

UC Berkeley

Earlier Faculty Research

Title

An Analysis of Variability of Travel Behavior within One-Week Period based on GPS

Permalink

<https://escholarship.org/uc/item/541616c9>

Authors

Zhou, Jianyu (Jack)
Golledge, R G

Publication Date

2003

An Analysis of Variability of Travel Behavior within One-Week Period Based on GPS

By

Jianyu (Jack) Zhou

Department of Geography and
Research Unit in Spatial Cognition and Choice

University of California Santa Barbara,
Santa Barbara, CA 93106-4060, USA

Telephone: (805) 971-5033

Email: zhou@geog.ucsb.edu

And

Reginald Golledge

Department of Geography and
Research Unit in Spatial Cognition and Choice

University of California Santa Barbara,
Santa Barbara, CA 93106-4060, USA

Telephone: (805) 893-2731

Fax: (805) 893-7782

Email: golledge@geog.ucsb.edu

Presented at IGERT Conference, UC Davis, U.S., April 2000

Acknowledgement: We are grateful to DOT for providing us with a CD-ROM of the Lexington Study and to UCTC Grant #DTRS99-G009 for the financial support.

Abstract

In 1997 the Department of Transportation carried out a one-week study in Lexington, Kentucky in which the cars of 100 households were equipped with GPS and in-car computers. Every stop was logged by the GPS receiver and the purpose of the stop was recorded at real time on an in-car computer. The final report of the study gave descriptions of travel behavior but performed little analysis on the data so collected.

Provided a CD-ROM data record of all the transactions from DOT, we propose to address questions such as:

1. How does the week period influence different types of people's travel activities in a general way?
2. How does the week period influence the variation of people's travel choices on different days of week?
3. To what extent is the automatic-device-collected data more accurate than the data collected by using traditional methods?

In this paper, two physical measurements of trips (duration and frequency) are analyzed to differentiate people's activity patterns among the days in a week period in terms of types of activities pursued. MONOVA analysis is applied first to illustrate the day-to-day activity variability across the week. Then time series analysis is used further reveal the temporal characteristics of the trip series. Accompanying these, the advantages and disadvantages of using GPS-integrated devices as a means of collecting travel activity data are analyzed.

1. INTRODUCTION

1.1 Goals

An understanding of variability is central to the modeling of travel behavior. Until into the late 80's, little attention had been paid to the question of day-to-day variability in travel behavior. Past attempts have usually ignored the problem in conventional transportation studies by surveying travel on a common weekday or by collecting and analyzing one-day data from different weekdays to obtain a picture of typical travel patterns averages across individuals and days of the week. Comparison and contrast of day-to-day differences in travel behavior were rarely practiced. Now, however, development in travel behavior

analysis and transportation policy is leading to a greater awareness of the need to examine day-to-day variability in travel behavior. Obviously a thorough understanding of variability would provide us the chance to make Transportation Management and Information Systems (TMIS) much more efficient or make road network design more closely matched to the profile of travel demands.

To capture the variability of travel behavior over a longer period, easily accessible and highly accurate multi-day data is essential for research input. While characteristics of daily travel behavior have been determined from analyses of the reconstructed household travel behavior in travel diaries, such reconstruction is subject to serious criticism. It was commonly known that people might lie or falsely recall information about destination, times of travel, trip purpose, trip destination and other critical characteristics, such as under-reporting of short trips and the number of stops in a trip chain. With the availability of GPS, it becomes possible for us to examine the actual behavior of people in a more accurate approach by integrating and applying GPS and computer technology in data collection process. Our knowledge of individual and household travel behavior gained from traditional diary and survey methods could be evaluated and complemented by adding the effects of real time on site data collection.

For addressing the problem of variability of travel behavior, various methods for measurement exist. Total trip rates or a vector of descriptive attributes (number of journeys, number of stops, travel mode used, duration of journeys, etc) have been used to compare activity pattern by Koppelman & Pas (1984) and Hanson and Huff (1982) respectively. However, their researches mainly focus on inter- or intra-person variation of travel pattern rather than on day to day variation, specifically, one day-of-week to another day-of-week variation. In this paper, measures of activity-travel behavior and its variability among the seven different day-of-week are presented. As part of a preliminary study of using GPS-collected data in travel behavior research, two physical measurements of trips (time duration and frequency), are analyzed to discriminate how people's activities show different patterns among days in a week in terms of types of activities pursued. Time series analysis is then used to further prove the conclusion derived in the former analysis. Accompanying these, the advantages and disadvantages of using GPS-integrated devices as a reliable means of collecting travel activity data is analyzed. Finally, suggestions about how to improve the design of experiment involving GPS-integrated data-collecting devices are elaborated. It is anticipated that our examination of the dynamics of travel behavior across the sampled week period will further our

knowledge of several still unresearched questions on repetition behavior, multi-stop trips, cyclic travel patterns and the relevance of single models for predicting travel behavior.

1.2 Objectives

Our objectives are to complement and evaluate knowledge gained from traditional diary and survey methods, by adding the effects of real-time on-site data collection using GPS and in car computer data entry. While the GPS-involved data collection methodology is not expected to supplant the traditional data collection method in behavioral science within a short period of time, we expect that it would provide behavioral researchers a more robust alternative for defining personal travel than the current method. By pursuing a variety of analytical techniques on the GPS-collected survey data set, we attempt to address the following problems:

1. How does the calendar periodicity—week period— influence people's travel activity in a general way?
2. How does the week period influences the variation of people's travel choices on different days of week in terms of trip frequency, trip purposes and trip duration?
3. To what extent the automatic-device-collected data (involving GPS) are more accurate than the data collected using traditional methods? Is there any possible inaccuracy involved that may potentially harm our research conclusions?

To behavioral geographers after the 1980's, the limited availability of multi-day travel data is no longer a constraint. Multi-day travel diary data have been used in the past in a lot of studies (e.g. Hanson, 1980; Hanson and Huff, 1982; Hanson and Huff, 1988; Pas and Koppelman, 1984,1985). It has been found that day to day variation of activities within a longer period could be more complicated than we thought. The amount and the nature of repetition and variability in individuals' daily activity patterns are under the cover of entangles of socio-economic factors, personal characteristics, urban transportation facility configuration, etc. Longitudinal observation of repeated travel decisions (e.g. work trip choice over a week) has made it possible to examine the stochastic nature of the choice. However, in the surge of activity variation within a

multi-day period, there is no trace of efforts that have been put on examining how the typical social institution (week-period) affects people's travel choice.

In our research, we followed an exploring approach for the analysis of weekly travel data. We delved into human behavior patterns along a time axis at an aggregate level. Concerning the temporal aspects, activities of various types are related to the frequency and regularity with which a particular social group chooses to participate in a specified activity. The possible form that such regularities might take are to a certain extent determined by the regional characteristics of the study area, age composition of the selected social group, or the local social-cultural environment. We expect to see that trips for different purposes such as work trips, shopping trips or social and recreational trips exhibit quite contrasting time distributions.

2. RESEARCH AREA AND DATA COLLECTION METHOD

The data set used in our study comes from Lexington Area Travel Survey. Travel data are collected using a GPS integrated device. The development and field test of this device are the result of the efforts of two Federal Highway Administration offices. The survey area is located in the Lexington area, central Kentucky. This area includes two counties – Fayette and Jessamine counties, which encompass an area of approximately 461 square miles with a total population of approximately 350,000. Travel data were collected using the automatic data collection device mentioned above. As implemented in Lexington area travel data collection test (1997), it collected self-reported travel-related information and also automatically recorded real time GPS position information of the vehicles in use by the respondents. These devices were deployed in the survey area to record information about personal travel behavior of a group of 100 volunteer respondents. This new data collection method, compared to the approach of recall-interview or travel diary that was used a lot in the past, has its advantage of accuracy. By adding trip-related information into a data collector at real time, the chance of omitting very short trips or having trips times rounded to 10, 15 and 30 minutes interval, which often happen when using traditional self-reporting methods, is greatly reduced.

The participants for this travel survey were recruited using a sample plan based on demographic factors. In addition to gender, the sampling objectives were satisfied with the following categories.

Age 18 –24 with no children

Age 18 --24 with children.

Age 25 – 49 with no children

Age 25 – 49 with children

Age 50 – 64 with or without children.

Age 65 + with or without children.

During the recruitment process, efforts were made to assure some degree of geographic distribution among the participants within the Fayette and Jessamine County planning areas. The adjustment was achieved by altering the recruiting telephone calling patterns based on the postal zip code of households.

3.METHODOLOGY

3.1 K-group Multivariate Analysis of Variance and Discriminant Analysis

Since time can affect people's travel choices in different ways. The first step is to create an approximately complete set of activity choices in order to evaluate the potential influence of time on people's actions. This provides the basic temporal framework of the sample's activity spaces and will allow us to make comparisons say between the temporal pattern and activity structure on Thursday as compared to Friday, or Sunday as opposed to Wednesday. The specific classes of activities in the Lexington data included trips to pick up passengers, drop off passengers, work trips, return home trips, shopping, religion, work-related business, trips to school, college, or university, eating out, social or recreational, medical or dental and other errands.

Comparing all possible combination of two days in a week with respect to household travel behavior in terms of trip frequency and trip duration, may or may not yield significant differences between the two patterns (e.g. Maybe people's activity patterns on Monday and Friday are similar and correlated, while Sunday and Wednesday are not). Although the information is useful for us to know if trip-related measures (such as frequency or duration) differ between two arbitrary days of week, it does not contain enough information on how people's daily activity structure and temporal pattern contributed to this difference. By applying multiple measures as criteria in variance analysis (multivariate analysis of variance

- MANOVA) and discriminate analysis on the data set, we expect to get a more detailed and informative breakdown of the influence of weekly period on people's travel behavior.

Based on the days of the week the next step is to reformat the collected trip count and trip duration from the Lexington Travel Survey data into seven daily groups (Monday through Sunday). Each of the two measures will be further divided based on different trip purposes or trip types as dependent variables. Using the K-group MANOVA capability 13 different dependent variables (trip types) can be compared simultaneously for each of seven survey days with a null hypotheses that no significant difference exists between the travel patterns produced on any given day. In other words, the null hypothesis suggests there is no significant difference between people's activities across the seven days of the week. While a number of travel diary studies have given empirical evidence that trip making does vary significantly on different days (e.g. Hanson and Huff, 1982, 1983, 1985, 1988; Timmermans and Golledge, 1990), no statistical testing has been put forward by explicitly measure the degree of coincidence of trips across an entire seven-day week period. Consequently the null hypothesis is expected to be rejected and the generally accepted conclusion will be accepted (i.e. people's activities differ over the set of 13 trip type variables across the seven days of the week).

Following MANOVA analysis discriminant analysis will be used for describing major differences among the seven-day groups. Using 7 days (Independent variables) and 13 trip purposes (dependent variables) the number of possible discriminant functions is 6. The coefficients for each of the trip variables on the six discriminant functions will then be examined. The structure matrix will also be examined to show the correlation between each discriminant function and each of the trip purposes. Generally, it is assumed that greater stability of the correlation exists in small or- medium sized samples, especially when there are high or fairly high interrelations among the variables. Also the correlation gives a direct indication of which variables are most closely aligned with the unobserved trait which the canonical variate (discriminant function) represents. Usually, we use the correlation for substantive interpretation of the discriminant functions, but use the coefficients to determine which of the variables are redundant given that others are also in the set. This will help us to know which subsets of trip purposes maximizes the difference

of people's travel behavior within a weekly period, as well as giving insight into the preferred travel patterns of local people (their preference for certain trip purpose over others on different days of the week).

The above procedures will be applied to reformatted trip count, trip duration data (derived from Lexington travel survey data) separately in order to examine the travel pattern of the sampled household from different perspectives. We expect that trips with various purposes will present quite different patterns on the two trip measures (count and duration) across the week period.

3.2 Time Series Analysis of Trip Activities

It is necessary to identify the temporal aspects as well as spatial aspects of people's activities. Concerning the temporal aspects, movement to a certain place is related to the frequency and regularity with which an individual chooses to participate in a certain activity. Although this inherent frequency associated with a certain kind of trip activity may be disturbed by some random factors, it is still possible to pick out the periodicity from an accurate time records of the trips under study by using time series analysis. We may determine the degree to which a certain type of activities tends to lead or lag behind others by using cross-correlation technique.

Cullen and Godson (1975) used time series to study survey data on activities and their various attributes collected for half-hour time periods throughout the whole day over 14 consecutive days. Using time series analysis on data collected using recall survey or travel diary, however, is subject to the inaccuracy induced by people's recall error or tendency to round trip start time and end time to multiples of 5 minutes following the hours. Using GPS-collected travel data, in contrast, records of the trip start time and end time have the significant unit of one or two minutes (due to set up delay of the devices). Therefore the conclusions resulted from time series analysis on the GPS-collected data set is expected to show much more detailed periodic or non-periodic (noise) features in the analysis results. Considering the limited sampling period of Lexington travel survey (7 consecutive days), we expect but only hourly period or daily period associated with a certain trip purpose may be picked up in the final result.

4. RESULTS

4.1 MONOVA and Discriminant Analysis

Based on days of week, we reformatted the collected data from Lexington Travel Survey into 7 groups – Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday. Variability of two types of trip measurements (trip counts and trip duration) was studied separately by using MONOVA analysis. For each day of the week, the measurement was further divided into different groups based on purposes associated with the trip or trip type. Variability of different types of trips undertaken by our respondents within the week was our interest. They are treated as dependent variables. Table 1 shows the trip types used. Because of the limited number of trips recorded for trip types -9, 13, 14, 16, 17 and 18, they are not used as dependent variables in this study. With the K group MONOVA capability provided by SPSS, we are comparing the 7 day-of-week groups on the leftover thirteen dependent variables simultaneously. Our null hypothesis for MONOVA analysis is:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7$$

(Population mean vectors are equal. Namely, there is no difference on people's travel activities across the week.)

Table 1. Activity Types

- Purp-9 Unknown
- Purp1 Pick Up Passenger
- Purp2 Drop Off Passenger
- Purp3 Work Place
- Purp4 Work-Related Business
- Purp5 School, College, University
- Purp6 Shopping
- Purp7 Other Errands
- Purp8 Eat Out
- Purp9 Social or Recreational
- Purp10 Medical or Dental
- Purp11 Return Home
- Purp12 Religious Activities
- Purp13 Volunteer Work
- Purp14 Community Meetings
- Purp15 Other
- Purp16 To Day Care or Preschool
- Purp17 Go Along For The Ride
- Purp18 Work or School

As we choose 0.05 as the criterion for rejection, the significance of F's from MONOVA analysis indicates that we should reject the null hypothesis on trip counts and trip time. So we conclude that people's travel activities differs overall on the set of 13 trip variables in terms of trip frequency and trip duration.

Table 2. Post Hoc Procedure

Difference of travel behavior across a week (time)

The trip types that significantly contribute to the overall trip difference are:

Variable	Trip type	sig. Of F
Purp3	Work Place	0.048
Purp6	Shopping	0.004
Purp9	Social Recreational	0.047
Purp11	Return Home	0

Difference of travel behavior across a week (frequency)

The trip types that significantly contribute to the overall trip difference are:

Variable	Trip type	sig. Of F
Purp3	Work Place	0
Purp4	Work-Related Business	0.015
Purp12	Religious Activities	0.008

After finding that the groups differ, we would now like to determine which of the variables are contributing to the overall difference of people's travel behavior across the week. Here we use univariate tests as the post hoc procedures, each at the 0.05 level. The results are listed in Table 2.

From the table, we can easily see that the difference of travel time across the week mainly comes from four types of activity -- (go to) work place, (go) shopping, social or recreational and return home. This implies that people's expenditure of their time on these four types of activities is not even across the sample week. Similarly, the difference of travel frequency mainly comes from three types of activity --(go to) work place, work-related business and religious activities. This is can be easily proved from our life experience. Typically people go to work place or on work-related business on weekdays, but not on weekends; and people go to church on weekends, but not on weekdays. Referring to the former list in

travel-time table, two types of activities -- (go) shopping and social recreational activities are excluded in the travel-frequency table. This may suggest that for our research subjects, making their trips on shopping and social recreational activities on each-day-of-the-week is, to a certain extent, their daily routines, but time spent on these two types of activities differs depending on which day of the week the specific activity was performed.

Next, we used Discriminant analysis for describing major differences among the seven day-of-the-week groups in MANOVA. As we have $k=7$ groups and $p=13$ dependent variables, then the number of possible discriminant functions is the minimum of p and $(k-1)$, which is 6. After the test procedure is performed for determining how many of the discriminant functions, only the first discriminant functions remain. The coefficients for each of the trip variables of the six discriminant functions are listed in table 3, 4 for trip counts and trip duration data separately.

Table 3. Standardized Canonical Discriminant Function Coefficients (trip counts)

	Function					
	1	2	3	4	5	6
PURP1	.114	.389	-.288	.049	-.227	-.392
PURP10	.307	.060	.083	.264	.466	.562
PURP11	.007	-.095	-.485	-.816	-.391	.652
PURP12	-.530	.699	.150	.164	.476	-.051
PURP15	.140	-.249	-.187	.113	-.169	.274
PURP2	.130	.317	.336	-.086	.052	.161
PURP3	.595	-.098	.444	-.228	.325	-.348
PURP4	.283	.415	-.108	.655	-.375	.033
PURP5	.259	.224	.037	.053	.003	-.070
PURP6	-.057	.080	-.013	.177	.231	-.237
PURP7	.114	-.372	-.520	.268	.544	-.293
PURP8	.168	-.096	.313	.119	-.058	.032
PURP9	-.072	-.230	.459	.304	-.166	.130

Table 4 Standardized Canonical Discriminant Function Coefficients (trip duration)

	Function					
	1	2	3	4	5	6
PURP1	.343	-.032	.010	-.020	-.233	.148
PURP2	.047	.323	.601	-.578	-.037	.181
PURP3	.332	.051	.542	.187	.767	.129
PURP4	-.088	.240	.263	.778	-.519	.777
PURP5	.225	.414	.359	.357	-.123	-.632
PURP6	.358	.001	-.194	-.358	-.229	-.358
PURP7	.053	.438	-.231	.116	.266	.344
PURP8	-.015	-.554	.419	-.706	-.312	-.060
PURP9	.162	-.161	-.572	-.219	-.725	-.267
PURP10	.202	.074	-.002	.114	-.075	-.117
PURP11	.476	-.400	.053	-.113	.366	.033
PURP12	-.076	-.605	.426	.285	.123	.070
PURP15	.396	.564	-.598	.271	.763	.017

Another useful table in discriminant analysis of MANOVA is the Structure Matrix, which shows the correlation between each discriminant function and each of the original variables (in this case, trip with specific purpose, e.g. Purp1). Similarly, each structure matrix is listed for trip counts and trip duration data separately (in table 5 and table 6).

Table 5 Structure Matrix (trip counts)

	Function					
	1	2	3	4	5	6
PURP3	.635(*)	.151	.318	-.371	.184	-.214
PURP5	.367(*)	.246	-.128	-.117	.024	.018
PURP12	-.343	.614(*)	.054	-.084	.360	.197
PURP1	.320	.374(*)	-.254	-.103	-.165	-.366
PURP2	.249	.262(*)	.121	-.175	.110	.113
PURP7	.221	-.208	-.531(*)	.148	.449	-.130
PURP9	-.062	-.217	.374(*)	.216	-.188	.154
PURP8	.207	-.058	.251(*)	.064	.014	.071
PURP4	.344	.389	-.168	.518(*)	-.377	.110
PURP11	.247	.252	-.323	-.465(*)	-.010	.413
PURP6	.010	.010	-.205	.094	.309(*)	-.042
PURP10	.308	.055	-.007	.247	.478	.573(*)
PURP15	.137	-.111	-.204	.108	-.069	.402(*)

Table 6 Structure Matrix (travel duration)

	Function					
	1	2	3	4	5	6
PURP11	.645(*)	-.271	.034	.014	.056	.104
PURP6	.509(*)	-.083	-.035	.004	-.332	.082
PURP3	.409(*)	-.062	.138	.017	.262	-.046
PURP9	.402(*)	-.118	-.203	-.118	-.168	-.112
PURP15	.319(*)	.095	-.218	-.034	.244	.217
PURP1	.313(*)	-.025	.018	-.038	-.241	.150
PURP10	.295(*)	.012	.002	.115	.053	-.056
PURP8	.270(*)	-.024	-.065	-.194	-.010	.235
PURP12	-.053	-.547(*)	.346	.318	.201	.065
PURP7	.096	.427(*)	-.199	.083	.264	.321
PURP2	.038	.341	.587(*)	-.585	-.028	.212
PURP5	.192	.402	.353	.367	-.125	-.629(*)
PURP4	.386	.053	.093	.338	-.439	.557(*)

There are two methods for interpreting the discriminant functions:

1. Examine the standardized coefficients--- these are obtained by multiplying the raw coefficient for each variable by the standard deviation for that variable.
2. Examine the discriminant function-variable correlation (structure matrix).

For both of these methods it is the largest (in absolute value) coefficients or correlation that are used for interpretation. The correlation gives a direct indication of which variables are most closely aligned with the unobserved trait that the canonical variate (discriminant function) represents. Usually, we use the correlation for substantive interpretation of the discriminant functions, but use the coefficients to determine which of the variables are redundant given that others are in the set. To name a function, we need to determine what the variables that correlate highly with the discriminant function have in common.

For interpreting the discriminant functions, as mentioned earlier, we use both the standardized coefficients and the discriminant function-variable correlation (showed in structure matrix). Since significant tests show that only the first discriminant functions are significant, we restricted our discussion

on them. Examining table 5 for the first discriminant function (in Table 3) of trip counts (frequency), we see that it is primarily the two variables—trip with purp3 (work place, correlation = 0.635) and trip with purp5 (trip to school, college, and university, correlation = 0.367) that define the function, with purp12 (religious activities) and purp4 (work-related business) secondarily involved (correlation of -0.343 and 0.344 respectively). Since the correlation for purp12 (religious activities) is negative, this means that the groups that have higher purp12 trip counts (Saturday group and Sunday group) scored lower on the first discriminant function.

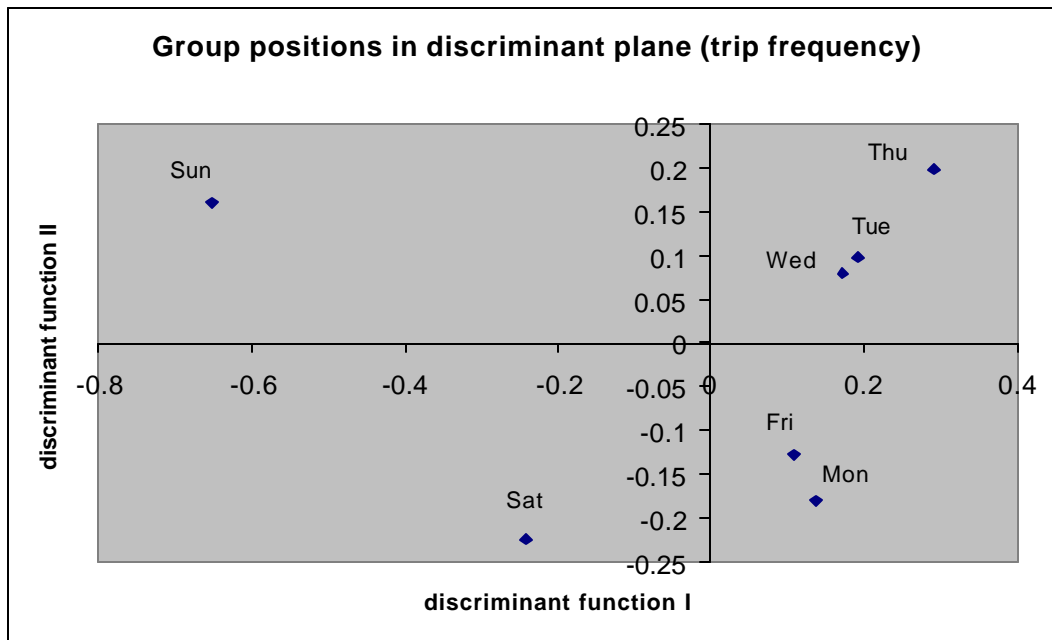
Now, examining the standardized coefficients (Table 3) to determine which of the variables are redundant given others in the set, we see that purp12 and purp3 are not redundant (coefficients of -0.53 and 0.595 separately), but that purp11, purp6 and purp9 are redundant since their coefficients are close to zero. Combined with the information from the coefficients and discriminant function-variable correlation, we can say that the first discriminant function of trip counts (frequency) is characterized as work—school—religious activity dominant. The three kinds of activities maximize the difference of people's activity-frequency across the days of the week. And on the other hand, we know that return home (purp11), shopping (purp6) and social recreational activities (purp9) show not much variation within the period of one week in terms of travel frequency. This conclusion is close to what we derive from the Post Hoc procedures.

Similarly, examining Table 6 for the first discriminant function (in Table 4) of trip duration, we see it is primarily the six variables—trip with purp11 (return home, correlation = 0.645), trip with purp6 (shopping, correlation = 0.509), trip with purp3 (work place, correlation = 0.409), trip with purp9 (social or recreational), trip with purp15 (other trips, correlation = 0.321), and trip with purp1 (pick up passenger, correlation = 0.315) that define the function. Then examining the standardized coefficients (Table 4), we see that all these six variables are not redundant (coefficients above 0.300 except trip with purp9, coefficient = 0.162), but purp8 (eat out)'s coefficient is close to zero. Therefore, we can draw our conclusion that the first discriminant function of trip duration is characterized as return-home—shopping—work place—social or recreational—pickup passenger activity dominant (we overlook the type “other

trips” here for that it doesn’t have any practical meaning). These five types of activities maximize the difference of people’s activity-time expenditure across the days of the sample week. On the contrary, we know the time spent on eating out does not vary too much within the one-week period. Again, the result we derived agrees with what we found through post hoc procedures.

When there are two or more discriminant functions, then a useful device for determining directional differences among the groups is to graph them in the discriminant plane. The horizontal direction corresponds to the first discriminant function and thus lateral separation among the groups indicates how much they have been distinguished on this function. The vertical dimension corresponds to the second discriminant function and thus vertical separation tells us which groups are being distinguished in a way unrelated to the way they were separated on the first discriminant function. (Figure 1--trip frequency and Figure 2--trip duration, shows the positions of the daily groups for Lexington’s travel survey data in discriminant plane defined by discriminant functions 1 & 2).

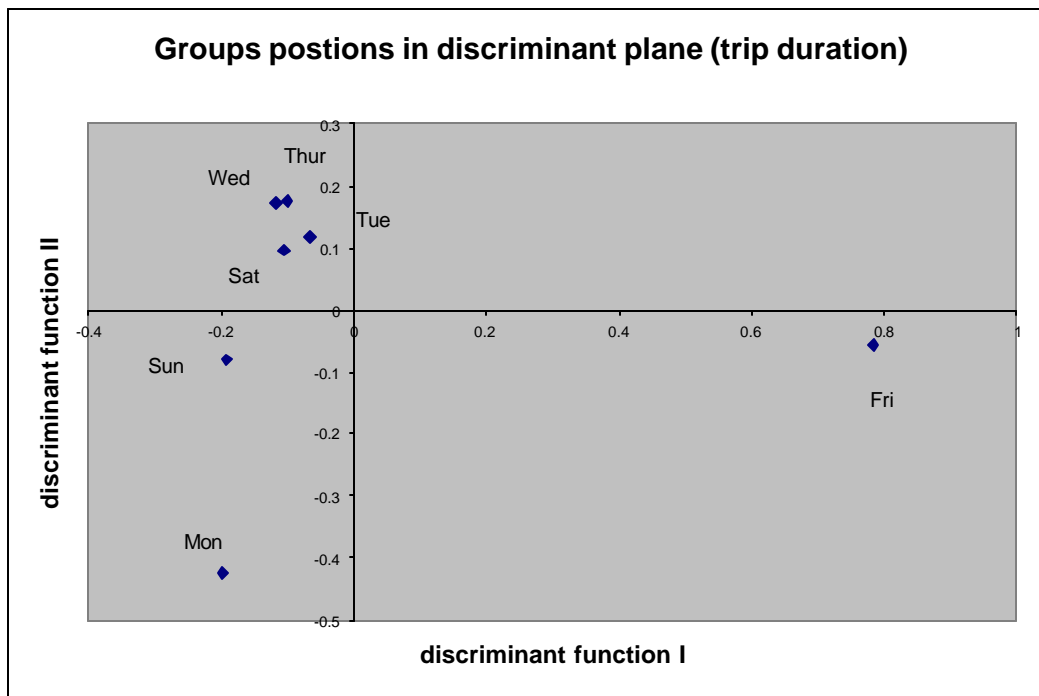
Figure 1



From Figure 1, we can clearly see that people’s activity intensity drops from weekdays to weekends. And this drop (combined the information we have from the data) mainly comes from decreased

(go to) work trips and school trips. Note Sunday is characterized as most activity-depressed. Furthermore, we can classify the activity intensities on different day-of-week into classes based on Figure 1 (with Monday and Friday in class 1--1, Tuesday and Wednesday in class 2--2, Thursday in class 3--3, Saturday in class 4-- -1 and Sunday in class 5-- -2). Therefore we may get a picture of variation of people’s activity intensity across the sample week. The activity intensity is mostly depressed during the weekend. Then it starts from Monday at “warm up” level and gradually increases through Tuesday and Wednesday until reaches its peak on Thursday. Finally on Friday, it backs to the “warm up” level.

Figure 2



Now, let us look at people’s travel activity from the perspective of time spent (Figure 2). Note Friday is far separated from other days-of-the-week. It suggests that Friday distinguish itself from other days in terms of trip time spent by the respondents. In another word, people are spending more time on roads on Friday than other days-of-the-week.

4.2 Time Series Analysis

The original GPS recorded data are formulated to a format suitable to time series analysis. The sampling interval is chosen to be one hour. Therefore one whole week period is divided into a series of consecutive hour intervals (168), starting from the midnight of the former weekend, ending on the midnight of current weekend. The Data is composed of the hourly time label within one week and the number of trips happened during that one-hour interval. We divided the data based on trip purposes associated with a particular trip for the convenience of further analysis. In total, there are eight trip types under consideration. They are Working trip, Eat-out trip, College trip, Social or recreational trip, Medical or dental trips, Religious trips, Go-home trip and Shopping trip. Unix Version SPLUS was used to perform the time series analysis task.

There are two general approaches to analyzing time series. One is to use time domain methods in which the values of the process are used directly. The other is to use frequency domain methods. Frequency methods investigate the periodic properties of the process. In this study, we used both the two approaches to address a series of questions related to trip frequency, trip characteristics of various trip types and schedule relationship between different trip types.

4.2.1 Time Series Plots

As the first step, we use the extracted data to plot time series plots for each trip type presented above. These plots look like the traditional bar plots. But what is different is that the x axis we see now is on a temporal scale of 168 hours rather than just a quantitative scale. By comparing the amplitudes of the time series plots of the eight trip types, we may obtain an impression of the relative intensity of their trip occurrences. Results show that among the eight trip types, go-home trip has the highest intensity then followed by work trips. Medical or dental trip and religious happened least frequently on average. And the occurrence intensities of the other four trip types—Eat-out, College, Social or recreational and shopping go between them. There is no doubt to see go-home trip and go-work trips happened most frequently as home and work place are the two centers of one person's activity space. The two places are the most important components in the spatial environment within which people's activities occur. Go-work is more or less the

daily routine performed, at least on weekdays, while Go-home trip must be the ending trip of a trip series with origin at home, no matter what trip types the trip series start with and how the trip series are composed.

Figure 3

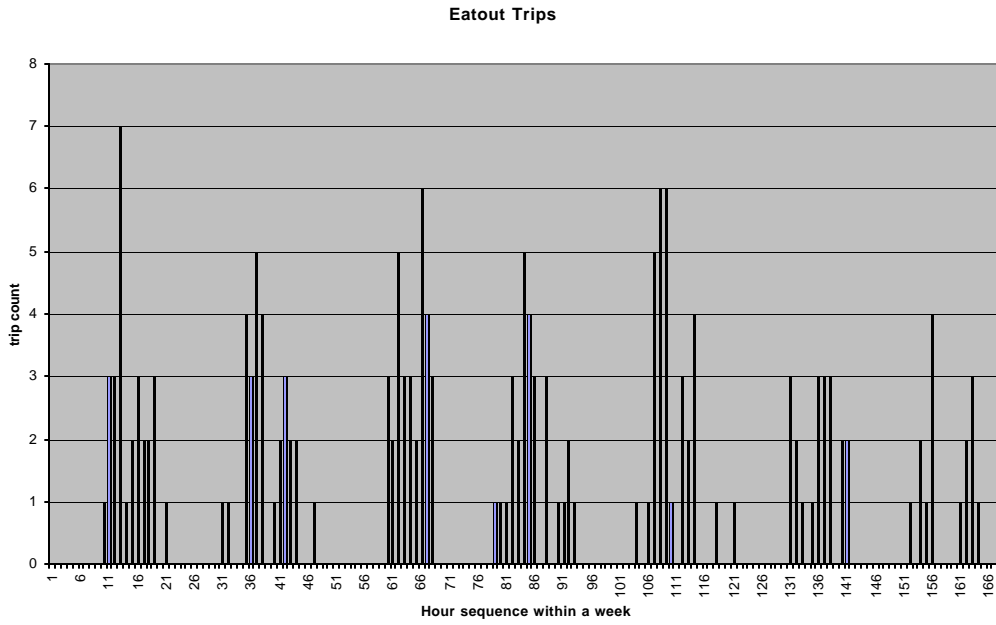


Figure 4

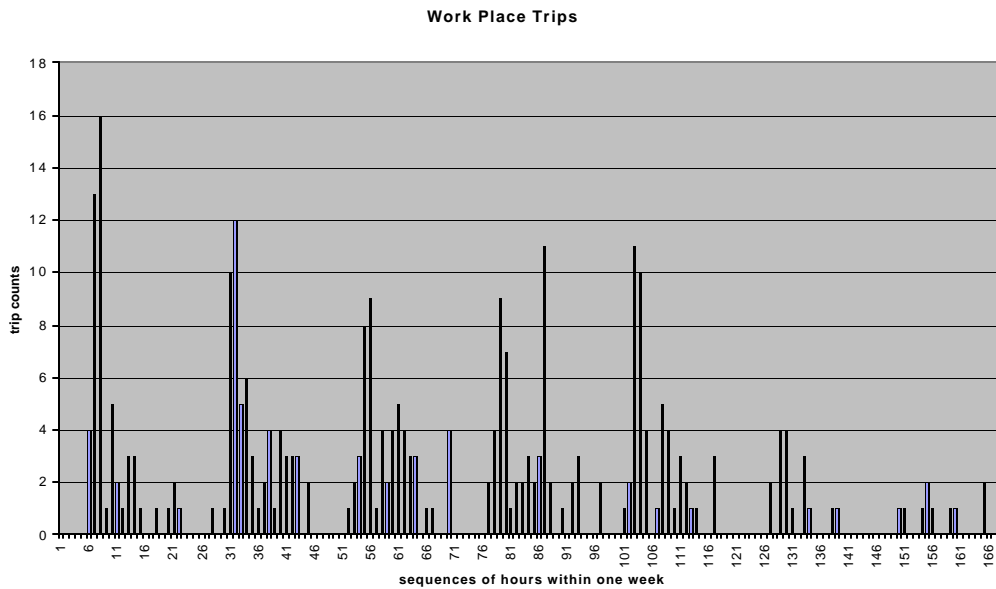
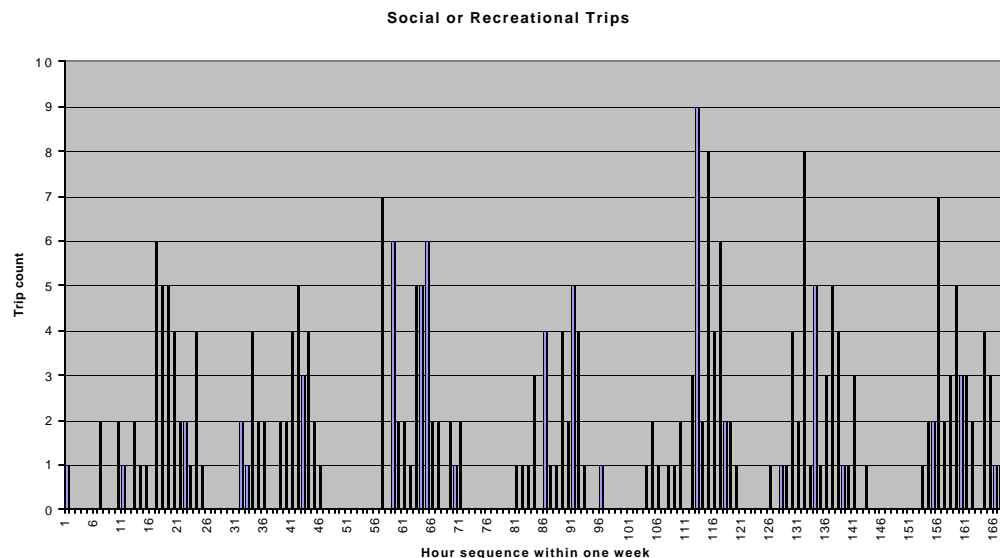


Figure 5



An insight into characteristics of different trip types could be obtained through visual examination of these plots. Go-to-work-place trips (Figure 4) mainly happen in the morning 7, 8 or 9 o'clock. That is, the trip counts peaks in the morning during weekdays usually. Except on Thursday, two peaks show up, one is in the morning, one is 3 o'clock in the afternoon. This could be related to some events happened or working scenario of the sample area. There is a general tendency existing for these daily peak trip counts. It decreases from Monday to Wednesday gradually and bounces back a little on Thursday and Friday. This may be an indication that working efficiency goes down as time goes from Monday and bouncing up again because of the approach of weekends. In other words, some psychological factors may be affecting people's go-work behavior. People may form their expectation for a weekly period during their life.

Eat-out trips (Figure 3) mainly happen during lunch hour or early afternoon during weekdays. They occur during working intervals. We could term it as "working eat-out trip". Most of Eat-out trips belong to this type. However, it is interesting to notice that the highest peak on Wednesday occur at early

evening. This could be a short family reunion or meeting with friends. It is reasonable to see it appear in the middle of week if we consider it as a short break of a busy life. Eat-out trips count decreases at the coming of weekends. This may be an indication that local people would more like to spend their weekend with their family and enjoy homemade food than going out for meals. However, referring back to our conclusion from MONOVA analysis, we know this is not necessarily true for every household. Eat-out trip time doesn't vary significantly across the week. Therefore, what we found about travel patterns on weekends might be reduced eat-out trip frequency but prolonged trip time.

Social or recreational trips (Figure 5) mainly occur during the early night. The highest peak in a week appears at 5 o'clock on Friday. Seconded by Saturday and Sunday noon peaks. If we look at the trip distribution for each day, we may find that the trip-count distribution presents reverse F distribution during weekdays (a little exception on Wednesday, which has two peaks). Usually the biggest bulge appears at evening on weekdays, but on weekends the distribution looks more like an F distribution—the biggest bulge appears at noon and decrease gradually as time goes. This change indicates the relaxed time schedule on weekends.

4.2.2 Autocorrelation

Autocorrelation is an important tool for describing the temporal dependence structure of a univariate time series. The max lag chosen for the eight trip types is 35 hours. For all these trip types, there exists a 24-hour maximum positive autocorrelation in their plots (Figure 6 and 7). However, the degree of correlation varies with the change of trip types. For those trip types performed more on a daily basis, like go-work, eat-out, go-home, social or recreational and shopping activities, the 24-hour correlation is more obvious. For trip types performed more or less sporadically, the feature of 24-hour autocorrelation is not obvious, like college, religious and medical or dental trips. For college trips and medical or dental trips, this 24-hour autocorrelation is less than 0.3. For religious trips, this 24-hour autocorrelation is less than 0.1. Religious trip shows its second-maximum autocorrelation at a 2-hour lag, which may be explained with the clustered religious activities on Sunday morning.

Figure 6 Auto-correlation of Work, Eatout, College and Social or Recreational Trips

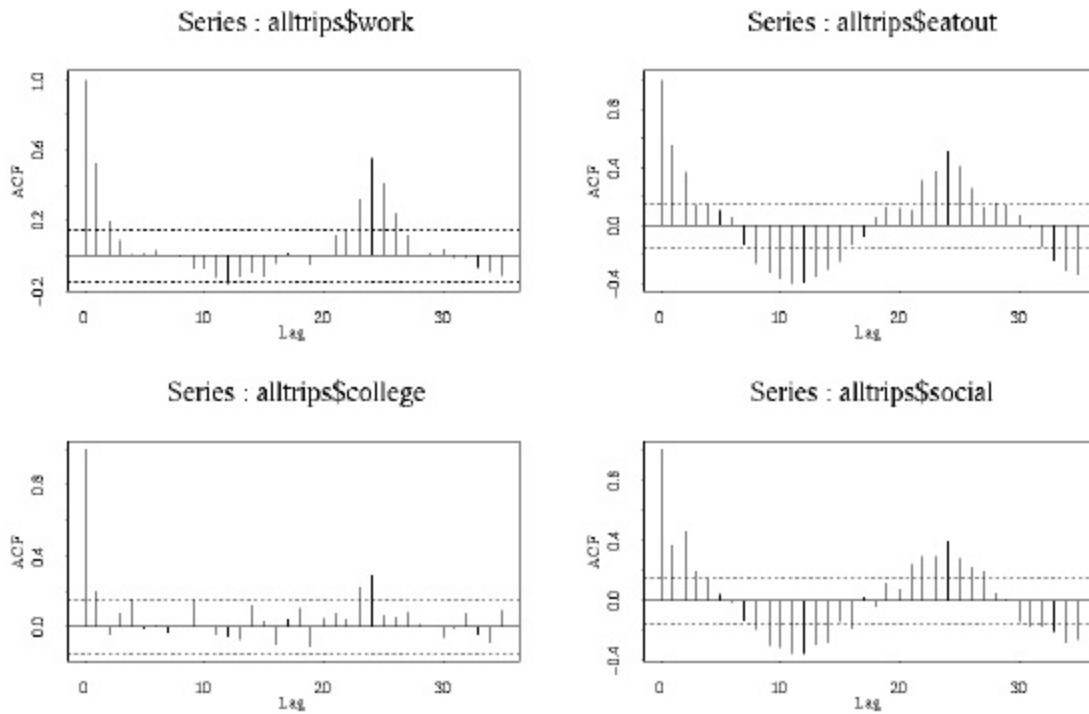
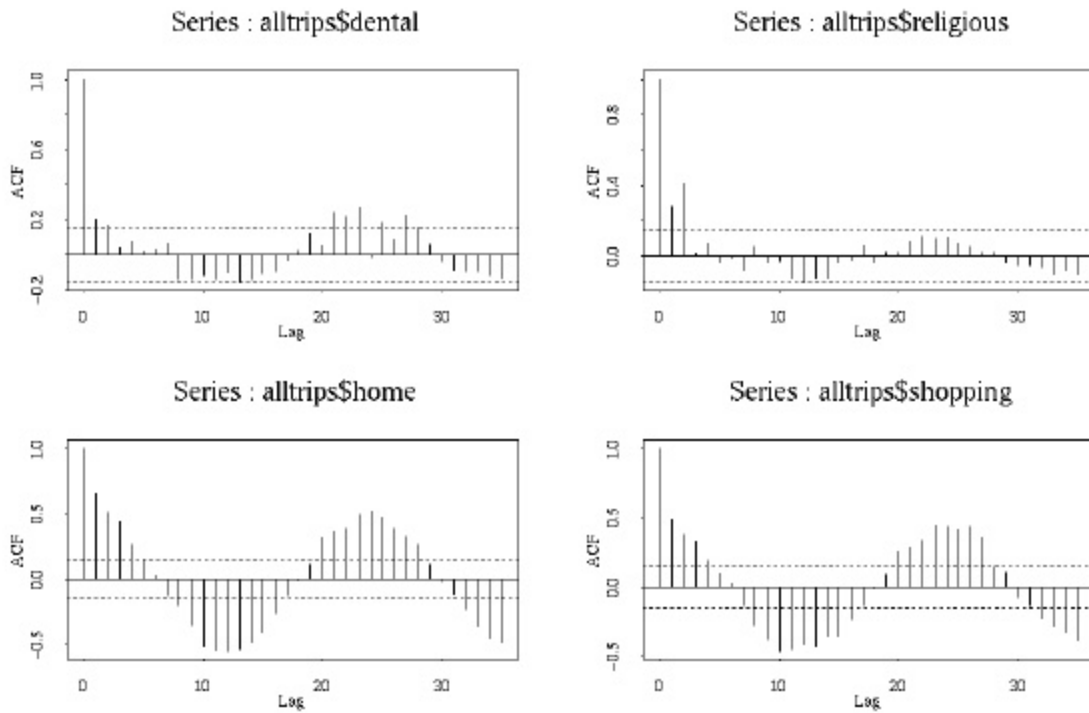


Figure 7 Auto-correlation of Dental or Medical, Religious, Go-home and Shopping Trips

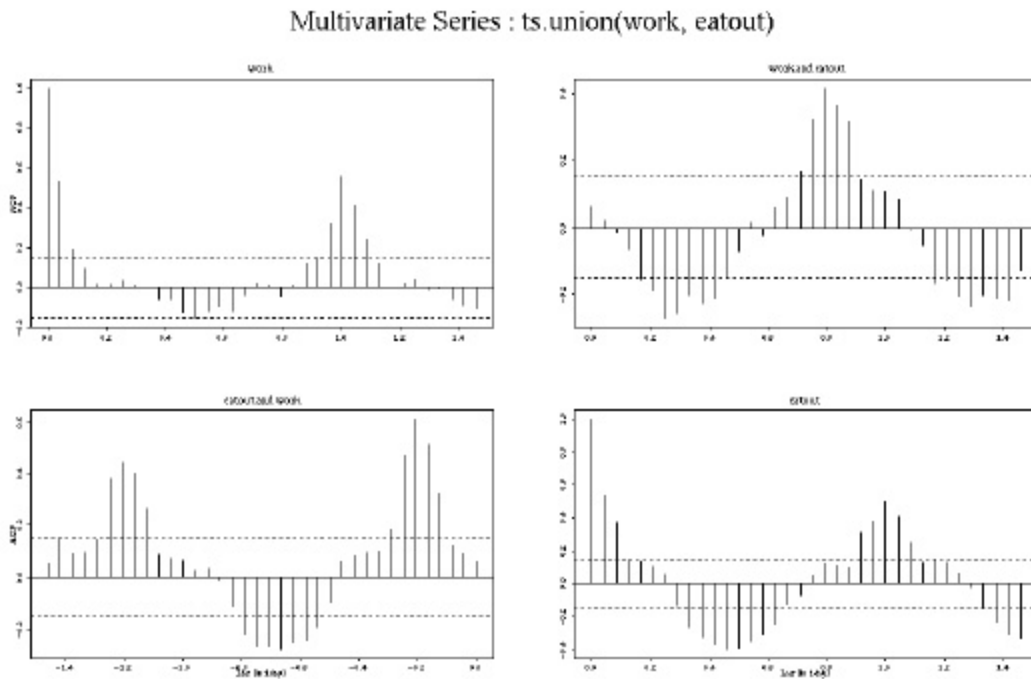


In Figure 6 and 7, the widths of sinusoidal peaks convey to us another kind of information—the degree of flexibility associated with a certain type of trip. Go-work trips ACF (autocorrelation function) plot has a peak width of only 2 or 3 hour interval. This indicates us that go-work trips are more or less obligatory activity type, which are subject to the working-hour constraints. In contrast, the width of go-home and shopping trips autocorrelation plots’ sinusoidal-peak is longer than five hours, which indicates much greater degree of flexibility associated with these trip types.

4.2.3 Cross-correlation between different trip types

Cross correlation is used in our research to study the mutual relationship between two different types of trips. We ran the cross correlation function provided in SPLUS for three activity-type pairs - eat-out trips and go-to-work trips, social or recreational trips and shopping trips, return-home trips and shopping trips. The results are shown in the following (Figure 8 ,9, and 10).

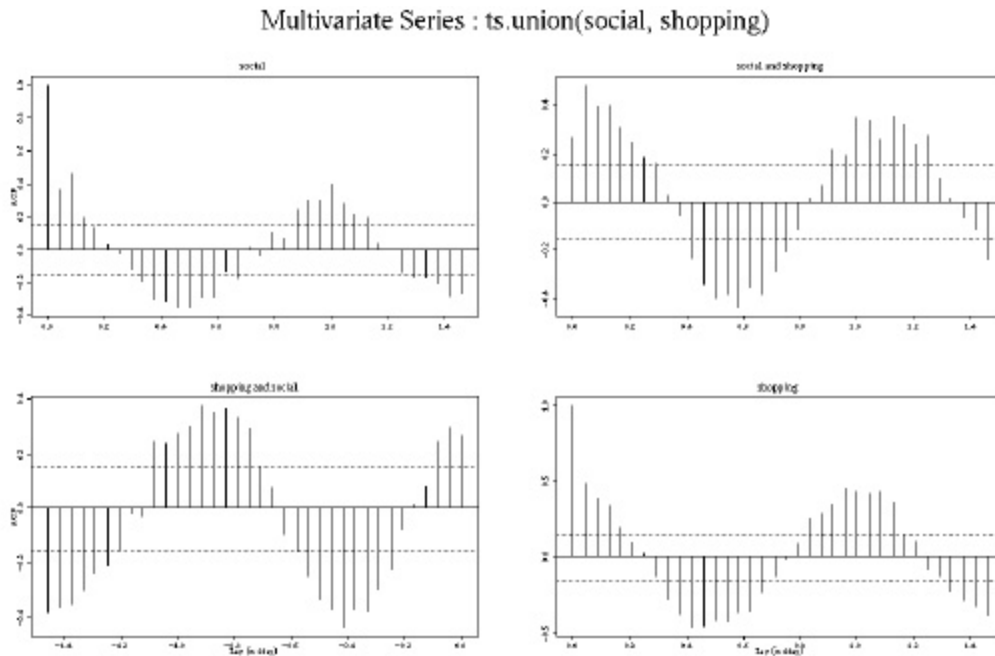
Figure 8 Cross-correlation Between Go-to Work Trips and Eat-out Trips



The cross-correlation plot between eat-out trips and go-work trips (Figure 8) shows that eat-out trips has the maximum correlation with go-work trips at -6 hour lag, which indicates that eat-out trips

typically lags behind go-work trips by 6 hours. These “working lunch” trips usually occurs at 1 or 2 o’clock in the afternoon.

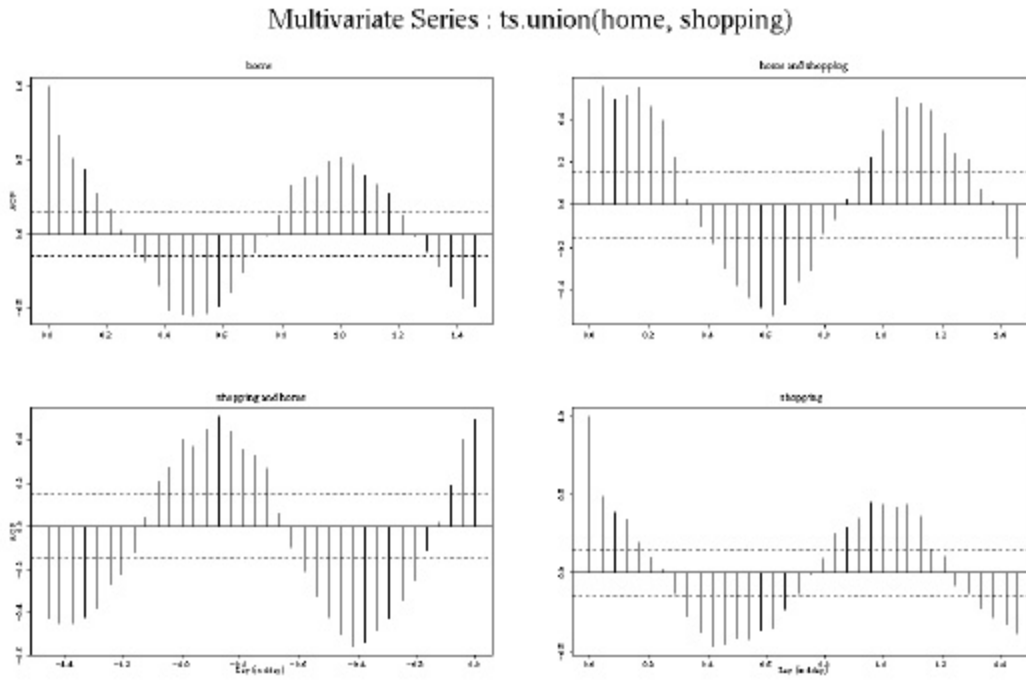
Figure 9 Cross-correlation between Social or Recreational Trips and Shopping Trips



The cross-correlation plot between social or recreational trips and shopping trips (Figure 9) shows no fixed schedule relationship between the two. However, the plot indicates, in most cases, shopping activities are scheduled close to social or recreational activities and in most cases two or three hours before them.

Similarly, the cross-correlation plot between return-home trips and shopping trips (Figure 10) shows no fixed schedule relationship between the two. Shopping behavior could happen either before return home trip or after it. This result seemingly does not make sense at first glance. However, considering the flexibility associated with return-home activity and its extensive relationship with other types of activities, it is possible.

Figure 10 Cross-correlation Between Return-home Trips and Shopping Trips



5 DISCUSSION AND CONCLUSION

5.1 Regularities in Trip Periodicity

As what is supposed to be found, there exist considerable differences in travel behavior between weekdays and weekends. However, past researchers have ignored the difference between Saturday and Sunday. Sunday is characterized with most (relative to other day-of-the-week) depressed travel-activity intensity. But Saturday is not. Most time of Saturday is devoted to relaxing or “clean-up” activities—finish something that hasn’t been done over the week.

Even among weekdays, when people's activities seem pretty routinized because of work or study constraints, such differences also exist. The variability of activity pattern on weekdays mainly comes from the flexibility associated with noon, early afternoon or evening time slot. Activities performed in these time slot may be eat-out, shopping, social or recreational activities—these activities are typically less obligatory.

As for trip intensity, we found an asymmetrical bell curve exists in trip counts plot across the week. It peaks on Thursday and falls on the lowest point on Sunday. This indicates people's activities are indeed influenced and shaped by a certain institutional period like week. As many social institutional rules are made based on the period, it affects people's decision making on allocation of time. Furthermore, the travel behavior of the former days may affect that of next day-of-week. Inertia exists in change of people's activity intensity across the week.

Note Friday in our MONOVA analysis shows its importance in terms of people's allocation of time on travel. The phenomenon has never been revealed in former researches. Combined with the research results derived from time series analysis part, we tend to attribute the increase of time spent on travel to the increase of time spent on shopping and social or recreational activities.

The time series analysis part revealed the periodicity associated with each type of trip. Most types of trips are performed on a routine basis across the week period—at least once a day—except religious and dental or medical trips. Some trips tend to be performed more frequently during a day (such as work trips, social-recreational trips, or eat-out trips) than other types of trips (such as return-home trips and shopping trips).

5.2 Defects that lies in GPS collected data

In the process of compiling and using data collected with the GPS-integrated device, we found the data collection procedure and technique are yet to be furnished to meet the up-to-date needs of behavior and transportation research.

In the Lexington travel survey, travel data are collected in a general way in terms of the sampling method used. Sampled households are spread evenly throughout the study area. And the sampled people in the households evenly come from different age groups. But due to some reason, the socio-demographic information associated with each sampled driver is not completely recorded, which impedes us from continuing to relate the revealed travel pattern to various socio-demographic factors.

In addition, the collected travel records are restricted to travels made with motorized vehicles. Short trips made by bicycle or on foot are ignored and not recorded. This is due to the fact that the size and weight of GPS-integrated device made individuals difficult to travel with them when biking or walking. Power supply is also a problem. Sometimes, the respondent simply forgot to turn on the recording device and enter the trip data into it. That causes us to lose some trip information too. In cases that the trip is relatively short, the GPS module may not gain enough time to get a positional fix for the record. What is recorded is just a bunch of useless information and has to be discarded during the map-matching phase. About 97 percent of the GPS collected trips finally got matched up in digital maps. 87 percent of the corrupted trips have distances less than 0.16 kilometers. This means that a lot of short trips were missed. Therefore, when using a GPS-integrated device for collecting travel data, we fixed the problem of “human memory malfunction”, but introduced “machine memory malfunction”. Furthermore, although more than 1800 trips are traced and recorded, when breaking trips into different trip types, the trip counts are not statistically large for analysis.

Another problem with the data set is the classification schema for activities (Table1). The classification schema is easy to use for survey (since it is a general classification) but not necessarily good for research purpose. For example, a more detailed classification scheme is needed for researchers who are interested in time-budget studies. It will be a blessing if future travel surveys could adopt some standardized schemas and fits the trips made by the respondents into more detailed classes. This is essential for making comparative studies possible and will make researchers able to examine the dataset in a more comprehensive way.

Following the study, we found that the household data in Lexington study was incomplete and thus we have to reduce the household set from 115 to 100. This is still a significant number. There are also some problems with the digitized base map; a preliminary search through the CD obtained from DOT shows that only one of the two counties was thoroughly geo-coded. Thus we will have to obtain an equivalent mapping of the second county so that members of the activities of sample residing in that area can be fully taken into consideration for further location-related analysis. In our future research, we will focus on two areas: (1) adding a touch to the relationship between the found weekly travel pattern with the demographic data of sample household. As what was mentioned before, demographic data we have is not complete, but still useful. We hope this analysis will lead us into the understanding of the underlying mechanism that produces the revealed activity patterns; (2) examining directionality in trip making using circular statistics. We will examine the directional relation between different trip types, as well as the relation of trip direction and the distribution of various potential activity sites of the study area.

REFERENCES:

- Cullen, I.G., Godson, V. (1975). Urban networks: The structure of activity pattern In D. Diamond & J. B. MacLaughlin (Eds), *Progress in Planning: Part I* (pp1-96). Oxford: Pergamon.
- Hanson, S. (1980) The importance of Multi-Purpose Journey to work in Urban Travel Behavior, *Transportation*, 9, 229-248.
- Hanson, S and J.O.Huff (1982) Assessing day-to-day variability in Complex Travel Patterns, *Transportation research Record*, No. 891, 18-24.
- Hanson, S. (1982) The determinants of daily travel-activity patterns: Relative location and socio-demographic factors. *Urban Geography*, 3, 179-202
- Hanson, S and Huff, J (1988) Repetition and day-to day variability in individual travel patterns: implications for classification. *Behavior and Environment—Psychological and Geographical Approaches*, 249-266.

Huberty, C.J. (1994). Applied discriminant analysis. New York: Wiley.

Kitamura, R.(1987) An analysis of weekly activity patterns and travel expenditure, in Golledge, R. and H.Timmermanns (Eds.) Behavioral modeling approaches in geography and planning.

Koppelman, F. & Pas E. I. (1984) Estimation of disaggregate regression model of person trip generation with multi-day data. In : J.Volmuller & r. Hamerstag(Eds.) Proceedings, International Symposium on Transportation and Traffic Theory. VNU Science Press, Utrecht

Lexington Area Travel Data collection Test: Global Positioning Systems for Personal Travel Surveys (October 9, 1997) Battelle 505 King Avenue columbus, Ohio 43201

Pas,E.I. and F.S. Koppelman (1984) Intrapersonal Variability in Weekday Urban Travel and Related Behavior: formulation and Examination of some Hypothesis, Paper presented at the 63rd Annual Meeting of Transportation Research Board, Washington, D.C, January.

Pas, E.I. and F.S. Koppelman (1985) Analysis of Multiday Travel-Activity Patterns, Paper presented at the 64th Annual Meeting of the Transportation Research Board, Washington, D.C., January

Timmermans, H., and Golledge, R.G. (1990) Applications of Behavioral research on spatial problems II: Preference and choice. Progress in Human Geography, 14, 311-354.