# Protein Threading Algorithms Used in Protein Structure Prediction 

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## Outline

Background

Introduction

Sequence Profile-Profile Alignment(PPAs)

Profile-Hidden Markov Models(HMMs)

Summary

## Background

Amino Acids

- Amino acids, also called residues.
- 20 different amino acids
- Unique single letter
- Primary Structure, linear combination of amino acids
- Secondary Structure, natural folds
- Tertiary Structure, 3-D structure


## Background

Protein Structure


Figure: Protein Structure

## Introduction

- Why predicting protein structure?
- Basic Strategy
- Template-Based Modeling


## Introduction

Why predicting protein structure?

- One important topic
- Functionality is closely related to structures
- Discovering novel drugs for diseases


## Introduction

## Basic Strategy

- Unknown protein's primary structure (target)
- Currently known protein structures (templates).
- Constructing target's structure based on templates' structures


## Introduction

## Basic Strategy

- Protein Data Bank (PDB):
- Templates
- Coordinate Files
- Atoms in each protein, and their 3D location in space
- Modeling Method
- Template-Based Modeling
- Free Modeling


## Introduction

Template-Based Modeling


Figure: Protein Threading

## Introduction

Template-Based Modeling

- Aligned Regions
- Unaligned Regions


## Sequence Profile-Profile Alignment(PPAs)

- Sequence
- Pairwise Sequence Alignment
- Multiple Sequence Alignment and Profile
- PPA Program
- Improvement


## Sequence Profile-Profile Alignment(PPAs)

Sequence

Sequence 1: L E V K Sequence 2: LDIR Sequence 3: L E I K Sequence 4: L D V E

L --- Leucine
E --- Glutamic Acid
D --- Aspartic Acid
V --- Valine
| --- Isoleucine
K --- Lysine
R --- Arginine

## Sequence Profile-Profile Alignment(PPAs)

Pairwise Sequence Alignment

- There are many ways to align two protein sequences, and for each amino acid pair, we can find either a match (blue), a mismatch (red) or an insertion or deletion ("-" represents a gap)


Sequence 1: L E V - K
Sequence 2: L D - I K

Figure: Pairwise Sequence Alignment

## Sequence Profile-Profile Alignment(PPAs)

Pairwise Sequence Alignment

- If we adopt a scoring method for each possible alignment, the best alignment is therefore the one with the highest score.

```
                                    Match +2
                                    Mismatch 0
                                    Gap -1
Index: 0 1 2 3 4
Sequence 1: L E V - K
Sequence 2: L D - I K
        +2+0-1-1 +2 =2
```

Figure: Pairwise Sequence Alignment

## Sequence Profile-Profile Alignment(PPAs)

Multiple Sequence Alignment

- A profile is a 20 by $L$ table of frequencies for a multiple sequence alignment with length $L$. Each entry $p_{i, j}$ represents the probability of amino acid type $i$ occur in the $j$ th column.
- Profile is a better representation for multiple sequence alignment.


## Sequence Profile-Profile Alignment(PPAs)

Profile

L --- Leucine<br>E --- Glutamic Acid<br>D --- Aspartic Acid<br>V --- Valine<br>I --- Isoleucine<br>K --- Lysine<br>Sequence 1: L E V K Sequence 2: L D I R Sequence 3: LEIK Sequence 4 : L D V E

Figure: Protein Sequence Examples

## Sequence Profile-Profile Alignment(PPAs)

Profile

|  | Index 0 | Index 1 | Index 2 | Index 3 |
| :---: | :---: | :---: | :---: | :---: |
| D | - | 0.5 | - | - |
| E | - | 0.5 | - | 0.25 |
| L | 1 | - | - | - |
| I | - | - | 0.5 | - |
| V | - | - | 0.5 | - |
| R | - | - | - | 0.25 |
| K | - | - | - | 0.5 |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |

## Sequence Profile-Profile Alignment(PPAs)

PPA program

- I-TASSER
- PPA program reduces multiple sequence alignments to pairwise alignment between profiles


## Sequence Profile-Profile Alignment(PPAs)

PPA program

- Use target sequence as input, and search through PDB using PSI-BLAST
>NP_002583.1 proliferating cell nuclear antigen [Homo sapiens] MFEARLVQGSILKKVLEALKDLINEACWDISSSGVNLQSMDSSHVSLVQL TLRSEGFDTYRCDRNLAMGVNLTSMSKILKCAGNEDIITLRAEDNADTLA LVFEAPNQEKVSDYEMKLMDLDVEQLGIPEQEYSCVVKMPSGEFARICRD LSHIGDAVVISCAKDGVKFSASGELGNGNIKLSQTSNVDKEEEAVTIEMN EPVQLTFALRYLNFFTKATPLSSTVTLSMSADVPLVVEYKIADMGHLKYYLA PKIEDEEGS


## Sequence Profile-Profile Alignment(PPAs)

PPA program


## Sequence Profile-Profile Alignment(PPAs)

PPA program

- Construct target profiles
- Align target profiles against all pre-calculated profiles in database, where each profile represents a specific set of protein families


## Sequence Profile-Profile Alignment(PPAs)

## PPA program Scoring function

- Use dynamic programming to find the overall best alignment



## Sequence Profile-Profile Alignment(PPAs)

New Improvement in I-TASSER Suite

- Added structural environment fitness score, $E\left(j, A A_{q}(i)\right)$
- torsion angle
- solvent accessibility
- secondary structure

$$
S_{\mathrm{Env}-\mathrm{PPA}}(i, j)=S(i, j)+c_{2} E\left(j, A A_{q}(i)\right)
$$

## Profile-Hidden Markov Models(HMMs)

- Structures
- Coin Toss Example
- Profile-HMM
- Pairwise Profile-HMM Alignment
- Scoring function
- Improvements


## Profile-Hidden Markov Models(HMMs)

Structures

- Two layers structure:
- Visible layer
- Invisible layer
- Markov chain


## Profile-Hidden Markov Models(HMMs)

## Coin Toss Example

- Given two coins that has different probability of heads and tails:

|  | Coin A | Coin B |
| :---: | :---: | :---: |
| Head (H) | 0.5 | 0.3 |
| Tail (T) | 0.5 | 0.7 |

- Suppose we are given an observation sequence of HHTHTH
- Without knowing which coin was used for each toss
- What would the best explanation for an observations of such sequence?


## Profile-Hidden Markov Models(HMMs)

Coin Toss Example

- Transition probabilities are given as below:

|  | Coin A | Coin B |
| :---: | :---: | :---: |
| Coin A | 0.9 | 0.2 |
| Coin B | 0.1 | 0.8 |



Figure: Hidden Markov Model for Coin Toss Example

## Profile-Hidden Markov Models(HMMs)

Coin Toss Example


- If the coin sequence is $A A B A A B$
- The probability for observations HHTHTH is:

$$
\begin{aligned}
P & =\mathbf{0 . 5} * 0.9 * \mathbf{0 . 5} * 0.1 * \mathbf{0 . 7} * 0.2 * \mathbf{0 . 5} * 0.9 * \mathbf{0 . 5} * 0.1 * \mathbf{0 . 3} \\
& =2.12625 * 10^{-5}
\end{aligned}
$$

## Profile-Hidden Markov Models(HMMs)

## Profile-HMM

- HHpred


Figure: Example of a Profile-Hidden Markov Model

## Profile-Hidden Markov Models(HMMs)

Profile

|  | Index 0 | Index 1 | Index 2 | Index 3 |
| :---: | :---: | :---: | :---: | :---: |
| D | - | 0.4 | - | - |
| E | - | 0.4 | - | 0.2 |
| L | 0.8 | - | - | - |
| I | - | - | 0.4 | - |
| V | - | - | 0.4 | - |
| R | - | - | - | 0.2 |
| K | - | - | - | 0.4 |
| Insert | 0.1 | 0.1 | 0.1 | 0.1 |
| Delete | 0.1 | 0.1 | 0.1 | 0.1 |

## Profile-Hidden Markov Models(HMMs)

## Profile-HMM



## Profile-Hidden Markov Models(HMMs)

Pairwise Profile-HMM Alignment

- Example of a pairwise profile-HMM alignment:



## Profile-Hidden Markov Models(HMMs)

Profile-HMMs Scoring Function

- Five possible pair states can co-emit amino acids or gaps: MM, MI, IM, DG and GD
- Log-sum-of-odds Score:

$$
S_{L S O}=\log \sum_{x_{1}, \ldots, x_{L}} \frac{P\left(x_{1}, \ldots, x_{L} \mid \text { co-emission on path }\right)}{P\left(x_{1}, \ldots, x_{L} \mid \text { Null }\right)}
$$

## Profile-Hidden Markov Models(HMMs)

Profile-HMMs Scoring Function

- Log-sum-of-odds Score:

$$
S_{L S O}=\sum_{k: X_{k} Y_{k}=M M} S_{a a}\left(q_{i(k)}, p_{j(k)}\right)+\log \mathcal{P}_{t r}
$$

- Column Score:

$$
S_{a a}\left(q_{i}, p_{j}\right)=\log \sum_{a=1}^{20} \frac{q_{i}(a) p_{j}(a)}{f(a)}
$$

- Also use dynamic programming, with a dynamic matrix for each co-emit state pair, to determine the best alignment


## Profile-Hidden Markov Models(HMMs)

New Improvement

- Reaserchers Xin Deng and Jianlin Cheng from University of Missouri-Columbiacan
- Additional structural information
- protein solvent accessibility
- torsion angles
- Improved alignment accuracy


## Summary

- Critical Assessment of protein Structure Prediction (CASP)
- The I-TASSER server (zhang-server) - top 3 places
- The HHpred server - top 10 places


## Summary

- We looked at two different and popular approaches used in protein threading process
- Many different improvements have been proposed for both methods
- However, there is no single method outperforms all others on every target yet, which leaves room for improvement


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Questions?

Thank You!


