UrbanRhythm: Revealing Daily Urban Dynamics Hidden in Mobility Data

ABSTRACT

Understanding the regularity of urban residents’ behaviors, or urban dynamics, is of urgent demand for building an efficient and livable city. Nonetheless, this is challenging due to the expanding urban population and city size. In this paper, we propose a novel system UrbanRhythm to reveal the urban dynamics hidden in human mobility data from the view of the city, which is a new perspective. To obtain UrbanRhythm, we first divide the city into different time slots. For each urban region in each time slot, we define its mobility feature as the number of people staying in, leaving from and arriving at this region. Then we utilize an image processing method Saak transform to capture the mobility spatial distribution pattern in the city for each time slot and classify time slots into hierarchical city states. Finally, we characterize the urban dynamics as the transform of city states along time axis. We evaluate our proposed system on two real-life datasets. Several city states are identified and interpreted. Interestingly, we not only discover general states which correspond to residents’ daily behaviors like sleeping, working and relaxing, but also distinguish sub-states such as deep-sleeping and light-sleeping. We find that the urban temporal dynamics are highly daily repeated except that the regularity are different in working day and non-working day. Besides, we implement an App analysis to further validate the detected city states. This study sheds light on urban dynamics hidden in human mobility and can further pave the way for more complicated mobility behavior modeling and deeper urban understanding.

CCS CONCEPTS
- Information systems → Spatial-temporal systems; Data mining; • Human-centered computing → Empirical studies in ubiquitous and mobile computing; • Computing methodologies → Machine learning.

KEYWORDS
Urban dynamics, mobility data, Saak transform, hierarchical clustering.

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1 INTRODUCTION

As reported by UN[^1], up to 2018, 55% of the world’s population lives in urban areas, and this proportion is expected to increase to 68% by 2050. With the increasingly number of urban residents, the rapid urbanization brings the increasingly complicated city structure. These complexities are reflected in the changeable intensity and distribution of the city resources at different time, which raise challenges to city governing, ranging from traffic monitoring, resource scheduling to city planning. Those city resources, including but not limited to population, traffic, are further determined by residents’ behaviors. For example, at rush hours when most residents are on the way to home with crowded traffic, the city belongs to a state; while in mid-night when most residents are asleep, the city belongs to another state. In order to build smart cities which are both efficient and livable, understanding the regularity of residents’ behaviors, i.e., urban dynamics, has become an urgent demand for policymaker, city governors and urban planners.

Previous understanding of residents’ behaviors comes from conducting surveys on human agents, which provides detailed information about people’s behaviors. However, collecting such kind of data is costly, and also has limitations in terms of generalization and geographical scope. Luckily, smart phones and mobile network are popular and ubiquitous everywhere, which makes it available for us to collect large-scale mobility data. Recently, many works have investigated urban dynamics through resident’ mobile behaviors. Sofiane et al. [1] built activity time series for different cities and found that close neighborhoods tend to share similar rhythms. Louail et al. [23] demonstrated that the city shape and hot-spots change with the course of the day. Fabio et al. [25] captured the spatio-temporal activity in a city across multiple temporal resolutions, and visualized different activity levels in different time slots. Xia et al. [33] revealed the daily activity patterns by learning offline mobility and online App usage together. However, these previous works are either based on statics [1, 23] or case studies of several regions [15, 25, 33] which do not consider the all the regions in the city and their spatial relationship, thus are not able to present urban dynamics from the view of the whole city in a concise way.

To bring meaningful and useful insights to researchers and governments, in this paper, we propose a system called UrbanRhythm, to understand the daily urban dynamics hidden in mobility data from the view of the whole city. For a better and deeper understanding, UrbanRhythm needs to answer the following three key questions:

1. What features should be used to characterize urban dynamics from high-dimensional activities?
2. What are the basic components of urban dynamics?
3. What is the regularity of urban dynamics within one day? How does it vary from week to month?

To answer these questions, UrbanRhythm has some specific design. Firstly, we divide the mobility data into different time slots and look into the dynamics reflected by the mobility changing with these time slots. Yuan et al. [36] has proved the moving-in and moving-out flow can be used to discover urban functional regions, and commuting is the most important activity in the city. Thus, for each region in the city in each time slot, we extract staying, leaving, arriving three features to represent the mobility within it.

To detect urban dynamics from the view of the whole city, for each time slot, we map the mobility of different regions in the city to a three-channel city image, where a pixel on the image represents a region, and three channels correspond to staying, leaving, arriving three mobility features. Then image processing methods could be utilized to capture the mobility spatial distribution pattern in the city. Compared with ordinary image processing tasks, we lack supervision and enough data to train a deep learning network. Thus we choose an unsupervised image processing method Saak transform and redefine it to suit our problem.

To answer the second question, we detect city states, i.e., several specific kinds of mobility, by utilizing unsupervised clustering after calculating mobility distribution patterns for each time slot. Specifically, we use hierarchical clustering to investigate not only city states, but also their inclusion relationships. Several city states and sub-states are identified. We interpret them by analyzing the temporal distribution pattern of states, the spatial distribution pattern of mobility, and the relationship between states and sub-states. As a result, we find that city states highly correspond to people’ daily behaviors like working, sleeping, relaxing and commuting. And the differences on the intensity and spatial distribution of mobility further lead to their division to sub-states like deep-sleeping state and light-sleeping state.

For the third question, we visualize the urban dynamics by full time mapping and 24-hour mapping; the regularity of urban dynamics within a day and between days can be observed. We find that the urban dynamics are highly daily repeated except that the regularity are different in weekday, weekends and festival holidays. By further comparing different dynamics, some other interesting dynamic patterns can be found, like the very symmetric night and the unexpected peace in some non-weekday afternoons.

Finally, we carry out two experiments on two real-life datasets of Beijing and Shanghai. Besides answering the above three questions, we employ a TF-IDF analysis [27] on the relation between the App usage and city states to further validate our detection and interpretation of city states.

To summarize, the contribution of our work is three-fold:

- We propose a novel system UrbanRhythm to reveal daily urban dynamics from the view of the whole city. We divide the city into different time slots and classify time slots into hierarchical city states. We characterize the urban dynamics as the transform of city states along time axis.
- We identify specific city states including working time, sleeping time, relaxing time, rush hours and other states corresponding to people’s daily life. These found states can be further divided into sub-states. We find that the urban dynamics are highly daily repeated except that the regularity are different in weekday, weekends and festival holidays.
- We evaluate our method in two mobility datasets from different sources in different cities. Similar as well as different city states are identified between this two cities. Urban dynamics in two cities are revealed, visualized and interpreted. Moreover, we validate our detection and interpretation of city states by employing a TF-IDF analysis on the relationship between App usage and city states.

2 OVERVIEW

2.1 Problem Definition

With the following definitions, we characterize urban dynamics from mobility data.

Definition 1 (Region) In this problem, we partition a city into a $I \times J$ grid map based on the longitude and latitude where a grid denotes a region, as shown in Fig. 1(a). Here, region in $i$-th row and $j$-th column is denoted by $R_{i,j}$.

Definition 2 (City Image) After dividing a city into $I \times J$ grids, we can describe the characters of the city by a three-channel image, where each channel presents one character and each pixel presents one region. Here we define the channels of an image as a staying-channel, a leaving-channel and an arriving-channel presenting that how many people stay at, leave from and arrive in the region during a given time slot, respectively [36]. The 3-channel image of a given time slot is shown in Fig. 1(b).

Definition 3 (City Image Series) City images at different time slots form a city image series, which reveal the variation of human mobility along with the time. A city image series is shown in Fig. 1(c), where $N$ is the total number of time slots. We denote the city image series by $M = M_1, M_2, ..., M_n, ..., M_N$ with $M_n$ denoting the
We use Saak transform to calculate the spatial distribution pattern of mobility. Kuo and Chen [22] proposed the Saak transform recently. The Saak transform converts a single-channel image $A_n$ to a feature vector $F_n$ in spectral space by implement Karhunen-Loeve transform (KLT) step by step. Chen et al. [10] put forward lossy saak transform, in which he uses the principal component analysis (PCA) instead of KLT to save time and space.

**Definition 4 (City state)** We divide city images into several kinds. A city state represent a typical kind of city images and further represent a typical kind of mobility. Similar city images share the same city state. We define the total number of city states to be $K$ and the state of city image $M_n$ to be $S_n$, where $S_n = 0, 1, ..., K - 1$

**Definition 5 (Urban Dynamics)** We classify each city image in city image series to a city state and define urban dynamics as the transform of city states along with time.

In this paper, we aim to transform mobility data to city images series, detect city states from it, and finally reveal urban dynamics by these identified states.

### 2.2 System Framework

**Figure 2: A illustration of UrbanRhythm system.**

Our system is shown in Fig. 2. First, we extract the mobility features staying, leaving, arriving at different time slots to form the city image series $M$. Then, we conduct multi-channel Saak transform on each city image, and finally use the transform outputs as input for the hierarchical clustering to detect city states. Urban dynamics could be revealed by these states at different time slots.

To get deeper insight and answer the second and third questions, i.e., to understand the basic components and the regularity of urban dynamics, we interpret physical meaning of each city state, visualize urban dynamics and investigate special dynamic patterns by comparing different kinds of urban dynamics. In the end, we take an App usage analysis to validate our detection and interpretation of city states.

### 3 ALGORITHM DESIGN

#### 3.1 Saak transform

We use Saak transform to calculate the spatial distribution pattern of mobility. Kuo and Chen [22] proposed the Saak transform recently. The Saak transform converts a single-channel image $A_n$ to a feature vector $F_n$ in spectral space by implement Karhunen-Loeve transform (KLT) step by step. Chen et al. [10] put forward lossy saak transform, in which he uses the principal component analysis (PCA) instead of KLT to save time and space.

**Figure 3: The first stage of Saak transform.** We assemble each four adjacent regions into a grid, then apply PCA on all grid vectors and conduct a S/P transform on the outputs vectors of PCA. Finally, we refill the transformed vectors to their original grids and generate new images.

Under our problem definition, with images series as input, each stage of Saak transform has the following three steps:

1) **Assemble adjacent regions:** We first choose the size of area in which we calculate the local distribution pattern. In practice, we choose the basic scale of $2 \times 2$. Let value in region $R_{i,j}$ denoted by $r_{i,j} \in R^D$, $i,j = 1, 2, \ldots, L_{in}$, where $L_{in}$ is the input width and height. For each city image, assemble each 4 adjacent regions to be a new grid, denoted as $G_{i,j} \in R^{4D}$, $i,j = 1, 2, \ldots, L_{out}$.

$$g_{i,j} = \text{Concatenate}(r_{2i-1,2j-1}, r_{2i-1,2j}, r_{2i,2j-1}, r_{2i,2j})$$  \hspace{1cm} (1)

$$L_{out} = L_{in}/2$$  \hspace{1cm} (2)

2) **Calculate local distribution pattern:** We conduct principal component analysis (PCA) on grids vectors from all $N$ city images. In this way, for each grid $G_{i,j}$, a comparison with other grids among all city images is implemented and the variation pattern is calculated and expressed as output vectors $G_{i,j}^{\text{out}}$.

To avoid the change of sign in two consecutive stage, we conduct a sign-to-position (S/P) transform , with $G_{i,j}^{\text{in}}$ as input and $G_{i,j}^{\text{out}}$ as output.

$$g_{2k-1} = \text{Relu}(g_{k}^{\text{out}}), k = 1, 2, \ldots, 4D$$

$$g_{2k} = \text{Relu}(-g_{k}^{\text{out}}), k = 1, 2, \ldots, 4D$$

3) **Generate new image:** Refill each grid $G_{i,j}$ with the transform vector $g_{i,j}^{\text{out}} \in R^{4D}$. Form $N$ new images with half the original width and height. The spatial relationship between grids are kept for the next stage transform.

The scale of $2 \times 2$ is the smallest scale we can choose. Using bigger scale like $3 \times 3$ or $4 \times 4$ may miss the influence of small district pattern to city state. And the same as Chen et al. did, we reserve components with explained variance ratios lager than $3\%$ in PCA, which has been proved to be an acceptable compromise between efficiency and reserving discriminative information [10].

The first stage of Saak transforms is illustrated in Fig. 3. In $k$ stage of Saak transform, the local spatial pattern of $2^k \times 2^k$ scale is calculated. Put together the outputs of all stages, the spatial distribution pattern of mobility is calculated.

#### 3.2 Multi-channel Saak transform

The original Saak transform only deals with one channel at one single time. We can’t directly concatenate three channels of city images and apply Saak transform because people’s staying, leaving, arriving are obviously correlated.
Thus we design Multi-channel Saak transform. We apply KLT on channels to do decorrelation and use KLT-transformed images as input for Saak transform. For each city image, put together the outputs for all stages of Saak transform as the feature vector for this city image.

3.3 Clustering
After Saak transform, each city image $M_n$ can be represented as feature vectors $F_n(n = 1, 2 \ldots N)$. To save time and space for clustering, we apply PCA on feature vectors to reduce their dimensions to 128, uniformly. The choice of this dimension is under the consideration of the explained variance ratio of PCA.

Intuitively, human mobility behaviors usually have intrinsic periods of day and week; city state of different time could be alike. Thus unsupervised clustering method can be utilized on city images to find those with similar mobility features. However, the problem of totally unsupervised clustering is that we don’t have a specific standard to evaluate the cluster results and due to that it’s hard for us to specify a number of clusters. On the other hand, we’re not only curious about a specific set of city states or a specific kind of city dynamics, but also their inclusion relationships. So to better understand the process of clustering and the relationship between clusters, we use hierarchical clustering method to cluster feature vectors.

We conduct hierarchical clustering in these obtained feature vectors $F_n(n = 1, 2 \ldots N)$ of city images. The basic idea of hierarchical clustering is to generate a tree of clusters where two son clusters merge to form a father cluster. The leaf node of this tree is the input $N$ feature vectors. And then from bottom to up iteratively merge the most suitable two clusters until the stop condition is met. We define the suitability of two clusters' merging according to Ward’s method [19], to minimize the variance of the clusters after merging. From these two figures, we can explicitly observe that in the feature space, the time slots of the same state distribute closely to each other, while the time slots of different states generally have a larger distance. Therefore, it demonstrates that the Saak and PCA transform is effective to represent the feature of time slots.

4.4.1 Hierarchical Clustering Structure. Since hierarchical clustering is utilized, the structure of clustering results from up to bottom could be clearly observed. By default, we display the cluster hierarchy using several circles, where child clusters are nested within their parent cluster. For Beijing, we show the 3-level results for 3, 7, 11 clusters exhibited in circles with the color from blue to white in Fig. 5. We also label the semantics for each state when the time slots are divided into 11 clusters. Obviously, the outermost three circles represent three basic states in city that people are working, relaxing and sleeping. When the number of clusters increases, the time slots can be divided into more detailed states. For example, the basic sleeping state of Beijing can be divided into four states Home, Sleep 1, Sleep 2 and Sleep 3, which represent different levels of people’s staying home and movement in the city. The latter three sub-states could be further interpreted as different levels of how many people.

4.4 Clustering Results
By hierarchical clustering, we can detect city states and further answer the second and third question by the analysis on clustering results.

Privacy and ethical concerns: We have taken the following procedures to address the privacy and ethical concerns. First, all of the researchers have been authorized by data provider to utilize the data for research purposes only. Second, the data is completely anonymized. Third, we store all the data in a secure off-line server.
Table 1: Key features of two real world mobility datasets we utilize.

<table>
<thead>
<tr>
<th>City</th>
<th>Sources</th>
<th>Localization Method</th>
<th>Duration</th>
<th>Number of Users</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beijing, China</td>
<td>Mobile apps</td>
<td>GPS module</td>
<td>1 Apr. ~ 30 Apr. (2018)</td>
<td>18,916,166</td>
</tr>
<tr>
<td>Shanghai, China</td>
<td>Cellular network</td>
<td>Cellular base station</td>
<td>21 Apr. ~ 25 Apr. (2016)</td>
<td>1,700,000</td>
</tr>
</tbody>
</table>

Figure 5: Hierarchical clustering results with different cluster numbers.

Figure 6: Visualization of dynamics for Beijing when the number of clusters is 11. In (a), we show the transform of city state along with time within 30 days. In (b), we visualize dynamics for 4 kinds of days, i.e., weekday, weekends, May Day and Qingming Festival.

1) Full time mapping: Since N city images of N time slots could be regarded as a time series, we go back to time series and plot each slot with its identified state, forming a state series that present the transform of state over time. By doing this, we hope to reveal the period of human mobility and the regularities of urban dynamics.

2) 24-hour mapping: To analyze the variation of city state in a day, we show each 48 time slots in the same day as a 24-hour pie chart. Besides, we divide the time slots into weekend, weekday and holidays to show 24-hour pie charts respectively. By doing this, dynamics within a day can be observed and different kinds of dynamics are presented and compared.

For Beijing, the state series is shown in Fig. 6(a), and the 24-hour pie chart is shown in Fig. 6(b). Since the dataset of Beijing covers a whole month, we can easily observe the period of day and week in the state transform process. The distribution of state on the time axis is very symmetrical and neat, which is consistent with the regularity of people’s daily commuting. To explain these states in more detail, we align the states on the time axis and display them in 24-hour pie chart, where each circle presents one day and time slots...
we conclude in these states most people are at work. Besides, in
reflected by high values of official areas in staying-channel. Thus,
appearing in only weekdays. In these state, most people are working
and arriving.
Compared to Rush 1, people presents more staying, less leaving
off-work rush. Rush 2 appears both weekdays are non-weekdays.
Rush 1 only appears in weekdays, corresponding to go-to-work and
distribution of people in city address the main road. Specifically,
in arriving-channel and leaving-channel than staying-channel. The
states, most people are moving in traffics, reflected by bigger value
surprised to find it also appears in some non-weekdays afternoons.
according to the clustering structure in Fig. 6. However we are
channel and smaller value in leaving-channel and arriving-channel,
in all days. It is similar to Relax states, for they belong to the same
root state according to Fig. 5. However the values of leaving-channel
in all three channels decrease from Sleep 3 to Sleep 2 to Sleep 1, which
means more and more people become asleep.
Home State: This state usually covers 23:00-23:30 and 7:00-7:30
in all days. It is similar to Sleep states with larger value in staying-
channel and smaller value in leaving-channel and arriving-channel,
according to the clustering structure in Fig. 6. However we are
surprised to find it also appears in some non-weekdays afternoons.
Rush States: These states include Rush 1 and Rush 2. In these
states, most people are moving in traffics, reflected by bigger value
in arriving-channel and leaving-channel than staying-channel. The
distribution of people in city address the main road. Specifically,
Rush 1 only appears in weekdays, corresponding to go-to-work and
off-work rush. Rush 2 appears both weekdays are non-weekdays.
Compared to Rush 1, people presents more staying, less leaving
and arriving.
Work States: These state include Work 1 and Work 2 state, both
appearing in only weekdays. In these state, most people are working
reflected by high values of official areas in staying-channel. Thus,
we conclude in these states most people are at work. Besides, in
Work 2, people’s movement is more frequent than in Work 1. We
are surprised to find that people’s movement in noon is close to
that in the beginning and end of office time.
Relax States: These states include Relax 1,2,3. Relax 1 covers
most day-time in holidays when many people travel far away from
the city. Relax 2 covers day-time in weekends, 22:00-23:30 and
7:30-8:00 in weekdays and it presents larger value in all three chan-
nels than Relax 1. Relax 3 appears mostly after Relax 2 or in non-
weekdays mornings, with much lower arriving value and leaving
value than Relax 2.
For Shanghai, the state time series is shown in Fig. 7(a), and the
24-hour pie chart is shown in Fig. 7(b). Since the dataset of Shanghai
covers only five days, we can only observe the period of day. But
the distribution of state on the time axis is still very symmetrical
and neat. We summarize the characters of each state as follows:
Sleep State: This state mainly covers 23:30-06:00. Most people
are sleeping and few people are moving in the city. Values in
arriving-channel and leaving-channel are very low.
Work States: These states include Work 1 and Work 2. Most
people are at work and slight movement in the specific office
district. Specifically, people in Work 2 state have more movement
than Work 1.
Rush States: These states include Morning rush, Afternoon
rush and Saturday morning. In these rush states, people’s moving
is much stronger than work and sleep states. Movement in theses
states addresses downtown areas. The value of leaving-channel in
Morning rush higher than that of arriving-channel. However, it
is just opposite in Afternoon rush. In Saturday morning, value in
both leaving-channel and arriving-channel is high, suggesting the
movement in Saturday morning is more directionless than that in
weekdays.
Relax States: These states include Weekends relax and Evening
relax. The movement is more frequent than work hours and less
frequent than rush hours, as well as less concentrated in office areas
and downtown areas. This indicates people are moving all around
the city without very heavy traffic. Thus we conclude people are
moving for relaxing in these two states.
Home State: This state usually covers 21:30-23:30 and 6:00-7:00
in all days. It is similar to Relax states, for they belong to the same
root state according to Fig. 5. However the values of leaving-channel
and arriving-channel are smaller than that in Relax states, but larger
than that in Sleep states. Thus Home state corresponds to the time
when people are at home with few movement.
To conclude, observing the state in the 24-hour pie chart from
clockwise, we have that the dynamics of city from morning to night,
from day to month, which reveal the regularity of people’s mobility
behavior from inactive to active, and last back to inactive in circle
of one day.
4.4.3 Special States Patterns. For Beijing’s data covers longer time,
we compare its dynamics between different days and find some
spatial patterns. Some of our results well match people’s intuition
while some give surprises.
Weekends VS Holidays: Two holidays are detected through
our method, i.e., Qingming Festival and May Day. People have
intuition that weekends and holidays are different, but wonder why and how. As showed in Fig. 6, in weekends, Relax 3 covers very morning time and Relax 2 covers other day time and some evening time. However in holidays like Qingming Festival and May day, Relax 1 covers almost all the time. Relax 3 covers very morning time and almost all the evening time. This shows that people’s movements pattern are similar in weekends’ and holidays’ mornings and evenings, while differ in their day-time. we conclude that in holidays’ day-time, people tend to travel far away from the city, while in mornings and evenings, people haven’t set off or have backed the city, following the same pattern as weekends.

**Last night of holidays:** We usually have a sense that on the last night of holidays, our pace of life back to normal. Interestingly, we find that in the last night of Qingming Festival, city’s dynamic back to weekends patterns, where a Rush 2 state appears first, then followed Relax 2 and Relax 3. It matches with our intuition that people come back city in the last day of holiday, causing a traffic jam, then most people get home while some people still hang out. Note that our data only covers the first two days of May Day, so this pattern doesn’t appear in May Day.

**Symmetric night:** We find that sleep states are more symmetric than expected. This pattern is for all the days, regardless weekdays or not. As showed in Figure 6, city’s states in night are : Home - Sleep 3 - Sleep 2 - Sleep 1 - Sleep 2 - Sleep 3 - Home. Though this comes from people’s movement patterns, but well matched people’s sleeping habits. The government can properly arrange resources like illumination and construction according to this night dynamics.

**Unexpected peace in afternoons:** We find Home state surprisingly appears in two holiday afternoons and one weekend afternoon. This suggests people’s slight movement, which means at these moments, the city is as ‘quite’ and ‘peaceful’ as about-to-sleep hours.

### 4.4.4 City Images for States

To further explain the states obtained through hierarchical clustering, we show the spatial distribution of the three original mobility features for different time slots and compare their difference. Limited by space, we only compare Morning rush, Afternoon rush, Sleep 1, Work 1 states in Shanghai, whose physical meanings are go-to-work rush, off-work rush, sleeping, working as shown Fig. 8. The heatmap is colored with the relative density.

1) Compared with working state, in sleeping state, people’s staying is distributed more uniformly with low arriving and leaving. However, for working state, people are staying in some specific area with higher arriving and leaving than sleeping state. The reasonable explanation is that people are staying at home and the living area in the city is distributed more uniformly than office areas.

2) As for go-to-work rush and off-work rush, the arriving-channel and leaving-channel have higher values than other states. The distribution of mobility in city address the downtown area and main road. These show that these two states are much about traffic. Interestingly, staying people in off-work rush are more than those in go-to-work rush. And this may due to that people usually have a uniform time to go to work, but do not have uniform off work time. Someone keep staying office while others are on the way home. We also find that the arriving-channel and leaving-channel in go-to-work rush is similar to the leaving-channel and arriving-channel of off-work rush. This implies that off-work rush is the opposite process of go-to-work rush.

### 4.5 Validation with App Usage

Considering that the numbers of Apps in each App category are different, we can not compare the absolute usage count in the same state directly. In order to address this problem, we use TF-IDF statistic to analyze the relationship between App usage and city states [27]. We denote $U$ as the absolute usage count of each App, where $U_{i,j}$ means the usage of i-th App under j-th state. Thus, the transformed App usage $U'$ can be calculated as follows,

$$U'_{i,j} = \frac{U_{i,j}}{\sum_j U_{i,j}} \times \log \frac{\sum_i U_{i,j}}{U_{i,j}}. \quad (3)$$

The result is shown in Table 2, where we can observe that:

1) In Sleep state, the usage of all Apps are lowest.
5 RELATED WORK

Urban dynamics modeling: Forrester first summarized the previous researches about modeling bits and pieces of urban areas as urban dynamics models in [16]. [6, 20] proved and extended the model proposed by Forrester. In addition, Batty et al. [5] utilized fine-grained cellular automata to model urban activities, which can be adapted to simulate urban development over very different time periods. In recent years, [11] detected city areas depicting a snapshot of activity patterns of its people. With more attention to temporal dimension, [21] used a Topic model to characterize urban dynamics; [37] used the geo-tagged social data to analyze urban dynamics; [15] modeled city dynamics in a basic life pattern space. We also see urban dynamics view the spatial distribution patterns as the transform of city states along the time axis. Different from previous works, we divide the city into different hierarchical states and characterize urban dynamics as the transform of city states. Moreover, we consider the spatial distribution of human mobility in the city as a factor influencing urban dynamic and use an image processing method to capture such distribution patterns.

Mobility pattern revealing: Revealing the hidden pattern in mobility data becomes popular these years [7, 9, 29, 30]. From the view of individuals, [26, 28, 31] revealed the pattern of people's behaviors. From the view of regions, [3] explored significant places; [35, 38] predicted the function of regions; [15] used a non-negative tensor factorization approach to decompose human mobility into variations among regions and times; [33] revealed the daily activity pattern of specific regions. From the view of events, [13] detected special event by analyzing spatio-temporal data; [8] analyzed cell-phone mobility and the relationship between events and attendees. To best of our knowledge, we are first to use mobility data to understand urban dynamics from the whole view of the whole city. Our analyzing target is not a single region, but the whole city composed of numerous regions. Thus we use image processing method Saak to capture the spatial distribution pattern of human mobility. Our analysis of App usage gives more interpretation to our results.

Image transformation and its application: In this paper, we use Saak transform [22] to extract the spatial distribution pattern of mobility for city images. Saak transform is a spatial-spectral transform like the discrete cosine transform [2] and the Wavelet transform [12]. There have been a lot of applications for these transforms, like image coding [4], image compression [32], face recognition [18], etc. To best of our knowledge, we are the first to apply image transformation in urban dynamics detection. There are also deep learning methods for image transform, i.e., unsupervised feature extraction [14, 17, 34]. However, they are hard to train and require a large number of training samples, making it not realistic in our problem.

6 CONCLUSION

In this paper, we propose a novel system UrbanRhythm to reveal urban dynamics hidden in human mobility data from the view of the city. We divide the city into different time slots, classify those time slots into hierarchical city states and finally characterize the urban dynamics as the transform of city states along time axis. Extensive experiments on two real-life datasets of different cities demonstrate the efficiency of our method. We give interpretations for the identified city states which pave the way for more applications, such as traffic monitoring, resource scheduling and urban planning. We employ a TF-IDF analysis on the relationship between App usage and city states to validate our interpretation. Some special dynamic patterns are discovered and analyzed as well. Our work opens a new perspective to investigate urban dynamics and to reveal the patterns in mobility data.

After the detection of city states and urban dynamics, the following question is what factors cause the change of city states. For example, which regions influence city state most and how? Short-term factors like a event or weather, long-term factors like season may influence city states and dynamics as well. These need further investigations.