Introduction to Reinforcement Learning

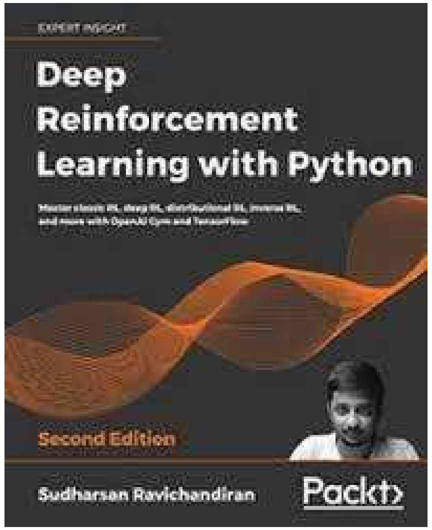
Dept. of Computer Engineering,

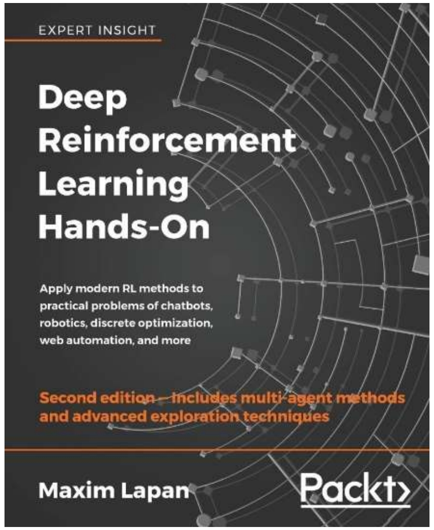
Sogang University

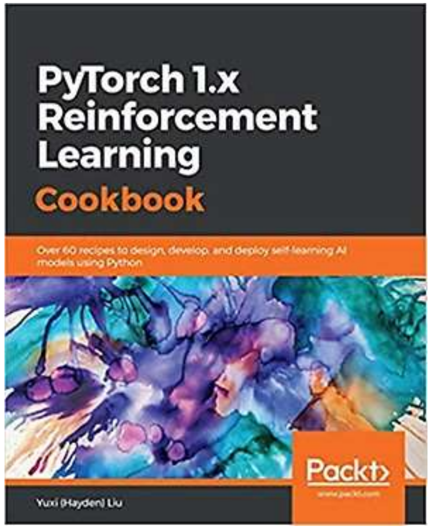
Course Info

- Instructor: Jungmin So (AS-1013, jso1@sogang.ac.kr)
- Lecture slides and other information will appear at http://cyber.sogang.ac.kr.

- Slides are based on the following books
  - Sutton and Barto, "Reinforcement Learning: An Introduction, 2nd Ed."
  - S. Ravichandiran, "Deep Reinforcement Learning with Python, 2nd Ed."
  - M. Lapan, "Deep Reinforcement Learning Hands-On, 2nd Ed."
  - Y. Liu, "PyTorch 1.x Reinforcement Learning Cookbook"







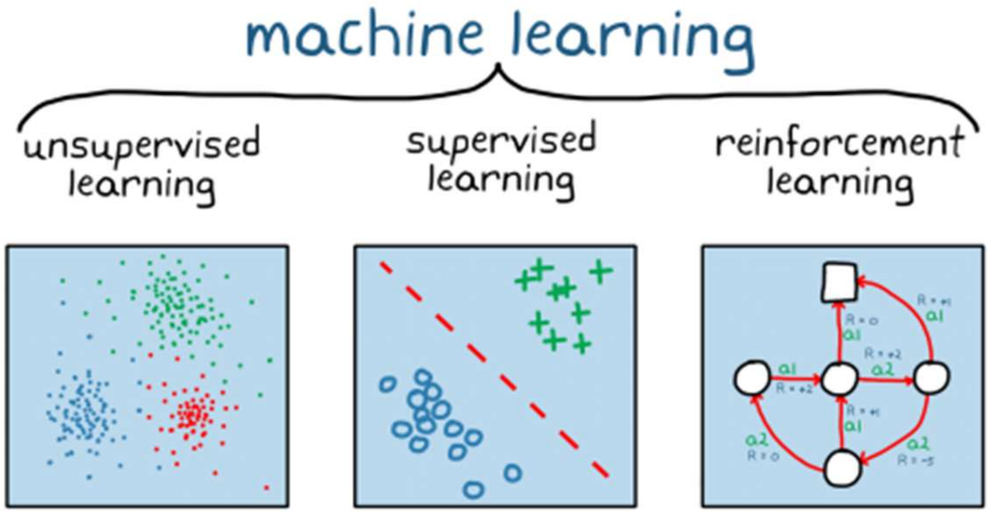
Evaluation

- 1 Mid-term Exam
- 1 Final Exam
- 1 Individual Project
  - Using reinforcement learning to solve problems

Reinforcement Learning

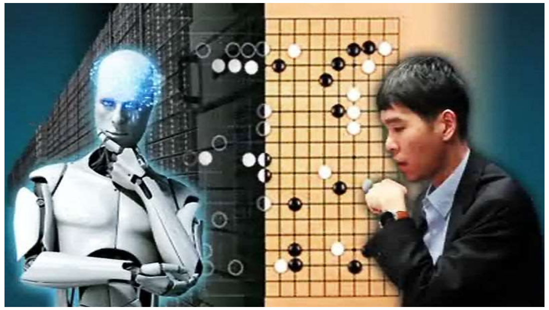
- Definition from Wikipedia
  - Reinforcement learning (RL) is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward.

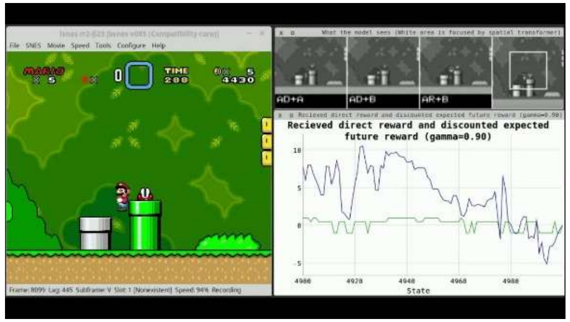
- Different types of machine learning



Reinforcement Learning - Applications

- self-driving cars
- industry automation
- trading and finance
- natural language processing
- healthcare
- news recommendation
- gaming
- marketing and advertising
- robotics
- and many more!





Reinforcement Learning - Topics

- introduction and concepts
- Bellman equation and dynamic programming (DP)
- Monte Carlo methods (MC)
- temporal difference (TD) learning
- deep reinforcement learning (DQN)
- policy gradient method (PG)
- actor-critic methods (AC)
- multi-agent reinforcement learning
- advanced topics
  - deep deterministic policy gradient (DDPG)
  - soft actor-ctiric (SAC)
  - trust region policy optimization (TRPO)
  - proximal policy optimization (PPO)

Our goal in this course

- Understands concepts of RL and can run toy examples like FrozenLake

- Understands various methods of reinforcement learning and the differences between them

- Can apply reinforcement learning to solve new problems

- Understands math behind algorithms and why they are designed like that

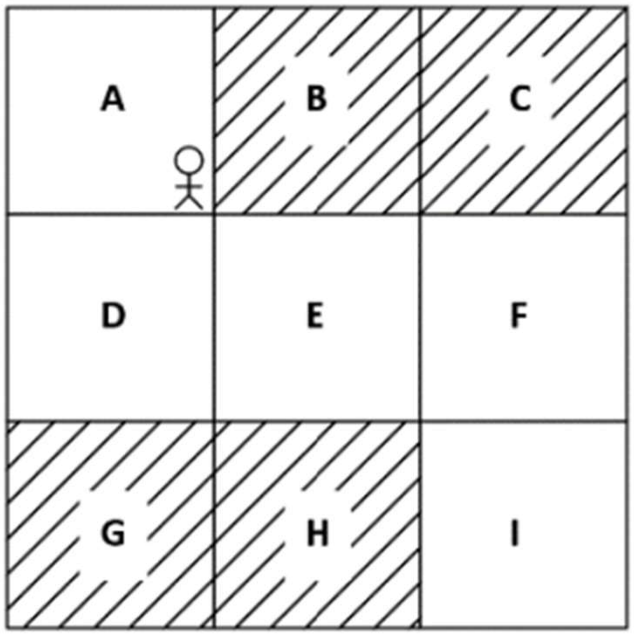
- Can design new types of reinforcement learning algorithms and methods

Fundamentals of Reinforcement Learning

Introduction

An Example Problem

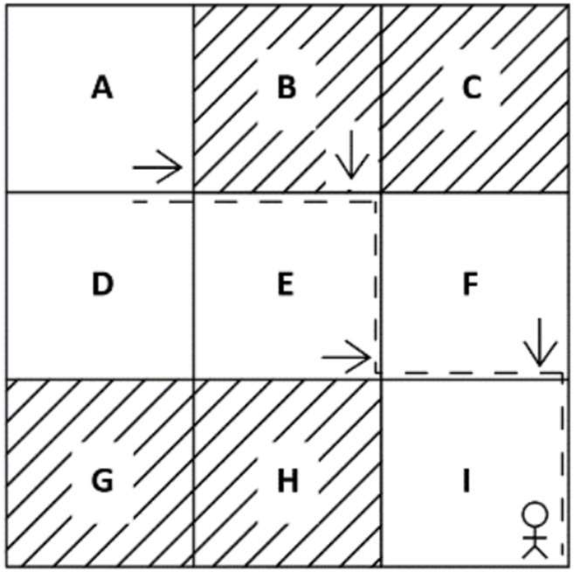
- Suppose there is a person in a grid world.
- The person starts at position A.
- His/her goal is to move to position I.
- The person can move in only two directions: right or down.
- The shaded locations (B, C, G, and H) are to be avoided, otherwise the person gets a penalty.
- What path should the person take in order to reach the goal?



Reinforcement Learning Approach

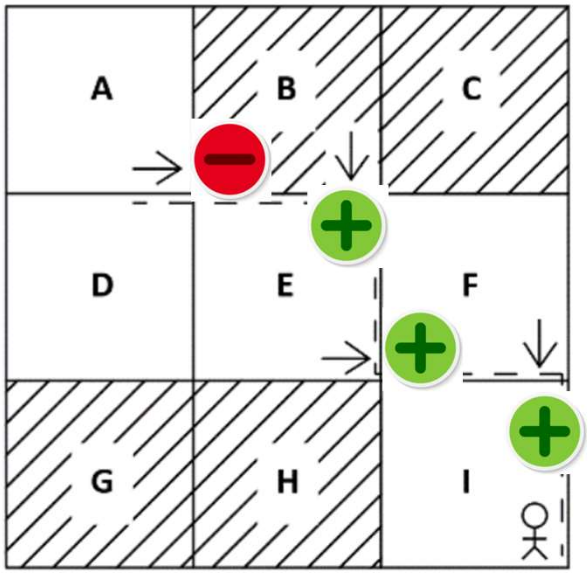
- Try and learn from experience!

- Iteration (episode) 1
  - The person (agent) has no experience, so it chooses to perform a random action among possible actions. It moves right and reaches location (state) B.
  - Still taking random actions, the agent moves down from B to reach state E, moves right to reach state F, and moves down to reach state I.
  - State I is defined as a terminal state, so the iteration ends there.



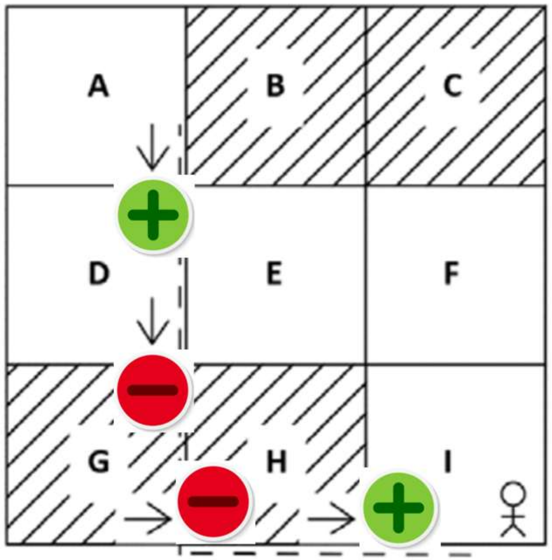
Reinforcement Learning Approach

- How does the agent learn from experience?
  - Based on the concept of reward!
- Reward in the grid world
  - If the agent moves to a shaded state, it receives a negative reward.
    - The agent learns that the move was a 'bad' action.
  - If the agent moves to an unshaded state, it receives a positive reward.
    - The agent learns that the move was a 'good' action.
  - The reward is given to a specific action on a specific state.
    - (state, action) pair



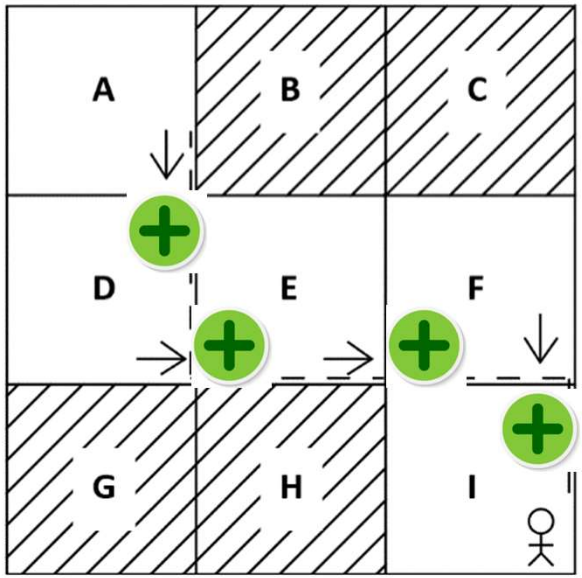
Reinforcement Learning Approach

- Episode 2
  - This time, the agent moves down from state A to reach state D.
  - Since state D is a unshaded state, the agent receives a positive reward.
  - From this experience, the agent learns that moving down from state A is a good action.
  - Similarly, the agent moves in the path A → D → G → H → I. It receives positive rewards for actions A→D and H→I, but receives negative rewards for actions D→G and G→H.



Reinforcement Learning Approach

- Episode 3
  - In this iteration, the agent moves in the path A→D→E→F→I. For all actions, the agent receives positive rewards.

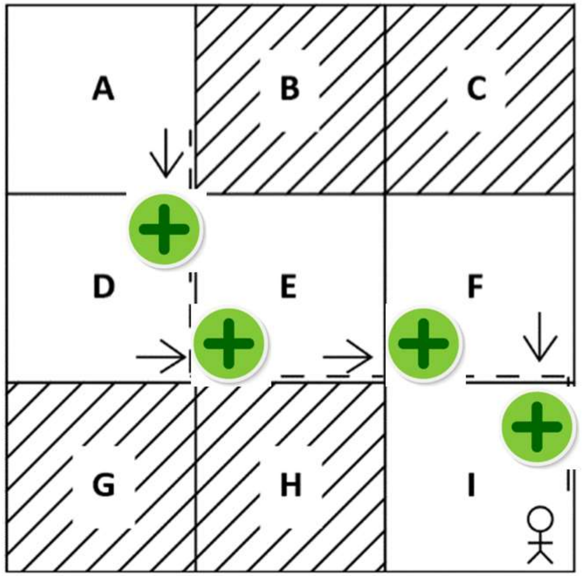


Reinforcement Learning Approach

- Learning from experience
  – After each iteration, the agent records the reward for each (state, action) pair.

states	actions	rewards
A	move right	-1
	move down	+1

  – As the experience builds up, the agent <u>leans towards taking actions with high reward</u> → does the task better. That's why it is called reinforcement learning!

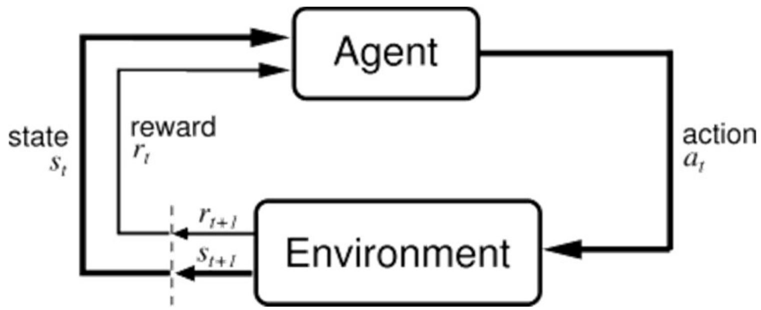


Reinforcement Learning Approach

- Basic reinforcement learning algorithm
  1) The agent interacts with the environment by performing an action.
  2) By performing an action, the agent moves from one state to another.
  3) The agent receives a reward based on the action it performed.
  4) Based on the reward, the agent understands whether the action is good or bad.
  5) If the action was good, that is, if the agent received a positive reward, the agent will prefer performing that action, else the agent will try performing other actions in search of a positive reward.

Terms used in RL

- Agent
  - a software program that learns to make intelligent decisions
    - e.g.) chess player, Mario in a Super Mario Bros. game.
- Environment
  - the world where the agent stays within
    - e.g.) chess board, the world of Mario
- State
  - a snapshot of moment in the environment (including the agent.)
    - e.g.) In a 3x3 grid world, the player can be in 1 of the 9 locations. Each location of the player is a state.
- Action
  - a move performed by the agent.
    - e.g.) Moving to a new location in the grid world, moving a chess piece in a chess board
- Reward
  - a feedback given for an action
    - e.g.) taking opponent's chess piece, reaching a goal



Reinforcement Learning vs. Other Learning Paradigms

- Supervised learning
  - Trains a model using a labeled dataset, which is a set of (input, label) pairs.
  - The model learns the relationship between input and its label (function approximation)
  - When an input is presented to the trained model, the model can predict its label

- Unsupervised learning
  - Trains a model using dataset without labels.
  - The trained model can organize data into clusters or find abnormal data

- Reinforcement learning
  - An agent interacts with the given environment by taking actions.
  - The agent learns to take good actions from feedback (reward) obtained from previous episodes.

Fundamentals of Reinforcement Learning

Markov Decision Process

Markov Property and Markov Chain

- Markov Decision Process (MDP)
  - A mathematical framework for solving optimization problems
  - Used in RL to solve problems as well

- Markov property
  - "Future depends only on the present and not on the past."
  - a memoryless property

- Markov chain (Markov process)
  - Sequence of states that strictly obey the Markov property
  - A probabilistic model that solely depends on the current state to predict the next state (and not the previous states)
    - The future is conditionally independent of the past
  - e.g.) "today is cloudy, so it is likely to be rainy tomorrow."

Elements of Markov Chain

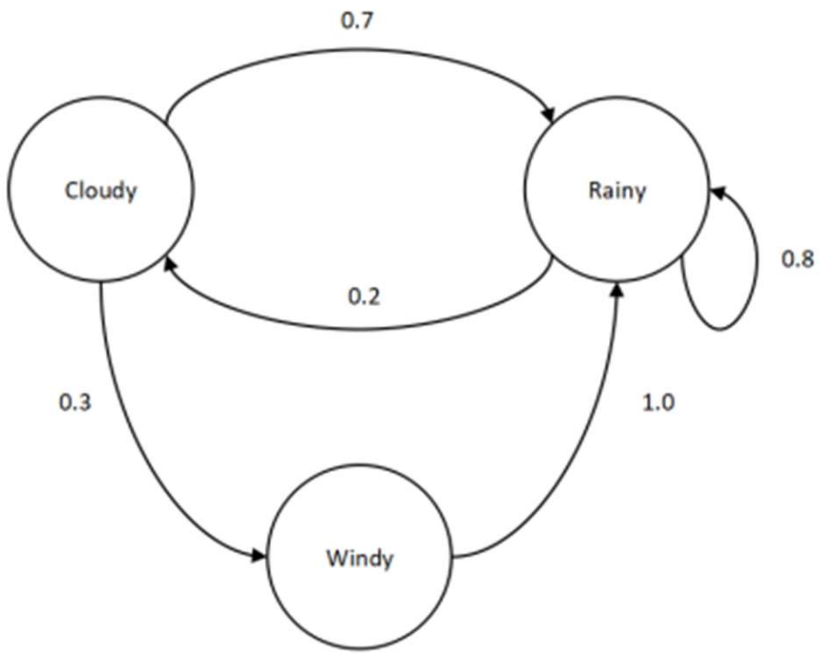
- States
  - A set of all possible states
  - e.g. [cloudy, windy, rainy]

- Transition probability
  - Probability of moving from one state to another

Current State	Next State	Transition Probability
Cloudy	Rainy	0.7
Cloudy	Windy	0.3
Rainy	Rainy	0.8
Rainy	Cloudy	0.2
Windy	Rainy	1.0

Representation of Markov Chain

- State diagram of a Markov chain



- Transition matrix

$$
\begin{array}{c} \\ \text{Cloudy} \\ \text{Rainy} \\ \text{Windy} \end{array}
\begin{array}{c}
\begin{array}{ccc} \text{Cloudy} & \text{Rainy} & \text{Windy} \end{array} \\
\begin{bmatrix} 0.0 & 0.7 & 0.3 \\ 0.2 & 0.8 & 0.0 \\ 0.0 & 1.0 & 0.0 \end{bmatrix}
\end{array}
$$

Markov Reward Process (MRP)

- Extension of Markov chain with the reward function

- Markov Chain = states + transition probability

- Markov Reward Process = states + transition probability + reward function
  - States: s
  - Transition probability: $P(s'|s)$
  - Reward function: $R(s)$

- Reward function
  - A reward function defines reward obtained in each state
  - E.g.) reward in state cloudy, reward in state windy, reward in state rainy

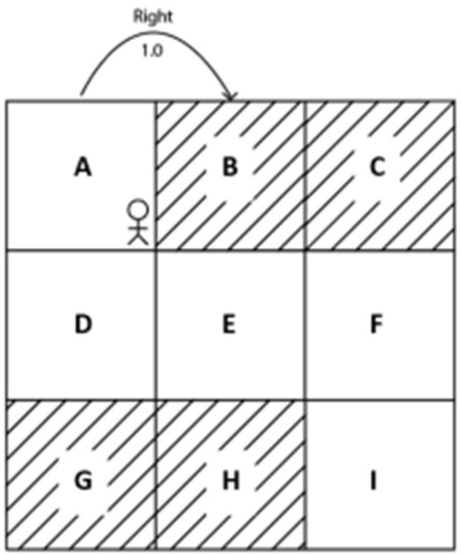
Markov Decision Process (MDP)

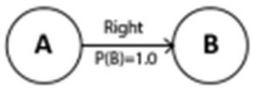
- Extension of Markov Reward Process

- Markov Chain = states + transition probability
- Markov Reward Process = states + transition probability + reward function
- Markov Decision Process = states + transition probability + reward function + actions
  - States: s
  - Actions: a
  - Transition probability: $P(s'|s,a)$
    - Probability of moving to state s' when the agent takes action a in state s.
  - Reward function: $R(s,a,s')$
    - Reward the agent obtains when moving from state s to s' while performing action a.
- Actions
  - A set of actions that our agent can perform in each state
  - An agent performs an action and moves from one state to another

Formulating Grid World using MDP

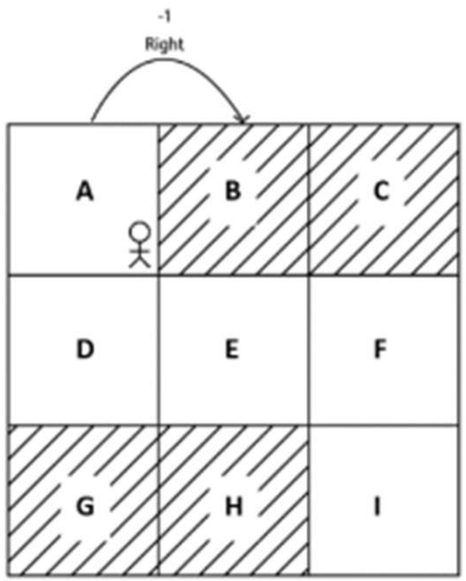
- States: the set of locations {A, B, …, I}.
- Actions: the set of actions {down, right}.
- Transition Probability
  - E.g.) $P(B|A, right)$ is the probability of the agent ends up in state B when taking action "right" in state A.
  - In our previous 3x3 Grid World example, the agent <u>always</u> moves to state B from state A when it moves "right".
    - $P(B|A, right) = 1.0$
    - In some environment, an action may probabilistically lead the agent to multiple states.





Formulating Grid World using MDP

- Reward function
  - Reward for (current state, action, next state) triple
  - E.g.) $R(A, right, B)$: reward when the agent performs action "right" in state A, and moves to state B.
  - In the 3x3 Grid World, agent receives reward -1 when it moves to state B, because it is a shaded state.
    - $R(A, right, B) = -1.0$
    - Reward can be different when one of current state, action, next state is different.



Fundamentals of Reinforcement Learning

Concepts of RL

Recap: Expectation (1)

- Suppose we have a random variable X.
- The random variable takes values based on a random experiment.
  - E.g.) rolling a dice, tossing a coin
- Suppose X is an outcome of rolling a fair dice.
- The possible outcomes are 1, 2, 3, 4, 5, and 6.
- Probability of occurrence for each value is 1/6.

X	1	2	3	4	5	6
P(x)	1/6	1/6	1/6	1/6	1/6	1/6

- For a random variable X, its expectation E(X) is defined as:

$$E(X) = \sum_{i=1}^{N} x_i p(x_i)$$

- When rolling a dice, the expectation is 3.5.

Recap: Expectation (2)

- We can define expectation of a function of a random variable X.

- Suppose we roll a dice, and we get a score of x^2 when the outcome is x.
  - If the outcome of dice is 5, we get a score of 25.
  - What is the expected score we get, when we roll the dice?

X	1	2	3	4	5	6
f(x)	1	4	9	16	25	36
P(x)	1/6	1/6	1/6	1/6	1/6	1/6

- The expectation of a function of a random variable is defined as:

$$\mathbb{E}_{x \sim p(x)}[f(X)] = \sum_{i=1}^{N} f(x_i)p(x_i)$$

- For the dice game, the expected score is 15.167.

Action Space

- The set of possible actions
  - E.g.) {right, down} in the Grid World.
  - E.g.) {right, left, stay, fire} in the Atari Breakout.

- Two types of action spaces
  - Discrete action space
  - Continuous action space

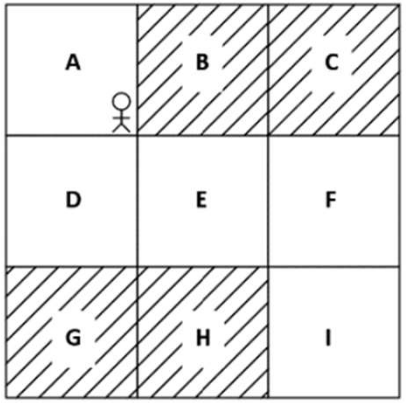
- Discrete action space
  - Action space consists of discrete actions, e.g.) up, down, left, right

- Continuous action space
  - Action space consists of continuous actions
  - E.g.) self-driving cars: speed of the car, number of degrees to rotate the wheel

Policy

- A policy defines the agent's behavior in an environment
  - Action taken by the agent in each state

states	actions
A	right
B	right
C	down
F	down

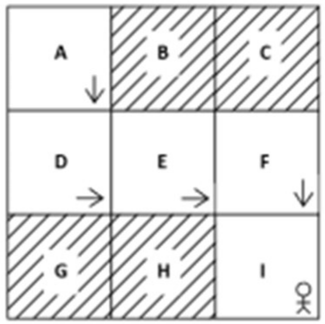


- When the agent first interacts with the environment, it uses a random policy.
  - The agent chooses a random action in every state.

- Optimal policy
  - The best policy in the environment
  - E.g.) The agent can reach the goal state without going through shaded states

Optimal Policy

State	Action
A	Down
D	Right
E	Right
F	Down



Policy: Deterministic vs. Stochastic Policy

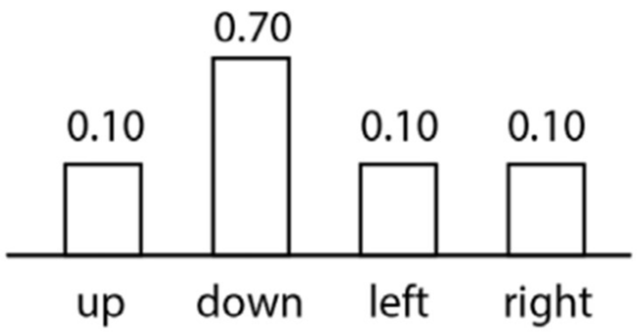
- Deterministic Policy
  - The agent performs one particular action in a state.
  - Denoted by μ → $a_t = \mu(s_t)$
  - If the agent moves down in state A, then: $\mu(A) = \text{Down}$

- Stochastic Policy
  - In each state, the agent probabilistically selects one of the possible actions
  - The agent may take different actions in a state in different episodes
  - For example, in state A, the agent moves right 70% of the time, and moves down 30% of the time.
  - The probability distribution over actions [right, down] in state A is [0.7, 0.3].
  - The probability distribution is denoted as π.
  - Expressions for stochastic policy

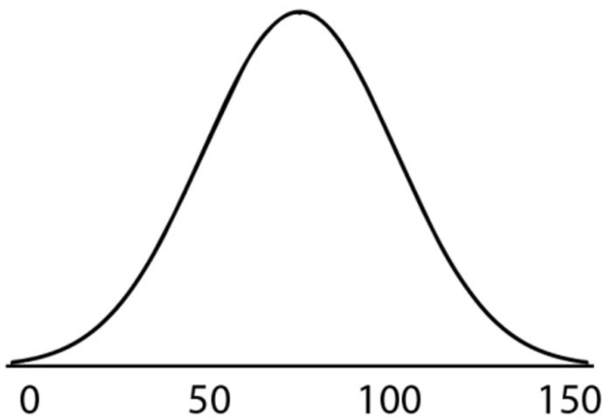
$$a_t \sim \pi(s_t) \qquad\qquad \pi(a_t | s_t)$$

Stochastic Policy: Categorical Policy vs. Gaussian Policy

- Categorical policy
  - action space is discrete
  - E.g.) actions: up, down, left, right



- Gaussian Policy
  - action space is continuous
  - E.g.) action: speed of a car, range of values: 0 to 150 kmph.
  - Probability of selecting a speed



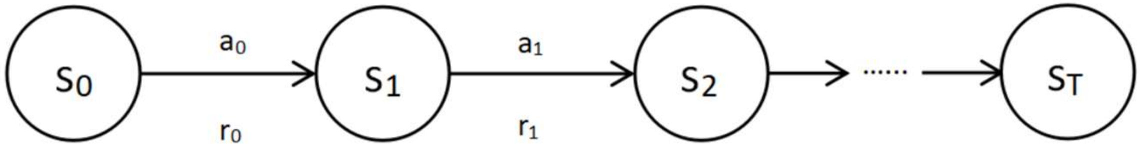
Episode

- The agent interacts with the environment by performing some actions, starting from the initial state until it reaches the final (terminal) state.
- One iteration of this interaction is called an episode.
- E.g.) In a car racing video game, the player starts racing from the starting point and moves to the endpoint. It is considered an episode.
- An episode is often called a trajectory, and is denoted by τ.

- In reinforcement learning, the agent goes through multiple episodes in order to find the optimal policy.
  - When playing a game, the user can learn good strategies to win the game by playing the game repeatedly.

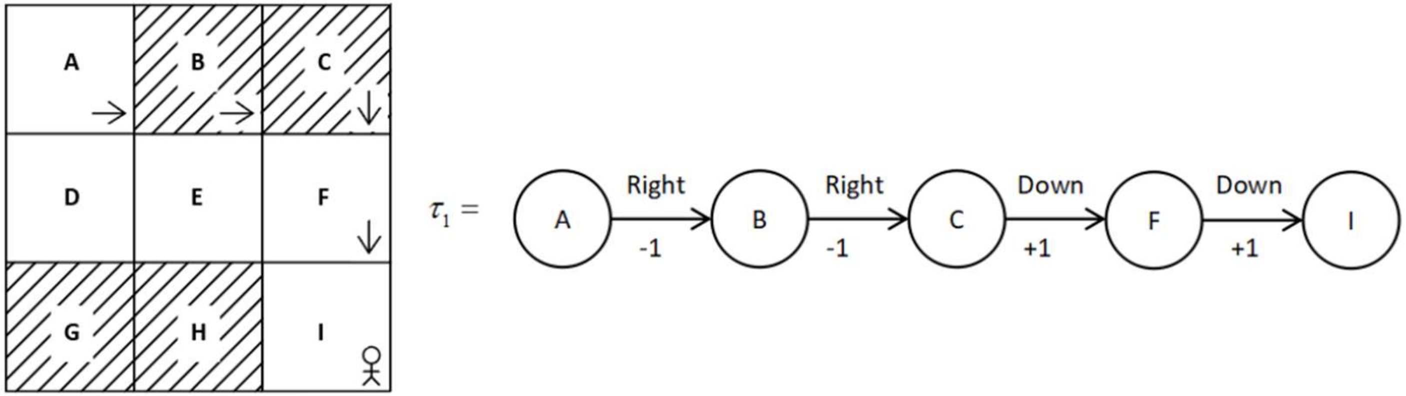
- An episode can be represented by a sequence of (state, action, reward).

$$(s_0, a_0, r_0, s_1, a_1, r_1, \ldots, s_T)$$

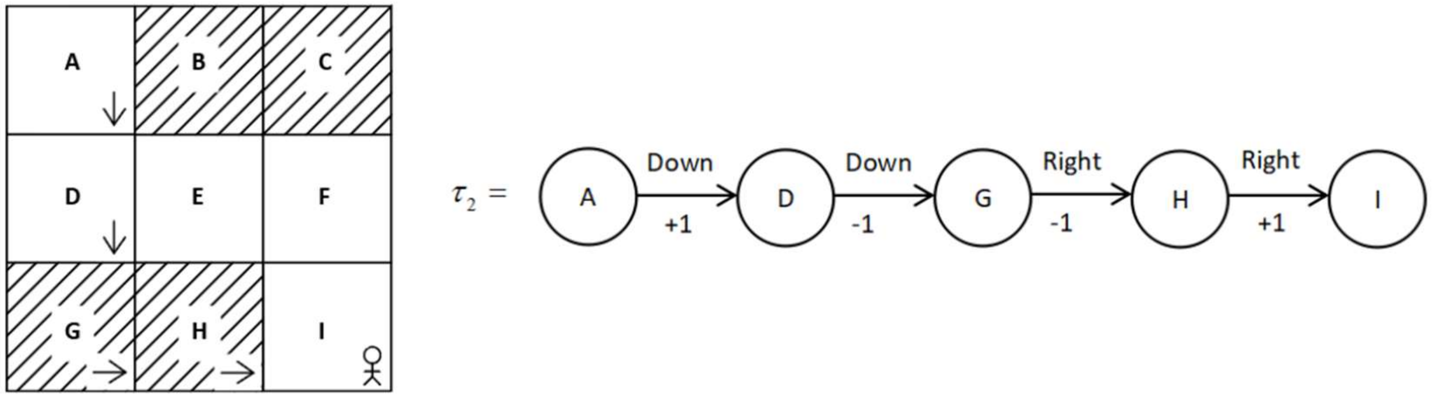


Learning Optimal Policy from Episodes (1)

- Episode 1: with no experience, the agent uses a random policy.

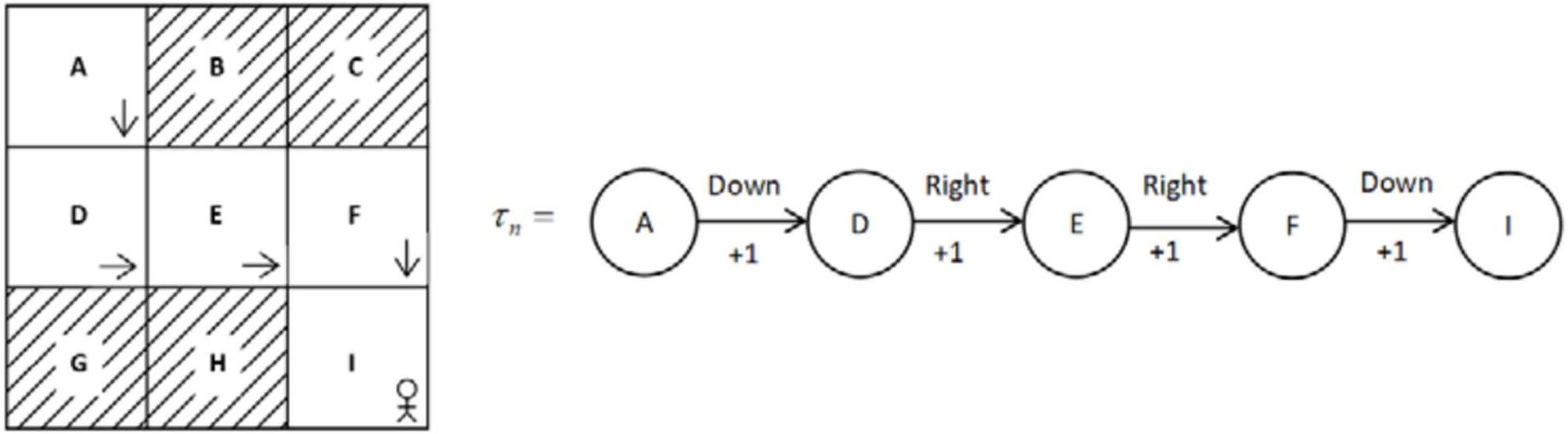


- Episode 2: since moving right in state A leads to a negative reward, the agent tries a different action this time and moves down.



Learning Optimal Policy from Episodes (2)

- Episode n: over a series of episodes the agent learns the optimal policy.



Episodic Task vs. Continuous Task

- Episodic Task
  - A task that has a terminal/final state.
  - Episodic tasks are tasks made up of episodes with terminal states.
  - E.g.) A car racing game where a car starts from the starting point and reaches the destination (final point).

- Continuous Task
  - Continuous tasks do not contain episodes, and they do not have any terminal state.
  - Continuous tasks are tasks that never end.
  - E.g.) A personal assistance robot

Horizon

- Horizon is the time step until which the agent interacts with the environment.

- Finite horizon
  - The agent-environment interaction stops at a particular time step
  - In an episodic task, an agent interacts with the environment by starting from the initial state at time step t=0 and reaches the final state at time step T.

- Infinite horizon
  - The agent-environment interaction never stops
  - In a continuous task, the agent-environment interaction does not terminate.

Return

- A return can be defined as the sum of rewards obtained in an episode.
- Denoted by R or G.
- If the agent starts an episode from the initial state at time step 0 and reaches the final state at time step T,

$$R(\tau) = r_0 + r_1 + r_2 + \ldots + r_T \qquad R(\tau) = \sum_{t=0}^{T} r_t$$

$$\begin{tikzcd}
s_0 \arrow[r, "a_0", "+2"'] & s_1 \arrow[r, "a_1", "+2"'] & s_2 \arrow[r, "a_2", "+1"'] & s_3 \arrow[r, "a_3", "+2"'] & s_4
\end{tikzcd}$$

$$R(\tau) = 2 + 2 + 1 + 2 = 7$$

- If the task is a continuous task that does not end,

$$R(\tau) = r_0 + r_1 + r_2 + \ldots + r_\infty$$

- The goal of agent is to learn an optimal policy that maximizes return.

Discount Factor

- Let us consider a continuous task that does not end.
- The return of this task can be defined as:

$$R(\tau) = r_0 + r_1 + r_2 + \ldots + r_\infty$$

- Suppose the rewards are all defined as nonnegative values.
- Then, the return sums to infinity regardless of what actions the agent takes.
- We cannot maximize return that goes to infinity.

- In order to deal with this problem, we introduce a discount factor γ.
- Discount factor is chosen from range [0, 1].
- With the discount factor, the return is defined as:

$$R(\tau) = \gamma^0 r_0 + \gamma^1 r_1 + \gamma^2 r_2 + \ldots + \gamma^n r_\infty \qquad R(\tau) = \sum_{t=0}^{\infty} \gamma^t r_t$$

- When $\gamma < 1$, the return is prevented from reaching infinity.

Small Discount Factor vs. Large Discount Factor

- Small discount factor: discount factor close to 0.
  - Suppose $\gamma = 0.2$, then return is:

$$\begin{aligned} R &= (\gamma)^0 r_0 + (\gamma)^1 r_1 + (\gamma)^2 r_2 + \dots \\ &= (0.2)^0 r_0 + (0.2)^1 r_1 + (0.2)^2 r_2 + \dots \\ &= (1) r_0 + (0.2) r_1 + (0.04) r_2 + \dots \end{aligned}$$

  - More importance is given to the immediate reward.
  - When $\gamma = 0$, the return is just the immediate reward r_0. Agent does not learn.
- Large discount factor: discount factor close to 1.
  - Suppose $\gamma = 0.9$, then return is:

$$\begin{aligned} R &= (\gamma)^0 r_0 + (\gamma)^1 r_1 + (\gamma)^2 r_2 + \dots \\ &= (0.9)^0 r_0 + (0.9)^1 r_1 + (0.9)^2 r_2 + \dots \\ &= (1) r_0 + (0.9) r_1 + (0.81) r_2 + \dots \end{aligned}$$

  - More importance is given to future rewards.
  - If $\gamma = 1$, the return becomes infinity in continuous tasks. Learning does not converge.
- The best discount factor depends on the task.

Value Function

- The value function, or the state value function, denotes the value of a state.

- The value of a state is the return an agent would obtain starting from that state following policy π.

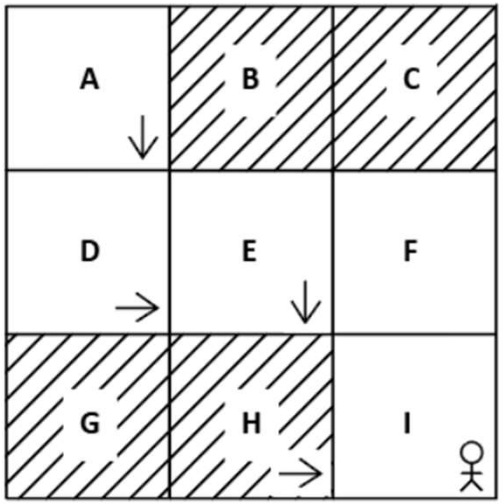
- Denoted as $V(s)$

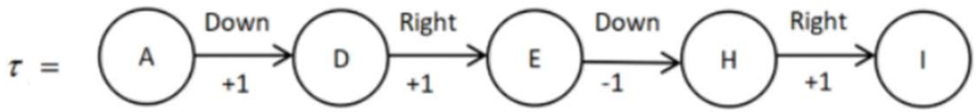
$$V^{\pi}(s) = [R(\tau) | s_0 = s]$$

- $s_0 = s$ means the starting state is s.

Value Function: Example

- In the Grid World, suppose the agent's policy is shown in the figure below.
  - A: down, D: right, E: down, H: right
- Assume we set discount factor as 1.
- V(A): return of trajectory starting from state A → 1 + 1 - 1 + 1 = 2
- V(D): return of trajectory starting from state D → 1 - 1 + 1 = 1
- V(E): return of trajectory starting from state E → -1 + 1 = 0
- V(H): return of trajectory starting from F → 1.
- V(I): terminal state → 0.





Value Function with Stochastic Policies

- When the policy is stochastic, actions in states are chosen probabilistically.
- Because of that, we use the expected return.

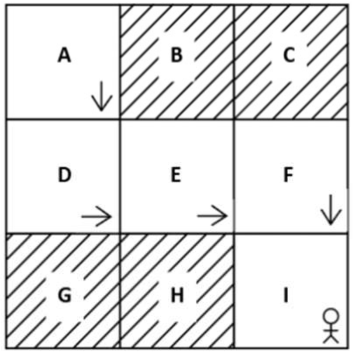
$$V^{\pi}(s) = \underset{\tau \sim \pi}{\mathbb{E}}\left[R(\tau) | s_0 = s\right]$$

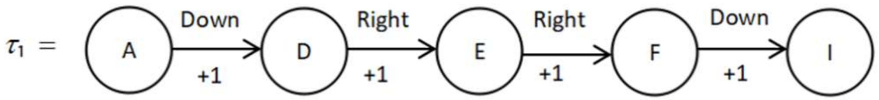
Value Function with Stochastic Policies: Example

- Let us assume the actions in all states except state A are deterministic.
- In state A, the agent moves down 80% of the time, and moves right 20% of the time.
- What is the value of state A?

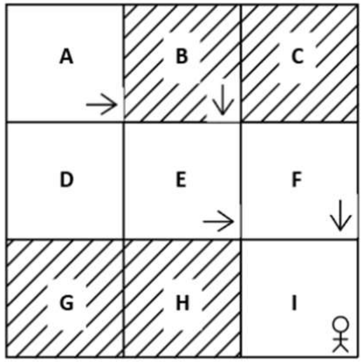
$$V^{\pi}(A) = \mathop{\mathbb{E}}_{\tau\sim\pi}[R(\tau)|s_0 = A] = \sum_i R(\tau_i)\pi(a_i|A)$$

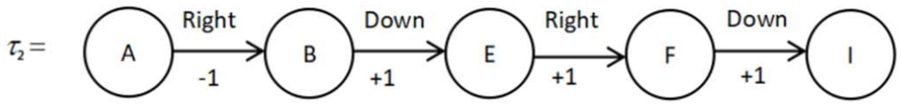
$$= R(\tau_1)\pi(\text{down}|A) + R(\tau_2)\pi(\text{right}|A)$$
$$= 4(0.8) + 2(0.2)$$
$$= 3.6$$





$$V(A) = R(\tau_1) = 1 + 1 + 1 + 1 = 4$$





$$V(A) = R(\tau_2) = -1 + 1 + 1 + 1 = 2$$

Value Function and Policy

- The value function $V(s)$ depends on the policy.
  - The value of a state varies based on the policy we choose, because the policy determines what actions are chosen in each state.

- The optimal value function $V^*(s)$ yields the maximum value compared to all other functions

$$V^*(s) = \max_{\pi} V^{\pi}(s)$$

- The policy that maximizes value of all states is called the optimal policy π^*.
  - Proof of existence of the optimal policy in finite MDPs.
    - *https://towardsdatascience.com/why-does-the-optimal-policy-exist-29f30fd51f8c*

- Value table: a table that records values of all states
  - $V(s_1) > V(s_0)$ means that it is better to be in state s_1 than s_0.
  - A state that has the maximum value is called the optimal state.

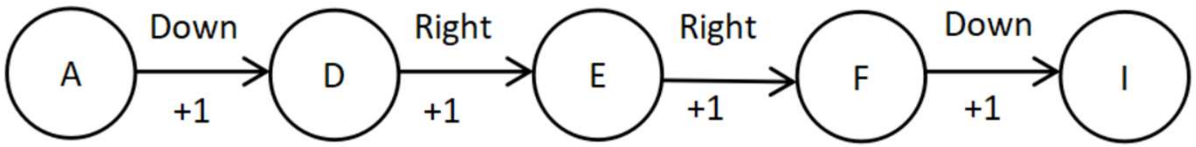
State	Value
s_0	7
s_1	11

Q Function

- The value function defines value of a state.
- The Q function defines value of a state-action pair.
- The value of a state-action pair is the return the agent would obtain starting from state s and performing action a following policy π.
- Denoted as $Q(s, a)$

$$Q^{\pi}(s, a) = [R(\tau) | s_0 = s, a_0 = a]$$

- Suppose the agent follows the policy:



- $Q^{\pi}(A, down) = [R(\tau) | s_0 = A, a_0 = down] = 1 + 1 + 1 + 1 = 4$
- $Q^{\pi}(D, right) = [R(\tau) | s_0 = D, a_0 = right] = 1 + 1 + 1 = 3$
- We can compute Q value of all state-action pairs similarly.

Q Function

- To address stochasticity, we use the expected return.

$$Q^{\pi}(s,a) = \underset{\tau\sim\pi}{\mathbb{E}}\left[R(\tau)|s_0 = s, a_0 = a\right]$$

- Similar to the value function, the Q function depends on the policy.
- The optimal Q function: one that has the maximum Q value over other Q functions.

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

- The optimal policy: the policy that gives the maximum Q value.
- Q table: represents Q values of all possible state-action pairs

State	Action	Value
s_0	0	9
s_0	1	11
s_1	0	17
s_1	1	13

Q Function and Optimal Policy

- The optimal policy can be extracted from the Q table.
  - For each state, select the action that yields the highest Q value.

Q Table

State	Action	Value
s_0	0	9
s_0	1	11
s_1	0	17
s_1	1	13

→

Optimal policy

State	Action
s_0	1
s_1	0

- Note: When we have the Q table, we can extract a policy based on the table.

Model-based Learning vs. Model-free Learning

- Here, the "model" means assumptions on the environment.

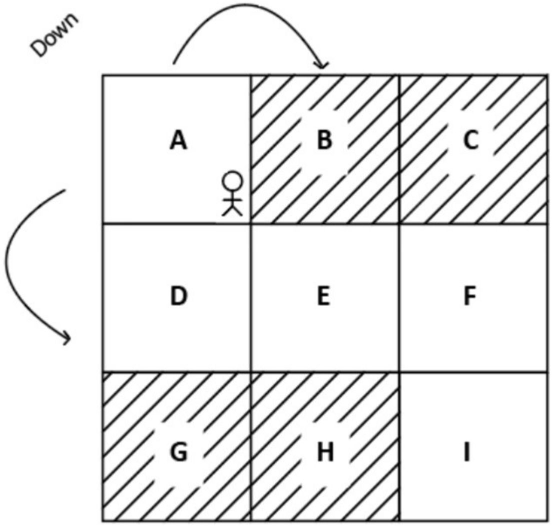
- Model-based learning
  - The environment dynamics is known.
    - Transition probability for a state-action pair.
    - Reward function is known.
  - For example, in a game of Go, the rules of the game is known.
    - The next state is determined based on the action (putting a stone on the board)
    - The rules on winning the game is also known.

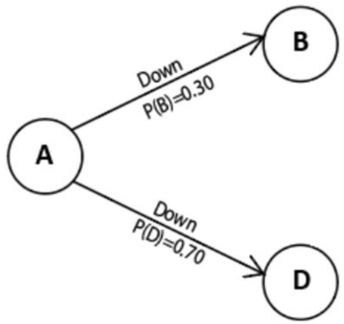
- Model-free learning
  - The agent does not know the environment dynamics.

Different Types of Environments

- The environment is the world of the agent.
  - The agent lives/stays within the environment.

- Determinisitic vs. Stochastic environments
  - Determinisitic environment: when an agent performs action a in state s, its next state is always the same.
  - Stochastic environment: when an agent performs action a in state s, its next state is determined probabilistically.
    - When the agent moves "down" in state A, the agent successfully arrive at state D 70% of the time, but it fails and ends up in state B 30% of the time.





Different Types of Environments

- Discrete vs. Continuous environments
  - Discrete environment: action space is discrete. E.g.) [up, down, left, right]
  - Continuous environment: action space is continuous. E.g.) car's speed, rotating the wheel

- Episodic vs. Non-episodic environments
  - Episodic environment: the agent's current action does not affect future actions
    - e.g.) asking a question to a bot
  - Non-episodic environment: the agent's current action affects future actions
    - Also called sequential environment
    - e.g.) chessboard

- Single vs. Multi-agent environments
  - Single-agent environment: The environment consists of a single agent.
    - e.g.) a game that is played by a single player
  - Multi-agent environment: Multiple agents are in the environment
    - e.g.) playing a soccer match

Different Types of Environments

- Fully Observable vs. Partially Observable environments
  - Fully observable environment: driving a car on the road
  - Partially observable environment: playing card games such as Poker or Blackjack

- Static vs. Dynamic environments
  - Static environment: the environment does not change while the agent is sensing the environment
    - e.g.) cleaning a room using a robot cleaner
  - Dynamic environment: the environment changes when the agent is sensing the environment
    - e.g.) playing a soccer match

Applications of Reinforcement Learning

- Manufactoring
  - Intelligent robots are trained using RL to place objects in the right position.
- Dynamic pricing
  - Based on demand and supply, an RL agent learns to determine price of products with the goal of maximizing revenue.
- Inventory management
  - RL is used for tasks such as supply chain management, demand forecasting, and handling warehouse operations (distributing products in warehouses.)
- Recommendation system
  - The RL agent learns the user's preference and recommends books, songs, or movies.
- Neural architecture search
  - RL is used to find the best neural architecture for a given task with the goal of maximizing accuracy
- Natural language processing
  - RL is used in NLP tasks such as abstractive text summarization and chatbots.
- Finance
  - RL is used in financial portfolio management, which is the process of constant redistribution of a fund into different financial products

End of Chapter

- Do you remember these keywords?

- agent
- environment
- state
- action
- reward
- action space
- policy
- episode
- episodic and continuous task
- horizon
- return
- discount factor
- value function
- Q function
- Model-based and model-free learning
- deterministic and stochastic environment

Homework: Install Python Environment + Gym Toolkit

- The Gym toolkit is a software developed and maintained by OpenAI.
  - https://gym.openai.com/
  - The toolkit provides simulated environments for training RL agents.

- Until next class, prepare a python environment and install the Gym toolkit on your computer.

- IDE: Visual Studio Code
  - https://code.visualstudio.com/
  - Install Python extension

- Virtual Environment Manager: Anaconda
  - https://www.anaconda.com/products/individual-d

Homework: Install Python Environment + Gym Toolkit

- Goal: you can successfully import the gym library in your python program.

- Try running the following code and see if you get a printout of the Frozen Lake environment.

```
[1]
import gym
env = gym.make("FrozenLake-v0")
state = env.reset()
env.render()

SFFF
FHFH
FFFH
HFFG
```

End of Class

Questions?

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