

Shortest Paths in DAG

- $f[i]$: length of the shortest path from 1 to i

$$f[i] = \begin{cases} 0 & i = 1 \\ \min_{j:(j,i) \in E} \{f(j) + w(j,i)\} & i = 2, 3, \dots, n \end{cases}$$

Shortest Paths in DAG

- Use an adjacency list for incoming edges of each vertex i

Shortest Paths in DAG

```
1:  $f[1] \leftarrow 0$   
2: for  $i \leftarrow 2$  to  $n$  do  
3:    $f[i] \leftarrow \infty$   
4:   for each incoming edge  $(j, i)$  of  $i$  do  
5:     if  $f[j] + w(j, i) < f[i]$  then  
6:        $f[i] \leftarrow f[j] + w(j, i)$ 
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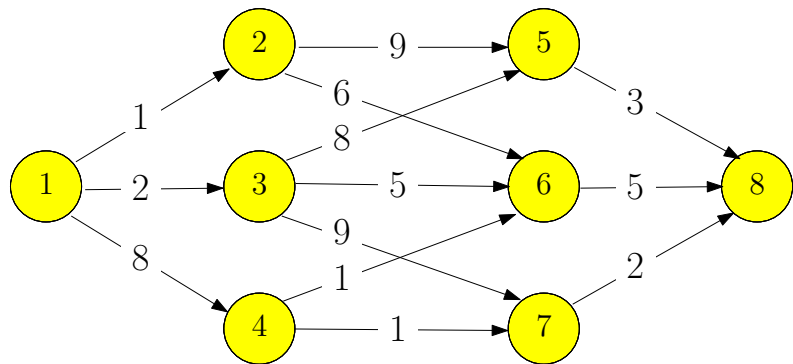
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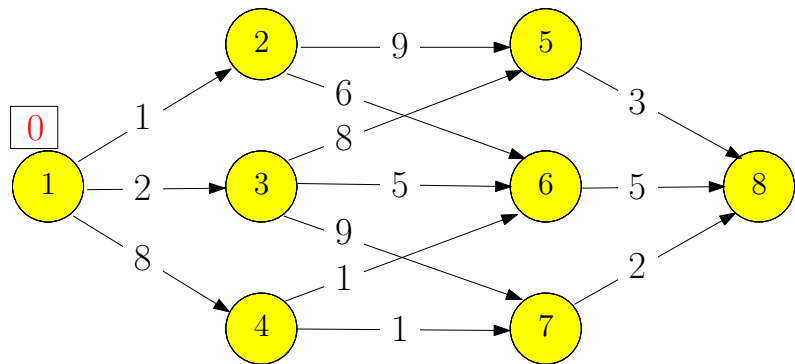
print-path(t)

```
1: if  $t = 1$  then
2:   print(1)
3:   return
4: print-path( $\pi(t)$ )
5: print(", ",  $t$ )
```

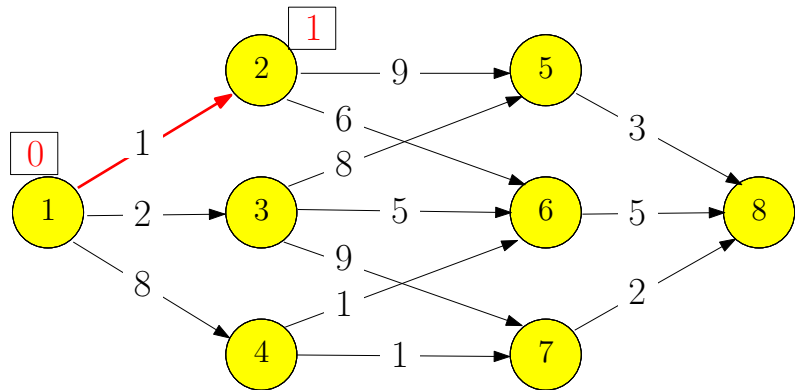
Example



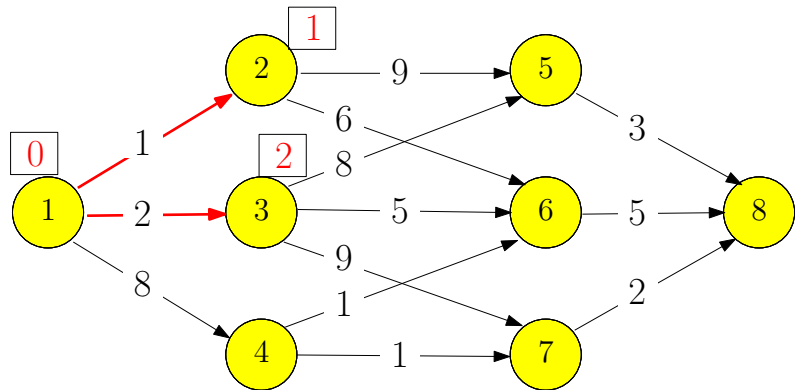
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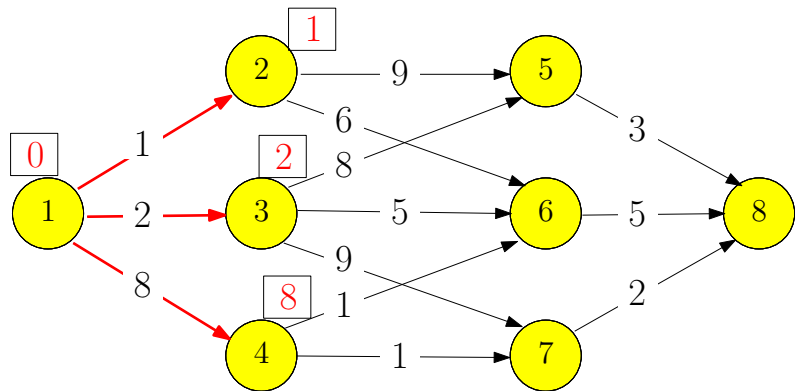
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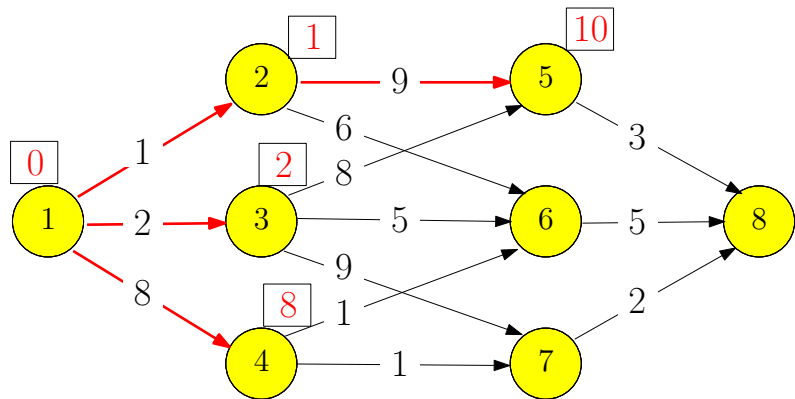
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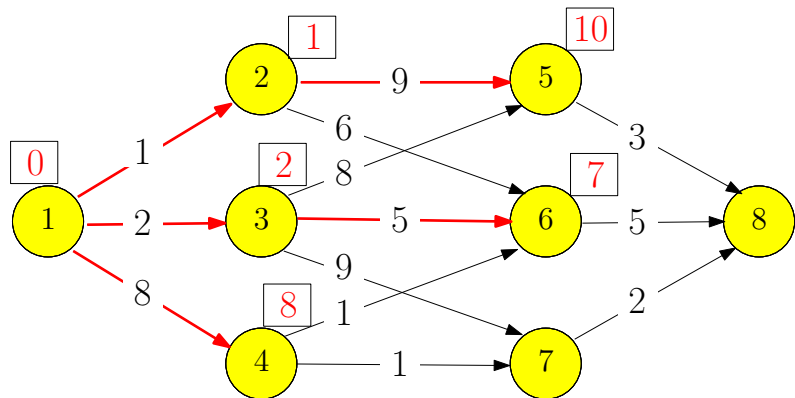
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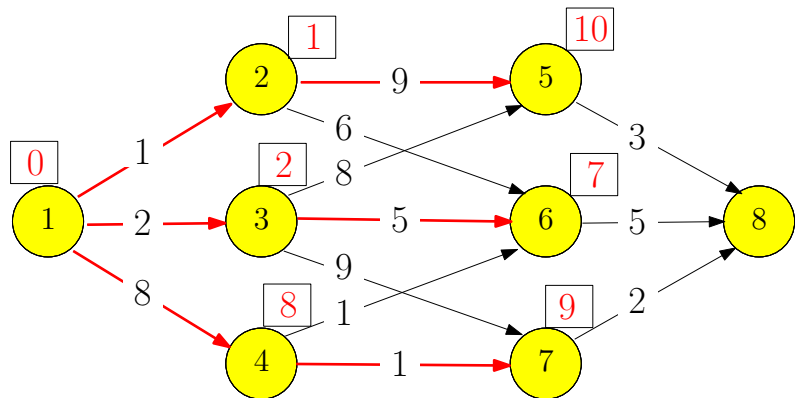
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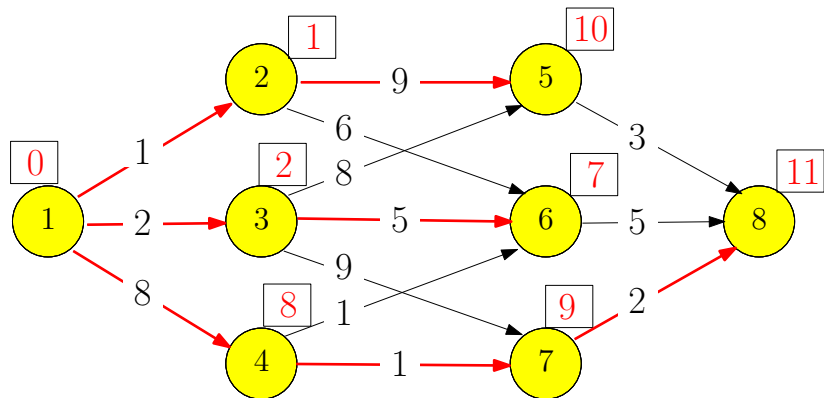
Example



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Example



Variant: Heaviest Path in a Directed Acyclic Graph

Heaviest Path in a Directed Acyclic Graph

Input: directed acyclic graph $G = (V, E)$ and $w : E \rightarrow \mathbb{R}$.

Assume $V = \{1, 2, 3, \dots, n\}$ is topologically sorted: if $(i, j) \in E$, then $i < j$

Output: the path with the **largest** weight (the **heaviest** path) from 1 to n .

- $f[i]$: weight of the **heaviest** path from 1 to i

$$f[i] = \begin{cases} & i = 1 \\ & i = 2, 3, \dots, n \end{cases}$$

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- 6 Matrix Chain Multiplication**
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Matrix Chain Multiplication

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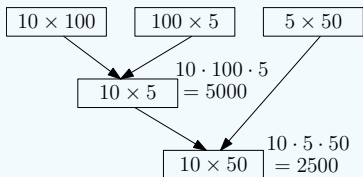
Input: n matrices A_1, A_2, \dots, A_n of sizes $r_1 \times c_1, r_2 \times c_2, \dots, r_n \times c_n$, such that $c_i = r_{i+1}$ for every $i = 1, 2, \dots, n - 1$.

Output: the order of computing $A_1 A_2 \dots A_n$ with the minimum number of multiplications

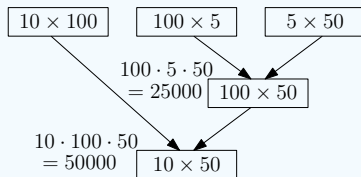
Fact Multiplying two matrices of size $r \times k$ and $k \times c$ takes $r \times k \times c$ multiplications.

Example:

- $A_1 : 10 \times 100$, $A_2 : 100 \times 5$, $A_3 : 5 \times 50$



$$\text{cost} = 5000 + 2500 = 7500$$

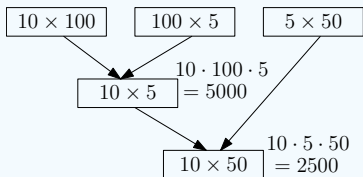


$$\text{cost} = 25000 + 50000 = 75000$$

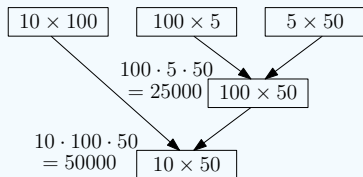
- $(A_1A_2)A_3: 10 \times 100 \times 5 + 10 \times 5 \times 50 = 7500$
- $A_1(A_2A_3): 100 \times 5 \times 50 + 10 \times 100 \times 50 = 75000$

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Matrix Chain Multiplication: Design DP

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- $opt[i, j]$: the minimum cost of computing $A_iA_{i+1} \cdots A_j$

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- $opt[i, j]$: the minimum cost of computing $A_iA_{i+1} \cdots A_j$

$$opt[i, j] = \begin{cases} 0 & i = j \\ \min_{k:i \leq k < j} (opt[i, k] + opt[k + 1, j] + r_i c_k c_j) & i < j \end{cases}$$

Matrix Chain Multiplication: Design DP

matrix-chain-multiplication($n, r[1..n], c[1..n]$)

```
1: let  $opt[i, i] \leftarrow 0$  for every  $i = 1, 2, \dots, n$ 
2: for  $\ell \leftarrow 2$  to  $n$  do
3:   for  $i \leftarrow 1$  to  $n - \ell + 1$  do
4:      $j \leftarrow i + \ell - 1$ 
5:      $opt[i, j] \leftarrow \infty$ 
6:     for  $k \leftarrow i$  to  $j - 1$  do
7:       if  $opt[i, k] + opt[k + 1, j] + r_i c_k c_j < opt[i, j]$  then
8:          $opt[i, j] \leftarrow opt[i, k] + opt[k + 1, j] + r_i c_k c_j$ 
9: return  $opt[1, n]$ 
```

Recover the Optimum Way of Multiplication

matrix-chain-multiplication($n, r[1..n], c[1..n]$)

```
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7:       if  $opt[i, k] + opt[k + 1, j] + r_i c_k c_j < opt[i, j]$  then
8:          $opt[i, j] \leftarrow opt[i, k] + opt[k + 1, j] + r_i c_k c_j$ 
9:          $\pi[i, j] \leftarrow k$ 
10: return  $opt[1, n]$ 
```

Constructing Optimal Solution

Print-Optimal-Order(i, j)

```
1: if  $i = j$  then  
2:   print("A" $i$ )  
3: else  
4:   print("(")  
5:   Print-Optimal-Order( $i, \pi[i, j]$ )  
6:   Print-Optimal-Order( $\pi[i, j] + 1, j$ )  
7:   print(")
```

matrix	A_1	A_2	A_3	A_4	A_5
size	3×5	5×2	2×6	6×9	9×4

$$\text{opt}[1, 2] = \text{opt}[1, 1] + \text{opt}[2, 2] + 3 \times 5 \times 2 = 30, \quad \pi[1, 2] = 1$$

$$\text{opt}[2, 3] = \text{opt}[2, 2] + \text{opt}[3, 3] + 5 \times 2 \times 6 = 60, \quad \pi[2, 3] = 2$$

$$\text{opt}[3, 4] = \text{opt}[3, 3] + \text{opt}[4, 4] + 2 \times 6 \times 9 = 108, \quad \pi[3, 4] = 3$$

$$\text{opt}[4, 5] = \text{opt}[4, 4] + \text{opt}[5, 5] + 6 \times 9 \times 4 = 216, \quad \pi[4, 5] = 4$$

$$\begin{aligned} \text{opt}[1, 3] &= \min\{\text{opt}[1, 1] + \text{opt}[2, 3] + 3 \times 5 \times 6, \\ &\quad \text{opt}[1, 2] + \text{opt}[3, 3] + 3 \times 2 \times 6\} \\ &= \min\{0 + 60 + 90, 30 + 0 + 36\} = 66, \quad \pi[1, 3] = 2 \end{aligned}$$

$$\begin{aligned} \text{opt}[2, 4] &= \min\{\text{opt}[2, 2] + \text{opt}[3, 4] + 5 \times 2 \times 9, \\ &\quad \text{opt}[2, 3] + \text{opt}[4, 4] + 5 \times 6 \times 9\} \\ &= \min\{0 + 108 + 90, 60 + 0 + 270\} = 198, \quad \pi[2, 4] = 2, \end{aligned}$$

matrix	A_1	A_2	A_3	A_4	A_5
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$$\begin{aligned}
 \text{opt}[3, 5] &= \min\{\text{opt}[3, 3] + \text{opt}[4, 5] + 2 \times 6 \times 4, \\
 &\quad \text{opt}[3, 4] + \text{opt}[5, 5] + 2 \times 9 \times 4\} \\
 &= \min\{0 + 216 + 48, 108 + 0 + 72\} = 180,
 \end{aligned}$$

$$\pi[3, 5] = 4,$$

$$\begin{aligned}
 \text{opt}[1, 4] &= \min\{\text{opt}[1, 1] + \text{opt}[2, 4] + 3 \times 5 \times 9, \\
 &\quad \text{opt}[1, 2] + \text{opt}[3, 4] + 3 \times 2 \times 9, \\
 &\quad \text{opt}[1, 3] + \text{opt}[4, 4] + 3 \times 6 \times 9\} \\
 &= \min\{0 + 198 + 135, 30 + 108 + 54, 66 + 0 + 162\} = 192,
 \end{aligned}$$

$$\pi[1, 4] = 2,$$

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size	3×5	5×2	2×6	6×9	9×4

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 &\quad \text{opt}[2, 4] + \text{opt}[5, 5] + 5 \times 9 \times 4\} \\
 &= \min\{0 + 180 + 40, 60 + 216 + 120, 198 + 0 + 180\} = 220,
 \end{aligned}$$

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 &\quad \text{opt}[1, 4] + \text{opt}[5, 5] + 3 \times 9 \times 4\} \\
 &= \min\{0 + 220 + 60, 30 + 180 + 24, \\
 &\quad 66 + 216 + 72, 192 + 0 + 108\} \\
 &= 234,
 \end{aligned}$$

$$\pi[1, 5] = 2.$$

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opt, π	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$
$i = 1$	0, /	30, 1	66, 2	192, 2	234, 2
$i = 2$		0, /	60, 2	198, 2	220, 2
$i = 3$			0, /	108, 3	180, 4
$i = 4$				0, /	216, 4
$i = 5$					0, /

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$i = 5$					0, /

Print-Optimal-Order(1,5)

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 Print-Optimal-Order(4, 4)

 Print-Optimal-Order(5, 5)

Optimum way for multiplication: $((A_1A_2)((A_3A_4)A_5))$

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Optimum Binary Search Tree

Def. Binary search tree (BST), also called an ordered or sorted binary tree, is a rooted binary tree data structure with the key of each internal node being greater than all the keys in the respective node's left subtree and less than the ones in its right subtree.

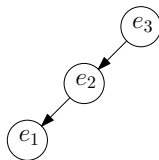
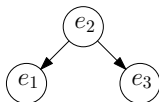
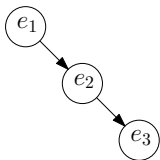
Optimum Binary Search Tree

- n elements $e_1 < e_2 < e_3 < \dots < e_n$
- e_i has frequency f_i
- goal: build a binary search tree for $\{e_1, e_2, \dots, e_n\}$ with the minimum accessing cost:

$$\sum_{i=1}^n f_i \times (\text{depth of } e_i \text{ in the tree})$$

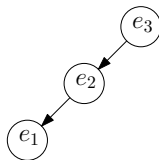
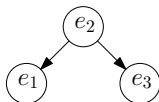
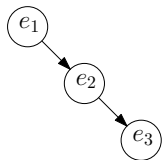
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- Example: $f_1 = 10, f_2 = 5, f_3 = 3$



Optimum Binary Search Tree

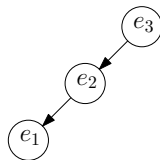
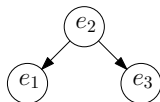
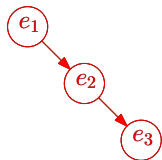
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- $10 \times 1 + 5 \times 2 + 3 \times 3 = 29$
- $10 \times 2 + 5 \times 1 + 3 \times 2 = 31$
- $10 \times 3 + 5 \times 2 + 3 \times 1 = 43$

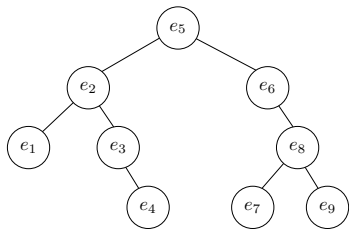
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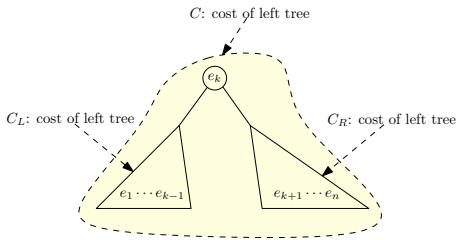


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- suppose we decided to let e_k be the root
- e_1, e_2, \dots, e_{k-1} are on left sub-tree
- $e_{k+1}, e_{k+2}, \dots, e_n$ are on right sub-tree
- d_j : depth of e_j in our tree
- C, C_L, C_R : cost of tree, left sub-tree and right sub-tree



- $d_1 = 3, d_2 = 2, d_3 = 3, d_4 = 4, d_5 = 1,$
- $d_6 = 2, d_7 = 4, d_8 = 3, d_9 = 4,$
- $C = 3f_1 + 2f_2 + 3f_3 + 4f_4 + f_5 + 2f_6 + 4f_7 + 3f_8 + 4f_9$
- $C_L = 2f_1 + f_2 + 2f_3 + 3f_4$
- $C_R = f_6 + 3f_7 + 2f_8 + 3f_9$
- $C = C_L + C_R + \sum_{j=1}^9 f_j$



$$\begin{aligned}
 C &= \sum_{\ell=1}^n f_{\ell} d_{\ell} = \sum_{\ell=1}^n f_{\ell} (d_{\ell} - 1) + \sum_{\ell=1}^n f_{\ell} \\
 &= \sum_{\ell=1}^{k-1} f_{\ell} (d_{\ell} - 1) + \sum_{\ell=k+1}^n f_{\ell} (d_{\ell} - 1) + \sum_{\ell=1}^n f_{\ell} \\
 &= C_L + C_R + \sum_{\ell=1}^n f_{\ell}
 \end{aligned}$$

$$C = C_L + C_R + \sum_{\ell=1}^n f_{\ell}$$

- In order to minimize C , need to minimize C_L and C_R respectively

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$$opt[1, n] = (opt[1, k-1] + opt[k+1, n]) + \sum_{\ell=1}^n f_{\ell}$$

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$$opt[1, n] = \min_{k: 1 \leq k \leq n} (opt[1, k-1] + opt[k+1, n]) + \sum_{\ell=1}^n f_{\ell}$$

$$C = C_L + C_R + \sum_{\ell=1}^n f_{\ell}$$

- In order to minimize C , need to minimize C_L and C_R respectively
- $opt[i, j]$: the optimum cost for the instance $(f_i, f_{i+1}, \dots, f_j)$

$$opt[1, n] = \min_{k:1 \leq k \leq n} (opt[1, k-1] + opt[k+1, n]) + \sum_{\ell=1}^n f_{\ell}$$

- In general, $opt[i, j] =$

$$\begin{cases} 0 & \text{if } i = j + 1 \\ \min_{k:i \leq k \leq j} (opt[i, k-1] + opt[k+1, j]) + \sum_{\ell=i}^j f_{\ell} & \text{if } i \leq j \end{cases}$$

Optimum Binary Search Tree

- 1: $fsum[0] \leftarrow 0$
- 2: **for** $i \leftarrow 1$ to n **do** $fsum[i] \leftarrow fsum[i - 1] + f_i$
 $\triangleright fsum[i] = \sum_{j=1}^i f_j$
- 3: **for** $i \leftarrow 0$ to n **do** $opt[i + 1, i] \leftarrow 0$
- 4: **for** $\ell \leftarrow 1$ to n **do**
- 5: **for** $i \leftarrow 1$ to $n - \ell + 1$ **do**
- 6: $j \leftarrow i + \ell - 1, opt[i, j] \leftarrow \infty$
- 7: **for** $k \leftarrow i$ to j **do**
- 8: **if** $opt[i, k - 1] + opt[k + 1, j] < opt[i, j]$ **then**
- 9: $opt[i, j] \leftarrow opt[i, k - 1] + opt[k + 1, j]$
- 10: $\pi[i, j] \leftarrow k$
- 11: $opt[i, j] \leftarrow opt[i, j] + fsum[j] - fsum[i - 1]$

Print-Tree(i, j)

```
1: if  $i > j$  then  
2:   return  
3: else  
4:   print('(')  
5:   Print-Tree( $i, \pi[i, j] - 1$ )  
6:   print( $\pi[i, j]$ )  
7:   Print-Tree( $\pi[i, j] + 1, j$ )  
8:   print('')
```