

Characterizing Evolution of Extreme Public Transit Behavior Using Smart Card Data

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Abstract—Existing studies have extensively used temporal-spatial data to mining the mobility patterns of different kinds of travelers. Smart Card Data (SCD) collected by the Automated Fare Collection (AFC) systems can reflect a general view of the mobility pattern of the whole bus and metro riders in urban area. Most existing work focusing on mobility pattern usually ignore a special group of people who travel in abnormal patterns or mechanisms. In this paper, we focus on the evolution extreme transit behaviors of travelers in urban area by using SCD in 2010 and 2014. We have several aspects of descriptive statistics of the SCD with a view to better understanding the dynamic process and evolution of the extreme transit behavior. By combining the SCD’s temporal information and the amount of travel behavior, we also proposed a concept of Extreme Index (EI) based on the mixture Gaussian model to depict the extreme level of the passengers’ travel pattern. According to our analysis, the normal transit behavior of the two year have nearly the same temporal distribution. Although the regularities of the two years’ SCD are not correlated, the EI models of the two years are very similar, which can be applied in further discussion for urban transit or transportation analysis.

I. INTRODUCTION

The continuum of human spatial immobility-mobility at varying geographic and temporal scales poses fascinating topics and challenges for researchers and governments to make right decisions on urban development and traffic assignment. As a major urban transit method, the public transit has made a great contribution to mitigate congestion and save energy. Although, many works are carried out focusing on the analysis of passengers’ travel pattern, there is still a group of people we need to pay more attention, whose behavior always reflect the extreme events and mechanisms in the city.

Extreme travelers have received increasing attention in recent years, when we experiencing the backdrops of the global financial crisis, increased numbers of the unemployed, rise of telecommuters and low-paying jobs relocated to cheaper places inside or outside a region/country. But it needs a more general criteria to evaluate these phenomenon and estimate the evolving of these special travel patterns. In this paper, we focus on the evolution extreme transit behaviors of travelers in urban area by using SCD in 2010 and 2014. We have several aspects of descriptive statistics of the SCD with a view to better understanding the evolution of the extreme transit behavior.

We also proposed a concept of Extreme Index (EI) based on the mixture Gaussian model to depict the extreme level of the passengers’ travel pattern.

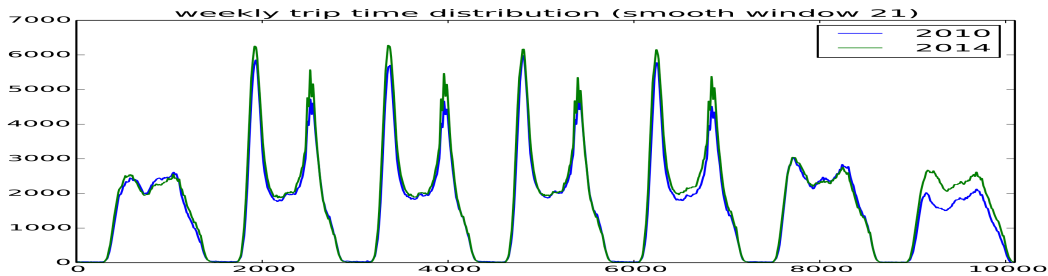
The paper is organized as follows. In the next section, we describe some previous work related to extreme transit behavior. We then give a brief dataset description in the Section III. Several descriptive statistics of the SCD are demonstrated and the regularity of passenger’s travel pattern is analyzed in the Section IV. Section V mainly characterizes the level of extreme transit behavior and define the Extreme Index (EI). We conclude this paper and have a discussion of future work in Section VI.

II. RELATED WORK

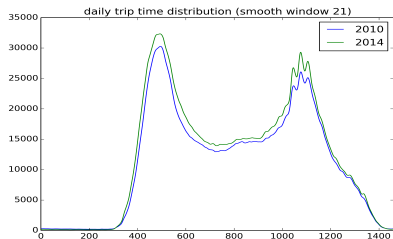
Hanson [3] is among the first researchers to focus on stability and show analyzing individuals’ stability requires also analyzing their mobility. Based on this idea, James et al. [1] concentrate on detailed substructures and spatiotemporal flows of mobility to show that individual mobility is dominated by small groups of frequently visited, dynamically close locations, forming primary ”habitats” capturing typical daily activity. To measure residents’ transit behavior in urban area, SCD in public transit is one of the most widely used data. In their work, public transit riders are classified into four groups of different types of extreme transit behaviors to identify the spatiotemporal patterns of these four extreme transit behaviors. Further, Neal et al. [4] discuss personalizing transport information services based on SCD. Zheng et al. [10] show us several typical applications based on SCD, like building more accurate route planners. Legara et al.[5] infer passenger type from commuter eigentravel matrices by focusing on passengers’ usual and unusual travel patterns. Also Cui et al. [2] have perspectives on Stability and Mobility of Passenger’s Travel Behavior through SCD. Only Long et al.[6] seek to understand extreme public transit riders in Beijing using both traditional household surveys and SCD and we combine his work to show our findings in this paper.

III. DATASET DESCRIPTION

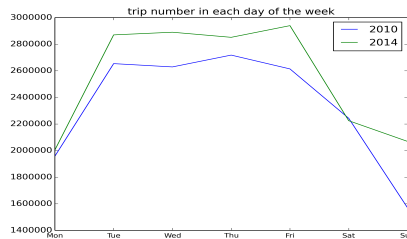
To evaluate the evolution of extreme transit, we look into movements of public transit users with in Beijing by using



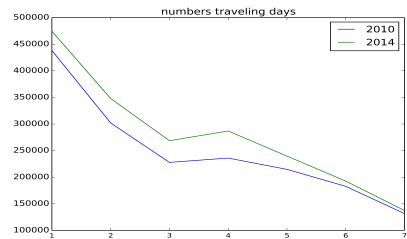
(a) Weekly Trip time distribution of 2010 and 2014. X-axis represents the time lasting for one week with 1 minute interval. Y-axis indicates the number of trips. The curves are smoothed by Hanning function with the window size of 21. Monday in each year is a holiday



(b) Weekly Trip time distribution. X-axis & Y-axis are with the same meanings of Fig.1(a)



(c) Distribution of numbers of trips in each day



(d) Distribution of numbers of smart card holders whose traveling days ranging from 1 to 7 in one week. Y-axis is the number of card holders

Fig. 1. descriptive statistics of the data in 2010 and 2014

smart card data. The SCD contains transit riders' records for both the bus and metro systems. There were two types of AFC system on Beijing buses: flat fares and distance-based fares. In this paper, no matter what kind of fare system, we consider the transaction (paying) time as the time for one ride for simplicity.

We select SCD with shared card IDs from two datasets in 2010 and 2014. Both the selected datasets of 2010 and 2014 last for one week and come from the first complete week in April. The two datasets contain the same smart card IDs with the amount of 1.9 million, representing 1.9 million passengers lived in Beijing at least from 2010 to 2014. We assume each smart card represents an anonymous passenger, without considering the situation of passengers' changing card, which is not common in Beijing. Moreover, even though someone discards the smart card or returns it back to public transit company, the smart card's ID will not be assigned to others any more in Beijing. Each record of the SCD consists of 1) smart card ID, 2) boarding or alighting time, and 3) station ID of boarding or alighting line. As we do not have the longitudinal information of public transit stations, we only use the temporal information of passengers' boarding and alighting time for each ride.

IV. DATA STATISTICS & ANALYSIS

To better understand the travel pattern of public transit user, we carry out several aspects of descriptive statistics of the data. Although we do not have the spatial information of the SCD, to characterize the passengers' extreme travel activity, we first

introduce the trips' temporal distribution and card holders' trip number distribution into our analysis. Then, we do our analysis in an opposite direction that we focus on the travel regularity.

A. Temporal distribution analysis

We count smart card's travel activities (trips) with an interval of 1 minute and thus, the whole smart card records can be represented as a vector with 10080 ($7 \times 24 \times 60$) components. Figure 1(a) shows the weekly trip time distributions of the SCD in 2010 and 2014. The two years' curve are very similar during the whole week. There are 7 obvious curves in the figure which demonstrate the 7 days' trip pattern. Each of the 7 curve has two peaks which represent the morning peak and the evening peak. One special case we need to look at is the first curve for Monday, which is obviously different from the other weekdays. As we checked, the first Mondays of April in both 2010 and 2014 are the part of a national holiday of China, the Tomb Sweeping Day. Thus, it is reasonable that the trip amount of Monday is less than that of the other weekdays.

Figure 1(b) shows the distribution of daily travel time during the whole week in each year of 2010 and 2014. The curves have been smoothed by the Hanning function with a window size of 21. The curve nearly starts from 5:00am (the 300th point in the figure) and last until the end of the day (the 1400th point). There are two obvious peak in each curve and the evening peak is scattered with 3 sub-peaks which demonstrates there are mainly 3 kinds of time for workers leaving office. That may be one of the features of a megacity, like Beijing, which has different leaving office time to spread the evening peak over several hours to mitigate the traffic congestion.

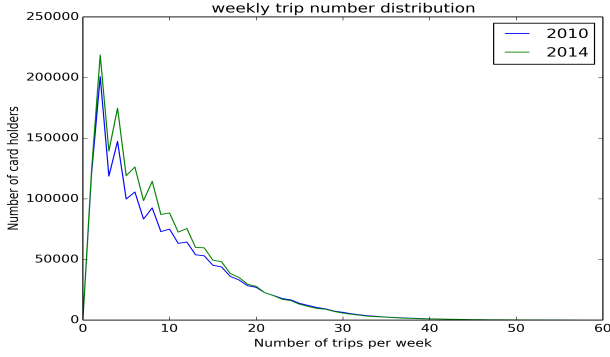


Fig. 2. Trip number distribution with respect to smart card holders during one week

The distribution of trip numbers in each day of the week is demonstrated in Figure 1(c). The trips of each day, except Saturday, in 2014 are more than that of 2010, which indicates the people holding the smart cards in our dataset increase their public transit travel times after 4 years. Figure 1(d) shows the distribution of numbers of traveling day for each smart card holder. We may expect the curve in this figure would be a monotonically decreasing function. But actually, people who traveling in 4 days a week is more than that of 3 days a week. Considering Monday is a holiday and only 4 days (Tuesday to Friday) are weekdays in this case, the commuters with high possibility to travel in 4 days of the week, accounting for a large proportion of the whole dataset, are one of the major groups of people we need to analysis.

B. Travel times distribution analysis

After we count the travel times of all the card holders, we get a trip number distribution shown in Figure 2. The number of holders who only have 1 public transit trips per week reach the peak of the curves. Then the number of holders decreases as the number of trip increase. One interesting phenomenon in this figure is that both the curves appear to be serrated and the card holder number with odd trip number is mostly smaller than that with the even trip number adjacent. It seems like if people choose to travel by public transit, they mostly would like to travel a round trip other than a single trip.

C. Regularity Analysis

In this section, we aim to figure out the relation between passengers' regularity between the two years. The large amount of SCD in 2010 and 2014 can help us understand each passenger's weekly travel regularity.

1) *Defining Distance between Smart Card Records*: As the time span of SCD in 2010 and 2014 both cover one week, we estimate each passenger's trip activities using a "weekly profile", a vector contains 168 (7×24) variables describing the distribution of the trip activities. Each variable in the vector represents the number of smart card's transaction time over each hour in each day of the week. Figure 3 illustrates weekly profiles of passengers' transaction time.

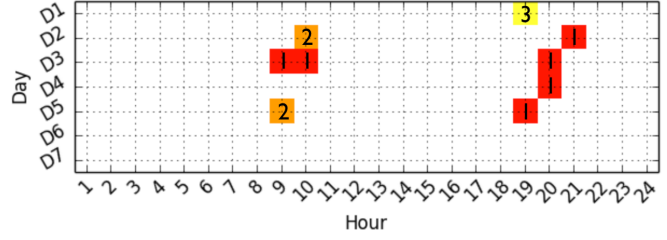


Fig. 3. Weekly profiles of two passengers' transaction time. The transaction time (colored squares) reflects their different travel pattern. Numbers in squares represent times of transaction in that hour. D1-D5: weekdays, D6: Saturday, D7: Sunday.

We count the transaction time of SCD in each hour of the week to form a vector consisted of 168 ($24 \text{ hours} \times 7 \text{ days}$) variables, $V = [v_0, \dots, v_{167}] \in N$. We define a method to compute the distance between two vectors as **Transaction Distance** (D_{tran}). Since non-extreme passengers' vectors are mostly sparse vectors. We define the distance between the two vectors, u and v , by computing the sum of i th component distance (D_i) between u_i and v_i . The component distance (D_i) consists of two parts, the time interval (T_i) and the absolute difference of the two components' value ($A_i = |u_i - v_i|$). As for the time interval T_i , if one of u_i and v_i equals to 0, T_i equals the smaller value of the previous and the next time intervals between non-zero components in different vectors, namely $T_i = \min\{T_i^P, T_i^N\}$. If u_i and v_i both do not equal to 0, $T_i = 0$. Then, the Transaction Distance between vectors u and v can be represented as:

$$D_{tran} = \sum_{i=0}^{167} \min\{T_i^P, T_i^N\} + k * |u_i - v_i|, \quad s.t. \quad u_i \neq v_i \quad (1)$$

Here, k , ranging from 0 to 3, is a parameter to balance the weights of T and A , as we tested. Figure 4 shows an example of computing the transaction distance. $T_j = \min\{T_j^P, T_j^N\}$ equals 1 and $T_l = 0$. If a non-zero component in one vector cannot find a previous or next non-zero component in the other vector, like the situation of u_i , its T_i^P equals $\min\{i, 167 - i\}$.

2) *Regularity Analysis*: We take three aspects of weekly regularity into consideration:

- Travel frequency of the week, $W = \frac{d}{7} \in [\frac{1}{7}, 1]$. Here, d is the number of days when passengers travelled by public transit.
- Travel frequency of every day. We count the number of

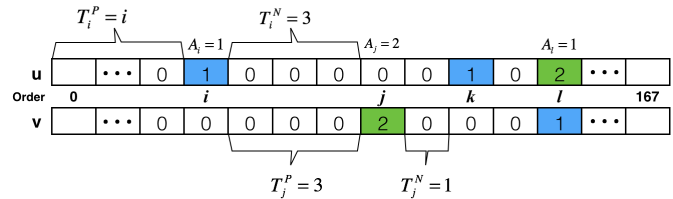


Fig. 4. Example of the distance between two vectors, u and v

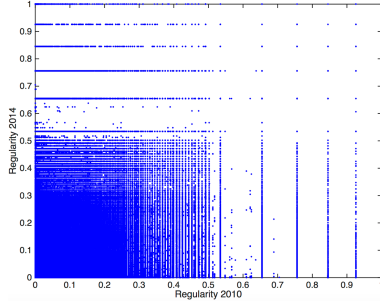


Fig. 5. Relationship between passengers' travel regularities of 2010 and 2014

trips in each day of the week, $D = \{D_i | i = 1, \dots, 7\}$. The standard deviation of D is calculated as D_{sd} .

- Temporal differences between daily trips. We acquire the temporal differences of n daily trips in one week, $DIST = \{Dist_i | i = 1, \dots, \frac{n*(n-1)}{2}\}$, by using the distance calculating method presented in Section IV-C1. $DIST_{sd}$ is the standard deviation of $DIST$.

Then, since D_{sd} and $DIST_{sd}$ is negative correlated with regularity, we defined passenger's regularity (RE) as:

$$RE = W \times e^{-D_{sd}} \times e^{-DIST_{sd}}, RE \in (0, 1] \quad (2)$$

We also acquire each passenger's stability (Sta), which subject to the variance between each passenger's regularities in 2010 and 2014 (RE_{10} and RE_{14}), $Sta = RE_{14}/RE_{10}$. Figure 5(a) shows the relation between RE_{10} and RE_{14} , and the correlation coefficient is 0.0485. Figure 5 (b) shows the relation between RE_{10} and Sta , and the correlation coefficient is -0.00059. This two coefficients are both less than 0.1, which means the regularities of passengers between 4 years are nearly irrelevant. We may assert that the regularity between long-time intervals cannot be predicted.

V. CHARACTERIZE THE LEVEL OF EXTREME TRANSIT

Our previous work [6] has proposed several definitions of extreme transit behavior. We first define and identify the extreme travelers here. But several kinds of extreme transit behavior cannot completely reflect passengers' extreme travel pattern. Thus, we then propose a more general definition with regard to the extreme pattern based on the SCD analysis above.

A. Four Extreme Transit Behavior

Four types of extreme travelers are defined based on their behaviors in weekdays, by setting several thresholds and combining empirical knowledge of Beijing as depicted in Table I. For example, since most people's working hours start on 8:30 or 9:00 am in Beijing, public transit boarding time before 6:00 am would be considered as an unusually early situation.

According to [6], [7], commuting journeys, which are required by the TIs, can be constructed based on commuters' job and home location. Even though our dataset does not have spatial information about bus/metro station, we can substitute the station's number for the location to identify passenger's job and home location.

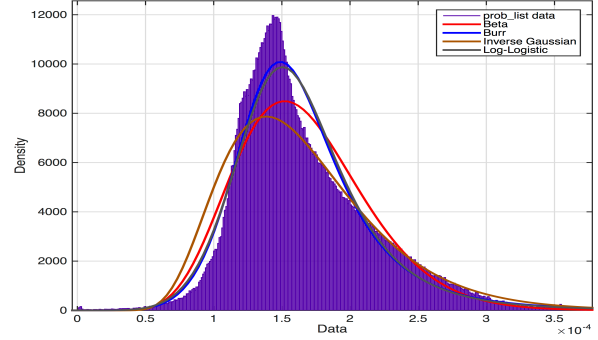


Fig. 6. Distribution of the probability of SCD's travel time probability of 2010

B. Extreme Index

As we can see in the four extreme transit above, the EBs and NOs is defined according to the time of travel activities, while the TIs and RIs is defined based on the amount (frequency) of travel activities. Thus, we may conclude that the extreme transit pattern is influenced by two aspects of the travel activities, time and amount. The earlier or later passengers travel, the more extreme their transit is. Also the larger the amount of trips is, the more extreme the travel pattern is. To generate a general definition of extreme transit behavior, we define the extreme level of each passenger's travel pattern as **Extreme Index** (EI) combining the travel time and travel amount. The larger the EI is, the more extreme the card holder's travel pattern is.

1) *Travel Time Probability*: In order to be better aware of whether the travel time of a card holder is extreme or not, we acquire the probability of each minute in the week from weekly travel time distribution shown in Figure 1(a). Taking the data of 2010 for an example, on entry of smart card record has k trips in the week, whose travel time sequence, T , is represented as $T = \{t_i | i = 1, \dots, k; 0 < k < 10080\}$. The total quantity of trips in the week is N . The number of trips at time t_i is n_{t_i} . Thus, the empirical probability of occurrence of a trip at time t_i is represented as $p_{t_i} = n_{t_i}/N$. For a smart card record, its travel time probability can be described as $TTP = \sum_{i=1}^k p_{t_i}/N$. Here, we get the distribution of TTP of all the SCD of 2010, shown in Figure 6. Some common-used

TABLE I
DEFINITIONS OF EXTREME TRAVELERS

Type	Definition
Early Birds (EBs)	First trip < 6AM, more than two days in five weekdays (60% of weekdays)
Night Owls (NOs)	Last trip > 10PM, more than two days in five weekdays (60% weekdays)
Tireless Itinerants (TIs)	\geq one and a half hours commuting, more than two days in a week
Recurring Itinerants (RIs)	\geq 30 trips in weekdays of a week (\geq 6 trips per day)

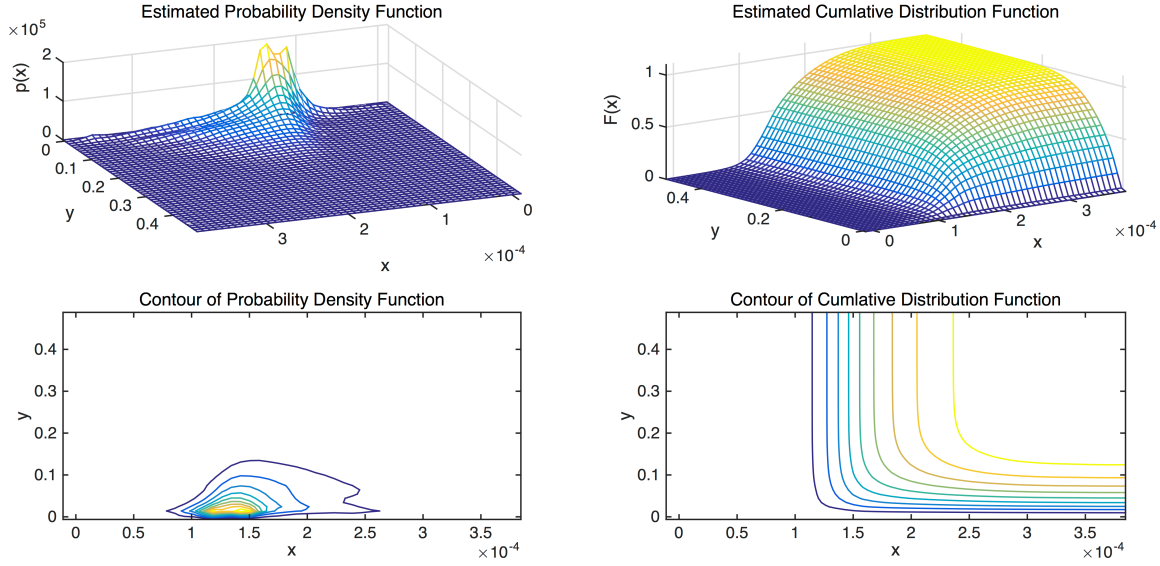


Fig. 7. 2-dimensional PDF and CDF of TTP and ATT of the data in 2010

distribution function was tried to fitting the TTP distribution, but the performance is not good. Thus, we will deal with the fitting problem in the following sections.

2) *Extreme Index*: After the computation in the above section, each smart card has a attribute of TTP . The TTP can show the extreme level for a small TTP demonstrating a few passengers will choose this kind of travel time. But two card holders' travel pattern with the same amount of TTP can also be different. For example, the travel pattern with a TTP acquired by 10 travel activities is definitely differ from that acquired by 2 travel activities. Thus, we estimate the traveller's EI by considering two aspects, TTP and the amount of travel times in the whole week (ATT), and acquire 2-dimensional distribution shown in Figure 7.

We use Bivariate Gaussian Kernel Density Estimation to fit the $TTP-ATT$ distribution. We also get the contour of the probability density function (PDF) and cumulative distribution function (CDF) which can help us have a better view of the distribution. As the 2d distribution can be represented as a mixture gaussian distribution, we fits the model by maximum likelihood using the Expectation-Maximization (EM) algorithm to get parameters. The mixture gaussian distribution can be represented by the distribution function F:

$$F(x) = \sum_{i=0}^n \omega_i P_i(x) \quad (3)$$

As the vector $x = \{x_1, x_2\}$ obey normal distribution:

$$\mathcal{N}(x|\mu, \Sigma) = \frac{1}{(2\pi|\Sigma|)^{1/2}} e^{-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)} \quad (4)$$

We use EM algorithm to estimate the n tuples of parameter (ω, μ, Σ) . But the first thing we need to do is determine the value of n . There are several criteria that can evaluate the

quality of the model and the goodness of fit of the model, like Akaike information criterion (AIC), Bayesian information criterion (BIC) and negative log likelihood (NLL). After we test the n ranging from 3 to 6. We get the the criteria listed in the Table II. We use the three criteria mentioned above to measure the number of component of the distribution. As we can see in the table, no matter what the sample size is and no matter which criteria is, when n is larger than 4, the value of the criteria decrease very little. Especially for the case in the BIC with 2000 sample tested, when n equals 4 (in the gray grid), the value is larger than the value when n equals 5. Thus, considering the simplicity of a model and the goodness of the fit, we choose n equals 4 in this model. Figure ?? shows the contour of our mixture gaussian distribution model. For the 2010 case, the parameters with 4 tuples (ω, μ, Σ) of the model is described as: $\{((\omega_1 = 0.327), (\omega_2 = 0.198), (\omega_3 = 0.161), (\omega_4 = 0.314)); (\mu_1 = (0.0019, 10.24), (\mu_2 = (0.0013, 1.46), (\mu_3 = (0.0020, 2.57), (\mu_4 = (0.0014, 5.47)); ((\Sigma_1 = \begin{pmatrix} 0.0000 & -0.0009 \\ -0.0009 & 24.8318 \end{pmatrix}), (\Sigma_2 = \begin{pmatrix} 0.0000 & 0.0000 \\ 0.0000 & 0.4341 \end{pmatrix}), (\Sigma_3 = \begin{pmatrix} 0.0000 & -0.0002 \\ -0.0002 & 1.6797 \end{pmatrix}), (\Sigma_4 = \begin{pmatrix} 0.0000 & 0.0001 \\ 0.0001 & 6.0962 \end{pmatrix}))\}$. The parameters of 2014 is described as: $\{((\omega_1 = 0.190), (\omega_2 = 0.358), (\omega_3 = 0.138), (\omega_4 = 0.314)); (\mu_1 = (0.0017, 10.48), (\mu_2 = (0.0021, 5.52), (\mu_3 = (0.0013, 1.33), (\mu_4 = (0.0014, 3.12)); ((\Sigma_1 = \begin{pmatrix} 0.0000 & 0.0001 \\ 0.0001 & 24.5545 \end{pmatrix}), (\Sigma_2 = \begin{pmatrix} 0.0000 & -0.0006 \\ -0.0006 & 8.9095 \end{pmatrix}), (\Sigma_3 = \begin{pmatrix} 0.0000 & 0.0000 \\ 0.0000 & 0.3349 \end{pmatrix}), (\Sigma_4 = \begin{pmatrix} 0.0000 & 0.0001 \\ 0.0001 & 2.3395 \end{pmatrix}))\}$.

Then Figure 8 shows the estimated contour of the PDF. Thus, up to now, we have the model of EI and let EI equals the distribution function shown the equations in the Eq. 3 and 4. Given a SCD, we can quickly compute the TTP and ATT as the input variables to get the value of EI. The smaller the EI, the more extreme the transit pattern is.

As we checked, although the data's regularities in 2010 and

TABLE II
CRITERIA OF THE DATA OF 2010 TO DETERMINE THE COMPONENT SIZE n

n	2,000 samples			20,000 samples			200,000 samples			Total data (nearly 2,000,000)		
	AIC	BIC	NLL	AIC	BIC	NLL	AIC	BIC	NLL	AIC	BIC	NLL
1	1.0e+4	1.0e+4	1.0e+3	1.0e+5	1.0e+5	1.0e+4	1.0e+6	1.0e+6	1.0e+5	1.0e+7	1.0e+7	1.0e+6
1	-1.2905	-1.2877	-6.4576	-1.2988	-1.2984	-6.4944	-1.2955	-1.2955	-6.4776	-1.1216	-1.1216	-5.6082
2	-1.3791	-1.3730	-6.9066	-1.3840	-1.3831	-6.9212	-1.3798	-1.3797	-6.8992	-1.2094	-1.2094	-6.0470
3	-1.4298	-1.4202	-7.1658	-1.4357	-1.4344	-7.1802	-1.4247	-1.4245	-7.1235	-1.2199	-1.2198	-6.0990
4	-1.4595	-1.4466	-7.3205	-1.4521	-1.4503	-7.2629	-1.4398	-1.4396	-7.1995	-1.2475	-1.2475	-6.2378
5	-1.4623	-1.4460	-7.3403	-1.4581	-1.4558	-7.2932	-1.4576	-1.4573	-7.2882	-1.2570	-1.2570	-6.2851
6	-1.4688	-1.4492	-7.3792	-1.4681	-1.4654	-7.3442	-1.4639	-1.4635	-7.3197	-1.2645	-1.2645	-6.3225
7	-1.4718	-1.4488	-7.4001	-1.4697	-1.4664	-7.3525	-1.4655	-1.4651	-7.3278	-1.2674	-1.2673	-6.3770

2014 are irrelevant, the EI models of 2010 and 2014 are very similar according to their parameter tuples. We also find that the average EI of the four extreme pattern is lower than the average of the whole dataset, which can in return prove the legitimacy of the EI model.

VI. CONCLUSION

In this paper, we focus on the evolution of extreme public transit behaviors of travelers by using the SCD of Beijing in the year of 2010 and 2014. We carry out several descriptive statistics of the SCD in order to have a better understanding of the dynamic process and evolution of the extreme transit behavior. These distributions based on the SCD's temporal information reveals several interesting phenomena and corroborate each other with the datasets' background. We also define a distance between SCD to characterize the regularity of travel patterns. By combining the SCD's temporal information and the amount of travel behavior, we proposed a concept of Extreme Index (EI) based on the mixture Gaussian model to depict the extreme level of the passengers' travel pattern.

According to our analysis, the normal transit behavior of the two years have nearly same temporal distributions. The definition of the SCD's distance may be useful for further research. By using this distance, we define and analyze an opposite concept of extreme, regularity. Although the regularities of the two years' SCD are not correlated, the EI models of two years, which are the main contribution of this paper,

are very similar. With the EI model, every smart card will have an attribute of EI, which can be introduced to further cross comparisons analysis. We will also improve the EI model with respect to the variation of trips' temporal information and entropy of the occurrence of travel activities. The EI model can definitely be applied in further discussion for urban transit and passengers' behavior and status analysis.

VII. ACKNOWLEDGMENTS

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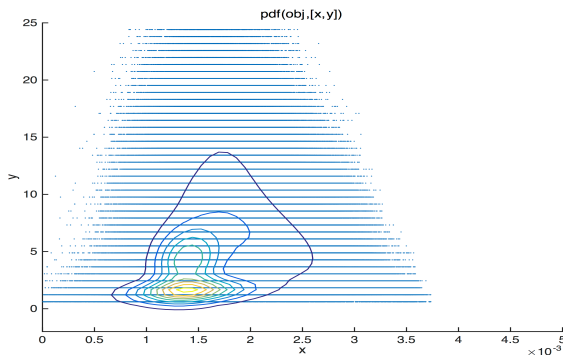


Fig. 8. Estimated contour of the mixture gaussian distribution of 2010 data. X-axis represents the TTP and y-axis represents the ATT