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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.

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 (Skinner, 1953). 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 (Turner and Killian, 1957). 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 (Zheng et al., 2010); analyzing collective social activities can help design personalized location based services (Gavalas et al., 2014).

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 (Ostrom, 2000). 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 (Yang et al., 2015). 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

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[1] https://foursquare.com/

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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 is 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 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) (Brooke, 1996) 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. Sections 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 (1949) 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 (1974) studied biological bases of human social behavior. In sociology, Park (1915) investigated the human behavior in social environment in cities. In economics, Shiller (1999) 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 (Ostrom, 2000). 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. (2014) 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. (2011) conducted an empirical study of geographic user activity patterns based on check-in data in Foursquare. Cranshaw et al. (2012) studied the dynamics of a city based on user collective behavior in LBSNs. Wang et al. (2014) 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 (Yang et al., 2013b) and search (Yang et al., 2013a). Sarwat et al. (2013) 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 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 Fig. 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

[2] http://www.nationmaster.com/