Computer Engineering Department

Offline Reinforcement Learning

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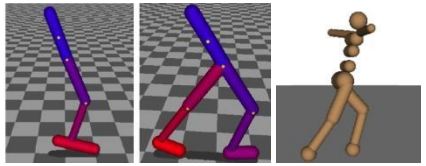
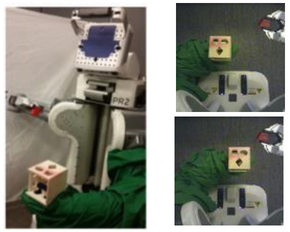
Slides are adopted from CS 285, UC Berkeley.

The generalization gap

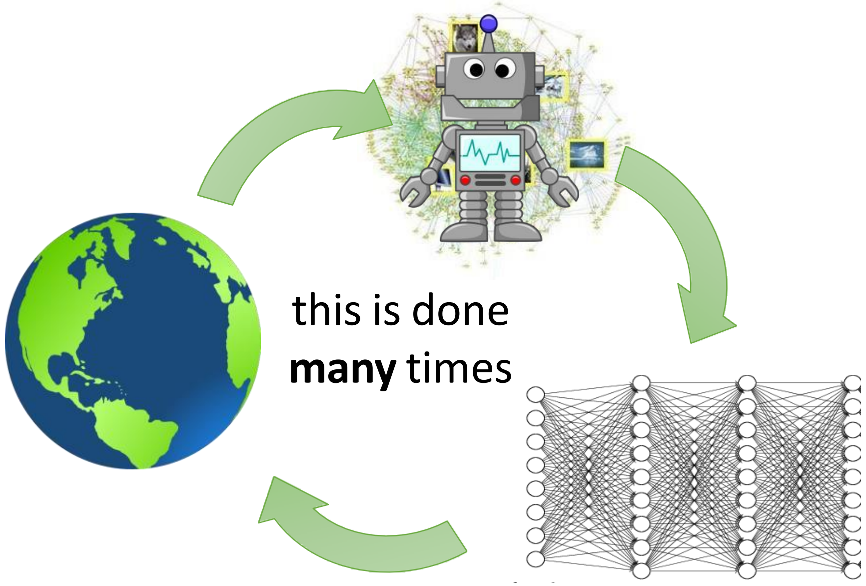
Mnih et al. '13

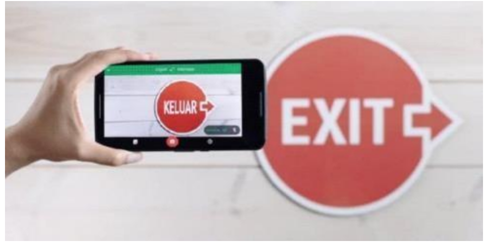


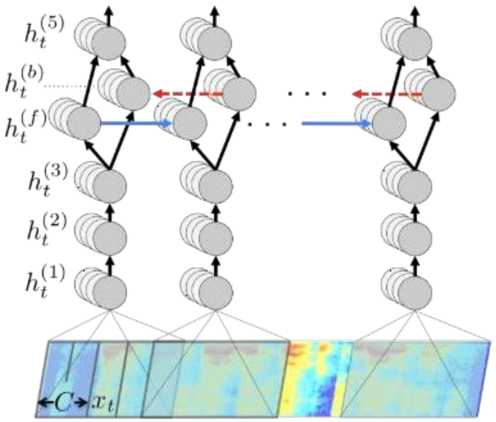
Schulman et al. '14 & '15

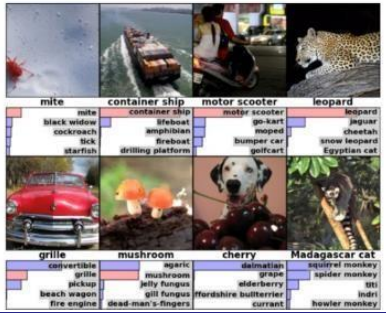


Levine*, Finn*, et al. '16



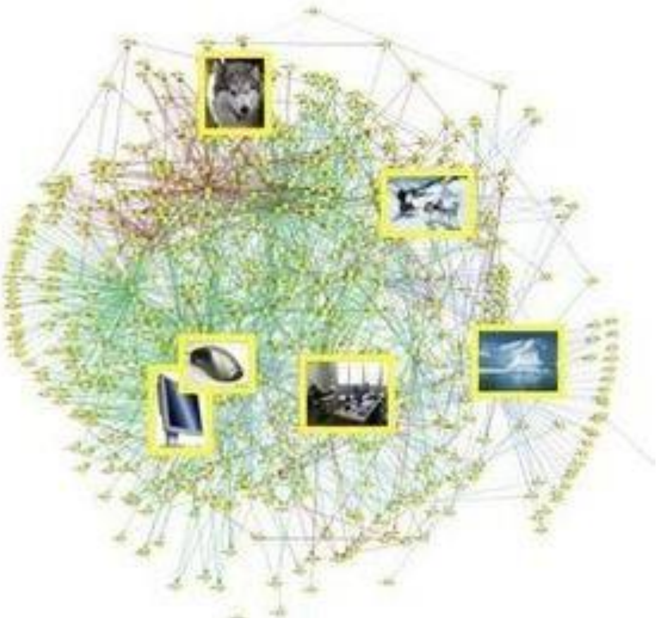


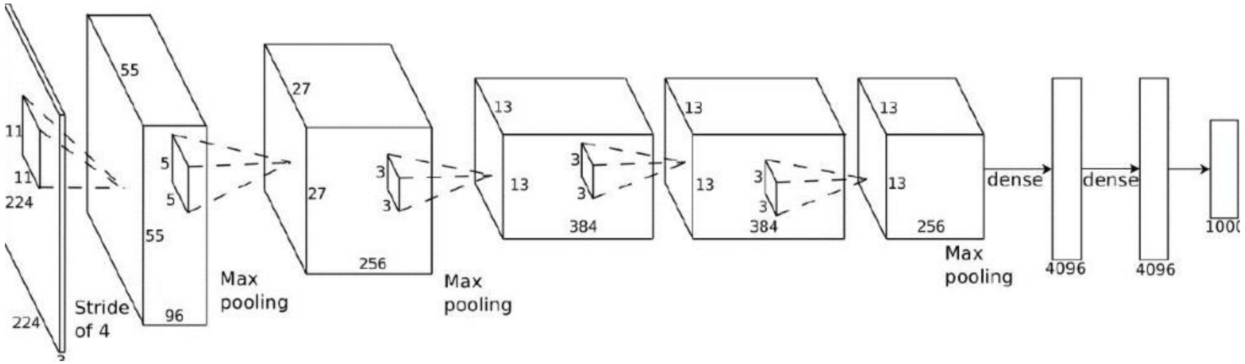


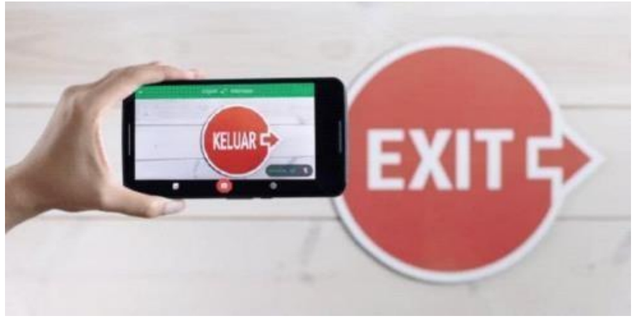


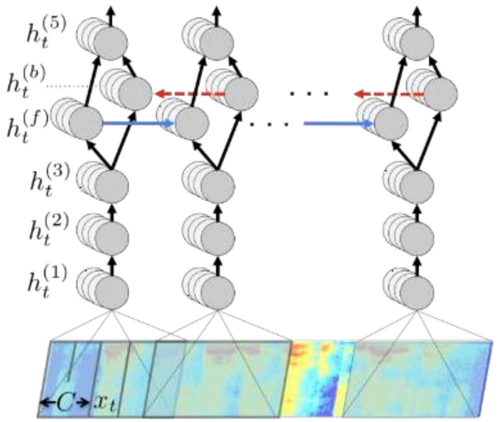
enormous gulf

What makes modern machine learning work?

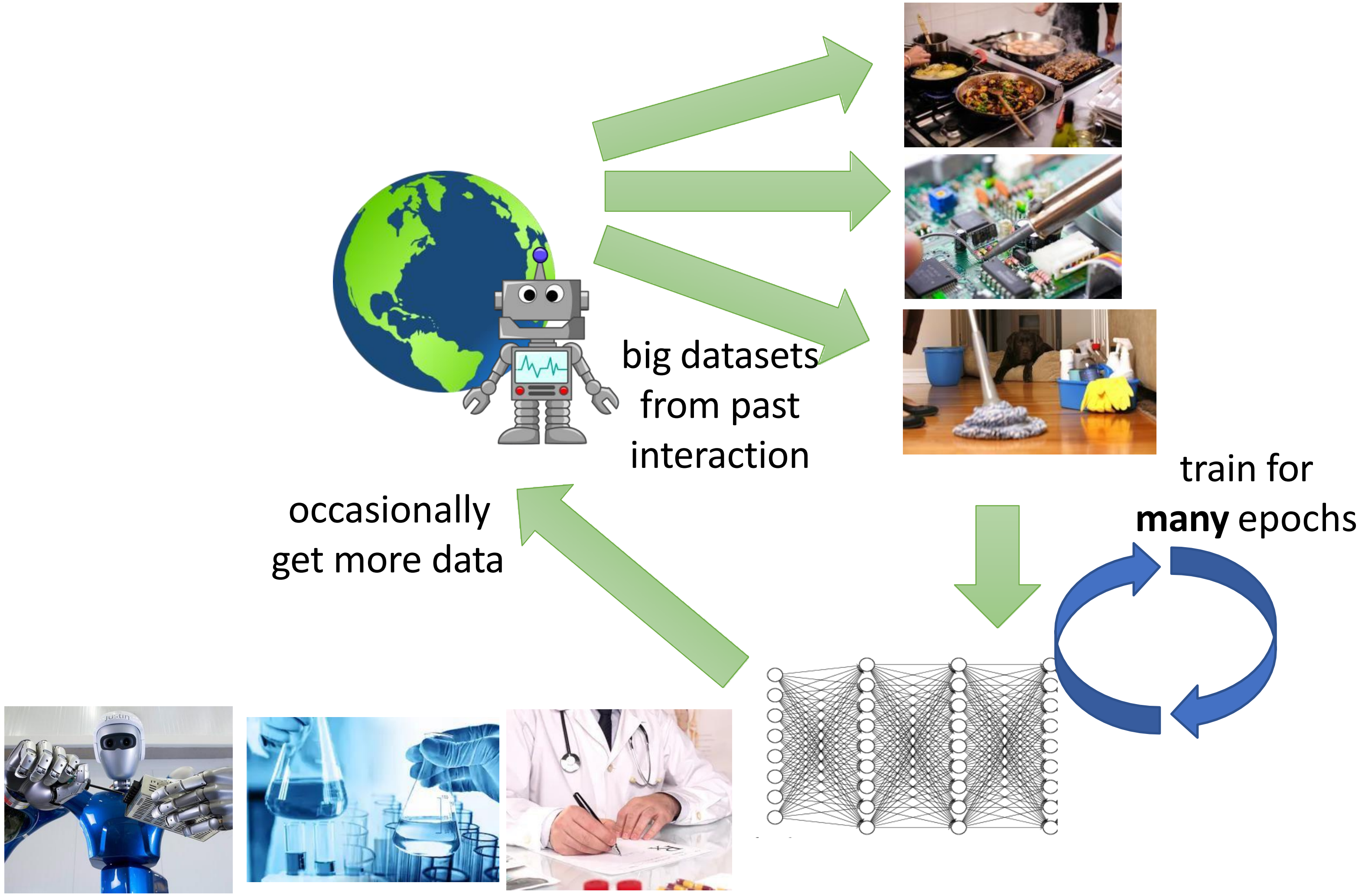








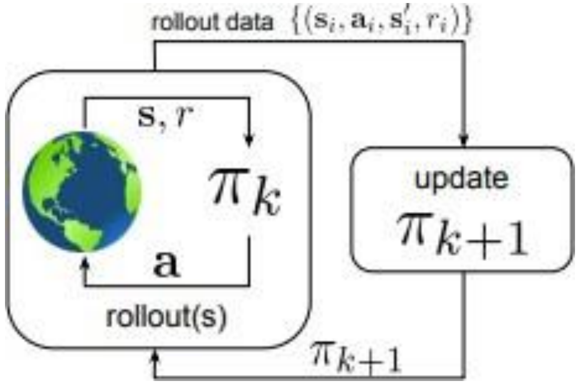
Can we develop data-driven RL methods?



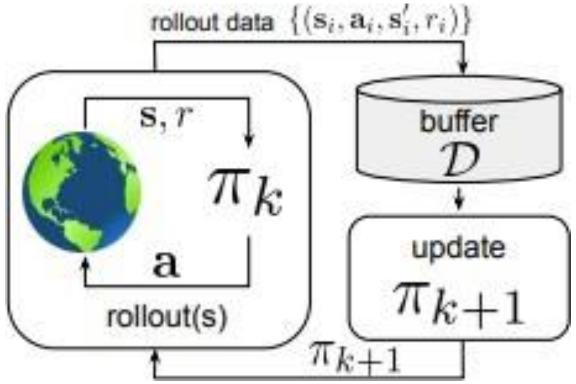
Levine, Kumar, Tucker, Fu. **Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.** ‘20

What does offline RL mean?

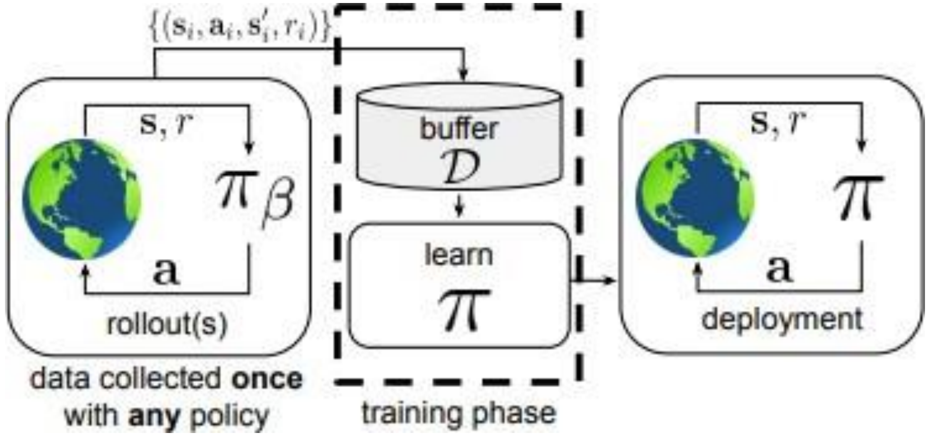
on-policy RL



off-policy RL



offline reinforcement learning



Formally:

$$\mathcal{D} = \{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$$

$$\mathbf{s} \sim d^{\pi_\beta}(\mathbf{s})$$
$$\mathbf{a} \sim \pi_\beta(\mathbf{a}|\mathbf{s})$$
$$\mathbf{s}' \sim p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$$
$$r \leftarrow r(\mathbf{s}, \mathbf{a})$$

generally **not** known

RL objective: $\max_\pi \sum_{t=0}^{T} E_{\mathbf{s}_t \sim d^\pi(\mathbf{s}), \mathbf{a}_t \sim \pi(\mathbf{a}|\mathbf{s})}[\gamma^t r(\mathbf{s}_t, \mathbf{a}_t)]$

Levine, Kumar, Tucker, Fu. **Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.** ‘20

Types of offline RL problems

$$\mathcal{D} = \{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$$

$$\mathbf{s} \sim d^{\pi_\beta}(\mathbf{s})$$
$$\mathbf{a} \sim \pi_\beta(\mathbf{a}|\mathbf{s})$$
$$\mathbf{s}' \sim p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$$
$$r \leftarrow r(\mathbf{s}, \mathbf{a})$$

off-policy evaluation (OPE):

given $\mathcal{D}$, estimate $J(\pi) = E_\pi\left[\sum_{t=1}^{T} r(\mathbf{s}_t, \mathbf{a}_t)\right]$

offline reinforcement learning: (a.k.a. batch RL, sometimes fully off-policy RL)

given $\mathcal{D}$, learn the best possible policy π_θ

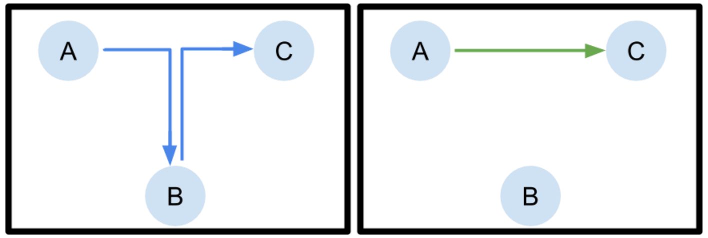
not necessarily obvious what this means

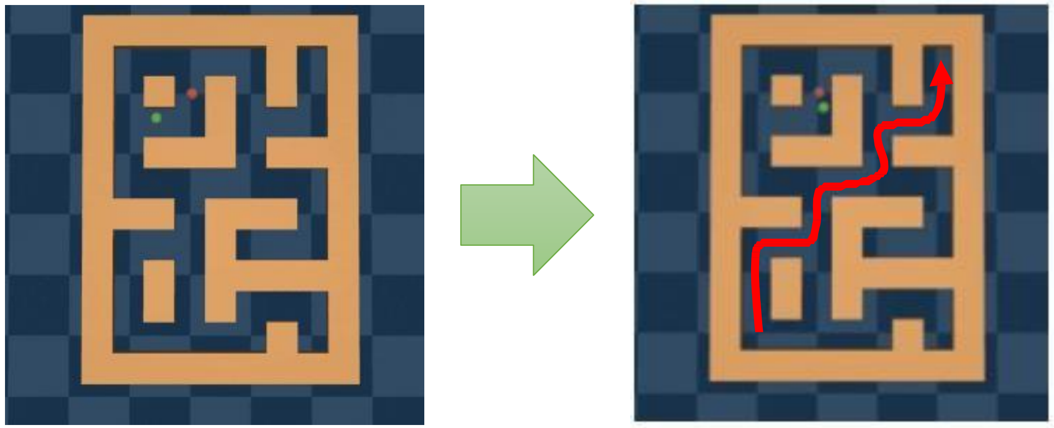
How is this even possible?

1. Find the “good stuff” in a dataset full of good and bad behaviors

2. Generalization: good behavior in one place may suggest good behavior in another place

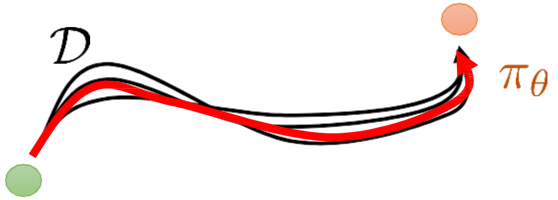
3. “Stitching”: parts of good behaviors can be recombined





What do we expect offline RL methods to do?

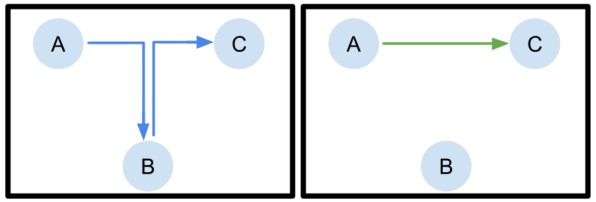
Bad intuition: it's like imitation learning



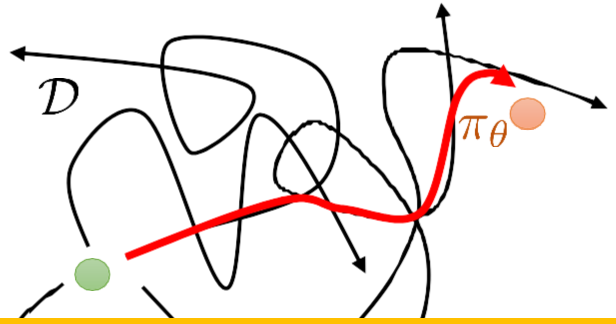
Though it can be shown to be **provably** better than imitation learning even with optimal data, under some structural assumptions!

See: Kumar, Hong, Singh, Levine. Should I Run Offline Reinforcement Learning or Behavioral Cloning?

Better intuition: get order from chaos



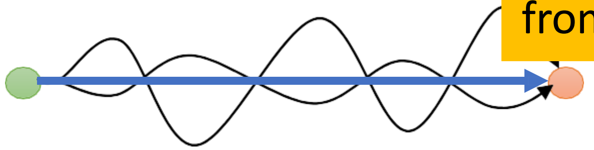
"Macro-scale" stitching



If we have algorithms that properly perform dynamic programming, we can take this idea much further and get near-optimal policies from highly suboptimal data

But this is just the clearest example!

"Micro-scale" stitching:

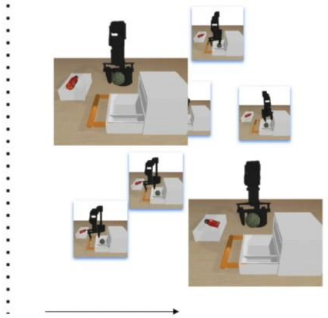


A vivid example

RL policies typically don't generalize to initial conditions that were not seen during training

Training time

Can we use previously collected, unlabeled datasets to extend learned skills?



training task

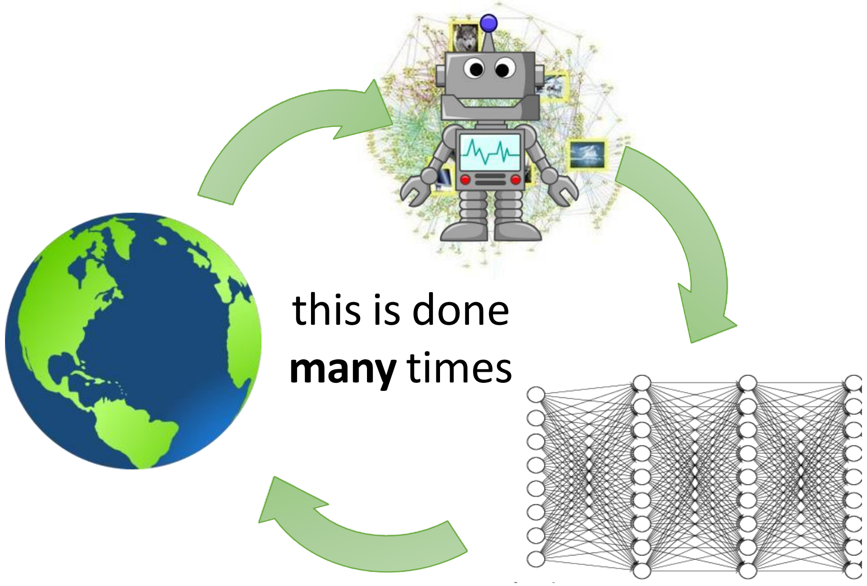
closed drawer

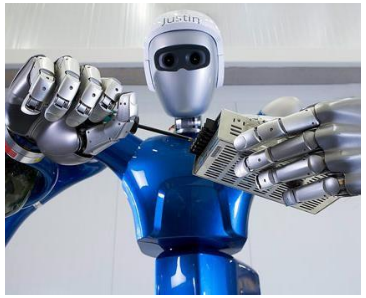
blocked by drawer

blocked by object

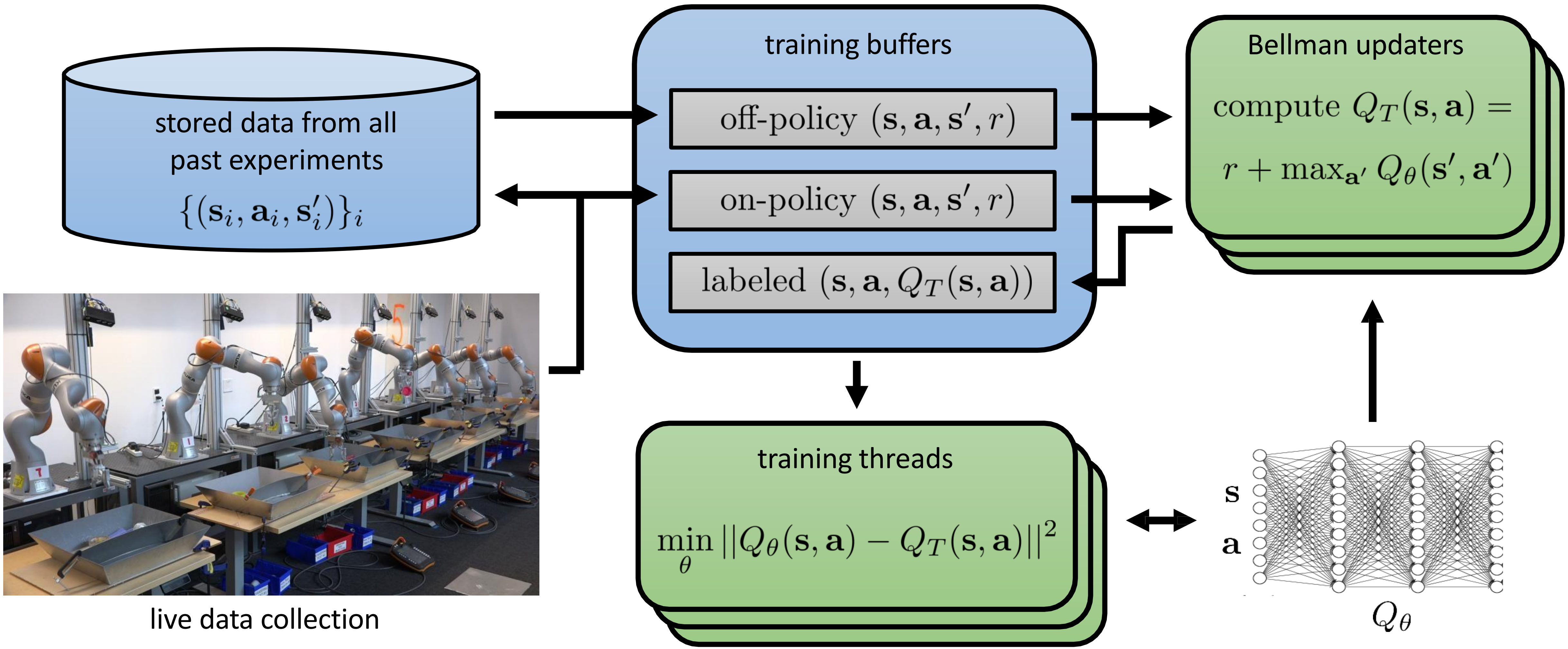
Singh, Yu, Yang, Zhang, Kumar, Levine. **COG: Connecting New Skills to Past Experience with Offline Reinforcement Learning.** '20

Why should we care?





Does it work?



Kalashnikov, Irpan, Pastor, Ibarz, Herzong, Jang, Quillen, Holly, Kalakrishnan, Vanhoucke, Levine. **QT-Opt: Scalable Deep Reinforcement Learning of Vision-Based Robotic Manipulation Skills**

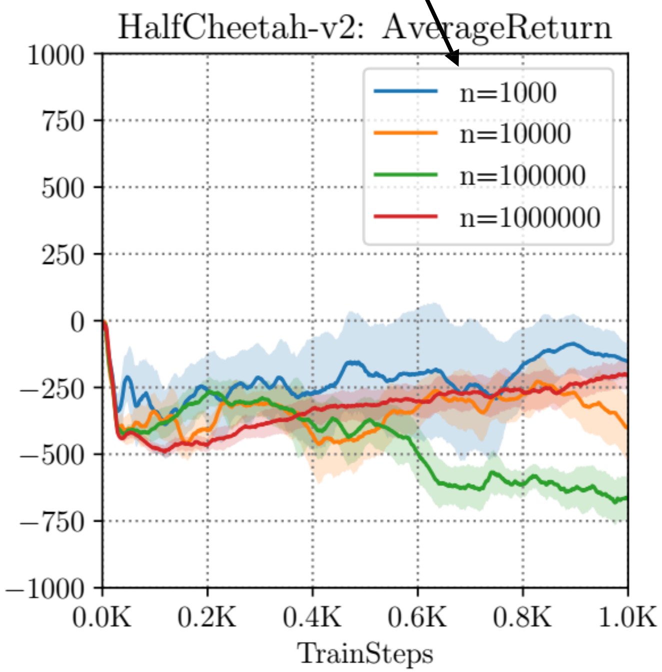
Does it work?

Method	Dataset	Success	Failure
Offline QT-Opt	580k offline	87%	13%
Finetuned QT-Opt	580k offline + 28k online	**96%**	**4%**

Kalashnikov, Irpan, Pastor, Ibarz, Herzong, Jang, Quillen, Holly, Kalakrishnan, Vanhoucke, Levine. **QT-Opt: Scalable Deep Reinforcement Learning of Vision-Based Robotic Manipulation Skills**

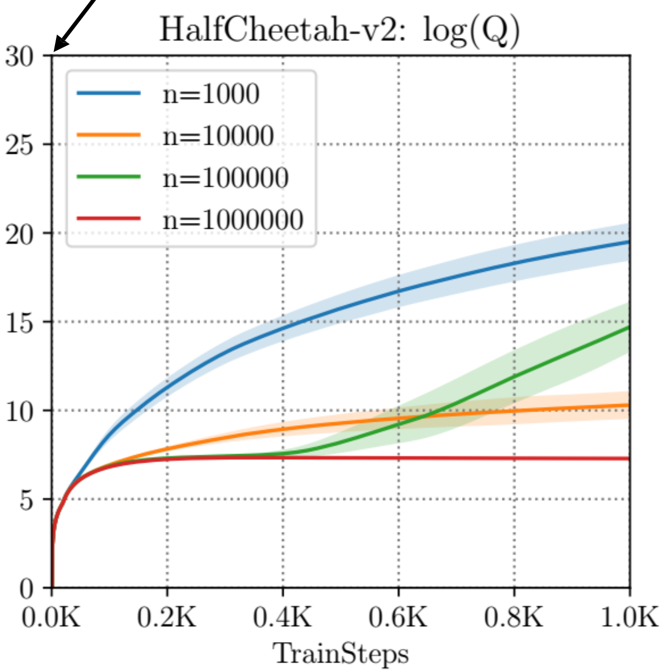
Why is offline RL hard?

amount of data



how well it does

log scale (massive overestimation)



how well it *thinks* it does (Q-values)

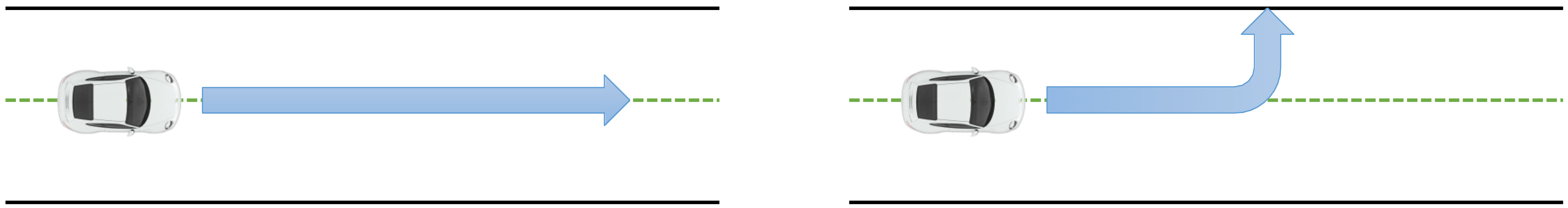
Kumar, Fu, Tucker, Levine. **Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction.** NeurIPS '19

Why is offline RL hard?

Fundamental problem: counterfactual queries

Training data

What the policy wants to do



Is this good? Bad? How do we know if we didn't see it in the data?

Online RL algorithms don't have to handle this, because they can simply **try** this action and see what happens

Offline RL methods must somehow account for these unseen ("out-of-distribution") actions, ideally in a safe way

…while still making use of generalization to come up with behaviors that are better than the best thing seen in the data!

Levine, Kumar, Tucker, Fu. **Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.** '20

Distribution shift in a nutshell

Example empirical risk minimization (ERM) problem:

$$\theta \leftarrow \arg\min_\theta E_{\mathbf{x}\sim p(\mathbf{x}),y\sim p(y|\mathbf{x})}\left[(f_\theta(\mathbf{x})-y)^2\right]$$

given some $\mathbf{x}^\star$, is $f_\theta(\mathbf{x}^\star)$ correct?

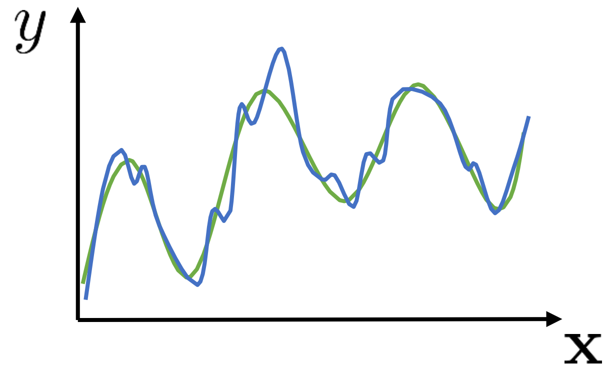
$E_{\mathbf{x}\sim p(\mathbf{x}),y\sim p(y|\mathbf{x})}\left[(f_\theta(\mathbf{x})-y)^2\right]$ is low

$E_{\mathbf{x}\sim \bar{p}(\mathbf{x}),y\sim p(y|\mathbf{x})}\left[(f_\theta(\mathbf{x})-y)^2\right]$ is not, for general $\bar{p}(\mathbf{x}) \neq p(\mathbf{x})$

what if $\mathbf{x}^\star \sim p(\mathbf{x})$? not necessarily...

usually we are not worried – neural nets generalize well!

what if we pick $\mathbf{x}^\star \leftarrow \arg\max_{\mathbf{x}} f_\theta(\mathbf{x})$?



Kumar, Fu, Tucker, Levine. **Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction.** NeurIPS '19

Where do we suffer from distribution shift?

$$\cancel{Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + \max_{\mathbf{a}'} Q(\mathbf{s}',\mathbf{a}')}$$

$$Q(\mathbf{s},\mathbf{a}) \leftarrow \underbrace{r(\mathbf{s},\mathbf{a}) + E_{\mathbf{a}'\sim\pi_{\text{new}}}[Q(\mathbf{s}',\mathbf{a}')]}_{y(\mathbf{s},\mathbf{a})}$$

what is the objective?

$$\min_Q E_{(\mathbf{s},\mathbf{a})\sim\pi_\beta(\mathbf{s},\mathbf{a})}\left[(Q(\mathbf{s},\mathbf{a}) - y(\mathbf{s},\mathbf{a}))^2\right]$$

behavior policy

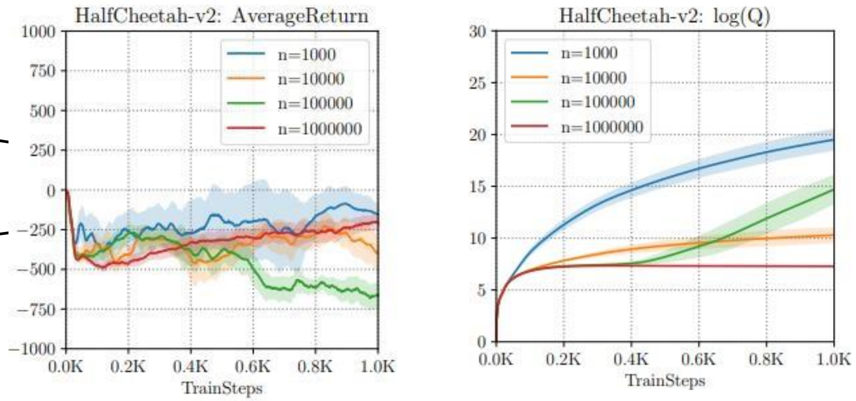
target value

expect good accuracy when $\pi_\beta(\mathbf{a}|\mathbf{s}) = \pi_{\text{new}}(\mathbf{a}|\mathbf{s})$

how often does *that* happen?

even *worse*: $\pi_{\text{new}} = \arg\max_\pi E_{\mathbf{a}\sim\pi(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})]$

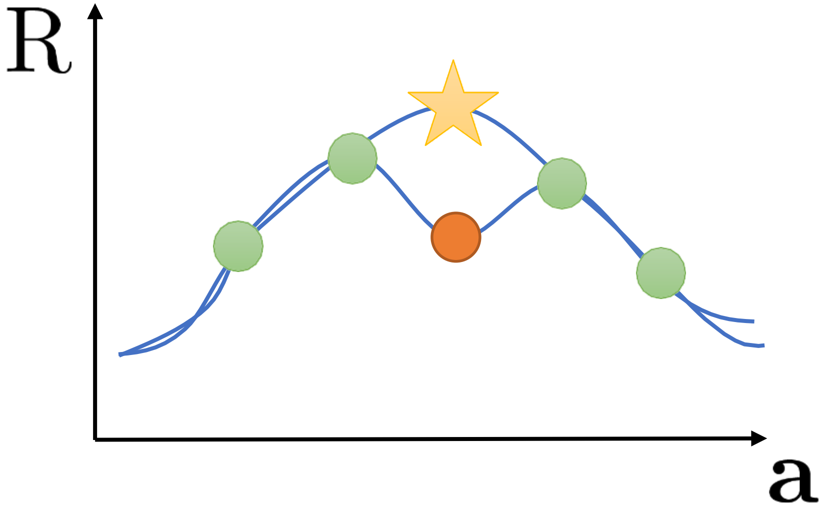
(what if we pick $\mathbf{x}^\star \leftarrow \arg\max_{\mathbf{x}} f_\theta(\mathbf{x})$?)



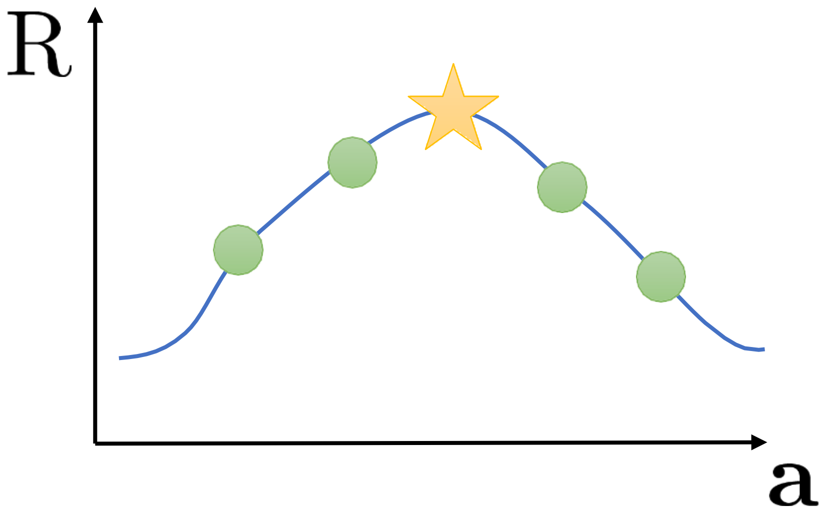
Kumar, Fu, Tucker, Levine. **Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction.** NeurIPS '19

Issues with generalization are not corrected

online RL setting



offline RL setting



Existing challenges with sampling error and function approximation error in standard RL become **much more severe** in offline RL

Offline RL Solutions

Policy Constraint Methods

How do prior methods address this?

$$Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + E_{\mathbf{a}'\sim\pi_{\text{new}}}[Q(\mathbf{s}',\mathbf{a}')]$$

$$\pi_{\text{new}}(\mathbf{a}|\mathbf{s}) = \arg\max_{\pi} E_{\mathbf{a}\sim\pi(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] \text{ s.t. } D_{\text{KL}}(\pi\|\pi_\beta) \leq \epsilon$$

This solves distribution shift, right?

No more erroneous values?

Issue 1: we usually don't know the behavior policy $\pi_\beta(\mathbf{a}|\mathbf{s})$

- human-provided data
- data from hand-designed controller
- data from many past RL runs
- all of the above

Issue 2: this is both *too pessimistic* and *not pessimistic enough*

"policy constraint" method

very old idea (but it had no single name?)

Todorov et al. [passive dynamics in linearly-solvable MDPs]

Kappen et al. [KL-divergence control, etc.]

trust regions, covariant policy gradients, natural policy gradients, etc.

used in some form in recent papers:

Fox et al. '15 ("Taming the Noise…")

Fujimoto et al. '18 ("Off Policy…")

Jaques et al. '19 ("Way Off Policy…")

Kumar et al. '19 ("Stabilizing…")

Wu et al. '19 ("Behavior Regularized…")

Levine, Kumar, Tucker, Fu. **Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.** '20

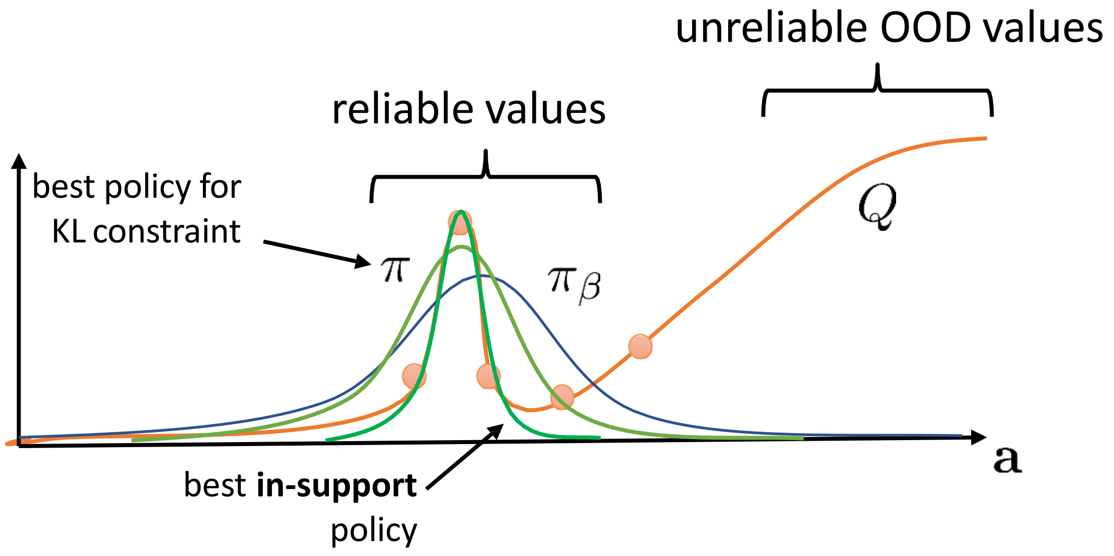
Explicit policy constraint methods

What kinds of constraints can we use?

KL-divergence: $D_{\mathrm{KL}}(\pi \| \pi_\beta)$

+ easy to implement (more on this later)

- not necessarily what we want



support constraint: $\pi(\mathbf{a}|\mathbf{s}) \geq 0$ only if $\pi_\beta(\mathbf{a}|\mathbf{s}) \geq \epsilon$

can approximate with MMD

- significantly more complex to implement

+ much closer to what we really want

For more information, see:

Levine, Kumar, Tucker, Fu. **Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.** '20

Kumar, Fu, Tucker, Levine. **Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction.** '19

Wu, Tucker, Nachum. **Behavior Regularized Offline Reinforcement Learning.** `19

Explicit policy constraint methods

How do we implement constraints?

Lagrange multiplier

easy to compute and differentiate
for Gaussian or categorical policies

1. Modify the actor objective

$$\cancel{\theta \leftarrow \arg\max_\theta E_{\mathbf{s}\sim D}\left[E_{\mathbf{a}\sim\pi_\theta(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})]\right]}$$

$$\theta \leftarrow \arg\max_\theta E_{\mathbf{s}\sim D}\left[E_{\mathbf{a}\sim\pi_\theta(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a}) + \lambda \log \pi_\beta(\mathbf{a}|\mathbf{s})] + \lambda\mathcal{H}(\pi(\mathbf{a}|\mathbf{s}))\right]$$

$$D_{\text{KL}}(\pi\|\pi_\beta) = E_\pi[\log \pi(\mathbf{a}|\mathbf{s}) - \log \pi_\beta(\mathbf{a}|\mathbf{s})] = -E_\pi[\log \pi_\beta(\mathbf{a}|\mathbf{s})] - \mathcal{H}(\pi)$$

2. Modify the reward function

$$\bar{r}(\mathbf{s},\mathbf{a}) = r(\mathbf{s},\mathbf{a}) - D(\pi,\pi_\beta)$$

simple modification to directly penalize divergence
also accounts for **future** divergence

See: Wu, Tucker, Nachum. **Behavior Regularized Offline Reinforcement Learning.** `19

generally, the best modern offline RL methods do not do either of these things

Implicit policy constraint methods

$$\pi_{\text{new}}(\mathbf{a}|\mathbf{s}) = \arg\max_{\pi} E_{\mathbf{a}\sim\pi(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] \text{ s.t. } D_{\text{KL}}(\pi\|\pi_\beta) \leq \epsilon$$

$$\pi^\star(\mathbf{a}|\mathbf{s}) = \frac{1}{Z(\mathbf{s})}\pi_\beta(\mathbf{a}|\mathbf{s})\exp\left(\frac{1}{\lambda}A^\pi(\mathbf{s},\mathbf{a})\right)$$

straightforward to show via duality

See also:
Peters et al. (REPS)

approximate via **weighted** max likelihood!

$$\pi_{\text{new}}(\mathbf{a}|\mathbf{s}) = \arg\max_{\pi} E_{(\mathbf{s},\mathbf{a})\sim\pi_\beta}\left[\log\pi(\mathbf{a}|\mathbf{s})\overbrace{\frac{1}{Z(\mathbf{s})}\exp\left(\frac{1}{\lambda}A^{\pi_{\text{old}}}(\mathbf{s},\mathbf{a})\right)}^{w(\mathbf{s},\mathbf{a})}\right]$$

samples from dataset
$\mathbf{a}\sim\pi_\beta(\mathbf{a}|\mathbf{s})$

critic can be used to give us this

Peng*, Kumar*, Levine. **Advantage-Weighted Regression.** ‘19

Implicit policy constraint methods

$$\mathcal{L}_C(\phi) = E_{(\mathbf{s},\mathbf{a},\mathbf{s}')\sim D}\left[\left(Q_\phi(\mathbf{s},\mathbf{a}) - (r(\mathbf{s},\mathbf{a}) + \gamma E_{\mathbf{a}'\sim\pi_\theta(\mathbf{a}'|\mathbf{s}')}[Q_\phi(\mathbf{s}',\mathbf{a}')])\right)^2\right]$$

$$\mathcal{L}_A(\theta) = -E_{(\mathbf{s},\mathbf{a})\sim\pi_\beta}\left[\log\pi_\theta(\mathbf{a}|\mathbf{s})\frac{1}{Z(\mathbf{s})}\exp\left(\frac{1}{\lambda}A^{\pi_{\text{old}}}(\mathbf{s},\mathbf{a})\right)\right]$$

1. $\phi \leftarrow \phi - \alpha\nabla_\phi\mathcal{L}_C(\phi)$
2. $\theta \leftarrow \theta - \alpha\nabla_\theta\mathcal{L}_A(\theta)$

$$Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + E_{\mathbf{a}'\sim\pi_{\text{new}}}[Q(\mathbf{s}',\mathbf{a}')]$$

$$\pi_{\text{new}}(\mathbf{a}|\mathbf{s}) = \arg\max_\pi E_{\mathbf{a}\sim\pi(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] \text{ s.t. } D_{\text{KL}}(\pi\|\pi_\beta) \leq \epsilon$$

Peng*, Kumar*, Levine. **Advantage-Weighted Regression.** '19

Can we also avoid all OOD actions in the Q update?

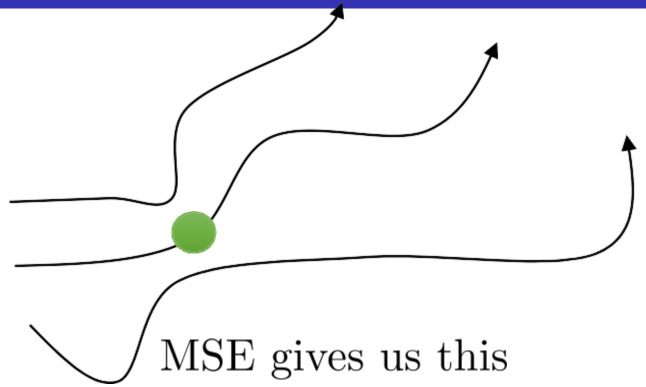
$$Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + \underbrace{E_{\mathbf{a}'\sim\pi_{\text{new}}}[Q(\mathbf{s}',\mathbf{a}')]}_{V(\mathbf{s}')}$$

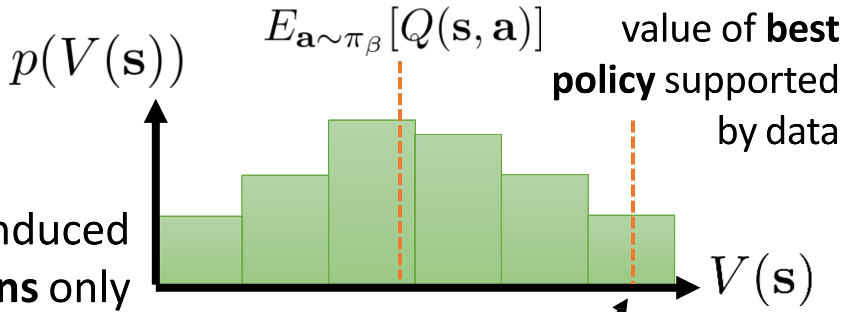
just another neural network

$$V \leftarrow \arg\min_V \frac{1}{N}\sum_{i=1}^{N} \ell(V(\mathbf{s}_i), Q(\mathbf{s}_i,\mathbf{a}_i))$$

e.g., MSE loss $(V(\mathbf{s}_i) - Q(\mathbf{s}_i,\mathbf{a}_i))^2$

this action comes from π_β not from π_{new}

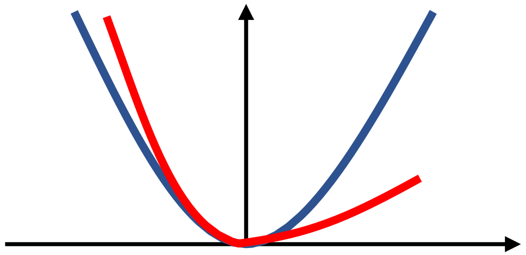




distribution is induced by **actions** only

could **another** loss give us this?

expectile: $\ell_2^\tau(x) = \begin{cases} (1-\tau)x^2 & \text{if } x > 0 \\ \tau x^2 & \text{else} \end{cases}$



$$V(\mathbf{s}) \leftarrow \max_{\mathbf{a}\in\Omega(\mathbf{s})} Q(\mathbf{s},\mathbf{a})$$

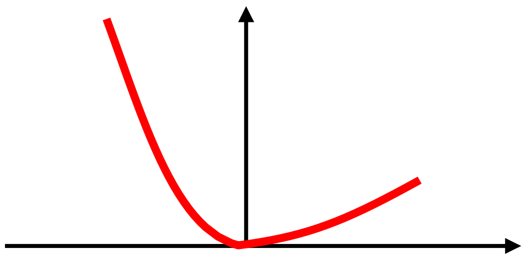
$$\Omega(\mathbf{s}) = \{\mathbf{a} : \pi_\beta(\mathbf{a}|\mathbf{s}) \geq \epsilon\}$$

if we use ℓ_2^τ for big τ

Kostrikov, Nair, Levine. **Offline Reinforcement Learning with Implicit Q-Learning.** '21

Implicit Q-learning (IQL)

$$Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + V(\mathbf{s}') \qquad V \leftarrow \arg\min_V \frac{1}{N}\sum_{i=1}^{N} \ell_2^\tau(V(\mathbf{s}_i), Q(\mathbf{s}_i,\mathbf{a}_i))$$



$$V(\mathbf{s}) \leftarrow \max_{\mathbf{a}\in\Omega(\mathbf{s})} Q(\mathbf{s},\mathbf{a})$$

$$\Omega(\mathbf{s}) = \{\mathbf{a} : \pi_\beta(\mathbf{a}|\mathbf{s}) \geq \epsilon\}$$

if we use ℓ_2^τ for big τ

$$Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + \max_{\mathbf{a}'\in\Omega(\mathbf{s}')} Q(\mathbf{s}',\mathbf{a}')$$

"implicit" policy

$$\pi_{\text{new}}(\mathbf{a}|\mathbf{s}) = \delta(\mathbf{a} = \arg\max_{\mathbf{a}\in\Omega(\mathbf{s})} Q(\mathbf{s},\mathbf{a}))$$

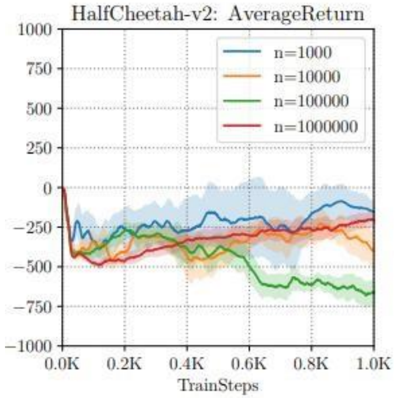
Now we can do value function updates without ever risking out-of-distribution actions!

Kostrikov, Nair, Levine. **Offline Reinforcement Learning with Implicit Q-Learning.** '21

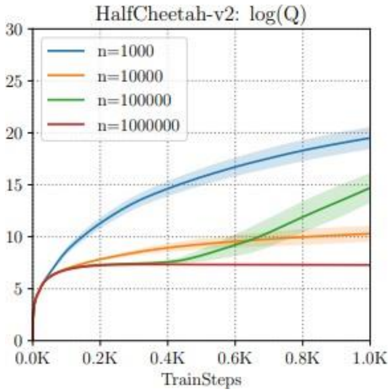
Offline RL Solutions

Conservative Q-Learning

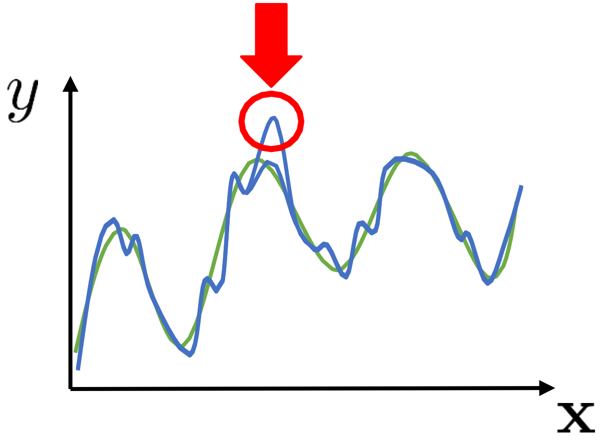
Conservative Q-learning (CQL)



how well it does



how well it *thinks* it does (Q-values)



$$\hat{Q}^{\pi} = \arg\min_{Q} \max_{\mu} \underbrace{\alpha E_{\mathbf{s}\sim D,\mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})]}_{\text{term to push down big Q-values}}$$

$$\underbrace{+E_{(\mathbf{s},\mathbf{a},\mathbf{s}')\sim D}\left[\left(Q(\mathbf{s},\mathbf{a}) - (r(\mathbf{s},\mathbf{a}) + E_{\pi}[Q(\mathbf{s}',\mathbf{a}')])\right)^2\right]}_{\text{regular objective}}$$

can show that $\hat{Q}^{\pi} \leq Q^{\pi}$ for large enough α

true Q-function

Conservative Q-learning (CQL)

A *better* bound:

always pushes Q-values down

push up on (**s**, **a**) samples in data

$$\left.\begin{aligned}\hat{Q}^\pi = \arg\min_Q \max_\mu \alpha E_{\mathbf{s}\sim D, \mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] - \alpha E_{(\mathbf{s},\mathbf{a})\sim D}[Q(\mathbf{s},\mathbf{a})] \\ + E_{(\mathbf{s},\mathbf{a},\mathbf{s}')\sim D}\left[(Q(\mathbf{s},\mathbf{a}) - (r(\mathbf{s},\mathbf{a}) + E_\pi[Q(\mathbf{s}',\mathbf{a}')]))^2\right]\end{aligned}\right\} \mathcal{L}_{\mathrm{CQL}}(\hat{Q}^\pi)$$

no longer guaranteed that $\hat{Q}^\pi(\mathbf{s},\mathbf{a}) \leq Q^\pi(\mathbf{s},\mathbf{a})$ *for all* $(\mathbf{s},\mathbf{a})$

but guaranteed that $E_{\pi(\mathbf{a}|\mathbf{s})}[\hat{Q}^\pi(\mathbf{s},\mathbf{a})] \leq E_{\pi(\mathbf{a}|\mathbf{s})}[Q^\pi(\mathbf{s},\mathbf{a})]$ *for all* $\mathbf{s} \in D$

Kumar, Zhou, Tucker, Levine. **Conservative Q-Learning for Offline Reinforcement Learning.** ‘20

Conservative Q-learning (CQL)

1. Update $\hat{Q}^\pi$ w.r.t. $\mathcal{L}_{\text{CQL}}(\hat{Q}^\pi)$ using $\mathcal{D}$
2. Update policy π

if actions are discrete:

$$\pi(\mathbf{a}|\mathbf{s}) = \begin{cases} 1 \text{ if } \mathbf{a} = \arg\max_{\mathbf{a}} \hat{Q}(\mathbf{s}, \mathbf{a}) \\ 0 \text{ otherwise} \end{cases}$$

if actions are continuous:

$$\theta \leftarrow \theta + \alpha \nabla_\theta \sum_i E_{\mathbf{a} \sim \pi_\theta(\mathbf{a}|\mathbf{s}_i)}[\hat{Q}(\mathbf{s}_i, \mathbf{a})]$$

Kumar, Zhou, Tucker, Levine. **Conservative Q-Learning for Offline Reinforcement Learning.** '20

Conservative Q-learning (CQL)

regularization

$$\left.\begin{aligned}\hat{Q}^{\pi} = \arg\min_{Q}\max_{\mu}\, &\alpha E_{\mathbf{s}\sim D,\mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] - \alpha E_{(\mathbf{s},\mathbf{a})\sim D}[Q(\mathbf{s},\mathbf{a})] - \mathcal{R}(\mu) \\ &+ E_{(\mathbf{s},\mathbf{a},\mathbf{s}')\sim D}\left[\left(Q(\mathbf{s},\mathbf{a}) - (r(\mathbf{s},\mathbf{a}) + E_{\pi}[Q(\mathbf{s}',\mathbf{a}')])\right)^2\right]\end{aligned}\right\} \mathcal{L}_{\mathrm{CQL}}(\hat{Q}^{\pi})$$

$\text{common choice:} \quad \mathcal{R} = E_{\mathbf{s}\sim D}[\mathcal{H}(\mu(\cdot|\mathbf{s}))]$ maximum entropy regularization

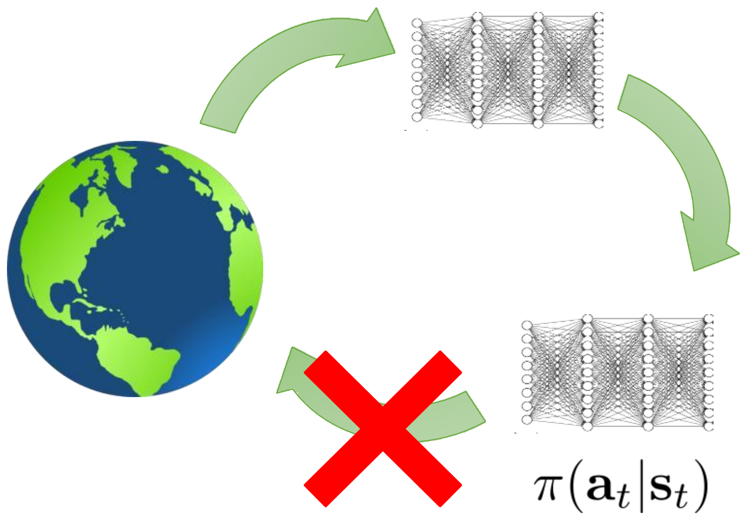
Kumar, Zhou, Tucker, Levine. **Conservative Q-Learning for Offline Reinforcement Learning.** ‘20

Offline RL Solutions

Model-Based Offline RL

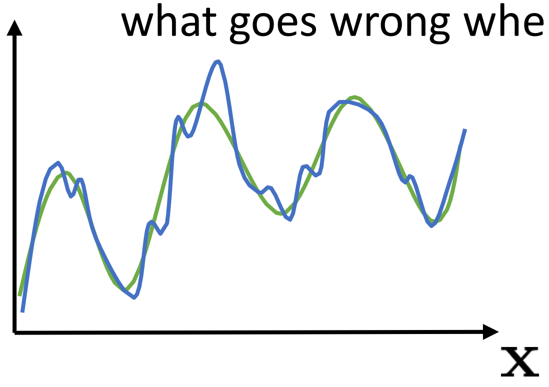
How does model-based RL work?

$\hat{p}(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$



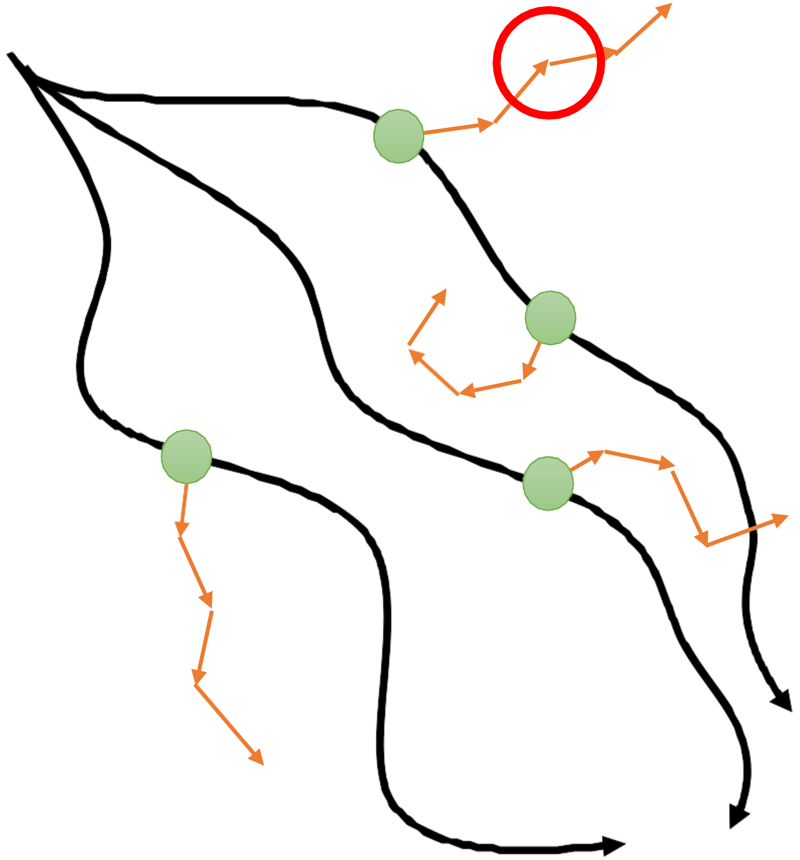
$\pi(\mathbf{a}_t|\mathbf{s}_t)$

what goes wrong when we can't collect more data?



...so the model's predictions are invalid

these states are OOD



the model answers "what if" questions

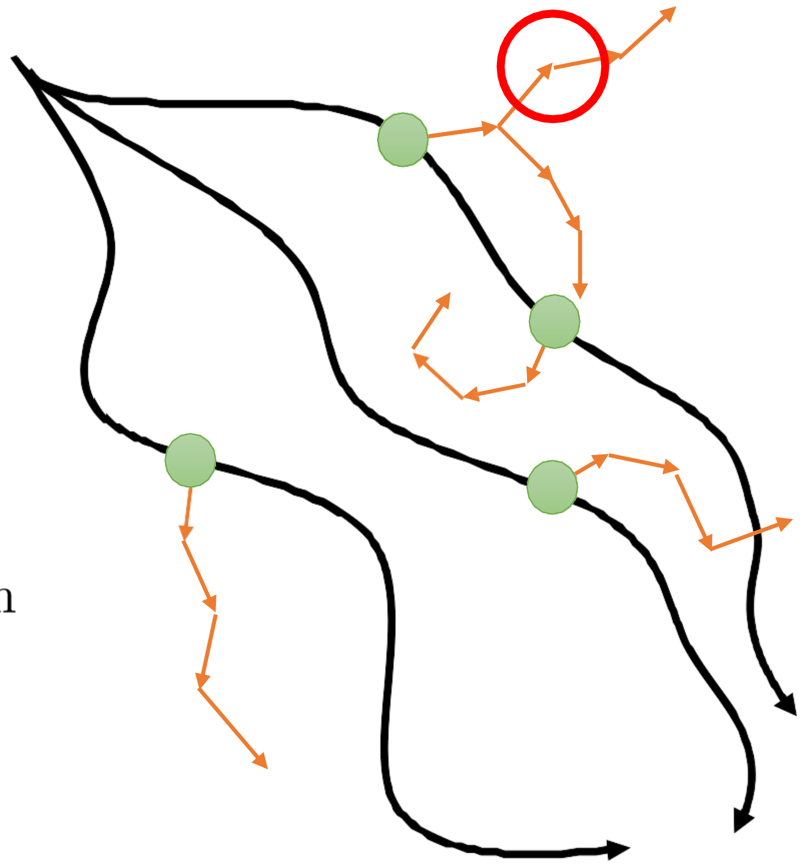
Model-Based Offline RL

solution: "punish" the policy for exploiting

$$\tilde{r}(\mathbf{s},\mathbf{a}) = r(\mathbf{s},\mathbf{a}) - \lambda u(\mathbf{s},\mathbf{a})$$

uncertainty penalty

...and then use any existing model-based RL algorithm



Yu*, Thomas*, Yu, Ermon, Zou, Levine, Finn, Ma. **MOPO: Model-Based Offline Policy Optimization.** '20

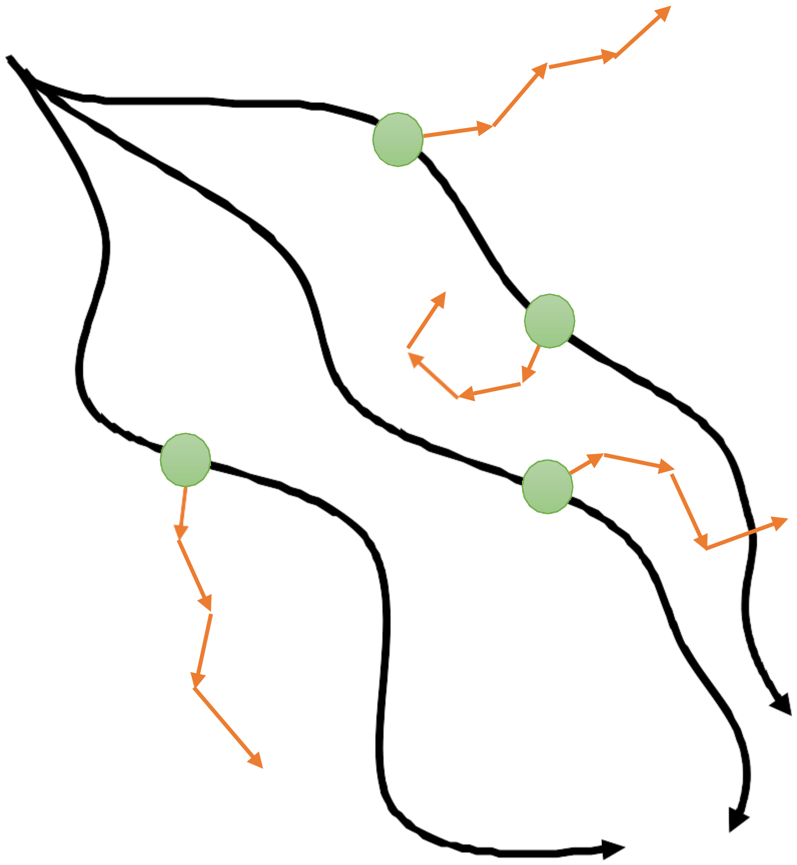
See also: Kidambi et al., **MOReL : Model-Based Offline Reinforcement Learning.** '20 (concurrent)

Conservative Model-Based RL

Basic idea: just like CQL minimizes Q-value of policy actions, we can minimize Q-value of model state-action tuples

state-action tuples from the model

$$\hat{Q}^{k+1} \leftarrow \arg\min_{Q} \beta \left(\mathbb{E}_{\mathbf{s},\mathbf{a} \sim \rho(\mathbf{s},\mathbf{a})}[Q(\mathbf{s},\mathbf{a})] - \mathbb{E}_{\mathbf{s},\mathbf{a} \sim \mathcal{D}}[Q(\mathbf{s},\mathbf{a})] \right) + \frac{1}{2} \mathbb{E}_{\mathbf{s},\mathbf{a},\mathbf{s}' \sim d_f} \left[\left(Q(\mathbf{s},\mathbf{a}) - \widehat{\mathcal{B}}^{\pi} \hat{Q}^{k}(\mathbf{s},\mathbf{a}) \right)^2 \right]. \quad (4)$$



Intuition: if the model produces something that looks clearly different from real data, it's easy for the Q-function to make it look bad

Yu, Kumar, Rafailov, Rajeswaran, Levine, Finn. **COMBO: Conservative Offline Model-Based Policy Optimization**. 2021.

Summary, Applications, Open Questions

Which offline RL algorithm do I use?

If you want to *only* train offline…

Conservative Q-learning + just one hyperparameter + well understood and widely tested

Implicit Q-learning + more flexible (offline + online) - more hyperparameters

If you want to *only* train offline and finetune online

Advantage-weighted actor-critic (AWAC) + widely used and well tested

Implicit Q-learning + seems to perform much better!

If you have a good way to train models in your domain

COMBO + similar properties as CQL, but benefits from models

- not always easy to train a good model in your domain!

The power of offline RL

standard real-world RL process

1. instrument the task so that we can run RL
   - safety mechanisms
   - autonomous collection
   - rewards, resets, etc.

2. wait a long time for online RL to run

3. change the algorithm in some small way

4. throw it all in the garbage and start over for the next task

offline RL process

1. collect initial dataset
   - human-provided
   - scripted controller
   - baseline policy
   - all of the above

2. Train a policy offline

3. change the algorithm in some small way

4. collect more data, add to growing dataset

5. keep the dataset and use it again for the next project!

Takeaways, conclusions, future directions

current offline RL algorithms

“the gap”

“the dream”

1. Collect a dataset using any policy or mixture of policies
2. Run offline RL on this dataset to learn a policy
3. Deploy the policy in the real world

- An offline RL **workflow**
  - Supervised learning workflow: train/test split
  - Offline RL workflow: **???**
- Statistical **guarantees**
  - Biggest challenge: distributional shift/counterfactuals
  - Can we make any guarantees?
- Scalable methods, large-scale applications
  - Dialogue systems
  - Data-driven navigation and driving