



Chapter 3

Dynamic Programming

Algorithm Theory
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„*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

Knapsack

- n items $1, \dots, n$, each item has **weight** w_i and **value** v_i
- Knapsack (bag) of capacity W
- Goal: pack items into knapsack such that **total weight** is at most W and **total value is maximized**:

$$\begin{aligned} \max \quad & \sum_{i \in S} v_i \\ \text{s. t.} \quad & S \subseteq \{1, \dots, n\} \text{ and } \sum_{i \in S} w_i \leq W \end{aligned}$$

- E.g.: jobs of length w_i and value v_i , server available for W time units, try to execute a set of jobs that maximizes the total value

Recursive Structure?

- Optimal solution: \mathcal{O}
 - If $n \notin \mathcal{O}$: $\text{OPT}(n) = \text{OPT}(n - 1)$
 - What if $n \in \mathcal{O}$?
 - Taking n gives value v_n
 - But, n also occupies space w_n in the bag (knapsack)
 - There is space for $W - w_n$ total weight left!
- $\text{OPT}(n) = w_n +$ **optimal solution with first $n - 1$ items and knapsack of capacity $W - w_n$**

A More Complicated Recursion

$OPT(k, x)$: value of **optimal solution** with **items $1, \dots, k$**
and knapsack of **capacity x**

Recursion:

Dynamic Programming Algorithm

Set up table for all possible $OPT(k, x)$ -values

- Assume that all weights w_i are integers!

	0	1	2	3	...								W
0													
1													
2													
3													
⋮													
n													

Row i , column j :
 $OPT(i, j)$

Example

- 8 items: (3,2), (2,4), (4,1), (5,6), (3,3), (4,3), (5,4), (6,6)
 Knapsack capacity: 12

weight value

- $OPT(k, x) = \max\{OPT(k - 1, x), OPT(k - 1, x - w_k) + v_k\}$

	1	2	3	4	5	6	7	8	9	10	11	12
1												
2												
3												
4												
5												
6												
7												
8												

Running Time of Knapsack Algorithm

- **Size of table:** $O(n \cdot W)$
- Time per table entry: $O(1)$ → **overall time: $O(nW)$**
- Computing solution (set of items to pick):
Follow $\leq n$ arrows → **$O(n)$ time** (after filling table)
- Note: Time depends on W → can be exponential in n ...
- And it is problematic if weights are not integers.

String Matching Problems

Edit distance:

- For two given strings A and B , efficiently compute the **edit distance** $D(A, B)$ (# edit operations to transform A into B) as well as a minimum sequence of edit operations that transform A into B .
- Example:** mathematician \rightarrow multiplication:

m u t i p l a t i o ~~i~~ ~~a~~ n
 └──┬──┘ └──┬──┘
 l i c

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

Edit Distance – Cost Model

- Cost for **replacing** character a by b : $c(a, b) \geq 0$
- Capture insert, delete by allowing $a = \varepsilon$ or $b = \varepsilon$:
 - Cost for **deleting** character a : $c(a, \varepsilon)$
 - Cost for **inserting** character b : $c(\varepsilon, b)$

- **Triangle inequality:**

$$c(a, c) \leq c(a, b) + c(b, c)$$

→ each character is changed at most once!

- **Unit cost model:** $c(a, b) = \begin{cases} 1, & \text{if } a \neq b \\ 0, & \text{if } a = b \end{cases}$

Recursive Structure

- Optimal “alignment” of strings (unit cost model)

bbcadfagikccm and abbagflrgikacc:

```

- b b c a g f a - g i k - c c m
a b b - a d f l r g i k a c c -

```

- Consists of optimal “alignments” of sub-strings, e.g.:

```

-bbcagfa      and      -gik-ccm
abb-adfl      rgikacc-

```

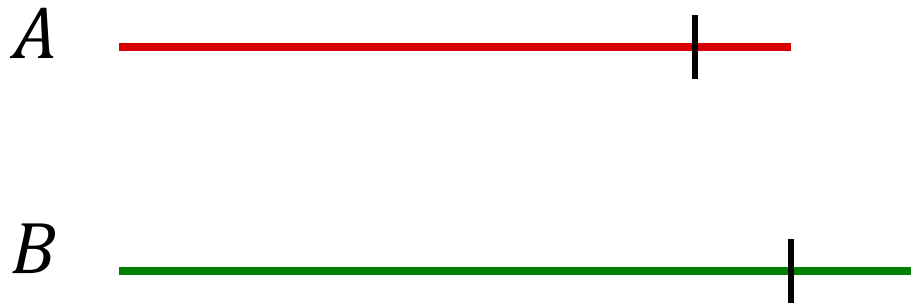
- Edit distance between $A_{1,m} = a_1 \dots a_m$ and $B_{1,n} = b_1 \dots b_n$:

$$D(A, B) = \min_{k, \ell} \{ D(A_{1,k}, B_{1,\ell}) + D(A_{k+1,m}, B_{\ell+1,n}) \}$$

Computation of the Edit Distance

Let $A_k := a_1 \dots a_k$, $B_\ell := b_1 \dots b_\ell$, and

$$D_{k,\ell} := D(A_k, B_\ell)$$



Computation of the Edit Distance

Three ways of ending an “alignment” between A_k and B_ℓ :

1. a_k is replaced by b_ℓ :

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

2. a_k is deleted:

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

3. b_ℓ is inserted:

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

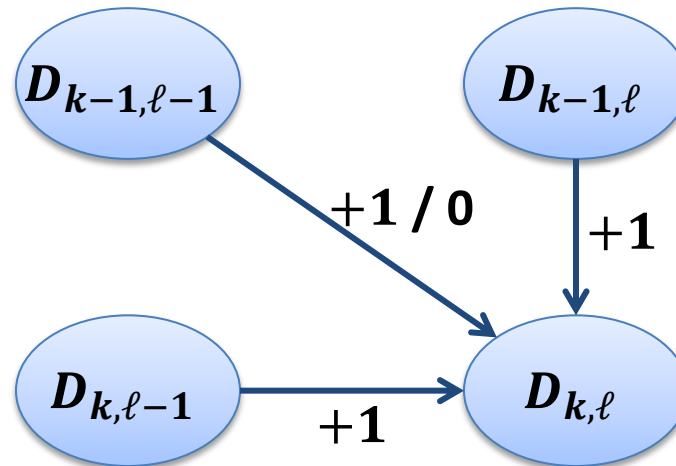
Computing the Edit Distance

- 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 $0 \leq i \leq k, 0 \leq j \leq \ell$:



Base cases:

$$D_{0,0} = D(\varepsilon, \varepsilon) = 0$$

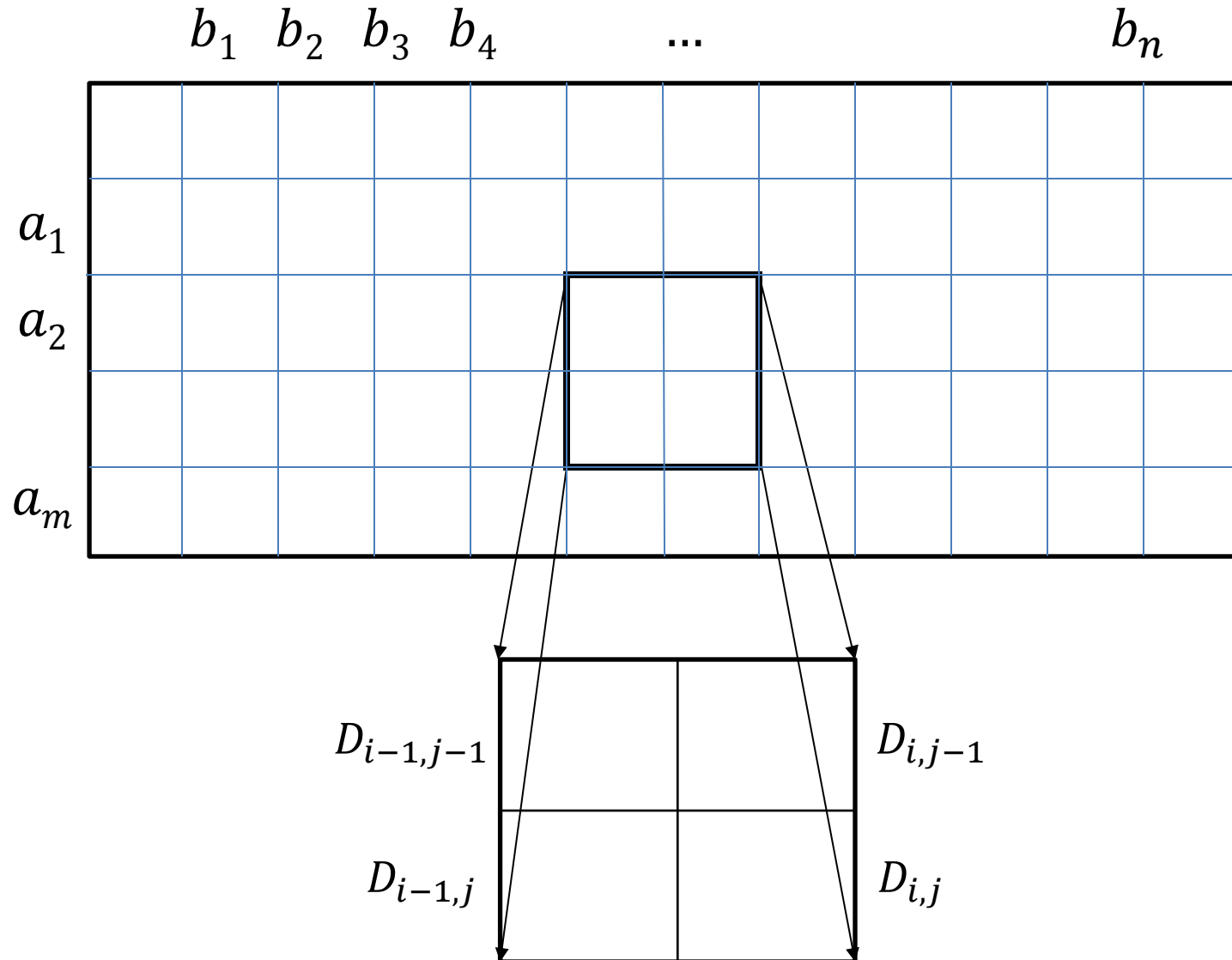
$$D_{0,j} = D(\varepsilon, B_j) = D_{0,j-1} + c(\varepsilon, b_j)$$

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

Recurrence relation:

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

Order of solving the subproblems



Algorithm for Computing the Edit Distance



Algorithm *Edit-Distance*

Input: 2 strings $A = a_1 \dots a_m$ and $B = b_1 \dots b_n$

Output: matrix $D = (D_{ij})$

1 $D[0,0] := 0;$

2 **for** $i := 1$ **to** m **do** $D[i, 0] := i;$

3 **for** $j := 1$ **to** n **do** $D[0, j] := j;$

4 **for** $i := 1$ **to** m **do**

5 **for** $j := 1$ **to** n **do**

6 $D[i, j] := \min \left\{ \begin{array}{l} D[i-1, j] \quad + 1 \\ D[i, j-1] \quad + 1 \\ D[i-1, j-1] + c(a_i, b_j) \end{array} \right\};$