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Offline Reinforcement Learning

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Foreword

- Introduction into the offline RL topic
- Focus on the intuition on the problem and existing solutions
  - Some details on a few approaches
- Many references to 2020 NeurIPS tutorial on Offline RL by Levine and Kumar
  - Highly useful resource for more details on the methods mentioned here

Success in Machine Learning

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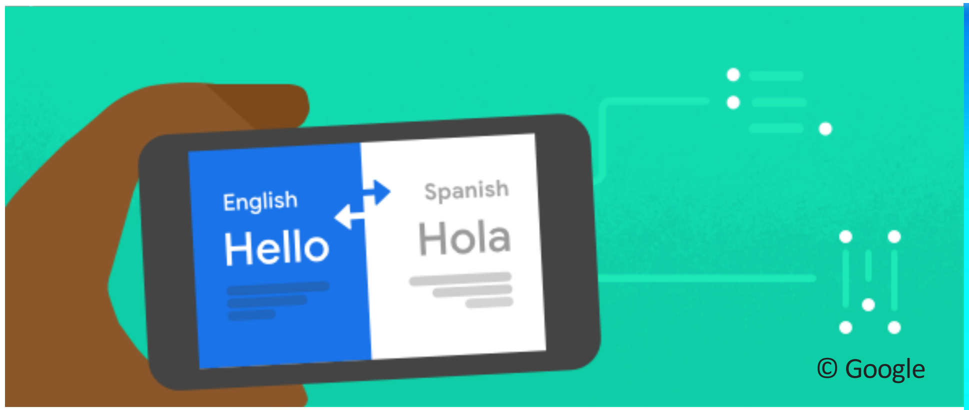
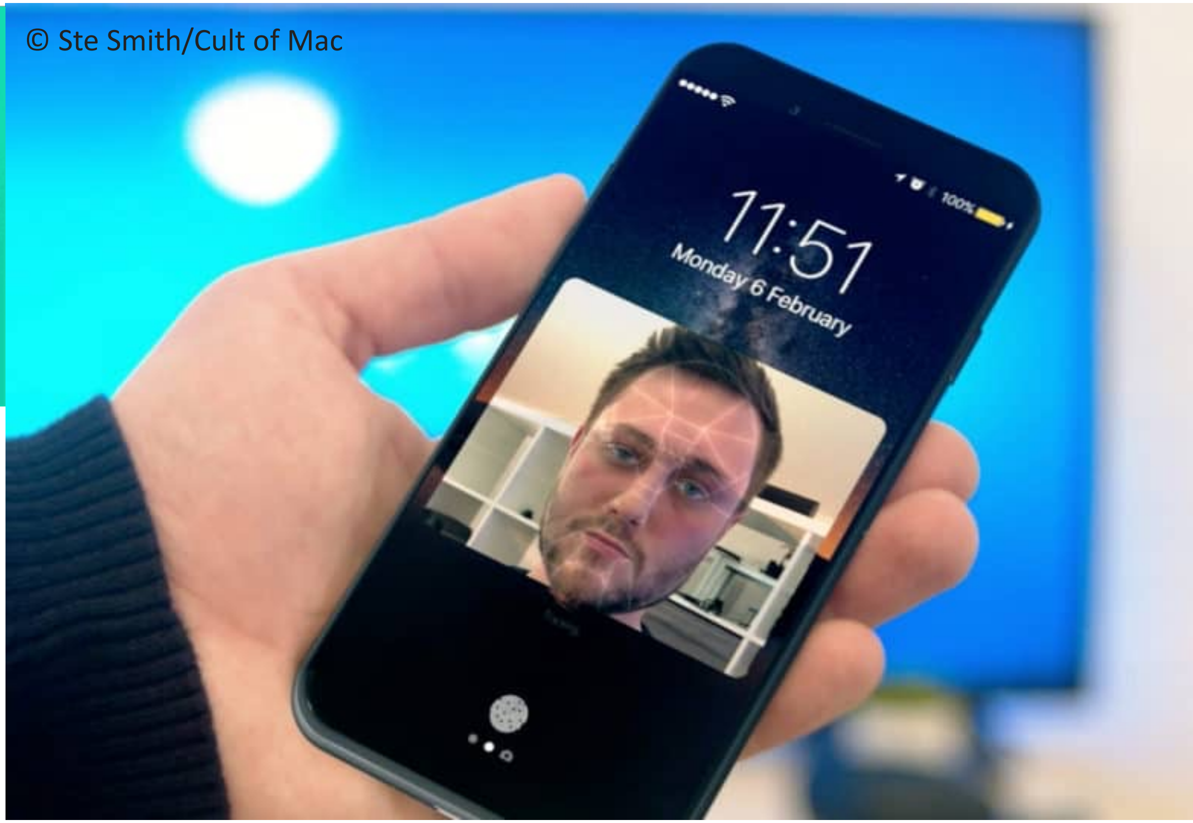
Universität Düsseldorf





Huge models that generalize well, trained with huge amount of data

Success in Machine Learning

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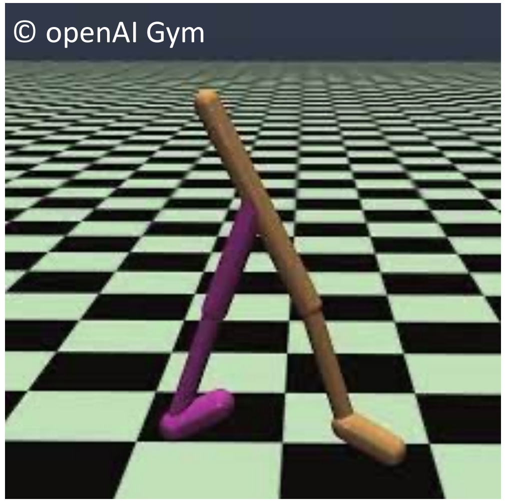
Supervised learning...

- Large amounts of data
- Deep NNs
- Generalizes to open world settings

In contrast, reinforcement learning...

- Learning through interactions
- Learn on specific tasks and small domains
- Lacking in terms of generalization



I'm looking for a hotel in the south

What price range do you want?

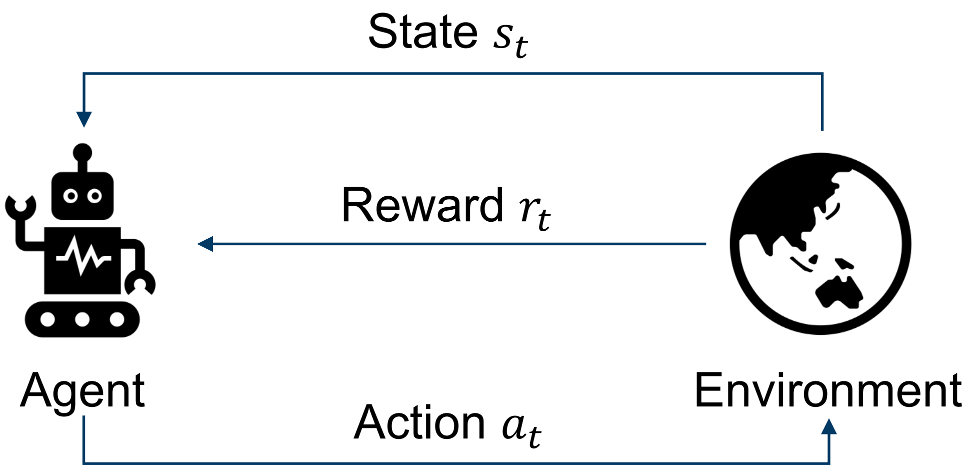
The Need for Data-driven RL

- Some environments are high-risk
  - Factory monitoring, self-driving cars, ..
- Some behavior we want to learn are highly complex
  - Medical field, education, ...
- Learning from online interaction can be expensive and time consuming
  - Dialogue systems
- Simulators?
  - Has its own challenges and limitations
  - Unnecessary in other learning paradigms

Can we leverage offline data to learn a policy?

RL Primer

RL Primer: Notations



- Through interactions with the environment, the agent try to find the best policy based on some measure of reward.
- Huge amount of interactions are needed

Trajectory τ
Sequence of state, action, reward tuples from a sequence of time steps (we assume a finite horizon case)

Return R_t
Discounted cumulative reward

$$R_t = \sum_{n \geq t} \gamma^{n-t} r_n$$

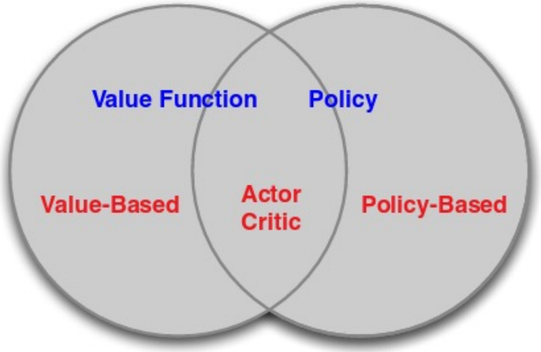
Policy $\pi(a|s)$
Probability distribution over actions in a given state

Value functions

- $V^{\pi}(s)$ expected return of being in state s and following policy π afterwards
- $Q^{\pi}(s, a)$ expected return of being in state s, taking action a, and following policy π afterwards

RL Primer: Learning Methods

- **Value-based**: Learn the optimal Q-function Q^* and act greedily
  - Starting with an arbitrary value function $Q(s,a)$, update at each time step to enforce the Bellman equation
    - $Q(s,a) = r(s,a) + \gamma \mathbb{E}_{a' \sim \pi(a'|s')} Q(s',a')$
  - For example with temporal difference (TD) target
  - Policy is defined implicitly
    - $\pi(s) = argmax_{a'}\, Q^*(s,a')$



- **Policy-based**: Directly parametrise the policy $\pi_\theta(a|s)$ using θ
  - For instance using a neural that outputs a softmax over possible actions given a state
  - REINFORCE (Williams, 1992): Update paramater to encourage actions that maximize return
    - $\nabla_\theta J(\theta) = \mathbb{E}_\theta[\sum_{t=0}^{T} R_t \nabla_\theta \log p_\theta(a_t|s_t)]$
- **Actor-Critic**: Learn both an actor $\pi_\theta(a|s)$ and a critic $\mathrm{Q}_\psi(s,a)$
  - Critic tries to approximate $Q^\pi(s,a)$
  - Improves on policy-based methods by trying to reduce variance

Slide adapted from Chris' talk on RL in 2020

RL Primer: Set Ups

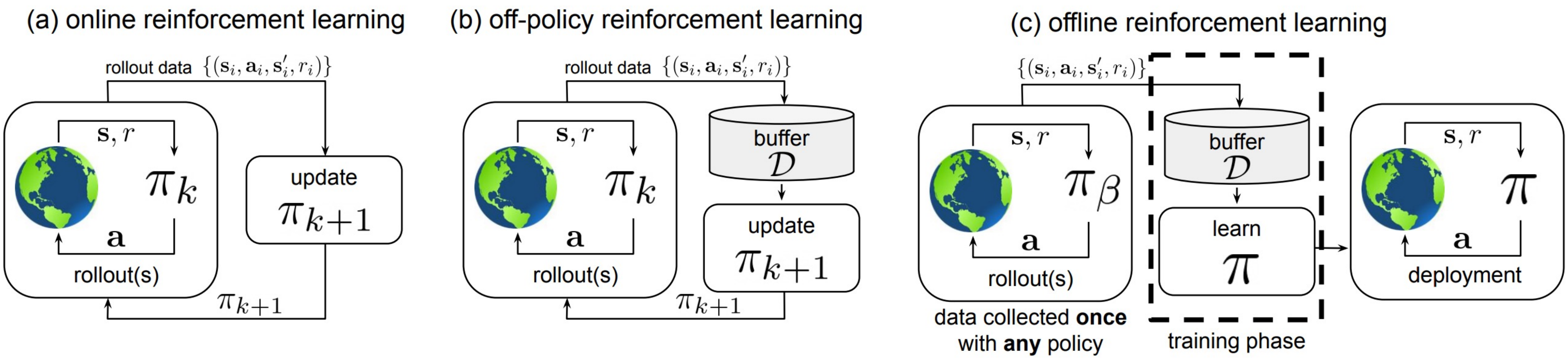


Figure from (Levine et al., 2020)

What makes offline RL challenging?

- Counterfactual decision making
  - Taking a different action than shown in data
  - A necessity in offline RL
- Distributional shift
  - State distribution
    - π has different state distribution than π_β
    - Even though we get high value on data, policy still could be bad during deployment
  - Sampling and estimation error
    - Erroneous estimates for unseen state and action pairs are not corrected
    - Exacerbated by choosing action to maximize the value function

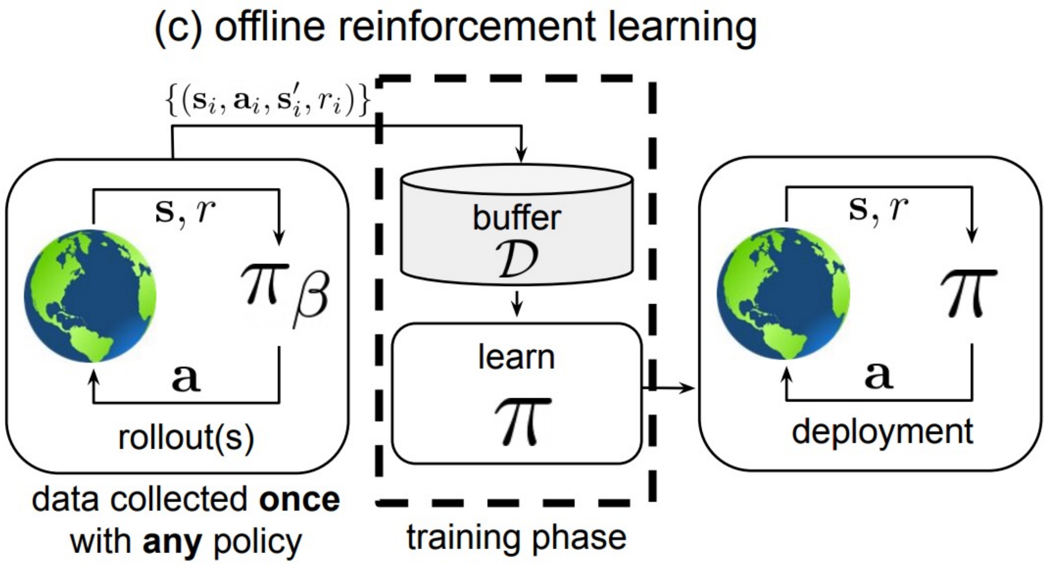


Figure from (Levine et al., 2020)

Offline RL methods

- Importance sampling
- Policy constraints
- Value regularization
- Model-based methods
- Uncertainty based methods
- ...

Importance sampling

Off-policy evaluation for offline RL

How can we estimate the return of our current policy, given trajectories from another policy?

- **Importance sampling** (Rubinstein, 1981) can be used to derive and unbiased estimator of $J(\pi)$ based on trajectories sampled from the behavior policy (Precup, 2000)
  - $J(\pi_\theta) = \mathbb{E}_{\tau \sim \pi_\beta(\tau)}\left[\frac{\pi_\theta(\tau)}{\pi_\beta(\tau)} \sum_{t=0}^{T} \gamma^t r(s_t, a_t)\right]$
  - $\frac{\pi_\theta(\tau)}{\pi_\beta(\tau)} = \prod_{t=0}^{T} \frac{\pi_\theta(a_t|s_t)}{\pi_\beta(a_t|s_t)}$
- Drawbacks: very high variance and potentially unbounded

Off-policy evaluation for offline RL

How can we estimate the return of our current policy, given trajectories from another policy?

- Some solutions to reduce variance (in tradeoff with some bias) (Precup, 2000)
  - Self-normalizing: divide with the sum of weights
  - Per-decision importance sampling estimator: drop the weights from future time steps
- We can also use an estimate of the value $\hat{Q}(s_t, a_t)$ in place of the reward (Jiang and Li, 2015; Thomas and Brunskill 2016)
  - Reduces variance while keeping the estimate unbiased if π_β is known or $\hat{Q}(s_t, a_t)$ is correct

Off-policy evaluation for offline RL

Can we use this to estimate a policy gradient, and use that for policy update?

- Importance sampling can also be used to directly estimate policy *gradients* using trajectories from π_β
  - REINFORCE:

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_{\tau\sim\pi_\beta(\tau)}\left[\frac{\pi_\theta(\tau)}{\pi_\beta(\tau)}\sum_{t=0}^{T}\gamma^t\nabla_\theta\log\pi_\theta(a_t|s_t)\,r(s_t,a_t)\right]$$

- The objective can also be derived for per-decision importance weight (Precup, 2000), or with value estimate instead of the return (Gu et al., 2017; Cheng et al., 2019; ...)

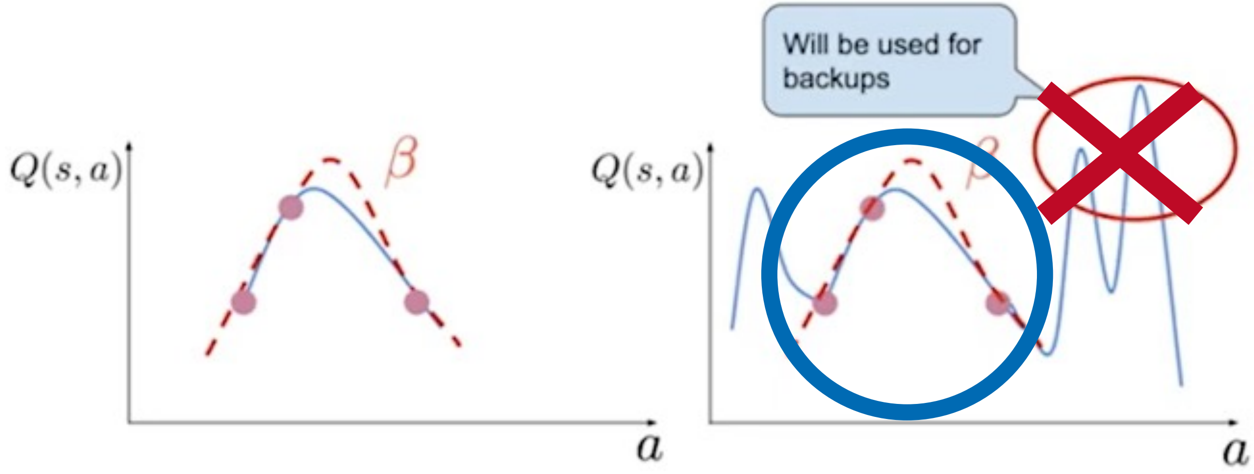
Challenges and open problems

- Typically used in off-policy setting, where we assume that we can collect additional data from interaction
- Application in offline RL has been limited
  - In practice, the variance is too high to work well in problems of interest
  - In sequential problems (with long horizon), exponential blowup could happen
- If π_β is too far from π_θ, the weights quickly become degenerate

Constraint methods

Policy constraints

- Constraining the action distribution of $\pi(a|s)$ to match the density of $\pi_\beta(a|s)$
  - Make sure that the actions taken by the learned policy is close enough to the action density of the behavior policy
  - $D\left(\pi(a|s), \pi_\beta(a|s)\right) \leq \epsilon$

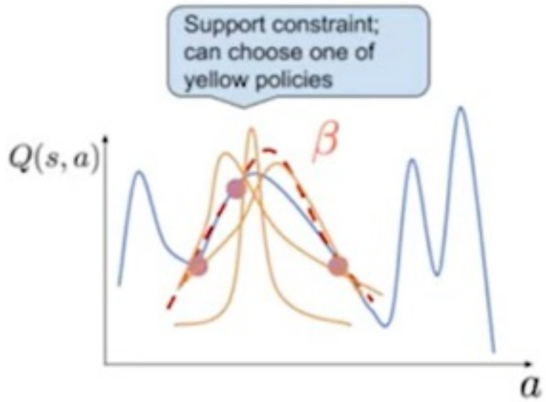


- Constraints can be solved explicitly
  - KL-Divergence (Jacques et al., 2019; Wu et al., 2019a)
  - F-Divergence (Wu et al., 2019b)
- Or implicitly
  - Add distance minimization into the objective, and express in closed form (Pang et al., 2019; Seigel et al., 2019; Wang et al., 2020; Nair et al. 2020)

Figures from NeurIPS 2020 tutorial on Offline RL

Support constraints

- Consider only actions that are within the support of the behavior policy π_β
  - Support: a set of action that are likely under the behavior policy
- Instead of matching the density of $\pi_\beta(a|s)$ as in policy constraints, here we compare the samples
  - Results in a more spiked density

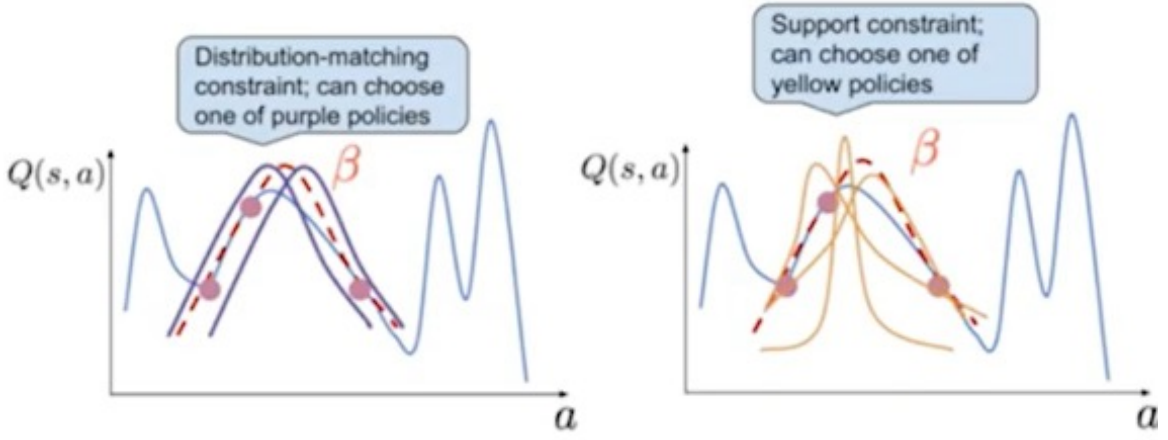


  - $argmax_{a \in \mathcal{D}[s]} Q(s,a)$ (Fujimoto et al., 2019; Ghasemipour et al., 2020; ...)

Figures from NeurIPS 2020 tutorial on Offline RL

Which one works better?

- *In theory*, support constraints
  - Can choose actions deterministically
  - More flexibility in choosing a policy
- With distribution matching, we always match the distribution even in suboptimal cases
  - May be too conservative



- Support constraints can outperform behavior cloning, but do not work well yet in more complex environments (Fu et al., 2020; Wu et al., 2020)
  - One major shortcoming is the need to estimate behavior policy π_β
  - If π_β is wrongly estimated, the learned policy will fail
    - as is the case in more complex environments

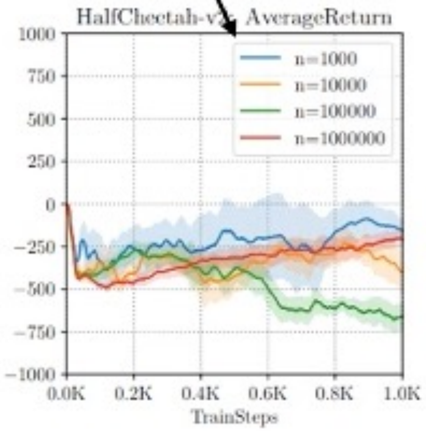
Figures from NeurIPS 2020 tutorial on Offline RL

Value regularization methods

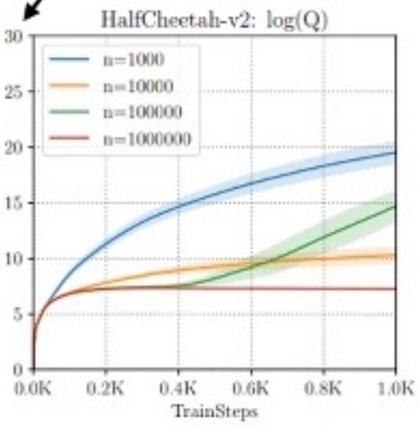
Overconfidence in Q-value estimation

amount of data

log scale (massive overestimation)



how well it does

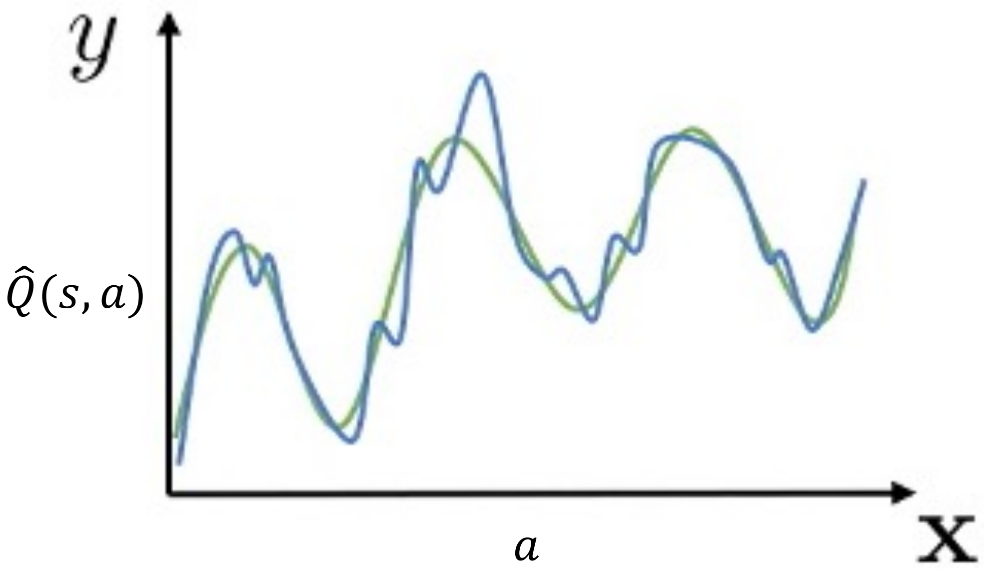


how well it *thinks* it does (Q-values)

- Huge discrepancy between its estimation and real return
  - Not something that larger amount of data can fix
- Value estimation on OOD actions can be unpredictable
- We expect good estimation when $\pi_\beta(a|s) = \pi(a|s)$
  - However, that is rarely the case, and may even be an *undesirable* case.

Figures from Kumar et al. (2019)

Overconfidence in Q-value estimation



Figures from NeurIPS 2020 tutorial on Offline RL

- Huge discrepancy between its estimation and real return
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- Value estimation on OOD actions can be unpredictable
- We expect good estimation when $\pi_\beta(a|s) = \pi(a|s)$
  - However, that is rarely the case, and may even be an *undesirable* case.
  - Even worse, by choosing an action that maximizes the Q-value, we essentially choose actions where the estimate is most overconfident

Pessimistic value functions

Learning a conservative Q-function to act as a lowerbound of the true value

- Avoid overestimation, especially on OOD state-action pairs, where the estimation could be erroneously high

- We can add penalty to the value function based on the distance between the policies
  - $Q(s,a) \leftarrow r(s,a) + \gamma \mathbb{E}_{a' \sim \pi(a'|s')} Q(s',a') - \alpha D(\pi_\theta, \pi_\beta)$
  - For example, with KL-control (Jacques et al., 2018) or BRAC-v (Wu et al., 2019)
  - Drawback: still needs to estimate π_β

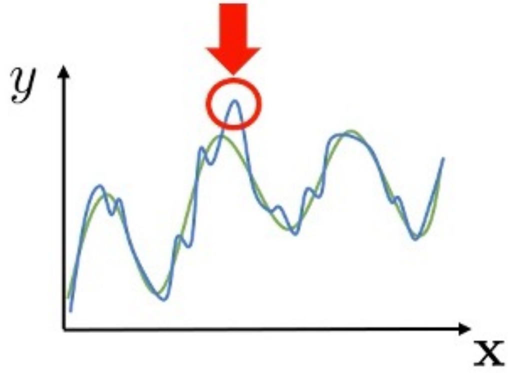
Conservative Q-learning

- We can regularize the objective directly to make this behavior inherent (Kumar et al., 2020)
  - Big Q-values for actions that are likely under the current policy is minimized
  - Q-values for state action pairs in the data will still be pushed up by the TD error
  - Shown to learn a lowerbound of Q-values on state action pairs contained in the data

$$\min_{Q}\max_{\mu} \overbrace{\mathbb{E}_{\mathbf{s}\sim\mathcal{D}}\mathbb{E}_{\mathbf{a}\sim\mu(\mathbf{a}|\mathbf{s})}\left[Q(\mathbf{s},\mathbf{a})\right]}^{\text{Minimize the “big” Q-values}} + \frac{1}{2\alpha}\overbrace{\mathbb{E}_{\mathbf{s},\mathbf{a},\mathbf{s}'\sim\mathcal{D}}\left[\left(Q(\mathbf{s},\mathbf{a}) - y(\mathbf{s},\mathbf{a})\right)^2\right]}^{\text{Standard TD error objective}}$$

$$y(\mathbf{s},\mathbf{a}) = r(\mathbf{s},\mathbf{a}) + \gamma\mathbb{E}_{\mathbf{a}'\sim\pi_\theta(\mathbf{a}'|\mathbf{s}')}\left[Q(\mathbf{s}',\mathbf{a}')\right]$$

Target values



  - The learned Q-function can then be used in a standard Q-learning or actor-critic algorithms
  - Shown to work on more complex simulation environments
- Drawback: the policy and the value function works in an adversarial manner, so training can be unstable

Figures from NeurIPS 2020 tutorial on Offline RL

Open challenges

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- Conservative value estimation may underfit on small data, leading to excessive pessimism
  - Value for undersampled actions may be estimated too low
  - How to balance the risk of overestimation while still exploring OOD actions?

Other approaches

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- Model-based
  - Train an ensemble of dynamics model
  - Use their agreement as a measure of uncertainty to penalize the reward
- Other uncertainty-based methods
  - Train multiple Q-functions and use multiple predictions to estimate uncertainty
- ...

Applications

- Robotics
  - Object grasping is particularly interesting as it requires generalization.
  - Navigating a room using human demonstration
- Healthcare
  - Exclusively offline, due to high risk of online exploration
  - Works towards treatments for epilepsy, schizophrenia, and more
- Autonomous driving
  - More datasets containing human driving activity are being released
  - Offline RL hasn't been successfully applied yet
- Advertising and recommender systems
  - Off policy evaluation is commonly used to perform A/B testing
  - Optimize visit and clicks based on user activity logs
- Language and Dialogue
  - Learning from readily available human dialogue, e.g. dialogue data from customer service

Conclusion

- Offline RL aims to learn a policy using previously collected data, without further interaction with the deployment environment
  - Towards scalable RL towards solving more complex real-world problems
- Major challenges:
  - Counterfactual decision making
  - Distributional shift
- Some solutions:
  - Importance sampling to address the distribution mismatch
  - Constrained policy update, making sure the policy stays close to the behavior policy
  - Conservative value estimation, underestimate the value on OOD state-action pairs
  - ...
- Have been applied in various fields, from robotics to dialogue
- Actively developing area of research

References

Levine, Sergey, et al. "Offline reinforcement learning: Tutorial, review, and perspectives on open problems." *arXiv preprint arXiv:2005.01643* (2020).

Papers cited in this talk can be found on the bibliography