Adaptive Self-Supervised Dynamic Influence Learning for GNN-based Multi-Agent Traffic Signal Control

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1. Methodology

To address the problem of evolving spatial and temporal dependencies in urban traffic systems, we propose a novel adaptive self-supervised learning framework for constructing dynamic traffic-influence graphs, which are subsequently integrated into a Graph Neural Network-based Multi-Agent Reinforcement Learning (GNN-MARL) system. This integrated approach aims to coordinate signal control policies in real-time, reducing congestion propagation and improving network traffic efficiency.

1.1 Traffic State Encoding

· Each traffic intersection is considered as an agent that observes its environment via sensors capturing data such as:

· - Vehicle counts per incoming lane

· - Queue lengths at intersections

· - Inflow and outflow rates

· - Current and previous signal phases

· To convert these raw traffic metrics into a format suitable for downstream learning, we propose a spatiotemporal encoding mechanism:

· - Temporal features are processed using LSTM or Temporal Convolutional Networks (TCNs) to model traffic flow trends.

· - Signal phase information is embedded as learnable vectors.

· - Features are concatenated and passed through a dense encoding layer to form a fixed-size latent representation per intersection.

· These latent vectors serve as node features for the influence graph construction process.

1.2 Dynamic Influence Learning

To learn about evolving relationships between intersections, we design a self-supervised dynamic influence learning module that constructs a weighted adjacency matrix in real-time.

· Key components:

· - Graph Attention Mechanism: Assigns attention weights to neighboring nodes based on their encoded features.

· Contrastive Learning: Uses dropout and feature masking to maximize agreement between positive node pairs.

· - Mutual Information Maximization: Preserves meaningful global dependencies.

· The resulting dynamic traffic-influence graph updates at every timestep, capturing short- and long-range dependencies.

1.3 GNN-MARL Integration

· We integrate the dynamically constructed graphs into a GNN-based MARL system, where a local agent controls each intersection.

· Observation: Node features and messages from dynamically identified influential neighbors.

· Policy Network: GAT layer followed by a policy head (e.g., PPO or DQN).

· Action: Agent selects the next signal phase.

· Reward: Based on local traffic efficiency.

· This setup allows agents to learn coordinated policies using both local and non-local context.

1.4 Performance Evaluation

· We evaluate the proposed framework on standard benchmarks using the following metrics:

· Average Waiting Time per vehicle

· Average Queue Length at intersections

· Throughput: Number of vehicles reaching destinations

· Average Travel Time

. Comparison with static-topology MARL baselines will highlight improvements in congestion reduction and flow stability.

1.5 Scalability and Robustness

· Scalability: Achieved through GNNs and attention mechanisms with graph sampling or hierarchical clustering.

· Robustness: Tested under sensor faults, incidents, and varying densities using dropout regularization and online graph refinement.

2. Novelty Justification and Model Comparison

2.1 Comparative Analysis

Model	Graph Type	Coordination	Dependency Capture	Adaptability	Learning Type
CoLight	Static	Graph Attn.	No	Low	MARL + GAT
PressLight	Static	Pressure Rule	No	None	Rule-based
MA2C	Static	Local Info	Partial (fixed)	Low	A2C (shared)
Ours	Dynamic	GNN + Attention	Yes	High	Self-supervised + MARL

2.2 Limitations of Existing Models

- CoLight assumes a fixed graph, failing to adapt to real-time traffic fluctuations.
- PressLight relies on handcrafted pressure metrics; it lacks global coordination.
- MA2C shares limited local info, and does not learn influence dynamically.

2.3 Key Differentiators

- Learns real-time evolving influence graphs using self-supervision.
- Embeds temporal traffic dynamics with LSTM/TCN encoders.
- Integrates attention-based GNNs within a multi-agent RL system.
- Adapts to non-stationary traffic patterns and unexpected events.
- Enhances coordination across distant intersections via influence propagation.
- Robust against noise, scalable to larger networks.

3. System Architecture Diagram