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# Semantics-Guided Dynamic Hypergraph Network for Human Mobility Nowcasting in Disaster

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***Abstract*—Human mobility nowcasting is crucial for public safety, especially during disasters when human mobility significantly differs from normal patterns, posing unique challenges. Recent studies have shown a correlation between disaster-related social media information and abnormal patterns in human mobility. However, these studies mainly focus on text counts while neglecting semantic text, which limits the effective use of social media data and reduces model prediction performance. The social text semantics reveal inherent non-pairwise relationships between regions in human mobility, posing a challenge to traditional graph neural network approaches. Thus, we propose a Semantics-Guided Dynamic Hypergraph Convolutional Network (SG-DyHGCN) for human mobility nowcasting in disaster. The model leverages semantic information to guide dynamic hypergraph construction, enabling flexible adjustments to the hypergraph structure, effectively capturing non-pairwise relationships between regions, and enhancing prediction performance. Experimental results validate the effectiveness of our method.**

***Index Terms*—Semantics, Hypergraph, Human mobility in disasters**

## I. Introduction

The world has witnessed a surge in devastating disasters, posing significant threats to human lives and properties. Accurate nowcasting of human mobility during disasters is crucial for effective disaster management and response, aligning with the United Nations' Sustainable Development Goals [1]. Currently, numerous studies employ deep learning models to nowcasting human mobility, including crowd, taxi, and bike. Spatiotemporal graph networks are a dominant approach [2]–[4]. However, these models primarily focus on learning periodic patterns of human mobility under normal conditions. In contrast, disaster events are inherently unique and unpredictable, rendering current methods challenging to apply directly in anomalous disaster scenarios.

On the other hand, previous studies [1] have shown that the "hills" of the number of social media-related texts coincide with abnormal patterns of human mobility in various disaster contexts. Therefore, incorporating social media information into spatiotemporal graph prediction models can enhance the effectiveness of human mobility prediction in disaster scenarios.

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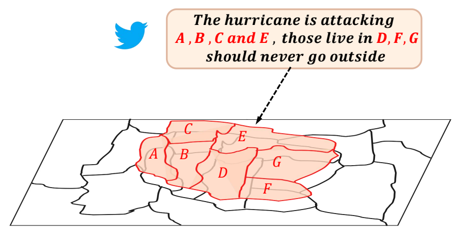



Fig. 1. Example of the inherent non-pairwise relationship between regions in human mobility revealed by social text semantics.

Despite the effectiveness, we argue that they overlook the rich semantic information embedded in social media. Social media users often discuss specific events related to disasters, including disaster types, locations, and severity [5], which is crucial for future prediction in disaster [6]–[8]. Therefore, the motivation of this paper is to leverage social text's semantic information to further enhance the performance of human mobility prediction in disaster. However, as shown in Fig.1, the explicit semantics of social text reveal inherent non-pairwise relationships between regions in human mobility, posing a challenge to traditional spatiotemporal graph networks. For instance, a single event mentioned in a social text may span multiple regions, and accurately capturing these non-pairwise relationships is crucial for precise prediction.

To address this challenge, we develop a Semantics-Guided Dynamic Hypergraph Convolutional Network (SG-DyHGCN) for human mobility nowcasting in disasters. By learning regional social text semantic knowledge, SG-DyHGCN can effectively capture non-pairwise relationships between regions in human mobility, enhancing the ability to capture spatiotemporal relationships. As shown in Fig.2, our approach consists of two main components: Regional Social Semantics Relationship (RSSR) construction and spatiotemporal (ST) learning module. The RSSR construction aims to leverage social text to enhance regional relationship representation. The ST learning module aims to utilize this relationship to effectively predict future human mobility, comprising multiple DyHGCN layers that explore semantics to guide dynamic hypergraph construction and learn non-pairwise relationships between regions. We conduct extensive experiments to verify the effectiveness of our model for human mobility nowcasting in disaster. The experimental results show that our model consistently outperforms the compared methods.

The main contributions of the paper are: (1) To our knowledge, this is the first work to leverage social text semantics for human mobility nowcasting in disaster. (2) We propose SG-DyHGCN that models disaster-related semantic representations to guide dynamic hypergraph construction and learn non-pairwise relationships between regions. (3) Experiments on two real-world disaster datasets show that SG-DyHGCN outperforms other methods, achieving state-of-the-art performance.

## II. Methodology

### A. Problem Definition

Followed by [1], we define human mobility as $X \in \mathbb{R}^{T\times N\times C}$, where $T$ is the number of timestamps, and $N$ is the number of regions, $C$ is the types of human mobility. Additionally, we collect disaster-related tweets (tweet ID, timestamp, location, text) and transfer them into a tensor $P \in \mathbb{R}^{T\times N\times N}$, which represents the RSSR.

Formally, we define the problem as follows: given human mobility and RSSR from the past $\alpha$ timestamps, we aim to build a model $F$ with learnable parameters $\theta$ to predict the human mobility in the next $\epsilon$ timestamps, denoted as follows.

$$F_\theta([X_{\tau-\alpha+1},...,X_\tau];[P_{\tau-\alpha+1},...,P_\tau]) \rightarrow [\hat{X}_{\tau+1},...,\hat{X}_{\tau+\epsilon}] \tag{1}$$

### B. Hypergraph Definition

We first define a hypergraph represented as $G = (V, E)$, where $V$ is the set of nodes and $E$ is the set of hyperedges. Unlike traditional graphs, hypergraphs allow multiple nodes to be connected by a single hyperedge, and a node can be associated with multiple hyperedges. To charaterize the structure of a hypergraph, we employ an incidence matrix $\Lambda \in \mathbb{R}^{|V|\times|E|}$. The incidence matrix's rows represent nodes, while the columns represent edges. If node $v_i$ belongs to hyperedge $e_j$, the element in the $i$-th row and $j$-th column of the incidence matrix is 1; otherwise, it is 0.

### C. Regional Social Semantic Relationship Construction

In RSSR construction, we first compute the social text semantic representation of regions, and then build semantic relationship $P$. Specifically, inspired by the significant advances of large language model (LLM) in text summarization and text clustering [9]–[12], we develop a zero-shot prompt-based text representation method, which forms online representations related to regions from a large number of samples. Specifically, we construct prompts to semantically summarize the text information associated with each region, and then leverage the summary as the representative of the region. The prompt template is defined as follows:

> PROMPT (P1): According to the text: [*Given Texts*], sum up the extent of the disaster in the area in one sentence.

We then feed the summarized tweet into BERT [13] for vectorized encoding, denoted as $s_i^t \in \mathbb{R}^{1\times1\times768}$. This approach, commonly used in natural language processing, effectively captures contextual information and semantic relationships in the tweet.

Subsequently, we propose a proximity semantic correlation (PSC) layer, which considers spatial relations in semantic correlations. Formally, we incorporate social semantics $S$ and the spatial relationships of regions to construct $P$ as follows.

$$P^t_{v_j,v_i} = \begin{cases} \dfrac{e^{S^t_{v_j}}}{\sum\limits_{v_k\in\mathcal{N}(v_i)} e^{S^t_{v_k}}} & \text{if } v_j \in \mathcal{N}(v_i), \\ 0 & \text{else} \end{cases} \tag{2}$$

Here, $P^t_{v_j,v_i}$ refers to the strength of semantics correlation between region $v_j$ and region $v_i$ at timestamp $t$, $\mathcal{N}(v_i)$ means all neighbors of node $v_i$. After calculating all nodes and stacking $P^t_{v_j,v_i}$ for all timestamps, we can obtain $P \in \mathbb{R}^{T\times N\times N}$.

### D. DyHGCN Layer

As shown in Fig. 2, the DyHGCN layer consists of two steps: dynamic hypergraph learning and the hypergraph convolutional operation. The first step leverages regional social semantics to guide dynamic hypergraph learning, whereas the second step explores the hypergraph convolutional operator to learn spatiotemporal correlations based on the learned hypergraph.

First, we construct a semantic-guided dynamic hypergraph to explicitly model non-pairwise relationships between regions. Specifically, we parameterize the $P$ to jointly optimize with the hypergraph structure and network parameters. At $l$-th layer, the incidence matrix $\Lambda^{(l)}$ of the dynamic hypergraph is defined as follows.

$$\Lambda^{(l)} = softmax(H^{(l-1)}W_1 + PW_2), \tag{3}$$

where $H^{(l-1)} \in \mathbb{R}^{TN\times C}$ denotes the output of $(l-1)$-th layer, and $H^0$ is equal to $X$. $W_1 \in \mathbb{R}^{C\times d}$ and $W_2 \in \mathbb{R}^{N\times d}$ are trainable parameters, $d$ is the number of hyperedges.

Second, we apply a hypergraph convolution operation to capture spatiotemporal correlations from the constructed dynamic hypergraphs. Specifically, we obtain the hyperedge embeddings $E^{(l)}$ by aggregating information from all connected nodes as follows.

$$E^{(l)} = \phi(W_3\Lambda^{(l)\top}H^{(l-1)}) + \Lambda^{(l)\top}H^{(l-1)}, \tag{4}$$

where $W_3 \in \mathbb{R}^{d\times d}$ is a learnable matrix to characterize the implicit relations among hyperedges. Then, these hyperedge embeddings $E^{(l)}$ are further aggregated to obtain the output of $l$-th layer:

$$H^{(l)} = \Lambda^{(l)}E^{(l)} \tag{5}$$

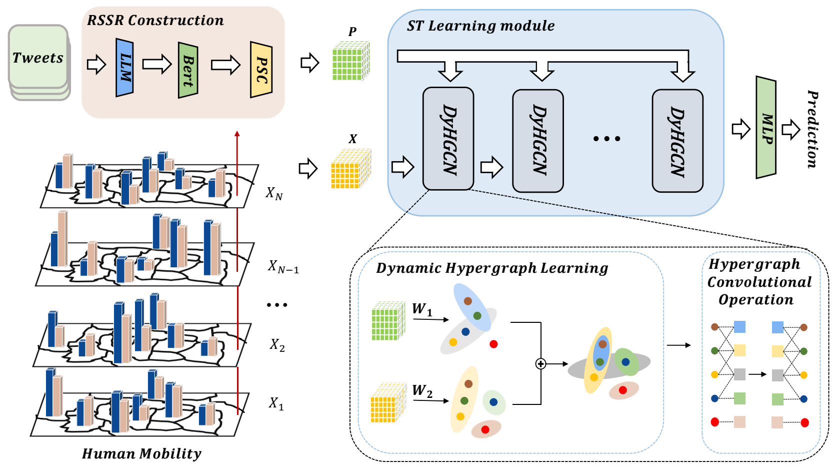



Fig. 2. Framework of SG-DyHGCN.

TABLE I
SUMMARY OF DATASETS

| Dataset | Hurricane-US | Storm-New York |
|---|---|---|
| Time | 2019/7/1-2019/9/10<br>72 days by hour | 2014/1/1-2014/1/26<br>26 days by hour |
| Space | 67 counties in Florida | 223 areas in New York |
| Mobility | POI visit volume | Inflow and outflow volume |
| Twitter | Disaster-related tweets | |

By feeding $H^{(l)}$ into a fully-connected layer, we can obtain the final predictions. The model is optimized using the mean absolute error (MAE) loss $\mathcal{L}$ as follows.

$$\mathcal{L} = \sum_{\tau=1}^{T} \sum_{i=1}^{\epsilon} |X_{\tau+i} - \hat{X}_{\tau+i}| \tag{6}$$

where $X_{\tau+i}$ is the ground truth, and $\hat{X}_{\tau+i}$ is the predcition values.

## III. EXPERIMENT

### A. Dataset

We select two real-world disasters as our experimental targets: the 2019 Atlantic Hurricane Season and the 2014 Storm in New York. The details of the datasets are summarized in Table I. Each dataset contains two subsets: mobility and social media tweets. The mobility data are collected from hurricane-US repository [1] and the NYC Taxi data[1]. The social media tweets of both datasets are collected from Twitter[2]. After spatial-temporal aggregation, the dimensions of the mobility data are (1728, 67, 9) for hurricane-US and (601, 223, 9) for Storm-New York. The dimensions of the Twitter data are (1728, 67, 67) for hurricane-US and (601, 223, 223) for Storm-New York.

[1]https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page
[2]https://developer.twitter.com/apitools/

### B. Baselines and Metrics

We select several baseline methods for comparison: including STGCN [4], GW-Net [14], ASTGCN [15], GMAN [16], MTGNN [17], STD-MAE [18], and MemeSTN [1]. To facilitate a fair comparison, we augment the baseline methods with tweet information. We evaluate the performance of our model using two common metrics: mean absolute error (MAE) and root mean square error (RMSE).

### C. Settings

Followed by [19], we split each dataset into training, validation, and testing sets with a ratio of 6:2:2 in chronological order. The testing set includes both normal days and disaster days to evaluate the model's performance. Empirically, the hyperparameters for each dataset are set as follows: for Hurricane-US, the learning rate is set as 0.01 with 274 hyperedges; for Storm-New York, the learning rates are 0.01 (inflow) with 1024 hyperedges and 0.002 (outflow) with 515 hyperedges. Following [19], we also employ a multi-scale framework to train our model. We train our model for up to 200 epochs with an early stopping strategy, terminating training if the validation loss does not improve for 10 consecutive epochs. We run the method 10 times and report the average score for our method. The model uses the past 6 timestamps to predict the next 6 timestamps. Our implementation uses PyTorch 1.12.0 with Nvidia A100.

### D. Overall Performance

Table II presents a comprehensive summary of our experiments across all datasets. From the result, we can observe that our SG-DyHGCN consistently outperforms all other methods, demonstrating its superiority in terms of performance metrics. Notably, simply concatenating social media information with traditional GCN-based methods yields poor performance, indicating that social information cannot be effectively integrated into the current predictive model through direct concatenation. MemeSTN, on the other hand, outperforms conventional

TABLE II
AVERAGE PERFORMANCE WITH MODELS

| Model | Hurricane-US | | Storm-New York | | | |
|---|---|---|---|---|---|---|
| | POI Visit | | Inflow | | Outflow | |
| | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| STGCN | 1111.6 | 387.0 | 245.5 | 72.8 | 247.0 | 71.3 |
| GW-Net | 786.6 | 266.9 | 187.8 | 63.5 | 250.1 | 97.1 |
| ASTGCN | 883.8 | 278.3 | 261.8 | 40.6 | 315.0 | 64.3 |
| GMAN | 992.4 | 312.2 | 208.3 | 64.9 | 267.9 | 63.2 |
| MTGNN | 901.7 | 317.0 | 229.9 | 76.4 | 267.7 | 106.0 |
| MemeSTN | 718.6 | 247.2 | 172.3 | 48.6 | 227.3 | 72.7 |
| STD-MAE | 693.5 | 250.4 | 150.9 | 47.1 | 220.0 | 78.3 |
| **SG-DyHGCN** | **670.3** | **225.0** | **109.3** | **26.8** | **121.8** | **27.9** |
| w/o DyHGCN | 731.3 | 253.7 | 111.4 | 28.1 | 126.1 | 28.7 |
| w/o PSC | 787.5 | 282.9 | 121.5 | 30.6 | 126.4 | 29.4 |
| w/o DH | 679.9 | 229.0 | 110.6 | 27.3 | 122.6 | 28.3 |

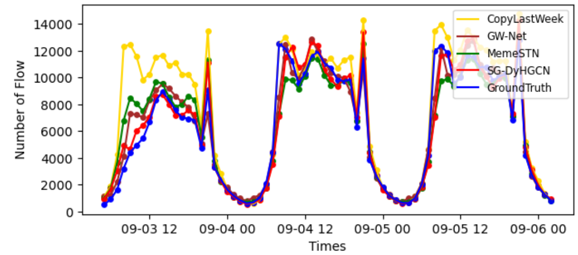
GCN-based methods by customizing the fusion of social information. However, this approach solely relies on the number of tweet postings, failing to effectively utilize semantic information. Furthermore, STD-MAE employs spatial-temporal decoupling to enhance remote contextual feature learning capabilities still underperforms in disaster. In contrast, our approach consistently outperforms existing methods, which we attribute to the effective design of our semantics-guided dynamic hypergraph convolutional network. By leveraging semantic information, our model enhances its ability to capture non-pairwise relationships and correlations between multiple nodes, leading to improved predictive performance in disaster scenarios.

### E. Ablation Study

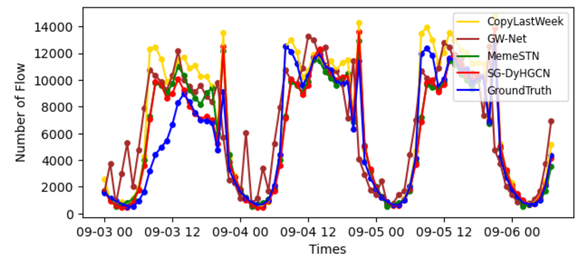
To investigate the impact of each part on SG-DyHGCN, we propose serval variants as follows: 1) w/o PSC, which removes PSC layer, 2) w/o DH, which removes the dynamic hypergraph learning, 3) w/o DyHGCN, which replaces DyHGCN layers with interactive graph convolution [19]. As shown in Table II, comparing w/o DH and SG-DyHGCN, we observe that removing the semantics- guided module degrades model performance, underscoring the importance of disaster-related content on social media for human mobility nowcasting in disaster. Furthermore, we find that the DyHGCN layers also substantially impact our method's performance, indicating that it effectively captures non-pairwise relationships between regions, thereby enhancing predictive performance. Finally, as expected, combining all modules yields the best results, achieving state-of-the-art performance, which verifies the effectiveness of the components we proposed.

### F. Case Study

Hurricane Dorian made landfall in Florida on September 1, 2019, causing significant impact from September 1 to September 3. To validate our model's adaptability to disaster, we selected Broward County, Florida, as a case study and plotted 1-hour and 6-hour ahead predictions. As shown in Fig.3, these baselines achieve relatively good overall performance, with satisfactory results in both normal conditions.




(a) Visualization of 1-hour ahead prediction




(b) Visualization of 6-hour ahead prediction

Fig. 3. A case study on Hurricane-US dataset.

However, they struggle to perform well during the disaster phase. In contrast to previous work MemeSTN that enhances prediction performance in disaster scenarios by incorporating social media tweet counts, our approach integrates semantic information and outperforms them, particularly in the more challenging 6-hour prediction task (from 09-03 00 to 09-04 00). We attribute this improvement to two factors: the effective incorporation of social text semantics, which helps learn non-pairwise relationships, and our semantic-guided hypergraph module, which successfully integrates social text semantic information to enhance performance in disaster scenarios.

## IV. CONCLUSION

In this paper, we propose an SG-DyHGCN for human mobility nowcasting in disaster scenarios. Our approach leverages regional social text semantic knowledge to capture non-pairwise relationships between regions, enhancing spatiotemporal relationship modeling. SG-DyHGCN consists of two key components: regional social semantics relationship construction and spatio-temporal learning module. Extensive experiments demonstrate the effectiveness of our model, consistently outperforming compared methods. Future work will focus on integrating additional data sources, such as sensor data and satellite imagery, to further improve the accuracy and robustness of our model.

## ACKNOWLEDGMENTS

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