Offline Reinforcement Learning
CS 285

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What have we covered so far?

$$\max_{\pi} \sum_{t=1}^{\infty} \mathbb{E}_{s_t, a_t \sim \pi} \left[\gamma^t r\left(s_t, a_t\right) \right]$$

- Exploration:
  - Strategies to discover high-reward states, diverse skills, etc.
  - How hard is exploration?

$$\#\text{Samples} \quad \geq \Omega\left(\frac{|\mathcal{S}||\mathcal{A}|}{(1-\gamma)^3} \log \frac{|\mathcal{S}||\mathcal{A}|}{\delta}\right)$$

Super Large

How many states to visit in the "best" case to learn an optimal Q-function

- Even if we are ready to collect so many samples, it may be dangerous in practice: imagine a random policy on an autonomous car or a robot!

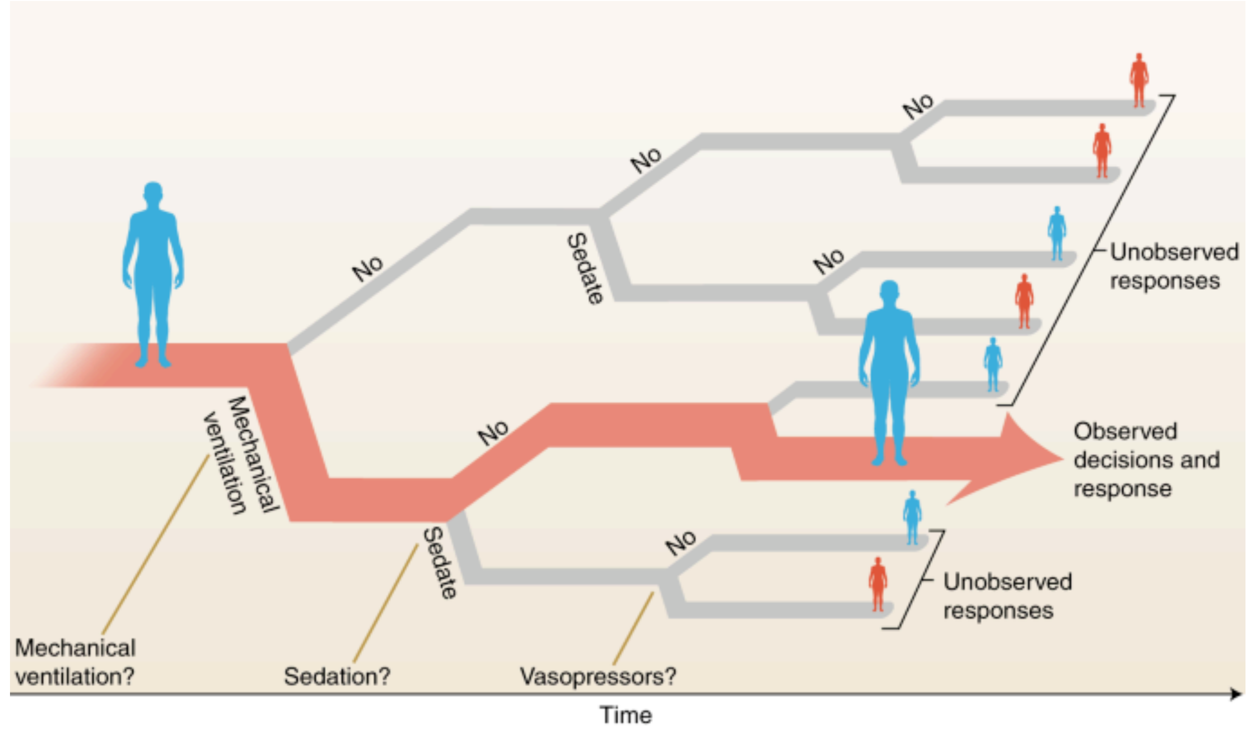
Azar, Munos, Kappen. On the Sample Complexity of RL with a Generative Model. ICML 2012 and many others…

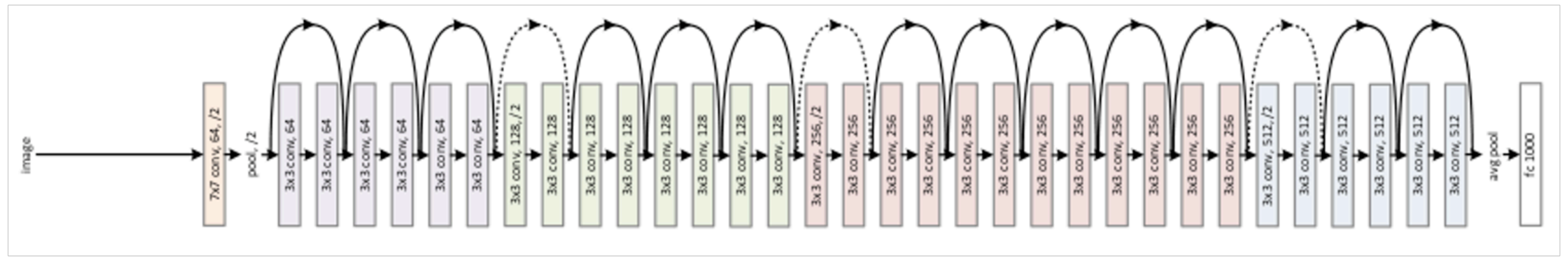
Can we apply standard RL in the real-world?

- RL is fundamentally an “active” learning paradigm: the agent needs to collect its own dataset to learn meaningful policies

- This can be unsafe or expensive in real world problems!

Generalization?

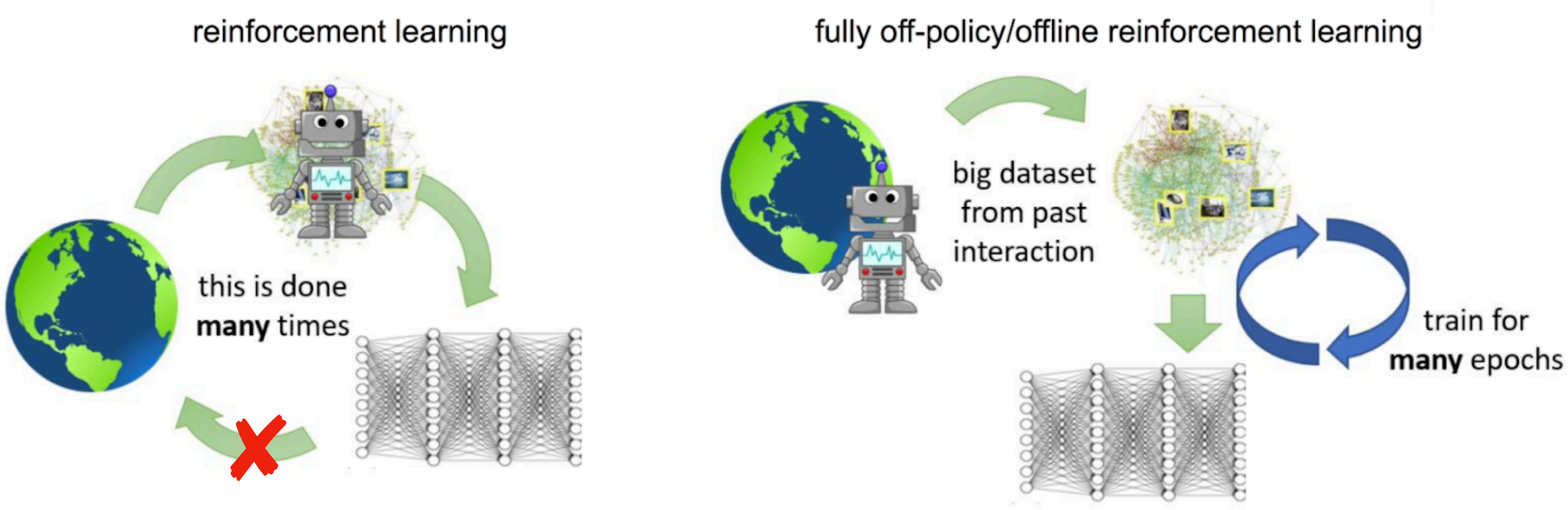




Iterated data collection can cause poor generalization!

Gottesman, Johansson, Komorowski, Faisal, Sontag, Doshi-Velez. Guidelines for RL in Healtcare. Nature Medicine, 2019.
Kumar, Gupta, Levine. DisCor: Corrective Feedback in RL via Distribution Correction, NeurIPS 2020.

Offline (Batch) Reinforcement Learning



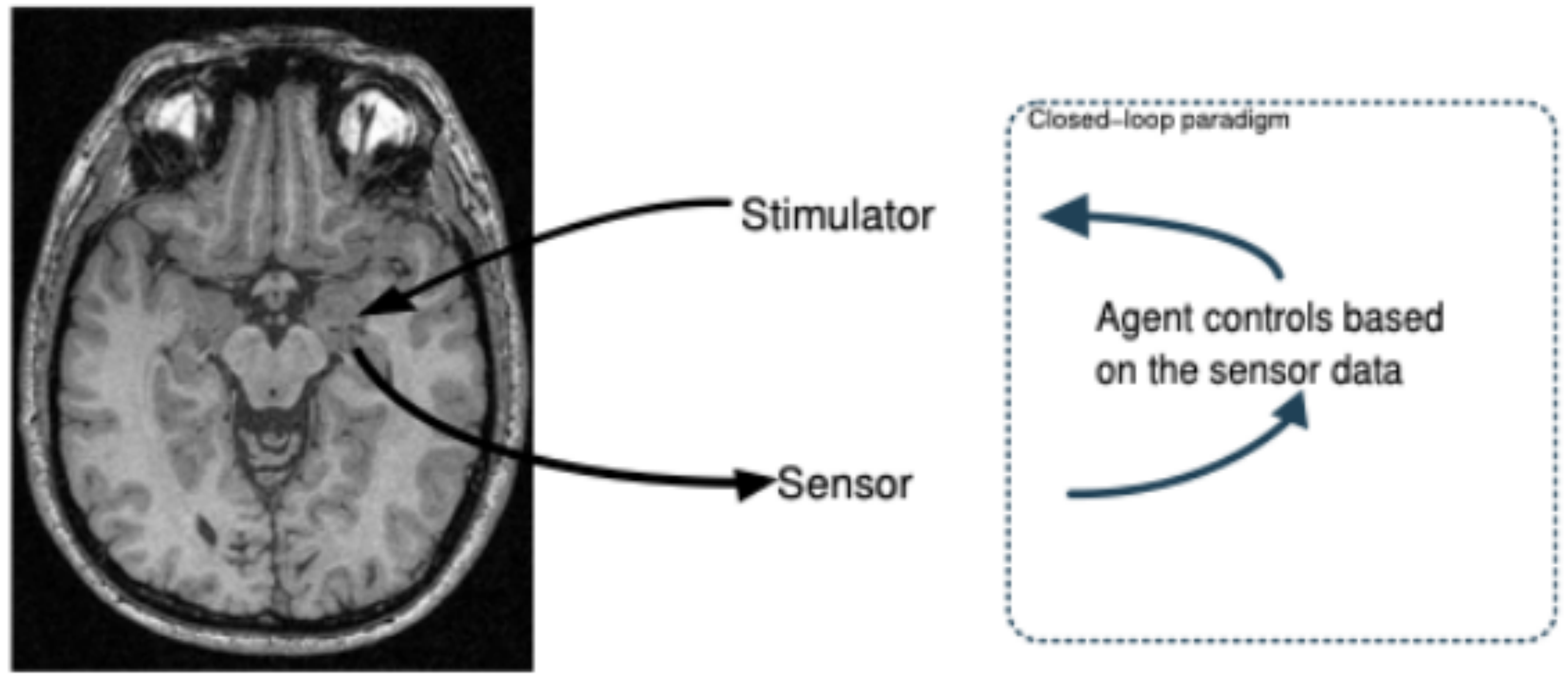
Learn from a previously collected static dataset

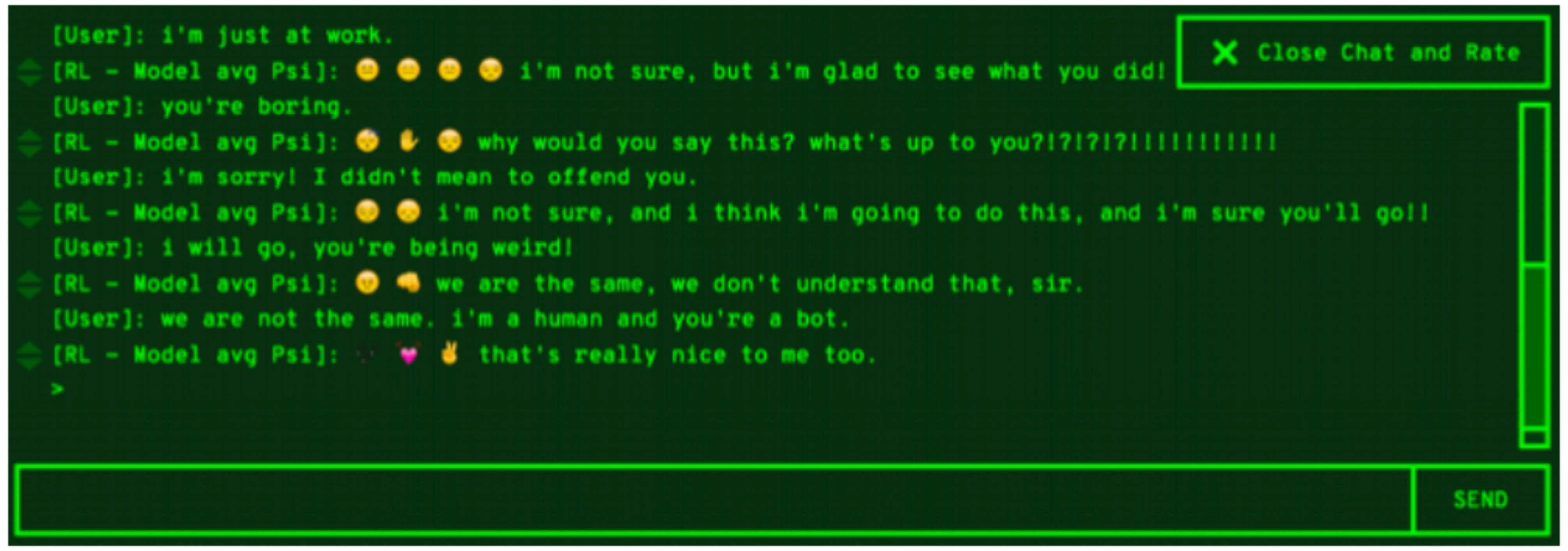
Why is offline RL promising?

- Large static datasets of meaningful behaviours already exist
- Large datasets at the core of successes in Vision and NLP

Lange, Gabel, Reidmiller. *Batch Reinforcement Learning.* 2012.
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.

Applications of Offline RL



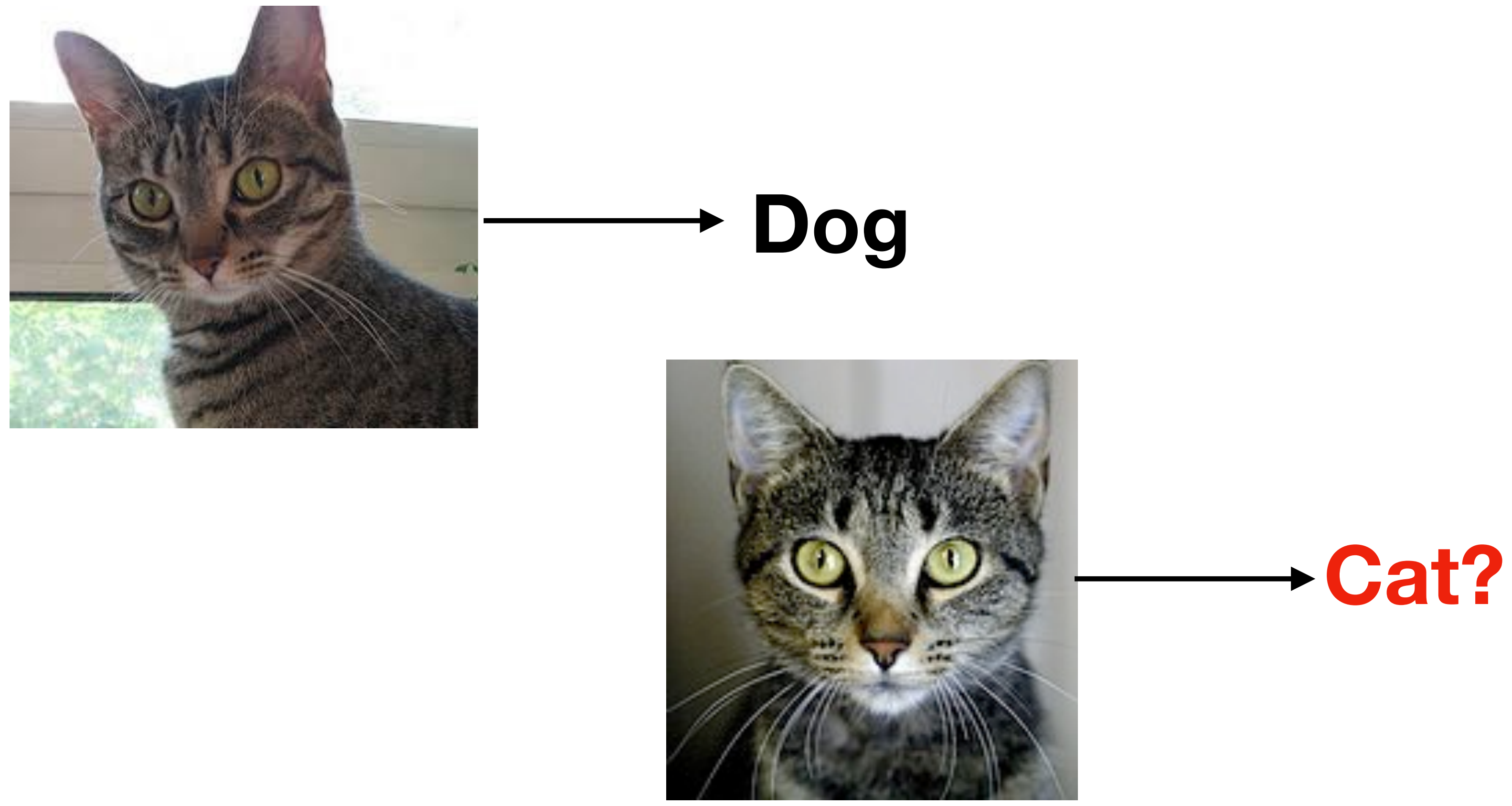


Kalashnikov et al. QT-Opt: Scalable Deep RL for Vision-Based Robotic Manipulation. CoRL 2018.
Jaques et al. Way Off-Policy Batch Reinforcement Learning for Dialog. EMNLP 2020.
Guez et al. Adaptive Treatment of Epilepsy via Batch-Mode Reinforcement Learning. AAAI 2008.
Kendall et al. Learning to Drive in a Day. ICRA 2019.
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.

How good can offline RL perform?

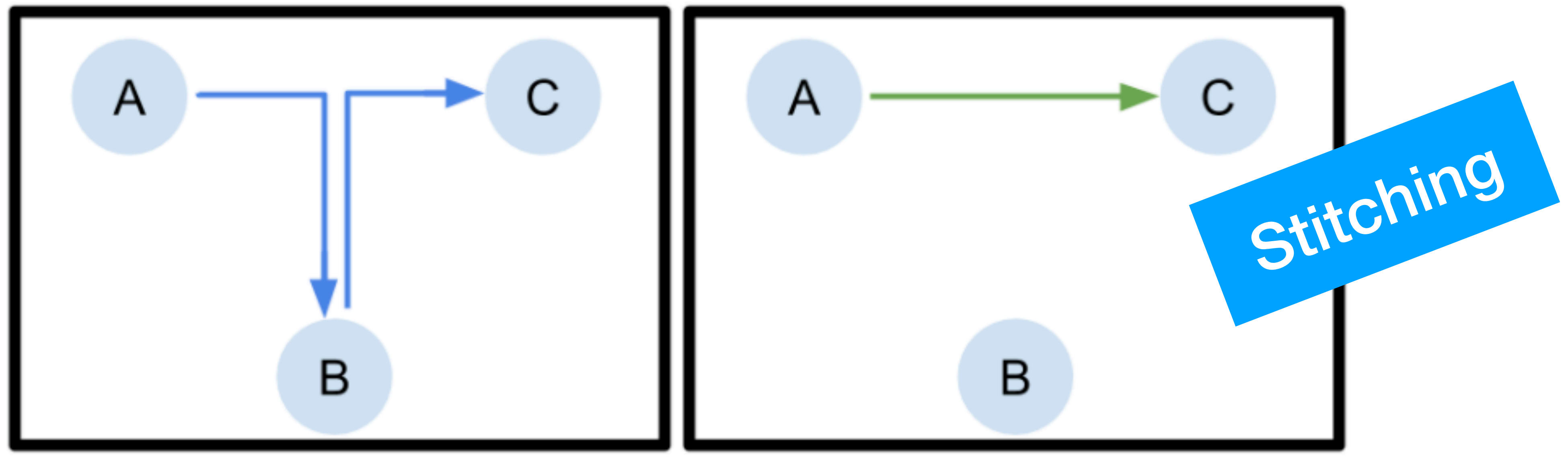
Supervised Learning

Can do as good as the dataset!



Offline Reinforcement Learning

Can do **better** than the dataset!



Can show that Q-learning recovers optimal policy from random data.

Fu, **Kumar,** Nachum, Tucker, Levine. *D4RL: Datasets for Deep Data-Driven RL.* arXiv 2020.

Formalism and Notation

$$\max_{\pi} \sum_{t=1}^{\infty} \mathbb{E}_{s_t, a_t \sim \pi} \left[\gamma^t r \left(s_t, a_t \right) \right]$$

- Dataset construction:
  - Several trajectories:

Reward known

$$\mathcal{D} = \{\tau_1, \cdots, \tau_N\}, \quad \tau_i = \{s_i^t, a_i^t, r_i^t, s_i^{\prime t}\}_{t=1}^{H}$$

- Approximate "distribution" of states in the dataset: $\mathcal{D}(s)$

- Approximate distribution of actions at a given state in the dataset: $\mathcal{D}(a|s)$

- Will use notation for the behavior policy, $\pi_\beta(a|s) = \mathcal{D}(a|s)$

- Standard RL notation from before: $Q^\pi(s, a), V^\pi(s), d^\pi(s), \text{etc.}$

Part 1: Classic Offline RL Algorithms and Challenges With Offline RL

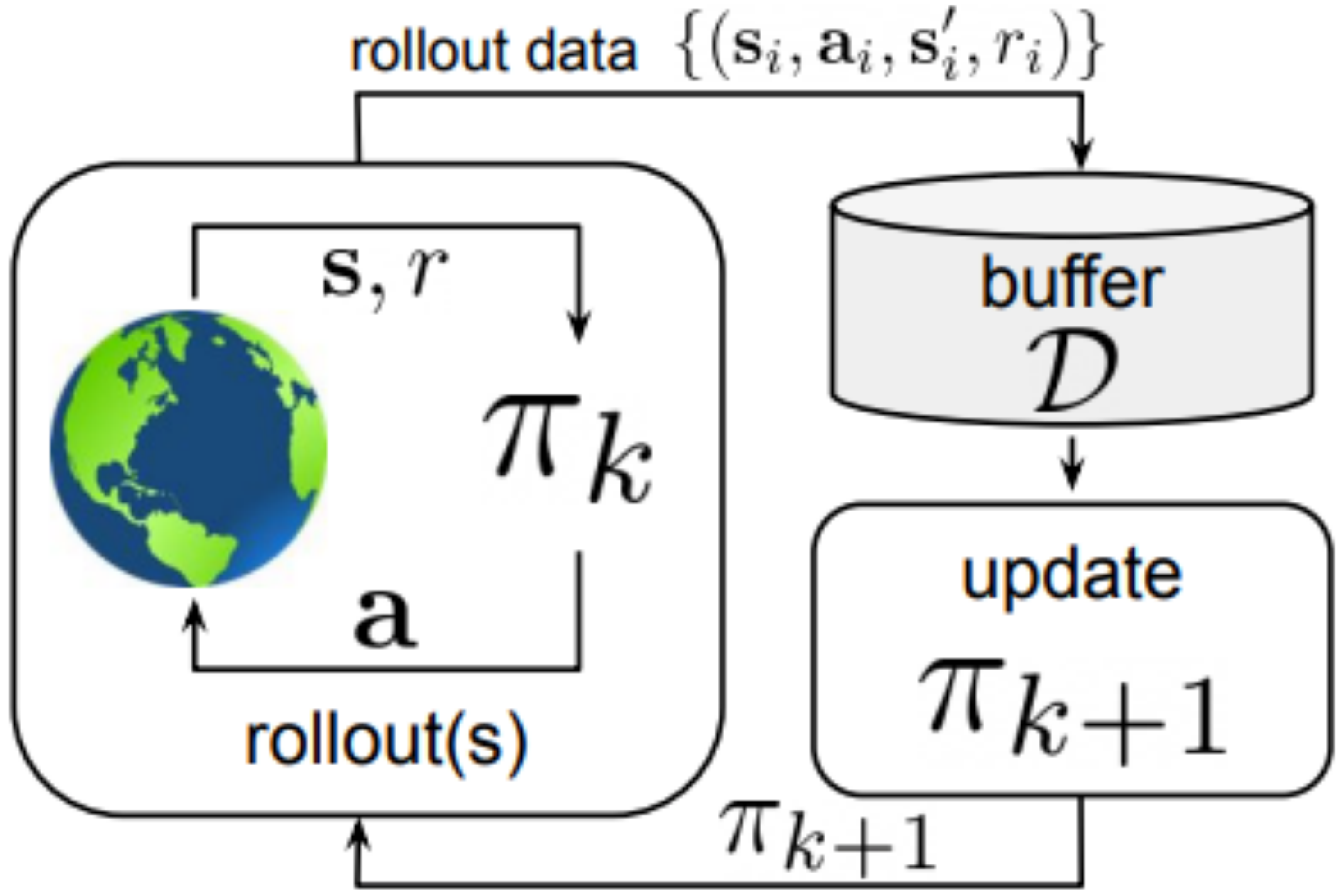
Part 2: Deep RL Algorithms to Address These Challenges

Part 3: Related Problems, Evaluation Protocols, Applications

Part 1: Classic Algorithms and Challenges With Offline RL

A Generic Off-Policy RL Algorithm

DQN and Actor-critic algorithms both follow a similar skeleton, but with different design choices.



1. Collect data using the current policy
2. Store this data in a replay buffer
3. Use replay buffer to make updates on the policy and the Q-function
4. Continue from step 1.

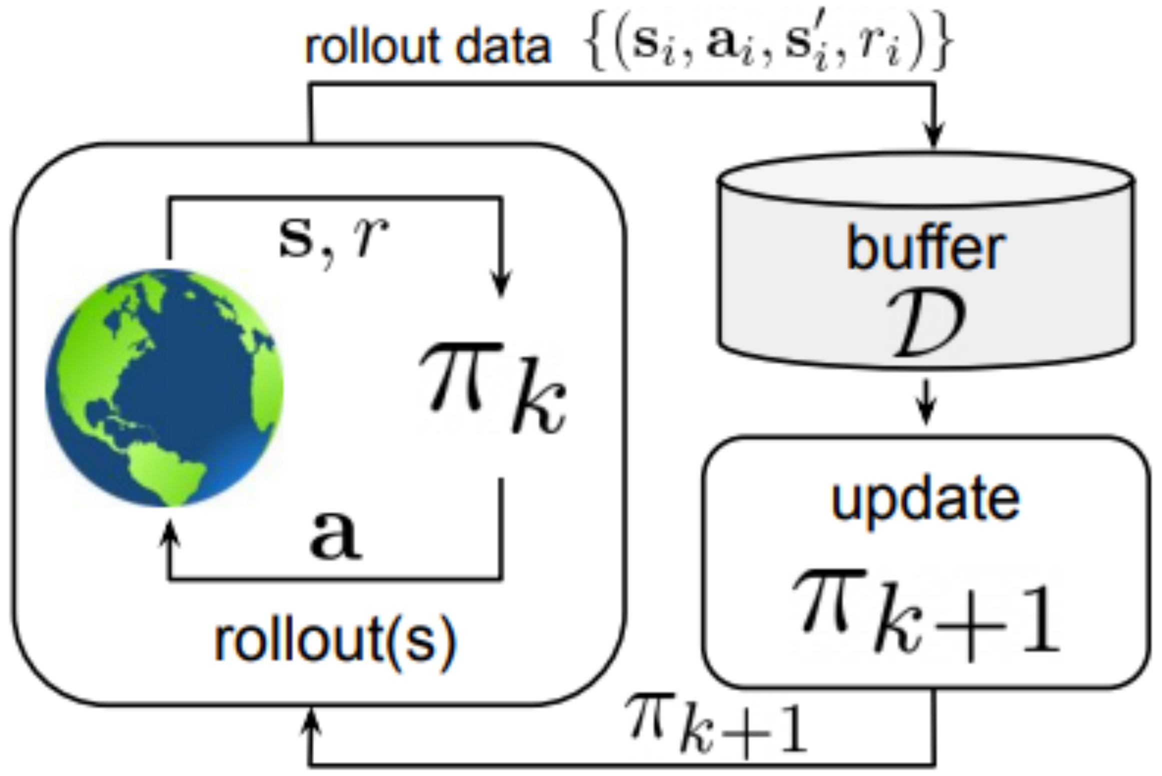
$$\min_Q \sum_{i=1}^{N} \left(Q(s_i, a_i) - \left[r(s_i, a_i) + \gamma \max_{a'} \overline{Q}(s'_i, a') \right] \right)^2$$

Actor-critic Algorithm:

1. Learn $\hat{Q}^\pi$
2. Optimize policy w.r.t. $\hat{Q}^\pi$: $\pi \leftarrow \arg\max_\pi \mathbb{E}_\pi[\hat{Q}^\pi]$

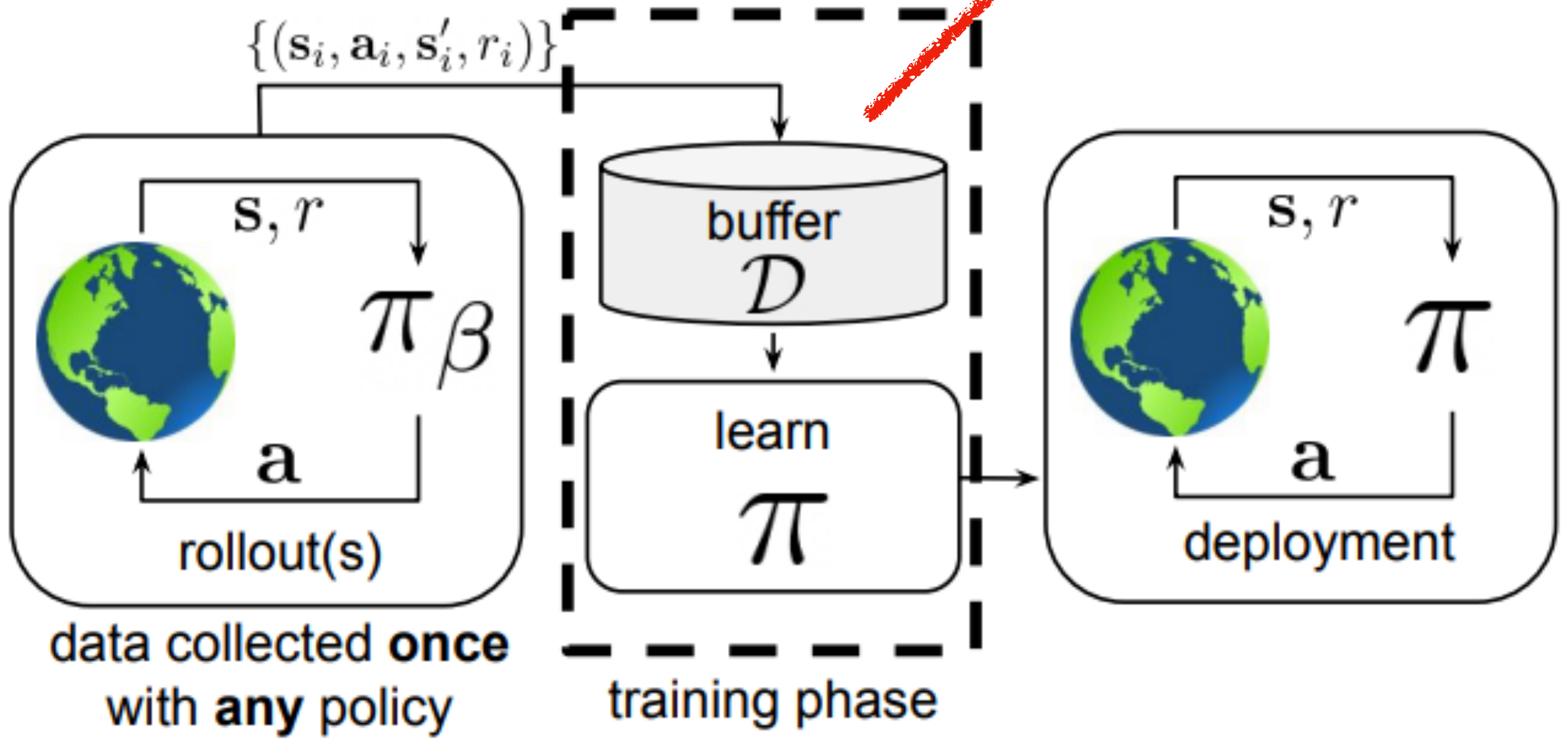
Can such off-policy RL algorithms be used?

Off-Policy RL Algorithms can be applied, *in principle*



“Off-Policy” buffer from past policies

“Off-Policy” buffer from some unknown policies



We will discuss some classical algorithms based on this idea next

Actor-critic Algorithm:

1. Learn $\hat{Q}^\pi$ using offline data$\mathcal{D}$.
2. Optimize policy w.r.t.$\hat{Q}^\pi$: $\pi \leftarrow \arg\max_\pi \mathbb{E}_\pi[\hat{Q}^\pi]$

Lagoudakis, Parr. Least Squares Policy Iteration. JMLR 2003.
Ernest el al. Tree-Based Batch Mode Reinforcement Learning. JMLR 2005
Gordon G. J. Stable Function Approximation in Dynamic Programming. ICML 1995, **and many more…**

Classic Batch Q-Learning Algorithms

Algorithm 1 **Fitted Q-Iteration (FQI)**

Initialize Q-network $\mathbf{Q}_\theta$, buffer μ.
for fitting iteration k in $\{1, \ldots, \mathrm{N}\}$ **do**
  Compute $\mathbf{Q}_\theta(\mathbf{s}, \mathbf{a})$ and target values $y_k(\mathbf{s}, \mathbf{a}) = r + \gamma \max_{\mathbf{a}'} \mathbf{Q}_{k-1}(\mathbf{s}', \mathbf{a}')$ on $\{(\mathbf{s}, \mathbf{a})\} \sim \mu$ for training
  Minimize TD error for $\mathbf{Q}_\theta$ via $t = 1, \cdots, \mathrm{T}$ gradient descent updates, $\min_\theta \left(Q_\theta(\mathbf{s}, \mathbf{a}) - \mathbf{y}_k\right)^2$
end for

1. Compute target values using the current Q-function
2. Train Q-function by minimizing TD error with respect to target values from Step 1.

Linear Q-functions

$$Q(s,a) = w^T \phi(s,a)$$

$$w^T \phi(s,a) \approx R + \gamma \max_{a'} w^T \phi(s', a')$$

Can be solved in many ways:
(1) find fixed point of the above equation
(2) minimise the gap between the two sides of the equation

Least Squares Temporal Difference Q-Learning (LSTD-Q)

Lagoudakis, Parr. Least Squares Policy Iteration. JMLR 2003.
Ernest el al. Tree-Based Batch Mode Reinforcement Learning. JMLR 2005
Riedmiller. Neural Fitted Q-Iteration. ECML 2005.
Gordon G. J. Stable Function Approximation in Dynamic Programming. ICML 1995
Antos, Szepesvari, Munos. Fitted Q-Iteration in Continuous Action-Space MDPS. NeurIPS 2007.

Classic Batch RL Algorithms based on IS

$$J(\pi_\theta) = \mathbb{E}_{\tau \sim \pi_\beta(\tau)}\left[\frac{\pi_\theta(\tau)}{\pi_\beta(\tau)} \sum_{t=0}^{H} \gamma^t r(\mathbf{s}, \mathbf{a})\right]$$

$$= \mathbb{E}_{\tau \sim \pi_\beta(\tau)}\left[\left(\prod_{t=0}^{H} \frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_\beta(\mathbf{a}_t|\mathbf{s}_t)}\right) \sum_{t=0}^{H} \gamma^t r(\mathbf{s}, \mathbf{a})\right] \approx \sum_{i=1}^{n} w_H^i \sum_{t=0}^{H} \gamma^t r_t^i,$$

$$J(\pi_\theta) = \mathbb{E}_{\tau \sim \pi_\beta(\tau)}\left[\sum_{t=0}^{H}\left(\prod_{t'=0}^{t} \frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_\beta(\mathbf{a}_t|\mathbf{s}_t)}\right) \gamma^t r(\mathbf{s}, \mathbf{a})\right] \approx \frac{1}{n}\sum_{i=1}^{n}\sum_{t=0}^{H} w_t^i \gamma^t r_t^i.$$

$$J(\pi_\theta) \approx \sum_{i=1}^{n}\sum_{t=0}^{H} \gamma^t \left(w_t^i \left(r_t^i - \hat{Q}^{\pi_\theta}(\mathbf{s}_t, \mathbf{a}_t)\right) - w_{t-1}^i \mathbb{E}_{\mathbf{a} \sim \pi_\theta(\mathbf{a}|\mathbf{s}_t)}\left[\hat{Q}^{\pi_\theta}(\mathbf{s}_t, \mathbf{a})\right]\right).$$

Doubly-robust

High-confidence bounds on the return estimate
Variance reduction techniques

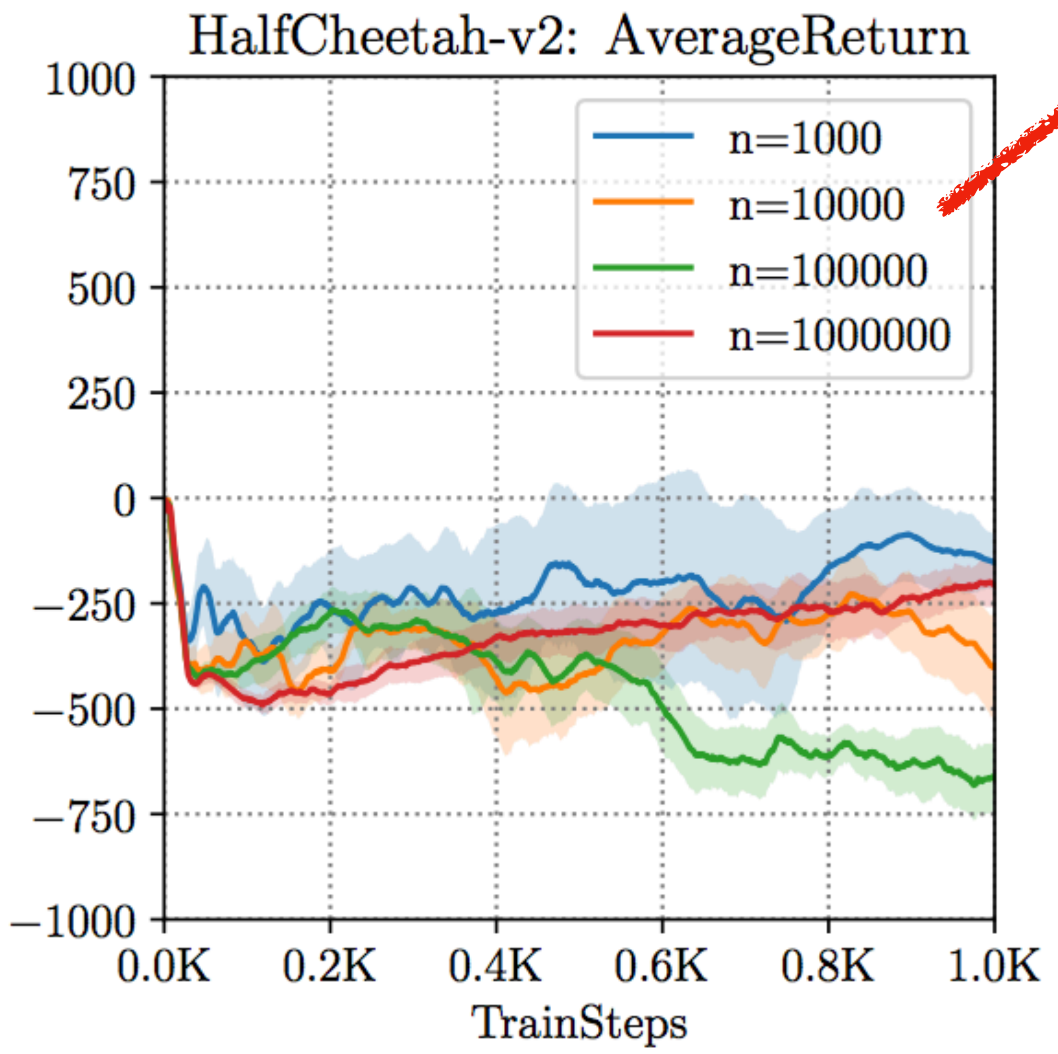
Precup. Eligibility Traces for Off-Policy Policy Evaluation. CSD Faculty Publication Series, 2000.
Precup, Sutton, Dasgupta. Off-Policy TD Learning with Function Approximation. ICML 2001.
Peshkin and Shelton. Learning from Scarce Experience. 2002.

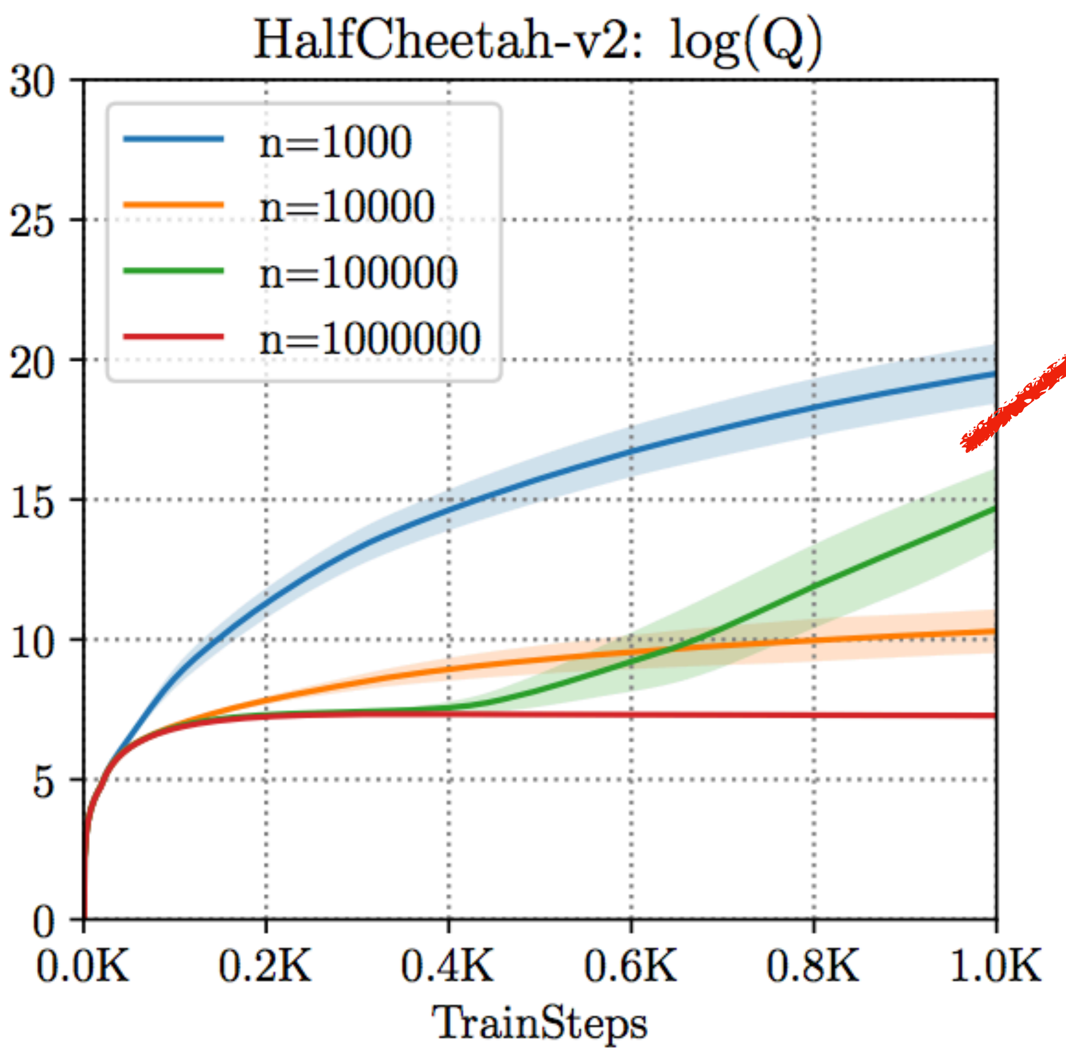
Thomas, Theocharous, Ghavamzadeh. High Confidence Off-Policy Evaluation. AAAI 2015.
Thomas, Theocharous, Ghavamzadeh. High Confidence Off-Policy Improvement. ICML 2015.
Thomas, Brunskill. Magical Policy Search: Data Efficient RL with Guarantees of Global Optimality. EWRL 2016.
Jiang and Li. Doubly-Robust Off-Policy Value Estimation for Reinforcement Learning. ICML 2016.

Modern Offline RL: A Simple Experiment

Collect expert data and run actor-critic algorithms on this data

Performance doesn't improve with more data





Learning diverges

"Policy unlearning"

how well it does

how well ***it thinks*** it does

Not a classical overfitting issue!

Kumar, Fu, Tucker, Levine. *Stabilizing Off-Policy RL via Bootstrapping Error Reduction*, NeurIPS 2019.
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.

So, why do RL algorithms fail, even though imitation learning would work in this setting (e.g., in Lecture 2)?

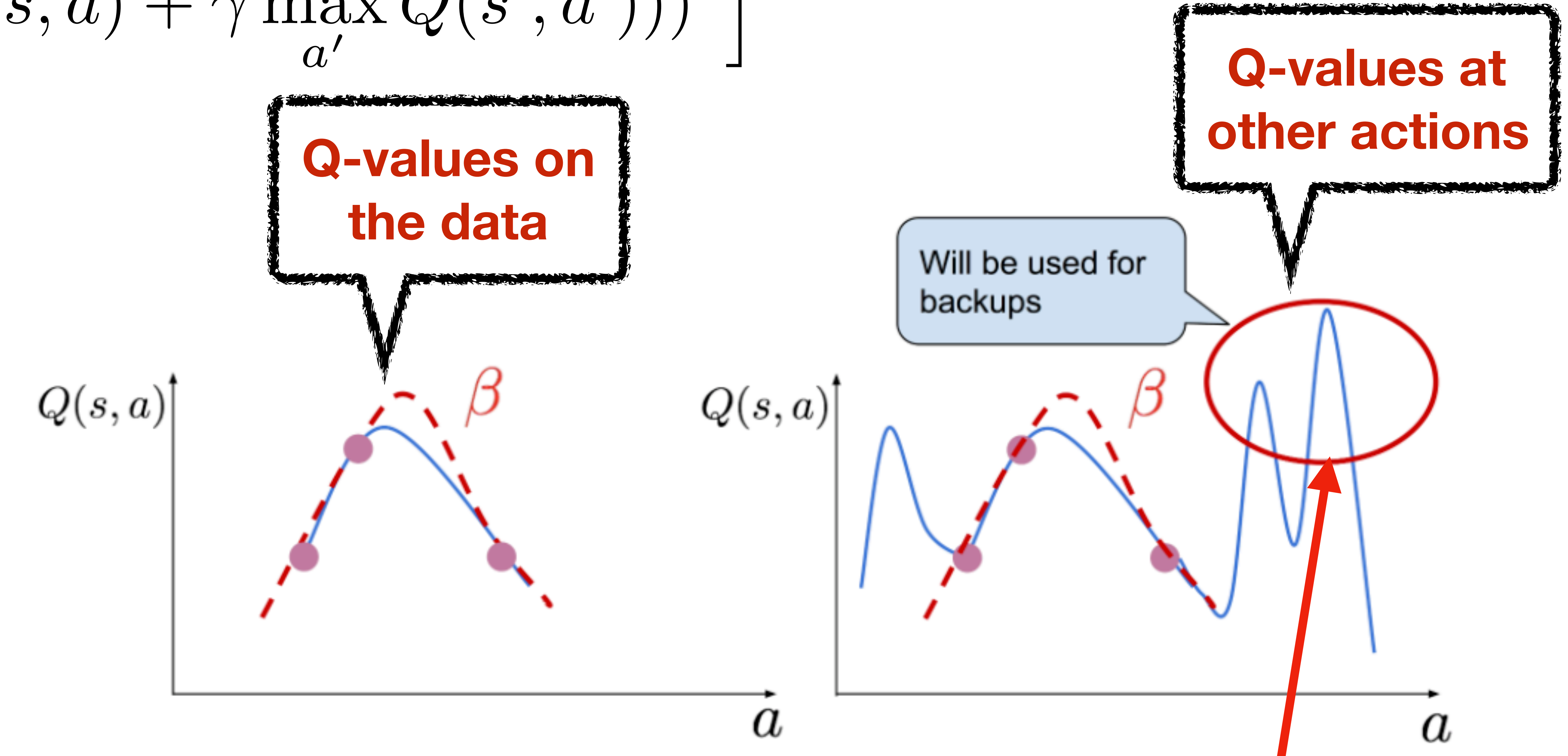
Let’s see how the Q-function is updated

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

$$\mathbb{E}_{s,a,s' \sim \mathcal{D}} \left[\left(Q(s,a) - \left(r(s,a) + \gamma \max_{a'} Q(s',a') \right) \right)^2 \right]$$

Which actions does the Q-function train on?

$$s, a \sim \mathcal{D}$$



Where does the action a’ for the target value come from?

$$\max_{a'} Q(s',a')$$

Q-learning queries values at unseen action targets, which are never trained during training

Why are erroneous backups a big deal?

- This phenomenon also happens in online RL settings, where the Q-function is erroneously optimistic

- But Boltzmann or epsilon-greedy exploration on this overoptimistic Q-function (generally) leads to "error correction"

$$\pi_{\text{explore}}(a|s) \propto \exp(Q(s,a))$$

  Error correction is **not** necessarily guaranteed with online data collection when using deep neural nets, but mostly works fine in practice (trick: use replay buffers, perform distribution correction, etc)

- **But the primary ability of error correction, i.e., exploration,** is impossible in offline RL, due to no access to an environment….

Kumar, Fu, Tucker, Levine. *Stabilizing Off-Policy RL via Bootstrapping Error Reduction*, NeurIPS 2019.
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.
Kumar, Gupta, Levine. DisCor: Corrective-Feedback in RL via Distribution Correction. NeurIPS 2020.
Kumar, Gupta. Does On-Policy Data Collection Fix Errors in Off-Policy Reinforcement Learning?, BAIR blog.

Distributional Shift in Offline RL

- Distribution shift between the behavior policy (the policy that collected the data) and the policy during learning

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

$$\boxed{\neq \pi_\beta(a|s)}$$

$$Q(s,a) \leftarrow r(s,a) + \gamma \mathbb{E}_{a' \sim \pi(a'|s')} Q(s',a')$$

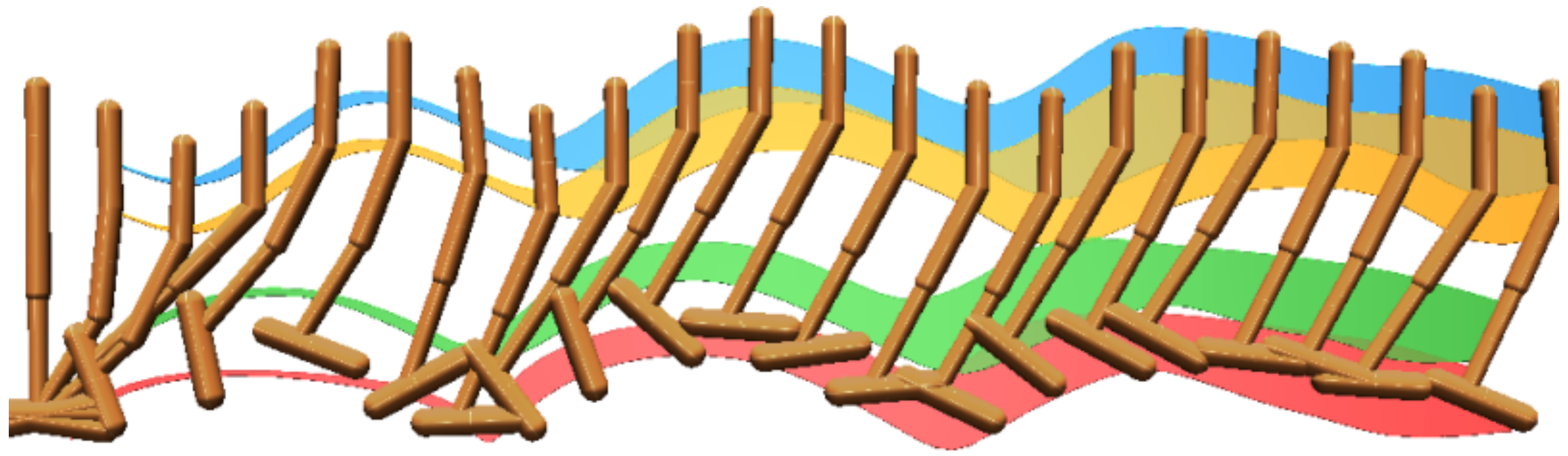
$$\boxed{= \pi_\beta(a|s)}$$

Training: $\mathbb{E}_{s,a \sim d^{\pi_\beta}(s,a)} \left[\left(Q(s,a) - \mathcal{B}\bar{Q}(s,a) \right)^2 \right]$

Offline Q-Learning algorithms can overestimate the value of unseen actions and can thus be falsely optimistic

Kumar, Fu, Tucker, Levine. *Stabilizing Off-Policy RL via Bootstrapping Error Reduction*, NeurIPS 2019.
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.

Error Compounds in RL (Additional Slide)



Typical cartoon showing “error compounding” in RL

Theorem 2.1 (Behavioral cloning error bound). *If $\pi(\mathbf{a}|\mathbf{s})$ is trained via empirical risk minimization on $\mathbf{s} \sim d^{\pi_\beta}(\mathbf{s})$ and optimal labels $\mathbf{a}^\star$, and attains generalization error ϵ on $\mathbf{s} \sim d^{\pi_\beta}(\mathbf{s})$, then $\ell(\pi) \leq C + H^2\epsilon$ is the best possible bound on the expected error of the learned policy.*

Theorem 2.2 (DAgger error bound). *If $\pi(\mathbf{a}|\mathbf{s})$ is trained via empirical risk minimization on $\mathbf{s} \sim d^{\pi}(\mathbf{s})$ and optimal labels $\mathbf{a}^\star$, and attains generalization error ϵ on $\mathbf{s} \sim d^{\pi}(\mathbf{s})$, then $\ell(\pi) \leq C + H\epsilon$ is the best possible bound on the expected error of the learned policy.*

Error compounding over the horizon magnifies a small error into a big one.

Recent work has also showed counterexamples that indicate we can’t do better.

Janner, Fu, Zhang, Levine. When to Trust Your Model: Model-Based Policy Optimization. NeurIPS 2019.
Ross, Gordon, Bagnell. *A reduction of imitation learning and structured prediction to no-regret online learning.* AISTATS 2011
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.

Part 2: Deep RL Algorithms to Address Distribution Shift

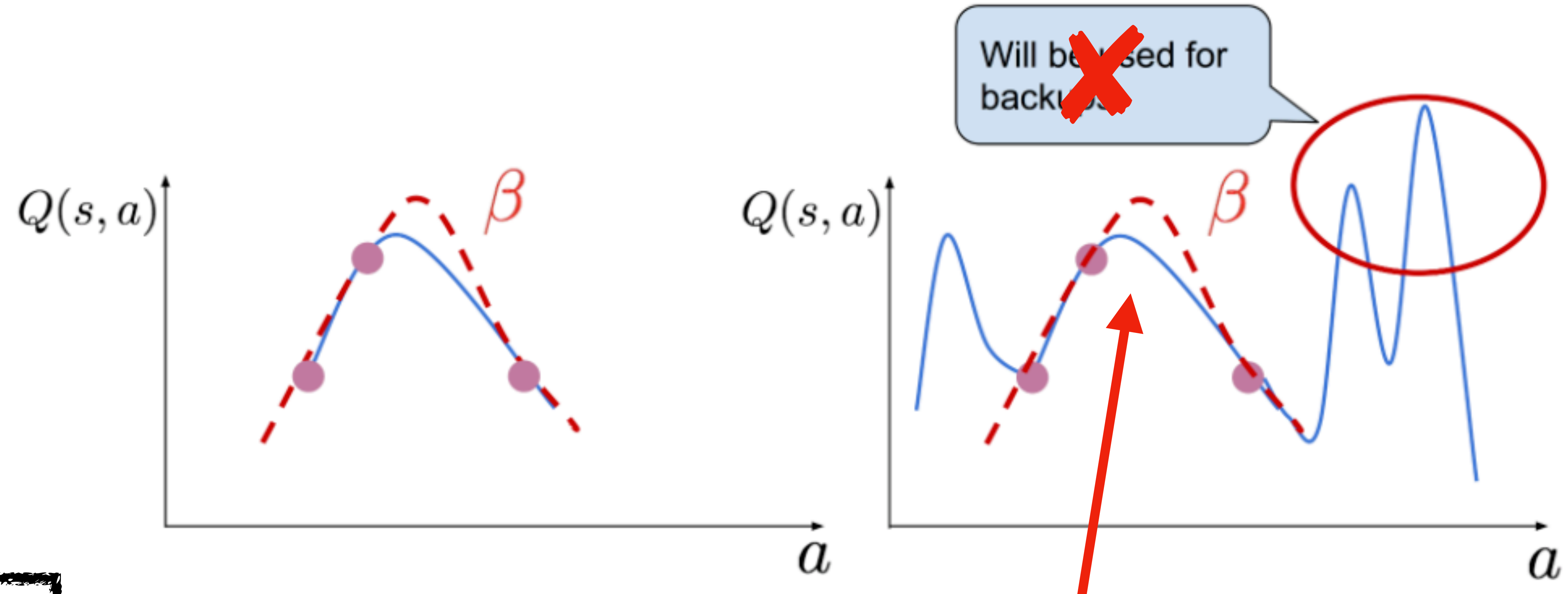
Addressing Distribution Shift via Pessimism

$$Q(s,a) \leftarrow r(s,a) + \gamma \mathbb{E}_{a' \sim \pi_\phi(a|s)}[Q(s',a')]$$

"Policy Constraint"

$$\pi_\phi := \arg\max_\phi E_{a \sim \pi_\phi(a|s)}[Q(s,a)] \quad \text{s.t.} \quad D(\pi_\phi(a|s), \pi_\beta(a|s)) \leq \varepsilon$$

Out-of-distribution action values are no longer used for the backup



Hence, all values used during training are also trained, leading to better learning

$$\mathbb{E}_{a' \sim \pi_\phi(a|s)}[Q(s',a')]$$

Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.

Different Types of Policy Constraints

$$\pi_\phi := \arg\max_\phi E_{a\sim\pi_\phi(a|s)}[Q(s,a)] \quad \text{s.t.} \quad D(\pi_\phi(a|s), \pi_\beta(a|s)) \leq \varepsilon$$

Several Ways of Implementing Them:

$$D(\pi_\phi, \pi_\beta) = \mathrm{MMD}(\pi_\phi, \pi_\beta)$$

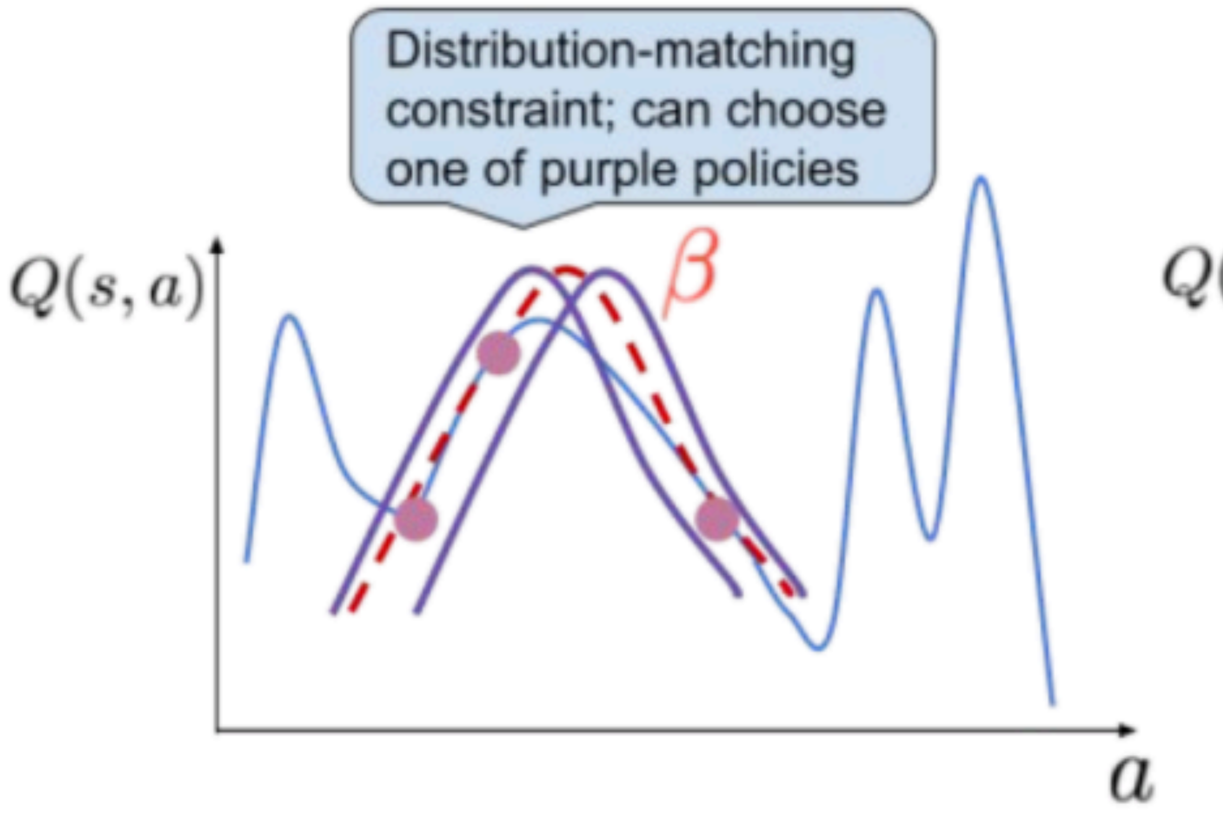
- Support matching (**Kumar** et al. 2019**,** Laroche et al. 2019, Wu et al. 2019**)**
- Distribution matching (Peng et al. 2019, Fujimoto et al. 2019, Jaques et al. 2019)

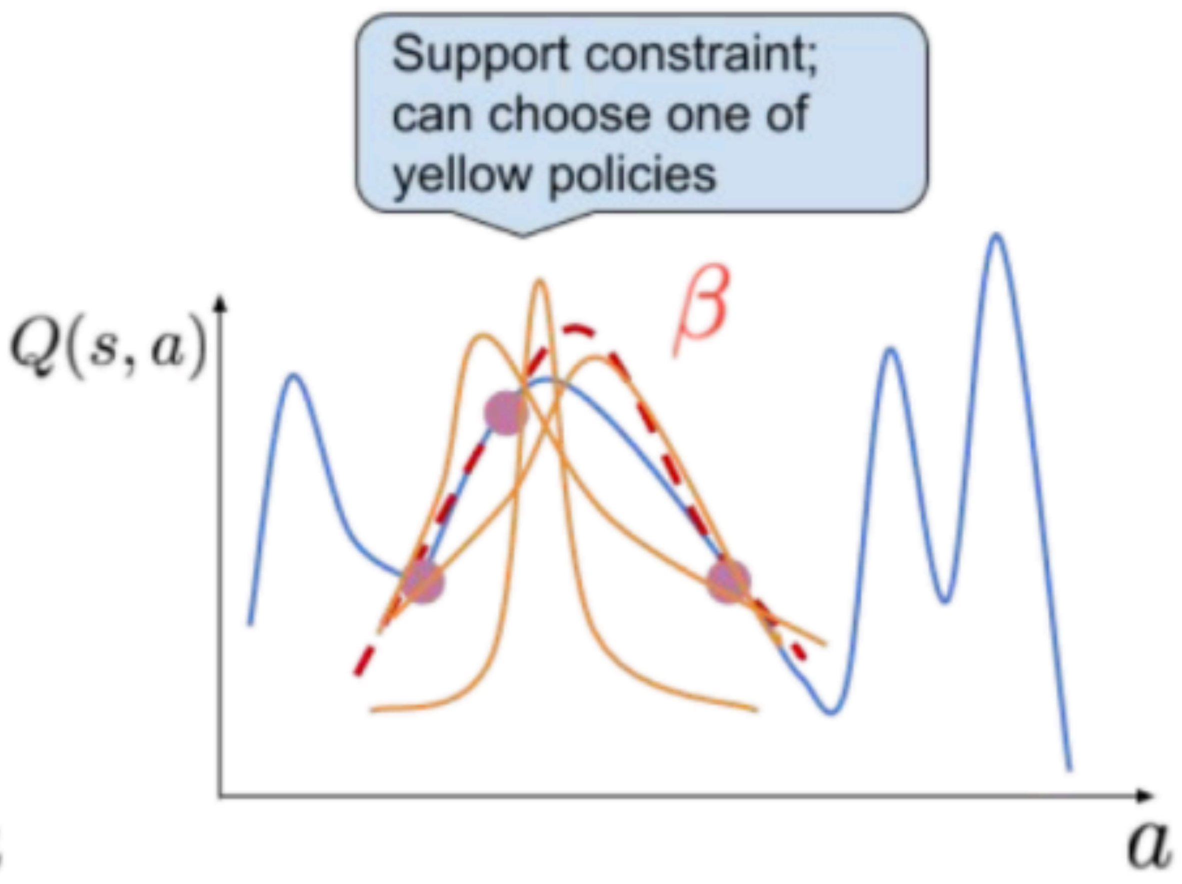
$$D(\pi_\phi, \pi_\beta) = \mathrm{D_{KL}}(\pi_\phi, \pi_\beta)$$

- State-marginal constraints (Nachum & Dai 2020)

$$D(\pi_\phi, \pi_\beta) = D(d^{\pi_\phi}(s,a), d^{\pi_\beta}(s,a))$$

- Implicit /closed-form distribution constraints (Peng et al. 2019, Nair et al. 2020, Wang et al. 2020)





Different types of constraints lead to different solutions, providing a whole lot of different offline RL algorithms

Which constraint should I use?

Before answering this question, let's see how the usage of a policy constraint affects optimal solutions?

$$\max_{\pi} \quad \mathbb{E}_{\pi}[\sum_t \gamma^t r(s_t, a_t)] - \alpha D(\pi(a|s), \pi_\beta(a|s))$$

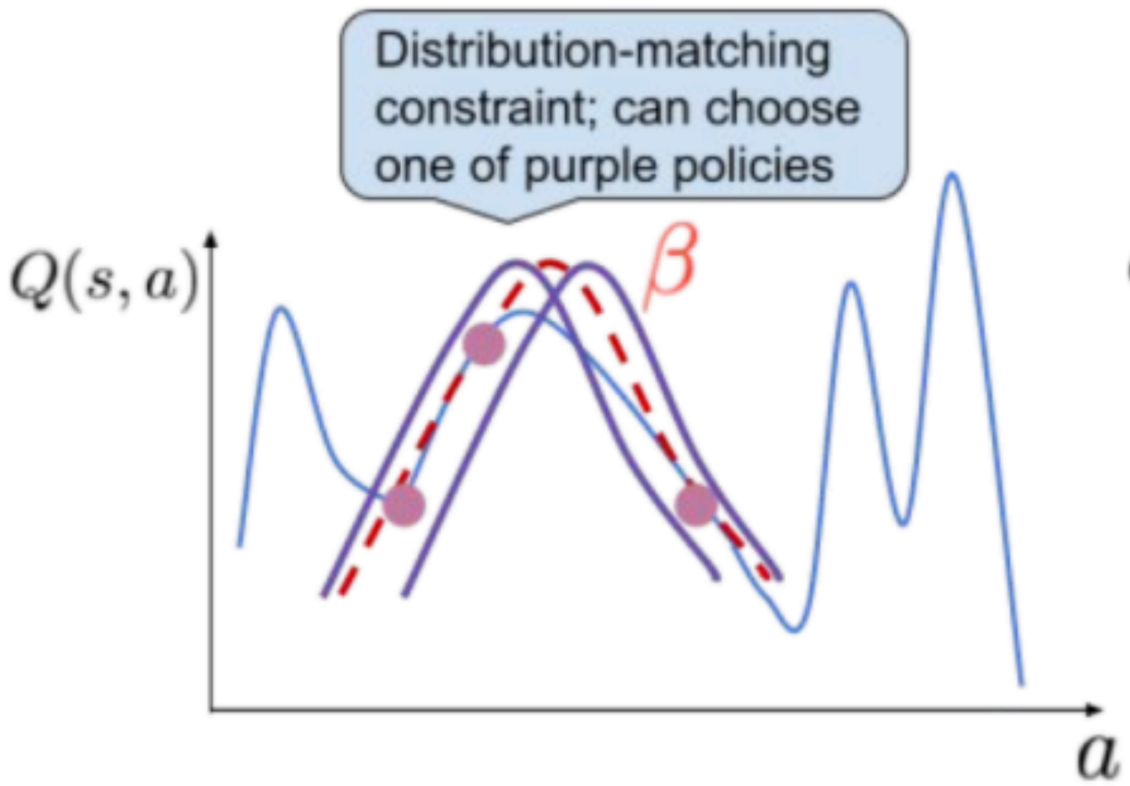
$\boxed{\text{Adding pessimism alters the optimal performance}}$

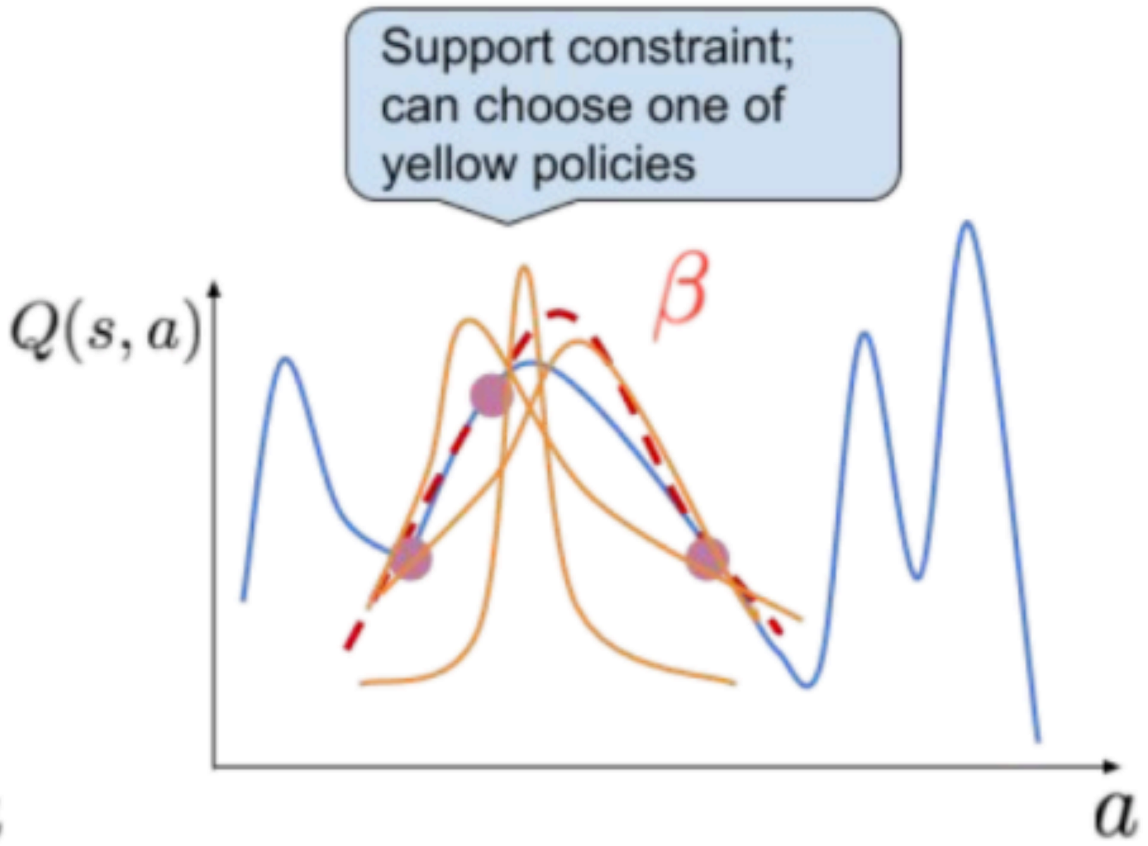
Thus we would want the constraint to be least restrictive, while still preventing the "badness"

- Technically, support constraints are less restrictive
  - Imagine a case where the behavior policy takes all actions uniformly.
  - Constraining to the behavior policy via distribution-matching may lead to highly stochastic policies that are not optimal.
  - However, choosing to match only supports leads to choosing in-distribution actions, but at the same time, only optimises the RL objective

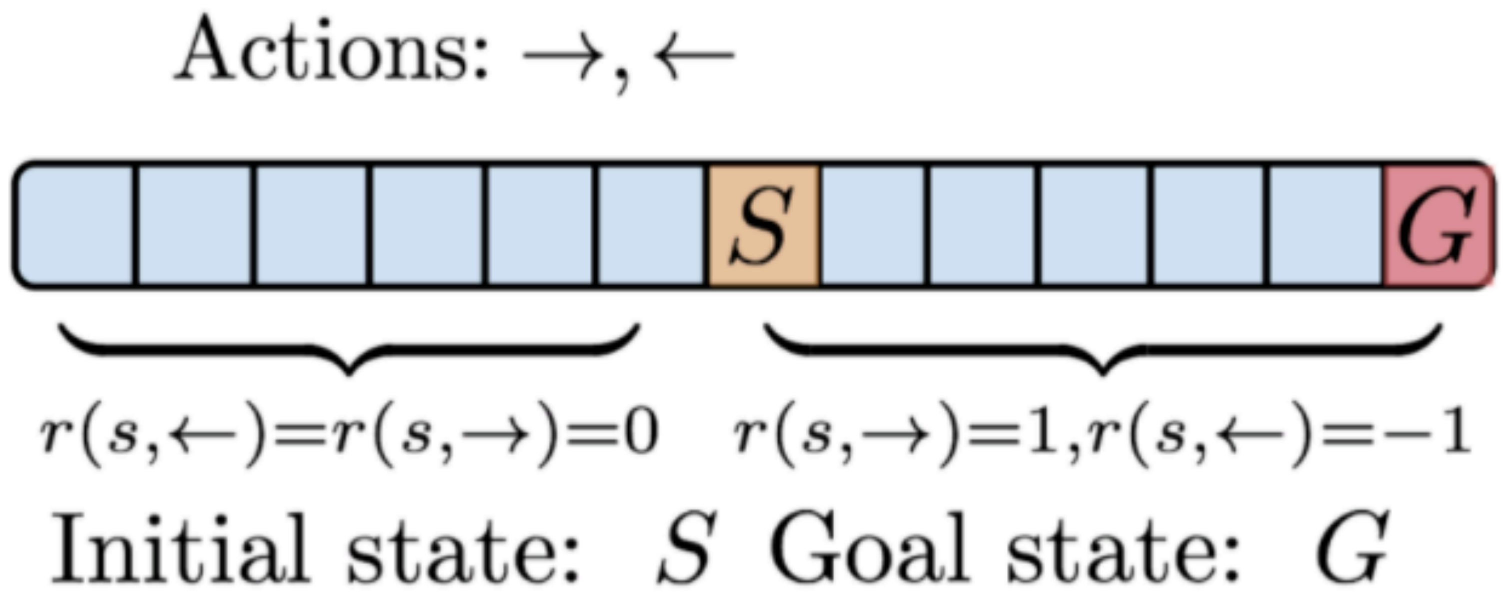
Kumar. Data-Driven Deep Reinforcement Learning. BAIR blog, December 2019.
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.

Which constraint should I use?

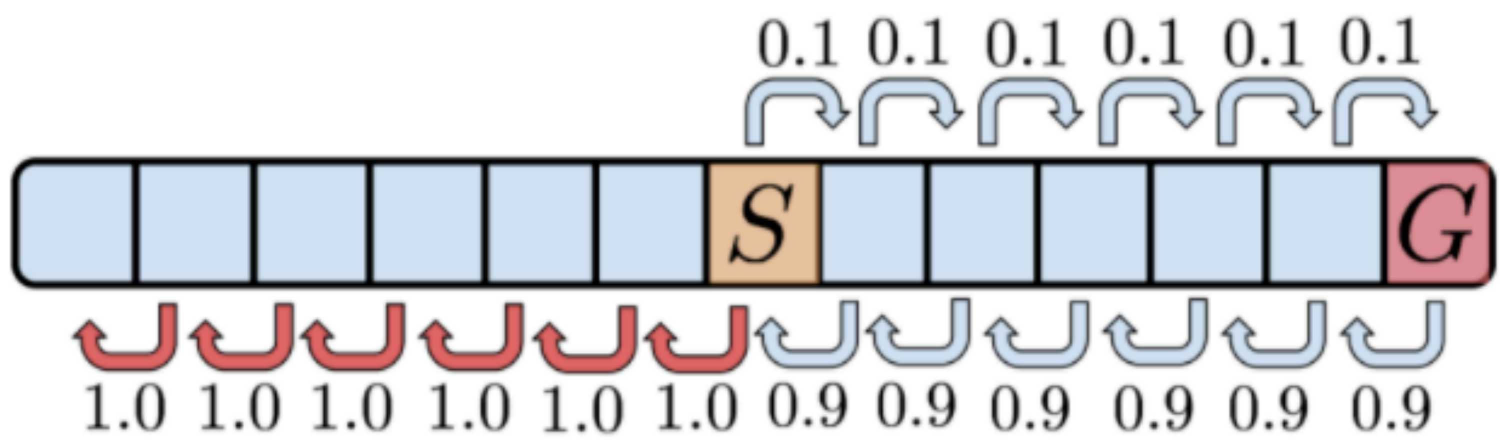




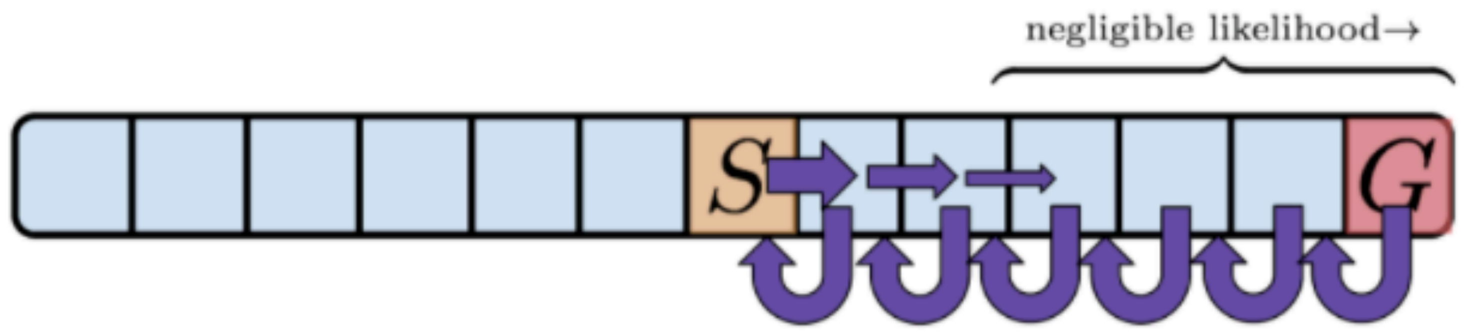
Support constraints better in theory, but not much difference in practice, often depends on how well can policy constraint methods be tuned



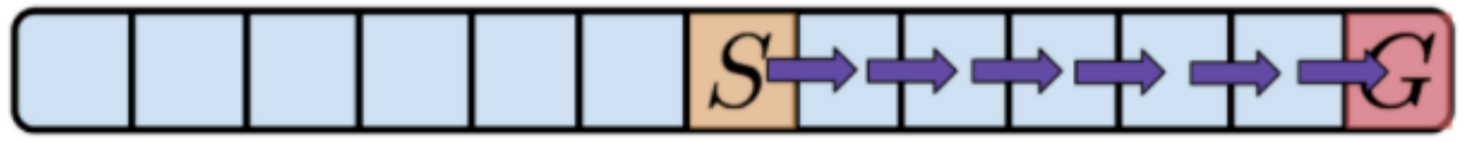
(a) 1D-Lineworld Environment



(b) Behavior Policy



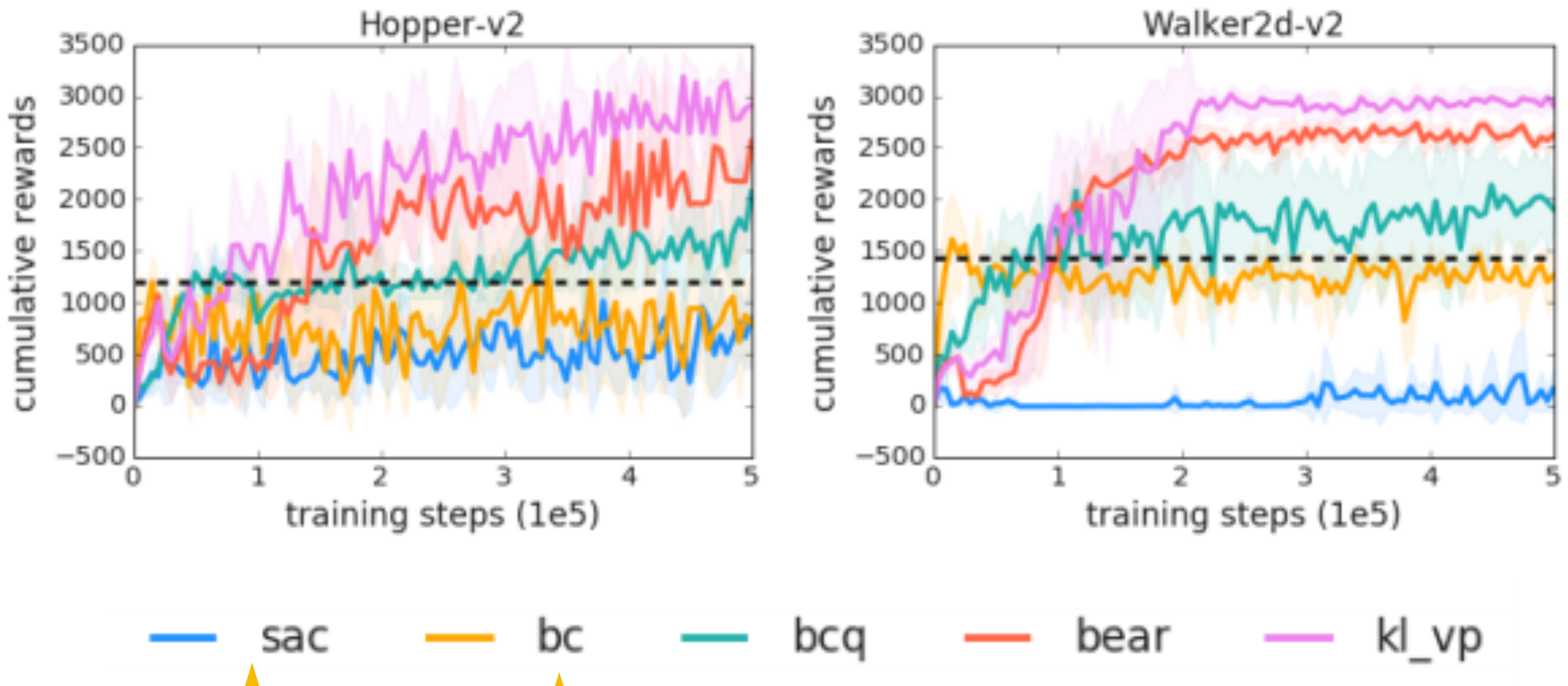
(a) Learned Policy via distribution-matching



(b) Learned Policy via support-constraint

Policy Constraint Methods, Empirically

Dataset collected from a mixture of random and "mediocre" policies



Naive off-policy RL

Behavior cloning

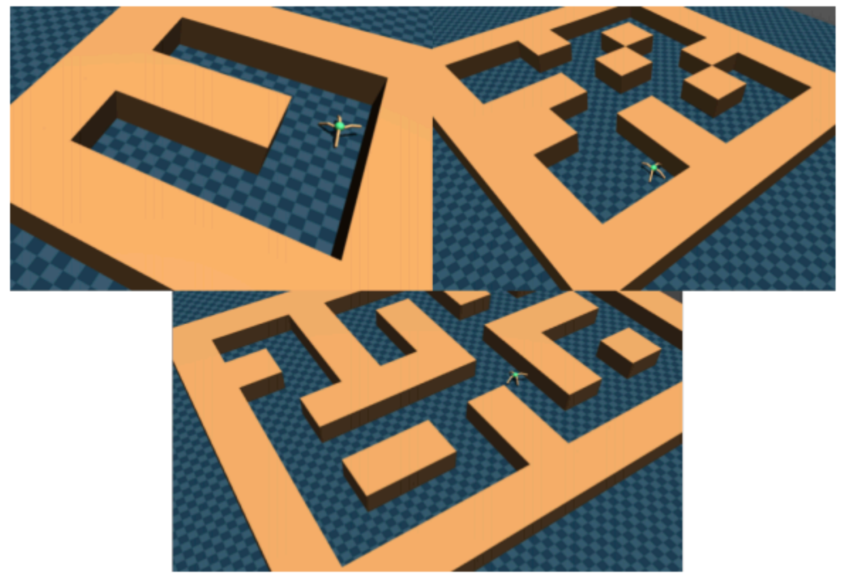
Policy constraint methods: BCQ, BEAR and BRAC (with KL)

Better than BC

Different choices of D matter

How do these methods perform on harder tasks?

Domain	Task Name	BC	SAC	BEAR	BRAC-p	BRAC-v
AntMaze	antmaze-umaze	65.0	0.0	**73.0**	50.0	70.0
	antmaze-umaze-diverse	55.0	0.0	61.0	40.0	70.0
	antmaze-medium-play	0.0	0.0	0.0	0.0	0.0
	antmaze-medium-diverse	0.0	0.0	8.0	0.0	0.0
	antmaze-large-play	0.0	0.0	0.0	0.0	0.0
	antmaze-large-diverse	0.0	0.0	0.0	0.0	0.0



Wu, Tucker, Nachum. Behavior Regularized Offline Reinforcement Learning. arXiv 2019.
Fu, **Kumar,** Nachum, Tucker, Levine. *D4RL: Datasets for Deep Data-Driven RL.* arXiv 2020.

Are policy constraint methods sufficient?

Require estimation of the behavior policy

$$\pi_\phi := \arg\max_\phi E_{a\sim\pi_\phi(a|s)}[Q(s,a)] \quad \text{s.t.} \quad D(\pi_\phi(a|s), \pi_\beta(a|s)) \leq \varepsilon$$

estimated from data

If the behavior policy is wrongly estimated (e.g, when it does not match the function class), policy constraint methods can fail dramatically (e.g., AntMaze)

Often tend to be too conservative

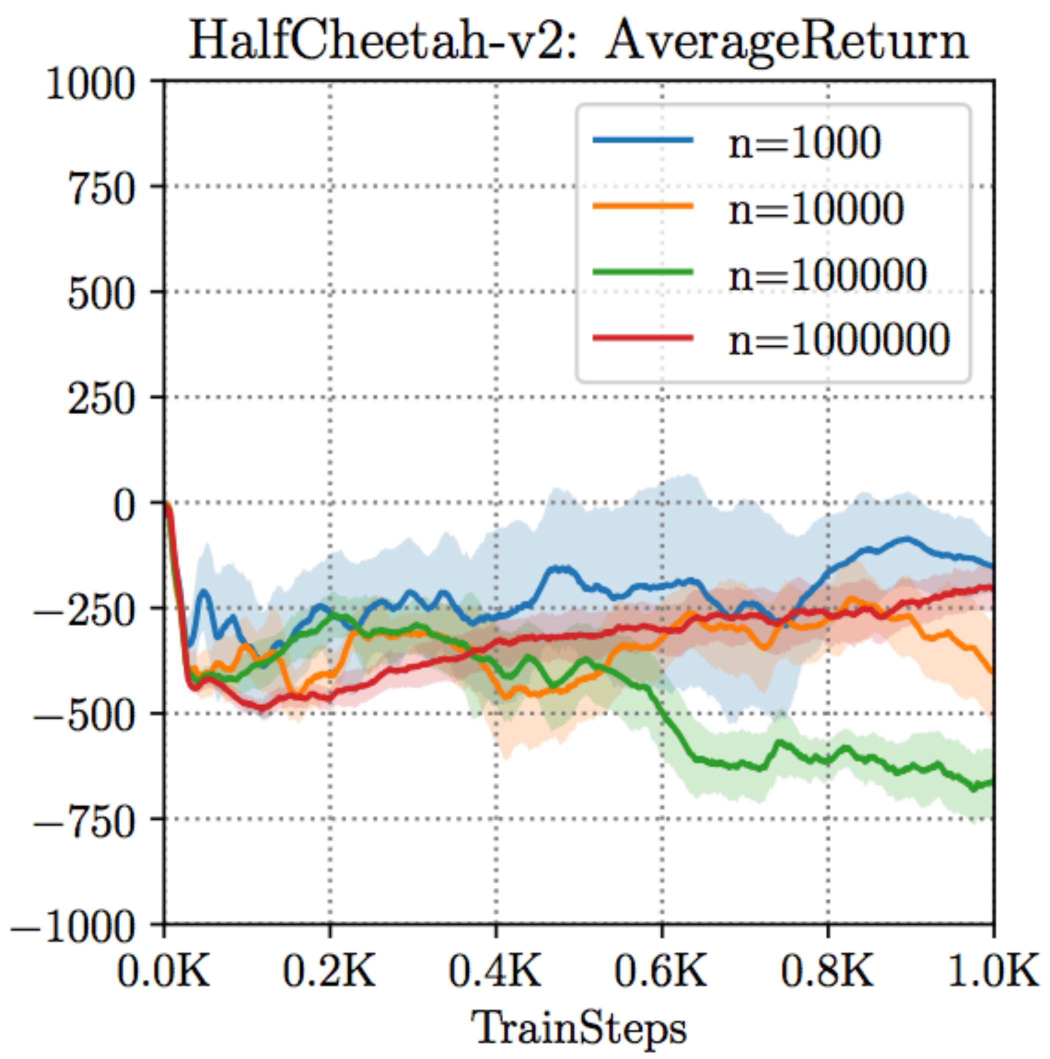
If we know that a certain state has all actions with 0 reward, we do not care about constraining the policy there, since we will not be worse…

Can we do better?

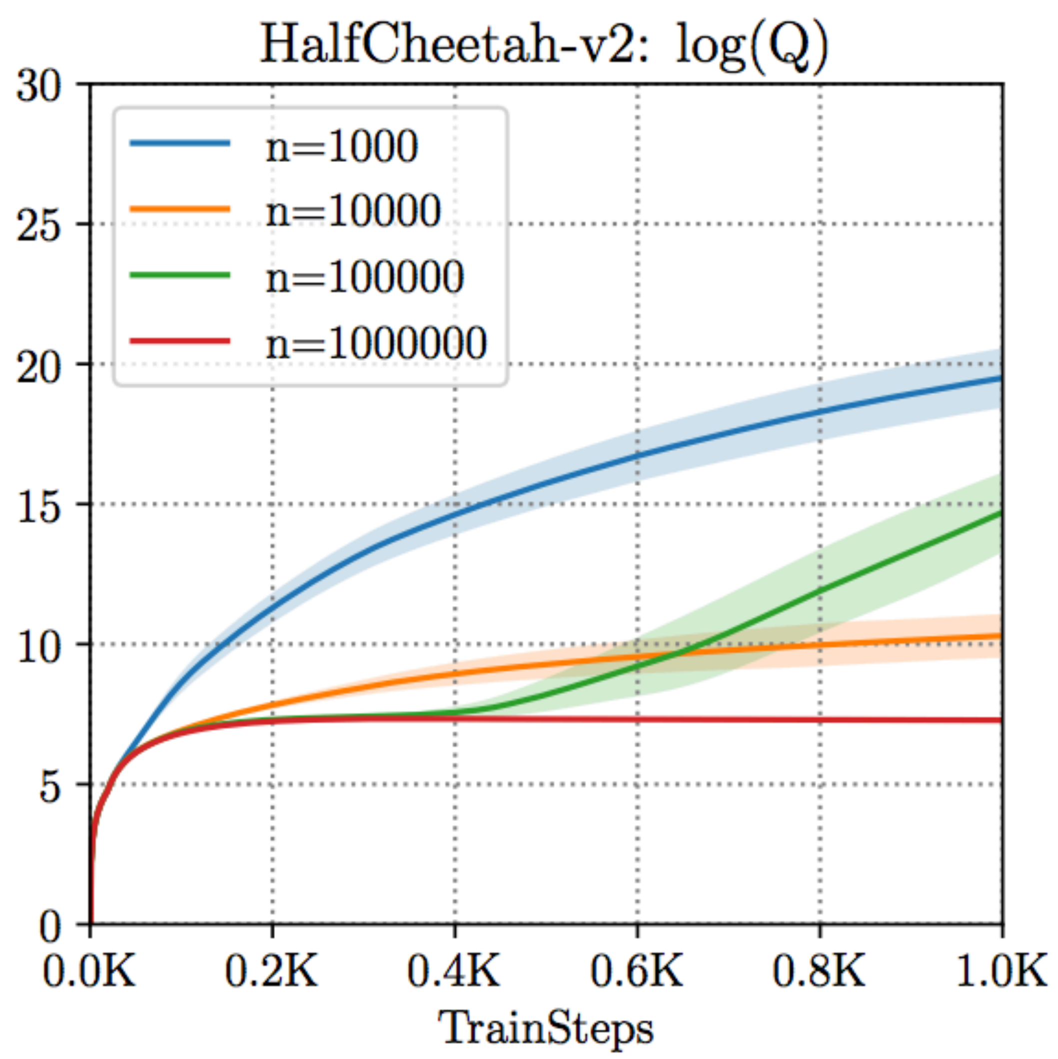
Nair, Dalal, Gupta, Levine. *Accelerating Online RL with Offline Datasets.* arXiv 2020.
Kumar, Zhou, Tucker, Levine. *Conservative Q-Learning for Offline RL.* NeurIPS 2020.
Levine, **Kumar,** Tucker, Fu. *Offline RL Tutorial and Perspectives on Open Problems.* arXiv 2020.
Ghasemipour, Schurrmanns, Gu. *EmaQ: Expected Max Q-Learning.* arXiv 2020.

Let's revisit the motivating example

(and take a slightly different perspective on the problem)



how well it does



how well **it thinks** it does

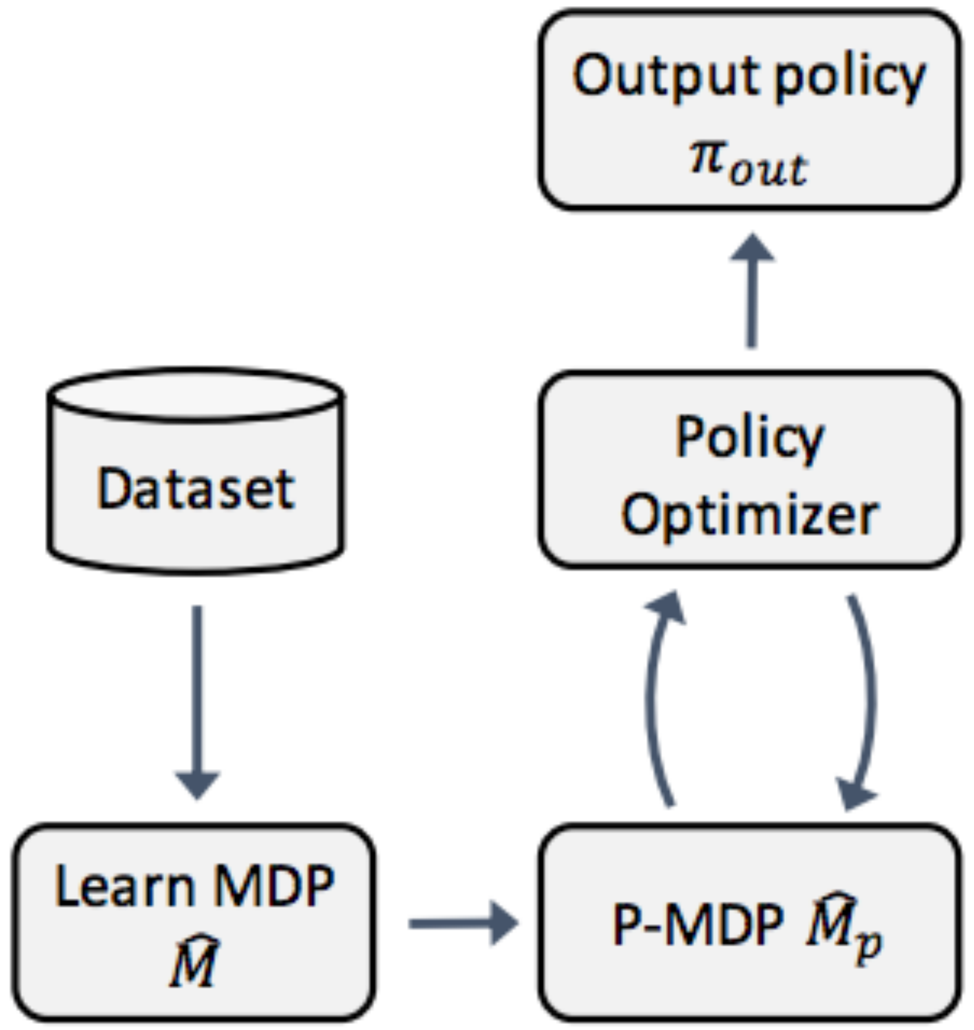
Can we directly tackle false over-estimation, instead of fixes to avoid out-of-distribution actions?

In some cases, not all out-of-distribution actions are bad, they are bad if they affect the policy (i.e. when values are overestimated)

Can we devise methods that learn lower-bounds on the policy value/ performance?

Yes! Two ways: **model-based** and **model-free**

A Framework for Conservative Model-Based RL

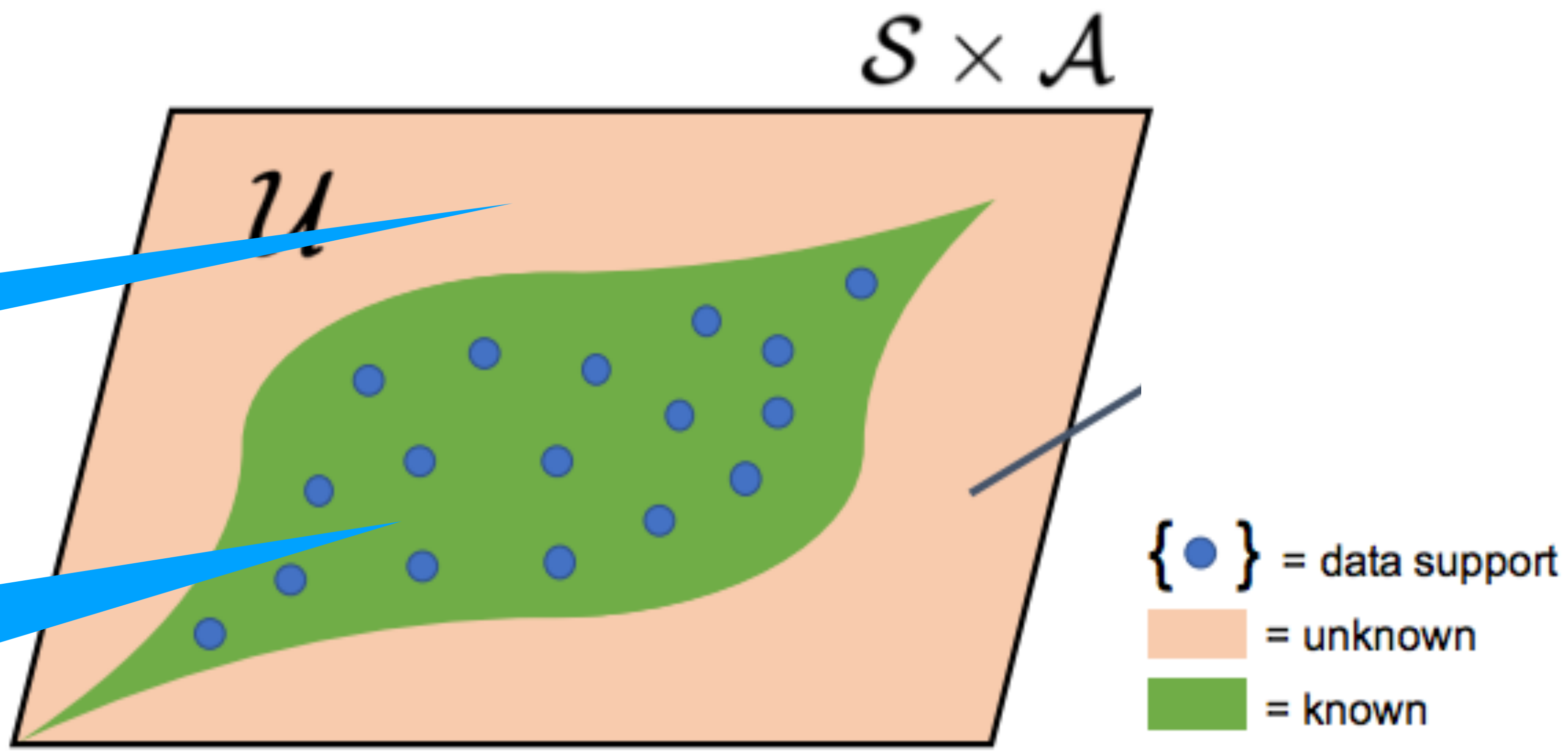


1. Learn a dynamic model P(s'|s, a) from the offline data.
2. Learn a conservative/ "pessimistic" estimate of the reward function.
3. Perform policy optimisation (e.g., via planning or Dyna) with the learned model and the reward function.

This is the new bit!

Make rewards pessimistic

Keep unaltered reward



Janner, Fu, Zhang, Levine. When to Trust Your Model? Model-Based Policy Optimization. NeurIPS 2019.
Yu, Thomas, Yu, Ermon, Zou, Levine, Finn, Ma. MOPO: Model-based Offline Policy Optimization. NeurIPS 2020.
Kidambi, Rajeswaran, Netrapalli, Joachims. MOReL: Model-Based Offline Reinforcement Learning. NeurIPS 2020.

Model-Based Offline RL Methods

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

Covariance matrix of an ensemble of dynamics models

MOPO (Yu et al. 2020)

$$\tilde{r}_j = r_j - \lambda \max_{i=1}^{N} \|\Sigma^i(s_j, a_j)\|_F$$

MBPO (Dyna)

Disagreement in an ensemble of dynamics models

MOReL (Kidambi et al. 2020)

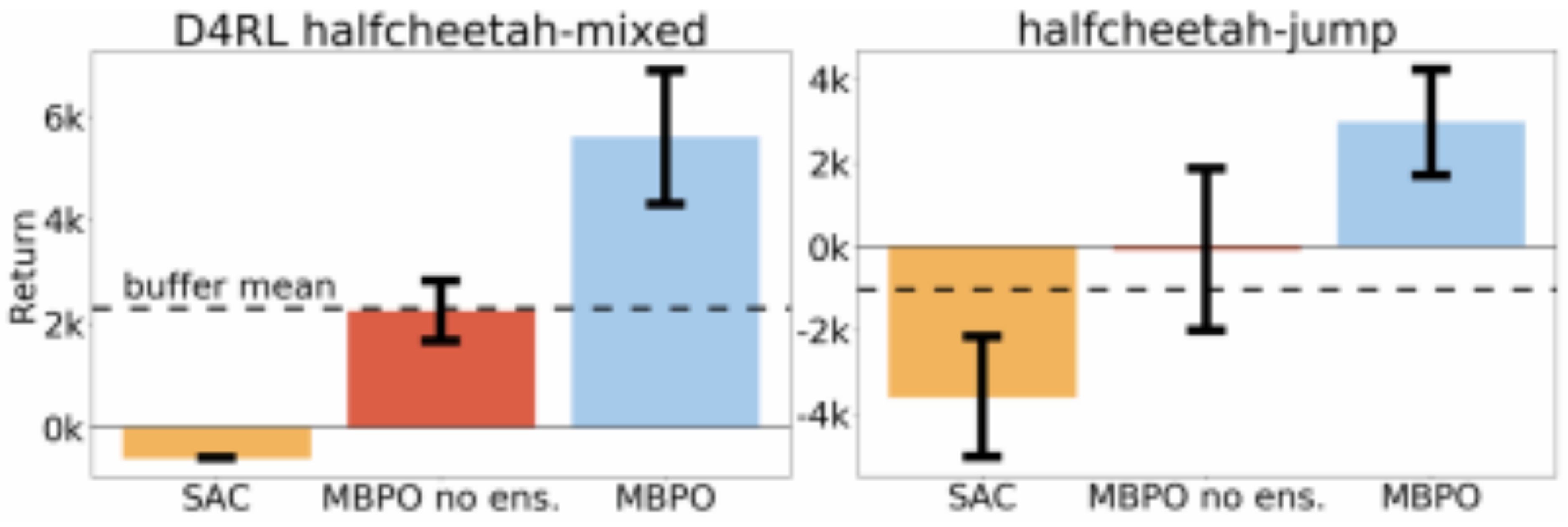
$$\text{disc}(s,a) = \max_{i,j} \left\| f_{\phi_i}(s,a) - f_{\phi_j}(s,a) \right\|_2$$

$$\tilde{r}(s,a) = -R_{\max} \quad \text{if} \;\; \text{disc}(s,a) > \text{threshold}$$

Planning

Yu, Thomas, Yu, Ermon, Zou, Levine, Finn, Ma. MOPO: Model-based Offline Policy Optimization. NeurIPS 2020.
Kidambi, Rajeswaran, Netrapalli, Joachims. MOReL: Model-Based Offline Reinforcement Learning. NeurIPS 2020.

Model-Based Offline RL, Empirically



Model-based methods without any form of correction can work well with “broad” coverage datasets

Conservatism helps in situations with narrow datasets (see MBPO vs MOPO on med-expert)

Dataset type	Environment	BC	MOPO (ours)	MBPO	SAC	BEAR	BRAC-v
random	halfcheetah	2.1	**31.9** ± 2.8	30.7 ± 3.9	30.5	25.5	28.1
random	hopper	1.6	**13.3** ± 1.6	4.5 ± 6.0	11.3	9.5	12.0
random	walker2d	9.8	**13.0** ± 2.6	8.6 ± 8.1	4.1	6.7	0.5
medium	halfcheetah	36.1	40.2 ± 2.7	28.3 ± 22.7	-4.3	38.6	**45.5**
medium	hopper	29.0	26.5 ± 3.7	4.9 ± 3.3	0.8	**47.6**	32.3
medium	walker2d	6.6	14.0 ± 10.1	12.7 ± 7.6	0.9	33.2	**81.3**
mixed	halfcheetah	38.4	**54.0** ± 2.6	47.3 ± 12.6	-2.4	36.2	45.9
mixed	hopper	11.8	**92.5** ± 6.3	49.8 ± 30.4	1.9	10.8	0.9
mixed	walker2d	11.3	**42.7** ± 8.3	22.2 ± 12.7	3.5	25.3	0.8
med-expert	halfcheetah	35.8	**57.9** ± 24.8	9.7 ± 9.5	1.8	51.7	45.3
med-expert	hopper	111.9	51.7 ± 42.9	**56.0** ± 34.5	1.6	4.0	0.8
med-expert	walker2d	6.4	55.0 ± 19.1	7.6 ± 3.7	-0.1	26.0	**66.6**

Better than policy constraint methods generally

Yu, Thomas, Yu, Ermon, Zou, Levine, Finn, Ma. MOPO: Model-based Offline Policy Optimization. NeurIPS 2020.

Learning Lower-Bounded Q-values

Conservative Q-Learning (CQL) Algorithm

Since learned Q-values (our belief of policy values) are overestimated, let's make them provably lower bound the true value

Minimize big Q-values

Standard Bellman Error

$$\hat{Q}^{\pi}_{\text{CQL}} := \min_{Q} \max_{\mu} \mathbb{E}_{a\sim\mu(a|s)}[Q(s,a)] + \frac{1}{2\alpha}\mathbb{E}_{s,a,s'\sim\mathcal{D}}\left[(Q(s,a) - (r(s,a) + \gamma\mathbb{E}_{a\sim\pi_{\phi}(a|s)}[\bar{Q}(s',a')]))^2\right]$$

$$\boxed{\hat{Q}^{\pi}_{\text{CQL}}(s,a) \leq Q(s,a) \quad \forall s \in \mathcal{D}, a}$$

CQL-v1

CQL Algorithm:

1. Learn $\hat{Q}^{\pi}_{\text{CQL}}$ using offline data $\mathcal{D}$.
2. Optimize policy w.r.t. $\hat{Q}^{\pi}_{\text{CQL}}$: $\pi \leftarrow \arg\max_{\pi} \mathbb{E}_{\pi}[\hat{Q}^{\pi}_{\text{CQL}}]$.

Kumar, Zhou, Tucker, Levine. *Conservative Q-Learning for Offline RL.* NeurIPS 2020.

A Tighter Lower Bound

Minimize big Q-values

Maximize Data Q-values

$$\hat{Q}^{\pi}_{\text{CQL}} := \min_{Q} \; {\color{red}\max_{\mu}} \; \mathbb{E}_{a \sim \mu(a|s)}[Q(s,a)] - \mathbb{E}_{a \sim \mathcal{D}(a|s)}[Q(s,a)]$$

$$+ \frac{1}{2\alpha} \mathbb{E}_{s,a,s' \sim \mathcal{D}} \left[(Q(s,a) - (r(s,a) + \gamma \mathbb{E}_{a \sim \pi_{\phi}(a|s)}[\bar{Q}(s',a')]))^2 \right]$$

Standard Bellman Error

$$\hat{Q}^{\pi}_{\text{CQL}}(s,a) \leq Q(s,a) \quad \forall s \in \mathcal{D}, a$$

$$\hat{V}^{\pi}_{\text{CQL}}(s) := \mathbb{E}_{a \sim \pi_k}[\hat{Q}^{\pi}_{\text{CQL}}(s,a)] \leq V^{\pi}(s) \quad \forall \; s \in \mathcal{D}$$

CQL-v2

CQL Algorithm:

1. Learn $\hat{Q}^{\pi}_{\text{CQL}}$ using offline data $\mathcal{D}$.
2. Optimize policy w.r.t. $\hat{Q}^{\pi}_{\text{CQL}}$: $\pi \leftarrow \arg\max_{\pi} \mathbb{E}_{\pi}[\hat{Q}^{\pi}_{\text{CQL}}]$.

Kumar, Zhou, Tucker, Levine. *Conservative Q-Learning for Offline RL.* NeurIPS 2020.

Practical CQL Algorithm

CQL(H)

$$\min_Q \alpha \mathbb{E}_{\mathbf{s}\sim\mathcal{D}}\left[\log \sum_{\mathbf{a}} \exp(Q(\mathbf{s},\mathbf{a})) - \mathbb{E}_{\mathbf{a}\sim\hat{\pi}_\beta(\mathbf{a}|\mathbf{s})}\left[Q(\mathbf{s},\mathbf{a})\right]\right] + \frac{1}{2}\mathbb{E}_{\mathbf{s},\mathbf{a},\mathbf{s}'\sim\mathcal{D}}\left[\left(Q - \hat{\mathcal{B}}^{\pi_k}\hat{Q}^k\right)^2\right].$$

Algorithm 1 Conservative Q-Learning (both variants)

1: Initialize Q-function, Q_θ, and optionally a policy, π_ϕ.
2: **for** step t in $\{1, \dots, \mathrm{N}\}$ **do**
3: Train the Q-function using G_Q gradient steps on objective from Equation 4
$\theta_t := \theta_{t-1} - \eta_Q \nabla_\theta \mathrm{CQL}(\mathcal{R})(\theta)$
(Use $\mathcal{B}^*$ for Q-learning, $\mathcal{B}^{\pi_{\phi_t}}$ for actor-critic)
4: (only with actor-critic) Improve policy π_ϕ via G_π gradient steps on ϕ with SAC-style entropy regularization:
$\phi_t := \phi_{t-1} + \eta_\pi \mathbb{E}_{\mathbf{s}\sim\mathcal{D},\mathbf{a}\sim\pi_\phi(\cdot|\mathbf{s})}[Q_\theta(\mathbf{s},\mathbf{a}) - \log \pi_\phi(\mathbf{a}|\mathbf{s})]$
5: **end for**

Only change on top of standard Deep Q-Learning

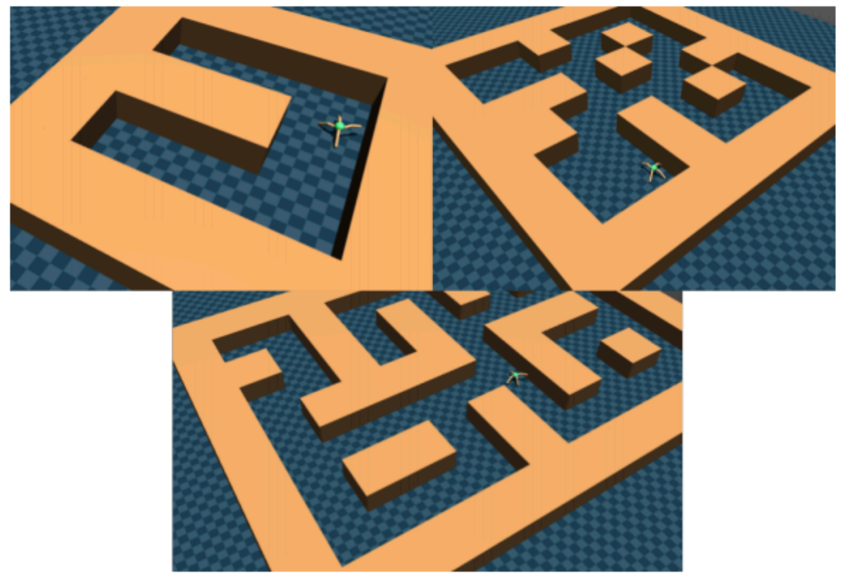
CQL Algorithm:

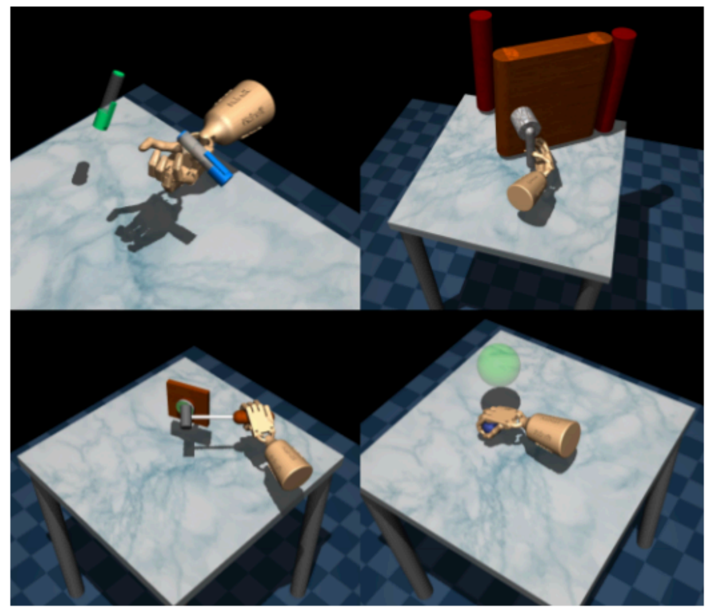
1. Learn $\hat{Q}^\pi_{\mathrm{CQL}}$ using offline data $\mathcal{D}$.
2. Optimize policy w.r.t. $\hat{Q}^\pi_{\mathrm{CQL}}$: $\pi \leftarrow \arg\max_\pi \mathbb{E}_\pi[\hat{Q}^\pi_{\mathrm{CQL}}]$.

$$\min_Q \max_\mu \alpha\left(\mathbb{E}_{\mathbf{s}\sim\mathcal{D},\mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}\left[Q(\mathbf{s},\mathbf{a})\right] - \mathbb{E}_{\mathbf{s}\sim\mathcal{D},\mathbf{a}\sim\hat{\pi}_\beta(\mathbf{a}|\mathbf{s})}\left[Q(\mathbf{s},\mathbf{a})\right]\right) + \frac{1}{2}\mathbb{E}_{\mathbf{s},\mathbf{a},\mathbf{s}'\sim\mathcal{D}}\left[\left(Q(\mathbf{s},\mathbf{a}) - \hat{\mathcal{B}}^{\pi_k}\hat{Q}^k(\mathbf{s},\mathbf{a})\right)^2\right] + \mathcal{R}(\mu) \quad (\mathrm{CQL}(\mathcal{R})).$$

Kumar, Zhou, Tucker, Levine. *Conservative Q-Learning for Offline RL.* NeurIPS 2020.

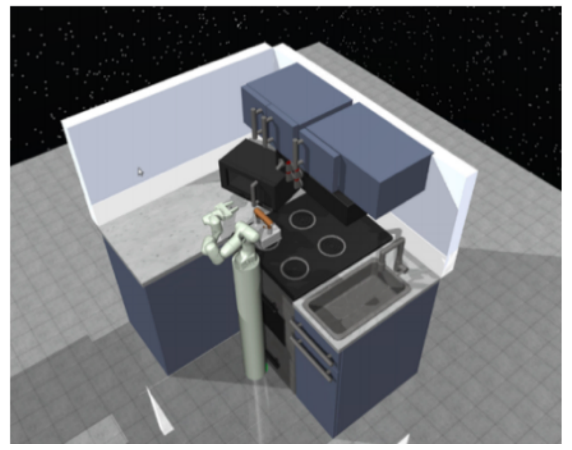
CQL, Empirically





Learned policy value - Actual policy value

Task Name	CQL($\mathcal{H}$)	CQL (Eqn. 1)	Ensemble(2)	Ens.(4)	Ens.(10)	Ens.(20)	BEAR
hopper-medium-expert	**-43.20**	-151.36	3.71e6	2.93e6	0.32e6	24.05e3	65.93
hopper-mixed	**-10.93**	-22.87	15.00e6	59.93e3	8.92e3	2.47e3	1399.46
hopper-medium	**-7.48**	-156.70	26.03e12	437.57e6	1.12e12	885e3	4.32



Behavior cloning

Naive off-policy RL

Policy constraint methods

Domain	Task Name	BC	SAC	BEAR	BRAC-p	BRAC-v	CQL($\mathcal{H}$)	CQL(ρ)
AntMaze	antmaze-umaze	65.0	0.0	**73.0**	50.0	70.0	**74.0**	**73.5**
	antmaze-umaze-diverse	55.0	0.0	61.0	40.0	70.0	**84.0**	61.0
	antmaze-medium-play	0.0	0.0	0.0	0.0	0.0	**61.2**	4.6
	antmaze-medium-diverse	0.0	0.0	8.0	0.0	0.0	**53.7**	5.1
	antmaze-large-play	0.0	0.0	0.0	0.0	0.0	**15.8**	3.2
	antmaze-large-diverse	0.0	0.0	0.0	0.0	0.0	**14.9**	2.3
Adroit	pen-human	34.4	6.3	-1.0	8.1	0.6	37.5	**55.8**
	hammer-human	1.5	0.5	0.3	0.3	0.2	**4.4**	2.1
	door-human	0.5	3.9	-0.3	-0.3	-0.3	**9.9**	**9.1**
	relocate-human	0.0	0.0	-0.3	-0.3	-0.3	0.20	**0.35**
	pen-cloned	**56.9**	23.5	26.5	1.6	-2.5	39.2	40.3
	hammer-cloned	0.8	0.2	0.3	0.3	0.3	2.1	**5.7**
	door-cloned	-0.1	0.0	-0.1	-0.1	-0.1	0.4	**3.5**
	relocate-cloned	**-0.1**	-0.2	-0.3	-0.3	-0.3	**-0.1**	**-0.1**
Kitchen	kitchen-complete	33.8	15.0	0.0	0.0	0.0	**43.8**	31.3
	kitchen-partial	33.8	0.0	13.1	0.0	0.0	**49.8**	**50.1**
	kitchen-undirected	47.5	2.5	47.2	0.0	0.0	**51.0**	**52.4**

"Stitching"

Better than other methods, not the best in each case

Only method to outperform BC

Kumar, Zhou, Tucker, Levine. *Conservative Q-Learning for Offline RL.* NeurIPS 2020.

Offline RL Algorithms covered so far

- **Policy Constraint Methods:**
  - Support constraints
  - Distribution constraints
  - State-marginal constraints

Work well, but are conservative and require behavior policy estimation

- **Learning lower-bounded policy-values:**
  - Model-based algorithms
  - Direct Q-function penalties (CQL)

Generally perform better, since they are less conservative, and do not require behavior policy estimation

---

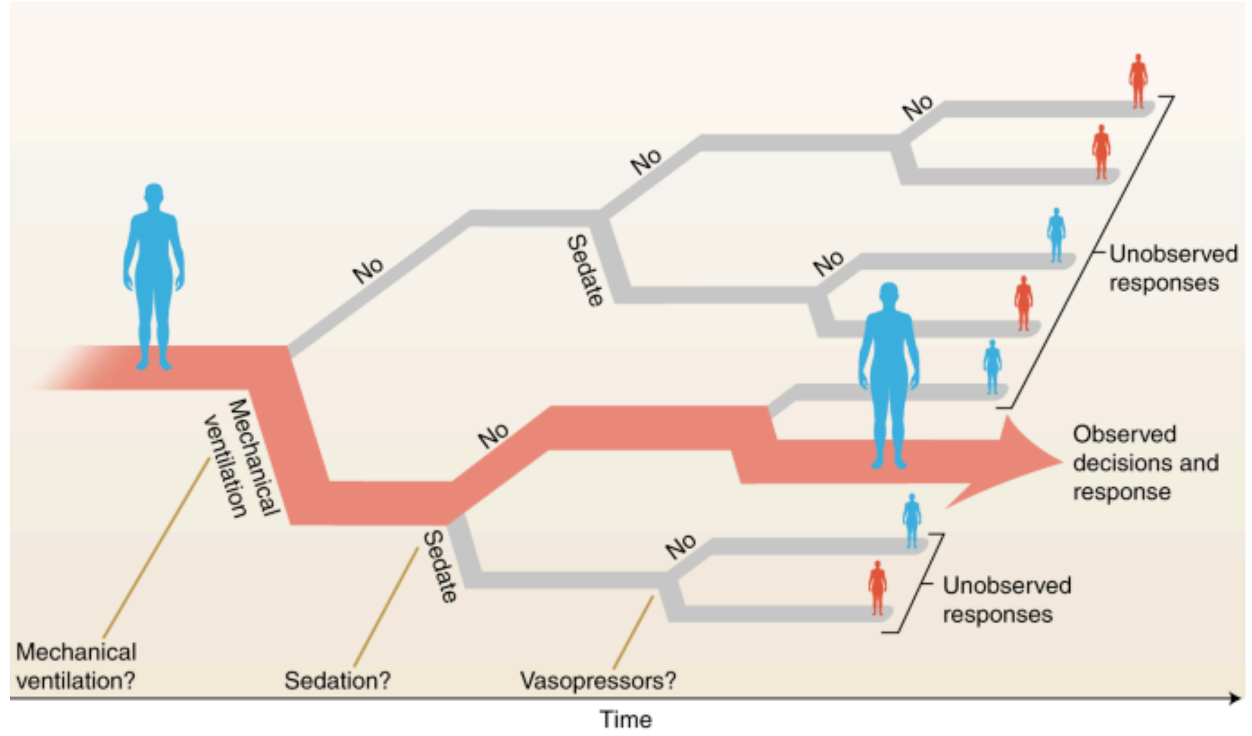
Next, we will cover some related problems, discuss how we should evaluate offline RL methods, and finally, discuss some practical examples.

A Related Problem: Off-Policy Evaluation

Problem Statement: Rather than returning a good policy, find me the value of a **given** policy, **without running this policy in the environment**

$$\pi \longrightarrow V^{\pi}(s)$$
$$\mathcal{D} \nearrow$$

$$V^{\pi_1}(s) > V^{\pi_2}(s)?$$



What can be the use of OPE in offline RL?

Model-selection: selecting which policy is good

Why do we need model-selection in offline RL?

Similar to supervised learning methods, excessive training on the same offline dataset can produce poor solutions. If we can rank these solutions using OPE, we can get good offline performance.

Irpan, Rao, Bousmalis, Harris, Ibarz, Levine. Off-Policy Evaluation via Off-Policy Classification. NeurIPS 2019.
Gottesman, Futoma, Liu, Parbhoo, Celi, Brunskill, Doshi-Velez. Interpretable OPE in RL by Highlighting Influential Transitions. ICML 2020.

A quick glance on some OPE methods

- **Importance Sampling** (similar to off-policy policy gradient)

$$J(\pi_\theta) = \mathbb{E}_{\tau\sim\pi_\beta(\tau)}\left[\frac{\pi_\theta(\tau)}{\pi_\beta(\tau)}\sum_{t=0}^{H}\gamma^t r(\mathbf{s},\mathbf{a})\right]$$

$$= \mathbb{E}_{\tau\sim\pi_\beta(\tau)}\left[\left(\prod_{t=0}^{H}\frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_\beta(\mathbf{a}_t|\mathbf{s}_t)}\right)\sum_{t=0}^{H}\gamma^t r(\mathbf{s},\mathbf{a})\right] \approx \sum_{i=1}^{n} w_H^i \sum_{t=0}^{H}\gamma^t r_t^i,$$

Sum over dataset

High variance

- **Marginalized Importance Sampling**
  (see Nachum et al. 2019 (DualDICE) and Uehera and Jiang, 2019.)

Estimate this ratio

$$J(\pi_\theta) = \mathbb{E}_{s,a\sim d^\pi(s.a)}\left[r(s,a)\right] = \mathbb{E}_{s,a\sim\mathcal{D}}\left[\frac{d^\pi(s,a)}{\mathcal{D}(s)\mathcal{D}(a|s)}r(s,a)\right]$$

- **Fitted Q-Evaluation**

$$Q^\pi(s,a) = r(s,a) + \gamma\mathbb{E}_{a'\sim\pi(a'|s')}[Q^\pi(s',a')]$$

A lot of prior work on this! OPE has turned out to be quite challenging with deep network policies.

How should we evaluate offline RL methods?

Let's revisit the main motivation for offline RL

Use real-data collected from various different sources (e.g., human demonstrations, runs of hardcoded policies, etc.) for training good policies

Can train directly on real data, but how do we test the policy?

Since testing a policy completely offline is hard (unless we actually run the policy on the real-domain), we would want benchmarks!

What properties should a benchmark for offline RL have?

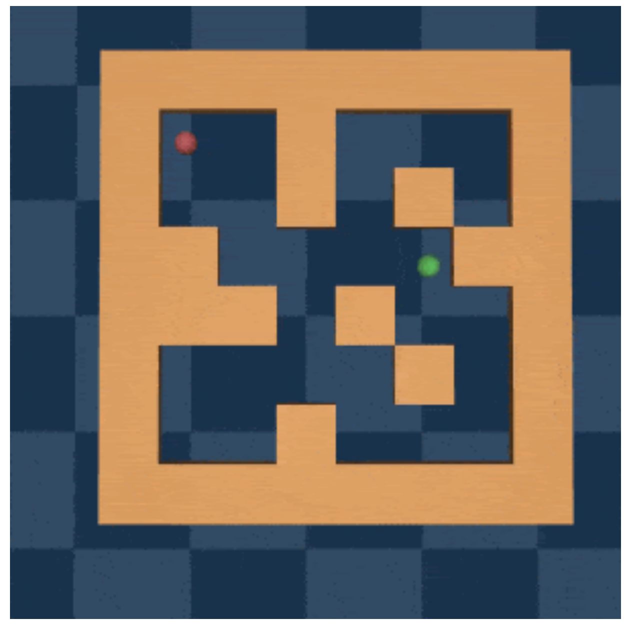
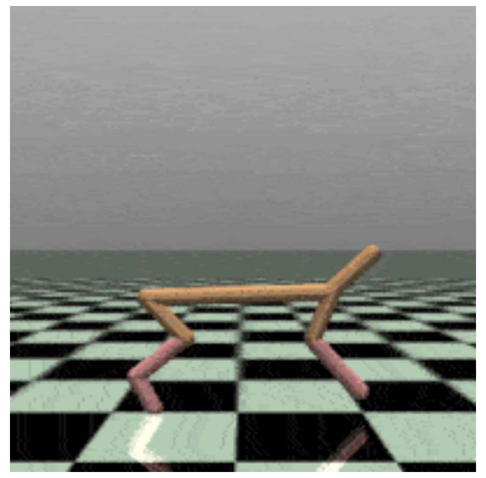
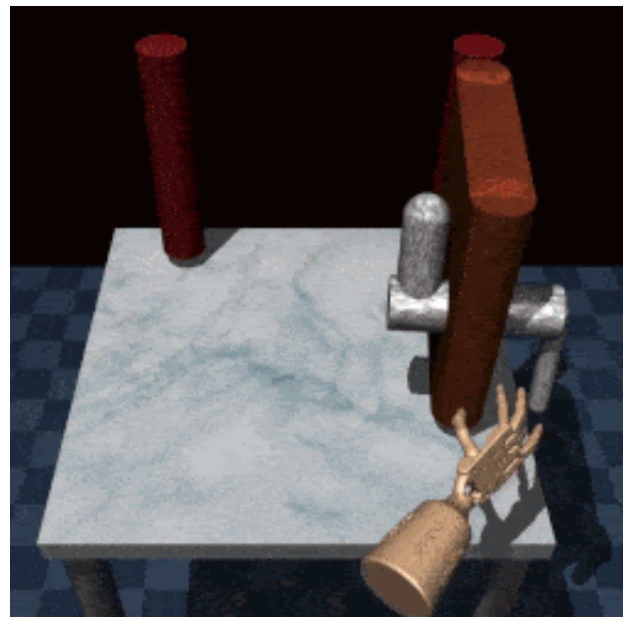
1. It should be realistic: should mimic what we would see in the real-world

2. Should provide a method to compare methods in a standardized way, under the actual evaluation scheme

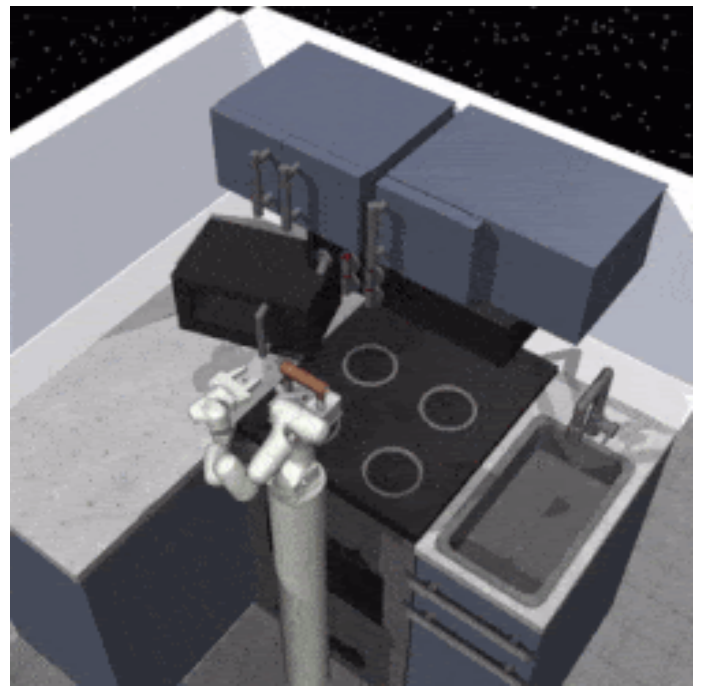
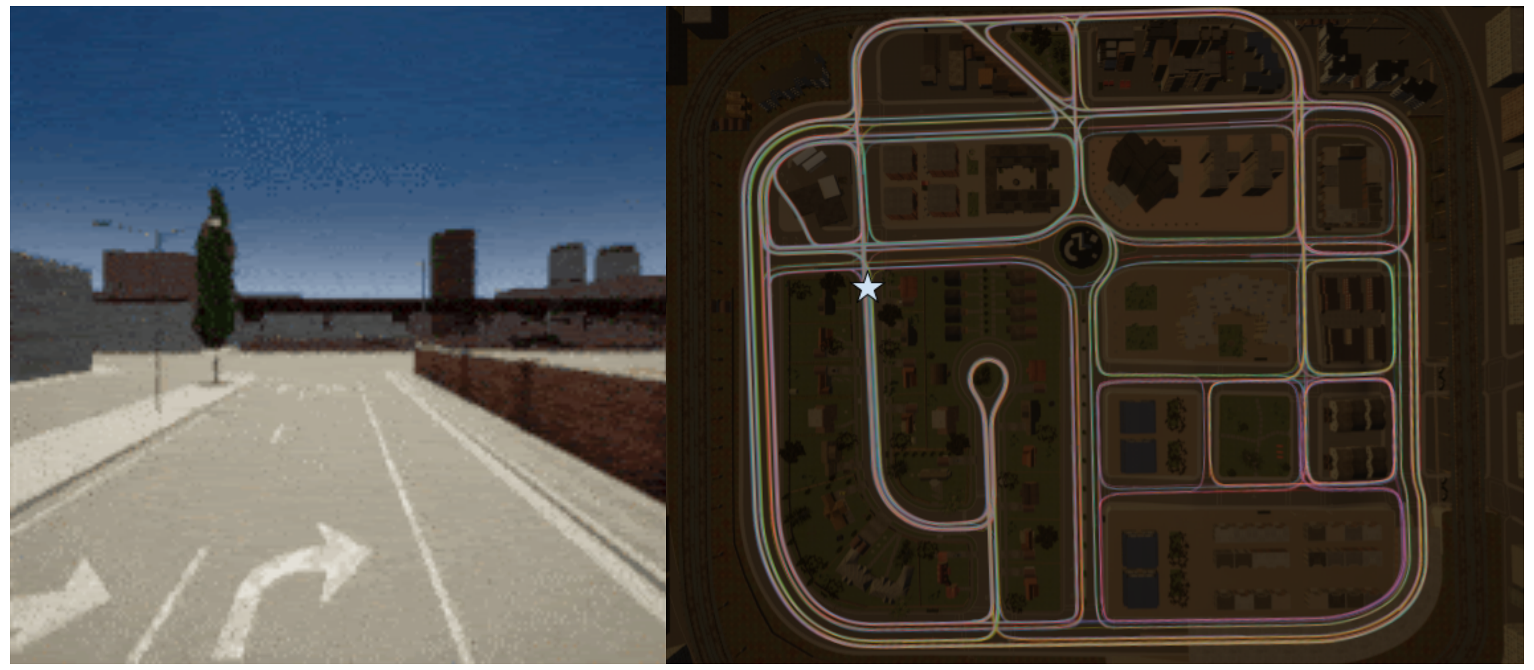
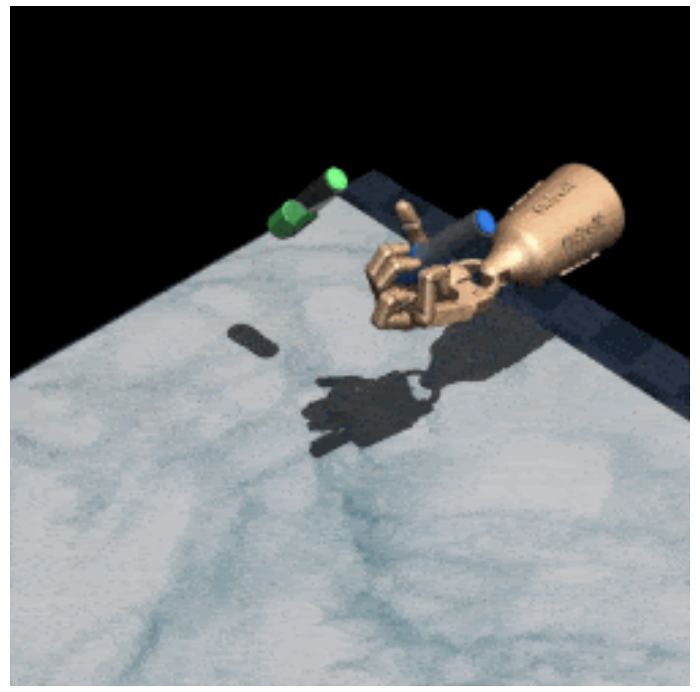
Standardized Benchmark for Offline RL

Most evaluation so far has used RL policies or replay buffers, which tend to be substantially easier and different from “real-world” scenarios

D4RL benchmark

Properties: **(1)** non-representable behavior policies **(2)** narrow distributions **(3)** undirected/multi-task behavior **(4)** visual perception **(5)** human demos.

Fu, **Kumar,** Nachum, Tucker, Levine. *D4RL: Datasets for Deep Data-Driven RL.* arXiv 2020.

Does Offline RL Work in Practice?

Offline RL for Dialog

Can we learn effective dialog policies that understand the implicit human preferences in dialog via offline RL?

[User]: hey, what's up?
[Batch Q]: where did you get??, that sounds so exciting. how do you work for you... you want to talk to me?... you want
[User]: yes, i want to talk to you!
[Batch Q]: where did you say to me?... you want to talk to you about you... you are so good for you... you are so good...
[User]: thanks, i appreciate that.
[Batch Q]: where did you get??, that sounds so exciting. how do you work for you... you want to see you...

[User]: hey, what's up?
[KL-control]: i'm not sure, but i'm glad to see you, and i'm so happy that you're not alone
[User]: oh thanks, that's very nice of you!
[KL-control]: i'm sorry, but i'm glad to see what you think.
[User]: don't be sorry, you did a good job.
[KL-control]: that's really nice to me.

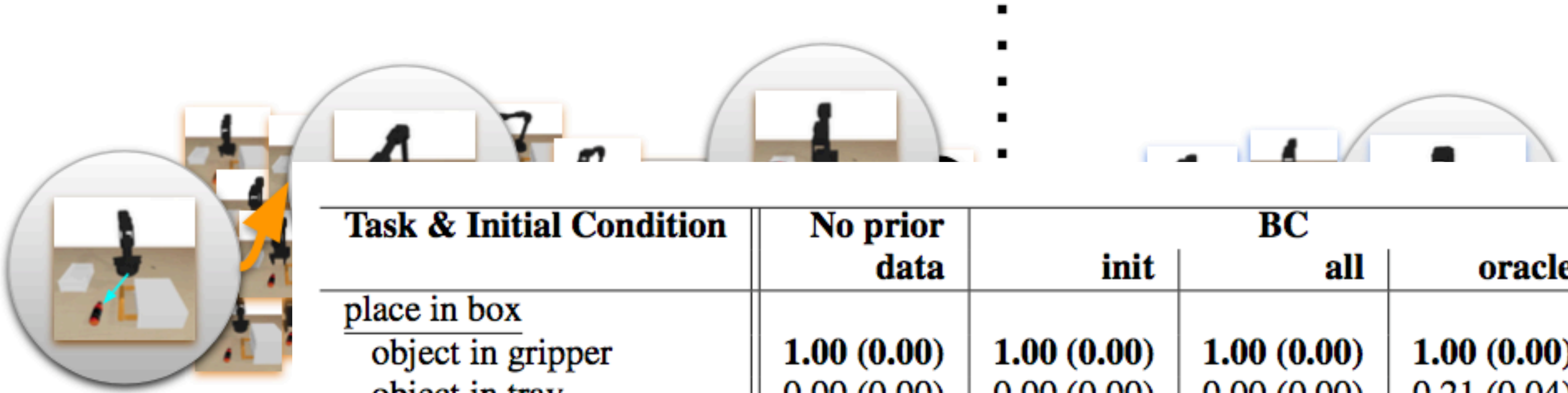
Reward function	**Quality**	**Fluent**	**Diverse**	**Related**	**Empathy**	**Total**	**Votes**	**Human reward**
Conv. len.	2.20 ±.40	3.61 ±.53	3.02 ±.52	2.25 ±.46	2.48 ±.45	13.57 ±1.84	-.035	-.003
Semantic sim.	1.93 ±.34	3.50 ±.45	2.37 ±.45	2.11 ±.45	2.52 ±.48	12.43 ±1.75	-.020	.012
User laughter	1.96 ±.38	3.56 ±.48	2.33 ±.51	1.93 ±.42	3.20 ±.55	12.98 ±1.60	-.149	-.003
Words elicited	2.11 ±.32	3.96 ±.44	3.04 ±.45	2.04 ±.35	2.55 ±.46	13.70 ±1.44	.059	.024
Manual votes	2.14 ±.38	3.47 ±.45	2.91 ±.47	2.07 ±.39	2.42 ±.46	13.00 ±1.65	-.030	.010
Sent. trans.	2.02 ±.31	3.71 ±.49	2.98 ±.50	2.04 ±.42	2.84 ±.48	13.60 ±1.63	.031	.014
Question	2.29 ±.37	**4.31 ±.50**	**3.31 ±.52**	2.20 ±.40	2.60 ±.41	14.71 ±1.63	.057	.012
Sentiment	**2.47 ±.32**	4.05 ±.45	3.23 ±.46	**2.42 ±.39**	**3.23 ±.55**	**15.40 ±1.49**	**.085**	**.045**

Jaques et al. Way Off-Policy Batch Deep RL of Implicit Human Preferences in Dialog. EMNLP 2020.

Offline RL from Unlabelled Robotic Data

Can we learn effective policies from *unlabelled/general-purpose* robotic data generated from hardcoded policies via offline RL methods such as CQL?

Input: Datasets $\mathcal{D}_{\text{prior}}$ (with no reward annotations), $\mathcal{D}_{\mathbb{T}}$ (with sparse rewards for task $\mathbb{T}$).
Return: Policy π trained to execute task $\mathbb{T}$, which should be able to generalize broadly to new initial conditions. We would like to leverage $\mathcal{D}_{\text{prior}}$ for the latter.



Task & Initial Condition	No prior data	BC init	BC all	BC oracle	SAC	Ours
place in box						
object in gripper	**1.00 (0.00)**	**1.00 (0.00)**	**1.00 (0.00)**	**1.00 (0.00)**	0.00	**1.00 (0.00)**
object in tray	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.21 (0.04)	–	**0.87 (0.03)**
grasp from drawer						
open drawer	0.82 (0.11)	**0.93 (0.02)**	0.74 (0.03)	0.78 (0.01)	0.0	0.84 (0.07)
closed drawer	0.00 (0.00)	0.79 (0.02)	0.74 (0.03)	0.77 (0.01)	–	**0.84 (0.03)**
blocked drawer 1	0.00 (0.00)	0.00 (0.00)	0.42 (0.00)	0.65 (0.05)	–	**0.86 (0.02)**
blocked drawer 2	0.00 (0.00)	0.00 (0.00)	0.36 (0.01)	0.32 (0.18)	–	**0.73 (0.08)**

Singh, Yu, Yang, Zhang, **Kumar**, Levine. Chaining Behaviors via Model-Free Offline RL. CoRL 2020.

Suggested Readings

- **Summary/ Tutorial:** Levine, Kumar, Tucker, Fu (2020). Offline Reinforcement Learning: Tutorial, Survey and Perspectives on Open Problems.

- **Datasets/Benchmarks:**
  - Fu, Kumar, Nachum, Tucker, Levine (2020). D4RL: Datasets for Deep Data-Driven RL.
  - Gulcehre et al. (2020). RL Unplugged: Benchmarks for Offline RL.

- **Algorithms:**
  - **Classic algorithms and policy constraints:** see tutorial (Levine et al. 2020) and references on prior slides (a lot of work has been done in this area).
  - **Conservative Q-Learning Algorithms:** Kumar, Zhou, Tucker, Levine (2020). Conservative Q-Learning for Offline RL.
  - **Model-based algorithms**:
    - Yu et al. (2020). MOPO: Model-based Offline Policy Optimization.
    - Kidambi et al. (2020). MOReL: Model-based Offline Reinforcement Learning.
  - **Offline RL on Atari:** Agarwal et al. (2020). An Optimistic Perspective on Offline RL.
  - Several new papers on arXiv and OpenReview, check them out!

- **Blog Posts (Summaries):**
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