"One learns from books and example only that certain things can be done. Actual learning requires that you do those things."

Frank Herbert, *Children of Dune*

CMPUT 365
Introduction to RL

Marlos C. Machado

https://www.duneawakening.com/en/developer-update-2-sounds-of-arrakis

Class 31/35

Coursera Reminder

You **should be enrolled in the private session** we created in Coursera for CMPUT 365.

I **cannot** use marks from the public repository for your course marks.

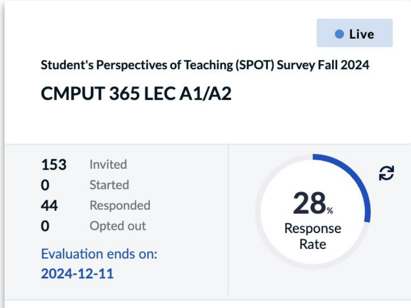
You **need** to **check**, **every time**, if you are in the private session and if you are submitting quizzes and assignments to the private section.

The deadlines in the public session **do not align** with the deadlines in Coursera.

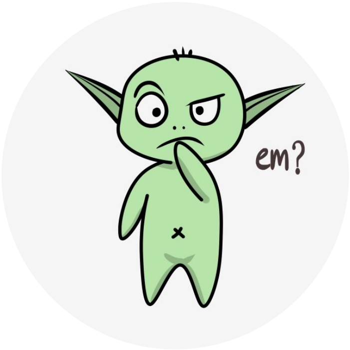
If you have any questions or concerns, **talk with the TAs** or email us `cmput365@ualberta.ca`.

Reminders and Notes

- The last quiz of the course is due on Monday, and the last programming assignment is due on Wednesday. Both are on Policy Gradient.
- Rich Sutton will give a guest lecture Dec 9th, Monday. Spread the word.
- A note on the final exam:
    - The required reading from the syllabus does not mean that's what will be covered in the final exam. There are some mismatches. Anything we discussed in class is fair game, including Maximization Bias and Double Learning (Section 6.7), and Nonlinear Function Approximation: Artificial Neural Networks (Section 9.7).
    - Final will be *2 hours long*, and questions will cover the whole term.
- SPOT Survey is now available for you.



Please, interrupt me at any time!



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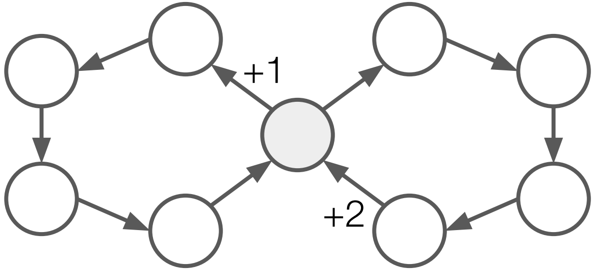
Last Class: Average Reward Problem Formulation

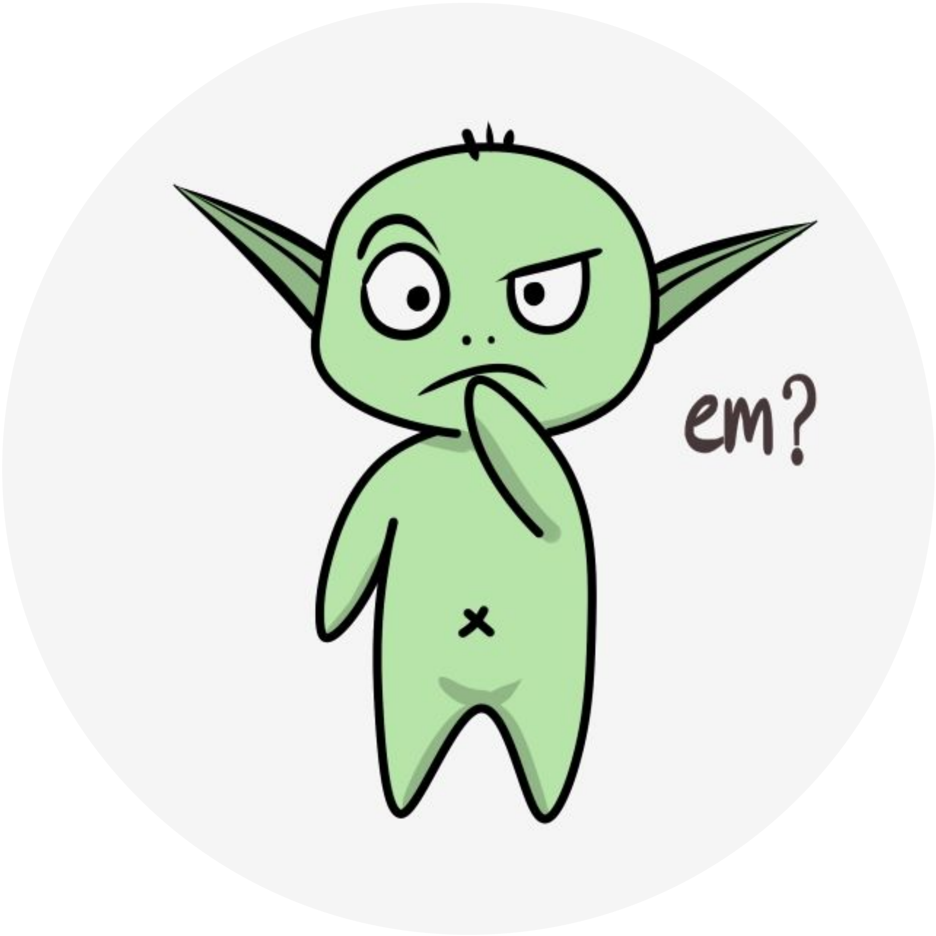
- Continuing problems without discounting.
  - The agent cares about all rewards equally.



- Quality of a policy is defined by the average rate of reward, r(π):

$$
\begin{aligned}
r(\pi) &\doteq \lim_{h\to\infty} \frac{1}{h} \sum_{t=1}^{h} \mathbb{E}[R_t \mid S_0, A_{0:t-1} \sim \pi] \\
&= \lim_{t\to\infty} \mathbb{E}[R_t \mid S_0, A_{0:t-1} \sim \pi], \\
&= \sum_s \mu_\pi(s) \sum_a \pi(a|s) \sum_{s',r} p(s', r \mid s, a) r
\end{aligned}
$$

If the MDP is *ergodic*: the starting state and any early decision made by the agent can have only a temporary effect; in the long run the expectation of being in a state depends only on the policy and the MDP transition probabilities.



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Avg. Reward: A Problem Setting for Continuing Tasks

- (Differential) Return:

$$G_t \doteq R_{t+1} - r(\pi) + R_{t+2} - r(\pi) + R_{t+3} - r(\pi) + \cdots .$$

Avg. Reward: A Problem Setting for Continuing Tasks

- (Differential) Return:

$$G_t \doteq R_{t+1} - r(\pi) + R_{t+2} - r(\pi) + R_{t+3} - r(\pi) + \cdots .$$

- Differential value functions:

$$v_\pi(s) = \sum_a \pi(a|s) \sum_{r,s'} p(s', r|s, a)\Big[r - r(\pi) + v_\pi(s')\Big],$$

$$q_\pi(s,a) = \sum_{r,s'} p(s', r|s, a)\Big[r - r(\pi) + \sum_{a'} \pi(a'|s') q_\pi(s', a')\Big],$$

$$v_*(s) = \max_a \sum_{r,s'} p(s', r|s, a)\Big[r - \max_\pi r(\pi) + v_*(s')\Big], \text{ and}$$

$$q_*(s,a) = \sum_{r,s'} p(s', r|s, a)\Big[r - \max_\pi r(\pi) + \max_{a'} q_*(s', a')\Big]$$

Avg. Reward: A Problem Setting for Continuing Tasks

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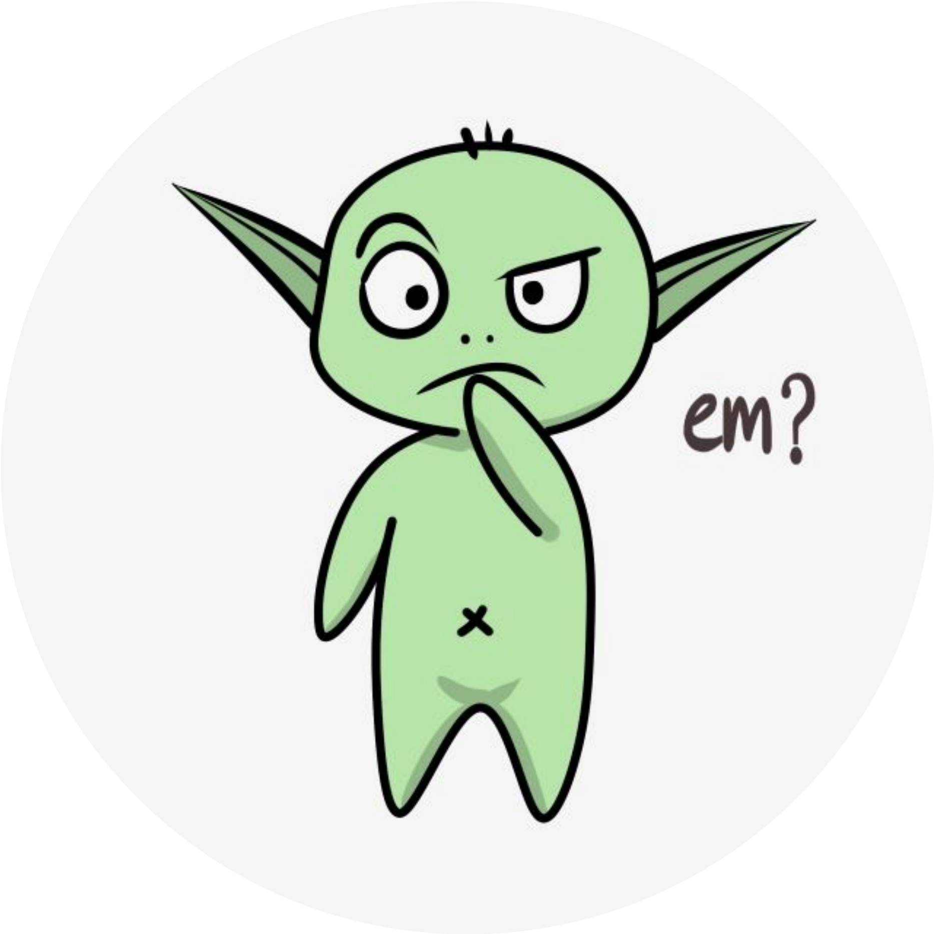
$$q_*(s, a) = \sum_{r,s'} p(s', r | s, a) \Big[r - \max_\pi r(\pi) + \max_{a'} q_*(s', a') \Big]$$

- Differential TD error:

$$\delta_t \doteq R_{t+1} - \bar{R}_t + \hat{v}(S_{t+1}, \mathbf{w}_t) - \hat{v}(S_t, \mathbf{w}_t),$$

$$\delta_t \doteq R_{t+1} - \bar{R}_t + \hat{q}(S_{t+1}, A_{t+1}, \mathbf{w}_t) - \hat{q}(S_t, A_t, \mathbf{w}_t).$$



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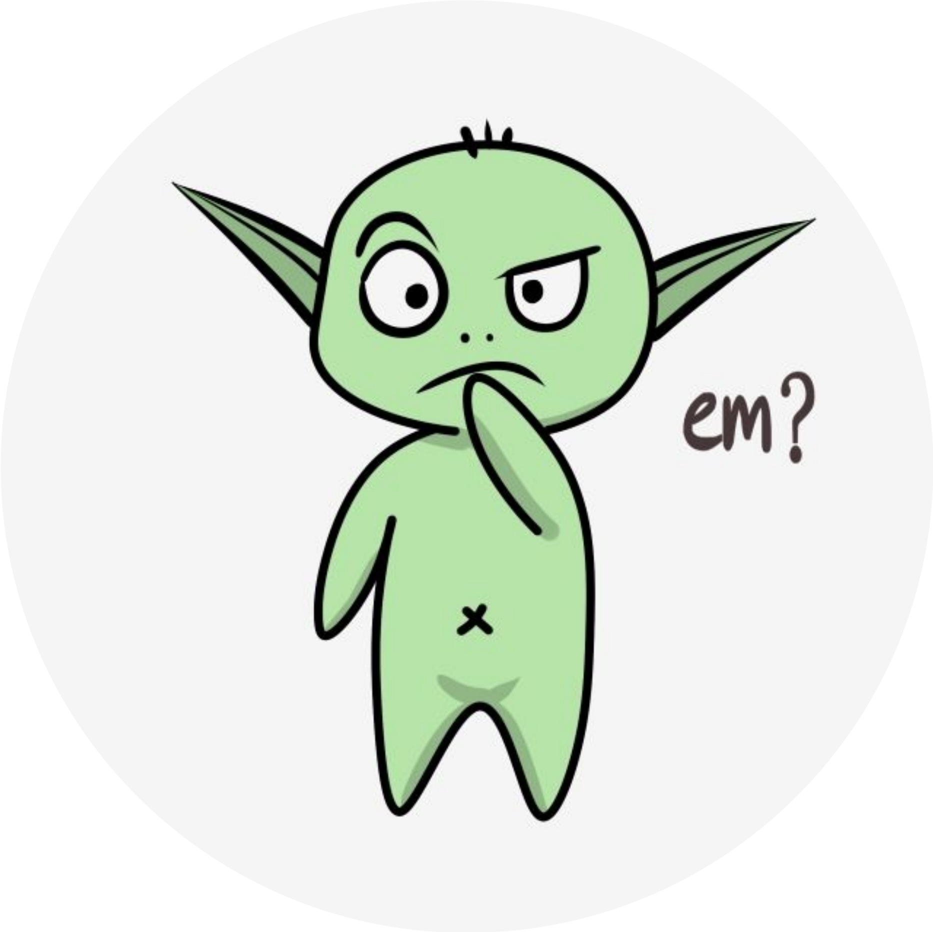
Differential semi-gradient Sarsa

Differential semi-gradient Sarsa for estimating $\hat{q} \approx q_*$

Input: a differentiable action-value function parameterization $\hat{q} : \mathcal{S} \times \mathcal{A} \times \mathbb{R}^d \to \mathbb{R}$
Algorithm parameters: step sizes $\alpha, \beta > 0$, small $\varepsilon > 0$
Initialize value-function weights $\mathbf{w} \in \mathbb{R}^d$ arbitrarily (e.g., $\mathbf{w} = \mathbf{0}$)
Initialize average reward estimate $\bar{R} \in \mathbb{R}$ arbitrarily (e.g., $\bar{R} = 0$)

Initialize state S, and action A
Loop for each step:
    Take action A, observe R, S'
    Choose A' as a function of $\hat{q}(S', \cdot, \mathbf{w})$ (e.g., ε-greedy)
    $\delta \leftarrow R - \bar{R} + \hat{q}(S', A', \mathbf{w}) - \hat{q}(S, A, \mathbf{w})$
    $\bar{R} \leftarrow \bar{R} + \beta\delta$
    $\mathbf{w} \leftarrow \mathbf{w} + \alpha\delta\nabla\hat{q}(S, A, \mathbf{w})$
    $S \leftarrow S'$
    $A \leftarrow A'$



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The Arcade Learning Environment: An Evaluation Platform for General Agents

Marc G. Bellemare MG17@CS.UALBERTA.CA
University of Alberta, Edmonton, Alberta, Canada

Yavar Naddaf YAVAR@EMPIRICALRESULTS.CA
Empirical Results Inc., Vancouver,
British Columbia, Canada

Joel Veness VENESS@CS.UALBERTA.CA
Michael Bowling BOWLING@CS.UALBERTA.CA
University of Alberta, Edmonton, Alberta, Canada

Abstract

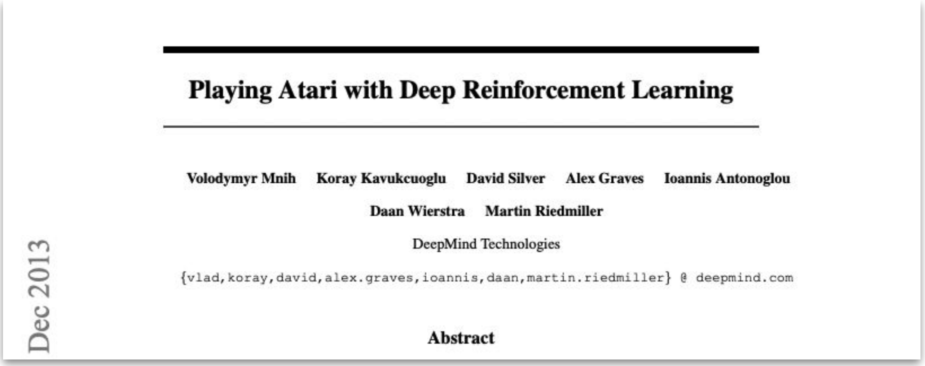
In this article we introduce the Arcade Learning Environment (ALE): both a challenge problem and a platform and methodology for evaluating the development of general, domain-independent AI technology. ALE provides an interface to hundreds of Atari 2600 game environments, each one different, interesting, and designed to be a challenge for human players. ALE presents significant research challenges for reinforcement learning, model learning, model-based planning, imitation learning, transfer learning, and intrinsic motivation. Most importantly, it provides a rigorous testbed for evaluating and comparing approaches to these problems. We illustrate the promise of ALE by developing and benchmarking domain-independent agents designed using well-established AI techniques for both reinforcement learning and planning. In doing so, we also propose an evaluation

Arcade Learning Environment

Over 50 Domains in 8 Minutes 23 Seconds

Deep Q-Network (and Deep RL)

[Mnih et al., 2013, 2015]



Dec 2013

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih Koray Kavukcuoglu David Silver Alex Graves Ioannis Antonoglou
Daan Wierstra Martin Riedmiller
DeepMind Technologies
{vlad,koray,david,alex.graves,ioannis,daan,martin.riedmiller} @ deepmind.com

Abstract

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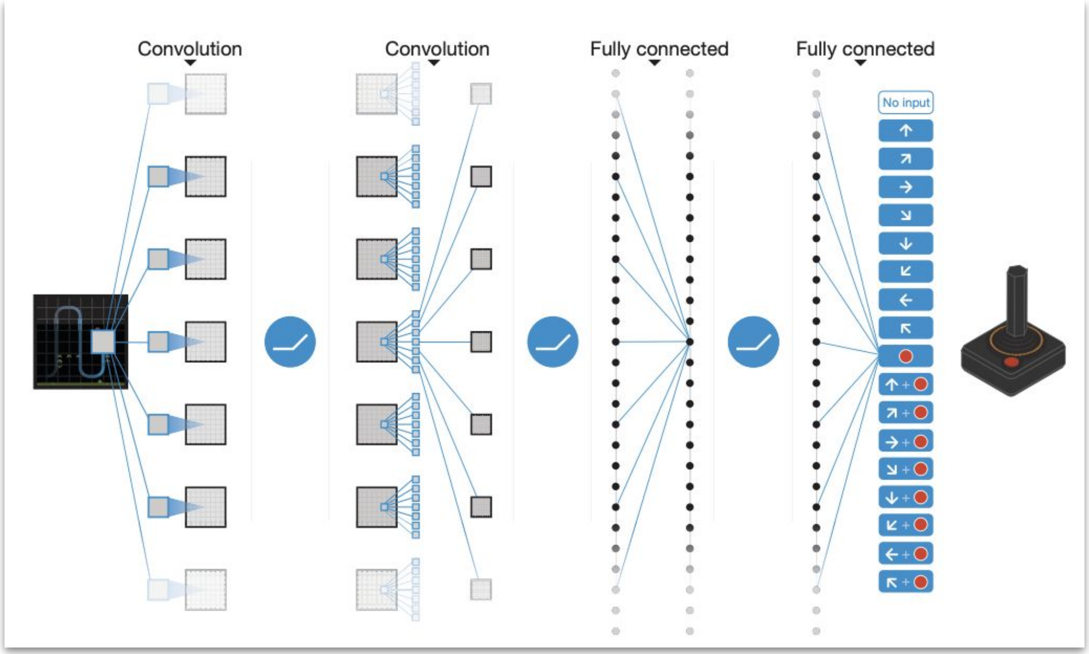

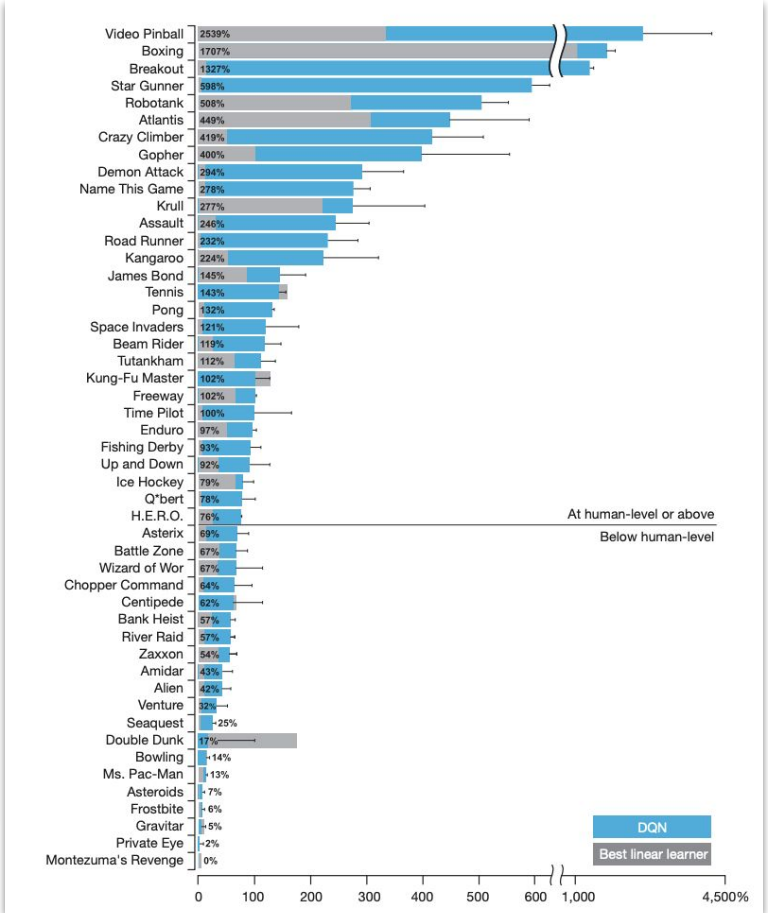

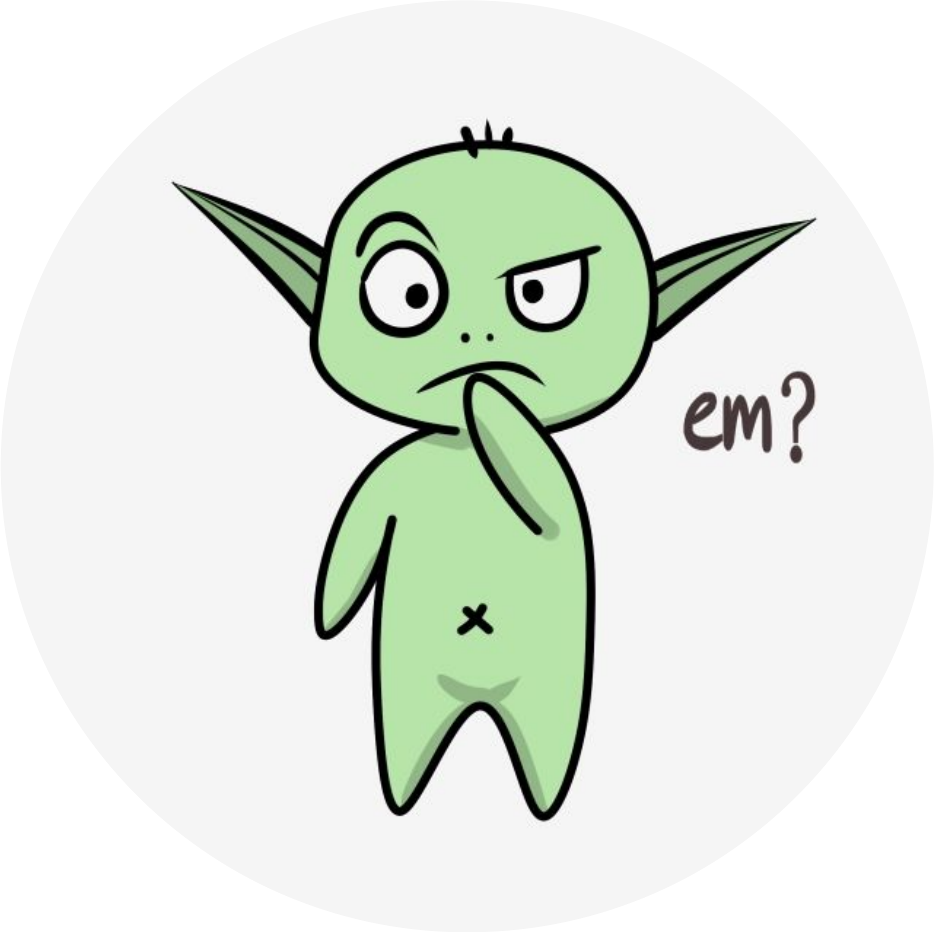

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Deep Q-Network (DQN)

[Mnih et al., 2013, 2015]

Stacked frames **-1, 0, +1 rewards** **Clipped error term**

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

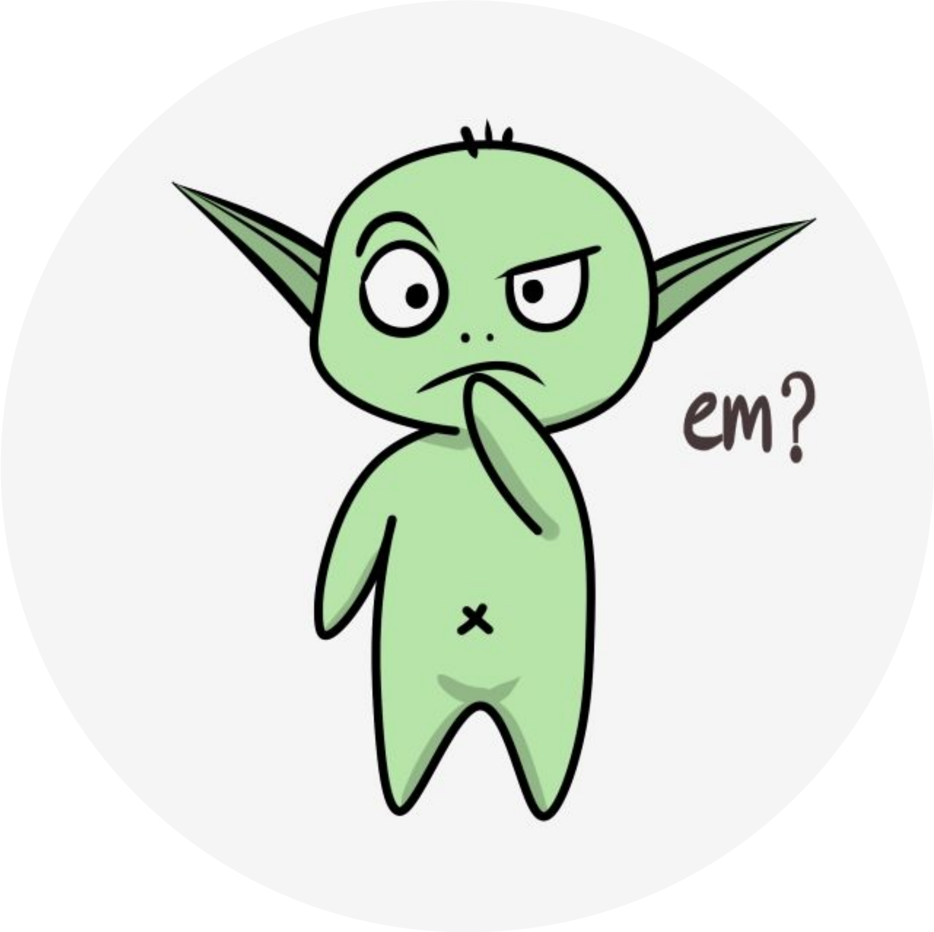
Experience replay buffer (Lin, 1993)
Original size: 1M frames

Target network
Original update frequency: 10k

ε decay
Originally, from 1.0 to 0.1 over 1M frames

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \alpha\left[R_{t+1} + \gamma \max_{a' \in \mathcal{A}} Q(S_{t+1}, a'; \boldsymbol{\theta}^{-}) - Q(S_t, A_t, \boldsymbol{\theta}_t)\right]\nabla_{\boldsymbol{\theta}_t} Q(S_t, A_t; \boldsymbol{\theta}_t)$$

RMSProp



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Deep Q-Network (DQN)

[Mnih et al., 2013, 2015]

Game	Random Play	Best Linear Learner	Contingency (SARSA)	Human	DQN (± std)	Normalized DQN (% Human)
Alien	227.8	939.2	103.2	6875	3069 (±1093)	42.7%
Amidar	5.8	103.4	183.6	1676	739.5 (±3024)	43.9%
Assault	222.4	628	537	1496	3359(±775)	246.2%
Asterix	210	987.3	1332	8503	6012 (±1744)	70.0%
Asteroids	719.1	907.3	89	13157	1629 (±542)	7.3%
Atlantis	12850	62687	852.9	29028	85641(±17600)	449.9%
Bank Heist	14.2	190.8	67.4	734.4	429.7 (±650)	57.7%
Battle Zone	2360	15820	16.2	37800	26300 (±7725)	67.6%
Beam Rider	363.9	929.4	1743	5775	6846 (±1619)	119.8%
Bowling	23.1	43.9	36.4	154.8	42.4 (±88)	14.7%

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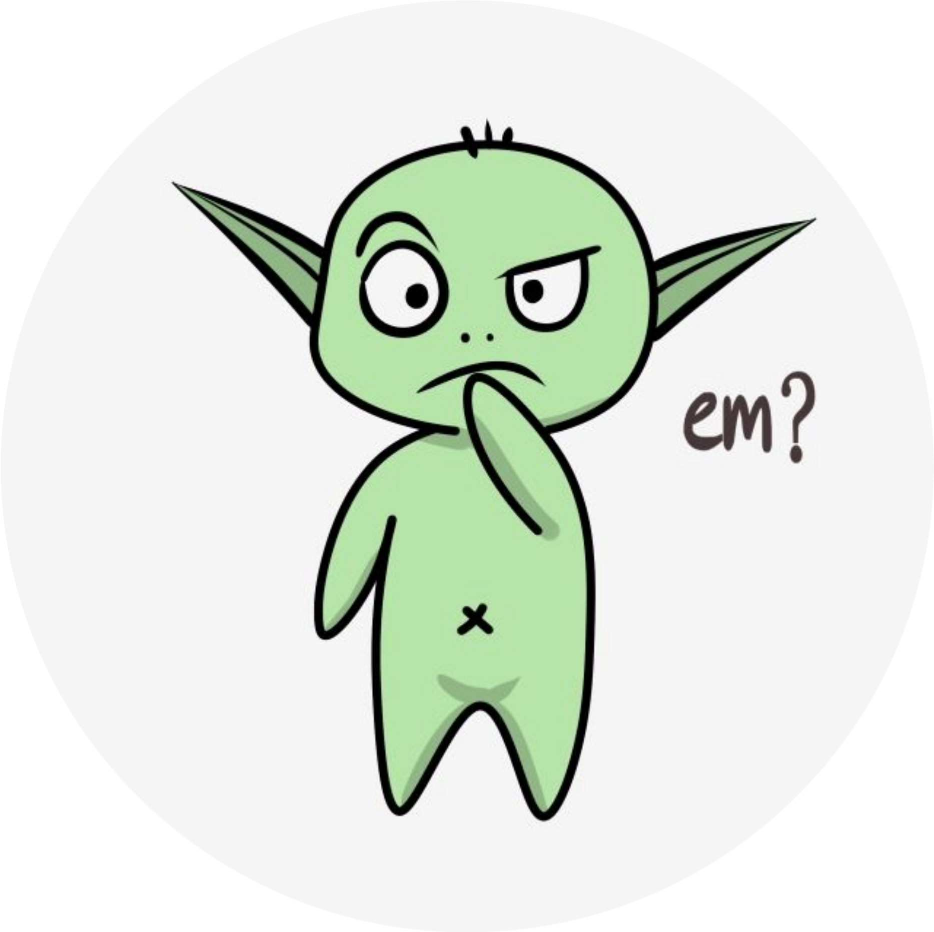
Tables can be misleading
[Machado et al., 2018]

- Tables imply an apples-to-apples comparison, even when they are not:

- DQN saw much more data than the baselines.
- DQN measured its performance differently than the baselines.
- DQN used domain knowledge other baselines didn’t:
    - Lives signal
    - Action set



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Exercise

In the context of control algorithms *with function approximation*, please provide:

(a) The general form of the update rule for semi-gradient one-step Q-Learning.

(b) The the specific update, with no generic gradient terms, for semi-gradient one-step Q-learning *with linear function approximation*.

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$$\mathbf{w} \leftarrow \mathbf{w} + \alpha\big[R + \gamma \max_{a'} \hat{q}(S', a', \mathbf{w}) - \hat{q}(S, A, \mathbf{w})\big]\nabla_{\mathbf{w}}\hat{q}(S, A, \mathbf{w})$$

(b) The the specific update, with no generic gradient terms, for semi-gradient one-step Q-learning *with linear function approximation*.

$$\mathbf{w} \leftarrow \mathbf{w} + \alpha\big[R + \gamma \max_{a'} \mathbf{w}^\top \mathbf{x}(S', a') - \mathbf{w}^\top \mathbf{x}(S, A)\big]\mathbf{x}(S, A)$$