CitySpectrum: A Non-negative Tensor Factorization Approach

Zipei Fan, Xuan Song, Ryosuke Shibasaki
Center for Spatial Information Science, The University of Tokyo, Japan
fanzipei@iis.u-tokyo.ac.jp

ABSTRACT
People flow at a citywide level is in a mixed state with several basic patterns (e.g. commuting, working, commercial), and it is therefore difficult to extract useful information from such a mixture of patterns directly. In this paper, we proposed a novel tensor factorization approach to modeling city dynamics in a basic life pattern space (CitySpectral Space). To obtain the CitySpectrum, we utilized Non-negative Tensor Factorization (NTF) to decompose a people flow tensor into basic life pattern tensors, described by three bases i.e. the intensity variation among different regions, the time-of-day and the sample days. We apply our approach to a big mobile phone GPS log dataset (containing 1.6 million users) to model the fluctuation in people flow before and after the Great East Japan Earthquake from a CitySpectral perspective. In addition, our framework is extensible to a variety of auxiliary spatial-temporal data. We parametrize a people flow with a spatial distribution of the Points of Interest (POIs) to quantitatively analyze the relationship between human mobility and POI distribution. Based on the parametric people flow, we propose a spectral approach for a site-selection recommendation and people flow simulation in another similar area using POI distribution.

Author Keywords
Human Mobility; Non-negative Tensor Factorization

ACM Classification Keywords

INTRODUCTION
Understanding and modeling a people flow on a citywide level play critical roles in urban planning, emergency management, and post-disaster recovery. As is well known, the Great East Japan Earthquake caused severe damage to the north-eastern part of Japan. With insight into people flow, the government plans to improve the efficiency of its humanitarian relief after disasters and during post-disaster reconstruction. Moreover, a better understanding of people flow will also bring about financial profits. Since the Great East Japan earthquake in 2011, the Japanese government has proposed a variety of policies for urban renaissance. To revitalize the economy, Priority Development Areas [23] have been designated to stimulate regional momentum, and many factors need to be taken into consideration for site-selection. Factors such as local demand and purchasing power are difficult to measure by traditional approaches. However, they underlie in city dynamics such that we can infer the latent factors by analyzing the people flow.

Meanwhile, the Fukushima Daiichi nuclear accident caused by the Great East Japan Earthquake turned out to be an unprecedented composite disaster that significantly impacted lives of those in Fukushima prefecture. The impact of this is twofold: First, materially, the collapse of buildings caused homelessness, the deformation of railroad tracks wreaked havoc on railway transportation, and people evacuated the exclusion zone owing to the radioactive leak caused nuclear accident, and second, psychologically, people have been unwilling to go outside because they are faced with uncertain aftershocks, whereas having a home or shelter would provide them with a sense of security. This has led to a fluctuation in their patterns (e.g. commuting pattern has dropped, and whereas their stay-at-home pattern has increased) as well as a shift in their geographical life patterns (moving to a new area without a nuclear power plant). Confronting such catastrophic disas-
ters, modeling and understanding a people flow before and after a disaster is of great significance, in both short (emergency management) and long (post-disaster recovery and rehabilitation) terms.

However, research on modeling and understanding a people flow at the citywide level is very hard to conduct, owing to the difficulties in collecting representative longitudinal data in locations where infrastructure and social order have collapsed and where study populations are moving across vast geographical areas. More recently, GPS log data from mobile phones [19], location-based online social networking data [3, 10], and Integrated Circuit (IC) card data [20] have emerged and are increasing explosively. This increase in human mobile sensing data becomes the “big data”, and offers a new way to circumvent methodological problems of earlier research for people flow modeling because such data offer a high temporal and spatial resolution, are instantaneously available, have no interviewer bias, and provide longitudinal data for very large populations. Therefore, in this paper, we collected “Big Human Mobile Sensing Data” (1.6 million mobile phone users with GPS capacity) over a three-year period to understand and model a people flow at the citywide level.

A city is a complex system, and it is therefore difficult to provide a straightforward interpretation of a people flow at the citywide level. Cities function quite distantly at different regions, at different times and on different days. Imagine a commercial area at 7 p.m. on a weekend. The people in this region would probably be drinking with friends, shopping, coming or leaving using public transportation. Comparatively, at 7 a.m. on a weekday, the same region may mainly act as a commuting hub. Thus, we assume that a people flow is a mixture of various underlying latent components such as commuting and working patterns. Under this assumption, our objective is to infer the underlying components from an integrated people flow and to correlate the components with other spatio-temporal data in a general unified framework.

Consider the manner in which astronomers analyze an newly discovered star: they pass the light of the star through a spectrograph to obtain its light spectrum. The components of light with different frequencies are separated. Thereafter, the deficiency of certain frequencies in the spectrum may indicate the existence of certain elements in the star. Similarly, in this paper, we regard a city as an newly discovered star, and the people flow as the observable light of the star. An intuitive example is given in Figure 1, the upper part of which is a people flow in a mixed state. Some regions are more likely to be a workplace (high density during working hours), other regions are more likely to be a transit station (high density in the morning and evening rush hours), and still some regions may be a combination of the two. Our research objective is to decompose a mixed people flow into a few basic people flows, each of which characterizes one human life pattern in the city, for example, a working pattern or commuting pattern, as shown in the lower part of Figure 1.

To find the proper “spectrograph”, we adapted the Non-negative Tensor Factorization (NTF) algorithm [2], which belongs to the family of matrix/tensor factorization algorithms. The philosophy of such algorithms is to approximate the matrix/tensor through a linear combination of a few basic tensors (rank 1) under certain constraints according to the application scenarios. There are two commonly used constraints to factorization. The first is the orthogonality (e.g. singular value decomposition), which applies a constraint in that the bases that are factorized out should be orthogonal to each other. The second is non-negativity (e.g. NTF), which assumes that every entry in the bases have to be non-negative. In our scenarios, there are two reasons why we prefer non-negativity:

- the density of a people flow cannot be negative, and
- the difference between each pattern is not so significant as to be orthogonal.

Our method is a step toward a future smart government that harnesses human mobility data sufficiently for fast responses to disasters and effective urban planning. The main contribution of this paper can be summarized as follows:

- We provide a novel perspective to the modeling of large-scale human mobility in a CitySpectral space.
- We applied our method to a big GPS log dataset, and present several real-world applications.

DATA AND PREPROCESSING
To model real-world human mobility, we collected a GPS log dataset anonymously from about 1.6 million real mobile-phone users in Japan over a three-year period (from August 1, 2010 to July 31, 2013). This dataset contains about 30 billion GPS records, or more than 1.5 terabytes. The data collection was conducted by a mobile operator and private company under an agreement with mobile phone users. By default, the positioning function on the users’ mobile phones is activated every 5 min, and their positioning data are uploaded onto the server. However, the data acquisition is affected by several factors such as a loss of signal or battery power. In addition, to save power, when a mobile phone is evenly placed, the positioning function is automatically turned off.

Original Data
Consider a set of city-wide GPS log data \( D = \{l_1, l_2, \ldots, l_M\} \), where \( l_i \) is the \( i \)-th record of the GPS log with in the city. Each record is a tuple in the form of \( l_i = (uid, time, latitude, logitude) \), where \( uid \) is the unique id for each mobile user.

People Flow Tensor
Before we begin analyzing the people flow at the citywide level, we need to find the proper data structure to represent people flow. When analyzing the interrelationship between two discrete attributes (for example, spatial and temporal), the use of matrix is commonly the first choice. However, in people flow modeling scenarios, a periodic appearance (in this paper, we consider this periodicity as daily) turns out to be an important preliminary for defining a pattern. Hence, in order to model daily recurring patterns, we need to fork the temporal dimension into “sample days” and “time-of-day”. Therefore, we introduced a three-way tensor \( Y \in \mathbb{R}^{N_t \times N_t \times N_d} \) to
formulate a people flow, where $N_r$, $N_t$, $N_d$ are the numbers of regions, time-slices and sample days respectively.

To construct a people flow tensor from a raw GPS record dataset, in the first step, we need to discretize the time and coordinates. We selected 30 min as the time interval therefore divided one day into 48 time-slices. In addition, we meshed the city into $\Delta d_{lat}$ and $\Delta d_{lon}$. Based on the definition of latitude and longitude, the east-west distance on the earth is variant according to latitude. To guarantee a square meshed the city into $\Delta d_{lat} \times \Delta d_{lon}$ on a map of Fukushima.

However, human coordinates are not recorded uniformly in terms of time, because the localization function is not activated when no movement of the user’s mobile phone is detected. As shown in Figure 2, the number of GPS points from 8:00 to 8:29 is about 11 times larger than that from 4:00 to 4:29. This bias leads to a very serious mis-estimation of the actual population density. In this paper, we construct a people flow tensor using the proportion of GPS points in each region over the entire city:

$$y_{r_0,t_0,d_0} = \frac{\text{Count}(r_0,t_0,d_0)}{\sum_{r=1}^{N_r} \text{Count}(r,t_0,d_0)}$$

where $r_0$, $t_0$, and $d_0$ are the index of the region, the time-slice and the sample day respectively; $N_r$ is the total number of regions, and $\text{Count}(r,t,d)$ calculates the number of GPS points at time $t$ on $d$-th days within region $r$.

CITYSPECTRAL SPACE

In this section, we give a formal description of the terminology used in people flow factorization and detail the NTF algorithm for people flow factorization. For simplicity, by default the tensors mentioned in the remainder of this paper are three-way (region, time, and day) tensors.

Definition 1 (basic tensor): A basic tensor can be expressed as the outer product of three unit vectors. It is notable that a basic tensor has a rank of 1.

Definition 2 (CitySpectral Space): Let $Y$ denote the people flow tensor defined in the previous section. A CitySpectral space is a space spanned by $K$ bases of basic tensors $\{Y(1), Y(2), \ldots, Y(K)\}$. Therefore, the city-wide people flow tensor could be approximately expressed as a linear combination of basic tensors in the CitySpectral space (as shown in Figure 3), with the coefficients of $\omega_1, \omega_2, \ldots, \omega_K$ that best approximate $Y$ through

$$Y \approx \sum_{k=1}^{K} \omega_k Y(k)$$

Definition 3 (region-basis, time-basis and day-basis): For each basic tensor $Y(k)$, we denote $u(k), v(k)$ and $w(k)$ as the unit vectors whose outer product is $Y(k)$:

$$Y(k) = u(k) \odot v(k) \odot w(k)$$

Therefore, the region-basis, time-basis and day-basis are defined as the collinear vectors with $u(k), v(k)$ and $w(k)$ respectively. Without losing generality, the bases are set to be $\sqrt{\omega_k}u(k), \sqrt{\omega_k}v(k)$ and $\sqrt{\omega_k}w(k)$ by default.

Definition 4 (basic life pattern): We define $\omega_k Y(k)$ as the $k$-th basic life pattern. Equivalently, a basic life pattern can also be described as the triple of (region—basis, time—basis, day—basis) as well.

CitySpectral Approach to People Flow Modeling

Intuition of CitySpectral Approach

A people flow at citywide level is in a mixed state composed of a variety of life patterns. Most regions are not monofunctional. As the result of such mixture, in a spatio-temporal space, it is impossible to tell one pattern from another if we analyze the population density at each time within each region in isolation. However, the term “Pattern” as defined in a dictionary, is a regular and repeated way in which something occurs or is conducted. Therefore, a holistic viewpoint gives a possible solution to generate a natural separation of such patterns by finding the regular presence of a small number of prototypes, namely, the bases of the basic life patterns. As shown in Figure 4, each basic pattern we factorized out in the form of a tensor is the most economic model of patterns occurring in real life, where the models are the bases of patterns in the CitySpectral space.
in Figure 1 (for simplicity of visualization, we omitted the “day” dimension and formulated a one-day people flow into a matrix form) can be described by the outer product of the basis vectors. From the property of the outer product, each row vector in a people flow matrix is collinear with the time-basis and each column vector is collinear with Region-basis; that is, each basic pattern is the repeated spatial presence of the time-basis, as well as the repeated temporal presence of the region-basis. Following this intuition, the essence of the CitySpectral approach is to approximate a city-wide people flow tensor with a linear combination of only a small number of basic tensors characterizing the basic life patterns underlying the people flow.

Formulation

Considering each entry in the people flow tensor characterizing the regional population density, which cannot be negative, we may assume that all bases describing the basic life patterns we factorized out should be non-negative as well. Thus we formulated the latent basic life patterns inference problem through Non-negative Tensor Factorization, the essence of which is to minimize the error reconstructed by $K$ triples of bases:

$$L(U, V, W) = \left\| Y - \sum_{k=1}^{K} u^{(k)} \circ v^{(k)} \circ w^{(k)} \right\|_F^2 + \Phi(U, V, W)$$

with non-negativity constraints of

$$U \geq 0, V \geq 0, W \geq 0$$

Here the region-basis $u^{(k)}$, time-basis $v^{(k)}$ and day-basis $w^{(k)}$ are the $k$-th column vector of $U$, $V$ and $W$ respectively, and $\circ$ is the operator of the outer product. In addition, $K$ is the number of basic life patterns that we want to infer, and $\|*\|_F^2$ is the Frobenius norm of the tensor based on the Euclidean distance. The function $\Phi$ is a generalized regularization term which can be used for extension of this framework.

NTF is an extensible framework in that a wide range of auxiliary spatio-temporal data such as the spatial distribution of POIs can be easily incorporated into a unified framework [4, 21], when conducting a variety of new applications such as comparative and parametric people flow. In the “Real-world Applications” section, we discuss the applications based on the two extensions of the NTF framework.

Pattern Labeling

Each rank-one tensor we discovered can be represented using three vectors, namely, the time-basis, the location-basis and the day-basis. These triple bases describe the spatio-temporal characteristics of the components of a people flow implied by a rank-one tensor. For simplicity and clarity of further analysis, we manually named the labels summarizing what kind of pattern the bases describe. For example, in Figure 5, we show the bases of the rank-one tensor we factorized out. In the top-right of the figure, the regions with the highest values are the major stations in Tokyo, and we can see that the regions with a high value are approximately aligned along the mainlines (railway) in Tokyo. As for the time-basis, we can see two peaks at about 8:30 and 19:00 which could be interpreted as the morning and evening rush hours. Weekly periodic behavior can be easily observed from the day-basis diagram with the exception of the “golden week” in Japan. In the “golden week”, Tuesday to Friday are national holidays. As a result, the people flow behaves similarly as that found on the weekend. Therefore, we labeled the rank-one tensor in Figure 5 as a “commuting pattern”.

REAL-WORLD APPLICATIONS

Disaster Behaviour Analysis

A good modeling of a people flow during a disaster can greatly improve the efficiency and effectiveness of the emergency response from the government. However, a people flow may appear to be more chaotic during a disaster, and as a result it may be hard for the government to evaluate the impact of the disaster on the daily life of the residents. The CitySpectral approach provides a novel perspective in modeling a people flow during a disaster in that disaster impact of the disaster on each basic life pattern can be quantitatively characterized. We acquired the people flow tensors to model the people flow in Fukushima for four continuous months before and after The Great East Japan Earthquake. The sample
days ranged from Feb. 1 to May 31, 2011. We annotated each basic life pattern by considering the day-basis, time-basis and region-basis comprehensively. Experimentally, we obtained nine basic life patterns, and annotated these patterns as “home (1,2,3,4)”, “commercial (1,2)”, “working”, “entertaining” and “commuting” patterns. Figure 6 shows the days-basis before and after the Great East Japan Earthquake, characterizing the fluctuation of the pattern intensity. In this part, we focus on the home patterns. As the results show, the home pattern is affected by the earthquake so significantly that it cannot simply be described as a single basic life patterns. The factorization algorithm separates a home pattern into four sub-patterns.

The most obvious peak in Figure 6 is the dramatic increase of “home 1” pattern in the three days following the earthquake. In the first row of Figure 7, the time-basis (the first column) describes the “home 1” life pattern as “staying at home (or somewhere nearby within the region) for the whole day”, since there is little variation of the pattern intensity during one day. From the third row, “home 3” is characterized as “spending most time at home while sometimes going outside during the daytime”. As shown in region-basis, “home 1” represents a more concentrated pattern of spatial distribution than “home 3”, because “home 1” describes the pattern that people at a very low level of mobility while “home 3” describes the pattern that people mobility is partially recovered. In addition, “home 1” and “home 3” have in common that both have very low intensity in the coastal regions, where are severely damaged by Tsunami.

From the day-basis perspective, Figure 6, we can see that the peak of “home 1” follows with the earthquake, this is because after the earthquake the transportation system broke down and people were unable to go anywhere far from their home or shelter. In addition, people felt insecure, preferring to stay at home or their temporary shelter. About three days later, “home 1” decreases sharply while “home 3” rises. This reflects people regained some mobility and started to go out to buy daily necessities or receive relief supplies.

Note that “home 3” does not describe the life pattern of people who needed to regularly go to work place during daytime. This home pattern is given in “home 2” and “home 4”, in which nightime density is obviously higher than that of the daytime, which is the life pattern of a typical salaryman. Although they are quite similar to each other in the time-basis, from a day-basis perspective, “home 2” and “home 4” behave in an opposite fashion. After the earthquake, “home 2” gradually increases whereas “home 4” decreases sharply. Therefore, the “home 4” represents a home pattern that was severely affected by the earthquake, while “home 2” was...
served after disaster, because the impact of the disaster was
long-term geographical shift of human mobility was ob-
Post Disaster Human Mobility Shift
A long-term geographical shift of human mobility was ob-
seen. In the middle area of the coastal region, we can see
slightly affected and represents a “new home” (namely a sec-
second house or a relative’s home) of those whose were more
significantly affected by the earthquake. With the help of
regions-basis, we can see that “home 2” excludes the regions
within 20 km of the Fukushima Daiichi Nuclear Power Sta-
where a catastrophic accident resulted from the release of
radioactive materials. This 20-km region is the exclusion
zone that the government announced [9] as being heavily pol-
luted by radioactive materials, and from where all residents
had to evacuate. “Home 4” which includes this exclusion
zone, dropped dramatically after the earthquake occurred.

Similarly, as shown in Figure 8, there are two commercial
patterns in the factorization results: one representing the commer-
cial regions most affected by the earthquake (the first row)
and another representing regions not substantially affected
by the earthquake (the second row). Specifically, tourism,
which is an important part of commerce, is very vulnerable
to disasters, because the majority of contributors to tourism,
namely tourists, are not local residents, usually their destina-
tion is far from their home, instead of preferring somewhere
near. Tourists therefore have multiple destination choices and
the negative news of a disaster may easily discourage them
from going to the disaster area. The center of Figure 8 shows
the region-basis of “commercial 2” (a heavily affected area)
in the Mount Bandai area. Mount Bandai is the most fa-
mous sightseeing area in Fukushima, however, because of
the earthquake, and particular based on the negative report of
radioactive materials beging released in Fukushima, people
have been unwilling to choose Fukushima as their travel des-
tination. This could be evidenced from the news that the first
tourist group from China to visit Fukushima after the earth-
quake did so in May of 2012 [22], more than one year after
the disaster. Note that the region with highest value is at the
peak of Mount Bandai, which is the hub where people can
access a cable-car.

Post Disaster Human Mobility Shift
A long-term geographical shift of human mobility was ob-
erved after disaster, because the impact of the disaster was
of different degrees at different locations. A proper estima-
tion of this shift is critical to the redevelopment planning.

In this subsection, we model the geographical shift of peo-
ple’s life patterns in February of 2011 (before the Great East
Japan Earthquake) and February of 2012 (after the Great East
Japan Earthquake). There are two possible solutions from our
previous algorithm. 1) Concatenate the people flow tensors in
2011 and 2012 into a single tensor by way of “sample days”. Then
similar to our first example of factorizing the people
flow of Fukushima before and after the earthquake, for each
pattern we are interested, we will obtain two (or even more)
basic life patterns, with one describing the pattern in 2011
and the other pattern in 2012. 2) Factorize the two people
flow tensors separately, and compare the patterns with the
same annotation. This solution has no mathematical restric-
tion on the similarity of the time-basis, region-basis between
the patterns in 2011 and 2012, so it is so flexible that for each
pattern, all the three bases can be different. However, for a
comparison, we need to control the variables. In this appli-
cation, we compared the basic life patterns before and after
the earthquake by controlling the time-basis variable and co-
factorizing [4] the two tensors using the shared time-basis.

We acquired two people flow tensors for 2011 and 2012, shar-
ting the time-basis with the people flow tensor for 2011. To
measure the geographical shifts in the patterns, we defined
$\Delta u^{(k)} = u^{(k)}_{2012} - u^{(k)}_{2011}$ as the variation of spatial distribution
of the $k$-th basic life pattern. We classify regions $\Delta u^{(k)}$ into
three categories: 1) “increase” (red regions in Figure 9) re-
gions where the “home” pattern increased by over 10%, 2)
“remain unchanged” (green) regions where the life pattern
dropped or increased within 10%, and 3) “decrease” (blue)
regions where the life pattern decreased by more than 10%.

Figure 9 visualizes the spatial variation in the “Home” pat-
ttern. In the middle area of the coastal region, we can see
Table 1. POI Categories and counts in Tokyo 2011.

<table>
<thead>
<tr>
<th>Index</th>
<th>POI Category</th>
<th>POI Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bank, Insurance</td>
<td>10466</td>
</tr>
<tr>
<td>2</td>
<td>House Agency</td>
<td>26901</td>
</tr>
<tr>
<td>3</td>
<td>Transportation(Land)</td>
<td>682</td>
</tr>
<tr>
<td>4</td>
<td>Transportation(Sea)</td>
<td>1293</td>
</tr>
<tr>
<td>5</td>
<td>Transportation(Air)</td>
<td>483</td>
</tr>
<tr>
<td>6</td>
<td>Warehouse</td>
<td>7083</td>
</tr>
<tr>
<td>7</td>
<td>Communication</td>
<td>22738</td>
</tr>
<tr>
<td>8</td>
<td>Electricity, Gas</td>
<td>1252</td>
</tr>
<tr>
<td>9</td>
<td>Technician Related</td>
<td>25000</td>
</tr>
<tr>
<td>10</td>
<td>Sports Facilitate</td>
<td>3468</td>
</tr>
<tr>
<td>11</td>
<td>Sports Shop</td>
<td>1661</td>
</tr>
<tr>
<td>12</td>
<td>Entertainment, Restau</td>
<td>90218</td>
</tr>
<tr>
<td>13</td>
<td>Sightseeing</td>
<td>10318</td>
</tr>
<tr>
<td>14</td>
<td>Hospital</td>
<td>40643</td>
</tr>
<tr>
<td>15</td>
<td>Supermarket, Shopping Mall</td>
<td>9007</td>
</tr>
<tr>
<td>16</td>
<td>Convenient Shop</td>
<td>109474</td>
</tr>
<tr>
<td>17</td>
<td>Car related</td>
<td>10896</td>
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<tr>
<td>18</td>
<td>Education</td>
<td>20504</td>
</tr>
<tr>
<td>19</td>
<td>Bureau</td>
<td>6494</td>
</tr>
<tr>
<td>20</td>
<td>Others</td>
<td>12419</td>
</tr>
</tbody>
</table>

Table 1. POI Categories and counts in Tokyo 2011.

a large area of “blue” regions including exclusion zone and
neighbourhood area caused by the accident at the Fukushima
Daiichi Nuclear Power Station. As surveyed by the Interna-
tional Medical Corps, the top-four destinations of the evac-
uees within Fukushima are given in the right side of Figure 9,
as shown in our results, these regions are labeled with a dom-
inating percentage of “increase” regions as compared with
“decrease” regions.

Parametric People Flow in Urban Planning
A parametric people flow is used to quantitatively model the
interrelationship between people’s lives and the key factors
e.g. the distribution of POIs from statistical data) effecting
their mobility. A quantitative characterization of how POIs
affect human mobility plays an important role in urban plan-
ing. In particular, by comparing the existing POIs (defined
as the POI distribution data directly from the POI dataset)
and estimated POIs (defined as the POI distribution estimated
by the quantitative functional relationship between the POIs
and a people flow), we can evaluate whether the existing POI
within this region is able to satisfy the demand, and therefore
recommend suitable locations for planning a new POI.

To describe the spatial distribution of POIs, we defined the
auxiliary POI-region matrix \( Z \). The first dimension of this
matrix is the indexes of the regions we analyzed, and the sec-
dond dimension is the categories of POIs. Therefore, each en-
try in the matrix is calculated by:

\[
Z_{ij} = \frac{n_{ij}}{\sum_k n_{k,j}}
\]

where \( n_{ij} \) is the number of the \( j \)-th category of POIs within
region \( i \).
closely related to “commercial” pattern as well, however it has a very low value in our factorization results. This could be explained as the “entertaining and restaurant” related life pattern being underlain in “entertaining” pattern. As shown in Figure 11, although the “entertaining” pattern has a very strong spatial distribution similarity with the “commercial” pattern, the time-basis and day-basis are quite different. We can see that people prefer “entertaining” on Friday and Saturday, and at night rather than during the day. This is because some restaurants especially drinking places are closed on Sundays [1] and because people have to go back to work on Mondays, they may prefer to go back home earlier and have a good rest on Sundays. We successfully separated these two patterns and determined the POI categories most related to these patterns.

POI Recommender System

A tensor-factorization based recommender system has been successfully applied to a wide range of application scenarios [27, 13]. In our application, the recommendation of the site-selection of certain type of POIs could be made by observing the positivity or negativity of spectral residue $E_Z$ defined as:

$$E_Z = Z - \sum_{k=1}^{K} u^{(k)} \circ p^{(k)} \tag{5}$$

From the definition of spectral residue, we can imply the entry $e_{i,j}$ of category $j$ in region $i$ as follows:

$$\begin{cases} 
\text{existing POI < estimated POI}, & \text{if } e_{i,j} > 0 \\
\text{existing POI > estimated POI}, & \text{if } e_{i,j} < 0 
\end{cases} \tag{6}$$

The recommendation of “entertainment, restaurant” is shown in Figure 12. The regions in the red oval (in Nakano Ward) are where we find that the existing POI for entertainment is insufficient compared with what the people flow indicates. Nakano Ward has a high density population especially for ages 25 to 45 (as shown in the bottom-left corner of Figure 12, the data is from national census statistics, 2012 [18]) who are most potential group of consumers of entertainment places and restaurants, while there are fewer existing local entertainment places. Besides, Nakano is adjacent to Shinjuku Ward, which is the most famous entertainment hub in Tokyo. All those stated above make Nakano Ward an ideal place for opening a new entertainment place or restaurant. In comparison, the regions in the blue oval are traditional commercial and entertainment places in Tokyo and have been developing for decades and therefore the existing entertaining places has already relatively satiated and stable. Although this area has a very high intensity of entertainment activity (from Figure 11), by taking existing POI distribution into account, this area is not recommended from our algorithm. Note that some regions in this area that has high recommendation value, especially at Tokyo Station and Akihabara Station. The reason for this outlier is the huge building at the station which takes up a large proportion of this region, and there are few entertainment places within the building. However, the “entertaining” people flow is intense here because people who come for entertainment purposes have to take the train to come and leave this area.

People Flow Simulation

Human mobility is one of the most important considerations of infrastructure planning. Simulating a possible people flow under every spatial infrastructure layout will provide a novel and intuitive way to evaluate a city design. In our application, a people flow in an unknown area is simulated using the given spatial distribution of the POIs. The people flow simulation is generated from the time-basis $v^{(k)}$ and day-basis $w^{(k)}$ in CitySpectral space ($k = 1, \cdots, K$) we discovered in the known area used as the training set, along with the region-basis $u_{new}^{(k)}$ defined as:

$$u_{new}^{(k)} := \arg \min_{u^{(k)}} \left\| Z_{new} - \sum_{k=1}^{K} u^{(k)} \circ p^{(k)} \right\|_2^2 \tag{7}$$

which minimizes the reconstruction error of the new POI-region matrix $Z_{new}$ using the POI-basis $p^{(k)}$ that we discovered. Therefore, the people flow tensor in the new region $\hat{Y}_{new}$ can be simulated by:

$$\hat{Y}_{new} = \sum_{k=1}^{K} u_{new}^{(k)} \circ v^{(k)} \circ w^{(k)} \tag{8}$$

Figure 13 shows a visualization of the simulated people flow at 18:30 on May 17 (Tuesday) as compared with the ground truth (people flow tensor calculated directly from GPS log data). The upper-left corner and upper-right corners are both regions with schools and businesses, and share a similar POI distribution. However, upper-left corner is simulated close to
the ground truth, while the people flow in upper-right corner is over-estimated. This could not be simply explained by the POI distribution, and the topology of the road network or the latent attributes of the schools and businesses (such as the working hours) may be the reason of such difference.

**EVALUATION**

**Metric**

To quantitatively evaluate our experimental results, we reconstruct the people flow tensor based on the sum of outer products of the bases, and calculated the element-wise correlation \( \eta^{(K)} \) with the origin tensor and reconstructed tensor:

\[
\eta^{(K)} = Cor \left( \sum_{k=1}^{K} u^{(k)} \otimes v^{(k)} \right)
\]

(9)

where \( \hat{Y} \) is the reconstructed tensor defined as \( \hat{Y} = \sum_{k=1}^{K} u^{(k)} \otimes v^{(k)} \) and \( Cor(*) \) is the function of calculating two matrices/tensors correlation.

However, this metric loses the information of where the error comes from. To have a better understanding of error source, we defined the correlation with respect to Region, Time, and Day.

\[
\eta^{(K)}_{\text{Region}} (r) = Cor \left( \sum_{1}^{R} \sum_{1}^{T} \hat{Y}_{r,t,d} \right)
\]

\[
\eta^{(K)}_{\text{Time}} (t) = Cor \left( \sum_{1}^{T} \sum_{1}^{R} \hat{Y}_{r,t,d} \right)
\]

(10)

\[
\eta^{(K)}_{\text{Day}} (d) = Cor \left( \sum_{1}^{D} \sum_{1}^{T} \hat{Y}_{r,t,d} \right)
\]

where, \( \sum_{1}^{R} \sum_{1}^{T} \hat{Y}_{r,t,d} \) are defined as the matrix the \( r \)-th/\( t \)-th/d-th slice of the tensor from corresponding way.

**Regions**

In the following subsections, we show the reconstruction correlation with respect to the region, time and sample day. We can see from the top-left image in Figure 14, urban areas have a much higher reconstruction correlation than rural areas, which could be explained as a city-wide people flow having a very imbalanced spatial distribution. In urban areas, the people flow is over 1000 times denser than country areas, where there are only a few GPS points in our sample days. As a result, people flow in rural areas is highly uninterpretable. In addition, in our factorization framework, those regions having a smaller people flow will naturally have less weight in the optimization phase.

**Time**

The top-right image of Figure 14 shows the reconstruction correlation with respect to time. We can see that the errors of reconstruction mainly come from the night-time data. As mentioned in the “Data and Preprocessing” subsection, the GPS uploading function is not activated if there is no mobile phone movement. As a result, there are probably only two or three GPS points during the night-time while with one point for every few minutes during the daytime. Although this smaller weight problem was rectified by normalizing, sparser data points still led to higher randomness during the night-time.

**Sample Days**

The bottom image of Figure 14 shows the reconstruction correlation with respect to the sample days. During the first week after the earthquake, the correlation declined. This declination can be explained as human activity being quite different from other days during this period, and thus the emergence of human activities such as the evacuation could seem to be somewhat random without much prior knowledge, and can therefore only be roughly described by the \( K \) basic life patterns. In the future, in accordance to the limitation, a spectral residue based abnormal people flow approach may be a promising extension to our algorithm. In addition, more prior knowledge is extended into this framework to improve a description of the people flow during a disaster.

**Evaluation of People Flow Simulation**

We separated the dataset utilized in “POI Recommender System” subsection into training and testing set. From the training set, we discovered the basic life patterns correlated with the POI distribution, and used the POI distribution in the testing set to simulate the people flow, and quantitatively evaluated by calculating the correlation \( \eta^{(K)} \) defined in Equation 9 between the simulated people flow tensor and the ground truth tensor (the people flow tensor generated from GPS log dataset).

<table>
<thead>
<tr>
<th>Ward/City</th>
<th>Number of Regions</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shinjuku</td>
<td>123</td>
<td>0.7759</td>
</tr>
<tr>
<td>Chuoou</td>
<td>130</td>
<td>0.5813</td>
</tr>
<tr>
<td>Minato</td>
<td>76</td>
<td>0.6487</td>
</tr>
<tr>
<td>Bunkyo</td>
<td>104</td>
<td>0.7082</td>
</tr>
<tr>
<td>Meguro</td>
<td>273</td>
<td>0.5883</td>
</tr>
<tr>
<td>Oota</td>
<td>100</td>
<td>0.8215</td>
</tr>
<tr>
<td>Shibuya</td>
<td>106</td>
<td>0.5956</td>
</tr>
<tr>
<td>Nakano</td>
<td>92</td>
<td>0.8442</td>
</tr>
<tr>
<td>Toshima</td>
<td>75</td>
<td>0.8944</td>
</tr>
</tbody>
</table>

Table 2. Quantitative evaluation on People Flow Simulation.
Quantitative evaluation details are given in Table 2. In our evaluation, the total number of discrete regions in Tokyo is 6516. Each time, we take one ward or city in Tokyo out as the testing data while the remaining regions as the training data. The numbers of discrete regions of the testing set are listed in the second column. Note that in this application, we simulated the people flow based on POIs, and each region was simulated independently (no topological relationship of the regions was taken into account). From Table 2, we can see our simulation reached 0.7 correlation on average, ranging from 0.5134 to 0.8944. These results can be further improved using a more sophisticated people flow simulation model fusing more sources of information such as road network, which will be included in our future work.

RELATED WORK

Urban computing using human mobility data: The emergence of a variety of available human mobility datasets [5, 26] has stimulated a wide-range of research interests on urban computing in recent years. Urban computing has provided a novel perspective on the traditional social issues such as zone regularity [25], air pollution [28], disaster evacuation [19] etc. Y. Zheng provided [29] a comprehensive review on the recent researches, methodologies and challenges of urban computing using human mobility data.

Matrix/Tensor Factorization: Matrix/tensor factorization has been researched for decades in the fields of computer vision [17], signal processing [16], urban computing [27] etc. Lee et al. [14] described the application of Non-negative Matrix Factorization on a face image analysis, and a variety of successful researches [4, 24, 21, 15, 11] in a wide-range of fields have also been published. The positivity constraint in NMF/NTF makes the factorization results more interpretable, and characterize the data space more essentially in many application scenarios. A. Cichocki [2] reviewed the techniques and applications of NMF/NTF, and herein, we refer to the formulation of NTF in this book. For co-factorization with auxiliary spatio-temporal data, the authors in [4] proposed a Simultaneous NMF for extracting gene expression profiles and [21] presented a Non-negative Multiple Tensor Factorization algorithm in analysing the users’ check-in and reviews on geo-locations. We referred to these two works for co-factorization algorithm.

The matrix factorization method has also been introduced into the analysis of spatio-temporal human mobility. N. Eagle et al. [8] modeled the daily human activities from Call Detail Record (CDR) data and factorized into EigenBehaviors using principal component analysis. F. Calabrese et al. [6] modeled the digital signature of on-campus WiFi, and clustering different functional regions in the campus. J. Reades et al. [12] used the telecoms usage data to find the life patterns in Rome. [21] introduced NTF into the analysis of human mobility, however, the check-in data they used is biased on the activities of “entertaining”, and they model check-in tensor accumulated with respect to the day of week, so that their application will be limited (e.g. it is not suitable for modeling the crowd behaviour during disaster time).

Compared with previous work, our novelty can be summarized in the following aspects: 1) We modeled the people flow as a tensor, and thus the life pattern we found out is analyzed from a citywide perspective, rather than analyzing each region independently and annotate the patterns as the ranking of the eigenvalue with the region. 2) We adapted Non-negative Tensor Factorization rather than Principal Component Analysis as our factorization algorithm, and the positivity constraint on the factorization process is more desirable for a people flow analysis as compared to the orthogonality constraint. 3) Finally, in this paper, we proposed an extensible framework and derived four real-world applications from this framework.

CONCLUSION

This paper proposed a spectral analysis framework for decomposing a people flow at a citywide level into basic life patterns. A variety of real-world applications can be derived by fusing spatial or temporal data into this framework. For example, in this paper, we factorized the spatial distribution of POIs simultaneously using a people flow tensor to model the relationship of POIs and human mobility. A site-selection recommendation and people flow simulation are two applications of this co-factorization. In addition, to model geographical shift of the “home” pattern, we co-factorized two people flow tensors of different years in a unified framework.

We note several limitations of our work. First, the GPS Log dataset was constructed by mobile phones and did not cover the portion of population who did not own mobile devices or did not register GPS service. As a result, the dataset was slightly biased towards younger people who are more likely to use GPS service than older people. However, this bias can be reduced by using regional statistics data, which will be included in our future work. Another limitation would be the difficulty of evaluation. In this paper, we quantitatively evaluated the predictability of POIs in the CitySpectral space and partially evidenced our interpretation of our results by the news or other reliable information sources.

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