IASD M2 at Paris Dauphine

Deep Reinforcement Learning

13: Model-Based Policy Learning

Eric Benhamou - Thérèse des Escotais

PSL UNIVERSITÉ PARIS   Dauphine UNIVERSITÉ PARIS   ENS ÉCOLE NORMALE SUPÉRIEURE   MINES ParisTech

Homework 3 : Q-Learning and Actor-Critic Algorithms

Due on Wed **27 March**.

Dauphine | PSL Moodle

3 outputs to submit:

1. Report (pdf)
2. (code) Submit.zip
3. Google colab notebook

Any homework submitted late will not be graded

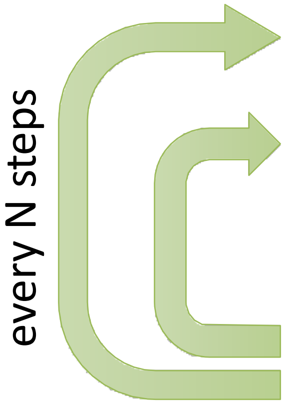
Ask your questions on Moodle and answer to others

Acknowledgement

These materials are based on the seminal course of Sergey Levine CS285

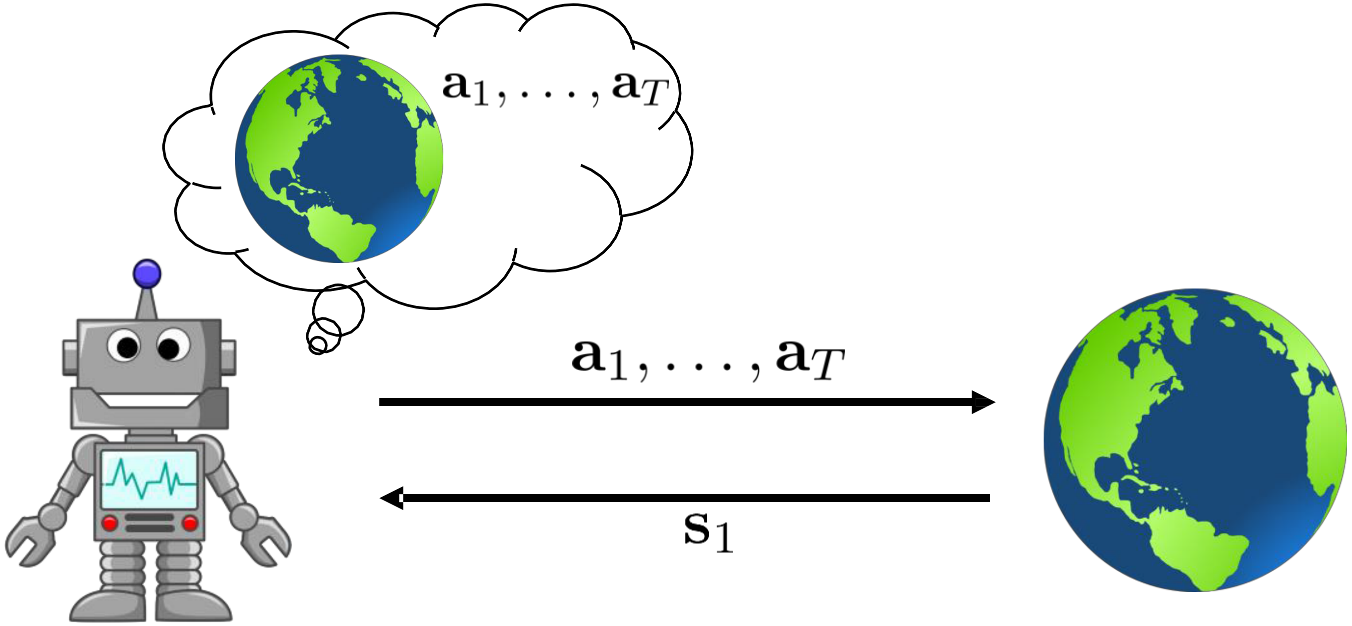
Last time: model-based RL with MPC

model-based reinforcement learning version 1.5:



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 dynamics model $f(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. plan through $f(\mathbf{s}, \mathbf{a})$ to choose actions
4. execute the first planned action, observe resulting state $\mathbf{s}'$ (MPC)
5. append $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to dataset $\mathcal{D}$

The stochastic open-loop case

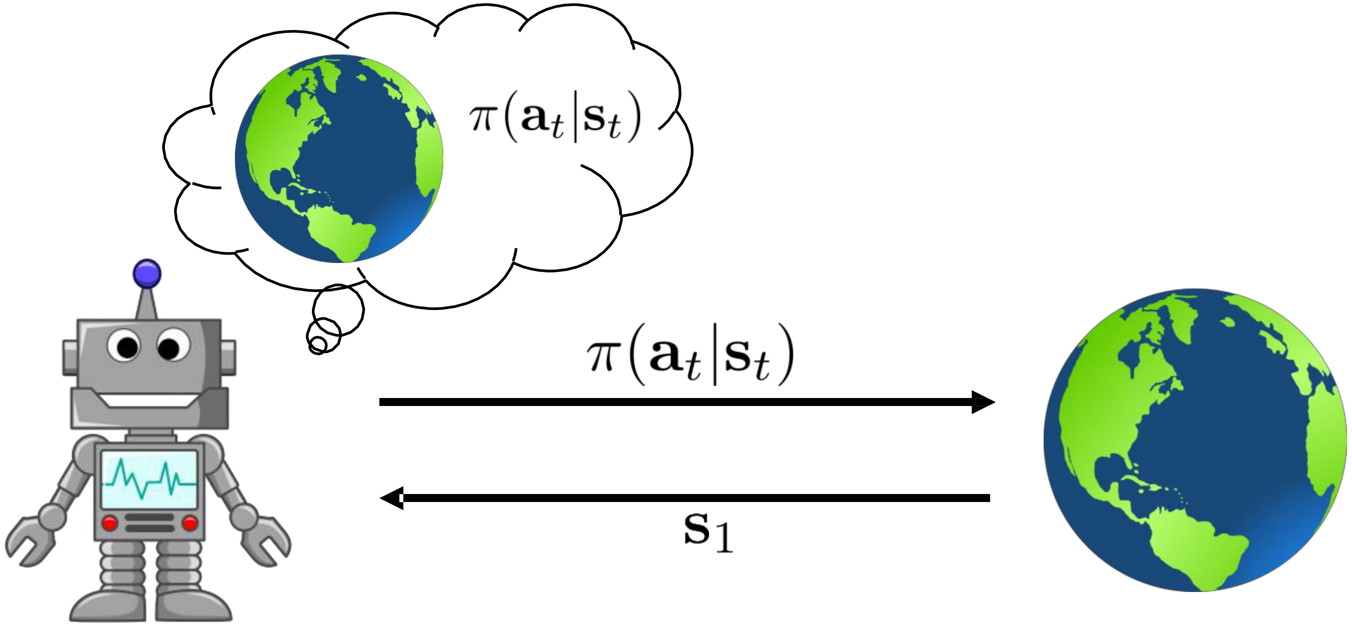


$$p_\theta(\mathbf{s}_1, \dots, \mathbf{s}_T | \mathbf{a}_1, \dots, \mathbf{a}_T) = p(\mathbf{s}_1) \prod_{t=1}^{T} p(\mathbf{s}_{t+1} | \mathbf{s}_t, \mathbf{a}_t)$$

$$\mathbf{a}_1, \dots, \mathbf{a}_T = \arg \max_{\mathbf{a}_1, \dots, \mathbf{a}_T} E\left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) | \mathbf{a}_1, \dots, \mathbf{a}_T\right]$$

why is this suboptimal?

The stochastic closed-loop case



form of π?

neural net — global

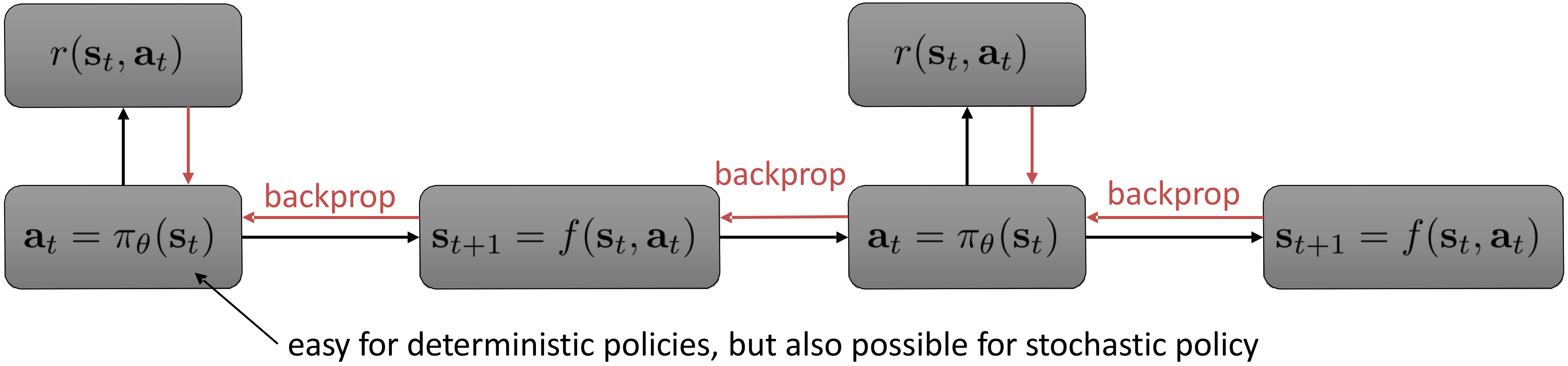
time-varying linear

$\mathbf{K}_t\mathbf{s}_t + \mathbf{k}_t$ — local

$$p(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T) = p(\mathbf{s}_1) \prod_{t=1}^{T} \pi(\mathbf{a}_t|\mathbf{s}_t) p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$$

$$\pi = \arg\max_{\pi} E_{\tau \sim p(\tau)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right]$$

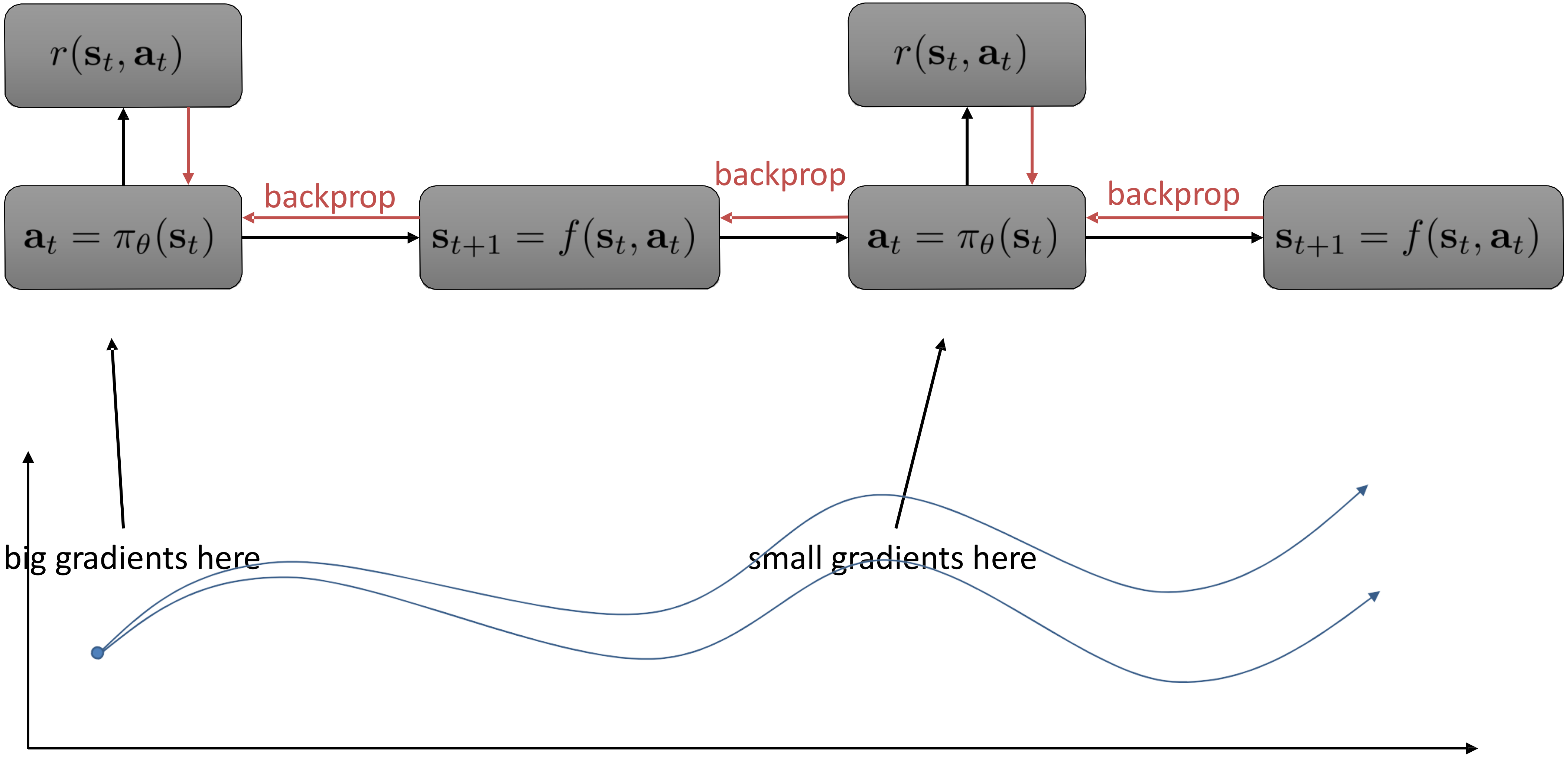
Backpropagate directly into the policy?



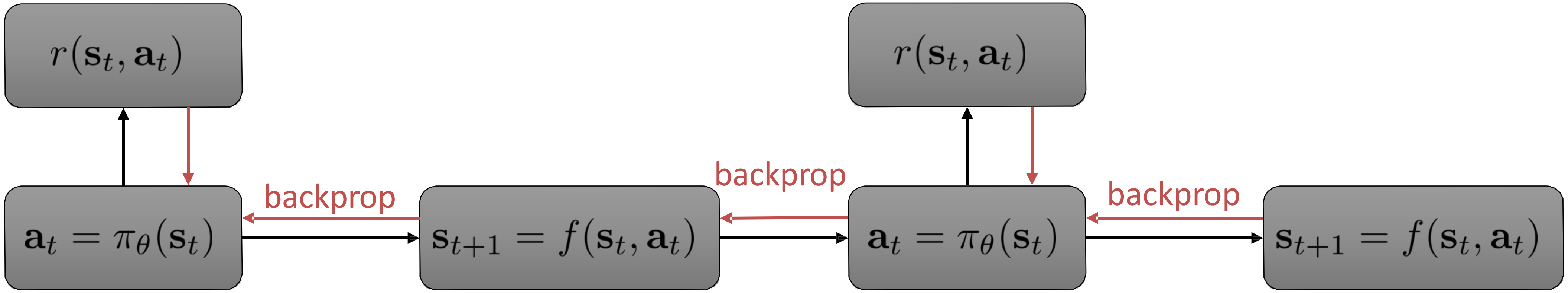
model-based reinforcement learning version 1.5:

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 dynamics model $f(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. backpropagate through $f(\mathbf{s}, \mathbf{a})$ into the policy to optimize $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$
4. run $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$, appending the visited tuples $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to $\mathcal{D}$

What's the problem with backprop into policy?



What's the problem with backprop into policy?



- Similar parameter sensitivity problems as shooting methods
  - But no longer have convenient second order LQR-like method, because policy parameters couple all the time steps, so no dynamic programming
- Similar problems to training long RNNs with BPTT
  - Vanishing and exploding gradients
  - Unlike LSTM, we can't just "choose" a simple dynamics, dynamics are chosen by nature

What's the solution?

- Use derivative-free ("model-free") RL algorithms, with the model used to generate synthetic samples
  - Seems weirdly backwards
  - Actually works very well
  - Essentially "model-based acceleration" for model-free RL

Model-Free Learning With a Model

Model-free optimization with a model

Policy gradient: $$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \hat{Q}^\pi_{i,t}$$

Backprop (pathwise) gradient: $$\nabla_\theta J(\theta) = \sum_{t=1}^{T} \frac{d\mathbf{a}_t}{d\theta} \frac{d\mathbf{s}_{t+1}}{d\mathbf{a}_t} \left(\sum_{t'=t+1}^{T} \frac{dr_{t'}}{d\mathbf{s}_{t'}} \left(\prod_{t''=t+2}^{t'} \frac{d\mathbf{s}_{t''}}{d\mathbf{a}_{t''-1}} \frac{d\mathbf{a}_{t''-1}}{d\mathbf{s}_{t''-1}} + \frac{d\mathbf{s}_{t''}}{d\mathbf{s}_{t''-1}} \right) \right)$$

- Policy gradient might be more *stable* (if enough samples are used) because it does not require multiplying many Jacobians
- See a recent analysis here:
  - Parmas et al. ‘18: PIPP: Flexible Model-Based Policy Search Robust to the Curse of Chaos

Model-based RL via policy gradient

model-based reinforcement learning version 2.5:

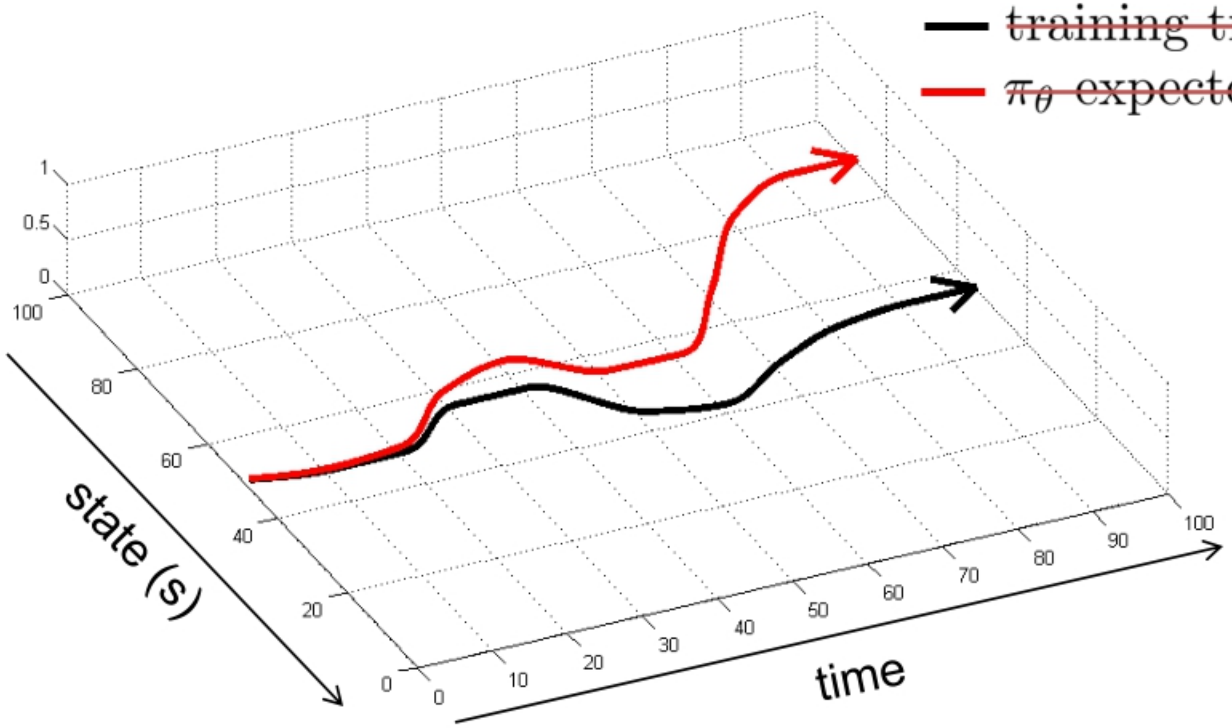
1. run base policy $\pi_0(\mathbf{a}_t|\mathbf{s}_t)$ (e.g., random policy) to collect $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. learn dynamics model $f(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. use $f(\mathbf{s}, \mathbf{a})$ to generate trajectories $\{\tau_i\}$ with policy $\pi_\theta(\mathbf{a}|\mathbf{s})$
4. use $\{\tau_i\}$ to improve $\pi_\theta(\mathbf{a}|\mathbf{s})$ via policy gradient
5. run $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$, appending the visited tuples $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to $\mathcal{D}$

What's a potential **problem** with this approach?

The curse of long model-based rollouts

~~training trajectory~~ run π_θ with true dynamics

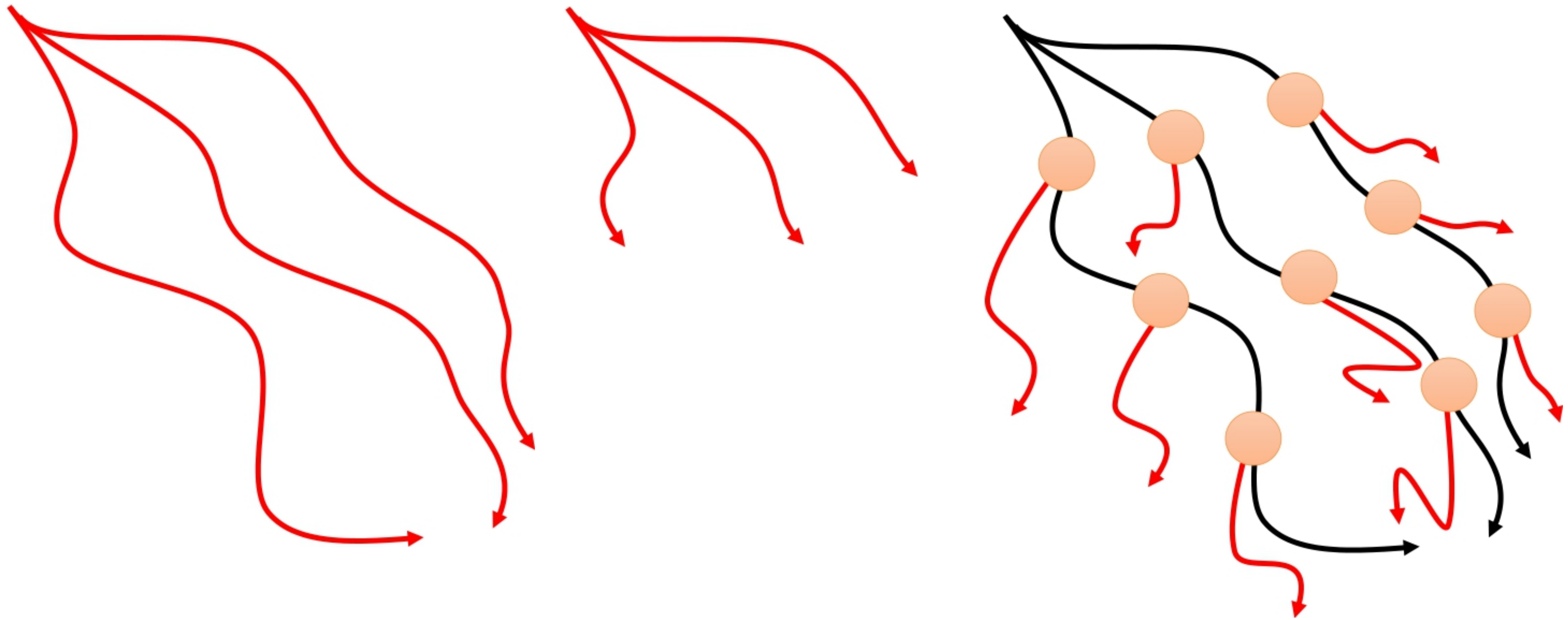
~~π_θ expected trajectory~~ run π_θ with learned model



How quickly does error accumulate?

$$\mathcal{O}(\epsilon T^2)$$

How to get away with **short** rollouts?



- huge accumulating error

+ much lower error
- never see later time steps

+ much lower error
+ see all time steps
- wrong state distribution

Model-based RL with **short** rollouts

model-based reinforcement learning version 3.0:

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 dynamics model $f(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. pick states $\mathbf{s}_i$ from $\mathcal{D}$, use $f(\mathbf{s}, \mathbf{a})$ to make *short* rollouts from them
4. use *both* real and model data to improve $\pi_\theta(\mathbf{a}|\mathbf{s})$ with *off-policy RL*
5. run $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$, appending the visited tuples $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to $\mathcal{D}$

Dyna -Style Algorithms

Model-based RL with **short** rollouts

model-based reinforcement learning version 3.0:

1. run base policy $\pi_0(\mathbf{a}_t|\mathbf{s}_t)$ (e.g., random policy) to collect $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
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4. use *both* real and model data to improve $\pi_\theta(\mathbf{a}|\mathbf{s})$ with *off-policy RL*
5. run $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$, appending the visited tuples $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to $\mathcal{D}$

Model-free optimization with a model

Dyna

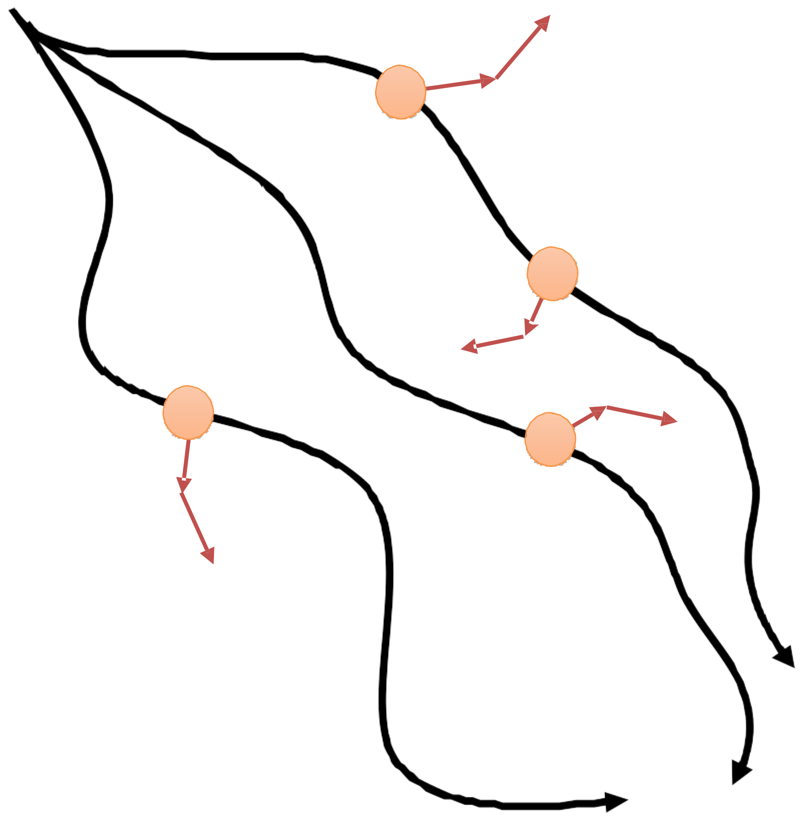
online Q-learning algorithm that performs model-free RL with a model

1. given state s, pick action a using exploration policy
2. observe s' and r, to get transition (s, a, s', r)
3. update model $\hat{p}(s'|s, a)$ and $\hat{r}(s, a)$ using (s, a, s')
4. Q-update: $Q(s, a) \leftarrow Q(s, a) + \alpha E_{s',r}[r + \max_{a'} Q(s', a') - Q(s, a)]$
5. repeat K times:
   6. sample $(s, a) \sim \mathcal{B}$ from buffer of past states and actions
   7. Q-update: $Q(s, a) \leftarrow Q(s, a) + \alpha E_{s',r}[r + \max_{a'} Q(s', a') - Q(s, a)]$

Richard S. Sutton. Integrated architectures for learning, planning, and reacting based on approximating dynamic programming.

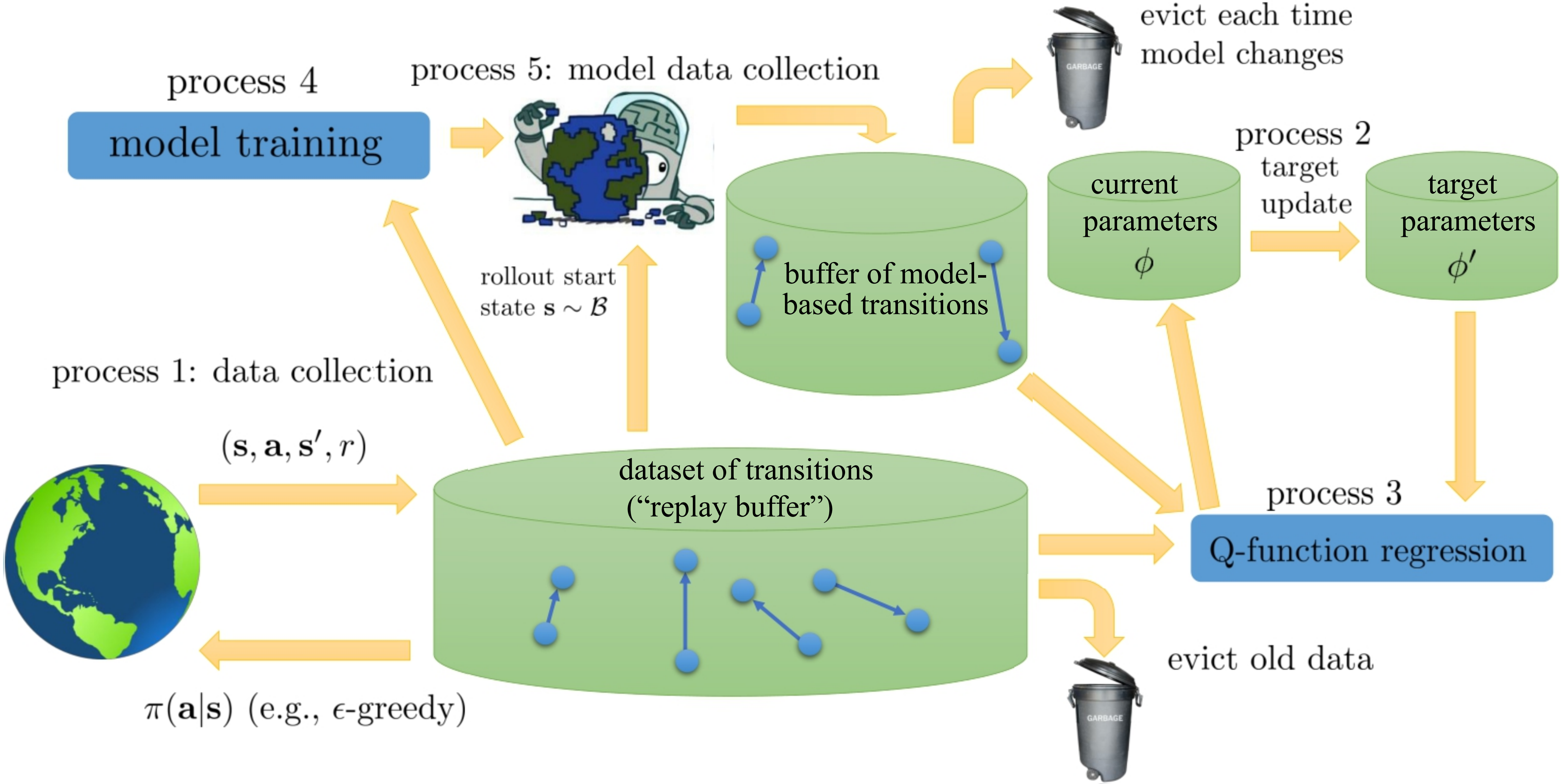
General “Dyna-style” model-based RL recipe

1. collect some data, consisting of transitions (s, a, s', r)
2. learn model $\hat{p}(s'|s, a)$ (and optionally, $\hat{r}(s, a)$)
3. repeat K times:
    4. sample $s \sim \mathcal{B}$ from buffer
    5. choose action a (from $\mathcal{B}$, from π, or random)
    6. simulate $s' \sim \hat{p}(s'|s, a)$ (and $r = \hat{r}(s, a)$)
    7. train on (s, a, s', r) with model-free RL
    8. (optional) take N more model-based steps



+ only requires short (as few as one step) rollouts from model
+ still sees diverse states

Model-accelerated off -policy RL

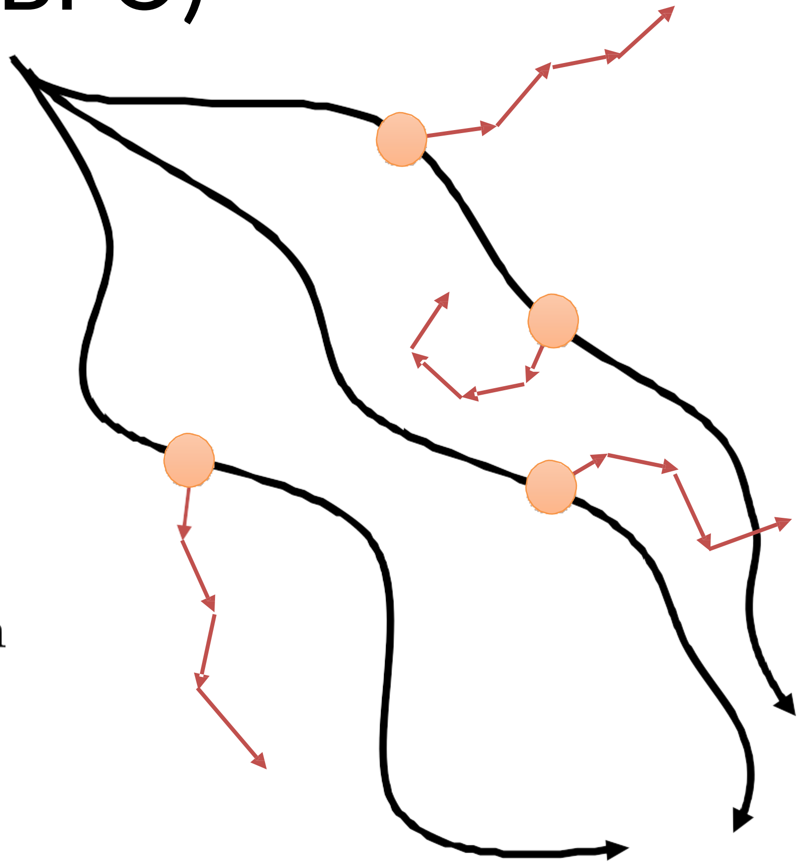


Model-Based Acceleration (MBA)
Model-Based Value Expansion (MVE)
Model-Based Policy Optimization (MBPO)

1. take some action $\mathbf{a}_i$ and observe $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$, add it to $\mathcal{B}$
2. sample mini-batch $\{\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j, r_j\}$ from $\mathcal{B}$ uniformly
3. use $\{\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j\}$ to update model $\hat{p}(\mathbf{s}'|\mathbf{s}, \mathbf{a})$
4. sample $\{\mathbf{s}_j\}$ from $\mathcal{B}$
5. for each $\mathbf{s}_j$, perform model-based rollout with $\mathbf{a} = \pi(\mathbf{s})$
6. use all transitions $(\mathbf{s}, \mathbf{a}, \mathbf{s}', r)$ along rollout to update Q-function

+ why is this a *good* idea?

- why is this a *bad* idea?



Gu et al. Continuous deep Q-learning with model-based acceleration. ‘16
Feinberg et al. Model-based value expansion. ’18
Janner et al. When to trust your model: model-based policy optimization. ‘19

Multi-Step Models & Successor Representations

What kind of model do we need to **evaluate** a policy?

The job of the model is to **evaluate** the policy

(if you can evaluate it, you can make it better)

$$J(\pi) = E_{s\sim p(s_1)}[V^\pi(s_1)]$$

$$V^\pi(s_t) = \sum_{t=t'}^{\infty} \gamma^{t'-t} E_{p(s_{t'}|s_t)} E_{\mathbf{a}_{t'}\sim\pi(\mathbf{a}_{t'}|\mathbf{s}_{t'})}[r(\mathbf{s}_{t'}, \mathbf{a}_{t'})]$$

let's keep it simple

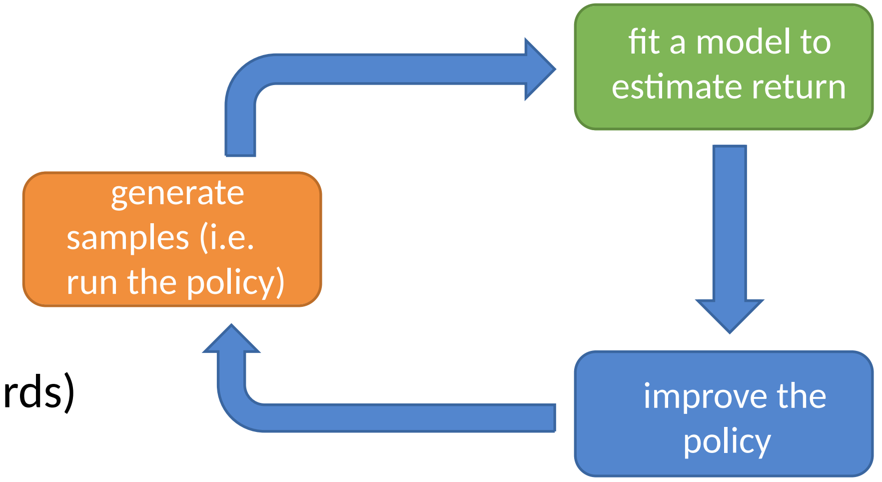
$$= \sum_{t=t'}^{\infty} \gamma^{t'-t} E_{p(s_{t'}|s_t)}[r(\mathbf{s}_{t'})]$$

(easy to re-derive for action-dependent rewards)

$$= \sum_{t=t'}^{\infty} \gamma^{t'-t} \sum_{\mathbf{s}} p(\mathbf{s}_{t'} = \mathbf{s}|\mathbf{s}_t) r(\mathbf{s})$$

$$= \sum_{\mathbf{s}} \left(\sum_{t=t'}^{\infty} \gamma^{t'-t} p(\mathbf{s}_{t'} = \mathbf{s}|\mathbf{s}_t) \right) r(\mathbf{s})$$

fit model $f(\mathbf{s}, \mathbf{a})$



What kind of model do we need to **evaluate** a policy?

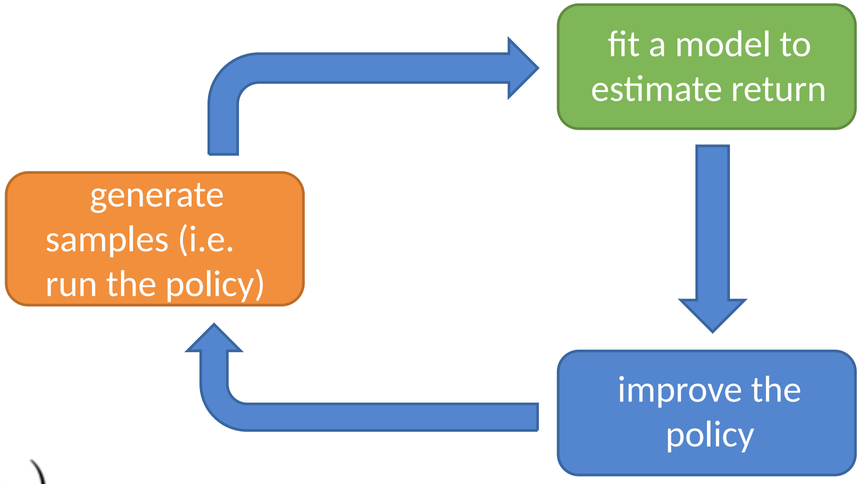
$$V^\pi(\mathbf{s}_t) = \sum_{t=t'}^{\infty} \gamma^{t'-t} E_{p(s_{t'}|s_t)}[r(\mathbf{s}_{t'})]$$

$$= \sum_{\mathbf{s}} \underbrace{\left(\sum_{t=t'}^{\infty} \gamma^{t'-t} p(\mathbf{s}_{t'} = \mathbf{s}|s_t) \right)}_{p_\pi(\mathbf{s}_{\text{future}} = \mathbf{s}|\mathbf{s}_t)} r(\mathbf{s})$$

$$p_\pi(\mathbf{s}_{\text{future}} = \mathbf{s}|\mathbf{s}_t) = \underbrace{(1-\gamma)}_{\text{just to ensure it sums to 1}} \sum_{t'=t}^{\infty} \gamma^{t'-t} p(\mathbf{s}_{t'} = \mathbf{s}|\mathbf{s}_t)$$

(if you can evaluate it, you can make it better)

fit model $f(\mathbf{s}, \mathbf{a})$



What kind of model do we need to **evaluate** a policy?

$$p_\pi(\mathbf{s}_{\text{future}} = \mathbf{s}|\mathbf{s}_t) = (1-\gamma)\sum_{t'=t}^{\infty} \gamma^{t'-t} p(\mathbf{s}_{t'} = \mathbf{s}|\mathbf{s}_t)$$

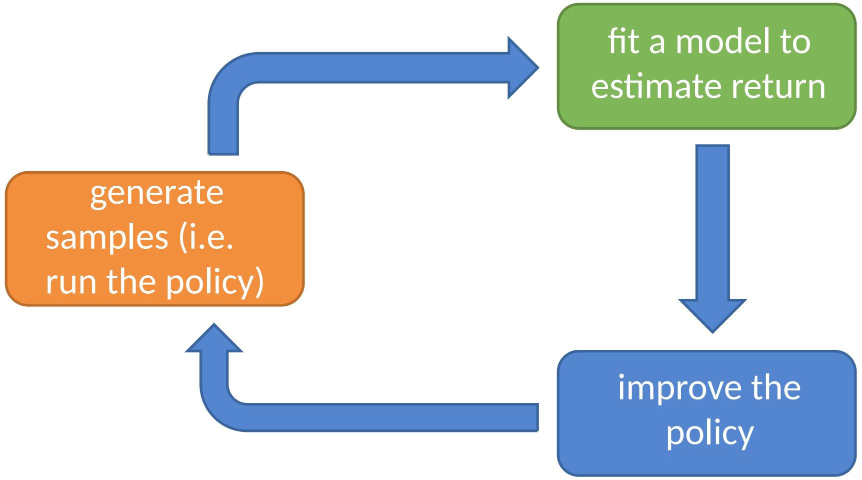
$$V^\pi(\mathbf{s}_t) = \frac{1}{1-\gamma} \underbrace{\sum_{\mathbf{s}} p_\pi(\mathbf{s}_{\text{future}} = \mathbf{s}|\mathbf{s}_t) r(\mathbf{s})}_{\mu^\pi(\mathbf{s}_t)^T \vec{r}}$$

$$\mu_i^\pi(\mathbf{s}_t) = p_\pi(s_{\text{future}} = i|\mathbf{s}_t)$$

This is called a **successor representation**

(if you can evaluate it, you can make it better)

fit model $f(\mathbf{s}, \mathbf{a})$



Dayan. **Improving Generalisation for Temporal Difference Learning: The Successor Representation** . 1993.

Successor representations

$$\mu_i^\pi(\mathbf{s}_t) = (1-\gamma)\sum_{t'=t}^{\infty}\gamma^{t'-t}p(\mathbf{s}_{t'}=i|\mathbf{s}_t)$$

$$= (1-\gamma)\delta(\mathbf{s}_t=i) + \gamma E_{\mathbf{a}_t\sim\pi(\mathbf{a}_t|\mathbf{s}_t),\mathbf{s}_{t+1}\sim p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)}[\mu_i^\pi(\mathbf{s}_{t+1})]$$

like a Bellman backup with "reward" $r(\mathbf{s}_t) = (1-\gamma)\delta(\mathbf{s}_t = i)$

in practice, we can use vectorized backups for all i at once

A few issues…

- ➢ Not clear if learning successor representation is easier than model - free RL
- ➢ How to scale to large state spaces?
- ➢ How to extend to continuous state spaces ?

Successor features

$$\mu_i^\pi(\mathbf{s}_t) = (1-\gamma)\sum_{t'=t}^{\infty}\gamma^{t'-t}p(\mathbf{s}_{t'} = i|\mathbf{s}_t)$$

$$\psi_j^\pi(\mathbf{s}_t) = \sum_{\mathbf{s}}\mu_{\mathbf{s}}^\pi(\mathbf{s}_t)\phi_j(\mathbf{s})$$

$$\psi_j^\pi(\mathbf{s}_t) = \mu^\pi(\mathbf{s}_t)^T\vec{\phi}_j$$

$$V^\pi(\mathbf{s}_t) = \mu^\pi(\mathbf{s}_t)^T\vec{r}$$

if $r(\mathbf{s}) = \sum_j \phi_j(\mathbf{s})w_j = \phi(\mathbf{s})^T\mathbf{w}$

then $V^\pi(\mathbf{s}_t) = \psi^\pi(\mathbf{s}_t)^T\mathbf{w}$

$$= \sum_j \psi_j^\pi(\mathbf{s}_t)w_j$$

$$= \sum_j \mu^\pi(\mathbf{s}_T)^T\vec{\phi}_j\mathbf{w}$$

$$= \mu^\pi(\mathbf{s}_T)^T\sum_j\vec{\phi}_j\mathbf{w} = \mu^\pi(\mathbf{s}_t)^T\vec{r}$$

so what?

If the number of features is much less than the number of states, learning them is much easier!

Successor features

$$\mu_i^\pi(\mathbf{s}_t) = (1-\gamma)\delta(\mathbf{s}_t = i) + \gamma E_{\mathbf{a}_t \sim \pi(\mathbf{a}_t|\mathbf{s}_t), \mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}[\mu_i^\pi(\mathbf{s}_{t+1})]$$

$$\psi_j^\pi(\mathbf{s}_t) = \phi_j(\mathbf{s}_t) + \gamma E_{\mathbf{a}_t \sim \pi(\mathbf{a}_t|\mathbf{s}_t), \mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}[\psi_j^\pi(\mathbf{s}_{t+1})]$$

special case with
$\phi_i(\mathbf{s}_t) = (1-\gamma)\delta(\mathbf{s}_t = i)$

can also construct a "Q-function-like" version:

$$\psi_j^\pi(\mathbf{s}_t, \mathbf{a}_t) = \phi_j(\mathbf{s}_t) + \gamma E_{\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t), \mathbf{a}_{t+1} \sim \pi(\mathbf{a}_{t+1}|\mathbf{s}_{t+1})}[\psi_j^\pi(\mathbf{s}_{t+1}, \mathbf{a}_{t+1})]$$

$Q^\pi(\mathbf{s}_t, \mathbf{a}_t) \approx \psi^\pi(\mathbf{s}_t, \mathbf{a}_t)^T \mathbf{w}$ when $r(\mathbf{s}_t) \approx \phi(\mathbf{s}_t)^T \mathbf{w}$

Using successor features

Idea 1: recover a Q -function very quickly

1. Train $\psi^\pi(\mathbf{s}_t, \mathbf{a}_t)$ (via Bellman backups)
2. Get some reward samples $\{\mathbf{s}_i, r_i\}$
3. Get $\mathbf{w} \leftarrow \arg\min_{\mathbf{w}} \sum_i ||\phi(\mathbf{s}_i)^T \mathbf{w} - r_i||^2$
4. Recover $Q^\pi(\mathbf{s}_t, \mathbf{a}_t) \approx \psi^\pi(\mathbf{s}_t, \mathbf{a}_t)^T \mathbf{w}$

Is this the **optimal** Q -function?

$$\pi'(\mathbf{s}) = \arg\max_{\mathbf{a}} \psi^\pi(\mathbf{s}, \mathbf{a})^T \mathbf{w}$$

Equivalent to **one step** of policy iteration

Better than nothing, but **not** optimal

Using successor features

Idea 2: recover many Q -functions

1. Train $\psi^{\pi_k}(\mathbf{s}_t, \mathbf{a}_t)$ for many policies π_k (via Bellman backups)
2. Get some reward samples $\{\mathbf{s}_i, r_i\}$
3. Get $\mathbf{w} \leftarrow \arg\min_{\mathbf{w}} \sum_i ||\phi(\mathbf{s}_i)^T \mathbf{w} - r_i||^2$
4. Recover $Q^{\pi_k}(\mathbf{s}_t, \mathbf{a}_t) \approx \psi^{\pi_k}(\mathbf{s}_t, \mathbf{a}_t)^T \mathbf{w}$ for every π_k

$$\pi'(\mathbf{s}) = \arg\max_{\mathbf{a}} \max_k \psi^{\pi_k}(\mathbf{s}, \mathbf{a})^T \mathbf{w}$$

Finds the highest reward policy in **each state**

Barreto et al. **Successor Features for Transfer in Reinforcement Learning** . 2016.

Continuous successor representations

$$\mu_i^\pi(\mathbf{s}_t) = (1-\gamma)\delta(\mathbf{s}_t = i) + \gamma E_{\mathbf{a}_t \sim \pi(\mathbf{a}_t|\mathbf{s}_t), \mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}[\mu_i^\pi(\mathbf{s}_{t+1})]$$

always zero for any sampled state if states are continuous

Framing successor representation as *classification*:

$$p^\pi(F = 1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}}) = \frac{p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t)}{p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t) + p^\pi(\mathbf{s}_{\text{future}})}$$

binary classifier

$F = 1$ means $\mathbf{s}_{\text{future}}$ is a future state from $\mathbf{s}_t, \mathbf{a}_t$ under π

$$\mathcal{D}_+ \sim p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t) \qquad \mathcal{D}_- \sim p^\pi(\mathbf{s})$$

Continuous successor representations

$$\mathcal{D}_+ \sim p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t) \qquad \mathcal{D}_- \sim p^\pi(\mathbf{s})$$

$$p^\pi(F=1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}}) = \frac{p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t)}{p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t) + p^\pi(\mathbf{s}_{\text{future}})}$$

$$p^\pi(F=0|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}}) = \frac{p^\pi(\mathbf{s}_{\text{future}})}{p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t) + p^\pi(\mathbf{s}_{\text{future}})}$$

$$\frac{p^\pi(F=1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}})}{p^\pi(F=0|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}})} = \frac{p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t)}{p^\pi(\mathbf{s}_{\text{future}})}$$

$$\frac{p^\pi(F=1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}})}{p^\pi(F=0|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}})} p^\pi(\mathbf{s}_{\text{future}}) = p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t)$$

constant independent of $\mathbf{a}_t, \mathbf{s}_t$

The C-Learning algorithm

$$\mathcal{D}_+ \sim p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t) \qquad \mathcal{D}_- \sim p^\pi(\mathbf{s})$$

$$p^\pi(F=1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}}) = \frac{p^\pi(F=1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}})}{p^\pi(F=1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{\text{future}}) + p^\pi(\mathbf{s}_{\text{future}})}$$

To train:

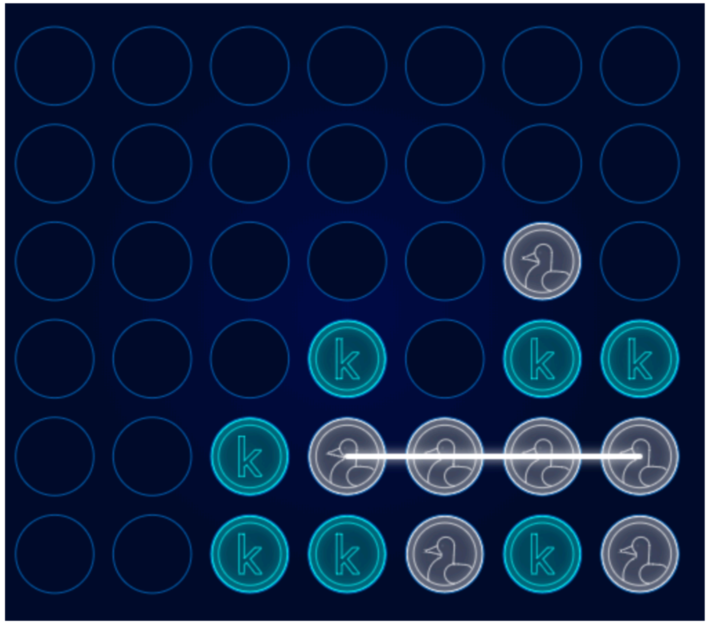
1. Sample $\mathbf{s} \sim p^\pi(\mathbf{s})$ (e.g., run policy, sample from trajectories)
2. Sample $\mathbf{s} \sim p^\pi(\mathbf{s}_{\text{future}}|\mathbf{s}_t, \mathbf{a}_t)$ (e.g., pick $\mathbf{s}_{t'}$ where $t' = t+\Delta$, $\Delta \sim \text{Geom}(\gamma)$)
3. Update $p^\pi(F=1|\mathbf{s}_t, \mathbf{a}_t, \mathbf{s})$ using SGD with cross entropy loss

This is an **on policy** algorithm

Could also derive an **off policy** algorithm

Eysenbach , Salakhutdinov, Levine. **C- Learning: Learning to Achieve Goals via Recursive Classification** . 2020.

Kaggle competition: Connect X



Dauphine | PSL Moodle

Submit your code on Moodle on **Sunday 10 March**.
Presenting your solution on Wednesday 13 March.
Graded on the stabilized version of March 18.

Don’t submit after March 10 midnight Paris time, otherwise you will be disqualified.

20 points: 18 from your score and 2 from your oral presentation.

Good luck!