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Intelligence Artificielle pour les systèmes autonomes (IAA)

Reinforcement Learning (RL)

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Basé sur le cours du Prof. A. Geiger

Summary

Today's lesson

→ **Reinforcement learning**

On the previous lecture: supervised techniques

Imitation learning and direct perception

→ Supervised learning

- Using expert demonstration
- Imitation learning: computing the differences between the result of our action and the expert's action (loss function → try to minimize the loss)
- Direct perception: computing the loss on the affordance indicators

→ Today's lecture: reinforcement learning

- Learning models based on the loss that we actually care about
  - Minimize time to get to a location
  - Minimize number of collisions
  - …

Three types of learning

Supervised, unsupervised, reinforcement learning

→ Supervised

- We have a dataset of samples x_i with labels y_i: we want to learn the mapping of $x \rightarrow y$
- Examples: classification (NNs), regression, imitation learning, affordance learning, etc.

→ Unsupervised

- We have a dataset (x_i) and we want to discover the underlying structure
- Examples: clustering

→ Reinforcement Learning (RL)

- Agent interacting with an environment that provides numeric rewards
- Goal: taking actions to maximize the reward
- Example: learning of manipulation and control tasks

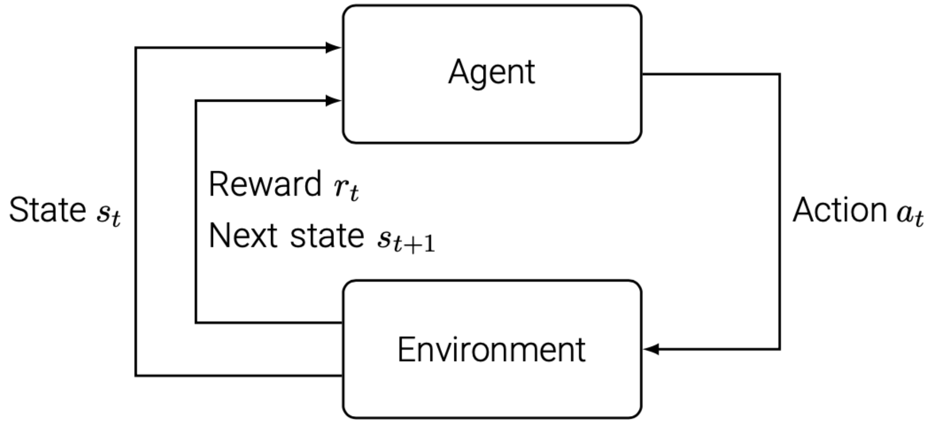
Reinforcement Learning

Overview

→ Agent observes environment state s_t at time t

→ Send an action at at time t to the environment

→ Environment returns the reward and its new state



→ **Goal**: selecting actions that maximize the reward.

→ Knowing that:

- Actions may have long-term consequences
- Reward may be delayed, not instantaneaous
- It might be better to sacrifice immediate reward to gain more long-term reward

Examples

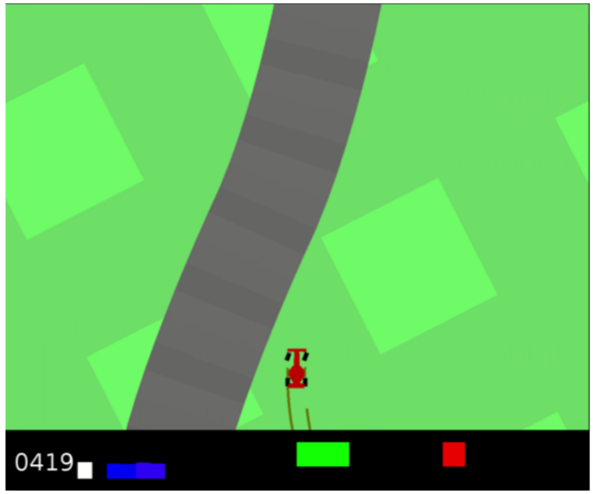
Atari game, AlphaGo, Car racing

https://openai.com/research/gym-retro

- **Objective:** Maximize game score
- **State:** Raw pixels of screen (210x160)
- **Action:** Left, right, up, down
- **Reward:** Score increase/decrease at t

https://deepmind.google/technologies/alphago/

- **Objective:** Winning the game
- **State:** Position of all pieces
- **Action:** Location of next piece
- **Reward:** 1 if game won, 0 otherwise



- **Objective:** Lane Following
- **State:** Image (96x96)
- **Action:** Acceleration, Steering

How do we know which actions to take

A simple grid example

→ Goal: reaching one of the terminal states (marked with *) in the least number of actions possible

→ Penalty: negative “reward” given for every transition made

actions = {
1. right →
2. left ←
3. up ↑
4. down ↓

}

states

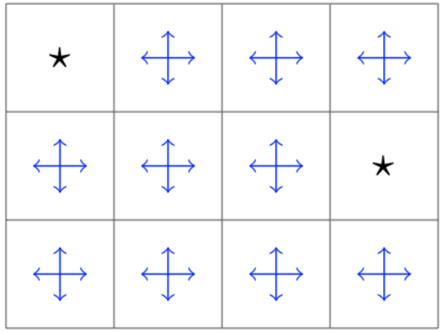
$\star$			
			$\star$

reward: $r = -1$ for each transition

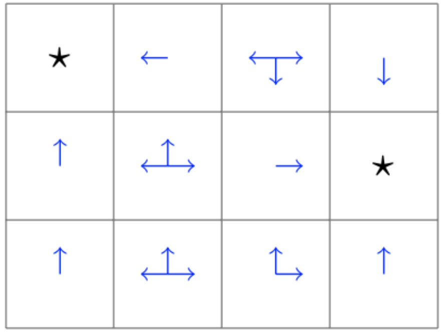
The simple grid example

Random policy vs optimal policy

→ Arrows indicate equal probability of moving into each direction



Random Policy



Optimal Policy

→ How do we choose how to cover the possible space of actions in RL?

Q-learning

A model-free algorithm for RL for learning the value of an action

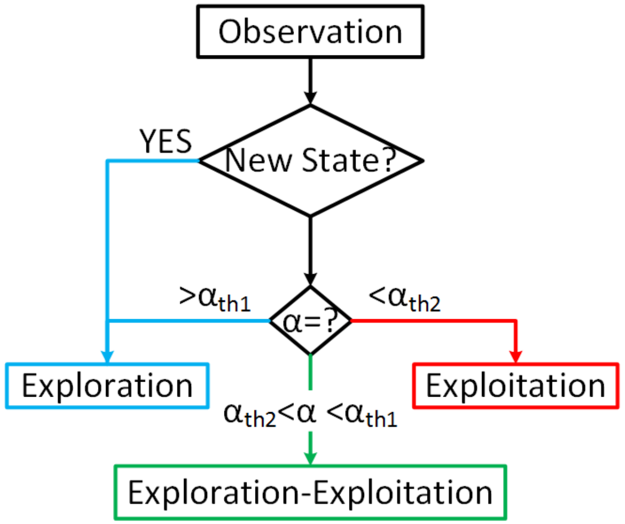
→ The algorithm calculates the Quality of a state-action combination

- Trying to maximize total reward over any and all successive steps

→ Builds and updates the Quality of a sequence of actions iteratively

→ Implementation:

- Initialize Q-table and initial state randomly
- Repeat:
  - Observe state, choose action using epsilon-greedy strategy
  - Observe reward and next state
  - Compute error
  - Update Q-tables
- Explore new states until a certain threshold is achieved, then exploit what has been learned



$$Q^{new}(S_t, A_t) \leftarrow (1 - \underbrace{\alpha}_{\text{learning rate}}) \cdot \underbrace{Q(S_t, A_t)}_{\text{current value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \overbrace{\left(\underbrace{R_{t+1}}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(S_{t+1}, a)}_{\text{estimate of optimal future value}} \right)}^{}$$

$$\underbrace{\qquad\qquad\qquad\qquad\qquad\qquad}_{\text{new value (temporal difference target)}}$$

Q-learning example

The mouse finding the cheese in the maze

Problem

Q-table

	←	→	↑	↓
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0

https://huggingface.co/deep-rl-course/unit2/q-learning-example?fw=pt

What’s the main issue of Q-learning?

Scalability, and how to solve it

→ Scalability: tables don’t scale to high-dimensional state/action pairs

→ Solution:
- Multi-agent reinforcement learning: splitting the environment, agents collaborate/compete observing parts of it
- Deep Q-learning: use a function approximator (a neural network) to represent Q(s,a)

→ Deep Q-learning:
- Very popular today, but has shortcomings
- Long training times, simplistic exploration strategy, action space limited

“Learn to drive in a day”

Real world RL demo for self-driving by Wayve

→ Input: single camera image

→ Action: steering and speed

→ Reward: distance travelled without safety driver taking control

→ No maps / localization required

→ 4 Conv layers / 2 FC layers

→ Only 35 training episodes

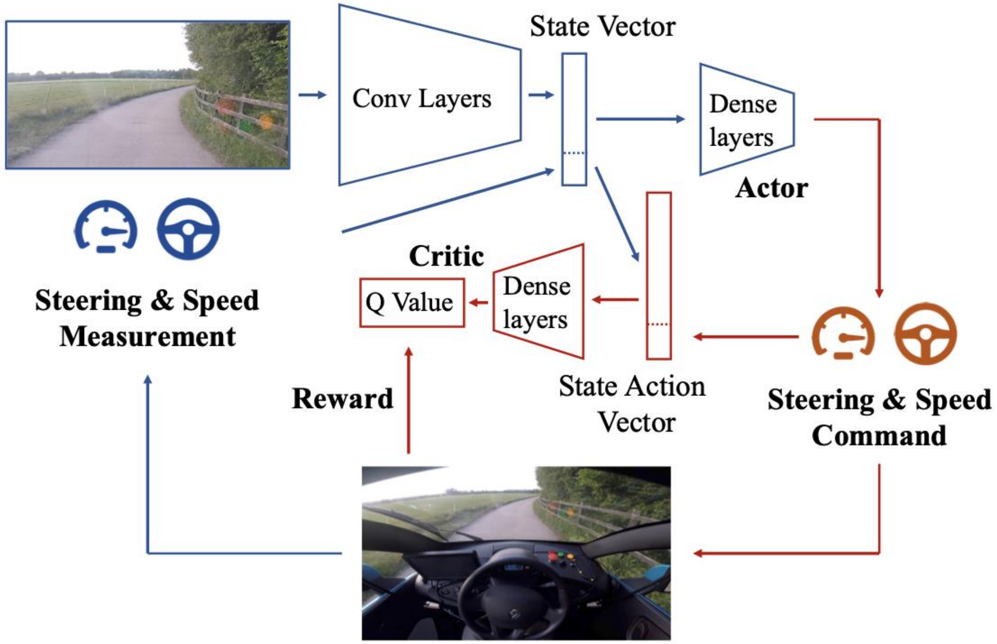


Fig. 1: We design a deep reinforcement learning algorithm for autonomous driving. This figure illustrates the actor-critic algorithm which we use to learn a policy and value function for driving. Our agent maximises the reward of distance travelled before intervention by a safety driver.

https://wayve.ai/thinking/learning-to-drive-in-a-day/
https://arxiv.org/pdf/1807.00412.pdf

“Learn to drive in a day”

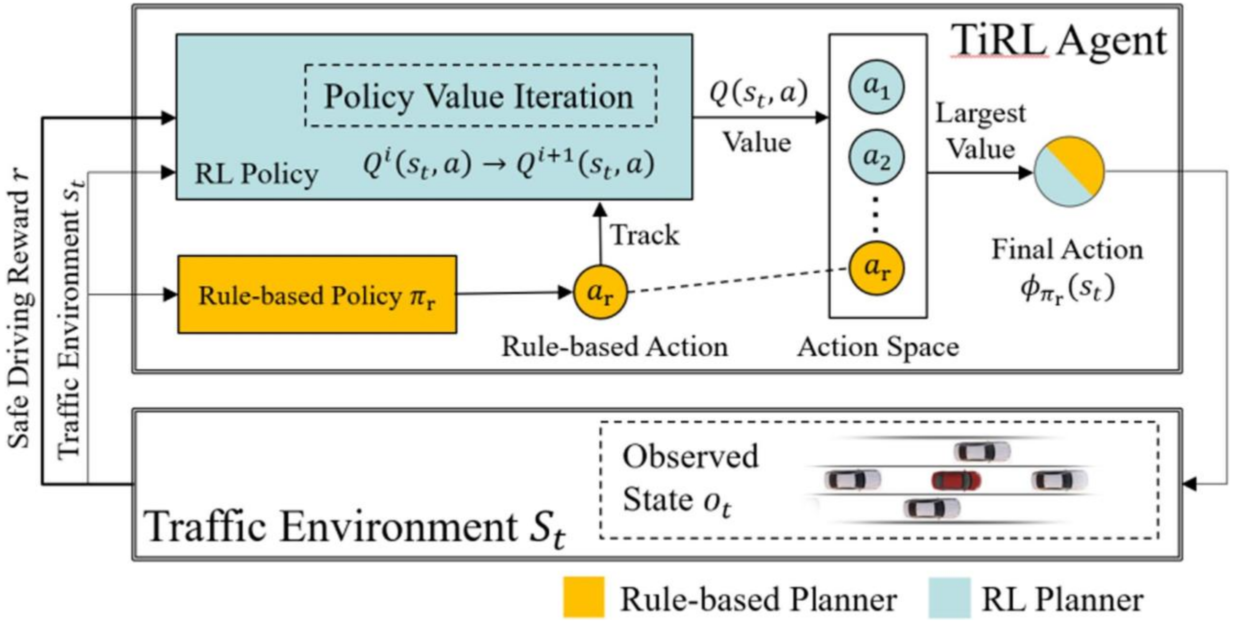
Youtube video

https://www.youtube.com/watch?v=eRwTbRtnT1I&t=5s

Expert and Reinforcement learning

Take the best of the two worlds

Trustworthy improvement RL (TiRL)



https://www.sciencedirect.com/science/article/pii/S0968090X22000997

Reinforcement learning for safety validation

→ Finding corner cases and safety-critical events is hard

→ Use reinforcement learning to generate such events

→ https://www.nature.com/articles/s41586-023-05732-2

TODO’s for last lecture

Exercises

1. Analysis of the Dronet running on the Crazyflie (papers provided on Cyberlearn)

2. Conditional Imitation Learning

3. Conditional Affordance Learning

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TODO’s for today

Exercises

1. Understand the mouse and cheese problem

2. Checking the Wayve paper and demo
(”Learn to drive in a day”)

3. RL using Deep Q-Learning (Deep Q Networks)
Using OpenAI Gym (Car Racing environment)

    - https://github.com/andywu0913/OpenAI-GYM-CarRacing-DQN
    - https://towardsdatascience.com/applying-a-deep-q-network-for-openais-car-racing-game-a642daf58fc9
    - https://scientific-python.readthedocs.io/en/latest/notebooks_rst/6_Machine_Learning/04_Exercices/02_Practical_Work/02_RL_2_CarRacing.html

4. Take a look at the RL Zoo
https://github.com/DLR-RM/rl-baselines3-zoo

REDS
Institut
Reconfigurable
and Embedded
Digital Systems

Hes·so
Haute Ecole Spécialisée
de Suisse occidentale