# CS 747, Autumn 2023: Lecture 24

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# 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.

  David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel, and Demis Hassabis, Nature: 529:484–489, 2016.

- Mastering the game of Go without human knowledge.

  David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, Yutian Chen, Timothy Lillicrap, Fan Hui, Laurent Sifre, George van den Driessche, Thore Graepel, and Demis Hassabis, Nature, 550:354–358, 2017.

- A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play.

  David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, Timothy Lillicrap, Karen Simonyan, and Demis Hassabis, Science: 362(6419):1140–1144, 2018.

# 2016: AI Conquers Go

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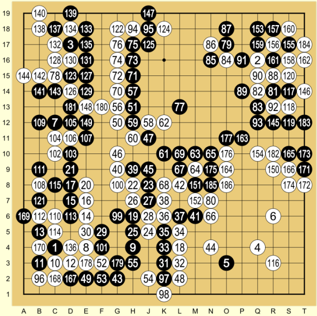

Lee Sedol (B) vs AlphaGo (W) - Game 1

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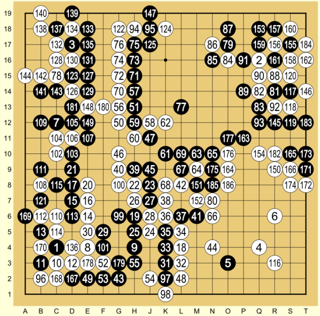

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- 19 $\times$ 19 board; turn-based; black and white stones.
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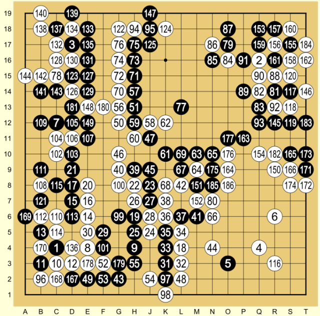

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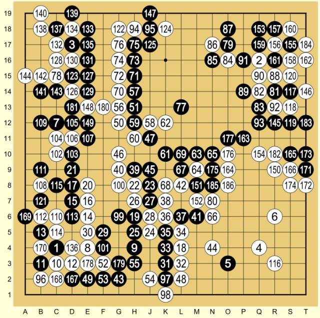

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  How learned, how used?

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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 $3ms$ for $p_\sigma$).

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  - Reward: $+1$ for win, $-1$ for loss, $0$ for all other states.
  - $p_\rho$ (without search) has win record
    - 80% against $p_\sigma$ (without search),
    - 85% against Pachi (independent agent using MCTS).

# 3. Policy Evaluation

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- 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

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

- Observe that $p_\sigma$ guides exploration within the tree, but $v_\theta$ (trained to approximate $V^{p_\rho}$) is used for evaluating leaves.

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

# Performance

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- Watch "AlphaGo - The Movie":
  `https://www.youtube.com/watch?v=WXuK6gekU1Y`.

# 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.
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- 2019: Lee Sedol retires from professional play.

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- Usually needs lots of computation, data (hence simulators).
- Not the method of choice across all domains.

# Next Steps for Interested Students

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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; ....