



**Figure 5.2** A two-ply game tree. The  $\triangle$  nodes are “MAX nodes,” in which it is MAX’s turn to move, and the  $\nabla$  nodes are “MIN nodes.” The terminal nodes show the utility values for MAX; the other nodes are labeled with their minimax values. MAX’s best move at the root is  $a_1$ , because it leads to the state with the highest minimax value, and MIN’s best reply is  $b_1$ , because it leads to the state with the lowest minimax value.

MIN, then MAX’s moves in the states resulting from every possible response by MIN to those moves, and so on. This is exactly analogous to the AND-OR search algorithm (Figure 4.11) with MAX playing the role of OR and MIN equivalent to AND. Roughly speaking, an optimal strategy leads to outcomes at least as good as any other strategy when one is playing an infallible opponent. We begin by showing how to find this optimal strategy.

Even a simple game like tic-tac-toe is too complex for us to draw the entire game tree on one page, so we will switch to the trivial game in Figure 5.2. The possible moves for MAX at the root node are labeled  $a_1$ ,  $a_2$ , and  $a_3$ . The possible replies to  $a_1$  for MIN are  $b_1$ ,  $b_2$ ,  $b_3$ , and so on. This particular game ends after one move each by MAX and MIN. (In game parlance, we say that this tree is one move deep, consisting of two half-moves, each of which is called a **ply**.) The utilities of the terminal states in this game range from 2 to 14.

Given a game tree, the optimal strategy can be determined from the **minimax value** of each node, which we write as  $\text{MINIMAX}(n)$ . The minimax value of a node is the utility (for MAX) of being in the corresponding state, *assuming that both players play optimally* from there to the end of the game. Obviously, the minimax value of a terminal state is just its utility. Furthermore, given a choice, MAX prefers to move to a state of maximum value, whereas MIN prefers a state of minimum value. So we have the following:

$$\text{MINIMAX}(s) = \begin{cases} \text{UTILITY}(s) & \text{if TERMINAL-TEST}(s) \\ \min_{a \in \text{Actions}(s)} \text{MINIMAX}(\text{RESULT}(s, a)) & \text{if PLAYER}(s) = \text{MAX} \\ \max_{a \in \text{Actions}(s)} \text{MINIMAX}(\text{RESULT}(s, a)) & \text{if PLAYER}(s) = \text{MIN} \end{cases}$$

Let us apply these definitions to the game tree in Figure 5.2. The terminal nodes on the bottom level get their utility values from the game’s **UTILITY** function. The first MIN node, labeled  $B$ , has three successor states with values 3, 12, and 8, so its minimax value is 3. Similarly, the other two MIN nodes have minimax value 2. The root node is a MAX node; its successor states have minimax values 3, 2, and 2; so it has a minimax value of 3. We can also identify

the **minimax decision** at the state with the highest utility. This definition of minimax value is used to show (Exercise 5.2) that opponents may do better against optimal play.

### 5.2.1 The minimax algorithm

The **minimax** algorithm uses a simple implementation of the tree. It winds, left node to right node, up value or down value. Finally, we take the maximum of the values.

The **minimax algorithm** is:

If the maximum depth of the tree is  $d$ , the time complexity of the minimax algorithm is  $O(n^d)$ , where  $n$  is the number of actions at once, or  $O(n^d)$  one at a time (see page 87). For real games, of course, the algorithm serves as the basis for the mathematical analysis of practical algorithms.

### 5.2.2 Optimal decisions in multiplayer games

Many popular games allow more than two players. Let us examine how to extend the idea to multiplayer games. This is straightforward from the technical viewpoint, but some interesting new conceptual issues.

First, we need to replace the single value for each node with a **vector** of values with each node. For terminal states, this vector gives the utility of the state from each player’s viewpoint. (In two-player, zero-sum games, the two-element vector can be reduced to a single value because the values are always opposite.) The simplest way to implement this is to use the **UTILITY** function return a vector of utilities.

Now we have to consider nonterminal states. Consider the node marked  $X$  in the tree shown in Figure 5.4. In that state, player  $C$  chooses what to do. The two choices to terminal states with utility vectors  $\langle v_A = 1, v_B = 2, v_C = 6 \rangle$  and  $\langle v_A = 4, v_B = 2, v_C = 6 \rangle$ . Since 6 is bigger than 3,  $C$  should choose the first move. This means that if state  $X$  is reached, subsequent play will lead to a terminal state with utilities  $\langle v_A = 1, v_B = 2, v_C = 6 \rangle$ . If the backed-up value of  $X$  is this vector. The backed-up value of a node  $n$  is always the

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CONTINUOUS DOMAINS

Constraint satisfaction problems are widely used in the world and are widely used in the start and finish of experiments on the must obey a variety of category of constraints must be in time position and objectives of the program

UNARY CONSTRAINT  
BINARY CONSTRAINT

