CSC 2515: Introduction to Machine Learning

AlphaGo and game-playing

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Recap of different learning settings

So far the settings that you’ve seen imagine one learner or agent.

**Supervised**

Learner predicts labels.

**Unsupervised**

Learner organizes data.

**Reinforcement**

Agent maximizes reward.
Today

We will talk about learning in the context of a **two-player game**.

This lecture only touches a small part of the large and beautiful literature on game theory, multi-agent reinforcement learning, etc.
Game-playing in AI: Beginnings

• (1950) Claude Shannon proposes explains how games could be solved algorithmically via tree search
• (1953) Alan Turing writes a chess program
• (1956) Arthur Samuel writes a program that plays checkers better than he does
• (1968) An algorithm defeats human novices at Go

slide credit: Profs. Roger Grosse and Jimmy Ba
Game-playing in AI: Successes

- (1992) TD-Gammon plays backgammon competitively with the best human players
- (1996) Chinook wins the US National Checkers Championship
- (1997) DeepBlue defeats world chess champion Garry Kasparov

slide credit: Profs. Roger Grosse and Jimmy Ba
Today

- Game-playing has always been at the core of CS.
  - Simple well-defined rules, but mastery requires a high degree of intelligence.
- We will study how to learn to play Go.
  - The ideas in this lecture apply to all zero-sum games with finitely many states, two players, and no uncertainty.
  - Go was the last classical board game for which humans outperformed computers.
  - We will follow the story of AlphaGo, DeepMind’s Go playing system that defeated the human Go champion Lee Sedol.
- Combines many ideas that you’ve already seen.
  - supervised learning, value function learning...
The game of Go: Start

- Initial position is an empty $19 \times 19$ grid.
The game of Go: Play

- 2 players alternate placing stones on empty intersections. Black stone plays first.
- (Ko) Players cannot recreate a former board position.
The game of Go: Play

- **(Capture)** Capture and remove a connected group of stones by surrounding them.
The game of Go: End

- **(Territory)** The winning player has the maximum number of occupied or surrounded intersections.
Outline of the lecture

To build a strong computer Go player, we will answer:

- What does it mean to play optimally?
- Can we compute (approximately) optimal play?
- Can we learn to play (somewhat) optimally?
Why is this a challenge?

• Optimal play requires searching over $\sim 10^{170}$ legal positions.
• It is hard to decide who is winning before the end-game.
  • Good heuristics exist for chess (count pieces), but not for Go.
• Humans use sophisticated pattern recognition.
Optimal play
Game trees

- Organize all possible games into a tree.
  - Each node $s$ contains a legal position.
  - Child nodes enumerate all possible actions taken by the current player.
  - Leaves are terminal states.
  - Technically board positions can appear in more than one node, but let's ignore that detail for now.

- The Go tree is finite (Ko rule).
Game trees

black stone’s turn

white stone’s turn
Evaluating positions

• We want to quantify the utility of a node for the current player.

• Label each node \( s \) with a value \( v(s) \), taking the perspective of the black stone player.
  • +1 for black wins, -1 for black loses.
  • Flip the sign for white’s value (technically, this is because Go is zero-sum).

• Evaluations let us determine who is winning or losing.
Evaluating leaf positions

Leaf nodes are easy to label, because a winner is known.

```
-1 +1 +1 +1 -1 -1 +1 +1 +1 -1 -1 -1 -1 -1 +1 -1
```

black stones win white stones win
Evaluating internal positions

- The value of internal nodes depends on the strategies of the two players.
- The so-called maximin value $v^*(s)$ is the highest value that black can achieve regardless of white's strategy.
- If we could compute $v^*$, then the best (worst-case) move $a^*$ is

$$a^* = \arg \max_a \{v^*(\text{child}(s, a))\}$$
Evaluating positions under optimal play
Evaluating positions under optimal play
Evaluating positions under optimal play

$max$

$min$

$max$

$min$

$v^*(s) = +1$
Value function $v^*$

- $v^*$ satisfies the **fixed-point equation**

$$v^*(s) = \begin{cases} 
\max_a\{v^*(\text{child}(s, a))\} & \text{black plays} \\
\min_a\{v^*(\text{child}(s, a))\} & \text{white plays} \\
+1 & \text{black wins} \\
-1 & \text{white wins}
\end{cases}$$

- Analog of the optimal value function of RL.
- Applies to other two-player games
  - Deterministic, zero-sum, perfect information games.
What is the maximin value $v^*(s)$ of the root?

1. -1?
2. +1?

Recall: black plays first and is trying to maximize, whereas white is trying to minimize.
Quiz!

$v^*(s) = +1$

What is the maximin value $v^*(s)$ of the root?

1. -1?
2. +1?

Recall: black plays first and is trying to maximize, whereas white is trying to minimize.
In a perfect world

• So, for games like Go, all you need is $v^*$ to play optimally in the worst case:

$$a^* = \arg \max_a \{v^*(\text{child}(s, a))\}$$

• Claude Shannon (1950) pointed out that you can find $a^*$ by recursing over the whole game tree.

• Seems easy, but $v^*$ is wildly expensive to compute...
  • Go has $\sim 10^{170}$ legal positions in the tree.
Approximating optimal play
Depth-limited Minimax

- In practice, recurse to a small depth and back off to a static evaluation \( \hat{v}^* \).
  - \( \hat{v}^* \) is a heuristic, designed by experts.
  - Other heuristics as well, e.g. pruning.
  - For Go (Müller, 2002).
Progress in Computer Go

Minimax search for Go

adapted from Sylvain Gelly & David Silver, Test of Time Award ICML 2017
Expected value functions

- Designing static evaluation of $v^*$ is very challenging, especially so for Go.
  - Somewhat obvious, otherwise search would not be needed!
- Depth-limited minimax is very sensitive to misevaluation.
- Monte Carlo tree search resolves many of the issues with Minimax search for Go.
  - Revolutionized computer Go.
  - To understand this, we will introduce expected value functions.
Expected value functions

If players play by rolling fair dice, outcomes will be random.

This is a decent approximation to very weak play.
Expected value functions

Averaging many random outcomes $\rightarrow$ expected value function.

$$v(s) = -1/9$$
Consider two players that pick their moves by flipping a fair coin, what is the expected value \( v(s) \) of the root?

1. 1/3?
2. 1/2?
Consider two players that pick their moves by flipping a fair coin, what is the expected value $v(s)$ of the root?

1. $1/3$?
2. $1/2$?
**Expected value functions**

- Noisy evaluations $v_n$ are cheap approximations of expected outcomes:

$$v_n(s) = \frac{1}{n} \sum_{i=1}^{n} o(s'_i)$$

$$\approx \mathbb{E}[o(s') := v(s)]$$

$o(s) = \pm 1$ if black wins / loses.

- Longer games will be underweighted by this evaluation $v$, but let’s ignore that.
Monte Carlo tree search

• Ok expected value functions are easy to approximate, but how can we use $v_n$ to play Go?
  • $v_n$ is not at all similar to $v^*$.
  • So, maximizing $v_n$ by itself is probably not a great strategy.
  • Minimax won’t work, because it is a pure exploitation strategy that assumes perfect leaf evaluations.

• Monte Carlo tree search (MCTS; Kocsis and Szepesvári, 2006; Coulom, 2006; Browne et al., 2012) is one way.
  • MCTS maintains a depth-limited search tree.
  • Builds an approximation $\hat{v}^*$ of $v^*$ at all nodes.
Monte Carlo tree search

- **Select** an existing leaf or **expand** a new leaf.
- Evaluate leaf with Monte Carlo **simulation** $v_n$.
- Noisy values $v_n$ are **backed-up the tree** to improve approximation $\hat{v}^*$.

(Browne et al., 2012)
Monte Carlo tree search

• Selection strategy greedily descends tree.

• MCTS is robust to noisy misevaluation at the leaves, because the selection rule balances exploration and exploitation:

\[ a^* = \arg \max_a \left\{ \hat{v}^*(\text{child}(s,a)) + \sqrt{\frac{2 \log N(s)}{N(\text{child}(s,a))}} \right\} \]

• \( \hat{v}^*(s) = \) estimate of \( v^*(s) \), \( N(s) \) number of visits to node \( s \).

• MCTS is forced to visit rarely visited children.

• Key result: MCTS approximation \( \hat{v}^* \rightarrow v^* \) (Kocsis and Szepesvári, 2006).
Progress in Computer Go

Monte Carlo tree search for Go

adapted from Sylvain Gelly & David Silver, Test of Time Award ICML 2017
Scaling with compute and time

- The strength of MCTS bots scales with the amount of compute and time that we have at play-time.
- But play-time is limited, while time outside of play is much more plentiful.
- How can we improve computer Go players using compute when we are not playing? Learning!
  - You can try to think harder during a test vs. studying more beforehand.
Learning to play Go
This is where Chris came in

- 2014 Google DeepMind internship on neural nets for Go.
  - Working with Aja Huang, David Silver, Ilya Sutskever, he was responsible for designing and training the neural networks.
  - Others came before (e.g., Sutskever and Nair, 2008).
- Ilya Sutskever’s (Chief Scientist, OpenAI) argument in 2014: expert players can identify a good set of moves in 500 ms.
  - This is only enough time for the visual cortex to process the board—not enough for complex reasoning.
  - At the time we had neural networks that were nearly as good as humans in image recognition, thus we thought we would be able to train a net to play Go well.

- **Key goal: can we train a net to understand Go?**
Neural nets for Go

Neural networks are powerful parametric function approximators.

board \( s \)

\[ \text{net}(s, x) \]

parameters \( x \)

Idea: map board position \( s \) (input) to a next move or an evaluation (output) using simple convolutional networks.
Neural nets for Go

• We want to train a neural policy or neural evaluator, but how?
• Existing data: databases of Go games played by humans and other compute Go bots.
• The first idea that worked was **learning to predict expert’s next move.**
  • Input: board position \( s \)
  • Output: next move \( a \)
Policy Net (Maddison et al., 2015)

- **Dataset:** KGS server games split into board / next-move pairs $(s_i, a_i)$
  - 160,000 games $\rightarrow$ 29 million $(s_i, a_i)$ pairs.

- **Loss:** negative log-likelihood,

  $$-\sum_{i=1}^{N} \log \pi_{\text{net}}(a_i | s_i, x).$$

- **Use trained net as a Go player:**

  $$a^* = \arg \max_a \{ \log \pi_{\text{net}}(a | s, x) \}.$$
Like learning a better traversal

As supervised accuracy improved, searchless play improved.
Progress in Computer Go

Progress in my internship

Adapted from Sylvain Gelly & David Silver, Test of Time Award ICML 2017
Can we improve MCTS with neural networks?

- These results prompted the formation of big team inside DeepMind to combine MCTS and neural networks.
- To really improve search, we needed strong evaluators.
  - **Recall**: an evaluation function tells us who is winning.
  - $\pi_{\text{net}}$ rollouts would be a good evaluator, but this is too expensive.
- Can we learn one?
Value Net (Silver et al., 2016)

Failed attempt.

- **Dataset**: KGS server games split into board / outcome pairs $(s_i, o(s_i))$
- **Loss**: squared error,

\[
\sum_{i=1}^{N} (o(s_i) - v_{\text{net}}(s_i, x))^2.
\]

- **Problem**: Effective sample size of 160,000 games was not enough.
Value Net (Silver et al., 2016)

Successful attempt.

- Use Policy Net playing against itself to generate millions of unique games.
- **Dataset**: Board / outcome pairs \((s_i, o(s_i))\), each from a unique self-play game.

- **Loss**: squared error,

\[
\sum_{i=1}^{N} (o(s_i) - \nu_{\text{net}}(s_i, x))^2.
\]

(Silver et al., 2016)
AlphaGo (Silver et al., 2016)

- The Value Net was a very strong evaluator.

- The final version of AlphaGo used rollouts, Policy Net, and Value Net together.
  - Rollouts and Value Net as evaluators.
  - Policy Net to bias the exploration strategy.
Progress in Computer Go

AlphaGo Team (Silver et al., 2016)

adapted from Sylvain Gelly & David Silver, Test of Time Award ICML 2017
Impact
2016 Match—AlphaGo vs. Lee Sedol

- Best of 5 matches over the course of a week.
- Most people expected AlphaGo to lose 0-5.
- AlphaGo won 4-1.
Human moments

Lee Sedol is a titan in the Go world, and achieving his level of play requires a life of extreme dedication.

It was humbling and strange to be a part of the AlphaGo team that played against him.
Game 2, Move 37


