Offline Reinforcement Learning Part 2

CS 285

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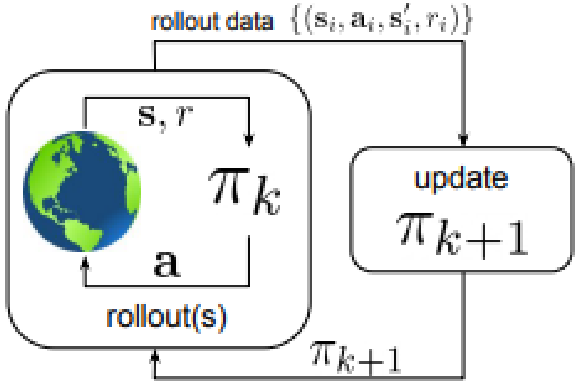
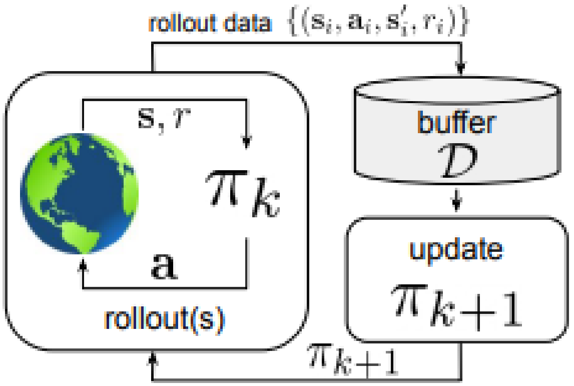
UC Berkeley

Offline Reinforcement Learning

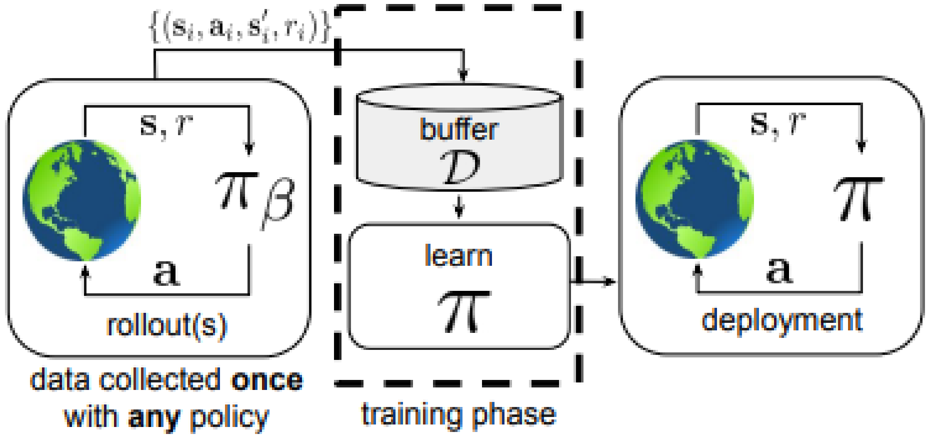
on-policy RL



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

Where do we suffer from distribution shift?

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

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

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

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

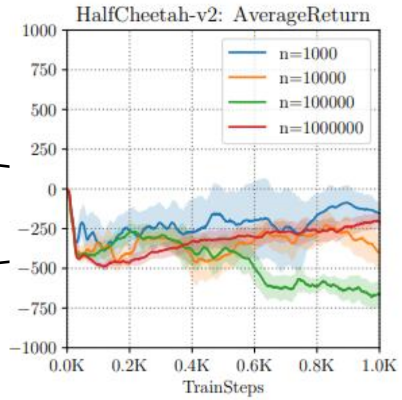
what is the objective?

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

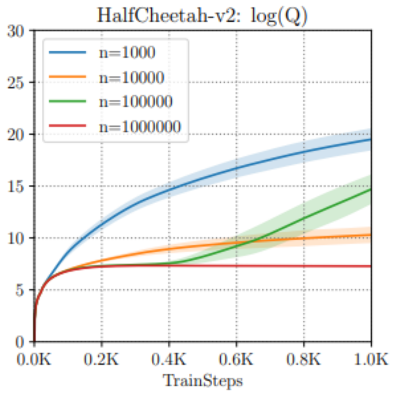
behavior policy

target value

how often does *that* happen?



how well it does



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

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

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

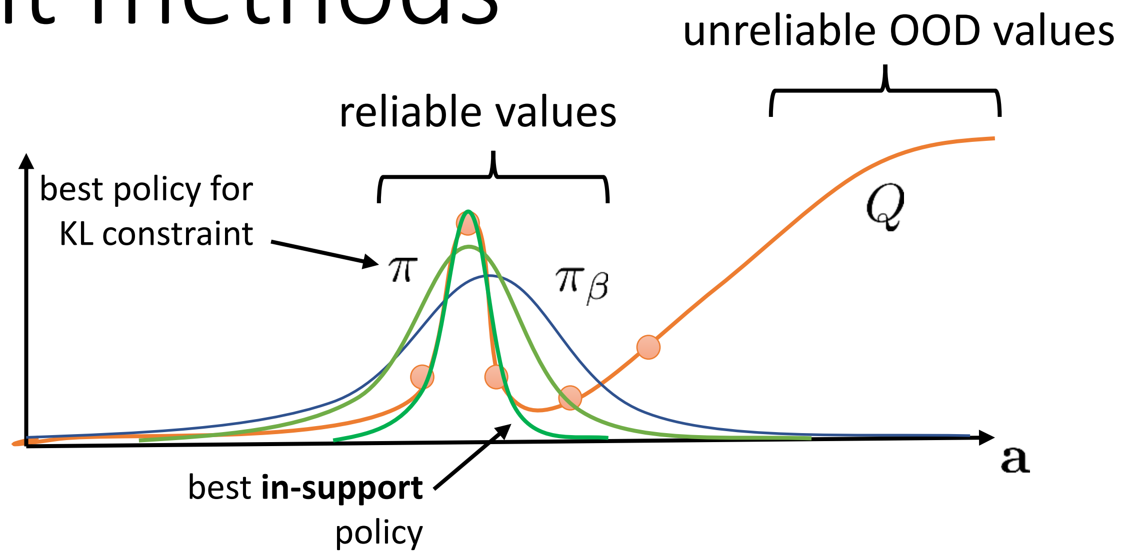
Explicit policy constraint methods

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

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

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

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

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)
Rawlik et al. ("psi-learning")
…many follow-ups

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

Nair, Dalal, Gupta, Levine. **Accelerating Online Reinforcement Learning with Offline Datasets.** '20

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

Nair, Dalal, Gupta, Levine. **Accelerating Online Reinforcement Learning with Offline Datasets.** ‘20

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

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

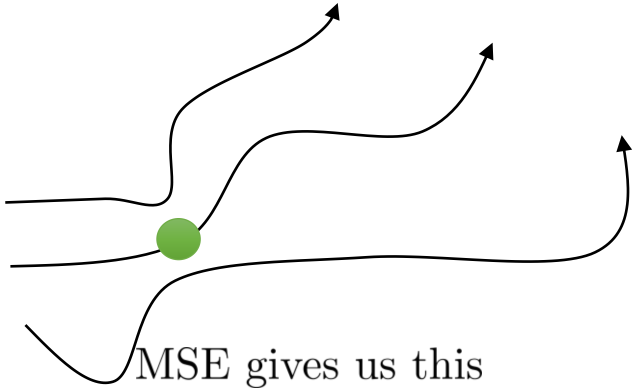
$V(\mathbf{s}')$ ← just another neural network

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

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}

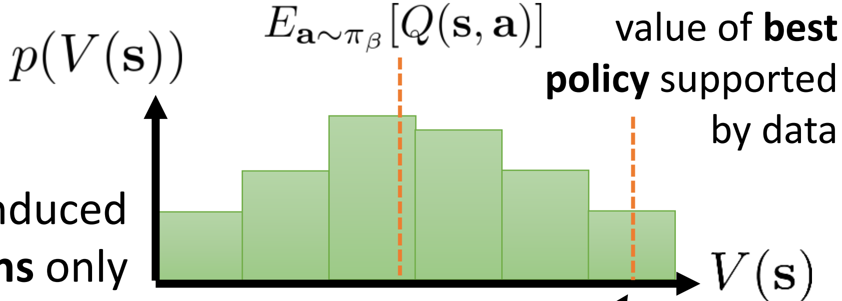
$$\text{expectile: } \ell_2^\tau(x) = \begin{cases} (1-\tau)x^2 & \text{if } x > 0 \\ \tau x^2 & \text{else} \end{cases}$$



MSE gives us this

$E_{\mathbf{a}\sim\pi_\beta}[Q(\mathbf{s},\mathbf{a})]$

value of **best policy** supported by data



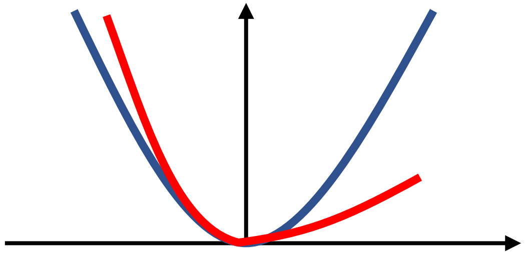
distribution is induced by **actions** only

could **another** loss give us this?

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

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

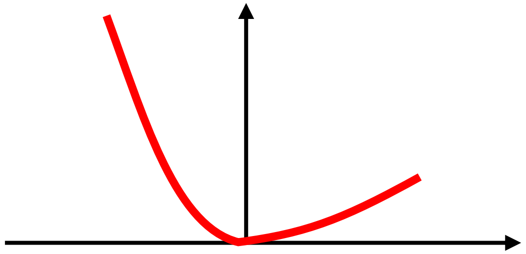
if we use ℓ_2^τ for big τ



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

Implicit Q-learning (IQL)

Q-learning with *implicit* policy improvement



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

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

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

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

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

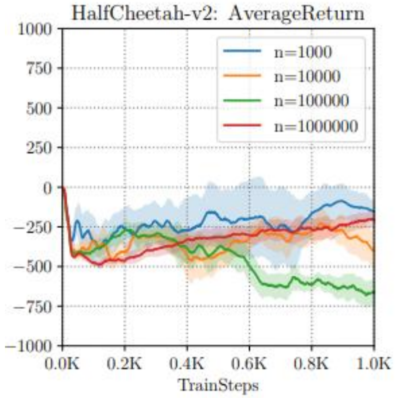
Now we can do value function updates without ever risking out-of-distribution actions!

We'll see results soon, but first let's talk about **Option 2**…

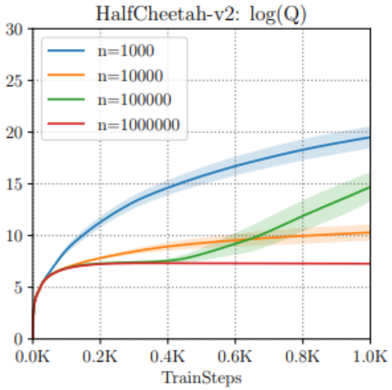
Kostrikov, Nair, Levine. **Offline Reinforcement Learning with Implicit Q-Learning.** '21

Conservative Q-Learning

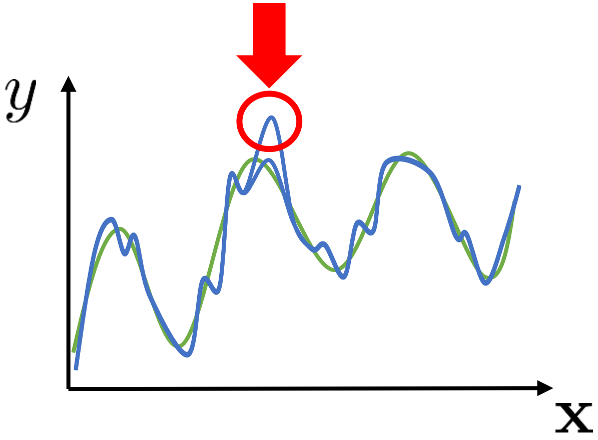
Conservative Q-learning (CQL)



how well it does



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



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

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

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

true Q-function

Conservative Q-learning (CQL)

A *better* bound:

<u>always</u> pushes Q-values down

push <u>up</u> on (**s**, **a**) samples in data

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

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

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

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

optimal choice: $\mu(\mathbf{a}|\mathbf{s}) \propto \exp(Q(\mathbf{s},\mathbf{a}))$

$$E_{\mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})] = \underline{\log\sum_{\mathbf{a}}\exp(Q(\mathbf{s},\mathbf{a}))}$$

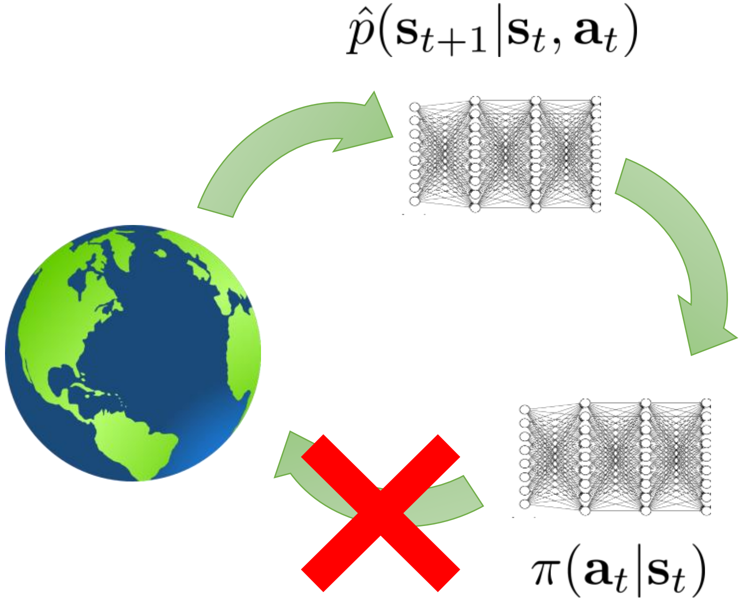
for discrete actions: just calculate directly

for continuous actions: use importance sampling to estimate $E_{\mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}[Q(\mathbf{s},\mathbf{a})]$

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

Model-Based Offline RL

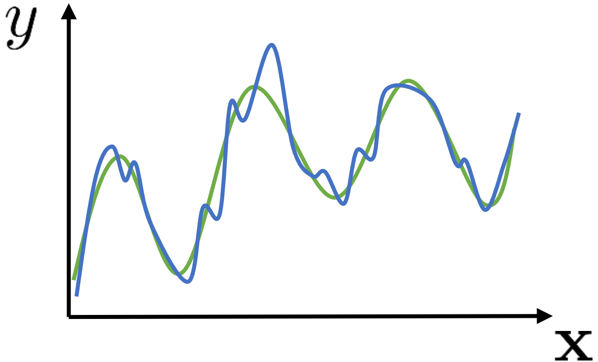
How does **model-based** RL work?



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

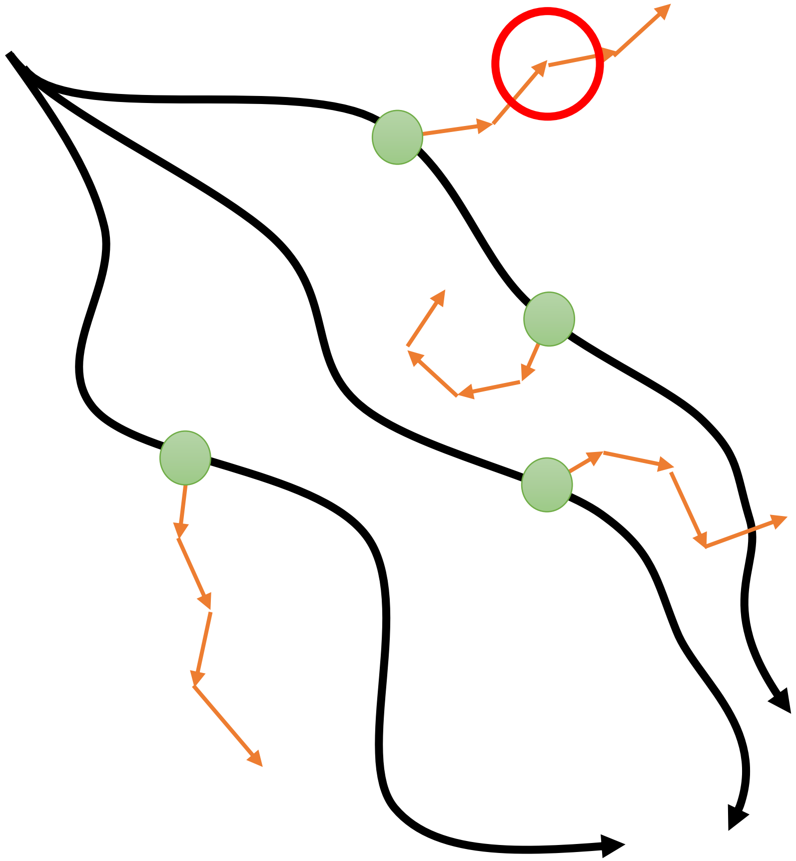
$\pi(\mathbf{a}_t|\mathbf{s}_t)$

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

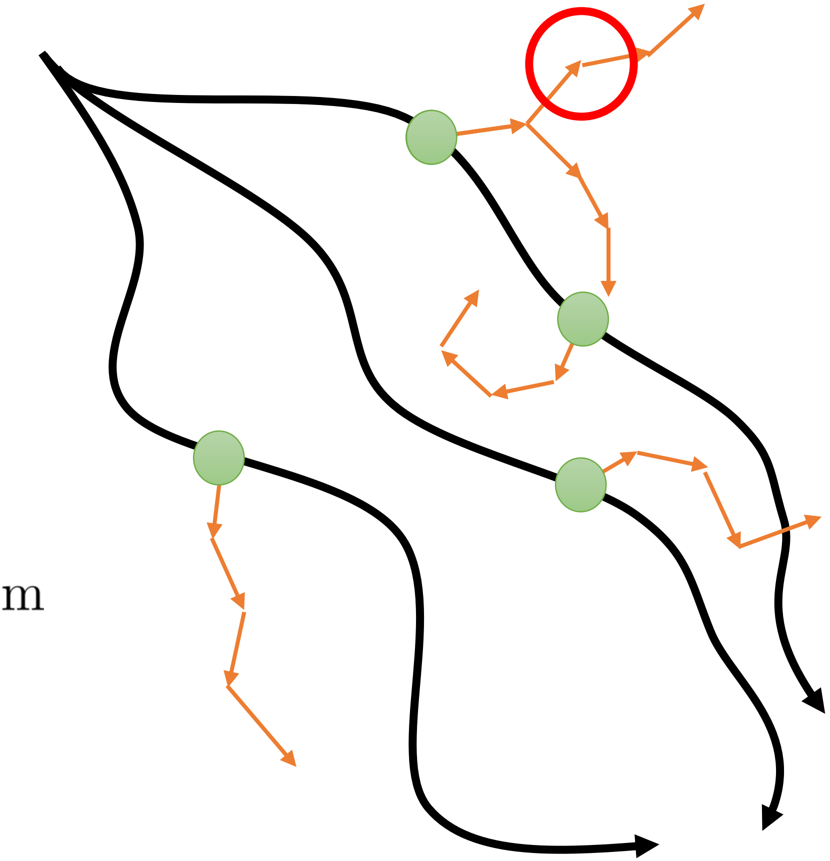
MOPO: Model-Based Offline Policy Optimization

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

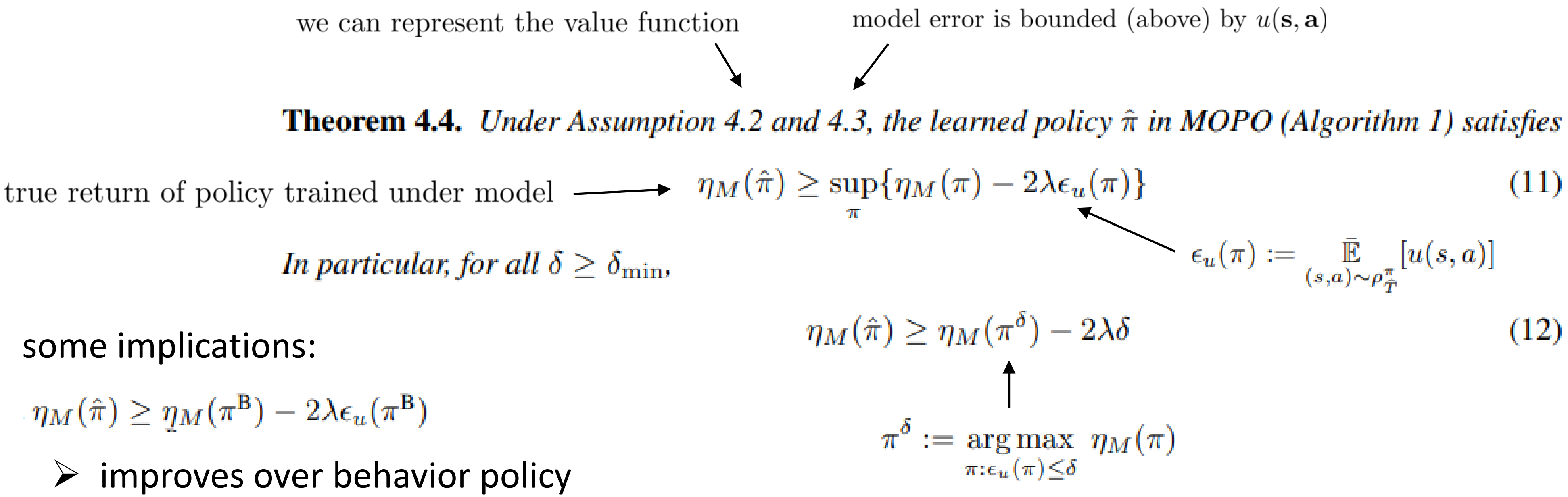


Yu*, Thomas*, Yu, Ermon, Zou, Levine, Finn, Ma. **MOPO: Model-Based Offline Policy Optimization.** '20

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

MOPO: Theoretical Analysis

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



we can represent the value function

model error is bounded (above) by $u(\mathbf{s},\mathbf{a})$

Theorem 4.4. *Under Assumption 4.2 and 4.3, the learned policy $\hat{\pi}$ in MOPO (Algorithm 1) satisfies*

true return of policy trained under model

$$\eta_M(\hat{\pi}) \geq \sup_{\pi}\{\eta_M(\pi) - 2\lambda\epsilon_u(\pi)\} \tag{11}$$

$$\epsilon_u(\pi) := \mathop{\bar{\mathbb{E}}}_{(s,a)\sim\rho^{\pi}_{\hat{T}}}[u(s,a)]$$

In particular, for all $\delta \geq \delta_{\min}$,

$$\eta_M(\hat{\pi}) \geq \eta_M(\pi^{\delta}) - 2\lambda\delta \tag{12}$$

$$\pi^{\delta} := \mathop{\arg\max}_{\pi:\epsilon_u(\pi)\leq\delta} \ \eta_M(\pi)$$

some implications:

$$\eta_M(\hat{\pi}) \geq \eta_M(\pi^{\mathrm{B}}) - 2\lambda\epsilon_u(\pi^{\mathrm{B}})$$

- ➢ improves over behavior policy

$$\eta_M(\hat{\pi}) \geq \eta_M(\pi^{\star}) - 2\lambda\epsilon_u(\pi^{\star})$$

- ➢ quantifies “optimality gap” in terms of model error

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

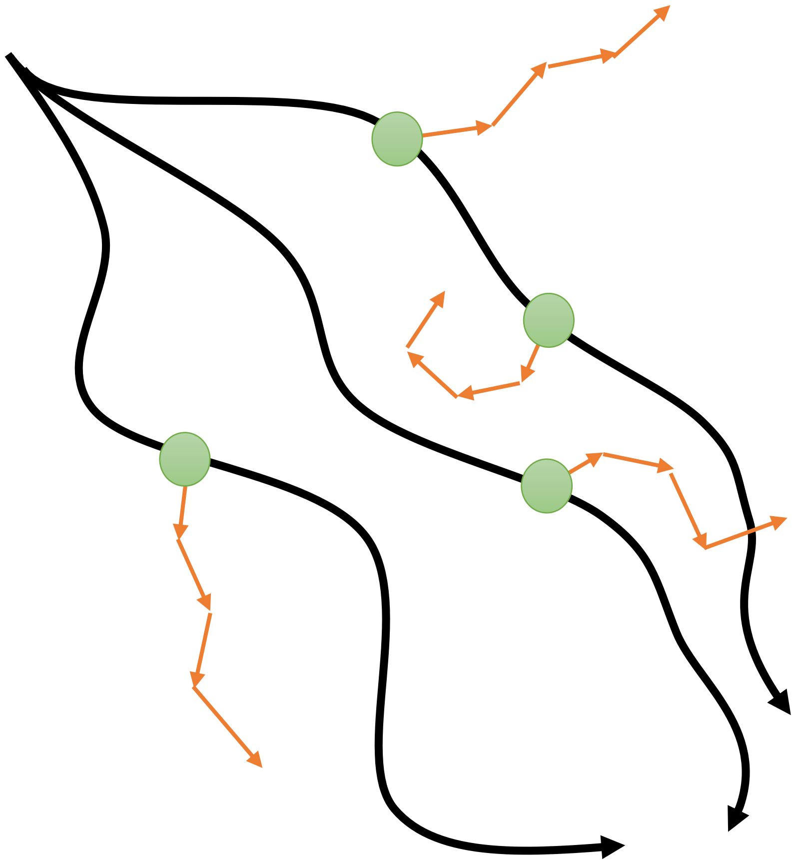
COMBO: Conservative Model-Based RL

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

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

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.

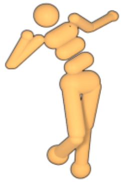
Trajectory Transformer

Basic ideas:

1. train a joint state-action model:

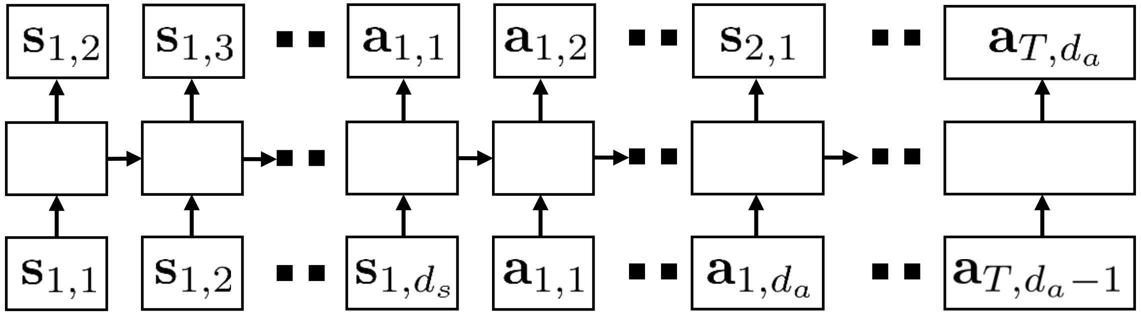
$$p_\beta(\tau) = p_\beta(s_1, a_2, \ldots, s_T, a_T)$$

2. use a big expressive model (a Transformer)



Trajectory Transformer making accurate predictions to hundreds of steps

The model:



How to do control:

beam search, but use $\sum_t r(\mathbf{s}_t, \mathbf{a}_t)$ instead of probability

1. given current sequence, sample next tokens from model
2. store top K tokens with highest cumulative reward
3. move on to next token

Why does this work?

generating high-probability trajectories avoids out-of-distribution states & actions

using a really big model works well in offline mode (lots of compute, captures complex behavior policies)

Janner, Li, Levine. **Reinforcement Learning as One Big Sequence Modeling Problem**. 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

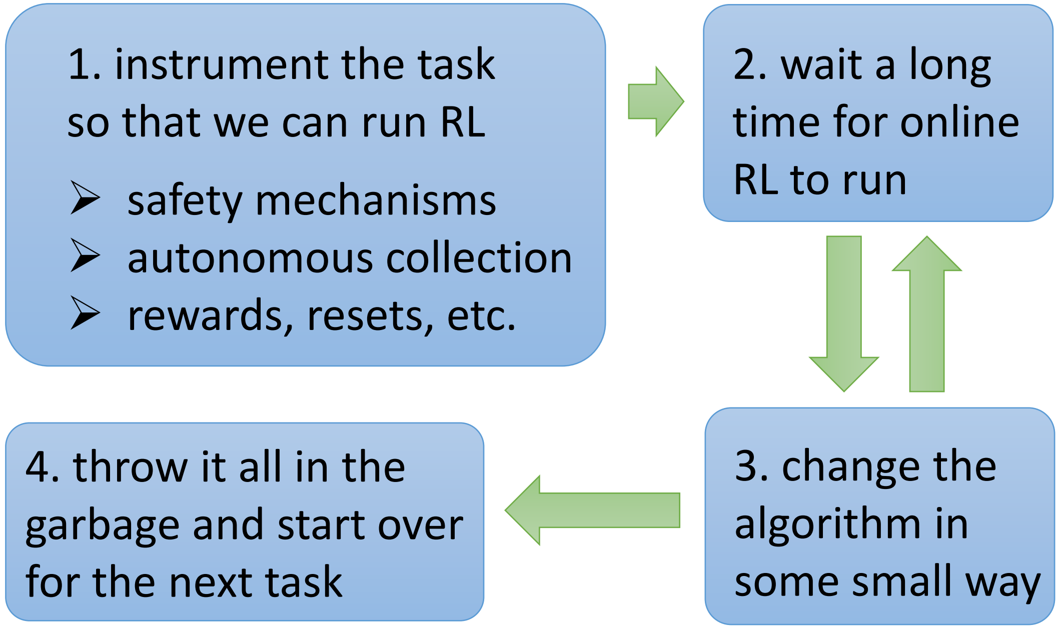
Advantage-weighted actor-critic (AWAC)	+ widely used and well tested
Implicit Q-learning	+ seems to perform much better!

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!
Trajectory transformer	+ very powerful and effective models - extremely computationally expensive to train and evaluate

The power of offline RL

standard real-world RL process



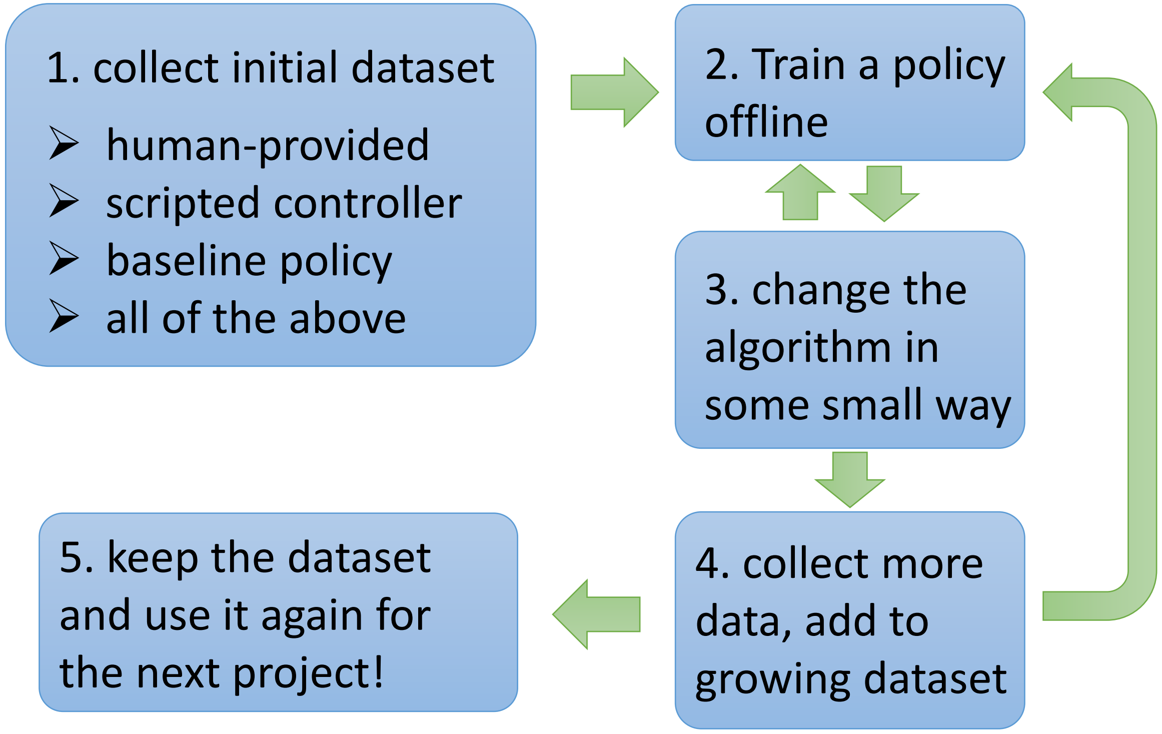
1. instrument the task so that we can run RL
   - safety mechanisms
   - autonomous collection
   - rewards, resets, etc.

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

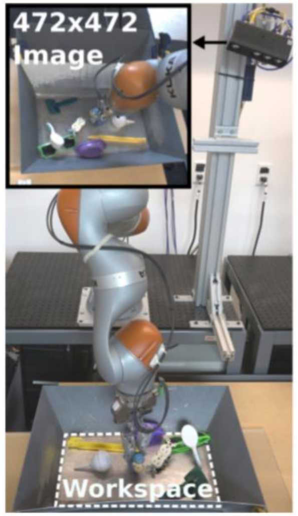
2. Train a policy offline

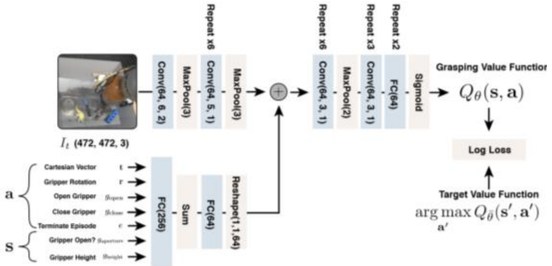
3. change the algorithm in some small way

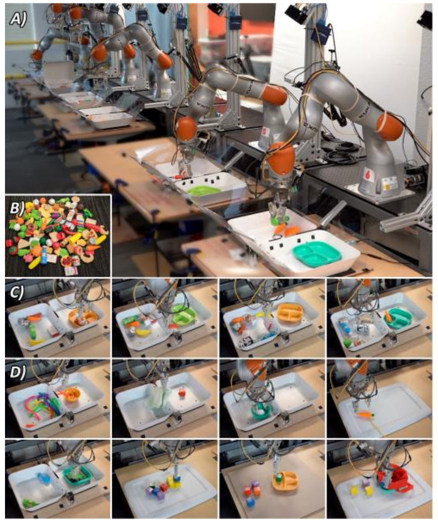
4. collect more data, add to growing dataset

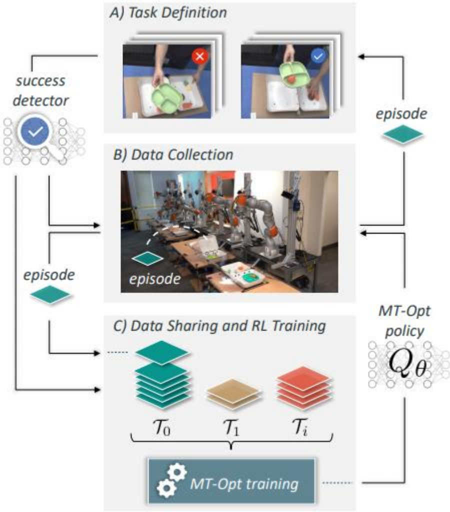
5. keep the dataset and use it again for the next project!

Offline RL in robotic manipulation: MT-Opt, AMs









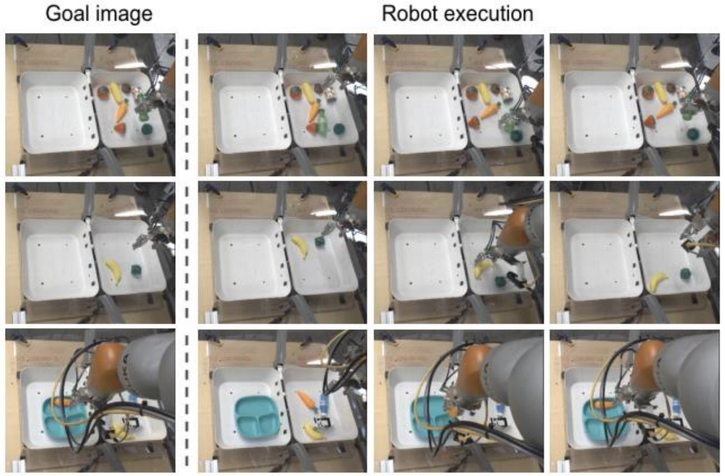
Kalashnikov, Irpan, Pastor, Ibarz, Herzong, Jang, Quillen, Holly, Kalakrishnan, Vanhoucke, Levine. **QT-Opt: Scalable Deep Reinforcement Learning of Vision-Based Robotic Manipulation Skills**

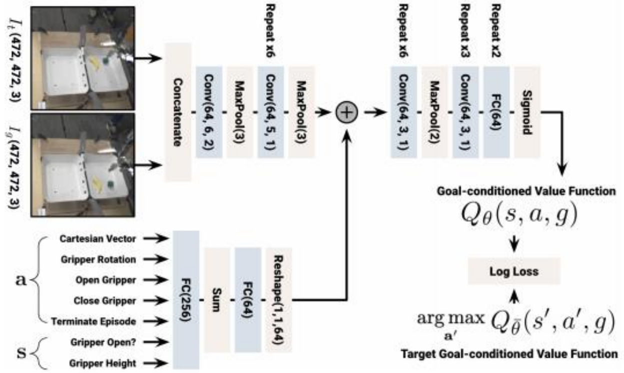
- 12 different tasks
- Thousands of objects
- Months of data collection

reuse the **same exact** data

Kalashnikov, Varley, Chebotar, Swanson, Jonschkowski, Finn, Levine, Hausman. **MT-Opt: Continuous Multi-Task Robotic Reinforcement Learning at Scale.** 2021.

New hypothesis: could we learn these tasks **without** rewards using goal-conditioned RL?

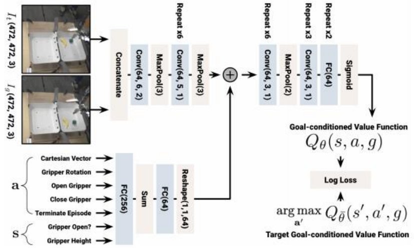




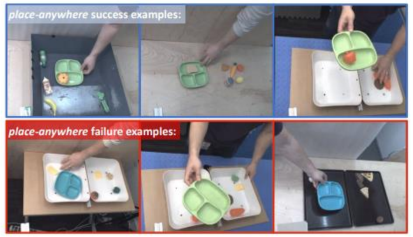
Actionable Models: Offline RL with Goals

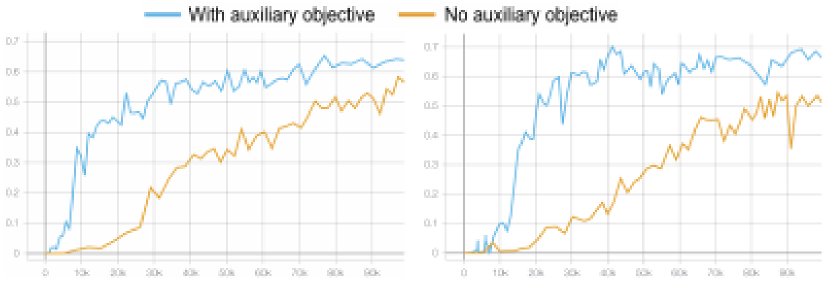
- ➢ No reward function at all, task is defined entirely using a **goal image**!
- ➢ Uses a conservative offline RL method designed for goal-reaching, based on CQL
- ➢ Works very well as an **unsupervised pretraining** objective!

1. Train **goal-conditioned** Q-function with offline RL



2. Finetune with a **task reward** and limited data





(c) Bottle grasping (d) Banana grasping

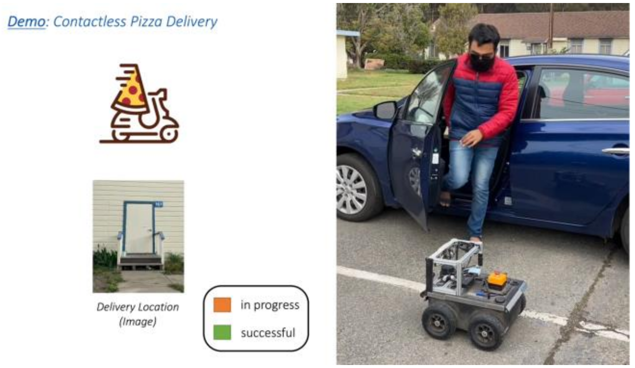
Chebotar, Hausman, Lu, Xiao, Kalashnikov, Varley, Irpan, Eysenbach, Julian, Finn, Levine. **Actionable Models: Unsupervised Offline Reinforcement Learning of Robotic Skills.** 2021.

More examples

Early 2020: Greg Kahn collects 40 hours of robot navigation data

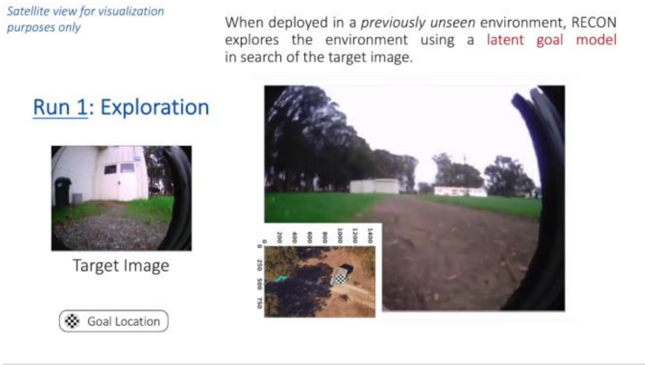
Kahn, Abbeel, Levine. **BADGR: An Autonomous Self-Supervised Learning-Based Navigation System.** 2020.

Late 2020: Dhruv Shah uses it to build goal-conditioned navigation system



Shah, Eysenbach, Kahn, Rhinehart, Levine. **ViNG: Learning Open-World Navigation with Visual Goals.** 2020.

Early 2021: Dhruv Shah uses the **same** dataset to train an exploration system



When deployed in a *previously unseen* environment, RECON explores the environment using a latent goal model in search of the target image.

Shah, Eysenbach, Rhinehart, Levine. **RECON: Rapid Exploration for Open-World Navigation with Latent Goal Models.** 2020.

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

A starting point: Kumar, Singh, Tian, Finn, Levine. **A Workflow for Offline Model-Free Robotic Reinforcement Learning**. CoRL 2021