ML Meeting

Idea Proposals

12/28

Idea Proposals

Offline Reinforcement Learning

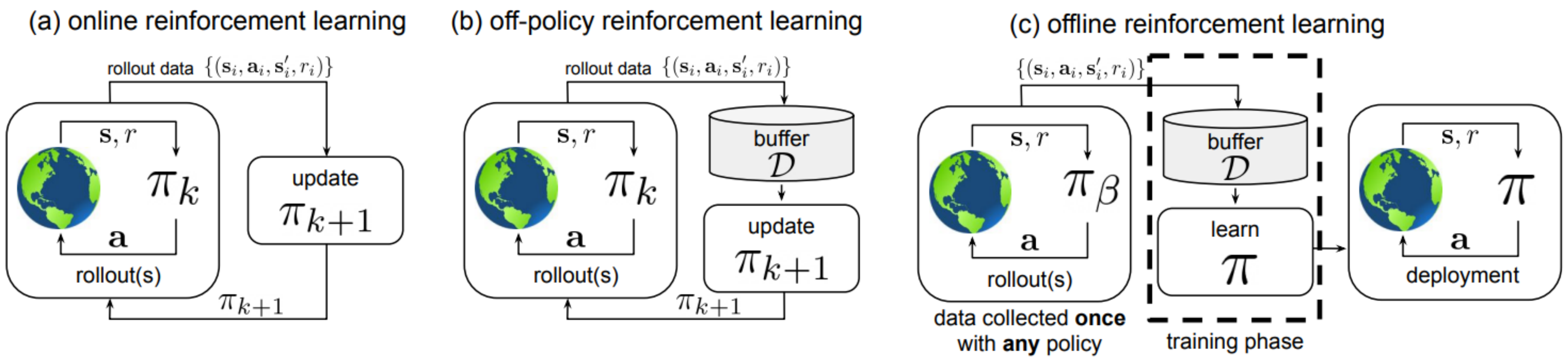
- NTK + uncertainty-based offline RL
- Decision Transformer + NTK

Imitation Learning

- GA-NTK + GAIL
- Behavior Cloning + NTK

NLP

Offline RL


(a) online reinforcement learning
rollout data $\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$
$\mathbf{s}, r$
π_k
$\mathbf{a}$
rollout(s)
update
π_{k+1}
π_{k+1}
(b) off-policy reinforcement learning
rollout data $\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$
buffer
$\mathcal{D}$
update
π_{k+1}
$\mathbf{s}, r$
π_k
$\mathbf{a}$
rollout(s)
π_{k+1}
(c) offline reinforcement learning
$\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$
$\mathbf{s}, r$
π_β
$\mathbf{a}$
rollout(s)
data collected **once** with **any** policy
buffer
$\mathcal{D}$
learn
π
training phase
$\mathbf{s}, r$
π
$\mathbf{a}$
deployment

We aim to learn a policy π from the history of trajectories $\mathcal{D} = \{s_t, a_t, s'_t, r_t\}$ generated by behavioral policy π_β s.t. the performance $\pi \geq \pi_\beta$(Which means we want to train an agent's policy π only from the history of trajectories $\mathcal{D}$)

$$\hat{Q}^{\pi}_{k+1} \leftarrow \arg\min_{Q} \mathbb{E}_{(\mathbf{s},\mathbf{a},\mathbf{s}')\sim\mathcal{D}} \left[\left(Q(\mathbf{s}, \mathbf{a}) - \left(r(\mathbf{s}, \mathbf{a}) + \gamma \mathbb{E}_{\mathbf{a}'\sim\pi_k(\mathbf{a}'|\mathbf{s}')}[\hat{Q}^{\pi}_{k}(\mathbf{s}', \mathbf{a}')] \right) \right)^2 \right]$$

$$\pi_{k+1} \leftarrow \arg\max_{\pi} \mathbb{E}_{\mathbf{s}\sim\mathcal{D}} \left[\mathbb{E}_{\mathbf{a}\sim\pi(\mathbf{a}|\mathbf{s})}[\hat{Q}^{\pi}_{k+1}(\mathbf{s}, \mathbf{a})] \right] \text{ s.t. } D(\pi, \pi_\beta) \leq \epsilon.$$

Challenge

- Extrapolation Error
  - Because the agent's policy isn't the same as the behavioral policy. The agent may overestimate unseen $Q^\pi(s, a)$.
  - In the offline setting, the policy cannot correct such over-optimistic Q-values.

Extrapolation Error

- **Final Buffer**: train a DDPG agent for 1 million time steps, adding $\mathcal{N}(0, 0.5)$ Gaussian noise to actions for high exploration.
- **Concurrent**: We concurrently train the off-policy and behavioral DDPG agents, for 1 million time steps. A standard $\mathcal{N}(0, 0.1)$ Gaussian noise is added to action
- **Imitation**: A trained DDPG agent acts as an expert, and is used to collect a dataset of 1 million transitions.

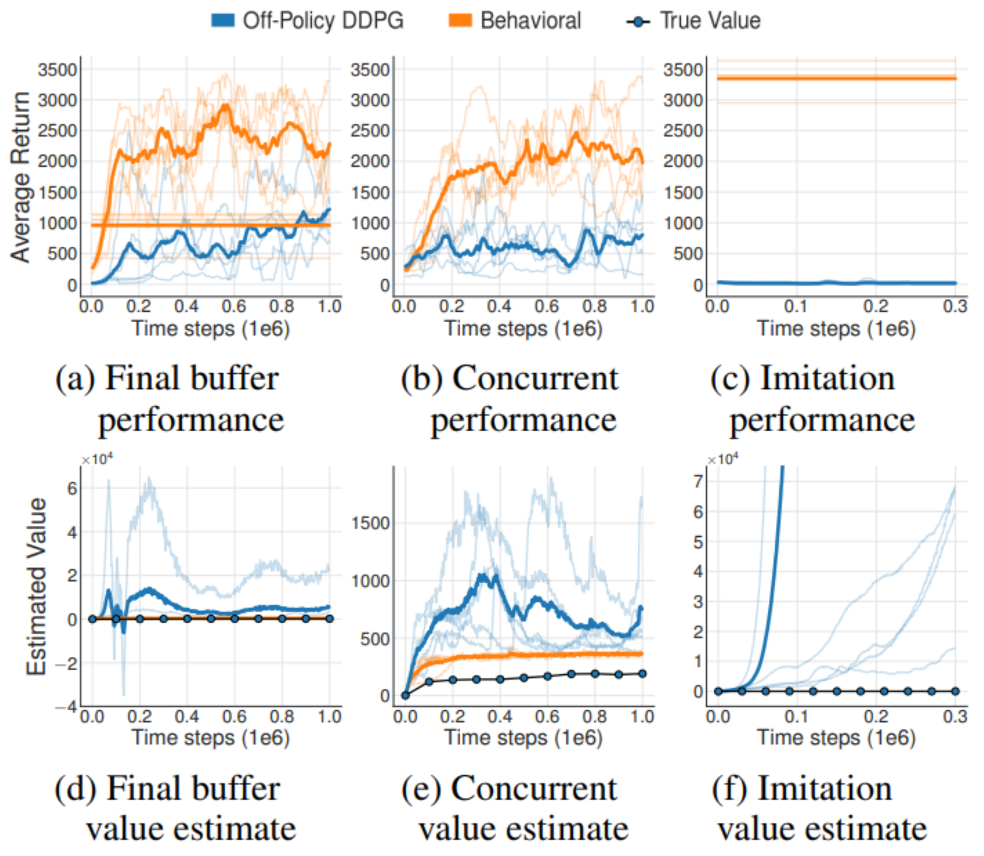


Figure 1. We examine the performance (top row) and corresponding value estimates (bottom row) of DDPG in three batch tasks on Hopper-v1. Each individual trial is plotted with a thin line, with the mean in bold (evaluated without exploration noise). Straight lines represent the average return of episodes contained in the batch (with exploration noise). An estimate of the true value of the off-policy agent, evaluated by Monte Carlo returns, is marked by a dotted line. In all three experiments, we observe a large gap in the performance between the behavioral and off-policy agent, even when learning from the same dataset (*concurrent*). Furthermore, the value estimates are unstable or divergent across all tasks.

Extrapolation Error

- In each task, the off-policy agent performances significantly worse than the behavioral agent, even in the concurrent experiment.

Uncertainty-Based Offline RL

- Uncertainty Estimation: Penalize the unseen action on $Q^{\pi}(s,a)$
  - Challenges: Hard to measure the uncertainty. The SOTA algorithm EDAC trains 10 ~ 500 Q-networks to estimate the uncertainty.

$$\pi_{k+1} \leftarrow \arg\max_{\pi} \mathbb{E}_{\mathbf{s}\sim\mathcal{D}} \underbrace{\left[\mathbb{E}_{\mathbf{a}\sim\pi(\mathbf{a}|\mathbf{s})}\left[\mathbb{E}_{Q^{\pi}_{k+1}\sim\mathcal{P}_{\mathcal{D}}(Q^{\pi})}[Q^{\pi}_{k+1}(\mathbf{s},\mathbf{a})] - \alpha \mathrm{Unc}(\mathcal{P}_{\mathcal{D}}(Q^{\pi}))\right]\right]}_{\text{conservative estimate}}, \quad (24)$$

IDEA 2: Use NTK to measure uncertainty

However, there is another way to tackle the offline RL problem.

How about we take offline RL problem as a sequence modeling problem?

Decision Transformer(DT)

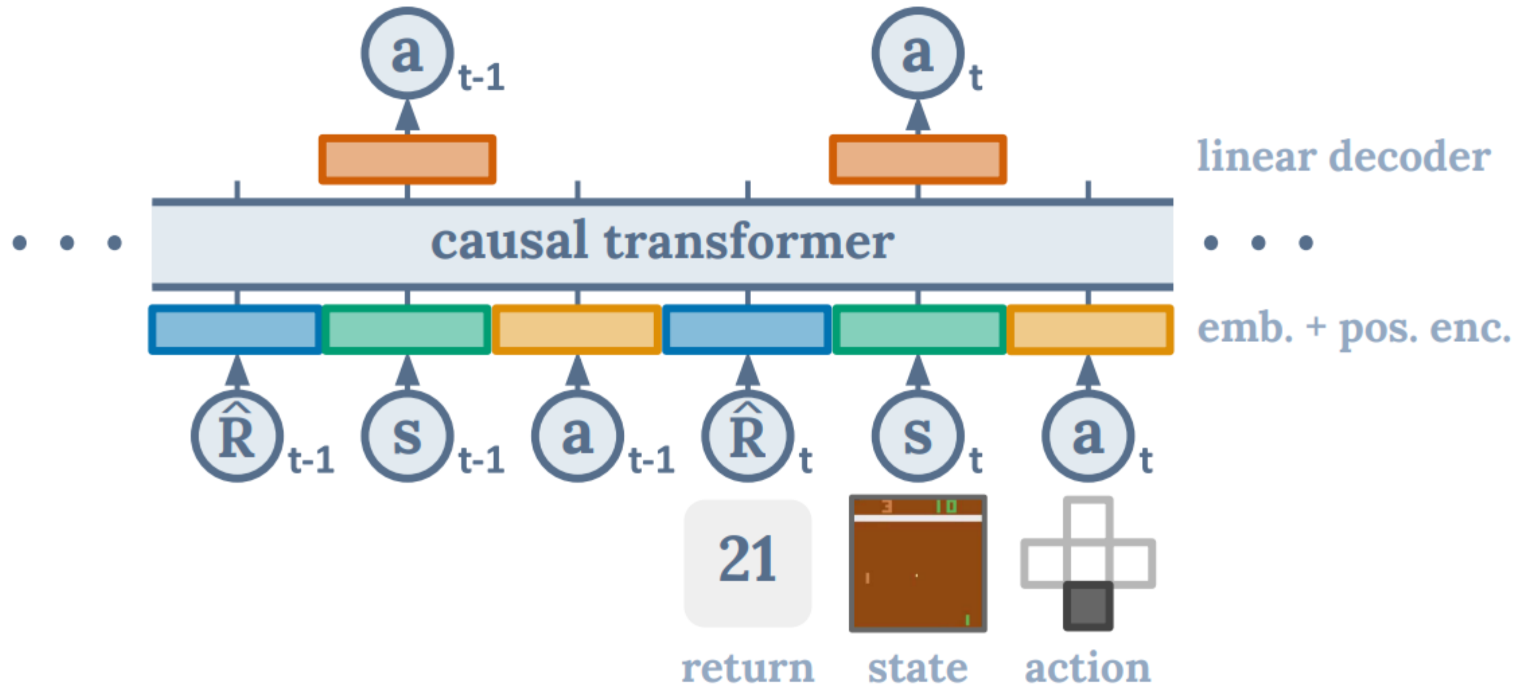


Figure 1: Decision Transformer architecture[1]. States, actions, and returns are fed into modality-specific linear embeddings and a positional episodic timestep encoding is added. Tokens are fed into a GPT architecture which predicts actions autoregressively using a causal self-attention mask.

DT use GPT model. Denote s_t is state, a_t is action and, r_t is reward at time step t.

$\hat{R}_i$ is the reward-to-go, which means $\hat{R}_{t-1} = \sum_{i=t}^{T} r_i$ for a sequence with length T.

But Why It Work?

Actually, Decision Transformer is a Conditional Policy Generator(In My Opinion).

Decision Transformer As Conditional Policy Generator

- The original paper gives an explanation in the view of shortest path. But I don't think it's convincing.
- If we see the Decision Transformer as a **Conditional Policy Generator**. I think the Decision Transformer has 3 assumptions.
  - Assume the **decay of the reward** $\gamma = 1$
  - Assume the environment is **non-stochastic Hidden Markov Chain**
  - Assume **deterministic policy**

Decision Transformer As Conditional Policy Generator

- Denote the actions space as $a \in \mathcal{A}$, state space as $s \in \mathcal{S}$, value function of policy π as $V_\pi(s)$, the decay factor of the reward as γ, and the reward function as $r(s, a)$.
- We consider the **assumption: deterministic policy**

$$V_\pi(s_t) = \sum_{s_{t+1} \in \mathcal{S}} P(s_{t+1} | s_t, \pi(s_t))(r(s_t, \pi(s_t)) + \gamma V_\pi(s_{t+1}))$$

Decision Transformer As Conditional Policy Generator

- While considering the **assumption: non-stochastic MDP** and denote the transition function as $t(s_t, a_t) = s_{t+1}$, the transition probability reduce to a Dirac-Delta distribution which means $\delta(s'|s, \pi(s)) = P(s'|s, \pi(s)) = 1$ if $t(s, a) = s'$, otherwise $= 0$. Thus, we can derive

$$V_\pi(s_t) = r(s_t, \pi(s_t)) + \gamma V_\pi(s_{t+1})$$

- Finally, consider the **assumption: decay of the reward** $\gamma = 1$

$$V_\pi(s_t) = r(s_t, \pi(s_t)) + V_\pi(s_{t+1})$$

Trivially, $V_\pi(s_t)$ is reward-to-go $\hat{R}_t$

Decision Transformer As Conditional Policy Generator

- First, we consider to learn a policy generator G

$$G(\hat{R}_0;\theta) = \pi \quad s.t. \quad \hat{R}_0 = V_\pi(s_0)$$

- Next, we can expand the model G as a **Conditional Policy Generator** H

$$H(\hat{R}_t, s_t;\theta) = \hat{a}_t \quad s.t. \quad \hat{R}_t = V_\pi(s_t)$$

$$\arg\min_\theta \sum_{t=0}^{T} ||\hat{a}_t - a_t||_2$$

- Consider the transformer is an auto-regressive model, it models the environment as a **hidden markov chain** corresponding to the assumption.

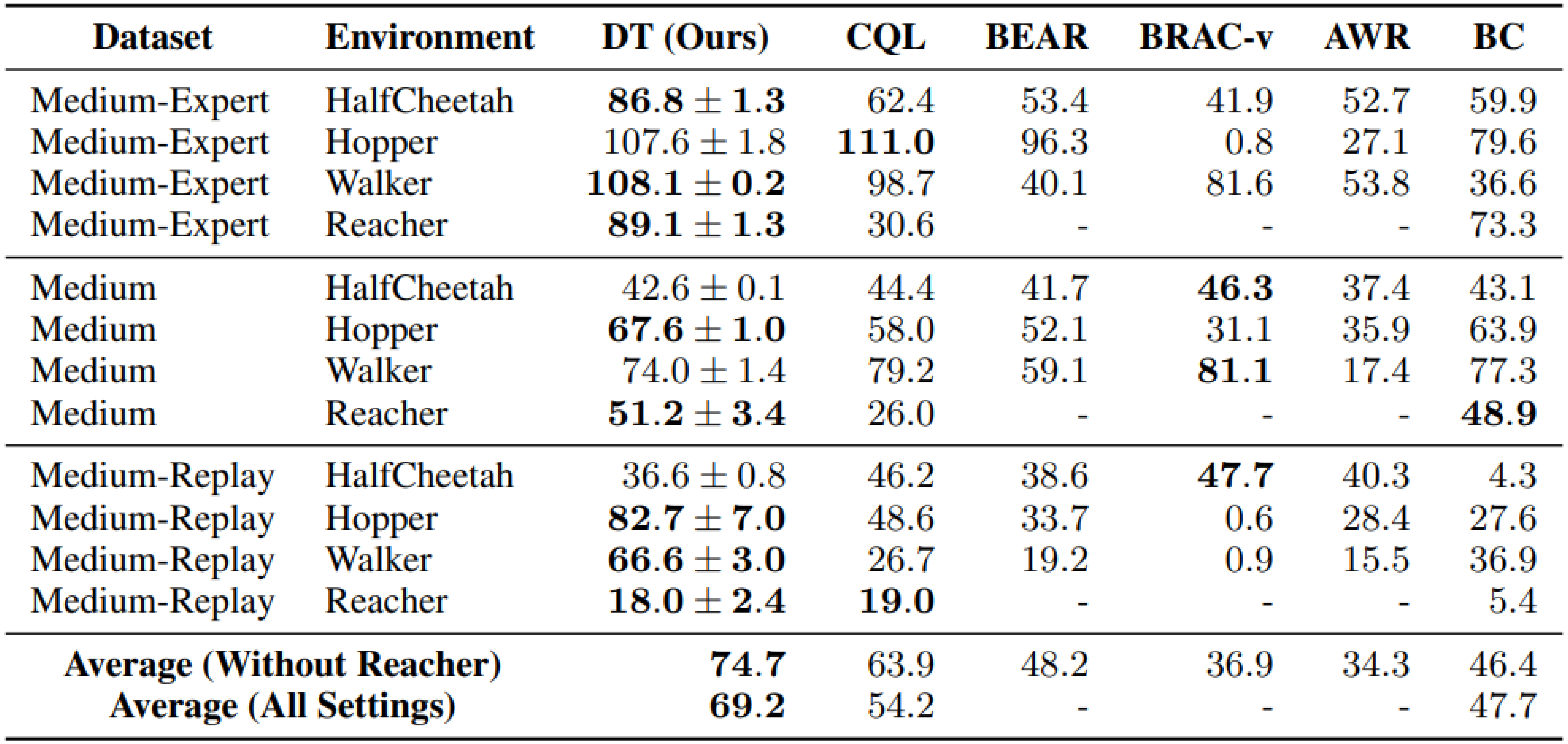
Disadvantages

- Cannot use the model online, since we need to produce the reward-to-go and feed it into the model.
- Poor performance in stochastic environments.
- The performance during testing time would highly depends on the given value of reward-to-go. If the first reward-to-go $\hat{R}_0$ we give is too high, DT would behave unexpectedly.

Advantages

- Provide competitive performance compared to SOTA offline RL algorithm in most of environment.

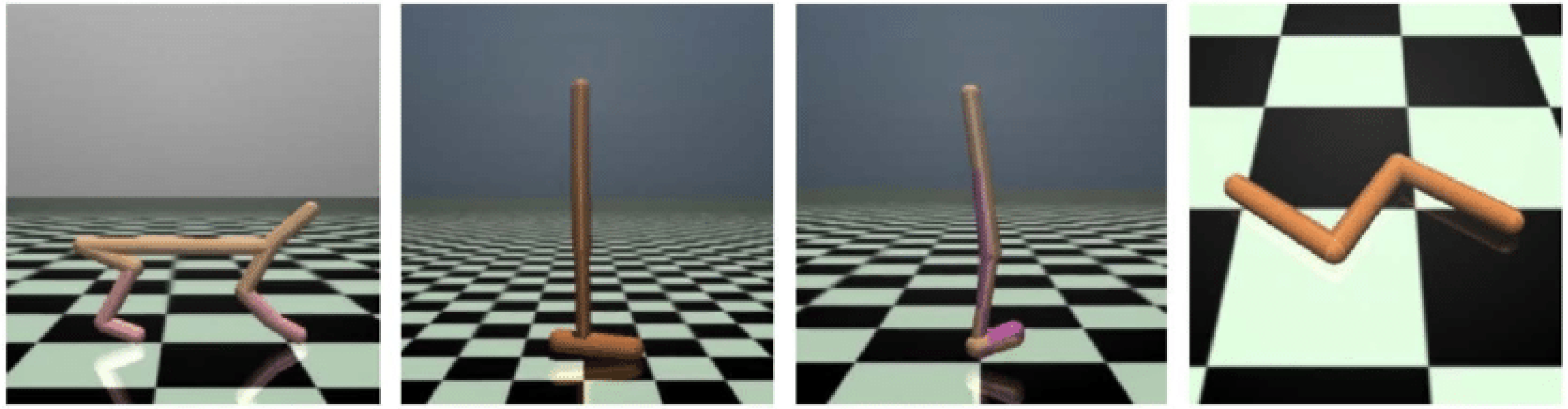
Performance



Dataset	Environment	DT (Ours)	CQL	BEAR	BRAC-v	AWR	BC
Medium-Expert	HalfCheetah	**86.8 ± 1.3**	62.4	53.4	41.9	52.7	59.9
Medium-Expert	Hopper	107.6 ± 1.8	**111.0**	96.3	0.8	27.1	79.6
Medium-Expert	Walker	**108.1 ± 0.2**	98.7	40.1	81.6	53.8	36.6
Medium-Expert	Reacher	**89.1 ± 1.3**	30.6	-	-	-	73.3
Medium	HalfCheetah	42.6 ± 0.1	44.4	41.7	**46.3**	37.4	43.1
Medium	Hopper	**67.6 ± 1.0**	58.0	52.1	31.1	35.9	63.9
Medium	Walker	74.0 ± 1.4	79.2	59.1	**81.1**	17.4	77.3
Medium	Reacher	**51.2 ± 3.4**	26.0	-	-	-	**48.9**
Medium-Replay	HalfCheetah	36.6 ± 0.8	46.2	38.6	**47.7**	40.3	4.3
Medium-Replay	Hopper	**82.7 ± 7.0**	48.6	33.7	0.6	28.4	27.6
Medium-Replay	Walker	**66.6 ± 3.0**	26.7	19.2	0.9	15.5	36.9
Medium-Replay	Reacher	**18.0 ± 2.4**	**19.0**	-	-	-	5.4
Average (Without Reacher)		**74.7**	63.9	48.2	36.9	34.3	46.4
Average (All Settings)		**69.2**	54.2	-	-	-	47.7

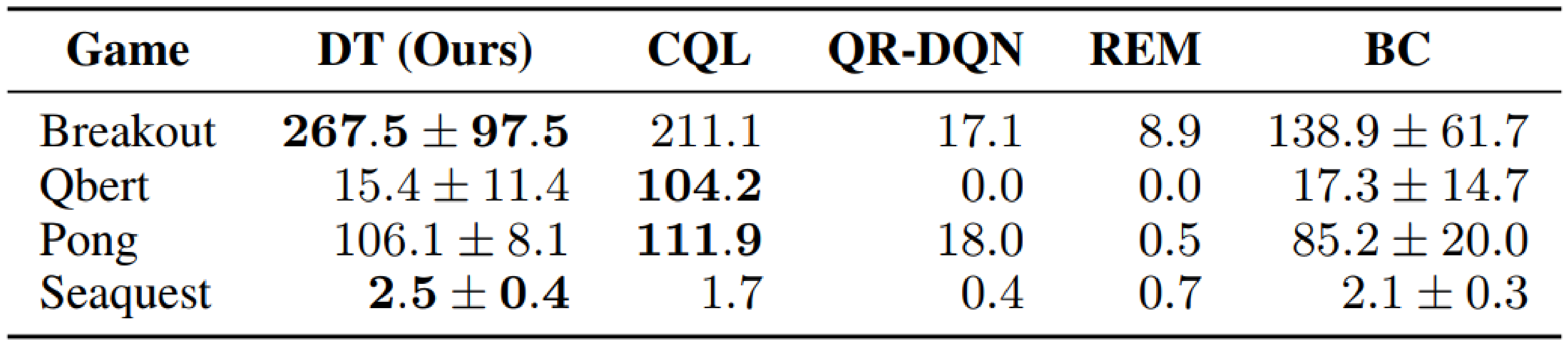
Table 2: Results for D4RL datasets[3]. We report the mean and variance for three seeds. Decision Transformer (DT) outperforms conventional RL algorithms on almost all tasks.

D4RL Dataset



Halfcheetah-v2, Hopper-v2, Walker2d-v2 and Swimmer-v2 tasks environment

Performance

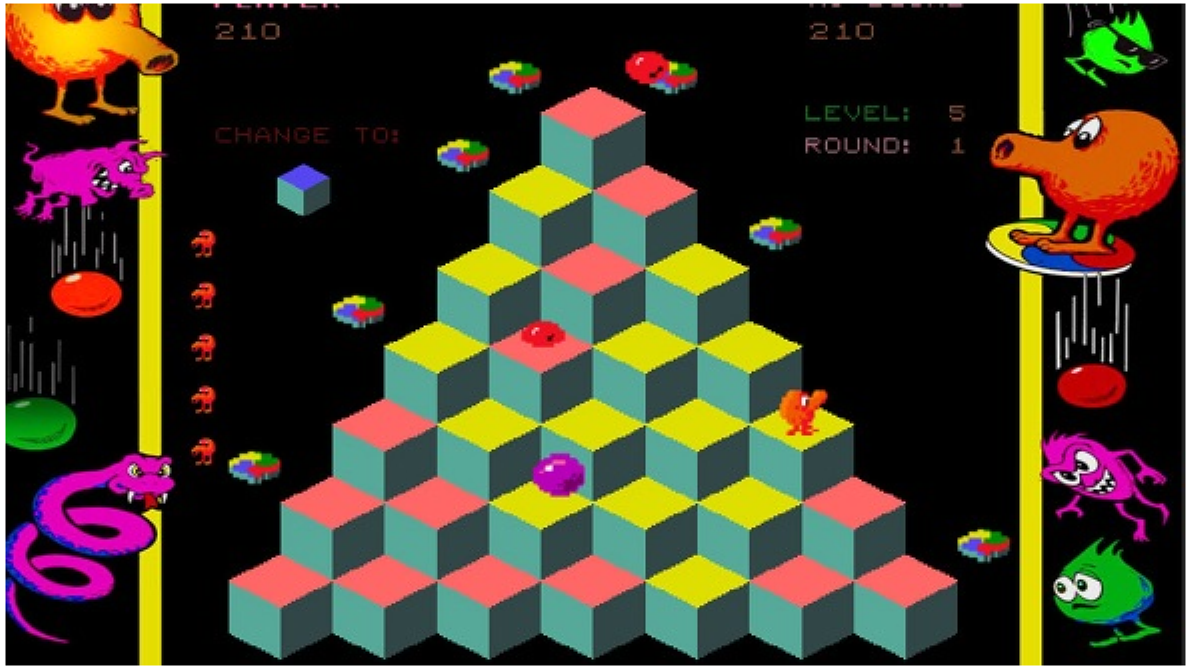


Game	DT (Ours)	CQL	QR-DQN	REM	BC
Breakout	**267.5 ± 97.5**	211.1	17.1	8.9	138.9 ± 61.7
Qbert	15.4 ± 11.4	**104.2**	0.0	0.0	17.3 ± 14.7
Pong	106.1 ± 8.1	**111.9**	18.0	0.5	85.2 ± 20.0
Seaquest	**2.5 ± 0.4**	1.7	0.4	0.7	2.1 ± 0.3

Table 1: Gamer-normalized scores for the 1% DQN-replay Atari dataset. We report the mean and variance across 3 seeds. Best mean scores are highlighted in bold. Decision Transformer (DT) performs comparably to CQL on 3 out of 4 games, and outperforms other baselines in most games.

- In Qbert, DT is extremely poor, since Qbert has highly stochastic environment.

QBert



Idea 3: Kernelize Conditional Policy Generator

- Predict action a_{t-1} and next reward-to-go $\hat{R}_t$ at time step $t-1$.

$$H(\hat{R}_t, s_t; \theta) = \hat{a}_t, \hat{R}_{t+1} \quad s.t. \quad \hat{R}_{t+1} = V_\pi(s_{t+1})$$

$$\arg\min_\theta \sum_{t=0}^{T} ||\hat{a}_t - a_t||_2$$

- Then kernelize it.

Advantage

- Since the loss is defined as MSE. We can **use NTK-GP compute the agent without training.**
- Can be applied on **both offline RL and real-time situation**
- Avoid over-fitting(Bayesian) naturally. High sample efficiency.
- The next reward-to-go is predicted and we only need to give the first reward-to-go.

Disadvantage

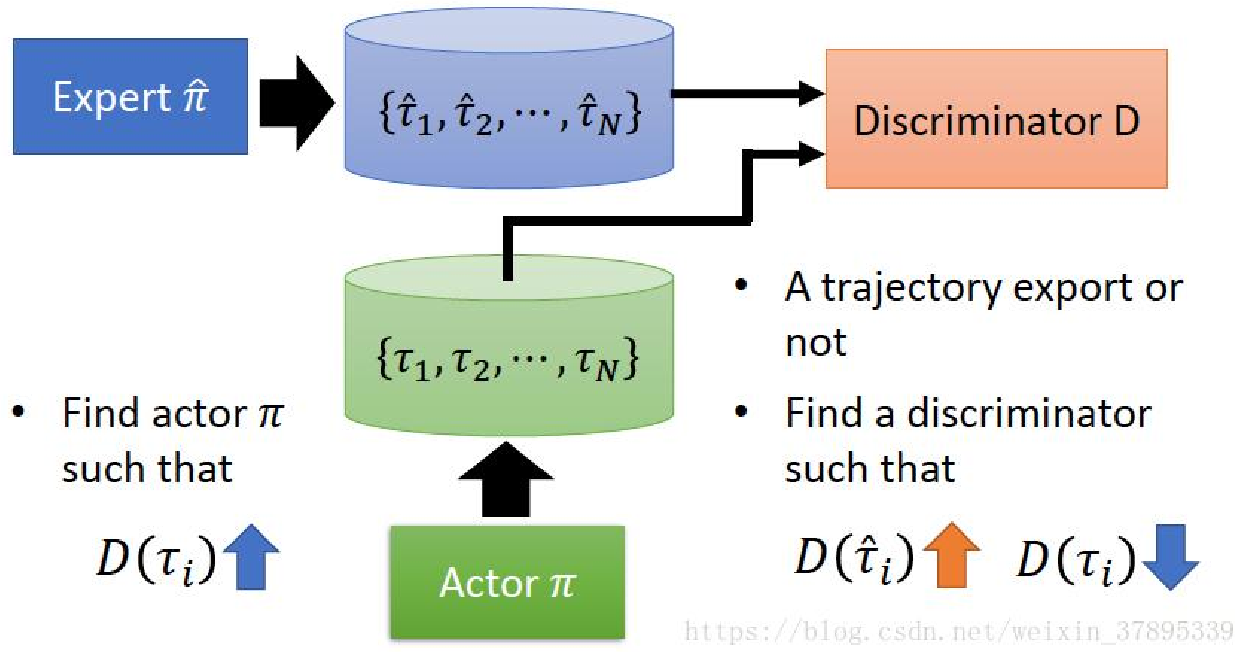
- If we want to extend the Decision Transformer to stochastic MDP, we need to **work around the estimation of $\hat{R}_t$ in stochastic MDP and stochastic policy.**

Imitation Learning

Generative Adversarial Imitation Learning(GAIL)

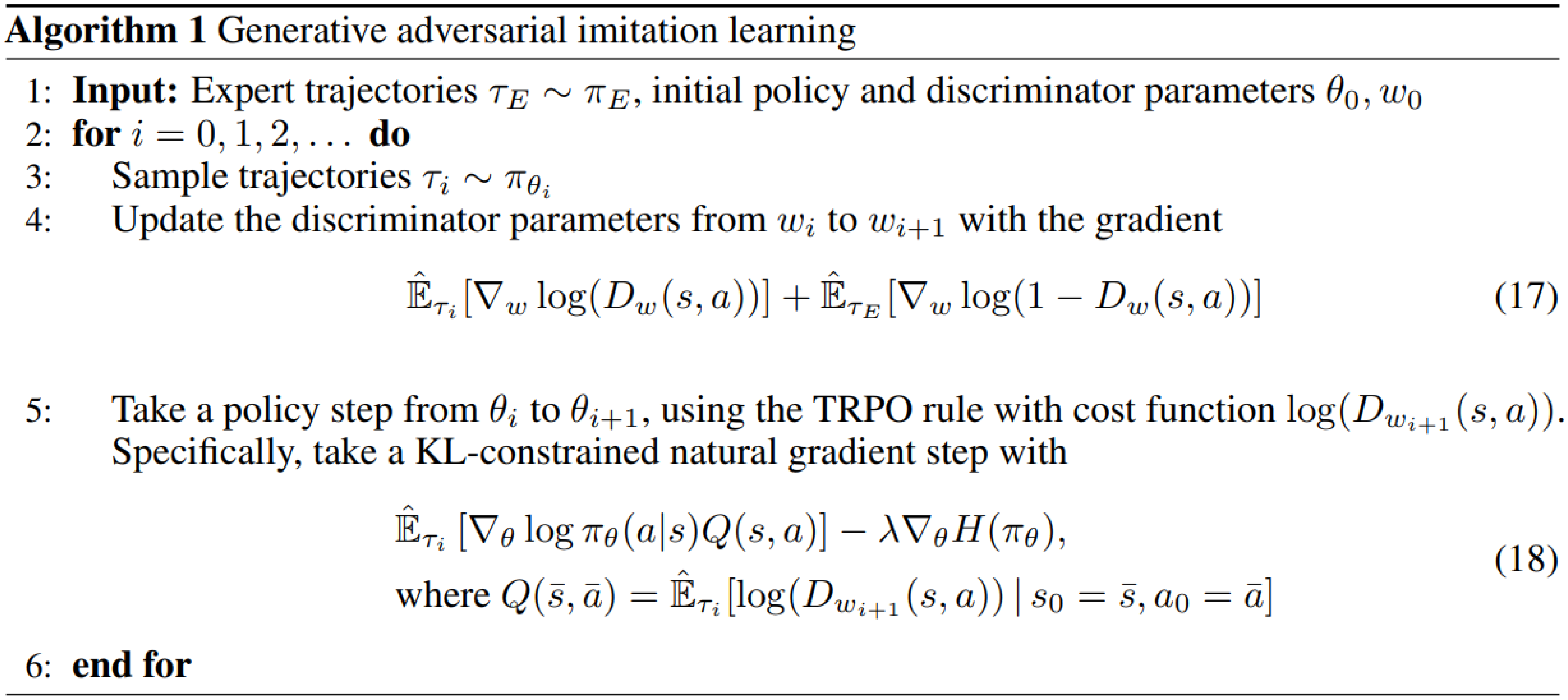
Given expert trajectory $\hat{\tau}$ generated by expert policy $\hat{\pi}$ as ground truth and the generated trajectory τ by generator(agent) π.

Discriminator D need to distinguish which trajectory is generated by the generator(fake).



Expert $\hat{\pi}$
$\{\hat{\tau}_1, \hat{\tau}_2, \cdots, \hat{\tau}_N\}$
Discriminator D
$\{\tau_1, \tau_2, \cdots, \tau_N\}$
• A trajectory export or not
• Find actor π such that
$D(\tau_i)$↑
Actor π
• Find a discriminator such that
$D(\hat{\tau}_i)$↑ $D(\tau_i)$↓
https://blog.csdn.net/weixin_37895339

Generative Adversarial Imitation Learning(GAIL)



Algorithm 1 Generative adversarial imitation learning

```
1: Input: Expert trajectories $\tau_E \sim \pi_E$, initial policy and discriminator parameters $\theta_0, w_0$
2: for $i = 0, 1, 2, \ldots$ do
3:     Sample trajectories $\tau_i \sim \pi_{\theta_i}$
4:     Update the discriminator parameters from $w_i$ to $w_{i+1}$ with the gradient

           $\hat{\mathbb{E}}_{\tau_i}[\nabla_w \log(D_w(s,a))] + \hat{\mathbb{E}}_{\tau_E}[\nabla_w \log(1 - D_w(s,a))]$        (17)

5:     Take a policy step from $\theta_i$ to $\theta_{i+1}$, using the TRPO rule with cost function $\log(D_{w_{i+1}}(s,a))$.
       Specifically, take a KL-constrained natural gradient step with

           $\hat{\mathbb{E}}_{\tau_i}[\nabla_\theta \log \pi_\theta(a|s) Q(s,a)] - \lambda \nabla_\theta H(\pi_\theta),$
                                                                                                   (18)
           where $Q(\bar{s},\bar{a}) = \hat{\mathbb{E}}_{\tau_i}[\log(D_{w_{i+1}}(s,a)) \mid s_0 = \bar{s}, a_0 = \bar{a}]$

6: end for
```

Issues of GAIL

Most of them are te same as GANs

- Mode collapse, unstable training, low sample efficiency
- Recent search What Matters for Adversarial Imitation Learning? argues that
    - GAILs only synthetic demonstrations may lead to algorithms which perform poorly in the more realistic scenarios with human demonstrations, which means that GAILs doesn't generalize well on the reality.
    - But performs well on low-dimension tasks.
- Challenged by Offline RL, which usually can perform well on non-expert dataset

Idea: GA-NTK + GAIL

Advantages

- Avoid mode collapse, unstable training, low sample efficiency
- Interpolation on small training dataset, same as GAIL. But in continuous control(robotic tasks), interpolation may not be a bad thing.

Another Trivial Idea: Behavior Cloning + NTK

- Directly kernelize behavior cloning with NTK-GP

$$J(\pi) = \mathbb{E}_{s\sim d_{\pi^*}}\left[||\pi^*(\cdot|s) - \pi(\cdot|s)||_2\right]$$

Advantages

- Since NTK-GP is Bayesian, the action would be smoother than MLE, which is great for robotic tasks.

It's trivial(stupid), but in ICLR'21 spotlight, Disagreement-Regularized Imitation Learning if it is outside of it. These two criteria are addressed by combining two losses: a standard behavior cloning loss, and an additional loss which represents the variance over the outputs of an ensemble $\Pi_{\mathrm{E}} = \{\pi_1, ..., \pi_E\}$ of policies trained on the demonstration data $\mathcal{D}$. We call this the uncertainty cost, which is defined as:

$$C_{\mathrm{U}}(s,a) = \mathrm{Var}_{\pi \sim \Pi_{\mathrm{E}}}(\pi(a|s)) = \frac{1}{E}\sum_{i=1}^{E}\left(\pi_i(a|s) - \frac{1}{E}\sum_{i=1}^{E}\pi_i(a|s)\right)^2$$

The motivation is that the variance over plausible policies is high outside the expert's distribution, since the data is sparse, but it is low inside the expert's distribution, since the data there is dense. Minimizing this cost encourages the policy to return to regions of dense coverage by the expert. Intuitively, this is what we would expect the expert policy $\pi^\star$ to do as well. The total cost which the algorithm optimizes is given by:

$$J_{\mathrm{alg}}(\pi) = \underbrace{\mathbb{E}_{s\sim d_{\pi^\star}}[||\pi^\star(\cdot|s) - \pi(\cdot|s)||]}_{J_{\mathrm{BC}}(\pi)} + \underbrace{\mathbb{E}_{s\sim d_\pi, a\sim\pi(\cdot|s)}[C_{\mathrm{U}}(s,a)]}_{J_{\mathrm{U}}(\pi)}$$

NLP

IDEA: NLP models are so large, according to NTK theorem, it should converge within a few epochs? Actually, we don't need to train so many epochs?