CSE 473: Artificial Intelligence
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Adversarial Search
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Most of these slides originate from Ross, Dan Klein, and Pieter Abbeel.

Game Playing State-of-the-Art

- Chess: 1997: Deep Blue defeats human champion Gary Kasparov in a six-game match. Deep Blue examined 200M positions per second, used very sophisticated evaluation and undisclosed methods for extending some lines of search up to 40 ply. Current programs are even better, if less historic.

Adversarial Games

- Many different kinds of games!
- Axes:
  - Deterministic or stochastic?
  - One, two, or more players?
  - Zero sum?
  - Perfect information (can you see the state)?
- Want algorithms for calculating a strategy (policy) which recommends a move from each state

Behavior from Computation

Video of Demo Mystery Pacman

Types of Games
Deterministic Games

- Many possible formalizations, one is:
  - States: \( S \) (start at \( s_0 \))
  - Players: \( P = \{1,...,N\} \) (usually take turns)
  - Actions: \( A \) (may depend on player / state)
  - Transition Function: \( S \times A \rightarrow S \)
  - Terminal Test: \( S \rightarrow \{t,f\} \)
  - Terminal Utilities: \( S \times P \rightarrow R \)

- Solution for a player is a policy: \( S \rightarrow A \)

Zero-Sum Games

- Zero-Sum Games
  - Agents have opposite utilities (values on outcomes)
  - Lets us think of a single value that one maximizes and the other minimizes
  - Adversarial, pure competition

- General Games
  - Agents have independent utilities (values on outcomes)
  - Cooperation, indifference, competition, and more are all possible
  - More later on non-zero-sum games

Adversarial Search

Value of a State

- Value of a state: The best achievable outcome (utility) from that state

Value of a State

- Value of a state: \( V(s) = \max_{a \in A(s)} V(s,a) \)

Value of a State

- Terminal States: \( V(s) = \text{known} \)

- Non-Terminal States: \( V(s) = \max_{a \in A(s)} V(s,a) \)

Single-Agent Trees

Adversarial Game Trees

- Adversarial Game Trees
  - Terminal States: \( V(s) = \text{known} \)

- Non-Terminal States: \( V(s) = \max_{a \in A(s)} V(s,a) \)
Minimax Values

States Under Agent’s Control:
\[ V(s) = \max_{a' \in \text{Children}(s)} V(s') \]

States Under Opponent’s Control:
\[ V(s') = \min_{a' \in \text{Children}(s')} V(s') \]

Terminal States:
\[ V(s) = \text{Utility} \]

Tic-Tac-Toe Game Tree

Adversarial Search (Minimax)

- Deterministic, zero-sum games:
  - Tic-tac-toe, chess, checkers
  - One player maximizes result
  - The other minimizes result
- Minimax search:
  - A state-space search tree
  - Players alternate turns
  - Compute each node’s minimax value: the best achievable utility against a rational (optimal) adversary

Minimax Implementation

```python
def min_value(state):
    initialize v = +\infty
    for each successor of state:
        v = min(v, max_value(successor))
    return v

def max_value(state):
    initialize v = -\infty
    for each successor of state:
        v = max(v, min_value(successor))
    return v
```

Minimax Implementation (Dispatch)

```python
def value(state):
    if the state is a terminal state: return the state’s utility
    if the next agent is MAX: return max_value(state)
    if the next agent is MIN: return min_value(state)
```

Minimax Example
Minimax Efficiency

- How efficient is minimax?
  - Just like (exhaustive) DFS
  - Time: $O(b^m)$
  - Space: $O(bm)$

- Example: For chess, $b \approx 35$, $m \approx 100$
  - Exact solution is completely infeasible
  - But, do we need to explore the whole tree?

Minimax Properties

Optimal against a perfect player. Otherwise?

Video of Demo Min vs. Exp (Min)

Video of Demo Min vs. Exp (Exp)

Resource Limits

- Problem: In realistic games, cannot search to leaves!
- Solution: Depth-limited search
  - Instead, search only to a limited depth in the tree
  - Replace terminal utilities with an evaluation function for non-terminal positions
- Example:
  - Suppose we have 100 seconds, can explore 10K nodes / sec
  - So can check 1M nodes per move
  - $\alpha-\beta$ reaches about depth 8 – decent chess program
- Guarantee of optimal play is gone
- More plies makes a BIG difference
- Use iterative deepening for an anytime algorithm
**Depth Matters**

- Evaluation functions are always imperfect.
- The deeper in the tree the evaluation function is buried, the less the quality of the evaluation function matters.
- An important example of the tradeoff between complexity of features and complexity of computation.

**Video of Demo Limited Depth (2)**

**Video of Demo Limited Depth (10)**

**Evaluation Functions**

- Evaluation functions score non-terminals in depth-limited search.
- Ideal function: returns the actual minimax value of the position.
- In practice: typically weighted linear sum of features:
  \[ \text{Eval}(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s) \]
- e.g. \( f(s) \) = (num white queens – num black queens), etc.

**Evaluation for Pacman**
Why Pacman Starves

- A danger of replanning agents!
  - He knows his score will go up by eating the dot now (west, east)
  - He knows his score will go up just as much by eating the dot later (east, west)
  - There are no point-scoring opportunities after eating the dot (within the horizon, two here)
  - Therefore, waiting seems just as good as eating: he may go east, then back west in the next round of replanning!
Alpha-Beta Pruning

- General configuration (MIN version)
  - We're computing the MIN-VALUE at some node \( n \)
  - We're looping over \( n \)'s children
  - \( n \)'s estimate of the children's min is dropping
  - Who cares about \( n \)'s value? MAX
  - Let \( a \) be the best value that MAX can get at any choice point along the current path from the root
  - If \( n \) becomes worse than \( a \), MAX will avoid it, so we can stop considering \( n \)'s other children (it's already bad enough that it won't be played)

- MAX version is symmetric

Alpha-Beta Implementation

```python
def min_value(state, α, β):
    initialize v = +∞
    for each successor of state:
        v = min(v, value(successor, α, β))
    if v ≤ α return v
    β = min(β, v)
    return v

def max_value(state, α, β):
    initialize v = -∞
    for each successor of state:
        v = max(v, value(successor, α, β))
    if v ≥ β return v
    α = max(α, v)
    return v
```

- \( α \): MAX's best option on path to root
- \( β \): MIN's best option on path to root

Alpha-Beta Pruning Properties

- This pruning has no effect on minimax value computed for the root!
- Values of intermediate nodes might be wrong
  - Important: children of the root may have the wrong value
  - So the most naive version won’t let you do action selection
- Good child ordering improves effectiveness of pruning
- With "perfect ordering":
  - Time complexity drops to \( O(b^{m/2}) \)
  - Doubles solvable depth!
  - Full search of, e.g. chess, is still hopeless...
- This is a simple example of metareasoning (computing about what to compute)
Iterative Deepening uses DFS as a subroutine:

1. Do a DFS which only searches for paths of length 1 or less. (DFS gives up on any path of length 2)
2. If "1" failed, do a DFS which only searches paths of length 2 or less.
3. If "2" failed, do a DFS which only searches paths of length 3 or less.
   ...and so on.

Why do we want to do this for multiplayer games?

Note: wrongness of eval functions matters less and less the deeper the search goes!