Pascal Bercher

Many thanks to Stephen Gould!
Slides partially build upon his lecture from 2019.

Planning & Optimization Group
College of Engineering and Computer Science
the Australian National University (ANU)

August 21, Semester 2, 2020
Outline for Today

- Motivation: Why Solving Games Automatically Anyways?
- What are Games? (A few Definitions)
- Solving Small Games
  - MiniMax
  - \(\alpha/\beta\) Pruning
- Games with Chance
- Solving Large Games
- Defeating Dragons with AI
- Game AI Success Story
Why Bother? Why Solving Games Automatically?

- Game AIs for computer games (modern ones or board game adaptations).
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  - Robotics or Multi-Agent-Planning (though this is often cooperative, whereas we take a look at antagonistic games)
  - Economics! Cf. game theory (look up: Nash Equilibrium and Prisoner’s Dilemma)
What are Games? Which Kinds Exist?

A game consists of a set of one or more players, a set of moves for the players, and a specification of payoffs (outcomes) for each combination of strategies (also called policy).

What kinds of restrictions can games have?
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- Zero-sum games vs. non-zero-sum games
- Games with chance (randomness) vs. games without chance
What’s a Strategy?

A **strategy** defines a complete plan of action for a given player.

Given enough processing time an **optimal strategy** can be found for games of **perfect information** by enumerating paths of a **game tree**. However, in practice this can only be done for small games.
What are we Looking For?

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- Game AI (strategy) vs. game theoretic outcome!

What’s the game theoretic outcome?

- The outcome of the game assuming all players play *rational*.
- Rationality = optimization of expected reward.
- Outcome is known? → The respective game is “solved”.
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- Game AI (strategy) vs. game theoretic outcome!
- Just because we have an AI that beats all humans, it doesn’t mean the game is solved!

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Motivation | Games? | Solving Small Games | Games with Chance | Solving Large Games | Defeating Dragons with AI | Game AI Success Story
---|---|---|---|---|---|---

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MiniMax — How to Solve Small Games?

Using search to solve a game:

- If the game tree is “sufficiently small” we can search in it to find and extract a strategy.
- But we still need to do that *efficiently*!
MiniMax — How to Solve Small Games?

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- But we still need to do that *efficiently*!

Consider two players, MAX and MIN. MAX tries to maximize his/her own score, and player MIN tries to minimize it.

We assume that the players are rational.
The MiniMax algorithm allows each player to compute their optimal move on a game tree of alternating MAX and MIN nodes.

The value of a node is the payoff for a game that is played optimally from that node until the end of the game.

```
max-value(s)
if state s is a leaf then
  return payoff(s)

v := -∞
forall successor states s' of s do
  v := max {v, min-value(s')}
return v
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MiniMax — Example: Tic Tac Toe

MAX player plays X, MIN plays O. Outcomes (black boxes) are from the perspective of the MAX player (i.e., 1 is a win, -1 a loss, 0 a draw).
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$\text{MAX}$ player plays $X$, $\text{MIN}$ plays $O$. Outcomes (black boxes) are from the perspective of the $\text{MAX}$ player (i.e., 1 is a win, -1 a loss, 0 a draw).
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What is the runtime of MiniMax?

- Time: All nodes have to be visited! How many are there?
- Assume each game ends after \( d \) moves (tree depth).
  Each player has at most \( b \) moves (branching factor)
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What is the space requirement of MiniMax?

- We perform a depth-first search!
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  Each player has at most $b$ moves (branching factor)

→ Runtime is in $O(b^d)$ (exponential!)

What is the space requirement of MiniMax?

- We perform a depth-first search!
- So only the longest path needs to be stored.

→ Space is in $O(b \cdot d)$ (linear)
α/β Pruning — Can we do better?

- MiniMax suffers from the problem that the number of game states it has to examine is *always* exponential in the number of moves.

- α/β pruning is a method for reducing the number of nodes that need to be evaluated by only considering nodes that may be reached in game play.

- Alpha-beta pruning places bounds on the values appearing anywhere along a path:
  - $\alpha$ is the best (highest) value found so far for MAX
  - $\beta$ is the best (lowest) value found so far for MIN

$\alpha$ and $\beta$ propagate down the game tree. $v$ propagates up the game tree.
### α/β Pruning — The MiniMax Algorithm Extended By α/β Pruning

Keep in mind:

- \( \alpha \) is the best value found so far for \( \text{MAX} \), initialize with \(-\infty\).
- \( \beta \) is the best value found so far for \( \text{MIN} \), initialize with \(\infty\).

#### max-value

\[
\text{max-value}(s, \alpha, \beta) \quad \begin{align*}
\text{if } & \text{state } s \text{ is a leaf then} \\
& \text{return } \text{payoff}(s) \\
\quad v := & -\infty \\
\text{forall successor states } s' \text{ of } s \text{ do} \\
& v := \max \{ v, \text{min-value}(s', \alpha, \beta) \} \\
& \text{if } v \geq \beta \text{ then} \\
& \quad \text{return } v \\
& \quad \alpha := \max \{ \alpha, v \}
\end{align*}
\]

\text{return } v

#### min-value

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\text{forall successor states } s' \text{ of } s \text{ do} \\
& v := \min \{ v, \text{max-value}(s', \alpha, \beta) \} \\
& \text{if } v \leq \alpha \text{ then} \\
& \quad \text{return } v \\
& \quad \beta := \min \{ \beta, v \}
\end{align*}
\]

\text{return } v
α/β Pruning — Idea Behind Pruning: When and Why?

\[ \alpha = -\infty \quad \beta = \infty \]
\[ \alpha = -\infty \quad \beta = 5 \]
\[ \alpha = 2 \quad \beta = 5 \]
\[ v = 5 \]
\[ v = 2 \]
\[ v = 7 \]

**MIN** chooses the left move with \( v = 5 \) so there is no point investigating the branch below.

\( (v = 7) \geq (\beta = 5) \)

\[ V \]

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**Motivation**

Games?

Solving Small Games

Games with Chance

Solving Large Games

Defeating Dragons with AI

Game AI Success Story

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**α/β Pruning** — Example: Tic Tac Toe

Start with $\alpha = -1$ (rather than $-\infty$) and $\beta = 1$ (rather than $\infty$)

Max

$v = -\infty$ (or $-1$)

$\alpha = -1, \beta = 1$
\( \alpha/\beta \) Pruning — Example: Tic Tac Toe

Start with \( \alpha = -1 \) (rather than \(-\infty\)) and \( \beta = 1 \) (rather than \(\infty\))

\[
\begin{align*}
\text{MAX} & \quad & \text{MIN} \\
O & O & X & o & o & x & o & o & x & o & o & x & o & x & x \\
X & & X & o & x & x & o & x & x & o & x & x & o & x & x \\
\end{align*}
\]

\( v = -\infty \) (or \(-1\))
\( \alpha = -1, \beta = 1 \)

(2)

\( v = \infty \) (or 1)
\( \alpha = -1, \beta = 1 \)

\( v = ??? \)
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α/β Pruning — Example: Tic Tac Toe

Start with $\alpha = -1$ (rather than $-\infty$) and $\beta = 1$ (rather than $\infty$)

\[
\begin{align*}
\text{MAX} & : \quad \alpha = -1, \beta = 1 \\
\text{MIN} & : \quad \alpha = -1, \beta = 1 \\
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because $(\nu = -1) \leq (\alpha = -1)$
α/β Pruning — Example: Tic Tac Toe

Start with $\alpha = -1$ (rather than $-\infty$) and $\beta = 1$ (rather than $\infty$)

because $(v = -1) \leq (\alpha = -1)$

$\alpha = -1, \beta = 1$

$\alpha = ???, \beta = ???$

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α/β Pruning — Example: Tic Tac Toe

Start with $\alpha = -1$ (rather than $-\infty$) and $\beta = 1$ (rather than $\infty$)

![Diagram of Tic Tac Toe game with alpha-beta pruning example](image-url)
Start with $\alpha = -1$ (rather than $-\infty$) and $\beta = 1$ (rather than $\infty$)
What is the runtime (and space requirements) of $\alpha/\beta$ pruning?

- In the worst case: identical to MiniMax! If nothing can be pruned.
- On average: Complexities omitted. (Due to lack of time.)
- This can happen depending on the order in which edges are traversed/payoffs are discovered.
- In practice, it is very unlikely that no pruning occurs, so always choose $\alpha/\beta$ pruning over MiniMax!
How to Deal with Randomness?

- A random decision can be regarded as the move of yet another player!
- Certainly that’s not another MAX player! I.e, the “environment” (the random decision) will not always play in our favor!
- But what is it, then?
  - Another MIN player? (Too pessimistic...)
  - If we want to play rational, we maximize the expectation!

\[
\text{value}(s) = \sum_{\text{successor states } s'} P(s') \cdot \text{value}(s')
\]
Illustration For a 2-Player Game With Throwing Two Dice, Counting Their Sum

\[
\begin{align*}
P(sum = 2) &= \frac{1}{36} \\
P(sum = 7) &= \frac{6}{36} \\
P(sum = 12) &= \frac{1}{36}
\end{align*}
\]
The “Size” of Games

When is using MiniMax and $\alpha/\beta$ Pruning still feasible?

- Recall that the complexity of MiniMax (and $\alpha/\beta$) is exponential! I.e., in $O(b^d)$, with
  - $b$, the branching factor (available moves per state)
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- For some games that is simply too large!
- So, let’s take a look at some examples...
The “Size” of Games: Tic Tac Toe

Examples for (estimated) number of reachable (game) states:
(Source: https://en.wikipedia.org/wiki/Game_complexity)
The “Size” of Games: Tic Tac Toe

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- Rough maximum: $3^9 = 19,683$ (including invalid states)
- Actual maximum: 5,478
- Maximum after duplicating symmetries: 765
- There are still 26,830 possible games!
  (For those states with eliminated duplicates.)

What’s a “game”?
A path in the MiniMax tree!
The “Size” of Games: Connect 4

Examples for (estimated) number of reachable (game) states:

(Source: https://en.wikipedia.org/wiki/Connect_Four)

- Rough maximum: $3^{7 \cdot 6} < 1.110^{20}$ (including invalid states)
- Actual maximum: $4,531,985,219,092 \approx 4.5 \cdot 10^{12}$ (still including symmetries)
- First solved, independently, by James Dow Allen (October 1, 1988), and Victor Allis (October 16, 1988).
- Note that today it can also be solved using $\alpha/\beta$ pruning!
The “Size” of Games: Blokus

Examples for (estimated) number of reachable (game) states:
(Source: by Stephen Gould, previous year(s))

Approximately 58 moves, not all symmetries eliminated.
The “Size” of Games: Blokus

Examples for (estimated) number of reachable (game) states:
(Source: by Stephen Gould, previous year(s))

approx. 2 \cdot 58 \text{ moves, symmetries as before}

approx. 116 \text{ moves, symmetries as before}
The “Size” of Games: Blokus

Examples for (estimated) number of reachable (game) states:
(Source: by Stephen Gould, previous year(s))

- 21 pcs, 58 moves: $58 \cdot 116 = 6,728$ moves
- 20 pcs, ??? moves
- $58 \cdot 116 \cdot 116 = 780,448$ moves
- $58 \cdot 116 \cdot 116 \cdot 58 = 45,265,984 \approx 4.5 \cdot 10^7$ moves
Examples for (estimated) number of reachable (game) states:

(Source: https://en.wikipedia.org/wiki/Shannon_number)

- Some maximum: $5 \cdot 10^{52}$
- Lower limit on game tree size: $10^{123}$
- More conservative estimate on lower limit of game tree size, eliminating obvious bad moves: $10^{40}$
The “Size” of Games: Go

Examples for (estimated) number of reachable (game) states:

(Source: https://en.wikipedia.org/wiki/Shannon_number_number)

- Legal positions: $2.08168199382 \cdot 10^{170}$
- Lower limit on number of games: $10^{10^{48}}$
- Upper limit on number of games: $10^{10^{171}}$
How to deal with large games?

So, what to do for (too) large games?

- Don’t compute the entire game tree!
- Stop at certain nodes and *estimate* their payoff!
How to deal with large games?

So, what to do for (too) large games?

- Don’t compute the entire game tree!
- Stop at certain nodes and estimate their payoff! But how?
  - hand-crafted heuristics

![Chess Board](image)

<table>
<thead>
<tr>
<th>Piece</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>pawn</td>
<td>1 pt</td>
</tr>
<tr>
<td>knight/bishop</td>
<td>3 pts</td>
</tr>
<tr>
<td>rook</td>
<td>5 pts</td>
</tr>
<tr>
<td>queen</td>
<td>9 pts</td>
</tr>
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</table>

Estimate: Black: 7 pts versus White: 6 pts
→ Black leading! (Only very slightly.)
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  - hand-crafted heuristics
  - learned heuristics

Machine learning techniques are often used to find a good static evaluation function based on a linear combination of features:

\[
\hat{v}(s) = w_1 f_1(s) + \cdots + w_n f_n(s)
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\hat{v}(s) = w_1 f_1(s) + \cdots + w_n f_n(s)
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Note the similarity to chess!

- \( w_1 = 1, f_1(s) = \text{number of pawns in } s \)
- \( w_2 = 3, f_2(s) = \text{number of knights/bishops in } s \)
- ...
How to deal with large games?

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- Don’t compute the entire game tree!
- Stop at certain nodes and *estimate* their payoff! But how?
  - hand-crafted heuristics
  - learned heuristics
  - simulate a game, use the outcome as estimate

**Monte-Carlo Tree Search** is a well-known algorithm exploiting this idea. It works in four phases:

- *Selection* (select a non-terminal leaf based on current strategy)
- *Expansion* (expand the selected node)
- *Simulation* (play a random game to the end)
- *Backpropagation* (use the outcome to update strategy)

Interested? See, e.g.,
https://www.youtube.com/watch?v=UXW2yZnd17U
(15:30, lecture by Dr. John Levine from Univ. of Strathclyde)
**When to use heuristics?**

- In standard MiniMax or *alpha/beta* pruning, we make a **terminal test** to obtain the payoff, or continue expanding. With heuristics, we instead make a **cut-off test** to check whether we should stop expansion and *estimate* the payoff of the current node.
When to use heuristics?

- In standard MiniMax or alpha/beta pruning, we make a **terminal test** to obtain the payoff, or continue expanding. With heuristics, we instead make a **cut-off test** to check whether we should stop expansion and **estimate** the payoff of the current node.

- What about using a fixed depth as cut-off test? → Suffers from the **horizon problem**:

![Chess Board](image)

**Black to move**

### Title:  *Artificial Intelligence: A Modern Approach (3rd Ed.)*

### Authors:  *Stuart Russel and Peter Norvig*

### URL:  [https://aima.cs.berkeley.edu/](https://aima.cs.berkeley.edu/)

White can promote a pawn into a queen on his next move! So the cut-off test should be negative in this state.
But let’s start with Tsudo, the “underlying game mechanics”.

Figure: YouTube video: https://www.youtube.com/watch?v=MGvY3jsLN1I (1:25) Code: M-G-v-Y-3-j-s-L-N-1(one)-l(capital-i)
The Assignment: Tsuro of the Seas

Tsuro of the Seas: Ultra-short introduction

Figure: YouTube video: https://www.youtube.com/watch?v=ziQS8rcT5EA (we just take a glance from 5:04 to 5:58) Code: z-i-Q-S-8-r-c-T-5-E-A

Regarding the game rules: Please stick to the ones officially provided by Steve Blackburn!
Mile Stones in AI Game Playing

1959  Arthur Samuel develops Checkers playing program
### Mile Stones in AI Game Playing

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Milestones in AI Game Playing

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Motivation

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2016  Google DeepMind’s AlphaGo beats Lee Sedol, Korea

2017  AlphaZero learns Go, Chess, and Shogi from scratch (and beats AlphaGo)
Picture is *public domain*
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The game Tsuro, is used as assignment for this lecture.


By Stuart Russel and Peter Norvig from their book *Artificial Intelligence: A Modern Approach (3rd Ed.)*

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