Foundations of Artificial Intelligence

45. AlphaGo and Outlook

Malte Helmert and Thomas Keller

University of Basel

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Board Games: Overview

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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

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 $B(n) \propto \frac{p_0(n)}{1+N(n)}$

$\rightsquigarrow$ 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

Neural Networks

Neural Networks in AlphaGo

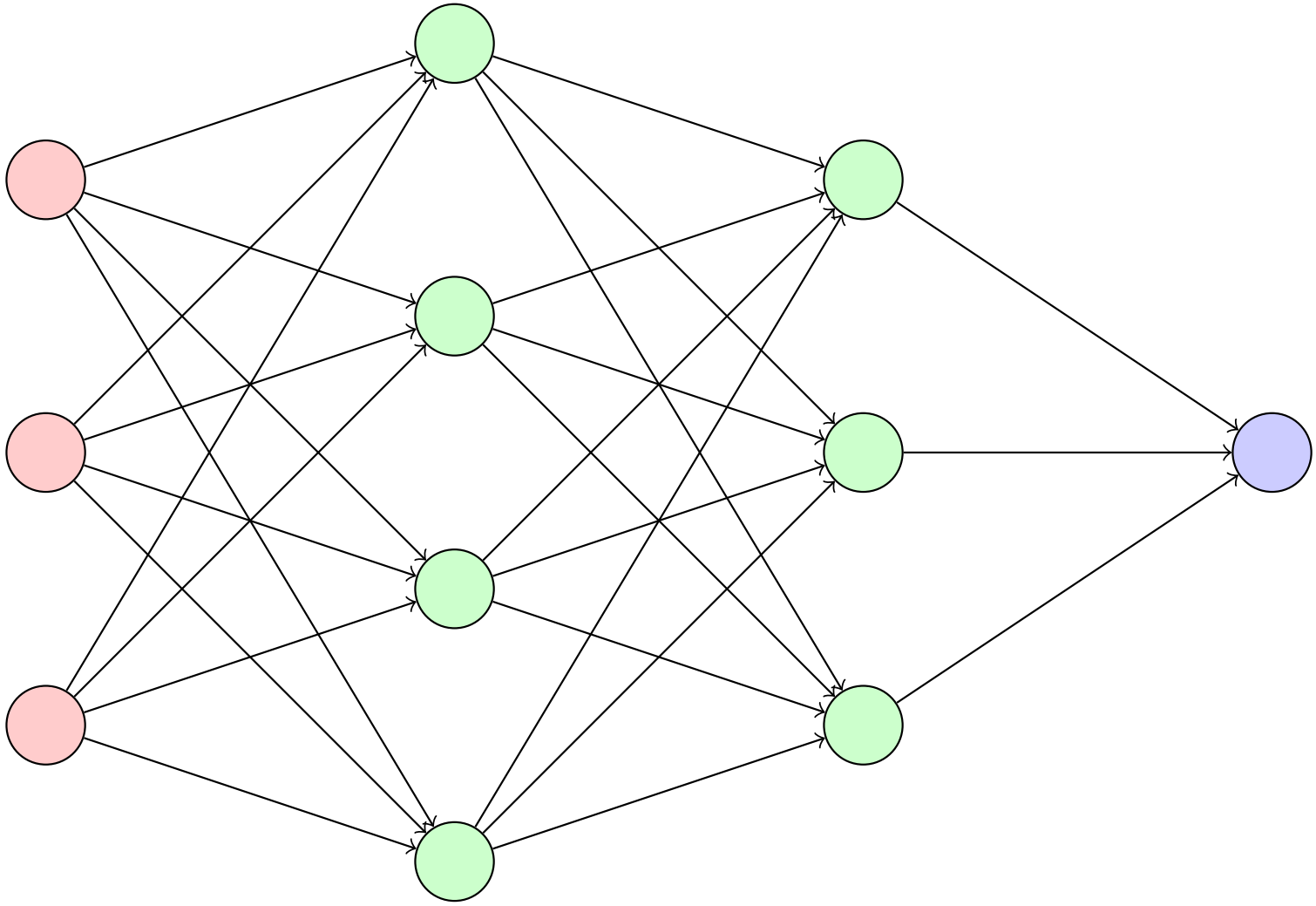
AlphaGo computes four neural networks:

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



input layer 1st hidden layer 2nd hidden layer output layer

SL Policy Network: Architecture

input nodes:

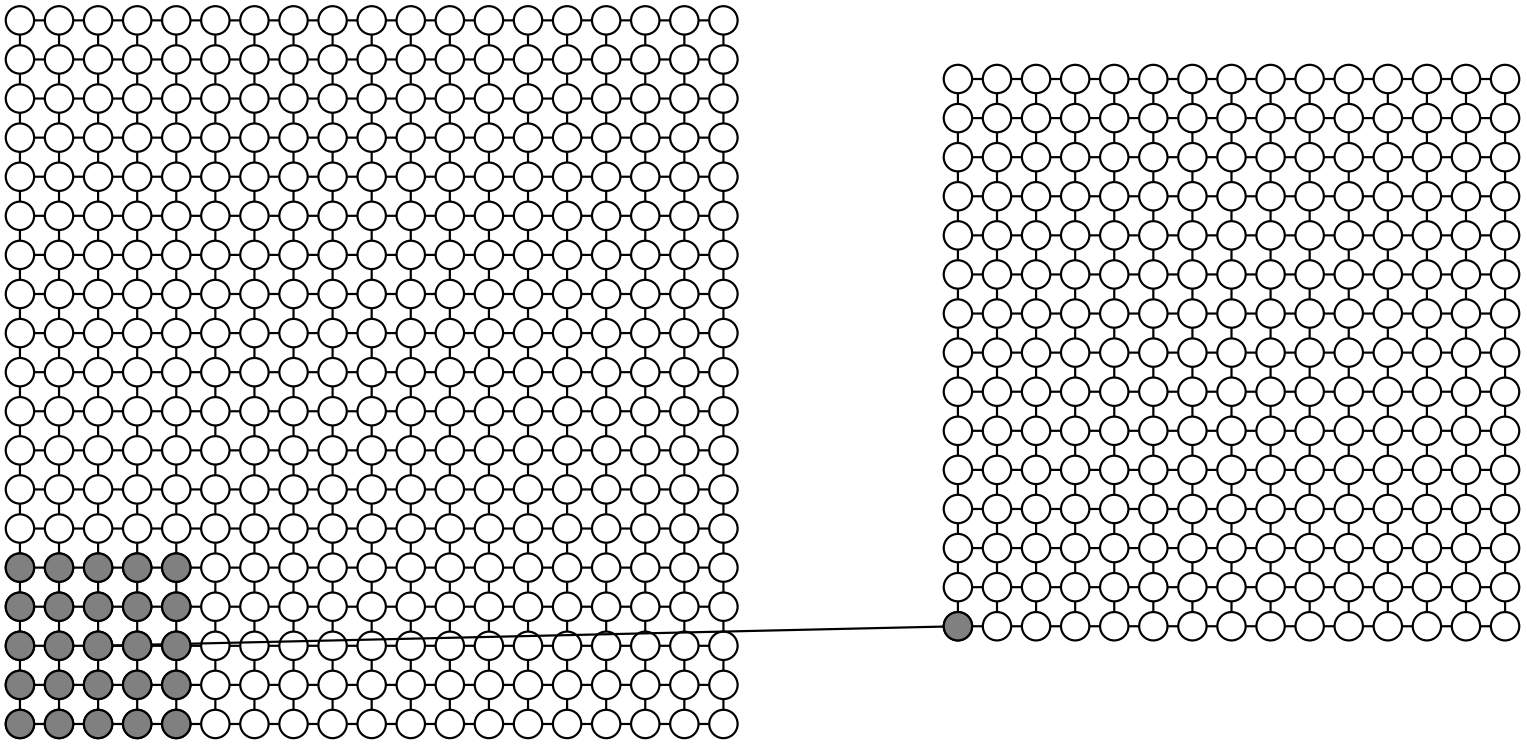
- the current position
- (limited) move history
- additional features (e.g., related to ladders)

hidden layer:

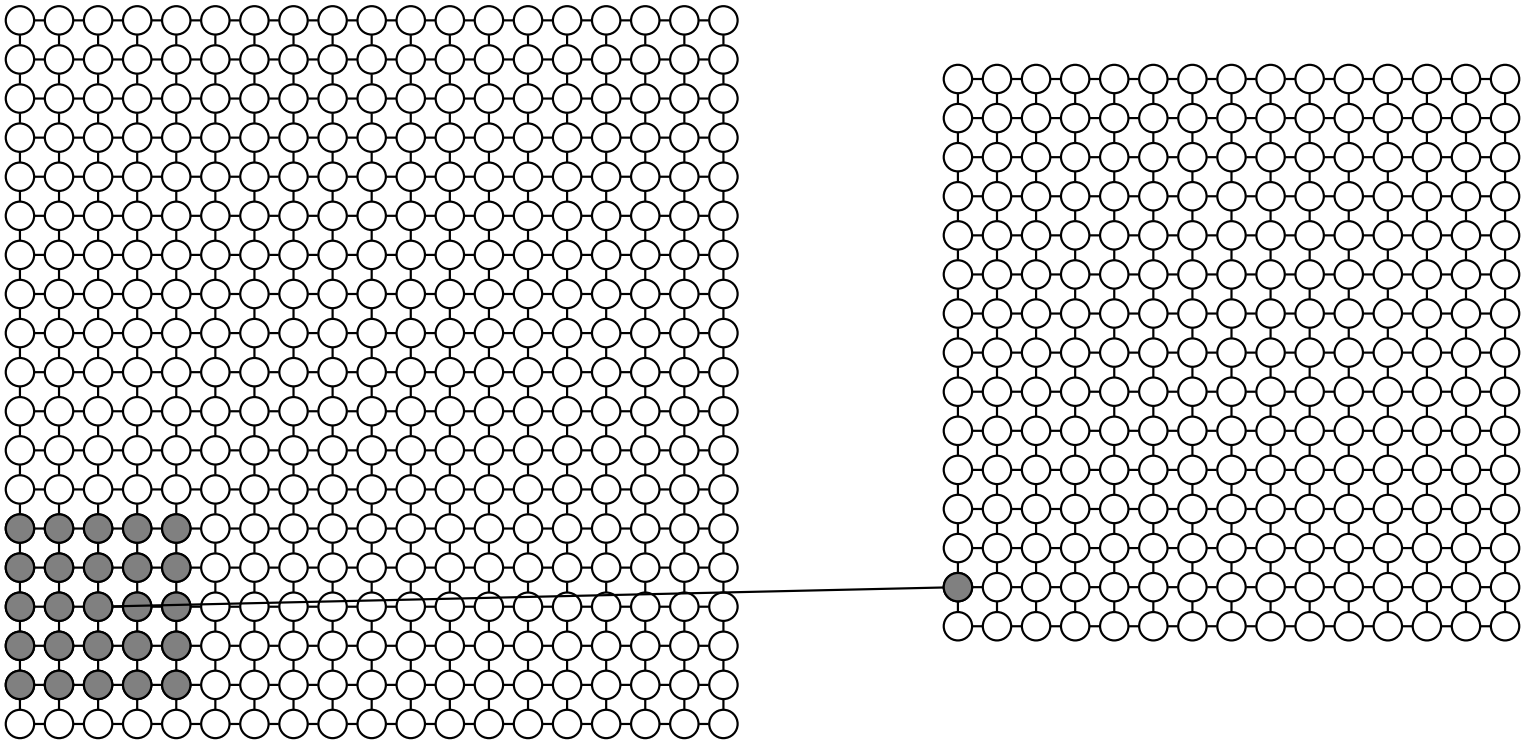
- several convolutional layers:
  - combine local information
    $\rightsquigarrow$ only partial connections between layers
  - weights are shared between connections of the same type
- final linear softmax layer
  - converts weights to probabilities

output nodes: a probability distribution over all legal moves

SL Policy Network: Convolutional Layers



SL Policy Network: 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 $\rightsquigarrow$ 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^*
  $\rightsquigarrow$ 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 $\rightsquigarrow$ only minimal overfitting
- slightly worse accuracy than using RL Policy Network as default policy
- but 15000 times faster

well informed and fast $\rightsquigarrow$ 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
- 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