The background features a collection of 3D-rendered spheres in various colors including pink, yellow, green, and blue, scattered across the frame. A large, irregular, purple-colored blob is positioned behind the main title text.

# **강화학습 기반의 자율주행 전기차 이동충전소**

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The background of the slide is a light gray. It is decorated with numerous 3D-rendered spheres of various sizes and colors, including shades of purple, blue, green, yellow, and pink. A large, irregular, purple blob-like shape is positioned on the left side, partially overlapping the word 'Contents'.

# Contents

- *Introduction*
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- *Method*
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# Introduction

## 1. Background

### ○ Problem

- 국내에 보급된 전기차에 비해 전기차 충전소 인프라가 부족
- 지역별 전기차 충전소 분포가 고르지 않음

## 2. Importance

- 강화학습을 활용하여 실시간으로 이동식 전기차 충전소가 최적의 경로로 자율주행 하여 전기차를 충전
- 이를 통해 전기차 충전소 인프라 부족 현상을 유연하게 해결하고자 함



# Related Works

## 1. MADDPG

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**Algorithm 1:** Multi-Agent Deep Deterministic Policy Gradient for  $N$  agents

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**for** episode = 1 to  $M$  **do**

Initialize a random process  $\mathcal{N}$  for action exploration

Receive initial state  $\mathbf{x}$

**for**  $t = 1$  to max-episode-length **do**

for each agent  $i$ , select action  $a_i = \boldsymbol{\mu}_{\theta_i}(o_i) + \mathcal{N}_t$  w.r.t. the current policy and exploration

Execute actions  $a = (a_1, \dots, a_N)$  and observe reward  $r$  and new state  $\mathbf{x}'$

Store  $(\mathbf{x}, a, r, \mathbf{x}')$  in **replay buffer**  $\mathcal{D}$

$\mathbf{x} \leftarrow \mathbf{x}'$

**for** agent  $i = 1$  to  $N$  **do**

Sample a random minibatch of  $S$  samples  $(\mathbf{x}^j, a^j, r^j, \mathbf{x}'^j)$  from  $\mathcal{D}$

Set  $y^j = r^j + \gamma Q_i^{\mu'}(\mathbf{x}'^j, a'_1, \dots, a'_N)|_{a'_k = \boldsymbol{\mu}'_k(o_k^j)}$

Update **critic** by minimizing the loss  $\mathcal{L}(\theta_i) = \frac{1}{S} \sum_j (y^j - Q_i^{\boldsymbol{\mu}}(\mathbf{x}^j, a_1^j, \dots, a_N^j))^2$

Update **actor** using the sampled policy gradient:

$$\nabla_{\theta_i} J \approx \frac{1}{S} \sum_j \nabla_{\theta_i} \boldsymbol{\mu}_i(o_i^j) \nabla_{a_i} Q_i^{\boldsymbol{\mu}}(\mathbf{x}^j, a_1^j, \dots, a_i, \dots, a_N^j)|_{a_i = \boldsymbol{\mu}_i(o_i^j)}$$

**end for**

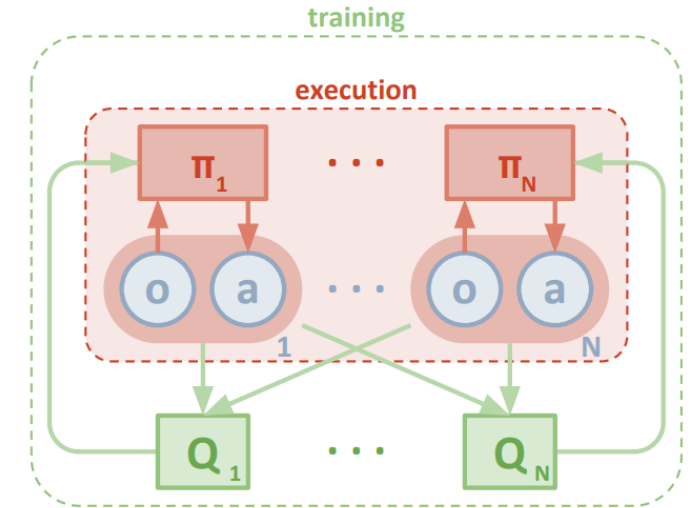
Update target network parameters for each agent  $i$ :

$$\theta'_i \leftarrow \tau \theta_i + (1 - \tau) \theta'_i$$

**end for**

**end for**

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# Related Works

## 2. Auction Theory

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1: /* Bidding Submission of  $d_i$  */
2: Each buyer  $d_i$  requests the energy trading and
   provides its bid vector,  $\mathbb{B}_i$ 
3: /* Winning Bid Determination at  $s_j$  */
4:  $x_{ij}^{temp} = 0, p_j^t = 0, \forall d_i \in \mathcal{D}; s_j \in \mathcal{S}; W_j^{can} = \emptyset$ .
5: Determine the set of feasible buyers
    $W_j^{temp} = \{d_i | e_i \leq E_j, t_i \leq T_j, \forall d_i \in \mathcal{D}\}$ .
6: Sort the bids of buyers  $d_i \in W_j^{temp}$  in non-increasing
   order:
    $W_j^{order} = (d_{j1}, d_{j2}, \dots, d_{jK})$  such that
    $b_{j1j} \geq b_{j2j} \geq \dots \geq b_{jKj}$  with  $K = |W_j^{temp}|$ .
7: Pick out  $|c_j|$  bidders having the highest bids


$$W_j^{cons} = \begin{cases} (d_{j1}, d_{j2}, \dots, d_{j_{c_j}}), & \text{if } c_j < K, \\ W_j^{order}, & \text{otherwise.} \end{cases}$$


8: if  $\sum_{d_i \in W_j^{cons}} e_i \leq E_j$  then
9:    $W_j^{can} = W_j^{cons}; x_{ij}^{temp} = 1, \forall d_i \in W_j^{can}$ .
    $p_j^t = b_{mj}$  where
   
$$m = \begin{cases} \arg \max_i \{d_i | d_i \in W_j^{order} \setminus W_j^{cons}\} & \text{if } c_j < K, \\ \arg \min_i \{d_i | d_i \in W_j^{order}\} & \text{otherwise.} \end{cases}$$


```

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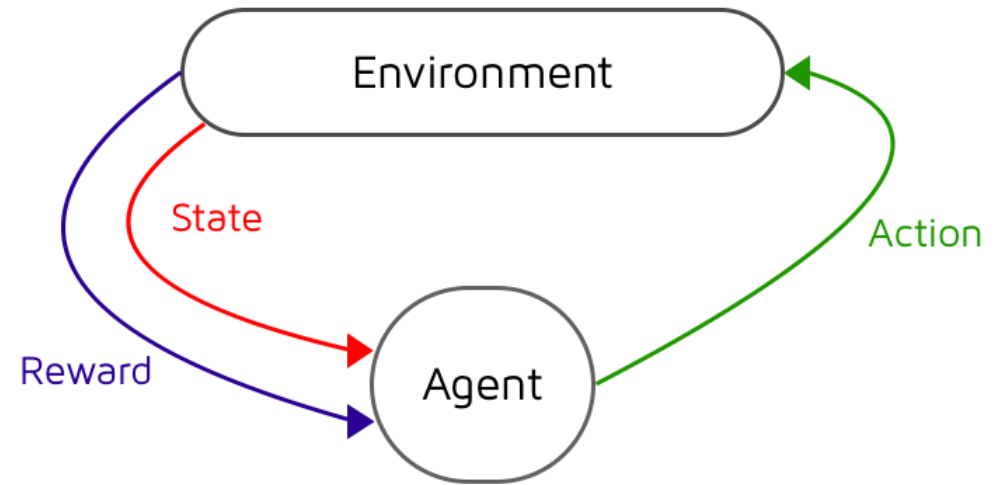
10: if  $\sum_{d_i \in W_j^{cons}} e_i > E_j$  then
11:    $h = \arg \max_h \sum_{h'=1}^h e_{h'} \leq E_j, \forall d_{h'} \in W_j^{cons}$ .
12:    $W_j^{can} = \{d_{h'} | 1 \leq h' \leq h\}; x_{h'j}^{temp} = 1$ .
    $p_j^t = b_{(h+1)j}$ .
13: /* Final seller determination at  $d_i$  */
14: for  $j = 1$  to  $S$  do
15:    $x_{ij} = 0; p_i^d = 0$ .
16:   if  $\sum_{j=1}^M x_{ij}^{temp} = 0$  then
17:      $x_{ij} = 0, \forall j; p_i^d = 0$ .
18:   if  $\sum_{j=1}^M x_{ij}^{temp} = 1$  then
19:     for  $j = 1$  to  $M$  do
20:       if  $x_{ij}^{temp} = 1$  then
21:          $x_{ij} = 1; p_i^d = p_j^t$ .
22:   if  $\sum_{j=1}^M x_{ij}^{temp} > 1$  then
23:     for  $j = 1$  to  $M$  do
24:       if  $x_{ij}^{temp} = 1$  then
25:          $U_{ij}^d = (v_{ij} - p_j^t)e_i$ .
26:      $j^* = \arg \max_j \{U_{ij}^d | x_{ij}^{temp} = 1, \forall j \in M\}$ .
27:      $x_{ij^*} = 1; p_i^d = p_{j^*}^t$ .

```

# Method

## 1. Definition

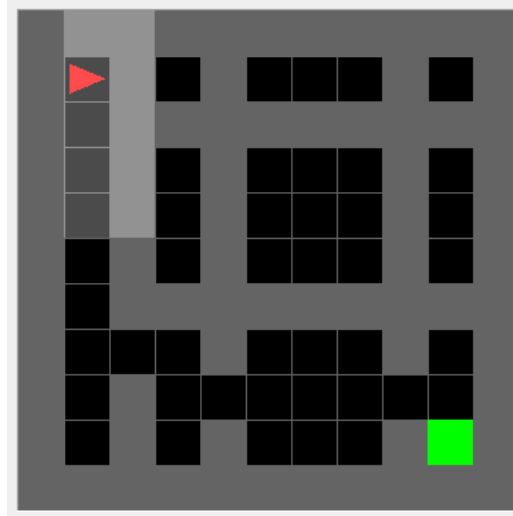
- Action Space
  - 주어진 환경에서 가능한 모든 action의 set
  - Move = {right, left, up, down, no-operation}
- Observation Space (State)
  - Environment의 현재 상태에 대한 정보
  - Agent인 전기차 충전소는 자신의 근처(상하좌우)에 있는 전기차를 알 수 있음
- Policy
  - Agent가 어떤 Action을 취할지 선택하는 Rule
  - 확률적(Stochastic) 접근 : Move\_Probability = {0.175, 0.175, 0.175, 0.175, 0.3}



# Method

## 2. Environment

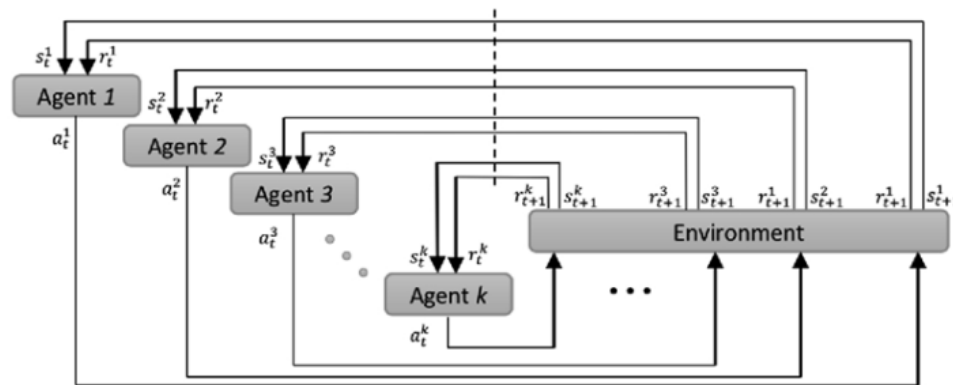
- OpenAi/gym : gridworld



- Multi Agent

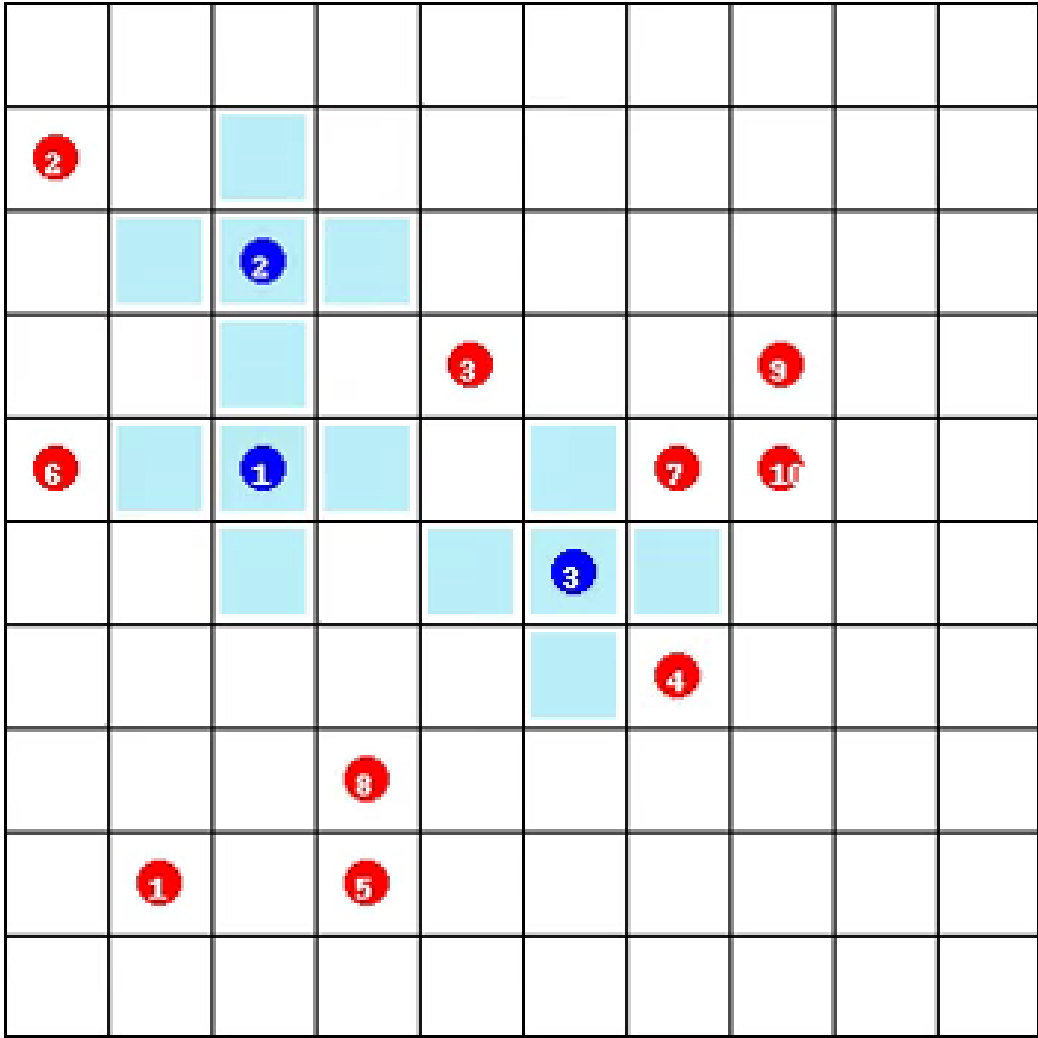


(a) Single Agent



(b) Multi-Agents

# Experiments





# Conclusion

## 1. 기대효과

- 전기차 충전소 인프라의 시간, 공간적 제약 극복
- 전기차 충전소가 최적의 경로로 자율주행

## 2. 추후 연구 계획

- 모델 경량화
- 임베디드 환경에서 실험