Deep Reinforcement Learning (1)

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ADL x MLDS

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Slides credited from Dr. David Silver & Hung-Yi Lee

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

Markov Decision Process

Reinforcement Learning Approach
- Value-Based
- Policy-Based
- Model-Based

Problems within RL
- Learning and Planning
- Exploration and Exploitation

RL for Unsupervised Model

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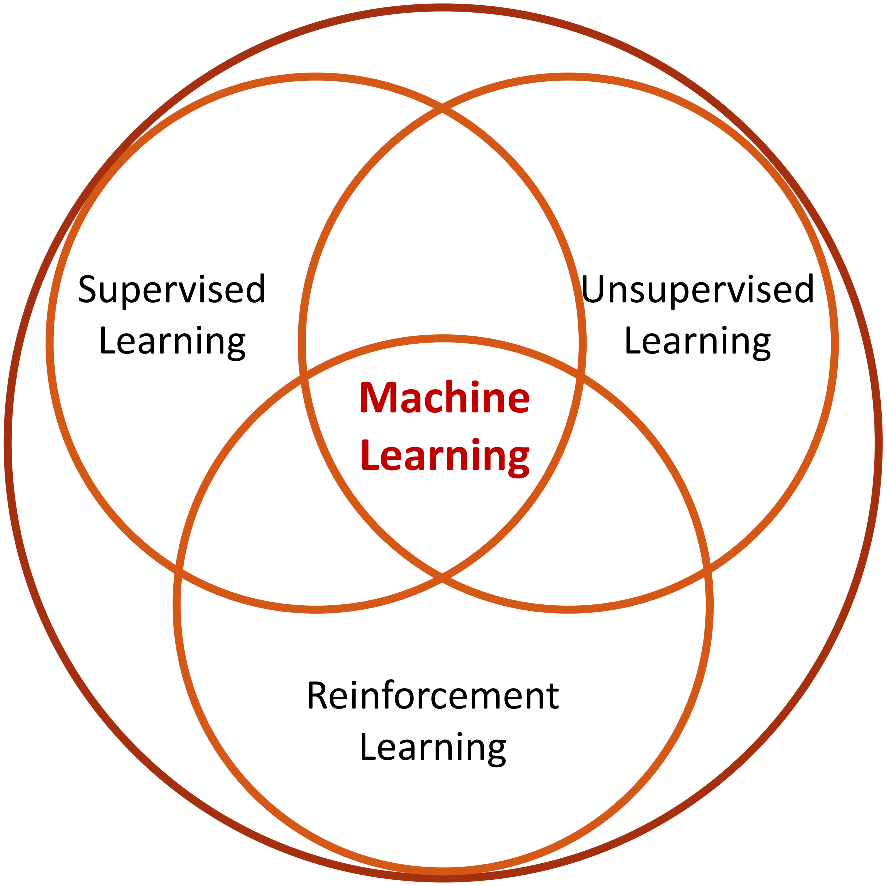
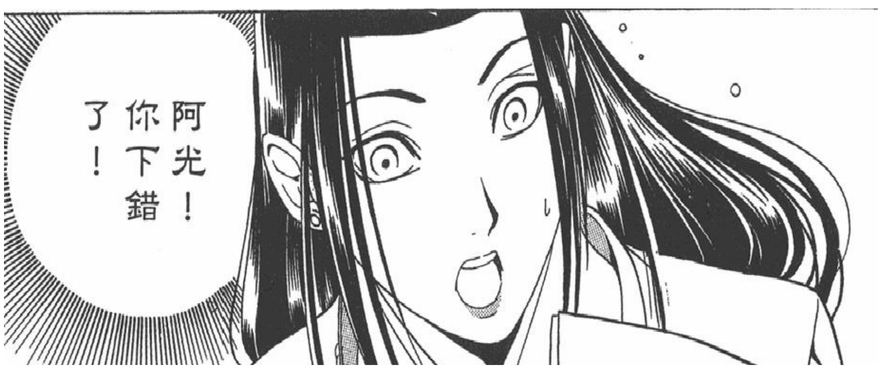
Machine Learning



Supervised v.s. Reinforcement

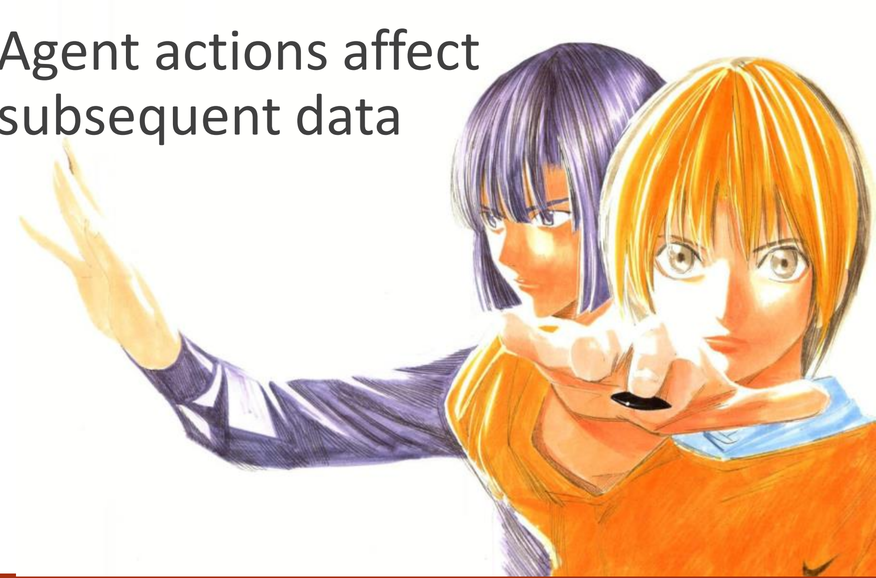
Supervised Learning

- 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

"Hello"

"Bye bye"

Say "Hi"

Say "Good bye"

Reinforcement

…….

…….

Hello ☺

……

……

Bad

Learning from critics

Reinforcement Learning

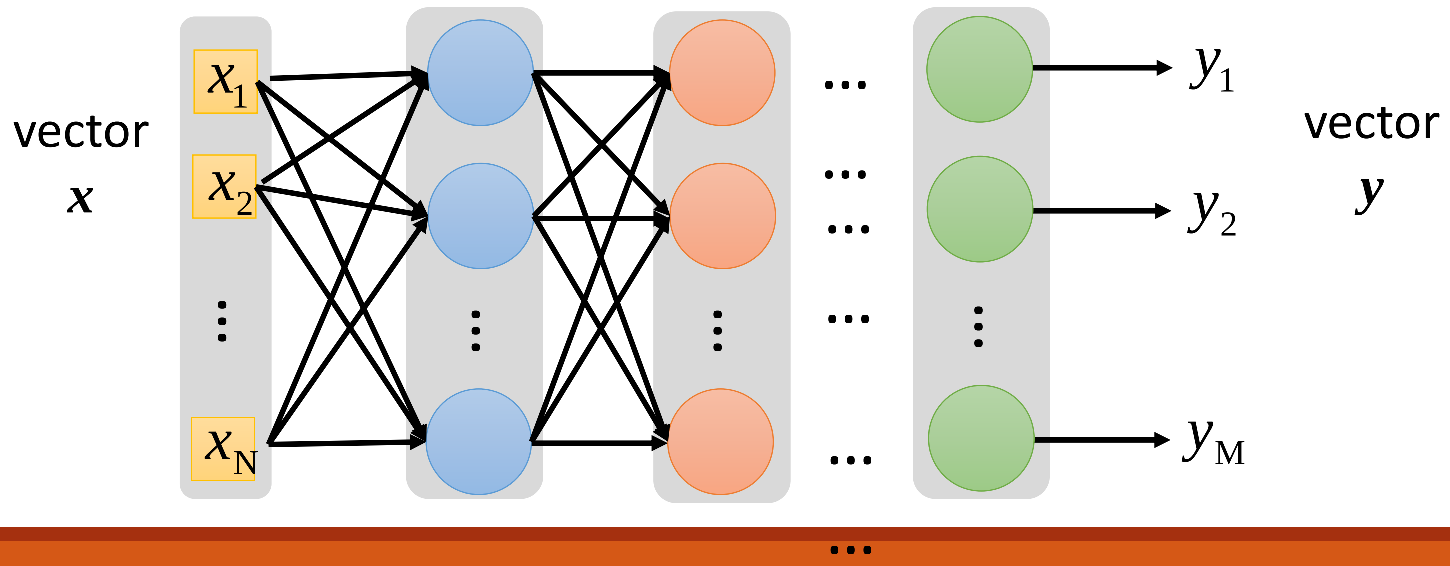
RL is a general purpose framework for **decision making**

- 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, …

Introduction to RL

Reinforcement Learning

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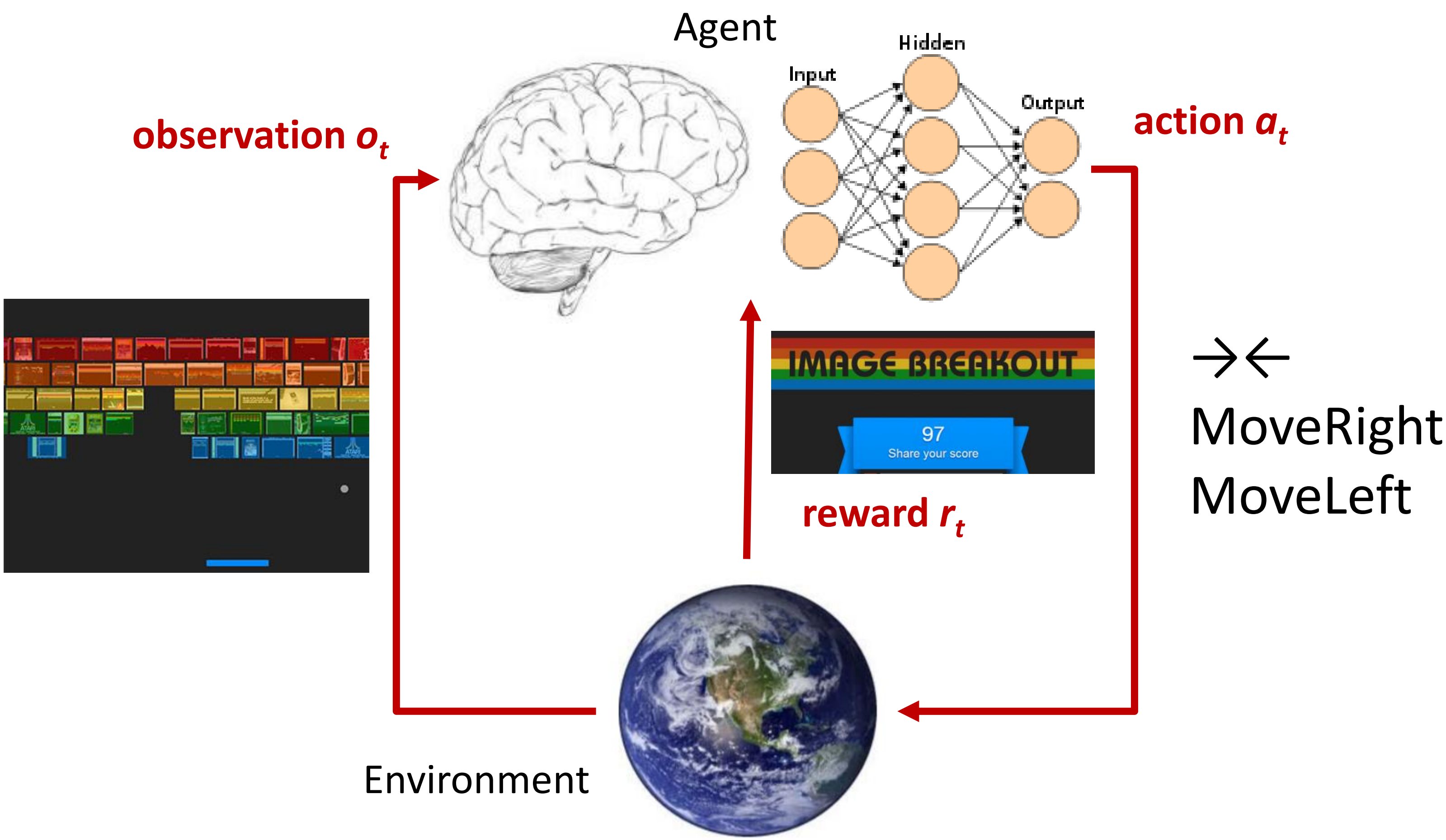
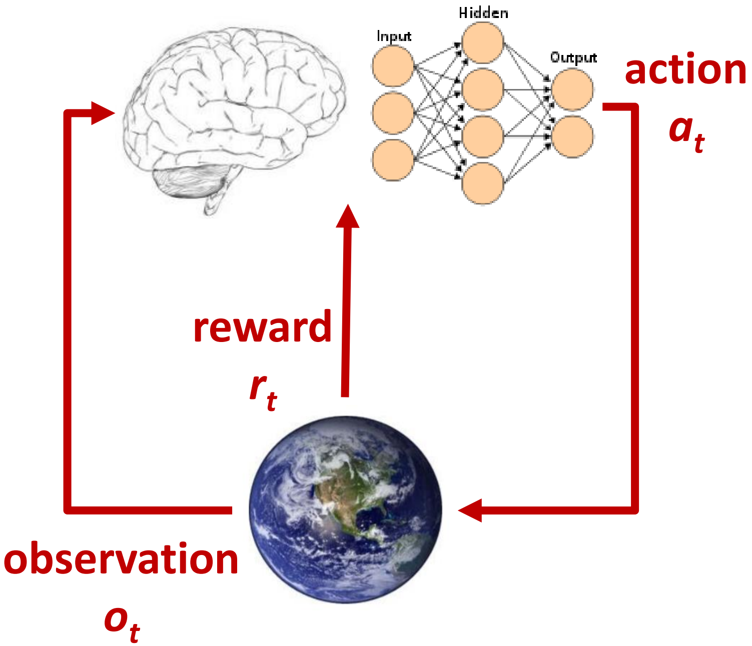
- Each *action* influences the agent's future *state*
- Success is measured by a scalar *reward* signal

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

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

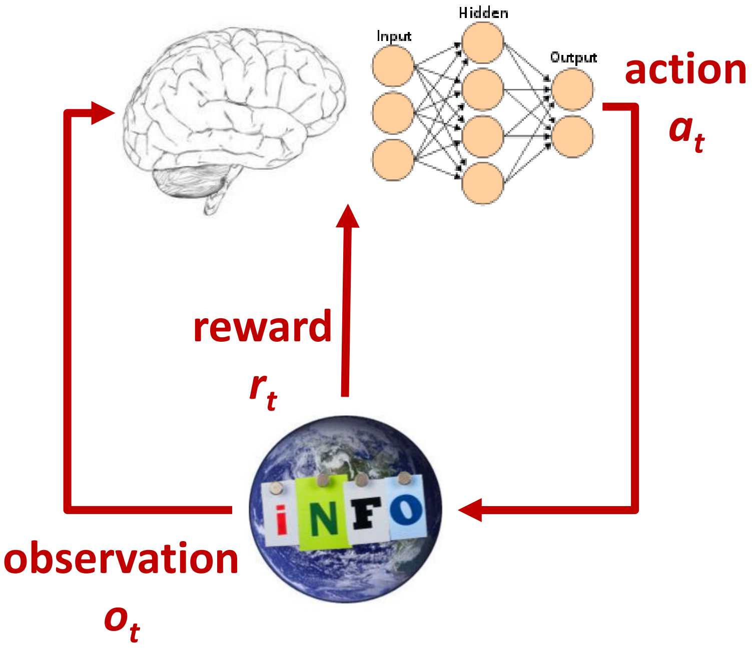
State is the information used to determine what happens next

- 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

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

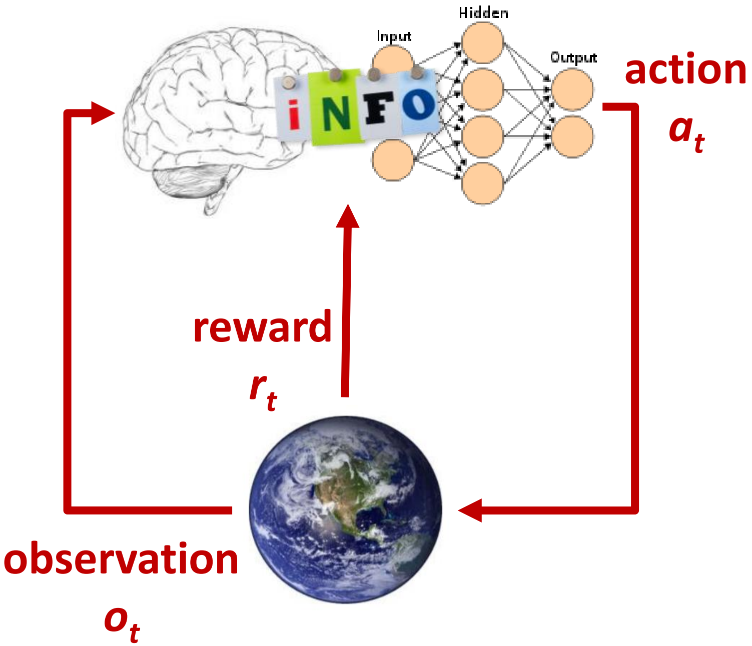
Environment State



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 *indirectly* 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

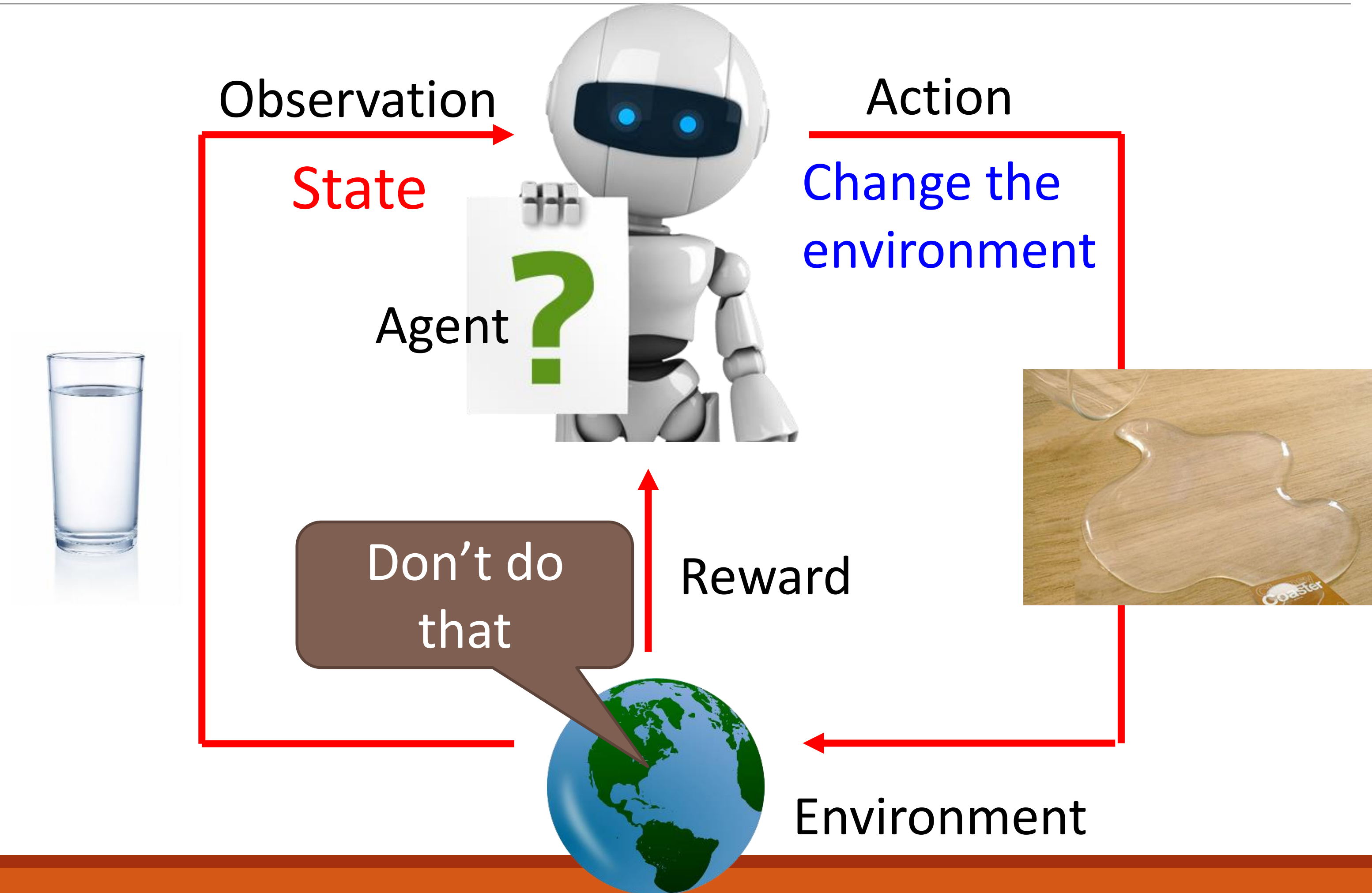
Reward hypothesis: all agent goals can be desired by maximizing expected cumulative reward

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



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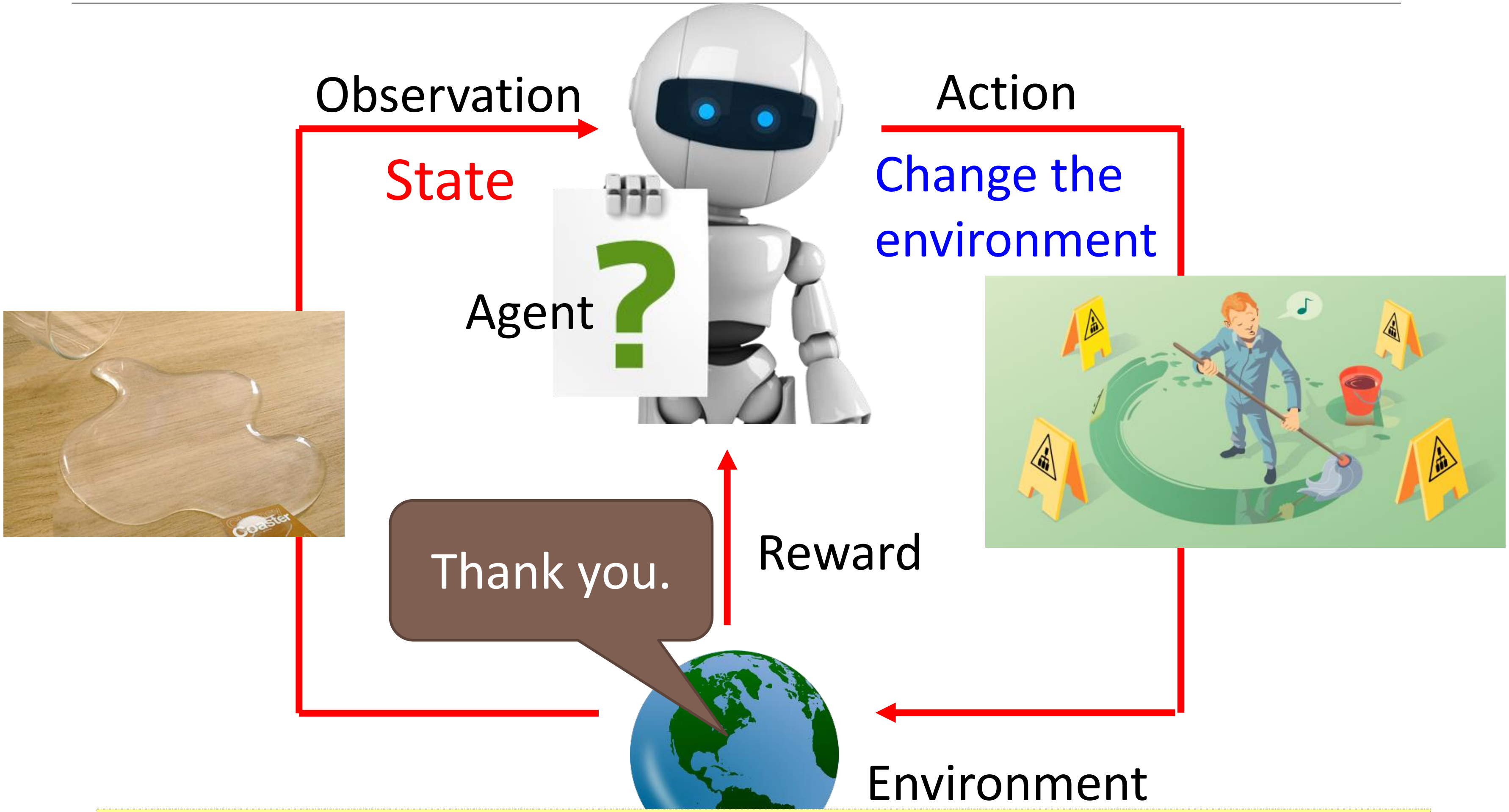
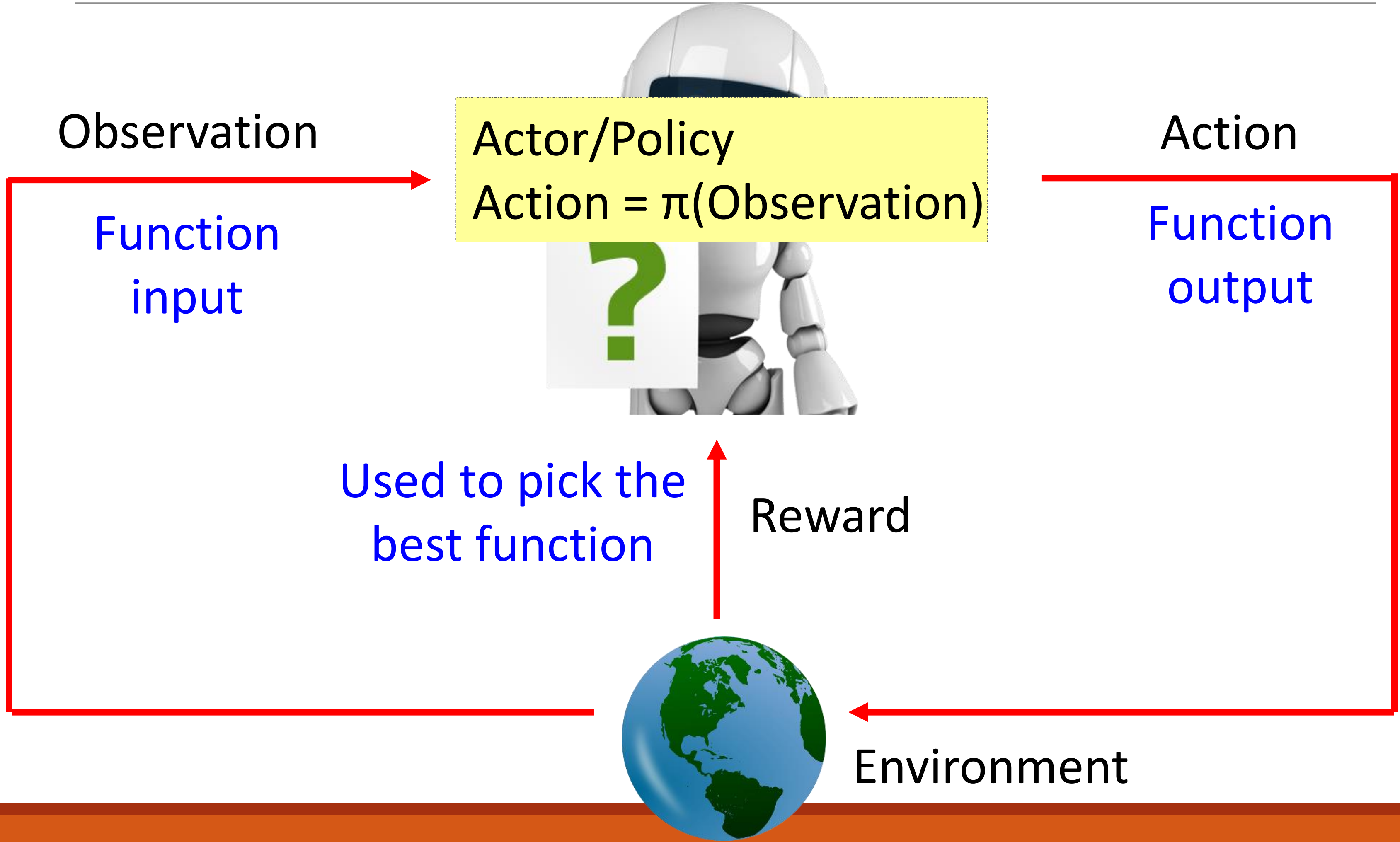
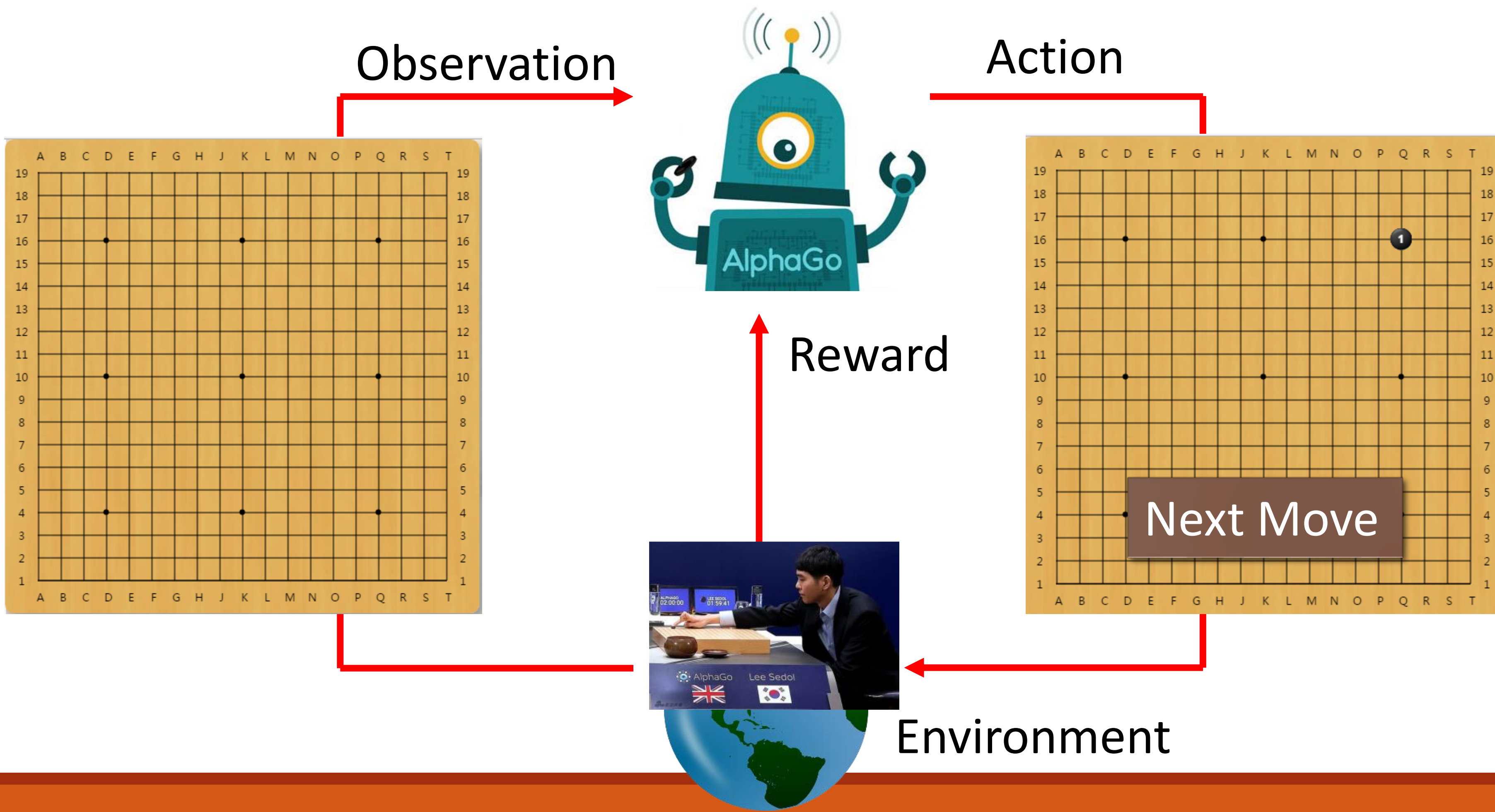


Agent learns to take actions maximizing expected reward.

Machine Learning ≈ Looking for a Function



Learning to Play Go



Learning to Play Go

reward = 0 in most cases

If win, reward = 1

If loss, reward = -1

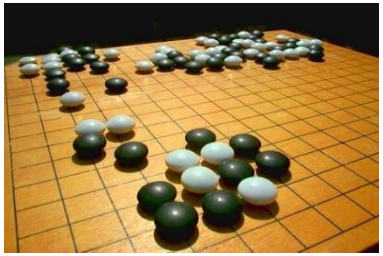
Agent learns to take actions maximizing expected reward.

Learning to Play Go

Supervised

Learning from teacher

Next move: "5-5"



Next move: "3-3"

Reinforcement Learning

Learning from experience

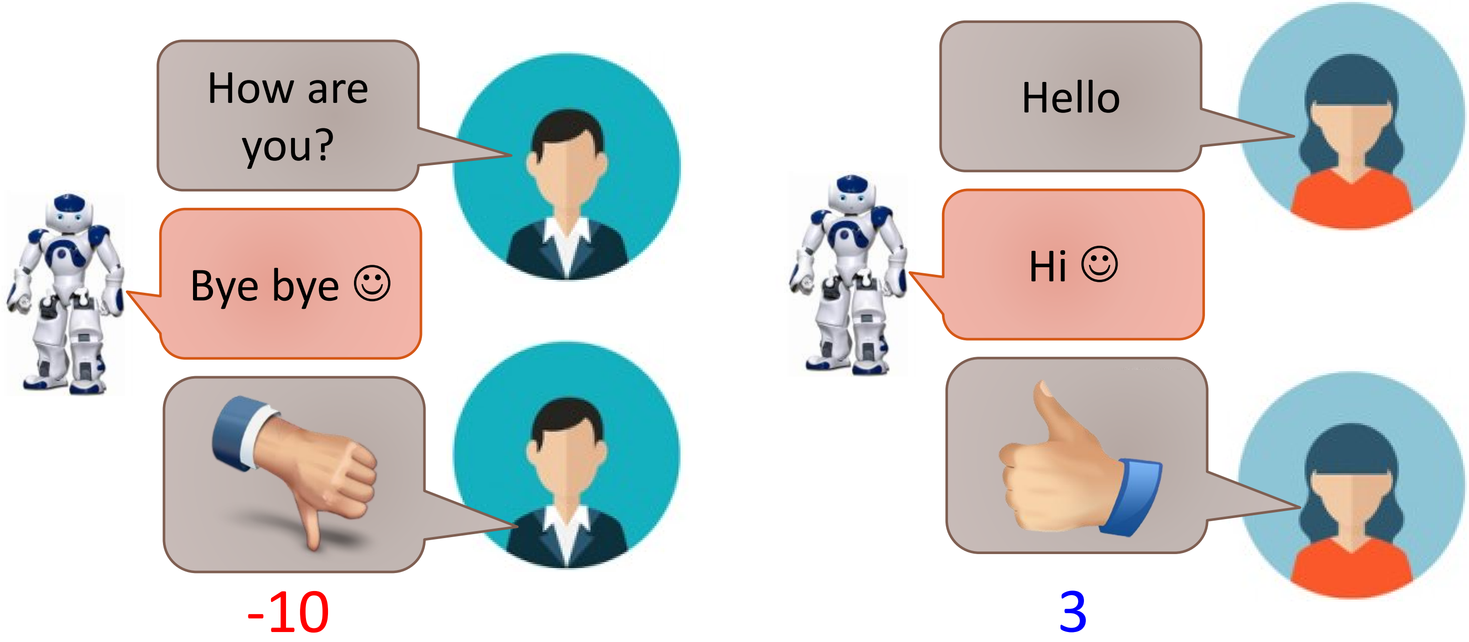
First move → …… many moves …… → Win!

(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)

How old are you?

See you.

See you.

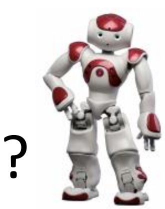
See you.

How old are you?

I am 16.

I though you were 12.

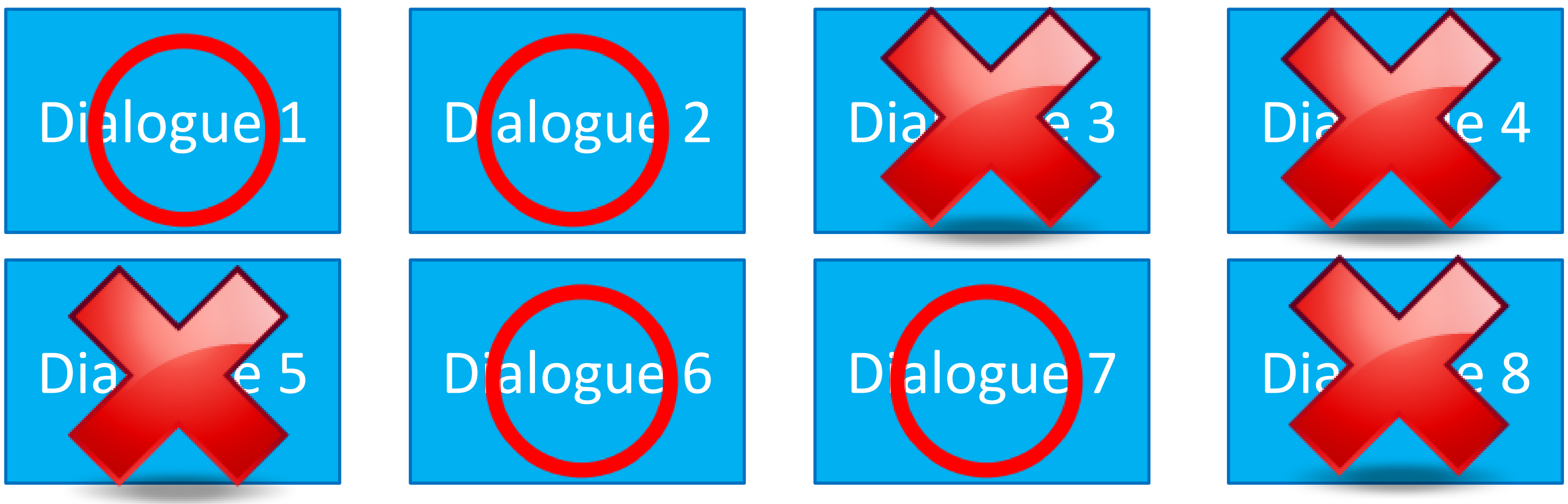
What make you think so?



Learning a chat-bot

By this approach, we can generate a lot of dialogues.

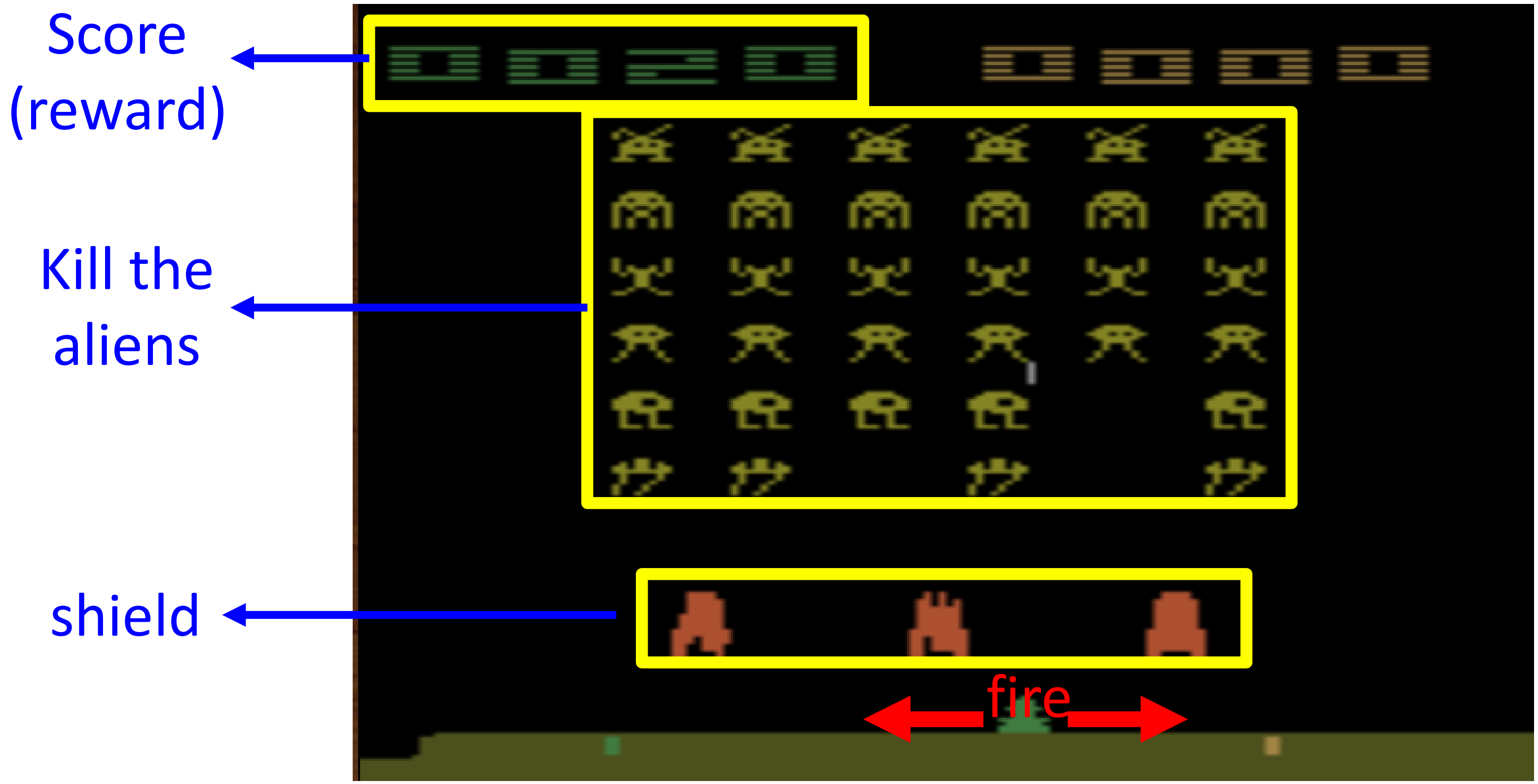
Use pre-defined rules to evaluate the goodness of a dialogue



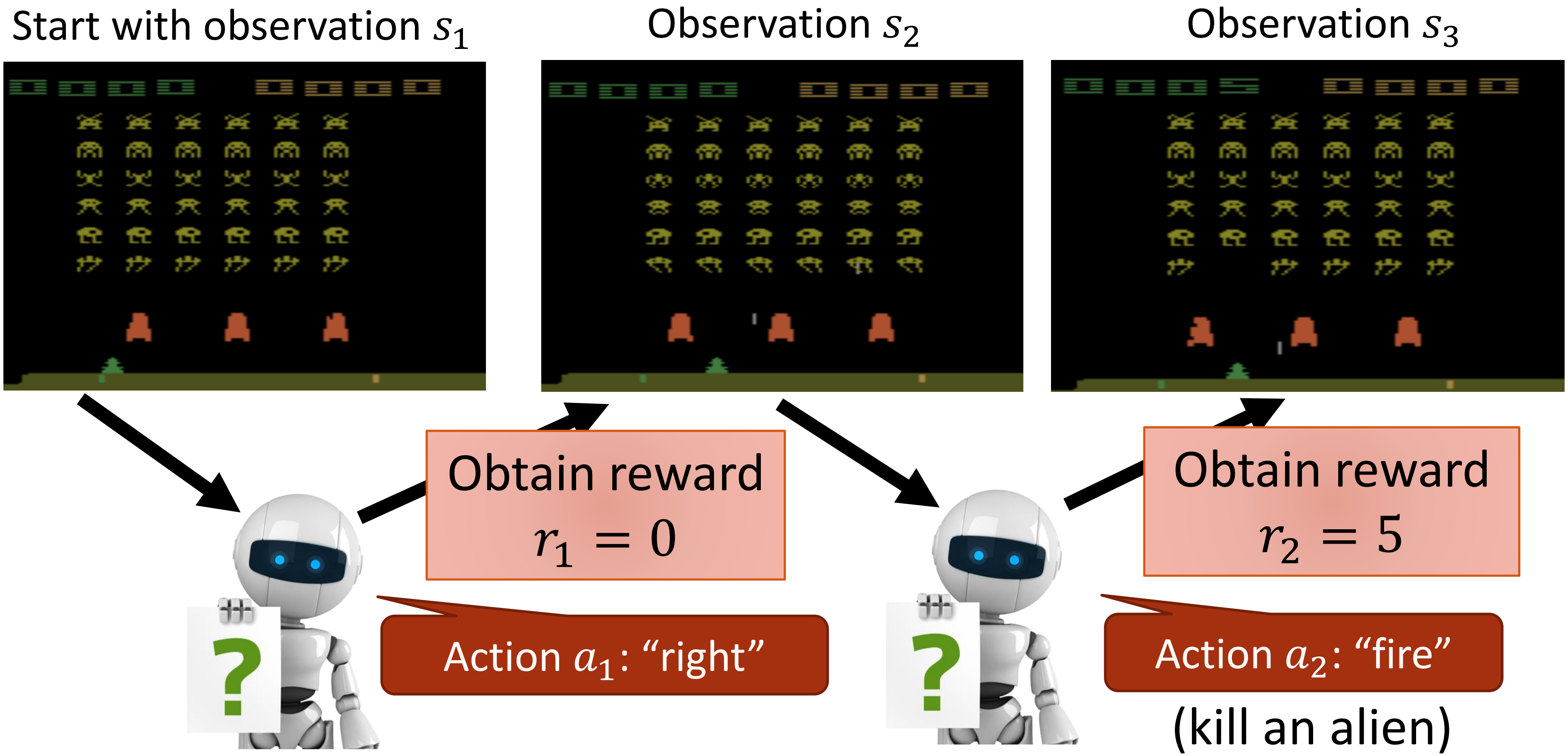
Machine learns from the evaluation as rewards

Learning to Play Video Game

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



Learning to Play Video Game

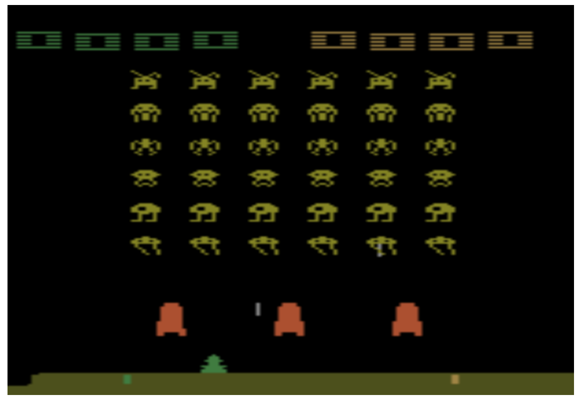


Usually there is some randomness in the environment

Learning to Play Video Game

Start with observation s_1

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

Markov Decision Process

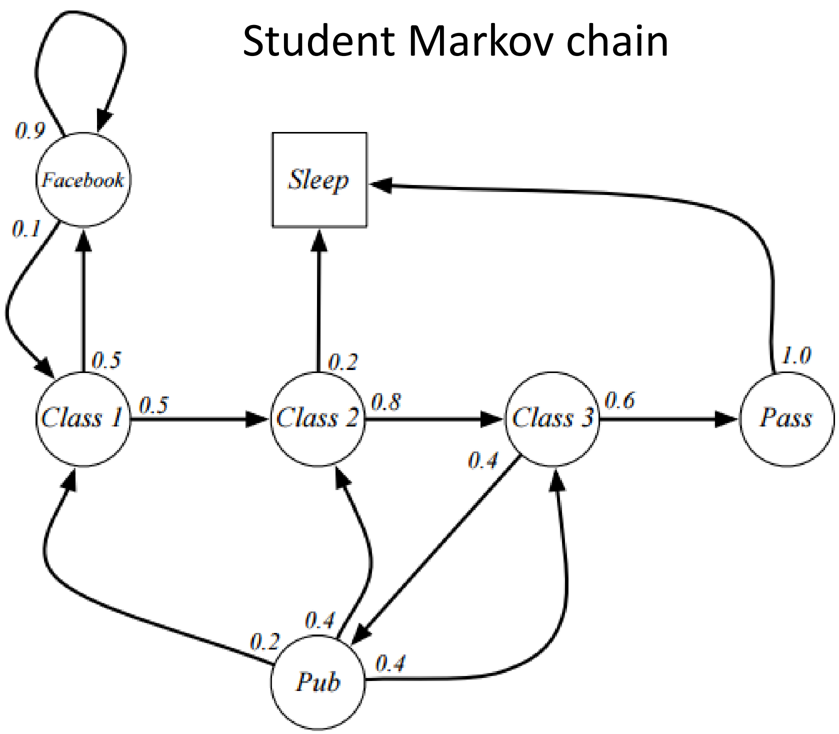
Fully Observable Environment

Outline

Markov Process

Markov process is a memoryless random process

- i.e. a sequence of random states S_1, S_2, ... with the Markov property



Student Markov chain

Sample episodes from S_1=C1

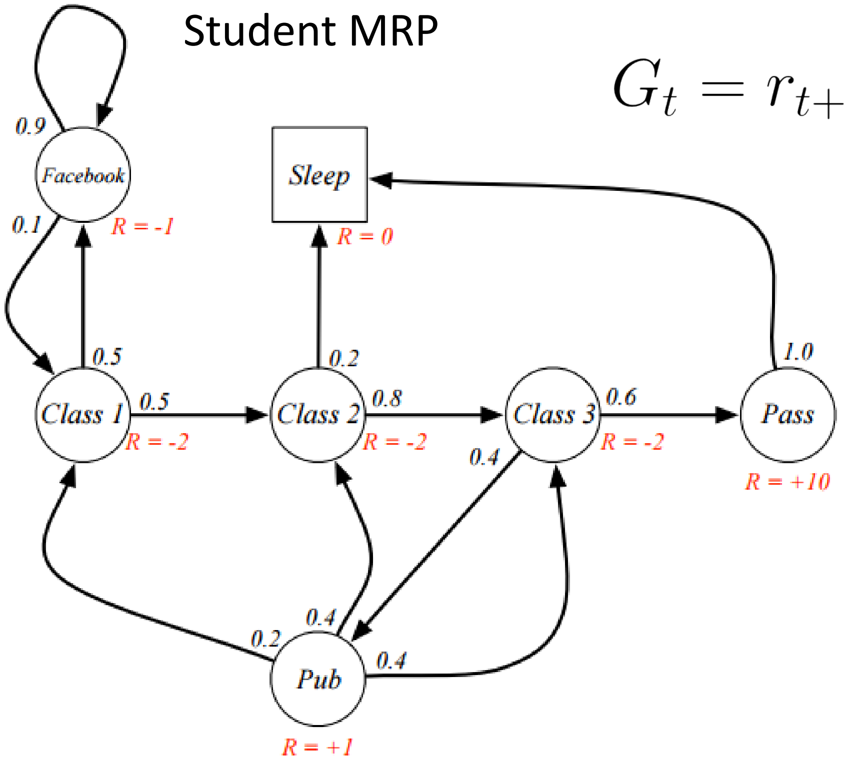
- C1 C2 C3 Pass Sleep
- C1 FB FB C1 C2 Sleep
- C1 C2 C3 Pub C2 C3 Pass Sleep
- C1 FB FB C1 C2 C3 Pub
- C1 FB FB FB C1 C2 C3 Pub C2 Sleep

Markov Reward Process (MRP)

Markov reward process is a Markov chain with values

- The return G_t is the total discounted reward from time-step t

Student MRP



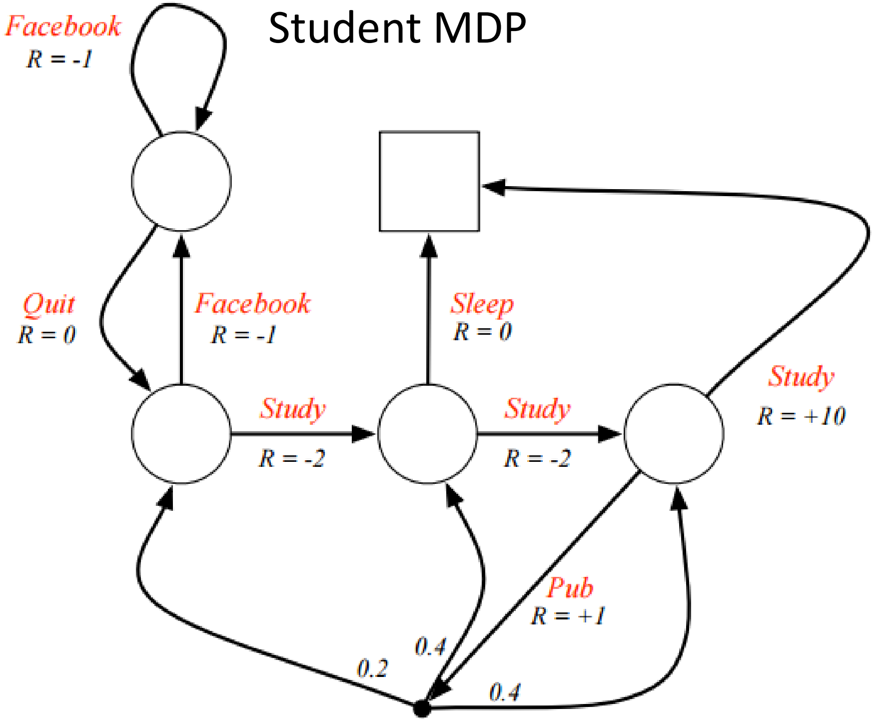
$$G_t = r_{t+1} + \gamma r_{t+2} + \ldots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

Markov Decision Process (MDP)

Markov decision process is a MRP with decisions

- It is an environment in which all states are Markov

Student MDP



Markov Decision Process (MDP)

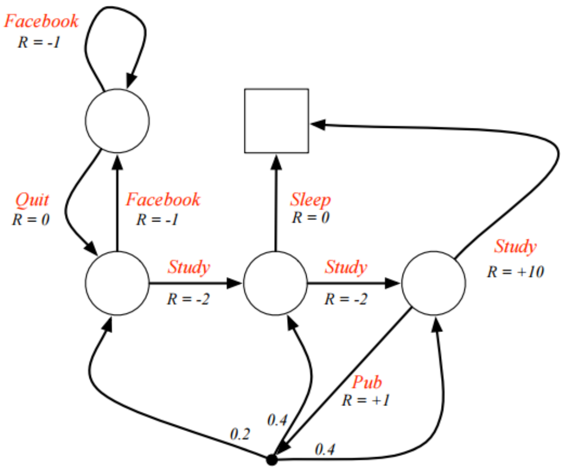
S : finite set of states/observations

A : finite set of actions

P : transition probability

R : immediate reward

γ : discount factor



Goal is to choose policy π at time *t* that maximizes expected overall **return**:

$$\sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$$

Reinforcement Learning

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RL for Unsupervised Model

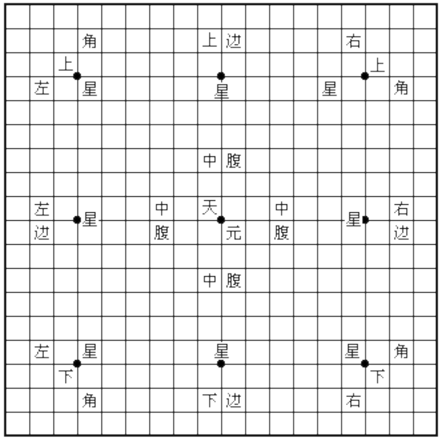
Major Components in an RL Agent

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

Value Function

A value function is a prediction of future reward (with action *a* in state *s*)



Q-value function gives expected total reward

- from state s and action a
- under policy π
- with discount factor γ

$$Q^{\pi}(s,a) = \mathbb{E}\left[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots \mid s,a\right]$$

Value functions decompose into a Bellman equation

$$Q^{\pi}(s,a) = \mathbb{E}_{s',a'}\left[r + \gamma Q^{\pi}(s',a') \mid s,a\right]$$

Optimal Value Function

An optimal value function is the maximum achievable value

$$Q^*(s,a) = \max_\pi Q^\pi(s,a) = Q^{\pi^*}(s,a)$$

The optimal value function allows us act optimally

$$\pi^*(s) = \arg\max_a Q^*(s,a)$$

The optimal value informally maximizes over all decisions

$$\begin{aligned} Q^*(s,a) &= r_{t+1} + \gamma \max_{a_{t+1}} r_{t+2} + \gamma^2 \max_{a_{t+2}} r_{t+3} + \ldots \\ &= r_{t+1} + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1}) \end{aligned}$$

Optimal values decompose into a Bellman equation

$$Q^*(s,a) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q^*(s',a') \mid s,a]$$

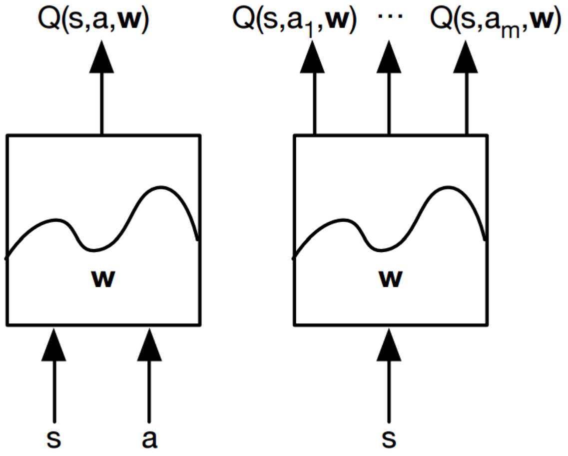
Value Function Approximation

Value functions are represented by a *lookup table*

$$Q(s, a) \quad \forall s, a$$

- too many states and/or actions to store
- too slow to learn the value of each entry individually

Values can be estimated with *function approximation*

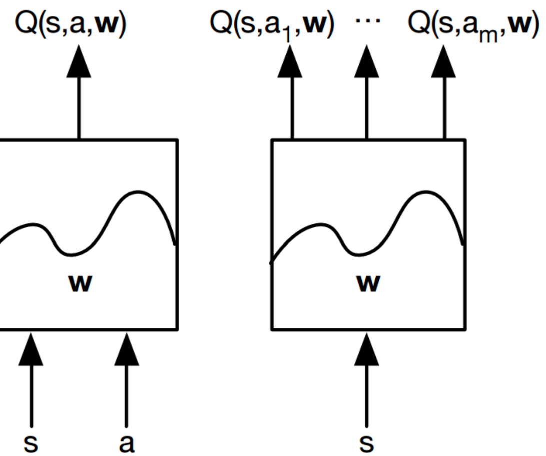


Q-Networks

Q-networks represent value functions with weights w

$$Q(s, a, w) \approx Q^*(s, a)$$

- generalize from seen states to unseen states
- update parameter w for function approximation



Q-Learning

Goal: estimate optimal Q-values

- Optimal Q-values obey a Bellman equation

$$Q^*(s,a) = \mathbb{E}_{s'}\Big[\boxed{r + \gamma \max_{a'} Q^*(s',a')} \mid s,a\Big]$$

learning target

- *Value iteration* algorithms solve the Bellman equation

$$Q_{i+1}(s,a) = \mathbb{E}_{s'}\big[r + \gamma \max_{a'} Q_i(s',a') \mid s,a\big]$$

Policy

A policy is the agent's behavior

A policy maps from state to action

- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a) = P(a \mid s)$

Policy Networks

Represent policy by a network with weights u

$$a = \pi(a \mid s, u) \qquad a = \pi(s, u)$$

stochastic policy　　　deterministic policy

Objective is to maximize total discounted reward by SGD

$$L(u) = \mathbb{E}\left[r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots \mid \pi(\cdot, u)\right]$$

Policy Gradient

The gradient of a stochastic policy $\pi(a \mid s, u)$ is given by

$$\frac{\partial L(u)}{\partial u} = \mathbb{E}_s\left[\frac{\partial \log \pi(a \mid s, u)}{\partial u} Q^{\pi}(s, a)\right]$$

The gradient of a deterministic policy $\pi(s, u)$ is given by

$$\frac{\partial L(u)}{\partial u} = \mathbb{E}_s\left[\frac{\partial Q^{\pi}(s, a)}{\partial a}\frac{\partial a}{\partial u}\right] \qquad a = \pi(s, u)$$

How to deal with continuous actions

Model

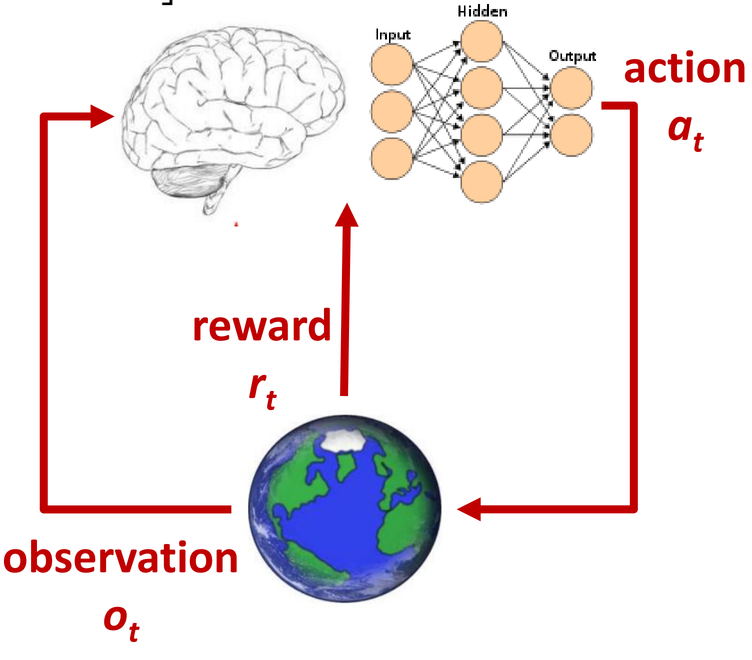
A model predicts what the environment will do next

- P predicts the next state

$$\mathcal{P}^a_{ss'} = \mathbb{P}[s_{t+1} = s' \mid s_t = s, a_t = a]$$

- R predicts the next immediate reward

$$\mathcal{R}^a_s = \mathbb{E}[r_{t+1} \mid s_t = s, a_t = a]$$



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

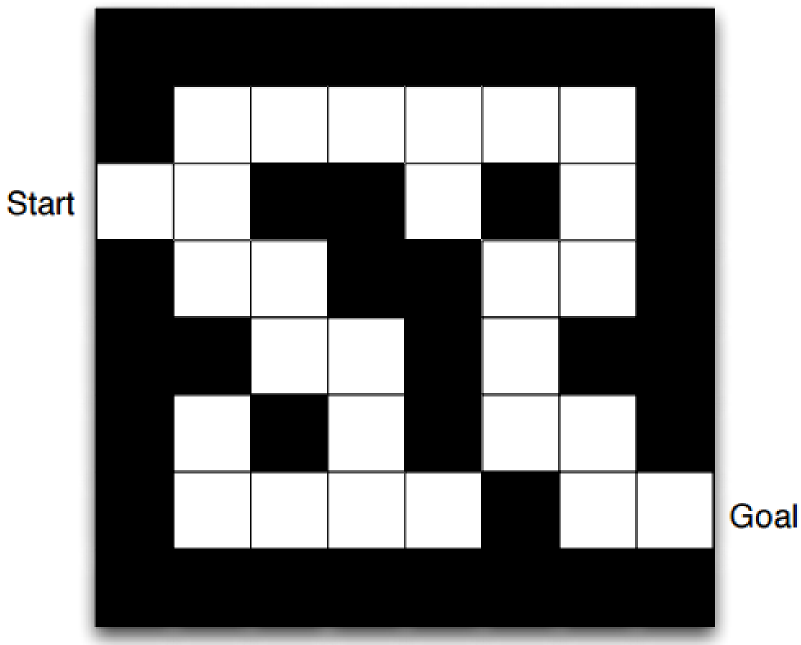
- Search directly for optimal policy π^*

π^* 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

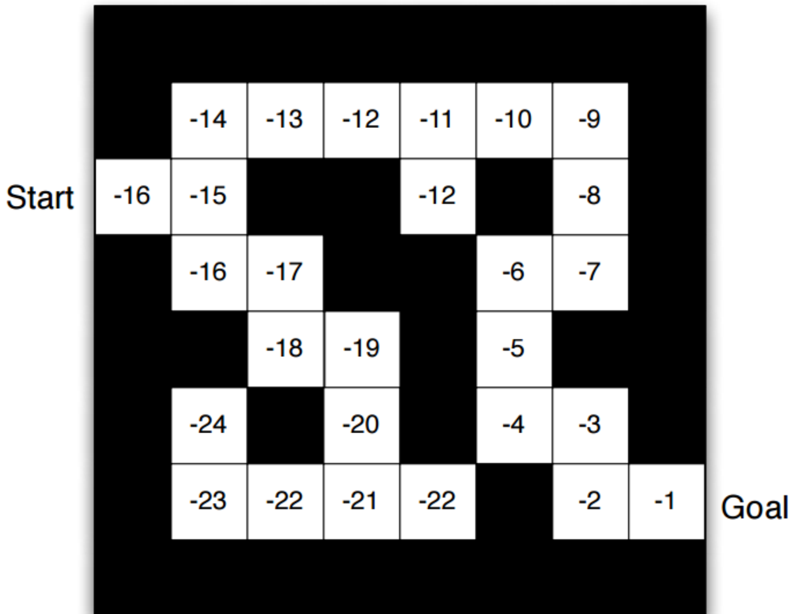


Rewards: -1 per time-step

Actions: N, E, S, W

States: agent's location

Maze Example: Value Function



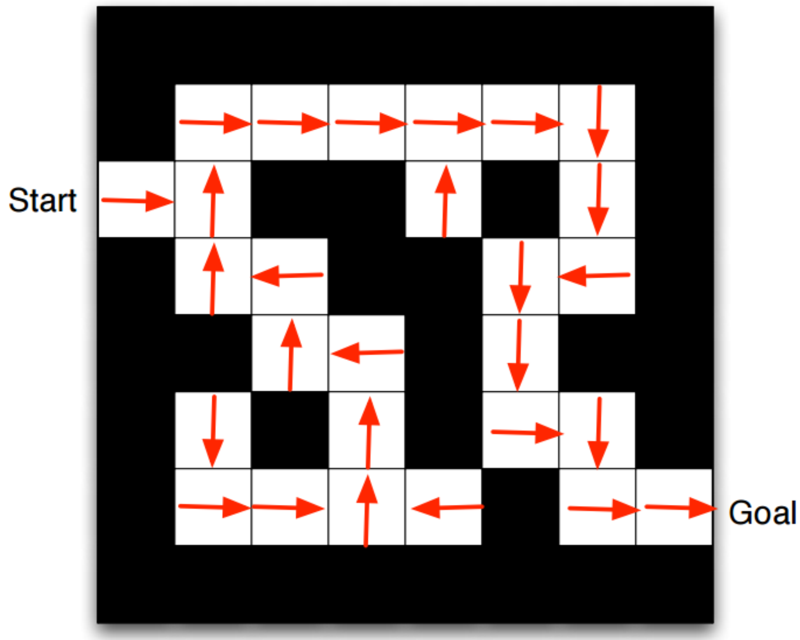
Rewards: -1 per time-step

Actions: N, E, S, W

States: agent's location

Numbers represent value $Q_\pi(s)$ of each state s

Maze Example: Policy



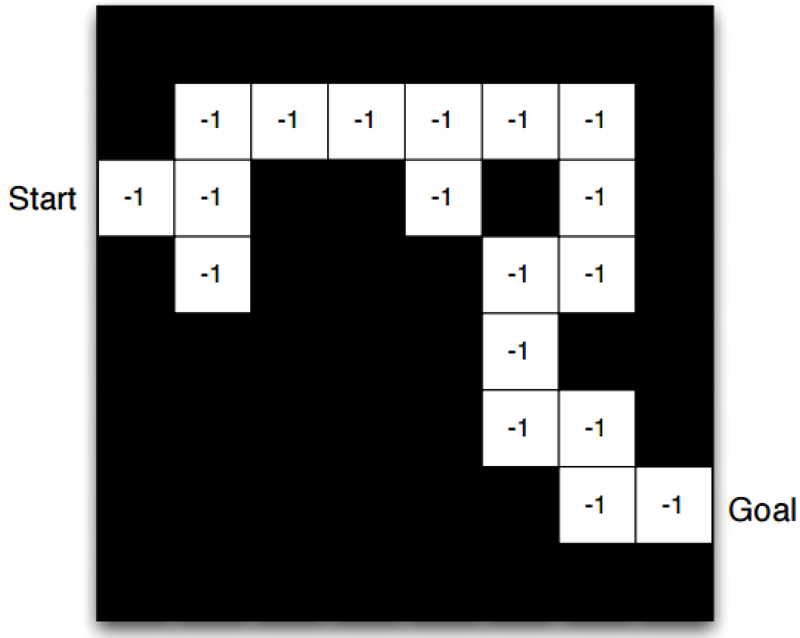
Rewards: -1 per time-step

Actions: N, E, S, W

States: agent's location

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

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*)

Categorizing RL Agents

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

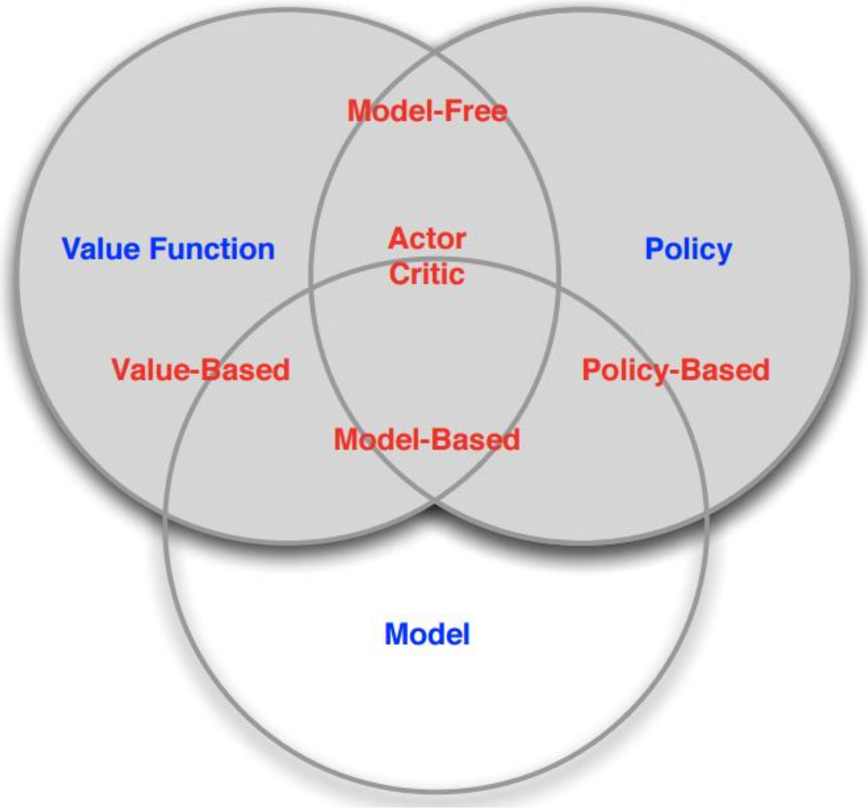
Policy-Based
- Policy
- No Value Function

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



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Learning and Planning

In sequential decision making

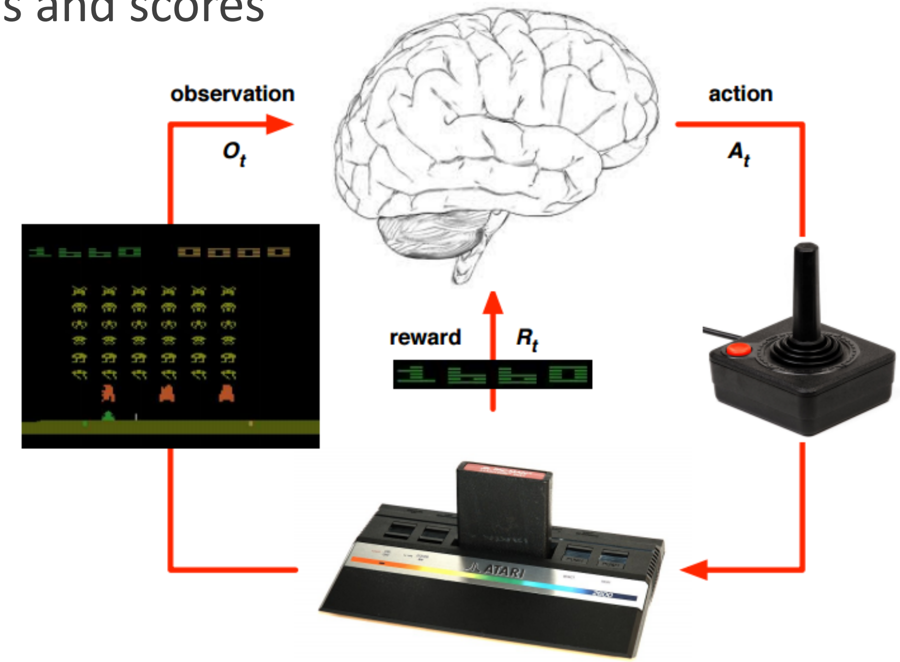
- Reinforcement learning
  - The environment is initially unknown
  - The agent interacts with the environment
  - The agent improves its policy
- Planning
  - A model of the environment is known
  - The agent performs computations with its model (w/o any external interaction)
  - The agent improves its policy (a.k.a. deliberation, reasoning, introspection, pondering, thought, search)

Atari Example: Reinforcement Learning

Rules of the game are unknown

Learn directly from interactive game-play

Pick actions on joystick, see pixels and scores



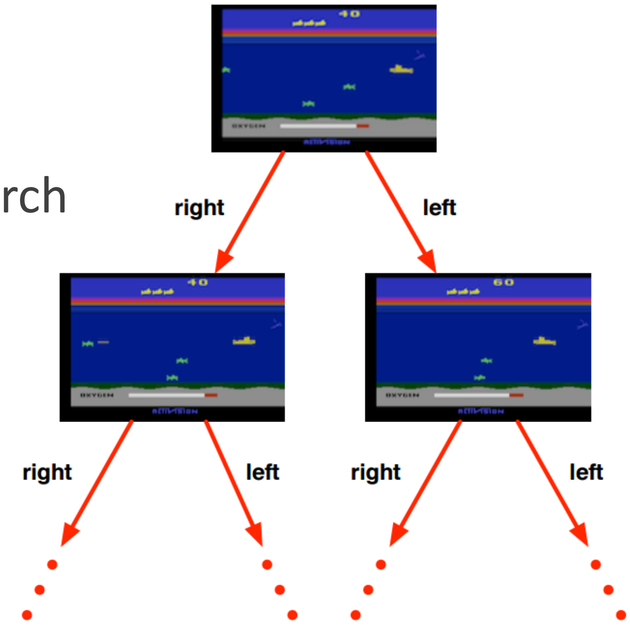
Atari Example: Planning

Rules of the game are known

Query emulator based on the perfect model inside agent's brain

- If I take action a from state s:
  - what would the next state be?
  - what would the score be?

Plan ahead to find optimal policy e.g. tree search



Exploration and Exploitation

Reinforcement learning is like trial-and-error learning

The agent should discover a good policy from the experience without losing too much reward along the way

When to try?

Exploration finds more information about the environment

Exploitation exploits known information to maximize reward

It is usually important to explore as well as exploit

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

Markov Decision Process

Reinforcement Learning
- Policy-Based
- Value-Based
- Model-Based

Problems within RL
- Learning and Planning
- Exploration and Exploitation

RL for Unsupervised Model

RL for Unsupervised Model: **Modularizing Unsupervised Sense Embeddings (MUSE)**

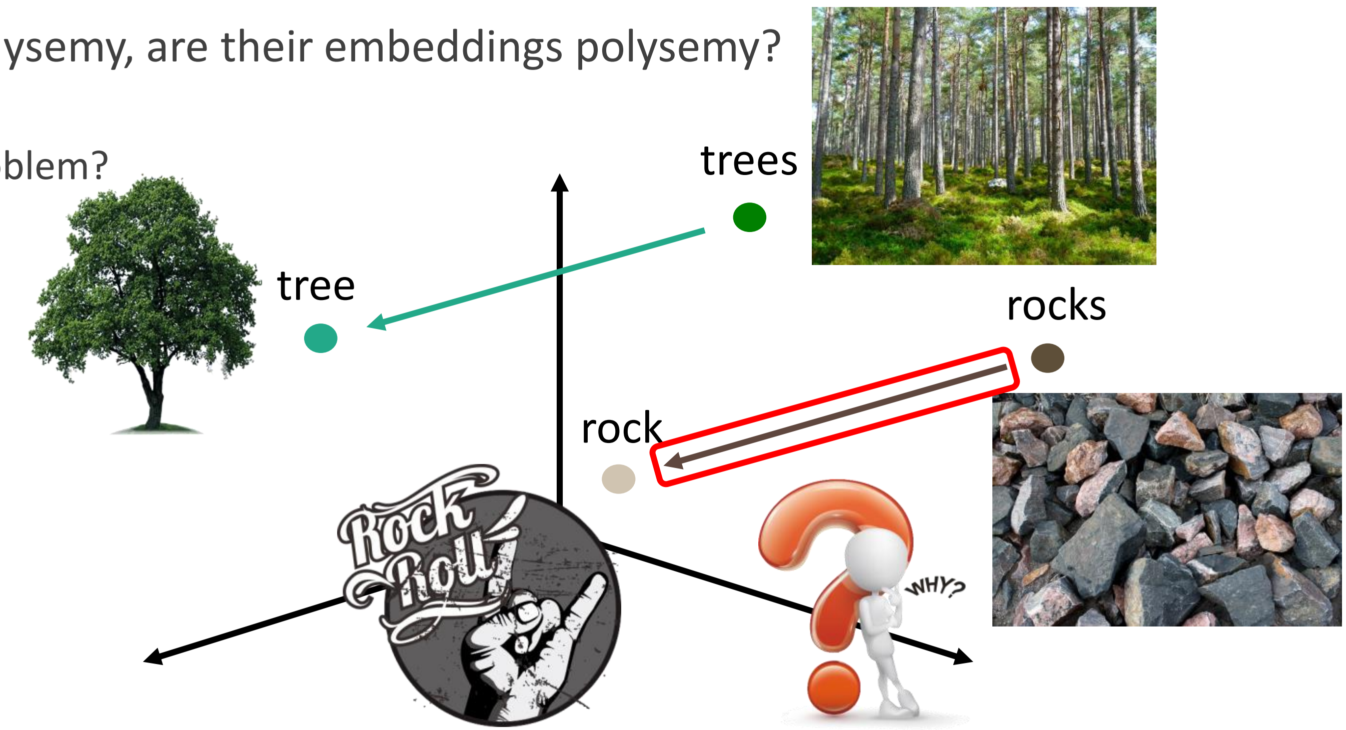
Word2Vec Polysemy Issue

Words are <u>polysemy</u>

- An apple a day, keeps the doctor away.
- Smartphone companies including apple, …

If words are polysemy, are their embeddings polysemy?

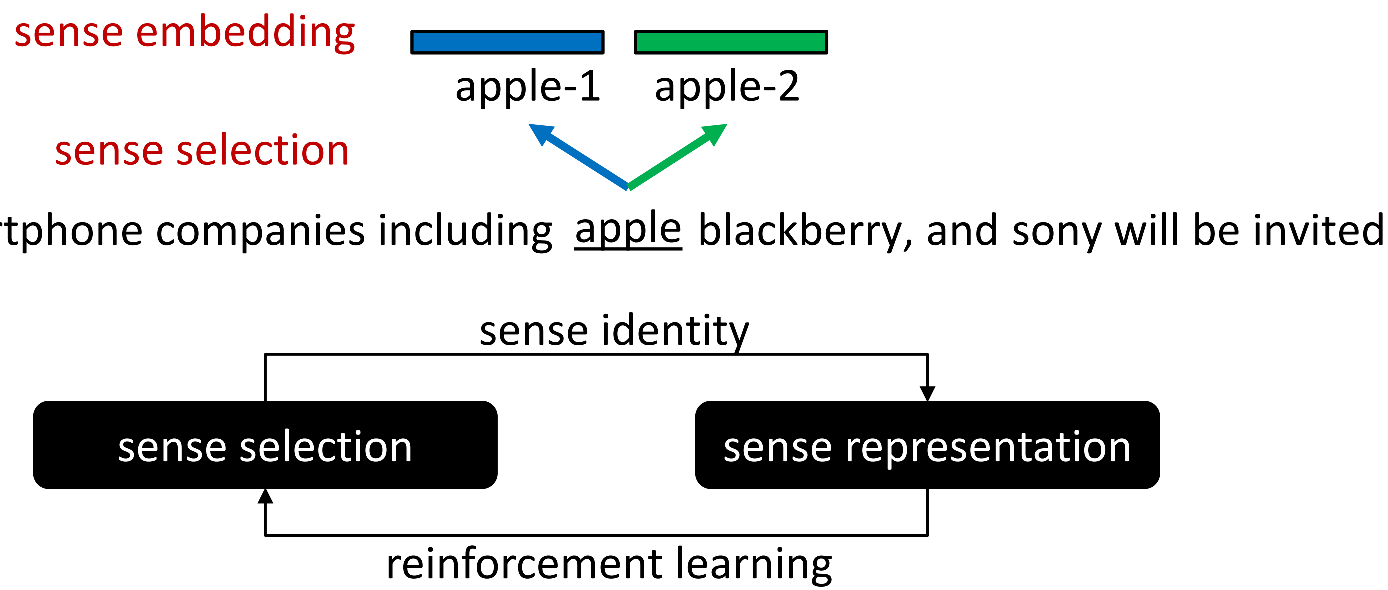
- No ☹
- What's the problem?



Modular Framework

Two key mechanisms

- **Sense selection** given a text context
- **Sense representation** to embed statistical characteristics of sense identity



Sense Selection Module

Input: a text context $\bar{C}_t = [C_{t-m}, \dots, C_t = w_i, \dots, C_{t+m}]$

Output: the fitness for each sense $z_{i1}, \dots, z_{i3}$

Model architecture: Continuous Bag-of-Words (CBOW) for efficiency

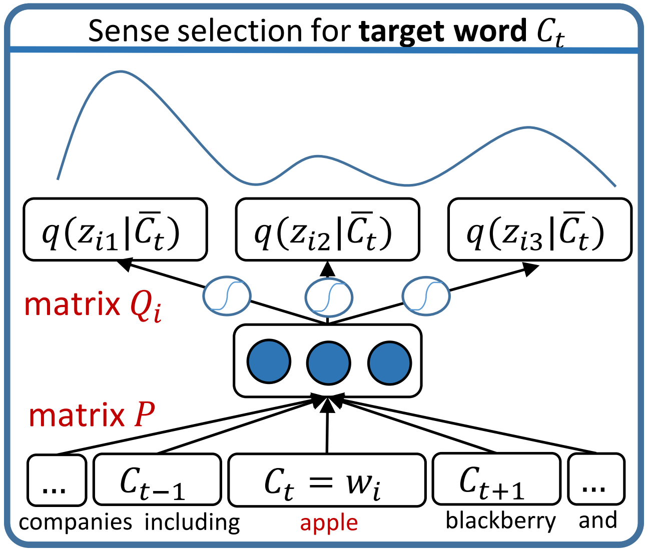
Sense selection

- Policy-based

$$\pi(z_{ik} \mid \bar{C}_t) = \frac{\exp(Q_{ik}^T \sum_{j \in \bar{C}_t} P_j)}{\sum_{k' \in Z_i} \exp(Q_{ik'}^T \sum_{j \in \bar{C}_t} P_j)}$$

- Value-based (Q-value)

$$q(z_{ik} \mid \bar{C}_t) = \sigma(Q_{ik}^T \sum_{j \in \bar{C}_t} P_j)$$



Sense Selection Module

Sense Representation Module

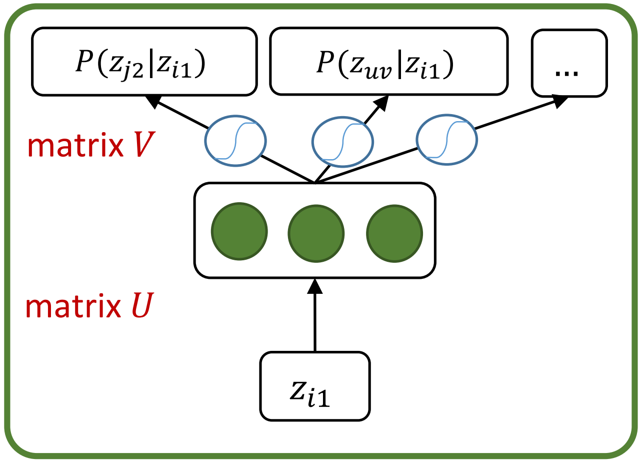
Input: sense collocation z_{ik}, z_{jl}

Output: collocation likelihood estimation

Model architecture: skip-gram architecture

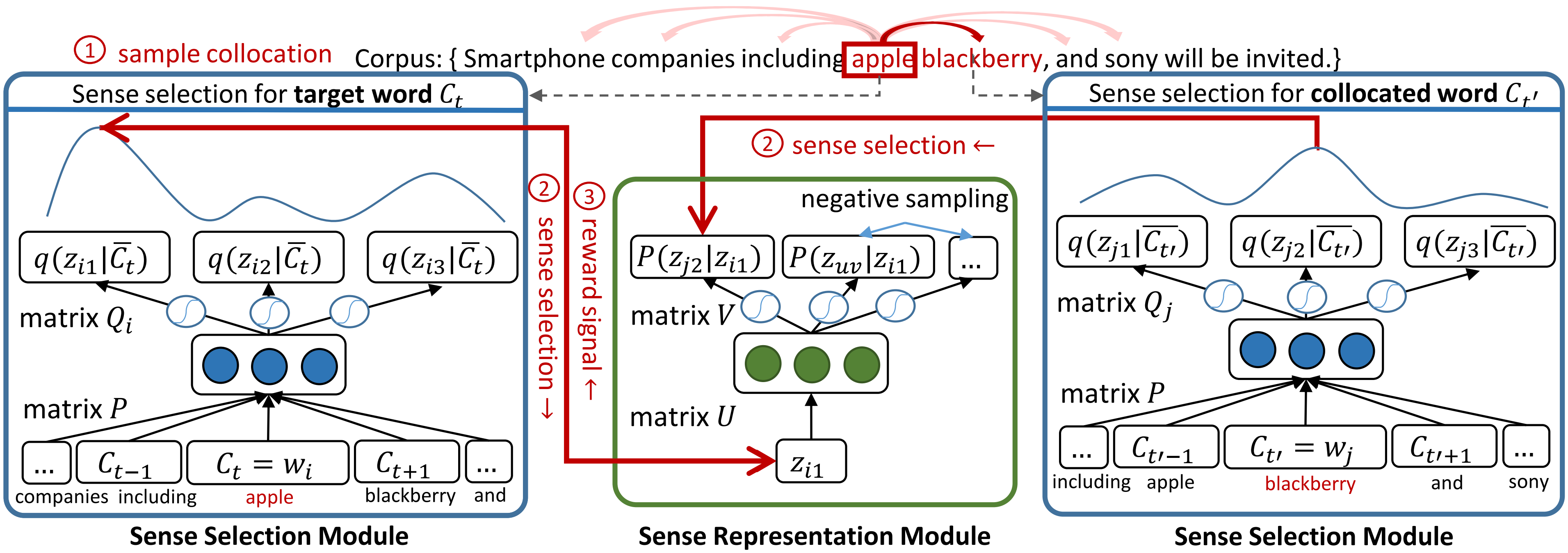
Sense representation learning

$$\log \bar{\mathcal{L}}(z_{jl} \mid z_{ik}) = \log \sigma(U_{z_{ik}}^T V_{z_{jl}}) + \sum_{v=1}^{M} \mathbb{E}_{z_{uv} \sim p_{neg}(z)} [\log \sigma(-U_{z_{ik}}^T V_{z_{uv}})]$$



Sense Representation Module

A Summary of MUSE



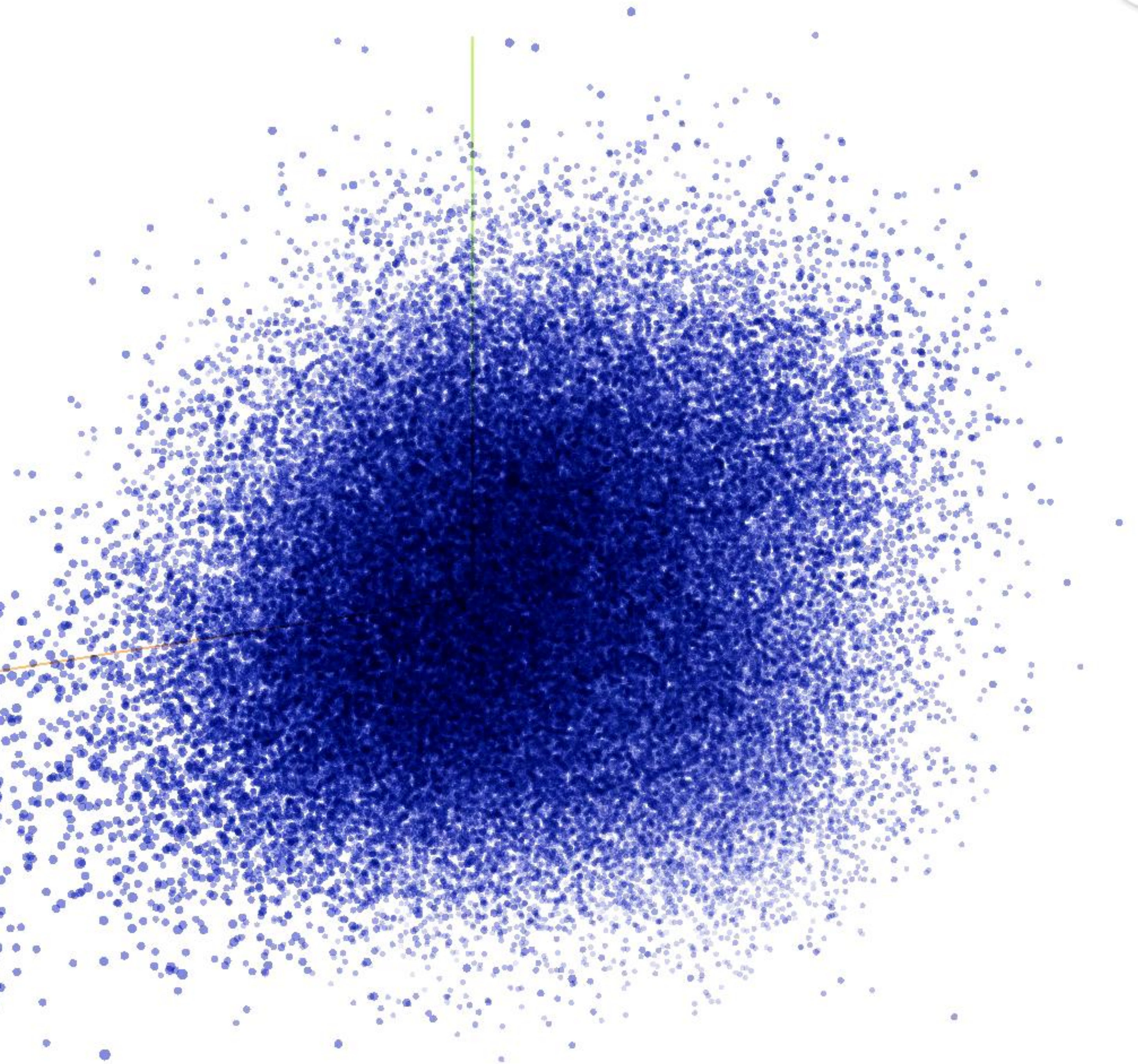
The first purely sense-level embedding learning with efficient sense selection.

Qualitative Analysis

Context	… braves finish the season in **tie** with the los angeles dodgers …	… his later years proudly wore **tie** with the chinese characters for …
k-NN	scoreless otl shootout 6-6 hingis 3-3 7-7 0-0	pants trousers shirt juventus blazer socks anfield
Figure		

Qualitative Analysis

Context	… of the mulberry or the **blackberry** and minos sent him to …	… of the large number of **blackberry** users in the us federal …
k-NN	cranberries maple vaccinium apricot apple	smartphones sap microsoft ipv6 smartphone
Figure		



Search

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*

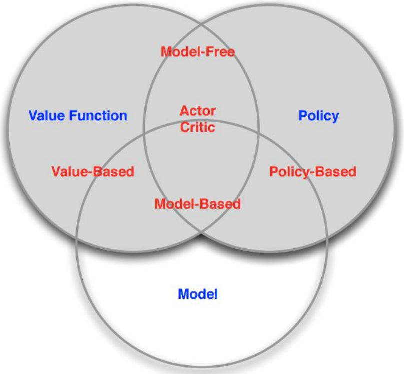
action

state

reward

An RL agent may include one or more of these components

- Value function: how good is each state and/or act
- Policy: agent's behavior function
- Model: agent's representation of the environmen



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