

Lecture 10

Sequence Alignments

Part 1: Alignments Between Sequences

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

Sequence Alignments

- 1 Alignments Between Sequences
- 2 Representing and Scoring Alignments
- 3 Dynamic Programming Algorithms
- 4 Evaluation

Alignments Between Sequences

We have two related sequences of possibly different lengths.

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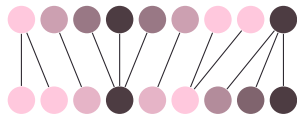
find the best sequence of edits between strings

(e.g., spell checking etc)

kitten-
sitting

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	...

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We need to figure out:

1. How to score an alignment
2. How to compute argmax over alignments
3. How to compute logsumexp over alignments

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We need to figure out:

0. How to represent alignments
1. How to score an alignment
2. How to compute argmax over alignments
3. How to compute logsumexp over alignments

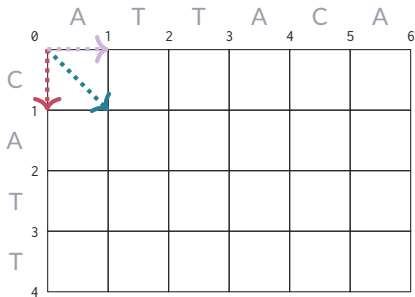
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Sequence Alignments

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Alignment Tables



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

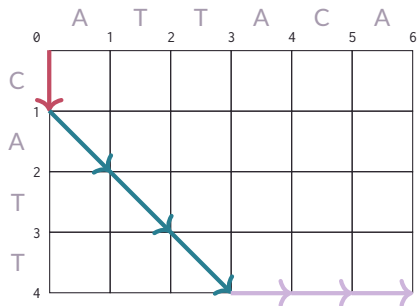
M: match tokens i in seq1 to j in seq2,

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Some alignments and corresponding trajectories:

Alignment Tables



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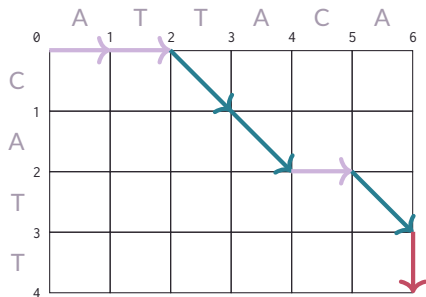
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- **I**MMMD**D**D: CATT---
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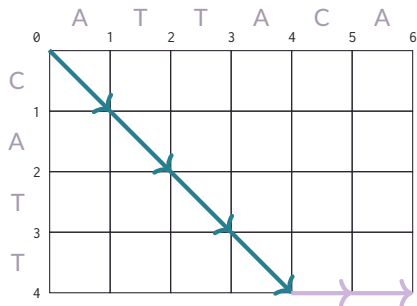
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- DDMMDMI: --CA-TT
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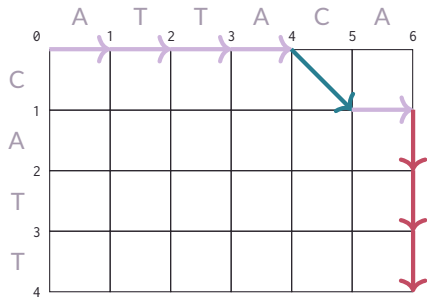
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Some alignments and corresponding trajectories:

- **I**MMDD: CATT---
-ATTACA
- DD**M**DM**I**: --CA-TT
ATTACA-
- **M**MMDD: CATT--
ATTACA

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- **I**MMMDDD: CATT---
-ATTACA
- DD**M**MD**I**: --CA-TT
ATTACA-
- **M**MMMD**D**: CATT--
ATTACA
- DDD**D**MD**I****I****I**: ----C-ATT
ATTACA---

Alignment Tables

	A	T	T	A	C	A	
0							6
C							
1							
A							
2							
T							
3							
T							
4							

DAG representation:

Nodes at grid points

$$V = \{(i, j) : 0 \leq i \leq n, 0 \leq j \leq m\}$$

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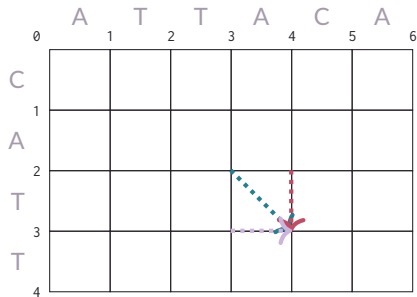
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Alignment Tables



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Three incoming edges for each node.

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Alignment Tables


		A	T	T	A	C	A	
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C								
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DAG representation:

Nodes at grid points

$$V = \{(i, j) : 0 \leq i \leq n, 0 \leq j \leq m\}$$

Three incoming edges for each node.

 Number of paths from $(0, 0)$ to (n, m) :

$$D(n, m) = \sum_{k=0}^{\min(n, m)} \binom{m}{k} \binom{n}{k} 2^k \text{ (Delannoy numbers)}$$

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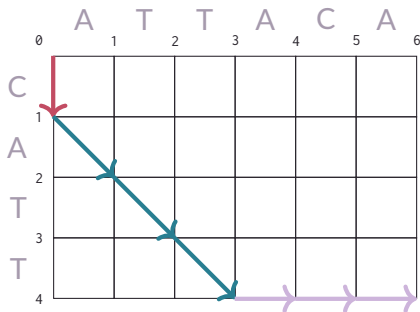
Scoring an alignment

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	0	1	2	3	4	5	6	
C								
1								
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A “default” scoring strategy:

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

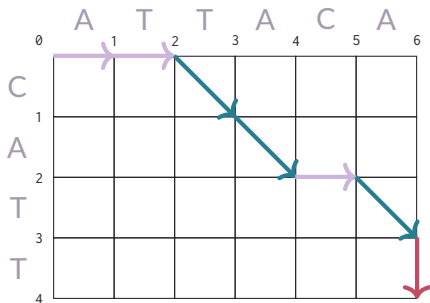
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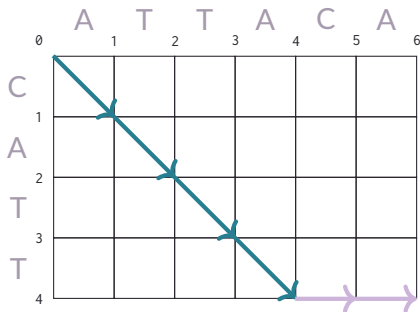
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C								
A	1							
T	2							
T	3							
	4							

let \mathbf{A} a score array of shape $(n + 1, m + 1, 3)$:

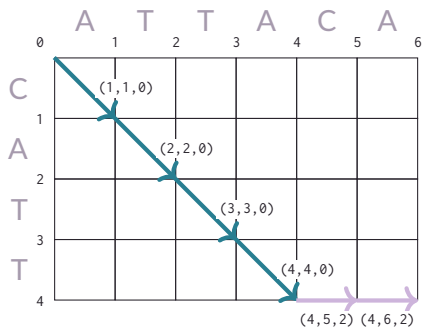
- $a_{i,j,0}$ is the score for Matching token i in seq1 with token j in seq2.
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note: in these slides, we use zero-indexing into \mathbf{A} , but one-indexing into the sequences.

We can set the specific values of \mathbf{A} to replicate the default scoring from before.

But this parametrized version lets us learn how to score alignments.

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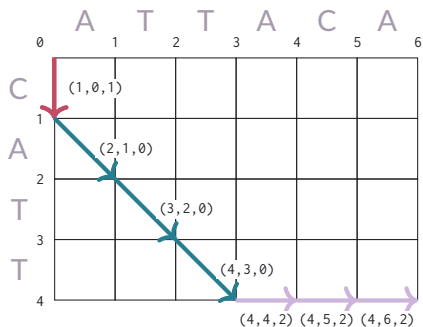
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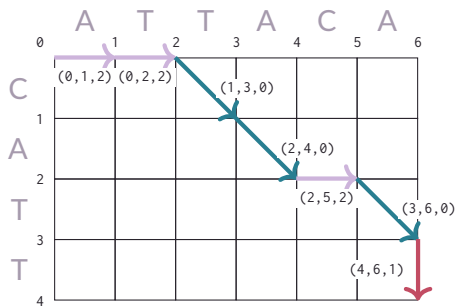
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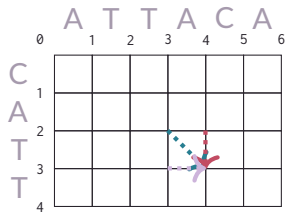
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Sequence Alignments

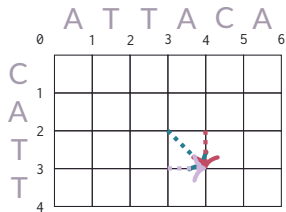
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Dynamic Programming for Alignments



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Dynamic Programming for Alignments



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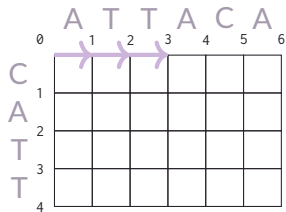
Computing the max score:

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

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

What is a topological order?

Dynamic Programming for Alignments



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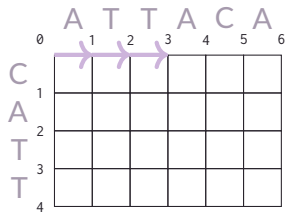
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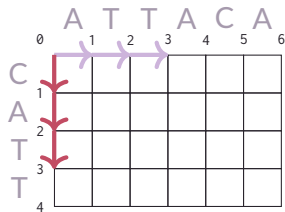
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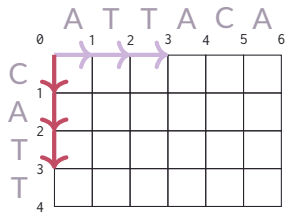
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Dynamic Programming for Alignments



$F =$

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a_{101}						
$a_{101} + a_{201}$						
...						

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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 compiling / 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 \mathbf{A} ($(n+1) \times (m+1) \times 3$ array), zero-indexed

initialize \mathbf{F} , same shape as \mathbf{A} ,

$$M_{00} = 0, \quad M_{i0} = \sum_{k=1}^i a_{k,0,1}, \quad M_{0j} = \sum_{k=1}^j a_{0,k,2}.$$

Forward: compute max. scores recursively

for $i = 1$ to n **do**

for $j = 1$ to m **do**

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

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

Backward: follow backpointers

$$i = n, j = m, \mathbf{y}^* = ()$$

while $(i, j) \neq (0, 0)$ **do**

 insert π_{ij} at the front of \mathbf{y}^* ,

 decrease i, j , or both, depending on π_{ij}

output: The highest-scoring alignment path \mathbf{y}^* , and its total score f^* .

Forward algorithm for alignments

input: Scores \mathbf{A} ($(n+1) \times (m+1) \times 3$ array), zero-indexed

initialize \mathbf{F} , same shape as \mathbf{A} ,

$$F_{00} = 0, \quad F_{i0} = \sum_{k=1}^i a_{k,0,1}, \quad F_{0j} = \sum_{k=1}^j a_{0,k,2}.$$

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

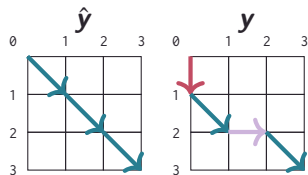
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Evaluating Alignments

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

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

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



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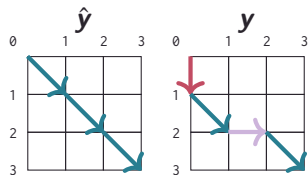
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Alignment-level accuracy always an option.
Finer-grained eval?

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.



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

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

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.