CSC321 Lecture 23: Go

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Final Exam

- Friday, April 20, 9am-noon
  - Last names A–Y: Clara Benson Building (BN) 2N
  - Last names Z: Clara Benson Building (BN) 2S
- Covers all lectures, tutorials, homeworks, and programming assignments
  - 1/3 from the first half, 2/3 from the second half
  - If there's a question on Lectures 22 or 23, it will be easy
- Emphasis on concepts covered in multiple of the above
- Similar in format and difficulty to the midterm, but about 3x longer
- Practice exams are posted

Overview

- Most of the problem domains we've discussed so far were natural application areas for deep learning (e.g. vision, language)
  - We know they can be done on a neural architecture (i.e. the human brain)
  - The predictions are inherently ambiguous, so we need to find statistical structure
- Board games are a classic AI domain which relied heavily on sophisticated search techniques with a little bit of machine learning
  - Full observations, deterministic environment — why would we need uncertainty?
- This lecture is about AlphaGo, DeepMind's Go playing system which took the world by storm in 2016 by defeating the human Go champion Lee Sedol
- Combines ideas from our last two lectures (policy gradient and value function learning)

Overview

Some milestones in computer game playing:

- 1949 — Claude Shannon proposes the idea of game tree search, explaining how games could be solved algorithmically in principle
- 1951 — Alan Turing writes a chess program that he executes by hand
- 1956 — Arthur Samuel writes a program that plays checkers better than he does
- 1968 — An algorithm defeats human novices at Go

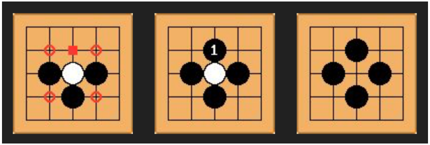
...silence...

- 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

After chess, Go was humanity's last stand

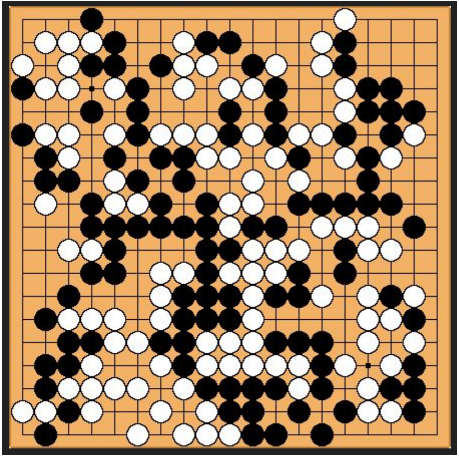
Go

- Played on a 19×19 board
- Two players, black and white, each place one stone per turn
- Capture opponent's stones by surrounding them



Go

- Goal is to control as much territory as possible:



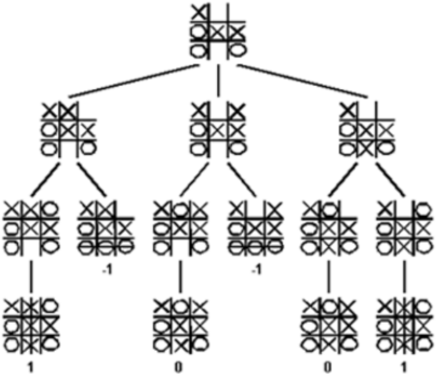
Go

What makes Go so challenging:

- Hundreds of legal moves from any position, many of which are plausible
- Games can last hundreds of moves
- Unlike Chess, endgames are too complicated to solve exactly (endgames had been a major strength of computer players for games like Chess)
- Heavily dependent on pattern recognition

Game Trees

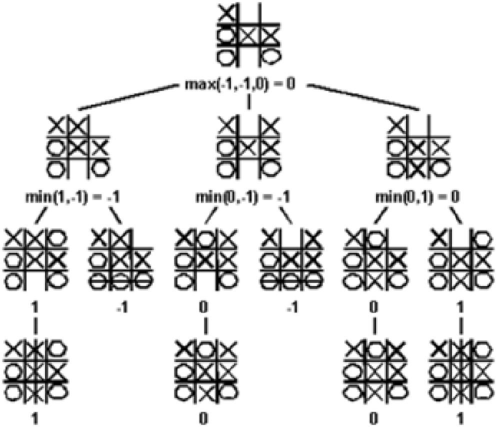
- Each node corresponds to a legal state of the game.
- The children of a node correspond to possible actions taken by a player.
- Leaf nodes are ones where we can compute the value since a win/draw condition was met



https://www.cs.cmu.edu/~adamchik/15-121/lectures/Game%20Trees/Game%20Trees.html

Game Trees

- To label the internal nodes, take the max over the children if it's Player 1's turn, min over the children if it's Player 2's turn



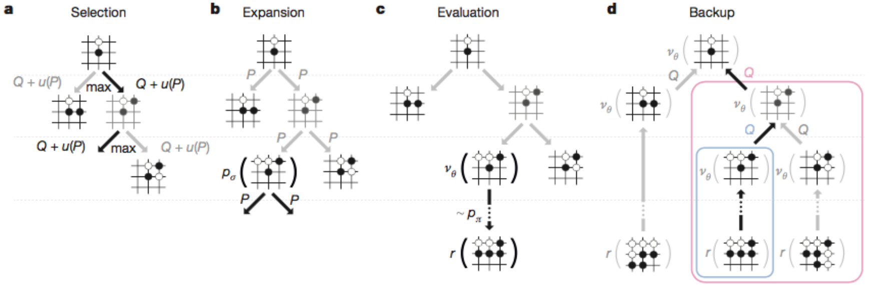
https://www.cs.cmu.edu/~adamchik/15-121/lectures/Game%20Trees/Game%20Trees.html

Game Trees

- As Claude Shannon pointed out in 1949, for games with finite numbers of states, you can solve them in principle by drawing out the whole game tree.
- Ways to deal with the exponential blowup
  - Search to some fixed depth, and then estimate the value using an evaluation function
  - Prioritize exploring the most promising actions for each player (according to the evaluation function)
- Having a good evaluation function is key to good performance
  - Traditionally, this was the main application of machine learning to game playing
  - For programs like Deep Blue, the evaluation function would be a learned linear function of carefully hand-designed features

Monte Carlo Tree Search

- In 2006, computer Go was revolutionized by a technique called Monte Carlo Tree Search.



Silver et al., 2016

- Estimate the value of a position by simulating lots of rollouts, i.e. games played randomly using a quick-and-dirty policy
- Keep track of number of wins and losses for each node in the tree
- Key question: how to select which parts of the tree to evaluate?

Monte Carlo Tree Search

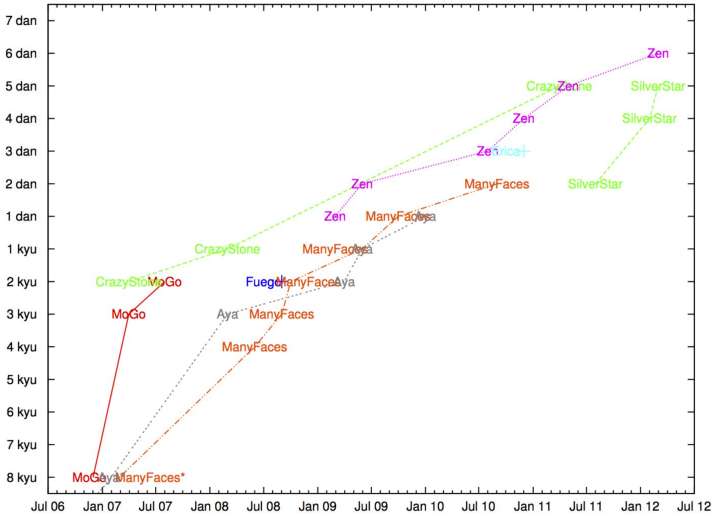
- The selection step determines which part of the game tree to spend computational resources on simulating.
- This is an instance of the exploration-exploitation tradeoff from last lecture
  - Want to focus on good actions for the current player
  - But want to explore parts of the tree we're still uncertain about
- Uniform Confidence Bound (UCB) is a common heuristic; choose the node which has the largest frequentist upper confidence bound on its value:

$$\mu_i + \sqrt{\frac{2 \log N}{N_i}}$$

- μ_i = fraction of wins for action i, N_i = number of times we've tried action i, N = total times we've visited this node

Monte Carlo Tree Search

Improvement of computer Go since MCTS (plot is within the amateur range)



Now for DeepMind's computer Go player, AlphaGo...

Predicting Expert Moves

- Can a computer play Go without any search?
- Ilya Sutskever's argument: experts players can identify a set of good moves in half a second
  - This is only enough time for information to propagate forward through the visual system — not enough time for complex reasoning
  - Therefore, it ought to be possible for a conv net to identify good moves

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- **Input:** a 19×19 ternary (black/white/empty) image — about half the size of MNIST!
- **Prediction:** a distribution over all (legal) next moves
- **Training data:** KGS Go Server, consisting of 160,000 games and 29 million board/next-move pairs
- **Architecture:** fairly generic conv net
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- When playing for real, choose the highest-probability move rather than sampling from the distribution
- This network, which just predicted expert moves, could beat a fairly strong program called GnuGo 97% of the time.
  - This was amazing — basically all strong game players had been based on some sort of search over the game tree

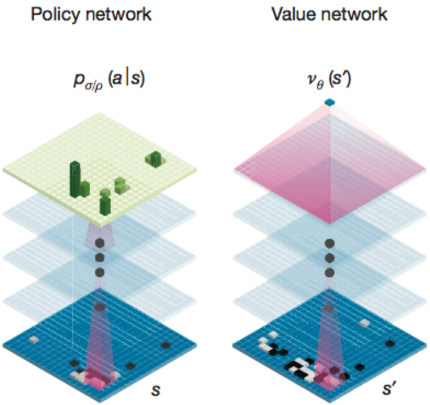
Self-Play and REINFORCE

- The problem from training with expert data: there are only 160,000 games in the database. What if we overfit?
- There is effecitvely infinite data from self-play
  - Have the network repeatedly play against itself as its opponent
  - For stability, it should also play against older versions of itself
- Start with the policy which samples from the predictive distribution over expert moves
  - The network which computes the policy is called the policy network
- REINFORCE algorithm: update the policy to maximize the expected reward r at the end of the game (in this case, $r = +1$ for win, -1 for loss)
- If $\boldsymbol{\theta}$ denotes the parameters of the policy network, a_t is the action at time t, and s_t is the state of the board, and z the rollout of the rest of the game using the current policy

$$R = \mathbb{E}_{a_t \sim p_{\theta}(a_t \mid s_t)}[\mathbb{E}[r(z) \mid s_t, a_t]]$$

Policy and Value Networks

- We just saw the policy network. But AlphaGo also has another network called a value network.
- This network tries to predict, for a given position, which player has the advantage.
- This is just a vanilla conv net trained with least-squares regression.
- Data comes from the board positions and outcomes encountered during self-play.



Silver et al., 2016

Policy and Value Networks

- AlphaGo combined the policy and value networks with Monte Carlo Tree Search
- Policy network used to simulate rollouts
- Value network used to evaluate leaf positions

AlphaGo Timeline

- **Summer 2014** — start of the project (internship project for UofT grad student Chris Maddison)
- **October 2015** — AlphaGo defeats European champion
  - First time a computer Go player defeated a human professional without handicap — previously believed to be a decade away
- **January 2016** — publication of Nature article "Mastering the game of Go with deep neural networks and tree search"
- **March 2016** — AlphaGo defeats gradmaster Lee Sedol
- **October 2017** — AlphaGo Zero far surpasses the original AlphaGo without training on any human data
- **Decemter 2017** — it beats the best chess programs too, for good measure

AlphaGo

- Most of the Go world expected AlphaGo to lose 5-0 (even after it had beaten the European champion)
- It won the match 4-1
- Some of its moves seemed bizarre to human experts, but turned out to be really good
- Its one loss occurred when Lee Sedol played a move unlike anything in the training data

AlphaGo

Further reading:

- Silver et al., 2016. Mastering the game of Go with deep neural networks and tree search. *Nature* http://www.nature.com/nature/journal/v529/n7587/full/nature16961.html
- Scientific American: https://www.scientificamerican.com/article/how-the-computer-beat-the-go-master/
- Talk by the DeepMind CEO: https://www.youtube.com/watch?v=aiwQsa_7ZIQ&list=PLqYmG7hTraZCGIymT8wVVIXLWkKPNBoFN&index=8