Hochschule
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Interactive Reinforcement Learning

Guest Lecture

June 13th, 2024

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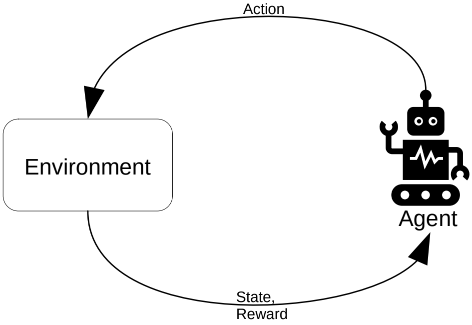
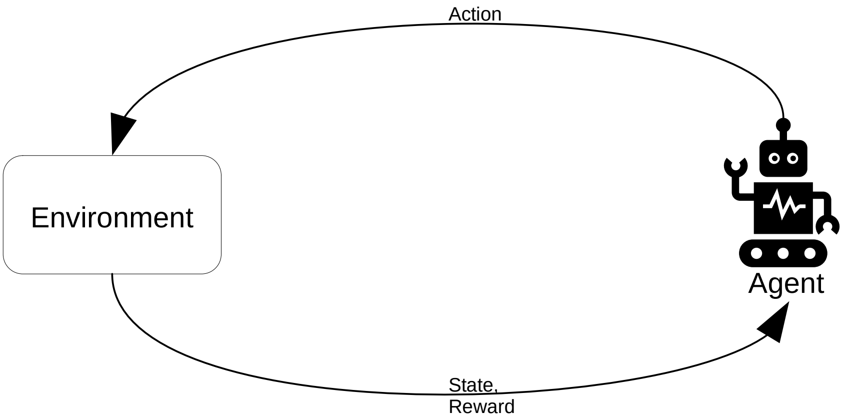
Reinforcement Learning (RL)

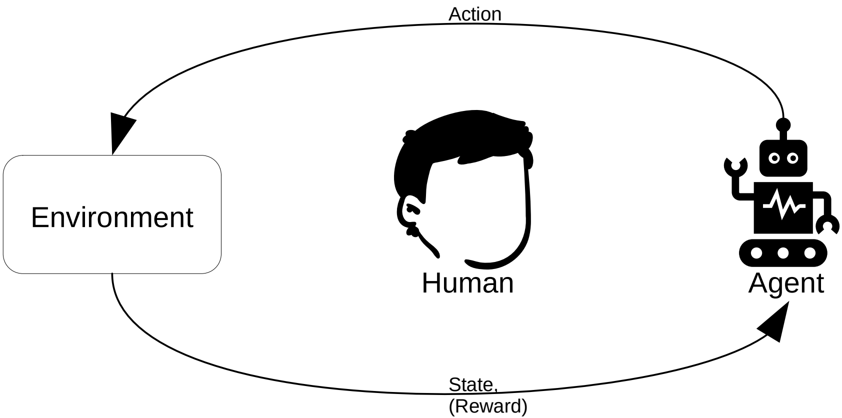
- RL allows an agent to learn an optimal policy that maximises the **cumulative reward** by interacting with an environment.
- In real-world tasks, the agent is faced with the **sample efficiency problem**, making the learning slow.



Reinforcement Learning



(Interactive) Reinforcement Learning



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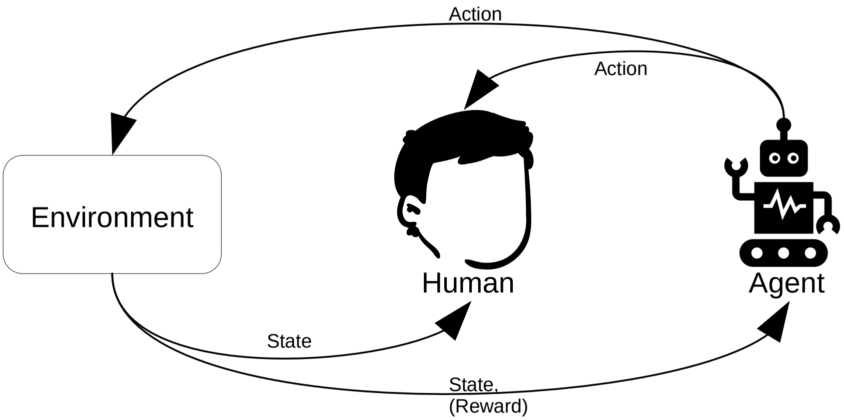
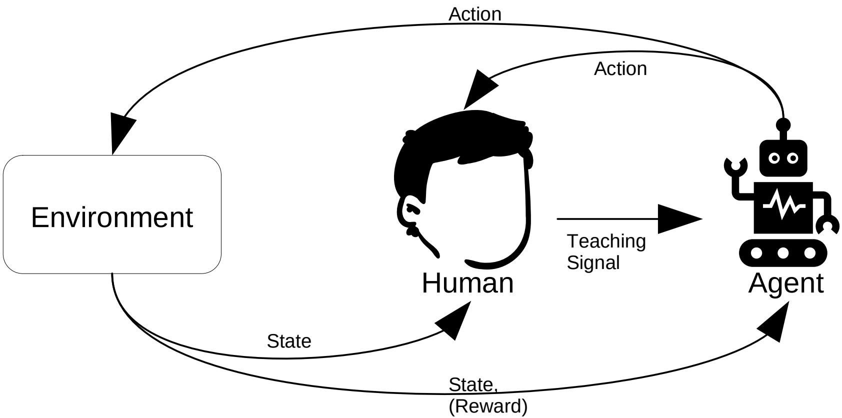


Interactive Reinforcement Learning (IRL)



Advantages of IRL

- Humans possess **knowledge** about the environment and have **experience** in acting in that environment.
- Human input could be used to guide and **accelerate the robot's learning**, or to change its optimal behaviour (personalisation).

Teaching Signals

Feedback

✓ Human feedback is provided with the intention of **evaluating** the robot's action.

✓ The value of the **evaluative feedback** depends on the last action performed by the robot.

Demonstration

✓ Demonstration is produced with the intention of **showing** a **state-action sequence** to robot.

✗ Teaching with a demonstration strategy imposes a **significant burden** on the human teacher.

Instruction

✓ An instruction is produced with the intention of **communicating** the **action** to be performed in a given task state.

✓ Learning from instructions - mapping instructions (e.g. natural language) to a sequence of executable actions.

[1] M. Chetouani, "Interactive Robot Learning: An Overview," ECCAI Advanced Course on Artificial Intelligence, pp. 140–172, 2021

Teaching Signals

Teaching signals		Feedback	Demonstration	Instruction
Nature	Notation	$H(s, a)$	$D = \{(s_t, a_t^*), (s_{t+1}, a_{t+1}^*) \ldots\}$	$I_\pi(s) = a_t^*$
	Value	Binary/Scalar	State-Action pairs	Probability of an action
Time-step	t − 1		✓	✓
	t		✓	
	$t + 1$	✓		
Human	Intention	Evaluating/Correcting	Showing	Telling
	Teaching cost	Low	High	Medium
Robot	Interpretation	State-Action evaluation Reward-/Value-like	Optimal actions Policy-like	Optimal action Policy-like
	Learning cost	High	Low	High

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How Can Humans Deliver Evaluative Feedback?

Two **ways** of delivering evaluative **feedback**:

- Hardware
- Natural interaction modalities

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- Natural interaction modalities

Two **types** of evaluative **feedback**:

- **Explicit** - user gives **direct feedback** to the robot e.g. through the graphical interface.
- **Implicit** - **spontaneous behaviour** of the human user is analysed and used as feedback. Feedback is estimated based on social signals such as valence, engagement, facial expressions.

Arity of Human Evaluative Feedback

- Unimodal $\rightarrow$ Only one feedback modality is used.
- Multimodal:
  - Multiple modalities are used either **disjunctively** (OR) or **conjunctively** (AND).
  - If **one** modality is unavailable, then the others can be used $\rightarrow$ **robustness**.
  - If **all** are available, then the feedback is more **reliable**.
  - Examples:
    - Speech and gesture
    - Laugh (audio) and smile (visual)
    - Facial expressions of emotions + task-related features
- Human evaluative feedback can also be combined with a pre-defined environmental reward function.

Challenges with Human Feedback

- Delayed feedback
  - E.g. Due to reaction times involved in evaluating the action and providing the feedback.
  - To which action should the feedback be mapped?
- Interpersonal variability
  - E.g. The reaction times differ from person to person.
  - The social signals used for feedback vary in modality, in expression, and in intensity.
  - The same teacher might change the feedback strategy or type over time (e.g. change from binary to categorical feedback).

Challenges with Human Feedback

- Decay in feedback frequency
  - Intense feedback at the beginning, sparse feedback later.
- Multiple feedback
  - Should the feedback be aggregated or should only one of those multiple feedback be used?
- Noise in feedback channel
  - Discrepancies between what the teacher intends to convey and what the agent actually observes.

Human-centered RL

- TAMER [2]
  - Human feedback is mapped to numeric value.
- SABL [3]
  - Human feedback is mapped to categorical strategies.
- COACH [4]
  - Human feedback is mapped to agent's policy (selecting actions).

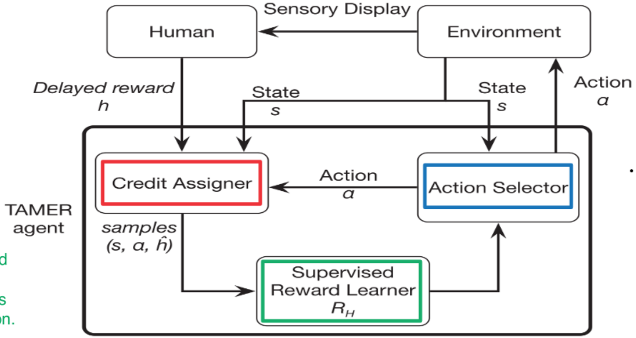
[2] W. B. Knox and P. Stone, "Interactively shaping agents via human reinforcement: The TAMER framework," in **Proc. of the Fifth Int. Conf. on Knowledge Capture**, 2009, pp. 9–16

[3] R. Loftin **et al.**, "A Strategy-Aware Technique for Learning Behaviors from Discrete Human Feedback," in **Proc. of the AAAI Conf. on Artificial Intelligence**, vol. 28, no. 1, 2014

[4] J. MacGlashan **et al.**, "Interactive Learning from Policy-Dependent Human Feedback," in **Proc. of the 34th Int. Conf. on Machine Learning**, ser. Proc. of Machine Learning Research, D. Precup and Y. W. Teh, Eds., vol. 70. PMLR, 06–11 Aug 2017, pp. 2285–2294

TAMER

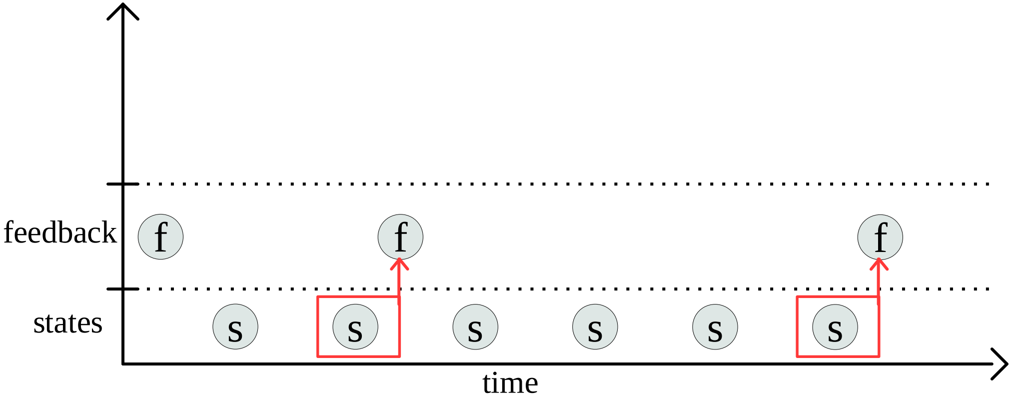
- Probabiliy density function to model the feedback delay.
- Learns a parameterised model for expected human reward, which is used for action selection.



- Myopic rewards (γ=0) under the assumption that the human takes the long-term consequences into account in their evaluative feedback.

[5] W. B. Knox, "Learning from human-generated reward," Ph.D. dissertation, University of Texas at Austin, 2012

Without Credit Assignment



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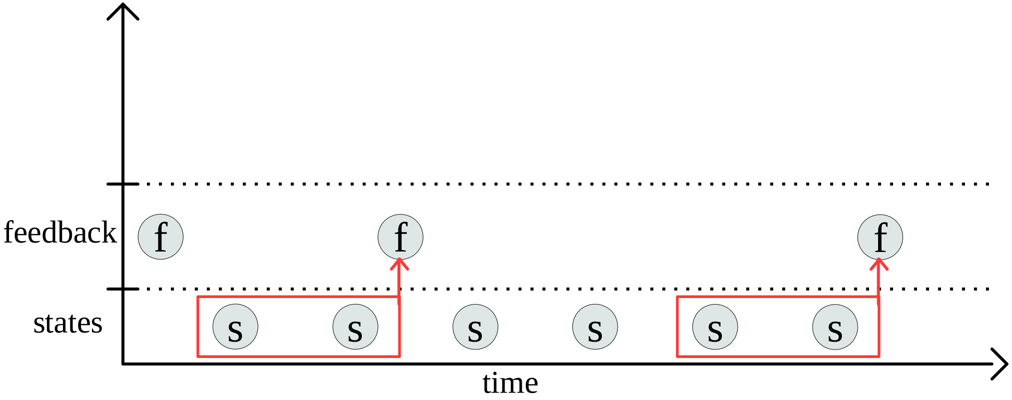


Practical Example

- Agent is deployed in a simple **Mountain Car** environment, with
  - **continuous state space** - position of the car along the x-axis and velocity of the car
  - **discrete action space** - accelerate to the left, don't accelerate, accelerate to the right
- The **user** can give positive/negative **feedback** using the keyboard or no feedback (by not giving any input)

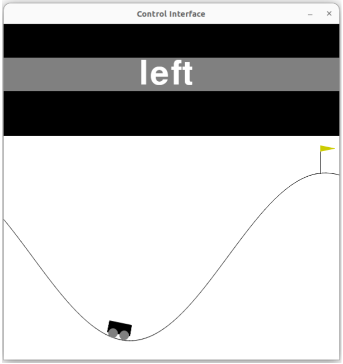
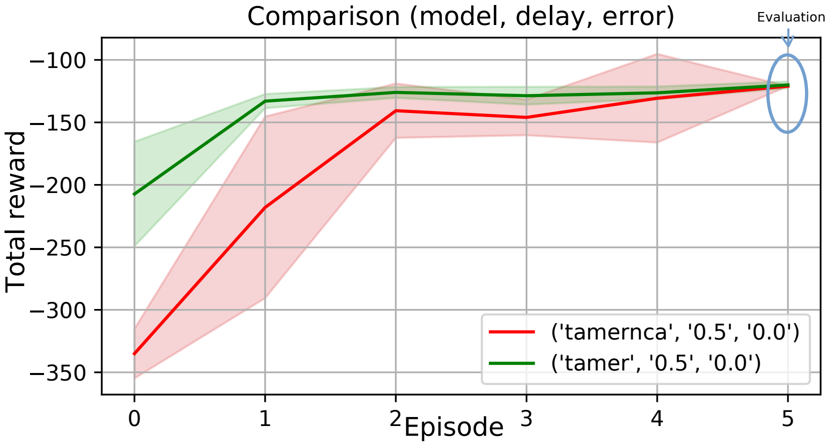


Figure 1: View of the deployment environment

Advantage of Credit Assignment



Going "deeper" ...

- One needs to find features (e.g. x car position, velocity) that can sufficiently define a state for TAMER.
- Would be easier if TAMER finds these features itself based on the image (like humans do).
- This problem is addressed by Deep TAMER [6].

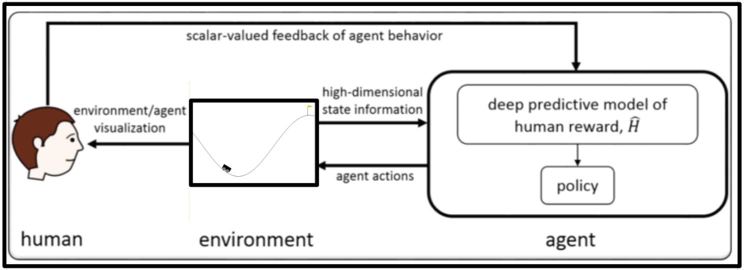


Figure 2: Based on [6]

[6] G. Warnell, N. Waytowich, V. Lawhern, and P. Stone, “Deep TAMER: Interactive Agent Shaping in High-Dimensional State Spaces,” in **Proc. of the AAAI Conf. on Artificial Intelligence**, vol. 32, no. 1, 2018

Is Deep TAMER a Solution?

- Needs pretraining of the encoder part (a lot of data necessary).
- Needs two input images for some environments (e.g. to estimate velocity).
- Hard to assess the quality of the extracted features.

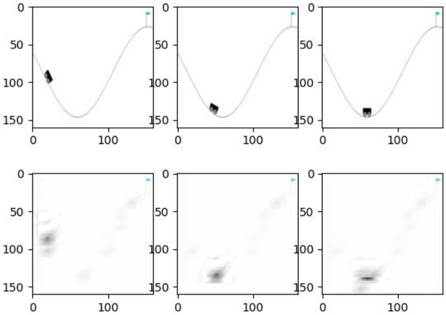


Figure 3: Reconstruction of the images from the features extracted by the encoder part of Deep TAMER

Categorical Feedback Strategies

A human teacher's feedback can be categorized into four types (inspired by behaviourism and animal training):

- Positive reward (R+)
  - Explicit feedback for correct behaviour.
- Negative reward (R-)
  - No feedback for correct behaviour.
- Positive punishment (P+)
  - Explicit feedback for wrong behaviour.
- Negative punishment (P-)
  - No feedback for wrong behaviour.

Categorical Feedback Strategies

- Different combinations of these feedback types are possible and it forms the teacher's feedback strategy.
  - Reward-focused $\rightarrow$ R+/P-
  - Punishment-focused $\rightarrow$ P+/R-
  - Balanced $\rightarrow$ R+/P+ (explicit reward and explicit punishment)
  - Inactive $\rightarrow$ R-/P- (rarely gives explicit feedback)

- The teacher can change the strategy during the course of training.
  - Teacher's feedback modelled probabilistically [7] and used with SABL algorithm.
  - Parameters:
    - » $\mu+$ $\rightarrow$ Probability that teacher will not give explicit feedback for correct behaviour
    - » $\mu-$ $\rightarrow$ Probability that teacher will not give explicit feedback for wrong behaviour
    - » ϵ $\rightarrow$ Probability that teacher misjudges the correctness of an action

[7] R. Loftin **et al.**, "Learning behaviors via human-delivered discrete feedback: modeling implicit feedback strategies to speed up learning," **Autonomous Agents and Multi-Agent Systems**, vol. 30, pp. 30–59, 2016

Strategy-Aware Bayesian Learning (SABL)

- Bayessian inference.
- Assumes that teacher's strategy is **known**, i.e. $\mu+$ and $\mu-$ are known.
- Policy is updated based on the categorical probability of the given human feedback.
- Can be used only for low-dimensional discrete state space.
- Variant: **Inferring-SABL** or **I-SABL**
  - In reality, the teacher's strategy (i.e. $\mu+$ and $\mu-$) is **unknown**.
  - I-SABL **infers** the **teacher's strategy** by analyzing the feedback history.

Motivation for COACH

The following **characteristics** of training strategies used by humans:

- Correct actions are given **less positive feedback** progressively, as the **agent learns** to use that action succesfully.
- **Strength** of feedback varies depending on how much **improvement** or **deterioration** is observed in the agent's behaviour.
- Suboptimal actions may receive **positive** feedback if it **improves** the agent's behaviour; after the behaviour improves, the same suboptimal actions are given **negative feedback**.

[4] J. MacGlashan **et al.**, "Interactive Learning from Policy-Dependent Human Feedback," in **Proc. of the 34th Int. Conf. on Machine Learning**, ser. Proc. of Machine Learning Research, D. Precup and Y. W. Teh, Eds., vol. 70. PMLR, 06–11 Aug 2017, pp. 2285–2294

COnvergent Actor-Critic by Humans (COACH)

- COACH [4] is actor-critic-based reinforcement learning algorithm where human feedback is used as an **advantage function**.
  - advantage function - function that describes an **advantage** of selecting a certain action **over** the agent's policy

- The **sparse feedback** (also delayed feedback) problem is faced with **eligibility traces** which can smooth observed human feedback over past transitions.

- **Deep COACH** [8], namely COACH for **high-dimensional** input.

[4] J. MacGlashan **et al.**, "Interactive Learning from Policy-Dependent Human Feedback," in **Proc. of the 34th Int. Conf. on Machine Learning**, ser. Proc. of Machine Learning Research, D. Precup and Y. W. Teh, Eds., vol. 70. PMLR, 06–11 Aug 2017, pp. 2285–2294
[8] D. Arumugam, J. K. Lee, S. Saskin, and M. L. Littman, "Deep Reinforcement Learning from Policy-Dependent Human Feedback," **arXiv preprint arXiv:1902.04257**, 2019

Improving Learning from Evaluative Feedback

- **Human feedback** is usually:
  - **dense** (at the beginning of the interaction)
  - **flawed** (people generally make mistakes evaluating the agent's behaviour)
- On the other hand, **environmental reward** is usually:
  - **sparse**
  - **flawless** (determines optimal behaviour)
- Why not combine **human feedback** (HF) and **environmental reward** (ER) for agent learning?

Combining HF and ER

- **Reward shaping**
  - Modelled human feedback $\hat{H}$ is interpreted as a **reward**.
  - $r'(s,a) = r(s,a) + \beta * \hat{H}(s,a)$
- **Value shaping**
  - Modelled human feedback $\hat{H}$ is interpreted as **action-value function** (expected cumulative reward given that the agent starts with action a from s following policy π).
  - $Q'(s,a) = Q(s,a) + \beta * \hat{H}(s,a)$
- **Policy shaping**
  - Modelled human feedback $\hat{H}$ employed to directly influence the agent's **policy**.
  - e.g. $P(a = argmax(\hat{H}(s,a))) = min(\beta, 1)$

[1] M. Chetouani, "Interactive Robot Learning: An Overview," **ECCAI Advanced Course on Artificial Intelligence**, pp. 140–172, 2021

[9] W. B. Knox and P. Stone, "Combining manual feedback with subsequent MDP reward signals for reinforcement learning," in **Proc. of the 9th Int. Conf. on Autonomous Agents and Multiagent Systems: volume 1-Volume 1**. Citeseer, 2010, pp. 5–12

Example: Social Robotics

https://www.youtube.com/watch?v=VN1-bToWlac

[10] H. W. Park, I. Grover, S. Spaulding, L. Gomez, and C. Breazeal, "A Model-Free Affective Reinforcement Learning Approach to Personalization of an Autonomous Social Robot Companion for Early Literacy Education," in **Proceedings of the AAAI Conference on Artificial Intelligence**, vol. 33, no. 01, 2019, pp. 687–694

Summary

- Human input can be used to **speed-up robot learning** in real-world tasks.
- Human input can take the form of **demonstrations**, **instruction**, or **evaluative feedback**.
- Learning from human evaluative feedback is called **human-centered reinforcement learning**.
- There are several **challenges** associated with obtaining, interpreting and using human input.
- Frameworks and methods that use human evaluative feedback include **TAMER**, **SABL** and **COACH**, to name a few.
- There are methods to combine human evaluative feedback and environmental reward including **reward shaping**, **value shaping** and **policy shaping**.

Thank you for your attention!