Foundations of Artificial Intelligence

46. AlphaGo and Outlook

Thomas Keller

Universität Basel

May 30, 2016

Board Games: Overview

chapter overview:

Introduction

Go

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

Monte-Carlo Methods in Go: Brief History

- 1993: Brügmann applies Monte-Carlo methods to Go
- 2006: MoGo of Gelly et al. is the first Go AI 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 worlds best Go players, 9 dan professional Lee Sedol, with 4-1

MCTS in AlphaGo

MCTS in AlphaGo: Overview

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

MCTS in AlphaGo: Tree Policy

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

$\Rightarrow$ computes an upper confidence bound with a bonus term that resembles Boltzmann exploration

MCTS in AlphaGo: Iteration Evaluation

- Utility of an iteration is made up of two parts:
  - the result of a simulation $u_{\mathrm{sim}}(n)$ 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

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

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

MCTS in AlphaGo: Other

expansion phase:

- ignores restriction that unvisited successors must be created
- stores annotations in the parent node

final recommendation:

- return successor that has been visited most often rather than the one with highest utility estimate

Neural Networks

Neural Networks

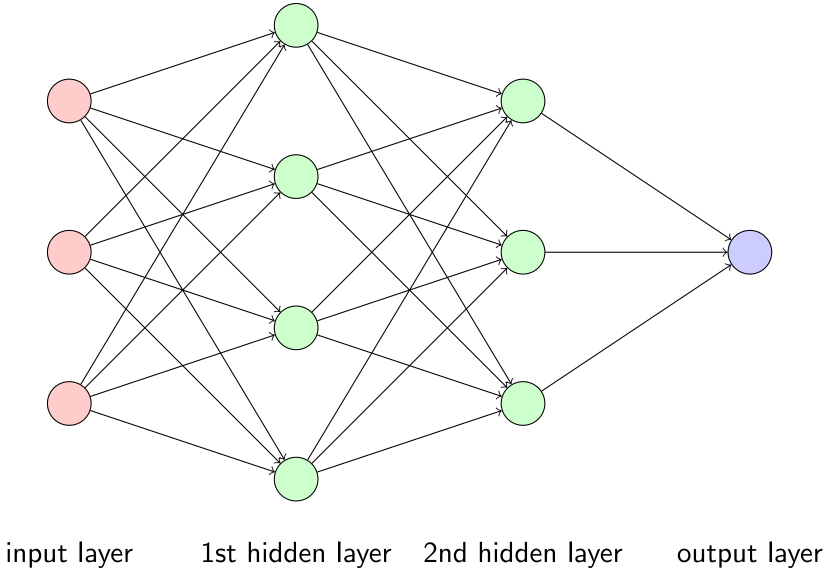
AlphaGo computes four neural networks:

- rollout policy network
  $\Rightarrow$ for initialization
- supervised learning (SL) policy network
  $\Rightarrow$ for prior probabilities
- reinforcement learning (RL) policy network
  (intermediate step only)
- value network
  $\Rightarrow$ for initialization

Neural Network

- 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:

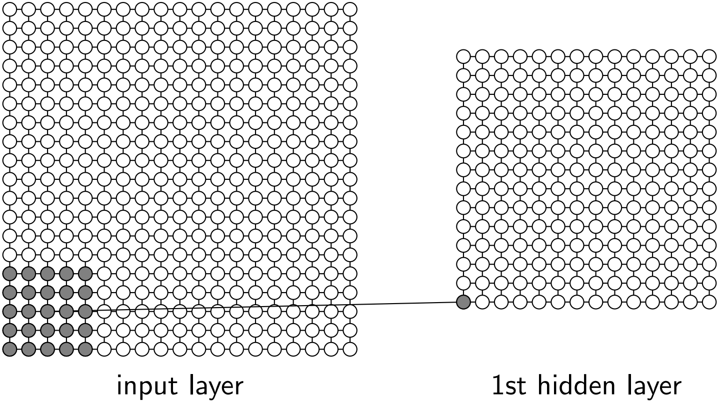
- the current position
- move history
- additional features (e.g., number of captured stones)

hidden layer:

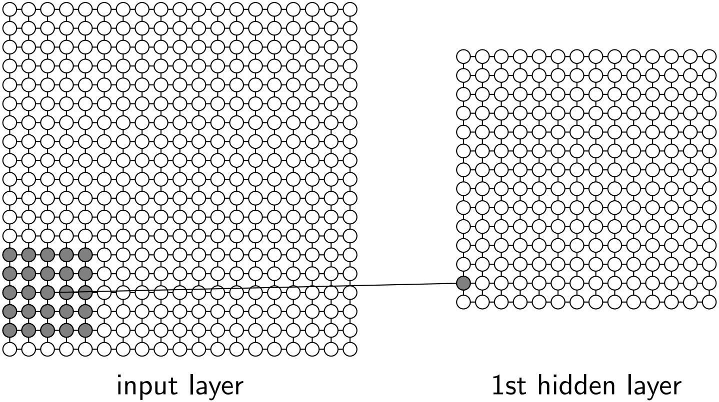
- several convolutional layers:
  - combine local information
  - allow less connections between layers
  - weights are shared between connections of the same type
- final linear softmax layer
  - converts weights to probabilities

output nodes: a probability distribution over all legal moves

SL Policy Network: Convolutional Layers



SL Policy Network: Convolutional Layers



SL Policy Network

- uses 30 million positions from strong human players on KGS
- uses supervised learning: the network learns to match given input to given output
(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 $\Rightarrow$ 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
$\Rightarrow$ 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 at random $\Rightarrow$ 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 state
  - sample a move according to the probabilities
  - play that move
  - repeat alternatingly 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 layer: similar to RL policy network

output node: utility estimate that approximates Q^*
$\Rightarrow$ the value network computes a heuristic

Value Network

- using state-outcome pairs from KGS Server leads to overfitting
- using too many positions from same game introduce bias (not enough data to use only a few)
- create a new dataset with 30 million self-plays of standalone RL policy network and itself
- each game only introduces a single state-outcome pair into the new dataset
- only minimal overfitting
- slightly worse win percentage than using RL Policy Network as default policy
- but 15000 times faster

very well informed and reasonably fast
$\Rightarrow$ good heuristic

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
- iterations are additionally evaluated with utility estimates, which are learned from humans and intensive self-play

Summary: Board Games

- board games are a topic that has 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 many games
- combination with neural networks allowed to beat a human professional in Go