Foundations of AI

6. Adversarial Search

Search Strategies for Games, Games with Chance, State of the Art

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Games & Game Theory

• When there is *more than one agent*, the future is not anymore easily predictable for the agent

• In *competitive* environments (when there are conflicting goals), adversarial search becomes necessary

• Mathematical *game theory* gives the theoretical framework (even for non-competitive environments)

• In AI, we usually consider only a special type of games, namely, board games, which can be characterized in game theory terminology as
  
  – *Extensive, deterministic, two-player, zero-sum* games with *perfect information*
Why Board Games?

• Board games are one of the oldest branches of AI (Shannon, Turing, Wiener, and Shanon 1950).
• Board games present a very abstract and pure form of competition between two opponents and clearly require a form on “intelligence”.
• The states of a game are easy to represent.
• The possible actions of the players are well defined.
• Realization of the game as a search problem
• The world states are fully accessible
• It is nonetheless a contingency problem, because the characteristics of the opponent are not known in advance.

➢ Note: Nowadays, we also consider sport games
Problems

• Board games are not only difficult because they are contingency problems, but also because the search trees can become astronomically large.

• Examples:
  - **Chess**: On average 35 possible actions from every position, 100 possible moves $\rightarrow 35^{100}$ nodes in the search tree (with “only” approx. $10^{40}$ legal chess positions).
  - **Go**: On average 200 possible actions with approx. 300 moves $\rightarrow 200^{300}$ nodes.
What are Our Goals?

- **Good game programs** try to
  - look ahead as many moves as possible
  - delete irrelevant branches of the game tree
  - use good evaluation functions in order to estimate how good a position is
Terminology of Two-Person Board Games

- **Players** are MAX and MIN, where MAX begins.
- **Initial position**, e.g. board arrangement
- **Operators** are the legal moves
- **Termination test** determines when the game is over. Terminal state = game over.
- **Utility function** computes the value of a terminal state, e.g., -1, 0, or 1.
- **Strategy**. In contrast to regular searches, where a path from beginning to end is simply a solution, MAX must come up with a strategy to reach a terminal state regardless of what MIN does → correct reactions to all of MIN’s moves.
Every step of the search tree, also called game tree, is given the player’s name whose turn it is (MAX- and MIN-steps).

When it is possible, as it is here, to produce the full game tree, the minimax algorithm computes an optimal strategy for MAX.
Minimax

1. Generate the complete game tree using depth-first search.
2. Apply the utility function to each terminal state.
3. Beginning with the terminal states, determine the utility of the predecessor nodes as follows:
   • Node is a MIN-node
     Value is the minimum of the successor nodes
   • Node is a MAX-node
     Value is the maximum of the successor nodes
   • From the initial state (root of the game tree), MAX chooses the move that leads to the highest value (minimax decision).

Note: Minimax assumes that MIN plays perfectly. Every weakness (i.e. every mistake MIN makes) can only improve the result for MAX.

Note: Human strategy may be different trying to exploit the weakness of the opponent.
Minimax Example
Minimax Algorithm

Recursively calculates the best move from the initial state.

```
function MINIMAX-DECISION(game) returns an operator
    for each op in OPERATORS[game] do
        VALUE[op] ← MINIMAX-VALUE(APPLY(op, game), game)
    end
    return the op with the highest VALUE[op]

function MINIMAX-VALUE(state, game) returns a utility value
    if TERMINAL-TEST[game](state) then
        return UTILITY[game](state)
    else if MAX is to move in state then
        return the highest MINIMAX-VALUE of SUCCESSORS(state)
    else
        return the lowest MINIMAX-VALUE of SUCCESSORS(state)
```
Evaluation Function

When the search space is too large, the game tree can be created to a certain depth only. The art is to correctly evaluate the playing position of the leaves, which are not terminal states.

Example of simple evaluation criteria in chess:

- Material worth: pawn=1, knight =3, rook=5, queen=9.
- Other: king safety, good pawn structure
- Rule of thumb: 3-point advantage = certain victory

The choice of evaluation function is decisive!

The value assigned to a state of play should reflect the chances of winning, i.e. the chance of winning with a 1-point advantage should be less than with a 3-point advantage.
Evaluation Function - General

The preferred evaluation functions are weighted, linear functions (easy to compute):

$$w_1 f_1 + w_2 f_2 + \ldots + w_n f_n$$

where the $w$'s are the weights, and the $f$'s are the features. (e.g., $w_1 = 3$, $f_1 =$ number of our own knights on the board)

**Assumption:** The criteria are independent.

The weights can be learned. The criteria, however, must be given (no one knows how they can be learned).
Cutting Off Search

• Fixed-depth search (so the goal limit is not overstepped)
• Better: iterative deepening search (with cut-off at time limit)
• … but only evaluate quiescent positions that won’t cause large fluctuations in the evaluation function in the following moves.
• … if bad situations can be pushed behind the horizon, try to search in order to find out.
Two Similar Positions

- Very similar positions, but in (b) black will lose
- Search for quiescent position
Horizon Problem

• Black has a slight material advantage
• … but will eventually lose (pawn becomes a queen)
• A fixed-depth search (<14) will not detect this because it thinks it can avoid it (on the other side of the horizon - because black is concentrating on the check with the rook, to which white must react).
Pruning Branches

• Often, it becomes clear early on that a branch cannot lead to better results than the one we have explored already

➤ Prune away such branches that cannot improve our results!

• What are the conditions under which we are allowed to do that?
Pruning Irrelevant Branches
Pruning Branches: General Idea

If $m > n$ we will never reach node $n$ in the game. Once we have enough information (an upper bound) about the node $n$, we can prune.
Alpha-Beta Pruning: The Method

• $\alpha = \text{the value of the best (i.e., highest value) choice we have found so far at any choice point along the path for MAX}$
  – In the example: $m$

• $\beta = \text{the value of the best (i.e., lowest value) choice we have found so far at any choice point along the path for MIN}$
When Can We Prune?

The following applies:

α values of MAX nodes can never decrease

β values of MIN nodes can never increase

(1) **Prune below** the MIN node whose β-bound is less than or equal to the α-bound of its MAX-predecessor node.

(2) **Prune below** the MAX node whose α-bound is greater than or equal to the β-bound of its MIN-predecessor node.

→ Delivers results that are just as good as with complete minimax searches to the same depth (because only irrelevant nodes are eliminated).
Alpha-Beta Search Algorithm

The $\alpha-\beta$ algorithm

<table>
<thead>
<tr>
<th>Function Definition</th>
<th>Code</th>
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| Alpha-Beta-Search($\text{state}$, $\text{game}$) returns an action | function \text{ALPHA-BETA-SEARCH}(\text{state}, \text{game}) \text{ returns an action} \\
| | \text{action, state} \leftarrow \text{the a, s in } \text{SUCCESSORS}[\text{game}](\text{state}) \\
| | \text{such that MIN-VALUE}(s, \text{game}, -\infty, +\infty) \text{ is maximized} \\
| | \text{return action} |

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| Max-Value($\text{state}$, $\text{game}$, $\alpha$, $\beta$) returns the minimax value of $\text{state}$ | function \text{MAX-VALUE}(\text{state}, \text{game}, \alpha, \beta) \text{ returns the minimax value of state} \\
| | \text{if CUTOFF-TEST}(\text{state}) \text{ then return Eval}(\text{state}) \\
| | \text{for each s in SUCCESSORS(\text{state}) do} \\
| | \quad \alpha \leftarrow \text{max}(\alpha, \text{MIN-VALUE}(s, \text{game}, \alpha, \beta)) \\
| | \quad \text{if } \alpha \geq \beta \text{ then return } \beta \\
| | \text{return } \alpha |

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| | \text{if CUTOFF-TEST}(\text{state}) \text{ then return Eval}(\text{state}) \\
| | \text{for each s in SUCCESSORS(\text{state}) do} \\
| | \quad \beta \leftarrow \text{min}(\beta, \text{MAX-VALUE}(s, \text{game}, \alpha, \beta)) \\
| | \quad \text{if } \beta \leq \alpha \text{ then return } \alpha \\
| | \text{return } \beta |

Initial call with MAX-VALUE($\text{initial-state}$,$\text{game}$,$-\infty$,$+\infty$)
Alpha-Beta Trace

\[
\alpha = -\infty, \\
\beta = +\infty
\]

\[
\alpha = -\infty, \\
\beta = +\infty
\]

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\alpha = -\infty, \\
\beta = +\infty
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\alpha = -\infty, \\
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Efficiency Gain

• The alpha-beta search **cuts the largest amount off the tree** when we examine the best move first.

• In the **best case** (always the best move first), the search cost is reduced to \( O(b^{d/2}) \).

• In the average case (randomly distributed moves), the search cost is reduced to \( O((b/\log b)^d) \).

• For \( b < 100 \), we get \( O(b^{3d/4}) \).

• **Practical case**: A simple ordering heuristic brings the performance close to the best case.

• I.e. we can search twice as deep in the same amount of time

• **Note**: **Iterative deepening search** can be used to enhance estimates
Transposition Tables

• As in search trees, also in game trees there is the problem of repeated states.
• In chess, e.g. the game tree may have $35^{100}$ nodes, but there are only $10^{40}$ different board positions.
• Similar to closed list in search, maintain a transposition table.
  ➢ Got its name from the fact that the same state is reached by a transposition of moves.
Games that Include an Element of Chance

White has just rolled 6-5 and has 4 legal moves.
Game Tree for Games with an Element of Chance

In addition to MIN- and MAX nodes, we need chance nodes (for rolling the dice).
Calculation of the Expected Value

• \textit{Expectiminimax} instead of \textit{Minimax}:

\[
\text{Expectiminimax}(n) =
\begin{align*}
&\text{Utility}(n) & \text{if } n \text{ is a terminal state} \\
&\max_{s \in \text{Successors}(n)} \text{Expectiminimax}(s) & \text{if } n \text{ is a MAX node} \\
&\min_{s \in \text{Successors}(n)} \text{Expectiminimax}(s) & \text{if } n \text{ is a MIN node} \\
&\sum_{s \in \text{Successors}(n)} P(s) \cdot \text{Expectiminimax}(s) & \text{if } n \text{ is a chance node}
\end{align*}
\]
Problems

- Order-preserving transformations on evaluation values change the best move:

  ![Game Tree Diagram]

  - **Search costs increase**: Instead of $O(b^d)$, we get $O(bxn)^d$, where $n$ is the number of possible dice outcomes.
  - In Backgammon ($n = 21, b = 20$ but can be 4000) the maximum $d$ is 3.
  - Variation of alpha-beta search can be used
Card Games

• Recently card games such as bridge and poker have been addressed as well

• One approach: simulate play with open cards and then average over all possible plays (or make a Monte Carlo simulation)
  – Averaging over clairvoyancy

• Although “incorrect”, seems to give reasonable results
State of the Art (1)

**Checkers, draughts** (by international rules): A program called *CHINOOK* is the official world champion in man-computer competition (acknowledged by ACF and EDA) and the highest-rated

**Backgammon**: The *BKG* program defeated the official world champion in 1980. A newer program called *TD-Gammon* (that used a reinforcement learning to learn the evaluation function) is among the top 3 players.

**Othello**: Very good, even on normal computers. Programs are not allowed at tournaments. *Logistello* defeated the world champion in 1997 the human world champion.
State of the Art (2)

**Bridge:** The Bridge Baron program won the 1997 computer bridge championship. GIB (using the averaging over clairvoyancy) won in 2000. In general, they are not a match for humans, though

**Tic-Tac-Toe, Go-Moku (five in a row), Nine-Men’s Morris** are all solved by exhaustive analysis.

**Go:** The best programs play a little better than beginners (10 kyu) (branching factor on average 200).

→ There is a $2 Mi. US-$ prize for the first program to defeat a world master.
Chess (1)

• Chess as “Drosophila” of AI research.

• A limited number of rules produces an virtually unlimited number of courses of play. In a game of 40 moves, there are $1.5 \times 10^{128}$ possible courses of play.

• Victory comes through logic, intuition, creativity, and previous experience.

• In 1997, the world chess master G. Kasparow was beaten by Deep Blue in a match of 6 games.

• January/February 2003, Kasparow played a draw against Deep Junior ($1,\frac{1}{2},0,\frac{1}{2},\frac{1}{2},\frac{1}{2}$)
Chess (2)

- **Deep Blue** (IBM Thomas J. Watson Research Center)
- **Special hardware** (32 processors with 8 chips, 2 Mi. calculations per second)
- Heuristic search
- Case-based reasoning and learning techniques
- 1996 Knowledge based on 600 000 chess games
- 1997 Knowledge based on 2 million chess games
- Training through grand masters
Chess (3)

Kasparow: There were moments when I had the feeling that these boxes are possibly closer to intelligence than we are ready to admit.

From a certain point on it seems, in chess at least, that great quantity translates into quality.

I see rather a great chance for fine creativity and brute force computational capacity to complement each other in a new form of information acquisition. The human and electronic brain together would produce a new quality of intelligence – an intelligence worthy of this name.
The Reasons for Success...

- Alpha-Beta-Search
- … with dynamic decision/making for uncertain positions
- Good (but usually simple) evaluation functions
- Large databases of opening moves.
- Very large end-game databases (for checkers, all 8-piece situations)
- And very fast and parallel processors!
Summary

• A game can be defined by the initial state, the operators (legal moves), a termination test and a utility function (outcome of the game).

• In two-player games, the minimax algorithm can determine the best move by enumerating the entire game tree.

• The alpha-beta algorithm produces the same result but is more efficient because it prunes away irrelevant branches.

• Usually, it is not feasible to construct the complete game tree, so the utility of some states must be determined by an evaluation function.

• Games of chance can be handled by an extension of the alpha-beta algorithm.