Mastering the Game of Go Without Human Knowledge

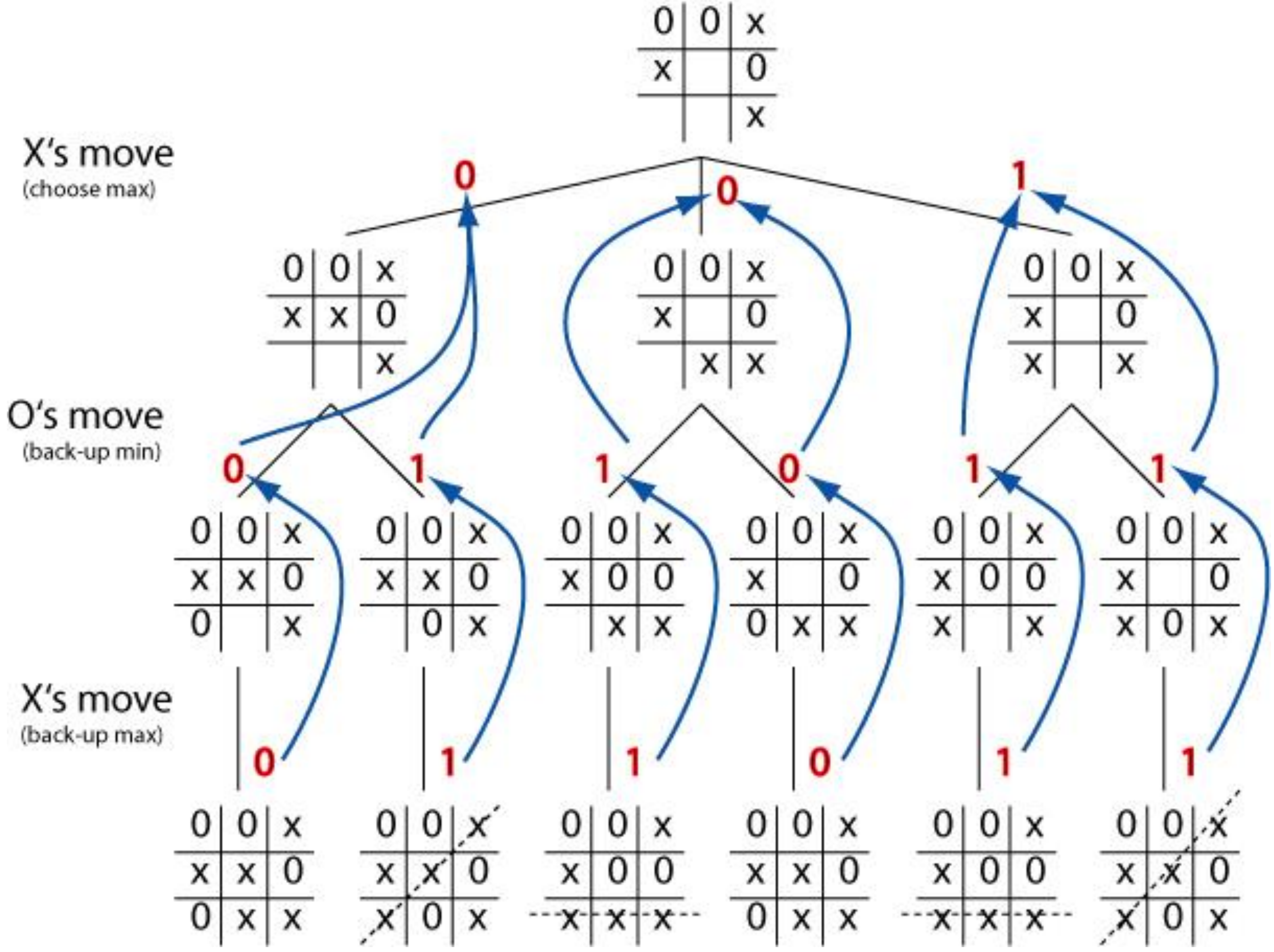
Lead: Liam Hinzman
Facilitators: Tahseen Shabab and Susan Cheng

AlphaGo Zero

Overview

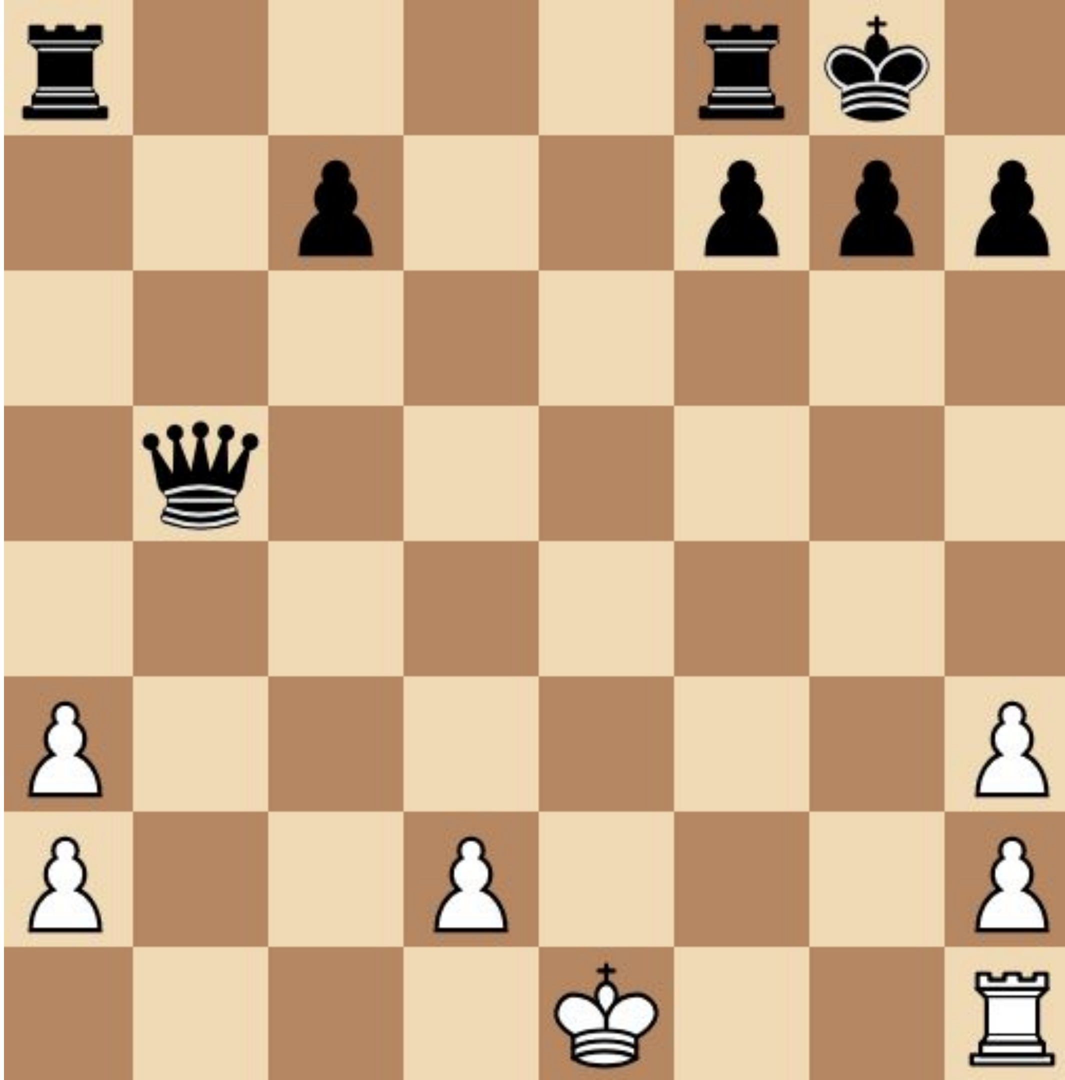
- Brief History of AI in Games
- What is Go and Why Should You Care?
- How AlphaGo Zero Works
- Results
- Discussion

Minimax


X's move
(choose max)
O's move
(back-up min)
X's move
(back-up max)
0
0
1
0
1
1
0
1
1
0
1
1
0
1
1

Heuristics

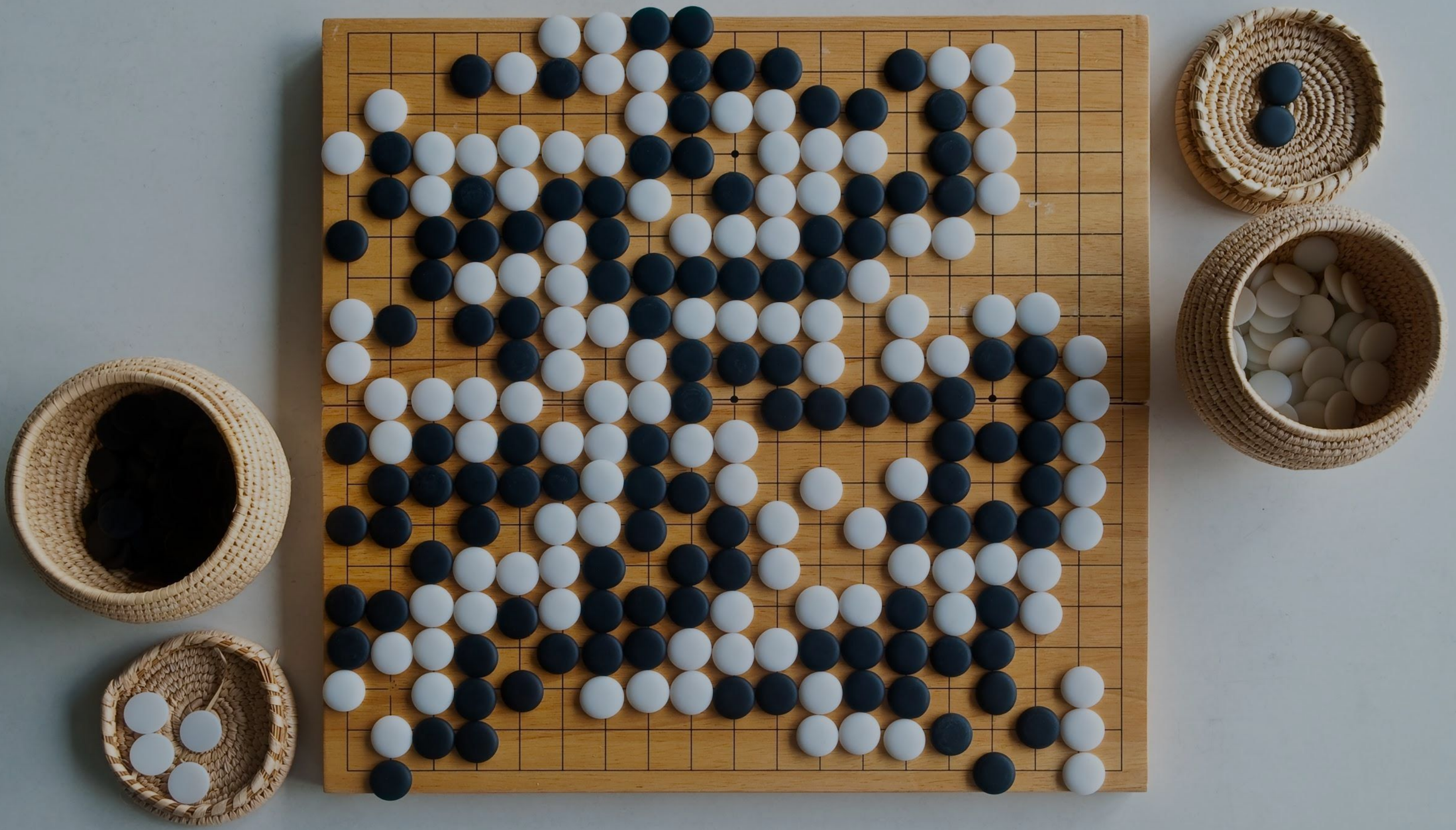
Reduces search depth

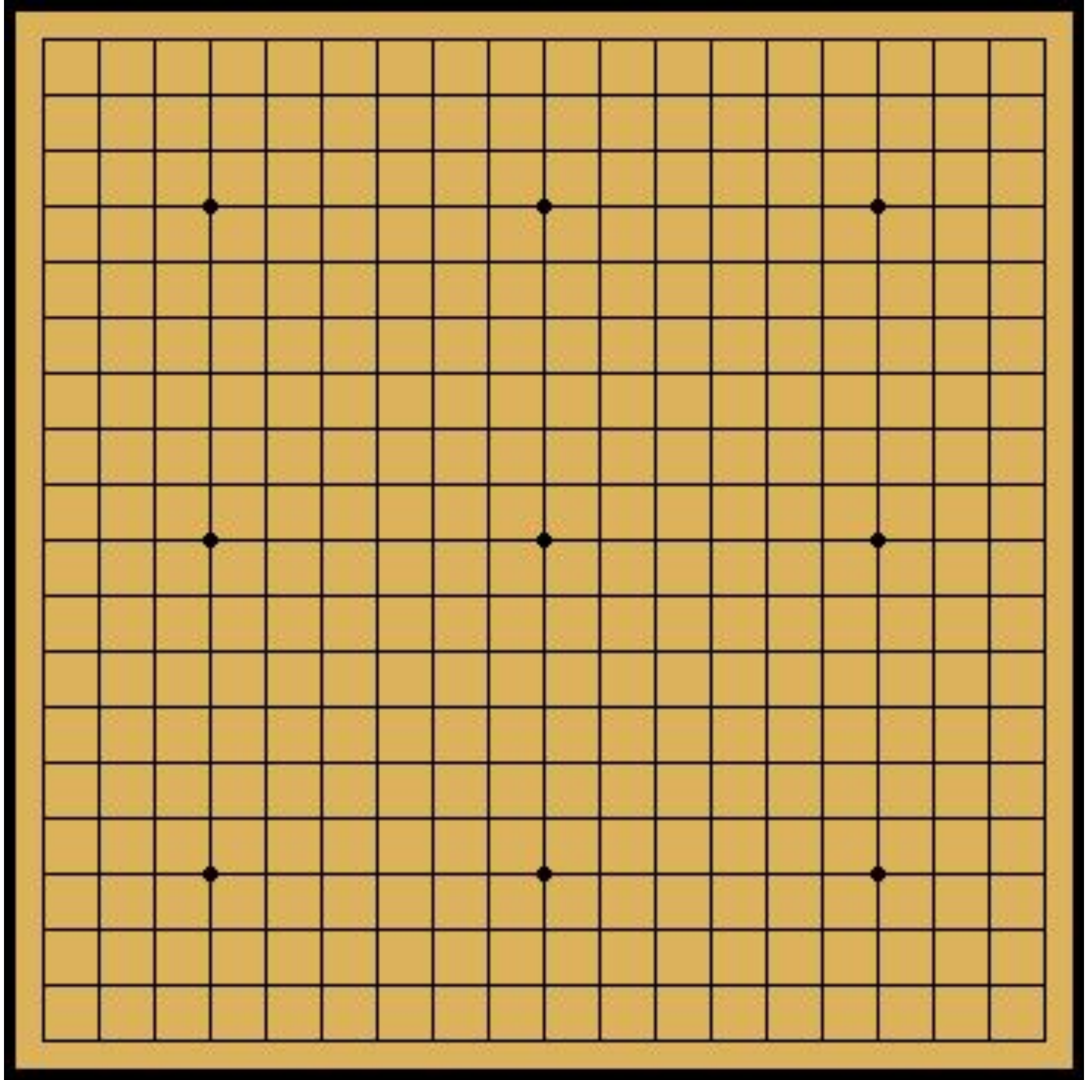


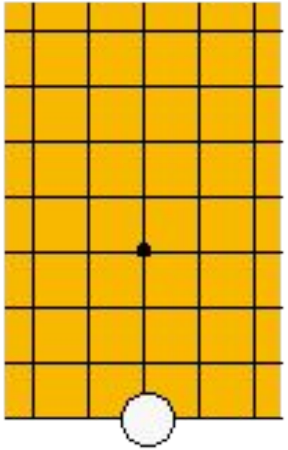
Deep Blue

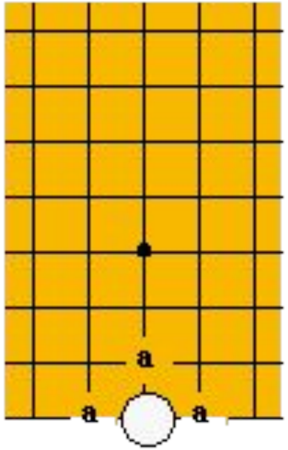
- 126 million positions per second
- Hand-designed Heuristics

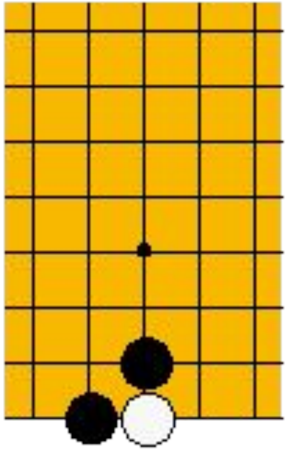
The Game of Go

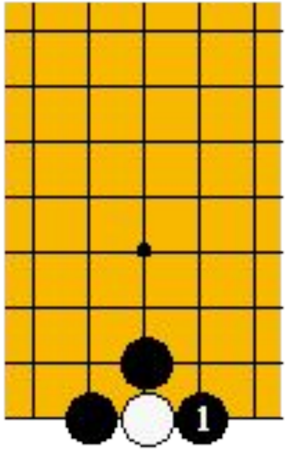


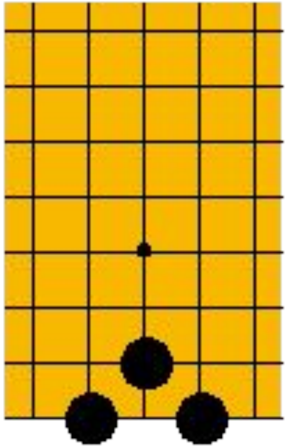





a
a
a

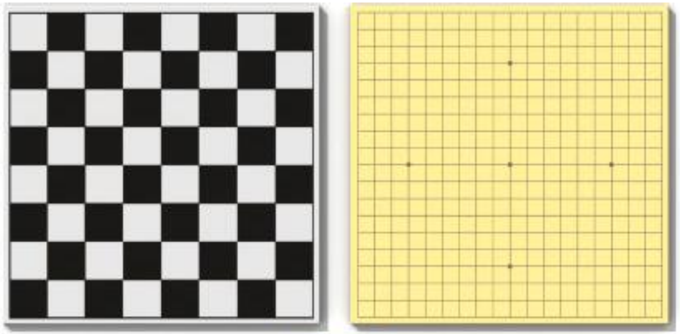



1



Go is Incredibly Complex

Go is Hard for Computers

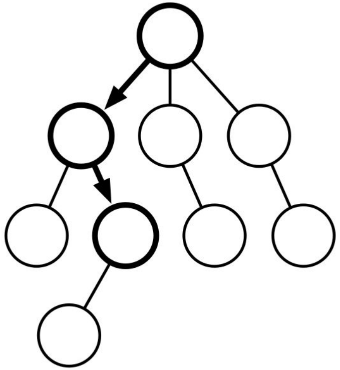


	GRID SIZE	
	8 x 8	19 x 19
	AVERAGE NUMBER OF MOVE CHOICES PER TURN	
	35	200–300
	LENGTH OF TYPICAL GAME	
	60 moves	200 moves
	NUMBER OF POSSIBLE GAME POSITIONS	
	10^{44}	10^{170}

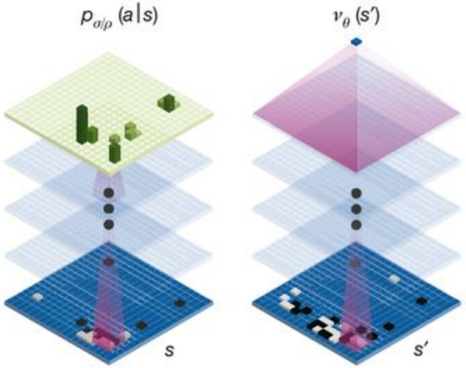
EXPLOSION OF CHOICES
(starting from average game position)

35	Move 1	200
1225	Move 2	40 000
42 875	Move 3	8 000 000
1 500 625	Move 4	1 600 000 000

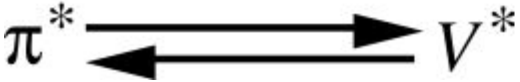
How AlphaGo Zero Works



Monte-Carlo Tree Search

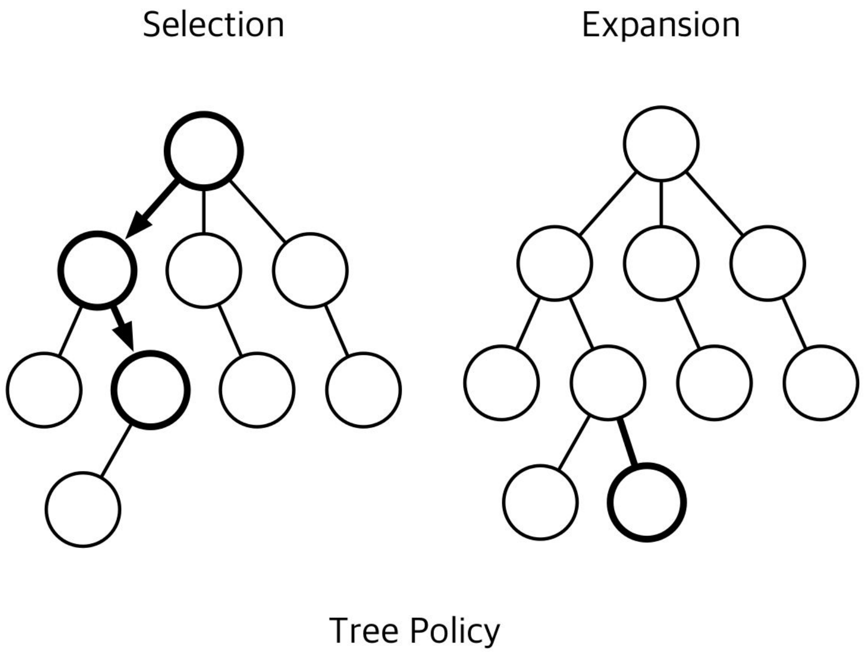


Residual Network

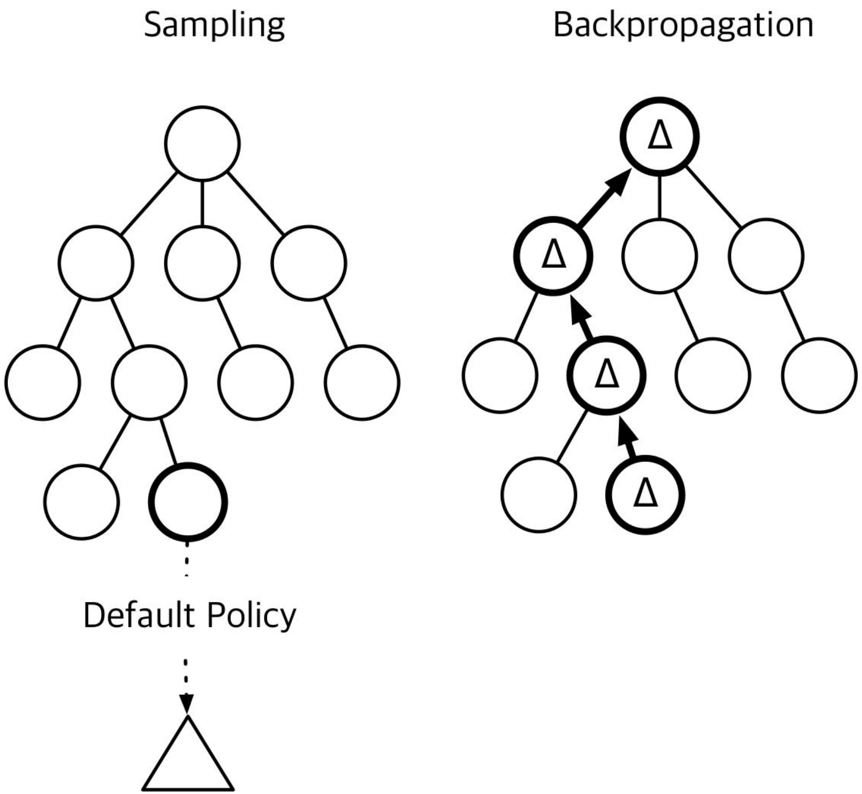


Policy Iteration

Monte-Carlo Tree Search (MCTS)



Monte-Carlo Tree Search (MCTS)



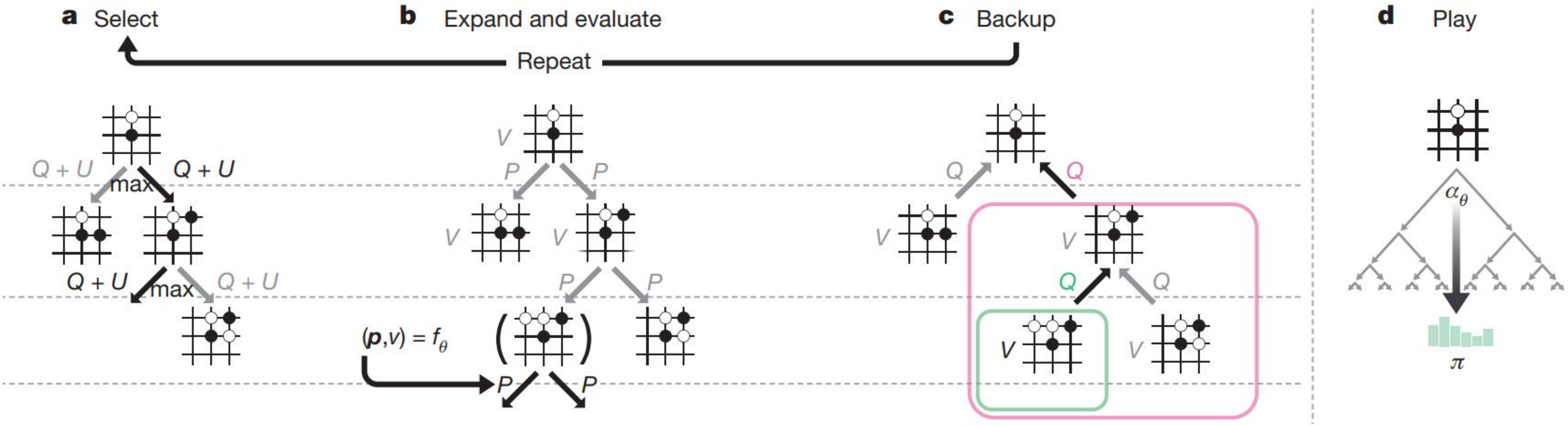
MCTS: Advantages

- Aheuristic
- Online-search
- Works well on large trees

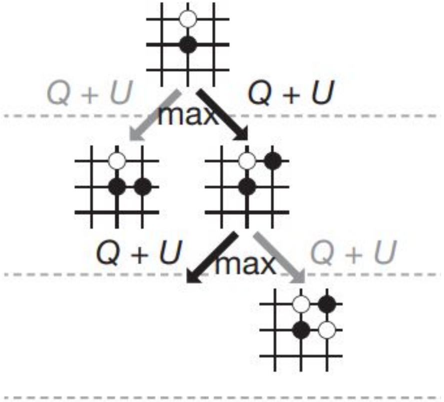
MCTS: Disadvantages

- Many simulation are required
- No generalization between similar states
- Performance is dependent on “rollout” policy

MCTS in AlphaGo Zero

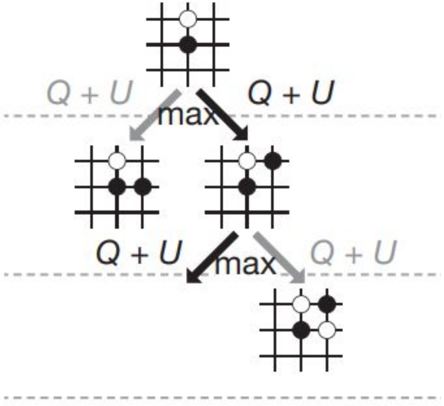


Upper Confidence Bound for Trees (UCT)



$$Q(s,a) + c_{puct} \cdot P(s,a) \cdot \frac{\sqrt{\Sigma_b N(s,b)}}{1 + N(s,a)}$$

Upper Confidence Bound for Trees (UCT)



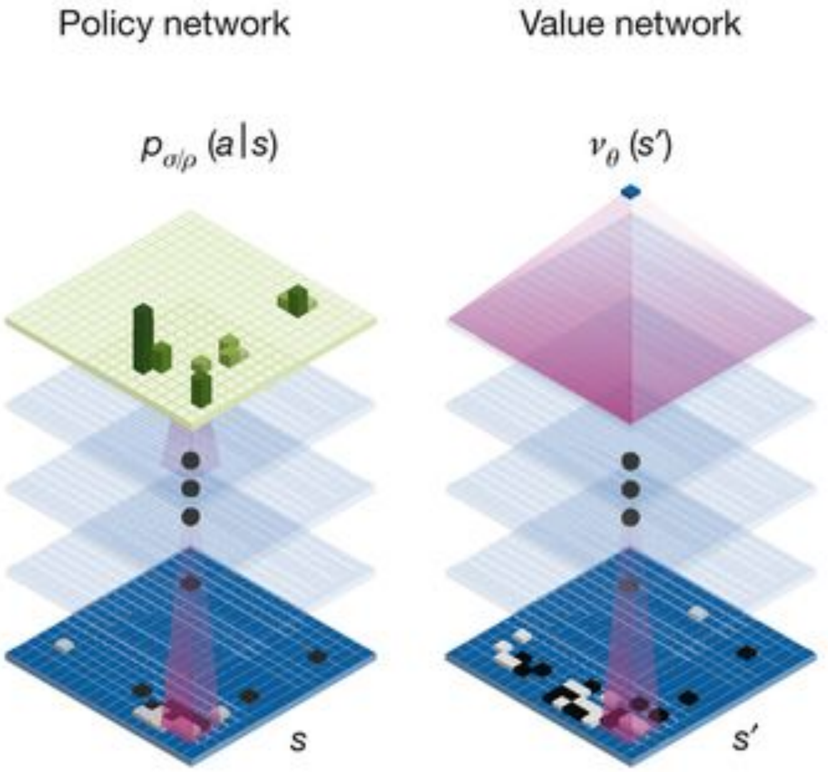
$$\underbrace{Q(s,a)}_{\text{Exploitation}} + \underbrace{c_{puct} \cdot P(s,a) \cdot \frac{\sqrt{\Sigma_b N(s,b)}}{1+N(s,a)}}_{\text{Exploration}}$$

Upper Confidence Bound for Trees (UCT)

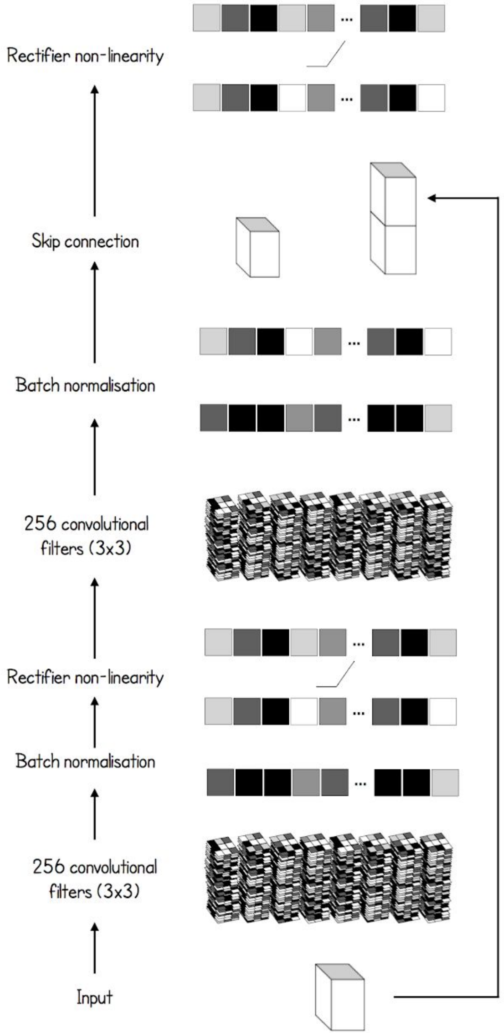
s	State
a	Action
Q(s, a)	Expected Reward
P(s, a)	Policy
N(s, a)	# of state visits
c_{puct}	Hyperparameter

$$\underbrace{Q(s,a)}_{\text{Exploitation}} + \underbrace{c_{puct} \cdot P(s,a) \cdot \frac{\sqrt{\Sigma_b N(s,b)}}{1 + N(s,a)}}_{\text{Exploration}}$$

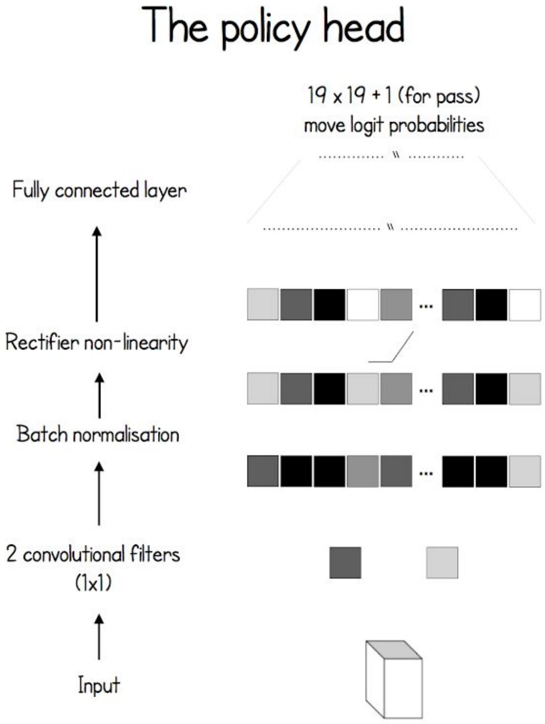
AlphaGo Zero’s Network Architecture

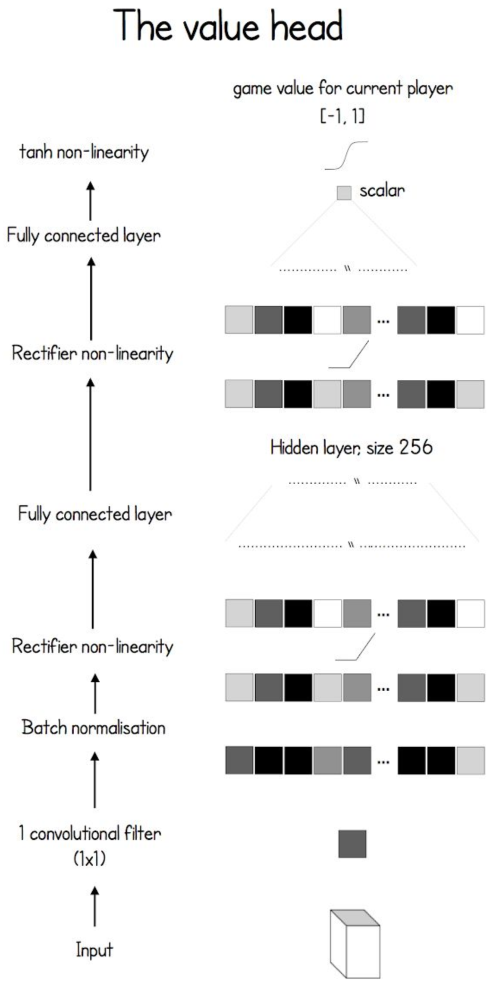


Residual Layer



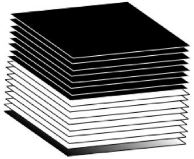
Dual Heads


The policy head
19 x 19 + 1 (for pass)
move logit probabilities
Fully connected layer
Rectifier non-linearity
Batch normalisation
2 convolutional filters
(1x1)
Input


The value head
game value for current player
[-1, 1]
tanh non-linearity
scalar
Fully connected layer
Rectifier non-linearity
Hidden layer, size 256
Fully connected layer
Rectifier non-linearity
Batch normalisation
1 convolutional filter
(1x1)
Input

Training

Self-play Worker



π

Training Worker

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

Evaluator

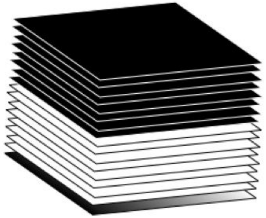
$$\pi' > \pi$$

How AlphaGo Zero Chooses a Move

1600
Simulations

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

Self-Play Workers



The game state

π

The search probabilities

The winner

Training Worker

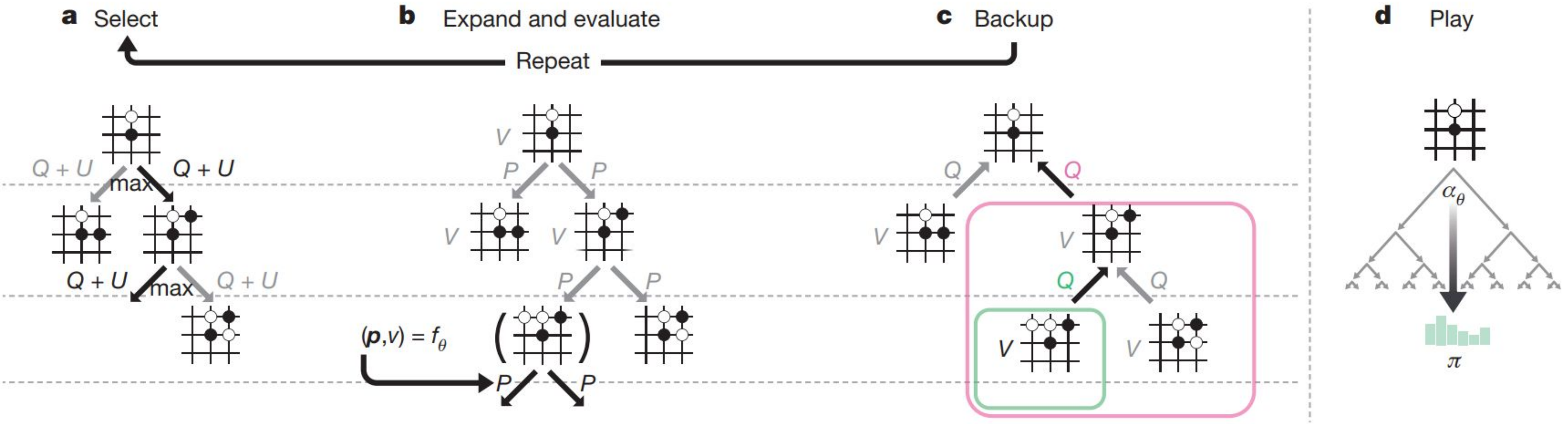
$$l = (z - v)^2 - \boldsymbol{\pi}^{\mathrm{T}} \log \boldsymbol{p} + c\|\theta\|^2$$

Evaluator

400 Games

55% Win Rate

MCTS in AlphaGo Zero

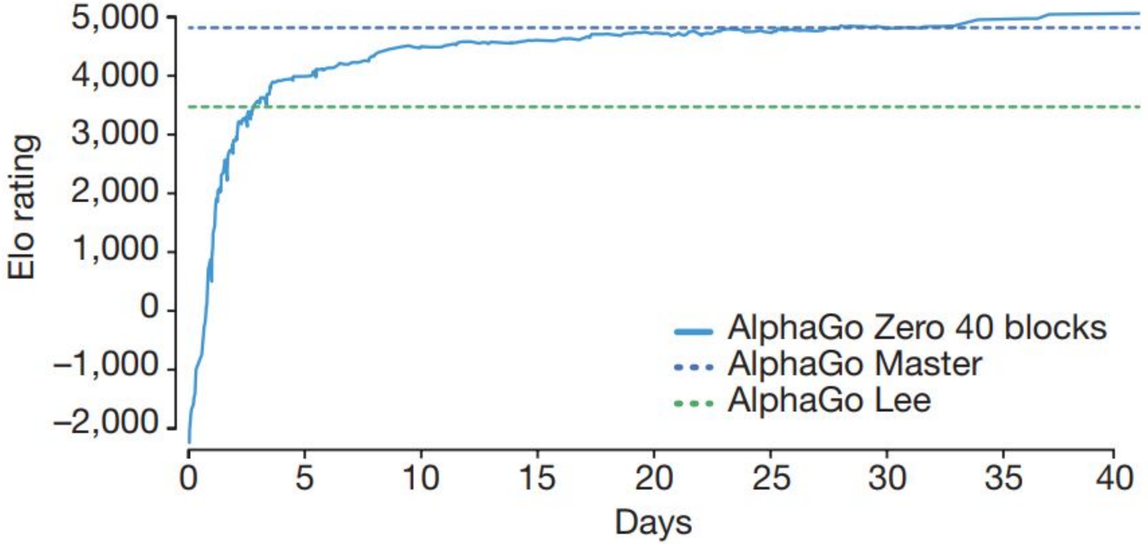


5 Minute Break

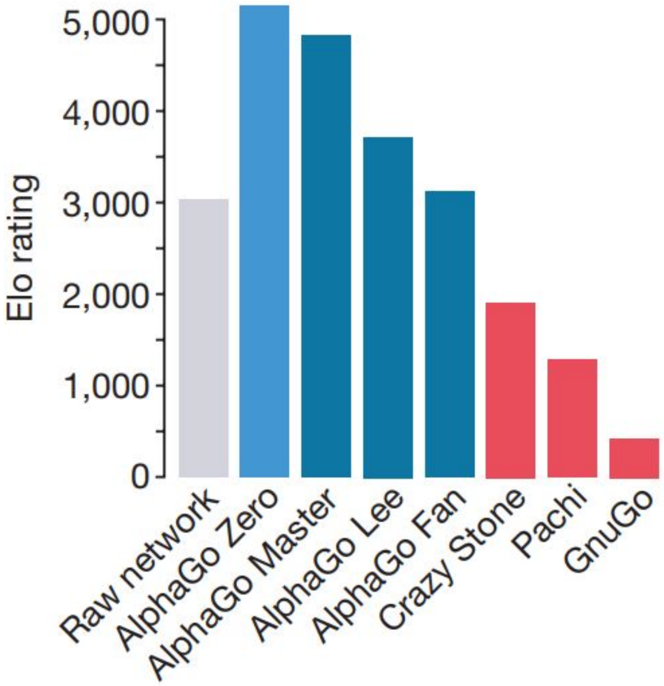
AlphaGo Zero vs AlphaGo

AlphaGo Zero	AlphaGo
Entirely self-play	Supervised learning + self-play
Input is game board	Input is hand-crafted features
Single network	Two networks
No rollouts	Rollouts were used

Results

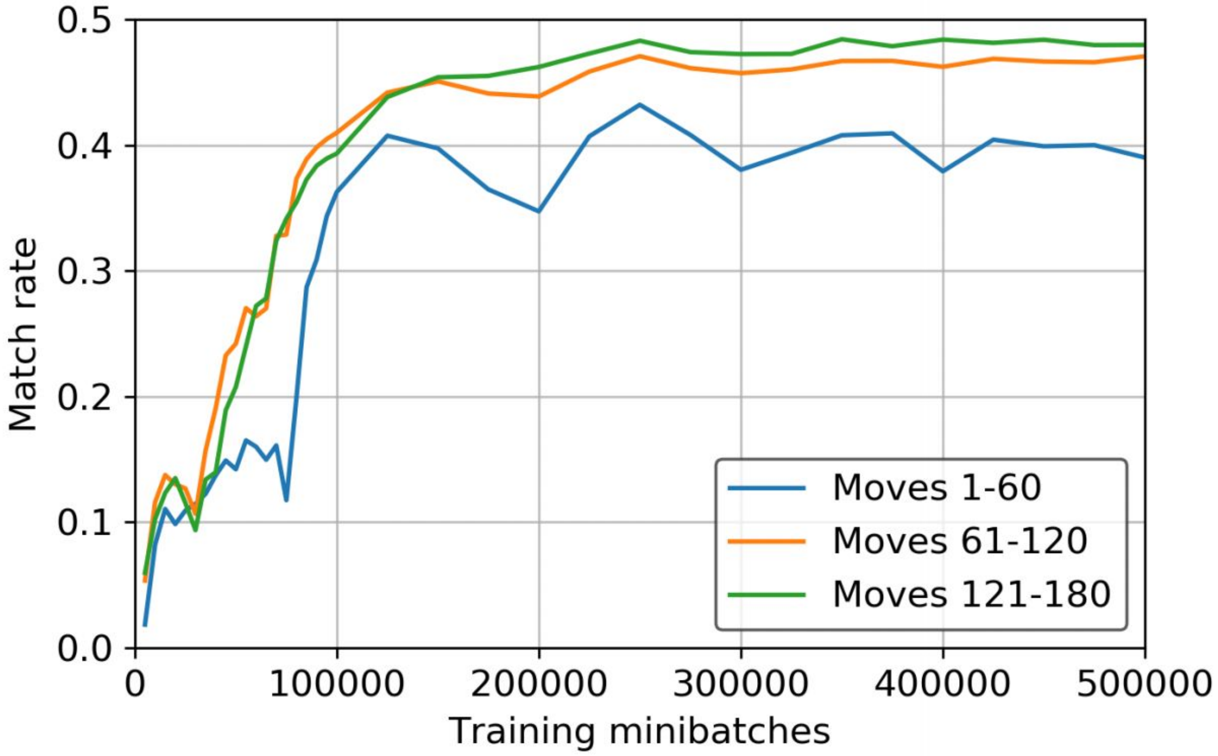


5,000
4,000
3,000
2,000
1,000
0
–1,000
–2,000
Elo rating
AlphaGo Zero 40 blocks
AlphaGo Master
AlphaGo Lee
0
5
10
15
20
25
30
35
40
Days

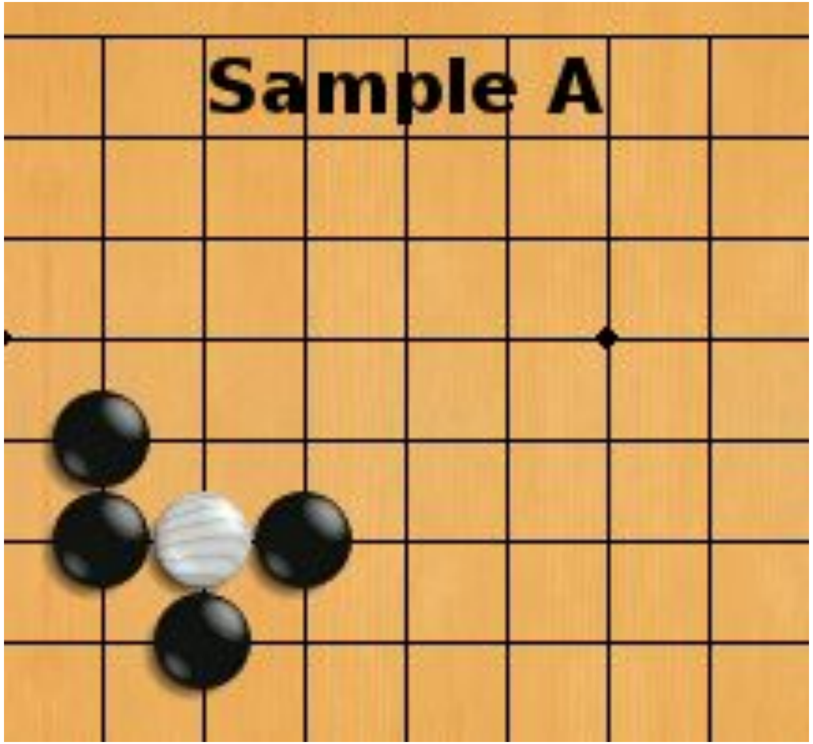


5,000
4,000
3,000
2,000
1,000
0
Elo rating
Raw network
AlphaGo Zero
AlphaGo Master
AlphaGo Lee
AlphaGo Fan
Crazy Stone
Pachi
GnuGo

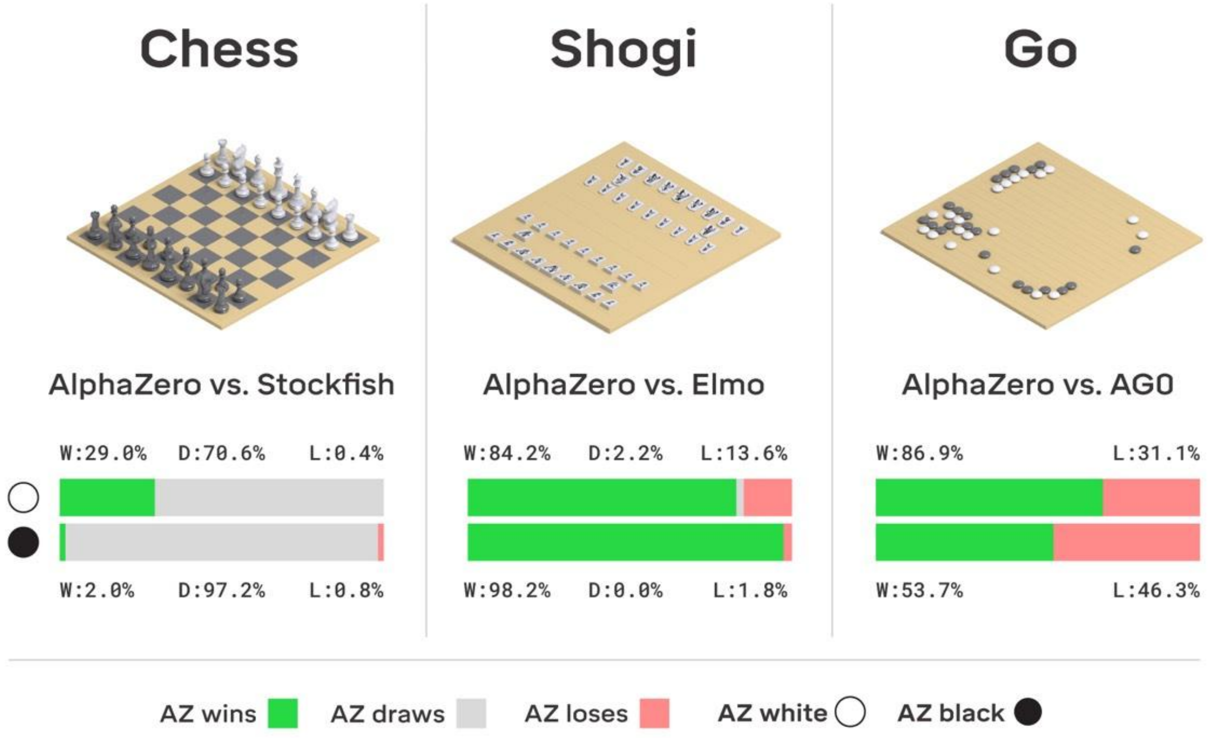
Learning Stages



Ladders



AlphaZero


Chess
Shogi
Go
AlphaZero vs. Stockfish
W:29.0%
D:70.6%
L:0.4%
W:2.0%
D:97.2%
L:0.8%
AlphaZero vs. Elmo
W:84.2%
D:2.2%
L:13.6%
W:98.2%
D:0.0%
L:1.8%
AlphaZero vs. AG0
W:86.9%
L:31.1%
W:53.7%
L:46.3%
AZ wins
AZ draws
AZ loses
AZ white
AZ black

AlphaGo Zero's Gift

Discussion

Discussion

How can the AlphaGo Zero algorithm be extended to different games?

How can the sample efficiency of AlphaGo Zero be improved?

A very stable training environment is need for the algorithm.
Can this be alleviated to let AlphaZero applied to real-world problems?

Resources

Mastering the Game of Go without Human Knowledge

David Silver 2017 NIPS Talk

ELF OpenGo: An Analysis and Open Reimplementation of AlphaZero

David Silver’s PhD Thesis: Reinforcement Learning and Simulation-Based Search in Computer Go

A Brief History of Game AI Up To AlphaGo - Andrey Kurenkov

AlphaGo Zero Demystified - Dylan Djian