

4. Dynamic Programming (DP)

"programming" refers to "tabular" method, not to writing program code.

DP is a general, powerful alg. design technique for solving optimisation problems

DP $\hat{=}$ type of very smart exhaustive search that can be applied if the problem can be "subdivided" into overlapping subproblems.

Exmp! Fibonacci numbers: $f(1) = f(2) = 1$
 $f(n) = f(n-1) + f(n-2)$
 $\Rightarrow 1, 1, 2, 3, 5, 8, 13, \dots$

Naive recursive way:

```
F(n)
{
  IF (n ≤ 2) f = 1
  ELSE f = F(n-1) + F(n-2)
  return f
}
```

Exponential time!

Why: Recurrence Nr:

$T(n)$ = time to compute n -th Fibnr.

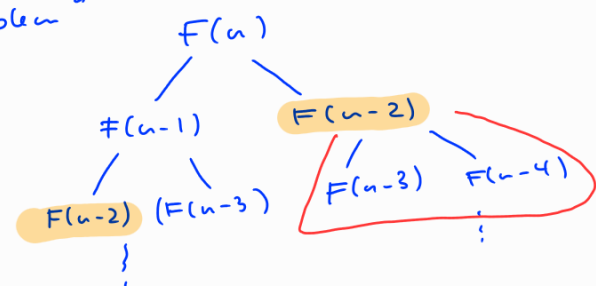
$$\Rightarrow T(n) = T(n-1) + T(n-2) + O(1)$$

$$\geq 2T(n-2)$$

$$\begin{matrix} T(n-1) \\ \geq T(n-2) \end{matrix} \geq 2 \cdot 2 T(n-4)$$

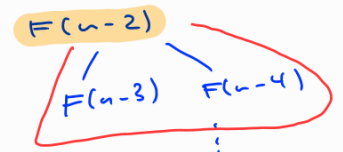
$$\geq 2^{\frac{n}{2}} = O(2^{\frac{n}{2}})$$

"problem"



We compute $F(n)$ several times, although it is enough to compute it ones

We can prune the entire search tree:



$\Rightarrow$ we must "memorise" the intermediate results.

memo = ϕ // dictionary

mF(n)

$\left[\begin{array}{l} \text{IF } (n \in \text{memo}) \text{ return memo}[n] \\ \text{IF } (n \leq 2) \quad f = 1 \\ \text{ELSE } f = \text{mF}(n-1) + \text{mF}(n-2) \\ \text{memo}[n] = f \\ \text{return } f \end{array} \right. \begin{array}{l} // \text{check if F[n] already} \\ \text{computed.} \\ \\ \} \text{ still the same} \\ \text{lines.} \end{array}$

Runtime

Sketch: $\Rightarrow$ mF(k) only recurses the first time it's called $\forall k$
& memoized calls cost $O(1)$

the nr of non-memoized calls is n :
 $\text{mF}(1), \text{mF}(2), \dots, \text{mF}(k), \dots, \text{mF}(n)$

$\Rightarrow$ runtime $O(n)$! (goes even faster)

In general, the design of DP-Arg consists of the following steps:

Step 1: characterize structure of optimal solution

Step 2: Recursively define value of opt. solution

Step 3: Compute value of opt solution (typically bottom up)

Step 4: Construct opt solution from computed information

IF we only want to know the values of opt. sol. then 1-3 are sufficient.

4.1. The Floyd-Warshall Algorithm

Aim: Find shortest $u-v$ -path $\forall u, v \in V(G)$.

Def: path $\langle v_0, \dots, v_k \rangle$ for vertices $v_1, \dots, v_{k-1}$ are inner vertices of path.

In what follows $V = \{1, 2, \dots, n\}$
 $V_k = \{1, 2, \dots, k\}$, $k \leq n$

Step 1: Characterize structure of shortest path in G with conservative weights

IDEA: let $i, j \in V$ & consider all $i-j$ -paths

s.t. all inner vertices are from V_k

Let P be one of such paths with minimum weight. = shortest $i-j$ -path with all inner vertices in V_k (not necessarily shortest $i-j$ -path in G)

Q: What is the relationship between P & shortest $i-j$ -path with all inner vertices in V_{k-1} ?

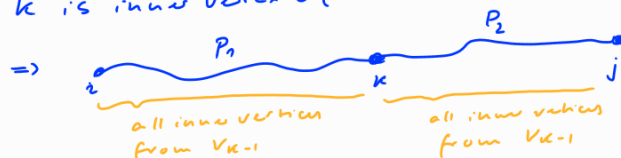
$\Rightarrow$ 2 cases:

- k is not inner vertex of P

$\Rightarrow$ all inner vertices of P are in V_{k-1}

$\Rightarrow$ shortest $i-j$ path with all inner vertices in V_{k-1} is also a shortest $i-j$ -path with all inner vertices in V_k

- k is inner vertex of P



By lemma 3.1 "subpath of shortest paths are shortest paths"

P_1 is shortest $i-k$ -path with inner vert. in V_{k-1}

P_2 is shortest $k-j$ -path with inner vert. in V_{k-1}

$\Rightarrow$ this generalizes to: for shortest $i-j$ -path P in G : all inner vertices are contained in $V_n = V$

If n not part of $P \Rightarrow P$ is shortest $i-j$ path in G with inner vertices in V_{n-1}
if n is part of $P \Rightarrow P$ composed of shortest $i-n$ path & $n-j$ path with inner vertices in V_{n-1} .

Step 2: Recursively def values of shortest paths

• $d_{ij}^{(k)}$ = weight of shortest i - j -path with inner vertices from V_k

$\text{If } \exists i\text{-}j\text{-path} \ \& \ k=0 \rightarrow (i,j) \in E \ \& \ d_{ij}^{(0)} = w(i,j)$

$$W_{ij} = \begin{cases} 0 & i=j \\ w(i,j) & i \neq j \ \& (i,j) \in E \\ \infty & i \neq j \ \& (i,j) \notin E \end{cases} \quad (\text{gives matrix } W)$$

Due to the discussion in (1):

$$d_{ij}^{(k)} = \begin{cases} W_{ij} & k=0 \\ \min(d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)}) & k \geq 1 \end{cases}$$

$\Rightarrow$ Since for any path it's inner vertices are from V_k
we obtain matrix $D^{(n)} = (d_{ij}^{(n)})$ with $d_{ij}^{(n)} = \delta(i,j) \ \forall i,j \in V$

Step 3: Computing values of shortest paths

(Bottom up) (matrix W as above)

FLOYD-WARSHALL($W, n = |V|$)

```
D0 = W
FOR (k=1..n) DO
  D(k) = (dij(k)) is new n x n matrix
  FOR (i=1..n) DO
    FOR (j=1..n) DO
      dij(k) = min { dij(k-1), dik(k-1) + dkj(k-1) }
Return D(n)
```

Theorem 4.1 Floyd-Warshall algorithm correctly computes $\delta(i,j) \ \forall i,j \in V$
in $\Theta(|V|^3)$ time for $G=(V,E)$ with conserv. weights

proof:

Runtime: clear $\Theta(|V|^3)$

Correctness: discussion above $\square$

(4) construct shortest i - j -path $\forall i, j \in V$

Step 4: similar to $d_{ij}^{(k)}$ def:

$$\pi_{ij}^{(0)} = \begin{cases} \text{NIL} & , i=j \text{ or } w_{ij} = \infty \\ i & , i \neq j \text{ \& } w_{ij} < \infty \end{cases}$$

// $\pi_{ij}^{(k)}$ = predecessor of j on shortest path from i to j with all inner vertices in V_k

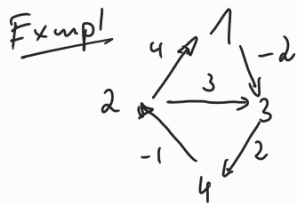
$k \geq 1$: Consider: $i \rightsquigarrow_k j$ (k is either part of this shortest i - j -path or not. within vertices in V_k)

IF $k \neq j \Rightarrow$ predecessor of j we choose is the same predecessor of j we choose on shortest k - j -path with vertices in V_{k-1}

$k=j \Rightarrow$ predecessor of j we choose the same predecessor of j we choose on shortest i - j path with all inner vertices in V_{k-1} or k is part of this path.

$$\Rightarrow \pi_{ij}^{(k)} = \begin{cases} \pi_{ij}^{(k-1)} & \text{if } d_{ij}^{(k-1)} \leq d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \\ \pi_{kj}^{(k-1)} & \text{if } d_{ij}^{(k-1)} > d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \end{cases}$$

[Exercise: Understand + incorporate in pseudocode].



FLOYD-WARSHALL ($W, n=|V|$)

```

 $D^0 = W$ 
FOR ( $k=1 \dots n$ ) DO
   $D^{(k)} = (d_{ij}^{(k)})$  is  $n \times n$  matrix
  FOR ( $i=1 \dots n$ ) DO
    FOR ( $j=1 \dots n$ ) DO
       $d_{ij}^{(k)} = \min \{ d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \}$ 
  RETURN  $D^{(n)}$ 

```

$D^{(0)}$

	1	2	3	4
1	0	∞	-2	∞
2	4	0	3	∞
3	∞	∞	0	2
4	∞	-1	∞	0

$D^{(1)}$

	1	2	3	4
1	0	∞	-2	∞
2	4	0	2	∞
3	∞	∞	0	2
4	∞	-1	∞	0

← shortest path cont. inner vertices from $V_1 = \{1\}$

(1) the first interesting case
is $k=1, i=2, j=3$

3 shorter path along 1
 $\Rightarrow$ update $d_{23}^{(1)} = d_{21}^{(0)} + d_{13}^{(0)}$
 $= 4 - 2$
 $= 2$

(2) next interesting case $k=2, i=4, j=1$

So far: $d_{41}^{(1)} = \infty$

→ but exist path from 4 to 1 with inner vertices from $V_2 = \{1, 2\}$



$$\Rightarrow d_{41}^{(2)} = d_{42}^{(1)} + d_{21}^{(1)}$$

$$= -1 + 4 = 3$$

$D^{(2)}$

	1	2	3	4
1	0	∞	-2	∞
2	4	0	2	∞
3	∞	∞	0	2
4	3	-1	1	0

next int. case: $k=2, i=4, j=3$

$$d_{43}^{(2)} = d_{42}^{(1)} + d_{23}^{(1)} = -1 + 2 = 1$$

next int case: $k=3, i=1, j=4$

$$d_{14}^{(2)} = \infty$$

$$d_{14}^{(3)} = d_{13}^{(2)} + d_{34}^{(2)}$$

$$= -2 + 2 = 0$$

$D^{(3)}$

	1	2	3	4
1	0	∞	-2	0
2	4	0	2	4
3	∞	∞	0	2
4	3	-1	1	0

next int case $k=3, i=2, j=4$

$$d_{24}^{(2)} = \infty$$

$$d_{24}^{(3)} = d_{23}^{(2)} + d_{34}^{(2)}$$

$$= 2 + 2 = 4$$

$D^{(4)}$

	1	2	3	4
1	0	-1	-2	0
2	4	0	2	4
3	5	-1	0	2
4	3	-1	1	0

$\parallel$
 $D^{(n)}$

next interesting case $k=4, i=1, j=2$

$$d_{12}^{(3)} = \infty$$

$$d_{12}^{(4)} = d_{14}^{(3)} + d_{42}^{(3)}$$

$$= 0 - 1 = -1$$

next case: $k=4, i=3, j=1$

$$d_{31}^{(3)} = \infty$$

$$d_{31}^{(4)} = d_{34}^{(3)} + d_{41}^{(3)}$$

$$= 2 + 3 = 5$$

$k=4, i=3, j=2$

$$d_{32}^{(3)} = \infty$$

$$d_{32}^{(4)} = d_{34}^{(3)} + d_{42}^{(3)}$$

$$= 2 + -1 = 1$$

4.2 The Longest Common Subsequence (LCS) problem

This is a classical problem in Bioinformatics,
where one wants to understand how "close"

DNA/protein sequences are.

= simply a string
some alphabet.

There are several ways to address this problem.
Here we consider one of them: LCS.

Def: Let $X = x_1 \dots x_m$ & $Z = z_1 \dots z_n$ be two strings (= sequences)

Z is a subsequence of X if

$\exists$ indices of X $i_1 \dots i_n$ st $i_1 < i_2 < \dots < i_n$
& $z_j = x_{i_j}$

Exmpl: $X = A B C B D A B$, $Z = B C D B$

$\Rightarrow Z$ can be obtained from X
by removing elements from X .
& keep order of remaining elements.

IF Z is subsequence of X & $Y \Rightarrow Z$ is common subsequ.
of X & Y .

Exmpl: $X = A B C B D A B$
 $Y = B D C A B A$

$Z = B C A$, $Z' = B C B A$, $Z'' = B D A B$ are common subsequ.
of X & Y .

Aim: Find longest common subsequ. (LCS) of X & Y .

Brute FORCE is not a good idea,
Since $X = x_1 \dots x_m$ has 2^m subsequences!

For $X = x_1 \dots x_m$, define the i -th prefix X_i of X
as $X_i = x_1 \dots x_i$, $1 \leq i \leq m$ & put $X_0 = \epsilon$ "empty sequ."

Step 1: Characterization of LCS.

Theorem 4.2
[opt. substructure
of LCS]

Let $X = x_1 \dots x_m$, $Y = y_1 \dots y_n$ be two sequences.
& $Z = z_1 \dots z_k$ be some LCS of X & Y .

- (1) $x_m = y_n \Rightarrow z_k = x_m = y_n$ & z_{k-1} is LCS of x_{m-1} & y_{n-1}
- (2) $x_m \neq y_n$ & $z_k \neq x_m \Rightarrow z$ is LCS of x_{m-1} & Y
- (3) $x_m \neq y_n$ & $z_k \neq y_n \Rightarrow z$ is LCS of X & y_{n-1} .

Illustration: (1) $X = A A B A C \boxed{D}$
 $Y = A B B C \boxed{D}$
LCS $Z = \underline{A B C} \boxed{\underline{D}}$
 z_3
 $\Rightarrow z_3$ is LCS of $x_5 = x_{m-1}$
 $y_4 = y_{n-1}$
 $m=6, n=5$
 $\Rightarrow$ can reduce problem to find
LCS of x_{m-1} & y_{n-1}

(2) $X = A A B A C A$
 $Y = A B B C D$
LCS $Z = A B C$
! this is independent of letter y_n
that is both cases may occur:
 $z_k = y_n$ or $z_k \neq y_n$
But since z_k never "matches" x_n ,
we can reduce the problem to find
LCS of x_{m-1} & Y

(3) analog to (2).

Proof: (1) $x_m = y_n \Rightarrow z_k = x_n$ [otherwise if $z_k \neq x_n$ we can append x_n to $z_1 \dots z_k$ & get larger subsequence $\hookrightarrow$ since z is LCS.]
 [Thm 4.2] already CS

$$\Rightarrow x_m = x_n = z_k$$

Now prefix z_{k-1} is a common subseq. of x_{m-1} & y_{n-1}

to show: z_{k-1} is LCS of x_{m-1} & y_{n-1}

But this is clear, since if there is a longer one,

say w then we could append $z_k + w$ to obtain a seq. which is longer than $z \hookrightarrow z$ is LCS

(2) Clearly if $z_k \neq x_m \Rightarrow z$ is common subseq. of x_{m-1} & y_n .

to show z is LCS of x_{m-1} & y_n .

Again, if there is a longer common subseq. w of x_{m-1} & y_n

then w is also a common subseq. of x & y ,

but longer than $z \hookrightarrow z$ is LCS

(3) analog to (2)

□

Step 2: recursive solution of LCS

By Thm 4.2: $x_m = y_n \Rightarrow$ Find LCS of x_{m-1} & y_{n-1} & append $x_m = y_n$ to this LCS.

$x_m \neq y_n \Rightarrow$ Find LCS of x_{m-1} & y or x & y_{n-1} whichever of these is longer is an LCS of x & y

Let C_{ij} = length (# of letters) of LCS of prefixes x_i & y_j

NOTE $x_0 = \epsilon, y_0 = \epsilon \Rightarrow C_{ij} = 0$, if $i=0$ or $j=0$

Recursive Formula:

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

Step 3: Computing length of LCS.

Based on recursive formula for c_{ij}
we get for free an exponential-time recursive alg.
But DP can be used to get it in polynomial time.

Let $X = x_1 \dots x_m$ & $Y = y_1 \dots y_n$

$LCS(X, Y)$

Let $b[1 \dots m, 1 \dots n]$
 $c[0 \dots m, 0 \dots n]$ be new arrays

// b used to construct LCS via backtracking
// c stores length.

FOR ($i = 0 \dots m$) DO $c[i, 0] = 0$
FOR ($j = 0 \dots n$) DO $c[0, j] = 0$

FOR ($i = 1 \dots m$) DO

FOR ($j = 1 \dots n$) DO

IF ($x_i = y_j$)

$c[i, j] = c[i-1, j-1] + 1$
 $b[i, j] = \nwarrow$

ELSE IF ($c[i-1, j] \geq c[i, j-1]$)

$c[i, j] = c[i-1, j]$
 $b[i, j] = \uparrow$

ELSE

$c[i, j] = c[i, j-1]$
 $b[i, j] = \leftarrow$

RETURN c & b .

// c :



$\Rightarrow x_i = y_j$
it's part of LCS



Step 4: construct LCS:

PRINT-LCS(b, X, i, j) // initial call: PRINT-LCS(b, X, m, n)

IF ($i = 0$ or $j = 0$) RETURN.

IF ($b[i, j] = \nwarrow$)

PRINT-LCS($b, X, i-1, j-1$)
print x_i

ELSE IF ($b[i, j] = \uparrow$)

PRINT-LCS($b, X, i-1, j$)

ELSE
PRINT-LCS($b, X, i, j-1$)

RUNTIME: $\Theta(m+n)$
since it decrements at most
one of i & j in each call

Exmpl:

$X = ABCB, Y = BDC$

j	0	1	2	3
i		B	D	C
0	0	0	0	0
1 A	0			
2 B	0			
3 C	0			
4 B	0			

j	0	1	2	3
i		B	D	C
0	0	0	0	0
1 A	0	0	0	0
2 B	0	1	1	1
3 C	0	1	1	2
4 B	0	1	1	2

now $i = 1 \dots m / j = 1 \dots m$

$i = 1, j = 1, 2, 3$

$i = 2, j = 1, 2, 3$

$x_2 = y_1$ "↖"

$i = 3, j = 1, 2, 3 \quad x_3 = x_2$ "↖"

$i = 4, j = 1, 2, 3 \quad x_4 = y_1$ "↖"

j	0	1	2	3
i		B	D	C
0	0	0	0	0
1 A	0	0	0	0
2 B	0	1	1	1
3 C	0	1	1	2
4 B	0	1	1	2

Backtracking:

start at $c[m, n]$

order "↖", "↑", "←"

but there might be further opt. solutions!

$b[3, 3] = \text{↖} \rightarrow \text{print 'C'}$

$b[2, 1] = \text{↖} \rightarrow \text{print 'B'}$

$\Rightarrow z = \underline{BC}$

↑
this value is
length of LCS

Theorem 4.3: $LCS()$ + $PRINT-LCS()$ correctly returns a length & LCS of given $X = x_1 \dots x_m$ & $Y = y_1 \dots y_n$ in $\Theta(mn)$ time.

Proof: correctness by Thm 4.2
runtime dominated by 2 FOR-loops ($i = 1 \dots m, j = 1 \dots n$)
 $\Rightarrow \Theta(mn)$

□