



3.3 DP and Optimization Problems

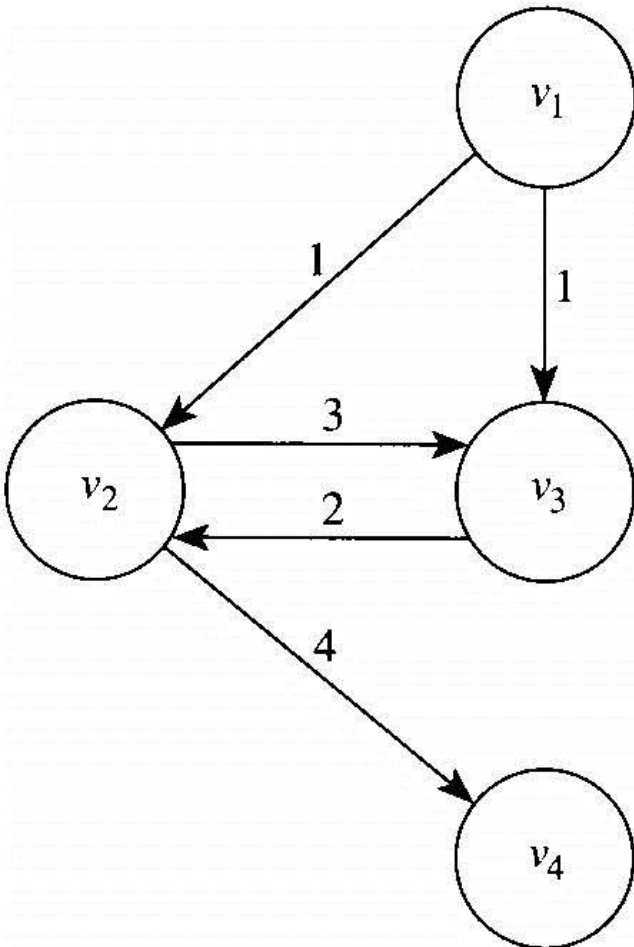
- P can be solved using DP if the principle of optimality applies in P.
- Def.: The **principle of optimality** is said to apply in a problem if an **optimal solution** to an instance of a problem always **contains optimal solutions to all subinstances**.
- Ex) *shortest path problem*
 - If the path from v_i to v_j is optimal, then the subpaths from v_i to v_k and from v_k to v_j must be optimal.

$$v_i \Rightarrow v_k \Rightarrow v_j$$

Counterexample

■ Ex) *longest path problem*

■ See Fig. 3.6 (consider simple path only)



$\underbrace{v_1 \rightarrow v_3}_{\text{NOT optimal}} \rightarrow v_2 \rightarrow v_4$ longest

$(v_1 \rightarrow v_2 \rightarrow v_3 \text{ optimal})$

Figure 3.6 A weighted, directed graph with a cycle.



3.4 Chained Matrix Multiplication

- **ijk multiplication** $A_{i \times j} \bullet B_{j \times k} = C_{i \times k}$

Ex) **A x B x C x D**

20x2 2x30 30x12 12x8

((AB)C)D 20x2x30+20x30x12+20x12x8 = 10,320

A((BC)D) 2x30x12+2x12x8+20x2x8 = 1,232

- **Goal:** determine the **optimal order** for multiplying n matrices



Basic Observation

- **Brute-force algorithm**

- Let t_n be the # of different orders in which we can multiply n matrices

$$\underbrace{A_1(A_2 \cdots A_n)}_{t_{n-1}} \quad \underbrace{(A_1 \cdots A_{n-1})A_n}_{t_{n-1}}$$

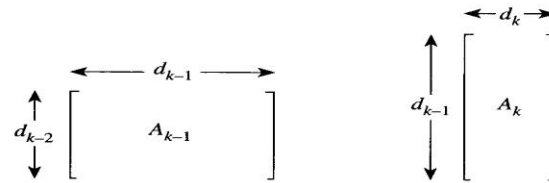
$$t_n \geq t_{n-1} + t_{n-1} = 2t_{n-1}$$

$$t_2 = 1 \quad t_n \geq 2^{n-2}$$

- **Principle of optimality applies?**

- If $A_1((((A_2A_3)A_4)A_5)A_6)$ is optimal
- $(A_2A_3)A_4$ is **also** optimal
- **Proof by contradiction**

Figure 3.7 The number of columns in A_{k-1} is the same as the number of rows in A_k .



Example

$$\begin{array}{ccccccc} A_1 & A_2 & \cdots & A_k & \cdots & A_n \\ d_0 \times d_1 & d_1 \times d_2 & & d_{k-1} \times d_k & & d_{n-1} \times d_n \end{array}$$

Let $M[i][j] = \min \# \text{ of multiplications needed}$
to multiply A_i through A_j $1 \leq i \leq j \leq n$

$$M[i][i] = 0 \quad \text{Want : } M[1][n]$$

Ex. 3.5

$$\begin{array}{cccccc} A_1 & A_2 & A_3 & A_4 & A_5 & A_6 \\ d_0 & d_1 & d_2 & d_3 & d_4 & d_5 & d_6 \\ 5 & 2 & 3 & 4 & 6 & 7 & 8 \end{array}$$

$$\#(A_4 A_5) A_6 = \underset{4}{d_3} \times \underset{6}{d_4} \times \underset{7}{d_5} + \underset{4}{d_3} \times \underset{7}{d_5} \times \underset{8}{d_6} = 392$$

$$\# A_4 (A_5 A_6) = \underset{6}{d_4} \times \underset{7}{d_5} \times \underset{8}{d_6} + \underset{4}{d_3} \times \underset{6}{d_4} \times \underset{8}{d_6} = 528$$

$$M[4][6] = \min(392, 528) = 392$$



Factorization (1/2)

- **Multiplying 6 matrices**

1. $(A_1)(A_2A_3A_4A_5A_6)$

2. $(A_1A_2)(A_3A_4A_5A_6)$

3. $(A_1A_2A_3)(A_4A_5A_6)$

4. $(A_1A_2A_3A_4)(A_5A_6)$

5. $(A_1A_2A_3A_4A_5)(A_6)$

- **One of these is optimal**

$$M[1][6] = \min_{1 \leq k \leq 5} (M[1][k] + M[k+1][6] + d_0 d_k d_6)$$

- **In general**

$$\begin{array}{cc} (A_i \cdots A_k) & (A_{k+1} \cdots A_j) \\ d_{i-1} \times d_k & d_k \times d_j \\ M[i][k] & M[k+1][j] \end{array}$$

$$M[i][j] = \min_{i \leq k \leq j-1} (M[i][k] + M[k+1][j] + d_{i-1} d_k d_j) \quad \text{if } i < j$$

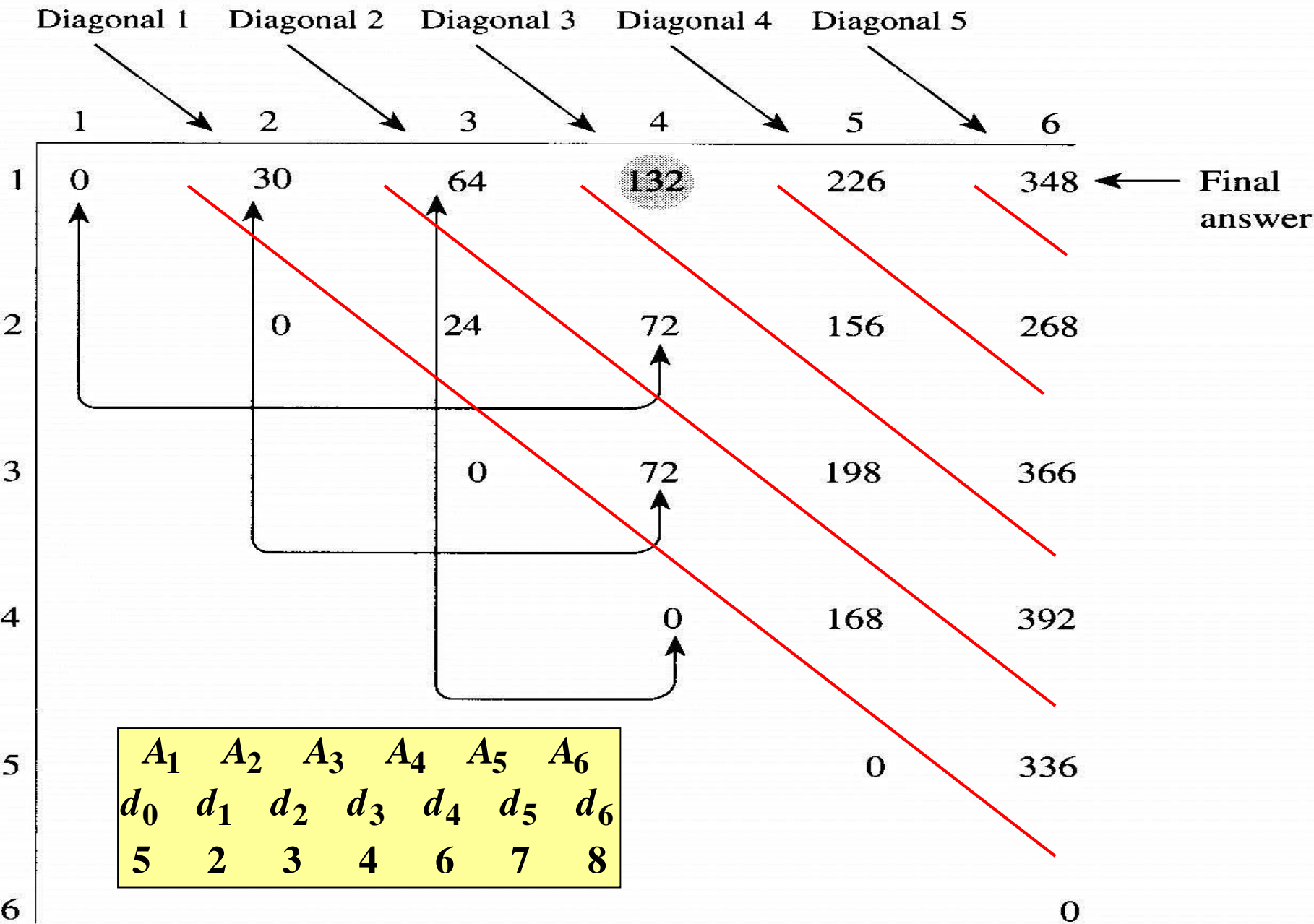
$$M[i][i] = 0$$



Factorization (2/2)

- **Computing order**
 - **From main diagonal ($j - i = 0$), diagonal 1 ($j - i = 1$), diagonal 2 ($j - i = 2$), etc.**
- **See Ex. 3.6 and Fig. 3.8**
- **See Alg. 3.6**

Figure 3.8 The array M developed in Example 3.6. $M[1][4]$, which is circled, is computed from the pairs of entries indicated.





Example 3.6 (1/2)

A_1	A_2	A_3	A_4	A_5	A_6	
d_0	d_1	d_2	d_3	d_4	d_5	d_6
5	2	3	4	6	7	8

- Compute **diagonal 0**:

$$M[i][i] = 0 \text{ for } 1 \leq i \leq 6$$

- Compute **diagonal 1**:

$$\begin{aligned} M[1][2] &= \min_{1 \leq k \leq 1} (M[1][k] + M[k+1][2] + d_0 d_k d_2) \\ &= M[1][1] + M[2][2] + d_0 d_1 d_2 \\ &= 0 + 0 + 5 \times 2 \times 3 = 30 \end{aligned}$$

$M[2][3]$, $M[3][4]$, $M[4][5]$, and $M[5][6]$

- Compute **diagonal 2**:

$$\begin{aligned} M[1][3] &= \min_{1 \leq k \leq 2} (M[1][k] + M[k+1][3] + d_0 d_k d_3) \\ &= \min(M[1][1] + M[2][3] + d_0 d_1 d_3, \\ &\quad M[1][2] + M[3][3] + d_0 d_2 d_3) \\ &= \min(0 + 24 + 5 \times 2 \times 4, 30 + 0 + 5 \times 3 \times 4) = 64 \end{aligned}$$

$M[2][4]$, $M[3][5]$, and $M[4][6]$



Example 3.6 (2/2)

A_1	A_2	A_3	A_4	A_5	A_6	
d_0	d_1	d_2	d_3	d_4	d_5	d_6
5	2	3	4	6	7	8

- Compute **diagonal 3**:

$$\begin{aligned} M[1][4] &= \min_{1 \leq k \leq 3} (M[1][k] + M[k+1][4] + d_0 d_k d_4) \\ &= \min(M[1][1] + M[2][4] + d_0 d_1 d_4, \\ &\quad M[1][2] + M[3][4] + d_0 d_2 d_4, \\ &\quad M[1][3] + M[4][4] + d_0 d_3 d_4, \\ &= \min(0 + 72 + 5 \times 2 \times 6, 30 + 72 + 5 \times 3 \times 6, \\ &\quad 64 + 0 + 5 \times 4 \times 6) = 132 \end{aligned}$$

$M[2][5]$, and $M[3][6]$

- Compute **diagonal 4**:

$M[1][5]$, and $M[2][6]$

- Compute **diagonal 5**:

$$M[1][6] = 348$$



Algorithm 3.6 Minimum Multiplications (1/2)

- **Problem**: Determining the **minimum number of elementary multiplications** needed to multiply n matrices and an **order** that produces that minimum number.
- **Inputs**: the number of matrices n , and an array of integers d , indexed from 0 to n , where $d[i - 1] \times d[i]$ is the dimension of the i -th matrix.
- **Outputs**: $minmult$, the minimum number of elementary multiplications needed to multiply the n matrices; a 2D **array** P from which the optimal order can be obtained. P has its rows indexed from 1 to $n - 1$ and its columns indexed from 1 to n . $P[i][j]$ is the **point where matrices i through j are split** in an optimal order for multiplying the matrices.

Algorithm 3.6 Minimum Multiplications (2/2)

```
int minmult(int n, const int d[ ], index P[ ][ ])
{
```

```
    index i, j, k, diagonal;
```

```
    int M[1..n][1..n];
```

```
    for (i = 1; i <= n; i++)
```

```
        M[i][i] = 0;
```

```
    for (diagonal = 1; diagonal <= n-1; diagonal ++)
```

```
        // diagonal-1 is just above the main diagonal.
```

```
        for (i = 1; i <= n - diagonal; i++){
```

```
            j = i + diagonal; // remember that “# of alternatives = diagonal”
```

```
            M[i][j] = minimum (M[i][k] + M[k+1][j] + d[i-1]*d[k]*d[j]);
                          i ≤ k ≤ j-1
```

```
            P[i][j] = a value of k that gave the minimum;
```

```
        }
```

```
    return M[1][n];
```

```
}
```

Figure 3.8 The array M developed in Example 3.6. M[1][4], which is circled, is computed from the pairs of entries indicated.

	Diagonal 1	Diagonal 2	Diagonal 3	Diagonal 4	Diagonal 5	
	1	2	3	4	5	6
1	0	30	64	132	226	348 ← Final answer
2		0	24	72	156	268
3			0	72	198	366
4				0	168	392
5					0	336
6						0

$$M[i][j] = \min_{i \leq k \leq j-1} (M[i][k] + M[k+1][j] + d_{i-1}d_kd_j) \text{ if } i < j$$

$$M[i][i] = 0$$



T(n) of Alg. 3.6

- **Basic operation:** instruction executed for each value of k and (min) comparison
- **Input size:** $n = (\# \text{ of matrices})$
- **Given diagonal**
 - **for i-loop** **n - diagonal**
 - **for k-loop** **$j-1 - i + 1 = i + \text{diagonal} - i = \text{diagonal}$**

$$\begin{aligned} T(n) &= \sum_{d=1}^{n-1} (n-d) \cdot d = n \cdot \frac{n(n-1)}{2} - \frac{(n-1)n(2n-1)}{6} \\ &= \frac{(n-1)n(n+1)}{6} \in \Theta(n^3) \end{aligned}$$

- **Note:** Yao(1982) $\Theta(n^2)$ Hu & Shing(1982,84) $\Theta(n \log n)$



Algorithm 3.7 Print Optimal Order (1/2)

- **Problem**: Print the **optimal order** for multiplying n matrices.
- **Inputs**: positive integer n , and the **array P produced by Alg. 3.6**. $P[i][j]$ is the point where matrices i through j are split in an optimal order for multiplying those matrices. (**$P[i][j] = \text{a value of } k \text{ that minimize } M[i][j]$**)
- **Outputs**: the **optimal order** for multiplying the matrices.

Algorithm 3.7 Print Optimal Order (2/2)

Figure 3.9 The array P produced when Algorithm 3.6 Example 3.5.

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

■ $P[2][5] = 4 \rightarrow (A_2A_3A_4)A_5$

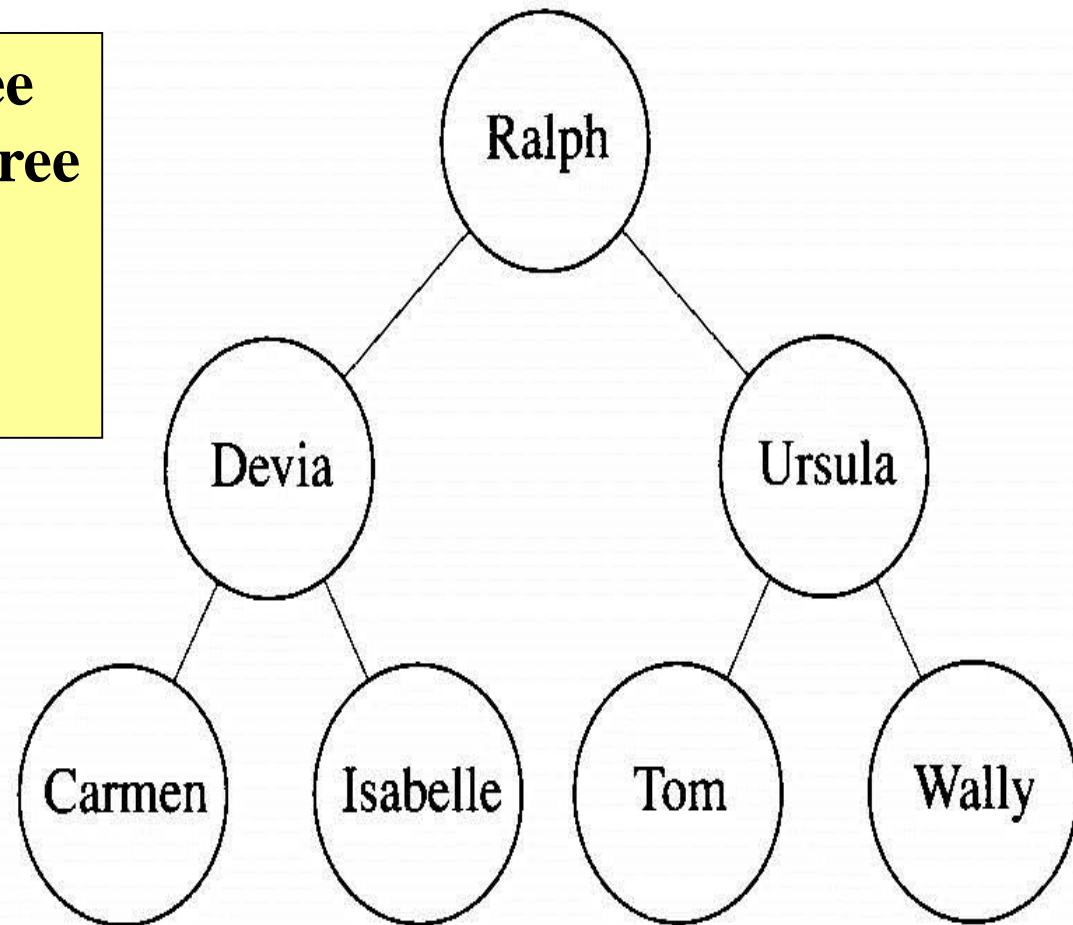
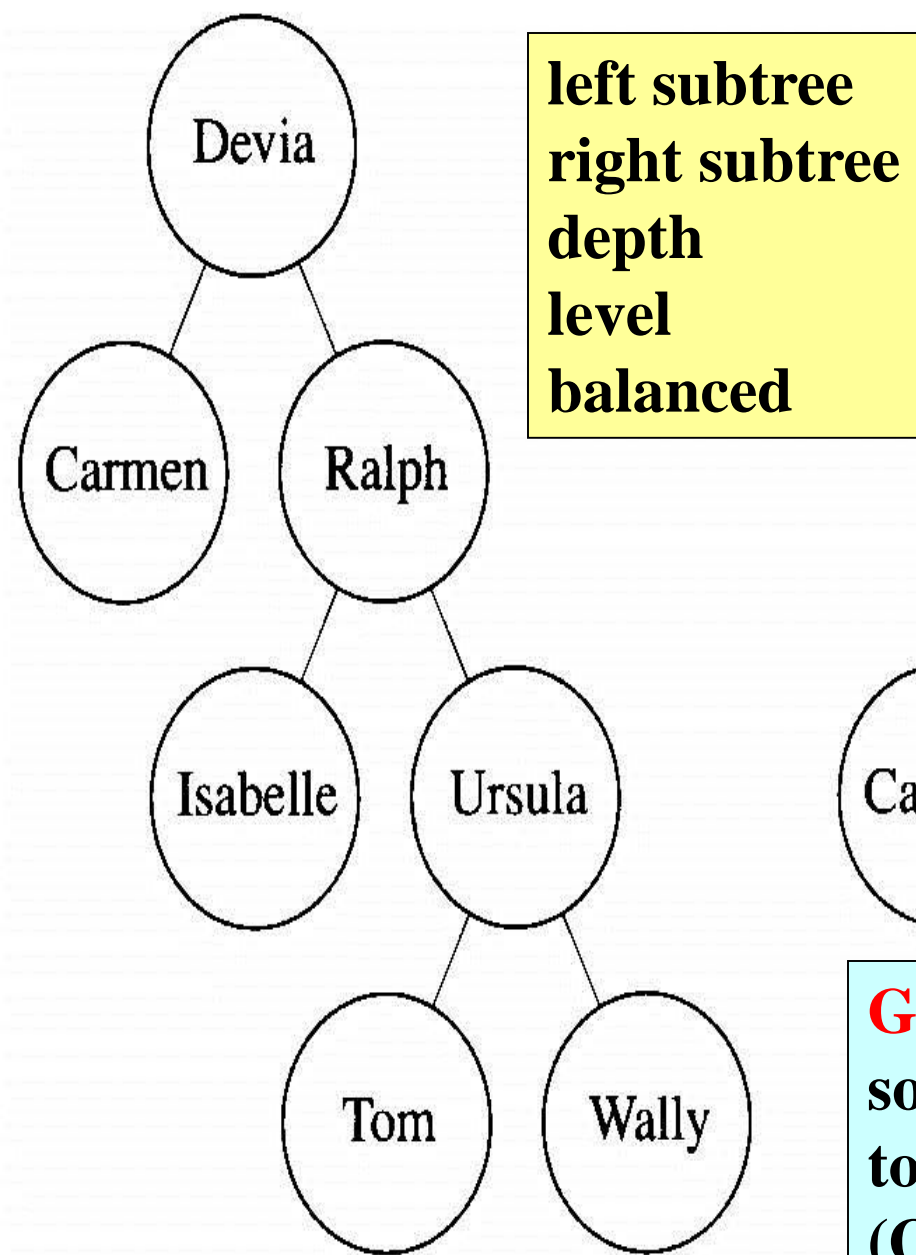
■ $P[1][6] = ?$

```
void order(index i, index j)
{
    if (i == j)
        cout << "A" << i;
    else {
        k = P[i][j];
        cout << "(";
        order(i, k);
        order(k + 1, j);
        cout << ")";
    }
}
```



3.5 Optimal Binary Search Trees

- **Def.: A BST is a binary tree of items (ordinary called keys), that come from an ordered set, such that**
 1. Each node contains one key.
 2. The keys in the **left subtree** of a given node are **less than or equal to** the key in that node.
 3. The keys in the **right subtree** of a given node are **greater than or equal to** the key in that node.



Goal: to organize the keys in a BST
so that the average time it takes
to locate a key is minimized
(Optimal BST)

Figure 3.10 Two binary search trees.



Data Type Used in Algorithm

```
struct nodetype  
{  
    keytype key;  
    nodetype* left;  
    nodetype* right;  
};  
typedef nodetype* node_pointer;
```



Algorithm 3.8 Search Binary Tree

- **Problem:** Determine the node containing a key in a BST. It is assumed that **the key is in the tree**.
- **Inputs:** a pointer *tree* to a BST and a key *keyin*.
- **Outputs:** a pointer *p* to the node containing the key.

```
void search(node_pointer tree, keytype keyin, node_pointer& p)
{
    bool found;
    p = tree;
    found = false;
    while (!found)
        if(p->key == keyin)
            found = true;
        else if(keyin < p->key)
            p = p->left;    // Advance to left child.
        else
            p = p->right;   // Advance to right child.
}
```

Search time for a given key
 $depth(key) + 1$



Average Search Time

- Let K_1, K_2, \dots, K_n be the n keys in order
 - Let p_i be the probability that K_i be the search key.
 - Let c_i be the number of comparisons needed to find K_i .

$$\text{minimize } \sum_{i=1}^n c_i p_i \quad \text{average search time}$$

Example 3.7

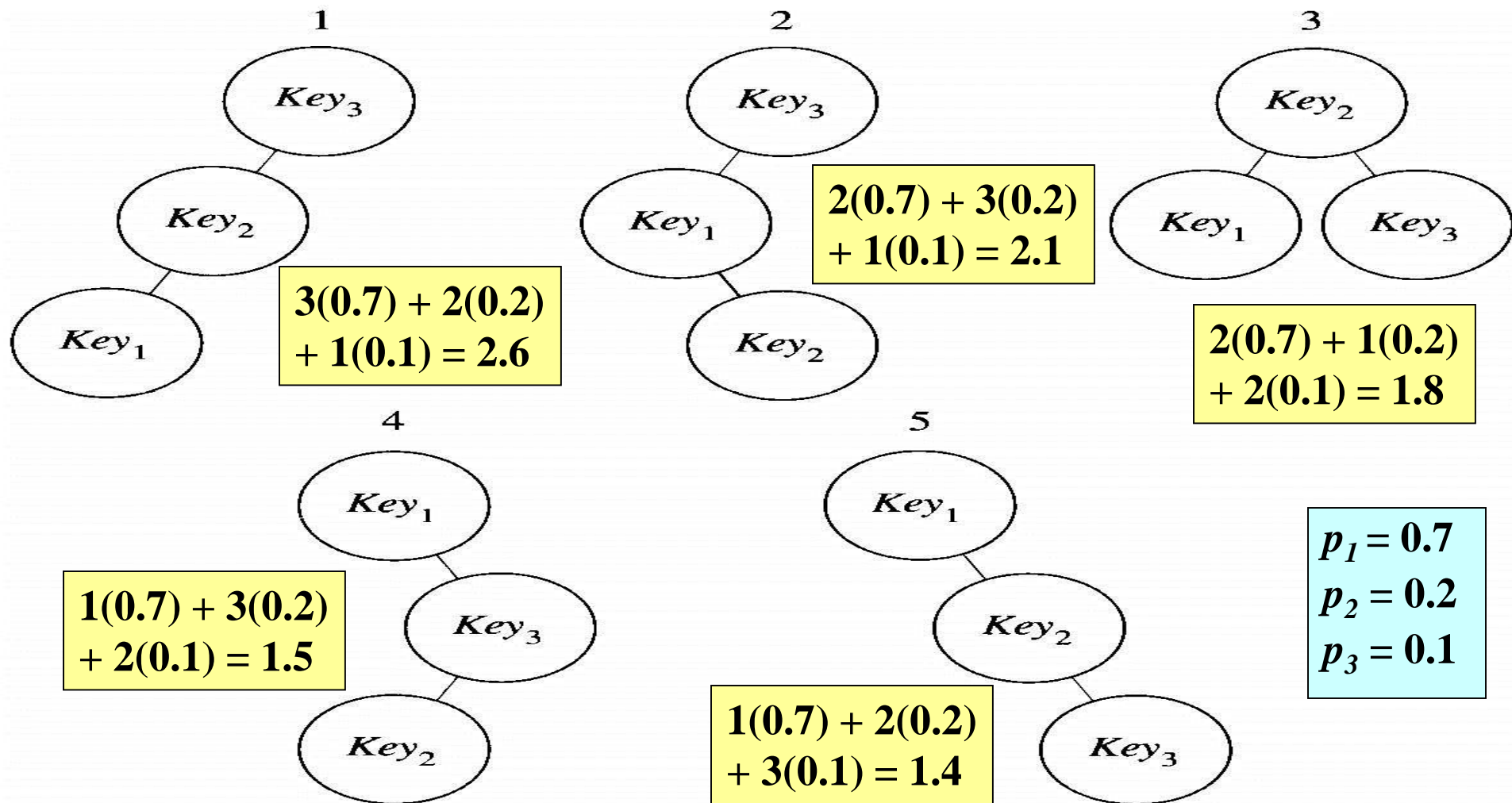


Figure 3.11 The possible binary search trees when there are three keys.



Principle of Optimality

- **Principle of optimality applies?**
 - **Any subtree of OBST is optimal.**
 - **Proof by contradiction.**



Formulation

- Suppose that K_i through K_j are arranged in a tree that minimize
$$\sum_{m=i}^j c_m p_m$$
- We will call such a tree **optimal**
- Let $A[i][j]$ denote the value of the OBST with K_i, \dots, K_j
 - $A[i][i] = p_i$

Example 3.8

- $p_1 = 0.7, p_2 = 0.2, p_3 = 0.1$.
- To determine $A[2][3]$, we must consider the two trees
 1. $1(p_2) + 2(p_3) = 1(0.2) + 2(0.1) = 0.4$
 2. $2(p_2) + 1(p_3) = 2(0.2) + 1(0.1) = 0.5$
- The first tree is optimal, and $A[2][3] = 0.4$.

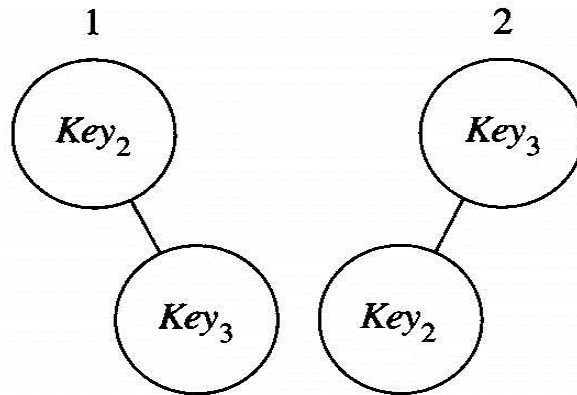
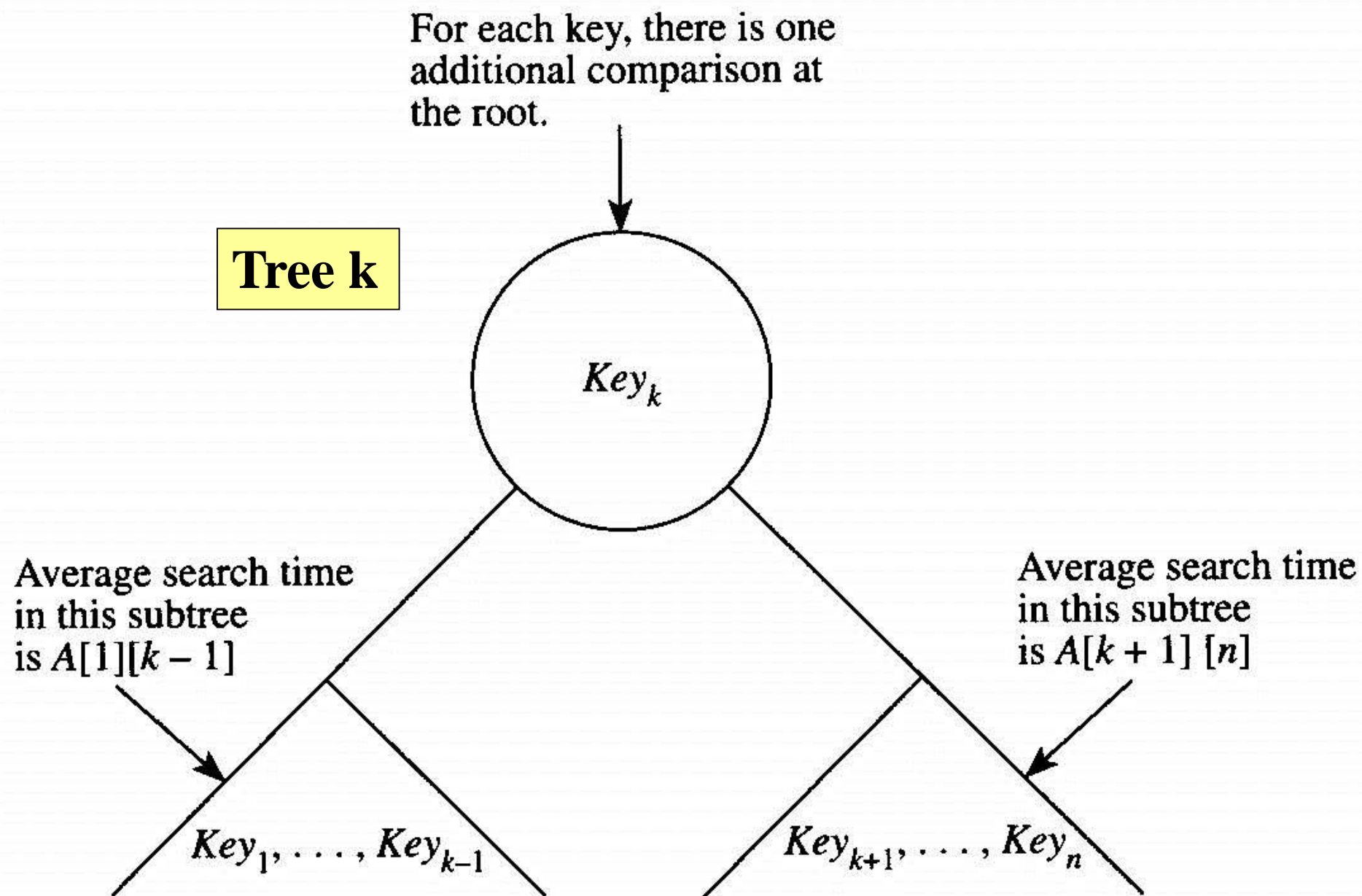


Figure 3.12 The binary search trees composed of Key_2 and Key_3 .

Figure 3.13 Optimal binary search tree given that Key_k is at the root.



Average search time for tree

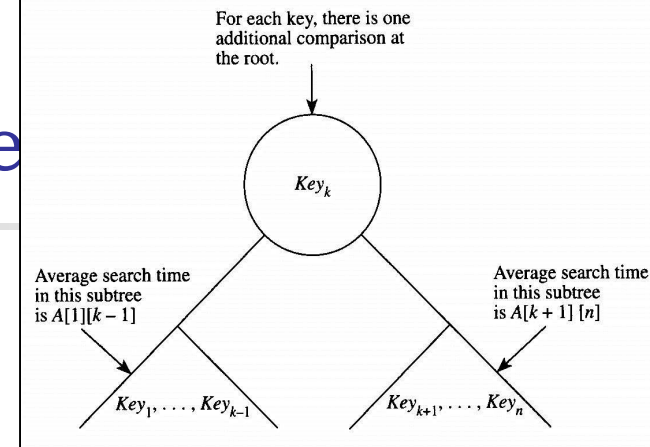
- $A[1][k-1] + (p_1 + \dots + p_{k-1}) + p_k + A[k+1][n] + (p_{k+1} + \dots + p_n)$
 - $A[1][k-1]$: average time in left subtree
 - $(p_1 + \dots + p_{k-1})$: additional time comparing at root
 - p_k : average time searching for root
 - $A[k+1][n]$: average time in right subtree
 - $(p_{k+1} + \dots + p_n)$: additional time comparing at root

$$= A[1][k-1] + A[k+1][n] + \sum_{m=1}^n p_m$$

$$A[1][n] = \min_{1 \leq k \leq n} (A[1][k-1] + A[k+1][n]) + \sum_{m=1}^n p_m$$

$$A[1][0] = A[n+1][n] = 0$$

Figure 3.13 Optimal binary search tree given that Key_k is at the root.





Generalization

$$A[i][j] = \min_{i \leq k \leq j} (A[i][k-1] + A[k+1][j]) + \sum_{m=i}^j p_m \quad ; \quad i < j$$

$$A[i][i] = p_i$$

$$A[i][i-1] = A[j+1][j] = 0$$

- Compute smaller $j - i$ first
- See Alg. 3.9
 - $R[i][j]$ has the root of OBST

$$W_{ij} = \sum_{m=i}^j p_m \quad W_{ij} = W_{i,j-1} + p_j$$



Algorithm 3.9 Optimal Binary Search Tree (1/3)

- **Problem**: Determine an OBST for a set of keys, each with a **given probability** of being the search key.
- **Inputs**: n , the number of keys, and an array of real numbers p indexed from 1 to n , where **$p[i]$ is the probability** of searching for the i -th key.
- **Outputs**: a variable $minavg$, whose value is the average search time for an OBST; and a 2D array R from which an optimal tree can be constructed. R has its rows indexed from 1 to $n + 1$ and its columns indexed from 0 to n . **$R[i][j]$ is the index of the key in the root of an optimal tree** containing the i -th through the j -th keys.



Algorithm 3.9 Optimal Binary Search Tree (2/3)

```
void optsearchtree(int n, const float p[ ], float& minavg, index R[ ][ ])
{
    index i, j, k, diagonal;
    float A[1..n+1][0..n];
    for (i = 1; i <= n; i++){
        A[i][i-1] = 0;
        A[i][i] = P[i];
        R[i][i] = i;
        R[i][i-1] = 0;
    }
```

$$A[i][i] = p_i$$

$$A[i][i-1] = A[j+1][j] = 0$$

Algorithm 3.9 Optimal Binary Search Tree (3/3)

$A[n+1][n] = 0;$

$R[n+1][n] = 0;$

$$A[i][j] = \min_{i \leq k \leq j} (A[i][k-1] + A[k+1][j]) + \sum_{m=i}^j p_m \quad ; \quad i < j$$
$$A[i][i-1] = A[j+1][j] = 0$$

for (diagonal = 1; diagonal <= n - 1; diagonal ++)

 // diagonal-1 is just above the main diagonal.

 for (i = 1; i <= n - diagonal; i++){

 j = i + diagonal; // remember that “# of alternatives = diagonal+1”

$A[i][j] = \underset{i \leq k \leq j}{\text{minimum}} (A[i][k-1] + A[k+1][j]) + \sum_{m=i}^j p_m \quad ;$

$R[i][j] = \text{a value of } k \text{ that gave the minimum};$

 }

 minavg = $A[1][n];$

}



$T(n)$ of Alg. 3.9

- **Basic operation:** instruction executed for each value of k and (min) comparison
- **Input size:** $n = (\# \text{ of keys})$

$$T(n) = \frac{(n-1)n(n+4)}{6} \in \Theta(n^3) \text{ similarly as Alg. 3.6}$$

- **Note:** Yao(1982) $\Theta(n^2)$



Algorithm 3.10 Build OBST (1/2)

- **Problem**: build an OBST.
- **Inputs**: n , the number of keys, an array Key containing the n keys in order, and the array R produced by Algorithm 3.9. $R[i][j]$ is the index of the key in the root of an optimal tree containing the i -th through the j -th keys.
- **Outputs**: a pointer *tree* to an OBST containing the n keys.



Algorithm 3.10 Build OBST (2/2)

```
node_pointer tree(index i, j )
{
    index k;
    node_pointer p;
    k = R[i][j];
    if (k == 0)
        return NULL;
    else {
        p = new nodetype;
        p->key = Key[k];
        p->left = tree(i, k-1);
        p->right = tree(k+1, j);
        return p;
    }
}
```

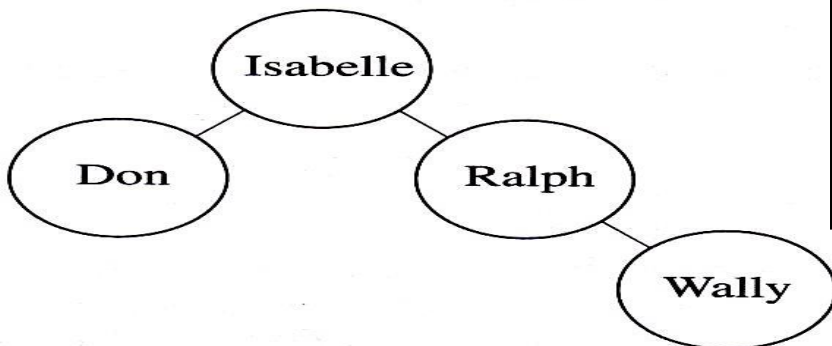
Example 3.9

	0	1	2	3	4		0	1	2	3	4
1	0	$\frac{3}{8}$	$\frac{9}{8}$	$\frac{11}{8}$	$\frac{7}{4}$	1	0	1	1	2	2
2		0	$\frac{3}{8}$	$\frac{5}{8}$	1	2		0	2	2	2
3			0	$\frac{1}{8}$	$\frac{3}{8}$	3			0	3	3
4				0	$\frac{1}{8}$	4				0	4
5					0	5					0

A *R*

Figure 3.14 The arrays *A* and *R*, produced when Algorithm 3.9 is applied to the instance in Example 3.9.

Figure 3.15 The tree produced when Algorithms 3.9 and 3.10 are applied to the instance in Example 3.9.



<i>Key</i> [<i>i</i>]	<i>Key</i> [1]	<i>Key</i> [2]	<i>Key</i> [3]	<i>Key</i> [4]
Instance	Don	Isabelle	Ralph	Wally
<i>p_i</i>	3/8	3/8	1/8	1/8



Example 3.7

$$A[1][1] = 0.7, A[2][2] = 0.2, A[3][3] = 0.1$$

$$A[1][2] = \min(A[1][0] + A[2][2], A[1][1] + A[3][2]) + (0.7 + 0.2) \\ = 1.1$$

$$R[1][2] = 1$$

$$A[2][3] = \min(A[2][1] + A[3][3], A[2][2] + A[4][3]) + (0.2 + 0.1) \\ = 0.4$$

$$R[2][3] = 2$$

$$A[1][3] = \min(A[1][0] + A[2][3], A[1][1] + A[3][3], \\ A[1][2] + A[4][3]) + (0.7 + 0.2 + 0.1) \\ = 1.4$$

$$R[1][3] = 1$$