# INT102 Algorithmic Foundations And Problem Solving Sequence Alignment by Dynamic Programming

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# Learning Outcomes

- >Longest Common Subsequence (LCS)
- >Pairwise Sequence Alignment Problem
  - 1. Global Alignment
  - 2. Local Alignment

# DNA Sequence Comparison A topic in Bioinformatics

 Finding sequence similarities with genes of known function is a common approach to infer a newly sequenced gene's function

 Gene similarities between two genes with known and unknown function alert biologists to some possibilities

 Computing a similarity score between two genes tells how likely it is that they have similar functions

# Aligning DNA Sequences

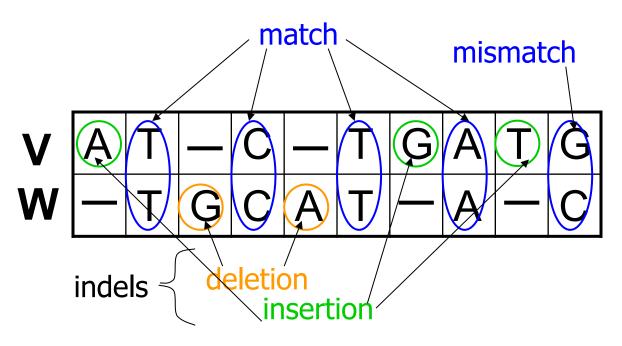
## Alignment: $2 \times k \text{ matrix } (k \geq m, n)$



n = 8

W = TGCATAC

m = 7



- 4 matches
- <sub>1</sub> mismatches
- 3 insertions
- 2 deletions

Longest Common Subsequence (LCS)

# Longest Common Subsequence (LCS)

- DNA analysis, two DNA string comparison.
- DNA string: a sequence of symbols A,C,G,T.
  - S=ACCGGTCGAGCTTCGAAT
- Subsequence (of X): is X with some symbols left out.
  - Z=CGTC is a subsequence of X=ACGCTAC.
- Common subsequence Z (of X and Y): a subsequence of X and also a subsequence of Y.
  - Z=CGA is a common subsequence of both X=ACGCTAC and Y=CTGACA.
- Longest Common Subsequence (LCS): the longest one of common subsequences.
  - -Z' =CGCA is the LCS of the above X and Y.
- LCS problem: given  $X=\langle x_1, x_2,..., x_m \rangle$  and  $Y=\langle y_1, y_2,..., y_n \rangle$ , find their LCS.

## LCS Intuitive Solution –brute force

- List all possible subsequences of X, check whether they are also subsequences of Y, keep the longer one each time.
- Each subsequence corresponds to a subset of the indices  $\{1,2,...,m\}$ , there are  $2^m$ . So exponential.
- Dynamic Programming (DP)

# Dynamic Programming (DP)

- Initialization
- Recursive Solution
- Trace Back

# **Analysis**

# LCS DP – Step 1: Optimal Substructure

Let 
$$X=\langle x_1, x_2, ..., x_m \rangle$$
 (=  $X_m$ ) and  $Y=\langle y_1, y_2, ..., y_n \rangle$  (=  $Y_n$ )

and

$$Z = \langle z_1, z_2, ..., z_k \rangle$$
 (=  $Z_k$ ) be any LCS of X and Y,

- 1. if  $x_m = y_n$ , then  $z_k = x_m = y_n$ , and  $Z_{k-1}$  is the LCS of  $X_{m-1}$  and  $Y_{n-1}$ .
- 2. if  $x_m \neq y_n$ , then  $z_k \neq x_m$  implies Z is the LCS of  $X_{m-1}$  and  $Y_n$ .
- 3. if  $x_m \neq y_n$ , then  $z_k \neq y_n$  implies Z is the LCS of  $X_m$  and  $Y_{n-1}$ .

For example: X = ABCD X = ABCD X = ABCD

Y = ACD Y = ABC Y = ECDF

Z = ACD and D = D = D Z = ABC and  $C \neq F$  Z = CD and  $D \neq F$ 

# **Analysis**

# LCS DP - Step 2: Recursive Solution

- What Step 1 says:
  - If  $x_m = y_{n}$ , find LCS of  $X_{m-1}$  and  $Y_{n-1}$ , then append  $x_m$ .
  - If  $x_m \neq y_{n_n}$  find LCS of  $X_{m-1}$  and  $Y_n$  and LCS of  $X_m$  and  $Y_{n-1}$ , take which one is longer.
- Overlapping substructure:
  - Both LCS of  $X_{m-1}$  and  $Y_n$  and LCS of  $X_m$  and  $Y_{n-1}$  will need to solve LCS of  $X_{m-1}$  and  $Y_{n-1}$ .
- c[i,j] is the length of LCS of  $X_i$  and  $Y_j$ .

$$c[i,j] = \begin{cases} 0 & \text{if } i=0, \text{ or } j=0 \\ c[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } x_i = y_j \\ \max\{c[i-1,j], c[i,j-1]\} & \text{if } i,j>0 \text{ and } x_i \neq y_j \end{cases}$$

## LCS Intuitive Solution – Dynamic Programming

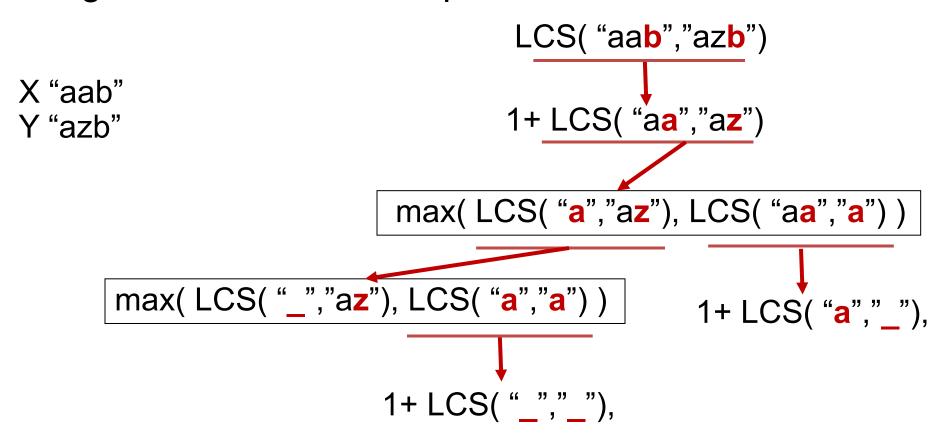
#### Longest Common Subsequence

```
X "aab"
Y "azb"
```

How to decompose the original problem?

## LCS Intuitive Solution – Dynamic Programming

#### Longest Common Subsequence



#### LCS DP Algorithm

```
LCS-LENGTH(X, Y)
 1 m \leftarrow length[X]
 2 n \leftarrow length[Y]
 3 for i \leftarrow 1 to m
 4 do c[i, 0] \leftarrow 0
 5 for j \leftarrow 0 to n
           do c[0, j] \leftarrow 0
     for i \leftarrow 1 to m
 8
            do for j \leftarrow 1 to n
                      do if x_i = y_j
10
                             then c[i, j] \leftarrow c[i - 1, j - 1] + 1
11
                                    b[i, j] \leftarrow " \setminus "
12
                             else if c[i - 1, j] \ge c[i, j - 1]
13
                                       then c[i, j] \leftarrow c[i-1, j]
14
                                             b[i,j] \leftarrow "\uparrow"
15
                                       else c[i, j] \leftarrow c[i, j-1]
16
                                             b[i, j] \leftarrow "\leftarrow"
17
      return c and b
```

## LCS DP – Step 3: Computing the Length of LCS

- Matrix c[0..m,0..n], where c[i,j] is defined as above.
  - -c[m,n] is the answer (length of LCS).
- b[1..m,1..n], where b[i,j] points to the table entry corresponding to the optimal subproblem solution chosen when computing c[i,j].
  - From b[m,n] backward to find the LCS.

## LCS Intuitive Solution – Dynamic Programming

#### Longest Common Subsequence

X "aab" Y "azb"

a a b
a
z
b

## LCS Intuitive Solution – Dynamic Programming

#### Longest Common Subsequence

X "aab" Y "azb"

		a	a	b
	0	0	0	0
a	0	1	1	1 —
Z	0	1	1	1
b	0	1	1	2

# LCS DP – Step 4: Constructing LCS

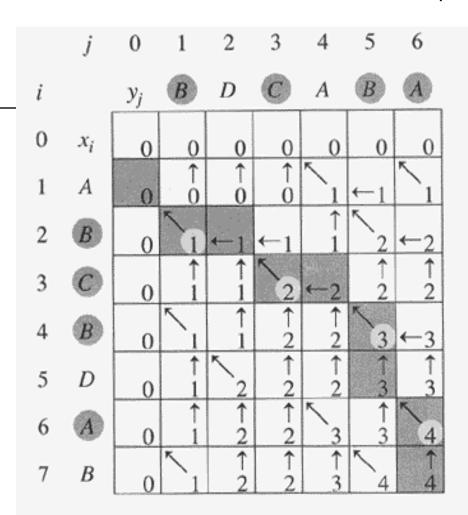
```
PRINT-LCS(b, X, i, j)
  if i = 0 or j = 0
      then return
3 if b[i, j] = "
"
      then PRINT-LCS(b, X, i-1, j-1)
           print x_i
   elseif b[i, j] = "\uparrow"
      then PRINT-LCS(b, X, i - 1, j)
   else PRINT-LCS(b, X, i, j - 1)
```

## LCS Intuitive Solution – Dynamic Programming

#### Longest Common Subsequence

X "aab" Y "azb" 

		а	a	b
	0	0	0	0
a	0	1	1	1 —
Z	0	1 1	1	1 1
b	0	1	1	2



**Figure 15.6** The c and b tables computed by LCS-LENGTH on the sequences  $X = \langle A, B, C, B, D, A, B \rangle$  and  $Y = \langle B, D, C, A, B, A \rangle$ . The square in row i and column j contains the value of c[i, j] and the appropriate arrow for the value of b[i, j]. The entry 4 in c[7, 6]—the lower right-hand corner of the table—is the length of an LCS  $\langle B, C, B, A \rangle$  of X and Y. For i, j > 0, entry c[i, j] depends only on whether  $x_i = y_j$  and the values in entries c[i-1, j], c[i, j-1], and c[i-1, j-1], which are computed before c[i, j]. To reconstruct the elements of an LCS, follow the b[i, j] arrows from the lower right-hand corner; the path is shaded. Each " $\nwarrow$ " on the path corresponds to an entry (highlighted) for which  $x_i = y_j$  is a member of an LCS.

## LCS Intuitive Solution – Dynamic Programming

Longest Common Subsequence: Exercise

X "acb" Y "czb"

	a	C	b
C			
Z			
b			

# Sequence Alignment



WHALE

HUMAN



@1998 GARLAND PUBLISHING



# Aligning DNA Sequences

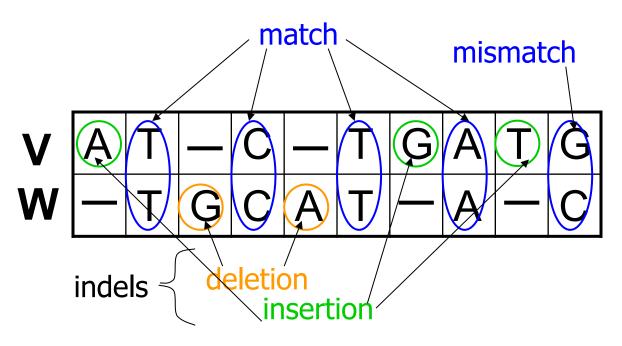
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## Pairwise Sequence Alignment Problem

- Given
  - a pair of sequences (DNA or protein)
  - a method for scoring a candidate alignment
- Do
  - find an alignment for which the score is maximized

What do we mean by this?

TREE V.S. REED

TREE TREE\_ TRE\_E\_ TRE\_E\_
REED \_REED \_REED RE ED ....

## Difficulty of Pairwise Sequence Alignment (PSA)

- Consider two sequences of length n
  - Number of possible global alignments

$$\binom{2n}{n} = \frac{(2n)!}{(n!)^2} \approx \frac{2^{2n}}{\sqrt{(\pi n)}}$$

- For n = 40, there are over  $10^{23}$  possible alignments
- Approaches
  - "Optimal" solution
    - Dynamic programming
  - Heuristic solutions
    - Dot matrix plot
    - FASTA
    - BLAST

# Dynamic Programming (DP)

#### Alignment

- Problem can be subdivided
- Optimal solutions

  1...n-1 nth
- Optimal alignment of n bases
  - 1. Incorporates optimal alignment of 1...n-1 bases
  - 2. Combine with best alignment for n<sup>th</sup> base

#### Bioinformatics application

Global alignment [Needleman-Wunsch 1970]

Local alignment [Smith-Waterman 1981]

### Complexity

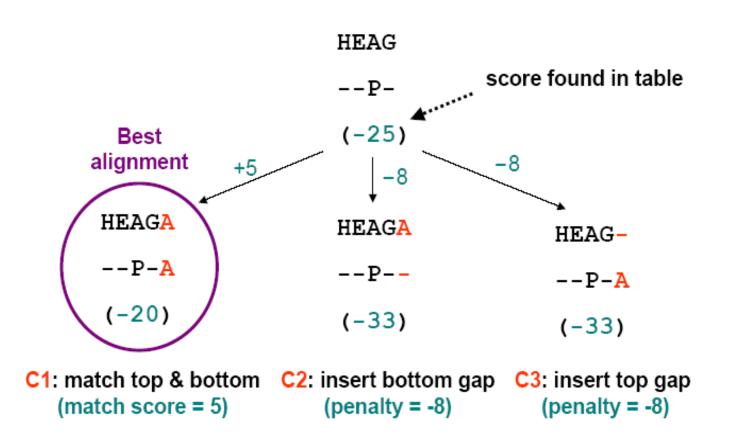
- O( $n^2$ ) or O( $n \times m$ ) algorithm (sequences of length n, m)
- Feasible for moderate-sized sequences, not entire genomes

# Dynamic Programming (DP)

- Dynamic programming usually consists of three components.
  - Recursive relation (Initialization)
  - Tabular computation (Matrix Filling)
  - Trace back (Trace Back)
- This efficient recursive method is used to search through all possible alignments and find the one with the optimal score.

# Intuition of Dynamic Programming

## Considering sequences: "HEAGA" and "PA"



# Intuition of Dynamic Programming

If we already have the optimal solution to:

XY

**AB** 

then we know the **next** pair of characters will either be:

```
XYZ or XY- or XYZ
ABC ABC AB-
(where "-" indicates a gap).
```

So we can extend the match by determining which of these has the highest score.

# DP (Global Alignment)

#### Recursive formula

$$F(i,j) = \max \begin{cases} F(i-1,j-1) + s(x_i, y_j) & \text{c1} \\ F(i-1,j) + d & \text{c2} \\ F(i,j-1) + d & \text{c3} \end{cases}$$

#### Notation

```
-x_i i<sup>th</sup> letter of string x
```

$$-y_i$$
 j<sup>th</sup> letter of string y

$$-x_{1..i}$$
 prefix of x from letters 1 through i

$$F(i, j)$$
 represents optimal score lining up  $x_{1..i}$  with  $y_{1..j}$ 

# Constant vs. Non-constant Gap Penalty

Constant gap penalty

$$F(i,j) = \max \begin{cases} F(i-1, j-1) + s(x_i, y_j), \\ F(i-1, j) + d, \\ F(i, j-1) + d. \end{cases}$$

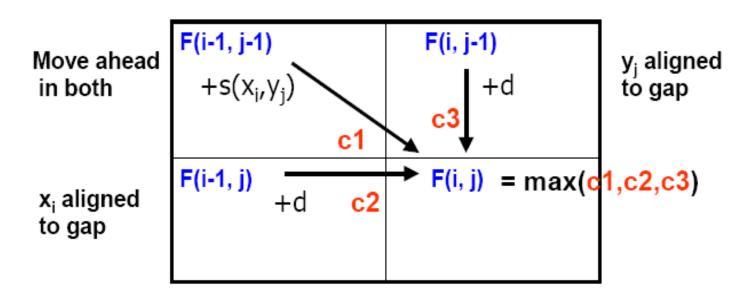
Non-constant gap penalty

$$F(i,j) = \max \begin{cases} F(i-1,j-1) + s(x_i, y_j), \\ F(k,j) + \gamma(i-k), & k = 0,..., i-1, \\ F(i,k) + \gamma(j-k), & k = 0,..., j-1. \end{cases}$$

# DP (Global Alignment)

## Algorithm

- Initialize: F(0,0) = 0,  $F(i,0) = i \times d$ ,  $F(0,j) = j \times d$  (gap penalties)
- Fill from top left to bottom right using recursive formula



While building the table, keep track of where optimal score came from, then reverse arrows

$$F(i,j) = \max \begin{cases} F(i-1,j-1) + s(x_i, y_j) & \text{c1} \\ F(i-1,j) + d & \text{c2} \\ F(i,j-1) + d & \text{c3} \end{cases}$$

# DP Example

## Sequences

– Seq1: HEAGAWGHEE

– Seq2: PAWHEAE

— Gap Penalty: -8 (Constant)

Scoring Matrix (Blosum 50)

	Н	Ε	Α	G	Α	W	G	Н	Ε	Ε
Р	-2	-1	-1	-2	-1	-4	-2	-2	-1	-1
Α	-2	-1	5	0	5	-3	0	-2	-1	-1
W	-3	-3	-3	-3	-3	15	-3	-3	-3	-3
Н	10	0	-2	-2	-2	-3	-2	10	0	0
Е	0	6	-1	-3	-1	-3	-3	0	6	6
Α	-2	-1	5	0	5	-3	0	-2	-1	-1
Е	0	6	-1	-3	-1	-3	-3	0	6	6

# DP Example

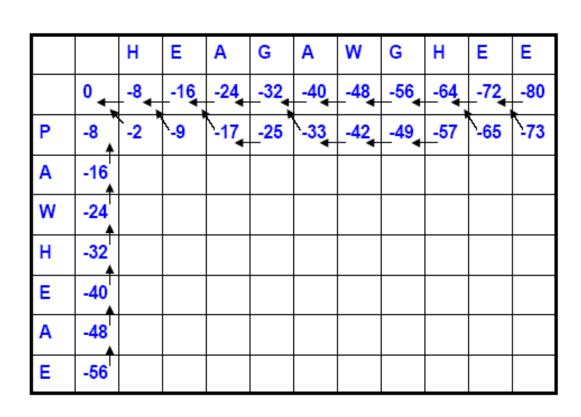
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Fill from top left to bottom right using recursive formula

#### Blosum 50

	Н	Е	Α	G	Α	W	G	Н	Ε	Е
Р	-2	-1	-1	-2	-1	-4	-2	-2	-1	-1
Α	-2	-1	5	0	5	-3	0	-2	-1	-1
W	-3	-3	-3	-3	-3	15	-3	-3	-3	-3
Н	10	0	-2	-2	-2	-3	-2	10	0	0
Е	0	6	-1	-3	-1	-3	-3	0	6	6
Α	-2	-1	5	0	5	-3	0	-2	-1	-1
Е	0	6	-1	-3	-1	-3	-3	0	6	6



$$F(i,j) = \max \begin{cases} F(i-1,j-1) + s(x_i,y_j) & \text{c1} \\ F(i-1,j) + d & \text{c2} \\ F(i,j-1) + d & \text{c3} \end{cases}$$

# DP Example

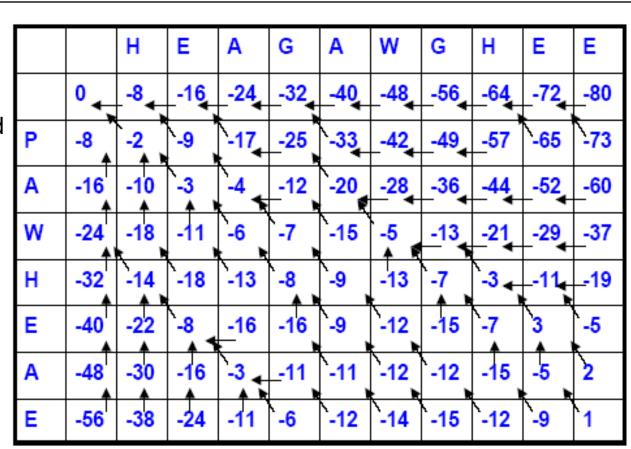
Algorithm

Initialize F(0,0) = 0,  $F(i,0) = i \times d$ ,  $F(0, j) = j \times d$  (gap penalties)

Fill from top left to bottom right using recursive formula

#### Blosum 50

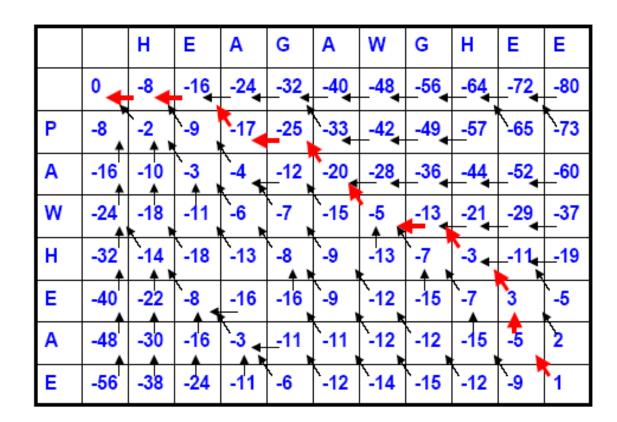
	Н	Е	Α	G	Α	W	G	Н	Е	Е
P	-2	-1	-1	-2	-1	-4	-2	-2	-1	-1
Α	-2	-1	5	0	5	-3	0	-2	-1	-1
W	-3	-3	-3	-3	-3	15	-3	-3	-3	-3
Н	10	0	-2	-2	-2	-3	-2	10	0	0
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$$F(i,j) = \max \begin{cases} F(i-1,j-1) + s(x_i, y_j) & \text{c1} \\ F(i-1,j) + d & \text{c2} \\ F(i,j-1) + d & \text{c3} \end{cases}$$

# DP Example (Traceback)

- Trace arrows from bottom right to top left
  - Diagonal both match
  - Up left sequence match a gap
    - Or insert a gap to top sequence
  - Left top sequence match a gap
    - Or insert a gap to left sequence



Optimal global alignment

HEAGAWGHE-E

## Global alignment vs. local alignment

- Global alignment: the entire sequence of each protein or DNA sequence is contained in the alignment.
- Local alignment: only regions of greatest similarity between two sequences are aligned

percent identity: ~26%

glycodelin: 23 QTKQDLELPKLAGTWHSMAMA-TNNISLMATLKAPLRVHITSLLPTPEDNLEIVLHRWEN 81

## Global alignment vs. local alignment

- Global alignment are often not effective for highly diverged sequences - do not reflect the biological reality that two sequences may only share limited regions of conserved sequence.
- Global methods are useful when you want to force two sequences to align over their entire length
- Local alignment is almost always used for database searches such as BLAST. It is useful to find domains (or limited regions of homology) within sequences.

# DP (Local Alignment)

- Make 0 minimal score (i.e., start new alignment)
- Alignment can start / end anywhere
  - Start at highest score(s)
  - End when 0 reached

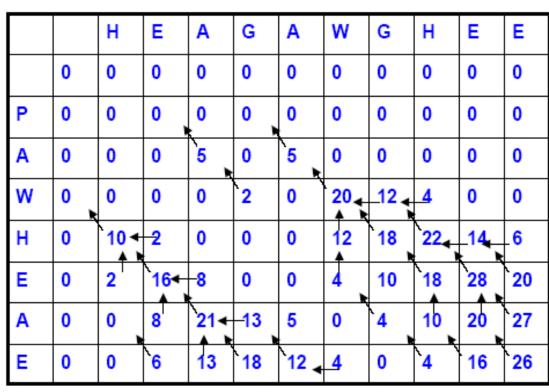
$$F(i, j) = \max \begin{cases} F(i-1, j-1) + s(x_i, y_j) \\ F(i-1, j) + d \\ F(i, j-1) + d \\ 0 \end{cases}$$

# DP (Local Alignment)

$$F(i,j) = \max \begin{cases} F(i-1,j-1) + s(x_i, y_j) \\ F(i-1,j) - 8 \\ F(i,j-1) - 8 \\ 0 \end{cases}$$

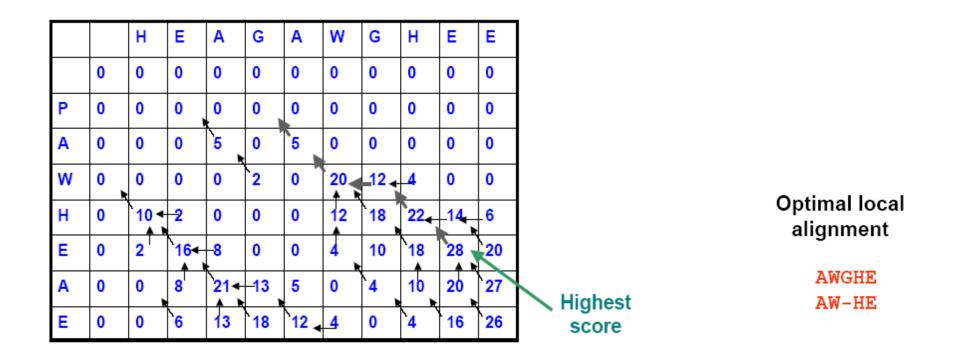
#### Blosum 50

	Н	Ε	Α	G	Α	W	G	Н	Ε	Е
P	-2	-1	-1	-2	-1	-4	-2	-2	-1	-1
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Н	10	0	-2	-2	-2	-3	-2	10	0	0
Е	0	6	-1	-3	-1	-3	-3	0	6	6
Α	-2	-1	5	0	5	-3	0	-2	-1	-1
Ε	0	6	-1	-3	-1	-3	-3	0	6	6



# DP (Local Alignment)

- Traceback
  - Start at highest score and trace arrows back to first 0



# Learning Outcomes

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