Time-series Stay Frequency for Multi-City Next Location Prediction using Multiple BERTs

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Abstract

Human Mobility Prediction Challenge 2024 was organized to compare human future movement prediction methods using a unified dataset. The challenge focuses on human movement prediction in multiple cities with varying numbers of users. Many existing movement prediction methods train deep learning models using large-scale movement histories from cities and make predictions. While cities with large users have sufficient training data, smaller cities with fewer users may face challenges due to insufficient data, raising concerns about lower prediction accuracy. Additionally, it is difficult to treat stay locations between different cities' movement histories due to differences in spatial area arrangement, making it challenging to share data across cities. To address this issue, we propose human movement prediction method that utilizes time-series stay frequency patterns, which can be commonly applied across different cities. This method demonstrated superiority in predicting movements in cities with fewer users compared to models trained and predicted using only the movement histories of the target city. Furthermore, the method achieved top 10 prediction accuracy in HuMob Challenge 2024.

CCS Concepts

• **General and reference** → *Estimation*; *Evaluation*; • **Social and professional topics** → *Geographic characteristics.*

Keywords

Next Location Prediction, BERT, Transformer, Urban Data

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1 Introduction

With the widespread adoption of mobile devices, it has become possible to collect large-scale location data in urban areas, leading to active research in urban planning, transportation planning, and disaster management utilizing such data[1][2][3]. Movement trends captured from movement histories based on location data provide clues for predicting users' future movements.

In many studies on human movement prediction, models are trained and tested on proprietary location datasets, making it difficult to compare methods across different studies. To address this, the Human Mobility Prediction Challenge 2024 (HuMob Challenge 2024) was organized to compare prediction methods using a unified open dataset[4].

In the challenge, movement history datasets from four cities were provided, and the task was to predict the 30-minute interval stay locations for the last 15 days of 3,000 users from each of the three cities: City B, City C, and City D. The number of users in each city is 100,000, 25,000, 20,000, and 6,000, respectively, raising concerns about lower prediction accuracy in cities with fewer users due to the limited amount of training data. Therefore, it is believed that leveraging movement trends from cities with more users can supplement the insufficient information available from cities with fewer users. However, a key challenge remains the difficulty of aligning stay locations across users' movement histories between different cities.

To address the issue, we propose a human movement prediction method using time-series stay frequency patterns that are common across different cities for each user. The time-series stay frequency

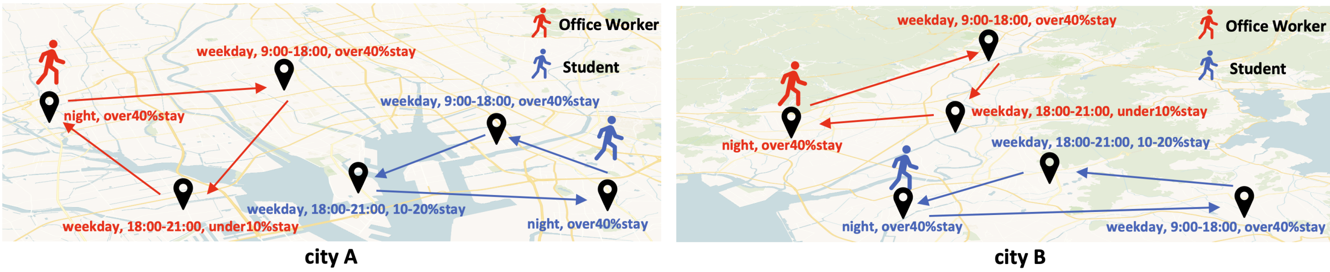

Figure 1: Time-series stay frequency patterns common across different cities

patterns for each user represent abstract stay tendencies without relying on spatial characteristics specific to each city. As shown in Figure 1, it is expected that common trends can be observed across cities based on user attributes.

Two BERT-based models (SF-BERT and CM-BERT) were used as encoders, and movement prediction was performed using LP-BERT[5]. SF-BERT (Time-series Stay Frequency BERT) captures time-series stay frequency patterns common across different cities, while CM-BERT (City Movement BERT) captures movement trends specific to each city. The movement histories were encoded using these two models, and the outputs were used as inputs to LP-BERT. Evaluation experiments demonstrated that, in cities with fewer users, the proposed method outperformed models trained and predicted using only the movement histories of the target city. Furthermore, the method achieved top 10 prediction accuracy in HuMob Challenge 2024.

	City A	City B	City C	City D
Records	111,535,175	24,375,898	18,456,528	8,418,135
Individuals	100,000	25,000	20,000	6,000
Valid mesh	34,032	26,523	9,208	21,113
Target Users	0	3,000	3,000	3,000

Table 1: Datasets Overview

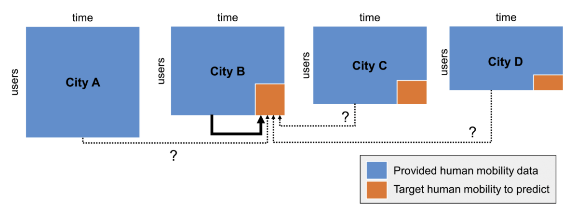

Figure 2: HuMob Challenge Overview

2 Related Work

With the ability to collect large-scale location data, research on human movement prediction has become increasingly active. Since movement trends are largely dependent on individual users, some models have been developed based on this concept, creating predictions for each user [6].

However, individual users' movement histories vary in the amount of data available, raising concerns about lower prediction accuracy for users with less data. In response, research has emerged using deep learning models such as RNNs and LSTMs to learn and predict large-scale movement trends of users in urban areas[7, 8].

Since the introduction of Transformer models, many movement prediction models leveraging the Attention mechanism have appeared. Attention enables the capture of long-term dependencies in movement histories, leading to improved prediction accuracy [5, 9, 10]. While large cities have sufficient movement histories to train deep learning models, smaller cities may face challenges due to insufficient data. Additionally, sharing movement histories across cities is difficult due to the challenge of aligning stay locations between different cities.

To supplement the data shortage in individual cities, research has been conducted on transfer learning for city prediction models [11, 12]. However, these studies are limited to predicting inflow and outflow volumes on a grid basis and do not address the matching and prediction of individual trajectories.

3 HuMob Challenge 2024

3.1 Datasets

Humob Challenge 2024 was organized to compare human movement prediction methods using a unified dataset[13]. The dataset includes 75 days of 30-minute interval movement histories from four cities in Japan. The number of records and users for each city is shown in Table1. The stay locations in the movement histories are divided into a grid of 500m by 500m, with each city containing approximately 40,000 grid cells.

3.2 Prediction Tasks

In the HuMob Challenge 2024, the task is to predict the 30-minute interval stay locations for the last 15 days for 3,000 individuals from each of the three cities—City B, City C, and City D—included in the dataset like in Figure 2. For training, the movement histories from days 0 to 74 of non-target users in each city, as well as the movement histories from days 0 to 59 of the target users, can be used.

3.3 Evaluation Metrics

The prediction performance is evaluated using two metrics, both of which take into account the spatial distance between the predictions and the ground truth.

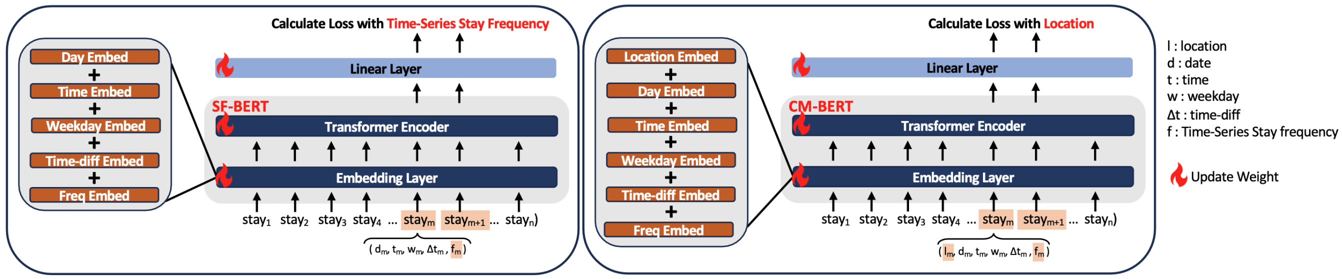

Figure 3: Overview of SF-BERT and CM-BERT pretraining

Day of Week	weekday
	weekend
Time Segments	0 - 11 or 42 - 47
	12 - 17
	18 - 35
	36 - 41
Visit Frequency	40% - 100%
	20% - 40%
	10% - 20%
	0% - 10%

Table 2: Time-series Stay Frequency

- **GEOBLEU[14]**
  GEOBLEU is an evaluation metric inspired by BLEU, which is used in the field of natural language processing. It is designed to evaluate local prediction accuracy, with higher values indicating better scores. If the prediction results and the actual results match perfectly, the value will be 1.
- **DTW[15]**
  DTW is a metric used to evaluate the similarity between the predicted trajectory and the actual trajectory over time. Lower values indicate better scores, and if the predicted trajectory and the actual trajectory match perfectly, the value will be 0.

4 Method

An overview of the training process for the SF-BERT and CM-BERT models used as encoders is shown in Figure 3. Additionally, the overall framework of the proposed method is shown in Figure 5

4.1 Time-series Stay Frequency

Time-series stay frequency refers to the visit frequency of each user to specific stay areas for each time segment. The time segments and stay frequency categories are shown in Table 2. Additionally, since the calculation is performed separately for weekdays and weekends, the time-series stay frequency is divided into 32 classes. It is expected that similar trends will emerge among users with similar attributes across different cities. For example, areas where students frequently stay during the daytime are likely to be schools, and areas where they frequently stay at night are likely to be their homes.

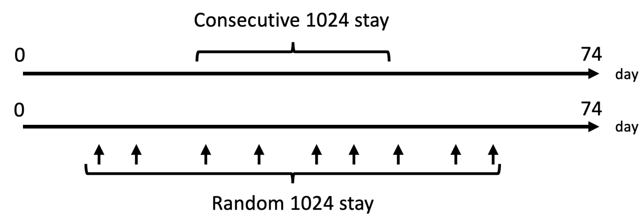

Figure 4: Datasets for SF-BERT and CM-BERT training

4.2 Time-Series Stay Frequency BERT (SF-BERT)

To learn time-series stay frequency patterns that are common across different cities, a dataset is created by mixing the movement histories of users from multiple cities. For each user, 1,024 consecutive movements and 1,024 randomly extracted time-series movement trajectories are used as training data like shown in Figure 4. It is expected that consecutive movements capture short-term movement trends, while random extractions capture long-term movement trends.

The structure of the model is shown in Figure 3. The input to the model consists of stay frequency classes, date, time, day of the week, and time differences between stays. During training, the stay frequency classes for 100 consecutive movements are masked, and the model is tasked with predicting the masked stay frequency classes. Cross-entropy is used as the loss function.

By using SF-BERT as an encoder, predictions can consider time-series stay frequency patterns learned from large-scale movement histories across multiple cities. This approach is expected to supplement the missing movement trends in cities with insufficient training data.

4.3 City Movement BERT (CM-BERT)

To learn the movement trends of each city, the movement histories of each city's users are used as training data. For each user, 1,024 consecutive movements and 1,024 randomly extracted time-series movement trajectories are used as training data like Figure 4.

The structure of the model is shown in Figure 3. The input to the model consists of location, date, time, day of the week, time differences between stays, and stay frequency classes. CM-BERT does not use user information as input, allowing it to learn general movement trends for each city. During training, the locations and

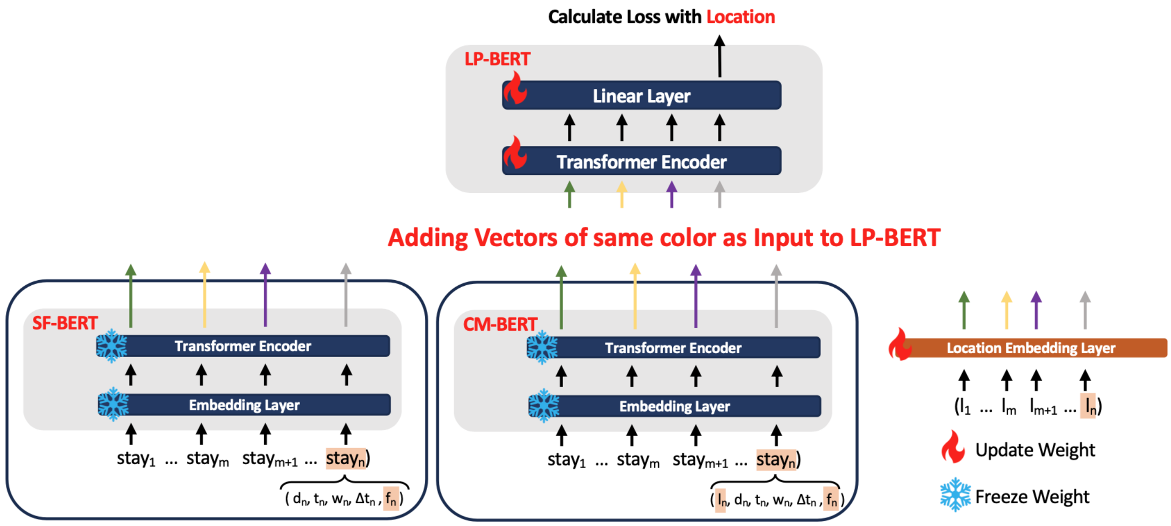

Figure 5: Overview of proposed method

stay frequency classes for 100 consecutive movements are masked, and the model is tasked with predicting the masked locations. Cross-entropy is used as the loss function.

4.4 Location Prediction

For movement prediction, two pre-trained models are used as encoders. During the training of LP-BERT, the parameters of the pre-trained models are not updated. The input consists of the entire movement history for each user, with each movement containing location, date, time, day of the week, time differences between stays, and time-series stay frequency class.

As shown in Figure 5, movement history is fed into each encoder, and the vectors output for each stay are summed. This sum is then added to the embedding of the location, which serves as the input for LP-BERT.

During training, the locations and stay frequency class for 15 consecutive days of movements are masked in each batch, and the model is tasked with predicting the masked locations. Cross-entropy is used as the loss function.

5 Experiment

5.1 Validation

An evaluation experiment was conducted to demonstrate the effectiveness of time-series stay frequency. The results of the comparative experiments are shown in Table 3. Five different input patterns to LP-BERT were compared.

- Embed
- SF-BERT + Embed
- SF-BERT + CM-BERT
- SF-BERT + CM-BERT + Embed
- SF-BERT + CM-BERT + Embed(Only Location)

The breakdown of the datasets for each city is shown in Table 5. The embedding size was set to 128 dimensions, and the batch size was set to 8 for City B and City C, and 4 for City D. Training was conducted for 400 epochs for each model. In Table 3, the best score for each city is highlighted in red, while the second-best score is highlighted in blue. The evaluation experiment results indicated that the best scores were achieved when using SF-BERT and CM-BERT as encoders and combining their output vectors with the location embeddings as the input to LP-BERT.

5.2 Parameter Tuning

We performed batch size tuning for the proposed model. The results are shown in Table 4. As a result, the final parameters were set with a batch size of 16 for City B and 8 for the remaining cities, City C and City D.

6 Conclusion and Future Work

In the Humob Challenge 2024, we proposed movement prediction method using time-series stay frequency patterns common across different cities. The method employed SF-BERT, trained on time-series stay frequency patterns using the movement histories of multiple cities, and CM-BERT, trained on the movement trends of individual cities, as encoders, with location prediction performed by LP-BERT. The proposed method demonstrated superiority in predicting movements in cities with fewer users compared to models trained and predicted using only the movement histories of a single city. In the future, we aim to compare multiple deep learning models as prediction models to find the optimal one and further improve prediction accuracy.

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	city B		city C		city D	
	GEOBLEU	DTW	GEOBLEU	DTW	GEOBLEU	DTW
Embed	0.3201	24.11	0.3176	16.83	0.3060	43.61
SF-BERT + Embed	0.3156	22.31	0.3101	16.44	0.3093	39.41
SF-BERT + CM-BERT	0.3354	23.83	0.3310	16.40	0.3212	41.13
SF-BERT + CM-BERT + Embed	0.3333	23.52	0.3283	16.40	0.3234	40.53
SF-BERT + CM-BERT + Embed (Only Location)	0.3357	23.64	0.3307	16.30	0.3255	40.44

Table 3: Performance Comparison of Input to LP-BERT

	city B		city C		city D	
batch_size	GEOBLEU	DTW	GEOBLEU	DTW	GEOBLEU	DTW
4	0.3352	23.82	0.3314	16.40	0.3255	40.44
8	0.3357	23.64	0.3307	16.30	0.3253	39.96
16	0.3358	23.46	0.3303	16.34	0.3188	40.23

Table 4: Performance Comparison for Different Batch Sizes

	city B	city C	city D
train	24000	19000	5800
test	3000	2000	1000
validation	1000	1000	200

Table 5: Data Split

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