Offline Reinforcement Learning

Slides developed from Prudencio et al. "A Survey on Offline Reinforcement Learning: Taxonomy, Review and Open Problems"

Bryce MacInnis

Offline Reinforcement Learning

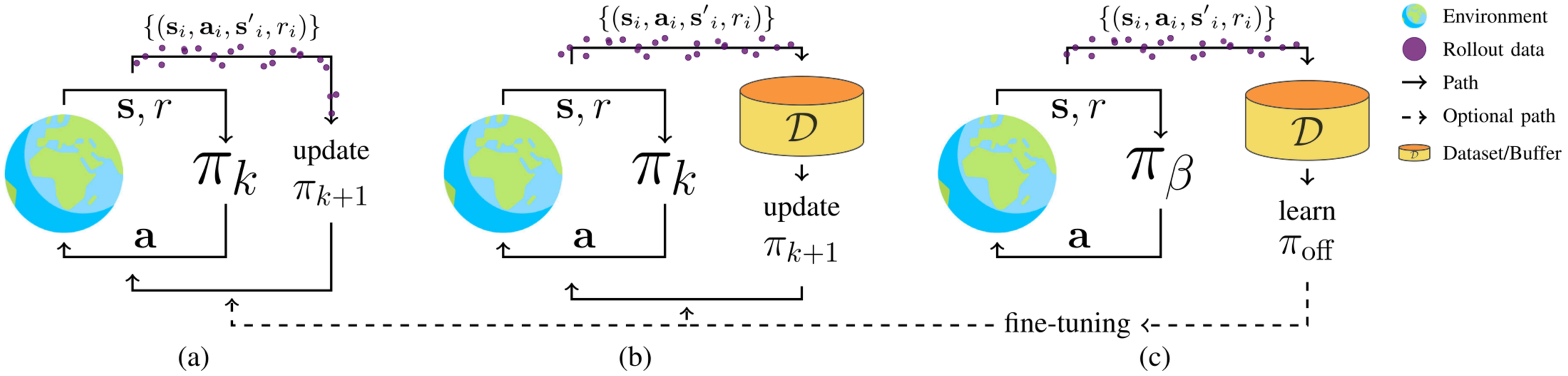


Figure taken from Prudencio et al. "A Survey on Offline Reinforcement Learning: Taxonomy, Review and Open Problems"

In Online Reinforcement Learning, every time you make a change to the policy you need to collect new data.

Offline Reinforcement Learning

Applications

- **Healthcare settings**: Offline RL can optimize treatment, medicine rates using historical patient data without experimenting on patients.
- **Autonomous vehicles:** Using pre-collected data directly from the sensors of the vehicle rather than learning from initially random behaviour (or fresh out of the simulator)
- **Robotics:** Controllers are easily damaged from locomotion failures, pre-training from a dataset collected from simulators may prevent damage.

Offline Reinforcement Learning

Motivation

- Reinforcement Learning isn't widely adopted in industry yet because of: safety concerns, cost of collecting data, challenge of modelling dynamic systems as simulators.
- Safety-critical RL requires pre-training to mind the gap from the simulator to the real-world.
- Collecting data can be expensive or infeasible depending on the application, online RL is inherently wasteful (low sample efficiency).
- Building simulators that can model the complexities of real-life is difficult (alignment gap).

In off-policy RL, we've already gone through the effort of collecting a dataset/replay buffer. Why can't we learn from that directly?

Offline Reinforcement Learning

$$\mathscr{D} = (s, a, r, s') \sim \beta(a \mid s)$$

$$\pi(a \mid s) = \arg\max_{\pi} \mathbb{E}_{\tau \sim \pi} \left[\sum_{t=0}^{T} \gamma^t r_t \right] \quad \text{s.t. } \pi \text{ is learned from } \mathscr{D}$$

Why not off-policy RL for offline RL?

- A replay buffer and an offline dataset are roughly equivalent, so the off-policy RL methods should work for offline RL right?
- Off-policy RL methods are likely to produce OOD actions that are positively biased.
- In Offline RL, you can't get feedback from the environment so these OOD actions are included in the policy and never evaluated by the environment.

Offline Reinforcement Learning

Challenges

- Can't correct bad behaviours without interacting with the environment
- Dealing with stochasticity and non-stationary environments
- Over-fitting vs under-fitting (bias-variance trade-off)
- Distributional shift

But first, a detour to look at Actor-Critic networks in more detail

Policy Gradients

Motivation

- DQN learns a Q-value for each state, action pair. Generating a policy is easy: choose whatever action maximizes the cumulative reward.
- What about for continuous actions? Which action (of an infinite possibilities) should we choose?
- Do we sample the action space and choose the best?
- Policy gradients directly optimize the policy (i.e. which actions to choose).

DDPG - Deep Deterministic Policy Gradient

Lillicrap et al. "Continuous control with deep reinforcement learning" (2015)

- Actor-Critic Architecture
  - Actor learns a deterministic policy π(s) that maximizes the Q-value.

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

  - Critic tries to minimize the TD error:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')}\left[\left(Q(s, a) - \left(r + \gamma Q(s', \pi(s'))\right)\right)^2\right]$$

DDPG - Deep Deterministic Policy Gradient

Problems

- The Q-values are a neural network (function approximator) which means that the Q-values are imperfect (positive bias)
- Because the actor is trained to maximize Q, the actor is going to exploit the imperfection in the Q-values / Critic network.
- These errors compound over time leading to poor performance.

TD3 - Twin Delayed DDPG

Fujimoto et al. "Addressing Function Approximation Error in Actor-Critic Methods" (2018)

1. Two critic networks: the conservative estimate of the Q-value is chosen.

$$\mathscr{L}_{\text{critic}} = \mathbb{E}_{(s,a,r,s')\sim\mathscr{D}}\left[\left(Q_1(s,a)-y\right)^2+\left(Q_2(s,a)-y\right)^2\right]$$

$$y = r + \gamma \cdot \min_{i=1,2} Q_i(s', \pi(s') + \epsilon)$$

$$\epsilon \sim \text{clip}(\mathcal{N}(0,\sigma), -c, c)$$

2. Clipped noise is added to the target action for smoothing

3. Actor network is updated less than the critic network

What is Advantage?

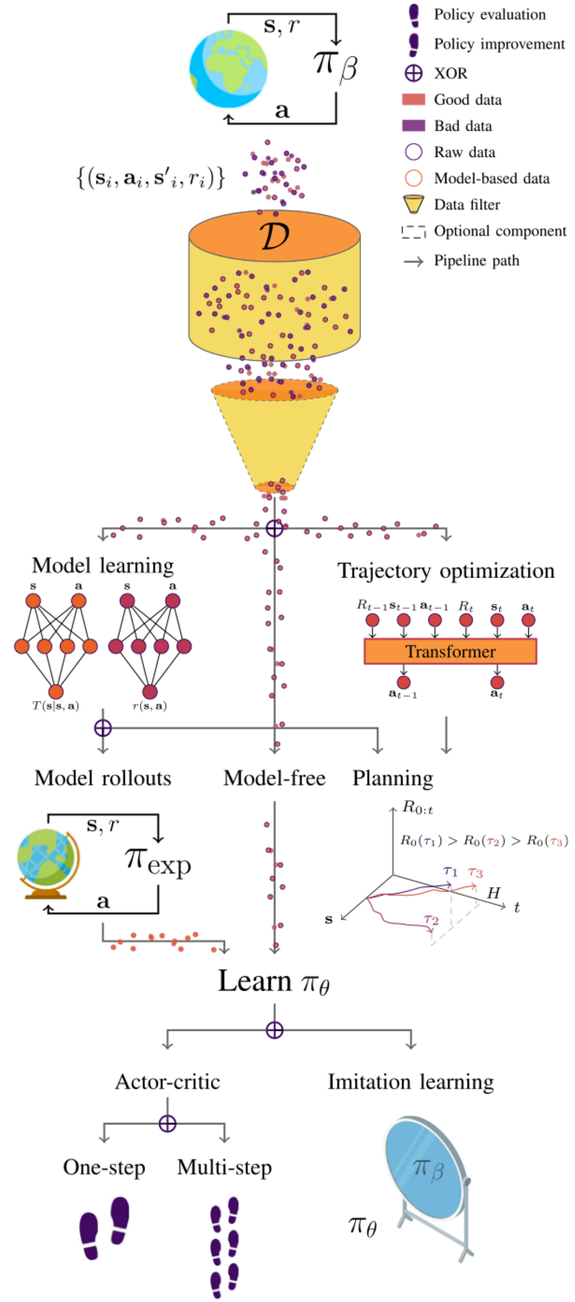
- The **advantage function** measures how much better (or worse) an action is compared to the average action at that state.

$$A(s, a) = Q(s, a) - V(s)$$

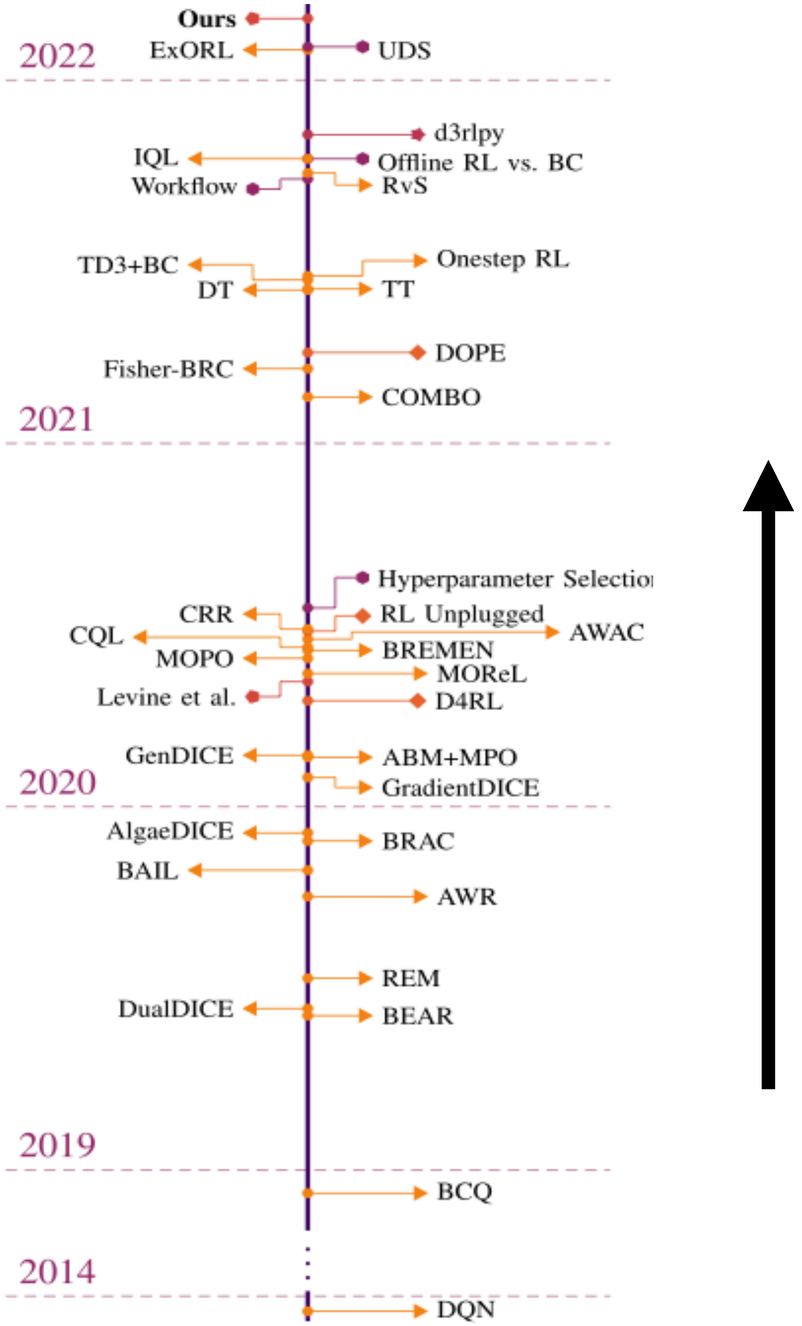
- Why use it?
  - Variance reduction: Helps stabilize learning by centering Q-values
  - Emphasizes actions that are better than average.

Offline Reinforcement Learning

- Policy constraints
- Policy regularization
- Model-based Offline RL
- Uncertainty Estimation
- Importance Sampling
- One-step methods
- Imitation Learning
- Trajectory Optimization



Development Timeline



Policy Constraints

- **Goal: Keep the learned policy close to the dataset to avoid out-of-distribution actions.**
- Variants:
  - Direct Constraints: Add a penalty for divergence from the behaviour policy.

$$D_{\text{KL}}(\pi(a \mid s) \;||\; \beta(a \mid s))$$

  - Implicit Constraints: Use MSE, advantage weighting, or other losses to naturally bias the policy away from OOD actions.
- Can be too pessimistic: "if we know that a certain state has all actions with zero reward, we should not care about constraining the policy."

Fitted Q-Iteration

Damien Ernst, Pierre Geurts, Louis Wehenkel (2005) "Tree-Based Batch Mode Reinforcement Learning"

- Reformulate Offline RL as a regression problem.

$$Q_n(s,a) = r + \gamma \max_{a'} Q_{n-1}(s',a')$$

$$Q_0(s,a) = 0$$

- The policy is determined by:

$$\pi(s) = \arg\max_{a} Q(s,a)$$

- Discrete actions only

You'll hear about this one again

BCQ - Batch Constrained Q-Learning

Scott Fujimoto, David Meger, Doina Precup (2018) "Off-Policy Deep Reinforcement Learning without Exploration"

- Learn a generative model (VAE) of the dataset's actions
- Sample potential actions from the model
- Choose the action with the highest Q-value among them
- Avoids Out-of-Distribution actions

BCQ - Batch Constrained Q-Learning

The Issue

- The policy is over-conservative i.e. performance is only as good as the demonstrated policy in the offline dataset.
- If we know the demonstrated policy in the offline dataset has poor performance in certain regions of the search space, should we still constrain it?

BEAR - Bootstrapping Error Reduction

Aviral Kumar, Justin Fu, George Tucker, Sergey Levine (2019) "Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction "

- BEAR directly constrains the policy to stay within the support of the dataset.
- BCQ has flaws: it relies on the generative model that produces "plausible" actions but not truly in-distribution points. It samples the action space.
- BEAR fixes this by: learning a stochastic Gaussian policy, uses MMD metric to measure similarity between the learned policy and the policy in the dataset.
- Penalizes deviation from the demonstrated policy.

BRAC - Behaviour Regularized Actor-Critic

Yifan Wu, George Tucker, Ofir Nachum (2019)

- Keeping the same policy as the original dataset is useful for the actions with high Q-values but if the original policy isn't good in the search region, deviate from the policy.
- Train an Actor-Critic network, estimate the advantage of each action. Imitate the actions with high advantage.
- Two variants: BRAC-p, BRAC-v.
  - BRAC-p: Modifies the objective to penalize divergence
  - BRAC-v: Uses the advantage-weighted imitation loss

TD3+BC

Scott Fujimoto, Shixiang Shane Gu (2021) "A Minimalist Approach to Offline Reinforcement Learning"

- Offline Reinforcement Learning has gotten too complicated: what's the least amount of effort or engineering that needs to be put into it.
- Two changes to TD3, everything else is the same:
  - Given that the dataset is offline, we know the mean and std of the data and therefore we can Z-score normalize it (easier function approximation).
  - Add a regularization term (MSE) to penalize deviations from the actions taken by the policy in the dataset.
- Basically today's state-of-the-art method.
- Lambda controls the effect of the regularization, 0 lambda is vanilla TD3, 1 lambda is behavioural cloning.

Regularization

- Adding penalty terms that aren't directly related to constraining the policy to the behavioural policy.
- Typically used to add pessimism to the Critic network

CQL: Conservative Q-Learning

Aviral Kumar, Aurick Zhou, George Tucker, Sergey Levine (2020) "Conservative Q-Learning for Offline Reinforcement Learning

- **Goal: Make Q-values smaller for actions not seen in the dataset, so the policy avoids choosing them.**

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

$$+\alpha \cdot \left(\mathbb{E}_{a\sim\pi(\cdot|s)}[Q(s,a)] - \mathbb{E}_{a\sim\mathscr{D}}[Q(s,a)] \right)$$

- A penalty to push down Q-values of actions outside of the dataset.

Uncertainty Estimation

- Uncertainty-based methods allow switching between conservative and naive off-policy RL methods based on how much we trust the model.
- If we're in a low-uncertainty region (lots of support from the dataset), we can relax the policy constraints.
- If we're in a high-uncertainty region (limited data coverage), we constrain the policy.

REM: Random Ensemble Mixture

Rishabh Agarwal, Dale Schuurmans, Mohammad Norouzi (2020) "An Optimistic Perspective on Offline Reinforcement Learning"

- Sample a random convex combination of Q-functions and use them to estimate the Q-value.

$$Q^{\text{REM}}(s, a; \mathbf{w}) = \sum_{i=1}^{K} w_i Q_i(s, a)$$

$$\text{where} \quad w_i \geq 0, \quad \sum_{i=1}^{K} w_i = 1$$

$$TDError = r + \gamma \max_{a'} Q_{\text{REM}}(s', a')$$

One-Step Methods

- Motivation: Avoid bootstrapping errors (like TD's overestimation bias)
- Strategy:

  1. Train $Q(s, a)$ on a dataset using a fitted Q-iteration method
  2. Freeze the $Q(s, a)$ network
  3. Train actor **once** by maximizing the reward through conventional methods.

IQL: Implicit Q-Learning

Ilya Kostrikov, Ashvin Nair, Sergey Levine (2021) Offline Reinforcement Learning with Implicit Q-Learning

- Train $Q(s, a)$ using the loss function:

$$\mathscr{L}_Q = \Big(Q(s,a) - \big[r + \gamma V(s')\big]\Big)^2$$

- Train $V(S)$ using the loss function:

$$\mathscr{L}_V = \left(V(s) - \mathbb{E}_{a\sim\beta(\cdot|s)}\left[\exp\left(\frac{Q(s,a) - V(s)}{\beta}\right) Q(s,a)\right]\right)^2$$

- Compute the advantage $A(s, a) = Q(s, a) - V(s)$
- Train $\pi(a \,|\, s)$ using the loss function:

$$\mathscr{L}_\pi = -\log \pi(a \mid s) \cdot \exp\left(\frac{Q(s,a) - V(s)}{\alpha}\right)$$

Imitation Learning

- Does not use reward information, simply tries to make the same predictions given an action as the critic.
- Subject to distributional shift.
- Often successful if the dataset consists of expert behaviour
- Objective: Filter out suboptimal data and then imitate the expert data in the dataset.

RvS: Offline RL via Supervised Learning

Scott Emmons, Benjamin Eysenbach, Ilya Kostrikov, Sergey Levine (2021) "RvS: What is Essential for Offline RL via Supervised Learning?"

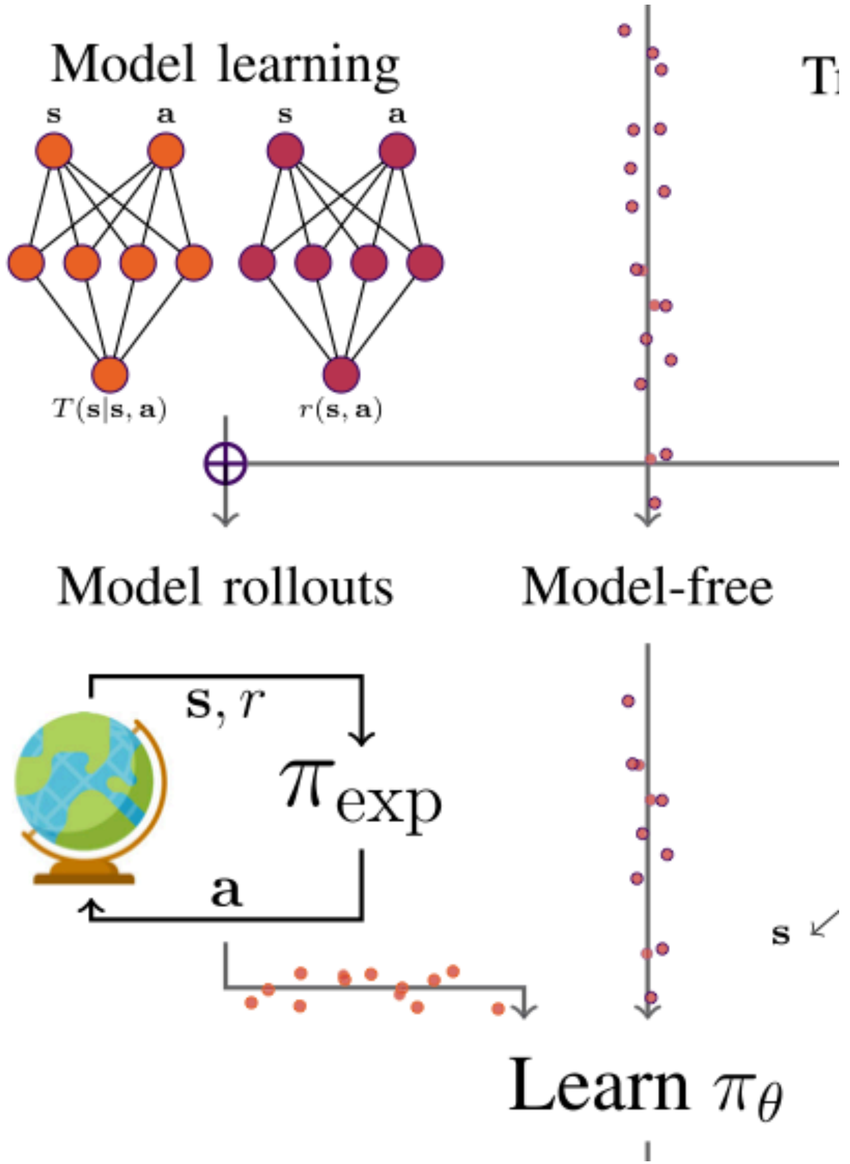
- The **Return-to-go** is an included input feature
- Otherwise, it's a behavioural cloning supervised learning regression problem.

$$\mathscr{L}(\theta) = \mathbb{E}_{(s_t, a_t, G_t) \sim \mathscr{D}} \left[\left\| \pi_\theta(s_t, R_t) - a_t \right\|^2 \right]$$

- Doesn't extrapolate or improve beyond the policy demonstrated in the dataset
- Works best with expert data: fails on suboptimal quality datasets.

Model-based Methods

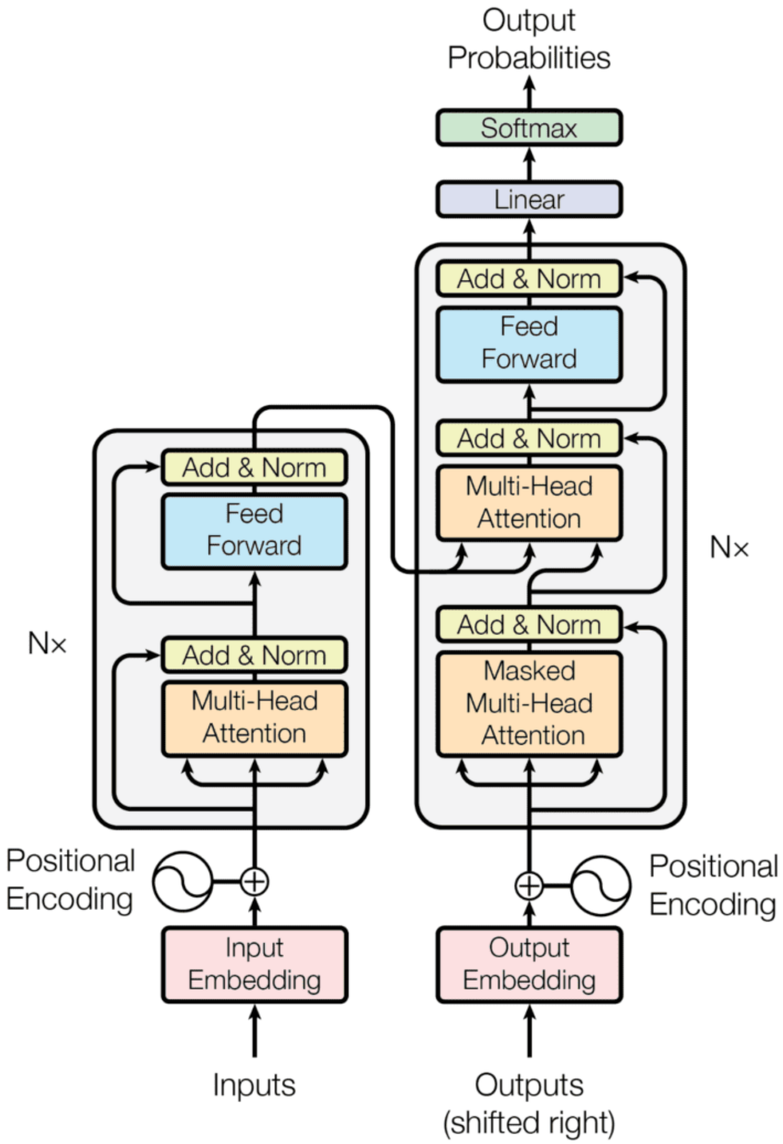
- Learn a model of the environment from the offline dataset, use the model to simulate online learning.
- Uses supervised learning to learn a dynamics model $T_{(s|s,a)}$ and $r(s,a)$
- Use policy gradients, imitation learning, etc to learn the policy.
- Depends on the quality and coverage of the model.



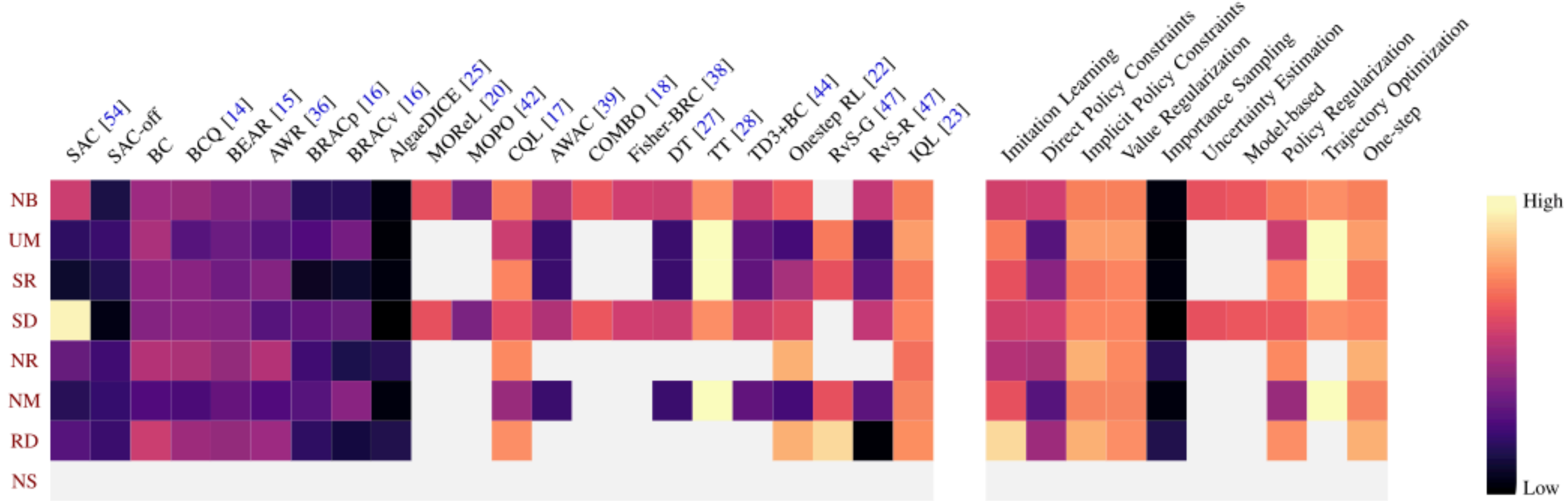
Trajectory Optimization Methods

Decision Transformer

- Reframe Reinforcement Learning as a Sequence Modelling task
- Treat trajectories like sentences and predict the next action like the next word.
- Based on Transformer architectures e.g. positional encoding, multi-head attention, etc.
- (RTG, s_0, [PAD]) -> a_0
- (RTG_1, s_1, a_0) -> a_1
- (RTG_2, s_2, a_1) -> a_2



Performance of Methods



Choosing an Offline RL method

You have **expert data** only?	**RvS**
You have **mixed-quality** data?	**IQL**, **CQL**
Want a **simple**, ready-to-go model?	**TD3+BC**

Off-policy Evaluation

- Evaluating the performance of Online RL is easy.
- Interact with the environment and then observe the reward.
- How do we evaluate the performance of an offline policy WITHOUT interacting with the environment?
- This is essential for hyper-parameter tuning and benchmarking offline RL methods.

Importance Sampling

Why do we need it?

- In Offline RL, our data comes from a behaviour policy
- But we want to learn a new policy Pi(A|S)
- Mismatch Problem: We don't have data from our learned policy, how can we estimate what the data would look like under Pi(A|S)

Importance Sampling

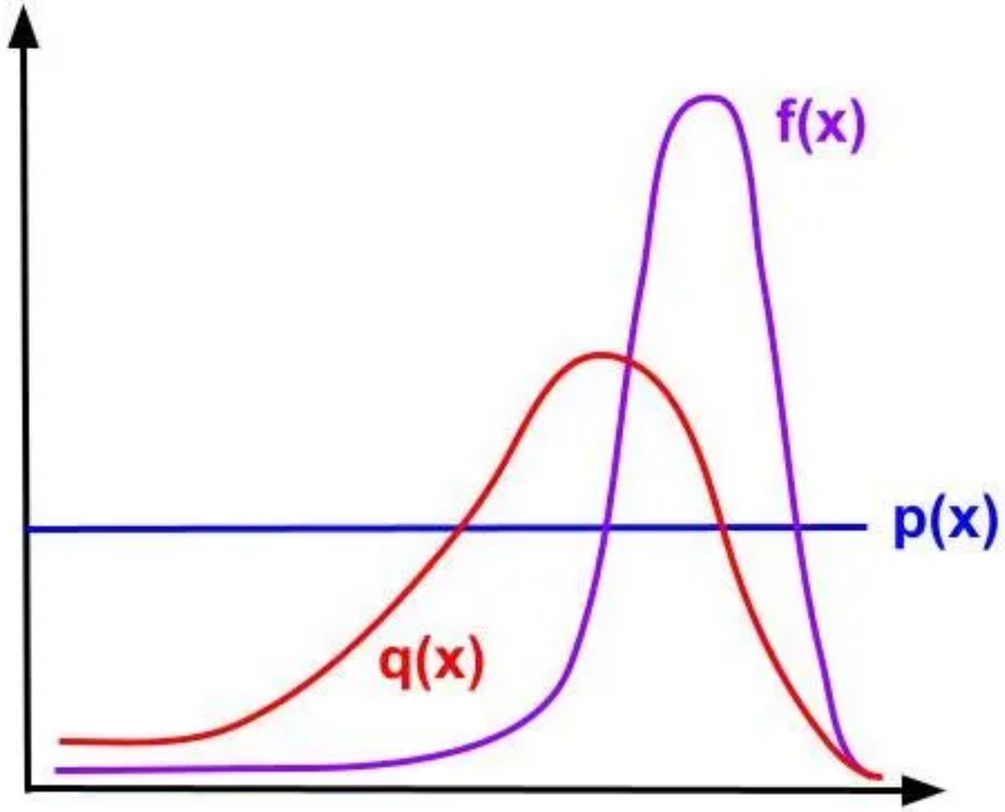
- Trick: Reweight samples collected under the behavioural policy to approximate expectations under Pi(S|A)

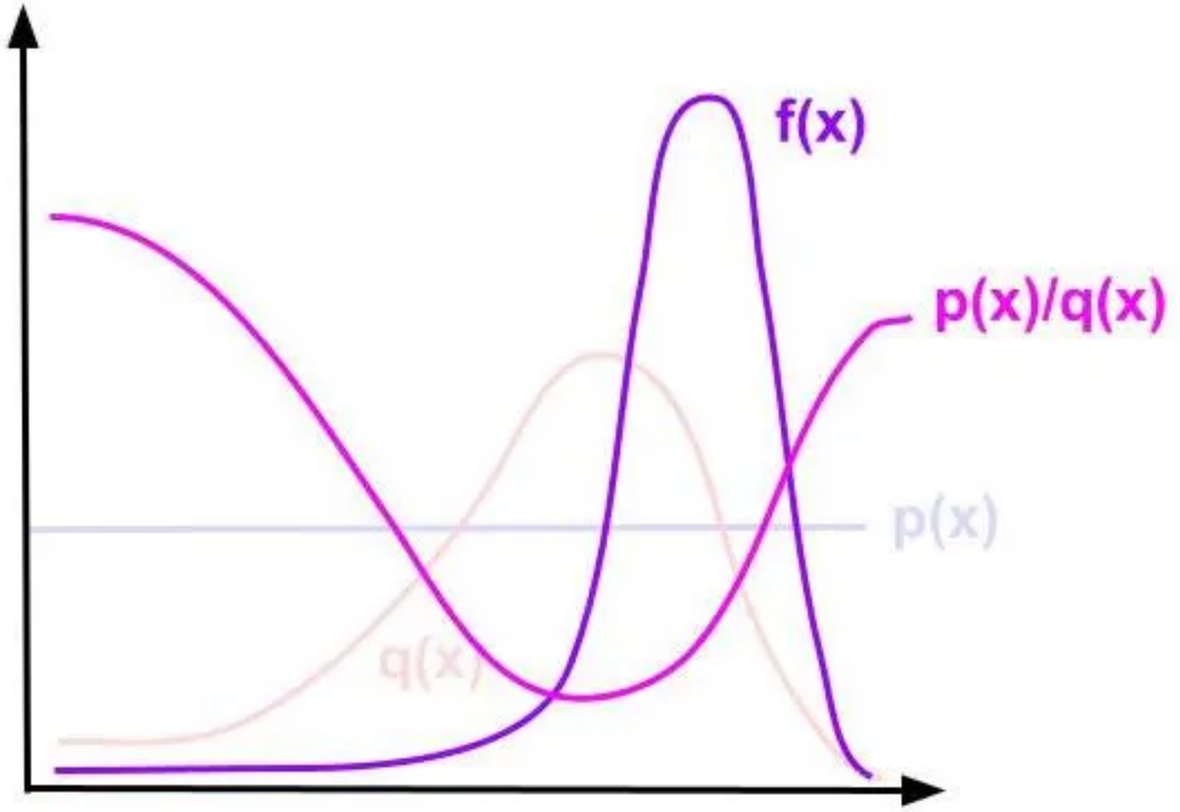
$$w(s,a) = \frac{\pi(a \mid s)}{\beta(a \mid s)}$$

$$\hat{V}^{\pi}(s) = \mathbb{E}_{(s,a)\sim\mathcal{D}}\left[w(s,a) \cdot Q(s,a)\right]$$

Importance Sampling

A Geometric Interpretation





Off-policy Evaluation

- Three existing methods:
    1. Model-based Evaluation
    2. Importance Sampling
    3. Fitted Q-Evaluation

Fitted Q-Evaluation

- Offline Q-learning from the dataset i.e. train a Q-network (typically a neural network)
- Use final $Q^{\pi}(s, a)$ to estimate each state, action pair of the learned policy.
- The value of the policy:

$$V^{\pi}(s) = E_{a \sim \pi} Q^{\pi}(s, a)$$

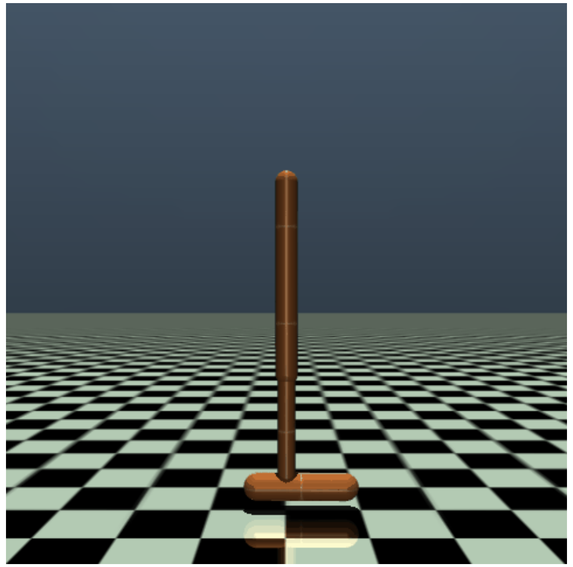
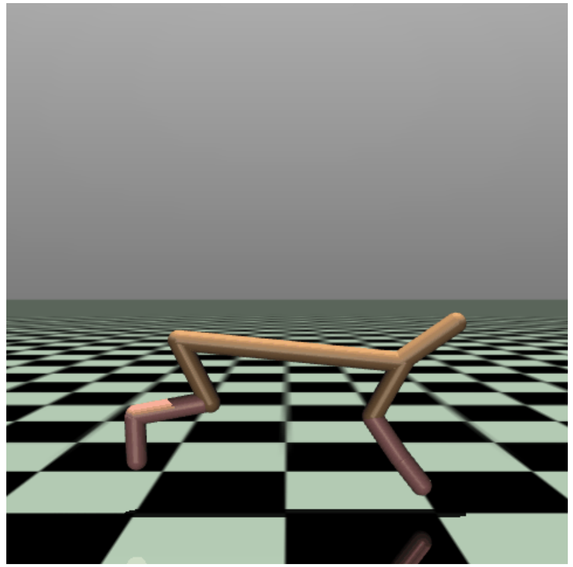
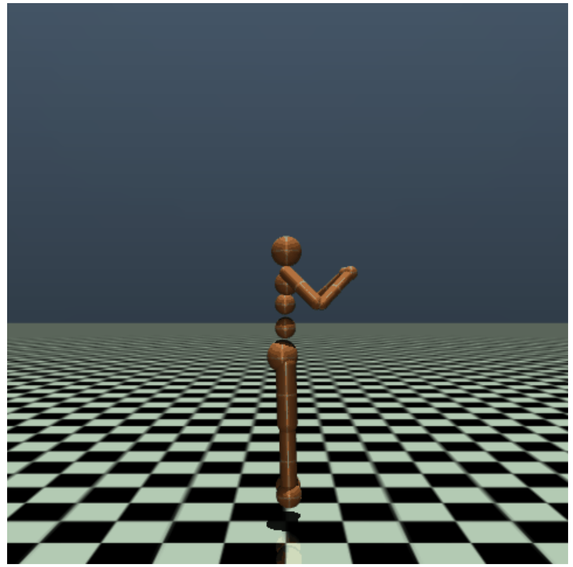
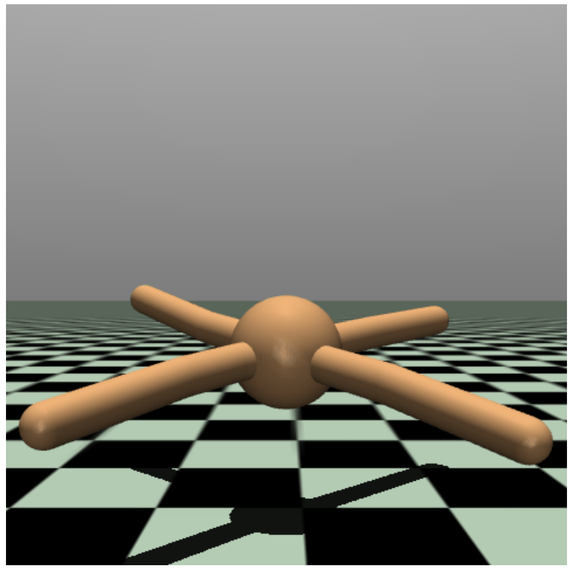
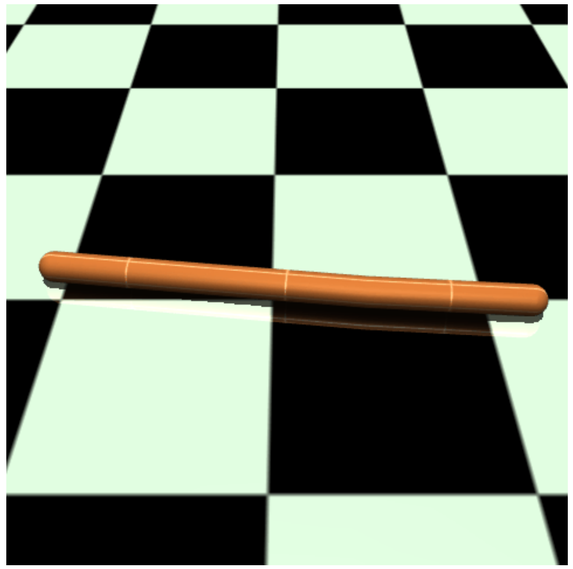
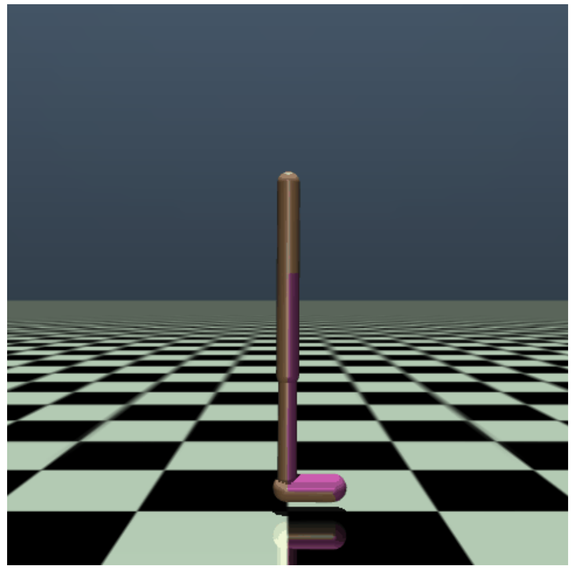
- Empirically, the best method for Offline Policy Evaluation right now.

Benchmarks

What makes a good Offline RL benchmark?

- Narrow and Biased Distributions: When data is limited or done only a certain way in human demonstrations, it's important that Offline RL is robust to this.
- Undirected Tasks: Assesses the ability of the method to stitch trajectories. I.e. solving a task even if none of the individual trajectories are complete solutions.
- Sparse Rewards: Difficult to solve due to the nature of the Bellman equation -- how do you bootstrap without a reward signal
- Suboptimal Data: How does the method perform when there are not expert demonstrations but instead low-quality trajectories.
- Realistic Domains: In order to assess real-world applicabilities, benchmarks should model complex systems as close to reality as possible.
- Nonstationarity: In Reinforcement learning, sometimes the distribution of the task changes and what works no longer does -- or occasionally there is an element of luck. Offline RL methods should be robust to this.

MuJoCo Environments

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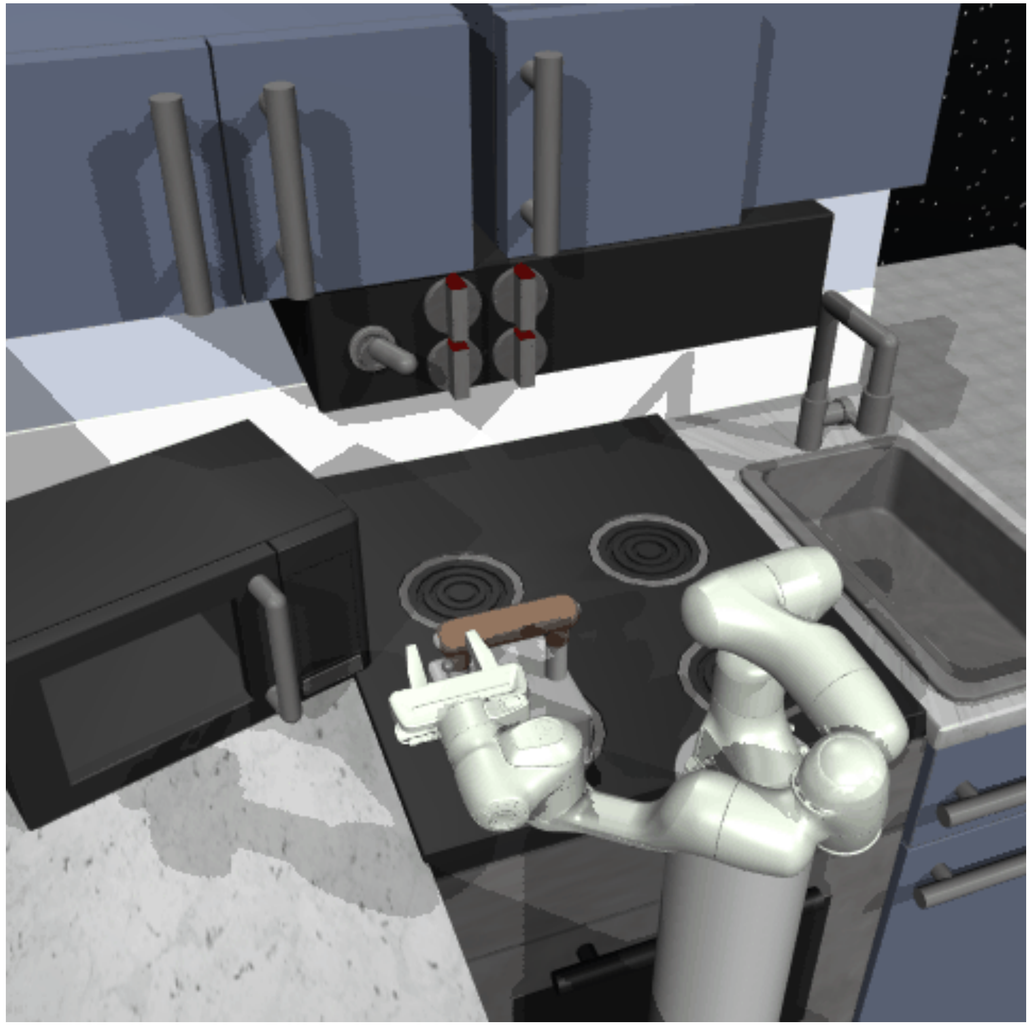
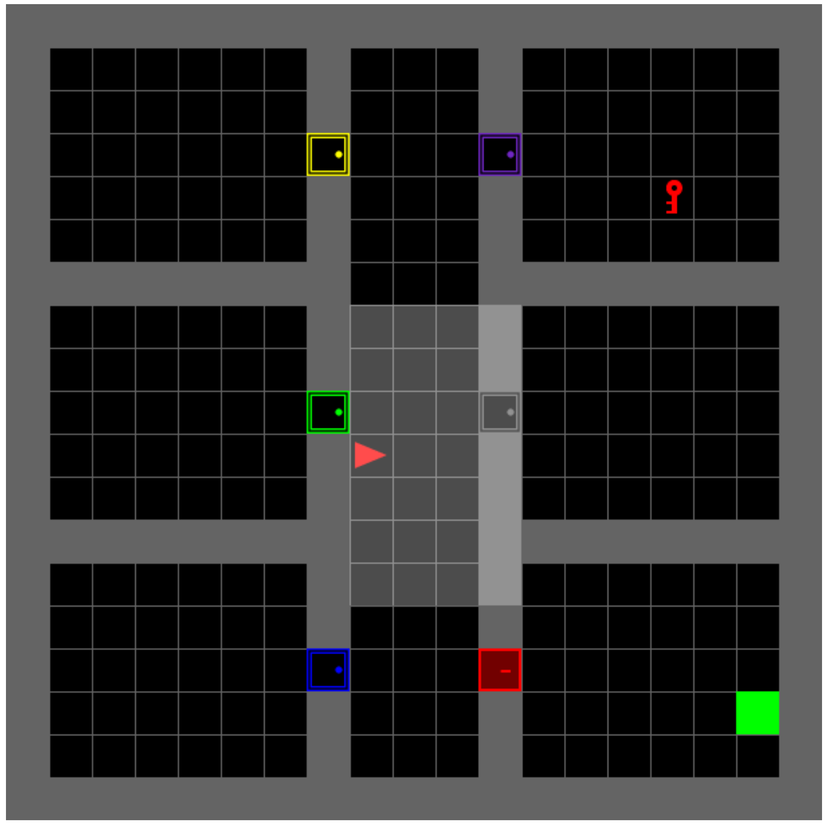
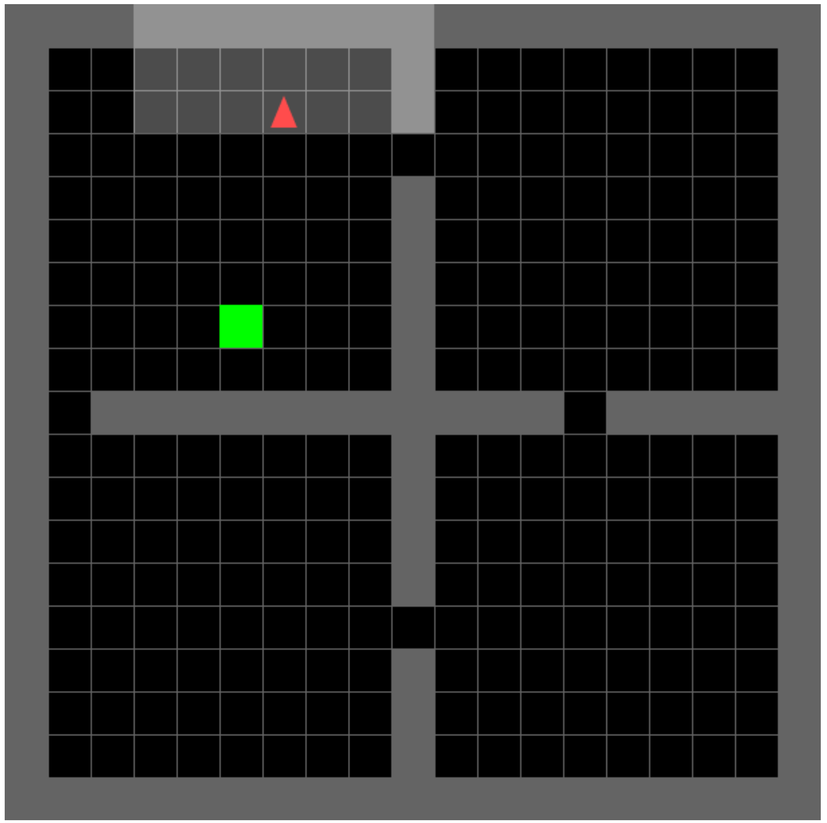


MiniGrid





Minari

- The best hub for Offline Reinforcement Learning datasets
- Released by the Farama Foundation (same maintainers as the Gymnasium environments)
- Makes creating and uploading datasets really easy.

```
(venv) bryce@brycelab2:~/Repos/offline-gp$ minari --help

 Usage: minari [OPTIONS] COMMAND [ARGS]...

 Minari is a tool for collecting and hosting Offline datasets for Reinforcement
 Learning environments based on the Gymnaisum API.

╭─ Options ──────────────────────────────────────────────────────────────────────╮
│ --version                -v      Show installed Minari version.                │
│ --install-completion             Install completion for the current shell.     │
│ --show-completion                Show completion for the current shell, to     │
│                                  copy it or customize the installation.        │
│ --help                           Show this message and exit.                   │
╰────────────────────────────────────────────────────────────────────────────────╯
╭─ Commands ─────────────────────────────────────────────────────────────────────╮
│ list       List Minari datasets in local or remote storage.                    │
│ show       Describe a local or remote dataset, and its environment.            │
│ delete     Delete datasets from local database.                                │
│ download   Download Minari datasets from Farama server.                        │
│ upload     Upload Minari datasets to the remote Farama server.                 │
│ combine    Combine multiple datasets into a single Minari dataset.             │
╰────────────────────────────────────────────────────────────────────────────────╯
```

Name	# Episodes	# Steps	Size	Author
mujoco/... *Group with 28 datasets*	54K	23M	24.26 GB	Kallinteris Andreas
minigrid/... *Group with 170 datasets*	170K	4M	7.51 GB	Omar G. Younis
metaworld/... *Group with 50 datasets*	2K	1M	474.9 MB	Omar G. Younis
webagents/weblinx-v0	969	24K	135.1 MB	Zdeněk Kasner, Siva Reddy, Xing Han Lù
D4RL/antmaze/medium-play-v1	1K	1M	605.2 MB	Alex Davey
D4RL/antmaze/umaze-diverse-v1	1K	1M	605.0 MB	Alex Davey
D4RL/antmaze/large-diverse-v1	1K	1M	605.2 MB	Alex Davey
D4RL/antmaze/large-play-v1	1K	1M	605.2 MB	Alex Davey
D4RL/antmaze/medium-diverse-v1	1K	1M	605.2 MB	Alex Davey
D4RL/antmaze/umaze-v1	1K	1M	605.0 MB	Alex Davey
D4RL/pointmaze/open-dense-v2	10K	1M	437.6 MB	Rodrigo Perez-Vicente
D4RL/pointmaze/umaze-v2	13K	1M	556.2 MB	Rodrigo Perez-Vicente
D4RL/pointmaze/large-dense-v2	3K	1M	239.2 MB	Rodrigo Perez-Vicente
D4RL/pointmaze/medium-v2	5K	1M	284.0 MB	Rodrigo Perez-Vicente
D4RL/pointmaze/umaze-dense-v2	13K	1M	556.2 MB	Rodrigo Perez-Vicente
D4RL/pointmaze/medium-dense-v2	5K	1M	284.0 MB	Rodrigo Perez-Vicente

Key Takeaways

- Offline RL is hard because we can't explore and we can't rely on feedback to correct bad behaviours
- The biggest issue is distributional shift: small errors compounding.
- Policy constraints, conservative value estimates, imitation learning are techniques to mitigate OOD actions.
- Importance sampling can be used to weight points based on their likelihood of relevancy to the new policy.
- Lots of diverse solutions: model-based methods, sequence modelling, **evolutionary algorithms.**

References

Fitted Q-Iteration

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