



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**:

$$\max \sum_{i \in S} v_i$$

$$\text{s. t. } \underline{S} \subseteq \{1, \dots, n\} \text{ and } \sum_{i \in S} \underline{w}_i \leq \underline{W}$$

- 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?

OPT(k)



- 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!

$$\text{OPT}(n) = \overset{v_n}{\cancel{w_n}} + \text{optimal solution with first } \underline{n - 1} \text{ items} \\ \text{and knapsack of capacity } \underline{W - w_n}$$

A More Complicated Recursion OPT(n, W)

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

n possibilities

Recursion:

only makes sense if $x - w_k \geq 0$

$$OPT(k, x) = \max \left\{ \underbrace{OPT(k-1, x)}_{\text{opt sol. if } k \text{ is not cont.}}, v_k + \underbrace{OPT(k-1, x - w_k)}_{\text{remaining cap. after taking } k} \right\}$$

Initialization:

$$OPT(0, x) = 0$$

$$OPT(k, 0) = 0$$

#possibilities for 2nd parameter: ∞ , exp.

assumption: weights are integers

→ $W + 1$ options for 2nd parameter

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	0	0	0	0	0	0
1	0				1	
2	0				1	
3	0	—	—	—	*	
...	0					
k	0					
...	0					
n	0					

← 2nd param.
Row i , column j :
 $OPT(i, j)$

*: $OPT(3, 5)$
items 1..3
cap. 5

↖ #items

Example

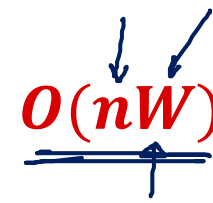
- 8 items: (3,2), (2,4), (4,1), (5,6), (3,3), (4,3), (5,4), (6,6)
- Knapsack capacity: 12

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	0	0	2	2	2	2	2	2	2	2	2	2
2	0	4	4	4	6	6	6	6				
3												
4												
5												
6												
7												
8										6	11	

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.
 weights are rational would be possible
another special case: values are integers
 - NP-hard problem
 - but, one can compute an arbitrarily close to opt. solution in poly. time

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 ic 10 operations

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

(Note: In the original image, red characters 'a', 'h', 'e', 'm', 'c' in the first row and 'u', 'l', 'i', 'p', 'l', 'i', 'o' in the second row are underlined. Blue characters 'u', 'l', 'i', 'p', 'l', 'i', 'o' in the second row are also underlined.)

Edit Distance – Cost Model

- Cost for **replacing** character a by b : $c(\underline{a}, \underline{b}) \geq 0$

$$c(a, a) = 0$$

- Capture insert, delete by allowing $a = \varepsilon$ or $b = \varepsilon$:

- Cost for **deleting** character a : $c(\underline{a}, \underline{\varepsilon})$

- Cost for **inserting** character b : $c(\underline{\varepsilon}, \underline{b})$

- **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-
  
```

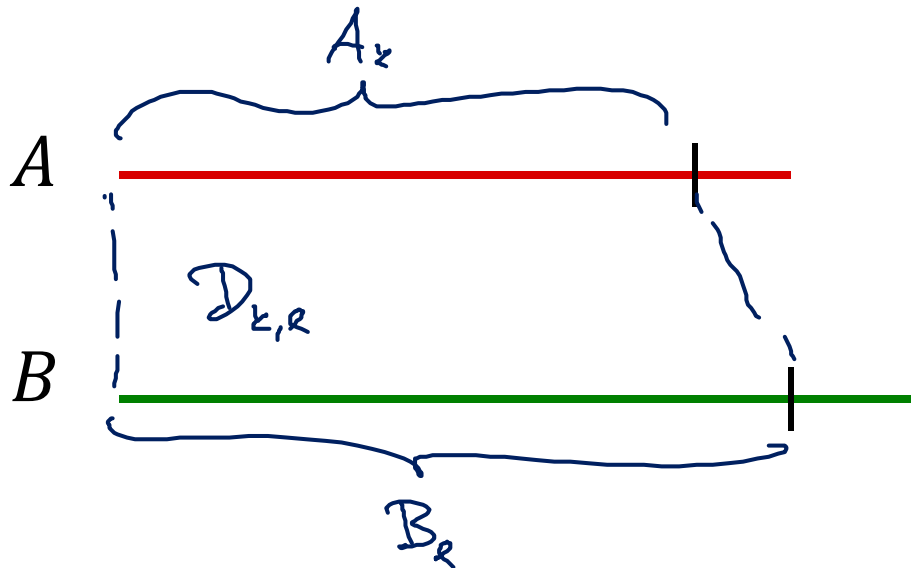
- Edit distance between $A_{1,m} = a_1 \dots a_m$ and $B_{1,n} = b_1 \dots b_n$:

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

Computation of the Edit Distance

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

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

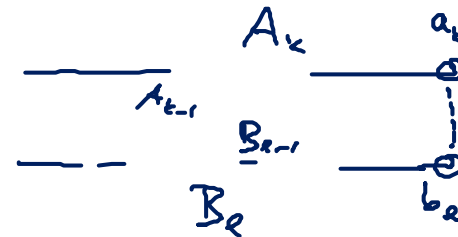


Computation of the Edit Distance

Three ways of ending an “alignment” between \underline{A}_k and \underline{B}_ℓ :

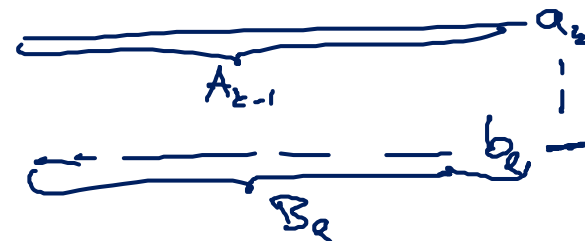
1. a_k is replaced by b_ℓ :

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



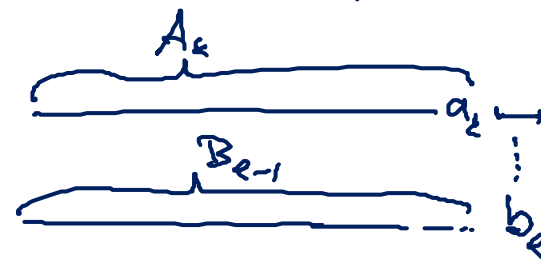
2. a_k is deleted:

$$\underline{D}_{k,\ell} = \underline{D}_{k-1,\ell} + c(\overset{\downarrow}{a_k}, \varepsilon)$$



3. b_ℓ is inserted:

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



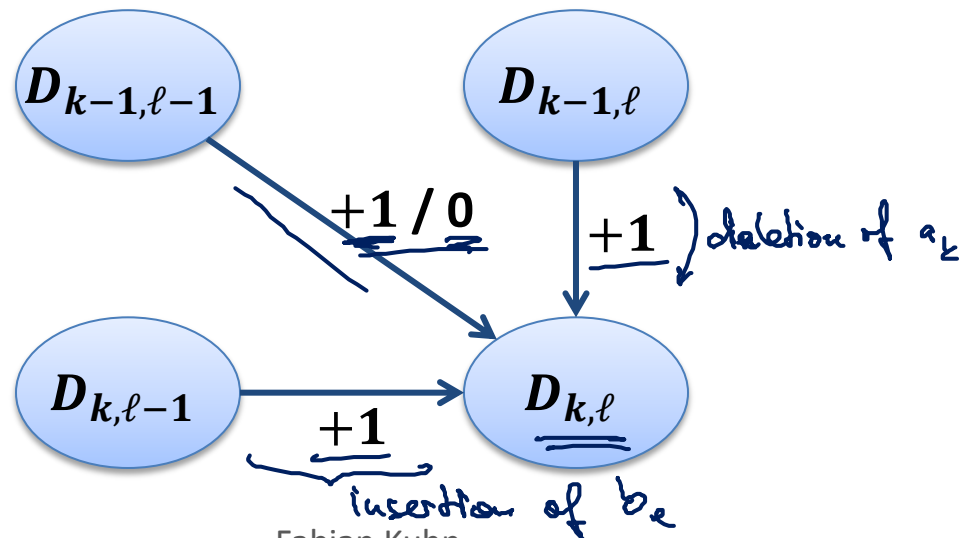
Computing the Edit Distance

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

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

unit cost model

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



Base cases:

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

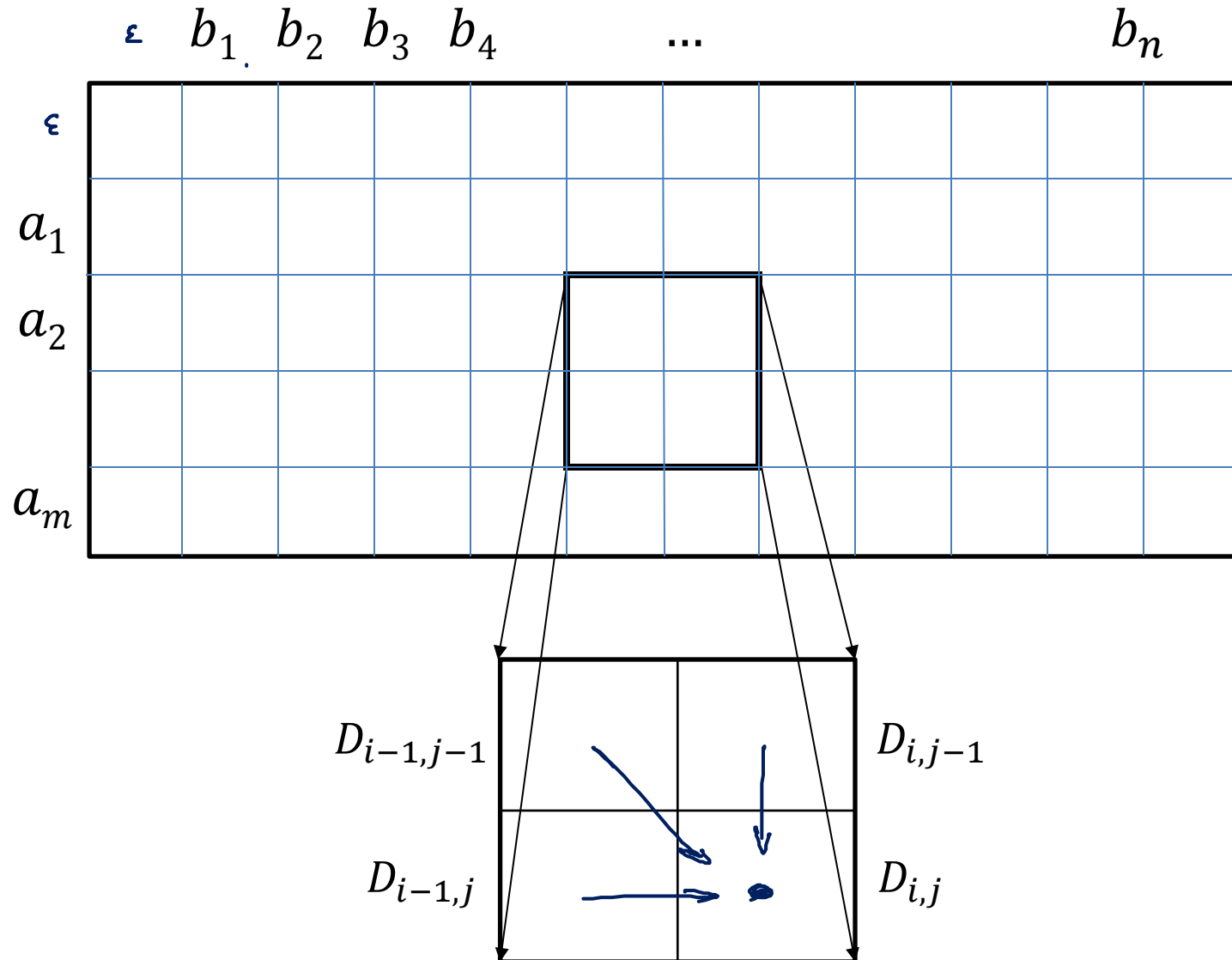
$$D_{\underline{0},\underline{j}} = D(\varepsilon, B_j) = D_{\underline{0},\underline{j-1}} + c(\varepsilon, b_j) \quad (= j \text{ in unit cost})$$

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

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