Actor Critic I

CISC 7404 - Decision Making

Steven Morad

University of Macau

Admin

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How is homework 2?

Admin

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Deadlines

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- 1 Quiz next week

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- Final project proposal due day after quiz

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- Final project proposal due day after quiz
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- Last quiz in ~ 1 month
- Final project ~ 6 weeks

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Quiz next week, topics:

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- Actor critic
  - Basic algorithm
  - Advantages
  - Off-policy gradient
  - Trust regions
  - Will not cover PPO

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Format/difficulty will be similar to last time (3-4 questions, 75 mins)

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Continue lecture after quiz next week? Will you be too tired?

Final Project

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Suggest project and group members by next Friday (28th)

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https://ummoodle.um.edu.mo/pluginfile.php/6900679/mod_resource/content/6/project.pdf

Review

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We previously computed the Monte Carlo policy gradient (REINFORCE)

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Question: Why don't we always use Monte Carlo?

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Answer: Requires collecting an infinite sequence of rewards!

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I want to quickly repeat the relationship between V and Q

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Now that V and Q are clear, back to policy gradient

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Replace MC return with V / Q in policy gradient, call it **actor-critic**

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Critic gives actor score

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$$\theta_{\pi, i+1} = \theta_{\pi, i} + \alpha \cdot \underbrace{V(s_0, \theta_{\pi, i}, \theta_{V, i})}_{\text{Expected return}} \cdot \nabla_{\theta_{\pi, i}} \log \pi(a_0 \mid s_0; \theta_{\pi, i})$$

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Can train policy with single transition s_0, a_0, s_1, r_0, d_0

Advantage Actor Critic

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Question: Any scenarios where reward is always negative?

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Similar results if reward is always positive

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$$\nabla_{\theta_\pi} \mathbb{E}[\mathcal{G}(\boldsymbol{\tau}) \mid s_0; \theta_\pi] = V(s_0, \theta_\pi) \cdot \nabla_{\theta_\pi} \log \pi(a_0 \mid s_0; \theta_\pi)$$

Question: Any scenarios where reward is always negative?

Answer: Distance to goal, $\mathcal{R}(s_{t+1}) = -(s_{t+1} - s_g)^2$

Question: What happens to return if reward is always negative?

Answer: Return always negative

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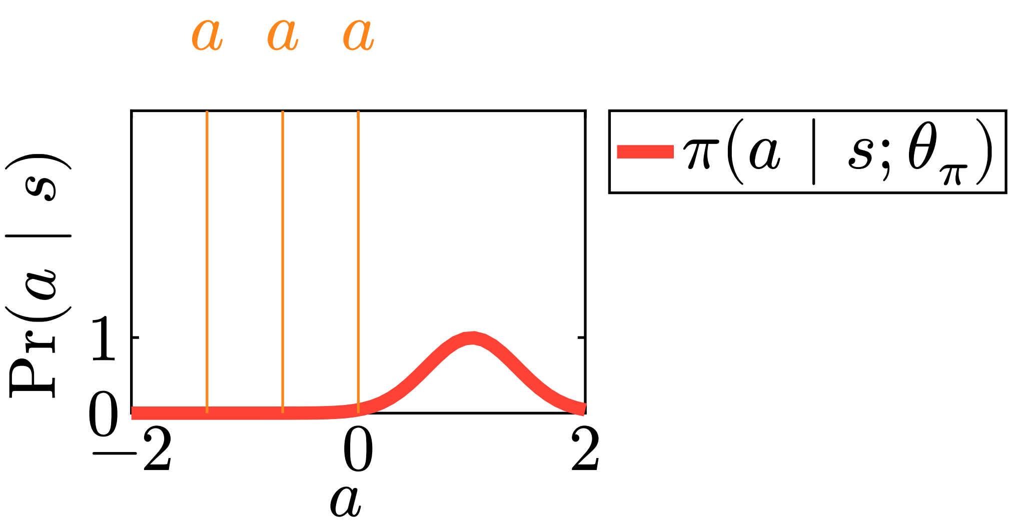

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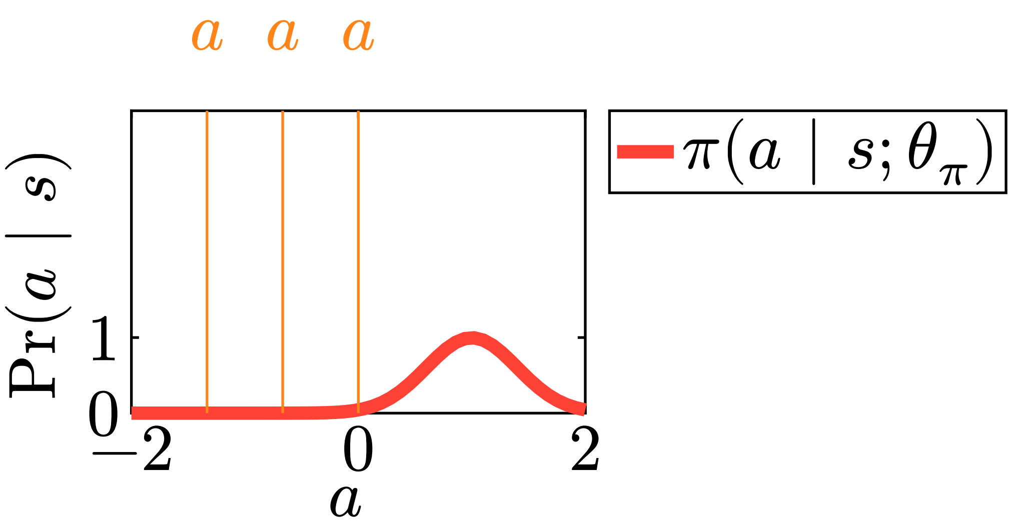

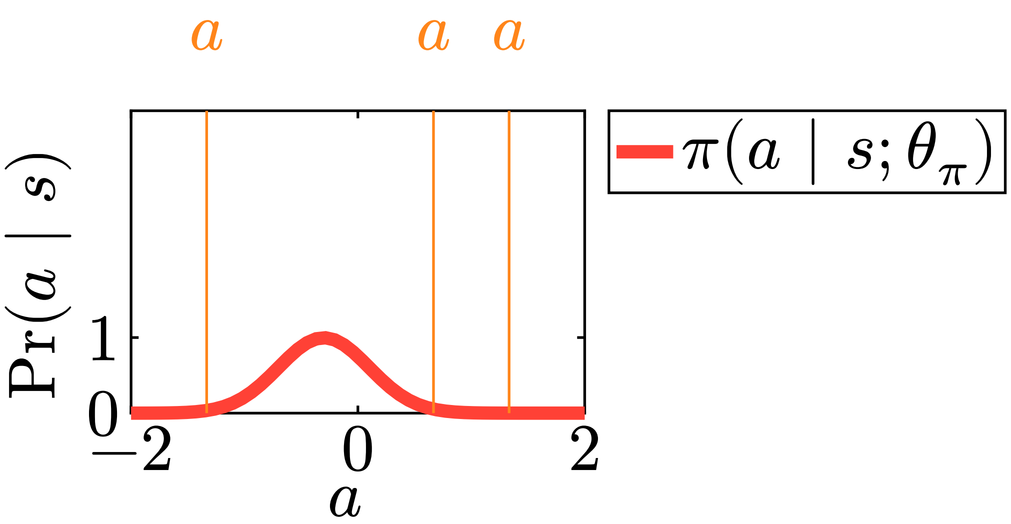

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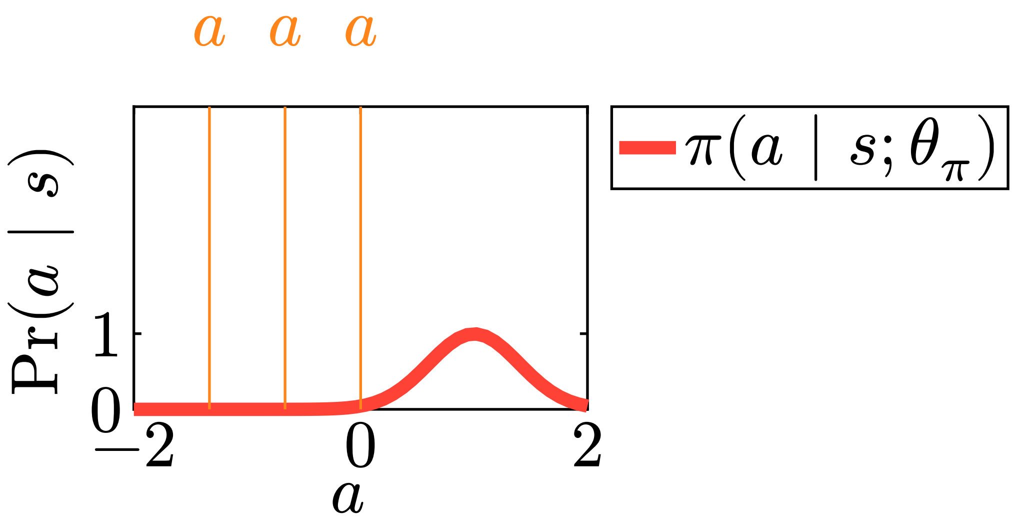
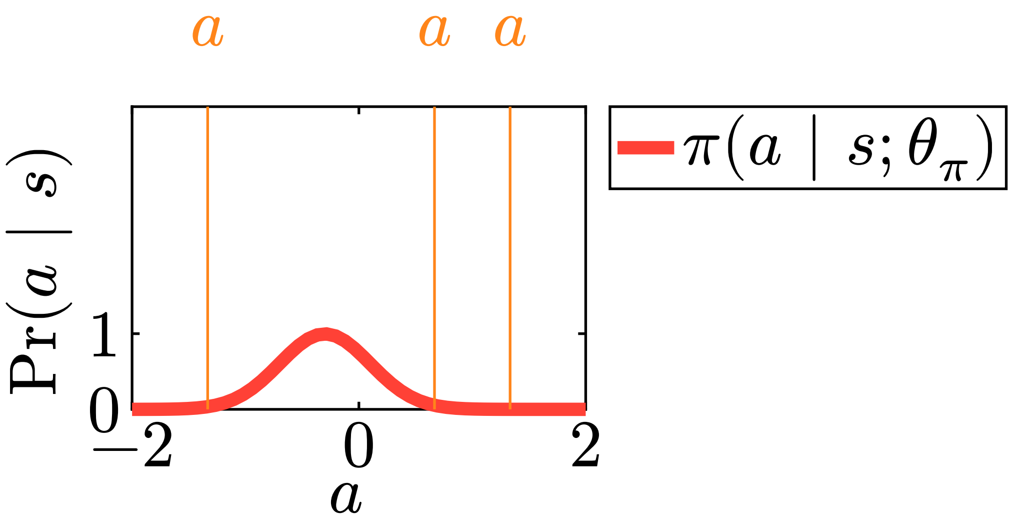
https://media0.giphy.com/media/v1.Y2lkPTc5MGI3NjExeGdqZm56NDgzcmY2Ym95dG13Ynczdm9lbDY0cGpjczdtMHBmcnJmMSZlcD12MV9pbnRlcm5hbF9naWZfYnlfaWQmY3Q9Zw/MVUyVpyjakkRW/giphy.gif

Advantage Actor Critic





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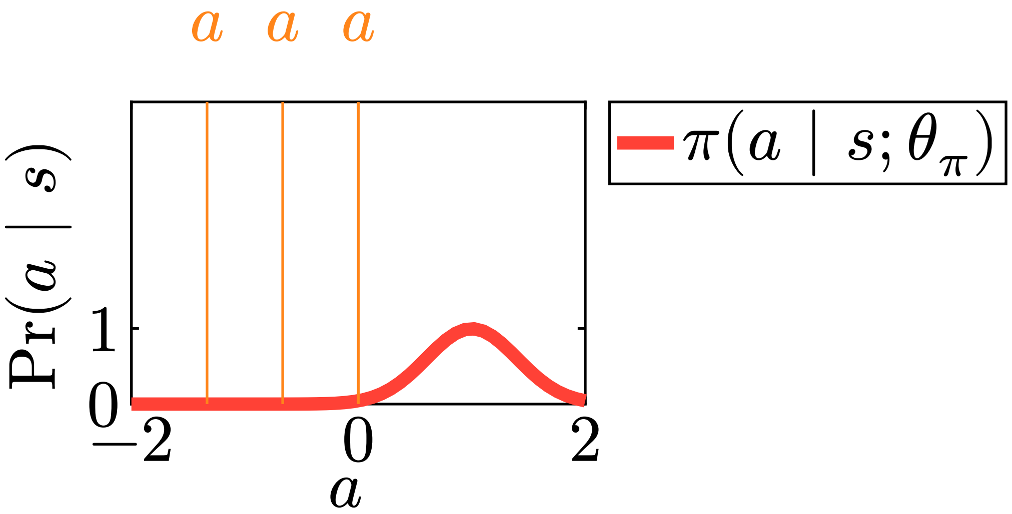

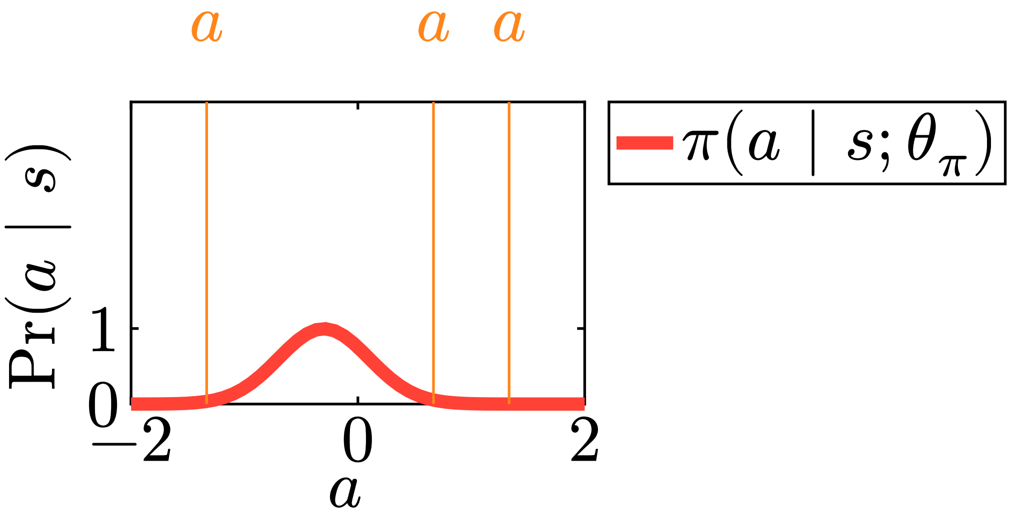

Policy keeps oscillating, can destabilize learning

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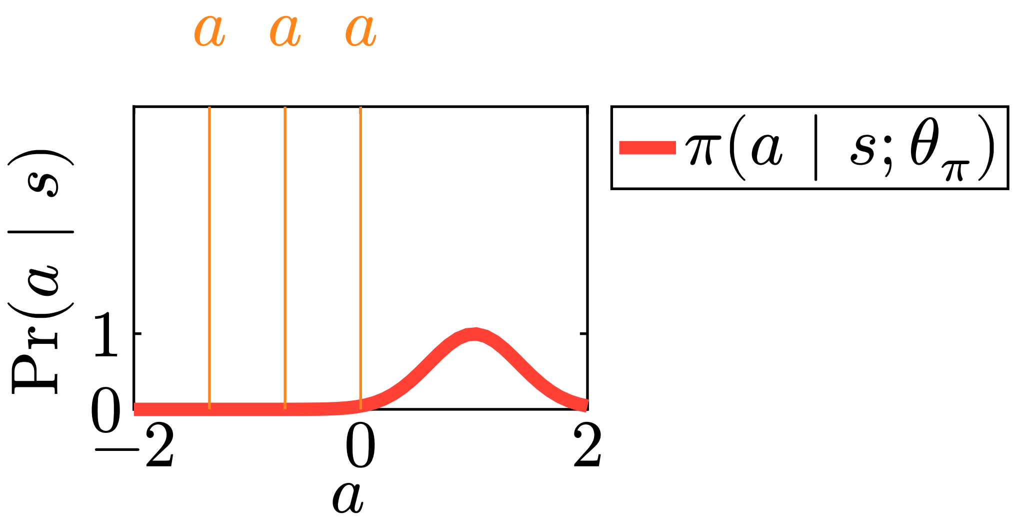

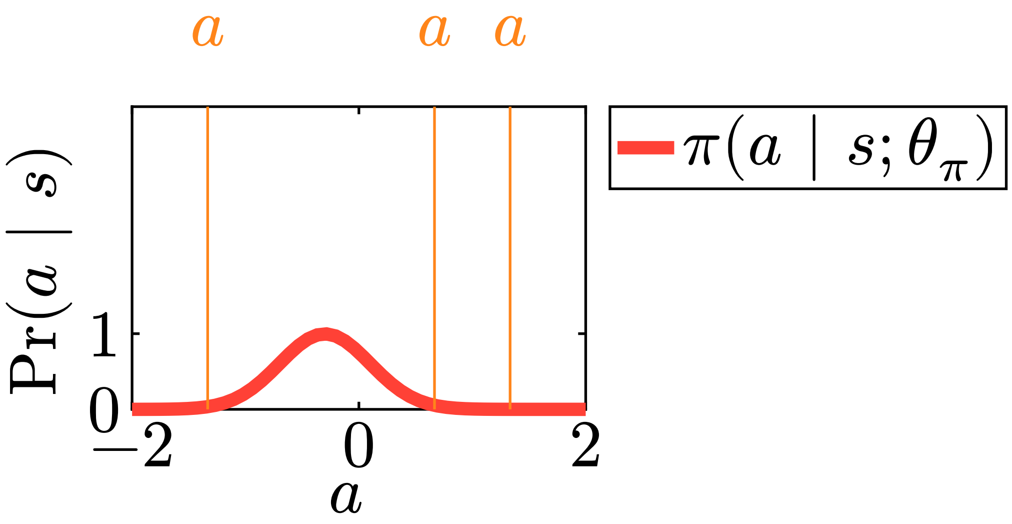

Policy keeps oscillating, can destabilize learning

Question: If we take 8 actions, will this fix it?

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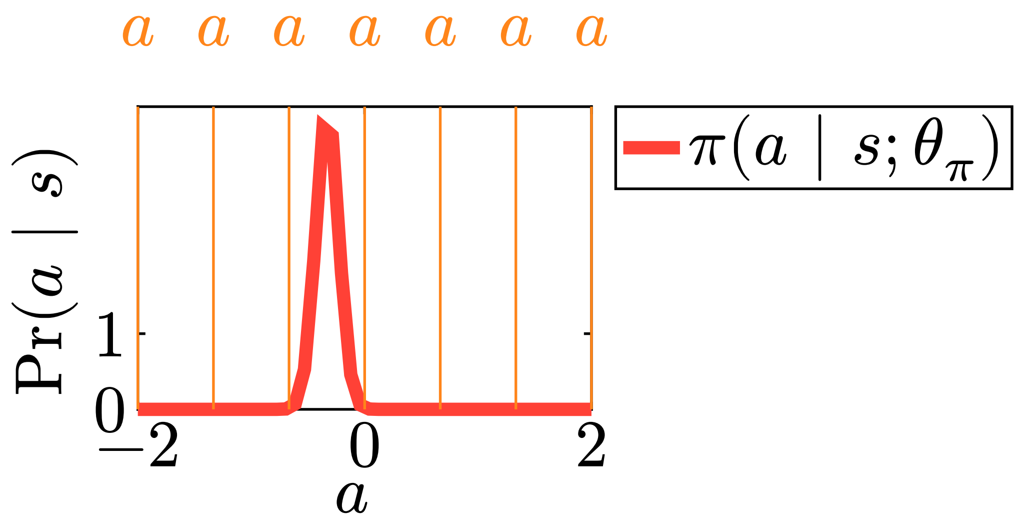

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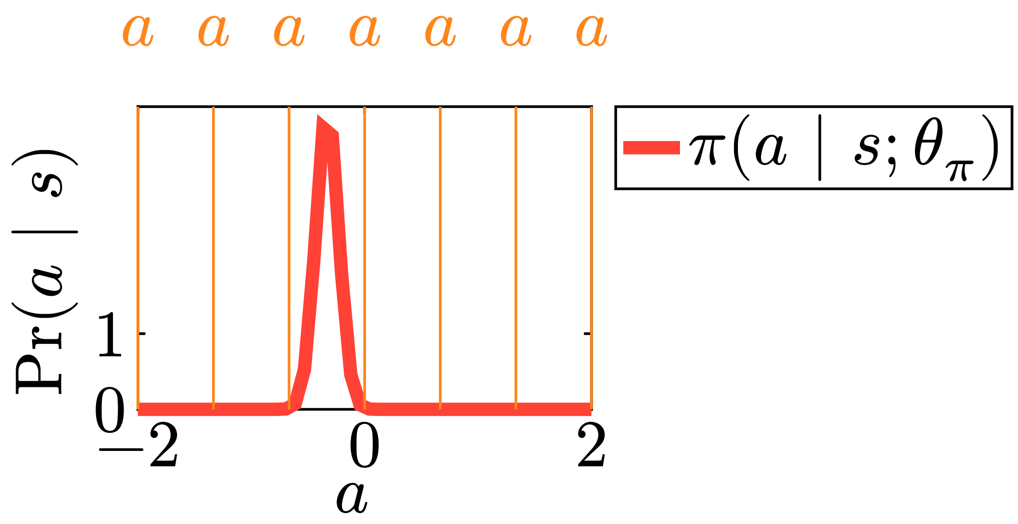

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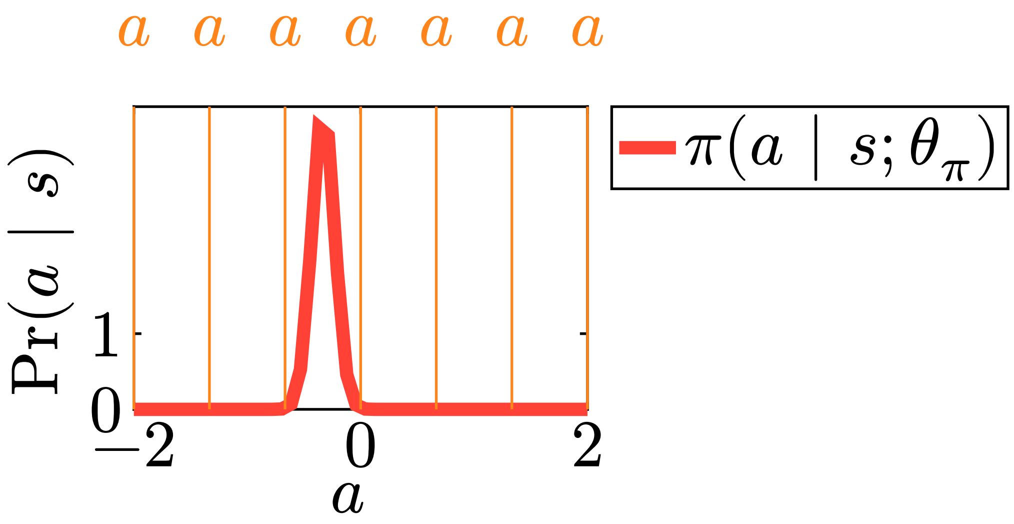

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Hint: Think about the mean of the return

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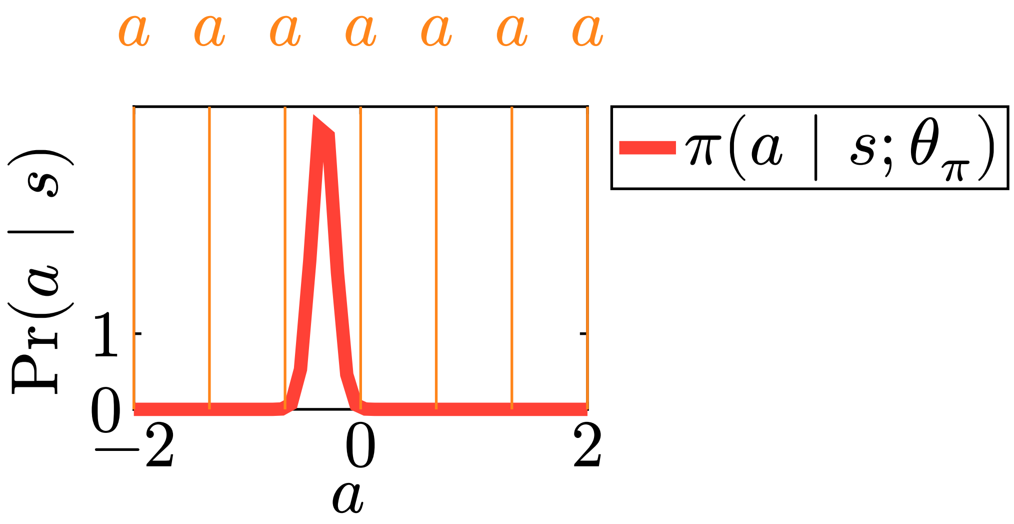

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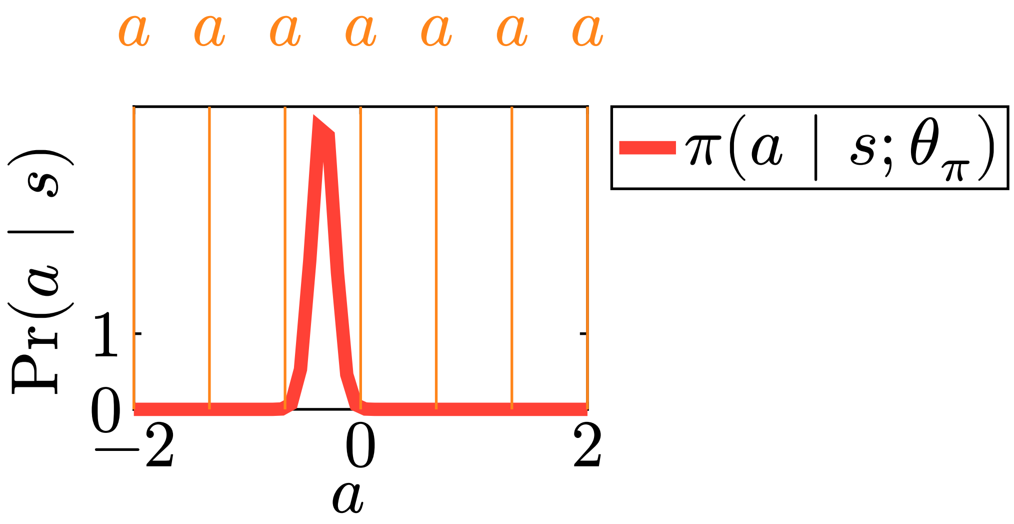

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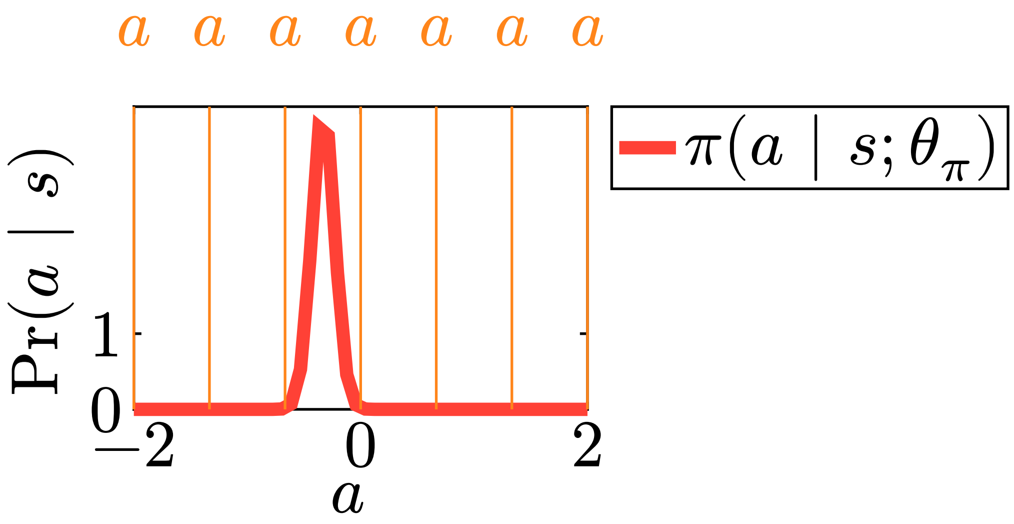

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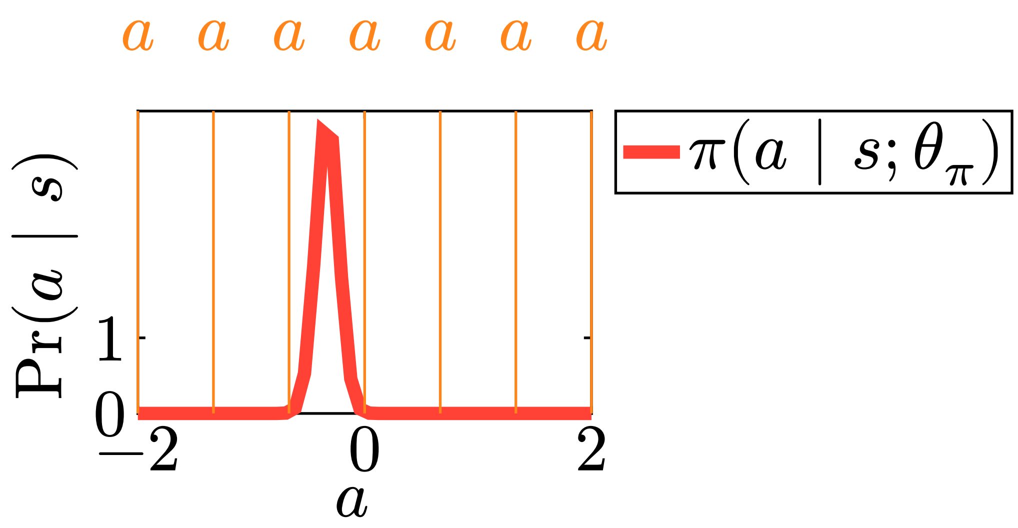

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What if we:

- Almost never update policy
- Update the policy **only** if action is better/worse than expected

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If action a_0 produced expected return, do nothing $\theta_{\pi,i+1} = \theta_{\pi,i} + 0$

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The policy will not oscillate – policy only changes if it improves return

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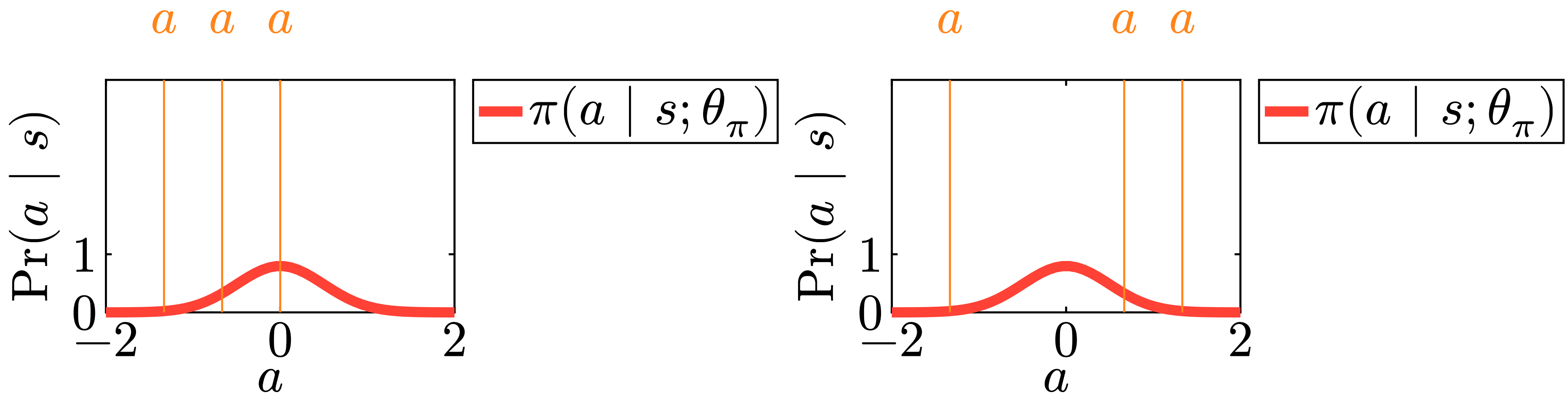

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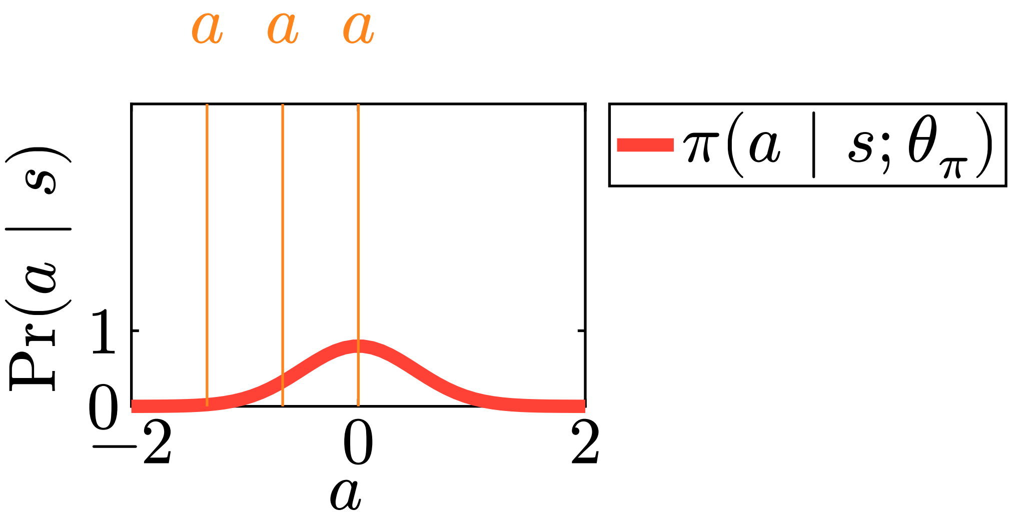

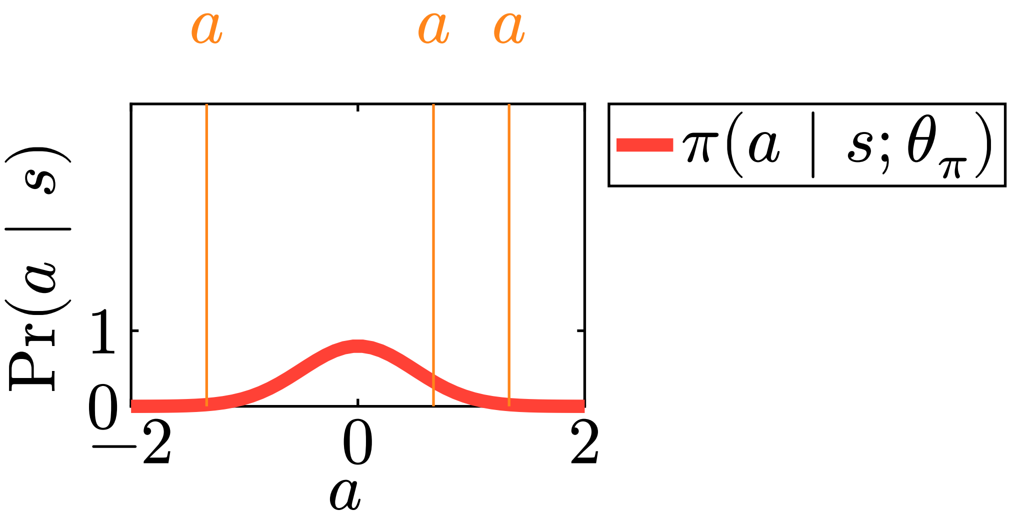

Results in more stable training and faster convergence

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Definition: The advantage A determines the relative advantage/ disadvantage of taking an action a_0 in state s_0 for a policy θ_π

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Better than expected: $|A| > 0$

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Better than expected: $|A| > 0$, worse than expected $|A| < 0$

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$$\theta_{V, i+1} =$$

$$\arg\min_{\theta_{V, i}} \underbrace{\left(V(s_0, \theta_{\pi, i}, \theta_{V, i}) - \left(\hat{\mathbb{E}}[\mathcal{R}(s_1) \mid s_0; \theta_\pi] + \neg d \gamma V(s_0, \theta_{\pi, i}, \theta_{V, i})\right)\right)^2}_{\text{TD error}}$$

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Question: What do we need to make policy gradient off-policy?

Off-Policy Gradient

$$\nabla_{\theta_\pi} \mathbb{E}[\mathcal{G}(\boldsymbol{\tau}) \mid s_0; \theta_\pi] = \mathbb{E}[\mathcal{G}(\boldsymbol{\tau}) \mid s_0; \theta_\pi] \cdot \nabla_{\theta_\pi} \log \pi(a_0 \mid s_0; \theta_\pi)$$

Question: Is policy gradient off-policy or on-policy?

Answer: On-policy, expected return depends on θ_π

Question: Why do we care about being off-policy?

Answer: Algorithm can reuse data, much more efficient

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Question: Any statistics students know how to do this?

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Reward following θ_β

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Off-Policy Gradient

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Left with expected reward following θ_π

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$$\prod_{t=0}^{\infty} \frac{\pi(a_t \mid s_t; \theta_\pi)}{\pi\left(a_t \mid s_t; \theta_\beta\right)} \rightarrow 0, \infty$$

Only works if $\pi(a_t \mid s_t; \theta_\pi) \approx \pi\left(a_t \mid s_t; \theta_\beta\right) \quad \forall t$

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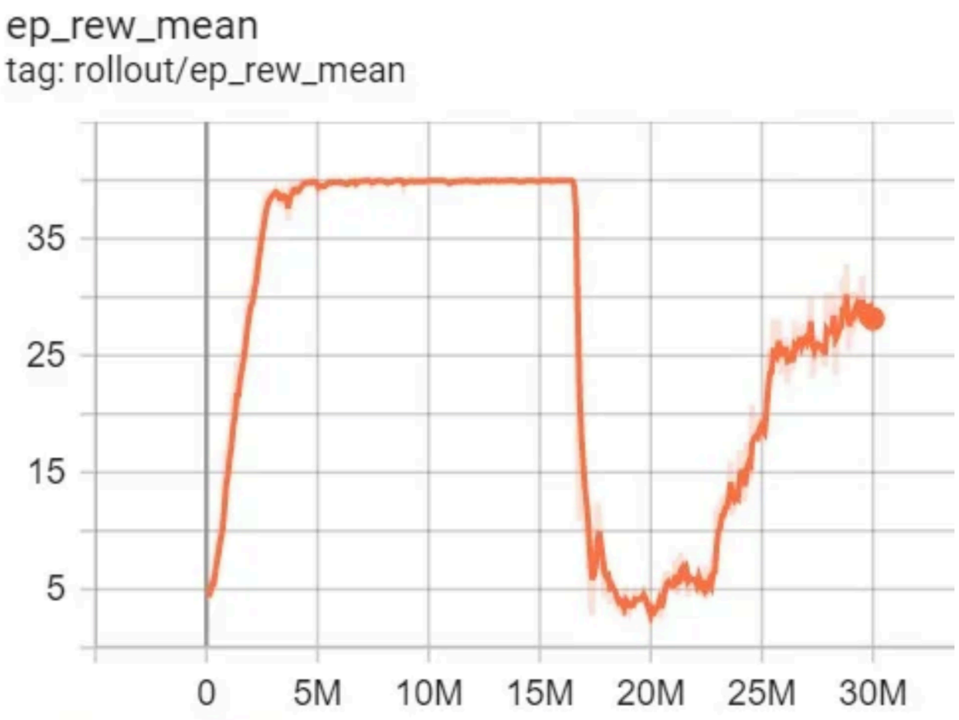

Trust Regions

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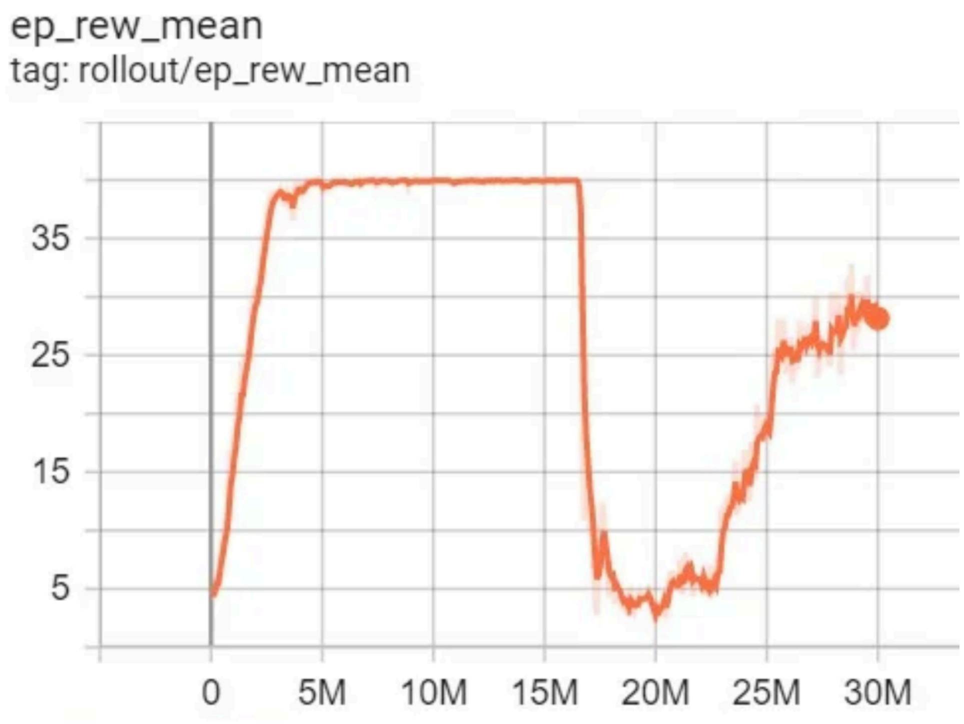
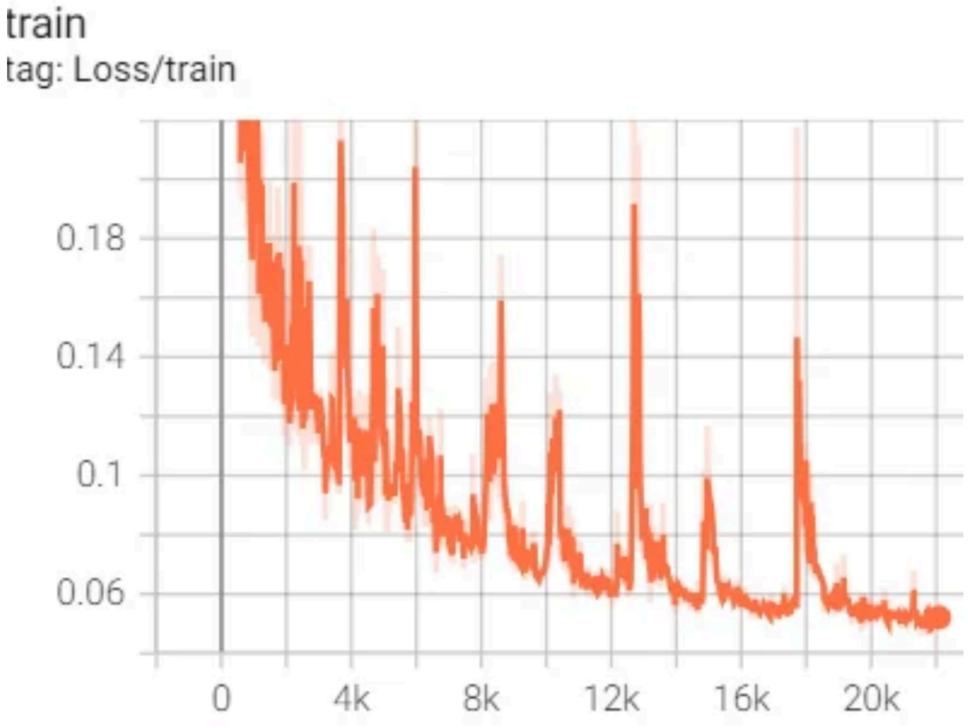


Question: Any idea why?

Trust Regions



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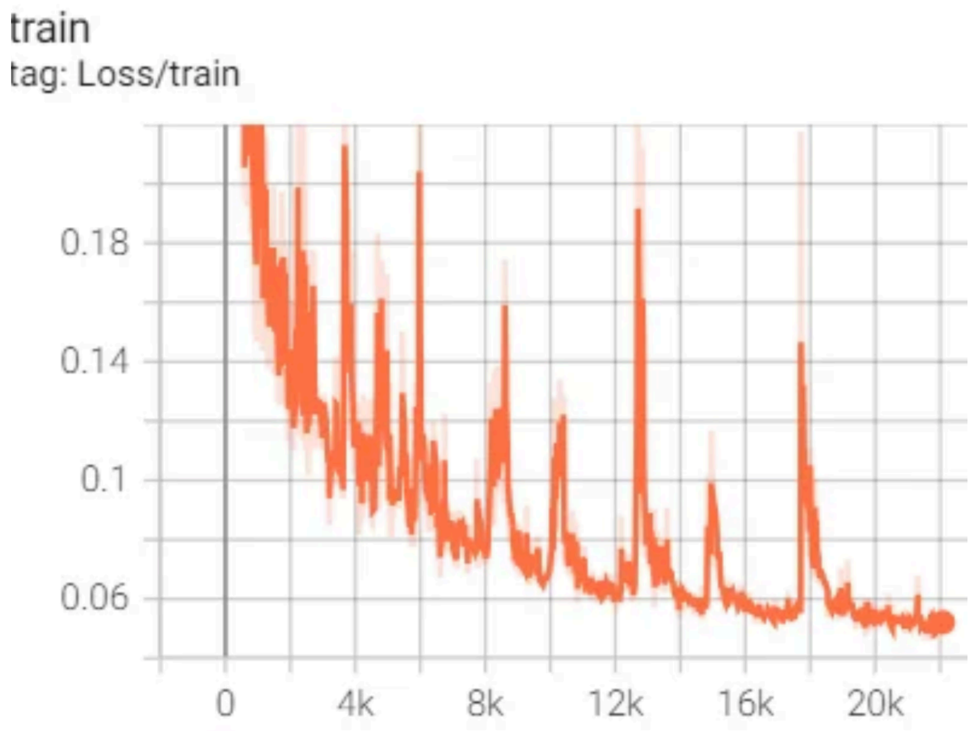
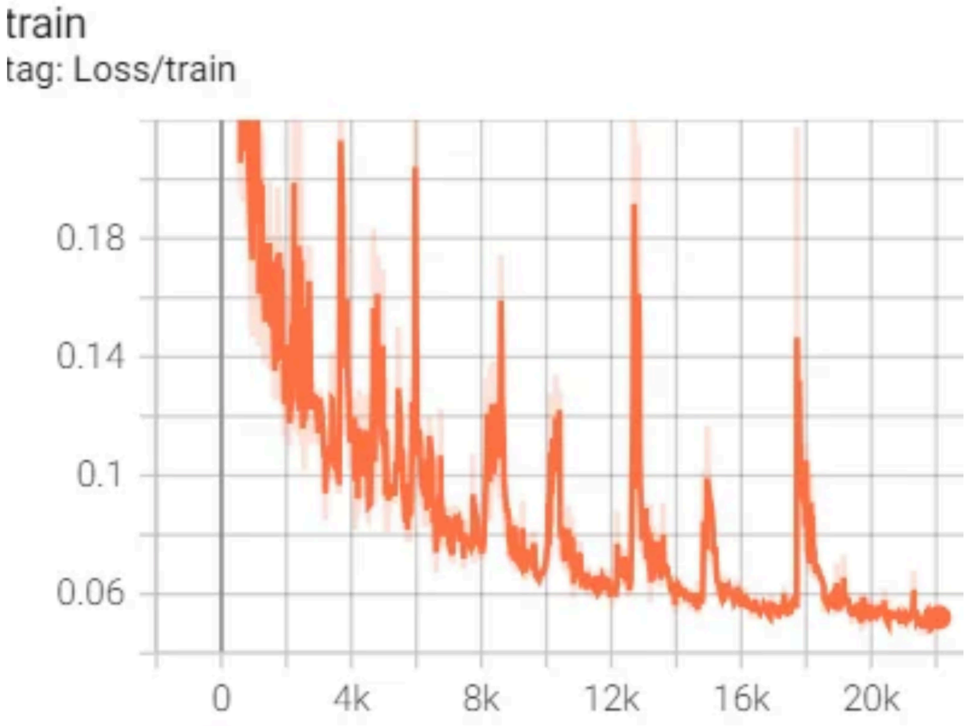


See it in supervised learning too

Trust Regions



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Sometimes, the gradient is inaccurate producing a bad update

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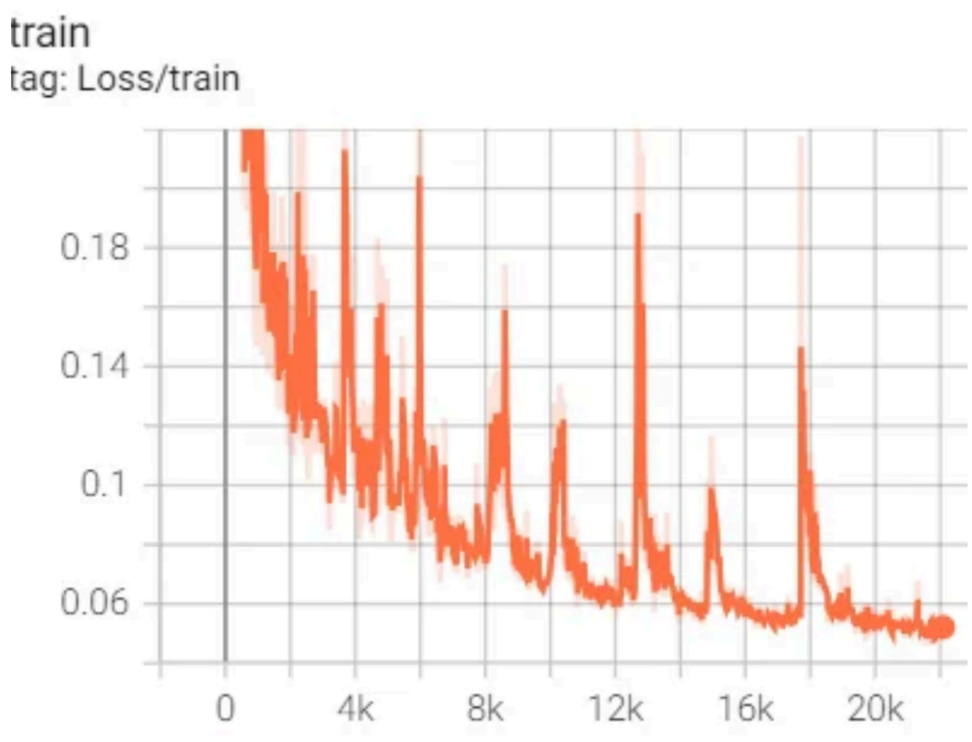

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In supervised learning, the network can easily recover

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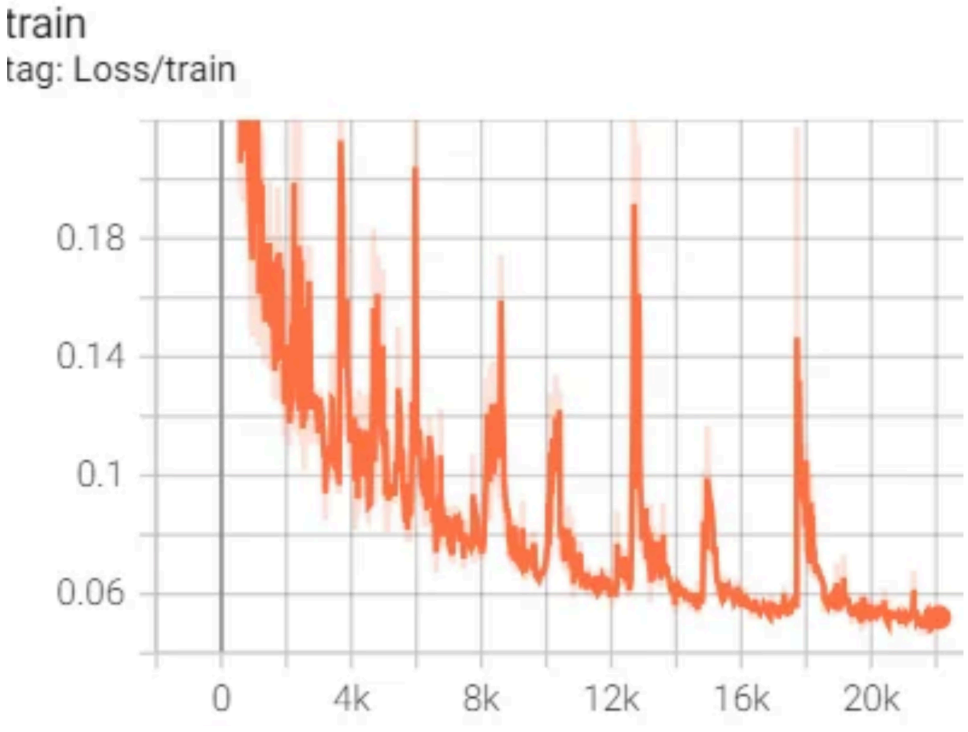

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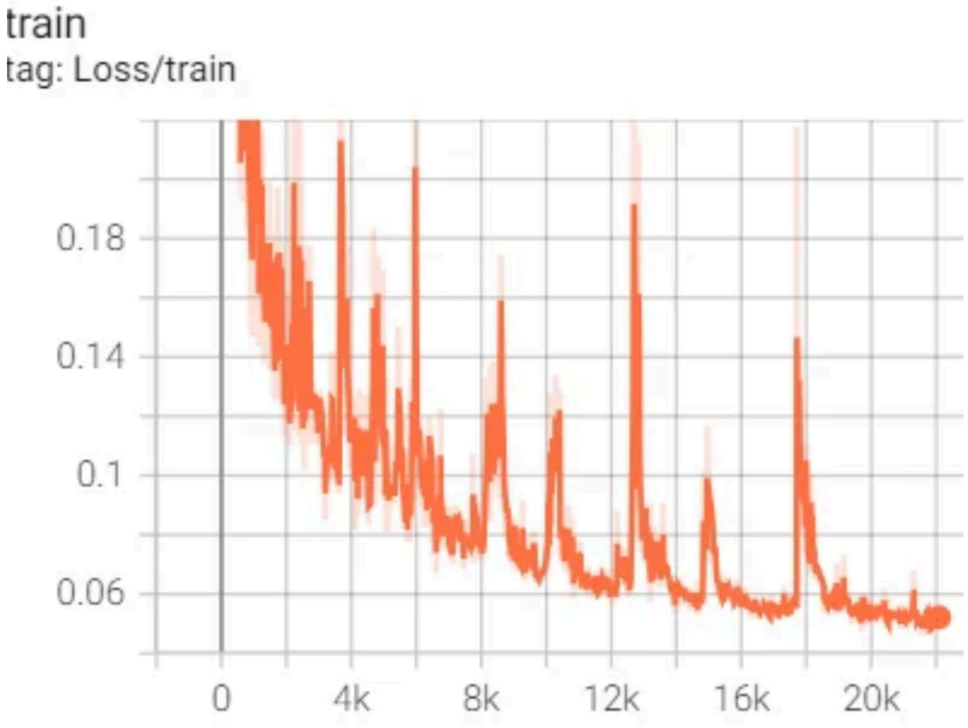

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Question: Why is it harder to recover with policy gradient?

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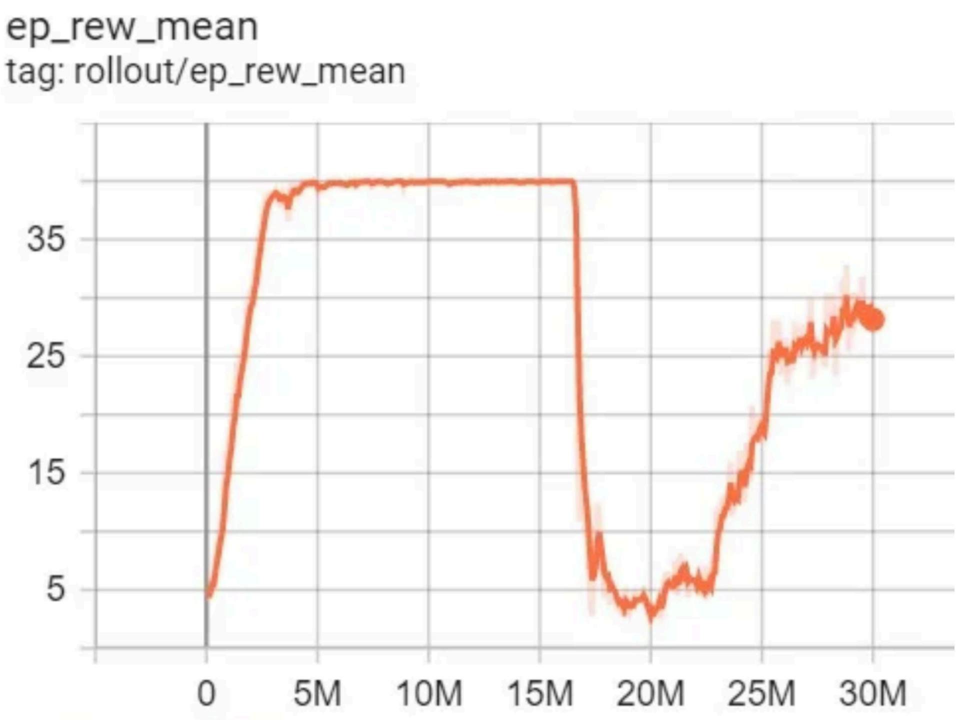

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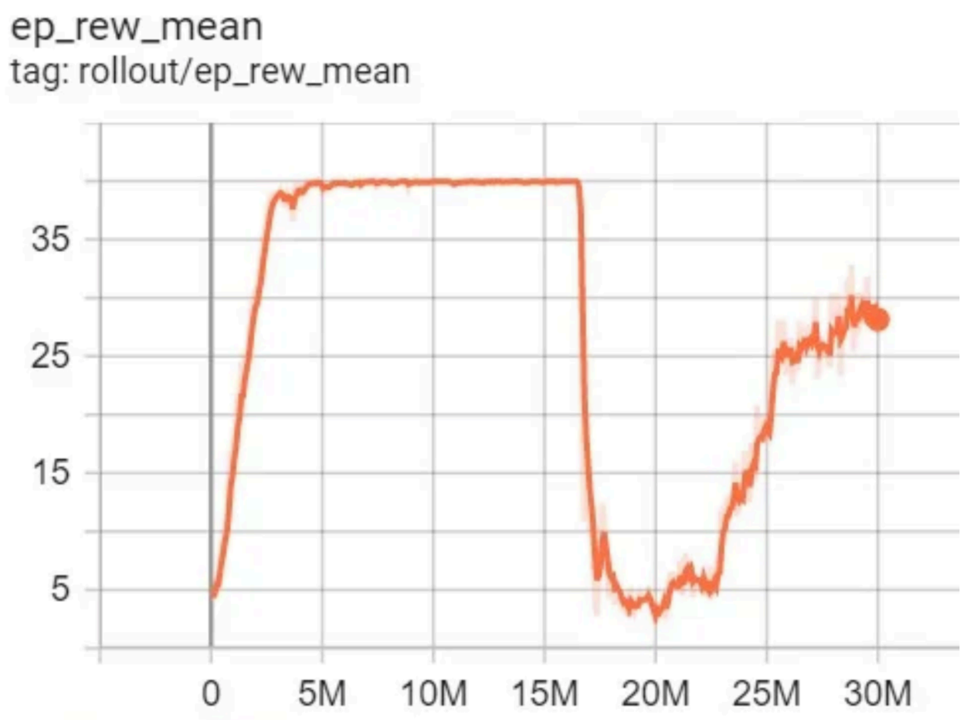

Our policy provides the training data $a \sim \pi(\cdot \mid s; \theta_\pi)$

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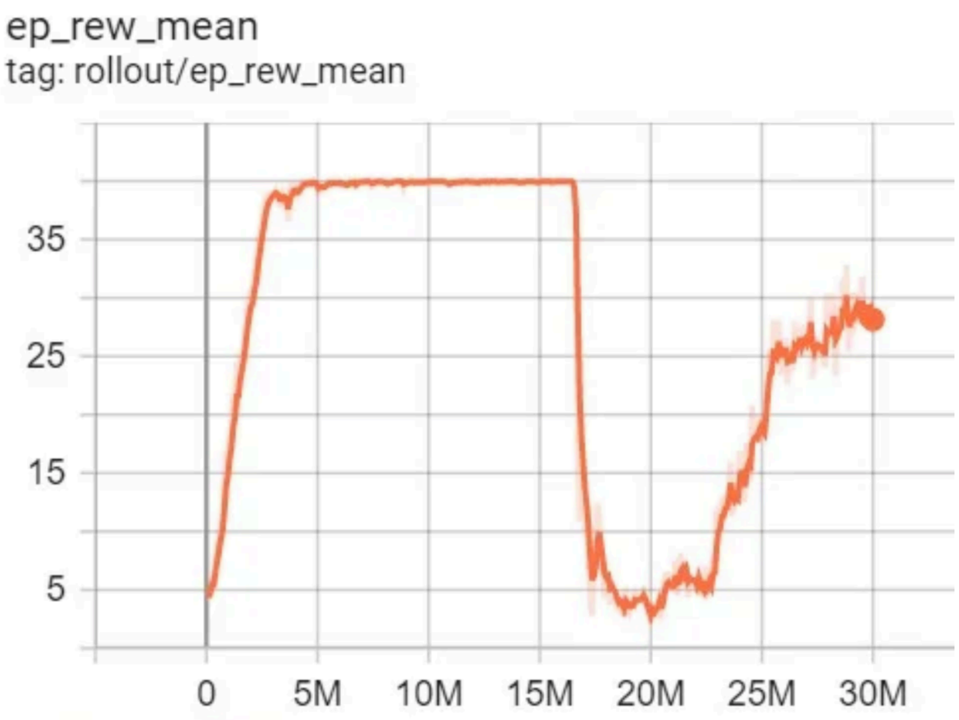

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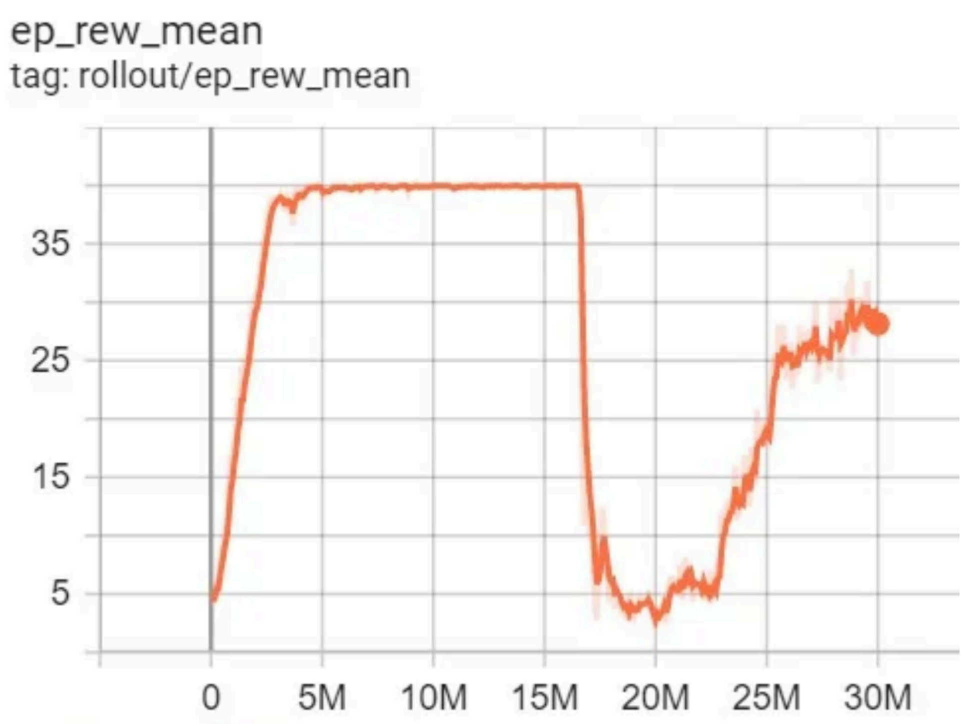

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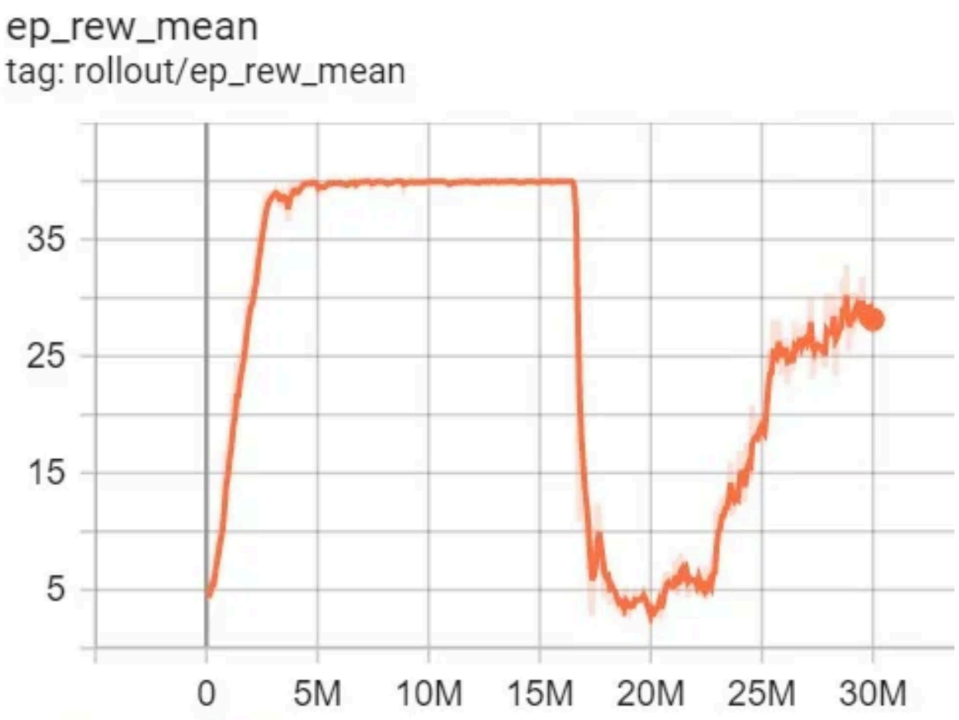

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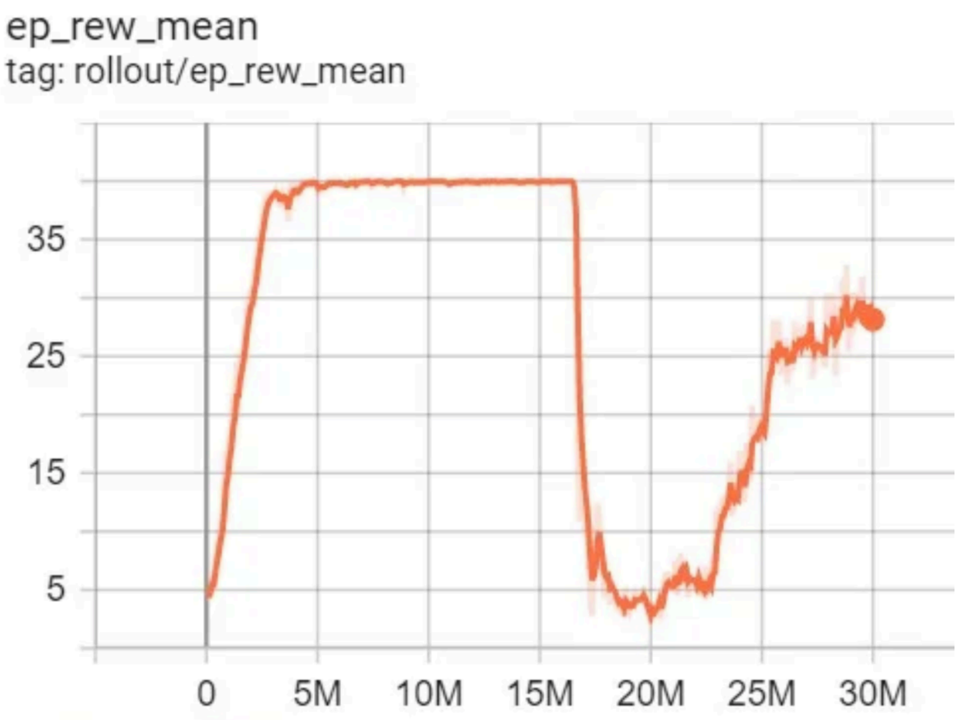

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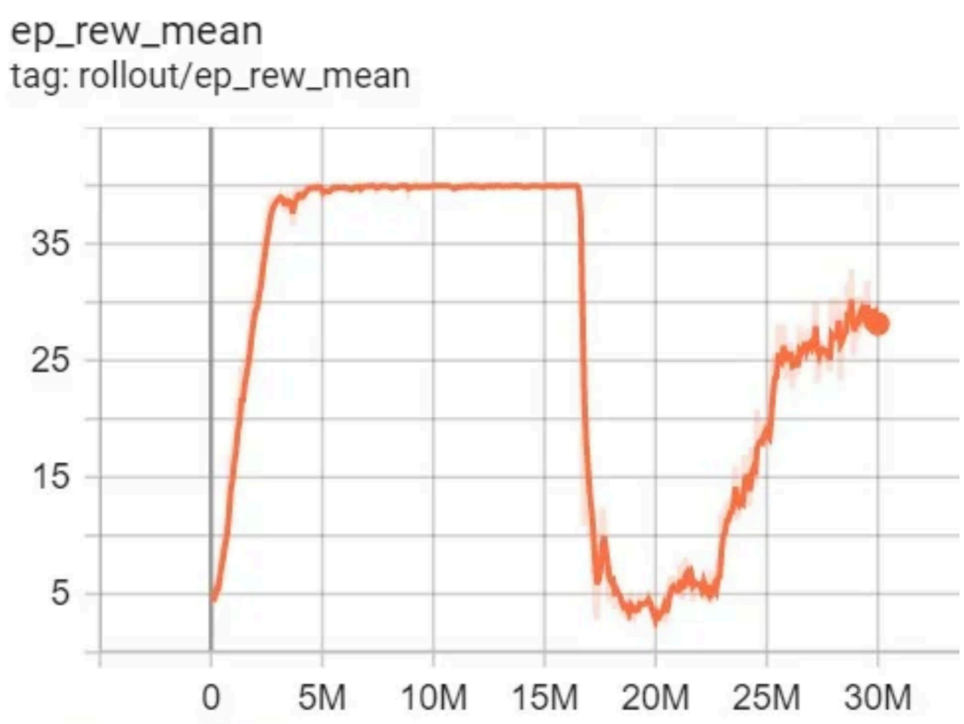

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Must be very careful when updating policy using on-policy algorithms

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We can fix this issue with small changes to the policy

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Answer: The action distributions

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See Trust Region Policy Optimization (TRPO), Natural Policy Gradient

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$$\theta_{\pi,i+1} = V(s_0, \theta_{\pi,i}) \cdot \nabla_{\theta_{\pi,i}} [\log \pi(a_0 \mid s_0; \theta_{\pi,i})]$$
$$-\rho \nabla_{\theta_{\pi,i+1}} [\mathrm{KL}[\pi(a \mid s; \theta_{\pi,i}), \pi(a \mid s; \theta_{\pi,i+1})]]$$

Proximal Policy Optimization

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Proximal policy optimization (PPO) combines all we learned today

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Let us see a pseudocode PPO update

Proximal Policy Optimization

```python
for epoch in range(epochs):
    batch = collect_rollout(theta_beta)
    # Minibatching learns much faster
    # but is very slightly off-policy!
    for minibatch in batch:
        theta_pi = update_pi(
            theta_pi, theta_beta, theta_V, batch
        )
        theta_V = update_V(theta_V, batch)
    theta_beta = theta_pi
```

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There are different variations of PPO

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- PPO clip
- PPO KL penalty
- PPO clip + KL penalty
- PPO clip + KL penalty + entropy bonus

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We will focus on the simplest version (PPO KL penalty)

Proximal Policy Optimization

$$\theta_{\pi, i+1} =$$

Proximal Policy Optimization

$$\theta_{\pi,i+1} = \theta_{\pi,i} + \alpha \cdot \underbrace{\left(\frac{\pi(a \mid s; \theta_{\pi,i})}{\pi(a \mid s; \theta_\beta)} \; A(s_0, s_1, r_0, \theta_\beta, \theta_V) \right)}_{\text{Value}}$$

$$\cdot \left(\nabla_{\theta_{\pi,i}} \left[\log \pi(a_0 \mid s_0; \theta_{\pi,i}) \right] - \rho \nabla_{\theta_{\pi,i+1}} \left[\mathrm{KL}\left[\pi(a_0 \mid s_0; \theta_\beta), \pi(a_0 \mid s_0; \theta_{\pi,i+1}) \right] \right] \right)$$

Proximal Policy Optimization

Off-policy correction for minibatch

$$\theta_{\pi,i+1} = \theta_{\pi,i} + \alpha \cdot \underbrace{\left(\frac{\pi(a \mid s; \theta_{\pi,i})}{\pi(a \mid s; \theta_{\beta})} A(s_0, s_1, r_0, \theta_\beta, \theta_V) \right)}_{\text{Value}}$$

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Off-policy correction for minibatch

Advantage

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Policy gradient

Trust region

$$A(s_0, s_1, r_0, \theta_\beta, \theta_V) = -V(s_0, \theta_\beta, \theta_V) + \left(\hat{\mathbb{E}}[\mathcal{R}(s_1) \mid s_0; \theta_\beta] + \neg d \gamma V(s_1, \theta_\beta, \theta_V) \right)$$

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$$\theta_{V,i+1} = \arg\min_{\theta_{V,i}} \left(V(s_0, \theta_\beta, \theta_{V,i}) - \left(\hat{\mathbb{E}}[\mathcal{R}(s_1) \mid s_0; \theta_\beta] + \neg d \gamma V(s_0, \theta_\beta, \theta_{V,i}) \right) \right)^2$$

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My suggestions:

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- Large batches and regularization (weight decay, layer norm) helpful
- You can make any algorithm work with enough effort!

Proximal Policy Optimization

PPO plays Pokemon!

Video describes the RL experiment process, helpful for your final project

https://youtu.be/DcYLT37ImBY?si=jJfZyYwFkPYMJYMy