

# Chapter 4

## HEURISTIC SEARCH

（启发式搜索）



## 4.0 Introduction

## 4.1 Hill Climbing and Dynamic Programming

### 4.1.1 Hill-Climbing

### 4.1.2 Dynamic Programming

## 4.2 The Best-First Search Algorithm

### 4.2.1 Implementing Best-First Search

### 4.2.2 Implementing Heuristic Evaluation Functions

### 4.2.3 Heuristic Search and Expert Systems

## 4.3 Admissibility, Monotonicity, and Informedness

### 4.3.1 Admissibility Measures

### 4.3.2 Monotonicity

### 4.3.3 When One Heuristic Is Better: More Informed Heuristics

## 4.4 Using Heuristics in Games

### 4.4.1 The Minimax Procedure on Exhaustively Searchable Graphs

### 4.4.2 Minimaxing to Fixed Ply Depth

### 4.4.3 The Alpha-Beta Procedure

## 4.5 Complexity Issues

## Exercises      P. 162



## 4.0 Introduction

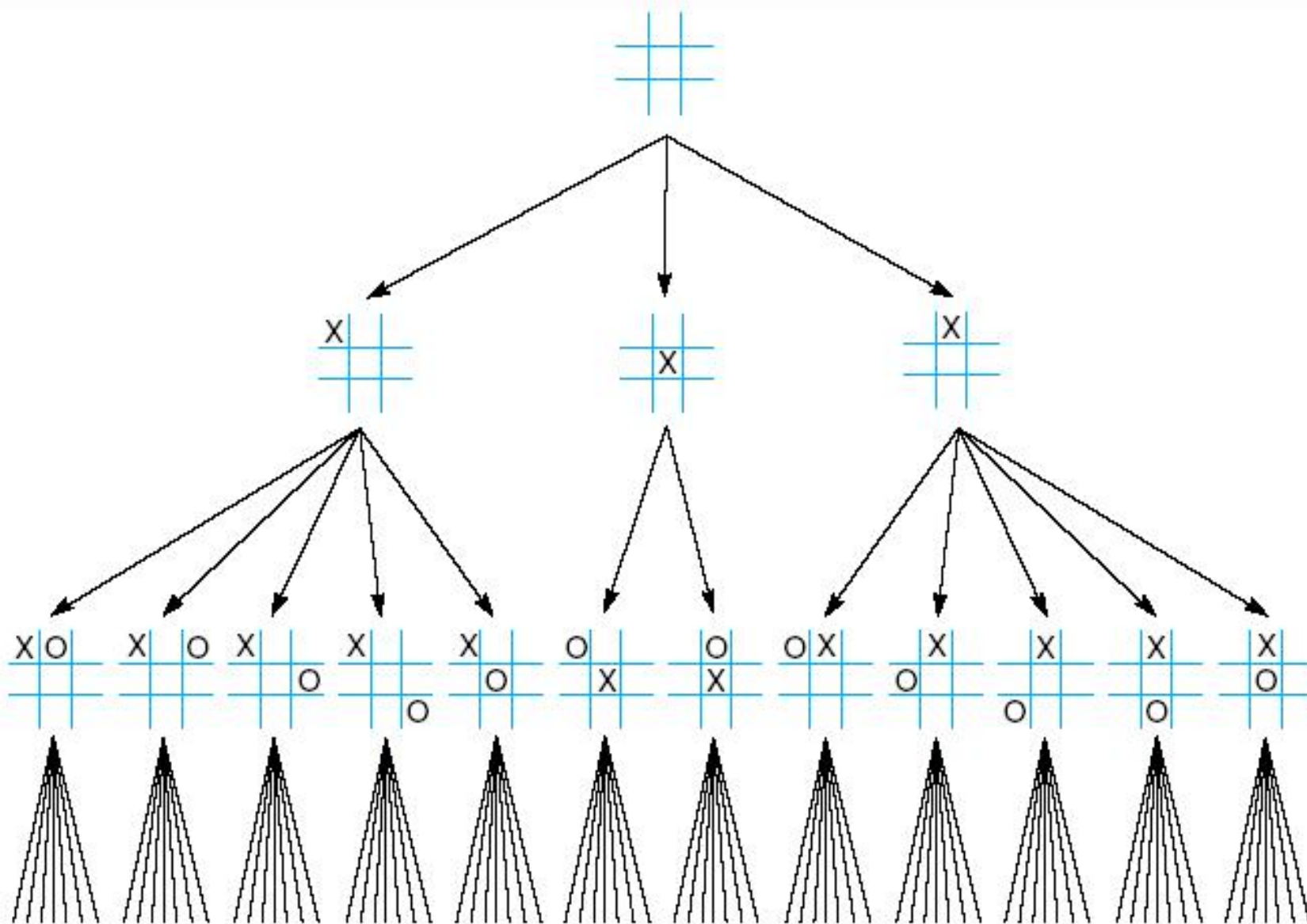
- In state space search, **heuristics** are formalized as **rules** (规则) **for choosing branches** that are most likely to lead to an **acceptable** (可接受的) **solution**.
  - AI problem solvers **employ heuristics** in two basic situations:
    - (1) A problem may not have an **exact solution** (精确解) because of **inherent ambiguities** (固有的含糊性) in the problem **statement** or **available data**.
      - **Medical diagnosis** is an example of this.
- A given set of **symptoms** (症状) may have several **possible causes** (病因) ;
- doctors use **heuristics** to choose **the most likely diagnosis** and formulate **a plan of treatment**.



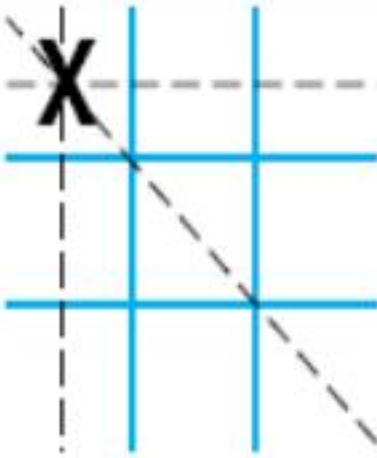
(2) A problem, may have an exact solution, but **the computational cost** may be **prohibitive** (过高) . In many problems (such as chess), **state space growth** is **combinatorially explosive** (组合爆炸的) , with the number of possible states increasing **exponentially** (按指数方式) or **factorially** (按阶乘方式) with the depth of the search.

- Expert systems research has affirmed (肯定) **the importance of heuristics**.
- The “rules of thumb” (经验法则) that **a human expert uses** to solve problems efficiently are **heuristic in nature**.

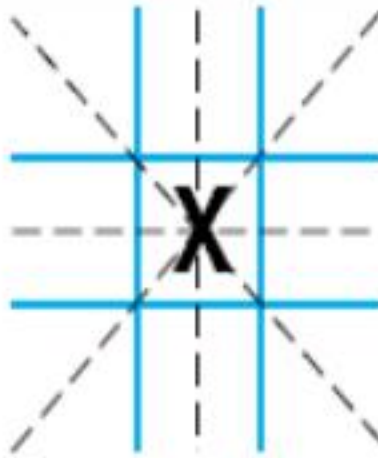




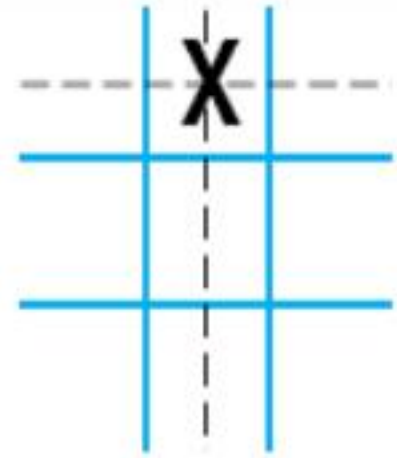
# The “**most wins**” heuristic applied to the first children in tic-tac-toe



Three wins through  
a corner square



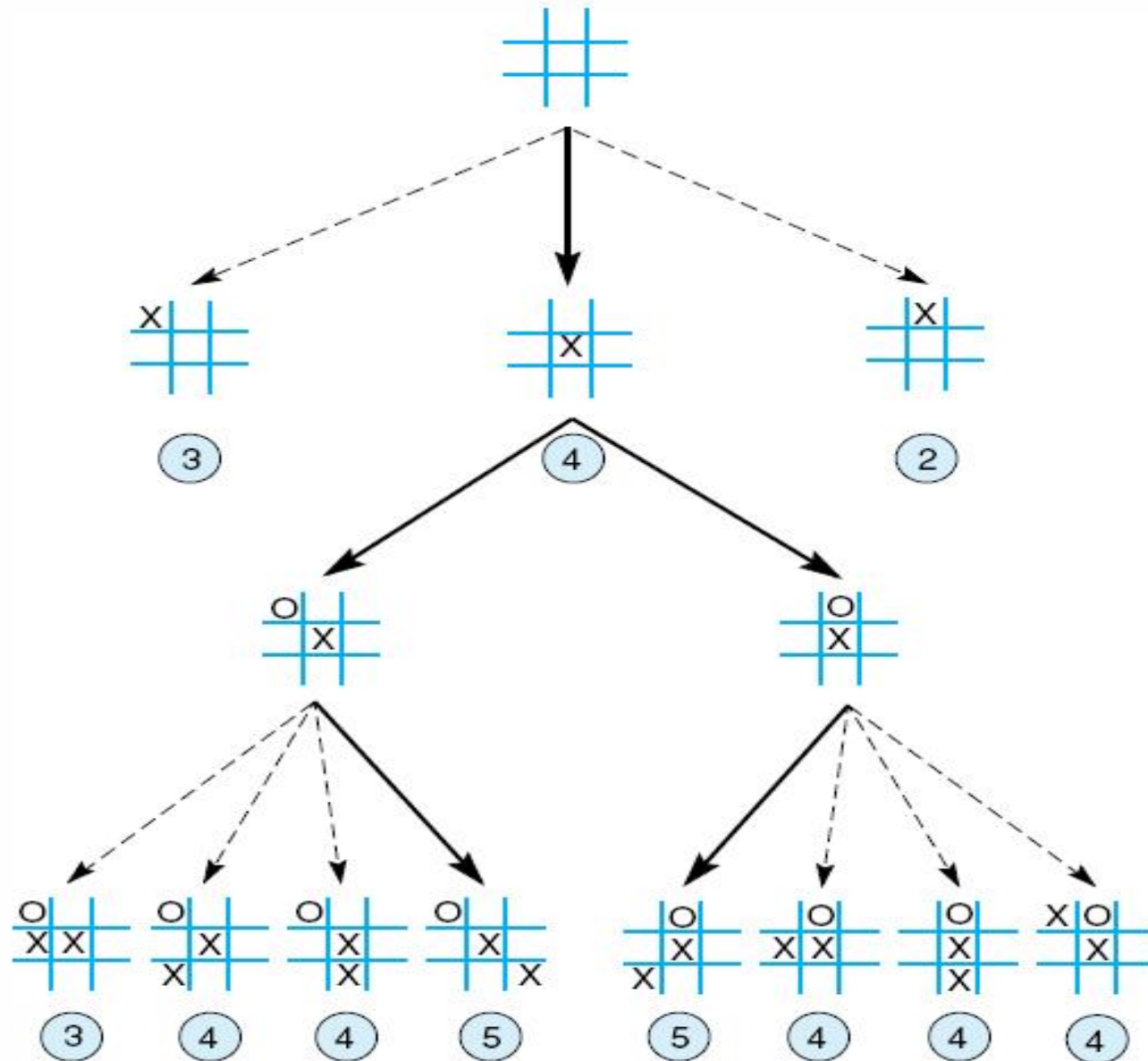
Four wins through  
the center square



Two wins through  
a side square



# Heuristically reduced state space for tic-tac-toe





# 4.1 Hill-Climbing and Dynamic Programming

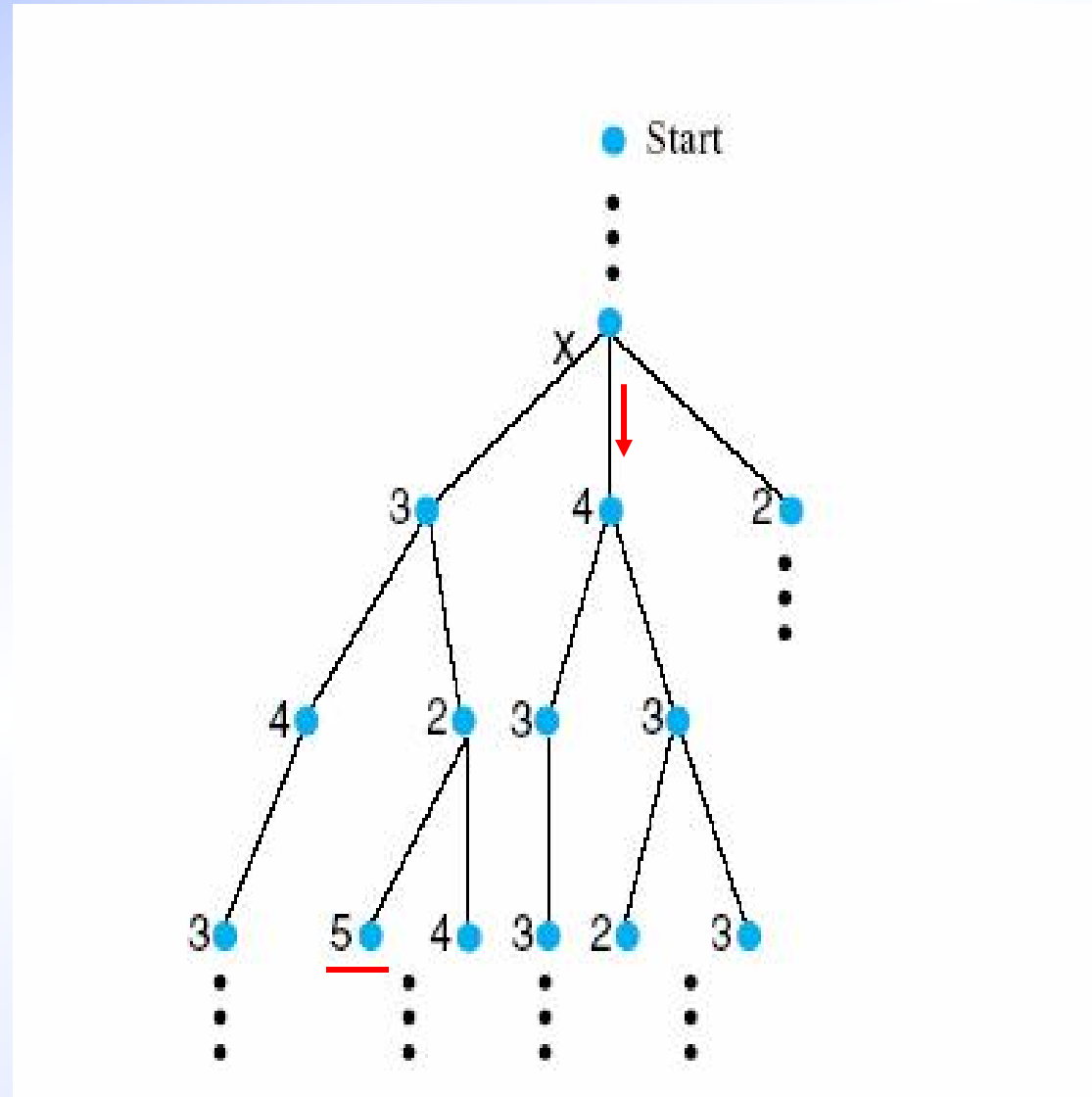
## 4.1.1 Hill-Climbing

- Hill-climbing strategies (爬山法) **expand** the current state and **evaluate** its children.
- The “**best**” child ( better than parent ) is selected for further expansion; **neither** its siblings **nor** its parent are **retained** (保留) .
- **Hill climbing** is named for the strategy that might be used by **an eager but blind** mountain climber : **go uphill along the steepest** (最陡) possible path until you can go no farther up.
- Because it **keeps no history**, it **cannot recover** (恢复) from failures .





- A major problem of hill-climbing strategy is the tendency to become stuck at local maxima (局部极大值).
- In this case, it may fail to find the best solution.



## 4.2 The Best-First Search Algorithm

### 4.2.1 Implementing Best-First Search

- open list : a **priority queue** (优先级队列) to keep track of **the current fringe** (边界结点) of the search
- closed list : to record states that **already visited**.
- An added step : **orders** (排序) the states on **open** according to some **heuristic estimate** (启发估值) of their “closeness” to a goal.
- Each iteration (迭代) considers **the most “promising” state** on the open list.



Function best-first-search;

begin

open := [Start]; % initialize

closed := [ ];

while open ≠ [ ] do % state remain

begin

remove the leftmost state from open, call it X;

if X=goal then return the path from Start to X

else begin

generate children of X;

for each child of X do

case

the child is not on open or closed:

begin

assign the child heuristic value;

add the child open

end;

the child is already on open:

if the child was reached by a shorter path

then give the state on open the shorter path

the child is already on closed:

if the child was reached by a shorter path then

begin

remove the state from closed;

add the child to open

end;

end; % case

put X on closed;

re-order states on open by heuristic merit ( best leftmost )

end

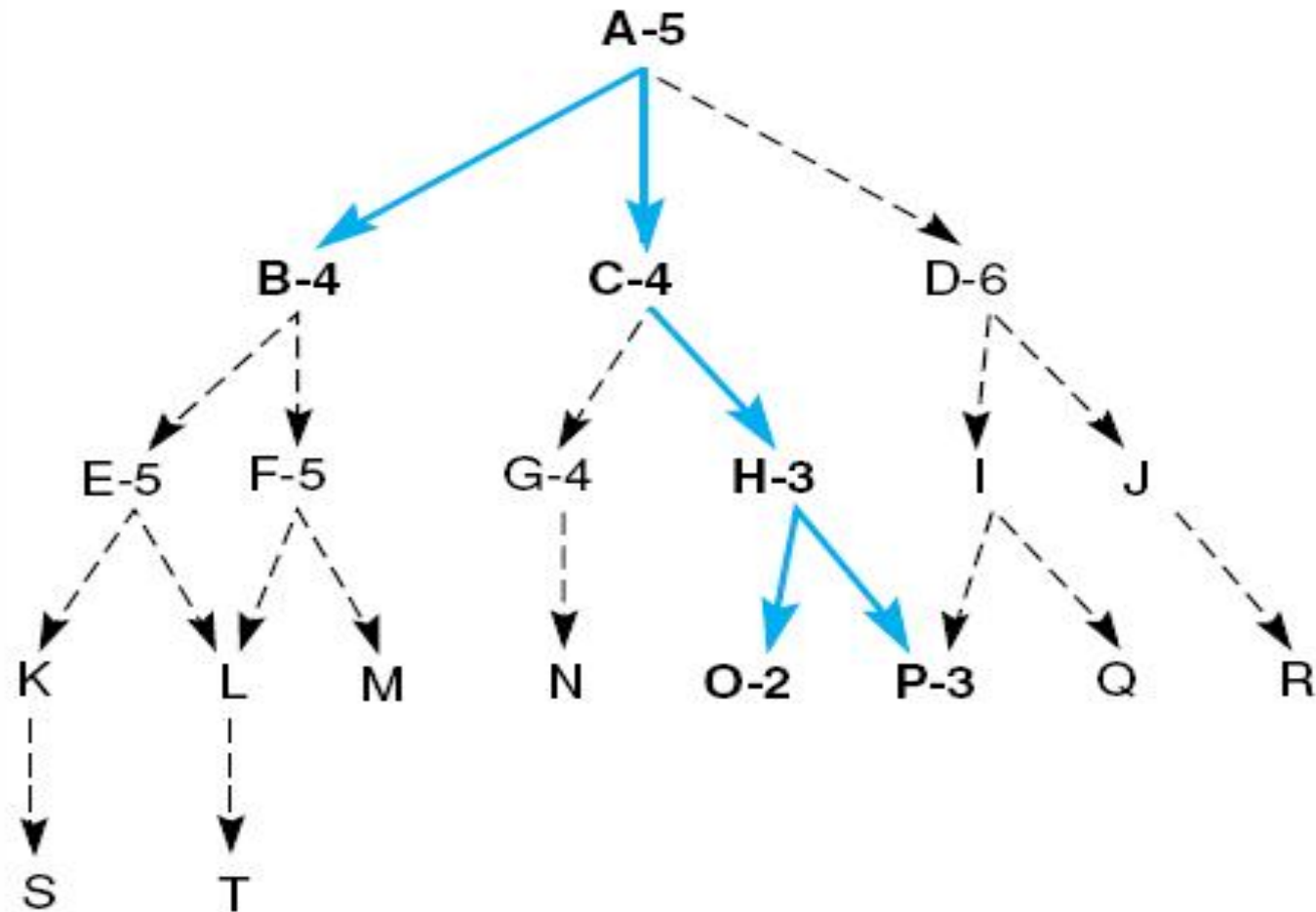
end;

return FAIL % open is empty

end



## best-first-search of a hypothetical (假想的) state space



## A trace of the execution of best-first-search

1. open=[**A5**]; closed=[ ]
2. evaluate **A5**; open=[**B4,C4,D6**]; closed=[**A5**]
3. evaluate **B4**; open=[**C4,E5,F5,D6**]; closed=[**B4,A5**]
4. evaluate **C4**; open=[**H3,G4,E5,F5,D6**];  
closed=[**C4,B4,A5**]
5. evaluate **H3**; open=[**O2,P3,G4,E5,F5,D6**];  
closed=[**H3,C4,B4,A5**]
6. evaluate **O2**; open=[**P3,G4,E5,F5,D6**];  
closed=[**O2,H3,C4,B4,A5**]
7. evaluate **P3**; the solution is found!

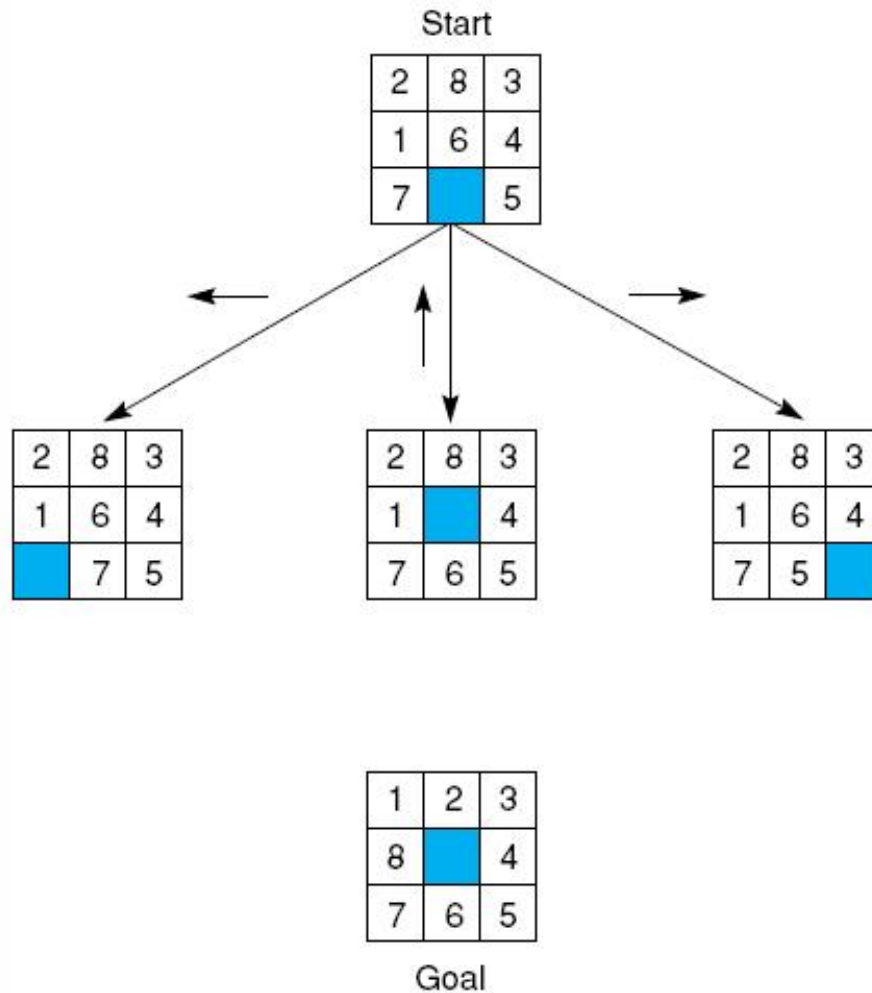


## 4.2.2 Implementing Heuristic Evaluation Functions

- We next evaluate **the performance** (性能) of **several different heuristics** for solving the 8-puzzle.
- Figure 4.12 shows a start and goal state for the 8-puzzle, along with the first three states generated in the search.



The start state, **first three moves**, and **goal state** for an example - 8 puzzle





- The **simplest** heuristic **counts the tiles** (将牌) **out of place** (错位) in each state when **compared with** the goal.
- A “**better**” heuristic would **sum all the distances** by which **the tiles are out of place**, one for each square **a tile must be moved to reach its position** in the goal state.



- Both of these heuristics can be criticized for failing to **acknowledge** (反映) the difficulty of **tile reversals** (逆转) .
- That is , **if two tiles are next to each other** and the goal requires **their being in opposite locations**, it takes (several) **more than two moves** to put them back in place, as the tiles must **“go around” each other** (Figure 4.13)



- A heuristic that **takes this into account multiplies a small number 2 :**

$$2 \times \text{num}$$

num is the number of **direct tile reversals**.

- Figure 4.14 shows the result of **applying each of these three heuristics** to the three child states of Figure 4.12



<table><tr><td>2</td><td>8</td><td>3</td></tr><tr><td>1</td><td>6</td><td>4</td></tr><tr><td></td><td>7</td><td>5</td></tr></table>	2	8	3	1	6	4		7	5	5	6	0
2	8	3										
1	6	4										
	7	5										
<table><tr><td>2</td><td>8</td><td>3</td></tr><tr><td>1</td><td></td><td>4</td></tr><tr><td>7</td><td>6</td><td>5</td></tr></table>	2	8	3	1		4	7	6	5	3	4	0
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2	8	3										
1	6	4										
7	5											
	Tiles out of place	Sum of distances out of place	2 x the number of direct tile reversals									

1	2	3
8		4
7	6	5

Goal



- A **forth** heuristic, which **may overcome the limitations** of the tile reversal heuristic :
- **adds the sum of the distances the tiles are out of place and 2 times the number of direct reversals.**



- Full evaluation function:

$$f(n) = g(n) + h(n)$$

- $g(n)$  is the length of the current shortest path from the start state to state  $n$
- $h(n)$  is a heuristic estimate of the distance from state  $n$  to a goal.



- In the 8-puzzle, we can define  $h(n)$  as follows:

$h(n)$  = the number of tiles out of place

- We can define  $g(n)$  as follows:

$g(n)$  = the depth of  $n$

- The full evaluation function is :

$f(n) = g(n) + h(n)$

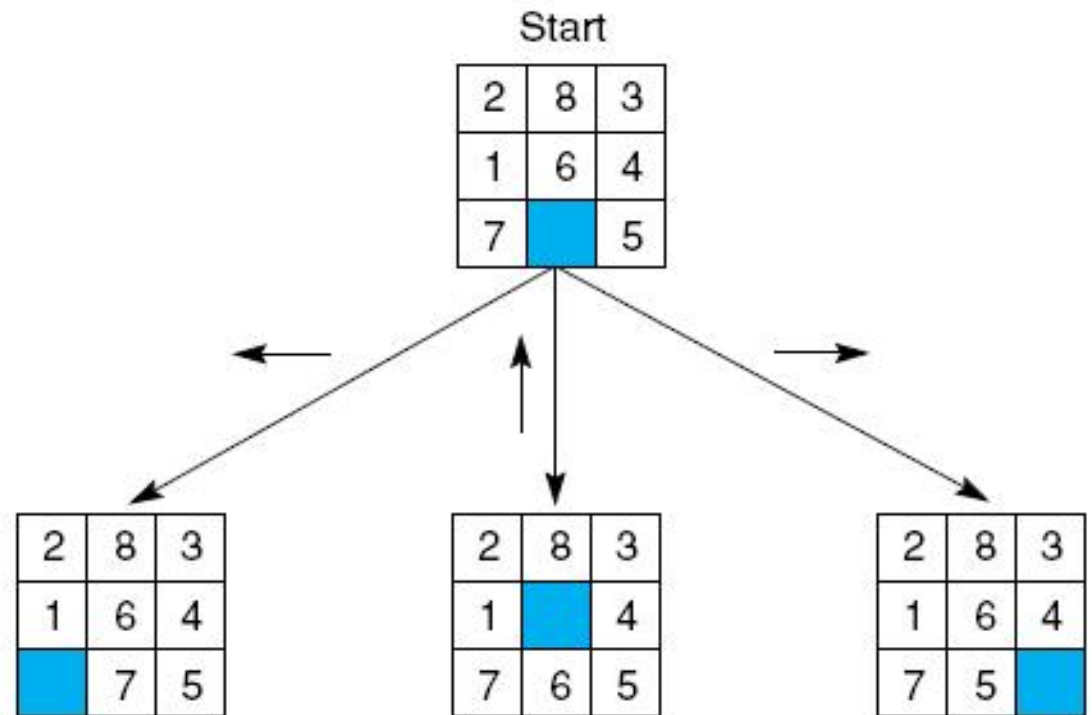
- When this evaluation is applied to each of the child states in Figure 4.12, their  $f$  values are 6, 4, and 6, respectively.





$$g(n) = 0$$

$$g(n) = 1$$



Values of  $f(n)$  for each state,

6

4

6

where:

$$f(n) = g(n) + h(n),$$

$g(n)$  = actual distance from  $n$   
to the start state, and

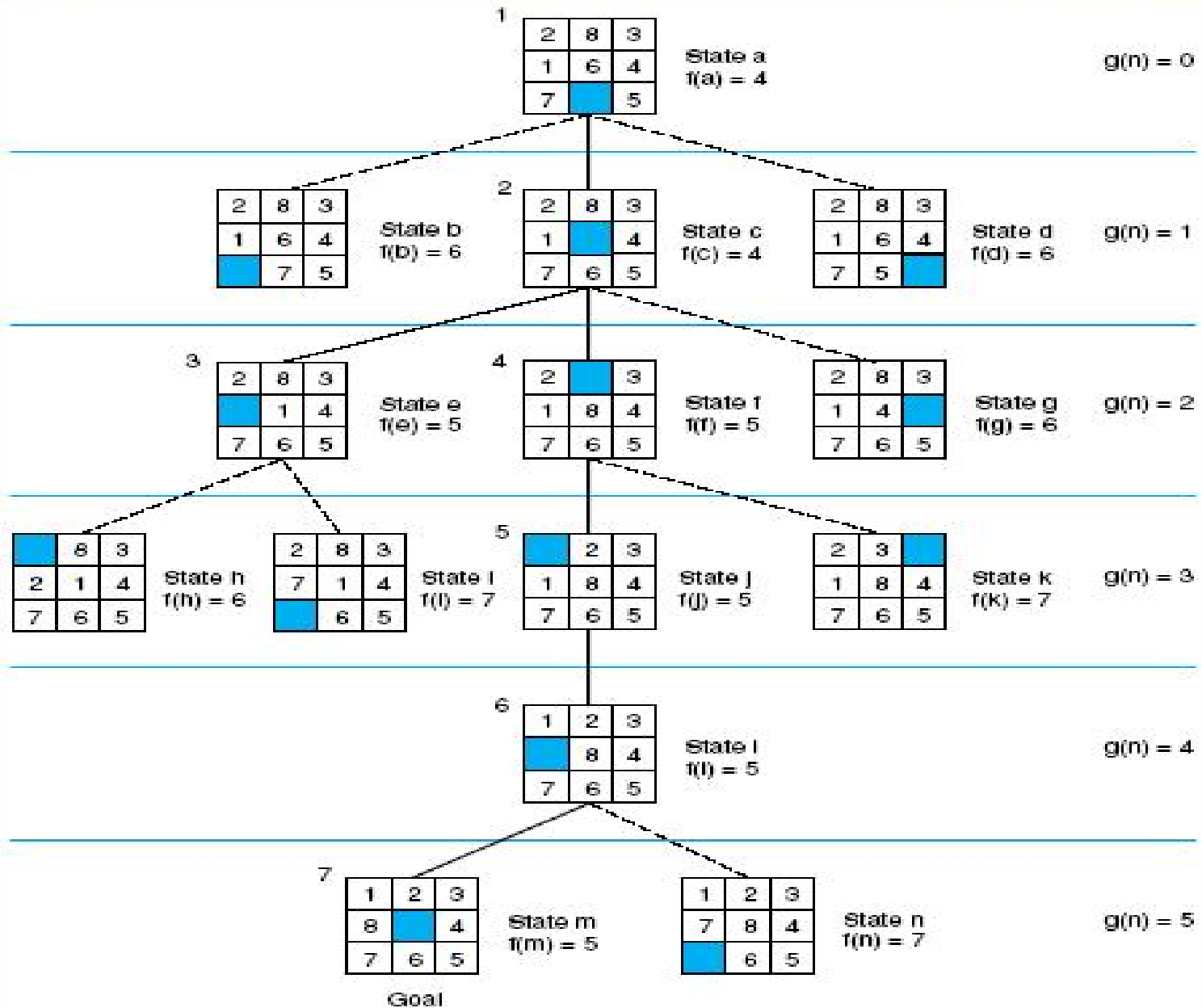
$h(n)$  = number of tiles out of place.

1	2	3
8		4
7	6	5

Goal

- The full best-first search of the 8-puzzle graph, using  $f$  as defined above, appears in Figure 4.16.
- Each state is labeled with a letter and its heuristic weight,  $f(n)=g(n)+h(n)$ .
- The number at the top of each state indicates the order in which it was taken off the open list.





- The **successive stages** of open and closed that generate this graph are:

- |    |                                |                             |
|----|--------------------------------|-----------------------------|
| 1. | open=[a4]                      | closed=[ ]                  |
| 2. | open=[c4,b6,d6]                | closed=[a4 ]                |
| 3. | open=[e5,f5,b6,d6,g6]          | closed=[a4,c4 ]             |
| 4. | open=[f5,h6,b6,d6,g6,i7]       | closed=[a4,c4,e5]           |
| 5. | open=[j5,h6,b6,d6,g6,k7,i7]    | closed=[a4,c4,e5,f5 ]       |
| 6. | open=[l5,h6,b6,d6,g6,k7,i7]    | closed=[a4,c4,e5,f5,j5 ]    |
| 7. | open=[m5,h6,b6,d6,g6,n7,k7,i7] | closed=[a4,c4,e5,f5,j5,l5 ] |
| 8. | m=goal ! success               |                             |



- To summarize:
  - ① Operations on a state **generate its children**.
  - ② Each new state is checked to see **whether it has occurred before**, thereby **preventing loops**.
  - ③ Each state **n** is given an **f** value equal to the sum of its **depth** in the search space **g(n)** and **a heuristic estimate of its distance to a goal** **h(n)**.
    - The **h value guides search** toward promising states
    - **the g value** can **prevent search from** persisting on a **fruitless path**.
  - ④ States on open are **sorted by their f values**. By keeping all states on open until they are examined or a goal is found, the algorithm **recovers from** dead ends.
  - ⑤ As an implementation point, **the algorithm's efficiency** can be improved through maintenance of the **open** as **heaps** (堆) or **leftist trees** (左偏树) .

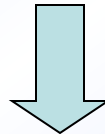


## 4.2.3 Heuristic Search and Expert Systems

### EXAMPLE 4.2.1

#### THE FINANCIAL ADVISOR, REVISITED

savings-account(adequate)  $\wedge$  income(adequate)



investment(stocks)

with **confidence = 0.8**



## 4.3 Admissibility, Monotonicity and Informedness

- Admissibility (可采纳性) : heuristics that find the shortest path to a goal **whenever it exists** are said to be *admissible*.
- Informedness (信息性) : In what sense is one heuristic **“better” than** another?
- Monotonicity (单调性) : When a state is **discovered ( examined )**, is there any guarantee that **the same state won't be found later at a cheaper cost** ( with a shorter path )?





## 4.3.1 Admissibility Measures

- A search algorithm is *admissible* (可采纳的) if it is guaranteed **to find a minimal path to a goal** whenever such a path exists.

- define an evaluation function  $f^*$  :

$f^*(n) = g^*(n) + h^*(n)$ , where  $g^*(n)$  is **the cost of the shortest path from the start to node  $n$**  and  $h^*$  returns **the cost of the shortest path from  $n$  to goal**.

- It follows that  $f^*(n)$  is **the cost of the optimal path from a start node to a goal node that passes through node  $n$**  (经过  $n$ ) .



- **DEFINITION**

(algorithm A, admissibility, algorithm A\*)

- Consider the evaluation function

$$f(n) = g(n) + h(n)$$

- if  $f(n)$  is used with the best\_first\_search algorithm, the result is called **algorithm A**

- If  $h(n)$  is less than or equal to  $h^*(n)$ , the algorithm is called **algorithm A\***

- It is now possible to state **a property of A\* algorithms:**

**All A\* algorithms are admissible.**



## 4.3.2 Monotonicity

- **DEFINITION ( MONOTONICITY )**

A heuristic function  $h$  is monotone (单调的) if

1. For all states  $n_i$  and  $n_j$ , where  $n_j$  is a **decedent** of  $n_i$ ,

$$h(n_i) - h(n_j) \leq \text{cost}(n_i, n_j)$$

2.  $h(\text{Goal})=0$



- If the heuristics function is monotone, the algorithm will be “**locally admissible**”
- That is, it will consistently find the **minimal path** to each state **x** when it is expanded,
- i.e.  $g(x) = g^*(x)$
- This means that **when finding a new path to a node x in CLOSED, we don't need to update the value of  $g(x)$ .**



- A simple argument can show that **any monotonic heuristic is admissible**.
- Considers **any solution path** in the space as a sequence of states  **$s_1, s_2, \dots, s_g$** , where  $s_1$  is the **start state** and  $s_g$  is the **goal**.
- For the sequence of moves in this path:

$$s_1 \text{ to } s_2 \quad h(s_1) - h(s_2) \leq \text{cost}(s_1, s_2)$$

$$s_2 \text{ to } s_3 \quad h(s_2) - h(s_3) \leq \text{cost}(s_2, s_3)$$

$$s_3 \text{ to } s_4 \quad h(s_3) - h(s_4) \leq \text{cost}(s_3, s_4)$$

.....

$$s_{g-1} \text{ to } s_g \quad h(s_{g-1}) - h(s_g) \leq \text{cost}(s_{g-1}, s_g)$$



- **Summing each column**

- $h(s_g) = 0$

we get :  $h(s_1) \leq \text{cost}(s_1, s_g)$

- When  $s_1, s_2, \dots, s_g$  is the **best solution path**,

there is :  $\text{cost}(s_1, s_g) = h^*(s_1)$

that is :  $h(s_1) \leq h^*(s_1)$

- Let  $s_1$  be **any state**  $x$ , then :

$$h(x) \leq h^*(x)$$

- This means that monotone heuristic  $h$  is **A\*** and admissible.



### 4.3.3 When One Heuristic Is Better : More Informed Heuristics

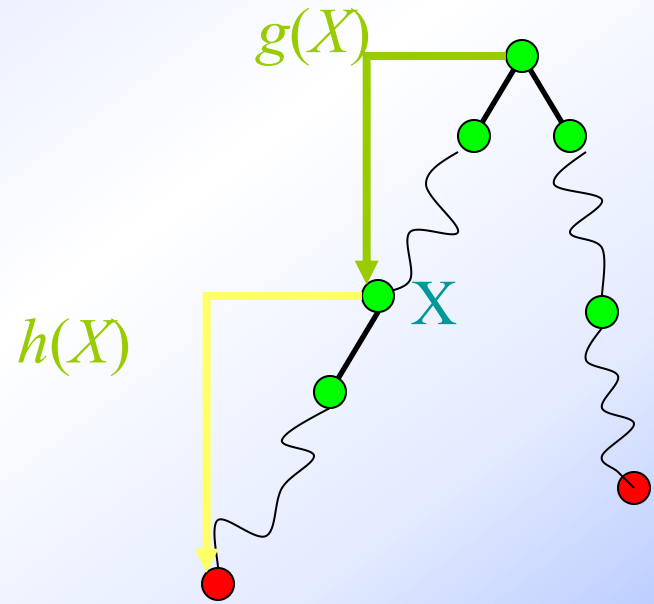
- DEFINITION : INFORMEDNESS (信息度)
  - For two **A\*** heuristics  $h_1$  and  $h_2$
  - if  $h_1(n) \leq h_2(n)$ , for all states  $n$  in the search space,
  - heuristic  $h_2$  is said to be **more informed** than  $h_1$





# 估价函数与择优搜索

- 估价函数概念：用于估价节点重要性的函数称为估价函数。
- 一般形式： $f(x) = g(x) + h(x)$ 
  - $g(x)$  为从初始节点  $S_0$  到节点  $x$  已经实际付出的代价；
  - $h(x)$  是从节点  $x$  到目标节点的最优路径的估计代价，它体现了问题的启发性信息，其形式要根据问题的特性确定。



❖ 八数码难题的启发函数  $h(x)$ ，可以定义为节点  $x$  中数码位置与目标节点相比不同的个数。



## A\*算法小结

- A\*算法引入了估价函数 $f(n)$ ，它是对价值函数 $f^*(n)$ 估计。
- 价值函数 $f^*(n)$ 表示从初始结点经过结点 $n$ 而到达目标结点最小花费的代价。
- $f^*(n)$  它分为两部份，一是从初始结点到结点 $n$ 的最小代价，记为 $g^*(n)$ ，另一部份是从结点 $n$ 到目标结点的最小代价，记为 $h^*(n)$ ；所以 $f^*(n) = g^*(n) + h^*(n)$ 。
- $f(n)$  是对函数 $f^*(n)$ 估计。



- $f(n)=g(n)+h(n)$ ，其中 $f(n)$ 是节点 $n$ 的估价函数。 $g(n)$ 是在状态空间中从初始节点到 $n$ 节点的实际代价， $h(n)$ 是从 $n$ 到目标节点最佳路径的估计代价。
- 条件：  $h(n) \leq h^*(n), g(n) \geq g^*(n)$
- 宽度优先搜索算法就是A\*算法的特例。  
 $f(n)=g(n)+h(n)$ ，其中 $g(n)$ 是节点所在的层数， $h(n)=0$ 。
- A\*算法找到的是初始状态到目标状态的最优路径，而并非在路径上每个状态都最优。而如果 $h(n)$ 满足单调性，则在这个路径上的每一处都是可纳的。



# A\*算法应用——搜索最短路径

## (一)

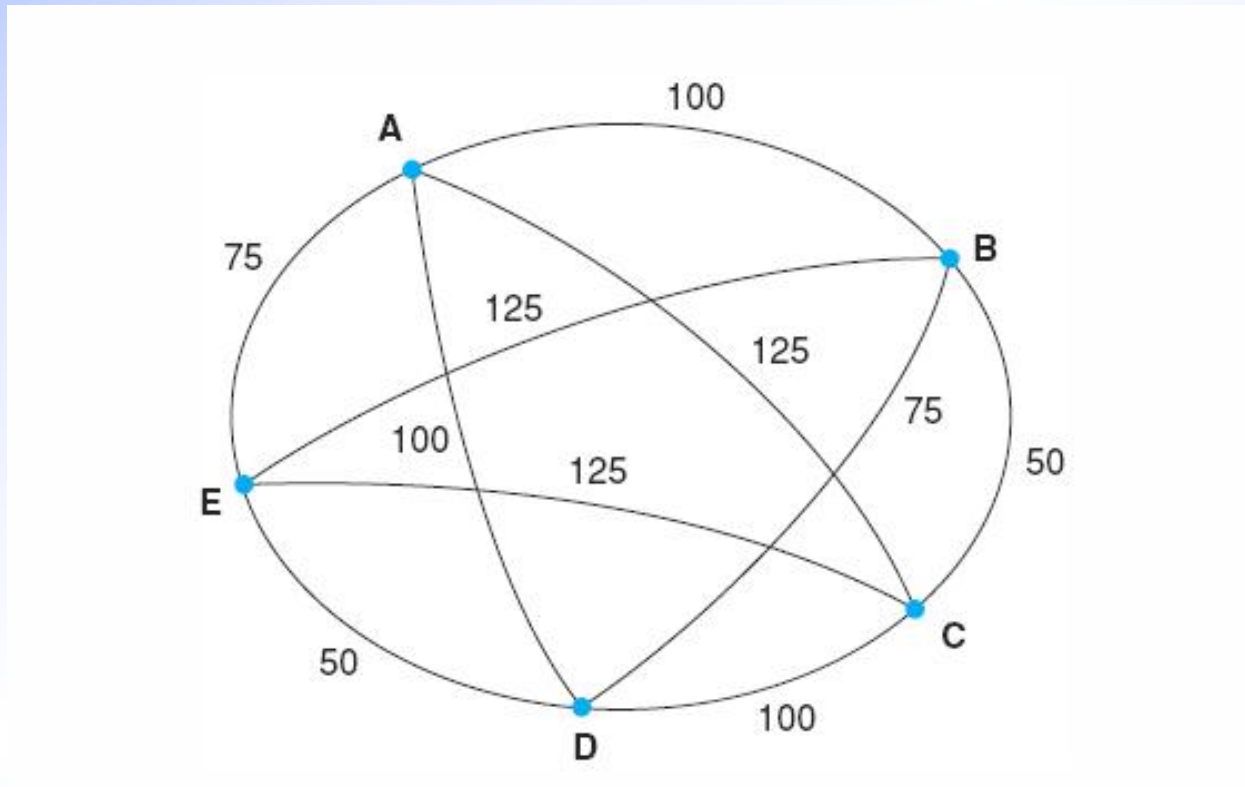
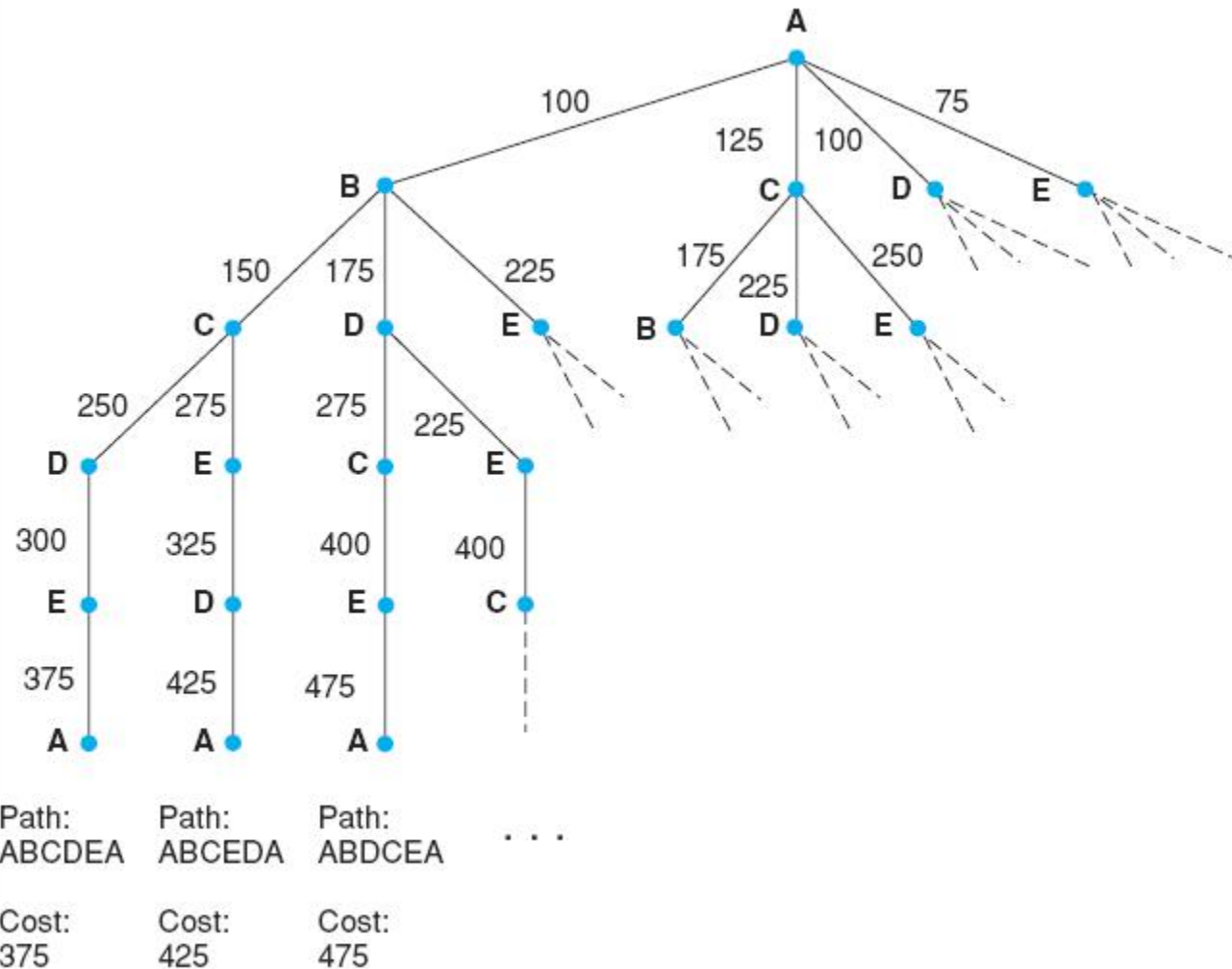


Fig 3.9 An instance of the travelling salesperson problem

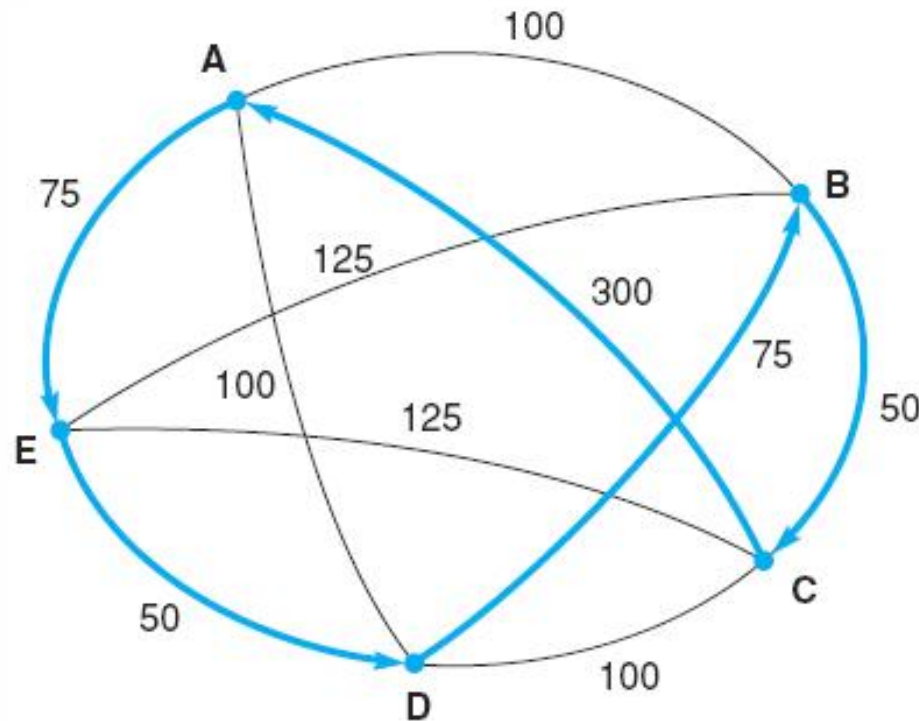


**Fig 3.10. Search for the travelling salesperson problem. Each arc is marked with the total weight of all paths from the start node (A) to its endpoint.**



**An instance of the travelling salesperson problem with the nearest neighbor path in bold.**

**Note this path (A, E, D, B, C, A), at a cost of 550, is not the shortest path. The comparatively high cost of arc (C, A) defeated the heuristic.**



# A\*算法应用——搜索最短路径

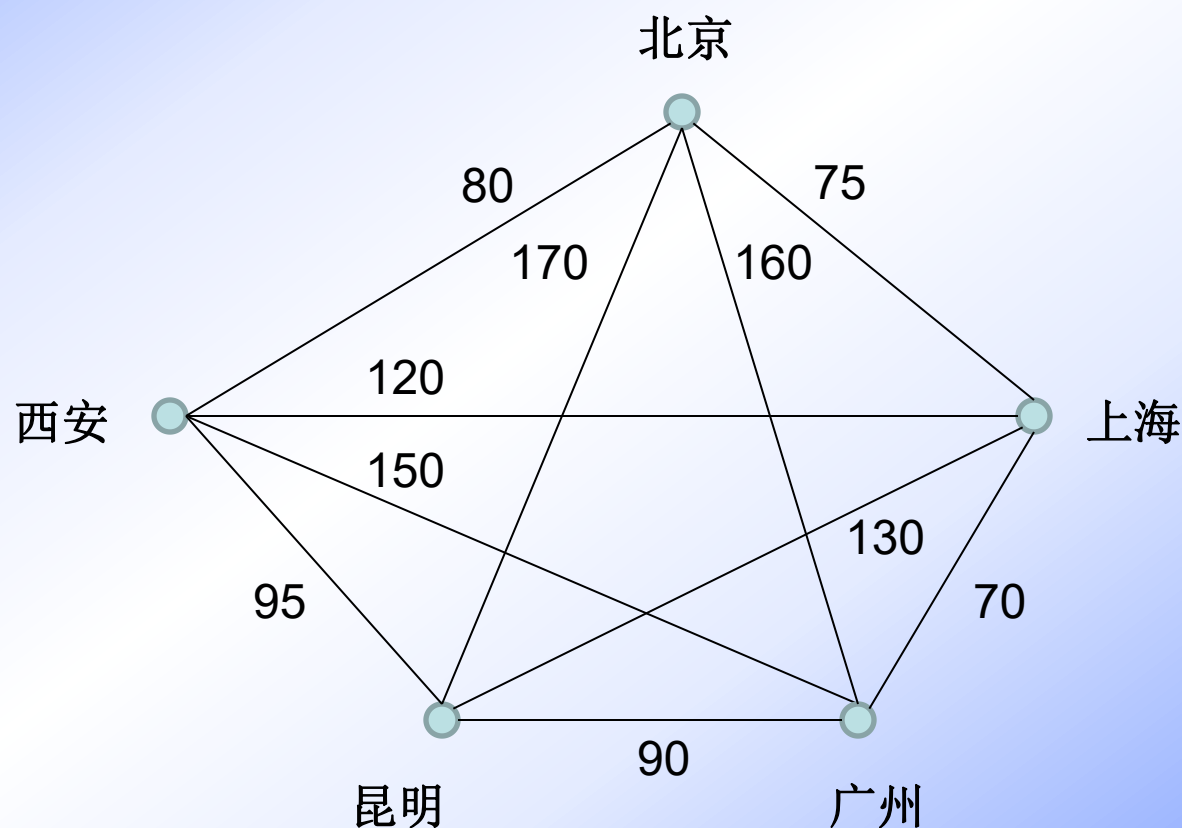
## (二)

- 假定:
- $h(x)=70$ ;  $x$ 属于集合{西安, 北京, 昆明, 上海}
- $H(\text{广州})=0$
- 西安 → 北京 → 上海 → 昆明 → 广州,
- 代价为375

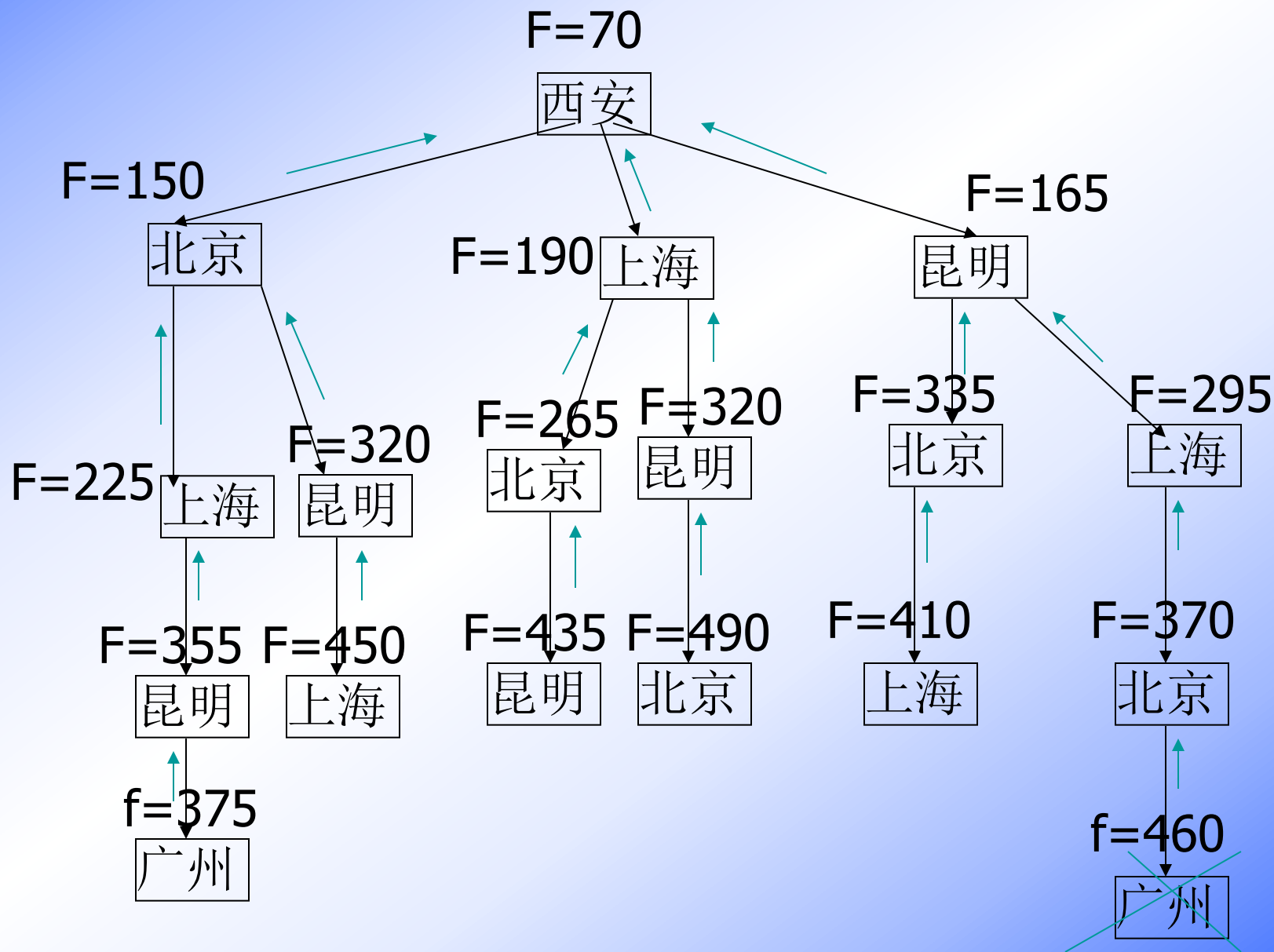




练习：五个城市之间的交通费用如图所示，若从西安出发，经过每个城市一次且一次，最后到达广州，请找出一条交通费用最少的路线。画出搜索树，并给出问题的解。

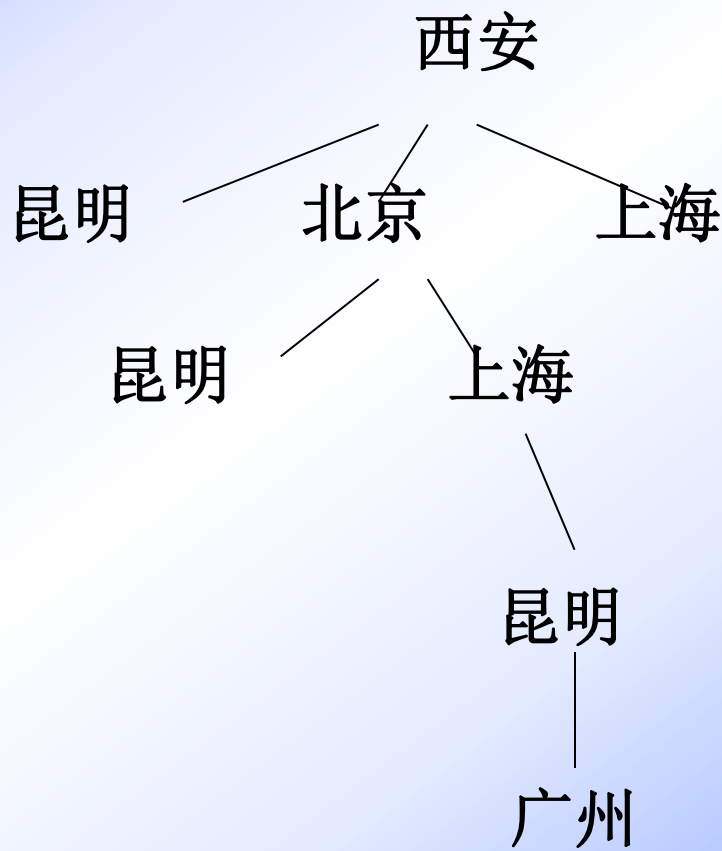






路径：西安→北京→上海→昆明→广州

最小代价为：375



# A\*算法应用——搜索最短路径

## (三)

- 一个问题的状态空间图是客观存在的。
- 应用时先给出问题的状态空间图。
- 注：如果是80个城市，在有限时间内给出全部状态空间图则不可能。
- 同一问题启发函数可以有多种设计方法



对本章的旅行商问题，定义两个h函数（非零），使其都满足A\*算法的条件。（右图为 $h(n)=0$ ）

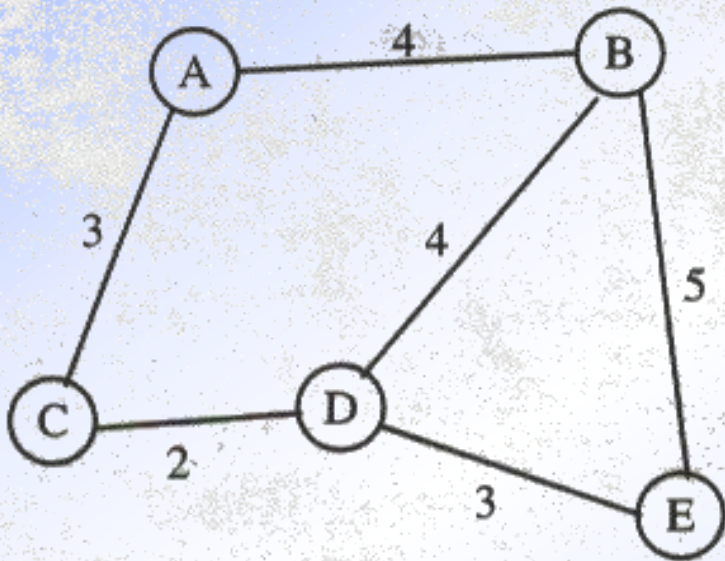


图 4.14 交通图

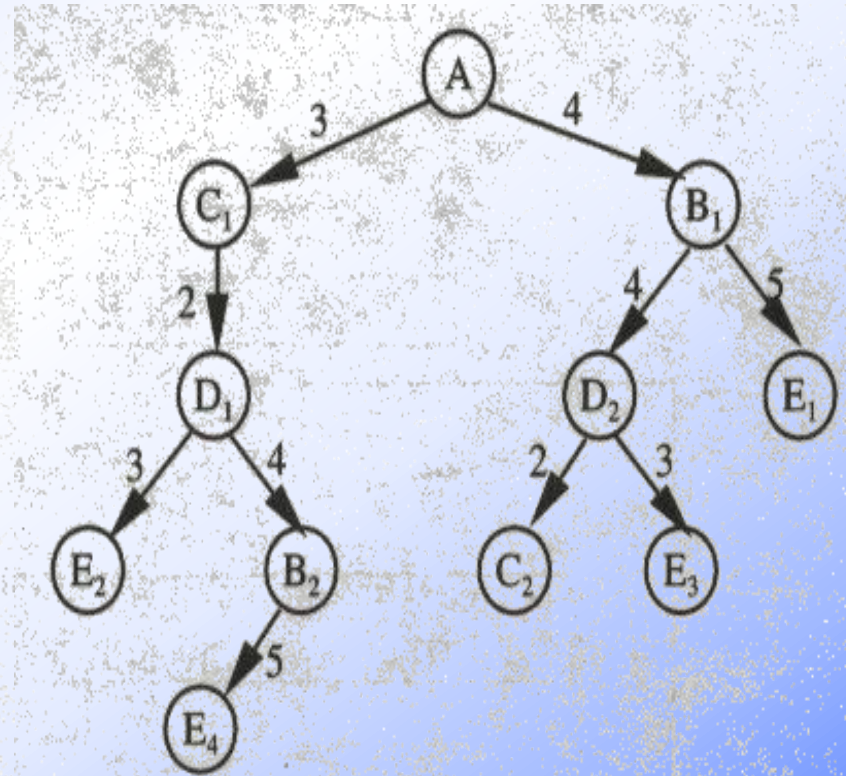


图 4.15 交通图的代价树



参考答案:

定义: (1)  $h_1 = n \times k$

其中  $n$  是还未走过的城市数,  $k$  是还未走过的城市间距离的最小值。

$$(2) h_2 = \sum_{i=1}^n k_i$$

其中  $n$  是还未走过的城市数,  $k_i$  是还未走过的城市间距离中  $n$  个最小的距离。



## A\*算法应用——八数码游戏

$$S_0 = \begin{bmatrix} 2 & 8 & 3 \\ 1 & & 4 \\ 7 & 6 & 5 \end{bmatrix}$$

$$S_g = \begin{bmatrix} 1 & 2 & 3 \\ 8 & & 4 \\ 7 & 6 & 5 \end{bmatrix}$$

- 在八数码问题中，启发式函数的选取如下： **$g(x)$** 表示节点 **$x$** 在搜索树中的深度， **$w(x)$** 表示节点 **$x$** 中不在目标状态中相应位置的数码个数，显然， **$h(x) \leq h^*(x)$** ，因此它满足**A\***算法的要求，所以找到的是最短路径。
- 还可以定义启发函数 **$h(n)=p(n)$** 为节点 **$n$** 的每一数码与其目标位置之间的距离总合。显然，相应的搜索算法也是**A\***算法。





- $p(n)$ 比 $w(n)$ 有更强的启发性信息，由 $h(n)=p(n)$ 构造的启发式搜索树，比 $h(n)=w(n)$ 构造的启发式搜索树节点树要少。
- 以下是三种不同启发函数下，扩展节点情况比较结果。

启发函数	$h(n)=0$	$h(n)=w(n)$	$h(n)=p(n)$
扩展节点	26	6	5
生成节点	46	12	10



第零层

2	8	3
1		4
7	6	5

S0

第一层

2	8	3
	1	4
7	6	5

B1

2		3
1	8	4
7	6	5

B2

2	8	3
1	4	
7	6	5

B3

2	8	3
1	6	4
7		5

B4

第二层

	8	3
2	1	4
7	6	5

C1

2	8	3
7	1	4
	6	5

C2

	2	3
1	8	4
7	6	5

C3

	2	3
1	8	4
7	6	5

C4

	2	8
1	4	3
7	6	5

C5

	2	8	3
1	8	5	
7	6		

C6

	2	8	3
1	6	4	
	7	5	

C7

	2	8	3
1	6	4	
7	5		

C8

第三层

8		3
2	1	4
7	6	5

D1

	2	8	3
7	1	4	
6		5	

D2

	1	2	3
		8	4
7	6		5

D3

	2	3	4
1	8		
7	6	5	

D4

	2		8
1	4	3	
7	6	5	

D5

	2	8	3
1	4	5	
7		6	

D6

	2	8	3
		6	4
1	7	5	

D7

	2	8	3
1	6		
7	5	4	

D8

第四层

8	3	
2	1	4
7	6	5

E1

8	1	3
2		4
7	6	5

E2

	2	8	3
7		4	
6	1	5	

E3

	2	8	3
7	1	4	
6	5		

E4

1	2	3
8		4
7	6	5

Sg

1	2	3
7	8	4
	6	5

E6

2	3	4
1		8
7	6	5

E7

找到目标状态，  
结束搜索

广度优先搜索





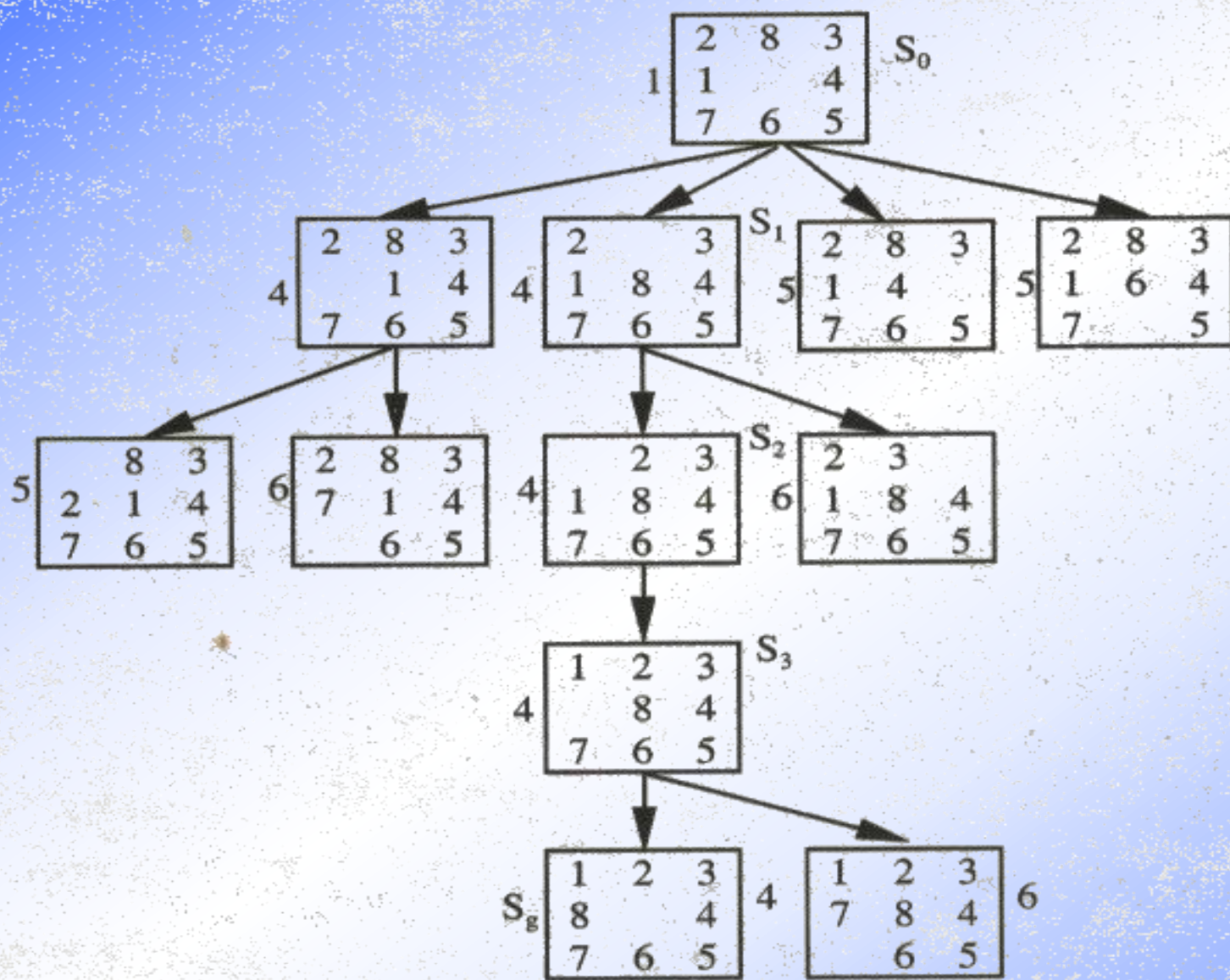
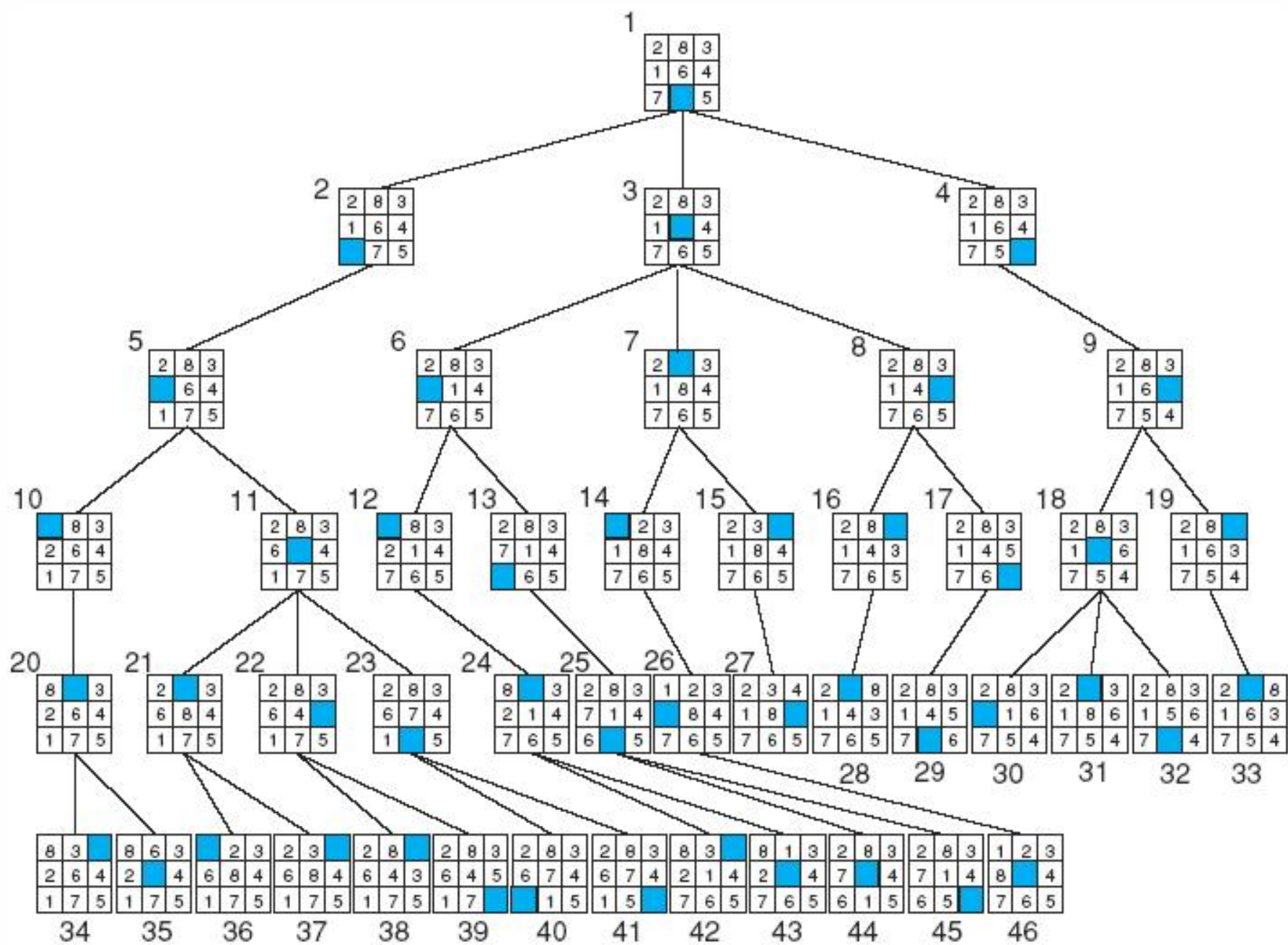
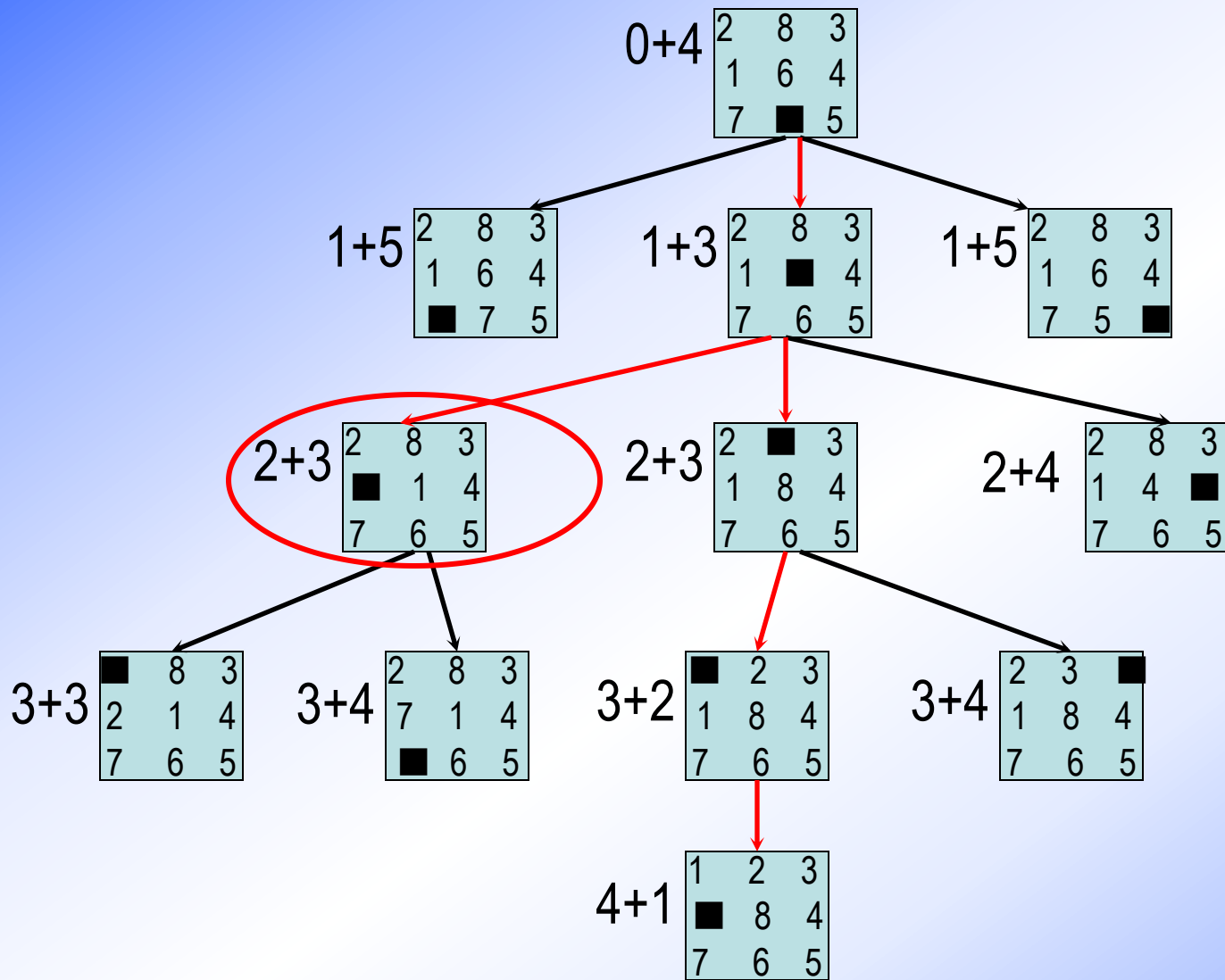


图 4.17 重排九宫问题的全局择优搜索树





Goal



目标



## 启发式搜索应用

- 给定4升和3升的水壶各一个。水壶上没有刻度。可以**向水壶中加水**。如何在4升的壶中准确地得到2升水？

提示：在这里用  $(x, y)$  表示4升壶里的水有 $x$ 升和3升壶里的水有 $y$ 升， $n$ 表示搜索空间中的任一节点，则给出下面的启发式函数：

$$\begin{aligned} h(n) &= 2, && \text{如果 } 0 < x < 4 \text{ 并且 } 0 < y < 3 \\ &= 4, && \text{如果 } 0 < x < 4 \text{ 或者 } 0 < y < 3 \\ &= 10, && \text{如果 (1) } x=0 \text{ 并且 } y=0 \\ &&& \text{或者 (2) } x=4 \text{ 并且 } y=3 \\ &= 8, && \text{如果 (1) } x=0 \text{ 并且 } y=3 \\ &&& \text{或者 (2) } x=4 \text{ 并且 } y=0 \end{aligned}$$





## 4.4 Using Heuristics in Games

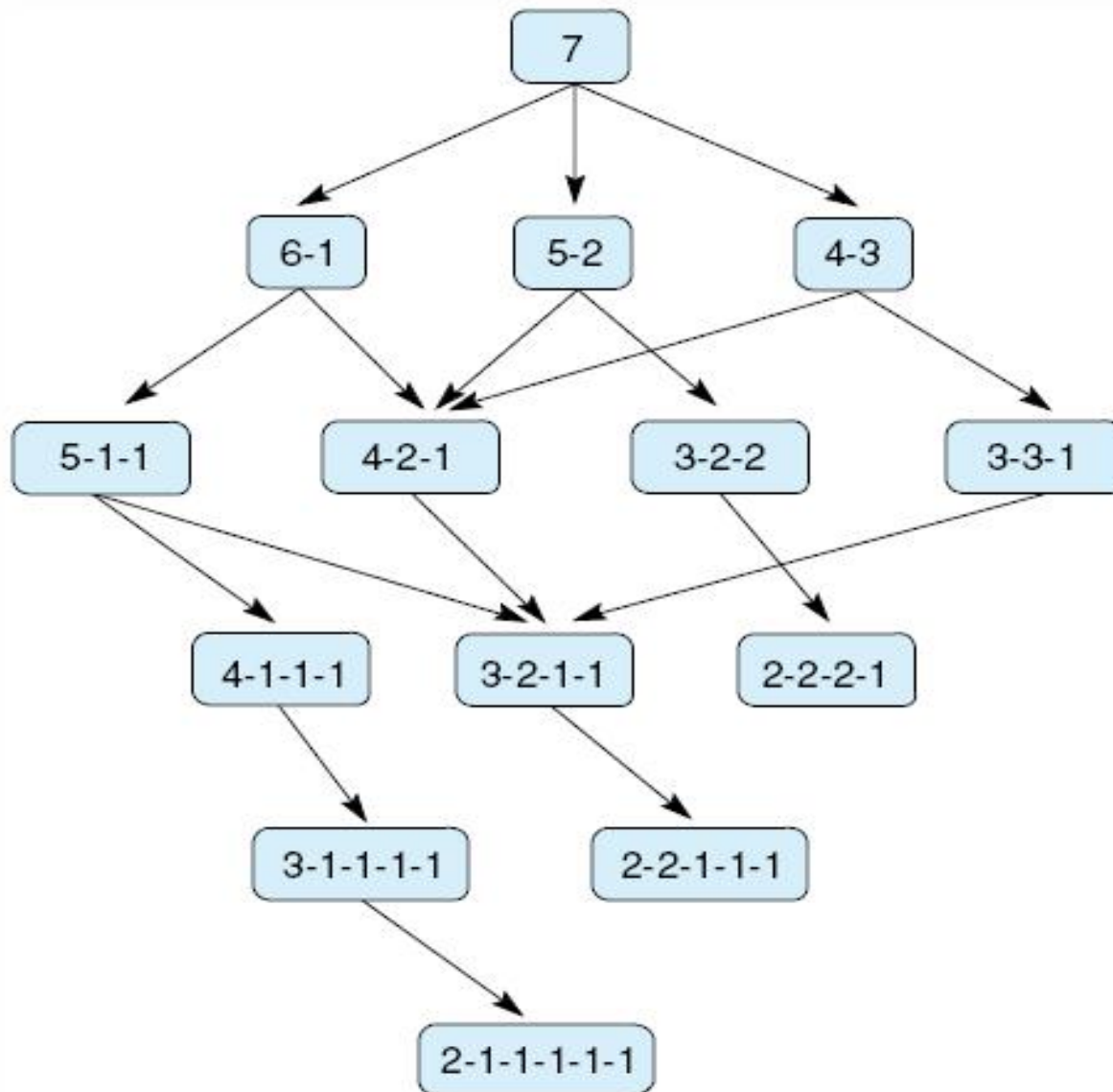
### 4.4.1 The Minimax Procedure (极大极小过程) on

#### Exhaustively Searchable Graphs

- we consider games whose state space is **small enough** to be exhaustively searched.
- We consider **a variant** (变体) of the game **nim** (余一棋, 取物游戏), at each move, the player must **divide a pile of tokens** (筹码) into **nonempty piles of different sizes**.
- The first player **who can no longer make a move** loses the game.



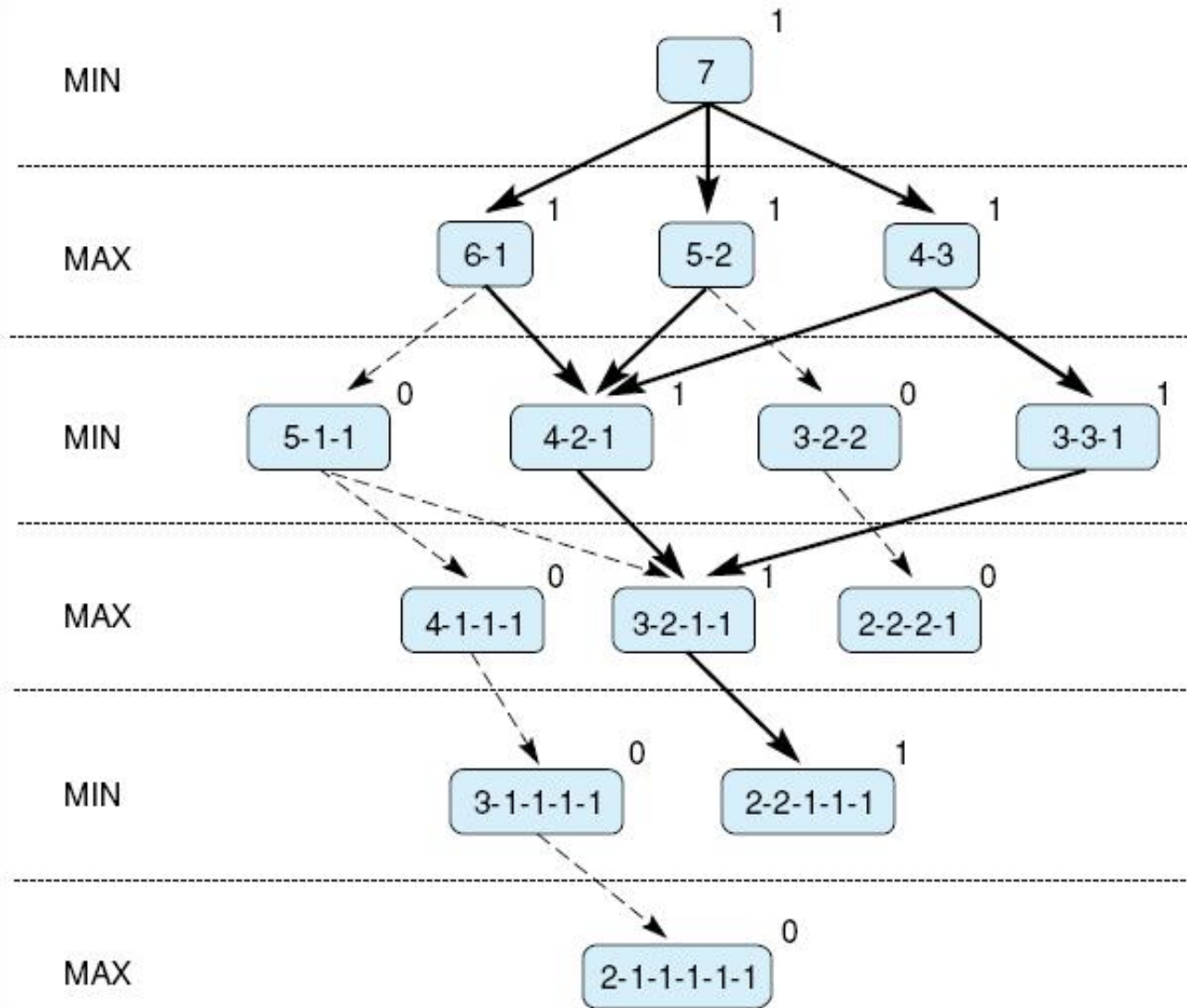
# State space for a variant of nim



- Each **leaf node** is given a value of **1** or **0**, depending on whether it is **a win for MAX** or **for MIN**.
- Minimax **propagates** (传播) these values **up the graph** through successive (连续的) parent nodes **according to the rule**:
  - if the parent is **a MAX node** (极大结点), give it **the maximum value** among its children.
  - if the parent is **a MIN node** (极小结点), give it **the minimum value** of its children.



# Exhaustive minimax for the game of nim





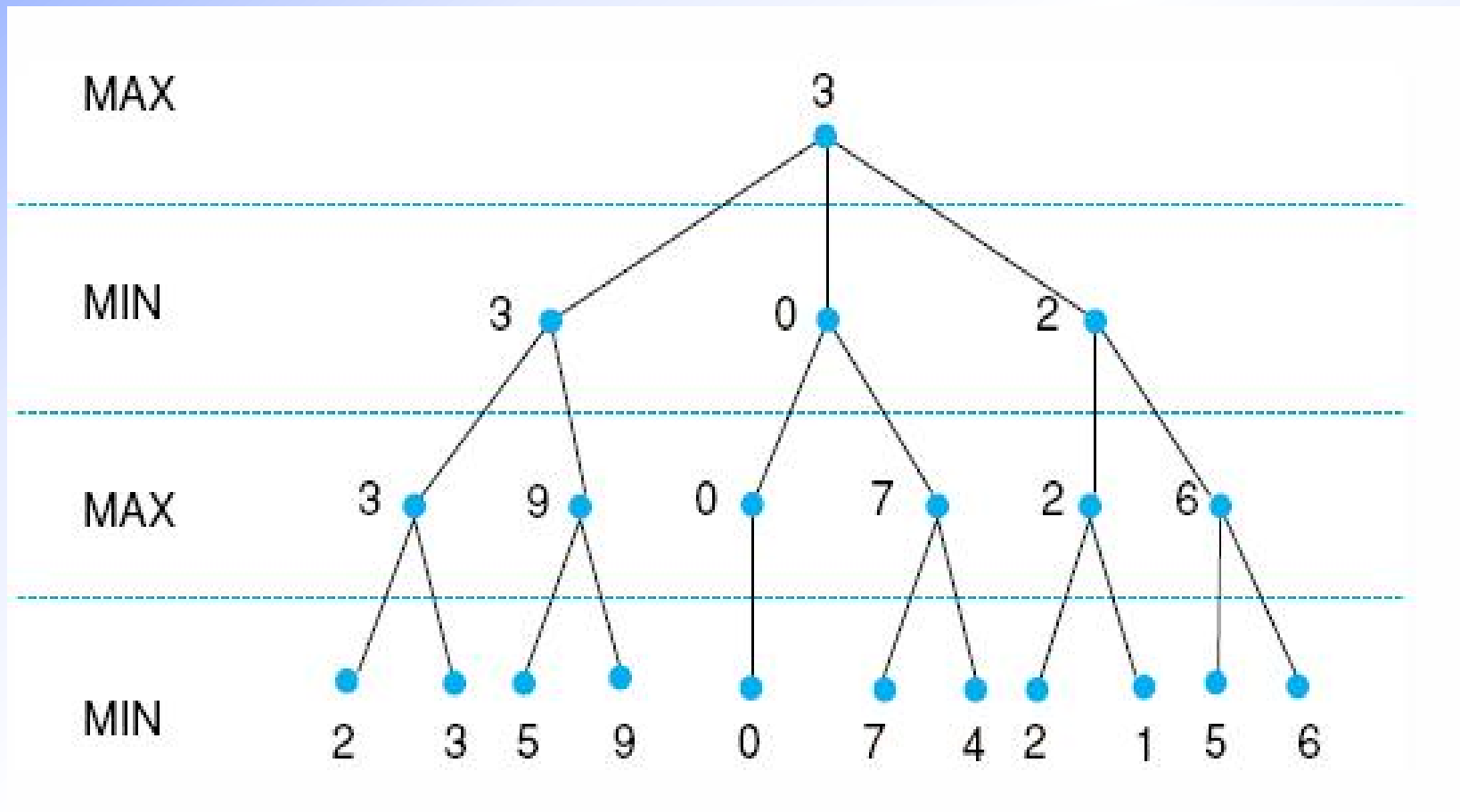
## 4.4.2 Minimizing to **Fixed Ply** Depth

- In applying **minimax** to complicated games, it is impossible **to expand the state space graph** out to **the final leaf nodes**.
- Instead, the state space is searched to **a predefined number of levels**.
- This strategy is called an ***n-ply look-ahead*** (**n 层预判**) .
- Each node **on level n** ( **current leaf node** ) is given a value according to some heuristic evaluation function.
- The value is **the estimation of the goodness** of the state.



# Minimax to a hypothetical state space

**Leaf states show heuristic values**  
**internal states show backed-up values**



**举例： 下图给出了计算博弈树倒推值的示例**

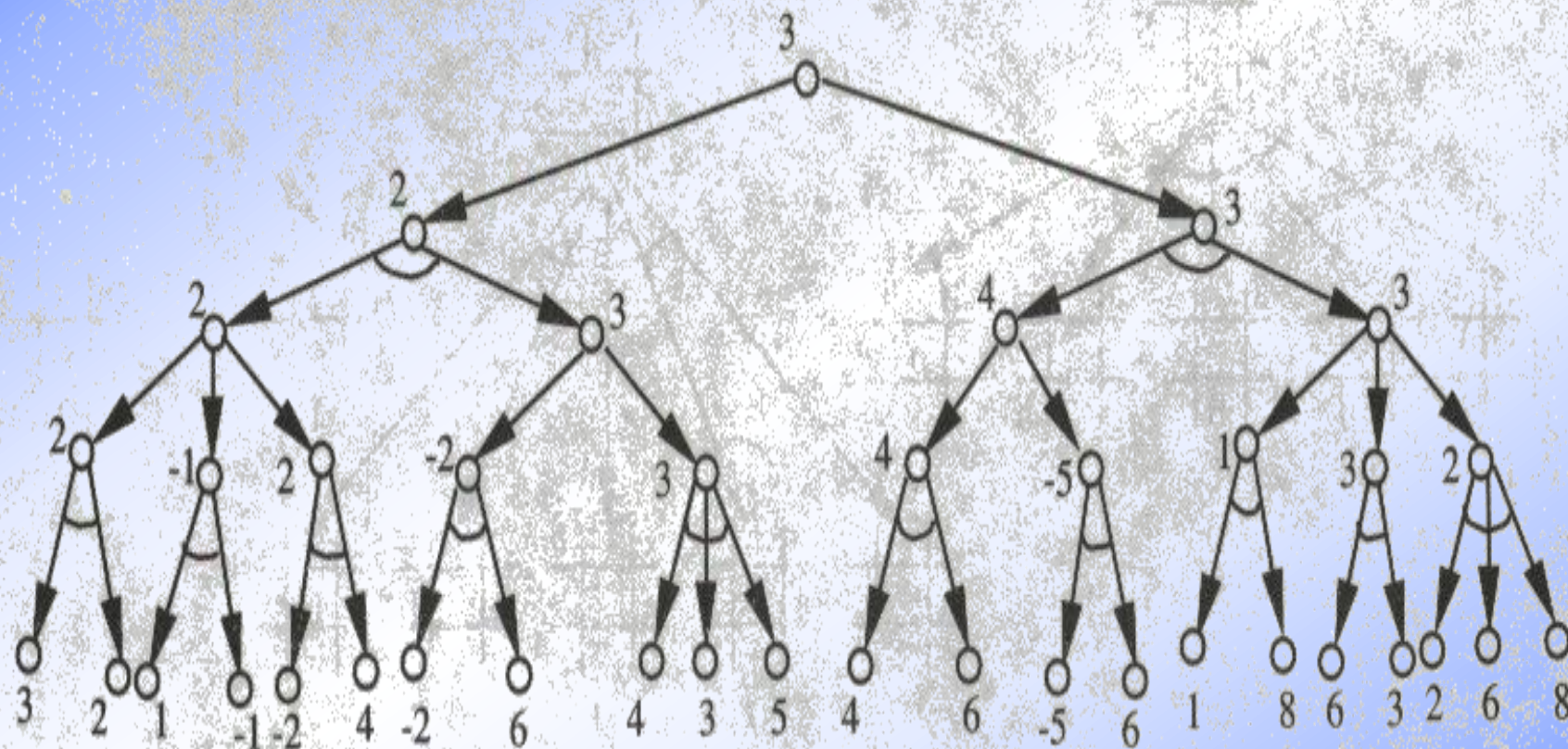
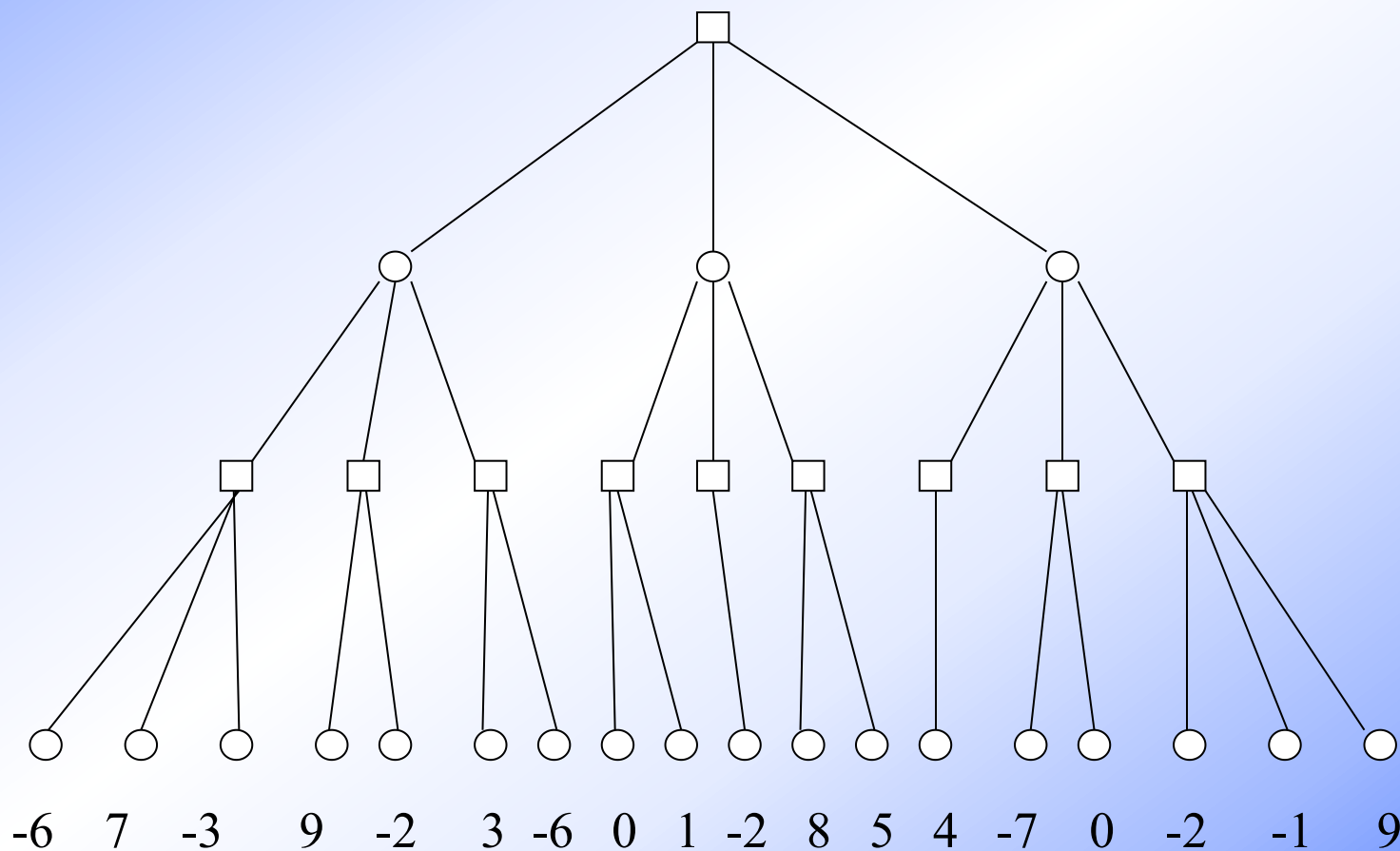


图 4.27 博弈树倒推值的计算



**举例：已知博弈树如图所示，其中方形结点为极大结点，圆形结点为极小结点。如何找出当前最佳棋步。**

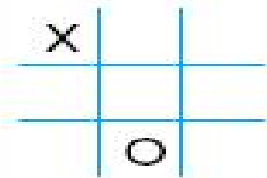


# An application of minimax to tic-tac-toe (一字棋)

- A more complex heuristic is used here.
- The heuristic counts the total winning lines (所有取胜线路) open to MAX, and then subtracts the total number of winning lines open to MIN
- The search attempts to maximize this difference.
- If a state is a forced win (必胜) for MAX, it is evaluated as  $+\infty$
- If a state is a forced win (必胜) for MIN, it is evaluated as  $-\infty$

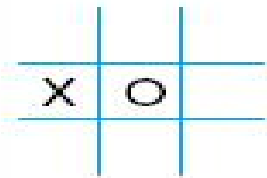
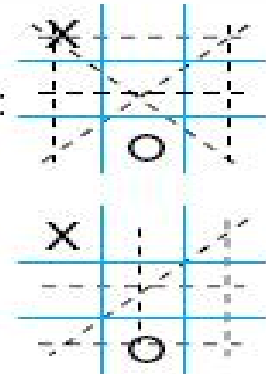






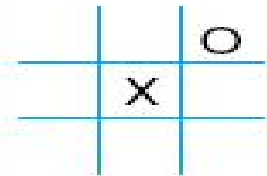
X has 6 possible win paths:  
O has 5 possible wins:

$$E(n) = 6 - 5 = 1$$



X has 4 possible win paths;  
O has 6 possible wins

$$E(n) = 4 - 6 = -2$$



X has 5 possible win paths;  
O has 4 possible wins

$$E(n) = 5 - 4 = 1$$

Heuristic is  $E(n) = M(n) - O(n)$

where  $M(n)$  is the total of My possible winning lines

$O(n)$  is total of Opponent's possible winning lines

$E(n)$  is the total Evaluation for state  $n$



① Start node

MAX's move

X  
-1

X  
1

X  
O

X  
O

X  
O

X  
O

X  
O

$6 - 5 = 1$   $5 - 5 = 0$   $6 - 5 = 1$   $5 - 5 = 0$   $4 - 5 = -1$

X  
-2

O  
X

O  
X

$5 - 4 = 1$   $6 - 4 = 2$

O  
X

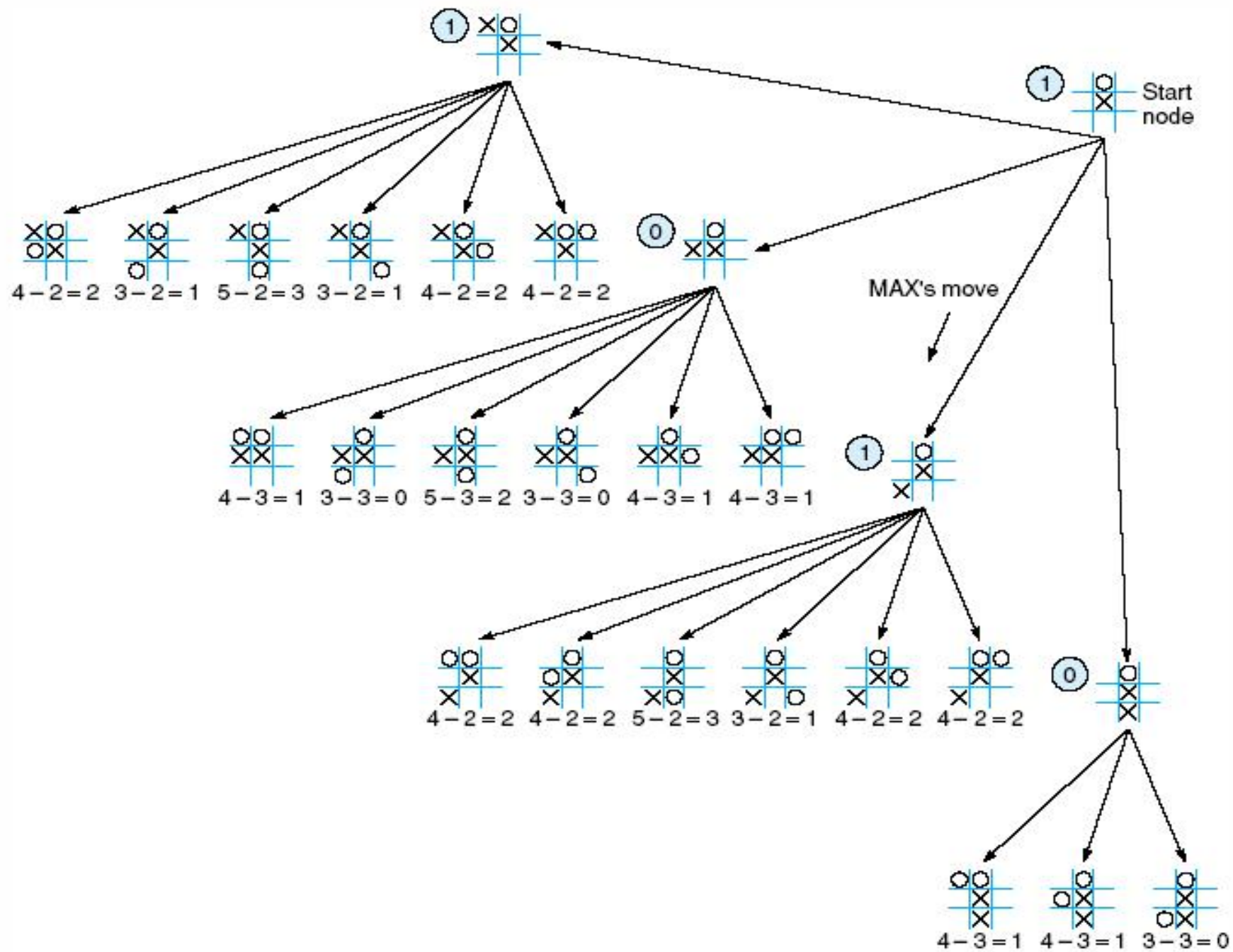
X  
O

X  
O

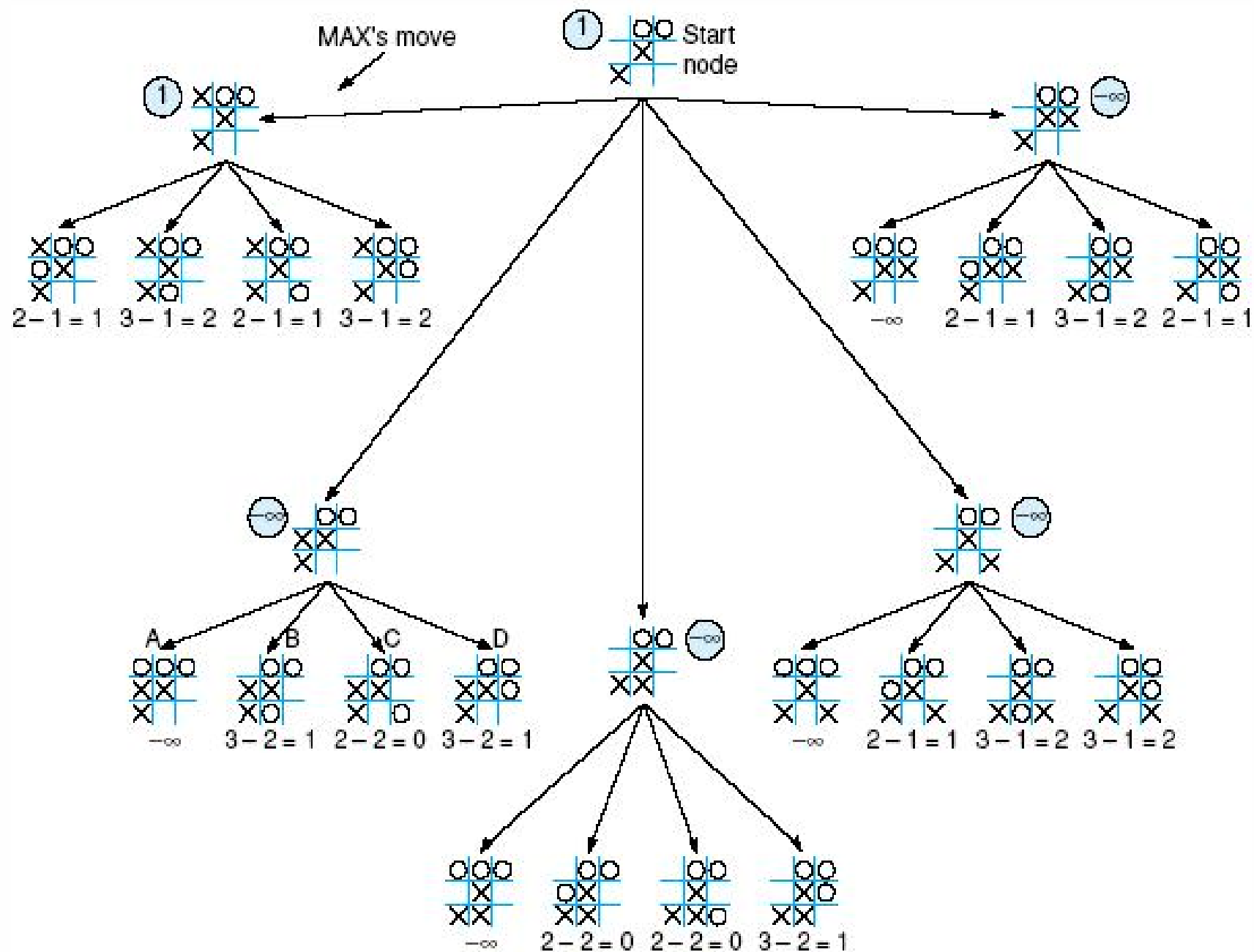
X  
O

X  
O

$5 - 6 = -1$   $6 - 6 = 0$   $5 - 6 = -1$   $6 - 6 = 0$   $4 - 6 = -2$







### 4.4.3 The Alpha-Beta Procedure

- **Straight minimax** requires a **two-pass** (两阶段) **analysis** of the search space,
  - the first **to descend** (向下) **to the ply depth** (预定层深) and **there** apply the heuristic
  - the second **to propagate values back up** the tree.
- Minimax pursues **all branches** in the space, including many that **could be ignored or pruned** (剪枝) .
- Researchers developed a class of search techniques called **alpha-beta pruning** (alpha-beta 剪枝) .



- The idea for alpha-beta search : **rather than searching the entire space to the ply depth (预定层深)** , search proceeds **in a depth-first fashion**.
- Two values, called ***alpha*** and ***beta***, are created during the search.
- The **alpha value (alpha 值)** , associated with **MAX nodes**, can **never decrease (减小)** , and the **beta value (beta 值)** , associated with **MIN nodes**, can **never increase (增大)** .



- Suppose a **MAX** node's **alpha value** is **6**. Then **MAX** need not consider any backed-up value (倒推值) less than or equal to **6** that is associated with any **MIN** node below it (子孙) .
- Similarly, if **MIN** has **beta value 6**, it dose not need to consider any **MAX** node below (子孙) that has a value of **6** or more.



- Two rules for terminating search (终止搜索), based on **alpha** and **beta** values, are:
  1. Search can be stopped below any **MIN** node having a **beta** value **less than** or **equal to** the **alpha** value of any of its **MAX** node **ancestors** ( **MAX** 祖先 ) . (  $\beta \leq \alpha$  )
  2. Search can be stopped below any **MAX** node having an **alpha** value **greater than** or **equal to** the **beta** value of any of its **MIN** node **ancestors** ( **MIN** 祖先 ) . (  $\alpha \geq \beta$  )

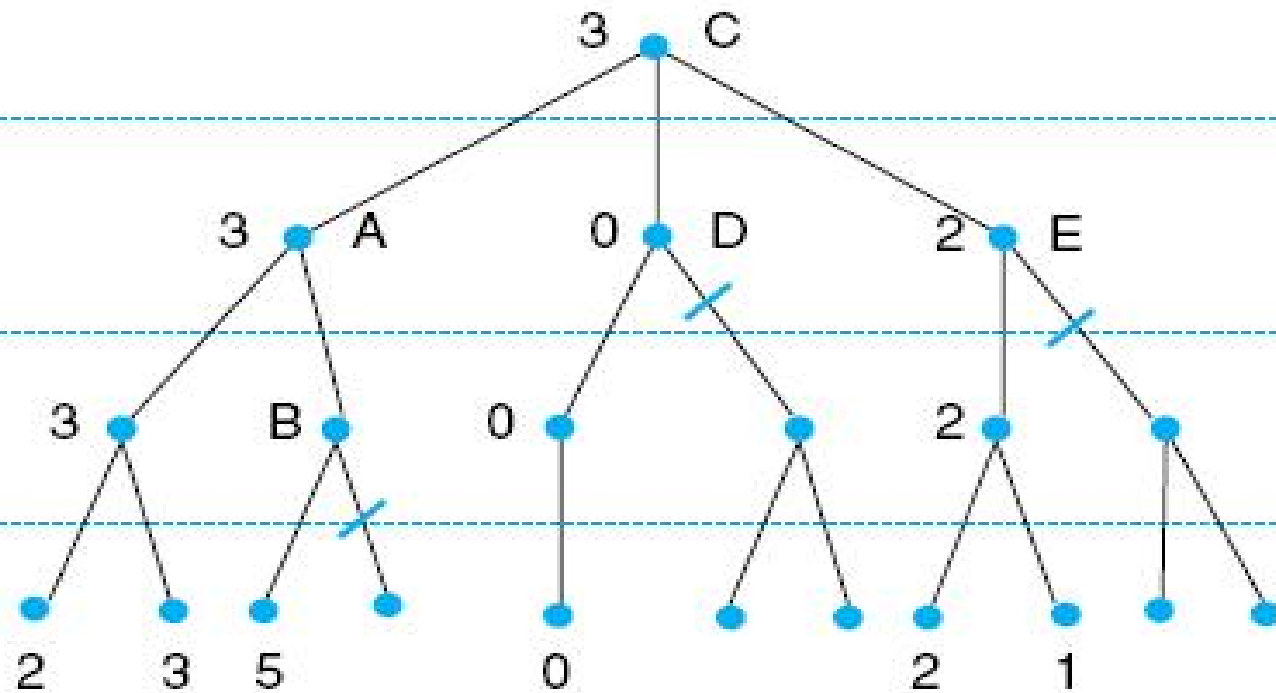


MAX

MIN

MAX

MIN



A has  $\beta = 3$  (A will be no larger than 3)

B is  $\beta$  pruned, since  $5 > 3$

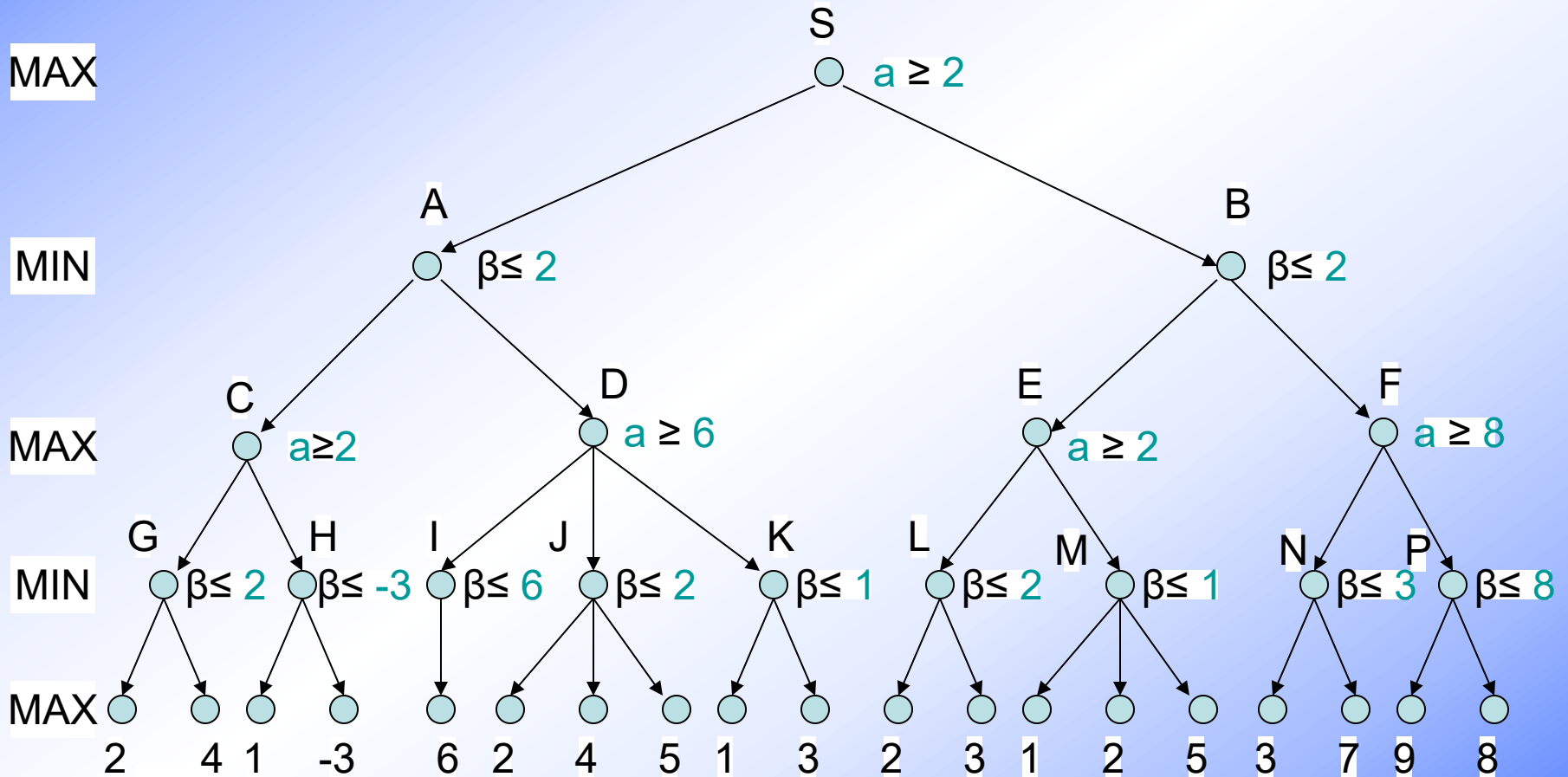
C has  $\alpha = 3$  (C will be no smaller than 3)

D is  $\alpha$  pruned, since  $0 < 3$

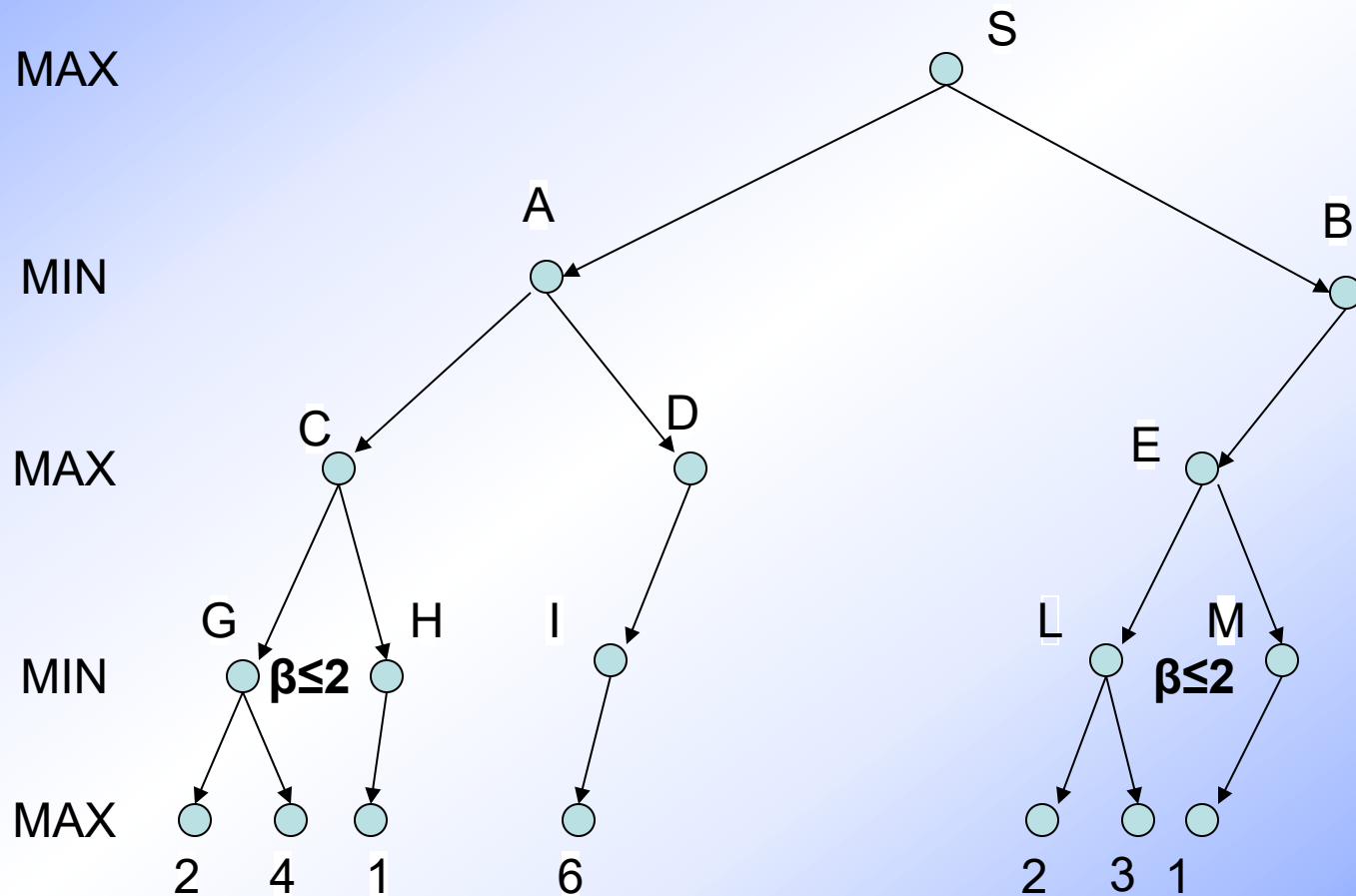
E is  $\alpha$  pruned, since  $2 < 3$

C is 3

# An example of alpha-beta search

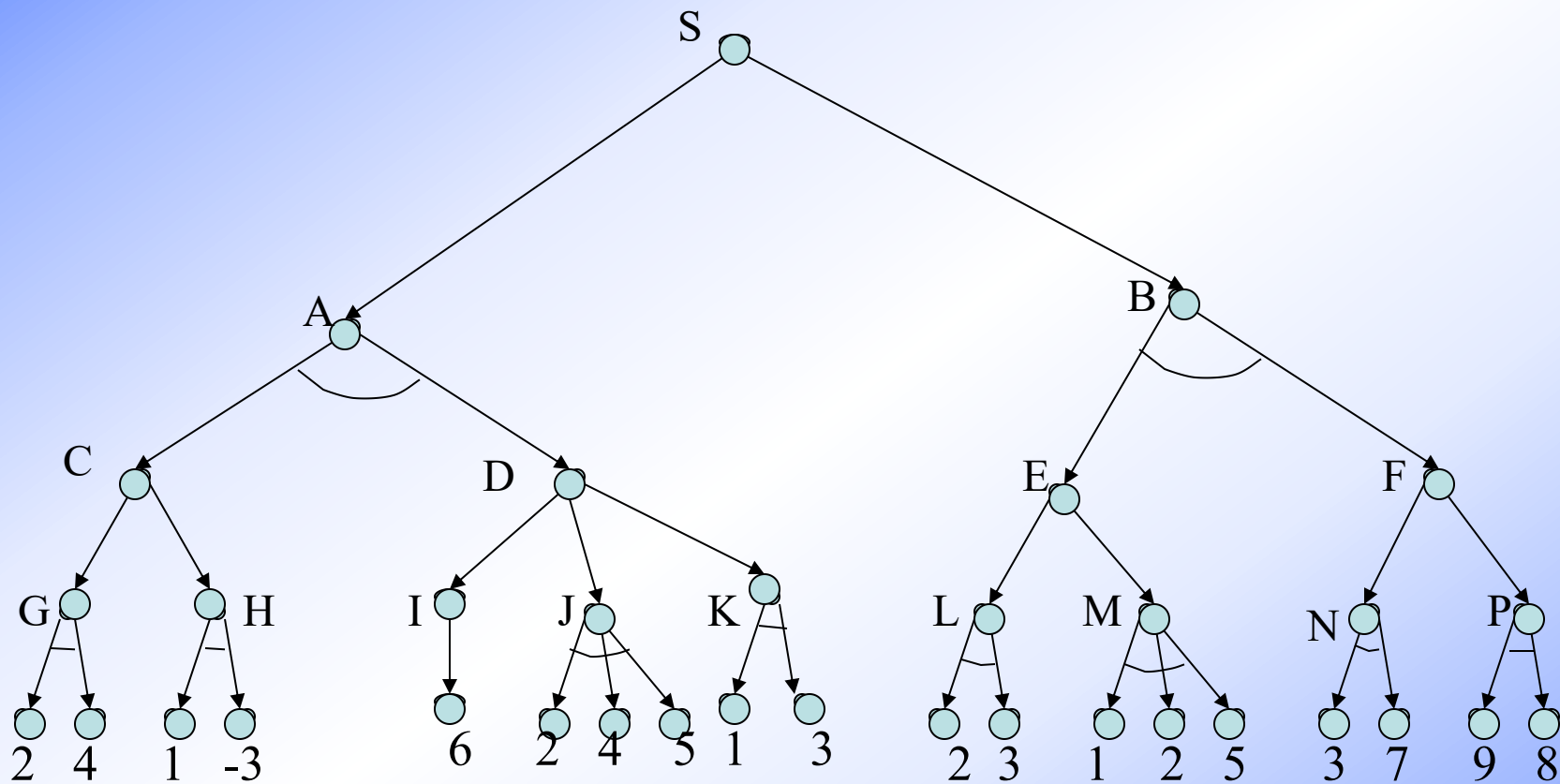


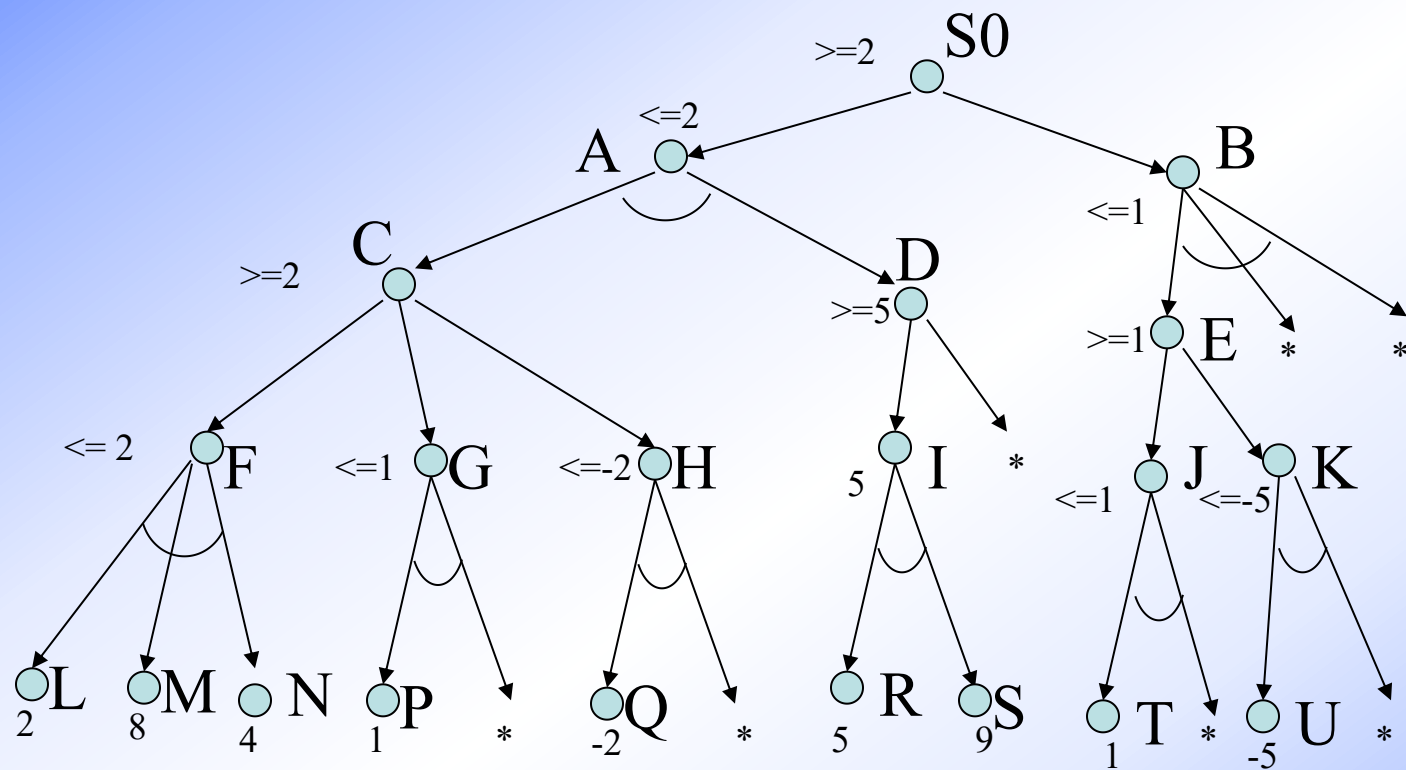
# An example of alpha-beta search





# 计算各节点倒推值



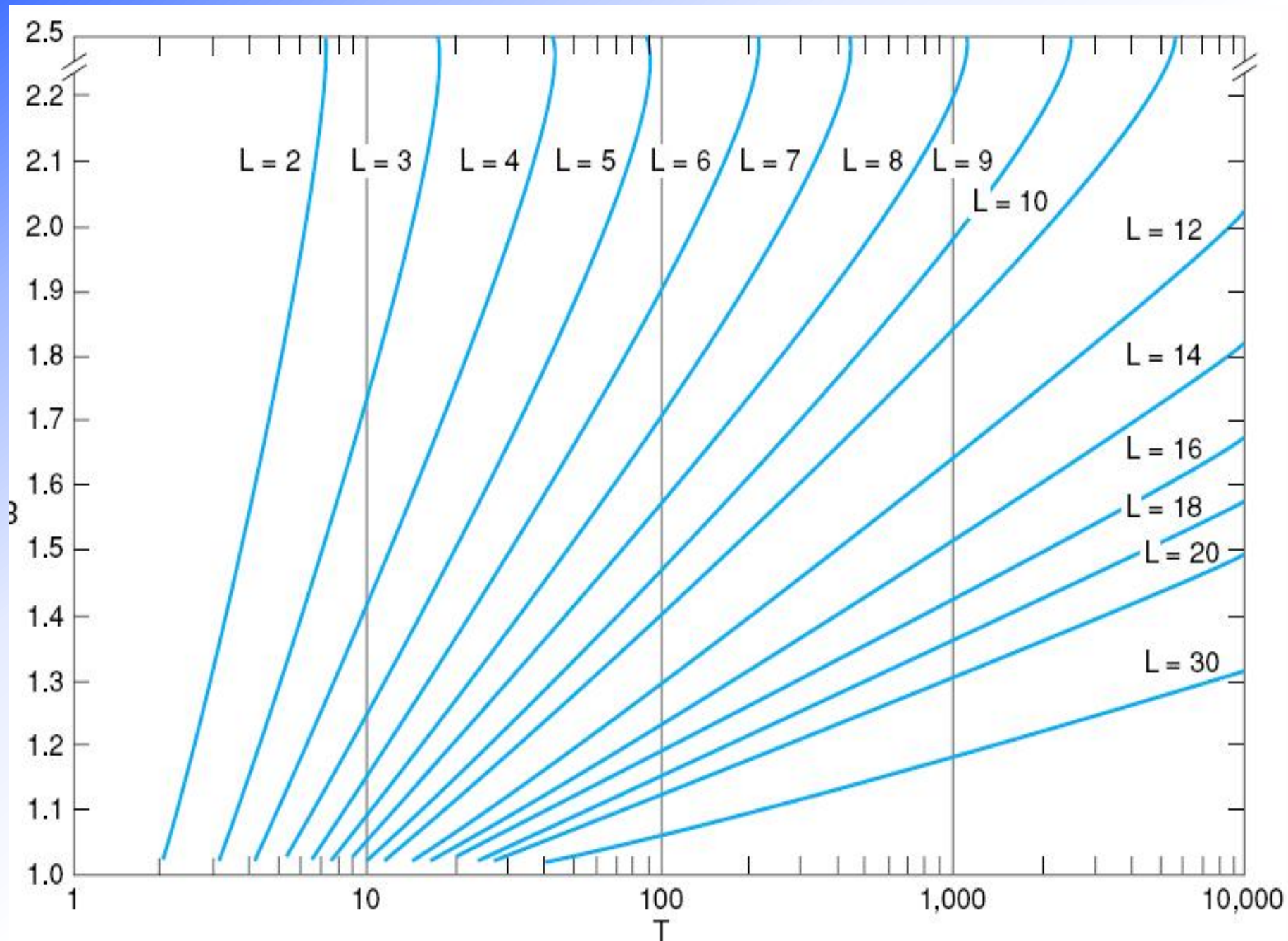


## 4.5 Complexity issues

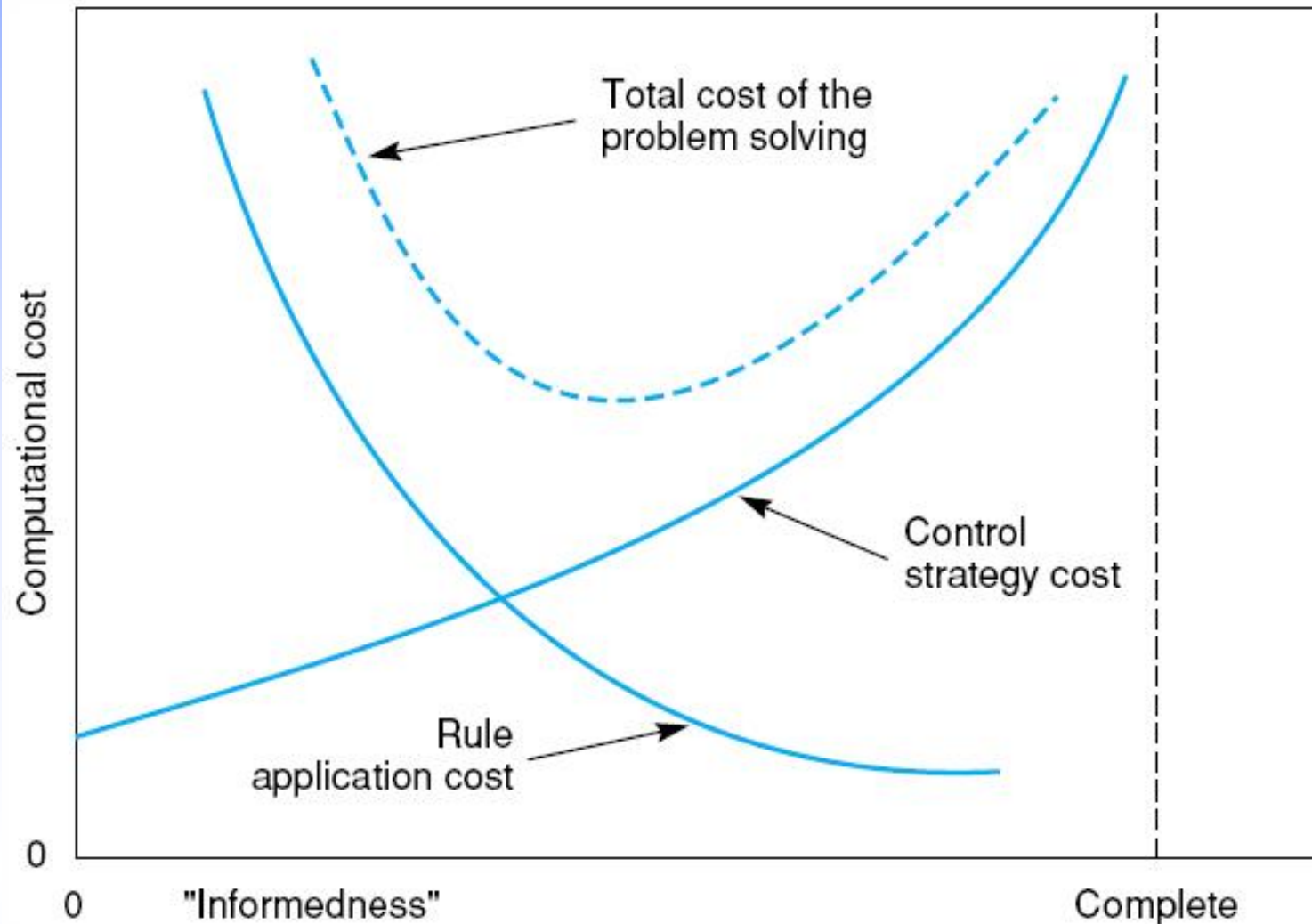
- The **branching factor** :  $B$
- **Depth** or search length :  $L$
- **Total number of states generated** :  $T$
- $T = B + B^2 + B^3 + \dots + B^L$
- The relating equation is :

$$T = B ( B^L - 1 ) / ( B - 1 )$$





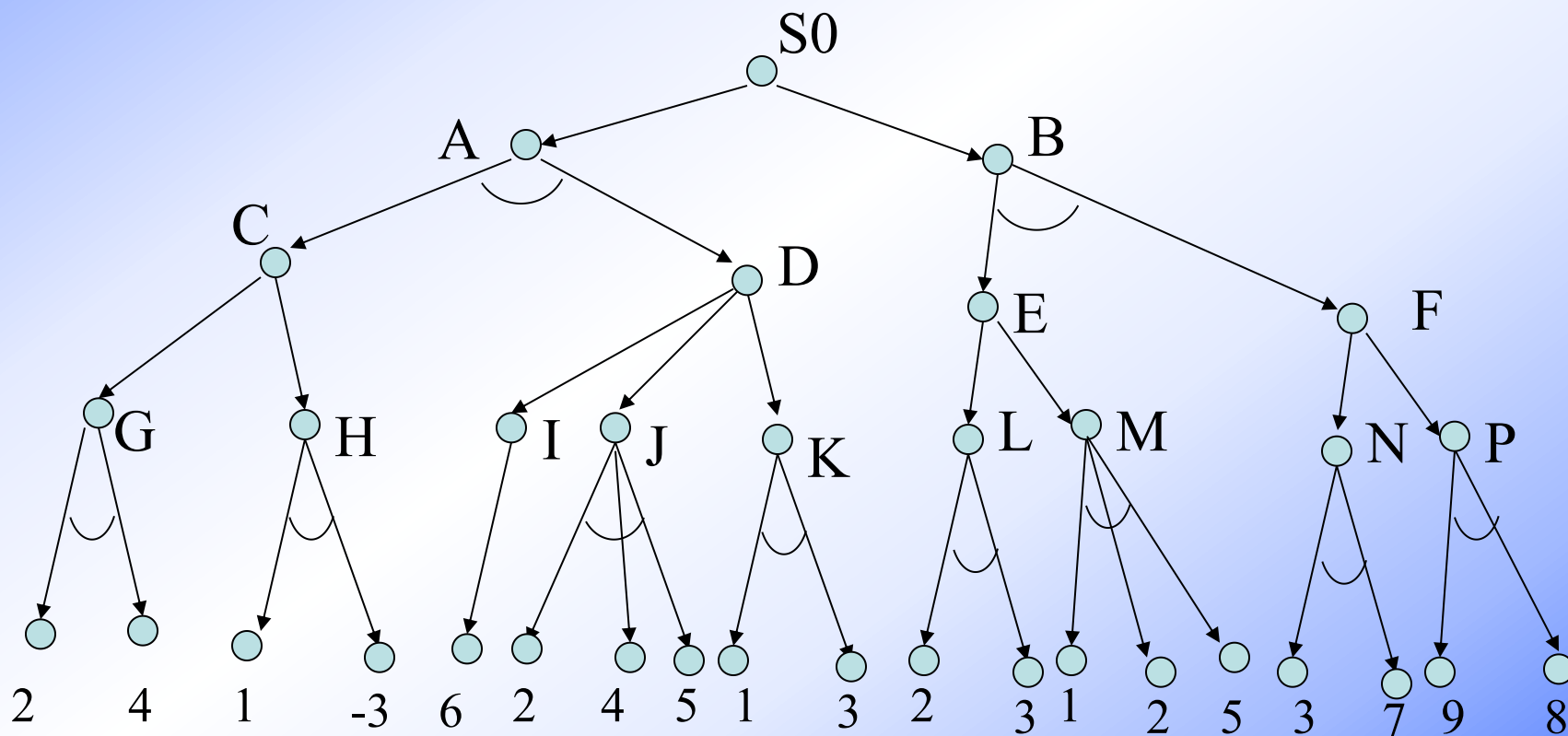
# Cost of searching and cost of computing heuristic evaluation



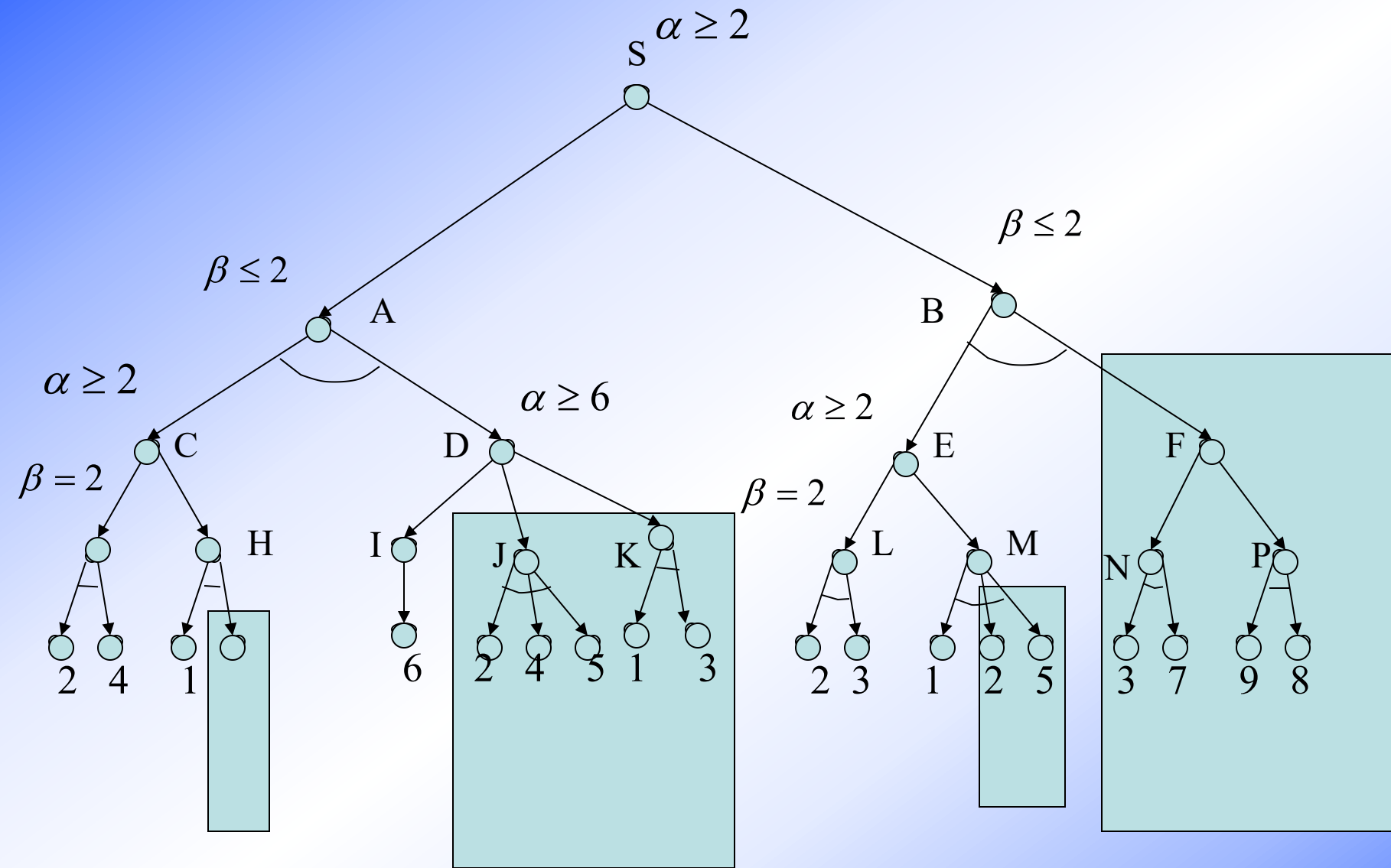
习题1.如图所示的博弈树,其中末一行的数字为假设的估值,

1)计算各节点的倒推值。

2)利用 $\alpha$ - $\beta$ 剪枝技术剪去不必要的分枝。





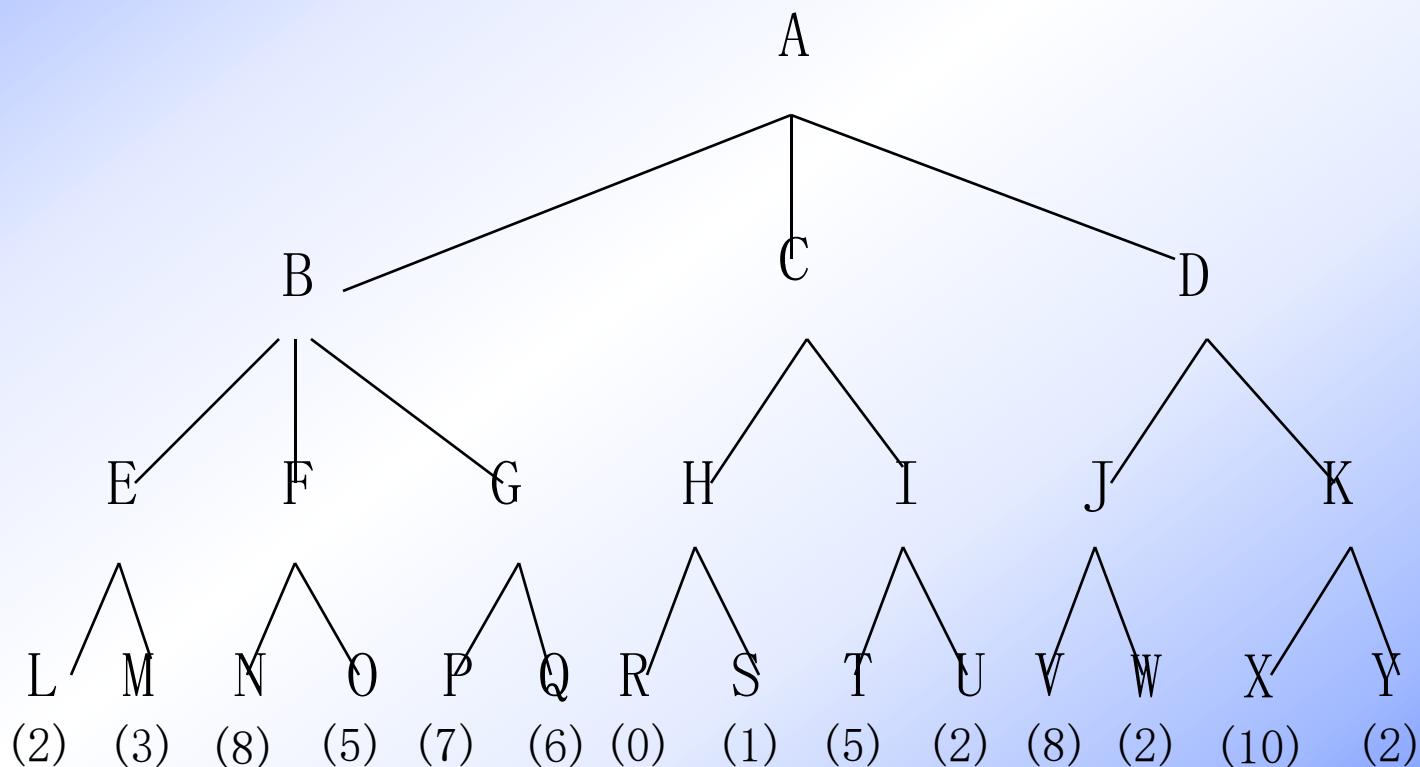




习题2. 假设第一个博弈者为MAX，如图所示。

(1) 第一个博弈者将选择什么移动？

(2) 假如采用  $\alpha - \beta$  剪枝算法，哪些节点无须检验（假设节点按从左到右的顺序检验）？



### 习题3. A\*算法12分（共3小题）

1. A\*算法采用怎样的启发函数？ (3分)
2. A\*算法有哪些特性？（3分）
3. 请用A\*算法求解重排九宫问题。（6分）

问题的初始状态 $S_0$ 和目标状态 $S_g$ 分别为：

$$S_0 = \begin{bmatrix} 2 & 8 & 3 \\ 1 & & 4 \\ 7 & 6 & 5 \end{bmatrix}$$

$$S_g = \begin{bmatrix} 1 & 2 & 3 \\ 8 & & 4 \\ 7 & 6 & 5 \end{bmatrix}$$



[解答]:

1. 如果有序搜索算法的估价函数 $f$ 满足如下限制, 则称为A\*算法:  
节点的估价函数为:  $f(x)=g(x)+h(x)$  , 其中 $h(x)\leq h^*(x)$ 。

2. A\*算法的有关特性: 可纳性、最优性、 $h(x)$  的单调性限制。

3. 用A\*算法重新求解重排九宫问题:

评价函数:  $f(x)=d(x)+h(x)$

其中:  $h(x)$ 为节点 $x$ 与目标节点 $S_g$  不相同的数码个数,  $d(x)$ 为节点 $x$ 的深度。

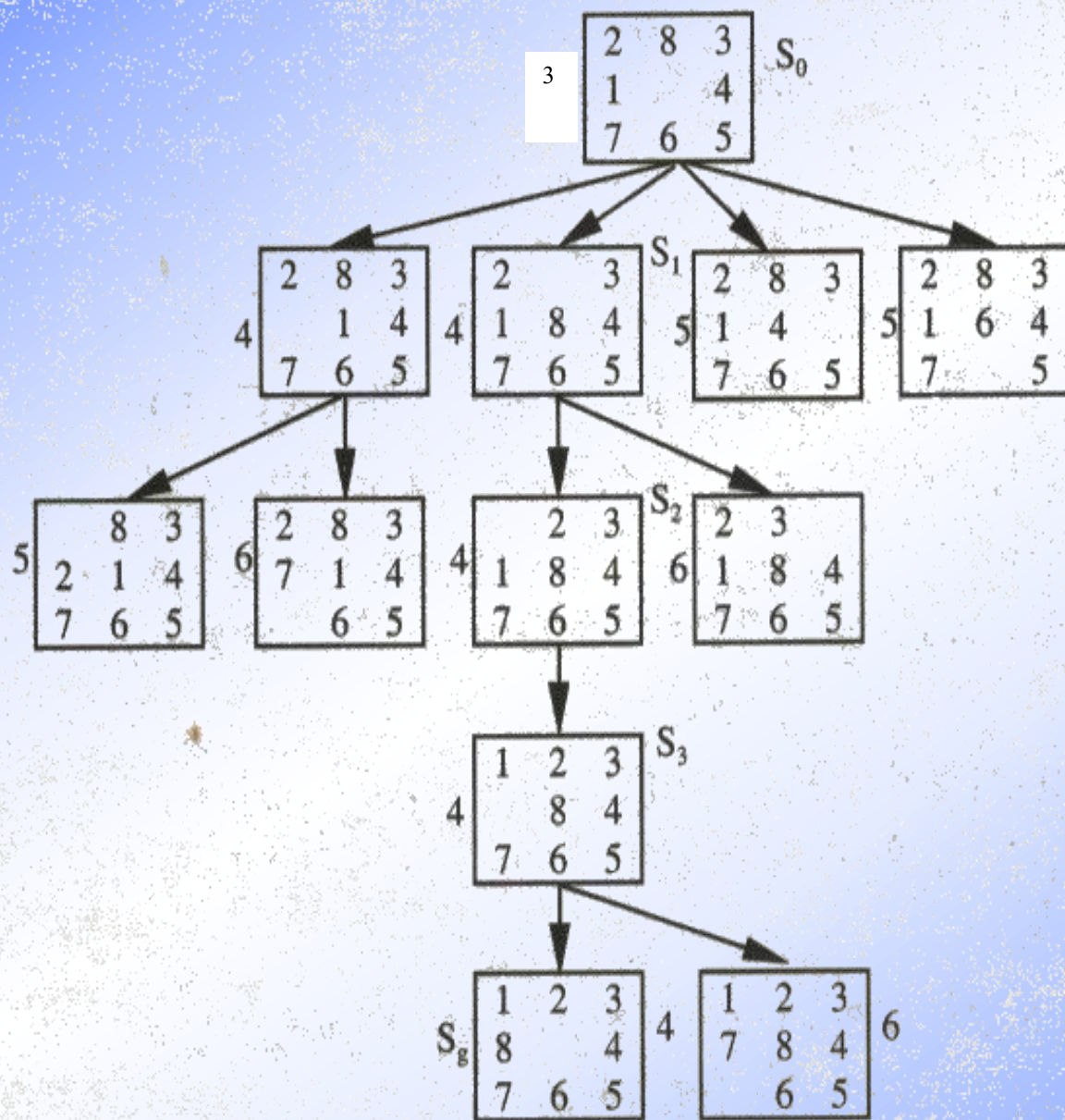
此评价函数 $f(x)$ 满足A\*算法的限制。

其搜索的状态空间图如下图。

则路径为:  $S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow S_g$

● [评分标准]: 定义占3分, 性质占3分, 搜索图占6分。





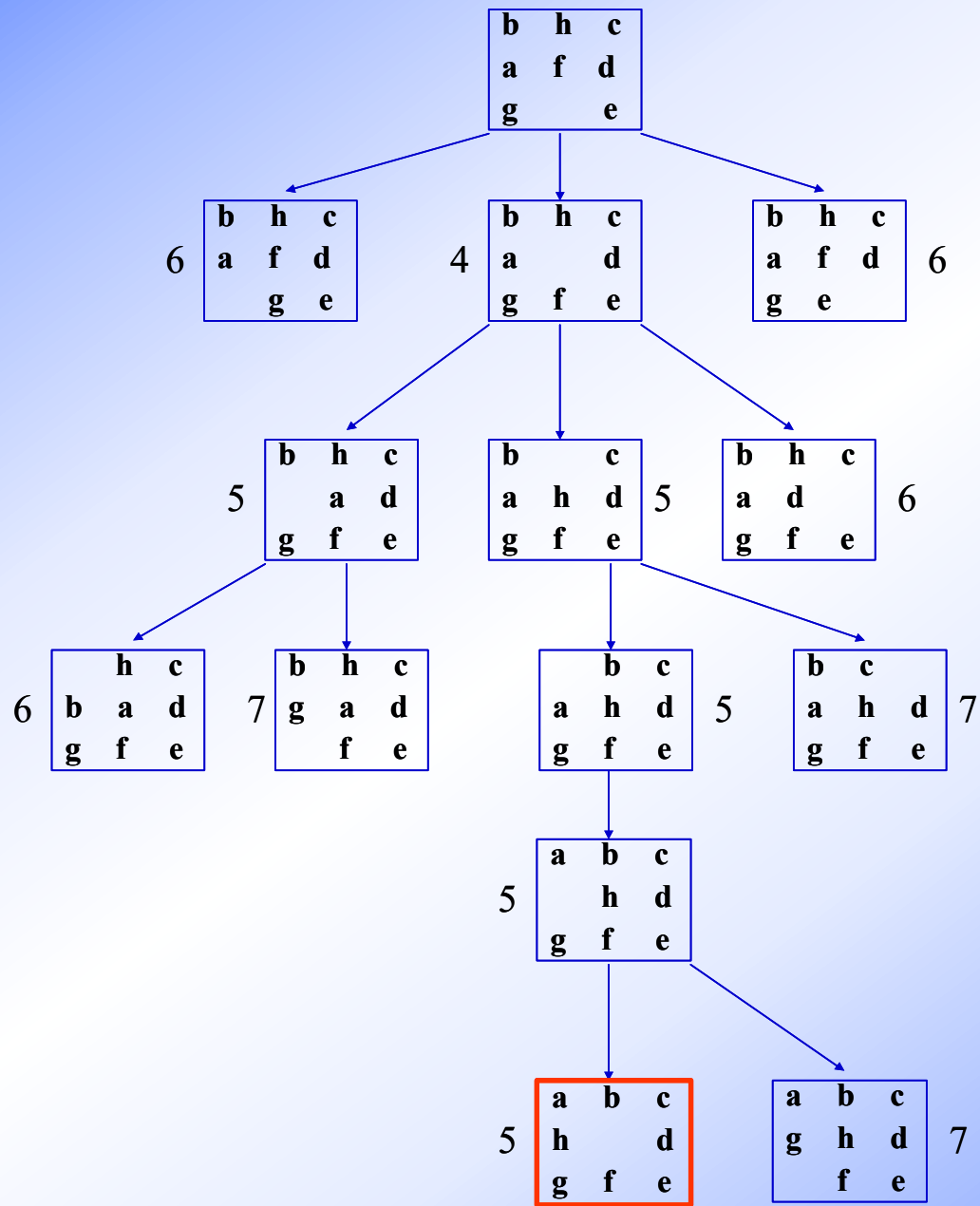
习题4. 用A\*算法求解九宫重排问题。问题的初始状态 $S_0$ 和目标状态 $S_g$ 分别为：

$$S_0 = \begin{array}{|c|c|c|} \hline b & h & c \\ \hline a & f & d \\ \hline g & & e \\ \hline \end{array}$$

$$S_g = \begin{array}{|c|c|c|} \hline a & b & c \\ \hline h & & d \\ \hline g & f & e \\ \hline \end{array}$$

可使用的算符有：空格左移、空格上移、空格右移、空格下移。设估价函数为： $f(x)=d(x)+h(x)$ ，其中 $d(x)$ 为结点 $x$ 的深度， $h(x)$ 为结点 $x$ 中还没有到位的字母个数。要求画出搜索图示，标出每个结点的估值，并指出解路径。







习题5. 用有界深度优先搜索法求解九宫重排问题。问题的初始状态 $S_0$ 和目标状态 $S_g$ 分别为：

$$S_0 = \begin{array}{|c|c|c|} \hline b & h & c \\ \hline a & f & d \\ \hline g & & e \\ \hline \end{array}$$

$$S_g = \begin{array}{|c|c|c|} \hline a & b & c \\ \hline h & & d \\ \hline g & f & e \\ \hline \end{array}$$

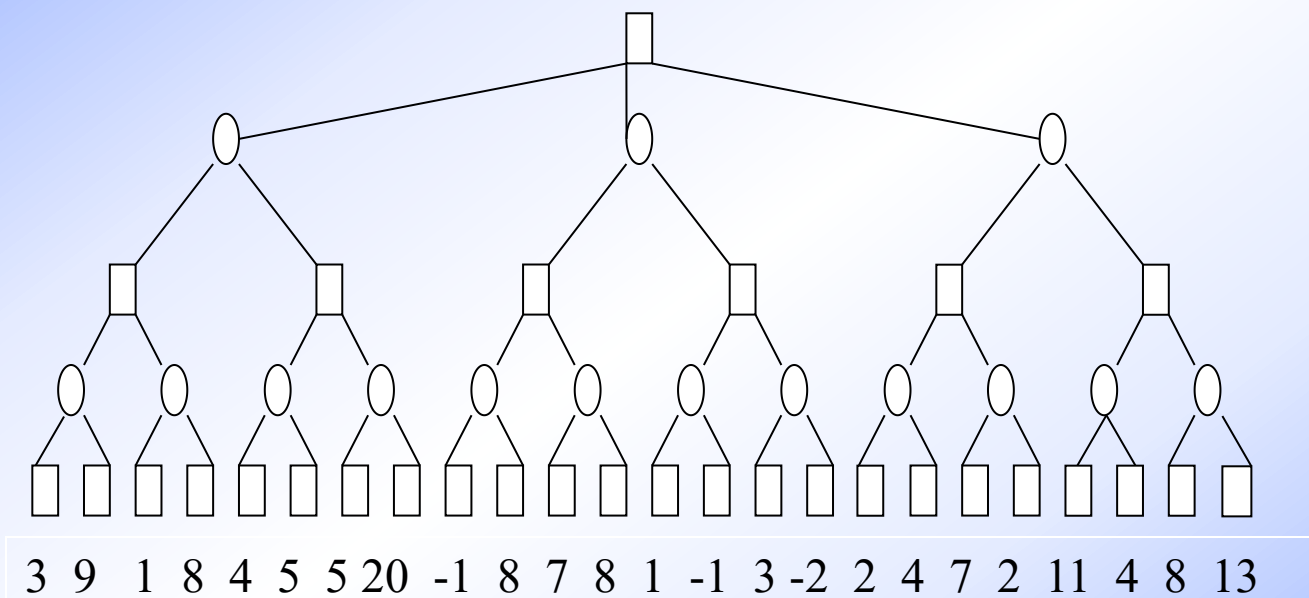
可使用的算符有：空格左移、空格上移、空格右移、空格下移。

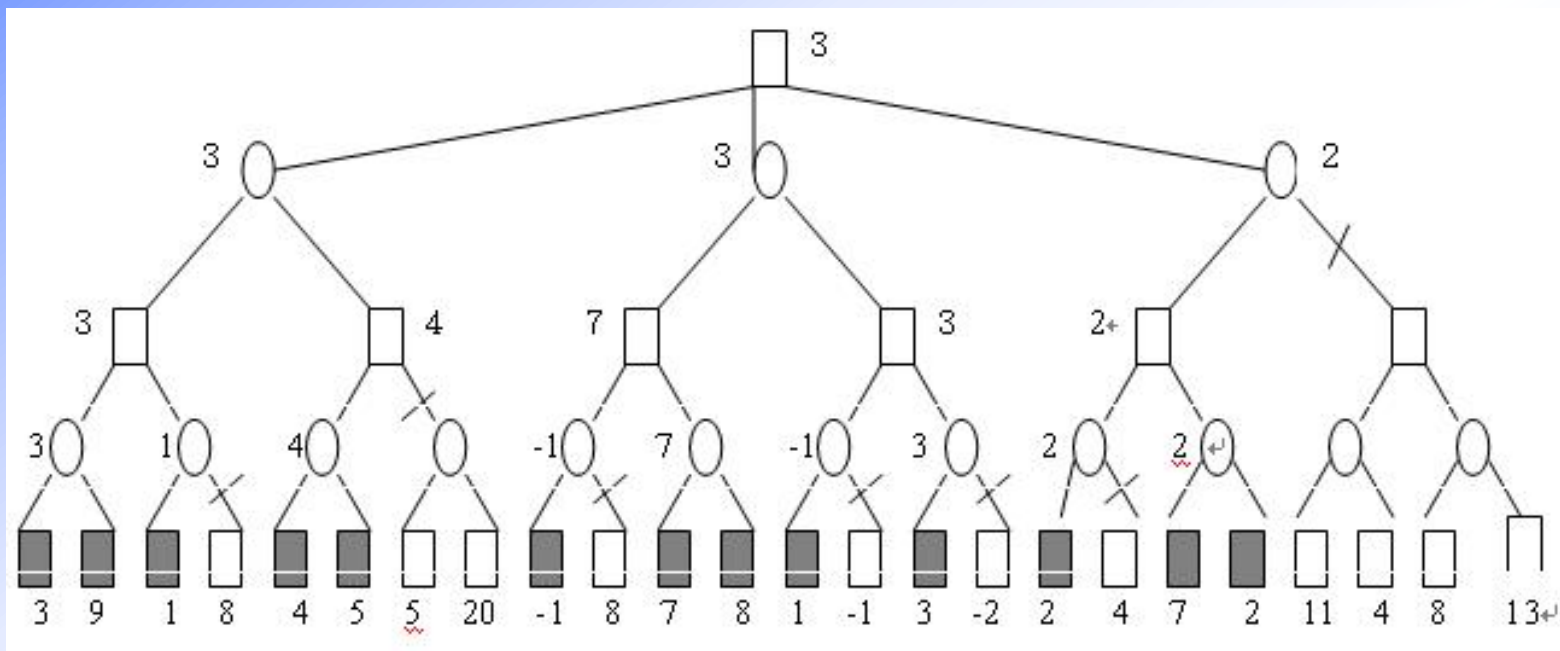
设搜索深度界限 $d_m=5$ ，要求画出搜索图示，并指出解路径。





习题6. 在如下所示博弈树中，按从左到右的顺序进行剪枝搜索，试标明各生成节点的倒退值，何处发生剪枝，及当前应选择的走步。





### [评分标准]:

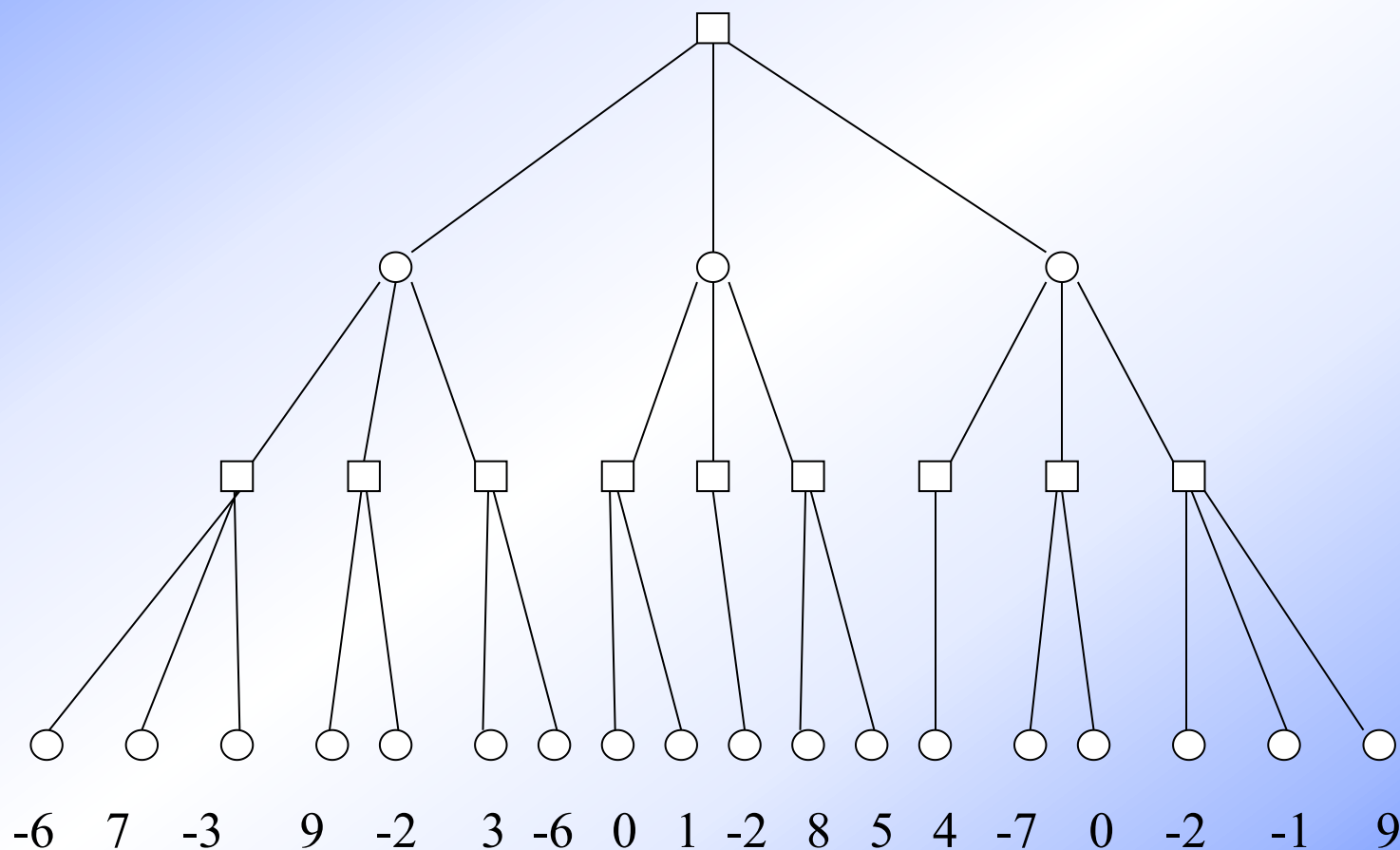
标明各生成节点的倒退值占2分;

标出发生剪枝位置占6分;

选出当前应选择的走步占2分。



习题7. 已知博弈树如图所示，其中方形结点为极大结点，圆形结点为极小结点。用  $\alpha$  -  $\beta$  剪枝法找出当前最佳棋步。  
(要求标明  $\alpha$ 、 $\beta$  值和剪枝位置)



## **Exercises P. 162**

**1.**

**6.**

**13.**

**14.**

**16. Figure 4.23、 4.25**



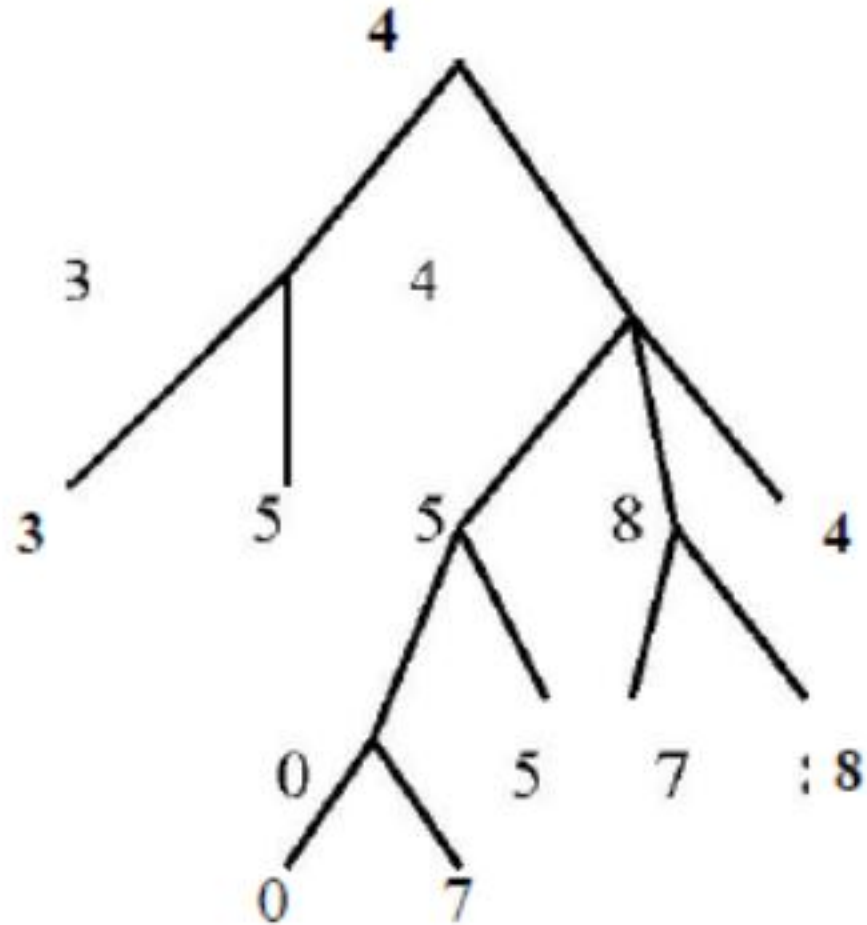
13. Perform MINIMAX on the tree shown in Figure 4.30.

MAX

MIN

MAX

MIN

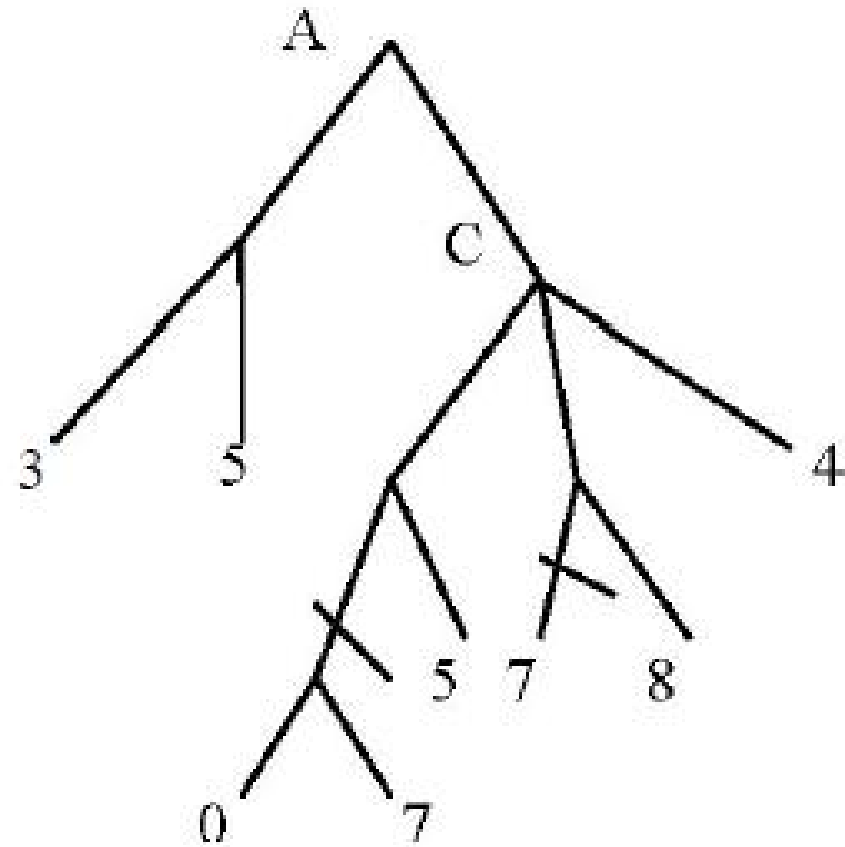


MAX

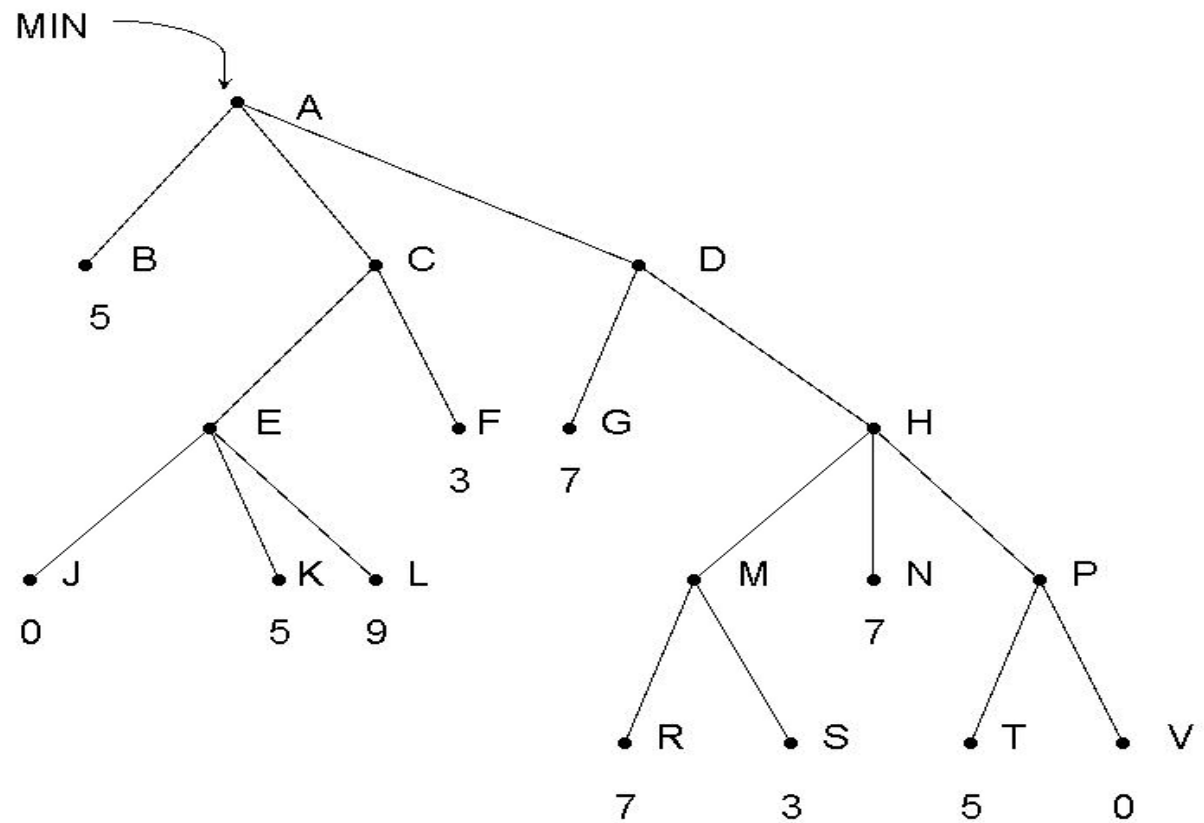
MIN

MAX

MIN

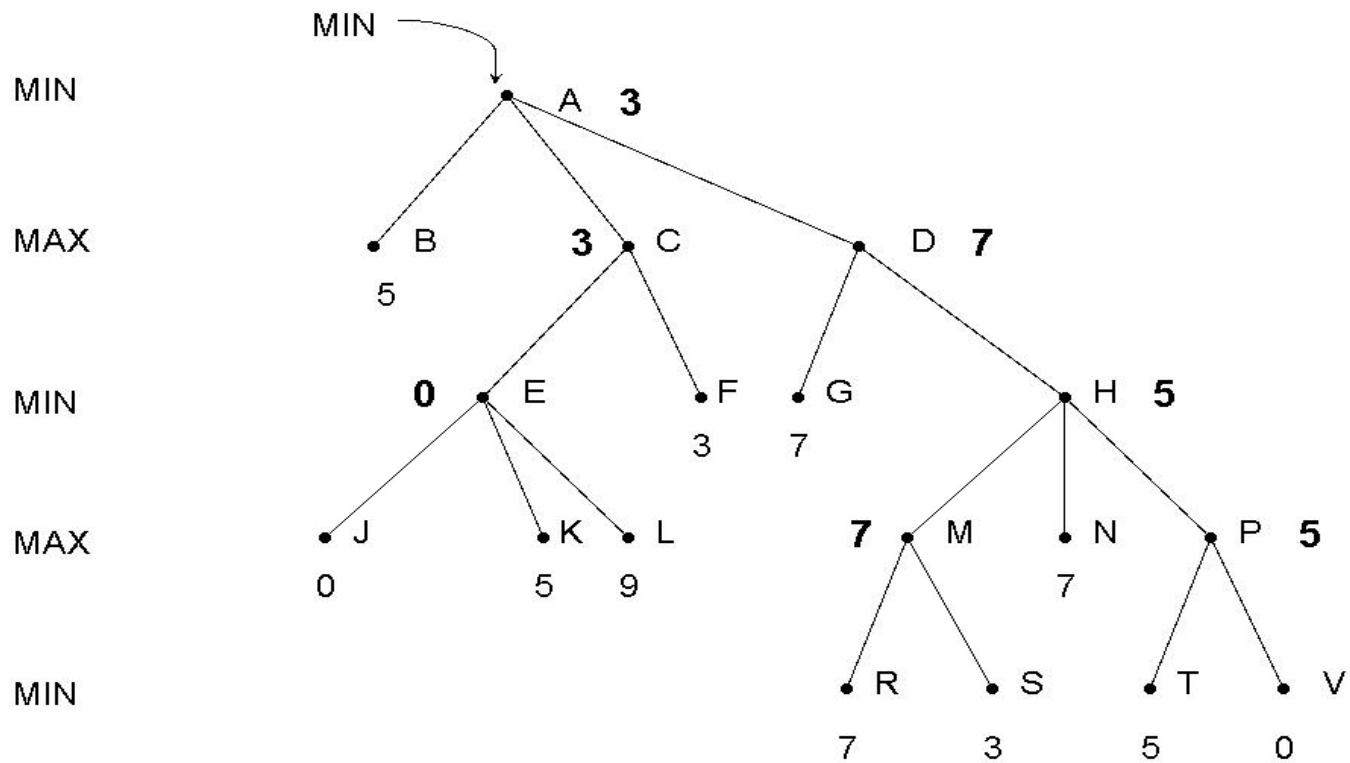


13. Perform minimax on the following tree.



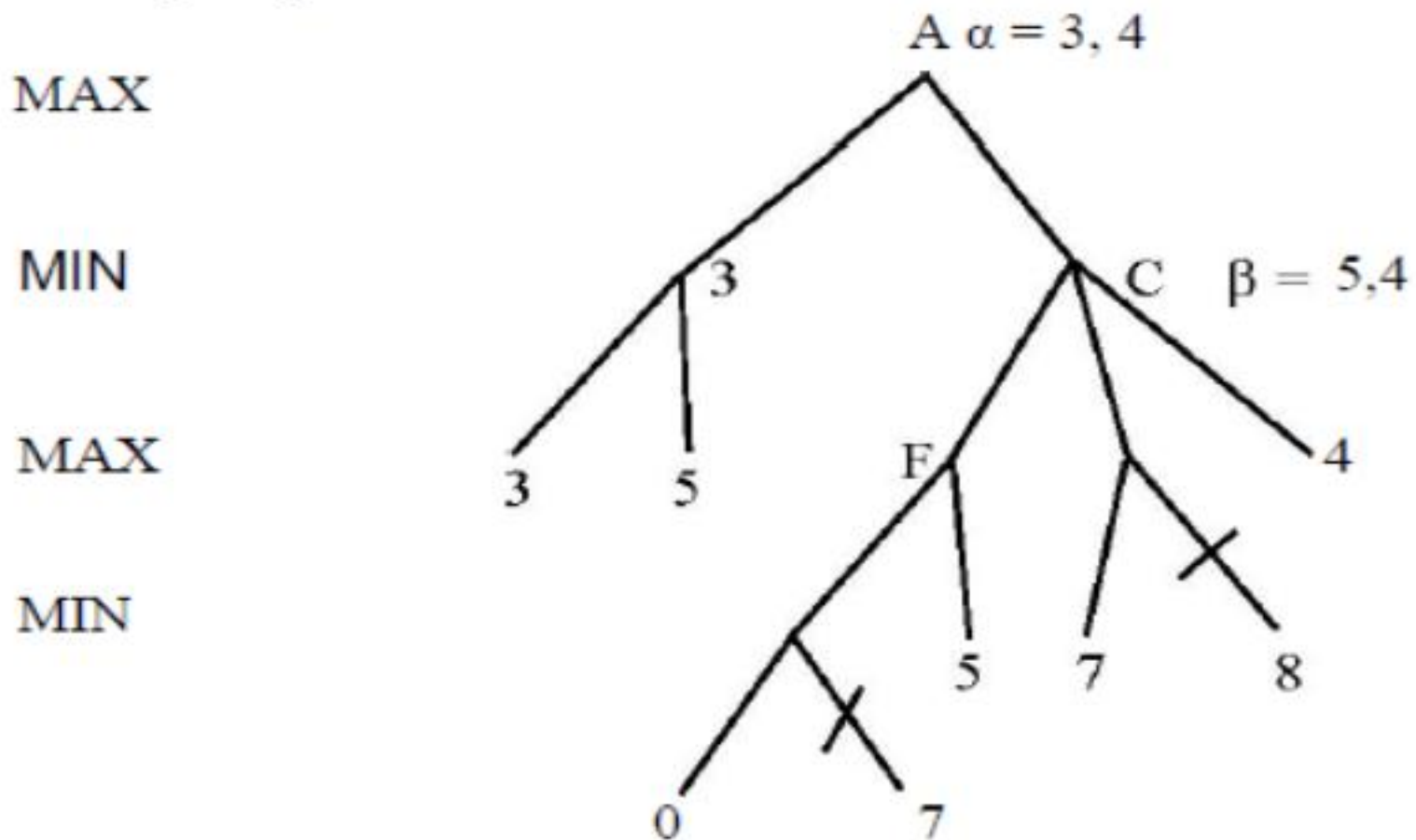


Solution:



**14.** Perform a left-to-right alpha-beta prune on the tree of Exercise 13. Perform a right-to-left prune on the same tree. Discuss why different pruning occurs.

Left-to-right alpha-beta:



MIN on left-most deepest subtree (3,5) to get  $\alpha$  at  $A = 3$ .

From next left-most deepest subtree (0,7), MIN of 0, prune.

F is now 5 and  $\beta$  at  $C = 5$ .

Subtree (7,8) is MAX, so with 7, 8 is  $\beta$  pruned.

Seeing the right-most 4,  $\beta$  at  $C = 4$ , and  $\alpha$  at  $A = 4$ , the final backed up value.

Right-to-left alpha-beta:

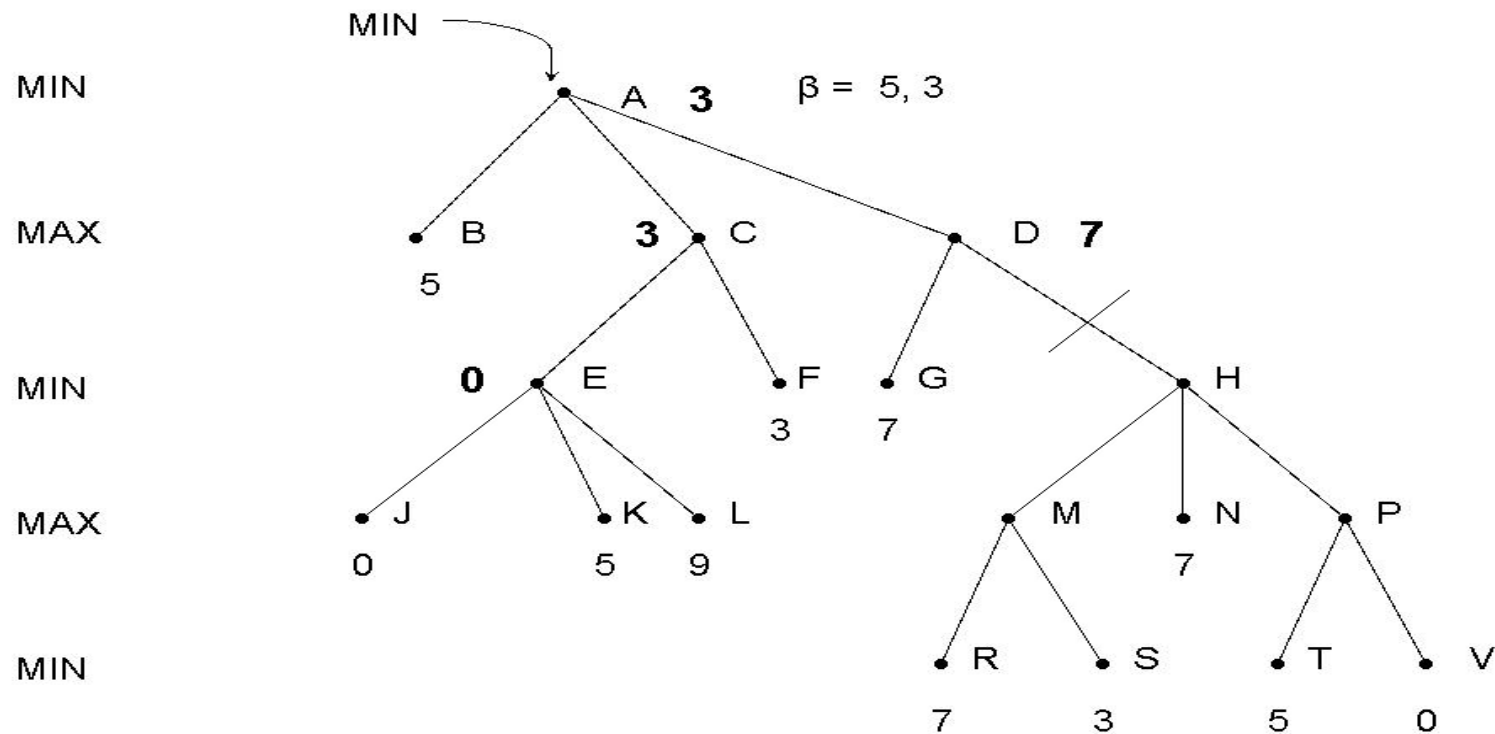


Starting at the right-most deepest subtree, 4 gives  $\beta$  of  $C = 4$ .  
Seeing 8 in subtree (7,8), 7 is  $\beta$ -pruned.  
Seeing 5 next the entire subtree (7,8) is  $\beta$ -pruned.  
A takes on the  $\alpha$  value of 4.  
5 and then 3 are examined (MIN) in the left-most subtree.  
The final value of  $A = 4$ .



14. Perform a left-to-right alpha-beta prune on the tree from Exercise 13. Perform a right-to-left prune on the same tree. Discuss why a different pruning occurs.

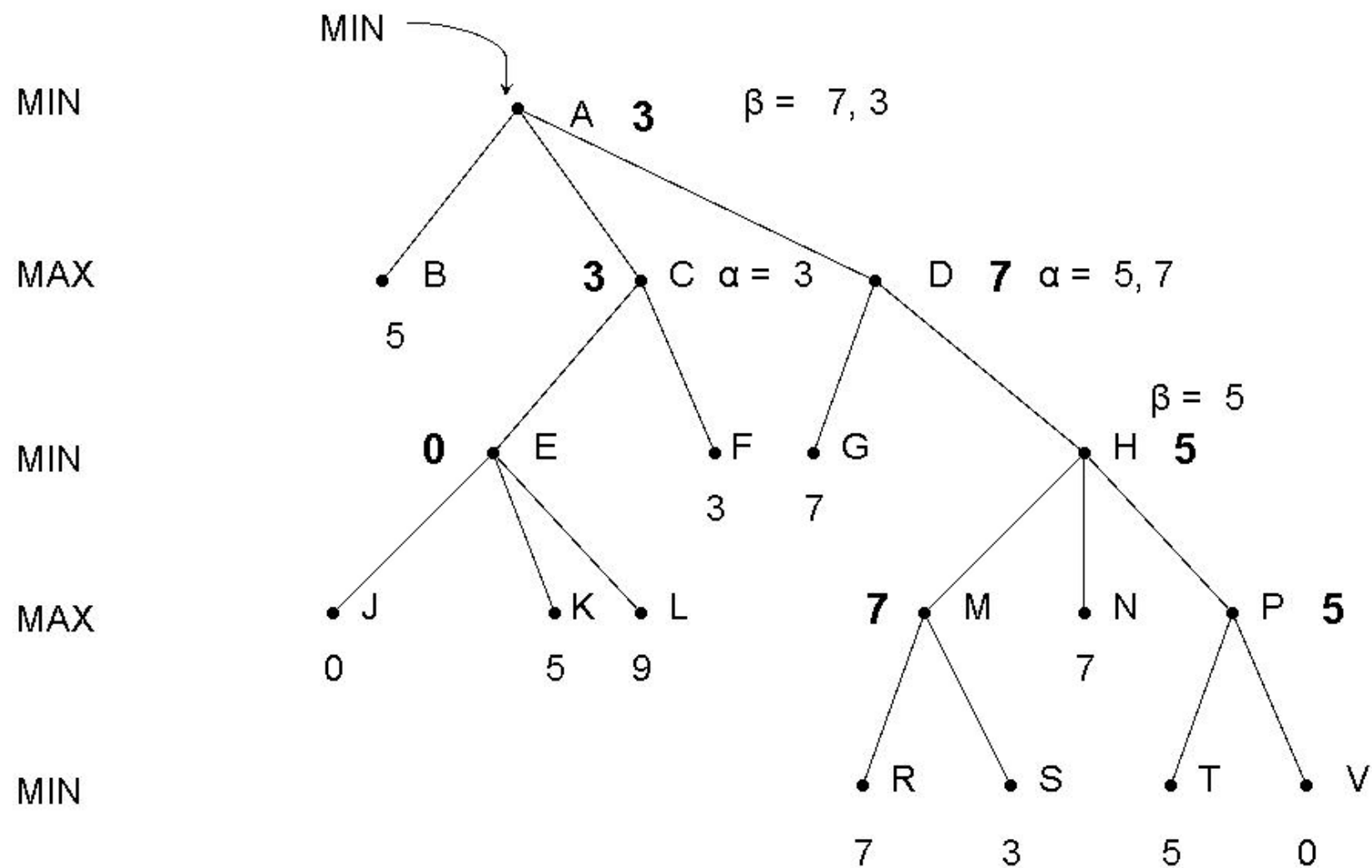
Solution:(Left-to-right)



The tree is searched depth-first from left to right. The value of 5 at node B is reported, and  $\beta$  set to 5. Next the min of (0,5,9) is evaluated and 0 passed to E. C takes the value 3 which is the max of (0,3) and 3 is assigned to  $\beta$ , since 3 is less than 5. When the 7 is found at node G, the right subtree below D can be  $\beta$ -pruned because the value of D will be at least as large as 7, which is greater than the most recent  $\beta$  value of 3.

Right-to-left:







The tree is searched depth first, right to left.  $(0,5)$  are compared, and P is assigned 5. The  $\beta$ -value associated with node H is set to 5, so no subtree below H with a value greater than 5 need be considered. We look next at node N, which is 7. We could not prune N because we had to look at it to determine its value. Next, node S is searched, which gives a value of 3. Since this will potentially change the value of  $\beta$  at H, we have to search R, which gives us 7 at M and 5 at H. We set the  $\alpha$  value at node D to 5 because we do not need to consider any min grandchild of D whose value is less than 5. D only has one other grandchild, and its value is 7, so the  $\alpha$  associated with D is set to 7.



The  $\beta$  value of the root node is set to 7, and no child of the root evaluating to more than 7 need to be considered further. The next node evaluated is F, which has a value of 3, and the  $\alpha$  value associated with C is set to 3, and no node whose value is greater than 3 need be considered. However, L, K, and J have to be evaluated because L, and K both have values greater than 3. Thus 0 is assigned to E, and 3 is assigned to the  $\beta$  value associated with the root. The final node, B, cannot be pruned because although its value is greater than the last  $\beta$  value of the root, it has to be examined to determine this.

