*Applied Deep Learning*

# Deep Reinforcement Learning

October 27th, 2022

http://adl.miulab.tw

National Taiwan University 國立臺灣大學

# Outline

- Machine Learning
  - Supervised Learning v.s. Reinforcement Learning
  - Reinforcement Learning v.s. Deep Learning
- Introduction to Reinforcement Learning
  - Agent and Environment
  - Action, State, and Reward
- Reinforcement Learning Approach
  - Value-Based
  - Policy-Based
  - Model-Based

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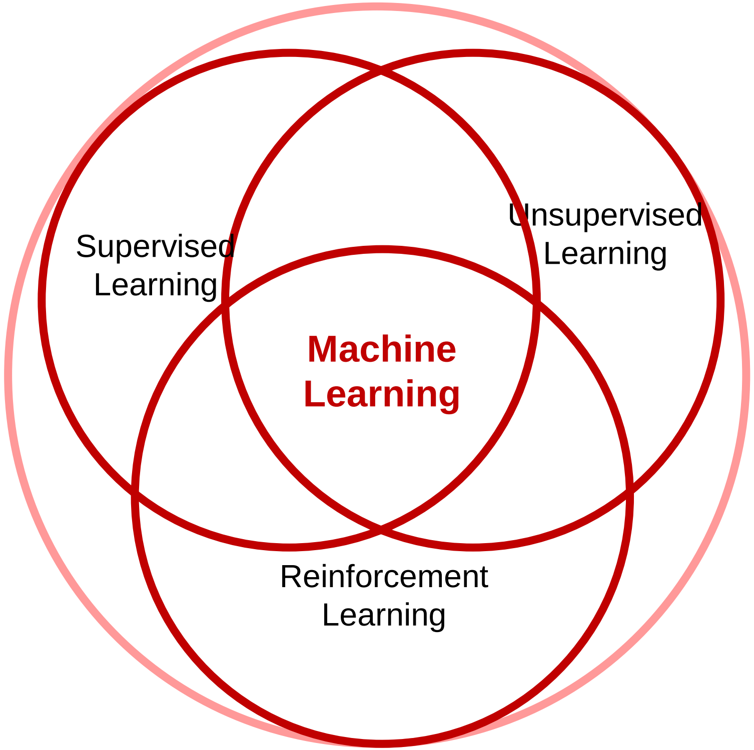
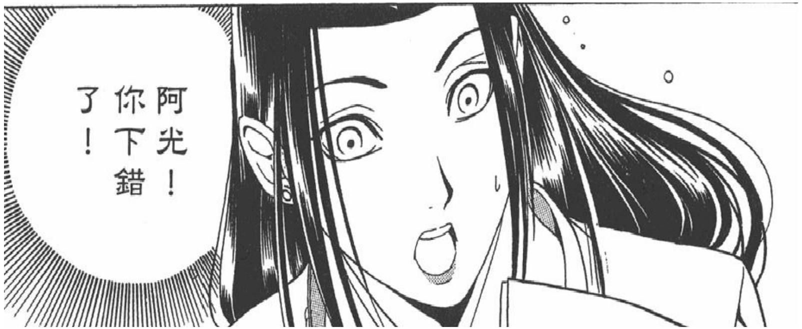
# Machine Learning



# Supervised v.s. Reinforcement

- Supervised Learning
  - Training based on supervisor/label/annotation
  - Feedback is instantaneous
  - Time does not matter

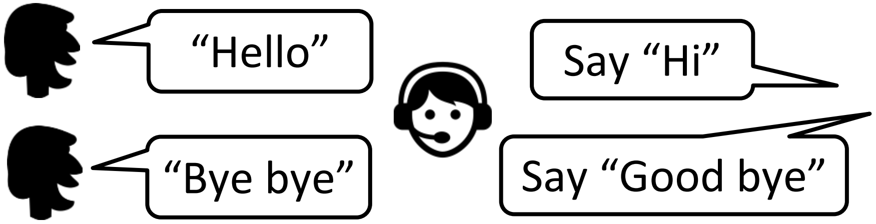
- Reinforcement Learning
  - Training only based on reward signal
  - Feedback is delayed
  - Time matters
  - Agent actions affect subsequent data



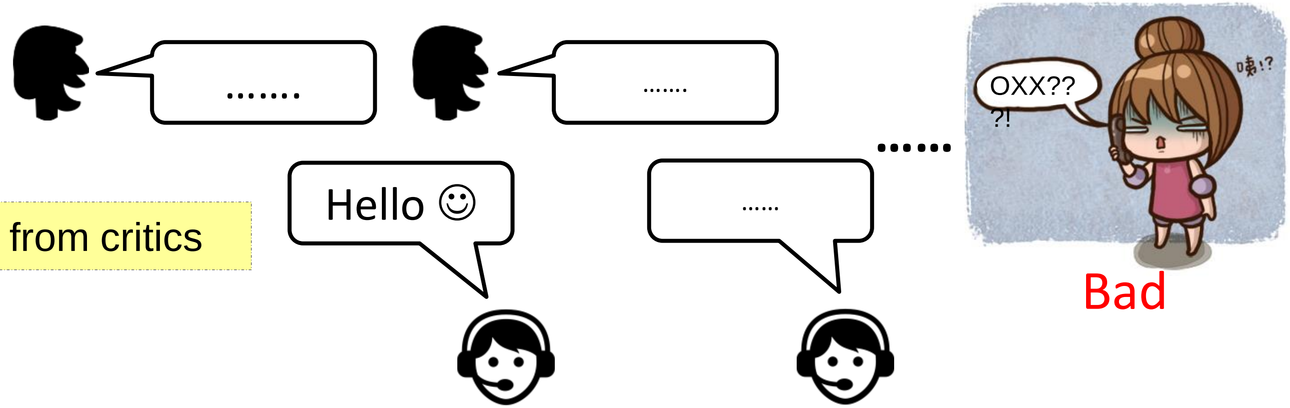

# Supervised v.s. Reinforcement

- Supervised

Learning from teacher




- Reinforcement



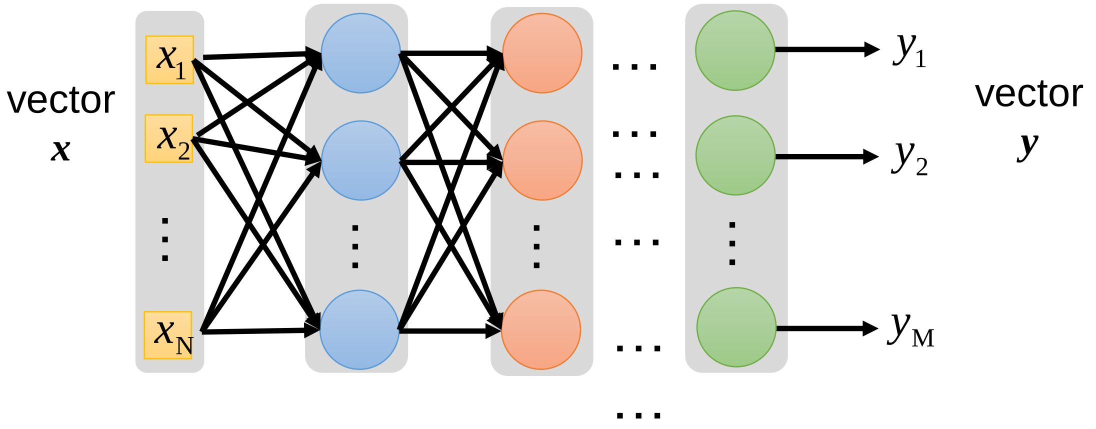

Learning from critics

# Reinforcement Learning

- RL is a general purpose framework for **decision making**
  - RL is for an *agent* with the capacity to *act*
  - Each *action* influences the agent’s future *state*
  - Success is measured by a scalar *reward* signal
  - Goal: *select actions to maximize future reward*

# Deep Learning

- DL is a general purpose framework for **representation learning**
  - Given an *objective*
  - Learn *representation* that is required to achieve objective
  - Directly from *raw inputs*
  - Use minimal domain knowledge



# Deep Reinforcement Learning

- AI is an agent that can solve human-level task
  - RL defines the objective
  - DL gives the mechanism
  - RL + DL = general intelligence


# Deep RL AI Examples

- Play games: Atari, poker, Go, …
- Explore worlds: 3D worlds, …
- Control physical systems: manipulate, …
- Interact with users: recommend, optimize, personalize, …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# Introduction to RL

Reinforcement Learning

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# Reinforcement Learning

- RL is a general purpose framework for **decision making**
  - RL is for an *agent* with the capacity to *act*
  - Each *action* influences the agent's future *state*
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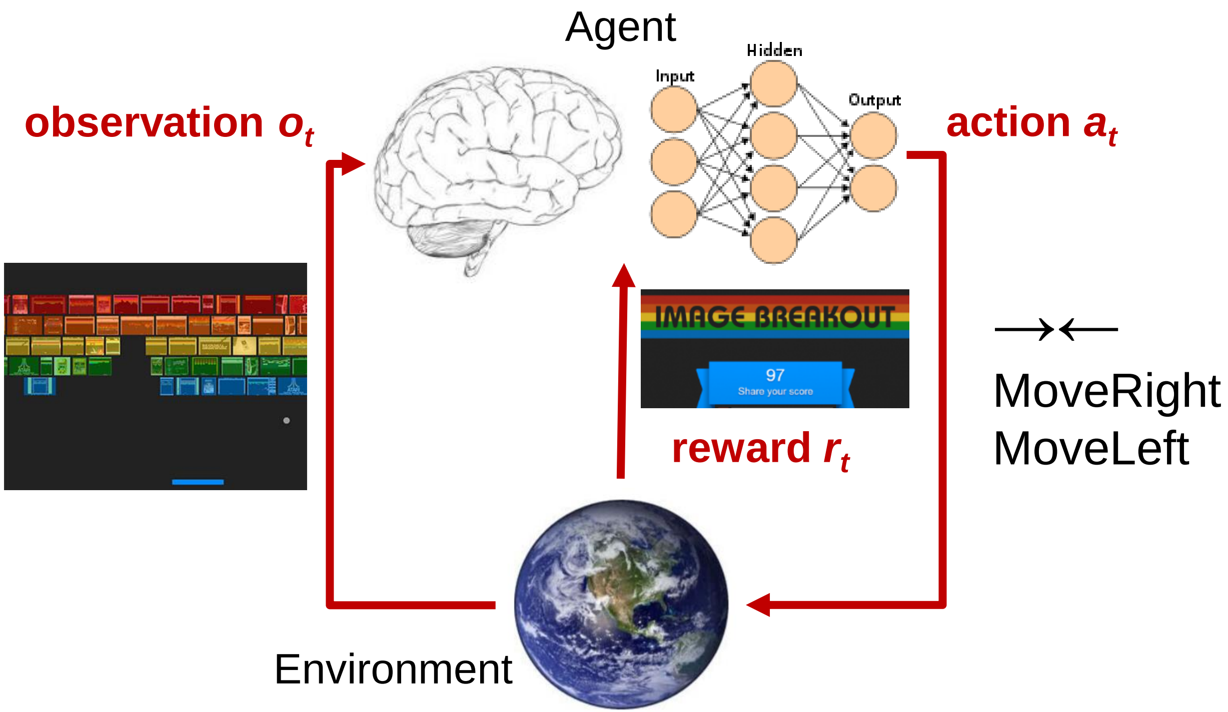
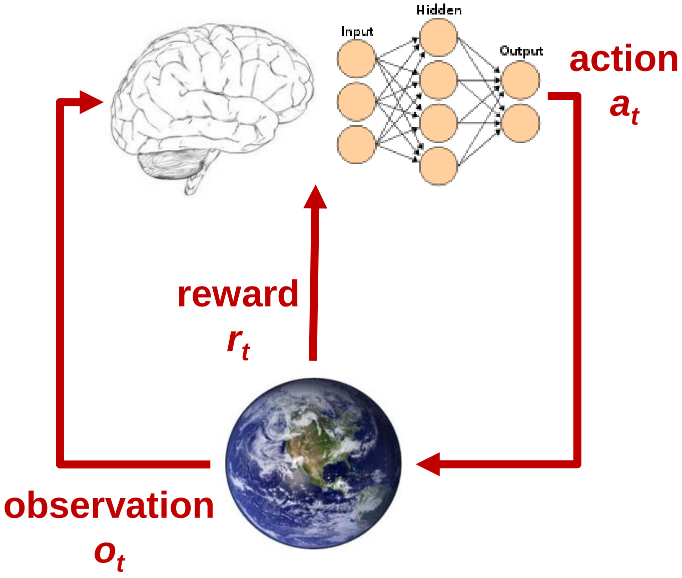
Big three: action, state, reward

# Agent and Environment



# Agent and Environment




- At time step $t$
  - The agent
    - Executes action $a_t$
    - Receives observation $o_t$
    - Receives scalar reward $r_t$
  - The environment
    - Receives action $a_t$
    - Emits observation $o_{t+1}$
    - Emits scalar reward $r_{t+1}$
  - $t$ increments at env. step

# State

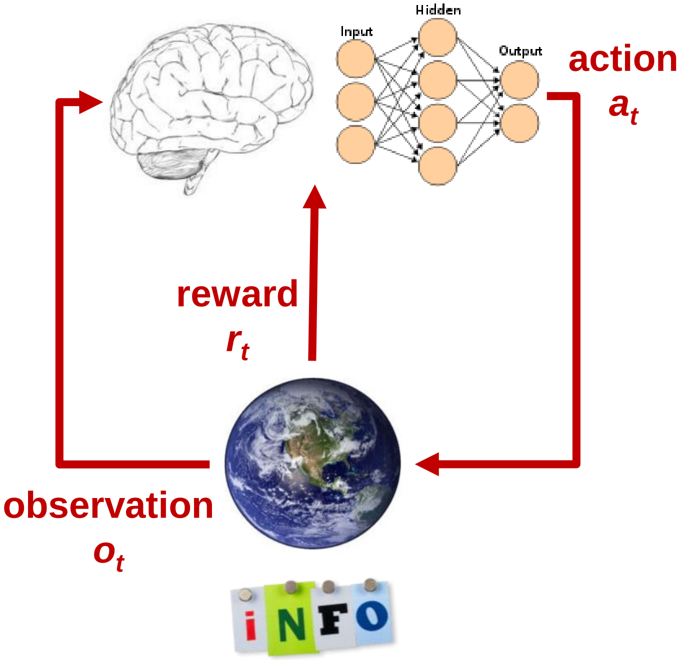
- Experience is the sequence of observations, actions, rewards

$$o_1, r_1, a_1, \ldots, a_{t-1}, o_t, r_t$$

- State is the information used to determine what happens next
  - what happens depends on the history experience
    - The agent selects actions
    - The environment selects observations/rewards
- The state is the function of the history experience

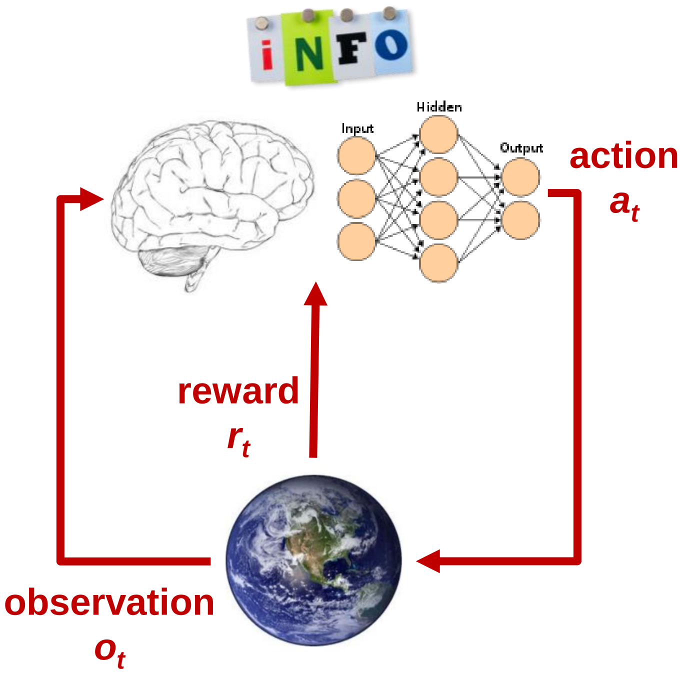
$$s_t = f(o_1, r_1, a_1, \ldots, a_{t-1}, o_t, r_t)$$

# Environment State




- The environment state $s_t^e$ is the environment's *private* representation
  - whether data the environment uses to pick the next observation/reward
  - may not be visible to the agent
  - may contain irrelevant information

# Agent State




- The agent state $s_t^a$ is the agent's *internal* representation
  - whether data the agent uses to pick the next action → information used by RL algorithms
  - can be any function of experience

# Information State

- An information state (a.k.a. Markov state) contains all useful information from history

A state is Markov iff $P(s_{t+1} \mid s_t) = P(s_{t+1} \mid s_1, ..., s_t)$

- The future is independent of the past given the present

$$H_t = \{o_1, r_1, a_1, ..., a_{t-1}, o_t, r_t\}$$

$$H_{1:t} \rightarrow s_t \rightarrow H_{t+1:\infty}$$

  - Once the state is known, the history may be thrown away
  - The state is a sufficient statistics of the future

# Fully Observable Environment

- Full observability: agent *directly* observes environment state

$$o_t = s_t^a = s_t^e$$

information state = agent state = environment state

This is a Markov decision process (MDP)

# Partially Observable Environment

- Partial observability: agent *<u>indirectly</u>* observes environment

$$s_t^a \neq s_t^e$$

agent state ≠ environment state

This is partially observable Markov decision process (POMDP)

- Agent must construct its own state representation $s_t^a$
  - Complete history: $s_t^a = H_t$
  - Beliefs of environment state: $s_t^a = \{P(s_t^e = s^1), ..., P(s_t^e = s^n)\}$
  - Hidden state (from RNN): $s_t^a = \sigma(W_s \cdot s_{t-1}^a + W_o \cdot o_t)$

# Reward

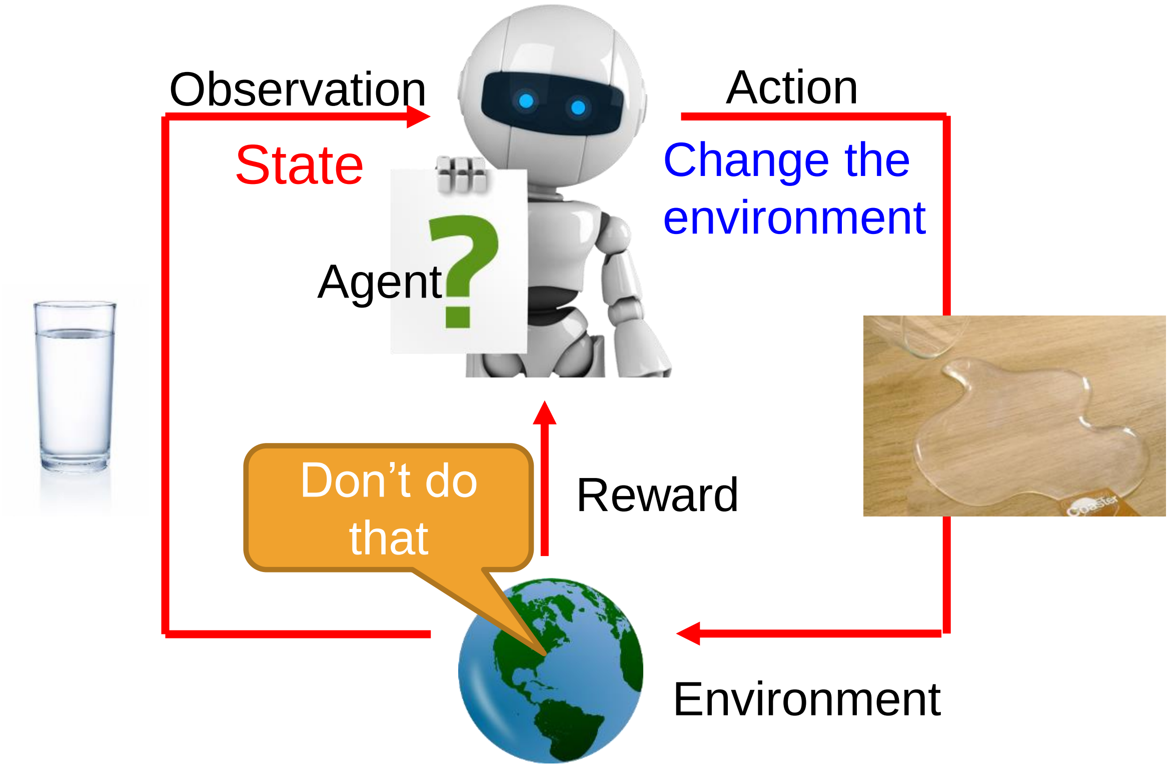
- Reinforcement learning is based on reward hypothesis
- A reward $r_t$ is a scalar feedback signal
  - Indicates how well agent is doing at step $t$

Reward hypothesis:
all agent goals can be desired by maximizing expected cumulative reward

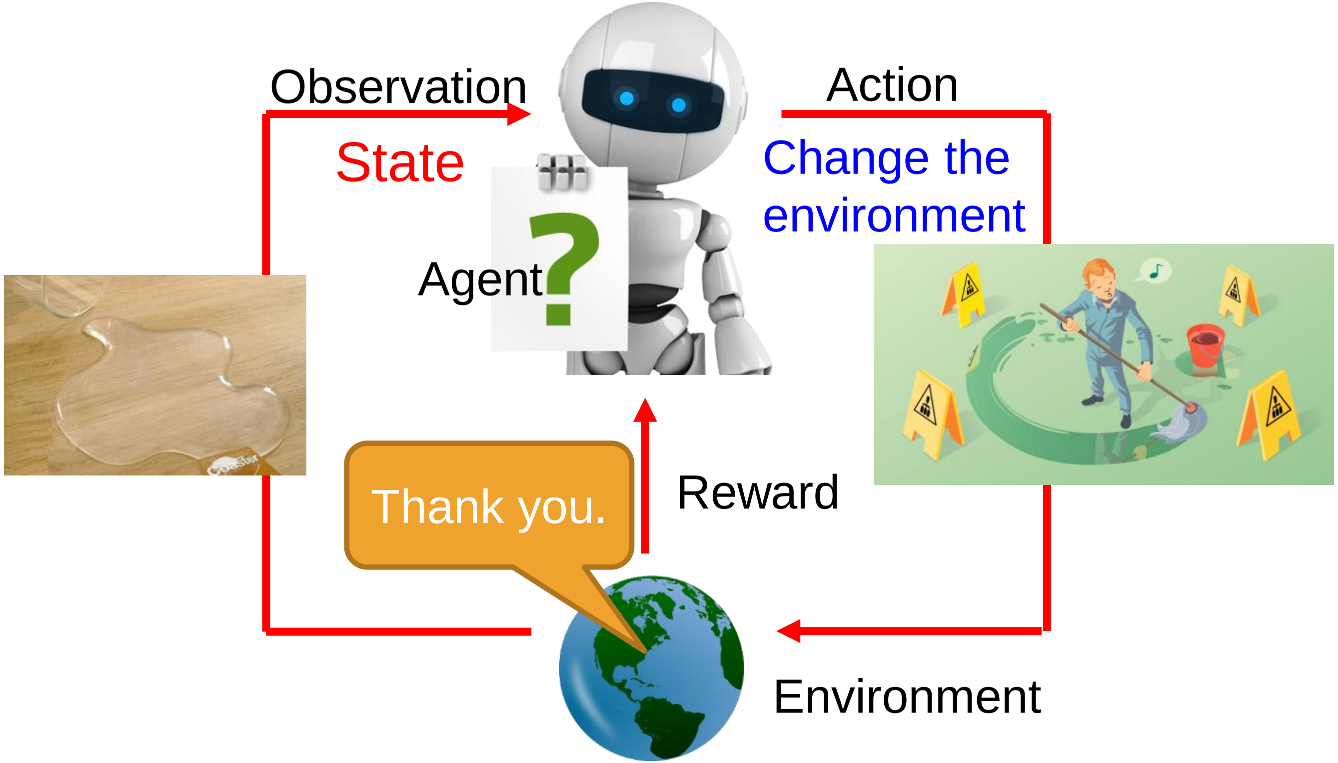
# Sequential Decision Making

- Goal: select actions to maximize total future reward
  - Actions may have long-term consequences
  - Reward may be delayed
  - It may be better to sacrifice immediate reward to gain more long-term reward


# Scenario of Reinforcement Learning

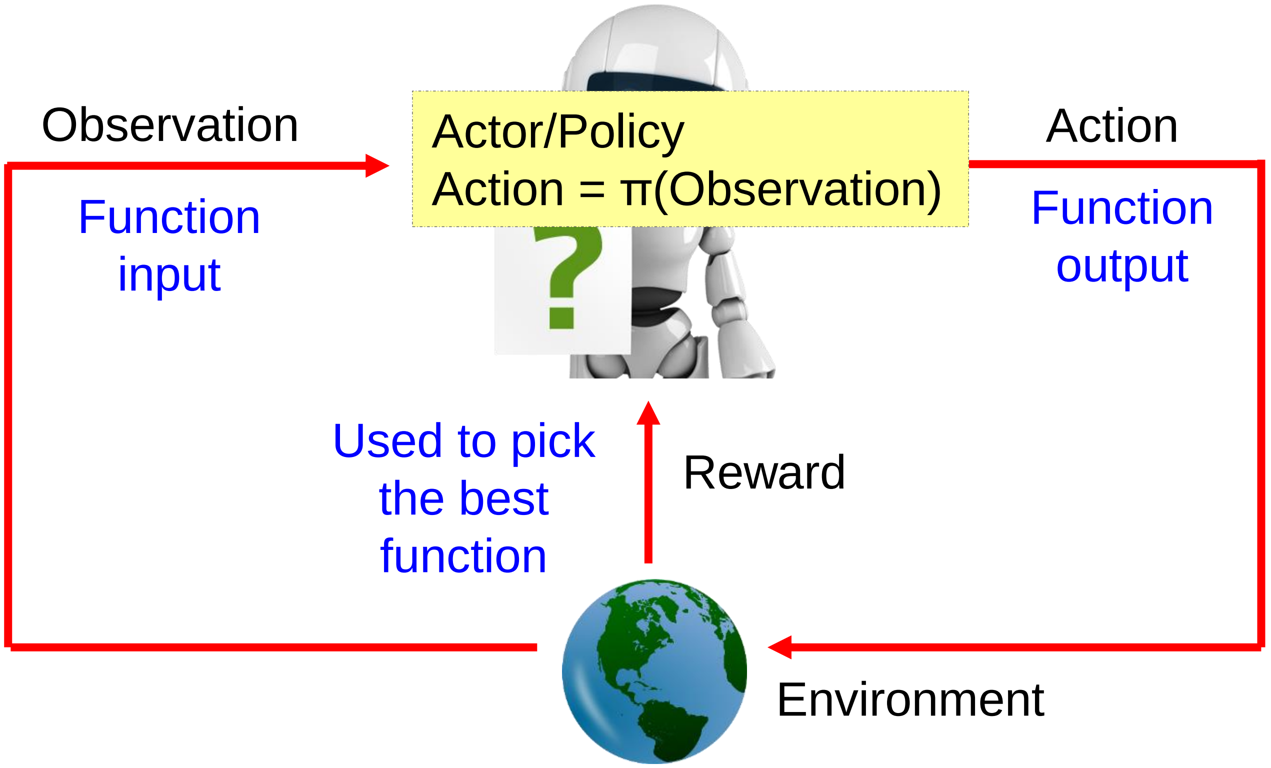


# Scenario of Reinforcement Learning

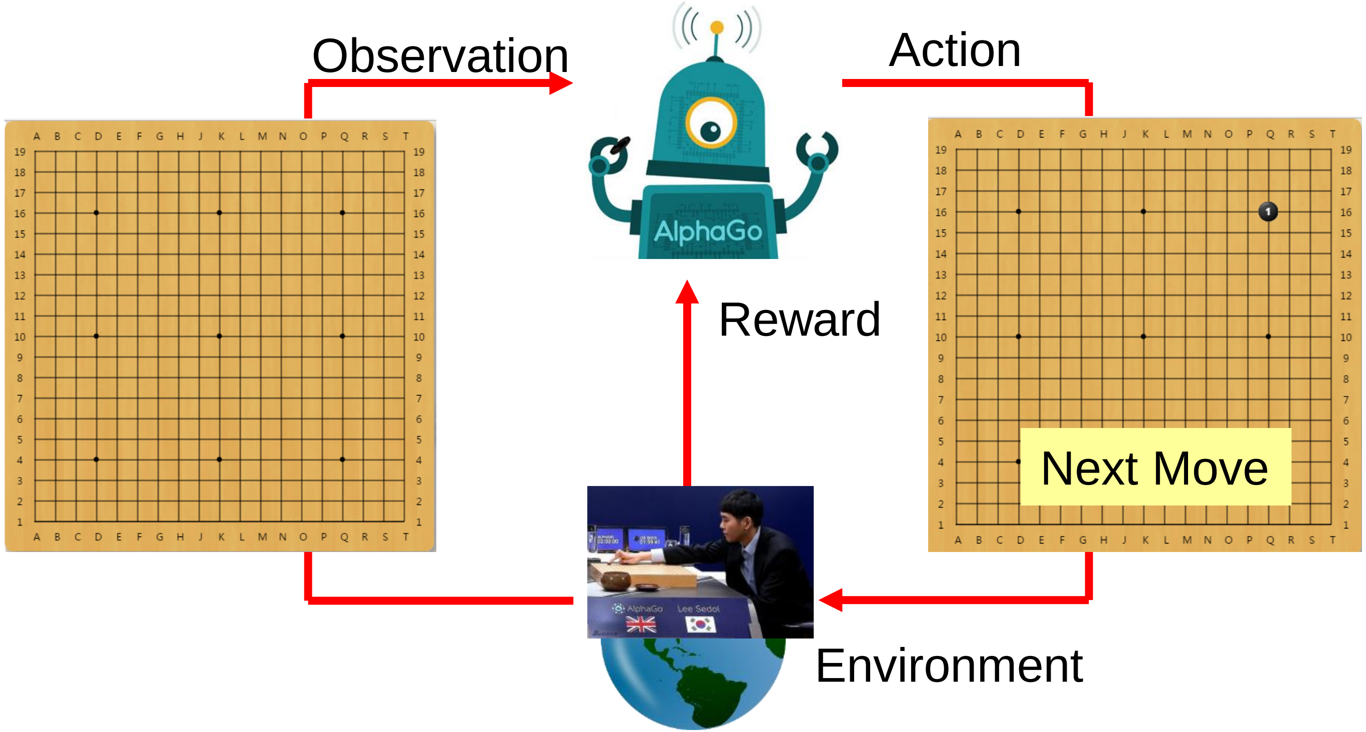



Agent learns to take actions maximizing expected reward.

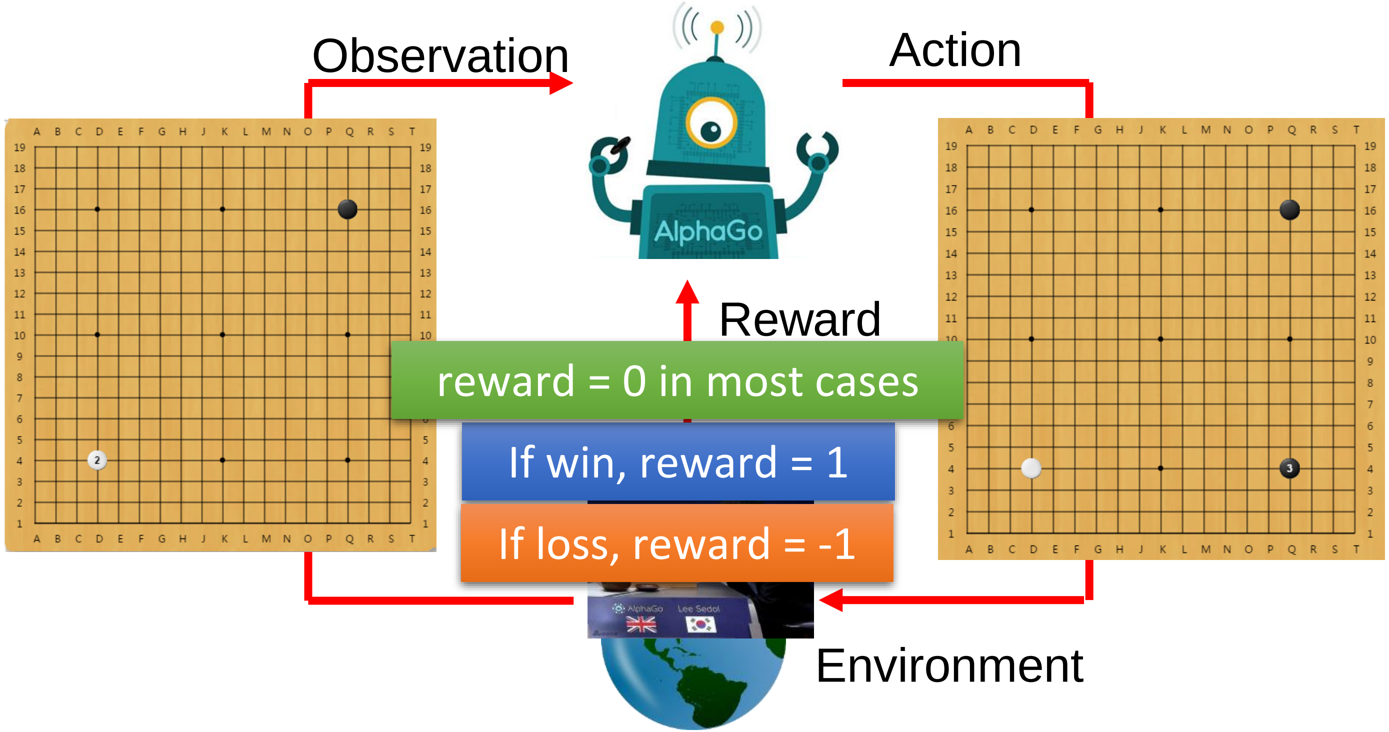
# Machine Learning ≈ Looking for a Function



# Learning to Play Go



# Learning to Play Go




Agent learns to take actions maximizing expected reward.

# Learning to Play Go

- Supervised

Learning from teacher

Next move: "5-5"

Next move: "3-3"

- Reinforcement Learning

Learning from experience

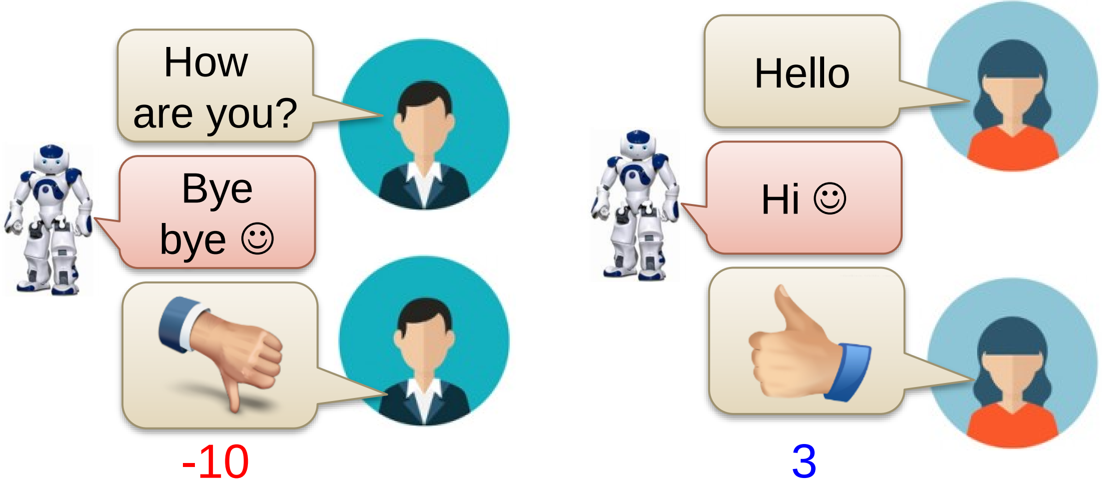
First move → …… many moves …… → Win!

(Two agents play with each other.)

AlphaGo uses supervised learning + reinforcement learning.

# Learning a Chatbot

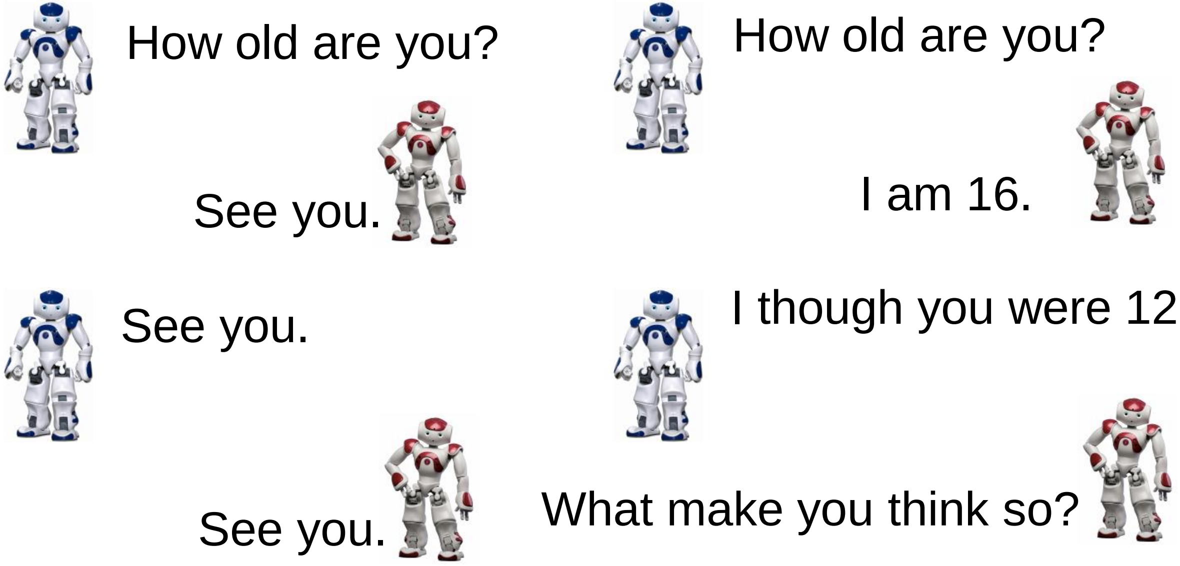
- Machine obtains feedback from user




Chatbot learns to maximize the ***expected reward***

# Learning a Chatbot

- Let two agents talk to each other (sometimes generate good dialogue, sometimes bad)



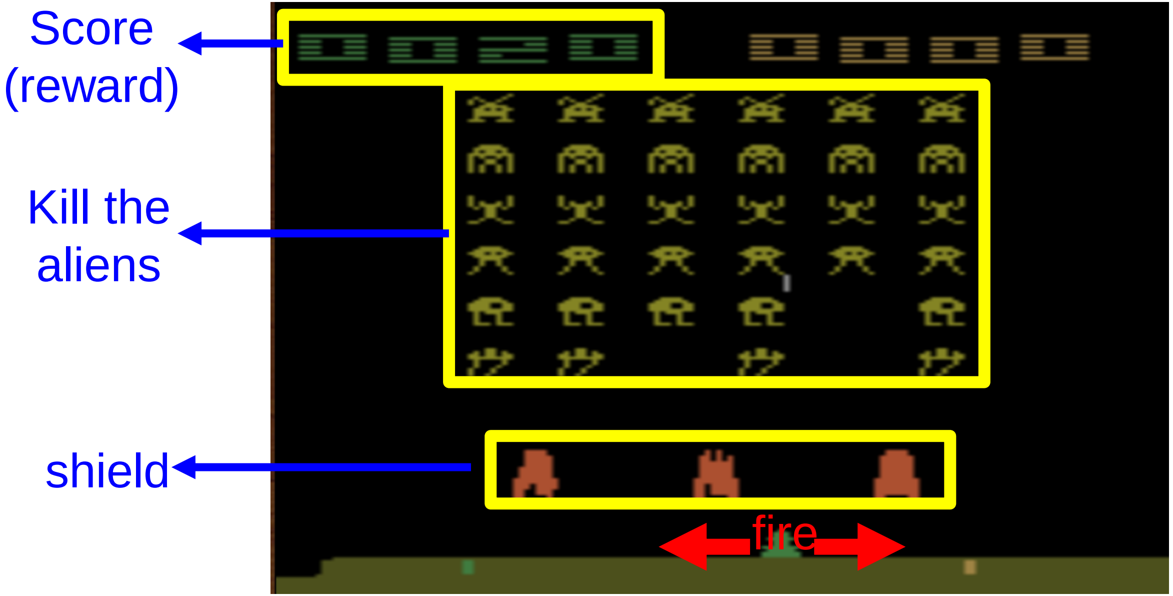
# Learning a chat-bot

- By this approach, we can generate a lot of dialogues.
- Use pre-defined rules to evaluate the goodness of a dialogue


Machine learns from the evaluation as rewards

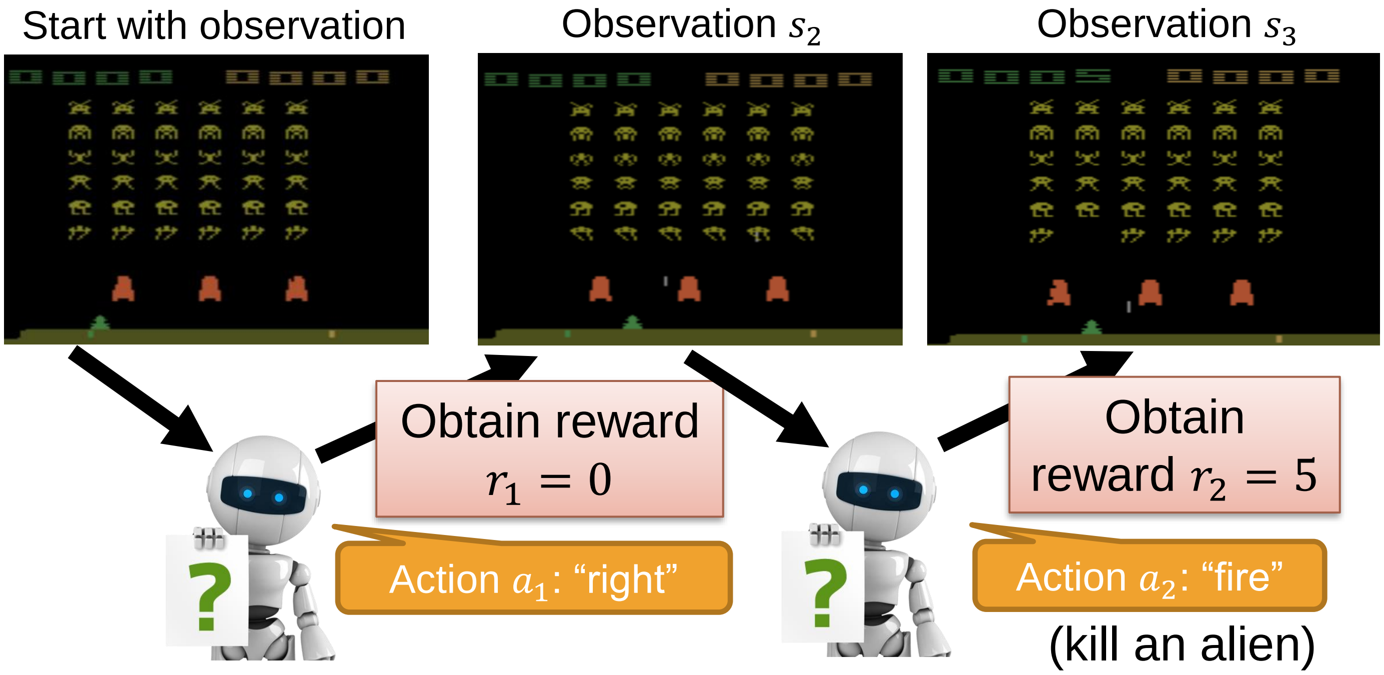
# Learning to Play Video Game

- Space invader: terminate when all aliens are killed, or your spaceship is destroyed




Play yourself: http://www.2600online.com/spaceinvaders.html
How about machine: https://gym.openai.com/evaluations/eval_Eduozx4HRyqgTCVk9ltw

# Learning to Play Video Game

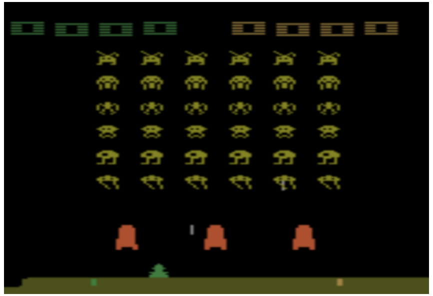



Usually there is some randomness in the environment

# Learning to Play Video Game

Start with observation

Observation $s_2$



Observation $s_3$

After many turns

Game Over (spaceship destroyed)

Action $a_T$

Obtain reward $r_T$

This is an ***episode***.

Learn to maximize the expected cumulative reward per episode

# More Applications

- Flying Helicopter
  - https://www.youtube.com/watch?v=0JL04JJjocc
- Driving
  - https://www.youtube.com/watch?v=0xo1Ldx3L5Q
- Robot
  - https://www.youtube.com/watch?v=370cT-OAzzM
- Google Cuts Its Giant Electricity Bill With DeepMind-Powered AI
  - http://www.bloomberg.com/news/articles/2016-07-19/google-cuts-its-giant-electricity-bill-with-deepmind-powered-ai
- Text Generation
  - https://www.youtube.com/watch?v=pbQ4qe8EwLo

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# Major Components in an RL Agent

- An RL agent may include one or more of these components
  - **Value function**: how good is each state and/or action
  - **Policy**: agent’s behavior function
  - **Model**: agent’s representation of the environment

# Reinforcement Learning Approach

- Value-based RL
  - Estimate the optimal value function $Q^*(s,a)$

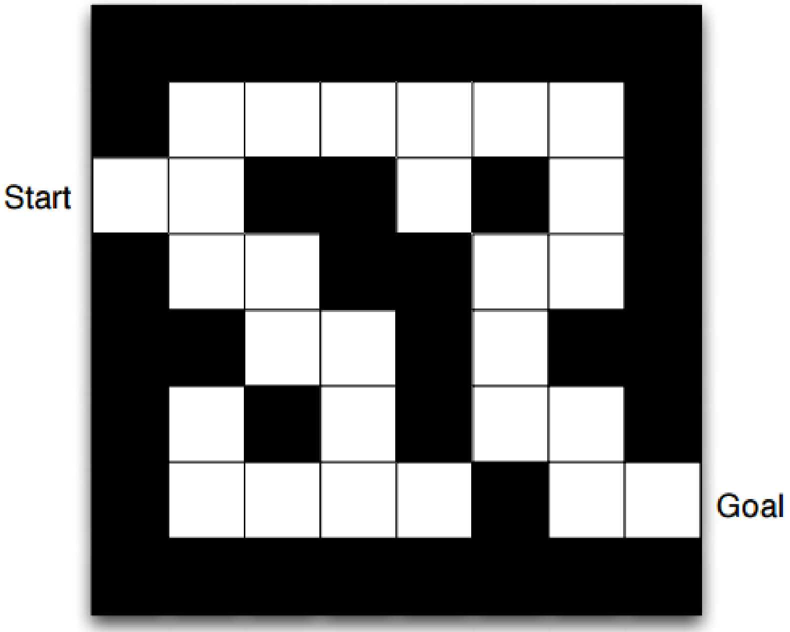
    $Q^*(s,a)$ is maximum value achievable under any policy

- Policy-based RL
  - Search directly for optimal policy $\pi^*$

    $\pi^*$ is the policy achieving maximum future reward

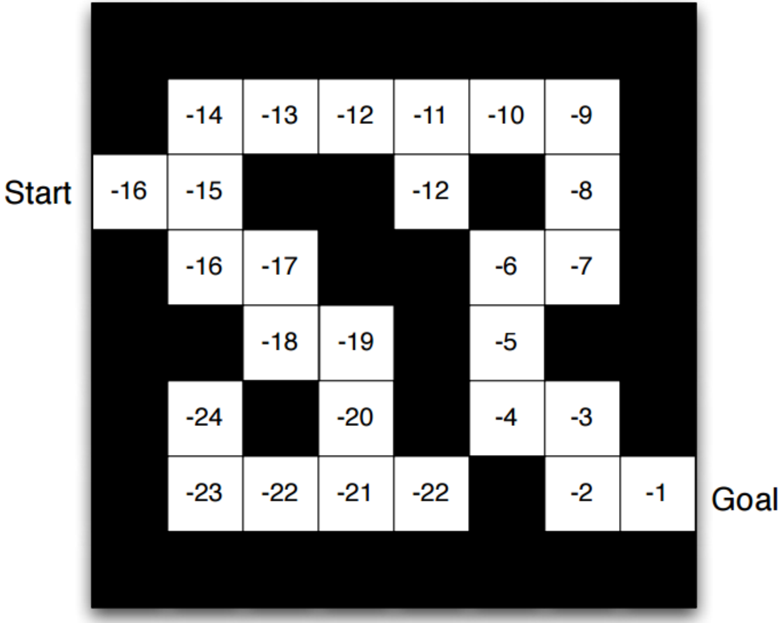
- Model-based RL
  - Build a model of the environment
  - Plan (e.g. by lookahead) using model

# Maze Example




- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: agent's location

# Maze Example: Value Function




- Rewards: -1 per time-step
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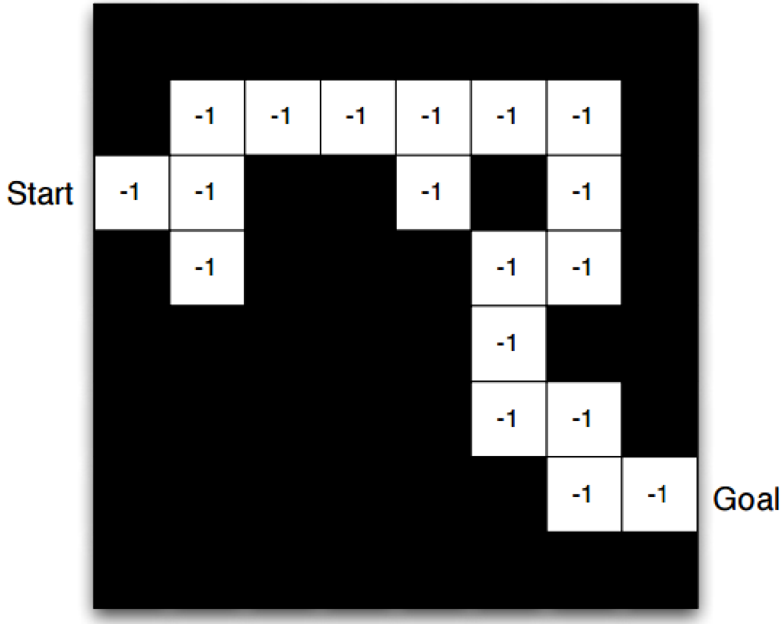
Numbers represent value $Q_{\pi}(s)$ of each state $s$

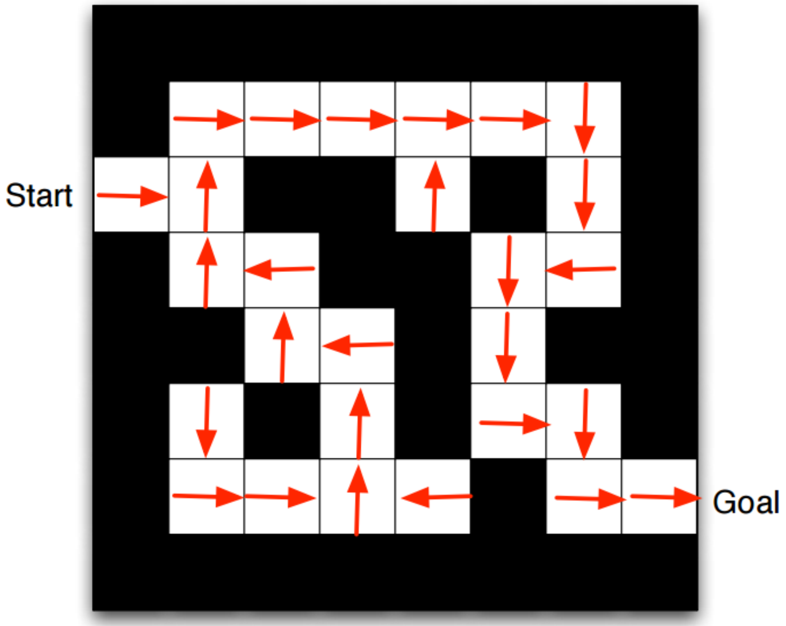
# Maze Example: Value Function




- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: agent’s location

Grid layout represents transition model *P*
Numbers represent immediate reward *R* from each state *s* (same for all *a*)

# Maze Example: Policy




- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: agent's location

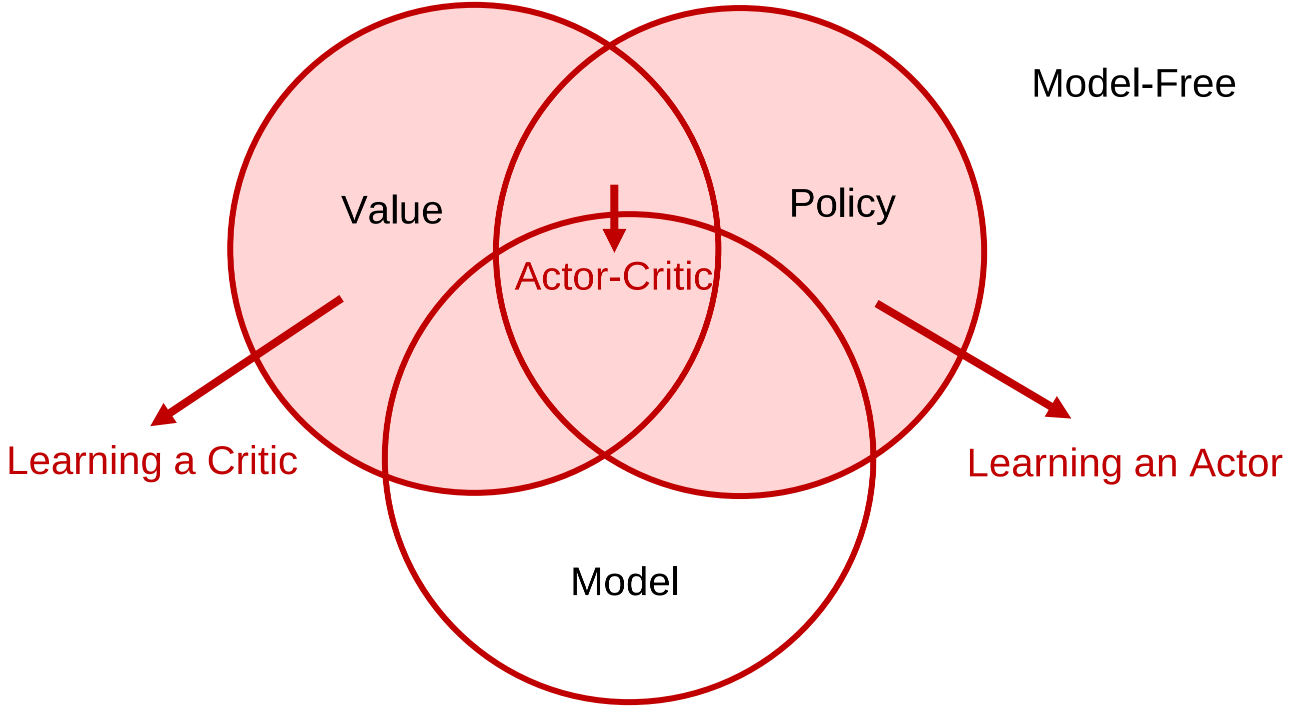
Arrows represent policy *π(s)* for each state *s*

# Categorizing RL Agents

- Value-Based
  - No Policy (implicit)
  - Value Function
- Policy-Based
  - Policy
  - No Value Function
- Actor-Critic
  - Policy
  - Value Function

- Model-Free
  - Policy and/or Value Function
  - No Model
- Model-Based
  - Policy and/or Value Function
  - Model

# RL Agent Taxonomy



# Concluding Remarks

- RL is a general purpose framework for **decision making** under interactions between *agent* and *environment*
  - RL is for an *agent* with the capacity to *act*
  - Each *action* influences the agent's future *state*
  - Success is measured by a scalar *reward* signal
  - Goal: *select actions to maximize future reward*

action

state

reward

- An RL agent may include one or more of these components
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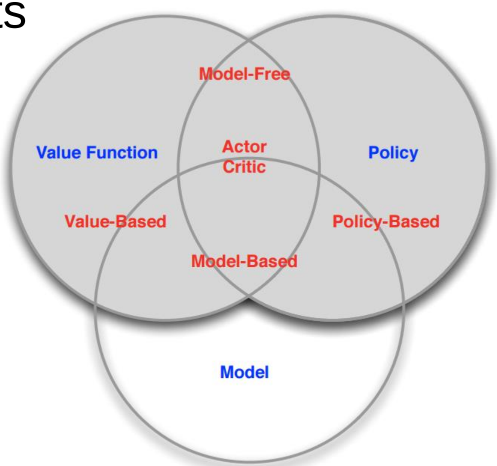
  - Policy: agent's behavior function
  - Model: agent's representation of the environment



# References

- Course materials by David Silver: http://www0.cs.ucl.ac.uk/staff/D.Silver/web/Teaching.html
- ICLR 2015 Tutorial: http://www.iclr.cc/lib/exe/fetch.php?media=iclr2015:silver-iclr2015.pdf
- ICML 2016 Tutorial: http://icml.cc/2016/tutorials/deep_rl_tutorial.pdf