



Dynamic

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programming

T H E O R E T I C A L M O D E L

March 28, 2005



Introduction

- **Dynamic Programming is a general algorithm design paradigm.**
- **Dynamic Programming is a technique for solving problems “bottom-up”:**
 - **first, solve small problems, and then use the solutions to solve larger problems.**
- **What kind of problems can Dynamic Programming solve efficiently?**



Introduction

- **Optimal substructure:** The optimal solution contains optimal solutions to sub-problems.
- **Overlapping sub-problems:** the number of different sub-problems is small, and a recursive algorithm might solve the same sub-problem a few times.



Optimization problems

- **Optimization problem is an important and practical class of computational problems. For most of these, the best known algorithm runs in exponential time.**

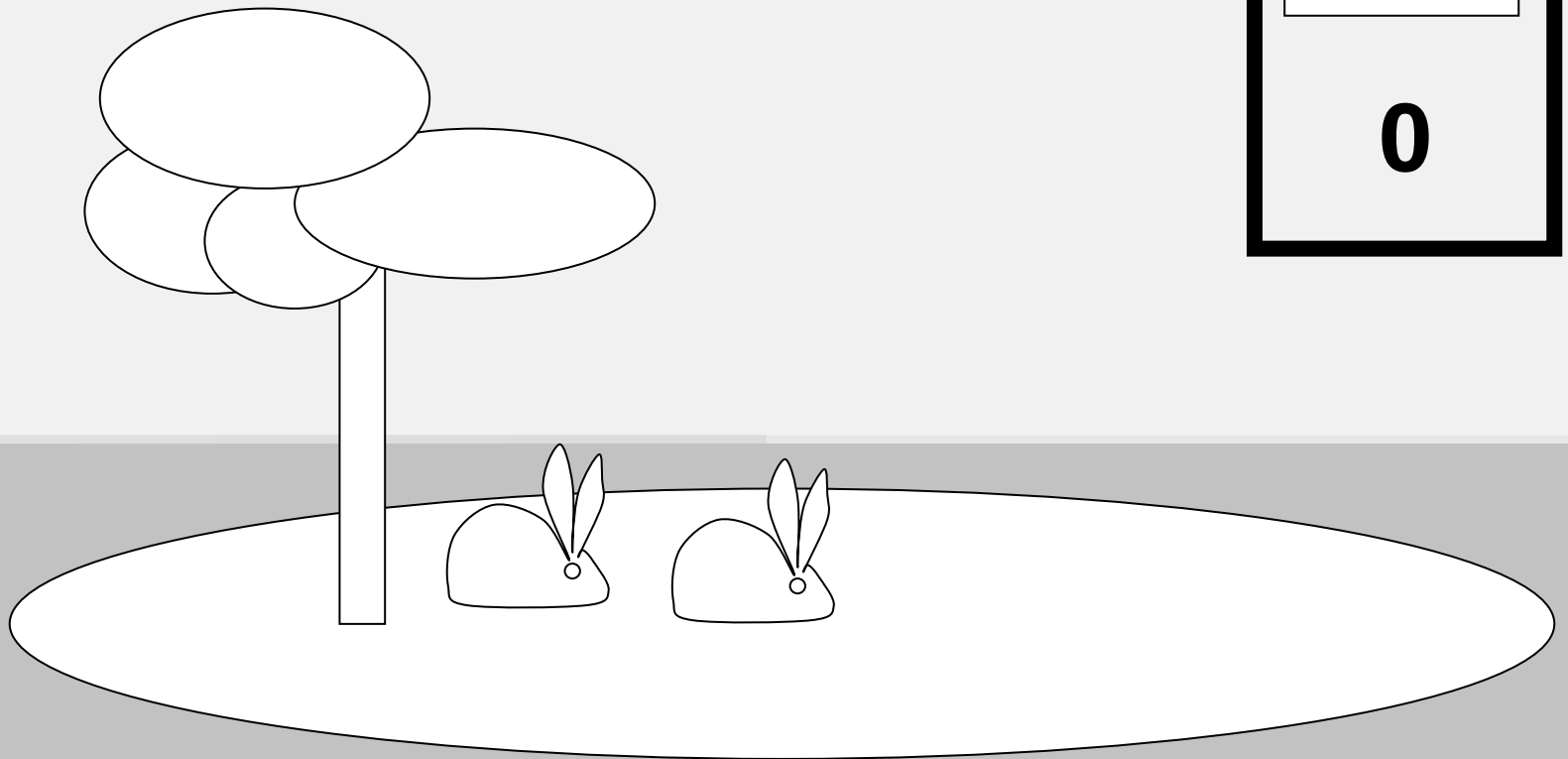


Rabbits on an island

By Leonardo di Pisa, 12th century

island

A pair of rabbits does not breed until they are two months old, then each pair produces another pair each month.



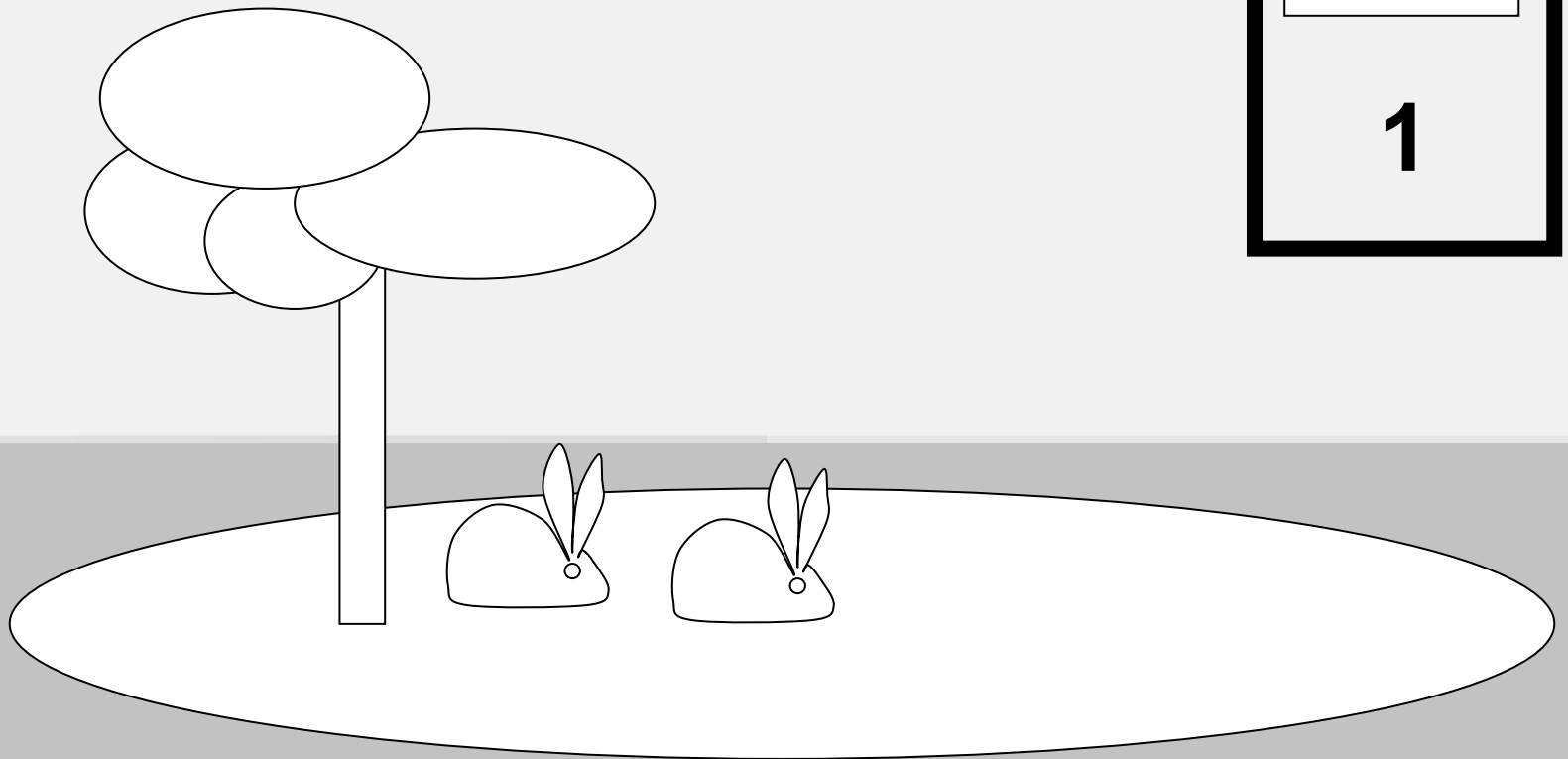


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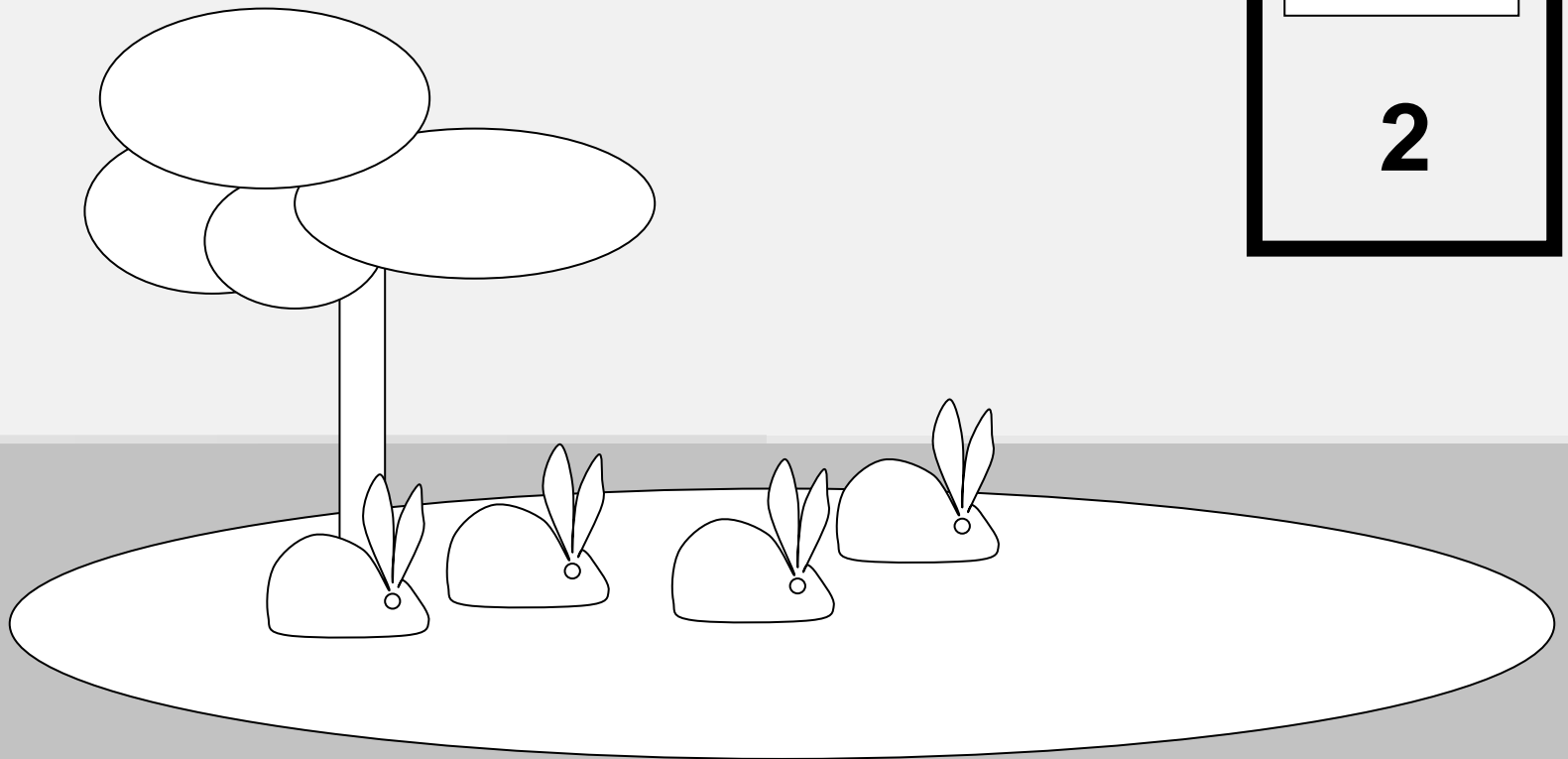
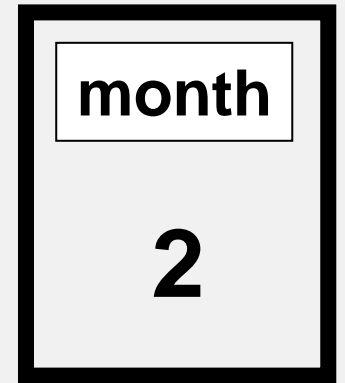


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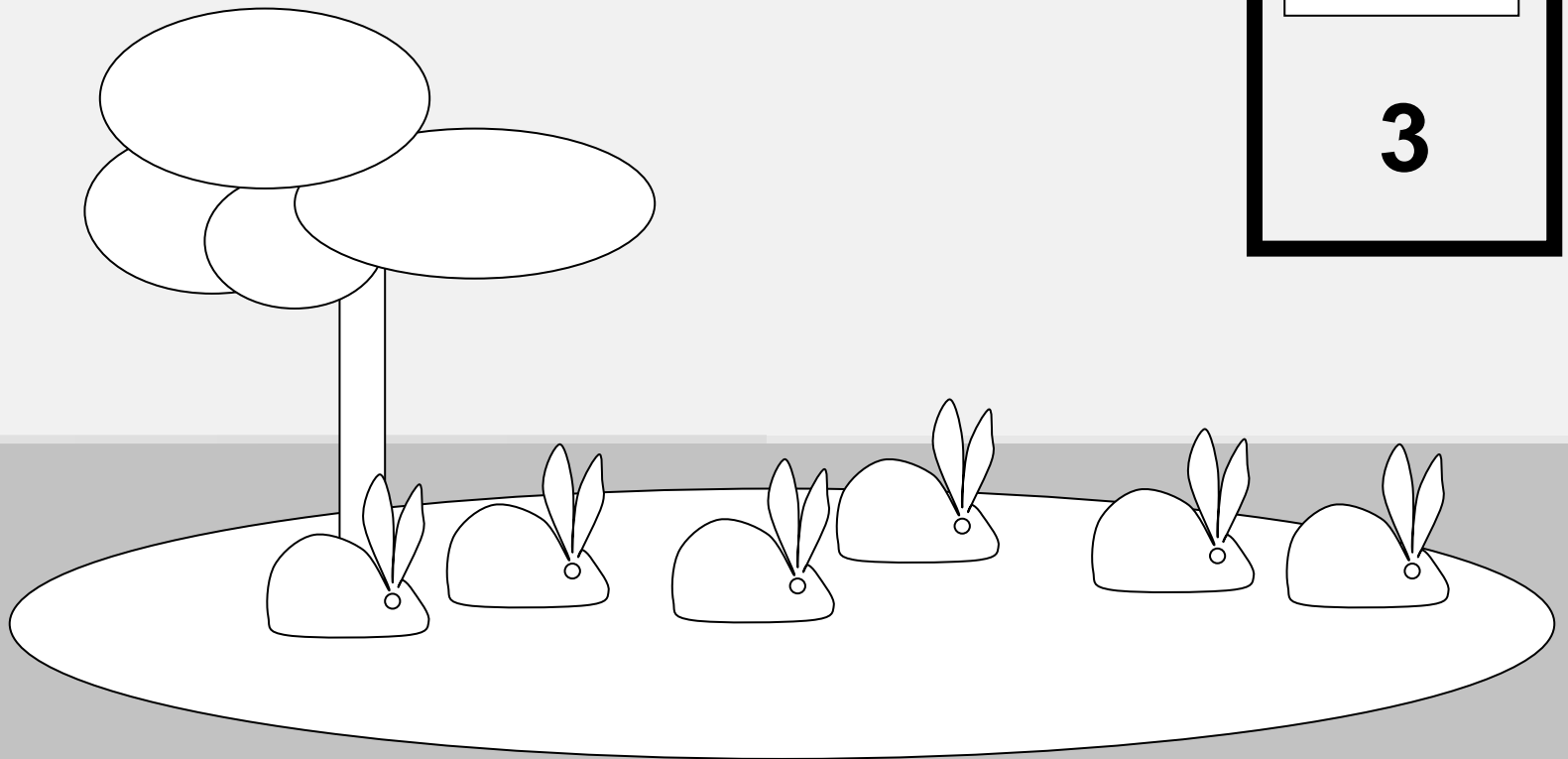
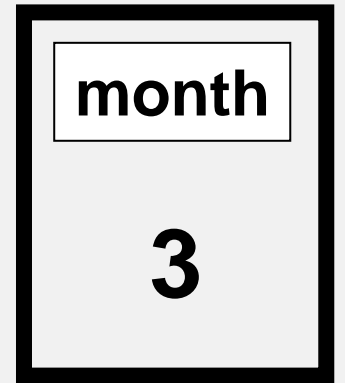


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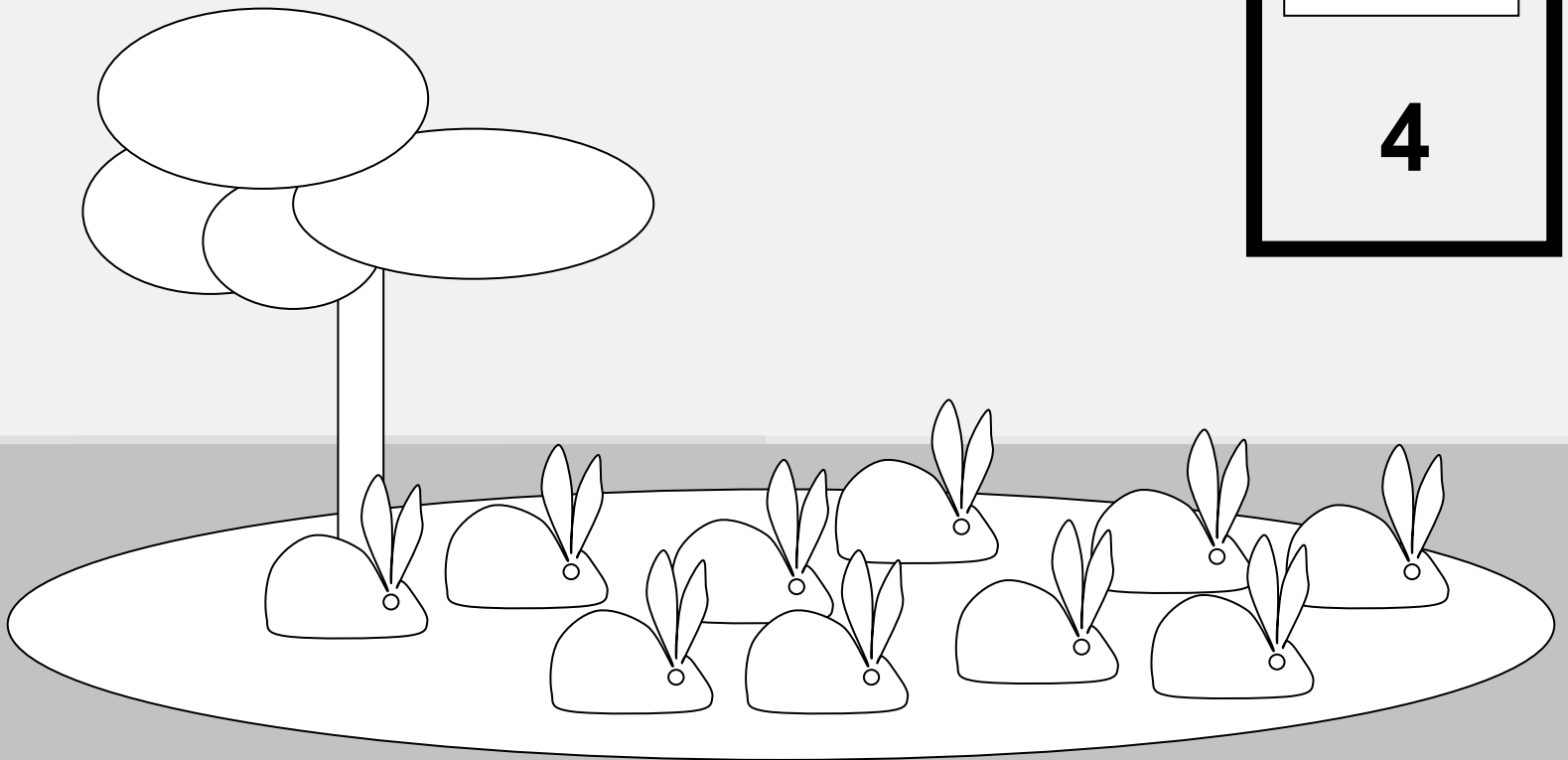
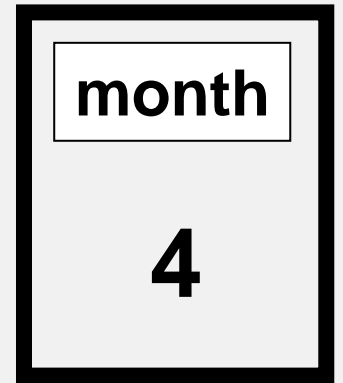


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Rabbits on an

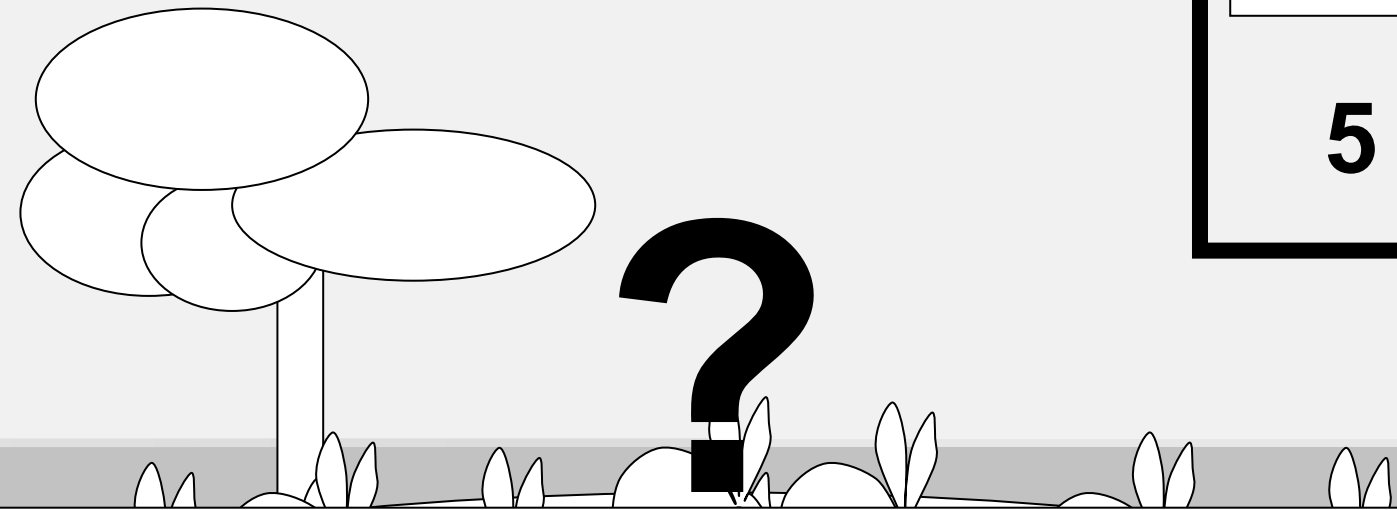
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island

A pair of rabbits does not breed until they are two months old, then each pair produces another pair each month.

month

5



Assuming that no rabbits ever die,
how many pairs of rabbits after n months.



Rabbits on an island

By Leonardo di Pisa, 12th century

Fibonacci Number

$$F_0 = 1$$

$$F_1 = 1$$

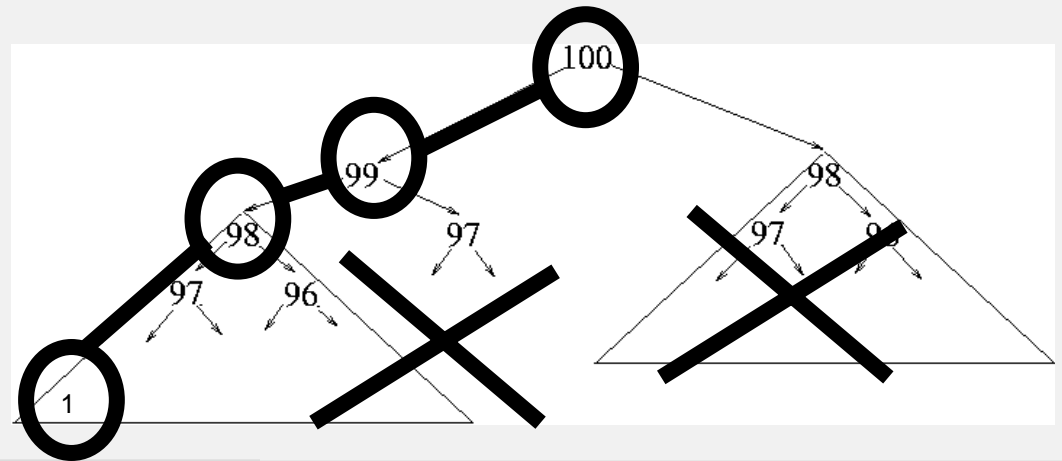
$$F_2 = F_0 + F_1 = 2$$

$$F_3 = F_1 + F_2 = 3$$

$$F_4 = F_2 + F_3 = 5$$

...

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



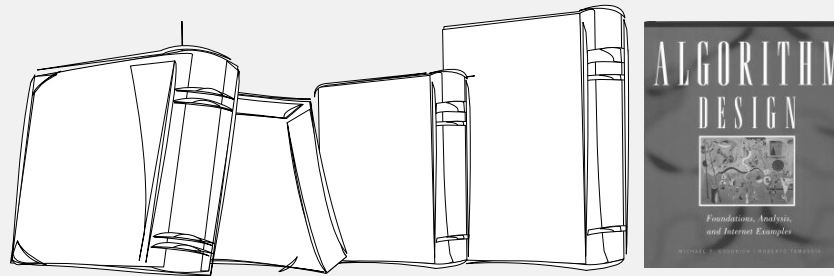
Exponential time → Linear time

OVERLAPPING SUBPROBLEMS



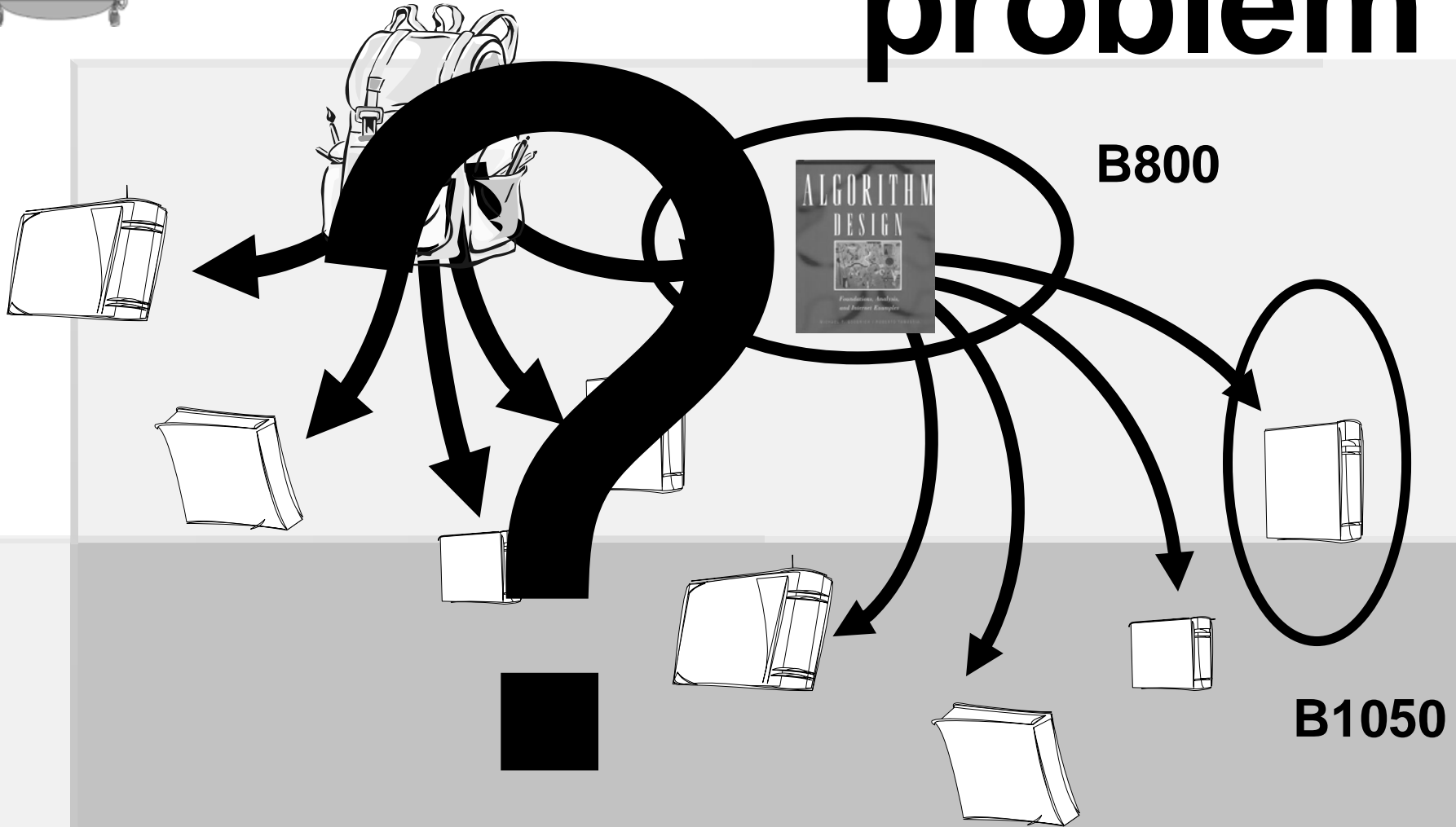
0/1 Knapsack problem

Choose items with maximum total benefit but with some limitation.

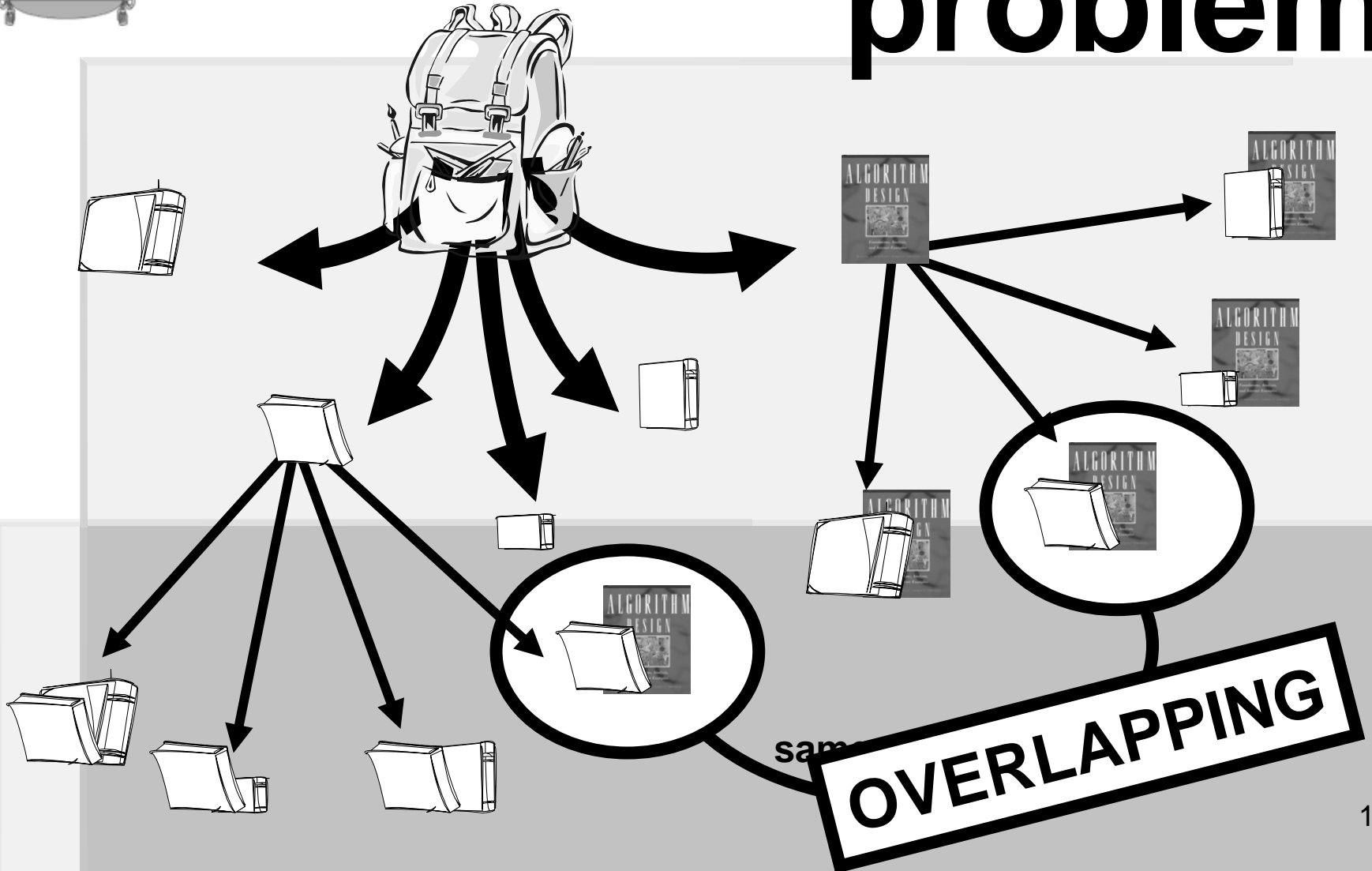


weight	4 kgs	2 kgs	2 kgs	6 kgs	2 kgs
value	B200	B30	B60	B250	B800

0/1 Knapsack problem



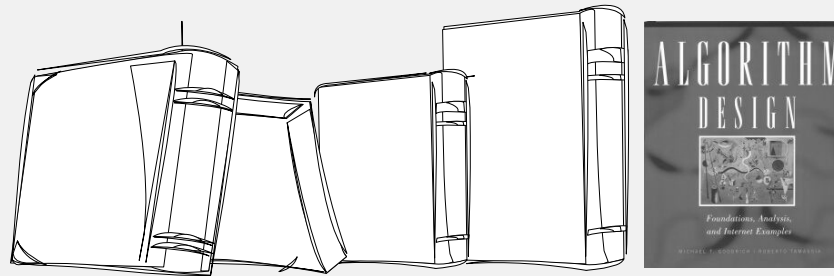
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0/1 Knapsack problem

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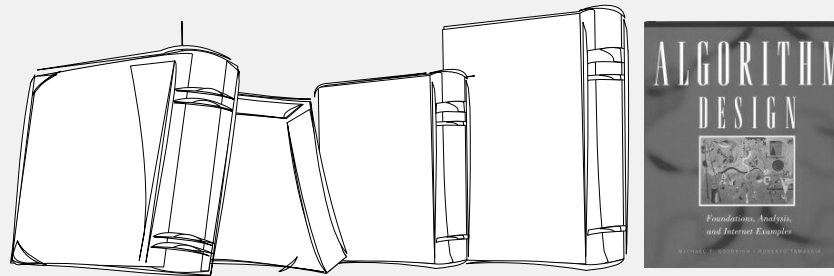
weight	4 kgs	2 kgs	2 kgs	6 kgs	2 kgs
value	B200	B30	B60	B250	B800

Number of solutions : 2^n (n : number of books)



0/1 Knapsack problem

Choose items with maximum total benefit but with some limitation.



weight	4 kgs	2 kgs	2 kgs	6 kgs	2 kgs
value	B200	B30	B60	B250	B800

OBJECTIVE FUNCTION:

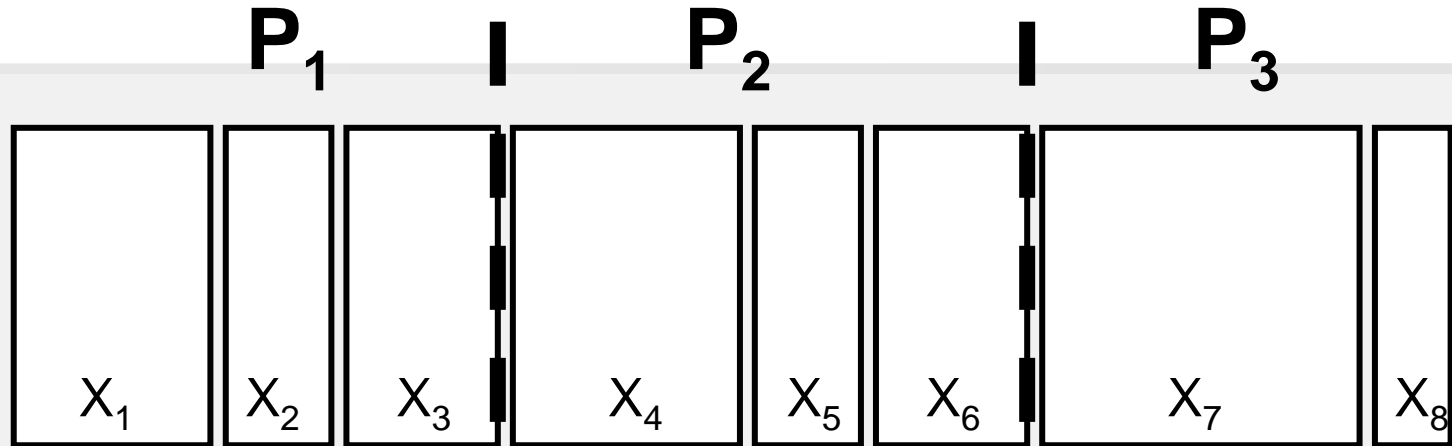
$$\max\left(\sum_{i=1}^n x_i v_i\right) \quad x_i = \begin{cases} 1 & \text{selected} \\ 0 & \text{otherwise} \end{cases}$$

$$\sum_{i=1}^n x_i w_i \leq W$$

CONSTRAINT



Linear Partition



Partition all fields into 3 groups with approximately the same size.

OBJECTIVE FUNCTION:

$$\min \left(\max \left(P_j = \sum_{i=s}^t x_i \right) \right)$$

NUMBER OF SOLUTIONS

$$C_{(n+k-1, k-1)}$$



Printing neatly

Application for word processor

Problem: English text with n words
word i with length w_i (no.of.chars)
Each line contains max M chars

Solution: Close to right justified text
 $(x_1, x_2, x_3, \dots, x_m)$ x_j : last wordth of line j .

Penalty: sum of right blank-end square.

$$S_i = M - \left[(x_i - (x_{i-1} + 1)) + \sum_{k=x_{i-1}+1}^{x_i} w_k \right]$$

blank-end of line i

Objective function $\min \left(\sum_{k=1}^m S_k^2 \right)$



Sequence of matrix multiplication

Given $M_1 M_2 M_3 M_4 \dots M_k$ with $d_{i-1} \times d_i$ dimension.

Find an algorithm for

$$M_1 \times M_2 \times M_3 \times M_4 \times \dots \times M_k$$

Example: $A_{5 \times 10} \times B_{10 \times 20} \times C_{20 \times 1} \times D_{1 \times 10}$

Cost of $((AB)C)D$ is $1000+100+50 = 1150$

Cost of $((AB)(CD))$ is $1000+100+50 = 1150$

Cost of $(A(B(CD)))$ is $1000+100+50 = 1150$

Cost of $(A(B(CD)))$ is $1000+100+50 = 1150$

HOW MANY SOLUTIONS ?



Sequence of matrix multiplication

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Example: $A_{5 \times 10} \times B_{10 \times 20} \times C_{20 \times 1} \times D_{1 \times 10}$

Number of solutions = number of sequence of multiplication



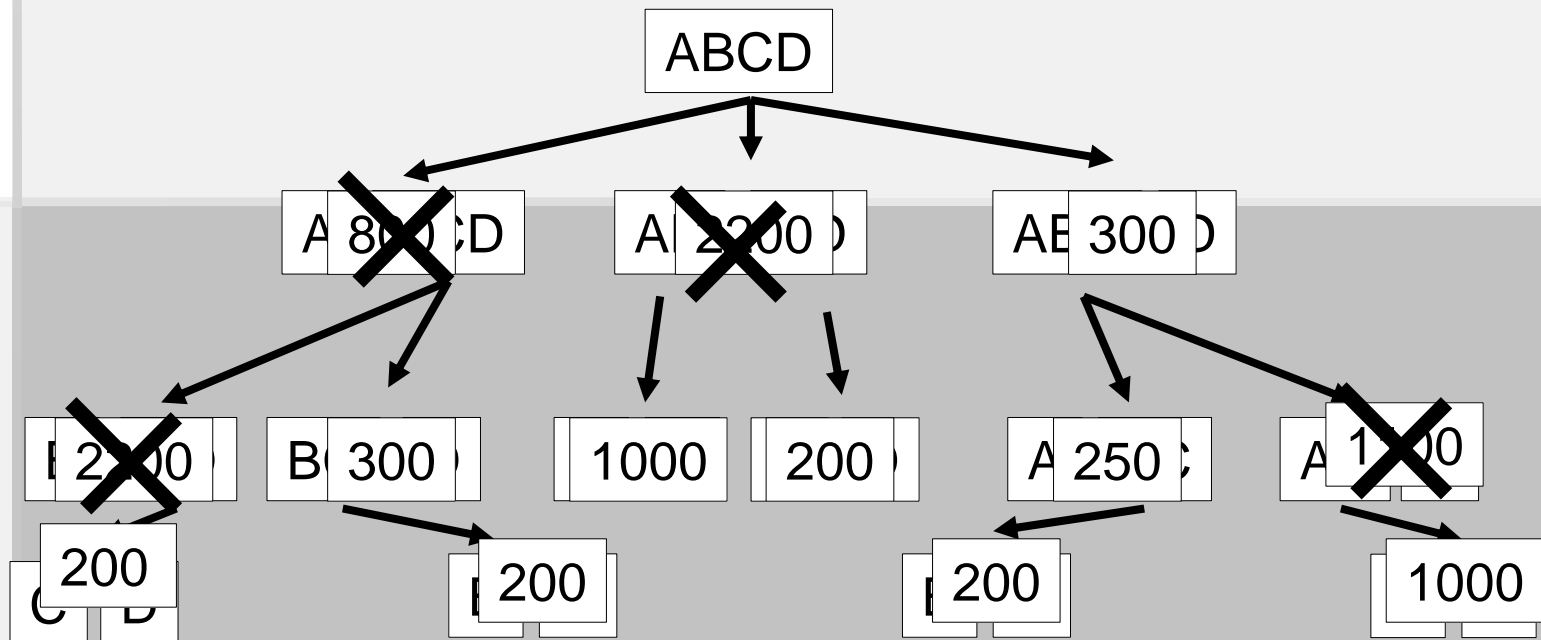
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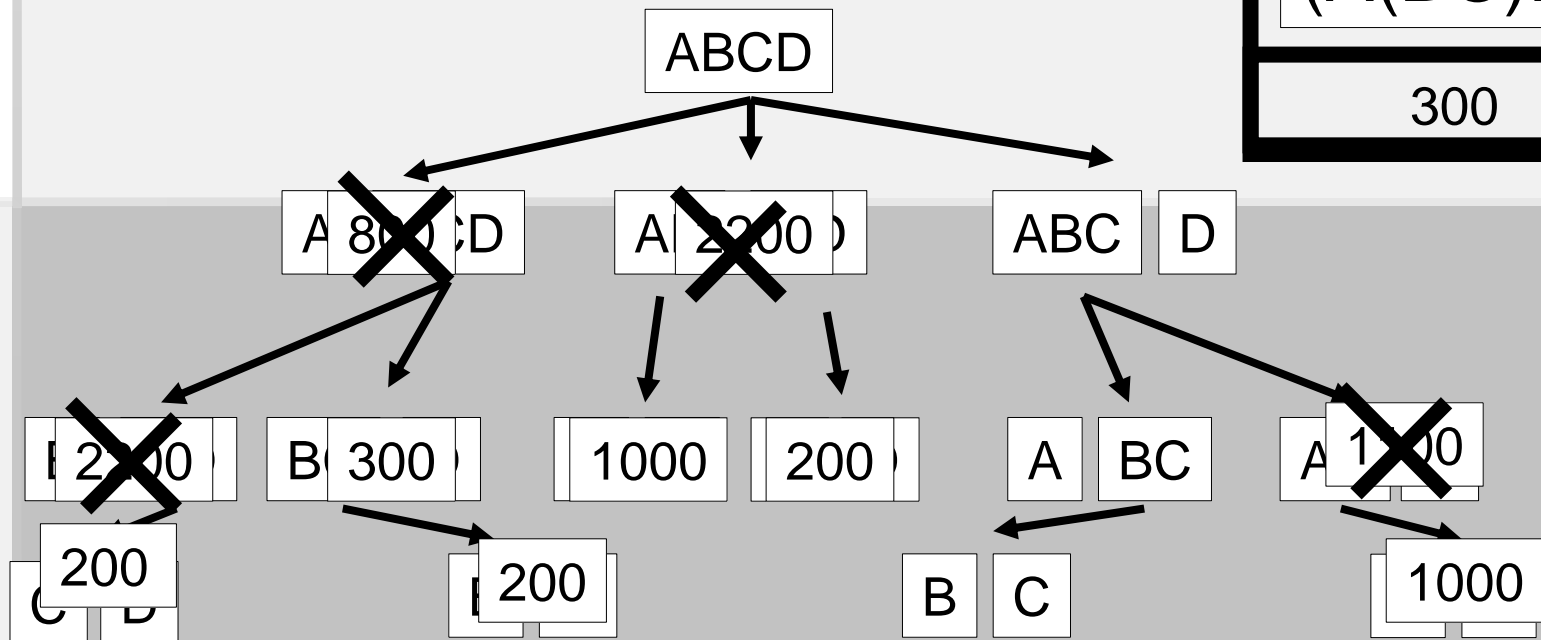
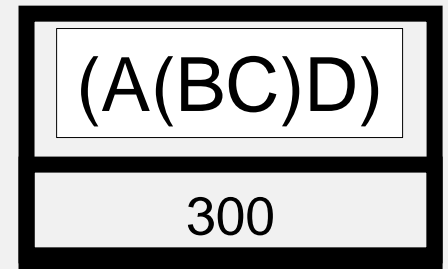
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Sequence of matrix multiplication

Given $M_1 M_2 M_3 M_4 \dots M_k$ with $d_{i-1} \times d_i$ dimension.

Find an algorithm for

$$M_1 \times M_2 \times M_3 \times M_4 \times \dots \times M_k$$

Let $T_{i,j}$ be the cost of multiplication of $M_i \dots M_j$

$$T_{i,j} = \min_{i \leq k \leq j-1} (T_{i,k} + T_{k+1,j} + d_i \times d_k \times d_j)$$

1								
2								
n								
	1	2						n

DICTIONARY



Sequence of matrix multiplication

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1								
2								
n								
	1	2						n

DICTIONARY



Sequence of matrix multiplication

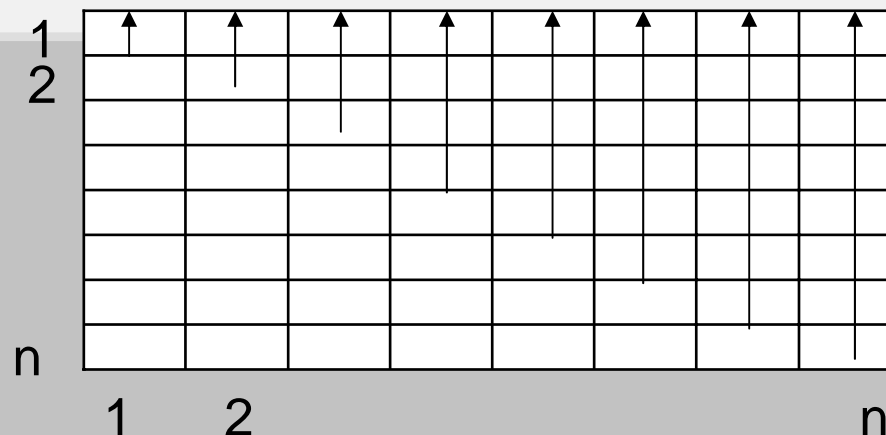
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DICTIONARY



Optimal binary search tree

Create an optimal binary search tree

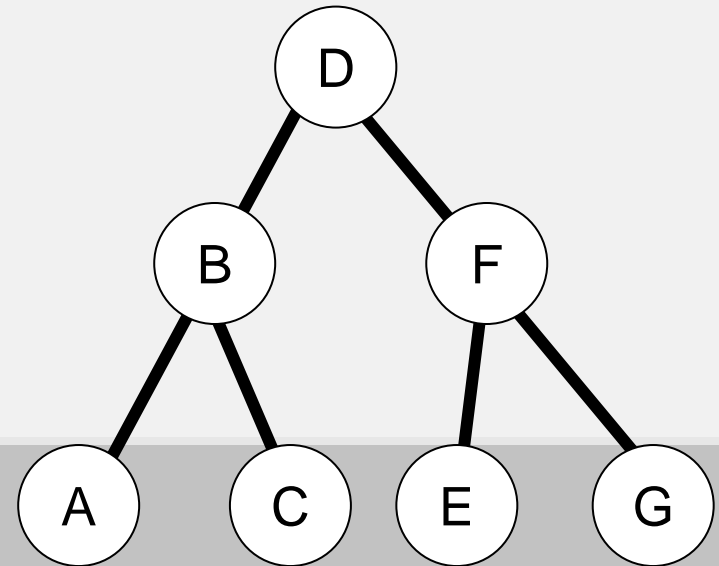
DATA	Probability
A	0.25
B	0.22
C	0.20
D	0.18
E	0.08
F	0.05
G	0.02



Optimal binary search tree

Create an optimal binary search tree

DATA	Probability	TIME
A	0.25	3
B	0.22	2
C	0.20	3
D	0.18	1
E	0.08	3
F	0.05	2
G	0.02	3



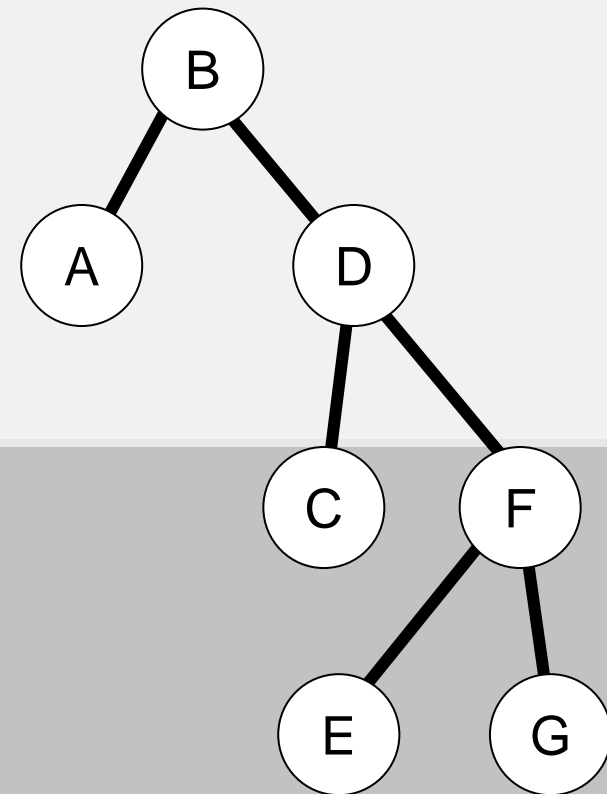
Average-time for searching **2.37**



Optimal binary search tree

Create an optimal binary search tree

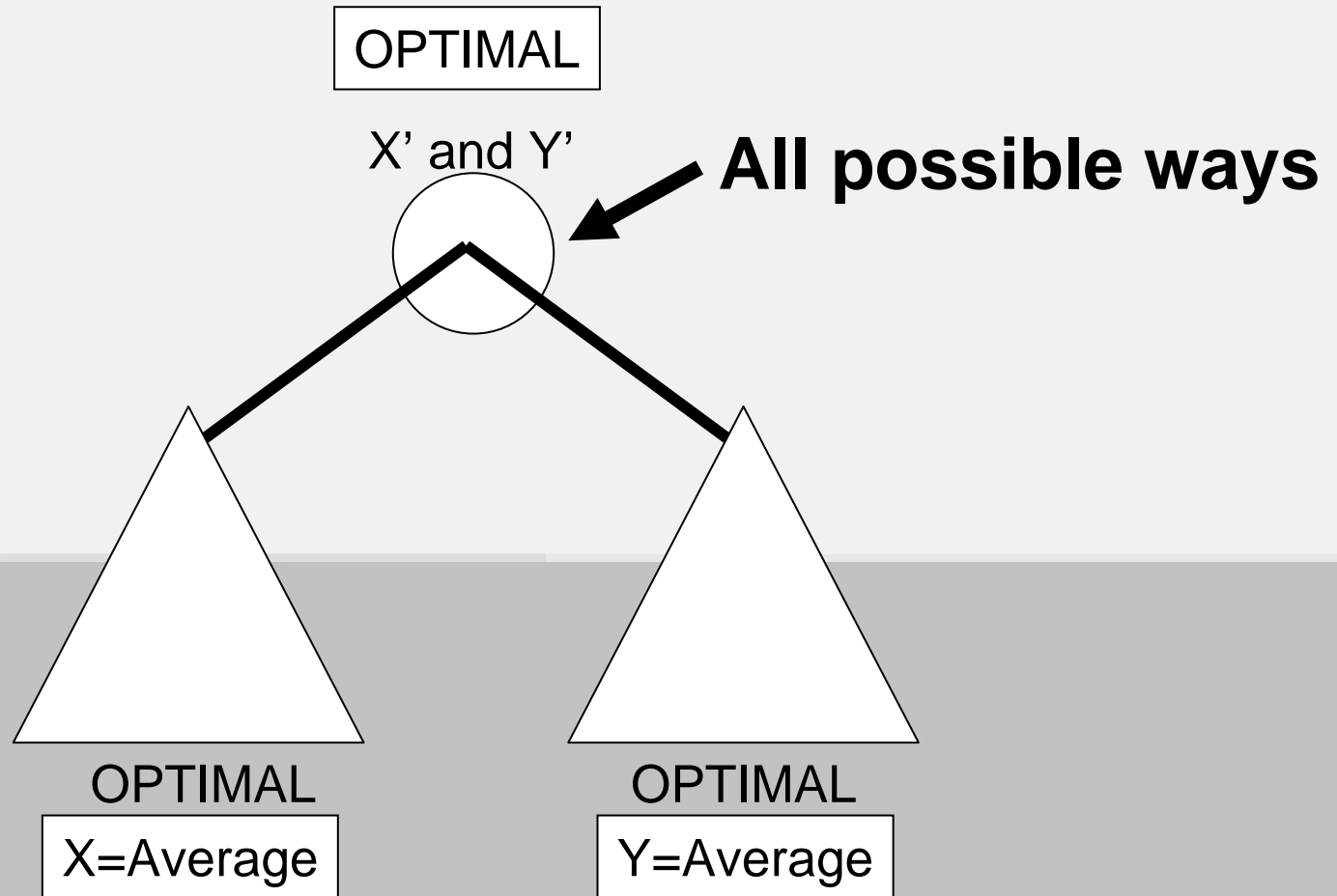
DATA	Probability	TIME
A	0.25	2
B	0.22	1
C	0.20	3
D	0.18	2
E	0.08	4
F	0.05	3
G	0.02	4



Average-time for searching **1.98**



Optimal binary search tree

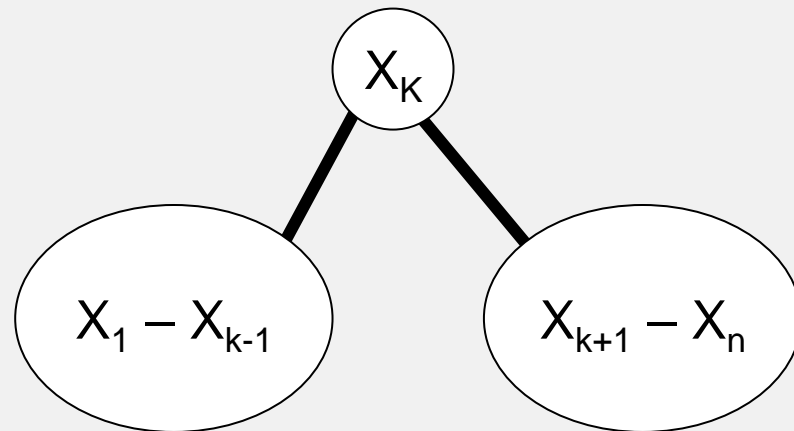




Optimal binary search tree

Create an optimal binary search tree

DATA	Probability
X_1	P_1
X_2	P_2
X_3	P_3
X_4	P_4
X_5	P_5
X_6	P_6
x_7	p_7

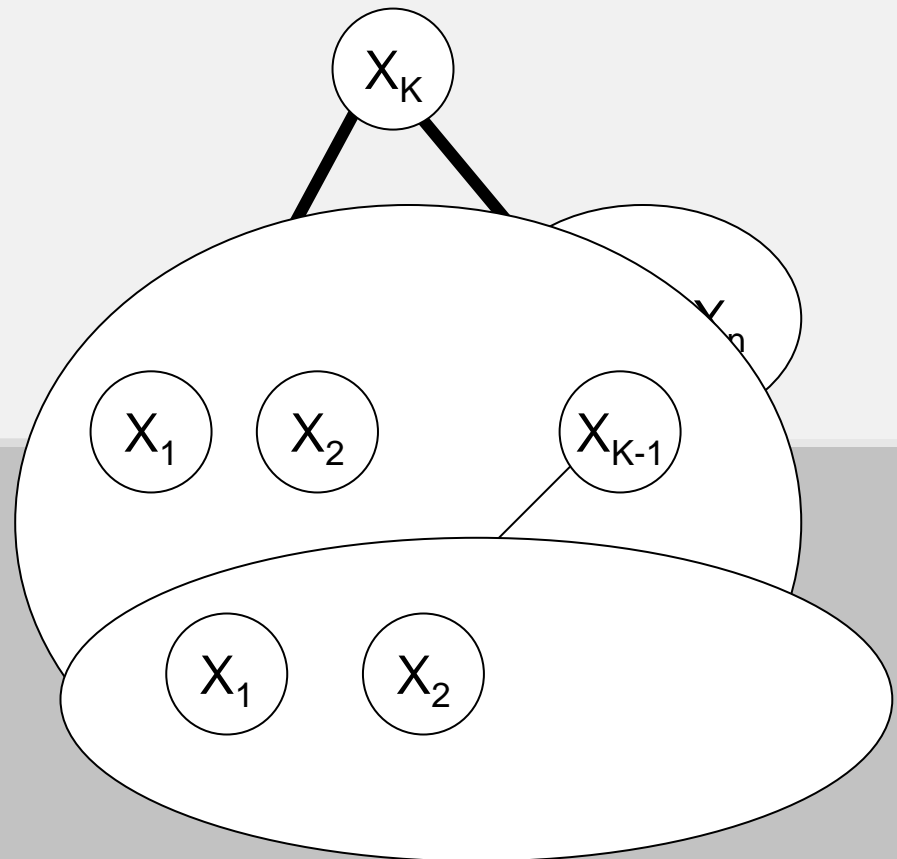




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X_2	P_2
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DICTIONARY

1								
2								
n								
	1	2						n



Optimal binary search tree

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DATA	Probability
X_1	P_1
X_2	P_2
X_3	P_3
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DICTIONARY

1								
2								
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	1	2						n



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DICTIONARY

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X_5	P_5
X_6	P_6
x_7	p_7

DICTIONARY

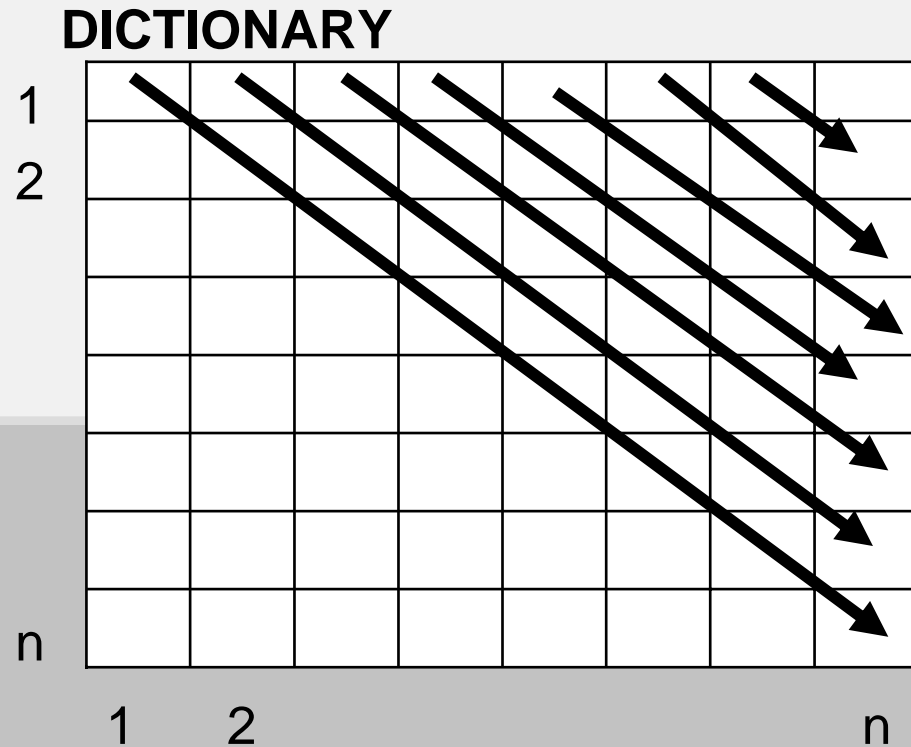
1								
2								
n								
	1	2						n



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X_4	P_4
X_5	P_5
X_6	P_6
X_7	p_7

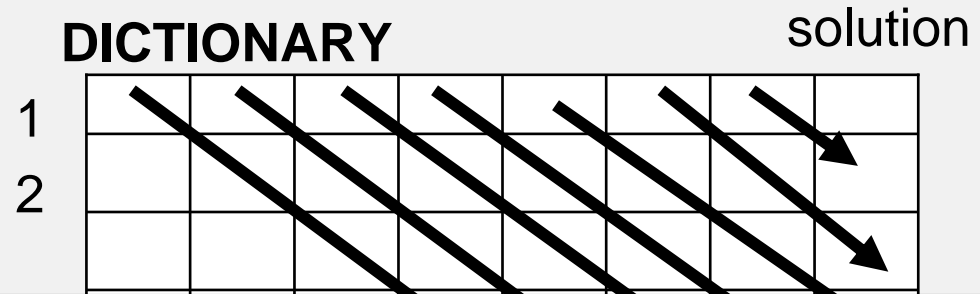




Optimal binary search tree

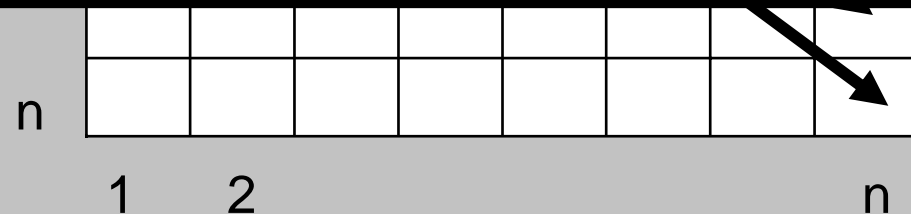
Create an optimal binary search tree

DATA	Probability
X_1	P_1
X_2	P_2
X_3	P_3



$$T_{i,j}(\min_{i \leq k \leq j} (P_k + T_{i,k-1} + T_{k+1,j} + P_{i,k-1} + P_{k+1,j}))$$

x_7	p_7
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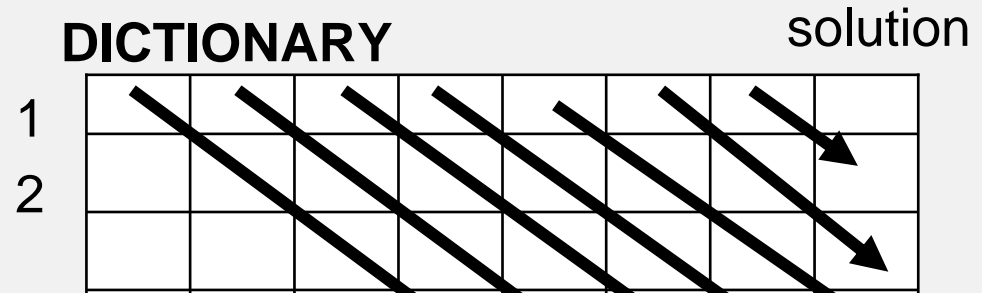




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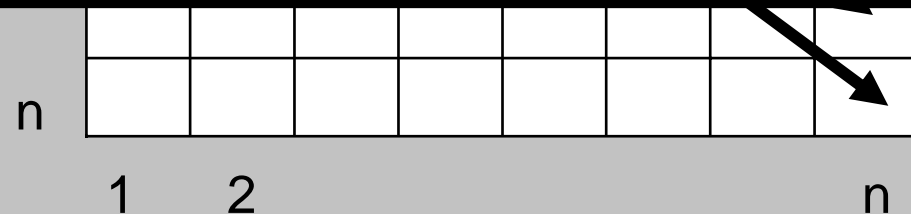
Create an optimal binary search tree

DATA	Probability
X_1	P_1
X_2	P_2
X_6	P_6



$$T_{i,j} (\min_{i \leq k \leq j} (P_{i,j} + T_{i,k-1} + T_{k+1,j}))$$

x_7	p_7
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Optimal binary search tree

Create an optimal binary search tree

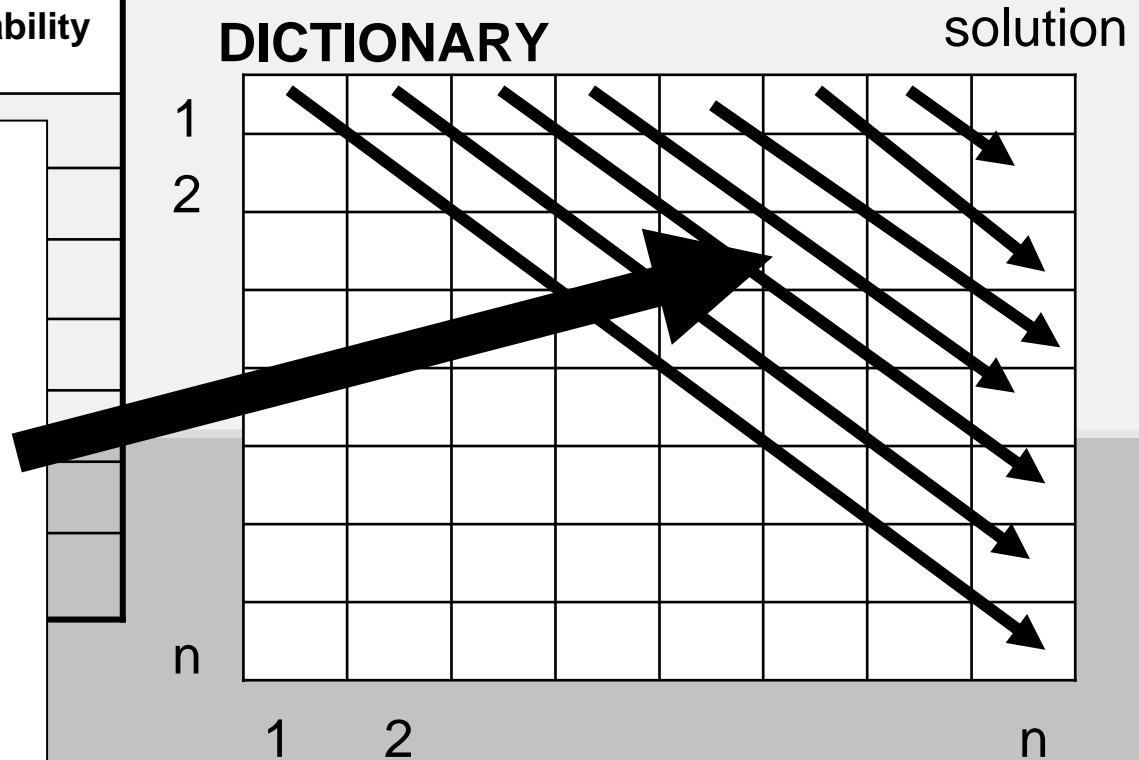
DATA	Probability
x	p

Min

$$T_{i+1,j}$$
$$T_{i,j} + T_{i+2,j}$$
$$T_{i,i+1} + T_{i+3,j}$$
$$T_{i,i+2} + T_{i+4,j}$$

...

$$T_{i,j-1}$$





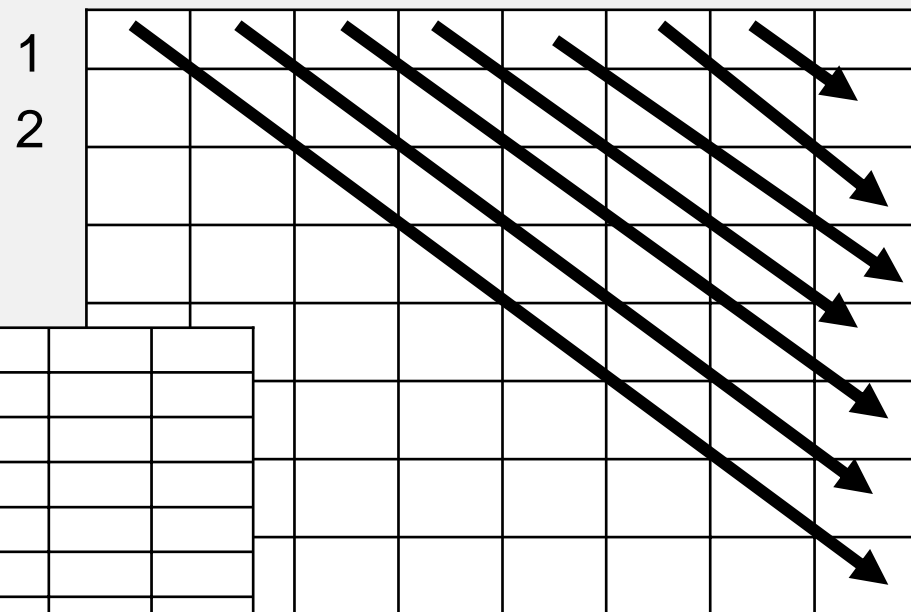
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X_2	P_2
X_3	P_3
X_4	P_4

1									
2									
n									

DICTIONARY

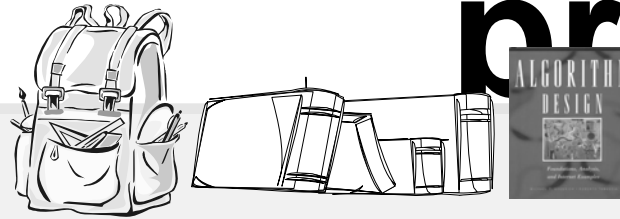


solution

PROBABILITY



0/1 Knapsack problem

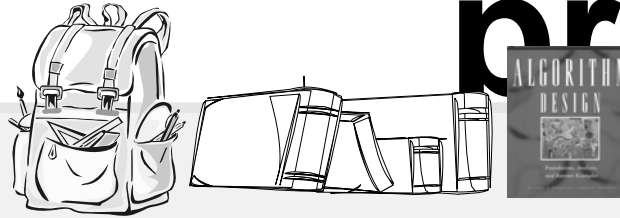


- S_k : Set of items numbered 1 to k .
- Define $B[k, w]$ = best selection from S_k with weight exactly equal to w
- Best subset of S_k with weight exactly w is either:
 - - the best subset of S_{k-1} weight w
 - - the best subset of S_{k-1} weight $w - w_k$ plus item k

$$B[k, w] = \begin{cases} B[k-1, w] & \text{if } w_k > w \\ \max \{B[k-1, w], B[k-1, w - w_k] + b_k\} & \text{otherwise} \end{cases}$$



0/1 Knapsack problem



- Since $B[k,w]$ is defined in terms of $B[k-1,*]$, we can reuse the same array

Algorithm *0-1Knapsack*(S, W):

Input: set S of items with benefit b_i
and weight w_i ; max. weight W

Output: value of best subset with weight $\leq W$

for $w \leftarrow 0$ to W do

$B[0,w] \leftarrow 0$

for $k \leftarrow 1$ to n do

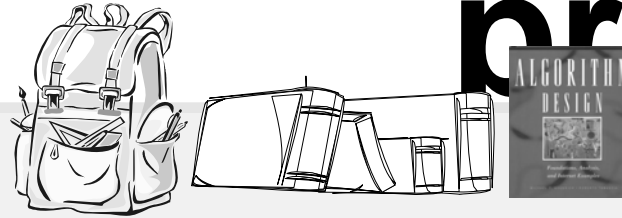
 for $w \leftarrow W$ down to w_k do

$B[k,w] \leftarrow \max(B[k-1,w],$

$B[k-1,w-w_k]+b_k)$



0/1 Knapsack problem



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for $k \leftarrow 1$ to n do

 for $w \leftarrow W$ downto w_k do

$B[k,w] \leftarrow \max(B[k-1,w],$

$B[k-1,w-w_k]+b_k)$

Running time: $O(nW)$.



All shortest Floyd-Warshapaths

Given a directed weighted graph $G = (V, E)$,
find all shortest paths between any two vertices in G .

Algorithm

- If we already know the all shortest paths whose intermediate vertices belong to the set $\{1, \dots, k-1\}$, how can we find all shortest paths with intermediate vertices $\{1, \dots, k\}$?
- Consider the shortest path p between (i, j) , whose intermediate vertices belong to $\{1, \dots, k\}$
- If k is not an intermediate vertex in p , then p is the path found in the previous iteration.
- If k is in p , then we can write p as $i \rightsquigarrow k \rightsquigarrow j$, where the intermediate vertices in $i \rightsquigarrow k$ and $k \rightsquigarrow j$ belong to $\{1, \dots, k-1\}$.

$$d_{i,j}(k) = \min(d_{i,j}(k-1), d_{i,k}(k-1) + d_{k,j}(k-1))$$



All shortest

Floyd-Warshapaths

Given a directed weighted graph $G = (V, E)$,
find all shortest paths between any two vertices in G .

Algorithm

The algorithm:

–Initialize: $D_{(0)} = W$

–For $k = 1 \dots |V|$

– For

Time complexity = $O(|V|^3)$

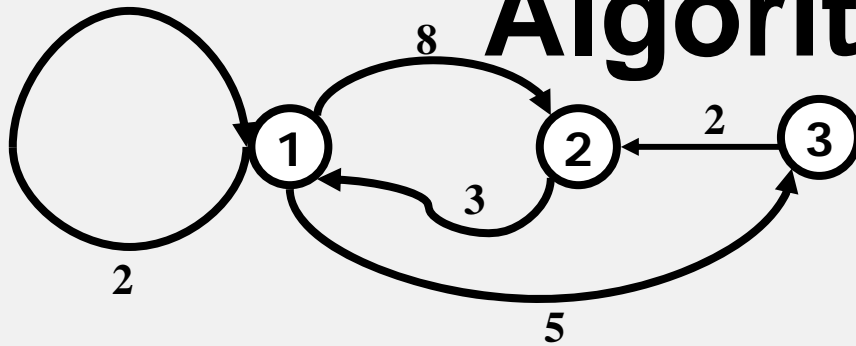
$$\gg d_{i,j}(k) = \min(d_{i,j}(k-1), d_{i,k}(k-1) + d_{k,j}(k-1))$$



All shortest

Floyd-Warshapaths

Algorithm



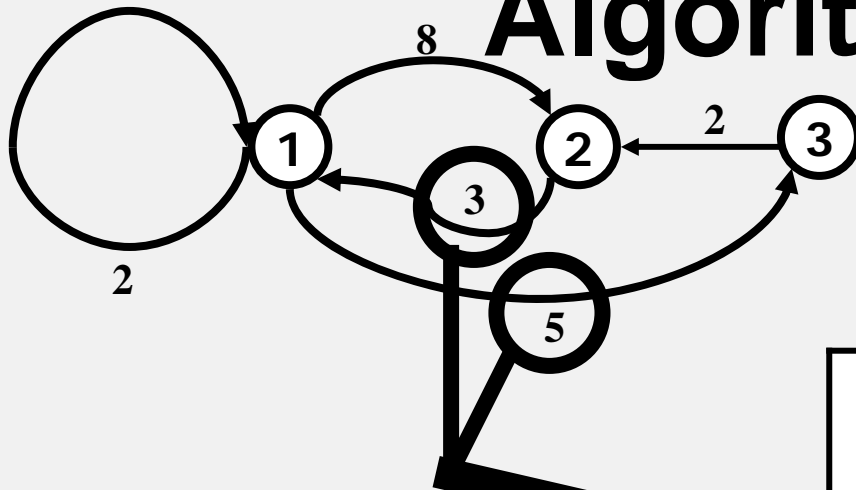
D_0	1	2	3
1	0	8	5
2	3	0	∞
3	∞	2	0



All shortest

Floyd-Warshapaths

Algorithm



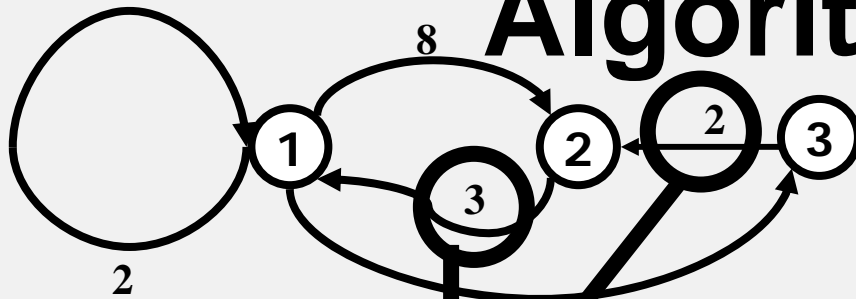
D_1	1	2	3
1	0	8	5
2	3	0	8
3	∞	2	0



All shortest

Floyd-Warshapaths

Algorithm



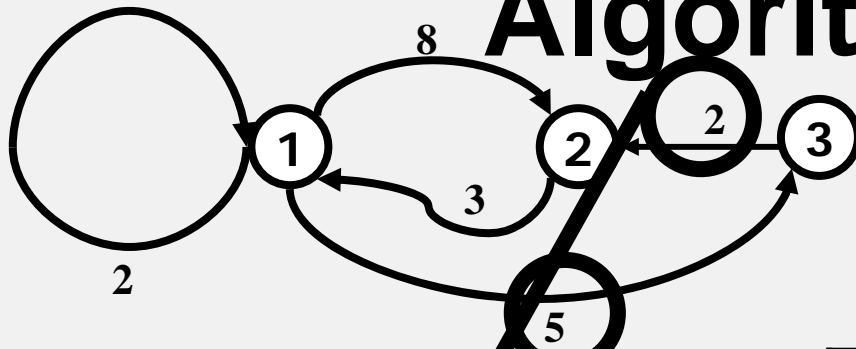
D_2	1	2	3
1	0	8	5
2	3	0	8
3	5	2	0



All shortest

Floyd-Warshapaths

Algorithm



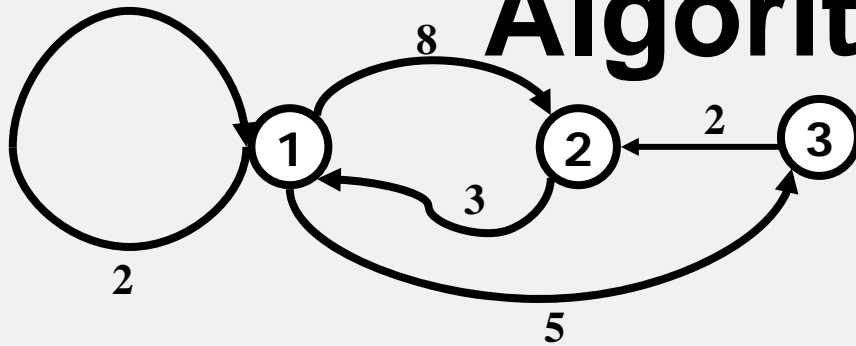
D_3	1	2	3
1		7	5
2	3	0	8
3	5	2	0



All shortest

Floyd-Warshapaths

Algorithm



D_3	1	2	3
1	0	7	5
2	3	0	8
3	5	2	0



Longest common subsequence

Given two sequences

- **X = ABCB**
- **Y = BDCAB**



Longest common subsequence

Find the longest common subsequence of two sequences

- **X = ABCB**
- **Y = BDCAB**

Brute force algorithm would compare each subsequence of X with the symbols in Y.

If $|X| = m$, $|Y| = n$, then there are 2^m subsequences of x; we must compare each with Y (n comparisons).

So the running time of the brute-force algorithm is $O(n 2^m)$.

Notice that the LCS problem has *optimal substructure*: solutions of subproblems are parts of the final solution.



Longest common subsequence

Find the longest common subsequence of two sequences

- **X = ABCB**
- **Y = BDCAB**

Define X_i , Y_j to be the prefixes of X and Y of length i and j respectively

Define $c[i,j]$ to be the length of LCS of X_i and Y_j

Then the length of LCS of X and Y will be $c[m,n]$

$$c[i, j] = \begin{cases} c[i-1, j-1] + 1 & \text{if } x[i] = y[j], \\ \max(c[i, j-1], c[i-1, j]) & \text{otherwise} \end{cases}$$



Longest common subsequence

	j	0	1	2	3	4	5
i	Yj		B	D	C	A	B
0	Xi	0	0	0	0	0	0
1	A	0	0				
2	B	0					
3	C	0					
4	B	0					



Longest common subsequence

	j	0	1	2	3	4	5
i	Yj	B	D	C	A	B	
0	Xi	0	0	0	0	0	0
1	A	0	0	0			
2	B	0					
3	C	0					
4	B	0					



Longest common subsequence

	j	0	1	2	3	4	5
i	Yj	B	D	C	A	B	
0	Xi	0	0	0	0	0	0
1	A	0	0	0	0		
2	B	0					
3	C	0					
4	B	0					



Longest common subsequence

		j	0	1	2	3	4	5
		Yj	B	D	C	A	B	
i	Xi							
0		0	0	0	0	0	0	0
1	A	0	0	0	0	0		
2	B	0						
3	C	0						
4	B	0						

An arrow points from the cell at (i=1, j=4) to the cell at (i=0, j=4), with the label "+1" next to it.



Longest common subsequence

		j					
		0	1	2	3	4	5
i	Yj		B	D	C	A	B
	Xi						
0	A	0	0	0	0	1	1
1	B	0	+1				
2	C	0					
3	B	0					



Longest common subsequence

	j	0	1	2	3	4	5
i	Yj		B	D	C	A	B
0	Xi	0	0	0	0	0	0
1	A	0	0	0	0	1	1
2	B	0	1	1	1	1	+1
3	C	0					
4	B	0					



Longest common subsequence

		j	0	1	2	3	4	5
		Yj		B	D	C	A	B
i	Xi							
0	A	0	0	0	0	0	1	1
1	B	0	1	1	1	1	1	2
2	C	0	↓					
3								
4	B	0						



Longest common subsequence

		j	0	1	2	3	4	5
i		Yj	B	D	C	A	B	
0	Xi	0	0	0	0	0	0	0
1	A	0	0	0	0	1	1	
2	B	0	1	1	1	1	2	
3	C	0	1	1				
4	B	0						

An arrow points from the cell at (i=3, j=4) to the cell at (i=2, j=3), with the label "+1" next to the arrowhead.



Longest common subsequence

		j					
		0	1	2	3	4	5
i	Yj		B	D	C	A	B
	Xi						
0	A	0	0	0	0	1	1
1	B	0	1	1	1	1	2
2	C	0	1	1	2	2	2
3	B	0	1				
4							

The table above shows the dynamic programming table for finding the Longest Common Subsequence (LCS) between the strings "ABC" (X) and "BDACB" (Y). The rows represent the string X and the columns represent the string Y. The value in each cell (i, j) represents the length of the LCS of the prefixes X[0..i] and Y[0..j].

Key features of the table:

- The cell at (0, 1) containing '0' is circled in black.
- The cell at (3, 1) containing '1' is circled in black.
- An arrow points from the cell at (3, 1) to the cell at (4, 2), which contains '+1', indicating the update rule: $dp[i][j] = dp[i-1][j-1] + 1$ when $X[i] = Y[j]$.

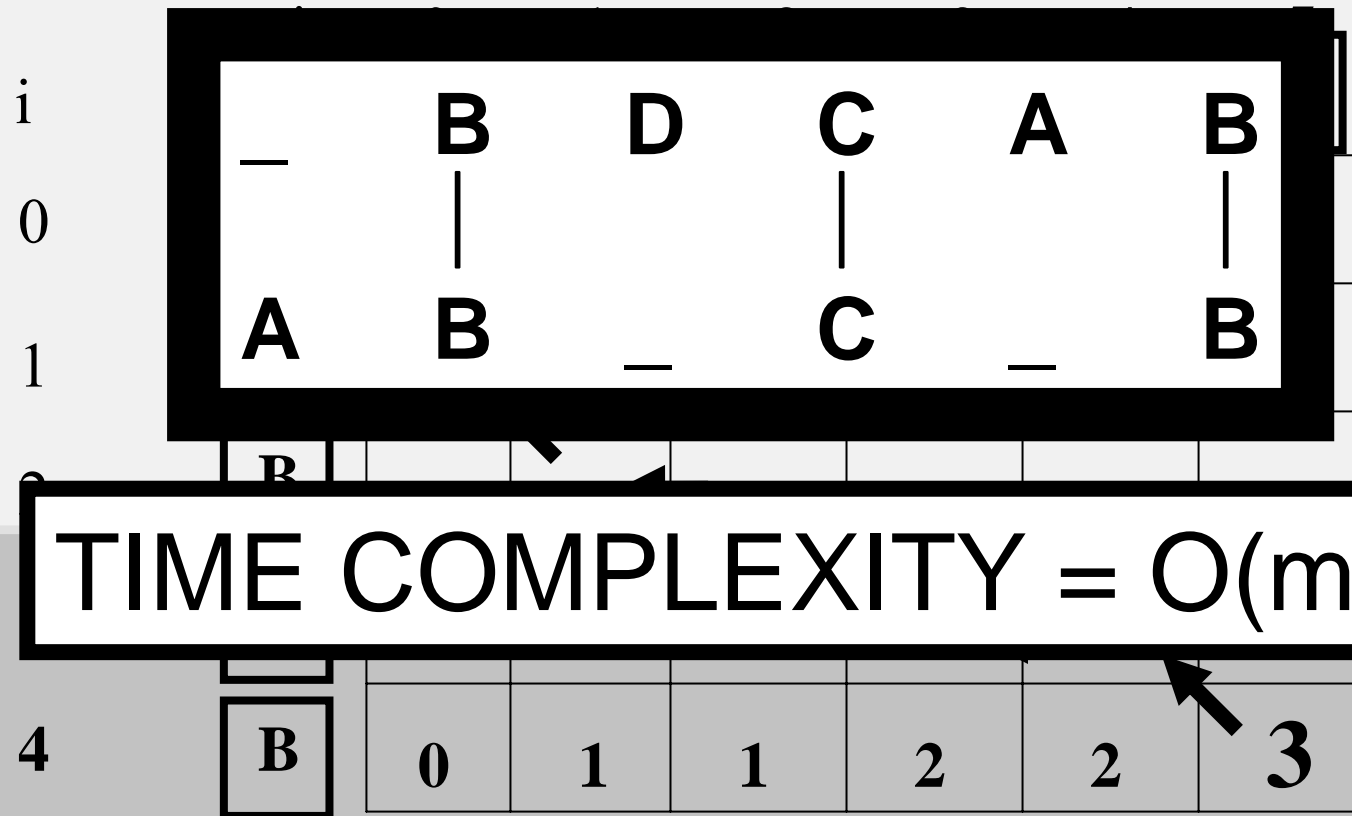


Longest common subsequence

	j	0	1	2	3	4	5
i	Yj		B	D	C	A	B
0	Xi	0	0	0	0	0	0
1	A	0	0	0	0	1	1
2	B	0	1	1	1	1	2
3	C	0	1	1	2	2	2
4	B	0	1	1	2	2	+1



Longest common subsequence





Natural language

Given a sentence (sequence of words)

John called Mary from Denver.

Find a grammar tree matched to X .

Given GRAMMAR

$S \rightarrow NP VP$

$VP \rightarrow V NP$

$NP \rightarrow NP PP$

$VP \rightarrow VP PP$

$PP \rightarrow P NP$

John NP

called V

Mary NP

from P

Denver NP



Natural language

John called Mary from Denver.

Given GRAMMAR

$S \rightarrow NP VP$

$VP \rightarrow V NP$

$NP \rightarrow NP PP$

$VP \rightarrow VP PP$

$PP \rightarrow P NP$

John NP

called V

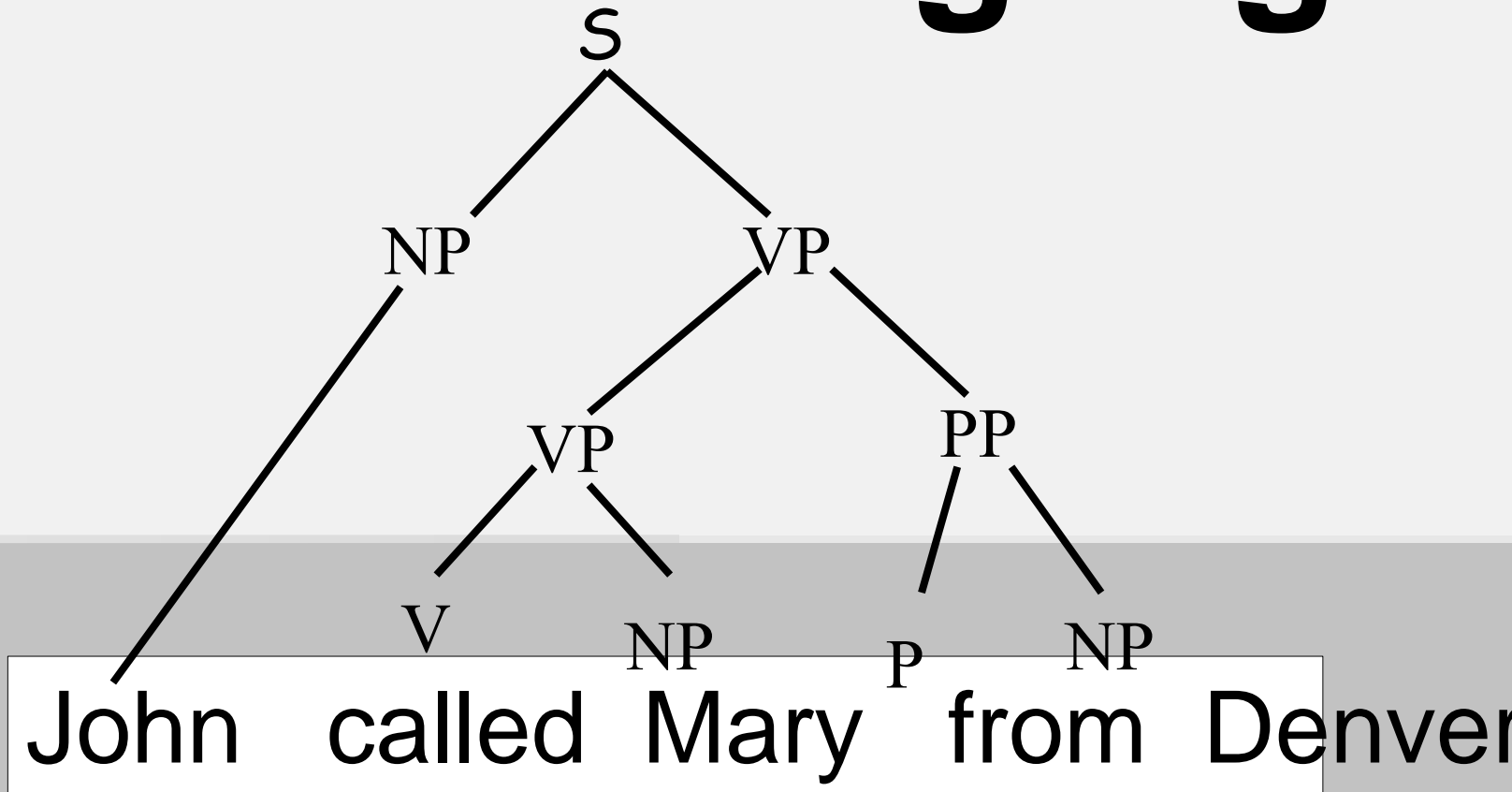
Mary NP

from P

Denver NP

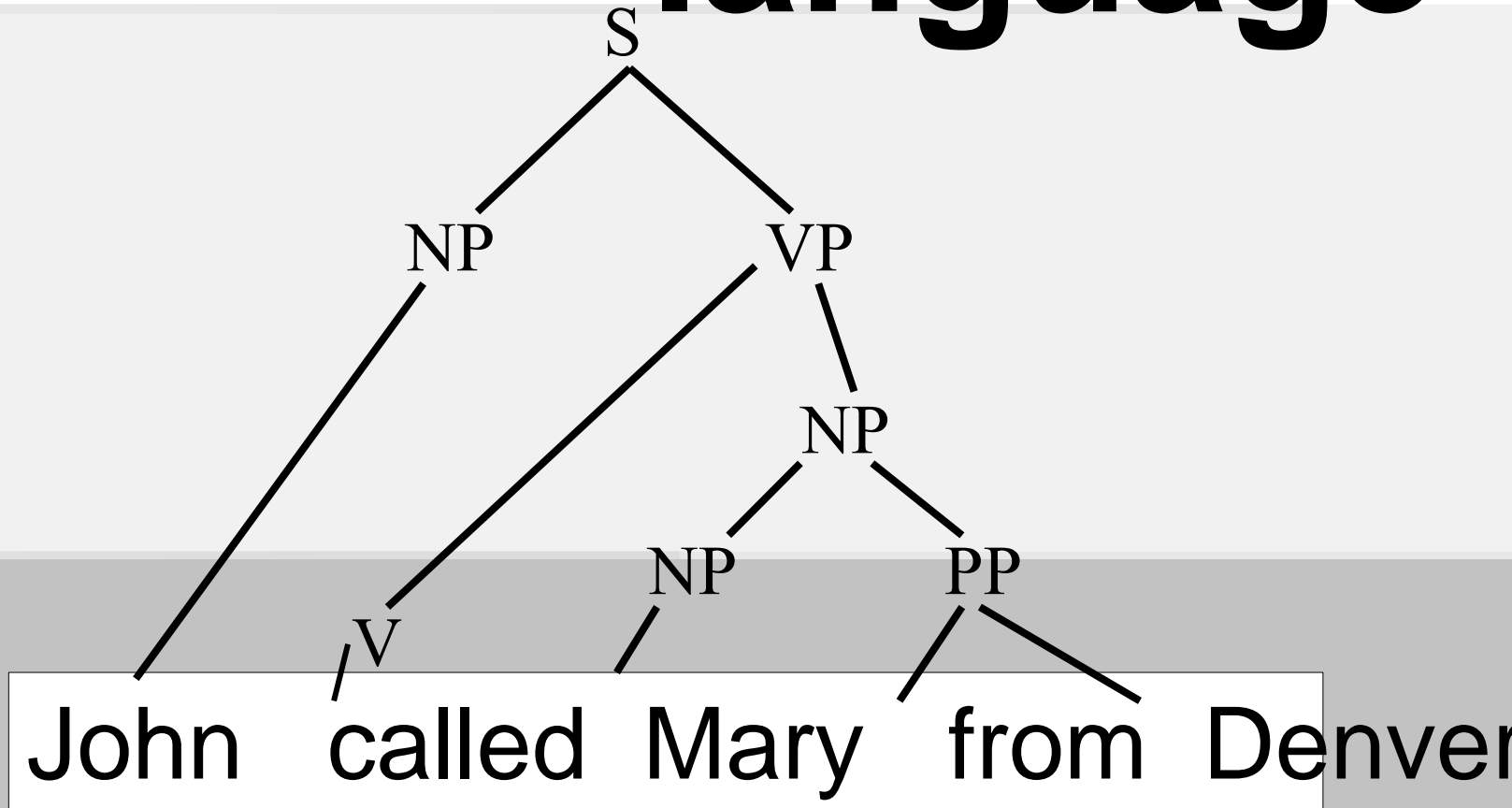


Natural language





Natural language





Natural language

John	called	Mary	from	Denver



Natural language

			P	Denver
		NP	from	
	V	Mary		
NP	called			
John				



Natural language

			P	Denver
		NP	from	
X	V	Mary		
NP	called			
John				



Natural language

			P	Denver
	VP →	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

		X	P	Denver
	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

		X	P	Denver
	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

		X	P	Denver
S →	VP	NP	from	
↓	V	Mary		
NP	called			
John				



Natural language

	X	X	P	Denver
S	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

		NP	P	NP
	X	↓	P	Denver
S	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

		NP	NP	NP
X	X	X	P	Denver
S	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

	VP	NP	PP	NP
X	X	X	P	Denver
S	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

	VP	NP	P	NP
X	X	X	P	Denver
S	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural language

	VP ₁ VP ₂	NP	PP	NP
X	X	X	P	Denver
S	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural

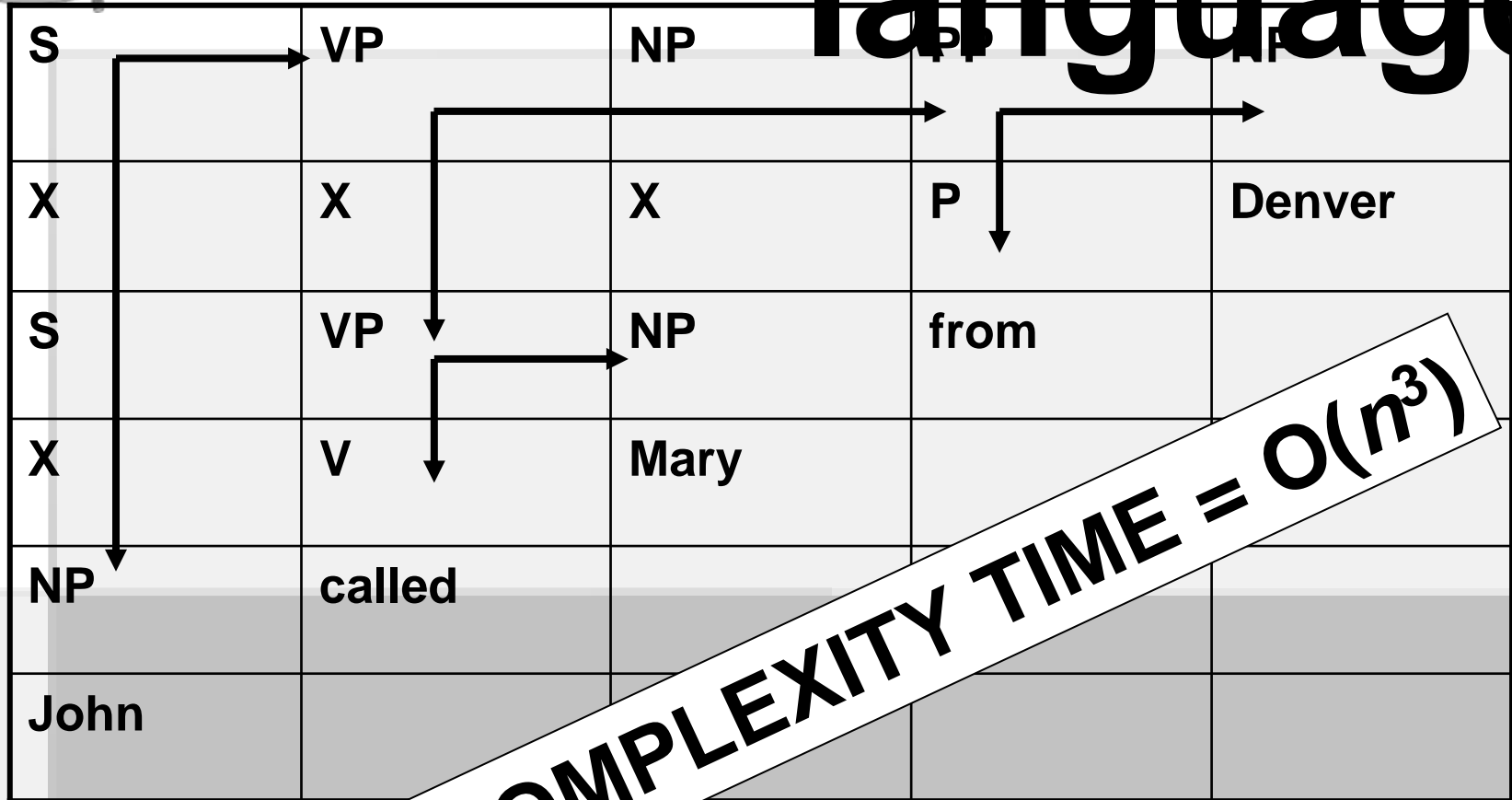
language

S	VP₁ VP₂	NP	PP	NP
X	X	X	P	Denver
S	VP	NP	from	
X	V	Mary		
NP	called			
John				



Natural

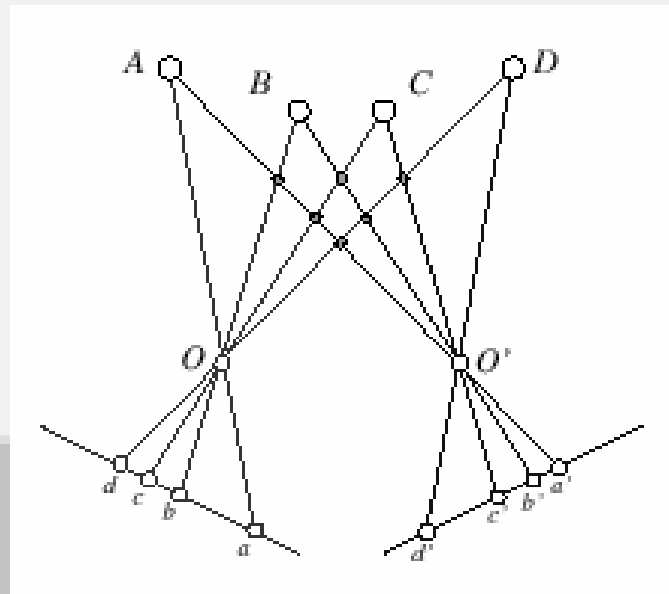
language



COMPLEXITY TIME = $O(n^3)$



Stereo vision



Ordering constraint...

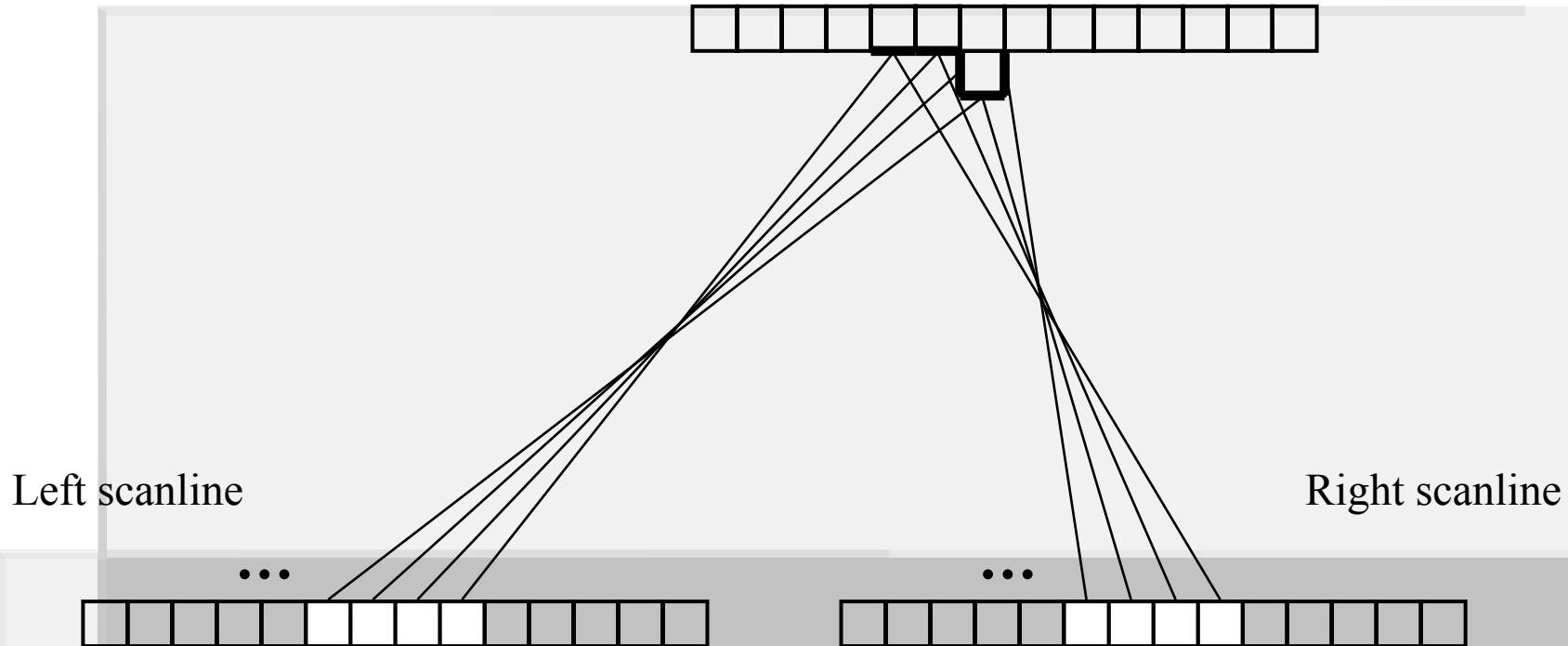


Stereo vision



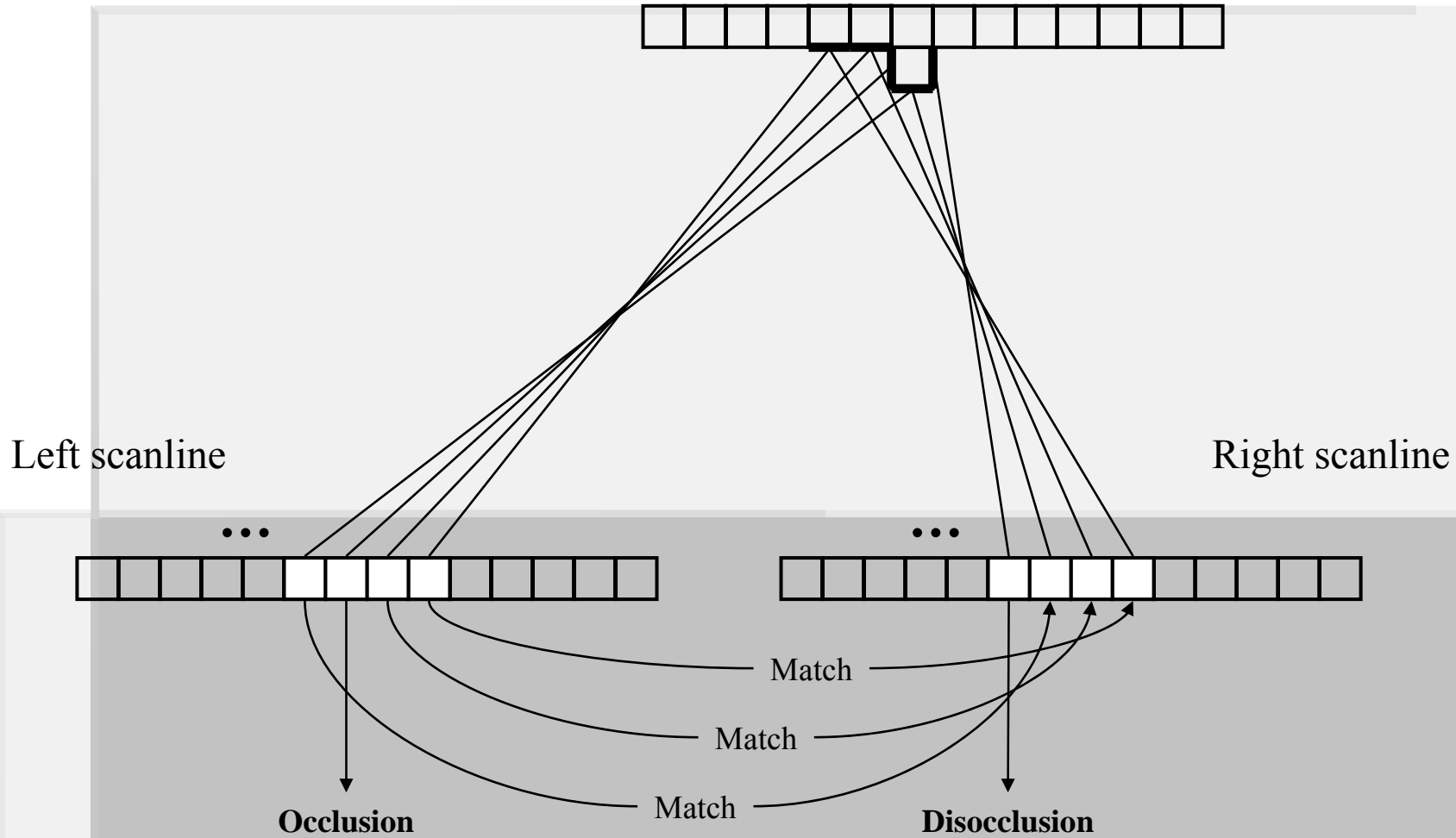


Stereo vision



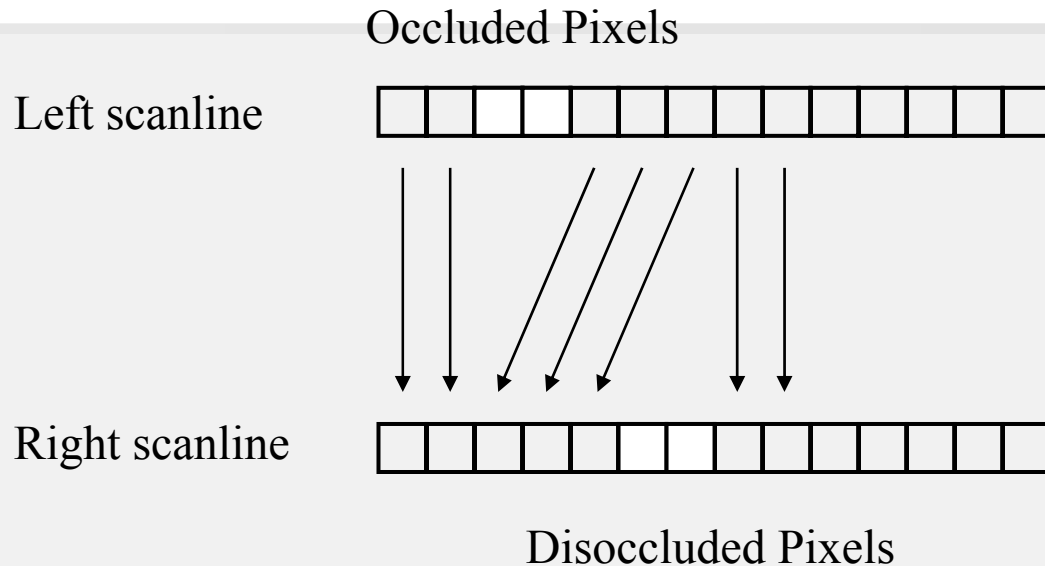


Stereo vision





Stereo vision

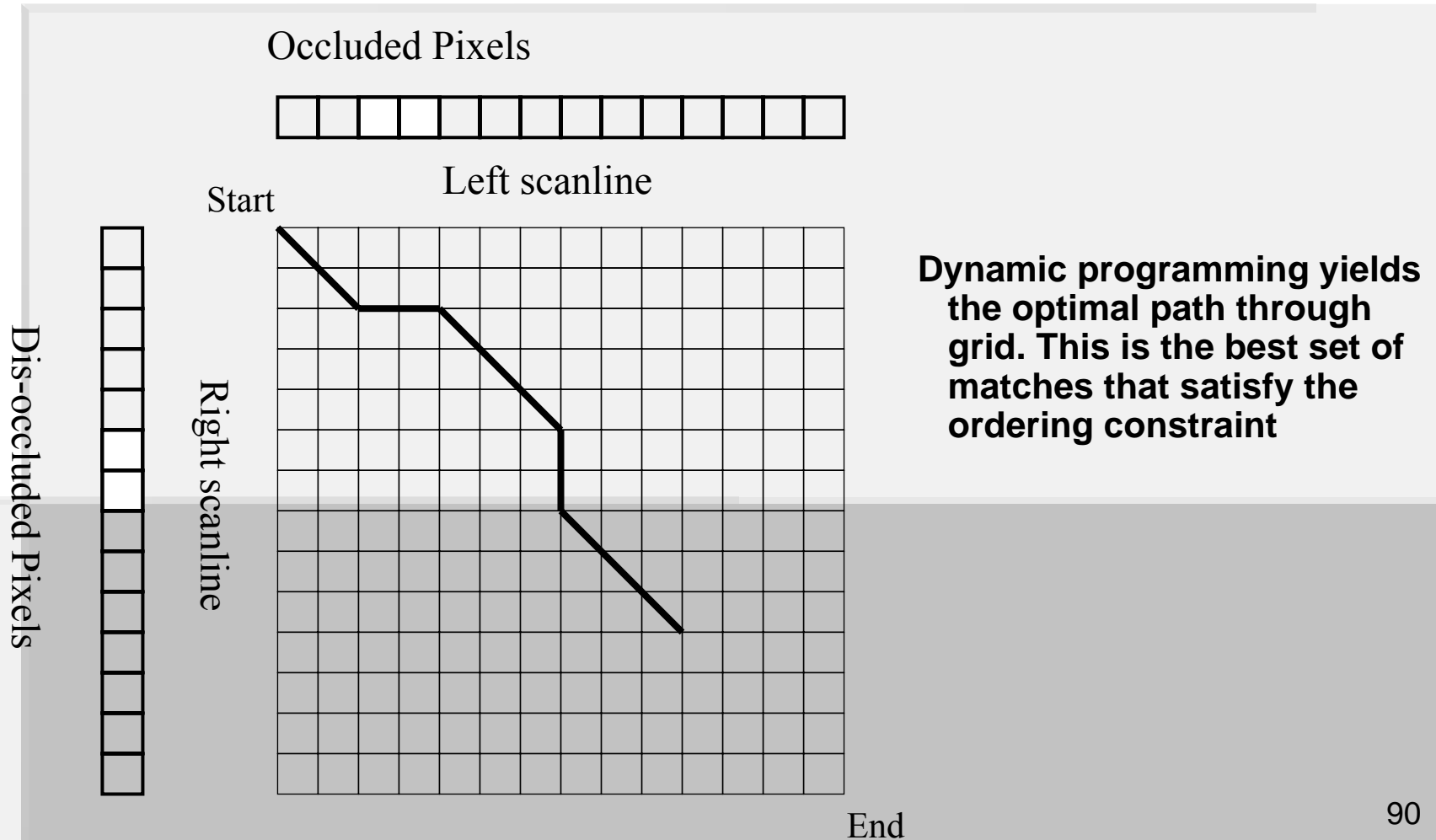


Three cases:

- Sequential – add cost of match (small if intensities agree)
- Occluded – add cost of no match (large cost)
- Disoccluded – add cost of no match (large cost)



Stereo vision





Stereo vision

Occluded Pixels

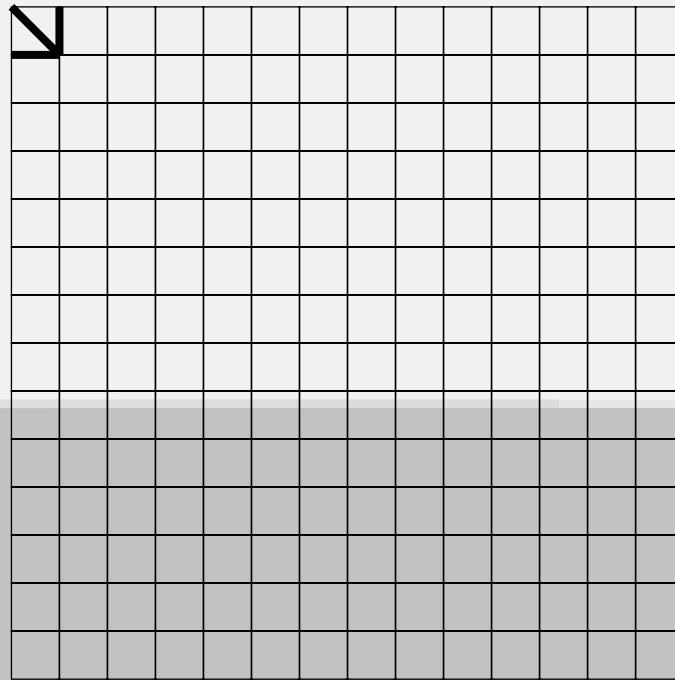


Left scanline



Dis-occluded Pixels

Right scanline



**Scan across grid computing optimal cost for each node given its upper-left neighbors.
Backtrack from the terminal to get the optimal path.**

Terminal



Stereo vision

Occluded Pixels

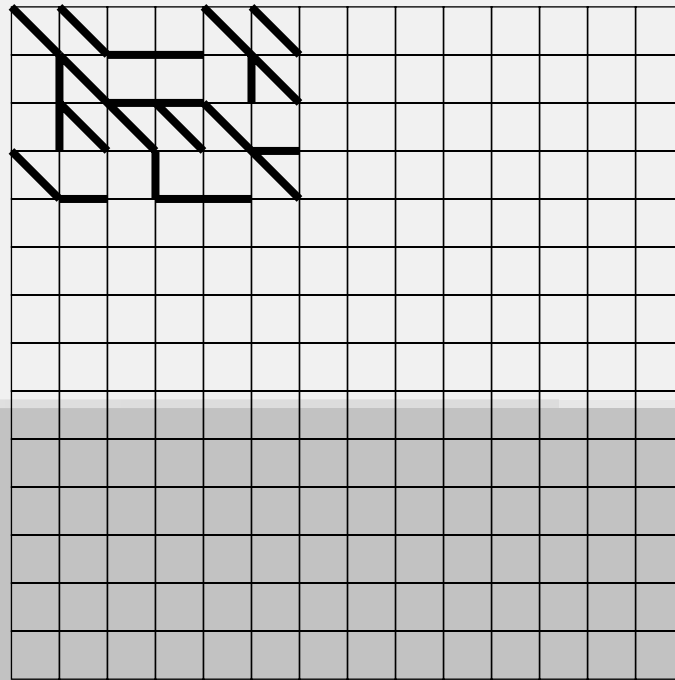


Left scanline



Dis-occluded Pixels

Right scanline



**Scan across grid computing optimal cost for each node given its upper-left neighbors.
Backtrack from the terminal to get the optimal path.**

Terminal



Stereo vision

Occluded Pixels

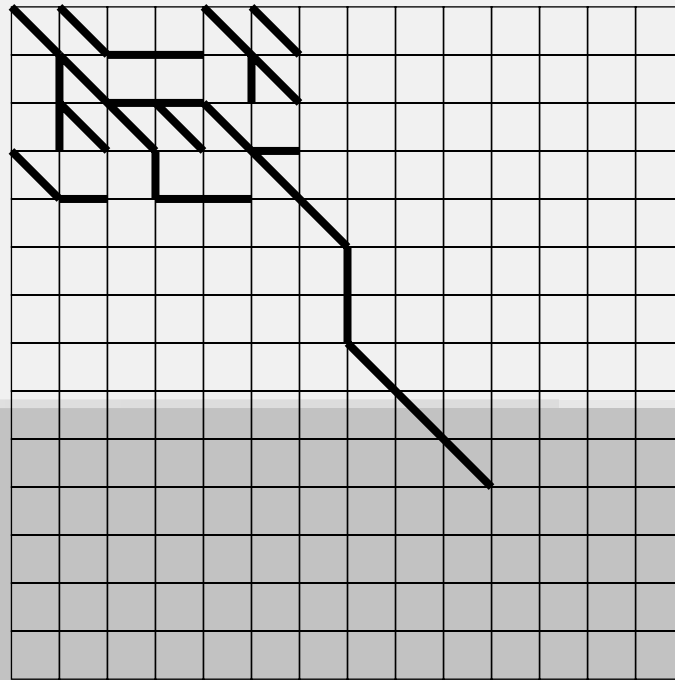


Left scanline



Dis-occluded Pixels

Right scanline



**Scan across grid computing optimal cost for each node given its upper-left neighbors.
Backtrack from the terminal to get the optimal path.**

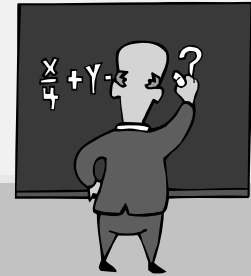
Terminal



Problems

Three groups of complexity problems

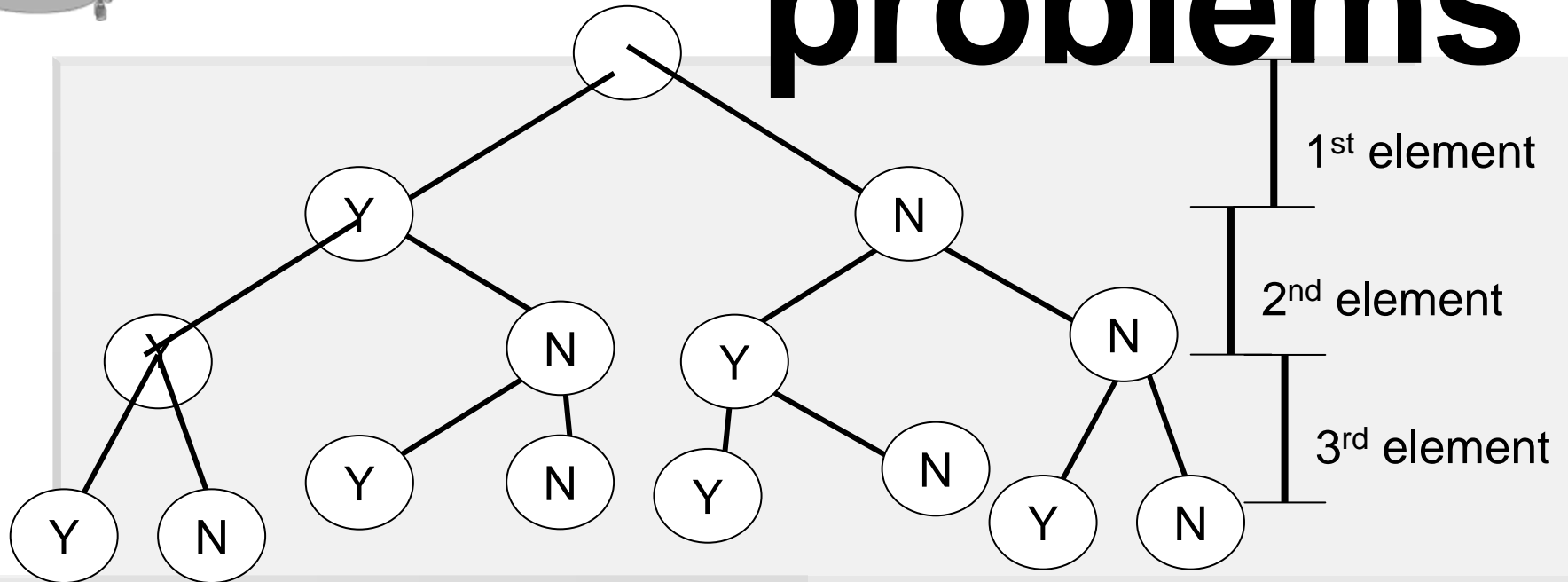
- **S**ubset problems (2^n)
- **P**ermutation problems ($n!$)
- **P**artition problems ($n!$)



State-space graph / tree



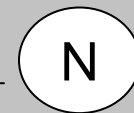
Subset problems



Number of nodes = $2^{n+1} - 1$



All yes

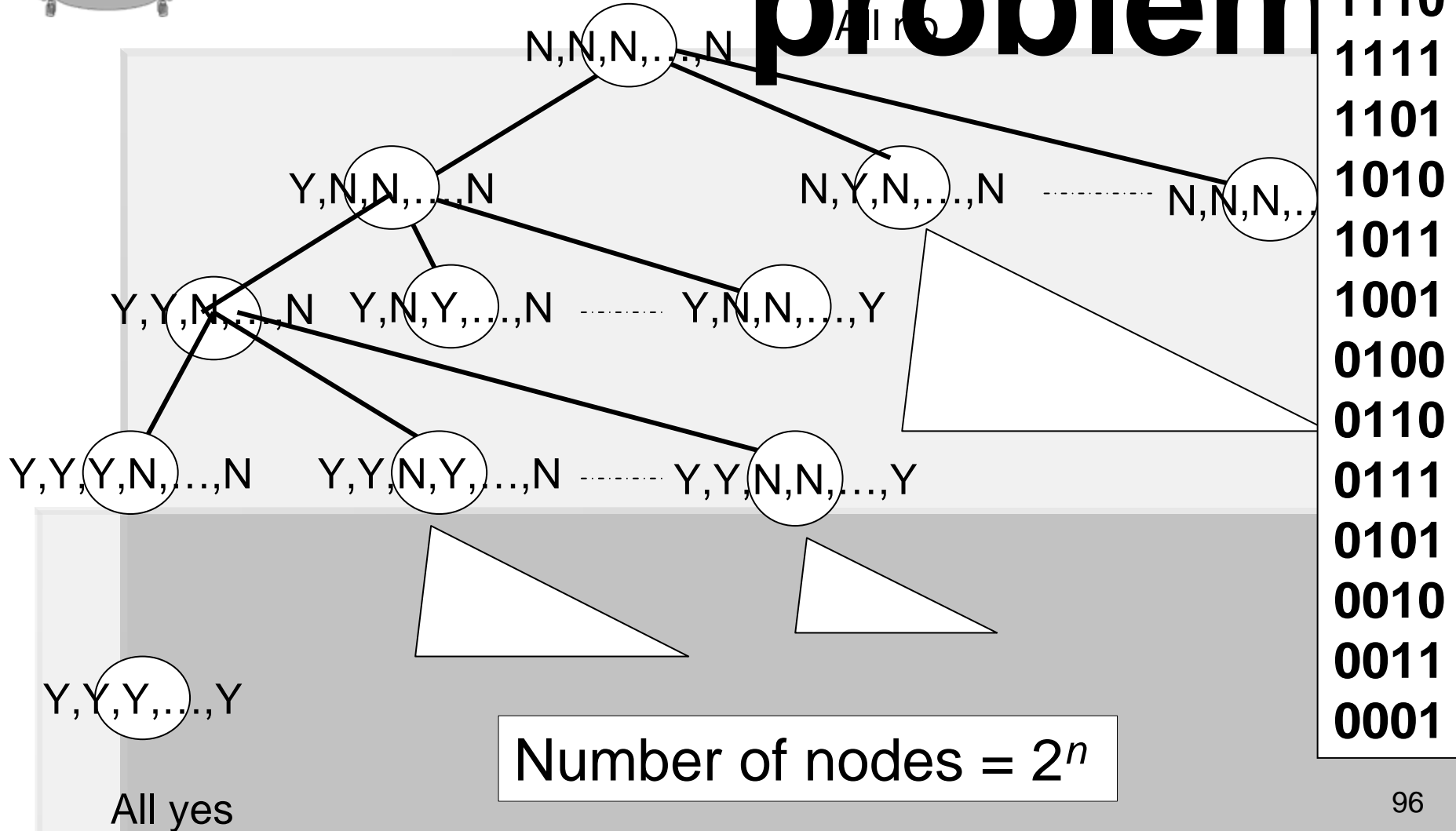


All no

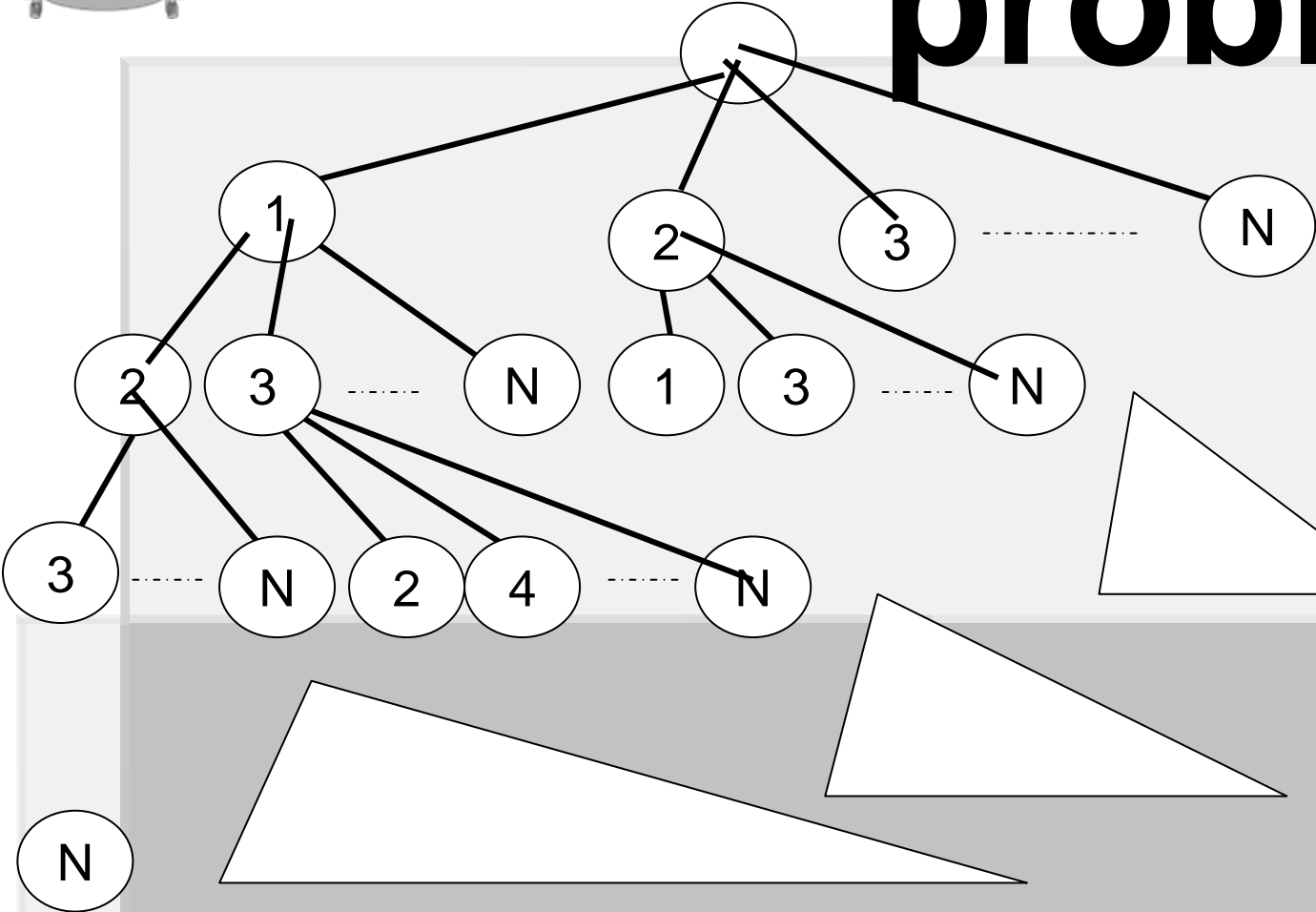
n^{th} element



Subsequence problem



Permutation problem



- 1234
- 1243
- 1324
- 1342
- 1423
- 1432
- 2134
- 2143
- 2314
- 2341
- 2413
- 2431
- 3124
- 3142
- ...
- 4312
- 4321

1st

2nd

3rd

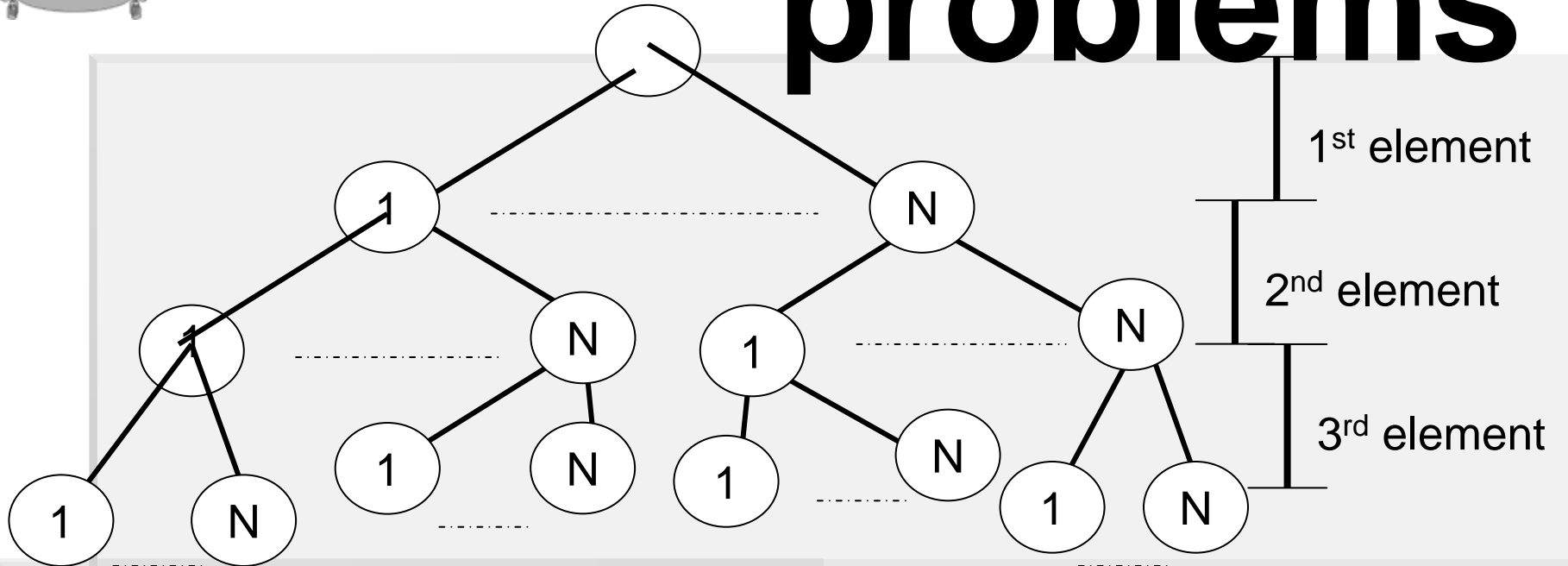
nth

n

n



Partition problems



Number of nodes = n^n

All 1

All n



Traversal

Three possible ways

- Depth-first technique
- Breadth-first technique
- Best-first technique



Back tracking

Technique

- **D**epth-first technique
- **K**eep track and return back when it cannot be branched.



Branch & bound

	1	2	3	4
A	10	7	13	15
B	12	5	16	12
C	14	9	14	20
D	11	7	14	13