Reinforcement Learning
Tutorial for Lecture 8

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Advantage Estimation

In the lecture we had a Quiz on how to do Advantage estimation.
Why is the following answer wrong?

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$$\hat{A}(s, a) = q(s, a) - \hat{v}(s)$$

Trust Region

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Why is it needed / a good idea for policy gradient?

- We make a very local estimate of our gradient
- The gradient estimate is noisy (noise in environment and policy)
- We cannot guarantee that a big step actually leads to an improvement

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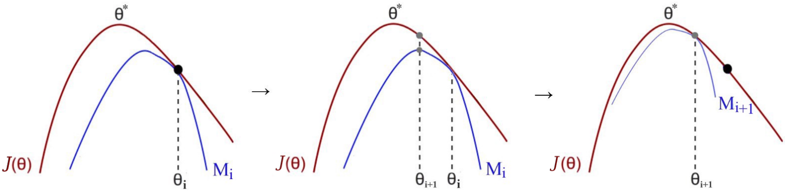
Why not measuring the distance in changes to the network parameter?

- a change in network weights can have drastic effects on the output / actions

TRPO uses the Minorization Maximization technique:



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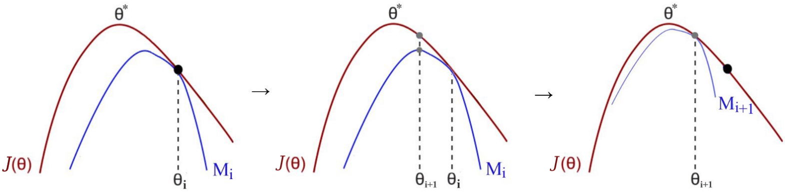

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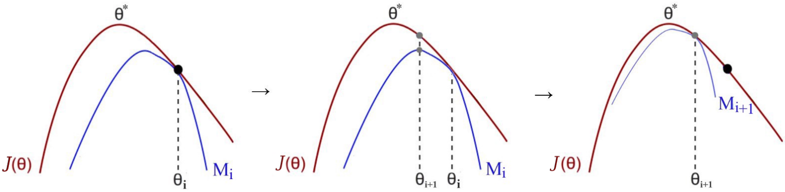

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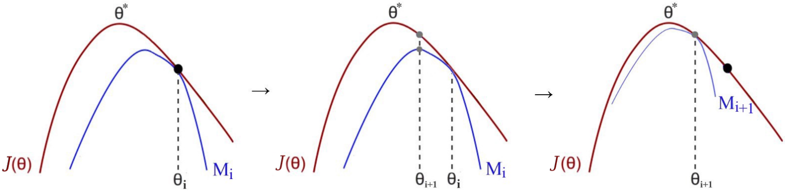

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So when is M actually a lower bound if J?

- We perform a Tailor expansion if J: if b is larger than the |second derivative| of J (it is negative as we are considering concav functions)

PPO

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- Parametrized policy: π_θ
- Parametrized value function: $\hat{v}(s, \mathbf{w})$
- Importance weights: $\rho_t(\theta) = \frac{\pi_\theta(s_t, a_t)}{\pi_{\theta^{\text{old}}}(s_t, a_t)}$
- Monte Carlo Returns: $G \leftarrow \sum_{k=t+1}^{T} \gamma^{k-t-1} r_k$
- Loss function for value function: $L^{\text{VF}}(\mathbf{w}) = (\hat{v}(s_t, \mathbf{w}) - G_t)^2$
- Loss function for policy:
  $L^{\text{CLIP}}(\theta) = \underset{\pi_{\theta^{\text{old}}}}{\mathbb{E}} \left[\min\left(\rho_t(\theta) A_t, \text{clip}\left(\rho_t(\theta), 1-\epsilon, 1+\epsilon\right) A_t\right)\right]$
- Entropy regularizer: $\mathcal{H}[\pi_\theta] = -\sum_a \pi_\theta(a \mid s) \log(\pi_\theta(a \mid s))$

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Initialise $\theta, \mathbf{w}$ arbitrarily
for each iteration:

1. $\theta_{\text{old}} \leftarrow \theta$
2. $\mathcal{D} = \emptyset$
3. for $e = 1$ to E episodes:
   3.1 $\tau^e \leftarrow \{s_1^e, a_1^e, r_2^e, \ldots, s_{T-1}^e, a_{T-1}^e, r_T^e\} \sim \pi_\theta$
   3.2 for $t = 1$ to $T-1$ timesteps:

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     - **3.2.1** $G_t^e \leftarrow \sum_{k=t+1}^{T} \gamma^{k-t-1} r_k^e$

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   - **3.2** for $t = 1$ to $T-1$ timesteps:
     - **3.2.1** $G_t^e \leftarrow \sum_{k=t+1}^{T} \gamma^{k-t-1} r_k^e$
     - **3.2.2** $A_t^e \leftarrow G_t^e - \hat{v}(s_t^e, \mathbf{w})$
     - **3.2.3** $\mathcal{D} = \mathcal{D} \cup (s_t^e, a_t^e, G_t^e)$
4. $\theta \leftarrow \theta + \alpha \nabla_\theta \mathbb{E}_{(s,a,G)\sim\mathcal{D}}\left[L^{\text{CLIP}}(\theta) + c_2 \mathcal{H}[\pi_\theta]\right]$
5. $\mathbf{w} \leftarrow \mathbf{w} + \alpha \nabla_{\mathbf{w}} \mathbb{E}_{(s,G)\sim\mathcal{D}}\left[(G - \hat{v}(s, \mathbf{w}))^2\right]$ value function loss: L^{VF}

return $\theta, \mathbf{w}$