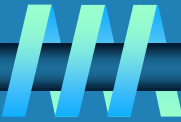


# Dynamic Programming

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**Prof. Sushree Sangita Jena**

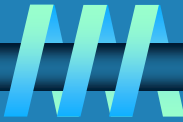
# Dynamic Programming



*Dynamic Programming* is a general algorithm design technique for solving problems defined by recurrences with overlapping subproblems

- Invented by American mathematician Richard Bellman in the 1950s to solve optimization problems and later assimilated by CS
- “Programming” here means “planning”
- Main idea:
  - set up a recurrence relating a solution to a larger instance to solutions of some smaller instances
  - solve smaller instances once
  - record solutions in a table
  - extract solution to the initial instance from that table

# Example 1: Fibonacci numbers



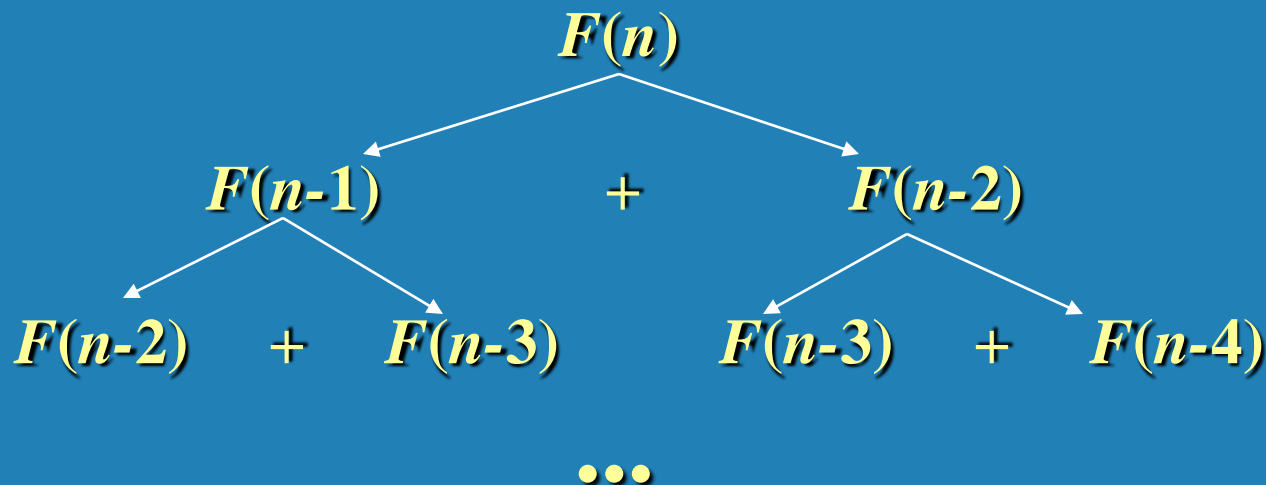
- Recall definition of Fibonacci numbers:

$$F(n) = F(n-1) + F(n-2)$$

$$F(0) = 0$$

$$F(1) = 1$$

- Computing the  $n^{\text{th}}$  Fibonacci number recursively (top-down):



# Example 1: Fibonacci numbers (cont.)

Computing the  $n^{\text{th}}$  Fibonacci number using bottom-up iteration and recording results:

$$F(0) = 0$$

$$F(1) = 1$$

$$F(2) = 1 + 0 = 1$$

...

$$F(n-2) =$$

$$F(n-1) =$$

$$F(n) = F(n-1) + F(n-2)$$

0	1	1	...	$F(n-2)$	$F(n-1)$	$F(n)$
---	---	---	-----	----------	----------	--------

Efficiency:

- time
- space



## Example 2: Coin-row problem

There is a row of  $n$  coins whose values are some positive integers  $c_1, c_2, \dots, c_n$ , not necessarily distinct. The goal is to pick up the maximum amount of money subject to the constraint that no two coins adjacent in the initial row can be picked up.

E.g.: 5, 1, 2, 10, 6, 2. What is the best selection?

Also try: 5, 1, 6, 10, 5, 2

# DP solution to the coin-row problem

Let  $F(n)$  = maximum amount that can be picked up from the first  $n$  coins in the row of coins.

To derive a recurrence for  $F(n)$ , we partition all the allowed coin selections into two groups:

those without last coin – the max amount is ?

those with the last coin -- the max amount is ?

Thus we have the following recurrence

$$F(n) = \max\{ \quad \quad \quad \} \text{ for } n > 1,$$

$$F(0) = 0, \quad F(1) = c_1$$

# DP solution to the coin-row problem

Let  $F(n)$  = maximum amount that can be picked up from the first  $n$  coins in the row of coins.

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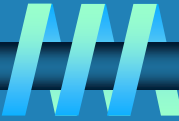
those with the last coin -- the max amount is ?

Thus we have the following recurrence

$$F(n) = \max\{c_n + F(n-2), F(n-1)\} \text{ for } n > 1,$$

$$F(0) = 0, F(1) = c_1$$

# DP solution to the coin-row problem (cont.)



$$F(n) = \max\{c_n + F(n-2), F(n-1)\} \text{ for } n > 1,$$
$$F(0) = 0, F(1) = c_1$$

index	0	1	2	3	4	5	6
coins	--	5	1	6	10	5	2
F( )	0, N	5 Y	5 N	11 Y	15 Y	16 Y	17 Y

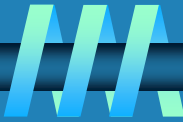
**Max amount:**            **Coins of optimal solution:**

**Time and space efficiency:**

**What's missing? ...**

**Note: All smaller instances were solved. Solution to subproblem may not be part of solution to larger problem. (Greedy algorithms don't solve all smaller and always use solution to smaller in larger.)**

# DP solution to the coin-row problem (cont.)



$$F(n) = \max\{c_n + F(n-2), F(n-1)\} \text{ for } n > 1,$$
$$F(0) = 0, F(1) = c_1$$

index	0	1	2	3	4	5	6
coins	--	5	1	6	10	5	2
F( )							

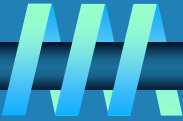
**Max amount:**            **Coins of optimal solution:**

**Time and space efficiency:**

**What's missing? Which coins to pick up! Any ideas?**

**Note: All smaller instances were solved. Solution to subproblem may not be part of solution to larger problem. (Greedy algorithms don't solve all smaller and always use solution to smaller in larger.)**

# DP solution to the coin-row problem (cont.)



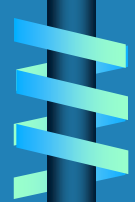
$$F(n) = \max\{c_n + F(n-2), F(n-1)\} \text{ for } n > 1,$$
$$F(0) = 0, F(1) = c_1$$

i	0	1	2	3	4	5	6
c(i)	--	5	1	6	10	5	2
F( i )	0	5	5	11	15	16	17

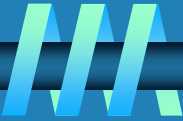
To find coins, remember choice at each step:

1. Add row P(n): 0/1 = leave/pickup coin n (at that point)
2. Fill in rows F and P together, left to right
3. For final choice, work backwards from right:

0=leave and move 1 left, 1=pickup and move 2 left



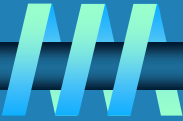
# DP solution to the coin-row problem (cont.)



$$F(n) = \max\{c_n + F(n-2), F(n-1)\} \text{ for } n > 1,$$
$$F(0) = 0, F(1) = c_1$$

i	0	1	2	3	4	5	6
c(i)	--	5	1	6	10	5	2
F(i)	0	5	5	11	15	16	17
Choice		1	0	1	1	1	1
Pick		1			1		1

# DP Steps



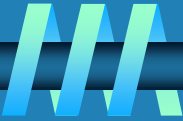
$$F(n) = \max\{c_n + F(n-2), F(n-1)\} \text{ for } n > 1,$$
$$F(0) = 0, F(1) = c_1$$

1. Recursive math function describing maximum
2. Recursive function solving problem, top down (too slow)
3. Iterative solution, bottom up
4. Add information to find how to get maximum
5. Work backward to find maximum



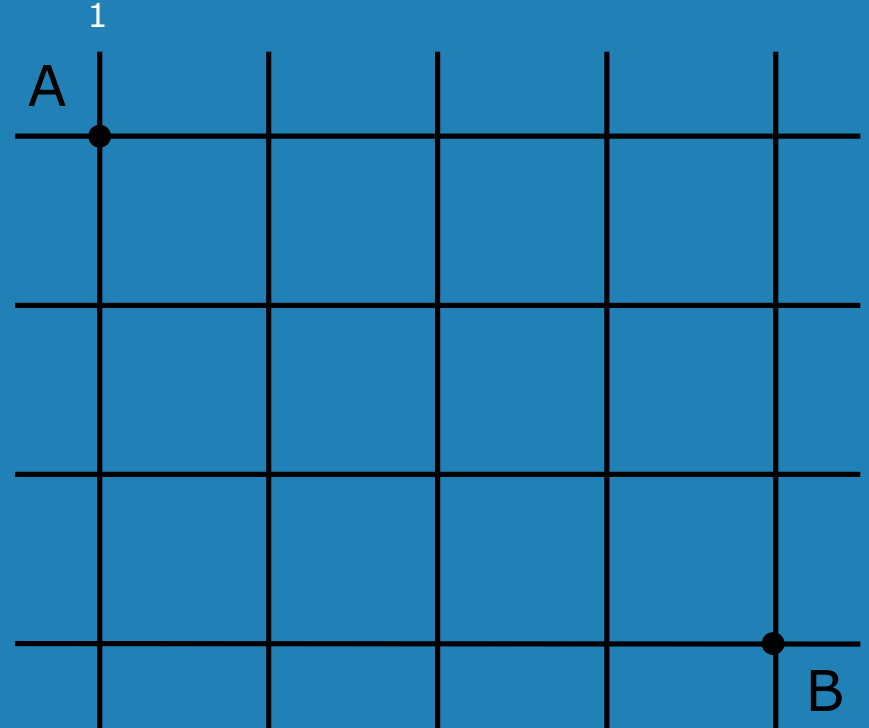


# Example 3: Path counting



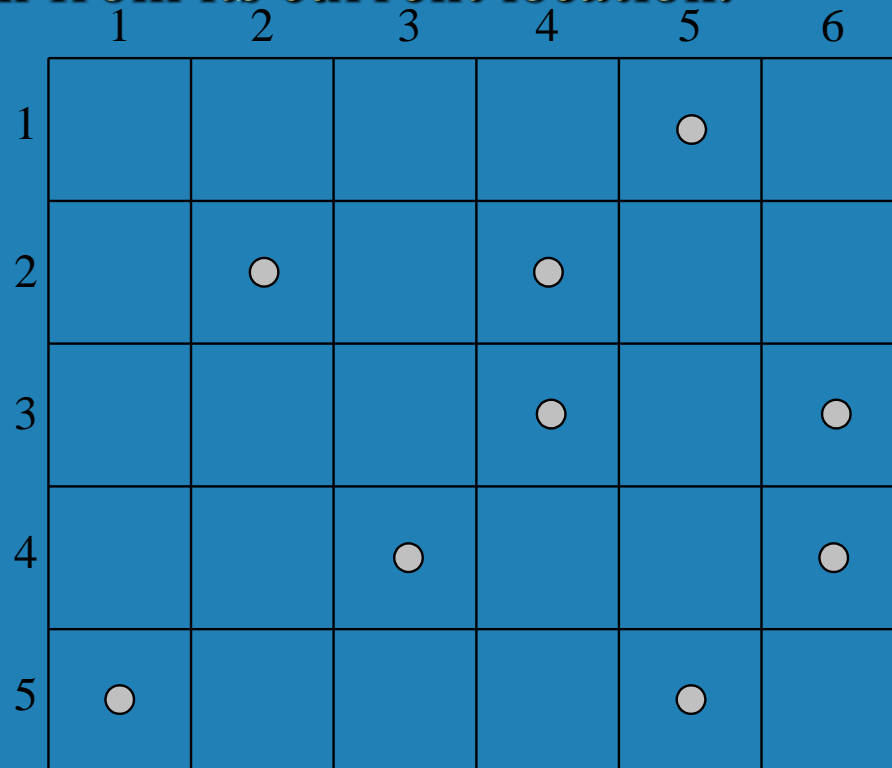
Consider the problem of counting the number of shortest paths from point A to point B in a city with perfectly horizontal streets and vertical avenues

$$F(i,j) = F(i-1,j) + F(i,j-1)$$



# Example 4: Coin-collecting by robot

Several coins are placed in cells of an  $n \times m$  board. A robot, located in the upper left cell of the board, needs to collect as many of the coins as possible and bring them to the bottom right cell. On each step, the robot can move either one cell to the right or one cell down from its current location.



# Solution to the coin-collecting problem

Let  $F(i,j)$  be the largest number of coins the robot can collect and bring to cell  $(i,j)$  in the  $i$ th row and  $j$ th column.

The largest number of coins that can be brought to cell  $(i,j)$ :

from the left neighbor ?

from the neighbor above?

The recurrence:

$$F(i,j) = \max\{F(i-1,j), F(i,j-1)\} + c_{ij} \quad \text{for } 1 \leq i \leq n, 1 \leq j \leq m$$
  
where  $c_{ij} = 1$  if there is a coin in cell  $(i,j)$ , and  $c_{ij} = 0$  otherwise

$$F(0,j) = 0 \text{ for } 1 \leq j \leq m \text{ and } F(i, 0) = 0 \text{ for } 1 \leq i \leq n.$$

# Solution to the coin-collecting problem (cont.)

$$F(i, j) = \max\{F(i-1, j), F(i, j-1)\} + c_{ij} \text{ for } 1 \leq i \leq n, 1 \leq j \leq m$$

where  $c_{ij} = 1$  if there is a coin in cell  $(i, j)$ , and  $c_{ij} = 0$  otherwise

$F(0, j) = 0$  for  $1 \leq j \leq m$  and  $F(i, 0) = 0$  for  $1 \leq i \leq n$ .

	1	2	3	4	5	6
1					●	
2		●		●		
3				●		●
4			●			●
5	●				●	

# Solution to coin-collecting problem (cont.)

$$F(i, j) = \max\{F(i-1, j), F(i, j-1)\} + c_{ij} \quad \text{for } 1 \leq i \leq n, 1 \leq j \leq m$$

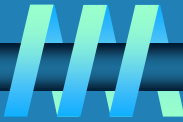
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$$F(0, j) = 0 \text{ for } 1 \leq j \leq m \text{ and } F(i, 0) = 0 \text{ for } 1 \leq i \leq n.$$

*Code (3 versions)? Storage? Path? Storage? Subproblems?*

	1	2	3	4	5	6
1					●	
2		●		●		
3				●		●
4			●			●
5	●				●	

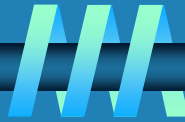
# Other examples of DP algorithms



- **Computing a binomial coefficient (# 9, Exercises 8.1)**
- **General case of the change making problem (Sec. 8.1)**
- **Some difficult discrete optimization problems:**
  - **knapsack (Sec. 8.2)**
  - **traveling salesman**
- **Constructing an optimal binary search tree (Sec. 8.3)**
- **Warshall's algorithm for transitive closure (Sec. 8.4)**
- **Floyd's algorithm for all-pairs shortest paths (Sec. 8.4)**



# Knapsack Problem by DP



Given  $n$  items of

integer weights:  $w_1 \ w_2 \ \dots \ w_n$

values:  $v_1 \ v_2 \ \dots \ v_n$

a knapsack of integer capacity  $W$

find most valuable subset of the items that fit into the knapsack

Recursive solution?

What is smaller problem?

How to use solution to smaller in solution to larger

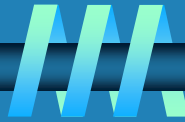
Table?

Order to solve?

Initial conditions?



# Knapsack Problem by DP (example)



Example: Knapsack of capacity  $W = 5$

<u>item</u>	<u>weight</u>	<u>value</u>
-------------	---------------	--------------

1	2	\$12
---	---	------

2	1	\$10
---	---	------

3	3	\$20
---	---	------

4	2	\$15
---	---	------

capacity  $j$

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

0	0	0	0	0	0	0
---	---	---	---	---	---	---

$w_1 = 2, v_1 = 12$	1	0	0			
---------------------	---	---	---	--	--	--

$w_2 = 1, v_2 = 10$	2					
---------------------	---	--	--	--	--	--

$w_3 = 3, v_3 = 20$	3					
---------------------	---	--	--	--	--	--

$w_4 = 2, v_4 = 15$	4					?
---------------------	---	--	--	--	--	---



# Knapsack Problem by DP (example)

Example: Knapsack of capacity  $W = 5$

<u>item</u>	<u>weight</u>	<u>value</u>
-------------	---------------	--------------

1	2	\$12
---	---	------

2	1	\$10
---	---	------

3	3	\$20
---	---	------

4	2	\$15
---	---	------

capacity  $j$

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

0	0	0	0	0	0	0
---	---	---	---	---	---	---

$w_1 = 2, v_1 = 12$	1	0	0	12	12	12	12
---------------------	---	---	---	----	----	----	----

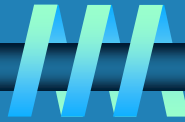
$w_2 = 1, v_2 = 10$	2	0	10	12	22	22	22
---------------------	---	---	----	----	----	----	----

$w_3 = 3, v_3 = 20$	3	0	10	12	22	30	32
---------------------	---	---	----	----	----	----	----

$w_4 = 2, v_4 = 15$	4	0	10	15	25	30	37
---------------------	---	---	----	----	----	----	----

?

# Knapsack Problem by DP



Given  $n$  items of

integer weights:  $w_1 \ w_2 \ \dots \ w_n$

values:  $v_1 \ v_2 \ \dots \ v_n$

a knapsack of integer capacity  $W$

find most valuable subset of the items that fit into the knapsack

Recursive solution?

What is smaller problem?

How to use solution to smaller in solution to larger

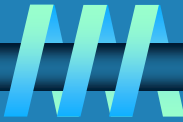
Table?

Order to solve?

Initial conditions?



# Knapsack Problem by DP



Given  $n$  items of

integer weights:  $w_1 \ w_2 \ \dots \ w_n$

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a knapsack of integer capacity  $W$

find most valuable subset of the items that fit into the knapsack

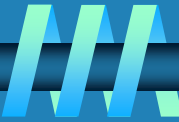
Consider instance defined by first  $i$  items and capacity  $j$  ( $j \leq W$ ).

Let  $V[i,j]$  be optimal value of such instance. Then

$$V[i,j] = \begin{cases} \max \{V[i-1,j], v_i + V[i-1,j-w_i]\} & \text{if } j-w_i \geq 0 \\ V[i-1,j] & \text{if } j-w_i < 0 \end{cases}$$

Initial conditions:  $V[0,j] = 0$  and  $V[i,0] = 0$

# Optimal Binary Search Trees



**Problem:** Given  $n$  keys  $a_1 < \dots < a_n$  and probabilities  $p_1 \leq \dots \leq p_n$  searching for them, find a BST with a minimum average number of comparisons in successful search.

Since total number of BSTs with  $n$  nodes is given by  $C(2n, n)/(n+1)$ , which grows exponentially, brute force is hopeless.

**Example:** What is an optimal BST for keys  $A, B, C$ , and  $D$  with search probabilities 0.1, 0.2, 0.4, and 0.3, respectively?

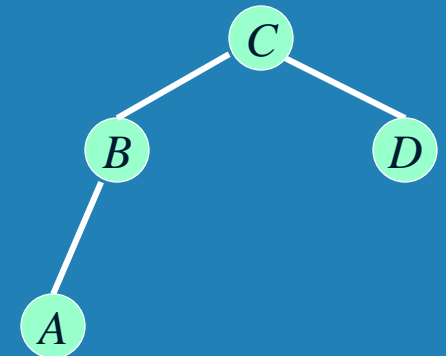
What smaller problems could we use?

Let's first look at an example.



# Optimal Binary Search Trees

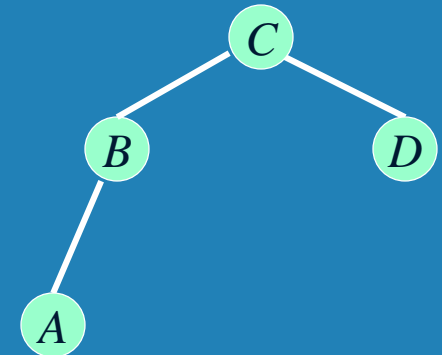
<b>Example:</b>	<b>key</b>	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>
	<b>probability</b>	<b>0.1</b>	<b>0.2</b>	<b>0.4</b>	<b>0.3</b>
		optimal BST			



Expected number of comparisons?

# Optimal Binary Search Trees

<b>Example:</b>	<b>key</b>	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>
	<b>probability</b>	<b>0.1</b>	<b>0.2</b>	<b>0.4</b>	<b>0.3</b>
		optimal BST			



Expected number of comparisons for optimal BST:

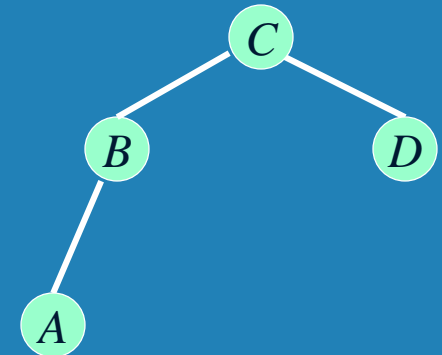
$$1*0.4 + 2*(0.2+0.3) + 3*(0.1) = 0.4+1.0+0.3=1.7$$

Non-optimal BST – Swap A and B:

$$1*0.4 + 2*(0.1+0.3) + 3*(0.2) = 0.4+0.8+0.6=1.8$$

# Optimal Binary Search Trees

<b>Example:</b>	<b>key</b>	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>
	<b>probability</b>	<b>0.1</b>	<b>0.2</b>	<b>0.4</b>	<b>0.3</b>
		optimal BST			



Expected number of comparisons for optimal BST:

$$1*0.4 + 2*(0.2+0.3) + 3*(0.1) = 0.4+1.0+0.3=1.7$$

Can factor out cost of visiting each node once:

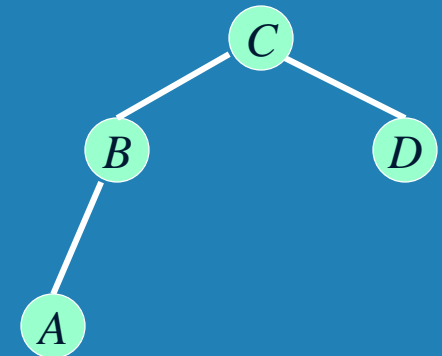
$$1*0.4 + 2*(0.2+0.3) + 3*(0.1) = 0*.4+1*.5+2*.1 + 1*(.4+.5+.1)$$

Moving subtree up or down changes total by weight of subtree

- BA at level 1/2 has cost  $1*.2 + 2*.1 = .4 =$
- BA at level 2/3 has cost  $2*.2 + 3*.1 = .7 = .4 + (.2 + .1)$
- BA at level 3/4 has cost ???

# Optimal Binary Search Trees

<b>Example:</b>	<b>key</b>	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>
	<b>probability</b>	<b>0.1</b>	<b>0.2</b>	<b>0.4</b>	<b>0.3</b>
		optimal BST			



Expected number of comparisons for optimal BST:

$$1*0.4 + 2*(0.2+0.3) + 3*(0.1) = 0.4+1.0+0.3=1.7$$

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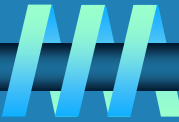
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Moving subtree up or down changes total by weight of subtree

- BA at level 1/2 has cost  $1*.2 + 2*.1 = 0.4 =$
- BA at level 2/3 has cost  $2*.2 + 3*.1 = 0.7 = .4 + (.2 + .1)$
- BA at level 3/4 has cost  $3*.2 + 4*.1 = 1.0 = .4 + (.2 + .1)$



# Optimal Binary Search Trees

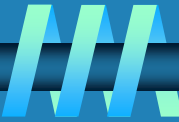


**Problem:** Given  $n$  keys  $a_1 < \dots < a_n$  and probabilities  $p_1 \leq \dots \leq p_n$  searching for them, find a BST with a minimum average number of comparisons in successful search.

**What smaller problems could we use?**



# Optimal Binary Search Trees



**Problem:** Given  $n$  keys  $a_1 < \dots < a_n$  and probabilities  $p_1 \leq \dots \leq p_n$  searching for them, find a BST with a minimum average number of comparisons in successful search.

What smaller problems could we use?

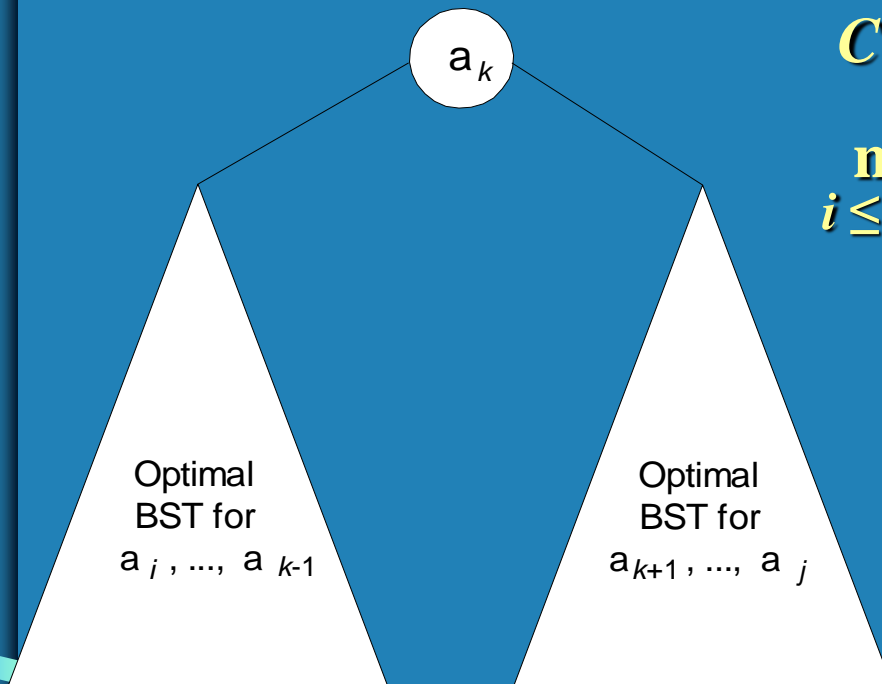
What if we let each element be the root?

What is needed then?



# DP for Optimal BST Problem

Let  $T[i,j]$  be optimal BST for keys  $a_i < \dots < a_j$ ,  $C[i,j]$  be minimum average number of comparisons made in  $T[i,j]$ , for  $1 \leq i \leq j \leq n$ . Consider optimal BST among all BSTs with some  $a_k$  ( $i \leq k \leq j$ ) as their root;  $T[i,j]$  is the best among them.



$$C[i,j] =$$

Min Num Comparisons

$$\min_{i \leq k \leq j} \{p_k \cdot 1 +$$

Best Tree

$$\sum_{s=i}^{k-1} p_s \cdot (\text{level } a_s \text{ in } T[i,k-1] + 1) +$$

$$\sum_{s=k+1}^j p_s \cdot (\text{level } a_s \text{ in } T[k+1,j] + 1)\}$$

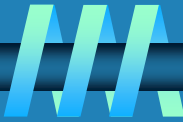
# DP for Optimal BST Problem (cont.)

After simplifications, we obtain the recurrence for  $C[i,j]$ :

$$C[i,j] = \min_{i \leq k \leq j} \{C[i,k-1] + C[k+1,j]\} + \sum_{s=i}^j p_s \quad \text{for } 1 \leq i \leq j \leq n$$
$$C[i,i] = p_i \quad \text{for } 1 \leq i \leq j \leq n$$

What table elements are involved?

# DP for Optimal BST Problem (cont.)



After simplifications, we obtain the recurrence for  $C[i,j]$ :

$$C[i,j] = \min_{i \leq k \leq j} \{C[i,k-1] + C[k+1,j]\} + \sum_{s=i}^j p_s \quad \text{for } 1 \leq i \leq j \leq n$$

$$C[i,i] = p_i \quad \text{for } 1 \leq i \leq j \leq n$$

	0	1					$j$	$n$
1	0	$p_1$						goal
		0	$p_2$					
$i$							$C[i,j]$	
								$p_n$
$n+1$								0

**Example:** key                    *A*    *B*    *C*    *D*  
    probability   0.1   0.2   0.4   0.3

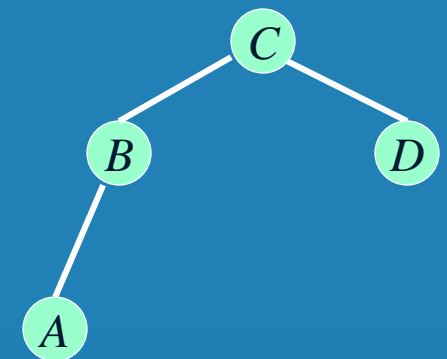
The left table is filled using the recurrence

$$C[i,j] = \min_{i \leq k \leq j} \{C[i,k-1] + C[k+1,j]\} + \sum_{s=i}^j p_s, \quad C[i,i] = p_i$$

The right saves the tree roots, which are the *k*'s that give the minima

<i>i j</i>	0	1	2	3	4
1	0	.1	.4	1.1	1.7
2		0	.2	.8	1.4
3			0	.4	1.0
4				0	.3
5					0

<i>i j</i>	0	1	2	3	4
1		1	2	3	3
2			2	3	3
3				3	3
4					4
5					



optimal BST

Tables filled diagonal by diagonal (remember what  $C[i,j]$  is).

## ALGORITHM *OptimalBST*( $P[1..n]$ )

//Finds an optimal binary search tree by dynamic programming  
//Input: An array  $P[1..n]$  of search probabilities for a sorted list of  $n$  keys  
//Output: Average number of comparisons in successful searches in the  
//        optimal BST and table  $R$  of subtrees' roots in the optimal BST  
**for**  $i \leftarrow 1$  **to**  $n$  **do**  
     $C[i, i - 1] \leftarrow 0$   
     $C[i, i] \leftarrow P[i]$   
     $R[i, i] \leftarrow i$   
 $C[n + 1, n] \leftarrow 0$   
**for**  $d \leftarrow 1$  **to**  $n - 1$  **do** //diagonal count  
    **for**  $i \leftarrow 1$  **to**  $n - d$  **do**  
         $j \leftarrow i + d$   
         $minval \leftarrow \infty$   
        **for**  $k \leftarrow i$  **to**  $j$  **do**  
            **if**  $C[i, k - 1] + C[k + 1, j] < minval$   
                 $minval \leftarrow C[i, k - 1] + C[k + 1, j]; kmin \leftarrow k$   
         $R[i, j] \leftarrow kmin$   
         $sum \leftarrow P[i];$  **for**  $s \leftarrow i + 1$  **to**  $j$  **do**  $sum \leftarrow sum + P[s]$   
         $C[i, j] \leftarrow minval + sum$   
**return**  $C[1, n], R$

# Analysis DP for Optimal BST Problem

**Time efficiency:**  $\Theta(n^3)$  but can be reduced to  $\Theta(n^2)$  by taking advantage of monotonicity of entries in the root table, i.e.,  $R[i,j]$  is always in the range between  $R[i,j-1]$  and  $R[i+1,j]$

**Space efficiency:**  $\Theta(n^2)$

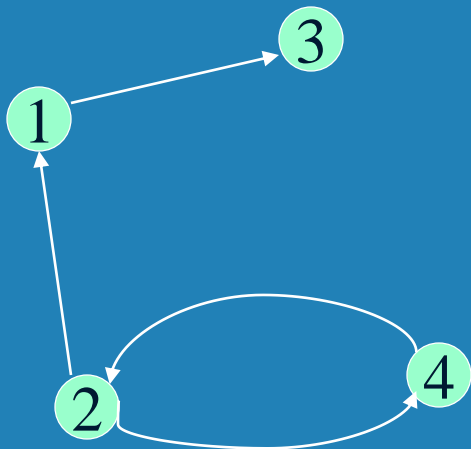
**Method can be expanded to include unsuccessful searches**



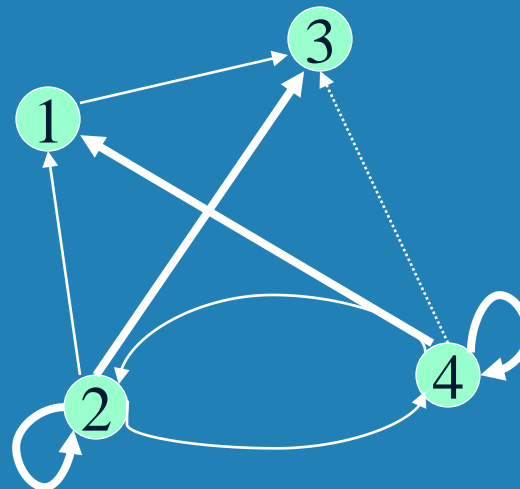
# Warshall's Algorithm: Transitive Closure

## SKIP

- Computes the transitive closure of a relation
- Alternatively: existence of all nontrivial paths in a digraph
- Example of transitive closure:



0	0	1	0
1	0	0	1
0	0	0	0
0	1	0	0

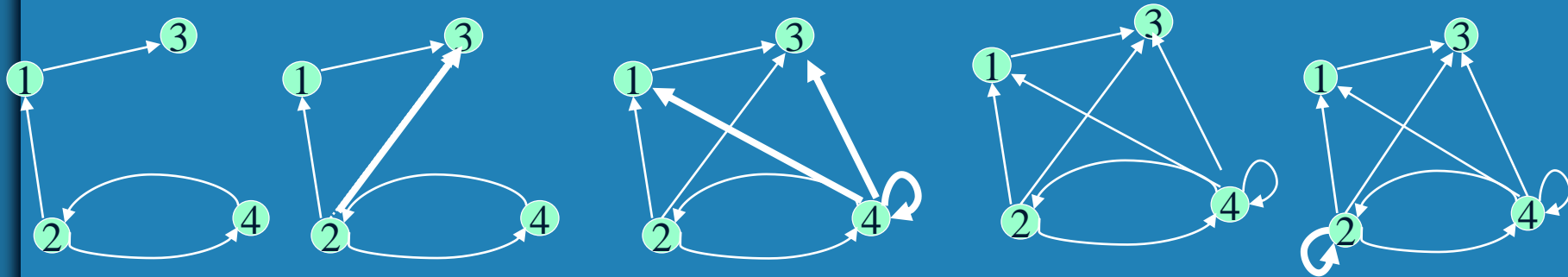


0	0	1	0
1	1	1	1
0	0	0	0
1	1	1	1

# Warshall's Algorithm

Constructs transitive closure  $T$  as the last matrix in the sequence of  $n$ -by- $n$  matrices  $R^{(0)}, \dots, R^{(k)}, \dots, R^{(n)}$  where  $R^{(k)}[i,j] = 1$  iff there is nontrivial path from  $i$  to  $j$  with only first  $k$  vertices allowed as intermediate

Note that  $R^{(0)} = A$  (adjacency matrix),  $R^{(n)} = T$  (transitive closure)

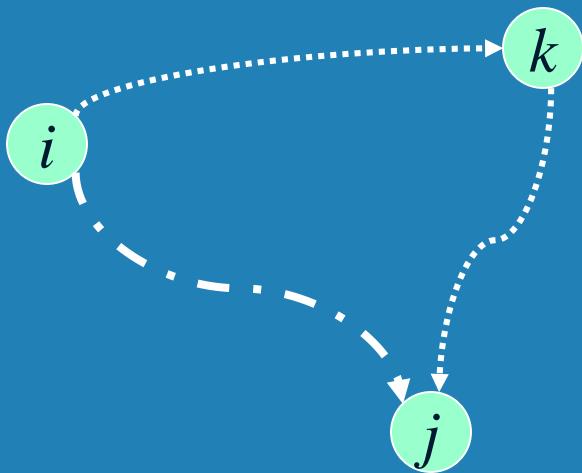


$R^{(0)}$	$R^{(1)}$	$R^{(2)}$	$R^{(3)}$	$R^{(4)}$
0 0 1 0	0 0 1 0	0 0 1 0	0 0 1 0	0 0 1 0
1 0 0 1	1 0 <b>1</b> 1	1 0 1 1	1 0 1 1	1 <b>1</b> 1 1
0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
0 1 0 0	0 1 0 0	<b>1</b> 1 <b>1</b> <b>1</b>	1 1 1 1	1 1 1 1

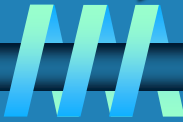
# Warshall's Algorithm (recurrence)

On the  $k$ -th iteration, the algorithm determines for every pair of vertices  $i, j$  if a path exists from  $i$  and  $j$  with just vertices  $1, \dots, k$  allowed as intermediate

$$R^{(k)}[i,j] = \begin{cases} R^{(k-1)}[i,j] & \text{(path using just } 1, \dots, k-1) \\ \text{or} \\ R^{(k-1)}[i,k] \text{ and } R^{(k-1)}[k,j] & \text{(path from } i \text{ to } k \\ & \text{and from } k \text{ to } j \\ & \text{using just } 1, \dots, k-1) \end{cases}$$



# Warshall's Algorithm (matrix generation)



Recurrence relating elements  $R^{(k)}$  to elements of  $R^{(k-1)}$  is:

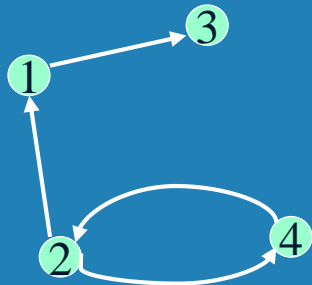
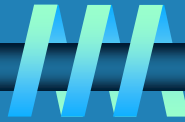
$$R^{(k)}[i,j] = R^{(k-1)}[i,j] \text{ or } (R^{(k-1)}[i,k] \text{ and } R^{(k-1)}[k,j])$$

It implies the following rules for generating  $R^{(k)}$  from  $R^{(k-1)}$ :

**Rule 1** If an element in row  $i$  and column  $j$  is 1 in  $R^{(k-1)}$ , it remains 1 in  $R^{(k)}$

**Rule 2** If an element in row  $i$  and column  $j$  is 0 in  $R^{(k-1)}$ , it has to be changed to 1 in  $R^{(k)}$  if and only if the element in its row  $i$  and column  $k$  and the element in its column  $j$  and row  $k$  are both 1's in  $R^{(k-1)}$

# Warshall's Algorithm (example)



$$R^{(0)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

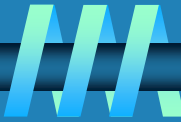
$$R^{(1)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$R^{(2)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

$$R^{(3)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

$$R^{(4)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

# Warshall's Algorithm (pseudocode and analysis)



**ALGORITHM** *Warshall*( $A[1..n, 1..n]$ )

//Implements Warshall's algorithm for computing the transitive closure

//Input: The adjacency matrix  $A$  of a digraph with  $n$  vertices

//Output: The transitive closure of the digraph

$R^{(0)} \leftarrow A$

**for**  $k \leftarrow 1$  **to**  $n$  **do**

**for**  $i \leftarrow 1$  **to**  $n$  **do**

**for**  $j \leftarrow 1$  **to**  $n$  **do**

$R^{(k)}[i, j] \leftarrow R^{(k-1)}[i, j] \text{ or } (R^{(k-1)}[i, k] \text{ and } R^{(k-1)}[k, j])$

**return**  $R^{(n)}$

**Time efficiency:**  $\Theta(n^3)$

**Space efficiency:** Matrices can be written over their predecessors

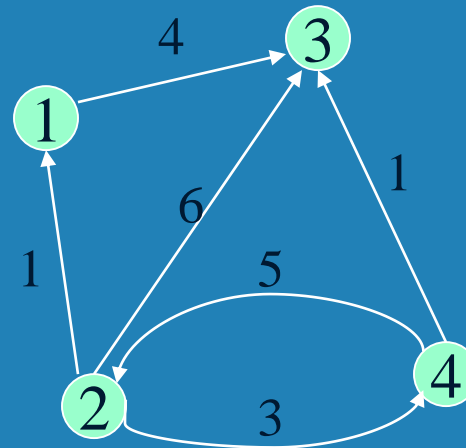
# Floyd's Algorithm: All pairs shortest paths

## SKIP

**Problem:** In a weighted (di)graph, find shortest paths between every pair of vertices

**Same idea:** construct solution through series of matrices  $D^{(0)}$ , ...,  $D^{(n)}$  using increasing subsets of the vertices allowed as intermediate

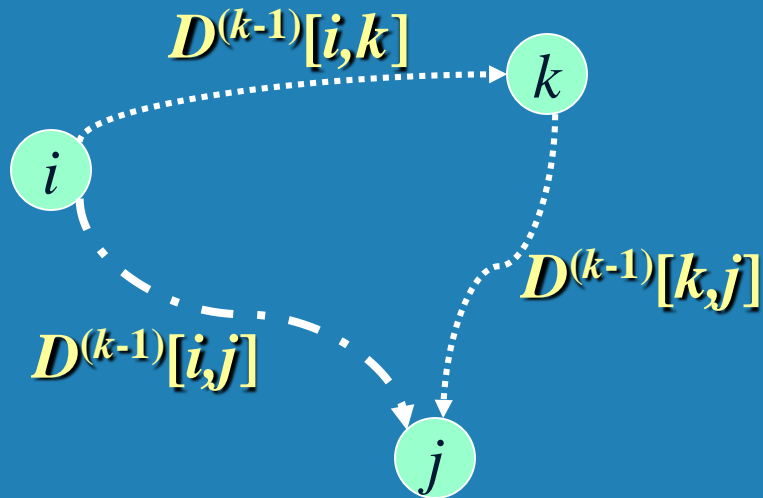
**Example:**



# Floyd's Algorithm (matrix generation)

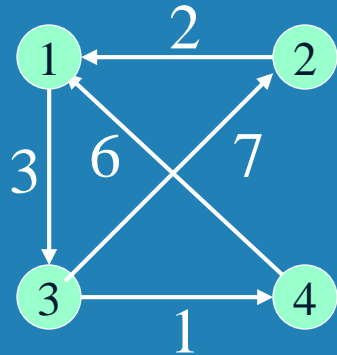
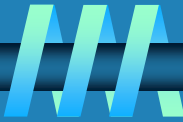
On the  $k$ -th iteration, the algorithm determines shortest paths between every pair of vertices  $i, j$  **that use only vertices among  $1, \dots, k$  as intermediate**

$$D^{(k)}[i,j] = \min \{D^{(k-1)}[i,j], D^{(k-1)}[i,k] + D^{(k-1)}[k,j]\}$$





# Floyd's Algorithm (example)



$$D^{(0)} =$$

0	$\infty$	3	$\infty$
2	0	$\infty$	$\infty$
$\infty$	7	0	1
6	$\infty$	$\infty$	0

$$D^{(1)} =$$

0	$\infty$	3	$\infty$
2	0	<b>5</b>	$\infty$
$\infty$	7	0	1
6	$\infty$	<b>9</b>	0

$$D^{(2)} =$$

0	$\infty$	3	$\infty$
2	0	5	$\infty$
<b>9</b>	7	0	1
6	$\infty$	9	0

$$D^{(3)} =$$

0	<b>10</b>	3	4
2	0	5	<b>6</b>
<b>9</b>	7	0	1
6	<b>16</b>	9	0

$$D^{(4)} =$$

0	10	3	4
2	0	5	6
<b>7</b>	7	0	1
6	16	9	0

D(3): 3 to 1 not allowing 4=9. D(4): 3 to 1 with allowing 4=7

# Floyd's Algorithm (pseudocode and analysis)

**ALGORITHM** *Floyd*( $W[1..n, 1..n]$ )

//Implements Floyd's algorithm for the all-pairs shortest-paths problem

//Input: The weight matrix  $W$  of a graph with no negative-length cycle

//Output: The distance matrix of the shortest paths' lengths

$D \leftarrow W$  //is not necessary if  $W$  can be overwritten

**for**  $k \leftarrow 1$  **to**  $n$  **do**

**for**  $i \leftarrow 1$  **to**  $n$  **do**

**for**  $j \leftarrow 1$  **to**  $n$  **do**

$D[i, j] \leftarrow \min\{D[i, j], D[i, k] + D[k, j]\}$

**return**  $D$

**Time efficiency:**  $\Theta(n^3)$

**Space efficiency:** Matrices can be written over their predecessors

**Note:** Shortest paths themselves can be found, too (Problem 10)