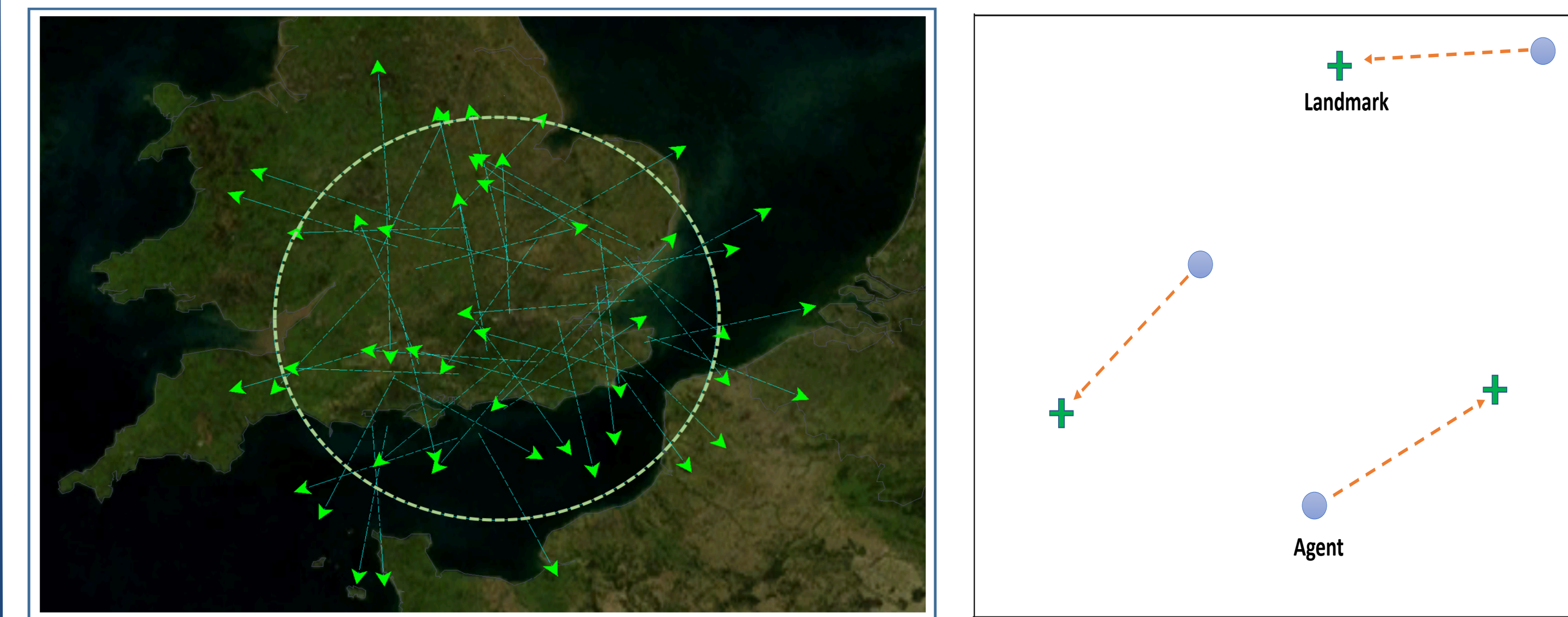


Introduction

We address the problem of multiagent credit assignment in large scale multiagent system. Our main contributions are:

- An approach to learn a differentiable reward model by exploiting the collective nature of interactions among agents.
- A principled method to analytically compute shaped rewards from the reward model.
- A model-based RL approach that uses learned shaped rewards addressing credit assignment problem.

Motivating Domains



Air Traffic Control

Cooperative Navigation

Challenges

- Empirical reward signal is not effective in addressing multiagent credit assignment problem.
- The credit assignment problem becomes more challenging with large number of agents.
- Current proposed approaches either do not scale well for large agent settings or their credit assignment mechanism is not effective.

Our work address these challenges.

Count Variables

State-Action Count Variable

$$n_t(s, a) = \sum_{m=1}^M \mathbb{I}[s_t^m = s, a_t^m = a; \mathbf{s}_t, \mathbf{a}_t], \forall s \in S$$

System Reward Approximator

Loss Function for Reward Approximator

$$\tilde{\mathcal{L}}(\mathbf{w}) = M \sum_{\xi \in \mathcal{B}} \sum_{s \in S} \sum_{a \in A} n_{\xi}(s, a) \cdot \left(\tilde{r}(s, a, \mathbf{n}_{\xi}^S) - r_{\mathbf{w}}(s, a, \mathbf{n}_{\xi}^S) \right)^2$$

Approximate DR – Discrete Action

Difference Rewards (DRs)

$$D^m(s_t^m, a_t^m) = r(s_t, \mathbf{a}_t) - r(s_t^{-m} \cup d_s, \mathbf{a}_t^{-m} \cup d_a)$$

Difference Rewards with Count Variables

$$D^m(s_t^m, a_t^m) = r_{\mathbf{w}}(\mathbf{n}_t^{SA}) - r_{\mathbf{w}}(\mathbf{n}_t^{SA - (s_t^m, a_t^m) + (d_s, d_a)})$$

Approximate Difference Rewards

$$D_t(s, a) \approx \frac{1}{M} \cdot \left(\frac{\partial r_{\mathbf{w}}(\tilde{\mathbf{n}}_t^{SA})}{\partial \tilde{\mathbf{n}}_t^{SA}(s, a)} - \frac{\partial r_{\mathbf{w}}(\tilde{\mathbf{n}}_t^{SA})}{\partial \tilde{\mathbf{n}}_t^{SA}(d_s, d_a)} \right)$$

Return with Difference Rewards

$$R_t^{dr} = \sum_{i=0}^{\infty} \gamma^i \left(\sum_{s \in S} \sum_{a \in A} n_{t+i}(s, a) \cdot D_{t+i}(s, a) \right)$$

Policy Gradient

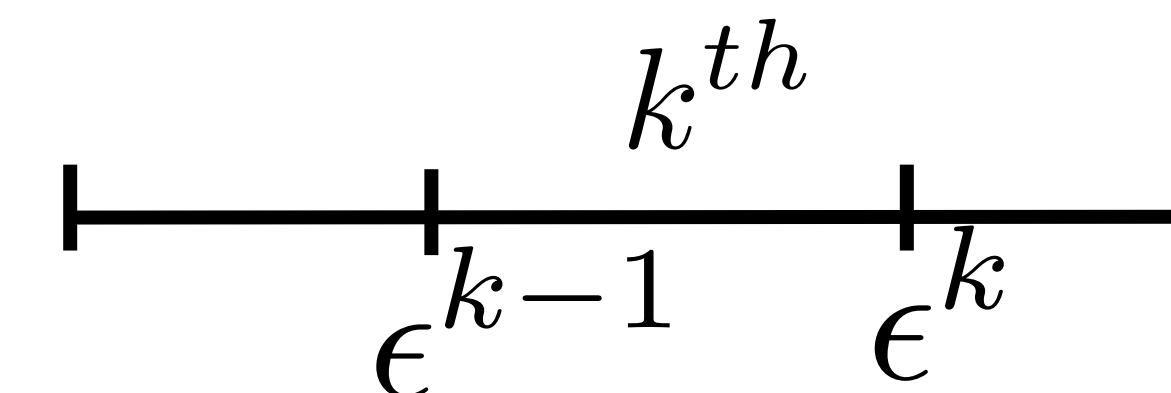
$$\nabla_{\theta} J(\pi_{\theta}) = \mathbb{E}_{s_0: \infty, a_0: \infty} \left[\sum_{t=0}^{\infty} \sum_{s \in S} \sum_{a \in A} n_t(s, a) \cdot \nabla_{\theta} \log \pi_{\theta}(a | s_t) \cdot R_t^{dr} \right]$$

Approximate DR - Continuous Actions

Continuous Action:

$$a^m = f_{\theta}(\epsilon^m; s^m)$$

Noise Partition



Difference Rewards

$$D^m(s_t^m, \epsilon_t^m) = r_{\theta}(s_t, \epsilon_t) - r_{\theta}(s_t^{-m} \cup d_s, \epsilon_t^{-m} \cup d_{\epsilon})$$

Approximate Difference Rewards

$$D_t(i, k) \approx \frac{1}{M} \left(\frac{\partial r_{\mathbf{w}}(\mathbf{n}_t^S, \mathbf{n}_t^{SP})}{\partial \mathbf{n}_t^S(i)} - \frac{\partial r_{\mathbf{w}}(\mathbf{n}_t^S, \mathbf{n}_t^{SP})}{\partial \mathbf{n}_t^S(d_s)} + \frac{\partial r_{\mathbf{w}}(\mathbf{n}_t^S, \mathbf{n}_t^{SP})}{\partial \mathbf{n}_t^{SP}(i, k)} - \frac{\partial r_{\mathbf{w}}(\mathbf{n}_t^S, \mathbf{n}_t^{SP})}{\partial \mathbf{n}_t^{SP}(d_s, d_{k^*})} \right)$$

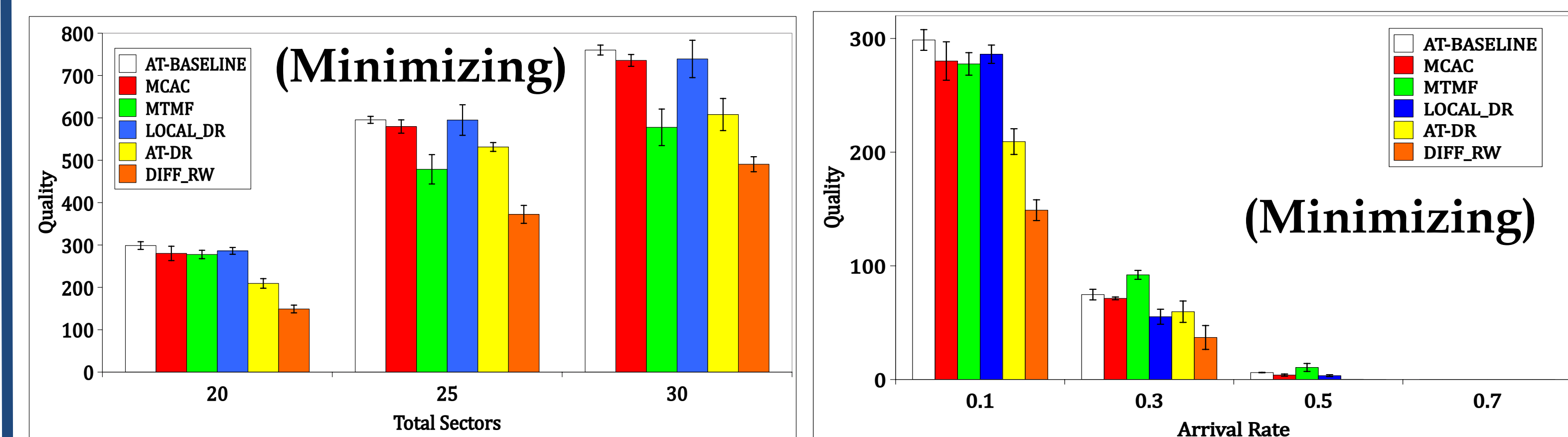
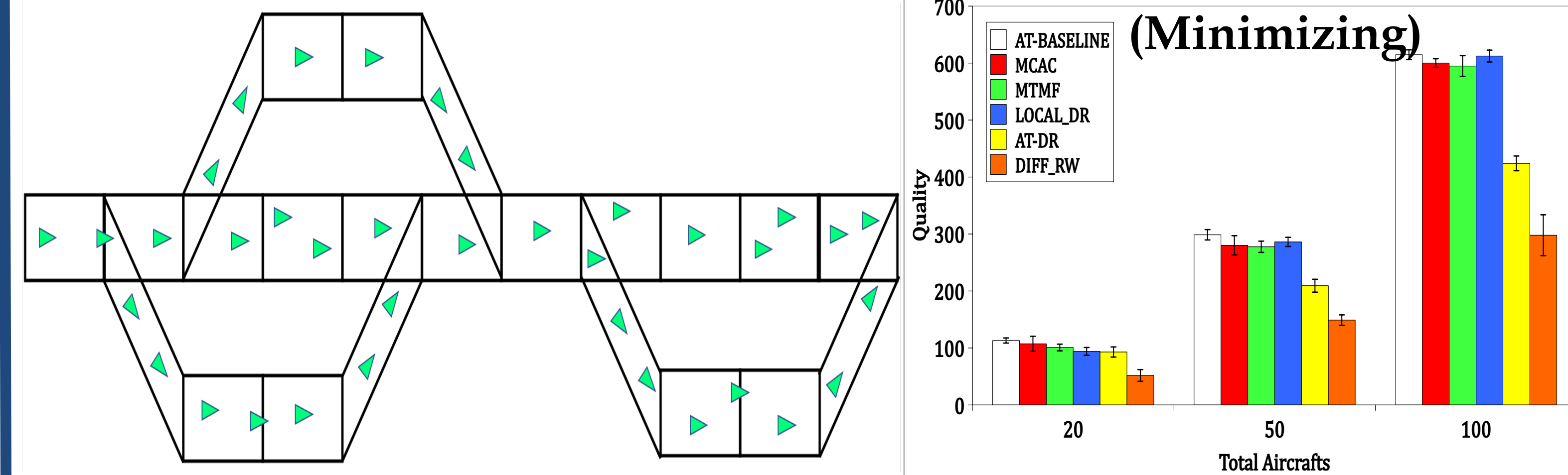
Soft Action-Critic with DR

$$\hat{Q}(o^m(s_t), a_t^m) = D_t(o^m(s_t), k^m) + \gamma \mathbb{E}_{s_{t+1}} [V_{\bar{\psi}}(o^m(s_{t+1}))]$$

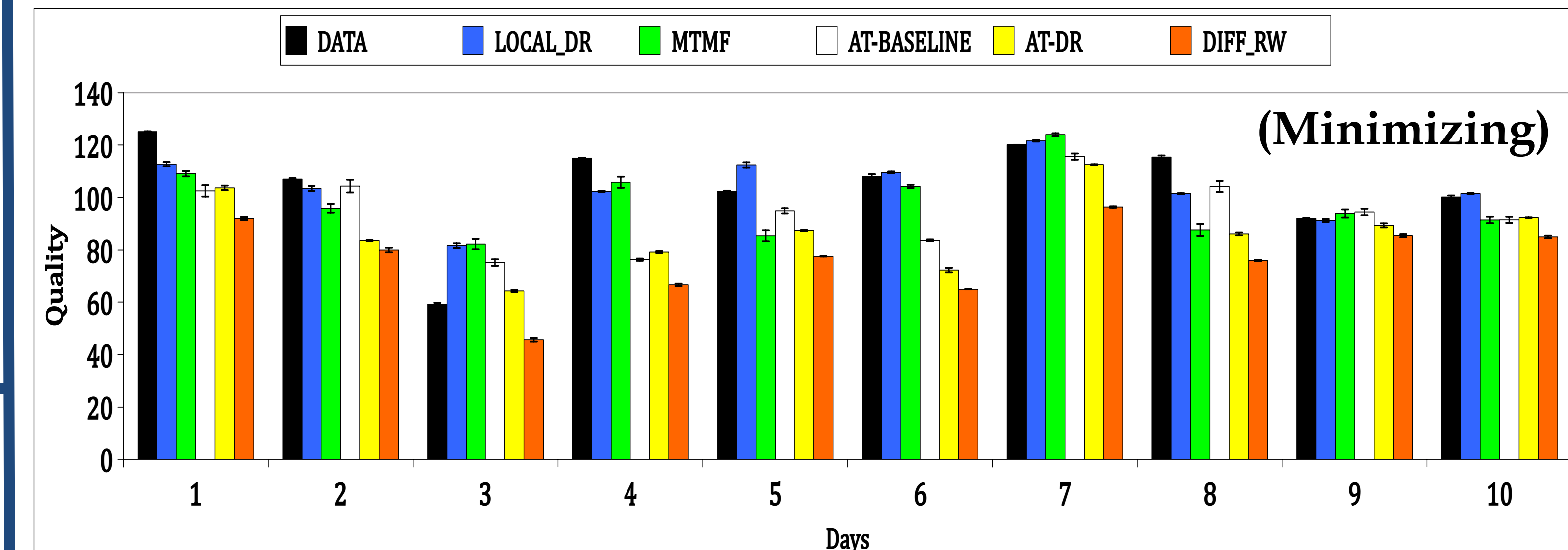
Experiments

Air Traffic Control Problem

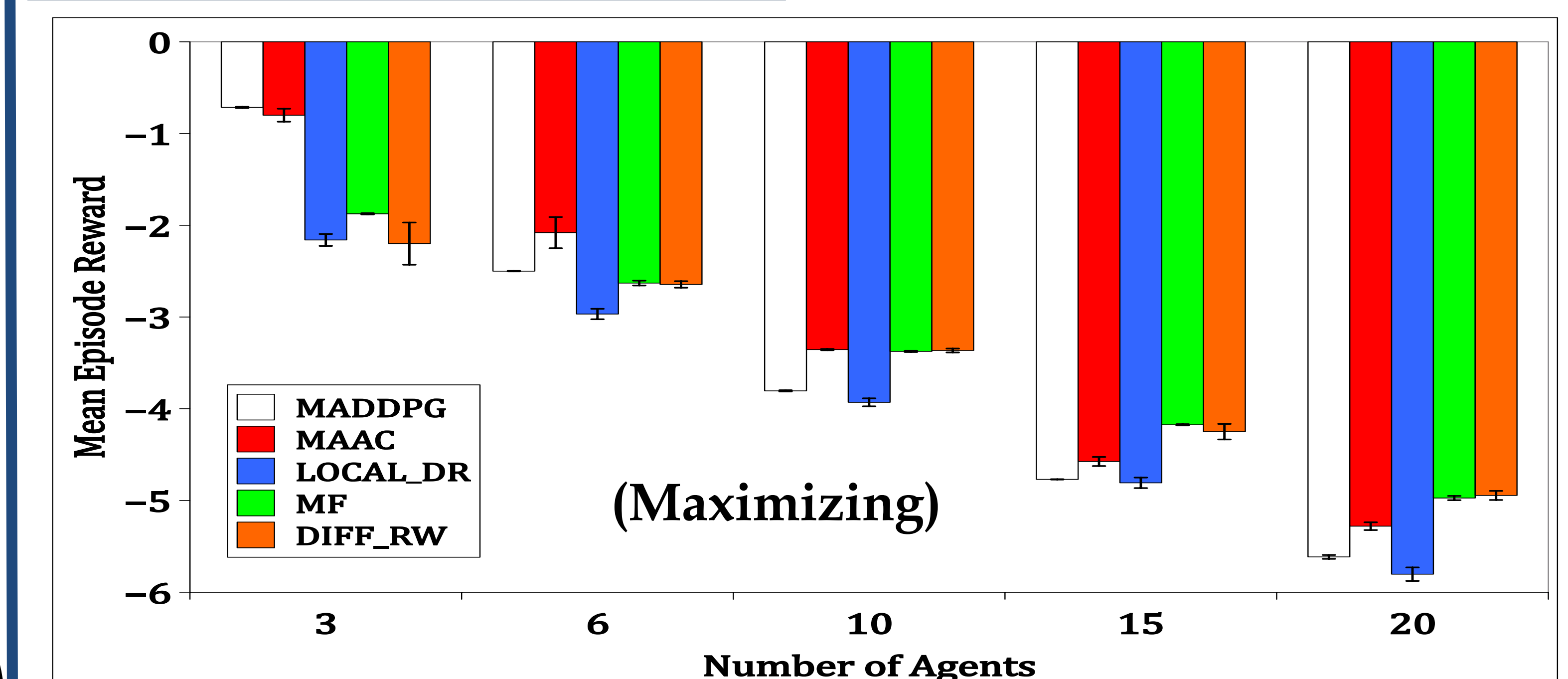
Synthetic Data:



Real world dataset (1 month data):



Cooperative Navigation



Acknowledgments

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