Artificial Intelligence and Mobility Lab

다중 에이전트 강화학습 이론 및 응용

Multi-Agent Deep Reinforcement Theory and its Application

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Now, we have curiosity about…

Q1. Should we wait for the scenario terminated?
Trajectory(Dataset): $\tau = \{s_0, a_0, r_0, s_1, a_1, \ldots, s_T\}$

A1. **No, I will introduce *A2C*. It will make objective function optimized FASTER.**

Q2. How can I maximize objective function efficiently?
Objective Function: $J(\theta) = E_\tau[\sum_{t=0}^{T} \gamma^t \cdot r(s_t, a_t)]$

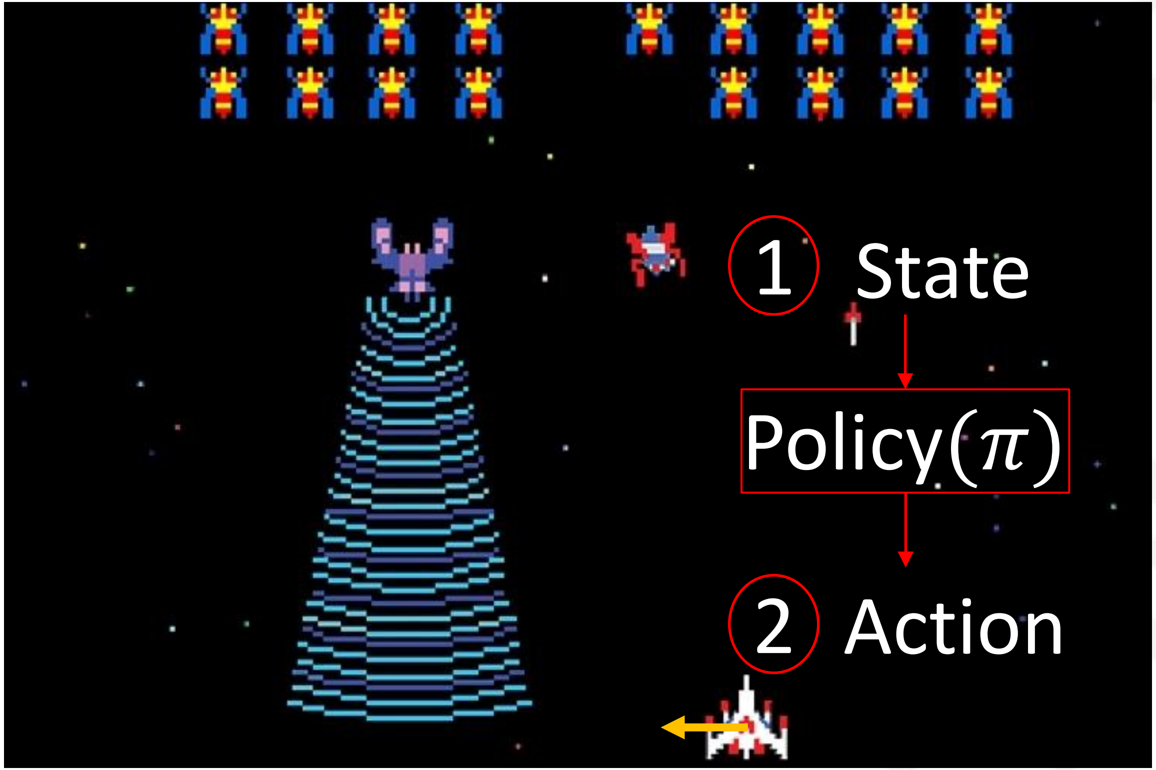
A2. **I will introduce *PPO* and *DDPG*. If you use it, you can maximize the objective function with BETTER PERFORMANCE.**

Q3.What about design DQN?

A3. **I will introduce *CommNet* and *G2ANet*.**

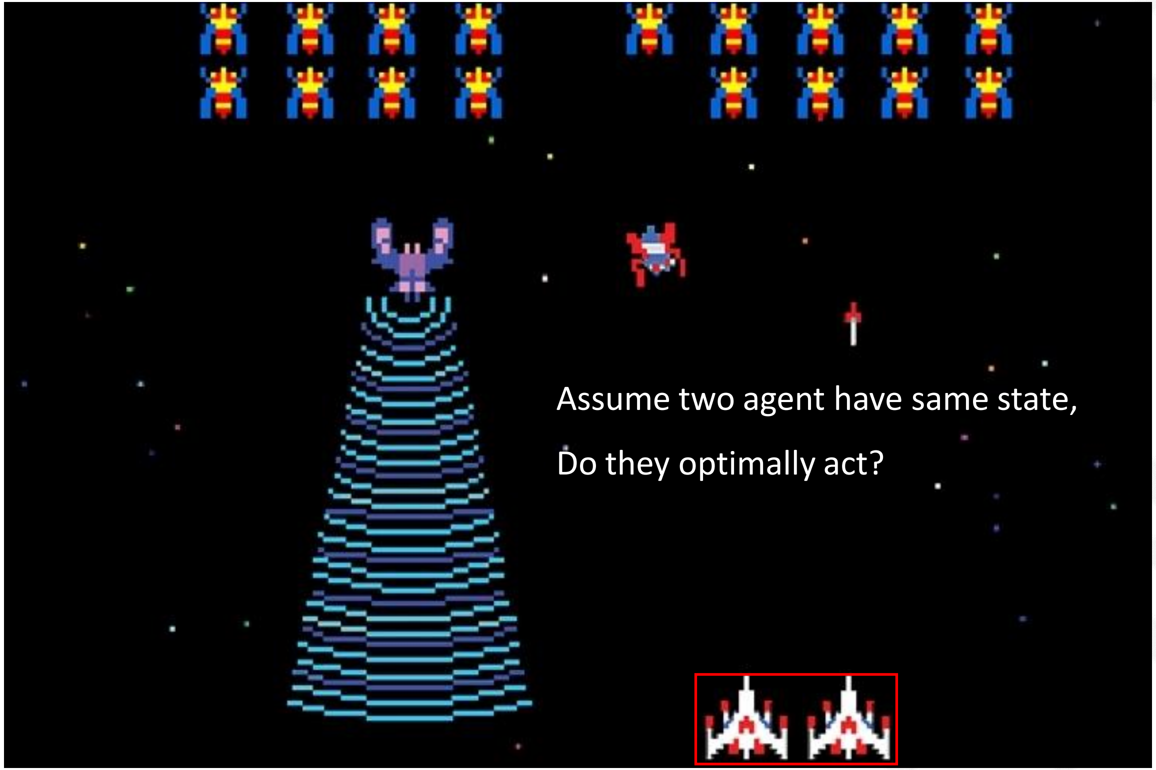
Q4. Any new idea?

A4. **I will introduce Value Decomposition Network.**

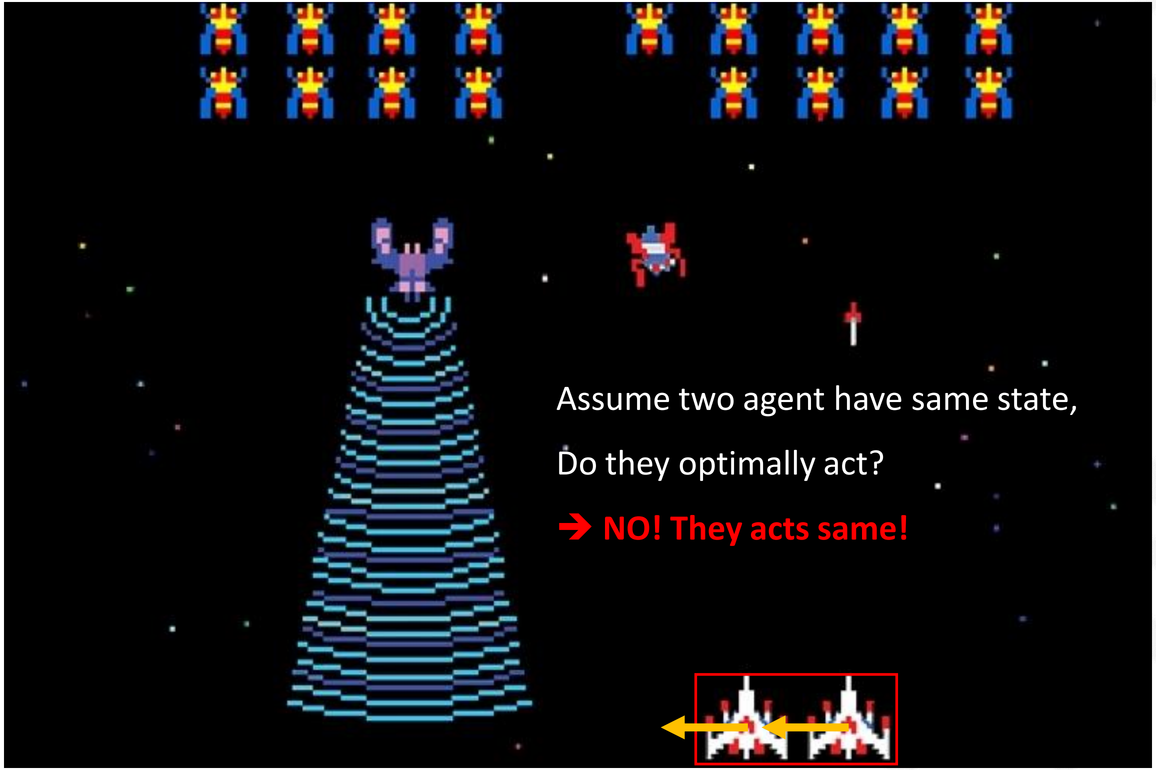


1 State
Policy(π)
2 Action

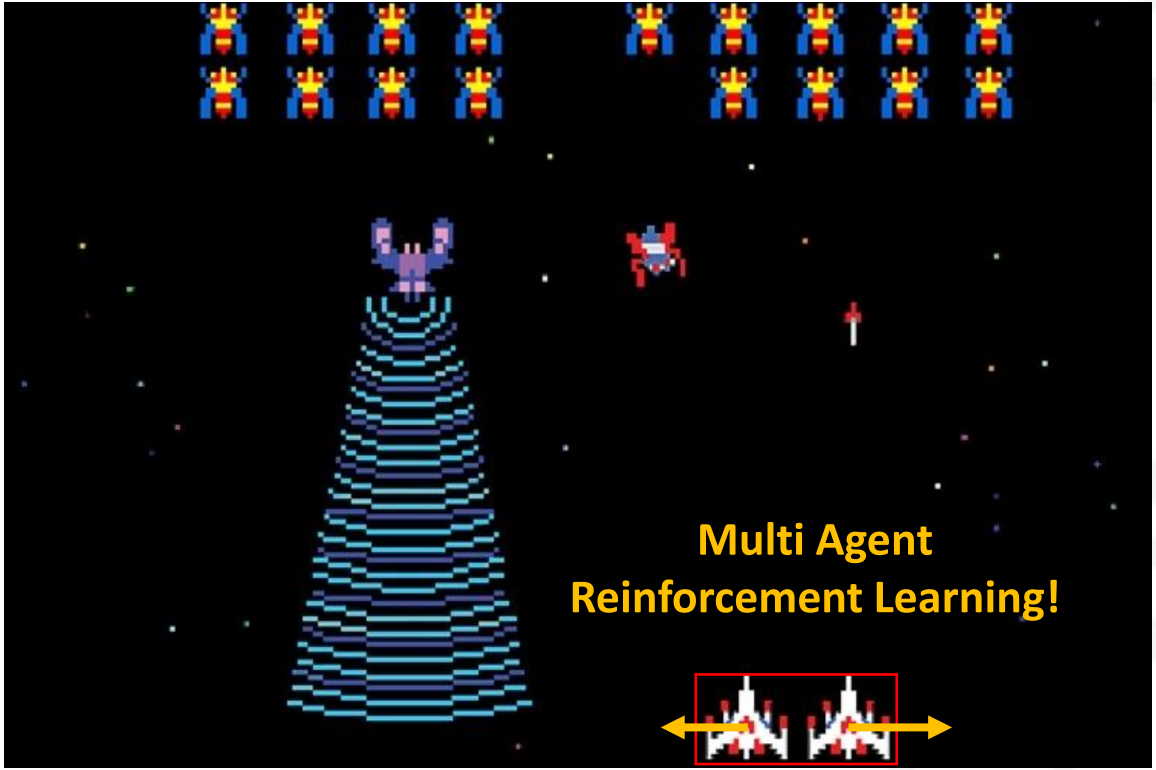
What if there exists more than one agent?



What if there exists more than one agent?

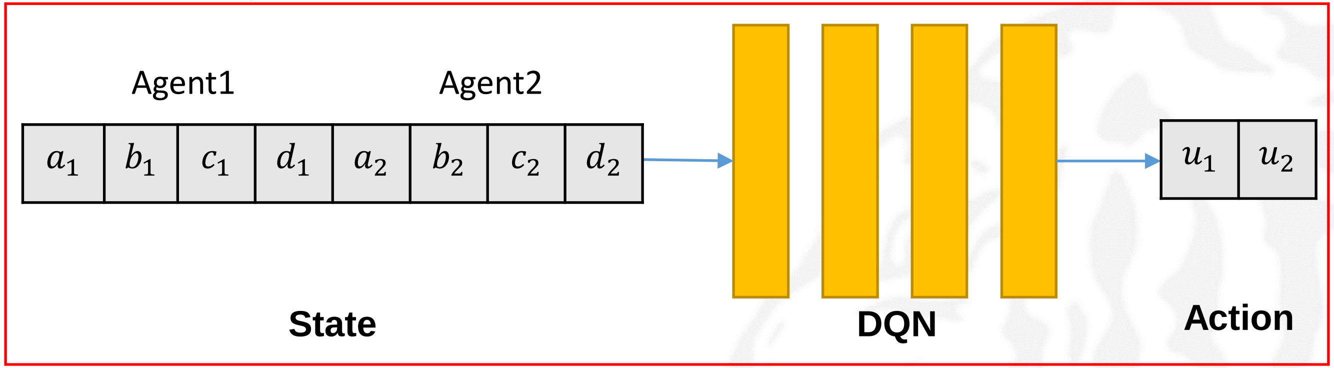


What we are going to learn is …

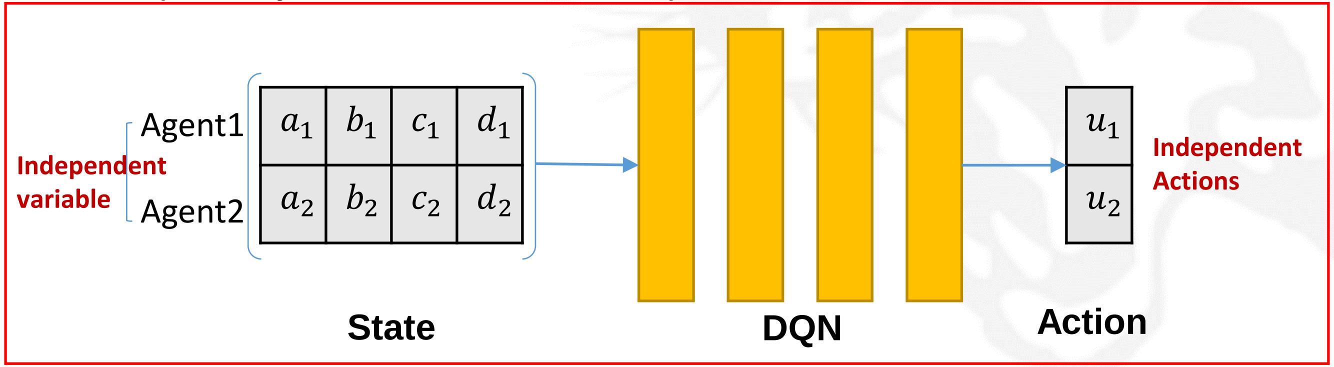


With Previous method.

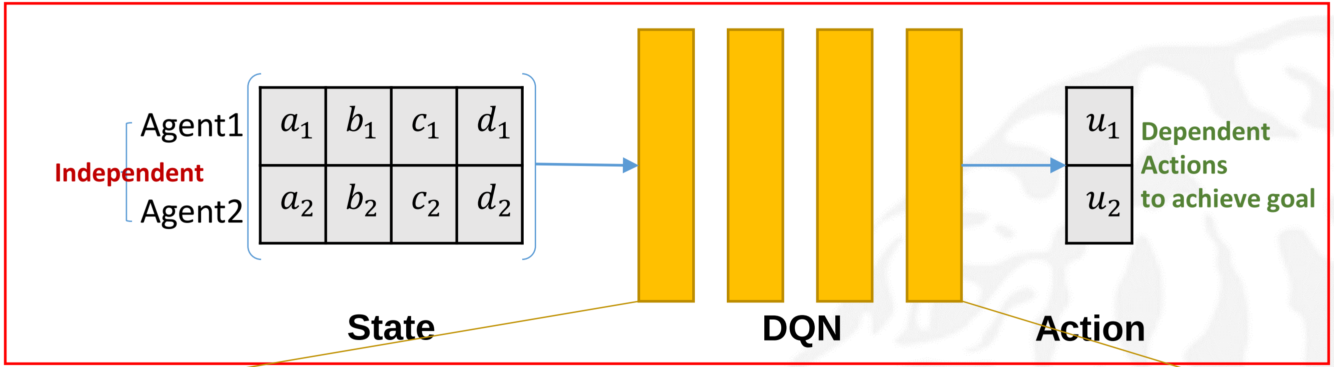
With DDPG (Fully Observable Environment) → **Hard to Converge**

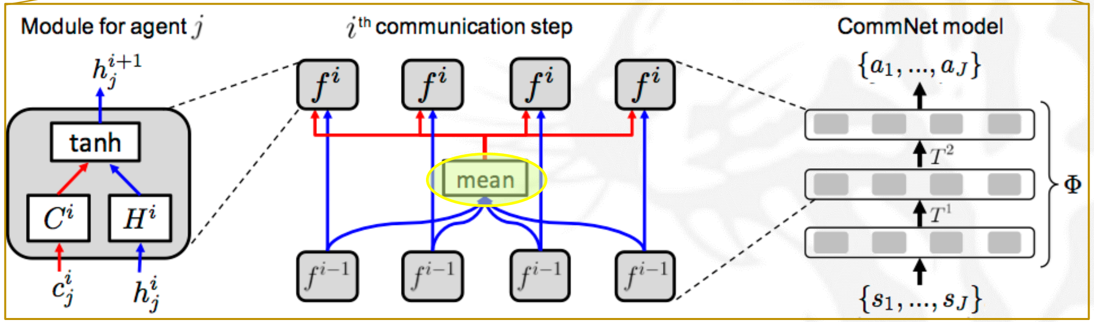


With DQN(Partially Observable Environment)



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

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

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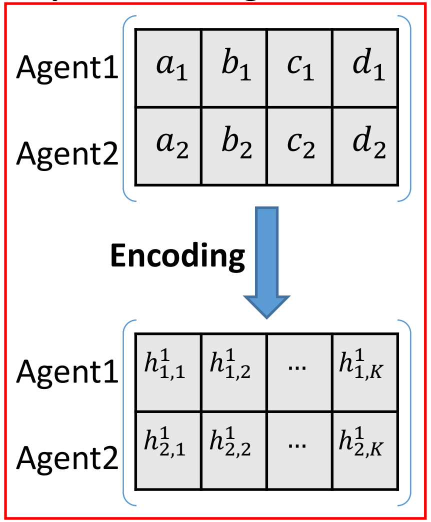
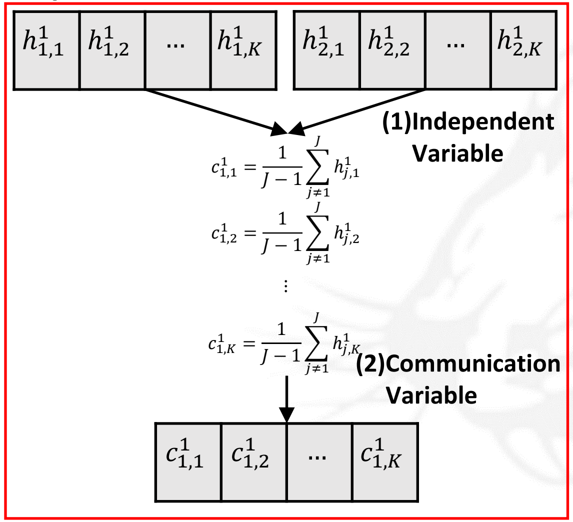
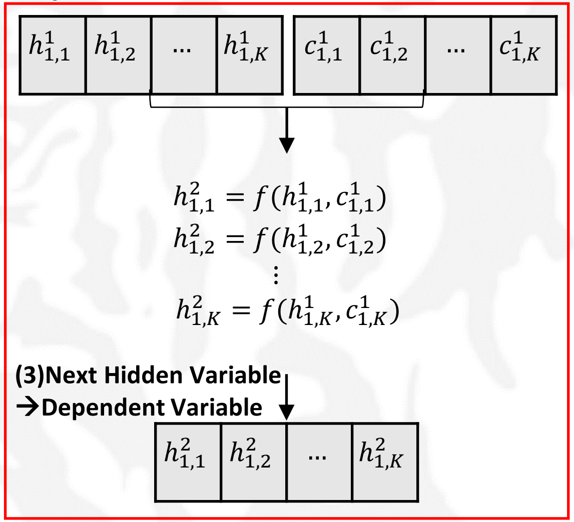
Step#1. Encoding



Step#2-1. Communication Variable



Step#2-2. Activation Function



CommNet Architecture

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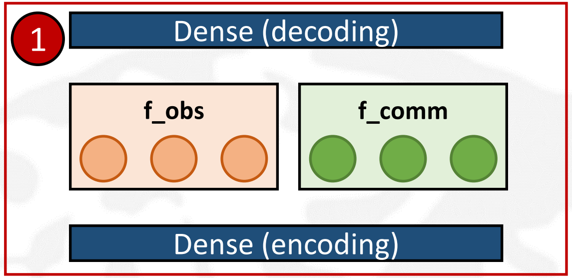
1

```
class CommNet(nn.Module):
    def __init__(self, input_shape):
        super(CommNet, self).__init__()
        self.encoding = nn.Linear(input_shape, rnn_dim)
        self.f_obs = nn.GRUCell(rnn_dim, rnn_dim)
        self.f_comm = nn.GRUCell(rnn_dim, rnn_dim)
        self.decoding = nn.Linear(rnn_dim, rnn_dim)
    def forward(self, obs, hidden_state):
        obs_encoding = torch.sigmoid(self.encoding(obs))
        h_in = hidden_state.reshape(-1,  rnn_dim)
        h_out = self.f_obs(obs_encoding, h_in)
        h = h.reshape(-1, n_agents, rnn_dim)
        c = h.reshape(-1, 1, n_agents*rnn_dim)
        c = c.repeat(1, n_agents, 1)
        mask = (1 - torch.eye(n_agents))
        mask = mask.view(-1, 1).repeat(1, rnn_dim).view(n_agents, -1)
        c = c * mask.unsqueeze(0)
        c = c.reshape(-1,  n_agents, n_agents, rnn_dim)
        c = c.mean(dim=-2)
        h = h.reshape(-1, rnn_dim)
        c = c.reshape(-1, rnn_dim)
        h = self.f_comm(c, h)
        weights = self.decoding(h)
        return weights, h_out
```



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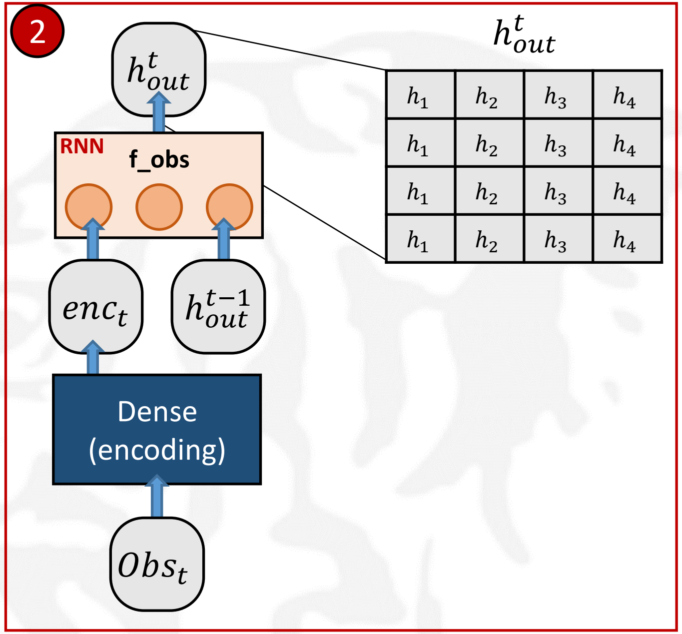
```

2



CommNet Architecture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```

3

c

h_1	h_2	h_3	h_4
h_1	h_2	h_3	h_4
h_1	h_2	h_3	h_4
h_1	h_2	h_3	h_4

*

mask

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

3

$$h_2 + h_3 + h_4$$
$$h_1 + h_3 + h_4$$
$$h_1 + h_2 + h_4$$
$$h_1 + h_2 + h_3$$

$$c_1 = (h_2 + h_3 + h_4)/(J-1)$$
$$c_2 = (h_1 + h_3 + h_4)/(J-1)$$
$$c_3 = (h_1 + h_2 + h_4)\,/(J-1)$$
$$c_4 = (h_1 + h_2 + h_3)\,/(J-1)$$

$$c_j^{i+1} = \frac{1}{J-1} \sum_{j' \neq j} h_{j'}^{i+1}.$$

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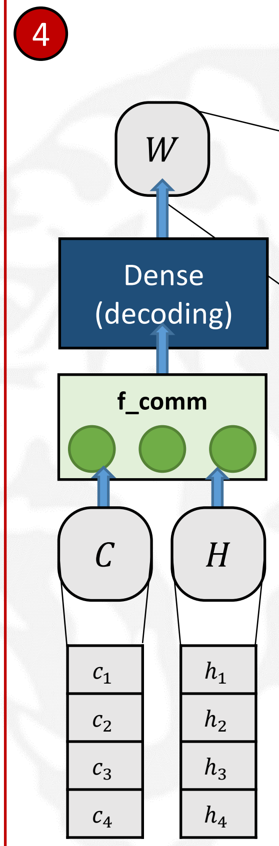
```

4



$p(a_1)$	$p(a_2)$	$p(a_m)$	$p(a_M)$
$p(a_1)$	$p(a_2)$	$p(a_m)$	$p(a_M)$
$p(a_1)$	$p(a_2)$	$p(a_m)$	$p(a_M)$
$p(a_1)$	$p(a_2)$	$p(a_m)$	$p(a_M)$

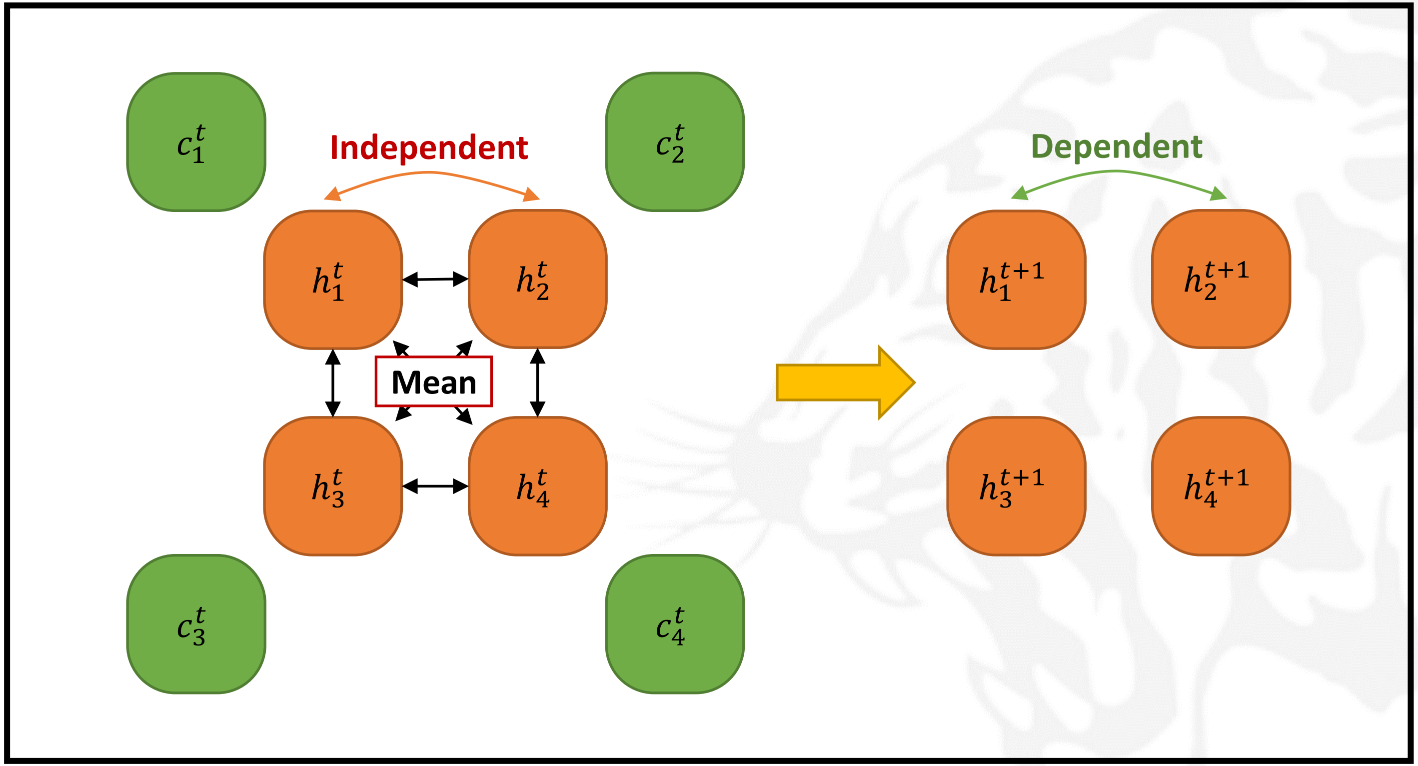
CommNet Performance

Model Φ	Training method: Supervised	Training method: Reinforcement
Independent	0.59	0.59
CommNet	**0.99**	**0.94**

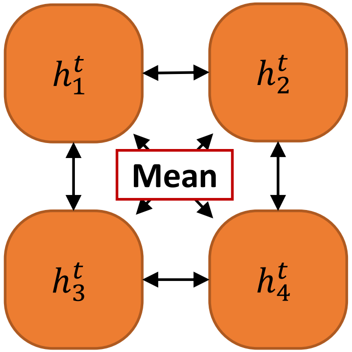
Model Φ	Other game versions: Easy (MLP)	Other game versions: Hard (RNN)
Independent	15.8± 12.5	26.9± 6.0
Discrete comm.	1.1± 2.4	28.2± 5.7
CommNet	**0.3**± **0.1**	22.5± 6.1
CommNet local	-	**21.1**± **3.4**

Model Φ	Module $f()$ type: MLP	RNN	LSTM
Independent	20.6± 14.1	19.5± 4.5	9.4± 5.6
Fully-connected	12.5± 4.4	34.8± 19.7	4.8± 2.4
Discrete comm.	15.8± 9.3	15.2± 2.1	8.4± 3.4
CommNet	**2.2**± **0.6**	**7.6**± **1.4**	**1.6**± **1.0**

Summary of CommNet



CommNet



In Graph Approach.

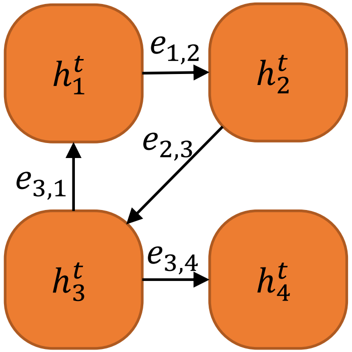
1. Should the agent communicate with all agent?

2. Can we transfer only essential information between agents?

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

Now we are curious that…

G2ANet



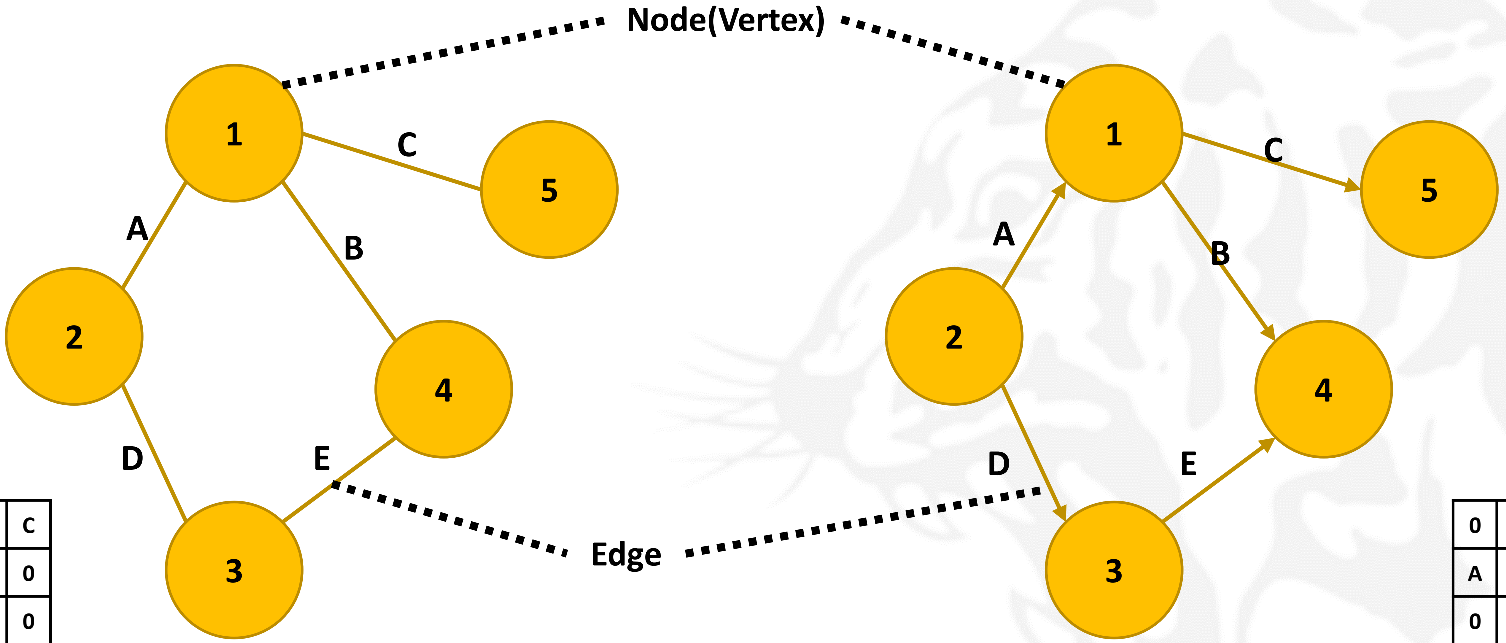
In Graph Approach.

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.**

- Graph



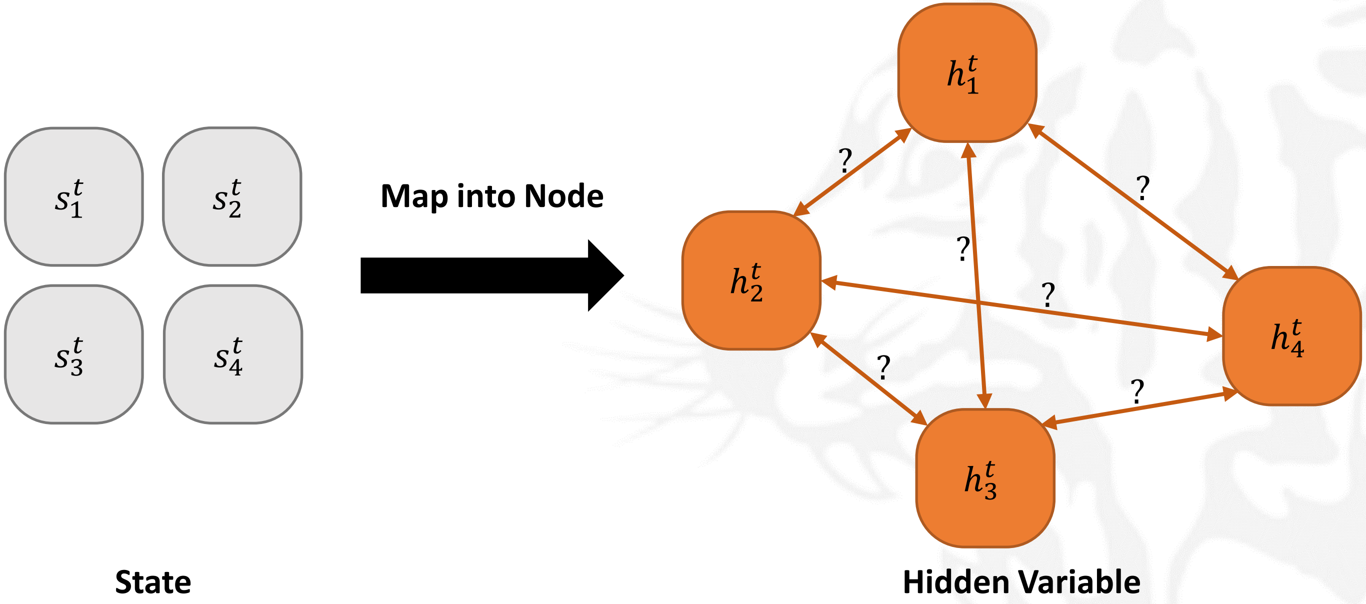
Undirected graph

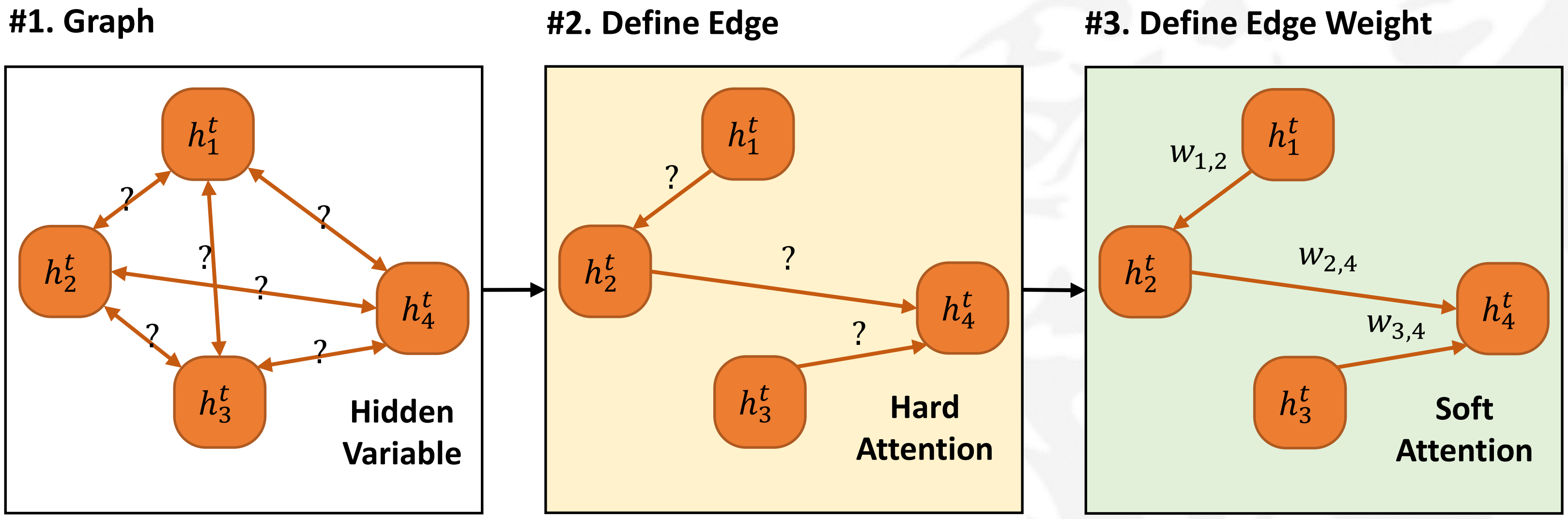
Directed graph

0	A	0	B	C
A	0	D	0	0
0	D	0	E	0
B	0	E	0	0
C	0	0	0	0

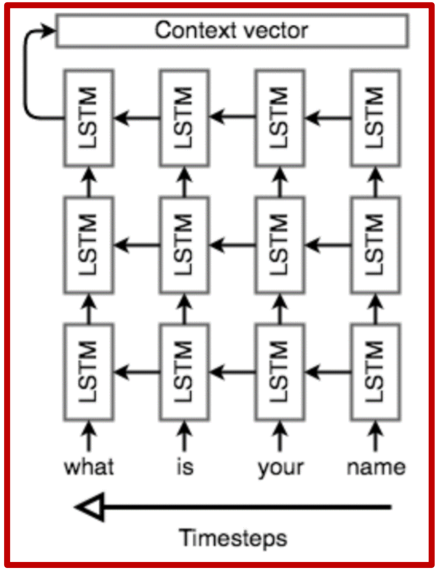
0	0	0	B	C
A	0	D	0	0
0	0	0	E	0
0	0	0	0	0
0	0	0	0	0

- States of agent are mapped into nodes(vertices).




#1. Graph
h_1^t
h_2^t
h_3^t
h_4^t
?
Hidden Variable
#2. Define Edge
h_1^t
h_2^t
h_3^t
h_4^t
?
Hard Attention
#3. Define Edge Weight
h_1^t
h_2^t
h_3^t
h_4^t
$w_{1,2}$
$w_{2,4}$
$w_{3,4}$
Soft Attention

- *Seq2Seq and attention* mechanism is widely used in natural language process(NLP).



- Query(Dictionary)

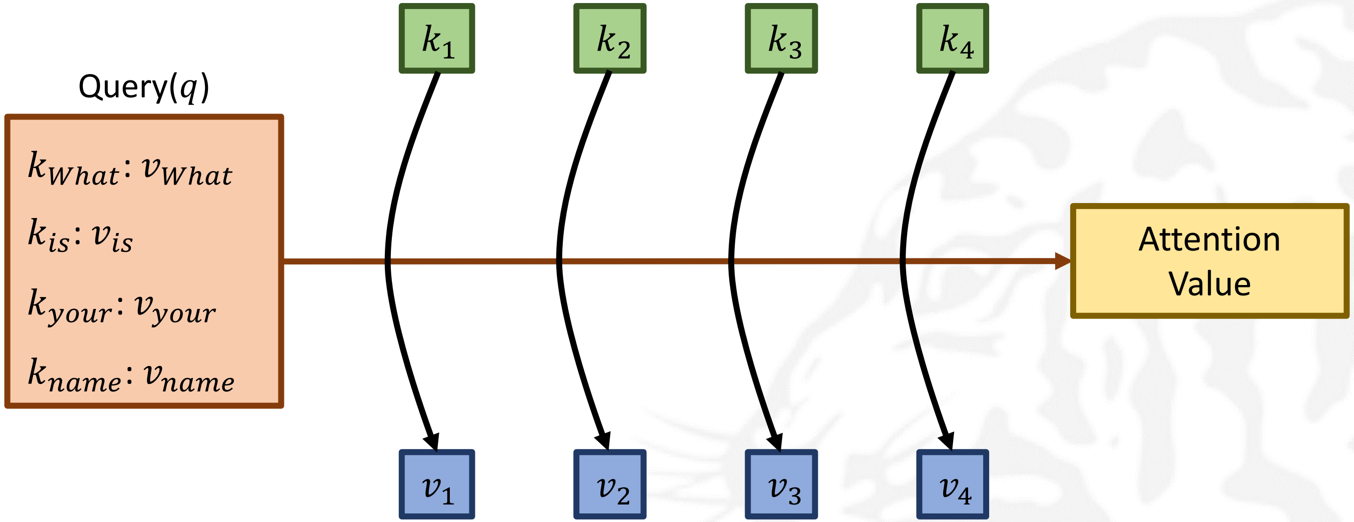
  $\{k_{What}: v_{What}\ ,k_{is}: v_{is}\ ,k_{your}: v_{your}, k_{name}: v_{name}\}$

- Key

  $k_{What}, k_{is}, k_{your}, k_{name}$

- Value

  $v_{What}, v_{is}, v_{your}, v_{name}$

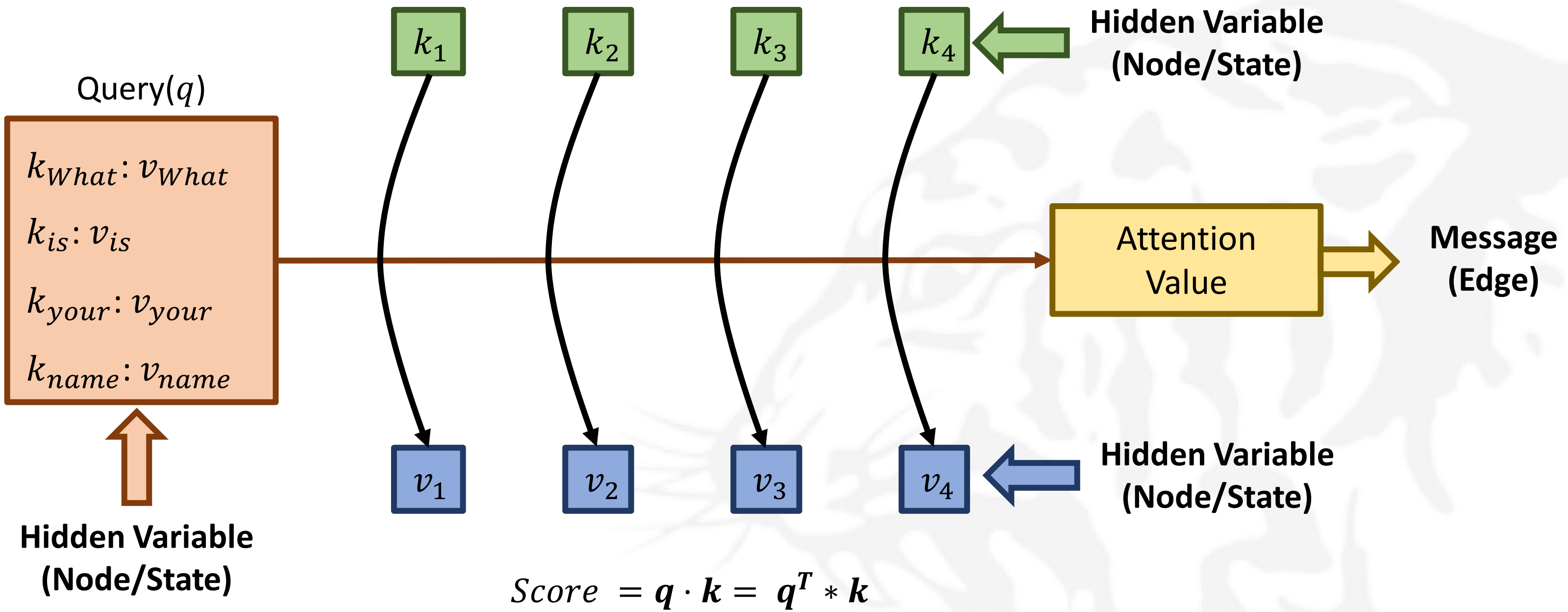


$$Score = \boldsymbol{q} \cdot \boldsymbol{k} = \boldsymbol{q}^{\boldsymbol{T}} * \boldsymbol{k}$$

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

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

Autoencoder: Hidden Variable(h_t) to Query, Key, Value



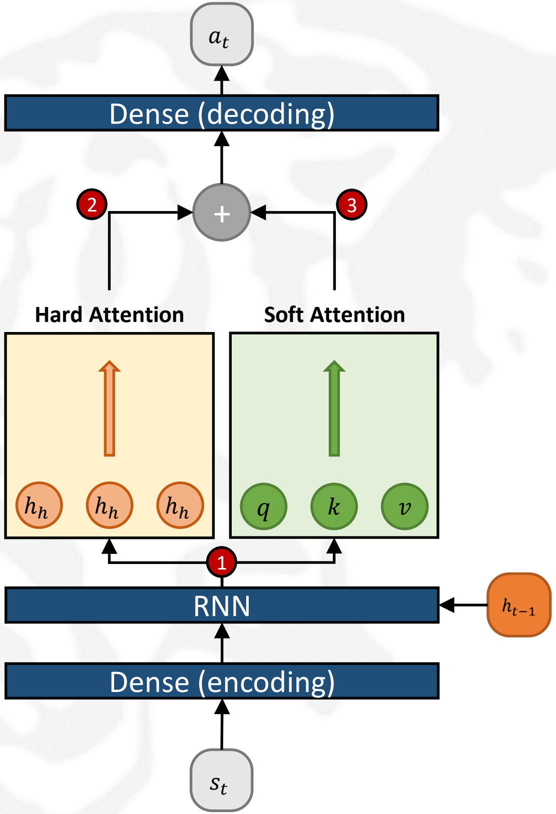
$$Score = \boldsymbol{q} \cdot \boldsymbol{k} = \boldsymbol{q}^T * \boldsymbol{k}$$

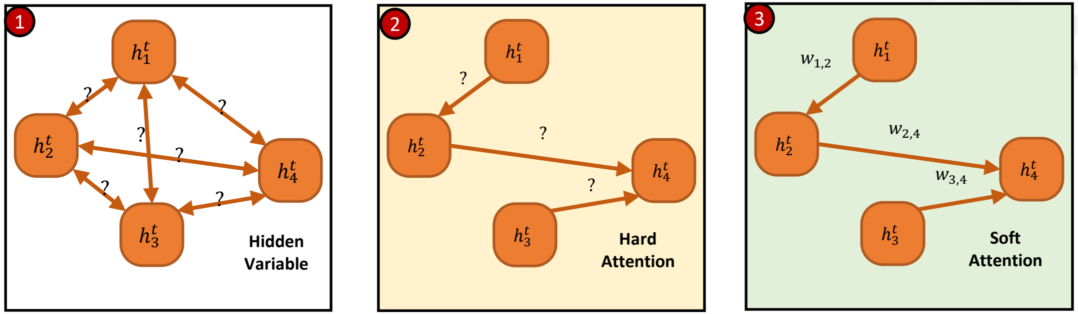
$$Score_{scaled} = \frac{Score}{\sqrt{n}}$$

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

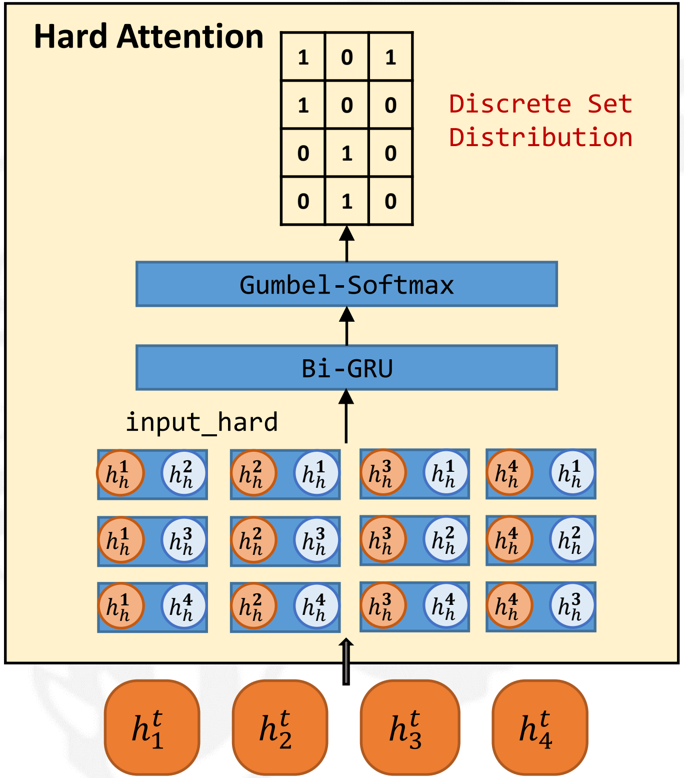
G2ANet Architecture

```python
class G2ANet(nn.Module):
    def __init__(self, input_shape, args):
        super(G2ANet, self).__init__()
        self.encoding = nn.Linear(input_shape, rnn_dim)
        self.h = nn.GRUCell(rnn_dim,  rnn_dim)
        self.hard_bi_GRU = nn.GRU(rnn_dim * 2,  rnn_dim, bidirectional=True)
        self.hard_encoding = nn.Linear(rnn_dim * 2, 2)
        self.q = nn.Linear(rnn_dim,  rnn_dim, bias=False)
        self.k = nn.Linear(rnn_dim,  rnn_dim, bias=False)
        self.v = nn.Linear(rnn_dim,  rnn_dim)
        self.decoding = nn.Linear(rnn_dim+attention_dim, n_actions)
        self.args = args
        self.input_shape = input_shape
```





```
def forward(self, obs, hidden_state):
    obs_encoding = f.relu(self.encoding(obs))
    h_in = hidden_state.reshape(-1,  rnn_dim)
    h_out = self.h(obs_encoding, h_in)
    h = h_out.reshape(-1, n_agents, rnn_dim)
    input_hard = []
    for i in range(n_agents):
        h_i = h[:, i]
        h_hard_i = []
        for j in range(n_agents):
            if j != i:
                h_hard_i.append(torch.cat([h_i, h[:, j]], dim=-1))
                h_hard_i = torch.stack(h_hard_i, dim=0)
                input_hard.append(h_hard_i)
            input_hard = torch.stack(input_hard, dim=-2)
            input_hard = input_hard.view(n_agents - 1, -1,  rnn_dim * 2)
    h_hard = torch.zeros((2 * 1, size, rnn_dim))
    h_hard, _ = self.hard_bi_GRU(input_hard, h_hard)
    h_hard = h_hard.permute(1, 0, 2)
    h_hard = h_hard.reshape(-1, rnn_dim * 2)
    hard_weights = self.hard_encoding(h_hard)
    hard_weights = f.gumbel_softmax(hard_weights, tau=0.01)
    hard_weights = hard_weights[:, 1].view(-1, n_agents, 1, n_agents-1)
    hard_weights = hard_weights.permute(1, 0, 2, 3)
```



Hard Attention

```python
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    h_hard = h_hard.reshape(-1, rnn_dim * 2)
    hard_weights = self.hard_encoding(h_hard)
    hard_weights = f.gumbel_softmax(hard_weights, tau=0.01)
    hard_weights = hard_weights[:, 1].view(-1, n_agents, 1, n_agents-1)
    hard_weights = hard_weights.permute(1, 0, 2, 3)
```

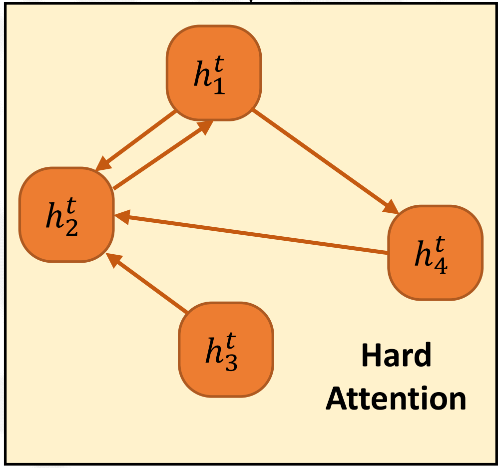
Hard Attention Output

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

Adjacency Matrix

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

Define Edge



Soft Attention

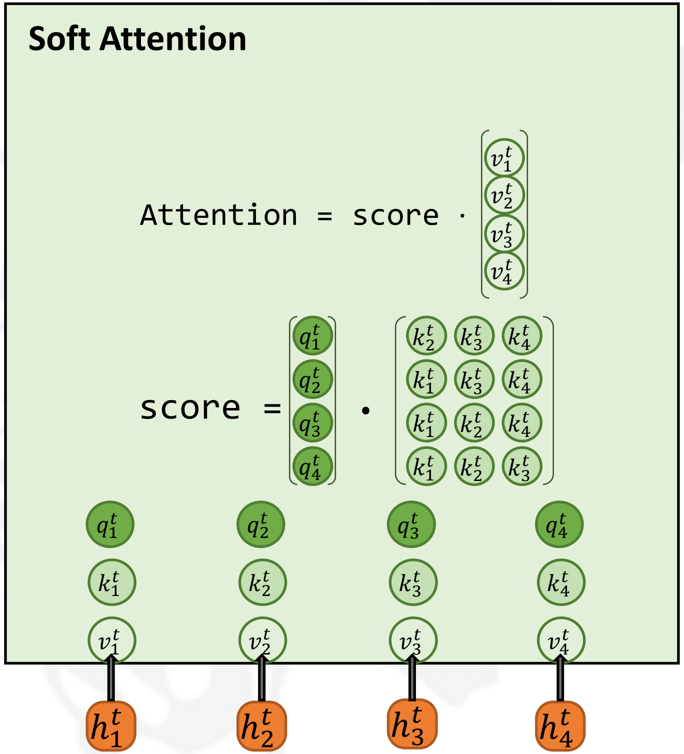

```
def forward(self, obs, hidden_state):
    q = self.q(h_out).reshape(-1, n_agents, attention_dim)
    k = self.k(h_out).reshape(-1, n_agents, attention_dim)
    v = f.relu(self.v(h_out)).reshape(1, n_agents, attention_dim)
    x = []
    for i in range(n_agents):
        q_i = q[:, i].view(-1, 1, attention_dim)
        k_i = [k[:, j] for j in range(n_agents) if j != i]
        v_i = [v[:, j] for j in range(n_agents) if j != i]

        k_i = torch.stack(k_i, dim=0)
        k_i = k_i.permute(1, 2, 0)
        v_i = torch.stack(v_i, dim=0)
        v_i = v_i.permute(1, 2, 0)
        score = torch.matmul(q_i, k_i)
        scaled_score = score / np.sqrt(attention_dim)
        soft_weight = f.softmax(scaled_score, dim=-1)
        x_i = (v_i * soft_weight * hard_weights[i]).sum(dim=-1)
        x.append(x_i)
    x = torch.stack(x, dim=1).reshape(-1, attention_dim)
    final_input = torch.cat([h_out, x], dim=-1)
    output = self.decoding(final_input)
    return output, h_out
```

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

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

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



Soft Attention

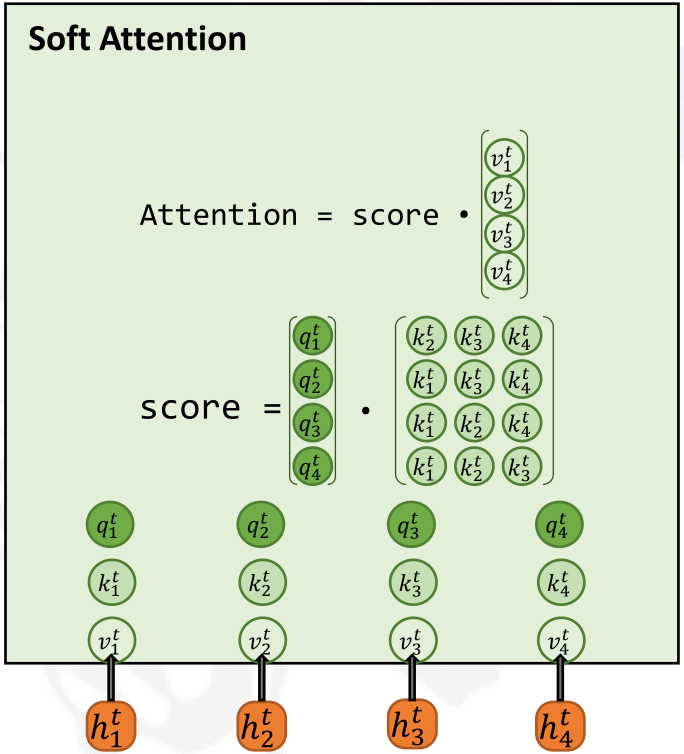
```python
def forward(self, obs, hidden_state):
    q = self.q(h_out).reshape(-1, n_agents, attention_dim)
    k = self.k(h_out).reshape(-1, n_agents, attention_dim)
    v = f.relu(self.v(h_out)).reshape(1, n_agents, attention_dim)
    x = []
    for i in range(n_agents):
        q_i = q[:, i].view(-1, 1, attention_dim)
        k_i = [k[:, j] for j in range(n_agents) if j != i]
        v_i = [v[:, j] for j in range(n_agents) if j != i]

        k_i = torch.stack(k_i, dim=0)
        k_i = k_i.permute(1, 2, 0)
        v_i = torch.stack(v_i, dim=0)
        v_i = v_i.permute(1, 2, 0)
        score = torch.matmul(q_i, k_i)
        scaled_score = score / np.sqrt(attention_dim)
        soft_weight = f.softmax(scaled_score, dim=-1)
        x_i = (v_i * soft_weight * hard_weights[i]).sum(dim=-1)
        x.append(x_i)
    x = torch.stack(x, dim=1).reshape(-1, attention_dim)
    final_input = torch.cat([h_out, x], dim=-1)
    output = self.decoding(final_input)
    return output, h_out
```

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

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

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

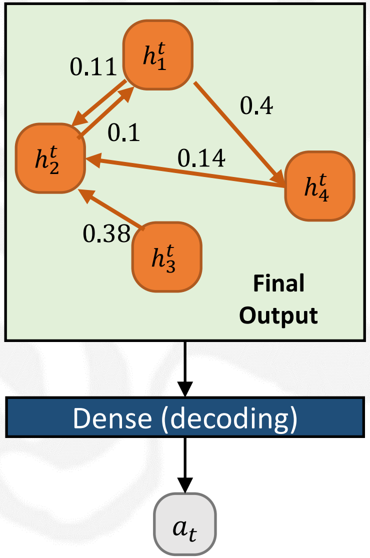


```python
def forward(self, obs, hidden_state):
    q = self.q(h_out).reshape(-1, n_agents, attention_dim)
    k = self.k(h_out).reshape(-1, n_agents, attention_dim)
    v = f.relu(self.v(h_out)).reshape(1, n_agents, attention_dim)
    x = []
    for i in range(n_agents):
        q_i = q[:, i].view(-1, 1, attention_dim)
        k_i = [k[:, j] for j in range(n_agents) if j != i]
        v_i = [v[:, j] for j in range(n_agents) if j != i]

        k_i = torch.stack(k_i, dim=0)
        k_i = k_i.permute(1, 2, 0)
        v_i = torch.stack(v_i, dim=0)
        v_i = v_i.permute(1, 2, 0)
        score = torch.matmul(q_i, k_i)
        scaled_score = score / np.sqrt(attention_dim)
        soft_weight = f.softmax(scaled_score, dim=-1)
        x_i = (v_i * soft_weight * hard_weights[i]).sum(dim=-1)
        x.append(x_i)
    x = torch.stack(x, dim=1).reshape(-1, attention_dim)
    final_input = torch.cat([h_out, x], dim=-1)
    output = self.decoding(final_input)
    return output, h_out
```

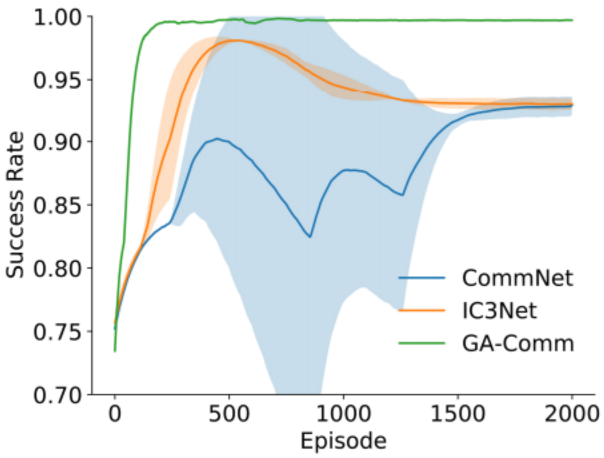
Hard Attention Output (connection) * **Soft Attention Output (message)** = **Final Output (connection & message)**

$$\begin{bmatrix} 1 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix} * \begin{bmatrix} 0.11 & 0.84 & 0.4 \\ 0.1 & 0.18 & 0.72 \\ 0.34 & 0.38 & 0.28 \\ 0.16 & 0.14 & 0.70 \end{bmatrix} = \begin{bmatrix} 0.11 & 0 & 0.4 \\ 0.1 & 0 & 0 \\ 0 & 0.38 & 0 \\ 0 & 0.14 & 0 \end{bmatrix}$$

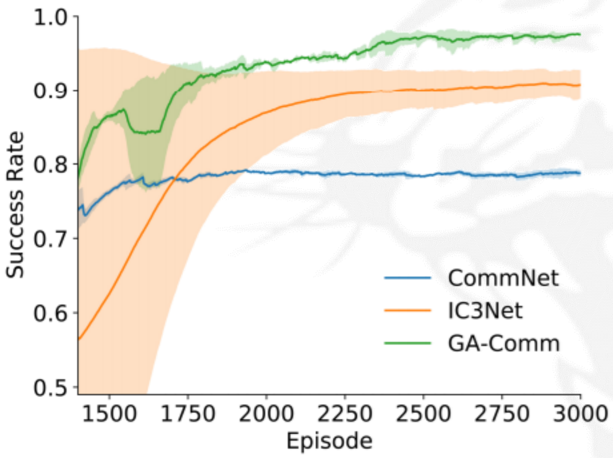


G2ANet Performance

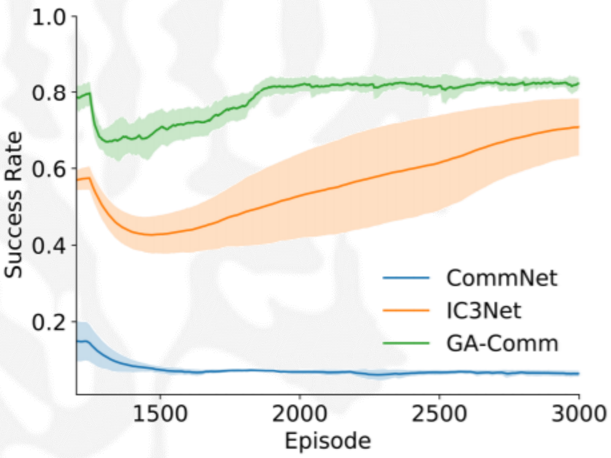
Algorithm	Easy	Medium	Hard
CommNet	93.5%	78.8%	6.5%
IC3Net	93.2%	90.8%	70.9%
GA-Comm	**99.7%**	**97.6%**	**82.3%**



(a) Easy



(b) Medium



(c) Hard

Thank you for your attention!

- More questions?
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