
	N	4	4	6	7	2	5	6	4	6	3	2	5	3	2	4	5	4	2	3	3
	D	5	4	8	11	1	7	10	5	6	3	2	5	3	1	4	5	5	1	2	3
	C	2	1	1	1	52	1	1	2	2	2	1	1	1	1	2	3	2	1	4	2
_	Q	3	5	5	6	1	10	7	3	7	2	3	5	3	1	4	3	3	1	2	3
acid	Е	5	4	7	11	1	9	12	5	6	3	2	5	3	1	4	5	5	1	2	3
0 2	G	12	5	10	10	4	7	9	27	5	5	4	6	5	3	8	11	9	2	3	7
amino	Н	2	5	5	4	2	7	4	2	15	2	2	3	2	2	3	3	2	2	3	2
	I	3	2	2	2	2	2	2	2	2	10	6	2	6	5	2	3	4	1	3	9
en	L	6	4	4	3	2	6	4	3	5	15	34	4	20	13	5	4	6	6	7	13
Replacement	K	6	18	10	8	2	10	8	5	8	5	4	24	9	2	6	8	8	4	3	5
lac	M	1	1	1	1	0	1	1	1	1	2	3	2	6	2	1	1	1	1	1	2
Rep	F	2	1	2	1	1	1	1	1	3	5	6	1	4	32	1	2	2	4	20	3
	P	7	5	5	4	3	5	4	5	5	3	3	4	3	2	20	6	5	1	2	4
	S	9	6	8	7	7	6	7	9	6	5	4	7	5	3	9	10	9	4	4	6
	T	8	5	6	6	4	5	5	6	4	6	4	6	5	3	6	8	11	2	3	6
	W	0	2	0	0	0	0	0	0	1	0	1	0	0	1	0	1	0	55	1	0
	Y	1	1	2	1	3	1	1	1	3	2	2	1	2	15	1	2	2	3	31	2
	V	7	4	4	4	4	4	4	5	4	15	10	4	10	5	5	5	7	2	4	17

Compare this to a PAMI matrix, and note the diagonal still has high scores but much information content is lost.

Dayhoff step 6 (of 7): from a mutation probability matrix to a relatedness odds matrix

$$R_{ij} = \frac{M_{ij}}{f_i}$$

A relatedness odds matrix reports the probability that amino acid *j* will change to *i* in a homologous sequence.

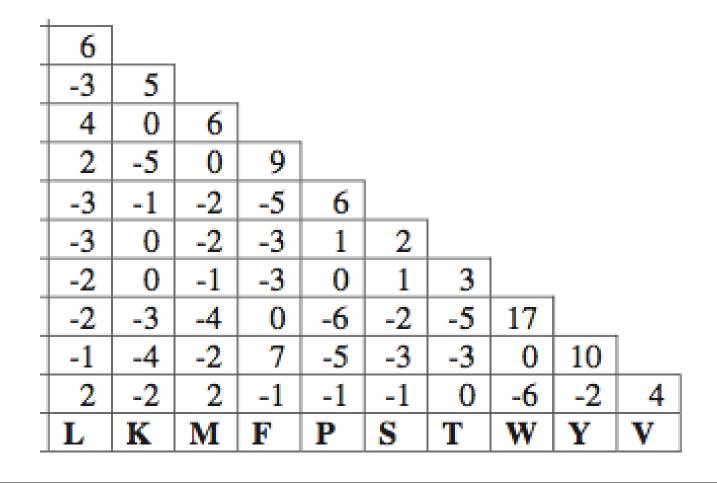
The numerator models the observed change. The denominator *fi* is the probability of amino acid residue *i* occurring in the second sequence by chance.

A positive value indicates a replacement happens more often than expected by chance. A negative value indicates the replacement is not favored.

Why do we go from a mutation probability matrix to a log odds matrix?

- We want a scoring matrix so that when we do a pairwise alignment (or a BLAST search) we know what score to assign to two aligned amino acid residues.
- Logarithms are easier to use for a scoring system. They allow us to sum the scores of aligned residues (rather than having to multiply them).

Log-odds matrix for PAM250



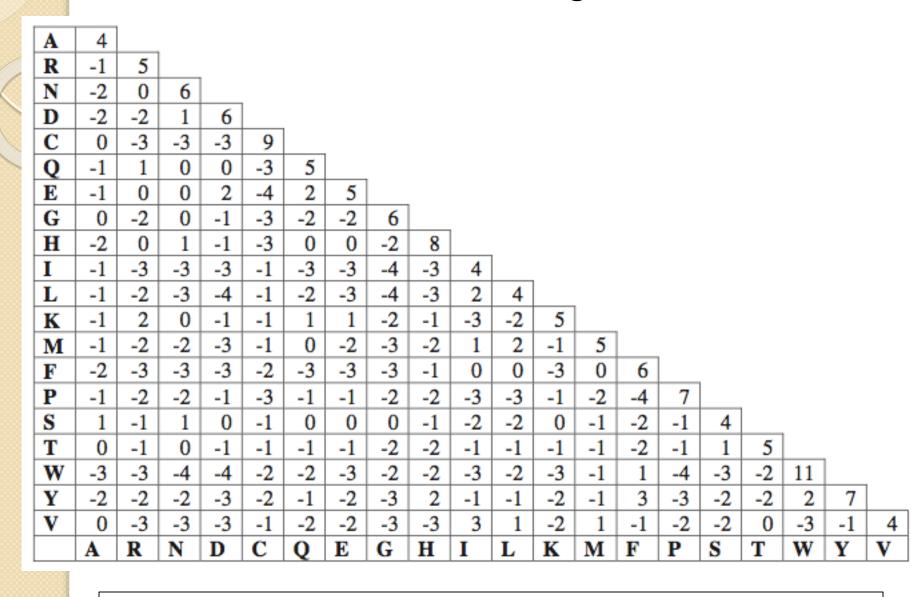
This is a useful matrix for comparing distantly related proteins. Note that an alignment of two tryptophan (W) residues earns +17 and a W to T mismatch is -5.

Log-odds matrix for PAMI0

		1																		
A	7																			
R	-10	9																		
N	-7	-9	9																	
D	-6	-17	-1	8																
C	-10	-11	-17	-21	10]														
Q	-7	-4	-7	-6	-20	9														
E	-5	-15	-5	0	-20	-1	8													
G	-4	-13	-6	-6	-13	-10	-7	7												
H	-11	-4	-2	-7	-10	-2	-9	-13	10											
I	-8	-8	-8	-11	-9	-11	-8	-17	-13	9										
L	-9	-12	-10	-19	-21	-8	-13	-14	- 9	-4	7]								
K	-10	-2	-4	-8	-20	-6	-7	-10	-10	-9	-11	7]							
M	-8	-7	-15	-17	-20	-7	-10	-12	-17	-3	-2	-4	12]						
F	-12	-12	-12	-21	-19	-19	-20	-12	- 9	-5	-5	-20	-7	9						
P	-4	-7	-9	-12	-11	-6	-9	-10	-7	-12	-10	-10	-11	-13	8					
S	-3	-6	-2	-7	-6	-8	-7	-4	- 9	-10	-12	-7	-8	-9	-4	7				
T	-3	-10	-5	-8	-11	-9	-9	-10	-11	-5	-10	-6	-7	-12	-7	-2	8			
W	-2	-5	-11	-21	-22	-19	-23	-21	-10	-20	-9	-18	-19	-7	-20	-8	-19	13		
Y	-11	-14	-7	-17	-7	-18	-11	-20	-6	-9	-10	-12	-17	-1	-20	-10	-9	-8	10	
v	-5	-11	-12	-11	-9	-10	-10	-9	- 9	-1	-5	-13	-4	-12	-9	-10	-6	-22	-10	8
	A	R	N	D	C	Q	E	G	H	I	L	K	М	F	P	S	T	W	Y	v

This is an example of a scoring matrix with "severe" penalties. A match of W to W earns +13, but a mismatch (e.g. W aligned to T) has a score of -19, far lower than in PAM250.

BLOSUM62 scoring matrix



BL62 is the default scoring matrix at the NCBI BLAST site.

BLOSUM Matrices

BLOSUM matrices are based on local alignments.

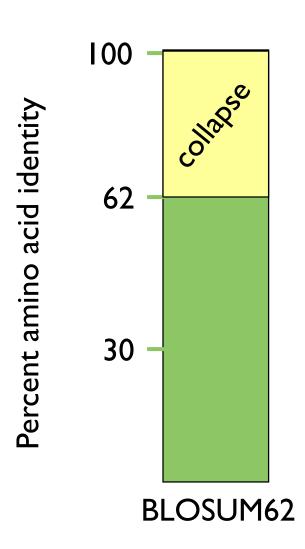
All BLOSUM matrices are based on observed alignments; they are not extrapolated from comparisons of closely related proteins.

BLOSUM stands for blocks substitution matrix.

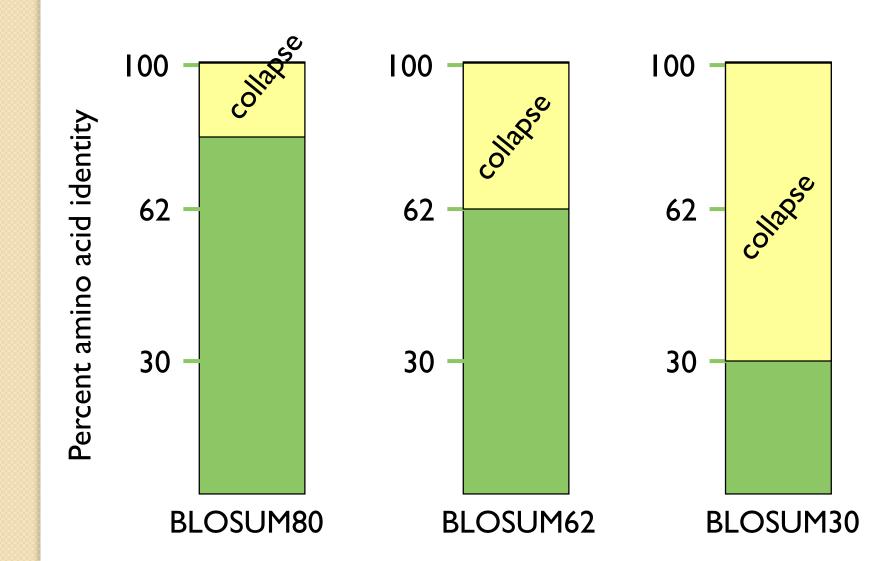
BLOSUM62 is a matrix calculated from comparisons of sequences with no less than 62% divergence.

BLOSUM62 is the default matrix in BLAST 2.0.

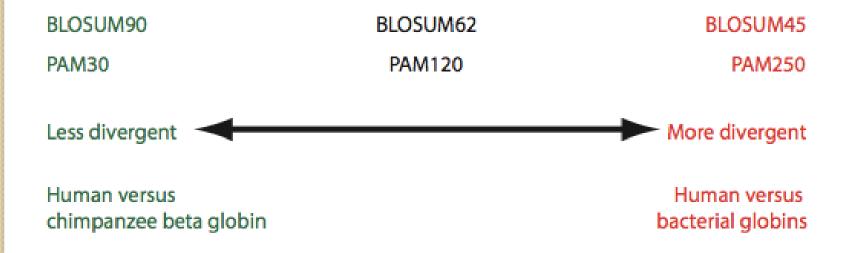
BLOSUM Matrices



BLOSUM Matrices



Summary of PAM and BLOSUM matrices



A higher PAM number, and a lower BLOSUM number, tends to correspond to a matrix tuned to more divergent proteins.

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Introduction

Protein alignment: often more informative than DNA alignment

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Pairwise alignment, homology, and evolution of life

Scoring matrices

Dayhoff model: 7 steps

Pairwise alignment and limits of detection: the "twilight zone"

Alignment algorithms: global and local

Global sequence alignment: algorithm of Needleman and

Wunsch

Local sequence alignment: Smith and Waterman algorithm

Rapid, heuristic versions of Smith-Waterman: FASTA and BLAST

Basic Local Alignment Search Tool (BLAST)

Pairwise alignment with dotplots

The statistical significance of pairwise alignments

Statistical significance of global alignments

Percent identity and relative entropy

Perspective

Two kinds of sequence alignment: global and local

We will first consider the global alignment algorithm of Needleman and Wunsch (1970).

We will then explore the local alignment algorithm of Smith and Waterman (1981).

BLAST, a heuristic version of Smith-Waterman.

Global alignment with the algorithm of Needleman and Wunsch (1970)

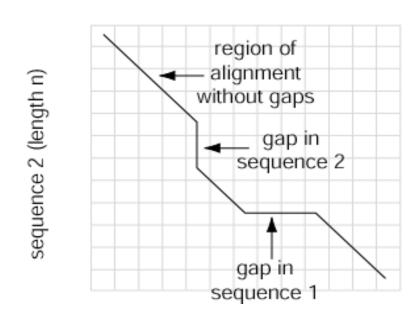
- Two sequences can be compared in a matrix along x- and y-axes.
- If they are identical, a path along a diagonal can be drawn
- Find the optimal subpaths, and add them up to achieve the best score. This involves
 - --adding gaps when needed
 - -- allowing for conservative substitutions
 - --choosing a scoring system (simple or complicated)
- N-W is guaranteed to find optimal alignment(s)

Three steps to global alignment with the Needleman-Wunsch algorithm

- [I] set up a matrix
- [2] score the matrix
- [3] identify the optimal alignment(s)

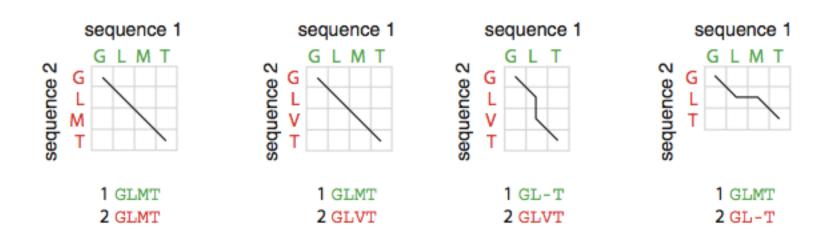
Four possible outcomes in aligning two sequences

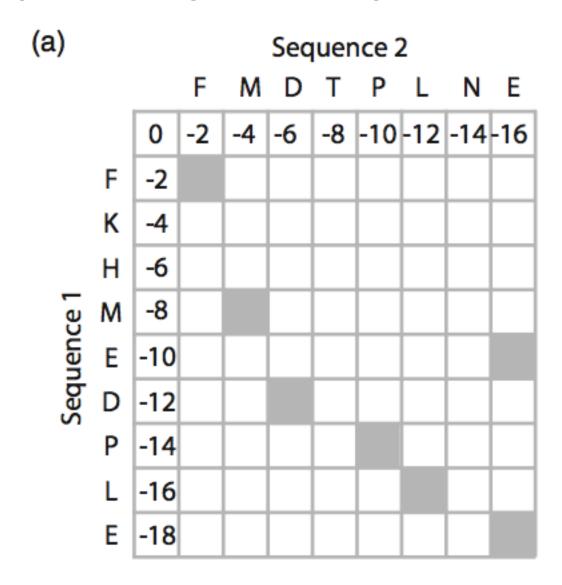
sequence 1 (length m)



- [1] identity (stay along a diagonal)
- [2] mismatch (stay along a diagonal)
- [3] gap in one sequence (move vertically!)
- [4] gap in the other sequence (move horizontally!)

Four possible outcomes in aligning two sequences

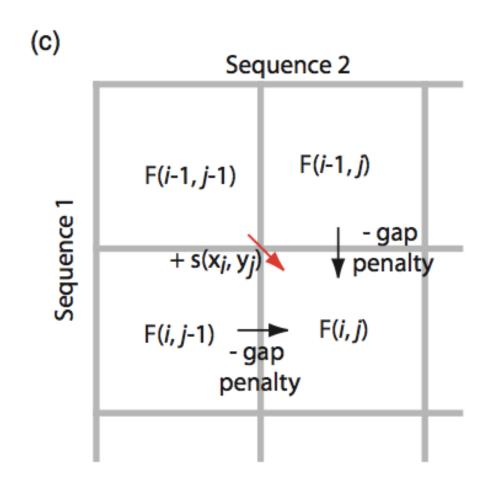




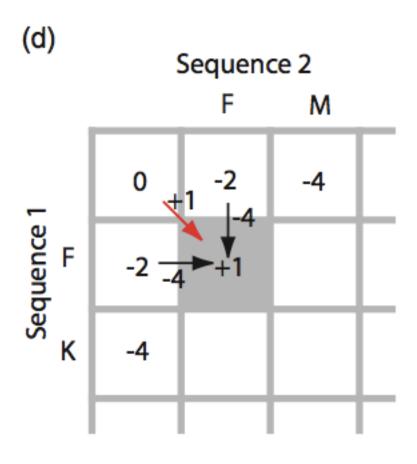
Identify positions of identity (shaded gray).

Score = Max
$$\begin{cases} F(i-1, j-1) + s(x_i, y_i) \\ F(i-1, j) - gap penalty \\ F(i, j-1) - gap penalty \end{cases}$$

Define an overall score that maximizes cumulative scores at each position of the pairwise alignment, allowing for substitutions and gaps in either sequence.

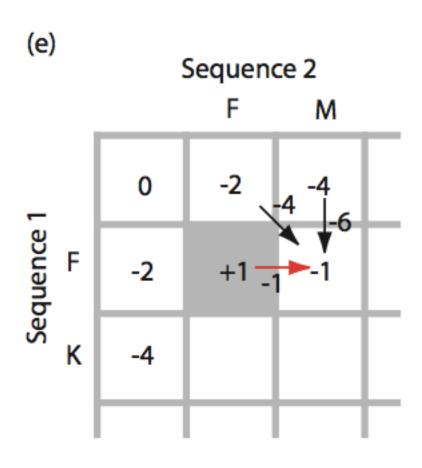


To decide how to align sequences I and 2 in the box at lower right, decide what the scores are beginning at upper left (not requiring a gap), or beginning from the left or top (each requiring a gap penalty).



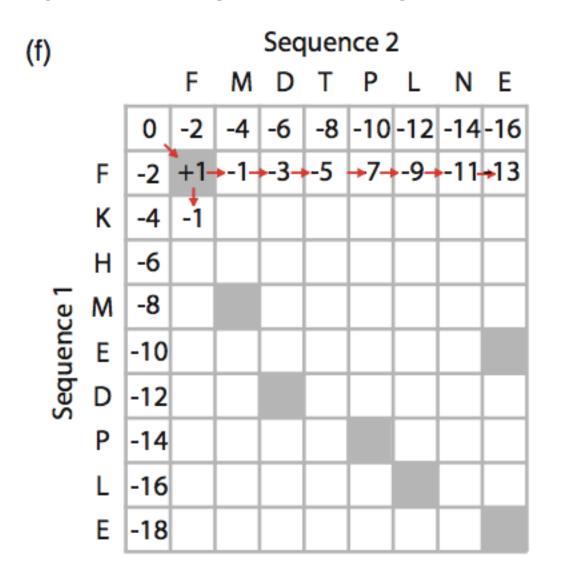
Here the best score involves +1 (proceed from upper left to gray, lower right square). If we instead select an alignment involving a gap the score would be worse (-4).

B&FG 3e Fig. 3-21 Page 98



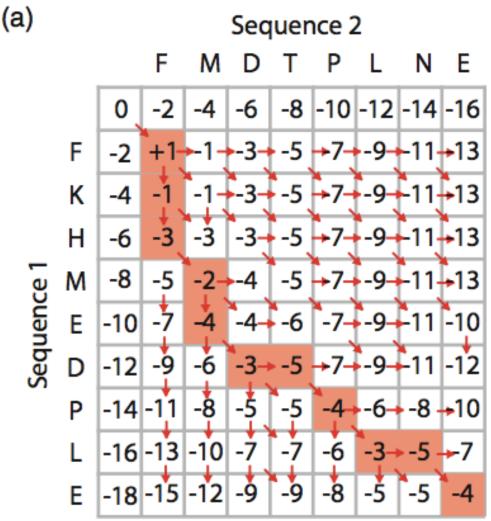
B&FG 3e Fig. 3-21 Page 98

Proceed to calculate the optimal score for the next position.

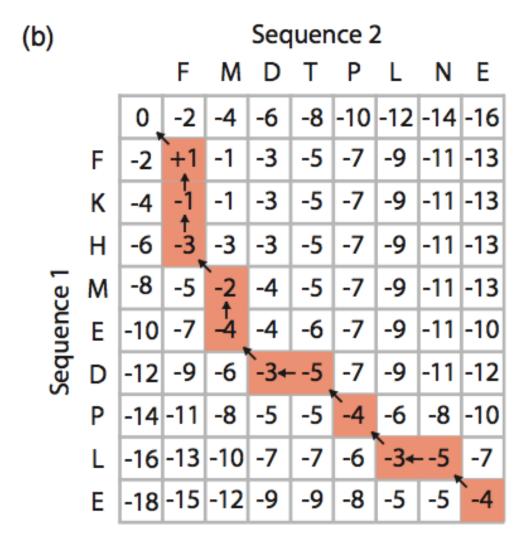


B&FG 3e Fig. 3-21 Page 98

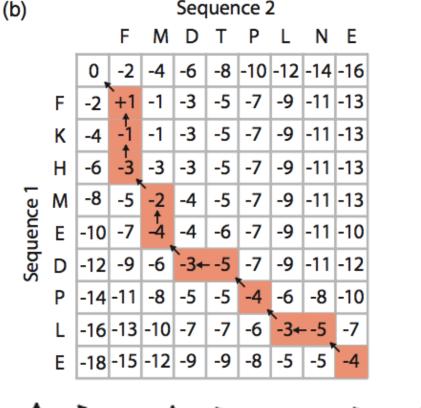
Continue filling in the matrix.

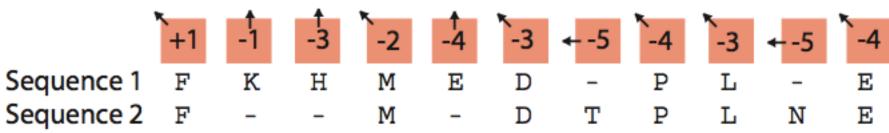


Highlighted cells indicate the optimal path (best scores), indicating how the two sequences should be aligned.



Equivalent representation, showing the traceback procedure: begin at the lower right cell and proceed back to the start.





Equivalent representation, showing the traceback procedure: begin at the lower right cell and proceed back to the start.

Needleman-Wunsch: dynamic programming

N-W is guaranteed to find optimal alignments, although the algorithm does not search all possible alignments.

It is an example of a dynamic programming algorithm: an optimal path (alignment) is identified by incrementally extending optimal subpaths.

Thus, a series of decisions is made at each step of the alignment to find the pair of residues with the best score.

Global alignment versus local alignment

Global alignment (Needleman-Wunsch) extends from one end of each sequence to the other.

Local alignment finds optimally matching regions within two sequences ("subsequences").

Local alignment is almost always used for database searches such as BLAST. It is useful to find domains (or limited regions of homology) within sequences.

Smith and Waterman (1981) solved the problem of performing optimal local sequence alignment. Other methods (BLAST, FASTA) are faster but less thorough.

Global alignment (top) includes matches ignored by local alignment (bottom)

(a)				
NP_824492.	1 1	MCGDMTVHTVEYIRYRIPEQQSAEFLAAYTRAAAQLAAAPQCVDYELARC	50	
NP_337032.	1 1		0	
NP_824492.	1 51	EEDFEHFVLRITWTSTEDHIEGFRKSELFPDFLAEIRPYISSIEEMRHYK	100	
NP_337032.	1 1		0	
NP_824492.	1 101	PTTVRGTGAAVPTLYAWAGGAEAFARLTEVFYEKVLKDDVLAPVFEGMAP :. :. :.	150	
NP_337032.	1 1		43	Global:
NP_824492.	1 151	EHAAHVALWLGEVFGGPAAYSETQGGHGHMVAKHLGKNITEVQRR	195	15% identity
NP_337032.	1 44	EDDLAGAEERLRMFLEQYWGGPRTYSE-QRGHPRLRMRHAPFRISLIERD	92	1070 12011010)
NP_824492.	1 196	RWVNLLQDAADDAGLPT-DAEFRSAFLAYAEWGTRLAVYFSGPDAVPPAE	244	
NP_337032.	1 93	AWLRCMHTAVASIDSETLDDEHRRELLDYLEMAAHSLVNSPF	134	
NP_824492.	1 245	QPVPQWSWGAMPPYQP 260		
NP_337032.	1 135	134		
(b)				
NP_824492.	1 113	TLYAWAGGAEAFARLTEVFYEKVLKDDVLAPVFEGMAPEHAAHVA	157	
NP_337032.	1 10	SFYDAVGGAKTFDAIVSRFYAQVAEDEVLRRVYPEDDLAGAEERLR	55	
NP_824492.	1 158	LWLGEVFGGPAAYSETQGGHGHMVAKHLGKNITEVQRRRWVNLLQDAADD :: .:: : :: :	207	Local:
NP_337032.	1 56	MFLEQYWGGPRTYSE-QRGHPRLRMRHAPFRISLIERDAWLRCMHTAVAS	104	30% identity
NP_824492.	1 208	AGLPT-DAEFRSAFLAYAE 225		
NP_337032.	1 105	IDSETLDDEHRRELLDYLE 123		

B&FG 3e Fig. 3-23 Page 101

NP_824492, NP_337032

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How the Smith-Waterman algorithm works

Set up a matrix between two proteins (size m+I, n+I)

No values in the scoring matrix can be negative! $S \ge 0$

The score in each cell is the maximum of four values:

```
[I] s(i-1, j-1) + the new score at [i,j] (a match or mismatch)
```

[2]
$$s(i,j-1)$$
 – gap penalty

[3]
$$s(i-1,j)$$
 – gap penalty

Where to use the Smith-Waterman algorithm

[1] Galaxy offers "needle" and "water" EMBOSS programs.

[2] EBI offers needle and water. http://www.ebi.ac.uk/Tools/psa/

[3] Try using SSEARCH to perform a rigorous Smith-Waterman local alignment: http://fasta.bioch.virginia.edu/

[4] Next-generation sequence aligners incorporate Smith-Waterman in some specialized steps.

Rapid, heuristic versions of Smith-Waterman: FASTA and BLAST

Smith-Waterman is very rigorous and it is guaranteed to find an optimal alignment.

But Smith-Waterman is slow. It requires computer space and time proportional to the product of the two sequences being aligned (or the product of a query against an entire database).

Gotoh (1982) and Myers and Miller (1988) improved the algorithms so both global and local alignment require less time and space.

FASTA and BLAST provide rapid alternatives to S-W.

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Basic Local Alignment Search Tool (BLAST)

Pairwise alignment with dotplots

The statistical significance of pairwise alignments

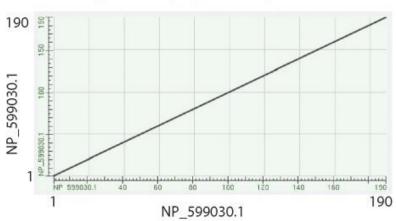
Statistical significance of global alignments

Percent identity and relative entropy

Perspective

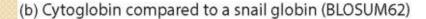
Pairwise alignment with dotplots

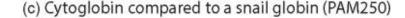




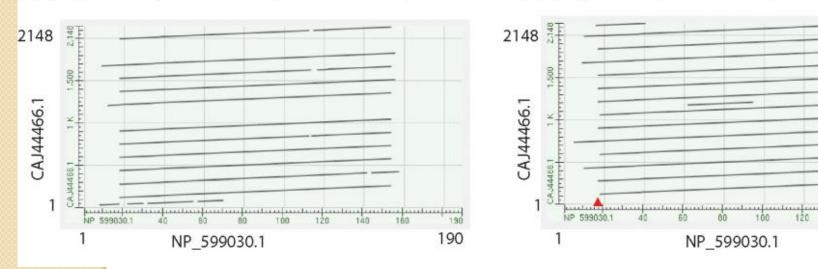
B&FG 3e Fig. 3-25 Page 105 A human globin searched against itself produces a unit diagonal on a dot plot (NCBI BLASTP, aligning 2 sequences).

Pairwise alignment with dotplots





190



Search human cytoglobin against a large snail globin (having many globin repeats). More repeats are observed using PAM250 than BLOSUM62.

To "read" this plot note that cytoglobin (x-axis) matches the snail globin (y-axis) at about a dozen locations across the snail protein. Red arrows indicate that the first few and last few amino acids of cytoglobin do not participate in this repeat structure.

Pairwise alignment with dotplots

haemoglobin type 1 [Biomphalaria glabrata]
Sequence ID: emb[CAJ44466.1] Length: 2148 Number of Matches: 15

Score		Expect	Method		Identities	Positives	Gaps	
55.0 b	its(189)	4e-13	Composition-ba	sed stats.	36/141(26%)	83/141(58%)	4/141(2	2%
Query	18		CAVQAMWARLYANCE				ER 74	
Sbjct	1529		RALDSSWKRLTAGEN				RA 158	В
Query	75		ACRVMGALNTVVENL			VEPVYFKILSGVI V YF LS I	LE 133	
Sbjct	1589		NVIVGGLKSFLDSV		DRVAEAHLSMDPV	VGVPYFSALSONI	HR 164	В
Query	134	VVAEEFAS	SDFPPETQRAWAKL	154				
Sbjct	1649	FIEISLGY	TADSDESQAWIDL	1669				

BLASTP output includes the various sequence alignments. One is shown here: human cytoglobin (residues 18-154) aligns to the snail globin (at residues 1529-1669). The expect value is convincing (4e-13), and this is one of a dozen sequence alignments.

Conclusion: the dotplot is an excellent way to visualize complex repeats.

Outline

Introduction

Protein alignment: often more informative than DNA alignment

Definitions: homology, similarity, identity

Gaps

Pairwise alignment, homology, and evolution of life

Scoring matrices

Dayhoff model: 7 steps

Pairwise alignment and limits of detection: the "twilight zone"

Alignment algorithms: global and local

Global sequence alignment: algorithm of Needleman and

Wunsch

Local sequence alignment: Smith and Waterman algorithm

Rapid, heuristic versions of Smith-Waterman: FASTA and BLAST

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Pairwise alignment with dotplots

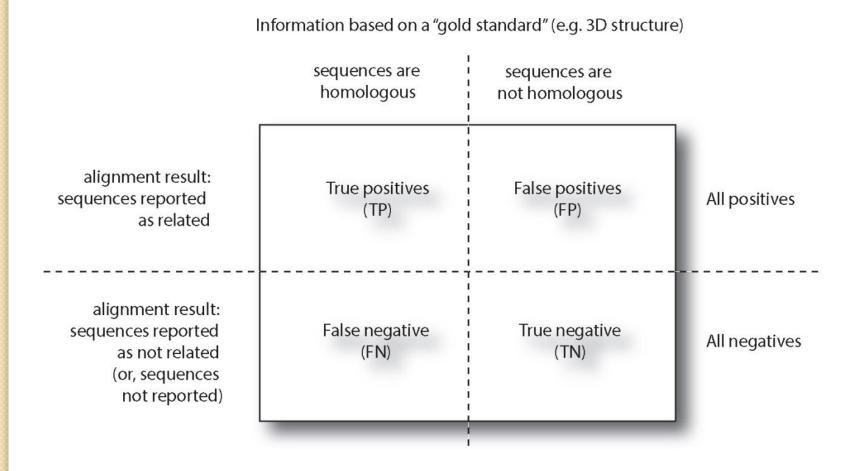
The statistical significance of pairwise alignments

Statistical significance of global alignments

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Statistical significance of pairwise alignments



Statistical significance of pairwise alignments

The statistical significance of global alignments is not well described. We can apply a z-score.

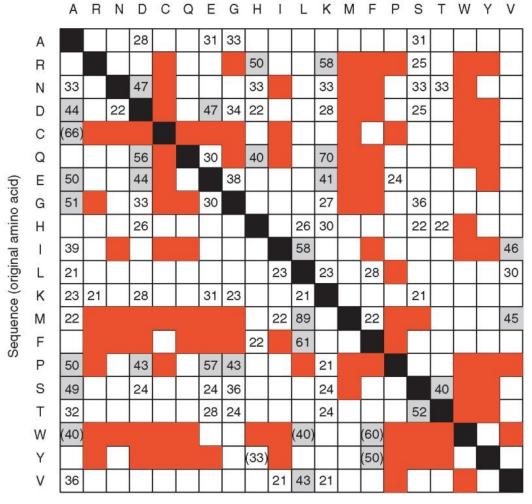
$$Z = \frac{x - \mu}{s}$$

For local alignment the statistical significance is thoroughly understood.

Perspective

Pairwise alignment is a fundamental problem in bioinformatics. We discussed concepts of homology, and global versus local alignment (e.g. Needleman-Wunsch versus Smith-Waterman algorithms).

Substituent residue
(Percentage of total residue sites at which the substituent occurs)



We end with a remarkable scoring matrix reported by Zuckerkandl and Pauling in 1965, soon after the very first protein sequences were identified. While the data set was very sparse, these authors already found patterns of amino acid substitutions that occur in nature.