# DS-GA 3001 001 | Lecture 1

## Reinforcement Learning

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# Week 1

1. Course Information

2. Introduction to Reinforcement Learning

# Course Information

# DS-GA 3001 RL Instructional Team

## Instructor:

- Dr. Jeremy Curuksu, jeremy.cur@nyu.edu

## Section Leaders:

- Akshitha Kumbam, ak11071@nyu.edu
- Kushagra Khatwani, kk5395@nyu.edu

## Graders:

- Akshitha Kumbam, ak11071@nyu.edu
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# DS-GA 3001 RL Schedule

## DS-GA 3001 RL Lecture:

- Wednesdays from 4:55pm to 6:35pm EST
- Location: 31 Washington Pl (Silver Ctr), Room 206

## DS-GA 3001 RL Lab:

- Thursdays from 5:55pm to 6:45pm EST
- Location: 31 Washington Pl (Silver Ctr), Room 206

# DS-GA 3001 RL Curriculum

## Reinforcement Learning:

- **1.** Introduction to Reinforcement Learning
- **2.** Multi-armed Bandit
- **3.** Dynamic Programming on Markov Decision Process
- **4.** Model-free Reinforcement Learning
- **5.** Value Function Approximation (Deep RL)
- **6.** Policy Function Approximation (Actor-Critic)
- **7.** Planning from a Model of the Environment (AlphaZero)
- **8.** Aligning AI systems to Human Preferences (ChatGPT)
- **TBC.** Examples of industrial applications
- **New.** Look Ma, no RL: Optimal control with convex models

# DS-GA 3001 RL Resources

- Lecture and lab practice code + lecture slides
- **Reinforcement Learning: An introduction** (2018) by R. Sutton and A. Barto
- Python RL libraries used in this course have free, recent and online documentations. The library we will use most is **OpenAI Gym** (maintained as **Gymnasium** since 2022)

# Advice to Succeed in this Course

- **Attend both lectures and labs**. Lectures and labs complement each other to set you up for success
- **Read book from Sutton & Barto** at least chapt 3-10 and 13
- **Read the Gym documentation**, at least the introduction
- **Before implementing a RL solution**, define the agent's goal, states, actions, and reward functions
- **Implement, Document, and Customize RL code.**
- **Ask questions!**

# Introduction to Reinforcement Learning

# Introduction to Reinforcement Learning

## Today's topics:

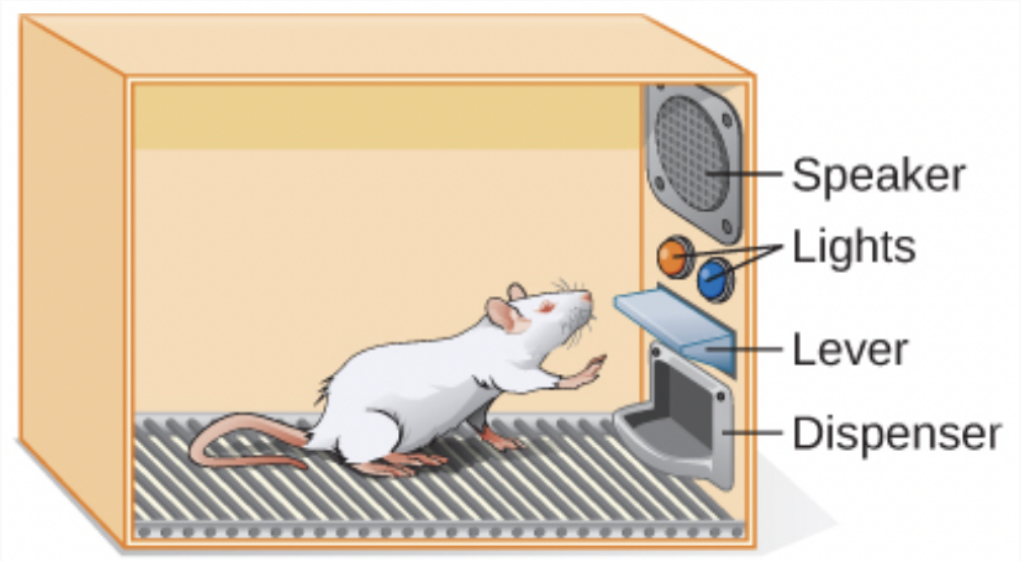
- What is Reinforcement Learning?
- Key components of Reinforcement Learning
- Examples of Reinforcement Learning problems
- Introduction to the Gym Python library

# What is Reinforcement Learning?

# What is Reinforcement Learning?

**Behavior is primarily shaped by reinforcement rather than free-will:**
*"Skinner saw human action as dependent on consequences of previous actions, a theory he called the principle of reinforcement: If the consequences to an action are bad, there is a high chance the action will not be repeated; if the consequences are good, the probability of the action being repeated becomes stronger"*

**On B. Skinner, 1904-1990 (in *Psychology*, Schacter, 2011)**



# What is Reinforcement Learning?

- **RL is the science of learning to make decisions from interactions with an environment**
  - **Industrial revolution and Machine Age (1750-1940)**
    Automation of repeated physical solutions
  - **Digital revolution and Information Age (1960-Now)**
    Automation of repeated mental solutions
  - **Artificial Intelligence revolution (Now -?)**
    Allow machines to find solutions themselves
- **Why learn by reinforcement?**
  - Find previously unknown solutions
  - Find solutions online for unforeseen circumstances

# Reinforcement Learning History

## In short...

- **1850-1911**: Trial-and-error learning in psychology: The *Law of Effect* (Thorndike)
- **1927**: Theory of conditioned reflexes (Pavlov)
- **1938**: Behaviorism and principle of reinforcement (Skinner)
- **1948**: Trial-and-error learning in a computer system (Turing)
- **1952-1954**: Maze-running mouse (Shannon), Reinforcement calculator (Minsky)
- **1957**: Dynamic programming to solve optimal control in MDP (Bellman)
- **1959**: Checkers-playing program (Samuel)
- **1960s-70s**: Learning automata, K-armed Bandits, Genetic algorithms
- **1972**: Model of classical conditioning based on temporal-difference (Klopf)
- **1983**: Actor–critic architecture to solve pole-balacing problem (Sutton, Barto)
- **1989**: Q-learning algorithm (Watkins)
- **1992**: Backgammon playing program (Tesauro's TD-Gammon)
- **2013**: Deep Q-Network reaches superhuman ability at Atari 2600
- **2016**: AlphaGo reaches superhuman ability at Go (Silver)
- **2022**: ChatGPT creates poetry

# Reinforcement Learning Examples

**Problem requiring to make decisions with a goal in mind:**

- Drive a car
- Fly a helicopter
- Manage a financial portfolio
- Play video or board game
- Control a power station
- Make a robot walk

# Reinforcement Learning Examples

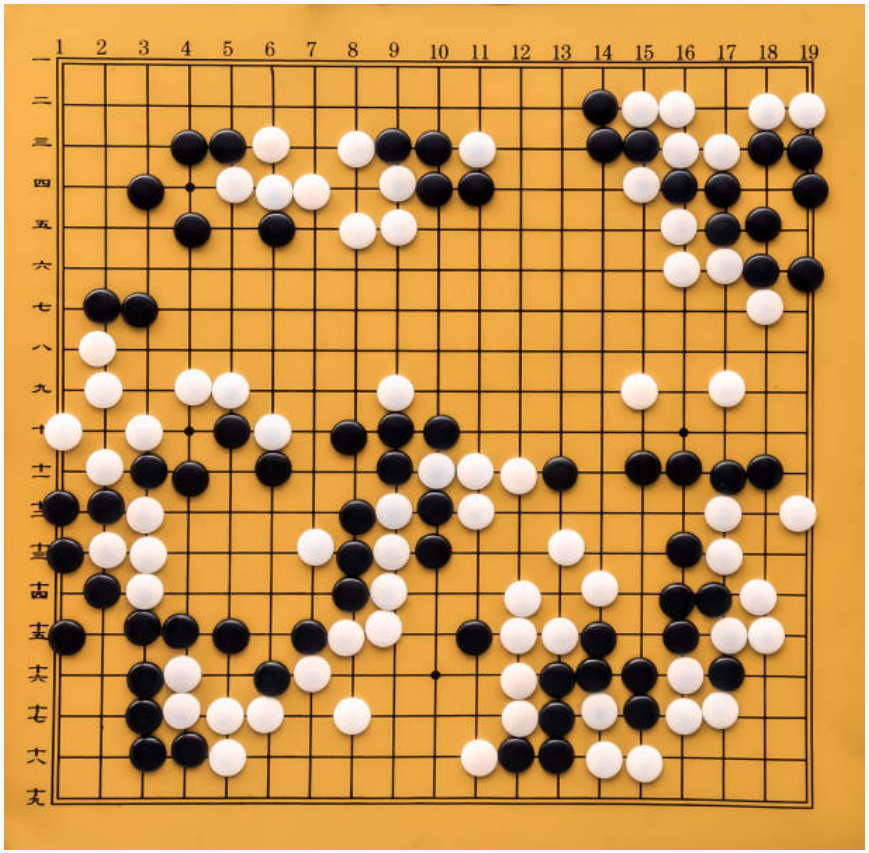
**Problem requiring to make decisions with a goal in mind:**

- Drive a car
- Fly a helicopter
- Manage a financial portfolio
- Play video or board game
- Control a power station
- Make a robot walk
- (New...) Human-level semantic reasoning

# Reinforcement Learning Examples

## Play Go (to win)

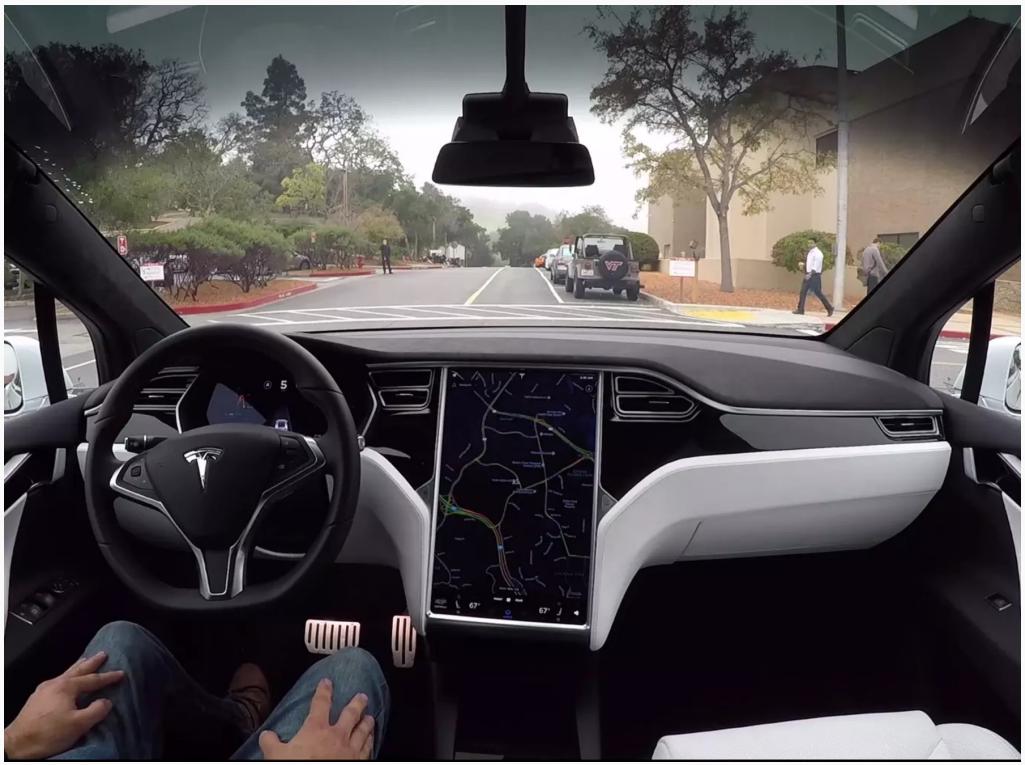
- **State**:
  Configuration of the playing board
- **Action**:
  Any valid move
- **Reward**:
  Win = +1
  Lose = -1
  Else = 0



# Reinforcement Learning Examples

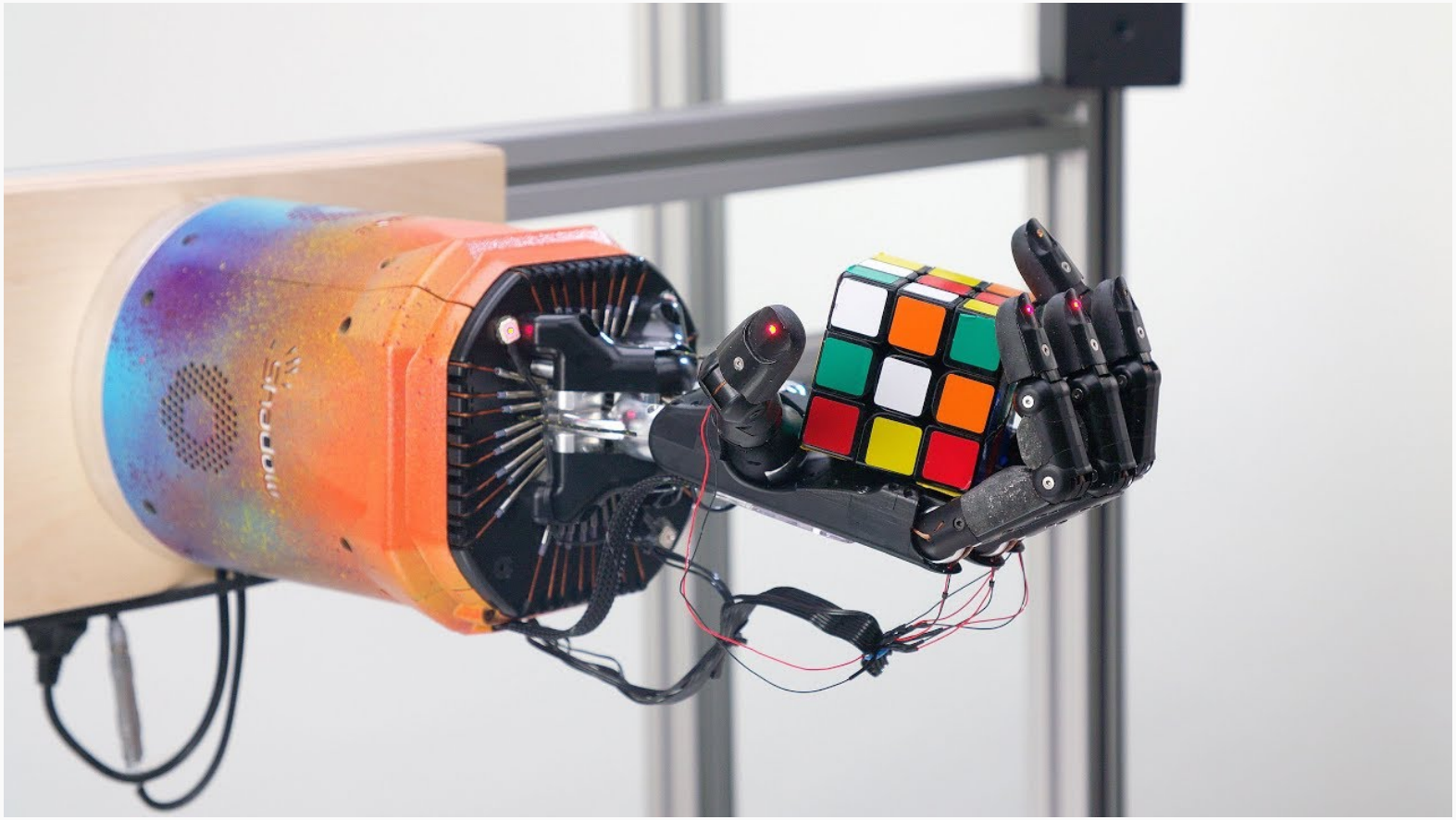
## Drive (safely to a destination)

- **State**:
  Camera pixels
  Traffic
  Weather
- **Actions**:
  Steering wheel
  Accelerator/Break
- **Reward**:
  Destination = +1
  Honking = -1
  Collision = -100



# Reinforcement Learning Examples

## Example of robot operating on its own



# How to formalize Reinforcement Learning?

- **To find unknown or online solutions, intelligent beings learn by interacting with their environment:**
  - Actively gather experience
  - Learn long-term consequences of actions
  - Predict an uncertain future
- **Supervised Learning formalism is limited:**

$$h_\theta\left(x^{(n)}\right) \longmapsto y^{(n)} \qquad \theta^{(k+1)} = \theta^k - \alpha \frac{\partial J}{\partial \theta}$$

$$J(\theta) = \frac{1}{2N} \sum_{n=1}^{N} \left(h_\theta\left(x^{(n)}\right) - y^{(n)}\right)^2$$

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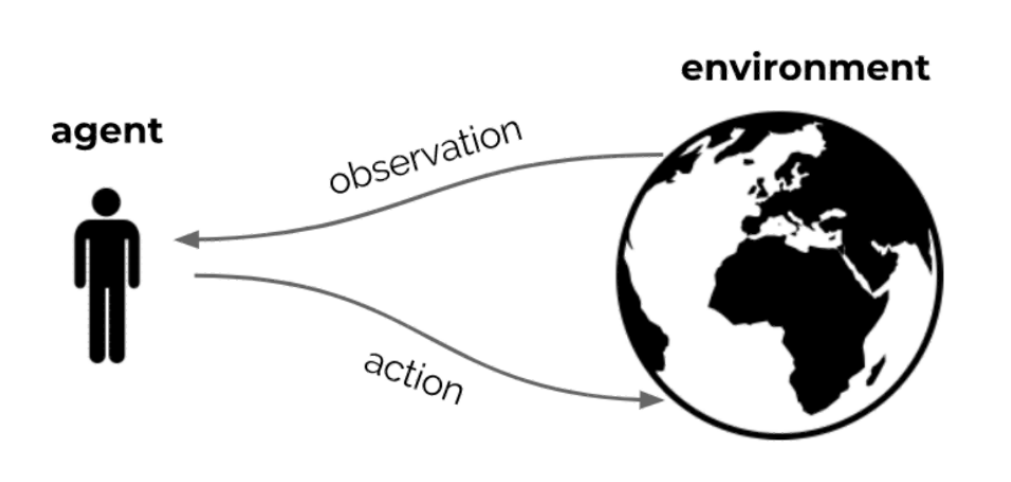
What if $y^{(n)}$ is not known?

# Formalizing Reinforcement Learning



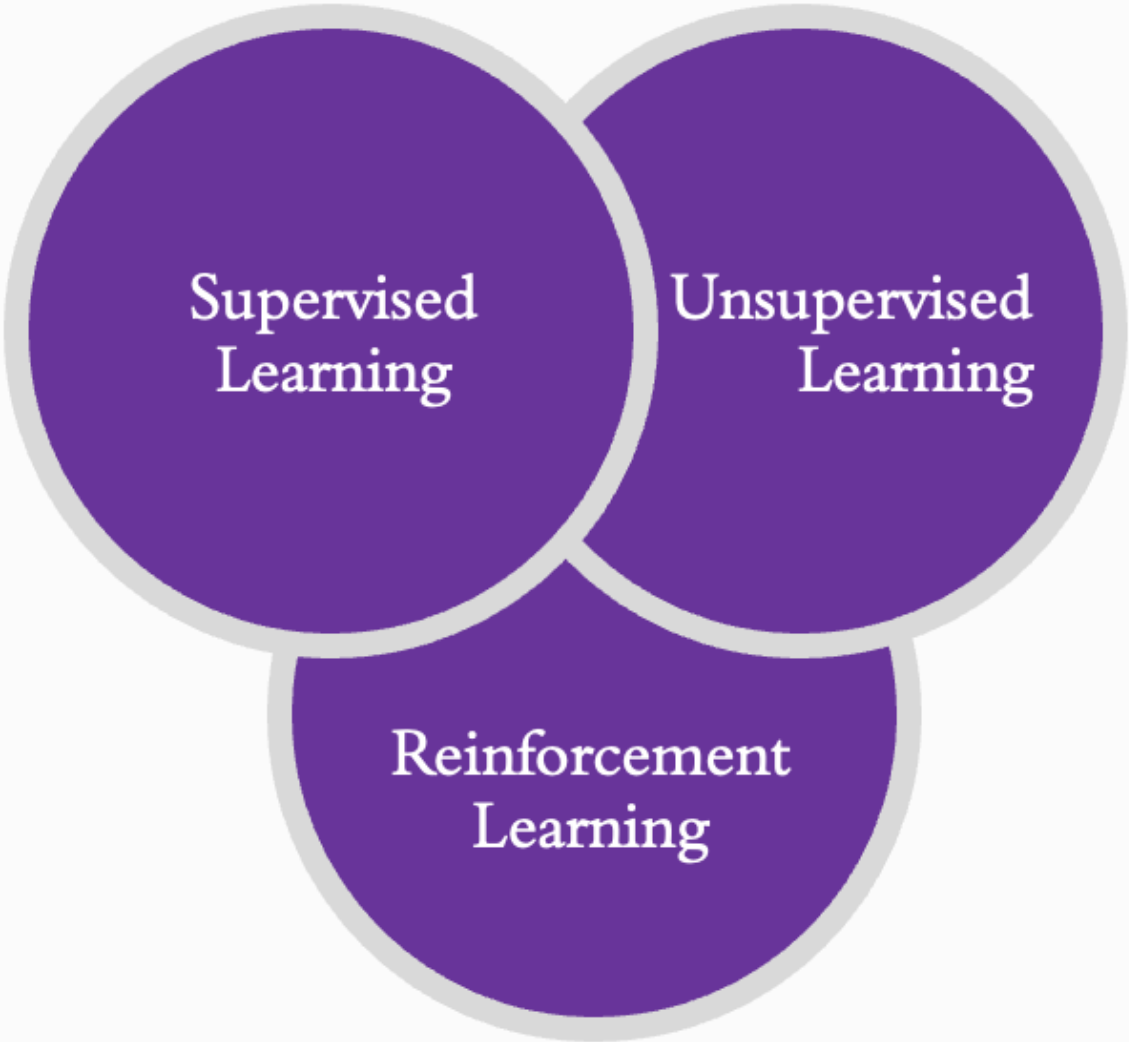

$$\pi_\theta : s_t \longmapsto p(a_t)$$

$$J(\theta) = ?$$

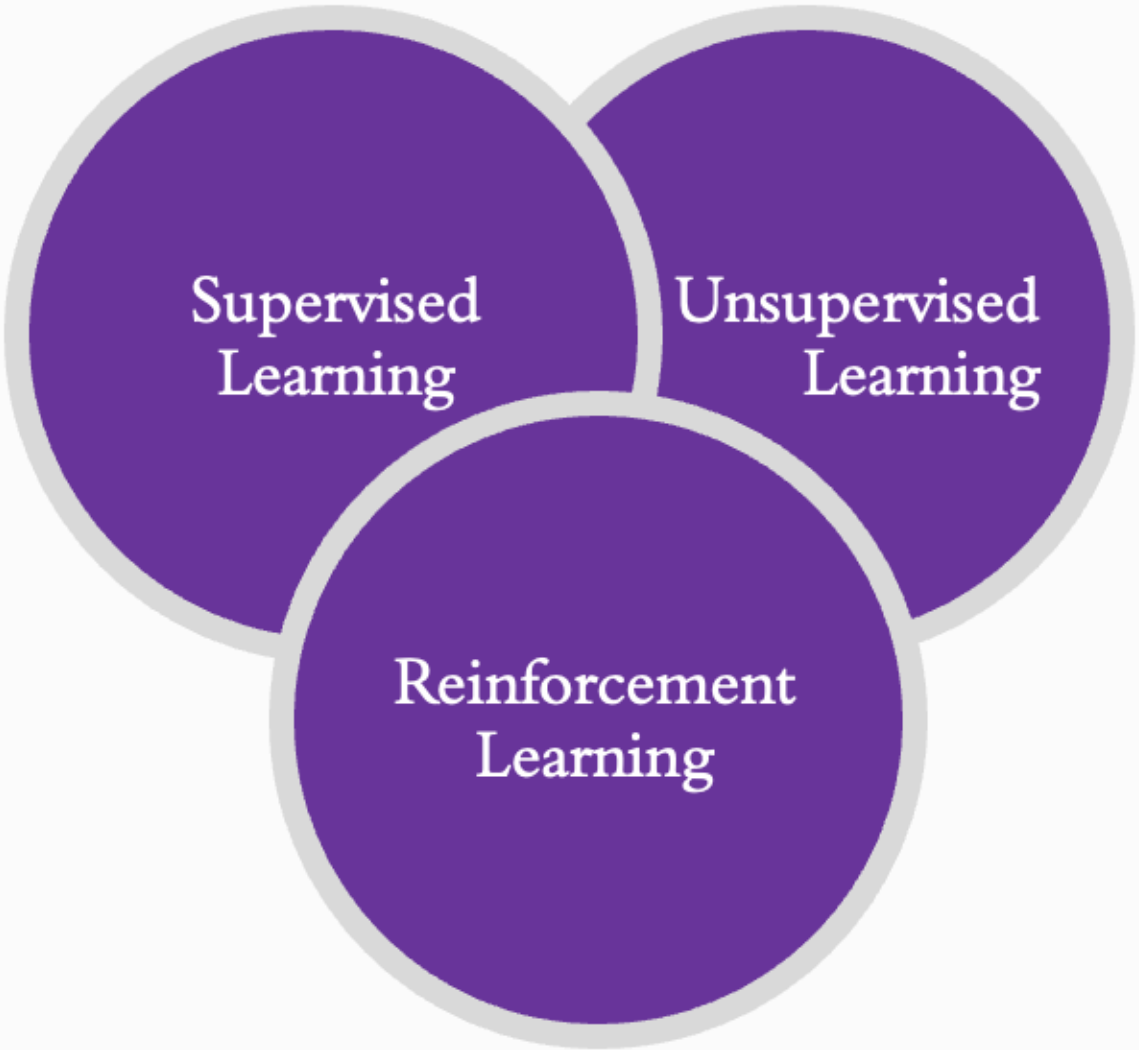
**Science of learning to make decisions from interactions**

- Sample experience by interacting with the environment
- No supervision, only reward signals
- Feedback can be delayed, time matters
- Goal-directed. Need to act across time to reach a goal

# Formalizing Reinforcement Learning

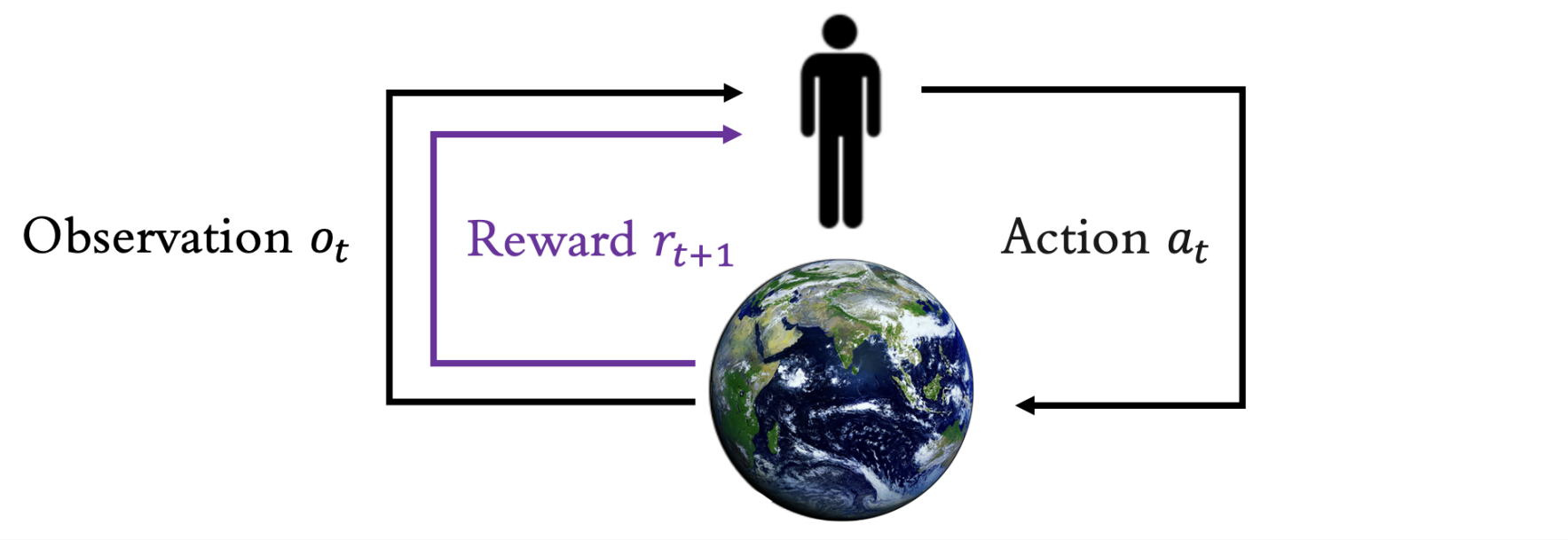


# Formalizing Reinforcement Learning



# Key Components of Reinforcement Learning

# Components of Reinforcement Learning




**At each step *t*, the agent:**

- Receives observation $o_t$
- Executes action $a_t$
- Receives reward $r_{t+1}$

**The environment:**

- Receives action $a_t$
- Send reward $r_{t+1}$
- Send observation $o_{t+1}$

# Components of Reinforcement Learning

**A Reinforcement Learning solution has 3 components:**

1. **The Environment**
2. **The Agent**:
   - States and Observations
   - Actions and Policies
   - Value Function (for states and/or actions)
   - Model of the environment dynamics
3. **A Reward signal**

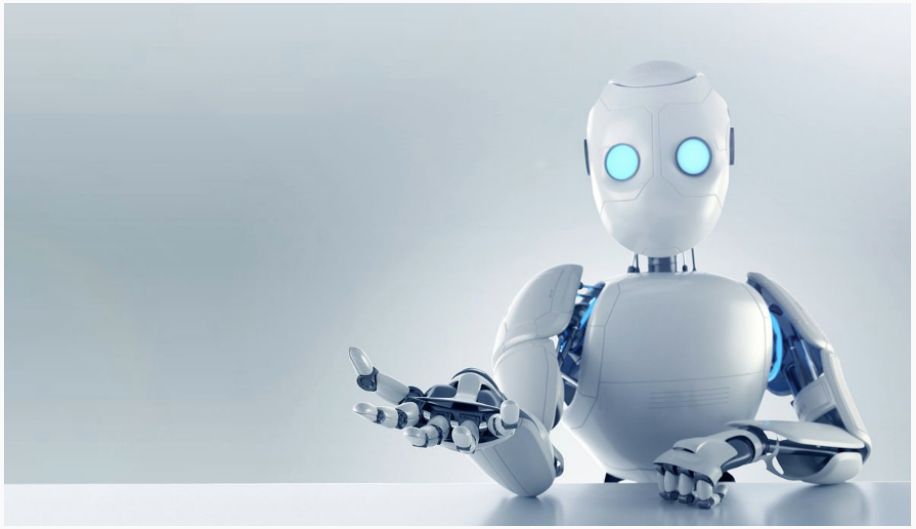
# The Environment

## = What is *not* defined as the agent

- Well-defined in simulation environment, but infinite in reality
- The environment has its own internal state which is not usually visible to the agent. It may contain lot of irrelevant information
- Can be defined relative to the agent: the environment is what the agent *perceives* from it = observations and rewards

# The Agent

**= An entity equipped with sensors, effectors, and goals**



- The agent performs actions to reach a goal
- It may learn *policies* mapping specific states to specific actions
- It may learn value functions for states or actions
- It may learn a model of the environment dynamics

# States and Observations

**The agent state $s_t$ captures information available to the agent at step $t$ about its environment**

- An observation a.k.a. sensation is the (raw) input of the agent's sensors such as measurements, images, tactile signals
- The agent state can be defined as a raw or processed observation, or even as a function of the history from past sequences of observations, actions and rewards:

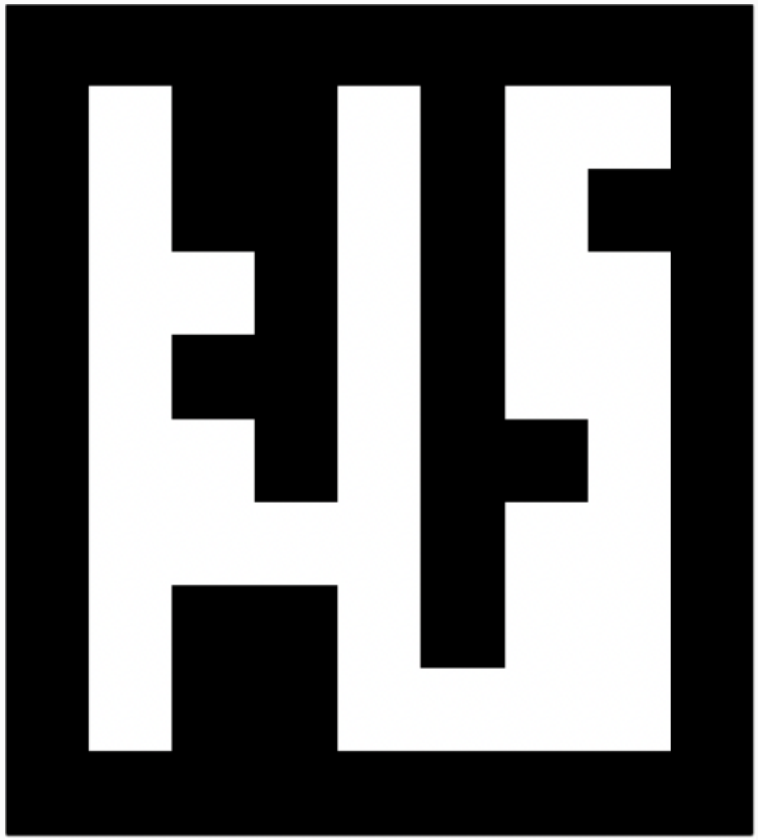
$$s_{t+1} = f(s_t, a_t, r_{t+1}, o_{t+1}) = f(\ldots, o_{t-1}, a_{t-1}, r_t, o_t, a_t, r_{t+1}, o_{t+1})$$

where $f$ is a *state update function*

- The agent state is often not the same as the environment state. It depends on what the agent observes on the environment

# Defining the Agent State

## Example of Maze Environment



- The agent may observe the full environment

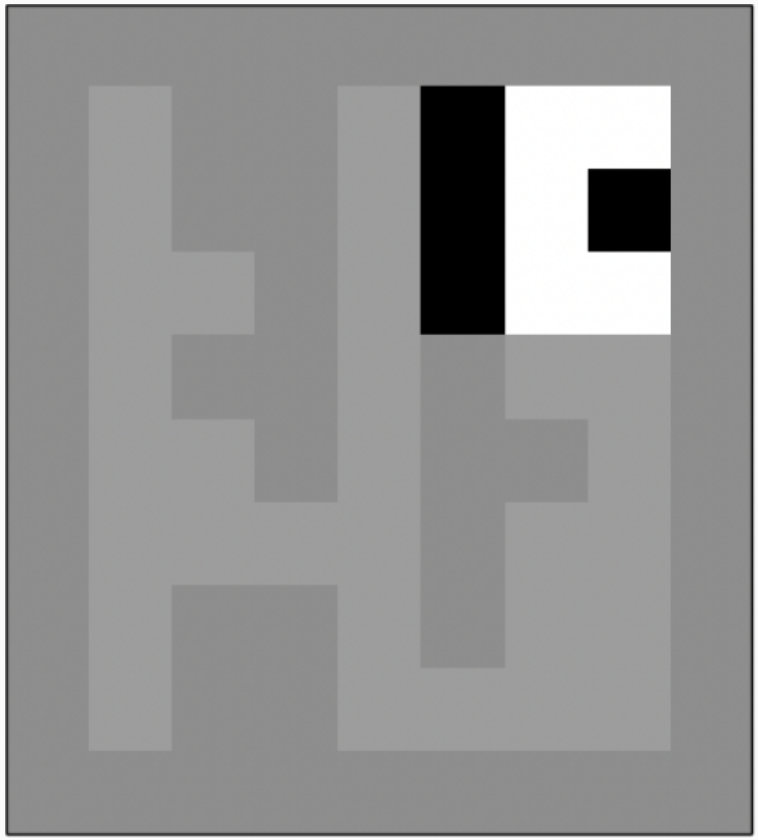
# Defining the Agent State

## Example of Maze Environment

- The agent may only partially observe the environment

# Defining the Agent State

## Example of Maze Environment



- The agent may only partially observe the environment

# Defining the Agent State

## Example of Maze Environment

- How would you construct the agent state to distinguish between these two locations?

# Actions and Policies

**The goal of the agent is to select actions to maximise expected accumulated reward across an entire policy**

- **Actions may have long term consequences** on future accessible states and reward: reward may be *delayed*
- **Examples of Actions**:
  - Suggest a song or a movie
  - Translate & rotate articulation joints of a robot
  - Manage a financial portfolio (may take months to mature)
  - Block opponent moves (help win game many moves later)
- **A policy is a function that maps states to actions**:
  - Deterministic policy: $\pi : s \longmapsto a$
  - Stochastic policy: $\pi : s \longmapsto p(a_1|s), p(a_2|s), ..., p(a_k|s)$

# Reward and Return

## A reward $r_t$ evaluates the action taken at time $t$

- $r_t$ is a scalar feedback signal *produced by* the environment, *received by* the agent, at time $t$.
- The goal of the agent is to maximize the accumulated rewards:

$$G_t = r_{t+1} + r_{t+2} + \ldots r_{\text{end}}$$

- $G_t$ is called the return
- **Examples**:
  - $r_T = +1$ or $r_T = 0$ (win or lose), $r_t = 0$ if $t \neq T$
  - $r_t = -n \times \text{price}$ or $r_t = n \times \text{price}$ (buy or sell $n$ stocks)
- **Reward Hypothesis**: *All goals/purposes can be mathematically encoded as maximizing the sum of accumulated rewards*.

# The True Value of a State... $v_\pi(s)$

**The value of a state is the expected return for that state**

- Value of a state $s$ for a given policy $\pi$:

$$v_\pi(s) = \mathop{\mathbb{E}}_{\pi}(G_t \mid s)$$

  $v_\pi(s)$ indicates how good it is to be in $s$ when following $\pi$

- **$G_t$ can be discounted to trade off short- vs. long-term rewards**:

$$G_t = r_{t+1} + \gamma\, r_{t+2} + \gamma^2\, r_{t+3} + \ldots \quad \text{where } \gamma \in [0, 1]$$

- **$G_t$ can be defined recursively, and so too can $v_\pi(s)$**:

$$G_t = r_{t+1} + \gamma\, G_{t+1}$$

$$v_\pi(s) = \mathop{\mathbb{E}}_{\pi}(r_{t+1} + \gamma\, G_{t+1} \mid s)$$

$$v_\pi(s) = \mathop{\mathbb{E}}_{\pi}(r_{t+1} + \gamma\, v_\pi(s_{t+1}) \mid s) \quad \text{(Bellman equation)}$$

# State-Action Value $q_\pi(s, a)$

## A value can also be defined for each action in a state

- Value of an action $a$ in a state $s$ for a given policy $\pi$:

$$q_\pi(s, a) = \mathop{\mathbb{E}}_{\pi}(G_t \mid s, a)$$

$q_\pi(s, a)$ indicates how good it is to choose $a$ in $s$ under $\pi$

- **Again $q_\pi(s, a)$ can be defined recursively**:

$$q_\pi(s, a) = \mathop{\mathbb{E}}_{\pi}(r_{t+1} + \gamma\, q_\pi(s_{t+1}, a_{t+1}) \mid s, a)$$

- **Bellman equations hold for optimal (=highest possible) values**:

$$q_*(s, a) = \mathbb{E}(r_{t+1} + \gamma \max_{a_k} q_*(s_{t+1}, a_k) \mid s, a)$$

They are used to create RL algorithms (example: Q-learning)

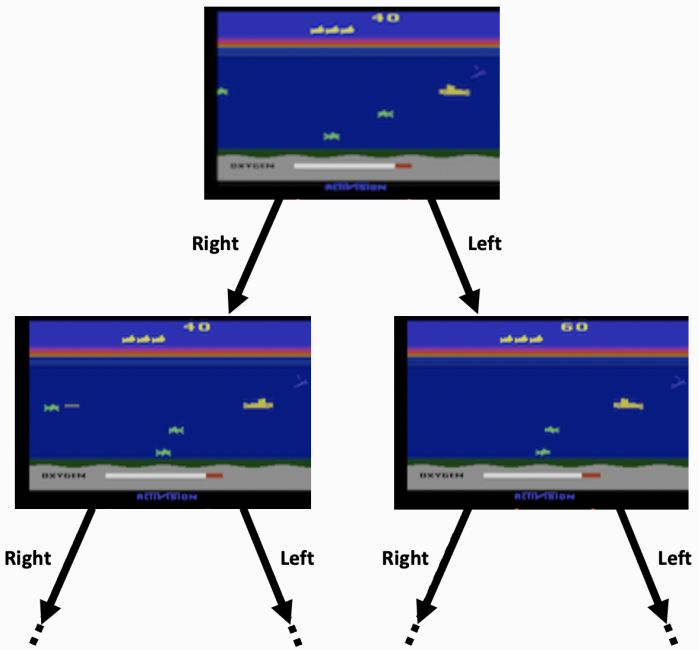
# Model of Environment Dynamics

## A model can be used to simulate an environment

- Transition function to predict next state and reward:

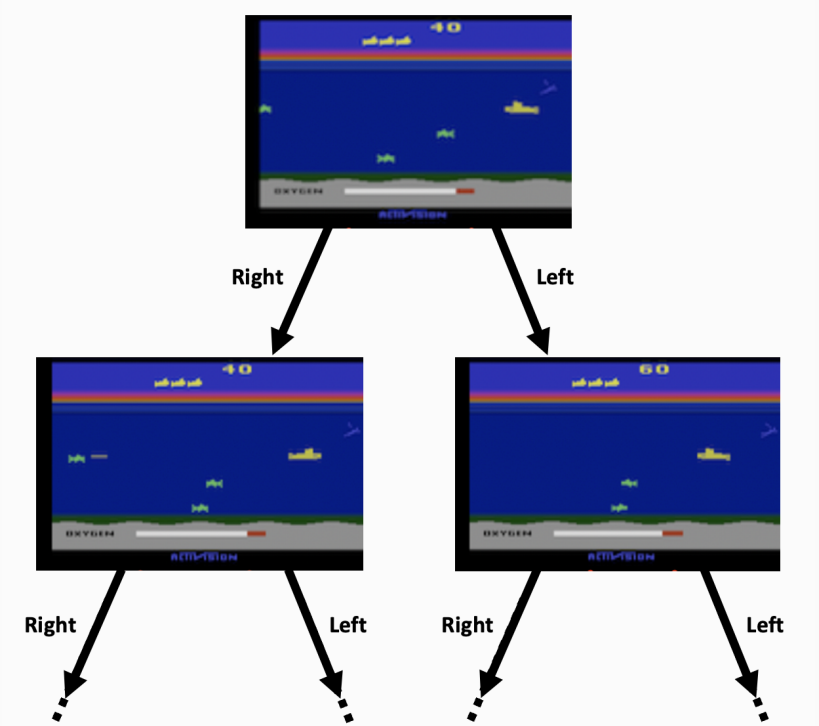
$$p(s', r \mid s, a) = p(s_{t+1} = s', r_{t+1} = r \mid s_t = s, a_t = a)$$

- A RL model does not infer policies (does not "act")
- **Example of model:** Querying a video game console is an example of "perfect model" (rules of the game are perfectly defined by the console)



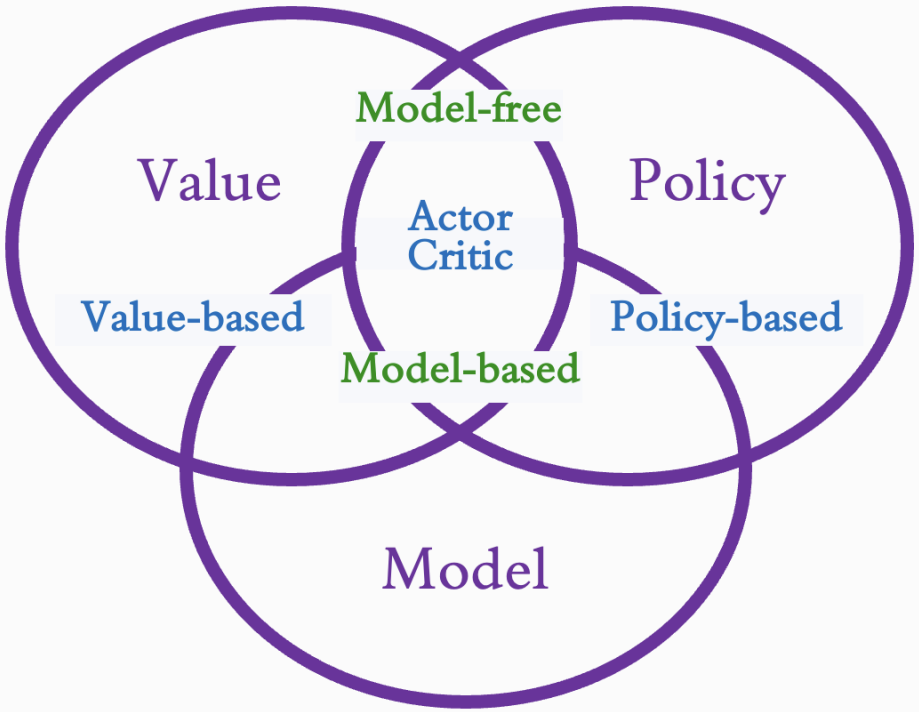
# Model of Environment Dynamics

**Planning from a model:**




- If the rules of the game are perfectly known, couldn't an agent plan ahead and find an optimal policy?
- An agent could "plan" (= think): *If I take action a from state s, what would the next state be? What would the score be?*

# RL Taxonomy




## Categories of RL agents:

- **Model-based**: Use a model to learn policy and/or value function (lecture 3, 7)
- **Model-free**: Learn policy and/or value function without model (lecture 4-5)
- **Value-based**: Learn value function, not policy function (lectures 4-5)
- **Policy-based**: Learn policy function, not value function (lecture 6)
- **Actor-Critic**: Learn policy and value functions (lecture 6)

# RL Challenges and Opportunities

1. **Control vs. Prediction**. How to search for optimal policies and estimate their values simultaneously?
2. **Exploration vs. Exploitation**. An agent must explore to find information, yet must exploit known information to get reward
3. **Generalization to large state-action spaces**. For example the game Go has over $10^{170}$ possible positions
4. **Combining Learning with Planning**: In addition to interact with the environment, an agent can learn and plan from a model
5. **Simulated vs. real experience**. *Trial-and-error* impractical
6. **Other forms of learning**: From rewards? From demonstrations? Imitations? Supervisions? What does Psychology teach us?
7. **Convergence vs. tracking and adaptability**

# Introduction to Python's Gym library

# Practice: RL in Gym environments

## What is Gym?

- An open source toolkit for testing RL algorithms
- Provides you with baseline RL environments
- Has a standard API to access these environments
- Up to you to create RL agents to interact with these environments
- Widely used, safe simulations

# Practice: RL in Gym environments

## Example of Gym environments: Atari 2600 video games


- Rules of games unknown by agent
- Agent can learn directly from interactive game-play
- Agent picks actions, sees pixels, receives scores

# Practice: RL in Gym environments

## Implementing a Gym environment

### 1. Instantiate environment

env = gym.make("name")

- Assign it to a variable
- Access it anytime later

### 2. Initialize environment

s = env.reset()

- Used to begin an episode
- Return initial state

### 3. Select actions

a = yourAgent(state)

- Apply your policy
- Map state to action(s)

### 4. Step through environment

s, r, done, info = env.step(action)

- Used at every step
- Test if episode should end

# What comes next...

## DS-GA 3001 RL Syllabus:

1. Introduction to Reinforcement Learning
2. Multi-armed Bandit
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5. Value Function Approximation (Deep RL)
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7. Planning from a Model of the Environment (AlphaZero)
8. Aligning AI systems to Human Preferences (ChatGPT)
9. Examples of industrial applications
10. Advanced topics and development platforms

# Thank you!