# 連合転移学習に基づくスパースモビリティデータの位置予測

Location Prediction of sparse mobility data based on federated transfer learning

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## 1.Introduction

Human mobility prediction is a key problem in urban computing, which could be beneficial to developing smart city applications. Short-term human mobility prediction could be utilized to provide advertisement and above it, long-term human mobility prediction help location-based AI applications in smart city in the future.

Nowadays we could have obtained a relatively high prediction accuracy of human mobility prediction when we have huge users and high time resolution. Unfortunately, there are still some issues reserved when we predict sparse human mobility data or use privacy GPS data. As a sequential problem, human mobility prediction has been studied by Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM). Sparse data means it lack of information, so it is difficult to generate an effective model. Some studies attempt to incorporate spatiotemporal factors into the neural network or use attention mechanism to solve the problem caused by the sparsity of human mobility data. To some extent, these studies improve the performance of prediction of sparse human mobility data. However, few studies devote to improving accuracy of sparse human mobility data by help of dense human mobility data.

Another problem is privacy issue. Although more and more human mobility data is collected in smart phones, use of these data is limited and companies couldn't use the data collaboratively with others due to privacy problem, which results in "isolated islands" issue. Federated learning is privacy-preserving model training in heterogeneous, distributed networks, which help companies collaborate to train a collective model that they can store their raw data locally and needn't to exchanged data with each other. In order to solve these problems, this study utilizes transferring learning to adapt the domain from dense data to sparse data to help improve performance of prediction of sparse human mobility data and uses federated learning to train a collective model among companies without exchange of data.

Combined with the two technologies, this study proposes a federated transfer learning model for modeling sparse human mobility data without exchange of raw data. This study uses two real-world GPS datasets that one is sparse dataset and another is dense dataset to model human mobility data. Result shows this model has great performance on prediction of sparse human mobility data by the help of dense data without exchange privacy.

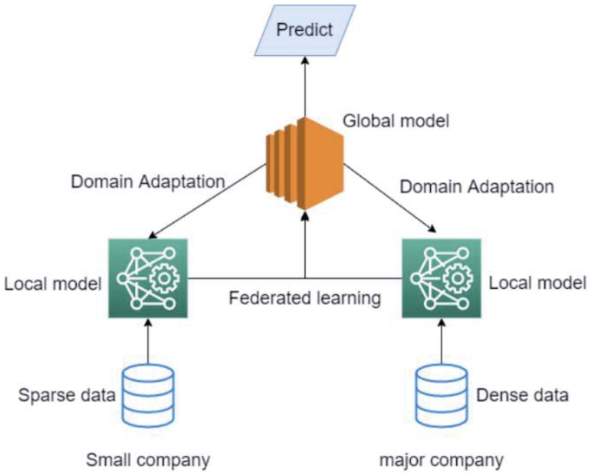


Figure 1: architecutre of this research

## 2. Methodology

### 2.1 Data preprocessing

In this research, I mainly use two datasets. Foursquare data (LBSNs sparse data) and zdc data (dense trace data). Because they all have many users in Tokyo and in same period from 2012~2013, I just consider data in Tokyo. Foursquare data has nearly 2273 users in Tokyo and average time interval of every check-in is 2.44 days. Zdc data has millions of users and average time interval is 15 minutes. Considering the size of whole zdc data is too large, I just use 3 months zdc data and randomly select 1/10 users in zdc dataset. Avoid confusing users from two datasets, I used different numbering methods that there is no intersection between user ids.Although foursquare data already has location id feature, we don't know how it is recorded and to fuse it with zdc data, label the two datasets by same method is necessary.

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In addition, considering types of the two datasets are greatly different. Foursquare data is check-in data that adjacent location is different in most times. Zdc data is dense traces, within 15 minutes, user is probably in same location. Therefore, it is necessary to make the two datasets more closely for data fusion in next step. I preprocess zdc data as the form of stay point, making the data shape more closely to foursquare data.

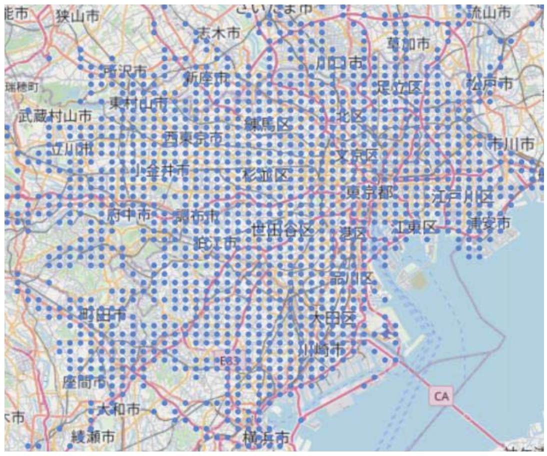

Figure 2:1600 common anchors in Tokyo

### 2.2 Model

This research attempts to predict long-term and sparse human mobility pattern. Therefore, it is practically impossible to have a great result if we just use RNN, even LSTM. Fortunately, there have some researches centralized in modeling sparse human mobility data and one of them is Flashback.

In RNN hidden state, it uses past hidden state by delta-time, delta-distance and hvc equation, it also considers spatial and temporal periodicity. For every past hidden state, it uses a weight w calculated by delta-time and delta-distance.

$$\begin{aligned}\mathcal{W}(\Delta T_{i,j}, \Delta D_{i,j}) &= w_T(\Delta T_{i,j}) \cdot w_S(\Delta D_{i,j}) \\ &= \mathrm{hvc}(2\pi \Delta T_{i,j}) e^{-\alpha \Delta T_{i,j}} e^{-\beta \Delta D_{i,j}}\end{aligned}$$

Compared with previous study, this framework has already a relatively great result when predicting sparse traces.

Based on this framework, I design two transfer learning model. One is discrepancy-based method, I calculate mmd loss when training.

$$MMD^2(X,Y) = \left\| \sum_{i=1}^{n_1} \phi(\mathbf{x}_i) - \sum_{j=1}^{n_2} \phi(\mathbf{y}_j) \right\|_{\mathcal{H}}^2$$

Another is adversarial-based method, except classifier, I add discriminator to it to predict which domain the data from. These two models both used domain adaptation to align two kinds of data to have a better result.

There are only two companies in this research. Two parts separately train their local models, then aggregate the two models as global model by federated learning. Afterwards, use global model to update the two local models and continue the circulation.

I used both federated learning and transfer learning in the final model. It adapts the inputs from source domain by adding an alignment layer. Both of the previous two transfer learning methods directly input data into the model during training. However, in consideration of privacy protection, direct interaction between data cannot be conducted.

Given the network from server and two users, I add a correlation alignment layer after fully connected layer in order to adapt the domains. This alignment function could be used to align the second-order statistics between the inputs. the loss function of this method is:

$$\arg\min l_u = \sum_{i=1}^{n_u} l(y_i^u, f_u(x_i^u)) + \eta L_{coral}$$

Where $\lambda$ demonstrates the trade-off parameter and $L_{coral}$ is correlation alignment loss. Figure 3 shows final federated transfer learning model.

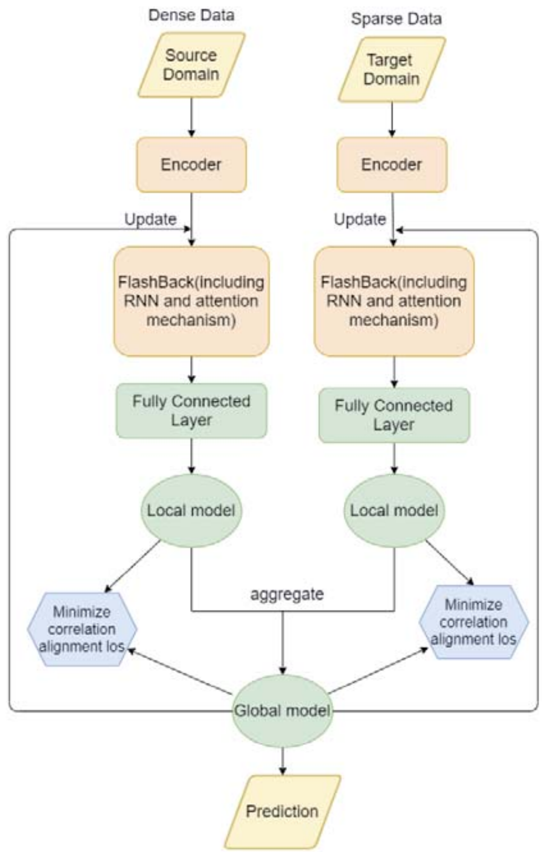


Figure 3: Federated transfer learning model

## 3.Experiment

Firstly, I conduct the experiment on original foursquare dataset and relabeled foursquare datasets by basic model Flashback. After that, I also use zdc dataset to complete same experiment.

Afterwards, I conduct the experiment of federated learning methods on foursquare and zdc dataset. I use method of FedAvg to aggregate two local model as global model except user embedding layer.

Then, two transfer learning models are used to predict next location of trajectories in foursquare dataset by the help of zdc data. Because we want to improve model performance of foursquare dataset, zdc data is source domain and foursquare data is target domain.

Finally, I use federated transfer learning model to predict human mobility data without privacy disclosure. Significantly, different from just transfer learning method, in this experiment, source domain is weight of global model and target domain is weight of local model, including local trainer of foursquare data and zdc data.

Unavoidably, federated learning method will decrease model accuracy to some extent trained by local data and updated by global model become closer, which means that two datasets are aligned to some extent. because domain adaptation is not directly done between two datasets. Virtually, the alignment of two local models trained by two datasets is completed by global model indirectly. Despite limited by federated learning, compared with basic model, our model based on federated transfer learning method has improved performance of basic model without exchanging data.

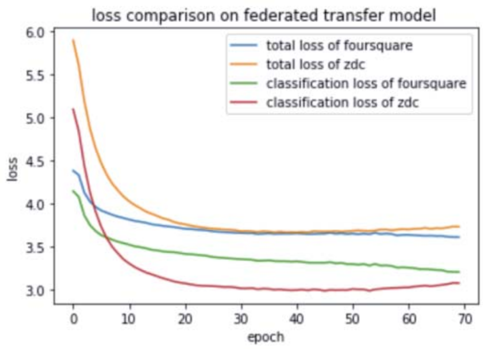


Figure 4: loss comparison on federated transfer learning model

| Data | mAP | Recall@10 | Model |
|---|---|---|---|
| Original fsq data | 48.354088% | 75.302128% | Flashback |
| Relabeled fsq data | 48.219626% | 75.302128% | Flashback |
| Zdc data(part) | 53.130656% | 77.117857% | Flashback |
| Relabeled fsq data | 47.98230% | 74.808568% | FedAvg method |
| Relabeled fsq data | 48.710939% | 75.575331% | DDC transfer method |
| Relabeled fsq data | 48.672451% | 75.680877% | DANN transfer method |
| **Relabeled fsq data** | **48.416047%** | **75.509106%** | **Federated transfer method** |

Table 1: Location prediction performance on different datasets with different models