# Model-Based Reinforcement Learning

CS 224R

# Course reminders

- Project proposal due this Wednesday (graded fairly lightly — really for your benefit!)
- Homework 2 due next Wednesday (**start early!**)

Following up on high-resolution feedback:

- Optional readings posted on course website
- The most math-dense lectures are behind us.
- Unfortunately don't have TA bandwidth to support live zoom questions
- Covering RL**HF** on Weds.

# The plan for today

1. A brief primer on sampling-based optimization
2. Model-based reinforcement learning
    a. How to get a good dynamics model?
    b. How to use a (learned) dynamics model?
3. Case study in dexterous robotic manipulation

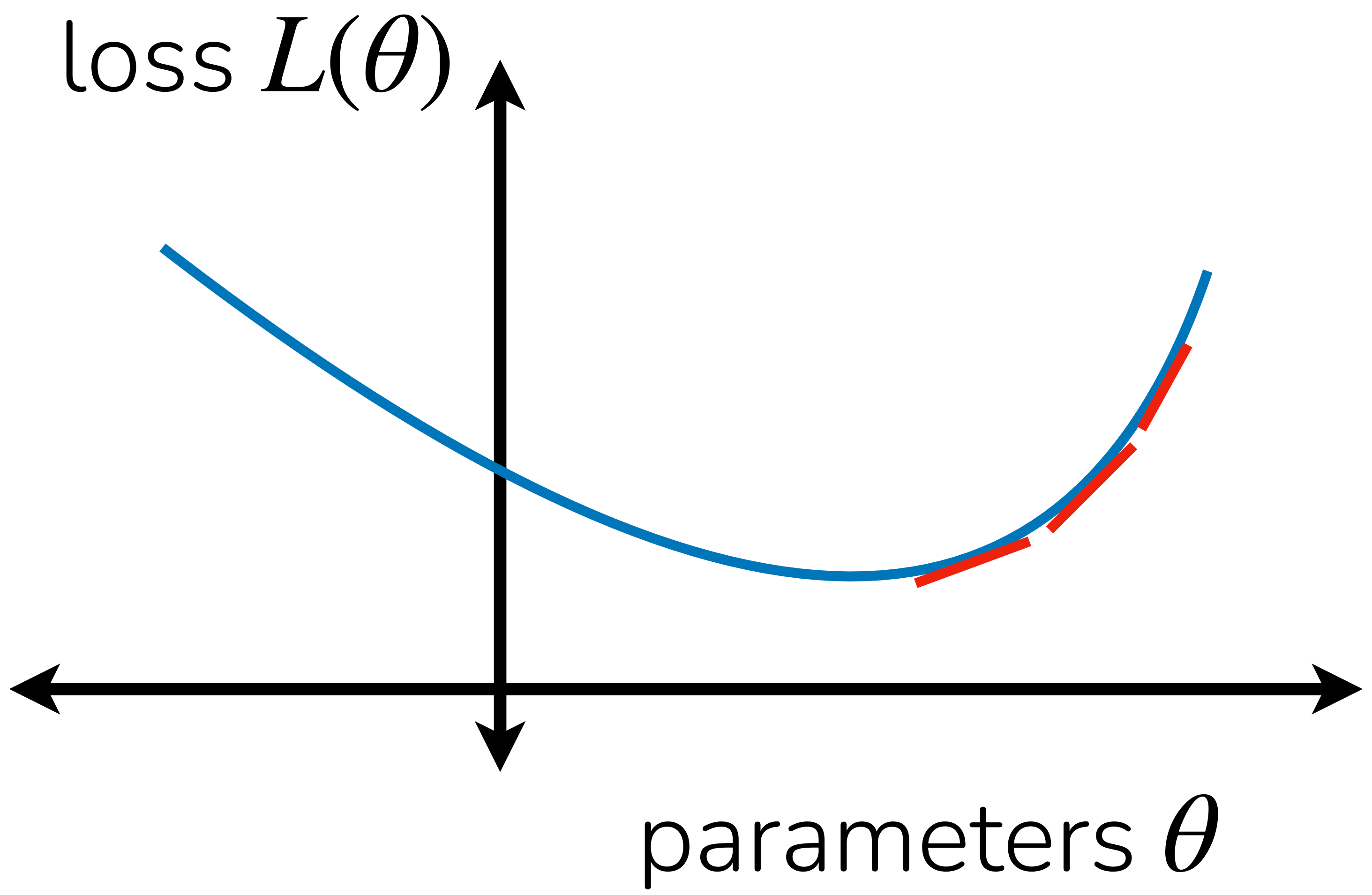
**Key learning goals**:

- model-based RL methods, and how to implement them
- the key challenges arising in model-based reinforcement learning
- tradeoffs between different model-based RL approaches

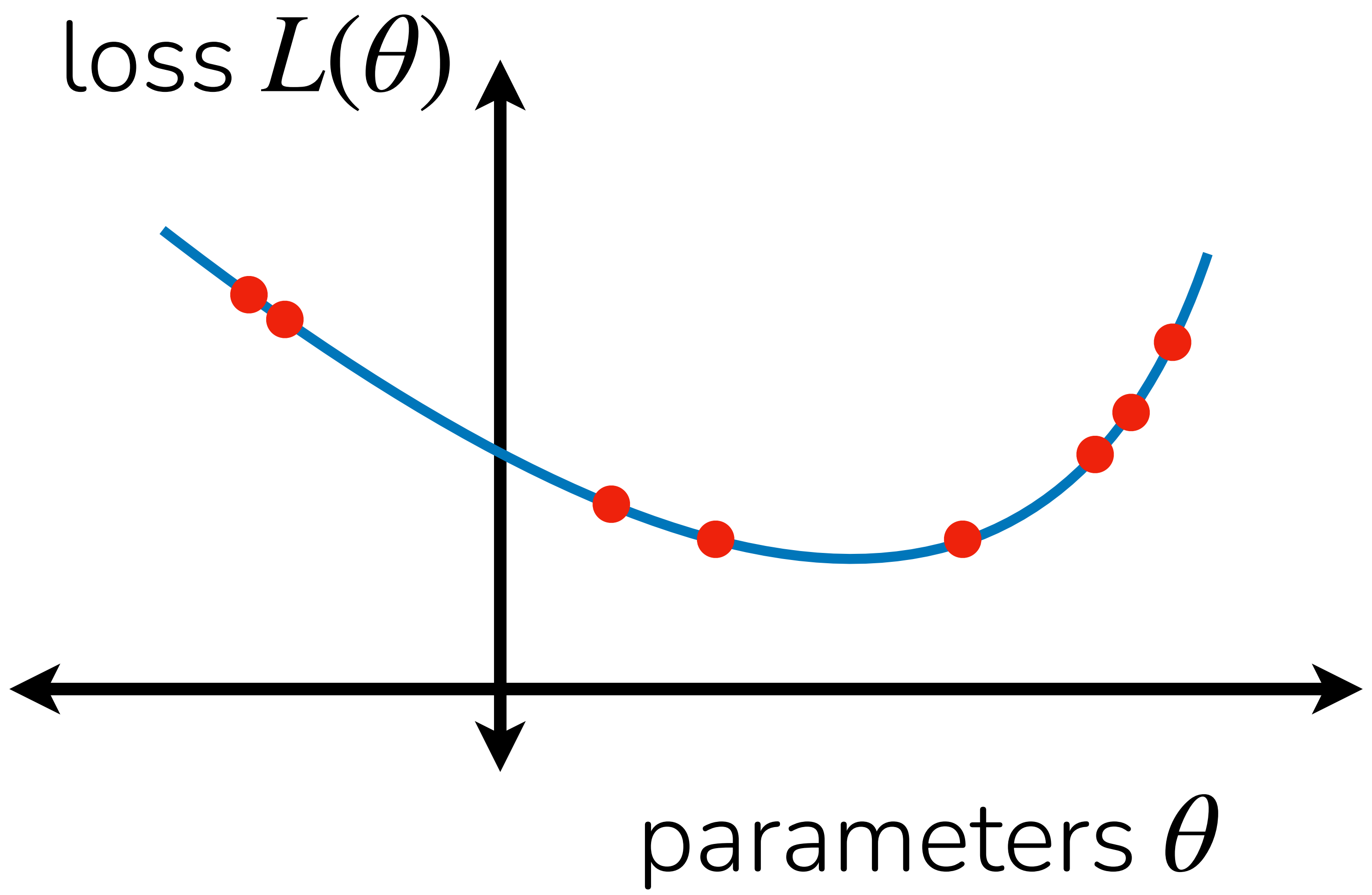
# Teaser: How to get a robot to learn this?

# Gradient-based vs. sampling-based optimization

## Gradient-based (1st order)




## Sampling-based (0th order)




**Cross-entropy method (CEM)** (Not to be confused with the cross-entropy loss!)

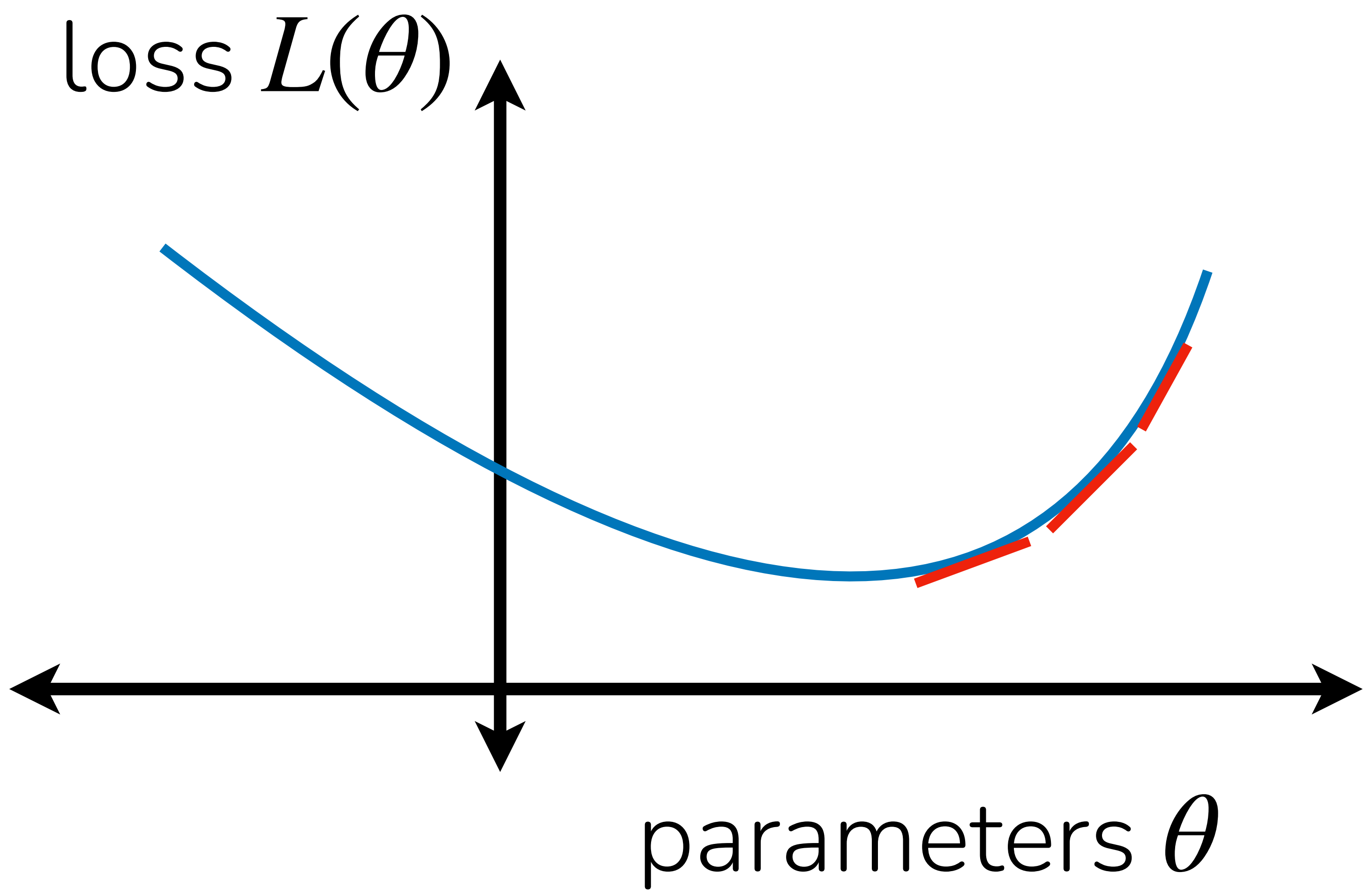
repeat

1. Sample from distribution $p_i(\theta)$
2. Rank samples according to loss $\theta_{1,\ldots,K}$
3. Fit Gaussian distribution $p_{i+1}$ to "elite" samples $\theta_{1\ldots k}$

Eventually return $\theta_1$

# Gradient-based vs. sampling-based optimization

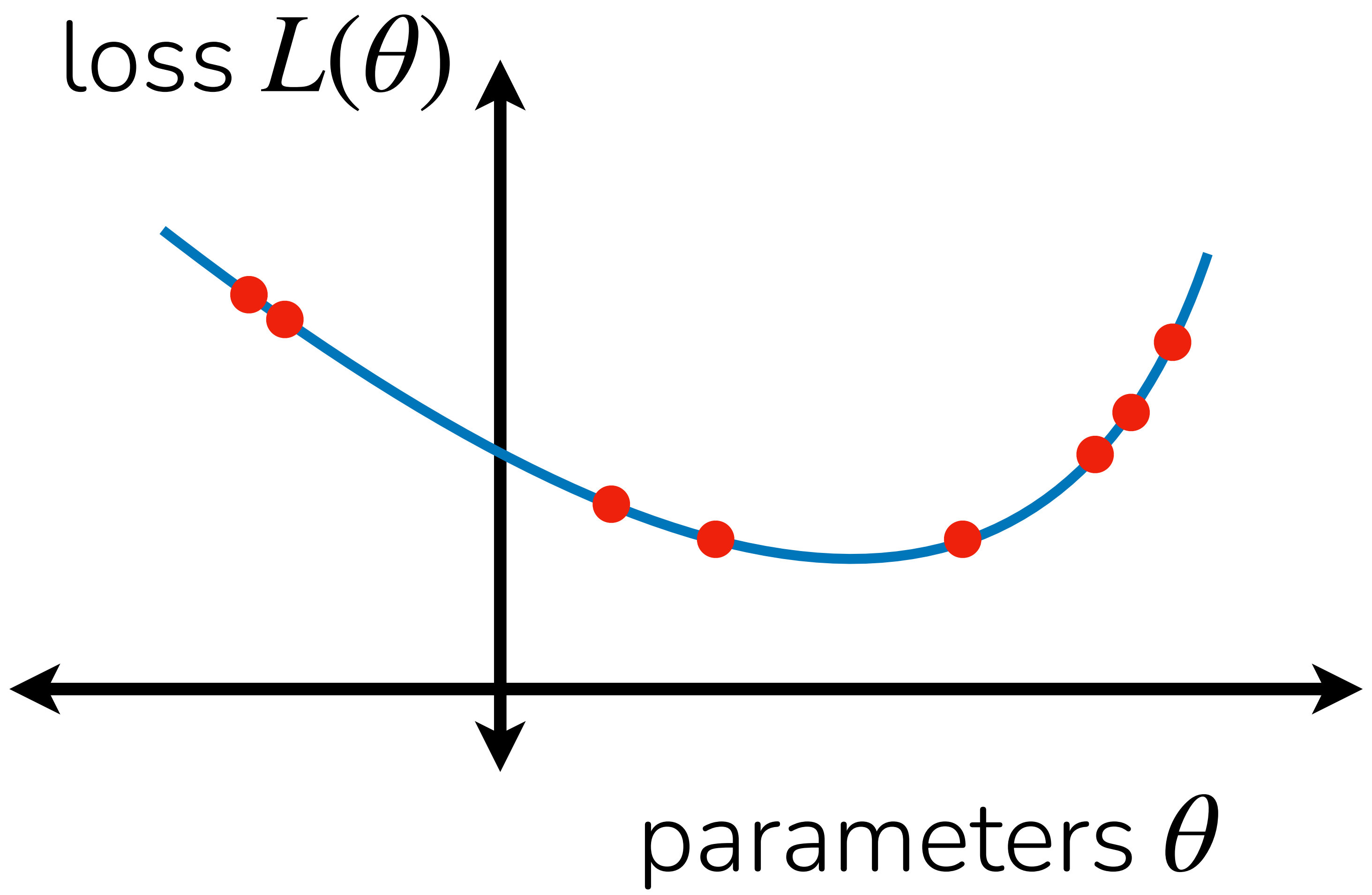
## Gradient-based (1st order)




+ scalable to high dimensions
+ works well *especially* in overparametrized regimes

- requires nice optimization landscape

## Sampling-based (0th order)




+ parallelizable
+ requires no gradient information

- scales poorly to high dimensions

# The plan for today

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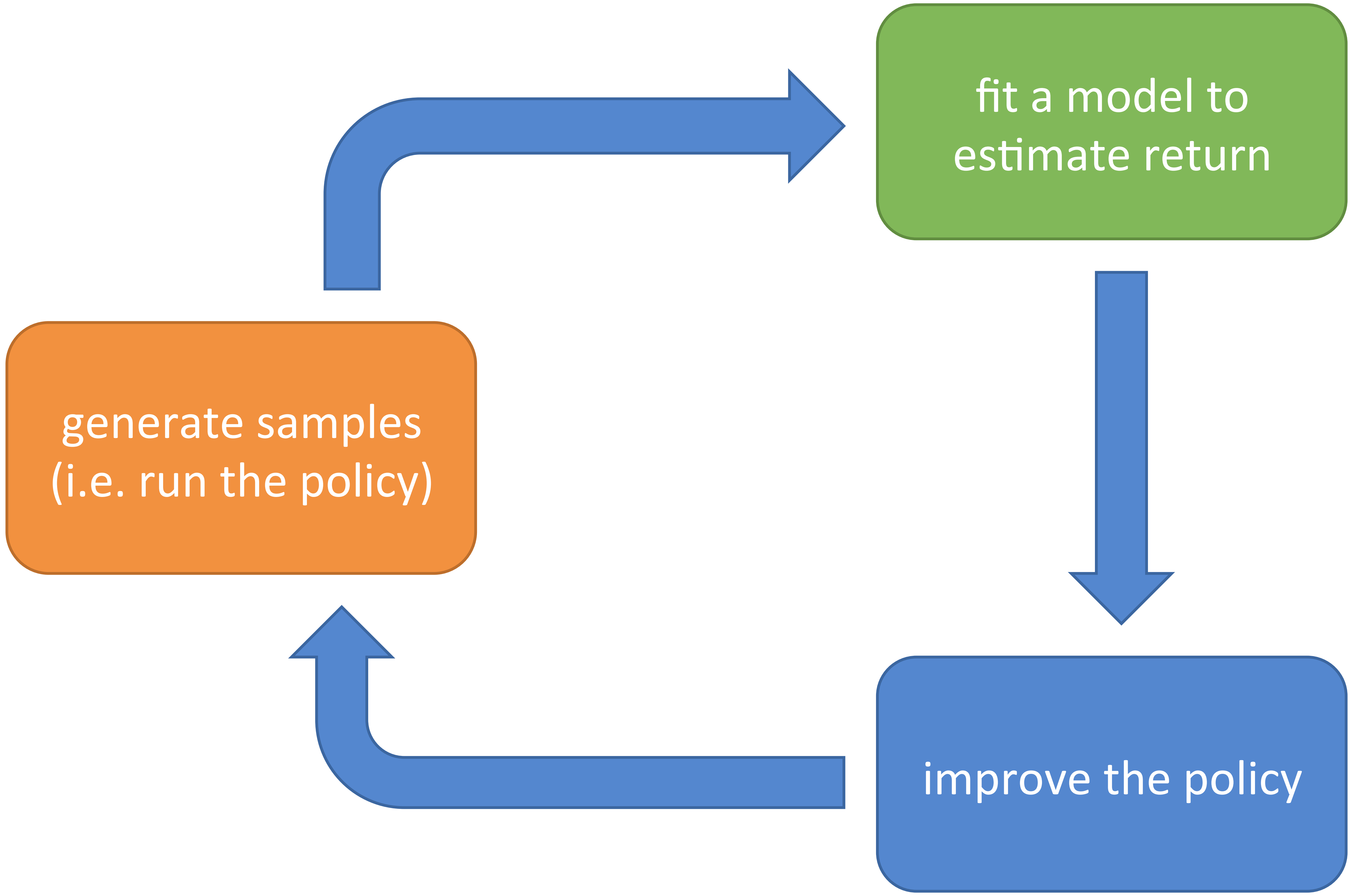
3. Case studies

# Recap: The anatomy of a reinforcement learning algorithm

**Previously**: introduced model-free RL methods (policy gradient, Q-learning)




compute $\hat{Q} = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$ (MC policy gradient)

fit $Q_\phi(\mathbf{s}, \mathbf{a})$ (actor-critic, Q-learning)

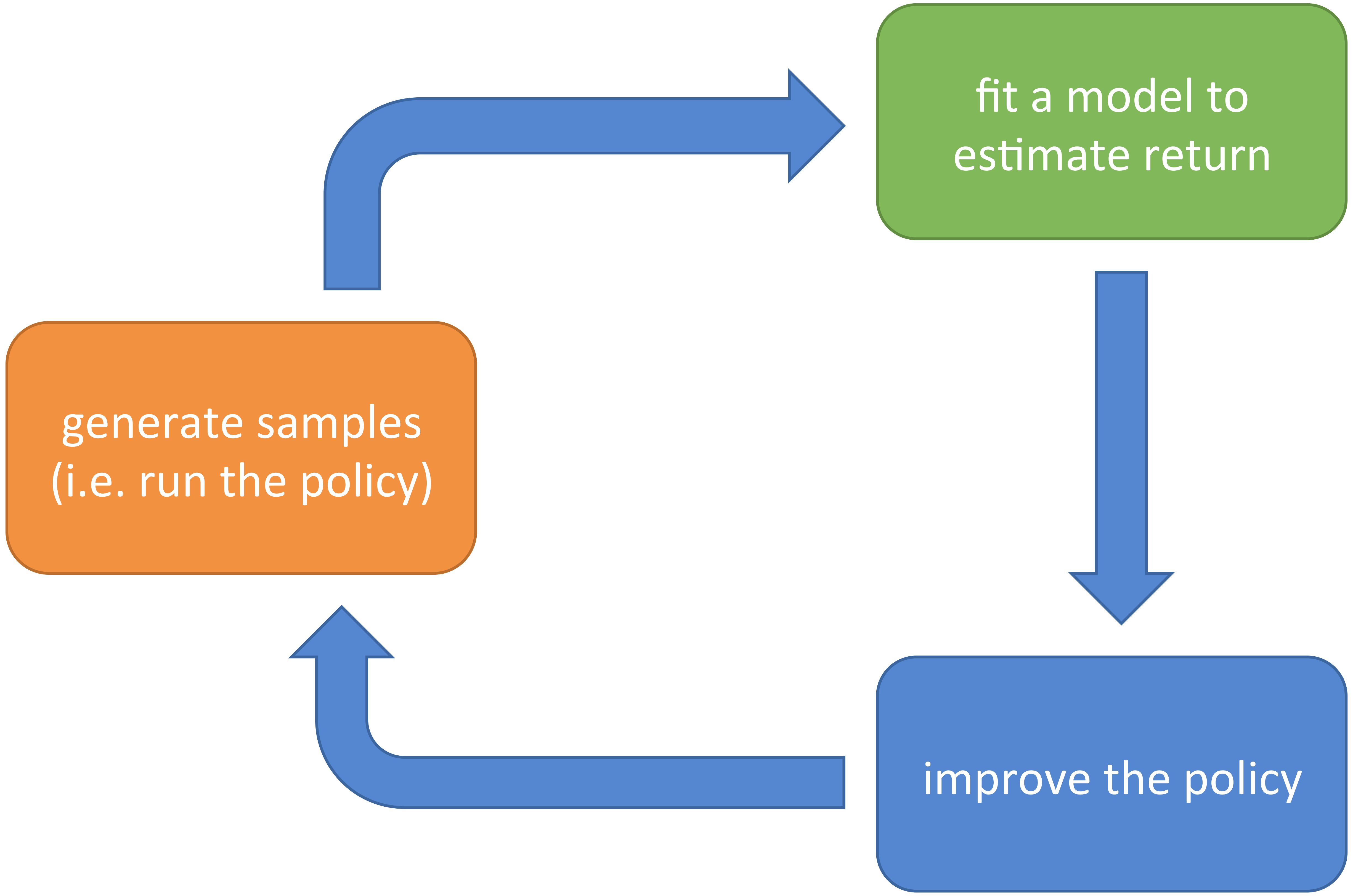
$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$ (policy gradient)

$\pi(\mathbf{s}) = \arg\max Q_\phi(\mathbf{s}, \mathbf{a})$ (Q-learning)

**This lecture**: focus on **model-based RL** methods

# Model-based reinforcement learning

**Key idea:** It would be useful if we could approximately simulate the world!
i.e. if we could predict the consequences of our actions




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)

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   a. **How to get a good dynamics model?**
   b. How to use a (learned) dynamics model?
3. Case study in dexterous robotic manipulation

# How to get a good dynamics model?

**Fit a predictive model**:

- input: s, a
- output: s'

**Example models**:

- robotics
  - video prediction model (possibly in some image representation space)
  - physics model some unknown free parameters
    (e.g. unknown coefficient of friction)
- dialog: large language model
- finance: stock market predictor

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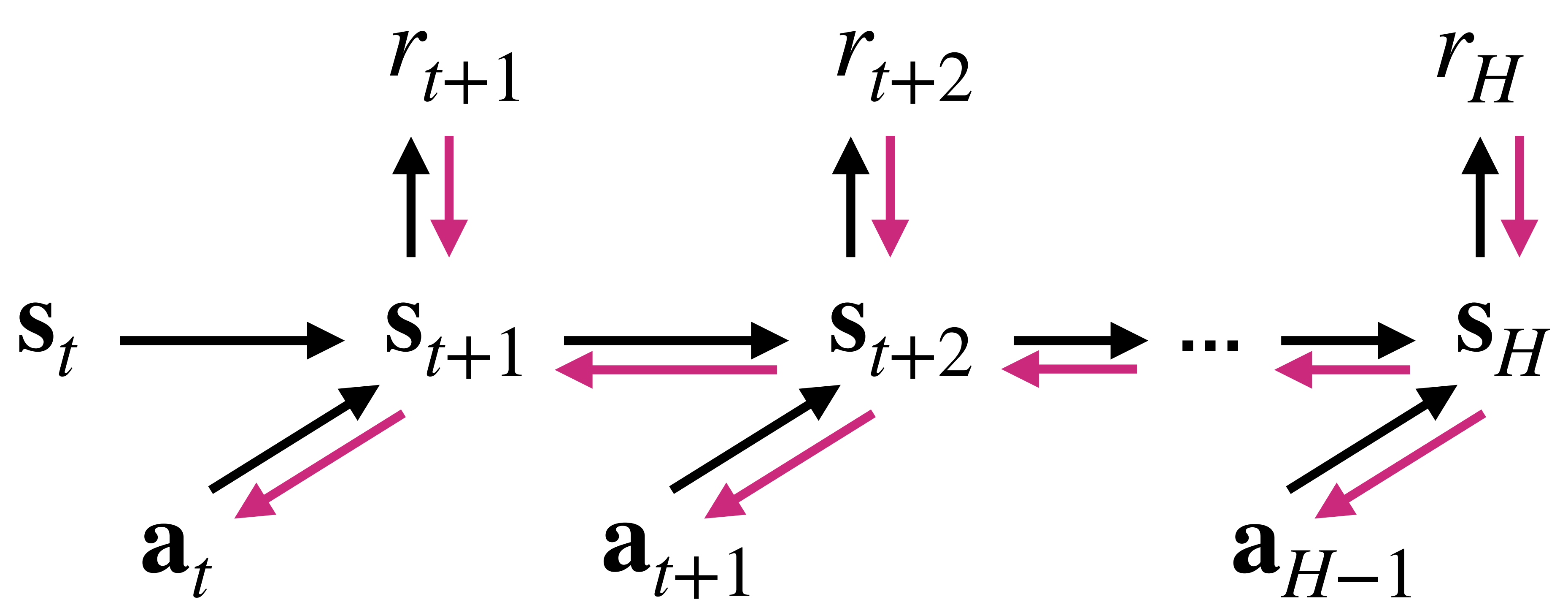
   a. How to get a good dynamics model?
   **b. How to use a (learned) dynamics model?**
3. Case study

- for planning
- for learning a policy

## Approach 1: Optimize over actions using model $\max_{\mathbf{a}_{t:t+H}} \sum_t r(\mathbf{s}_t, \mathbf{a}_t)$

"planning"




Approach 1a:
via *backpropagation*
(i.e. *gradient-based* optimization)

## Algorithm:

1. Run some policy (e.g. random policy) to collect data $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. Learn model $f_\phi(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. Backpropagate through $f_\phi(\mathbf{s}, \mathbf{a})$ to choose actions

## Approach 1: Optimize over actions using model $\max_{\mathbf{a}_{t:t+H}} \sum_t r(\mathbf{s}_t, \mathbf{a}_t)$

"planning"

$$
\begin{tikzcd}
 & r_{t+1} & r_{t+2} & & r_H \\
\mathbf{s}_t \arrow[r] & \mathbf{s}_{t+1} \arrow[u] \arrow[r] & \mathbf{s}_{t+2} \arrow[u] \arrow[r] & \dots \arrow[r] & \mathbf{s}_H \arrow[u] \\
\mathbf{a}_t \arrow[ur] & \mathbf{a}_{t+1} \arrow[ur] & & \mathbf{a}_{H-1} \arrow[ur] &
\end{tikzcd}
$$

Approach 1b:
via *sampling*
(i.e. *gradient-free* optimization)

## Algorithm:

1. Run some policy (e.g. random policy) to collect data $\mathscr{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. Learn model $f_\phi(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}_i'\|^2$
3. Iteratively sample action sequences, run through model $f_\phi(\mathbf{s}, \mathbf{a})$ to choose actions

# Sampling-Based Optimization

$$\text{Denote } \mathbf{A} := \mathbf{a}_t, \ldots, \mathbf{a}_{t+H}$$

## Version 1: guess & check

“random shooting”

a. Sample many $\mathbf{A}_1, \ldots, \mathbf{A}_N$ from some distribution (e.g. uniform)

b. Choose $\mathbf{A}_i$ based on $\arg\max_i \sum_{t'=t}^{t+H} r(\mathbf{s}_{t'}, \mathbf{a}_{t'})$

Can we improve this distribution?

## Version 2: cross-entropy method

a. Sample many $\mathbf{A}_1, \ldots, \mathbf{A}_N$ from $p(\mathbf{A})$

b. Evaluate $J(\mathbf{A}_i) = \sum_{t'=t}^{t+H} r(\mathbf{s}_{t'}, \mathbf{a}_{t'})$

c. Pick the elites $\mathbf{A}_{i_1}, \ldots, \mathbf{A}_{i_M}$ with the largest $J(\mathbf{A}_i)$, where $M < N$

d. Refit $p(\mathbf{A})$ to the elites $\mathbf{A}_{i_1}, \ldots, \mathbf{A}_{i_M}$

# Sampling-Based Optimization

Version 1: guess & check "random shooting"

Version 2: cross-entropy method

Pros:

+ fast, if parallelized

+ simple

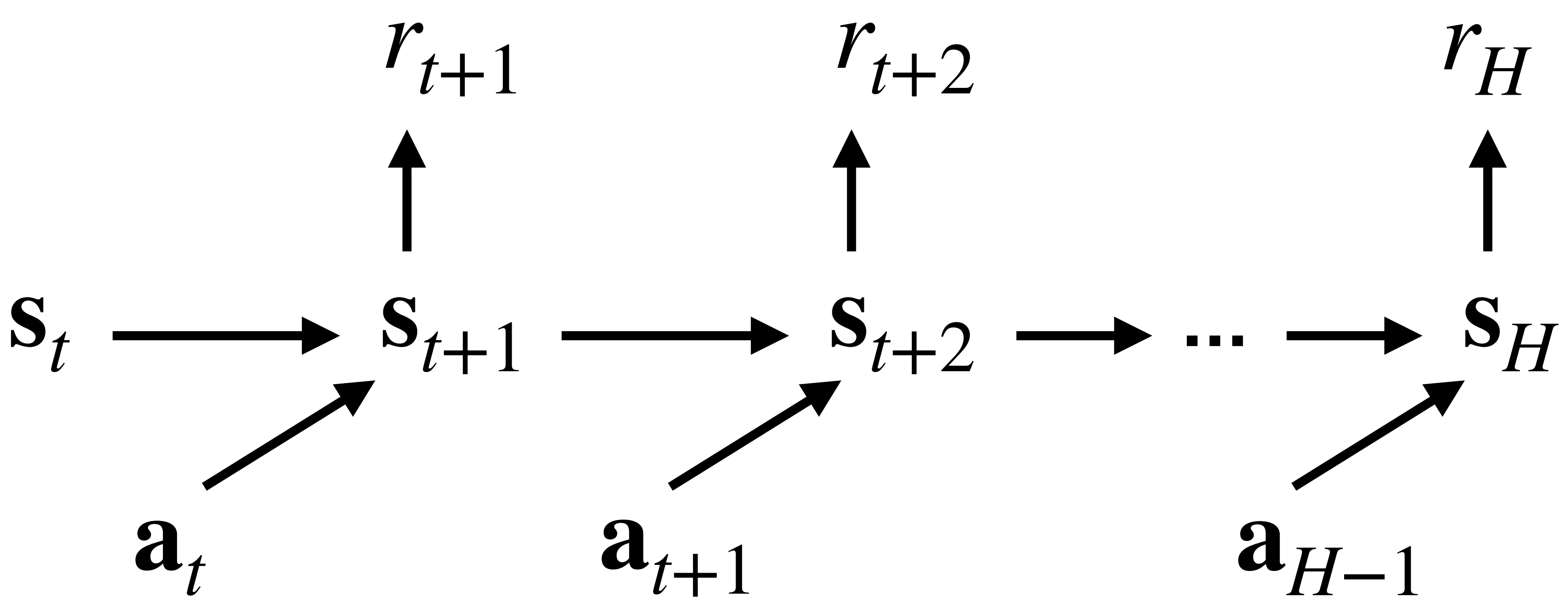
Cons:

- doesn't scale to high-dimensions

(Including both $H$ and $|\mathbf{a}|$)

## **Approach 1:** Optimize over actions using model $\max_{\mathbf{a}_{t:t+H}} \sum_t r(\mathbf{s}_t, \mathbf{a}_t)$

"planning"




Approach 1b:
via *sampling*
(i.e. *gradient-free* optimization)

## Algorithm:

1. Run some policy (e.g. random policy) to collect data $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. Learn model $f_\phi(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}_i'\|^2$
3. Iteratively sample action sequences, run through model $f_\phi(\mathbf{s}, \mathbf{a})$ to choose actions

(e.g. with random shooting or cross-entropy method)

# How can this approach fail?


1. Run some policy (e.g. random policy) to collect data $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. Learn model $f_\phi(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. Iteratively sample action sequences, run through model $f_\phi(\mathbf{s}, \mathbf{a})$ to choose actions

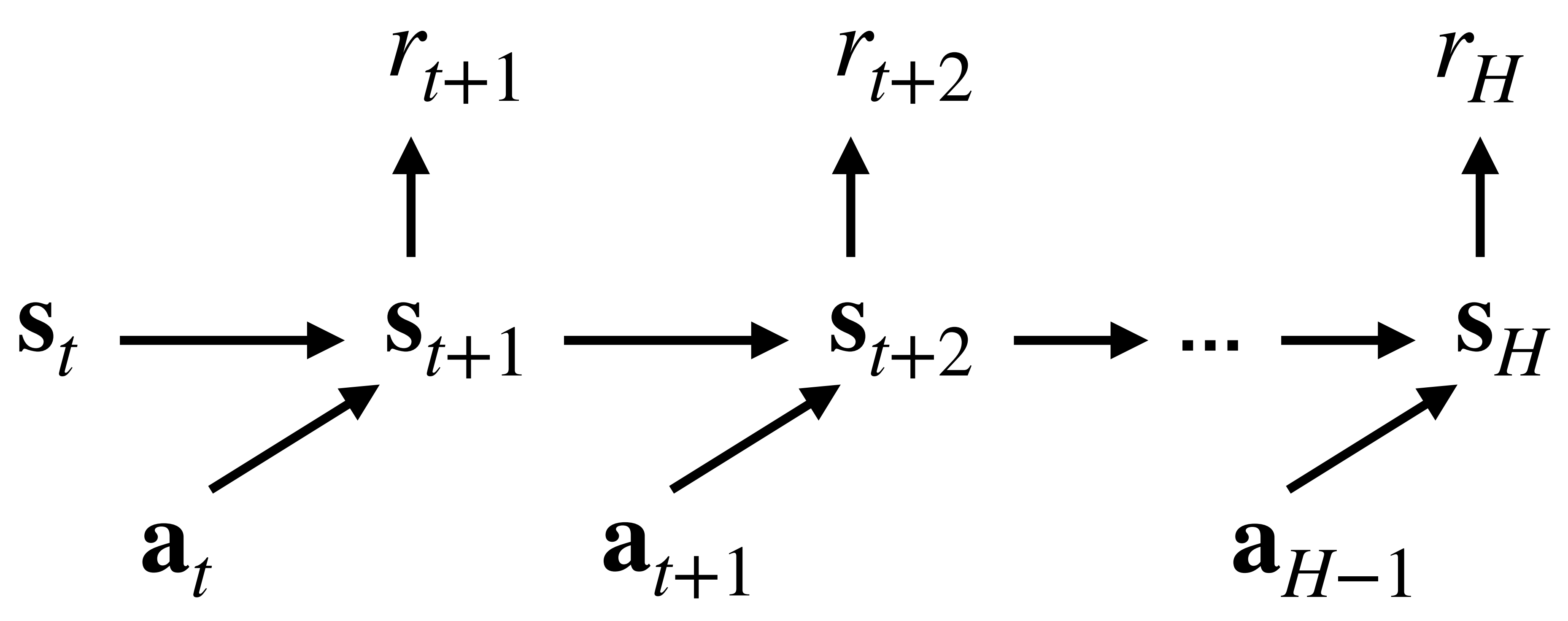
Data distribution mismatch

$$p_{\pi_0}(\mathbf{s}) \neq p_{\pi_f}(\mathbf{s})$$

Going right means that we can go higher!

**Thought Exercise:** How might you alleviate this issue?

**Approach 1:** Optimize over actions using model $\max_{\mathbf{a}_{t:t+H}} \sum_t r(\mathbf{s}_t, \mathbf{a}_t)$




Approach 1b:
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## Algorithm:

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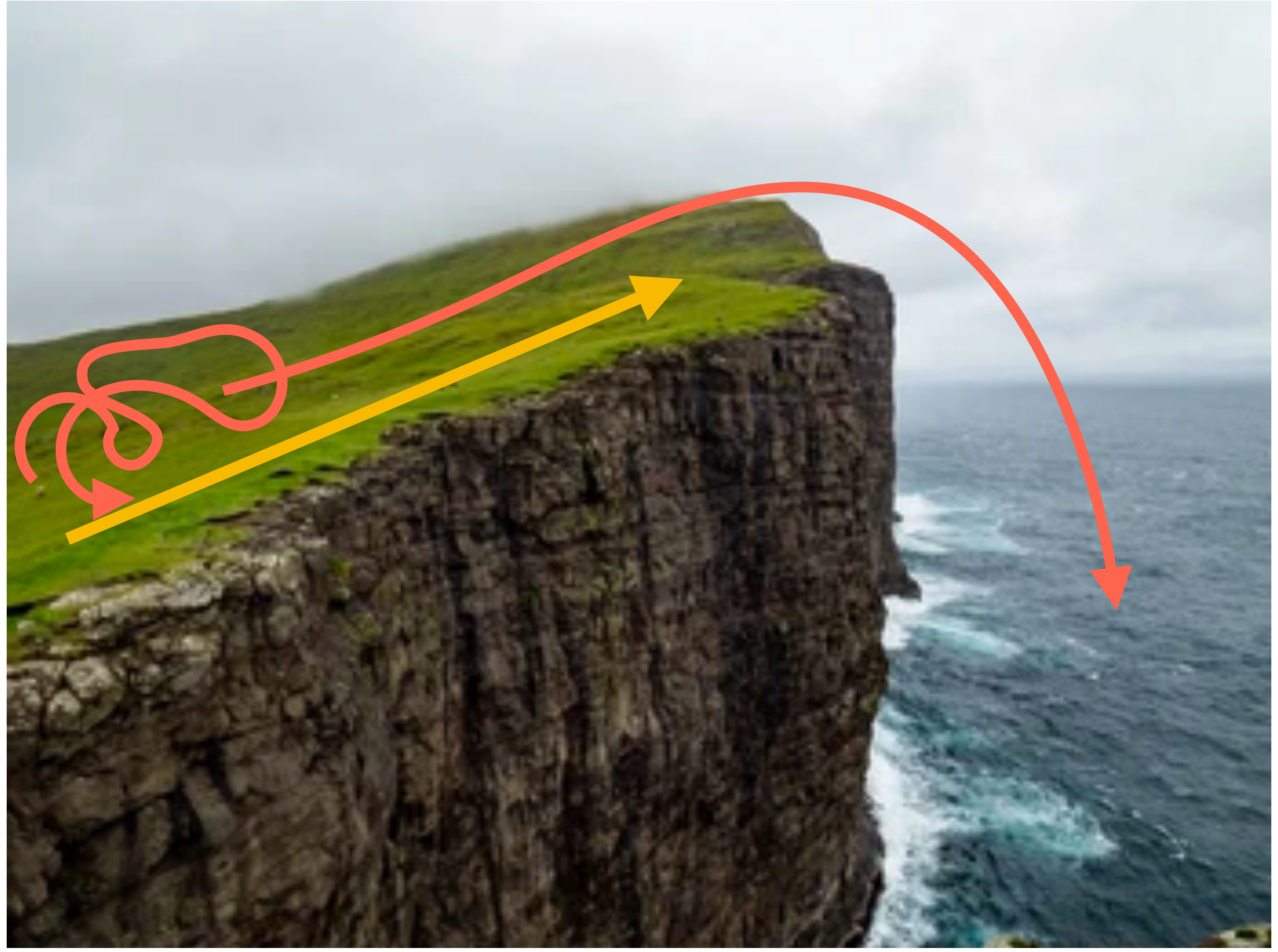
3. Iteratively sample action sequences, run through model $f_\phi(\mathbf{s}, \mathbf{a})$ to choose actions
4. Execute planned actions, appending visiting tuples $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to $\mathcal{D}$

# Revisiting the cliff



1. Run some policy (e.g. random policy) to collect data $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
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4. Execute planned actions, appending visiting tuples $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to $\mathcal{D}$

Going right means that we can go higher!

**Final policy**: go to the top and stop.

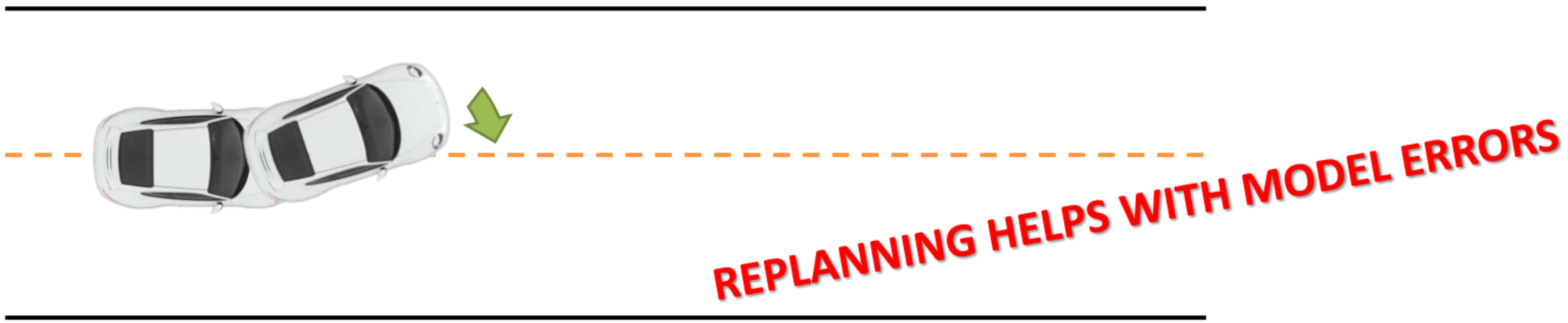
# Can we do better?

open-loop vs. closed-loop planning

# **Approach 2:** Plan & replan using model

*model-predictive control (MPC)*

1. run base policy $\pi_0(\mathbf{a}_t|\mathbf{s}_t)$ (e.g., random policy) to collect $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. learn model $f_\phi(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i ||f_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i||^2$
3. use model $f_\phi(\mathbf{s}, \mathbf{a})$ to optimize action sequence
4. execute the first planned action, observe resulting state $\mathbf{s}'$
5. append $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to dataset $\mathcal{D}$




+ replan to correct for model errors

- compute intensive

# So far: Planning with learned models

1. Can ***plan*** $\mathbf{a_1}$, ..., $\mathbf{a_H}$ with gradient-based or sampling-based optimization
2. ***Update the model*** using data collected with planning
3. ***Replan*** periodically to help account for mistakes.

+ Simple

+ Easy to plug in different goals / rewards (possibly even at test time!)

- Compute intensive at test time

- Only practical for short-horizon problems (or very shaped reward functions)

Why only short horizons?

(a) too compute expensive to make long plans

(b) model is not accurate for long horizons

Can we ***train a policy*** using a learned model?

# Model-based policy optimization

**Option 1**: Distill planner’s actions into a policy

(i.e. train policy to match actions taken by planner)

+ no longer compute intensive at test time

- still limited to short-horizon problems

How might we solve **longer-horizon** problems using a model?

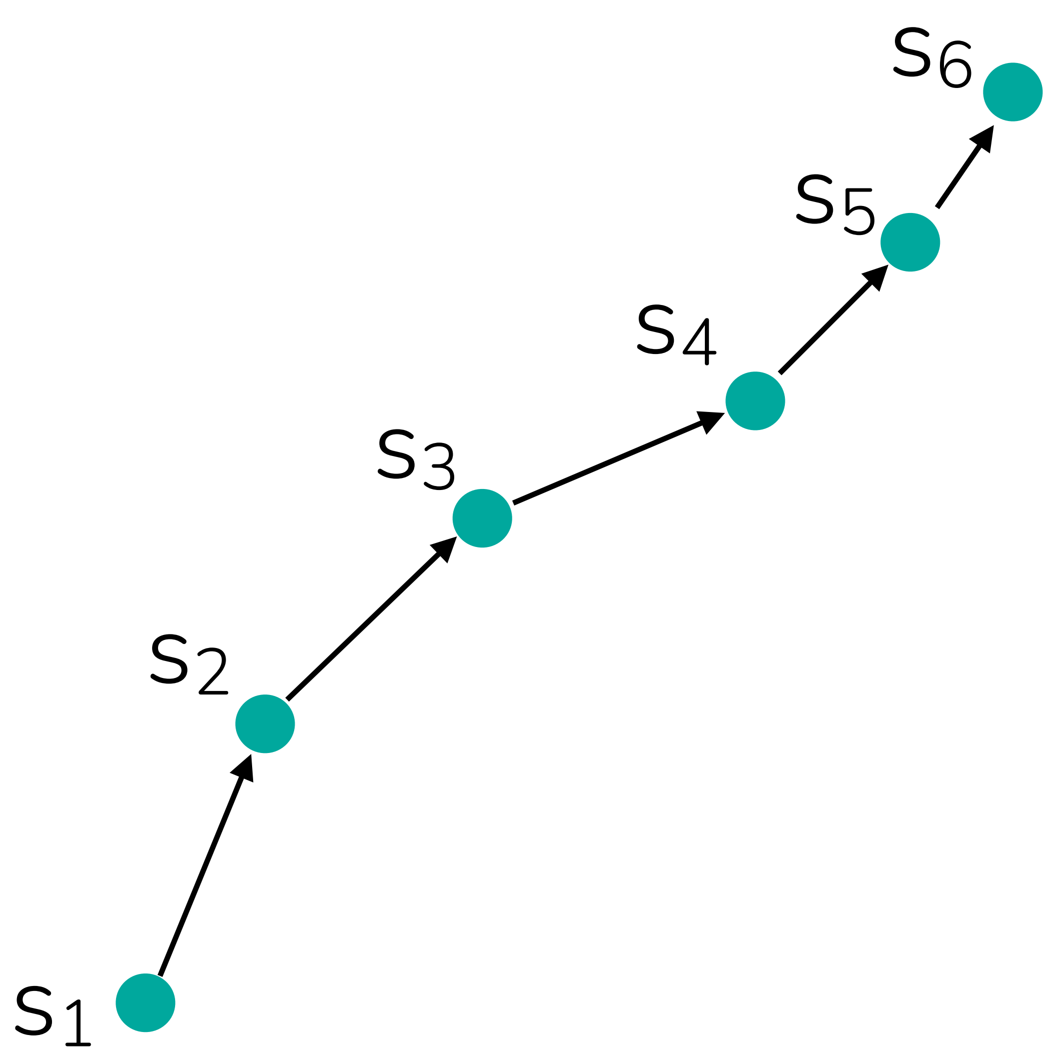
1. Plan with terminal value function
2. Augment model-free RL methods with data from model

Let’s focus on #2

# Model-based policy optimization

**Key idea**: augment data with model-simulated roll-outs.

Example real trajectory



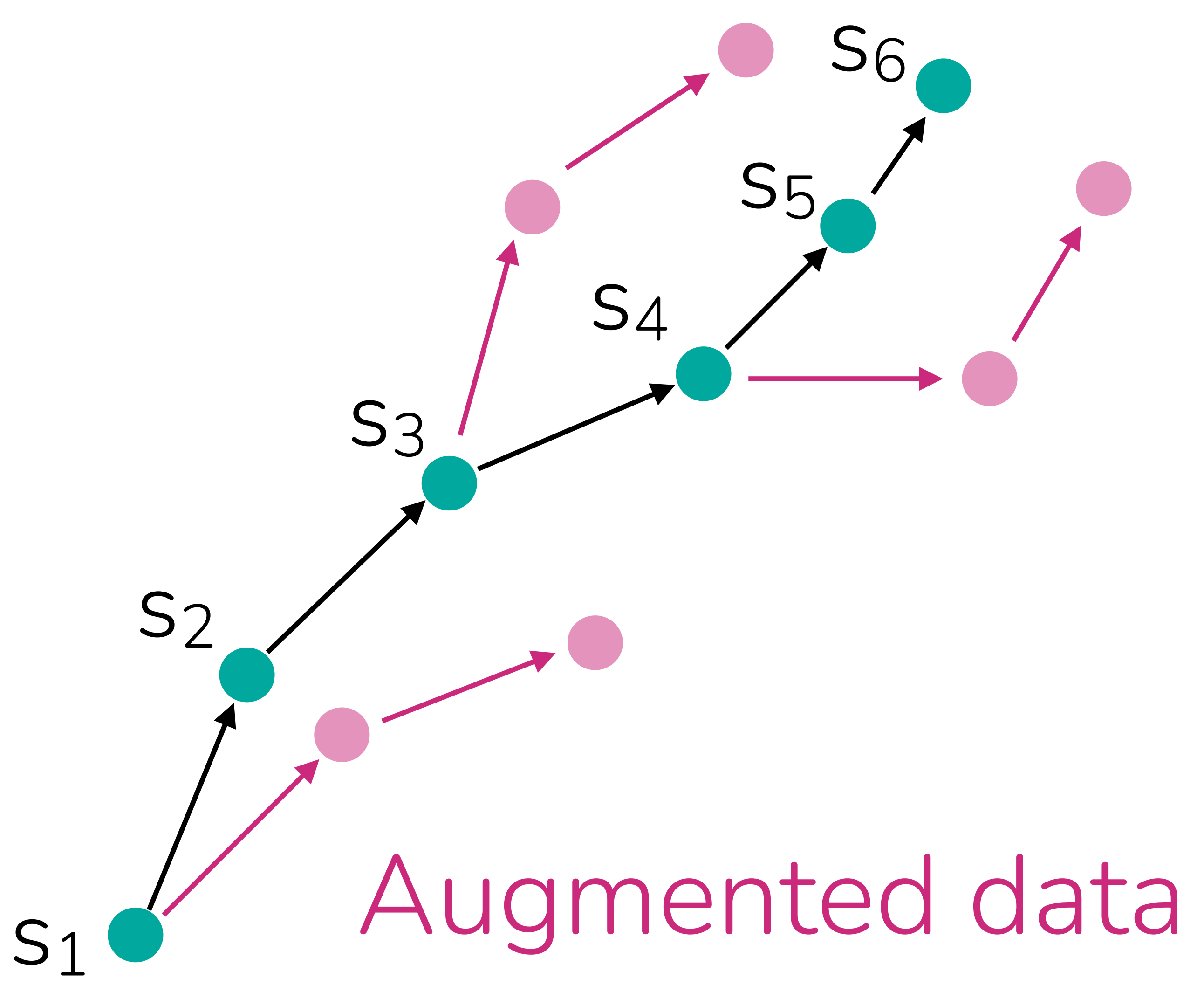

How to augment?

- generate full trajectories from initial states?
  - model may not be accurate for long horizons
- generate *partial trajectories* from initial states?
  - may not get good coverage of later states

# Model-based policy optimization

**Key idea**: augment data with model-simulated roll-outs.

Example real trajectory




How to augment?

- generate full trajectories from initial states?
  - model may not be accurate for long horizons
- generate *partial trajectories* from initial states?
  - may not get good coverage of later states
- generate *partial trajectories* from *all states* in the data

# Model-based policy optimization

**Key idea**: augment data with model-simulated roll-outs.

**Full algorithm**

1. Collect data using current policy $\pi_\phi$, add to $D_{env}$
2. Update model $p_\theta(s' | s, a)$ using $D_{env}$
3. Collect synthetic roll-outs using $\pi_\phi$ in model $p_\theta$ from states in $D_{env}$; add to $D_{model}$
4. Update policy $\pi$ (and critic $Q$) using $D_{model}$

Notes:
- compatible with variety of model-free RL methods (step 4)
- could additionally use $D_{env}$ in policy update

# When to use model-based RL?

+ Models are immensely useful if easy to learn
+ Model can be trained without reward labels (self-supervised)
+ Model is somewhat task-agnostic (can sometimes be transferred across rewards)
- Models don't optimize for task performance
- Sometimes harder to learn than a policy

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

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3. **Case study in dexterous robotic manipulation**

# Case study: Model-based RL for dexterous manipulation

**Deep Dynamics Models**
**for Learning Dexterous Manipulation**

Anusha Nagabandi, Kurt Konoglie, Sergey Levine, Vikash Kumar
Google Brain

September 2019

Still one of the most impressive results with five-fingered hands!

# Case study: Model-based RL for dexterous manipulation

**State space**: hand & object positions

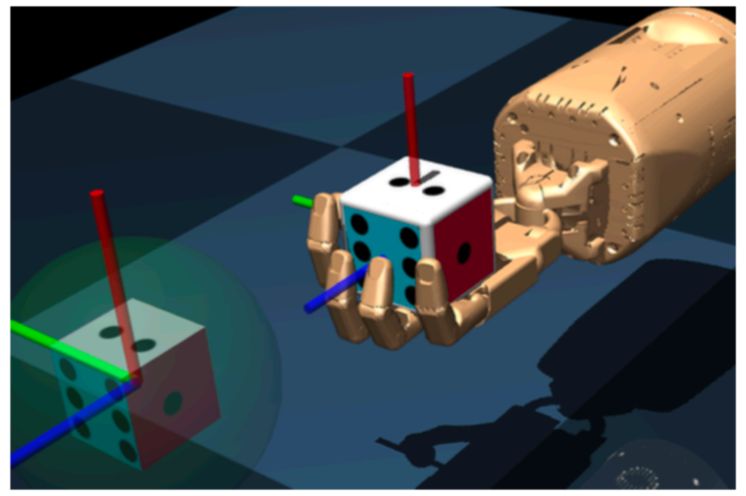
**Action space**: controlling 5-fingered hand (24 DoF)

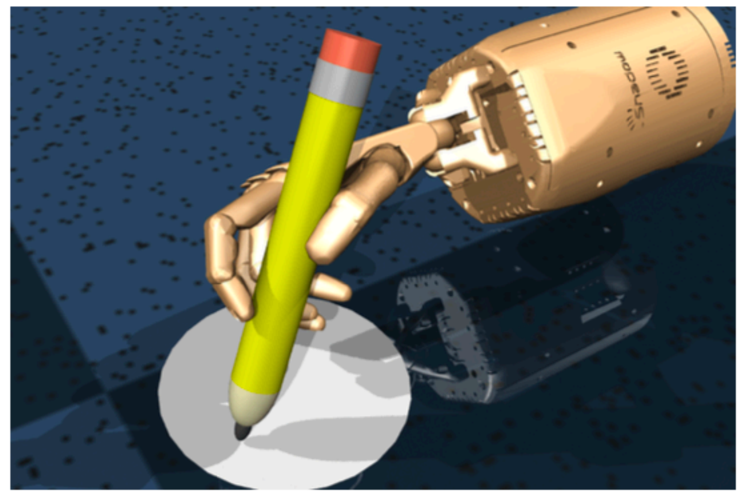
**Reward**: track target object trajectory + penalty for dropping

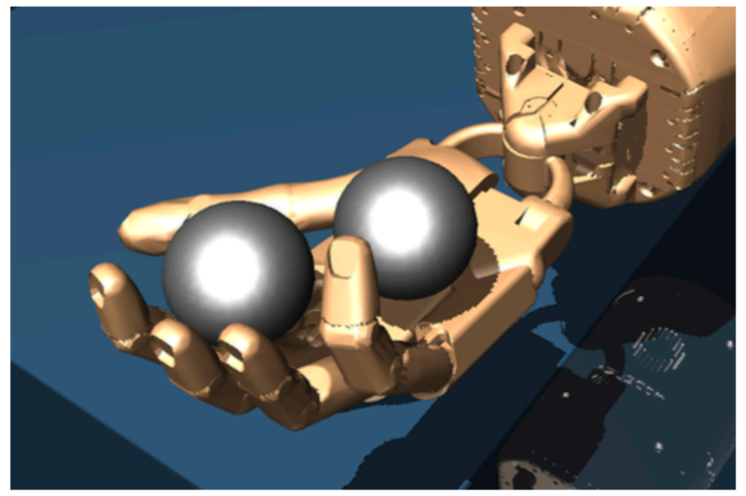
**Model**: Ensemble of 3 neural networks,
each with 2 hidden layers of size 500

**Planner**: modified version of CEM optimizer
softer reward-weighted mean & temporal smoothing on actions

Alternate between collecting ~30 trajectories with
planner & updating model.







# Case study: Model-based RL for dexterous manipulation

## Simulated experiments

### Model-free methods:

SAC: actor-critic method

NPG: policy gradient method

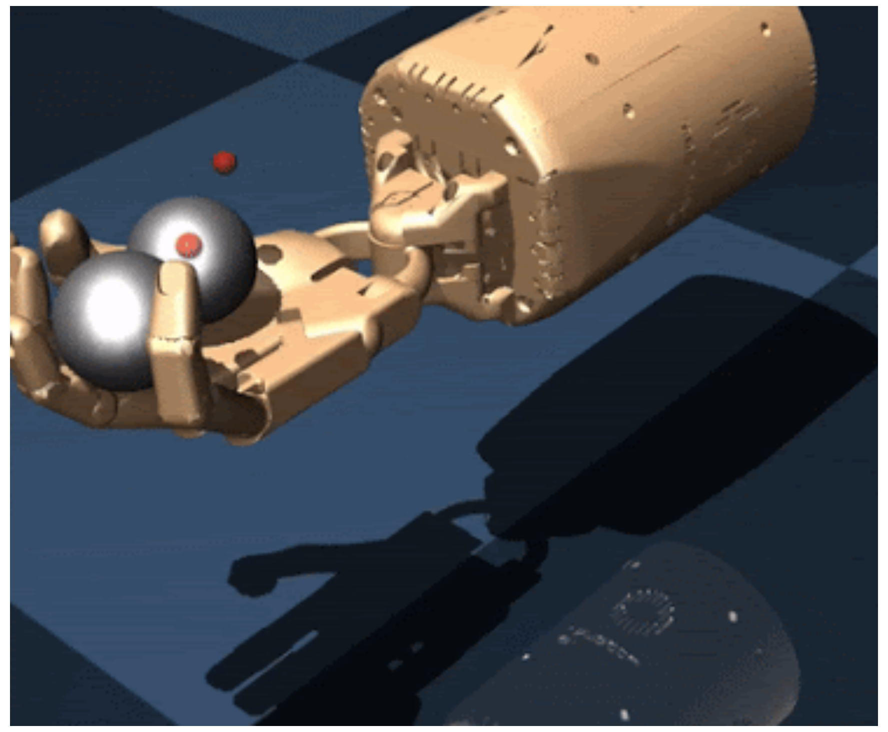
### Model-based methods:

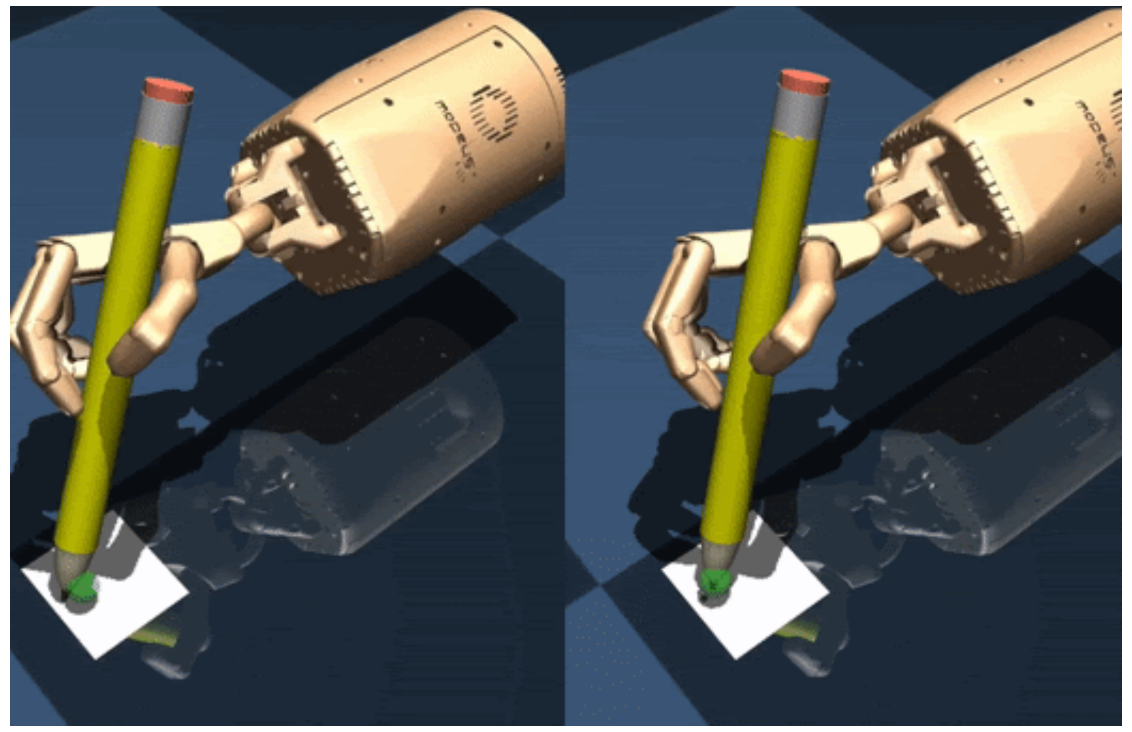
PDDM: proposed method

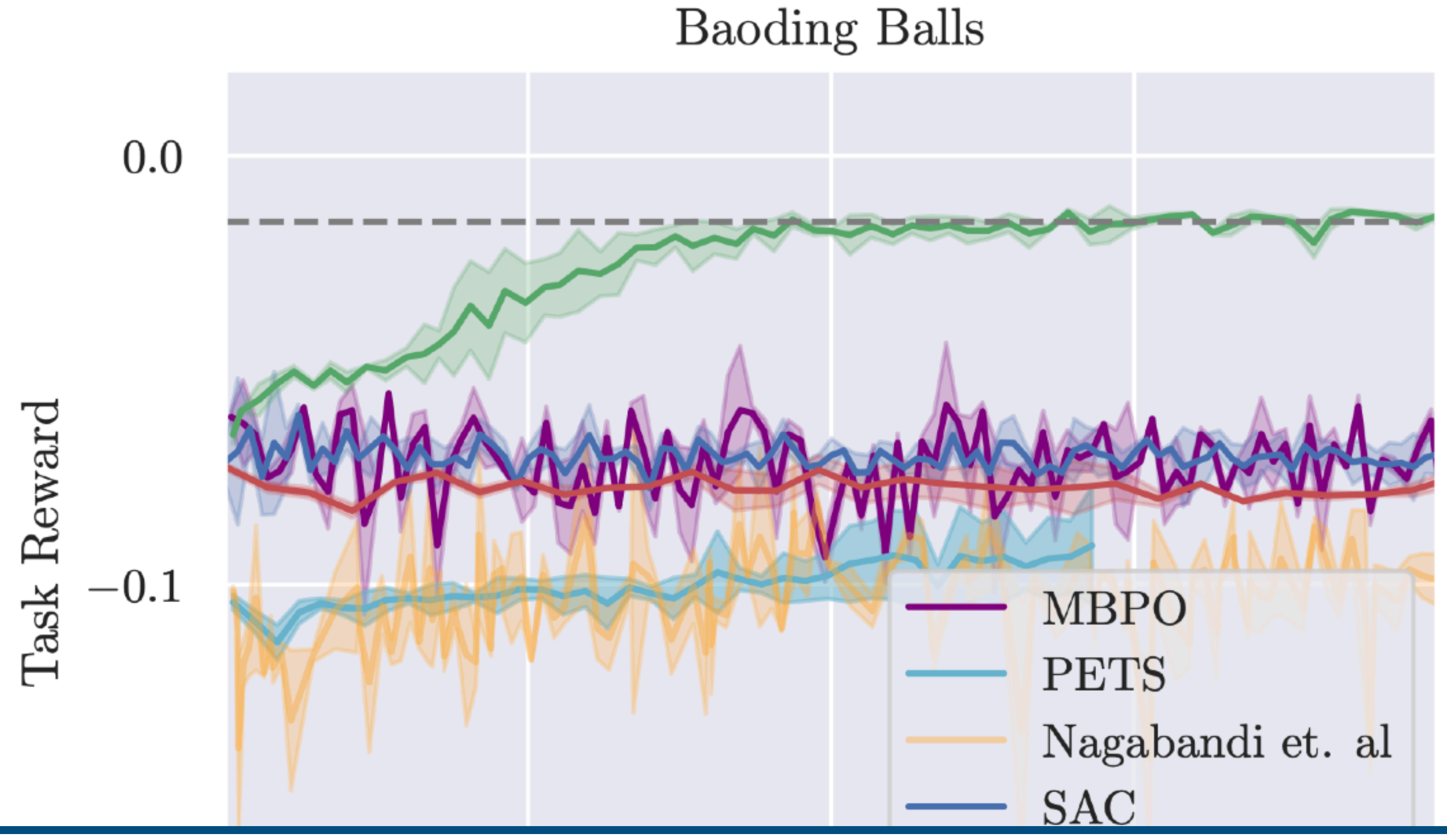
MBPO: RL with model-generated data

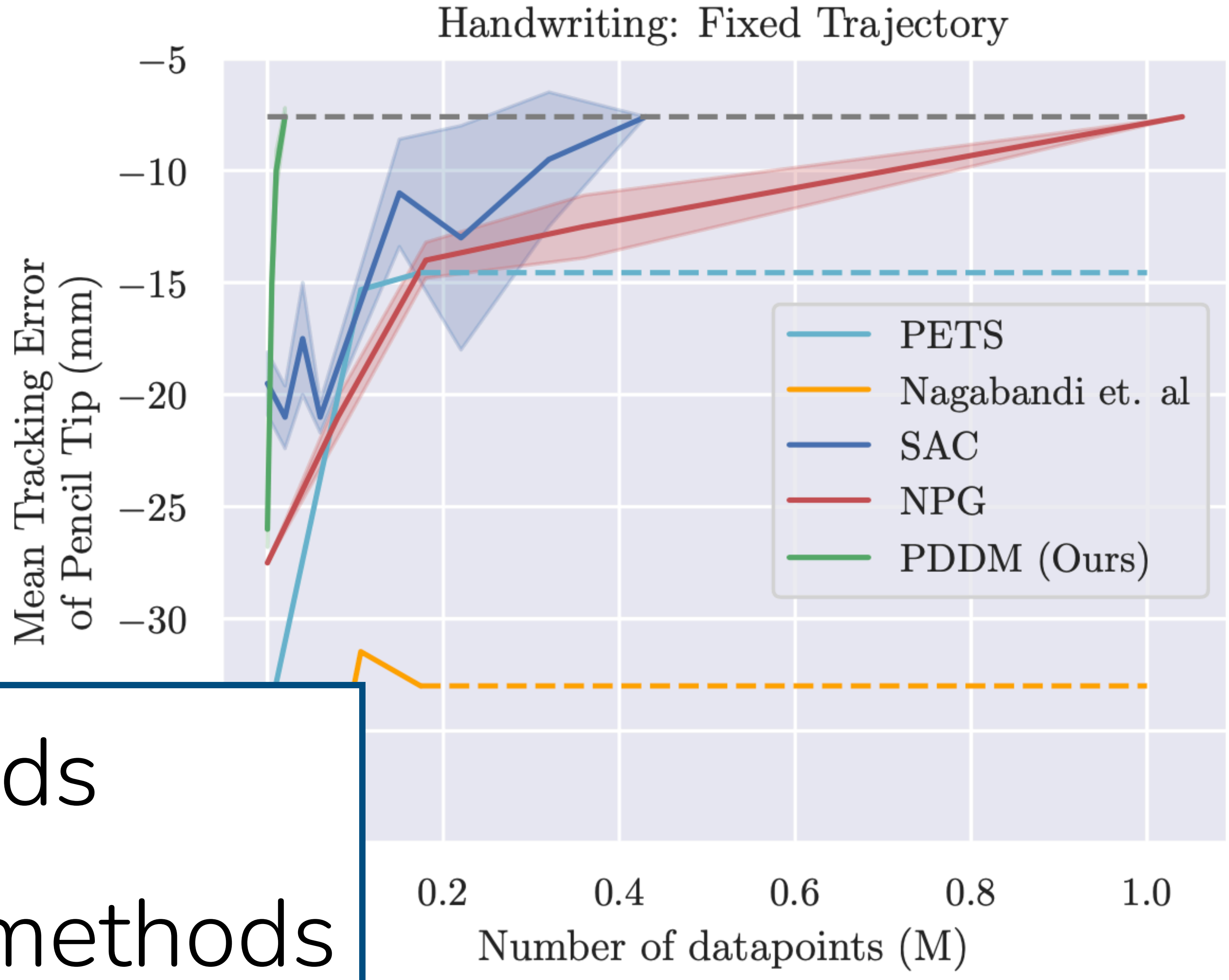
PETS: CEM-based planner

Nagabandi et al.: random shooting, no ensembles







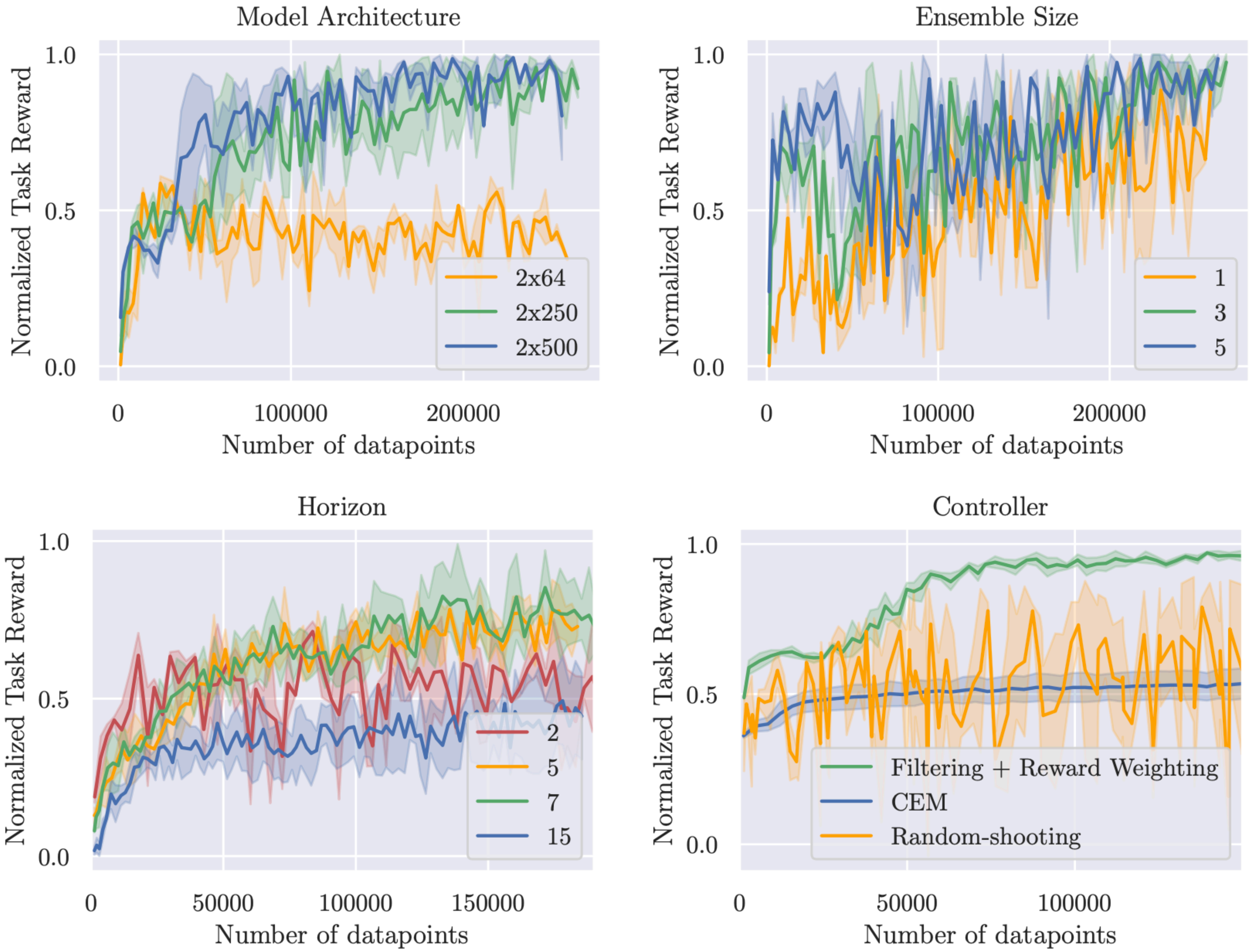




More efficient than model-free methods

More performant than other model-based methods

# Case study: Model-based RL for dexterous manipulation

## Simulated ablations

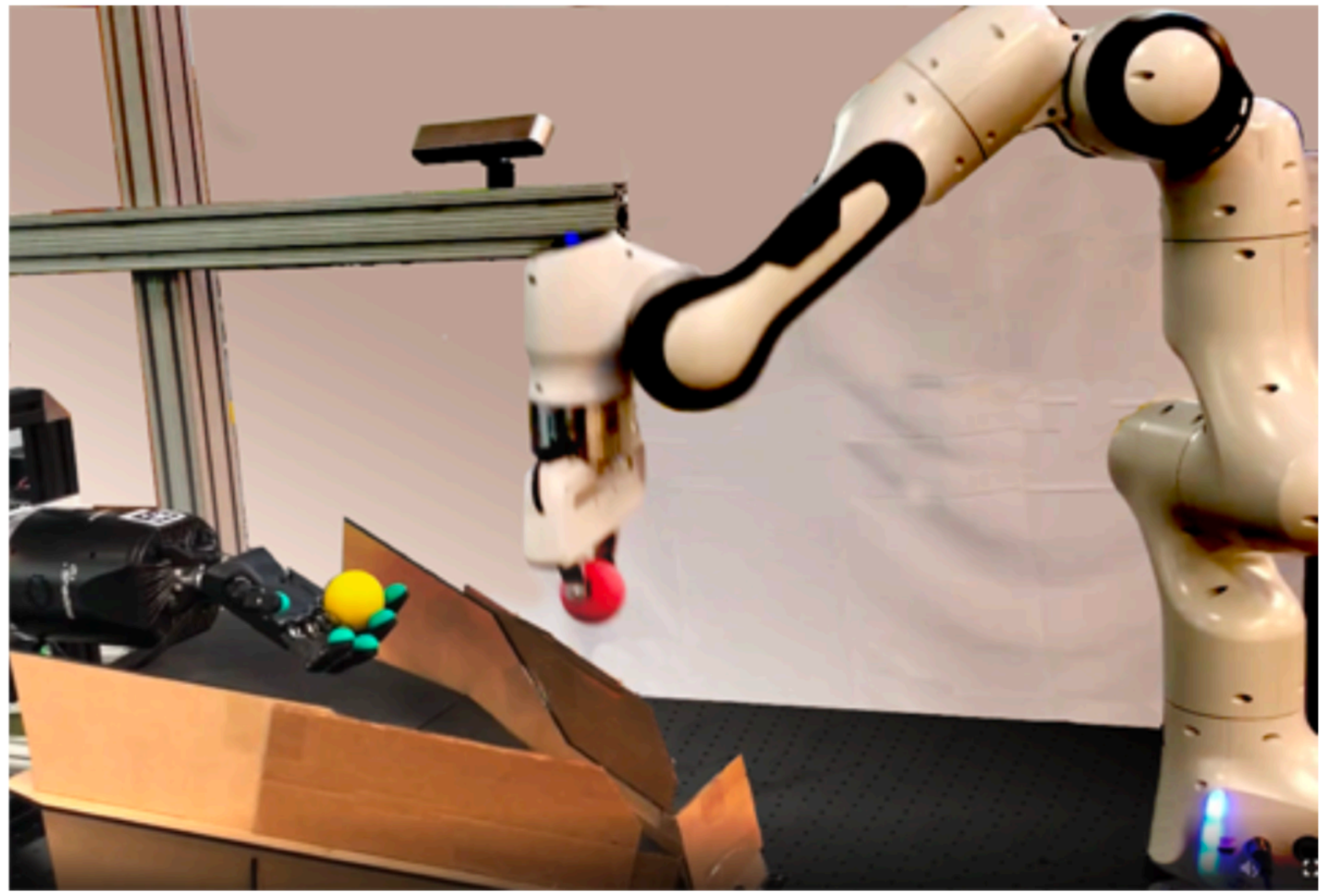



- Need sufficiently large model
- Need at least 3 ensemble members
- Planning horizon trade-offs
- Modified CEM is crucial

# Case study: Model-based RL for dexterous manipulation

Real-world dexterous control with ShadowHand

- Efficiency is key for fragile hardware
- Learns Baoding ball rotation in ~4 hours
- Ball is reset with another robot arm

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- the key challenges arising in model-based reinforcement learning
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- Homework 2 due next Wednesday (**start early!**)

**Next time**: Where do rewards come from? Can we learn them?