UrbanRhythm: Revealing Daily Urban Dynamics Hidden in Mobility Data

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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 datesets. 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. 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 is costly and 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

[1]https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html

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.

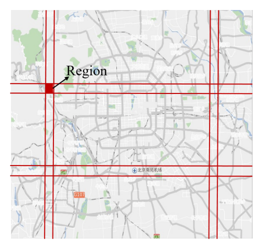
To summarize, the contribution of our work is three-fold:

- We propose a novel system UrbanRhythm to reveal daily urban dynamics from the view of the whole city.
- We 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. Some other interesting dynamics patterns are analyzed as well.
- We evaluate our method in two mobility datasets from different sources in different 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.

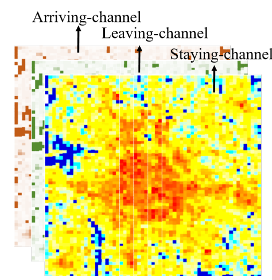
2 OVERVIEW

2.1 Problem Definition

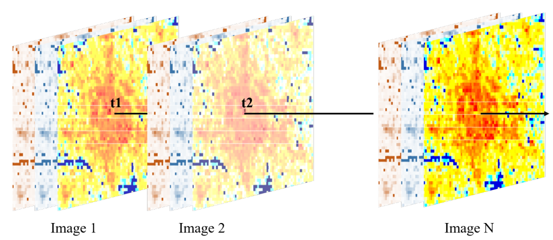
With the following definitions, we characterize urban dynamics from mobility data.



(a) Grid-based city partition



(b) Three-channel city image



(c) City image series

Figure 1: A illustration of definitions of region, city image and city image series.

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 an 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).

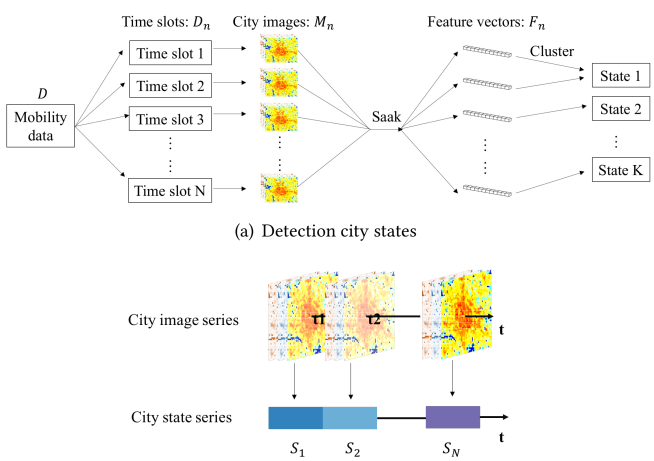
Definition 3 (City Image Series) City images at different time slots form a city image series, which reveal the variation of human mobility along with the time. A city image series is shown in Fig. 1(c), where N is the total number of time slots. We denote the city image series by $M = M_1, M_2, ..., M_n, .., M_N$ with M_n denoting the image at *n-th* time slot.

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



(a) Detection city states

(b) Reveal city dynamics

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.

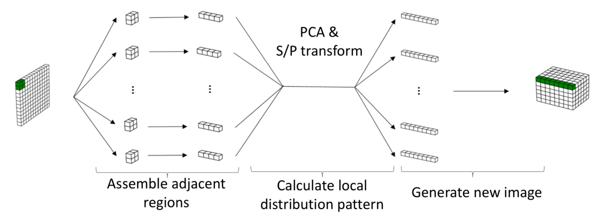


Figure 3: The first stage of Saak transform. We assemble each four adjacent regions into a grid, then apply PCA on all grid vectors and conduct a S/P transform on the outputs vectors of PCA. Finally, we refill the transformed vectors to their original grids and generate new images.

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 2×2. 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 $G_{i,j} \in R^{4D}$, $i, j = 1, 2 \ldots L_{out}$.

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

$$L_{out} = L_{in}/2 \quad (2)$$

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 $G^*_{i,j}$.

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

$$g'_{2k-1} = Relu(g^*_k), k = 1, 2 \ldots 4D$$
$$g'_{2k} = Relu(-g^*_k), k = 1, 2 \ldots 4D$$

3) **Generate new image:** Refill each gird $G_{i,j}$ with the transform vector $g'_{i,j} \in R^{8D}$. 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 2×2 is the smallest scale we can choose. Using bigger scale like 3*3 or 4*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. 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 $F_n(n = 1, 2 \dots N)$. 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 $F_n(n = 1, 2 \dots N)$ 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. By applying hierarchical clustering instead of distance-based or density-based clustering, we could analyze the dynamic states at different levels.

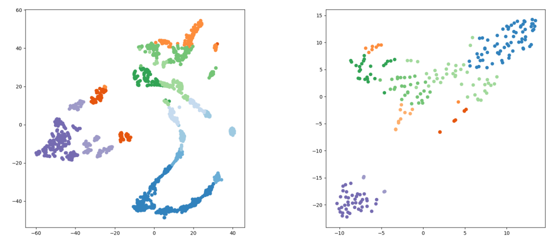
4 PERFORMANCE EVALUATION

In this section, we experiment our algorithm in two different datasets. We further answer the second and third question based on these results.

4.1 Datasets

We collect two large scale real world mobility datasets to apply and evaluate our methodology. The datasets are collected from two different metropolis: Beijing and Shanghai, China. The features of the datasets are presented in Table 1. Shanghai dataset also contains the mobile applications (App) the mobile users are currently using, by resolving the *URI* of *HTTP requests*. We use this App usage records to further validate the city states identified by analyzing mobility features.

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.



(a) t-SNE for Beijing (b) t-SNE for Shanghai

Figure 4: Feature visualization using 8 clusters to represent 8 states, where each point represents one time slot and time slots in the same state are presented in the same color.

4.2 Pre-processing

We divide Beijing into $1km \times km$ grids, and finally remain the areas in downtown with total grid number of 61×65. For Shanghai, to evaluate the flexibility of our framework, we divide its city areas into 256×256 grid map, where each grid has a granularity of $200m \times 200m$. Besides, we calculate the mobility features *staying, leaving, arriving* for each half hour. Thus, the number of city images for Beijing is 1440 and for Shanghai is 240.

4.3 Feature Space Visualization

We apply PCA on features vectors after Saak transform to reduce their dimensions and as the input for clustering. We conduct t-SNE [24] to visualize the relationship of all 128-dimensional features. Results for Beijing and Shanghai are shown in 4(a) and 4(b), respectively. 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 Clustering Results

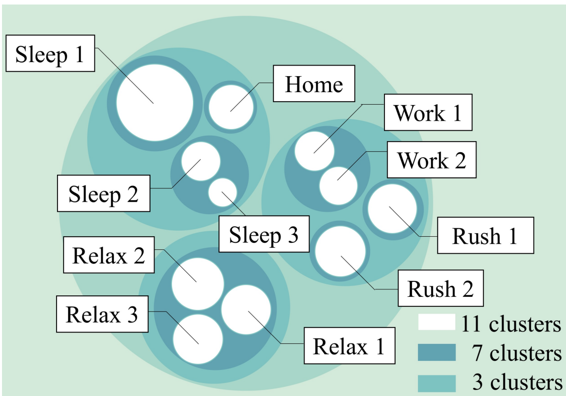
By hierarchical clustering, we can detect city states and further answer the second and third question by the analysis on clustering results.

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.

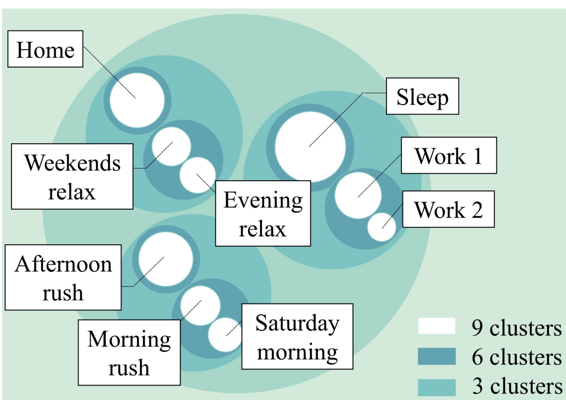
For Beijing, we show the 3-level results for 3, 7, 11 clusters exhibited in circles with the color from blue to white in Fig. 5. We also label the semantics for each state when the time slots are divided into 11 clusters. Obviously, the outermost three circles represent three basic states in city that 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

City	Sources	Localization Method	Duration	Number of Users
Beijing, China	Mobile applications	GPS module	1 Apr.~30 Apr. (2018)	18,916,166
Shanghai, China	Cellular network	Cellular base station	21 Apr.~25 Apr. (2016)	1,700,000

Table 1: Key features of two real world mobility datasets we utilize.



(a) Beijing clustering



(b) Shanghai clustering

Figure 5: Hierarchical clustering results with different cluster numbers.

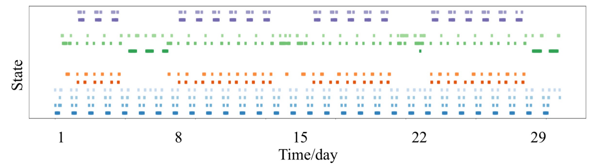
are sleeping, respectively. The same is to Shanghai. We show the 3-level results for 3, 6, 9 clusters in Fig. 5.

To conclude, the hierarchical relationships of different time slots is consistent with our intuitions to the states of city, which is pave the way for our understanding of urban dynamics.

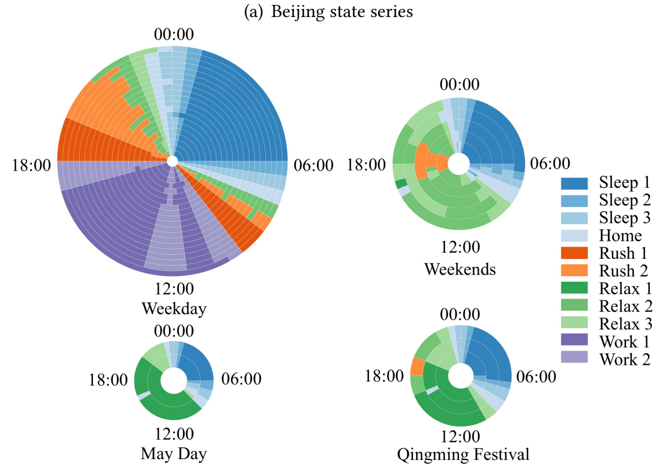
4.4.2 Urban Dynamics Analysis. To analyze specific city states and investigate how they correspond to residents' daily life, we set the number of clusters to be 11 and 9 for Beijing and Shanghai respectively and interpret the physical meaning of each state by analyzing the temporal distribution pattern of states, the spatial distribution pattern of mobility, and the relationship between states and sub-states.

To investigate the regularity of urban dynamics within a day and how it vary from day to day, we visualize the obtained urban dynamics in two aspects as follows:

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



(a) Beijing state series



(b) Beijing 24 hours pie charts

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.

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 in the same state are exhibited in the same color. We summarize the characters of each state as follows:

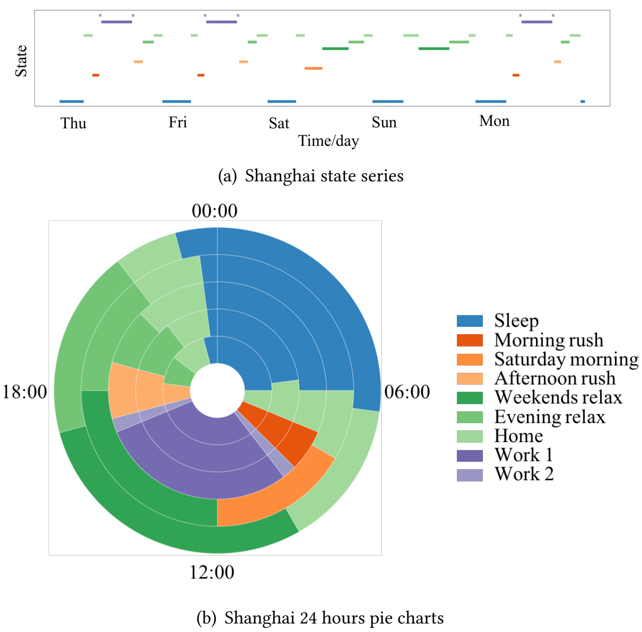


Figure 7: Visualization of dynamics for Shanghai when the number of clusters is 9. In (a), we show the transform of city state along with time within 5 days. In (b), to better compare dynamics between weekdays and weekends, we visualize dynamics for Mon, Thu, Fri, Sat, Sun from inner circle to outer circle.

Sleep States: These states include Sleep 1, Sleep 2 and Sleep 3. In these states, most people are sleeping and few people are moving in the city, reflected by bigger value in staying-channel than arriving-channel and leaving-channel. Besides, values in all three channels in Sleep states are much smaller than others states, suggesting few people are using the mobile application. Values 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 staying-channel in official areas. 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, 22:00-22:30 and 7:30-8:00 in weekdays and it presents larger value in all three channels 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 with 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.

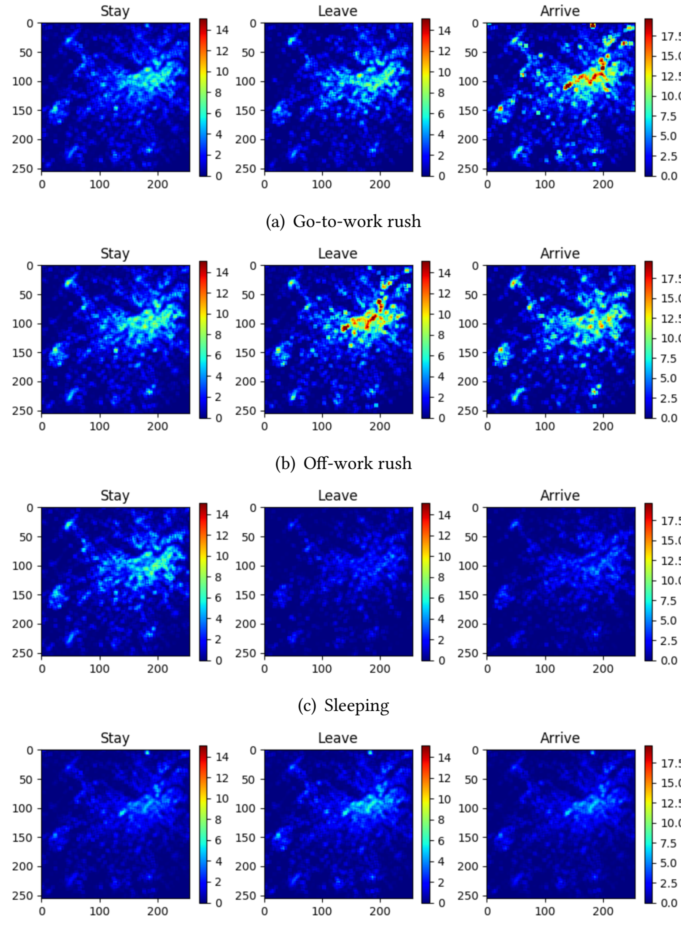
Symmetric night: We find that sleep states are more symmetric than expected. This pattern is for all the days, regardless weekdays or not. As showed in Figure 6, city's states in night are : Home - Sleep 3 - Sleep 2 - Sleep 1 - Sleep 2 - Sleep 3 - Home. Though this comes from people's movement patterns, 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.



(a) Go-to-work rush

(b) Off-work rush

(c) Sleeping

(d) Working

Figure 8: City images for Shanghai. We show the spatial distribution of the three original mobility features for four city states whose physical meaning are go-to-work rush, off-work rush, sleeping and working.

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,

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

The result is shown in Table 2,where we can observe that:
1) In Sleep state, the usage of all Apps are lowest.
2) In Work states, including Work 1 and Work 2, the usage of Stock and Office are highest.
3) In Rush states, the usage of Transportation Apps is high in Morning rush, Afternoon rush, and highest in Saturday morning. Interestingly, in Morning rush and Afternoon rush, the usage of Music and Restaurant is highest.

Usage	**Morning rush**	**Afternoon rush**	**Sat morning**	**Relax 1**	**Relax 2**	**Home**	**Work 1**	**Work 2**	**Sleep**
Social	0.326	0.418***	0.317	0.351	0.338***	0.22***	0.409	0.4	0.073
Video	0.342	0.412	0.336**	0.361***	0.36*	0.238*	0.376	0.367	0.091*
Music	0.446*	0.436**	0.302	0.316	0.309	0.217	0.344	0.391	0.07
Reading	0.441**	0.391	0.321	0.318	0.291	0.207	0.393	0.402	0.068
Game	0.398***	0.411	0.323	0.34	0.323	0.229**	0.379	0.381	0.087**
Shopping	0.338	0.413	0.31	0.353	0.308	0.189	0.427***	0.423***	0.059
Restaurant	0.226	0.461*	0.332***	0.439*	0.355**	0.143	0.398	0.357	0.041
Transportation	0.354	0.402	0.369*	0.374**	0.304	0.208	0.386	0.385	0.076
office	0.356	0.392	0.316	0.334	0.306	0.206	0.429**	0.424**	0.086***
stocks	0.192	0.195	0.074	0.062	0.092	0.058	0.815*	0.489*	0.016

Table 2: The TF-IDF results for App usage, where * means the most frequently used APP in each state, while ** and * means the second and the third frequently used APP in each state, respectively.**

4) In Relax states, including Relax 1 and Relax 2, the usage of Restaurant, Video, Transportation, Social Apps are high. Specifically, in Relax 1 state where some people tend to travel far in weekends, the usage of Transportation Apps is higher than that in Relax 2 state where people get fewer movement.
5) In Home state, the usage of all Apps is low and the usage of Video and Game are highest among them. People tend to stay home, rest and relax.

These observations and conclusions support our interpretation for the identified city states, and further demonstrate that urban dynamics could be revealed from human mobility behaviors.

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 period. In recent years, [11] detected city areas depicting a snap-shot 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 analyzed urban dynamics; [15] modeled city dynamics in a basic life pattern space. We also reveal urban dynamics from the view of temporal dimension. 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 cellphone 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 view of the whole city. Our analyzing target is not a single region, but the whole city composed with 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]. Applications for these transforms includes 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 datesets 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. This paper opens a new perspective to investigate urban dynamics and to reveal the patterns in mobility data. Our future work will be discovering how different factors influence city dynamics, including short-term factors like weather and long-term factors like season.

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