Computer Engineering Department

# Offline Reinforcement Learning

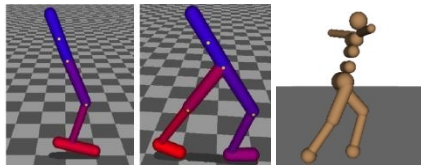
**Mohammad Hossein Rohban, Ph.D.**

Spring 2024

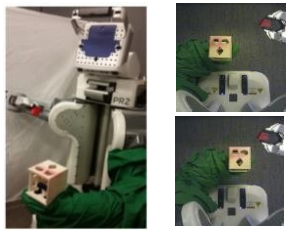
Slides are adopted from CS 285, UC Berkeley.

# The generalization gap

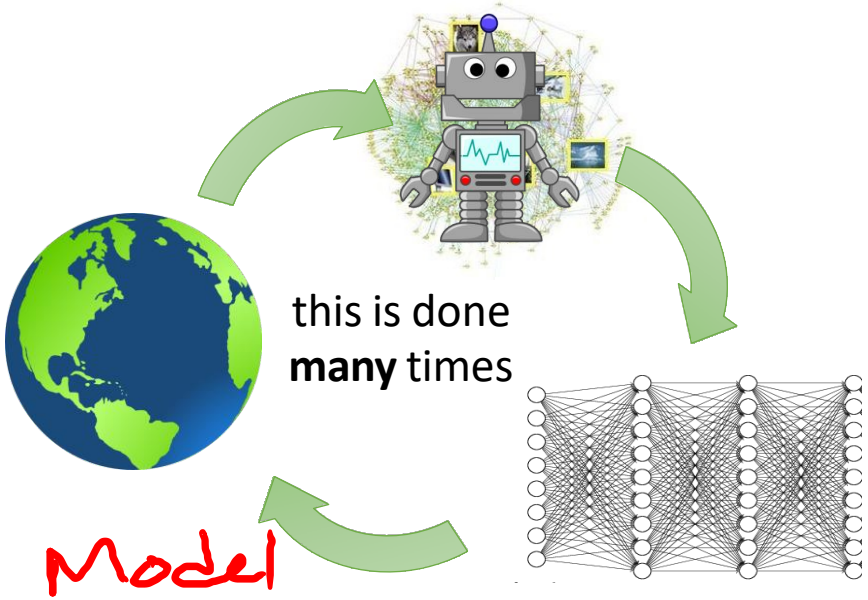
Mnih et al. ‘13



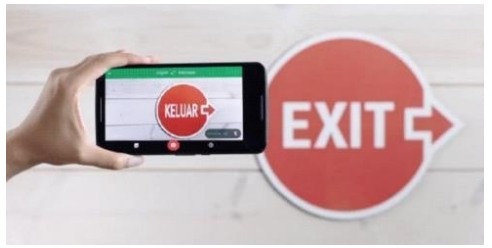
Schulman et al. ’14 & ‘15

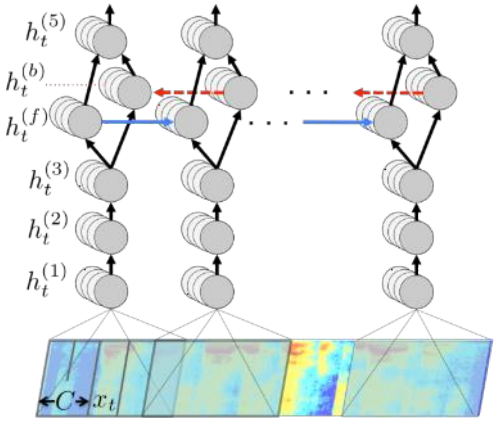


Levine*, Finn*, et al. ‘16

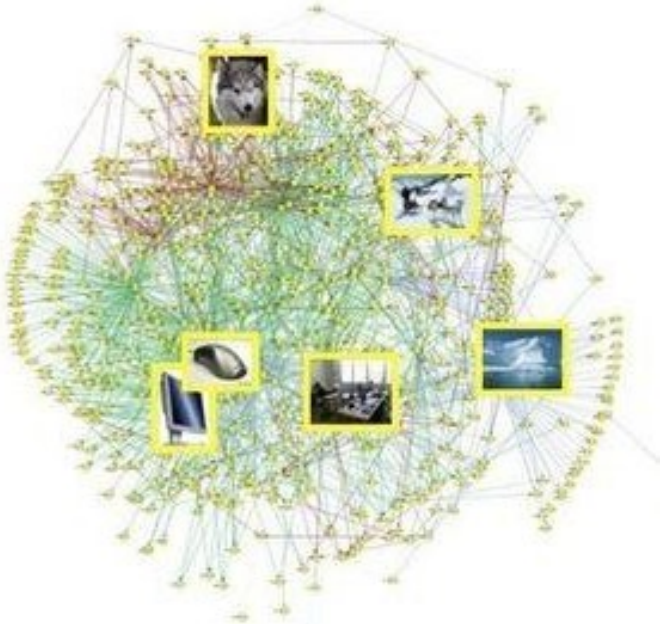




**enormous gulf**



# What makes modern machine learning work?



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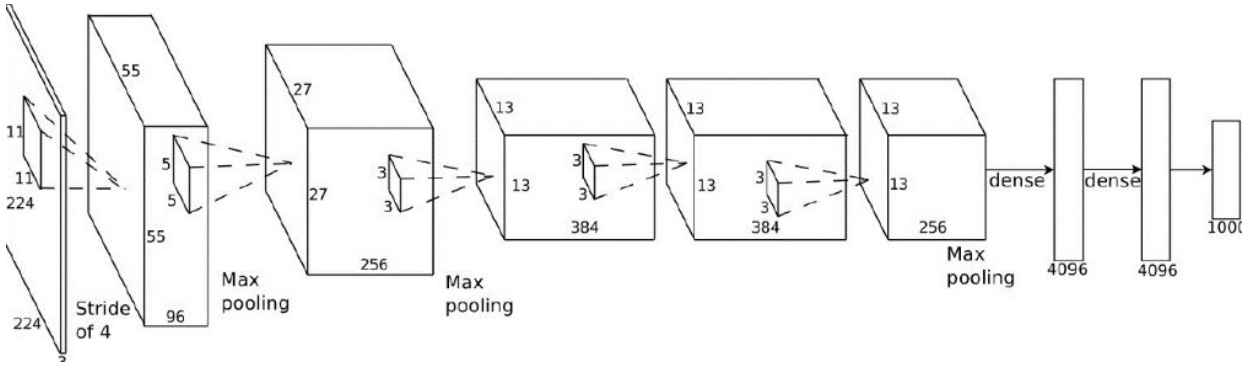
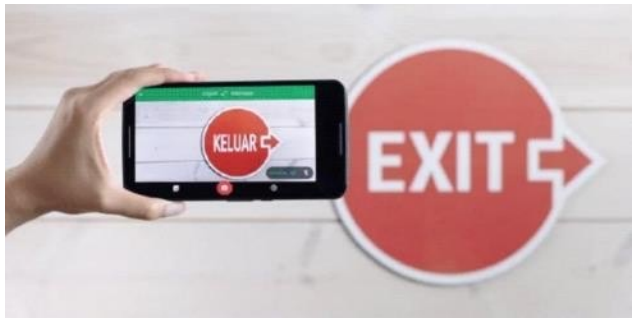
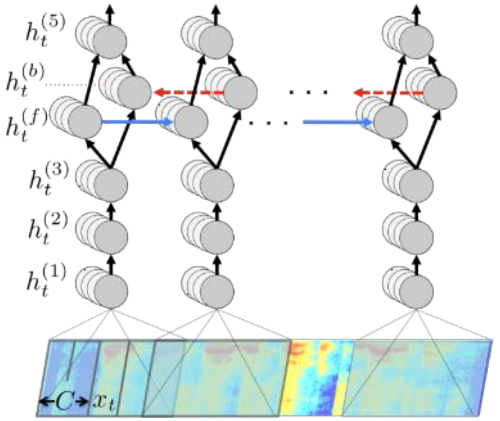
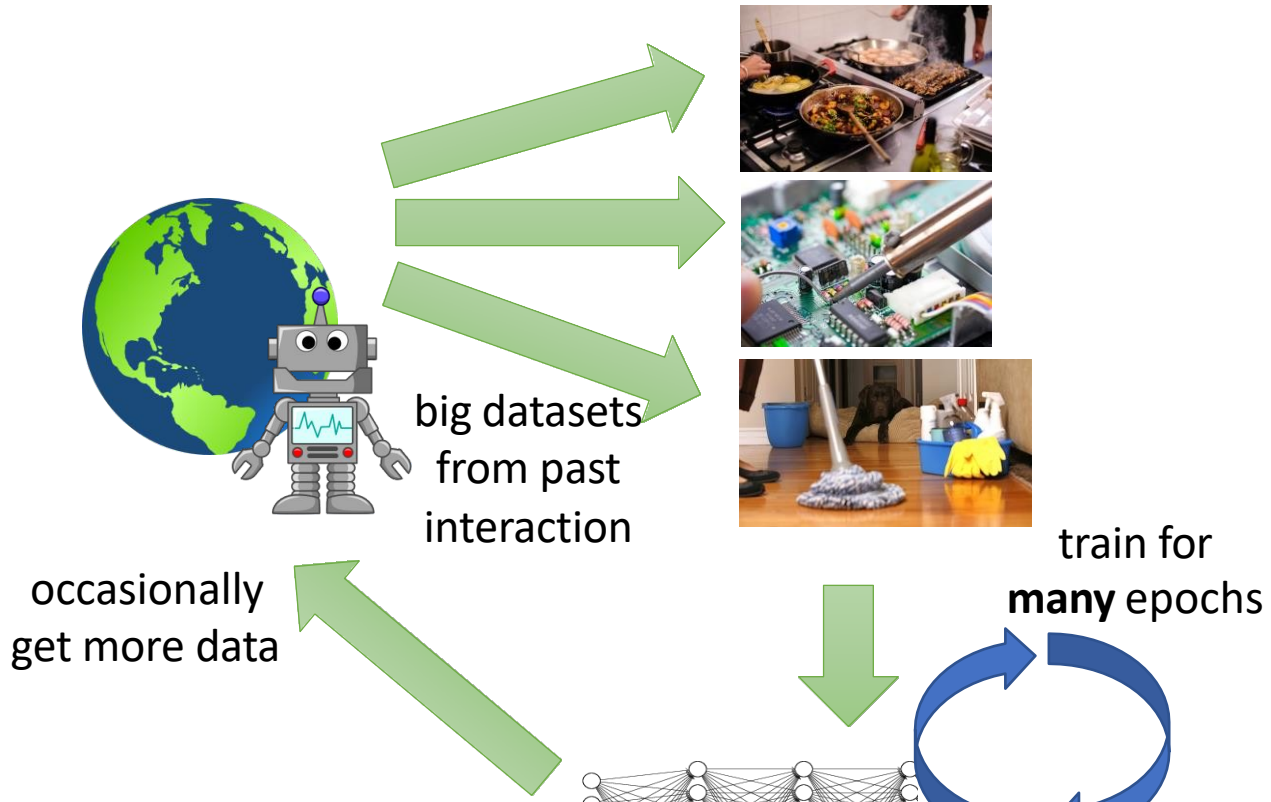


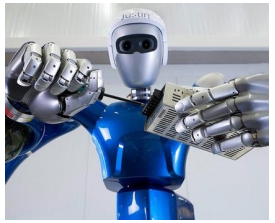




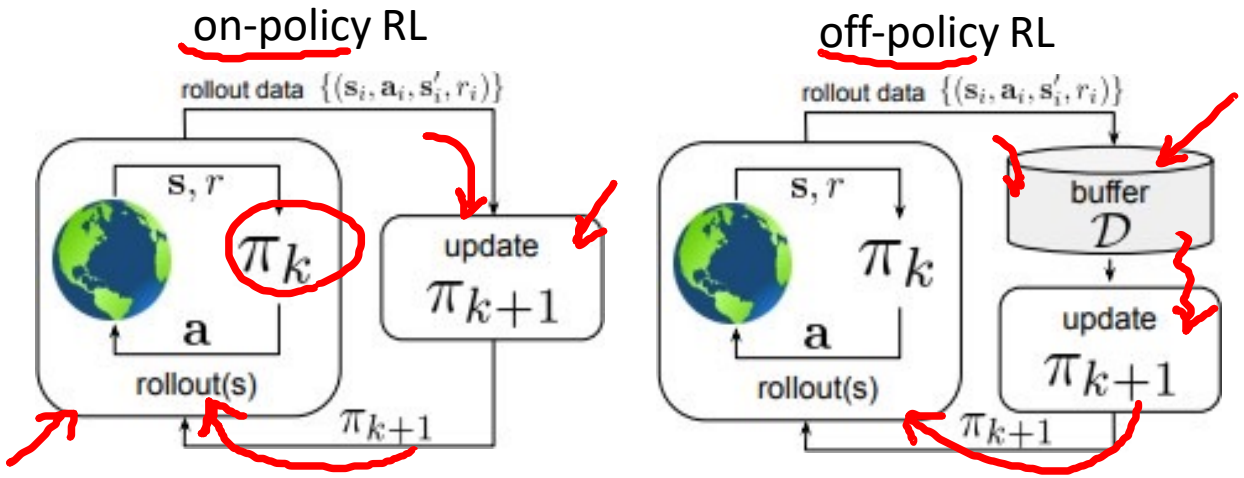
# Can we develop data-driven RL methods?

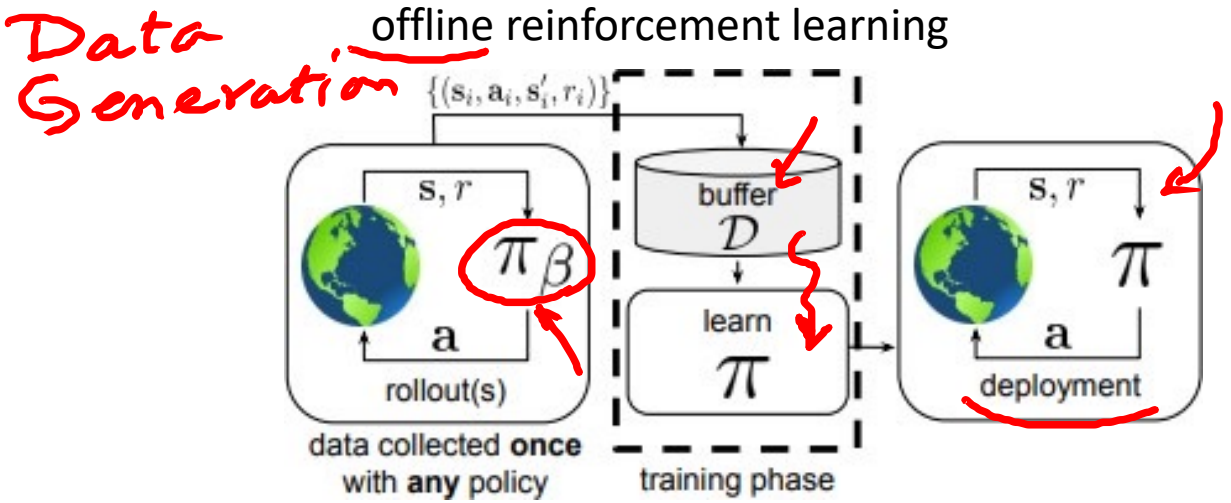


Levine, Kumar, Tucker, Fu. **Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems.** '20

# What does offline RL mean?




Formally:

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

$$\mathbf{s} \sim d^{\pi_\beta}(\mathbf{s})$$
$$\mathbf{a} \sim \pi_\beta(\mathbf{a}|\mathbf{s})$$ ← generally **not** known
$$\mathbf{s}' \sim p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$$
$$r \leftarrow r(\mathbf{s}, \mathbf{a})$$

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

off-policy evaluation (OPE):

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

$\pi_\beta \neq \pi$

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

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

not necessarily obvious what this means

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

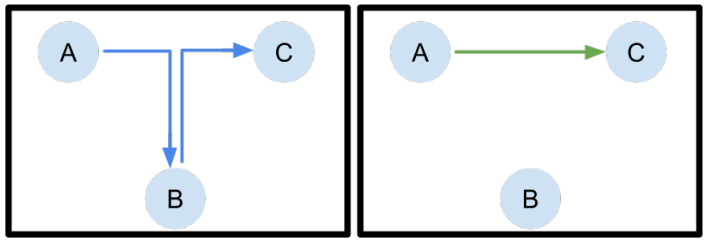
$\mathbf{s} \sim d^{\pi_\beta}(\mathbf{s})$
$\mathbf{a} \sim \pi_\beta(\mathbf{a}|\mathbf{s})$
$\mathbf{s}' \sim p(\mathbf{s}'|\mathbf{s}, \mathbf{a})$
$r \leftarrow r(\mathbf{s}, \mathbf{a})$

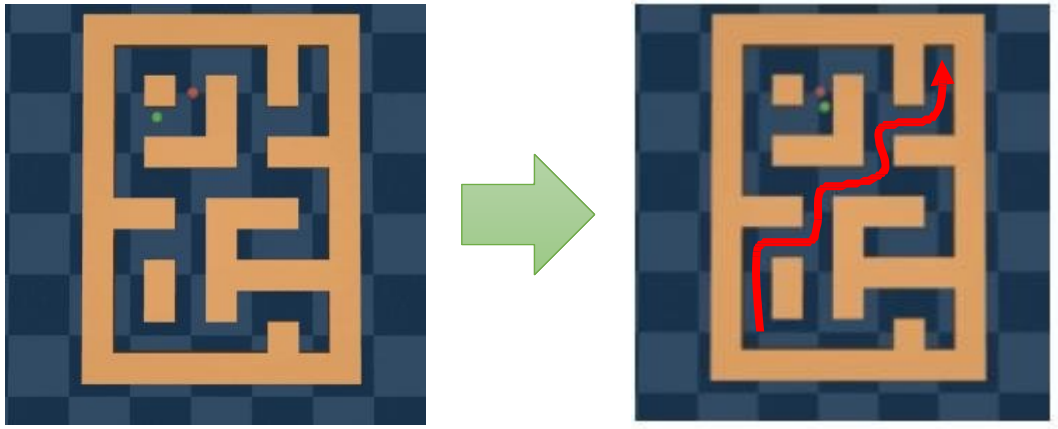
# How is this even possible?

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



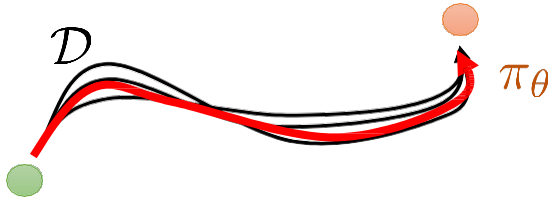



# What do we expect offline RL methods to do?

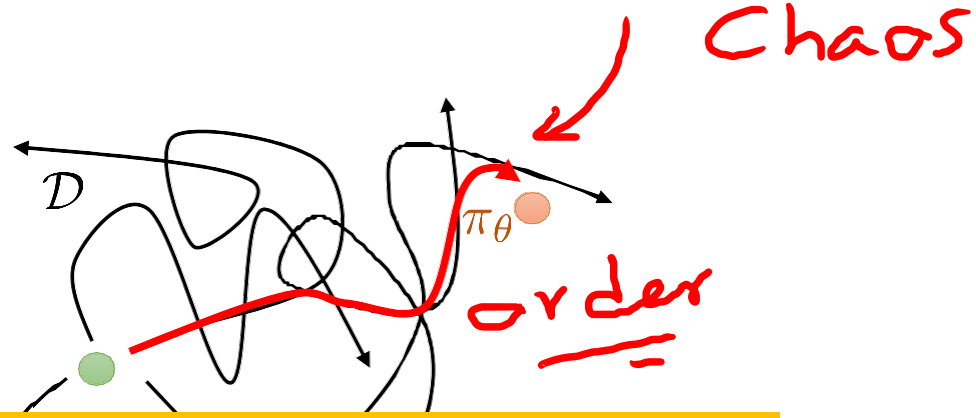
**Bad intuition:** it's like imitation learning

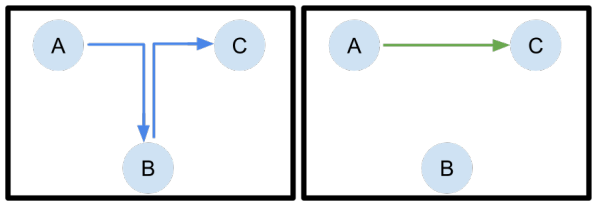
Though it can be shown to be **provably** better than imitation learning even with optimal data, under some structural assumptions!

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




**Better intuition:** get order from chaos

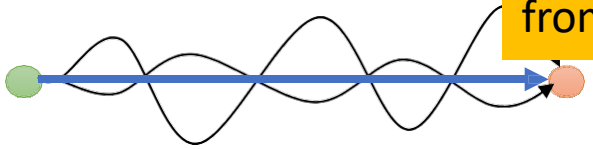



"Macro-scale" stitching

**But this is just the clearest example!**

"Micro-scale" stitching:

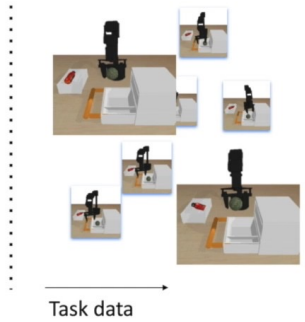


If we have algorithms that properly perform dynamic programming, we can take this idea much further and get near-optimal policies from highly suboptimal data

# A vivid example

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

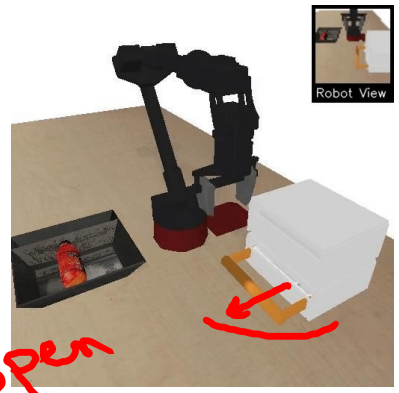

Can we use previously collected, unlabeled datasets to extend learned skills?




$D = [(s, a, s', r), \ldots]$

training task


closed drawer

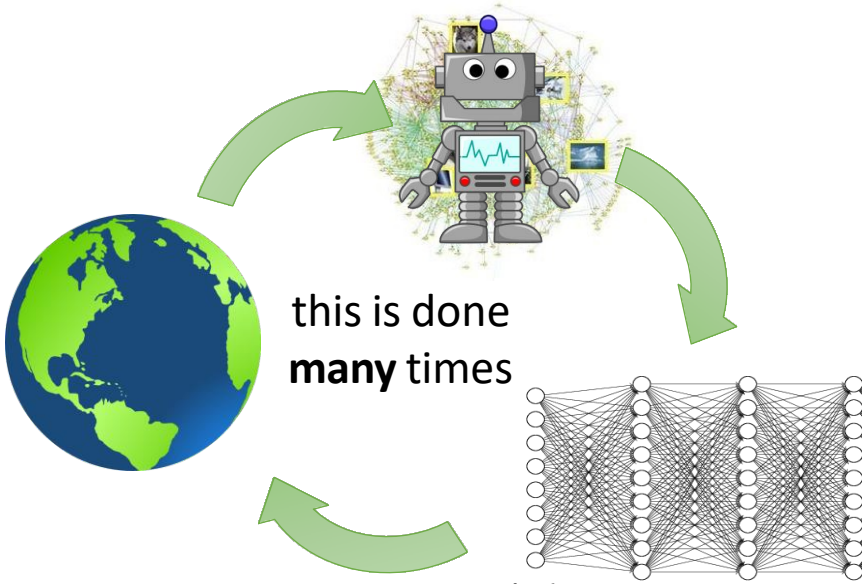


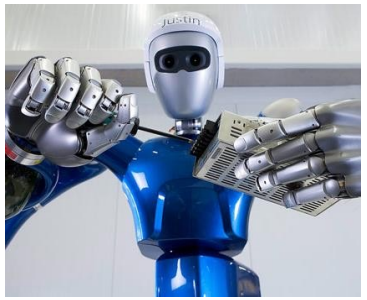

blocked by drawer


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?

live data collection

stored data from all past experiments

$\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i)\}_i$

training buffers

off-policy $(\mathbf{s}, \mathbf{a}, \mathbf{s}', r)$

on-policy $(\mathbf{s}, \mathbf{a}, \mathbf{s}', r)$

labeled $(\mathbf{s}, \mathbf{a}, Q_T(\mathbf{s}, \mathbf{a}))$

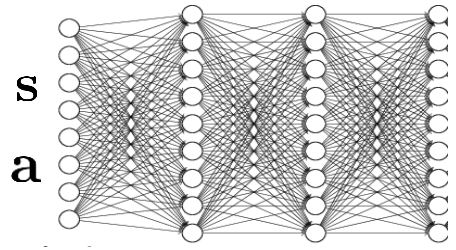
Bellman updaters

compute $Q_T(\mathbf{s}, \mathbf{a}) =$

$r + \max_{\mathbf{a}'} Q_\theta(\mathbf{s}', \mathbf{a}')$

training threads

$\min_\theta ||Q_\theta(\mathbf{s}, \mathbf{a}) - Q_T(\mathbf{s}, \mathbf{a})||^2$




$Q_\theta$

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?

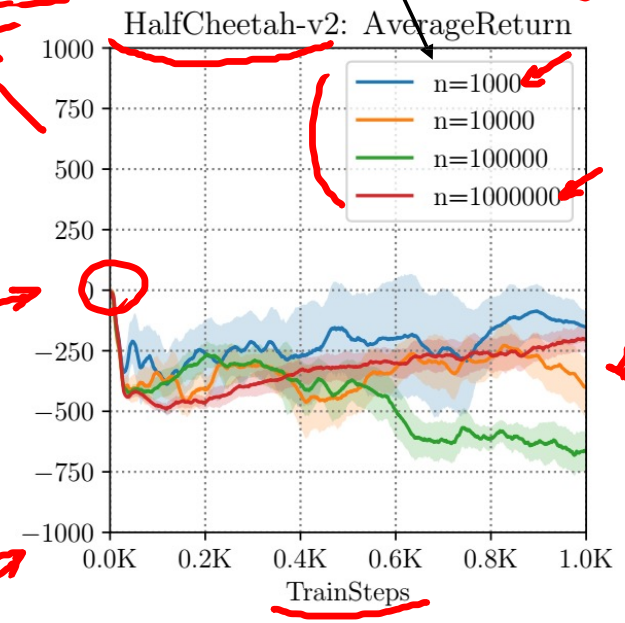


| Method | Dataset | Success | Failure |
|---|---|---|---|
| Offline QT-Opt | 580k offline | 87% | 13% |
| Finetuned QT-Opt | 580k offline + 28k online | **96%** | **4%** |

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

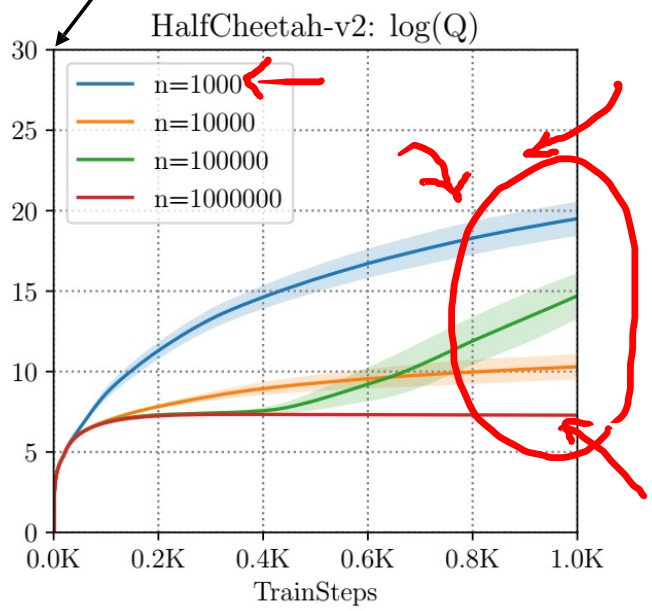
# Why is offline RL hard?

amount of data




how well it does

log scale (massive overestimation)

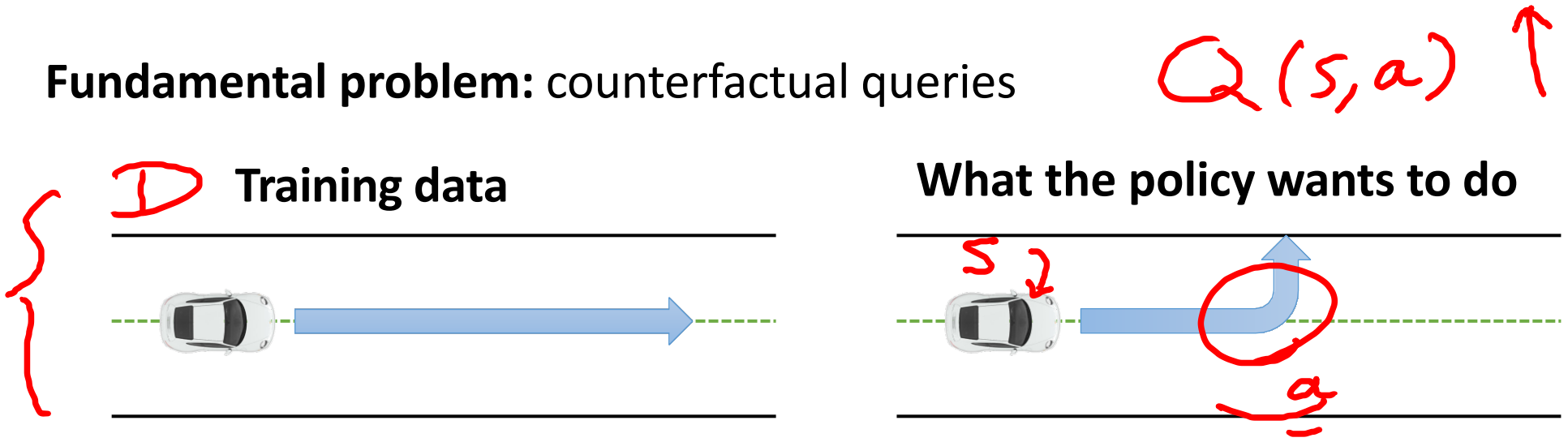



how well it *thinks* it does (Q-values)

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

# Why is offline RL hard?

**Fundamental problem:** counterfactual queries




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?

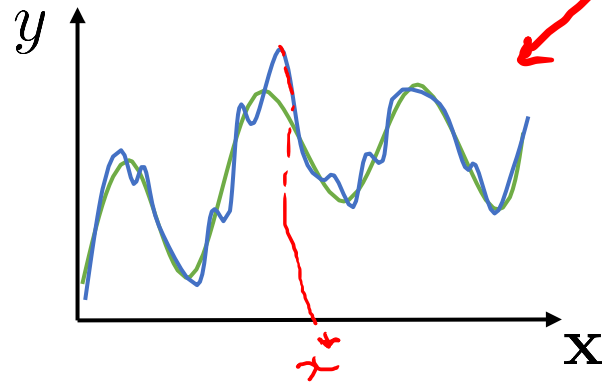
$E_{\mathbf{x}\sim p(\mathbf{x}),y\sim p(y|\mathbf{x})}\left[(f_\theta(\mathbf{x})-y)^2\right]$ is low

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

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

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

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

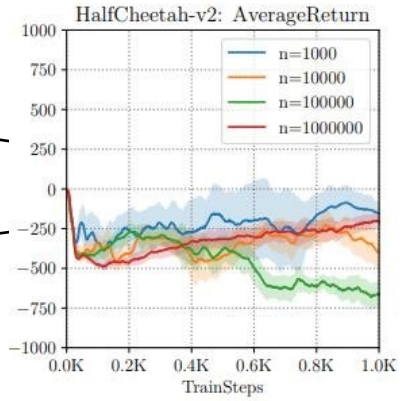
target value

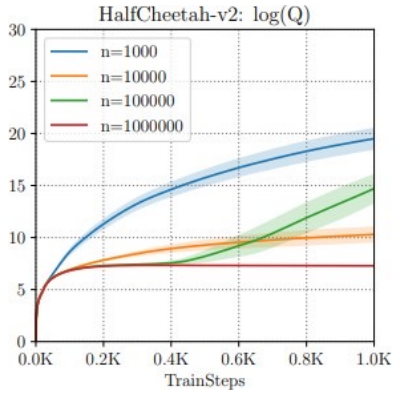
expect good accuracy when $\pi_\beta(\mathbf{a}|\mathbf{s}) = \pi_{\text{new}}(\mathbf{a}|\mathbf{s})$

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

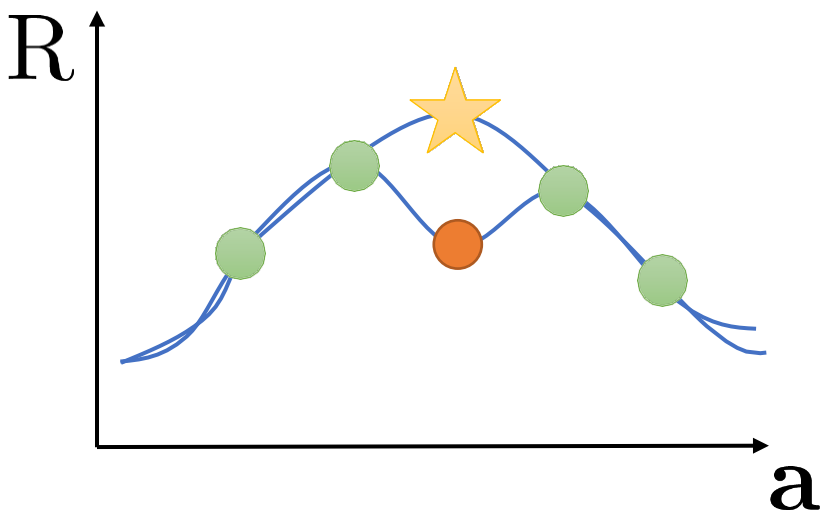


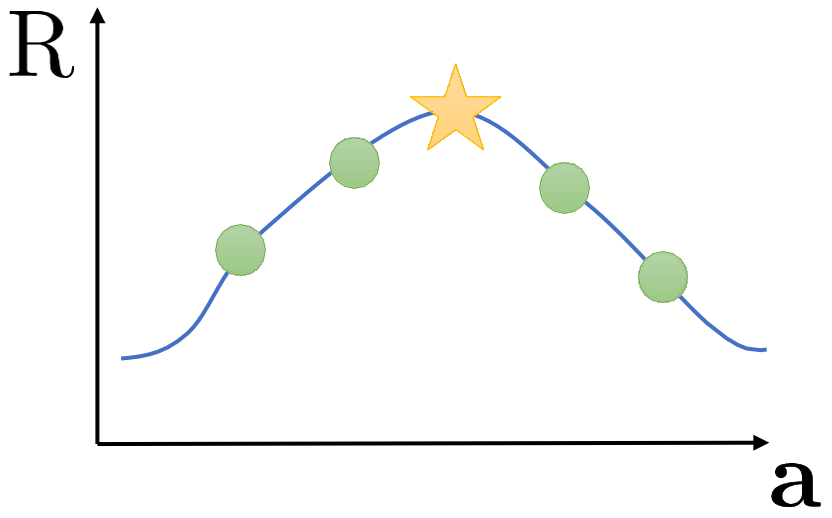

Kumar, Fu, Tucker, Levine. **Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction.** NeurIPS '19

# 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)

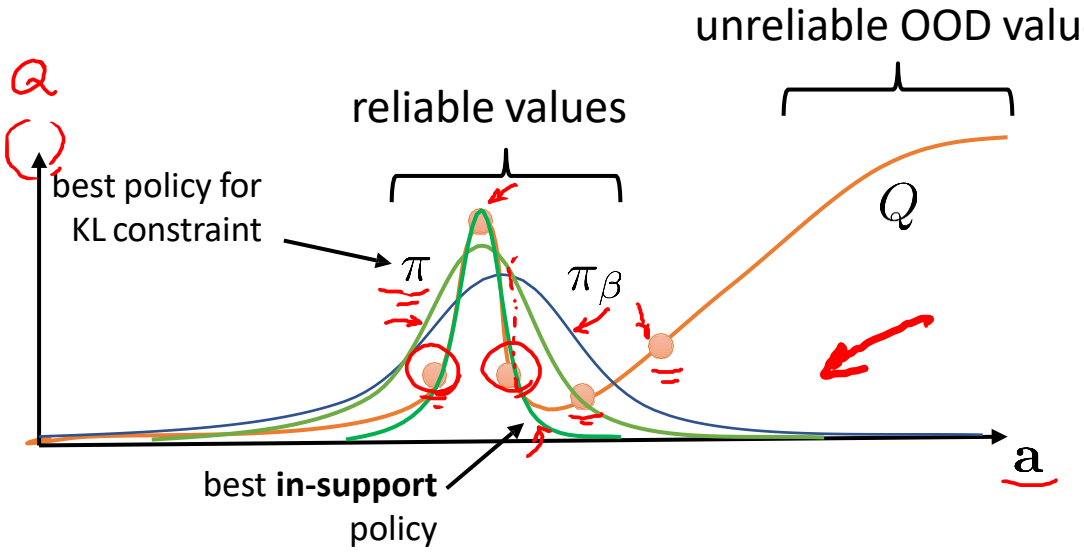
- not necessarily what we want

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?

1. Modify the actor objective

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

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

Lagrange multiplier

easy to compute and differentiate for Gaussian or categorical policies

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

Big Barrier

$\pi_\beta$

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!

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

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

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

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

Bellman Err. minimization

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

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

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

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

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

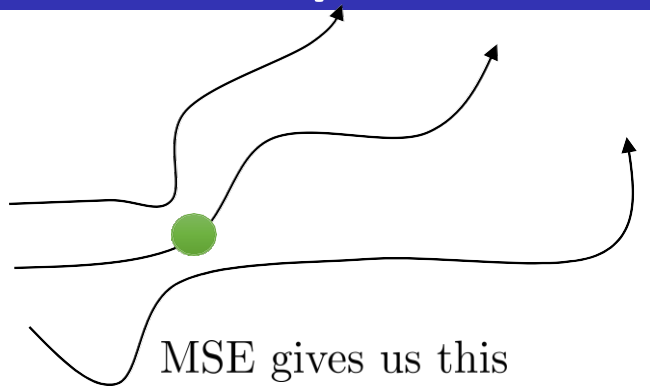
$$Q(\mathbf{s}, \mathbf{a}) \leftarrow r(\mathbf{s}, \mathbf{a}) + E_{\mathbf{a}' \sim \pi_{\text{new}}}[Q(\mathbf{s}', \mathbf{a}')]$$

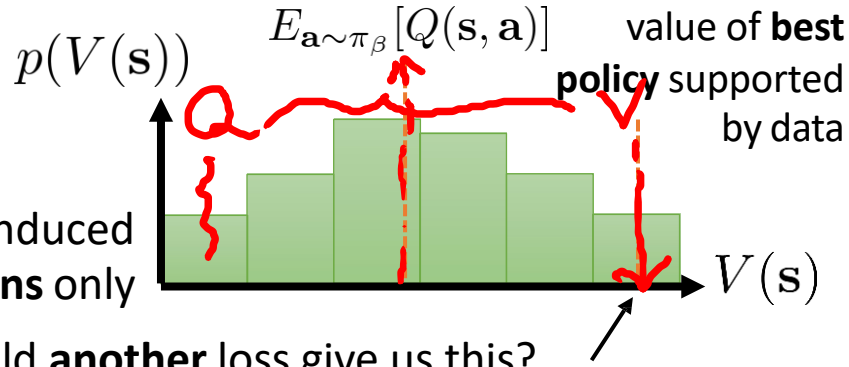
$V(\mathbf{s}')$ ← just another neural network

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

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

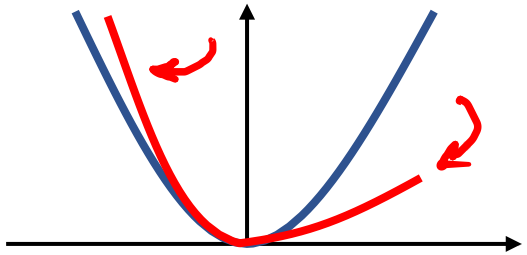
this action comes from $\pi_\beta$
not from $\pi_{\text{new}}$




could **another** loss give us this?

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



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

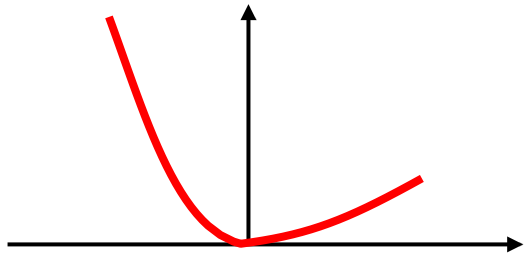
$$\Omega(\mathbf{s}) = \{\mathbf{a} : \pi_\beta(\mathbf{a}|\mathbf{s}) \geq \epsilon\}$$

if we use $\ell_2^\tau$ for big $\tau$

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 $\ell_2^\tau$ for big $\tau$

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

"implicit" policy

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

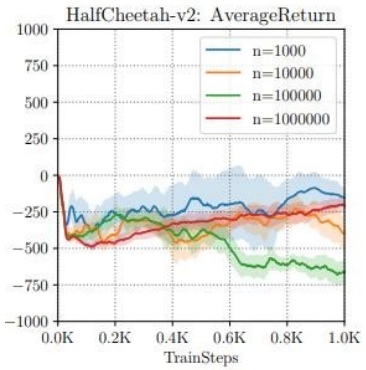
Now we can do value function updates without ever risking out-of-distribution actions!

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

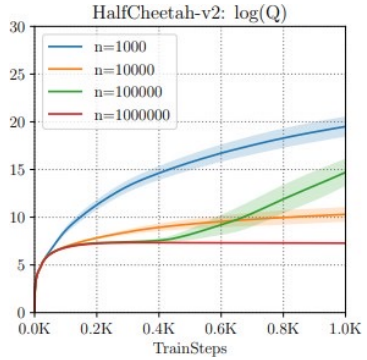
# Offline RL Solutions

Conservative Q-Learning

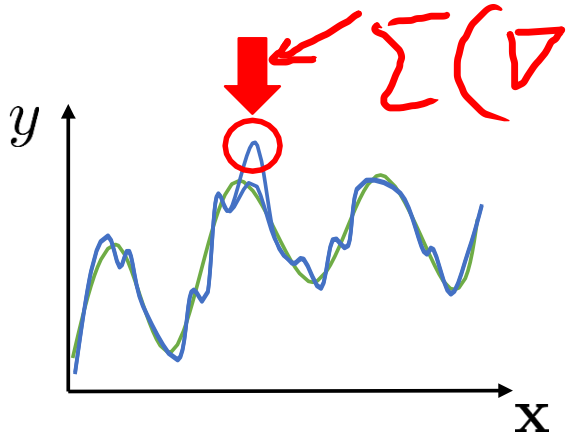
# Conservative Q-learning (CQL)




how well it does




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




$$\sum (\nabla \log \pi_\theta) Q(s,a)$$

$$\pi(s) = \arg\max_a Q(s,a)$$

$$\hat{Q}^\pi = \arg\min_Q \max_\mu \alpha E_{\mathbf{s}\sim D, \mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] + E_{(\mathbf{s},\mathbf{a},\mathbf{s}')\sim D}\left[\left(Q(\mathbf{s},\mathbf{a}) - (r(\mathbf{s},\mathbf{a}) + E_\pi[Q(\mathbf{s}',\mathbf{a}')])\right)^2\right]$$

term to push down big Q-values

regular objective

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

true Q-function

w.h.p.

$$\hat{Q}(s,a) = Q(s,a) + \underbrace{\quad}_{<0} + \underbrace{\quad}_{>0}$$

# Conservative Q-learning (CQL)

A *better* bound:

always pushes Q-values down

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

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

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 $\pi$

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)

$\mu \propto \exp(Q(s,a))$

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

regularization

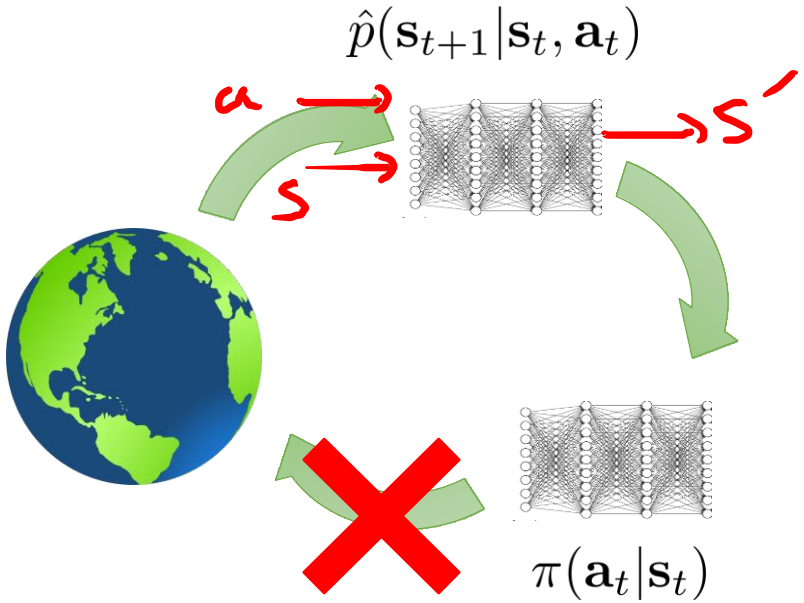
common choice: $\mathcal{R} = E_{\mathbf{s}\sim D}[\mathcal{H}(\mu(\cdot|\mathbf{s}))]$ maximum entropy regularization

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

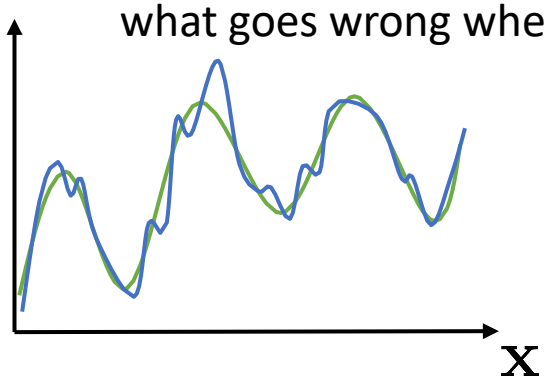
# Offline RL Solutions

## Model-Based Offline RL

# How does model-based RL work?

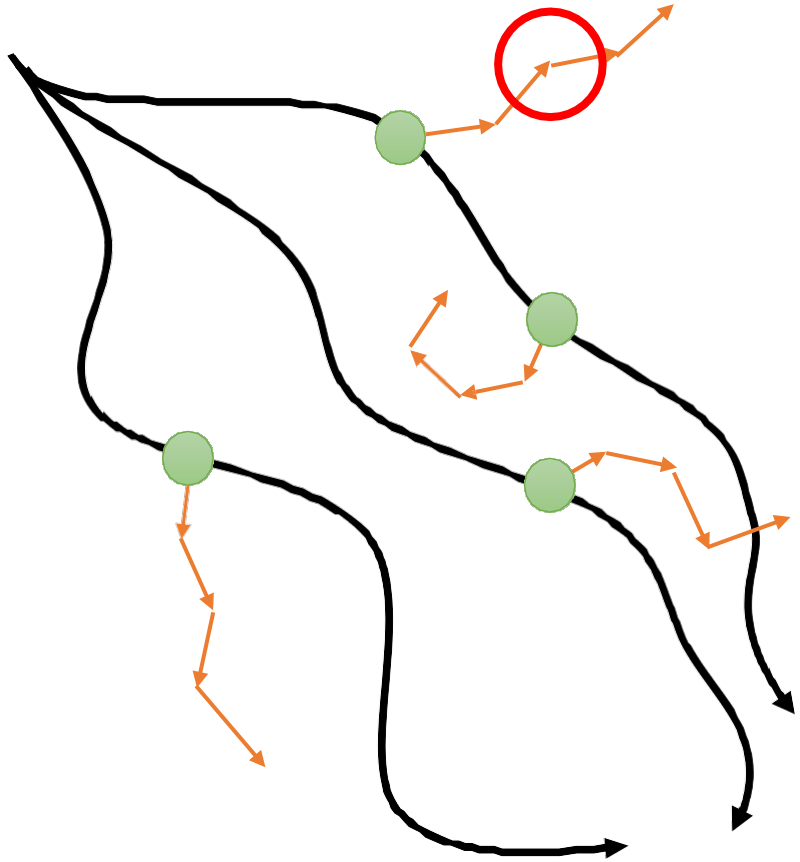



what goes wrong when we can't collect more data?




…so the model's predictions are invalid

these states are OOD



the model answers "what if" questions

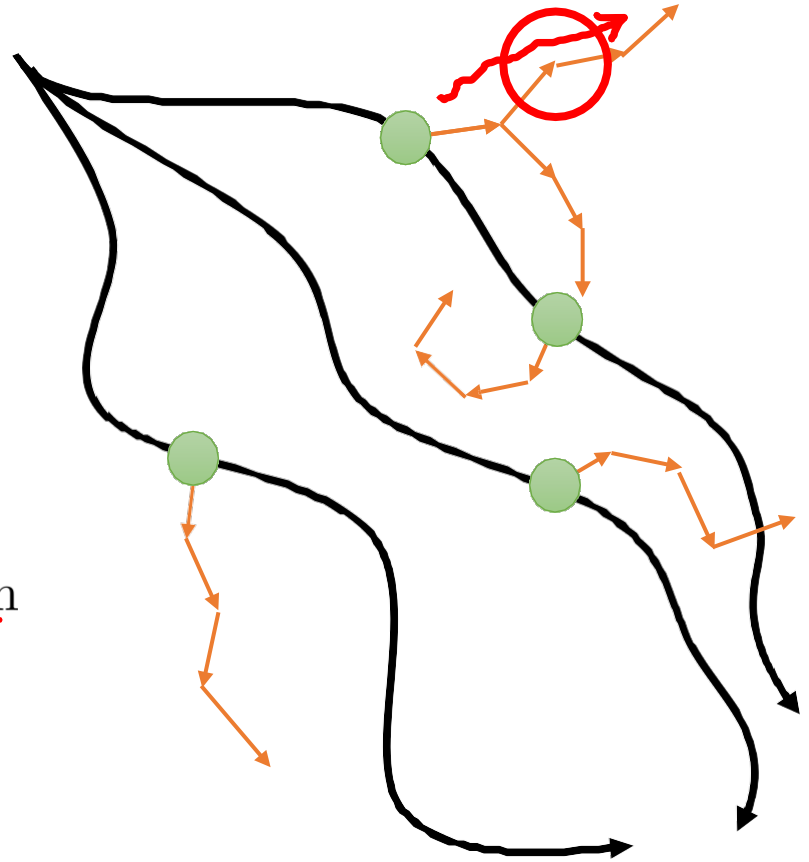
# Model-Based Offline RL

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

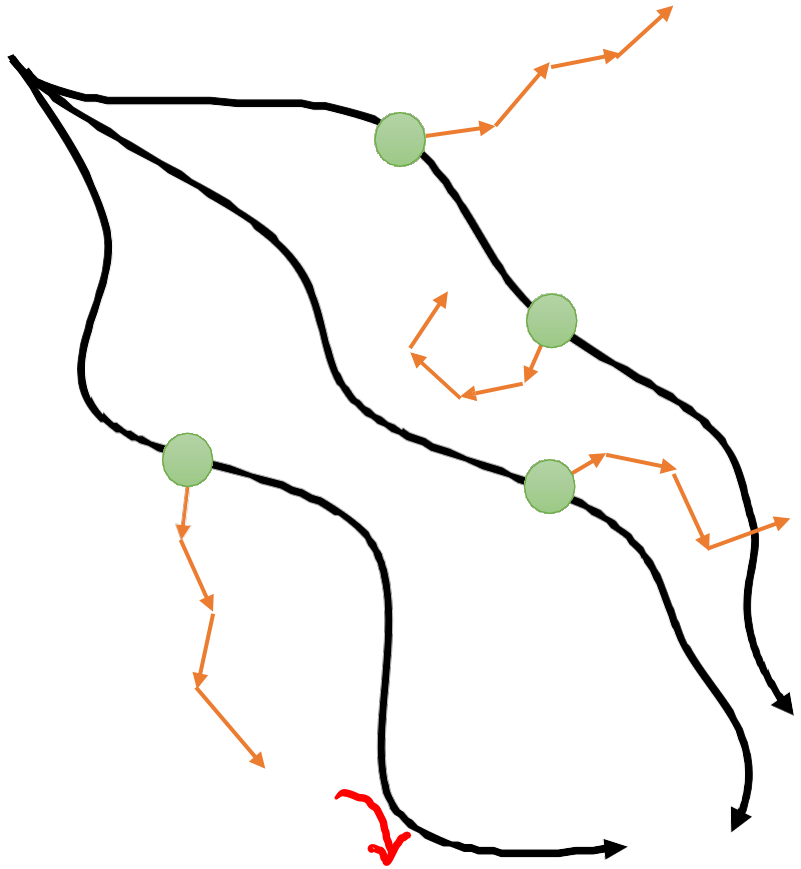
state-action tuples from the model

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

Dyna style

**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

$s, a, s'$



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

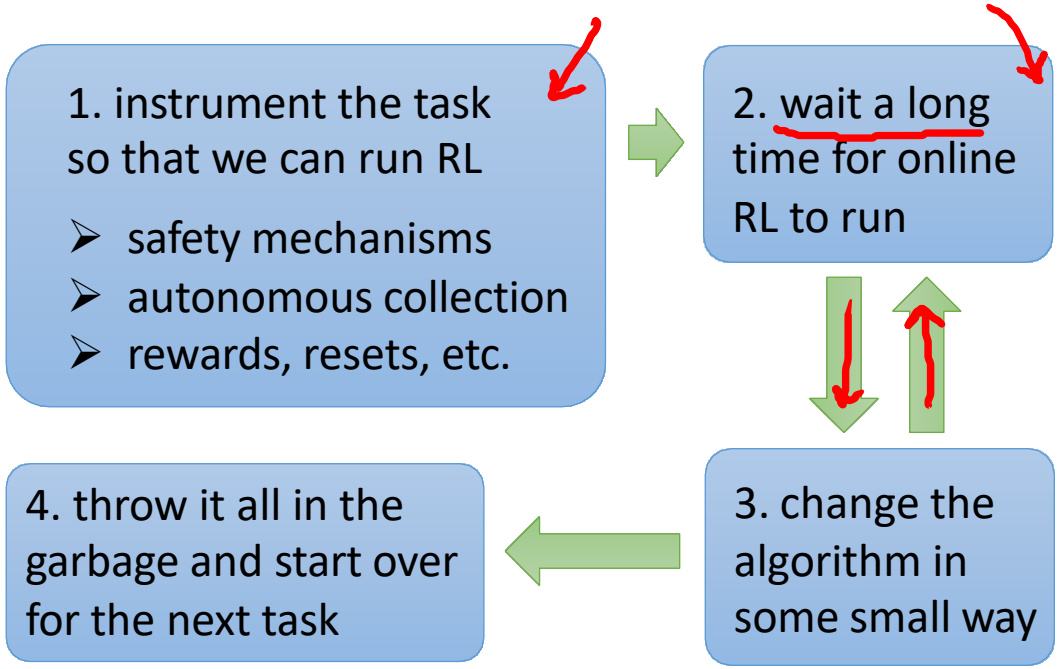
| | |
|---|---|
| Advantage-weighted actor-critic (AWAC) | + widely used and well tested |
| Implicit Q-learning | + seems to perform much better! |

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

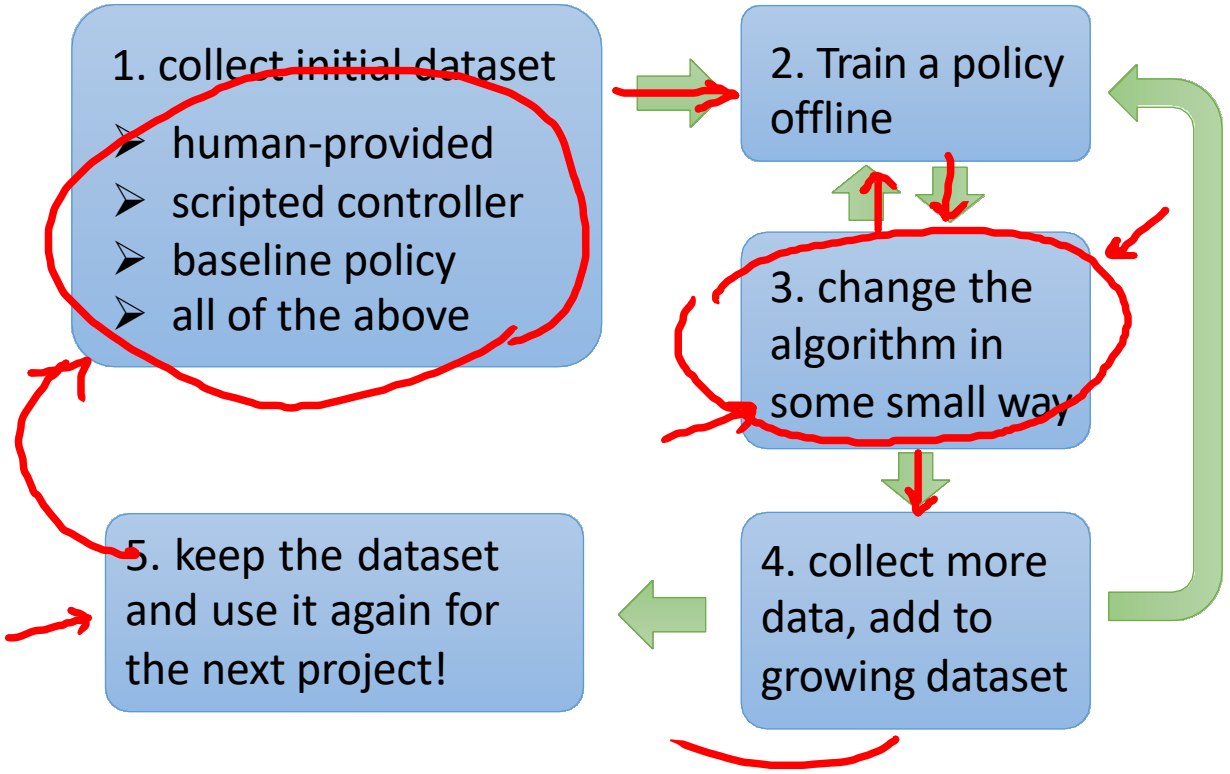
| | |
|---|---|
| COMBO | + similar properties as CQL, but benefits from models |
| | - not always easy to train a good model in your domain! |

# The power of offline RL

**standard real-world RL process**




**offline RL process**



# 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