PROJECT REPORT

MULTI-AGENT REINFORCEMENT LEARNING VIA ADAPTIVE KALMAN TEMPORAL DIFFERENCE AND SUCCESSOR REPRESENTATION

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INTRODUCTION

Challenges!

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Problem Formulation

- > Single Agent Reinforcement Learning
- > Off-Policy Temporal Difference (TD) Learning
- > Multi-Agent Setting
- > Multi-Agent SR

Problem Formulation

- > Single Agent Reinforcement Learning
- > Off-Policy Temporal Difference (TD) Learning
- Multi-Agent Setting
- > Multi-Agent SR

SINGLE AGENT REINFORCEMENT LEARNING

$$Q_{\pi}(\mathbf{s},a) = \mathbb{E}\left\{\sum_{k=0}^{T} \gamma^k r_k | \mathbf{s}_0 = \mathbf{s}, a_0 = a, a_k = \pi(\mathbf{s}_k)\right\}$$

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SINGLE AGENT REINFORCEMENT LEARNING

$$Q_{\pi}(s, a) = \mathbb{E}\left\{\sum_{k=0}^{T} \gamma^{k} r_{k} | s_{0} = s, a_{0} = a, a_{k} = \pi(s_{k})\right\}$$

$$a_k = \arg\max_{a \in \mathcal{A}} Q_{\pi^*}(s_k, a)$$

Problem Formulation

- > Single Agent Reinforcement Learning
- > Off-Policy Temporal Difference (TD) Learning
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TD LEARNING

$$Q_{\pi^*}(s_k, a_k) = Q_{\pi^*}(s_k, a_k) + \alpha \left(r_k + \gamma \max_{a \in \mathcal{A}} Q_{\pi^*}(s_{k+1}, a) - Q_{\pi^*}(s_k, a_k) \right)$$

Problem Formulation

- > Single Agent Reinforcement Learning
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TD LEARNING

$$Q_{\pi^*}(s_k, a_k) = Q_{\pi^*}(s_k, a_k) + \alpha \left(r_k + \gamma \max_{a \in \mathcal{A}} Q_{\pi^*}(s_{k+1}, a) - Q_{\pi^*}(s_k, a_k) \right)$$

$$a_k = \arg\max_{a \in \mathcal{A}} Q_{\pi^*}(s_k, a)$$

> Single Agent Reinforcement Learning

> Off-Policy Temporal Difference (TD) Learning

Multi-Agent Setting

MULTI AGENT SETTING

Agent *i*, for $(1 \le i \le N)$

$$\mathbb{S} = \{\mathcal{S}^{(1)}, \dots, \mathcal{S}^{(N)}\}$$

$$\mathbb{A} = \{\mathcal{A}^{(1)}, \dots, \mathcal{A}^{(N)}\}$$

$$\mathbb{Z} = \{\mathcal{Z}^{(1)}, \dots, \mathcal{Z}^{(N)}\}$$

$$r^{(i)} : \mathbb{S} \times \mathcal{A}^{(i)} \to \mathbb{R}$$

$$R^{(i)} = \sum_{i=1}^{T} \gamma^{t} (r^{(i)})^{t}$$

- > Single Agent Reinforcement Learning
- > Off-Policy Temporal Difference (TD) Learning
- Multi Agent Octung
- Multi-Agent SR

MULTI AGENT SR

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}^{(i)}, \boldsymbol{s'}^{(i)}, a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k} \mathbb{1}[\boldsymbol{s}_{k}^{(i)} = \boldsymbol{s'}^{(i)}] | \boldsymbol{s}_{0}^{(i)} = \boldsymbol{s}^{(i)}, a_{0}^{(i)} = a^{(i)}\right]$$

$$\begin{aligned} \mathbf{M}_{\pi^{(i)}}^{\text{new}}(\mathbf{s}_{k}^{(i)}, \mathbf{s'}^{(i)}, a_{k}^{(i)}) &= \mathbf{M}_{\pi^{(i)}}^{\text{old}}(\mathbf{s}_{k}^{(i)}, \mathbf{s'}^{(i)}, a_{k}^{(i)}) + \\ &\alpha \Big(\mathbb{1}[\mathbf{s}_{k}^{(i)} = \mathbf{s'}^{(i)}] + \gamma \mathbf{M}_{\pi^{(i)}}(\mathbf{s}_{k+1}^{(i)}, \mathbf{s'}^{(i)}, a_{k+1}^{(i)}) - \mathbf{M}_{\pi^{(i)}}^{\text{old}}(\mathbf{s}_{k}^{(i)}, \mathbf{s'}^{(i)}, a_{k}^{(i)}) \Big) \end{aligned}$$

$$Q_{\pi^{(i)}}(s_k^{(i)}, a_k^{(i)}) = \sum_{s'^{(i)} \in \mathcal{S}^{(i)}} \mathbf{M}(s_k^{(i)}, s'^{(i)}, a_k^{(i)}) R^{(i)}(s'^{(i)}, a_k^{(i)})$$

- > Single Agent Reinforcement Learning
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MULTI AGENT SR

$$M_{\pi^{(i)}}(s^{(i)}, s'^{(i)}, a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^k \mathbb{1}[s_k^{(i)} = s'^{(i)}] | s_0^{(i)} = s^{(i)}, a_0^{(i)} = a^{(i)}\right]$$

$$\begin{aligned} \boldsymbol{M}_{\pi^{(i)}}^{\text{new}}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{s}'^{(i)}, a_{k}^{(i)}) &= \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{s}'^{(i)}, a_{k}^{(i)}) + \\ \alpha \left(\mathbb{1}[\boldsymbol{s}_{k}^{(i)} = \boldsymbol{s}'^{(i)}] + \gamma \boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_{k+1}^{(i)}, \boldsymbol{s}'^{(i)}, a_{k+1}^{(i)}) - \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{s}'^{(i)}, a_{k}^{(i)}) \right) \end{aligned}$$

$$Q_{\pi^{(i)}}(\mathbf{s}_k^{(i)}, a_k^{(i)}) = \sum_{\mathbf{s}'^{(i)} \in \mathcal{S}^{(i)}} \mathbf{M}(\mathbf{s}_k^{(i)}, \mathbf{s}'^{(i)}, a_k^{(i)}) R^{(i)}(\mathbf{s}'^{(i)}, a_k^{(i)})$$

- > Single Agent Reinforcement Learning
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MULTI AGENT SR

$$M_{\pi^{(i)}}(s^{(i)}, s'^{(i)}, a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^k \mathbb{1}[s_k^{(i)} = s'^{(i)}] | s_0^{(i)} = s^{(i)}, a_0^{(i)} = a^{(i)}\right]$$

$$\begin{split} \boldsymbol{M}_{\pi^{(i)}}^{\text{new}}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{s'}^{(i)}, a_{k}^{(i)}) &= \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{s'}^{(i)}, a_{k}^{(i)}) + \\ &\alpha \Big(\mathbb{1}[\boldsymbol{s}_{k}^{(i)} = \boldsymbol{s'}^{(i)}] + \gamma \boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_{k+1}^{(i)}, \boldsymbol{s'}^{(i)}, a_{k+1}^{(i)}) - \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{s'}^{(i)}, a_{k}^{(i)}) \Big) \end{split}$$

$$Q_{\pi^{(i)}}(\mathbf{s}_k^{(i)}, a_k^{(i)}) = \sum_{\mathbf{s}'^{(i)} \in \mathcal{S}^{(i)}} \mathbf{M}(\mathbf{s}_k^{(i)}, \mathbf{s}'^{(i)}, a_k^{(i)}) R^{(i)}(\mathbf{s}'^{(i)}, a_k^{(i)})$$

$$Q_{\pi^{(i)*}}(\mathbf{s}_k^{(i)}, a_k^{(i)}) \approx r_k^{(i)} + \gamma \max_{a^{(i)} \in \mathcal{A}} Q_{\pi^{(i)*}}(\mathbf{s}_{k+1}^{(i)}, a^{(i)})$$

$$r_k^{(i)} = Q_{\pi^{(i)*}}(s_k^{(i)}, a_k^{(i)}) - \gamma \max_{a^{(i)} \in \mathcal{A}} Q_{\pi^*}(s_{k+1}^{(i)}, a^{(i)}) + v_k^{(i)}$$

 v_k is modeled as a zero-mean normal distribution with variance of $R^{(i)}$

$$Q_{\pi^{(i)*}}(\mathbf{s}_k^{(i)}, a_k^{(i)}) \approx r_k^{(i)} + \gamma \max_{a^{(i)} \in \mathcal{A}} Q_{\pi^{(i)*}}(\mathbf{s}_{k+1}^{(i)}, a^{(i)})$$

$$r_k^{(i)} = Q_{\pi^{(i)^*}}(s_k^{(i)}, a_k^{(i)}) - \gamma \max_{a^{(i)} \in \mathcal{A}} Q_{\pi^*}(s_{k+1}^{(i)}, a^{(i)}) + v_k^{(i)}$$

 v_k is modeled as a zero-mean normal distribution with variance of $R^{(i)}$

$$Q_{\pi^{(i)}}(s_k^{(i)}, a_k^{(i)}) = \phi(s_k^{(i)}, a_k^{(i)})^T \theta_k^{(i)}$$

$$r_k^{(i)} = \left[\phi(s_k^{(i)}, a_k^{(i)})^T - \gamma \max_{a^{(i)} \in \mathcal{A}} \phi(s_{k+1}^{(i)}, a^{(i)})^T \right] \theta_k^{(i)} + v_k^{(i)}$$

$$h_k^{(i)} = \phi(s_k^{(i)}, a_k^{(i)}) - \gamma \max_{a^{(i)} \in \mathcal{A}} \phi(s_{k+1}^{(i)}, a^{(i)})$$

$$r_k^{(i)} = [\boldsymbol{h}_k^{(i)}]^T \boldsymbol{\theta}_k^{(i)} + v_k^{(i)}$$

MAK-TD Framework

$$Q_{\pi^{(i)}}(s_k^{(i)}, a_k^{(i)}) = \phi(s_k^{(i)}, a_k^{(i)})^T \theta_k^{(i)}$$

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$$h_k^{(i)} = \phi(s_k^{(i)}, a_k^{(i)}) - \gamma \max_{a^{(i)} \in \mathcal{A}} \phi(s_{k+1}^{(i)}, a^{(i)})$$

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$$\boldsymbol{h}_{k}^{(i)} = \boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)}, a_{k}^{(i)}) - \gamma \max_{a^{(i)} \in \mathcal{A}} \boldsymbol{\phi}(\boldsymbol{s}_{k+1}^{(i)}, a^{(i)})$$

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$$r_k^{(i)} = [h_k^{(i)}]^T \theta_k^{(i)} + v_k^{(i)}$$

$$r_k^{(i)} = [\boldsymbol{h}_k^{(i)}]^T \boldsymbol{\theta}_k^{(i)} + v_k^{(i)}$$

$$x_{k} = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}$$

$$y_k = H_k x_k + v_k$$

$$E(w_k) = E(v_k) = 0$$
 $E(w_k w_j^T) = Q_k \delta_{k-j}$ $E(v_k v_j^T) = R_k \delta_{k-j}$ $E(v_k w_j^T) = 0$

$$x_{k} = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}$$

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$$r_k^{(i)} = [\boldsymbol{h}_k^{(i)}]^T \boldsymbol{\theta}_k^{(i)} + v_k^{(i)}$$

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$$x_{k} = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}$$

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$$r_k^{(i)} = [\boldsymbol{h}_k^{(i)}]^T \boldsymbol{\theta}_k^{(i)} + v_k^{(i)}$$

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 $E(w_k w_j^T) = Q_k \delta_{k-j}$ $E(v_k v_j^T) = R_k \delta_{k-j}$ $E(v_k w_j^T) = 0$

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} = P_k^+ H_k^T R_k^{-1}$$

$$\hat{x}_{k}^{+} = \hat{x}_{k}^{-} + K_{k}(y_{k} - H_{k}\hat{x}_{k}^{-})$$

$$P_k^+ = (I - K_k H_k) P_k^- = (I - K_k H_k) P_k^- (I - K_k H_k)^T + K_k R_k K_k^T$$

$$\begin{aligned} r_k^{(i)} &= [\boldsymbol{h}_k^{(i)}]^T \boldsymbol{\theta}_k^{(i)} + v_k^{(i)} \\ K_k &= P_k^- \boldsymbol{H}_k^T (\boldsymbol{H}_k P_k^- \boldsymbol{H}_k^T + R_k)^{-1} &= P_k^+ \boldsymbol{H}_k^T R_k^{-1} \\ \hat{x}_k^+ &= \hat{x}_k^- + K_k (\boldsymbol{y}_k - \boldsymbol{H}_k \hat{x}_k^-) \\ P_k^+ &= (I - K_k \boldsymbol{H}_k) P_k^- = (I - K_k \boldsymbol{H}_k) P_k^- (I - K_k \boldsymbol{H}_k)^T + K_k R_k K_k^T \end{aligned}$$

$$\mathbf{K}_{k}^{j(i)} = \mathbf{P}_{(\theta,k|k-1)}^{(i)} \mathbf{h}_{k}^{(i)} (\mathbf{h}_{k}^{T(i)} \mathbf{P}_{(\theta,k|k-1)}^{(i)} \mathbf{h}_{k}^{(i)} + R^{j(i)})^{-1}
\hat{\boldsymbol{\theta}}_{k}^{j(i)} = \hat{\boldsymbol{\theta}}_{(k|k-1)}^{(i)} + \mathbf{K}_{k}^{j(i)} (r_{k}^{(i)} - \mathbf{h}_{k}^{T(i)} \hat{\boldsymbol{\theta}}_{(k|k-1)}^{(i)})
\mathbf{P}_{\theta,k}^{j(i)} = (\mathbf{I} - \mathbf{K}_{k}^{j(i)} \mathbf{h}_{k}^{T(i)}) \mathbf{P}_{(\theta,k|k-1)}^{T}^{(i)} (\mathbf{I} - \mathbf{K}_{k}^{j(i)} \mathbf{h}_{k}^{T(i)}) + \mathbf{K}_{k}^{j(i)} \mathbf{K}_{k}^{j(i)} \mathbf{K}_{k}^{j}^{T(i)}$$

$$x_{k} = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}$$

$$\overline{x}_{k} = F_{k-1}\overline{x}_{k-1} + G_{k-1}u_{k-1}$$

$$P_{k} = F_{k-1} P_{k-1} F_{k-1}^{T} + Q_{k-1}$$

$$\hat{\boldsymbol{\theta}}_{k}^{(i)} = \sum_{j=1}^{M} \omega^{j(i)} \hat{\boldsymbol{\theta}}_{k}^{j(i)}
P_{\boldsymbol{\theta},k}^{(i)} = \sum_{j=1}^{M} \omega^{j(i)} \left(P_{\boldsymbol{\theta},k}^{j(i)} + (\hat{\boldsymbol{\theta}}^{j(i)} - \hat{\boldsymbol{\theta}}^{(i)}) (\hat{\boldsymbol{\theta}}^{j(i)} - \hat{\boldsymbol{\theta}}^{(i)})^{T} \right)$$

$$\boldsymbol{\phi}(s_k^{(i)}) = \left[\phi_1(s_k^{(i)}), \phi_2(s_k^{(i)}), \dots, \phi_{N_b-1}(s_k^{(i)}), \phi_{N_b}(s_k^{(i)})\right]^T$$

$$\phi_n(s_k^{(i)}) = \exp\{\frac{-1}{2}(s_k^{(i)} - \mu_n^{(i)})^T \Sigma_n^{(i)} - 1(s_k^{(i)} - \mu_n^{(i)})\}$$

where $\mu_n^{(i)}$ and $\Sigma_n^{(i)}$ are the mean and covariance of $\phi_n(s_k^{(i)})$, for $(1 \le n \le N_b)$

$$\boldsymbol{\phi}(s_k^{(i)}) = \left[\phi_1(s_k^{(i)}), \phi_2(s_k^{(i)}), \dots, \phi_{N_b-1}(s_k^{(i)}), \phi_{N_b}(s_k^{(i)})\right]^T$$

$$\phi_n(s_k^{(i)}) = \exp\{\frac{-1}{2}(s_k^{(i)} - \mu_n^{(i)})^T \Sigma_n^{(i)} - (s_k^{(i)} - \mu_n^{(i)})\}$$

where $\mu_n^{(i)}$ and $\Sigma_n^{(i)}$ are the mean and covariance of $\phi_n(s_k^{(i)})$, for $(1 \le n \le N_b)$

$$\boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)}, a_{k}^{(i)}) = [\phi_{1,a_{1}}(\boldsymbol{s}_{k}^{(i)}), \dots \phi_{N_{b},a_{1}}(\boldsymbol{s}_{k}^{(i)}), \phi_{1,a_{2}}(\boldsymbol{s}_{k}^{(i)}), \dots \phi_{N_{b},a_{D}(i)}(\boldsymbol{s}_{k}^{(i)})]^{T}$$

$$\phi(s_k^{(i)}, a_k^{(i)}) = [0, \dots, \phi_1(s_k^{(i)}), \dots, \phi_N(s_k^{(i)}), 0, \dots, 0]^T$$

$$L_k^{(i)} = (\boldsymbol{\phi}^T(s_k^{(i)}, a_k) \, \boldsymbol{\theta}_k^{(i)} - r_k^{(i)})^2$$

$$\Delta \mu^{(i)} = -\frac{\partial L_k^{(i)}}{\partial \mu^{(i)}} = -\frac{\partial L_k^{(i)}}{\partial Q_{\pi^{*(i)}}} \frac{\partial Q_{\pi^{*(i)}}}{\partial \phi^{(i)}} \frac{\partial \phi^{(i)}}{\partial \mu^{(i)}}$$
and
$$\Delta \Sigma^{(i)} = -\frac{\partial \Sigma_k^{(i)}}{\partial \mu^{(i)}} = -\frac{\partial L_k^{(i)}}{\partial Q_{\pi^{*(i)}}} \frac{\partial Q_{\pi^{*(i)}}}{\partial \phi^{(i)}} \frac{\partial \phi^{(i)}}{\partial \Sigma^{(i)}}$$



$$L_k^{(i)} = (\boldsymbol{\phi}^T(s_k^{(i)}, a_k) \, \boldsymbol{\theta}_k^{(i)} - r_k^{(i)})^2$$

$$\Delta \mu^{(i)} = -\frac{\partial L_k^{(i)}}{\partial \mu^{(i)}} = -\frac{\partial L_k^{(i)}}{\partial Q_{\pi^{*(i)}}} \frac{\partial Q_{\pi^{*(i)}}}{\partial \phi^{(i)}} \frac{\partial \phi^{(i)}}{\partial \mu^{(i)}}$$
and
$$\Delta \Sigma^{(i)} = -\frac{\partial \Sigma_k^{(i)}}{\partial \mu^{(i)}} = -\frac{\partial L_k^{(i)}}{\partial Q_{\pi^{*(i)}}} \frac{\partial Q_{\pi^{*(i)}}}{\partial \phi^{(i)}} \frac{\partial \phi^{(i)}}{\partial \Sigma^{(i)}}$$



$$a_k^{(i)} = \arg \max_{a} \left(\mathbf{h}_k^{(i)}(\mathbf{s}_k^{(i)}, a^{(i)}) R^{-1}{}^{(i)} \mathbf{h}_k^{T}{}^{(i)}(\mathbf{s}_k^{(i)}, a^{(i)}) \right)$$
$$= \arg \max_{a} \left(\mathbf{h}_k^{(i)}(\mathbf{s}_k^{(i)}, a^{(i)}) \mathbf{h}_k^{T}{}^{(i)}(\mathbf{s}_k^{(i)}, a^{(i)}) \right).$$

Algorithm 1 THE PROPOSED MAK-TD FRAMEWORK

```
1: Learning Phase:
  2: Set \theta_0, P_{\theta,0}, F, \mu_{n,i_d}, \Sigma_{n,i_d} for n = 1, 2, ..., N and i_d = 1, 2, ..., D
  3: Repeat (for each episode):
                  Initialize s_k
  5:
                  Repeat (for each agent i):
                      While s_{\nu}^{(i)} \neq s_T do:
  6:
                          a_k^{(i)} = \arg\max_{a} \left( h_k^{(i)}(s_k^{(i)}, a^{(i)}) h_k^{T(i)}(s_k^{(i)}, a^{(i)}) \right)
                           Take action a_k^{(i)}, observe s_{k+1}^{(i)}, r_k^{(i)}
  8:
                           Calculate \phi^{(i)}(s^{(i)}, a^{(i)}) via Equations (22) and (23)
  9:
                           h_k^{(i)}(s_k^{(i)}, a_k^{(i)}) = \phi^{(i)}(s_k^{(i)}, a_k^{(i)}) - \gamma \arg \max \phi^{(i)}(s_{k+1}^{(i)}, a^{(i)})
10:
                           \hat{\boldsymbol{\theta}}_{(k|k-1)}^{(i)} = \boldsymbol{F}^{(i)} \hat{\boldsymbol{\theta}}_k^{(i)}
11:
                           P_{(\theta,k|k-1)}^{(i)} = F^{(i)}P_{\theta,k-1}^{(i)}F^{T(i)} + Q^{(i)}
12:
                           for i = 1 : M do:
13:
                                    \mathbf{k}_{k}^{j(i)} = \mathbf{P}_{(\boldsymbol{\theta},k|k-1)}^{(i)} \mathbf{h}_{k}^{(i)} (\mathbf{h}_{k}^{T(i)} \mathbf{P}_{(\boldsymbol{\theta},k|k-1)}^{(i)} \mathbf{h}_{k}^{(i)} + \mathbf{R}^{j(i)})^{-1}
14:
                                     \hat{\boldsymbol{\theta}}_{k}^{j(i)} = \hat{\boldsymbol{\theta}}_{(\boldsymbol{\theta}|k|k-1)}^{(i)} + \boldsymbol{k}_{k}^{j(i)} (r_{k}^{j} - \boldsymbol{h}_{k}^{T(i)} \hat{\boldsymbol{\theta}}_{(k|k-1)}^{(i)})
15:
                                     P_{\theta k}^{(i)} = (I - K_k^{j(i)} h_k^{T(i)}) P_{(\theta k|k-1)}^{(i)} (I - K_k^{j(i)} h_k^{T(i)})^T + K_k^{j(i)} R^j K_k^{j}^{T(i)}
16:
17:
                           end for
```

```
Compute the value of c and w^{j^{(i)}} by using \sum_{i=1}^{M} w^{j^{(i)}} = 1 and Equation (19)
18:
                     \hat{\theta}_{k}^{(i)} = \sum_{i=1}^{M} w^{j(i)} \hat{\theta}_{k}^{j(i)}
19:
                     P_{\theta_k}^{(i)} = \sum_{j=1}^{M} \omega^{j(i)} \left( P_{\theta_{jk}}^{j(i)} + (\hat{\theta}^{j(i)} - \hat{\theta}^{(i)}) (\hat{\theta}^{j(i)} - \hat{\theta}^{(i)})^T \right)
20:
                      RBFs Parameters Update:
21:
                     L_{k}^{(i)} = (\boldsymbol{\phi}^{T}(s_{k}^{(i)}, a_{k}) \, \boldsymbol{\theta}_{k}^{(i)} - r_{k}^{(i)})^{2}
22:
                     if L_{\nu}^{(i)^{\frac{1}{2}}}(\boldsymbol{\theta}_{\nu}^{(i)^{T}}\boldsymbol{\phi}(\cdot)) > 0 then:
23:
                         Update \Sigma_{n,a_d} via Equation (29)
24:
25:
                      else:
26:
                          Update \mu_{n,a_d} via Equation (30)
27:
                      end if
                  end while
28:
      Testing Phase:
     Repeat (for each trial episode):
              While s_k \neq s_T do:
31:
                  Repeat (for each agent):
                     a_k = \arg\max_{a} \boldsymbol{\phi}(s_k, a)^T \boldsymbol{\theta}_k
33:
                      Take action a_k, and observe s_{k+1}, r_k
34:
35:
                      Calculate Loss S_k for all agents
              End While
36:
```

MAK-SR FRAMEWORK

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}^{(i)},:,a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k} \boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) | \boldsymbol{s}_{0}^{(i)} = \boldsymbol{s}^{(i)}, a_{0}^{(i)} = a^{(i)}\right]$$

$$r^{(i)}(\boldsymbol{s}_k^{(i)}, \boldsymbol{a}_k^{(i)}) \approx \boldsymbol{\phi}(\boldsymbol{s}_k^{(i)}, \boldsymbol{a}_k^{(i)})^T \boldsymbol{\theta}_k^{(i)}$$

$$Q(s_k^{(i)}, a_k^{(i)}) = \theta_k^{(i)^T} M(s_k^{(i)}, :, a_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_k^{(i)},:,\boldsymbol{a}_k^{(i)}) \approx \boldsymbol{M}_k \, \boldsymbol{\phi}(\boldsymbol{s}_k^{(i)},\boldsymbol{a}_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}^{\text{new}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) = \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) + \alpha \big(\boldsymbol{\phi^{(i)}}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) + \gamma \boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_{k+1}^{(i)},:,a_{k+1}^{(i)}) - \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)})\big)$$

MAK-SR FRAMEWORK

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}^{(i)},:,a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k} \boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) | \boldsymbol{s}_{0}^{(i)} = \boldsymbol{s}^{(i)}, a_{0}^{(i)} = a^{(i)}\right]$$

$$r^{(i)}(\boldsymbol{s}_k^{(i)}, a_k^{(i)}) \approx \boldsymbol{\phi}(\boldsymbol{s}_k^{(i)}, a_k^{(i)})^T \boldsymbol{\theta}_k^{(i)}$$

$$Q(s_k^{(i)}, a_k^{(i)}) = \theta_k^{(i)^T} M(s_k^{(i)}, :, a_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_k^{(i)},:,\boldsymbol{a}_k^{(i)}) \approx \boldsymbol{M}_k \, \boldsymbol{\phi}(\boldsymbol{s}_k^{(i)},\boldsymbol{a}_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}^{\text{new}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) = \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) + \alpha \left(\boldsymbol{\phi^{(i)}}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) + \gamma \boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_{k+1}^{(i)},:,a_{k+1}^{(i)}) - \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)})\right)$$

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}^{(i)},:,a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k} \boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) | \boldsymbol{s}_{0}^{(i)} = \boldsymbol{s}^{(i)}, a_{0}^{(i)} = a^{(i)}\right]$$

$$r^{(i)}(\boldsymbol{s}_k^{(i)}, \boldsymbol{a}_k^{(i)}) \approx \boldsymbol{\phi}(\boldsymbol{s}_k^{(i)}, \boldsymbol{a}_k^{(i)})^T \boldsymbol{\theta}_k^{(i)}$$

$$Q(s_k^{(i)}, a_k^{(i)}) = \theta_k^{(i)^T} M(s_k^{(i)}, :, a_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_k^{(i)},:,\boldsymbol{a}_k^{(i)}) \approx \boldsymbol{M}_k \, \boldsymbol{\phi}(\boldsymbol{s}_k^{(i)},\boldsymbol{a}_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}^{\text{new}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) = \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) + \alpha \left(\boldsymbol{\phi^{(i)}}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) + \gamma \boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_{k+1}^{(i)},:,a_{k+1}^{(i)}) - \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)})\right)$$

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}^{(i)},:,a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k} \boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) | \boldsymbol{s}_{0}^{(i)} = \boldsymbol{s}^{(i)}, a_{0}^{(i)} = a^{(i)}\right]$$

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$$M_{\pi^{(i)}}(s_k^{(i)},:,a_k^{(i)}) \approx M_k \phi(s_k^{(i)},a_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}^{\text{new}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) = \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) + \alpha(\boldsymbol{\phi^{(i)}}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) + \gamma \boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_{k+1}^{(i)},:,a_{k+1}^{(i)}) - \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}))$$

$$\boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}^{(i)},:,a^{(i)}) = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^{k} \boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) | \boldsymbol{s}_{0}^{(i)} = \boldsymbol{s}^{(i)}, a_{0}^{(i)} = a^{(i)}\right]$$

$$r^{(i)}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{a}_{k}^{(i)}) \approx \boldsymbol{\phi}(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{a}_{k}^{(i)})^{T} \boldsymbol{\theta}_{k}^{(i)}$$

$$Q(\boldsymbol{s}_{k}^{(i)}, \boldsymbol{a}_{k}^{(i)}) = \boldsymbol{\theta}_{k}^{(i)}{}^{T} \boldsymbol{M}(\boldsymbol{s}_{k}^{(i)}, :, \boldsymbol{a}_{k}^{(i)})$$

$$Q(s_k^{(i)}, a_k^{(i)}) = \theta_k^{(i)^T} M(s_k^{(i)}, :, a_k^{(i)})$$

$$M_{\pi^{(i)}}(s_k^{(i)},:,a_k^{(i)}) \approx M_k \phi(s_k^{(i)},a_k^{(i)})$$

$$\boldsymbol{M}_{\pi^{(i)}}^{\text{new}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) = \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}) + \alpha(\boldsymbol{\phi^{(i)}}(\boldsymbol{s}_{k}^{(i)},a_{k}^{(i)}) + \gamma \boldsymbol{M}_{\pi^{(i)}}(\boldsymbol{s}_{k+1}^{(i)},:,a_{k+1}^{(i)}) - \boldsymbol{M}_{\pi^{(i)}}^{\text{old}}(\boldsymbol{s}_{k}^{(i)},:,a_{k}^{(i)}))$$

$$\hat{\boldsymbol{\phi}}(\boldsymbol{s}_{k}^{(i)}, a_{k}^{(i)}) = \boldsymbol{M}^{\text{new}}(\boldsymbol{s}_{k}^{(i)}, :, a_{k}^{(i)}) - \gamma \boldsymbol{M}(\boldsymbol{s}_{k+1}^{(i)}, :, a_{k+1}^{(i)}) + \boldsymbol{n}_{k}^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = M_k \underbrace{\left[\phi(s_k^{(i)}, a_k^{(i)}) - \gamma \phi(s_{k+1}^{(i)}, a_{k+1}^{(i)})\right]}_{g_k^{(i)}} + n_k^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = (g^{(i)}_k^T \otimes I) m_k^{(i)} + n_k^{(i)}$$

$$m_{k+1}^{(i)} = m_k^{(i)} + \mu_k^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = M^{\text{new}}(s_k^{(i)}, :, a_k^{(i)}) - \gamma M(s_{k+1}^{(i)}, :, a_{k+1}^{(i)}) + n_k^{(i)}$$

$$\hat{\boldsymbol{\phi}}(s_k^{(i)}, a_k^{(i)}) = \boldsymbol{M}_k \underbrace{\left[\boldsymbol{\phi}(s_k^{(i)}, a_k^{(i)}) - \gamma \boldsymbol{\phi}(s_{k+1}^{(i)}, a_{k+1}^{(i)}) \right]}_{\boldsymbol{g}_k^{(i)}} + \boldsymbol{n}_k^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = (g^{(i)}_k^T \otimes I) m_k^{(i)} + n_k^{(i)}$$

$$m_{k+1}^{(i)} = m_k^{(i)} + \mu_k^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = M^{\text{new}}(s_k^{(i)}, :, a_k^{(i)}) - \gamma M(s_{k+1}^{(i)}, :, a_{k+1}^{(i)}) + n_k^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = M_k \underbrace{\left[\phi(s_k^{(i)}, a_k^{(i)}) - \gamma \phi(s_{k+1}^{(i)}, a_{k+1}^{(i)})\right]}_{g_k^{(i)}} + n_k^{(i)}$$

$$\hat{\boldsymbol{\phi}}(\boldsymbol{s}_k^{(i)}, \boldsymbol{a}_k^{(i)}) = (\boldsymbol{g^{(i)}}_k^T \otimes \boldsymbol{I}) \boldsymbol{m}_k^{(i)} + \boldsymbol{n}_k^{(i)}$$

$$m_{k+1}^{(i)} = m_k^{(i)} + \mu_k^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = M^{\text{new}}(s_k^{(i)}, :, a_k^{(i)}) - \gamma M(s_{k+1}^{(i)}, :, a_{k+1}^{(i)}) + n_k^{(i)}$$

$$\hat{\phi}(s_k^{(i)}, a_k^{(i)}) = M_k \underbrace{\left[\phi(s_k^{(i)}, a_k^{(i)}) - \gamma \phi(s_{k+1}^{(i)}, a_{k+1}^{(i)})\right]}_{g_k^{(i)}} + n_k^{(i)}$$

$$\hat{\boldsymbol{\phi}}(\boldsymbol{s}_k^{(i)}, \boldsymbol{a}_k^{(i)}) = (\boldsymbol{g}^{(i)}_k^T \otimes \boldsymbol{I}) \boldsymbol{m}_k^{(i)} + \boldsymbol{n}_k^{(i)}$$

$$m_{k+1}^{(i)} = m_k^{(i)} + \mu_k^{(i)}$$

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Algorithm 2 THE PROPOSED MAK-SR FRAMEWORK

- 1: Learning Phase:
- 2: **Initialize:** θ_0 , $P_{\theta,0}$, m_0 , $P_{M,0}$, μ_n , and Σ_n for n = 1, 2, ..., N
- 3: **Parameters:** Q_{θ} , Q_{M} , λ_{μ} , λ_{Σ} , and $\{R_{\theta}^{j}, R_{M}^{j}\}$ for j = 1, 2, ..., M
- 4: **Repeat** (for each episode):
- 5: Initialize s_k
- 6: **Repeat** (for each agent *i*):
- 7: While $s_k^{(i)} \neq s_T$ do:
- 8: Reshape m_k into $L \times L$ to construct 2-D matrix M_k .
- 9: $a_k^{(i)} = \arg\max_{a} \left(\mathbf{g}_k^{(i)}(\mathbf{s}_k^{(i)}, a) \mathbf{g}_k^{(i)}^T(\mathbf{s}_k^{(i)}, a^{(i)}) \right)$
- 10: Take action $a_k^{(i)}$, observe $s_{k+1}^{(i)}$ and $r_k^{(i)}$.
- 11: Calculate $\phi(s_k^{(i)}, a_k^{(i)})$ via Equations (23) and (25).
- 12: **Update reward weights vector:** Perform MMAE to update $\theta_k^{(i)}$.
- 13: **Update SR weights vector:** Perform KF on Equations (40) and (41) to update $m_k^{(l)}$.
- 14: **Update RBFs parameters:** Perform RGD on the loss function L_k to update Σ_n and μ_n .
- 15: **end while**



(d)

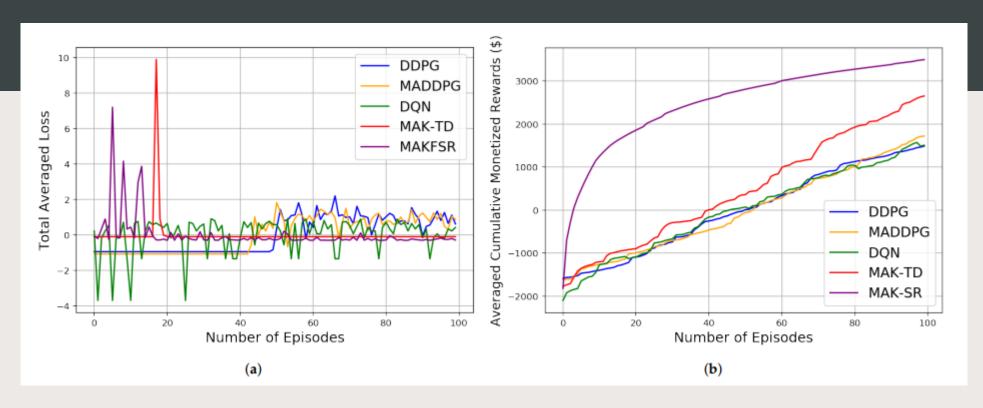
(c)

Table 1. Total loss averaged across all the episodes and for all the four implemented scenarios.

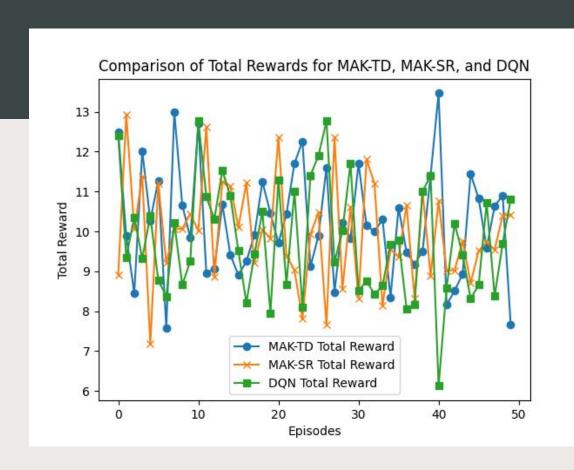
Environment	MAK-SR	MAK-TD	MADDPG	DDPG	DQN
Cooperation	8.93	2.4088	9649.84	10,561.16	10.93
Competition	0.43	4.9301	10,158.18	10,710.37	107.39
Predator-Prey 1v2	0.005	1.9374	6816.34	6884.33	8.21
Predator-Prey 2v1	8.87	1.2421	7390.18	6882.2	10.24

Table 2. Total received reward by the agents averaged for all the four implemented scenarios.

Environment	MAK-SR	MAK-TD	MADDPG	DDPG	DQN
Cooperation	-16.0113	-23.0113	-69.28	-66.29	-39.96
Competition	-0.778	-13.358	-63.30	-61.34	-14.49
Predator-Prey 1v2	-0.0916	-13.432	-46.17	-20.53	-23.451
Predator-Prey 2v1	-0.081	-17.0058	-55.69	-49.41	-44.32

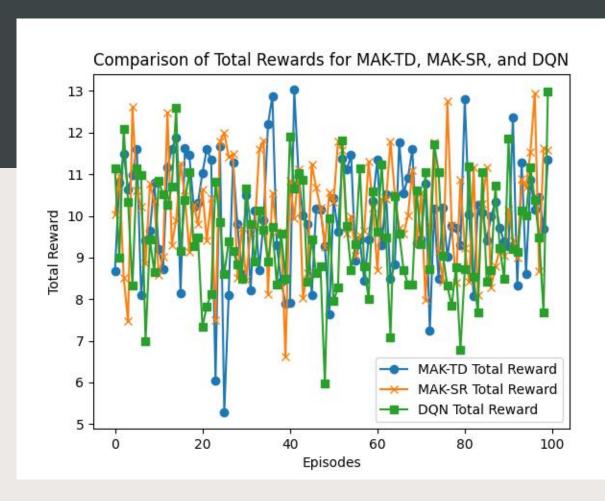


Simulation Results



Final Total Rewards after 50 Episodes:
MAK-TD Total Reward: 510.10918848452957
MAK-SR Total Reward: 498.1273978229948
DQN Total Reward: 488.53212117234517

Simulation Results



Final Total Rewards after 100 Episodes:
MAK-TD Total Reward: 996.1441199350996
MAK-SR Total Reward: 1003.7453232643612

DQN Total Reward: 955.8240584992651

Key Achievements:

- MAK-TD
- MAK-SR

CONCLUSIONS

THANK YOU!