Using Ensembles to address Bootstrapping Error in Offline RL

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Outline

Reinforcement Learning - A schematic view

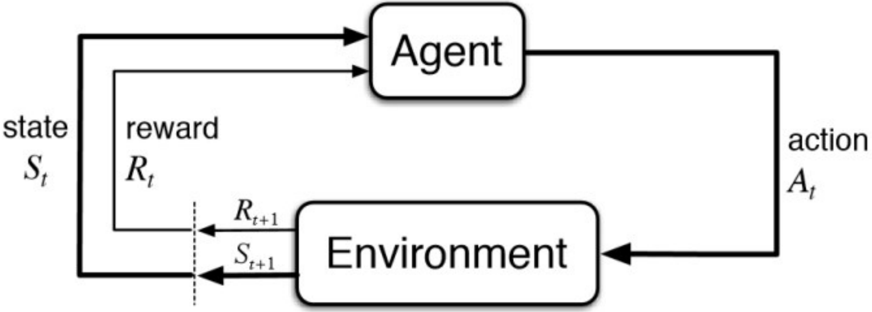


Figure 1: The agent-environment loop (Sutton and Barto, 2018)

Reinforcement Learning Problem Statement

- An agent seeking an optimal policy $\pi(s, a)$ - a mapping from states to action probabilities ($s \in \mathcal{S}$, $a \in \mathcal{A}$)
- Used in sequential decision making problems modeled as Markov decision process (*MDP*), enriched with a reward function $R(s, a) \colon \mathcal{S} \times \mathcal{A} \mapsto \mathbb{R}$
- Focus: *value-based*, *model-free* methods

RL Definitions

$$G_t = \sum_{k=0}^{T} \gamma^k r_{t+k} \qquad \text{(Discounted cumulative reward)}$$

$$Q^{\pi}(s, a) = \mathbb{E}\left[G_t | s_t = s, a_t = a, \pi\right] \qquad \text{(State-action value function)}$$

$$Q^{*}(s, a) = \mathbb{E}\ R(s, a) + \gamma \mathbb{E}_{s' \sim P} \max_{a \in \mathcal{A}} Q^{*}(s', a) \qquad \text{(Bellaman optimality equation)}$$

Reinforcement Learning (RL) - Offline

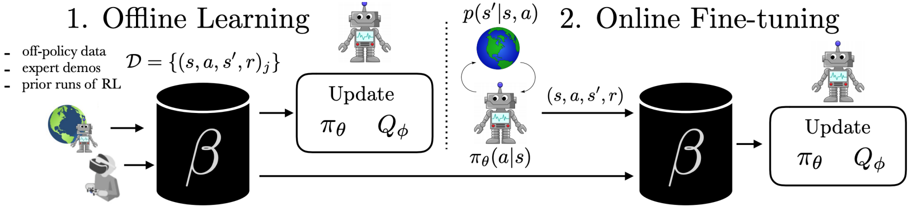


Figure 2: The learning loop in Offline RL, courtesy of Nair et al.

- Also called Batch Reinforcement Learning
- Behavior policy π_β generates dataset $\mathcal{D}$
- *Pure Batch* vs *Growing Batch* RL methods

Detrimental factors in Offline RL

- Function approximation errors in Deep RL (Neural Networks)
- Different state visitation frequencies under training and testing distributions
- Bootstrapping error (Kumar et al., 2019)

Bootstrapping Error

DQN objective function:

$$\mathcal{L}(\theta) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1} \rangle \sim D} \left[\left(r_t + \gamma \max_{a \in \mathcal{A}} Q(s_{t+1,a;\theta^-}) - Q(s_t, a_t; \theta) \right)^2 \right]$$

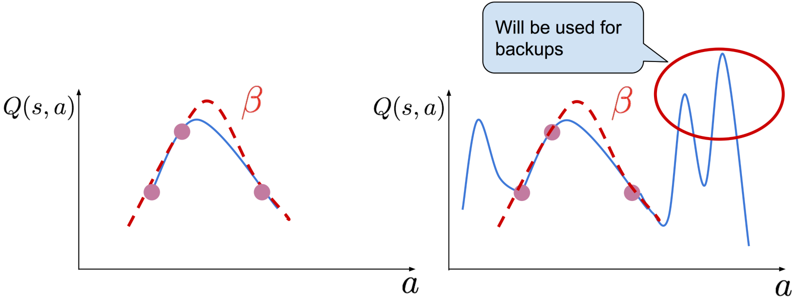


Figure 3: Incorrectly high Q-values for OOD actions may be used for backups, leading to accumulation of error. Figure and caption: Kumar, Aviral

Bootstrapping Error in the DQV[9] algorithmic family

- We want to check if the DQV and DQV-Max deep RL algorithms suffer from the Bootstrapping Error in the *offline* setting
- DQV objective functions:

$$\mathcal{L}(\phi) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}} \rangle \sim D} \left[\left(r_t + \gamma V(s_{t+1}, a; \phi^-) - V(s_t, a; \phi) \right)^2 \right] \tag{1}$$

$$\mathcal{L}(\theta) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}} \rangle \sim D} \left[\left(r_t + \gamma V(s_{t+1}, a; \phi^-) - Q(s_t, a_t; \theta) \right)^2 \right] \tag{2}$$

- DQV-Max objective functions:

$$\mathcal{L}(\phi) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}} \rangle \sim D} \left[\left(r_t + \gamma \max_{a \in \mathcal{A}} Q(s_{t+1}, a; \theta^-) - V(s_t, a; \phi) \right)^2 \right] \tag{3}$$

$$\mathcal{L}(\theta) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}} \rangle \sim D} \left[\left(r_t + \gamma V(s_{t+1}, a; \phi) - Q(s_t, a_t; \theta) \right)^2 \right] \tag{4}$$

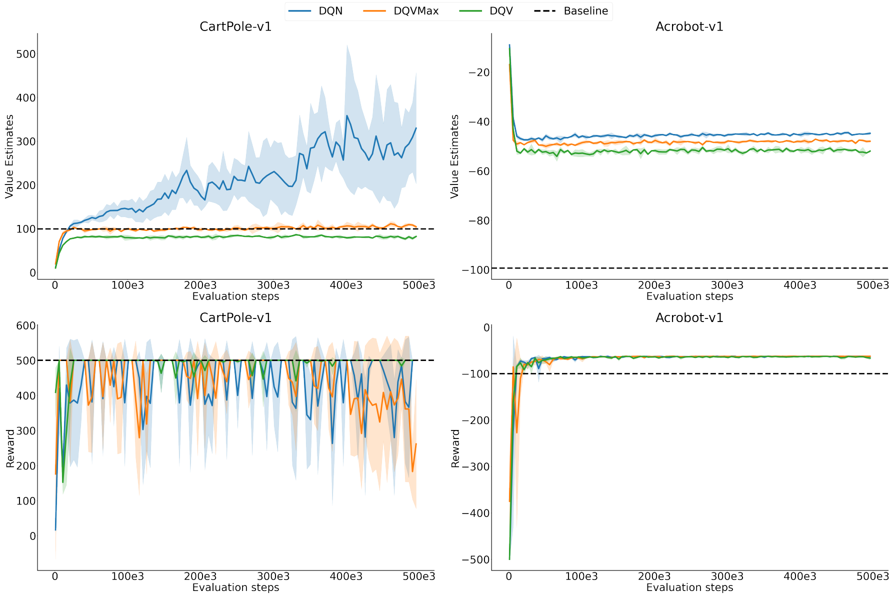
Experimental setup

- Classic control OpenAI Gym environments: `CartPole-v1` and `Acrobot-v1`
- Data collection: log every trajectory $\langle s, a, r, s' \rangle$ of a DQN[7] agent trained online for 500k steps
- Hyper-parameters and training scheme follow those of the Dopamine[3] framework
- Record estimates of $\max_{a \in \mathcal{A}} Q(s_{t_0}, a)$ at each evaluation round to track the value estimates evolution, then compare against ground truth

$$G_{t_0} = \sum_{k=0}^{T} \gamma^k r_{t+k}$$

T is the environment's finite time horizon, and r_t is constant across environments

Bootstrapping Error in the DQV algorithmic family - Results



Preventing the Bootstrapping Error - Online

Two ways of addressing the Bootstrapping Error:

1. Obtain unbiased Q-values by decoupling *selection* and *evaluation*, e.g.
   - **Double Q-Learning target**[11]

     $Q^*(s, a) = r + \gamma Q\left(s', \text{argmax}_{a \in \mathcal{A}} Q'(s', a)\right)$
   - **DQV-Max targets** in Eq.(3)
2. Reducing the variance of the Target Approximation Error (TAE)[2]
   - TAE: $Z_{s,a} = Q(s, a) - \mathbb{E}[r + \gamma \max_{a \in \mathcal{A}} Q(s', a) | s, a]$
   - Anschel et al. show that the magnitude of the bootstrapping bias in Q-learning is related to the *variance* of the TAE

Preventing the Bootstrapping Error - Offline

- In the offline setting, algorithms such as BCQ[4] and BEAR[5] mitigate the Bootstrapping Error by *regularizing* the learned policy to be *close* to the *training trajectories*
- One exception: Random Ensemble Mixture (REM)[1]
  - Dataset size and diversity are crucial for offline performance: DQN Replay Dataset on the Atari 2600 benchmark
  - REM idea: combining multiple noisy Q-functions creates a more robust Q-function

Focus: Offline DQV and DQV-Max

DQV and DQV-Max still incur in the Bootstrapping Error, but...

- Being an *on-policy* algorithm, DQV is less prone to it
- DQV-Max is *off-policy*, yet it uses multiple estimators to compute the expected Q-values $\rightarrow$ also more robust to the Bootstrapping Error
- Idea: can we use techniques for TAE reduction to improve resilience to the Bootstrapping Error in the DQV algorithmic family?
- Ensemble DQN[2]: training K Q-functions in parallel to obtain a $\frac{1}{K}$ variance reduction in Q-values
- Also motivated by REM's strong offline performance

Ensemble learning problem

- Ensemble DQN learning goal:

$$\mathcal{L}(\theta) = \frac{1}{K}\sum_{k=0}^{k-1}\mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}}\rangle \sim D}\left[\left(r_t + \gamma \max_{a\in\mathcal{A}} Q(s_{t+\mathbf{1},a;\theta_k^-}) - Q(s_t, a_t; \theta_k)\right)^2\right] \quad (5)$$

- The learning goal for DQV becomes:

$$\mathcal{L}(\phi) = \frac{1}{K}\sum_{k=0}^{k-1}\mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}}\rangle \sim D}\left[\left(r_t + \gamma V(s_{t+\mathbf{1}}, a; \phi_k^-) - V(s_t, a; \phi_k)\right)^2\right] \quad (6)$$

$$\mathcal{L}(\theta) = \frac{1}{K}\sum_{k=0}^{k-1}\mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}}\rangle \sim D}\left[\left(r_t + \gamma V(s_{t+\mathbf{1}}, a; \phi_k^-) - Q(s_t, a_t; \theta)\right)^2\right] \quad (7)$$

- The learning goal for DQV-Max becomes:

$$\mathcal{L}(\phi) = \frac{1}{K}\sum_{k=0}^{k-1}\mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}}\rangle \sim D}\left[\left(r_t + \gamma \max_{a\in\mathcal{A}} Q(s_{t+\mathbf{1}}, a; \theta_k^-) - V(s_t, a; \phi_k)\right)^2\right] \quad (8)$$

$$\mathcal{L}(\theta) = \frac{1}{K}\sum_{k=0}^{k-1}\mathbb{E}_{\langle s_t, a_t, r_t, s_{t+\mathbf{1}}\rangle \sim D}\left[\left(r_t + \gamma V(s_{t+\mathbf{1}}, a; \phi_k) - Q(s_t, a_t; \theta_k)\right)^2\right] \quad (9)$$

Ensemble Architecture

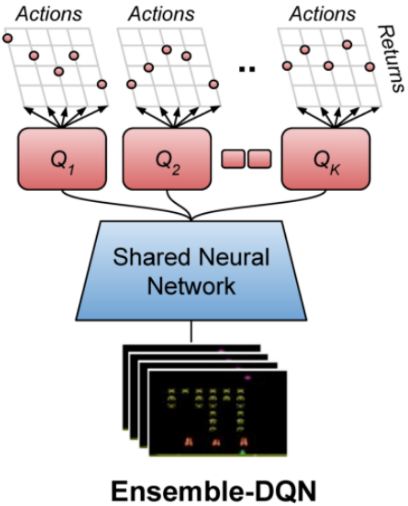
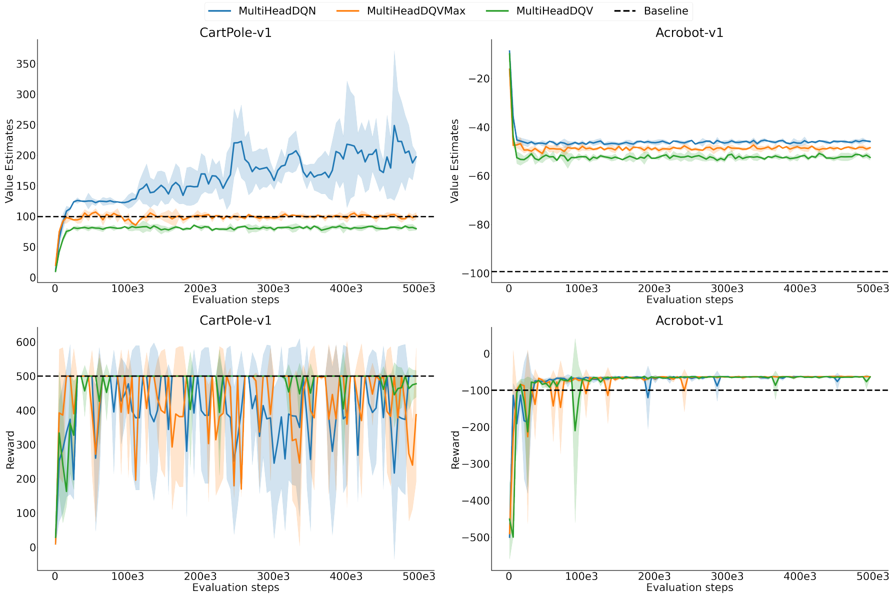


Figure 4: Multi-head Neural Network from Agarwal et al.

Bootstrapping Error with Multi-Headed DQV agents



Conclusions

- No real improvement over the traditional DQV algorithms
- The decoupling of estimation and update in the off-policy DQV-Max is stronger than the gains from multiple estimation observed with base DQN
- Rigorous analysis of the TAE for the DQV algorithms needed

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