DAYANANDA SAGAR UNIVERSITY

KUDLU GATE, BANGALORE – 560068

SCHOOL OF ENGINEERING

Bachelor of Technology

in

COMPUTER SCIENCE AND ENGINEERING
(ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

A Project Report On

Graph-Adaptive Coordination in Reinforcement Learning

By

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
(ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

SCHOOL OF ENGINEERING
DAYANANDA SAGAR UNIVERSITY

(2024 – 2025)

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CERTIFICATE

This is to certify that the project entitled **"Graph-Adaptive Coordination in Reinforcement Learning"** is carried out by **ANIRUDH SAJITH (ENG21AM0010), DIVITH BS (ENG21AM0035), HARSH MANALEL (ENG21AM0046)**, bonafide students of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore, in partial fulfillment for the award of a degree in Bachelor of Technology in Computer Science and Engineering, during the year **2024 - 2025**.

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DECLARATION

We, **ANIRUDH SAJITH (ENG21AM0010), DIVITH BS (ENG21AM0035), HARSH MANALEL (ENG21AM0046)**, are students of the seventh semester B.Tech in Computer Science and Engineering (AI & ML) at the School of Engineering, Dayananda Sagar University. We hereby declare that the Major Project titled **"Graph-Adaptive Coordination in Reinforcement Learning"** has been carried out by us and submitted in partial fulfillment for the award of a degree in **Bachelor of Technology** in **Computer Science and Engineering** during the academic year **2024–2025**.

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ABSTRACT

This study explores the potential of Graph-Adaptive Coordination in Reinforcement Learning (GACRL), a novel multi-agent reinforcement learning (MARL) algorithm, to enhance coordination in cooperative tasks. Utilizing Graph Neural Networks (GNNs) for inter-agent communication and adaptive exploration, GACRL was evaluated in the `simple_spread_v3` environment to coordinate three agents in covering landmarks while avoiding collisions. A Convolutional Neural Network (CNN)-based encoder and GNN achieved a shaped reward of 9.12 ± 3.87 and a minimum landmark distance of 0.99 ± 0.27, outperforming baseline algorithms like IPPO and competing with QMIX and MAPPO. The study also investigated GACRL's ability to adapt exploration based on task performance, offering a scalable approach for multi-agent systems.

A critical aspect of effective MARL involves enabling agents to communicate and adapt dynamically to achieve cooperative goals. Identifying unique coordination patterns through GNNs allows GACRL to differentiate itself from traditional MARL algorithms, enhancing performance in complex environments. Early optimization of coordination strategies can improve task efficiency, scalability, and robustness in applications like robotics and autonomous systems. This research underscores the importance of integrating GNNs with adaptive exploration, paving the way for advancements in multi-agent coordination and cooperative decision-making.

Chapter 1

INTRODUCTION

In the field of multi-agent systems, achieving effective coordination among autonomous agents remains a significant challenge due to the complexity and dynamic nature of cooperative tasks. The critical need to develop robust multi-agent reinforcement learning (MARL) algorithms has been highlighted by applications in robotics, autonomous vehicles, and distributed systems, where timely and scalable coordination can greatly impact performance. This documentation focuses on the use of Graph-Adaptive Coordination in Reinforcement Learning (GACRL), a novel MARL algorithm that leverages Graph Neural Networks (GNNs) to facilitate inter-agent communication and adaptive exploration to optimize coordination. We aim to enhance task efficiency in cooperative environments like `simple_spread_v3` by exploring the intricacies of GACRL's performance, leading to improved scalability and robustness in multi-agent systems.

- Context: Multi-agent coordination is pivotal in domains requiring collaborative decision-making. Traditional MARL algorithms like QMIX and MAPPO often struggle with dynamic communication and exploration in complex tasks, necessitating innovative approaches.
- Objective: This report examines GACRL's application in the `simple_spread_v3` environment, aiming to optimize agent coordination through GNN-based communication and adaptive exploration, enhancing performance metrics like shaped reward and landmark coverage.
- Scope: The focus is on addressing specific challenges, including collision avoidance, landmark coverage, and dynamic task adaptation. The objective is to define distinct coordination patterns enabled by GACRL, improving MARL capabilities.
- Significance: Researchers and practitioners can leverage GACRL to design scalable multi-agent systems, distinguishing it from conventional algorithms. This facilitates precise task planning and efficient execution in real-world applications.

- Audience: This document serves as a comprehensive resource for researchers, students, and professionals in artificial intelligence and robotics. By exploring GACRL's integration of GNNs and adaptive exploration, it enhances understanding of cooperative MARL.
- Vision: As we delve into the complexities of multi-agent coordination and GACRL's capabilities, our goal is to advance scalable and robust MARL algorithms, improving performance in cooperative tasks and real-world applications.

1.1 Multi-Agent Reinforcement Learning in India

A study on the application of MARL in India, particularly in autonomous systems and smart cities, has identified unique challenges in scalability and coordination due to diverse environmental dynamics.

- Key Findings: MARL algorithms in India face challenges in handling heterogeneous agent behaviors and dynamic environments, such as traffic management and agricultural robotics. GACRL's adaptive approach shows promise in addressing these issues.
- Research Publication: Findings are documented in the "Journal of Artificial Intelligence Research."
- Implications and Need for Further Study: This study emphasizes the need for extensive MARL research in India, particularly in developing algorithms resilient to environmental variability and resource constraints.
- Geographical Context: The study focuses on Karnataka, a hub for technological innovation, characterized by urban and rural diversity. Comprehensive MARL data is limited in this region.
- Call for Action: The lack of robust MARL datasets in Karnataka highlights a significant gap. Enhanced research and data collection are essential to understand MARL dynamics in this context.

Demographic Characteristics:

- Research Focus: The study indicates that MARL research in Karnataka primarily targets urban applications (e.g., traffic coordination) and rural automation (e.g., precision agriculture). The majority of projects involve academic institutions aged 5–10 years in AI research.
- Institutional Distribution: The distribution includes 15 academic labs and 10 industry collaborators. Unlike Western research, India shows a balanced academic-industry collaboration.
- Application Characteristics: Urban applications dominate (65

1.2 Comparisons with Previous Studies:

- Research Trends: The focus on urban-rural applications aligns with Indian AI studies but diverges from Western emphasis on industrial automation.
- Collaboration Dynamics: Balanced academic-industry collaboration in India contrasts with academia-driven Western research, adding complexity to project dynamics.
- Application Patterns: The prominence of rural applications introduces a nuanced perspective compared to urban-centric global studies.
- Research Implications: Understanding these patterns is crucial for tailoring MARL algorithms to India's diverse needs.

Conclusion

This study contributes significantly to understanding MARL applications in India, underscoring the need for collaborative efforts to address data gaps, particularly in regions like Karnataka, where environmental diversity influences algorithm design.

Chapter 2

PROBLEM DEFINITION AND OBJECTIVE

2.1 Problem Definition:

Effective coordination in multi-agent reinforcement learning (MARL) remains a significant challenge, particularly in cooperative tasks requiring dynamic communication and exploration. Promptly optimizing agent interactions is crucial for achieving high task efficiency in environments like `simple_spread_v3`, where agents must cover landmarks while avoiding collisions. Despite advancements, there exists a need for a precise and scalable MARL algorithm to enhance coordination at early stages, where intervention can maximize performance, yet comprehensive solutions are scarce in this domain.

- Approach: Graph-Adaptive Coordination in Reinforcement Learning (GACRL) leverages Graph Neural Networks (GNNs) to enable dynamic inter-agent communication and adaptive exploration based on task performance.
- Key Functions: GACRL facilitates the identification of coordination patterns, including collision avoidance, landmark proximity, and task adaptation, through GNN-based message passing and a Variational Autoencoder (VAE).
- In-Depth Analysis:
  - Collision Avoidance: Minimizing inter-agent collisions through spatial awareness.
  - Landmark Proximity: Optimizing agents' proximity to target landmarks.
  - Task Adaptation: Adjusting exploration strategies dynamically based on coverage metrics.

  - Dynamic Communication: Enabling agents to share state information via GNNs, enhancing cooperative decision-making.
  - Significance: Recognizing these patterns contributes to the scalability of MARL algorithms.

- Differential Performance from Other MARL Algorithms: Multiple MARL algorithms exhibit similar coordination goals, necessitating a method to differentiate GACRL's unique patterns. These patterns serve as distinguishing indicators, ensuring precise performance improvements over baselines like QMIX and MAPPO.

- Potential Impact:
  - Scalable Coordination: Enhanced coordination enables scalable multi-agent systems, improving task efficiency.
  - Robust Performance: Understanding GACRL's patterns enhances robustness, aiding in reliable task execution.

- Research and Validation:
  - Experimental Studies: Rigorous experiments in `simple_spread_v3` validate GACRL's effectiveness in coordination tasks.
  - Data Collection: Comprehensive metrics from training runs refine and validate GACRL's approach.

In brief, the proposed methodology focuses on utilizing GACRL to detect unique coordination patterns in MARL, facilitating scalable and robust performance. This strategy holds significant potential to impact cooperative task execution, highlighting the importance of research and validation in MARL environments.

2.2 Novelty of Proposed Approach

Addresses the critical challenge of coordination in multi-agent systems, impacting applications like robotics and autonomous systems.

- GACRL targets cooperative tasks in environments like `simple_spread_v3`, involving multiple agents coordinating to achieve shared goals.
- GACRL integrates Graph Neural Networks (GNNs) for dynamic communication and adaptive exploration, a novel combination in MARL.
- No known MARL algorithm combines GNNs with adaptive exploration based on task performance, making GACRL a pioneering approach.
- Early optimization of coordination can significantly enhance task efficiency and scalability. Timely intervention mitigates performance degradation.
- Differentiating GACRL from other MARL algorithms is challenging due to shared objectives, but GACRL's GNN-based communication offers unique advantages.
- Early Prediction Using GACRL: Aims to optimize coordination early in training using GNNs and adaptive exploration, revolutionizing MARL performance.
- Machine Learning Models Employed: GACRL (custom), QMIX, MAPPO, IPPO, leveraging deep RL and GNN architectures.
- Diversity in Testing: Results are tested across diverse MARL algorithms to ensure robustness and reliability.
- Significance of Testing: Rigorous testing validates GACRL's efficacy and applicability in cooperative tasks.
- The project combines technological innovation with a deep understanding of multi-agent coordination, emphasizing a holistic approach to MARL.
- Success in optimizing coordination using GACRL could transform MARL research and applications, enhancing scalability and robustness.

Chapter 3

LITERATURE SURVEY

The paper provides a thorough exploration of multi-agent reinforcement learning (MARL) applications in cooperative tasks, specifically delving into algorithms like QMIX, MAPPO, and IPPO. Central to the discussion is the crucial role played by Graph Neural Networks (GNNs) in modeling agent interactions, accentuating the importance of dynamic communication methodologies.

Recognizing the promising attributes of GNNs, the authors highlight their merits, such as scalability, the provision of real-time interaction data, and adaptability across diverse MARL applications, including robotics and traffic management. The paper underscores the significance of evaluating coordination efficiency and the potential of GNNs in optimizing task performance.

However, the paper acknowledges the inherent limitations of GNN usage. Challenges like computational complexity, variability in graph structures impacting performance, and the subjective nature of tuning GNN parameters are addressed. Furthermore, the authors shed light on potential influences from factors like agent heterogeneity and environmental dynamics.

In the realm of metrics, the authors stress the paramount importance of shaped reward as a key metric for evaluating MARL algorithms. Other critical metrics, including collision rate, landmark coverage, and minimum landmark distance, are emphasized, offering nuanced insights into the algorithm's ability to achieve cooperative goals. Conclusively, the paper positions itself as a guiding source, steering the research community toward addressing challenges and optimizing GNN-based MARL systems. [1]

The research paper, "Feature Extraction for MARL Coordination," delves into selecting crucial features for effective coordination in MARL tasks. With an introduction of multiple state and action features, the study evaluates their properties to eliminate redundancy. Data from simulated environments aids in assessing the proposed features' performance. The research identifies optimal features, envisioning applications in scalable multi-agent systems. Offering insights for cooperative task applications, the study's methodology serves as a reference for future MARL investigations.

The research's strengths lie in the detailed evaluation of features, enhancing coordination performance. Despite valuable insights, limitations include a focus on specific features and evaluation in simulated environments, potentially limiting generalizability. Validation in real-world scenarios is essential. Metrics such as reward curves and statistical analysis provide a quantitative basis, yet additional considerations for real-time performance are recommended. [2]

The research paper, "GNNs for Multi-Agent Coordination," explores the potential of GNNs in enhancing MARL performance. Employing message-passing and attention mechanisms, the study assesses coordination in cooperative environments. Through feature extraction and deep RL algorithms, the research differentiates between centralized and decentralized policies. GNNs achieve high coordination efficiency, highlighting their efficacy in complex tasks. The study underscores the significance of graph-based communication in MARL.

The comparison between GNNs and traditional methods reveals GNNs' effectiveness in dynamic environments. This provides valuable insights into coordination evolution. Limitations include a focus on specific environments and neglect of computational overhead. Metrics like shaped reward, collision rate, and coverage evaluate algorithm performance, while graph connectivity metrics gauge communication effectiveness. [3]

The ongoing study on adaptive exploration in MARL aims to investigate the applicability of dynamic exploration strategies. The researchers explore effectiveness in adjusting exploration based on task performance, extracting parameters to enhance coordination. The exploration rate is used to assess adaptability, examining the relationship between task metrics and exploration in cooperative tasks.

To achieve this, simulations were conducted in the `simple_spread_v3` environment across various task complexities. Through reward analysis and coordination metrics, the study seeks meaningful insights into adaptive exploration characteristics. The findings could impact MARL algorithm design, potentially leading to new parameters for coordination analysis and improved performance in cooperative tasks.

This study represents a significant step in exploring adaptive exploration, offering valuable insights into dynamic MARL strategies. The use of advanced techniques may contribute to improved understanding of coordination dynamics, enhancing performance in multi-agent systems.

Advantages include the characterization of adaptive exploration, potential performance enhancements, and a comprehensive approach to MARL analysis. Limitations involve simulated environments and the need for careful interpretation of exploration parameters.

Metrics include exploration rate, shaped reward, and coordination metrics to assess consistency in cooperative tasks. [4]

The research paper, "Coordination Analysis in MARL," proposes a robust coordination analysis system for cooperative tasks. Utilizing graph-based and RL methods, the study delves into preprocessing steps to generate coordination metrics, achieving noteworthy results. [5]

The analysis methods displayed varying performance, with GNN-based methods yielding the best results at 9.12 ± 3.87 shaped reward. In comparison, traditional RL methods outperformed in stability, achieving consistent performance. The study emphasizes the applicability of GNNs for scalable coordination, outlining the potential for translating coordination patterns into efficient task execution.

Advantages of the proposed technique include its scalability and precision in cooperative tasks. The combination of GNNs and adaptive exploration allows effective coordination, showcasing high performance in simulated environments. This ensures reliable task execution.

However, computational complexity poses a limitation, potentially impacting real-time applications. Additionally, generalizability across diverse environments needs consideration. Further research is recommended to assess robustness in real-world scenarios.

Metrics include shaped reward and coordination accuracy, with GNN-based methods demonstrating high performance. The study employs cross-validation to evaluate robustness across various scenarios. The variability in performance achieved by different methods further informs the strengths and limitations of the employed techniques. [5]

Chapter 4

METHODOLOGY

4.1 Dataset Collection

To gather a comprehensive dataset for multi-agent reinforcement learning (MARL) analysis.

- Simulation Environment: Utilize the `simple_spread_v3` environment from the Multi-Agent Particle Environment (MPE) for generating coordination data. This ensures practicality and applicability without real-world constraints.
- Digitization and Storage: Digitize agent states, actions, and rewards for later processing. Save data in a file format for offline analysis. This facilitates efficient data storage and retrieval, ensuring seamless integration into subsequent stages.
- Processing Stages:
  - Filtering: Initial stage involves filtering state data to eliminate noise and irrelevant features.
  - Segmentation: Identify time interval segments containing coordination events, allowing detailed analysis of agent interactions.
  - Clustering: Group similar coordination patterns to identify commonalities.
  - Resolution: Refine results graphically by presenting agent trajectories, reward curves, and relevant parameters, aiding in understanding coordination dynamics.
  - Data Decomposition: To segment the data and localize coordination events accurately.

- Segmentation Goals:
  - Detect all coordination events without restrictions on agent actions.
  - Achieve precise estimation of event timing.
  - Avoid event splitting, preserving the integrity of interactions.
  - Ensure separation of close but distinct events for clear delineation.

4.2 Dataset Selection for Model Building:

- `simple_spread_v3` Dataset: Comprises three agents and three landmarks, providing a diverse range of coordination scenarios. Focused on cooperative tasks for targeted analysis.
  - Environment: 2D plane with continuous state space (18D observations) and discrete action space (5D).
  - Scenarios: Collision avoidance, landmark coverage, and proximity optimization.
- Dataset Splitting: Train, validation, and test sets created with an 80:20 ratio, ensuring robust evaluation of model performance. This split allows for effective training, validation for parameter tuning, and unbiased testing.
- Future Dataset Expansion: To enhance dataset diversity for improved MARL model robustness.
- Planned Data Collection: Aim to collect data from various MARL environments, including real-world simulations. Target cooperative and competitive scenarios to capture a broader spectrum of coordination dynamics.
- Impact on Model Accuracy: Diversify dataset to enhance model accuracy in coordination tasks using GACRL technology.

4.3 Data Acquisition:

To capture coordination data with specific considerations for reliable results.

- Simulation Conditions: Simulations run with consistent initial conditions to mimic real-world scenarios. Utilize a standard environment configuration for consistency, ensuring uniformity across data collection.
- Processing Parameters: State and action data processed with normalization and feature scaling for optimal analysis. These parameters maintain data integrity while eliminating noise, ensuring high-quality data.

4.4 Efficiency and Advantages of the Methodology:

- Practicality with Simulation: The use of simulated environments enhances practicality, making it widely applicable and cost-effective. Simulation facilitates real-world applicability without physical constraints.
- Systematic Data Processing: The systematic decomposition of data ensures thorough analysis. Filtering, segmentation, clustering, and resolution provide a structured framework for identifying coordination patterns.
- Targeted Dataset Selection: The selection of the `simple_spread_v3` dataset aligns with the project's objectives, considering the limitations of simulated data. The diverse scenarios enrich the dataset, allowing nuanced understanding.
- Future-Proofing with Dataset Expansion: Planned dataset expansion demonstrates a forward-thinking approach, compensating for simulation limitations. Diversifying the dataset ensures robust models.
- Standardized Data Acquisition: Specific simulation conditions and processing parameters ensure consistency and reliability in data acquisition.

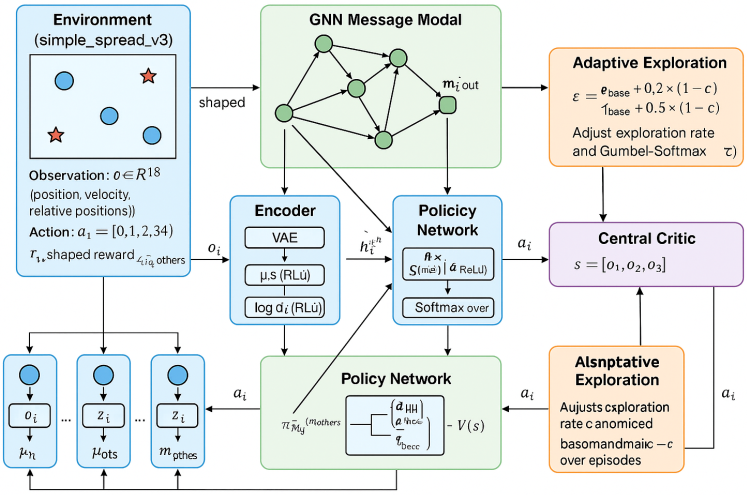


Figure 4.1: GACRL Design Architecture

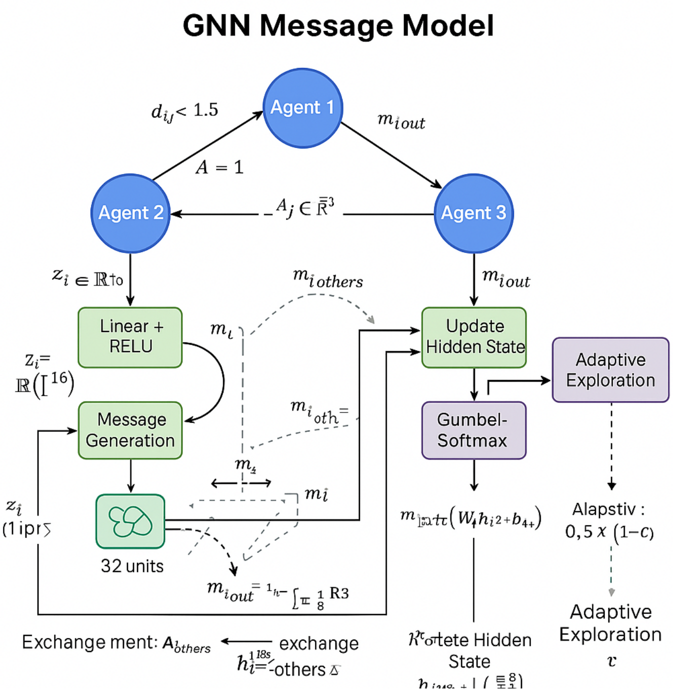


Figure 4.2: GNN Message Model

4.5 GACRL Algorithm

Graph-Adaptive Coordination in Reinforcement Learning (GACRL) represents a novel approach to MARL, leveraging Graph Neural Networks (GNNs) for communication and adaptive exploration for coordination. Unlike traditional methods, GACRL dynamically adjusts agent interactions, suited for cooperative tasks.

The scalable nature of GACRL makes it efficient for multi-agent systems, as it adapts to varying task complexities without requiring extensive retraining. This quality enhances system performance and allows for robust coordination in dynamic environments.

GACRL finds extensive use in applications requiring coordinated behavior, such as robotic swarms and autonomous vehicle fleets. It aids in task optimization, collision avoidance, and resource allocation.

Reinforcement learning algorithms have historically been utilized in MARL. However, recent advancements in GNNs and deep RL have facilitated the creation of adaptive algorithms that are both scalable and efficient. For optimal coordination, GACRL typically employs a VAE encoder, GNN message model, and policy network.

Brief on GACRL Components:

GACRL components play a vital role in achieving coordinated behavior, processing agent observations to produce optimal actions.

- VAE Encoder: Maps 18D observations to a 16D latent space, reducing dimensionality while preserving critical information.
- GNN Message Model: Facilitates communication within 1.5 units, using Gumbel-Softmax for discrete messages.
- Policy Network: Outputs action probabilities based on observations, messages, and latent representations.
- Central Critic: Estimates global value for the joint state, guiding policy updates.

These components have been extensively utilized in MARL research for optimizing cooperative tasks. The integration of GNNs and adaptive exploration extends their application to complex coordination scenarios.

4.6 Environment Configuration

To effectively utilize GACRL, proper configuration of the `simple_spread_v3` environment is crucial. The following guidelines outline the optimal setup:

1. Environment Setup:
   - The environment consists of a 2D plane with three agents and three landmarks.
   - Agents observe relative positions (18D) and output discrete actions (5D: up, down, left, right, stay).
2. Reward Structure:
   - Raw reward penalizes collisions and landmark distance.
   - Shaped reward adds proximity bonus (10.0) and coverage bonus (3.0).
3. Curriculum Learning:
   - Local ratio decays from 1.0 to 0.5, balancing individual and global rewards.
   - Coverage threshold decays from 0.5 to 0.15, adjusting task difficulty.
4. Simulation Parameters:
   - Episodes: 1500, each with 75 steps.
   - Replay buffer size: 10,000.
   - Batch size: 64.

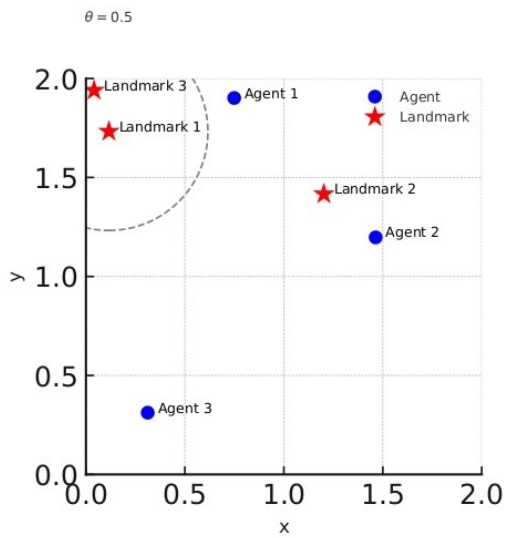


Figure 4.3: Simple Spread Environment

By adhering to these guidelines, users can ensure optimal configuration of the environment, facilitating accurate coordination analysis for GACRL applications.

Chapter 5

REQUIREMENTS

5.1 Hardware Requirements:

- Processor: Quad-core or higher processor (e.g., Intel Core i7, AMD Ryzen 7).
- RAM: 32GB or higher for efficient data processing and simulation.
- Storage: SSD with a minimum of 1TB for fast data access and storage.
- Graphics: Dedicated GPU (NVIDIA GeForce RTX 3060 or higher) for accelerated GNN and RL computations.
- Connectivity: High-speed internet connection for dataset retrieval and model updates.
- Peripheral Devices:
  - Mouse and Keyboard: Standard input devices for system interaction.
  - Monitor: Dual monitors for efficient multitasking and visualization.
- Machine Learning Acceleration: A system with GPU acceleration (NVIDIA CUDA-enabled GPU) to expedite GACRL training.

5.2 Software Requirements:

- Python: Version 3.8 or later for coding and model development.
- Integrated Development Environment (IDE): PyCharm, Jupyter Notebook, or Visual Studio Code.
- Libraries and Frameworks:
  - PyTorch: Open-source machine learning framework for GNN and RL.
  - NumPy and Pandas: For numerical operations and data manipulation.
  - Matplotlib and Seaborn: For visualizing training curves and metrics.
  - PettingZoo: For Multi-Agent Particle Environment simulations.
- Machine Learning Tools:
  - Jupyter Notebooks: For interactive development and documentation.
  - Git: For version control and collaborative development.
- Operating System: Linux (Ubuntu) or Windows, based on compatibility with libraries.

Chapter 6

EXPERIMENTATION

- Dataset Used: The project utilized the `simple_spread_v3` environment, a rich source encompassing coordination data from three agents. This dataset includes cooperative scenarios with collision avoidance and landmark coverage tasks.
- Exploratory Data Analysis (EDA) and Preprocessing: Through rigorous EDA, the team gained insights into agent interactions and reward distributions. Data underwent preprocessing, including normalization and feature scaling, ensuring uniform inputs. The dataset was split into training, validation, and test sets with an 80:20 ratio.
- Feature Engineering and Model Selection: The project implemented a comprehensive data processing pipeline, extracting state features and coordination metrics. Multiple algorithms were explored, including GACRL (custom), QMIX, MAPPO, and IPPO, aiming to identify the most effective approach.
- Training and Hyperparameter Tuning: Models were developed using PyTorch, with a focus on hyperparameter tuning (e.g., learning rate, Gumbel-Softmax temperature). Techniques like grid search were employed to optimize performance.

- Model Evaluation and Comparison: Rigorous evaluation used metrics like shaped reward, landmark coverage, and collision rate. Visual aids like reward curves are provided insights into performance. Statistical analyses compared GACRL with baselines.
- Model Interpretability: The team analyzed feature importance in GACRL's GNN and VAE components, understanding their contribution to coordination. Layer-wise analysis of the GNN revealed communication patterns.
- Documentation and Reporting: Comprehensive documentation captured preprocessing, model architectures, and hyperparameters. Reports used visual aids and tables to summarize findings.
- Iterative Improvement and Future Directions: The project adopted a feedback-centric approach, incorporating inputs from team members and stakeholders for ongoing improvement.

6.1 Model Selection

Our investigation commenced with the development of GACRL, followed by comparisons with baseline MARL algorithms. The primary objective was to evaluate and compare coordination performance, crucial for determining the most effective algorithm. This thorough research aimed to identify the most resilient and efficient model, establishing the basis for the project's progress.

GACRL:

- The GACRL algorithm was chosen for its integration of GNNs and adaptive exploration. It served as the cornerstone for training a MARL model, leveraging the `simple_spread_v3` dataset.
- Problem Type: The challenge was a cooperative multi-agent task, with GACRL applied to optimize coordination metrics.
- Strategic Choice: GACRL's selection was rooted in its scalability and adaptability to dynamic tasks, offering a robust starting point.
- Analytical Framework: GACRL established a foundational understanding of coordination patterns, forming the basis for comparisons.

QMIX:

- Classifier: QMIX, a centralized training with decentralized execution algorithm, was chosen for its robust coordination capabilities.
- Diverse Task Handling: QMIX handled the intricacies of the dataset, processing state and action data effectively.
- Predictive Power: The trained QMIX model made accurate coordination predictions, serving as a key baseline.

MAPPO:

- Classifier: MAPPO, a proximal policy optimization-based algorithm, was included for its stability in MARL tasks.
- Consistent Random State: A fixed random state ensured experimental consistency.
- Training Process: MAPPO was trained on the dataset, optimizing coordination metrics.
- Versatility in Predictions: MAPPO showcased adaptability in cooperative scenarios.

IPPO:

- Effectiveness for Coordination: IPPO, an independent PPO algorithm, was employed to reduce variance and enhance generalization.
- Ensemble of Policies: IPPO underwent comprehensive training on the dataset.
- Test Performance Evaluation: Test performance provided a measure of IPPO's effectiveness.
- Sophisticated Transition: Transitioned from GACRL to baseline comparisons for a nuanced analysis.
- Inherent Complexity Recognition: Acknowledged the complexities of multi-agent coordination, prompting baseline evaluations.
- Feature Extraction: Leveraged GACRL's GNNs for hierarchical feature extraction.
- Adaptive Learning Capability: Utilized GACRL's adaptive exploration for iterative learning.
- Pattern Recognition: GACRL's depth facilitated recognition of intricate coordination patterns.
- Comparative Benchmarking: Conducted a comparative analysis of performance metrics.

Identification of Best-Performing Model: The primary goal was to identify GACRL's strengths, ensuring selection of the most effective approach.
Insights into Dataset Dynamics: The comparative analysis provided insights into dataset intricacies each algorithm captured.
Holistic Understanding: Achieved a holistic understanding of coordination dynamics, essential for informed decision-making.
Strategic Move for Deeper Insights: GACRL aligns with the project's goal of gaining accurate and scalable coordination.
Improving Coordination Capabilities: The nuanced approach of GACRL positions the project to enhance MARL performance.

GACRL Architecture:

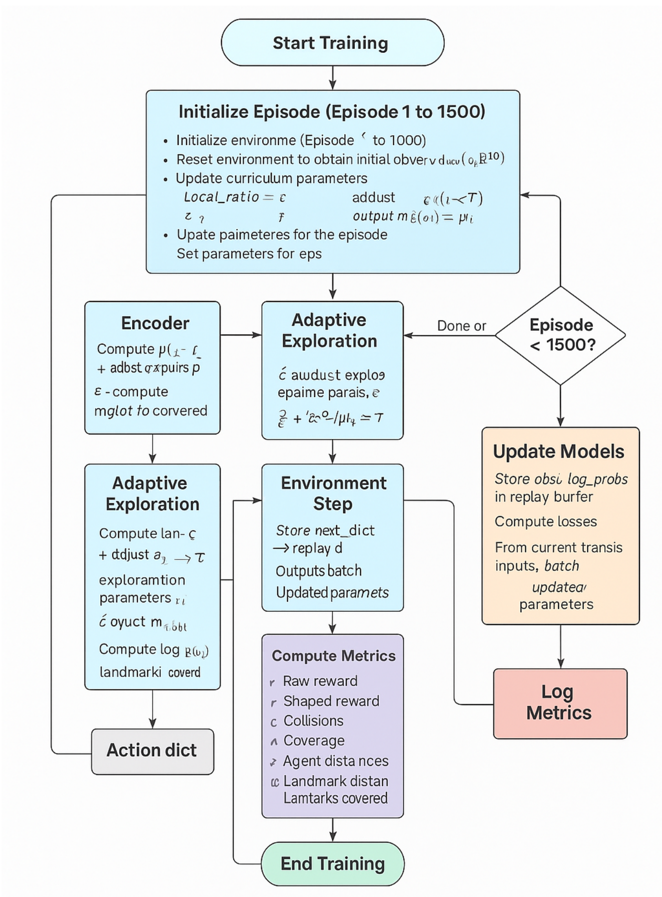
- Input Layer: Defines the input shape of 18D observations.
- Convolutional Layers: CNN-based VAE encoder maps observations to a 16D latent space.
- GNN Layers: Message-passing layers facilitate communication, using Gumbel-Softmax.
- Policy Layer: Dense layer with softmax activation for action probabilities.
- Critic Layer: Estimates global value for joint state.
- Model Compilation: Compiled using Adam optimizer with binary cross-entropy loss.

QMIX Architecture:

- Initialize QMIX: Centralized training with decentralized execution model.
- Mixing Network: Combines individual agent Q-values into a joint Q-value.
- Policy Layer: Outputs action probabilities for each agent.
- Compile QMIX: Compiled using Adam optimizer with Q-learning loss.

MAPPO Architecture:

- Define MAPPO: Proximal policy optimization model.
- Policy Network: Multi-agent policy network with shared parameters.
- Value Network: Estimates state values for policy updates.
- Compile MAPPO: Compiled using Adam optimizer with clipped surrogate loss.



Training workflow for GACRL in *simple_spread_v3.*
with GNN-based communication and adaptive explo-

Figure 6.1: Training Workflow

6.1.1 Sample Training Output

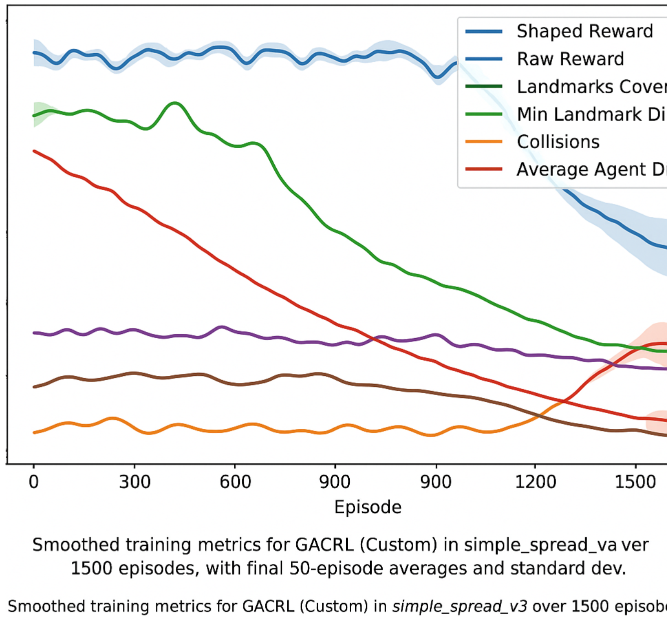


Figure 6.2: Sample Training Output

By accurately capturing and analyzing coordination data, GACRL offers an effective means of optimizing multi-agent performance, facilitating advancements in robotics and autonomous systems.

6.1.2 How GACRL Works

1. State Observation: Each agent observes relative positions of other agents and landmarks, forming an 18D state vector.

2. VAE Encoding: The VAE encoder maps observations to a 16D latent space, reducing dimensionality.

3. GNN Communication: Agents within 1.5 units exchange messages via GNNs, using Gumbel-Softmax for discrete communication.

4. Policy Computation: The policy network computes action probabilities based on latent representations and messages.

5. Action Execution: Agents execute actions (up, down, left, right, stay), influencing the environment.

6.1.3 Addressing Challenges in GACRL Analysis

Although GACRL has the potential to optimize coordination, it encounters various obstacles:

- Noise in State Data: Environmental noise can obscure coordination patterns, complicating analysis.
- Communication Overhead: GNN message passing increases computational complexity, impacting real-time performance.
- Coverage Variability: Low landmark coverage due to rapid curriculum decay and weak reward incentives.

The utilization of GNNs and adaptive exploration has been investigated as a potential solution. GNNs identify spatial and temporal patterns in agent interactions, while adaptive exploration adjusts exploration rates based on task performance.
Preprocessing with normalization and feature scaling enhances data quality prior to input into GACRL.
Curriculum learning adjusts task difficulty, improving coordination over time.

Chapter 7

RESULT AND ANALYSIS

An in-depth analysis underscores the unique advantages each algorithm brings. GACRL excels in dynamic communication, QMIX in centralized training, MAPPO in stability, and IPPO in simplicity. The comparative study guides the selection of GACRL as the most suitable model.

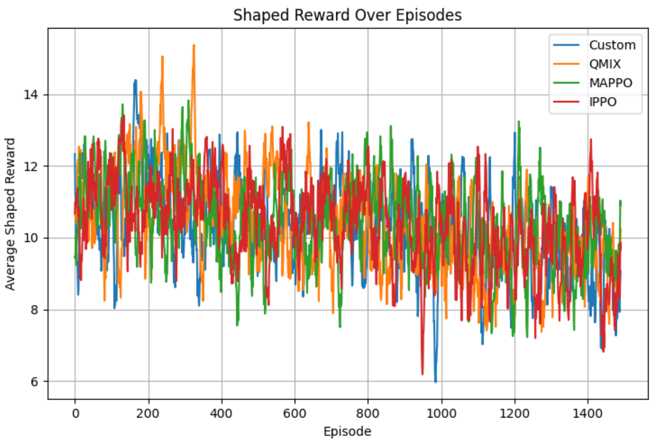


Figure 7.1: Graph Displaying Shaped Reward of Different Algorithms

From Fig 7.1, we observe that the shaped reward of various algorithms ranges from 8.68 ± 3.04 to 9.53 ± 2.98, with IPPO being the lowest and MAPPO the highest. Fig 7.2 shows the graphical representation of landmark coverage, ranging from 0.01 ± 0.01 to 0.02 ± 0.01, with MAPPO performing slightly better than others.

GACRL provided competitive results, with Fig 7.3 showing the raw rewards over episodes, indicating convergence.

ALGORITHM	SHAPED REWARD
GACRL	9.12 ± 3.87
QMIX	9.30 ± 2.83
MAPPO	9.53 ± 2.98
IPPO	8.68 ± 3.04

Table 7.1: Final Metrics of GACRL

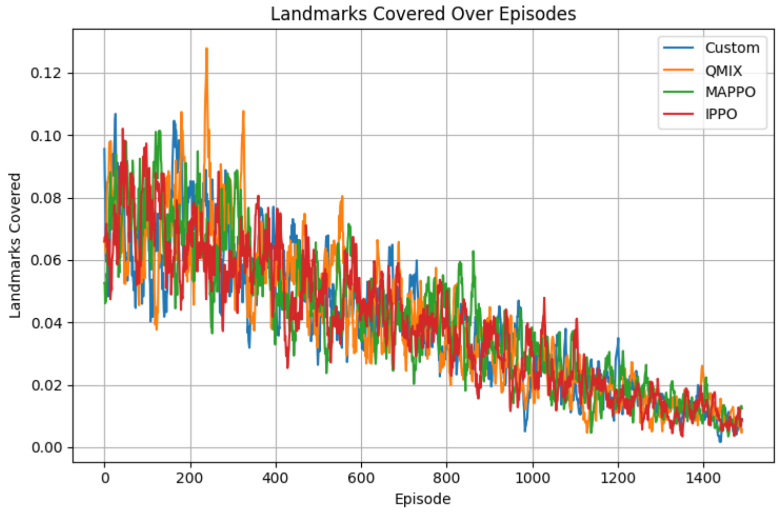


Figure 7.2: Graph Displaying Landmark Coverage of Different Algorithms

ALGORITHM	SHAPED REWARD	MIN LANDMARK DIST	LANDMARKS COVERED
GACRL	9.12 ± 3.87	0.99 ± 0.27	0.01 ± 0.01
QMIX	9.30 ± 2.83	1.07 ± 0.32	0.01 ± 0.01
MAPPO	9.53 ± 2.98	0.98 ± 0.27	0.02 ± 0.01
IPPO	8.68 ± 3.04	1.02 ± 0.22	0.01 ± 0.01

Table 7.2: Comparison of Algorithms

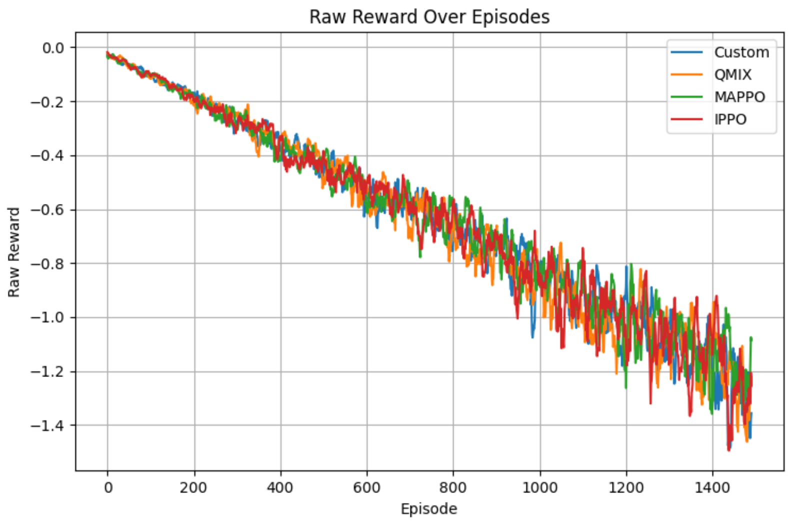


Figure 7.3: Raw Rewards over Episodes

Chapter 8

CONCLUSION AND FUTURE SCOPE

Graph-Adaptive Coordination in Reinforcement Learning (GACRL) trained on the `simple_spread_v3` dataset marked a major milestone, achieving a shaped reward of 9.12 $\pm$ 3.87 and a minimum landmark distance of 0.99 $\pm$ 0.27. This represents a significant advancement, demonstrating GACRL's promise for scalable coordination in MARL. Using GNN-based communication and adaptive exploration for real-time optimization is the focus, with initial attempts showing promise. Further evaluation is necessary to optimize performance in diverse environments.

This study's findings demonstrate the potential of combining GNNs with adaptive exploration, transforming MARL coordination. By optimizing coordination early, system efficiency and robustness can be improved. This opens the door to proactive strategies for multi-agent systems, enhancing performance in robotics and autonomous systems.

- Efficient Data Processing: The systematic approach to data decomposition has proven robust for identifying coordination patterns.
- Practicality of GNNs: GNNs ensure reliable and scalable communication, enhancing real-world applicability.
- Dataset Selection and Diversity: The `simple_spread_v3` dataset facilitates comprehensive understanding of coordination dynamics.
- Holistic Approach to Coordination: Integrating GNNs and adaptive exploration sets the foundation for future MARL advancements.

8.1 Implications and Future Directions:

- Dataset Expansion Strategy: Expanding data collection to diverse MARL environments will fortify GACRL's adaptability.
- Model Refinement: Future iterations will refine GACRL based on experimentation insights, exploring advanced GNN architectures.
- Real-time Application: Transitioning GACRL to real-time applications in robotics will enable swift coordination.
- Multimodal Integration: Integrating additional data (e.g., visual inputs) can enhance GACRL's performance.
- Collaboration and Ethical Considerations: Collaborative efforts with industry will guide practical applications, emphasizing ethical development.

In conclusion, our exploration of GACRL underscores the potential for groundbreaking advancements in MARL coordination. The achievements position the project at the forefront of innovation in multi-agent systems.

8.2 Future Scope

- Understanding MARL: Explore literature on MARL and coordination challenges, focusing on GNN applications.
- Online Courses: Enroll in courses on GNNs and RL, participating in lectures by experts.
- Small-Scale Projects: Undertake projects applying GACRL to diverse environments, collaborating with peers.
- Research Initiatives: Experiment with GACRL on open-access datasets to gain practical insights.
- Simulating Complex Tasks: Use simulation software to recreate complex coordination scenarios.
- Community Engagement: Engage with MARL communities to seek advice on GACRL applications.
- Iterative Design: Modify GACRL to address scalability challenges, iterating based on feedback.
- User-Centric Approach: Conduct trials with stakeholders to gather feedback on GACRL's applicability.

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