PSI-BLAST

Fishing in the (sequence) twilight zone

Introduction to Bioinformatics, Faroe Islands 2024 Bent Petersen

(With some borrowed concepts / slides from Morten Nielsen, Rasmus Wernersson / Henrik Nielsen and Anders Gorm Pedersen)

THE PROBLEM WITH PAIRWISE ALIGNMENTS

Part 1

Reminder: how BLAST works

Use pairwise alignments to search databases for similar sequences

Database

BLASTP output

(Example from the BLAST exercise: At the protein level it was quite evident, that the unknown sequence was a serine peptidase)

BLASTP alignment

(Example from the BLAST exercise: At the protein level it was quite evident, that the unknown sequence was a serine peptidase)

Not all positions are biological equal

>ref|WP_006953704.1| **peptidase** [Prevotella micans] Conserved region:

Is likely important for the function of the enzyme

Identities = 117/211 (55%), Positives = 145/211 (69%), Gaps = 14/211 (7%)

Variable region: Is likely not that important for the function of the enzyme

Scoring of pairwise alignments

- In a normal pairwise alignment the same scores (the same matrix) is used for all positions
- As we saw before the selection pressure on the different parts of the sequence is not equal, and ideally we should take this into account
- IMPORTANT: if the sequences is of high enough similarity, this is usually not a big issue

Reminder: Dot-plot

- 1. Place two sequences along axes of plot
- 2. Place dot at grid points where two sequences have identical residues
- 3. Diagonals correspond to conserved regions

Dot-plot with BLOSUM colors

1PLC._ (Plastocyanin)

IPLC._(Plastocyanin)

Relationship can be detected using BLASTP

Dot-plot with BLOSUM colors

Relationship can be detected using BLASTP

Color dot-plot of low-similarity sequences

1PLC._ (Plastocyanin

 \subset

Relationship CANNOT be detected using BLASTP

THOUGHTS ABOUT HOW TO SOLVE THE PROBLEM

Part 2

Idea catalog

- We would like to build a **scoring model** for pairwise alignments that more closely resembles what happens in **real sequence evolution**
	- Highly conserved sites/regions should have a high weight
	- Non-conserved regions should have a low weight (be allowed to vary without counting too much against the alignment score)
- IMPORTANT: Different protein families are under different selection pressure, so our model needs to account for this

Protein families

- Tools we can use, to identify the selective pressure on protein families:
	- Data sets of truly related proteins
	- Multiple alignment
	- Logo plots
	- Weight matrices

Protein family data sets

- How we can build such data sets:
	- Already known collections (literature, curated data sets)
		- Limitation: What have other people looked at before
	- "Text based" search in protein data bases (e.g. UniProt)
		- Limitation: Coverage, how well are the sequences described
	- BlastP (!)
		- Limitation: We only expect to find sequences of moderate to high similarity

Signal across multiple sequences

LOGO example

Small section of a LOGO from 1500 aligned bacterial serine proteases

Going back to pairwise alignments

Alignment: Bacterial serine peptidase ("Savinase") vs. human PCSK9

Going back to pairwise alignments

Goal: combine observations from large data set (1500 sequences) into the scoring scheme for the pairwise alignment

Naïve approach

- A naïve approach that would actually work:
	- When calculating the alignment score, look at how much information is in the LOGO plot (from the large data set) at the corresponding position.
	- Then scale the score from the BLOSUM62 matrix according to this.
	- That would mean that highly conserved regions would count more and variable regions would count less in the alignment score.

But we can actually do better

- Some things the naïve approach do not cover:
	- From the LOGO plot, a clear preference for certain amino acids at certain positions is seen.
	- We would like to build this into the model.

Weight matrices to the rescue

- Weight matrices:
	- Built from large data sets of aligned sequences.
	- Is essentially log2(observed/expected) AA frequencies (the pseudo-frequencies is a trick to cope with small data sets).
	- A score for how well new sequences match the pattern in the matrix can easily be calculated.

How to construct a WM

• A weight matrix is given as

 $W_{ij} = log_2(p_{ij}/q_j)$

Notice the LOG transform

- where i is a position in the motif, and j an amino acid. q_i is the background frequency for amino acid j.
- $-$ if $p_{ij} = 0$, we cannot apply the logarithm, so we have to add pseudocounts.

- W is a L x 20 matrix, L is motif length
- Wij > 0, Amino acid is seen **more** often than expected from random
- Wij < 0, Amino acid is seen **less** often than expected from random

Scoring a sequence

• Score sequences to weight matrix by looking up and adding L values from the matrix

A R N D C Q E G H I L K M F P S T W Y V 1 0.6 0.4 -3.5 -2.4 -0.4 -1.9 -2.7 0.3 -1.1 1.0 0.3 0.0 1.4 1.2 -2.7 1.4 -1.2 -2.0 1.1 0.7 2 -6.5 -5.4 -2.5 -4.0 -4.7 -3.7 -6.3 1.0 $\left(5.3 \right)$ -3.7 3.1 -4.2 -4.3 -4.2 -0.2 -5.9 -3.8 **3** 0.2 -1.3 0.1 **1.5** 0.0 -1.8 -3.3 0.4 0.5 -1.0 **0.3** -2.5 1.2 1.0 -0.1 -0.3 -0.5 3.4 1.6 0.0 **0.1** -0.1 -0.1 -2.0 **2.0** -1.6 0.5 0.8 2.0 -3.3 0.1 **1.4** -1.0 -2.2 -1.6 1.7 -0.6 -0.2 1.3 -6.8 -0.7 **4** -0.1 -0.1 -2.0 $(2-0.1 - 1.6 0.5 0.8 2.0 - 3.3 0.1 1.7 - 1.0 - 2.2 - 1.6)$ **5 -1.6 -0.1 0.1 -2.2 -1.2 0.4 -0.5 1.9 1.2 -2.2 -0.5 -1.3 -2.2 1.7 1.2 -2.5 -0.1 1.7 1.5 1.0 6** -0.7 -1.4 -1.0 \rightarrow -1.1 -1.3 -1.4 -0.2 -1.0 1.8 0.8 -1.9 0.2 1.0 -0.4 -0.6 0.4 -0.5 **7 1.1 -3.8 -0.2 -1.3 1.3 -0.3 -1.3 -1.4 2.1 0.6 0.7 -5.0 1.1 0.9 1.3 -0.5 -0.9 2.9 -0.4 0.5 8 -2.2 1.0 -0.8 -2.9 -1.4 0.4 0.1** -0.4 0.2 -0.0 1.1 -0.5 -0.5 0.7 -0.5 0.8 0.8 -0.7 1.3 **9 -0.2 -3.5 -6.1 -4.5 0.7 -0.8 -2.5 -4.0 -2.6 0.9 2.8 -3.0 -1.8 -1.4 -6.2 -1.9 -1.6 -4.9 -1.6 4.5**

RLLDDTPEV GLLGNVSTV ALAKAAAAL 11.9 Which peptide is most likely to bind? Which peptide second?

Scoring a sequence

• Score sequences to weight matrix by looking up and adding L values from the matrix

A R N D C Q E G H I L K M F P S T W Y V 1 0.6 0.4 -3.5 -2.4 -0.4 -1.9 -2.7 0.3 -1.1 1.0 0.3 0.0 1.4 1.2 -2.7 1.4 -1.2 -2.0 1.1 0.7 2 -1.6 -6.6 -6.5 -5.4 -2.5 -4.0 -4.7 -3.7 -6.3 1.0 5.1 -3.7 3.1 -4.2 -4.3 -4.2 -0.2 -5.9 -3.8 0.4 3 0.2 -1.3 0.1 1.5 0.0 -1.8 -3.3 0.4 0.5 -1.0 0.3 -2.5 1.2 1.0 -0.1 -0.3 -0.5 3.4 1.6 0.0 4 -0.1 -0.1 -2.0 2.0 -1.6 0.5 0.8 2.0 -3.3 0.1 -1.7 -1.0 -2.2 -1.6 1.7 -0.6 -0.2 1.3 -6.8 -0.7 5 -1.6 -0.1 0.1 -2.2 -1.2 0.4 -0.5 1.9 1.2 -2.2 -0.5 -1.3 -2.2 1.7 1.2 -2.5 -0.1 1.7 1.5 1.0 6 -0.7 -1.4 -1.0 -2.3 1.1 -1.3 -1.4 -0.2 -1.0 1.8 0.8 -1.9 0.2 1.0 -0.4 -0.6 0.4 -0.5 -0.0 2.1 7 1.1 -3.8 -0.2 -1.3 1.3 -0.3 -1.3 -1.4 2.1 0.6 0.7 -5.0 1.1 0.9 1.3 -0.5 -0.9 2.9 -0.4 0.5 8 -2.2 1.0 -0.8 -2.9 -1.4 0.4 0.1 -0.4 0.2 -0.0 1.1 -0.5 -0.5 0.7 -0.3 0.8 0.8 -0.7 1.3 -1.1 9 -0.2 -3.5 -6.1 -4.5 0.7 -0.8 -2.5 -4.0 -2.6 0.9 2.8 -3.0 -1.8 -1.4 -6.2 -1.9 -1.6 -4.9 -1.6 4.5

Which peptide is most likely to bind? Which peptide second? **14.7**

Where have we seen this before?

Estimation of the BLOSUM 62 matrix

- Use the BLOCKS database (ungapped alignments of especially conserved regions of multiple alignments)
- For each alignment in the BLOCKS database the sequences are grouped into clusters with at least 62% identical residues (for BLOSUM 62)
- All pairs of sequences are compared *between* clusters, and the **observed pair frequencies** are noted

BLOSUM score = log2(observed pair freq/expected pair freq)

IMPORTANT: This means that BLOSUM is **not** position specific – it is a kind of an averaged across all alignment positions.

Idea: merge BLOSUM and WMs

- Pairwise alignment:
	- Alignment score = sum(BLOSUM(for each AA pair))
	- $-$ + penalty for gaps
	- IMPORTANT: 2 sequences
- Weight matrix:
	- WM score = sum(WM_score(for each AA, for each position))
	- IMPORTANT: single sequence

Idea: merge BLOSUM and WMs

- "New BLOSUM":
	- Use protein family data set to estimate AA pair frequencies **per position**.
	- We need to apply the **pseudo-count** approach to account for AAs we do not observe.

Idea: merge BLOSUM and WMs

- "New alignment":
	- Look up alignment score per position
	- Sum up score + penalize for gaps the usual way

HOW PSI-BLAST ACTUALLY WORKS

Part 3

PSI-BLAST

- **P**osition-**S**pecific **I**terative BLAST
- Start with one sequence (as with BLASTP)
- Build protein family model on the fly:

- Ø **Step 0:** Start with an alignment model build purely on BLOSUM 62*
	- **Step 1: Find set of related sequences**
	- Ø **Step 2:** Build refined **position specific** alignment model based on the identified related

sequences

Ø **Step 3:** Re-**iterate** step 1-2 until model does not improve anymore (in practice 3-4 iterations)

PSSM

- PSSM (pronounced "**P**o**SS**o**M**"):
	- **P**osition-**S**pecific **S**coring **M**atrix
- Start by creating a n^{*}20 matrix $-$ n = length of input sequence
- For each AA in the input sequence look up the corresponding row in the BLOSUM62 matrix and copy in the values

PSSM visualization

- Trick:
	- The PSSM can be visualized as a LOGO plot
	- Here's what it can look like initially (after the trivial seeding with BLOSUM62):

PSSM adjusted after each iteration

Seed: Savinase (p29600) – database: NR

After iteration 2

PSSM adjusted after each iteration

Seed: Savinase (p29600) – database: NR

After iteration 3

PSSM adjusted after each iteration

Seed: Savinase (p29600) – database: NR

After iteration 4

ENTERFO 0 G SEQU **NA** SIS CBS

Example (SGNH active site)

Saving a PSSM for later use

- Very important:
	- The PSSM you have arrived at after all your iterations can be saved for later use
- Uses:
	- **Scenario 1:** Visualize your PSSM to assess the patterns picked up.
	- **Scenario 2:** Run your search again (perhaps ½ year later) without having to go through all the iterations.
	- **Scenario 3:** Search **a different database** using your PSSM
		- For example: train a rock solid PSSM for detecting prokaryotic serine peptidases on the big "NR" database, then save it and use it to hunt for human/mouse remote homologs.
		- You'll HAVE TO do it this way, as it's highly unlikely to find sufficiently good homologs to build the model in the restricted data set.

PSI-BLAST summary

- Is much better at finding remote homologs compared to BLASTP
	- If used correctly!
	- Remember to build your PSSM on the best possible data set, and potentially re-apply it in the actual data set you want to search
- Great for building data sets of related sequences
	- In the NCBI interface you can save all found sequences as a single pre-aligned multi FASTA file