Computing Science (CMPUT) 455

Search, Knowledge, and Simulations

James Wright

Department of Computing Science
University of Alberta
james.wright@ualberta.ca

Fall 2021

455 Today - Lecture 22

- Quiz 11 review
- AlphaGo - overview and early versions
- Coursework:
  - Work on Assignment 4 (due **Tue, Dec 14**)
  - Reading: AlphaGo Zero paper
  - Quiz 12: Reinforcement Learning and AlphaGo

Quiz 11

- 73 attempts, average 93%
- Lowest: Q2: 65%; Q18: 87%

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  - **True**: E.g., ReLU is $f(x) = x$ for $x \geq 0$, so this is actually an advantage.
- Your NN will no longer be able to perform classification.
  - **False**: If your problem can be linearly classified, your NN will still work.

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Compared to move evaluation with simple features, Deep Convolutional NN typically return a larger number of good moves for one input position.

- **False:** Deep CNNs typically return a very confident prediction of a small number of actions, whereas move evaluation with simple places moderate weight/probability on a larger number of moves. (*why?*)

AlphaGo Introduction

- High-level overview
- History of DeepMind and AlphaGo
- AlphaGo components and versions
- Performance measurements
- Games against humans
- Impact, limitations, other applications, future

About DeepMind

- Founded 2010 as a startup company
- Bought by Google in 2014
- Based in London, UK, **Edmonton (from 2017)**, Montreal, Paris
- Expertise in reinforcement learning, deep learning and search

DeepMind and AlphaGo

nature
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
At last – a computer program that can beat a champion Go player PAGE 484
ALL SYSTEMS GO
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POPULAR SCIENCE
WHEN GENES GOT 'SELFISH'
Dawkins's calling card 40 years on
PAGE 462
NATUREASIA.COM

Image source:

`https://www.nature.com`

- A DeepMind team developed AlphaGo 2014-17
- Result: Massive advance in playing strength of Go programs
- Before AlphaGo: programs about 3 levels below best humans
- AlphaGo/Alpha Zero: far surpassed human skill in Go
- Now: AlphaGo is retired
- Now: Many other super-strong programs, including open source
- All are based on AlphaGo, Alpha Zero ideas

DeepMind and UAlberta

- UAlberta has deep connections
- Faculty who work part-time or on leave at DeepMind
  - Rich Sutton, Michael Bowling, Patrick Pilarski, Csaba Szepesvari (all part time)
- Many of our former students and postdocs work at DeepMind
  - David Silver - UofA PhD, designer of AlphaGo, lead of the DeepMind RL and AlphaGo teams
  - Aja Huang - UofA postdoc, main AlphaGo programmer
  - Many from the computer Poker group
- Some are starting to come back to Canada (DeepMind Edmonton and Montreal)

State of Computer Go before AlphaGo

Summary of previous work, and of our course so far

- Search - MCTS, quite strong
- Simulations - OK, hard to improve
- Knowledge
    - Good for move selection
    - Considered **hopeless for position evaluation**
- Strength: about 3 handicap levels below best humans
- Quick progress considered unlikely - see next slide

Online Betting Market - Computer Go Program Beats Human Champion

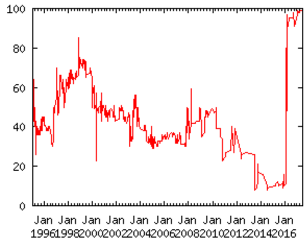

Image source:

`http://www.ideosphere.com/`

`fx-bin/Claim?claim=GoCh`

- Online "play-money" betting market
- Claim: A machine will be the best Go player in the world, sometime before the end of 2020
- Before AlphaGo, chances were considered low, and falling
- First Nature paper changed it around completely

AlphaGo Versions and Publications

- Worked on Go program for about 2 years, mostly kept secret
- DCNN paper published in 2015 (see previous lecture)
- Fall 2015
  Match **AlphaGo Fan** vs
  European champion Fan Hui (2 dan professional)
  - AlphaGo won 5:0 in official games,
    lost some other games
  - Match kept secret until January 2016
- January 2016
  Article in Nature describes this version of AlphaGo

AlphaGo Versions and Publications (continued)

- March 2016
  Match **AlphaGo Lee** vs top-level human player Lee Sedol, wins 4 - 1
- January 2017
  AlphaGo Master plays 60 games on internet vs top humans, wins 60 - 0
- May 2017
  Match vs world #1 Ke Jie, wins 3 - 0
  AlphaGo retires from match play
- October 2017
  AlphaGo Zero article in Nature
  Learns without human game knowledge
- December 2017/December 2018
  Alpha Zero article preprint/final - chess and shogi

AlphaGo Project

Image source: `http://sports.sina.com.cn/go/2016-12-19/`

- AlphaGo project was “Big Science”
- Dozens of developers
- World experts in RL, game tree search and MCTS, neural nets, deep learning
- Many millions of dollars in hardware and computing costs
- Huge engineering effort

AlphaGo vs Fan Hui

Image source:

`https://www.geekwire.com/2016/`

- Fall 2015 - early AlphaGo version **AlphaGo Fan Hui**
- Fan Hui: trained in China, 2 dan professional
- Lives in Europe since 2000, French citizen
- European champion 2013 - 2015
- AlphaGo beat Fan Hui by 5:0 in official games
- Fan Hui won some faster, informal games

AlphaGo Article in Nature

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Image source:

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- Nature and Science are the top two scientific journals
- Papers on computing science are rare
- Papers on games are very rare
- Games articles from our dept:
  - Checkers Is Solved, Science 2007
  - Heads-up limit hold'em poker is solved, Science 2015
- January 2016
  AlphaGo on title page of Nature
- Describes version that beat Fan Hui

AlphaGo Fan Design

As described in January 2016 article in Nature

- Search: MCTS (pretty standard, parallel MCTS)
  - Modified UCT combines simulation result and value network evaluation
- Simulation (rollout) policy: relatively normal
  - Uses small, fast network for policy
- Supervised Learning (SL) policy network
  - DCNN, similar to their 2015 paper
  - Learns move prediction from master games
  - Improved in details, more data

AlphaGo Fan Design (continued)

- **New: strong RL policy network**
  - Learns by Reinforcement Learning (RL) from self-play
- **New: value network**
  - Learns from labeled game data created by strong RL policy
- Main contributions
  - Reinforcement learning for training DCNN policy net
  - Value network for state evaluation
  - Large, extremely well-engineered learning and playing system

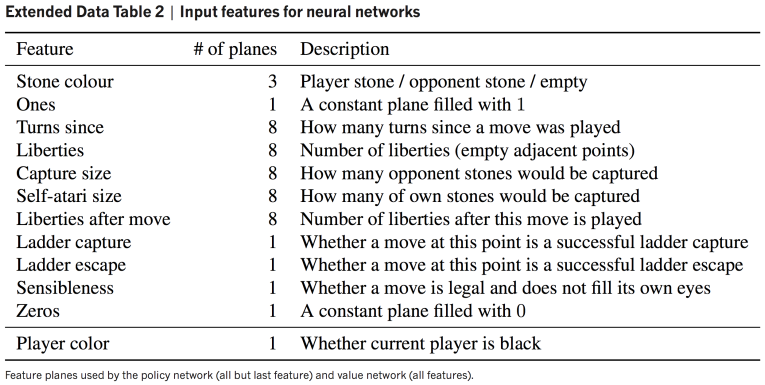
Rollout Policy Network

- Used for simulations in MCTS
- Designed to be simple and fast
- “Linear softmax of small pattern features”
- Probabilistic move selection as in Coulom’s paper, Go4
- Weights trained by RL instead of MM
- Slightly larger patterns/extended features
- 24.2% move prediction rate
- 2μs per move selection (500,000 simulated moves/second)

AlphaGo Fan Deep Network Architecture

- Three “big” networks
    - SL policy network, RL policy network, RL value network
- Same overall design for all three
- 13-layer deep convolutional NN
- 192 filters in convolutional layers
- 4.8ms evaluation on GPU
    - About 200 Evaluations/second/GPU
    - More than 2000x slower than simulation policy evaluation
    - Can learn and represent **much more complex** information

Input Features for NN



Extended Data Table 2 | Input features for neural networks

Feature	# of planes	Description
Stone colour	3	Player stone / opponent stone / empty
Ones	1	A constant plane filled with 1
Turns since	8	How many turns since a move was played
Liberties	8	Number of liberties (empty adjacent points)
Capture size	8	How many opponent stones would be captured
Self-atari size	8	How many of own stones would be captured
Liberties after move	8	Number of liberties after this move is played
Ladder capture	1	Whether a move at this point is a successful ladder capture
Ladder escape	1	Whether a move at this point is a successful ladder escape
Sensibleness	1	Whether a move is legal and does not fill its own eyes
Zeros	1	A constant plane filled with 0
Player color	1	Whether current player is black

Feature planes used by the policy network (all but last feature) and value network (all features).

Image

source: AlphaGo paper

- Pretty similar input as previous nets

Value Network

- Learn a *state evaluation function*
- Given a Go position
- Computes probability of winning
- No search, no simulation!
- Learns mapping
  - From state s
  - To expected outcome $\mathbb{E}[z]$ of the game
- Network architecture mostly same as policy nets
- Difference: output layer
- Value net outputs single number: evaluation of s
  - Compare policy nets: output = probability distribution

AlphaGo Fan Learning Pipeline and Play

- Training Pipeline
- AlphaGo program
- Performance measurements
- Games against humans

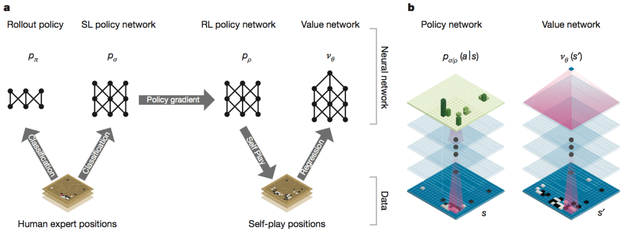
AlphaGo Fan Training Pipeline

Supervised Learning (SL)

- Rollout policy
- SL policy network

Reinforcement Learning

- RL policy network
- Value network



Supervised Learning (SL) Policy Network

- Trained from 30 million positions from the KGS Go Server
- Maximize likelihood of human move
- 57% move prediction when using all simple input features
- 55.7% when using only raw board input
- “Small improvements in accuracy led to large improvements in playing strength”
- MCTS with this network is already much better than all previous Go programs

RL Policy Network

- Learns from self play
- Learning: adjust weights of net to learn from winner of each game
- Exactly same network architecture as SL net
- Weights initialized from SL net
- Then plays many millions of games
- Keeps a pool of previous networks as opponents to avoid overfitting

Rewards and RL Training Procedure

- Goal: learn improved weights ρ for current network
- Play full game
  - Reward z only at end
  - +1 for winning, -1 for losing
- Update weights ρ by stochastic gradient ascent
- Ascent: go in the direction that maximizes expected outcome of game
- Formula from REINFORCE learning method (Williams 1992)

REINFORCE Update Formula

REINFORCE update formula

$$\Delta\rho = \alpha \frac{\partial \log p_\rho(a \mid s)}{\partial \rho} z$$

- $\Delta\rho$ .. change in weight ρ
- α step size for gradient ascent
- $p_\rho(a \mid s)$ .. probability of playing the move a which was played in the game from state s
- z .. game result (+1 or -1)

RL Policy Network vs Other Go Programs

- Tested RL Policy Network as a standalone player
- No search, only one call to network
- Plays move by sampling from p_ρ
- Won 80% against SL policy net
- Won 85% vs MCTS Go program `pachi` which used 100,000 simulations/move (!)

Training the Value Net

- Value net computes a function $v_\theta(s)$
- Function arguments:
  - input state s
  - Value net weights θ
- Output: $v_\theta(s)$ is a single real number
- Training: minimize squared error between
  - Value net prediction $v_\theta(s)$
  - True game outcome z_i

$$\text{Squared error} = \sum_i (v_\theta(s_i) - z_i)^2$$

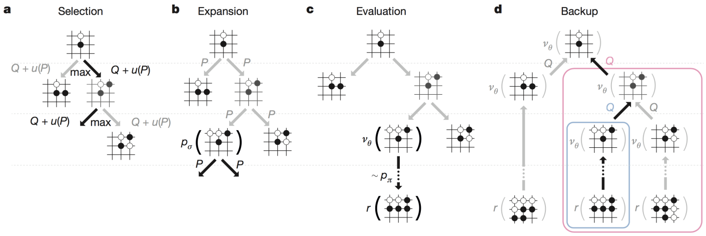
- Measure mean squared error (MSE):
  - Squared error / number of training items

Training Data for Value Net

- Played 30 million self-play games using the RL policy player
- Randomly sample *one single* state s from each game
    - Why only one state? Because of overfitting problems
- Label s with the outcome z of the game
- Result: 30 million training points (s_i, z_i)
- Learn the value net by trying to predict z_i from s_i
- This was called “reinforcement learning of value networks” in the paper
- It is really supervised learning from game data
- Game data was produced by the RL policy

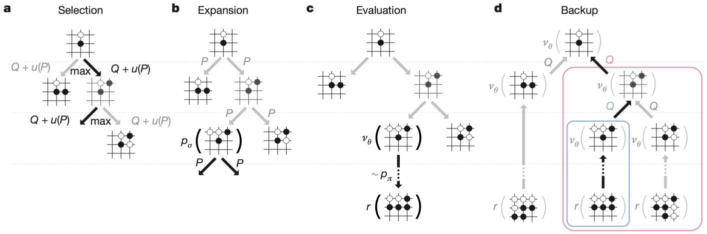
MCTS in AlphaGo Fan Player

- Player uses MCTS - search and simulations
- Neural nets used as (very strong) in-tree knowledge
  - Policy net guides tree search
  - Value net helps evaluate leaf nodes
- 3 values stored on each edge (s,a) of game tree
- Winrate Q, visit count N, prior probability P from policy net



In-tree Move Selection

- Choose move which maximizes $Q + u$
- Winrate Q, exploitation term
- u exploration term, with multiplicative knowledge
- Decay by $u = C\frac{P}{1+N}$
- Exploration constant C



Computing $V(s_L)$

- Value estimate $V(s_L)$ of leaf node s_L
- $V(s_L)$ is weighted average of two different evaluations
- $v_\theta(s_L)$ = Value network evaluation of s_L
- z_L = win/loss result of single simulation from s_L
- Combined by $V(s_L) = (1 - \lambda)v_\theta(s_L) + \lambda z_L$
  - $\lambda = 0.5$, equal weight

Which Prior Probability *P* to Use?

- Remember meaning of knowledge term in MCTS:
  - Give prior to good moves that should be searched
- Problem of RL policy in AlphaGo Fan:
  - It was optimized to play well
  - It learned a very strong prior for a **single** move
  - It was not optimized to produce a good **set** of moves to search in MCTS

SL vs RL policy network in MCTS

- Search with RL policy was too narrow
- Quality of other candidate moves not as good as in SL network
- Result: they ended up using the SL policy network, not the RL policy network in AlphaGo Fan
- SL net worked better in MCTS, even though it is much weaker in move prediction
- SL net gave a better set of good moves to search, not just a single strong move
- In AlphaGo Zero, this problem was finally solved by defining a different learning target for the policy net

Evaluation and Parallel Search

- Evaluating policy and value networks is expensive!
- Asynchronous multi-threaded search
- Simulations run on CPUs
- Policy and value networks evaluated on GPUs
- In match vs Fan Hui:
  40 search threads, 1,202 CPUs and 176 GPUs

Elo Model of Playing Strength

- Numerical rating scale
- Developed for chess
- Works well for many games of skill
- Basic idea: difference in rating corresponds to winning probability
- In Go, 100 Elo is roughly 1 stone handicap
- Formula: Difference d, win probability $1/(1 + 10^{d/400})$
- Example: 200 Elo stronger = wins about 80% of games

AlphaGo Fan Playing Strength - 2016 Nature Paper

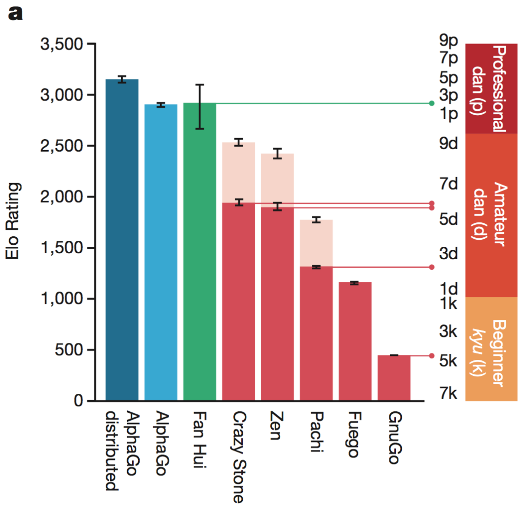


Image source: AlphaGo paper

Engineering and Technical Contributions

- Massive amounts of self-play training for the neural networks
- Massive amounts of testing/tuning
- Parallel training algorithms
- Large-scale parallel asynchronous search
- Large hardware:
- 1202 CPU, 176 GPU used vs Fan Hui

AlphaGo vs Lee Sedol

Image source:

`http://time.com/4257406/go-google-alphago-lee-sedol/`

- 5 game match in March 2016
- First ever match computer vs top player on 19 $\times$ 19 board, with no handicap
- Lee Sedol was the world's top Go player for more than a decade
- Won large number of international tournaments
- Still very strong at time of match, about world #3
- AlphaGo won the match 4:1
- Lee won game #4

AlphaGo Movie

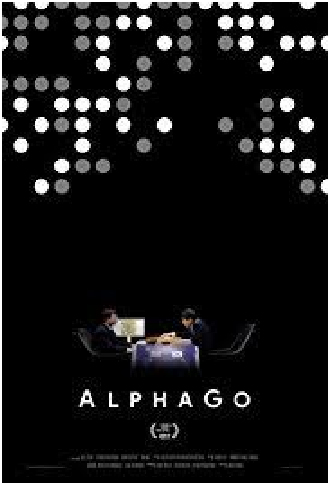


Image source: `http://www.imdb.com/title/tt6700846/`

- `https://www.alphagomovie.com`
- Story of AlphaGo development and match vs Lee Sedol
- Director Greg Kohs
- Very good movie, focus on human aspects

AlphaGo Lee

- Version used for Lee Sedol match, March 2016
- Much more RL training than for Fan Hui match
- Trained from **AlphaGo selfplay games**,
  not from RL policy games anymore
- Larger neural net
- Better hardware to evaluate neural nets
- About 2000 CPU, 48 TPU used
- 1 TPU: maybe 30x faster than 1 GPU
- Strength: 3 handicap stones stronger than AlphaGo Fan in self-play

AlphaGo Master

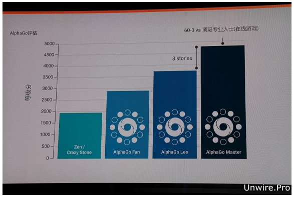


Image source:

`https://unwire.pro/2017/05/25`

- Played online end of December 2016 - early January 2017
- 60 fast games, many against top human players
- Score 60 wins no losses

AlphaGo Master Architecture

- Mostly same architecture as AlphaGo Zero (next lecture)
- Some parts were still the same as in previous AlphaGo, different from Zero:
  - Still uses handcrafted input features
  - Still uses rollouts as part of evaluation
  - Still uses initialization by SL net
- Reduced hardware:
  4 TPU, “single machine”
- Strength:
  - Far surpasses humans
  - 3 handicap stones stronger than AlphaGo Lee in direct match

AlphaGo vs Ke Jie

Image source:

- Match in May 2017 at “Future of Go Summit”
- AlphaGo played world #1 Ke Jie
- AlphaGo won 3:0
- Program: similar to AlphaGo Master
- Also on reduced hardware: 4 TPU, “single machine”

Summary

- Discussed the earlier versions of AlphaGo
- AlphaGo Fan, AlphaGo Lee, AlphaGo Master
- Main architecture: MCTS + neural networks for knowledge
- Policy net for biasing in-tree move selection
- Value net plus simulations for evaluating leaf nodes in tree
- Massively parallel implementation on CPU for simulations + GPU or TPU for nets
- Quantum leap in performance of Go-playing programs
- Reached, then surpassed level of best human Go players