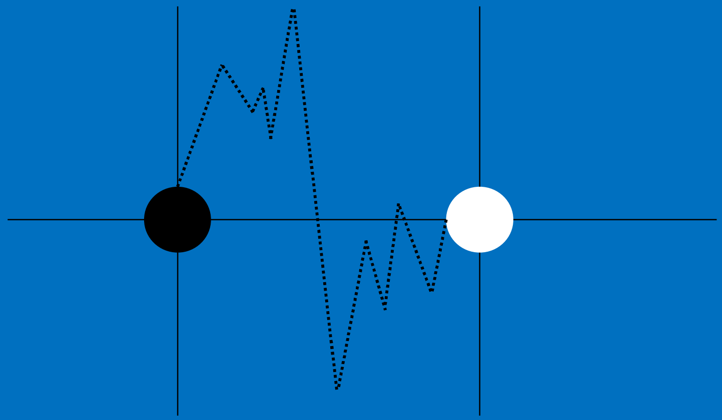
From AlphaGo to AlphaZero

1. Mastering the Game of Go with Deep Neural Networks and Tree Search (2016)
2. Mastering the Game of Go without Human Knowledge (2017)
3. Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm (2017)

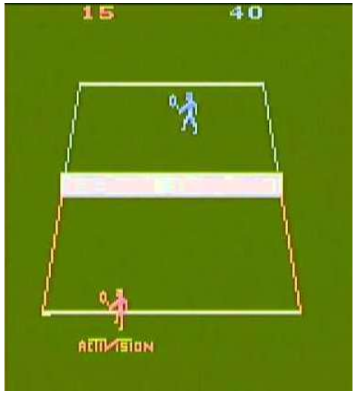


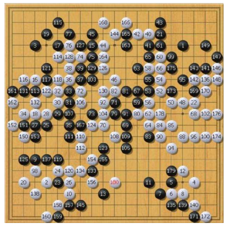
- By Harvey

- 2022

1. Deep Reinforcement Learning in Different Games

Assumption: AI can only see/do what humans can see/do



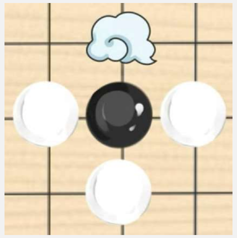


Games	Atari	Board Game	Dota / LOL	Starcraft II
Agents	1	2	≥ 1 (Generally 5 vs. 5)	≥ 2 (Generally 1 vs. 1)
Information	Perfect information	Perfect Information	Imperfect information (fog of war)	Imperfect information (fog of war)
State space	Limited	Limited but large	Unlimited	Unlimited
Action space	Limited	Limited but large	Limited but large	Unlimited
AI vs. Human	AI dominated	AI dominated	AI won in 1 vs. 1 Completely failed in 5 vs. 5 (OpenAI)	Completely failed in any competitive game but learn to do simple tasks (DeepMind)

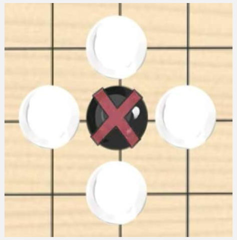
1. Go Game: Basic Rules

How to play

Liberty

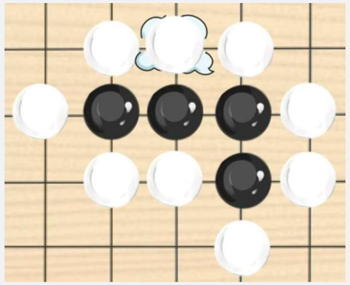


- Liberty is when the area surrounding the go has no other go



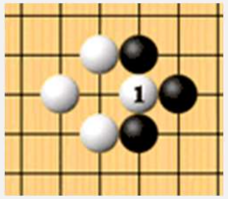
- If a go has no liberty, it is consider "dead" and will be taken out

Liberty (Multiple Go)



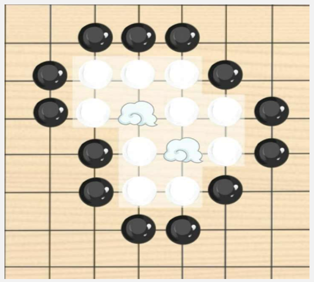
- In this case, black gos are "dead" and will be taken out

Ko Rule



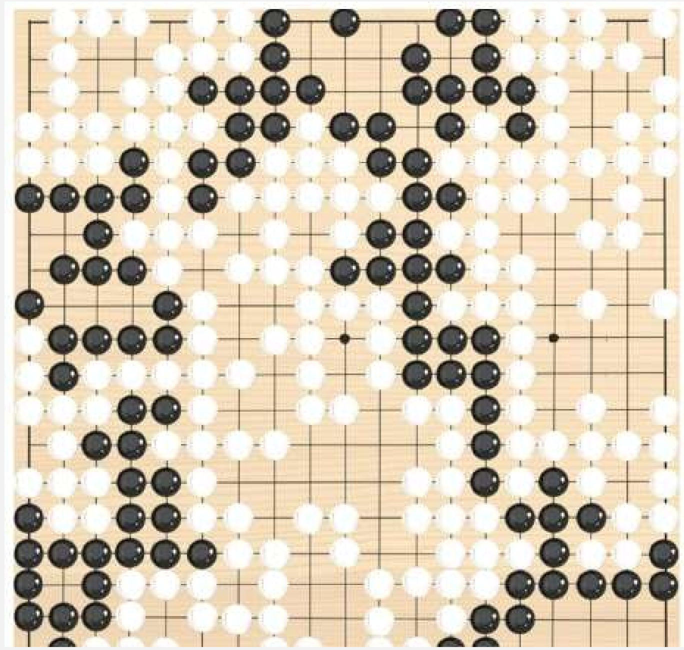
- One cannot place the go in "dead" area unless you can eat them
- Forbid sequential eat in the same position
- Unless you make a move that significantly changes the board position

Life



- If go is surrounded and the area has more than two liberties (i.e. they cannot be taken out with one step), then this area of go is considered to be "alive" (life)
- In the case shown in the left, black gos cannot be placed inside the white gos. Hence, white gos are considered to be "alive"

How to win



The winner is:

1. whoever occupies more areas of the board.
2. whoever has a larger number of "alive" go on the board .
3. rules are geo-dependent but with minor difference.

Versions

Version	Training hardware	Elo rating	When	
AlphaGo Fan	176 GPUs	3144	Oct 2015	5:0 against Fan Hui
AlphaGo Lee	48 TPUs distributed	3738	Mar 2016	4:1 against Lee Sedol
AlphaGo Master	4 TPUs, single machine	4858	May 2017	60:0 against professional players
AlphaGo Zero	4 TPUs, single machine	5185	Oct 2017	100:0 against AlphaGo Lee
AlphaZero	4 TPUs, single machine	5018	Dec 2017	60:40 against AlphaGo Zero

TPU: tensor processing unit

AlphaGo

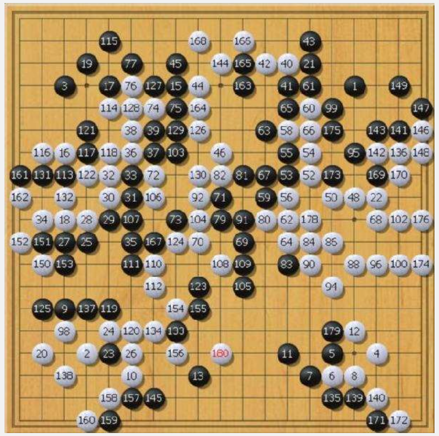
An “interesting” fact about AlphaGo:
The most powerful version consists of ~1900 CPUs and ~200 GPUs
Electricity bill is ~$3000 per game, training phase: 160,000 game ≈ $480 million

Networks

- Policy network
  - Given state s, probability of action.
- Value network
  - Given state s, expected value of winning the game.
- Fast rollout
  - A much faster (smaller) network to make decisions.

2. Why Go and Prior Work

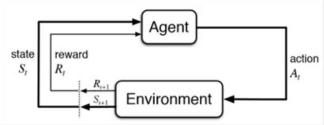
Why Go Game?



- The most challenging classic board games from a computational perspective.
- 19 X 19 board positions.
- 250^{150} possible sequences of moves (chess: 35^{80}).
- The objective is to occupy more territory.
    - Leads to highly sophisticated evaluation functions
    - No one before AlphaGo has successfully build an effective evaluation function.
- Exhaustive search is infeasible.

Prior Work

Reinforcement Learning



Self-play

Linear Value Function

$$V_\theta(s) = \phi(s)^T\theta$$

Tree Search

Minimax (Alpha-Beta) Tree Search

- Most game too large for Minimax Tree Search because it requires one to go all the way to the end of the game
- Truncate the tree by using approximated value function $V_\theta(s) \approx v^*(s)$
- Super-human performance in chess
- Not effective in Go

Monte Carlo Tree Search

- Double approximation
- $V^n(s) \approx v^{p^n}(s) \approx v^*(s)$
- First, use *n* Monte Carlo simulations to estimate the value function of a policy p^n
- Second, use the value function to approximate the optimal value function
- Why does it work? In the limit they are equivalent (mathematically).

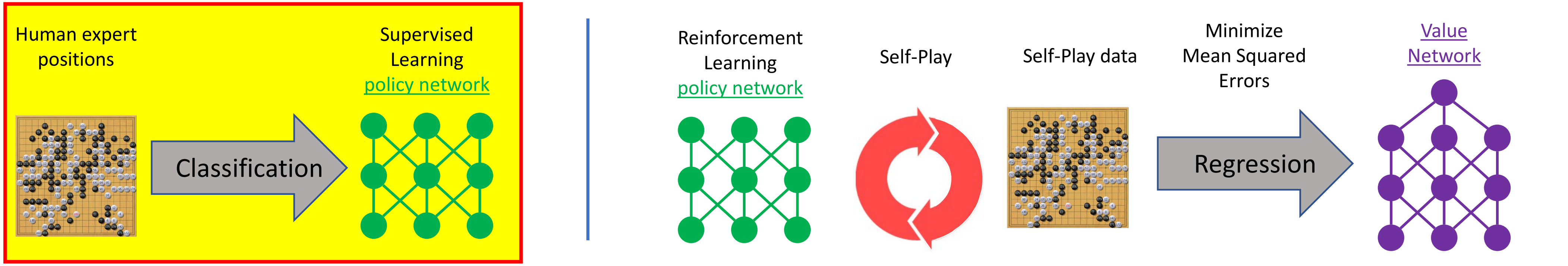
Why?

Reinforcement Learning: Neurobiology foundations

Tree Search: Players tend to make forecasts (truncated) and predictions

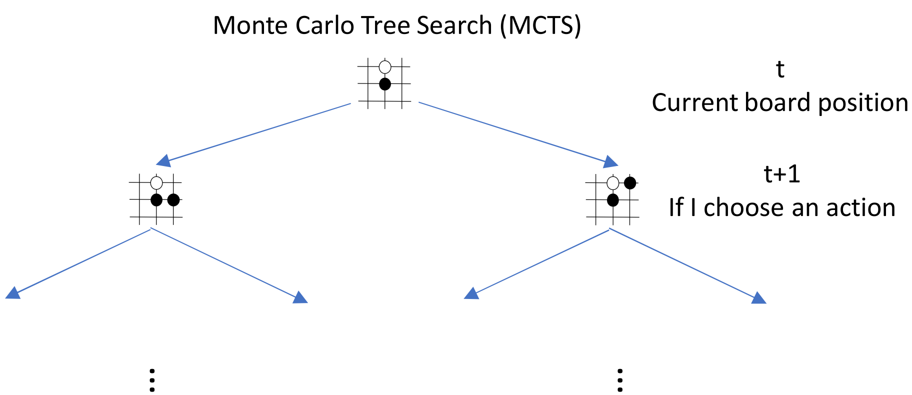
2. AlphaGo: Structure Breakdown

Training Pipeline



(Silver et al. 2016)

Testing/Tournament



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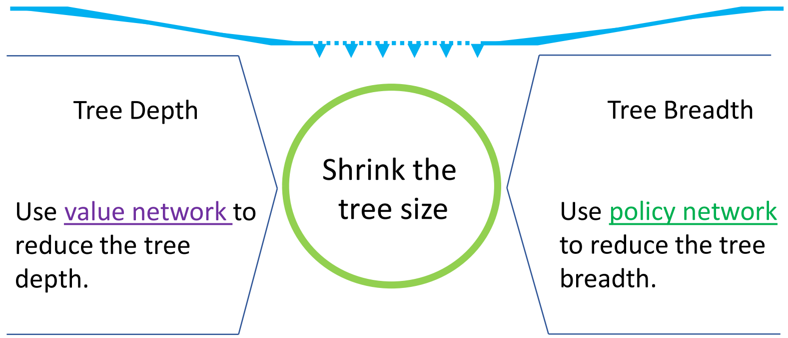
Problems with a full-scale MCTS

- Tree depth: need to simulate all the way to the end of the game
- Tree breadth: enormous amounts of choices per time step



2. AlphaGo: Supervised Learning of Policy Networks

Convolutional Neural Network

CNN Training and Testing

- To predict human experts' move.
- 160,000 games (professional players).
- 29.4 million moves (28.4 million training and 1 million testing).
- Stochastic Gradient Descent update to maximize the action log likelihood

Prediction accuracy: 55-57%

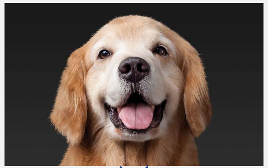
If I feed the neural network with a board status (state), the neural network can predict, on average 55-57% chance, the correct move that a human expert will do under the same board condition.

Better accuracy or higher chances of winning?
After all, human (including experts) make mistakes/their strategy may not be optimal strategy

Supervised learning is not enough

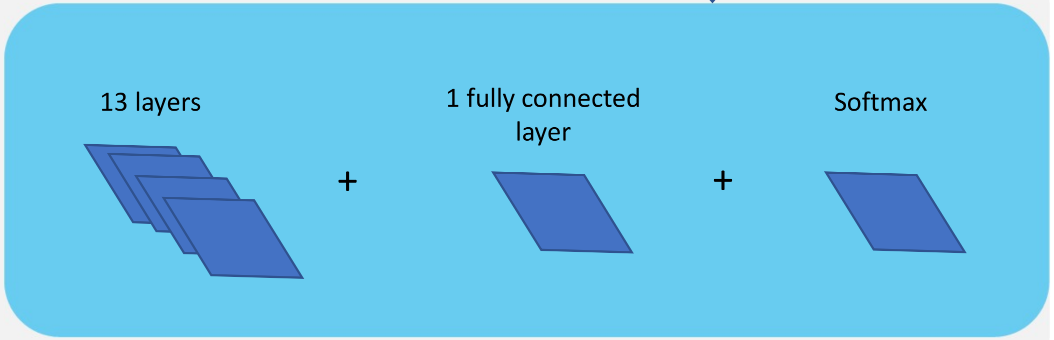
(Smiling) Puppy picture

Pixels



Human expert positions

48 feature planes (each 19 X 19)
19 X 19 X 48



In the picture, there is a

- (Smiling) Puppy (80%)
- (Angry) puppy (60%)
- Kittie (10%)
- Baby (1%)
- …

Human experts will take a move in

- Position 1 (56%)
- Position 2 (30%)
- Position 3 (20%)
- …

2.1 AlphaGo: Policy and Policy Network

Policy Based Learning

$P(a|s)$ **Formally, a policy maps states to actions**

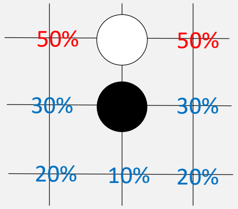
- In policy gradient framework, it is a probability distribution over all states and actions (vs. value framework).
- Policy will tell the probability of I choose a particular action under current state.
- No value function, states and actions are allowed to be continuous and infinite.
- Often parameterized, a function $P_\theta(a|s)$.

Policy Network in AlphaGo

Take board position **s** as input

$P_\theta(a|s)$

Action probability distribution/matrix



50%	n/a	50%
30%	n/a	30%
20%	10%	20%

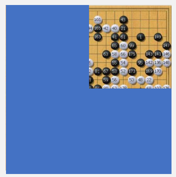
Training:
Stochastic gradient ascent to maximize the log likelihood

Rollout Policy vs. Supervised Learning Policy

Trade off between speed and accuracy

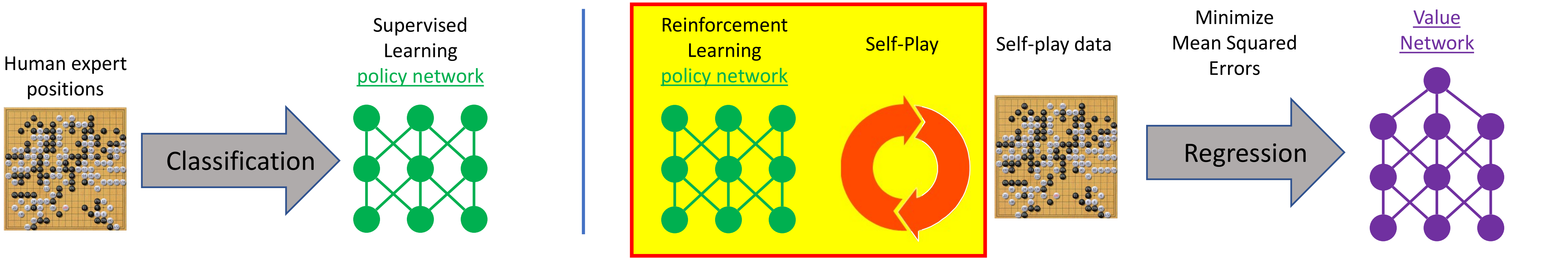
Choose an action	Rollout Policy	SL Policy
Speed	$2\mu s$	$3ms$
Accuracy	24.4%	57%

The key differences

Structure	Rollout Policy	SL Policy
activation function	Linear	Non-linear
Feature fed into CNN	Small feature size (A simple demo) 	Full size (19 X 19 X 48) 
Notation	$P_\pi(a|s)$	$P_\sigma(a|s)$

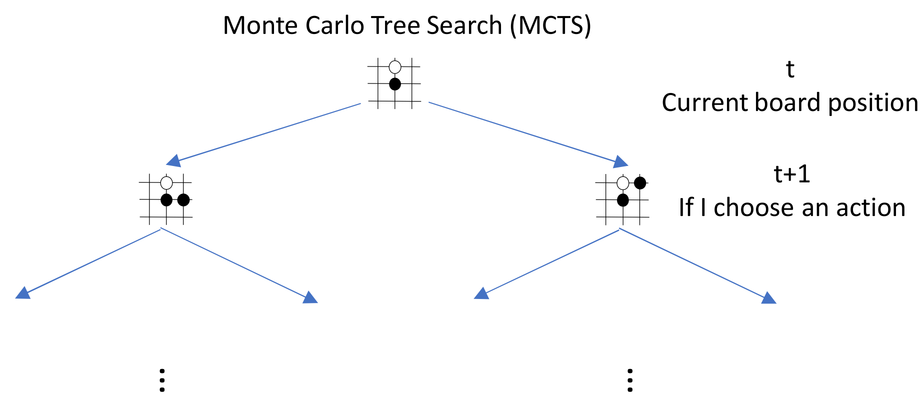
2. AlphaGo: Structure Breakdown

Training Pipeline



(Silver et al. 2016)

Testing/Tournament



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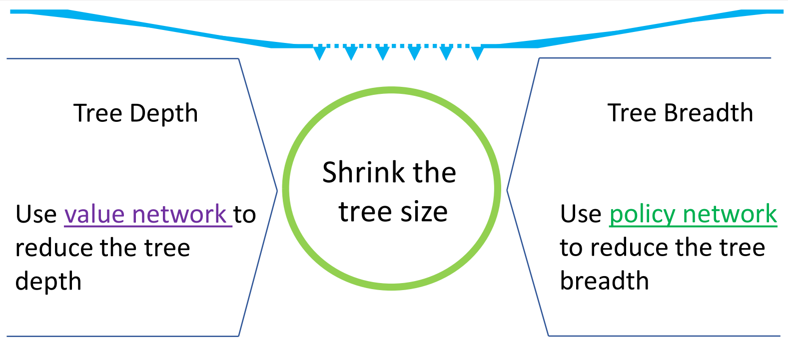
Problems with a full-scale MCTS

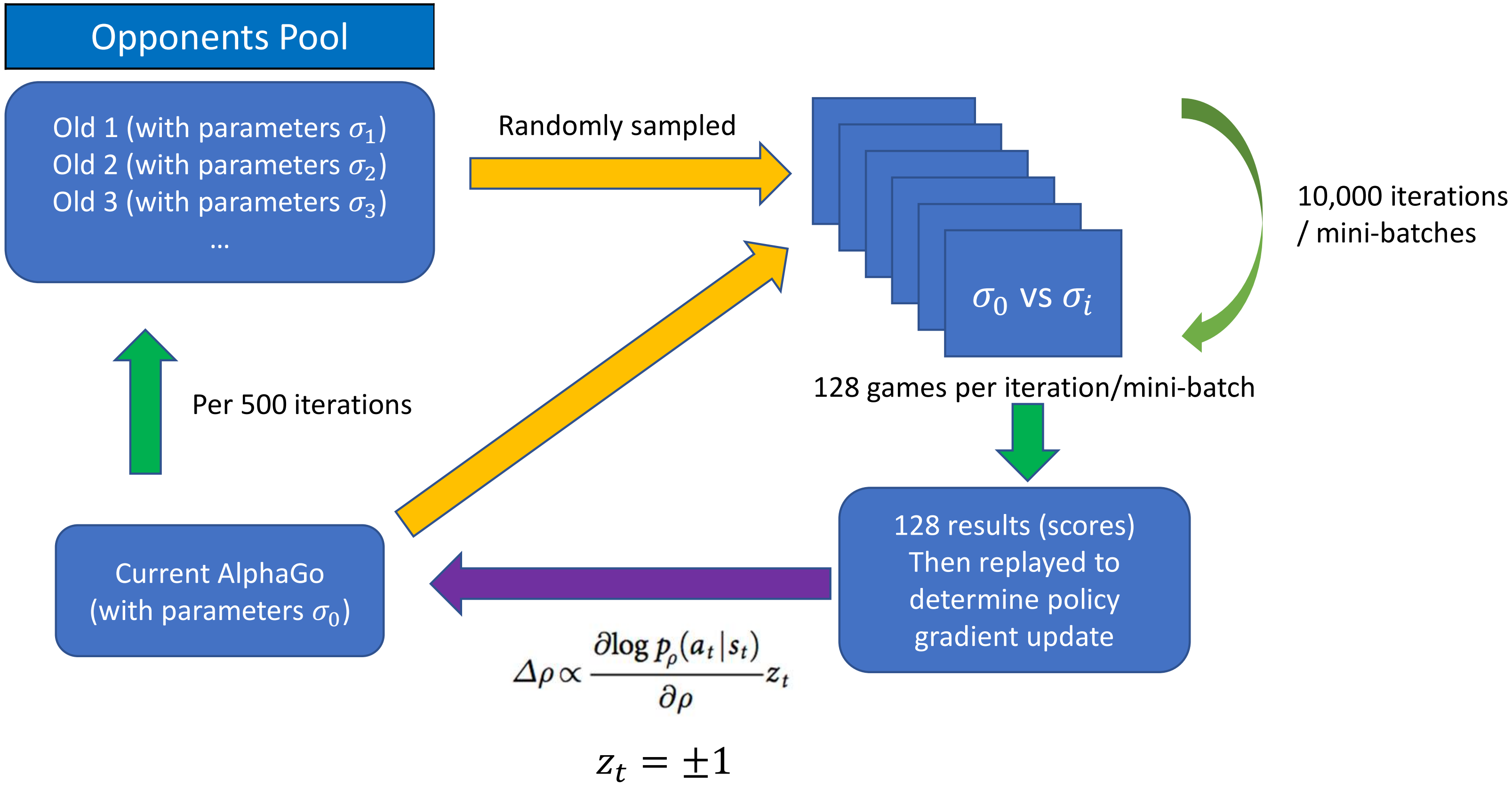
- Tree depth: need to simulate all the way to the end of the game
- Tree breadth: enormous amount of choices per time step



2.2 Reinforcement Learning: Policy Network Iterations

The aim here is to allow the policy to be improved by letting the AI play against itself

$$P_\sigma(a|s) \Rightarrow P_\rho(a|s), \sigma \text{ and } \rho \text{ are weight parameters}$$



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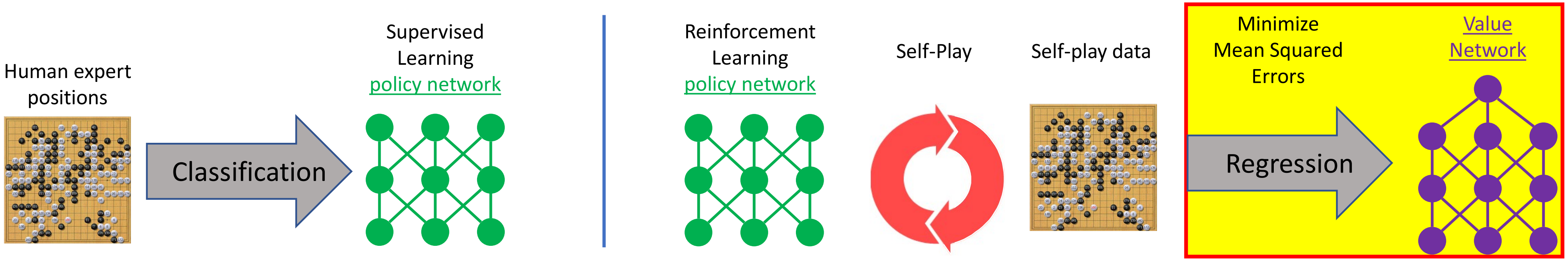
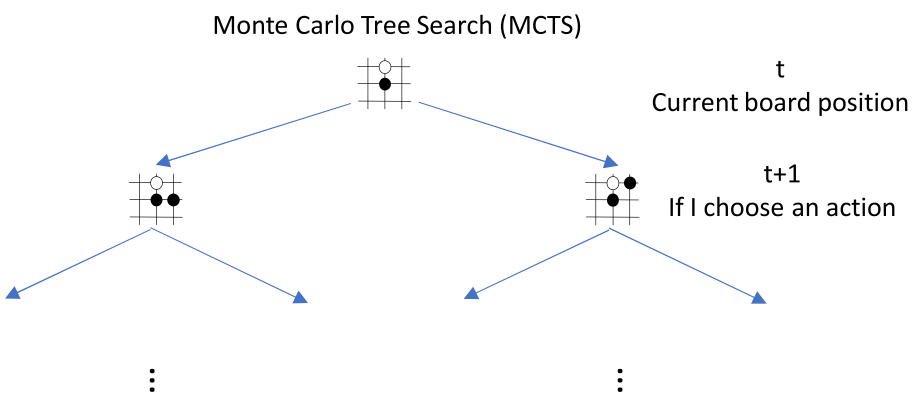


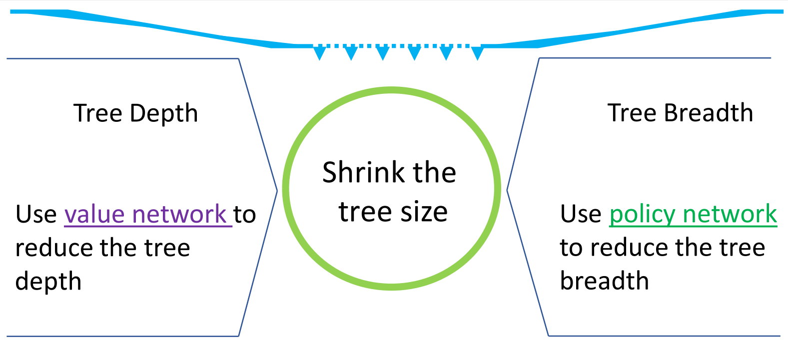
(Silver et al. 2016)

Testing/Tournament



(Silver et al. 2016)

Problems with pure MCTS
• Tree depth: need to simulate all the way to the end of the game
• Tree breadth: enormous amount of choices per time step



2.3 Reinforcement Learning: Value Network and Position Evaluation

Now we have a better policy (strategy), we want to predict the outcome of game when we make a move

i.e., given the current board position, how likely will I win the game.

Value Function

$$v^p(s) = \mathbb{E}[z_t | s_t = s,\ a_{t\ldots T} \sim p]$$

- **Interpretation:** the value (chances of win) of the current state under the policy p.
- **Problem:** we do not know the optimal value function under perfect play $v^*(s)$
- **Solution:** use approximation
  - $v_\theta(s) \approx v^{p_\rho}(s) \approx v^*(s)$

Training

- Parameterized value function $v_\theta(s)$ with weights θ
- We know the game results for a given state (board position) under the strongest policy p_ρ, i.e. $v_\theta(s)$.
- **Optimization problem:** optimize θ so that $v_\theta(s)$ is close to $v^{p_\rho}(s)$
- **Approach:** standard regression (projection) method
- Minimize Mean Squared Errors:
  - $\left(v_\theta(s) - z^k\right)^2$ where $z^k = \pm 1$

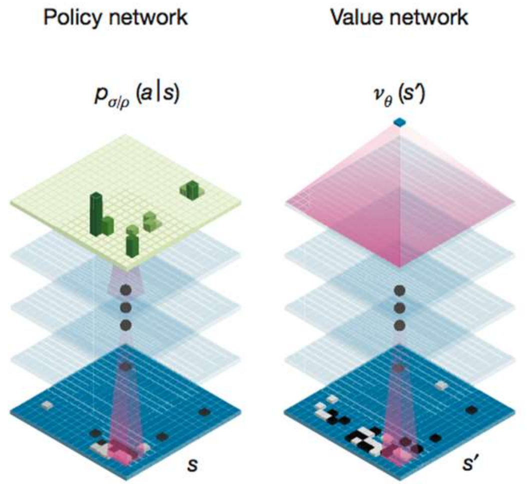
Overfitting

Naïve approach leads to overfitting

- **Training:** Mean Squared Errors of 0.19
- **Testing:** Mean Squared Errors of 0.37

Solution and approach

- A new self-play dataset consisting of 30 million distinct positions, each sampled from a separate game
- Each game between the RL policy network and itself
- MSEs: 0.226 (Training) and 0.234 (Testing)



(Silver et al. 2016)

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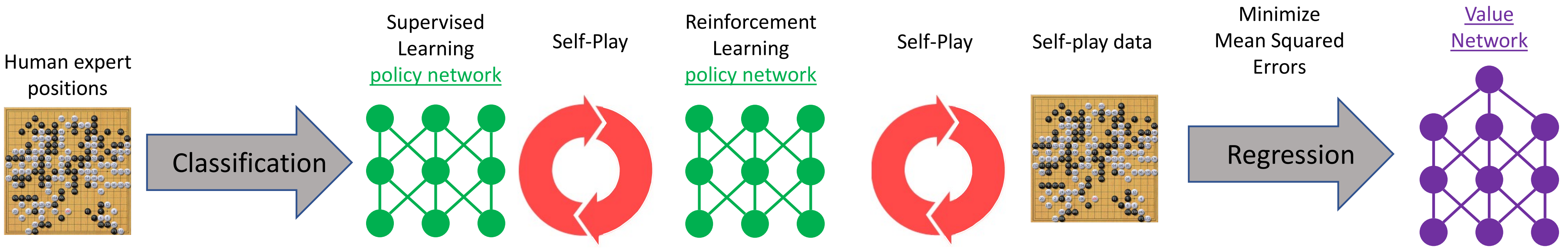
Training Pipeline



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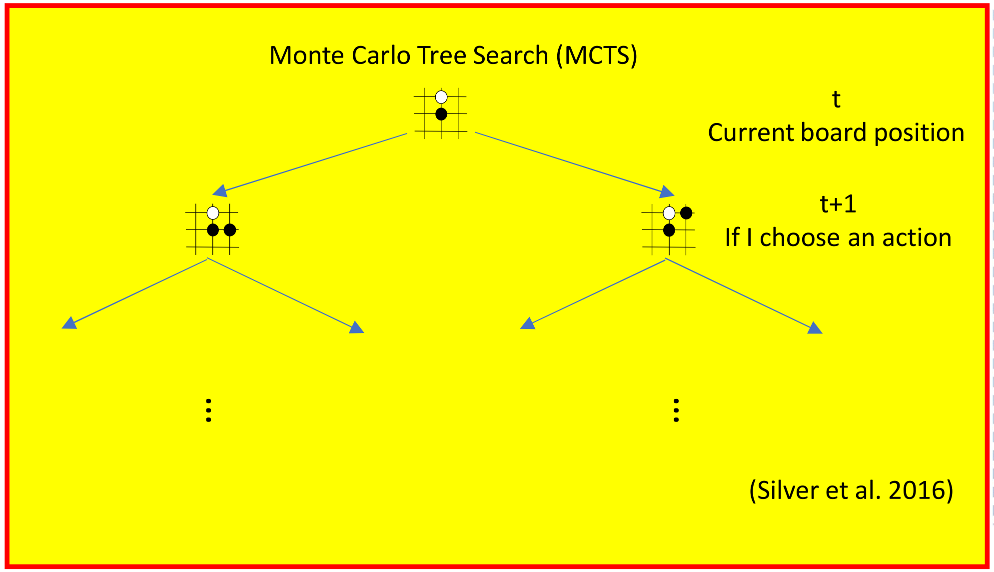
Testing/Tournament



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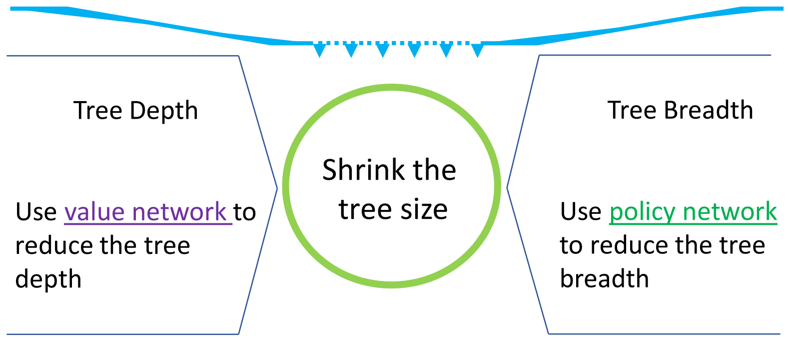
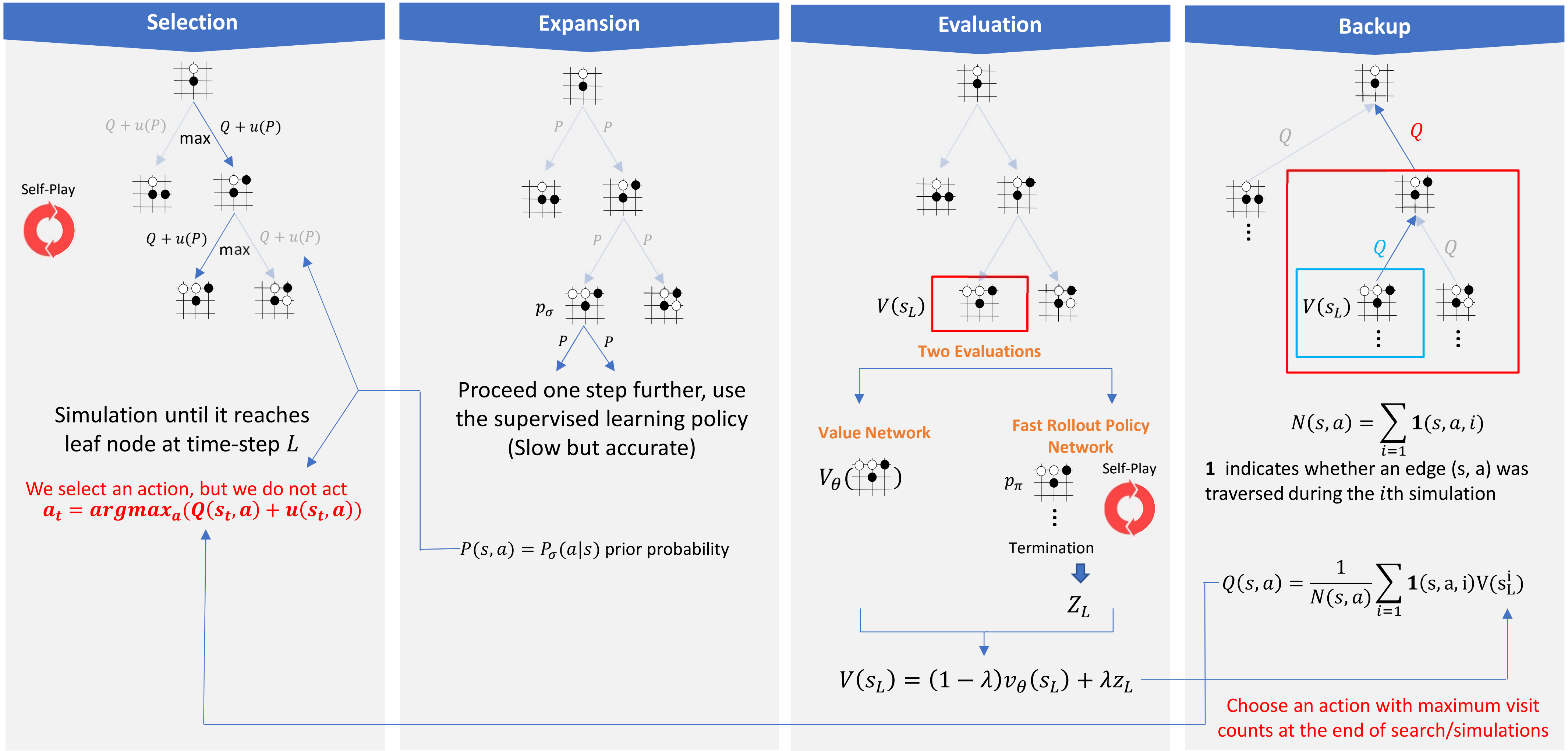


2.4 Monte Carlo Tree Search: Search with Policy and Value Networks

Asynchronous Policy and Value Monte Carlo Tree Search (APV-MCTS)



AlphaGo Zero

Simple Neural Network Structure
Completely tablua Rasa

An “interesting” fact about AlphaGo Zero:
The system consists of only 4 TPUs,
each of which is 15-30 times more efficient than GPUs in performance per-watt
And 64 GPUs, 19 CPUs.

Improvements from AlphaGo

- No supervised learning
- Simplified input features (from 19x19x48 -> 19x19x17)
- Change network structure from CNN to ResNet.

3.1 Deep Neural Network- Structure Breakdown

Single Neural Network Head

$$(p, v) = f_\theta(s)$$

Policy Network

$p_a = \Pr(a|s)$ probability of selecting each move from the current position

Value Network

v scalar evaluation, estimating the probability of current players winning from the current position

But two outputs

Core RL Concepts

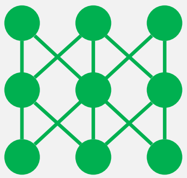
Policy Evaluation → Value Function

Policy Iteration

Policy Improvement

Training Pipeline

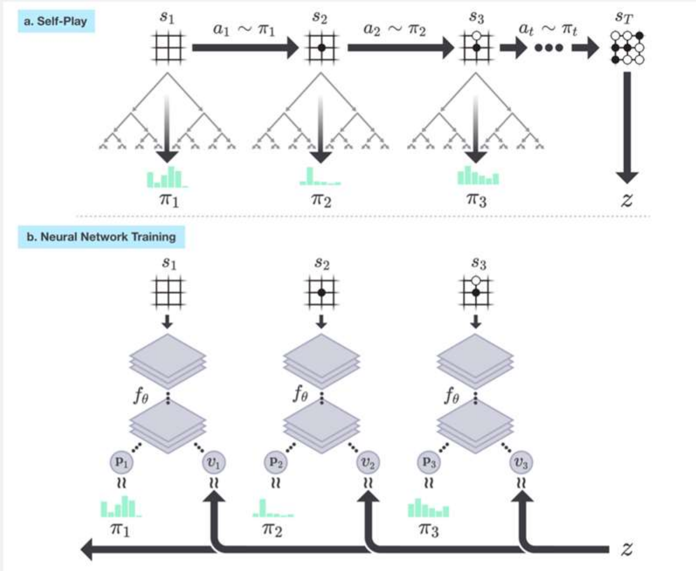
Reinforcement Learning
Neural Network



Self-Play

Policy Evaluation

MCTS ⇒ π_t, a move is selected according to **search policy** $a_t \sim \pi_t$
Terminal state s_T will give us a game winner Z



Policy Improvement

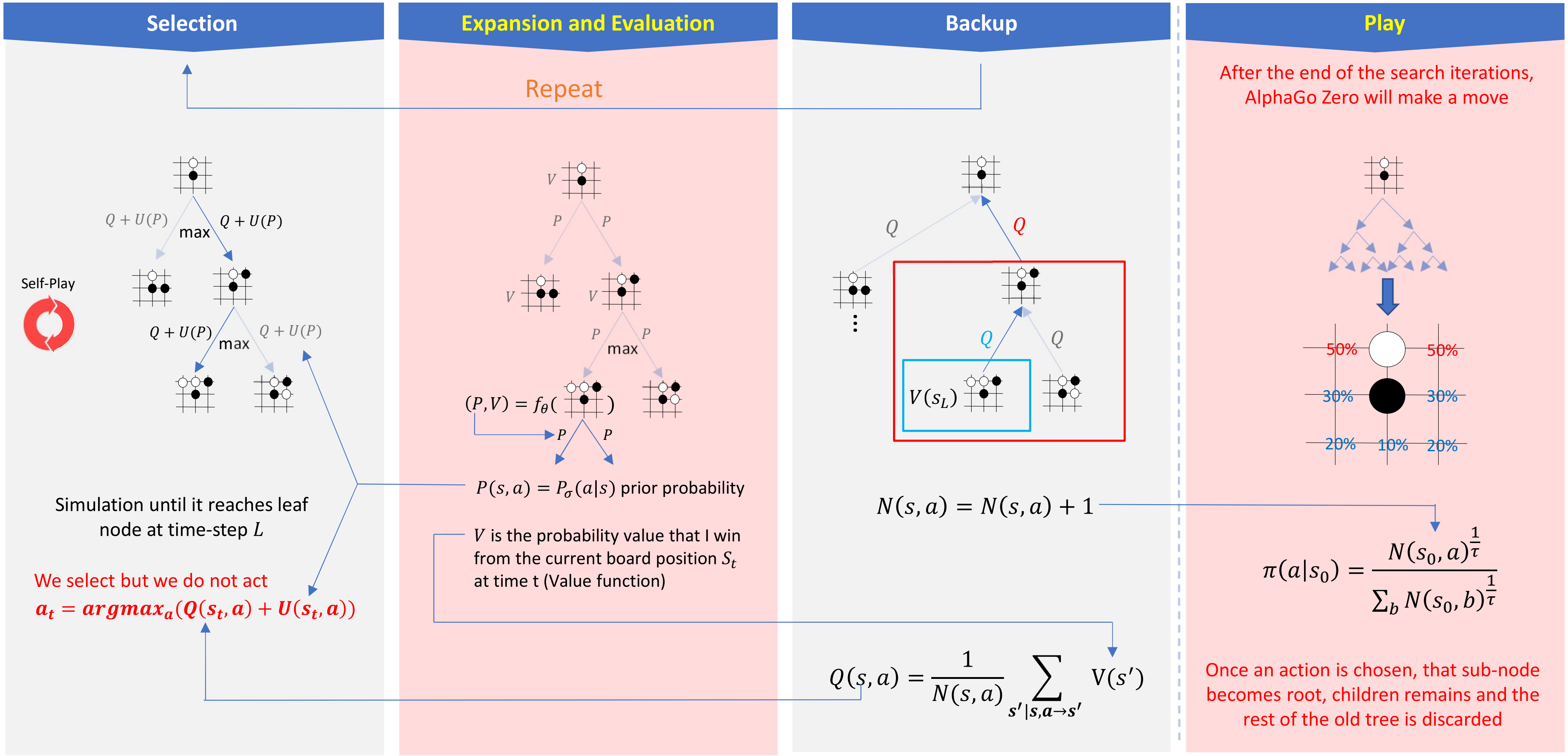
At time t, feed the board position s_t into policy $f_\theta(s)$ = $f_\theta(s_t)$, which gives us p_t and v_t.

Optimization problem: optimize weight parameters θ to minimize prediction errors $\boldsymbol{v_t} - \boldsymbol{Z_t}$ and maximize the similarity between neural network probability $\boldsymbol{p_t}$ and search probability $\boldsymbol{\pi_t}$

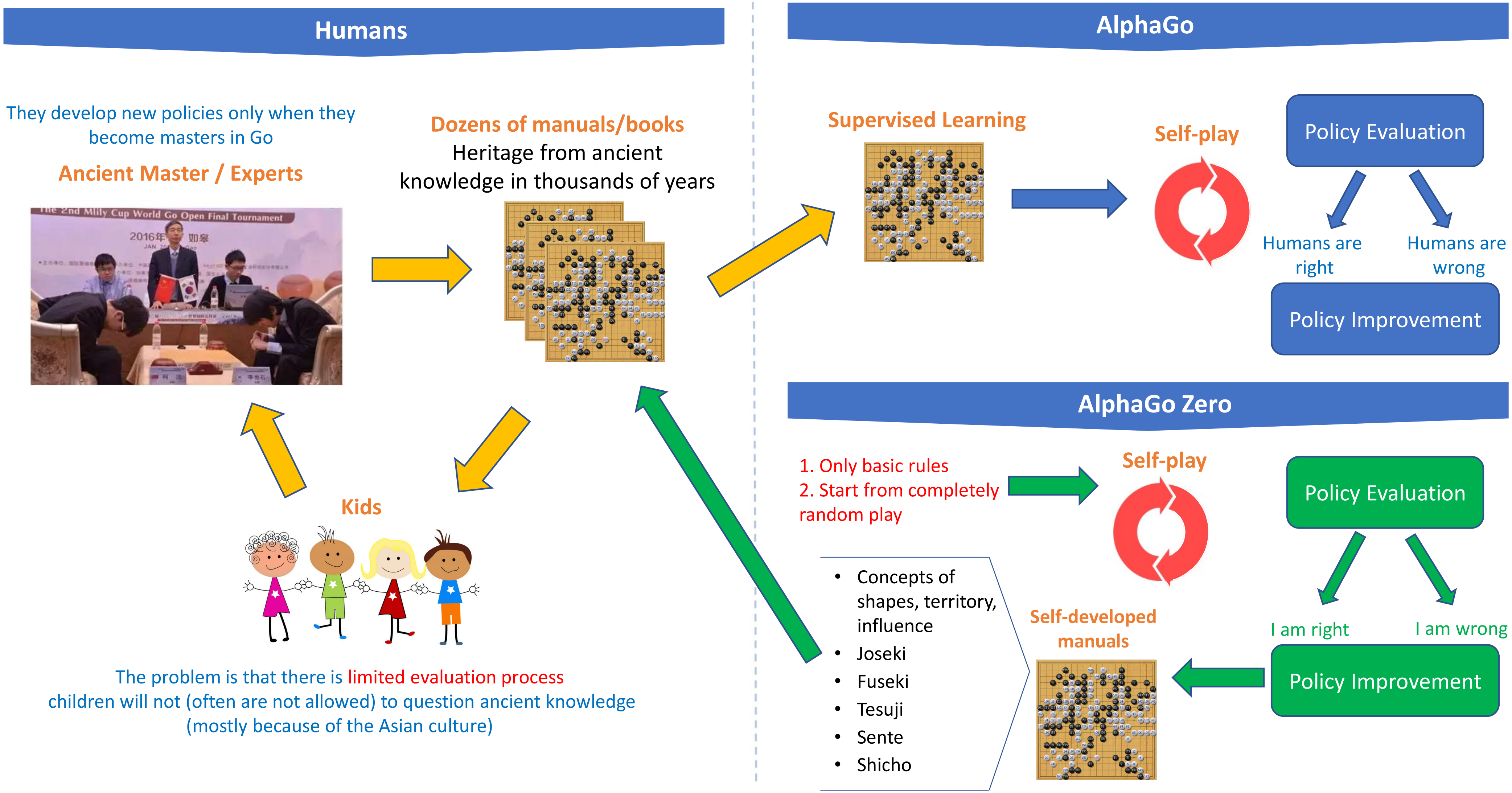
⇒ **Minimize Loss Function:** $l = (z - v)^2 - \pi^T \log \mathbf{p} + \mathbf{c}||\theta||^2$

3.2 Monte Carlo Tree Search: Search with a Single Neural Networ

Asynchronous Policy and Value Monte Carlo Tree Search (APV-MCTS)



4. Humans, AlphaGo and AlphaGo Zero



5. Discussions

Human vs. Artificial Intelligence

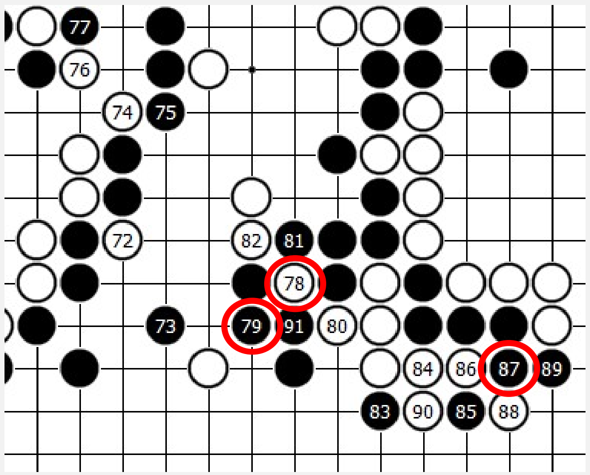
Humans in Go game

- Humans are often wrong.
- Master manuals are more like guidance rather than mandatory knowledge.
- Self-evaluation and improvement are key to learning.
- The concept of tabula rasa is crucial in learning theories.

AI in Go game

- Algorithms are much more important than data (model-based).
- People tend to assume that machine learning is all about big data and massive computations, which is wrong.
- AlphaGo Zero does not use any human data whatsoever, it always has the opponent at just right level (self-play), and improves itself from self-learning.
- Yet it performs much better, and significantly less computational requirement.

The only game that AlphaGo resigned



- AlphaGo (Black) calculated that the probability of Lee Sedol making move 78 is 0.01%.
- Value network informed AlphaGo that move 79 had a winning probability of 70%.
- It realised (re-calculated) that the winning probability was 55% after move 87.

6. AlphaZero: General Version

Generalize AlphaGo Zero in board games

AlphaGo Zero vs. AlphaZero

	AlphaGo Zero	AlphaZero
Value Function	Binary win/loss Probability of Winning	Expected outcome (Chess has win, loss, draw)
Rotation and Reflection	Invariance (faster training)	Variance (Asymmetric rules)
Policy Improvement	Current best player vs. New player after each iteration If win by 55% then update the policy	Updated continuously, even during the iterations

Neural network architecture in different games

	Chess	Shogi	Go
Input Feature	119	362	17
Policy Plane	8 X 8 X 73	9 X 9 X 139	19 X 19 + 1
Training Time	9h	12h	34h
Training Games	44 million	24 million	21 million