

# メタ学習パラダイムに基づくリアルタイム軌跡予測システム

## A Real-Time Trajectory Prediction System Based on the Meta-Learning Paradigm

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### Abstract

Human mobility prediction is crucial for developing smart cities in the digital twin framework. As a digital replica of the real world, the digital twin of the traffic system has been built from real-time data transmitted by GPS sensors attached to cars and developed to extract congestion and accidents. Today, as many people have become accustomed to carrying their smartphones, human mobility can be enriched by the location records of these smart devices, which can contribute to constructing a digital twin of human movement for prediction. However, predictive models in previous research are not flexible enough in real-time systems as they are computationally intensive and time-consuming. Also, they lack some mechanisms to help the models distinguish differences between real-time and historical data. Based on the above issues and considerations, this study introduced the meta-learning paradigm to help predict people's movements with a GRU model at different times and a retrieval-based historical trajectory database to enrich the predicted outcomes. Finally, this research proposed a simulated real-time system and embedded the proposed model to verify the framework's performance using a simulated real-time data stream.

**Keywords:** human mobility, trajectory prediction, meta-learning paradigm, real-time system

### Introduction

The rapid development of today's world has driven the era of big data, with billions of data being generated by people every day. Human mobility analysis with mobile data has been considered a core component of creating smart transportation systems. In transportation, the digital twin is applied to detect the traffic flow in real-time to reduce congestion and accidents. More importantly, patterns in human mobility have a great potential to help us estimate the system's future state. These patterns are also constrained by the type of travel patterns and regional or wide-area events and, conversely, change the environment. As a result, the study of human mobility is crucial due to its essential role in many aspects of our society, such as urban planning, pollution management, infectious disease control, and natural disasters.

According to previous research, by the end of 2021, smartphones worldwide would reach 3.8 billion. Therefore, millions of location records will be generated daily to show human mobility in a large-scale urban range. These records provide data support for building a digital twin of a smart city. Furthermore, the recent rapid development of computer science has made it possible to handle such large amounts of data, and the powerful Artificial Intelligence (AI) also made it easier to analyze big data with complicated structures to complete predictive tasks.

The next-location prediction is an essential part

of human mobility-related research, which will focus on individual mobility. With a sequential set of independent human mobility records like GPS data, the prediction will capture patterns hidden in such data to indicate human spatiotemporal regularity and finally output the future location. The next-location prediction will present more information for its ability to analyze users separately. Since analyzing individual-based movement patterns and associated predictions can be more specific and challenging, this research will focus on this topic.

### Previous research

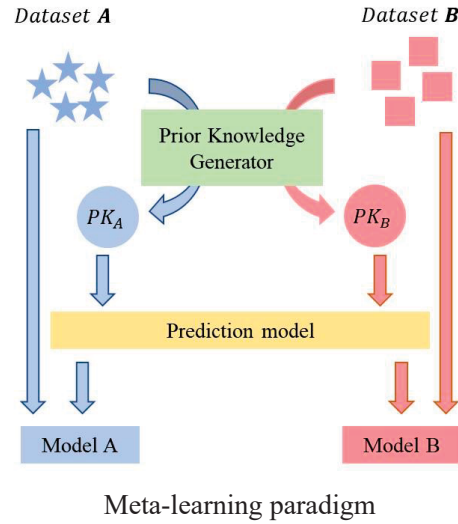
Given a series of historical trajectories, the next-location prediction requires us to understand hidden patterns and underlying features in historical trajectories through both spatial and temporal perspectives. With the increasing performance of deep learning methods, more and more works have introduced deep learning models and related mechanisms. Human mobility exhibits strong spatiotemporal regularities, and with that in mind, previous research started to use historical trajectories as input for next-location prediction with deep learning models.

Consequently, Recurrent Neural Network (RNN), a famous structure to deal with time-series predictive tasks, is widely used in next-location prediction, including its variants (LSTM and GRU). Deepmove designed a multi-model embedding RNN to capture sequential transitions in human mobility and utilize the periodical nature of history trajectories to augment mobility prediction. Flashback, combined with distance in spatial and temporal dimensions, was proposed by modeling sparse mobility traces and finding the hidden historical patterns with high predictive power as attention weights for location prediction.

On the other side, the real-time mobility data

stream is filled with high-frequency unlabeled data, and the implementation of a real-time prediction algorithm is challenging to process and has more fluctuating instability.

To that end, we introduced the meta-learning paradigm, which can modify the prediction procedure adapted to different prediction tasks with corresponding prior knowledge. In the supervised case, AI and deep learning leverage the paradigm to extract appropriate prior knowledge, as the following figure shows. Memory-based approaches, which can be regarded as meta-learning, learn to find the proper weights of an RNN so that the time-dependent indicators can effectively track the global state of the current task.



In this research, we proposed a next-location prediction method from the perspective of the meta-learning paradigm. We investigated how the introduction of a meta-learning indicator (prior knowledge generator) will improve the performance of our proposed GRU predictive model. Then, we built a history trajectory retrieval mechanism to enrich the predictive results and implemented the predictive model into a simulated real-time system to evaluate our design system.

## Methodology

Before describing the proposed model in this research, some preprocessing is necessary for raw GPS datasets.

Firstly, we forward-filled the raw GPS data in a 15-minute interval after map-matching, then interpolated and sampled these data in 5 minutes. After that, we had users' trajectories with the same 288 lengths. Secondly, we indexed continuous coordinate data with the h3 engine and selected 3600 hexagons for all the locations. Finally, we have indexed the cluster-level trajectory dataset for our predictive model training.

### • Proposed model

After preprocessing, the indexed cluster-level trajectory in our dataset is similar to check-in data. As we want to design a prior knowledge generator under the meta-learning paradigm, we introduced the **GRU** model as our initial base model for a different design.

Next, as memory-based approaches can help the predictive model modify its outcomes, we thought that the hidden state was not enough to represent the collective mobility patterns in our dataset, so we introduced the crowd context generated from a function and named it **GRU\_crowd\_context**. The updated model here calculated the average hidden state of all the users' trajectories as the prior knowledge generator. Also, we made the hidden state fuse the spatial information of the real world instead of indexes locations, for the hidden state for every iteration could consist of potential predictive power, referencing the Flashback Attention mechanism:

$$\begin{aligned} h_0 &= \mathbf{0} \\ w_s(\Delta D) &= e^{-\beta \Delta D} \\ merged &= (EL(TRC[t + \tau]), ET(t), EW(d)) \\ \Phi_{\Delta t} &= Pooling(h_{\Delta T}) \\ \Delta H &= [h_0, h_1 \dots h_{\Delta T}] \\ o_T &= SoftMax(MLP(\Delta H), \Phi_{\Delta t}) \end{aligned}$$

We regarded the optimized GRU model as our proposed predictive model.

Besides two bolded model names, we tested two famous baselines to evaluate results: **Deepmove** and the **MAML** framework.

### • Historical trajectory database

We aim to use historical trajectories to fill up the predicted results and the last observation to express more information. As a result, we built a database with a historical GPS dataset and design a mechanism to extract trajectory from it. Our database is built with the following steps: Divide the processed GPS dataset by user id, date, and time, and set the key as the above strings. The value should be the trajectory in that time; Create two cluster-level origin-destination-based index files with a GPS dataset, one's value is the coordinate and time information, and another is the corresponding database index.

With this database, we can find the most similar trajectory once we get the predicted result, the last observation, and time information.

### • Simulated real-time system

This research also designed a real-time system structure with a simulated data stream with our historical data. Also, the model modification mechanism was tested with an irregular event (earthquake) simultaneously.

## Data

In this research, we used a national dataset "Konzatsu-Tokei(R)" generated by individual location data sent from smartphones with enabled AUTO-GPS function under user's consent, through the "Docomo map Navi" service provided by NTT DOCOMO, INC. we used one month of data (from 2011.02.01 to 2011.02.28) for training the proposed methodology, and 12 days of data (from 2011.03.01 to 2011.03.12) for evaluation.

## Experiment

### • Cluster-level prediction & Time Efficiency

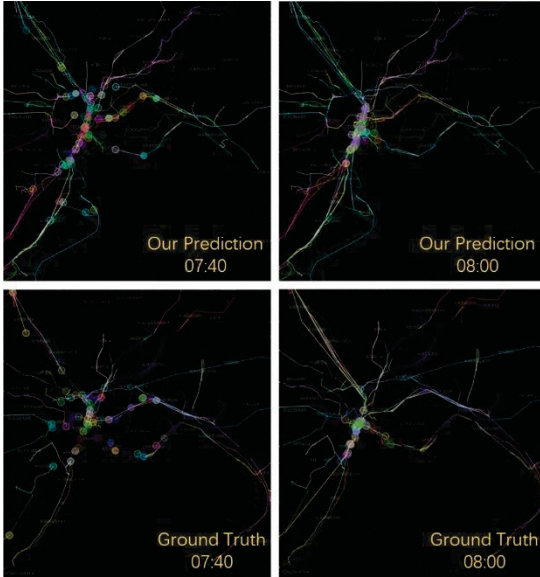
We evaluated our proposed model with baselines and the mentioned two baselines, and the following chart used the cross-entropy Loss as an indicator:

	Loss	Time
GRU	1.3463	169.45s
GRU_crowd_context	1.3530	173.88s
MAML	1.4773	160.62s
Deepmove	0.9442	633.82s
Ours	1.3350	172.04s

For presentation purposes, we have also added the time efficiency comparison of the subsequent complete process to the above table.

### • Node-level prediction

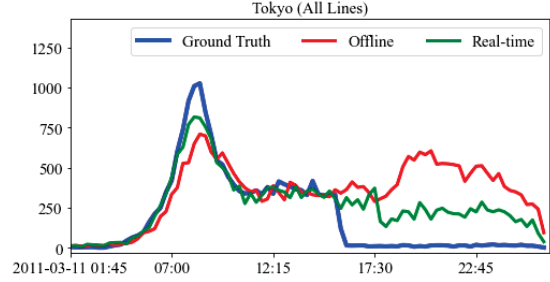
Node-level means extracted trajectories from the database. We visualized the predicted results of the proposed model and baselines and counted the visit volume to main train stations in Tokyo:



	RMSE/MAE/MAPE
GRU	65.7 / 90.4 / 0.4338
GRU_crowd_context	88.2 / 51.3 / 0.7917
MAML	54.4 / 41.3 / 1.2345
Deepmove	102.4 / 68.7 / 1.1203
Ours	<b>47.1 / 35.0 / 0.7081</b>

### • Simulated real-time system

In this experiment, we created a simulated real-time data stream for our system design and tested its performance for different events, as follows the most irregular event – an earthquake.



## Conclusion

This paper proposed a real-time trajectory prediction system structure with the meta-learning paradigm. We evaluated our proposed model with some intermediate products while designing the prior knowledge generator and the other baselines. We found that crowd context and spatial information fusion enhanced the model's performance with a slight temporal cost, compared with Deepmove, which showed good cluster-level performance. However, its low time efficiency made it unable to be implemented in a real-time system. In the node-level prediction, our proposed model performed the best compared with other baselines.

Regarding our simulated real-time system, our designed structure can detect irregularities, but the predicted trajectories show that some people were heading to train stations. That is because of the lack of corresponding historical information in our historical trajectory database.

In the future, we want to design a more reasonable meta-learning prior knowledge generator to detect events. We would like to produce some dummy data to simulate human mobility in different events and fuse those data into our database. Finally, building the system in a more robust method with other programming languages is necessary.