Fine-Grained Urban Event Detection and Characterization Based on Tensor Co-Factorization

Longbiao Chen, Jérémie Jakubowicz *Member, IEEE*, Dingqi Yang, Daqing Zhang *Member, IEEE*, Gang Pan*

***Abstract*—Understanding the irregular crowd movement and social activities caused by urban events such as city festivals and concerts can benefit event management and city planning. Although various urban data can be exploited to detect such irregularities, the crowd mobility data (e.g., bike trip records) are usually in a mixed state with several basic patterns (e.g., eating, working, recreation), making it difficult to separate concurrent events happening in the same region. The social activity data (e.g., social network check-ins) are usually over-sparse, hindering the fine-grained characterization of urban events. In this paper, we propose a tensor co-factorization based data fusion framework for fine-grained urban event detection and characterization leveraging crowd mobility data and social activity data. First, we adopt a Nonnegative Tensor Co-Factorization (NTCoF) approach to decompose the crowd mobility tensor into several basic patterns, with the help of the auxiliary social activity tensor. We then use a Multivariate Outlier Detection (MOD) based method to identify irregularities from the decomposed basic patterns, and aggregate them to detect and characterize the associated urban events. We evaluate the performance of our framework using real-world bike trip data and check-in data from New York City and Washington, D.C, respectively. Results show that by fusing the two types of urban data, our method achieves fine-grained urban event detection and characterization in both cities, and consistently outperforms the baselines.**

***Keywords*-event detection; tensor factorization; urban data**

I. Introduction

The rapid progress of urbanization has modernized many people's lives. Today, 54% of the world's population lives in urban areas [1]. With the increasing population in cities, one of the key challenges faced by urban authorities is the management of *urban events*, i.e., the notable occurrences that attract large crowds of people gathering at specific venues for certain activities during a period of time, such as public concerts, sports games, and festival parades [2], [3]. Such urban events usually incur significant and unusual irregularities of human movement and activities, bringing issues such as traffic congestion and potential security risks [4]. For example, during the opening game of the FIFA World Cup 2010, a traffic jam occurred for more than four hours around Johannesburg, South Africa, where the game was taking place. Understanding the irregularities associated with urban events can help urban authorities gain a panoramic view of these events, especially in the following aspects [5]:

- **The influenced regions of an event**: citywide events such as parades and fireworks shows usually attract large crowds to different regions, which might be different from the pre-arranged routes and venues by event organizers.
- **The gathering time for an event**: people might start to gather for events earlier than scheduled. For example, the audiences of lawn concerts and sport games usually arrive much earlier before the starting time.
- **The popular activities of an event**: people might perform different activities during an urban event. For example, on Independence Day in Washington, D.C., many people might gather at parks for picnic, attend public concerts, and watch fireworks.

The above-mentioned fine-grained characterization of urban events can not only benefit decision making in future urban event management [4]–[6], but also help long-term city planning such as building new stadiums or making evacuation plans for urban centers [7]–[9]. Traditionally, urban authorities usually collect event information from organizers before the events take place [5]. However, such information might not align well with the real-world situation, resulting in potentially sub-optimal urban event management and city planning.

Fortunately, with the ubiquity of urban sensing infrastructures and paradigms, the large-scale digital traces that people leave while interacting with urban spaces can be well captured [10]–[12]. These *urban data* [13] provide us with new opportunities to understand the crowd movement and social activities associated with urban events. In particular, the following two categories of urban data have been exploited by researchers: (1) *crowd mobility data*, which can be collected from bike trip records in bike sharing systems [14], GPS trajectories of taxis and cars [15], [16], and cell-phone traces in cellular networks [6], etc., and (2) *social activity data*, which include users' check-ins in Location-Based Social Networks (LBSNs) [17], Mobile Crowdsensing platforms [18], [19], and noise or traffic complaints reported to government services [20].

Based on these urban data, various kinds of urban event detection methods have been proposed [2], [3], [21]. On one hand, by exploiting the crowd mobility data, one can model

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the crowd movement in a region by estimating a probability distribution, and then identify irregular occurrences associated with urban events [2]. However, since crowd movement is usually a mixture of various basic patterns [22] (e.g. working, eating, recreation), such method can not separate irregularities caused by concurrent events taking place in the same region (e.g., a parade and a lawn concert near a park). Moreover, the detected crowd movement irregularities do not carry semantic information about people's activity (e.g., gathering for parade or for concert), hindering the fine-grained characterization of the associated urban events. On the other hand, the social activity data contain rich semantic information [6], [23], which can be used to describe the fine-grained characteristics of urban events. For example, a crowd of people checking-in at a music stadium may correspond to a concert event. However, such data are often very *sparse* in the spatio-temporal dimensions due to the way they are collected [24], [25] (in our check-in dataset, only 1.16% of the entries are non-zero). For example, people may not check-in in certain place and time [20], [24]. Detecting urban events directly from such sparse data is very difficult [21] and might lead to unreliable results.

Recently, researchers have started to exploit both categories of data for better event detection and characterization [21], [26], [27]. The common approach is to detect irregularities in the crowd mobility data as urban events, and find the semantic explanations from the social activity data to characterize the events. However, as the crowd mobility data is a mixture of basic patterns, the semantic explanation of the irregularity can be diverse and difficult to interpret. Moreover, due to the sparse nature of the social activity data, directly splitting the crowd mobility data according to the percentage of activity types is usually inconsistent and error prone. To address these issues, in this paper, we propose a *tensor co-factorization based data fusion framework* to augment the crowd mobility data with semantic information from the social activity data, and decompose the crowd mobility data into several basic patterns, each corresponding to a set of social activities. By identifying the irregularities in each crowd mobility basic pattern, we can detect the associated urban events and characterize the influenced regions, gathering time, and popular activities of these events. The main contributions of this work include:

- We propose a tensor co-factorization based data fusion framework to augment the crowd mobility data with semantic information from the social activity data for fine-grained urban event detection and characterization. We first adopt a Nonnegative Tensor Co-Factorization (NTCoF) approach to decompose the crowd mobility tensor into several basic patterns, with the help of the auxiliary social activity tensor. We then use a Multivariate Outlier Detection (MOD) based method to detect significant and unusual human flow irregularities from these basic patterns, and aggregate the irregularities to detect and characterize the associated urban events. Such a framework can separately detect concurrent urban events taking place in the same region, and leads to fine-grained characterization of these events.
- We evaluate the performance of our framework using real-world bike sharing system data and LBSN check-in data collected from Washington, D.C. and New York City for one year. Results show that our framework achieves fine-grained urban event detection and characterization in both cities, and outperforms baselines that separately detect urban events from bike trip data and check-in data.

The rest of this paper is organized as follows. We first present the related work in Section II, and then analyze the collected datasets in Section III. In Section IV we propose our data fusion framework, and then detail the human flow decomposition and urban event detection steps in Section V and VI, respectively. We report the evaluation results in Section VII. We discuss several issues in Section VIII and conclude the work in Section IX.

II. Related Work

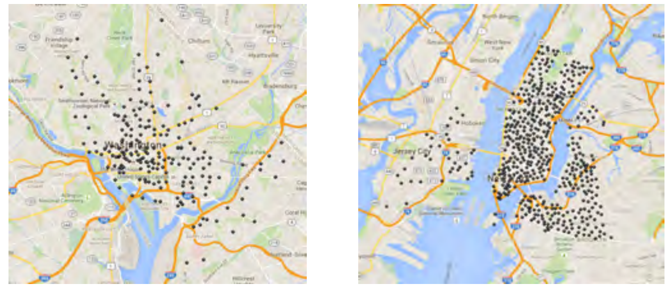
With the wide deployment of urban sensing infrastructures and the increasingly popularity of crowd sensing paradigms [18], [19], [28], the urban digital footprints that people leave while interacting with cyber-physical spaces are accumulating in an unprecedented pace [10]. Research on understanding the urban dynamics by mining these urban data has drawn extensive attention in recent years, especially in urban planning [7], [8], [29], urban environment monitoring [20], [30], [31], and urban event detection [2], [21]. In this section, we first survey the research work on urban event detection, and then focus on existing data fusion methods for urban event detection.

A. Urban Event Detection

Urban event detection has been extensively studied by researchers, especially in the urban computing community [13]. The research interests include detecting anomalous taxi trajectories [32], diagnosing traffic anomalies [7], [26], and predicting abnormal crowd gathering patterns [4], [25]. Two main categories of urban data, i.e., social activity data and crowd mobility data, have been exploited in urban event detection. For example, Liang et al. [25] used LBSN check-ins to model the size, duration, and temporal dynamics of short-lived crowds formed in urban events. However, as the user-contributed LBSN data are often noisy and sparse [17], directly detecting urban events from the sparse social activity data can be very difficult and unreliable [17], [24]. Zhang et al. [2] took a different approach, leveraging taxi GPS traces to extract crowd mobility patterns in urban areas, and proposed a probability-based method to detect urban events based on the social activeness of a region. Similarly, Fan et al. [4] proposed an online approach for predicting crowd movement during urban events leveraging large-scale mobile phone GPS log data. However, these methods might not be able to separate concurrent events taking place in the same region, as the semantic information of these irregularities is often unavailable and needs to be inferred indirectly.

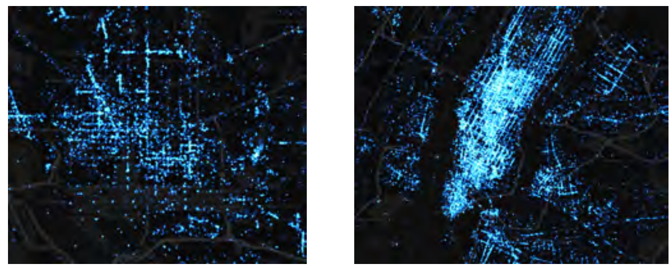
B. Data Fusion Methods for Urban Event Detection

Recently, researchers have started to combine multiple datasets to detect urban events [21], [33]. For example, Pan et al. [26] proposed a successive data fusion approach to first detect traffic anomalies from vehicle GPS trajectories, and then analyze the causes of anomalies using the correlated social media data. However, since the trajectories represent a mixture of various traffic patterns, it is difficult to correspond one traffic anomaly to an event in the social network. Coffey et al. [27] separately decomposed mobility flows and social media data into components using different topic models, and presented a correlation and causation analysis between irregularities of mobility flows and social media streams. However, since the two data are decomposed separately, corresponding the irregularities in the two datasets require intensive human interaction [27]. Yao et al. [34] propose a crowd mobility tensor decomposition method to predict a person's future mobility event, however this work focuses on individual mobility instead of crowd mobility, which is more significant in describing urban events. In this paper, we directly augment the crowd mobility data with the semantic information from the social activity data by leveraging a tensor co-factorization technique proposed in [35]. In this way, the fine-grained spatio-temporal-semantic characteristics of the associated urban events can be captured.



(a) Washington, D.C. **(b)** New York City

Fig. 1: The distributions of bike stations in both cities, respectively.



(a) Washington, D.C. **(b)** New York City

Fig. 2: The heat maps of one years' check-ins collected in DC (01/01/2012–12/31/2012) and NYC (01/01/2014–12/31/2014).

III. Dataset Analysis

In this section, we describe the data collection process, and present an empirical study on the collected datasets. In particular, we first present essential details about the crowd mobility data from bike sharing system, and the social activity data from LBSN user check-ins. We then study the spatial, temporal, and semantic characteristics of these datasets.

A. Data Collection

1) Crowd Mobility Datasets: crowd mobility data can be collected from various sources in the urban space, including bike sharing systems [14], GPS-equipped taxicabs [29], and cellular network users [6], [22]. In this paper, we use the *bike trip records* from the bike sharing systems as a proxy of the crowd mobility data, since bike sharing systems have become an important transportation means for citizens to attend social events [36], [37]. We collect bike trip records from Washington, D.C. Capital Bikeshare System[1] and New York Citi Bike System[2]), respectively. In particular, each bike trip record contains the following fields *(departure_station, departure_time, arrival_station, arrival_time)*. The GPS coordinates and the IDs of stations are also available from both cities. Based on the bike trip records, we count the number of bikes arriving at each station in each time span (e.g. one hour), which we refer to as the *bike arrival number*.

2) Social Activity Datasets: social activities in urban environment can be captured from various sources, including location-based social networks [24] and mobile crowdsensing platforms [28], [38]. We collect social activity data from the popular LBSN service Foursquare[3], which has a wide coverage in many cities for several years since 2009. In foursquare, users' activities are mainly represented by *check-ins*, which indicate that users visited certain venues at certain time. Based on the category of the venue, we can semantically characterize the users' social activities [6], [17]. For example, if users are checking-in at a restaurant at 19:00, they might probably be having dinner there. We collect Foursquare check-in data and venue category information in Washington, D.C. and New York City by crawling the Foursquare-tagged geo-tweets from Twitter Public Stream[4] [39]. In particular, each check-in record contains the following fields: *(venue_id, venue_location, venue_category, check-in_time)*, where the venue location is manually selected by user from a list provided by Foursquare based on the user's current location to avoid GPS positioning errors, and the venue category is defined by the Foursquare Venue Category API[5]. Based on the check-in records, we count the number of check-ins in each venue category in each time span (e.g. one hour) and define it as the *check-in number*.

3) Urban Neighborhood Dataset: we aggregate bike stations and check-in venues into *regions* as the minimal units to study human flow in urban areas. Each region consists of a number of blocks and communities, standing for a neighborhood structure that might have a similar human flow constitution. Simply adopting a uniform grid-based urban partition [22] might lose the semantic information of such neighborhood structure, while a partition using ZIP codes is often too coarse [20]. Therefore, we use a region partition based on *census block* [40]. Census blocks are neighborhood units established by the Bureau of Census for analyzing populations and urban social dynamics [40], [41]. We retrieve the 2010 census block datasets from U.S. Government Open Data

[1]http://www.capitalbikeshare.com/system-data
[2]https://www.citibikenyc.com/system-data
[3]http://foursquare.com
[4]https://dev.twitter.com/docs/streaming- apis/streams/public
[5]https://developer.foursquare.com/categorytree

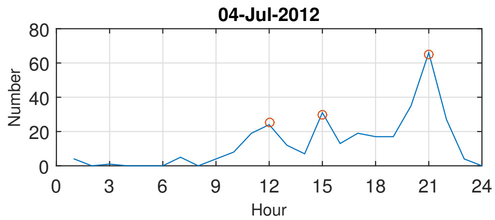


Fig. 3: The human flow in the region of the National Mall during the 2012 Independence Day (July 4th).

Portal[1] for Washington, D.C. and New York City respectively. Based on the region partition, we aggregate the bike arrival number and check-in number in the same region to denote the crowd mobility and LBSN user activity, respectively.

B. Empirical Study

1) Spatio-Temporal Patterns of the Bike Arrival Data: Fig.1 presents the geographical distributions of the bike stations in Washington, D.C. and New York City, respectively, where each black dot represents one bike station. In practice [37], [42], bike sharing stations are usually deployed in regions with Urban Activity Centers (UACs) [9], such as stadiums, urban parks, shopping malls, and university campus, making it convenient to rent public bikes for attending sports games, concerts and city festivals. By counting and comparing the number of bikes arriving in a region during different periods of time, we can infer the potential events causing the large human flow. However, such human flow extracted from bike trips do not carry semantic information, making it difficult to separate concurrent events and characterize the associated events. In particular, when a region contains many UACs and several urban events take place concurrently, the mixed human flow irregularities are difficult to interpret. For example, Fig.3 shows the human flow in the region of the National Mall during the 2012 Independence Day (July 4th). The three irregularities (denoted by red circles in Fig.3) might correspond to various celebrations taken place in the National Mall region, such as parades, picnics, and outdoor concerts. Without further semantic information about these irregularities, we are not able to separate them apart, or capture the fine-grained characteristics (e.g. popular activities) of these events.

2) Semantic Information of the Check-in Data: Fig.2 shows the heat maps of the check-ins in Washington, D.C. and New York City, respectively, where the brighter areas observe more check-ins. Most check-ins are performed by users when they go to restaurants, stores, concerts, games, and etc., providing a proxy for depicting their activities [6], [23], [43]. More specifically, by investigating the categories of check-in venues in a region during a period of time, we can infer the corresponding human activities [6], [17]. For example, Fig.4 presents the percentage of three check-in categories during each hour of a typical-day in the National Mall region (check-ins are aggregated over one month's weekdays since the original data is sparse). Based on the venue categories, we can infer the working activities around 9:00, eating activities around 13:00, and recreation activities around 15:00, respectively.

[1]http://www.data.gov/

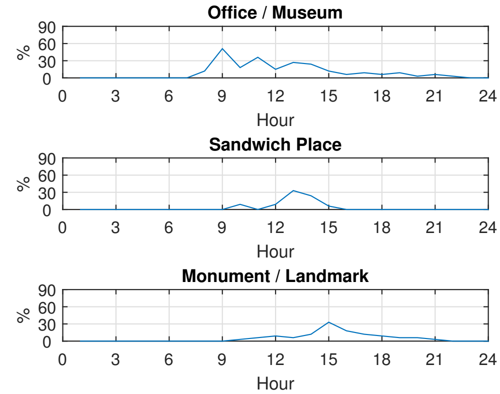


Fig. 4: Check-in percentage of three main categories during each hour of a typical-day in the National Mall region (aggregated over one month's weekdays). Red circles denote irregularities.

In summary, the bike trip records capture the spatio-temporal patterns of crowd mobility, while the check-in records depict the semantic information of collective activities. In order to better detect and characterize urban events, we need to fuse them together to exploit the spatio-temporal-semantic information from both datasets.

IV. Framework Overview

We propose a framework for fine-grained urban event detection characterization leveraging urban data, as shown in Figure 5. Our framework consists of three phases, i.e., crowd mobility decomposition, urban event detection, and urban event characterization. In the first phase, we construct two tensors from urban data, i.e., the crowd mobility tensor and social activity tensor, and adopt the Nonnegative Tensor Co-Factorization (NTCoF) method to decompose the crowd mobility tensor into basic patterns, with the help of the auxiliary social activity tensor. In the second phase, we use a Multivariate Outlier Detection (MOD) based method to detect significant and unusual irregularities from the decomposed crowd mobility basic patterns, and aggregate these irregularities to detect the associated urban events. In the third phase, we characterize different aspects of the detected events in terms of the influenced regions, gathering time, and popular activities. We detail the framework in the following sections.

V. Crowd Mobility Tensor Decomposition

In this phase, our objective is to decompose the crowd mobility data into several basic patterns, such as working, eating, and recreation. To this end, we first find the corresponding structure to represent the crowd mobility data and the social activity data, and then design an effective approach to decompose the crowd mobility data into basic patterns.

More specifically, we first construct a two-dimensional *crowd mobility tensor* to capture the spatio-temporal human flow patterns. We then need to decompose this tensor into several basic patterns, as illustrated in Fig.6. A common approach is Non-negative Tensor Factorization (NTF) [4], [34]. The philosophy of the NTF algorithm is to approximate the tensor through the multiplication of a few latent, low-rank

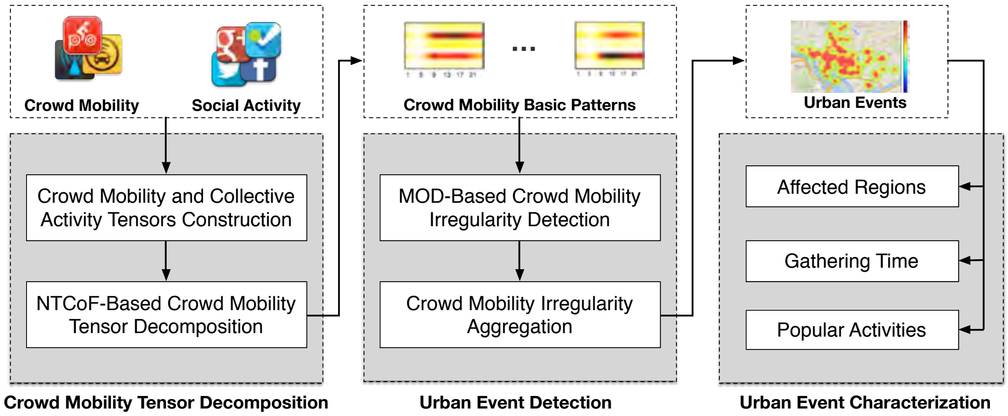


Fig. 5: Framework overview.

factors (matrices) under the non-negative constraints [35]. Then each basic pattern can be formed by the multiplication of a column of the factor matrices, respectively. For example, as shown in Fig.7, the crowd mobility tensor $\mathcal{A}$ is factorized into two rank-K matrices R and T, indicating K basic patterns. However, these decomposed basic patterns do not necessarily carry semantic information, hindering the semantic interpretation of each basic pattern.

To address this issue, we adopt a Non-negative Tensor Co-Factorization (NTCoF) [35] approach to incorporate the semantic information from the social activity tensor in the tensor decomposition, as illustrated in Fig.7. We construct an auxiliary social activity tensor with three dimensions, i.e., *regions*, *time span*, and *venue categories*, where the venue category dimension carries rich semantic information about social activity [6], [17]. We then decompose both tensors simultaneously using the NTF algorithm, while forcing the two tensors to share the spatial and temporal factor matrices R and T, respectively. In this way, the semantic information of the venue category factor C (i.e. social activity) is propagated to the crowd mobility tensor.

A. Tensors Construction

We construct the crowd mobility tensor from the bike arrival data and the social activity tensor from the Foursquare check-in data as follows.

1) Crowd Mobility Tensor: we build a tensor $\mathcal{A} \in \mathbb{R}^{N_r \times N_t}$ with two dimensions denoting N_r regions and N_t time spans, respectively:

- *Region dimension*: we map bike stations to the corresponding regions $\boldsymbol{r} = [r_1, r_2, \ldots, r_{N_r}]$.
- *Time span dimension*: we divide the duration of observation into equal time spans $\boldsymbol{t} = [t_1, t_2, \ldots, t_{N_t}]$, each time span lasts for a period of time, e.g., one hour.

Correspondingly, an entry $\mathcal{A}(r, t)$ stores the number of bikes arriving at region $\boldsymbol{r}_r$ during time span $\boldsymbol{t}_t$.

2) Social Activity Tensor: we build the check-in tensor $\mathcal{B} \in \mathbb{R}^{N_r \times N_t \times N_c}$ with three dimensions denoting N_r regions, N_t time spans, and N_c categories, respectively:

- *Region dimension*: we map check-in venues to the corresponding regions $\boldsymbol{r} = [r_1, r_2, \ldots, r_{N_r}]$.

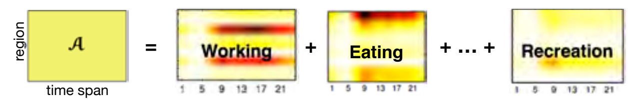


Fig. 6: Illustration of crowd mobility data tensor decomposition.

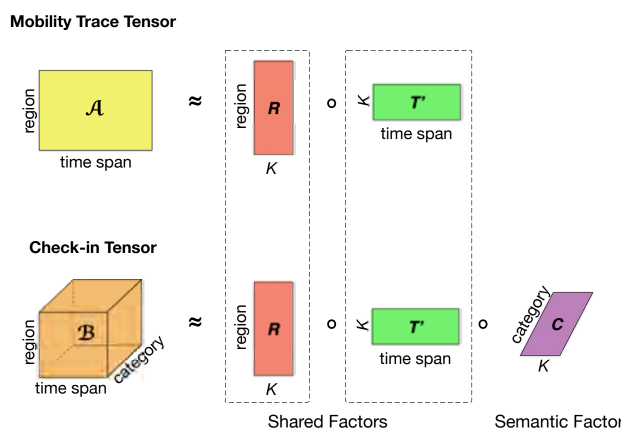


Fig. 7: Illustration of the Nonnegative Tensor Co-Factorization Approach.

- *Time span dimension*: we divide the duration of observation into equal time spans $\boldsymbol{t} = [t_1, t_2, \ldots, t_{N_t}]$, each time span lasts for a period of time, e.g. one hour.
- *Venue category dimension*: we organize check-ins according to their venue category $\boldsymbol{c} = [c_1, c_2, \ldots, c_{N_c}]$.

As a result, $\mathcal{B}(r, t, c)$ stores the total number of check-ins in region $\boldsymbol{r}_r$ during time span $\boldsymbol{t}_t$ of category $\boldsymbol{d}_c$. We note that tensor $\mathcal{B}$ itself is usually very sparse. For example, in Washington, D.C. only 1.16% entries of tensor $\mathcal{B}$ have values. Detecting urban events from such a sparse tensor is very difficult. Moreover, decomposing tensor $\mathcal{B}$ solely based on its non-zero entries is not accurate enough neither [20]. Therefore, we need to combine the two tensors together to for further event detection and characterization.

B. NTCoF-Based Crowd Mobility Tensor Decomposition

With the crowd mobility tensor $\mathcal{A}$ and the social activity tensor $\mathcal{B}$ at hand, we now simultaneously decompose them into low-rank, latent factors, and force the spatial and temporal factors to be shared. As illustrated in Fig.7, we model each factor as a rank-K matrix, where K denotes the number of latent basic patterns. Correspondingly, we obtain the region factor $\boldsymbol{R} \in \mathbb{R}^{N_r \times K}$, the time factor $\boldsymbol{T} \in \mathbb{R}^{N_t \times K}$, and the venue category factor $\boldsymbol{C} \in \mathbb{R}^{N_c \times K}$. In order to absorb differences in scale between factorizations, we introduce two rank-K diagonal core tensors [35] $\mathcal{S}_{\mathcal{A}} = diag(\boldsymbol{u})$ and $\mathcal{S}_{\mathcal{B}} = diag(\boldsymbol{v})$ for each tensor $\mathcal{A}$ and $\mathcal{B}$ respectively, where $\boldsymbol{u}, \boldsymbol{v} \in \mathbb{R}^{1 \times K}$, $\mathcal{S}_{\mathcal{A}} \in \mathbb{R}^{K \times K}$, and $\mathcal{S}_{\mathcal{B}} \in \mathbb{R}^{K \times K \times K}$. Finally, we use the Canonical decomposition model [44] to decompose the two tensors as follows:

$$\hat{\mathcal{A}} = \mathcal{S}_{\mathcal{A}} \times_R \boldsymbol{R} \times_T \boldsymbol{T} \tag{1}$$

$$\hat{\mathcal{B}} = \mathcal{S}_{\mathcal{B}} \times_R \boldsymbol{R} \times_T \boldsymbol{T} \times_C \boldsymbol{C} \tag{2}$$

The symbol $\times_n$ denotes the mode-n tensor product with matrix [20]. We define the objective function to control the error of the coupled decomposition as

$$\begin{aligned} \mathcal{L}(\mathcal{S}_{\mathcal{A}}, \mathcal{S}_{\mathcal{B}}, \boldsymbol{R}, \boldsymbol{T}, \boldsymbol{C}) = \|\mathcal{A} - \mathcal{S}_{\mathcal{A}} \times_R \boldsymbol{R} \times_T \boldsymbol{T}\|^2 \\ + \|\mathcal{B} - \mathcal{S}_{\mathcal{B}} \times_R \boldsymbol{R} \times_T \boldsymbol{T} \times_C \boldsymbol{C}\|^2 \\ + (\|\boldsymbol{R}\|^2 + \|\boldsymbol{T}\|^2 + \|\boldsymbol{C}\|^2 + \|\mathcal{S}_{\mathcal{A}}\|^2 + \|\mathcal{S}_{\mathcal{B}}\|^2) \end{aligned} \tag{3}$$

where $\|\mathcal{A} - \mathcal{S}_{\mathcal{A}} \times_R \boldsymbol{R} \times_T \boldsymbol{T}\|^2$ and $\|\mathcal{B} - \mathcal{S}_{\mathcal{B}} \times_R \boldsymbol{R} \times_T \boldsymbol{T} \times_C \boldsymbol{C}\|^2$ are used to control the error of decomposing $\mathcal{A}$ and $\mathcal{B}$, respectively, and $\|\boldsymbol{R}\|^2 + \|\boldsymbol{T}\|^2 + \|\boldsymbol{C}\|^2 + \|\mathcal{S}_{\mathcal{A}}\|^2 + \|\mathcal{S}_{\mathcal{B}}\|^2$ is a regularization penalty to avoid over-fitting. As there is no closed-form solution for finding the global optimal result of the objective function (Equation 3), we resort to a numeric method to find a local optimization. More specifically, we adopt the Nonlinear Least Square (NLS) method to iteratively improve an initial (random) solution with additive updates obtained by minimizing a second-order approximation of the objective function based on first-order derivatives [35].

Finally, we decompose the crowd mobility tensor $\mathcal{A}$ into the multiplication of $\mathcal{S}_{\mathcal{A}}$, $\boldsymbol{R}$, and $\boldsymbol{T}$. Since $\mathcal{S}_{\mathcal{A}}$ is a diagonal tensor $\mathcal{S}_{\mathcal{A}} = diag(\boldsymbol{u})$, the values of each entry of $\mathcal{A}$ can then be approximated by:

$$\hat{\mathcal{A}}(r,t) = \sum_{k=1}^{K} \boldsymbol{u}(k) \cdot \boldsymbol{R}(r,k) \cdot \boldsymbol{T}(t,k) \tag{4}$$

In other words, we can approximate tensor $\mathcal{A}$ by the sum of a number of basic patterns $\hat{\mathcal{A}}^{(k)}$:

$$\hat{\mathcal{A}} = \sum_{k=1}^{K} \hat{\mathcal{A}}^{(k)} \tag{5}$$

In this way, the semantic information of each basic pattern is expressed by the venue category matrix $\boldsymbol{C}$, each column of which corresponds to a specific basic pattern. For example, the *working* pattern can be represented by a column having relatively large intensity in venue categories such as office, government building, and subway station. We present the expression of basic patterns in the evaluation part.

VI. Urban Event Detection

In this phase, our goal is to detect urban events from the crowd mobility basic patterns. The rationale behind this approach is that when an urban event takes place in a region at a time span, the intensity of the related basic patterns will probably be higher than usual [3]. For example, during Independence Day, the *recreation* pattern is more significant than usual in major parks and streets. Therefore, by capturing the *significant and unusual* irregularities in the decomposed basic patterns, we can detect the associated urban events. We note that irregularities with unusually low intensity might be relevant to bad weather, device malfunction, etc., which is out of the scope of urban event detection.

Although we can detect irregularities in each basic pattern separately and then aggregate them together, this method requires individual thresholds to control the irregularity significance for each basic pattern and each region. Instead, we detect irregularities from all basic patterns at once using a Multivariate Outlier Detection [45] method. More specifically, we first model the basic patterns of a region by a set of K-dimensional vectors, where each vector corresponds to a time span, and each vector element corresponds to a basic pattern intensity. We then detect the unusual vectors using a clustering-based approach, and select the significant irregularities with higher intensities than normal samples in history. Finally, we aggregate the irregularities based on their temporal co-occurrence to detect the associated urban events. We detail the steps of this approach in the following steps.

A. MOD-Based Crowd Mobility Irregularity Detection

As illustrated in Equation 5, the crowd mobility intensity $\mathcal{A}(r,t)$ of region r and time span t can be approximated by the sum of K basic patterns. We arrange these basic pattern components into a vector $\boldsymbol{\theta}$, i.e.,

$$\boldsymbol{\theta}(r,t) = (\theta_1, \theta_2, \ldots, \theta_K) \tag{6}$$

where $\theta_k = \hat{\mathcal{A}}^{(k)}(r,t)$. We model the crowd mobility basic patterns of region r along all time spans as a set of vectors:

$$\boldsymbol{\Theta}(r) = \{\boldsymbol{\theta}(r,1), \boldsymbol{\theta}(r,2), \ldots, \boldsymbol{\theta}(r,N_t)\} \tag{7}$$

In this way, we model the crowd mobility basic patterns of a region as a multivariate variable with the observation samples $\boldsymbol{\Theta}(r)$. We take an example to elaborate on the modeling. Using 6 consecutive weeks of data from May to July, 2012, we decompose the crowd mobility data into three basic patterns, i.e., *working*, *eating*, and *recreation*. We draw a set of basic pattern vectors for the National Mall region from 9:00 to 10:00. Fig.8 shows the distributions of these vectors in a ternary plot. In this plot, each apex represents a basic patterns, while each point corresponds to a vector. The distance between a point and an apex is inversely proportional to the intensity of the corresponding vector element intensity. We can find two clusters in this ternary plot: the top-left cluster features days with high *working* intensity, which may correspond to regular workdays, and the bottom-right cluster contains days with high *recreation* intensity, which may indicate the weekend crowd mobility patterns. The two outliers in the red circles correspond to two national holidays, i.e., Memorial Day (05/28/2012) and Independence Day (07/04/2012). The significant increase in the *recreation* patterns may corresponds to the picnic and sightseeing activities in National Mall and

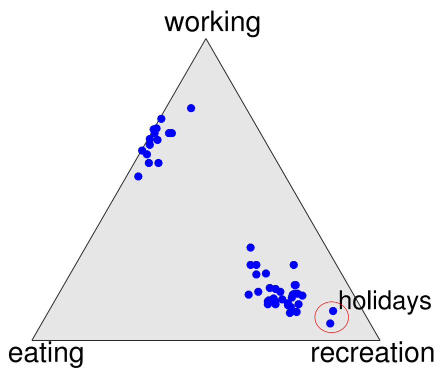


Fig. 8: An ternary plot of the three example basic pattern vectors in the National Mall region from 9:00 to 10:00 over 6 consecutive weeks (05/28/2012–07/08/2012).

the surrounding monuments and landmarks. Based on the crowd mobility basic pattern modeling, we turn the urban event detection into a Multivariate Outlier Detection problem [46]. We first perform outlier detection for each vector set $\boldsymbol{\Theta}(r)$ in region r to identify unusual irregularities, and then select the significant ones using a threshold.

1) Finding unusual crowd mobility irregularities: for the crowd mobility vector set $\boldsymbol{\Theta}(r)$ of region r, we define the *unusual* outliers as vectors that are distant from other vector clusters in the basic pattern space. In order to detect such outliers, we first adopt the density-based clustering method OPTICS [47] to identify clusters of vectors. OPTICS generates an R-tree to order the data and identify the n nearest neighbors. It can identify clusters of arbitrary shape and varying density, and autonomously determine the number of clusters. The algorithm requires a parameter $MinPts$ to be specified, i.e., the minimum number of points required to form a cluster. We detail the parameter selection in evaluation. Finally, we mark vectors not belonging to any clusters as outliers.

2) Detecting significant crowd mobility irregularities: for each outlier $\boldsymbol{\theta}'(r,t) = (\theta'_1, \theta'_2, \dots, \theta'_K)$, we compare it with the historical observation samples in the same hour $\boldsymbol{\Theta}(r)' = \{\boldsymbol{\theta}(r, t-24), \theta(r, t-48), ...\}$. we define $\theta'(r,t)$ as a *significant* irregularity if the intensity of its largest dimension is higher than the average value of the dimension in $\boldsymbol{\Theta}(r)'$, and the difference is larger than three times of the standard deviation [21]. We then determine the *irregularity type* based on the largest dimension. For example, the types of the two outliers in Fig.8 is detected as significant irregularities, and their types being *recreation*, since they have relatively large intensity in that dimension.

B. Crowd Mobility Irregularity Aggregation

Since an urban event might cause multiple crowd mobility irregularities in more than one region and time span, we need to aggregate these irregularities to correspond them to the associated event. We note that irregularities associated with the same urban event are usually detected concurrently (i.e. temporal close to each other), however these irregularities might occur in different regions. For example, during the evening of Independence Day, people might gather at different regions to watch the 4th of July Fireworks show. Therefore, we derive a heuristic rule to guide the irregularities aggregation procedure: the irregularities associated with an event should occur within several hours range.

TABLE I: A summary of the datasets

Dataset	Item	Washington, D.C.	New York City
Bike trip	Duration	01/01–12/31, 2012	01/01–12/31, 2014
	# Station	203	328
	# Bike	3,296	4,077
	# Record	1,869,980	8,081,188
Check-in	Duration	01/01–12/31, 2012	01/01–12/31, 2014
	# Venue	26,740	62,240
	# Category	266	287
	# Check-in	259,770	404,256
Neighborhood	# Census blocks	198	317

Formally, given the set of detected irregularities $\boldsymbol{\Theta'}$, the formed subset $\boldsymbol{\Theta'_i} \subset \boldsymbol{\Theta'}$ associated with a potential urban event should meet the following criterion:

$$\forall \boldsymbol{\theta'_1} \in \boldsymbol{\Theta'_i}, \boldsymbol{\theta'_2} \in \boldsymbol{\Theta'_i}, |\boldsymbol{\theta'_1}.t - \boldsymbol{\theta'_2}.t| \leq \delta_t \tag{8}$$

where $\boldsymbol{\theta'}.t$ denotes the corresponding time span of the irregularity. δ_t is a time threshold controlling the temporal distance of the irregularities in the same subset. We empirically set δ_t to 3 hours, since most urban events, such as concerts and football games, usually last for only one or two hours. Finally, we associate each subset of irregularities $\boldsymbol{\Theta'_i}$ with a detected urban event e_i, i.e.,

$$\boldsymbol{\Theta'_i} \rightarrow e_i \tag{9}$$

VII. Evaluation

We evaluate the performance of our framework using datasets collected from Washington, D.C. and New York City, respectively. We first present the experiment settings including dataset statistics and the evaluation metrics. We then conduct a parameter tuning process to select optimal parameters for our model. Finally, we present the experiment results on crowd mobility decomposition and urban event detection, and conduct a series of case studies on urban event characterization.

A. Experiment Settings

1) Datasets: we collect the bike trip datasets, the check-in datasets, and the neighborhood datasets from DC and NYC, respectively. The statistics of the collected datasets are shown in Table I. We then aggregate bike stations and check-ins venues into regions, and count the bike arrival number and check-in number in different regions, respectively.

2) Evaluation Plan: we split the datasets into two parts, and use one half for model tuning and the other half for testing. We adopt an interleaving splitting scheme, i.e., using every second day for training and testing, respectively. In order to reduce the impact of seasonality, we use the bike trip data and the check-in data in the recent two months for modeling the crowd mobility and social activity patterns, respectively.

TABLE II: 10 important UACs in DC and NYC, respectively

No.	Washington, D.C.	New York City
1	National Mall	Times Square
2	Nationals stadium	Madison Square Garden (Stadium)
3	Verizon Center	Manhattan Center
4	RFK Stadium	Radio City Music Hall
5	Capitol Hill	Herald Square
6	Washington Convention Center	Jacob K. Javits Convention Center
7	West Potomac Park	New York Botanical Garden
8	Library of Congress	New York Public Library
9	National Gallery of Art	Metropolitan Museum of Art
10	The White House	Greenwich Village

3) Ground Truth Data: evaluating urban events in a real-world setting is an open challenge [21], since it is difficult to obtain a complete set of ground truth recording all events happened in the city. In this paper, we compile a list of urban events that took place in the important Urban Activity Centers (UACs) in both cities, such as stadiums, parks, and museums, during the time span of the experiment dataset. We select UACs of DC according to the map published by DC Metropolitan Washington Council of Governments[1], and select UACs of NYC based on the "Selected Facilities and Program Sites" list published by NYC Department of City Planning[2]. We then retrieve the event name, scheduled venue, scheduled time, and event descriptions from the corresponding official websites and Facebook Event pages[3] of these UACs. Table II shows 10 important UACs in each city, respectively. In summary, we obtain 103 urban events from the 10 important UACs in Washington, D.C. during 2012, and 142 urban events from the 10 important UACs in New York City during 2014.

4) Evaluation Metrics: we compute the accuracy of the urban event detection results to evaluate the proposed framework. More specifically, we compare the event detection results with the ground truth event list to compute the *precision* and *recall*. For each detected event, if a real-world event in the ground truth list has a temporal overlapping with the detected event, we mark the detection as a hit, and otherwise a miss. Based upon this, the precision and recall are calculated as follows:

$$precision = \frac{|\{\text{real-world event}\} \cap \{\text{detected event}\}|}{|\{\text{detected event}\}|} \tag{10}$$

$$recall = \frac{|\{\text{real-world event}\} \cap \{\text{detected event}\}|}{|\{\text{real-world event}\}|} \tag{11}$$

In addition, we compute the *F1-Score* as

$$F1\text{-}Score = \frac{2 \cdot precision \cdot recall}{precision + recall} \tag{12}$$

to assess the overall performance of our model and assist in the model parameter selection.

B. Parameter Selection

There are two important parameters in our framework. First, in the crowd mobility decomposition phase, the number of basic patterns K determines the number of semantic features involved in the tensor factorization process. Decomposition with small values of K may result in mixed basic patterns that are not able to approximate the tensors well, while decomposition with large K will make it difficult to interpret the meanings of the basic patterns. Second, in the urban event detection phase, the minimum number of points to form a cluster $MinPts$ determines the sensitivity of irregularities to be detected, and thus affecting event detection accuracy. We study the impact of these two parameters in both cities.

[1]http://www.mwcog.org/store/item.asp?PUBLICATION

[2]http://www1.nyc.gov/site/planning/data-maps/open-data/dwn-selfac.page

[3]e.g., https://www.facebook.com/NationalMallNPS/events

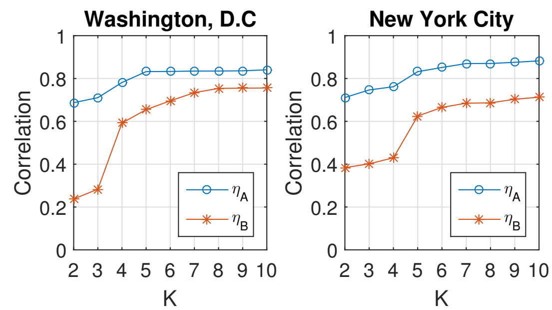


Fig. 9: Parameter selection of the basic pattern numbers in DC and NYC, respectively.

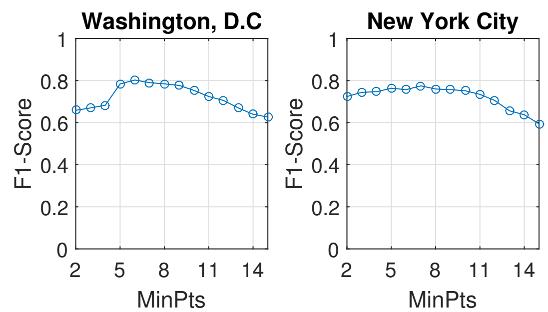


Fig. 10: Parameter selection of the irregularity sensitivity in DC and NYC, respectively.

1) Determining Basic Pattern Number: in order to quantitatively evaluate the performance of the decomposition, we compute the element-wise correlation $\eta^{(K)}$ between the reconstructed tensors and the original tensors [22]:

$$\eta_{\mathcal{A}}^{(K)} = Corr(\hat{\mathcal{A}}^{(K)}, \mathcal{A}), \quad \eta_{\mathcal{B}}^{(K)} = Corr(\hat{\mathcal{B}}^{(K)}, \mathcal{B}) \tag{13}$$

We vary K from 3 to 10. Fig.9 reports the correlation results in both cities. We see that with the increase of the basic pattern number, the correlations also increase. We observe no significant improvement in correlation values for K larger than 5, which indicates the convergence in therms of basic patterns. Therefore, we set $K = 5$ for both cities.

2) Determining Irregularity Detection Sensitivity: varying the value of $MinPts$ directly changes the number of detected irregularities, and thus affecting the accuracy of the event detection results. On one hand, setting a large $MinPts$ results in small clusters to be detected as irregularities, and may lead to low precision. On the other hand, setting $MinPts$ to a relative small value only excludes isolated points as irregularities, which will result in low recall as few irregularities are detected. Taking the overall accuracy into consideration, we determine the optimal value of $MinPts$ based on the *F1-score*, as shown in Fig.10. We set $MinPts = 7$ for both cities in the following experiments.

C. Baseline Methods

We compare our framework with the following baselines.

- *Multi-dataset-skyline method*: We compare our method with a start-of-the-art event detection method using multiple spatio-temporal datasets, which follows the similar idea as in [21]. More specifically, this method combines the bike trip dataset and the check-in dataset in a topic model to infer the distributions of the check-in data, since the check-in data itself is over-sparse to describe a distribution. It then generates irregularity candidates in each dataset by testing the likelihood of the null and alternative models given the estimated distribution, and use a heuristic skyline detection algorithm [48] to further select the most significant irregularities across different datasets. Finally it aggregates the irregularities to detect urban events by applying spatio-temporal constraints. Although this method fuses both datasets together to address the data sparsity problem, the irregularities in each dataset are detected separately and the semantic information is not shared.
- *Single-dataset-bike method*: this baseline method directly detects irregularities from the bike trip dataset using a deviation-based method, and then aggregates these irregularities to detect urban events, as described in our previous paper [3]. More specifically, if the deviation of the bike arrival number of a station is greater than three times of the standard deviation, it is marked as an irregularity. Although this method can detect some urban events, it fails to separate concurrent events apart if the human flow irregularities are mixed together. Moreover, the semantic information of the human flow related to the events can not be interpreted.
- *Single-dataset-check-in method*: this baseline method directly detects irregularities from the check-in dataset. As such a dataset is usually very sparse, the deviation-based method can not be directly applied. Instead, we first use a tensor completion method to decompose and reconstruct the check-in tensor, as proposed in [17], [20], and then apply the deviation-based method to detect irregularities.

D. Crowd Mobility Data Decomposition Results

We perform the NTCoF algorithm for crowd mobility data decomposition in both cities. For each city, we obtain five basic patterns. To visualize the spatio-temporal-semantic features of each pattern, we employ (1) *tag cloud* [17] to represent the most popular check-in venues, (2) *city map* to show the most visited regions in a basic pattern, and (3) *temporal plot* to demonstrate the temporal distribution of a basic pattern, respectively. We aggregate crowd mobility data into a typical day in the temporal plot for a clear visualization.

We present the visualization of the basic patterns of both cities in Fig.11. Based on the corresponding tag clouds, we label the five basic patterns as *working*, *recreation*, *eating*, *nightlife*, and *sports & concert*. For example, the *recreation* activities are mostly observed in museums and parks during afternoon hours, while the *sports & concert* activities correspond to sports games in the stadiums during after-work hours.

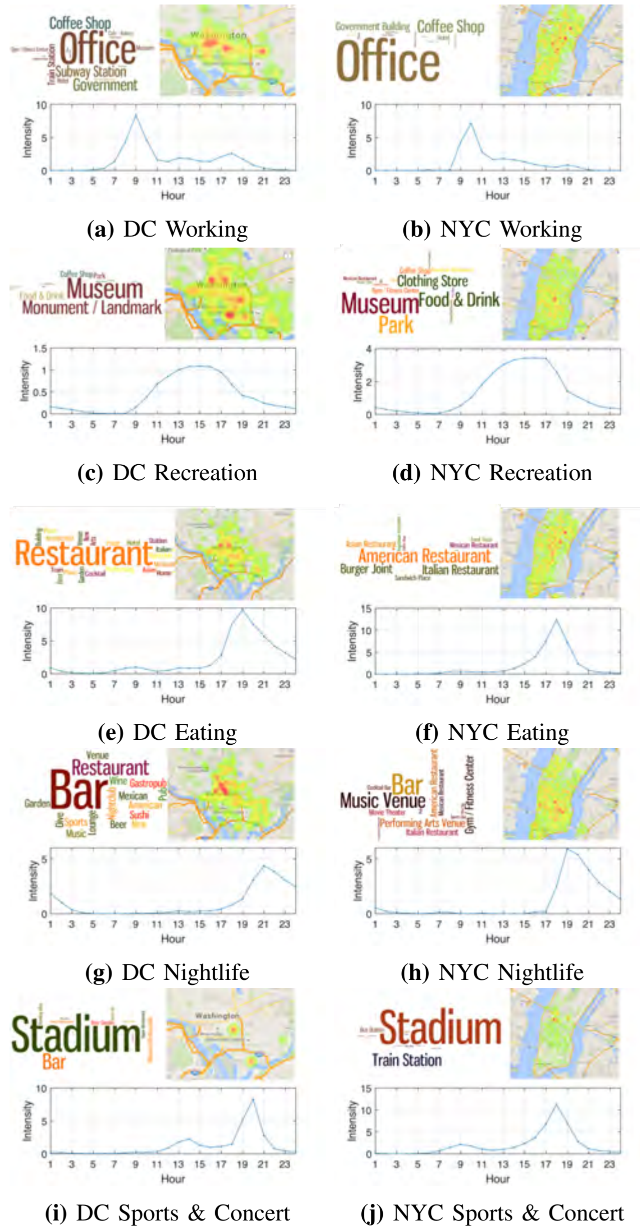


Fig. 11: The spatio-temporal-semantic distributions of the five decomposed crowd mobility basic patterns in DC and NYC.

E. Urban Event Detection Results

The urban event detection results in both cities are presented in Fig.12. Our method is consistently better than the baselines over all metrics, achieving 77.1% and 75.9% F1-Score in DC and NYC, respectively. The two single dataset baselines do not achieve balanced precision and recall scores. Specifically, the *single-dataset-bike* method achieves relatively low precision score as it detects many pseudo irregularities which can not be correspond to urban events (e.g., 172 events detected with only 74 events hit in DC), while the *single-dataset-check-in* method achieves relatively low recall score as it detects less irregularities than the ground truth. The *multi-dataset-skyline* baseline does not perform well regarding the recall score as it detects 16% less events compared to the ground truth in both cities. We investigate the results of this method and find out that many of these missing events correspond to irregularity

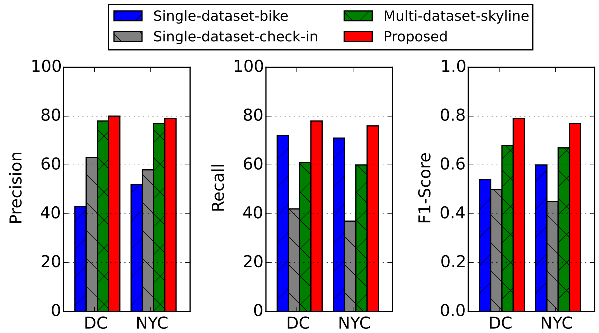
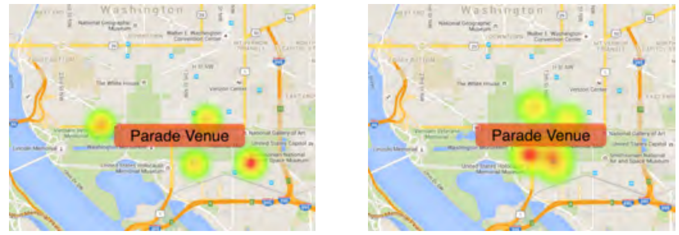


Fig. 12: Urban event detection accuracy in DC and NYC.



(a) 11:00–12:00, *recreation* **(b)** 12:00–13:00, *eating*

Fig. 13: Crowd mobility irregularities associated with *A National Parade*.

(a) 15:00–16:00, *recreation* **(b)** 21:00–22:00, *nightlife*

Fig. 14: Crowd mobility irregularities associated with *A Capitol Fourth Concert* and *Fourth of July Fireworks*, respectively.

points close to the skyline. As the scales of urban events may vary, less significant events are covered by larger events (i.e., the skyline points) and thus being omitted. In contrast, our method achieves consistently higher precision and recall scores as well as the F1-Scores in both cities.

F. Case Studies on Urban Event Characterization

In order to evaluate the urban event characterization results, we conduct case studies on DC and NYC, respectively. In each case study, we present (1) the *influenced regions* where large crowds of people gather for the event[1], (2) the *gathering time* for the event, and (3) the *popular activities* in different regions and time during the event.

1) Independence Day in DC: serving as the capital of the United States, Washington, D.C. hosts a series of grand celebrations on Independence Day each year, which attract large crowd of people gathering to the city center. Understanding the spatial, temporal, and semantic patterns of the crowd mobility is of great importance for urban authorities managing these events. Using the proposed framework, we separately detect and characterize the following important events on the 2012 Independence Day.

- *A National Parade*: The parade takes place at around 12:00 on Constitution Avenue. However, people might arrive at early to secure a spot and have picnic in the nearby National Mall after the parade. As shown in Fig.13, we detect a human flow irregularity of *recreation* during 11:00–12:00, corresponding to the early arrival of the audience. We also detect an *eating* irregularity after the parade, indicating the lunch or picnic activities of the crowd after the parade in nearby regions.
- *A Capitol Fourth Concert*: The outdoor concert takes place at the West Lawn of the U.S. Capitol Building at around 20:00. Interestingly however, the audience starts to gather at the West Lawn from nearby transit stations very early at about 15:00, as shown in Fig.14a. The probable reason is that the general admission gates for public opens at 15:00[2]. Knowing when and where people are gathering for the concert might help urban authorities make responsive decisions when emergency occurs, such as temporarily closing several transit stations to control gathering flow when the region becomes over-crowded.
- *Fourth of July Fireworks*: This famous fireworks show is usually launched at around 21:30 from the the Lincoln Memorial Reflecting Pool in the National Mall. During the fireworks show (21:00–22:00), we observe significant *nightlife* activities in the surrounding areas. We note that besides the National Mall region, the downtown areas are also the influenced regions for the fireworks show. This can be explained that many people might choose to watch the show from nearby nightlife venues, probably in bars and rooftop restaurants, which are also recommended spots to watch the fireworks on the local guide[3].

2) Lady Gaga Concert in New York City: in 05/13/2014, Lady Gaga performed at a sold out concert in Madison Square Garden (MSG)[4], a major stadium in New York City. Our method successfully detects this event by identifying several *sports & concert* irregularities in the nearby regions, as illustrated in Fig.15a. In contrast, the *single-dataset-bike* baseline method misses irregularities near the Pennsylvania Station (PS) and United States Post Office (USPO) region, as highlighted by the yellow circle in Fig.15b. The probable reason is that the concert crowd is overwhelmed by the daily commuting crowd at PS and the sightseeing crowd at USPO (which is a famous land mark and keeps open from 9:00 to 22:00 on weekdays). Since the *single-dataset-bike* baseline method models crowd mobility as a whole, the concert crowd near PS and USPO is not significant enough to be detected as irregularities. In contrast, by detecting irregularities in the decomposed basic pattern space, our method effectively captures such irregularity.

VIII. Discussion

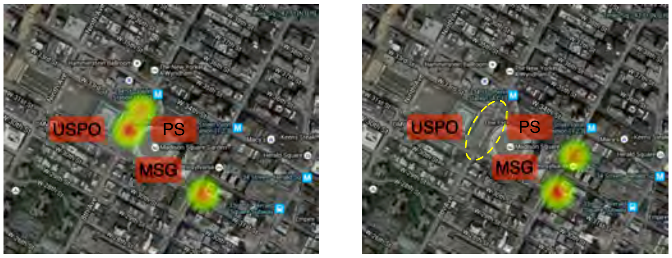
We discuss the following limitations of our work.

[1]To better represent the crowd scale in a region, we use the corresponding bike station location to denote the region center, as shown in Fig.13–15.

[2]http://www.pbs.org/a-capitol-fourth/about/faqs/

[3]http://washington.org/DC-focus-on/top-spots-catch-fireworks

[4]http://www.rollingstone.com/music/news/lady-gagas-live-artflop-nyc-ghosts-and-flowers-20140514



(a) *Sports & concert* irregularities detected by the proposed method.

(b) Mixed crowd mobility irregularities detected by the single-dataset-bike method.

Fig. 15: Crowd mobility irregularities detected for the *the Lady Gaga Concert* in MSG during 19:00–20:00 in 05/13/2014.

1) *Data bias in bike sharing and LBSN users*. The user communities of bike sharing and LBSNs are not completely representative of all the citizens, i.e., some strata of the population are more visible than others. Previous studies [17], [49] have shown that the bike sharing and LBSN users tend to be youngsters. The urban events we detect, such as lawn concerts, sports games, city festivals, and fireworks, are attractive to the communities. Therefore, by capturing the crowd mobility and social activity patterns of the communities, we can still detect and characterize many types of urban events. In the future, we plan to incorporate more urban data sources to better model the crowd mobility and social activity.
2) *Seasonality of bike usage patterns*. We observe seasonal patterns in the bike trip data, i.e., there are usually more bikes arriving at each region in the summer than in the winter. Such seasonality may hinder the effective modeling of the crowd mobility patterns. Hence, in this work, we only use two month's data before to model the crowd mobility patterns, as mentioned in the evaluation plan. In the future, we plan to explore streaming methods for modeling such time-varying patterns.

IX. Conclusion

With the increasing ubiquity of urban sensing infrastructures and social network services, rich urban data about crowd mobility and social activity has become available, providing us with new opportunities to understand urban events at a low-cost and automatic manner. In this paper, we proposed a data fusion framework to detect and characterize urban events from crowd mobility and social activity data. We augment the crowd mobility data with semantic information from the social activity data, leveraging a proposed Nonnegative Tensor Co-Factorization (NTCoF) approach. A Multivariate Outlier Detection (MOD) based method is adopted to identify crowd mobility irregularities from the decomposed basic patterns. Evaluations on real-world datasets from DC and NYC show that our framework effectively detects and characterize urban events in a fine-grained manner, and outperforms baselines that separately detect urban events from individual dataset.

In the future, we plan to incorporate more urban data sources to better model the crowd mobility and social activity, including taxi trace data [15], 311 complain data [21], and event-based social network data [50]. We also intend to explore real-time detection and prediction of crowd mobility associated with urban events.

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