Multiple Systems Combination to Improve Human Mobility Prediction

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ABSTRACT

This paper describes a human mobility prediction system which build by KDDI Research, Inc. to submit for Human Mobility Prediction Challenge (HuMob Challenge) 2024. The system consists of 6 human mobility prediction subsystems: 5 transformer-based subsystems; LSTM (Long Short-Term Memory) based subsystem. The system selects the best prediction result out of 6 outputs. Since a task of HuMob Challenge 2024 is to predict human mobility of day 61 to 75 using given human mobility data of day 1 to 60, the selection logic is built by the prediction performance of day 45 to 60 data. Although the selection logic is based on the prediction results on closed data set, the selection thought to work precisely.

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CCS CONCEPTS

• Computing methodologies → Natural language generation;

Spatial and physical reasoning.

KEYWORDS

Human mobility, Trajectory generation, Mobility model Transformer

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1 Introduction

Prediction of human mobility in urban areas is an important technology that is expected to be applied in various fields, including marketing such as advertising strategies, urban planning, traffic control during incidents and accidents, infection forecasting during pandemics and so on.

On the other hand, by wide spreading of GPS-equipped smart phone in recent years, it has become easier to collect human mobility data. And advances in artificial intelligence-related techniques such as deep learning [1,2,3], will lead to data-driven human mobility prediction is expected to develop further in the future. In particular, deep learning models developed in the field of natural language processing (NLP) have been applied as a sequential processing in fields [4] other than NLP. And they have shown high performance in various fields. Similar things are happening in the human mobility prediction research field. Many of top 10 teams [4,6,7] in the previous HumMob Challenge in 2023, used transformer-based models.

In this paper, we describe a method for improving the human mobility prediction system by using multiple prediction models composed of different architectures such as LSTM (Long Short-Term Memory) and Transformer in data-driven human mobility prediction.

Section 2 describes the proposed method, and section 3 presents experimental results using actual data. Finally, section 4 presents the conclusion and future works.

2 Proposed system

This section describes configuration of human mobility prediction system which is built by the KDDI Research, Inc. for HuMob Challenge 2024. The system consists of human mobility prediction parts and a system selection part. For human mobility prediction part, we built 6 subsystems: 5 transformer-based subsystems; 1 LSTM based subsystem (with 9,000 kinds parameter settings).

Table 1: Outlines of subsystems

Model architecutre	LSTM	BERT	
Number of trained models in 1 city	3,000	1	4
Pretraining data	NA	All data of 4 cities	
Fine tuning	Each user	Each city	Each user clasuters

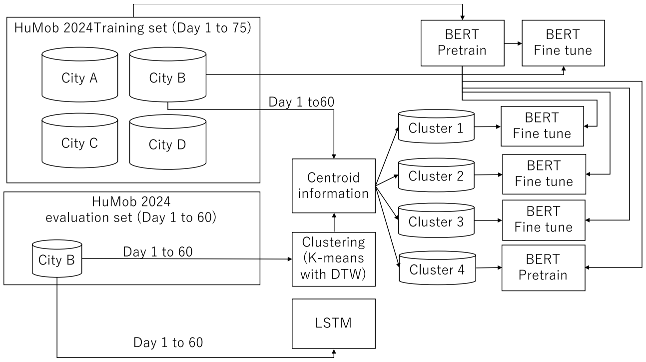

Figure 1: Data usage of the model training (In case of City B)

2.1 Outline of the system

Table 1 shows the outlines of each subsystem. Transformer-based subsystems are pretrained on whole data sets, then fine tune on each city or user clusters in each city. Meanwhile, LSTM-based system is trained for each user in HuMob challenge 2024 evaluation set. There are differences not only the model architecture, but also in the features used for prediction and the way of data selection to train the models.

2.2 Transformer-based Subsystem

For the transformer-based method, we use BERT architecture, referring to the conventional method [4]. We only used coordinates, date and time, and exclude Δt from input features. It is the only difference between our subsystem and the conventional method [4].

Figure 1 shows the actual data usage of the model training in case of City B. As shown in the figure, we apply pretraining, by considering data from four cities as a single data set on the same coordinates. This pretraining model are used for the following fine tuning by city or by user cluster.

We apply fine tuning in 5 conditions for 1 city. The first fine tuning simply uses the whole data of the target city. The other fine tunings use data sets of clustered users.

The clustering base fine tuning is performed in the following manner. We apply the following step 2 to reduce computational cost.

Step1: By using evaluation set of the target city, apply k-means clustering with dynamic time warp (DTW) as distance function. Here, human mobility trajectory of day 1 to 60 are used for the clustering.

Step2: By using centroid information given by step 1, assign each user of target city training data to one of the clusters by calculating DTW between user and centroids.

Table 2: Number of users in clusters

Area	Cluster name	Number of members in cluster(Evaluation set)	Number of members in cluster (Training set)
City B	B-1	2,350	19,690
	B-2	229	1,967
	B-3	266	2,119
	B-4	155	1,224
City C	C-1	373	2,645
	C-2	709	4,737
	C-3	152	1,043
	C-4	1,766	11,575
City D	D-1	939	1,862
	D-2	1,275	2,536
	D-3	251	518
	D-4	535	1,084

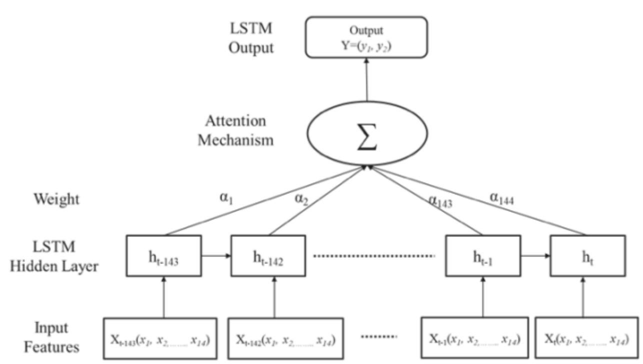

Figure 2: LSTM architecture for human mobility prediction

Step3: Apply fine tunings on each cluster. Here, number of clusters is set to be 4.

Table 2 shows number of users in clusters. The 3rd and 4th lows of the table are the number of users in Step1 and Step3, respectively.

2.3 LSTM-based Subsystem

LSTM-based subsystem does not use training set of HuMob challenge 2024. The system only uses the evaluation set of 60 days trajectory to train LSTM-based subsystem. LSTM models are trained for each user in evaluation set, i.e. 9,000 kinds (3,000 users in each 3 cities) of LSTM parameters sets are trained. Since the 1 LSTM model uses human mobility data of 1 user for training, it is less versatile, however, it sometimes provides high performance for individual user.

Figure 2 shows the network architecture of the LSTM. The model is trained to predict the position of user by using sequence whose length is 144. Outputs from 144 hidden layers are given to attention layer. Then, current coordinate is predicted by using output from the attention layer.

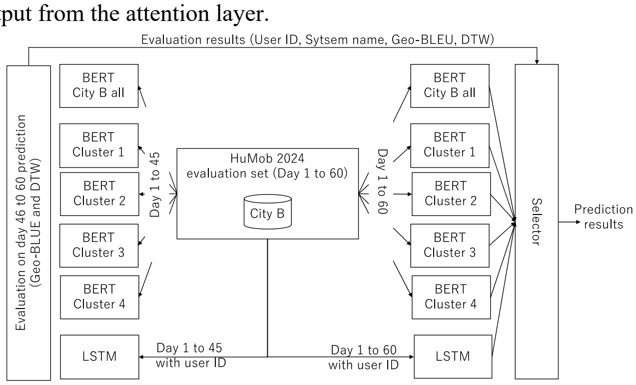

Figure 3: Output selection scheme

Table 3: Number of subsystems used for the final submission

	Cluster name	Used number of the system
City B	B-Cluster1	271
	B-Cluster2	212
	B-Cluster3	202
	B-Cluster4	281
	B-All	1,675
	LSTM	359
City C	C-Cluster1	192
	C-Cluster2	300
	C-Cluster3	155
	C-Cluster4	411
	B-All	1,563
	LSTM	379
City D	D-Cluster1	270
	D-Cluster2	182
	D-Cluster3	228
	D-Cluster4	315
	B-All	1644
	LSTM	361

The model uses following features as input features to LSTM.

- Day of the week (value of 0 to 6)
- Date information calculated by the following formulae

$$\sin \pi(d/7) \tag{1}$$

$$\cos \pi(d/7) \tag{2}$$

where d is the date expressed by 1 to 75.

- Time information calculated by the following formulae

$$\sin \pi(t/48) \tag{3}$$

$$\cos \pi(t/48) \tag{4}$$

where t is the time expressed by 1 to 48.

- Binary flag for weekend
- Binary flag for night time (10 p.m. to 6 a.m.)
- Distance from estimated home position

$$\Delta x\_home = x - x\_home \tag{5}$$

$$\Delta y\_home = y - y\_home \tag{6}$$

Where x_home, y_home is the most frequent location during night hours (10 p.m. to 6 a.m.)

- Distance from estimated work location

$$\Delta x\_work = x - x\_work \tag{7}$$

$$\Delta y\_work = y - y\_work \tag{8}$$

where x_work, y_work is the most frequent location during work hours (9 a.m. to 5 p.m.)

- Binary flag for being at the estimated home location
- Binary flag for being at the estimated work location
- Coordinate (x, y)

The following is the detailed information of LSTM-based model including key hyperparameters:

- LSTM Architecture:
  - Number of layers: 2
  - Hidden size: 128 units per layer
  - Sequence length: 144 (3 days of data)
- Attention Mechanism:
  - Type: Periodic Attention
  - Period: 48 (corresponding to daily cycle)
- Training Settings:
  - Batch size: 64
  - Number of epochs: 100
  - Early stopping patience: 10 epochs
  - Initial learning rate: 0.001
  - Optimizer: Adam (weight decay: 1e-5)
- Loss Function:
  - Custom combination of MSE and DTW
  - MSE weight (α): 0.5
  - DTW weight (1-α): 0.5

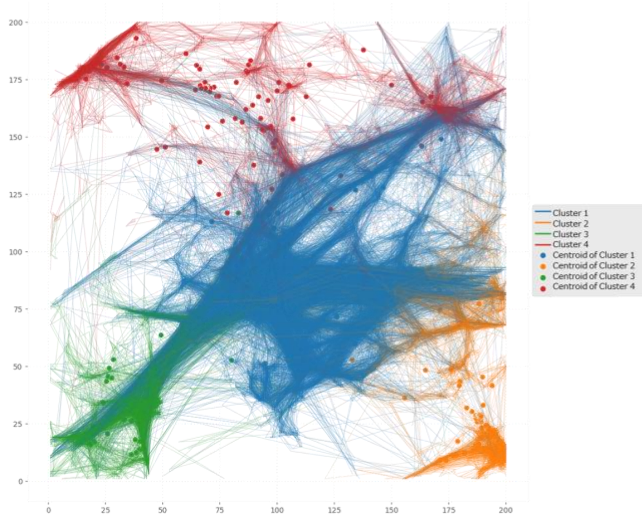

Figure 4: Visualization of the clustering results of City B

For the 10 p.m. to 6 a.m. time period, LSTM prediction results are adopted with 20% probability. For remaining 80%, estimated home position is adopted as the predicted location.

2.4 System Selection

Figure 3 shows the system selection scheme of our human mobility prediction system. By using 6 subsystem including LSTM and transformer-based ones, the systems can predict human mobility trajectory of day 46 to 60, by given the trajectory of day 1 to 45. Since the evaluation set includes the trajectory of day 46 to 60, we can evaluate performance on day 46 to 60 prediction. Here, we use Geo-BLEU and DTW as evaluation metrices. By using the evaluation results, we can obtain optimal system for each user and evaluation metric as follows.

$$Max\_System = \mathrm{argmax}_{system \in S}\, GeoBLEU(user, system) \quad (9)$$
$$Min\_System = \mathrm{argmin}_{system \in S}\, DTW(user, system) \quad (10)$$

Heuristic given by the following pseudocode determines the final output for each user.

if (GeoBLEU(user,Max_System) > 0.3)
final_system = Max_System
else
final_system = Min_System

3 Experiments

For the experiments, we use all data provided by HuMob2024 organizer [8]. Table 3 shows the number of subsystems used for the final submission.

As shown in the table, transformer-based system with city-wide finetuning used for half of users. And, the other 5 subsystems are used with similar frequency.

Figure 4 shows the visualized results clusters in City B. In the figure, only human mobility trajectory of one day (day 40) are used for visualization. As visualized in the figure, we can observe the 4 spatially separated clusters of trajectories. Therefore, DTW-based clustering is thought to work appropriately.

4 Conclusions and future works

In this paper, we explain a human mobility prediction system which build by KDDI Research to submit for Human Mobility Prediction Challenge (HuMob Challenge) 2024. We built multiple human mobility prediction models. Then, based on the prediction accuracy of day 46 to 60, the model used for the final predictions was determined.

Currently, we have not been able to evaluate individual subsystem because the evaluation set is not publicly available. As soon as the data becomes available, we would like to verify the effects of using multiple models.

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