Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm

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Chess, Shogi, and Go

Chess

• Pieces have varying movement abilities, goal is to capture opponent's king

Shogi

• Similar to chess, but larger board and action space

Go

• Much larger board, but all pieces have same placement rules





Properties of Chess, Shogi, Go

Rules	Go	Chess and Shogi
Translational Invariance	Yes	Partial (e.g. pawn moves, promotion)
Local	Yes (based on adjacency)	No (e.g. queen moves)
Symmetry	Yes (dihedral)	No (e.g. pawn moves, castling)
Action Space	Simple	Compound (move from/to)
Game Outcomes	Binary (look at prob. of winning)	Win / lose / draw (look at expected value)

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Go seems more amenable to CNNs



Computer Chess and Shogi: Prior Approaches

Computer chess is the most studied domain in AI

- Highly specialized approaches have been successful
- Deep Blue defeated World Champion G. Kasparov in 1997
- Before AlphaGo, state-of-the-art was Stockfish

Shogi only recently achieved human world champion level

• Previous state-of-the-art was Elmo

Engines like Stockfish and Elmo are based on alpha beta search

• Domain specific evaluation functions tuned by grandmasters



AlphaZero, starting from first principles

AlphaZero assumes no domain specific knowledge other than rules of the game

- Compare with Stockfish and Elmo's evaluation functions
- Previous version AlphaGo started by training against human games
 - It also exploited natural symmetries in Go both to augment data and regularize MCTS

Instead, AlphaZero relies solely on reinforcement learning

• Discovers tactics on its own



Agent receives information about its environment and learns to choose actions that will maximize some reward¹

Compare with supervised learning, but instead of learning from a label, we learn from a time delayed label called reward

• Learn good actions by trial and error



This framework is better suited to games like GO

In theory a network could learn to play using supervised learning, taking recorded human Go games as input

- Large suitable datasets may not exist
- More importantly, the network will only learn to perform like a human expert, instead of learning true optimal strategy

RL can be done through self play

- Using current weights, play out an entire match against self
- Update weights according to results



<u>AlphaZero</u>

Deep Neural Network $\mathbf{f}_{\boldsymbol{\theta}}$ with parameters $\boldsymbol{\theta}$

Input:

• Raw board representation, s

Output:

- Policy vector, **p**
- Expected value of board position, v

Loss:

$$Loss = (z - v)^2 - \pi^{\mathsf{T}} \log(\mathsf{p}) + \mathsf{c} ||\theta||^2$$

Where π , z come from tree search and self-play



<u>AlphaZero</u>

Input 256 conv. filters (3x3) Batch norm ReLu 256 conv. filters (3x3) **Batch Norm** ReLu

Architecture?

- Not stated explicitly (implied to be same as AlphaGo Zero)
- 20 (or 40) residual blocks of convolutions



Skip Connection

<u>AlphaZero</u>

Monte Carlo Tree Search

Goal: Reduce depth and breadth of search

- Move distribution **p** helps reduce breadth
- Value v helps reduce depth

Not *exactly* what happens

It's best to see a picture!



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Monte Carlo Tree Search In a Picture

D Silver et al. Nature 550, 354–359 (2017) doi:10.1038/nature24270

Training



Algorithm Pseudocode

Initialize $\mathbf{f}_{\boldsymbol{\theta}}$

Repeat: Play Game: While game not over: MCTS from state s Compute π Pick new s from π Update θ : For each (s, π , z) Back propagate



D Silver *et al. Nature* **550**, 354–359 (2017) doi:10.1038/nature24270

Results



- Many game series versus previous state-of-the-art
- Convincingly beat Stockfish, Elmo
- Slight improvement over AG0



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-and-go/

Public Criticism

- Unfair advantages over competition
- Hard to replicate

Future Work

- Hybrid approach
- AlphaStar (Starcraft 2 AI)



Thank You



WE ARE PURDUE. WHAT WE MAKE MOVES THE WORLD FORWARD.

EA/EOU



Bonus Slides

D. Silver et al. Science 07 Dec 2018: Vol. 362, Issue 6419, pp. 1140-1144 DOI: 10.1126/science.aar6404