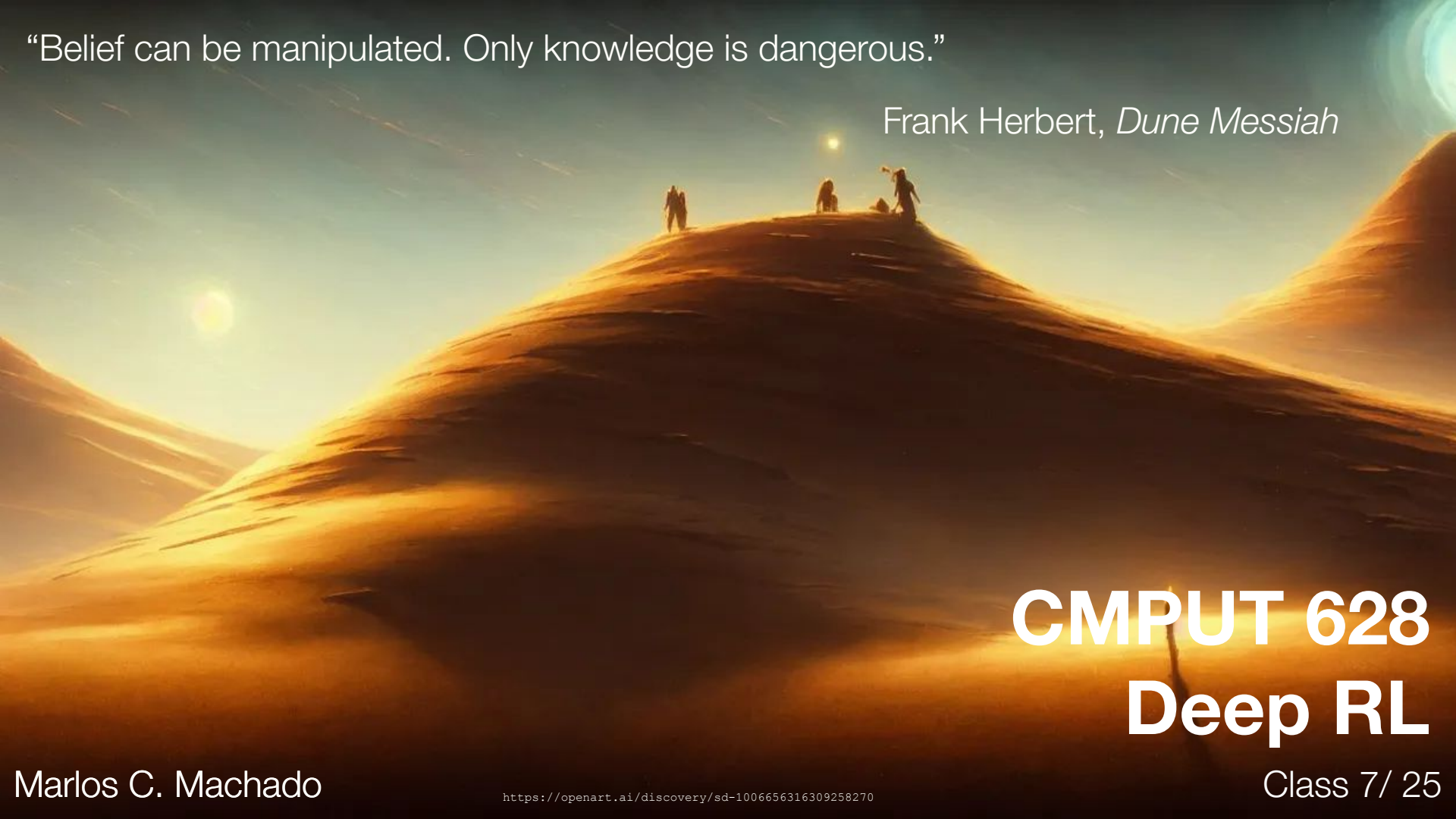
“Belief can be manipulated. Only knowledge is dangerous.”
Frank Herbert, *Dune Messiah*
CMPUT 628
Deep RL
Marlos C. Machado
https://openart.ai/discovery/sd-1006656316309258270
Class 7/ 25

Reminders & Notes

- Assignment 2 is coming …
- We will be marking Assignment 1 this week.
- I will release instructions about seminar and paper review during the reading week (Feb 16 – Feb 20)

Please, interrupt me at any time!

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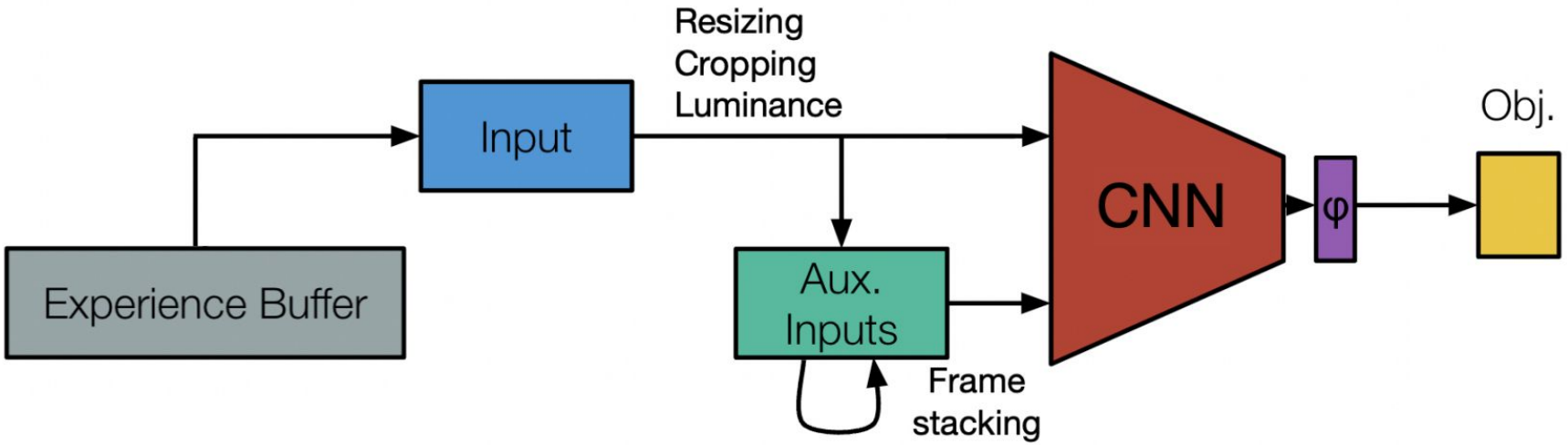
Last class: DQN



DQN's objective function

$$\mathcal{L}^{\text{DQN}} = \mathbb{E}_{(o,a,r,o')\sim U(\mathcal{D})}\left[\left(R_{t+1} + \gamma \max_{a'\in\mathcal{A}} Q(O_{t+1}, a'; \boldsymbol{\theta}^-) - Q(O_t, A_t; \boldsymbol{\theta}_t)\right)^2\right]$$

or , equivalently,

$$Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}^-) = R_{t+1} + \gamma \max_{a'\in\mathcal{A}} Q\left(O_{t+1}, a'; \boldsymbol{\theta}^-\right)$$

$$\mathcal{L}^{\text{DQN}} = \mathbb{E}_{(o,a,r,o')\sim U(\mathcal{D})}\left[\left(Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}^-) - Q(O_t, A_t; \boldsymbol{\theta}_t)\right)^2\right].$$

Maximization bias

- Q-learning uses a maximization to get its target policies.
- *Maximization bias*: A maximum over estimated values is used implicitly as an estimate of the maximum value, which can lead to a significant positive bias.

Example: Maximization bias

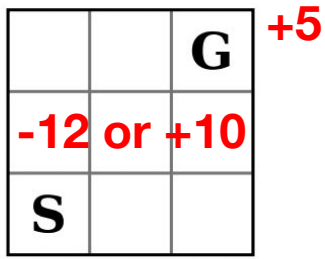




Actions	*Action 1*	*Action 2*	*Action 3*	*Action 4*	*Action 5*
Outcome	3, 1, 3, 1, 3	6, 3, 3, 2, 4	7, 1, 4, 6, 7	5, 3, 2, 5, 1	1, 10, 6, 2, 4
Average	2.2	3	5	3.2	4.6

3, 8, 2, 4, 8, 4, 2, 6, 4, 1 → Avg = 4.2

Q-learning overestimates [van Hasselt 2010]



Double learning

- The issue is that we use the same samples to determine the maximizing action and to estimate its value. One should not be using the maximum of the estimates as an estimate of the maximum of true values.
- In Bandits:
  - Split the data, learn $Q_1(a)$ and $Q_2(a)$ to estimate $q(a)$.
  - Choose actions according to one estimate and get estimate from the other:
    $A^* = \text{argmax}_a\ Q_1(a)$ $\quad\quad$ $Q_2(A^*) = Q_2(\text{argmax}_a\ Q_1(a))$
  - This leads to unbiased estimates, that is: $\mathbb{E}[Q_2(A^*)] = q(A^*)$

$$Q_1(S_t, A_t) \leftarrow Q_1(S_t, A_t) + \alpha \left[R_{t+1} + \gamma Q_2\left(S_{t+1}, \arg\max_a Q_1(S_{t+1}, a)\right) - Q_1(S_t, A_t) \right]$$

Double Q-Learning [van Hasselt 2010]

Double Q-learning, for estimating $Q_1 \approx Q_2 \approx q_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q_1(s, a)$ and $Q_2(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, such that $Q(\mathit{terminal}, \cdot) = 0$

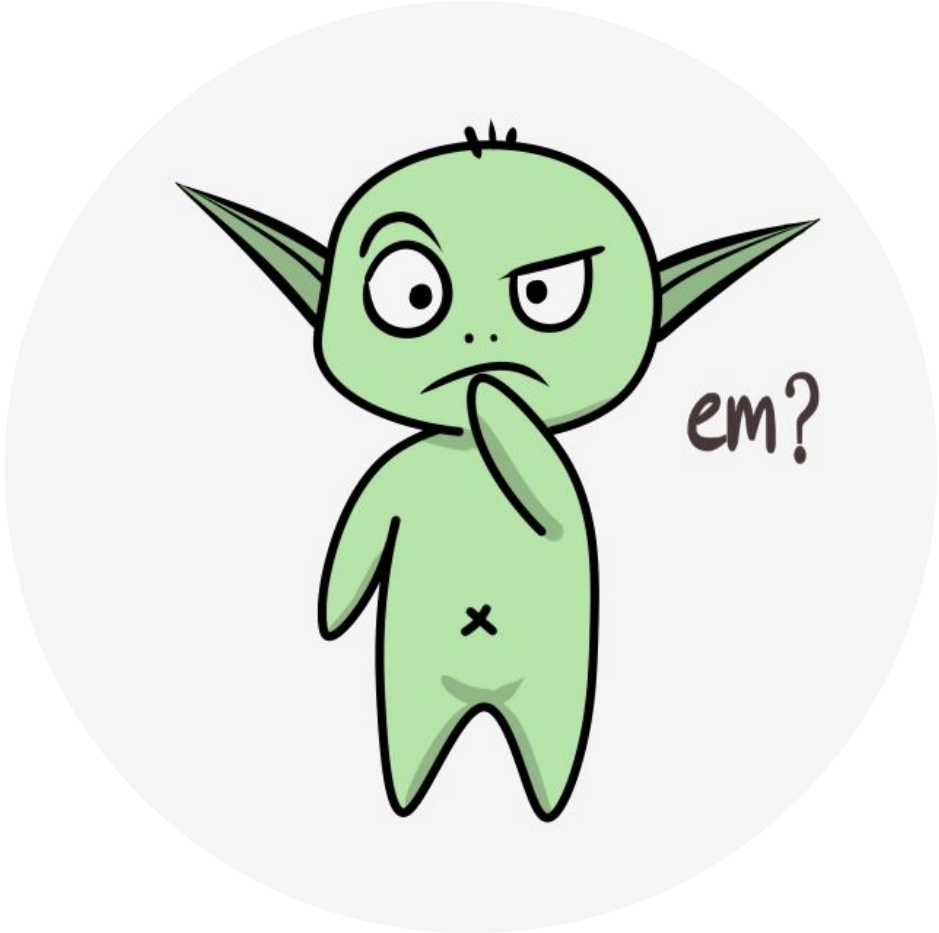
Loop for each episode:
  Initialize S
  Loop for each step of episode:
    Choose A from S using the policy ε-greedy in $Q_1 + Q_2$
    Take action A, observe R, S'
    With 0.5 probabilility:

$$Q_1(S, A) \leftarrow Q_1(S, A) + \alpha\Big(R + \gamma Q_2\big(S', \operatorname{argmax}_a Q_1(S', a)\big) - Q_1(S, A)\Big)$$

    else:

$$Q_2(S, A) \leftarrow Q_2(S, A) + \alpha\Big(R + \gamma Q_1\big(S', \operatorname{argmax}_a Q_2(S', a)\big) - Q_2(S, A)\Big)$$

    $S \leftarrow S'$
  until S is terminal



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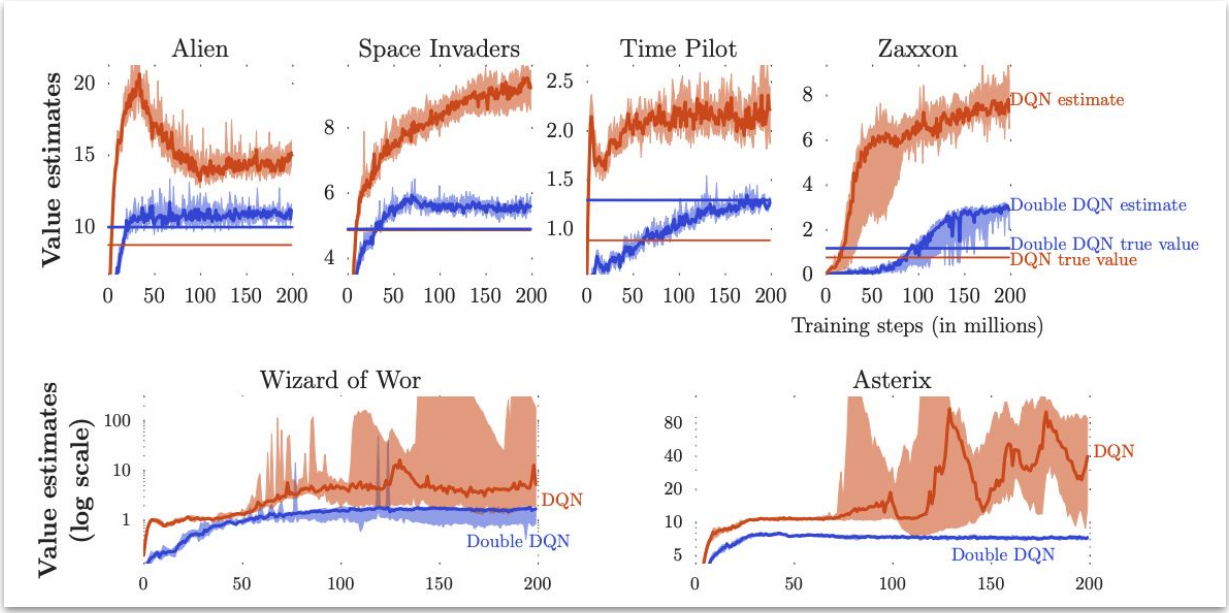
Do we observe maximization bias in DQN? [van Hasselt, Guez, & Silver 2016]



* “6 different random seeds with the hyper-parameters employed by Mnih et al. (2015). The darker line shows the median over seeds and we average the two extreme values to obtain the shaded area (i.e., 10% and 90% quantiles with linear interpolation).”

Now what?

$$Y_t^{\text{Q}} = R_{t+1} + \gamma Q(S_{t+1}, \underset{a}{\text{argmax}}\, Q(S_{t+1}, a; \boldsymbol{\theta}_t); \boldsymbol{\theta}_t)$$

$$Y_t^{\text{DoubleQ}} \equiv R_{t+1} + \gamma Q(S_{t+1}, \underset{a}{\text{argmax}}\, Q(S_{t+1}, a; \boldsymbol{\theta}_t); \boldsymbol{\theta}'_t)$$

Double DQN [van Hasselt, Guez, & Silver 2016]

- Main idea: use the target network as a second value function
- Update is the same as in DQN, but with a different target:

$$Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t) = R_{t+1} + \gamma Q\left(O_{t+1}, \arg\max_{a \in \mathcal{A}} Q(O_{t+1}, a; \boldsymbol{\theta}_t); \boldsymbol{\theta}^-\right)$$

$$\mathcal{L}^{\text{DDQN}} = \mathbb{E}_{\tau \sim U(\mathcal{D})}\left[\left(Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t) - Q(O_t, A_t; \boldsymbol{\theta}_t)\right)^2\right]$$

- “This version of Double DQN is perhaps the minimal possible change to DQN towards Double Q-learning. The goal is to get most of the benefit of Double Q-learning, while keeping the rest of the DQN algorithm intact for a fair comparison, and with minimal computational overhead.”

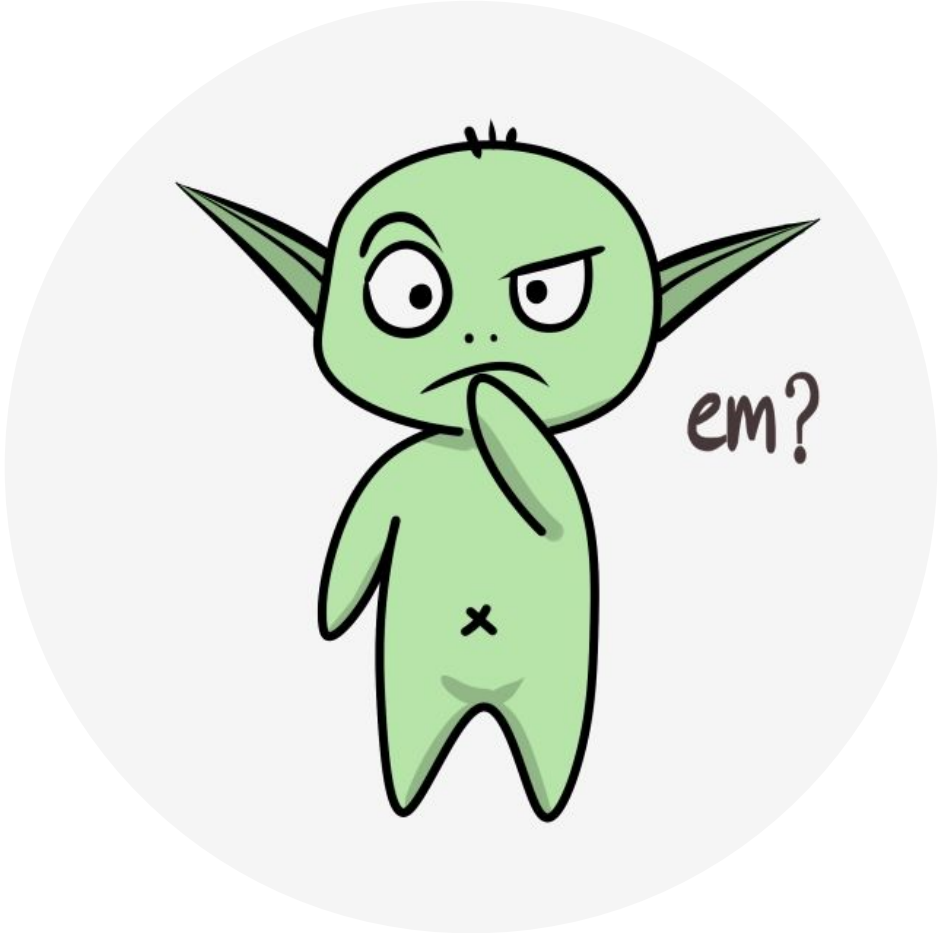
DQN vs Double DQN

$$Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}^-) = R_{t+1} + \gamma \max_{a' \in \mathcal{A}} Q\big(O_{t+1}, a'; \boldsymbol{\theta}^-\big)$$

$$\mathcal{L}^{\mathrm{DQN}} = \mathbb{E}_{(o,a,r,o') \sim U(\mathcal{D})} \Big[\big(Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}^-) - Q(O_t, A_t; \boldsymbol{\theta}_t) \big)^2 \Big].$$

$$Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t) = R_{t+1} + \gamma Q\big(O_{t+1}, \arg\max_{a \in \mathcal{A}} Q(O_{t+1}, a; \boldsymbol{\theta}_t); \boldsymbol{\theta}^-\big)$$

$$\mathcal{L}^{\mathrm{DDQN}} = \mathbb{E}_{\tau \sim U(\mathcal{D})} \Big[\big(Y(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t) - Q(O_t, A_t; \boldsymbol{\theta}_t) \big)^2 \Big],$$



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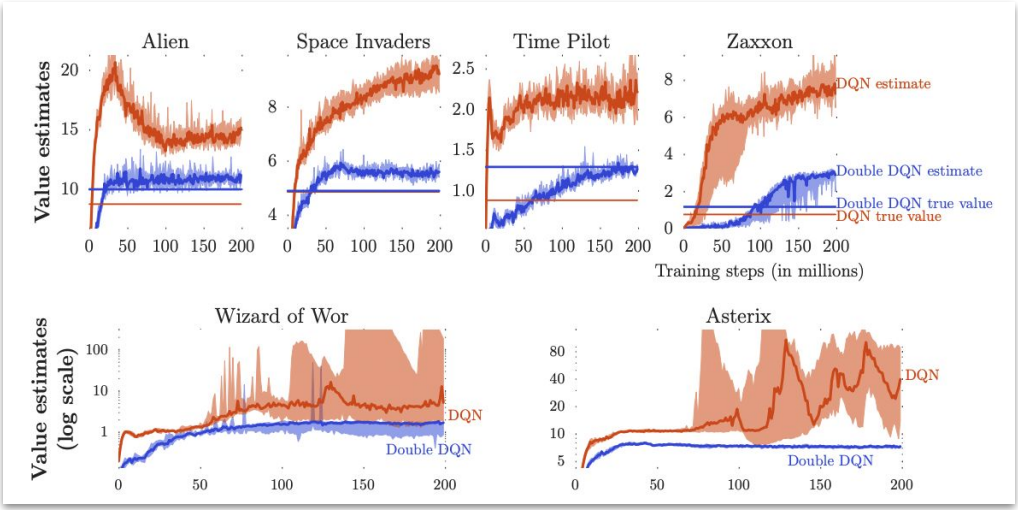
It seems to work ¯_ (ツ)_/¯

- “We closely follow the experimental setting and network architecture outlined by Mnih et al. (2015). (...) The network takes the last four frames as input and outputs the action value of each action. On each game, the network is trained on a single GPU for 200M frames, or approximately 1 week.” [van Hasselt, Guez, & Silver 2016]



Quality of the learned policies

[van Hasselt, Guez, & Silver 2016]

- “Overoptimism does not always adversely affect the quality of the learned policy. For example, DQN achieves optimal behavior in Pong despite slightly overestimating the policy value. Nevertheless, reducing overestimations can significantly benefit the stability of learning.” [van Hasselt, Guez, & Silver 2016]

- “As described by Mnih et al. (2015) each evaluation episode starts by executing a special no-op action that does not affect the environment up to 30 times, to provide different starting points for the agent. Some exploration during evaluation provides additional randomization. For Double DQN we used the exact same hyper-parameters as for DQN, to allow for a controlled experiment focused just on reducing overestimations. The learned policies are evaluated for 5 mins of emulator time (18,000 frames) with an ε-greedy policy where ε = 0.05. The scores are averaged over 100 episodes.”

Quality of the learned policies

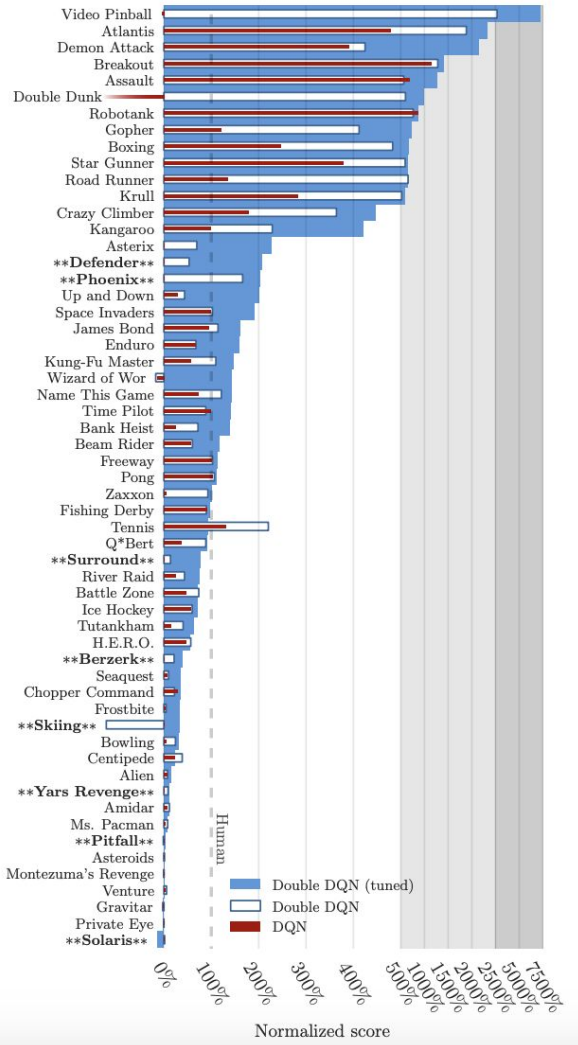
[van Hasselt, Guez, & Silver 2016]

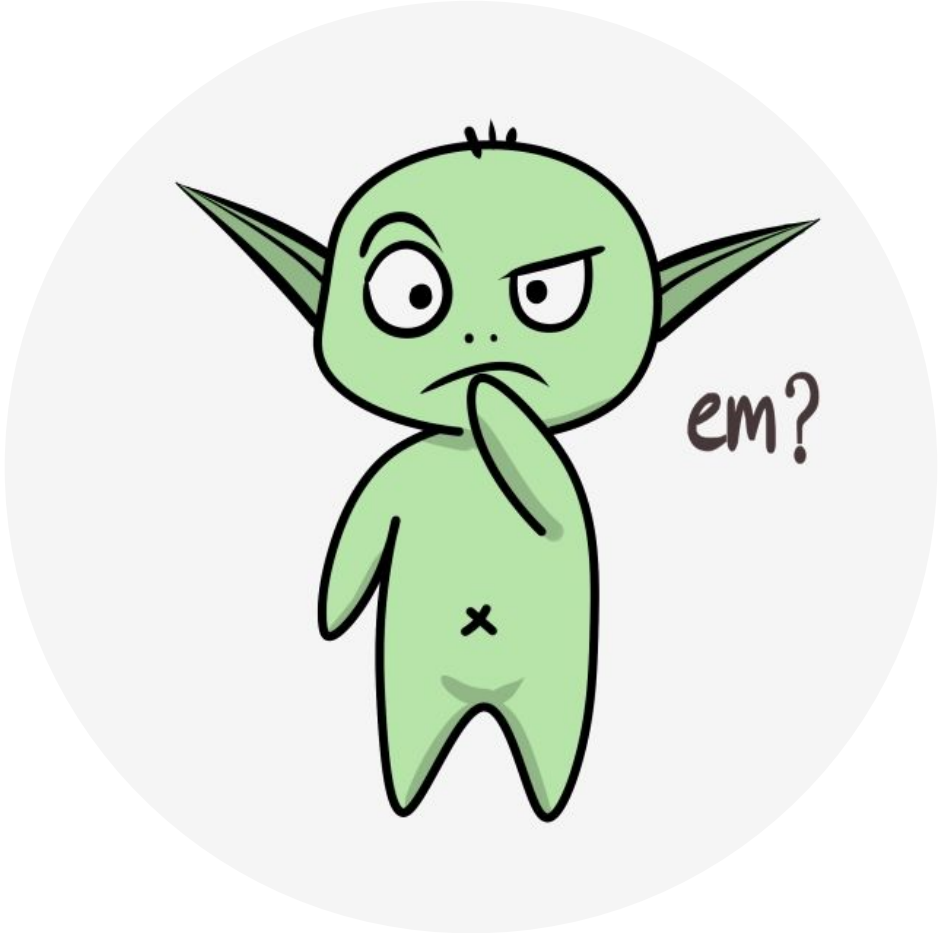
	DQN	Double DQN	Double DQN (tuned)
Median	47.5%	88.4%	116.7%
Mean	122.0%	273.1%	475.2%

$$\text{score}_{\text{normalized}} = \frac{\text{score}_{\text{agent}} - \text{score}_{\text{random}}}{\text{score}_{\text{human}} - \text{score}_{\text{random}}}$$

Game	Random	Human	DQN	Double DQN
Alien	227.80	6875.40	3069.33	2907.30
Amidar	5.80	1675.80	739.50	702.10
Assault	222.40	1496.40	3358.63	5022.90
Asterix	210.00	8503.30	6011.67	15150.00
Asteroids	719.10	13156.70	1629.33	930.60
Atlantis	12850.00	29028.10	85950.00	64758.00
Bank Heist	14.20	734.40	429.67	728.30
Battle Zone	2360.00	37800.00	26300.00	25730.00
Beam Rider	363.90	5774.70	6845.93	7654.00
Bowling	23.10	154.80	42.40	70.50
Boxing	0.10	4.30	71.83	81.70
Breakout	1.70	31.80	401.20	375.00
Centipede	2090.90	11963.20	8309.40	4139.40

* 1 seed?





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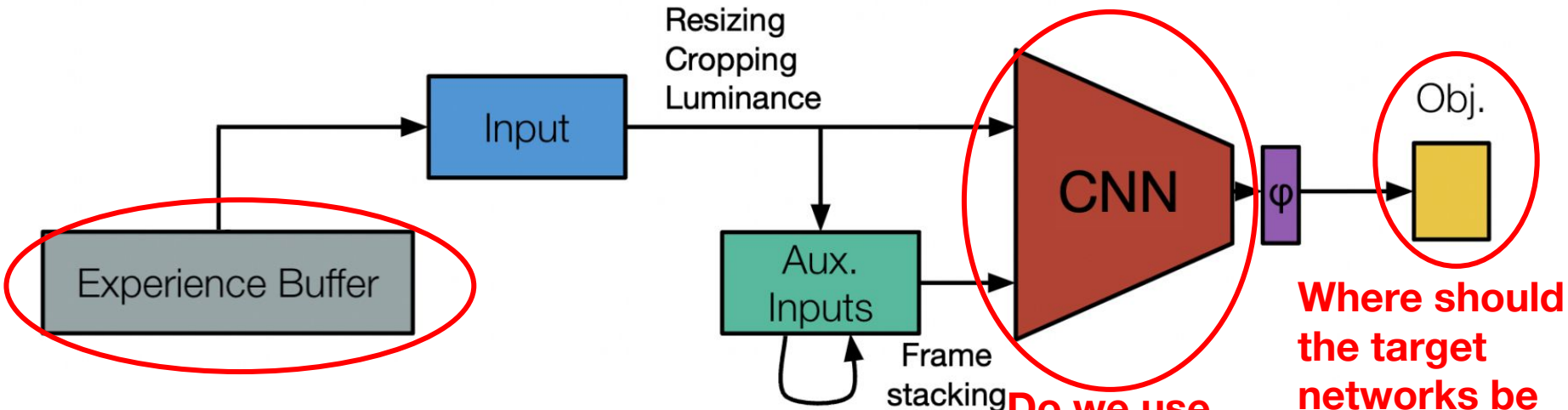
But this is deep RL: Which components should we change?



The Different Update Rules [Nagarajan et al., 2025]

- Two experience replay buffers, no target network:

$$Y_{\mathrm{v}_1}(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t^1, \boldsymbol{\theta}_t^2) = R_{t+1} + \gamma Q\big(O_{t+1}, \arg\max_{a \in \mathcal{A}} Q(O_{t+1}, a; \boldsymbol{\theta}_t^1); \boldsymbol{\theta}_t^2\big)$$

$$\mathcal{L}_{\mathrm{v}_1}^{\mathrm{DDQL}} = \mathbb{E}_{\tau \sim U(\mathcal{D}^1)}\Big[\big(Y_{\mathrm{v}_1}(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t^1, \boldsymbol{\theta}_t^2) - Q(O_t, A_t; \boldsymbol{\theta}_t^1)\big)^2\Big]$$

- Two independent estimators, but using a target network:

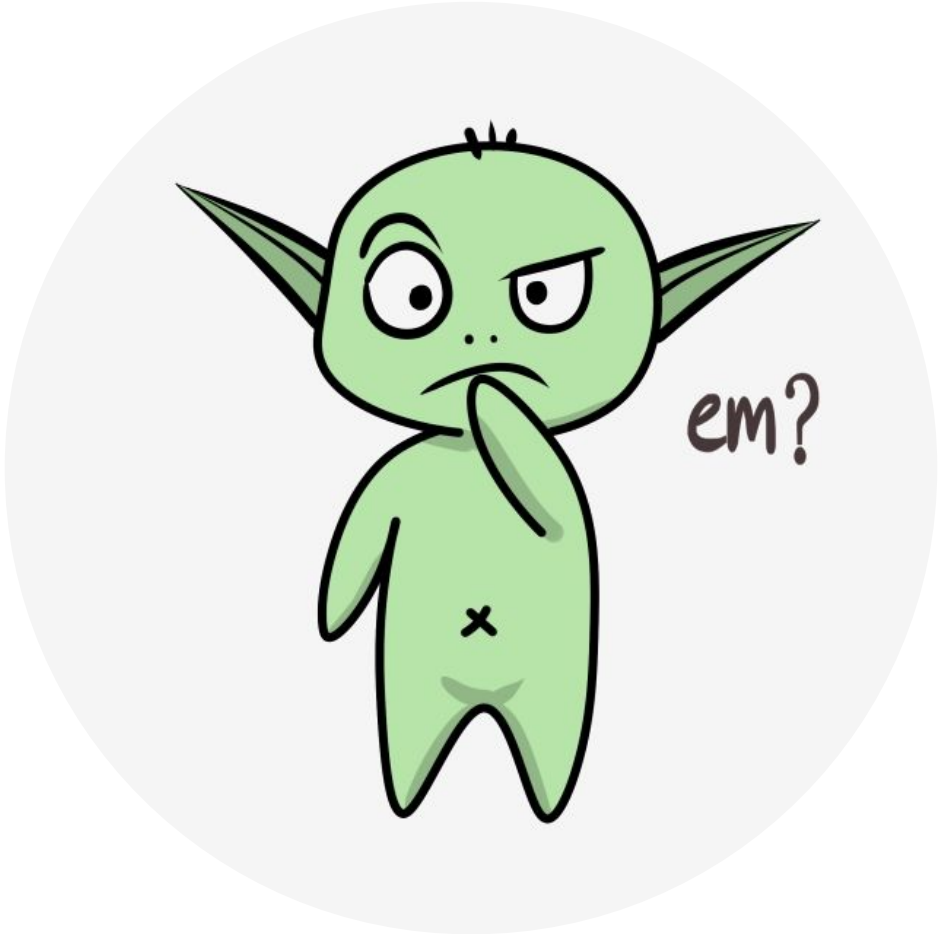
$$Y_{\mathrm{v}_2}(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t^{-1}, \boldsymbol{\theta}_t^{-2}) = R_{t+1} + \gamma Q\big(O_{t+1}, \arg\max Q(O_{t+1}, a; \boldsymbol{\theta}_t^{-1}); \boldsymbol{\theta}_t^{-2}\big)$$

$$\mathcal{L}_{\mathrm{v}_2}^{\mathrm{DDQL}} = \mathbb{E}_{\tau \sim U(\mathcal{D}^1)}\Big[\big(Y_{\mathrm{v}_2}(R_{t+1}, O_{t+1}; \boldsymbol{\theta}_t^{-1}, \boldsymbol{\theta}_t^{-2}) - Q(O_t, A_t; \boldsymbol{\theta}_t^1)\big)^2\Big]$$

The Different Update Rules [Nagarajan et al., 2025]

Action-value estimator	Action selector	Algorithm
θ	θ	OQLNN / DQN (no target)
θ	θ^-	Inverse Double DQN
θ^-	θ	Double DQN
θ^-	θ^-	DQN

Action-value estimator	Action selector	Algorithm
θ_2	θ_1	DDQL (no target)
θ_2^-	θ_1^-	Inverse Double DQN
θ_2^-	θ_1	True DDQN?
θ_2	θ_1^-	Inverse True DDQN?



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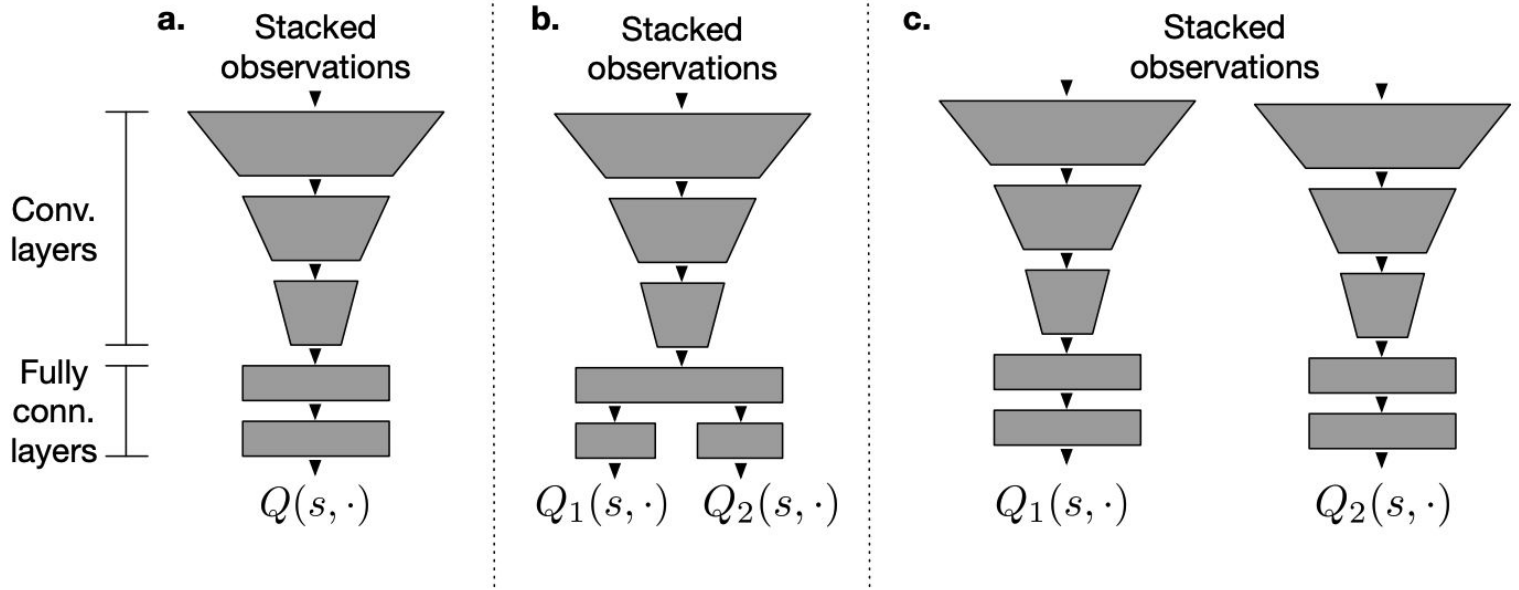
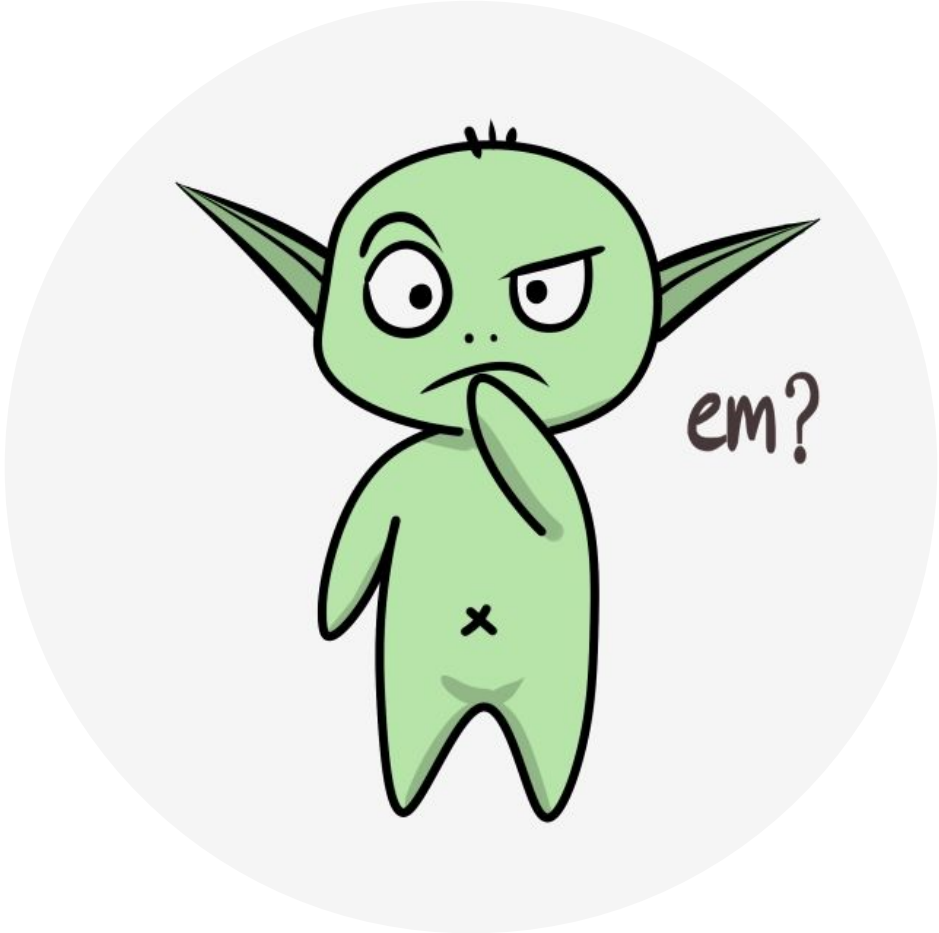
Different Neural Network Architectures [Nagarajan et al., 2025]

Arguably, this is a more faithful implementation of double learning



The Many Instantiation Choices [Nagarajan et al., 2025]

Double Q-learning Defining Feature		Double DQN	DH-DDQL	DN-DDQL
(1)	Target bootstrap decoupling?	✓	✓	✓
(2)	Double estimation?	-	✓	✓
(2a)	No parameter sharing?	-	✗	✓
(3)	Dataset partitioning?	-	✓	✓
(3a)	Train on distinct buffers?	-	✗	✗



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Overall Results: Overestimation [Nagarajan et al., 2025]

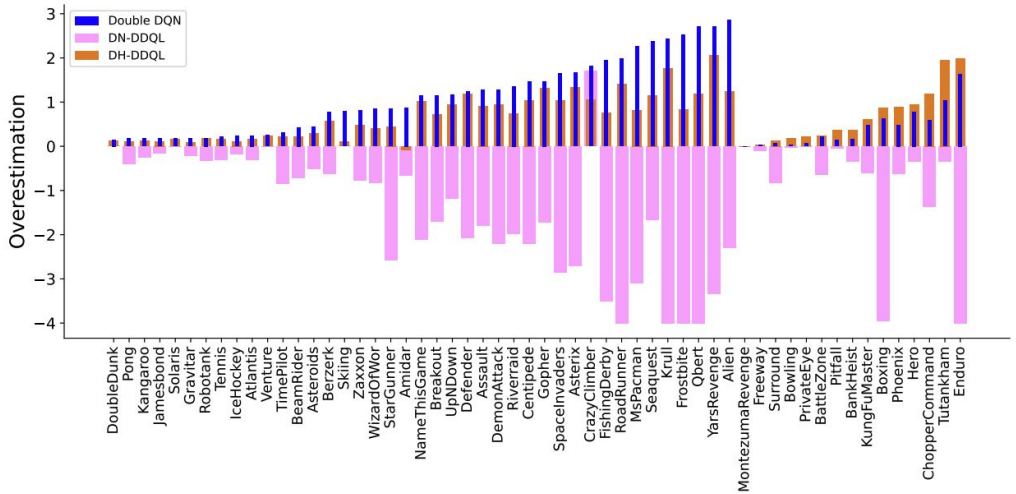


Figure 3: Final overestimations averaged across five seeds of Double DQN, DH-DDQL, and DN-DDQL. VIDEOPINBALL is omitted for visibility. The underestimation is clipped to -4 for visibility. Figure 13 depicts all 57 environments without clipping. Double DQN overestimates the most. DH-DDQL overestimates less. DN-DDQL overestimates the least, largely underestimating.

Overall Results: Performance [Nagarajan et al., 2025]

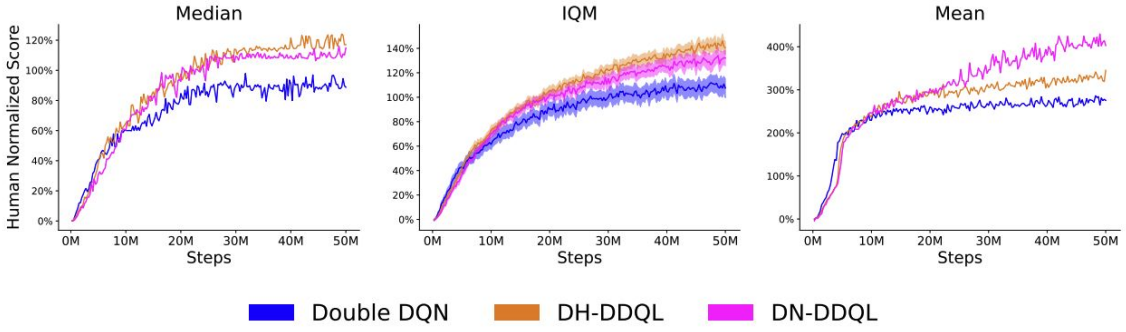


Figure 4: Human-normalized scores throughout training. Note that the scale of the y-axes are different across metrics. In all three metrics, DDQL outperforms Double DQN. The shaded region is a 95% stratified bootstrap confidence interval (Agarwal et al., 2021).

There are some other details (with ablations in the paper):

- Same initialization
- Lower number of gradient updates per environment transition
- Target network update interval

Two Buffers doesn't Improve Performance [Nagarajan et al., 2025]

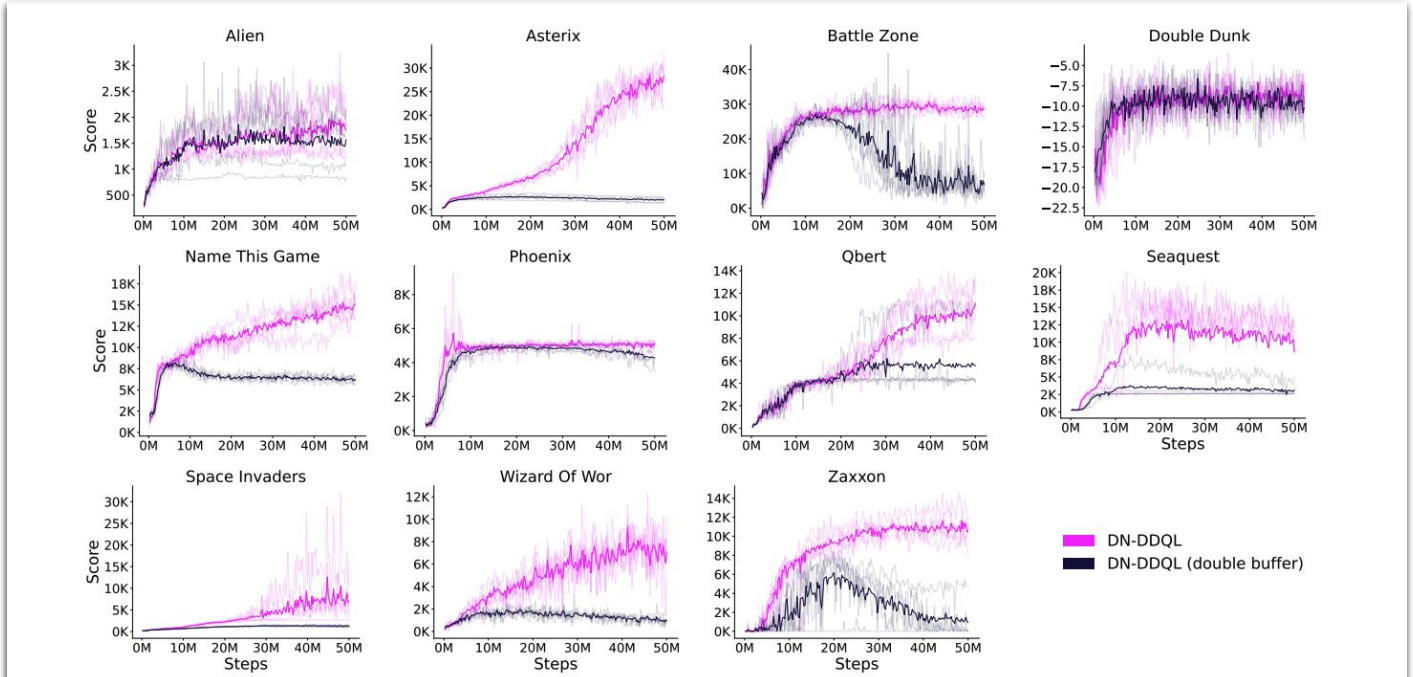


Figure 8: Performance of DN-DDQL compared to DN-DDQL (double buffer). DN-DDQL (double buffer) performs quite poorly.

But Two Buffers Reduce Overestimation [Nagarajan et al., 2025]

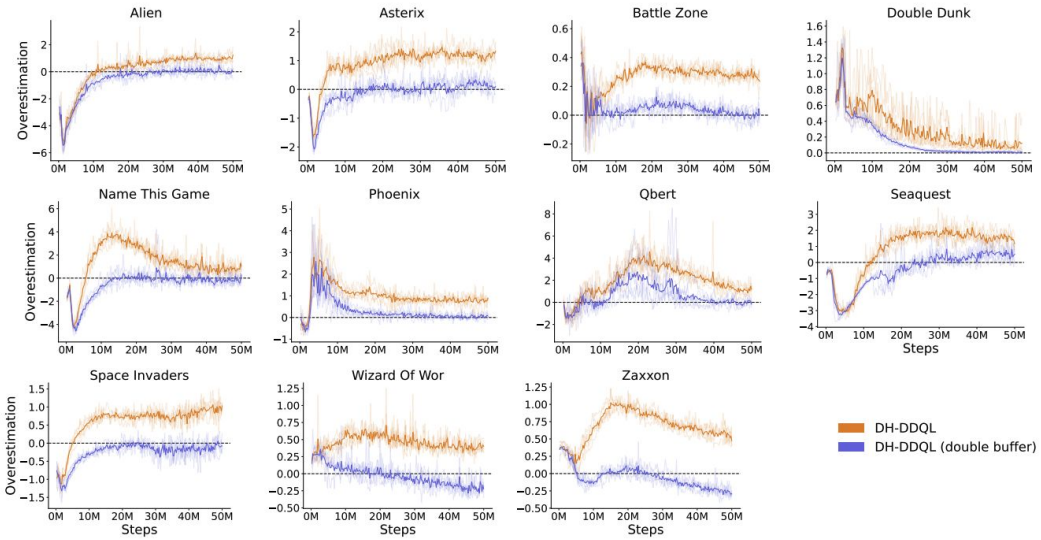


Figure 7: Overestimation of DH-DDQL compared to DH-DDQL (double buffer). The double buffer strategy reduces overestimation.

Some Preliminary Results [Nagarajan et al., 2025]

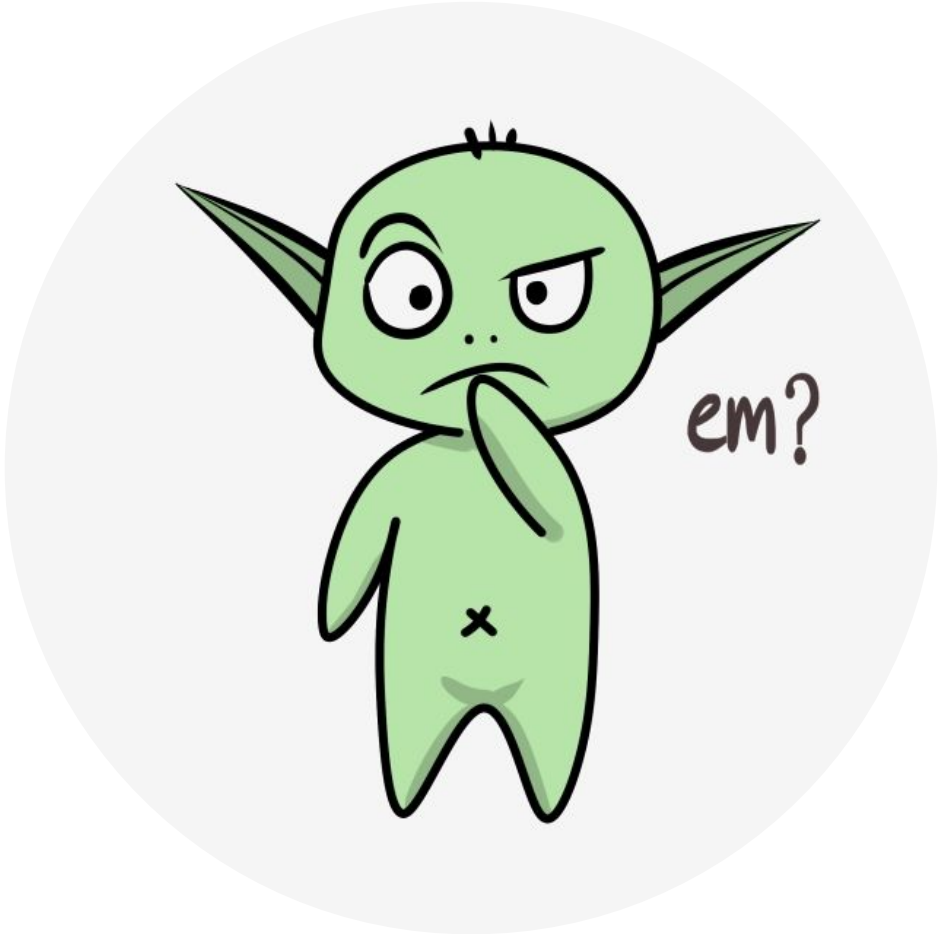
- The optimizer (Adam vs RMSProp) and the loss (MSE vs Huber) can have a big impact not only on performance, but also on overestimation
- Using two independent experience replay buffers has very little impact on the performance we observe (both for overestimation and the policy itself)
- Using two different networks drastically reduces overestimation, sometimes even leading to underestimation
- Reducing overestimation does not immediately lead to performance improvements

Some Preliminary Results [Nagarajan et al., 2025]

On the Development and Analysis of Algorithm Variations

Making definitive claims about an algorithm is difficult because:

- Hyperparameters need to be properly swept and hyperparameters are not independent from each other.
- Sometimes it is not easy to make apples-to-apples comparison (e.g., number of networks vs number of gradient updates)



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Next class

- What I plan to do:
  - Continue discussing different instantiations of deep RL algorithms through the objective function, more specifically, multi-step methods.
- What I recommend YOU to do for next class:
  - Read

    - *Chapters 7 and 12 by Sutton and Barto (2018)*

    - *[Optional] Daley, B., White, M., Amato, C., and Machado, M. C. (2023). Trajectory-aware eligibility traces for off-policy reinforcement learning. In Proceedings of the International Conference on Machine Learning*
  - Work on Assignment 2!