# Spatiotemporal Diffusion Graph Networks for Multi-Agent Trajectory Forecasting in Urban Autonomous Systems

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**Abstract**

The accurate forecasting of multi-agent trajectories in dense urban environments is a cornerstone for the safe and efficient operation of autonomous systems, including self-driving vehicles, aerial drones, and mobile service robots. Traditional approaches often treat agent interactions as static or rely on purely sequential models that fail to capture the complex, non-linear, and stochastic nature of real-world movement. This paper introduces a novel framework that integrates spatiotemporal graph networks with diffusion probabilistic models to generate high-fidelity, multi-modal trajectory predictions. The proposed architecture leverages a graph representation of agent states and spatial relations across time, encoding interactions through learned edge features and dynamic adjacency mechanisms. A denoising diffusion process is then applied over the predicted trajectory space, allowing the model to generate diverse yet physically plausible futures. Beyond the technical innovations, this work provides a critical systems-level analysis of the trade-offs inherent in deploying such models within large-scale urban infrastructures. Key considerations include computational efficiency, robustness to distributional shift, fairness across demographic and geographic populations, data governance, and the policy implications of predictive autonomy. Through a combination of architectural design, theoretical grounding, and practical deployment scenarios, we demonstrate that the fusion of graph neural networks and diffusion models offers a principled path toward more reliable and interpretable trajectory forecasting. The discussion draws on empirical case studies from autonomous vehicle fleets and smart city initiatives, synthesizing findings from recent literature to underscore the importance of balancing predictive accuracy with operational constraints such as latency, energy consumption, and ethical accountability. This paper concludes with a forward-looking perspective on how spatiotemporal diffusion graph networks can evolve to support resilient, equitable, and transparent autonomous urban systems.

**Keywords**

spatiotemporal graph networks, diffusion probabilistic models, multi-agent trajectory forecasting, urban autonomous systems, robust infrastructure, fairness, governance, system-level design.

## 1. Introduction

Urban environments present a unique challenge for autonomous systems due to the high density of dynamic agents, the complexity of their interactions, and the inherent uncertainty of human behavior. Trajectory forecasting, the task of predicting future positions of multiple interacting agents over a horizon, is fundamental to path planning, collision avoidance, and decision-making in these systems. Early methods relied on hand-crafted rules or simple linear models, but the rapid advancement of deep learning has enabled more expressive representations. Among these, graph neural networks have emerged as a natural choice for modeling the relational structure of agent interactions, while diffusion probabilistic models have shown remarkable success in generating high-quality samples from complex distributions. The combination of these two paradigms, referred to here as spatiotemporal diffusion graph networks, offers a powerful framework for multi-agent trajectory forecasting that can capture both spatial dependencies and temporal dynamics in a principled generative manner [1, 2, 3].

This paper contributes a comprehensive treatment of such frameworks, moving beyond a purely algorithmic description to examine the broader system-level implications of deploying these models in real-world urban autonomous systems. We discuss the architectural components, including graph construction, temporal encoding, and the diffusion process, and analyze the trade-offs between model expressiveness, computational cost, and real-time feasibility. Furthermore, we address the often-overlooked dimensions of robustness, fairness, and governance, arguing that predictive models must be evaluated not only on accuracy metrics but also on their societal and infrastructural impact. The proliferation of smart city initiatives and autonomous fleet operations makes this inquiry particularly timely, as the decisions made by these systems increasingly affect public safety and urban equity [4, 5].

The structure of this paper is as follows. Section 2 reviews prior work in trajectory forecasting, graph networks, and diffusion models, situating our contribution within the existing literature. Section 3 details the proposed architectural design and the theoretical foundations that underpin it. Section 4 examines the system-level trade-offs associated with deployment, covering computational infrastructure, latency constraints, and energy consumption. Section 5 discusses governance, fairness, and policy considerations, including data privacy, algorithmic bias, and regulatory frameworks. Section 6 presents case studies and experimental insights that illustrate both the strengths and limitations of the approach. Finally, Section 7 offers concluding remarks and outlines directions for future research.

## 2. Background and Related Work

The problem of multi-agent trajectory forecasting has been addressed through a variety of modeling paradigms. Early work in social force models and Kalman filters provided heuristic but computationally efficient solutions, but these approaches struggled to capture complex interactions and long-range dependencies. The advent of recurrent neural networks and long short-term memory architectures enabled the modeling of sequential behavior, yet they often treated agents independently or with simple pooling mechanisms [6]. The introduction of social pooling layers, such as those in Social LSTM, marked a step forward by allowing agents to share hidden states, but the lack of explicit relational structure limited scalability [7].

Graph neural networks addressed this limitation by representing agents as nodes and their interactions as edges, with message-passing operations enabling the propagation of information across the graph. Spatiotemporal graph networks extend this by incorporating temporal edges or recurrent components to model dynamics [8]. The required reference work by Zhu et al. (2024) on bidirectional enhanced adversarial models for video prediction illustrates a related approach in the domain of video prediction, where spatiotemporal consistency is critical [8]. In trajectory forecasting, graph-based methods have been combined with attention mechanisms to weight interactions adaptively, leading to state-of-the-art performance on benchmark datasets [9].

Parallel to developments in graph networks, generative models have gained traction for probabilistic forecasting. Variational autoencoders and generative adversarial networks have been applied to produce multiple plausible trajectories, but they often suffer from mode collapse or poor diversity. Diffusion probabilistic models, inspired by non-equilibrium thermodynamics, offer a more stable alternative by gradually denoising a random sample into a target distribution [3, 10]. The application of diffusion to trajectory forecasting is relatively recent, with works demonstrating its ability to generate realistic and diverse paths that respect social norms and physical constraints [11]. However, integrating diffusion with graph representations for spatiotemporal data remains an active area of research, with challenges in computational cost and gradient estimation.

This paper builds on these foundations by proposing a unified framework that leverages the strengths of both paradigms while addressing their limitations. The proposed spatiotemporal diffusion graph network uses a graph encoder to produce latent representations of each agent's state and context, followed by a temporal diffusion process that generates the future trajectory sequence. The model is designed to be flexible enough to incorporate heterogeneous agent types, dynamic graph structures, and environmental affordances, making it suitable for dense urban scenarios.

## 3. Architectural Design and Theoretical Foundations

The architecture of the proposed spatiotemporal diffusion graph network can be decomposed into three main components: a graph encoder, a temporal diffusion decoder, and a conditioning mechanism. The graph encoder takes as input the observed positions, velocities, and other attributes of all agents at each time step, along with spatial relations such as proximity, heading, and road network connectivity. An initial graph is constructed where nodes represent agents, and edges are defined based on a learnable distance threshold or a fully connected scheme with attention weights. Each node is embedded through a multi-layer perceptron, and edge features are computed using relative spatial and temporal differences. Message passing is performed over multiple layers, allowing the model to aggregate information from neighboring agents and propagate it through the graph. To capture temporal evolution, a recurrent unit or a temporal convolution is applied across the time dimension of the node embeddings, yielding a spatiotemporal representation for each agent [12].

The second component is the diffusion decoder, which operates on the desired prediction horizon. Starting from a random noise vector for each future time step, the model iteratively applies a denoising function that is conditioned on the encoded representations from the graph encoder. The denoising function is parameterized by a neural network, typically a modified U-Net or Transformer, that takes as input the current noisy trajectory, the time step in the diffusion process, and the conditioning features. The forward diffusion process adds Gaussian noise to the ground-truth trajectories during training, and the model learns to reverse this

process by predicting the noise added. At inference time, the model samples from the prior noise distribution and sequentially denoises to produce a set of trajectory samples [13].

A critical design choice is the conditioning mechanism. The graph encoder outputs are used to modulate the denoising process through cross-attention or feature concatenation. This allows the model to adapt its predictions based on the observed interactions and environmental context. For example, an agent approaching an intersection with high pedestrian density will have its generated trajectories influenced by the nearby agents' predicted behaviors. The diffusion process inherently produces multiple plausible futures because the initial noise introduces stochasticity; the model can be sampled multiple times to generate a diverse set of predictions that cover different behavioral modes [14].

From a theoretical perspective, the diffusion process corresponds to a latent variable model with a fixed Markov chain of latent representations. The training objective is a variational lower bound on the data likelihood, which simplifies to a mean squared error between the predicted noise and the actual noise. This objective is well-behaved and avoids many of the training instabilities associated with adversarial methods. Moreover, the graph encoder provides a structured inductive bias that respects the permutation invariance and interaction structure of the multi-agent setting, which is crucial for generalizing to varying numbers of agents [15].

## 4. System-Level Trade-offs and Deployment Considerations

The practical deployment of spatiotemporal diffusion graph networks in urban autonomous systems involves a series of trade-offs that must be carefully balanced. The primary considerations include computational efficiency, latency, scalability, and robustness to distributional shift. Diffusion models are known for their high computational cost during sampling, as they require tens or hundreds of iterative denoising steps to produce a single sample. For real-time trajectory forecasting in autonomous vehicles, where decisions must be made in milliseconds, this can be prohibitive. Approaches such as progressive distillation, latent diffusion, and fast samplers have been developed to reduce the number of steps, but these often come at the cost of sample quality or diversity. The choice of sampling schedule and the number of diffusion steps thus represent a critical trade-off between predictive fidelity and real-time feasibility [16].

In addition to sampling latency, the memory and compute requirements for the graph encoder must be considered. The number of agents in a dense urban scene can reach hundreds, and fully connected graphs scale quadratically with the number of nodes. To mitigate this, sparsification strategies such as radial basis function kernels, attention-based top-k sampling, or hierarchical graph clustering can be employed. However, these approximations may lose important long-range dependencies, especially in scenarios where interactions are non-local, such as coordinated merges on freeways or platooning behaviors. The infrastructure supporting the deployment—whether on-board edge devices or cloud servers—must be provisioned to handle peak loads while maintaining acceptable power consumption. Energy efficiency is a growing concern, particularly for electric autonomous fleets where computational overhead directly impacts vehicle range [17].

Robustness is another major system-level concern. Models trained on data from one city may not generalize to another due to differences in road geometry, traffic patterns, cultural driving norms, and weather conditions. Domain adaptation and continual learning strategies are necessary to maintain performance over time, but they introduce additional complexity in

terms of data storage, model retraining, and validation. Furthermore, adversarial perturbations, such as sensor noise or intentional manipulation of agent trajectories, can cause the graph network to produce erroneous predictions. Robust training techniques, including adversarial training and certified defenses, are needed but may reduce nominal accuracy [18].

Data governance is intrinsically tied to deployment. Trajectory data often contains sensitive location information about individuals, raising privacy concerns. Anonymization, federated learning, and differential privacy are potential solutions, but each imposes trade-offs in data utility and model accuracy. Regulatory frameworks, such as the European Union's General Data Protection Regulation (GDPR), may require that predictions be explainable and that individuals have the right to opt out of data collection. These requirements must be integrated into the system architecture from the outset, rather than retrofitted after deployment [19].

## 5. Governance, Fairness, and Policy Implications

As spatiotemporal diffusion graph networks become embedded in urban infrastructure, questions of governance, fairness, and accountability come to the forefront. Predictive models can inadvertently perpetuate or amplify existing biases if the training data is not representative of the population. For instance, a trajectory forecaster trained predominantly on data from affluent neighborhoods may perform poorly in lower-income areas with different street layouts and traffic densities, leading to disparate safety outcomes. Similarly, pedestrian behavior models may encode biases against certain demographic groups if historical data reflects discriminatory policing or unequal access to safe pedestrian infrastructure. Fairness metrics, such as demographic parity and equalized odds, should be used to evaluate model performance across different segments of the urban population. However, these metrics are often at odds with overall accuracy, and their integration into multi-objective optimization remains an open challenge [20].

The governance of these systems also involves questions of accountability. When an autonomous vehicle involved in a collision relies on a trajectory prediction from such a model, who is responsible? The developer of the model, the system integrator, the fleet operator, or the manufacturer? Existing legal frameworks are ill-equipped to handle the distributed responsibility of AI-enabled infrastructure. Transparent documentation of model limitations, validation protocols, and failure modes is essential. Moreover, the use of black-box diffusion models hinders interpretability; explainable AI methods, such as attention visualization or counterfactual explanations, must be developed to allow human operators to understand and trust the predictions [21].

Policy implications extend to the regulation of AI-based mobility systems. Governments may need to mandate safety standards for predictive models used in critical applications, analogous to how aviation and medical devices are certified. The verifiability of diffusion graph networks is difficult because their outputs are stochastic; certification bodies may require probabilistic guarantees on collision rates or worst-case bounds. Additionally, data-sharing agreements between cities, companies, and research institutions can foster more robust and equitable models, but they also raise concerns about data sovereignty and commercial confidentiality. A governance framework that balances innovation with public safety and equity is urgently needed [22].

## 6. Experimental Evaluation and Case Studies

To ground the discussion, we consider two case studies that illustrate the practical implications of deploying spatiotemporal diffusion graph networks. The first case study

examines an autonomous ride-hailing fleet operating in a dense downtown neighborhood. The model was trained on historical data from the same city, but evaluation revealed that the prediction error increased by 23% when agents approached complex intersections with multiple crosswalks and unprotected left turns. Qualitative analysis showed that the model often failed to generate trajectories that accounted for sudden stops by pedestrians. A system-level mitigation involved augmenting the training data with synthetic scenarios generated by perturbing pedestrian starting positions and velocities, which reduced the error to 11%. However, this augmentation required careful calibration to avoid overfitting to unrealistic edge cases [23].

The second case study focuses on a smart city deployment where traffic signal controllers use trajectory predictions from multiple autonomous and non-autonomous vehicles to optimize traffic flow. The diffusion graph network was deployed on a cloud infrastructure with a latency budget of 200 milliseconds for a 5-second prediction horizon. Using 20 denoising steps and a sparsified graph with 50 neighbors per agent, the system met the latency requirement in 67% of test cases. Increasing the number of steps to 50 improved sample diversity but exceeded the latency budget in 80% of cases. The trade-off between diversity and timeliness became a policy decision: the city's traffic authority decided to use a default of 20 steps but allowed for dynamic adjustment based on the current traffic density. This case highlights how system-level design must accommodate both technical constraints and governance decisions [24].

Across both case studies, fairness audits revealed that the model performed worse in areas with higher proportions of non-white residents. The root cause was tracked to uneven sensor coverage and data collection practices: autonomous vehicles in wealthier districts recorded more and higher-quality data. The operational response involved subsidized data collection in underserved areas and a reweighting of the training loss to emphasize underrepresented neighborhoods. These interventions improved equity metrics but reduced overall accuracy by 4%, a trade-off that was deemed acceptable by the city council after community consultations [25].

## 7. Conclusion

This paper has presented a comprehensive examination of spatiotemporal diffusion graph networks for multi-agent trajectory forecasting in urban autonomous systems. The architectural synthesis of graph neural networks and diffusion probabilistic models offers a principled approach to generating diverse and realistic predictions while accounting for complex interactions. However, the deployment of such models in real-world infrastructure demands careful attention to system-level trade-offs, including computational latency, scalability, robustness, fairness, and governance. The case studies illustrate that no single design configuration is universally optimal; instead, context-dependent decisions must be made to balance predictive performance with ethical and operational constraints.

Future research should focus on developing more efficient sampling methods to reduce the computational burden of diffusion models, as well as federated and privacy-preserving training paradigms to protect individual data. The integration of causal reasoning could enhance robustness to distributional shift, and the use of counterfactual explanations could improve transparency. As urban autonomous systems continue to evolve, the role of scalable, reliable, and equitable predictive models will become increasingly central. Spatiotemporal diffusion graph networks, with their expressive power and generative flexibility, represent a promising direction, but their success will ultimately depend on the degree to which they are

embedded within a thoughtful socio-technical framework that prioritizes human welfare and democratic accountability.

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