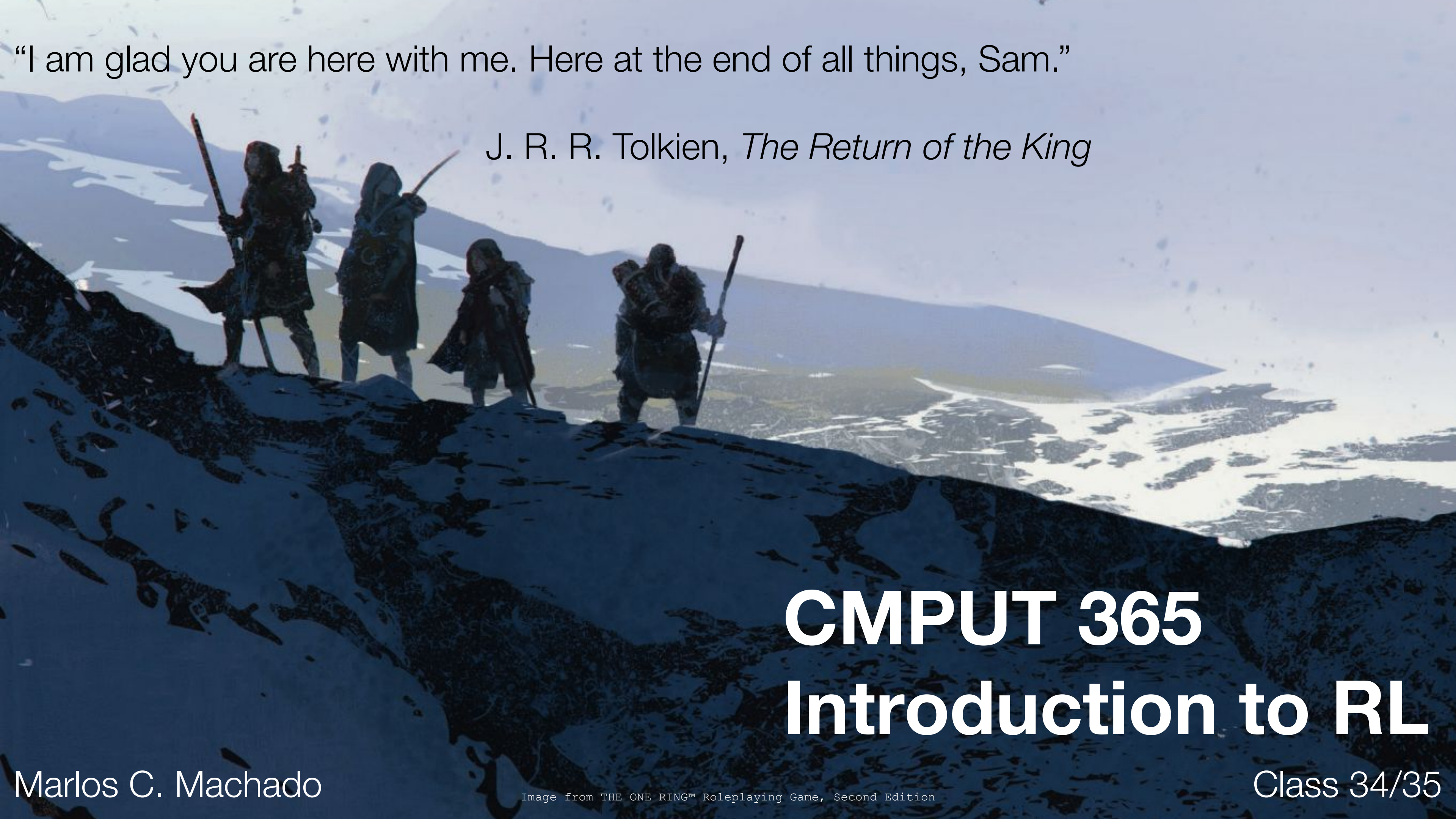
“I am glad you are here with me. Here at the end of all things, Sam.”

J. R. R. Tolkien, *The Return of the King*



CMPUT 365
Introduction to RL

Marlos C. Machado

Image from THE ONE RING™ Roleplaying Game, Second Edition

Class 34/35

Reminder I

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.

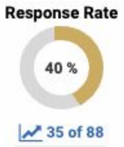
You **need** to **check**, **every time**, if you are in the private session and if you are submitting quizzes and assignments to the private section.

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`.

Reminder II

- Final Exam Schedule released
  - 12/14/2023 at 14:00 in CCIS L1-160. It will be 90 minutes long.
- The last programming assignment is due today.
  - Prediction and Control with FA: Control with approximation
- If you want extra marks, you can complete the last week of the 3rd module in Coursera by Friday, December 8th.
  - Policy Gradient methods
- The Student Perspectives of Teaching (SPOT) Survey is now available.



UNIVERSITY OF ALBERTA Department of Computing Science
Equity, Diversity, and Inclusion Committee

WHAT EXACTLY IS RESEARCH?

IS GRAD SCHOOL RIGHT FOR ME?

DEMYSTIFYING GRAD SCHOOL

HOW DO I APPLY TO GRAD SCHOOL?

WHAT ARE THE REQUIREMENTS?

Virtual Workshop

December 6, 5-7pm

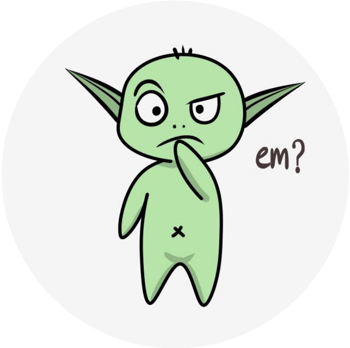
Open to all undergrad students!

Scan below to RSVP and send questions!

ALL YOUR GRAD SCHOOL QUESTIONS ANSWERED HERE!

bit.ly/cs-edi-workshop23

Please, interrupt me at any time!



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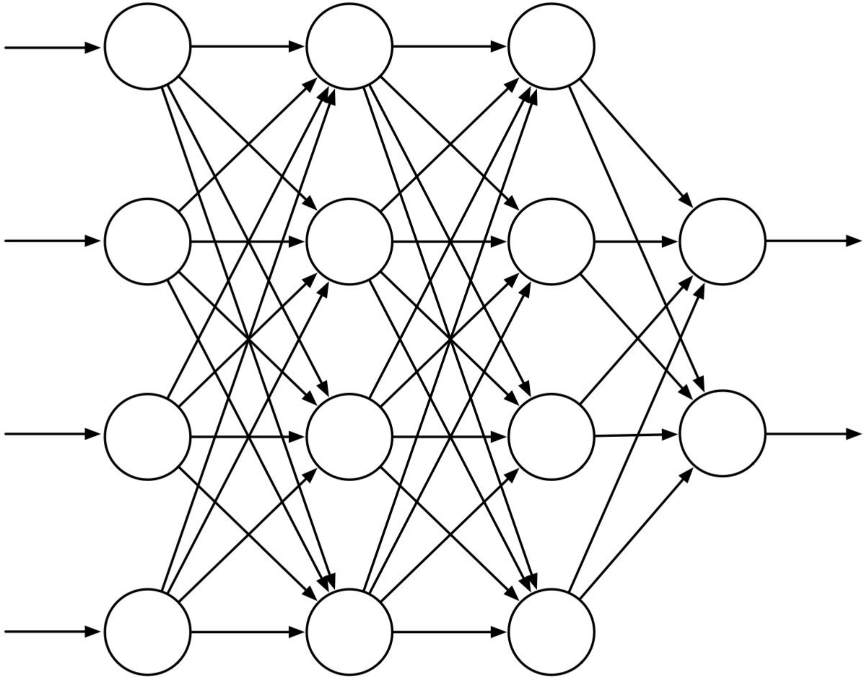
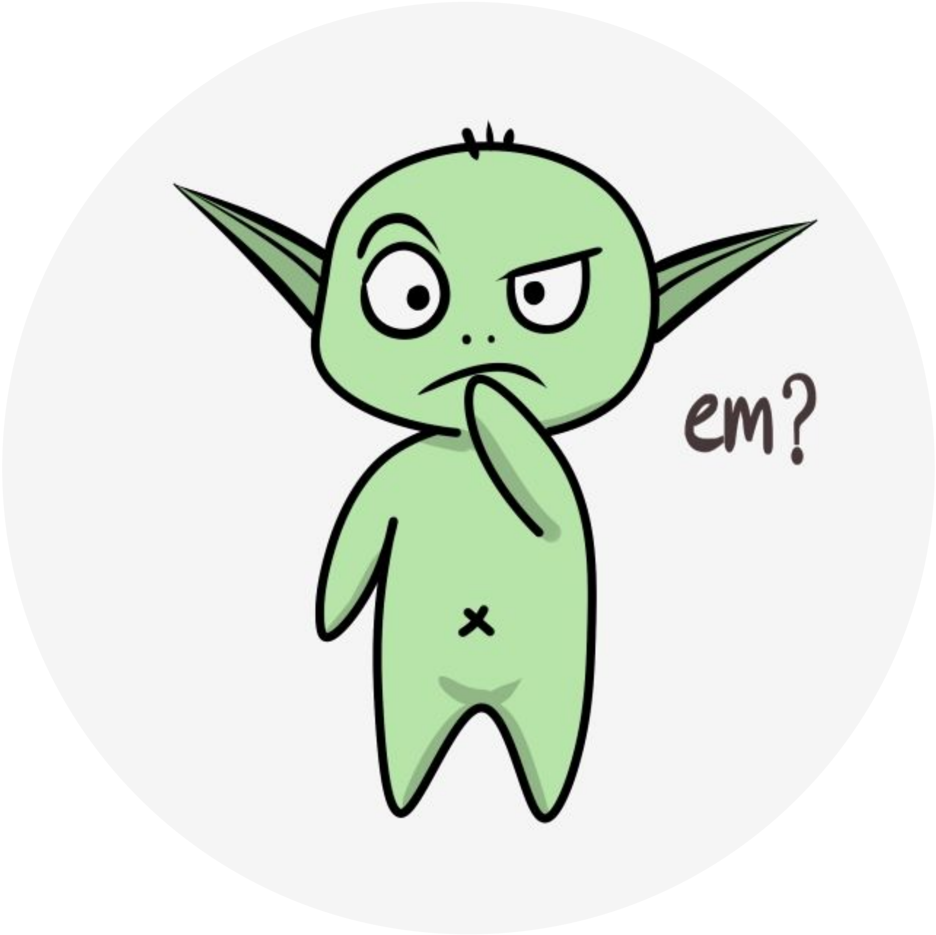
Last Class: Neural Networks





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Deep Convolutional Network

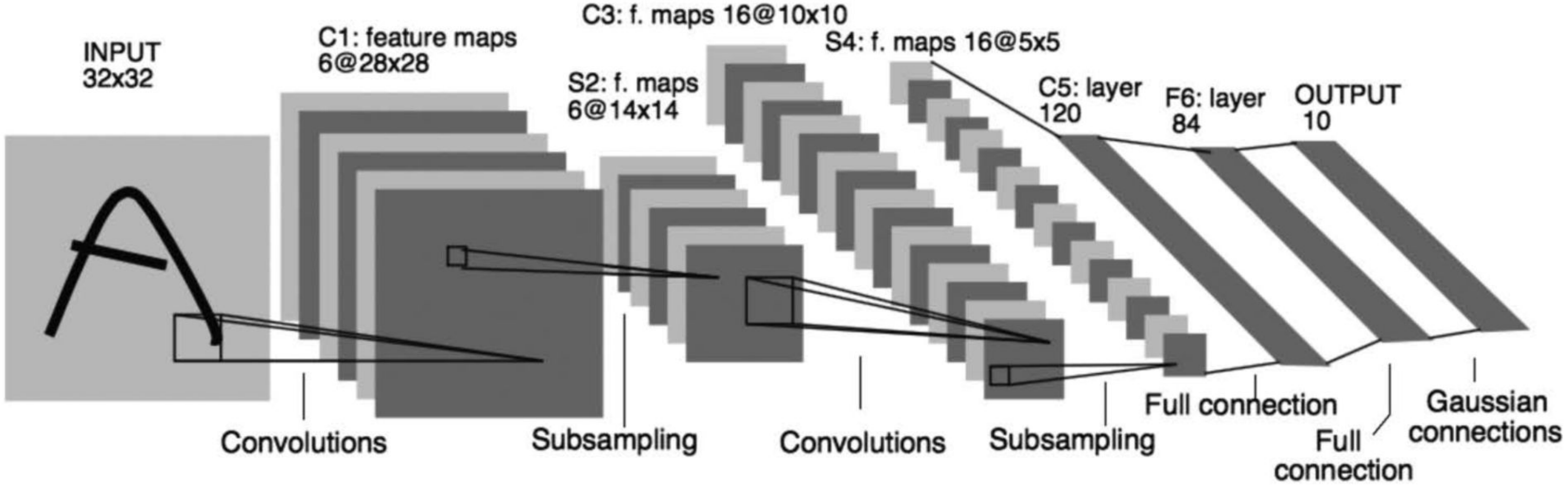
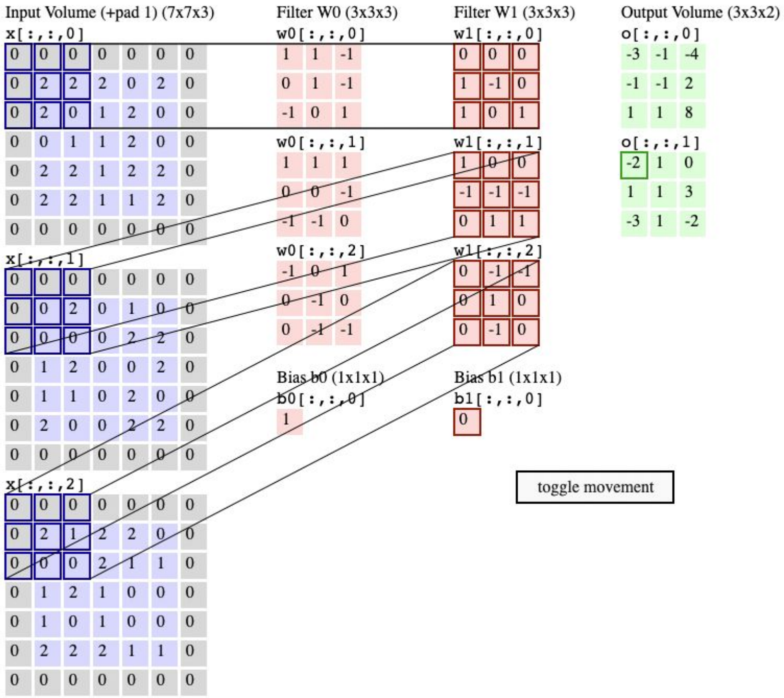


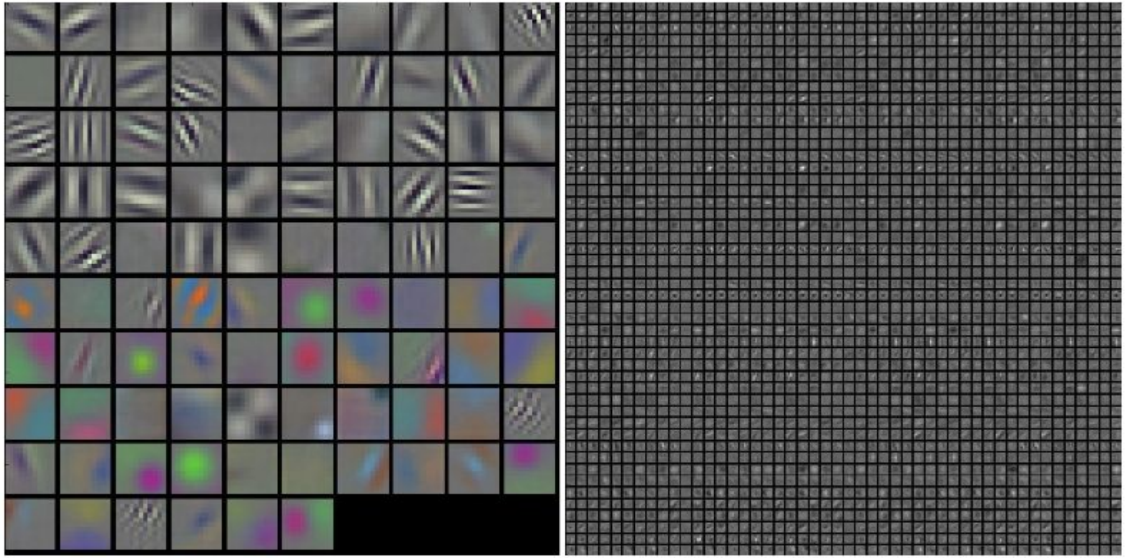
Figure 9.15: Deep Convolutional Network. Republished with permission of Proceedings of the IEEE, from Gradient-based learning applied to document recognition, LeCun, Bottou, Bengio, and Haffner, volume 86, 1998; permission conveyed through Copyright Clearance Center, Inc.

Deep Convolutional Network



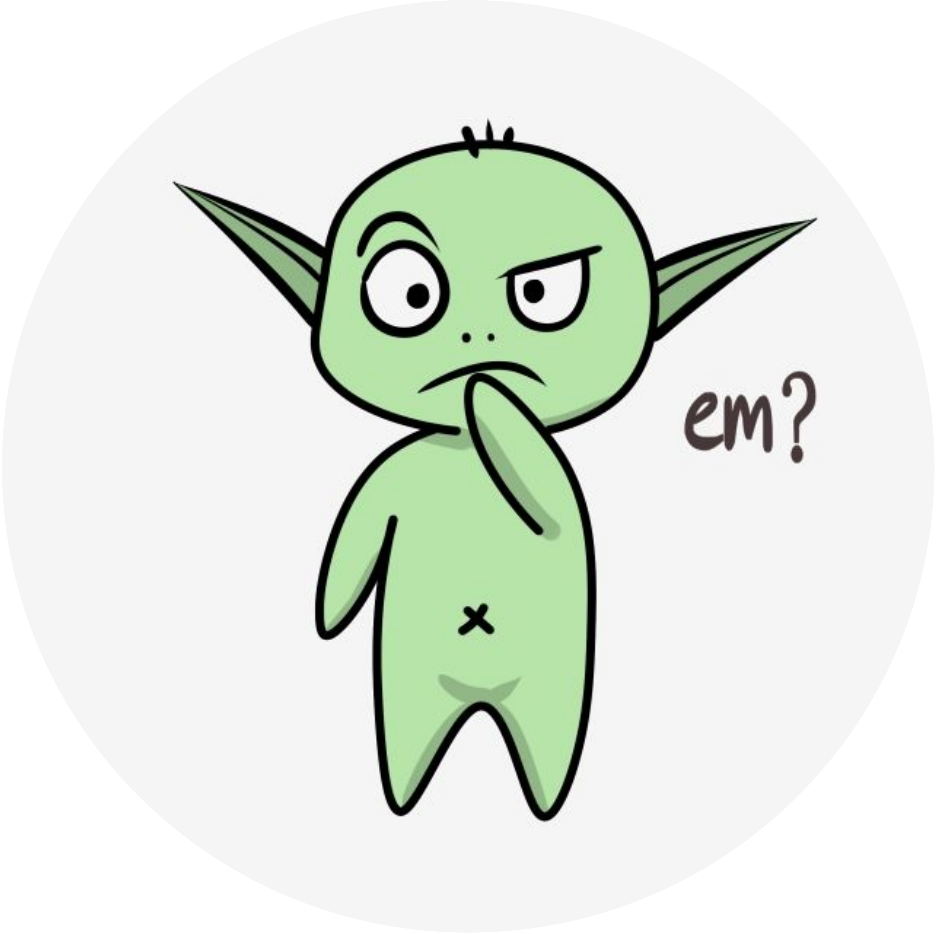
[Figure from demo in https://cs231n.github.io/convolutional-networks/]

Learned Representations



Typical-looking filters on the first CONV layer (left), and the 2nd CONV layer (right) of a trained AlexNet. Notice that the first-layer weights are very nice and smooth, indicating nicely converged network. The color/grayscale features are clustered because the AlexNet contains two separate streams of processing, and an apparent consequence of this architecture is that one stream develops high-frequency grayscale features and the other low-frequency color features. The 2nd CONV layer weights are not as interpretable, but it is apparent that they are still smooth, well-formed, and absent of noisy patterns.

[Figure from https://cs231n.github.io/understanding-cnn/]



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Episodic Semi-gradient Control

- We need to approximate the action-value function now, $\hat{q} \approx q_\pi$, that is represented as a parameterized function form with weight vector **w**.
- Before (until last class): $S_t \mapsto U_t$.
  Now: $S_t, A_t \mapsto U_t$.

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  Now: $S_t, A_t \mapsto U_t$.
- Action-value prediction:

$$\mathbf{w}_{t+1} \doteq \mathbf{w}_t + \alpha \Big[U_t - \hat{q}(S_t, A_t, \mathbf{w}_t) \Big] \nabla \hat{q}(S_t, A_t, \mathbf{w}_t)$$

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- Episodic semi-gradient one-step *Sarsa*:

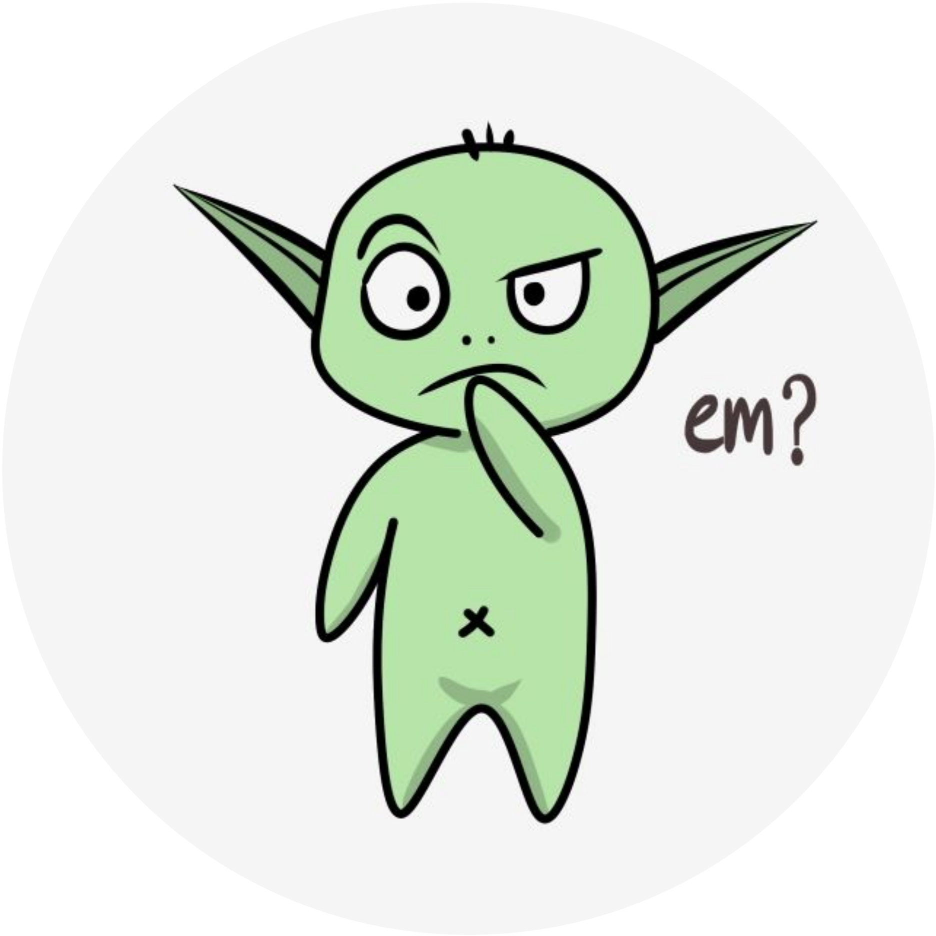
$$\mathbf{w}_{t+1} \doteq \mathbf{w}_t + \alpha \Big[R_{t+1} + \gamma \hat{q}(S_{t+1}, A_{t+1}, \mathbf{w}_t) - \hat{q}(S_t, A_t, \mathbf{w}_t) \Big] \nabla \hat{q}(S_t, A_t, \mathbf{w}_t)$$

Episodic Semi-gradient Sarsa

Episodic 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 size $\alpha > 0$, small $\varepsilon > 0$
Initialize value-function weights $\mathbf{w} \in \mathbb{R}^d$ arbitrarily (e.g., $\mathbf{w} = \mathbf{0}$)

Loop for each episode:
  $S, A \leftarrow$ initial state and action of episode (e.g., ε-greedy)
  Loop for each step of episode:
    Take action A, observe R, S'
    If S' is terminal:
      $\mathbf{w} \leftarrow \mathbf{w} + \alpha\big[R - \hat{q}(S, A, \mathbf{w})\big]\nabla\hat{q}(S, A, \mathbf{w})$
      Go to next episode
    Choose A' as a function of $\hat{q}(S', \cdot, \mathbf{w})$ (e.g., ε-greedy)
    $\mathbf{w} \leftarrow \mathbf{w} + \alpha\big[R + \gamma\hat{q}(S', A', \mathbf{w}) - \hat{q}(S, A, \mathbf{w})\big]\nabla\hat{q}(S, A, \mathbf{w})$
    $S \leftarrow S'$
    $A \leftarrow A'$



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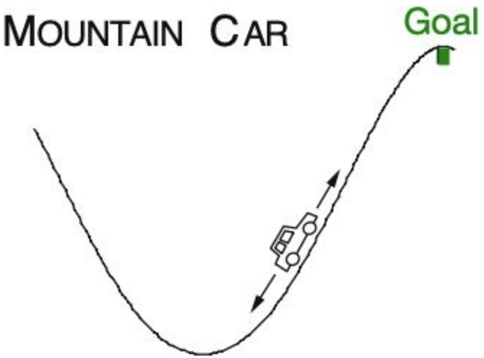
Example: Mountain Car Task

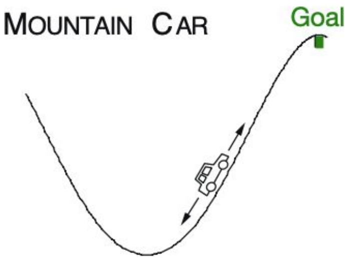
- Observations: $(x, \dot{x})$
- Actions:
  - Full throttle forward: +1
  - Full throttle reverse: -1
  - Zero throttle: 0
- Rewards: -1 at every time step, until end of episode.
- Dynamics:



$$x_{t+1} \doteq bound\big[x_t + \dot{x}_{t+1}\big]$$

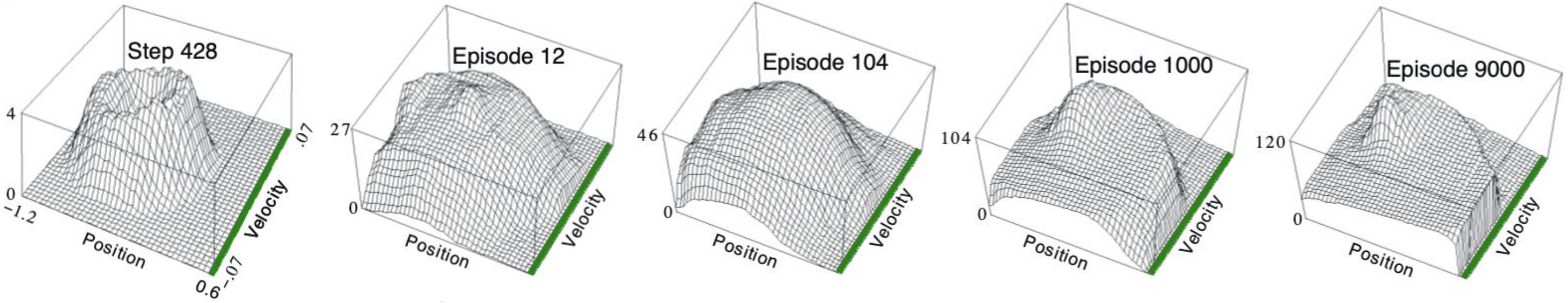
$$\dot{x}_{t+1} \doteq bound\big[\dot{x}_t + 0.001A_t - 0.0025\cos(3x_t)\big]$$

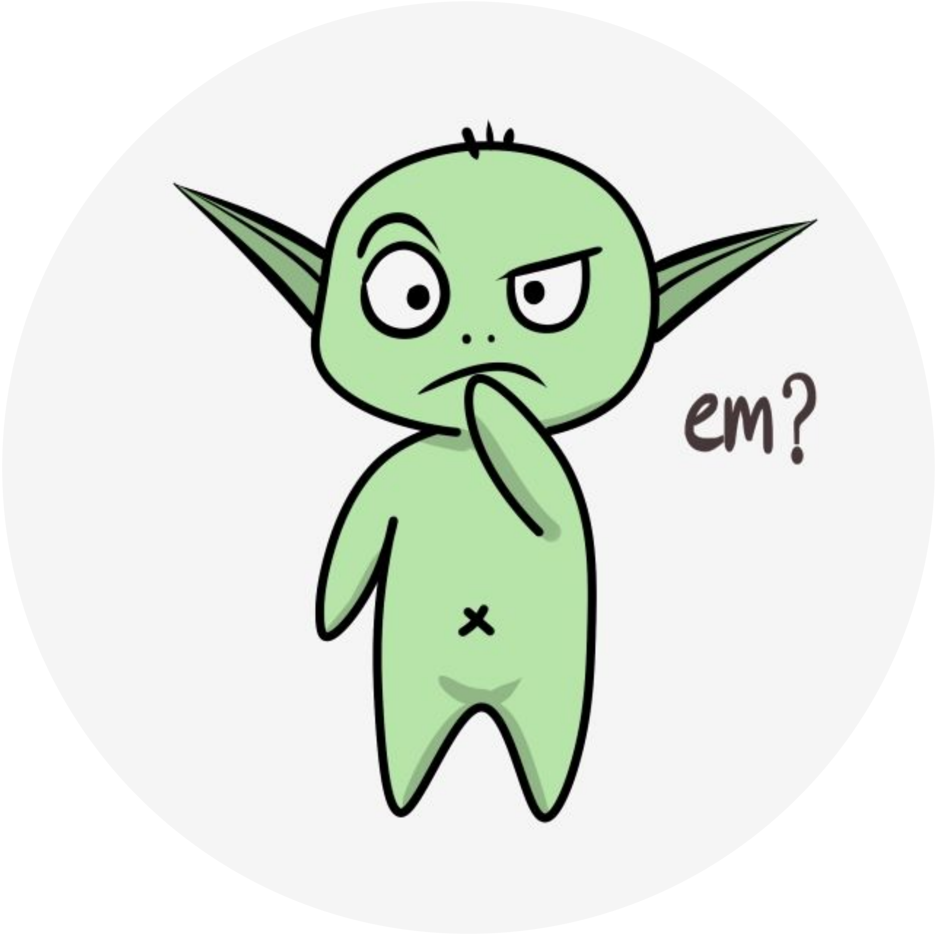
$$-1.2 \leq x_{t+1} \leq 0.5 \text{ and } -0.07 \leq \dot{x}_{t+1} \leq 0.07$$



“Solution”: Mountain Car Task

- Feature representation:
    - Grid-tilings with 8 tilings and asymmetrical offsets.
    - $\hat{q}(s, a, \mathbf{w}) \doteq \mathbf{w}^\top \mathbf{x}(s, a) = \sum_{i=1}^{d} w_i \cdot x_i(s, a)$
- Sarsa
    - Weights initialized at zero. Effectively optimistic initialization.





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Avg. Reward: A Problem Setting for Continuing Tasks

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

Avg. Reward: A Problem Setting for Continuing Tasks

- 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.

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:

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

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

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

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

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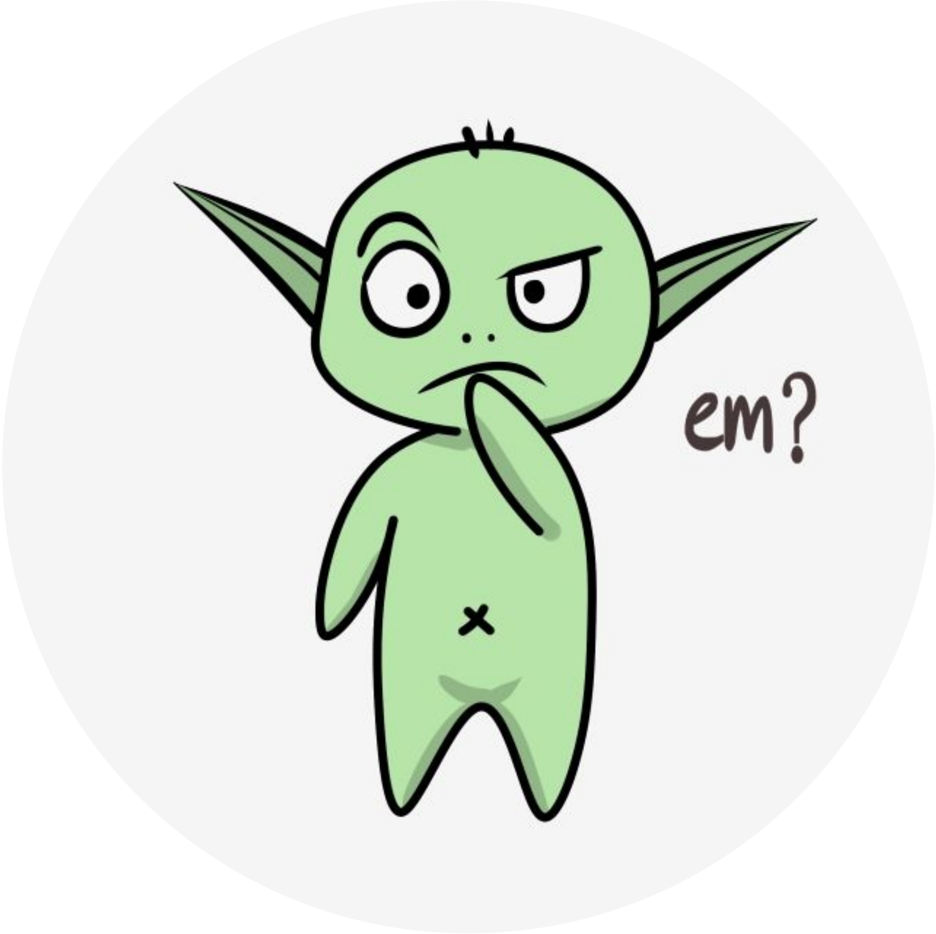
$$q_*(s,a) = \sum_{r,s'} p(s',r|s,a)\Big[r - \max_\pi r(\pi) + \max_{a'} q_*(s',a')\Big]$$

- 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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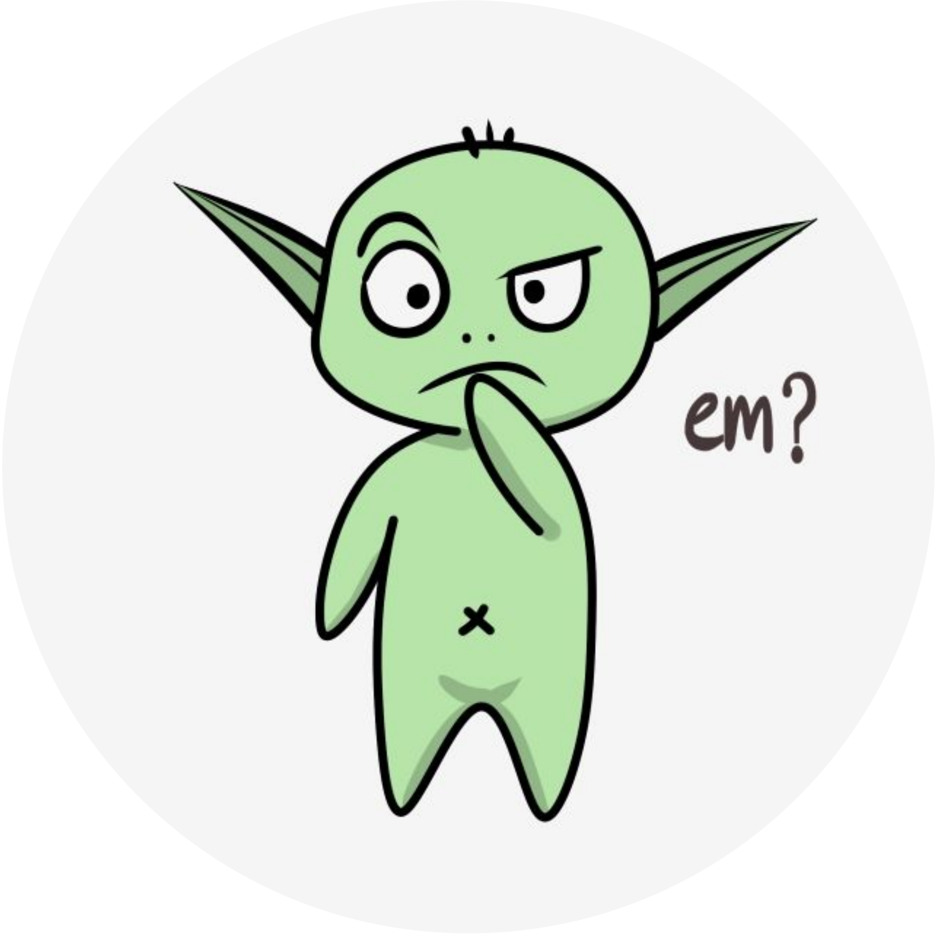
Differential semi-gradient Sarsa

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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