Offline Reinforcement Learning: Part 2
Course reminders

- Homework 2 due tonight.
- Homework 3 out today.
- Project proposal feedback coming out soon.

Announcements

- Moving two office hours (Dilip, Ansh) from in-person to hybrid
The plan for today

Offline RL: Part 2
1. Recap
2. Revisiting imitation learning for offline RL
   a. Weighted imitation learning
   b. Conditional imitation
3. Offline evaluation & hyperparameter tuning
4. Applications

Key learning goals:
- two approaches for offline RL (+ when they work & don’t work!)
- important considerations for tuning offline RL methods
Recap: Offline RL, data constraints, conservativeness

**Why offline RL?** Online data is expensive. *Reusing offline data* is good!

**Key challenge:** Overestimating Q-values because of shift between $\pi_{\beta}$ and $\pi_{\theta}$

- can explicitly constrain to the data by modeling $\pi_{\beta}$
  + fairly intuitive  - often too conservative in practice
- implicitly constrain to data by penalizing Q-values
  + simple  + can work well in practice  - need to tune alpha

Trajectory stitching allows offline RL methods to improve over imitation.
Recap: Why offline RL versus imitation learning?

Offline data may not be optimal!

—> Offline RL can leverage reward information to outperform behavior policy.

—> Good offline RL methods can \textit{stitch} together good behaviors.

(Recall: Imitation methods can’t outperform the expert.)

\begin{itemize}
  \item \(s_1 \rightarrow s_3\) is good behavior
  \item \(s_7 \rightarrow s_9\) is good behavior
\end{itemize}

 Offline RL methods can learn a policy that goes from \(s_1\) to \(s_9\)!
Other ways to leverage reward information in imitation?

If we have reward labels: imitate only the good trajectories?

Filtered behavior cloning:

1. Rank trajectories by return $r(\tau) = \sum_{(s_t, a_t) \in \tau} r(s_t, a_t)$
2. Filter dataset to include top k% of data $\tilde{D} : \{\tau | r(\tau) > \eta\}$
3. Imitate filtered dataset: $\max_{\pi} \sum_{(s, a) \in \tilde{D}} \log \pi(a \mid s)$

A very primitive approach to using reward information.
Therefore, a good baseline to test against!
Better way to do weighted imitation learning?

Could we weight each transition depending on how good the action is?

How do you measure how good an action is?  
Recall: advantage function $A$

\[
A^\pi(s_t, a_t) = Q^\pi(s_t, a_t) - V^\pi(s_t): \text{how much better } a_t \text{ is}
\]

\[
\theta \leftarrow \arg \max_{\theta} E_{s,a \sim D} \left[ \log \pi_\theta(a | s) \exp(A(s, a)) \right]
\]

standard imitation learning with advantage weights

Aside: Can show that advantage-weighted objective approximates KL-constrained objective.

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

See Peters et al. (REPS), Rawlik et al. ("psi-learning")
Better way to do weighted imitation learning?

Could we weight each transition depending on how good the action is?

How do you measure how good an action is? Recall: advantage function $A$

$$A^\pi(s_t, a_t) = Q^\pi(s_t, a_t) - V^\pi(s_t): \text{how much better } a_t \text{ is}$$

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

standard imitation learning with advantage weights

Advantage of which policy? We'll use $A^\pi_\beta$ for now.

Key question: How to estimate the advantage function?
Advantage-weighted regression

Could we weight each transition depending on how good the action is?

\[
\theta \leftarrow \arg \max_{\theta} E_{s,a \sim D} \left[ \log \pi_{\theta}(a | s) \exp(A(s, a)) \right]
\]

standard imitation learning with advantage weights

Key question: How to estimate the advantage function?

Estimate \(V^{\pi_\theta}(s)\) with Monte Carlo,
\[
\min_{V} E_{s,a \sim D} \left[ (R_{s,a} - V(s))^2 \right]
\]

Approximate \(\hat{A}^{\pi_\theta}(s, a) = R_{s,a} - V(s)\)

empirical return

Peng, Kumar, Zhang, Levine. Advantage-Weighted Regression. '19
Advantage-weighted regression

**Full AWR algorithm**

1. Fit value function: $\hat{V}^{\pi_\beta}(s) \leftarrow \arg\min_V E_{(s,a)\sim D} \left[ (R_{s,a} - V(s))^2 \right]$

2. Train policy: $\hat{\pi} \leftarrow \arg\max_{\pi} E_{s,a \sim D} \left[ \log \pi(a | s) \exp \left( \frac{1}{\alpha} \left( R_{s,a} - \hat{V}^{\pi_\beta}(s) \right) \right) \right]$  

+ Simple
+ Avoids querying or training on any OOD actions!

- Monte Carlo estimation is noisy
- $\hat{A}^{\pi_\beta}$ assumes weaker policy than $\hat{A}^{\pi_\theta}$

Peng, Kumar, Zhang, Levine. Advantage-Weighted Regression. '19
Advantage-weighted regression

Estimate advantage function with TD updates instead of Monte Carlo?

1. Estimate $Q^\pi$-function:
$$\min_Q E_{(s,a,s')\sim D} \left[ \left( Q(s, a) - \left( r + \gamma E_{a'\sim\pi(.|s)}[Q(s', a')] \right) \right)^2 \right]$$

2. Estimate advantage as:
$$\hat{A}^\pi(s, a) = \hat{Q}^\pi(s, a) - E_{\bar{a}\sim\pi(.|s)}[\hat{Q}^\pi(s, \bar{a})]$$

3. Update policy as before:
$$\hat{\pi} \leftarrow \arg\max_{\pi} E_{s,a\sim D} \left[ \log \pi(a|s) \exp \left( \frac{1}{\alpha} \hat{A}^\pi(s, a) \right) \right]$$

“What might go wrong?”

+ Policy still only trained on actions in data.
+ Temporal difference updates instead of Monte Carlo.

What might go wrong?

- Possibly querying OOD actions!

Nair, Gupta, Dalal, Levine. AWAC. ’20
Wang et al. Critic Regularized Regression. NeurIPS ’20
Can we do better?

Want to estimate advantages using TD updates, without querying $Q$ on OOD actions.

**AWAC**: Estimate $Q$-function: 

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

“SARSA algorithm”
Can we do better?

Want to estimate advantages using TD updates, without querying $Q$ on OOD actions.

**SARSA update:**

$$
\hat{Q}^{\pi_\beta} \leftarrow \arg \min_Q E_{(s,a,s',a') \sim D} \left[ (Q(s,a) - (r + \gamma Q(s',a')))^2 \right] 
$$

Can we estimate $Q$ for a policy that is better than $\pi_\beta$?

**Idea:** Use an asymmetric loss function

Can we use another loss to get this?

Histogram of $V(s)$

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

$V(s)$ for best policy in data support

$\ell_2$ loss gives us this!

Can we use another loss to get this?
Aside: Expectile regression

Instead of getting the mean of a random variable, can we get a higher or lower expectile?

Expectile regression loss:

\[
\ell_2^\tau(x) = \begin{cases} 
(1 - \tau)x^2 & \text{if } x < 0 \\
\tau x^2 & \text{otherwise}
\end{cases}
\]

Example with a 2D random variable
Can we do better?

Want to estimate advantages using TD updates, without querying $Q$ on OOD actions.

**Full algorithm**

Fit $V$ with expectile loss: $\hat{V}(s) \leftarrow \arg\min_V E_{(s,a) \sim D} \left[ \ell^\tau_2 \left( V(s) - \hat{Q}(s, a) \right) \right]$ using small $\tau < 0.5$

Update $Q$ with typical MSE loss: $\hat{Q}(s, a) \leftarrow \arg\min_Q E_{(s,a,s') \sim D} \left[ \left( Q(s, a) - \left( r + \gamma \hat{V}(s') \right) \right)^2 \right]$

Extract policy with AWR: $\hat{\pi} \leftarrow \arg\max_\pi E_{s,a \sim D} \left[ \log \pi(a | s) \exp \left( \frac{1}{\alpha} \left( \hat{Q}(s, a) - \hat{V}(s) \right) \right) \right]$

+ Never need to query OOD actions!
+ Policy (still) only trained on actions in data.
+ Decoupling actor & critic training $\rightarrow$ computationally fast

You will implement IQL in homework 3!
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   b. **Conditional imitation**
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4. Applications
Revisiting Filtered Behavior Cloning

If we have reward labels: imitate only the good trajectories?

**Filtered behavior cloning:**

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A very primitive approach to using reward information.

For some datasets, filtered BC can actually work really well!

What if we feel bad about discarding data?
Return-conditioned policies

1. Imitate entire dataset: \[
\max_{\pi} \sum_{(s,a) \in D} \log \pi(a | s, R_s, a)
\]

Condition policy on (empirical) return to go.

- Policy will learn to mimic good and poor behaviors (and everything in between!)
- Pass in high return at test time
- Can use a sequence model:

Referred to as: upside-down RL, reward-conditioned policies, decision transformers

Question: Can this approach do data stitching?

Question: When would a sequence model be helpful?
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Hyperparameter tuning for offline RL

Train policy $\pi_\theta$ using offline dataset $D$. True objective: $\max_{\theta} \sum_t \mathbb{E}_{s_t \sim d^{\pi_{\theta}(\cdot)}, a_t \sim \pi_{\theta}(\cdot \mid s_t)} [r(s_t, a_t)]$

**How good is the policy $\pi_\theta$?** Is policy $\pi_{\theta_1}$ better than policy $\pi_{\theta_2}$? “offline policy evaluation”

There’s no general, reliable way to evaluate offline. 😞 Also true for imitation learning!

**Strategies:**

- Roll-out policy in real world
  + accurate  - can be expensive, risky  ~ no longer purely offline (consider using online data!)
- Evaluate in high-fidelity simulator or model
  + might be good enough for comparing policies  - developing simulator is hard
- Sometimes can use heuristics
  + easy & cheap  - not reliable, general-purpose
Hyperparameter tuning for offline RL

How good is the policy $\pi_\theta$? Is policy $\pi_{\theta_1}$ better than policy $\pi_{\theta_2}$? “offline policy evaluation”

Strategies:
- Sometimes can use heuristics
  + easy & cheap
  - not reliable, general-purpose

Example heuristic for early stopping with CQL:
Look at peak average Q-value before decline

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Some example applications

Optimizing policy for sending notifications to users on LinkedIn

Prabhakar, Yuan, Yang, Sun, Muralidharan. Multi-Objective Optimization of Notifications Using Offline RL. ‘22

<table>
<thead>
<tr>
<th>Metric</th>
<th>DDQN vs. Baseline</th>
<th>DDQN + CQL vs. Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sessions</td>
<td>not stat sig</td>
<td>+ 0.24%</td>
</tr>
<tr>
<td>WAU</td>
<td>-0.69%</td>
<td>+ 0.18%</td>
</tr>
<tr>
<td>Volume</td>
<td>+7.72%</td>
<td>-1.73%</td>
</tr>
<tr>
<td>CTR</td>
<td>-7.79%</td>
<td>+2.26%</td>
</tr>
</tbody>
</table>

Table 1: Online A/B test results for DDQN with and without CQL
Some example applications

Annie Chen, Alex Nam, Suraj Nair develop algorithm for scalably collecting robot data.

Rafael Rafailov reuses same dataset to train a policy with new offline RL method

1. Label 200 images as drawer open vs. closed.
2. Train classifier (for a reward signal)
3. Run offline RL with LOMPO. (precursor to COMBO)

Chen*, Nam*, Nair*, Finn. Batch Exploration with Examples for Scalable Robotic RL, ICRA/RA-L ‘21

Rafailov*, Yu*, Rajeswaran, Finn. Offline RL from Images with Latent Space Models, L4DC ‘21
Some example applications

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76% success rate
Which offline RL algorithm to use?

If you only want to train offline:

Filtered behavior cloning: Good first approach to using offline data.
Implicit Q-learning: Can stitch data & explicitly constrained to data support
Conservative Q-learning: Just one hyperparameter

If you want offline pre-training + online fine-tuning:

Implicit Q-learning: Seems most performant.

If you have a good way to train a dynamics model:

COMBO: Similar to CQL, but benefits from learned model

Note: Still an active area of research!
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