INTELLIGENT SYSTEMS FOR
PATTERN RECOGNITION
A.Y. 2020/2021

MIDTERM 4

MASTERING THE GAME OF GO WITH DEEP NEURAL NETWORKS AND TREE SEARCH

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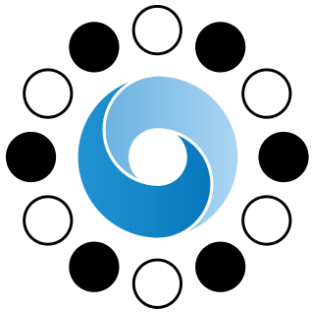


AlphaGo

HTTPS://GITHUB.COM/ELIAPICCOLI/ISPR-PROJECTS

ALPHA GO – THE CHALLENGE

GO

- The game is 2500 years old and still counts over 20M players
- Usually played on 19x19, 13x13, 9x9 board
- Very easy rules but complex game

IDEA : Given a position of the board the model should be able to find the best possible move that will lead to victory

Can be solved by recursevely computing the optimal value in a search tree

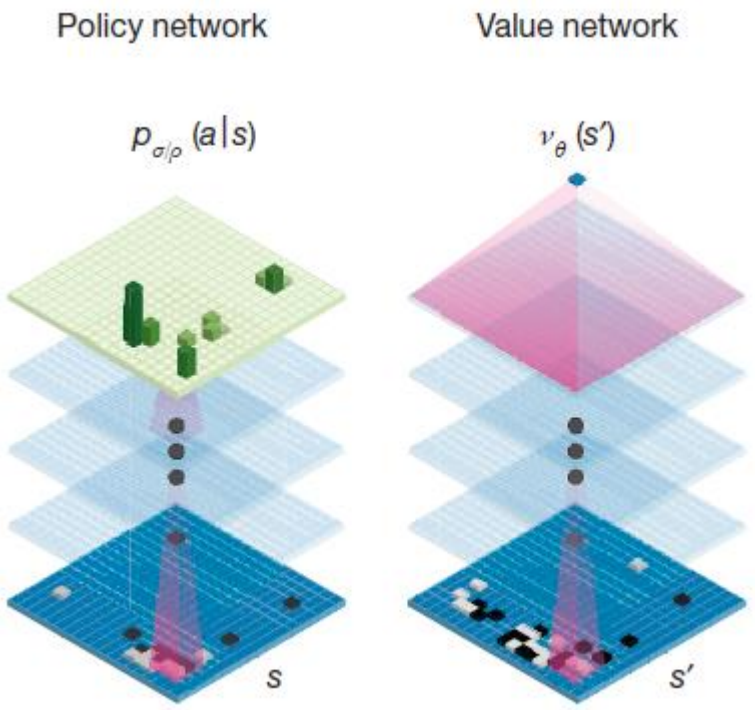
Unfeasible search space: b^d
($b \approx 250$, $d \approx 150$)

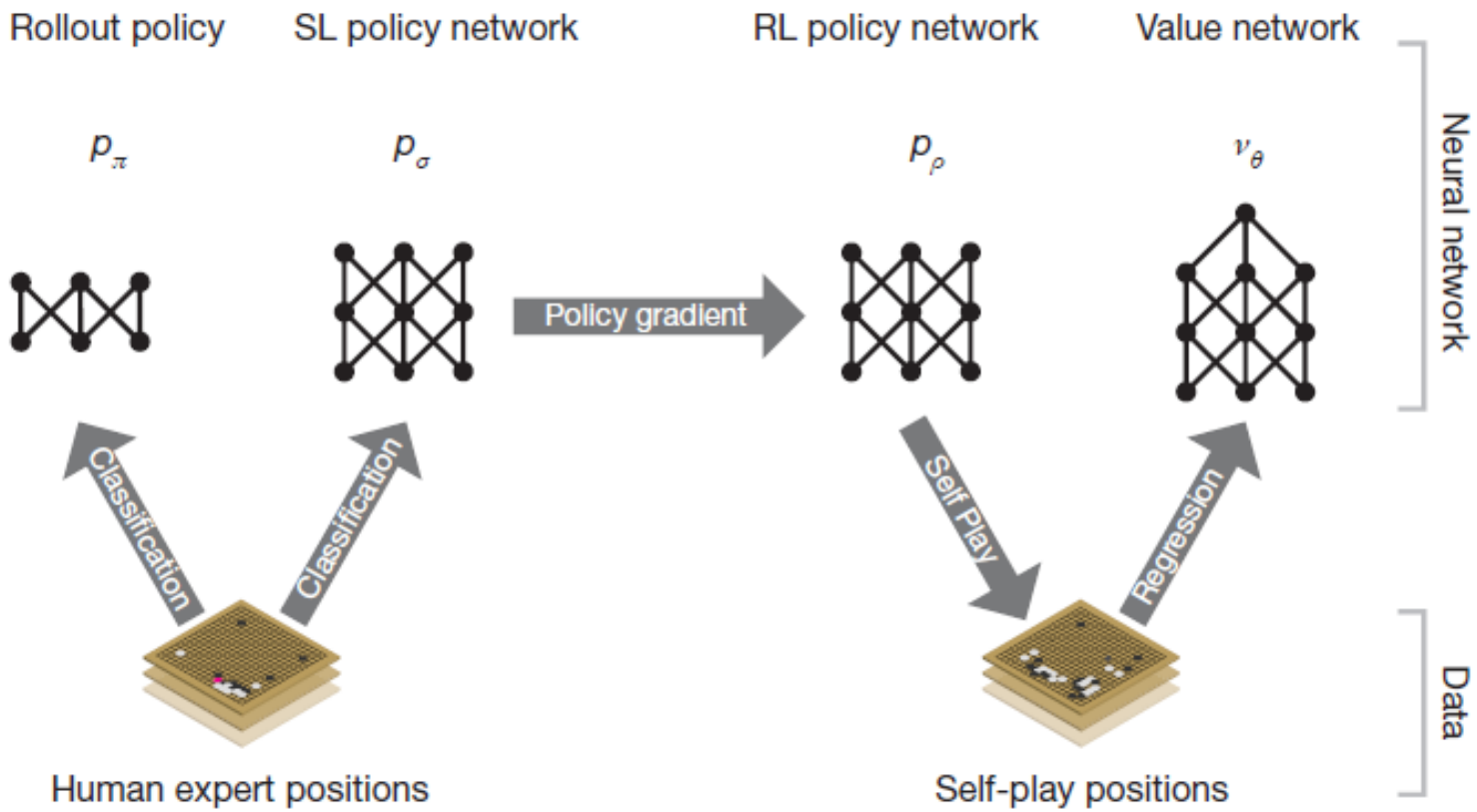
Narrow the depth of the trees using a value functon $v(s) \approx v^*(s)$

ALPHA GO – ARCHITECTURE

GO: abstraction is the key to win

CNN: abstraction is its *forte*





ALPHA GO – SL POLICY NETWORK

Training Data

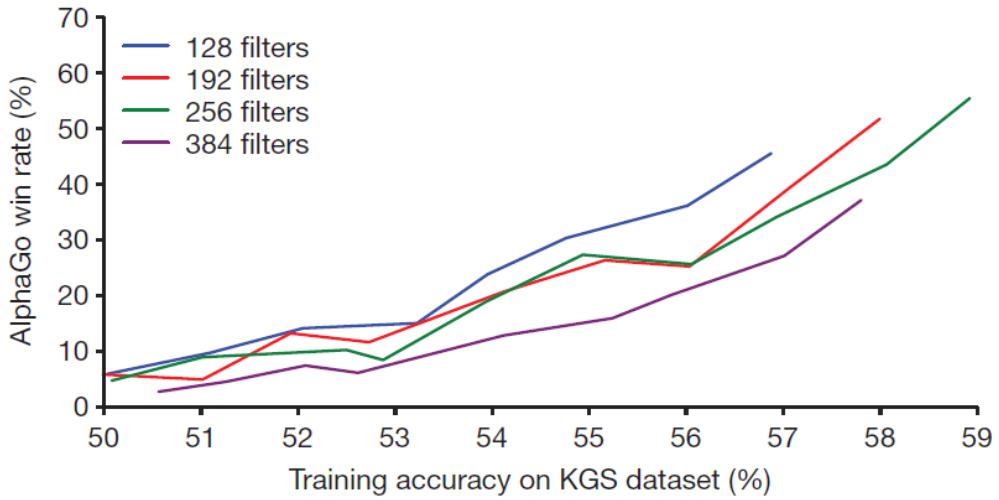
Trained to classify positions according to expert moves played in the KGS data set. This data set contains 29.4 million positions from 160,000 games played by KGS 6 to 9 *dan* human players.

Feature	# of planes	Description
Stone colour	3	Player stone / opponent stone / empty
Ones	1	A constant plane filled with 1
Turns since	8	How many turns since a move was played
Liberties	8	Number of liberties (empty adjacent points)
Capture size	8	How many opponent stones would be captured
Self-atari size	8	How many of own stones would be captured
Liberties after move	8	Number of liberties after this move is played
Ladder capture	1	Whether a move at this point is a successful ladder capture
Ladder escape	1	Whether a move at this point is a successful ladder escape
Sensibleness	1	Whether a move is legal and does not fill its own eyes
Zeros	1	A constant plane filled with 0

Neural Network architecture

- The input is a 19 × 19 × 48 image stack consisting of 48 feature planes
- First hidden layer pads to 23 x 23 images and then apply first convolutional layer with 192 filter of size 5 x 5 followed by rectified non-linearities
- Layer 2 to 12 pads to 21 x 21 images and then apply 192 filters of size 3x3 followed by rectified non-linearities
- Layer 12 apply 1 filter of size 1 x 1 followed by a softmax

- 3 weeks of training



ALPHA GO – FAST POLICY NETWORK

Training Data

Trained from 8 million positions from human games on the Tygem server to maximize log likelihood by stochastic gradient descent.

Neural Network architecture

- Use a small set of features as input considering 'response' patterns and 'non-response' patterns
- Simple Softmax layer

- The aim of this model is not accuracy - only 24% - but speed require just 2 μs to select an action (vs 3ms SL policy network)

- Will be exploited during MCTS to rapidly compute rollouts

Feature	# of patterns	Description
Response	1	Whether move matches one or more response pattern features
Save atari	1	Move saves stone(s) from capture
Neighbour	8	Move is 8-connected to previous move
Nakade	8192	Move matches a *nakade* pattern at captured stone
Response pattern	32207	Move matches 12-point diamond pattern near previous move
Non-response pattern	69338	Move matches 3 × 3 pattern around move

ALPHA GO – RL POLICY NETWORK

Training – Self Play

Each iteration consisted of a minibatch of *n* games played between the current policy network p_ρ and an opponent $p_{\rho-}$ randomly sampled from a pool of opponents (network at previous iteration)

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- Layer 13 apply 1 filter of size 1 x 1 followed by a softmax

- The network is initialized with the same weights of the SL policy network
- One day of training

- The aim of this model is to fine tune the SL policy network towards a winning policy

- It is trained using a sparse reward function that return *1* for victory and *-1* for defeat

- 80% winrate vs SL policy network
- 85% winrate vs Pachi

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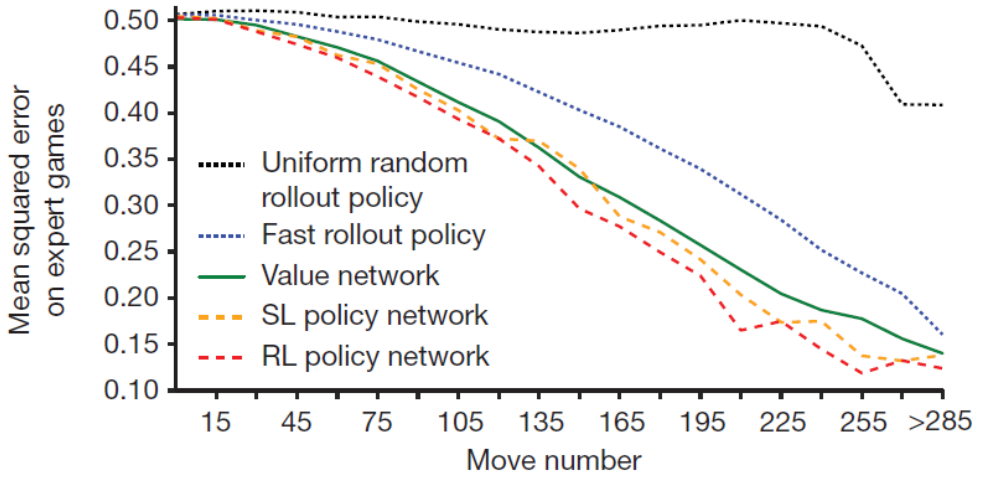
ALPHA GO – VALUE NETWORK

Training Data

To avoid overfitting due to very correlated data (successive moves) is created during the phase of self-play considering one random position and the outcome of that game (s_{U+1}, z_{U+1})



Neural Network architecture

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- Layer 2 to 12 pads to 21 x 21 images and then apply 192 filters of size 3x3 followed by rectified non-linearities
- Layer 13 apply 1 filter of size 1 x 1 followed by a rectified non-linearities
- Layer 14 is a fully connected layer with 256 rectifier units
- Output is a fully connected layer with 1 tanh unit

- One week of training

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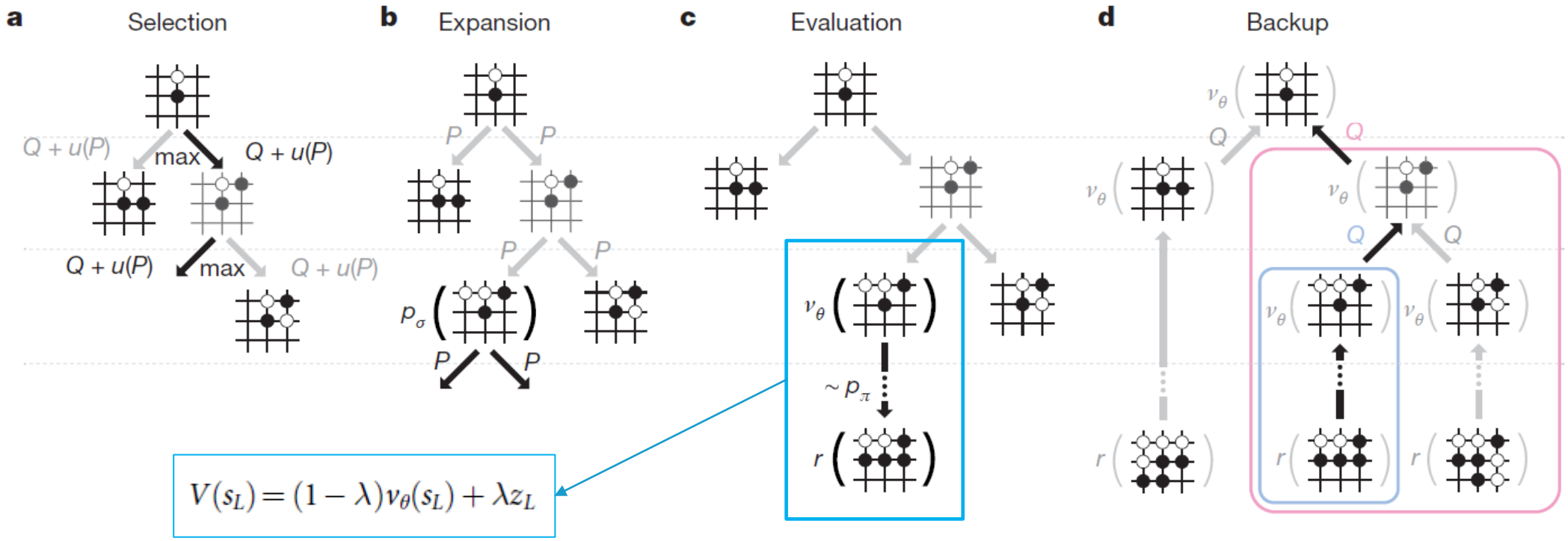
Zeros	1	A constant plane filled with 0
Player color	1	Whether current player is black

ALPHA GO – SEARCHING

- AlphaGo combines the policy and value networks in an MCTS algorithm

- Each edge (s, *a*) of the search tree stores an action value *Q*(s, *a*), visit count *N*(s, *a*), and prior probability *P*(s, *a*).



ALPHA GO – EVALUATION

VS Programs

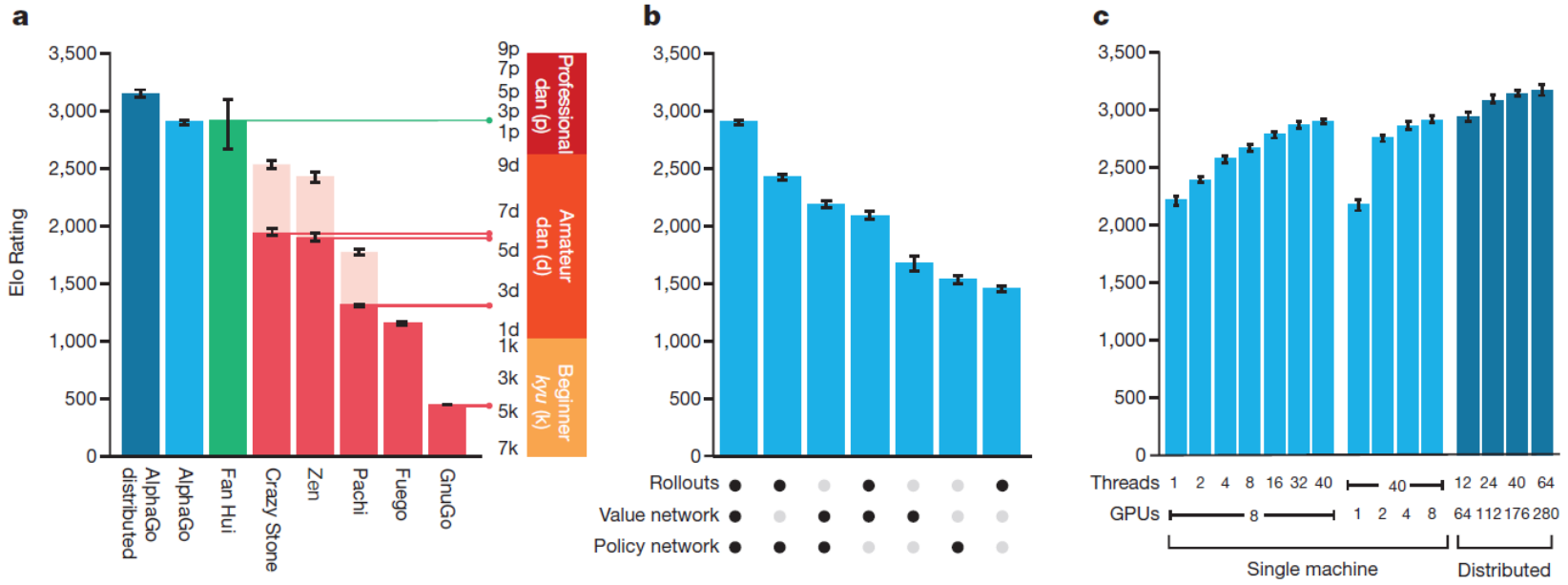
To evaluate AlphaGo, we ran an internal tournament among variants of AlphaGo and several other Go programs (CrazyStone, Zen, Pachi etc.)

- AlphaGo won 494 out 495 games
- AlphaGo won 77%, 86%, and 99% of handicap games against Crazy Stone, Zen and Pachi, respectively
- Distributed AlphaGo won 77% games versus single-machine AlphaGo

VS Humans

- 5–9 October 2015 AlphaGo and Fan Hui (2013/14/15 European Go champion) competed in a formal five-game match.
- 9-15 March 2016 AlphaGo and Lee Sedol (18-time Go world champion) competed in a formal five-game match.

- AlphaGo won 5-0 vs Fan Hui
- AlphaGo won 4-1 vs Lee Sedol



ALPHA GO – FINAL CONSIDERATION AND FUTURE WORK

- AlphaGo brought huge improvement with respect to the previous results obtained in GO
- Effective move selection and position evaluation functions for Go, based on deep neural networks that are trained by a novel combination of supervised and reinforcement learning.
- Differently from DeepBlue – handcrafted evaluation function - AlphaGo neural networks learns through supervised and reinforcement learning
- In 2017 DeepMind published AlphaGo Zero [1], a new version, that wins 100-0 vs Alpha Go starting from zero knowledge

I strongly suggest you to watch DeepMind's film about this huge achievement in AI world.
https://www.youtube.com/watch?v=WXuK6gekU1Y

[1] Silver, D., Schrittwieser, J., Simonyan, K. et al. Mastering the game of Go without human knowledge.