

WS 2021/22

Algorithms

Chapter 6

Dynamic Programming

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Chapter 6: Dynamic Programming (DP)

Algorithm paradigm for **optimization problems**. Typical:

- Define (many) **“subproblems”** (of an input instance)
- Identify simple **base cases**
- Formulate a version of the property

Substructures of optimal structures are optimal

- Find recursion equations for **values** of optimal solutions:

Bellman’s optimality equations

- Calculate optimal values (and structures) **iteratively**

6.3 Edit distance

Problem statement: Let A be alphabet. (Example: Latin alphabet, ASCII alphabet, $\{A,C,G,T\}$.) Then A^* denotes the set of all strings (or words) over A .

If $x = a_1 \dots a_m \in A^*$ and $y = b_1 \dots b_n \in A^*$ are two strings over A , we ask how **similar** (or different) they are.

“Arbeit” (*work*) and “Freizeit” (*leisure time*) are not identical, but intuitively more similar than “informatics” and “camping”.

How to measure “being more or less similar”?

We define elementary steps (“edit operations”), which change a string:

- Delete a letter: From uav obtain uv ($u, v \in A^*$, $a \in A$). Example: be**a**t \rightarrow bet.
- Insert a letter: From uv obtain uav ($u, v \in A^*$, $a \in A$). Example: bet \rightarrow be**a**t.
- Replace a letter: From uav obtain ubv ($u, v \in A^*$, $a, b \in A$).
Example: be**a**t \rightarrow be**s**t.

The “distance” or **edit distance** $d(x, y)$ of x and y is the minimal number of edit operations one needs to transform x into y .

Obvious: $d(x, y) = d(y, x)$. (Insertion and deletion are inverses, replacement is self-inverse.)

Observe: Transforming is equivalent to aligning:

A	r	b	e	i	-	-	-	t				
F	r	-	e	i	z	e	i	t				
<hr/>												
i	n	f	o	r	m	a	t	-	i	c	s	
c	-	-	-	-	-	a	m	p	i	n	g	

One aligns strings with some extra dashes below each other, where the two lines without dashes give x and y . The **cost** of such an alignment is the number of positions where letters in the two lines differ.

Claim: The cost of such an alignment is the same as the number of edit operations in a sequence of operations that transforms one word into the other. (In the examples: **5** and **10**, resp.) Hence: The **minimal** cost of an alignment is exactly the edit distance. (In the examples: **4** (!) and **10**, resp.)

The problem “edit distance” is the following:

Input: Strings $x = a_1 \dots a_m$, $y = b_1 \dots b_n$ from A^* .

Task: Calculate $d(x, y)$ (and a sequence of edit operations resp. an alignment that transforms x into y of cost $d(x, y)$).

Strategy: **Dynamic programming**

Our example: $x = \text{exponentiell}$ und $y = \text{polynomiell}$.

Step 1: Identify relevant **subproblems**.

Consider prefixes $x[1..i] = a_1 \dots a_i$ and $y[1..j] = b_1 \dots b_j$, and let

$$\mathbf{E}(i, j) := d(x[1..i], y[1..j]), \text{ for } 0 \leq i \leq m, 0 \leq j \leq n$$

In the example: **$E(7, 6)$** means we are to calculate $d(\text{exponen}, \text{polyno})$
(because $x[1..7] = \text{exponen}$ und $y[1..6] = \text{polyno}$).

In order to obtain Bellman equations, we consider relations among subproblems. For this we utilize the idea of aligning words as on slide 3.

Consider (nonempty) prefixes $x[1..i] = a_1 \dots a_i$ and $y[1..j] = b_1 \dots b_j$, for $1 \leq i \leq m$, $1 \leq j \leq n$.

If $x[1..i]$ and $y[1..j]$ are aligned optimally, with cost $E(i, j)$, there are three possibilities for the **last position** in the alignment:

Case 1 (copy/replace)	Case 2 (delete)	Case 3 (insert)
$x[1..i - 1] \ a_i$	$x[1..i - 1] \ a_i$	$x[1..i] \ -$
$y[1..j - 1] \ b_j$	$y[1..j] \ -$	$y[1..j - 1] \ b_j$

Case 1 (copy/replace)	Case 2 (delete)	Case 3 (insert)
$x[1..i-1]$ a_i	$x[1..i-1]$ a_i	$x[1..i]$ -
$y[1..j-1]$ b_j	$y[1..j]$ -	$y[1..j-1]$ b_j

Case 1: There is a replacement in the last position, with cost

$$\text{diff}(a_i, b_j) := [a_i \neq b_j] = \begin{cases} 1 & \text{if } a_i \neq b_j \\ 0 & \text{if } a_i = b_j \end{cases}.$$

$x[1..i-1]$ und $y[1..j-1]$ must be optimally aligned (“optimal substructure”).

$$\Rightarrow E(i, j) = E(i-1, j-1) + \text{diff}(a_i, b_j).$$

Case 2: There is a deletion in the last position, with cost 1.

$x[1..i-1]$ and $y[1..j]$ must be optimally aligned.

$$\Rightarrow E(i, j) = E(i-1, j) + 1.$$

Case 3: There is an insertion in the last position, with cost 1.

$x[1..i]$ and $y[1..j-1]$ must be optimally aligned.

$$\Rightarrow E(i, j) = E(i, j-1) + 1.$$

Among the three cases the one/s with the smallest cost is/are relevant.
Altogether, we obtain:

Bellman optimality equations for edit distance:

$$E(i, j) = \min\{E(i - 1, j - 1) + \text{diff}(a_i, b_j), E(i - 1, j) + 1, E(i, j - 1) + 1\}.$$

Base cases: Empty prefixes $\varepsilon = x[1..0]$ and $\varepsilon = y[1..0]$.

Obvious: $E(i, 0) = d(x[1..i], \varepsilon) = i$, for $0 \leq i \leq m$, and
 $E(0, j) = d(\varepsilon, y[1..j]) = j$, for $0 \leq j \leq n$.

(One has to delete/insert all letters.)

The numbers $E(i, j)$ are computed iteratively, entering them into a matrix $E[0..m, 0..n]$. This is already the “dynamic programming algorithm” for edit distance.

Initialization:

$E[i, 0] \leftarrow i$, for $i = 0, \dots, m$;

$E[0, j] \leftarrow j$, for $j = 0, \dots, n$.

Then we fill in the matrix (i.,e.) row by row, following the Bellman equations:

for i **from** 1 **to** m **do**

for j **from** 1 **to** n **do**

$E[i, j] \leftarrow \min\{E[i-1, j-1] + \text{diff}(a_i, b_j), E[i-1, j] + 1, E[i, j-1] + 1\}$;

return $E[m, n]$.

Time: $O(m \cdot n)$.

Remark: For doing the calculation by hand it saves time to identify the pairs (i, j) with $\text{diff}(a_i, b_j) = 0$, or $a_i = b_j$, beforehand (red, underlined).

E		p	o	l	y	n	o	m	i	e	l	l
	0	1	2	3	4	5	6	7	8	9	10	11
e	1									—		
x	2											
p	3	—										
o	4		—				—					
n	5					—						
e	6									—		
n	7					—						
t	8											
i	9								—			
e	10									—		
l	11				—						—	—
l	12				—						—	—

Base values $E(i, 0)$ and $E(0, j)$, markers for $\text{diff}(a_i, b_j) = 0$.

E		p	o	l	y	n	o	m	i	e	l	l
	0	1	2	3	4	5	6	7	8	9	10	11
e	1	1	2	3	4	5	6	7	8	<u>8</u>	9	10
x	2	2	2	3	4	5	6	7	8	9	9	10
p	3	<u>2</u>	3	3	4	5	6	7	8	9	10	10
o	4	3	—				—					
n	5					—						
e	6									—		
n	7					—						
t	8											
i	9								—			
e	10									—		
l	11				—						—	—
l	12				—						—	—

Filled in row by row up to $E(4, 1)$.

E		p	o	l	y	n	o	m	i	e	l	l
	0	1	2	3	4	5	6	7	8	9	10	11
e	1	1	2	3	4	5	6	7	8	<u>8</u>	9	10
x	2	2	2	3	4	5	6	7	8	9	9	10
p	3	<u>2</u>	3	3	4	5	6	7	8	9	10	10
o	4	3	<u>2</u>				—					
n	5					—						
e	6									—		
n	7					—						
t	8											
i	9								—			
e	10									—		
l	11			—							—	—
l	12			—							—	—

$$E(4, 2) = \min\{\mathbf{2} + \mathbf{0}, \mathbf{3} + 1, \mathbf{3} + 1\} = \mathbf{2}.$$

<i>E</i>		p	o	l	y	n	o	m	i	e	l	l
	0	1	2	3	4	5	6	7	8	9	10	11
e	1	1	2	3	4	5	6	7	8	<u>8</u>	9	10
x	2	2	2	3	4	5	6	7	8	9	9	10
p	3	<u>2</u>	3	3	4	5	6	7	8	9	10	10
o	4	3	<u>2</u>	3			—					
n	5					—						
e	6									—		
n	7					—						
t	8											
i	9								—			
e	10									—		
l	11										—	—
l	12											—

$$E(4, 3) = \min\{\mathbf{3} + 1, \mathbf{3} + 1, \mathbf{2} + 1\} = \mathbf{3}.$$

<i>E</i>		p	o	l	y	n	o	m	i	e	l	l
	0	1	2	3	4	5	6	7	8	9	10	11
e	1	1	2	3	4	5	6	7	8	<u>8</u>	9	10
x	2	2	2	3	4	5	6	7	8	9	9	10
p	3	<u>2</u>	3	3	4	5	6	7	8	9	10	10
o	4	3	<u>2</u>	3	4	5	<u>5</u>	6	7	8	9	10
n	5	4	3	3	4	<u>4</u>	5	6	7	8	9	10
e	6	5	4	4	4	5	5	6	7	<u>7</u>	8	9
n	7	6	5	5	5	<u>4</u>	5	6	7	8	8	9
t	8	7	6	6	6	5	5	6	7	8	9	9
i	9	8	7	7	7	6	6	6	<u>6</u>	7	8	9
e	10	9	8	8	8	7	7	7	7	<u>6</u>	7	8
l	11	10	9	<u>8</u>	9	8	8	8	8	7	<u>6</u>	<u>7</u>
l	12	11	10	<u>9</u>	9	9	9	9	9	8	<u>7</u>	<u>6</u>

Matrix is filled completely. Result: $d(x, y) = E(12, 11) = 6$, lower right corner!

Discovering an optimal edit sequence in time $O(m + n)$

Given x and y , one wants not only $d(x, y)$, but also the sequence of operations that transforms x into y in $d(x, y)$ steps.

If we have the matrix $E[0..m, 0..n]$, this is easy:

We walk a path from (m, n) to $(0, 0)$. From (i, j) we go to

$$\begin{aligned} (i - 1, j - 1), & \quad \text{if } E(i, j) = E(i - 1, j - 1) + \text{diff}(a_i, b_j), \\ (i - 1, j), & \quad \text{if } E(i, j) = E(i - 1, j) + 1, \\ (i, j - 1), & \quad \text{if } E(i, j) = E(i, j - 1) + 1. \end{aligned}$$

If more than one of the equations hold, we can choose arbitrarily.

The path we find ends in $(0, 0)$. This path, read backwards, from $(0, 0)$ to (m, n) , represents a transformation of x into y , where letters are left alone, replaced, inserted, or deleted. One reads $x = x[1..m]$ from left to right and generates $y[1..n]$ from left to right.

- (1) $(i - 1, j - 1) \xrightarrow{b} (i, j)$ corresponds to copying a_i ($b = 0$) or replacing it by b_j ($b = 1$);
- (2) $(i - 1, j) \xrightarrow{1} (i, j)$ corresponds to deleting a_i ;
- (3) $(i, j - 1) \xrightarrow{1} (i, j)$ corresponds to inserting b_j .

<i>E</i>		p	o	l	y	n	o	m	i	e	l	l
	0	1	2	3	4	5	6	7	8	9	10	11
e	1	1	2	3	4	5	6	7	8	8	9	10
x	2	2	2	3	4	5	6	7	8	9	9	10
p	3	2	3	3	4	5	6	7	8	9	10	10
o	4	3	2	3	4	5	5	6	7	8	9	10
n	5	4	3	3	4	4	5	6	7	8	9	10
e	6	5	4	4	4	5	5	6	7	7	8	9
n	7	6	5	5	5	4	5	6	7	8	8	9
t	8	7	6	6	6	5	5	6	7	8	9	9
i	9	8	7	7	7	6	6	6	6	7	8	9
e	10	9	8	8	8	7	7	7	7	6	7	8
l	11	10	9	8	9	8	8	8	8	7	6	7
l	12	11	10	9	9	9	9	9	9	8	7	6

In the example: $(0, 0) \xrightarrow{1} (1, 0) \xrightarrow{1} (2, 0) \xrightarrow{0} (3, 1) \xrightarrow{0} (4, 2) \xrightarrow{1} (5, 3) \xrightarrow{1} (6, 4) \xrightarrow{0} (7, 5) \xrightarrow{1} (8, 6) \xrightarrow{1} (8, 7) \xrightarrow{0} (9, 8) \xrightarrow{0} (10, 9) \xrightarrow{0} (11, 10) \xrightarrow{0} (12, 11)$, cost 6.

This yields the following alignment/transformation, where the six “chargeable” positions are marked in red:

e	x	p	o	n	e	n	t	-	i	e	l	l
-	-	p	o	l	y	n	o	m	i	e	l	l

One more example:

$x = \text{speziell}$ (*special*) and $y = \text{beliebig}$ (*arbitrary*).

Filling in the matrix gives:

E		b	e	l	i	e	b	i	g
	0	1	2	3	4	5	6	7	8
s	1	1	2	3	4	5	6	7	8
p	2	2	2	3	4	5	6	7	8
e	3	3	<u>2</u>	3	4	<u>4</u>	5	6	7
z	4	4	3	3	4	5	5	6	7
i	5	5	4	4	<u>3</u>	4	5	<u>5</u>	6
e	6	6	<u>5</u>	5	4	<u>3</u>	4	5	6
l	7	7	6	<u>5</u>	5	4	4	5	6
l	8	8	7	<u>6</u>	6	5	5	5	6

Red, underlined: the positions (i, j) with $a_i = b_j$.

Retracing yields the following sequence of operations (one possibility among others):

$(0, 0) \rightarrow (1, 1) \rightarrow (2, 1) \rightarrow (3, 2) \rightarrow (4, 3) \rightarrow (5, 4) \rightarrow (6, 5) \rightarrow (6, 6) \rightarrow (7, 7) \rightarrow (8, 8)$.

This yields the following alignment:

```
  s p e z i e - l l
  -----
  b - e l i e b i g
```

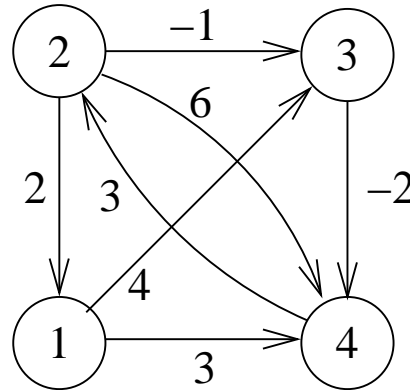
There are other alignments with cost 6, e.g.

```
  s p e z i e l l -
  -----
  - b e l i e b i g
```

6.6 The All-Pairs-Shortest-Paths problem

Central example for dynamic programming: The “**APSP** problem”.
“shortest paths between all nodes”.

Input:



Directed graph $G = (V, E, c)$

with $V = \{1, \dots, n\}$ and $E \subseteq \{(v, w) \mid 1 \leq v, w \leq n, v \neq w\}$.

$c: E \rightarrow \mathbb{R} \cup \{+\infty\}$: **Weight/cost/length function.**

Cost/Length of a walk $p = (v = v_0, v_1, \dots, v_r = w)$ is

$$c(p) = \sum_{1 \leq s \leq r} c(v_{s-1}, v_s).$$

Task: For all (v, w) , $1 \leq v, w \leq n$, find a walk from v to w with minimal cost/length $c(p)$ (“shortest path”).

Here: **Floyd-Warshall algorithm**.

We demand:

No **cycles** have negative total weight:

$$(*) \quad (v = v_0, v_1, \dots, v_r = v) \text{ cycle} \Rightarrow \sum_{1 \leq s \leq r} c(v_{s-1}, v_s) \geq 0.$$

Reason: If there is a negative cycle from v to v , and some walk from v to w , then there are walks from v to w with negative length of arbitrarily large absolute value – the question for a “shortest path” does not make sense.

Consequences: (1) If p is a walk from v to w , then there is a (simple) path p' from v to w with $c(p') \leq c(p)$.

Reason: Cut out (u, \dots, u) -segments from p , repeatedly, until no repetition remains. The walk cannot get longer by this operation.)

(2) If there is a walk from v to w at all, then there also is one with minimal length (a “**shortest path**”).

Reason: Because of (1) it suffices to consider simple paths (with at most $n - 1$ edges); of these there are only finitely many.

But: There may be several “shortest paths” from v to w . (Simple paths and maybe walks with cycles of length 0.)

First: Determine **length** $S(v, w)$ of a shortest path from v to w , for all $v, w \in V$. (∞ , if no path exists.)

Output: matrix $S = (S(v, w))_{1 \leq v, w \leq n}$.

W.l.o.g.: $E = V \times V - \{(v, v) \mid v \in V\}$

Edges (v, w) that are not present (v, w) are represented by $c(v, w) = \infty$.

First step: Identify suitable **subproblems**.

Given k , $0 \leq k \leq n$, consider paths from v to w that **in between** (excepting start and end node) visit only nodes in $\{1, \dots, k\}$.

$k = 0$: Cannot visit any node on the way;
only edges (v, w) with $c(v, w) < \infty$, or paths (v, v) of length 0.

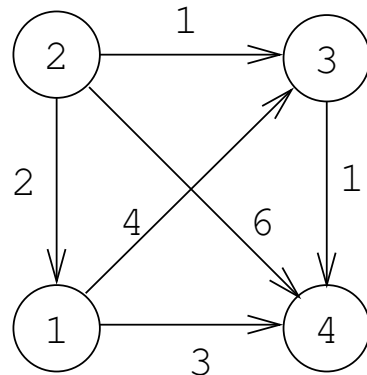
$k = 1$: Possible paths: (v, w) ((v) if $v = w$) and $(v, 1, w)$.

$k = 2$: Possible paths: (v, w) ((v) if $v = w$), $(v, 1, w)$, $(v, 2, w)$, $(v, 1, 2, w)$, and $(v, 2, 1, w)$.

Etc.

$S(v, w, k)$:= length of a shortest path from v to w using only nodes in $\{1, \dots, k\}$ underway.
 (= ∞ , if there is no such path.)

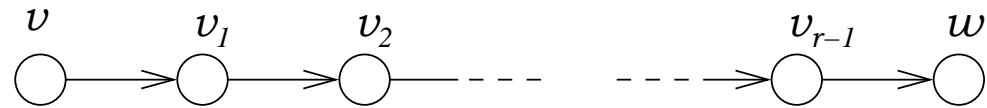
Example:



$$\begin{array}{r}
 S(2, 4, 0) = 6 \\
 S(2, 4, 1) = 5 \\
 S(2, 4, 2) = 5 \\
 S(2, 4, 3) = 2
 \end{array}
 \begin{array}{l}
 | \\
 \downarrow \text{monotonically} \\
 \downarrow \text{decreasing}
 \end{array}$$

“Bellman equations”:

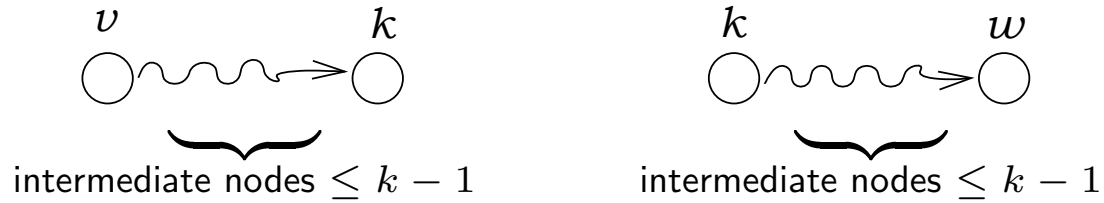
Consider path $p = (v_0, \dots, v_r)$ from v to w ; intermediate nodes v_1, \dots, v_{r-1} are from $\{1, \dots, k\}$:



Assume this path is optimal. Node k appears once or not at all.

1) If k is not on the path p ,
then p is optimal for intermediate nodes $1, \dots, k - 1$.

2) If k is not on the path p , then p has two parts



both optimal with respect to $\{1, \dots, k - 1\}$ (otherwise one could replace the part by something cheaper, contradicting the optimality of p).

1) and 2) express that substructures (subpaths) of an optimal solution (shortest path) have to be optimal.

Bellman optimality equations for the Floyd-Warshall algorithm:

$$S(v, w, k) = \min\{S(v, w, k - 1), S(v, k, k - 1) + S(k, w, k - 1)\},$$
$$\text{for } 1 \leq v, w \leq n, 1 \leq k \leq n.$$

Base cases: $S(v, v, 0) = 0$.

$S(v, w, 0) = c(v, w)$, for $v \neq w$.

We describe an **iterative** algorithm.

Intermediate results are stored in an array $S[1..n, 1..n, 0..n]$, initialized by

$$S[v, w, 0] \leftarrow c(v, w), \quad 1 \leq v, w \leq n, \quad v \neq w;$$

$$S[v, v, 0] \leftarrow 0, \quad 1 \leq v \leq n.$$

The algorithm fills S according to growing k :

```
for k from 1 to n do
  for v from 1 to n do
    for w from 1 to n do
       $S[v, w, k] \leftarrow \min\{S[v, w, k-1], S[v, k, k-1] + S[k, w, k-1]\}.$ 
```

Correctness: Follows from previous considerations:

The algorithm calculates all values $S(v, w, k)$ according to the Bellman equations.

Running time: There are three nested loops: $\Theta(n^3)$.

We are wasting space since for the k -th execution of the loop we only need the $(k - 1)$ -components of S .

Easy: Need only two matrices. An “old” one ($(k - 1)$ -version) and a “new” one (k -version), between which we can switch back and forth.

Then space is $O(n^2)$, time is $O(n^3)$.

Further improvement: We have:

$$(*) \quad \begin{aligned} S(v, k, k) &= S(v, k, k - 1) \text{ and} \\ S(k, w, k) &= S(k, w, k - 1), \text{ für } 1 \leq v, w, k \leq n, \end{aligned}$$

since node k cannot occur in the interior of a path from v to k or from k to w .

So one does not need an “old” and a “new” array, but only one: $S[1..n, 1..n]$.

```
S[v, v] ← 0;
S[v, w] ← c(v, w), für 1 ≤ v, w ≤ n, v ≠ w;
for k from 1 to n do
  for v from 1 to n do
    for w from 1 to n do
      S[v, w] ← min{S[v, w], S[v, k] + S[k, w]}.
```

We do not only want to know the **cost** of the shortest paths, but we also want to be able to calculate such a path for given v, w .

For this: Auxiliary array $I[1..n, 1..n]$, in which throughout rounds $k = 0, 1, \dots, n$ for each pair (v, w) the following information is kept:

What is the node with the largest number that has been used for a path from v to w of length $S(v, w, k)$?

Adding this feature gives the complete Floyd-Warshall algorithm.

Algorithm Floyd-Warshall($C[1..n, 1..n]$)

Input: $C[1..n, 1..n]$: matrix of edge costs/lengths

Output: $S[1..n, 1..n]$, with $S(v, w)$ the cost of a shortest path from v to w

$I[1..n, 1..n]$: minimal maximal nodes on shortest (v, w) path

```
(1)  for v from 1 to n do
(2)    for w from 1 to n do
(3)      if v = w then S[v,w] ← 0; I[v,w] ← 0
(4)      else S[v,w] ← C[v,w];
(5)      if S[v,w] < ∞ then I[v,w] ← 0 else I[v,w] ← -1;
(6)  for k from 1 to n do
(7)    for v from 1 to n do
(8)      for w from 1 to n do
(9)        if S[v,k] + S[k,w] < S[v,w] then
(10)         S[v,w] ← S[v,k] + S[k,w]; I[v,w] ← k;
(11)  return S[1..n, 1..n] , I[1..n, 1..n] .
```

Correctness: Loop invariant:

After the k -th execution of the loop we have $S[v, w] = S(v, w, k)$.

(Proof by induction on k , using the Bellman equations and $(*)$.)

And: $I[v, w]$ is the smallest ℓ such that among the

shortest paths from v to w over only nodes in $\{1, \dots, k\}$

there is one with **maximal** node ℓ .

(Proof by induction on k .)

Then a shortest path from v to w can be printed using a simple recursive procedure “printPathInner”, on the basis of $I[1..n, 1..n]$.

Algorithm printPathInner(v, w)**Global:** $I[1..n, 1..n]$: matrix of minimal maximal nodes on shortest paths**Input:** $v, w \in V$ **Output:** over print function

- (1) **if** $v \neq w$ **then**
- (2) $k \leftarrow I[v, w]$;
- (3) **if** $k > 0$ **then**
- (4) **printPathInner**(u, k); **print**(k); **printPathInner**(k, w);

Algorithm printPath(v, w)**Global:** $I[1..n, 1..n]$: matrix of minimal maximal nodes on shortest paths**Input:** $v, w \in V$ **Output:** over print function

- (1) **if** $v = w$
- (2) **then print**(v , "length 0")
- (3) **else if** $I[v, w] < 0$ **then print**("no path")
- (4) **else print**(v); **printPathInner**(v, w); **print**(w);

Exercise: Carry this out on an example. Why is the output correct?

Theorem

Floyd and Warshall's algorithm solves the All Pairs Shortest Paths problem in time $O(n^3)$ and space $O(n^2)$.

The result is a data structure of size $O(n^2)$ (a matrix), that enables calculating a shortest path from v to w , for any given pair (v, w) of nodes. The running time for such a call is $O(\#(\text{edges on the path}))$.

That's it!
Thanks for coming to the class, and
all the best for the exam!