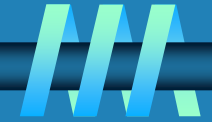


Lecture 9

Dyna c ro ra n

Dynamic Programming

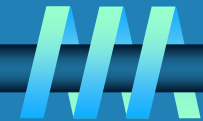


Dynamic Programming is a natural order design technique for solving problems defined by recurrence with overlapping subproblems

- Invited by A can be calculated by B and C
- Memoization
- Mandates
 - Start up a recurrence relation as output to a array instance to store solutions of subproblems
 - Record solutions in a table
 - Extract solution to the instance from the table



Example: Fibonacci numbers



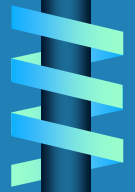
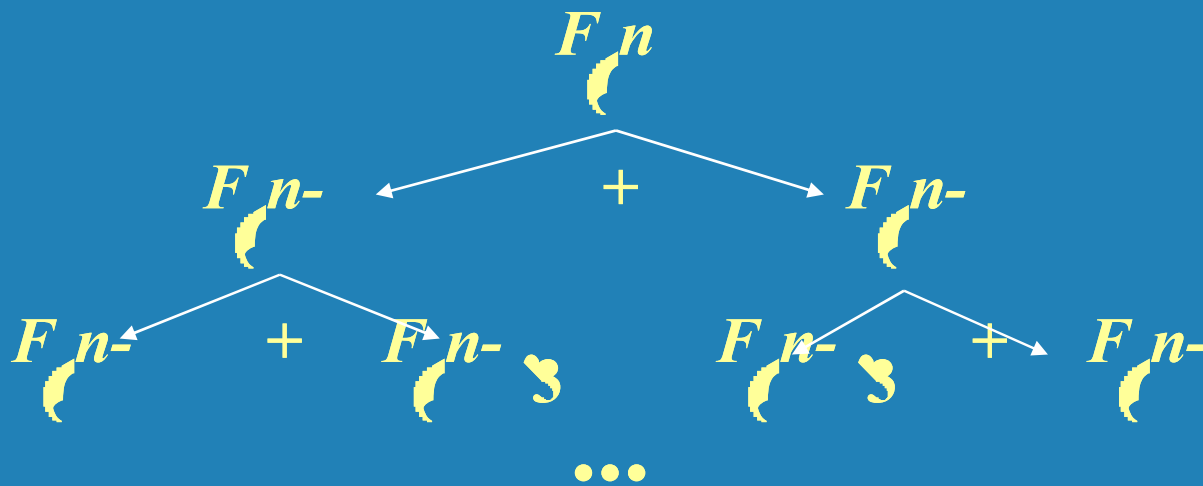
- calculate n th Fibonacci number

$$F_n = F_{n-1} + F_{n-2}$$

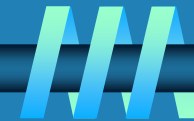
$$F_{n-1} = F_{n-2} + F_{n-3}$$

$$F_{n-2} = F_{n-3} + F_{n-4}$$

- Compute n th Fibonacci number recursively, top down



Example: Fibonacci numbers (cont.)



Computing the n^{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	...	$F(n-2)$	$F(n-1)$	$F(n)$
---	---	---	-----	----------	----------	--------

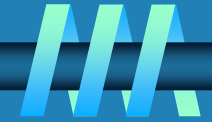
Efficiency:

- time

- space



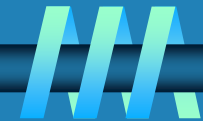
Examples of DP algorithms



- Computing a binomial coefficient
- Matrix multiplication or transitive closure
- Floyd's algorithm or a shortest path
- Constructing an optimal binary search tree
- Dynamic programming optimization problems
 travelling salesman
 knapsack



Computing a binomial coefficient by DP



Binomial coefficients are coefficients of the binomial formula:

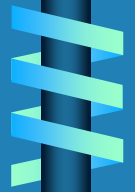
$$(a + b)^n = C(n,0)a^n b^0 + \dots + C(n,k)a^{n-k}b^k + \dots + C(n,n)a^0 b^n$$

Recurrence: $C(n,k) = C(n-1,k) + C(n-1,k-1)$ for $n > k > 0$

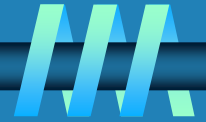
$$C(n,0) = 1, \quad C(n,n) = 1 \quad \text{for } n \geq 0$$

Value of $C(n,k)$ can be computed by filling a table:

	0	1	2	...	$k-1$	k
0	1					
1	1	1				
⋮						
⋮						
⋮						
$n-1$					$C(n-1,k-1)$	$C(n-1,k)$
n						$C(n,k)$



Computing $C(n, k)$: pseudocode and analysis



ALGORITHM *Binomial*(n, k)

//Computes $C(n, k)$ by the dynamic programming algorithm

//Input: A pair of nonnegative integers $n \geq k \geq 0$

//Output: The value of $C(n, k)$

for $i \leftarrow 0$ **to** n **do**

for $j \leftarrow 0$ **to** $\min(i, k)$ **do**

if $j = 0$ **or** $j = i$

$C[i, j] \leftarrow 1$

else $C[i, j] \leftarrow C[i - 1, j - 1] + C[i - 1, j]$

return $C[n, k]$

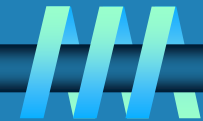
$C(n, k) = \Theta(n^k)$

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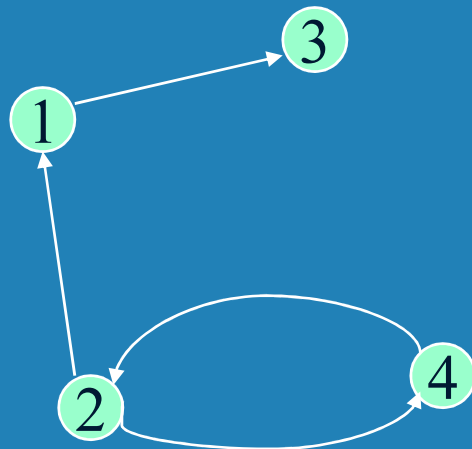
$C(n, k) = \Theta(n^k)$



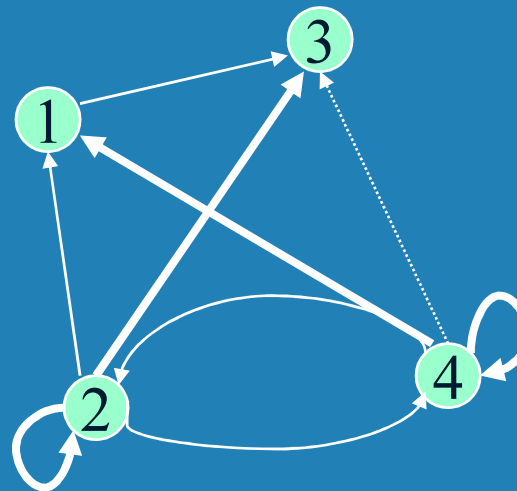
Warshall's Algorithm: Transitive Closure



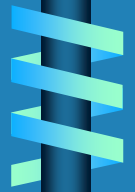
- Compute the transitive closure of a relation
- An arbitrary sequence of nontrivial paths is added
- Example of transitive closure



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

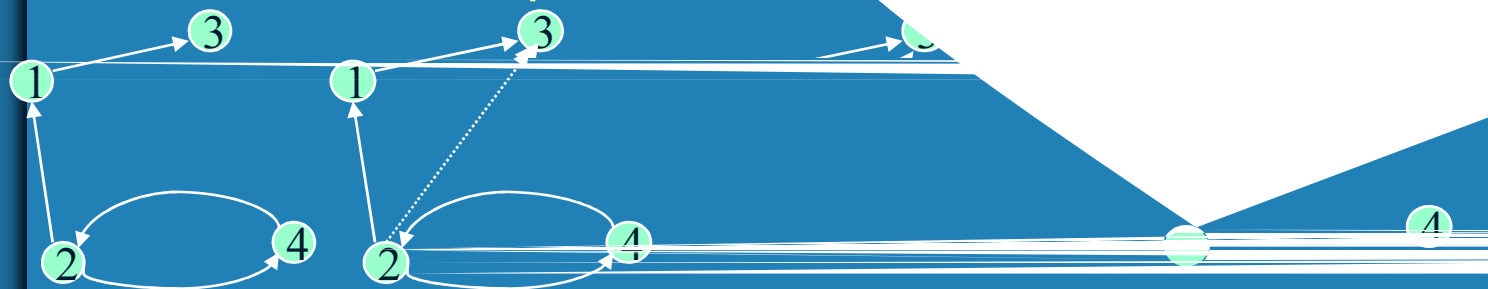


0	0	1	0
1	1	1	1
0	0	0	0
1	1	1	1



Warshall's Algorithm

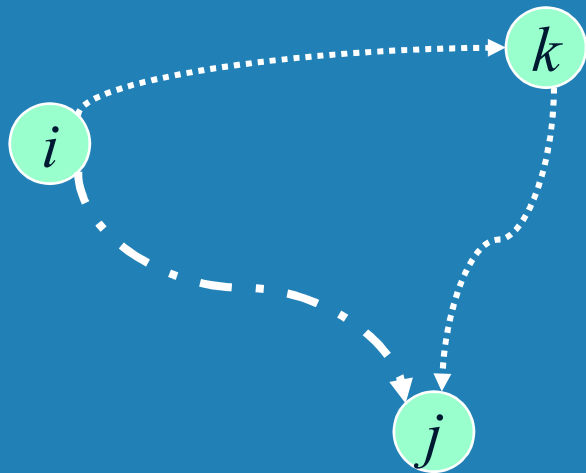
Constructs transitive closure T as transitive closure of
on by n matrix $R^{(0)}$. $R^{(k)}$ is the transitive closure of
 $R^{(k)}$ if j is not a vertex in $R^{(k)}$ then $R^{(k)}$ is the transitive closure of
vertices a and b in $R^{(k)}$.
Not that $R^{(0)}$ is adjacency matrix of A .



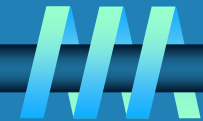
Warshall's Algorithm (recurrence)

Let $R^{(k-1)}$ be a $n \times n$ boolean matrix representing the reachability of vertices i and j with just vertices $1, \dots, k-1$ allowed as intermediate vertices.

$$R^{(k)}(i,j) = \begin{cases} R^{(k-1)}(i,j) & \text{if there is a path from } i \text{ to } j \\ & \text{using only vertices } 1, \dots, k-1 \\ \text{or} \\ R^{(k-1)}(i,k) \text{ and } R^{(k-1)}(k,j) & \text{if there is a path from } i \text{ to } k \\ & \text{and a path from } k \text{ to } j \\ & \text{using only vertices } 1, \dots, k-1 \end{cases}$$



Warshall's Algorithm (matrix generation)



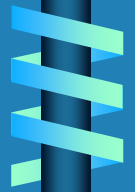
current entries $R^{(k)}$ to entries of $R^{(k-1)}$ is

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

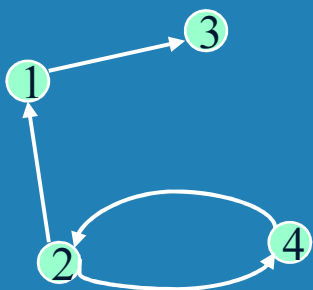
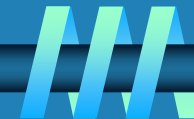
It proceeds row by row for $R^{(k)}$ from $R^{(k-1)}$

using information from row i and column j in $R^{(k-1)}$ to generate $R^{(k)}$

using information from row i and column j in $R^{(k-1)}$ to generate $R^{(k)}$ and on the other hand, information from row i and column k and from row k and column j in $R^{(k-1)}$



Warshall's Algorithm (example)



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

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

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

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

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



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**

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

return $R^{(n)}$

Complexity $\Theta(n^3)$

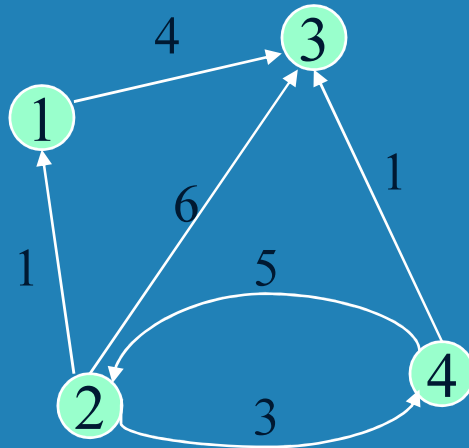
Adjacency Matrices can be written over the processors

Floyd's Algorithm: All pairs shortest paths

Problem: In a weighted undirected graph with n vertices and m edges, find the shortest path between every pair of vertices.

Algorithm: Construct a matrix $D^{(0)}$ where $D^{(0)}_{ij}$ is the weight of the edge between i and j , or ∞ if there is no edge. Then iteratively compute $D^{(k)}$ for $k=1, 2, \dots, n$ using the recurrence:

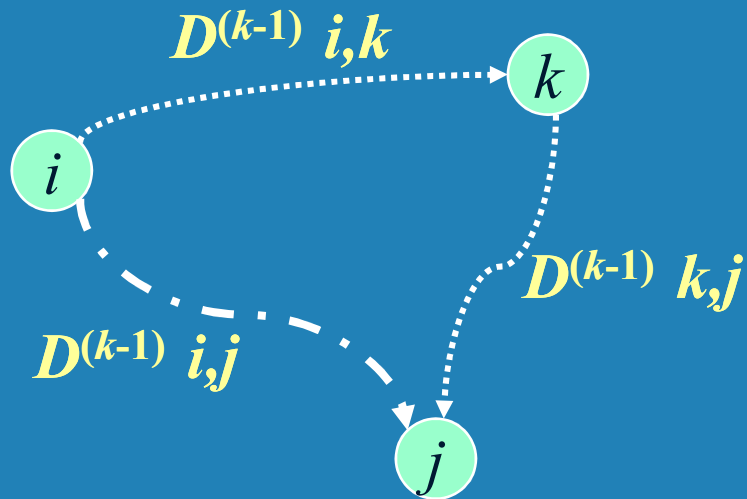
Example



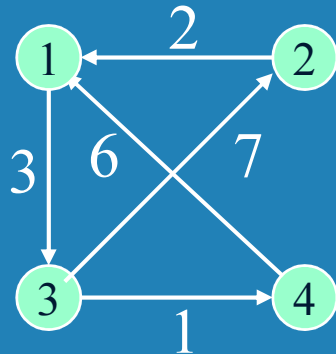
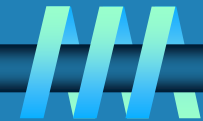
Floyd's Algorithm (matrix generation)

- In the k -th iteration, a shortest path between i and j is updated as

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



Floyd's Algorithm (example)



$$D^{(0)} = \begin{bmatrix} 0 & \infty & 3 & \infty \\ 2 & 0 & \infty & \infty \\ \infty & 7 & 0 & 1 \\ 6 & \infty & \infty & 0 \end{bmatrix}$$

$$D^{(1)} = \begin{bmatrix} 0 & \infty & 3 & \infty \\ 2 & 0 & & \infty \\ \infty & 7 & 0 & 1 \\ 6 & \infty & & 0 \end{bmatrix}$$

$$D^{(2)} = \begin{bmatrix} 0 & \infty & 3 & \infty \\ 2 & 0 & 5 & \infty \\ 7 & 7 & 0 & 1 \\ 6 & \infty & 9 & 0 \end{bmatrix}$$

$$D^{(3)} = \begin{bmatrix} 0 & & 3 & \\ 2 & 0 & 5 & \\ 9 & 7 & 0 & 1 \\ 6 & & 9 & 0 \end{bmatrix}$$

$$D^{(4)} = \begin{bmatrix} 0 & 10 & 3 & 4 \\ 2 & 0 & 5 & 6 \\ 7 & 7 & 0 & 1 \\ 6 & 16 & 9 & 0 \end{bmatrix}$$


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**

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

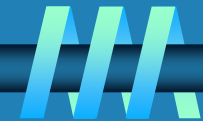
return D

Complexity $\Theta(n^3)$

Space Complexity: Matrixes can be written over it. Predecessors

Not: Shortest paths. Negative weights can be found too.

Optimal Binary Search Trees

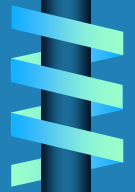


Problem: Given n keys a_1, \dots, a_n and probabilities p_1, \dots, p_n search for a key in a BWT. The average number of comparisons is

The total number of nodes is n by

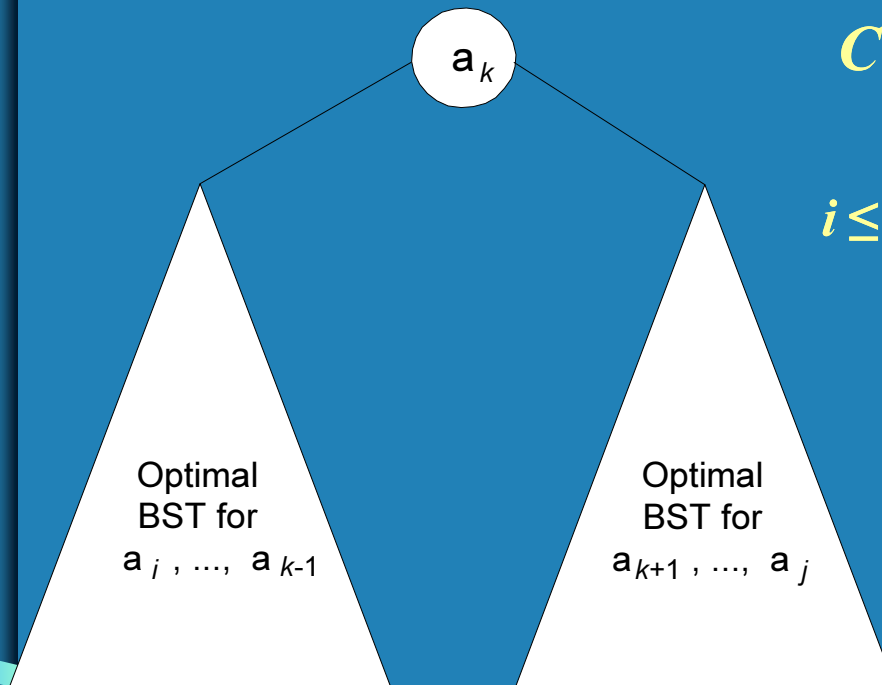
C_{n-1} ways to choose a root.

Example: An optimal BWT for keys A, B, C and D with probabilities $\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{8}$ respectively.



DP for Optimal BST Problem

Let $C_{i,j}$ be the minimum number of comparisons needed to construct an optimal BST for keys a_i, \dots, a_j . Consider an optimal BST with root a_k for keys a_i, \dots, a_j .



$C_{i,j}$

$$C_{i,j} = \sum_{s=i}^{k-1} p_s + \sum_{s=k+1}^j p_s + p_k$$

$$\sum_{s=i}^{k-1} p_s + \sum_{s=k+1}^j p_s + p_k$$

$$C_{i,j} = \sum_{s=i}^{k-1} p_s + \sum_{s=k+1}^j p_s + p_k$$

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

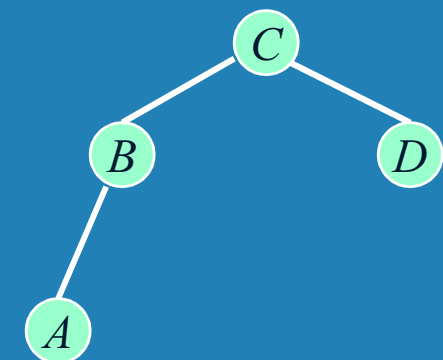
tab s b ow ar d d a o n a b y d a o n a t t o n s d
 us n t r curr nc

$$C_{i,j} = \min_{i \leq k \leq j} (C_{i,k} + C_{k,j} + \sum_{s=i}^j p_s) \cdot C_{i,i} \cdot p_i$$

t r t o n o r t r s r o o t s r c o r d s k s v a u s v n t n a

<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					



opt a B

Optimal Binary Search Trees

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  $C[1, n], R$ 
```

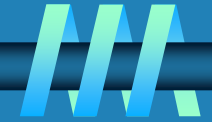
Analysis DP for Optimal BST Problem

Complexity n^3 but can be reduced to n^2 by taking advantage of monotonicity of optimal root table $R_{i,j}$ since ways not change between $R_{i,j}$ and i

Space complexity n^2

Method can be extended to include unsuccessful searches

Knapsack Problem by DP



Given n items

with weights w_1, w_2, \dots, w_n

and values v_1, v_2, \dots, v_n

and a knapsack of capacity W

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

Consider a subproblem defined by i items and capacity j , $j \leq W$.

Let $V[i, j]$ be the optimal value of such a subproblem.

$$\text{max } V[i, j] = v_i + V[i, j - w_i] \quad \text{if } j - w_i \geq 0$$

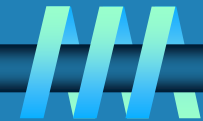
$V[i, j]$

$$V[i, j] = V[i, j] \quad \text{if } j - w_i < 0$$



In the conditions $V[i, j]$ and $V[i, j]$

Knapsack Problem by DP (example)



Example Knapsack of capacity W

t w t v a u

⌋

⌋

capacity j

⌋

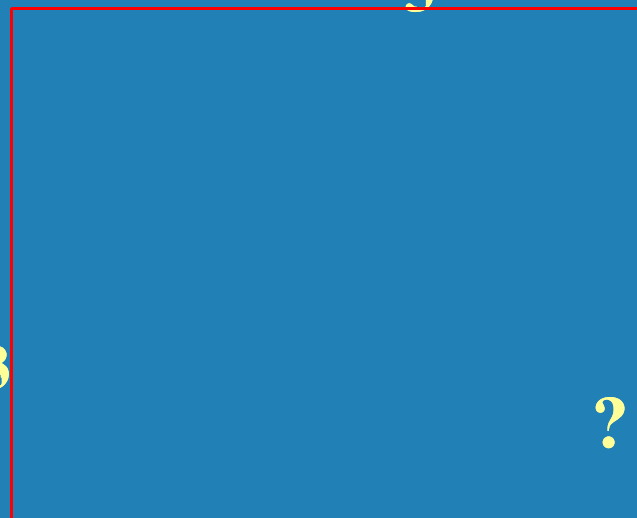
w_1 $v_1 =$

w_2 $v_2 =$

w_3 ⌋ $v_3 =$

w_4 $v_4 =$

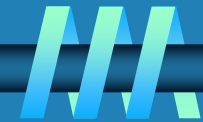
⌋



?



Excercise



ct on ,
ct on ,
ct on , 3 7
ct on ,

