AdverSAR – An Attentive Reasoning Framework for Multi Agent Cooperative Navigation under Adversarial Communication

Jayanth Bhargav[1], Himanshu Sharma[2], Arnab Bhattacharya[2], Ted Fujimoto[2], Aowabin Rahman[2], Sayak Mukherjee[2], Thiagarajan Ramachandran[2], Samrat Chatterjee[2]
[1]Purdue University, [2]Pacific Northwest National Laboratory

Introduction

- Communication is a critical aspect of Multi-Agent Reinforcement Learning (MARL) for cooperative tasks
- Communication based policies are prone to severe issues due to noise or attacks on the communication channels

Figure 1: Multi-Agent Cooperative Navigation Scenario

MARL Framework

- Centralized Training and Decentralized Execution (CTDE) for learning communication-based policies

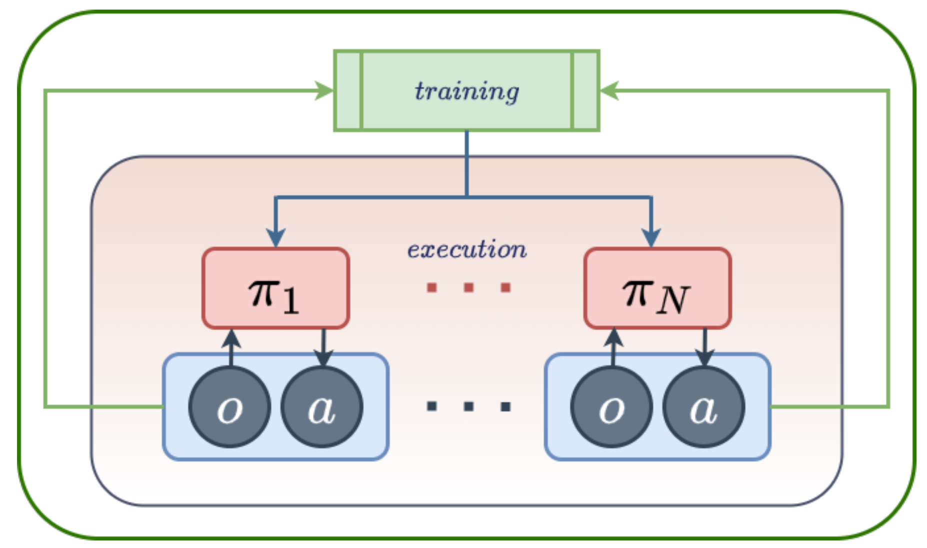

Figure 2: Centralized Actor-Critic Reinforcement Learning

- Central critic receives local actions of all agents and evaluates a centralized action-value function

Attentive Reasoning Network

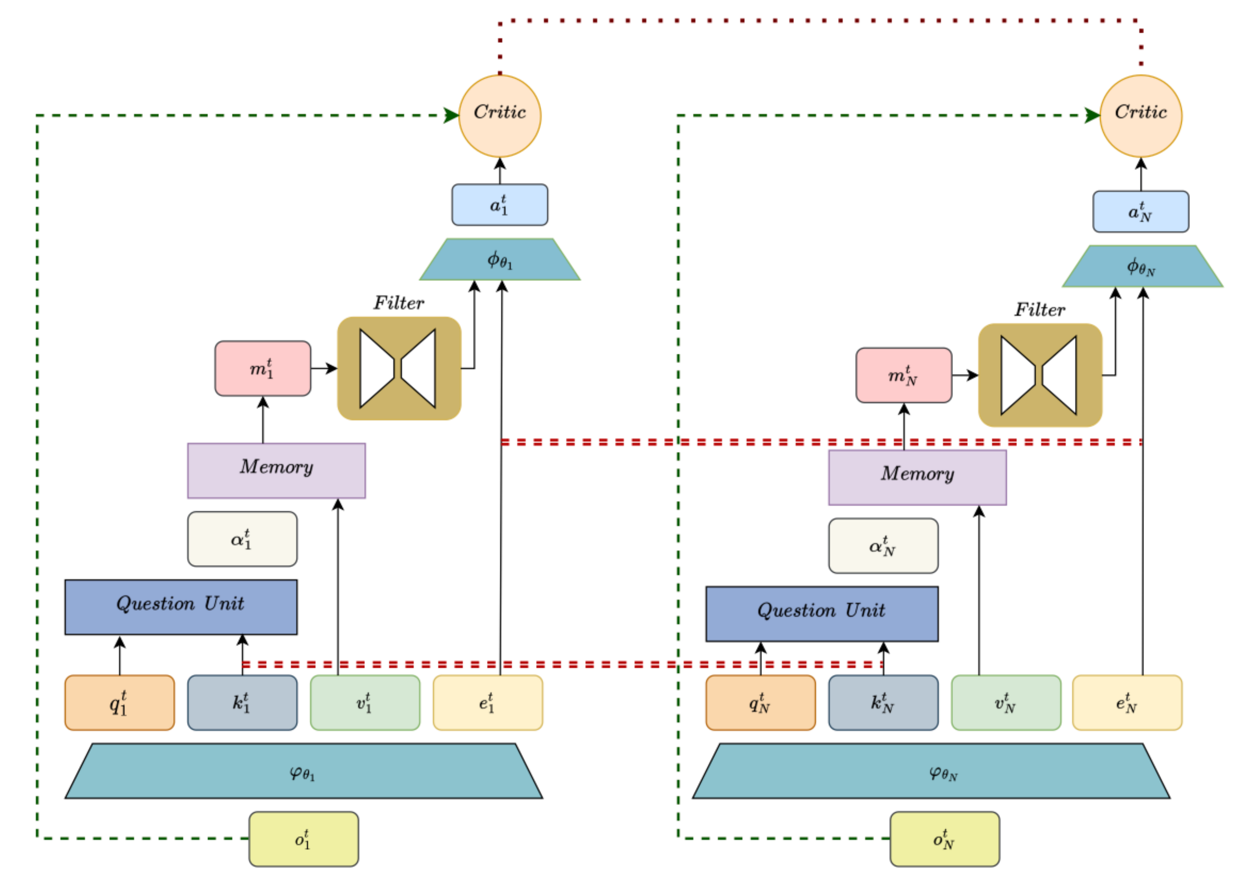

Figure 3: Network Architecture - Multi-Agent Structured Attentive Reasoning Network for Adversarial Communication (Adver-SAR)

Adversarial Commmunication

- Agents are cooperative and have no adversarial intent (adversaries are external only)
- Inter-agent communication is potentially corrupted by noise in the communication channels
- Filter unit has an Auto-Encoder for anomaly detection.

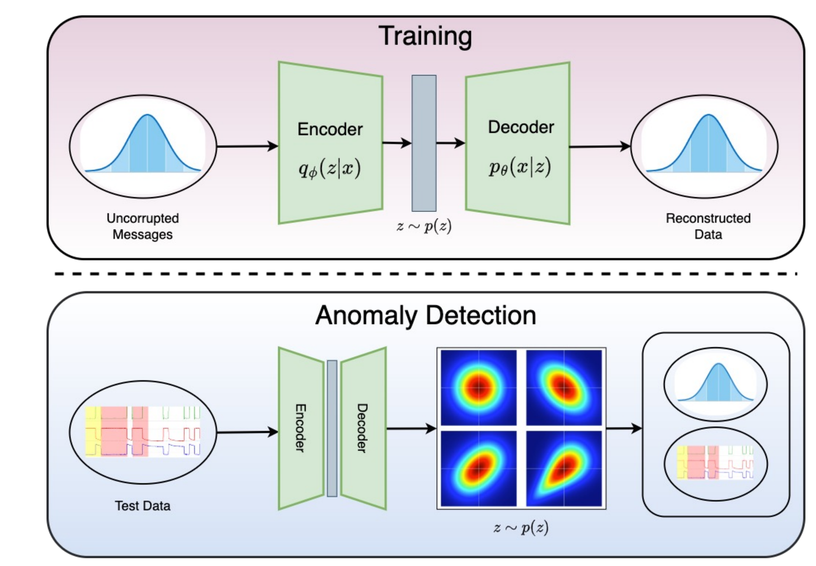

Figure 4: Anomaly Detection using Generative Models

- Auto-Encoder (AE) network is trained under a non-adversarial setting to learn the distribution of uncorrupted messages
- Filtering unit uses this AE network to identify if the communicated messages are corrupted (i.e., out of distribution (OOD))

Experiments

- **Empirical evaluation:** Cooperative navigation tasks of varying levels of difficulty
- **Environment:** OpenAI Gym Traffic Junction v0
- **Difficulty Levels:** Easy (1 junction), Medium (4 junctions) and Hard (8 junctions)
- **Noise Model:** Zero-Mean Gaussian Noise
- **Evaluation Baseline:** SARNet - State of the art attention-based MARL framework
- **Evaluation Metric:** Success Rate (% of collision free episodes)
- **Message Sizes:** 8-bit, 16-bit and 32-bit messages
- **Number of Agents:** 3, 6, 10 agents

Msg Size →	8 bit		16 bit		32 bit	
Num Agents ↓	SARNet	AdverSAR	SARNet	AdverSAR	SARNet	AdverSAR
3	84.41 ± 3.83	86.26 ± 1.30	77.34 ± 2.06	80.94 ± 3.03	85.61 ± 2.14	88.15 ± 2.45
6	61.03 ± 1.28	66.47 ± 2.35	72.53 ± 1.60	76.83 ± 3.23	78.31 ± 1.79	80.02 ± 2.50
10	58.10 ± 2.10	59.23 ± 1.39	65.42 ± 2.38	69.36 ± 3.21	72.70 ± 3.72	78.73 ± 1.03

Table 1: Comparison of Success Rate (%) for SARNet vs. AdverSAR with varying message sizes and number of agents with difficulty level Medium

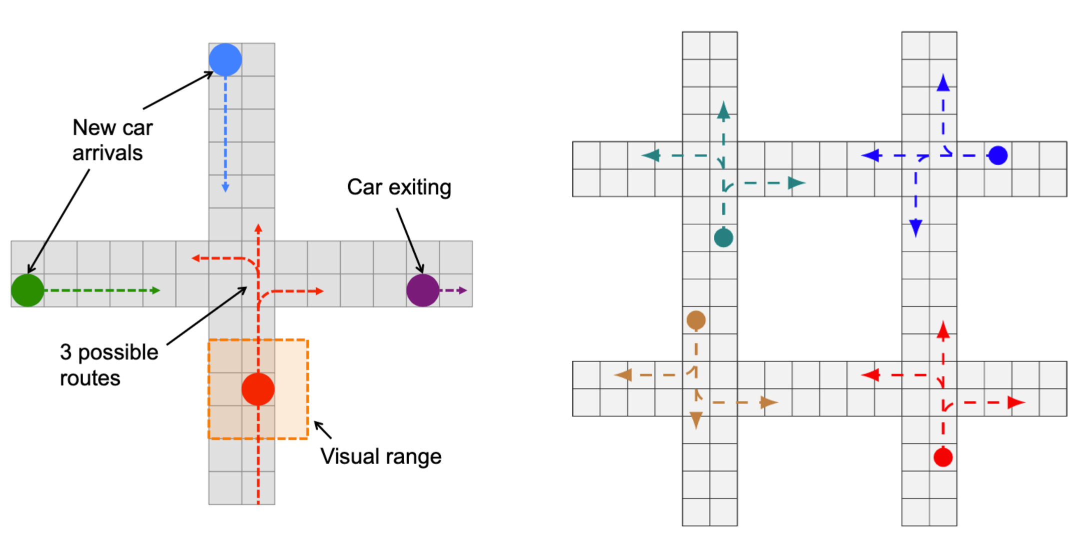

Figure 5: Traffic Junction Environment – (**left**) Easy, (**right**) Medium

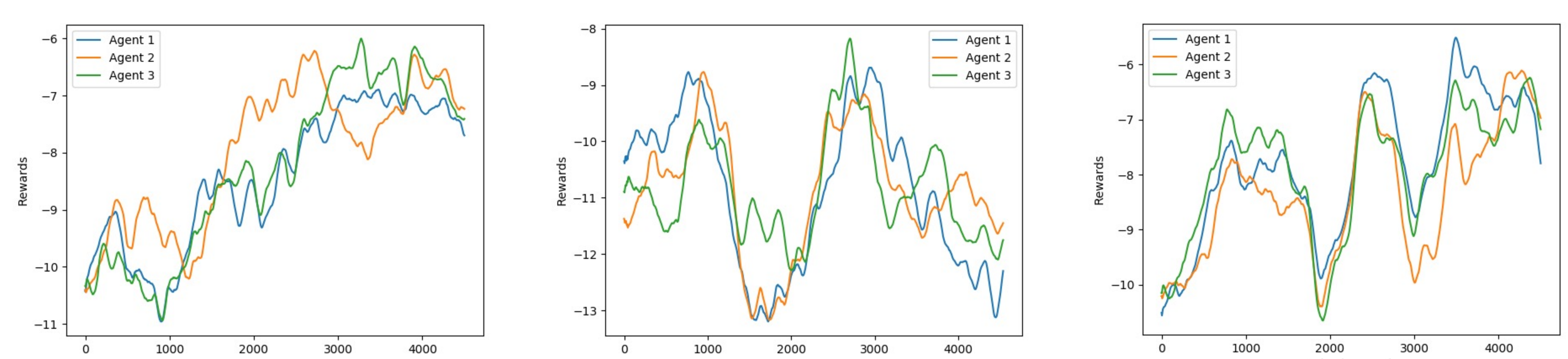

Figure 6: Reward Curves – (**left**) No Noise, (**center**) SARNet with Noise, (**right**) AdverSAR with noise

Conclusions & Future Work

Conclusions:

- Proposed a novel framework for multi-agent cooperative navigation under corrupted communication
- Demonstrated improve performance on cooperative navigation tasks with increasing levels of difficulty

Future Work:

- Test the framework on a variety of multi-agent cooperative tasks like Predator-Prey, StarCraft etc.
- Extend the framework to multi-agent tasks with adversarial agents and competitive tasks

References

1. Rangwala, Murtaza, and Ryan Williams. "*Learning multi-agent communication through structured attentive reasoning.*" Advances in Neural Information Processing Systems 33 (2020).
2. Singh, Amanpreet, Tushar Jain, and Sainbayar Sukhbaatar. "*Learning when to Communicate at Scale in Multiagent Cooperative and Competitive Tasks.*" International Conference on Learning Representations (2018).
3. Sukhbaatar, Sainbayar, and Rob Fergus. "*Learning multiagent communication with backpropagation.*" Advances in Neural Information Processing Systems 29 (2016).

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