



UNIVERSITÄT  
DES  
SAARLANDES



**ZBI** ZENTRUM FÜR  
BIOINFORMATIK

# Multiple Sequence Alignment I

Algorithms for Sequence Analysis

Sven Rahmann

Summer 2021

# Overview

## Multiple sequence Alignment

- Basic Definitions
- Why Multiple sequence comparison?
- Multiple Alignment Problem
- Sum-of-Pairs Scores

### Algorithms:

- Generalization of the Universal Alignment Algorithm
- The Center Star approximation

# Basics

## Definition

**Multiple Sequence Alignment (MSA)** is generalization of pairwise alignment with more than two sequences.

## Applications

- Compute motifs (eg. transcription factor binding sites)
- Detect homologous residues and estimate their conservation
- Predict the secondary structures of proteins
- Infer the evolutionary history of the sequences

*One or two homologous sequences whisper...  
a full multiple alignment shouts out loud.* (Hubbard et al., 1996)

# MSA example (60S acidic ribosomal protein P0)

```

Q5E940_BOVIN  -----MPREDRATWKSNYFLKIIQLLDDYPKCFIVGADNVGSKMQQIRMSLRGK-AVVLMGKNTMMRKAIRGHLENN--PALE  76
RLA0_HUMAN   -----MPREDRATWKSNYFLKIIQLLDDYPKCFIVGADNVGSKMQQIRMSLRGK-AVVLMGKNTMMRKAIRGHLENN--PALE  76
RLA0_MOUSE   -----MPREDRATWKSNYFLKIIQLLDDYPKCFIVGADNVGSKMQQIRMSLRGK-AVVLMGKNTMMRKAIRGHLENN--PALE  76
RLA0_RAT     -----MPREDRATWKSNYFLKIIQLLDDYPKCFIVGADNVGSKMQQIRMSLRGK-AVVLMGKNTMMRKAIRGHLENN--PALE  76
RLA0_CHICK   -----MPREDRATWKSNYFMKIIQLLDDYPKCFIVGADNVGSKMQQIRMSLRGK-AVVLMGKNTMMRKAIRGHLENN--PALE  76
RLA0_RANSY   -----MPREDRATWKSNYFLKIIQLLDDYPKCFIVGADNVGSKMQQIRMSLRGK-AVVLMGKNTMMRKAIRGHLENN--SALE  76
Q7ZUG3_BRARE -----MPREDRATWKSNYFLKIIQLLDDYPKCFIVGADNVGSKMQTIRLSLRGK-AVVLMGKNTMMRKAIRGHLENN--PALE  76
RLA0 ICTPU   -----MPREDRATWKSNYFLKIIQLLDDYPKCFIVGADNVGSKMQTIRLSLRGK-AIVLMGKNTMMRKAIRGHLENN--PALE  76
RLA0_DROME   -----MVRENKAAWKAQYFIKVVLFDFEPKCFIVGADNVGSKMONIRTSLRGL-AVVLMGKNTMMRKAIRGHLENN--PQLE  76
RLA0_DICDI   -----MSGAG-SKRKKLFIEKATKLFETTIDKMIVAEADFVGGSSQLQKIRKSIIRGI-GAVLMGKNTMIRKVIIRDLDASK--PELD  75
Q54LP0_DICDI -----MSGAG-SKRKNVFIEKATKLFETTIDKMIVAEADFVGGSSQLQKIRKSIIRGI-GAVLMGKNTMIRKVIIRDLDASK--PELD  75
RLA0_PLAF8   -----MAKLSKQKKQMYIEKSSLIQQYSKLLIVHVDNVGSSNOMASVRSKSLRGK-ATILMGKNTIRRTALKKNLQAV--PQIE  76
RLA0_SULAC   -----MIGLAVTTTKIAKWVDEVAELTEKLTHTKTIIANIEGFPADKLIHIRKKLRGK-ADIKVTKNLNFNIALKNAG----YDTE  79
RLA0_SULTO   -----MRIMAVITQERKIAKWKIEEYKLEKLRKYHTIIANIEGFPADKLIHIRKKMRGM-AEIKVTKNLFLGIAAKNAG----LDVS  80
RLA0_SULSO   -----MKRLALALQKRVASWVLEEVKELTELIKNSNTILICNLGFPADKLIHIRKKLRGK-ATIKVTKNLFLKIAAKNAG----IDIE  80
RLA0_AERPE   MSVSVLVGQMYKREKTIPEWKTLMLELELEFSKRVVLFADLTGDPFVVRVRRKLLWKK-YPMVAVAKRRIILRAMKAAGLE--LDDN  86
RLA0_PYRAE   -----MMLAVIKRRRYVTRQYPAKRVKIVSEATELLQKPYVFLDHLGSLSRILHEVRYRLRRY-GVIKIIPKPLFKIAFTKVYGG--IPAE  85
RLA0_METAC   -----MAEERHHTHEIPQWKKDEIENIKELIQSHKVFQMVGTEGLLATKMKIRRDLDKDV-AVLKVSNTLTERALNQLG----ETIP  78
RLA0_METMA   -----MAEERHHTHEIPQWKKDEIENIKELIQSHKVFQMVRIEGLATKOKIRRDLDKDV-AVLKVSNTLTERALNQLG----ESIP  78
RLA0_ARCFU   -----MAAVRGS-----PPEYKVRAVEEIKRMISSKPVVAIVSRNVPAGQMKIRREFRGK-AEIKVVTNLLERALDALG--GDYL  75
RLA0_METKA   MAVKAKGQPPSGEYEPKVAEWKRREYKELKLMDEYENGLVDLEGIPAPQLQEIIRAKLREERDIIIRMSRNTLMRIALEEKLER--PELE  88
RLA0_METTH   -----MAHVAEWKKKEVQELHDLIKQYEVVGIANLADIPAROLQKMRQTLDS-ALIRMSKKTLLISLAKAKREL--ENVD  74
RLA0_METTL   -----MITAESEHKIAPWKIEEYVNLKLELLKNGQIVALVDMMEVPAROLQEIIRDKIR-GTMTLKMRSNTLIERAIKEVAEETGNPEFA  82
RLA0_METVA   -----MIDAKSEHKIAPWKIEEYVNLKLELLKSNVIALIDMMEVPAPQLQEIIRDKIR-DQMTLKMRSNTLIRKRAVEEVAETGNPEFA  82
RLA0_METJA   -----METKVAHVAPWKIEEYKTLKGLIKSKPVVAIVDMMEVPAPQLQEIIRDKIR-DKVKLRMSRNTLIERAIKAAEELNPNFLA  81
RLA0_PYRAB   -----MAHVAEWKKKEVEELANLIKSPVIALVDVSSMPAYPLSQMRRLIRENGGLLRVSRNTLIELAIKKAAGELGKPELE  77
RLA0_PYRHO   -----MAHVAEWKKKEVEELAKLIKSPVIALVDVSSMPAYPLSQMRRLIRENGGLLRVSRNTLIELAIKKAAGELGKPELE  77
RLA0_PYRFU   -----MAHVAEWKKKEVEELANLIKSPVIALVDVSSMPAYPLSQMRRLIRENNGLLRVSRNTLIELAIKKAAGELGKPELE  77
RLA0_PYRKO   -----MAHVAEWKKKEVEELANLIKSPVIALVDVAGVPAYPLSKMRDKLR-GKALLRVSNTLIELAIKRAAGELGQPELE  76
RLA0_HALMA   -----MSAESERKTETIPEWQEEVDIVMIESYESVGVVNIAGIPSRLODMRRDLHGT-AELRVSNTLIERALDDVD--DGLE  79
RLA0_HALVO   -----MSESEVRQTEVIPQWKRREVDLDFIESYESVGVVGVGIPSRLOSMRRELHGS-AAVRMSRNTLVNRLDEVN--DGFE  79
RLA0_HALSA   -----MSAEQRTTEEYPEWKRQVEAELVDLLETYDSVGVVNVGTIPSKLODMRRGLHGQ-AALRMSRNTLLVRALEEAG--DGLD  79
RLA0_THEAC   -----MKEVSQOKKELVNEITDRIKASRSVAIVDLAGIRTRQIODIRGKNRGK-INLKVIKKTLLFKALENLGD--EKLS  72
RLA0_THEVO   -----MRKINPKKKEIVSELAQDITKSKVAIVDIKIVTRROMODIRAKNRDK-VKIKVVKKTLFLKALDSIND--EKLT  72
RLA0_PICTO   -----MTEPAQWKIDFYKMLENEINSRKVAIVSIKGLRNNEFQKIRNSIRDK-ARIKVSRRARLLRLAIENTGK--NNIV  72
ruler 1.....10.....20.....30.....40.....50.....60.....70.....80.....90

```

By Miguel Andrade, CC-BY-SA 3.0, wikipedia:RPLP0\_90 ClustalW aln.gif

# Definition

## Multiple Alignment Alphabet

- Let  $\Sigma$  be the character alphabet.
- Then  $\mathcal{A}(k) := (\Sigma \cup \{-\})^k \setminus \{(-)^k\}$  is the **multiple alignment alphabet** of  $k$  sequences.

## Example

For  $k = 3$  and  $\Sigma = \{A, G\}$ , there are 26 elements:

$$\mathcal{A}(3) = \begin{pmatrix} A & A & A & A & A & A & A & A & A & \dots \\ A & A & A & G & G & G & - & - & - & \dots \\ A & G & - & A & G & - & A & G & - & \dots \end{pmatrix}$$

# Global MSA

## Global Multiple Sequence Alignment (MSA)

A **global multiple alignment**  $A$  of  $s_1, \dots, s_k \in \Sigma^*$  is a sequence over  $\mathcal{A}(k)$  with projections  $\pi_{\{i\}}(A) = s_i$  for all  $i = 1, \dots, k$ .

### Definition: Projections

The **projection**  $\pi_{\{i\}}$  of an alignment **column**  $c$  to the  $i^{\text{th}}$  sequence is the function  $\mathcal{A}(k) \rightarrow \Sigma^? := \Sigma^0 \cup \Sigma^1$  with

$$\pi_{\{i\}}(c = \begin{pmatrix} a_1 \\ \vdots \\ a_k \end{pmatrix}) := \begin{cases} a_i & \text{if } a_i \neq -, \\ \epsilon & \text{if } a_i = -. \end{cases}$$

The **projection** of a **multiple sequence alignment**  $A = c_1 \cdots c_n$  to sequence  $i$  is the concatenation of the projections of the respective columns:

$$\pi_{\{i\}}(A = (c_1, \dots, c_n)) := \pi_{\{i\}}(c_1) \cdots \pi_{\{i\}}(c_n).$$

# Projection to Index Set

## Definition

The **projection**  $\pi_{\mathcal{I}}$  of an alignment **column**  $c$  to the **index set**  $\mathcal{I} = \{i_1, \dots, i_q\}$  is the function  $\mathcal{A}(k) \rightarrow \mathcal{A}(q)$  with:

$$\pi_{\mathcal{I}}\left(c = \begin{pmatrix} a_1 \\ \vdots \\ a_k \end{pmatrix}\right) := \begin{cases} \epsilon & \text{if } \begin{pmatrix} a_{i_1} \\ \vdots \\ a_{i_q} \end{pmatrix} = \begin{pmatrix} - \\ \vdots \\ - \end{pmatrix}, \\ \begin{pmatrix} a_{i_1} \\ \vdots \\ a_{i_q} \end{pmatrix} & \text{otherwise.} \end{cases}$$

The **projection** of a **multiple sequence alignment**  $A = c_1 \cdots c_n$  to **index set**  $\mathcal{I}$  is the concatenation of the projections of the respective columns:

$$\pi_{\mathcal{I}}(A) = \pi_{\mathcal{I}}(c_1) \cdots \pi_{\mathcal{I}}(c_n).$$

# Example

$$A = \begin{pmatrix} - & A & C & C & - & - & A & T & G \\ - & A & - & C & G & A & A & T & - \\ T & A & C & C & - & - & A & G & G \\ - & A & - & C & C & A & A & T & G \end{pmatrix}$$



# Example

$$A = \begin{pmatrix} - & A & C & C & - & - & A & T & G \\ - & A & - & C & G & A & A & T & - \\ T & A & C & C & - & - & A & G & G \\ - & A & - & C & C & A & A & T & G \end{pmatrix}$$

$$\pi_{\{1,2\}}(A) = \begin{pmatrix} A & C & C & - & - & A & T & G \\ A & - & C & G & A & A & T & - \end{pmatrix}$$

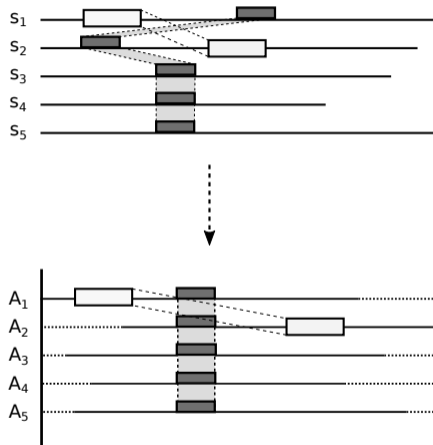
# Example

$$A = \begin{pmatrix} - & A & C & C & - & - & A & T & G \\ - & A & - & C & G & A & A & T & - \\ T & A & C & C & - & - & A & G & G \\ - & A & - & C & C & A & A & T & G \end{pmatrix}$$

$$\pi_{\{1,2\}}(A) = \begin{pmatrix} A & C & C & - & - & A & T & G \\ A & - & C & G & A & A & T & - \end{pmatrix}$$

$$\pi_{\{3,4\}}(A) = \begin{pmatrix} T & A & C & C & - & - & A & G & G \\ - & A & - & C & C & A & A & T & G \end{pmatrix}$$

# Why multiple sequence comparison



# Why multiple sequence comparison

Pairwise alignment ambiguities may be resolved by additional information.

## Example

$s_1 = \text{VIEQLA}$  and  $s_2 = \text{VINLA}$  may be aligned in the two different ways:

$$A_1 = \begin{pmatrix} V & I & E & Q & L & A \\ V & I & N & - & L & A \end{pmatrix}$$

and

$$A_2 = \begin{pmatrix} V & I & E & Q & L & A \\ V & I & - & N & L & A \end{pmatrix}$$

Additional sequence  $s_3 = \text{VINQLA}$  shows that alignment  $A_1$  is probably the correct one.

# Multiple Alignment Problem

## Multiple Sequence Alignment Problem

Given  $k$  sequences  $s_1, s_2, \dots, s_k$  and alignment score (cost) function  $S$  ( $D$ ), find an alignment  $A^{\text{opt}}$  of  $s_1, s_2, \dots, s_k$  such that  $S(A^{\text{opt}})$  is maximal ( $D(A^{\text{opt}})$  is minimal) among all possible alignments of  $s_1, s_2, \dots, s_k$ .

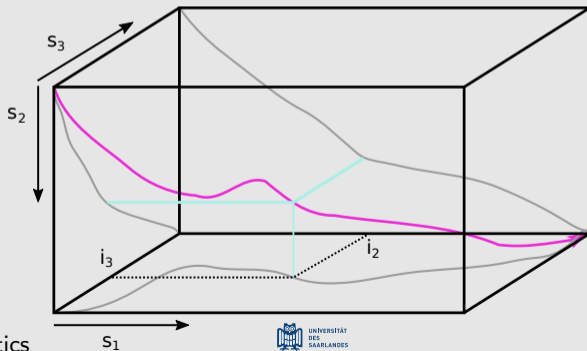
Such an alignment  $A^{\text{opt}}$  is called an **optimal alignment**, and  $S(s_1, s_2, \dots, s_k) := S(A^{\text{opt}})$  is the **optimal alignment score** and  $D(s_1, s_2, \dots, s_k) := D(A^{\text{opt}})$  is the **optimal alignment cost** of  $s_1, s_2, \dots, s_k$ .

# (Weighted) Sum-of-Pairs Score (Cost)

## Definition

Score a multiple alignment by the sum of scores of all pairwise projections.

$$S_{[W]SP}(A) := \sum_{1 \leq p < q \leq k} [w_{p,q}] \cdot S(\pi_{\{p,q\}}(A))$$



## Example: Weighted Cost of an Alignment

### [Weighted] Cost/Distance

$$D_{[W]SP}(A) := \sum_{1 \leq p < q \leq k} [w_{p,q}] \cdot D(\pi_{\{p,q\}}(A))$$

Let  $s_1 = \text{CGCTT}$ ,  $s_2 = \text{ACGGT}$ ,  $s_3 = \text{GCTGT}$ .

$$A_2 = \begin{pmatrix} C & G & C & T & - & T \\ - & A & C & G & G & T \\ - & G & C & T & G & T \end{pmatrix}$$

Let  $D$  be the unit cost edit distance.

Then  $D_{SP}(A) = 4 + 2 + 2 = 8$ ,

and  $D_{WSP}(A) = 4w_{1,2} + 2w_{1,3} + 2w_{2,3}$ .

## Example: Sum-of-Pairs MSA

Let  $s_1 = \text{CGCG}$ ,  $s_2 = \text{ACGC}$  and  $s_3 = \text{GCGA}$ .

In a unit cost scenario, the (only) optimal alignment of  $s_1$  and  $s_2$  is:

$$A^{(1,2)} = \begin{pmatrix} - & C & G & C & G \\ A & C & G & C & - \end{pmatrix}$$

with cost  $D(A^{(1,2)}) = 2$ .

The (only) optimal alignment of  $s_1$  and  $s_3$  is

$$A^{(1,3)} = \begin{pmatrix} C & G & C & G & - \\ - & G & C & G & A \end{pmatrix}$$

with cost  $D(A^{(1,3)}) = 2$ .



## Example: Sum-of-Pairs MSA

Combining the two alignments into one multiple alignment, using the common sequence  $s_1$  as seed, yields the multiple alignment

$$A^{((1,2),(1,3))} = \begin{pmatrix} - & C & G & C & G & - \\ A & C & G & C & - & - \\ - & - & G & C & G & A \end{pmatrix}$$

with cost  $D(A^{((1,2),(1,3))}) = 2 + 2 + 4 = 8$ .

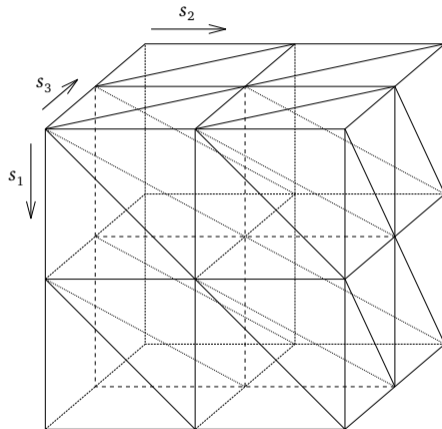
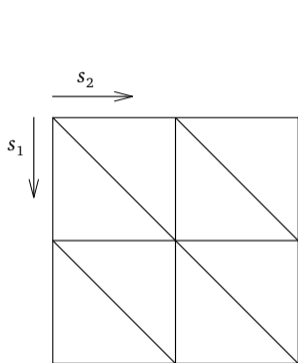
However, this is not the sum-of-pairs optimal alignment, which is

$$A^{\text{opt}} = \begin{pmatrix} - & C & G & C & G \\ A & C & G & C & - \\ G & C & G & A & - \end{pmatrix}$$

with cost  $D(A^{\text{opt}}) = 2 + 3 + 2 = 7$ .

# Algorithms for Sum-of-Pairs Multiple Alignment

# Alignment Graph: From 2 to $k$ Dimensions



# An Exact Solution: Universal Alignment Algorithm

The Needleman-Wunsch algorithm for pairwise global alignment can be generalized for the multiple alignment of  $k$  sequences  $s_1, s_2, \dots, s_k$  of lengths  $n_1, n_2, \dots, n_k$ , respectively.

# An Exact Solution: Universal Alignment Algorithm

The Needleman-Wunsch algorithm for pairwise global alignment can be generalized for the multiple alignment of  $k$  sequences  $s_1, s_2, \dots, s_k$  of lengths  $n_1, n_2, \dots, n_k$ , respectively.

- k-dimensional weighted edit graph
- Edge  $e$  corresponds to a possible alignment column  $c$
- Each edge weighted by its corresponding alignment score  $w(e) = S(c)$
- Optimal alignment = maximum scoring path from source to sink.

# An Exact Solution: Universal Alignment Algorithm

The Needleman-Wunsch algorithm for pairwise global alignment can be generalized for the multiple alignment of  $k$  sequences  $s_1, s_2, \dots, s_k$  of lengths  $n_1, n_2, \dots, n_k$ , respectively.

- k-dimensional weighted edit graph
- Edge  $e$  corresponds to a possible alignment column  $c$
- Each edge weighted by its corresponding alignment score  $w(e) = S(c)$
- Optimal alignment = maximum scoring path from source to sink.

## Minimization version

For each vertex  $v$  in the edit graph in topological order:

$$D(v) = \min\{D(v') + w(v' \rightarrow v) \mid v' \text{ is a predecessor of } v\}.$$

# Universal Algorithm Explicitly

$D(0, 0, \dots, 0) = 0$  and

$$D(\overbrace{i_1, i_2, \dots, i_k}^v) = \min_{\substack{\Delta_1, \dots, \Delta_k \in \{0, 1\} \\ \Delta_1 + \dots + \Delta_k \neq 0}} \left\{ D(\overbrace{i_1 - \Delta_1, i_2 - \Delta_2, \dots, i_k - \Delta_k}^{\text{predecessor } v'}) + D_{\text{SP}} \left( \overbrace{\begin{pmatrix} \Delta_1 s_1[i_1 - 1] \\ \vdots \\ \Delta_k s_k[i_k - 1] \end{pmatrix}}^{\text{alignm.col.}} \right) \right\}.$$

**Notation:** For  $c \in \Sigma$ , let  $\Delta c := c$  if  $\Delta = 1$  and  $\Delta c = \text{" - "}$  if  $\Delta = 0$ .

# Universal Algorithm Explicitly

$D(0, 0, \dots, 0) = 0$  and

$$D(\overbrace{i_1, i_2, \dots, i_k}^v) = \min_{\substack{\Delta_1, \dots, \Delta_k \in \{0, 1\} \\ \Delta_1 + \dots + \Delta_k \neq 0}} \left\{ D(\overbrace{i_1 - \Delta_1, i_2 - \Delta_2, \dots, i_k - \Delta_k}^{\text{predecessor } v'}) + D_{\text{SP}} \left( \overbrace{\begin{pmatrix} \Delta_1 s_1[i_1 - 1] \\ \vdots \\ \Delta_k s_k[i_k - 1] \end{pmatrix}}^{\text{alignm.col.}} \right) \right\}.$$

**Notation:** For  $c \in \Sigma$ , let  $\Delta c := c$  if  $\Delta = 1$  and  $\Delta c = "-"$  if  $\Delta = 0$ .

**Observation:** In general, a node has  $2^k - 1$  predecessors.



# Space and Time Complexity of Sum-of-Pairs Multiple Alignment

## Space Complexity

The space complexity is the size of the  $k$ -dimensional edit graph:

$O(n_1 n_2 \dots n_k) = O(n^k)$  if  $n$  is the maximum sequence length.

# Space and Time Complexity of Sum-of-Pairs Multiple Alignment

## Space Complexity

The space complexity is the size of the  $k$ -dimensional edit graph:

$O(n_1 n_2 \dots n_k) = O(n^k)$  if  $n$  is the maximum sequence length.

We can save one dimension if we do not need traceback:  $O(n^{k-1})$ .

# Space and Time Complexity of Sum-of-Pairs Multiple Alignment

## Space Complexity

The space complexity is the size of the  $k$ -dimensional edit graph:

$O(n_1 n_2 \dots n_k) = O(n^k)$  if  $n$  is the maximum sequence length.

We can save one dimension if we do not need traceback:  $O(n^{k-1})$ .

## Time Complexity

- $O(n^k)$  nodes to compute
- For each node: minimization/maximization over  $O(2^k)$  predecessors
- For each predecessor: Compute edge cost/score:  $O(k^2)$  (sum-of-pairs)

**Total** (for linear gap costs):  $O((2n)^k \cdot k^2)$

# Space and Time Complexity of Sum-of-Pairs Multiple Alignment

## Space Complexity

The space complexity is the size of the  $k$ -dimensional edit graph:

$O(n_1 n_2 \dots n_k) = O(n^k)$  if  $n$  is the maximum sequence length.

We can save one dimension if we do not need traceback:  $O(n^{k-1})$ .

## Time Complexity

- $O(n^k)$  nodes to compute
- For each node: minimization/maximization over  $O(2^k)$  predecessors
- For each predecessor: Compute edge cost/score:  $O(k^2)$  (sum-of-pairs)

**Total** (for linear gap costs):  $O((2n)^k \cdot k^2)$

## NP Hardness

Optimal Multiple Alignment with both weighted and unweighted sum-of-pairs score (or distance) is an NP-hard optimization problem in  $k$  (Wang and Jiang, 1994).

# Approximation Algorithms

## $c$ -approximation, $c \geq 1$

For  $c \geq 1$ , an algorithm for a cost or distance minimization problem is a  **$c$ -approximation** if its output solution has cost at most  $c$  times the optimal solution:

$$\text{output} \leq c \cdot \text{opt}_{\min}$$

For a maximization problem, an algorithm is called a  $c$ -approximation if its output solution has score at least  $\frac{1}{c}$  times the optimal solution:

$$\text{output} \geq \text{opt}_{\max}/c$$

# Approximation Algorithms

## $c$ -approximation, $c \geq 1$

For  $c \geq 1$ , an algorithm for a cost or distance minimization problem is a  **$c$ -approximation** if its output solution has cost at most  $c$  times the optimal solution:

$$\text{output} \leq c \cdot \text{opt}_{\min}$$

For a maximization problem, an algorithm is called a  $c$ -approximation if its output solution has score at least  $\frac{1}{c}$  times the optimal solution:

$$\text{output} \geq \text{opt}_{\max}/c$$

## Opinion

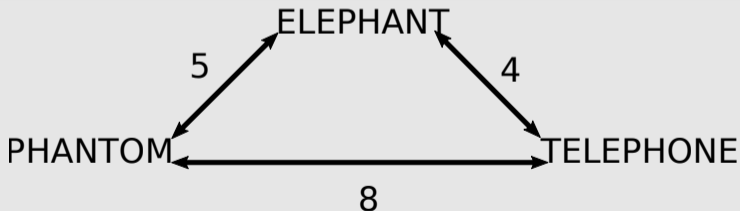
Theoretical computer scientists like approximation algorithms. I don't:  
Even a 2-approximation algorithm is bad in practice (in the worst case).  
Good:  $(1 + \epsilon)$  approximation algorithm for every  $\epsilon$ , polynomial time.

# The Center Star Approximation

## Algorithm

The **center star algorithm** (Gusfield, 1991, 1993) is a 2-approximation for the sum-of-pairs **distance** multiple alignment problem if the underlying weighted edit distance satisfies the **triangle inequality**.

## Example



# The Center Star Approximation

## Overall distance

For each sequence  $s_p$ ,  $1 \leq p \leq k$ , its total distance  $d_p$  to the other sequences is the sum of the pairwise optimal alignment costs:

$$d_p = \sum_{1 \leq q \leq k} d(s_p, s_q)$$

## Idea

let  $s_c$  be the sequence that minimizes this overall distance, called **center sequence**. A multiple alignment  $A_c$  is constructed from all pairwise optimal alignments where the center sequence is involved, i.e., all the optimal alignments of  $s_c$  and the other  $s_p$ ,  $p \neq c$ , are combined into one multiple alignment  $A_c$ .



# Center Star Theorem

## Theorem

The Center Star algorithm is a 2-approximation for the optimal sum-of-pairs multiple alignment:  $D_{SP}(A_c) \leq 2 \cdot D_{SP}(A^*)$ .

# Center Star Theorem

## Theorem

The Center Star algorithm is a 2-approximation for the optimal sum-of-pairs multiple alignment:  $D_{\text{SP}}(A_c) \leq 2 \cdot D_{\text{SP}}(A^*)$ .

## Proof.

Write  $D_{ij}^c$  for the cost of the induced pairwise alignment  $\pi_{\{i,j\}}(A^c)$ , and  $D_{ij}^*$  for  $A^*$ . Write  $d(s_i, s_j)$  for the (optimal) pairwise distance between  $s_i$  and  $s_j$ .

**Lemma:**  $D_{ij}^c \leq d(s_i, s_c) + d(s_c, s_j)$  for all  $i, j$  (proof follows).

# Center Star Theorem

## Theorem

The Center Star algorithm is a 2-approximation for the optimal sum-of-pairs multiple alignment:  $D_{\text{SP}}(A_c) \leq 2 \cdot D_{\text{SP}}(A^*)$ .

## Proof.

Write  $D_{ij}^c$  for the cost of the induced pairwise alignment  $\pi_{\{i,j\}}(A^c)$ , and  $D_{ij}^*$  for  $A^*$ . Write  $d(s_i, s_j)$  for the (optimal) pairwise distance between  $s_i$  and  $s_j$ .

**Lemma:**  $D_{ij}^c \leq d(s_i, s_c) + d(s_c, s_j)$  for all  $i, j$  (proof follows).

Then,  $2D_{\text{SP}}(A_c) = \sum_{i \neq j} D_{ij}^c \leq \sum_{i \neq j} [d(s_i, s_c) + d(s_c, s_j)] = 2(k-1) \cdot \sum_{j \neq c} d(s_c, s_j)$ .  
Also,  $2D_{\text{SP}}(A^*) = \sum_{i \neq j} D_{ij}^* \geq \sum_{i \neq j} d(s_i, s_j) = \sum_i \sum_{j \neq i} d(s_i, s_j) \geq k \cdot \sum_{j \neq c} d(s_c, s_j)$   
by the choice of  $c$ .

# Center Star Theorem

## Theorem

The Center Star algorithm is a 2-approximation for the optimal sum-of-pairs multiple alignment:  $D_{\text{SP}}(A_c) \leq 2 \cdot D_{\text{SP}}(A^*)$ .

## Proof.

Write  $D_{ij}^c$  for the cost of the induced pairwise alignment  $\pi_{\{i,j\}}(A^c)$ , and  $D_{ij}^*$  for  $A^*$ . Write  $d(s_i, s_j)$  for the (optimal) pairwise distance between  $s_i$  and  $s_j$ .

**Lemma:**  $D_{ij}^c \leq d(s_i, s_c) + d(s_c, s_j)$  for all  $i, j$  (proof follows).

Then,  $2D_{\text{SP}}(A_c) = \sum_{i \neq j} D_{ij}^c \leq \sum_{i \neq j} [d(s_i, s_c) + d(s_c, s_j)] = 2(k-1) \cdot \sum_{j \neq c} d(s_c, s_j)$ .  
Also,  $2D_{\text{SP}}(A^*) = \sum_{i \neq j} D_{ij}^* \geq \sum_{i \neq j} d(s_i, s_j) = \sum_i \sum_{j \neq i} d(s_i, s_j) \geq k \cdot \sum_{j \neq c} d(s_c, s_j)$   
by the choice of  $c$ .

It follows that  $D_{\text{SP}}(A_c)/D_{\text{SP}}(A^*) \leq 2(k-1)/k \leq 2$  for any  $k$ . □

# Proof of Lemma

## Lemma

$$D_{ij}^c \leq d(s_i, s_c) + d(s_c, s_j) \text{ for all } i, j$$

# Proof of Lemma

## Lemma

$D_{ij}^c \leq d(s_i, s_c) + d(s_c, s_j)$  for all  $i, j$

## Proof.

Because the cost function satisfies the triangle inequality, we have for all  $i, j$ :

$$D_{ij}^c \leq D_{ic}^c + D_{cj}^c.$$

Because the induced alignments involving the center sequence are by construction optimal, we have  $D_{ic}^c = d(s_i, s_c)$  and  $D_{cj}^c = d(s_c, s_j)$ . The lemma follows. □

# Time and Space Complexity

## Time complexity

- Phase 1: Compute  $\binom{k}{2}$  pairwise alignments; pick center:  $O(k^2n^2)$
- Phase 2: Combine  $k - 1$  alignments into one multiple alignment:  $O(k^2n)$
- Overall running time:  $O(k^2n^2)$

# Time and Space Complexity

## Time complexity

- Phase 1: Compute  $\binom{k}{2}$  pairwise alignments; pick center:  $O(k^2n^2)$
- Phase 2: Combine  $k - 1$  alignments into one multiple alignment:  $O(k^2n)$
- Overall running time:  $O(k^2n^2)$

## Space complexity

- $O(n + k)$  for computing and storing  $k$  computed values of  $d_p$
- $O(k^2n)$  to store  $k$  pairwise alignments and intermediate/final multiple alignments (size of multiple alignment: up to  $O(nk)$  columns, typically only  $O(n)$ )
- Overall space complexity:  $O(k^2n)$



# Summary

## Multiple Sequence Alignment (MSA)

- Sum-of-pairs objective function
- Universal DP algorithm: exponential space and time in  $k$ ; NP-hard
- The Center Star 2-approximation:  $O(n^2k^2)$  time,  $O(k^2n)$  space

## Possible Exam Questions

- Define a global multiple sequence alignment (MSA).
- What is the advantage of an MSA compared to a pairwise alignment?
- Define the sum-of-pairs objective for MSA.
- Do you know an algorithm to find the optimal MSA (wrt this objective)?
- What is its time and space complexity?
- Is there an exact algorithm with running time polynomial in the number of sequences  $k$ ?
- What is an approximation algorithm?
- Explain the Center Star algorithm and its assumptions.
- What is its running time?
- Can you sketch the ideas for proving it to be a 2-approximation?