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NationTelescope: Monitoring and Visualizing Large-Scale Collective Behavior in LBSNs

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Abstract

The research of collective behavior has attracted a lot of attention in recent years, which can empower various applications, such as recommendation systems and intelligent transportation systems. However, in traditional social science, it is practically difficult to collect large-scale user behavior data. Fortunately, with the ubiquity of smartphones and Location Based Social Networks (LBSNs), users continuously report their activities online, which massively reflect their collective behavior. In this paper, we propose NationTelescope, a platform that monitors, compares and visualizes large-scale nation-wide user behavior in LBSNs. First, it continuously collects user behavior data from LBSNs. Second, it automatically generates behavior data summary and integrates an interactive map interface for data visualization. Third, in order to compare and visualize the behavioral differences across countries, it detects the discriminative activities according to the related traffic patterns in different countries. By implementing a prototype of NationTelescope platform, we evaluate its effectiveness and usability via two case studies and a system usability scale survey. The results show that the platform can not only efficiently capture, compare and visualize nation-wide collective behavior, but also achieve good usability and user experience.

Keywords: Participatory Sensing, Collective Behavior, Location Based Social Networks, System Usability Scale

1. Introduction

In the long history of human development, human behavior has been widely studied across various disciplines, such as psychology, biology, sociology and economics[1]. By studying human behavior, we can understand not only individual's behavior, such as one's gestures and facial expressions, but also collective behavior, such as crowd mobility and social movement. In this work, we focus on collective human behavior, which can be defined as the behavior of aggregates whose interaction is affected by some sense that they constitute a group but who do not have procedures for selecting or identifying leaders or members [2]. For example, people in New York city usually go to central business districts for work from residential areas in the morning; French people often go to French restaurants in the evening for dinner while Japanese usually go to bars after work. Understanding such collective behavior can benefit various applications. For example, understanding collective human mobility in urban area can improve the efficiency of urban transportation systems [3]; analyzing collective social activities can help design personalized location based services [4].

Figure 1. Screenshot of Nation Master (comparison between the United States and Japan)

However, it is practically difficult to collect large-scale collective behavior. In current literature, traditional collective behavior studies are usually conducted based on some dedicatedly designed experiments [5]. Due to such setting, it is hard to carry out collective behavior experiments on a large population and collect large-scale data.

Fortunately, the increasing popularity of Location Based Social Networks (LBSNs) makes large-scale user behavior data become attainable. In LBSNs, users can share their real time presence with their friends by checking in at Points of Interest (POIs). Along with the POI category, we are able to understand the semantic meaning of the check-in activity [6]. For example, a user's check-in in office probably means the user's current activity is working. By interacting with LBSNs, users left a significant volume of check-in data. For example, Foursquare[1], one of the well-known LBSN services, attracts more than 45 million users globally and contains more than 5 billion check-ins by January 2014, with millions more everyday. This data massively implies the physical behavior of users and provides us with an unprecedented opportunity to explore large-scale collective behavior. For example, by analyzing the check-in data across different populations (e.g., people in different countries), we may discover certain behavioral differences between them.

In order to select an appropriate granularity of populations for our study, we focus on collective behavior in individual countries, because countries are usually the subject of inquiry of both politics and economy. For example, the mobility of citizens are usually bounded by the territories of their countries; the "rules of games" (e.g., legal rules and code of ethics) also vary across different countries; various macroeconomic statistics, such as gross domestic product (GDP) and inflation rate, are usually reported with country granularity. There exists also a Web service named "Nation Master"[2] that collects social and economic data by country from various sources and provides different visualization of the data. Figure 1 illustrates its screenshot for comparison between two countries (i.e., the United States and Japan).

When studying collective behavior with country granularity, one of the primary tasks is to understand the behavioral differences between countries. For example, when an American would like to travel to Japan for the first time and intends to enjoy a concert there, she may be wondering whether "Japanese people usually go to concert earlier than Americans do?", in order to better plan her trips. To answer such a question, we need to study the traffic patterns (i.e., visiting frequency at different time) of concert halls in the United States and Japan. The collective check-ins in LBSNs massively imply the traffic patterns of each POI category. By extracting and comparing such traffic patterns in different countries, we are able to discover their behavioral differences.

In this paper, we present NationTelescope, a platform that monitors and visualizes large-scale nation-wide collective behavior in LBSNs, and supports the collective behavior comparison between countries. Specifically, it incorporates three unique features.

- First, as users continuously report their activities (i.e., check-ins) in LBSNs, it collects user behavior

[1] https://foursquare.com/
[2] http://www.nationmaster.com/

data on a global scale via check-in data streams from LBSNs.

- Second, in order to efficiently visualize such large-scale data, it automatically generates data summary (i.e., various statistics of collective behavior) and integrates a map interface to visualize the summarized data using interactive map techniques.

- Third, in order to efficiently identify and visualize behavioral differences between countries, it incorporates a discriminative traffic pattern search method to detect discriminative activities (represented by POI categories) between countries.

By developing a prototype of NationTelescope platform, we evaluate its effectiveness and usability via two case studies and a System Usability Scale (SUS) [7] survey. The results show that the platform can efficiently capture and visualize the collective behavior in countries, and effectively compare collective behavior across different countries. The SUS survey with 18 participants proves the good usability of the platform. To the best of our knowledge, NationTelescope is the first platform to monitor and collect global-scale collective behavior in LBSNs.

The rest of the paper is organized as follows. Section 2 presents the related work. Section 3 and 4 illustrate the design of NationTelescope platform and its functionalities, respectively. Section 5 presents the evaluation including both the case studies and SUS survey, followed by discussion in Section 6. We conclude our work in Section 7.

2. Related Work

Human behavior has been widely studied in various disciplines. For example, in phycology, Zipf [8] systematically studied the human behavior and the principle of least effort, and showed that the principle of least effort can be widely interpreted and applied in studying human behavior. In biology, Hinde [9] studied biological bases of human social behavior. In sociology, Park [10] investigated the human behavior in social environment in cities. In economics, Shiller [11] studied the relationship between human behavior and the efficiency of the financial system.

Among these works, collective human behavior has been mostly studied, which represents the behavior of a group of people, such as crowd mobility and social movement. In the early stage of studying collective behavior, since it is difficult to monitor large-scale collective behavior in practice, a lot of studies are conducted based on the results of some dedicatedly designed experiments [5]. Due to such setting, these experiments are usually impossible to be carried out on a large population, leading to the unavailability of large-scale user behavior data.

With the popularity of social networks, users leave a large volume of digital footprints online. For example, by analyzing repost behavior in social networks, Lu et al. [12] studied predictability of the content dissemination trends. However, in traditional social networks, users' behavior such as posting blogs, sharing photos and uploading videos, does not necessarily reflect their daily activities. Location based social networks, where users can share their realtime activities by checking in at POIs, provide a novel data source to study the collective behavior. In current literature, collective behavior analysis in LBSNs has gained increasing popularity in academia. For example, Noulas et al. [13] conducted an empirical study of geographic user activity patterns based on check-in data in Foursquare. Cranshaw et al. [14] studied the dynamics of a city based on user collective behavior in LBSNs. Wang et al. [15] investigated the community detection and profiling problem using users' collective behavior in LBSNs. In addition, the analysis of collective behavior in LBSNs can also enable various applications. For example, by analyzing users' check-in data in LBSNs, Yang et al. studied the personalized location based services such as POI recommendation [16] and search [17]. Sarwat et al. [18] introduced the Plutus framework that assists different POI (e.g., restaurants or shopping malls) owners in growing their business by recommending potential customers.

Although these works provide insight into the characteristics and regularities of user collective behavior in LBSNs, they are usually limited by the collected datasets, i.e., fixed datasets with a small or moderate scale (e.g., check-in data in a city or a country during several weeks or months). In this paper, aiming at

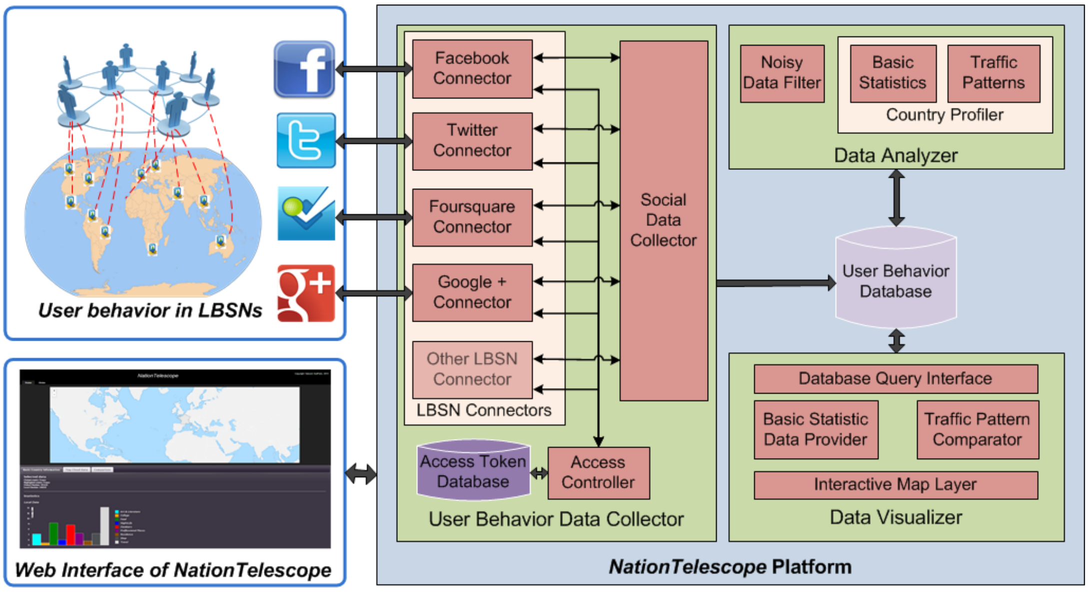


Figure 2. Architecture of NationTelescope Platform

studying the large-scale collective behavior, we introduce the NationTelescope platform to collect, analyze and visualize the user check-in behavior in LBSNs on a global scale.

3. Platform Design

In this section, we present the architecture of NationTelescope platform. As shown in Figure 2, it mainly consists of four parts, viz., User Behavior Data Collector, Data Analyzer and Data Visualizer, as well as a User Behavior Database. First, when users interact with LBSNs, they voluntarily report their behavior data online. This data is then collected by the User Behavior Data Collector and stored in the User Behavior Database. Second, the Data Analyzer regularly accesses the User Behavior Database to conduct basic analysis, and generates summarization of the collected behavior data, such as POI visiting patterns. The summarized data is also stored in the User Behavior Database. Third, the Data Visualizer provides various visualization of the summarized collective behavior data. In the following, we present the design and characteristics of each part.

3.1. User Behavior Data Collector

The User Behavior Data Collector is responsible for collecting user behavior data (i.e., check-in data) from various LBSNs services. As illustrated in Figure 2, it is composed of several LBSN Connectors, a Social Data collector, an Access Controller and an Access Token Database. The consideration of such a design is mainly due to the access control scheme of individual LBSNs. Specifically, due to the privacy protection of users' personal data, most LBSNs integrate the OAuth protocol[3], an open standard for authorization. In order to access the data stream from LBSNs, an authentication process is required with specific access tokens. Therefore, we implement the Access Controller and Access Token Database for authentication with various LBSNs. In addition, since different LBSNs usually provide different Application Programming Interfaces (APIs), the corresponding LBSN connector is implemented under the specification of each LBSN.

After the authentication with LBSNs, the Social Data Collector component continuously gathers user behavior data. In order to handle the data heterogeneity across different LBSNs, we adopt OpenSocial API[4],

[3]http://oauth.net/
[4]http://opensocial.org/

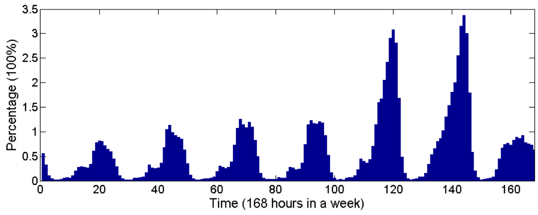


Figure 3. Traffic pattern of bar related activities in the United States

which is a public specification of social network Web framework supporting an extendable data structure for different social networks. Moreover, such a design of data collector also ensures the scalability of the platform when adding new LBSNs. Specifically, we can easily incorporate new LBSNs in our platform by only implementing the corresponding LBSN connectors.

3.2. Data Analyzer

The Data Analyzer component is responsible for conducting some basic data analysis tasks including noisy data filtering and country profiling in terms of nation-wide collective behavior. As shown in Figure 2, it is composed of Noisy Data Filter, and Country Profiler.

First, the raw check-in data stream from LBSNs usually contains various types of noisy data which need to be eliminated by the Noisy Data Filter. For example, some check-ins are conducted without the POI semantic information (e.g., POI category and description). Since the semantic information is indispensable for understanding collective behavior, these check-ins are thus considered as noise and need to be filtered out.

Second, based on the filtered check-in data, the Country Profiler component extracts various features to characterize the collective behavior in each country. Specifically, two types of features are extracted, viz., basic statistics and traffic patterns. The Basic Statistics of a country include the total number of check-ins, and the check-in frequency of each category of POIs (i.e., percentage of check-ins in individual POI categories). In LBSNs, POIs are classified into different categories. For example, Foursquare organizes its POIs with a three-level hierarchical category classification[5]. It contains 9 root categories (i.e. Arts & Entertainment, College & University, Food, Great Outdoors, Nightlife Spot, Professional & Other Places, Residence, Shop & Service, Travel & Transport) which are further classified into 291 categories at the second level. However, only a part of second-level categories are divided into sub-categories at the third level. Due to the incompleteness of the third-level categories, we choose to use the first-level and second-level categories to semantically characterize collective behavior in each country and calculate the visiting frequency for each category in a country.

In addition, in order to capture the temporal aspect of collective behavior, we also extract the traffic patterns in a “typical week”[6] for each POI category in a country, which are represented by the percentages of check-ins in each hours in a week. Figure 3 presents the traffic pattern of bars in the United States. We observe that bars are frequently visited in the evening and their traffic peaks appear on Friday and Saturday evening.

3.3. Data Visualizer

The Data Visualizer is responsible for providing user behavior data visualization in an interactive manner, i.e., via an interactive map. As presented in Figure 2, it is composed of four components. First, the Database Query Interface provides the access to the User Behavior Database. Second, the Basic Statistic Data Provider takes charge of fetching the basic statistics from a country profile and normalizing the data for visualization. Third, for each POI category, the Traffic Pattern Comparator provides the detailed comparison

[5]https://developer.foursquare.com/docs/venues/categories
[6]We extract weekly mean traffic patterns with hour granularity.

of traffic patterns from different countries. In order to efficiently identify the significant behavioral differences between countries, it incorporates a sliding-window based discriminative traffic pattern search method that will be elaborated in the next section. Fourth, all the data visualization are built upon the Interactive Map Layer. The interactive map is implemented using Leaflet[7], a light-weight cross-platform JavaScript library for interactive maps.

The design of the Data Visualizer ensures the scalability when adding new visualization components, such as tag cloud, bar chart and line chart, etc. Specifically, due to the fact that the data access and basic visualization are ensured by the Database Query Interface and Interactive Map Layer respectively, the new visualization components can be easily developed using the above two interfaces.

4. Platform Functionalities

In this section, we present the main functionalities of NationTelescope platform and the associated graphic user interface. Specifically, we first show the basic visualization of user behavior, including the global check-in distribution on the 3D world map, the bar charts of check-in frequency of different POI categories and the tag clouds of the checked POI categories in a specific country. We then present the visualization of the traffic pattern comparison between countries and introduce the proposed sliding-window based discriminative traffic pattern search method.

4.1. Basic Visualization

NationTelescope platform provides basic visualization of the summarized data. First, in order to quantitatively illustrate the collective behavior in LBSNs across the world, we present the global check-in distribution on the 3D world map by leveraging the WebGL technology[8]. WebGL (Web Graphics Library) is a powerful JavaScript API for creating interactive 3D graphics and 2D graphics within web browser without the use of plug-ins. Figure 4(a) shows the screenshot of the global check-in distribution. The 3D earth can be rotated or zoomed. The height of the bar indicates the total check-in number. We observe that most of the check-ins happened in big cities. Furthermore, cities in Turkey, South Asia, and South America contain a large number of active LBSN users and thus show high check-in number. Similar results have also been found in an empirical study of Foursquare usage[9].

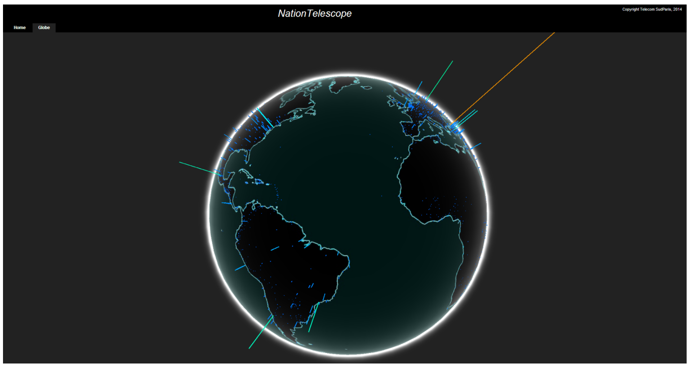
Second, we present the bar charts of check-in frequency of different POI categories. As shown in Figure 4(b), users can select a country by directly clicking on the interactive map. The check-in frequency of the top level POI categories is displayed as a bar chart. The bar chart is plotted using the D3.js technology[10], which is a data-driven documents JavaScript library for manipulating documents based on data. Figure 4(b) illustrates the check-in frequency of nine POI categories in France. We observe that travel, food, outdoor, art and entertainment related spots are frequently visited by French LBSN users.

Third, in order to understand the detailed semantics of collective behavior in a country, we look into the check-in frequency of the second-level POI categories. Due to the large number of categories (i.e., 291 categories in total), the bar chart visualization is not suitable. Therefore, we leverage the tag cloud representation to visualize the data as demonstrated in Figure 4(c). Larger font size of POI categories implies higher visiting frequency, and vice versa. We observe that, in Figure 4(c), besides the daily routine POIs, such as train stations, offices and home, French restaurants are preferred by French LBSN users.

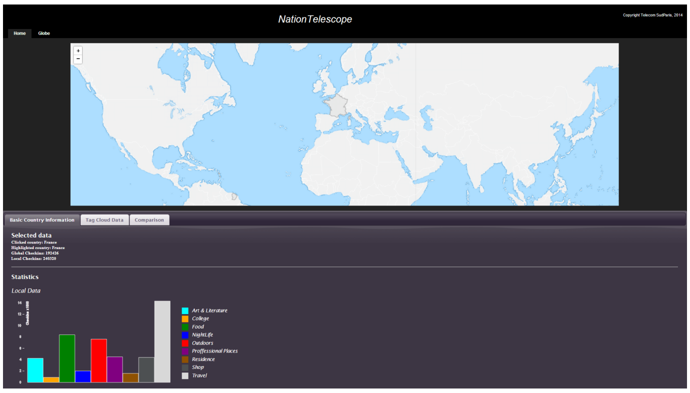
4.2. Traffic Pattern Visualization

In order to explore the behavioral differences between countries, NationTelescope platform supports the traffic pattern visualization functionality, which compares the traffic pattern of each POI category between two countries. However, due to a large number of POI categories (i.e., 291 categories), it is inefficient to

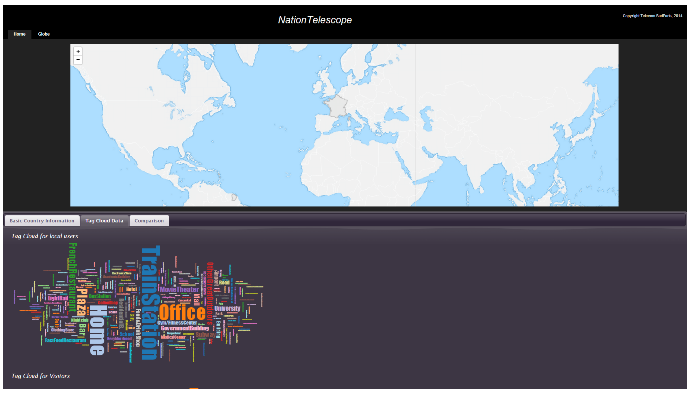
[7]http://leafletjs.com/
[8]http://www.khronos.org/webgl/
[9]http://www.appappeal.com/maps/foursquare
[10]http://d3js.org/



(a) Global Check-in Distribution



(b) Bar charts of check-in frequency of top-level POI categories



(c) Tag Cloud of check-in frequency of second-level POI categories

Figure 4. Basic visualization in NationTelescope

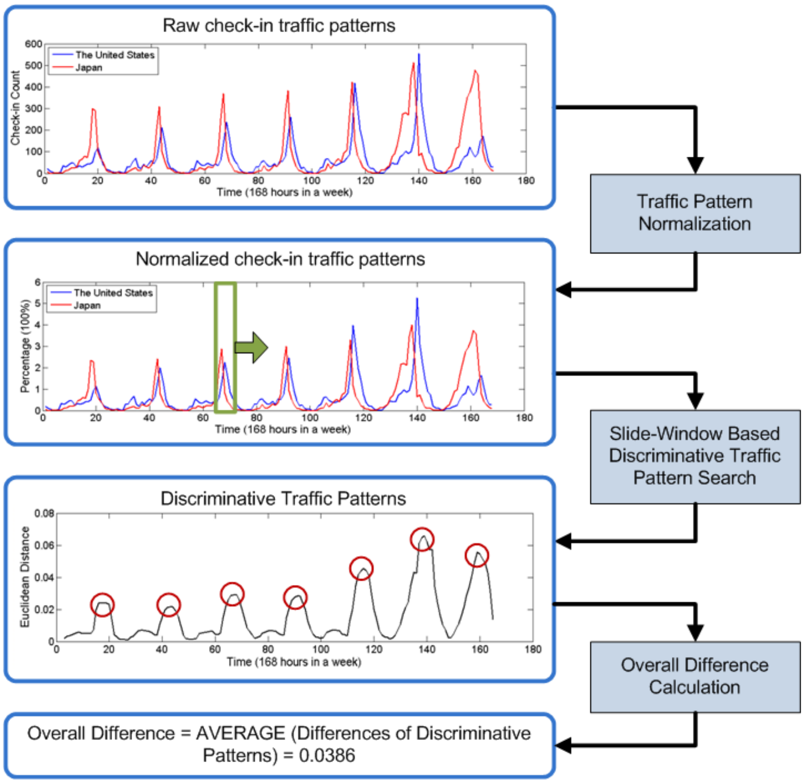


Figure 5. Traffic pattern comparison scheme and an example of "Concert Hall" category comparison between the United States and Japan)

visualize all the traffic patterns in a long list and let users explore the list to find the discriminative POI categories by scrolling the screen. Moreover, traffic patterns of some POI categories may be quite similar to each other. For example, the museum visiting patterns are probably similar in different countries. Intuitively, when comparing collective behavior between two countries, users may probably be interested in the POI categories whose traffic patterns exhibit significant difference. In the following, we first present the traffic pattern comparison scheme and then demonstrate the graphic user interface for traffic pattern visualization.

4.2.1. Traffic Pattern Comparison

For two given countries, in order to identify the most discriminative POI categories whose traffic patterns are significantly different, we propose a sliding-window based discriminative traffic pattern search method. Specifically, for each POI category in two countries, we first normalize the two traffic patterns and then use a sliding-window to compare them in order to identify the discriminative traffic patterns and the associated difference measures. Finally, we calculate the overall difference between the two traffic patterns by averaging the difference measures of the detected discriminative traffic patterns. Figure 5 shows the detailed traffic pattern comparison scheme with an example of "Concert Hall" category between the United States and Japan. We present the details of each step as follows.

First, in order to focus on the temporal regularity of traffic patterns, we need to normalize the raw traffic patterns. Specifically, the raw check-in traffic patterns in countries are influenced by the number and the activeness of the users, which can not be directly compared. For example, it is inappropriate to compare the raw traffic patterns between a country with a large number of users and that with a small number of users. Therefore, in order to avoid the influence of the number of users and the activeness of them, we normalize each traffic pattern with regard to its total number of check-ins.

Second, given two normalized check-in traffic patterns, in order to quantitatively measure the differences

Figure 6. Graphical user interface for traffic pattern visualization

between them, we detect discriminative traffic patterns using a sliding-window based discriminative traffic pattern search method. Similar idea of discriminative feature selection has been widely used in various data mining problem, such as classification [19]. Specifically, we first leverage a sliding-window to compare the traffic patterns segment-by-segment to calculate their distance in each segment, and then detect the discriminative traffic patterns where the peaks of distance in all segments appear. In this work, we empirically set the size of the sliding-window as 6 hours and use Euclidean distance to quantitatively measure the difference in a segment between two traffic patterns. For example, as shown in Figure 5, we observe that the discriminative patterns appear in every evening. By investigating the normalized check-in traffic patterns, we see that Japanese usually go to concert earlier than Americans do in the evening.

Finally, we calculate the average difference of all discriminative traffic patterns and regard it as the overall difference between two countries with regard to a specific POI category. By calculating the difference for all the POI categories, we are able to assess how discriminative the individual POI categories are. In this work, we consider the top k most discriminative POI categories to display in the user interface, which are presented in the next section.

4.2.2. *Graphic User Interface*

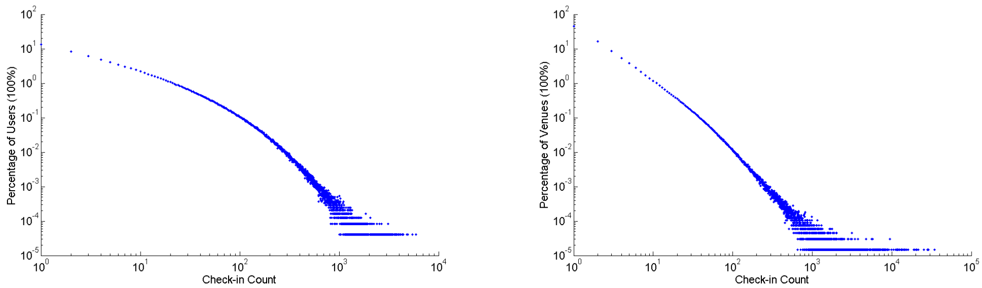
Figure 6 demonstrates the Web interface for traffic pattern visualization. Users can either input the complete country names or selecting them on the map. The comparison results are then visualized by different POI categories. As shown in Figure 6, the visualization leverages an accordion interface with 9 top-level POI categories. When selecting a top-level category, the detailed traffic patterns of the discriminative second-level POI categories, which are identified in the previous step, are illustrated. In the screenshot, we display the top five discriminative POI categories when comparing the traffic patterns between Japan and the U.S. We observe that the "Concert Hall" category appears as the 4th discriminative POIs. Specifically, the answer of the question in the introduction section, i.e., "Do Japanese people usually go to concert earlier than Americans do?", can be summarized as follows. Japanese usually go to concert in the early evening while Americans prefer to go to concert in the late evening. In addition, more Japanese go to concert on Sunday than Americans usually do.

5. Evaluation

In this section, we evaluate the effectiveness and usability of NationTelescope platform. Specifically, in order to accumulate representative user behavior data for evaluation, we implement the prototype of the platform and keep it running for about 6 months (from January to June 2014). We first conduct an overall statistical analysis on the collected dataset from our platform. We then evaluate it from the effectiveness and usability perspectives. First, in order to validate the effectiveness of NationTelescope platform, rather than

Table 1. Statistics of collected dataset

Check-in number	31,506,326
User number	1,394,556
Venue number	7,343,432
Average number of check-ins per user	22.59
Average number of check-ins per venue	4.29
Maximum number of check-ins per user	5,910
Maximum number of check-ins per venue	34,524
Country (according to ISO 3166-1 alpha-2) number	245
Average number of users per country	201,118



(a) Distribution by users

(b) Distribution by venues

Figure 7. Check-in count distribution

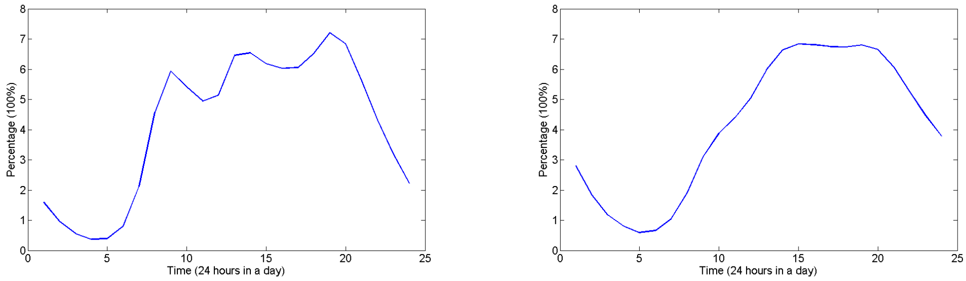
exhaustively presenting behavioral comparison across all countries, we conduct two case studies and present some interesting observations. The first case study compares collective behavior between an occidental country, i.e., the United States, and an oriental country, i.e., Japan, while the second case study compares two European countries, i.e., the United Kingdom and France. Second, in order to evaluate the usability of the platform from user experience perspective, we carry out a System Usability Scale (SUS) survey with 18 participants. In the following, we first present the overall statistical analysis on the collected dataset, followed by the case studies and the SUS study.

5.1. Statistical analysis on the collected dataset

In this section, we conduct a statistical analysis on the collected user behavior dataset using our platform. Table 1 presents the statistics of the collected dataset. It contains 1,394,556 users and 31,506,326 check-ins which were performed over 7,343,432 venues globally. The dataset covers 245 countries and dependent territories according to ISO 3166-1 alpha-2 two-letter country codes standardization, with 201,118 users on average per country.

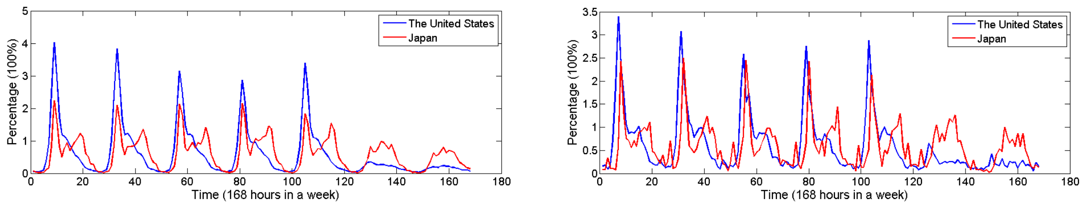
In the collected dataset, we find that, on average, one user has performed 22.59 check-ins and the most active user has contributed 5,910 check-ins. Meanwhile, the average check-in number for one venue is 4.29, and the most popular venue has attracted 34,524 check-ins. Such statistics imply a skew distribution of check-ins on venues and users. Figure 7 illustrates the check-in distribution by both users and venues (in log-log scale). The x-axis indicates the check-in count while the y-axis refers to the percentage of users or venues with that number of check-ins. We observe that both of the distributions follow the power-law, which is universal in social networks [20]. On the one hand, a large number of check-ins are performed by a small number of active users. On the other hand, many check-ins are reported at a few number of venues. For example, famous tourist spots usually attract a significant number of check-ins.

In addition, we demonstrates the overall traffic patterns of a typical day on the weekday and weekend, as shown in Figure 8. First, we observe that, on the weekday, user activities illustrate three major peaks around 9am, 13pm and 7pm, respectively. The diurnal pattern of human behavior is clearly displayed as most of



(a) Weekday (b) Weekend

Figure 8. Overall traffic patterns on the weekday and weekend



(a) Office (b) Factory

Figure 9. Traffic pattern comparison of working behavior between the United States and Japan

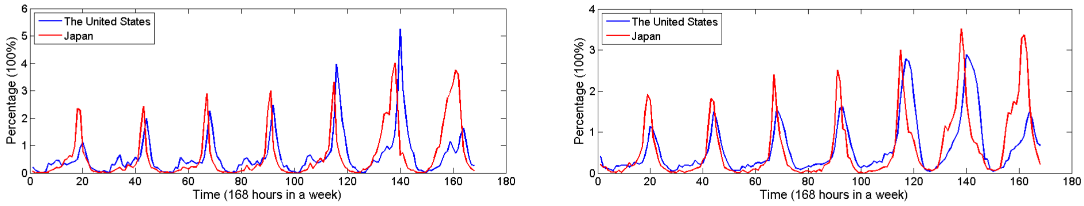
the users are active during the daytime than at night. Second, we find that the weekend pattern is obviously different from the weekday pattern. On the weekend, the morning peak around 9am disappears, and users are continuously active from noon to the evening. Moreover, they are more active at night than that on the weekday, as most of people do not work on the weekend and they often choose to enjoy more entertainment activities at night. As citizens from different nations usually behave differently with respect to activity categories and the related traffic patterns, in order to explore nation-wide collective activity differences, we present two case studies using our platform as follows.

5.2. Case Study I: The United States and Japan

According to social science study, the geographical isolation is an important factor for cultural diversity [21], which leads to the behavioral difference [22]. Therefore, we choose the United States and Japan in this case study since they are geographically distant. By exploring the behavioral differences between the United States and Japan using our platform, we discover a lot of behavioral differences across various daily activities, such as working, entertainment, eating and shopping, etc. Instead of exhaustively listing all the differences, in the following, we present some interesting findings from working and entertainment behavior perspectives.

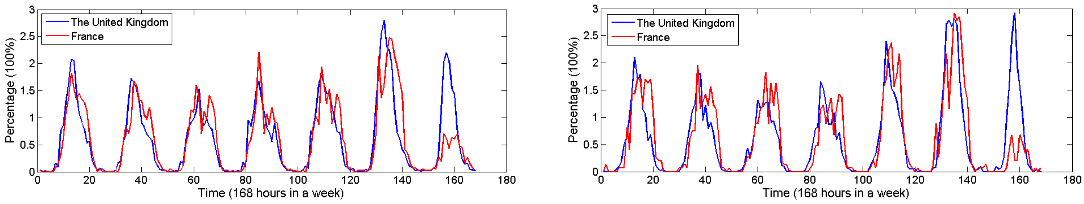
First, we find that Japanese work longer than Americans in general. We demonstrate in Figure 9 the traffic patterns of two POI categories (i.e., office and factory) among the top five discriminative working-related POI categories. We observe that Japanese daily working time is obviously longer than that of Americans, and a large number of Japanese work particularly in the evening. In addition, there are a lot of Japanese users working during the weekend. Similar observations have also been found in social and economy science with respect to Japanese working time [23] and the comparison of working time across different countries [24]. Compared to these traditional approaches in social and economy science that mainly consist of a large-scale survey, the advantages of NationTelescope are that it can provide timely results with significant less human effort.

Second, we find that Americans usually go to entertainment places later than Japanese in the evening, and less Americans prefer Sunday for entertainment activities than Japanese do. As shown in Figure 10, we



(a) Concert Hall (b) Music Venue

Figure 10. Traffic pattern comparison of entertainment behavior between the United States and Japan



(a) Mall (b) Department Store

Figure 11. Traffic pattern comparison of shopping behavior between the United Kingdom and France

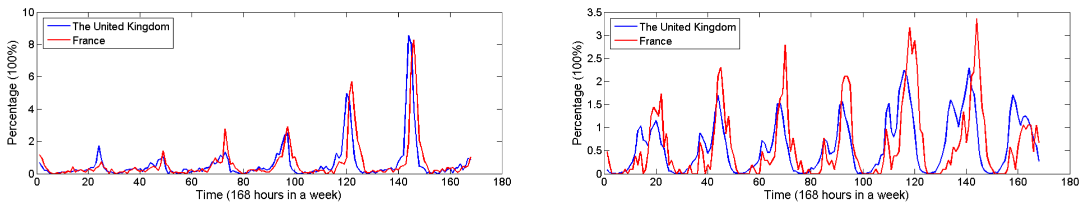
illustrate the traffic patterns of two POI categories (i.e., concert hall and music venue) among the top five discriminative entertainment related POI categories. We observe that the traffic peaks in the United States appear later than those in Japan. In addition, there is significant less traffic of entertainment activities on Sunday in the United States than that in Japan.

5.3. Case Study II: The United Kingdom and France

Although geographical isolation of two countries usually implies behavioral differences between the two populations, the collective behavior in two adjacent countries may still be different in some aspects. Therefore, in this case study, we choose the United Kingdom (UK) and France as the subjects of inquiry, and use our platform to explore the behavioral differences between them. In the following, we present notable differences from shopping and nightlife aspects.

First, we find that shopping activities on Sunday are significantly less in France than those in the UK. Specifically, as shown in Figure 11, we demonstrate two shopping related POI categories identified by our platform as the discriminative ones, i.e., “Mall” and “Department Store”. We observe that both categories have much lower traffic in France than that in the UK. This is mainly caused by the different “rules of games” (i.e., laws) in the two countries. Nowadays, the United Kingdom opens its shops on Sunday, while France have managed to keep most of theirs closed [25].

Second, we find that the French nightlife activities are generally later than those in the UK. As shown in



(a) Nightclub (b) Pub

Figure 12. Traffic pattern comparison of nightlife behavior between the United Kingdom and France

Table 2. System Usability Scale Scores (Higher scores imply better user experience. Note that the SUS scores for S1-S10, learnability and usability range from 0 to 4, while the overall SUS score ranged from 0 to 100.)

SUS Statements	Average Score
S1: I think that I would like to use this system frequently.	2.20
S2: I found the system unnecessarily complex.	2.87
S3: I thought the system was easy to use.	3.20
S4: I think that I would need the support of a technical person to be able to use this system.	3.13
S5: I found the various functions in this system were well integrated.	2.20
S6: I thought there was too much inconsistency in this system.	2.93
S7: I would imagine that most people would learn to use this system very quickly.	2.93
S8: I found the system very cumbersome to use.	3.06
S9: I felt very confident using the system.	2.80
S10: I need to learn a lot of things before I could get going with this system.	3.20
Learnability dimension (S4 and S7)	3.03
Usability dimension (other 8 statements)	2.81
Overall SUS score	**71.33**

Figure 12, we present two POI categories from the top five discriminative nightlife related POI categories, i.e., nightclubs and pubs. We observe that the traffic peaks in nightclubs and pubs in France appear later than the peaks in the UK.

5.4. Usability Study

In this study, we adopted the SUS developed by Brooke [7] in 1996, which had been widely adopted by both academia and industry. It contains a ten-item questionnaire based on Likert Scale [26], where a statement is made and respondents are supposed to indicate the degree of agreement with the statement. The SUS consists of ten statements, of which odd-numbered statements are worded positively and even-numbered statements are worded negatively. To use the SUS, participants should indicate their agreement with each statement using a five-point scale from 1 (anchored with "Strongly disagree") to 5 (anchored with "Strongly agree"). Afterwards, each statement's score contribution is determined, which ranges from 0 to 4. Concretely, for positively-worded statements (1, 3, 5, 7 and 9), the score contribution is the scale position minus 1. For negatively-worded statements (2, 4, 6, 8 and 10), it is 5 minus the scale position. Therefore, higher score for positively-worded statements implies more agreement on the statements, while higher score for negatively-worded statements implies less agreement on the statements. Finally, SUS yields a single score representing the overall usability, which is calculated by multiplying the sum of the statement score contributions by 2.5. Thus, the overall SUS score is range from 0 to 100. Higher scores imply better user experience.

In addition, Lewis et al. [27] conducted factor analysis on the SUS statement and then defined two dimensions, i.e., learnability and usability. According to their analysis, the learnability dimension includes the statement 4 and 10 while the usability dimension includes the statements 1, 2, 3, 5, 6, 7, 8, and 9. Please refer to [7] and [27] for more details.

We conducted a SUS survey of NationTelescope platform using Google Forms[11], and spread the survey via email and social network. Participants are provided with a brief guide of the platform functionalities and are required to use the platform for about 15 minutes before they start the survey. We also provided participants with some example tasks to let them better explore our platform, such as "finding the entertainment behavioral differences between the United States and Japan". In addition, in order to collect rich user feedback, we also allow participants to leave their comments about the platform in text. We recruited

[11]https://docs.google.com/forms

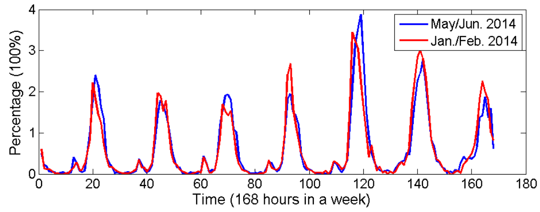


Figure 13. Example of collective behavioral seasonality (Traffic pattern comparison of bars in Japan in summer (May/Jun. 2014) and that in winter (Jan./Feb. 2014)).

18 participants in total, of which five were female. Most of the participants (i.e., 15 participants) are between 20-30 years. The professions of the participants are diverse, including computer scientists, engineers, university students, marketing managers, etc.

Table 2 shows the SUS statements and the results. Higher scores imply better user experience. We find that the overall SUS score is 71.33. According to the study of Bangor et al. [28] on adjective ratings (i.e, worst imaginable, awful, poor, OK, good, excellent, best imaginable) and SUS scores (from 0 to 100), our NationTelescope platform achieves a "good" SUS rating. Furthermore, our platform achieves high score for both usability and learnability. Specifically, the usability score and learnability score are 3.03 and 2.81 respectively. Note that the scores are ranging from 0 to 4, and higher scores imply better user experience.

In addition, by investigating the results of individual questions, we find that S3, S4, S8 and S10 have high scores, while S1 and S5 have relatively low scores. On the one hand, we understand that the NationTelescope is user-friendly and easy to use without specific preliminary knowledge. On the other hand, we understand that not all the participants would like to use the platform frequently and think that the integration of the platform can be further improved. By interviewing several participants, we find that the low score of S1 is mainly due to the fact that some of the participants are not interested in social network services, nor using social media. Moreover, some participants also mentioned that they would use the platform frequently if the platform can be integrated as an application in existing social network services, such as Facebook. According to users' comments, we find that the low score of S5 is also because they expected more integration of our platform with the existing social networks. Although it is not one of our original objectives in developing NationTelescope platform, we still plan to extend the current prototype as an integrated application in existing social networks in the future.

6. Discussion

Data bias in LBSNs. While the evaluation shows that NationTelescope platform can efficiently monitor and visualize large-scale collective behavior, we are aware that the platform has several limitations with respect to data bias. First, since users voluntarily report their activities in LBSNs, a user's check-in data is sparse and may not necessarily reflect her complete activity traces. By combining the individual behavior data, we believe that the collective behavior is still representative and valuable. Second, the collective behavior in LBSNs may be biased due to the targeted population. Concretely, users of LBSNs mainly consist of youngsters who frequently use social network services. Therefore, the collective behavior of such a population in a country may not be completely representative of the collective behavior of its whole population. However, it can still reflect the nation-wide collective behavior to some extent. Based on our case studies, we still find some interesting behavioral differences using NationTelescope.

Seasonality of collective behavior. Intuitively, collective behavior usually exhibits seasonality [29]. For example, due to the late sunset in summer, people may probably start nightlife activities later than they do in winter. Figure 13 demonstrates the comparison between the traffic patterns of bars in Japan in summer (May/Jun. 2014) and that in winter (Jan./Feb. 2014). We observe that the traffic peaks appear slightly later in summer than in winter. By studying such seasonality of collective behavior, we can conduct better behavioral comparison between countries. Therefore, although we do not fully explore such characteristics in this study due to the limited data collection time (i.e., about half a year), we plan to explore more about the seasonality of collective behavior in LBSNs and integrate new features in NationTelescope in the future.

7. Conclusion

In this paper, we introduce NationTelescope, a platform that monitors, compares and visualizes large-scale nation-wide user behavior in LBSNs. First, it collects the user behavior data in the check-in streaming from LBSNs. Second, it automatically generates the behavior data summary and integrates an interactive map interface for visualization. Third, it supports the collective behavior comparison functionality that detects and visualizes the discriminative behavioral differences between countries. To evaluate the effectiveness and usability of NationTelescope, we conduct two case studies and a system usability scale survey. The case studies show that our platform can efficiently capture and visualize the nation-wide collective behavior in LBSNs. The SUS survey with 18 participants proves that our platform achieves good usability.

In the future, we plan to extend NationTelescope platform in several directions. First, according to the SUS survey results and the participants' comments, we plan to better integrate NationTelescope with the existing social network services in order to improve the user experience. Second, since the current prototype of NationTelescope merely supports the basic check-in data, we plan to incorporate other data modalities, such as pictures, in the platform. Third, since NationTelescope platform continuously collects user behavior data, we intend to study the behavioral seasonality and evolution over time in the future. Finally, in order to make better use the collected user behavior data, we would like to design and implement a set of API to make the data accessible to public.

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