Application of RL to Go

- AlphaGo
- Summary and outlook
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Main References

- **Mastering the game of Go with deep neural networks and tree search.**
  

- **Mastering the game of Go without human knowledge.**
  

- **A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play.**
  
In 2016, Google DeepMind’s AlphaGo program (Silver et al., 2016) defeats Lee Sedol (international champion), 4–1.

[1] https://upload.wikimedia.org/wikipedia/commons/thumb/5/56/Lee_Sedol_%28B%29_vs_AlphaGo_%28W%29_-_Game_1.svg/734px-Lee_Sedol_%28B%29_vs_AlphaGo_%28W%29_-_Game_1.svg.png. CC image courtesy of Wesalius on WikiMedia Commons licensed under CC-BY-SA-4.0.
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- 19 × 19 board; turn-based; black and white stones.

- Surround opponent’s stones to capture them.

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- Value network $v_\theta$.
- Policy networks $p_\sigma$, $p_\rho$.
- Rollout policy network $p_\pi$.

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How learned, how used?

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1. Supervised Learning of Policy Networks

- $p_{\sigma}$ obtained by supervised learning on data (30 million moves) from expert games in KGS Go Server database.
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- $p_\pi$ trained similarly, to be used for rollouts.
  - Linear + softmax; accuracy $= 24\%$; much faster to compute ($2\mu s$ for forward pass, compared to $3 ms$ for $p_\sigma$).
2. Self-play, Reinforcement Learning

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Ensures stable progress in sequence of agents.
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Learning using REINFORCE with $v_\theta$ subtracted as baseline.

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- $p_\rho$ (without search) has win record
  . $80\%$ against $p_\sigma$ (without search),
  . $85\%$ against Pachi (independent agent using MCTS).
3. Policy Evaluation

- Evaluation function in search should ideally be $V^*$. Instead use $v_\theta$, an approximation of $V^{p_\rho}$ since $p_\rho$ is the best available policy.
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- $v_\theta$ trained using supervised learning; data generated by playing $p_\rho$ against itself.
- Trained to minimise **mean-squared error** with long-term reward (game outcome: $\pm 1$). No bootstrapping.
- Only **one training data point per game** (from self-play) to eliminate correlated inputs. Training set size: 30 million.
- Many orders of magnitude **faster to compute** than by rollout for similar error thresholds.
4. Decision-time Planning

- Uses a version of MCTS in which

\[
\text{ucb}(s, a) = Q(s, a) + \text{constant} \times p_\sigma(s, a) \times \frac{\sqrt{\text{visits}(s)}}{\text{visits}(s, a) + 1}.
\]

- Observe that \( p_\sigma \) guides exploration within the tree, but \( v_\theta \) (trained to approximate \( V^\rho \)) is used for evaluating leaves.
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- Value estimate at leaf \( s \) is

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- Standard version: 48 CPUs, 8 GPUs.
- Distributed version: 1200 CPUs, 176 GPUs.
Performance

- AlphaGo wins nearly 100% of games against other competitive (MCTS-based) agents.

- Defeats Fan Hui (winner of the 2013, 2014, and 2015 European Go championships) 5–0 in formal match. Program subsequently improved, with help from Fan Hui!

- In March 2016, AlphaGo defeats Lee Sedol (winner of 18 international titles), 4–1 in formal match.

- Move 37 by AlphaGo in Game 2 initially thought to be a "mistake" by commentators, but now praised in the Go world as "beautiful"! Unlike a move a human would play.

- Humans tend to optimise for win margin; AlphaGo optimises win probability.

Watch "AlphaGo - The Movie": [https://www.youtube.com/watch?v=WXuK6gekU1Y](https://www.youtube.com/watch?v=WXuK6gekU1Y).

Shivaram Kalyanakrishnan (2023)
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Getting Sleeker and Stronger

- **AlphaGo Zero** (Silver *et al.*, 2017)
  - Can be trained/run on single machine with 4 TPUs.
  - Tabula rasa learning; no bootstrapping from expert games.
  - Only raw features (black/white/empty) used.
  - No rollouts in MCTS.
  - Value and policy in single network (only outputs differ).
  - AlphaGo Zero beats AlphaGo Lee 100–0!

- **AlphaZero** (Silver *et al.*, 2018)
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2019: Lee Sedol retires from professional play.
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- (Atari 2600 DQN ∪ AlphaGo) ∩ CS 747:
  - Bandits/UCB, TD learning, Function approximation, Policy gradient methods, Batch RL, Multiagent RL, MCTS.

Neural networks a good choice of representation in many interesting domains (vision, audio, speech input).

Other applications of Deep RL: self-driving cars, speech/dialogue systems, computer games, algorithm discovery.

Successes have popularised RL, viewed as a fundamental ingredient of autonomous decision-making systems.

Published literature in RL has exploded in the last 5–10 years.

Usually needs lots of computation, data (hence simulators).

Not the method of choice across all domains.
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- **Related courses/areas** to explore:
  Game theory and multiagent systems; on-line learning; neural networks and deep learning; linear optimisation, MDPs, stochastic approximation; cognitive science, neuroscience; robotics; . . . .