Human Mobility Prediction using Personalized Spatiotemporal Models

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ABSTRACT

In this paper, I propose personalized spatiotemporal models based human mobility prediction method. The proposed method consists of three steps. Step1: we sin-cos transform the date and time data, and at the same time create variables representing timeslot from the time data, then use these variables to create node features. At the same time, we create edge features from human mobility trajectory data. Step2: the data prepared in Step1 are given to models that combine the Long Short-Term Memory (LSTM) layer on top of the Graph Neural Network (GNN) and trained. To the loss function during learning we set the cross-entropy. Step3: the output vectors from the trained model are given to Support Vector Classification (SVC) for prediction. At this time, a threshold is set for each city (cityB, cityC, cityD), and if the value of loss when epoch = 0 is greater than the threshold at the time of model training, the date and time data prepared in Step1, which are sin-cos transformed, and the variable representing the timeslot are given to SVC for prediction. Since there were 3,000 prediction targets in each city in this challenge, 9,000 models were created. The proposed method achieved high scores in both GEO-BLEU and Dynamic Time Warping (DTW) metrics for each city, confirming the high performance of personalized spatiotemporal models for prediction models of human mobility. This approach is expected to contribute to human mobility studies that consider the unique behavioral patterns of each individual.

CCS CONCEPTS

• Computing methodologies→Machine learning→Machine learning approaches

• Computing methodologies→Machine learning→Learning paradigms

• Applied computing→Operations research→Transportation

[†]GitHub: https://github.com/mukumuku-zero/HuMob2024

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KEYWORDS

Human Mobility, Personalized Model, Spatiotemporal Model, Graph Neural Network, Time Series, LSTM, Swish, Deep Learning, Machine Learning, GEO-BLEU, Dynamic Time Warping

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1 Introduction

These days, people use various means of transportation, such as walking, bicycles, and trains, to get to various locations. Human mobility has a significant impact on urban issues, and prediction problem of human mobility has become an important issue. Recently, various methods for predicting human mobility have been published, including those that utilize language models [1,2], models that utilize GNN [3], and models that utilize machine learning [4-6], which is a commonly used conventional method. However, it is difficult to make a fair evaluation of model performance because of the different acquisition methods and timing of the large amount of movement data [7-9] required to investigate human mobility.

In this context, HuMob Challenge 2024 (HuMob'24) [10] provided large-scale human mobility trajectory data obtained in each of a total of four metropolitan areas at the same time and in the same way. These data were provided by LY corporation, with human mobility trajectory data ranging from 6,000 to 100,000 persons per city. Other than the human mobility trajectory data, a processed date and a time representation (in 30-minute increments) were given so that it is not known when the data was acquired, and a POI with the name and location of the city not disclosed. All data was acquired over 75 days.

In this Challenge, to address these features of the data, I employed a method that focused on spatial and temporal features. It also assumes that people move differently for each individual and adopt a personalized approach. The following three methods were implemented:

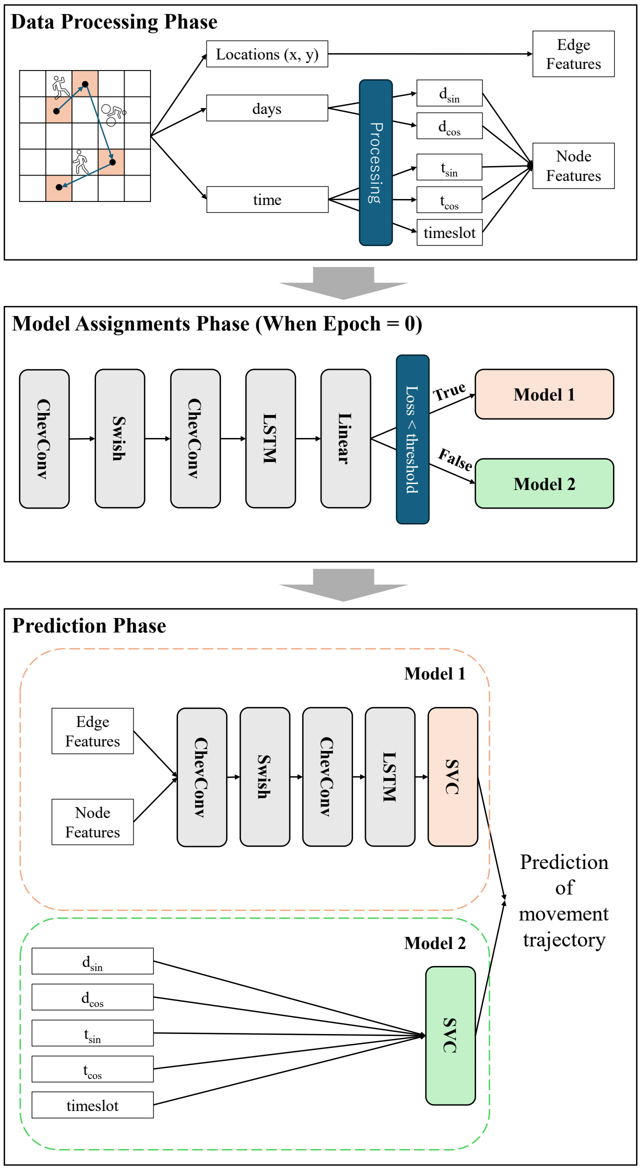

Figure 1: Overall diagram of the proposed method. In the Model Assignments Phase, edge and node features are given. Next, the model to be used in the prediction phase is selected from the value of loss at epoch = 0, according to the threshold set for each city.

① Spatial feature extraction using Graph Neural Network (GNN)

② Temporal features extraction using Long Short-Term Memory (LSTM)

③ Model building in each individual

Fig. 1 shows the overall image of the proposed method in this challenge. In this challenge, the movement trajectories of 3,000 people in each of the three designated metropolitan areas (cityB, cityC, and cityD) were predicted. The contributions of the proposed method are as follows:

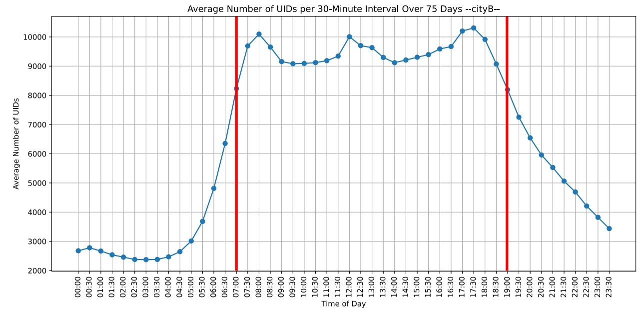

Figure 2: Example of the level of activity of human mobility in cityB at different times of the day. Other cities have similar characteristics.

- Fusing spatial and temporal features to create features that describe human mobility patterns
- Validating human mobility prediction performance through personalized model building

Chapter 2 below describes the proposed method. Chapter 3 describes the results. Chapter 4 presents the conclusions.

2 Proposed Method

In this challenge, I constructed personalized models utilizing GNN, LSTM and Support Vector Classification (SVC). As shown in Fig. 1, the proposed method consists of three phases: Data Processing Phase, Model Assignments Phase, and Prediction Phase. Since the model created was a personalized model, 3000 models were created in each of cityB, cityC, and cityD. In addition, objective variables, the locations (x, y), were combined into one in order to predict them simultaneously. Section 2.1 describes the data used and data processing methods. Section 2.2 describes the model composed of GNN and LSTM. Section 2.3 describes the model selection (assignments?) method, and Section 2.4 describes the prediction model.

2.1 Data Processing Phase

In this section, I describe the data to be used and how each of the data is processed. The data used are the objective variable, the location (x, y), the variable representing the date (d), and the variable representing the time (t). These variables are tied to each individual id and are independent for each individual. d has values from 0 to 74. t has values from 0 to 47. For data processing, since date and time are periodic variables, a sin-cos transformation is performed for two variables, d and t. Since d represents date, it has a period every week (7 days). t represents time, it has a period every day (48 times). Formula 1 and Formula 2 show the sin-cos transformation that captures the periodicity of each variable.

$$d_{sin} = \sin\left(\frac{2\pi}{7}d\right), d_{cos} = \cos\left(\frac{2\pi}{7}d\right), \{0 \leq d < 7\} \quad (1)$$

$$t_{sin} = \sin\left(\frac{\pi}{24}t\right), t_{cos} = \cos\left(\frac{\pi}{24}t\right), \{0 \leq t < 48\} \quad (2)$$

Next, Fig. 2 shows that there is a difference in the level of activity of people moving at different times of the day. From this, we prepare a variable (timeslot) that represents when people are active in moving and when they are not. Formula (3) shows how the timeslot is derived.

$$timeslot = \begin{cases} 1\ if\ 15 \leq t \leq 37 \\ 0\ if\ otherwise \end{cases} \tag{3}$$

We then create node features using the d_{sin}, d_{cos}, t_{sin}, t_{cos} and $timeslot$ we created, and create edge features from the locations (x, y).

From the next section, the variables created up to this point are used to build the model. For prediction, data with d ranging from 0 to 59 are used as training data, and data with d greater than 60 are used for prediction. This condition is assumed in the following explanation of the prediction.

2.2 GNN & LSTM Models

In order to implement models that take into account spatial and temporal features, I coupled the output layer of the GNN with a LSTM layer; for the graph convolution layer in the GNN, I used the Chebyshev spectral graph convolution (ChebConv) [11] and for the activation function, the Swish function [12]. I chose ChebConv because of its higher predictive accuracy, on average, for the 500 randomly selected samples in cityD compared to the other graph convolution layers. Table 1 shows the results of each model comparison. I used the data from cityD because cityD has data on 6,000 people, which is a smaller number than the other cities, and the confidence level of the results obtained from the sample size is higher than the other cities. 500 was set as a balance between the number of trials and the confidence level of the prediction results. The GEO-BLEU [13] and Dynamic Time Warping (DTW) [14] used in the HuMob'24 was used as evaluation metrics. AdamW with a weight decay set to 0.01 was used as the optimizer in the training. The epoch was set to 500 and early stopping was set to 15. The hidden layer value was set to 64 and the GNN consisted of two layers. Random seed was set to 42. The node and edge features created in Section 2.1 were used as explanatory variables. The Linear layer was used as the classifier to predict the location (x, y) and the loss function was cross-entropy.

2.3 Model Assignments Phase

Model assignments are done using thresholds set by each city. This section describes the models to be assigned and how the thresholds are set.

The first model to be assigned is the one in which the classifier of the model described in Section 2.2 is changed from the Linear layer to the SVC, which is commonly used because of its fast computation speed and high accuracy. Since I am building personalized models, I adopted them for the balance between speed and accuracy. The second model assigned is a simple SVC. The variables created in Section 2.1 are used as explanatory variables (d_{sin}, d_{cos}, t_{sin}, t_{cos}, $timeslot$). Table 2 shows the results when the classifier is changed from the Linear layer to the SVC and when the variables created in Section 2.1 are simply given to the SVC. Table 2 shows that changing from the Linear layer to the SVC improves accuracy without increasing inference time much. In addition, it can be seen that the GEO-BLEU values are not as high as those of the first model, but a good score is achieved in DTW when prediction is made with a simple SVC. Note that rbf was set for the kernel of the SVC.

Table 1: Results of GNN implementation with each graph convolutional layer

Model Name	GEO-BLEU↑	DTW↓
SAGEConv [15]	0.289	50.896
ChebConv [11]	0.301	53.968
EdgeConv [16]	0.253	43.907
GPSConv [17]	0.279	52.517

Model names are omitted for notational convenience. GEO-BLEU and DTW are averages over a sample size of 500. At the time of comparison, the ReLU function is used for the activation function.

We then set a threshold for each city based on the loss value at epoch = 0 for the model where the classifier is Linear. When loss is smaller than the threshold value, the model constructed in Section 2.2 is used, and when loss is larger than the threshold value, simple SVC is used. This is because as the threshold value increases, the increase in DTW is greater than in GEO-BLEU. I set the DTW as shown above because the Simple SVC takes a lower value when used. I varied the threshold between 4.0 and 6.0 in 0.1 increments, setting the threshold at 5.1 for cityB, 5.2 for cityC, and 5.3 for cityD, respectively.

Table 2: Prediction results for each classifier

Classifier Name	GEO-BLEU↑	DTW↓	Time (m)
Linear	0.308	61.052	22.11
SVC	0.317	47.790	24.73
Simple SVC	0.281	41.153	6.43

The Swish function is used for the activation function.

2.4 Prediction Phase

We use the models prepared in Section 2.3 with different thresholds for each city to make different predictions; the loss at epoch = 0 determines which model to use, thereby reducing the computational cost.

In the first model, a combination of GNN, LSTM and SVC, we train a two-layer combined GNN and LSTM model with epoch = 500, early stopping = 15, random seed = 42 and hidden layer value of 64. For the optimizer during training, we use AdamW with weight decay set to 0.01. The loss function is cross-entropy. The edge and node features created in Section 2.1 are used during training. We then feed the output vectors of this learned model for the node and edge features to the SVC for prediction.

The second model, SVC, is trained and predicted using the variables (d_{sin}, d_{cos}, t_{sin}, t_{cos}, $timeslot$) created in Section 2.1. The hyperparameters for training are set to default and the random seed is set to 42. These two models are used to make predictions for each individual in each city.

3 Results

Prediction results for each city are shown in Table 3. Table 3 includes the offline evaluation results for a sample size of 500 people and the online evaluation results for 3,000 actual prediction targets. From the results, it can be seen that the GEO-BLEU value is taken around 0.3 and the DTW value is kept low.

Table 3: Offline and Online Results

City	Offline		Online	
	GEO-BLEU↑	DTW↓	GEO-BLEU↑	DTW↓
B	0.310039	32.48897	0.291305	26.01827
C	0.304012	25.29710	0.289039	19.39015
D	0.317244	47.78991	0.304430	38.58666

4 Conclusion

In this challenge, I proposed a method to predict the movement trajectory of each individual by building a personalized model that takes into account spatial and temporal characteristics. This method contributes to the validation of the prediction performance of the personalized model and the effect of the fusion of spatial and temporal features representing people's movement patterns. Limitations of the proposed method include the hyperparameter optimization of each model in each individual and the limitation of the data used and model augmentation due to privacy protection of time and location. It is expected that finding a hyperparameter that fits each individual will enable more optimal prediction of movement trajectories. In addition, the structure of the model constructed in this challenge is simple, and models that consider more complexity should be constructed to further improve accuracy. In the after work, I would like to add the mobility characteristics of others to the personalized model, reduce the weight of the model, and compare it to other personalized models not used.

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