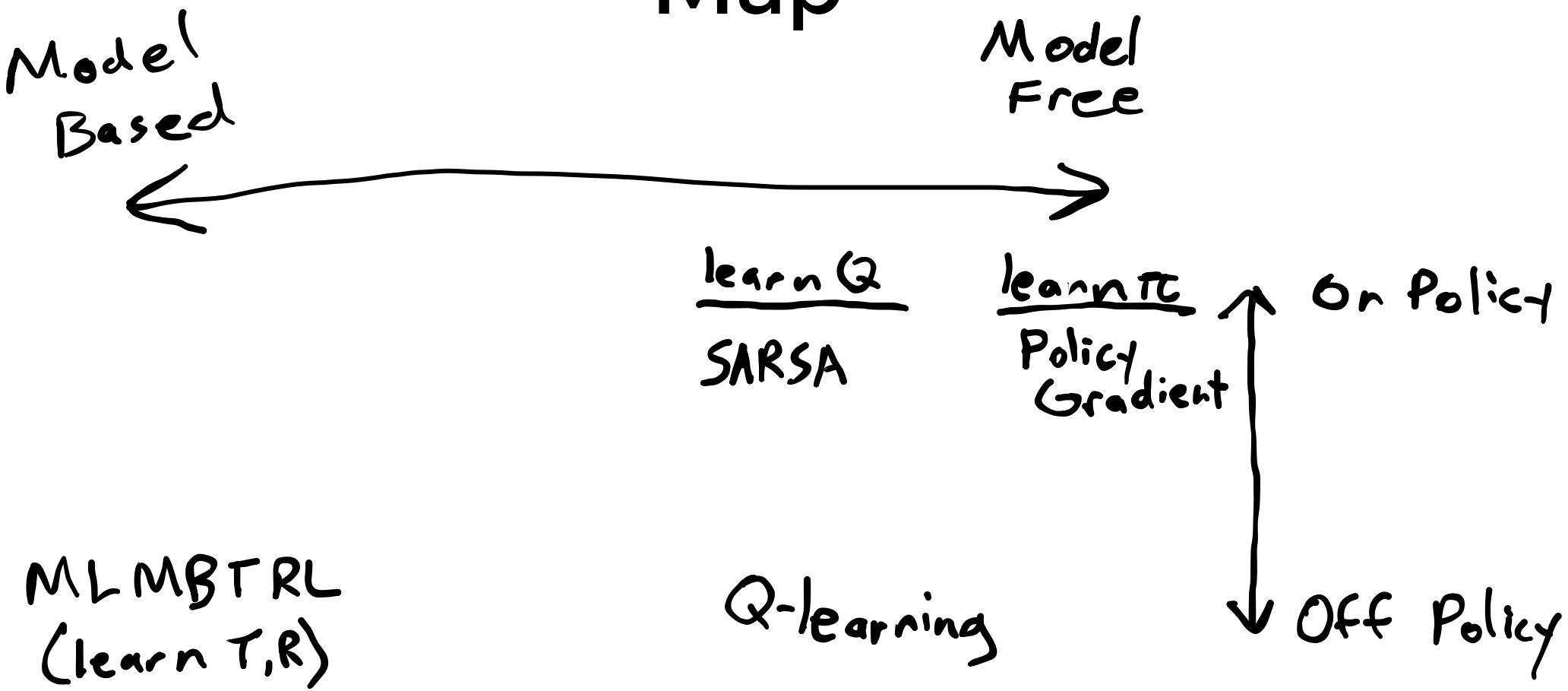
DQN and Advanced Policy Gradient

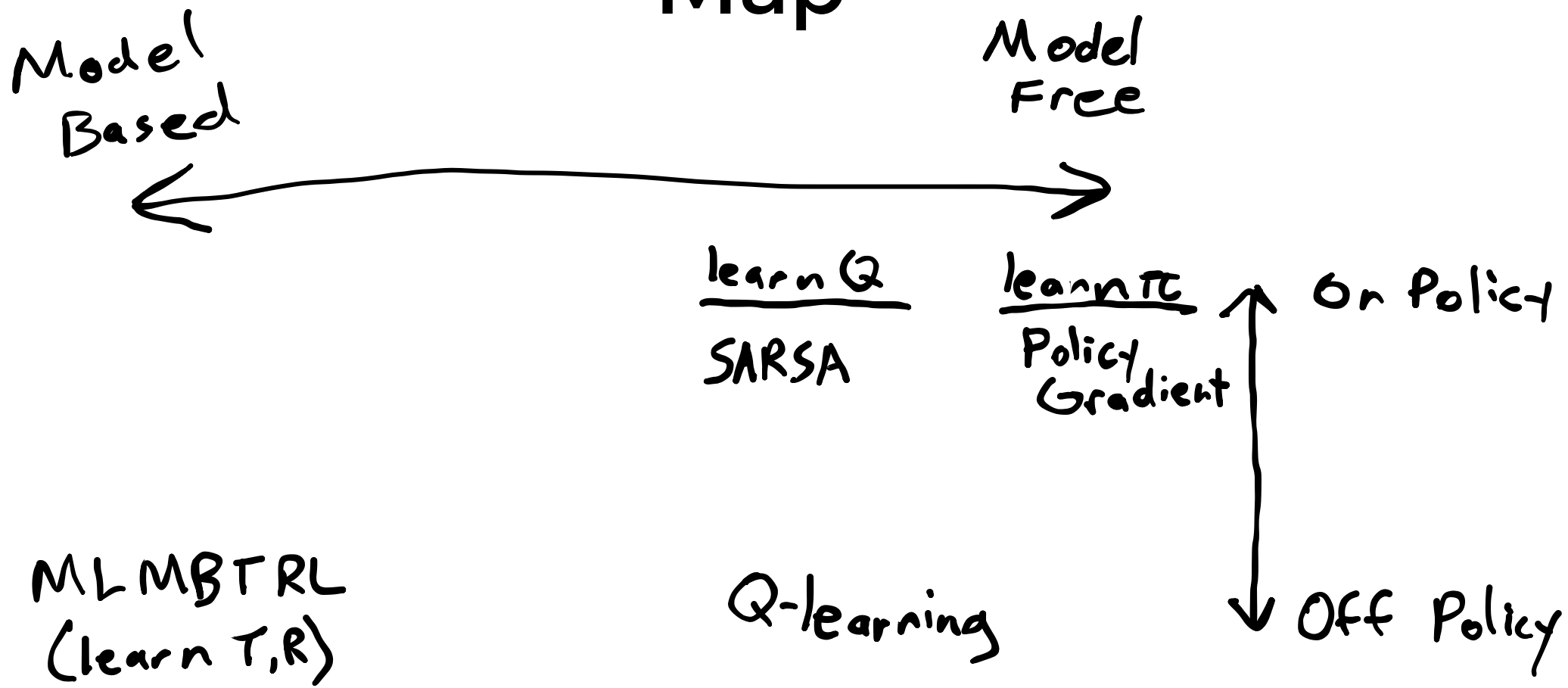
Map

Map

Map


Model Based
Model Free
learn Q
SARSA
learn π
Policy Gradient
On Policy
Off Policy
MLMBTRL
(learn T,R)
Q-learning

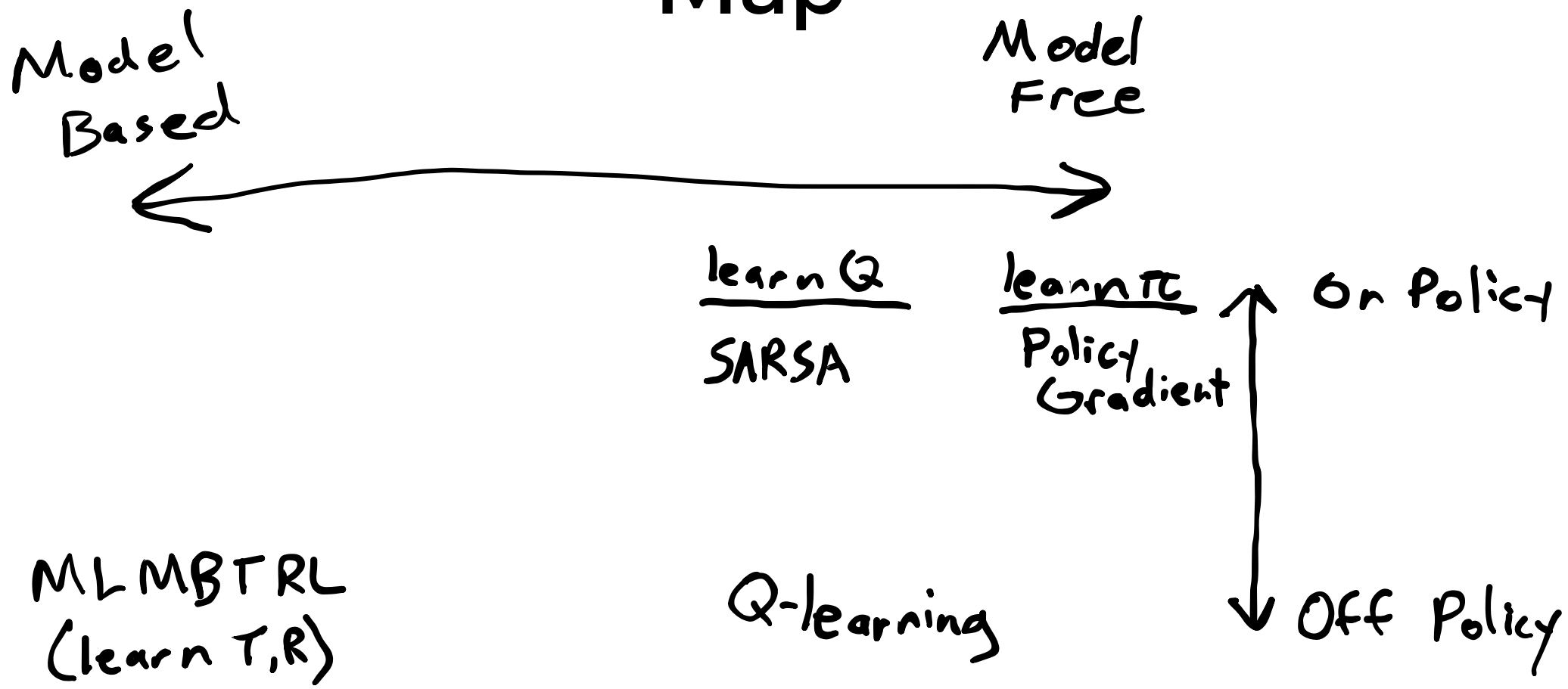
Map



Challenges:

1. Exploration vs Exploitation
2. Credit Assignment
3. Generalization

Map



Challenges:

1. Exploration vs Exploitation
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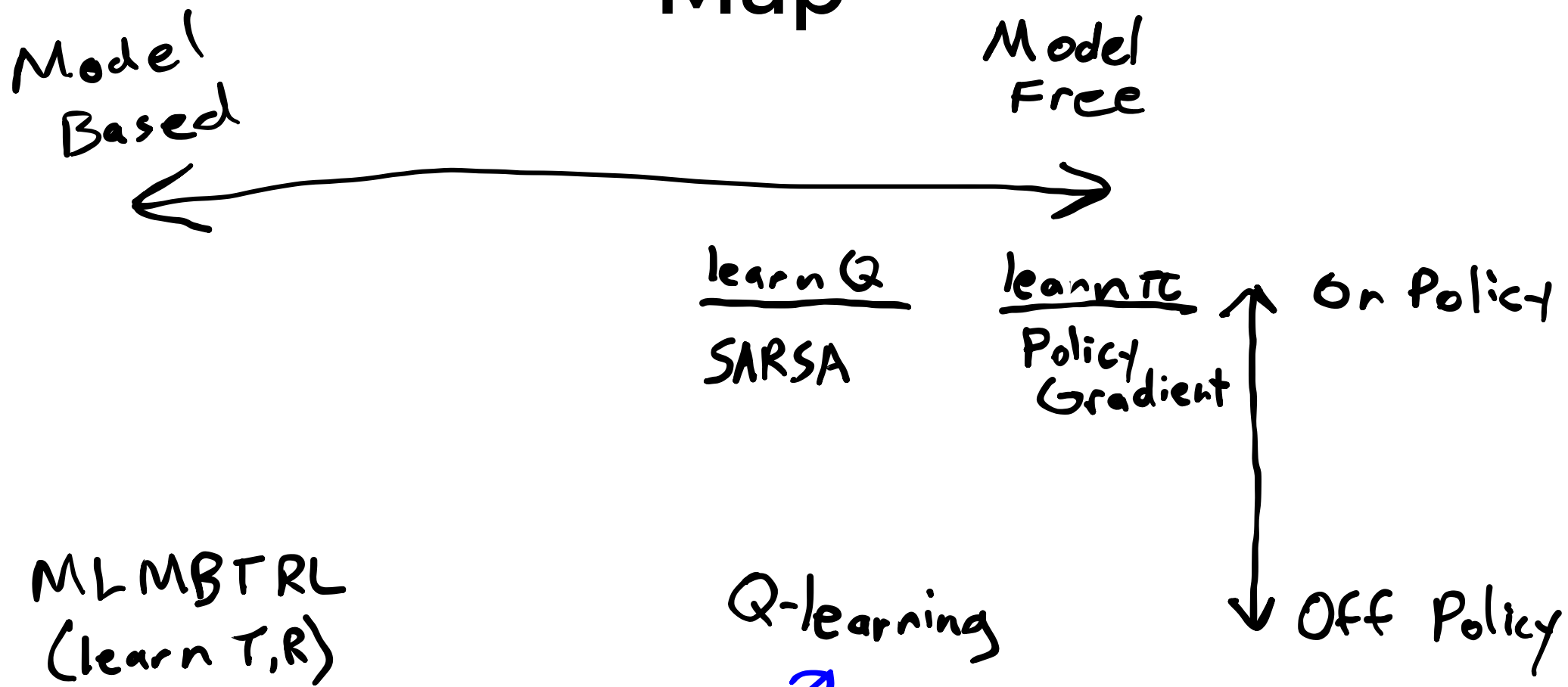
Last Time: Neural Networks

Map



Challenges:

1. Exploration vs Exploitation
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Last Time: Neural Networks

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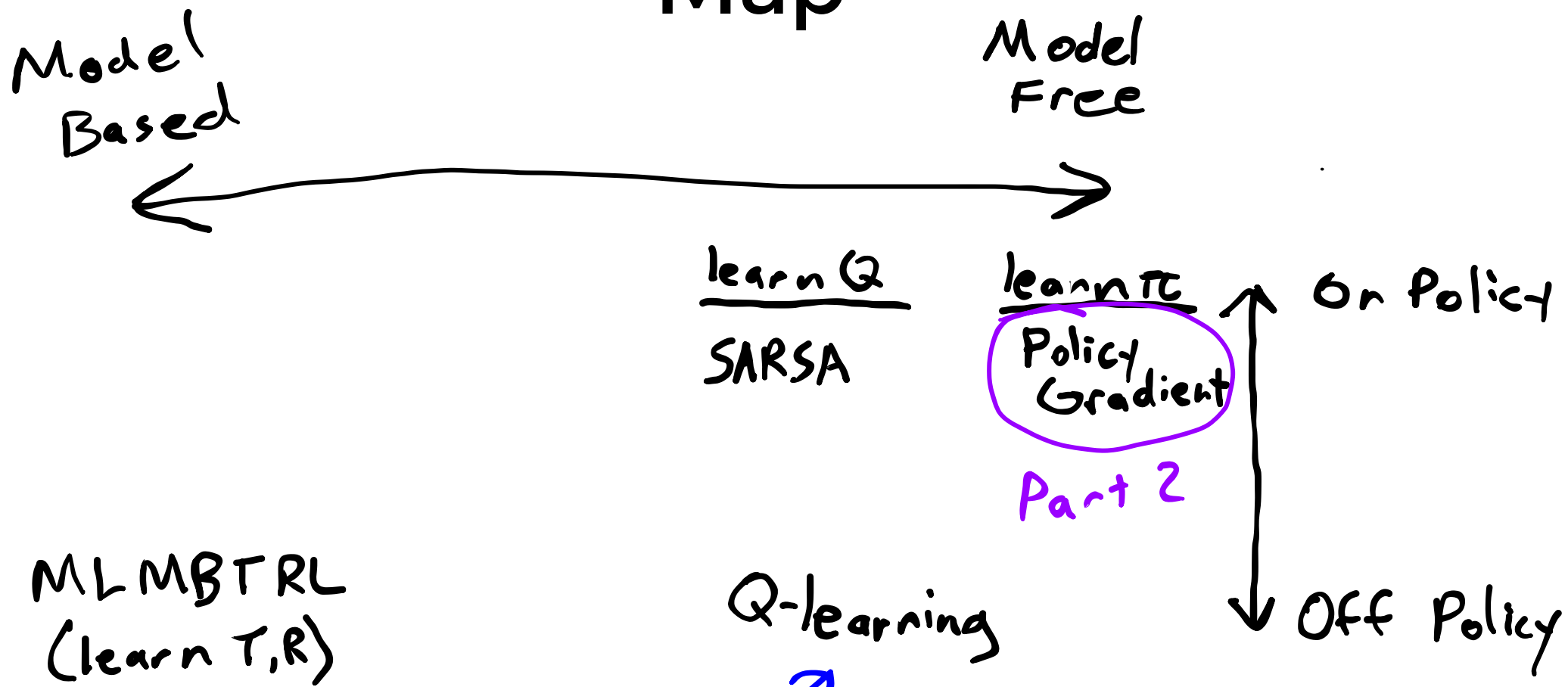

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Last Time: Neural Networks

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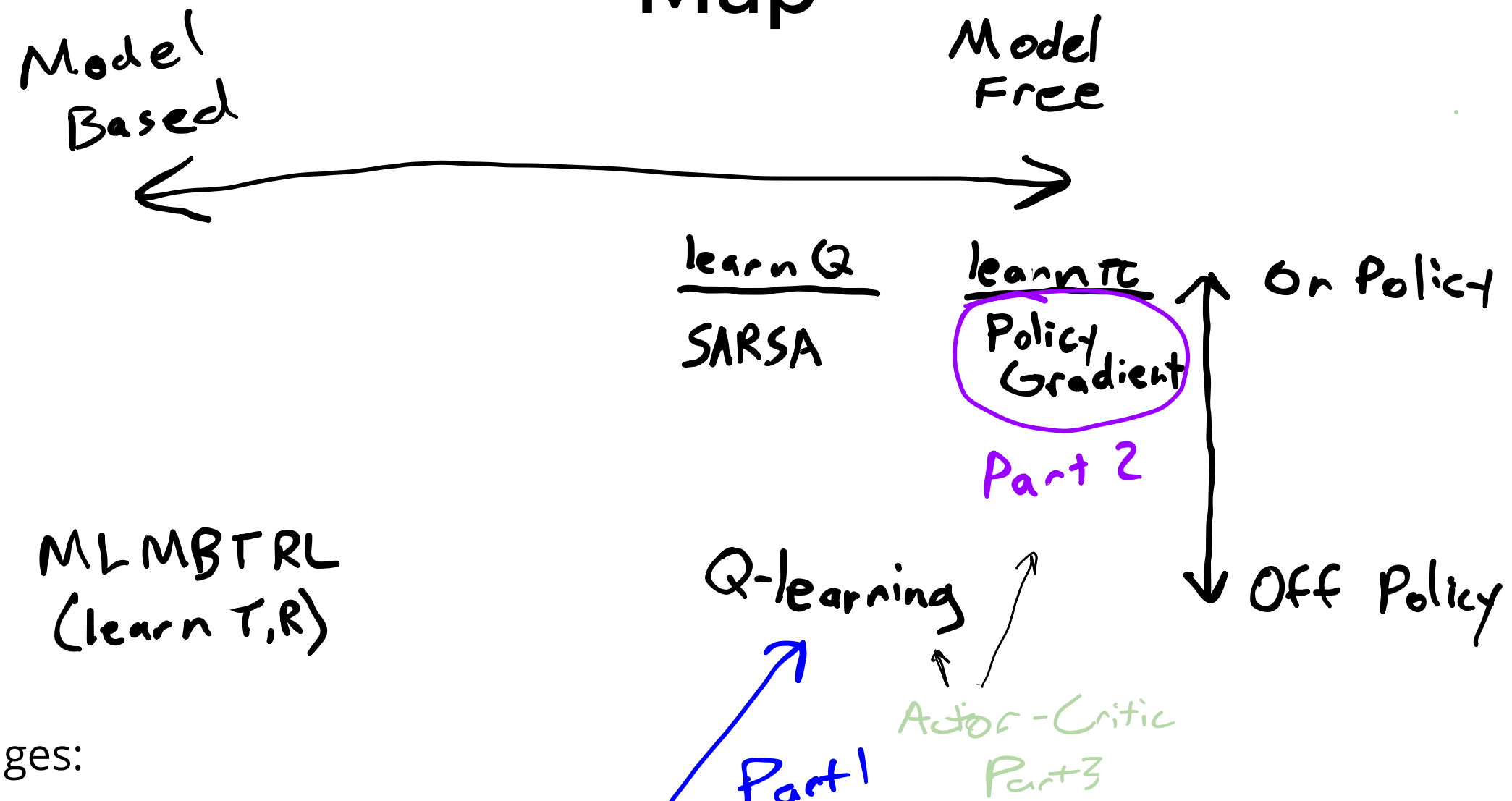

Challenges:

1. Exploration vs Exploitation
2. Credit Assignment
3. Generalization

Last Time: Neural Networks

Part I
DQN

Q-Learning with Neural Networks

Q-Learning with Neural Networks

Q-Learning:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left(r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$$

Q-Learning with Neural Networks

Q-Learning:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left(r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right)$$

Neural Networks

$$\theta^* = \arg\min_\theta \sum_{(x,y)\in\mathcal{D}} l(f_\theta(x), y)$$

$$\theta \leftarrow \theta - \alpha \overbrace{\nabla_\theta \, l(f_\theta(x), y)}$$

Q-Learning with Neural Networks

Q-Learning:

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Deep Q learning:

- Approximate Q with Q_θ

Q-Learning with Neural Networks

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Deep Q learning:

- Approximate Q with Q_θ
- What should (x, y) be?

Q-Learning with Neural Networks

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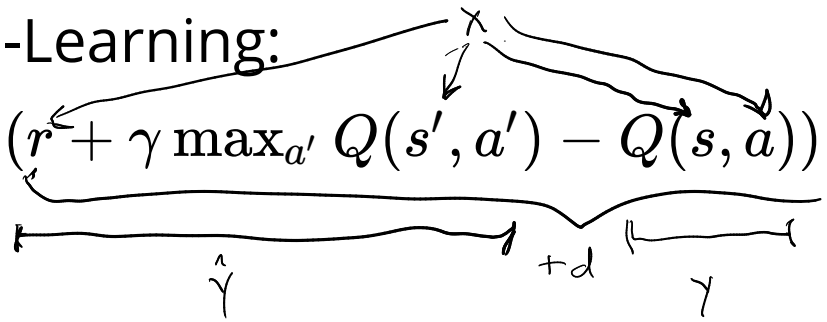

Neural Networks

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Deep Q learning:

- Approximate Q with Q_θ
- What should (x, y) be? (s,a,r,s')
- What should l be?

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

Q-Learning with Neural Networks

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$$Q(s,a) \leftarrow Q(s,a) + \alpha\ (r + \gamma \max_{a'} Q(s',a') - Q(s,a))$$

Neural Networks

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Deep Q learning:

- Approximate Q with Q_θ
- What should (x, y) be?
- What should l be?

Candidate Algorithm:

loop

$$a \leftarrow \text{argmax}\, Q(s,a) \text{ w.p. } 1-\epsilon, \quad \text{rand}(A) \text{ o.w.}$$

$$r \leftarrow \text{act!}(\text{env}, a)$$

$$s' \leftarrow \text{observe}(\text{env})$$

$$\theta \leftarrow \theta - \alpha \nabla_\theta \left(r + \gamma \max_{a'} Q_\theta(s',a') - Q_\theta(s,a)\right)^2$$

$$s \leftarrow s'$$

DQN: The Atari Benchmark

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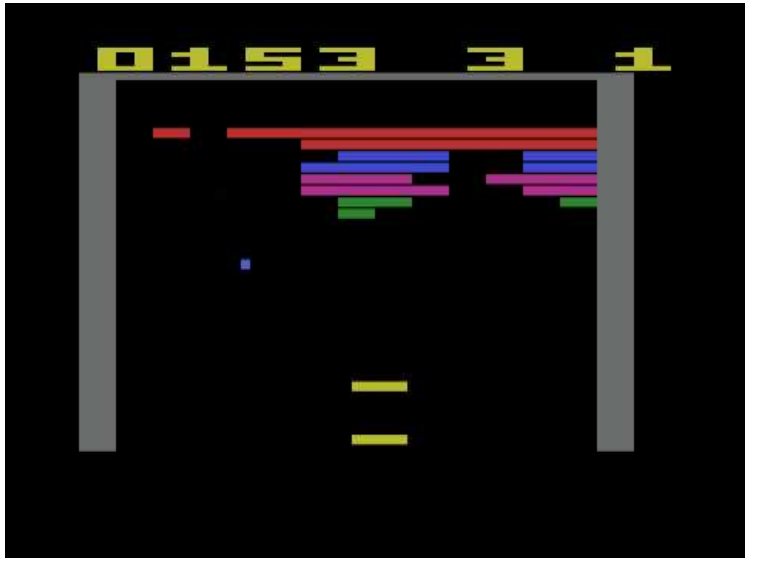

DQN: Problems with Naive Approach

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Problems:

1. Samples Highly Correlated

DQN: Problems with Naive Approach

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Problems:

1. Samples Highly Correlated
2. Size-1 batches

DQN: Problems with Naive Approach

Candidate Algorithm:

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$s \leftarrow s'$

Problems:

1. Samples Highly Correlated
2. Size-1 batches
3. Moving target

DQN: Problems with Naive Approach

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$$s \leftarrow s'$$

Problems:

1. Samples Highly Correlated
2. Size-1 batches
3. Moving target

} data buffer / experience replay

} periodically freeze target

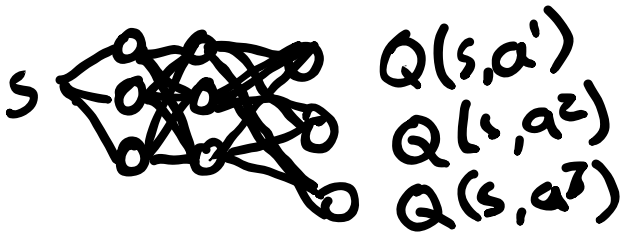
DQN

DQN

Q Network Structure:

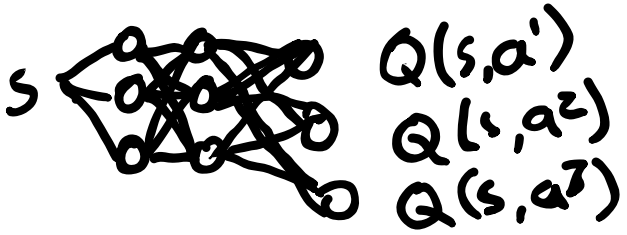
DQN

Q Network Structure:



DQN

Q Network Structure:

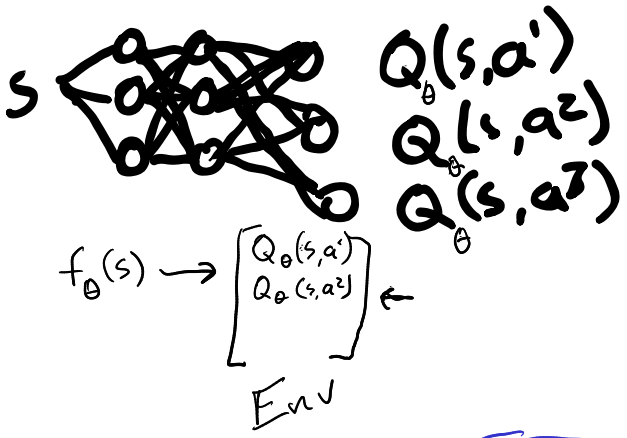


Experience Tuple: (s, a, r, s')

Trick 1: network structure

DQN

Q Network Structure:



Experience Tuple: (s, a, r, s')

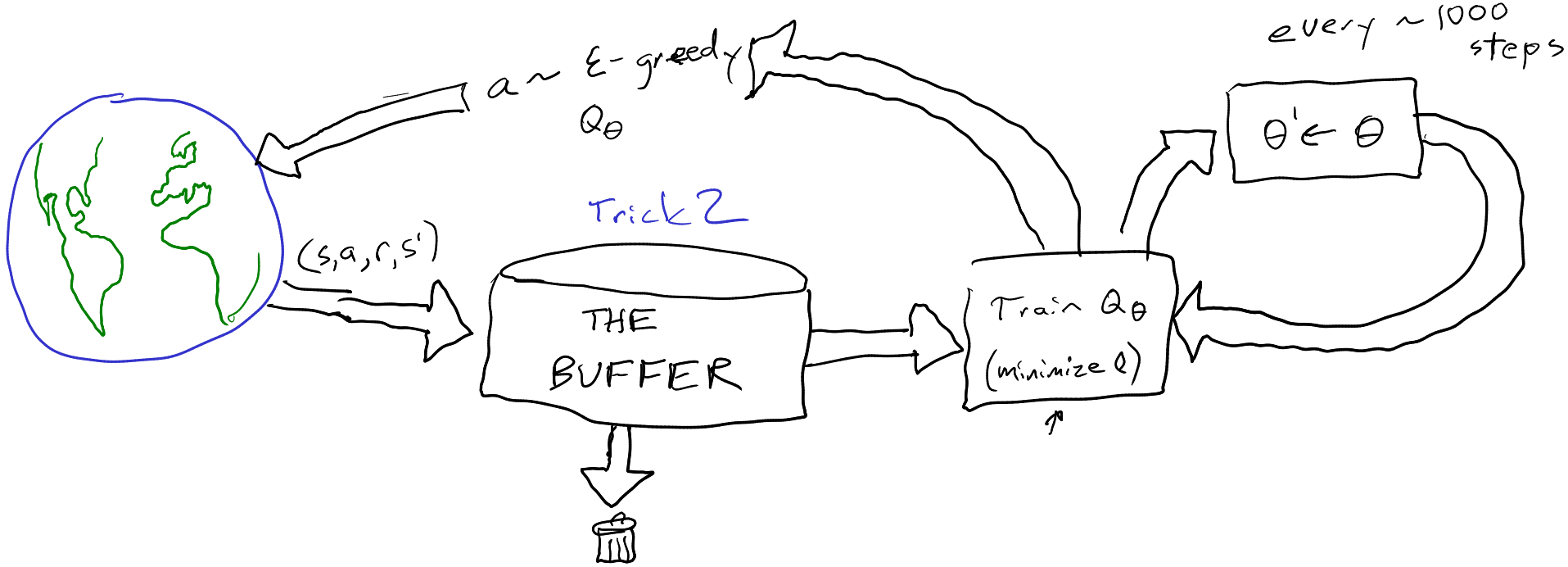
Loss:

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

updating slower

Trick 3

every ~1000 steps

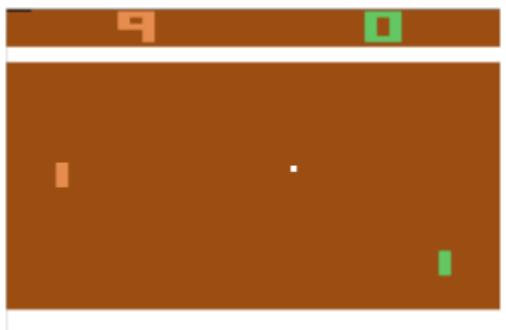


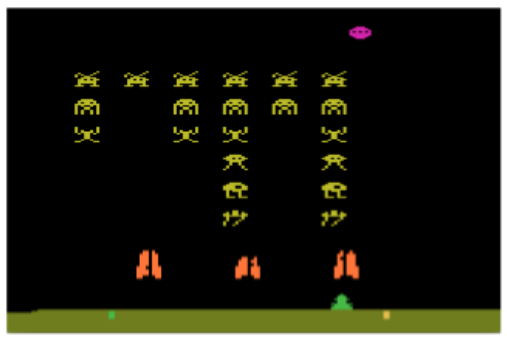
Playing Atari with Deep Reinforcement Learning

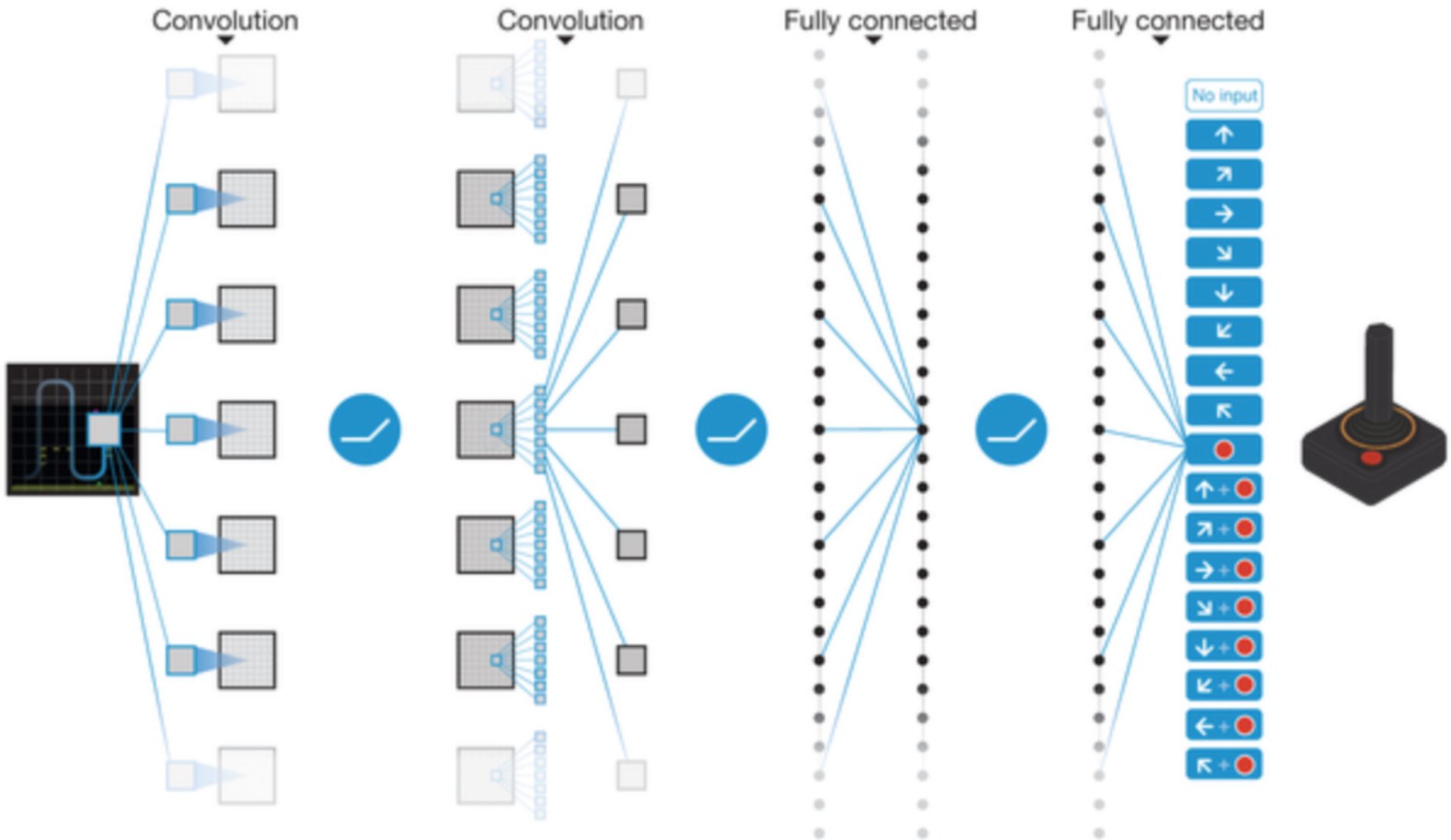
Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou**

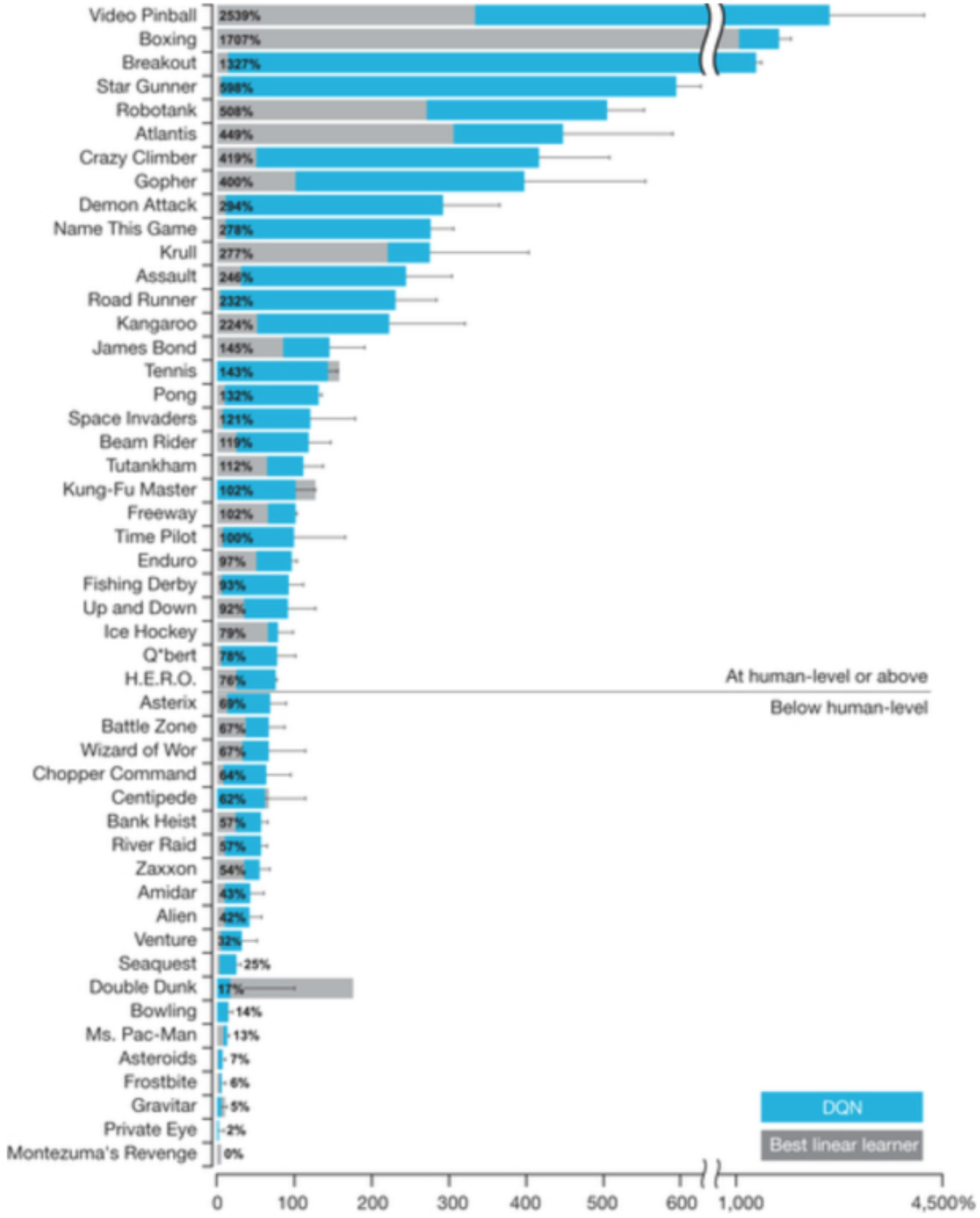
Daan Wierstra **Martin Riedmiller**

DeepMind Technologies

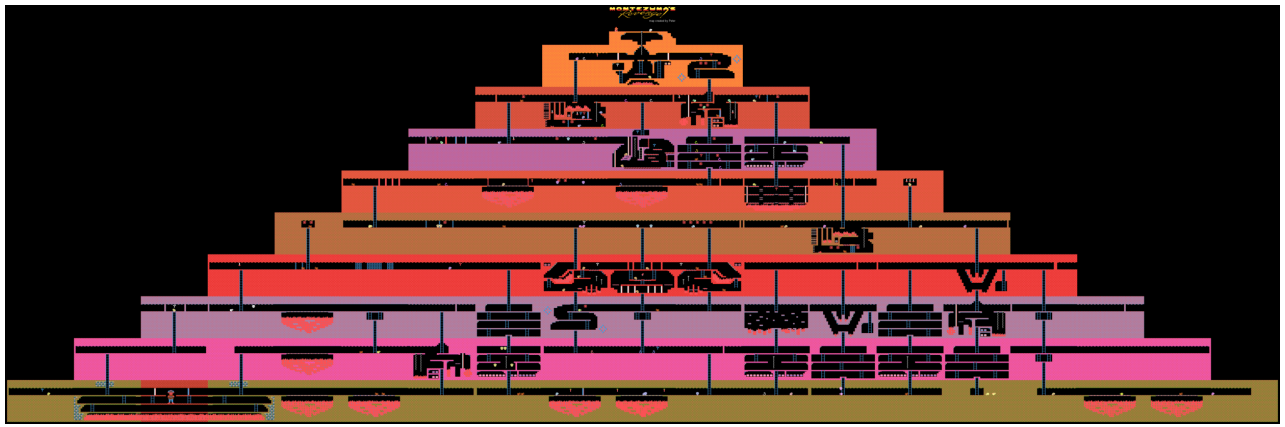






Convolution
Convolution
Fully connected
Fully connected
No input



https://www.youtube.com/watch?v=SuZVyOlgVek



Rainbow

Rainbow

- Double Q Learning

Rainbow

- Double Q Learning
- Prioritized Replay
  (priority proportional to last TD error)

Rainbow

- Double Q Learning
- Prioritized Replay
  (priority proportional to last TD error)
- Dueling networks
  Value network + advantage network
  $Q(s,a) = V(s) + A(s,a)$

Rainbow

- Double Q Learning
- Prioritized Replay
  (priority proportional to last TD error)
- Dueling networks
  Value network + advantage network
  $Q(s,a) = V(s) + A(s,a)$
- Multi-step learning
  $(r_t + \gamma r_{t+1} + \ldots + \gamma^{n-1} r_{t+n-1} + \gamma \max Q_\theta(s_{t+n}, a') - Q_\theta(s_t, a_t))^2$

Rainbow

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- Distributional RL
  predict an entire distribution of values instead of just Q

Rainbow

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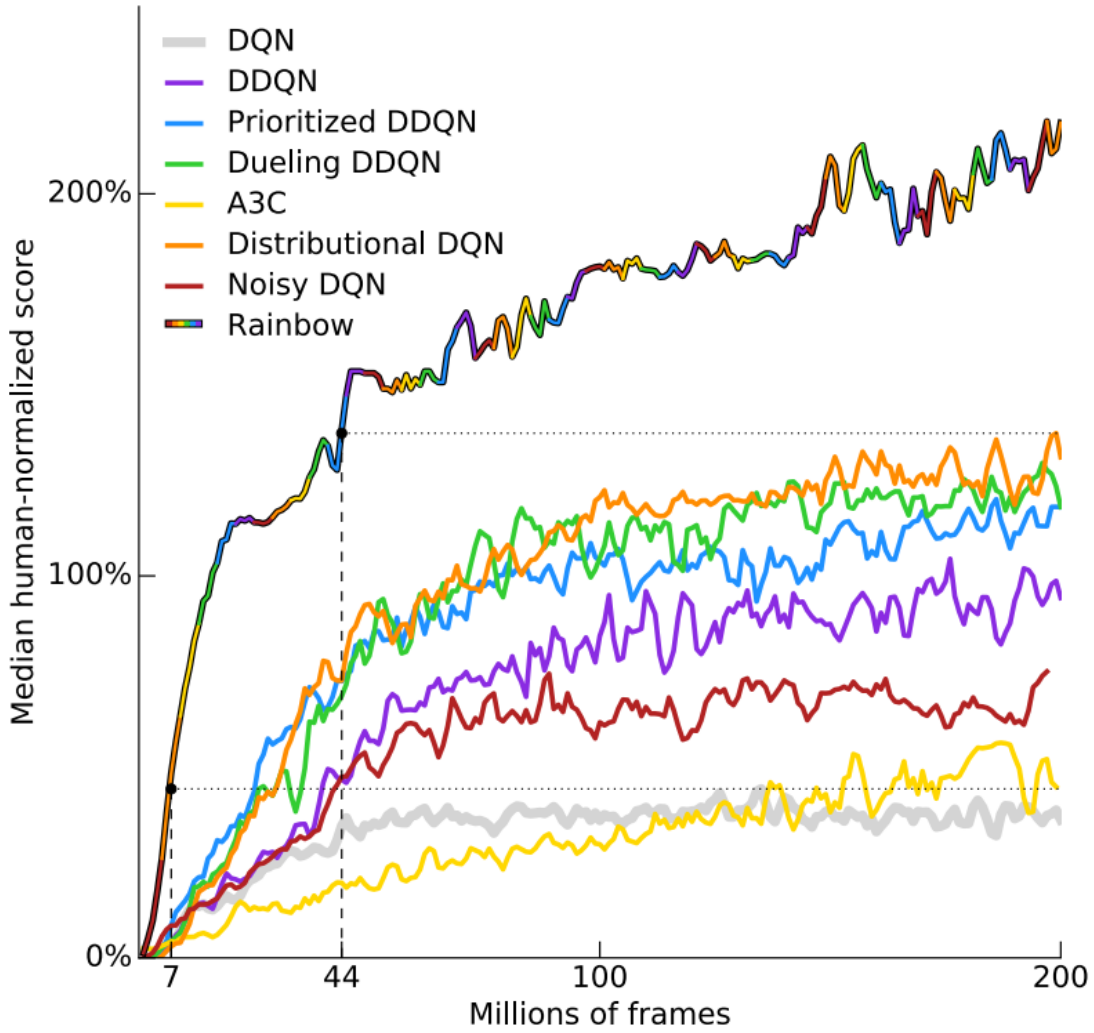
- Distributional RL
  predict an entire distribution of values instead of just Q
- Noisy Nets

Rainbow



- Double Q Learning
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Actual Learning Curves

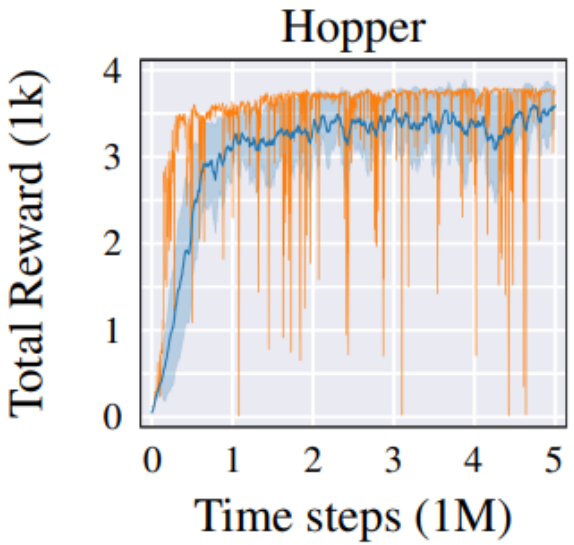

Figure 24: Standard presentation Single seed
The training curve as commonly presented in RL papers and the training curve of a single seed . Both curves are from the TD3 algorithm, trained for 5M time steps. The standard presentation is to evaluate every N_{freq} steps, average scores over N_{episodes} evaluation episodes and N_{seeds} seeds, then to smooth the curve by averaging over a window of N_{window} evaluations. (In our case this corresponds to $N_{\text{freq}} = 5000$, $N_{\text{episodes}} = 10$, $N_{\text{seeds}} = 10$, $N_{\text{window}} = 10$). The learning curve of a single seed has no smoothing over seeds or evaluations ($N_{\text{seeds}} = 1$, $N_{\text{window}} = 1$). By averaging over many seeds and evaluations, the training curves in RL can appear deceptively smooth and stable.

Paper: For SALE: State-Action Representation Learning for Deep Reinforcement Learning

Part II
Improved Policy Gradients

Restricted Gradient Update

Restricted Gradient Update

$$\widehat{\nabla U}(\theta) = \sum_{k=0}^{d} \nabla_\theta \log \pi_\theta(a_k \mid s_k) \gamma^k \left(r_{k,\text{to-go}} - r_{\text{base}}(s_k)\right)$$

.

Restricted Gradient Update

$$\widehat{\nabla U}(\theta) = \sum_{k=0}^{d} \nabla_\theta \log \pi_\theta(a_k \mid s_k) \gamma^k (r_{k,\text{to-go}} - r_{\text{base}}(s_k))$$

$$\theta' = \theta + \alpha \widehat{\nabla U}(\theta)$$

Restricted Gradient Update

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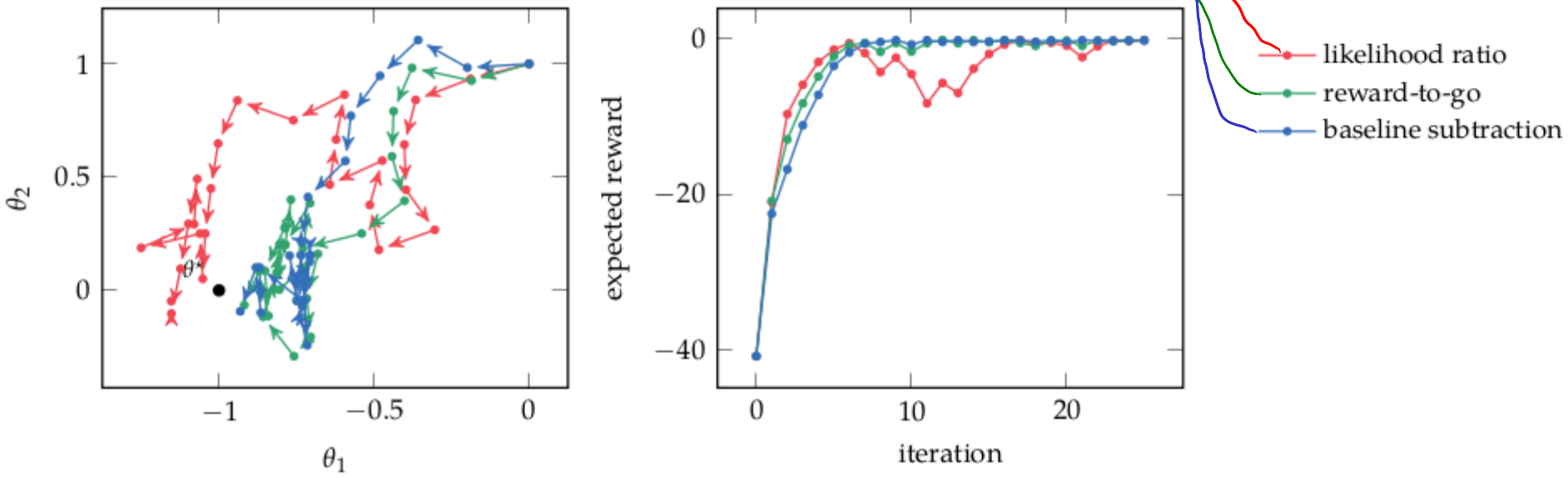

Restricted Gradient Update

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$$\theta' = \theta + \alpha \widehat{\nabla U}(\theta)$$

maximize θ' $\quad U(\theta') \approx U(\theta) + \nabla U(\theta)^\top (\theta' - \theta)$

subject to $\quad g(\theta, \theta') \leq \varepsilon$

$$g(\theta, \theta') = \|\theta - \theta\|_2^2 = \tfrac{1}{2}(\theta' - \theta)^\top (\theta' - \theta)$$

$$\theta' = \theta + u\sqrt{\frac{2\varepsilon}{u^\top u}} = \theta + \sqrt{2\varepsilon}\frac{u}{\|u\|}$$

$$u \equiv \nabla U(\theta)$$

Natural Gradient

$$g(\theta,\theta') \approx D_{KL}\left(p(\tau|\theta) \,||\, p(\tau|\theta')\right) \le \varepsilon$$

$$D_{KL}(p||q) = \int p(x) \log \frac{p(x)}{q(x)} dx$$

$$= -\int p(x) \log \frac{q(x)}{p(x)} dx$$

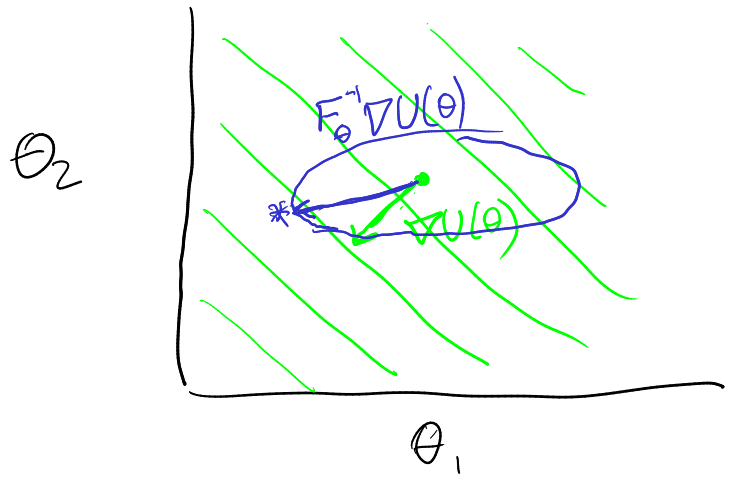
$$\text{maximize}_{\theta'} \; U(\theta') \approx U(\theta) + \nabla U(\theta)^T (\theta' - \theta)$$

$$\text{s.t.} \quad g(\theta,\theta') = \frac{1}{2}(\theta' - \theta)^T F_\theta (\theta' - \theta) \le \varepsilon$$

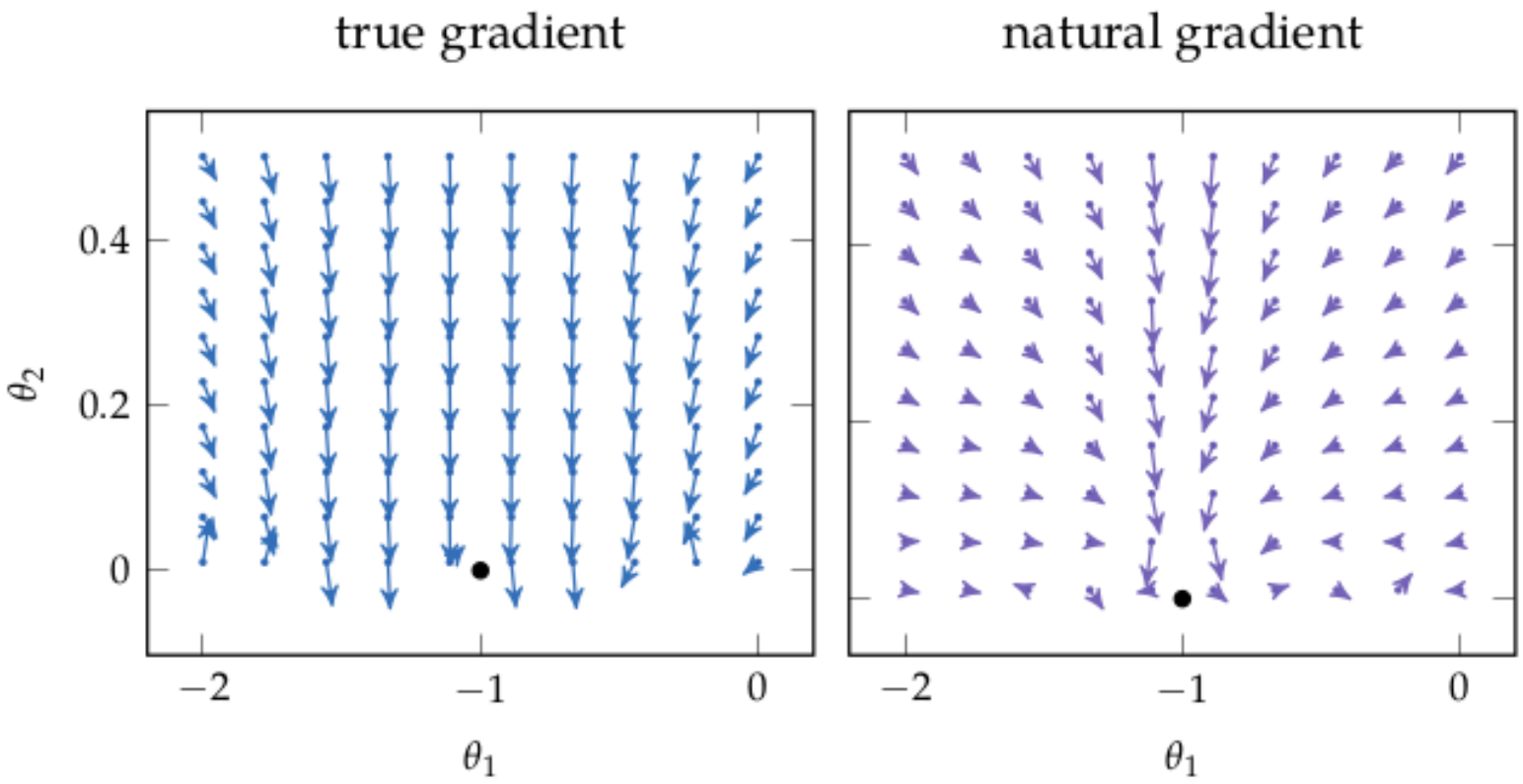
$$F_\theta = \int p(\tau|\theta) \nabla \log(p(\tau|\theta)) \nabla \log p(\tau|\theta)^T d\tau$$

$$= E_\tau\left[\nabla \log p(\tau|\theta) \nabla \log p(\tau|\theta)^T\right]$$

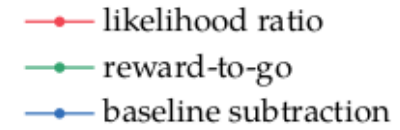
$$\theta' = \theta + u\sqrt{\frac{2\varepsilon}{\nabla U(\theta)^T u}} \qquad u = F_\theta^{-1} \nabla U(\theta)$$



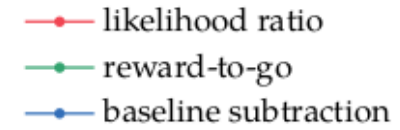
Natural Gradient



TRPO and PPO



TRPO and PPO



TRPO = Trust Region Policy Optimization

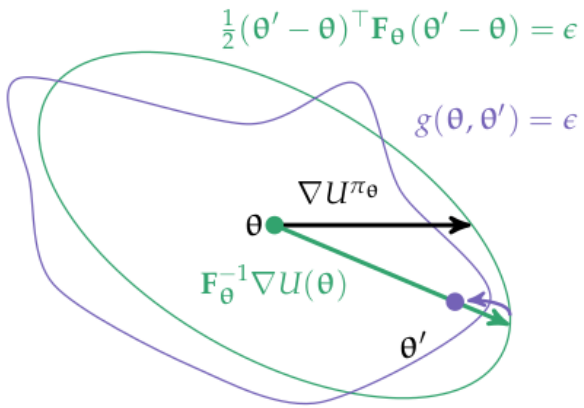
(Natural gradient + line search)

TRPO and PPO

likelihood ratio
reward-to-go
baseline subtraction

TRPO = Trust Region Policy Optimization

(Natural gradient + line search)



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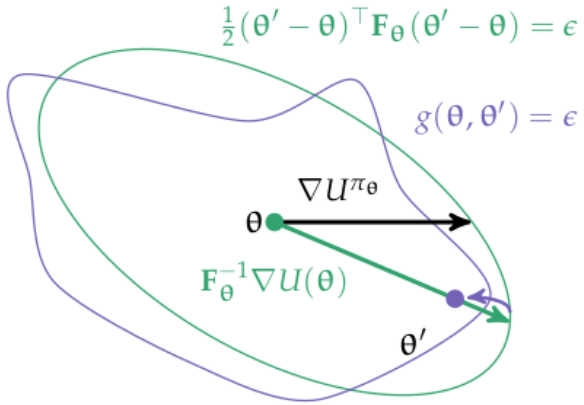
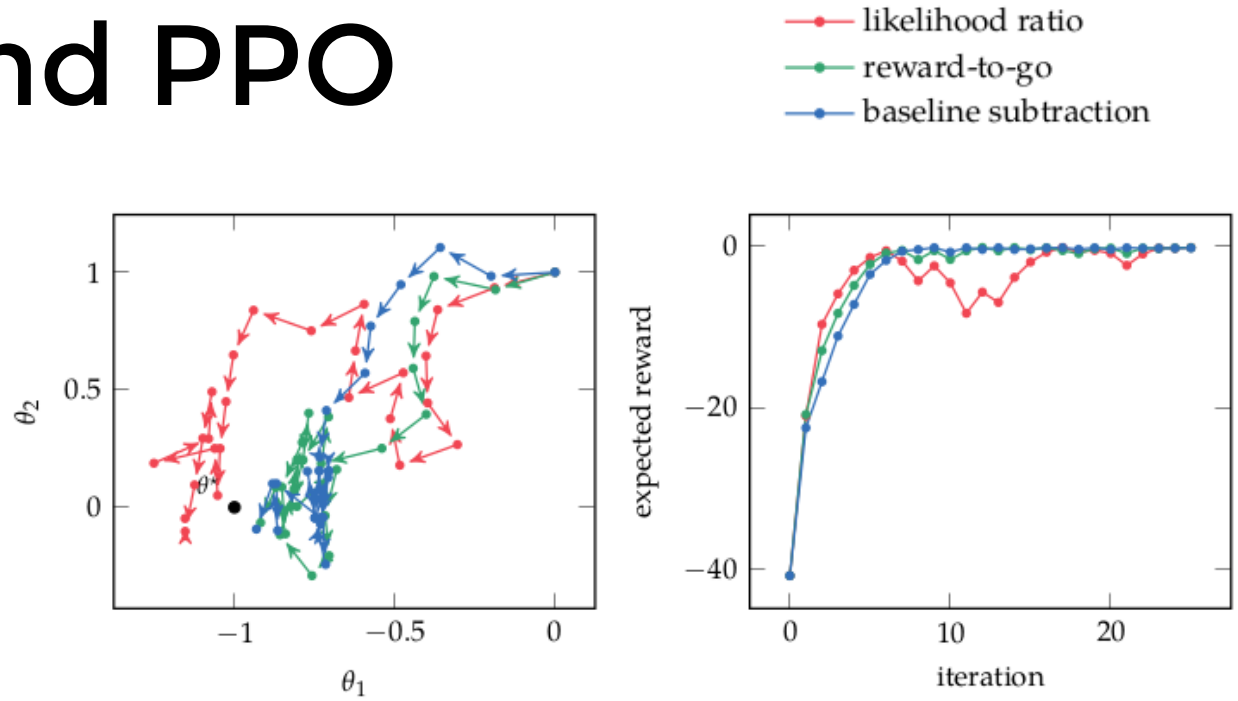
TRPO = Trust Region Policy Optimization

(Natural gradient + line search)





TRPO and PPO

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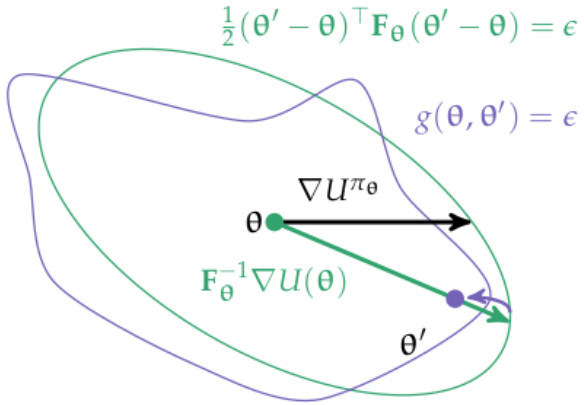

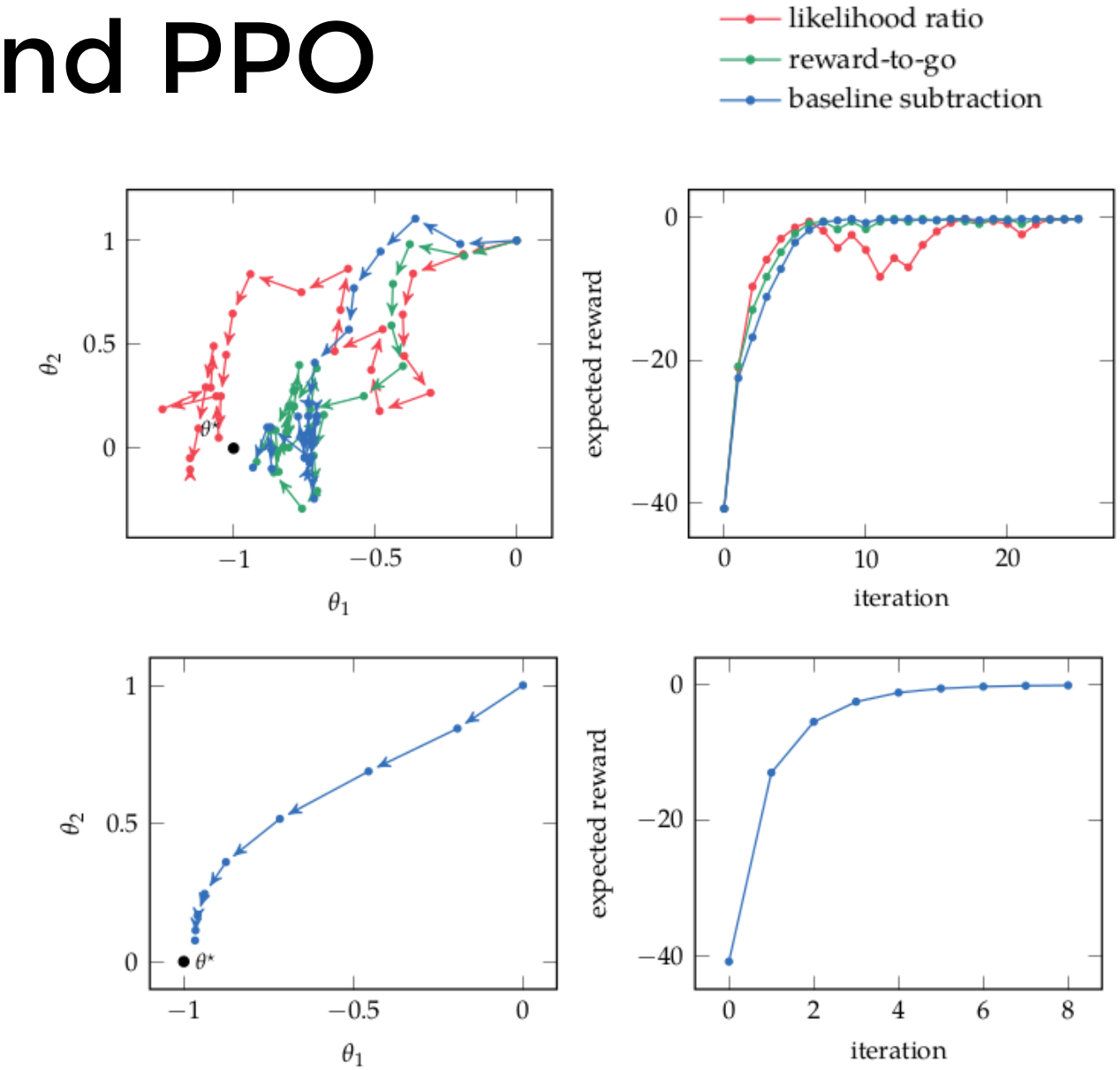

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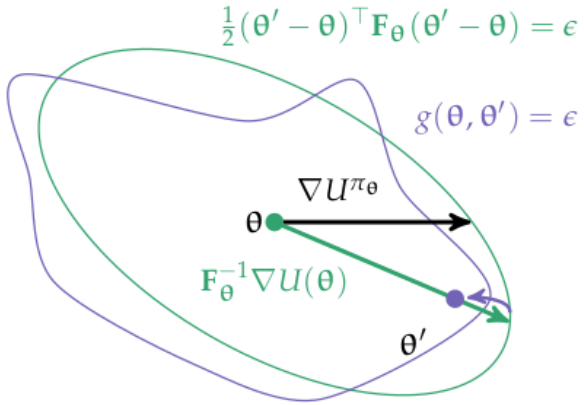
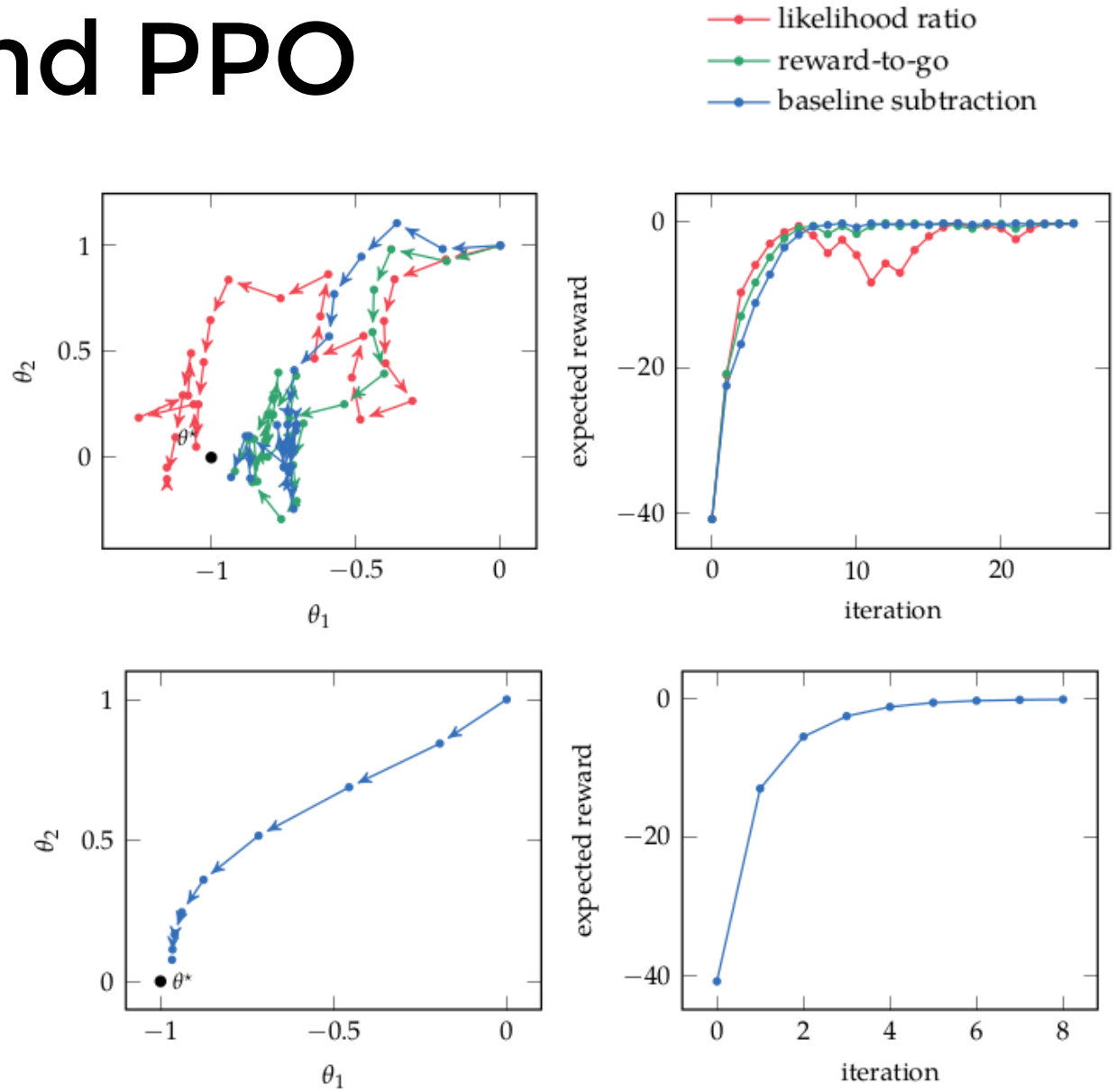


PPO = Proximal Policy Optimization

(Use clamped surrogate objective to remove the need for line search)



TRPO and PPO

TRPO = Trust Region Policy Optimization

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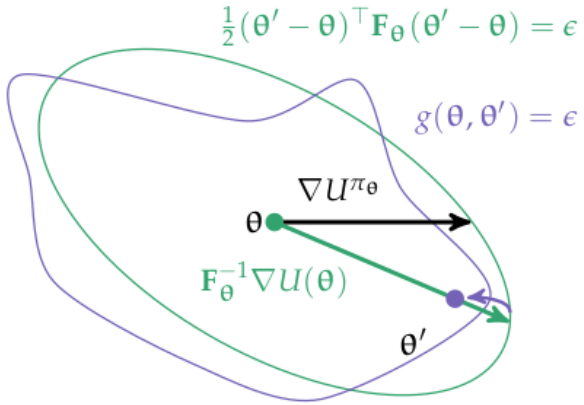

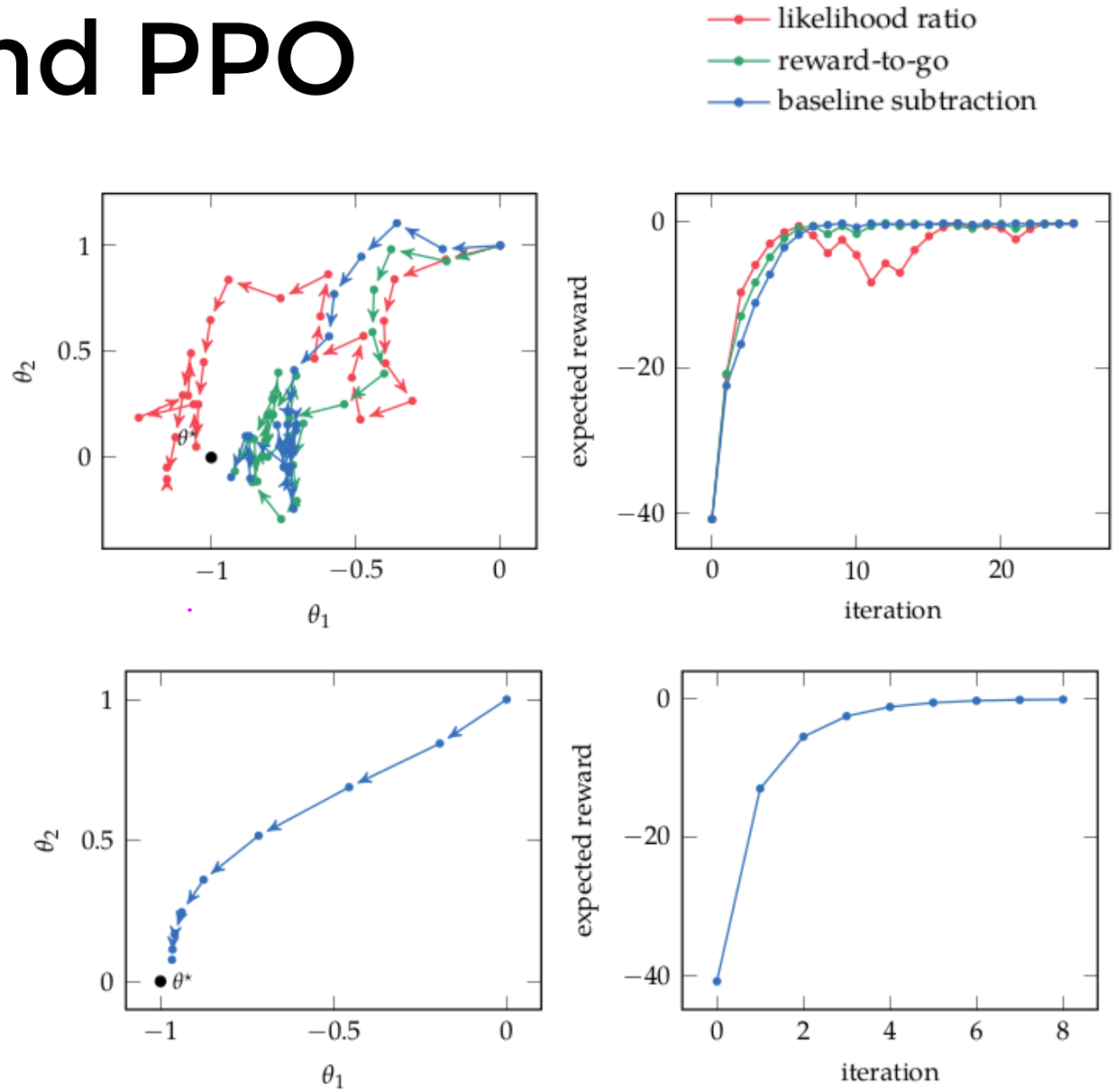

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(Use clamped surrogate objective to remove the need for line search)

https://openai.com/blog/openai-baselines-ppo/

Part III
Actor-Critic

Actor-Critic

Actor-Critic

Which should we learn? A, Q, or V?

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$$\nabla U(\theta) = E_\tau \left[\sum_{k=0}^{d} \nabla_\theta \log \pi_\theta(a_k \mid s_k) \gamma^k (r_k + \gamma V_\phi(s_{k+1}) - V_\phi(s_k)) \right]$$

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temporal difference residual

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$$l(\phi) = E\left[\left(V_\phi(s) - V^{\pi_\theta}(s) \right)^2 \right]$$

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↑ estimate with reward to go from sims

Generalized Advantage Estimation

Recap

Alpha Zero: Actor Critic with MCTS

Alpha Zero: Actor Critic with MCTS

1. Use π_θ and U_ϕ in MCTS

Alpha Zero: Actor Critic with MCTS

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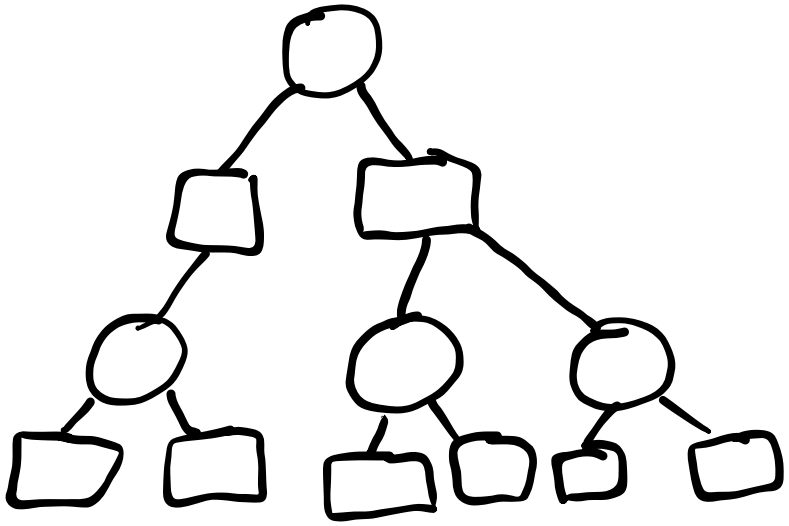

Alpha Zero: Actor Critic with MCTS

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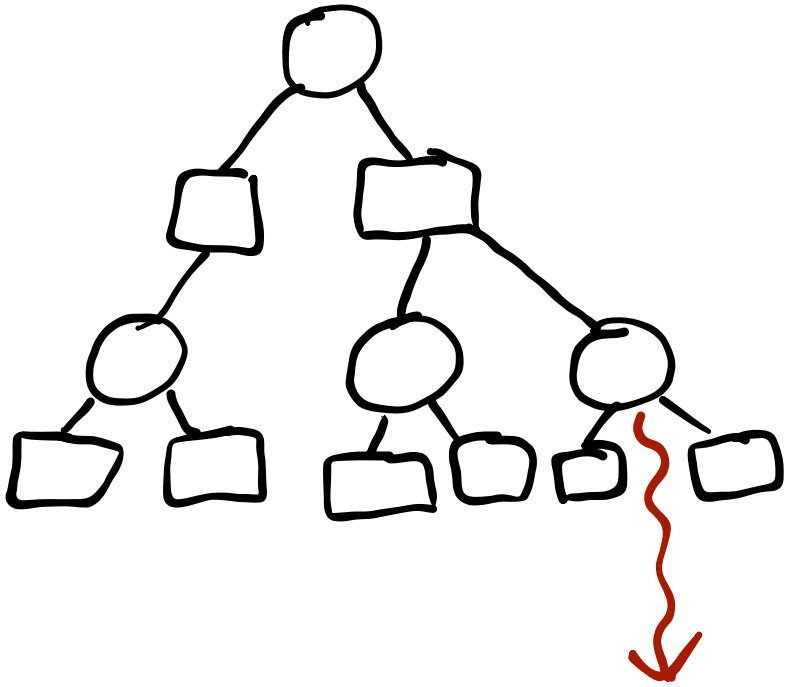

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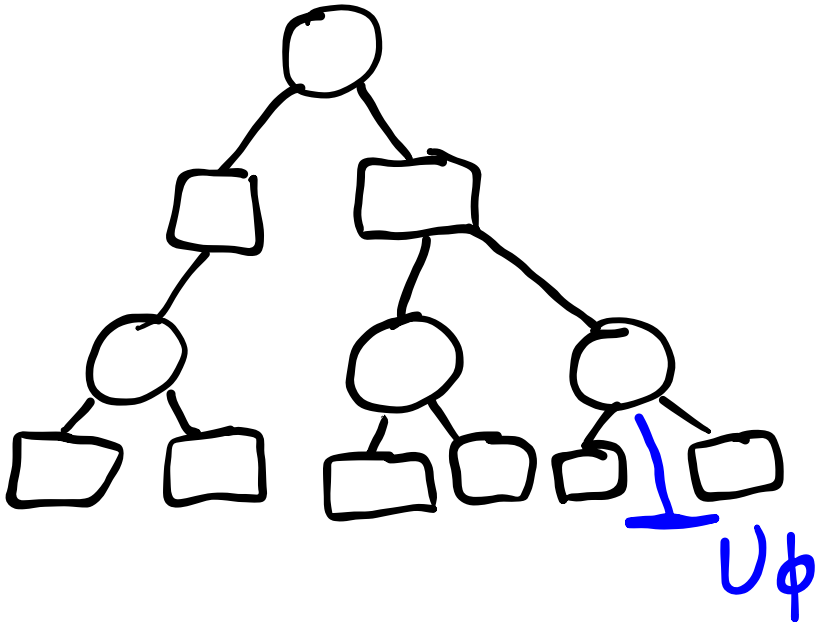

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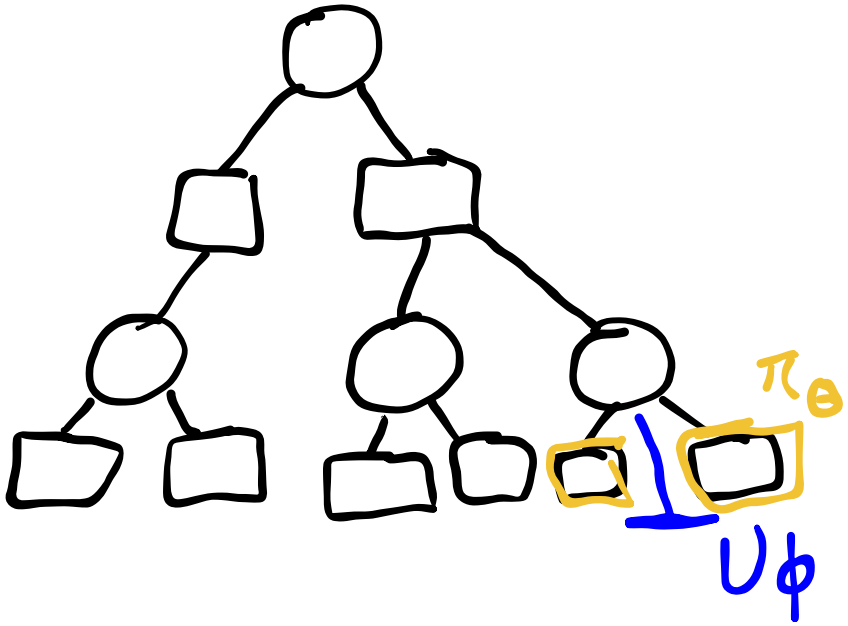
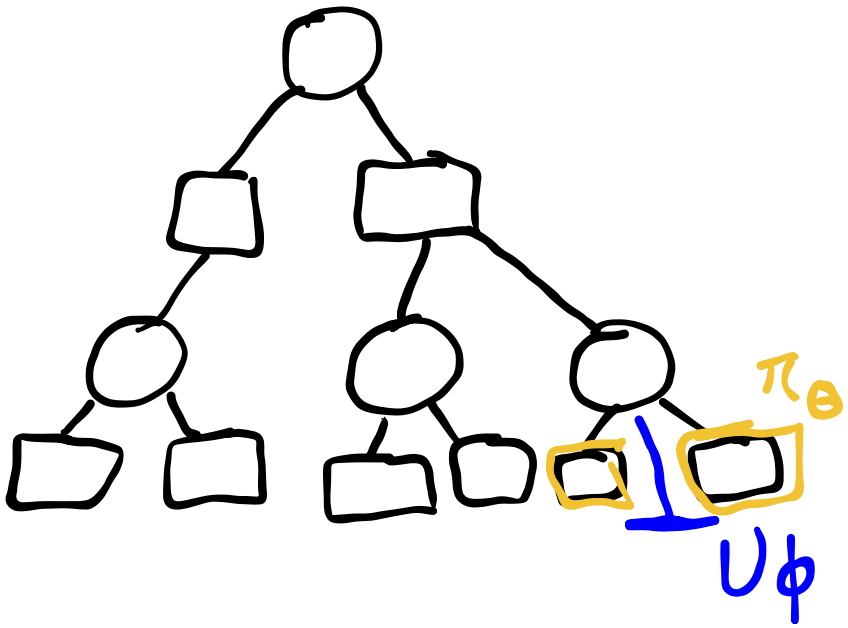


$$a = \arg\max_a Q(s,a) + c\pi_\theta(a \mid s)\frac{\sqrt{N(s)}}{1+N(s,a)}$$

Alpha Zero: Actor Critic with MCTS

1. Use π_θ and U_ϕ in MCTS
2. Learn π_θ and U_ϕ from tree



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Alpha Zero: Actor Critic with MCTS

1. Use π_θ and U_ϕ in MCTS
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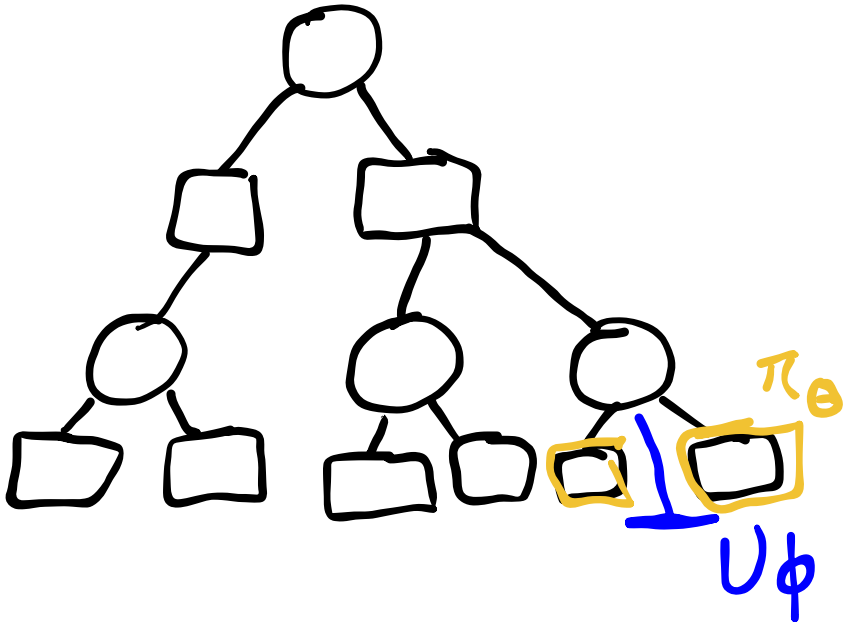
$$\ell(\theta) = -\mathbb{E}_s\left[\sum_a \pi_{\text{MCTS}}(a \mid s) \log \pi_\theta(a \mid s)\right]$$

$$\pi_{\text{MCTS}}(a \mid s) \propto N(s,a)^\eta$$



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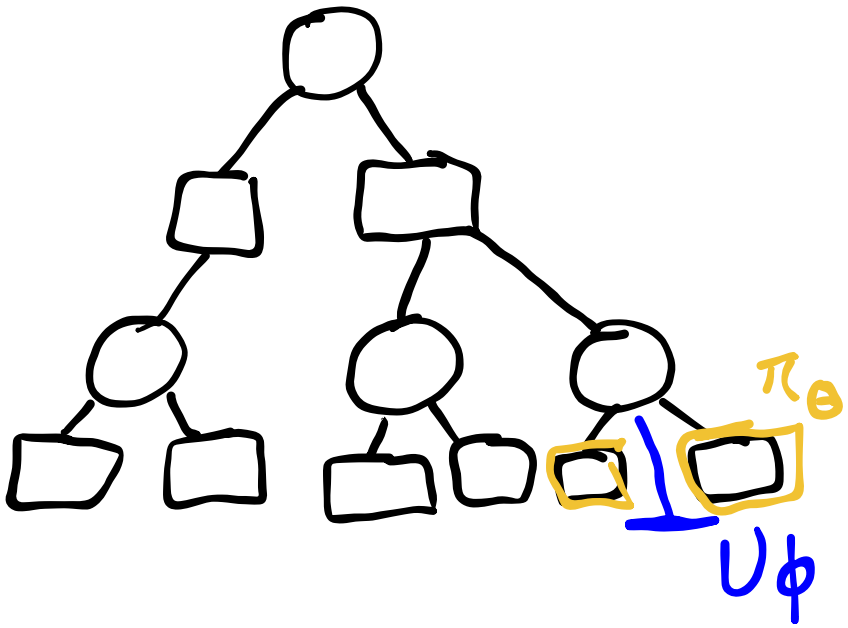

$$\ell(\phi) = \frac{1}{2}\mathbb{E}_s\left[\left(U_\phi(s) - U_{\text{MCTS}}(s)\right)^2\right]$$

$$U_{\text{MCTS}}(s) = \max_a Q(s,a)$$

$$a = \arg\max_a Q(s,a) + c\pi_\theta(a \mid s)\frac{\sqrt{N(s)}}{1+N(s,a)}$$