



# Chapter 3

# Dynamic Programming

**Algorithm Theory**  
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# Dynamic Programming = Recursion + Memoization



„Memoization“ for increasing the efficiency of a recursive solution:

- Only the *first time* a sub-problem is encountered, its **solution is computed** and then stored in a table. Each subsequent time that the subproblem is encountered, the value stored in the table is simply looked up and returned  
(without repeated computation!).
- *Computing the solution*: For each sub-problem, store how the value is obtained (according to which recursive rule).

# Dynamic Programming

Dynamic programming / memoization can be applied if

- **Optimal solution** contains **optimal solutions to sub-problems** (recursive structure)
- Number of sub-problems that need to be considered is small

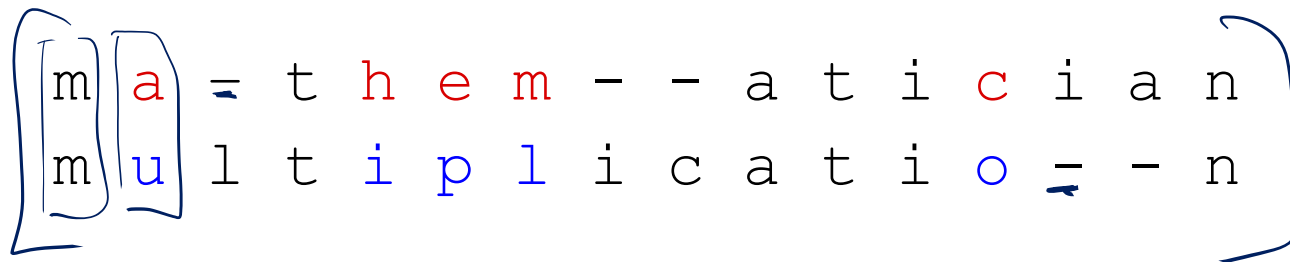
# Edit Distance

**Given:** Two strings  $A = a_1 a_2 \dots a_m$  and  $B = b_1 b_2 \dots b_n$

**Goal:** Determine the minimum number  $D(A, B)$  of edit operations required to transform  $A$  into  $B$

**Edit operations:**

- a) **Replace** a character from string  $A$  by a character from  $B$
- b) **Delete** a character from string  $A$
- c) **Insert** a character from string  $B$  into  $A$

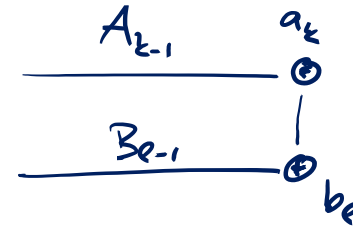

  
 m a = t h e m - - a t i c i a n  
 m u l t i p l i c a t i o - n

# Computation of the Edit Distance

Three ways of ending an “alignment” between  $A_k$  and  $B_\ell$ :

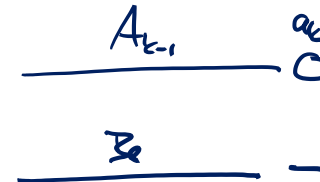
1.  $a_k$  is replaced by  $b_\ell$ :

$$\underline{D_{k,\ell}} = \underline{D_{k-1,\ell-1}} + \underline{c(a_k, b_\ell)}$$



2.  $a_k$  is deleted:

$$D_{k,\ell} = \underline{D_{k-1,\ell}} + \underline{c(a_k, \varepsilon)}$$



3.  $b_\ell$  is inserted:

$$\underline{D_{k,\ell}} = \underline{D_{k,\ell-1}} + \underline{c(\varepsilon, b_\ell)}$$

# Computing the Edit Distance

- Recurrence relation (for  $k, \ell \geq 1$ )

$$D_{k,\ell} = \min \left\{ \begin{array}{l} D_{k-1,\ell-1} + c(a_k, b_\ell) \\ D_{k-1,\ell} + c(a_k, \varepsilon) \\ D_{k,\ell-1} + c(\varepsilon, b_\ell) \end{array} \right\} = \min \left\{ \begin{array}{l} D_{k-1,\ell-1} + 1 / 0 \\ D_{k-1,\ell} + 1 \\ D_{k,\ell-1} + 1 \end{array} \right\}$$

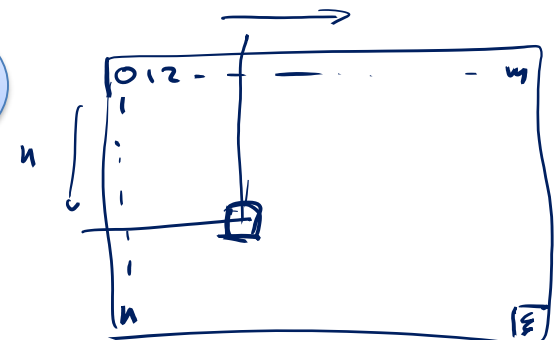
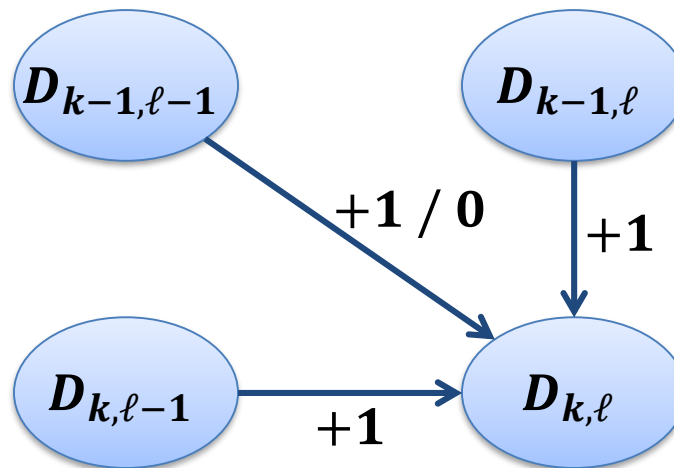
unit cost model

- Need to compute  $D_{i,j}$  for all  $0 \leq i \leq k, 0 \leq j \leq \ell$ :

$$D_{0,0} = 0$$

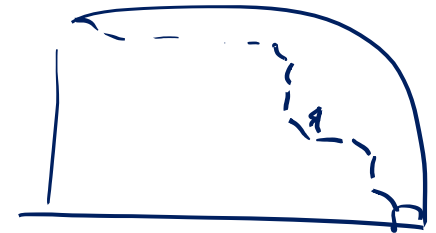
$$D_{0,j} = D_{0,j-1} + c(\varepsilon, b_j)$$

$$D_{i,0} = D_{i-1,0} + c(a_i, \varepsilon)$$



# Edit Distance: Summary

- Edit distance between two strings of length  $m$  and  $n$  can be computed in  $O(mn)$  time.
- Obtain the edit operations:
  - for each cell, store which rule(s) apply to fill the cell
  - track path backwards from cell  $(m, n)$
  - can also be used to get all optimal “alignments”
- Unit cost model:
  - interesting special case
  - each edit operation costs 1

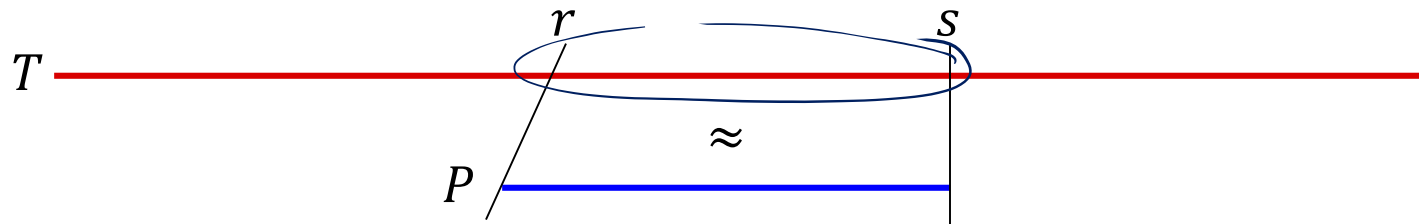


# Approximate String Matching $n \gg m$

**Given:** strings  $T = t_1 t_2 \dots t_n$  (text) and  $P = p_1 p_2 \dots p_m$  (pattern).

**Goal:** Find an interval  $[r, s]$ ,  $1 \leq r \leq s \leq n$  such that the sub-string  $T_{r,s} := t_r \dots t_s$  is the one with highest similarity to the pattern  $P$ :

$$\arg \min_{1 \leq r \leq s \leq n} D(T_{r,s}, P)$$





# Approximate String Matching

## Naive Solution:

**for all  $1 \leq r \leq s \leq n$  do**

    compute  $D(\underline{T}_{r,s}, \underline{P})$

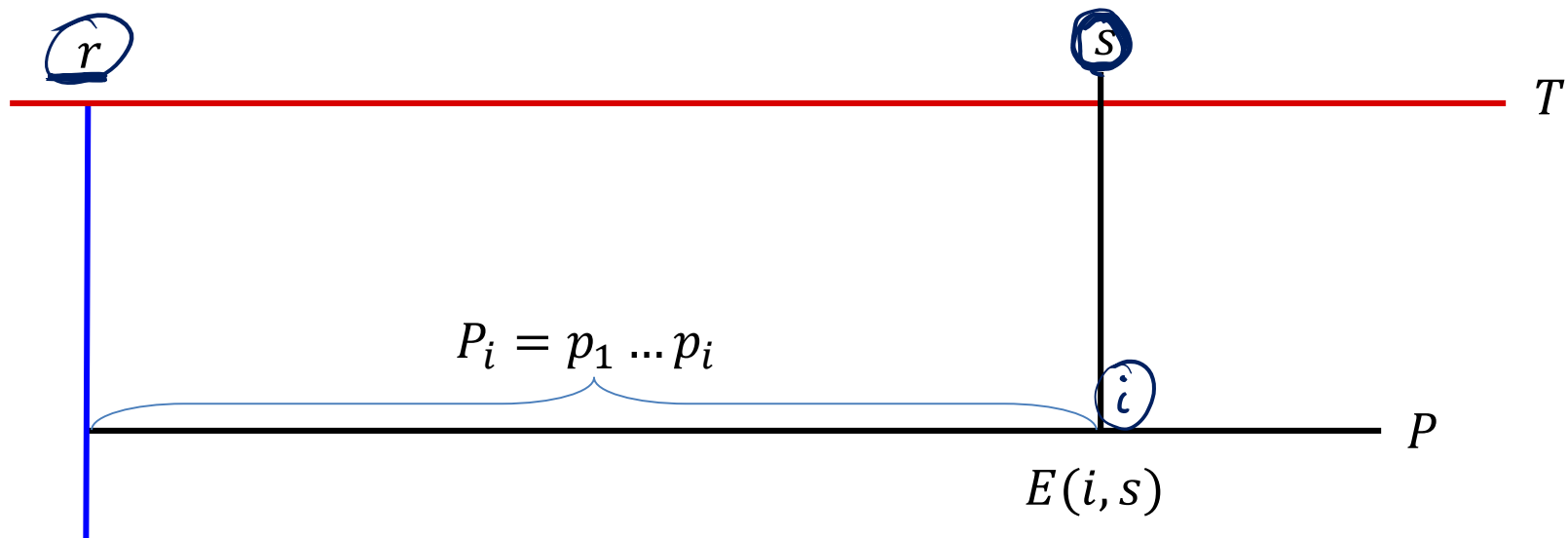
    choose the minimum

$$O(n^2 \cdot n \cdot m)$$

# Approximate String Matching

A related problem:

- For each position  $s$  in the text and each position  $i$  in the pattern compute the minimum edit distance  $E(i, s)$  between  $P_i = p_1 \dots p_i$  and any substring  $T_{r,s}$  of  $T$  that ends at position  $s$ .



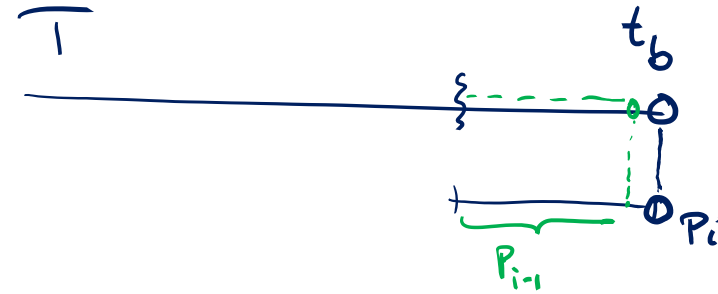
# Approximate String Matching



Three ways of ending optimal alignment between  $T_b$  and  $P_i$ :

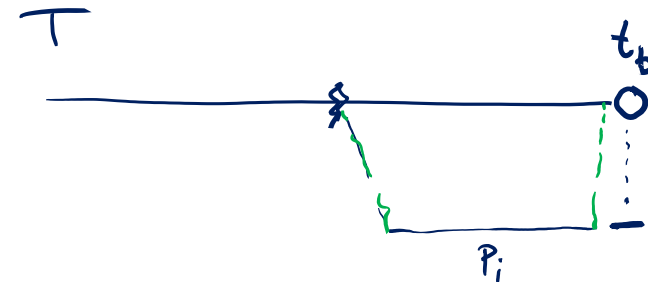
1.  $t_b$  is replaced by  $p_i$ :

$$\underline{E_{b,i}} = \underline{E_{b-1,i-1}} + c(t_b, p_i)$$



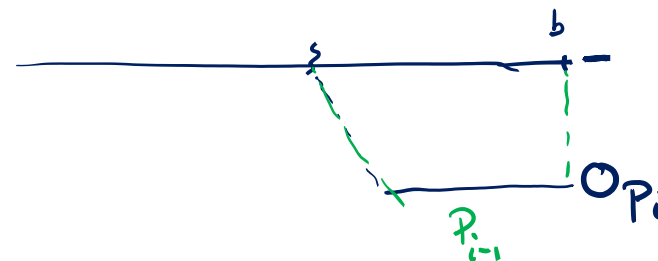
2.  $t_b$  is deleted:

$$E_{b,i} = E_{b-1,i} + c(t_b, \varepsilon)$$



3.  $p_i$  is inserted:

$$E_{b,i} = E_{b,i-1} + c(\varepsilon, p_i)$$



# Approximate String Matching

Recurrence relation (unit cost model):

$$E_{b,i} = \min \begin{cases} E_{b-1,i-1} + 1 \\ E_{b-1,i} + 1 \\ E_{b,i-1} + 1 \end{cases}$$

Base cases:

$$E_{0,0} = 0$$

$$E_{0,i} = i$$

$$E_{i,0} = 0$$

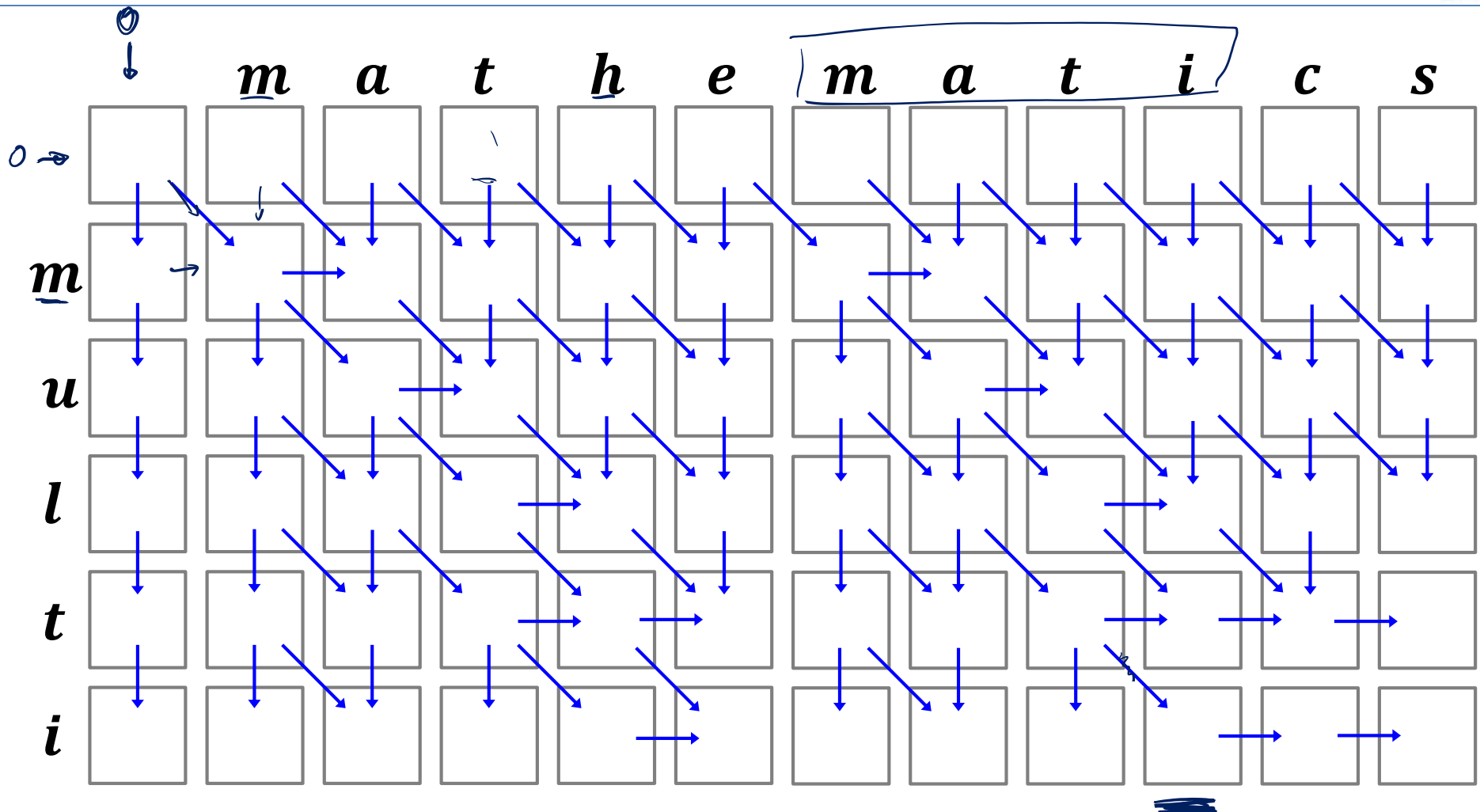


# Example

math

mathem

$O(m \cdot n)$



$E_{b,i}$  : cost of best alignment of  $P_i$  with a subst. of  $T$  ending in pos.  $b$

mathematics  
multic

# Approximate String Matching

- Optimal matching consists of optimal sub-matchings
- Optimal matching can be computed in  $O(mn)$  time
- Get matching(s):
  - Start from minimum entry/entries in bottom row
  - Follow path(s) to top row
- Algorithm to compute  $E(b, i)$  identical to edit distance algorithm, except for the initialization of  $E(b, 0)$

## Sequence Alignment:

Find optimal alignment of two given DNA, RNA, or amino acid sequences.

```
G A - C G G A T T A G
G A T C G G A A T - G
```

## Global vs. Local Alignment:

- Global alignment: find optimal alignment of 2 sequences
- Local alignment: find optimal alignment of sequence 1 (patter) with sub-sequence of sequence 2 (text)