ucc
Coláiste na hOllscoile Corcaigh, Éire
University College Cork, Ireland

CS4618 Artificial Intelligence I

Today: Adversarial Search ($\widehat{=}$ Games)

Thomas Jansen

October 12^{th}

Plans for Today

1. Optimal Game Play
   - Alpha-Beta-Pruning And Beyond
2. Real-Time Game Play
   - Evaluation and Cutting Off
   - Forward Pruning and Lookup
3. Other Games
   - Stochastic Games
   - Partially Observable Games
4. Summary
   - Summary & Take Home Message

Optimal Game Play

Remember

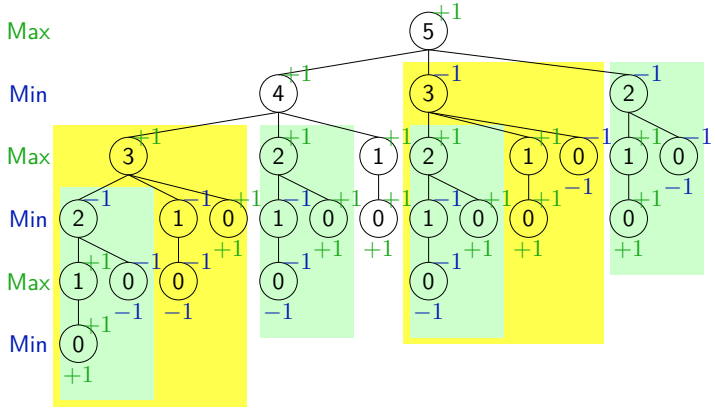
- two-player zero-sum games
- minimax algorithm to compute optimal moves
  - go over all actions
  - recursively compute values for resulting nodes
  - maximise or minimise (as required by current player) over these values
- alpha-beta pruning to improve over minimax search without sacrificing optimality
  - keep bounds α and β of what Max and Min can achieve
  - prune subtrees where nodes have values above/below these values

Now

one further improvement
without sacrificing optimality

Transposition Table

Remember



Observation identical sub-trees explored multiple times

Improvement store states in hash table
check before exploring
transposition table
('transposing' moves leading to identical states)

Problem size of transposition table
heuristics for deciding about which states to store

Remark minimax search $\leftrightarrow$ graph search
tranposition table $\leftrightarrow$ explored queue

Real-Time Game Play

Sad Fact alpha-beta pruning still much too slow for realistic games

Idea make search practical by introducing
cutoff-test to decide when to stop search at a non-terminal
eval assigns heuristic value to non-terminals
(effectively turning them into terminals)

Definition for an arbitrary state s

$$\text{h-minimax}(s,d) = \begin{cases} \text{eval}(s) & \text{if cutoff-test}(s,d) \\ \max_{a \in \text{actions}(s)} \text{h-minimax}(\text{result}(s,a), d+1) & \text{if player}(s) = \text{Max} \\ \min_{a \in \text{actions}(s)} \text{h-minimax}(\text{result}(s,a), d+1) & \text{if player}(s) = \text{Min} \end{cases}$$

On Evaluation Functions

Facts

- evaluation functions are heuristics
- evaluation functions are crucial

Guidelines

- respect ordering for terminals
- be strongly correlated with 'chances' of winning
- be not too computationally costly

Observation trade-off for evaluation functions
computational complexity vs. quality

Fact in chess simpler evaluation functions to be preferred

Example: Evaluation Functions for Chess

- expected values
  - classify states into categories
    (e. g., two pawns vs. one pawns)
  - obtain statistical evidence about outcomes
    (e. g., 72% wins $(+1)$, 8% draw $(+1/2)$, 20% loss (-1))
  - use expected value as result of evaluation
    (e. g., $.72 \cdot 1 + .08 \cdot (1/2) + .2 \cdot 0 = .76$)
  - problem (too) many categories, difficult to get sufficient data
- material values
  - assign values to pieces
    (e. g., pawn 1, knight 3, bishop 3, rook 5, queen 9)
  - add values as result of evaluation ($\widehat{=}$ weighted linear function)
  - problem often too simple and inaccurate (lacking incorporation of structural properties)
- non-linear weighting
  - use other factors to change values, incorporate structure
    (e. g., number of pieces in total, number of moves played, . . .)
  - problem concrete values difficult to obtain

On Cutting Off

Goal implement cutoff-test(s, d) for state s and depth d

Simple Idea fixed depth
return true of $d \geq d_{\max}$ or terminal reached

Slight Improvement iterative deepening search

Problems

- non-quiescent positions ($\widehat{=}$ extreme changes in evaluation after one move)
  solution attempt do not include these in evaluation (is called quiescence search)
- horizon effect (delay an ultimately unavoidable bad event thus making bad moves look good)
  solution attempt consider very promising move in greater depth (is called singular extension)

Forward Pruning

Idea for speeding-up search

forward pruning $\widehat{=}$ considering only a limited number of moves already in the beginning

Implementation beam search

consider only k most promising moves (parameter k)

Problem dangerous as best move may be difficult to identify (and thus missed)

Implementation probabilistic cut

extend alpha-beta pruning by estimating $[\alpha'; \beta']$-windows and cutting off like in alpha-beta pruning

Lookup

Idea avoid search completely
by looking up optimal solutions in a dictionary
when there are only sufficiently few states

When are there only 'sufficiently few' states?

Observation at the beginning and the end

Opening choose 'optimal' moves based on
expert domain knowledge
experience/statistics

Endgames compute 'optimal' moves using
retrogade minimax search (considering moves in reverse)
Note game tree size limited
$\rightsquigarrow$ exhaustive search feasible

Stochastic Games

Fact some games include randomness
example backgammon

Observation standard game trees fail to work
since choices of players are limited by random events

Idea introduce chance nodes
formally, another player 'Chance' with random choices
using the appropriate probability distribution

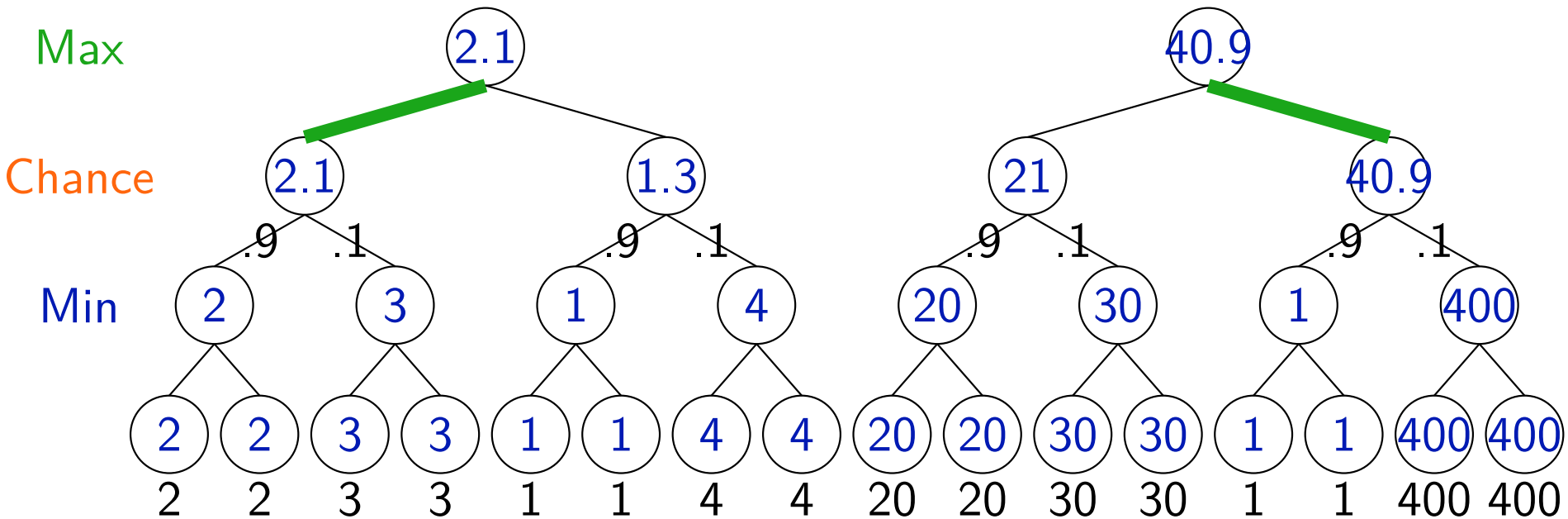
Definition for an arbitrary state s

$$\text{exp-MM}(s,d) = \begin{cases} \text{utility}(s) & \text{if terminal-test}(s) \\ \max\limits_{a \in \text{actions}(s)} \text{exp-MM}(\text{result}(s,a)) & \text{if player}(s) = \text{Max} \\ \min\limits_{a \in \text{actions}(s)} \text{exp-MM}(\text{result}(s,a)) & \text{if player}(s) = \text{Min} \\ \sum\limits_{r \in \text{rand. events(s)}} \text{Prob}\,(r)\, \text{exp-MM}(\text{result}(s,a)) & \text{if player}(s) = \text{Chance} \end{cases}$$

On Order-Preserving Transformations

Observation for deterministic games
only ordering of terminal-values important
$\Rightarrow$ order-preserving transformation without effect

Consider game tree for a tiny stochastic game



Observation optimal move changed

On Stochastic Games

Observations and Facts

- special care with evaluation function needed (due to sensitivity with respect to order-preserving transformations)
- chance nodes increase game tree size vastly
- alpha-beta pruning hardly useful
- adaptation of alpha-beta prunning feasible
  - needs upper and lower bounds on utility values
  - use bounds to bound expected utility values at nodes
  - apply alpha-beta pruning with respect to expected utility values
- Monte Carlo simulation helps
  - replace chance nodes by actual random decisions
  - apply 'normal' search algorithm (e. g., alpha-beta pruning)
  - repeat many tries, average results and pick 'average best' move

Partially Observable Games

Fact in some games the player's knowledge about states is restricted
example Kriegsspiel

Kriegsspiel

- partially observable variant of chess
- each player can only see the own pieces
- a referee announces illegal moves, takes them back and allows for another move
- a referee announces captures, check (with additional information), and end of game (stalemate, checkmate)

Approach perform state estimation
and search to belief states

Partially Observable Stochastic Games

Fact in some games the player's knowledge about states is restricted and the game includes random elements
example card games

Approach assume cards are dealt and treat as simple ($\widehat{=}$ fully observable) deterministic game

Problems

- probability space too large
  solution attempt apply Monte Carlo simulation
- assumption of fully observability unrealistic making reasonable moves impossible (e. g., information gathering, bluffing)
  solution attempt incorporate belief states

AI for Games – An Overview

- Chess
  routinely outperform best human players (at least since 2008)
- Checkers
  optimal game play feasible ($\Rightarrow$ routinely outperform best human players)
- Othello/Reversi
  routinely outperform best human players (at least since 2000)
- Backgammon
  competitive with top human players (since 1992)
- Go
  amateur level (good results on smaller boards)
- Bridge
  acceptable level of game play
- Scrabble
  competitive with top human players (since 2006)

Summary & Take Home Message

Things to remember

- transposition tables
- evaluation functions & cutoff, forward pruning, lookup
- stochastic games
- partially observable (stochastic) games

Take Home Message

- Games are a fascinating and motivating area for AI applications.
- Many games are a AI success story.
- If feasible 'brute force' is better than 'intelligence'.
- Stochastic games are much more challenging.
- Partially observable (stochastic) games present difficulties beyond our scope here.