

Foundations of Artificial Intelligence

45. AlphaGo and Outlook

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Board Games: Overview

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

~~ 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

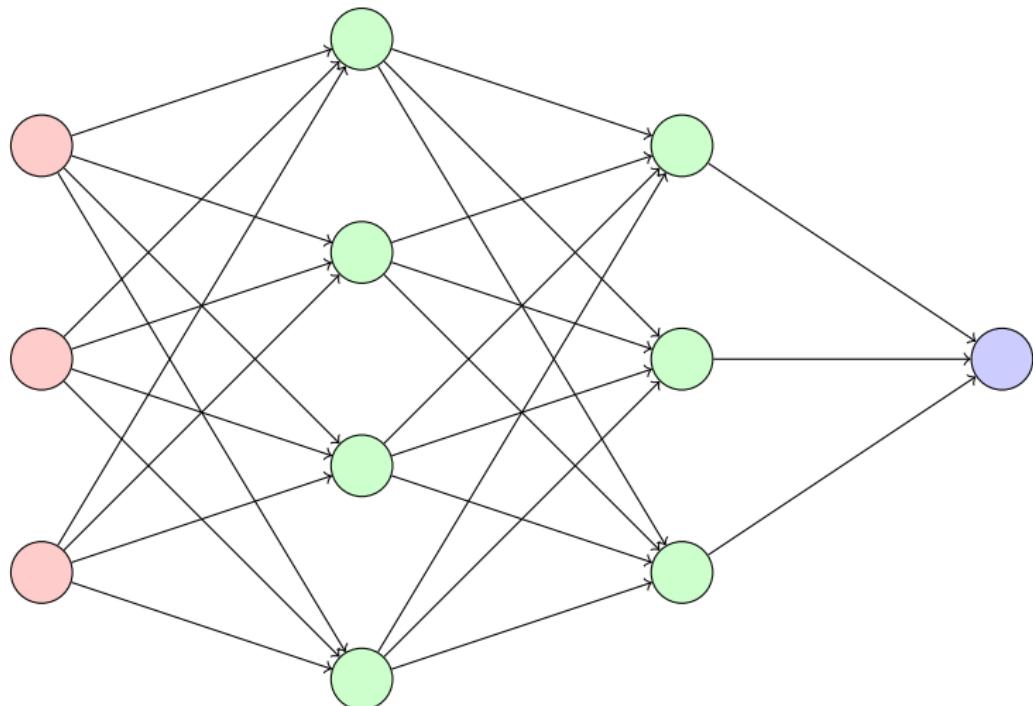
AlphaGo computes four neural networks:

- supervised learning (SL) policy network
~~ 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



input layer

1st hidden layer

2nd hidden layer

output layer

SL Policy Network: Architecture

input nodes:

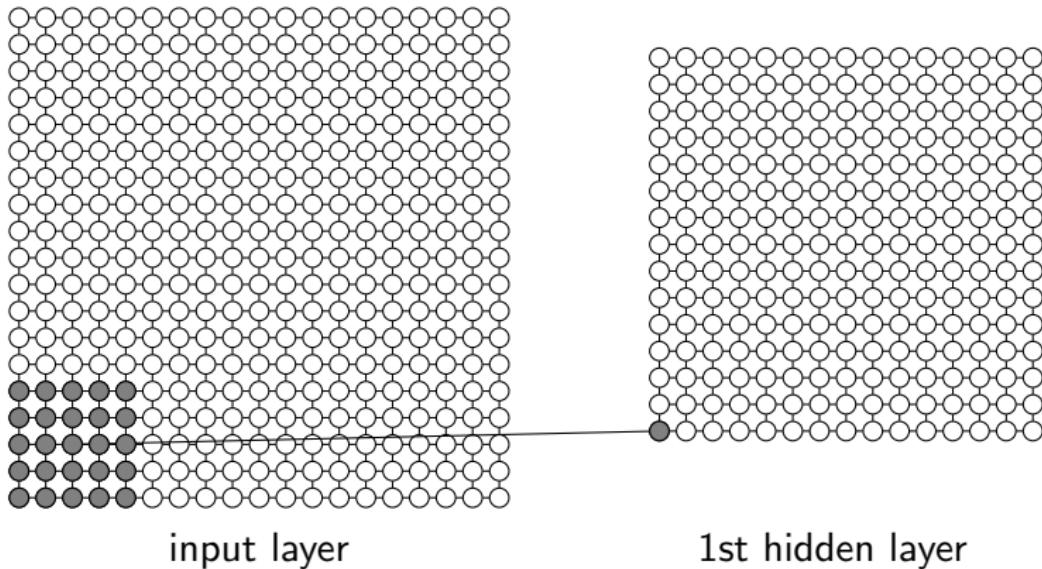
- the current **position**
- (limited) **move history**
- additional **features** (e.g., related to ladders)

hidden layer:

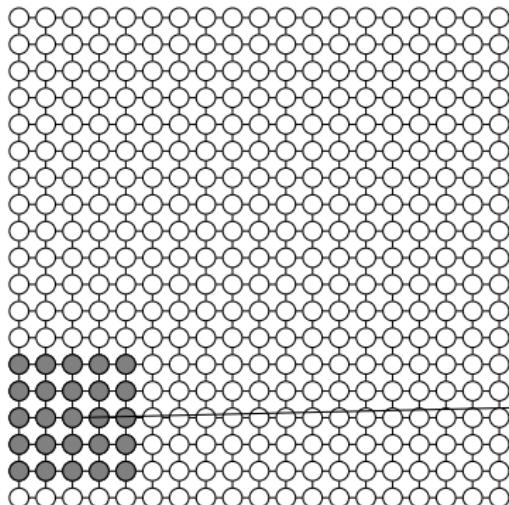
- several **convolutional layers**:
 - **combine local information**
~~ only **partial connections** between layers
 - weights are shared between connections of the same type
- final **linear softmax** layer
 - converts weights to **probabilities**

output nodes: a **probability distribution** over all legal moves

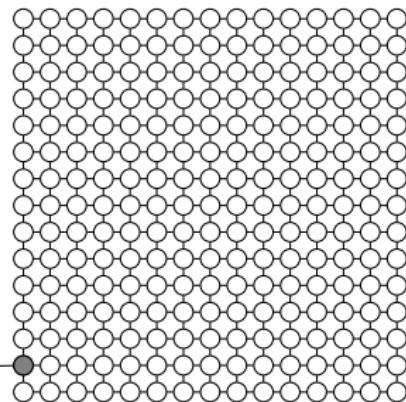
SL Policy Network: Convolutional Layers



SL Policy Network: Convolutional Layers



input layer



1st hidden layer

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 $2 \mu s$
(more than 1000 times faster than SL policy network)

reasonably informed yet cheap to compute
~~ 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^*
~~ 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**

MCTS
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Summary

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