Artificial Intelligence and Mobility Lab

Reinforcement Learning Algorithms and Applications

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Introduction and Preliminaries

Deep Reinforcement Learning Theory

Deep Reinforcement Learning Implementation

Imitation Learning

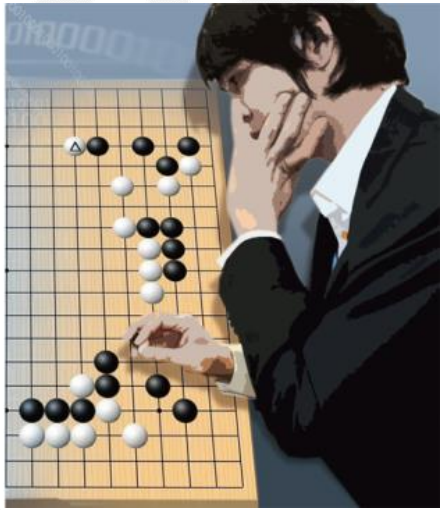
Autonomous Mobility Applications

- **Introduction and Applications**
- Q-Learning
- Dynamic Programming
- Markov Decision Process

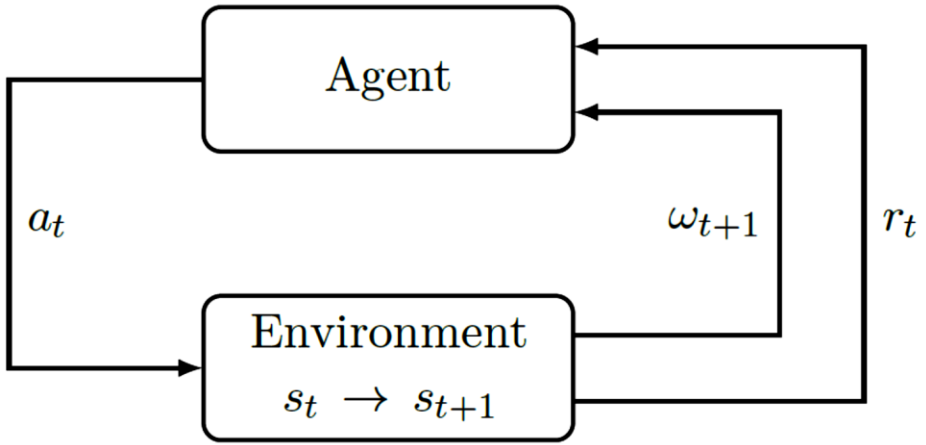
- Brief History and Successes
  - Minsky's PhD thesis (1954): Stochastic Neural-Analog **Reinforcement** Computer
  - Analogies with animal learning and psychology
  - Job-shop scheduling for NASA space missions (Zhang and Dietterich, 1997)
  - Robotic soccer (Stone and Veloso, 1998) – part of the world-champion approach

- When RL can be used?
  - Find the (approximated) **optimal action sequence** for **expected reward maximization (not for single optimal solution)**
  - Define **actions** and **rewards**. These are all we need to do.

- Action Sequence (also called **Policy**, later in this presentation)!



- **RL Setting**
  - The general RL problem is formalized as a **discrete time stochastic control process** where **an agent interacts with its environment** as follows:
    1. The agent starts
       in a given state within its environment $s_0 \in S$
       by gathering an initial observation $\omega_0 \in \Omega$.
    2. At each time step t,
       The agent has to take an action $a_t \in A$.
       It follows three consequences:
       1) Obtains a reward $r_t \in R$
       2) State transitions to $s_{t+1} \in S$
       3) Obtains an observation $\omega_{t+1} \in \Omega$



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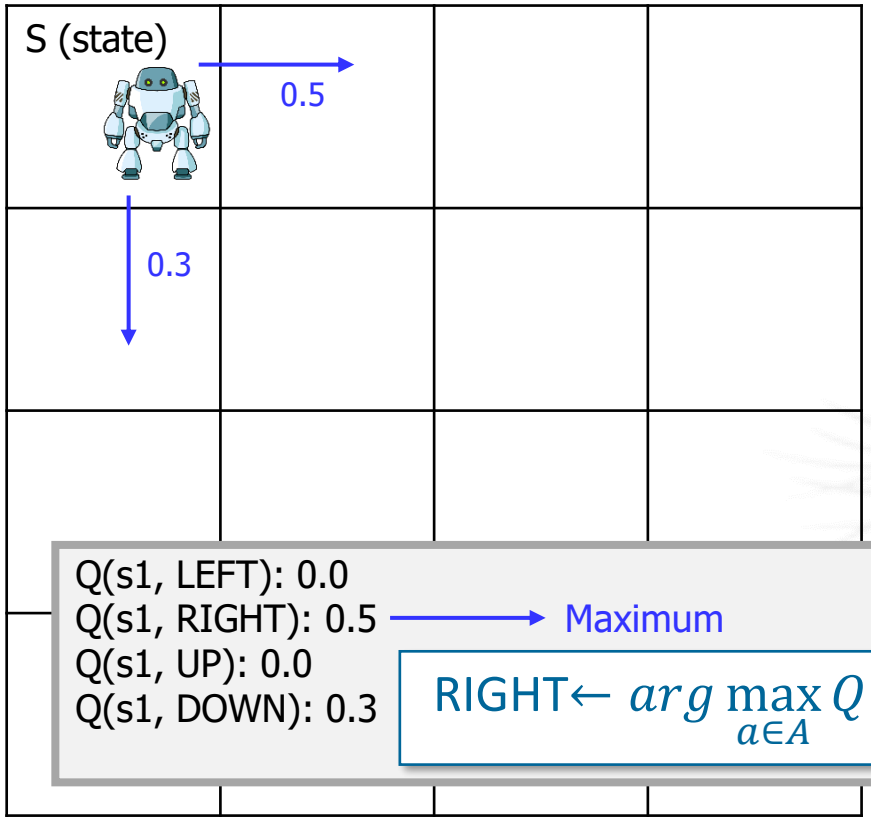
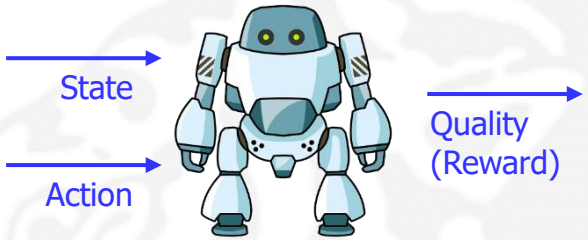


Q(s1, LEFT): 0.0
Q(s1, RIGHT): 0.5 → Maximum
Q(s1, UP): 0.0
Q(s1, DOWN): 0.3

RIGHT← $arg\max_{a \in A} Q(s_1, a)$

- Q-Function (State-action value)

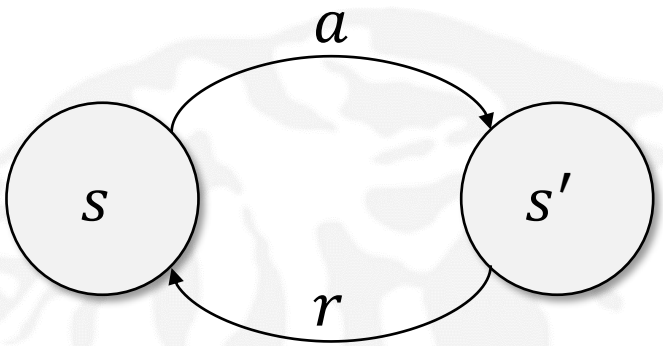


Q (state, action)

Optimal Policy π and Max Q

- Max Q = $\max_{a'} Q(s, a')$
- $\pi^*(s) = arg\max_{a} Q(s, a)$

- My condition
  - I am now in state s
  - When I do action a, I will go to s'.
  - When I do action a, I will get reward r
  - Q in s', it means $Q(s', a')$ exists.



- How can we express $Q(s, a)$ using $Q(s', a')$?

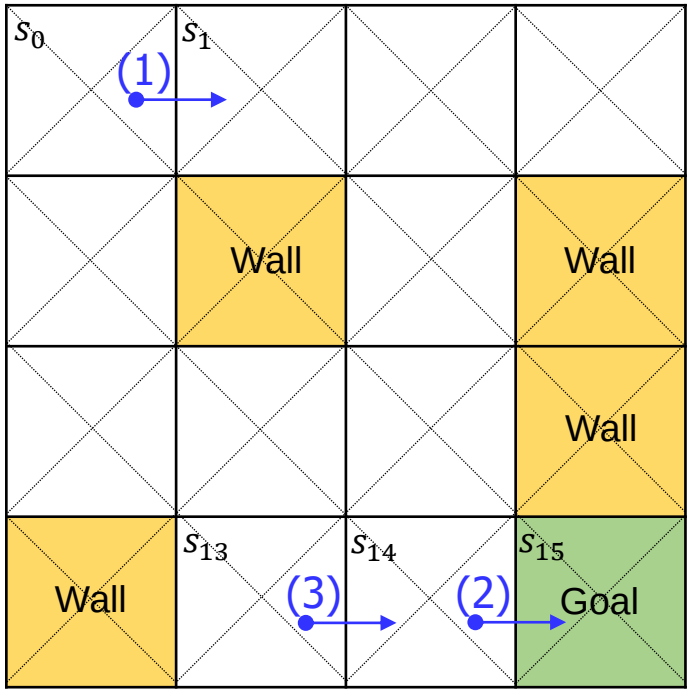
$$Q(s, a) = r + \max_{a'} Q(s', a')$$

Recurrence (e.g., factorial)

```
F(x){
        if (x != 1){ x * F(x-1) }
        if (x == 1){ F(x) = 1 }
        }
}
```

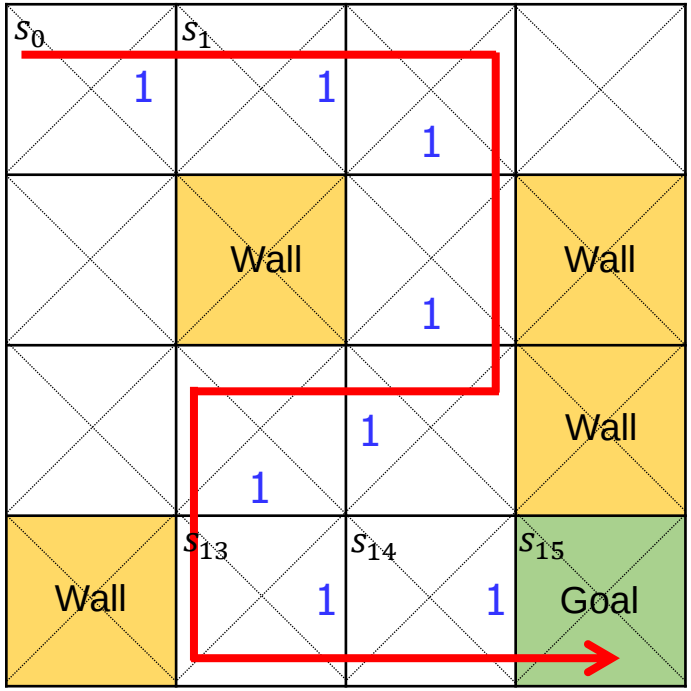
3! = F(3) = 3 * F(2)
= 3 * 2 * F(1)
= 3 * 2* 1 = 6

- 16 states and 4 actions (U, D, L, R)

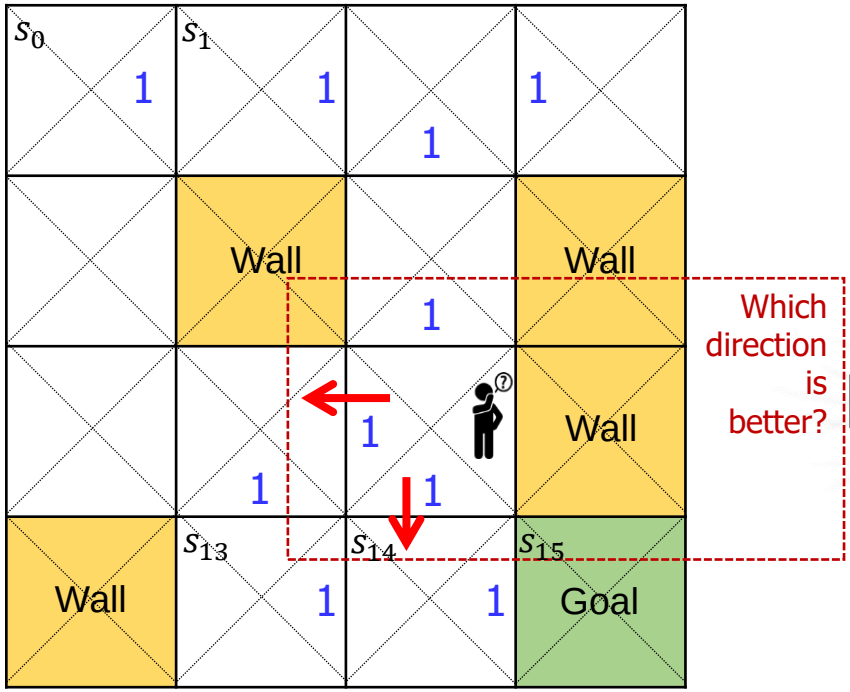


- Initial Status
  - All 64 Q values are 0,
  - Reward are all zero except $r_{s_{15},L} = 1$
- For (1), from s_0 to s_1
  - $Q(s_0, a_R) = r + \max_a Q(s_1, a) = 0 + \max\{0,0,0,0\} = 0$
- For (2), from s_{14} to s_{15} (goal)
  - $Q(s_{14}, a_R) = r + \max_a Q(s_{15}, a) = 1 + \max\{0,0,0,0\} = 1$
- For (3), from s_{13} to s_{14}
  - $Q(s_{13}, a_R) = r + \max_a Q(s_{14}, a) = 0 + \max\{0,0,1,0\} = 1$

- 16 states and 4 actions (U, D, L, R)



- 16 states and 4 actions (U, D, L, R)



Learning $Q(s,a)$ with Discounted Reward

$$Q(s,a) = r + \gamma \cdot arg\max_{a} Q(s',a')$$

$$0 < \gamma \leq 1$$

- For each s, a, initialize table entry $Q(s, a) \leftarrow 0$
- Observe current state s
- Do forever
  - Select an action a and execute it
  - Receive immediate reward r
  - Observe the new state s'
  - Update the table entry for $Q(s, a)$ as follows:

$$Q(s, a) \leftarrow r + \max_{a'} Q(s', a')$$

  - $s \leftarrow s'$

Q-Learning with Exploit and Exploration: ε-Greedy

Finding the Best Restaurant

- Try the best one during weekdays.
- Try new ones during weekends.

ε-Greedy

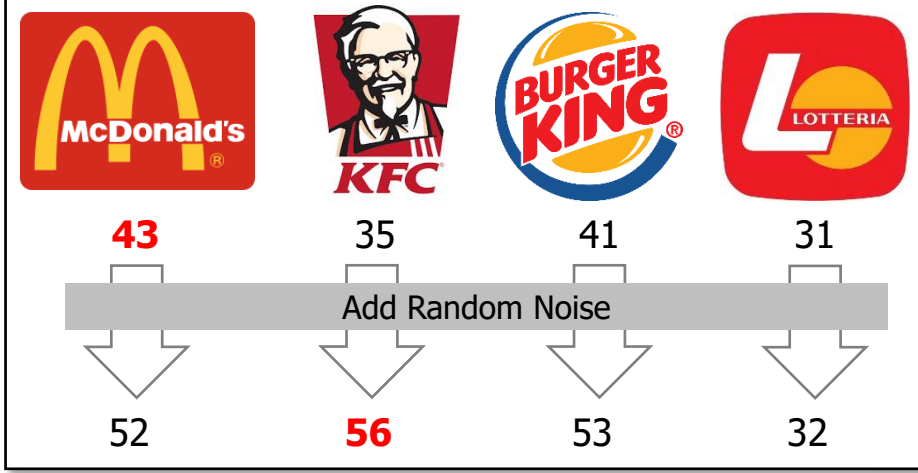
```
e=0.1
IF (random < e)
        a = random;
ELSE
        a = argmax(Q(s,a));
```

Decaying ε-Greedy

```
for i in range (1000); e=0.1 / (i+1);
IF (random < e)
        a = random;
ELSE
        a = argmax(Q(s,a));
```

Q-Learning with Exploit and Exploration: Add Random Noise

Finding the Best Restaurant



Add Random Noise

a = argmax(Q(s,a) + **random_values**);

Add Decaying Random Noise

for i in range (1000);
a = argmax(Q(s,a) + random**/(i+1)**);

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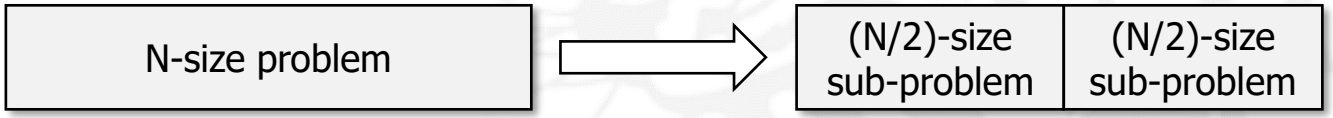
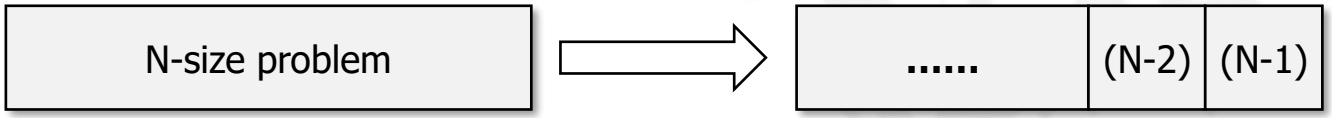
- **Introduction**
- Applications
  - Fibonacci Number
  - Pascal's Triangle
  - Knapsack Problem

- Dynamic Programming
  - The term “programming” stands for “planning”.
  - Usually used for optimization problems
  - In order to solve large-scale problems, (i) divide the problems into several sub-problems, (ii) solve the sub-problems, and (iii) obtain the solution of the original problem based on the solutions of the sub-problems, recursively
  - Difference from divide-and-conquer
    - Divide-and-conquer

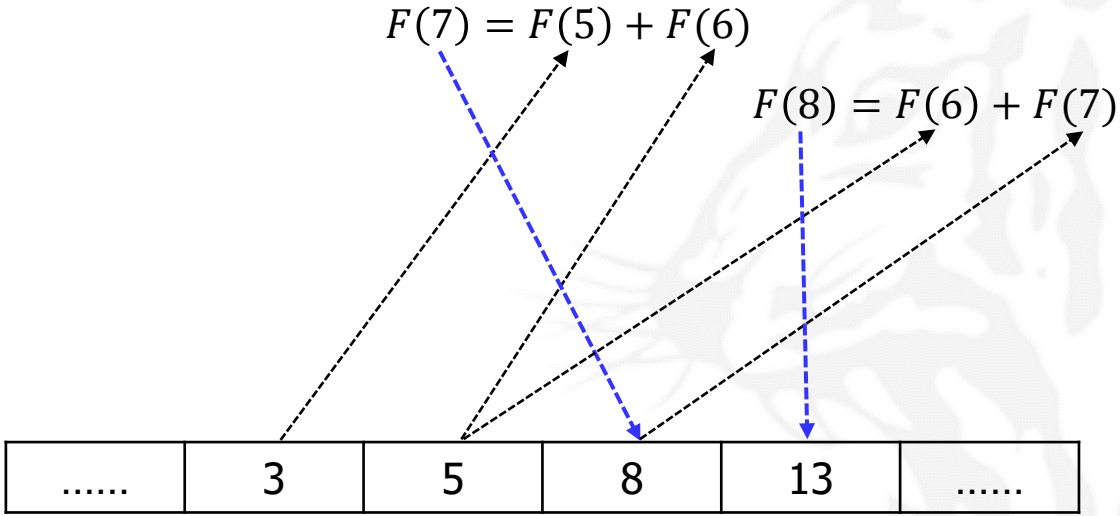


    - Dynamic programming



- Introduction
- Applications
  - **Fibonacci Number**
  - Pascal's Triangle
  - Knapsack Problem

- Fibonacci Number
  - 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, 233, ……
  - $F(N) = F(N-2) + F(N-1)$ where $F(1) = 0$ and $F(2) = 1$ (Recursive!)

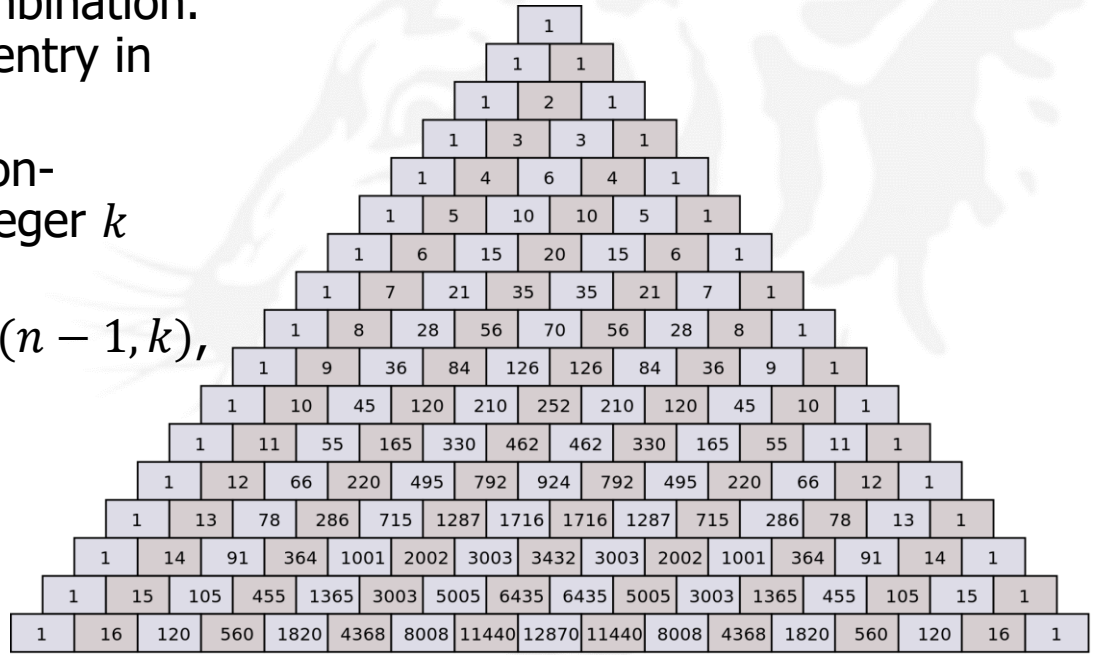


- Introduction
- Applications
  - Fibonacci Number
  - **Pascal's Triangle**
  - Knapsack Problem

- Pascal's Triangle
  - The entry in the n-th row and k-th column of Pascal's triangle is denoted $C(n,k)$ where C stands for combination. Note that the unique nonzero entry in the topmost row is $C(0,0) = 1$.
  - General Formulation for any non-negative integer n and any integer k between 0 and n:

    $$C(n,k) = C(n-1,k-1) + C(n-1,k),$$

  - Recursive!



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- **Markov Decision Process**

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Autonomous Mobility Applications

- Markov Decision Process (MDP) Components: $<S, A, R, T, \gamma>$
  - S: Set of states
  - A: Set of actions
  - R: Reward function
  - T: Transition function
  - γ: Discount factor

How can we use MDP to model agent in a maze?

- Markov Decision Process (MDP) Components: <S, A, R, T, γ>
  - **S: Set of states**
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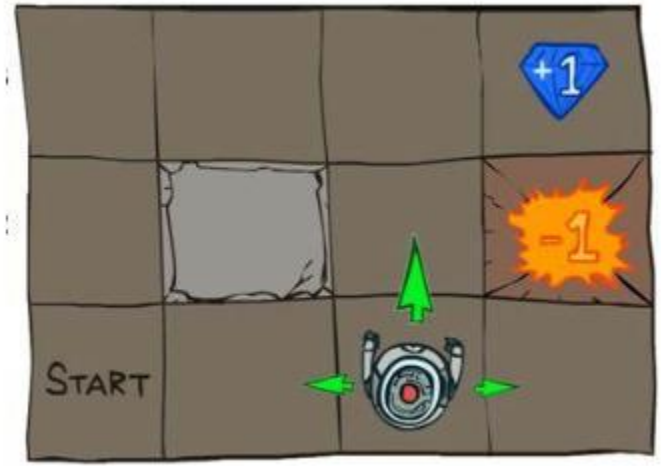

S: location (x, y) if the maze is a 2D grid
- s_0: starting state
- s: current state
- s': next state
- s_t: state at time t

- Markov Decision Process (MDP) Components: $<S, A, R, T, \gamma>$
  - S: Set of states
  - **A: Set of actions**
  - R: Reward function
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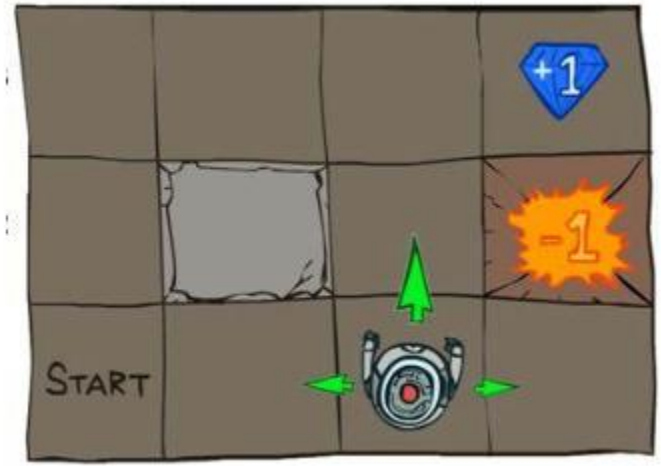

S: location (x, y) if the maze is a 2D grid

A: move up, down, left, or right

- $s \rightarrow s'$

- Markov Decision Process (MDP) Components: $<S, A, R, T, \gamma>$
  - S: Set of states
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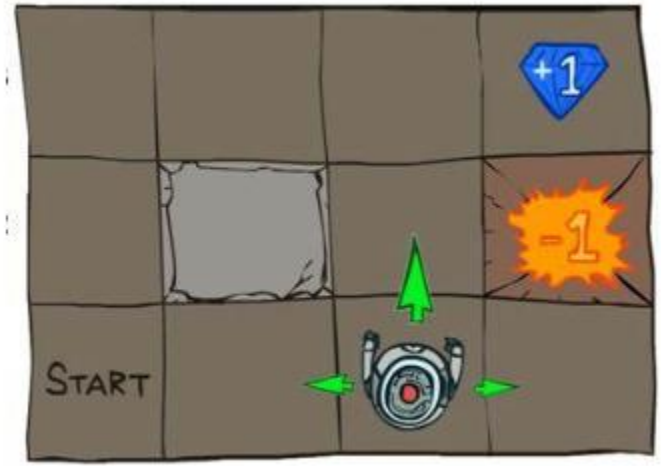

S: location (x, y) if the maze is a 2D grid
A: move up, down, left, or right
R: how good was the chosen action?
- $r = R(s, a, s')$
- -1 for moving (battery used)
- +1 for jewel? +100 for exit?

- Markov Decision Process (MDP) Components: $<S, A, R, T, \gamma>$
  - S: Set of states
  - A: Set of actions
  - R: Reward function
  - **T: Transition function**
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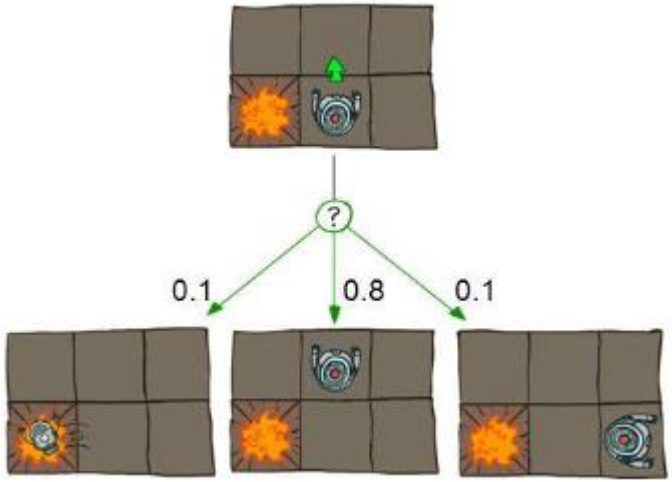


Stochastic Transition

S: location (x, y) if the maze is a 2D grid
A: move up, down, left, or right
R: how good was the chosen action?
T: where is the robot's new location?
- $T = P(s'|s, a)$

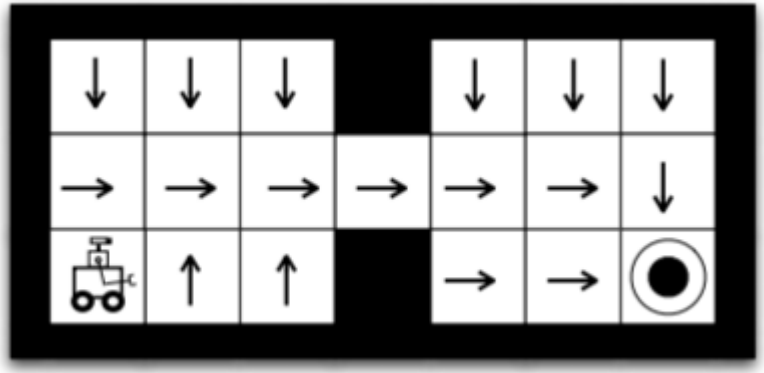
- Markov Decision Process (MDP) Components: <S, A, R, T, γ>
  - S: Set of states
  - A: Set of actions
  - R: Reward function
  - T: Transition function
  - **γ: Discount factor**

S: location (x, y) if the maze is a 2D grid
A: move up, down, left, or right
R: how good was the chosen action?
T: where is the robot's new location?
γ: how much does future reward worth?

- $0 \leq \gamma \leq 1$, [$\gamma \approx 0$: future reward is near 0 (immediate action is preferred)]

- Policy
  - $\pi: S \rightarrow A$
  - Maps states to actions
  - Gives an action for every state
- Return
  -

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$$



Our goal:
Find π that maximizes expected return!

- Action Value Function (Q)

$$Q^{\pi}(s,a) = E_{\pi}(R_t|s_t = s, a_t = a) = E_{\pi}\left(\sum_{k=0}^{\infty} \gamma^k r_{t+k} \,\middle|\, s_t = s, a_t = a\right)$$

  - Expected return of starting at state s, taking action a, and then following policy π
  - How much return do I expect starting from state s and taking action a?

- Our goal is to find the optimal policy

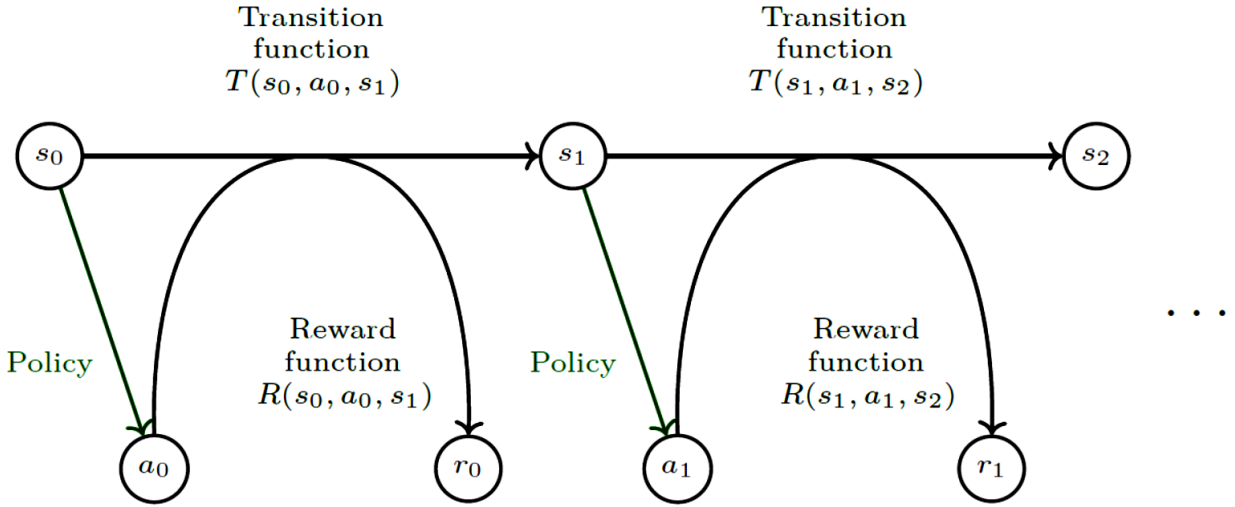
$$\pi^*(s) = \max_{\pi} R^{\pi}(s)$$

  - If $T(s'|s,a)$ and $R(s,a,s')$ are known, this is a **planning** problem.
  - We can use **dynamic programming** to find the optimal policy.

- **Markov Property**
  - [Definition (Markovian)] A discrete time stochastic control process is Markovian (i.e., it has the Markov property) if
    - $P(\omega_{t+1}|\omega_t, a_t) = P(\omega_{t+1}|\omega_t, a_t, \cdots, \omega_0, a_0)$, and
    - $P(r_t|\omega_t, a_t) = P(r_t|\omega_t, a_t, \cdots, \omega_0, a_0)$
  - The Markov property means that the future of the process only depends on the current observation, and the agent has no interest in looking at the full history.

- **Markov Property**
  - [Definition (MDP)] A Markov Decision Process (MDP) is a discrete time stochastic control process defined as follows. An MDP is a 5-tuple (S, A, T, R, γ) where:
    - S is the state space,
    - A is the action space,
    - $T: S \times A \times S \to [0,1]$ is the transition function (set of conditional transition probabilities between states),
    - $R: S \times A \times S \to R$ is the reward function, where R is a continuous set of possible rewards in a range $R_{\max} \in R^{+}$ (e.g., $[0, R_{\max}]$),
    - $\gamma \in [0,1)$ is the discount factor.

- **Markov Property**
  - The system in [Definition (MDP)] is fully observable in an MDP, which means that the observation is the same as the state of the environment: $\omega_t = s_t$.
  - At each time step t,
    - The probability of moving to s_{t+1} is given by the state transition function $T(s_t, a_t, s_{t+1})$ and the reward is given by a bounded reward function $R(s_t, a_t, s_{t+1}) \in R$.



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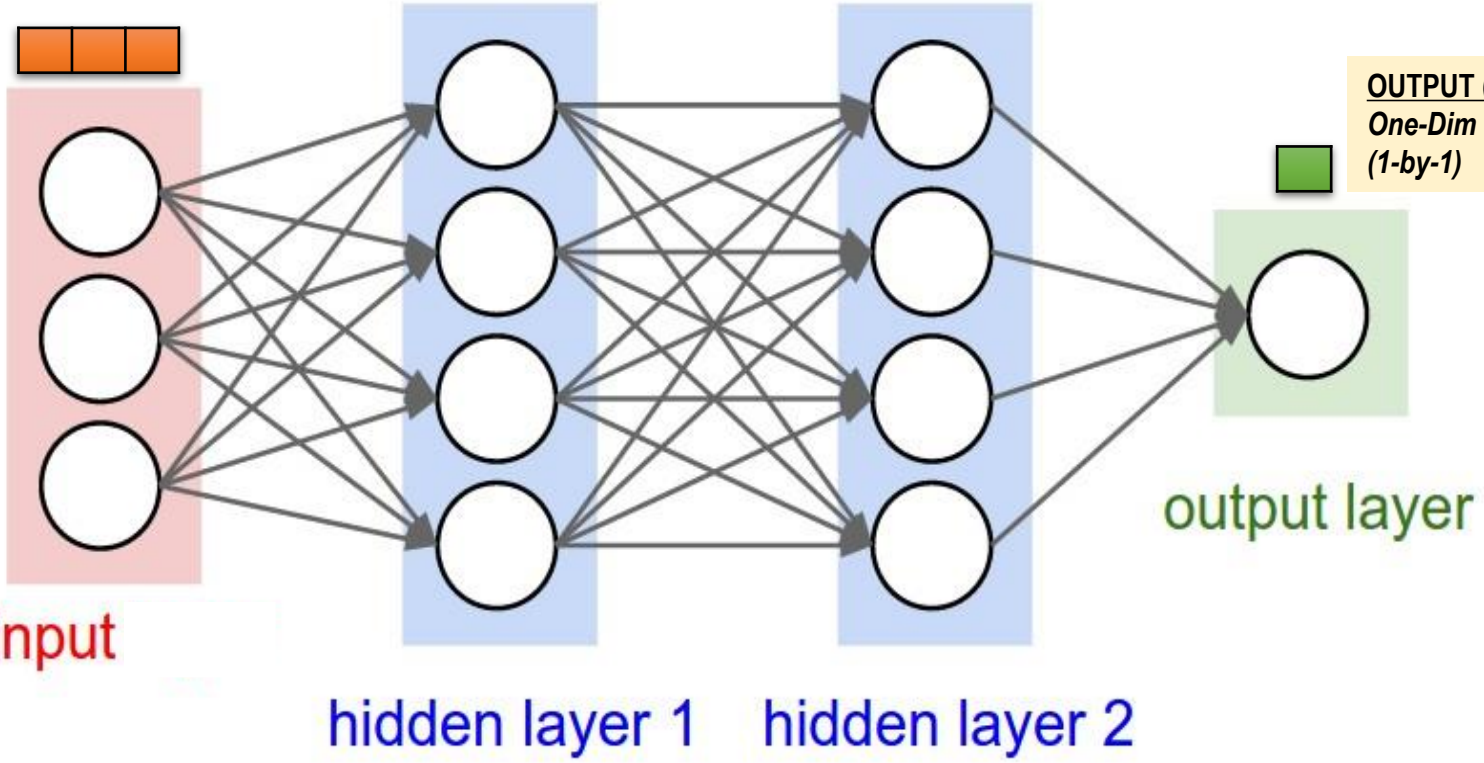
- **Deep Neural Network Summary**
- Deep Q-Network (DQN)

Reinforcement Learning (RL) vs. Deep Reinforcement Learning (DRL)

	RL (i.e., MDP)	DRL
Pros	Optimal	Fast Computation
Cons	Pseudo-Polynomial	Non-Optimal

- Toy Model

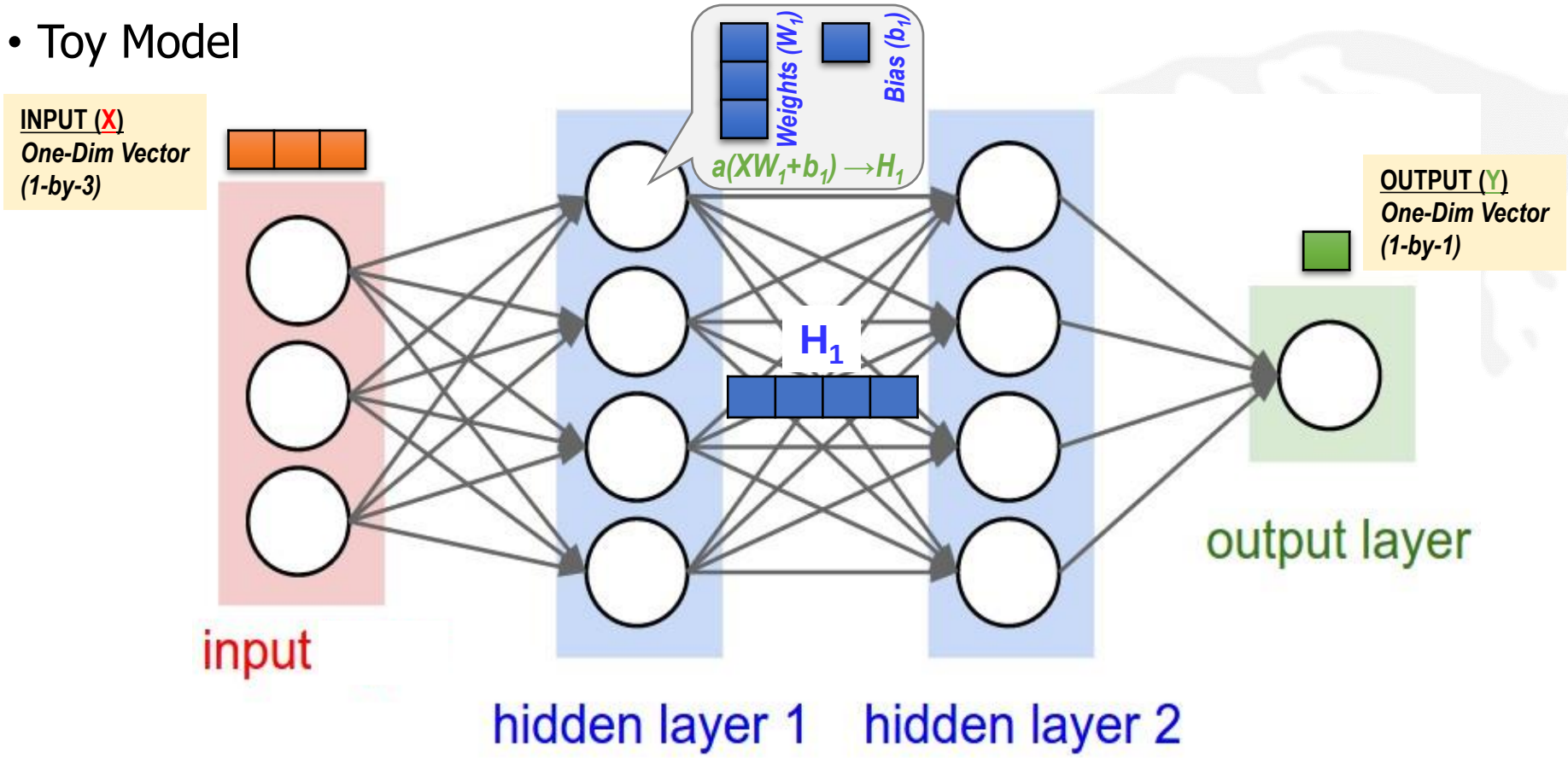
INPUT (X)
One-Dim Vector (1-by-3)



OUTPUT (Y)
One-Dim Vector (1-by-1)

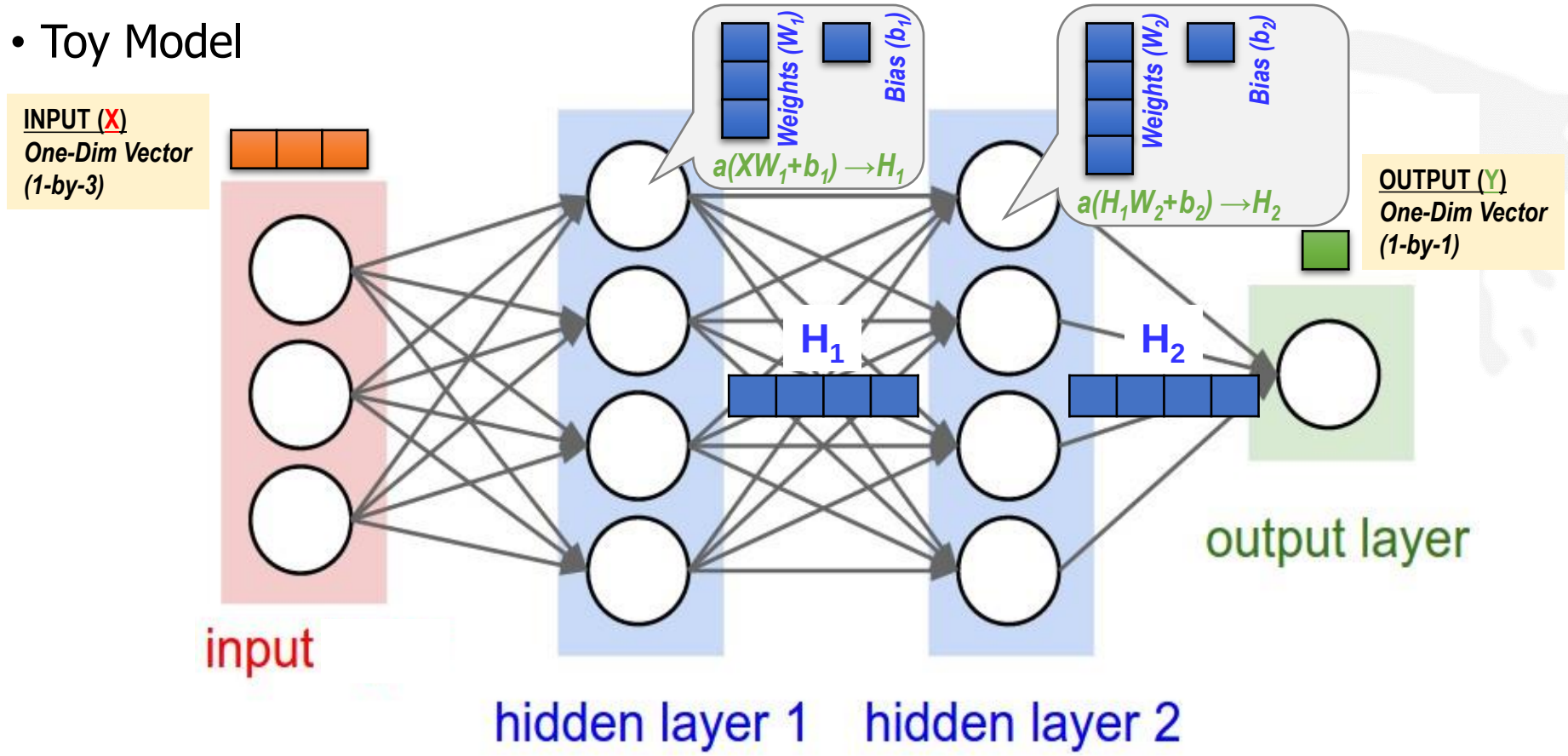
Conventional Deep Neural Network Training and Inference

- Toy Model



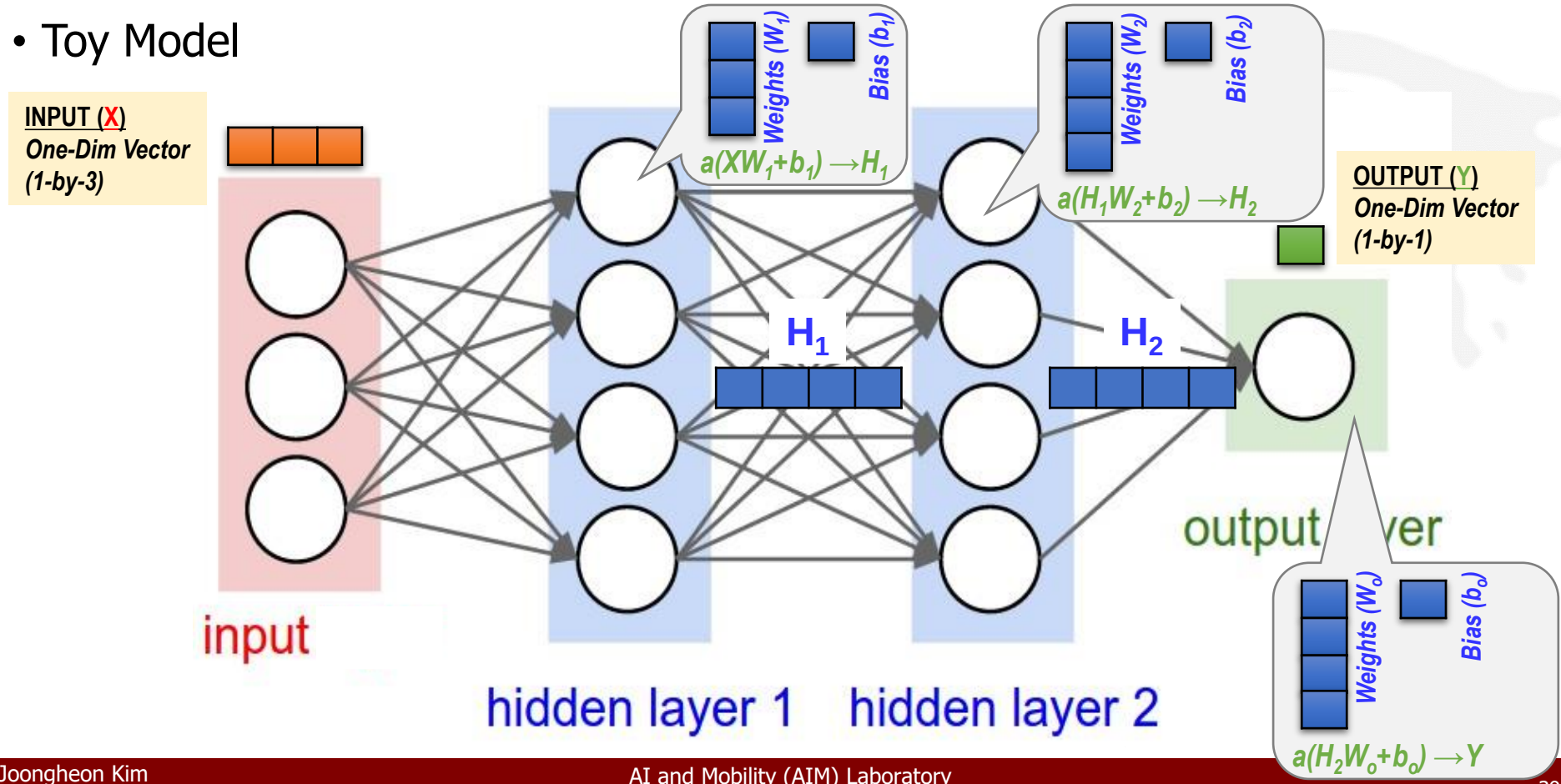
Conventional Deep Neural Network Training and Inference

- Toy Model



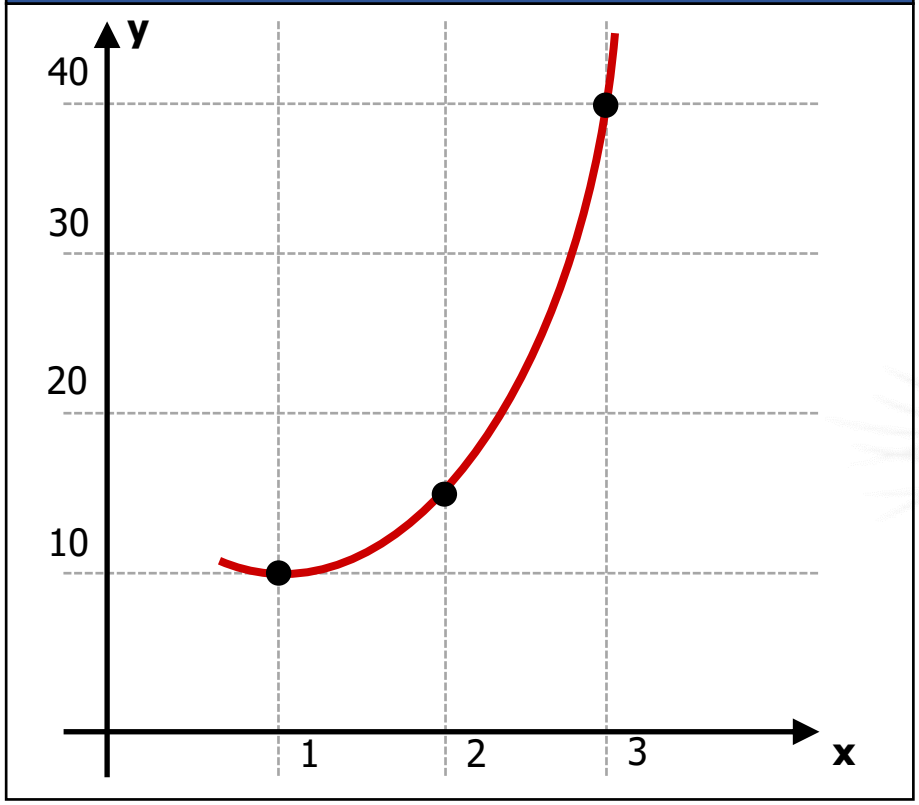
Conventional Deep Neural Network Training and Inference

- Toy Model

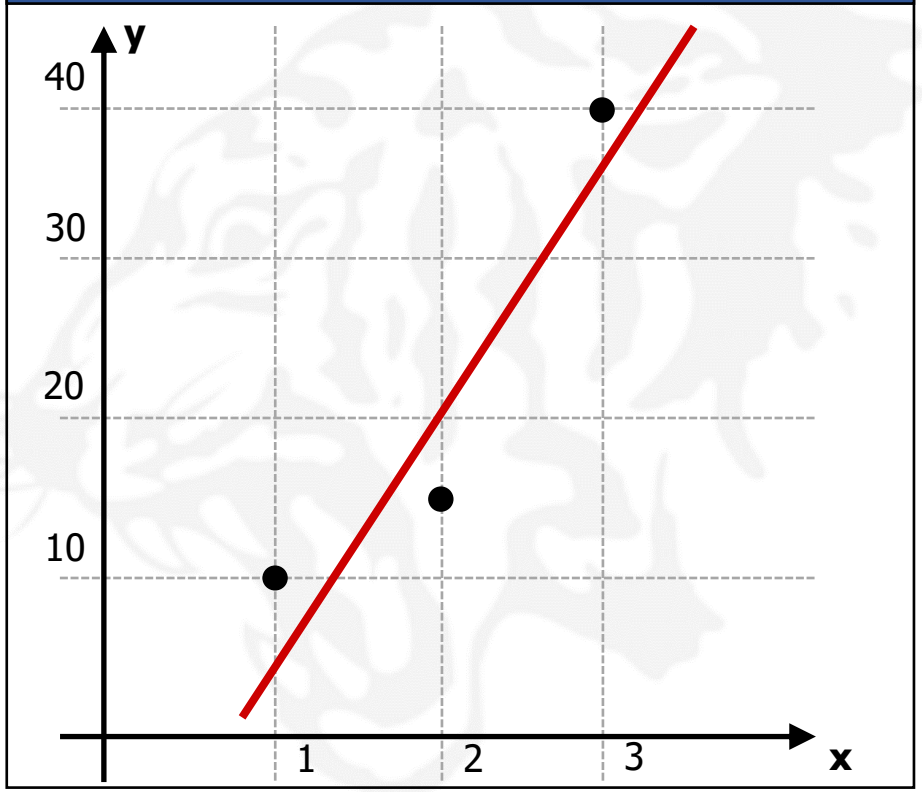


Interpolation vs. Linear Regression

Interpolation

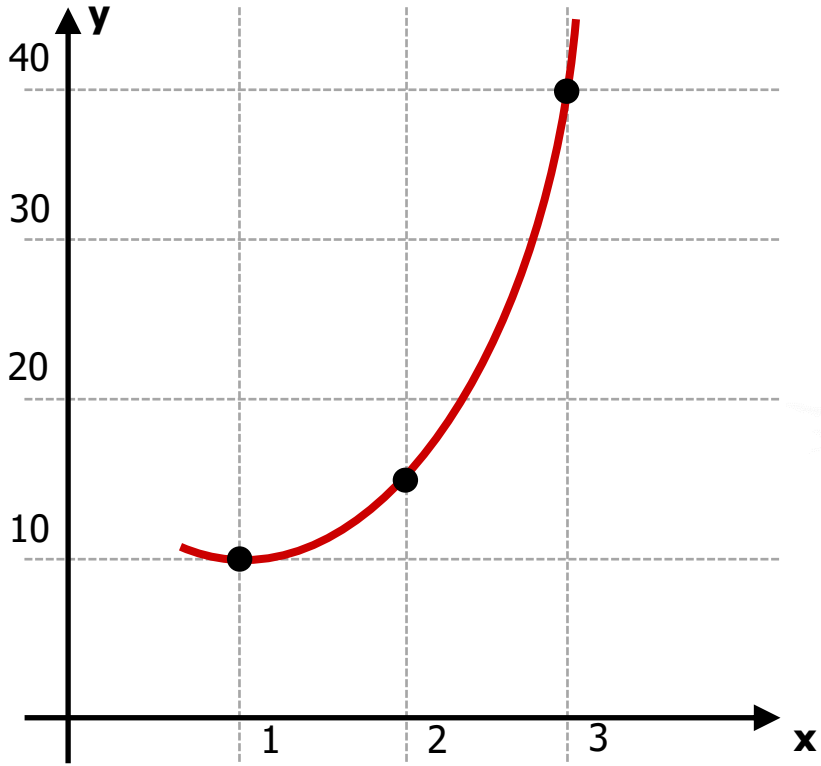


Linear Regression



Interpolation vs. Linear Regression

Interpolation

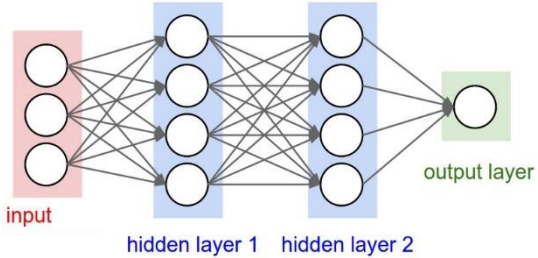


Interpolation with Polynomials

$$y = a_2 x^2 + a_1 x^1 + a_0$$

where three points are given.
→ Unique coefficients (a_0, a_1, a_2) can be calculated.

Is this related to
Neural Network Training?



$$Y = a(a(a(X \cdot W_1 + b_1) \cdot W_2 + b_2) \cdot W_o + b_o)$$

where training data/labels (X: data, Y: labels) are given.

→ Find $W_1, b_1, W_2, b_2, W_o, b_o$

→ This is the mathematical meaning of neural network training.

→ **Function Approximation**

→ The most well-known function approximation with neural network: **Deep Reinforcement Learning**

	RL (i.e., MDP)	DRL
Pros	Optimal	Fast Computation
Cons	Pseudo-Polynomial	Non-Optimal

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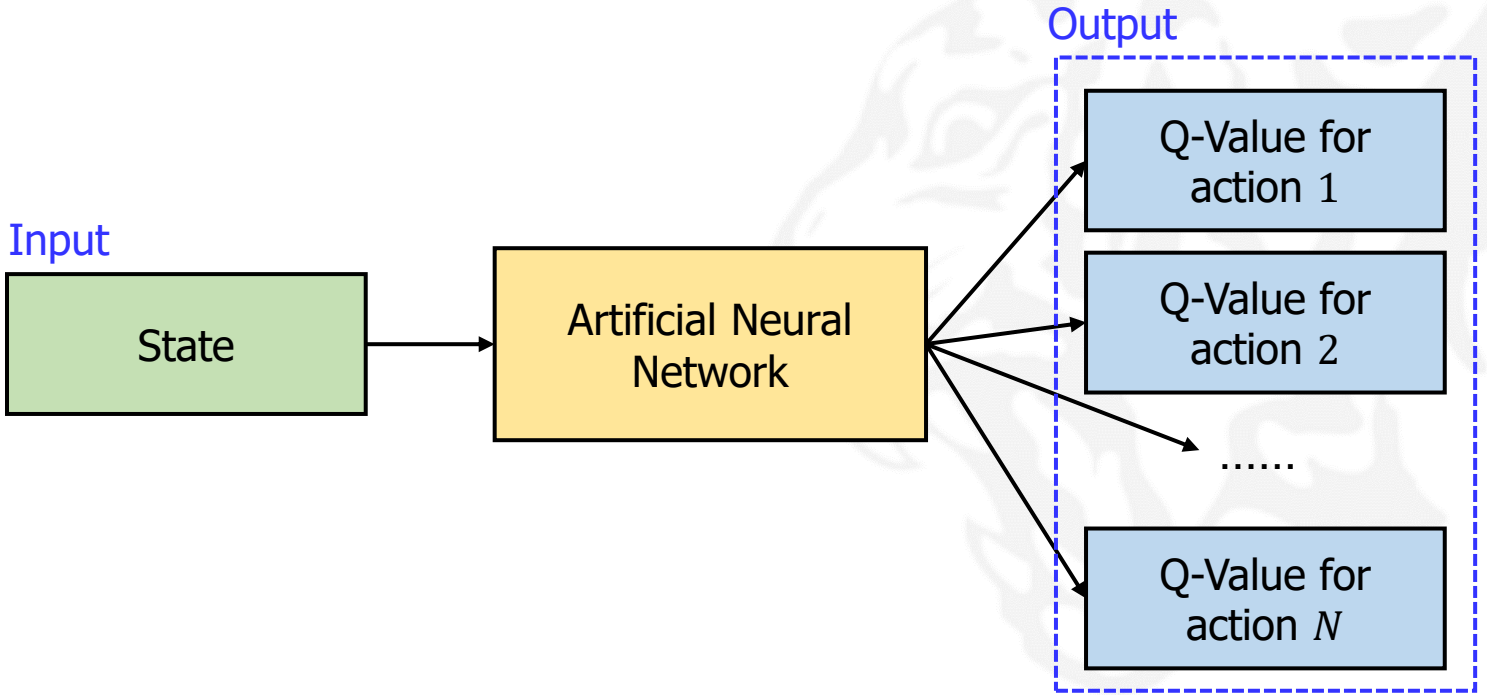
Autonomous Mobility Applications

- Large-Scale Q-Values
  - It is inefficient to make the Q-table for each state-action pair.
    → ANN is used to **approximate the Q-function**.



Lecture Roadmap

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Deep Reinforcement Learning Theory

Deep Reinforcement Learning Implementation

Imitation Learning

Autonomous Mobility Applications

- Gameplay

Pro-Gamer

Trained Agent

The goal of Imitation Learning is to train a policy to mimic **the expert's demonstrations**

- Problems of RL

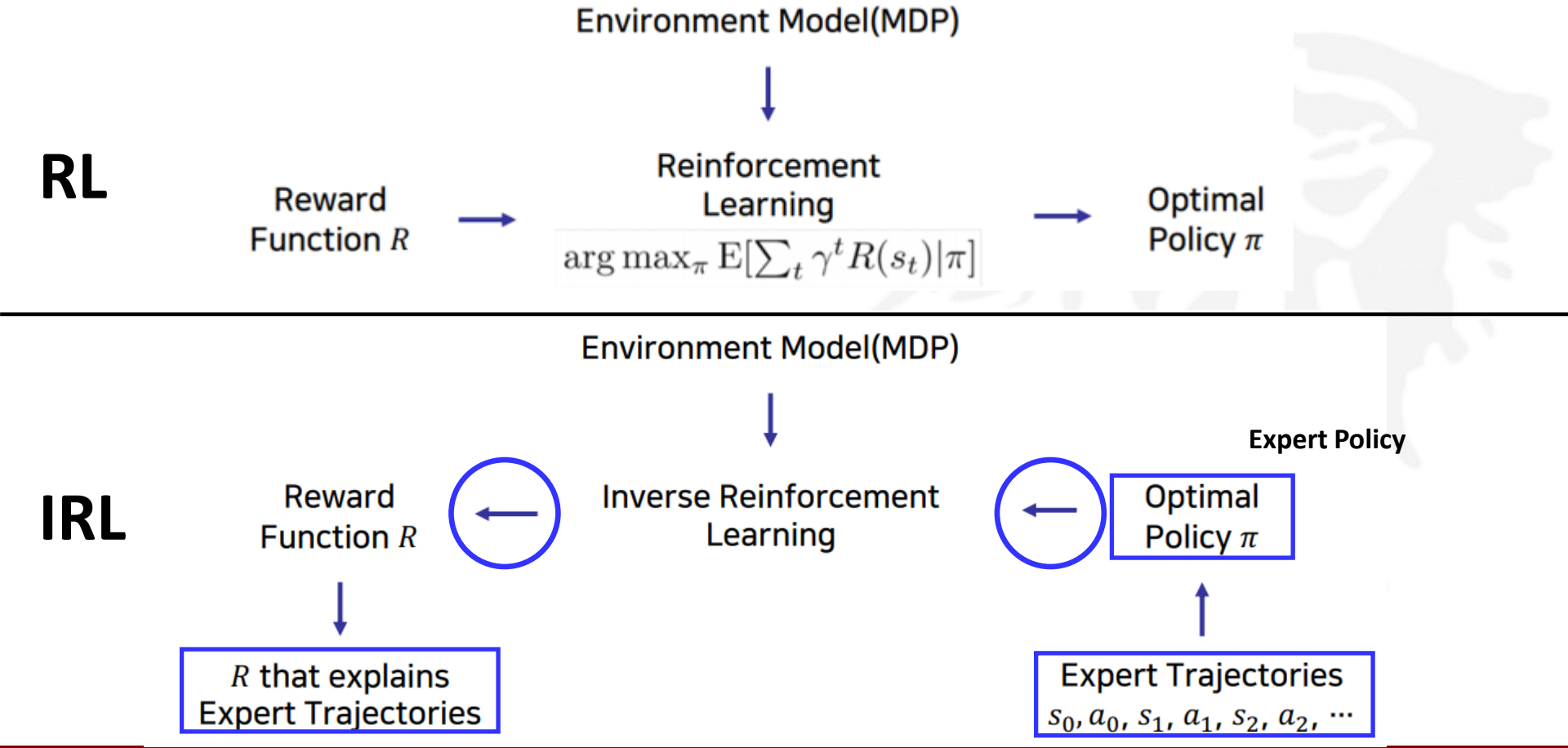
1. Reward Shaping

2. Safe Learning

3. Exploration process

Imitation Learning **handles with** these problems
through the demonstration of the experts.

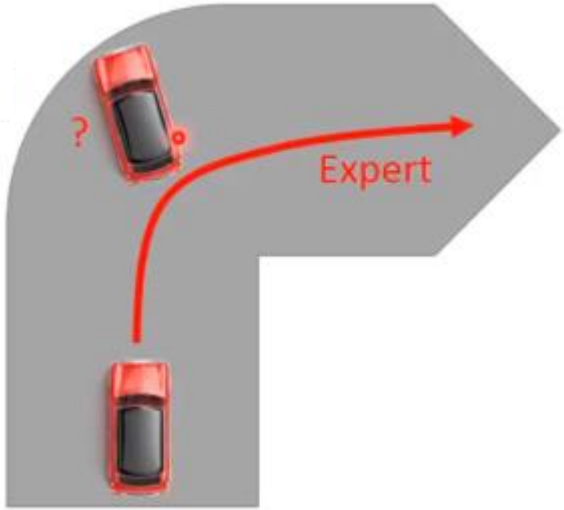
Inverse Reinforcement Learning (IRL)



- **Behavior Cloning**
  - Define $P^* = P(s|\pi^*)$ (distribution of states visited by **expert**)
  - **Learning objective**

$$argmin_{\boldsymbol{\theta}} E_{(s,a_E)\sim P^*} L(a_E, \pi_{\boldsymbol{\theta}}(s))$$
$$L\left(a_E, \pi_{\boldsymbol{\theta}}(s)\right) = \left(a_E - \pi_{\boldsymbol{\theta}}(s)\right)^2$$

  - **Discussion**
    - Works well when P^* close to the distribution of states visited by $\pi_{\boldsymbol{\theta}}$
    - **Minimize 1-step deviation error** along the expert trajectories



- Starcraft2

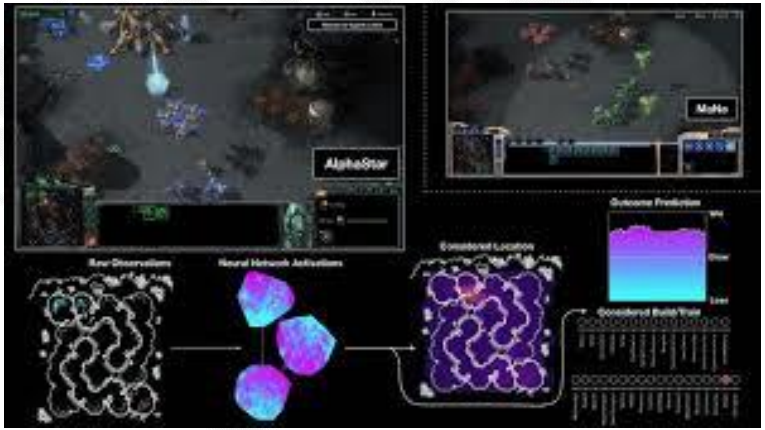
States: s = **minimap**, **screen**
Action: a **= select**, **drag**
Training set: $D = \{\tau := (s, a)\}$ from expert
Goal: learn $\pi_\theta(s) \rightarrow a$

States: s
Action: a
Policy: π_θ
- Policy maps states to actions : $\pi_\theta(s) \rightarrow a$
- Distributions over actions : $\pi_\theta(s) \rightarrow P(a)$

State Dynamics: $P(s'|s,a)$
- Typically not known to policy
- Essentially the simulator/environment

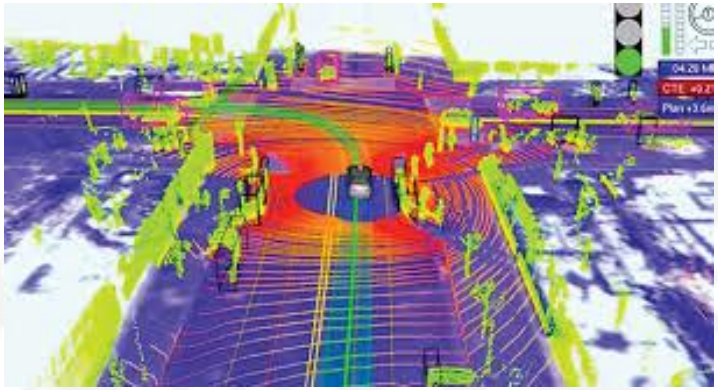
Rollout: sequentially execute $\pi_\theta(s_0)$ on initial state
- Produce trajectories $\boldsymbol{\tau}$

$\mathbf{P}(\boldsymbol{\tau}|\boldsymbol{\pi})$**:** distribution of trajectories induced by a policy
$\mathbf{P}(\mathbf{s}|\boldsymbol{\pi})$**:** distribution of states induced by a policy



- Autonomous Driving Control

States: s = **sensors**
Action: a = **steering wheel**, **brake**, …
Training set: $D = \{\tau := (s, a)\}$ from expert
Goal: learn $\pi_\theta(s) \rightarrow a$



- PPF/RFTN Injection Control in Medicine

States: s = **BIS**, **BP**, …
Action: a **= PPF**, **RFTN**, …
Training set: $D = \{\tau := (s, a)\}$ from expert
Goal: learn $\pi_\theta(\mathrm{s}) \rightarrow$ a

Lecture Roadmap

Introduction and Preliminaries

Deep Reinforcement Learning Theory

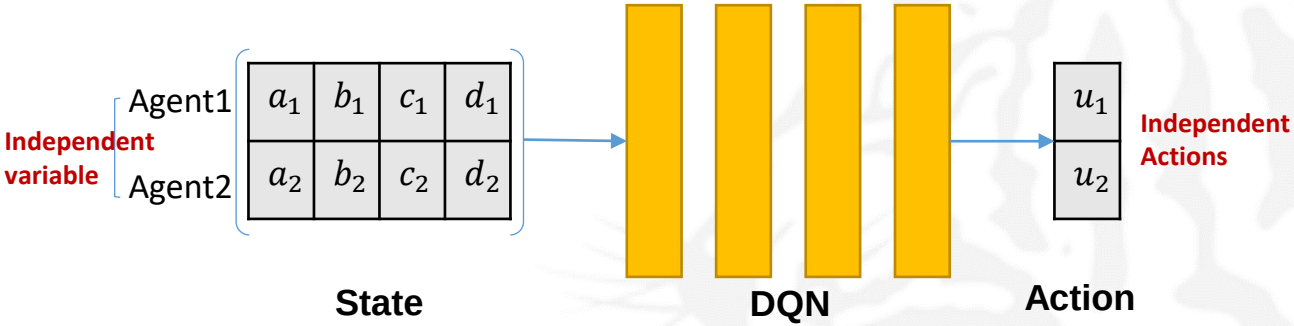
Deep Reinforcement Learning Implementation

Imitation Learning

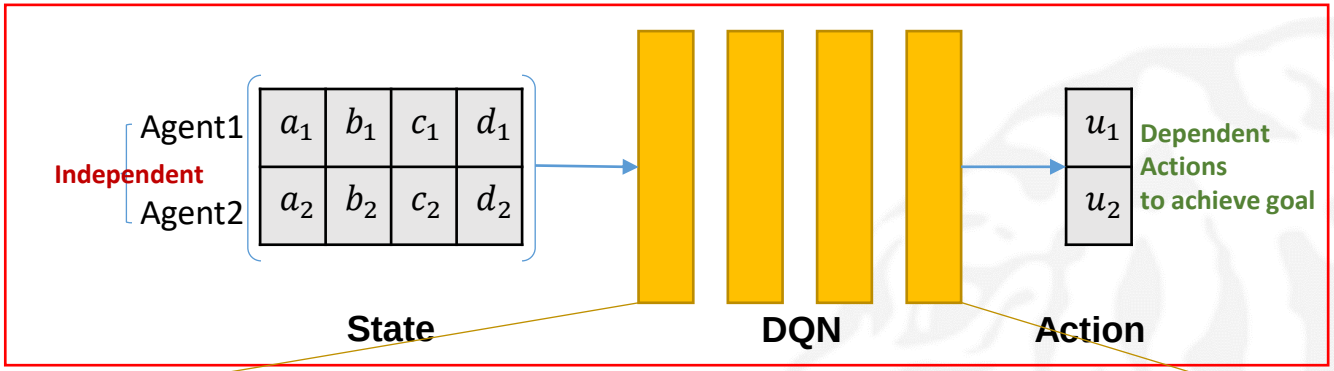
Autonomous Mobility Applications

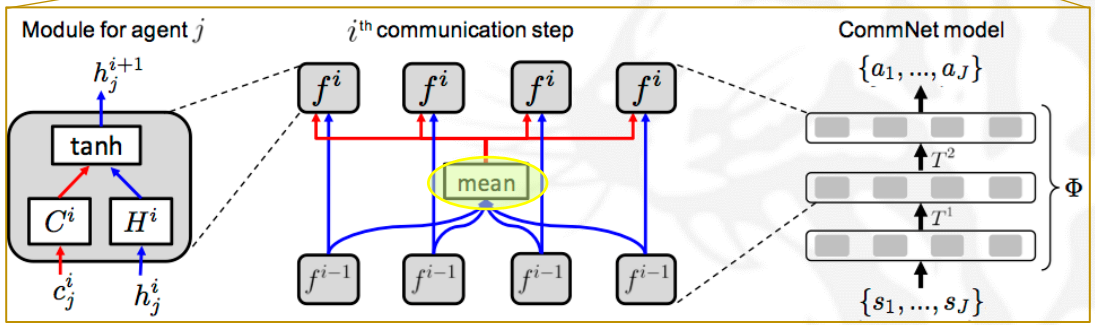
- **MADRL**
- Applications

- CTDE (Centralized Training and Distributed Execution)



DQN-based CommNet



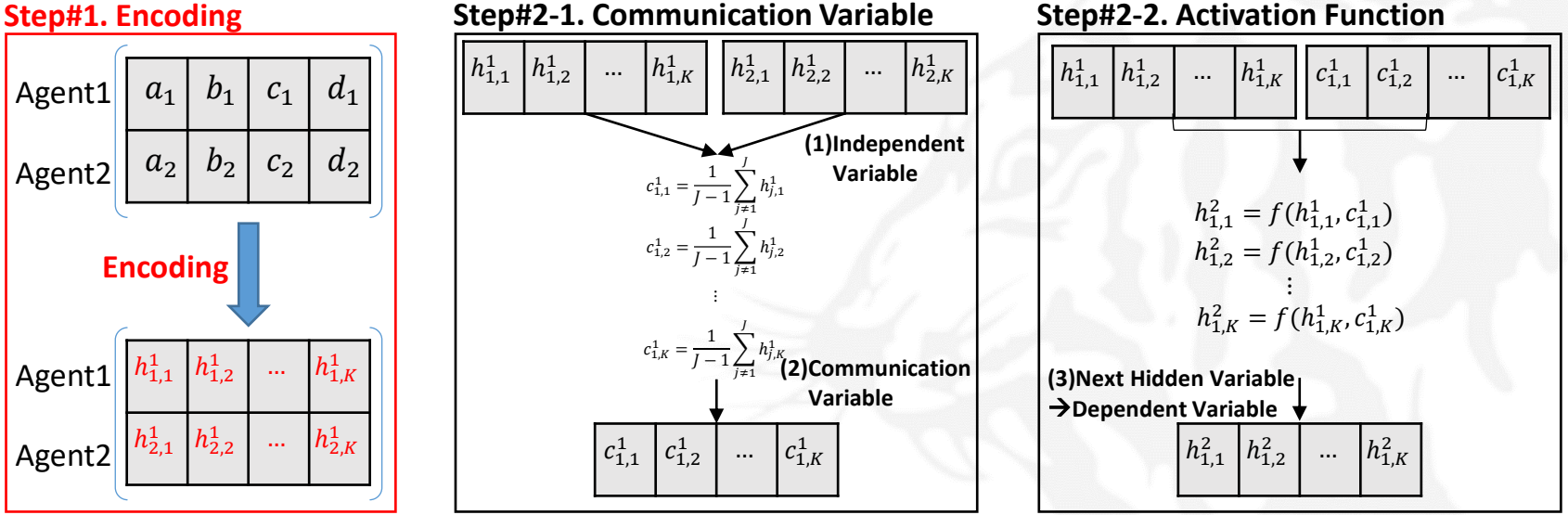


h_j^i : j-th agent's hidden state variable in i-th layer

c_j^i : j-th agent's communitive state variable in i-th layer

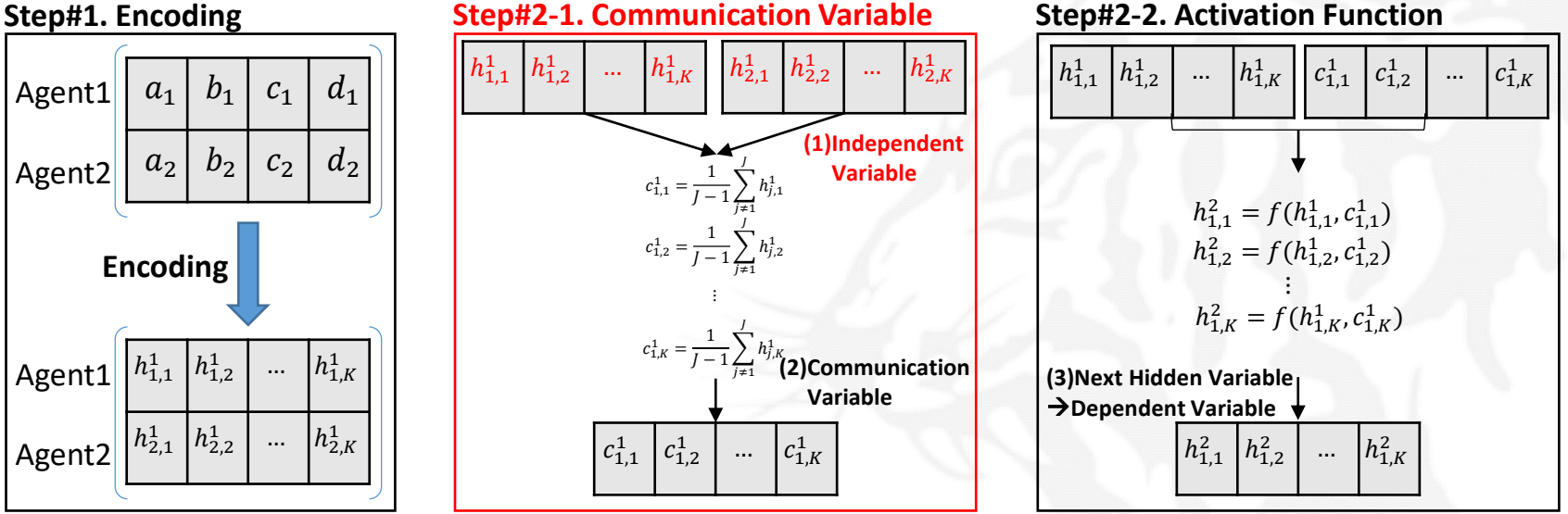
$$h_j^{i+1} = f^i(h_j^i, c_j^i)$$

CommNet Mechanism

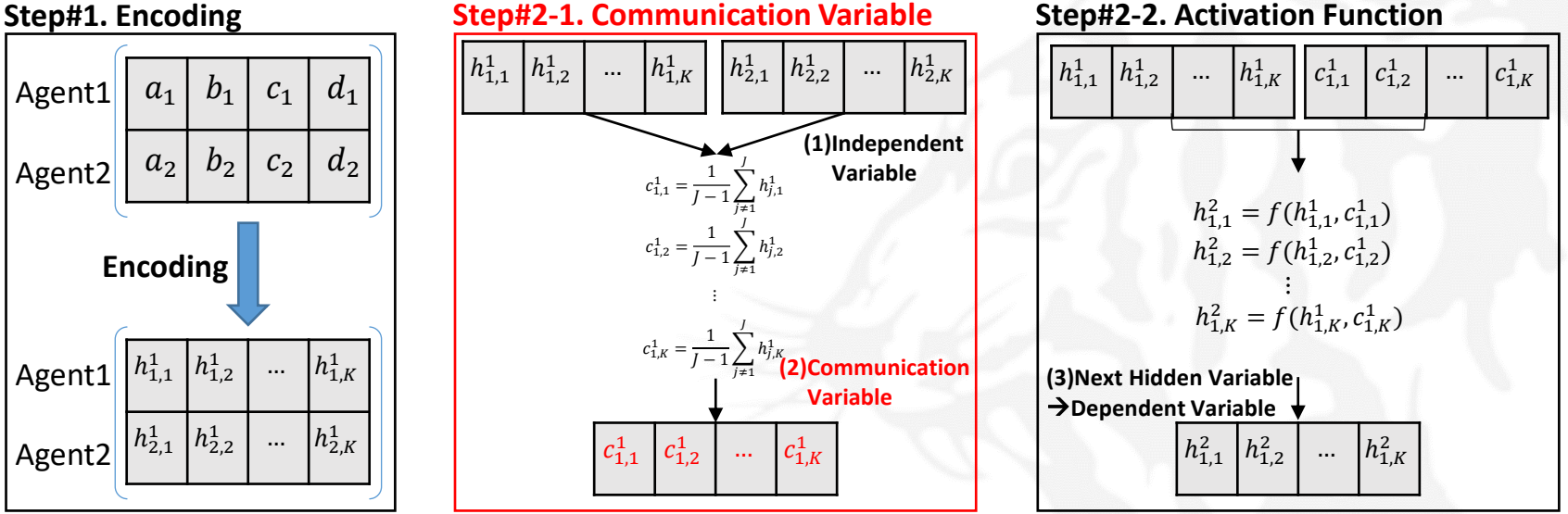


[3] S. Sukhbaatar et al., Learning Multiagent Communication with Backpropagation, *NIPS 2016*

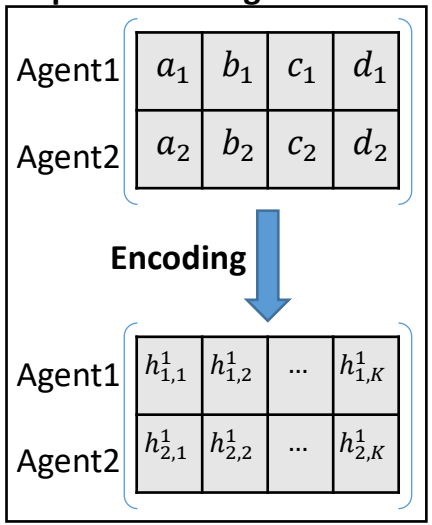
CommNet Mechanism

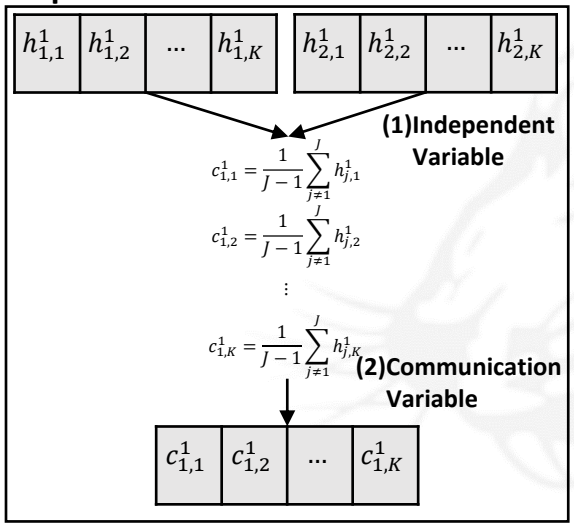


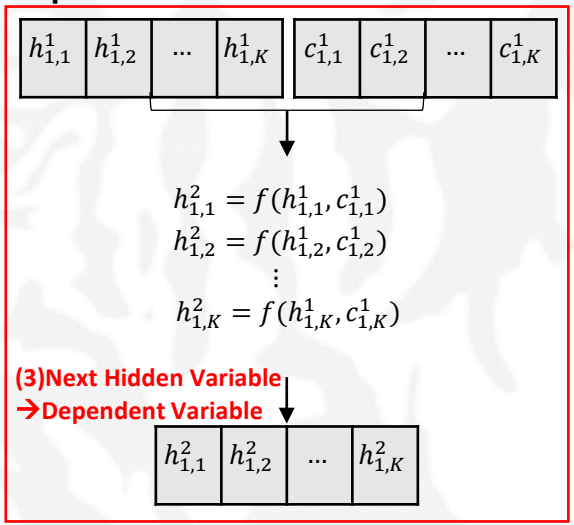
CommNet Mechanism

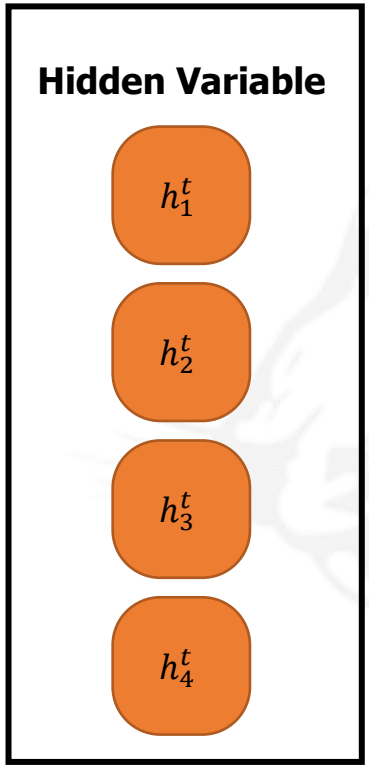


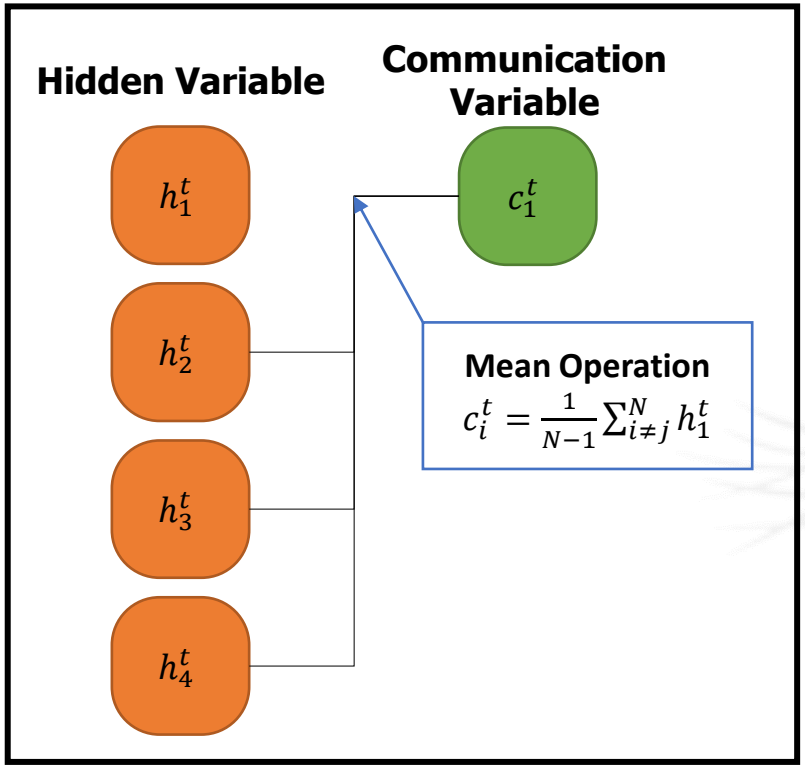
CommNet Mechanism

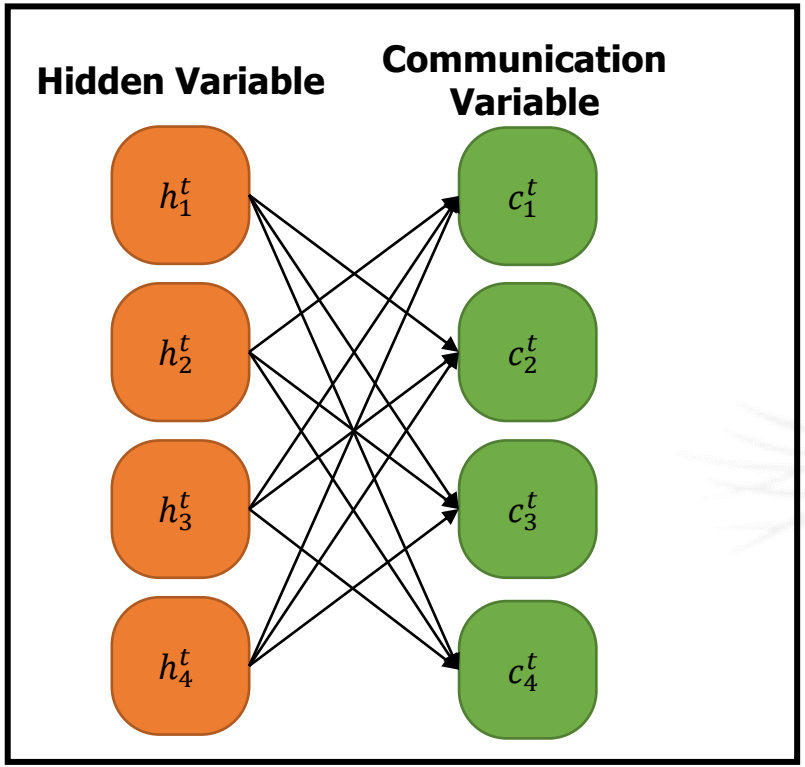


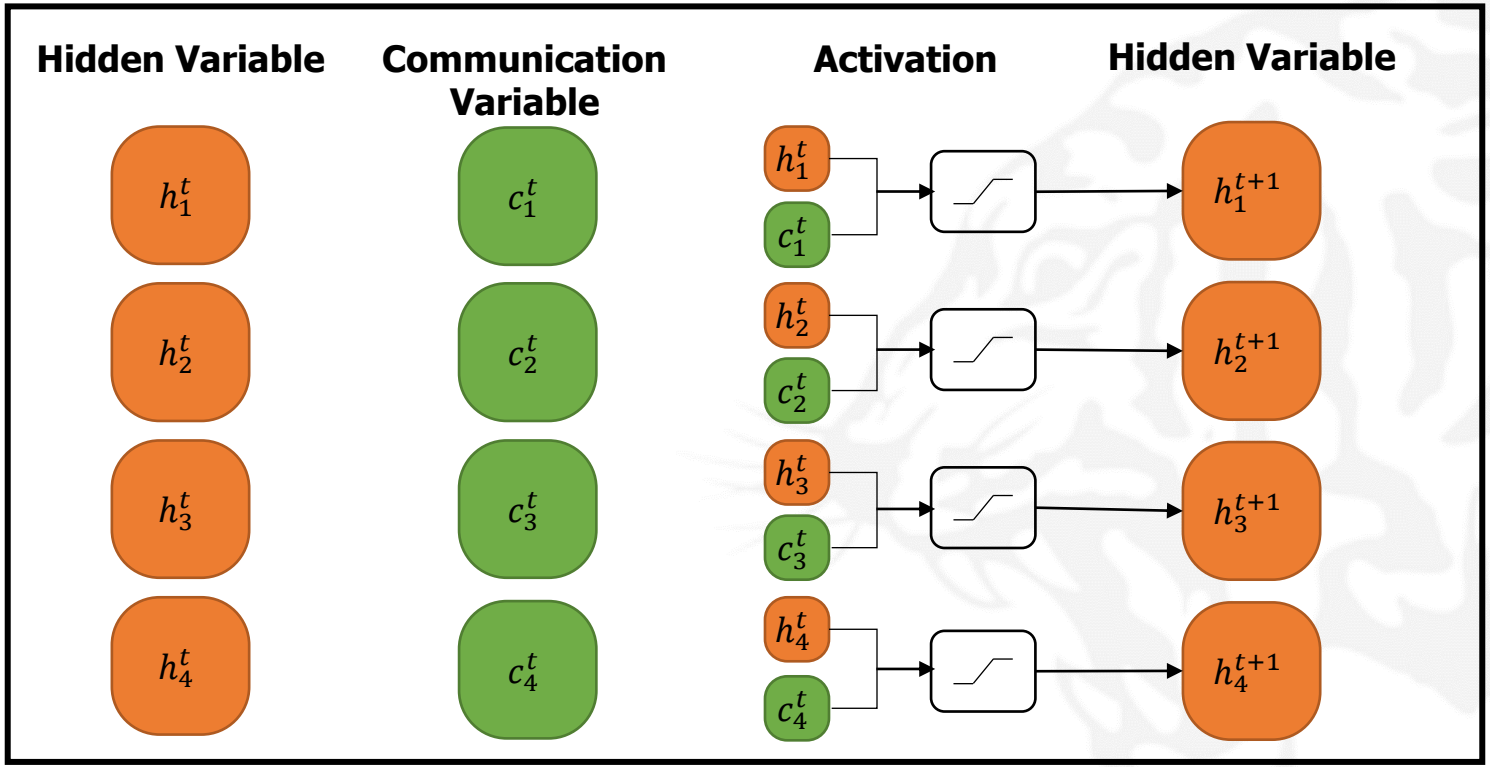





Hidden Variable
h_1^t
h_2^t
h_3^t
h_4^t

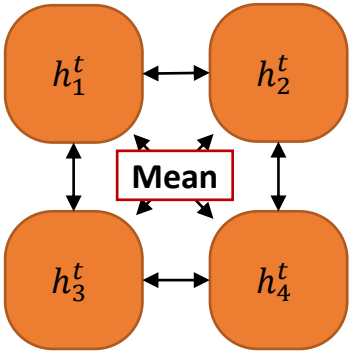

Hidden Variable
Communication Variable
h_1^t
h_2^t
h_3^t
h_4^t
c_1^t
Mean Operation
$c_i^t = \frac{1}{N-1}\sum_{i \neq j}^{N} h_1^t$


Hidden Variable
Communication Variable
h_1^t
h_2^t
h_3^t
h_4^t
c_1^t
c_2^t
c_3^t
c_4^t


Hidden Variable
Communication Variable
Activation
Hidden Variable
h_1^t
h_2^t
h_3^t
h_4^t
c_1^t
c_2^t
c_3^t
c_4^t
h_1^t
c_1^t
h_2^t
c_2^t
h_3^t
c_3^t
h_4^t
c_4^t
h_1^{t+1}
h_2^{t+1}
h_3^{t+1}
h_4^{t+1}

Now we are curious that…

CommNet



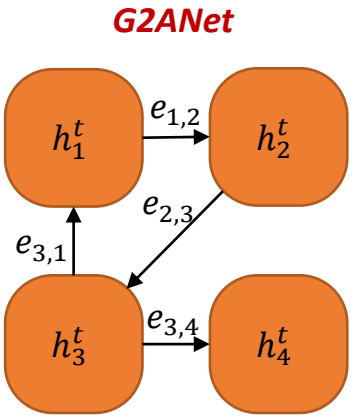
In Graph Approach.

1. Should the agent communicate with all agent?

2. Can we transfer only essential information between agents?

→ ***G2ANet will be the solution to the above problem.***

Now we are curious that…



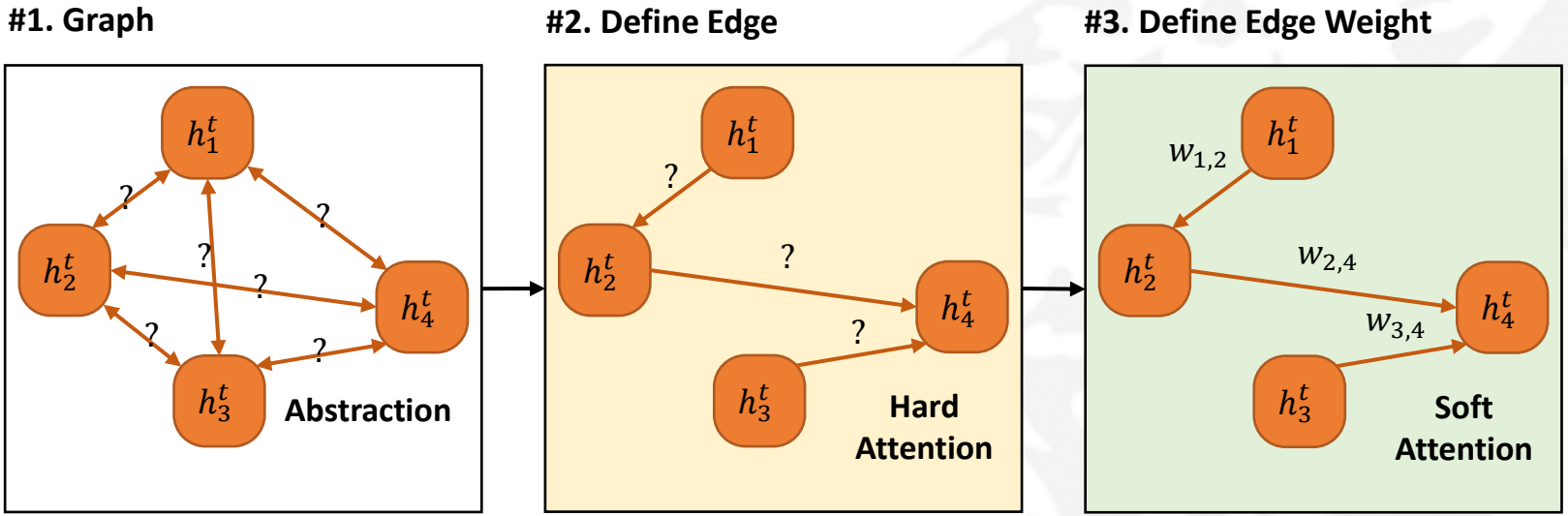
In Graph Approach.

1. Should the agent communicate with all agent?
2. Can we transfer only essential information between agents?

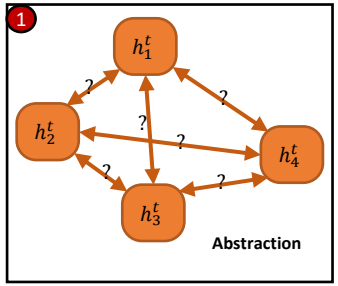
***G2ANet* will be the solution to the above problem.**

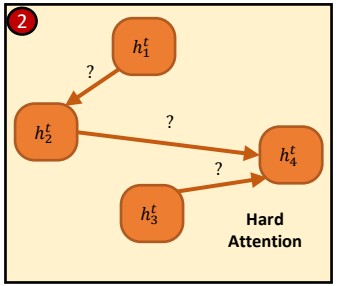
[4] Y. Liu et al., Multi-Agent Game Abstraction via Graph Attention Neural Network, *Proc. AAAI 2020*

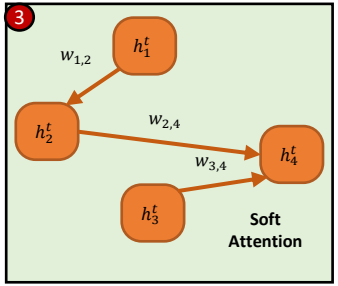
Before beginning *G2ANet …*

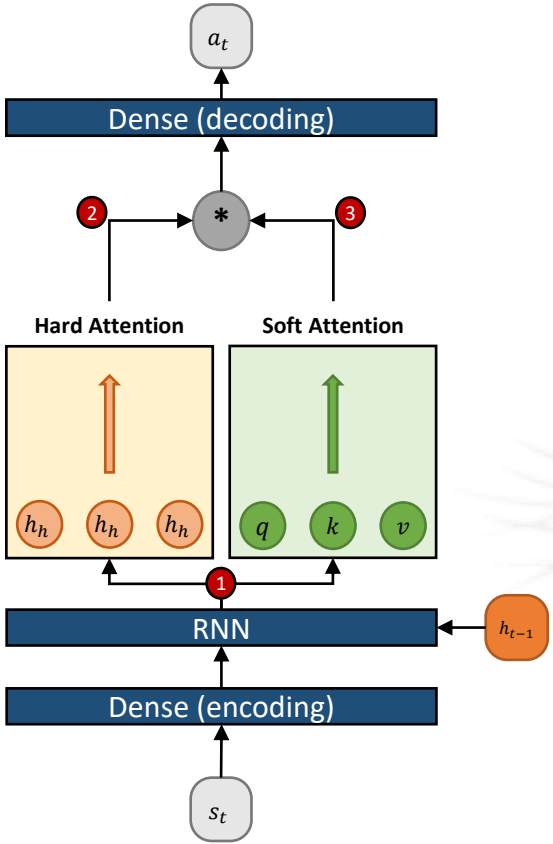


G2ANet Architecture

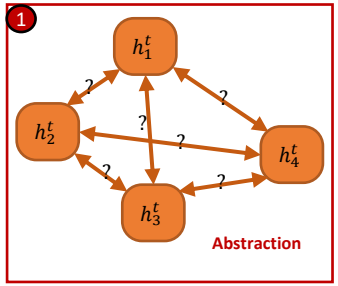


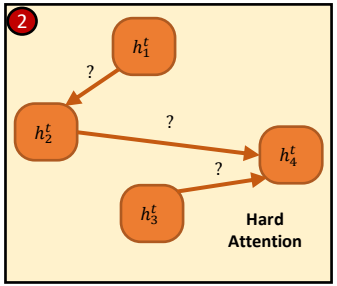


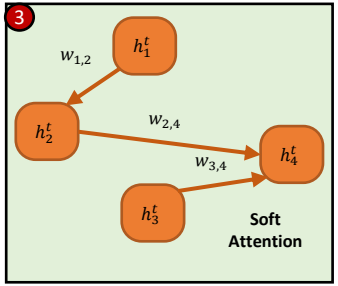


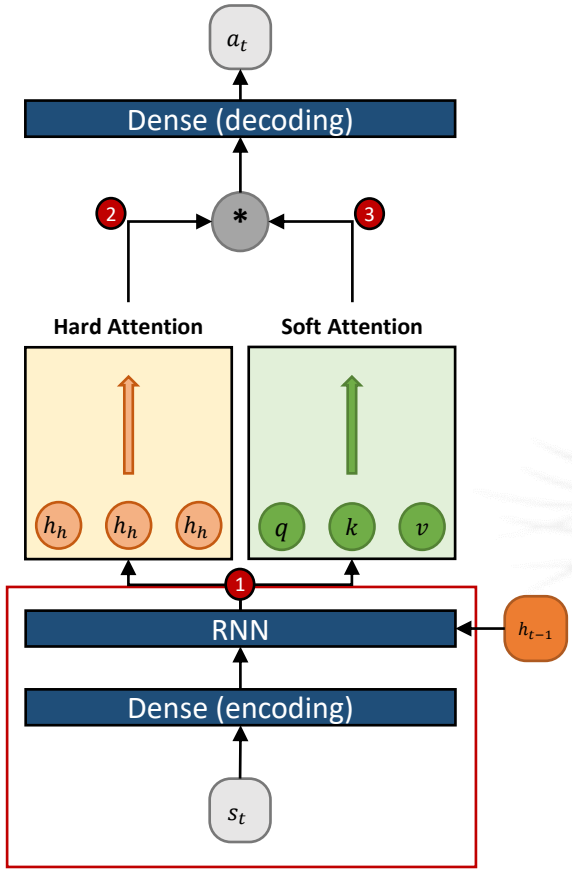


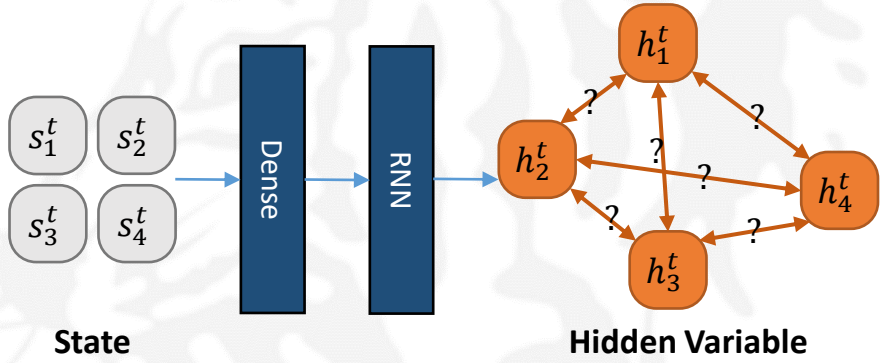
G2ANet Architecture: Abstraction



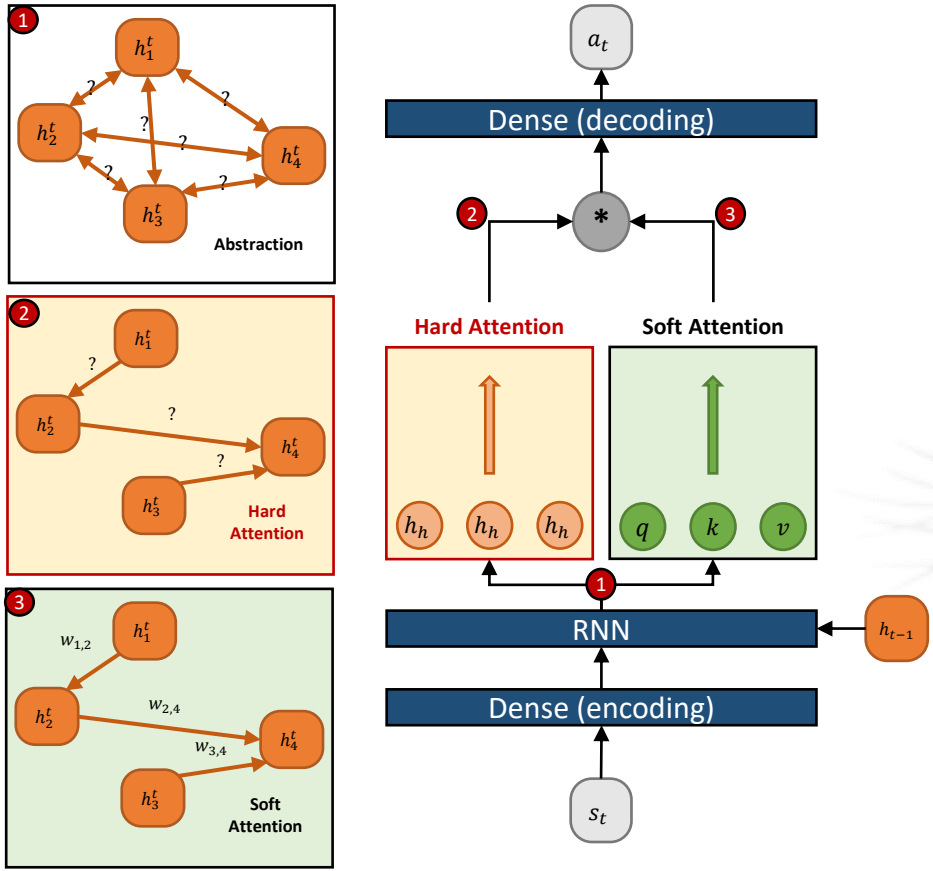




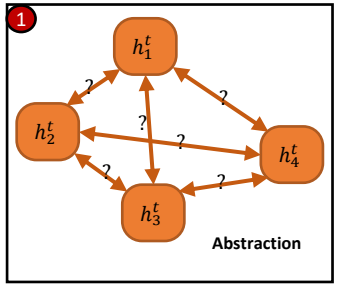


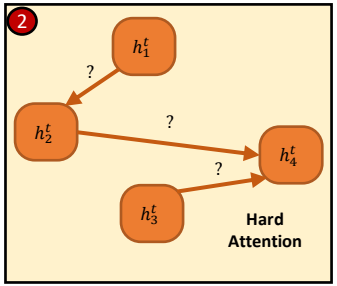


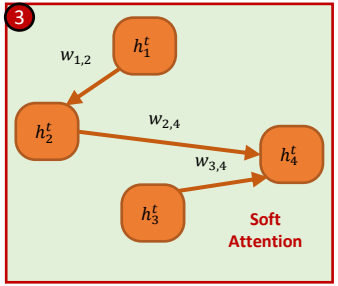
G2ANet Architecture: Hard Attention

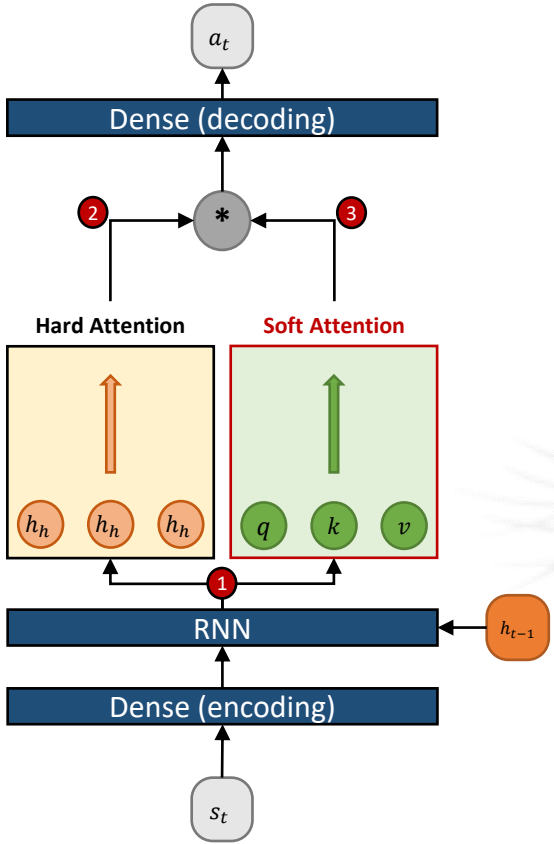


G2ANet Architecture: Soft Attention









Soft Attention

$$\text{Attention} = \text{score} \cdot \begin{bmatrix} v_1^t \\ v_2^t \\ v_3^t \\ v_4^t \end{bmatrix}$$

$$\text{score} = \begin{bmatrix} q_1^t \\ q_2^t \\ q_3^t \\ q_4^t \end{bmatrix} \cdot \begin{bmatrix} k_2^t & k_3^t & k_4^t \\ k_1^t & k_3^t & k_4^t \\ k_1^t & k_2^t & k_4^t \\ k_1^t & k_2^t & k_3^t \end{bmatrix}$$

Query q_1^t q_2^t q_3^t q_4^t

Key k_1^t k_2^t k_3^t k_4^t

Value v_1^t v_2^t v_3^t v_4^t

h_1^t h_2^t h_3^t h_4^t

$$Score = \boldsymbol{q} \cdot \boldsymbol{k} = \boldsymbol{q^T} * \boldsymbol{k}$$

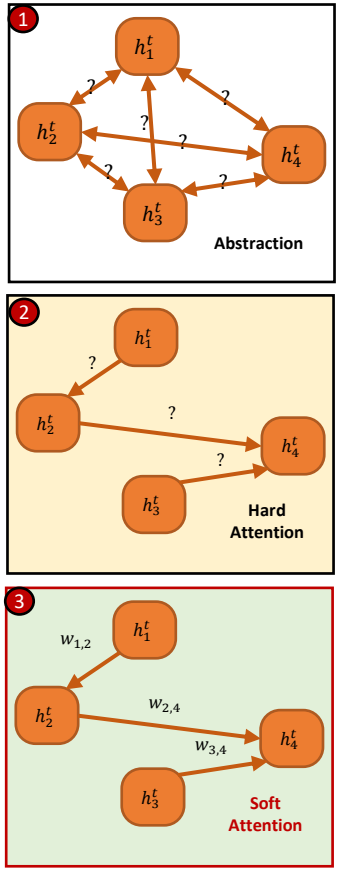
$$Score_{scaled} = \frac{Score}{\sqrt{n}}$$

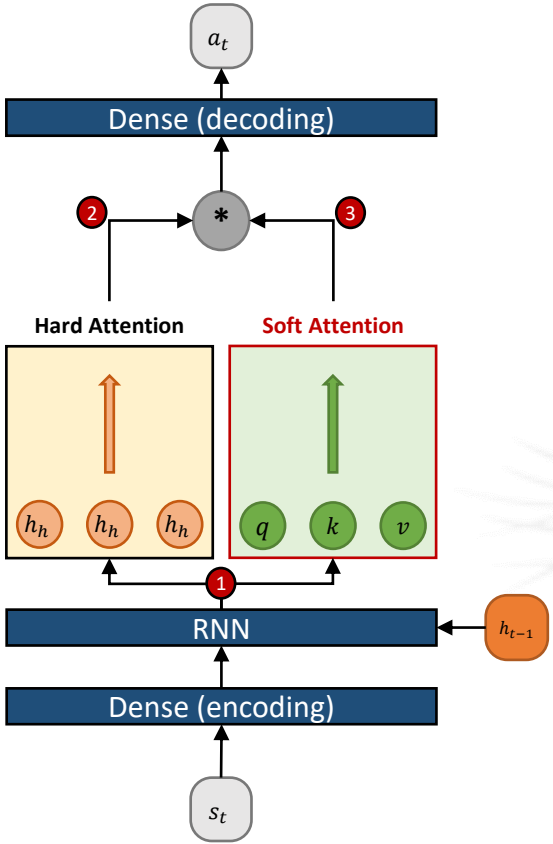
$$Attention(\boldsymbol{q}, \boldsymbol{k}, \boldsymbol{v}) = Score_{scaled} * \boldsymbol{v}$$

Soft Attention Output (message)

0.11	0.84	0.4
0.1	0.18	0.72
0.34	0.38	0.28
0.16	0.14	0.70

G2ANet Architecture: Soft Attention & GNN





Hard Attention Output (connection)

1	0	0
0	0	1
0	0	1
0	0	0

*

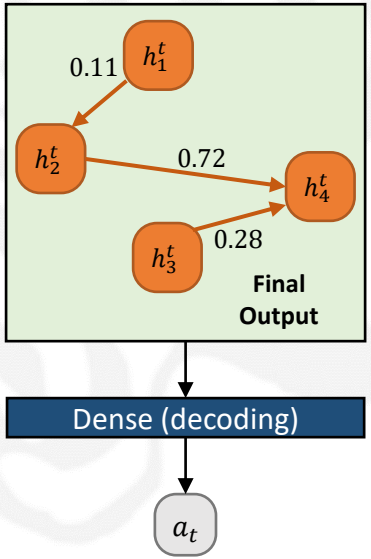
Soft Attention Output (message)

0.11	0.84	0.4
0.1	0.18	0.72
0.34	0.38	0.28
0.16	0.14	0.70

=

Final Output (connection & message)

0.11	0	0
0	0	0.72
0	0	0.28
0	0	0



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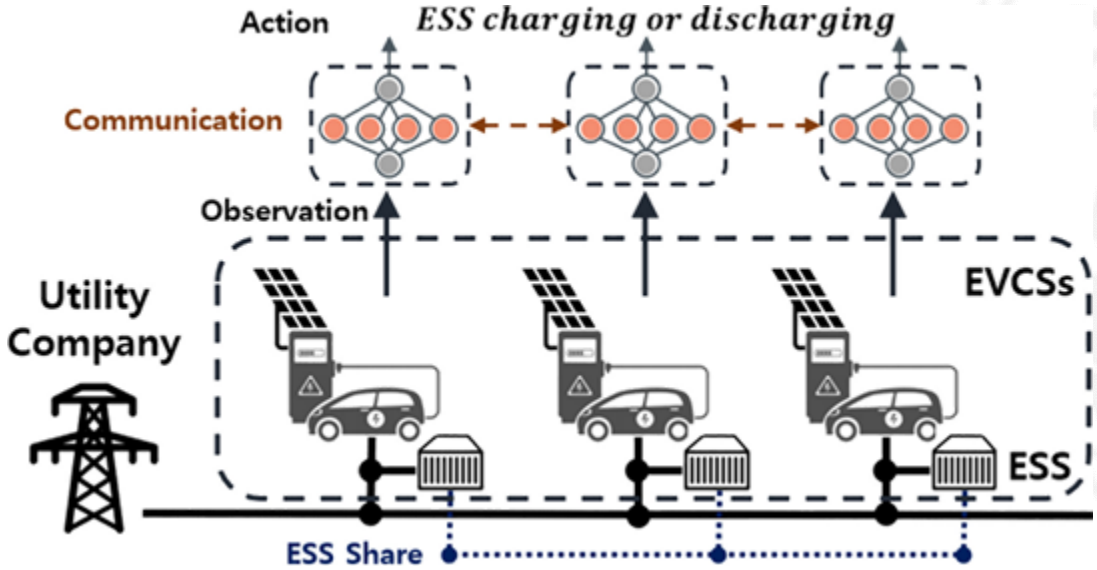
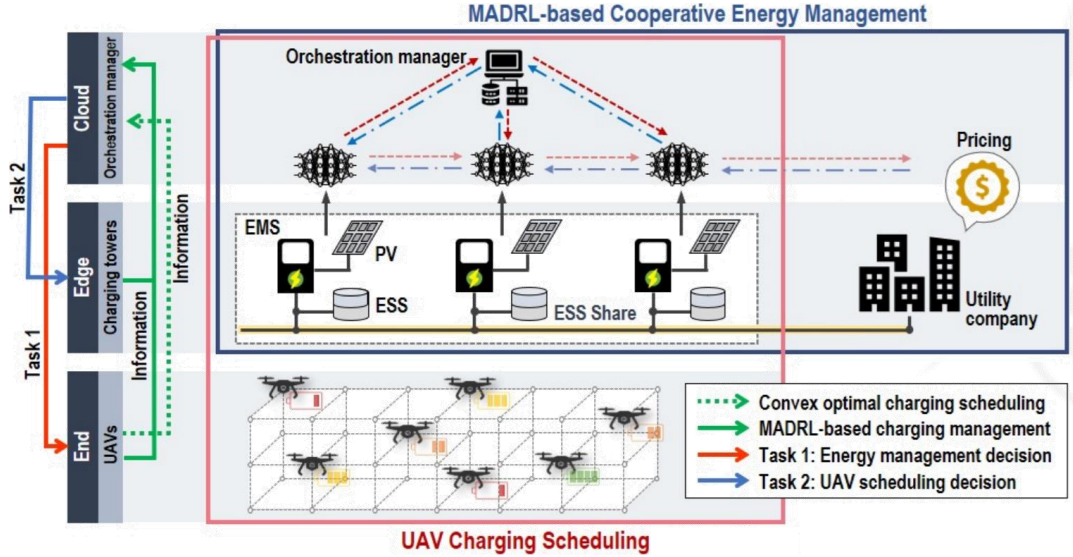
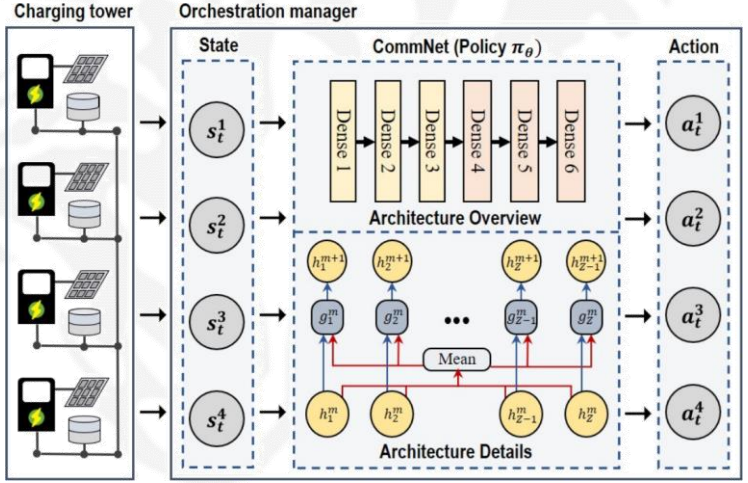
- MADRL
- **Applications**

- Electric Vehicle Charging
  - MyungJae Shin, Dae-Hyun Choi, and Joongheon Kim, "**Cooperative Management for PV/ESS-Enabled Electric-Vehicle Charging Stations: A Multiagent Deep Reinforcement Learning Approach**," IEEE Transactions on Industrial Informatics, 16(5):3493-3503, May 2020.

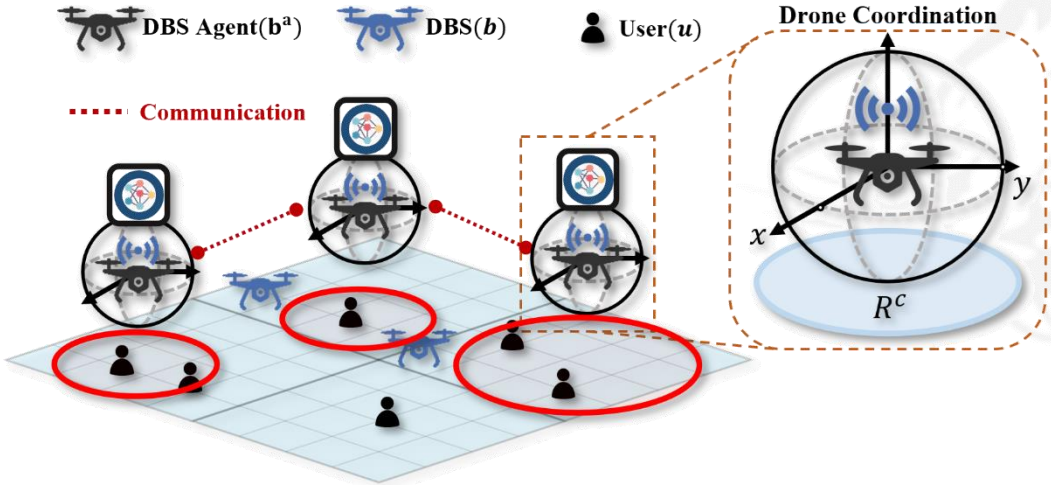


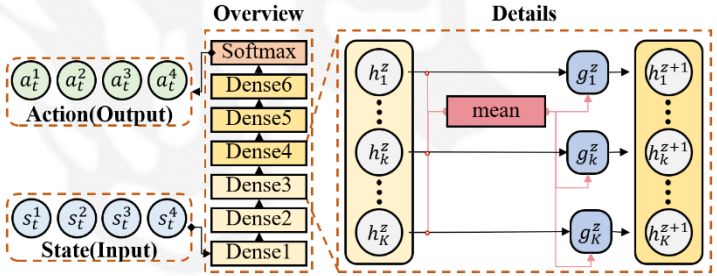
- Multi-UAV Charging
  - Soyi Jung, Won Joon Yun, MyungJae Shin, Joongheon Kim, and Jae-Hyun Kim, "**Orchestrated Scheduling and Multi-Agent Deep Reinforcement Learning for Cloud-Assisted Multi-UAV Charging Systems**," IEEE Transactions on Vehicular Technology, 70(6):5362-5377, June 2021.



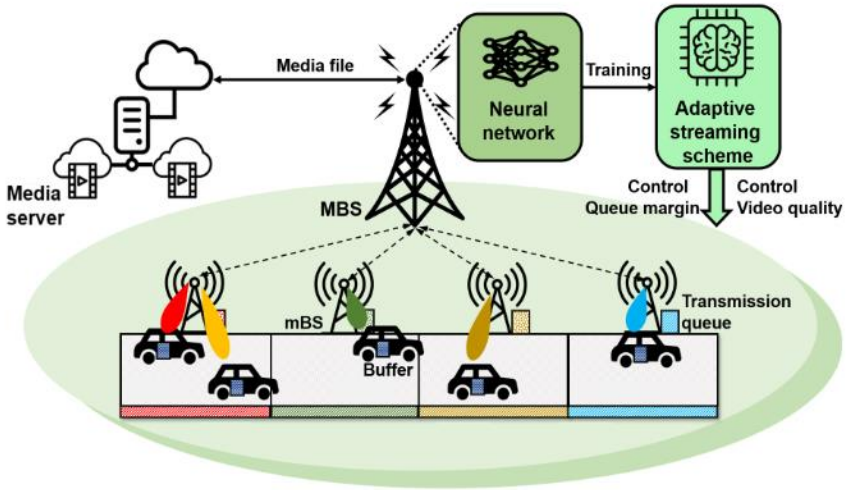


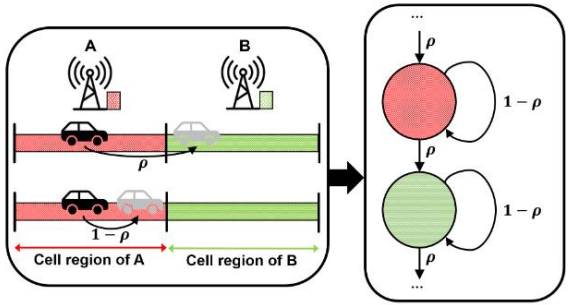
- Multi-UAV Surveillance
  - Won Joon Yun, Soohyun Park, Joongheon Kim, MyungJae Shin, Soyi Jung, David Mohaisen, and Jae-Hyun Kim, "**Cooperative Multi-Agent Deep Reinforcement Learning for Reliable Surveillance via Autonomous Multi-UAV Control**," IEEE Transactions on Industrial Informatics, (To Appear: October 2022).

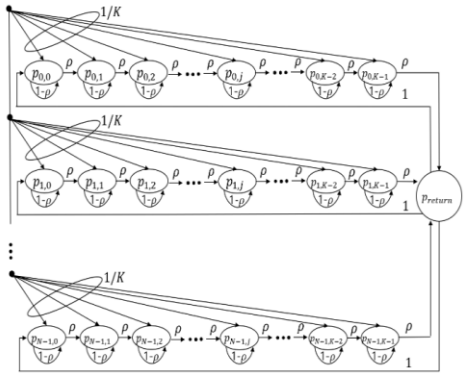




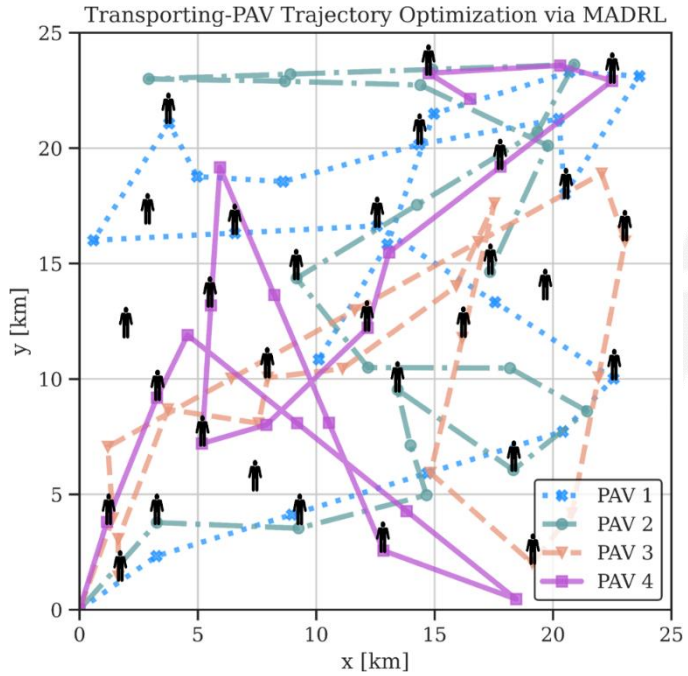
- Streaming in Connected Vehicles
  - Won Joon Yun, Dohyun Kwon, Minseok Choi, Joongheon Kim, Giuseppe Caire, and Andreas F. Molisch, "**Quality-Aware Deep Reinforcement Learning for Streaming in Infrastructure-Assisted Connected Vehicles**," IEEE Transactions on Vehicular Technology, 71(2):2002-2017, February 2022.

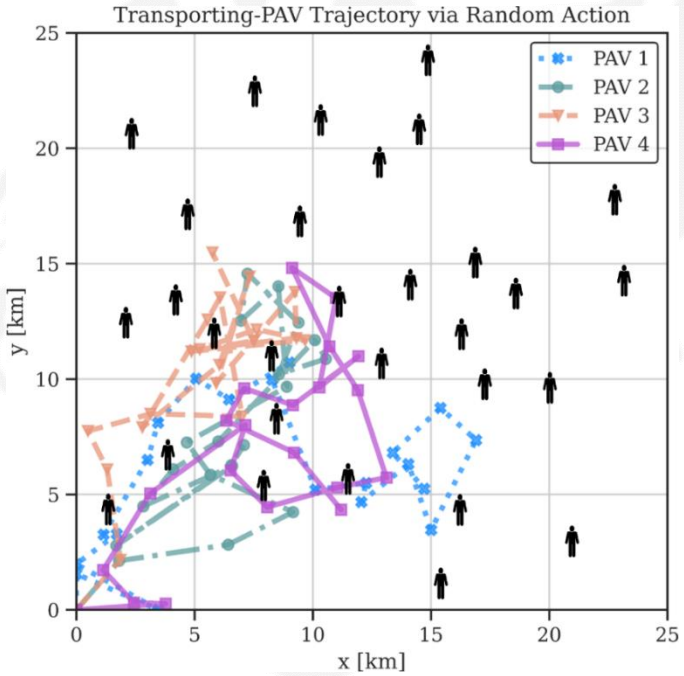






- Drone-Taxi Trajectory Learning
  - Won Joon Yun, Soyi Jung, Joongheon Kim, and Jae-Hyun Kim, "**Distributed Deep Reinforcement Learning for Autonomous Aerial eVTOL Mobility in Drone Taxi Applications**," ICT Express, 7(1):1-4, March 2021.





Thank you for your attention!

- More questions?
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