Adversarial Search

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Based on slides from Dan Klein, Peter Abbel, Ali Farhadi
Many slides over the course adapted from either Stuart Russell or Andrew Moore
Game Playing State-of-the-Art

- **Checkers**: Chinook ended 40-year-reign of human world champion Marion Tinsley in 1994. Used an endgame database defining perfect play for all positions involving 8 or fewer pieces on the board, a total of 443,748,401,247 positions. 2007: Checkers is now solved!

- **Chess**: Deep Blue defeated human world champion Gary Kasparov in a six-game match in 1997. Deep Blue examined 200 million 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.

- **Othello**: Human champions refuse to compete against computers, which are too good.

- **Go**: Human champions are beginning to be challenged by machines, though the best humans still beat the best machines. In go, b > 300, so most programs use pattern knowledge bases to suggest plausible moves, along with aggressive pruning.

- **Pacman**: unknown
General Game Playing

General Intelligence in Game-Playing Agents (GIGA'13)
(http://giga13.ru.is)

General Information

Artificial Intelligence (AI) researchers have for decades worked on building game-playing agents capable of matching wits with the strongest humans in the world, resulting in several success stories for games like chess and checkers. The success of such systems has been partly due to years of relentless knowledge-engineering effort on behalf of the program developers, manually adding application-dependent knowledge to their game-playing agents. The various algorithmic enhancements used are often highly tailored towards the game at hand.

Research into general game playing (GGP) aims at taking this approach to the next level: to build intelligent software agents that can, given the rules of any game, automatically learn a strategy for playing that game at an expert level without any human intervention. In contrast to software systems designed to play one specific game, systems capable of playing arbitrary unseen games cannot be provided with game-specific domain knowledge a priori. Instead, they must be endowed with high-level abilities to learn strategies and perform abstract reasoning. Successful realization of such programs poses many interesting research challenges for a wide variety of artificial-intelligence sub-areas including (but not limited to):

- knowledge representation and reasoning
- heuristic search and automated planning
- computational game theory
- multi-agent systems
- machine learning

The aim of this workshop is to bring together researchers from the above sub-fields of AI to discuss how best to address the challenges of and further advance the state-of-the-art of general game-playing systems and generic artificial intelligence.

The workshop is one-day long and will be held onsite at IJCAI during the scheduled workshop period August 3rd-5th (exact day is to be announced later).

Information for Authors

The workshop papers should be submitted online (see workshop webpage). Submitted papers must adhere to the IJCAI paper formatting instructions and not exceed 8 pages (including references). The papers must present original work that has not been published elsewhere. However, submissions of papers that are under review elsewhere are allowed, in particular we welcome papers submitted to the main technical track of IJCAI'13 or AAAI'13. All papers will be peer reviewed and non-archival working notes produced containing the papers presented at the workshop.

Important dates:
- Paper submission: April 20th, 2013
- Acceptance notification: May 20th, 2013
- Camera-ready papers due: May 30st, 2013
- Workshop date: August (3rd, 4th, or 5th) 2013

If you are interesting in attending the conference without submitting a paper please send a short statement of interest to either one of the organizers listed below before May 30st.

Workshop Organizers

Organizers:
Yngvi Björnsson, Reykjavik University
Michael Thielscher, University of New South Wales

Program Committee:
Tristan Cazenave, University of Paris-Dauphine
Stefan Edelkamp, University of Bremen
Hilmar Finnsson, Reykjavik University
Michael Genesereth, Stanford University
Lukasz Kaiser, University of Paris-Diderot
Gregory Kuhlmann, Apple Inc.
Abdallah Saffidine, University of Paris-Dauphine
Torsten Schaub, University of Potsdam
Stephan Schiffel, Reykjavik University
Sam Schreiber, Google Inc.
Nathan Sturtevant, University of Denver
Mark Winands, Maastricht University
Adversarial Search
Game Playing

- Many different kinds of games!

- Choices:
  - Deterministic or stochastic?
  - One, two, or more players?
  - Perfect information (can you see the state)?

- Want algorithms for calculating a strategy (policy) which recommends a move in each state
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: $S \rightarrow A$
Single-Agent Trees

Diagram of a tree structure with nodes labeled with numbers: 2, 0, 2, 6, 4, 6.
Value of States

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

Non-Terminal States:
\[ V(s) = \max_{s' \in \text{children}(s)} V(s') \]

Terminal States:
\[ V(s) = \text{known} \]
Deterministic Single-Player

- Deterministic, single player, perfect information:
  - Know the rules, action effects, winning states
  - E.g. Freecell, 8-Puzzle, Rubik’s cube
- … it’s just search!
- Slight reinterpretation:
  - Each node stores a value: the best outcome it can reach
  - This is the maximal outcome of its children (the max value)
  - Note that we don’t have path sums as before (utilities at end)
- After search, can pick move that leads to best node
Adversarial Game Trees
Minimax Values

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

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

Terminal States:
\[ V(s) = \text{known} \]
Deterministic Two-Player

- E.g. tic-tac-toe, chess, checkers
- Zero-sum games
  - Agents have opposite utilities
  - One player maximizes result
  - The other minimizes result
- Minimax search
  - A state-space search tree
  - Players alternate
  - Choose move to position with highest minimax value = best achievable utility against best play
Tic-tac-toe Game Tree
Minimax Example

A_1
/   \
A_{11} A_{12} A_{13}

A_2
/   \
A_{21} A_{22} A_{23}

A_3
/   \
A_{31} A_{32} A_{33}

3 12 8 2 4 6 14 5 2
Minimax Search

```python
function Max-Value(state) returns a utility value
    if Terminal-Test(state) then return Utility(state)
    \( v \leftarrow -\infty \)
    for \( a, s \) in Successors(state) do \( v \leftarrow \max(v, \text{Min-Value}(s)) \)
    return \( v \)
```

```python
function Min-Value(state) returns a utility value
    if Terminal-Test(state) then return Utility(state)
    \( v \leftarrow \infty \)
    for \( a, s \) in Successors(state) do \( v \leftarrow \min(v, \text{Max-Value}(s)) \)
    return \( v \)
```
Minimax Properties

- **Optimal?**
  - Yes, against perfect player. Otherwise?

- **Time complexity?**
  - $O(b^m)$

- **Space complexity?**
  - $O(bm)$

- **For chess, $b \approx 35$, $m \approx 100$**
  - Exact solution is completely infeasible
  - But, do we need to explore the whole tree?
Can we do better?
$\alpha$-$\beta$ Pruning Example

![Pruning Example Diagram]
**α-β Pruning**

- **General configuration**
  - α is the best value that MAX can get at any choice point along the current path.
  - If n becomes worse than α, MAX will avoid it, so can stop considering n’s other children.
  - Define β similarly for MIN.

![Diagram](attachment:image.png)
Alpha-Beta Pruning Example

α is MAX’s best alternative here or above
β is MIN’s best alternative here or above
Alpha-Beta Pseudocode

inputs: state, current game state
        α, value of best alternative for MAX on path to state
        β, value of best alternative for MIN on path to state
returns: a utility value

function MAX-VALUE(state, α, β)
    if TERMINAL-TEST(state) then
        return UTILITY(state)
    v ← −∞
    for a, s in SUCCESSORS(state) do
        v ← MAX(v, MIN-VALUE(s, α, β))
        if v ≥ β then return v
    α ← MAX(α, v)
    return v

function MIN-VALUE(state, α, β)
    if TERMINAL-TEST(state) then
        return UTILITY(state)
    v ← +∞
    for a, s in SUCCESSORS(state) do
        v ← MIN(v, MAX-VALUE(s, α, β))
        if v ≤ α then return v
    β ← MIN(β, v)
    return v
Alpha-Beta Pruning Example

α is MAX’s best alternative here or above
β is MIN’s best alternative here or above
Alpha-Beta Pruning Example

\[ \alpha \text{ is MAX's best alternative here or above} \]
\[ \beta \text{ is MIN's best alternative here or above} \]
Alpha-Beta Pruning Properties

- This pruning has **no effect** on final result at the root

- Values of intermediate nodes might be wrong!
  - but, they are bounds

- 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…
Resource Limits

- Cannot search to leaves
- Depth-limited search
  - Instead, search a limited depth of tree
  - Replace terminal utilities with an eval function for non-terminal positions
    - e.g., $\alpha$-$\beta$ reaches about depth 8 – decent chess program
- Guarantee of optimal play is gone
- Evaluation function matters
  - It works better when we have a greater depth look ahead
Depth Matters

depth 2
Depth Matters

SCORE: 0

depth 10
Evaluation Functions

- Function which scores non-terminals

- Ideal function: returns the utility of the position
- In practice: typically weighted linear sum of features:
  - e.g. $f_1(s) = (\text{num white queens} - \text{num black queens})$, etc.

$$Eval(s) = w_1f_1(s) + w_2f_2(s) + \ldots + w_nf_n(s)$$
What features would be good for Pacman?

\[ \text{Eval}(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s) \]
Evaluation Function
Evaluation Function
Bad Evaluation Function
Why Pacman Starves

- He knows his score will go up by eating the dot now
- He knows his score will go up just as much by eating the dot later on
- There are no point-scoring opportunities after eating the dot
- Therefore, waiting seems just as good as eating
Which algorithm?

$\alpha$-$\beta$, depth 4, simple eval fun
Which algorithm?

$\alpha$-$\beta$, depth 4, better eval fun
Minimax Example

Suicidal agent
Expectimax

- Uncertain outcomes are controlled by chance not an adversary
- Chance nodes are new types of nodes (instead of Min nodes)