solving go

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go: overview

- discuss game, rules
- uct + random rollouts —> MCTS
- MCTS + policy + value —> Alpha Go
- policy + value + self-play —> Alpha Go Zero
- Alpha Go Zero - Go —> Alpha Zero, demo

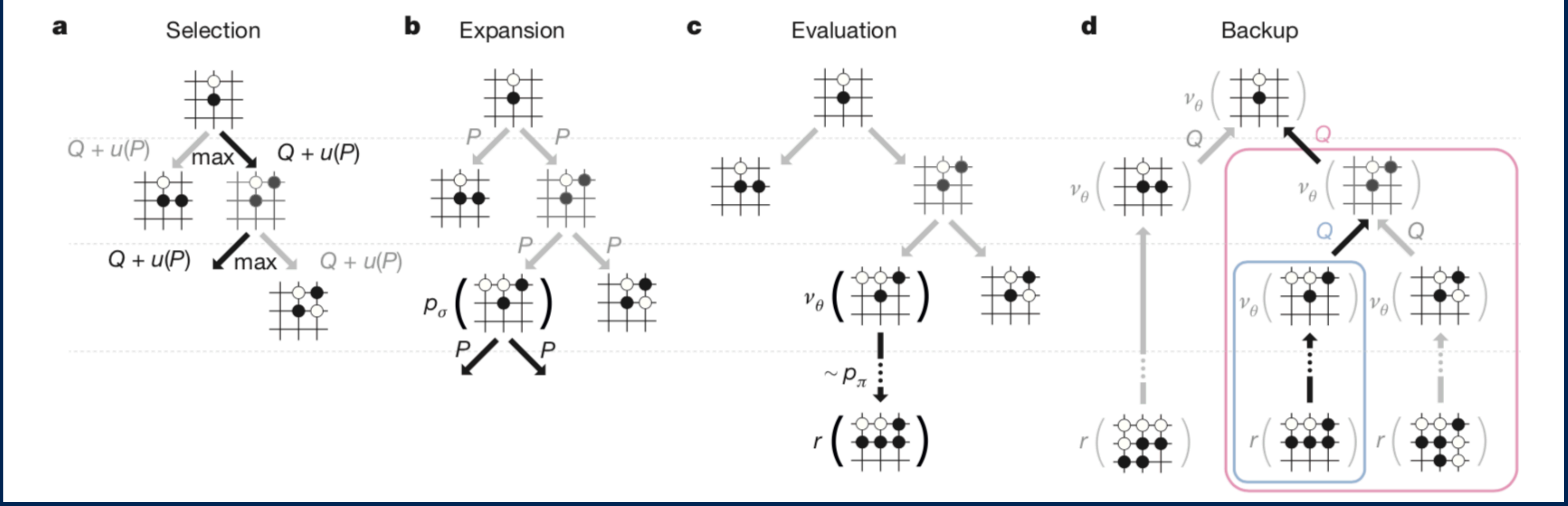
go: board

go: game/rules

- origin: asia, ~2500 years ago
- 19x19 board (361 squares), fill with stones
- squares + captures —> score (chinese)
- black - 7.5 (komi) > white —> winner (no draws)
- ~500 moves —> ~1e170 game complexity (chess: ~1e50, # atoms in universe: ~1e80)

uct (2006)

- multi-armed bandit problem: how do you win most money from room of slot machines, given X quarters?
- basic idea: explore new machines (policy), calculate reward of a machine (value)
- ucb: put statistical bound on losses —> maximize gains



random rollouts (2009)

- take current board state, pick candidate move to explore/evaluate
- alternate adding stones randomly till both sides cannot play (pass)
- score via chinese rules —> move win/loss predictor —> update value of candidate move
- uct + random rollouts —> mcts —> solves go! (minor bug: universe will die of heat death first)

alpha go (2016)

alpha go: fan/lee/master

- take mcts approach, but:
  - use policy network to quickly make moves (test good moves rather than random ones)
  - use value network to predict winning odds (cheaper predictions for faster exploration)
  - finally, use mcts to perform deeper evaluation as needed

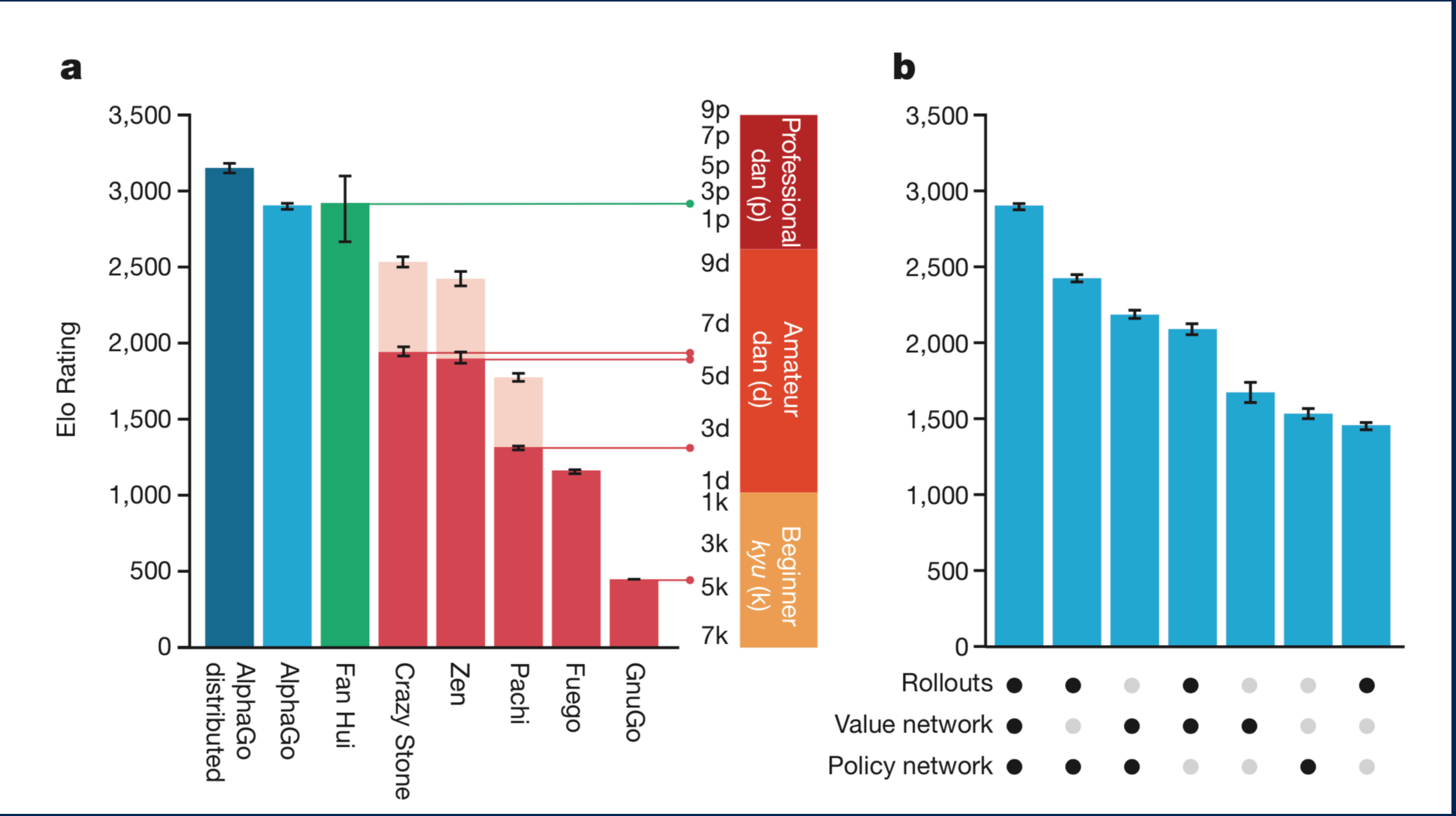
policy network

- human games (~150k) + supervised learning —> policy network (given position, predict next move)
- play games using policy network + MCTS —> more games (human + computer) —> train again —> better policy network (e.g. reinforcement learning)
- use policy network to make moves rapidly —>
    - 55% accuracy in 3ms, 24% accuracy in 2μs
    - policy network alone can defeat many engines*

value network

- from given input state, can we predict who will win, without performing a rollout simulation?
- build CNN to predict winning probability %
- train: mse between prediction and outcome
- overtrains to input games, so have to relax network (e.g. rotate/flip games)
- use value network to predict expected win/loss of moves without rollout (15000x faster)

alpha go: performance



alpha go: zero (2017)

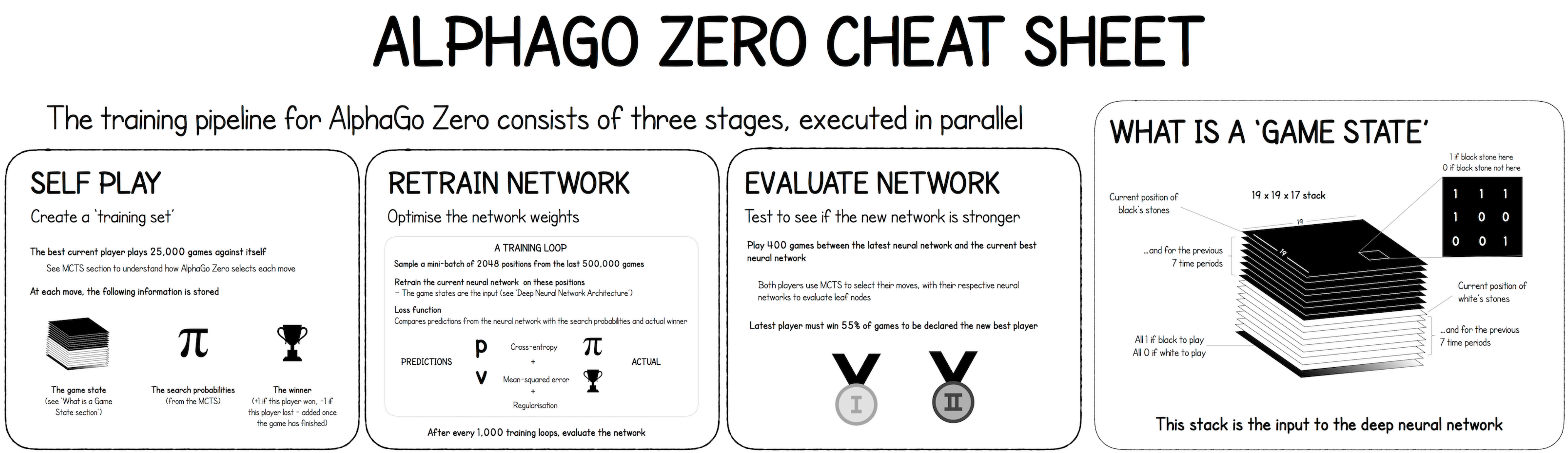
- input a position —> use single network (combined policy + value) to predict best move and winning odds —> build game tree

- play games against self (tabula rasa), train new network to categorize wins/losses and reduce prediction error

- evaluate new network against old, pick winner

- repeat 700k generations —> master level play

applied-data.science/blog/alphago-zero-cheat-sheet



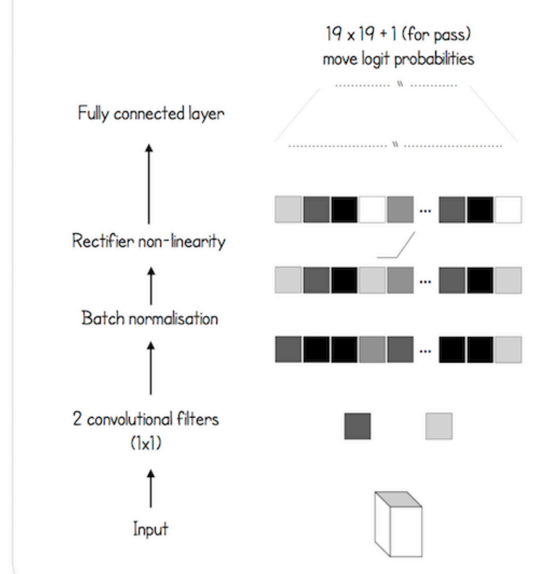
THE DEEP NEURAL NETWORK ARCHITECTURE

How AlphaGo Zero assesses new positions

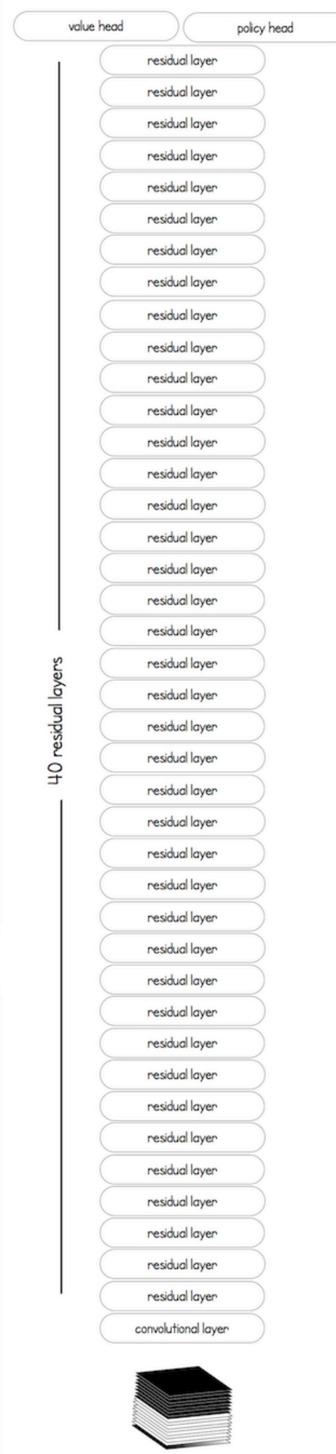
The network learns 'tabula rasa' (from a blank slate)

At no point is the network trained using human knowledge or expert moves

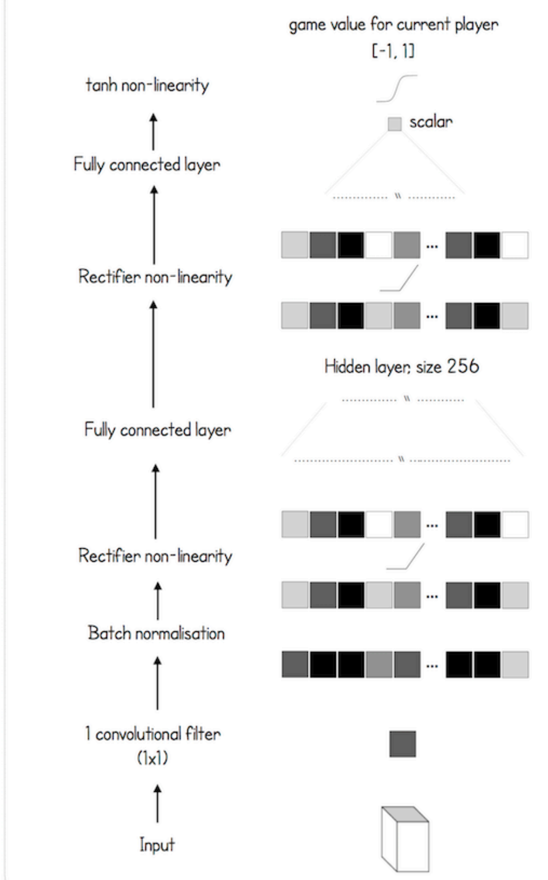
The policy head



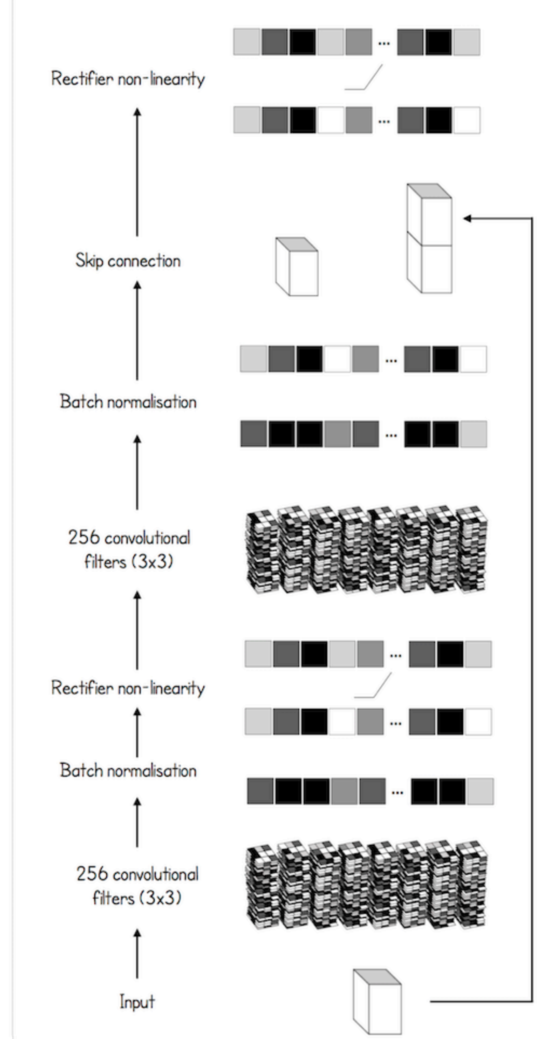
The network



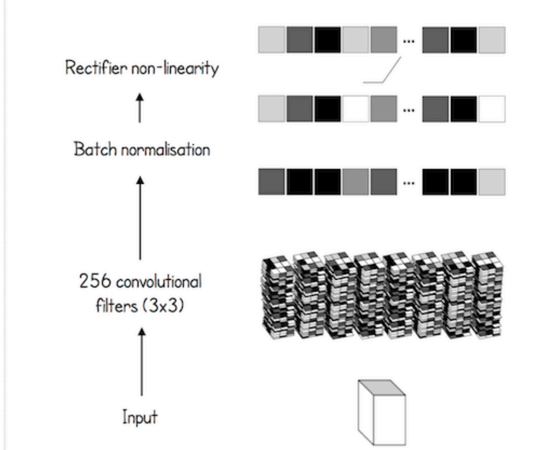
The value head



A residual layer

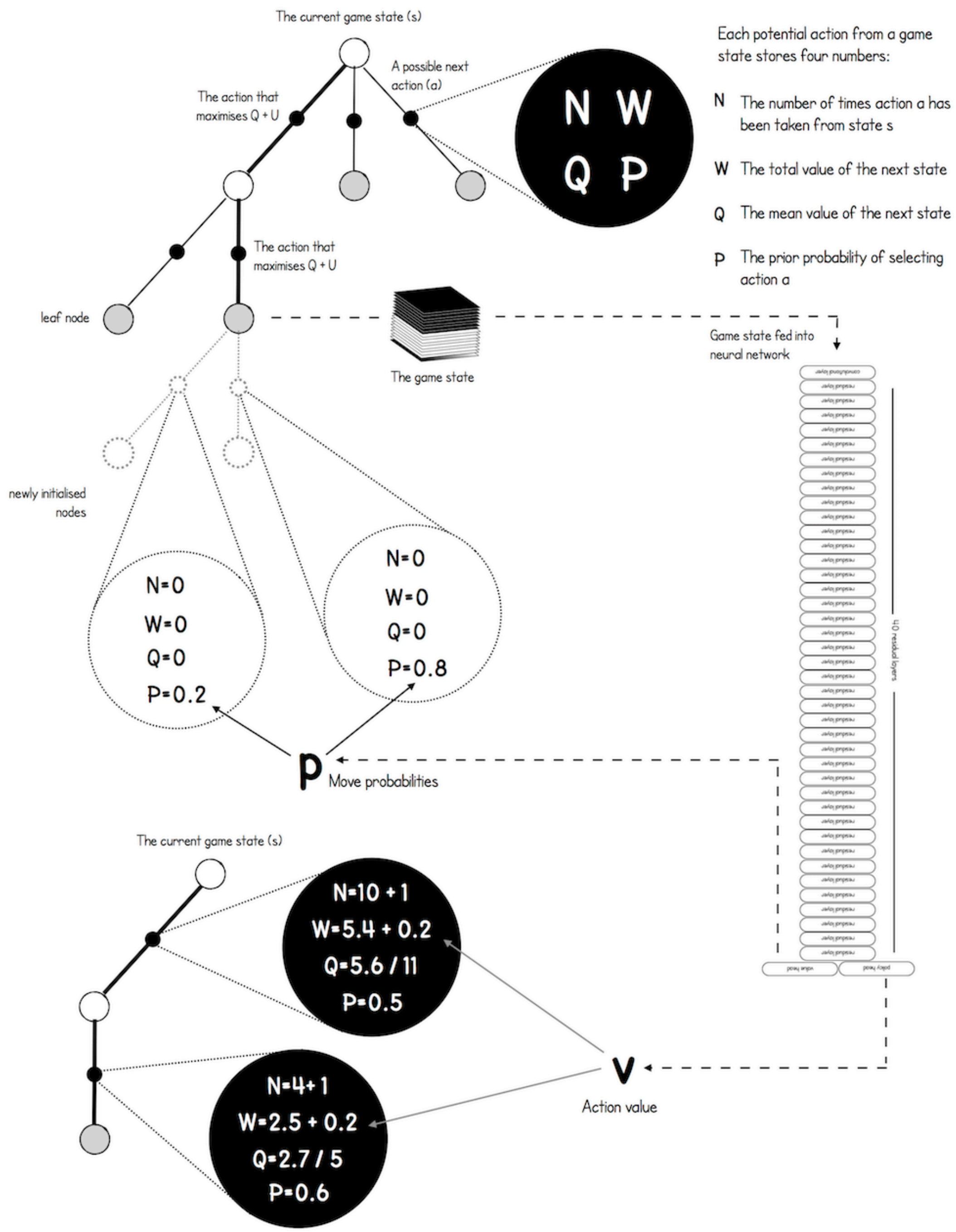


A convolutional layer



MONTE CARLO TREE SEARCH (MCTS)

How AlphaGo Zero chooses its next move



First, run the following simulation 1,600 times…

Start at the root node of the tree (the current game state)

1. Choose the action that maximises…

$$Q + U$$

The mean value of the next state

A function of P and N that increases if an action hasn't been explored much, relative to the other actions, or if the prior probability of the action is high

Early on in the simulation, U dominates (more exploration), but later, Q is more important (less exploration)

2. Continue until a leaf node is reached

The game state of the leaf node is passed into the neural network, which outputs predictions about two things:

p Move probabilities

v Value of the state (for the current player)

The move probabilities p are attached to the new feasible actions from the leaf node

3. Backup previous edges

Each edge that was traversed to get to the leaf node is updated as follows:

$$N \rightarrow N + 1$$
$$W \rightarrow W + v$$
$$Q = W / N$$

…then select a move

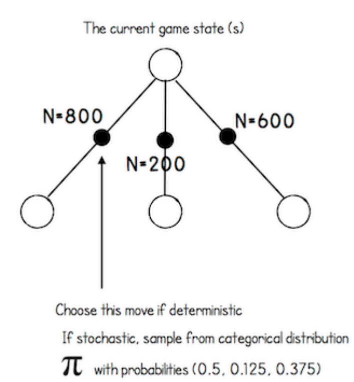
After 1,600 simulations, the move can either be chosen:

Deterministically (for competitive play)
Choose the action from the current state with greatest N

Stochastically (for exploratory play)
Choose the action from the current state from the distribution

$$\pi \sim N^{1/\tau}$$

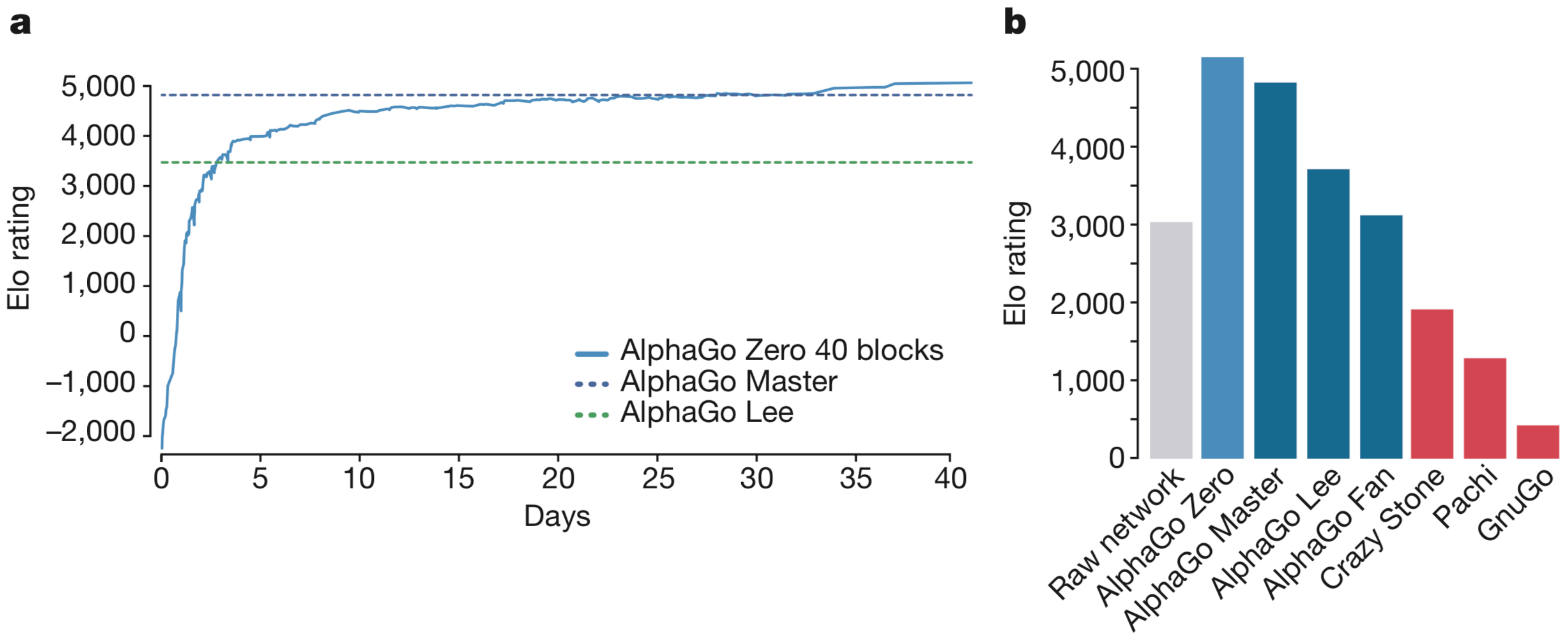
where τ is a temperature parameter, controlling exploration



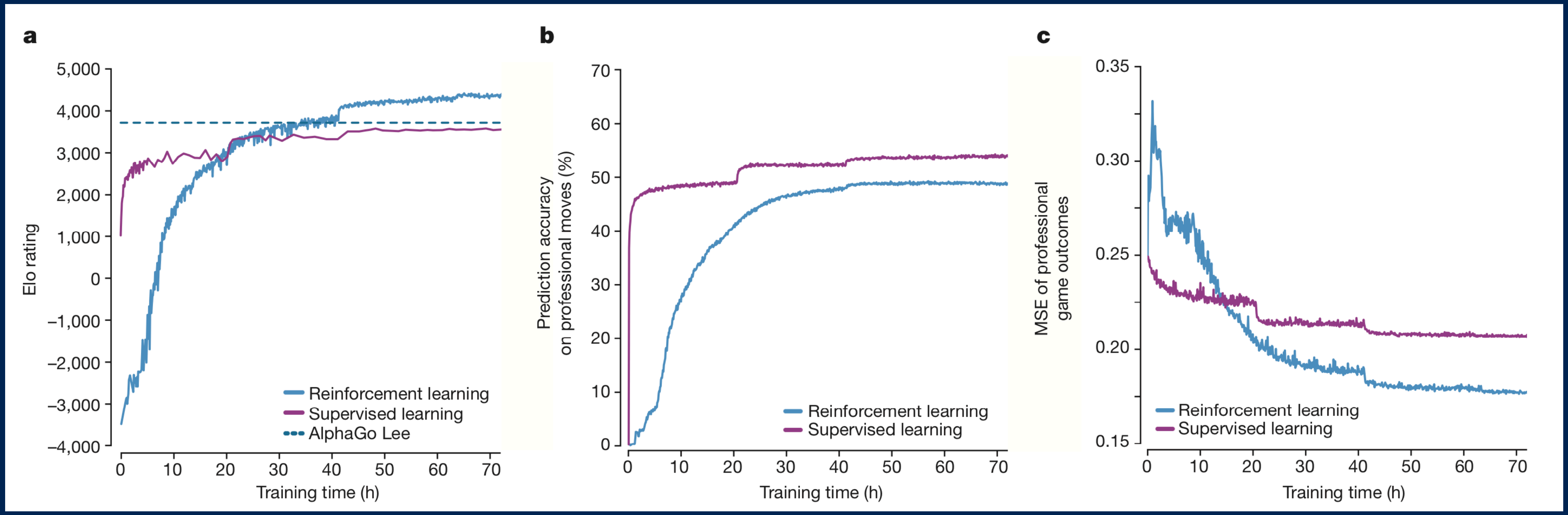
Other points

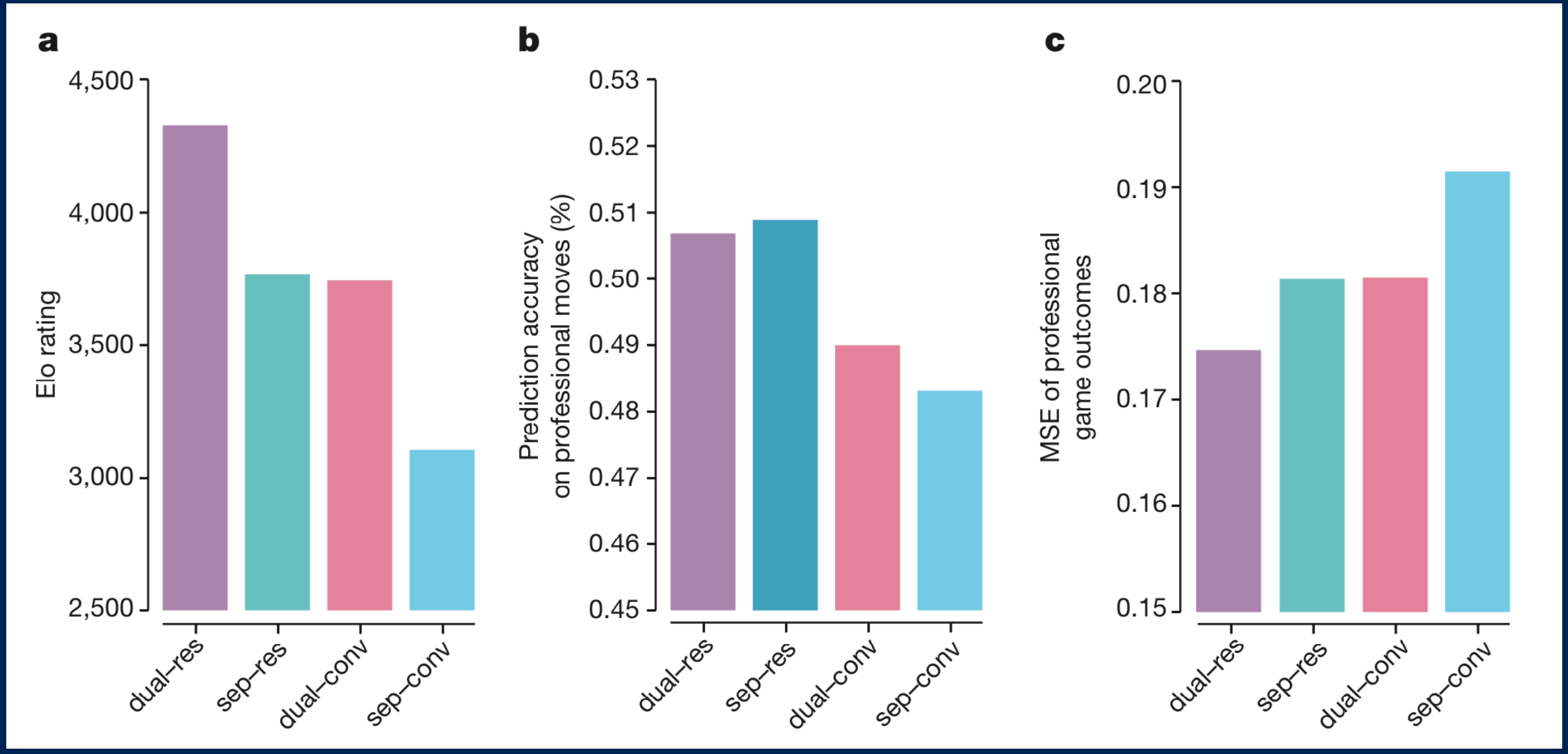
- The sub-tree from the chosen move is retained for calculating subsequent moves
- The rest of the tree is discarded

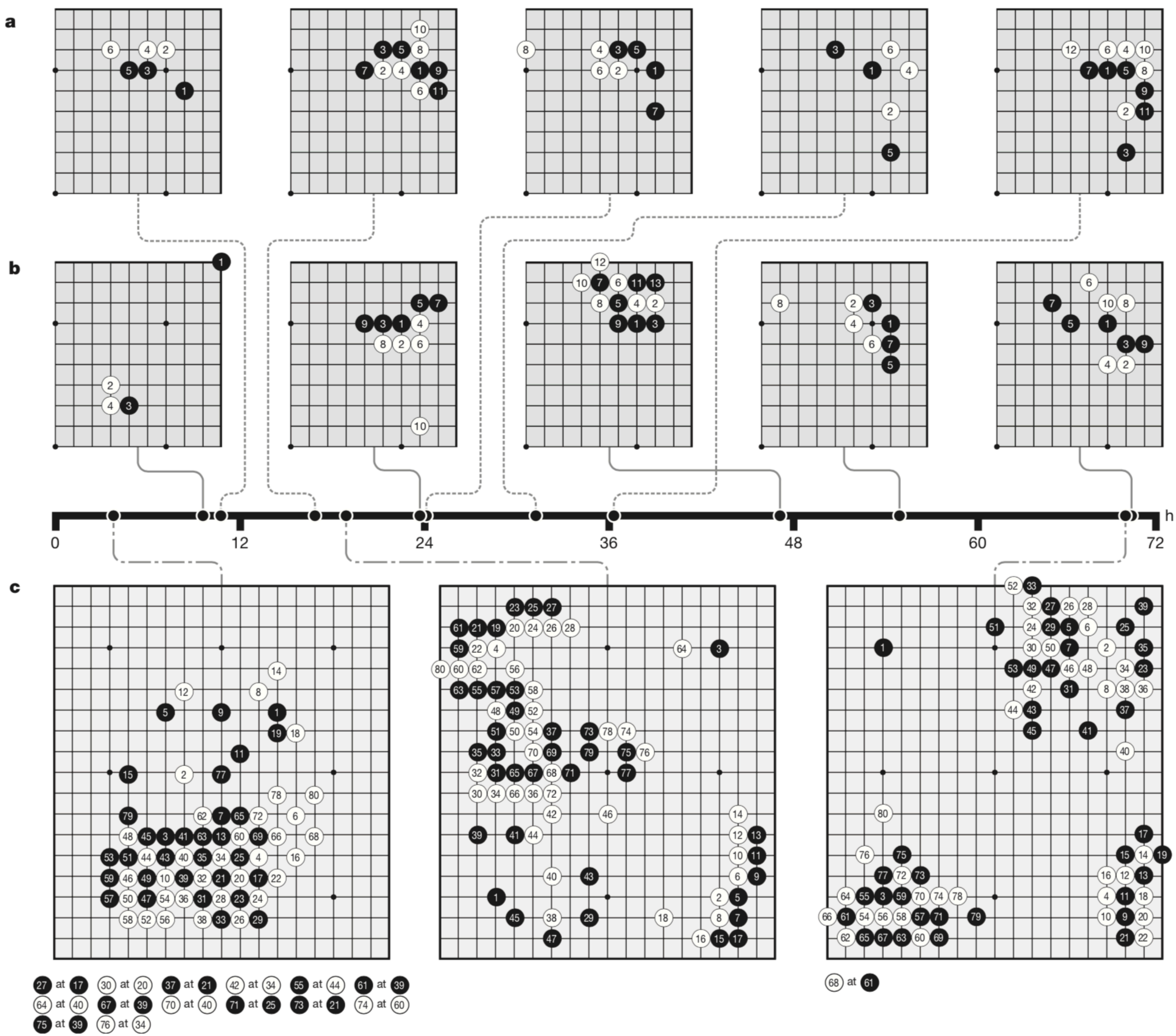
alpha go zero: train

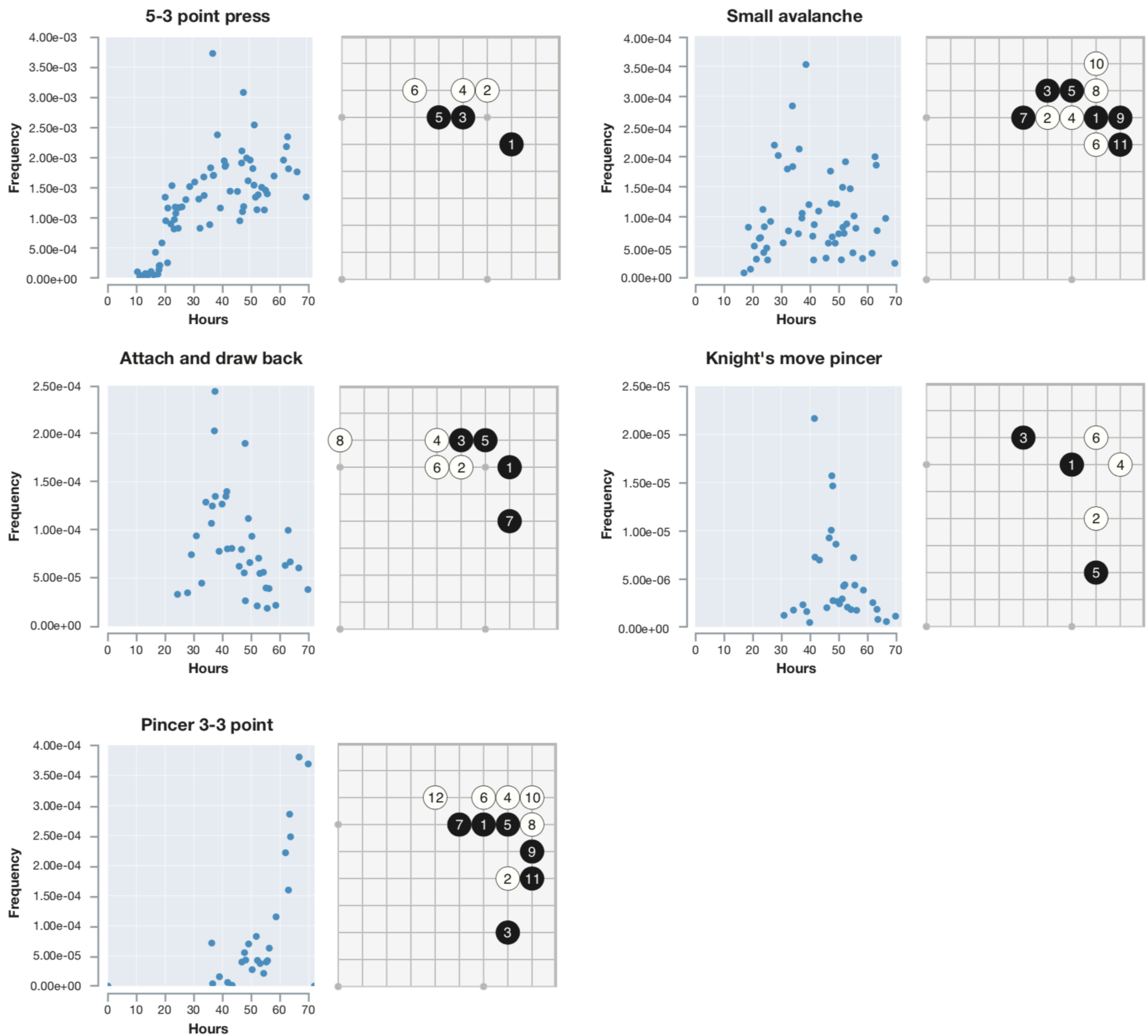


rl/sl + resnet/cnn



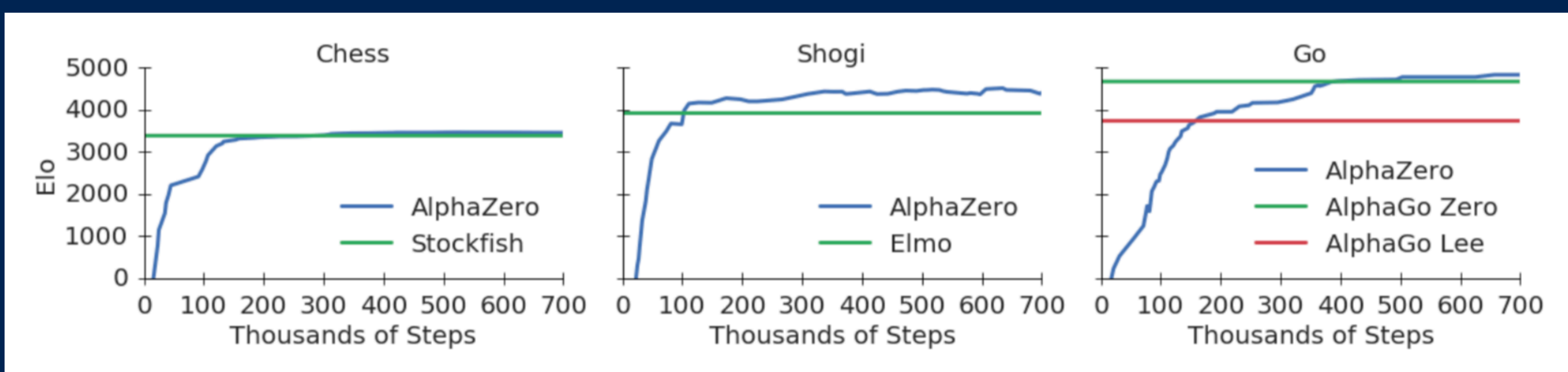



a
b
c
0 12 24 36 48 60 72 h
27 at 17 30 at 20 37 at 21 42 at 34 55 at 44 61 at 39
64 at 40 67 at 39 70 at 40 71 at 25 73 at 21 74 at 60
75 at 39 76 at 34
68 at 61

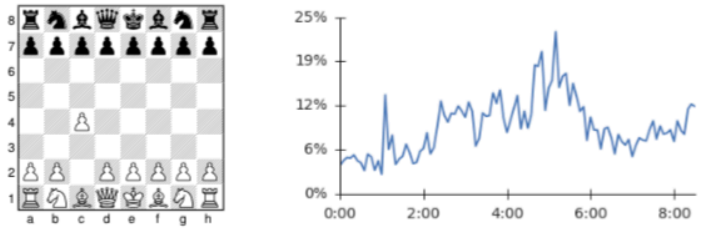

5-3 point press
Small avalanche
Attach and draw back
Knight's move pincer
Pincer 3-3 point
Frequency
Hours

alpha ~~go~~ zero (dec 17)

- generalized version of alpha go approach (no go-specific knowledge)
- input board state, possible moves, evaluation function —> generates policy/value networks via self play
- teaches self how to play, improves to master level

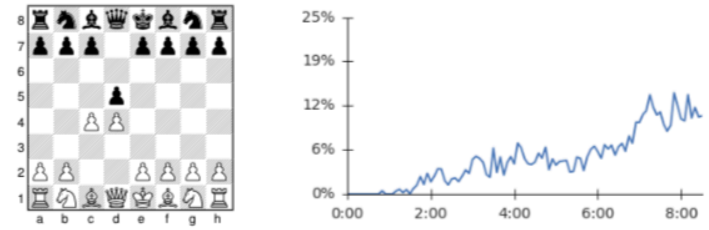


A10: English Opening



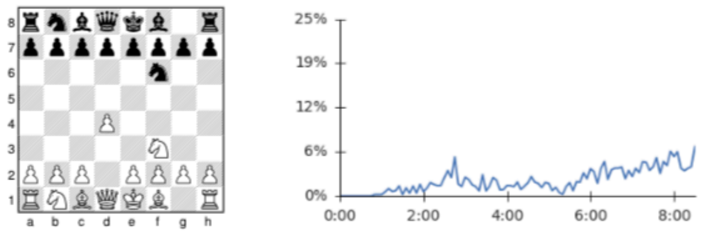
w 20/30/0, b 8/40/2 1...e5 g3 d5 cxd5 ♘f6 ♗g2 ♘xd5 ♘f3

D06: Queens Gambit



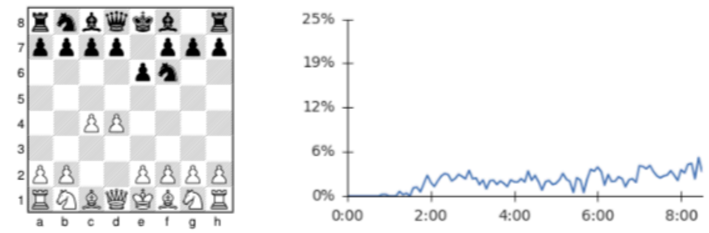
w 16/34/0, b 1/47/2 2...c6 ♘c3 ♘f6 ♘f3 a6 g3 c4 a4

A46: Queens Pawn Game



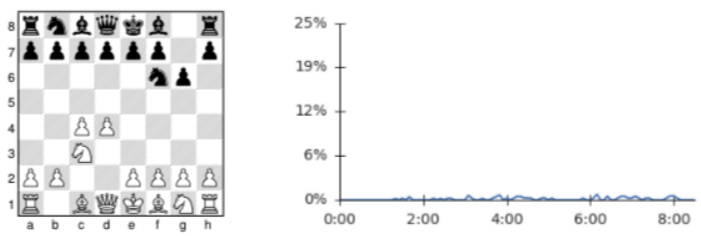
w 24/26/0, b 3/47/0 2...d5 c4 e6 ♘c3 ♗e7 ♗f4 O-O e3

E00: Queens Pawn Game



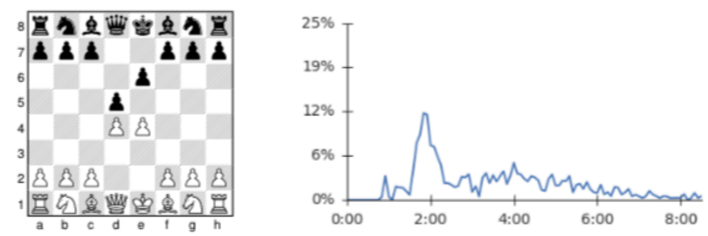
w 17/33/0, b 5/44/1 3.♘f3 d5 ♘c3 ♗b4 ♗g5 h6 ♕a4 ♘c6

E61: Kings Indian Defence



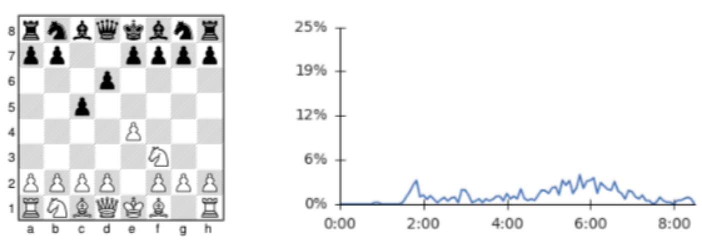
w 16/34/0, b 0/48/2 3...d5 cxd5 ♘xd5 e4 ♘xc3 bxc3 ♗g7 ♗e3

C00: French Defence



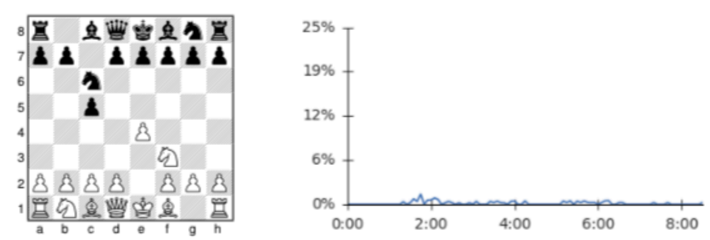
w 39/11/0, b 4/46/0 3.♘c3 ♘f6 e5 ♘d7 f4 c5 ♘f3 ♗e7

B50: Sicilian Defence



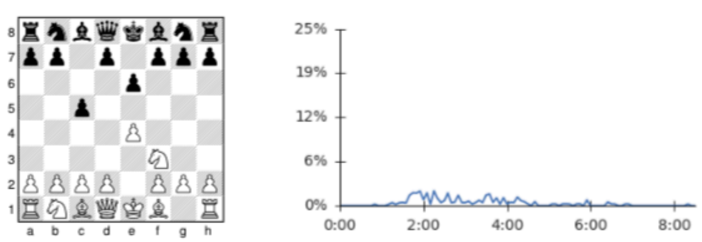
w 17/32/1, b 4/43/3 3.d4 cxd4 ♘xd4 ♘f6 ♘c3 a6 f3 e5

B30: Sicilian Defence



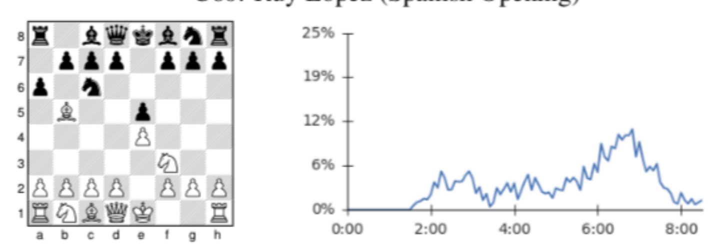
w 11/39/0, b 3/46/1 3.♗b5 e6 O-O ♘e7 ♖e1 a6 ♗f1 d5

B40: Sicilian Defence



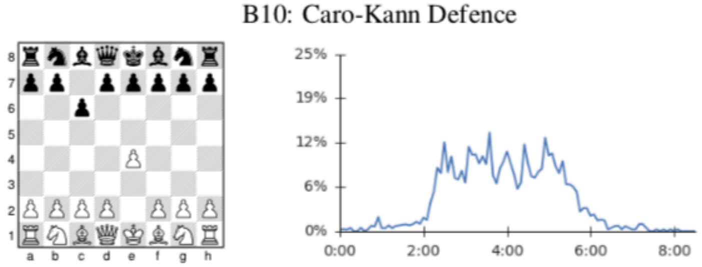
w 17/31/2, b 3/40/7 3.d4 cxd4 ♘xd4 ♘c6 ♘c3 ♕c7 ♗e3 a6

C60: Ruy Lopez (Spanish Opening)



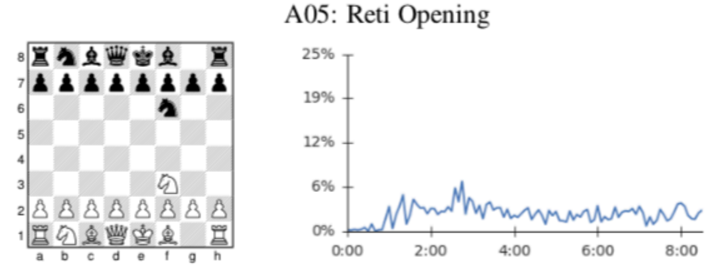
w 27/22/1, b 6/44/0 4.♗a4 ♗e7 O-O ♘f6 ♖e1 b5 ♗b3 O-O

B10: Caro-Kann Defence



w 25/25/0, b 4/45/1 2.d4 d5 e5 ♗f5 ♘f3 e6 ♗e2 a6

A05: Reti Opening



w 13/36/1, b 7/43/0 2.c4 e6 d4 d5 ♘c3 ♗e7 ♗f4 O-O

Total games: w 242/353/5, b 48/533/19 Overall percentage: w 40.3/58.8/0.8, b 8.0/88.8/3.2

tic-tac-toe

- github.com/evg-tyurin/alpha-zero-general
- thanks Surag Nair, Evgeny Tyurin!
- input: board, moves, evaluate
- play games against self, train (alpha zero + keras/tensorflow) to recognize winners/minimize losses, evaluate new network, repeat
- demo: play, train, test

recap

- mcts (uct + rollouts) “solves” go, but doesn’t scale
- combine expert knowledge (prior games) with value and policy networks (optimization) to surpass human players
- a single network randomly initialized can reach even greater performance via self-play
- this approach generalizes to other domains and is very human like

what is ai?

- chinese room example
- give beginner a board, rules, have them practice
- difference between master and beginner: knows what to seek, what to avoid —> they have experience
- casablanca: how many moves ahead do you think?

thanks for coming!

papers

- Reinforcement Learning and Simulation-Based Search in Computer Go (2009)
- Mastering the game of Go with deep neural networks and tree search (2016)
- Mastering the game of Go without human knowledge (2017)
- Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm (2017)

brettkoonce.com

- quarkworks.co
  - mobile apps for android and ios
  - custom solutions for solving problems on-device (edge computing)
  - keras, tensorflow lite, mobilenets, tf-coreml
  - traditional machine learning, analytics