Safely Exploring Policy Gradient

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Problem

- **Reinforcement Learning** for **continuous** control [Deisenroth et al., 2013]
- **Policy Gradient (PG)**: iteratively update **parametric** policy $\pi_{\boldsymbol\theta}$ via **gradient ascent** on performance $J(\boldsymbol\theta)$ (expected cumulative reward):

$$\boldsymbol\theta^{t+1} \leftarrow \boldsymbol\theta^t + \alpha \nabla J(\boldsymbol\theta^t)$$

- Convergence to local optimum guaranteed
- **Intermediate policies may be arbitrarily bad!**
- **Safe Exploration** [Amodei et al., 2016]: limit risks/costs of novel behavior

Motivation

- A working controller $\boldsymbol\theta^0$ is provided
- **Fine tuning**: improve it online via policy gradient
- Intermediate policies should never be worse than the initial $\boldsymbol\theta^0$ (baseline)
- *Economic safety*: losses and gains cancel out

State of the Art

Existing **safe PG** approaches [Pirotta et al., 2013, Papini et al., 2017]:

- Apply only to **Gaussian** policies with fixed variance:

$$\pi_{\boldsymbol\theta}(a|s) \sim \mathcal{N}(\mu_{\boldsymbol\theta}(s), \sigma^2)$$

⚠ The variance parameter regulates exploration and has a big impact on convergence speed

- Focus on **monotonic improvement** guarantees:

$$J(\boldsymbol\theta^{t+1}) - J(\boldsymbol\theta^t) \geq 0$$

⚠ Too strict for most practical scenarios

Contributions

- We adopt a more general definition of safety
- We extend the existing guarantees for Gaussian policies to the adaptive-variance case
- We introduce a **surrogate objective** for variance updates that explicitly encourages **exploration**
- We provide an algorithm (**SEPG**) for the **fine-tuning** scenario

Setting

- *Shallow* Gaussian policy parametrization:

$$\pi_{\boldsymbol\theta}(a|s) = \frac{1}{\sqrt{2\pi}\sigma_{\boldsymbol\theta}} \exp\left\{-\frac{1}{2}\left(\frac{a-\mu_{\boldsymbol\theta}(s)}{\sigma_{\boldsymbol\theta}}\right)^2\right\} \qquad \begin{aligned}\mu_{\boldsymbol\theta}(s) &= \boldsymbol v^T \boldsymbol\phi(s)\\ \sigma_{\boldsymbol\theta} &= e^w\end{aligned} \qquad \boldsymbol\theta = \begin{cases}\boldsymbol v \text{ mean parameter}\\ w \text{ variance parameter}\end{cases}$$

- **Safety requirement** (similar to Thomas et al. [2015]):

$$J(\boldsymbol\theta^{t+1}) - J(\boldsymbol\theta^t) \geq C^t \quad \text{with probability at least } 1-\delta$$

$C^t \geq 0$: *required improvement*
$C^t < 0$: *bounded worsening*

- Base algorithm: REINFORCE with separate mean and variance updates

$$\begin{cases}\boldsymbol v^{t+1} \leftarrow \boldsymbol v^t + \alpha\nabla_{\boldsymbol v} J(\boldsymbol v^t, w^t)\\ w^{t+1} \leftarrow w^t + \eta\nabla_w J(\boldsymbol v^{t+1}, w^t)\end{cases}$$

naive update: **too greedy!**

- **Adaptive PG**: we look for the *largest* step sizes guaranteeing safety at each iteration

Safe-Exploratory Updates

We introduce a surrogate **exploration objective** that accounts for long-term advantages of high policy variance:

$$\mathcal{L}(\boldsymbol v, w) = \underbrace{\frac{\|\nabla_{\boldsymbol v} J(\boldsymbol v, w)\|_2^2}{4mc_w}}$$

Largest **safe** performance improvement obtainable by updating the mean parameter $\boldsymbol v$ when $\sigma = e^w$

$$c_w = \frac{\overbrace{R}^{\text{max reward}}\ \overbrace{M^2}^{\text{max feature}}}{(1-\gamma)^2 e^{2w}}\left(\frac{\overbrace{|\mathcal{A}|}^{\text{volume of action space}}}{\sqrt{2\pi}e^w} + \frac{\overbrace{\gamma}^{\text{discount factor}}}{2(1-\gamma)}\right)$$

We provide a **safe** way to update the variance parameter according to this objective:

$$\begin{cases}\boldsymbol v^{t+1} \leftarrow \boldsymbol v^t + \overline\alpha\nabla_{\boldsymbol v} J(\boldsymbol v^t, w^t)\\ w^{t+1} \leftarrow w^t + \overline\eta\nabla_w \mathcal{L}(\boldsymbol v^{t+1}, w^t)\end{cases}$$

Largest safe step size $\overline\alpha$ from Papini et al. [2017]:

$$\overline\alpha = \frac{1}{2c_w}\left(1 + \sqrt{1 - \frac{4c_w C^t}{\|\nabla_{\boldsymbol v} J(\boldsymbol v^t, w^t)\|_\infty^2}}\right)$$

Largest safe-exploratory step size $\overline\eta$

$$\eta^* = \frac{\nabla_w J(\boldsymbol v^{t+1}, w^t)}{2d\nabla_w \mathcal{L}(\boldsymbol v^{t+1}, w^t)} \quad \text{(corresponds to naive update)}$$

$$\overline\eta = \eta^* + |\eta^*|\sqrt{1 - \frac{4dC^t}{\|\nabla_w J(\boldsymbol v^{t+1}, w^t)\|_\infty^2}}$$

$$d = \frac{R}{(1-\gamma)^2}\left(\frac{2(\sqrt{7}-2)e^{\sqrt{7}/2-2}|\mathcal{A}|}{\sqrt{2\pi}e^w} + \frac{\gamma}{1-\gamma}\right)$$

- Policy gradient $\nabla_w J$ (greedy) and surrogate $\nabla_w \mathcal{L}$ (explorative) typically *disagree* $\implies \eta^*$ typically negative
- Largest safe step size $\overline\eta$ can be positive (*exploration is allowed*) or negative (*greediness is required*) according to safety constraint C^t

Approximate Framework

- In practice, gradients $\nabla_{\boldsymbol v} J, \nabla_w J, \nabla_w \mathcal{L}$ must be estimated from batches of N trajectories
- We characterize estimation error $\epsilon = \left|\widehat\nabla_N J - \nabla J\right|$ using known statistical inequalities
- We obtain corrected step sizes with high-probability safety guarantees

References

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Fine Tuning

- We define the **exploration budget**

$$B^t := J(\boldsymbol\theta^t) - J(\boldsymbol\theta^0)$$

- "Never do worse than the initial policy" is equivalent to

$$J(\boldsymbol\theta^{t+1}) - J(\boldsymbol\theta) \geq -B^t$$

- **SEPG** algorithm

1. Keep track of the budget:

$$B^0 \leftarrow 0$$
$$B^{t+1} \leftarrow B^t + J(\boldsymbol\theta^{t+1}) - J(\boldsymbol\theta^t)$$

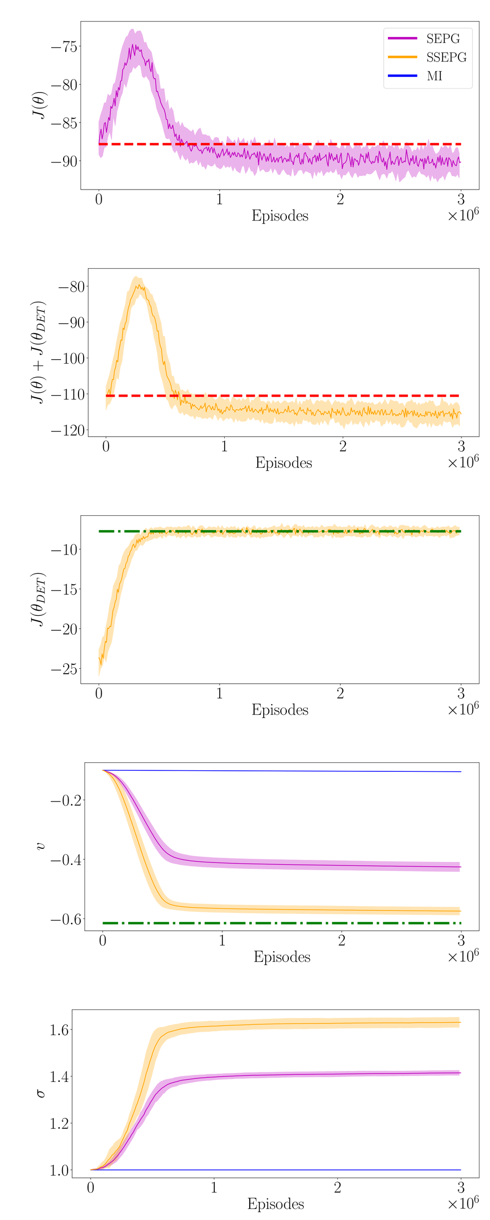
2. Update $\boldsymbol v$ and w alternately
3. Select $\overline\alpha$ and $\overline\eta$ according to $C^t = -B^t$

- **SSEPG** algorithm (*heuristic* variant):

+ Provide initial budget $B^0 > 0$ to encourage initial exploration
+ Test the corresponding **deterministic** policy ($\sigma = 0$) at each iteration to capture long-term advantages

Experiments

LQR



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