COMP 102: Excursions in Computer Science
Lecture 21: Game Playing

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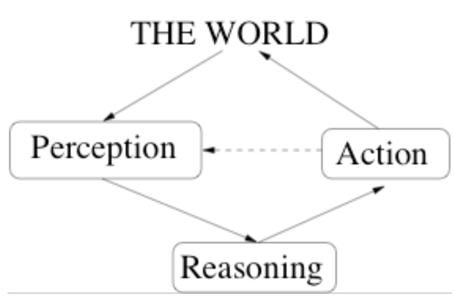
Overview of AI

- Typically three components:



Example AI system: Chess playing

IBM Deep Blue defeated Garry Kasparov (1997)

- Perception: advanced features of the board.
  Actions: choose a move.
- Reasoning: search and evaluation of possible board positions.

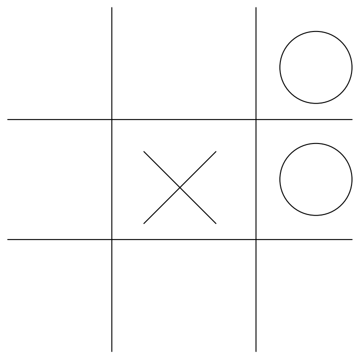
http://www-03.ibm.com

Game playing

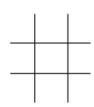
- One of the oldest, most well-studied domains in AI! Why?
  - People like them! People are good at playing them!
  - Often viewed as an indicator of intelligence.
    - State spaces are very large and complicated.
    - Sometimes there is stochasticity and imperfect information.
  - Clear, clean description of the environment.
  - Easy performance indicator.

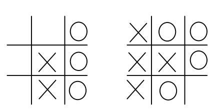
"Games are to AI as Grand Prix racing is to automobile design".

Start with an easy game: Tic-Tac-Toe



Defining a search problem for games

- **State space** S: all possible configurations of the domain.
  - **Initial state** $s_0 \in S$: the start state E.g. 
  - **Goal states** $G \subset S$: the set of end states

    E.g.  etc.
- **Actions** A: the set of moves available

Defining a search problem for games

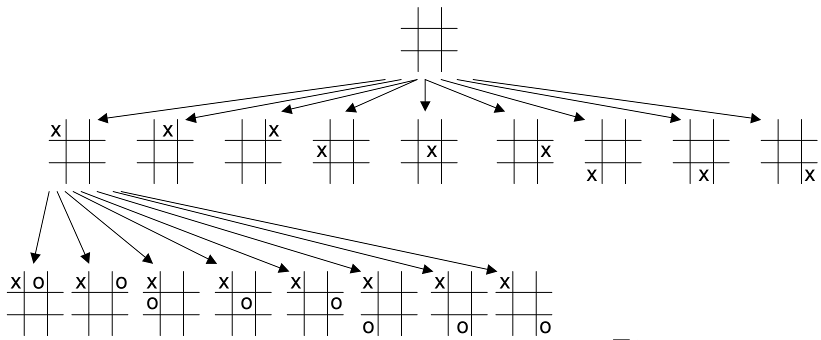
- **Path**: a sequence of states and operators.
- **Solution** of search problem: a path from s_0 to $s_g \in G$
- **Utility**: a numerical value associated with a state (higher is better, lower is worse).

  E.g. +1 if it's a win,
  -1 if it's a loss,
  0 if it's a draw or game not terminated.

Representing search: Graphs and Trees

- Visualize the state space search in terms of a graph.
- Graph defined by a set of nodes and a set of edges connecting the vertices.
  - Nodes correspond to states.
  - Edges correspond to actions.
- We search for a solution by building a search trees and traversing it to find a goal state.

Search tree for Tic-Tac-Toe

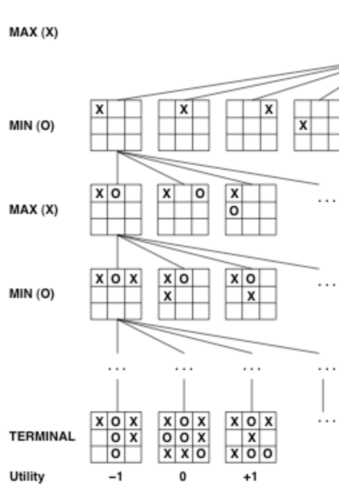


We want to find a strategy (i.e. way of picking moves) that wins the game.

Game search challenge

- Not quite the same as simple graph searching.
- There is an opponent! The opponent is malicious!
  - Opponent is trying to make things good for itself, and bad for us.
  - We have to simulate the opponent's decisions.
- **Key idea:**
  - Define a max player (who wants to maximize the utility)
  - And a min player (who wants to minimize the utility.)

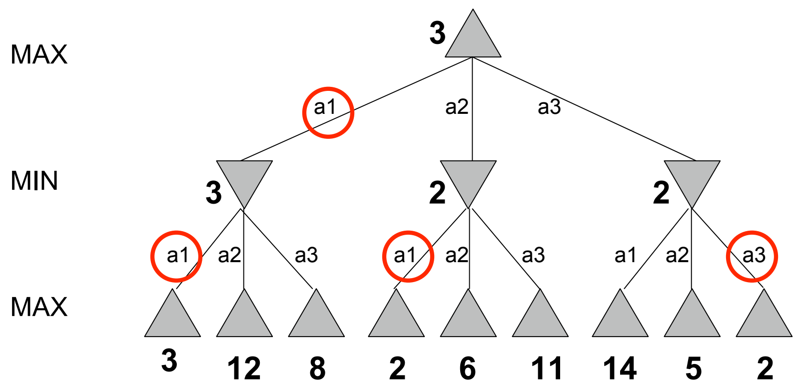
Example: Tic-Tac-Toe



Minimax search

- Expand complete search tree, until terminal states have been reached and their utilities computed.
- Go back up from leaves towards the current state of the game.
  - At each min node: backup the worst value among the children.
  - At each max node: backup the best value among the children.

A simple Minimax example



Properties of Minimax search

- Can we use minimax to solve any game?
  - Solve Tic-Tac-Toe? Yes!
  - Solve chess? No.

- Why not?
  - Large number of actions possible (I.e. large branching factor) b≈35.
  - Path to goal may be very long (I.e. deep tree) m≈100
  - Large number of states!

Coping with resource limitations

- Suppose we have 100 seconds to make a move, and we can search 10^4 nodes per second.
  – Can only search 10^6 nodes!
    (Or even fewer, if we spend time deciding which nodes to search.)

- Possible approach:
  – Only search to a pre-determined depth.
  – Use an evaluation function for the nodes where we cutoff the search.

Cutting the search effort

- Use an evaluation function to <u>evaluate non-terminal nodes</u>.
  – Helps us make a decision without searching until the end of the game.

- Minimax cutoff algorithm:

  Same as standard Minimax, except stop at some maximum depth *m* and use the evaluation function on those nodes.

Evaluation functions

- An evaluation function *v(s)* represents the "goodness" of a board state (e.g. chance of winning from that position).
  - Similar to a utility function, but approximate.
- If the features of the board can be evaluated independently, use a linear combination:

  $v(s) = f_1(s) + f_2(s) + \dots + f_n(s)$ (where *s* is board state)
- This function can be given by the designer or learned from experience.

Example: Chess

Black to move
White slightly better

White to move
Black winning

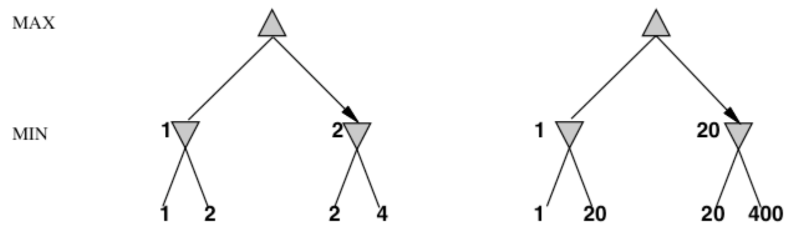
- Evaluation function: $v(s) = f_1(s) + f_2(s)$

  $f_1(s) = w_1$ * [(# white queens) - (# black queens)]

  $f_2(s) = w_2$ * [(# white pawns) - (# black pawns)]

How precise should the evaluation fn be?

- Evaluation function is only approximate, and is usually better if we are close to the end of the game.
- Only the order of the numbers matter: payoffs in deterministic games act as an ordinal utility function.



Minimax cutoff in Chess

- How many moves ahead can we search in Chess?

  >> 10^6 nodes with b=35 allows us to search 4 moves ahead!

- Is this useful?

  4-moves ahead ≈ novice player

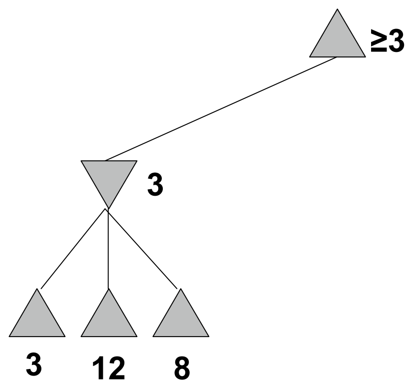
  8-moves ahead ≈ human master, typical PC

  12-moves ahead ≈ Deep Blue, Kasparov

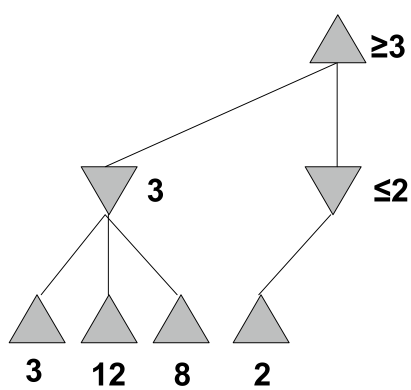
- Key idea:

  Search few lines of play, but search them deeply. **Need pruning!**

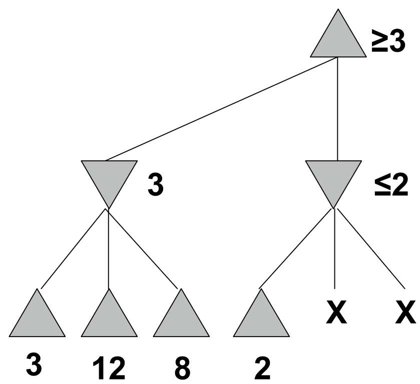
α-β Pruning example



α-β Pruning example



α-β Pruning example



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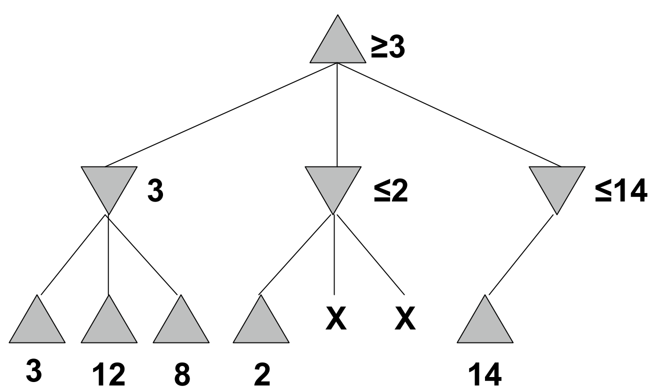
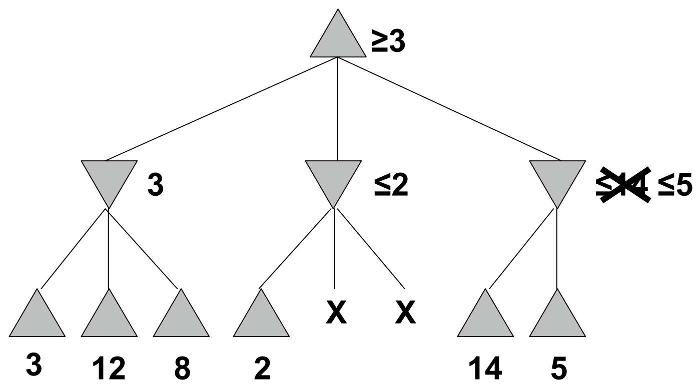
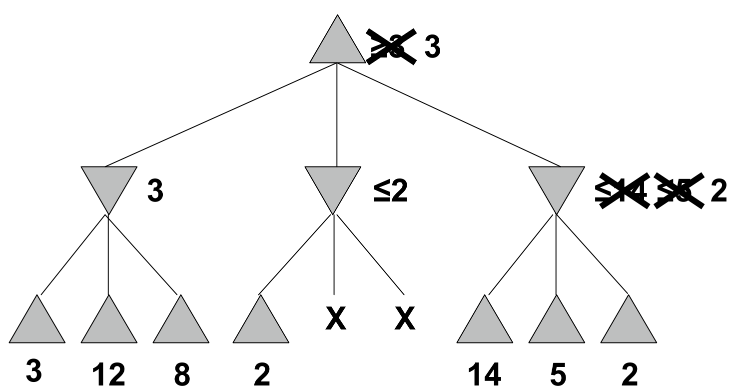


α-β Pruning example



α-β Pruning example



α-β Pruning

- Basic idea: if a path looks worse than what we already have, ignore it.
  - If the best move at a node cannot change (regardless of what we would find by searching) then no need to search further!
- Algorithm is like Minimax, but keeps track of best leaf value for our player (α) and best one for the opponent (β)

Properties of α-β pruning

- Pruning does not affect the final result! You will not play worse than without it.
- Good move ordering is key to the effectiveness of pruning.
  - With perfect ordering, explore approximately $b^{m/2}$ nodes.
    - Means double the search depth, for same resources.
    - In chess: this is difference between novice and expert player.
  - With bad move ordering, explore approximately b^m nodes.
    - Means nothing was pruned.
  - Evaluation function can be used to order the nodes.

The α-β pruning demonstrates the value of reasoning about which computations are important!

Human or computer - who is better?

Checkers:
- 1994: Chinook (U.of A.) beat world champion Marion Tinsley, ending 40-yr reign.

Othello:
- 1997: Logistello (NEC research) beat the human world champion.
- Today: world champions refuse to play AI computer program (because it's too good).

Chess:
- 1997: Deep Blue (IBM) beat world champion Gary Kasparov

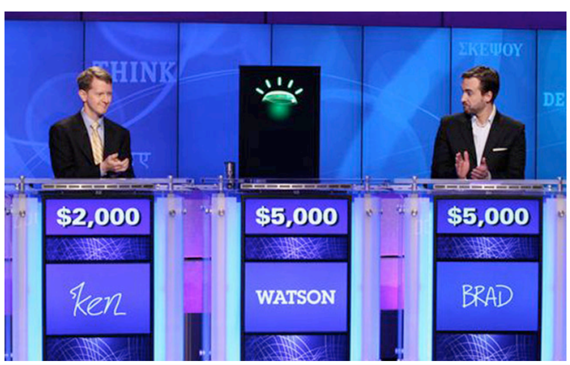
Backgammon:
- TD-Gammon (IBM) is world champion amongst humans and computers

Go:
- Human champions refuse to play top AI player (because it's too weak)

Bridge:
- Still out of reach for AI players because of coordination issue.

Jeopardy!

- In Winter 2011, Watson, a computer program created by IBM, made history by winning at Jeopardy!
  - Main innovation of Watson: ability to answer questions posed in natural language.



Jeopardy!

- How it works:
  - Watson isn't connected to the internet, but had access to 4TB of stored information (incl. all of Wikipedia).
  - When given a question, it extracts keywords, looks in database for related facts, compiles list of answers, and ranks them by confidence.
  - Watson is much better at buzzing in than its human opponents. So as long as it knows the answer, it has an edge.

Take-home message

- Understand the basic components (state space, start state, end state, utility function, etc.) required to represent the types of games discussed today.
- Know how to build the search tree.
- Understand the *how* and *why* of Minimax, Alpha-beta pruning, and evaluation functions.
- Have some intuition for what makes certain games harder than others.