Foundations of Artificial Intelligence

45. AlphaGo and Outlook

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Board Games: Overview

chapter overview:

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45.1 Introduction

Go

- more than 2500 years old
- long considered the hardest classical board game for computers
- played on 19×19 board
- simple rules:
  - players alternately place a stone
  - surrounded stones are removed
  - player with more territory plus captured stones wins

Monte-Carlo Methods in Go: Brief History

- 1993: Brügmann applies Monte-Carlo methods to Go
- 2006: MoGo by Gelly et al. is the first Go algorithm based on Monte-Carlo Tree Search
- 2008: Coulom's CrazyStone player beats 4 dan professional Kaori Aobai with handicap of 8 stones
- 2012: Ojima's Zen player beats 9 dan professional Takemiya Masaki with handicap of 4 stones
- 2015: AlphaGo beats the European Go champion Fan Hui, a 2 dan professional, 5–0
- 2016: AlphaGo beats one of the world's best Go players, 9 dan professional Lee Sedol, with 4–1

45.2 MCTS in AlphaGo

MCTS in AlphaGo: Overview

- based on Monte-Carlo Tree Search
- search nodes annotated with:
  - utility estimate $\hat{u}(n)$
  - visit counter $N(n)$
  - a (static) prior probability $p_0(n)$ from SL policy network

MCTS in AlphaGo: Tree Policy

- selects successor n that maximizes $\hat{u}(n) + B(n)$
- computes bonus term $B(n)$ for each node proportionally to prior and inverse number of visits as $B(n) \propto \frac{p_0(n)}{1+N(n)}$

⇝ rewards less frequently explored nodes (as in UCB1, but trailing off more quickly)

MCTS in AlphaGo: Simulation Stage

- Utility of an iteration is made up of two parts:
  - the result of a simulation $u_{\text{sim}}(n)$ with a default policy from a rollout policy network
  - a heuristic value $h(n)$ from a value network
- combined via a mixing parameter $\lambda \in [0, 1]$ by setting the utility of the iteration to

$$\lambda \cdot u_{\text{sim}}(n) + (1 - \lambda) \cdot h(n)$$

- mixing parameter in final version is $\lambda = 0.5$, which indicates that both parts are important for playing strength

MCTS in AlphaGo: Other

expansion phase:

- ignores restriction that unvisited successors must be created

finally selected move:

- move to child of root that has been visited most often rather than the one with highest utility estimate

45.3 Neural Networks

Neural Networks in AlphaGo

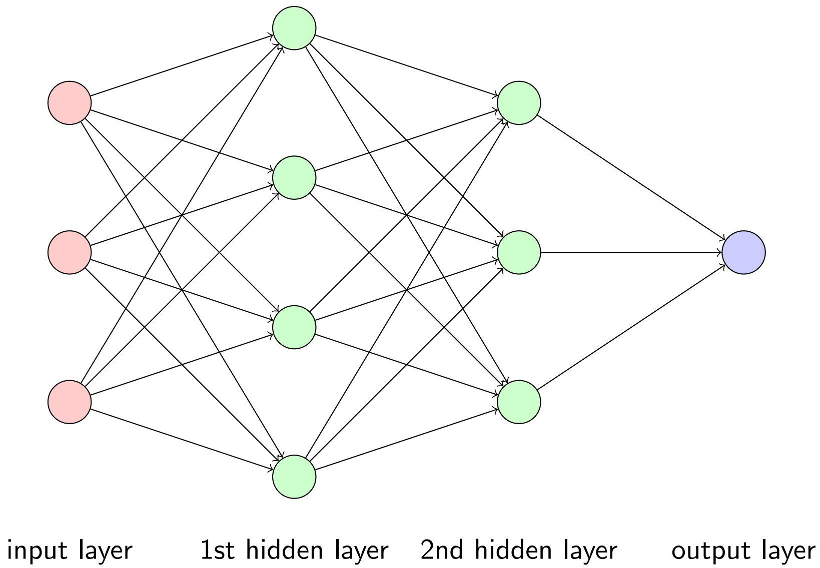
AlphaGo computes four neural networks:

- supervised learning (SL) policy network
  ⇝ for prior probabilities
- rollout policy network
  ⇝ for default policy in simulation phase
- reinforcement learning (RL) policy network
  (intermediate step only)
- value network
  ⇝ for heuristic in simulation phase

Neural Networks

- used to approximate an unknown function
- layered graph of three types of nodes:
  - input nodes
  - hidden nodes
  - output nodes
- iteratively learns function by adapting weights
  of connections between nodes

Neural Networks: Example



SL Policy Network: Architecture

input nodes:

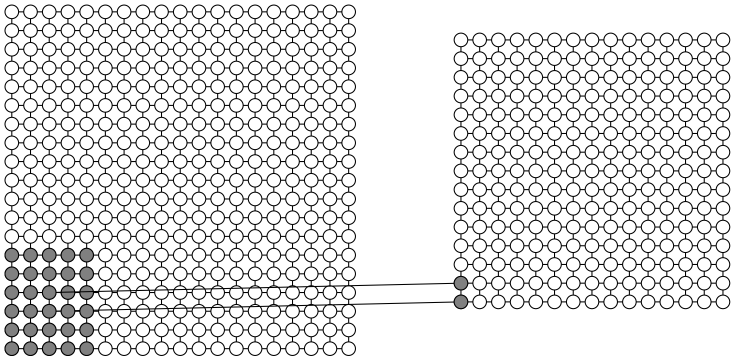
- the current position
- (limited) move history
- additional features (e.g., related to ladders)

hidden layer:

- several convolutional layers:
  - combine local information
    ⇝ only partial connections between layers
  - weights are shared between connections of the same type
- final linear softmax layer
  - converts weights to probabilities

output nodes: a probability distribution over all legal moves

SL Policy Network: Convolutional Layers



SL Policy Network

- uses 30 million positions and selected moves of strong human players from KGS Go Server
- supervised learning: network learns to match given inputs to given outputs (i.e., the given position to the selected move)
- most "human-like" part of AlphaGo: aims to replicate human choices, not to win
- prediction accuracy: 57%
- 3 ms per query

well-informed results with variance $\rightsquigarrow$ good for priors

Rollout Policy Network: Architecture

input nodes:

- only small set of features from small window around own and opponent's previous move
- does not look at the entire 19×19 board

hidden layer: a single linear softmax layer

output nodes: a probability distribution over all legal moves

Rollout Policy Network

- uses supervised learning with the same data as the SL policy network
- lower prediction accuracy: 24.2%
- but allows fast queries: just 2 μs (more than 1000 times faster than SL policy network)

reasonably informed yet cheap to compute
$\rightsquigarrow$ well-suited as default policy

Value Network: RL Policy Network

first create sequence of RL policy networks
with reinforcement learning

- initialize first RL policy network to SL policy network
- in each iteration, pick a former RL policy network uniformly randomly ⇝ prevents overfitting to the current policy
- play with the current network against the picked one:
  - compute the probability distribution over all legal moves for the current position
  - sample a move according to the probabilities
  - play that move
  - repeat until a final position is reached
- create new RL policy network by updating weights in the direction that maximizes expected outcome

Value Network: Architecture

then transform RL policy network to value network

- input nodes: same as in SL and RL policy network
- hidden layers: similar to RL policy network
- output node: utility estimate that approximates u^*
  ⇝ the value network computes a heuristic

Value Network

- using position-outcome pairs from KGS Server leads to overfitting
- using too many positions from same game introduces bias
- create a new dataset with 30 million self-play games of standalone RL policy network against itself
- each game only introduces a single position-outcome pair (chosen randomly) into the new dataset ⇝ only minimal overfitting
- slightly worse accuracy than using RL Policy Network as default policy
- but 15000 times faster

well informed and fast ⇝ good heuristic

45.4 Summary

Summary: This Chapter

- AlphaGo combines Monte-Carlo Tree Search with neural networks
- uses priors to guide selection strategy
- priors are learned from human players
- learns a reasonably informed yet cheap to compute default policy
- simulation steps are augmented with utility estimates, which are learned from humans and intensive self-play

Summary: Board Games

- board games have traditionally been important in AI research
- in most board games, computers are able to beat human experts
- optimal strategy can be computed with minimax
- alpha-beta pruning often speeds up minimax significantly
- introduction of Monte-Carlo Tree Search led to tremendous progress in several games
- combination with neural networks allowed to beat top human players in Go