Self-Supervised Spatiotemporal Graph Representation for Human Mobility and Trajectory Forecasting in Urban Environments

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Abstract

Human mobility prediction plays a critical role in urban planning, transportation management, and public safety. Traditional trajectory forecasting models rely heavily on large amounts of labeled data and are often limited by their inability to generalize across heterogeneous urban environments. This paper proposes a self-supervised spatiotemporal graph representation framework for human mobility and trajectory forecasting. The framework constructs dynamic spatiotemporal graphs from raw trajectory data without requiring explicit human supervision, leveraging contrastive and generative pretext tasks to learn transferable representations. We examine the architectural design choices, including the trade-offs between graph convolution, temporal attention, and modeling of long-range dependencies. The system-level discussion emphasizes deployment scalability, data governance, robustness to distribution shifts, and fairness implications across demographic groups. Cross-domain comparisons with traffic flow prediction, epidemic spread modeling, and social network analysis illustrate the broader applicability of self-supervised graph learning. We further address policy considerations regarding privacy, bias, and infrastructural resilience. The proposed approach demonstrates that self-supervision can reduce labeled data requirements while maintaining predictive accuracy, thereby enabling more sustainable and equitable urban mobility systems.

Keywords

spatiotemporal graph, self-supervised learning, human mobility, trajectory forecasting, urban infrastructure.

1. Introduction

The rapid urbanization of global populations has intensified the need for intelligent systems that can anticipate human movement patterns. Accurate trajectory forecasting supports a wide range of applications, including real-time traffic management, ride-hailing optimization, emergency evacuation planning, and public health interventions [1]. However, the inherent complexity of human mobility—characterized by irregular spatiotemporal dependencies, multi-scale periodicity, and individual heterogeneity—poses significant challenges for conventional machine learning approaches [2]. Most existing methods rely on supervised learning with large volumes of historical trajectory data, which are costly to annotate and often biased toward specific urban regions or time periods [3].

Recent advances in graph neural networks (GNNs) have provided a natural formalism for modeling spatial relationships among locations and temporal correlations across time steps [4]. Spatiotemporal graph convolutional networks (STGCNs) have demonstrated state-of-the-art performance in traffic forecasting by treating road networks as static graphs [5]. Yet human mobility trajectories involve dynamic, non-Euclidean spatial structures where the connectivity between points of interest changes continuously [6]. Moreover, labeled trajectory data for model training are scarce in many practical settings, especially for newly deployed systems or under-resourced regions [7].

Self-supervised learning (SSL) offers a promising avenue to address these limitations by enabling models to learn useful representations from unlabeled data through carefully designed pretext tasks [8]. In the context of spatiotemporal graphs, SSL can capture both local neighborhood patterns and global temporal dynamics without requiring ground-truth future trajectories [9]. This paper presents a comprehensive framework that integrates self-supervised objectives with spatiotemporal graph representation learning for human mobility forecasting. We discuss the architectural trade-offs, deployment considerations, and broader socio-technical implications of such a system.

2. Background and Related Work

Human mobility modeling has evolved from statistical models based on gravity laws and radiation principles to deep learning architectures that capture non-linear interactions [10]. Early neural approaches used recurrent neural networks (RNNs) and long short-term memory (LSTM) networks to model temporal sequences, but they struggled to incorporate spatial correlations [11]. The introduction of convolutional neural networks (CNNs) on grid-based representations offered spatial awareness but failed to handle irregular spatial layouts typical of urban environments [12].

Graph neural networks emerged as a more flexible alternative, representing locations as nodes and movement flows as weighted edges. The STGCN model by Yu et al. [5] combined graph convolutions with temporal convolutions for traffic prediction, while the diffusion convolutional recurrent neural network (DCRNN) by Li et al. [13] used graph diffusion processes to capture spatial dependencies. Subsequent works extended these ideas to human trajectory prediction by incorporating attention mechanisms and multi-scale temporal modules [14].

Self-supervised learning for graph data has gained momentum in recent years. Contrastive methods, such as GraphCL [15] and BGRL [16], maximize agreement between augmented views of the same graph, forcing the model to learn invariant features. Generative approaches like masked graph modeling (similar to masked language modeling in NLP) reconstruct missing node attributes or edges [17]. For spatiotemporal graphs, pretext tasks can involve predicting masked temporal segments or correlated spatial neighborhoods [9]. These methods reduce dependence on labeled data and improve generalization across domains.

3. System Architecture and Graph Construction

The proposed framework begins by constructing a dynamic spatiotemporal graph from raw GPS or cellular-based trajectory data. Each node represents a geographic location, such as a cell tower region or a road intersection, and edges represent either spatial proximity (e.g., Euclidean distance or road network connectivity) or temporal co-occurrence (e.g., frequent transitions between locations at similar times) [4]. Unlike static graphs used in traffic

forecasting, our graph evolves over time: node features (e.g., visitation counts, average dwell time) and edge weights (e.g., transition probabilities) are updated at each time step [6].

A key architectural choice involves the trade-off between fully connected graphs and sparse graphs. Dense graphs capture all possible interactions but incur high computational and memory costs, limiting scalability to large urban areas [2]. Sparse graphs, such as k-nearest neighbor graphs or thresholded similarity graphs, reduce complexity but may miss long-range dependencies essential for predicting sudden mobility shifts during events like festivals or disasters [1]. We adopt an adaptive graph learning module that dynamically reweights edges based on learned attention scores, balancing sparsity and expressiveness [9].

The temporal dimension is modeled through a combination of dilated temporal convolutions and recurrent layers. Dilated convolutions provide a large receptive field with fewer parameters, enabling the model to capture daily and weekly periodic patterns [5]. Recurrent layers, such as gated recurrent units (GRUs), handle irregularly sampled trajectories common in human mobility data [11]. The integration of these two mechanisms introduces a trade-off between computational efficiency and the ability to model long-term dependencies: convolutions are parallelizable but assume fixed temporal strides, while recurrent units are sequential but more flexible for variable-length sequences [14].

4. Self-Supervised Learning Paradigm

Self-supervision in our framework operates at both node and graph levels. Node-level pretext tasks include predicting the number of visits to a location in a masked time window or reconstructing the identity of a missing node given its neighbors [17]. Graph-level tasks involve contrasting pairs of temporal subgraphs from the same day versus different days, encouraging the model to learn time-sensitive representations [15]. These objectives are optimized jointly with the downstream forecasting task in a multi-task learning setting, though the representation can be transferred to other mobility tasks without retraining from scratch [8].

A critical design consideration is the choice of positive and negative samples in contrastive learning. If negative samples are too easy to discriminate (e.g., comparing locations from entirely different cities), the model may learn trivial features. Conversely, hard negatives—locations with similar visitation patterns but different spatial contexts—force the model to capture nuanced spatiotemporal correlations [16]. We employ an adaptive negative sampling strategy that selects negatives based on current representation distances, dynamically adjusting the difficulty during training [9].

Generative pretraining, such as masked autoencoding of spatiotemporal sequences, offers an alternative that does not require negative sampling. The model is trained to reconstruct randomly masked trajectory segments conditioned on the observed context [17]. This approach is particularly effective when the data contain strong periodic patterns because the model must infer missing information from surrounding spatiotemporal structure. However, generative objectives are computationally more demanding than contrastive ones, as they require decoding entire sequences rather than comparing representations [8]. The choice between these two paradigms depends on the available computational budget and the nature of the mobility data: contrastive learning excels when negative samples are abundant and informative, while generative learning performs better in data-sparse regimes [15].

5. Spatiotemporal Graph Representation

The learned representations from self-supervised pretraining are high-dimensional embeddings that encode each location's role within the urban mobility system. These embeddings capture not only static features such as land use (e.g., residential, commercial, industrial) but also dynamic behaviors such as rush-hour congestion or weekend leisure movements [2]. The spatiotemporal graph representation is inherently hierarchical: local neighborhoods aggregate into functional regions, and regions interact through commuting flows [10]. The framework leverages multi-scale graph pooling to summarize information at different spatial granularities, enabling forecasting at both individual and aggregate levels [4].

One challenge is ensuring that the representation is robust to distribution shifts. Human mobility patterns change over time due to seasonal variations, infrastructure changes, or policy interventions (e.g., lockdowns) [1]. A static pretrained model may quickly become outdated. We incorporate online adaptation mechanisms that update node embeddings using recent streaming data with a small memory budget, balancing stability and plasticity [6]. This is reminiscent of continual learning approaches in graph domains, where the model must avoid catastrophic forgetting of past patterns while accommodating new ones [14].

Another important property is the ability to transfer representations across cities or regions. A model pretrained on a large city like New York may not directly generalize to a smaller city with different layout and transit modes. However, self-supervised representations that capture universal mobility principles—such as distance decay, centrality attraction, and temporal rhythms—can serve as a strong initialization for fine-tuning on new urban environments [3]. We evaluate transfer learning by taking a model trained on data from three major cities and fine-tuning on a target city with only one week of labeled data, achieving within 10% of the performance of a fully supervised model trained on one month of data [9].

6. Trajectory Forecasting Mechanism

The forecasting module takes the learned spatiotemporal representations and generates probabilistic predictions of future trajectory sequences. Instead of outputting a single deterministic path, we use a variational encoder-decoder architecture that models the stochastic nature of human movement [11]. The decoder generates multiple plausible trajectories conditioned on the current state and a latent variable sampled from a learned prior distribution. This approach captures uncertainty and allows downstream applications to consider risk-averse versus risk-seeking decisions [2].

The integration of the self-supervised representation into the forecasting decoder raises issues of representation alignment. If the representation space is optimized for reconstruction or contrastive objectives, it may not align well with the forecasting objective's loss landscape. We address this by adding a projection head that maps the pretrained embeddings into a forecasting-specific space, similar to the information bottleneck principle [8]. End-to-end fine-tuning with a small learning rate preserves the structure learned during pretraining while adapting to the forecasting task [17].

We also explore multi-step forecasting by feeding predicted waypoints back into the spatiotemporal graph as new node features. This autoregressive approach can lead to error accumulation, especially for long horizons [5]. To mitigate this, we employ scheduled sampling during training, where the model is gradually exposed to its own predictions instead of ground-truth past observations [11]. Additionally, we incorporate a temporal attention mechanism that weighs the influence of each historical time step, allowing the model to focus on critical moments, such as the last observed location or a recurring pattern [14].

7. Deployment and Scalability Considerations

Deploying a self-supervised spatiotemporal graph model in a real urban infrastructure system requires careful attention to scalability, latency, and resource constraints. The graph construction and self-supervised pretraining phases are typically performed offline using historical data stored in a distributed data lake [1]. The pretrained model can then be deployed as a microservice that receives streaming trajectory data and returns forecasts with sub-second latency for real-time applications such as dynamic ride-pooling or traffic signal control [6].

Scalability challenges arise from the quadratic growth of graph adjacency matrices with the number of nodes. For a city with hundreds of thousands of locations, computing full graph convolutions becomes intractable. We use neighbor sampling and mini-batch training to reduce the memory footprint during both training and inference [4]. Furthermore, the self-supervised objectives can be approximated by random walk-based methods that do not require explicit storage of the entire graph [15].

Energy efficiency is another deployment concern. Training large self-supervised models on massive trajectory datasets consumes significant computational resources and carbon emissions [7]. We adopt mixed-precision training and gradient checkpointing to reduce power usage. Moreover, the flexibility of the framework allows for model compression via knowledge distillation, where a smaller student network learns to replicate the representations of the larger teacher network, enabling deployment on edge devices like traffic cameras or smartphones [13].

8. Robustness, Fairness, and Governance

Robustness to adversarial inputs is critical when the forecasting system informs safety-critical decisions. An attacker could manipulate a small number of trajectory samples to cause the model to mispredict congestion or reroute emergency vehicles [3]. We analyze the vulnerability of the spatiotemporal graph to adversarial perturbations in node features and edge weights. Self-supervised representations offer a degree of inherent robustness because they learn distributed, redundant features that are less sensitive to isolated corruption [16]. Nevertheless, we recommend adversarial training as a defense, where the model is exposed to perturbed examples during pretraining.

Fairness considerations arise because human mobility data often reflect societal inequalities. Certain neighborhoods, especially low-income or minority communities, may have sparser data collection due to fewer digital devices or less coverage from cellular networks [2]. A model trained on unevenly distributed data may produce biased forecasts, underestimating mobility demand in underserved areas and perpetuating inequitable resource allocation. We incorporate fairness constraints during the self-supervised phase by reweighting training samples to ensure that representations from different demographic regions are similarly well-learned [7]. Post-hoc fairness auditing using metrics such as demographic parity across income quintiles is employed to detect and rectify biases [10].

Governance of such systems requires clear policies on data ownership, consent, and transparency. Trajectory data are highly sensitive, revealing individuals' routines, associations, and personal habits. The self-supervised framework can operate on aggregated or differentially private data, adding noise to location counts before graph construction [1]. We advocate for a layered governance model where the data infrastructure is managed by a public authority (e.g., a city transportation department) while the forecasting algorithms are developed and audited by independent research organizations, ensuring accountability [3].

9. Case Illustrations and Cross-Domain Comparisons

To illustrate the framework's utility, we consider a case of emergency evacuation planning after a natural disaster. Traditional supervised models would require historical evacuation trajectories, which are rare and often not representative of real emergencies [14]. The self-supervised model, pretrained on routine daily mobility data, can adapt to the sudden shift by leveraging representations of high-traffic zones and bottleneck locations. In a simulated scenario, the model achieved 30% lower out-of-sample prediction error compared to a fully supervised baseline trained only on pre-disaster data [9].

Cross-domain comparisons reveal that the spatiotemporal graph representation is not limited to human mobility. The same architectural principles apply to traffic flow forecasting on road networks, where self-supervised pretraining on historical loops reduces the need for labeled incident data [5]. In epidemiological modeling, the graph nodes represent regions and edges represent population mobility flows, enabling prediction of disease spread without requiring extensive outbreak labels [13]. The contrast between mobility forecasting and these domains highlights the importance of graph construction: traffic graphs are typically static and deterministic, while mobility graphs are dynamic and probabilistic [4].

Another comparison with social network analysis shows that while the underlying mathematical tools overlap (e.g., graph convolutions, attention), the temporal dimension in mobility is non-negotiable. Social networks evolve slowly, but mobility networks change at sub-hourly scales [1]. Our framework's use of dilated temporal convolutions and recurrent units is specifically tailored for such rapid dynamics, whereas social network models often rely on static snapshots [10].

10. Future Directions and Policy Implications

The future of self-supervised spatiotemporal graph representation for mobility lies in integrating multi-modal data sources. Combining GPS trajectories with call detail records, public transit smart card data, and social media check-ins could enrich the graph with diverse behavioral signals [2]. However, this raises privacy risks that require federated learning approaches where raw data never leave individual devices [7].

Policy makers should consider regulatory frameworks that mandate fairness audits and interpretability for any AI system used in public infrastructure. The self-supervised paradigm offers an advantage: because representations are learned without explicit labels, they are less prone to encoding explicit discrimination, but they can still capture proxy variables that correlate with protected attributes [3]. We recommend that deployment be accompanied by a publicly available model card documenting data sources, performance across subgroups, and known limitations [8].

Sustainability of the system involves not only energy efficiency but also long-term maintainability. As cities evolve, the graph must be updated to reflect new infrastructure and land-use changes. A continuous pretraining pipeline that incrementally incorporates new data without retraining from scratch would reduce computational waste [14]. Finally, international cooperation on data standards and sharing protocols would enable cross-city transfer learning, benefiting developing cities that lack rich historical mobility datasets.

11. Conclusion

This paper has presented a comprehensive framework for self-supervised spatiotemporal graph representation in human mobility and trajectory forecasting. By leveraging contrastive

and generative pretext tasks, the framework learns robust and transferable representations from unlabeled trajectory data, significantly reducing the need for expensive annotation. We examined the architectural trade-offs between graph connectivity, temporal modeling, and self-supervised objectives, and discussed deployment scalability, robustness, fairness, and governance. Cross-domain comparisons illustrate the wide applicability of the approach beyond urban mobility. Future work should address multi-modal integration, privacy-preserving learning, and continuous model adaptation. The proposed system offers a path toward more sustainable, equitable, and resilient urban infrastructures that harness the power of unsupervised learning while respecting societal constraints.

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