Lecture 10

# **Sequence Alignments**

#### Part 1: Alignments: Definition, Construction

Machine Learning for Structured Data Vlad Niculae · LTL, UvA · https://vene.ro/mlsd

#### **Sequence Alignments**

#### **1** Alignments: Definition, Construction

**2** Dynamic Programming Algorithms



We have two related sequences of possibly different lengths.

How to best line them up using insertions / deletions (i.e., monotonically)?

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DNA, RNA, or protein sequences:	find the best sequence of edits between strings
align CAAT and ATTACA:	(e.g., spell checking etc)
CA-AT ATTACA-	kitten- sitting

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#### nlp:

find the best sequence of edits between strings

(e.g., spell checking etc)

kittensitting

#### signal processing:

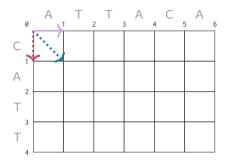
stretch or compress signals (e.g., audio) to match.



#### **Alignment Are Structures**

Alignments are structured objects: many possible alignments between same strings.

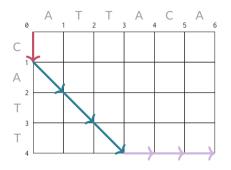
--CA-AT -CAAT- CAAT-- CAAT---- CAAT----- ATTACA- ATTACA ATTACA ----ATTACA ----ATTACA ...



At point (i, j) in the grid we either:

M: match tokens *i* in seq1 to *j* in seq2,

- I: skip token *i* in seq1,
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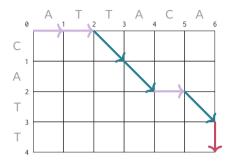
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Some alignments and corresponding trajectories:

• IMMMDDD: CATT----ATTACA

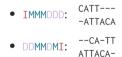


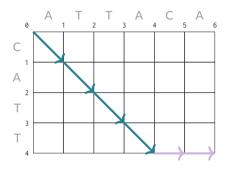
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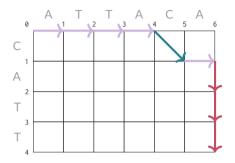


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- IMMMDDD: CATT----ATTACA
- DDMMDMI: --CA-TT ATTACA-
- MMMMDD: CATT--ATTACA



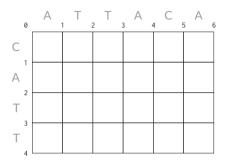
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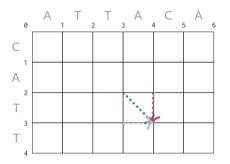
DAG representation:

Nodes at grid points  $V = \{(i, j) : 0 \le i \le n, 0 \le j \le m\}$  At point (i, j) in the grid we either:

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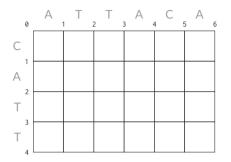
Three incoming edges for each node.

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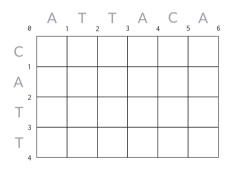
Number of paths from (0,0) to (*n*, *m*):  $D(n, m) = \sum_{k=0}^{\min(n,m)} {m \choose k} {n \choose k} 2^k \text{ (Delannoy numbers)}$ 

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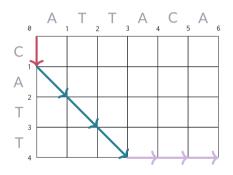
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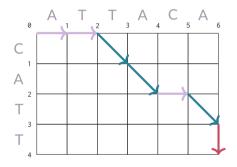
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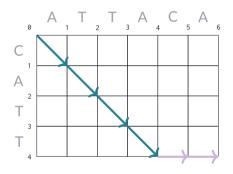
- Get a score of 1 for matching identical characters.
   i.e., if action M taken at grid position (*i*, *j*) and seq1[i] == seq2[j], add 1 to the score.
- Get a score of -1 for any insertion or deletion.



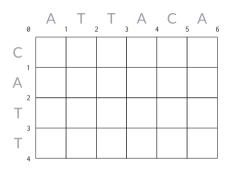
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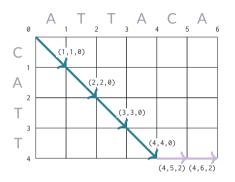


let **A** a score array of shape (n + 1, m + 1, 3):

- $a_{i,j,0}$  is the score for Matching token *i* in seq1 with token *j* in seq2.
- $a_{i,j,1}$  is the score for an Insertion at (i, j): skipping token *i* in seq1 when the cursor is at *j* in seq2.
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note: in these slides, we use zero-indexing into *A*, but one-indexing into the sequences.

We can set the specific values of **A** to replicate the default scoring from before.

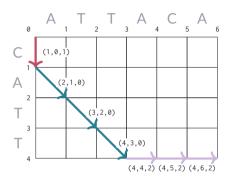


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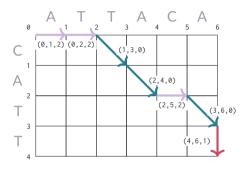


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# **Sequence Alignments**

#### Part 2: Dynamic Programming Algorithms

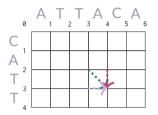
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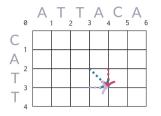
#### **1** Alignments: Definition, Construction







Alignments = paths in DAG from (0, 0) to (n, m).



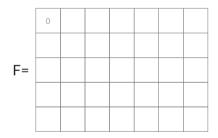
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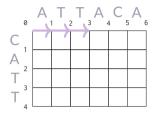
Computing the max score:

Fill in a table M, size (1 + n, 1 + m), s.t.  $m_{jj}$  = the max score up to (i, j).

$$m_{ij} = \begin{cases} m_{i-1,j-1} + a_{i,j,0} \\ m_{i-1,j} + a_{i,j,1} \\ m_{i,j-1} + a_{i,j,2} \end{cases} \text{ for any } i > 0, j > 0.$$

What is a topological order?







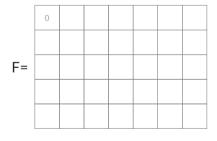
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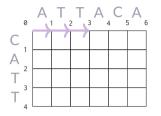
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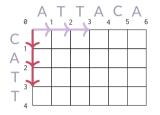
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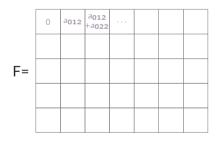
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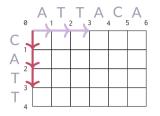
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 $m_{i0}$ : only one possible path for any *i*.

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a012 +a022

a101

a101

F=

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### **History of DP Alignments**

Small variants of this algorithm are known by many names and were reinvented many times:

- in biology: Needleman-Wunsch, and (with a small change) Smith-Waterman.
- in compling / information retrieval, Levenshtein / Edit Distance / Wagner-Fischer
- in time series / signal processing: Dynamic Time Warping (DTW)

As far as we know, the first inventor is actually Ukrainian mathematician Taras Vintsiuk, for speech applications.



#### Viterbi for alignments

**input:** Scores **A** ( $n + 1 \times m + 1 \times 3$  array), zero-indexed initialize **F**, same shape as **A**,  $M_{00} = 0$ ,  $M_{i0} = \sum_{k=1}^{i} a_{k,0,1}$ ,  $M_{0j} = \sum_{k=1}^{j} a_{0,k,2}$ .

```
Forward: compute max. scores recursively

for i = 1 to n do

for j = 1 to m do

M_{ij} = \max \begin{cases} M_{i-1,j-1} + a_{i,j,0} \\ M_{i-1,j} + a_{i,j,1} \\ M_{i,j-1} + a_{i,j,2} \end{cases}; \pi_{ij} = \arg \max \begin{cases} M_{i-1,j-1} + a_{i,j,0} \\ M_{i-1,j} + a_{i,j,1} \\ M_{i,j-1} + a_{i,j,2} \end{cases};

f^* = M_{n,m}
```

Backward: follow backpointers  $i = n, j = m, y^* = ()$ while  $(i, j) \neq (0, 0)$  do insert  $\pi_{ij}$  at the front of  $y^*$ , decrease i, j, or both, depending on  $\pi_{ij}$ 

output: The highest-scoring alignment path  $y^*$ , and its total score  $f^*$ .

#### Forward algorithm for alignments

**input:** Scores **A** ( $n + 1 \times m + 1 \times 3$  array), zero-indexed initialize **F**, same shape as **A**,  $F_{00} = 0$ ,  $F_{i0} = \sum_{k=1}^{i} a_{k,0,1}$ ,  $F_{0j} = \sum_{k=1}^{j} a_{0,k,2}$ .

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Forward: compute scores recursively

for i = 1 to n do

for j = 1 to m do

M_{ij} = \log \sum \exp \begin{cases} M_{i-1,j-1} + a_{i,j,0} \\ M_{i-1,j} + a_{i,j,1} \\ M_{i,j-1} + a_{i,j,2} \end{cases};

return M_{n,m}
```

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# **Sequence Alignments**

**Part 3: Evaluation** 

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**2** Dynamic Programming Algorithms

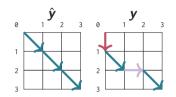


#### **Evaluating Alignments**

So far we are representing alignments as sequences of "moves" on a grid.

How to evaluate if we predict  $\hat{y} = MMM$ when the correct label is y = IMDM?

Alignment-level accuracy always an option. Finer-grained eval?



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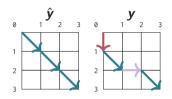
How to evaluate if we predict  $\hat{y} = MMM$ when the correct label is y = IMDM?

Alignment-level accuracy always an option. Finer-grained eval?

In protein alignment, we care most about getting the aligned indices (i, j) right.

(getting the M-edges right!)

- precision: n. correct M-edges / n. predicted M-edges
- recall: n. correct M-edges / n. true M-edges
- F-score: harmonic average of P and R.



indices $(\hat{y}) = \{(1, 1), (2, 2), (3, 3)\},\$ indices $(y) = \{(2, 1), (3, 3)\}.$ 

#### Summary

- Monotonic alignments between two sequences.
- Once again, dynamic programming gives us polynomial-time complexity.
- Algorithm rediscovered many times across many different fields under different names.