When to Trust Your Model: Model-Based Policy Optimization

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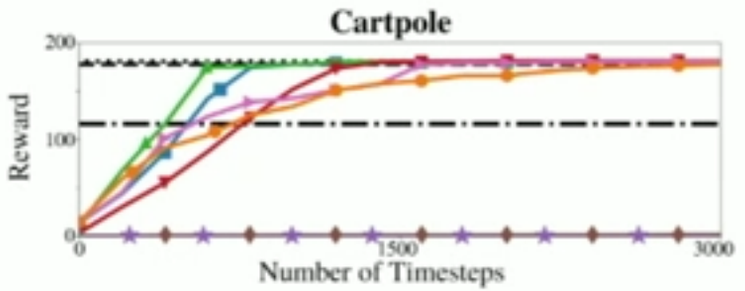
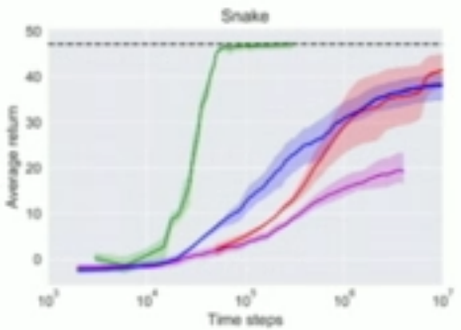
The problem of model bias

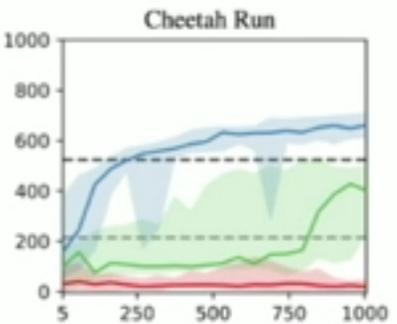
- Model-based reinforcement learning methods are fast!



PETS. Chua et al, 2018



ME-TRPO. Kurutach et al, 2018.



PlaNet. Hafner et al, 2019.

… but often have poor asymptotic performance on high-dimensional tasks due to modeling inaccuracies

- How can we best leverage a predictive model for learning a policy?

Outline

1. Model-based policy optimization (MBPO) algorithm
2. Monotonic improvement and model generalization in theory
3. Model generalization in practice
4. Experiments

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Algorithm 1 Model-Based Policy Optimization

1: Initialize data-collecting policy π
2: **for** N epochs **do**
3: Collect data with π in real environment
4: Train model p_θ on real data
5: Optimize policy π under predictive model

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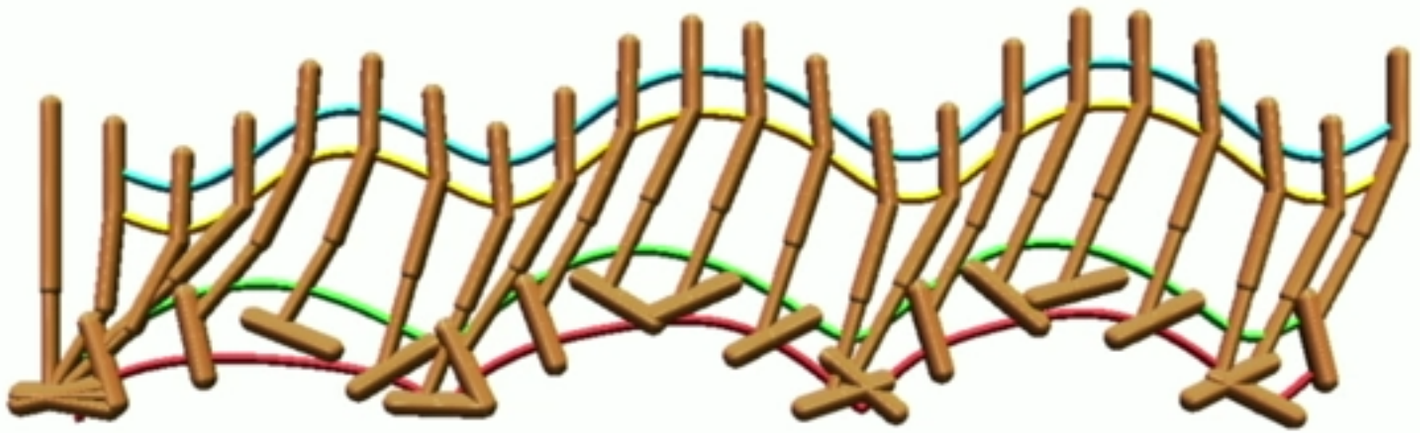
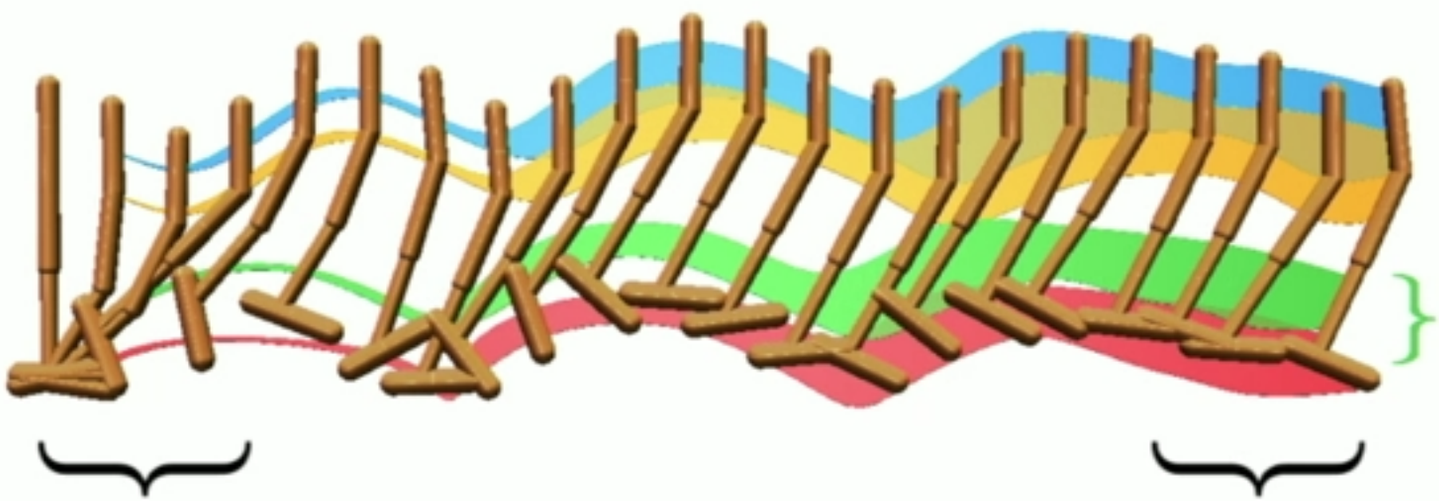
Little guidance on how to properly optimize a policy with a model

The problem with long rollouts



Environment rollout



Model rollout (x1000)

} mean prediction +/- std dev

accurate, low variance

low accuracy, high variance

Bounding returns

- Use policy performance under model rollouts to derive lower bound in real environment

$$\eta[\pi] \geq \eta^{\text{branch}}[\pi] - 2r_{\max}\Big[\underbrace{\frac{\gamma^{k+1}\epsilon_\pi}{(1-\gamma)^2} + \frac{(\gamma^k+2)\epsilon_\pi}{(1-\gamma)}}_{\text{discrepancy due to policy shift}} + \underbrace{\frac{k}{1-\gamma}(\epsilon_m + 2\epsilon_\pi)}_{\text{discrepancy due to model error}}\Big]$$

See also Luo et al, ICLR 2019 and Sun et al, NeurIPS 2018.

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- Real off-policy data is always preferable to model-generated on-policy data!

  → *k* = 0?

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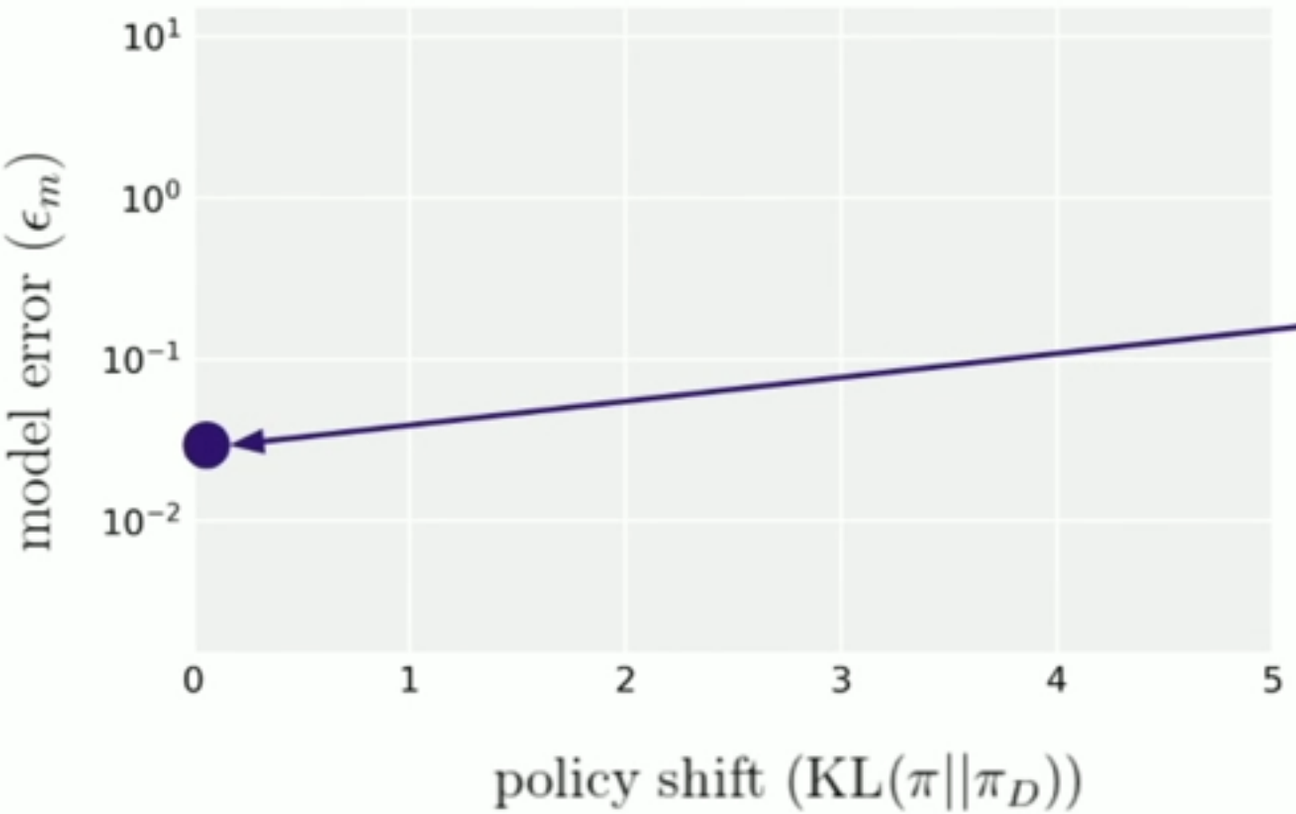
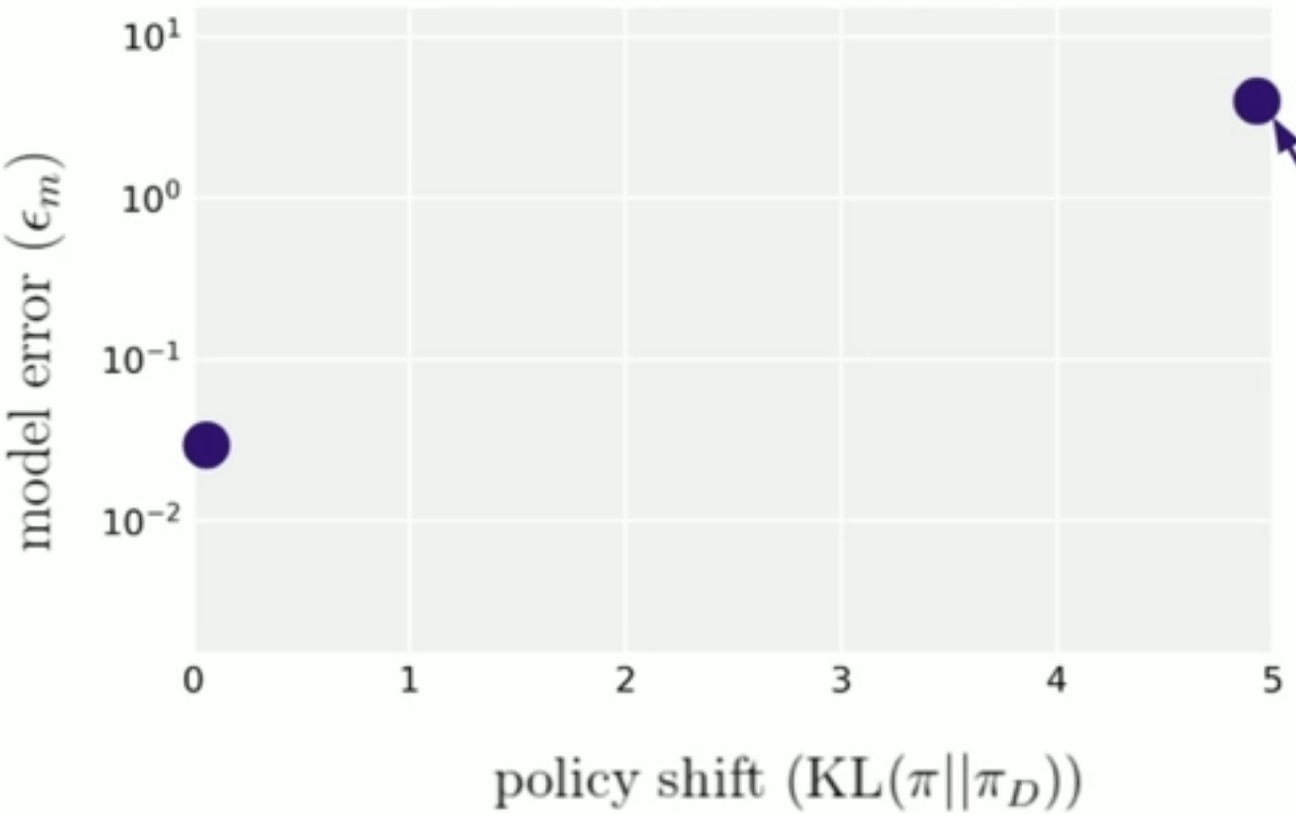
Model generalization in practice



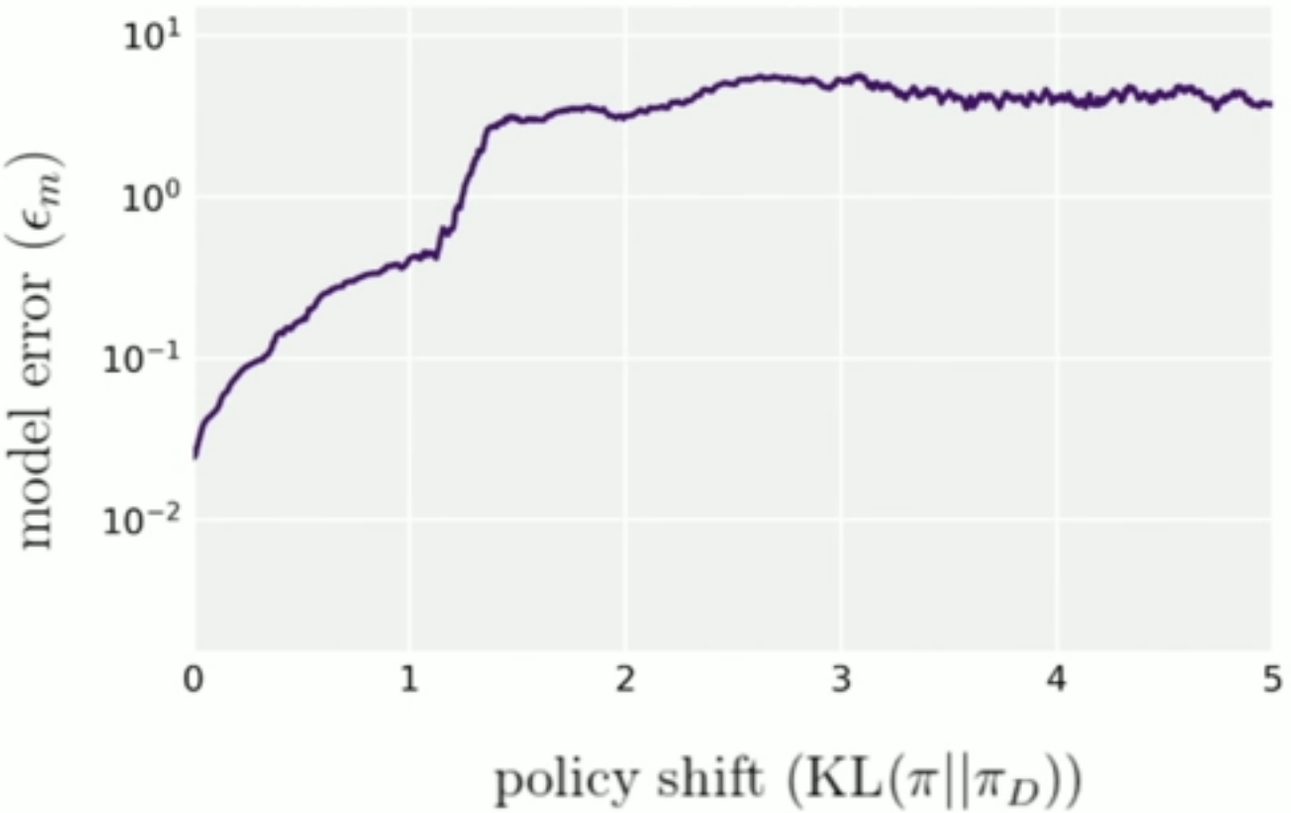
model error on data-collecting policy π_D

Model generalization in practice



model error on *different* policy

Model generalization in practice



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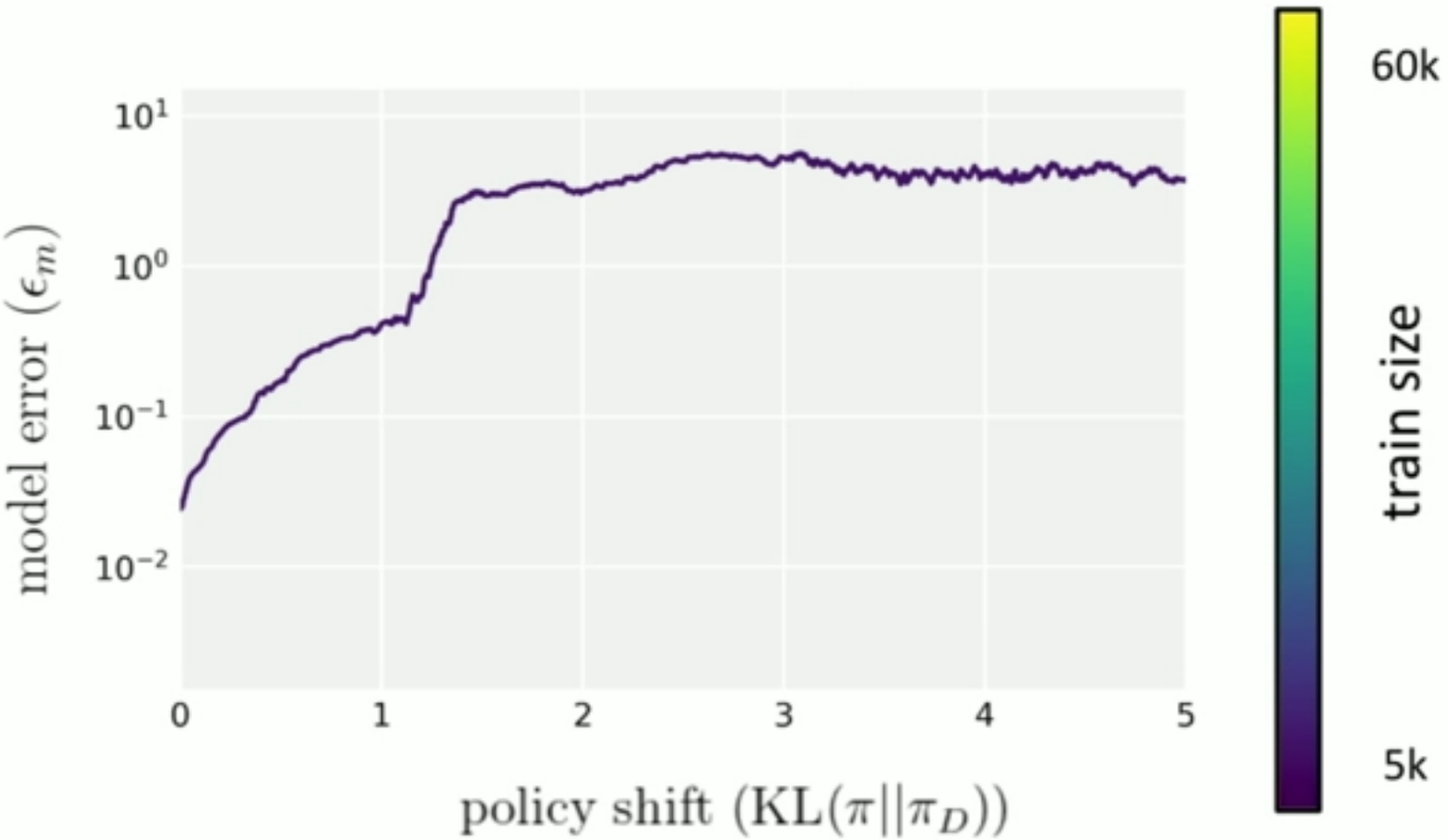

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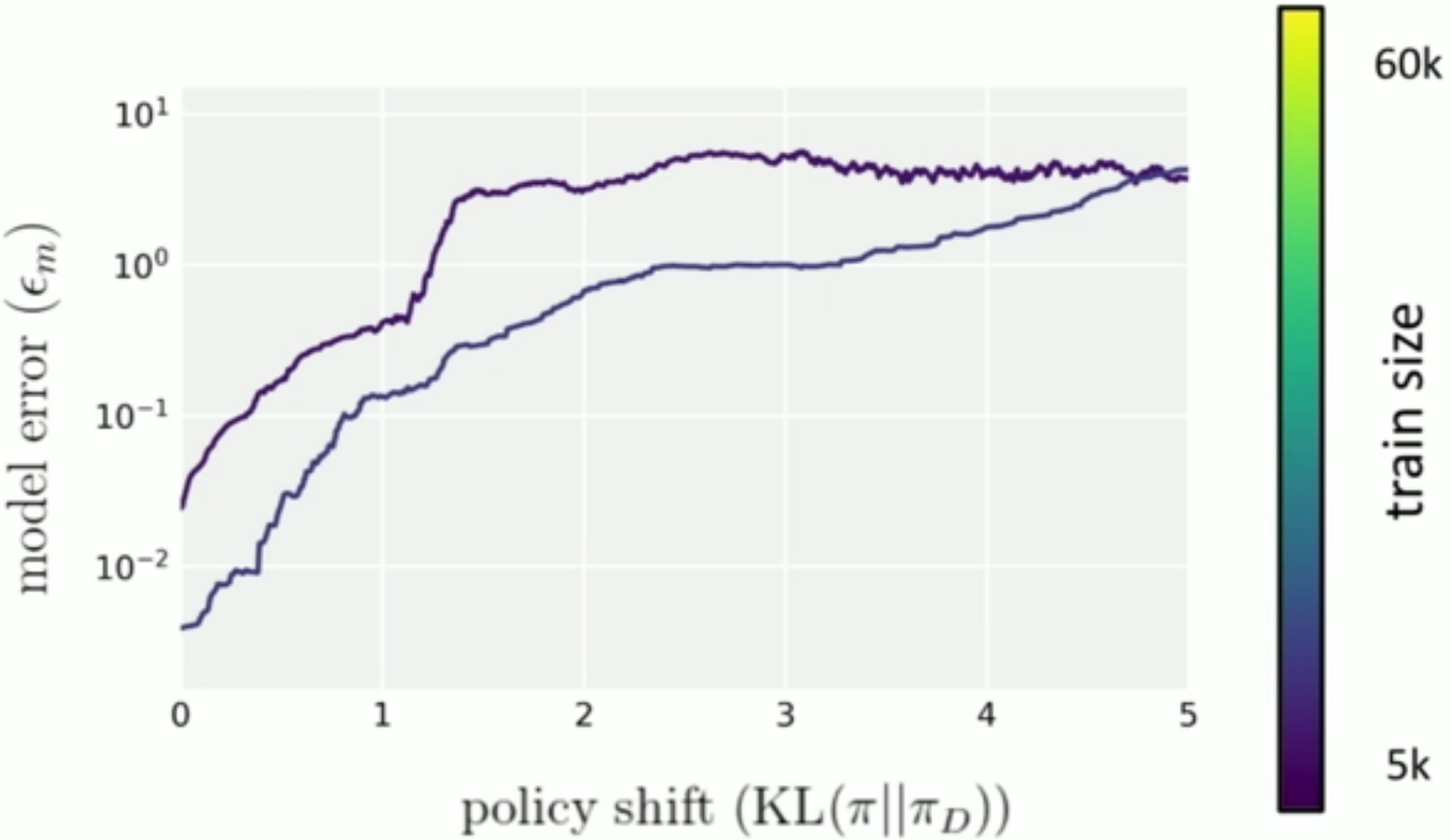

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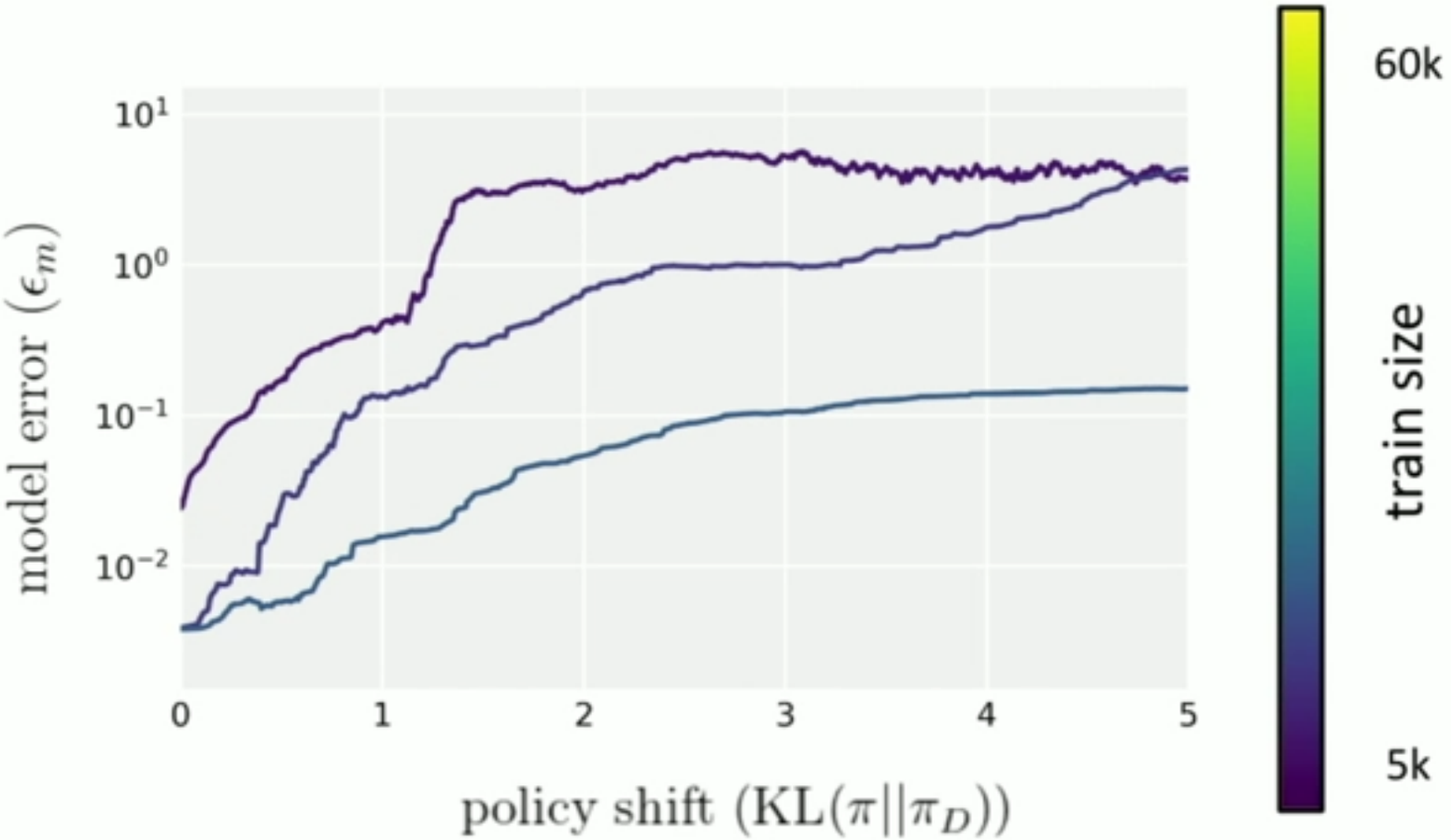

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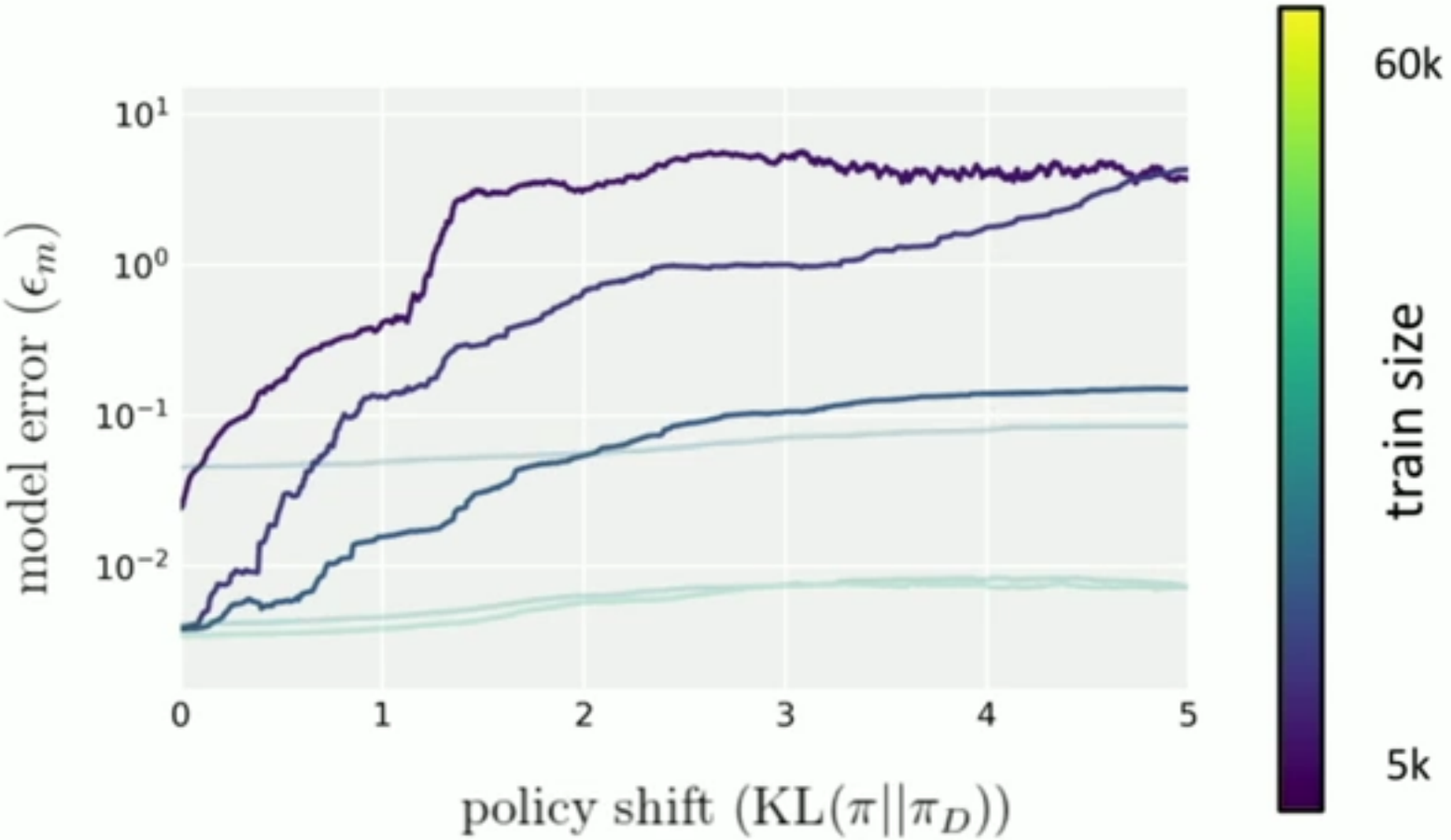

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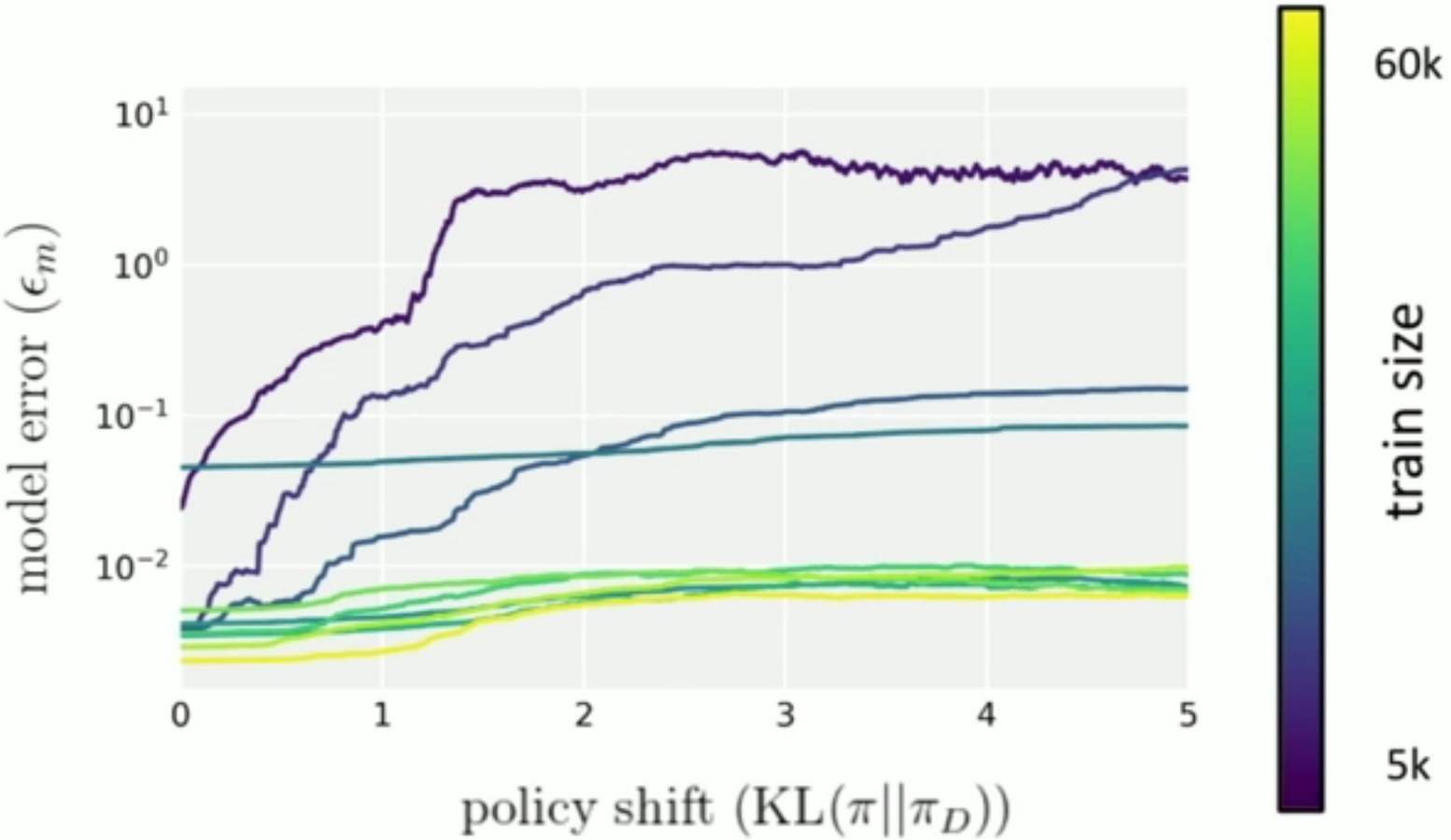

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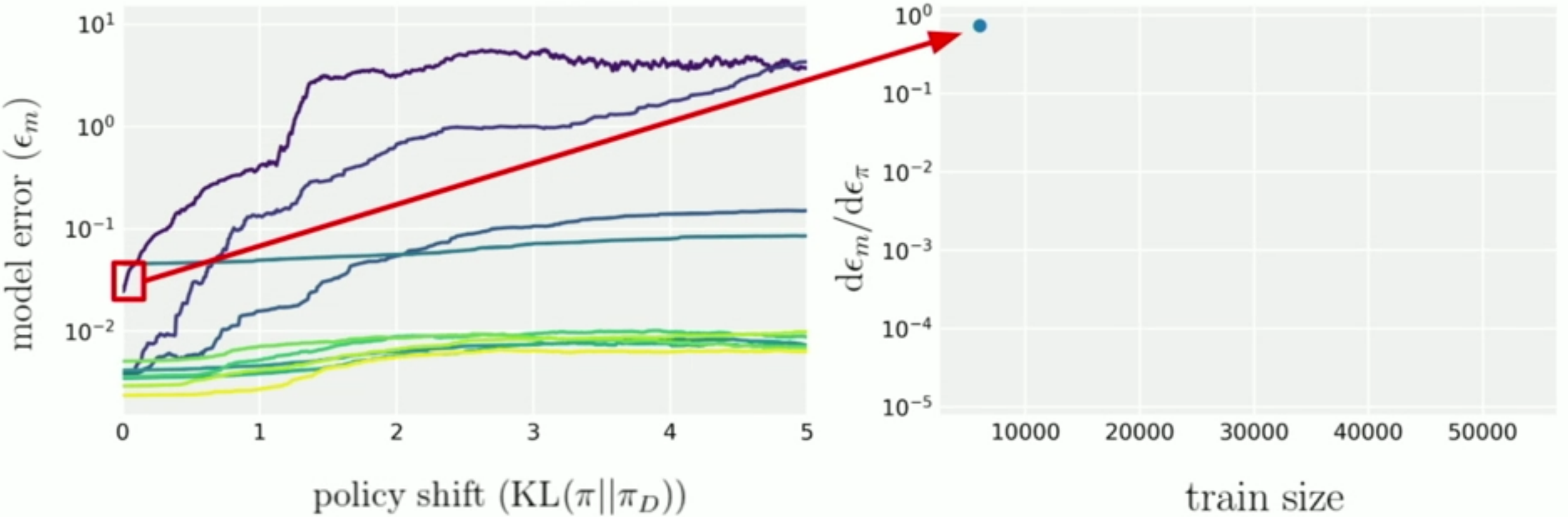

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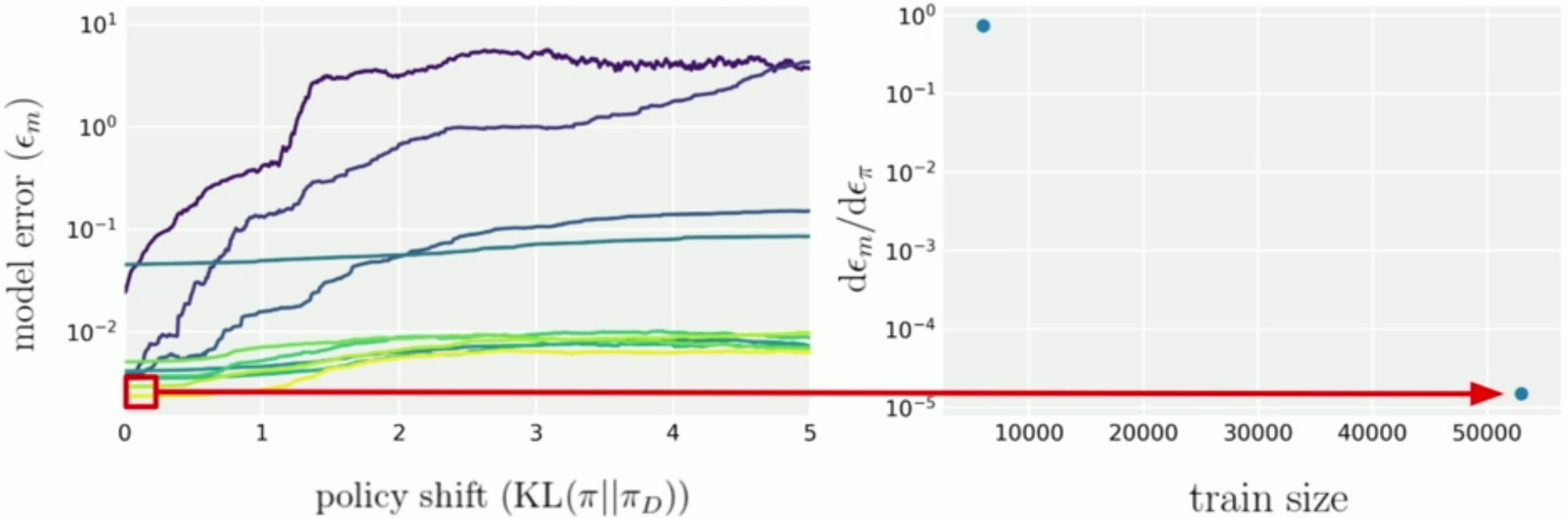

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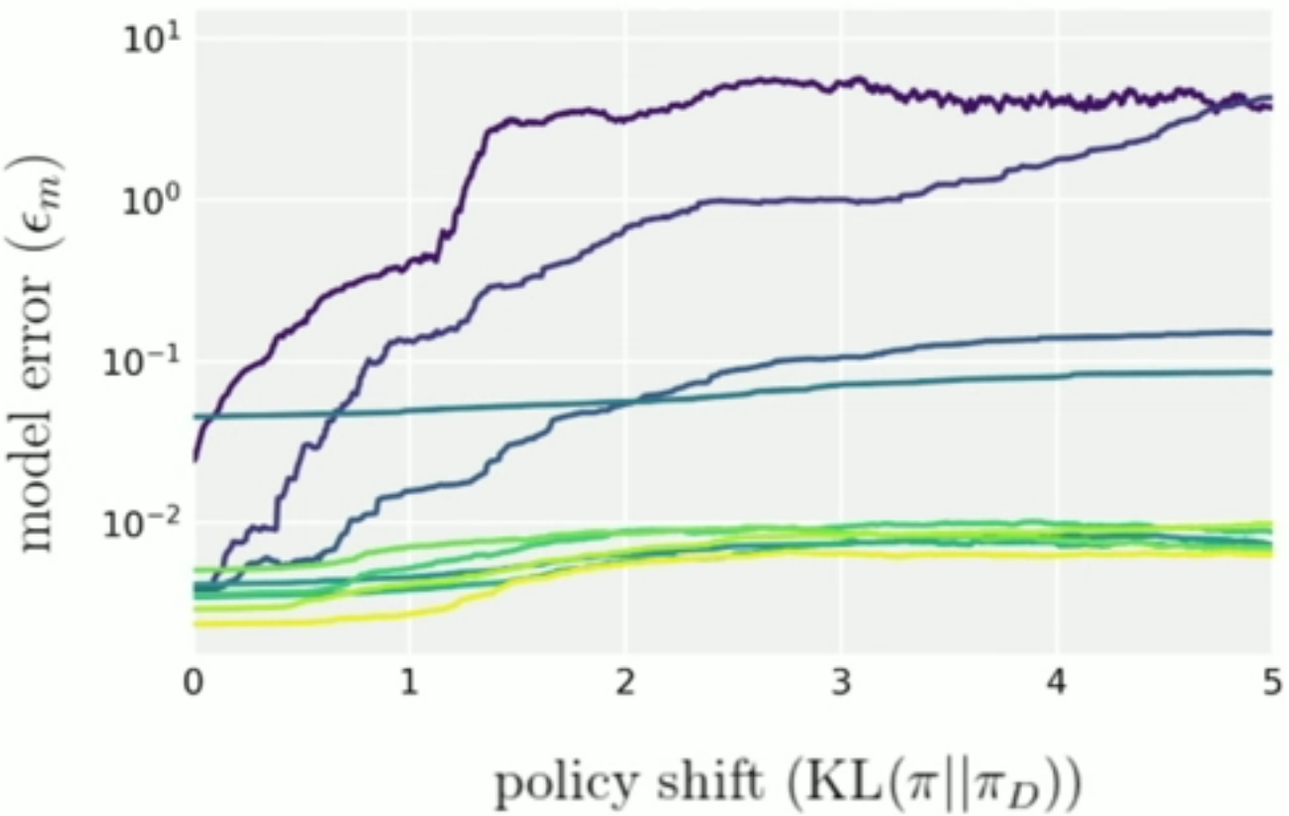

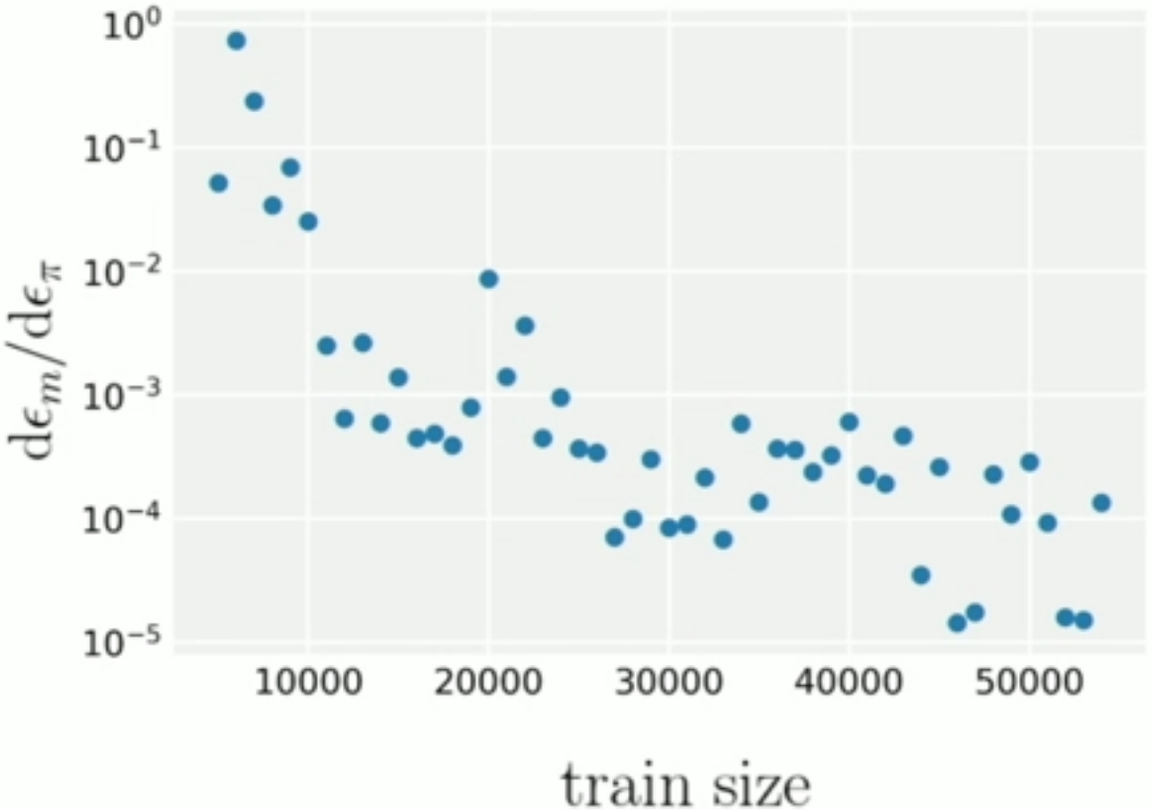

(Better) bounds on returns

- Use policy performance under model rollouts to derive lower bound in real environment

$$\eta[\pi] \geq \eta^{\text{branch}}[\pi] - 2r_{\max}\left[\frac{\gamma^{k+1}\epsilon_\pi}{(1-\gamma)^2} + \frac{(\gamma^k+2)\epsilon_\pi}{(1-\gamma)} + \frac{k}{1-\gamma}(\epsilon_m + 2\epsilon_\pi)\right]$$

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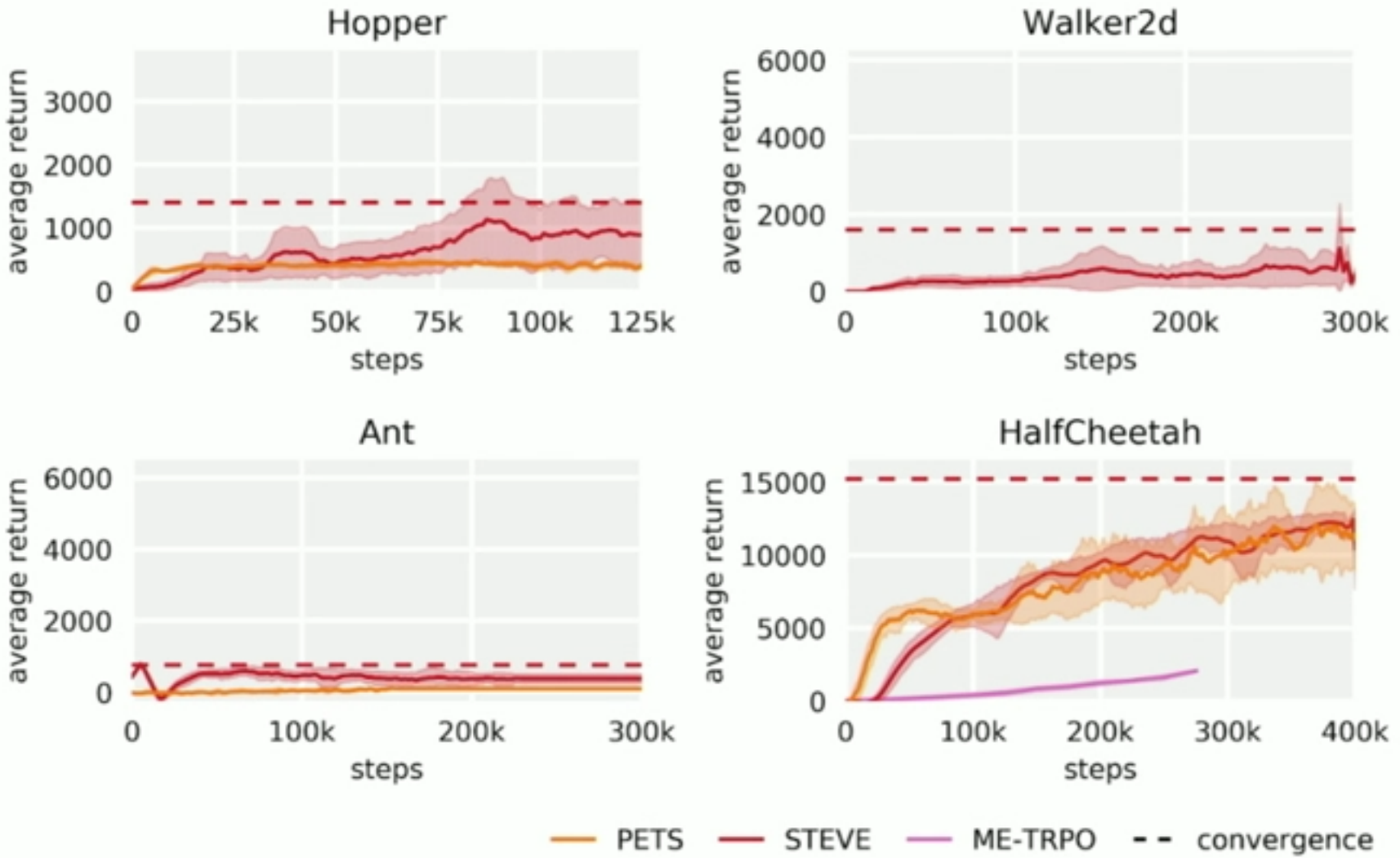
$$\epsilon_m + \frac{\mathrm{d}\epsilon_m}{\mathrm{d}\epsilon_\pi}$$

- Accounting for empirical model generalization motivates model usage

- If $\epsilon_\pi \approx \epsilon_m$, k will be small*

*When k=1, this corresponds to Dyna [Sutton, 1991]

MBPO Results



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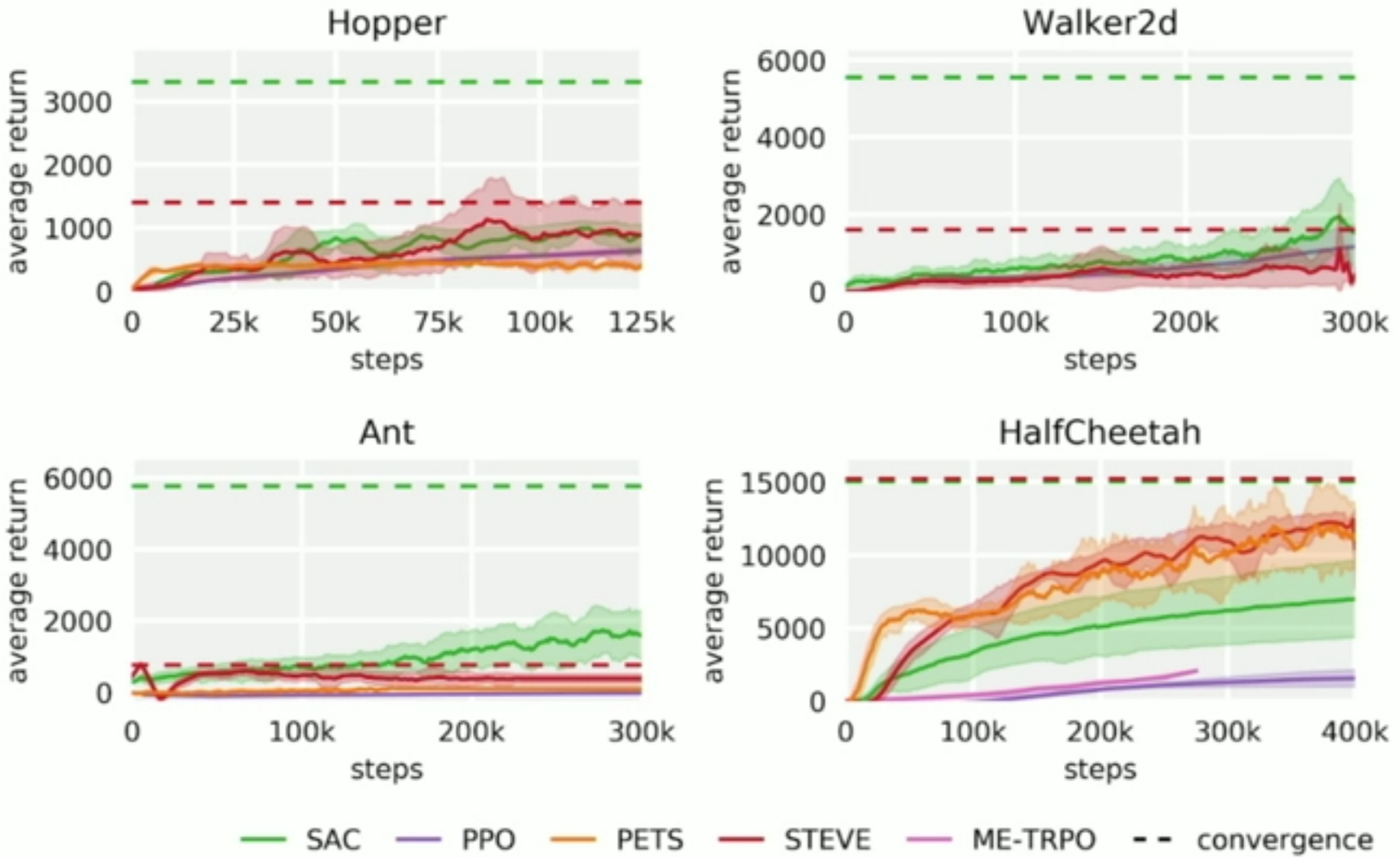

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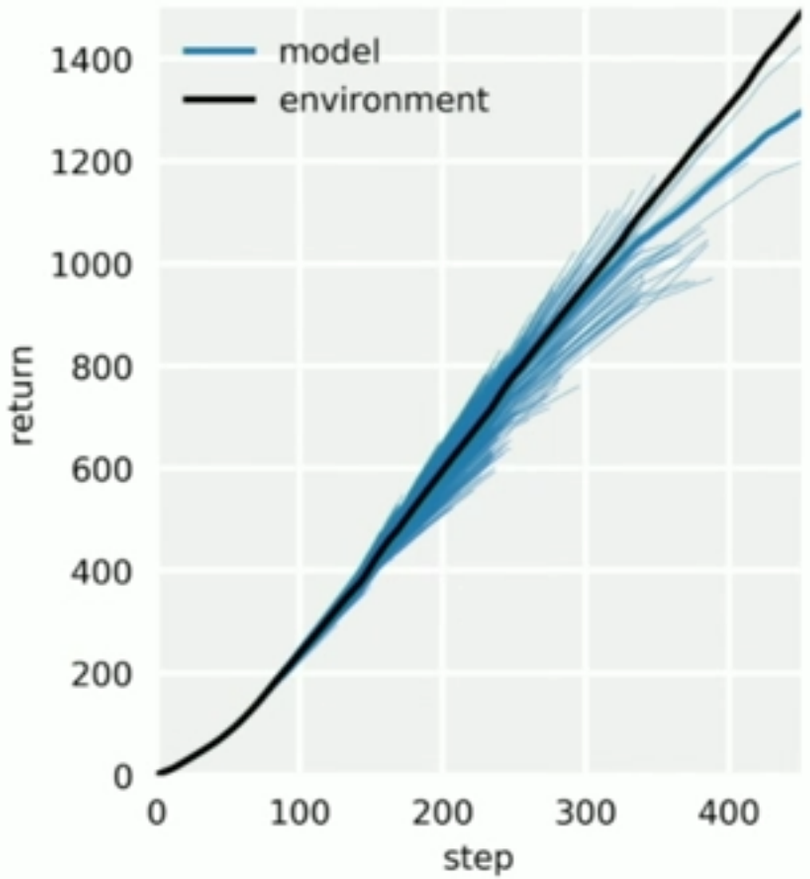

added benefit: no model exploitation!

Summary

- Empirical model generalization motivates model usage
- Short model rollouts give large benefits to policy optimization
- MBPO avoids model exploitation and scales to long-horizon tasks

people.eecs.berkeley.edu/~janner/mbpo/