Reinforcement Learning

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Recap

- Sometimes, it is better to learn a stochastic policy than a deterministic policy
- Policy gradient methods suffer from poor sample efficiency
- Importance sampling can help alleviate this problem
- However, we need to make sure that current policy is not far from policy with which we have collected trajectories
- Small changes in the policy parameters can unexpectedly lead to big changes in the policy.
- TRPO uses importance sampling to take multiple gradient steps and constrains the optimization objective in the policy space
- PPO does the same but approximately enforces KL constraint without computing natural gradients.

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- So far, we have only looked at model-free reinforcement learning

What is a Model?

- A model $\mathcal{M}$ is a representation of an MDP $< S, A, P, R >$
- We will assume state space S and action space A are known
- So a model $M =< P_\phi, R_\phi >$ represents state transitions $P_\phi \approx P$ and rewards $R_\phi \approx R$

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- We can also only learn one of state transitions and reward model

Model Learning

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- Learning $s, a \rightarrow s'$ is a density estimation problem
- We pick a loss function like MSE, KL Divergence etc., and then optimize

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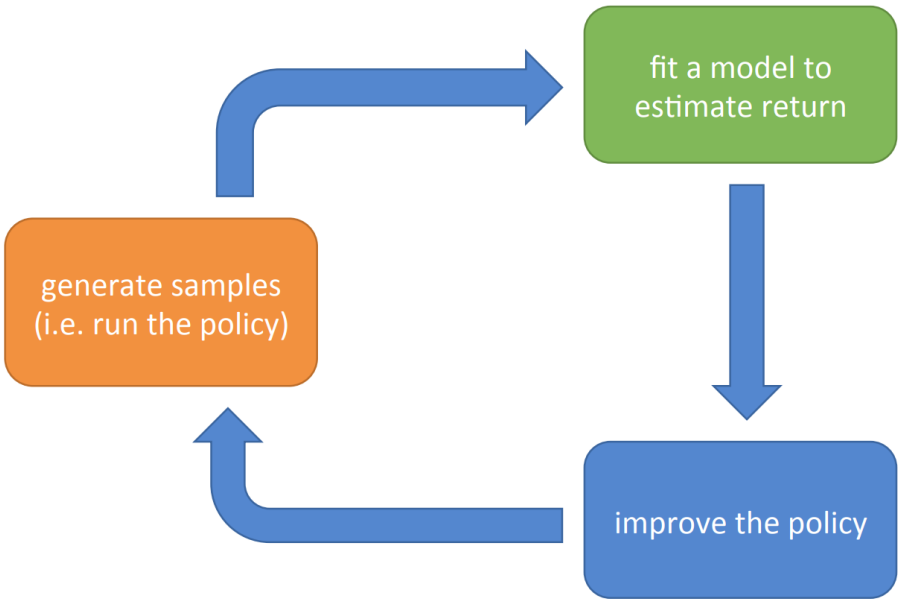
- Disadvantages:
  - First learn a model, then construct a value function. This means we will have two sources of approximation error

Model-Based RL



estimate $p(\mathbf{s}'|\mathbf{s},\mathbf{a})$ (model-based)

supervised learning

$$\min_{\phi} \sum_{i} ||f_{\phi}(\mathbf{s}_i,\mathbf{a}_i) - \mathbf{s}'_i||^2$$

optimize $\pi_{\theta}(\mathbf{a}|\mathbf{s})$ (model-based)

Model-Based RL

- So, now we have the following algorithm
  1. Run some policy (e.g. random policy) to collect data $\mathcal{D} = \{(s, a, s')_i\}$
  2. Learn model $f_\phi(s, a)$ to minimize $\sum_i ||f_\phi(s_i, a_i) - s'_i||$
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- Data distribution mismatch $p_{\pi_0}(s) \neq p_{\pi_f}(s)$

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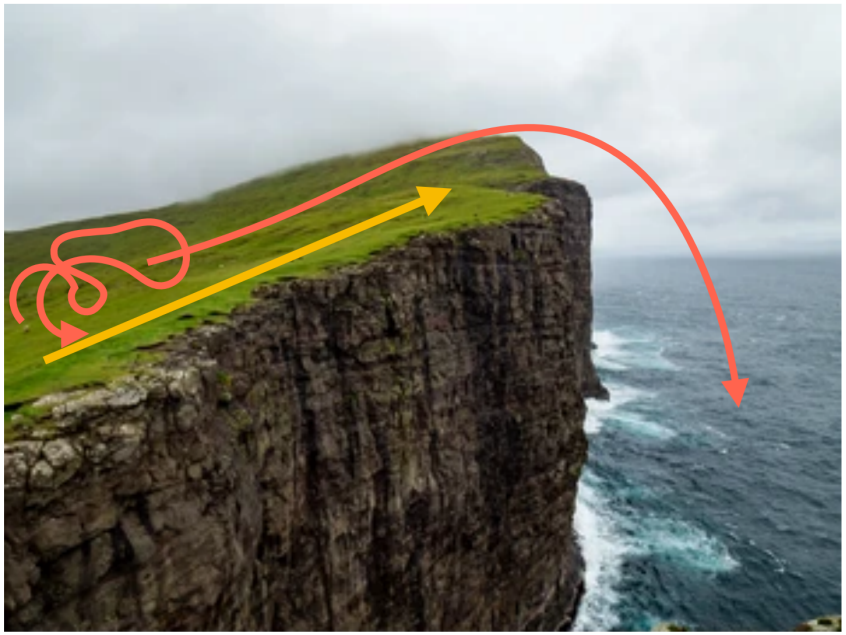
- Now, we update the model using data collected with planning
- Then, replan periodically to help account for mistakes.

Revisiting the Cliff



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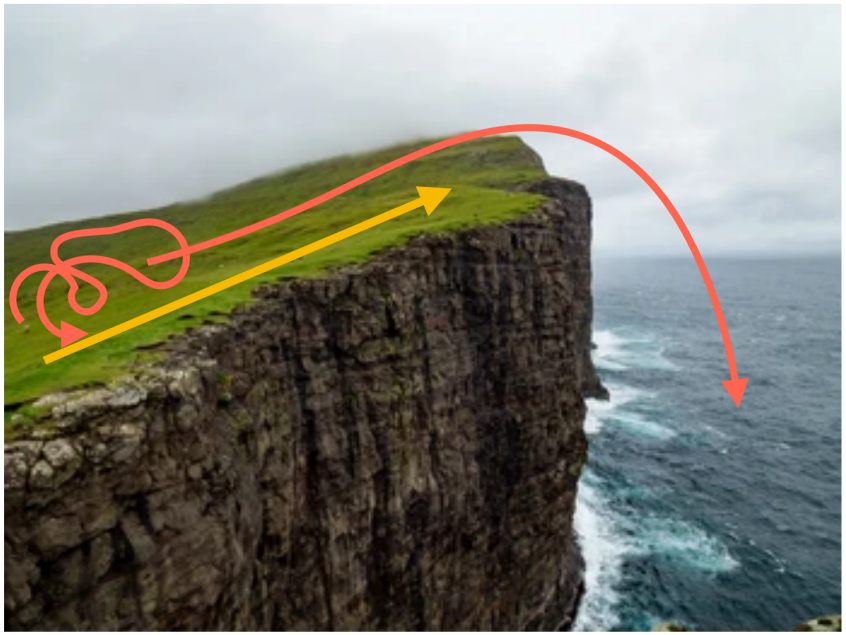

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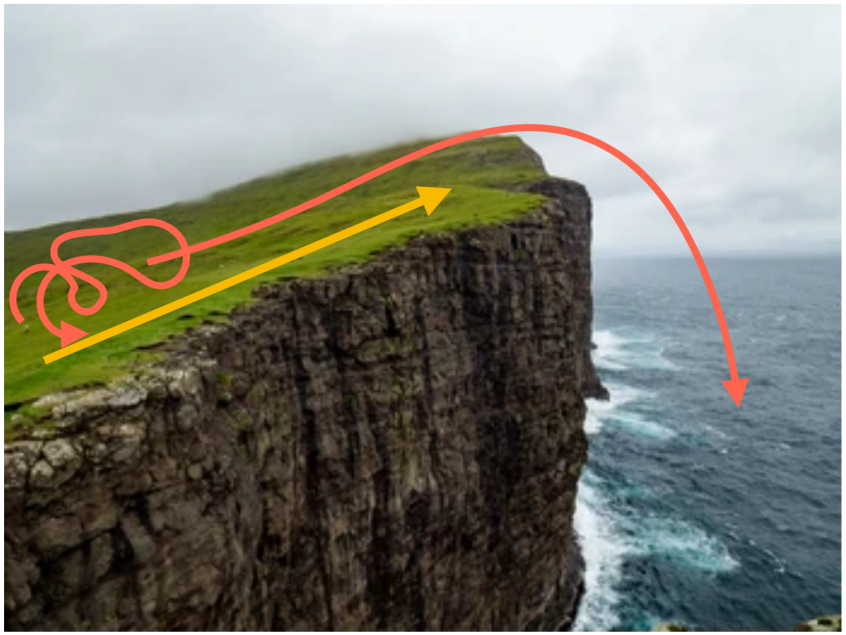

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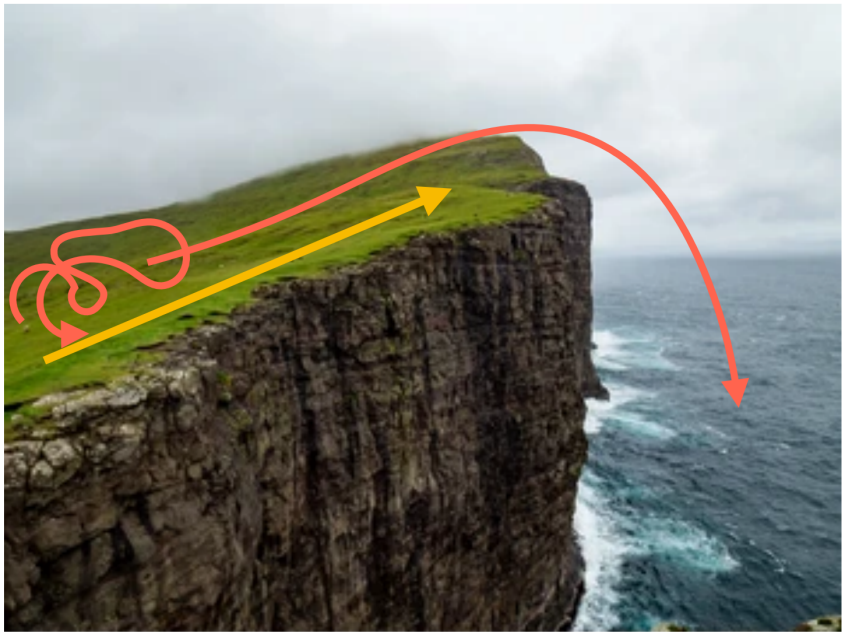

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- The final policy is different now. It learns to go to the top and stop.

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- Algorithm:
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  5. Go to step 1
- Compatible with variety of model-free RL methods
- Could additionally use D_{env} in policy update (step 4)

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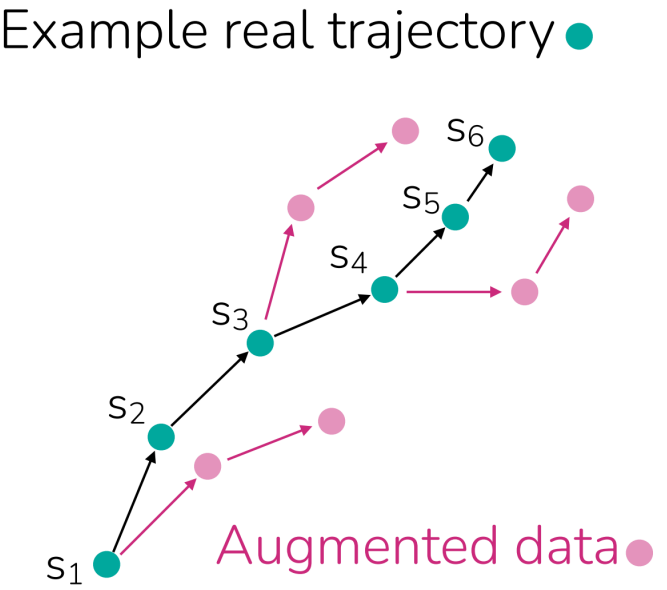

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Whether to use a model depends on how hard it is to learn!

Case study: Model-based RL for dexterous manipulation

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Model-free methods:

SAC: actor-critic method

NPG: policy gradient method

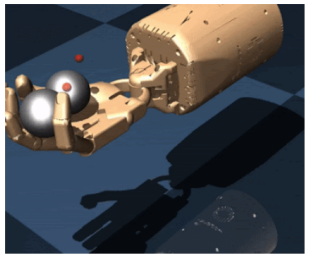
Model-based methods:

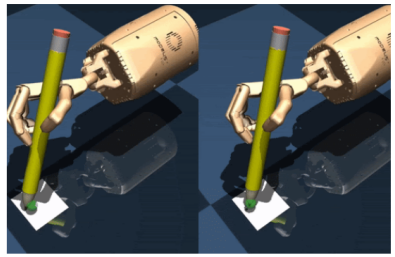
PDDM: proposed method

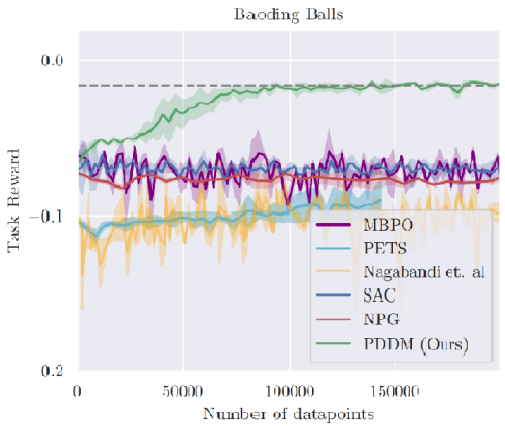
MBPO: RL with model-generated data

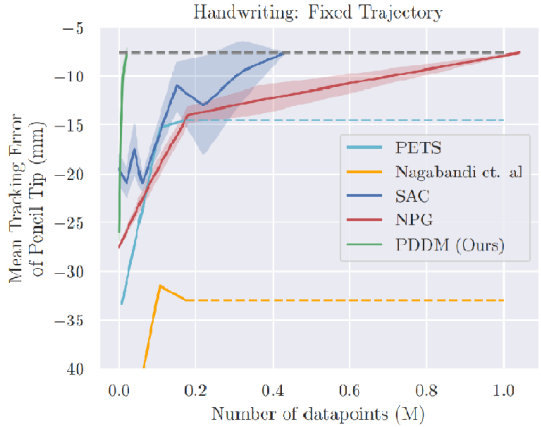
PETS: CEM-based planner

Nagabandi et al.: random shooting, no ensembles









[0]Nagabandi, et al. Deep Dynamics Models for Learning Dexterous Manipulation

Summary

- Reinforcement Learning can be categorised into Model-Based and Model-Free.
- In Model-Based RL, we also learn the model of the world i.e, the state transition model and/or the reward model
- Model-Based RL can be employed with both value and/or policy based methods
- We can use the model to augment the real environment data
- Models can be immensely useful if easy to learn but sometimes they can be harder to learn than a policy
- Whether to use a model depends on how hard it is to learn

References

These slides have been adapted from

- Chelsea Finn & Karol Hausman, Stanford CS224R: Deep Reinforcement Learning
- Sergey Levine, Berkeley CS285 Deep Reinforcement Learning
- David Silver, Deepmind: Introduction to Reinforcement Learning