POLITECNICO
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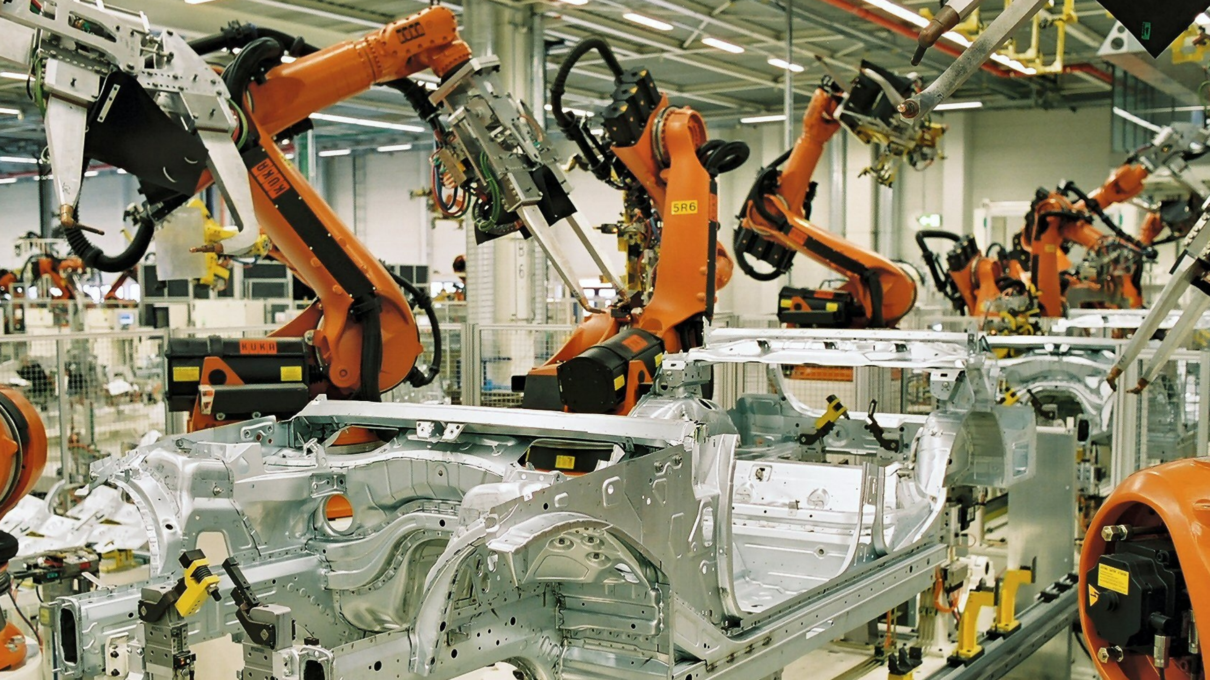
Balancing Learning Speed and Stability in Policy Gradient via Adaptive Exploration

Matteo Papini Andrea Battistello Marcello Restelli

The 23rd International Conference on Artificial Intelligence and Statistics, June 2020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Safe Exploration[1]

Learn safe behavior

[1]Amodei et al., "Concrete Problems in AI Safety", 2016.

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Learn safely $\implies$ Explore safely

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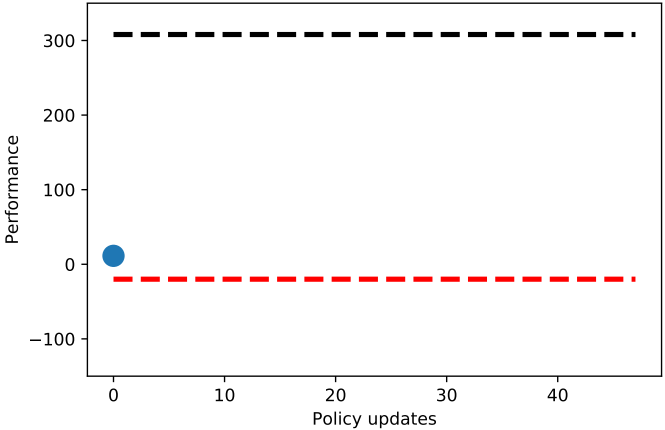
Monotonic Improvement



Data from Cart-Pole experiment

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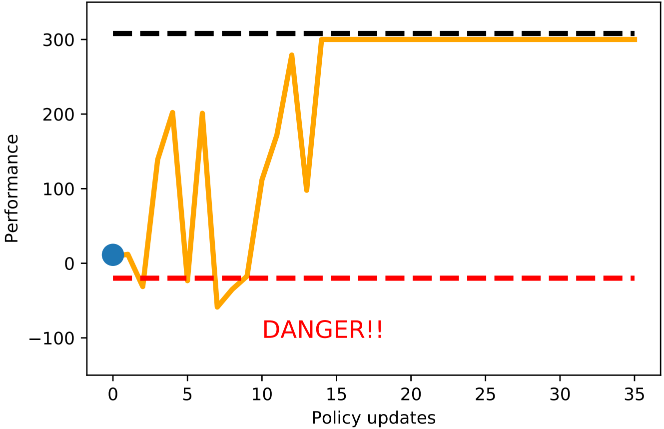

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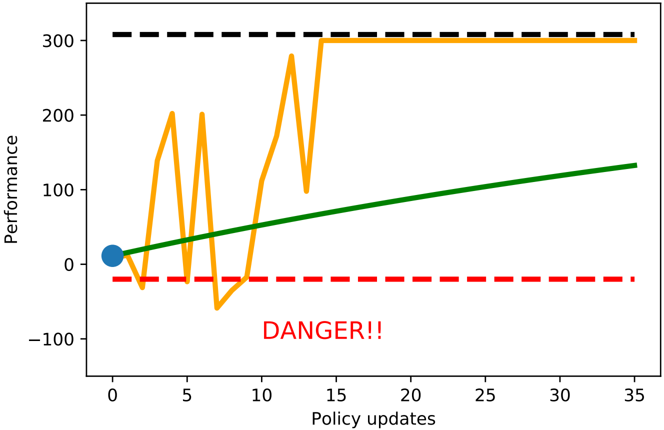

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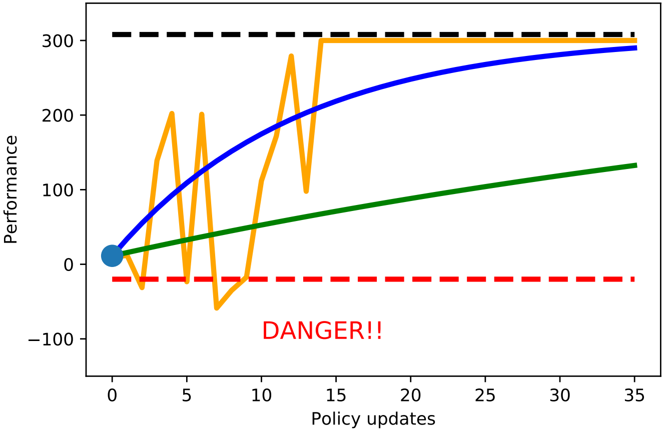

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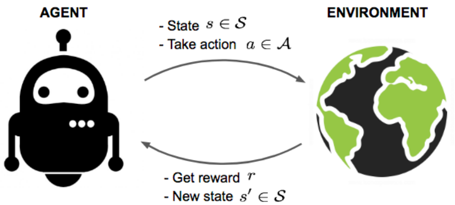
Continuous Reinforcement Learning[2]



- Policy $a \sim \pi(\cdot|s)$
- Goal: $\max_\pi \mathbb{E}\left[\sum_t \gamma^t r_{t+1} \mid a_t \sim \pi\right]$ (discount factor $\gamma \in (0,1)$)
- Continuous $\mathcal{S}, \mathcal{A} \subseteq \mathbb{R}^n$

[2] Sutton and Barto, *Reinforcement learning: An introduction*, 2018.

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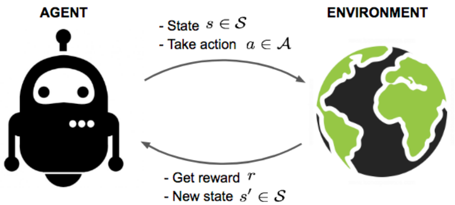

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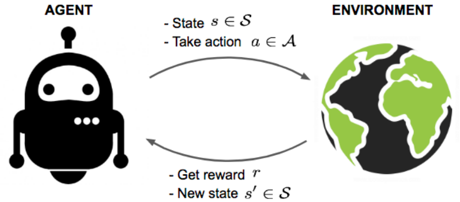

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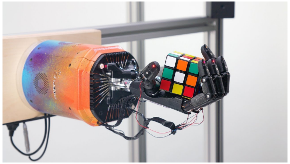
Policy Gradient

- Parametric policy $\pi_{\boldsymbol{\theta}}$ $(\boldsymbol{\theta} \in \mathbb{R}^d)$
- Performance $J(\boldsymbol{\theta}) = \mathbb{E}\left[\sum_t \gamma^t r_{t+1} \mid a_t \sim \pi_{\boldsymbol{\theta}}\right]$
- $\boldsymbol{\theta}' \leftarrow \boldsymbol{\theta} + \alpha \nabla J(\boldsymbol{\theta})$
- Best for continuous control [3]
  - Convergence guarantees
  - Robustness to noise
  - Freedom in policy design



OpenAI 2019

Google/BAIR 2020

[3] Deisenroth, Neumann, and Peters, "A Survey on Policy Search for Robotics", 2013

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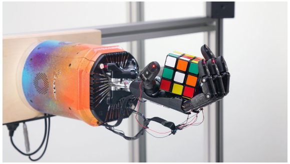

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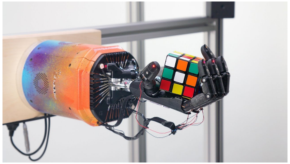

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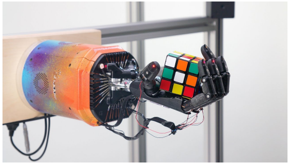

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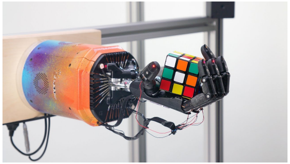

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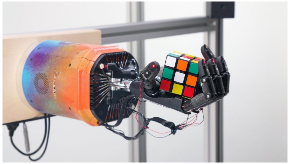

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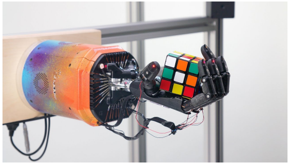

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Smoothing Policies

- $J(\boldsymbol{\theta})$ is nonconvex

- *Smooth* $J(\boldsymbol{\theta})$ allows *monotonic improvement*

$$J(\boldsymbol{\theta}') - J(\boldsymbol{\theta}) \geq 0$$

- Conditions on $\nabla \log \pi_{\boldsymbol{\theta}}, \nabla^2 \log \pi_{\boldsymbol{\theta}} \implies J(\boldsymbol{\theta})$ smooth [4]

[4] Papini, Pirotta, and Restelli, "Smoothing Policies and Safe Policy Gradients", 2019

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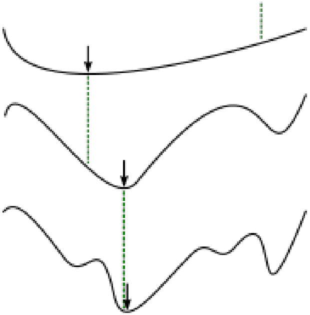

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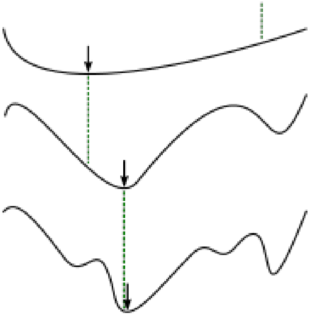

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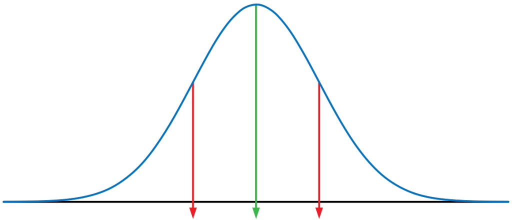
Gaussian Policy

$$\pi_{\boldsymbol{\theta}}(a|s) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(\mu_{\boldsymbol{\theta}}(s) - a)^2}{2\boldsymbol{\sigma^2}}\right\}$$



- Variance $\boldsymbol{\sigma^2}$ controls the *amount of exploration*
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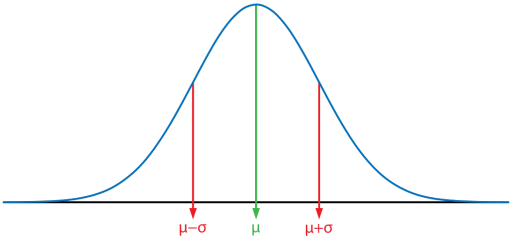

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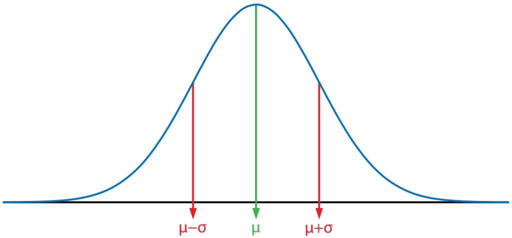

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Speed vs Safety

- $J(\boldsymbol{\theta})$ is $C/\sigma^{\mathbf{2}}$-smooth
- Larger $\sigma \implies$ faster convergence [6]
- Large $\sigma \implies$ not safe!

[6] Ahmed et al., "Understanding the Impact of Entropy on Policy Optimization", 2019

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Adaptive Exploration (State of the Art)

- ~~Hyper-parameter tuning~~
- Learn σ as any other parameter[7] $\implies$ *policy collapse*
- Entropy bonus[8]

[7] Duan et al., "Benchmarking Deep Reinforcement Learning for Continuous Control", 2016.
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Meta-Exploring Policy Gradient (MEPG)

1. Special exploration parameter ω

$$\sigma_\omega = e^\omega$$

2. Exploration-aware policy update

$$\boldsymbol{\theta}' \leftarrow \boldsymbol{\theta} + \alpha \sigma_\omega^{\mathbf{2}} \frac{\nabla_{\boldsymbol{\theta}} J_\omega(\boldsymbol{\theta})}{\|\nabla_{\boldsymbol{\theta}} J_\omega(\boldsymbol{\theta})\|}$$

3. Far-sighted update for ω:

$\mathcal{L}(\omega)$ (Exploratory objective)

$\nabla_\omega \mathcal{L} = \nabla_\omega J_\omega(\boldsymbol{\theta})$

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Sutton, "Adapting Bias by Gradient Descent: An Incremental Version of Delta-Bar-Delta", 1992

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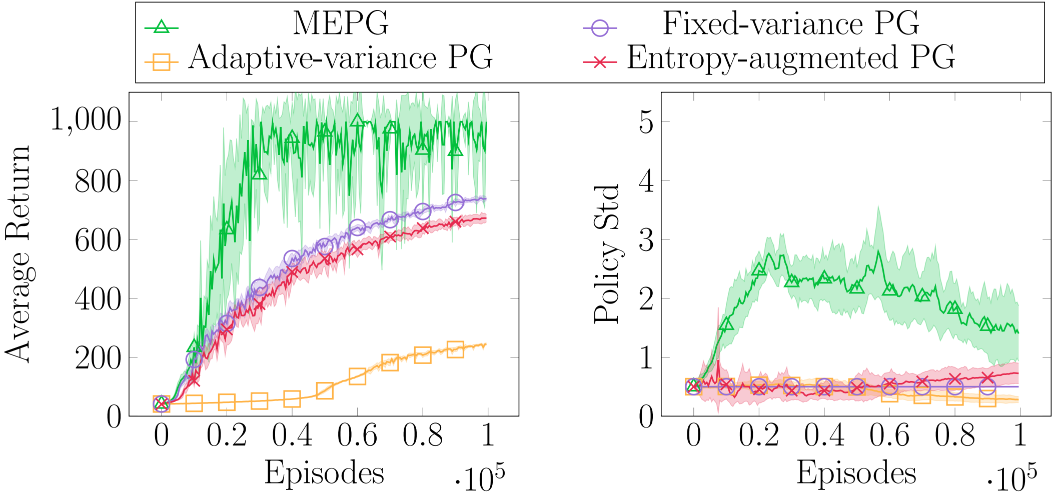

[9] Brockman et al., "OpenAI Gym", 2016.

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Monotonic improvement:

$$J_{\omega}(\boldsymbol{\theta}') - J_{\omega}(\boldsymbol{\theta}) \geq 0 \qquad \text{for sufficiently small } \alpha > 0$$
$$J_{\omega'}(\boldsymbol{\theta}) - J_{\omega}(\boldsymbol{\theta}) \geq 0 \qquad \text{for sufficiently small } \eta \in \mathbb{R}$$

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$J_{\omega'}(\boldsymbol{\theta}) - J_{\omega}(\boldsymbol{\theta}) \geq 0$ for sufficiently small $\eta \in \mathbb{R}$

η can be negative!

Safely-Exploring Policy Gradient (SEPG)

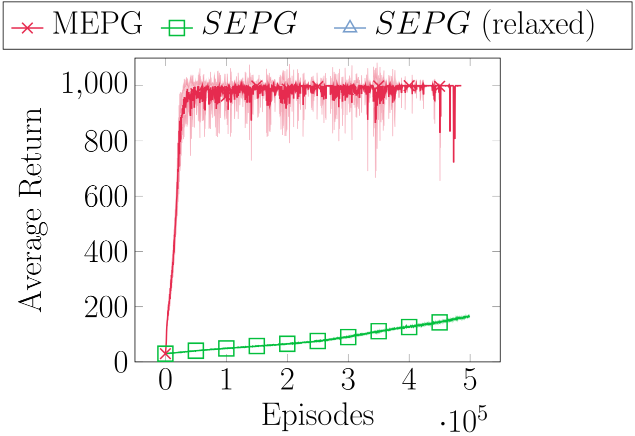
`Alternate:`

$$\boldsymbol{\theta}' \leftarrow \alpha^* \nabla_{\boldsymbol{\theta}} J_{\omega}(\boldsymbol{\theta})$$
$$\omega' \leftarrow \omega + \eta^* \nabla_{\omega} \mathcal{L}(\omega)$$

Largest safe step sizes (adaptive):

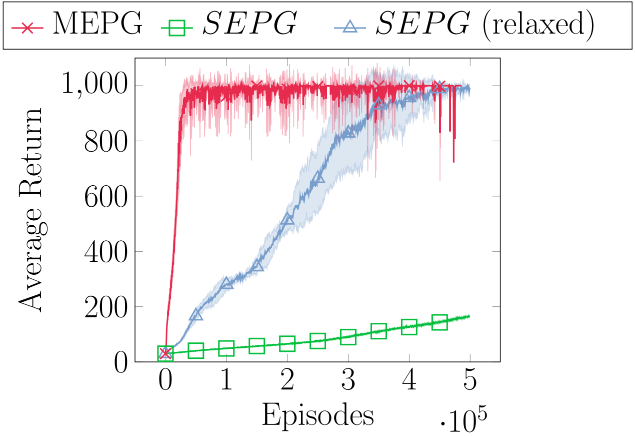
$$\alpha^* \propto \frac{\sigma_{\omega}^{\mathbf{2}}}{\|\nabla_{\boldsymbol{\theta}} J_{\omega}(\boldsymbol{\theta})\|}$$
$$\eta^* \propto \frac{1}{\|\nabla_{\omega} \mathcal{L}_{\omega}(\boldsymbol{\theta})\|}$$

Continuous Cart-Pole (cont.)



$$J(\boldsymbol{\theta}') - J(\boldsymbol{\theta}) \geq \quad 0$$

Continuous Cart-Pole (cont.)



$$J(\boldsymbol{\theta}') - J(\boldsymbol{\theta}) \geq 0$$

$$J(\boldsymbol{\theta}') - J(\boldsymbol{\theta}) \geq -C$$

Conclusion

- Adapting policy variance farsightedly is important
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- Gap between theory and practice
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- Remove random actions?

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Thanks for watching!

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