

Dynamic Programming

**Faculty Development Programme
Design and Analysis of Algorithms
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Outline

- * Introduction to dynamic programming
 - * Recursion with memoization (memory tables)
 - * Filling the table iteratively
- * Examples
 - * Floyd/Warshall algorithms
 - * Optimal search trees
 - * Others

Inductive definitions

- * Factorial
 - * $f(n) = n \times f(n-1)$
 - * $f(0) = 1$
- * Insertion sort
 - * $\text{isort}(\text{[]}) = \text{[]}$
 - * $\text{isort}(\text{[}x_1, x_2, \dots, x_n\text{]}) = \text{insert}(x_1, \text{isort}(\text{[}x_2, \dots, x_n\text{]}))$

... Recursive programs

```
int factorial(n):  
    if (n <= 0)  
        return(1)  
  
    else  
        return(n*factorial(n-1))
```

Sub problems

- * $\text{factorial}(n-1)$ is a **subproblem** of $\text{factorial}(n)$
 - * So is $\text{factorial}(n-2)$, $\text{factorial}(n-3)$, ..., $\text{factorial}(0)$
- * $\text{isort}([x_2, \dots, x_n])$ is a subproblem of $\text{isort}([x_1, x_2, \dots, x_n])$
 - * So is $\text{isort}([x_i, \dots, x_j])$ for any $1 \leq i \leq j \leq n$
- * Solution of $f(y)$ can be derived by combining solutions to subproblems

Evaluating subproblems

- * $\text{fib}(0) = 0$

$$\begin{array}{cccccccc} 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 \\ \underline{0} & \underline{1} & & & & & & \\ & & \underline{1} & & & & & \end{array}$$

- * $\text{fib}(1) = 1$

$$\begin{array}{cccccccc} & & & & & & & \\ & & & & & & & \\ & & & & & & & \underline{2} \end{array}$$

- * $\text{fib}(n) = \text{fib}(n-1) + \text{fib}(n-2)$

$$\begin{array}{cccccccc} & & & & & & & \\ & & & & & & & \\ & & & & & & & \underline{\underline{3}} \end{array}$$

- * Compute $\text{fib}(7)$?

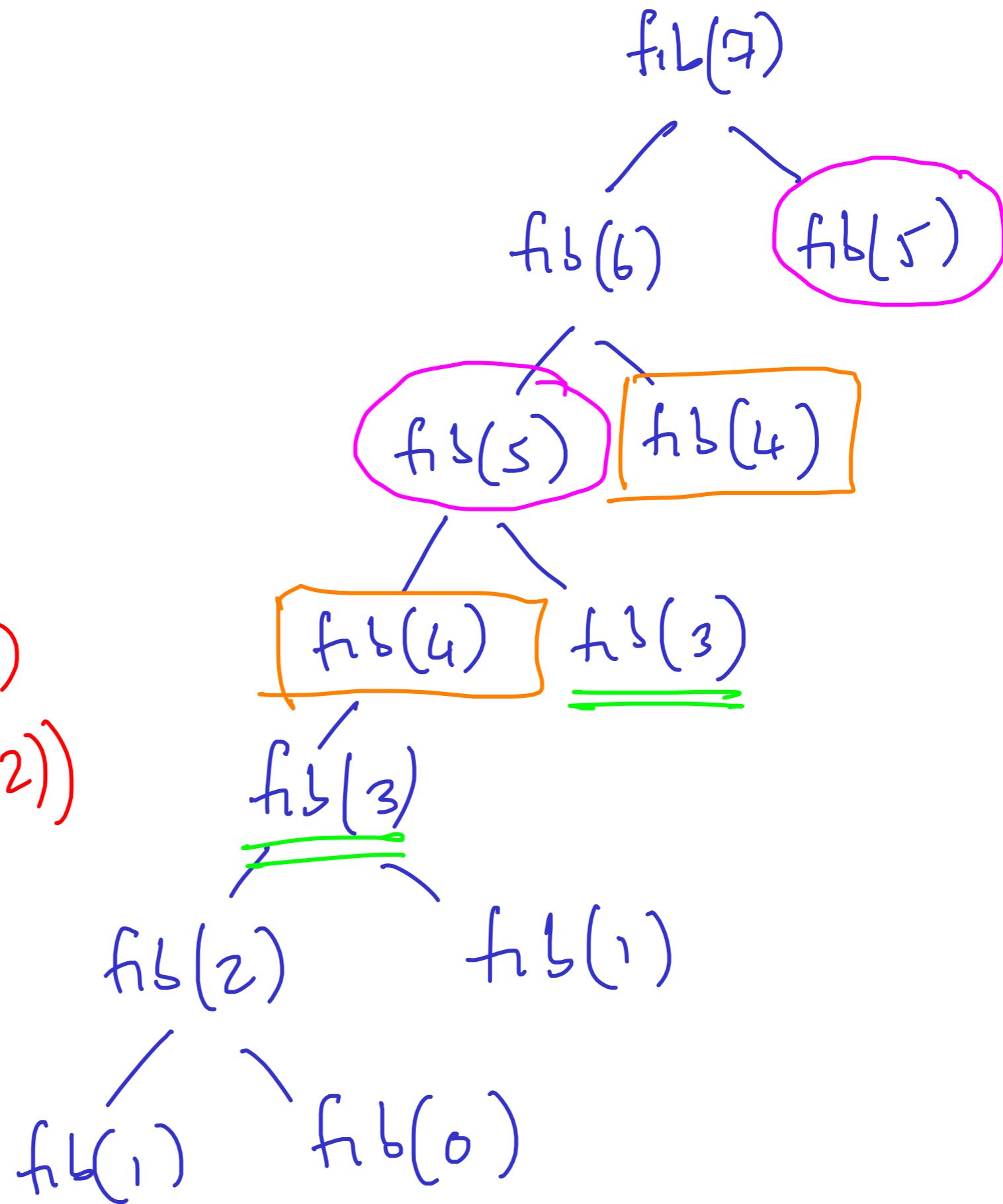
$$\begin{array}{cccccccc} & & & & & & & \\ & & & & & & & \\ & & & & & & & \underline{\underline{5}} \end{array}$$

13

```

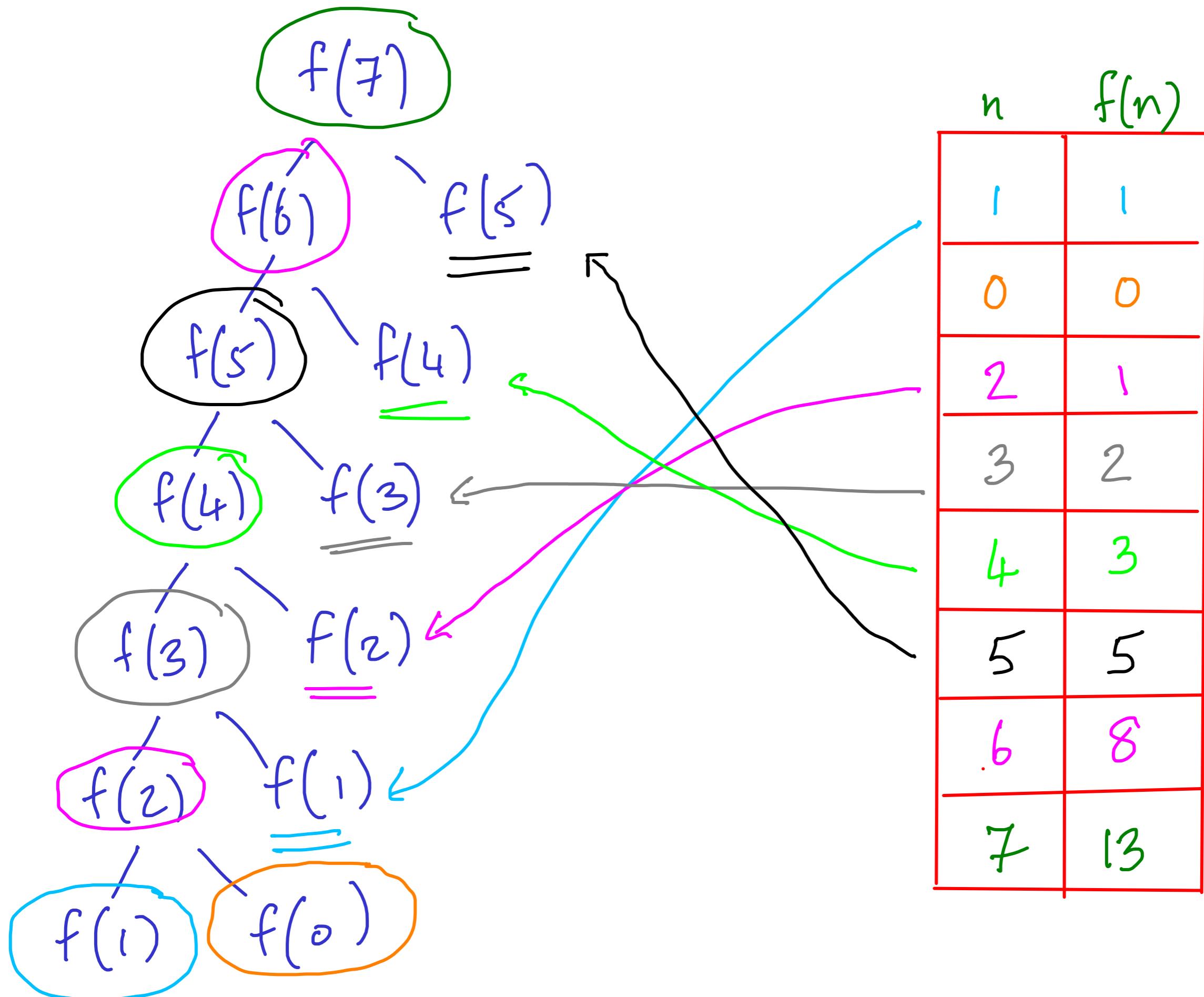
def fib(n):
    if n==0
        return(0)
    if n==1
        return(1)
    return(fib(n-1)
          +fib(n-2))

```



Never re-evaluate a subproblem

- * Build a table of values already computed
 - * Memory table
- * Memoization
 - * Remind yourself that this value has already been seen before



Memoized fibonacci

```
def fib(n):
    if fibtable[n]
        return(fibtable[n])
    if n == 0 or n == 1
        newvalue = n
    else
        newvalue = fib(n-1) + fib(n-2)
    fibtable[n] = newvalue
    return(newvalue)
```

In general

```
def f(x,y,z):
```

```
    if ftable[x][y][z]
```

```
        return(ftable[x][y][z])
```

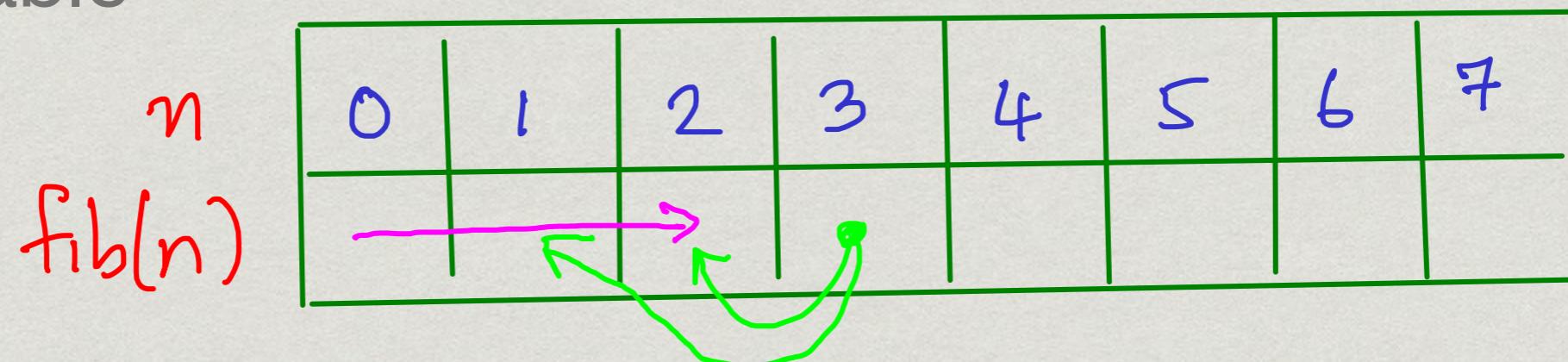
```
    newvalue = expression in terms of  
              subproblems
```

```
    ftable[x][y][z] = newvalue
```

```
    return(newvalue)
```

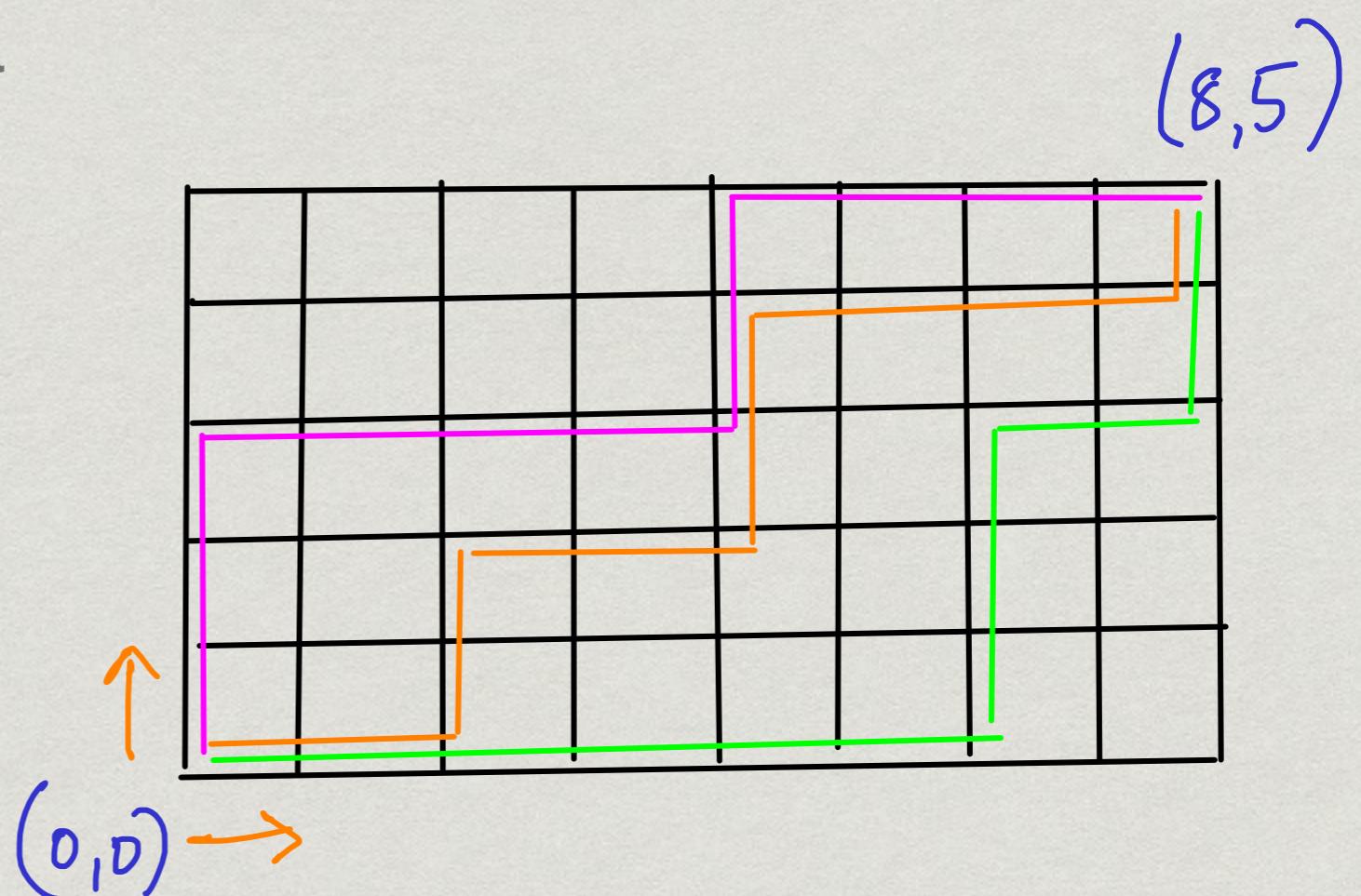
Dynamic programming

- * Anticipate what the memory table looks like
- * Fill it up iteratively
 - * For each new value, subproblems already filled in table



Grid Paths

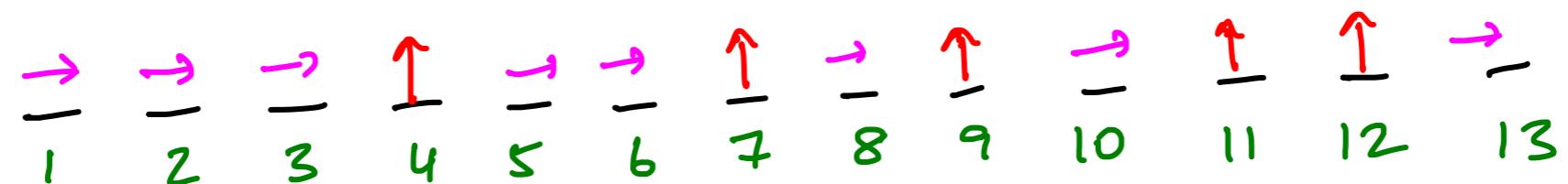
- * Roads arranged in a rectangular grid
- * Can only go up or right
- * How many different routes from $(0,0)$ to (m,n) ?



Analytic Solution

Every path takes exactly 8 steps →, 5 steps ↑

All paths have exactly 13 steps

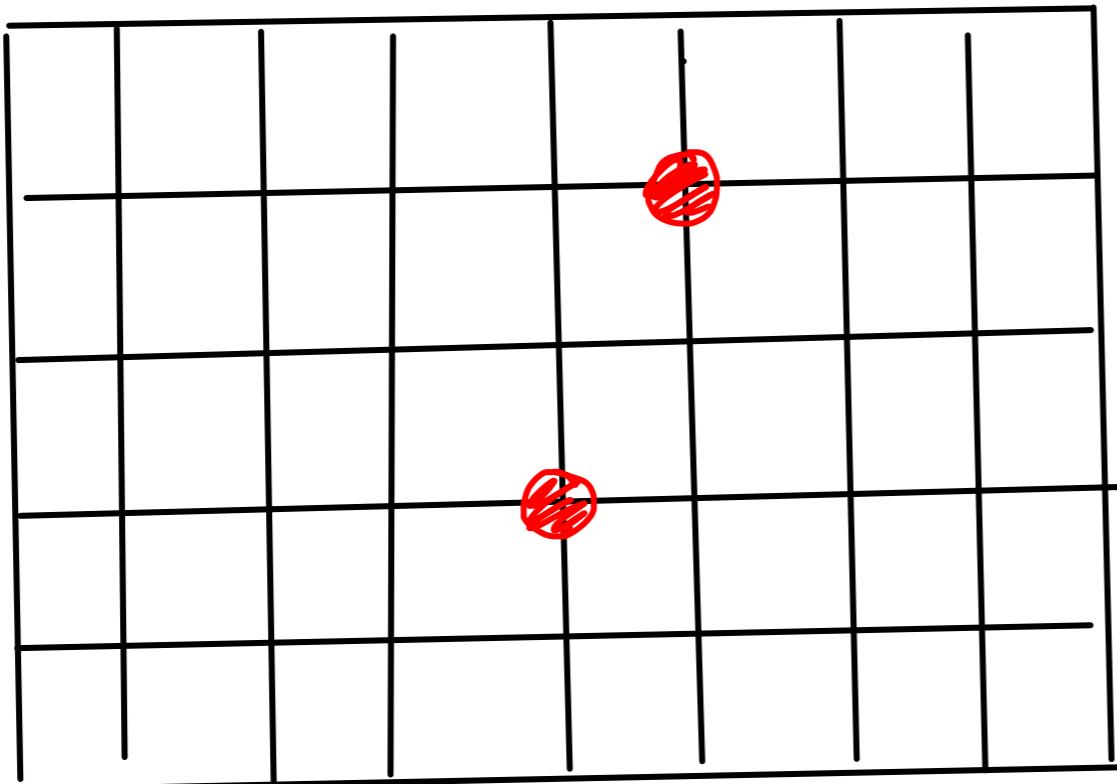


Identify 5 ↑ positions, rest must be →
8 → positions, rest must be ↑

$$\binom{13}{8}, \binom{n}{k} = \frac{n!}{k!(n-k)!} = \binom{n}{n-k} \quad \binom{13}{8} : \binom{13}{5} = \frac{13!}{5!8!}$$

In general, $(0,0)$ to $(m,n) \rightsquigarrow \binom{m+n}{m} = \binom{m+n}{n}$

What if some intersections are blocked?



(4,2), (5,4) blocked

Exclude paths passing through these

Paths through (4,2) =

Paths $(0,0)$ to $(4,2)$
x Paths $(4,2)$ to $(8,5)$

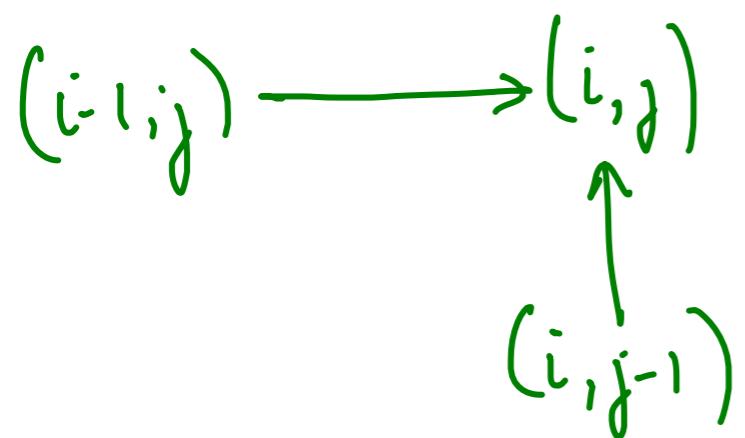
Paths through (4,2) and (5,4) excluded twice!

Add these back

Complicated "inclusion-exclusion" counting

Analytic solution does not scale well

Inductive formulation



- Paths to (i, j) must go through left or bottom neighbour
- No path can go via both neighbours
- Each path to neighbour has unique extension to (i, j)

$\text{Paths}(i, j) = \text{no. of paths from } (0, 0) \text{ to } (i, j)$

$$\begin{aligned}\text{Paths}(i, j) &= \text{Paths}(i-1, j) + \text{Paths}(i, j-1) \\ &= 0 \text{ if } (i, j) \text{ is a blocked intersection}\end{aligned}$$

Base Case : $\text{Paths}(0, 0) = 1$

$$\text{Paths}(0, j) = \text{Paths}(0, j-1)$$

$$\text{Paths}(i, 0) = \text{Paths}(i-1, 0)$$

What does our table look like?

To compute Paths(m, n), need Paths(i, j) , $0 \leq i \leq n$, $0 \leq j \leq m$

Base Cases

5	1	6	21	56	111	111	150	249	438
4	1	5	15	35	55	0	39	99	189
3	1	4	10	20	20	26	39	60	90
2	1	3	6	10	0	6	13	21	30
1	1	2	3	4	5	6	7	8	9
0	1	1	1	1	1	1	1	1	1

Start here

Table above filled row-wise



Can also fill column-wise ↑↑↑... or in diagonals



Memoization vs Dynamic Programming

		...								(m,n)	
0	0	0	0	0					
				0							
				0							
				
				
				0				0			
				0				0			

Target is unreachable from here - not touched by memoization

Memoization fills table
“on demand” - unreachable subproblems are not evaluated
D.P. blindly evaluates all subproblems

(0,0)

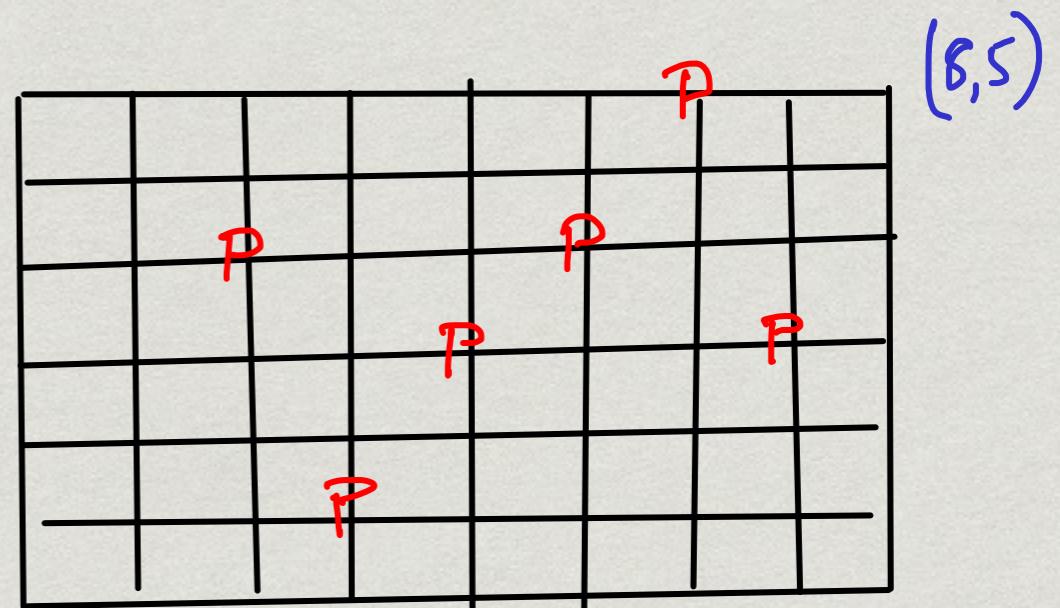
Given the grid configuration above

- Memoization explores $O(m+n)$ subproblems along boundary
- D.P. evaluates all $O(mn)$ subproblems

Nevertheless “wasteful” D.P. usually wins because of saving in iteration vs recursion

Picking prizes along a grid

- * Similar layout of roads, but objective is different
- * Some intersections have prizes
- * Find the maximum number of prizes you can pick up



(0,0)

$P(i,j)$ = max prizes from $(0,0)$ to (i,j)

$$= \max(P(i-1, j), P(i, j-1)),$$

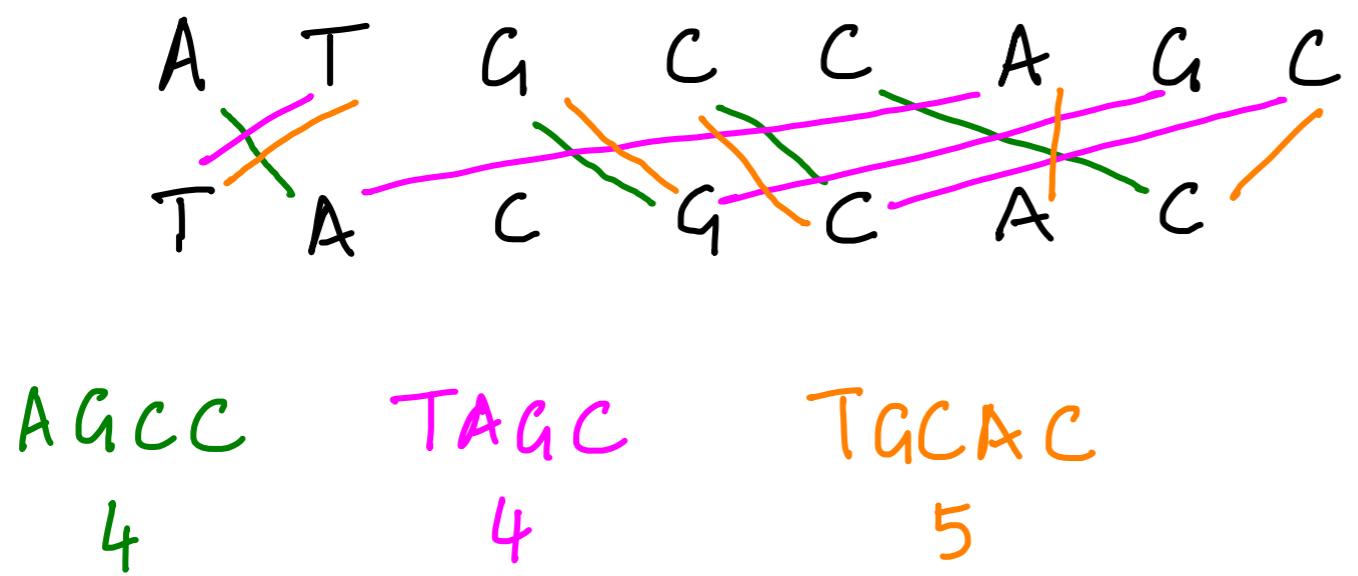
· if no prize at (i, j)

$$= 1 + \max(P(i-1, j), P(i, j-1)),$$

· if prize at (i, j)

Longest common subsequence

- * Two sequences, drawn from the same set of symbols
- * What is the maximum overlap?
- * Applications
 - * Comparing DNA sequences
 - * Comparing versions of text files (Unix `diff`)



Subsequence - omit some letters
 Find length of longest identical subsequence

s $s_1 \ s_2 \ s_3 \dots s_n$
 t $t_1 \ t_2 \ t_3 \dots t_m$

$\text{lcs}(s_1 \dots s_n, t_1 \dots t_m)$
 Subproblems?

In general, $\text{lcs}(s_1 \dots s_j, t_k \dots t_e)$

Our solution will use

$\text{lcs}(s_2 \dots s_n, t_2 \dots t_m)$
 $\text{lcs}(s_1 \dots s_n, t_2 \dots t_m)$
 $\text{lcs}(s_2 \dots s_n, t_1 \dots t_m)$

$$s = \begin{bmatrix} s_1 \\ s_2 & s_3 & \dots & s_n \end{bmatrix}$$

$$t = \begin{bmatrix} t_1 \\ t_2 & t_3 & \dots & t_m \end{bmatrix}$$

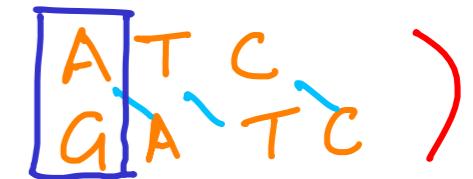
$$s_1 = t_1 ?$$

Match (s_1, t_1) and inductively solve rest
← Why is this always a good choice?

$$\text{lcs}(s_1 \dots s_n, t_1 \dots t_m) = 1 + \text{lcs}(s_2 \dots s_n, t_2 \dots t_m)$$

$$s_1 \neq t_1 ?$$

Drop either s_1 or t_1 (not both!)



$$\text{lcs}(s_1 \dots s_n, t_1 \dots t_m) =$$

$$\max \left(\text{lcs}(s_1 \dots s_n, t_2 \dots t_m), - \text{drop } t_1 \right)$$

$$\text{lcs}(s_2 \dots s_n, t_1 \dots t_{m-1}) - \text{drop } s_1$$

In general

$\text{lcs}(i, j)$ is solution for $(s_i s_{i+1} \dots s_n, t_j t_{j+1} \dots t_m)$

$$\begin{aligned}\text{lcs}(i, j) = & 1 + \text{lcs}(i+1, j+1), && \text{if } s_i = t_j \\ & \max(\text{lcs}(i, j+1), \text{lcs}(i+1, j)), && \text{if } s_i \neq t_j\end{aligned}$$

Convenient to let i, j go upto $n+1, m+1$

$$\text{lcs}(n+1, j) = 0 \quad \text{for all } j$$

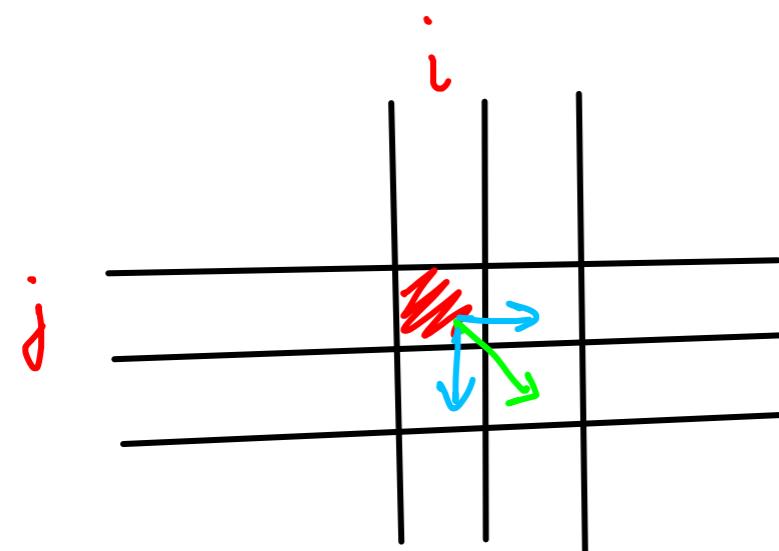
$$\text{lcs}(i, m+1) = 0 \quad \text{for all } i$$

Comparing empty sequence on
one side

	1	2	-	..	$n+1$
1					
2					
.					
$m+1$					

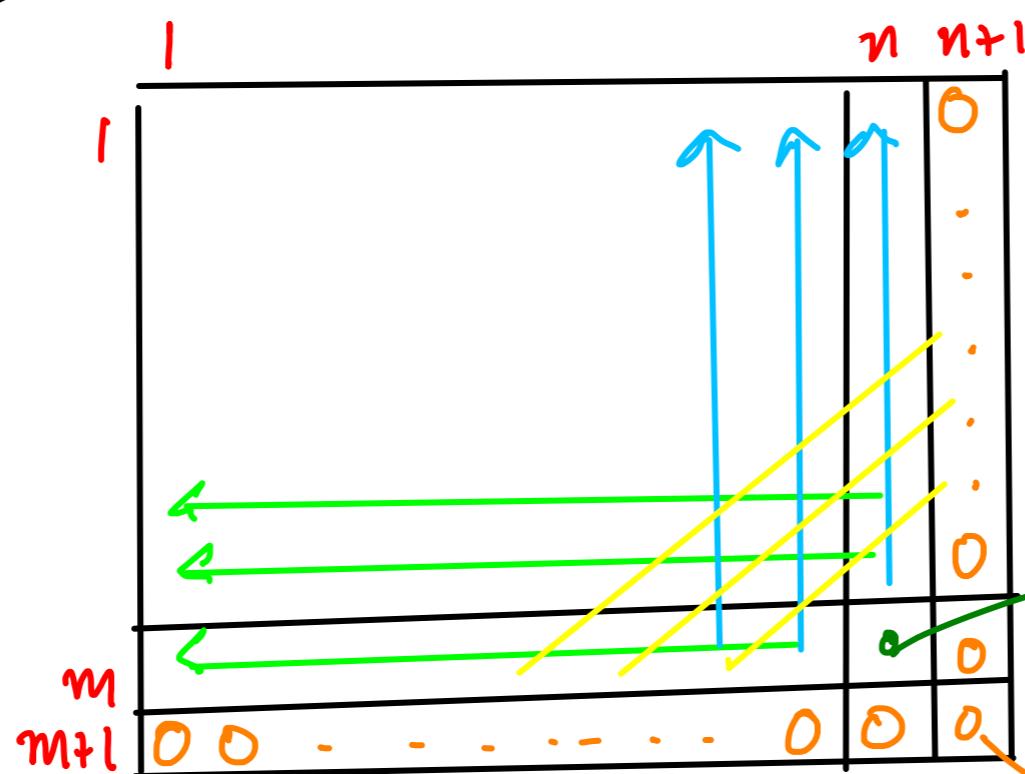
Table

What does taste entry $(i; j)$ depend on?



$$\text{lcs}(i, j) = \begin{cases} 1 + \text{lcs}(i+1, j+1) \\ \max(\text{lcs}(i, j+1), \text{lcs}(i+1, j)) \end{cases}$$

Filling up table



By row,
column,
or diagonal

- dependencies known

- Start here, base cases

1 2 3 4 5 6 +

 A T A C G A C

T G C A C B

1 2 3 4 5 6

Recovering the actual subsequence

- trace back how each table entry arose

- each time $\text{lcs}(l+1, j+1)$ is chosen, $s_i = t_j$ added to common subsequence
- when $\max(\text{lcs}(i, j+1), \text{lcs}(i+1, j))$ is chosen, have to make a choice if both are equal

	A	T	A	C	G	A	C	
T	(L)	4	3	3	3	2	1	0
G	3	3	(3)	(3)	(3)	2	1	0
C	3	3	(3)	(3)	2	2	1	0
A	2	2	2	2	2	2	1	0
C	1	1	1	1	1	1	0	0
B	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0

T C A C

T G A C

Two "witnesses"

Not unique, in general

Matrix multiplication

- * Multiplying matrices of dimensions $M \times N$ and $N \times P$ requires $O(MNP)$ arithmetic operations
 - * Product has size $M \times P$
 - * Each entry takes time $O(N)$ to compute
- * Multiplying $(M_1 M_2) M_3$ and $M_1 (M_2 M_3)$
 - * Same answer, but different complexity, in general

$$\begin{bmatrix} M_1 \\ M_2 \\ M_3 \end{bmatrix}$$

1×100

$r_1 \times c_1$

100×1

$r_2 \times c_2$

1×100

$r_3 \times c_3$

$M_1 M_2$ $r_1 c_1 c_2 = 100$ steps

1×1

$M_1 M_2 M_2$ $r_1 c_2 c_3 = 100$ steps
 1×100

$M_2 M_3$ $r_2 c_2 r_3 = 10000$ steps
 100×100

$\leftarrow 200$ steps
vs

20000 steps →

$M_1 M_2 M_3$ $r_1 c_1 r_3 = 10000$ steps
 1×100

Given

$$\begin{array}{ccccccc} M_1 & M_2 & M_3 & \dots & M_n \\ (r_1, c_1) & (r_2, c_2) & (r_3, c_3) & & (r_n, c_n) \end{array}$$

Dimensions match $c_i = r_{i+1}, 1 \leq i < n$

Find an optimal order to evaluate product

Final multiplication is of form

$$(M_1 \cdot M_2 \cdot \dots \cdot M_l) (M_{l+1} \cdot \dots \cdot M_n)$$

$r_1 \times c_i \qquad \qquad r_{l+1} \times c_n$

Final step costs $r_l \cdot c_i \cdot c_n$

Add cost of subproblems $(M_1 \cdot M_2 \cdot \dots \cdot M_l), (M_{l+1} \cdot \dots \cdot M_n)$

Which M_i to choose?

- No idea! Try them all and choose best

$$\text{Cost}(1, n) = \min_{1 \leq i < n} (r_1 \cdot c_i c_n + \text{Cost}(1, i) + \text{Cost}(i+1, n))$$

In general

$$\text{Cost}(i, j) = \min_{i \leq k < j} (r_i \cdot c_k c_j + \text{Cost}(i, k) + \text{Cost}(k+1, j))$$

\exists
Multiplying $M_i M_{i+1} \cdots M_j$

Base Case:

$$\text{Cost}(i, i) = 0$$

Cost of "multiplying"
single matrix M_i

Filling the table

$j \rightarrow$

$i \downarrow$	0						
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

$i \leq j$, so
this part
unused

Diagonal,
base case

Fill table diagonally
Need values to left
and below

$$\text{lcs}(2,7) = \min$$

$$\left\{ \begin{array}{ll} k=2 & r_2 c_2 c_7 + (2,2) + (3,7), \\ k=3 & r_2 c_3 c_7 + (2,3) + (4,7), \\ k=4 & r_2 c_4 c_7 + (2,4) + (5,7), \\ k=5 & r_2 c_5 c_7 + (2,5) + (6,7), \\ k=6 & r_2 c_6 c_7 + (2,6) + (7,7) \end{array} \right\}$$

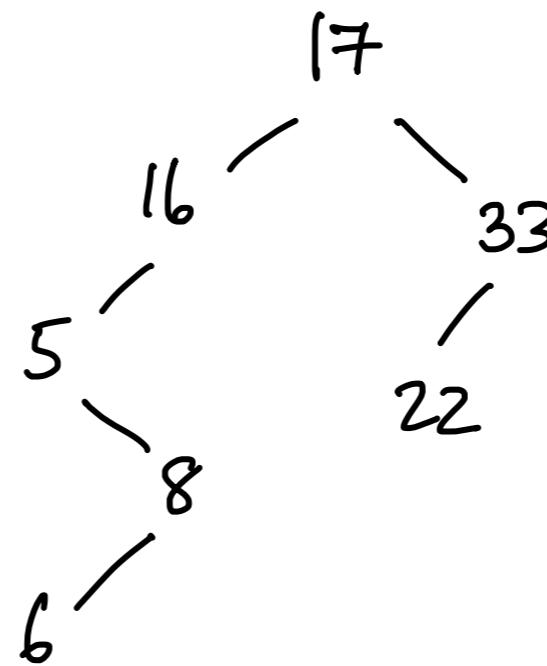
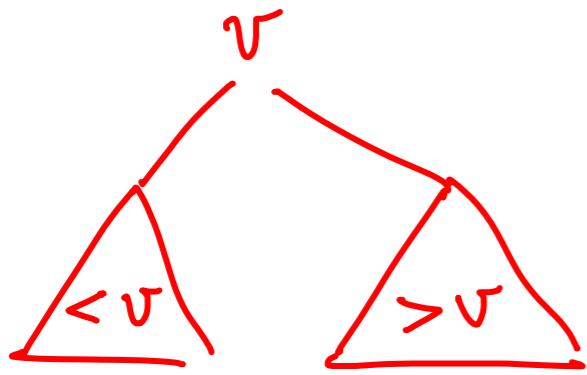
Need $O(j-i)$ steps to compute
entry (i,j)

Overall, $O(n^3)$ steps to fill
 $O(n^2)$ size table

Optimal search tree

- * Search tree
 - * No duplicate values
 - * At each node with value v
 - * Left subtree has values less than v
 - * Right subtree has values greater than v
 - * Search for a value like binary search

Search tree

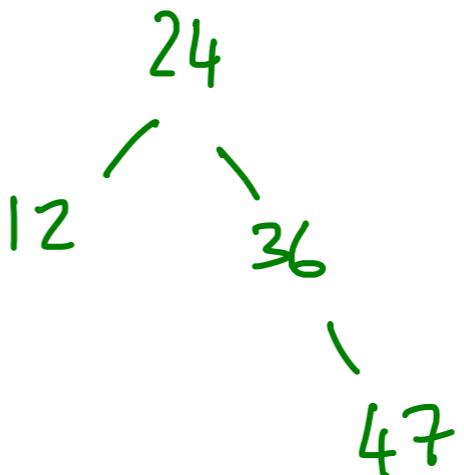


Different notions of optimality

- Search time proportional to tree height
- All values equally likely - "balance" the tree
- Suppose different values are searched with different probabilities

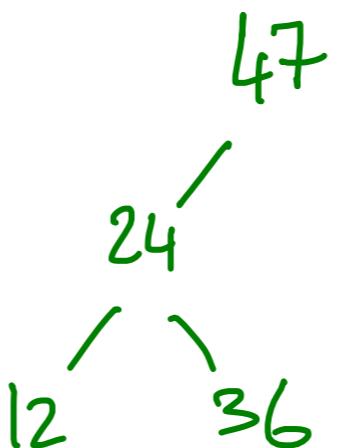
Values Probabilities

12	0.2
24	0.3
36	0.1
47	0.4



Expected search time

$$\begin{aligned}
 &= 0.3 \times 1 \quad (24) \\
 &+ 0.2 \times 2 \quad (12) \\
 &+ 0.1 \times 2 \quad (36) \\
 &+ 0.4 \times 3 \quad (47) \\
 &= 2.1
 \end{aligned}$$



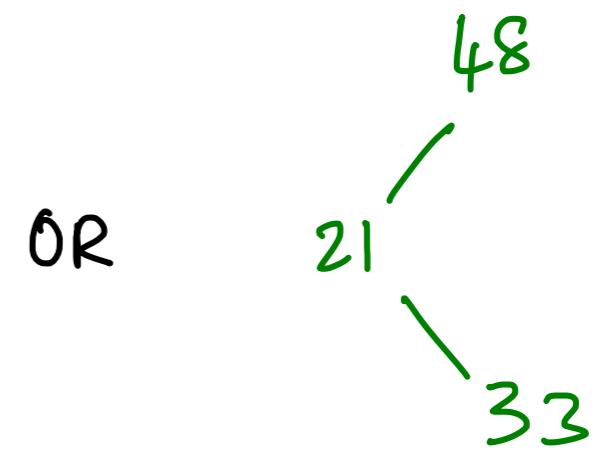
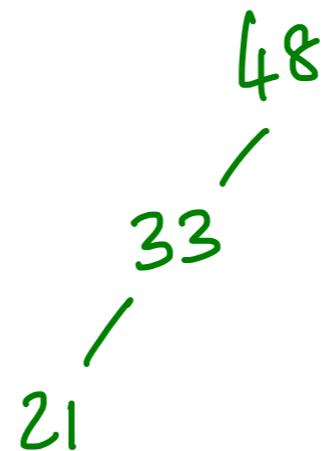
$$\begin{aligned}
 &0.4 \times 1 \quad (47) \\
 &+ 0.3 \times 2 \quad (24) \\
 &+ 0.2 \times 3 \quad (12) \\
 &+ 0.1 \times 3 \quad (36)
 \end{aligned}$$

$$= 1.9$$

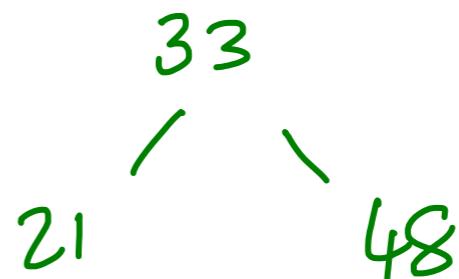
Second tree is better than first

Always make highest probability value root?

21	0.3
33	0.3
48	0.4



Both have cost $0.4 + 0.6 + 0.9 = 1.9$



Cost $\approx 0.3 + 0.6 + 0.8 = 1.7$

Given n values

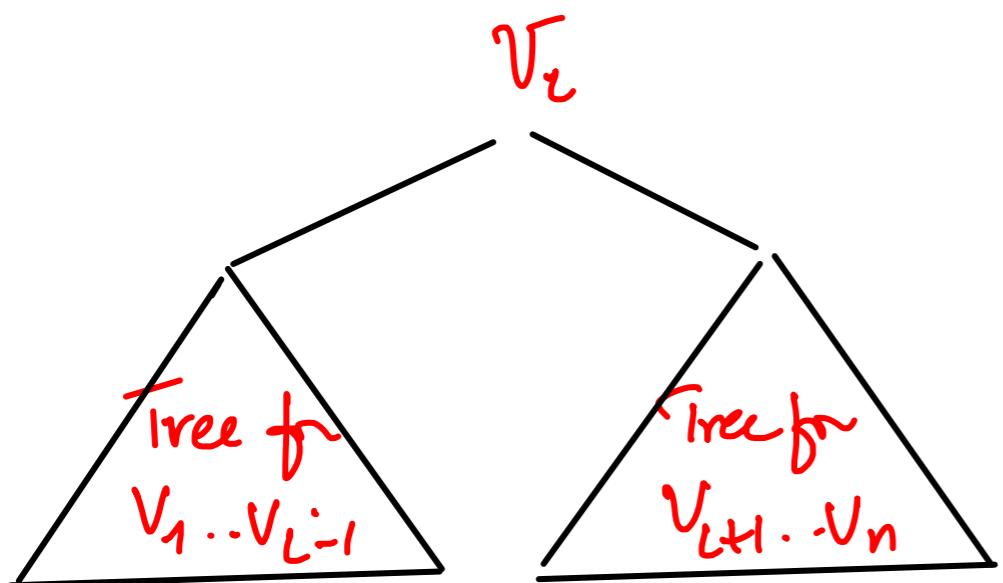
$$v_1 \quad v_2 \quad - \dots \quad v_n$$

probabilities

P_1, P_2, \dots, P_n

Assume w.l.o.g. values are sorted $v_1 < v_2 < \dots < v_n$

If we pick some v_i as root, the tree will look like



Expected lost =

$$\begin{aligned}
 & P_i = v_i \\
 & + \sum_{j=1}^{i-1} P_j (\text{depth of } v_j \text{ in } T_1 \dots L-1) + 1 \\
 & \equiv \overbrace{\quad\quad\quad}^{+1 \text{ because down one level}} + 1 \\
 & + \sum_{j=L+1}^n P_j (\text{depth of } v_j \text{ in } T_{L+1} \dots n) + 1 \\
 & \equiv \overbrace{\quad\quad\quad}^{v_j \text{ in right subtree}} + 1
 \end{aligned}$$

In general, subproblem is

$$v_i \ v_{i+1} \ \dots \ v_j$$

$$p_i \ p_{i+1} \ \dots \ p_j$$

$\text{Cost}(i, j) = \text{minimize cost over all choices for the root}$

$$= \min_{i \leq k \leq j} P_k + \sum_{l=i}^{k-1} P_l (\underset{\text{in } T_{i \dots l-1}}{\text{depth}(v_l)} + 1) + \sum_{l=l+1}^j P_l (\underset{\text{in } T_{l+1 \dots j}}{\text{depth}(v_l)} + 1)$$

Rearranging

$$= \min_{i \leq k \leq j} \sum_{l=1}^{k-1} P_l (\text{depth}(v_l)) + \sum_{l=l+1}^j P_l (\text{depth}(v_l)) + P_k + \sum_{l=1}^{k-1} P_l + \sum_{l=k+1}^j P_l$$

$$= \min_{i \leq k \leq j} \text{Cost}(i, k-1) + \text{Cost}(k+1, j) + \sum_{l=i}^j P_l$$

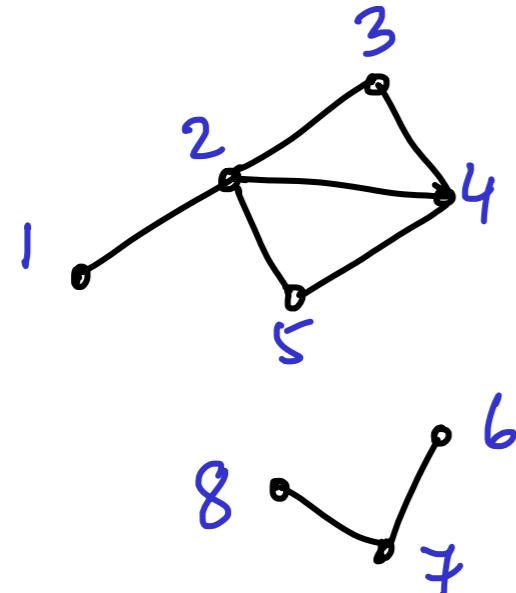
Assume $\text{Cost}(i+1, i) = 0$ (when $k=i$ or $k=j$)

Table filling is similar to matrix multiplication problem

- $\text{Cost}(i,j)$ needs value to left on same row
and below on same column
- Fill diagonally \diagup Only need values above diagonal, $i \leq j$
- Time taken is $O(j-i)$ for entry (i,j)
- Overall $O(n^3)$ steps to fill $O(n^2)$ table

Warshall, transitive closure

- * Given an undirected graph ...
 - * Edges represented by adjacency matrix A
- * ... compute which pairs of vertices are connected by a path (sequence of edges)
- * Connectivity = **transitive closure** of edge relation



Adjacency matrix

$A[i][j] = 1 \text{ iff } (i, j) \text{ is an edge}$

1	2	3	4	5	6	7	8
1	0	1	0	0	0	0	0
2	1	0	1	1	1	0	0
3	0	1	0	1	0	0	0
4	0	1	1	0	1	0	0
5	0	1	0	1	0	0	0
6	0	0	0	0	0	0	1
7	0	0	0	0	0	1	0
8	0	0	0	0	0	0	1

Want to compute a new matrix P (for paths)

$P[i][j] = 1 \text{ iff there is a path from } i \text{ to } j$

Warshall's algorithm

- Vertices are numbered $1, 2, \dots, k$
- Compute a sequence of matrices A^0, A^1, \dots, A^n

$A^k[i][j] = 1$ iff there is a path from v_i to v_j
where intermediate vertices are in $\{v_1, \dots, v_k\}$
Note that i, j can be bigger than k
- Clearly
 - $A^0 = A$ - no intermediate vertices - all paths are direct edges
 - $A^n = P$ - any vertex can appear on path

Computing A^k from A^{k-1}

$$A^k[i][j] = 1 \quad \text{if}$$

$$A^{k-1}[i][j] = 1$$

Path exists already,
 v_k not needed

OR

$$A^{k-1}[i][k] = 1, A^{k-1}[k][j] = 1$$

Paths from v_i to v_k, v_k to v_j only
use vertices in $\{v_1, \dots, v_{k-1}\}$

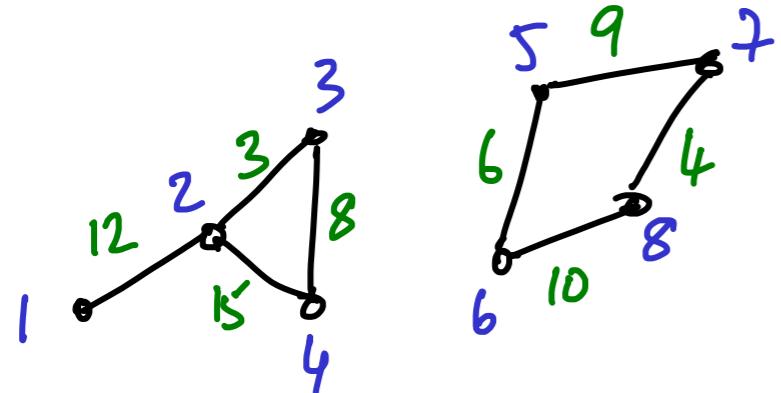
Updating A^k from A^{k-1} takes $O(n^2)$ time

Overall, n iterations, so $O(n^3)$

Simple nested loop implementation - See Levitin

Floyd, all pairs shortest path

- * Given an undirected graph with edge weights ...
 - * Weight represents cost—price, distance, time ...
 - * No edge— infinite cost
- * ... find the smallest weight path between any pairs of vertices
- * “All pairs shortest path”



- Find smallest weight path between v_i, v_j
- No path \Rightarrow Weight is ∞

(to implement, choose a value bigger than sum of all weights)

Initial adjacency matrix has weight information

$A[i][j] = \text{Weight of edge } (i,j)$, ∞ if no edge

Like Warshall's algorithm, define a sequence of matrices

A^0, A^1, \dots, A^n

$A^k[i][j] = \min \text{ weight of paths from } i \text{ to } j \text{ using intermediate vertices in } \{v_1, \dots, v_k\}$

Computing A^k from A^{k-1}

$$A^k[i][j] = \min \left(A^{k-1}[i][j], \begin{array}{l} \text{existing path, without} \\ \text{using } v_k \\ A^{k-1}[i][k] + A^{k-1}[k][j] \end{array} \right)$$

best new path via v_k

Again, each iteration $A^{k-1} \rightarrow A^k$ takes $O(n^2)$ time

Overall n iterations $\rightarrow O(n^3)$