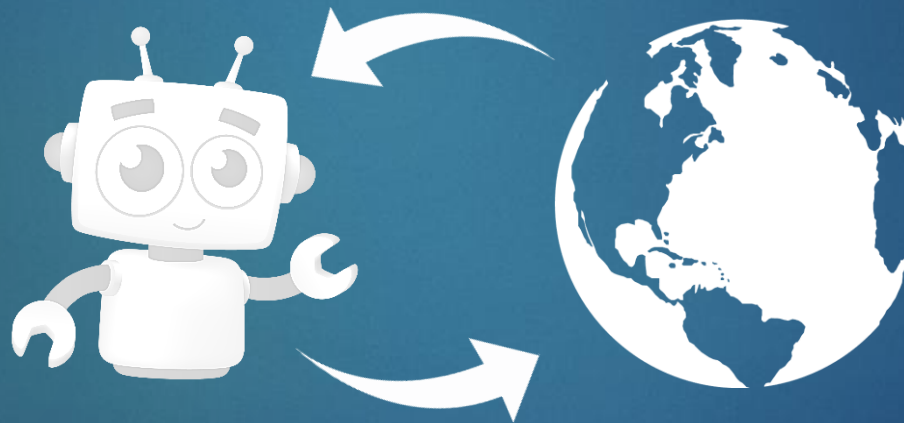


# Deep Learning from Scratch

## Session #9: Reinforcement Learning



by: Ali Tourani – Summer 2021

# Agenda

- ▶ Reinforcement Learning
- ▶ Applications of RL
- ▶ Deep RL Algorithms
- ▶ Deep Q-Learning

# Reinforcement Learning

- ▶ Different learning paradigms
  - ▶ Recall: [Session#3 – Feeding DNNs](#)

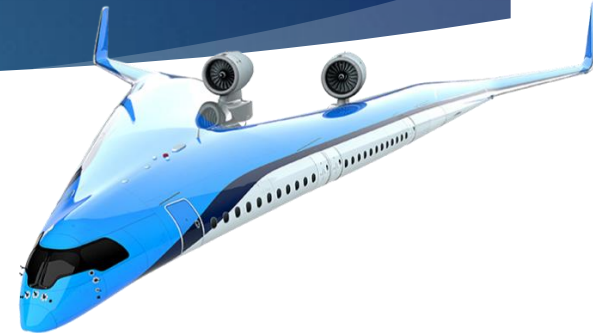


# Reinforcement Learning

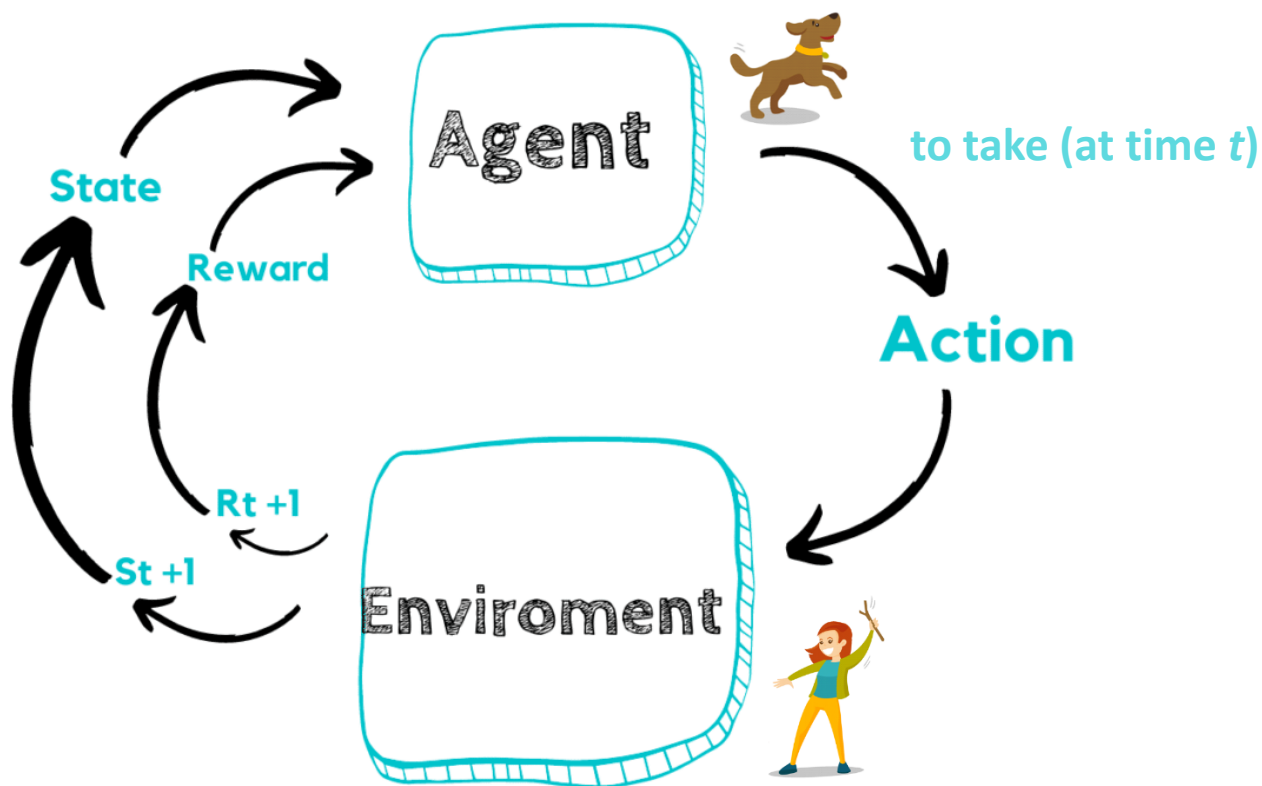
- ▶ Using DNNs to interact with real **dynamic environments**
  - ▶ **Data:** state(observations)-action(behaviors) pairs
  - ▶ **Goal:** Maximizing future rewards
- ▶ Trying to maximize the total (cumulative) reward
  - ▶ An agent learns to achieve a goal in an uncertain environment
  - ▶ Based on Reward and Penalty
- ▶ The model itself should find the solution with a **maximized reward**
  - ▶ Finding a solution with the lowest possible costs in future
  - ▶ Maybe even with trial and error

# Reinforcement Learning

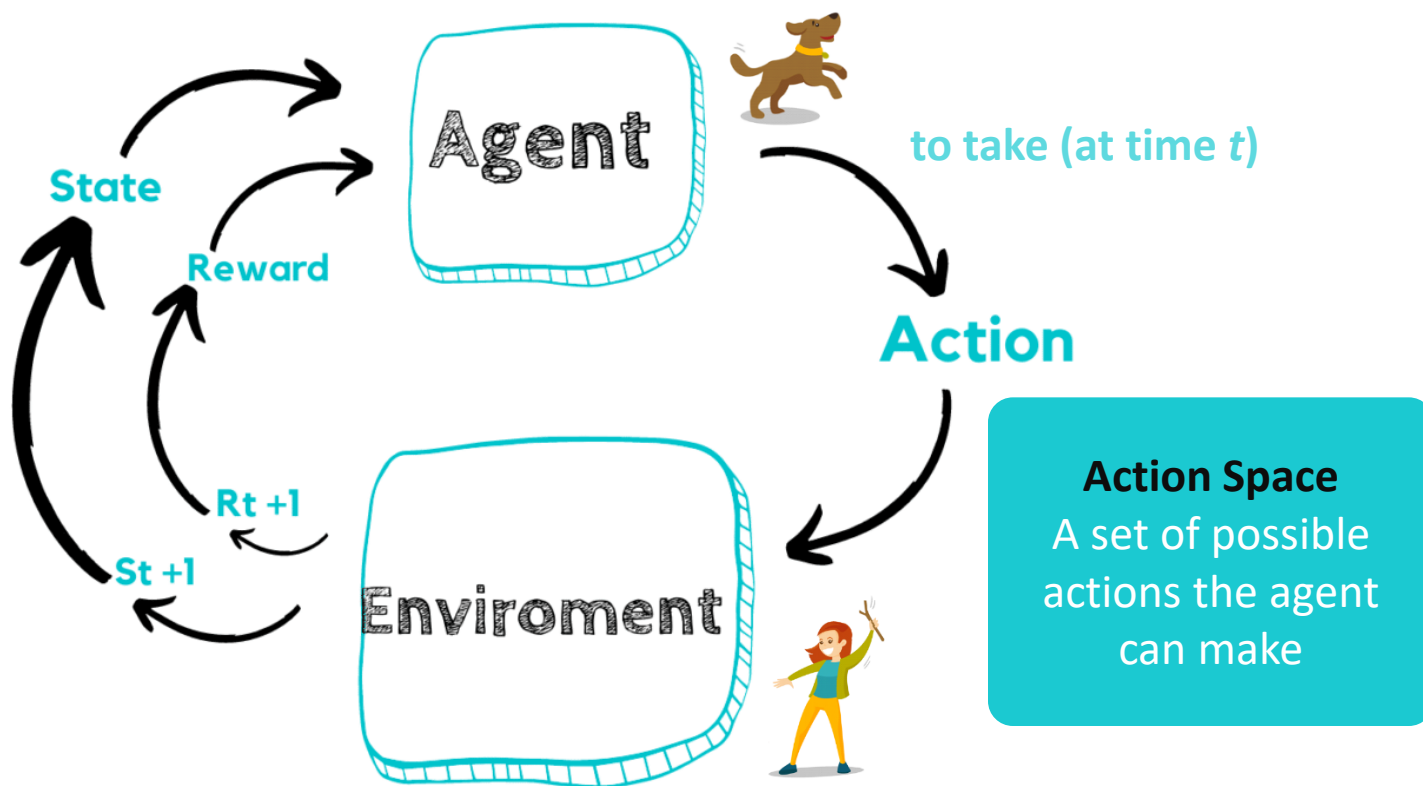
- ▶ Training models to make a sequence of decisions
- ▶ Very common in **game-like** situations
- ▶ **Advantage:** empowering machines' creativity!
  - ▶ How? By gathering experience from thousands of parallel routes
- ▶ **Challenges:**
  - ▶ Building a **realistic simulation** of environment
    - ▶ **Examples:** how to test a **self-driving airplane** in all possible challenging conditions?
  - ▶ Communication with the network through **controlling the agent**
  - ▶ Finding the **local optimum** for the agent (finishing the assigned tasks)



# Reinforcement Learning



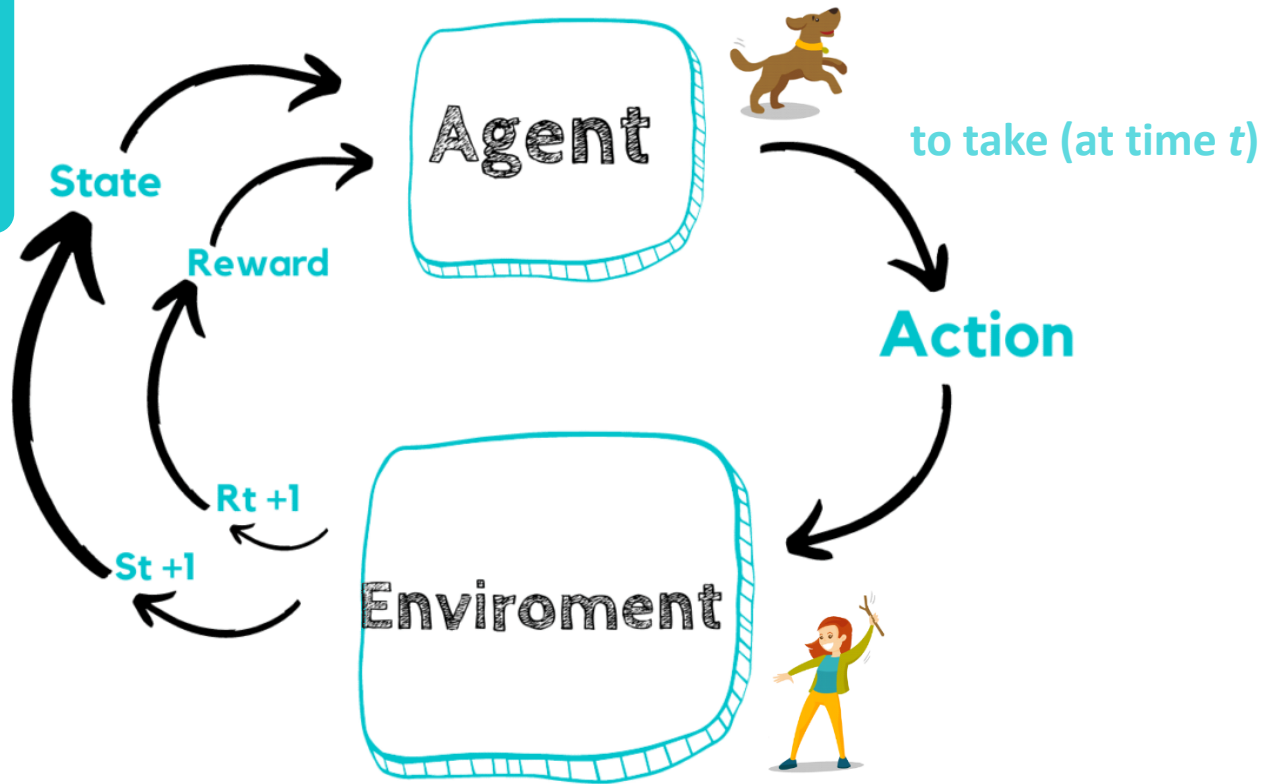
# Reinforcement Learning



# Reinforcement Learning

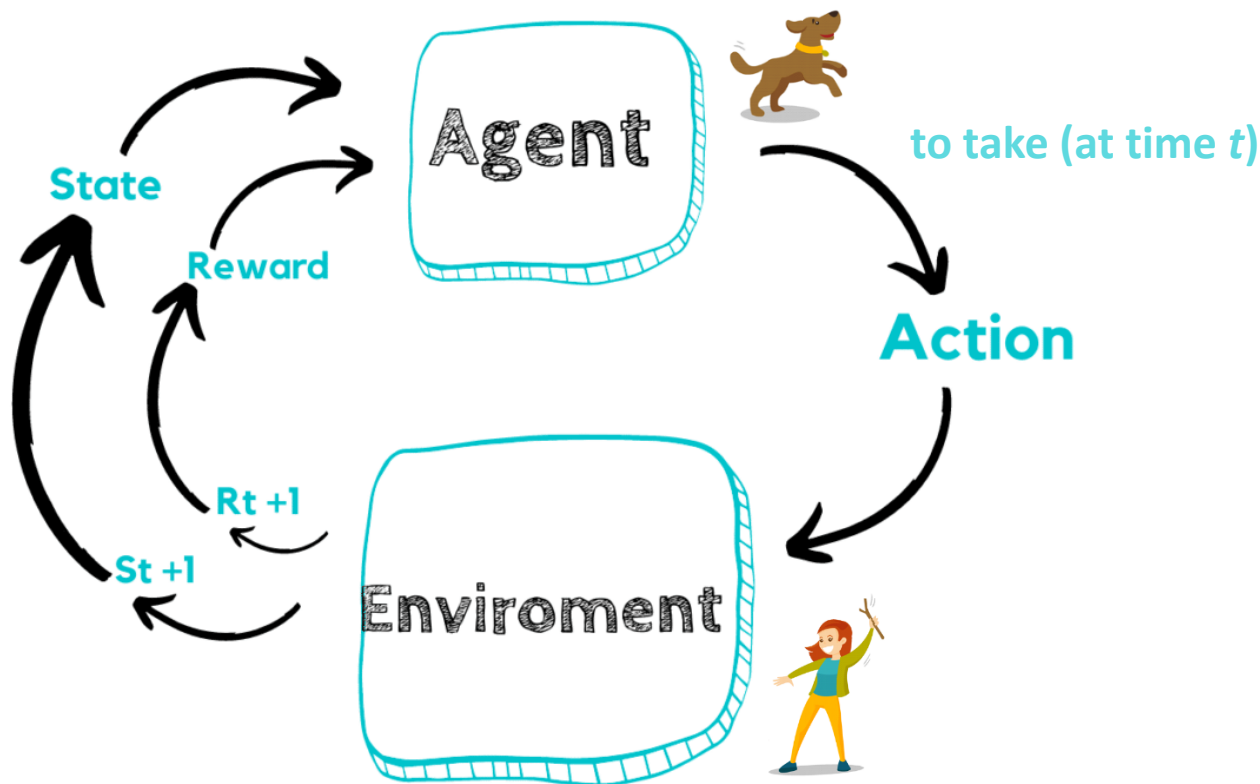
## State

a situation in which the agent finds itself





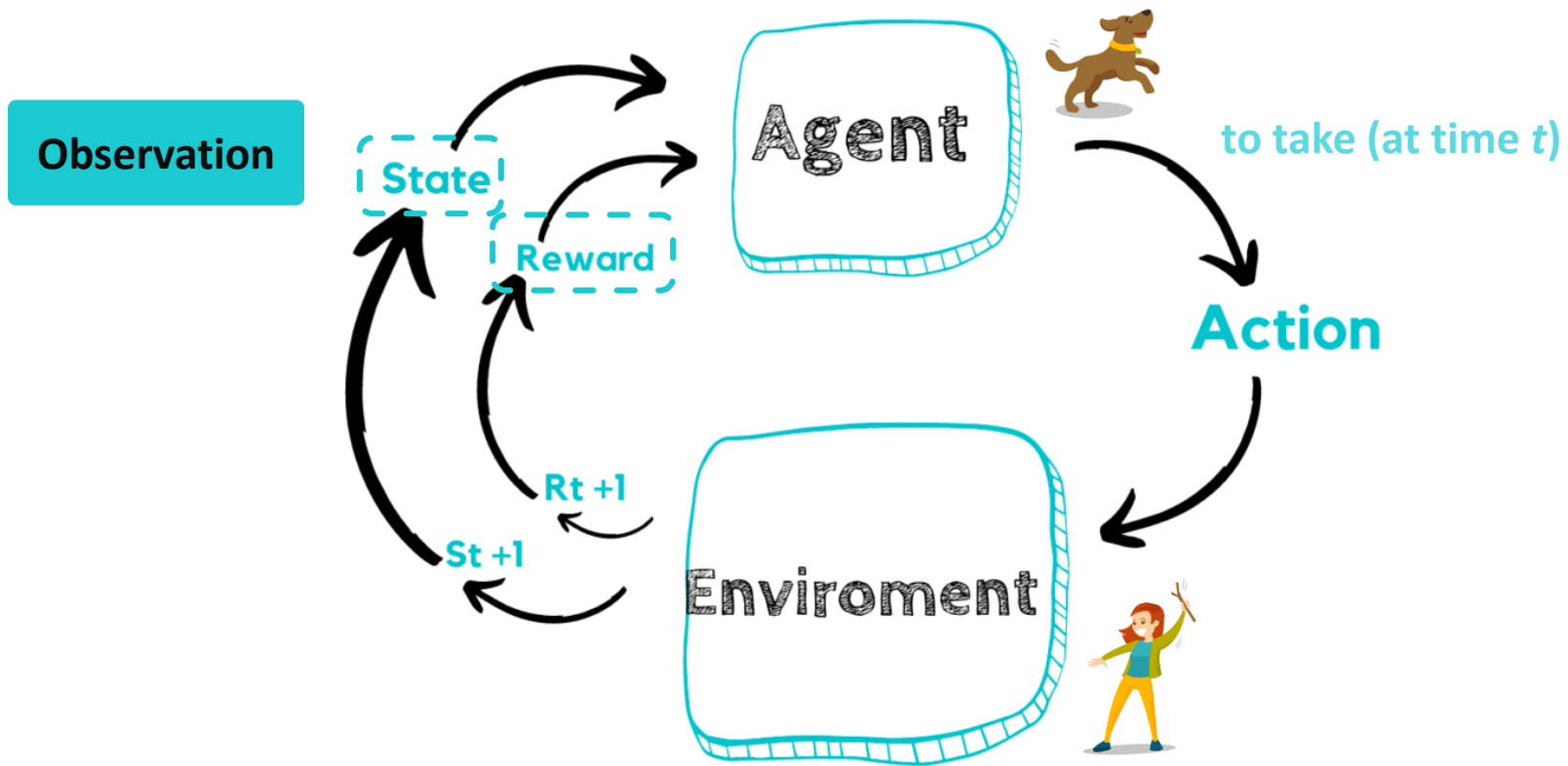
# Reinforcement Learning



**Reward**  
a feedback  
showing the  
success or failure  
of the action

Immediate or delayed

# Reinforcement Learning



# Reinforcement Learning



# Reinforcement Learning



# Reinforcement Learning



# Reinforcement Learning



# Reinforcement Learning



## Important notes on RL

- ▶ **Total Reward (TR)** is a key concept, which is equal to the sum of all rewards

$$R_{total} = \sum_{i=t}^{\infty} reward_i = \sum_{i=t}^{\infty} \gamma^i \cdot reward_i \quad (0 < \gamma < 1)$$

- ▶ Where  $\gamma$  is the **discounting factor** to make future rewards less effective
- ▶ **Goal:** enforcing **short-term learning** for the algorithm
- ▶ **Q-function** is another key concept that takes the current state and action, and returns the expected total reward

$$Q(state_t, action_t) = E[R_{total} \mid state_t, action_t]$$

# Reinforcement Learning



## Important notes on RL

- ▶ The main role of the Q-function is to define the best possible action
  - ▶ **How?** Just choose a policy to **maximize the future reward** when **different actions** are fed in a **known state**
- ▶ Agents in RL take **random decisions** in the environment to learn selecting the right choice
- ▶ A **policy** is a mapping  $s \rightarrow a$ 
  - ▶ Reinforcing the agent to learn to perform the best actions by experience





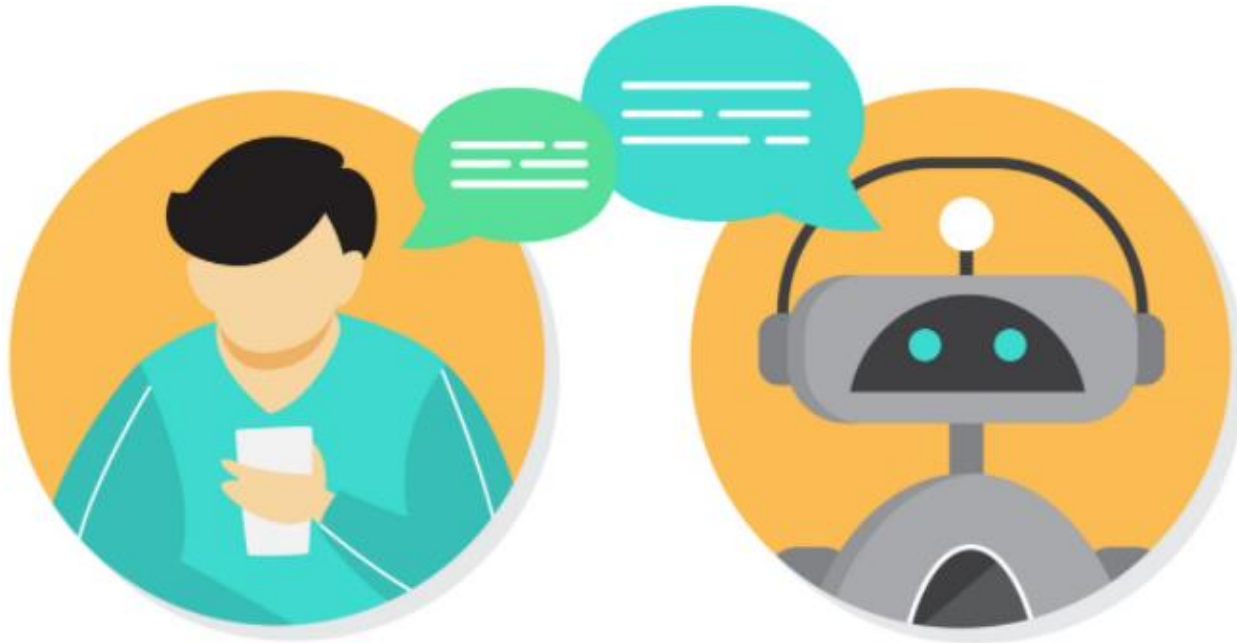
# Applications of RL

## Self-driving (autonomous) Cars



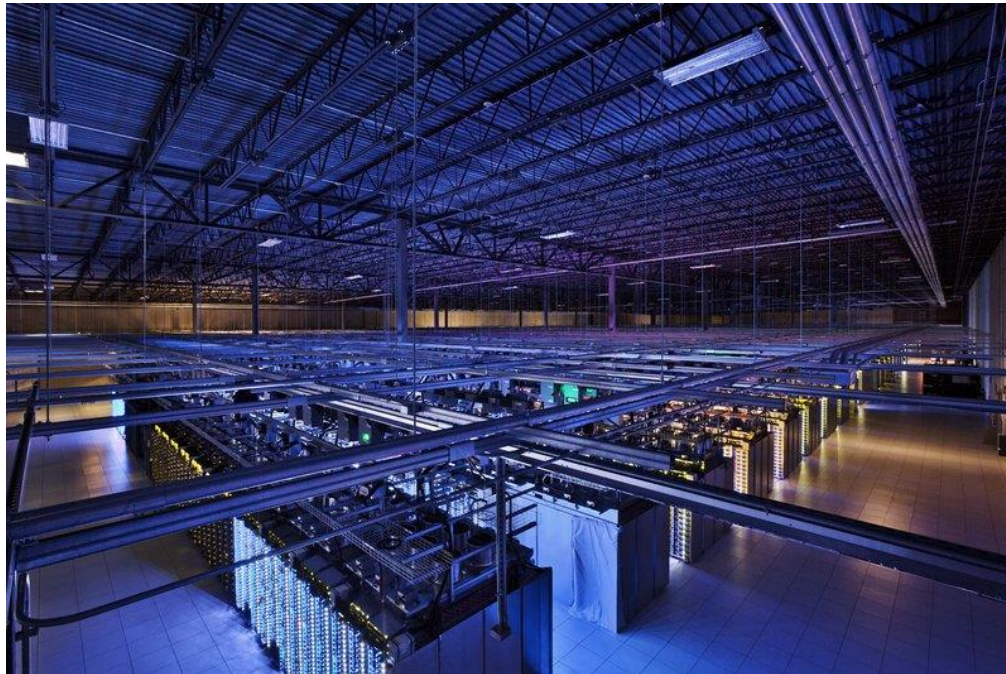
# Applications of RL

## Natural Language Processing (NLP): Question Answering



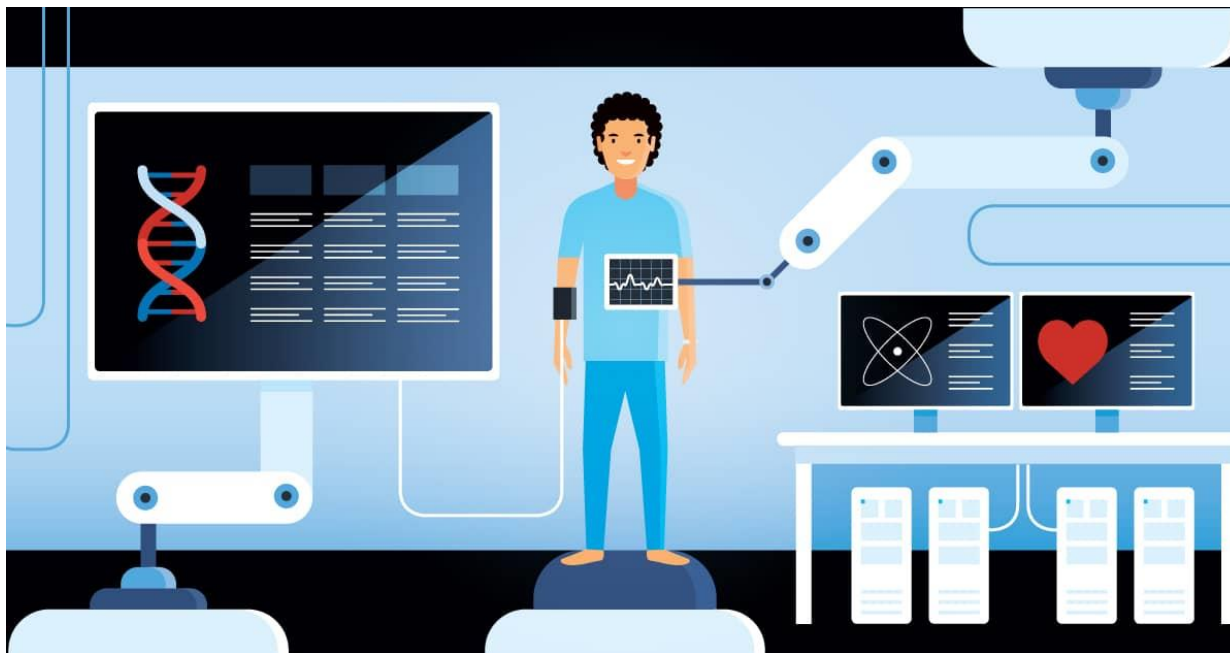
# Applications of RL

## DeepMind: Autonomous Data Center Cooling Systems



# Applications of RL

## Healthcare





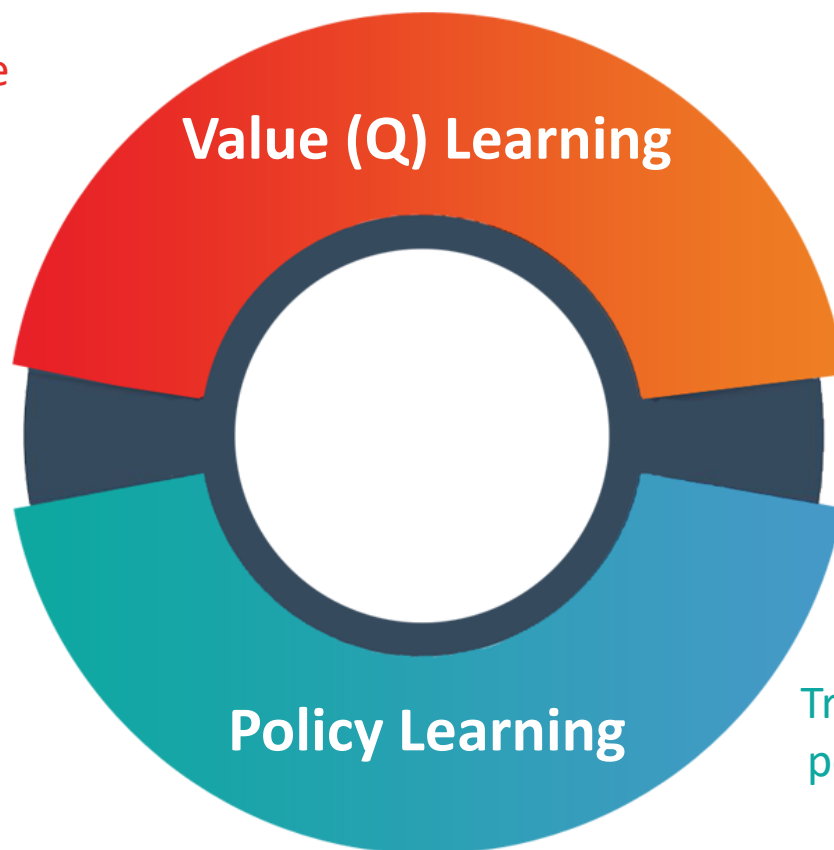
# Applications of RL

## Computer Games



# Deep RL Algorithms

Trying to calculate the Q-function instead of storing policies, and picking the action with max value



Trying to directly learn the policy (state to action mapping) showing what actions to take/avoid

# Deep RL Algorithms

## Value Learning (Q-Learning) Networks

- ▶ Calculating a **cumulative score** for each state (cheat sheet) and choosing the states with **most possible reward**
- ▶ Learning which actions should be performed at the current state to get maximum reward
  - ▶ **Example#1:** accelerate + →
  - ▶ **Example#2:** accelerate + ←
  - ▶ **Example#3:** brake + →
  - ▶ **Example#4:** brake + ←



# Deep RL Algorithms

## Policy Learning Networks

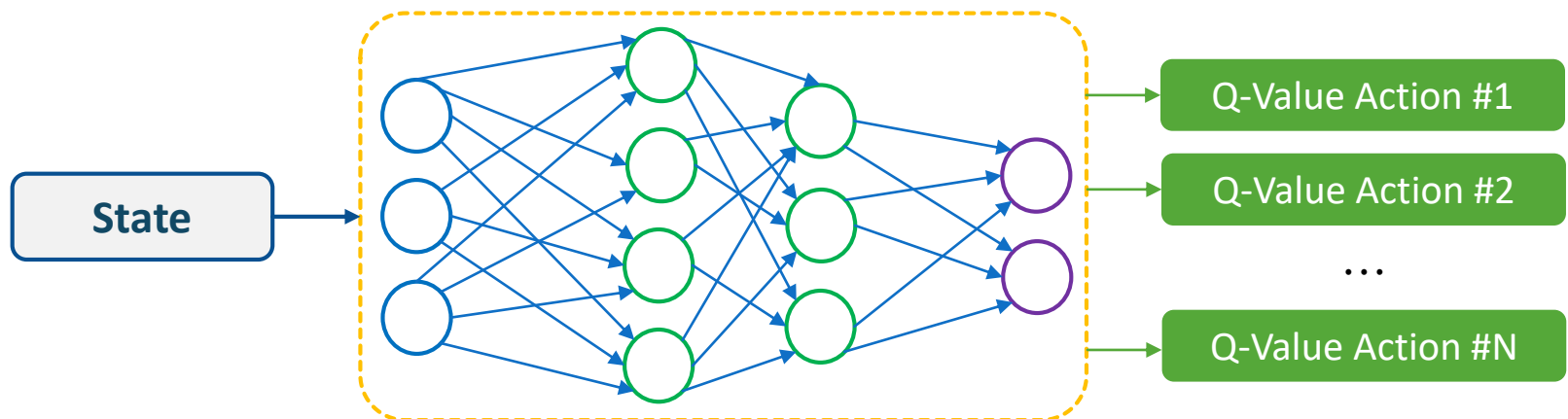
- ▶ Building a representation of a policy and keep it in memory during learning
- ▶ Learning to give a definite output by giving a particular input
  - ▶ **Example#1:**  $action_1$  will always result in  $state_1$
  - ▶ **Example#2:** staying on the road will always increase the  $score$
  - ▶ **Goal:** learn how to use  $action_1$  to stay on the road





# Deep Q-Learning

- ▶ **Goal:** to provide a cheat sheet for the agent to find the best action
  - ▶ We need more powerful infrastructure to control thousands of (states, actions)
- ▶ A Deep Q-Network (DQN) is designed for challenging scenarios!
  - ▶ Using DNNs to approximate the **Q-value function**
  - ▶ **Input:** current (candidate) state, **Output:** the Q-value of all possible actions

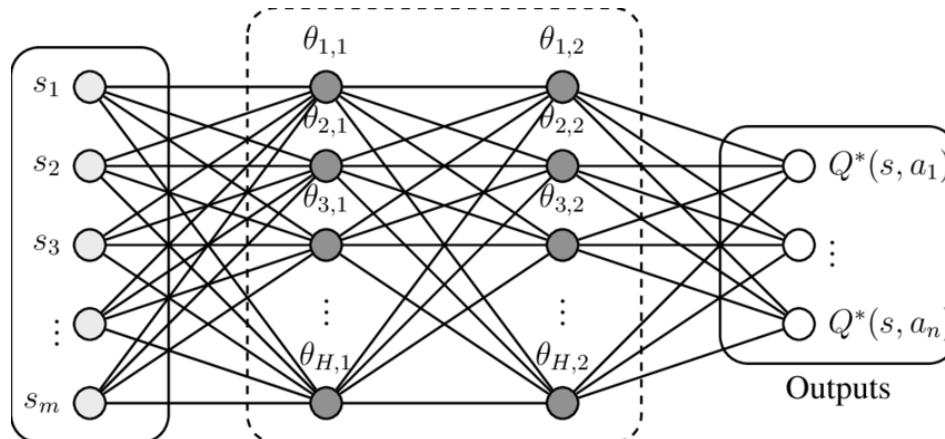


# Deep Q-Learning



## Important Notes on DQNs

- ▶ All the **past experiences** should be stored in memory
- ▶ The next action is actually the **maximum output of the Q-network**
- ▶ The loss function in a DQN is **MSE** of the predicted and target Q-value



# Deep Q-Learning

16 lines (11 sloc) | 938 Bytes

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## Deep Q-Networks (DQNs)

Reinforcement Learning is the usage of DNNs to interact with real dynamic environments and training models to make a sequence of decisions. A Deep Q-Network is a common architecture for RL. The main goal in DQNs is to provide a cheat sheet for the agent to find the best action! DQNs are used to approximate the Q-value function, where the input is current (candidate) state, and the output is the Q-value of all possible actions

Codes

#	File	Description
0	<a href="#">Basic introduction</a>	To be added soon

Full code on GitHub

# References

- ▶ <http://introtodeeplearning.com/>
- ▶ <https://towardsdatascience.com/policy-networks-vs-value-networks-in-reinforcement-learning-da2776056ad2>
- ▶ <https://deepsense.ai/what-is-reinforcement-learning-the-complete-guide/>
- ▶ <https://www.analyticsvidhya.com/blog/2019/04/introduction-deep-q-learning-python/>

# Questions?

