Success Stories of Deep RL

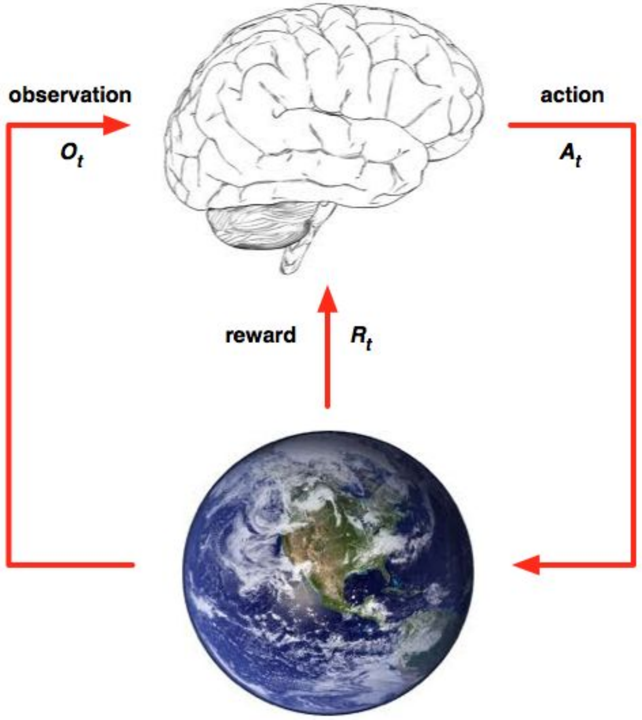
David Silver

Reinforcement Learning (RL)

RL is a general-purpose framework for decision-making

- An agent selects **actions**
- Its actions influence its future **observations**
- Success is measured by a scalar **reward** signal

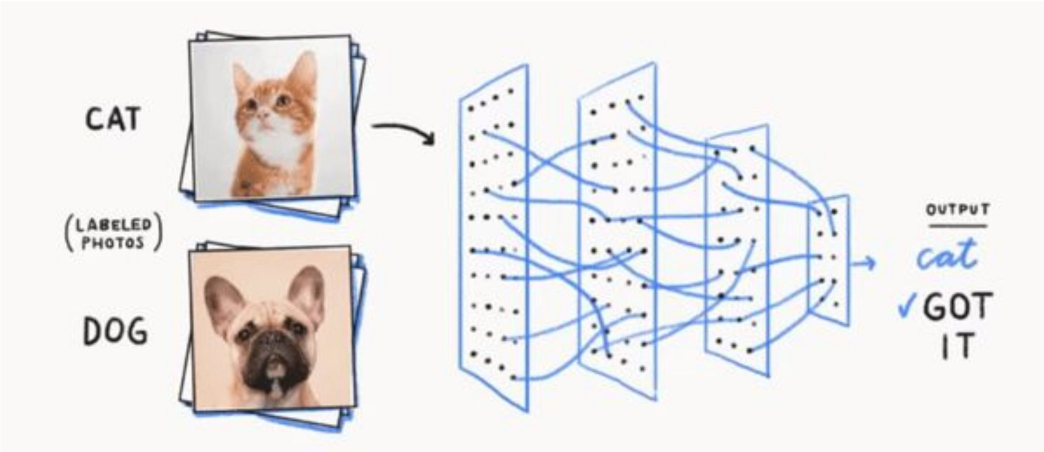
Goal: select actions to maximise future rewards



Deep Learning (DL)

Deep learning is a general-purpose framework for representation learning

- Given an **objective**
- Learn a **representation** that achieves objective
- Directly from **raw inputs**
- Using minimal domain knowledge



Deep Reinforcement Learning

We seek an agent that can solve any human-level task

- Reinforcement learning defines the objective
- Deep learning gives the mechanism

Conjecture: RL + DL = artificial general intelligence

Deep RL in Practice

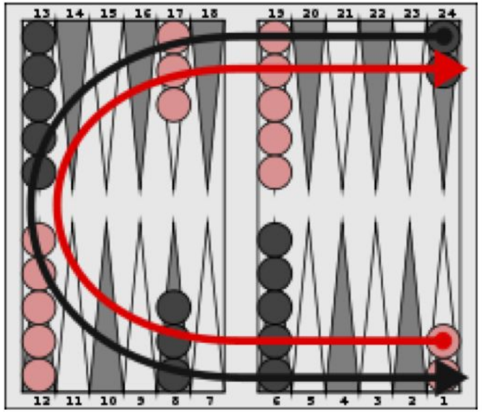
- Use neural networks to represent:
  - Value function
  - Policy
  - Model
- Optimise loss function end-to-end
  - e.g. by stochastic gradient descent

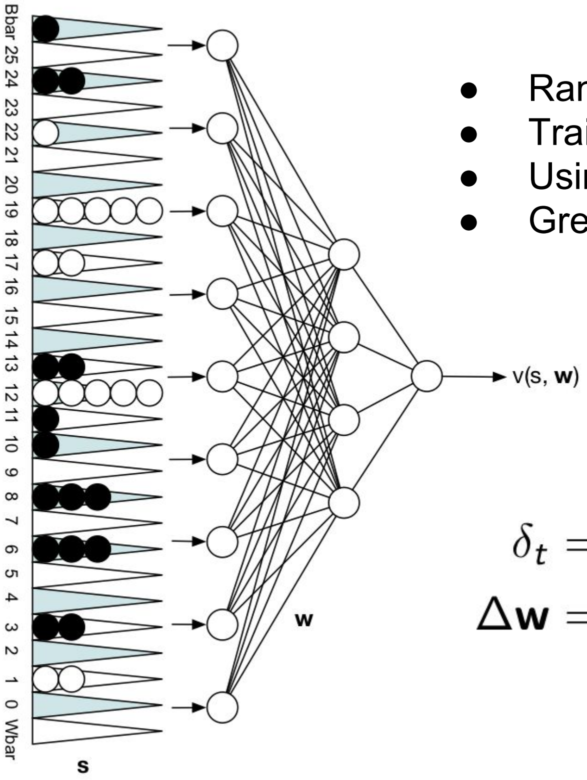
Tesauro 1992

TD Gammon

Success Story #1

Deep RL in Backgammon

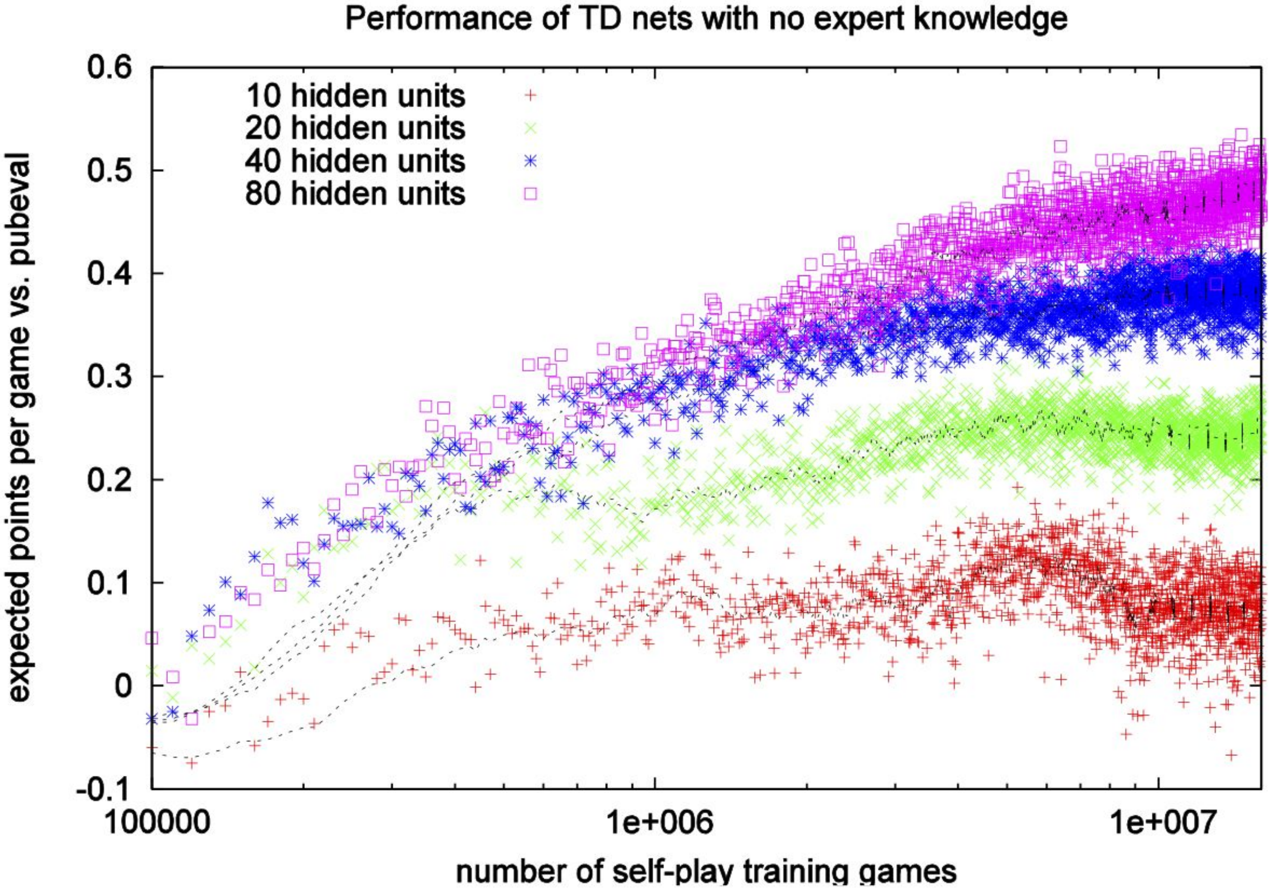




- Randomly initialised weights
- Trained by games of self-play
- Using temporal-difference learning
- Greedy action selection (using lookahead)

$$\delta_t = v(S_{t+1}, \mathbf{w}) - v(S_t, \mathbf{w})$$

$$\Delta \mathbf{w} = \alpha \delta_t \nabla_{\mathbf{w}} v(S_t, \mathbf{w})$$



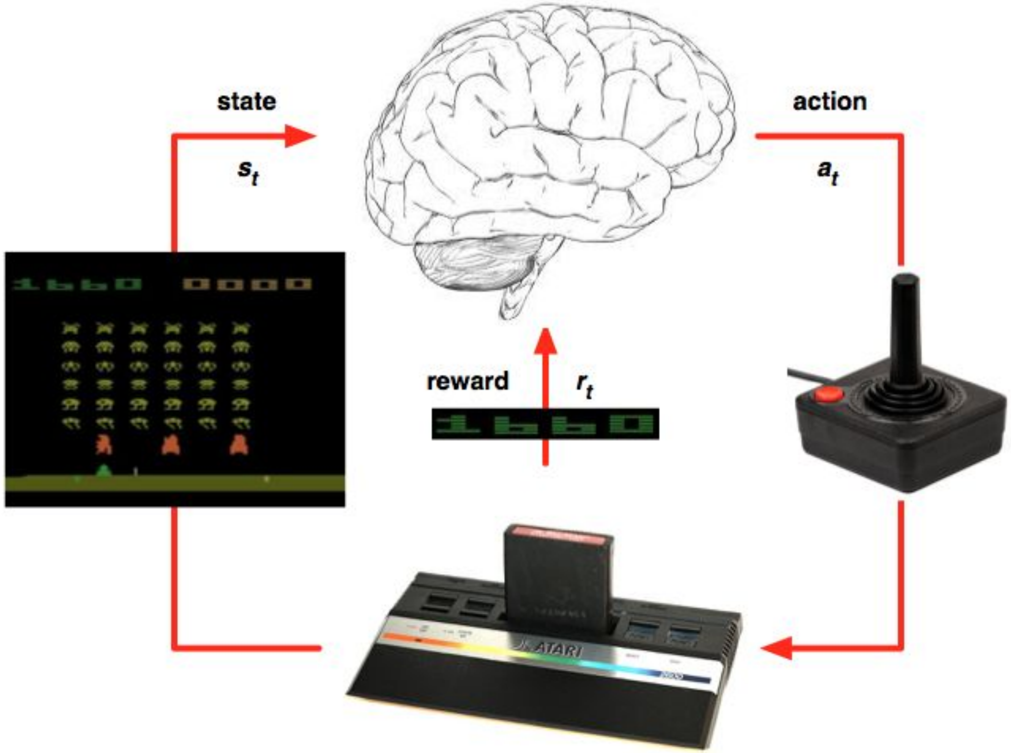
- In 1992, TD Gammon defeated world champion Luigi Villa 7-2
- It was trained by self-play
- Expert features were used
- Later results showed they could be removed

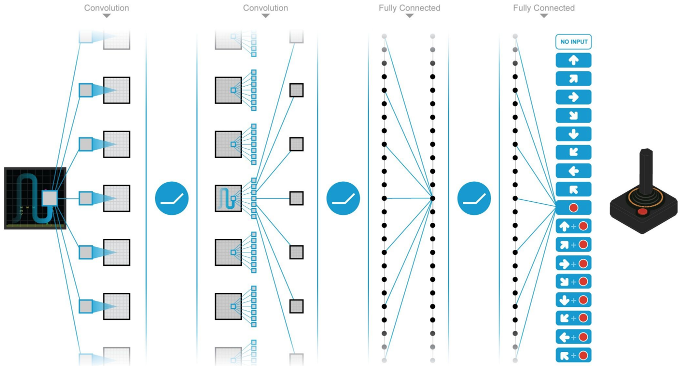
Mnih et al. 2015

DQN in Atari

Success Story #2

Deep Reinforcement Learning on Atari



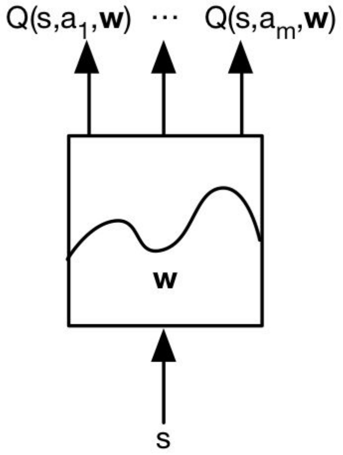


Mnih et al. 2015

Q-Networks

- Represent value function by Q-network with weights $\mathbf{w}$

$$Q(s, a, \mathbf{w}) \approx Q^*(s, a)$$



- Optimal Q-values should obey Bellman equation

$$Q^*(s, a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q^*(s', a') \mid s, a\right]$$

Deep Q-Networks (DQN): Experience Replay

To remove correlations, build data-set from agent's own experience

		s_1, a_1, r_2, s_2		
		s_2, a_2, r_3, s_3	$\rightarrow$	s, a, r, s'
		s_3, a_3, r_4, s_4		
		$\ldots$		
$s_t, a_t, r_{t+1}, s_{t+1}$	$\rightarrow$	$s_t, a_t, r_{t+1}, s_{t+1}$		

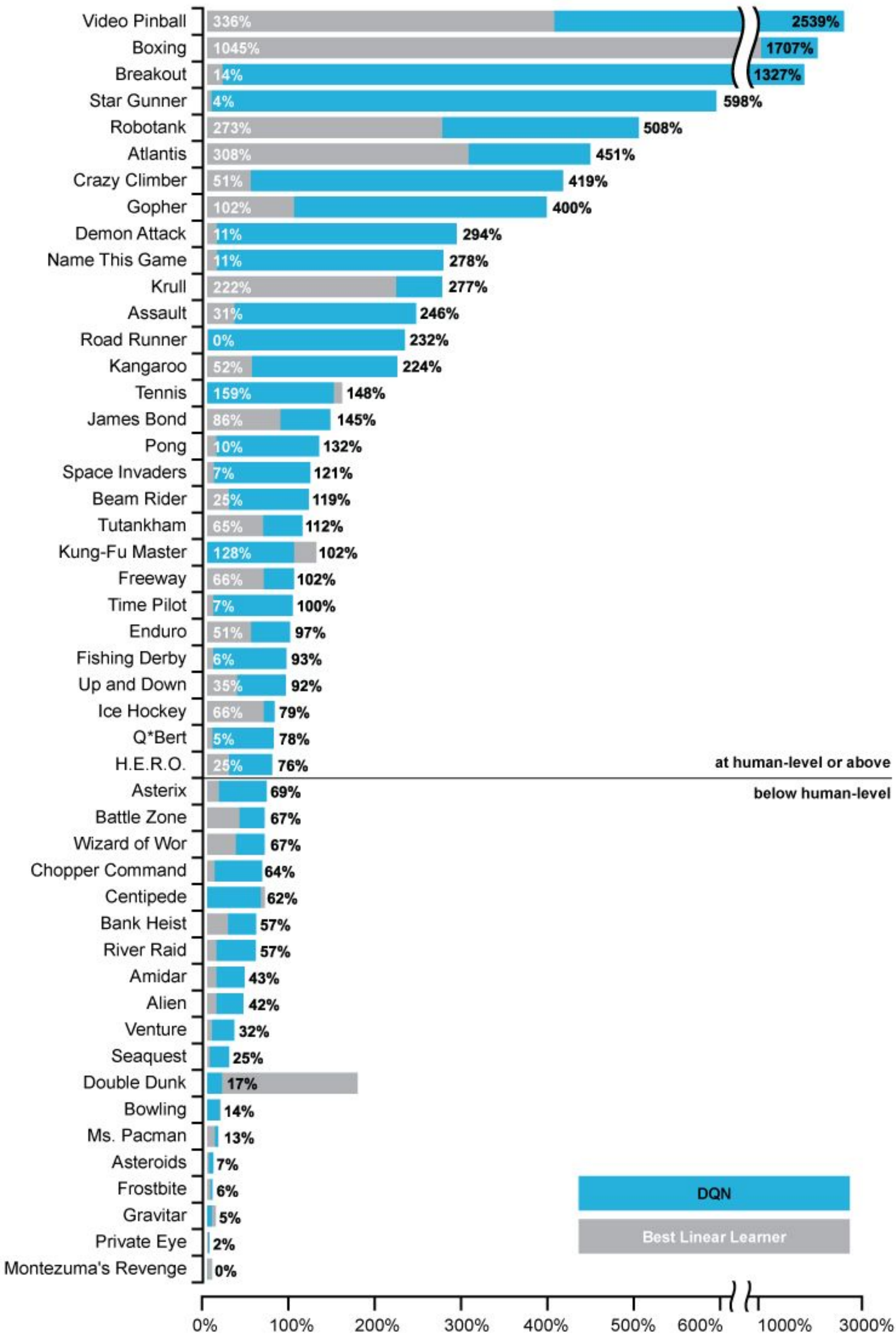
Sample experiences from data-set and apply update

$$l = \left(r + \gamma \max_{a'} Q(s', a', \mathbf{w}^-) - Q(s, a, \mathbf{w}) \right)^2$$

To deal with non-stationarity, target parameters $\mathbf{w}^-$ are held fixed

Learning to Play Atari 2600 Games

- Computer has never seen the game before and does not know the rules
- It learns by deep reinforcement learning to maximise its score
- Given only the pixels and game score as input
- Separately for 57 different games


Video Pinball 336% 2539%
Boxing 1045% 1707%
Breakout 14% 1327%
Star Gunner 4% 598%
Robotank 273% 508%
Atlantis 308% 451%
Crazy Climber 51% 419%
Gopher 102% 400%
Demon Attack 11% 294%
Name This Game 11% 278%
Krull 222% 277%
Assault 31% 246%
Road Runner 0% 232%
Kangaroo 52% 224%
Tennis 159% 148%
James Bond 86% 145%
Pong 10% 132%
Space Invaders 7% 121%
Beam Rider 25% 119%
Tutankham 65% 112%
Kung-Fu Master 128% 102%
Freeway 66% 102%
Time Pilot 7% 100%
Enduro 51% 97%
Fishing Derby 6% 93%
Up and Down 35% 92%
Ice Hockey 66% 79%
Q*Bert 5% 78%
H.E.R.O. 25% 76%
at human-level or above
below human-level
Asterix 69%
Battle Zone 67%
Wizard of Wor 67%
Chopper Command 64%
Centipede 62%
Bank Heist 57%
River Raid 57%
Amidar 43%
Alien 42%
Venture 32%
Seaquest 25%
Double Dunk 17%
Bowling 14%
Ms. Pacman 13%
Asteroids 7%
Frostbite 6%
Gravitar 5%
Private Eye 2%
Montezuma's Revenge 0%
DQN
Best Linear Learner
0% 100% 200% 300% 400% 500% 600% 1000% 3000%

Improvements since Nature DQN (1)

- Multi-step: propagate rewards on-policy over n steps

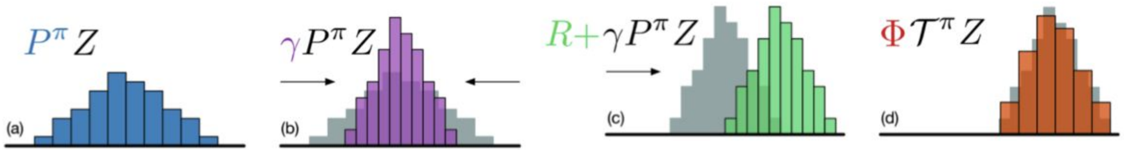
$$Q(s,a) \leftarrow r_{t+1} + \gamma r_{t+2} ... + \gamma^{n-1} r_{t+n} + \gamma^n \max_{a'} Q(s_{t+n}, a')$$

- Prioritised replay: Weight experience according to surprise
  - Store experience in priority queue according to DQN error

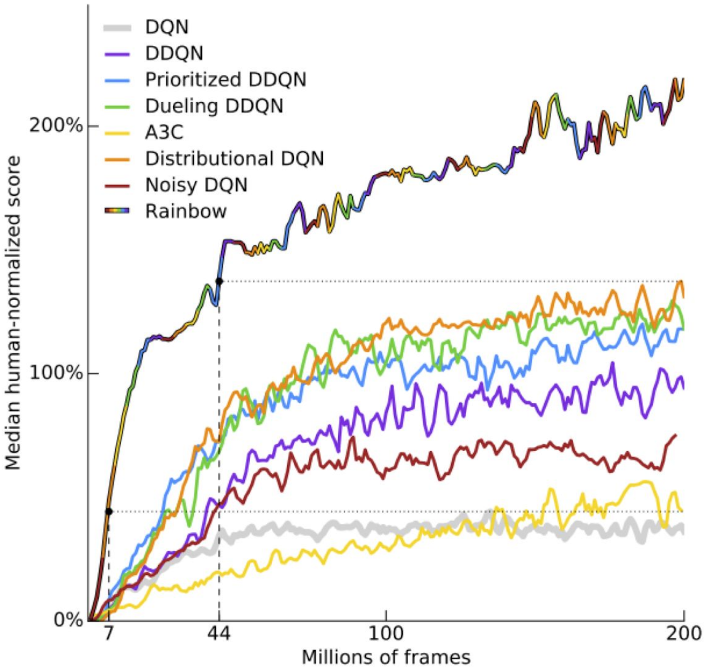
$$\left| r + \gamma \max_{a'} Q(s', a', \mathbf{w}^-) - Q(s, a, w) \right|$$

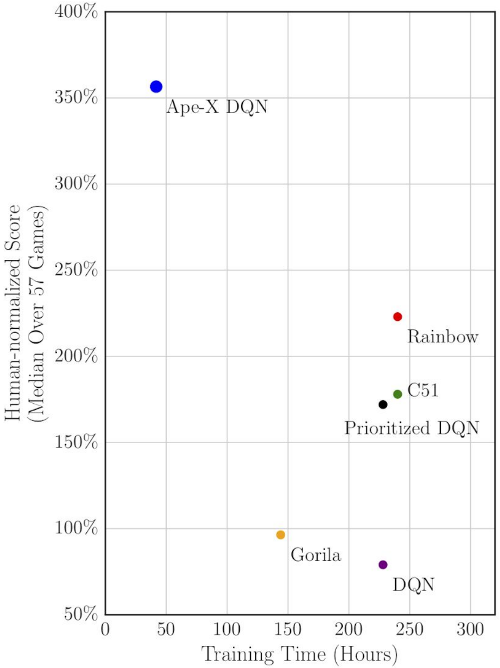
- Distributional values: update distribution over returns, instead of expectation over returns

$$d(s,a) \leftarrow r + \gamma d(s', a')$$



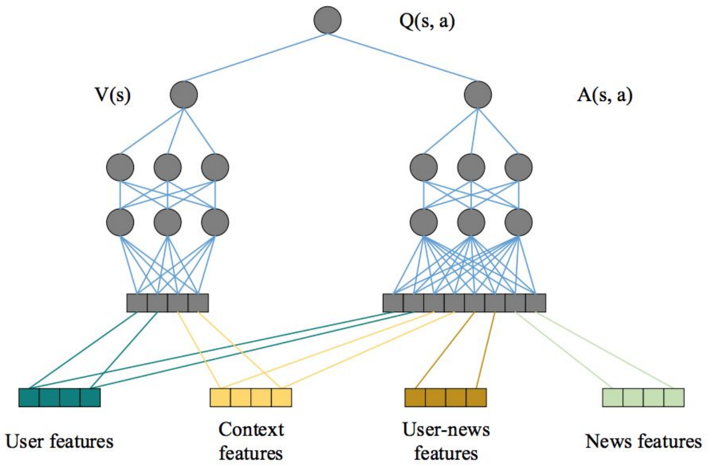
Recent Results on Atari 2600

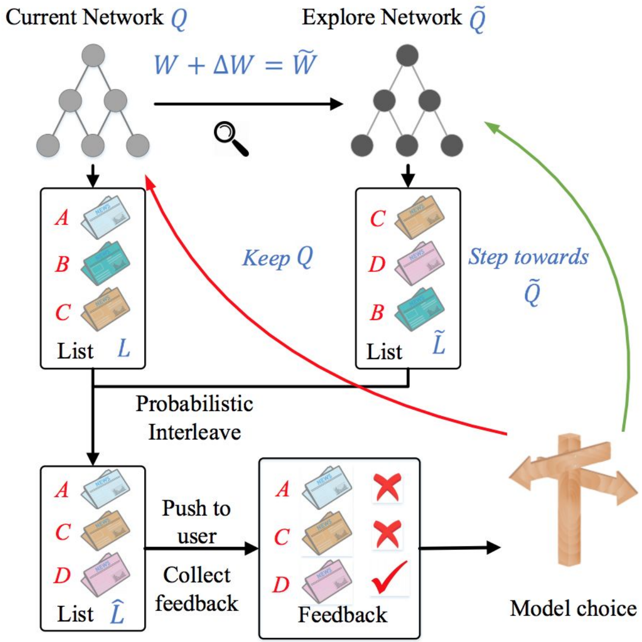




News Recommendation using DQN

Zhang et al. 2018





Deep RL in Robotics

Success Story #3

Actor-Critic Deep RL

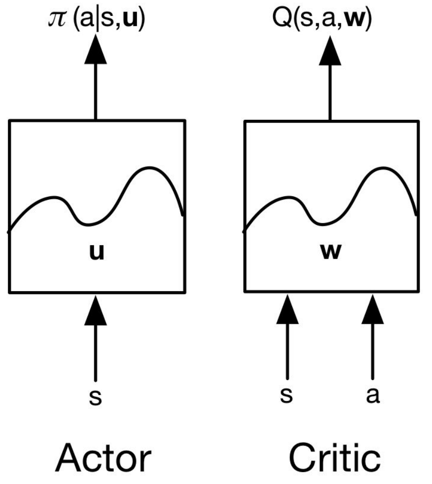
Actor π = Policy

Critic Q = Value Fn

Update critic by TD learning

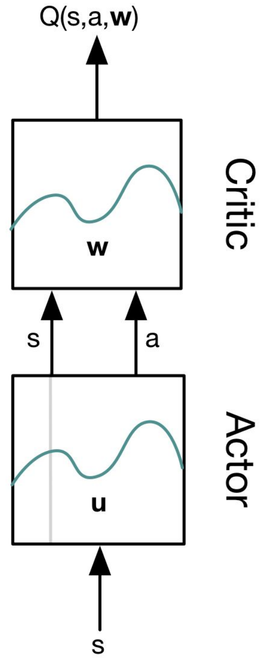
Update actor in direction of critic

Stochastic
Actor-Critic



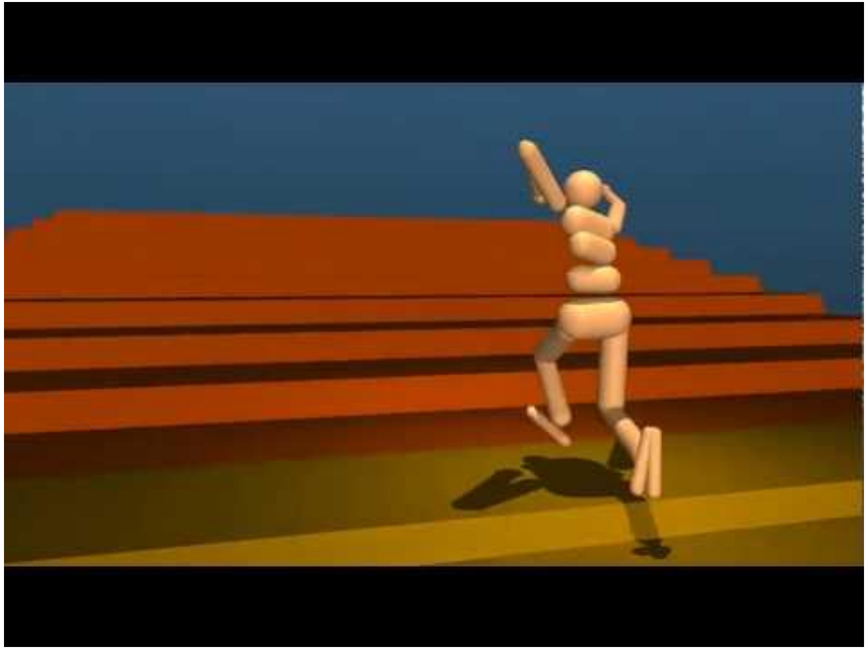
$$\frac{\partial l}{\partial \mathbf{u}} = \frac{\partial \log \pi(a|s,\mathbf{u})}{\partial \mathbf{u}} Q(s,a,\mathbf{w})$$

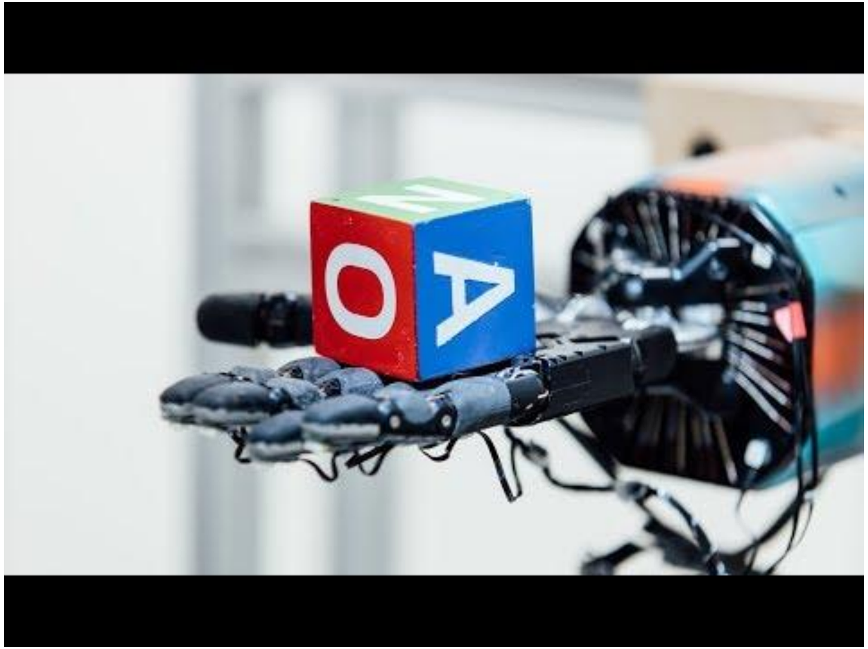
Deterministic
Actor-Critic



$$\frac{\partial l}{\partial \mathbf{u}} = \frac{\partial Q(s,a,\mathbf{w})}{\partial a} \frac{\partial a}{\partial \mathbf{u}}$$

Deep RL by Diverse Simulation

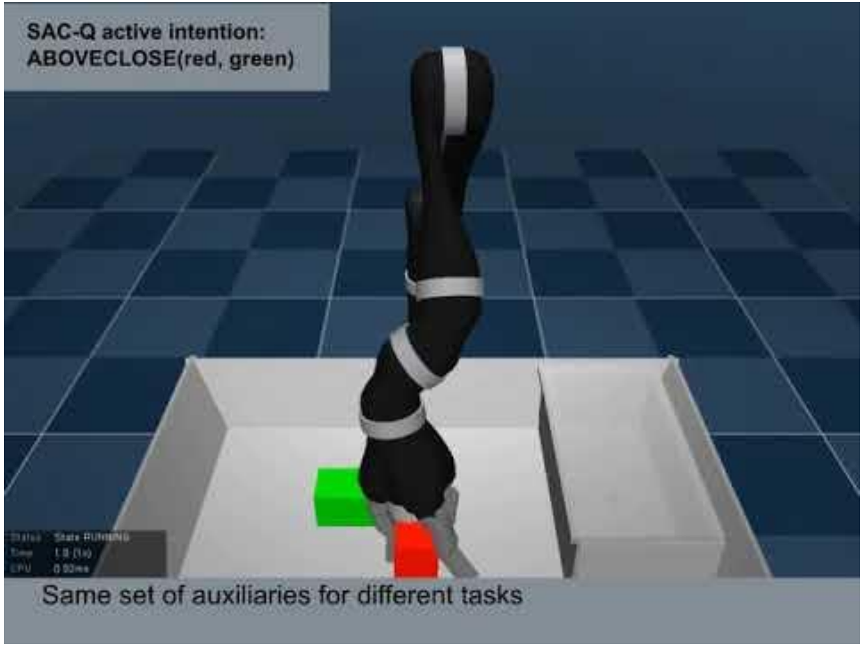




Heess et al. 2017

Andrychowicz 2018

Augmenting Data



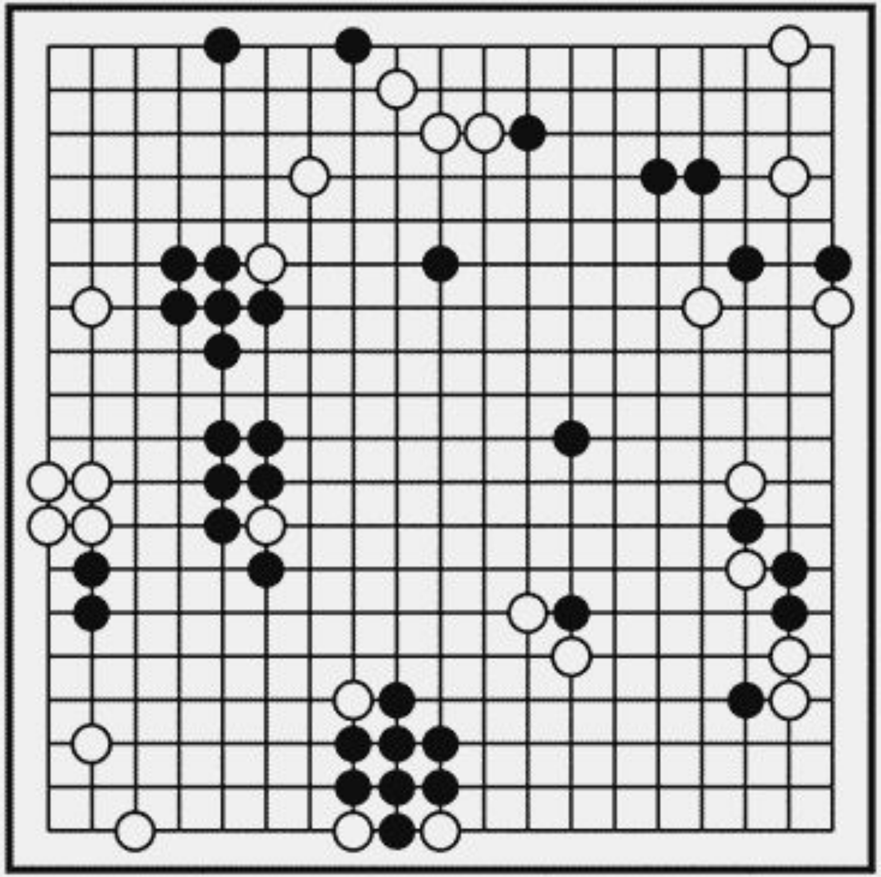
Kalshnikov et al. 2018

Riedmiller et al. 2018

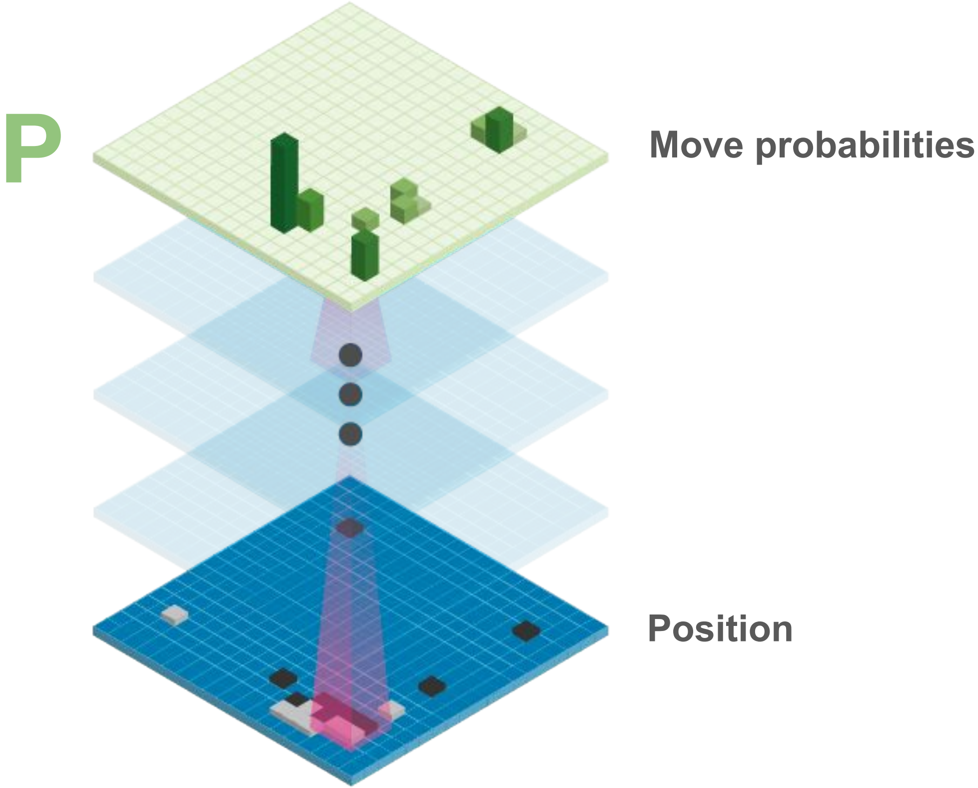
Silver et al. 2016

AlphaGo

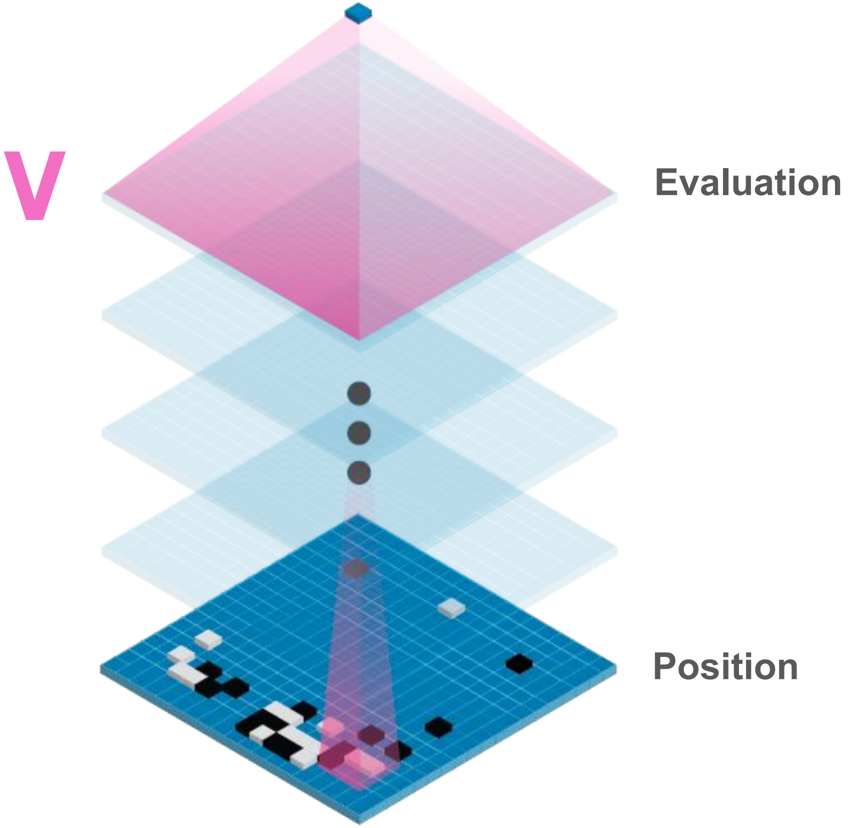
Success Story #4a



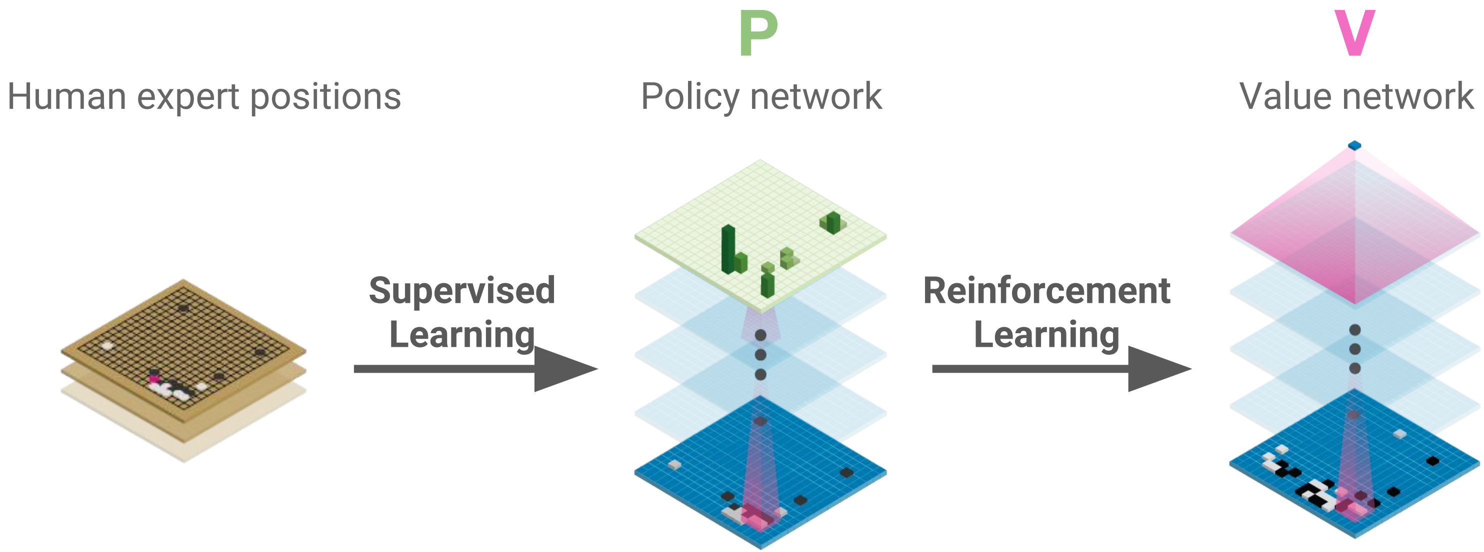
Policy network



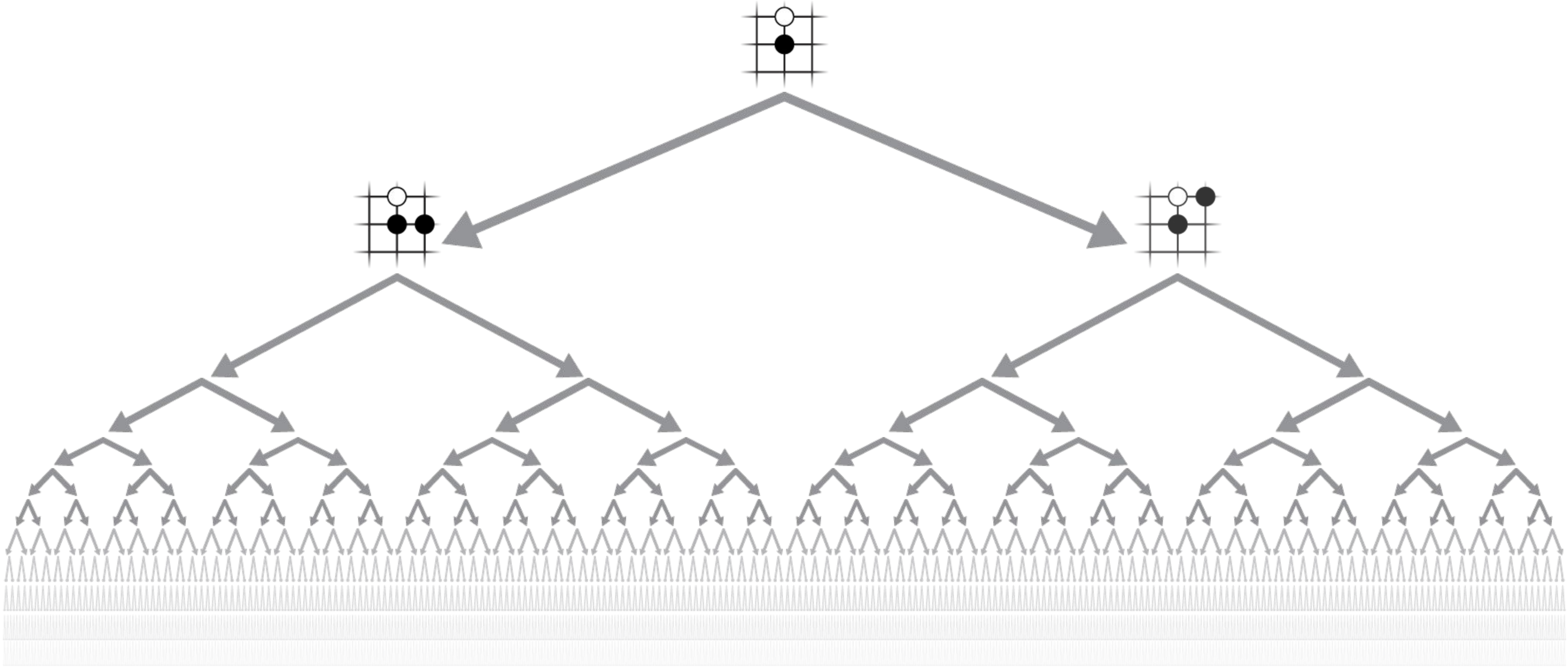
Value network



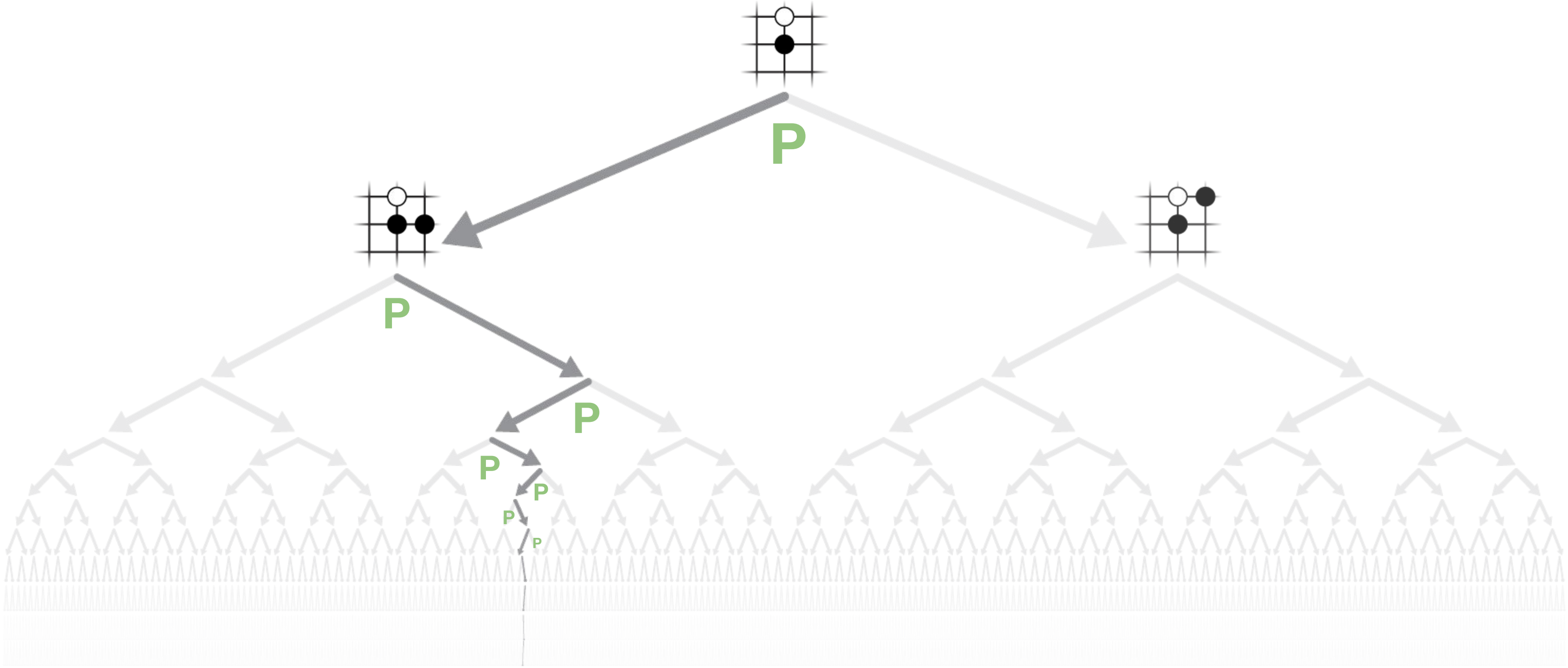
Training AlphaGo



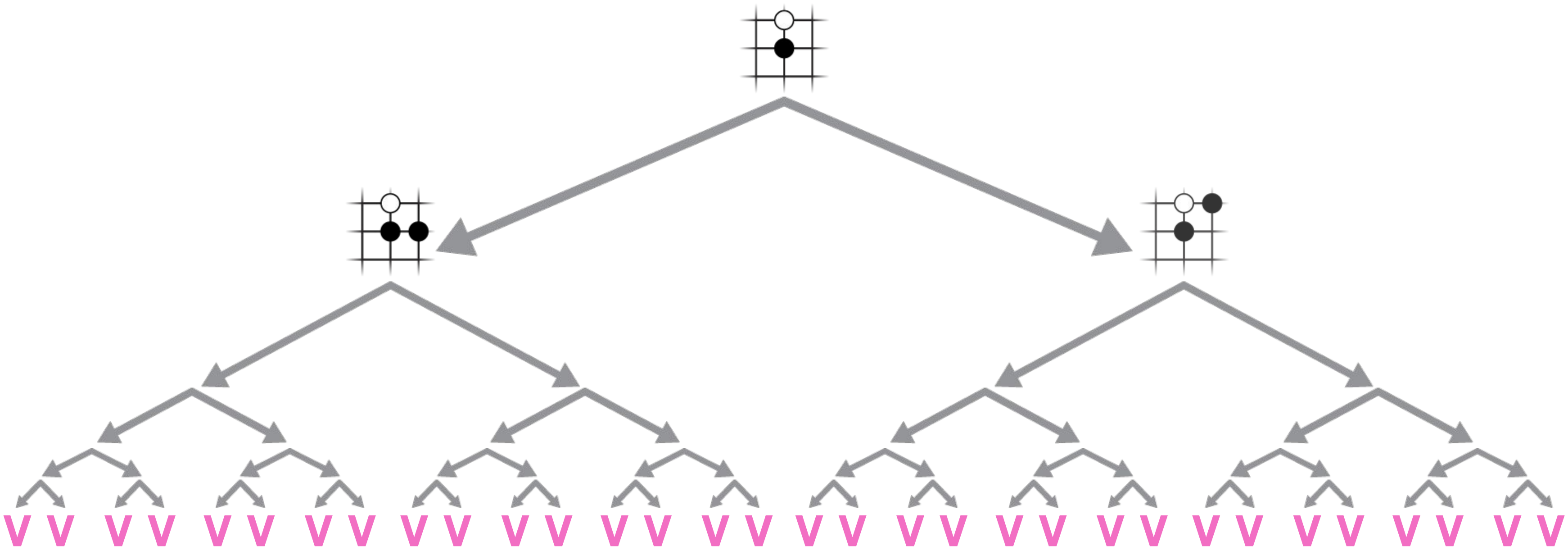
Exhaustive search



Reducing breadth with policy network



Reducing depth with value network



AlphaGo vs Lee Sedol

Lee Sedol (9p): winner of 18 world titles

Match was played in Seoul, March 2016

AlphaGo won the match 4-1

AlphaGo vs. Human World Champion Lee Sedol

Silver et al. 2017

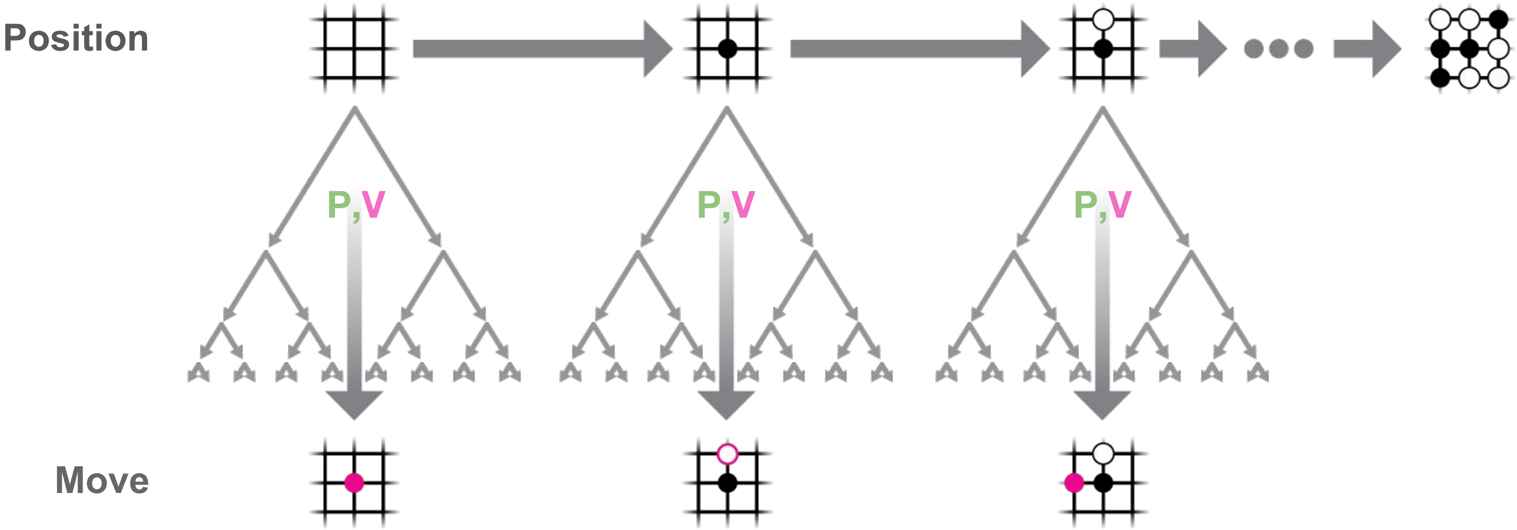
AlphaZero

Success Story #4b

AlphaZero: learning from first principles

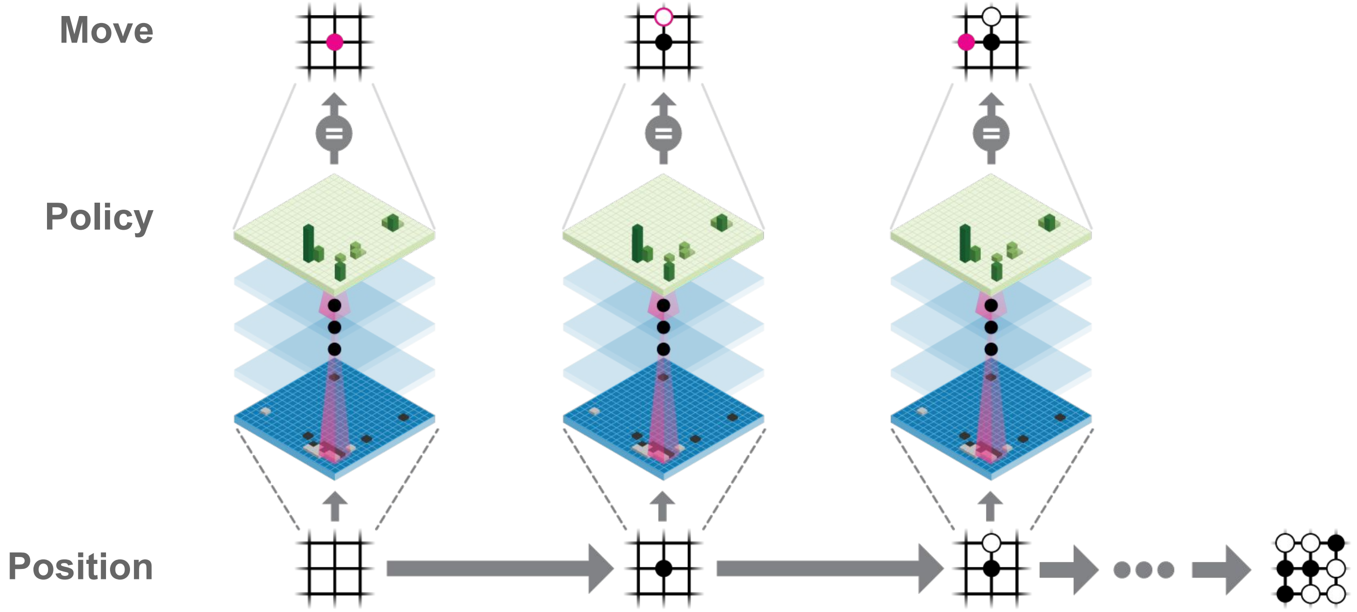
- **No human data**
  - Learns solely by self-play reinforcement learning, starting from random
- **No human features**
  - Only takes raw board as an input
- **Single neural network**
  - Policy and value networks are combined into one neural network (resnet)
- **Fully general**
  - Applicable to many domains, no special treatment for Go (symmetry etc.)

Reinforcement Learning in AlphaZero



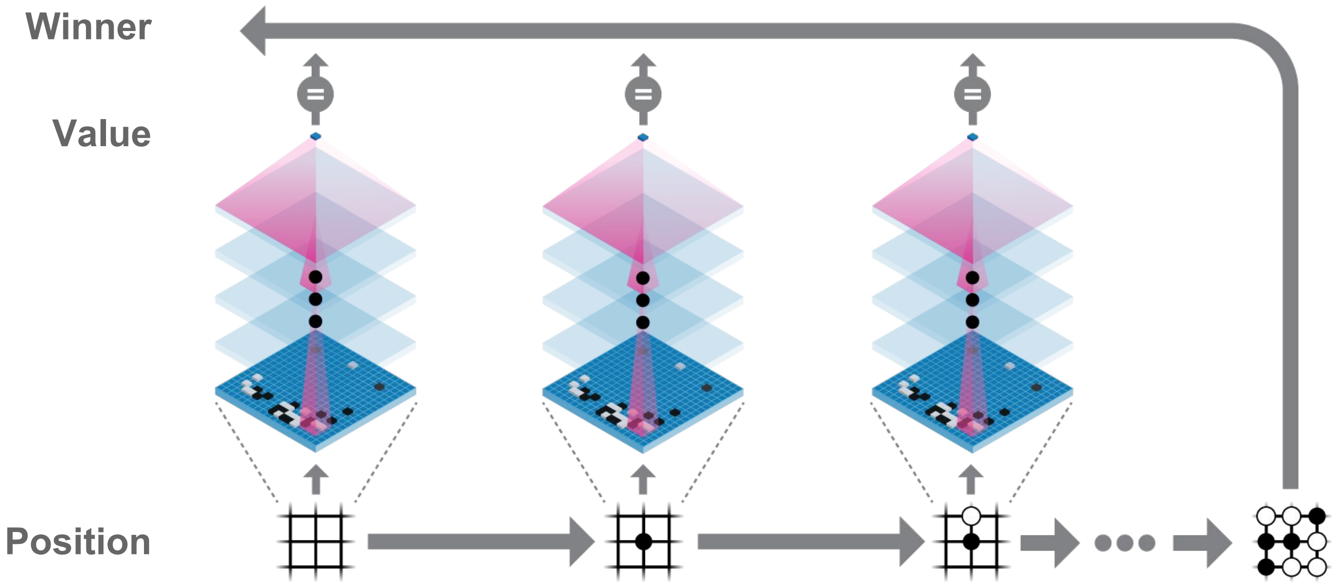
AlphaZero plays games against itself

Reinforcement Learning in AlphaZero



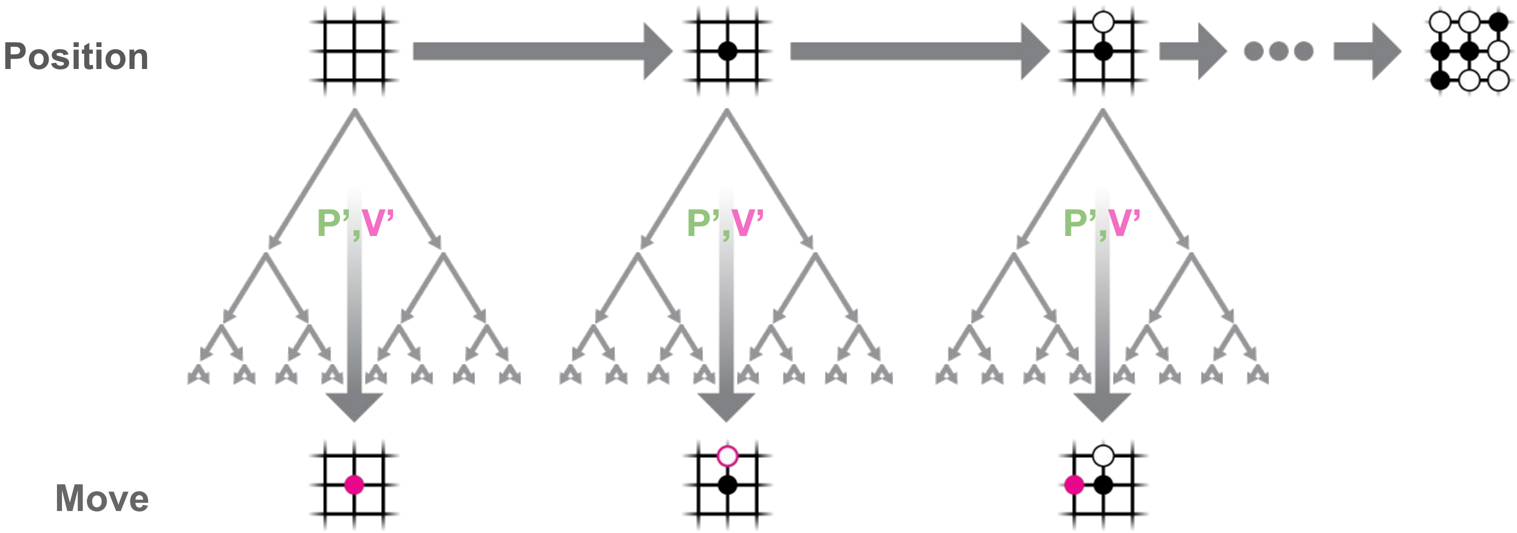
New policy network **P'** is trained to predict AlphaZero's moves

Reinforcement Learning in AlphaZero



New value network **V'** is trained to predict winner

Reinforcement Learning in AlphaZero



New policy/value network is used in next iteration of AlphaZero

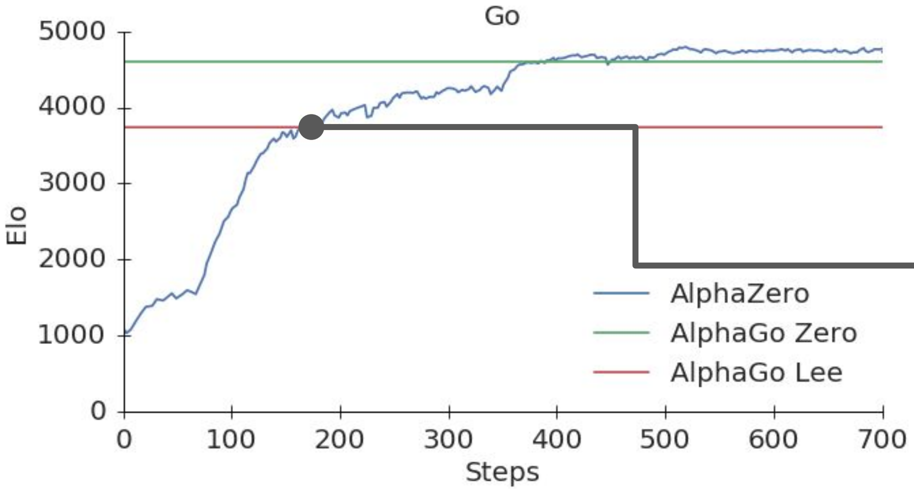
Search-Based Policy Iteration

- **Search-Based Policy Improvement**
  - Run MCTS search using current network
  - Actions selected by MCTS > actions selected by raw network

- **Search-Based Policy Evaluation**
  - Play self-play games using MCTS to select actions
  - Evaluate improved policy by the average outcome

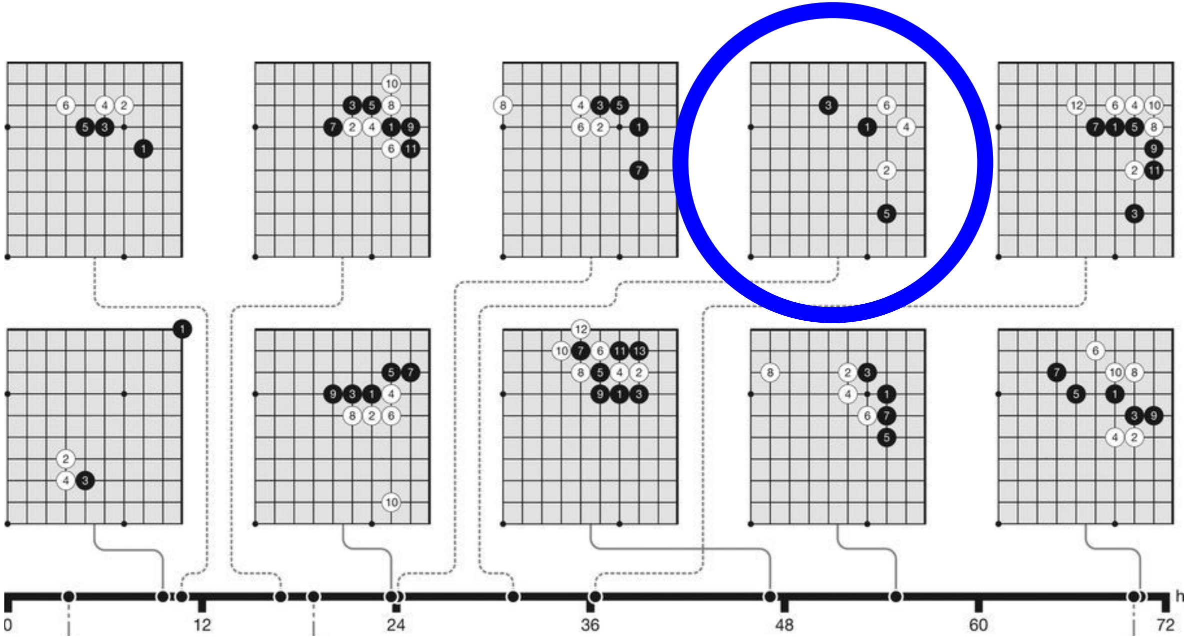
See also: Lagoudakis 03, Scherrer 15

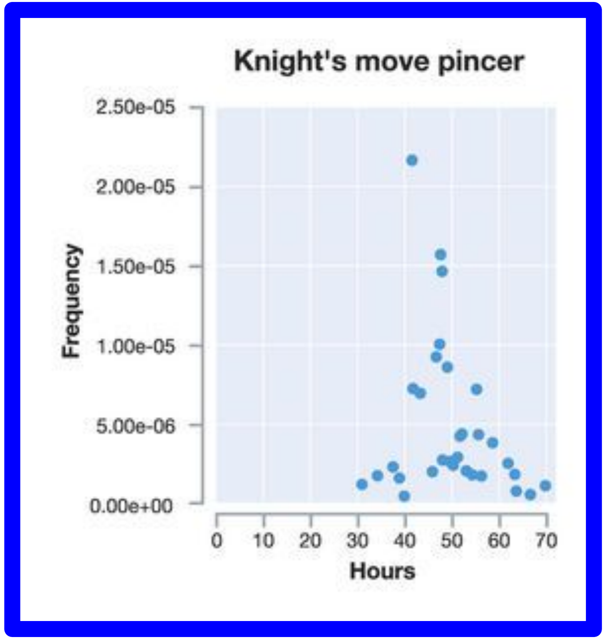
AlphaZero in Go



8 hours - *AlphaZero* surpasses *AlphaGo Lee*

Discovering and Discarding Human Go Knowledge





Known opening patterns (joseki) are discovered as training proceeds...

… But discarded if deemed inferior

Computer Chess

- Most studied domain in history of artificial intelligence
  - Studied by Babbage, Turing, Shannon, von Neumann
  - *Drosophila* of artificial intelligence for several decades
- Highly specialised systems have been successful in chess
  - Deep Blue defeated Kasparov in 1997
  - State-of-the-art now indisputably superhuman
- Shogi (Japanese chess) is more complex than chess
  - Larger board, larger action space (captured pieces dropped back into play)
  - Only recently achieved human world champion level
- State-of-the-art engines are based on alpha-beta search
  - Handcrafted evaluation functions optimised by human grandmasters
  - Search extensions that are highly optimised using game-specific heuristics

Anatomy of a World Champion Chess Engine

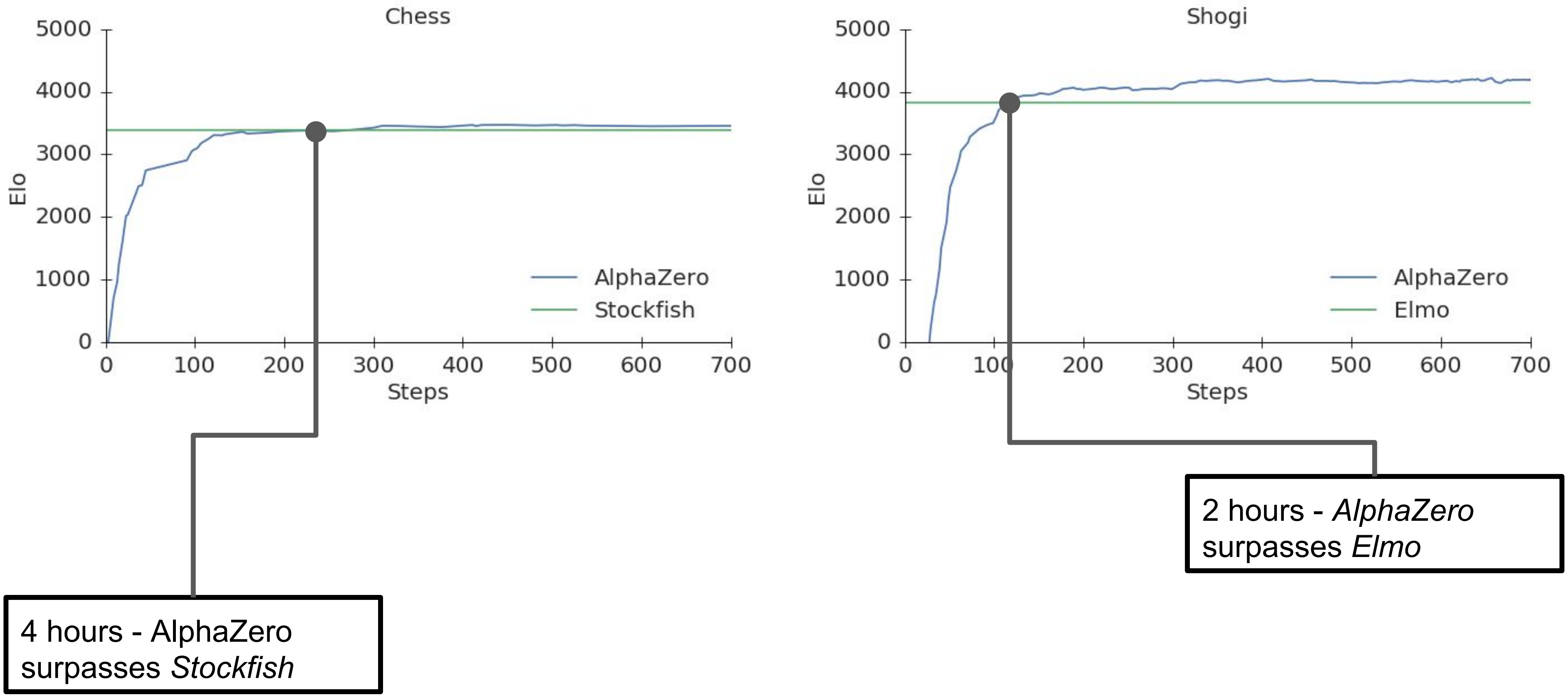
Domain knowledge, extensions, heuristics in 2016 TCEC world champion *Stockfish*:

Board Representation: Bitboards with Little-Endian Rank-File Mapping (LERF), Magic Bitboards, BMI2 - PEXT Bitboards, Piece-Lists, **Search:** Iterative Deepening, Aspiration Windows, Parallel Search using Threads, YBWC, Lazy SMP, Principal Variation Search. **Transposition Table:** Shared Hash Table, Depth-preferred Replacement Strategy, No PV-Node probing, Prefetch **Move Ordering:** Countermove Heuristic, Counter Moves History, History Heuristic, Internal Iterative Deepening, Killer Heuristic, MVV/LVA, SEE, **Selectivity:** Check Extensions if SEE >= 0, Restricted Singular Extensions, Futility Pruning, Move Count Based Pruning, Null Move Pruning, Dynamic Depth Reduction based on depth and value, Static Null Move Pruning, Verification search at high depths, ProbCut, SEE Pruning, Late Move Reductions, Razoring, Quiescence Search, **Evaluation:** Tapered Eval, Score Grain, Point Values Midgame: 198, 817, 836, 1270, 2521, Endgame: 258, 846, 857, 1278, 2558, Bishop Pair, Imbalance Tables, Material Hash Table, Piece-Square Tables, Trapped Pieces, Rooks on (Semi) Open Files, Outposts, Pawn Hash Table, Backward Pawn, Doubled Pawn, Isolated Pawn, Phalanx, Passed Pawn, Attacking King Zone, Pawn Shelter, Pawn Storm, Square Control, Evaluation Patterns, **Endgame Tablebases:** Syzygy TableBases

Anatomy of AlphaZero

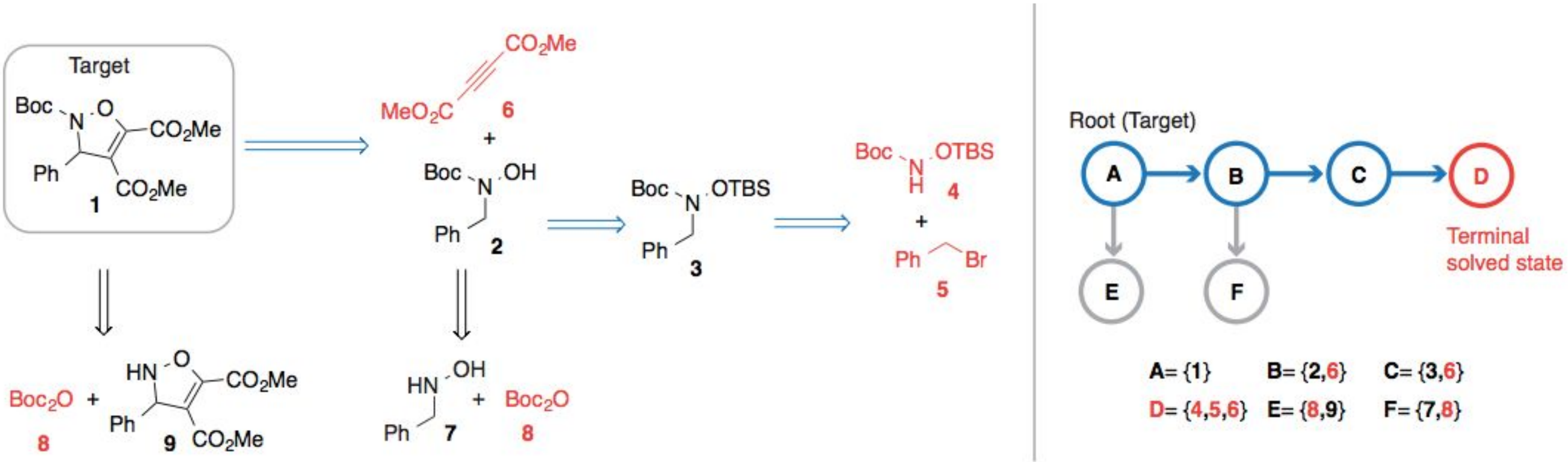
Self-play reinforcement learning + self-play Monte-Carlo search

~~**Board Representation**: Bitboards with Little-Endian Rank-File Mapping (LERF), Magic Bitboards, BMI2 - PEXT Bitboards, Piece-Lists, **Search:** Iterative Deepening, Aspiration Windows, Parallel Search using Threads, YBWC, Lazy SMP, Principal Variation Search. **Transposition Table:** Shared Hash Table, Depth-preferred Replacement Strategy, No PV-Node probing, Prefetch **Move Ordering:** Countermove Heuristic, Counter Moves History, History Heuristic, Internal Iterative Deepening, Killer Heuristic, MVV/LVA, SEE, **Selectivity:** Check Extensions if SEE >= 0, Restricted Singular Extensions, Futility Pruning, Move Count Based Pruning, Null Move Pruning, Dynamic Depth Reduction based on depth and value, Static Null Move Pruning, Verification search at high depths, ProbCut, SEE Pruning, Late Move Reductions, Razoring, Quiescence Search, **Evaluation:** Tapered Eval, Score Grain, Point Values Midgame: 198, 817, 836, 1270, 2521, Endgame: 258, 846, 857, 1278, 2558, Bishop Pair, Imbalance Tables, Material Hash Table, Piece-Square Tables, Trapped Pieces, Rooks on (Semi) Open Files, Outposts, Pawn Hash Table, Backward Pawn, Doubled Pawn, Isolated Pawn, Phalanx, Passed Pawn, Attacking King Zone, Pawn Shelter, Pawn Storm, Square Control, Evaluation Patterns, **Endgame Tablebases:** Syzygy TableBases~~


Chess
5000
4000
3000
2000
1000
0
Elo
0
100
200
300
400
500
600
700
Steps
AlphaZero
Stockfish
Shogi
5000
4000
3000
2000
1000
0
Elo
0
100
200
300
400
500
600
700
Steps
AlphaZero
Elmo
4 hours - AlphaZero surpasses *Stockfish*
2 hours - *AlphaZero* surpasses *Elmo*

AlphaChem

Segler et al., 2018



- Other Go programs (FineArt, LeelaZero, ELF, …)
- Hex (Anthony 2017)
- Bin packing (Laterre et al. 2018)

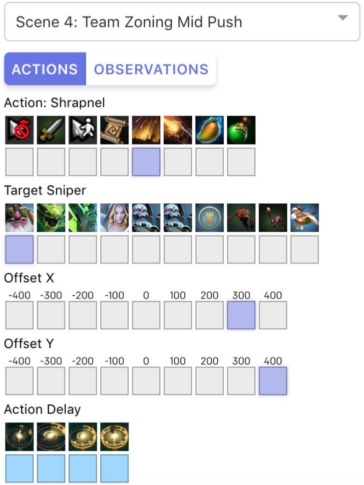
OpenAI 2018
(unpublished)

Dota 2

Success Story #5a

Dota 2

- 5v5 multi-player game with rich strategies
- 20,000 time-steps per game
- 170,000 discrete actions (~1,000 legal)
- 20,000 observations summarise information available to human



OpenAI Five

- Self-play training starting from random weights
- Actor-critic algorithm (PPO)
  - LSTM network represents policy and value
- 20% of games played against old weights
- Handcrafted reward shaping based on expert domain knowledge
- Exploits domain randomisations
- Simplified game rules (e.g. drafting)

1v1: defeated professional human (2017)

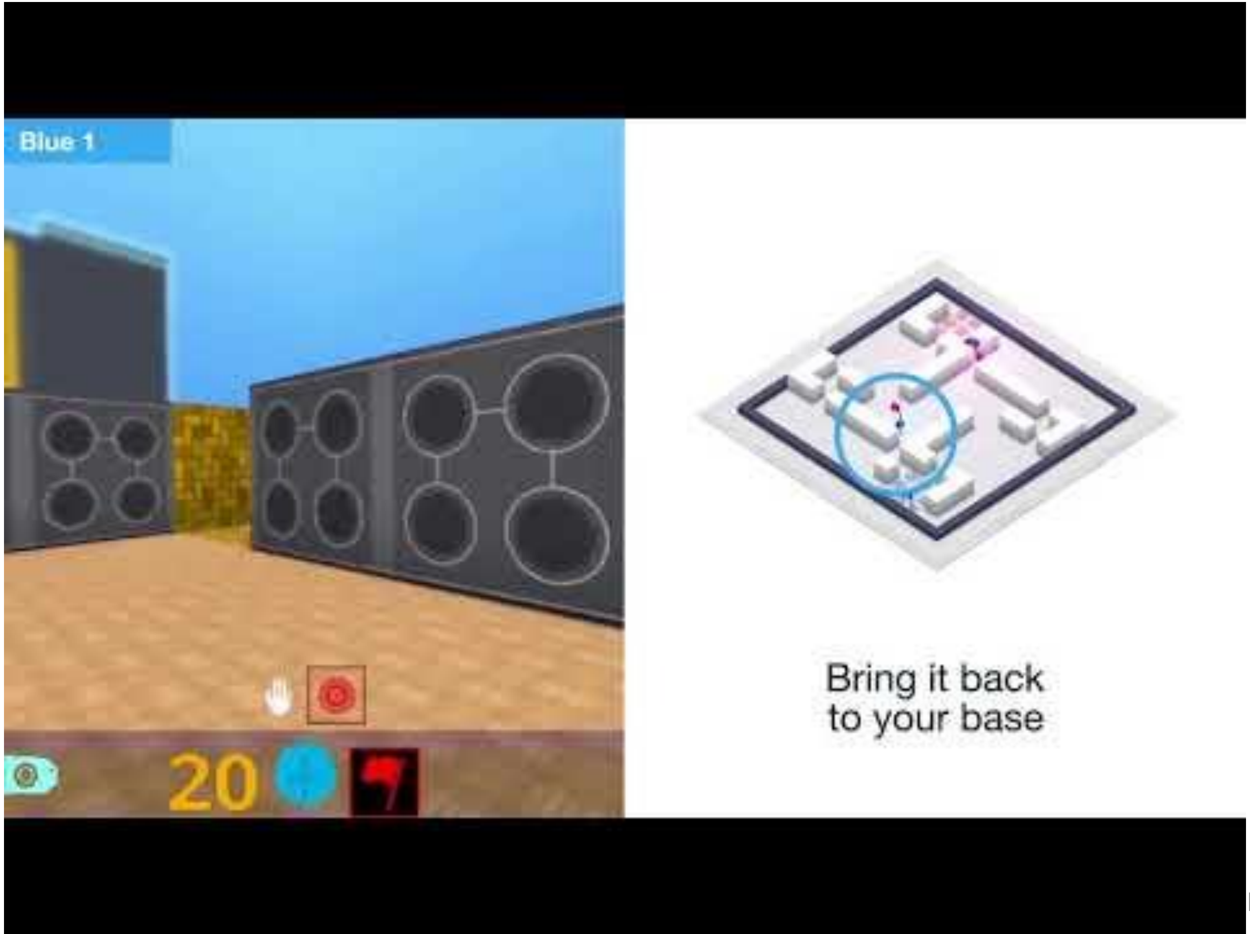
5v5: narrowly lost to professional human team (2018)

Jaderberg et al. 2018

Capture the Flag

Success Story #5b

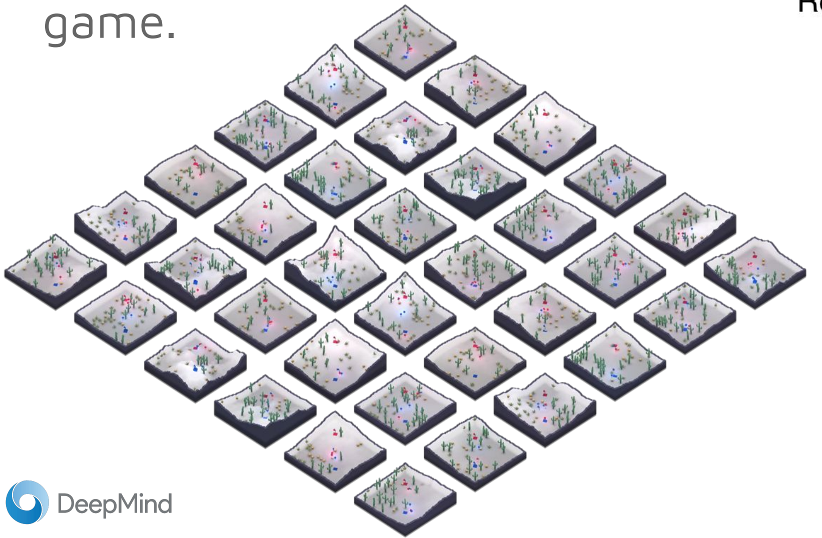
MULTI-AGENT RL: CAPTURE THE FLAG

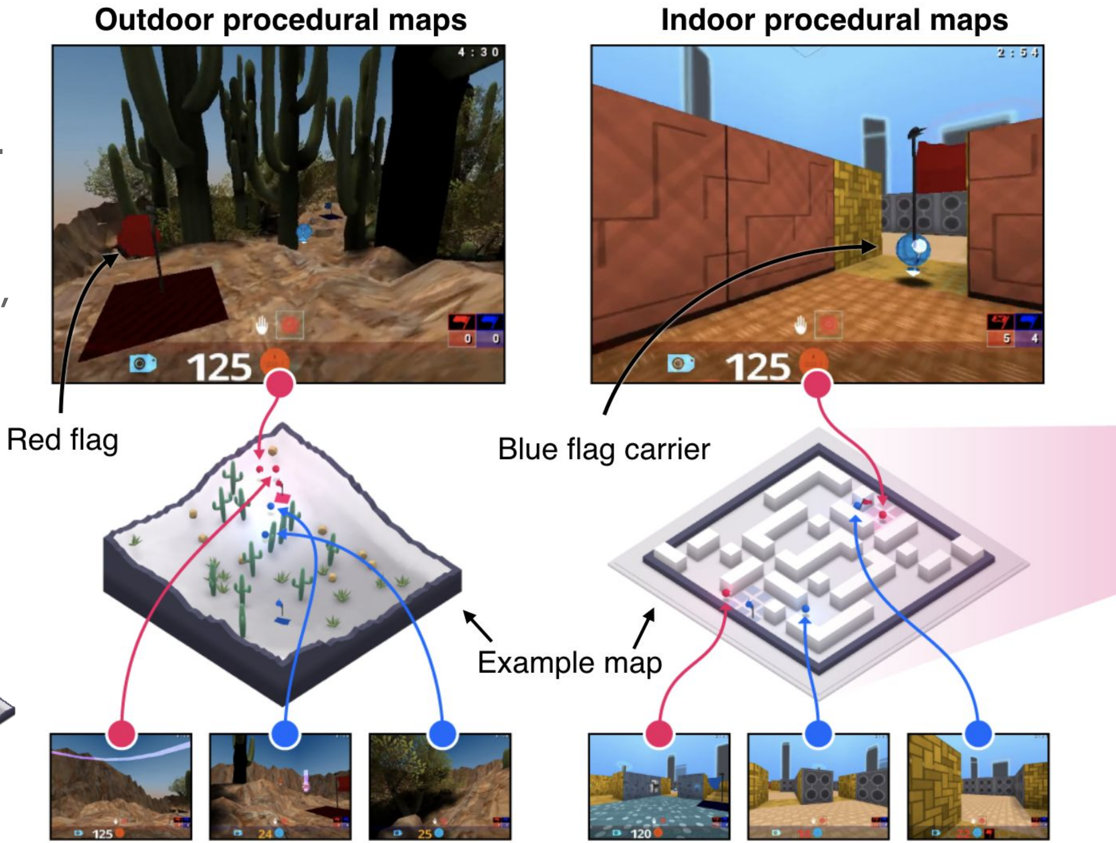


ENVIRONMENTS

Based on DMLab (Quake III Arena).

Train agents on two style of maps, **outdoor** and **indoor**. These are **procedurally generated** every game.

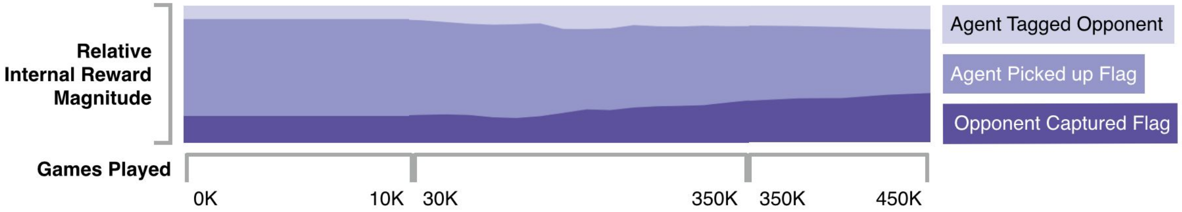




TRAINING ALGORITHM

Internal reward is adapted by population-based training to **maximise win rate**

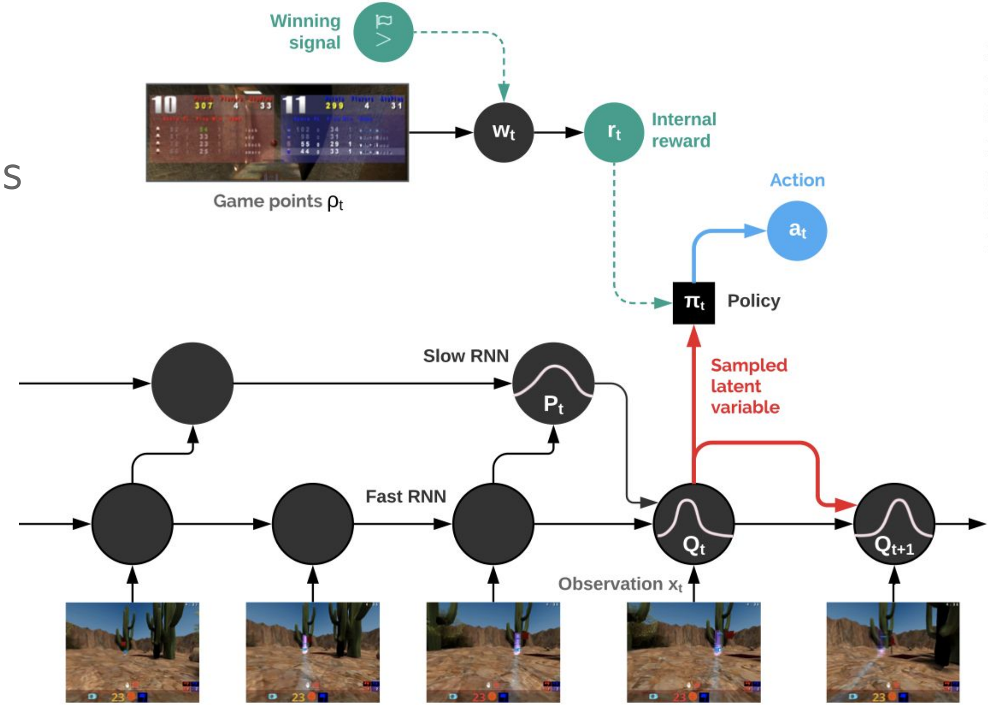
Policies/values are trained by actor-critic to **maximise internal rewards**



Network Architecture

Differentiable memory reads and writes latent variables

Temporal hierarchy: fast and slow timescales learn to work together



RESULTS