

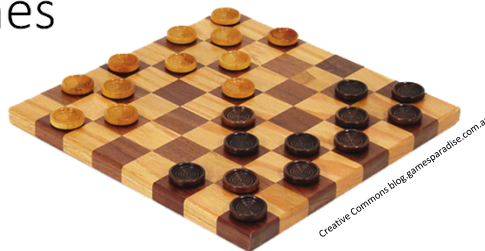


Adversarial Search

Professor Marie Roch
Chapter 5, Russell & Norvig



Two player games



Primary focuses

- Zero-sum games: What's good for you is bad for me
- turn-based (alternating)
- perfect information
- pruning: Removing portions of search tree



Game search problem

- initial state
- player – turn indicator
- actions – Set of legal actions
- $\text{result}(\text{state}, \text{action})$ – Result of player taking action
- $\text{terminal-test}(\text{state})$ – game over predicate
- $\text{utility}(\text{state}, \text{player})$ – utility of state for specified player

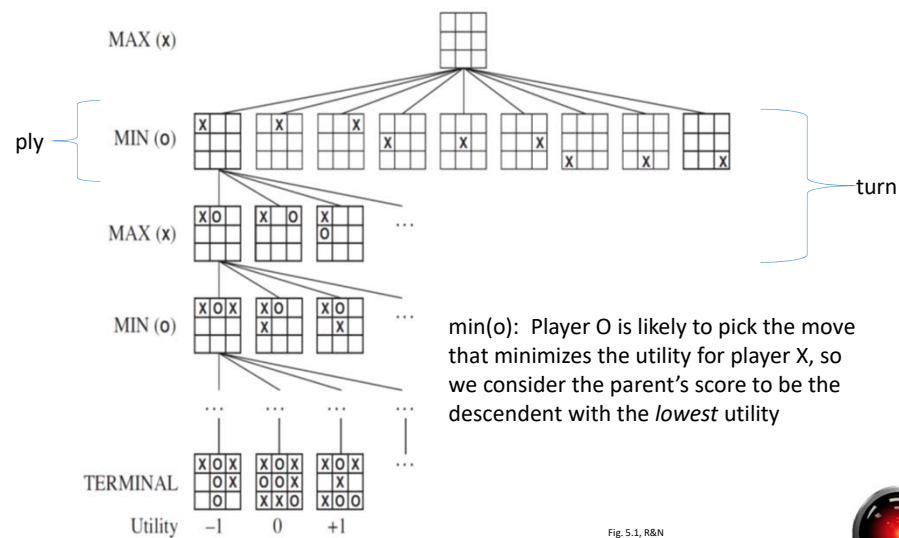


Game tree

- Game tree – exploration of the game search space
- Can be large
 - Chess – average branch factor 35
(about 10^{40} distinct nodes, and 10^{154} states in a 50 move game)
 - Checkers, about 10^{40}
- Turn consists of two plys
- Frequently use the same utility function, maximizing for one player and minimizing for the other



Tic-tac-toe



Minimax algorithm

```

minimax(state)
    return arg(maxa ∈ actions(state) minval(result(state,a)))

maxval(state)
    if terminal(state), v = utility(state)
    else
        v = -∞
        for a in actions(state)
            v = max(v, minval(result(state, a)))
        return v

minval(state)
    if terminal(state), v = utility(state)
    else
        v = ∞
        for a in actions(state)
            v = min(v, maxval(result(state, a)))
        return v

```

Trivial game tree

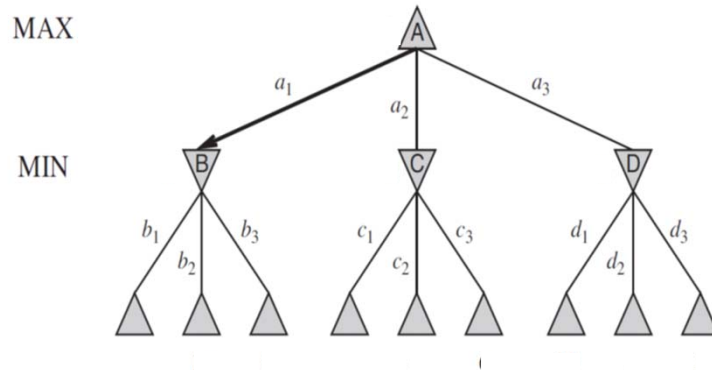


Fig. 5.2, R&N

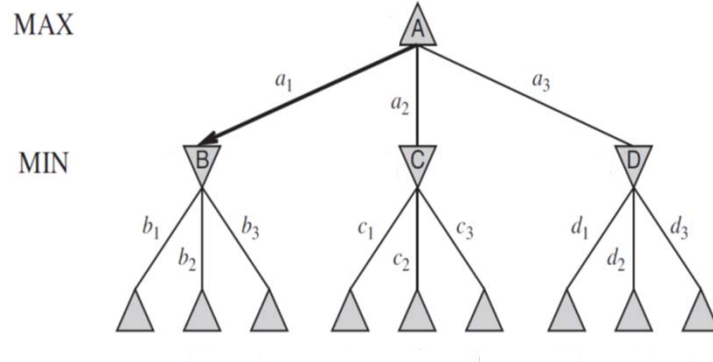


```

minimax(A)
  return arg(maxa ∈ actions={a1,a2,a3}(A) minval(result(A,a)))

minval(B)
  if terminal(B), v = utility(B)
  else
    v = ∞
    for a in {b1,b2,b3}
      v = min(v, maxval(result(B, a)))
  return v

```



Trivial game tree



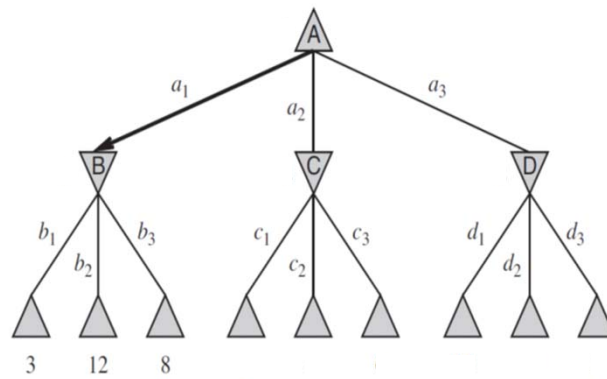
```

maxval(state)
  if terminal(state), v = utility(state)
  else
    v = -∞
    for a in actions(state)
      v = max(v, minval(result(state, a)))
  return v

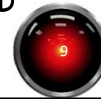
```

MAX

MIN



Trivial game tree



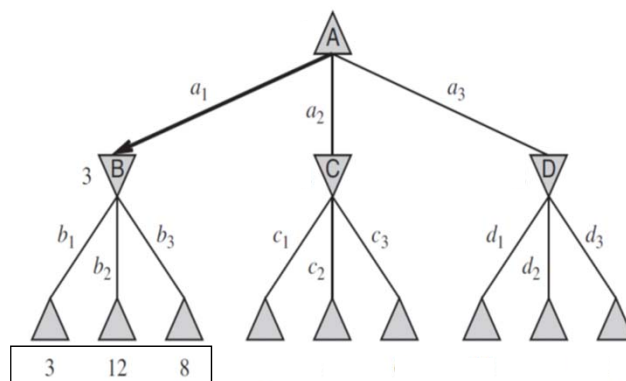
```

minval(B)
  if terminal(B), v = utility(B)
  else
    v = ∞
    for a in {b1, b2, b3}
      v = min(v, maxval(result(B, a)))
  return v

```

MAX

MIN



Trivial game tree



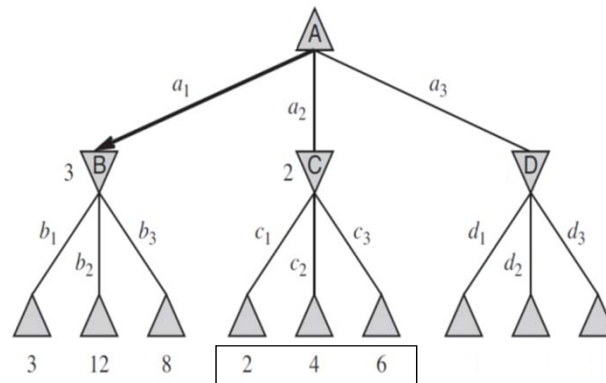
```

minval(C)
  if terminal(C), v = utility(C)
  else
    v = ∞
    for a in {c1, c2, c3}
      v = min(v, maxval(result(C, a)))
  return v

```

MAX

MIN



Trivial game tree



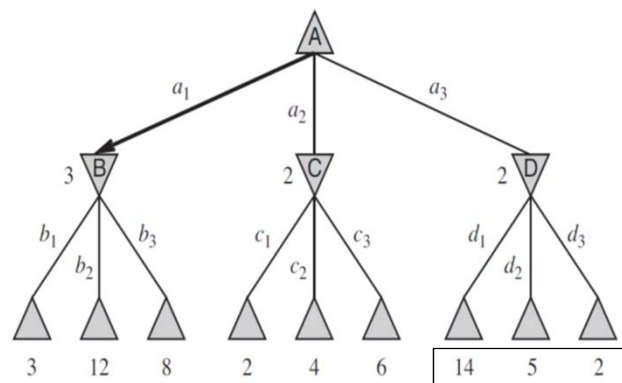
```

minval(C)
  if terminal(C), v = utility(C)
  else
    v = ∞
    for a in {c1, c2, c3}
      v = min(v, maxval(result(C, a)))
  return v

```

MAX

MIN



Trivial game tree



```

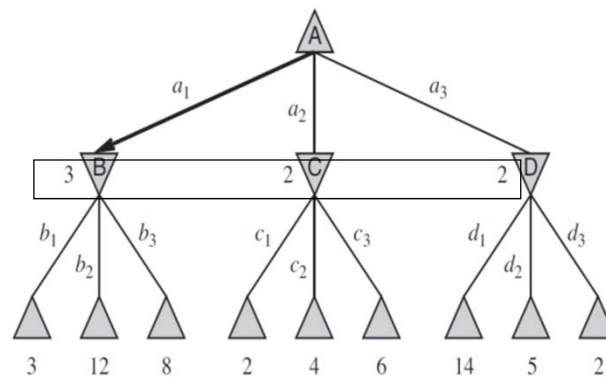
minimax(A)
  return arg(maxa ∈ {a1,a2,a3}(A) minval(result(A,a)))

best move a1!

```

MAX

MIN

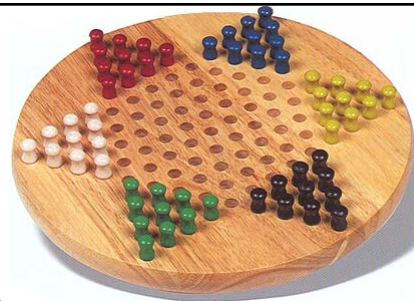


Trivial game tree



Multiplayer games

- Replace utility value with utility vector: $[u_1, u_2, \dots, u_N]$
- When evaluating nodes, utility is interpreted as a function of the utility vector and the agent that produced the node.
 - Every player for themselves: $u(i) = u_i$
 - Alliances $u(i) = f([u_1, u_2, \dots, u_N])$



Multiplayer games (u_A, u_B, u_C)

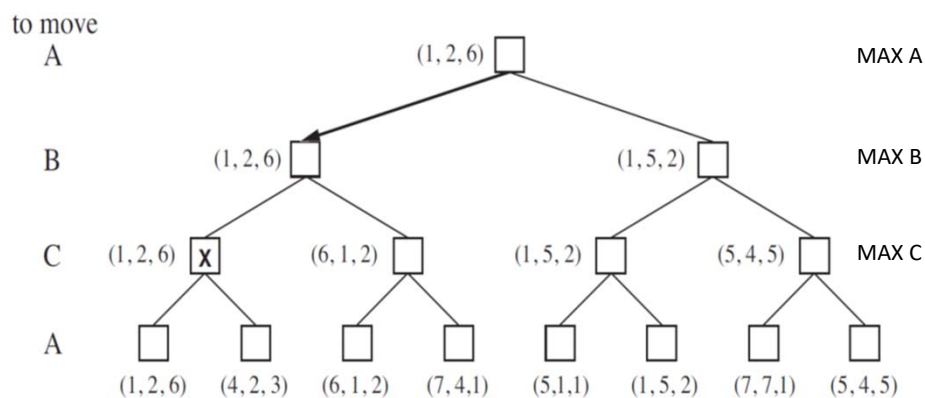


Fig. 5.3, R&N



Game tree size

- Non-trivial trees are large

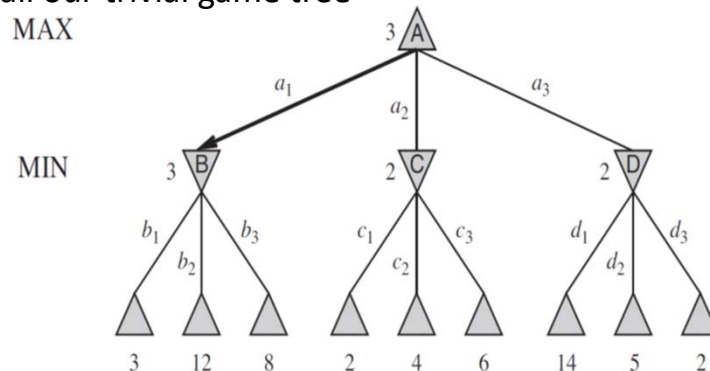


- Strategies to reduce search size:
 - alpha-beta pruning – Remove subtrees that can't influence the decision
 - move-ordering – order affects pruning performance
 - cutoff – Don't evaluate all the way to terminal nodes

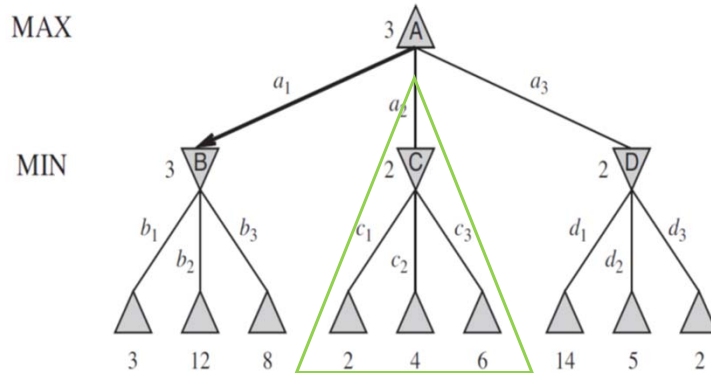


alpha-beta pruning

Recall our trivial game tree



alpha-beta pruning



depth 1
 $\max(3, 2, 2)$
 $\max(3, \min(2, 4, 6), 2)$

once we know 2, we don't need to look at siblings...



alpha-beta pruning

- Prune partial computations

- $\max(a_{\min}, \min(\dots < a_{\min} \dots))$
example from earlier slide
 $\max(\min(3, 12, 8), \min(2, 4, 6), \min(14, 5, 2))$

- $\min(a_{\max}, \max(\dots > a_{\max} \dots))$

- Can be applied at any depth in tree

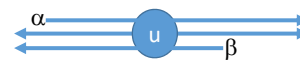
- Does not change minimax decision



Bounding a node

- Possible values for a node

- α - lower bound
 - β - upper bound



- α - β pruning looks for situations where $\alpha > \beta$



as these are not viable solutions

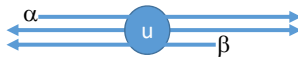


Bounding a node

- Try to increase lower bound of max nodes



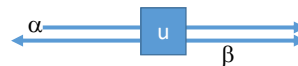
- Try to decrease upper bound of min nodes



Bounding a node

- Max nodes – loop children

If min node child value $\geq \beta$
 return child value
 else see if we can increase lower bound α



- Min nodes – loop children

if max node child value $\leq \alpha$
 return child value
 else see if we can decrease upper bound β

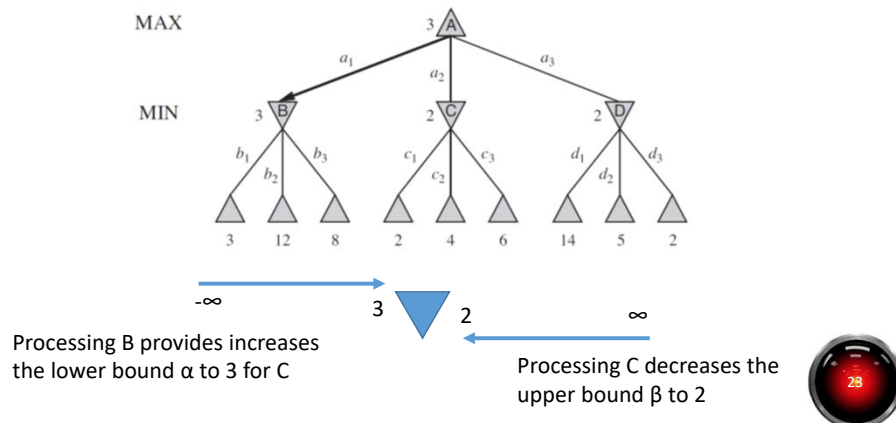


Formal algorithm later, this is just to build your intuition

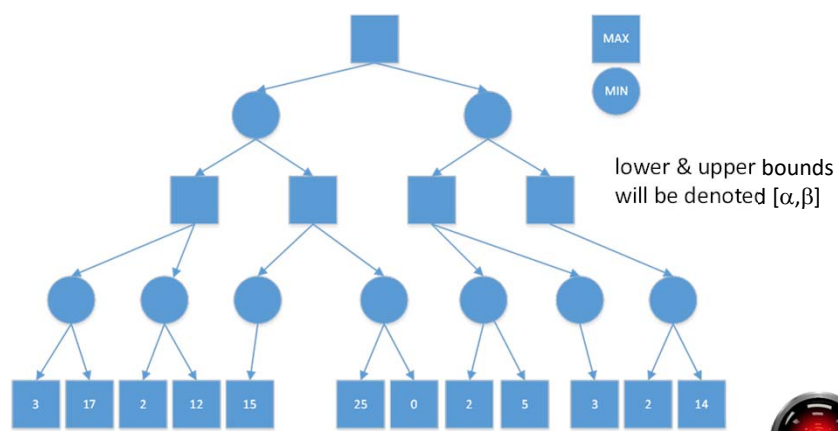


Bounding example:

$\max(\min(3, 12, 8), \min(2, 4, 6), \min(14, 5, 2))$

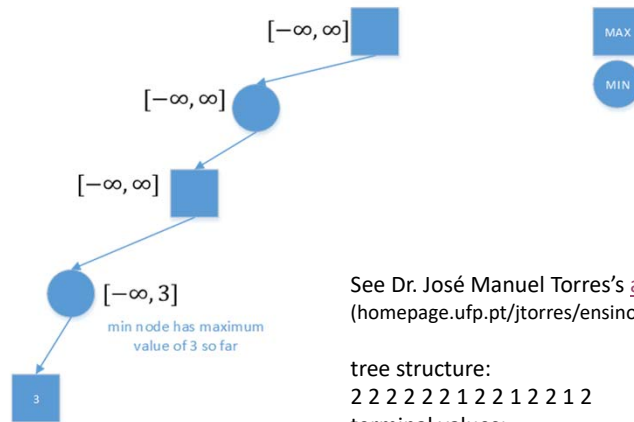


game tree

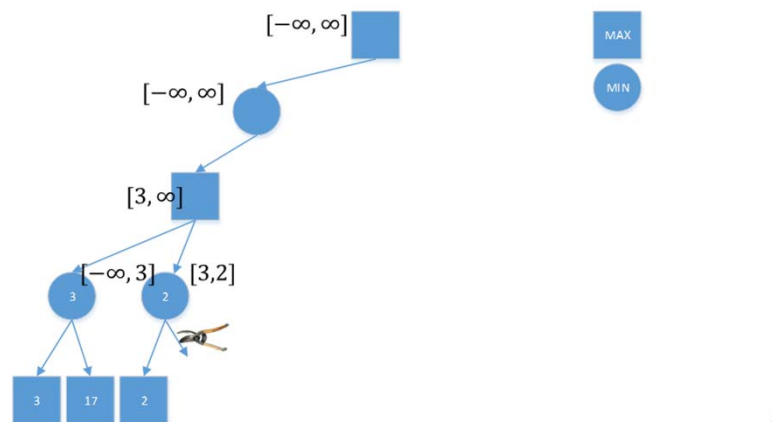


Game tree credit: Bruce Boncy, UCLA

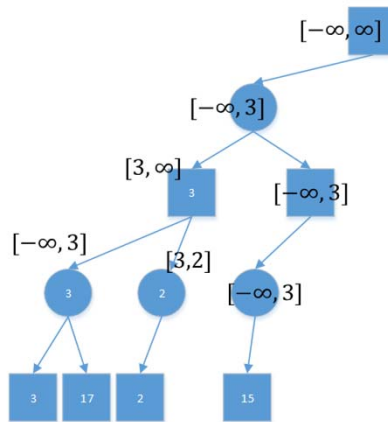
bounding a node



bounding a node



bounding a node



each node has $[\alpha, \beta]$
 α - lower bound
 β - upper bound



This case is tricky, let's look at the algorithm in detail before we proceed.



alpha-beta algorithm

```

alpha-beta search(state)
  v = maxvalue(state,  $\alpha=-\infty$ ,  $\beta=\infty$ )
  return action in actions(state) with value v

maxvalue(state,  $\alpha$ ,  $\beta$ )
  if terminal(state) then v = utility(state)
  else
    v =  $-\infty$ 
    for a  $\in$  actions(state)
      v = max(v, minvalue(result(state, a),  $\alpha$ ,  $\beta$ ))
      if v  $\geq$   $\beta$  then break else  $\alpha = \max(\alpha, v)$ 
    return v

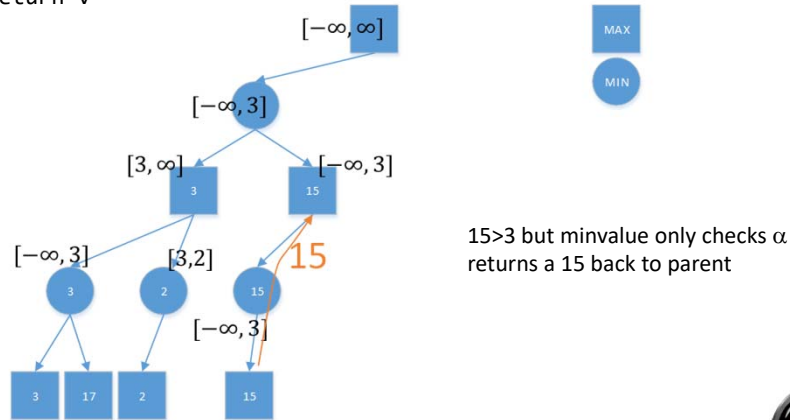
minvalue(state,  $\alpha$ ,  $\beta$ )
  if terminal(state) then v = utility(state)
  else
    v =  $\infty$ 
    for a  $\in$  actions(state)
      v = min(v, maxvalue(result(state, a),  $\alpha$ ,  $\beta$ ))
      if v  $\leq$   $\alpha$  then break else  $\beta = \min(\beta, v)$ 
    return v
  
```



```

minvalue(state,  $\alpha$ ,  $\beta$ )
  if terminal(state) then  $v$  = utility(state)
  else
     $v$  =  $\infty$ 
    for  $a \in \text{actions}(\text{state})$ 
       $v$  = min( $v$ , maxvalue(result(state,  $a$ ),  $\alpha$ ,  $\beta$ ))
      if  $v \leq \alpha$  then break else  $\beta$  = min( $\beta$ ,  $v$ )
  return  $v$ 

```



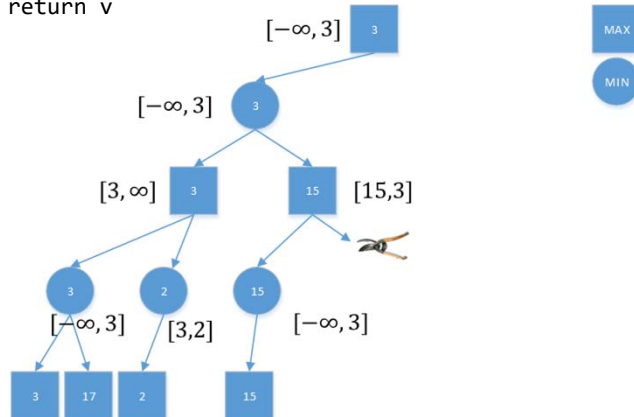
15 > 3 but minvalue only checks α
returns a 15 back to parent



```

maxvalue(state,  $\alpha$ ,  $\beta$ )
  if terminal(state) then  $v$  = utility(state)
  else
     $v$  =  $-\infty$ 
    for  $a \in \text{actions}(\text{state})$ 
       $v = \max(v, \text{minvalue}(\text{result}(\text{state}, a), \alpha, \beta))$ 
      if  $v \geq \beta$  then break else  $\alpha = \max(\alpha, v)$ 
  return  $v$ 

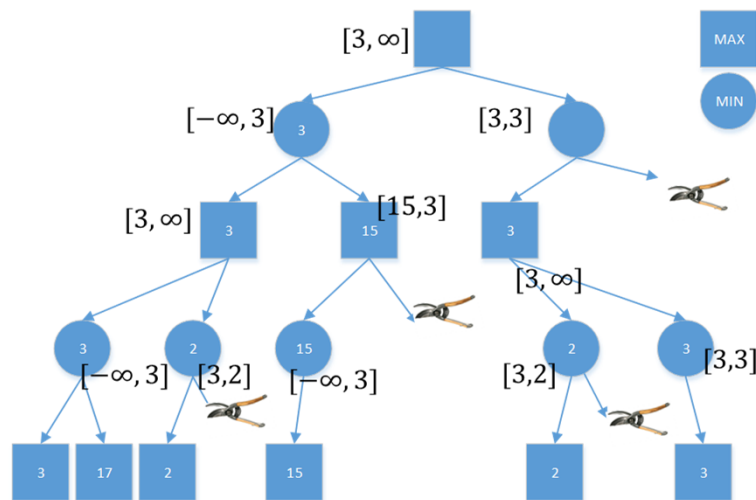
```



proceed along right subtree at home

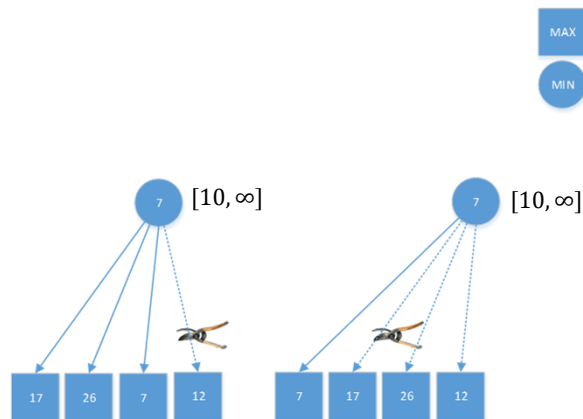


final tree



Move ordering

- α - β pruning sensitive to order value



Move ordering

- killer move heuristic
 - iterative deepening search to ply above
 - use heuristic value to order nodes
- games frequently have repeated states
 - *transposition table* stores heuristic of visited states
 - only store good states (heuristic required)
 - favor states in transposition table



Okay, so you're not Brad Pitt



Imperfect real-time decisions

- Replace utility function with an evaluation function
 - examines non-terminals
 - heuristic giving strength of current state
- How deep should we search?
 - cutoff test provides decision of whether to explore or apply evaluation function



Evaluation function

- Estimate of the expected utility
- Performance strongly linked to evaluation function choice.
- Guidelines
 - Order terminal states in the same order as the utility function, e.g. $u(a) \leq u(b) \leq u(c) \rightarrow e(a) \leq e(b) \leq e(c)$
 - Estimator should be
 - correlated with odds of winning
 - fast

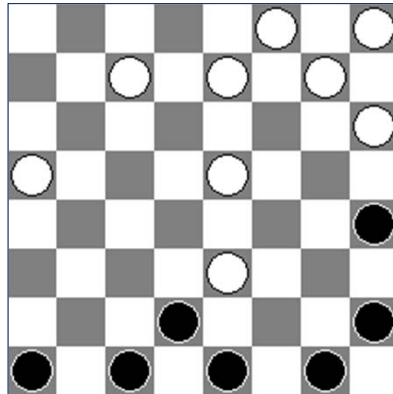


Features...

help us identify something based on state or percept.



Who has the better position?



Possible features for checkers?

Most features are relative to the opponent.
Count player & opponent and subtract one from other

- Number of pieces
- Number of kings
- Offense
 - Advance of pawns (# moves away from being kinged... sum, mean, max)
 - Number of possible: moves, captures (by pawn/king?)



Possible features for checkers?

- Defense, are pieces
 - On edges of board? (better defended)
 - protected by neighbors of the same color (good) or menaced by neighbors of the opposite color (bad)?
- These features need to be weighted and combined, typically as a weighted linear combination

$$f_{eval}(board) = \sum_{i=1}^{\#features} w_i f_i(board)$$

- Determine weights?
 - genetic algorithms?
 - other learning techniques? (beyond our reach for now)



Pruning search

- Game-tree search → \$\$\$
- Replace terminal-test with

if cutoff-test(state, depth), return $f_{eval}(board)$

- How do we define this?



Opening moves



excerpted from chess.com blog post by MonsterKing 2011/7/26

Lookup

- Reasonable to search billion game-tree nodes to move a pawn at beginning of game?
- Common to rely on table lookup for openings.
Rely on human experience

Lookup and retrograde search

- Endgames
 - Have a reduced search space
 - *retrograde search* - Backwards minimax search backwards from terminal states



Stochastic games

- Consist of
 - probability distributions
 - strategy contingent on probabilities
- Game trees need to somehow incorporate chance
- We will review a few concepts about probability before diving in



Probability Distributions

- Show the probability of an event happening.
 - Distributions are nonnegative
 - Must sum to 1
- Example with a die
 - $P(X=3)$ denotes the probability of rolling a 3
 - Fair die $\rightarrow P(X=3) = 1/6$
- Distributions of continuous variables are sometimes described by parameterized formulae



Probability distributions

- Some games depend on independent events
- Example – Roll two dice
- Probabilities that are independent can be multiplied.

$$P(R=1)P(G=6) = \frac{1}{6} \cdot \frac{1}{6} = \frac{1}{36}$$



- Many times, we only care about the probability of 1 and 6, not which die produced it. How do we do this?



Expectation operator

$$E[u(X)] = \sum_x u(X = x) P(X = x)$$

When $u(X) = X$, we call this the mean, or average value:

$$\mu = E[X]$$

Notes

- Distinguish between a random variable X and an instance of a random variable x .
- The $X=x$ notation is frequently dropped and just x is used.
- $P(x)$ is frequently denoted as $f(x)$



Backgammon

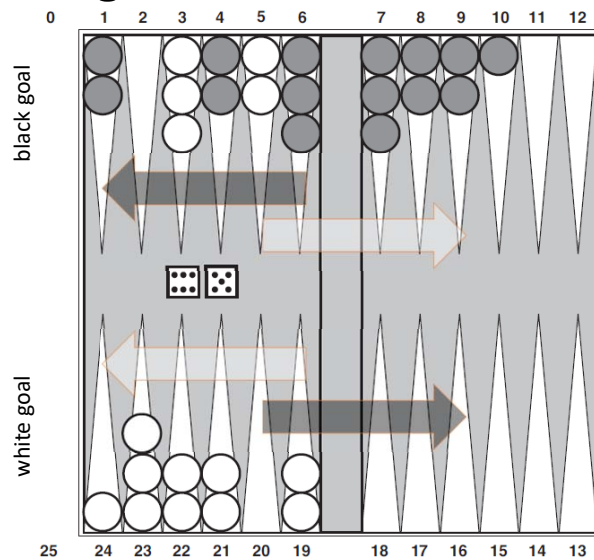
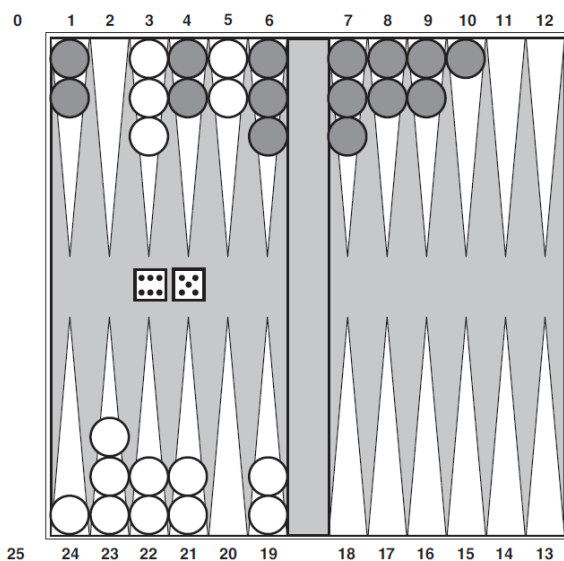


Fig. 5.10, R&N



Backgammon



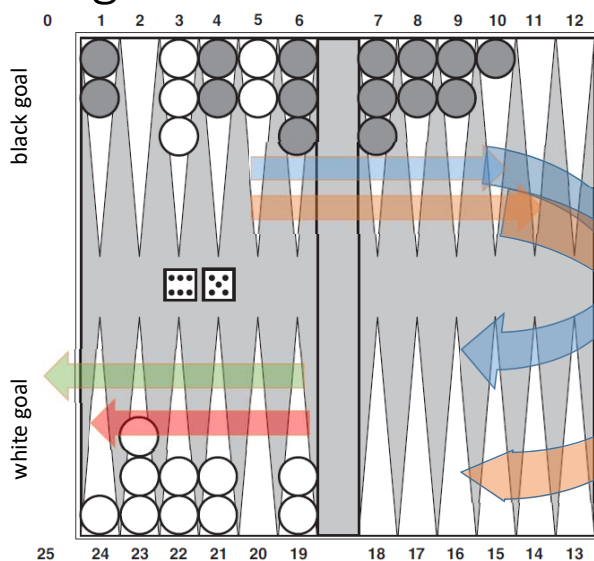
Rules in a nutshell
(not everything)



- Move into goal by exact count
- Can capture opponent and send to bar by landing on a *single* opponent.
- Roll can be divided amongst pieces or combined



Backgammon



moves

blue + orange

blue + blue

blue + green

orange + orange

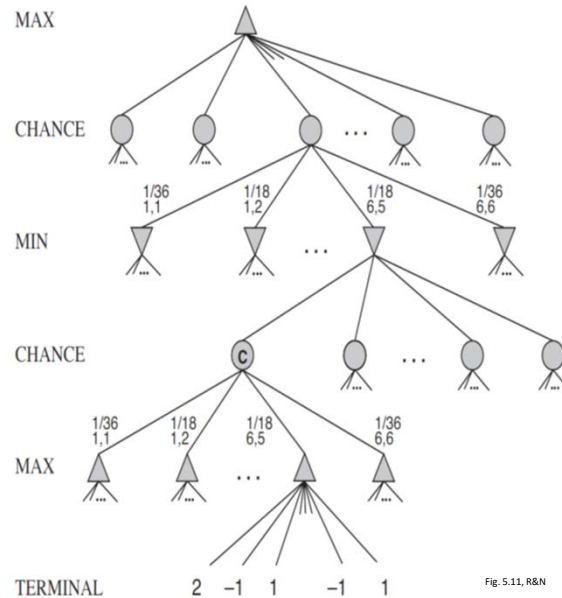
orange + red

green + red



Stochastic game search

- Incorporate chance nodes into min/max search tree
- Each edge denotes an outcome with a probability



Stochastic game search

- Minimax search is still the goal but how do we pick extrema in the face of uncertainty?
- For each chance node, compute the expected outcome



Stochastic minimax

```
Eminimax(searchnode):
    switch type of searchnode:
        case terminal:
            return utility(searchnode.state)
        case maxnode:
            return arg maxa ∈ actions (Eminimax(result(searchnode, a)))
        case minnode:
            return arg mina ∈ actions (Eminimax(result(searchnode, a)))
        case chance:
            Eminimax =  $\sum_{r \in \text{roll}} P(r) \text{Eminimax}(\text{result}(\text{searchnode}, r))$ 
```

note: multiple actions may be associated with a roll, so last case is a little more complicated.



Stochastic games and evaluation

- Not as clear as with deterministic games
- Consider possible values for three game states

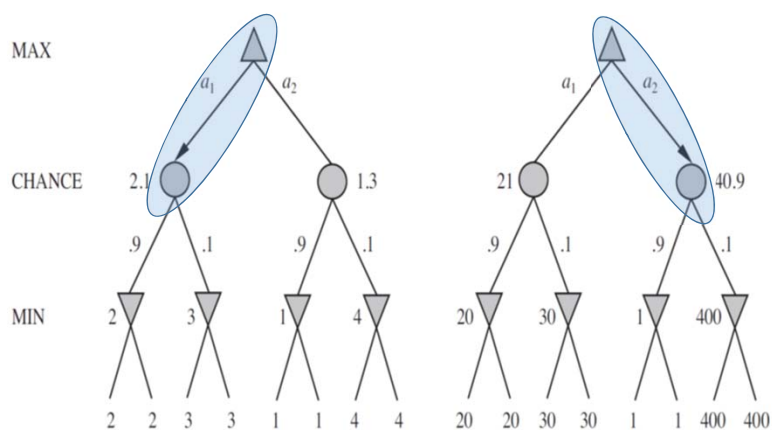
State	1	2	3	4
eval fn A	1	2	3	4
eval fn B	10	20	30	400

In a standard minimax routine, we would come up with the same solution, it is the relative ordering that is important.

What about here?



Stochastic games and evaluation



State	1	2	3	4
eval fn A	1	2	3	4
eval fn B	10	20	30	400



Stochastic minimax search

- Chance dramatically increases the branching factor
- Common not to search for more than a few plys
- It is possible to modify alpha-beta pruning to work on bounds of expected values [beyond our scope]



Stochastic search

Monte-Carlo simulations are an alternate strategy



- Play millions of games using some search algorithm
- Assign state values based on results of wins/losses of the millions of simulated games



Partial information

you will not be held responsible for this material

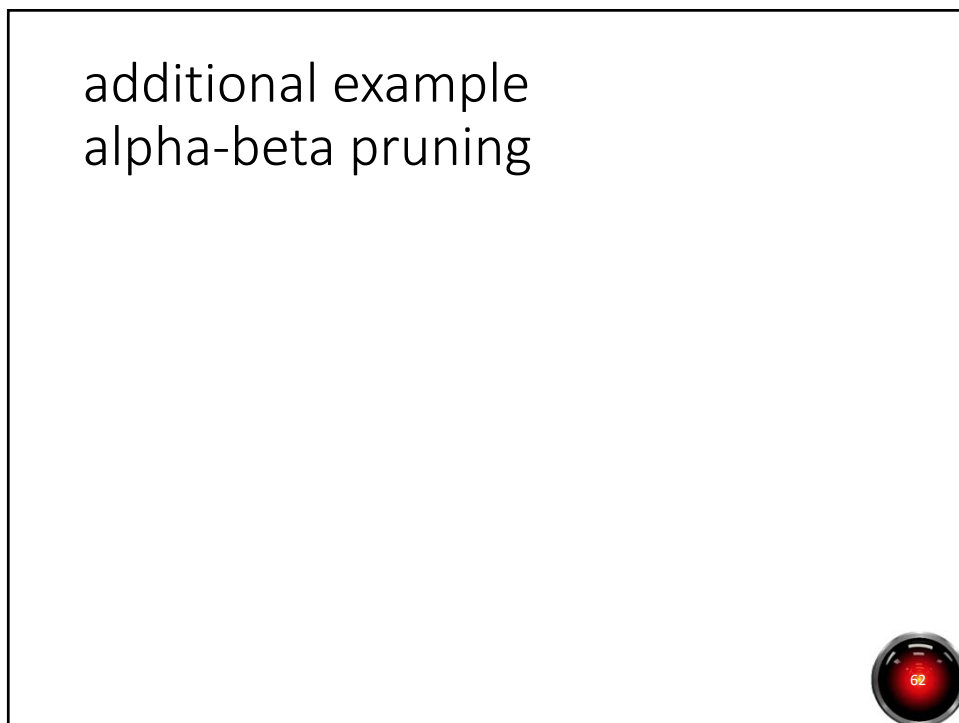


- Not all games fully observable
- Basic ideas
 - maintain a belief state
 - use and-or trees to represent possible states
 - problematic: lots of states





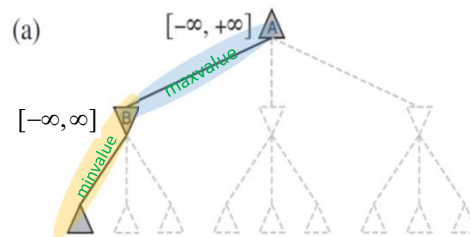
additional example
alpha-beta pruning



```

maxvalue(state,  $\alpha$ ,  $\beta$ )
  if terminal(state) then  $v$  = utility(state)
  else
     $v$  =  $-\infty$ 
    for  $a \in \text{actions}(\text{state})$ 
       $v$  =  $\max(v, \text{minvalue}(\text{result}(\text{state}, a), \alpha, \beta))$ 
      if  $v \geq \beta$  then break else  $\alpha = \max(\alpha, v)$ 
  return  $v$ 

```



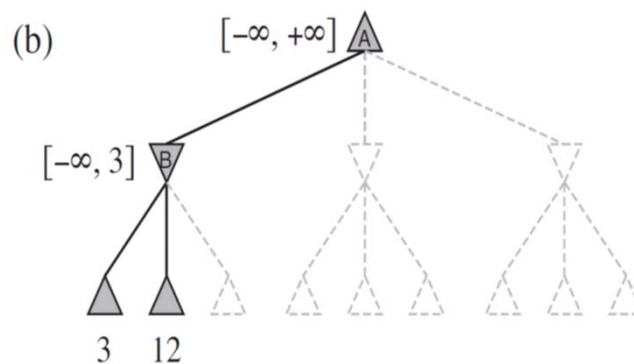
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       $v$  =  $\min(v, \text{maxvalue}(\text{result}(\text{state}, a), \alpha, \beta))$ 
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  return  $v$ 

```



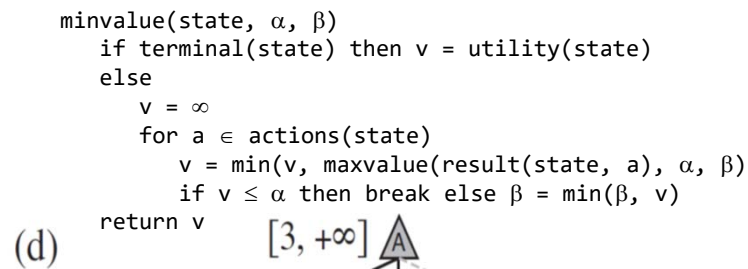
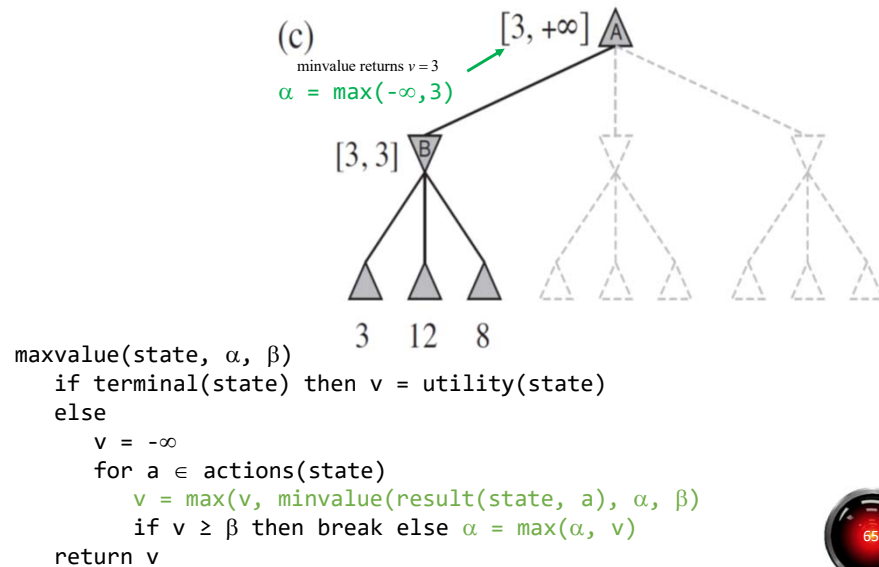
alpha-beta pruning example



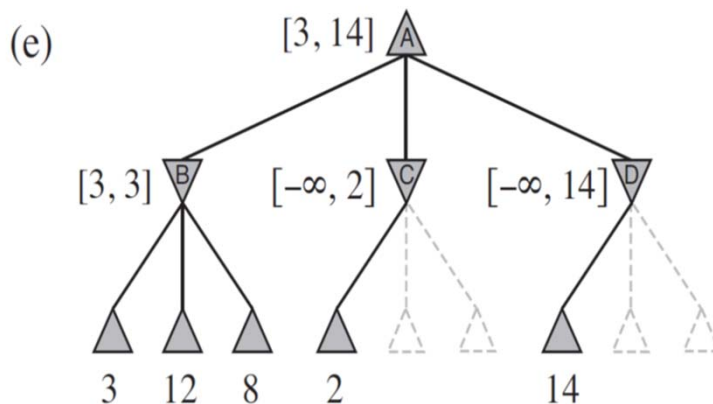
Note: When minvalue/maxvalue break their loop, they do not actually set α and β but for emphasis, we will show the values at nodes as if they did.



alpha-beta pruning example



alpha-beta pruning example



alpha-beta pruning example

