Review

- Uninformed Search
 - Breadth-first search
 - Uniform-cost search
 - Depth-first search
 - Depth-limited search
 - Iterative deepening search
- Informed Search
 - Greedy search
 - A* Search

HomeWorks

- Uninformed Search

 - Depth-first search

Breadth-first search Uniform-cost search HW 1 < Due: Jan 30>

- Informed Search

• A* Search \} HW 2 < Due: Feb 13>

MidTerm

- In-Class
- Wednesday, March 4

Adversarial Search

Adversarial Search

- In which we examine the problems that arise
 - when we try to plan ahead to get the best result
 - in a world that includes a <u>hostile</u> agent (other agent planning against us).

Games

- Adversarial search problems
 - Competitive environments in which goals of multiple agents are in conflict (often known as games)
- Game theory
 - Views any multi-agent environment as game
 - Provided the impact of each agent on the others is "significant"
- Classic AI games
 - Deterministic, turn-taking, two-player, perfect information
- Game playing is idealization of worlds in which hostile agents act so as to diminish one's well-being!
 - Games problems are like real world problems

Classic AI Games

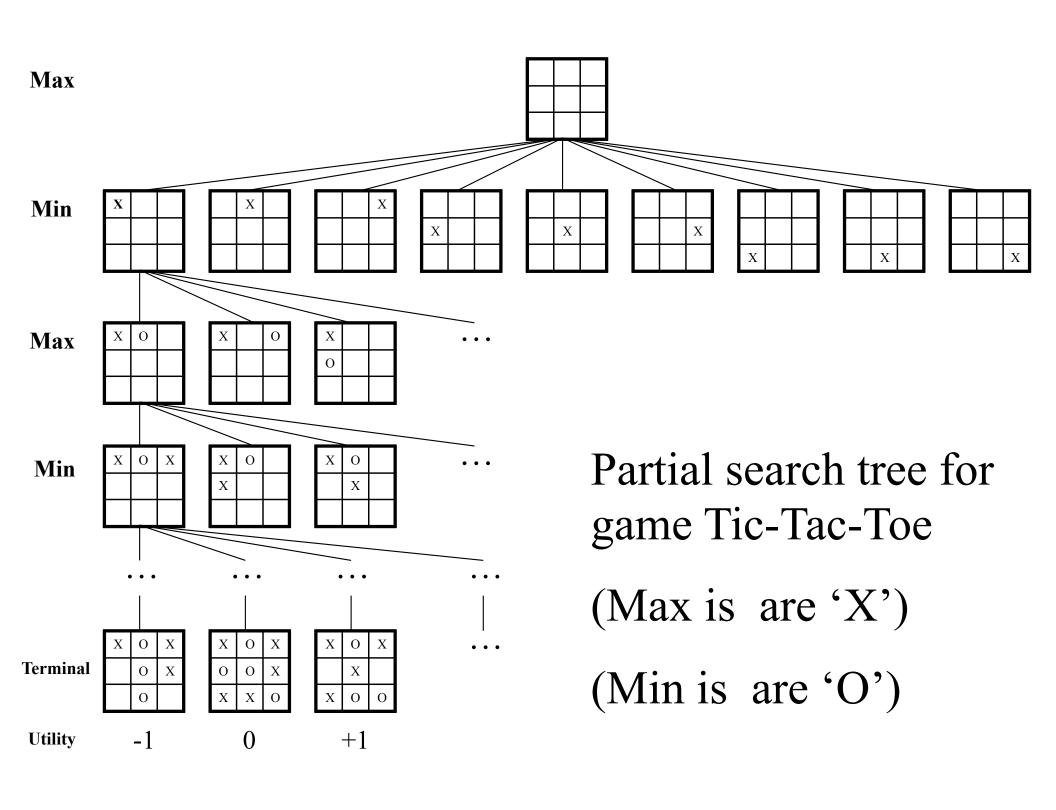
- State of game easy to represent
- Agents usually restricted to fairly small number of well-defined actions
- Opponent introduces uncertainty
- Games usually much too hard to solve
 - Chess
 - Branching factor 35
 - Often go to 50 moves by each player
 - About 352*50 = 35100 nodes!
- Good domain to study

AI Game Play

- Define optimal move and algorithm for finding it
- Ignore portions of search tree that make no difference to final choice
 - evaluation functions to approximate the true utility of a state without complete tree search.
 - Pruning

A Game Defined as Search Problem

- Initial state
 - Board position
 - Whose move it is
- Operators (successor function)
 - Defines legal moves and resulting states
- Terminal (goal) test
 - Determines when game is over (terminal states)
- Utility (objective, payoff) function
 - Gives numeric value for the game outcome at terminal states
 - $e.g., {win = +1, loss = -1, draw = 0}$



Optimal Strategies: Perfect Decisions in Two-Person Games

- Two players
 - MAX
 - MIN
- (Assume) MAX moves first, then they take turns moving until game over
- At end, points awarded to winning player
 - Or penalties given to loser
- Can formulate this gaming structure into a search problem

An Opponent

- If were normal search problem, then MAX (you/agent) need only search for sequence of moves leading to winning state
- But, MIN (the opponent) has input
- MAX must use a "strategy" that will lead to a winning state regardless of what MIN does
 - Strategy picks best move for MAX for each possible move by MIN

Techniques

- "Minimax"
- Alpha-beta pruning

Minimax

- Determines the best moves for MAX, assuming that MAX and opponent (MIN) play <u>perfectly</u>
 - MAX attempts to maximize its score
 - MIN attempts to minimize MAX's score
- Decides best first move for MAX
- Serves as basis for analysis of games and algorithms

Minimax

- Perfect play for deterministic, perfect-information games
- Two players: MAX, MIN
 - MAX moves first, then take turns until game is over
 - Points are awarded to winner
 - Sometimes penalties may be given to loser
- Choose move to position with highest *minimax* value
 - Best achievable payoff against best play
 - Maximizes the worst-case outcome for MAX

Minimax Algorithm

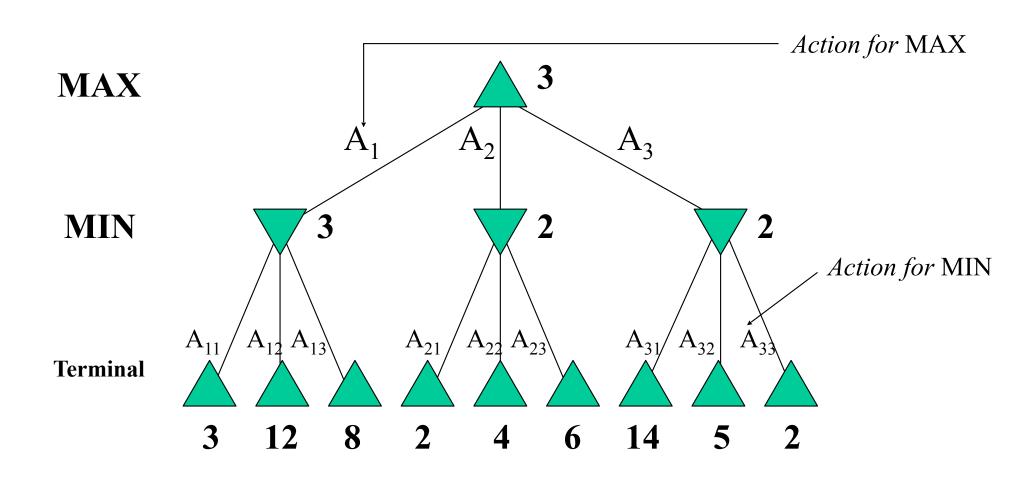
- Generate whole game tree (or from current state downward
 - depth-first process online)
 - Initial state(s) to terminal states

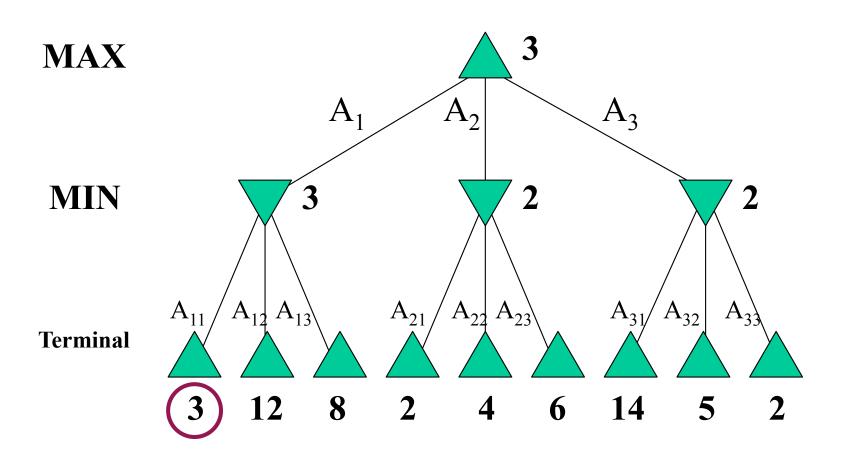
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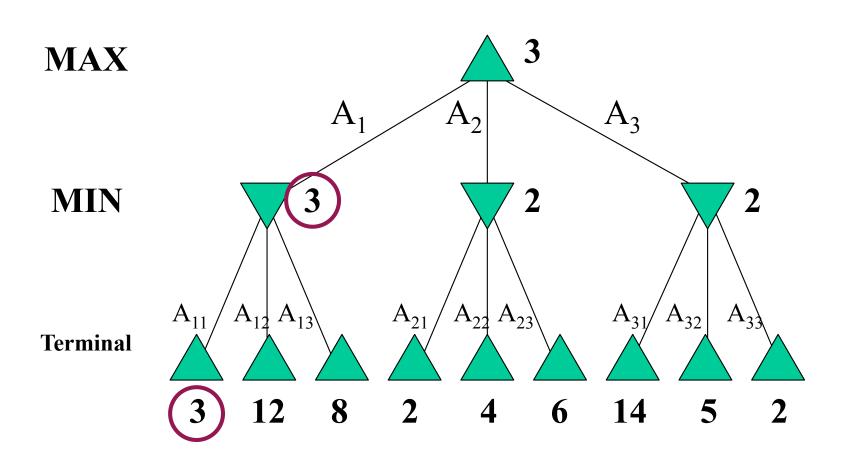
- Generate whole game tree (or from current state downward
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- Apply utility function to terminal states
- Use utilities at terminal states to determine utility of nodes one level higher in tree
 - Find MIN's best attempt to minimize high payoff for MAX at terminal level

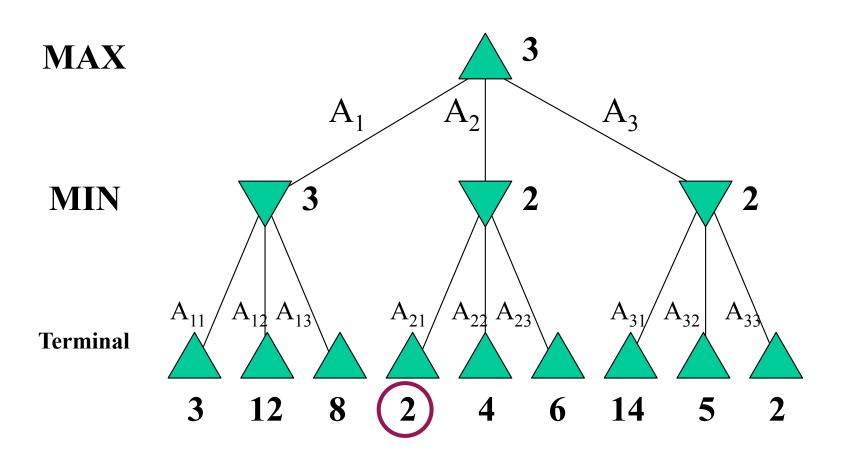
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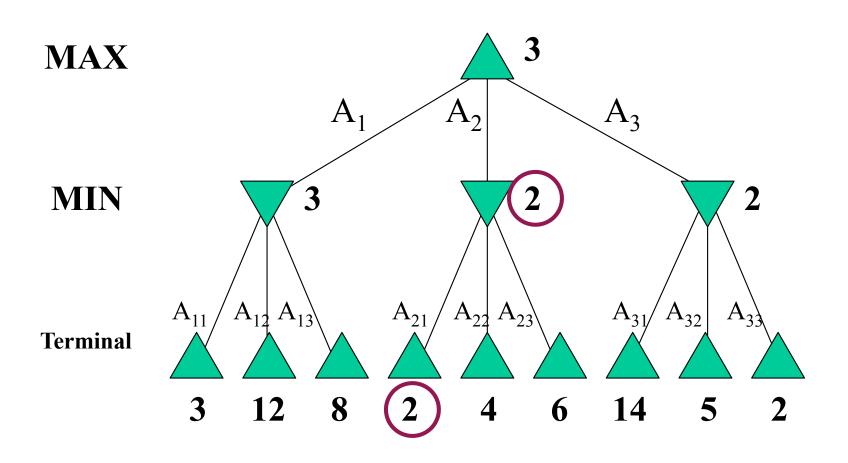
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- Continue backing up the values to the root
 - One layer at a time
- Value at root is determines the best payoff and opening move for MAX (minimax decision)

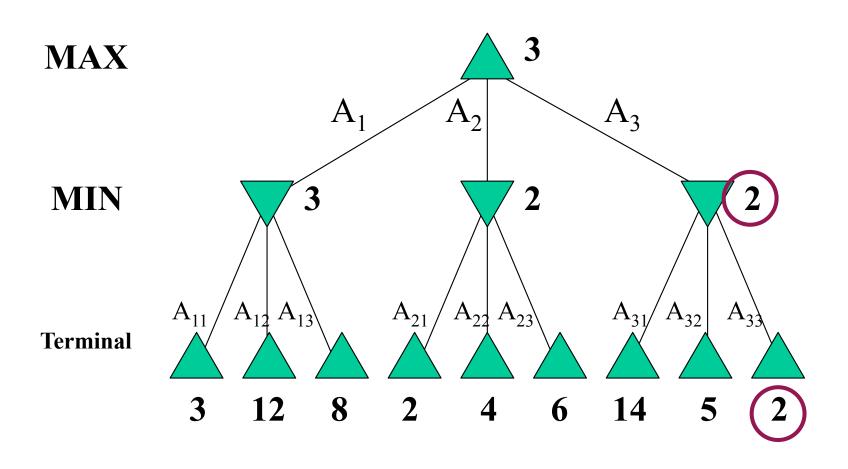


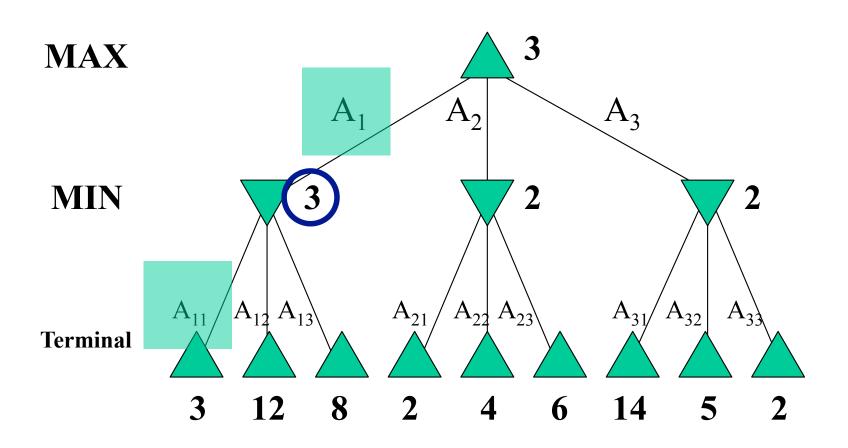


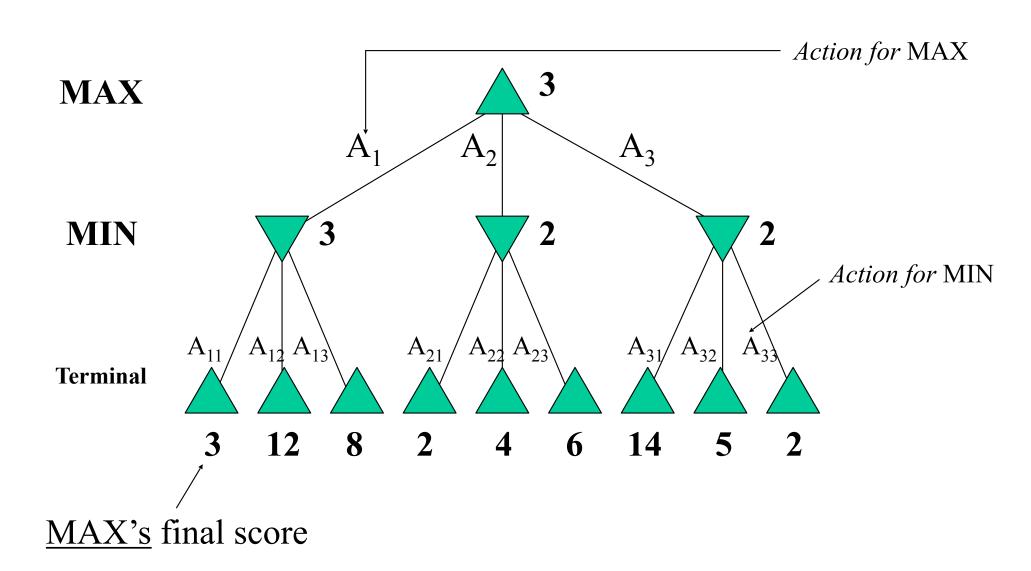












Properties of Minimax

- Complete
 - If tree is finite
- Time
 - Depth-first exploration
 - $O(b^m)$, max depth of m with b legal moves at each point (impractical for real games)
- Space
 - Depth-first exploration
 - -O(bm)
- Optimality
 - Yes against an optimal opponent
 - Does even better when MIN not play optimally

Pruning

- Minimax search has to search large number of states
- But possible to compute correct minimax decision without looking at every node in search tree
- Eliminating a branch of search tree from consideration (without looking at it) is called pruning

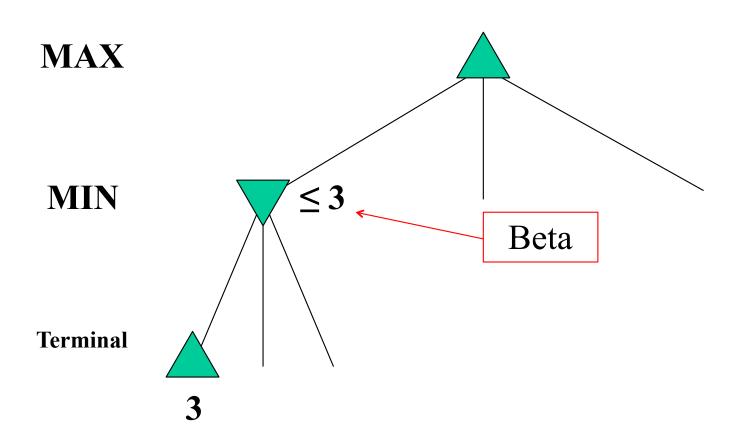
Alpha-beta pruning

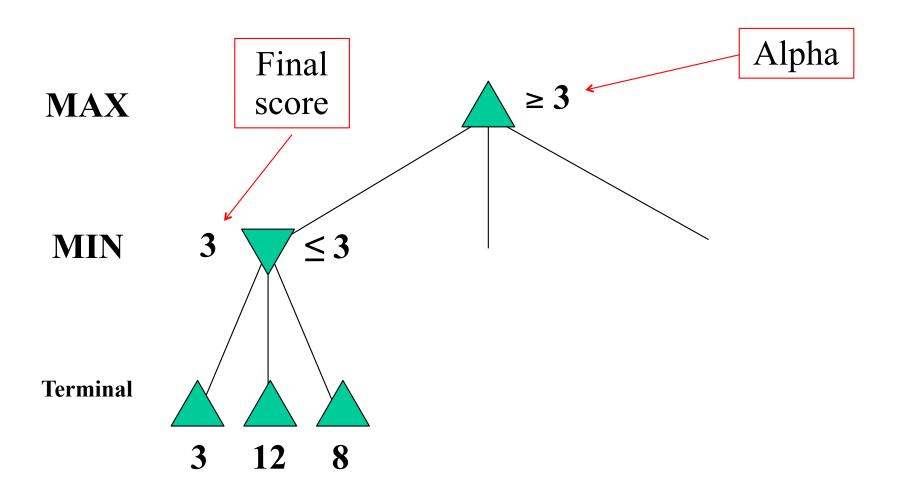
- Ignore portions of search tree that make no difference to final choice
- Prunes away branches that <u>cannot possibly</u> <u>influence</u> final minimax decision
- Returns same move as general minimax

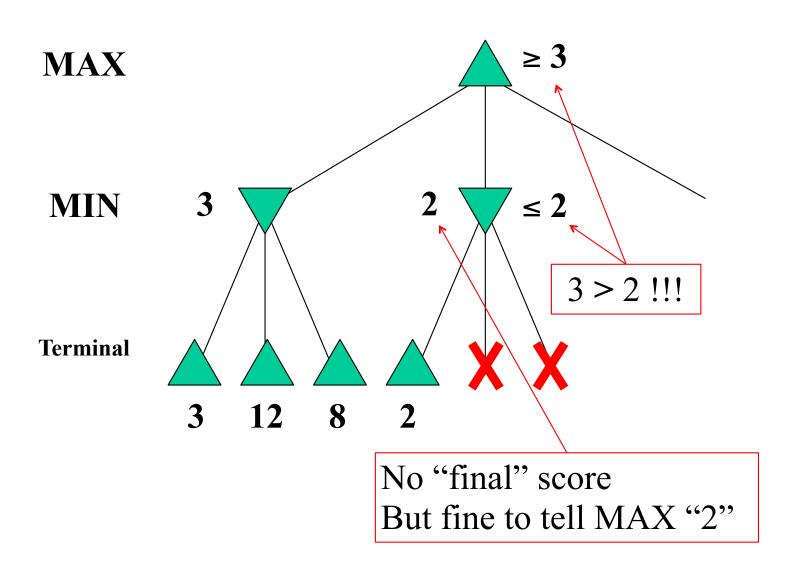
- Can be applied to trees of any depth
- Often possible to prune entire subtrees rather than just leaves

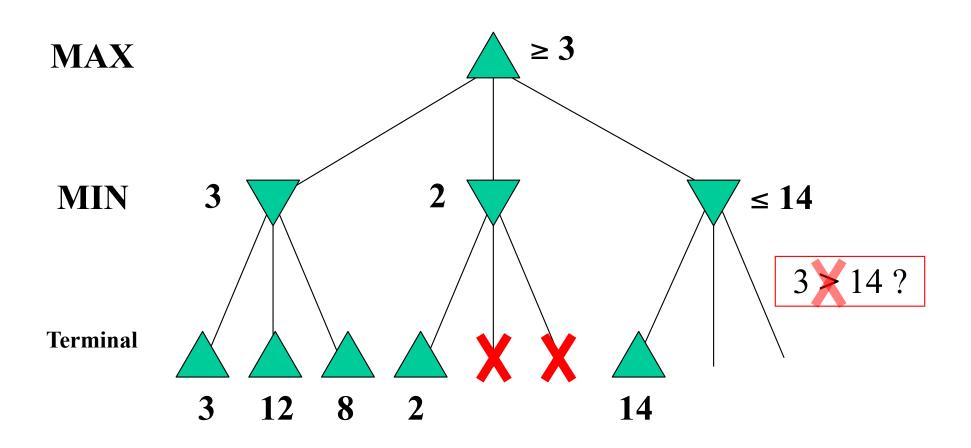
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 - Alpha = value of best (highest-value) choice found so far at any choice point along path for MAX
 - In other words, the worst score (lowest) MAX could possibly get
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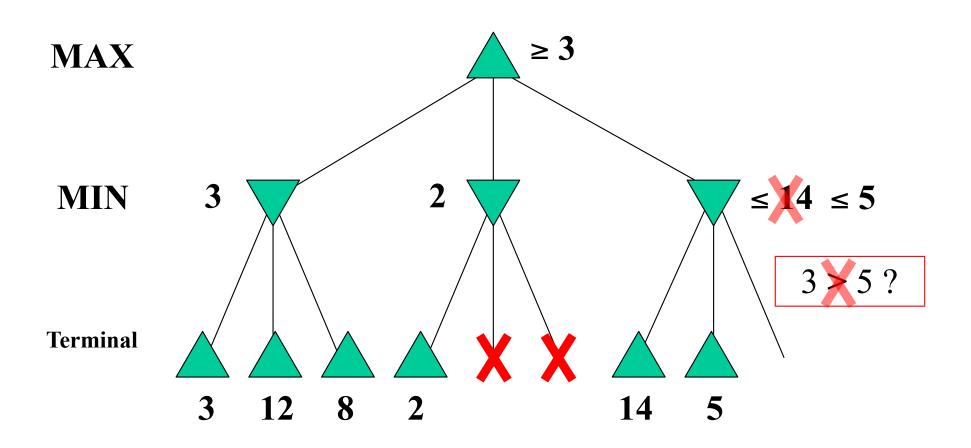




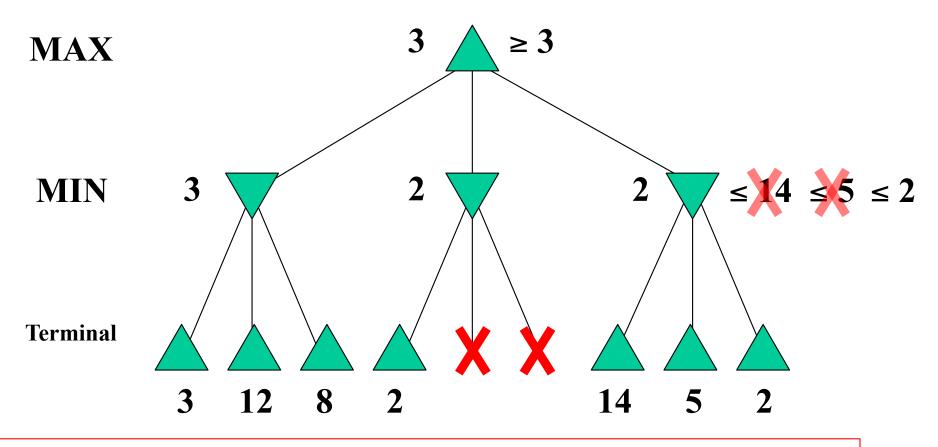




Alpha-Beta Pruning



Alpha-Beta Pruning



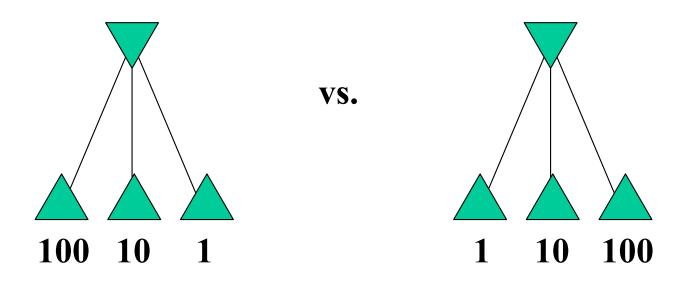
Note: Only showed MIN pruning here In general, both MIN <u>and</u> MAX check Alpha > Beta, prune

Properties of Alpha-Beta

- Pruning does not affect final result
- With "perfect ordering":
 - Time complexity $O(b^{m/2})$
- A simple example of the value of
 - "reasoning about which computations are relevant"

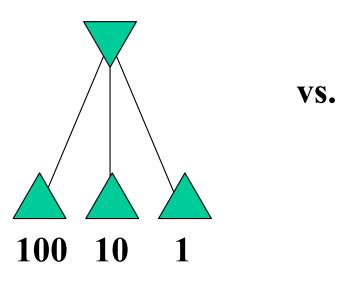
Node Ordering

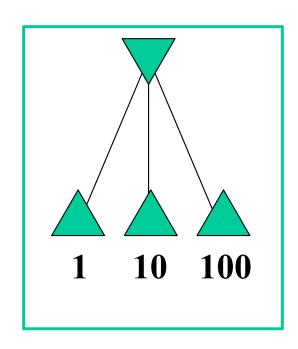
- Good move ordering would improve effectiveness of pruning
 - Try to first examine successors that are likely to be best
 - Prunes faster



Node Ordering

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- What if MAX ends up with multiple choices with the same (maximum) score?
 - According to basic MiniMax, doesn't matter which
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- Tie Breaking Strategies
 - Earliest Move
 - Latest Move
 - Random Make algorithm less predictable

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 - Latest Move
 - Random Make algorithm less predictable
- Also, consider adjusting utility function so less ties are possible

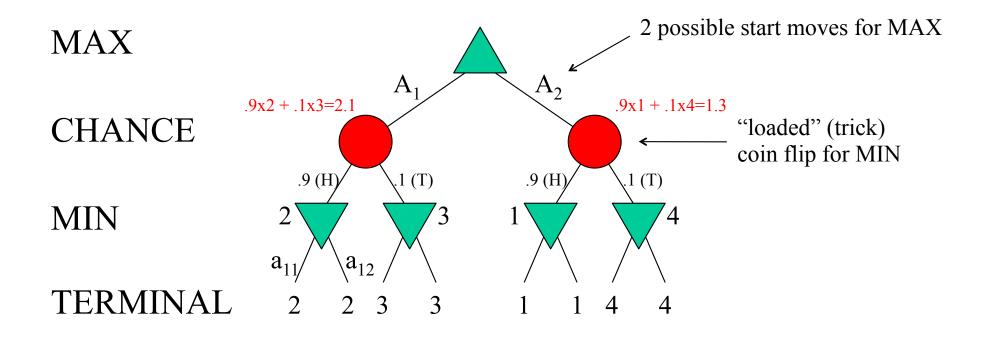
Games with Chance

- Many games have a random element
 - e.g., throwing dice to determine next move
- Cannot construct standard game tree as before
 - As in Tic-Tac-Toe
- Need to include "CHANCE nodes"
- Branches leading from chance node represent the possible chance-outcomes and probability
 - e.g., die rolls: each branch has the roll value (1-6) and its chance of occurring $(1/6^{th})$

Expecti-MiniMax

- TERMINAL, MAX, MIN nodes work same way as before
- CHANCE nodes are evaluated by taking weighted average of values (expected value) resulting from all possible chance outcomes (e.g., die rolls)
- Process is backed-up recursively all the way to root (as before)

Simple Example



Move A_1 is "expected" to be best for MAX

Alpha-Beta with Chance?

- Analysis for MAX and MIN nodes are same
- But can also prune CHANCE nodes

Summary

- Games can be defined as search problems
 - With complexity of real world problems
- Minimax algorithm determines the best move for a player
 - Assuming the opponent plays perfectly
 - Enumerates entire game tree
- Alpha-beta algorithm similar to minimax, but prunes away branches that are irrelevant to the final outcome
 - May need to cut off search at some point if too deep
- Can incorporate "chance"