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Estimating People's Position Using Matrix Decomposition

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Abstract

Human mobility estimation plays a key factor in a lot of promising applications including location-based recommendation systems, urban planning, and disease outbreak control. We study the human mobility estimation problem in the case where recent locations of a person-of-interest are unknown. Since matrix decomposition is used to perform latent semantic analysis of multi-dimensional data, we propose a human location estimation algorithm based on matrix factorization to reconstruct the human movement patterns through the use of information of persons with correlated movements. Specifically, the optimization problem which minimizes the difference between the reconstructed and actual movement data is first formulated. Then, the gradient descent algorithm is applied to adjust parameters which contribute to reconstructed mobility data. The experiment results show that the proposed framework can be used for the prediction of human location and achieves higher predictive accuracy than a baseline model.

Keywords: *Mobility prediction, Cellular network traces, Matrix factorization*

1. Introduction

Human mobility prediction can be beneficial for a variety of applications such as epidemiology and a data delivery algorithm in opportunistic networks. Therefore, this work considers the problem which predicts the next visiting places of a person or estimates the missing samples in human movement traces. In practice, human trajectories of a person could not be collected in cases where mobile devices are turned off to save the energy consumption or mobile phones are at the region with no signals, i.e., the historical locations of that person may not be available. Therefore, our work proposes a human mobility estimation algorithm to recover the missing samples in the human footprints and to predict the future locations of people, even when the recent location information of the person-of-interest is not provided.

There are several existing studies which addressed the future human mobility prediction [1-3]. For example, Pang *et. al* [3] extracted spatial and temporal movement information of people including location transition preference and pause time. Then, a modified Markov model which leverages the extracted mobility information was constructed to predict the next visiting location of people. Some works tried to approximate

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the human trajectory from mobile network data [4, 5]. For instance, Hotei *et. al* [4] examined the individual movement estimation using different interpolation methods including linear, cubic, and nearest interpolations. They concluded that the linear interpolation achieved the best estimation for sedentary people with the small radius of gyration. Whereas, the cubic interpolation is the most suitable method to describe movement of commuters who have a big radius of gyration. Nevertheless, the method described in [4] is limited to the mobility traces which provide the geographical positions of individuals.

Therefore, to address the limitation of [4], this paper introduces a human trajectory estimation framework which can be evaluated by using movement traces with symbolic locations (e.g., cellular traces and Wi-Fi logs). The objective of the proposed framework is to recover the missing movement patterns and to predict the next locations of people. There are two phases in the framework where the first phase seeks for persons with correlated movements (PCMs) of a person-of-interest and then the positional information of selected PCMs is sent to the second phase for predicting future or missing trajectories of the person-of-interest. We apply the matrix decomposition technique to extract latent factors of human mobility patterns. More particularly, the optimization problem is formulated to minimize the reconstruction error between the reconstructed and real movement patterns. Evaluation experiments are implemented to examine the prediction accuracy of the designed framework and the collected results show that the proposed framework can recover and predict human movement with high accuracy.

The rest of the paper is organized as follows. Section 2 presents preliminaries including the introduction of the matrix factorization and two considered datasets in this work. The two-phase human estimation framework and the predictive performance of the proposed framework are described in further details in Section 3 and 4, respectively. Finally, the conclusion remarks are drawn in Section 5.

2. Preliminaries

2.1 Matrix Decomposition

Matrix decomposition is a process in which a matrix of data is factorized into a product of matrices [6]. As a result, the latent association between participating entities (e.g., users and items) can be revealed. Matrix decomposition is used to build recommender systems which can help businesses to understand their customers and therefore to increase their sales through cross-selling.

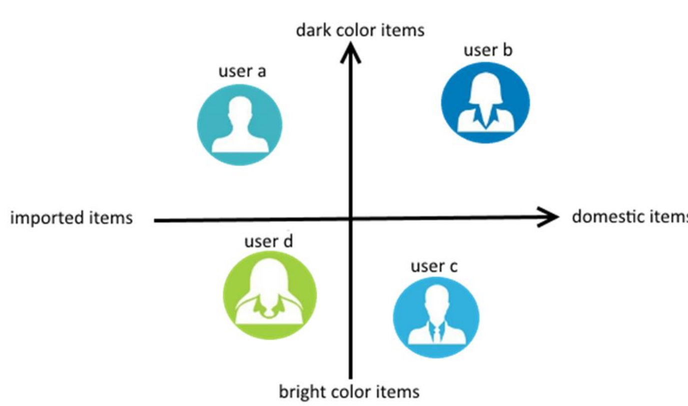

Figure 1. Visual representation of latent factors of several users

For example, we consider the data which provides people's scores on a variety of items on an online shopping website. In this case, matrix decomposition can allow this website to infer favorite items for each user. Assume that there are 4 different users, as shown in Figure 1. After performing matrix factorization, it is revealed that user a usually buys imported goods with dark color while user c tends to be interested in domestic items with bright color. Therefore, the website should implement a customized strategy which frequently suggests imported goods to users a and d while domestic items should be advertised to users b and c.

2.2 Datasets

In this work, the proposed algorithm is evaluated on two large datasets, the MIT dataset [7] and the Dartmouth dataset [8]. The following section briefly presents these datasets and how to extract people and locations from provided logs. The MIT traces provide mobility traces of 106 people belong to MIT over a 9-month period. Since most of participants are involved in the same educational institute, there are strong social connections between participants, thus leading to the highly correlated mobility patterns in the network. The MIT dataset provided cellular traces consisting of the cell handover events and a set of cell towers detected by the participants. Note that in cellular networks a mobile device connects to the tower which has the strongest signal among observed cell towers. Since small and short-range cell towers that provide communication within few hundred meters are more preferred in urban areas, human locations can be extracted by using the cellular logs.

Now, we present the extraction of people and locations in the MIT dataset. The 75-day overlapping period and 43 people with sufficient mobility traces are extracted [9, 10]. Note that time slot-based mobility data is considered in this work and a person may associate with several towers within a time slot. Therefore, a cell tower which reflects the human location during a time slot period should be determined. In this work, the time slot length is set to 30 minutes and the cell tower with which a person associates more than 15 minutes during a 30-minute time slot is regarded as the representative location of that person. We also remove positions at which people rarely stay and as a consequence 482 cell towers keep remaining in the MIT dataset. Let N and L denote the number of people and the number of locations, respectively, i.e., $N = 43, L = 482$.

The second dataset is the Wi-Fi association traces which provide the information about Wi-Fi association or disassociation events of people on the Dartmouth university campus. Thanks to the short range of Wi-Fi technology, an AP can be used to indicate the location of a person. Similar to the MIT dataset, in the Dartmouth traces, we select a 4-month period from 3 January to 30 April in which the academic campus was relatively stable. Also, we remove persons whose mobility data was provided less than 75% over the considered 4-month period and then there are 162 mobile users in the Dartmouth dataset, $N = 162$. The number of locations is 623 in the Dartmouth traces.

3. Two-phase Human Location Estimation Framework

In the following section, we present the two-phase framework which predicts locations of the person-of-interest (e.g., person p) at time t by using the position information of PCMs. As shown in Figure 2, the first phase chooses r PCMs who can help to predict locations of person p. Specifically, a measurement method is first proposed to estimate the score of $(m-1)$ other people, and then r PCMs with the highest score are chosen. Phase 2 leverages the information of these selected PCMs for estimating the location of person p. Note that observed location information of person p is sent to both phases in order to perform the training process. We name the algorithms in the first and second phases as PCMs selection based on matrix decomposition (PSMD) and location estimation based on matrix decomposition (LEMD), respectively. Now, the data structures of matrices in both phases are described and the reconstruction method is explained in the next subsections.

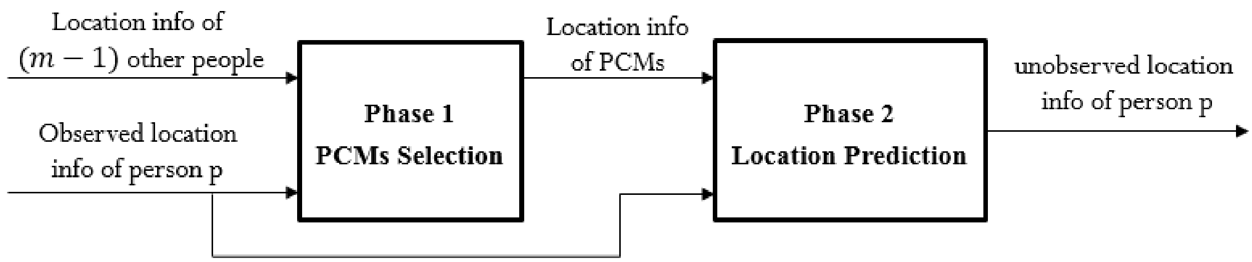

Figure 2. Location prediction framework

3.1 Data Structures in the Estimation Framework

In the PSMD method, we construct $(m-1)$ data matrices and matrix $M_q(q=[1,m], q \neq p)$ is used to measure the score of person q. Figure 3 shows the structure of matrix M_q which consists of 5 columns and k rows accounting for k instances in the dataset. The first column presents the location l_t^p of person p at current time t and the next two columns consist of position information of person q at the previous and current time slot. The last two columns include the temporal information, i.e., the current time and day indices. The unobserved samples on the validation set of person p are denoted by grey color elements with the question mark. Note that, the test dataset is not used in the first phase of the framework, as the test set is used only for performance evaluation of the prediction algorithm, LEMD, in the second phase. Cell tower indices are used to represent locations of person p. For instance, the first row shows that persons p and q are at the area covered by cell tower 5 and 2, respectively. After finding the reconstructed matrix $\widehat{M_q}$ from the original M_q through the use of the matrix factorization technique, we collect the predictive accuracy a_q on the unknown samples of the validation set. Then, r people who have the highest score are selected as PCMs for the next phase.

l_t^p	l_t^q	l_{t-1}^q	t	d
5	2	1	8 am	Mon
?	3	2	3 pm	Sun
5	4	3	10 am	Tue
3	2	1	1 pm	Mon
5	5	4	9 am	Sat

Figure 3. Structure of matrix M_q for PCMs selection

As presented in Figure 4, in the LEMD algorithm, the data matrix which represents the spatio-temporal movement of person p and person p's PCMs is constructed. Recall that l_t^p denotes the location of person p at current time t and day index d. Let $l_t^{PCM_1}$ represent the location of person p's first PCM. Figure 4 shows an example in which the matrix consists of location information of person p at current time t and spatial data of two PCMs at t and $(t-1)$. For example, person p stays at the region covered by cell tower 5 at 8 am on Monday while the first and second PCMs are in the locations 2 and 3, respectively. Unobserved locations of person p on the test set are denoted by grey color elements with the question mark.

l_t^p	$l_t^{PCM_1}$	$l_{t-1}^{PCM_1}$	$l_t^{PCM_2}$	$l_{t-1}^{PCM_2}$	t	d
5	2	1	3	1	8 am	Mon
?	3	2	2	2	3 pm	Sun
5	4	3	3	1	10 am	Tue
3	2	1	2	2	1 pm	Mon
5	5	4	3	1	9 am	Sat

Figure 4. Matrix structure in the LEMD algorithm where each row of the matrix represents spatio-temporal data of person p at time t and PCMs at time t and $(t-1)$.

Then, we leverage the matrix decomposition technique to find r PCMs and to compute reconstructed unknown mobility traces. More specifically, optimization problems are formulated to minimize the reconstruction error and the gradient descent algorithm is used to estimate the parameters of the model. The detail matrix factorization algorithm will be described in the next subsection.

3.2 Matrix Decomposition Algorithm

Now, we present the reconstruction process from the original matrix (named as matrix D). Matrix D is first converted to matrix A in the binary scale using the one-hot encoding. Specifically, the location element (e.g., $l_t^p, l_t^{PCM_1}, l_t^q$) is mapped to the indicator vector in $\mathbb{B}^L$. Time slot information t is represented by a three-dimensional vector where each dimension indicates one of three parts of a day (i.e., morning, afternoon, and evening). Meanwhile, a day-index vector in $\mathbb{B}^7$ is used to reflect the day index d in a week. Suppose that after performing one-hot encoding, D is mutated to A in $\mathbb{B}^{m\times n}$.

The proposed LEMD algorithm aims at reconstructing matrix A by leveraging UV decomposition which is an instance of matrix factorization [6]. More specifically, the reconstructed matrix, hereafter called $\hat{A}$, is decomposed into components U and V, i.e., $\hat{A} = UV$ where $\hat{A}, U,$ and V are matrices in $\mathbb{R}^{m\times n}, \mathbb{R}^{m\times c}$, and $\mathbb{R}^{c\times n}$, respectively. Note that matrices A and $\hat{A}$ have the same size. This work considers that $c = \lfloor 0.8n \rfloor$. Each element $\hat{a}_{i,j}$ in the reconstructed matrix is calculated as below:

$$\hat{a}_{i,j} = \sum_{k=1}^{c} u_{ik} v_{kj} \tag{1}$$

In the LEMD algorithm, we define the objective of the optimization problem which minimize the difference between matrices A and $\hat{A}$ as follows:

$$\min \|A - \hat{A}\| \tag{2}$$

where $\|x\|$ denotes the 2-norm value of vector x. The error function is defined as $e = \|A - \hat{A}\|^2 = \|A - U.V\|^2$. Then, the gradient descent method [6] is used to adjust the values of matrices U and V at epoch j as follows:

$$U^{(j)} = U^{(j-1)} - \eta\frac{\partial e}{\partial U} \tag{3}$$

$$V^{(j)} = V^{(j-1)} - \eta\frac{\partial e}{\partial V} \tag{4}$$

where η is the learning rate which is set to 0.001. The process of updating parameters ends when the number of iterations exceeds a given value which is set to 350. Note that while the values of matrix U are updated, parameters of matrix V is treated as constant values. In order to avoid overfitting, the L^2 weight decay method [6] is used and the cost function is modified as below:

$$e = \|A - U.V\|^2 + \alpha(\|U\|^2 + \|V\|^2) \tag{5}$$

The regularization coefficient is set to 0.3. Then, the parameters of two matrices U and V are updated accordingly.

4. Evaluation Results and Analysis

Evaluation experiments are conducted to examine the proposed location prediction framework on two datasets under the different number of PCMs. We divide the whole dataset into observed and unobserved sets at the ratio of 7:3. The observed one consists of training and validation sets. The training samples are used to reconstruct the original matrix and the validation set can help to select the appropriate initial values of matrices U and V. The results are collected on the unobserved set. The experiments are implemented in TensorFlow. We select the predictive accuracy as the performance metric for the evaluation of the designed framework. In order to better understand the predictability of the proposed framework, a baseline method named most frequent location (MFL) is used for performance comparison with our models. Specifically, MFL assumes that a person is likely to stay at the most visited position.

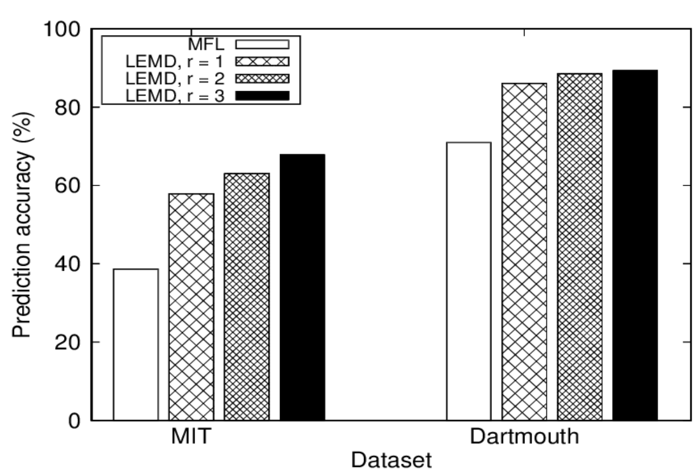

Figure 5. Performance results of the proposed prediction framework on the MIT and Dartmouth datasets

As shown in Figure 5, the designed framework outperforms the baseline MFL method with both considered datasets. For example, in the case of Dartmouth dataset, LEMD with $r = 1$ yields 86.04 % accuracy for the prediction of next locations, as compared with 70.97% accuracy of the MFL method. This result indicates that the location information of persons with correlated movements is beneficial for the location prediction task in the case where the recent historical locations of the person-of-interest is unknown.

Interestingly, increasing the number of PCMs results in the improved performance on both datasets. As presented in Figure 5, the LEMD produces the accuracy of 86.04%, 88.51%, and 89.33% when $r = 1,2,$ and 3, respectively, with the Wi-Fi Dartmouth traces. This observation is attributed to the fact that the person-of-interest may have similar movement patterns with different PCMs in the parts of a day. Therefore, the prediction model can estimate the mobility patterns more accurately in cases where the location information of more PCMs is fed into the prediction model. For example, person p usually goes to the office in the morning, visits the restaurant at lunch, then goes to the stadium for exercising with a family member in the afternoon. Person p is likely to have correlated movements with colleagues in the morning, friends at lunch time, and the family member in the afternoon. Therefore, intuitively using more PCMs can help to gain performance improvement of the prediction model.

5. Conclusion

This paper considers the problem which estimates future or missing trajectories of a given person in the case when the historical location information of that person is unavailable. We propose the two-phase prediction framework which first selects a number of persons with correlated movements and then leverages the location information of these selected persons to estimate future or missing movement of the person-of-interest. The matrix decomposition algorithm is used where the data matrix is first constructed. Then, the optimization problem which minimizes the reconstruction error is formulated and the gradient descent method is applied to find the approximate solution for the optimization problem. The experiment results show that, by using the information of persons with correlation movement, the proposed prediction framework can estimate the missing or future human movement without requiring the recent location information of that person.

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