Adversarial Search

CS 486/686: Introduction to Artificial Intelligence
Winter 2016

Introduction

- So far have only been concerned with single agents
- Today
  - Multiple agents planning against each other
    - Adversarial settings

Outline

- Games
- Minimax search
- Alpha-beta pruning
- Evaluation functions
- Coping with chance
- Game programs

Games

- Games are the oldest, most well-studied domain in AI
- Why?
  - They are fun
  - Easy to represent, rules are clear
  - State spaces can be very large
    - In chess, the search tree has ~10^{154} nodes
  - Like the “real world” in that decisions have to be made and time is important
  - Easy to determine when a program is doing well

Types of Games

- **Perfect vs Imperfect Information**
  - Perfect information: You can see the entire state of the game
  - Imperfect information:
- **Deterministic vs Stochastic**
  - Deterministic: change in state is fully controlled by the players
  - Stochastic: change in state is partially determined by chance

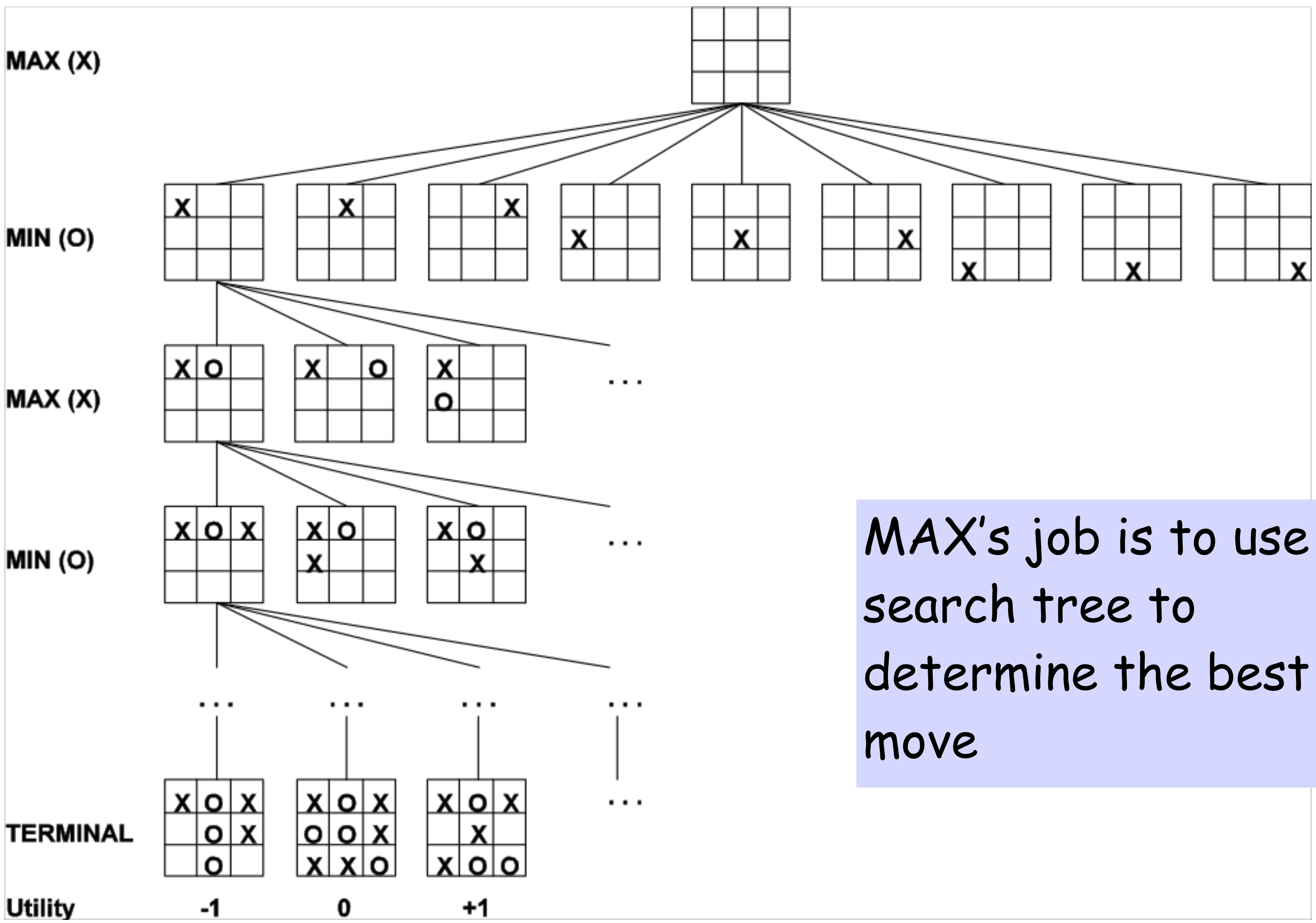
Games as Search Problems

- 2-player perfect information game
- **State**: board configuration plus the player who's turn it is to move
- **Successor function**: given a state, returns a list of (move,state) pairs indicating legal move and resulting state
- **Terminal state**: states where there is a win/loss/draw
- **Utility function**: assigns a numerical value to terminal states
- **Solution**: a strategy (way of picking moves) that wins the game

Game Search Challenge

- What makes game search challenging?
  - There is an opponent
  - The opponent is malicious
    - it wants to win (by making you lose)
  - We need to take this into account when choosing moves
- Notation:
  - **MAX** player wants to maximize its utility
  - **MIN** player wants to minimize its utility

Example



MAX's job is to use the search tree to determine the best move

Optimal Strategies

- In standard search
  - Optimal solution is sequence of moves leading to winning terminal state
- **Strategy** (from MAX's perspective)
  - Specify a move for the initial state
  - Specify a move for all possible states arising from MIN's response
  - Then all possible responses to all of MIN's responses to MAX's previous moves
  - ...

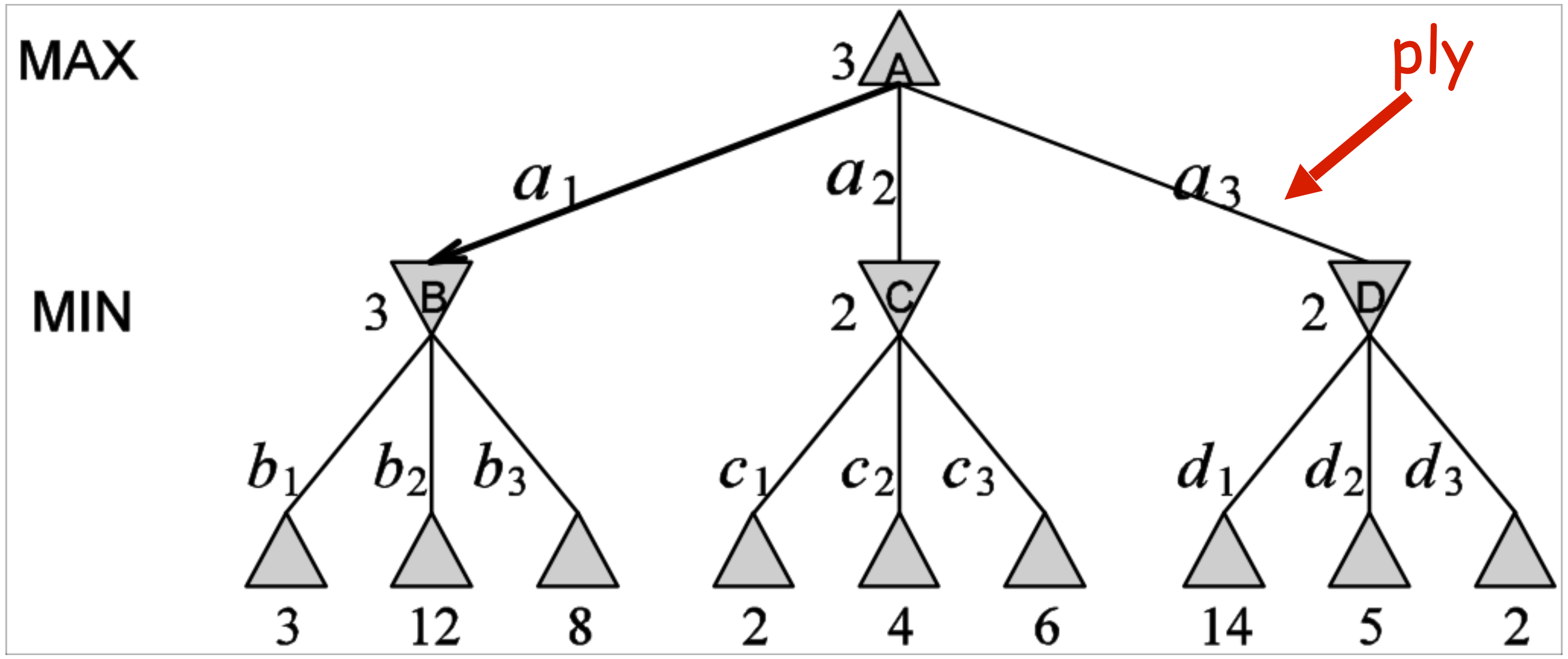
Optimal Strategies

- **Goal**: Find optimal strategy
- What do we mean by optimal?
  - Strategy that leads to outcomes at least as good as any other strategy, *given that MIN is playing optimally*
    - Equilibrium (game theory)
- Today we focus mainly on **zero-sum games of perfect information**
  - Easy games according to game theory

Minimax Value

MINIMAX-VALUE(n) =

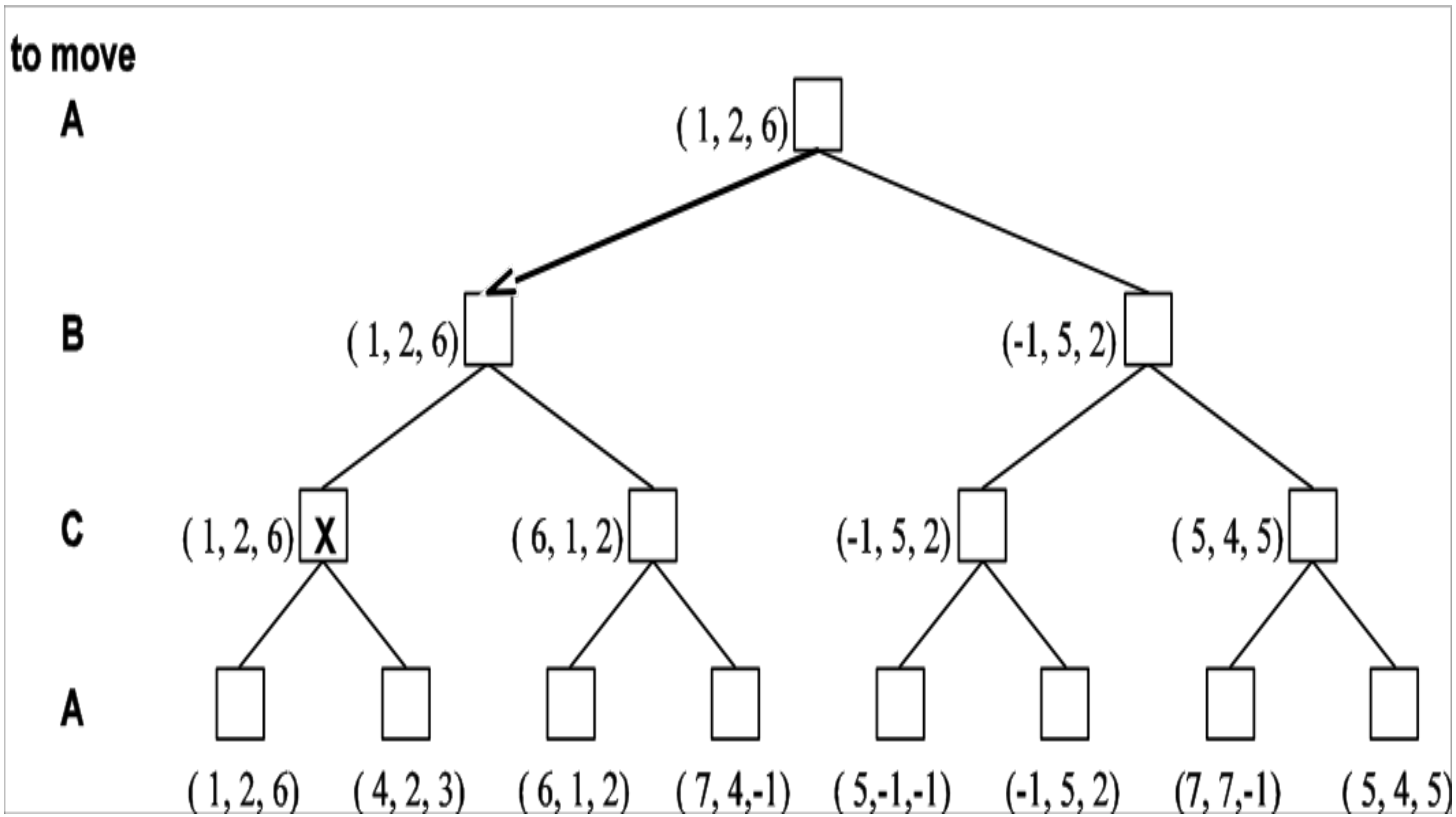
$$
\begin{cases}
\text{Utility}(n) & \text{if } n \text{ is a terminal state} \\
\text{Max}_{s \text{ in } Succ(n)} \text{ MINIMAX-VALUE}(s) & \text{if } n \text{ is a MAX node} \\
\text{Min}_{s \text{ in } Succ(n)} \text{ MINIMAX-VALUE}(s) & \text{is } n \text{ is a MIN node}
\end{cases}
$$



Properties of Minimax

- Complete if tree is finite
- Time complexity: $O(b^m)$
  - m is depth of tree
- Space complexity: O(bm)
  - It is DFS
- Optimal against an *optimal opponent*
  - If opponent is not playing optimally, then may be better off doing something else

Minimax and Multi-Player Games



Question

- Can we now write a program that will play chess reasonably well?

Question

- Can we now write a program that will play chess reasonably well
  - For chess b~35 and m~100

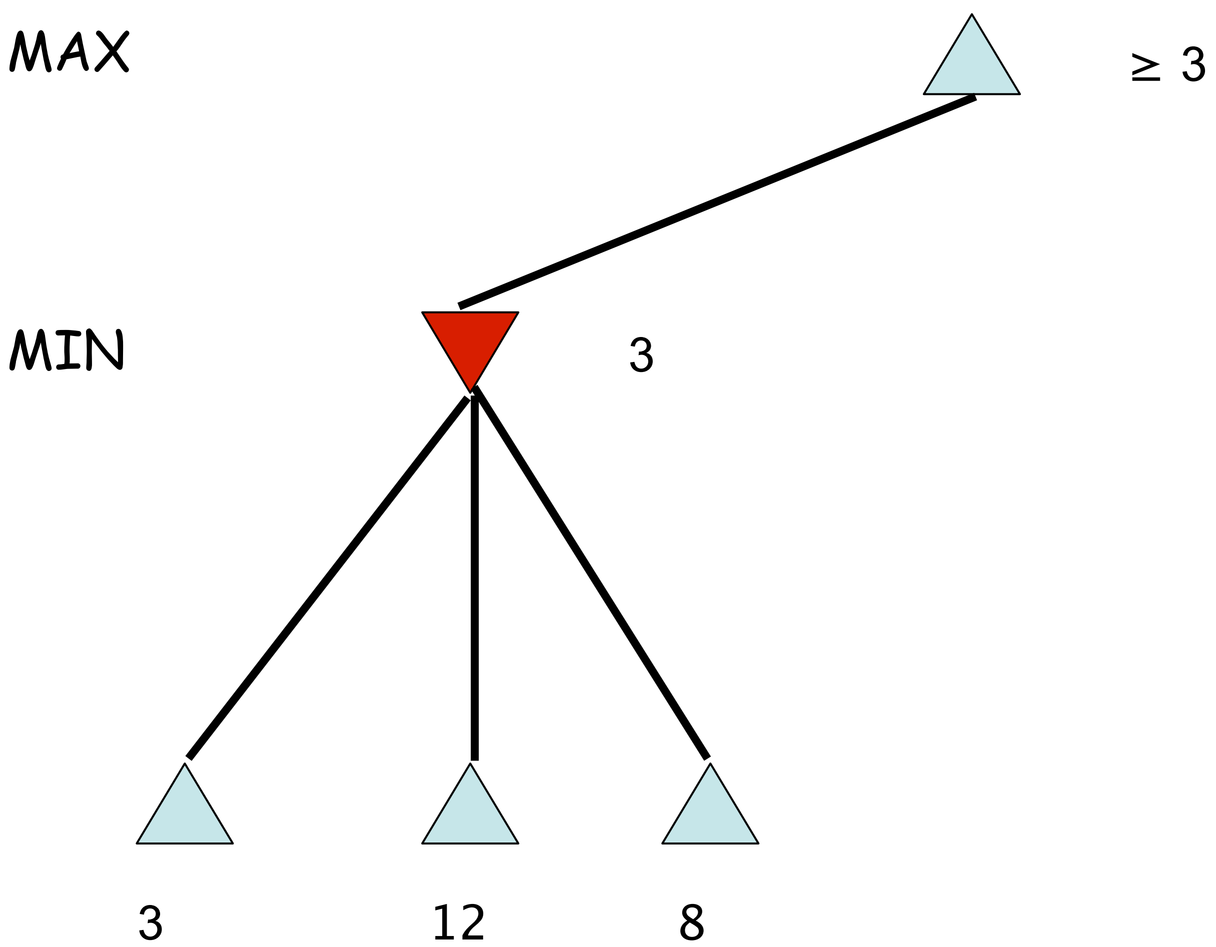
Alpha-Beta Pruning

- If we are smart (and lucky) we can do **pruning**
  - Eliminate large parts of the tree from consideration
- Alpha-beta pruning applied to a minimax tree
  - Returns the same decision as minimax
  - Prunes branches that cannot influence final decision

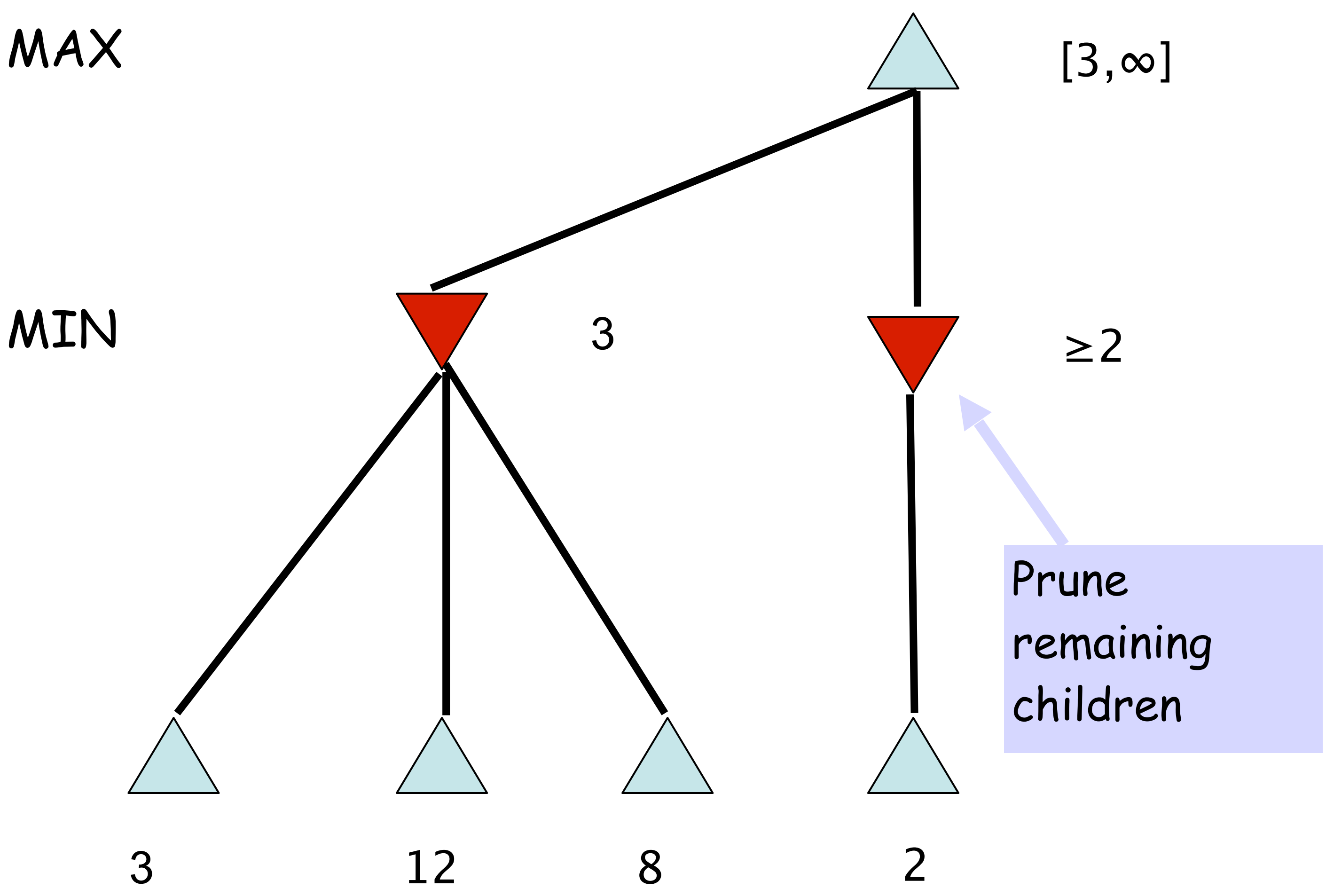
Alpha-Beta Pruding

- Alpha:
  - Value of best (highest value) choice we have found so far on path for MAX
- Beta:
  - Value of best (lowest value) choice we have found so far on path for MIN
- Update alpha and beta as search continues
- Prune as soon as value of current node is known to be worse than current alpha or beta values for MAX or MIN

Example



Example



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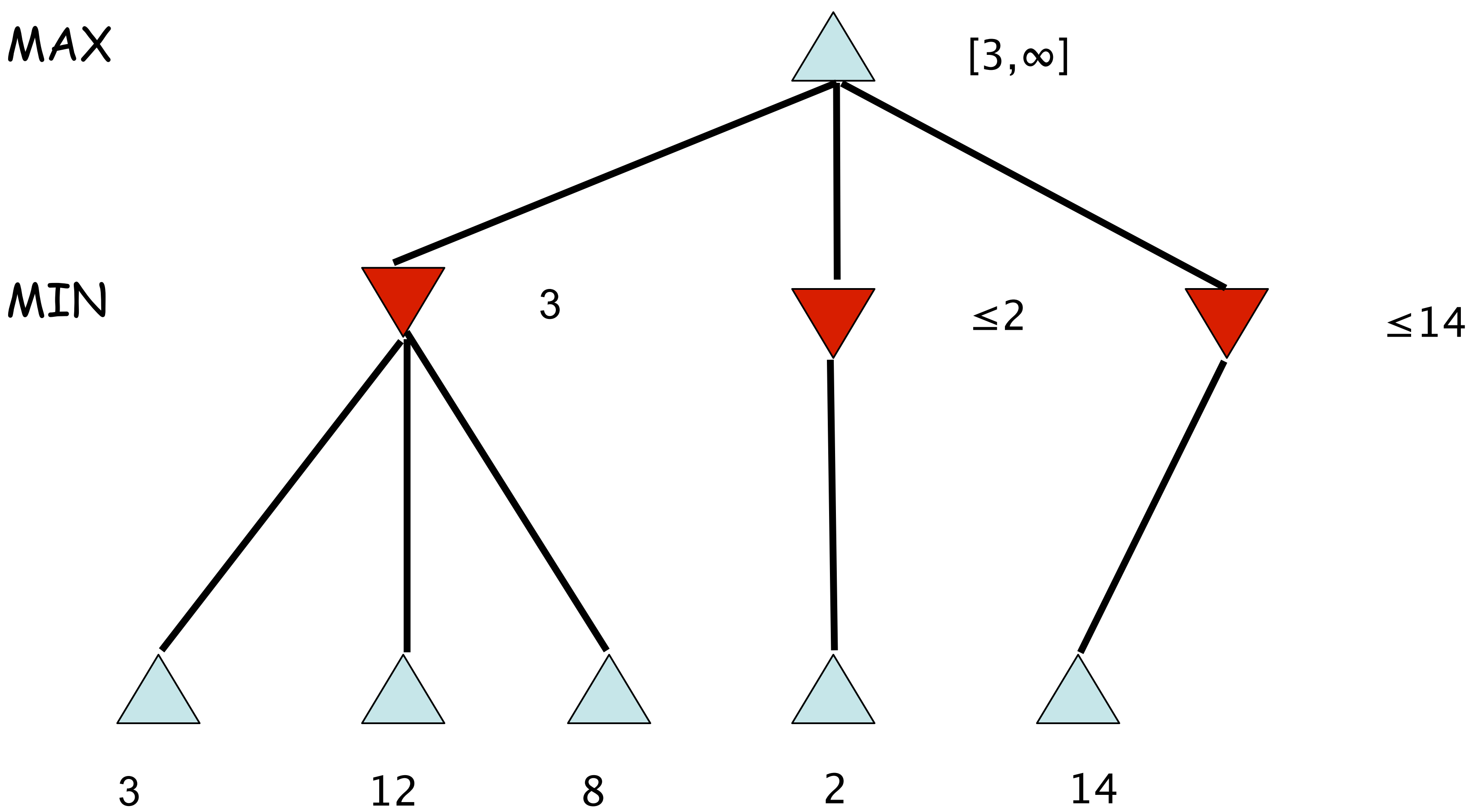

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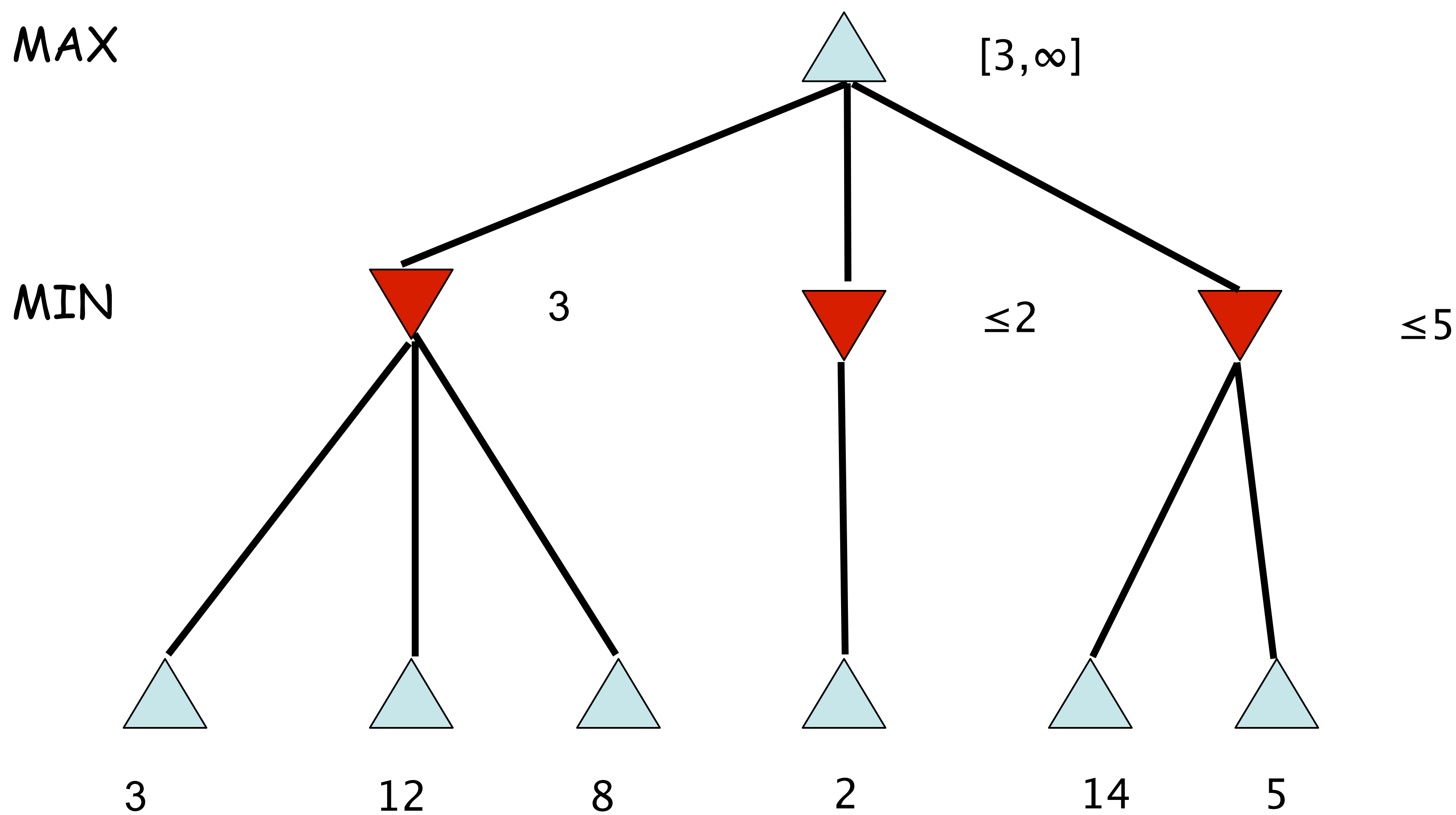

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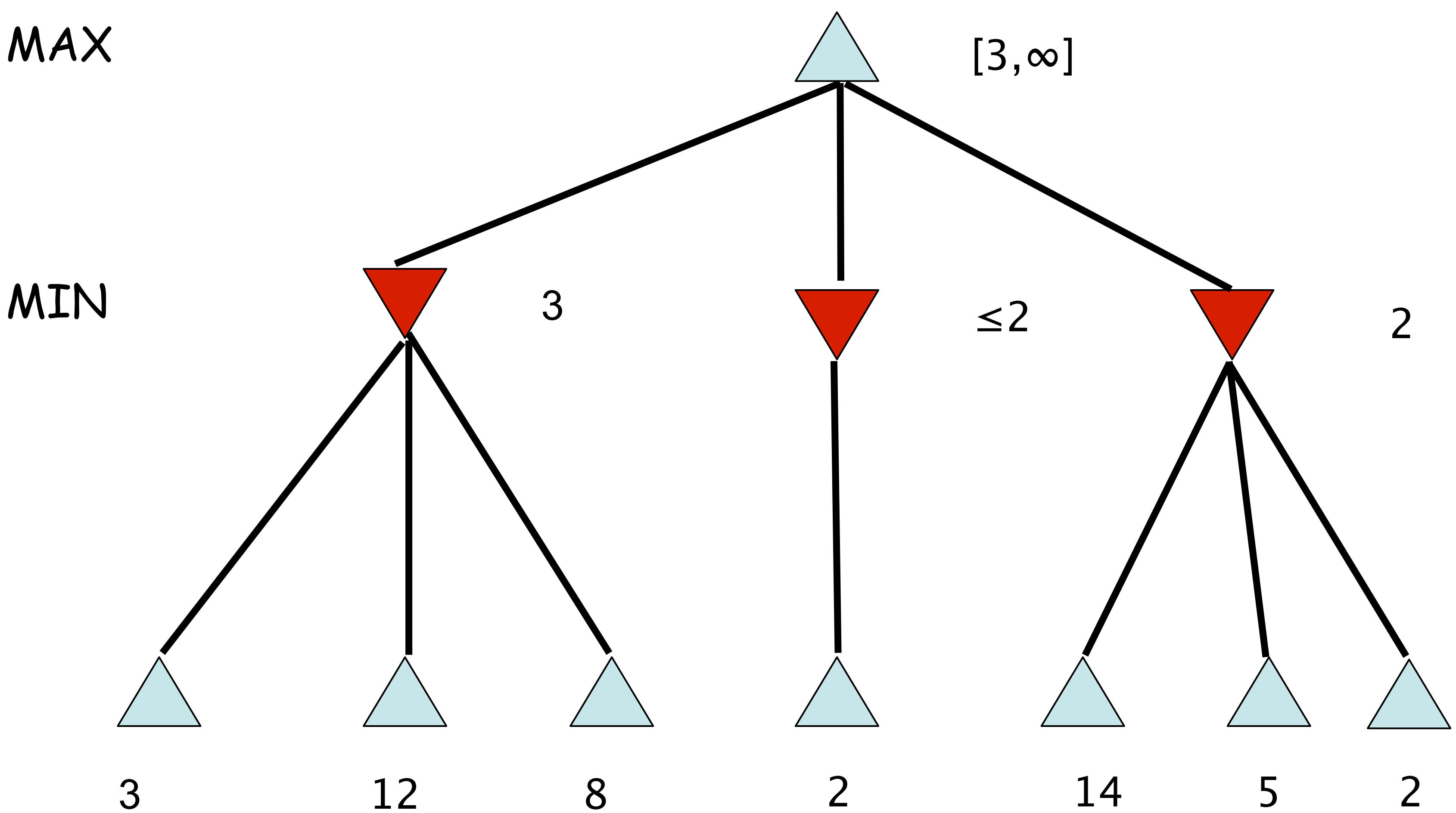


Properties of Alpha-Beta

- Pruning does not affect the final result
  - Why?
- Move ordering is important
- Alpha-beta demonstrates the value of reasoning about which computations are important

Real-Time Decisions

- Alpha-Beta can be a huge improvement over minimax
  - Still not good enough
    - Need to search to terminal states for at least part of search space
    - Need to make decisions quickly
- Solution
  - Heuristic evaluation function + cutoff tests

Evaluation Functions

- Apply an evaluation function to a state
  - If terminal state, function returns actual utility
  - If non-terminal, function returns estimate of the expected utility
- **Function must be fast to compute**

Evaluation Functions

- How do we get evaluation functions?
  - Expert knowledge
  - Learned from experience
- Look for features of states
  - Weighted linear function $Eval(s)=\sum_i w_i f_i(s)$

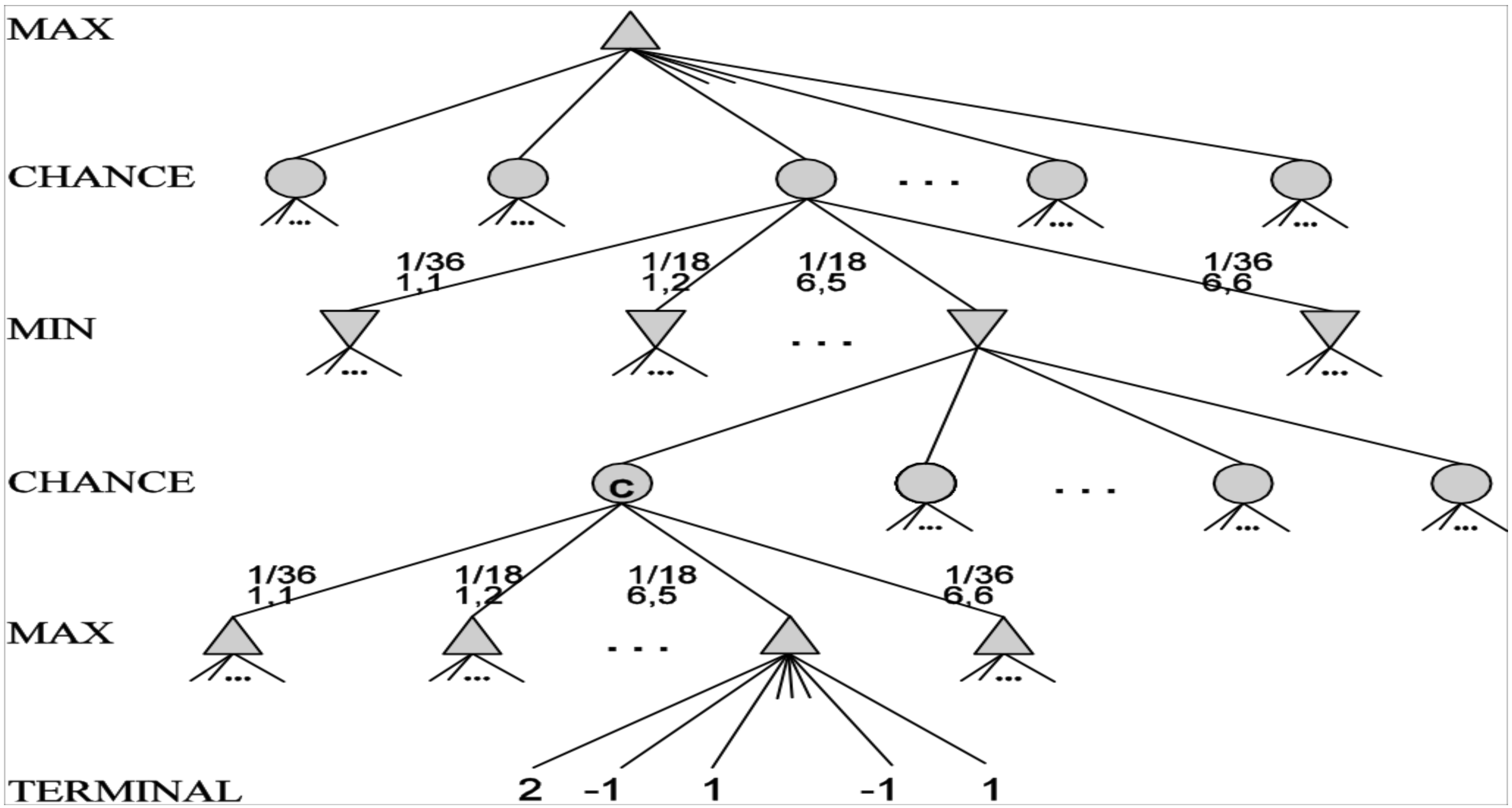
Cutting Off Search

- Do we have to search to terminal states?
  - No! Cut search early and apply evaluation function
- When?
  - Arbitrarily (but deeper is better)
  - Quiescent states
    - States that are “stable”
  - Singular extensions
    - Searching deeper when you have a move that is “clearly better”
    - Can be used to avoid the **horizon effect**

Cutting Off Search

- How deep?
  - Novice player
    - 5-ply (minimax)
  - Master player
    - 10-ply (alpha-beta)
  - Grandmaster
    - 14-ply + fantastic evaluation function, opening and endgame databases,...

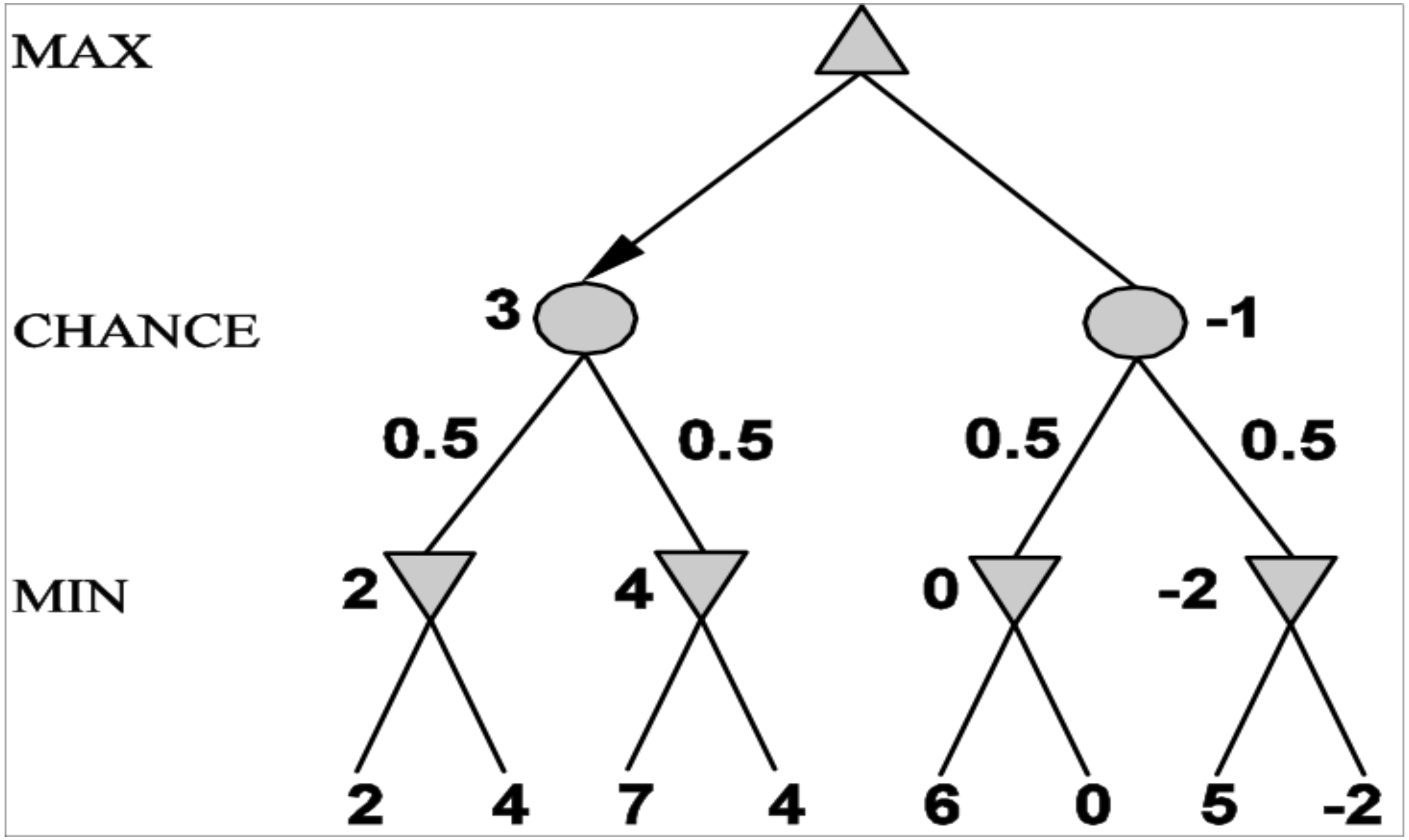
Stochastic Games



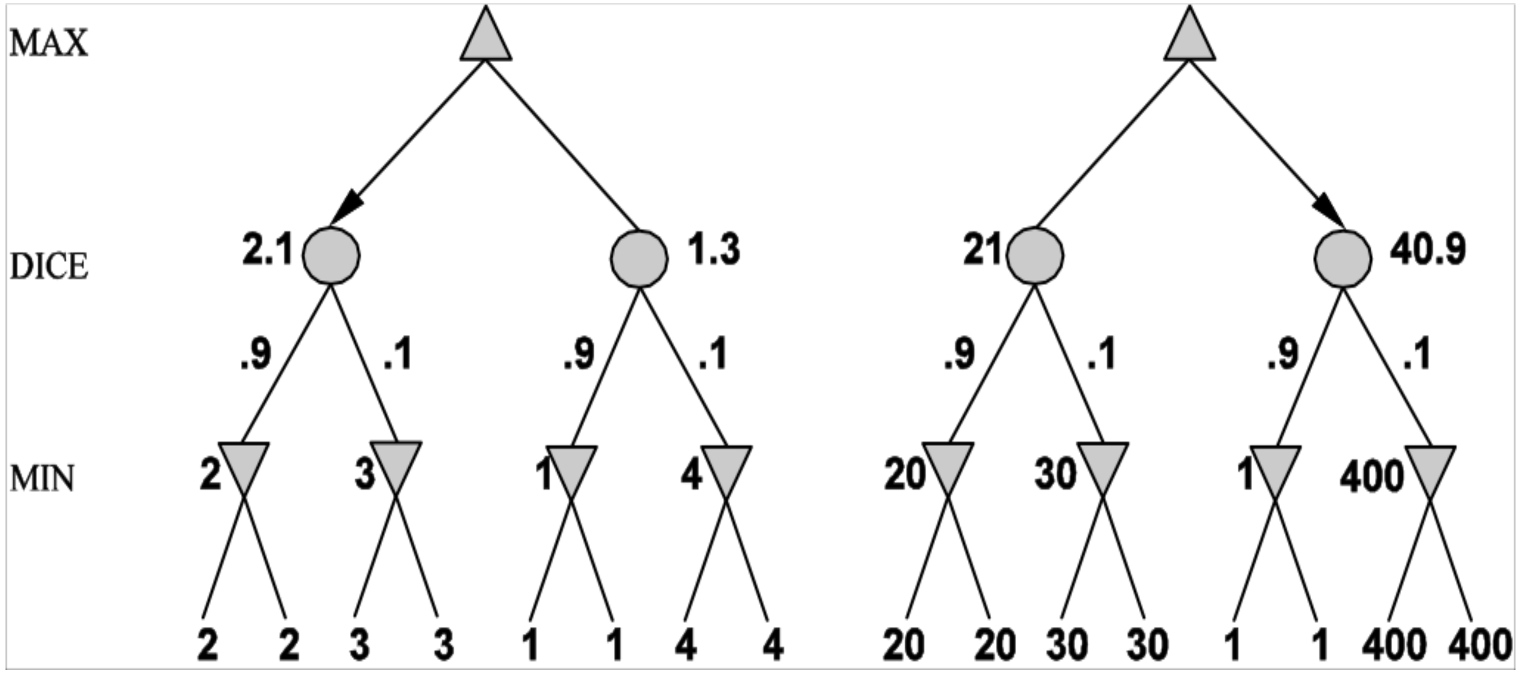
Stochastic Games

- Need to consider **best/worst cases + probability** they will occur
- Recall: Expected value of a random variable x $E[x]=\sum_{x \text{ in } X} P(x)x$
- **Expectiminimax**: minimax but at chance nodes compute the expected value

Expectiminimax



Expectiminimax



WARNING: exact values do matter! Order-preserving transformations of the evaluation function can change the choice of moves. Must have **positive linear transformations** only

Summary

- Games pose lots of fascinating challenges for AI researchers
- Minimax search allows us to play optimally against an optimal opponent
- Alpha-beta pruning allows us to reduce the search space
- A good evaluation function is key to doing well
- Games are fun!

Some Game Programs

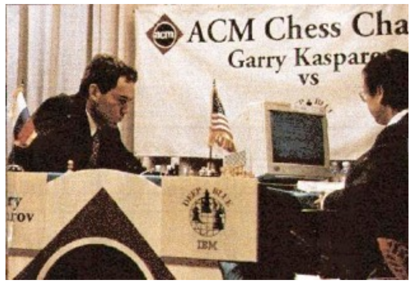
Checkers

Mr. Tinsley suffered his 4th and 5th losses **<u>ever</u>** against Chinook

Checkers

- Chinook (University of Alberta)
  - World Man-Machine Checkers Champion
  - Alpha-beta search
  - Opening database
- Secret weapon: **Endgame database**
  - Perfect knowledge into the search
- Checkers is now dominated by computers
  - Checkers is (weakly) solved

Chess: Kasparov vs. Deep Blue



1997: Deep Blue wins by 3 wins, 1 loss, and 2 draws

Kasparov		Deep Blue
5'10"	Height	6' 5"
176 lbs	Weight	2,400 lbs
34 years	Age	4 years
50 billion neurons	Computers	32 RISC processors + 256 VLSI chess engines
2 pos/sec	Speed	200,000,000 pos/sec
Extensive	Knowledge	Primitive
Electrical/chemical	Power Source	Electrical
Enormous	Ego	None

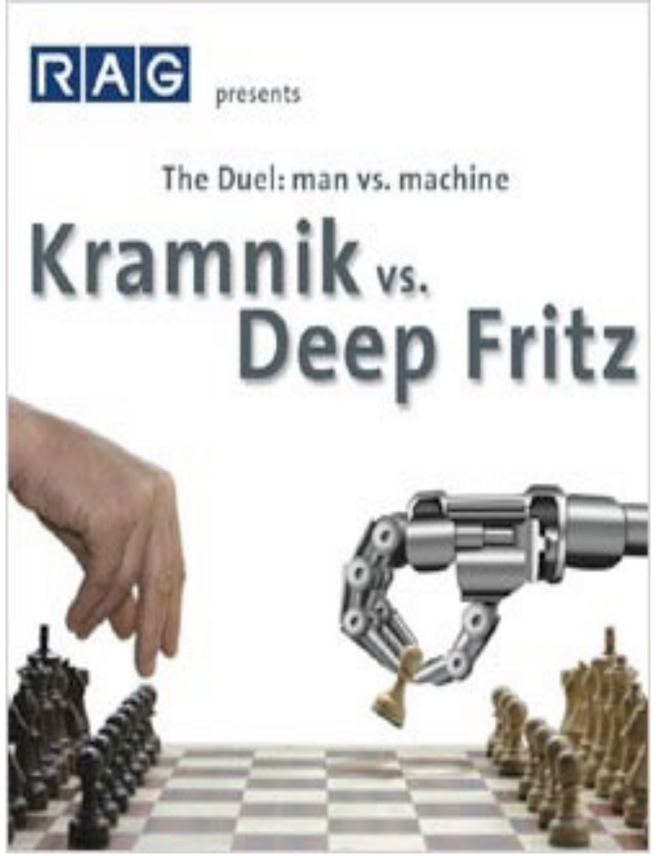
Jonathan Schaeffer

Chess

- Its secret:
  - Specialized chess processor + special-purpose memory optimization
  - Very sophisticated evaluation function
    - Expert features and hand-tuned weights
  - Opening and closing books
  - Alpha-beta + improvements (searching up to 40 ply deep)
  - Searched over 200 million positions per second

Chess

- There are now apps that are on par with human champions
- Is Chess still a human game or have computers conquered it?

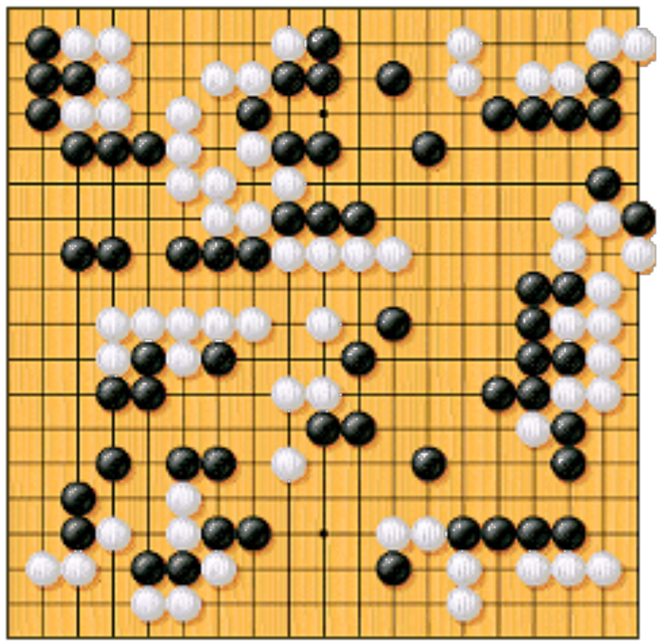


Backgammon

- TD-Gammon (Gerry Tesauro at IBM)
- One of the top players in the world
- Searches only two moves ahead!
- Its secret: **One amazing evaluation function**
  - Neural network trained with reinforcement learning during ~1 million games played against itself
  - Humans play backgammon differently now, based on what TD-Gammon learned about the game
  - Very cool AI ☺

Go

- Large branching factor makes Go too large to solve by classic search methods
    - pieces added to the board
    - evaluation function
    - ...
- Limited progress for decades

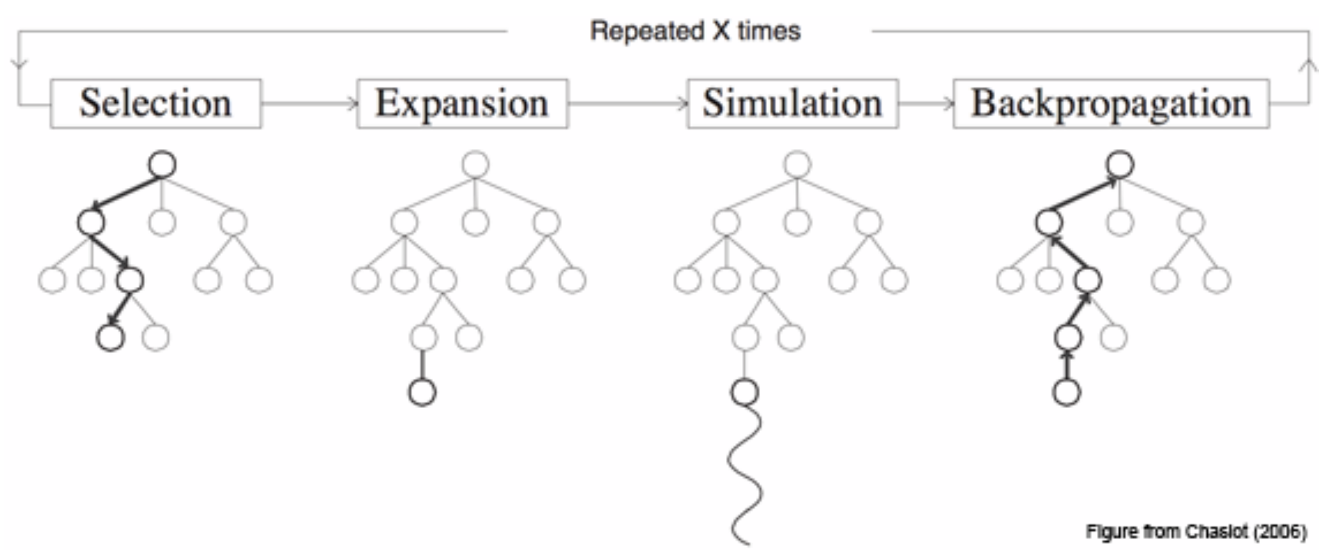


Go

- BUT computer Go has undergone a revolution in the past ~5 years
  - Close to perfection on 7x7 games
  - Reached top human level on 9x9 games
  - Still weaker than top humans on 19x9 boards

Go

- Monte-Carlo Tree Search (MCTS)
  - Build search tree according to outcomes of simulated plays



Upper Confidence Bounds for Trees (UCT): "Minimax search" using UCB

$$v_i + C\sqrt{\frac{\ln N}{n_i}}$$

Card Games

- Focus has been on Bridge and Poker
  - Humans are still winning...
  - But machines are catching up!
- Issues
  - Stochastic and partially observable
    - Ideas discussed today don't work well
    - New approaches are being developed