
Time-activity pattern observatory from mobile web logs

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Abstract: Air pollution has become a striking problem in recent years. When estimating the degree of human exposure to a particular air pollutant, time-activity pattern is one of the most important factors, which is able to quantify the time people spend in different micro-environments, such as indoor and outdoor. Traditional surveys use the method of questionnaires and telephone calls to explore the time-activity pattern. In this paper, we propose a novel method to analyse the time-activity pattern by utilising mobile web usage log. We test the method on two datasets covering about four million users. Experiments show that our method achieves an acceptable performance, and can truly measure the time-activity pattern of human beings.

Keywords: air pollution; time activity pattern; human exposure; micro-environments; mobile web log.

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1 Introduction

Air pollution has become a striking problem all over the world in recent years. Multiple air pollutants, including particulate matter (PM_{2.5}), ozone and various chemicals, are introduced into human beings' daily life owing to the increasing energy consumption, development of industry, usage of manufactured chemicals and so on. Human beings are exposed to various air pollutants all the time in all space and suffered from health risks. A study on global burden of disease (Lim et al., 2013) has indicated that indoor air pollution and atmospheric particle pollution ranked the 3rd and 7th place of the risk factors contributing to the burden of disease in 2010, respectively. It is also claimed (Samet et al., 2000) that fine particles are responsible for death due to all causes as well as cardiovascular diseases in 20 US cities from 1987 to 1994. Moreover, toxicologists have demonstrated that some ubiquitous air pollutants, such as polycyclic aromatic hydrocarbons (PAHs) and phthalates, are responsible for causing cancers, gene mutation and reproductive problems (Bostrom et al., 2002; Armstrong et al., 2004). Hence, protecting human beings from air pollution is urgent and crucial. Air pollutants undergo a complicated series of reactions when transporting from outdoor to indoor environments, together with the intricate indoor sources of air pollutants, leading to the difference in pollution level between indoor and outdoor environments. Thus, time-activity pattern is one of the most important exposure factors when assessing exposure to a particular air pollutant of human beings, which quantifies the fraction of time people spending in different micro-environments.

Since the time-activity pattern is critical to evaluate the exposure to air pollutant, many researches have been done to study the time-activity pattern. The time-activity pattern is not about one person's activity, but about a certain population's activity lasting for a relative long time (such as one year). What is more, the time-activity pattern varies from city to city. For example, the people in Sanya stay more time outdoor than in Harbin. Then, how to get the exact time fraction of activities for a period of time? The traditional way is through surveys (Chen et al., 2012a, 2012b; Wiley et al., 1991a, 1991b; Leech et al., 1996, 1999; Klepeis et al., 2001). Researchers use questionnaires and telephone interview to explore the time-activity pattern of different populations (about several hundreds to thousands of people), and get the statistical results. Researchers also used questionnaires for survey in different cities. However, survey is too subjective to record people's activity. It is very hard for people to memorise the exact time fraction of activities for several days or months. Besides, the sample size of survey is not large enough to reflect a population's activity. So far, there are normally several hundreds or thousands respondents in one city for the survey. Comparing to a city with a population of several million people, the sample size of respondents may not be large enough. Last but not least, survey is a time-consuming and money-consuming way.

The big data from mobile phone provides a new possibility to analyse the time-activity pattern. Nowadays,

almost every person brings a mobile phone with himself/herself and moves in the city. The moving or staying of the mobile phone can reflect the time-activity pattern of the person, such as the time spending in residences, working places, restaurants, bars, or vehicles. Through the automatic interaction between the cellular towers and mobile phones, the towers record the logs of connections of each cellular phone. The challenge is that the tower's location is the approximate location of people rather than the people's real locations. In this paper, we explore the time-activity pattern from mobile web log (HTTP requests and responses), combining with POI information and road network information. The result of our method achieves an acceptable performance. Comparing to the results of survey research, our method achieves three benefits. Firstly, the cellular phone's record is more objective and is more credible than people's memory. Secondly, the sample size of our method is much bigger. We analyse the mobile web log covering five million mobile phone users, which is almost one fourth of the city's population. Thirdly, our method costs less time and money.

The contributions of the paper include:

- 1 a novel method is proposed to analyse time-activity pattern by utilising mobile web usage log
- 2 a new approach is presented to estimate the moving status of people.

The rest of this paper is organised as follows: In Section 2, we describe recent related work on time-activity pattern analysis. In Section 3, we give an overview of the data we use, and describe some important characteristics of the data in several aspects. Section 4 describes the method we use for time-activity pattern analysis in detail. Section 5 describes the experimental results applied to our dataset, and gives detail analysis on the result. Finally, we conclude this paper in Section 6.

2 Related work

A lot of researches have been done by other researchers. Chen et al. (2012a) have evaluated the association between the ozone mortality and the total ozone exposure, accounting for the exposure occurring in both indoor and outdoor environments. It turned out that total exposure can partially reflect the intercity difference of ozone mortality coefficient, implying that total exposure, considering the difference between indoor and outdoor, is more reasonable to assess health risks than atmospheric pollutants concentrations. This conclusion has also been validated for PM₁₀ (particles with aerodynamic diameter smaller than 10 μm) by Chen et al. (2012b). The USA and Canada has conducted nationwide surveys, CAPS (Wiley et al., 1991a, 1991b), CHAPS (Leech et al., 1996, 1999) and NHAPS (Klepeis et al., 2001), of time-activity pattern from 1980s. All of the surveys utilised the method of diary and telephone interview to explore the time-activity pattern of different populations. Time-spent distribution in residences, working

places, restaurants and bars, vehicles, other indoor and outdoor environments of the target population were analysed based on the surveys. Duan et al. (2013) have promoted a nation-survey of exposure factors in China recently and collected time-activity pattern of people from every province by questionnaires. However, it is suspected that time-activity pattern resulting from these methods may be too subjective to reflect the real conditions. Human's memory can be influenced by enormous effects and may not be reliable enough to show the accurate time distribution in different micro-environment. Additionally, surveys based on a large population can be quite time-consuming and cost lots of money. Our method studies time-activity pattern from mobile web usage, which is both efficient and economic.

As the mobile web takes more and more proportions of people's total web usage, study of mobile web user behaviour also gains a great attention recently. Cui and Roto (2008) describe how people use the web on mobile devices by contextual inquiries, and analyse contextual factor as well as user activity patterns. Tseng and Lin (2006) mine user behaviour patterns in mobile web systems based on location trace, and do experiments using simulation. Liu et al. (2013) propose a data flow testing approach for web service compositions based on OWL-S. Phatak and Mulvaney (2002) propose a fuzzy clustering method on URLs and users based on a distance matrix, and further do user profiling and recommendation. Hashimoto et al. (2012) propose an effective measure to automatic determine the appropriate number of topics on social media. Do and Gatica-Perez (2010) mine user pattern through mobile app usage and web usage. Wang (2013) investigates the effects of social network sites on learning satisfaction and learning performance of college students. Verkasalo (2009) analyses contextual patterns in mobile service usage statistically, using handset-based data which includes location and web usage data. Most of the studies use mobile phone collected data, and hardly analyse the time-activity pattern. Our method mines time-activity pattern in mobile web usage from the mobile network service provider's perspective, which is both comprehensive and large-scale.

3 Data description and task definition

The data we use is the mobile web usage log (HTTP request log) of the cellular network (including 2G and 3G) of a mobile operator. The dataset covers the geographical range of Beijing, the capital of China. The data we use covers two urban districts, with an area of approximately 40 square kilometres. The area contains a major set of attractions, as well as one of the busiest business districts of the city. We own two datasets called dataset₁ and dataset₂. The time range of dataset₁ is from October 24 to November 14, 2012, and the time range of dataset₂ is from June 8 to June 20, 2013. Each row in the dataset corresponds to a HTTP request/response pair occurred using cellular network.

- *Overview.* There are totally 681,769,452 complete records in dataset₁, and 1,344,654,257 complete records in dataset₂.
- *Users.* There are 3,983,554 distinct users appearing in dataset₁, and 4,084,230 distinct users appearing in dataset₂. The average number of requests per user of each dataset is 171.14 and 329.23.
- *Locations.* 2,422 distinct cellular locations appear in dataset₁, and 3,134 distinct cellular locations appear in dataset₂.

For each row of the data, the mobile web logs can be formalised to:

- [userID, phoneID, time, towerID, host, agent]
- [towerID, latitude, longitude].

Besides the mobile web logs, other input data includes POI (point of interest) information and road network information. Then, the task of our research is to analyse the time fraction of indoor and outdoor (walk or in vehicle) for all the cellular users in the dataset.

4 Analyse time sequence

In this section, we cover the details about how we get time-activity pattern from mobile web usage log. First of all, we give some formal definitions of the concepts.

Definition 1: Time sequence: A time sequence represents one person's whole mobile web usage log in one day. One log includes a time point and a cellular location, so we use a tuple (l, t) to represent a log, t is a time point and l is a cellular location. A time sequence can be expressed as

$$(l_1, t_1), (l_2, t_2) \dots (l_n, t_n)$$

4.1 Data preprocess

Definition 2: Continuous action: If people do one thing over a period of time, we define this as a continuous action. For example, a person goes to work by bike from 7:50 to 8:25, stays at office from 8:25 to 11:40, and has lunch from 12:10 to 12:45. These are three continuous actions.

The mobile web usage logs last for a day or several days, so a time sequence may contain several continuous actions. In one time sequence, the adjacent log may share a same cellular location, we can merge these logs into one record.

Definition 3: For a time sequence:

$$(l_1, t_1), (l_2, t_2) \dots (l_n, t_n)$$

If

$$l_i = l_{i+1} = \dots = l_{i+m}$$

we merge

$$(l_i, t_i), (l_{i+1}, t_{i+1}) \dots (l_{i+m}, t_{i+m})$$

into (l_i, p_i) . We call p_i time period, it is the time between time point t_i and t_{i+m} .

Before we analyse one time sequence, we find that a person's cellular location may change very frequently in a short time period. This is because he is close to two cellular towers. In one time, he surf the web from one cellular tower, while in the next time the cellular tower is switched. Though he does not move, his cellular tower log changes. So, both towers should reflect people's one location.

Definition 4: For a time sequence:

$$(l_1, p_1), (l_2, p_2) \dots (l_n, p_n)$$

If

$$l_1 - l_3 = \dots = l_{2m-1}, l_2 = l_4 = \dots = l_{2m}$$

and the distance between l_1 and l_2 is less than 500 metre. We define l_1 and l_2 are switched towers, and merge

$$(l_1, p_1), (l_2, p_2) \dots (l_n, p_n)$$

into (l_1, p'_1) , p'_1 is a time period from time point t_1 (the beginning of p_1) to time point t_n (the end of p_n).

4.2 Distinguish home and working place

Now, we have a processed time sequence, and it is a series of continuous actions, how to identify each continuous action is an important task. First, we want to find this person's home and working place. We assume that people will show a regular action in a long time, i.e., in a month, so we can analyse which tower that people stay frequently at night and in the daytime.

Definition 5: At $hour_i, day_j$, the time duration that person spend in $tower_k$ is defined as $t_{i,j,k}$, where i is from 0 to 23. For example, in the first day, from 9:30 to 9:50, a person stays in the 5th tower, then $T_{9,1,5}$ is 20 minutes. The average time people spend in $tower_k, hour_i$

$$\overline{T_{i,k}} = \frac{\sum_{j=1}^{N_{day}} T_{i,j,k}}{N_{day}}$$

while N_{day} is the count of days.

Definition 6: For each i , if

$$\exists k, \overline{T_{i,k}} > 0.5 \text{ hour,}$$

we define $tower_k$ the most often appearing tower in $hour_i$:

$$MOAT_i = tower_k$$

For people's action is regular in a long time, so the tower people stay most at night must be his home, the tower he stays most in the daytime must be his working place.

After we get people's home and working place, we can easily tell the at-home action and at-office action in the time sequence, and calculate the time duration of home and working place.

4.3 Find other indoor environments

If a person is neither at home nor at office, but he stays at one location for a long time, how to judge he is indoor or outdoor? Since the location is only the tower's location, not person's real location, our idea is to judge according to the tower's surrounding environment.

The radius of a cellular tower is about 250 metre, and people's walking speed is about 5 km/h, which means a person needs about three minutes to walk away from a cellular tower. So if a person stays in a cellular tower longer than this time, we define he has a possibility to be indoor. To get this possibility, we use POI information.

POI is point of interest in short, which is a specific point location that someone may find useful or interesting. We use the term to refer to hotels, campsites, fuel stations or any other categories.

There are 21 main categories in our POI, shown in Table 1. We give a label to each category, label 0 means this category is mainly indoor environment, label 1 is mainly outdoor environment. So we can calculate the probability like this

$$P = \frac{\sum \text{the number of POI with label 1}}{\sum \text{the number of POI with label 0 and 1}}$$

The probability multiplies the time duration people spend in one place is the expected indoor duration.

Table 1 Twenty-one main categories in our POI information

Sights	Class unknown	Place name address information
Auto repair	Accommodation	Government agencies and community groups
Road ancillary facilities	Auto sales	Automotive services
Science, education and cultural services	Sports and leisure services	Corporate
Financial and insurance services	Business residential	Transportation facilities services
Living services	Catering services	Shopping service
Public facilities	Healthcare services	Motorcycle service

Figure 1 Cellular towers' distribution around (a) Tsinghua University and (b) SanLiTun (see online version for colours)



(a)

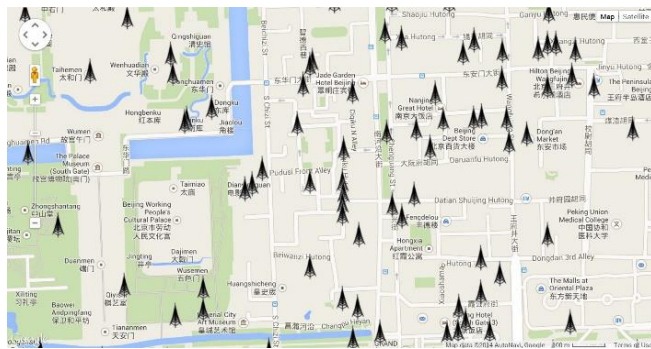


(b)

Figure 2 Cellular towers' distribution around (a) ZhongGuanCun and (b) WangFuJin (see online version for colours)



(a)



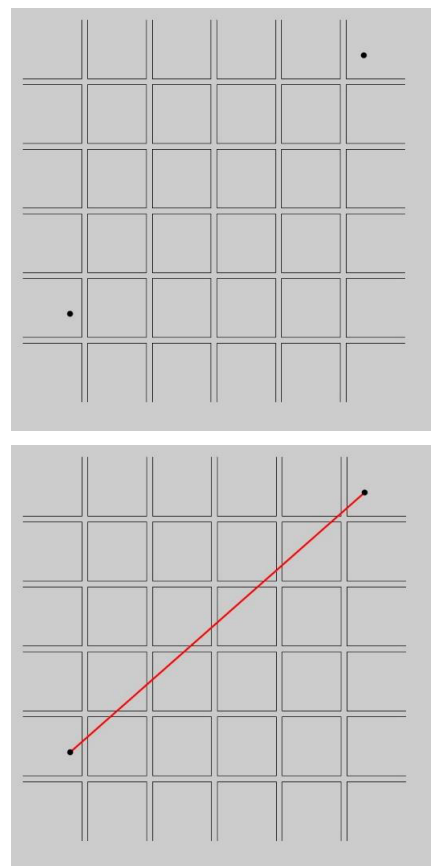
(b)

4.4 Estimate people's moving speed by road network

Excluding the time duration people stay still, the rest of the time is moving. The problem is how to identify whether the person is in a vehicle. We need to estimate the moving speed. First, we observe the cellular towers' distribution on the Google map, shown in Figure 1 and Figure 2.

Through the Google Map, we find that the distribution of towers is uniform, and nearly each street has a tower. The road in Beijing is almost straight from north to south, or straight from east to west, so we use a simple road map model to analyse the trace of person, which is described by Figures 2 to 5.

Figure 3 This is the simple road map model of Beijing, there are two cellular towers on it (see online version for colours)



Note: Assume a person moves from one cellular tower to the other, the red line is the straight way, but this is impossible.

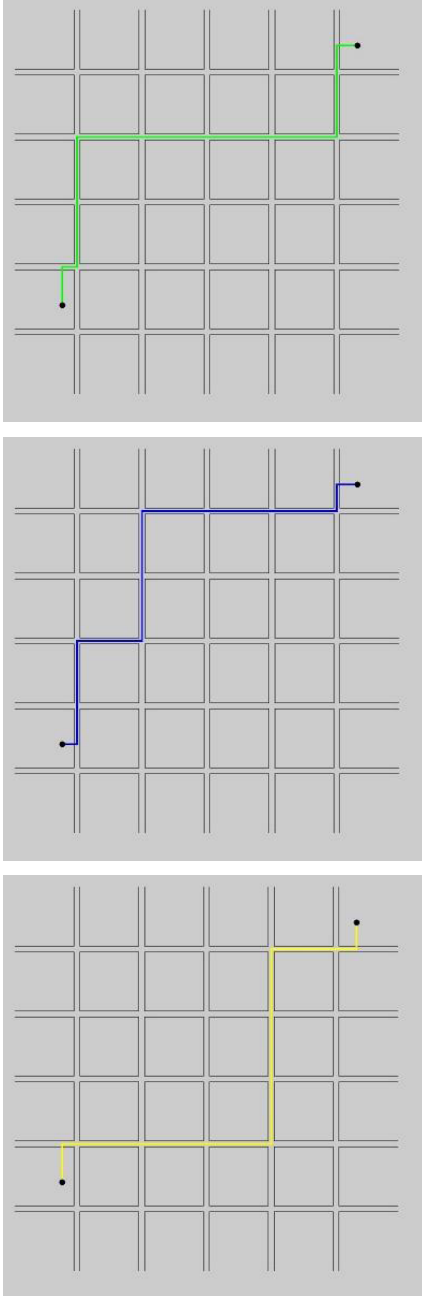
Through this model, we ignore the right way people will take, we just consider the length of the shortest way they will take, which can be easily calculated by the latitude and longitude of the two cellular towers, shown in Figure 6.

Now, we get the length of shortest way, so the speed V can be easily calculated. We can compare this speed with the normal speed of people walking and driving.

- If $V \geq 60$ km/h, he is in the vehicle.
- If $V \leq 5$ km/h, he is walking.

- If $5 \text{ km/h} < V < 60 \text{ km/h}$, he has a probability in the vehicle. How to get this probability?

Figure 4 We assume people always takes the shortest way, there are several possible shortest ways this people can move from one cellular tower to the other (see online version for colours)



$d_1, d_2 \dots d_n$

Figure 5 The lengths of these shortest ways are the same, they equal the length of the black line (see online version for colours)

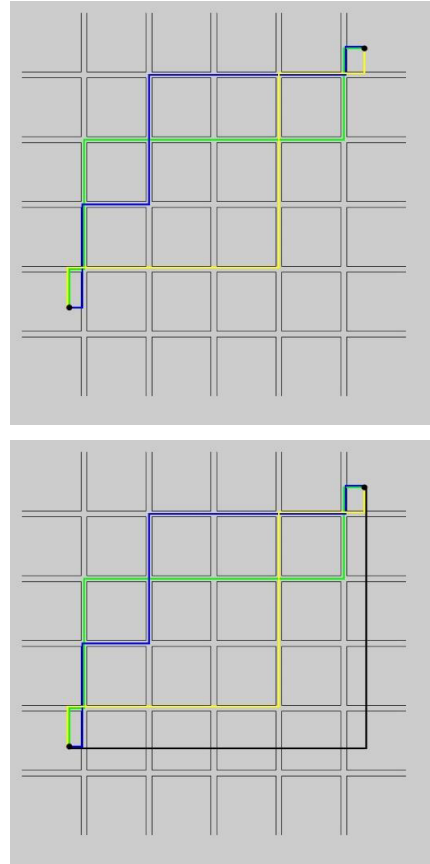
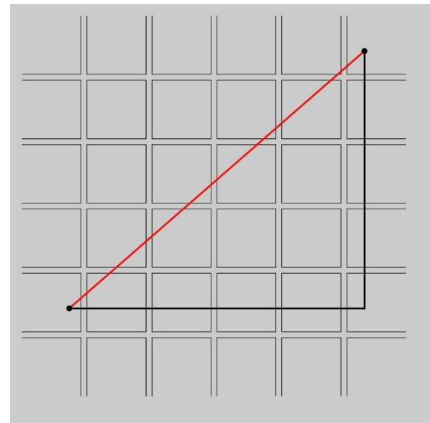


Figure 6 The length of the shortest way (black line) (see online version for colours)



4.5 Compare trace with road network

We use the road network to get the probability. Through the road network, we can calculate the distance between each cellular tower and its nearest road.

Definition 7: For a time sequence:

$$(l_1, p_1), (l_2, p_2) \dots (l_n, p_n)$$

and the distance between each tower and nearest road:

We get the probability by the following formula.

$$P_i = \begin{cases} 0.5 - \frac{\arctan\left(\frac{d_i - 1}{20}\right)}{\pi} & (d_i \geq 20) \\ 0.5 + \frac{\arctan\left(\frac{20}{d_i - 1}\right)}{\pi} & (d_i \leq 20) \end{cases}$$

The probability multiplied by the time people spend in one tower is the time duration that people will spend in the vehicle.

5 Experiments

In this section, we will demonstrate the experiment results and give analysis based on the experiments.

5.1 Data

We use the data described in Section 3 to conduct the experiment. Because we need to analyse people's whole-day action, we choose those who have record in 24 hours. The number of people who have whole-day record is shown in Table 2.

Table 2 Number of active user in two datasets

Summer		Autumn	
Date	Sample	Date	Sample
6/9	1,889	10/24	534
6/10	1,861	10/27	409
6/11	1,815	10/30	84
6/12	1,734	10/31	28
6/20	1,891	11/1	311
6/23	957	11/2	1,509
6/27	343	11/3	1,914
		11/7	321
		11/9	489
		11/10	128
		11/12	672
		11/13	217
		11/14	178

5.2 Time sequence analysis

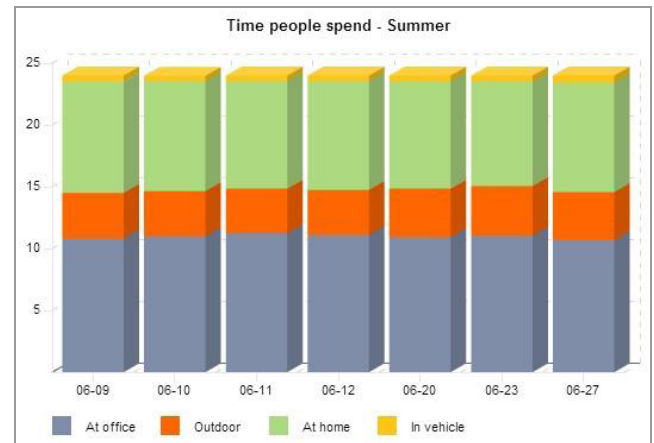
We use the method described in Section 4 on two datasets, and get the time people spend at home, at office, in vehicle and outdoor. To show intuitively, we use a histogram to display our result, shown in Figure 7.

Table 3 The comparison of three methods

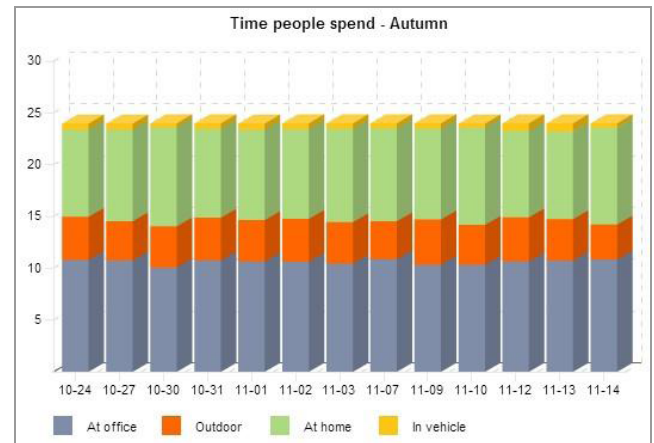
		<i>n5</i>	<i>n25</i>	<i>n50</i>	<i>n75</i>	<i>n95</i>	<i>Avg.</i>
Questionnaire	Outdoor	0.93	2.27	3.90	5.83	10.00	
	Indoor	23.07	21.73	20.10	18.17	14.00	
Summer	Outdoor	0.56	1.71	3.12	5.1	8.78	3.66
	Indoor	23.44	22.29	20.88	18.9	15.22	20.34
Autumn	Outdoor	0.62	1.87	3.36	5.6	9.43	4.01
	Indoor	23.38	22.13	20.64	18.4	14.57	19.99

We also compare our result with a survey result which is approved by industry (Duan et al., 2013), the comparison is shown in Table 3. From the comparison, we can see that our result is very close to the survey result (questionnaire), the difference is only about 0.5 hour. Such little difference is acceptable, which means our method can truly measure the time-activity pattern of human beings.

Figure 7 The four types of time show in histogram, (a) is summer, (b) is autumn (see online version for colours)



(a)



(b)

6 Conclusions

Time-activity pattern is one of the most important exposure factors when assessing exposure to a particular air pollutant of human beings. In this paper, we have presented a method for analysing the time-activity pattern on mobile web usage log. We have proposed a way to identify people's home and working place. We also have solved a problem of switching cellular towers and the length of the shortest trace. We have applied our method to two real-world large-scale datasets of Beijing, the capital of China, covering million users, and the output shows good performance in contrast to questionnaire result.

For future work, one possibility to extend the work is to explore the people who do not have all-day web usage log.

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