The Deep Quality-Value family of Deep Reinforcement Learning Algorithms

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Presentation outline

1. Model-Free Deep Reinforcement Learning (DRL)
2. The Deep Quality-Value Family of DRL Algorithms
3. Analysis of the Algorithms

Model-Free Reinforcement Learning

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In model-free RL we care about learning **value functions** which give us information about the policy π our agent is following.

The state-value (V) function

$$V^{\pi}(s) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^{k} r_{t+k} \middle| s_t = s, \pi\right].$$

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Deriving π

$$\pi^*(s) = \arg\max_{a \in \mathcal{A}} Q(s_{t+1}, a)$$

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

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The Deep Quality-Value Family of DRL Algorithms

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DQV vs DQN and DDQN

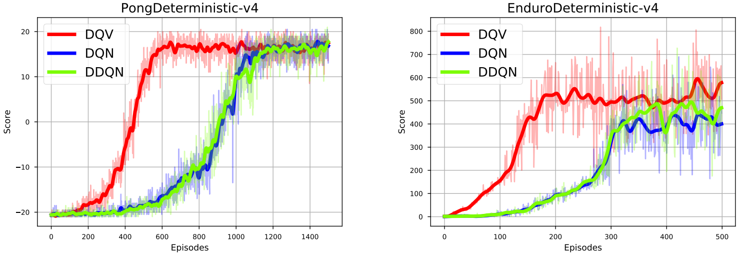

Figure: DQV learns significantly faster than DQN and DDQN [4]

[4] Sabatelli, Matthia, et al. "Deep Quality Value (DQV) Learning." Advances in Neural Information Processing Systems, Deep Reinforcement Learning Workshop. Montreal, 2018.

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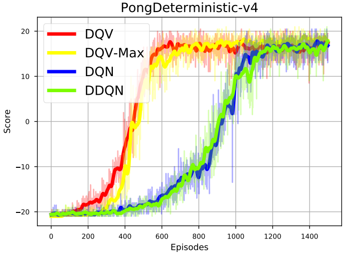

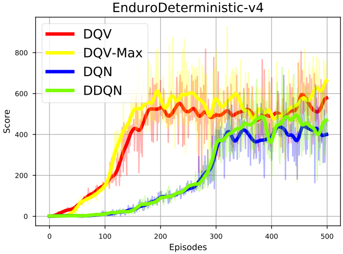

Figure: DQV-Max learns just as fast as DQV.

Empirical Results on the Atari Benchmark

TABLE I: The results obtained by DQV and DQV-Max on a subset of 15 `Atari` games. We can see that our newly introduced algorithms have a comparable, and often even better performance than DQN and DDQN. As highlighted by the green cells the overall best performing algorithm in our set of experiments is DQV-Max while the second-best performing algorithm is DQV (as reported by the yellow cells). Specific attention should be given to the games `BankHeist` and `Enduro` where DQV and DQV-Max are the only algorithms which can master the game with a final super-human performance.

Environment	Random	Human	DQN [6]	DDQN [7]	DQV	DQV-Max
Asteroids	719.10	13156.70	1629.33	930.60	1445.40	1846.08
Bank Heist	14.20	734.40	429.67	728.30	1236.50	1118.28
Boxing	0.10	4.30	71.83	81.70	78.66	80.15
Crazy Climber	10780.50	35410.50	114103.33	101874.00	108600.00	1000131.00
Enduro	0.00	309.60	301.77	319.50	829.33	875.64
Fishing Derby	-91.70	5.50	-0.80	20.30	1.12	20.42
Frostbite	65.20	4334.70	328.33	241.50	271.86	281.36
Gopher	257.60	2321.00	8520.00	8215.40	8230.30	7940.00
Ice Hockey	-11.20	0.90	-1.60	-2.40	-1.88	-1.12
James Bond	29.00	406.70	576.67	438.00	372.41	440.80
Montezuma's Revenge	0.00	4366.70	0.00	0.00	0.00	0.00
Ms.Pacman	307.30	15693.40	2311.00	3210.00	3590.00	3390.00
Pong	-20.70	9.30	18.90	21.00	21.00	21.00
Road Runner	11.50	7845.00	18256.67	48377.00	39290.00	20700.00
Zaxxon	32.50	9173.30	4976.67	10182.00	10950.00	8487.00

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1. A **function-approximator** is used when learning a value function
2. The algorithms rely on **bootstrapping** while the value function is regressed
3. The algorithms learn **off-policy**

These elements when combined enhance the **overestimation bias** of the Q function which characterizes the DQN algorithm.

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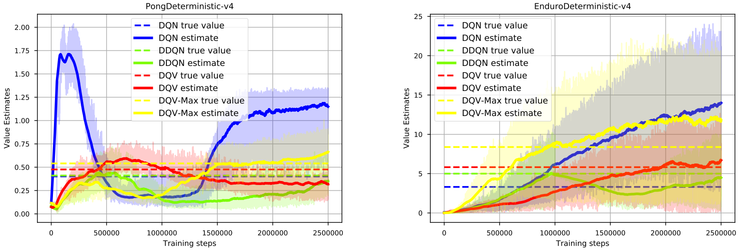

Figure: DQV and DQV-Max suffer less from the overestimation bias of the Q function.

On the neural capacity of the algorithms

1. Do we need two separately parametrized neural networks for successfully approximating $V(s)$ and $Q(s, a)$?

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2. We propose different extensions of the original DQV-Learning algorithm

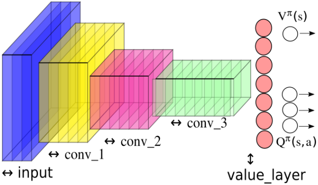

Figure: HARD-DQV Learning

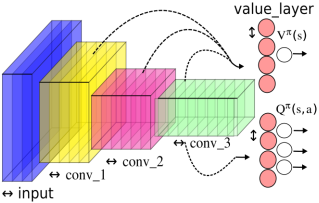

Figure: Dueling-DQV Learning

DQV-Learning Extensions

Two separate neural network with enough capacity are needed to exploit DQV's performance.

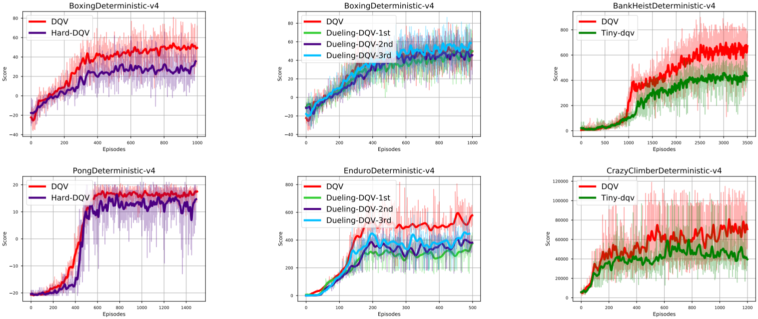

Figure: Results obtained by alternative versions of the DQV-Learning algorithm.

A final thank you note

   

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https://github.com/paintception/Deep-Quality-Value-Family