Mobile Big-Data-Driven Rating Framework: Measuring the Relationship between Human Mobility and App Usage Behavior

Yuanyuan Qiao, Xiaoxing Zhao, Jie Yang, and Jiajia Liu

Abstract

Smart devices bring us ubiquitous mobile access to the Internet, making it possible to surf the Internet in mobile environments. With the pervasiveness of mobile Internet, much evidence shows that human mobility has heavy impact on app usage behavior. However, the relationship between them has not been quantified in any form. In this article, a rating framework is presented to demonstrate the existence of their connection. The core idea of a rating framework selects the most significant mobility features that may influence app usage behavior. In particular, we focus on three aspects of human mobility in urban areas: individual mobility characteristics, location, and travel behavior, from both the crowd and individual points of view. At last, by using a limited number of selected mobility and time features, high forecast accuracy is achieved in terms of app usage behavior of crowds and individuals, which verifies the effectiveness of the rating framework.

The dynamics of many social, technological, and economic phenomena are driven by individual human actions, turning the quantitative understanding of human behavior into a central question of modern science [1]. Nowadays, human behavior is reshaped by the explosive growth of the Internet, which has utterly transformed the world, making studies about human behavior on the Internet a research hotspot. In the era of mobile Internet, a vast amount of mobile big data allows us to gain further insights into human activities (e.g., how people act, move, and respond to external events). Instead of finding the statistical law of Internet usage, many researchers try to find out what are the factors that "induce" people to surf on the Internet, the answer to which may bring new models to describe human activities.

It has been found that many factors may impact people's app usage behavior on smartphones, such as the devices people use, users' personalities, surrounding environments, and nearby users [2–6]. Recently, it has been proven that location has a strong influence on what kinds of apps we choose to use [7, 8]. For example, music apps prevail at home, social networking/email/news apps were mostly used outside the home and workplace, students liked to use the Android browser in classrooms, but consumed more traffic on ESPN and Pandora in the dorm. Time and travel behavior can also shape app usage behavior. Researchers found that people may use Angry Birds, Facebook, and Kindle before bedtime, and multimedia apps are more popular than travel apps when people are traveling [9].

Although lots of work has verified that location, movement frequency, and daily activities have influence on users' app usage behavior [7–9], the quantitative relationship between human mobility and app usage behavior in mobile Internet remains unknown. In this article, a rating framework is proposed to measure the relationship between human mobility and app usage behavior, which could be applied to all kinds of mobile big data collected from different areas. In particular, we try to find the answers to the following questions: "What mobility features have influence on people's app usage behavior?" "To what extent does human mobility impact people's app usage behavior?" "Are there rules connecting mobility features of crowds and individuals with app usage in urban areas?" We aim to give useful suggestions to service providers, and bring new insight to propose new models for app usage behavior and human mobility. More practically, building the bridge between human mobility and mobile Internet would tell us what people need in daily activities, which may help construct smart cities, benefit location-based services, and optimize network resources by content pre-fetching. The contributions of this article are highlighted as follows:

1. To the best of our knowledge, we are the first to measure the relationship between human mobility and app usage behavior. In order to reveal the internal mechanism of app usage behavior from the human mobility point of view, we focus on the impact of both crowd and individual mobility behavior on app usage. We found that although people usually have a wide range of preferences with app usage, a limited number of mobility and time features is enough to forecast app usage behavior of crowds and individuals with high accuracy.
2. The rating framework is designed to process traffic traces, select the significant features of human mobility, and forecast the app usage behavior. Although the selected features may vary with cities, regions, and countries, the rating framework can be applied to all kinds of mobile big data collected from different areas.
3. In order to discover the rules that govern human behavior, real mobile big data are essential. We do our experiments with real network traffic traces of mobile Internet collected

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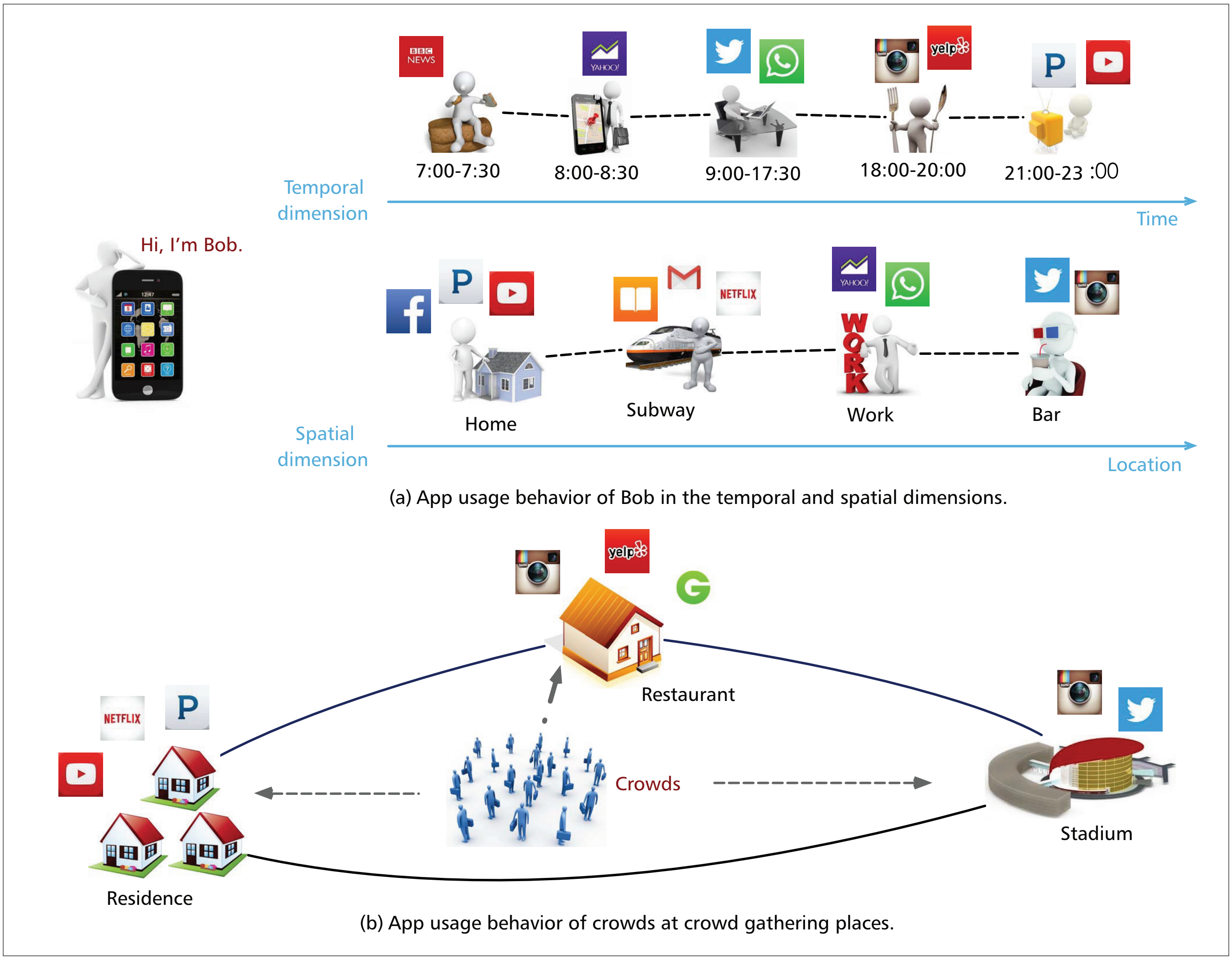

Figure 1. Regular app usage behavior in ordinary life: a) the app usage behavior of an individual exhibits a certain degree of time and space regularity; take Bob's daily behavior as an example; b) app usage behavior of crowds emerges at crowd gathering places.

from a typical city in China covering over 3 million people in 7 days.

The structure of the article is organized as follows. First, the results of statistical analysis based on real-world data are presented, which reveal there is strong correlation between app usage, location, and time for both individuals and crowds. Second, we provide the overall structure of the rating framework. It focuses on three aspects of human mobility features in urban area, including individual mobility characteristics (e.g., the trip distance distribution, the radius of gyration, and the number of visited locations over time), location (e.g., the places users frequently visited), and travel behavior (the movement/travel pattern, e.g., in commuting). Then we give experimental results and analysis from the rating framework. The most significant features of mobility pattern for both individuals and crowds, which have heavy impact on app usage behavior, are selected with a score value. Furthermore, the effectiveness of the framework is tested by forecasting app usage behavior with selected significant features. Finally, conclusions are drawn.

Movements Revealing the App Usage Behavior on Smartphones

Smartphones have touched so many different areas of our lives. It allows people to get news and updates immediately, whether it is through an application or the browser. Naturally, app usage behavior in ordinary life exhibits a certain degree of temporal/spatial regularity. For an individual, app usage behavior may vary with time and location. As shown in Fig. 1a, looking into Bob's app usage behavior on the temporal dimension, it is found that he usually sees the news after getting up in the morning, checks stock before work, chats on WhatsApp and browses social networks on the phone during daytime, views comments on Yelp and shares photos with friends during evening activities, and watches video and listens to music at night. Also, as for app usage in places/locations to which Bob often goes, some regular patterns are very obvious, such as that he likes to browse social networking, and watch videos and movies at home; on his way to work, he may read books, check emails, or watch a movie on the phone; at the workplace, Bob occasionally chats with friends and checks stock trends; and he shares photos on social networking apps when he is in a bar. In addition, for crowds, there are also regular patterns at crowd gathering places (Fig. 1b). For example, sharing photos and videos on social network while watching sports or a concert is very popular; checking reviews on Yelp or coupons on Groupon is very helpful at restaurants; and video, movie, and music apps are frequently used at home. All these daily behaviors show potential rules that connect app usage and mobility behavior.

In order to discover statistical patterns of app usage behavior from the temporal and spatial dimensions in a statistical

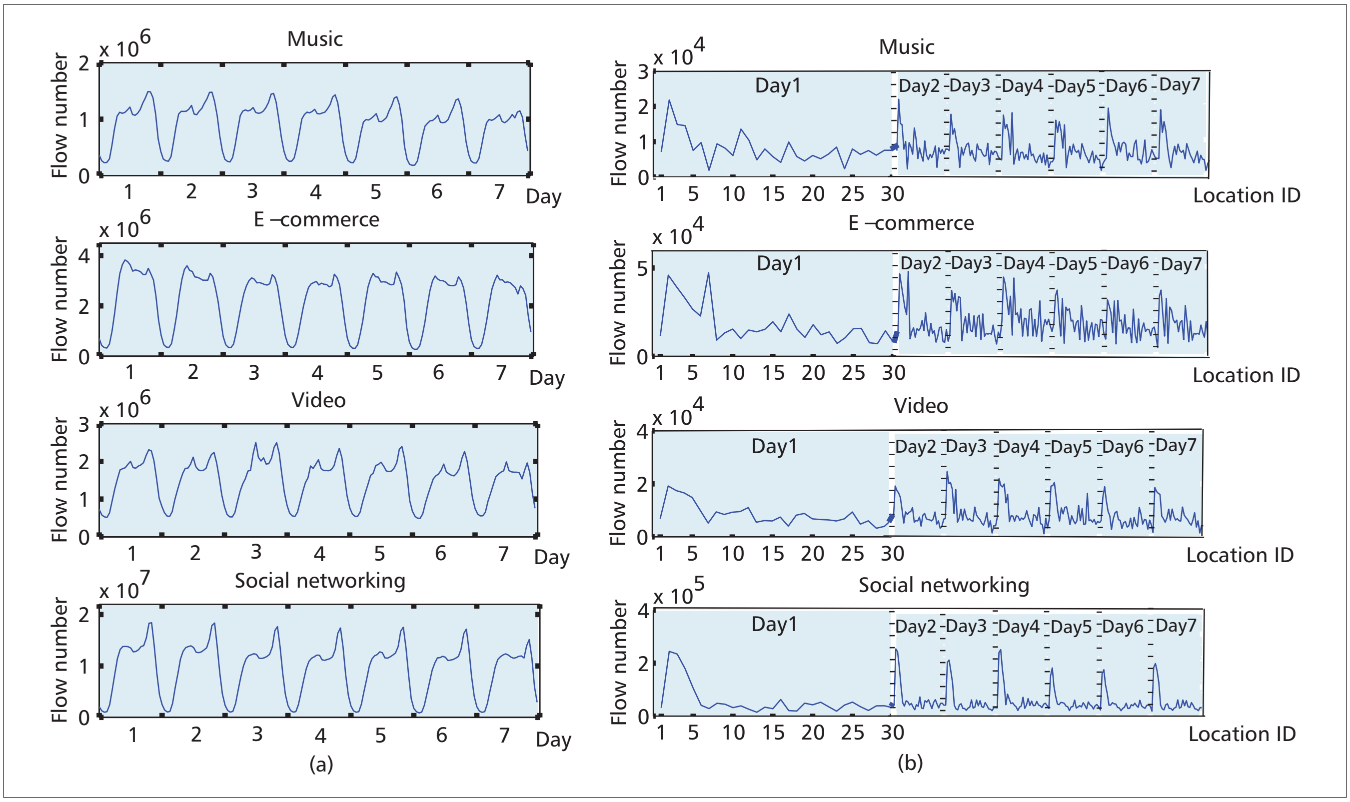

Figure 2. The flow number distributions of music, e-commerce, video, and communication apps varies with time and locations: a) flow number varies with time on different days; b) flow number varies with location on different days.

manner, the distributions of flow numbers of music, e-commerce, video, and communication apps at different time periods and locations are draw in Fig. 2. All flows are collected from a typical northern city in China that covers a population of nearly 300 million. Here, "flow" is defined as bidirectional data transmission at the usual 5-tuple {IP, destination IP, source port, destination port, and transport protocol} within a certain period of 64 s. For our dataset, location refers to the coverage of a cell tower through which users' smartphones connect, with an average error of 175 m (the density of a cell tower is much larger in an urban area than in a suburban or rural area due to the human population density). As shown in Fig. 2a, the flow number of apps changes periodically, so the trends of distinct apps over seven days are quite different. Communication apps such as WeChat (a mobile text and voice messaging communication service) and QQ (an instant messaging software service) averagely generate over 229 million flows each day during the whole week, the most intensive usage occurring around 9 p.m. What's more, e-commerce apps such as Taobao (the leading online consumer-to-consumer platform in China) and Jingdong (one of the largest business-to-customer online retailers in China) generate nearly 53 million flows each day, and reach their access peak at 11 a.m. or 8 p.m. everyday. In addition, the app usage in different locations is examined to find if there are similar "signatures" at similar locations. First, we sort the locations by generated flow numbers from large to small, and then draw the distribution of the flow number of the first 30 locations for music, e-commerce, video, and communication apps, as shown in Fig. 2b. It was found that the flow number of apps follows similar trends at the same location on different days, but distinct apps could easily be distinguished by the trends.

The flow number distributions of apps at locations of different functions are further studied. Sampled locations include a business zone, a restaurant, and a residential area (Fig. 3). Regular patterns of app usage behavior emerge at the same location on different days. People prefer to use mobile Internet in the business zone, generating over half a million flows in a day on average. The three most popular apps in business zones are map, weather, and communication apps; while music, news, and communication apps are more common in restaurants; and in residential areas, music, e-commerce, and video are the most frequently used apps.

All the above analyses show that app usage has a strong relationship with time and location, which drives us to quantify their relationship, and forecast current app usage based on the history of app usage and mobility behavior.

Framework to Measure the Relationship between Human Mobility and App Usage Behavior

In order to measure the relationship between human mobility and app usage behavior, it is essential to choose the most "significant" features of mobility behavior, which could be seen as the "fingerprint" of app usage to identify/forecast the app usage behavior of people. Here, we present a five-step rating framework to measure the relationship between app usage and mobility behavior, as shown in Fig. 4.

Step 1: Flows generated by users are collected from second/third/fourth generation (2G/3G/4G) networks.

Step 2: People's movement histories and used apps are extracted from flows in the form of 5-tuple {user ID, cell tower ID, timestamp, duration, app}. A cell tower's ID is replaced with its latitude and longitude, which turns the 5-tuple into a 6-tuple {user ID, latitude, longitude, timestamp, duration, app} as the input data of the third step.

Step 3: Calculate mobility features in view of individual mobility indicators, travel patterns, and locations.

Step 4: Mobility and time features with high score values are selected as significant features that may have heavy impact on app usage behavior.

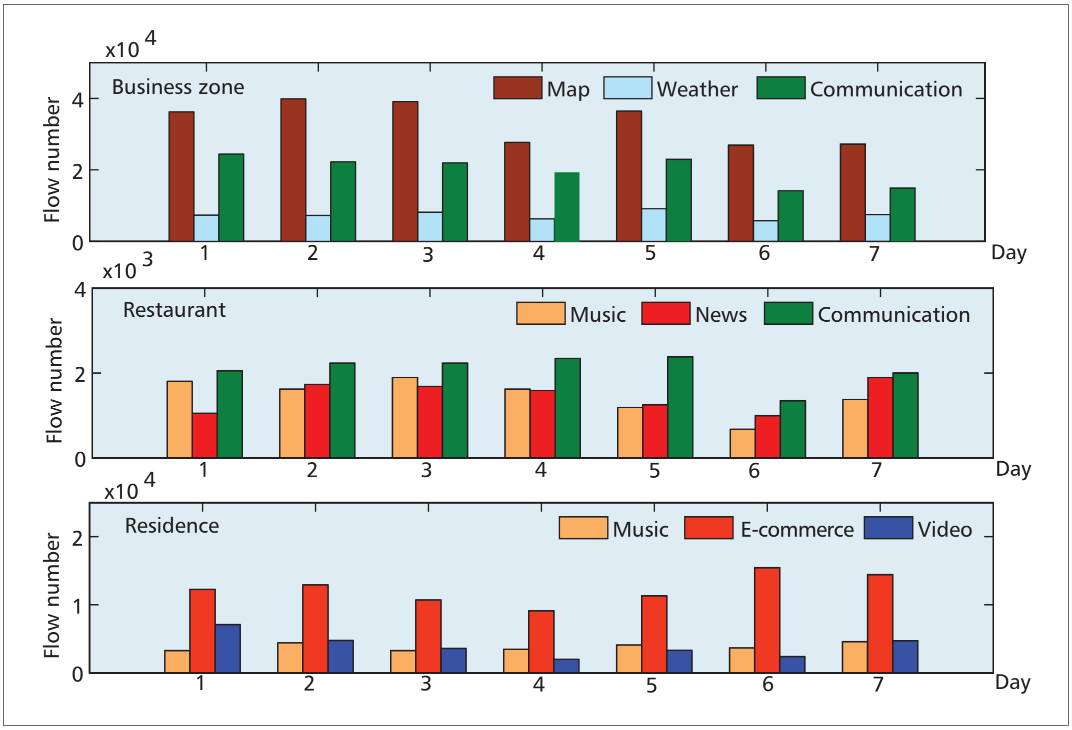

Figure 3. The flow number distributions of apps in locations of different functions.

Step 5: Selected significant features are used to forecast users' app usage behavior.

The forecast results are evaluated with a receiver operating characteristic (ROC) curve. The framework is suitable for analyzing mobile big data in different networks or countries, to discover the rules hidden in people's daily movements and app usage behavior. It is especially useful for location-based recommendation service and the study of human dynamics.

Data Description

The data packets in mobile networks are collected by our self-developed traffic monitoring system (TMS) [10], which monitors packets and aggregates them into flows in real time. In order to analyze users' app usage behavior, we focus on HTTP flows. Each HTTP flow contains the following details: a user's anonymized identity, timestamp, the URL accessed, and cell ID. As a result, the applications users use are distinguished by keywords in URLs, such as *twitter*, *mail.google*, and *map.google*. The location of users is positioned within the coverage of a cell tower.

As shown in Fig. 4, for our dataset, in 2G or 3G networks, a smartphone communicates with a base transceiver station (BTS) or NodeB, which transmits its network traffic to a base station controller (BSC) or radio network controller (RNC). TMS is deployed on a Gn interface, which is between the gateway general packet radio service (GPRS) support node (GGSN) and serving GPRS support node (SGSN). In 4G networks, an evolved NodeB (eNodeB) establishes the connection between user equipment and a mobility management entity (MME). TMS is deployed between a serving gateway (S-GW) and packet data network (PDN) gateway (P-GW) to collect user plane data, which carries the network user traffic.

Calculating the Features

Mobility Indicators: Nowadays, large-scale human mobility is described by three widely accepted indicators: the trip distance distribution, the radius of gyration, and the number of visited locations over time [12]. These three measures contain the basic ingredients to describe the individual trajectories, in which frequent travels occur between a limited number of places, with less frequent trips to new places outside an individual radius. The trip distance distribution $p(r)$ quantifies the relative probability of finding a displacement of length r in a short time. The radius of gyration of a user's trajectory refers to the root mean square distance of each location in the user's trajectory from the center of the trajectory. It reveals how extensively users move instead of capturing the practical distance. Visiting the same sequence of locations in a circle continuously does not increase the radius of gyration's value, while a straight line movement does. The number of visited distinct locations over time describes how frequently a user visits new places.

Locations: It is known that the app usage behavior of people is different at distinct locations. The source data records users' locations only at the granularity of a cellular antenna, which is accurate enough to define people's location in an urban area. Usually, a user's current position could be narrowed down to the range of a station, a commercial/residential area, an educational/industrial/government building, and so on. As a result, for crowds, we consider locations in the city as mobility features that could influence app usage behavior. For individuals, we only consider the five most frequently visited locations for each person.

Travel Patterns: Travel patterns may affect what apps people choose to use [9]. Discovering a pattern is a matter of finding maximal continuous movements. Therefore, we apply a modified version of the a priori algorithm to discover a maximal sequential pattern. The support value of discovered maximal continuous movements should be larger than the support threshold [13]. Here, support value is the ratio of pattern number p appearing in trajectories to the number of trajectories, and the support threshold is selected when all the patterns' average length reaches the longest. Travel patterns of individuals refer to the routine movements that happen every day for a particular person (e.g., commute from home to workplace every morning). For crowds, travel patterns show how large

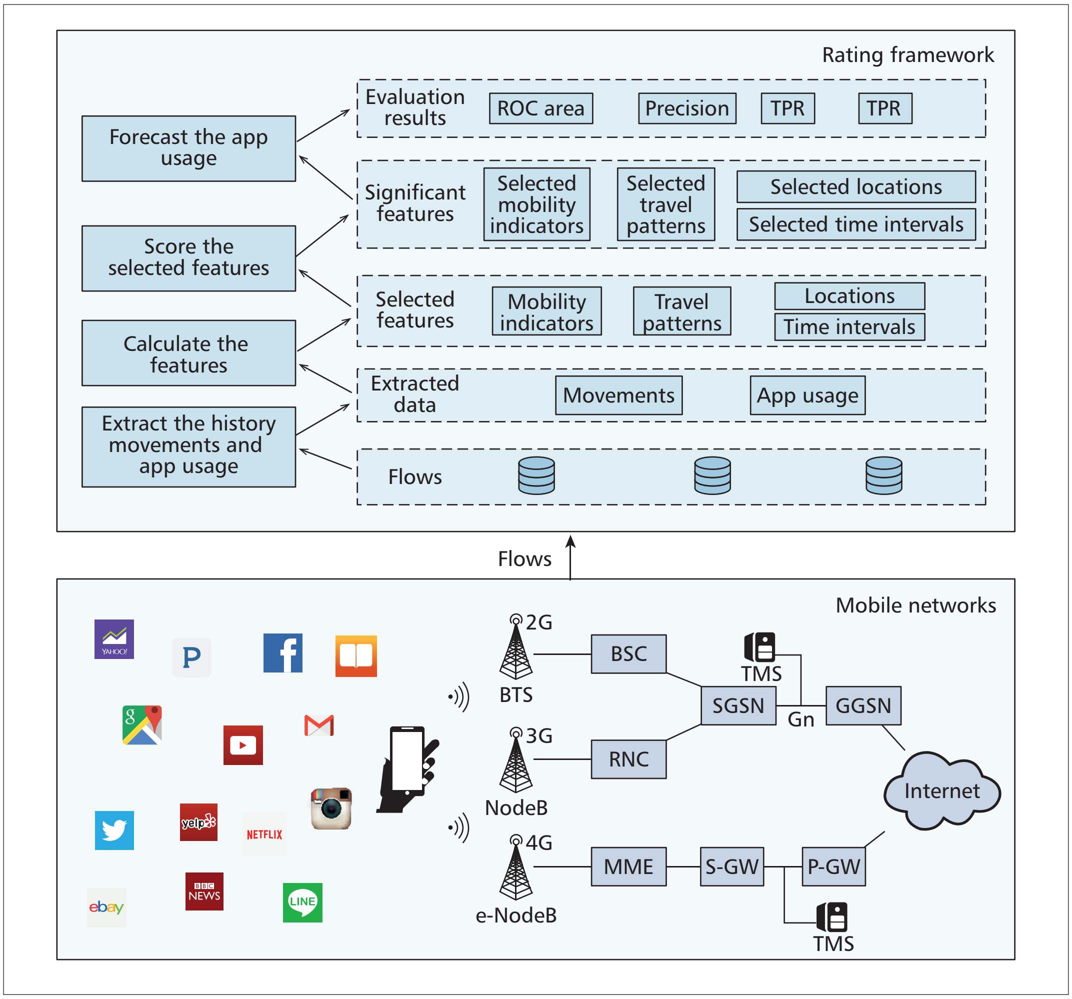

Figure 4. Overall architecture of the rating framework.

groups move in the city (e.g., a large group of people travel from suburban residential areas to the financial district at the core of the city every morning).

Scoring the Selected Features

In order to select mobility features that have big impacts on people's app usage behavior, we apply chi-squared statistic evaluation [14] to give a score value to each feature. Chi-squared statistic is commonly used for testing relationships on categorical variables. In our case, mobility features with high score values are the selected significant features, which can be used to quantify the relationship between mobility and app usage behavior.

Forecasting the App Usage

Selected mobility features are evaluated by adopting the nonlinear support vector machine (SVM) [15] to forecast people's future app usage behavior. SVM is a supervised learning model with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The prediction results of the rating framework are the classification results of SVM based on selected mobility and time features. Meanwhile, the efficiency of forecasting is measured on the basis of the ROC curve, and related characteristics are listed below:

- True positive rate (TPR)/false positive rate (FPR) defines how many correct/incorrect positive results occur among all positive/negative samples available during the test.
- Precision is the number of true positives divided by the total number of elements labeled as belonging to the positive class.
- The ROC curve is created by plotting the TPR against the FPR at various threshold settings. The best possible prediction method would yield a point in the upper left corner or coordinate (0,1) of the ROC space, representing 100 percent sensitivity (no false negatives) and 100 percent specificity (no false positives). In this perfect case, the area under the ROC curve is one.

Results and Analysis

In this section, the rating framework is tested by real network traffic traces from crowds' and individuals' points of view. An experimental dataset is collected from 2G/3G/4G networks, lasting for 7 days and covering nearly 3 million people. First, we introduce the apps used in the experiment. Then we calculate the mobility features and give each of them a score value to select the significant features that have big impacts on app usage behavior. Finally, the selected features are proved to have a strong relationship with app usage behavior only if they forecast future app usage behavior with high accuracy.

Measure the Relationship between Mobility and App Usage Behavior of Crowds

App Categories: In order to select the significant mobility features of crowds, we classify the popular apps by examining keyword of the URI field in each flow; for example, if there is a "Facebook" in the URI field of a flow, this flow will be

Feature set	Number of features	Number of correctly classified samples (%)	Precision	TPR	FPR	ROC area
Trip distance distribution	14	549 (52.890)	0.522	0.529	0.525	0.502
Radius of gyration	2	836 (80.540)	0.846	0.805	0.206	0.799
Number of visited locations over time	2	890 (85.742)	0.877	0.857	0.147	0.855
Locations	100	568 (54.721)	0.424	0.547	0.487	0.530
Travel pattern	10	547 (52.698)	0.303	0.527	0.526	0.501
Time	24	548 (52.794)	0.286	0.528	0.520	0.504
All features	152	942 (90.751)	0.918	0.908	0.092	0.908

Table 1. Forecast results for different features of crowds.

classified as "social network." We categorize the apps into eight groups, each category representing one type of app, including e-commerce (online shopping apps, e.g., Taobao, and Jingdong Mall), video (online video apps, e.g., iQIYI, and Youku), communication (mobile text and voice messaging communication, e.g., WeChat, and QQ), map (online video apps, e.g., Baidu Map and QQ Map), weather (weather information apps, e.g., China Weather and Xiaomi Weather), news (e.g., Tencent News), email, and life (apps for restaurant reviews, e.g., Dianping). Note that in the experiment we only take the flows generated by the above popular apps into consideration.

Selecting the Significant Features of Crowds with High Scores: As mentioned above, we focus on the time feature and three aspects of human mobility in an urban area. Significant features are selected according to the scoring results from our rating framework:

- Mobility indicators: We calculated the statistical value of three mobility indicators:
  1. Minimum, maximum, average, median, standard deviation, skewness, and kurtosis value of trip distance distribution in current day and hour
  2. The value of radius of gyration in current day and hour
  3. The number of visited locations at current day and hour

  The total number of selected features of mobility indicators are 18. Here, the value of mobility indicators at the current day or hour means calculating the duration value between (0 a.m., current time) or (the beginning of the current hour, current time).
- Location: The top 1000 locations with largest number of people in the city. Here, a distinct number of people that connected with each cell tower is counted.
- Travel pattern: 100 most popular/frequent movement patterns happening between the top 1000 locations. In our experiments, the support threshold is set to 0.01 to make sure the average mobility pattern length is the longest.
- Time: 24 time intervals (one hour for each interval) in a day.

We calculated the chi-squared value for each mobility and time feature (18 statistical features of mobility indicators, 1000 locations, 100 movement patterns, and 24 time intervals). At last, the remaining 152 features (900 locations and 90 travel patterns are removed; only 10 high score travel patterns between 100 selected locations remain) are selected to evaluate the rating framework by forecasting app usage behavior of crowds.

Evaluation: The experimental dataset only includes flows generated by selected popular apps, and generated in 100 selected locations. We randomly pick 10,978 flows as the training set and 1107 flows as the testing set.

The forecast results are listed in Table 1. If only some of the significant features are used to forecast the app usage behavior, the results are not sufficient. The combination of all features achieves 90.751 percent forecast accuracy. In addition, as shown in Fig. 5, we can clearly see that all significant features together reach the highest precision (0.908) with high ROC area (0.908), high TPR (0.918), and low FPR (0.092). For crowd behavior, the experiment only considers a limited number of locations, travel patterns, and people, but still, location-based service will benefit greatly if we know which group of people will prefer to use what kind of apps at some locations in the city.

Measure the Relationship between Mobility and App Usage Behavior of Individuals

Different from crowds' behavior, each individual only uses a limited number of apps, visits few locations, and most of individuals commute regularly between home and workplace in daily life. In order to study the correlation between one's mobility and app usage behavior, the proposed method will be applied to the data of each individual. And the rating framework can be deployed on an individual's smartphone to provide a personalized model, which selects the significant mobility features to predict future app usage of the current user totally based on his/her data.

Popular Apps for Individuals — Since individuals only have a limited number of interests (in our previous experiments, we found that the number of apps one user visited in a week is seven on average), we selected eight apps that contribute more to flows than other apps in our dataset to do the experiment for individuals, including WeChat (mobile text and voice messaging communication app), Baidu Map (online map and navigation app), Taobao (app for online customer-to-customer shopping), QQ Game (app for online games), QQ Music (online music app), Xiaomi Weather (weather information app), QQ News (news app), and Didi Dache (app of a taxi calling platform).

Selecting the Significant Features of Individuals with High Scores:

- Mobility indicators: The same as the selected features of mobility indicators for crowds.
- Location: Count and sort the number of flows the current user generated in visited locations from large to small; select the top five locations for the user.
- Travel pattern: The top five travel patterns between selected locations of current user.
- Time: 144 time intervals (10 minutes for each interval) in a day.

After calculating the chi-squared value for mobility and time features of each individual (18 statistical features of

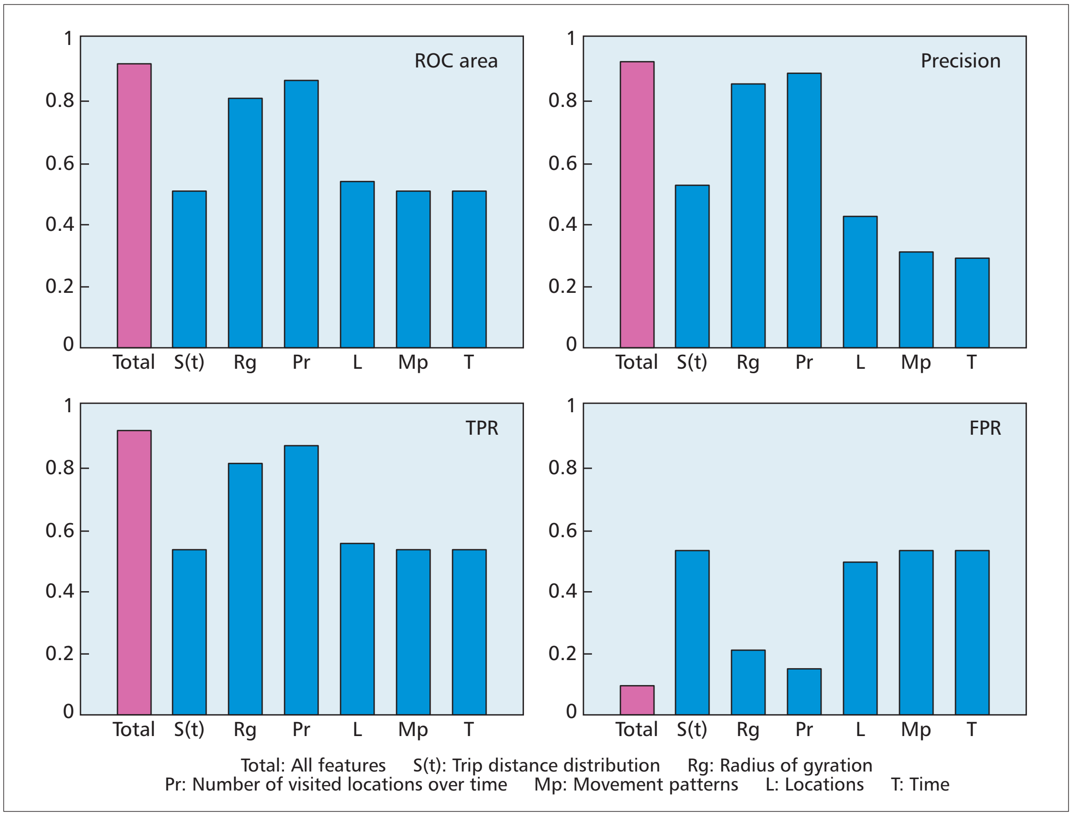

Figure 5. The value of ROC area, precision, TPR, and FPR for different features of crowds.

mobility indicators, 5 locations, 5 travel patterns, and 144 time intervals, 172 features in total for every user), features with low score values (i.e., the normalized chi-squared value is less than 0.1) are removed. The rating framework is tested with the remaining 167 significant features from the individual point of view.

Evaluation: The experiment was carried out on 100 users who generated more flows than others in 7 days. Flows of each user are divided into 10 folds; nine folds of flows are used for training, and the remaining one is the test set. On average, 94.312 percent forecast accuracy can be achieved.

Conclusion

In this article, we have proposed a mobile big-data-driven rating framework to measure the relationship between human mobility and app usage behavior. We focus on time and mobility features that have impact on app usage behavior from three aspects: individual mobility characteristics, location, and travel pattern. After processing mobile big data, selecting mobility features, and rating each feature, the significant features that are indicative of the mobility patterns of various users are used to verify the effectiveness of the rating framework. Results show that, based on significant features of mobility and time, 90.751 and 94.312 percent forecast accuracy are achieved by forecasting app usage behavior of crowds and individuals, respectively. This implies that a strong relationship exists between mobility and app usage behavior. The proposed rating framework is very useful to discover mobility features that have strong influence on app usage behavior, which can also be used to forecast app usage behavior of crowds and individuals. In the future, more applications will be studied through using the larger dataset. Specifically, a new model is expected to be proposed to predict individual app usage behavior based on our rating framework.

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