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GPS-Based Tracking of Daily Activities

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GPS-Based Tracking of Daily Activities

by

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Analysis of Variability of Weekly Travel Behavior Using GPS-Recorded Data

Preface: This project was initially conceived to investigate how the GPS-based recording of weekly travel behavior in Lexington (KY) could be integrated with the latest disaggregate travel behavior simulation models (SMASH & ALBATROSS) to determine if such recordings of data would improve model prediction capability. Funding limitations required drastic downsizing of the project. The revised project focused only on the GPS data for Lexington, and it was analyzed for patterns of spatial and temporal characteristics that may shed further light on individual and household travel. This Final Report summarizes the results of that work.

Executive Summary

Statement of Purpose

While characteristics of daily travel behavior have been determined from analyses of the reconstructed household travel behavior recorded in travel diaries, such reconstructions are subject to criticisms. Respondents in a survey may lie or falsely recall information about destinations, 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 (Brog, et al., 1982; Purvis, 1990). 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 in 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. Although the new GPS-involved data collection methodology is not expected to replace the traditional data collection method in behavioral science within a short period of time, it does provide a more robust alternative for defining personal travel than the current methods. After being provided with a CD data record of all the transactions by DOT, a variety of analytical techniques and methods were used on the GPS-collected survey data. Questions that drove these analyses included:

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

Answers to these questions are helpful for us to understand the relationship between daily travel activity patterns over a week period (see also Hirsh, et al., 1986; Kitamura, 1987; and Kitamura & Van der Hoorn, 1987), as well as the rationale that incorporates a time factor as a determinant of travel behavior.

A second objective is the evaluation of a new travel data collection method—GPS-integrated data collection. The data set that was generated from such a collection method is for the first time used in analyzing temporal characteristics of weekly travel activities. By adding the effects of real-time on-site data collection using GPS and in-car computer data entry, we aimed to complement and evaluate knowledge gained from traditional diary and survey methods.

Background and Procedures

An understanding of variability is central to the modeling of travel behavior (Jones & Clarke, 1988). Until the late 80's, comparatively little attention had been paid to the question of day-to-day variability in behavior. Past attempts usually handled the problem by surveying travel on a common weekday or by collecting and analyzing one-day data from different weeks to obtain a picture of typical travel pattern averaged across individuals and days of the week. Comparison and contrast of day-to-day differences in travel behavior were rarely practiced. For the past two decades, developments in travel behavior analysis and transport policy have led to a greater awareness of the need to examine day-to-day variability in travel behavior. It is hypothesized that a thorough understanding of variability would provide the chance to make traffic management systems (such as urban traffic control) more efficient or help ensure that road network design is more closely matched to the profile of travel demands. Improved knowledge of variability should also contribute to more efficient sampling procedures for short period traffic counts.

To capture the variability of travel behavior over a longer period, multi-day data is essential for research input. Specifically, with weekly data it becomes possible to answer a series of questions about the distribution of frequency of participation, rather than mean participation rates. The growing interest in longitudinal analysis, using repeat cross-sectional or panel data designs, has also highlighted the need to look at multi-day data sets.

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 patterns by Koppelman and Pas (1984) and Hanson and Huff (1982) respectively. However, their research mainly focused on inter- or intra-person variation of travel patterns rather than on day to day, or one day-of-week to another day-of-week patterns. In this project, measures of activity-travel behavior and its variability among the seven different days-of-week were used. As part of this study, the physical measurements of trips (time duration, distance, frequency, and direction) were analyzed using K-group MANOVA (multiple analysis of variance) procedures to examine how people's activities show different patterns among days in a week in terms of types of activities pursued. This was followed by a discriminant analysis (Huberty, 1994) of travel patterns for 13 specified trip purposes for each of the seven work days, and the structure matrix of the discriminant coefficients (Zhou & Golledge, 1999). Finally, post-hoc procedures (Hotelling's T^2 and univariate t-tests (see Olson, 1974) were used to determine which variables accounted for the associations found in the discriminant analysis). Then time series analysis (Zhou, 2000) was used to further prove the conclusion derived in the former analysis. Circular statistics (Mardia, 1976; Johnson &Wehrly, 1977) were used to examine travel directions. The advantages and disadvantages of using GPS-integrated devices as a reliable means of collecting travel activity data were then analyzed. Finally, suggestions about how to improve the design of experiments involving GPS-integrated data-collecting devices were elaborated.

Discussion of Results

As expected, there exist considerable differences in travel behavior between weekdays and weekends. However, past researchers have not empahsized the difference between Saturday and Sunday. Sunday is characterized with most (relative to other day-of-the-week) reduced travel-activity intensity. But Saturday is not.

As opposed to the research conclusion of Pas (1988), even “regular” travel-activity behavior was found dependent on day-of-the-week in this study. Among weekdays, when people's activities seem pretty routinized because of work or study constraints, differences of travel-activity patterns still exist. In Pas’s paper (1988), only the trip generation rate was considered as a comparison measure, which represents only one perspective of the people’s activity patterns. Our study examined the variation of travel behavior across the week not only from the aspect of trip frequency, but also from the aspects of trip duration and trip distance. Results of the comparisons of activities on week days using variables of trip duration, distance, frequency, and direction give the following results.

Pairwise multivariate tests (T^2’s) and univariate t tests are used to determine which pair of groups differ significantly on the set of trip variables. We used a loose criterion (set at the .05 level for univariate t tests) to determine which kind of trips contributed to the significant pairwise difference of people’s travel patterns on different paired days of the week. Some interesting results are shown as follows:

- Trips on Thursday - Friday: Not significantly different overall except for a significant difference on purp1 (pickup passenger).
- Trips on Tuesday – Thursday: Not significant.
- Trips on Monday – Thursday: Not significant except for purp4 (work-related business).
- Trips on Thursday – Saturday were significantly different; the difference was emphasized most in: purp1 (pickup passenger), purp3 (work place), purp4 (work-related business) purp5 (school, college, university), and purp11 (return home).
- Trips on Saturday - Sunday were significantly different, the emphasis mostly being on: purp7 (other errands) and purpl2 (religious activities).
- Trips on Wednesday - Sunday were significantly different, the main contribution to difference deriving from purp3 (work place), purp10 (medical or dental), and purpl2 (religious activities).
- Trips on Tuesday – Saturday were significantly different, the main contributors to difference being purp3 (work place).
- Trips on Monday - Tuesday were not significantly different.
- Trips on Wednesday – Saturday overall were not significantly different except for purp3 (work place) and purp10 (medical or dental).
- Trips on Friday – Saturday were significantly different, with major contributions from purp3 (work place), purp7 (other errands), and purpl2 (religious activity).

This analysis shows that the variability of activity patterns on weekdays mainly comes from the flexibility associated with the noon, early afternoon or the evening time slots. Activities performed in these time slots may be eat-out, shopping, social or recreational activities-- these activities are typically less obligatory.

With regard to trip intensity, we found an asymmetrical bell curve exists in the plots of trip counts across the week (Young & Willmott, 1973). It peaks on Thursday and falls to the lowest point on Sunday. This indicates people's activities are indeed influenced and shaped by institutional constraints (like the duration of a week). As many social institutional rules are made based on weekly periods, it affects people's decision-making with regard to the allocation of time and effort. Furthermore, the travel behavior of one day may affect that of the next day-of-week (e.g., by delaying trips when problems such as congestion do not allow completion of the original scheduling).

In our MANOVA analysis, Friday shows its importance in terms of people's allocation of time for travel. This phenomenon has not been explored in prior research. Combined with the research results derived from time series analysis, 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 revealed the periodicity associated with each type of trip. A rhythmic pattern (Shapcott & Steadman, 1978) for different types of trips was established. 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). To establish a reliable spectral signature for different trip purposes, however, we would need data from a longer time period (minimum of about 6 months).

As opposed to what we have assumed, the trip-direction-circular histograms that we produced were not exactly symmetrical about any arbitrary diameter of the base circle (see Zhou, 2000). There exists a mean vector to indicate the possible direction in which multi-purpose trips may have been undertaken. However, a sensible explanation for this effect needs to relate the direction preference to the local activity site distribution and socio-demographic features (as would be done if the data were to be used in the SMASH or ALBATROSS simulations). We hypothesized that direction data can be readily and accurately used in travel behavior and transportation research with the help of GPS. The attempt made in this study shows that the application of circular statistics to travel data is feasible. But more work needs to be done to make it a worthy tool of analysis in activity-related research.

<u>Defects in GPS Collected Data</u>

In the process of compiling and using data collected with the GPS-integrated device, we found the data collection procedure and technique as yet not sufficiently well developed to meet the up-to-date needs of behavior and transportation research.

In the Lexington travel survey, travel data were 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 are stratified by age groups. But, for some reason, the socio-demographic information associated with each sampled driver was not completely recorded, which impedes efforts to relate the revealed travel pattern to various socio-demographic factors (as would have been needed if SMASH and ALBATROSS had been used).

In addition, the collected travel records are restricted to travel 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 the GPS-integrated device made it difficult for individuals to travel with them when biking or walking. Power supply is also a problem. Another problem was that, at times, the respondent simply forgot to turn on the recording device and enter the trip data into it. That caused some loss of trip information, similar to forgetting to enter trips into a diary. In cases where 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 comparatively useless information and has to be discarded during the map-matching phase.

We were able to match about 97 percent of the GPS collected trips with digital maps. 87 percent of the corrupted trips have distances less than 0.16 kilometers. This means that probably some short trips were missed. Therefore, using a GPS-integrated device for collecting travel data fixed the problem of "human memory malfunction", but introduced "machine memory malfunction". Furthermore, although more than 1800 trips were traced and recorded, when breaking trips into different trip types, the trip counts were not large enough for statistical analysis.

Another problem with the data set was the classification schema for activities. The classification schema is easy to use for survey purposes (since it is a general classification), but it is not necessarily good for research purposes. 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 fit the trips made by the respondents into more detailed classes. This is essential for making daily comparative studies possible and will improve researchers' ability to examine the data set in a more comprehensive way.

Conclusions

In the attempts to reveal the determinants of variability of activity patterns, the earlier works by Hanson (1982) and Pas (1984) have identified their association with social-demographic and spatial or environment variables. The list of explanatory variables that potentially have influences on travel activities includes age, marital status, gender, employment status, education level, presence of young children, income, auto-ownership, residential density and the location of individual or household to potential destinations, such as shopping centers, churches, gas stations, etc. However, none of this literature addressed the role of the weekly period in the daily travel behavior. Kunert (1994) noticed how various life-cycle groups show distinctively different profiles of trip-making over the course of a week. But he considered the social constraint – the week period - only as a time frame for examining travel patterns instead of as an explanatory variable for them.

This study advanced our understanding of the unusual determinant (the weekly period) of activity pattern by a breakdown and analysis of its influence on travel distance, frequency, purpose, direction, and the type and temporal characteristics of activity pursued at an aggregate level. Kunert's finding (1994) that there is tendency of increasing trip making from Monday through Friday and relatively low trip making at the weekend was confirmed. As a bonus, Thursday was revealed with the highest trip intensity compared to other days of the week.

Another outcome of this study would be the evaluation of a new travel data collection method. The Lexington study was the first attempt to utilize a travel data collection based on GPS. The GPS-involved travel data collection method has its advantages in accuracy and reliability. In addition, the overall data post-processing procedure can be automated. Up to the time that LTS data was collected, the commercially available GPS-integrated device was still bulky and difficult to carry individually. This led to the fact that only travel by automobiles was recorded in the LTS data set, which potentially modifies any conclusion based on this data set. However, without losing generality, the research conclusions derived in this study are valid if we limit its applicability to motorized travel only. But we also recognize that hardware developments over the past 2-3 years have made GPS easily portable. This should lead to increased use of GPS to collect spatially accurate and complete data that obviates the need for recall from long-term memory and difficulties in remembering to complete surveys or diaries.

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Text of Proposal
UCTC Grant #DTRS99-G009

GPS DATA HANDLING FOR ACTIVITY BASED MODELING

Objectives

While characteristics of daily travel behavior have been determined from analyses of the reconstructed household travel behavior recorded in travel diaries, such reconstructions are subject to criticisms that people lie or falsely recall about destinations, times, trip purpose, and other critical characteristics, such as under-reporting of short trips and the number of stops in a trip chain. 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 that time on an in-car computer. The final report of the study gave descriptions of travel behavior but performed little detailed analysis on the data so collected. Using a CD-ROM data record of all the transactions, I propose to examine questions such as: To what extent were the travel behaviors recorded on each day highly correlated? Are there recurring cyclic patterns that show similar patterns of repetitive behavior on different days of the week? How well can a model calibrated for activity behavior on one day predict behavior on other days? To what extent do discrete choice models of travel behavior fit the data for different days with approximately the same parameters? To what extent did travelers use optimal travel routes (e.g. shortest path)? What proportion of different trip purposes were undertaken entirely on suburban streets and what proportion relied on different quantities of freeway travel? Knowing the answers to these questions provides some of the final pieces to the puzzle of repetitiveness in household travel behavior. It is of considerable importance to the calibration of predictive models of behavior, to selecting the GIS data structure representational formats, and to the selection of analytical tools to be included in any GIS that is to be used as a host for the data structure and as a decision support system for a planning agency.

Research plan, deliverables, and research contribution.

Much research over the last two decades has paid attention to the study of locational and spatial choice aspects of human activities. The development of GIS has provided an incentive to produce and use geocoded spatial databases and has consequently assisted in the determination of relevant variables for destination choice. The temporal sequencing of activities has also received increasing attention, but so far attempts to compare temporal sequences on a day-by-day bases across a standard period of time (a week) have not been fully pursued. Access to the GPS/in-car computer data record from the Lexington study provides an opportunity to remedy this lack.

Typically the study of human activities can be approached from the perspective of a spatial-temporal context. Following the fundamental ideas expressed in Hägerstrand's "Time Geography" (1970, 1976) and those of his followers such as Lentorp (1978), and more recently the works of Miller (1991, 1999), a spatio-temporal approach to the examination of people's activities should be able to focus on the correlation between daily trajectories. Various diary surveys have concluded that on a daily basis many activities are non-periodic, and destination choices are difficult to rationalize. Before we can adequately design and interpret a GIS model that suits the particular spatial/temporal movements and sequences that are typical of daily activities in the USA, we need more precise information about such movements. To achieve this objective, we need to look in detail at the actual time paths of individuals to determine to what extent time-paths of individuals or groups can be best fit by simple decision making models based on criteria such as shortest path and least time. We also plan to examine trip chains and discover what regularity exists both in the periodic occurrence of similar chains and the sequences in which particular activities are performed.

Basically we need data for different activities that take place more than once a week as well as those with other episodic frequencies. This will allow a clarification (using sequences of activities undertaken in trip chains) of the hypothesized "Sequencer" model embedded in the Gärling, Kwan, and Golledge (1994) computational process model. Given the budgetary restrictions of this project, we will not be able to collect the detailed data that we need. However, we have access to the DOT Lexington Study GPS-based data. By exhaustively examining this data, we can build a conceptual model of the necessary structure that could be implemented in future work.

Procedures

It is possible to delve into the behavior pattern along a time axis at both an individual and an aggregate level. Activity patterns are related to the frequency and regularity with which particular social groups choose to participate in those activities. The possible form that such regularities might take is to a certain extent determined by the study area itself, demographics of the local population, and the sociocultural environment. For different groups it appears that quite different patterns of work, social, recreational, and shopping trips occur (Janelle et al 1998).

In this study we plan to focus on variations or regularity of different kinds of trips across a seven day period. This time scale can reveal the underlying local patterns and help to identify changes of trip frequency and episodic intervals of trip making over the weekly period.

The participants for the Lexington study were recruited using a sample plan based on demographic factors in which gender, age, and presence or absence of children, were the critical differentiating variables. An effort was made to ensure that the sample population was widely geographically distributed in both counties.

Since time can effect people's travel choices in different ways, the first step in our methodology is to create a 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. This 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 activity in the Lexington data included trips to pick up passengers, work trips, return home trips, shopping, religion, drop off passengers, work related business, trips to school, college, or university, eating out, social or recreational, medical or dental, and other errands.

Comparing all possible combinations of two days in a week with respect to household travel behavior, may or may not yield significant differences between the two patterns (e.g. maybe Monday and Friday events will be correlated, while Sunday and Wednesday will not). Using multiple criterion measures such as the K-group multivariate analysis of variance (MANOVA) and discriminate analysis however can help determine if differences do exist.

Based on the days of the week the next step is to reformat the collected trip counts from the Lexington travel survey data into seven daily groups (Sunday through Saturday). Trip counts for each day of the week will then be further divided based on different trip purposes or trip types as dependent variables. Using the K-group MANOVA capability we can compare 13 different variables simultaneously for each of the seven working days with a null hypotheses of no significant difference between the 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), to my knowledge no statistical testing has been put forward that explicitly measures the degree of coincidence or the similarity of spectral properties of trips across an entire seven day week period. Consequently we anticipate we will reject the null hypothesis and support the generally accepted conclusion that people's activities differ over the set of 13 trip variables and the seven week days.

Following this we will use discriminate analysis for describing major differences among the seven day groups previously used in the multiple analysis of variance. Using seven week days and 13 trip purposes the number of possible discriminate functions is six. The coefficients for each of the trip variables on the six discriminate functions will then be examined. The structure matrix will also be examined to show the correlation between each discriminate function and each of the original trip purposes. Generally it is assumed that greatest stability of the function variable correlations found in the structure matrix exist in small or medium sized samples, especially when there are high or fairly high interrelations among the variables. Also the correlations give a direct indication of which variables are most closely aligned with the unobserved trait which the cononocal variables (discriminate function) represents. We will also determine variable redundancy. A useful device for determining directional differences among the groups when two or more discriminate functions exist is in to graph them in the discriminate plane. In the horizontal direction, correspondents of the first discriminate function and lateral separation among the groups indicates how much they have been differentiated on the basis of this function. The vertical dimension corresponds to the second discriminate function and tells which groups are being differentiated in a way unrelated to the way that they were separated on the first discriminate function. We will use this graphical display method to search for other regularities among variables and groups. This should help us decide which trip purposes are related to other trip purposes on which particular day or days of the week. This explores the basic nature of multi-purpose or multi-stop trips, as well as giving insights on trip sequencing.

Finally, post-hoc procedures using Hotelling's T^2 and univariate T tests will be undertaken. This is done to find out which groups and which variables are responsible for the overall association found in the discriminate analysis. Hotelling's multivariate tests (T^2) and univariate T-tests determine which pair or groups differ significantly on the set of trip variables. This should highlight which days of the week are most similar to each other and which trip purposes are most frequently repeated on those days to create the patterns of similarity.

A second problem will be to compare the trips made by individuals to those suggested by various optimization network flow models. At this stage we simply plan to use path selection models found in the ARC INFO NETWORK software, which includes TransCad. Basically the study area has been geocoded and the network exists as a node-link database. Using ArcInfo functionalities we can determine distance and times from specific origins to given destinations in the geocoded network, and compare them with the actual trips and temporal intervals between origin and destination GPS-based recordings of locations. Although many conceptual criticisms have been made of standard network flow optimization models, there have been very few opportunities to compare the specific routes taken by real-world travelers with those predicted by network models.

Analysis of Variability of Weekly Travel Behavior Using GPS-Recorded Data

By

Jianyu (Jack) Zhou

1. INTRODUCTION

1.1 Statement of Purpose

While characteristics of daily travel behavior have been determined from analyses of the reconstructed household travel behavior recorded in travel diaries, such reconstruction is subject to criticisms. Respondents in a survey may lie or falsely recall information about destinations, 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. 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 in 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. Although the new GPS-involved data collection methodology is not expected to replace the traditional data collection method in behavioral science within a short period of time, it does provide a more robust alternative for defining personal travel than the current method. Provided a CD data record of all the transactions by DOT, I used a variety of analytical techniques and methods on the GPS-collected survey data. This thesis summarizes my findings, which attempt to address the following problems related to the variation of travel behavior with change of time within a time period:

4. How does the calendar periodicity— week period –influence different types of people's travel activities in a general way?

5. What are the periodical variations of people's travel choices on different days of the week in terms of trip frequency, trip purposes, trip duration, trip distance, and trip direction?

6. To what extent is the automatic-device-collected data (involving GPS) more accurate than the data collected using traditional methods? Is there any possible inaccuracy involved that may potentially harm our research conclusions?

Answers to these questions are helpful for us to understand the relationship between daily travel activity patterns over a week period, as well as the rationale that incorporates a time factor as a determinant of travel behavior. A second objective is the evaluation of a new travel data collection method—GPS-integrated data collection method. The data set that was generated from such a collection method is for the first time used in analyzing temporal characteristics of weekly travel activities. By adding the effects of real-time on-site data collection using GPS and in-car computer data entry, I aim to complement and evaluate knowledge gained from traditional diary and survey method.

1.2 Overview of Variability of Travel Behavior

1.2.1 Background

An understanding of variability is central to the modeling of travel behavior. Until into late 80's, little attention had been paid to the question of day-to-day variability in 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 weeks to obtain a picture of typical travel pattern averaged across individuals and days of the week. Comparison and contrast of day-to-day differences in travel behavior were never practiced. Now, however, development in travel behavior analysis and transport 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 traffic management systems such as urban traffic control much more efficient or make road network design more closely matched to the profile of travel demands. Improved knowledge of variability might also contribute to more efficient sampling procedures for short period traffic counts.

To capture the variability of travel behavior over a longer period, multi-day data is essential for research input. Specifically, with weekly data it becomes possible to answer a whole series of questions about the distribution of frequency of participation, rather than mean participation rate. The growing interest in longitudinal analysis, using repeat cross-sectional or panel data has also highlighted the need to look at multi-day data sets.

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 research mainly focuses on inter- or intra-person variation of travel pattern rather than from day to day, or from one day-of-week to another day-of-week. In this thesis, measures of activity-travel behavior and its variability among the seven different days-of-week are presented. As part of a preliminary study of using GPS-collected data in travel behavior research, the physical measurements of trips (time duration, distance, frequency, and direction) are analyzed to discriminate how people's activities show different patterns among days in a week in terms of types of activities pursued. Then time series analysis is used to further prove the conclusion derived in the former analysis. Travel directions are also explored. The advantages and disadvantages of using GPS-integrated devices as a reliable means of collecting travel activity data are analyzed. Finally, suggestions about how to improve the design of experiments involving GPS-integrated data-collecting devices are elaborated.

The remainder of this thesis is organized as follows. Section 1.2 discusses the past literatures related to this study. Section 1.3 explains the traditional travel data collection method and GPS-integrated data collection method in detail. The LTS data set collected based on GPS is also briefly described in this part. Three analytic techniques (MONOVA, time series analysis, and trip direction analysis) are applied to the data set and results are presented in Section 2. In Section 3, the research reported here is discussed and the results are compared with the results of related research efforts. In addition, the conclusions that may be drawn from this work are presented.

1.2.2 Research Review

A concise definition of everyday activities may seem not necessary. After all, such activities are simply what we do each day. Some may be undertaken as routines, acting as pegs in the daily scheduling of activity programs. Some may just come up on specific days or a coincident of time. We may know exactly most of our own activities before we leave home in the morning. But some episodes also interfere in our schedule such that if activity patterns of our different days are faithfully recorded, more or less they are different from the original plans.

Activities constitute a stream of events, involving one or several persons, objects, and places. In this stream, units must be identified, classified, and counted or measured (Garling and Garvill, 1993). In other words, activities are usually organized within one-day units and are viewed as a series of episodes (e.g. went to work, went to lunch, returned to work, went home, went shopping, returned home). Before people perform these activities, typically a vague plan—schedule—is made in the brain.

Scheduling is thought of as the collection of all activities that will happen on a coming day. It is yet to happen. What really happened and passed by is the activity program—a series of activities really undertaken during a certain period of time, independently of the order of their occurrence. An activity pattern is defined as an activity program with its schedule.

During the past decades, growing out of dissatisfaction with traditional transportation studies that provide little insight into the potential individual motivations behind urban activities and people's everyday decision making, geographers have been putting more emphasis on a behavior approach for exploring the causes that create the myriad geo-spatial phenomena. Various methods have been utilized to collect behavior data on a small scale. The derived research results have helped us a lot in understanding the richness and uncertainty brought by human actors in the geo-related phenomenon under research.

Although the original desire is to find universal laws that govern behavior undertaken by human beings, various chores such as budget limits, privacy concerns, and lack of real-time recording methods, have put a lot of constraints on large scale data collecting practices. Up to now the most work we saw has been mainly small-scale qualitative as well as quantitative inquiries into human behavior in specific natural or designed experimental spatial contexts. Difficulties have been encountered when trying to transfer findings from one spatial context to another. However, the activity-based approach has enriched our understanding of a wide variety of urban problems. "By incorporating people's daily movements outside of home, activity studies lead to more accurate assessment of peoples' exposure to or interaction with various aspect of the physical and social environment (Hanson and Hanson, 1993, p254)".

For centuries, the diary has been known only for its historic value. Only in the 1960s and 1970s was the diary noticed for its use in drawing threads from structured records to weave an exploitable picture of daily activities of a large sample of people. Activity diary keeping quickly became a widespread data collecting method for recording what people do, where they do it, when they do it and studying why they do it. Differing from the ordinary diary, modern activity dairies for scientific use don't have names, locations and events interleaved without order among lines of text. Diaries follow a strict syntax and format and are well-structured tools for keeping selected information that behavior researchers are concerned with. Also “modern activity diaries do not usually include details of activities that take place at home (Hanson and Hanson, 1993, p250)” for privacy concerns. Depending on how we choose to measure and what we see as important in our behavior theory, specific aspects of activities (time, duration, distance, purpose, etc) are focused in the structural organization of activity diaries. The level of detail at which such things as time, distance, location, etc. are recorded varies. As for measuring time, for example, respondents may be asked to fill in arrival and departure times to the nearest minute or quarter hour, depending on the specific resolution desired by the researchers. Classifying activities, however, involves an interactive process—depending on how the researchers demarcate the different kinds of activities and how well the respondents understand the classification schema. Activities are most often measured in terms of four or five simple categories: work, social, recreation, personal business, or shopping. This general demarcation hides a lot of minute difference between similar activities under the same title. In only a few cases, the more detailed way in coding activity was taken. Its adoption was based on the issues researchers are interested in, because respondents could end up with confusion in terms of the dilemma of putting which activity into which category.

It is widely known that the observed behavior patterns are somehow related to the personal characteristics of the individual actors and to the nature of the environment within which the behavior takes place (Anderson, 1971; Chapin 1974; Cullen and Godson, 1975; Kutter, 1973; Lloyd and Jennings, 1978; Hanson, 1982). This notion has encompassed both non-psychological and psychological explanations of daily activity pattern. Non-psychological explanations mainly focus on the role of external circumstances, such as socio-demographic and environmental variables. These variables put constraints on a person's space-time path (Hagerstrand, 1970). To explain such paths or trajectories in space-time coordinates, primary emphasis must be given to basic constraining factors. "Explanations of daily activity based on psychological theories encompass external circumstances (situations, opportunities, constraints, and consequences), personality traits and abilities, motivations states (needs, drives and goals), and information processing (judgement, evaluations and decisions)" (Garling and Garvill, 1993, p275).

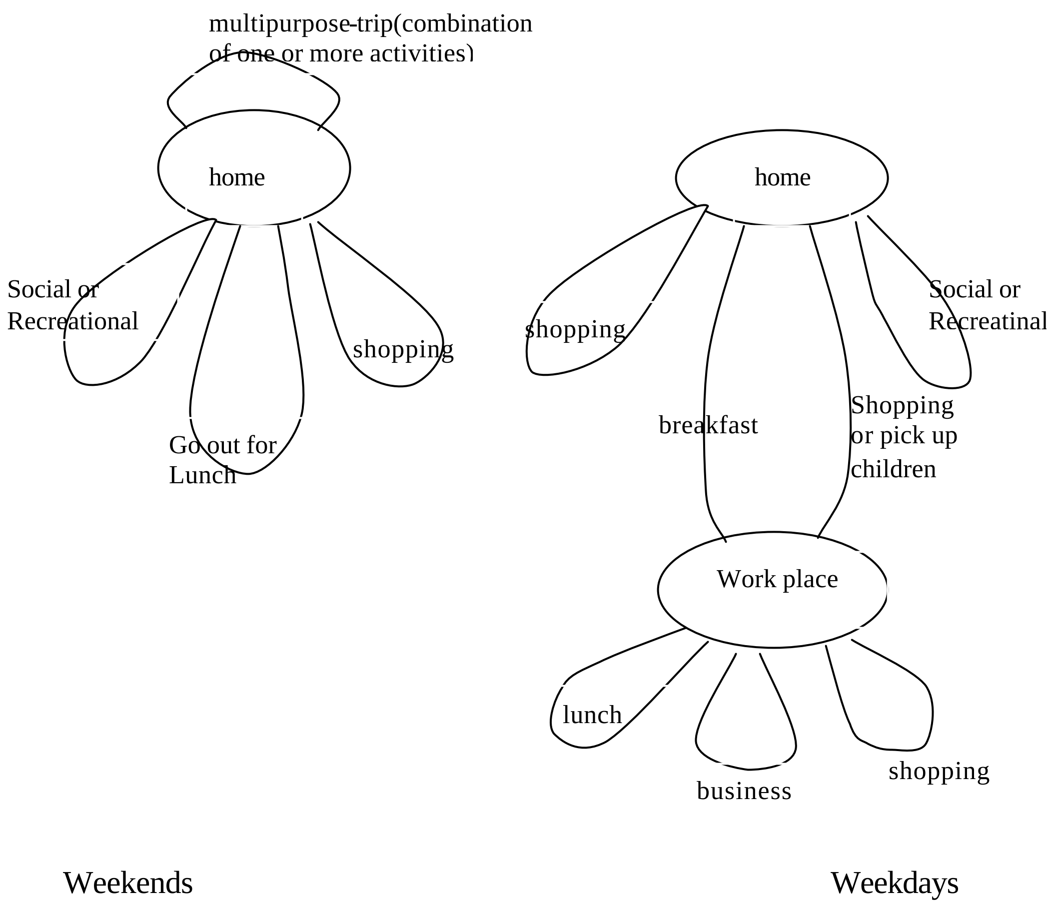
Three different subsystems constitute the theoretical framework of psychological explanations: a cognitive subsystem which acquires, transforms, and represents knowledge about the environment (including meta-knowledge about the person himself or herself); an emotional subsystem which evaluates the knowledge processed by the cognitive subsystem; and a separate motivational subsystem which represents and processes goals and activity tendencies.

Previous studies of activity behavior have been limited to daily patterns due to data limitations. Based on the assumption that that individual's daily travel patterns are largely habitual and that these habitual patterns are remarkably stable in the short run, a wide range of approaches have been employed to understand and predict various aspects of the daily activity behavior. Adler and Ben-Akiva(1979) examined the entire daily patterns of chained trips, rather than individual trip links, in modeling a daily travel pattern. It is logical to use a one-day time span as a study period as it is a natural physiological time unit that influences most of human behaviors. However, using a day as the basic cycle for modeling travel behavior has two major drawbacks: First the models do not capture changes in activity patterns over longer cycles. Secondly, they can not account for the systematic day-to-day variations in activity patterns (Hirsh, M., J. N. Prashkea & M.Ben-Akiva,1986). Although most people seem to think that activity patterns are indeed habitual, the repetition actually is based on a time period longer than a day. In other words, habitual behavior is characterized not only by repetition but also by variability. A natural derivation of this conclusion would be that a one-day snapshot might not be able to provide an excellent picture of a person's behavior within a longer period. Policy analysis in Hirsh, Prashikea and Ben-Akiva's (1986) weekly activity model shows that disregard of the weekly effects on shorter cycles, such as a day, may leads to biased activity predictions. In fact, in a policy context, there is a growing need for multi-day data to examine issues that affect general rather than one-day behavior. Analytically, multi-day data is needed to improve our ability to identify the mechanism behind travel behavior and to derive better empirical relationships among trips made (Jones and Clarke, 1988).

Since the1980's, the limited availability of multi-day travel data is no longer a constraint to behavioral geographers. Multi-day travel diary data have been used in the past in many studies. (e.g. Hanson, 1980; Hanson and Huff, 1982; Hanson and Huff, 1988, Pas 1985; 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 tangles 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, still little effort is put on examining how the man-made social tradition - week-period - put its effect on people's travel choice. With the work constraints relaxed on weekends, activities and trips are typically organized in a quite different way from what they are on weekdays. On weekends, home is the origin or center of one's activities. Trips made by people start from home and end at home. Trip cycles intersect each other at the location of home most frequently. On the contrary for weekdays, two centers or origins show themselves in people's activity structure -- home and work place. Here trip cycles formed from people's activities present as a two-level form (simplified), with home as the primary-level center and work place as the secondary-level center, and the journey to work and return-home link home and work places together. Typically, weekdays and weekends formed the two most distinct episodes within a one-week period. Based on similar arguments, day and night of weekdays may also form two distinct episodes for behavioral study. Once people returned home at night, only one origin - the home - becomes dominant in his or her activity structure again (See Figure 1).

Kitamura (1987) developed a framework for analysis of weekly travel activities. His model structure is based on the proposition that daily travel patterns vary from day to day around several representative patterns. This enables the statistical analysis of multi-day travel patterns using a frequently used measure of travel patterns, and at the same time recognizing typological differences across daily patterns. In his study, a statistical model was formulated with the assumption that travel behavior on a given day depends on past behavior. The model then was applied to a sample of workers from a Dutch travel survey dataset containing weekly travel diaries. Correlation of behavior of a given day with those of preceding days was found prevailing during the one-week diary period.

Figure 1. Variation of Activity Centers across a Week



Furthermore, the day of the week showed strong effects on the travel pattern of tested activity. An obvious pattern of weekly shopping participation is revealed. Kitamura (1997) explored the dynamic nature of weekly travel activity with the changed contributing factors in a travel environment. Two of the most important changes for household or personal attributes across the two waves of panel survey conducted in the Netherlands are identified--- increased car ownership (transitions from single-car to multi-car households) and changed employment status (either gained or lost employment during the six-month of survey interval). In his exploration of persistence of activity participation, two types of association between the regularity in activity participation and a person (or household) attributes are evaluated. The first is called "cross-sectional" association, indicating the correlation between the regularity in activity participation and a person attribute as observed at the beginning of the study period. The second is called "dynamic association," relating the regularity in behavior to the stability or change of the person attribute. As a result, no significant association between regularity in activity participation and change in person or household attributes is found. This could be an indication of people's strong adaptation ability or may be the case that the magnitude of changes for travel-related factors are not substantial enough to overwhelm the inertia of habitual activity patterns. However, we could also explain this as response lag--The expected behavioral pattern change hasn't happened in the sampled period.

In our research, we will follow an exploring approach for the analysis of weekly travel data. The dataset is collected differently from traditional methods.

1.3 Data Collection Method of Travel Behavior Study

1.3.1 Travel Diary and Activity Diary

Diary techniques have seen considerable use in technique-viewing surveys and in market research (in which a person lists in a diary the products they buy). Some use has also been seen in sociological studies. One of the most comprehensive uses of the diary technique is a sociological study by Young and Willmott (1973) of the manner in which people spend their time. This is very close to the traditional approach to collection of household-based travel data by taking the trip record in a diary format. The study of respondent's time budget is similar to the study of travel behavior in that respondents are asked to record details about a sequence of events.

As an example, Marble, Hanson, and Hanson (1972) administered a real travel diary to 1179 households in Uppsala, Sweden. Diaries were kept for a five-week period by all household members older than 16. The diary collected information on trip time, whether the respondent planned to make the stop before leaving the house, travel mode, vehicle occupancy, address at destination, and activities performed at each destination. A 17-page set of instruction with examples was given to each household to assure understanding of how to complete the diary. Also interviewers called respondents on a regular basis to see whether they had questions and respondents were given a telephone number to call if questions arose.

After the respondents completed the diaries, researchers retrieved the recorded travel information. Generally, there are two primary methods that can be used for diary retrieval: telephone retrieval and mail retrieval, each with its superiority in some aspects. It is hard to decide which method is better.

Proponents of telephone retrieval generally point to the following advantages of the method:

a) A higher response rate from households.
b) Potential for the surveyor to probe for information that may not have been recorded.
c) Capability to correct erroneous information during retrieval.

Proponents of mail retrieval generally point to the following advantages of the method:

a) A higher completion rate by responding households;
b) Availability of the hard copy record completed by each household member;
c) Ability to go back to the diary to construct or reconstruct other information.

Referring to Young and Willmott's study, mail retrieval is used for diary collection. 48 percent returned their diaries as intended; an additional 11 percent returned theirs after either a mail or personal follow-up. In total, about 60 percent of those interviewees accepted and completed their diary, which sounds satisfactory. However, of those who returned diaries, about 3 percent did not complete diary information for the weekend and 31 percent omitted the four weekday evenings. So a lot of desired information was not recorded. The response rate for the weekday evenings is so poor as to obviate any analysis.

In diary efforts, the desire is usually to have respondents complete information about travel or activities as they happen through the day. However, this is generally difficult for respondents to record complete information about trips right at the time activities or travel are undertaken, even when the diary instrument is provided in adequate time prior to the day or days identified for recording. Therefore, respondents are allowed to complete the information retroactively.

This could trigger one of the deficiencies associated with travel diary design and administration. In asking people to report on trips during the day, short trips, trips for relatively unimportant purposes are frequently forgotten. In addition, trips related to privacy are intentionally unreported in the finished diary.

The other deficiency is about vocabulary used by behavior scientists. The word "trip" does not have the same connotation in everyday language that it has in transportation planner's vocabulary, resulting in either a need to explain at length the transportation planning definition of a "trip," or requiring the use of other words, to describe the concept.

Despite the deficiencies with the diary-keeping method, a lot of large-scale household-based travel surveys were conducted in the past two or three decades in the form of travel diary. There has been a recent resurgence of activity and interest in collection of households-based travel data for the 1990s, to replace aging data bases used in many urban areas for travel forecasting and numerous policy and decision making activities (Purvis 1990). Most of the data collection methods used in these surveys are still paper and pencil-oriented. The biggest difference of the newer version of data collection method from the former ones is a user-friendlier format or the way of organizing the questions. Stopher(1992) has argued the advantage of using an activity-based diary rather than travel diary to collection travel data, which represents a shift of focus of the diary from travel to activities. Technically, the information collected by an activity diary is the same as that collected in a travel diary. But an activity-oriented diary could construct a query context that the author believes matches better the way in which people think and behave.

The advantages of using an activity diary instead of travel diary are direct corollaries of the disadvantages of travel diaries. Typically people are activity oriented in their behavior and recollections and are more likely to remember what they did than where they did it and how they got there. Therefore the notion of reporting on activities is far more easily explained. Activity is a word that is relatively unambiguous between the transportation planner and the survey respondent.

Stopher (1992) compared the information content of the two kinds of diary format in a table. It shows that the ordering of questions is only slightly different between the activity and the travel diaries.

Table 1. Comparison of the Question Contents of a Travel Diary and an Activity Diary

Travel Diary	Activity Diary
1. Where did you go?	1. What did you do?
2. What was the purpose?	2. When did you start?
3. When did you leave?	3. When did you Finish?
4. When did you arrive?	4. When did you do it?
5. How did you get there?	5. How did you get there?
6. Questions on Parking	6. Questions on Parking
7. Questions on fare	7. Questions on fare
8. Is this you last trip?	8. Was this the last thing you did?

From Stopher.R.(1992, p162)

Apart from the ordering, the information content is the same for both the activity and travel diaries. The activity diary, however, helps to trigger the memory for travel by focusing on the activity that required the travel to be undertaken. Also there appears to be strong evidence that the activity diaries measure more non-home-based trips than any prior measurement method. In a travel diary context, certain stops made during travel may not count as separate ends and starts of trips by the respondent as he or she might view them as an integral part of the whole travel. For example, a person leaves home in the car and drives to a gas station to fill up with gasoline, then drives a little further to drop mail at a postal box, before continuing on to his or her place of work. The individual reporting this in a travel context is likely to consider this as one work trip and to omit the incidental stops. The activity-focus diary would produce information about three activities with the potential to record these as three separate trips - one home-based followed by two non-homed-based - compared to the travel record production of one home-based work trip.

There are some common deficiencies when we use either travel or activity-oriented diary methods to collect travel or activity data. One of them is the problem of unreported trips, which has been mentioned in the former section. Three types of unreported trips could be distinguished:

a) Trips that were not reported by the respondents due to increasing lack of care in case of survey periods of multi-day length.
b) Trips that were not reported by the respondents because they forgot or considered them redundant.
c) Trips that the respondents did not want to report on the basis of their own deliberate decisions.

There exists a clear negative relationship between trip length and the probability that a trip will not be reported. Brog, Erl, Meyburg and Wermugh (1982) found in their research that a substantial number of non-reported trips are more likely attributable to carelessness rather than to conscious nondisclosure. The highest non-reported trip rate is evident for walking and bicycle trips. But under-reporting for motorized travel, due to its far higher service volume, could not be overlooked either. In computation, the relationships between travel modes (and associated activities) and reporting accuracy is statistically significant, but its magnitude varies a lot depending on the degree of flexibility related to associated activities. As an example, they showed that the non-reported trip rates are particularly low for motorized travel dedicated to regular activities; in contrast, the trip rates are particularly high for discretionary activities. Also, a correlation exists between non-reporting of trips and respondents' personal characteristics or socio-demographic characteristics in their research. Stratification of non-reported trips by means of respondents' socio-demographic characteristics showed that the level of non-reporting was particularly high for women, 10- to 15 year-olds, persons with poor education levels, and retired persons. Based on the result, they further attempted to test the observation that reported trip frequency might decrease over time due to more non-reported trips for surveys that include several survey days. However, in their research, the exact number of the trips happened could only be explored then compared with coded data. This inaccuracy undermines their conclusion.

Using a diary to collect data, which means measuring travel behavior by means of surveys, has quantitative as well as qualitative implications. The survey techniques to be employed usually prohibit their development on a massive scale due to time and budget constraints. Generally they can only be implemented in conjunction with a specific survey sampling technique. The quality of survey data typically is dependent on cooperation with the prospective respondent. Respondents obviously are individuals that are subject to a variety of human weaknesses. The means, as well as the manner in which the respondents are questioned, will influence the survey results to a considerable degree. Therefore, systematic error, or bias plays an important role in survey responses (Brog W. and Meyburg A. H., 1982). To reduce bias introduced when using a diary as the data collection method, attention should be paid to many issues. First, convincing respondents to participate in a travel diary survey implies the need for a reasonably significant incentive (monetary). Second, surveillance, either in the form of an appointment to pick up the travel or activity diary (for a 24-hour diary) or repeated visits (for a long-term diary), seems essential. Finally, the diary must be kept as simple as possible and explicit instructions must be provided.

An alternative method of collecting travel-behavior information is to intercept people in the process of making a trip. The roadside interview and the on-board transit survey are the most common (Sheskin, Spicack, Stopher, 1981). The significant advantage of such a technique is that respondents are surveyed at the time when they are least likely to forget trip details. On the other hand, such surveys, for logistical reasons, must be kept relatively short and brief, and it is impossible to construct a consistent multi-day trip record for the peculiar respondent and his or her household by using this method.

Another improved method is to use a travel or activity diary in which respondents are asked to report their own future behavior. Such a technique is a cross between observing behavior and a participatory survey. The major problem such a technique is designed to circumvent is that of memory. By presenting respondents with a document that needs to be filled out about travel planned for the next day, which can be filled out partly or fully while traveling or partly while traveling or partly at the end of the day, less information should be lost to memory problems. One problem not solved, of course, is that certain trips may end up non-reported due to personal concerns. Another problem is that the respondent may modify behavior by postponing trips to avoid having to spend time making entries in the diary.

Due to the various deficiencies associated with traditional travel data collection method, we turned to help from high technology.

1.3.2 <u>GPS-integrated Data Collection Device and Method</u>

1.3.2.1 Global Positioning System (GPS) and Its Applications

The Global Positioning System (GPS) is a worldwide radio-navigation system formed from a constellation of 24 satellites and their ground stations. GPS uses these "man-made stars" as reference points to calculate positions accurate to a matter of meters. In fact, with the advanced forms of GPS, measurements to better than a centimeter can be achieved. In a sense it's like giving every square meter on the planet a unique address.

The nominal GPS Operational Constellation consists of 24 satellites that orbit the earth in 12 hours. There are often more than 24 operational satellites as new ones are launched to replace older satellites. The satellite orbits repeat almost the same ground track (as the earth turns beneath them) once each day. The orbit altitude is such that the satellites repeat the same track and configuration over any point approximately each 24 hours (4 minutes earlier each day). There are six orbital planes (with nominally four satellites in each), equally spaced (60 degrees apart), and inclined at about fifty-five degrees with respect to the equatorial plane. This constellation provides the user with between five and eight satellites visible from any point on the earth.

GPS provides specially coded satellite signals that can be processed in a GPS receiver, enabling the receiver to compute position, velocity and time. GPS receivers have been miniaturized to just a few integrated circuits and so are becoming very economical. And that makes the technology accessible to virtually everyone. These days GPS is finding its way into cars, boats, planes, construction equipment, movie making gear, farm machinery, even laptop computers. Basic GPS is the most accurate radio-based navigation system ever developed. And for many applications it is sufficiently accurate. However, to meet the needs of some particular applications, engineers came up with "Differential GPS," a way to correct the various inaccuracies in the GPS system, pushing its accuracy even farther.

Differential GPS or "DGPS" can yield measurements correct to a couple of meters in moving applications and even better in stationary situations. That improved accuracy has a profound effect on the importance of GPS as a resource. With it, GPS becomes more than just a system for navigating boats and planes around the world. It becomes a universal measurement system capable of positioning things on a very precise scale. Differential GPS involves the cooperation of two receivers, one that's stationary and another that's roving around making position measurements. The stationary receiver is the key. It ties all the satellite measurements into a solid local reference.

In the early days of GPS, reference stations were established by private companies who had big projects demanding high accuracy - groups like surveyors or oil drilling operations. And that is still a very common approach. One buys a reference receiver and sets up a communication link with his roving receivers. But now there are enough public agencies transmitting corrections that potential users might be able to get them for free. The United States Coast Guard and other international agencies have established a large quantity of reference stations, especially around popular harbors and waterways. These stations often transmit on the radio beacons that are already in place for radio direction finding (usually in the 300kHz range). Anyone in the area can receive these corrections and radically improve the accuracy of their GPS measurements. Many new GPS receivers are being designed to accept corrections, and some are even equipped with built-in radio receivers.

GPS used in conjunction with communication links and computers can provide the backbone for systems tailored to applications in agriculture, mass transit, urban delivery, public safety, and vessel and vehicle tracking. So it's no surprise that police, ambulance, and fire departments are adopting systems like Trimble's GPS-based AVL (Automatic Vehicle Location) Manager to pinpoint both the location of the emergency and the location of the nearest response vehicle on a computer map. With this kind of clear visual picture of the situation, dispatchers can react immediately and confidently.

1.3.2.2 Use of GPS in Travel Data Collection

The fast growing GPS technology provides us an alternative to collect travel data. Traditional data collection methods have their inherent deficiency that is surmised to be subjectivity introduced by the use of the self-reported method. People likely omit very short stops made during a journey, like stopping at the post office, ATM, or video store. Other problems with the self-reported method include the tendency to round travel times to 10, 15 and 30-minute intervals. By combining GPS and computer technology, an automatic data collection device can be built that collects self-reported information along with automatically recording GPS position information. This device meets the need to attempt to both capture short trips and activity duration with a relatively high-degree of accuracy. Such a device was developed by Battelle Transportation Division and was tested in a travel activity survey undertaken in Kentucky in 1997 (Lexington Area Travel Data Collection Test, 1997)

Their device includes:

1. Mini-computer - for holding the user interface software and GPS control software, accepting GPS and user-input data.
2. GPS receiver - for receiving data from GPS satellites.
3. Personal travel survey software - user interface that identifies socio-demographic and travel-related information.
4. Accessories - Connecting cables and power supply.

The personal travel survey software developed for the device had two principal functions: (1) allowing the respondents to easily enter personal and trip-related information, and (2) capturing positional data from the GPS receiver associated with each respondent-initiated trip. Since the respondents would have a variety of backgrounds in operating an automatic machine, the software interface had to be user-friendly and self-explanatory.

1.3.2.3 GPS Errors in Data Collection

A principal objective of the real time data collection efforts with GPS was to capture Global Positioning System (GPS) positional data for the individual trips made by the respondents of a travel survey. These data, used in combination with some kinds of local base map (digital), permit analysis of the individual trips based on the information that is part of the map database. A key part of the assessment was matching the collected GPS data points with the individual links in the base map for this analysis. Both the accuracy and continuity of the collected GPS data influence the outcomes of this process.

GPS errors are a combination of noise, bias, and blunders. Noise errors are the combined effect of PRN code noises (around 1 meter) and noises within the receiver (around 1 meter). Bias errors result from Selective Availability (SA) and other signal disturbing factors. SA is the intentional degradation of the SPS signals by a time varying bias. SA is controlled by the Department of Defense (DOD) to limit accuracy for non-U.S. military and government users. The potential accuracy of the C/A code of around 30 meters is reduced to 100 meters (two standard deviations). The SA bias on each satellite signal is different, and so the resulting position solution is a function of the combined SA bias from each satellite used in the navigation solution. Differential GPS (DGPS) can reduce these errors substantially. Depending on the differential receiver in use, data errors are differentially correctable to a range of 1 to 5 meters (web page: http://gpscity.securesites.com/products/dgps_explained.html). (Note: As of May 2000, the US DOD has agreed to turn off Selective Availability. However, other errors remain, making DGPS still wanted when high accuracy is required.)

Compared to errors mentioned above, blunders (e.g. control segment error) can result in errors of hundred of kilometers. User mistakes, including incorrect geodetic datum selection, also can cause errors from 1 to hundreds of meters. Receiver errors from software or hardware failures can cause blunder errors of any size. Noise and bias errors combine, resulting in typical ranging errors of around fifteen meters for each satellite used in the position solution. Software communication problem could result in irregular recording of data. (Lexington Area Travel Data Collection Test, 1997)

Other factors may also affect the quality of collected data. During the data collection phase, the GPS receiver may not be able to achieve a positional fix due to the blocking of buildings or trees. Or the GPS receiver may experience a loss of fix during the trip, thus there is a time period where the data are unusable and must be discarded from the trip record. This typically happens at the beginning of a trip record, prior to the GPS receiver achieving its initial positional fix. However, loss of fix could also be observed during the middle of a trip record and the data record will show valid data points both before and after the loss of fix.

Due to the malfunction of the device or corrupt data record, a certain proportion of recorded trip data can be invalid and unusable. Data files with only a few valid GPS data points would also be discarded due to the paucity of positional data. In Lexington Travel Survey Data (Lexington Area Travel Data Collection Test, 1997), the actual travel route taken by the respondents was identified only by matching the GPS data points to a local map. Alternatively, help from the respondents would be needed to reconstruct these trips from their memory.

1.3.2.4. *Measurement of Travel Behavior Using GPS*

For each trip taken by a respondent, trip travel times could be measurable in two ways. Since at the beginning of each trip, the respondent will need to take his/ her time inputting trip related information, the trip time recorded by the personal travel survey software will be longer than the actual trip time. Another time recorded is the GPS time. The GPS time is the time interval from receiving the first valid GPS data record on the trip to the receipt of the last valid GPS record. The GPS time values are expected to be less than the trip time mentioned before. The GPS time markers are initiated based on when the GPS unit acquires a position fix after a trip is started and the time of the last valid position fix before the end of the trip. The difference between the two different kinds of time records can range from several seconds to several minutes.

Similarly, trip length can also be measurable in two ways. One is the GPS trip length, which is calculated from the individual GPS data points, using a point-to-point sum of the distance over a complete trip file. The other is the map trip length, which is calculated from the mapped trip on the local map. The trip length is a link-to-link sum of the routines over the map. Due to the errors existing in GPS records, it may be difficult to identify a matched path on a GIS map through an automatic procedure. Manual comparison may be necessary where too many errors make automatic matching impossible. With GPS equipment, more data like vehicle miles of travel (VMT) and travel speeds become easily accessible data within the travel survey. It is for sure that these new data will play an important role in future transportation research.

For some time, the data recorded in data collection equipment may be not continuous. The discontinuity of the GPS data collected can be related to two factors. First, there are gaps in the data stream due to receiver operation. These gaps are the time segment necessary for the receiver to establish a positional solution when it is first turned on (known as time to first fix) or after there has been a loss of signal, such as when vehicle moves into a parking garage, into a tunnel, or for some other reason the signal is blocked from reaching the receiver. The second factor affecting the data continuity is that the GPS data collected during the field test may be recorded at irregular time intervals due to a fault in the data collection equipment. This irregular spacing of the GPS data points in time adds to the complexity of assessing which segments on the reference map were actually traveled by the respondents.

1.3.2.5. *Benefit of Having a GPS-integrated Device for Travel Data Collection*

There are several distinct benefits to include GPS into a data collecting process:

1. Data are available that may provide information on route choice by the respondents.
2. More accurate travel time and distance data can be obtained. Actual travel departure times and speed (though not very accurate) are easily available using a GPS component.
3. Data can be accurately organized by highway functional class usage and travel speed.

Furthermore, the benefits could be beyond the list above. It is commonly known that diary data of a long duration contain more bias than short-duration data. This would be true if recording inaccuracies and tendencies to skip certain types of trips increase with time. Such biases are usually attributed to respondent fatigue or diminished motivation. By using an automatic device for recording at real time (record at the beginning of the trip), we may expect recording inaccuracies are reduced to below a certain level. Though respondent fatigue may not be entirely avoided, misreporting caused by memory loss would never happen. Another potential benefit could be time saving. If the time taken for the respondent to enter data at the beginning of each trip is 1 minute or less, nine or ten minutes of data entry time per day (assuming not more than 10 trips taken per day) are not perceived to be burdensome as spending 20 minutes on the telephone in one session or diary writing to report one day's travel. This approach helps eliminate the burden of the telephone interviewer contacting the respondents at a time that is not convenient for the respondent, or may also help eliminate the researchers' hard time of trying to read illegible handwriting by respondents.

1.3.3 A GPS Collected Data Set – Lexington Travel Survey Data (LTS Data)

The data set used in this study comes from the Lexington Area Travel Survey. Travel data (Lexington Area Travel Data Collection Test, 1997) were 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. It can be expected that data collected by this way will offer a more robust data source for defining personal travel then current methods, which rely on telephone interviews and daily travel diaries.

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 the Lexington area travel data collection test (1997), it collects self-reported travel-related information and also automatically records real time GPS position information of the vehicles in use by the respondents. These devices are 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. In the mode of inputting trip-related information into a data collector in real time, the chance of omitting very short trips or having trips times rounded to 10, 15 and 30 minutes interval, which often happened 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 (Lexington Area Travel Data Collection Test, 1997):

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.

The Lexington area base map (Figure 2) used in this study was composed from several sources in 1995. The map database contains over 10,200 roadway segments or links covering over 1,930 kilometers (1,200 miles) with street centerline accuracy from 2.1 meters (7 feet) to 4.5 meters (15 feet). The roadway database also includes the designation of six highway functional classes —freeway, arterial highway, major arterial, minor arterial, collector, and local through-street (functional classes are shown in the Figure 3). Non-intersecting segments and overpasses are properly handled because there are no node definitions at their graphical intersections and one-way streets and on- and off-ramps have proper directional indications. This Lexington base map includes only Fayette County, Kentucky. Since the local planning area, and thus the field test area, included both Fayette and Jessamine counties, the Lexington base map will be supplemented by the TIGER data set for Jessamine County for the subsequent analysis.

Figure 2. The Study Area in Central Kentucky

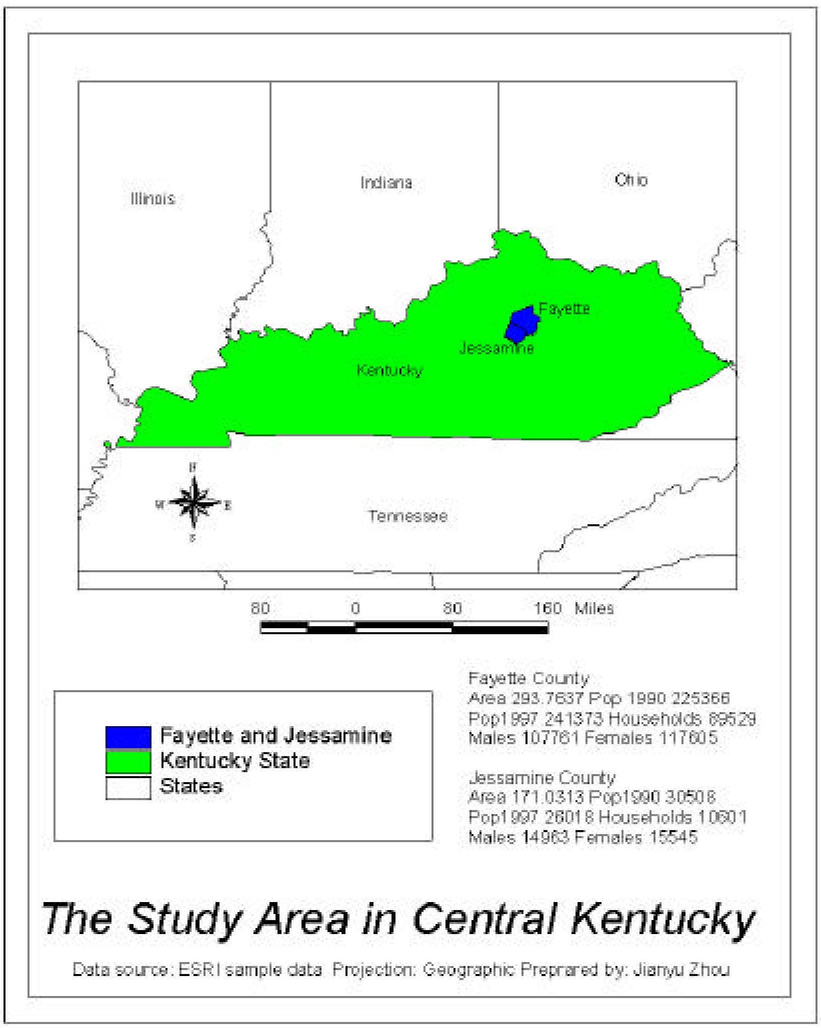
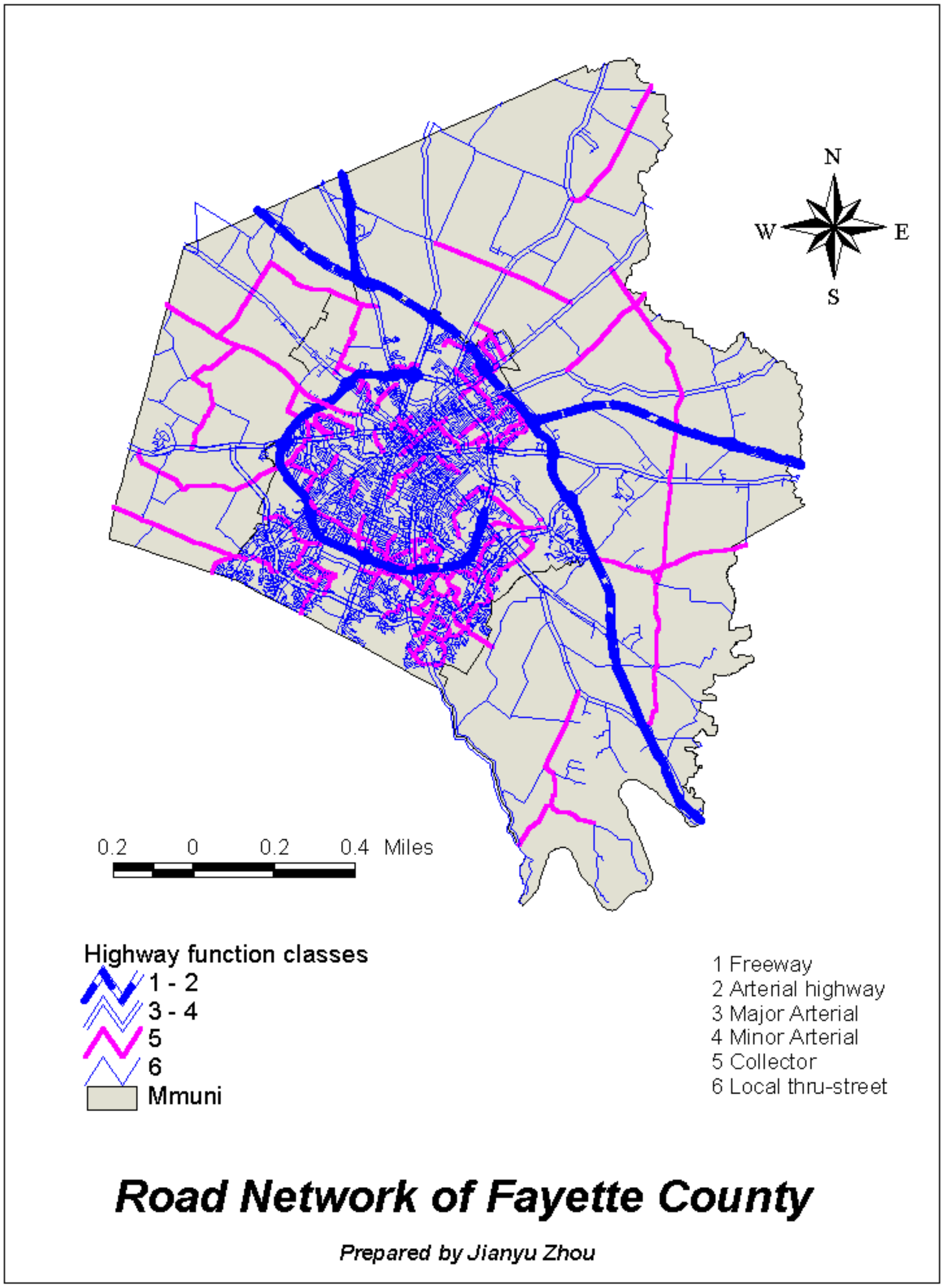


Figure 3. Road Network of Fayette County



2. METHODOLOGY AND RESULTS

In this section I am to describe three methodologies for analysis of weekly travel activity patterns. The MONOVA statistics are used to explore the variation of trip distance, trip frequency, and trip duration for different types of trips made across the sample week. The time series analysis is used to examine the temporal interrelationship between different trip types and the direction analysis section will focus mainly on the variation of travel directions between different days-of-the-week at an aggregate level.

2.1 K-group Multivariate Analysis of Variance and Discriminant Analysis

2.1.1 Outline for MONOVA

Studies in the social sciences comparing two or more groups very often measure their subjects on several criterion variables. There are three good reasons for using the multiple criterion measures in a study comparing the influence of environmental factors on the subjects:

1. Any factor will affect the subjects in more than one way. Hence the problem for the investigator is to determine in which specific ways the subjects will be affected, and then find sensitive measurement techniques for these variables.

2. Through the use of multiple criterion measures we can obtain a more complete and detailed description of the phenomenon under investigation.

3. The data collection process may be expensive to implement, while the cost of obtaining data on several more dependent variables is marginally small and maximizes information gains.

Multivariate analysis of variance (MANOVA) is the statistical analysis of two or more groups of subjects on several dependent variables simultaneously, focusing on cases where the variables are correlated and share a common conceptual meaning. That is, the dependent variables considered together make sense as a group. For example, they may be different dimensions of people's activity pattern on each day-of-the-week (shopping, social activity, recreation, work, etc). In contrast to univariate tests, which ignore important information (i.e., the correlation among the variables), the multivariate test incorporates the correlation (via the covariance matrix) right into the test statistic. This feature is ideal for us to jointly study different types of trips together rather than individually since the statistics have taken care of the variable interdependency.

Compared to the univariate t test, whose null hypothesis is:

H_0: $\mu_1 = \mu_2 = \ldots$(population means are equal),

The multivariate test has its null hypothesis:
H_0:

(population mean vectors are equal),which says that the vectors are equal implies that the

$$\begin{pmatrix} U11 \\ U21 \\ \ldots \\ Up1 \end{pmatrix} = \begin{pmatrix} U12 \\ U22 \\ \ldots \\ Up2 \end{pmatrix} = \ldots.$$

groups are equal on all p dependent variables.

In testing the multivariate null hypothesis, three assumptions should not be violated. They are (1) independence of the observations, (2) multivariate normality on the dependent variables in each population, and (3) equality of the covariance matrices. Actually, the multivariate test statistic arises naturally from the univariate t test. Simply the scalars (numbers) in the t test statistic are replaced by vectors and matrices.

2.1.2 <u>Outline for Discriminant Analysis</u>

As a supplement for MONOVA analysis, discriminant analysis is used for two purposes: (1) describing major differences among the groups in MANOVA, and (2) classifying subjects into groups on the basis of a battery of measurements. In this research, discriminant analysis is used only for the first purpose-- describing major differences of people's activity patterns among seven-days-of -the-week. Huberty (1994) classified the discriminant analysis with this focus as descriptive discriminant analysis. The major differences are revealed through the discriminant functions. By using discriminant analysis, we break down the total between association in MANOVA into additive pieces, through the use of the uncorrelated linear combinations of the original variables (these are the discriminant functions). An additive breakdown is obtained because the discriminant functions are derived to be uncorrelated. Discriminant analysis has two very nice features: (1) parsimony of description, and (2) clarity of interpretation. It can be quite parsimonious in that in comparing 7 groups of day-of-the week activities on say 13 activity-type variables, we may assume that the groups differ mainly on one or two major dimensions, i.e., the discriminant functions. It has clarity of interpretation in the sense that the separation of the groups along one function is unrelated to separation along a different function. If we can meaningfully name the discriminant functions and there is adequate sample size, the results will be generalizable.

2.1.3 <u>Application of MONOVA and Discriminant Analysis to LTS Data</u>

Time periods might affect people's travel choice in more then one way. An approximately complete set of activity choices may be formed to evaluate the potential influence of time feature--week on people's activity decision-making. The result derived will help us understand the temporal nature of activity spaces with respect to the overall mix of activities in which people participate. For instance, if we were comparing people's activities on the two days of a week, say, Thursday and Friday, we would obtain a more detailed and informative breakdown of the differential effects of time on people's travel behavior if they were split into their detailed types (such as pick up passenger, return home, work place. etc.). Comparing two days of a week on total trip counts made by a household might yield no significant difference; however, the multiple criterion measures mentioned above may be making a difference.

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 three types of trip measurements (trip counts, trip length, 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 2 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:

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

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

Table 2. 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

Table 3,4,5 gives the multivariate F's from the SPSS MANOVA run on the problem. As we choose 0.05 as the critical value for rejection, the significance of F indicates that we should reject the null hypothesis on trip counts and trip time and conclude that people's activities differs overall on the set of 13 trip variables. However, this is not the case for the comparison of trip distances of the seven day-of-the-week groups. This implies that the local people's travel behavior differs significantly across the sample week in terms of trip frequency and trip time (duration). But the distance traveled by the respondents on each day-of-the-week shows no significant difference.

Table 3. Multivariate F's for Trip Counts (frequency)

Multivariate Tests of Significance (S = 6, M = 3, N = 390 1/2)

Test Name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F

Pillais	.15292	1.58530	78.00	4728.00	.001
Hotellings	.16251	1.62784	78.00	4688.00	.000
Wilks	.85421	1.60697	78.00	4323.27	.001
Roys	.08744				

Note: Several statistics are available for testing the multivariate null hypothesis. Generally they lead to the same decision on H_0(Olson, 1974).

Table 4. Multivariate F's for Trip Distance

Multivariate Tests of Significance (S= 6, M = 3, N= 339 1/2)

Test Name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	.13683	1.22968	78.00	4110.00	.085
Hotellings	.14207	1.23555	78.00	4070.00	.080
Wilks	.86987	1.23287	78.00	3755.37	.082
Roys	.05654				

Table 5. Multivariate F's for Trip Duration

Multivariate Tests of Significance (S = 6, M = 3, N = 339 1/2)

Test Name	Value	Approx. F	Hypth. DF	Error DF	Sig. of F
Pillais	.15925	1.43879	78.00	4116.00	.007
Hotellings	.17128	1.49176	78.00	4076.00	.004
Wilks	.84782	1.46548	78.00	3760.88	.005
Roys	.09629				

Table 6. Post Hoc Procedure Results

Difference of travel behavior across a week (time)

The trip types that significantly contribute to the overall trip differrence 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

Difference of travel behavior across a week(distance)

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

Variable	Trip type	sig. Of F
Purp2	Drop off passenger	0.031
Purp3	Work place	0.028
Purp11	Return Home	0.044

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 .05 level. The results are listed in Table 6.

Although we didn't find that trip distances traveled by the respondents differs significantly on the seven day-of-the-week groups, we still included its univariate test for comparison with the other two measurements. From the table, we can easily see that the difference of travel time mainly comes from four types of activity -- (go to) work place, (go) shopping, social 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 obvious based on 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. Finally the travel-distance table indicates that the difference of people's travel distances mostly across the week comes from work-place, drop-off-passenger and return-home activities. The three types of distances traveled by the respondents vary significantly across the week.

Next, we attempt to use 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 7, 8, 9 for trip counts, trip duration, trip distance data separately.

Table 7. Standardized Canonical Discriminant Function Coefficients of Trip Counts

Activity		Function 1	2	3	4	5	6
Pick-up passenger	PURP1	.114	.389	-.288	.049	-.227	-.392
Medical or Dental	PURP10	.307	.060	.083	.264	.466	.562
Return Home	PURP11	.007	-.095	-.485	-.816	-.391	.652
Religious Activities	PURP12	-.530	.699	.150	.164	.476	-.051
Other	PURP15	.140	-.249	-.187	.113	-.169	.274
Drop Off Passenger	PURP2	.130	.317	.336	-.086	.052	.161
Work Place	PURP3	.595	-.098	.444	-.228	.325	-.348
Work-Related Business	PURP4	.283	.415	-.108	.655	-.375	.033
School/College	PURP5	.259	.224	.037	.053	.003	-.070
Shopping	PURP6	-.057	.080	-.013	.177	.231	-.237
Other Errands	PURP7	.114	-.372	-.520	.268	.544	-.293
Eat Out	PURP8	.168	-.096	.313	.119	-.058	.032
Social/Recreational	PURP9	-.072	-.230	.459	.304	-.166	.130

Table 8. Standardized Canonical Discriminant Function Coefficients of Trip Duration

Activity		Function 1	2	3	4	5	6
Pick-up passenger	PURP1	.343	-.032	.010	-.020	-.233	.148
Drop off Passenger	PURP2	.047	.323	.601	-.578	-.037	.181
Workplace	PURP3	.332	.051	.542	.187	.767	.129
Work-related Business	PURP4	-.088	.240	.263	.778	-.519	.777
School/College	PURP5	.225	.414	.359	.357	-.123	-.632
Shopping	PURP6	.358	.001	-.194	-.358	-.229	-.358
Other Errands	PURP7	.053	.438	-.231	.116	.266	.344
Eat Out	PURP8	-.015	-.554	.419	-.706	-.312	-.060
Social/Recreational	PURP9	.162	-.161	-.572	-.219	-.725	-.267
Medical or Dental	PURP10	.202	.074	-.002	.114	-.075	-.117
Return Home	PURP11	.476	-.400	.053	-.113	.366	.033
Religious Activities	PURP12	-.076	-.605	.426	.285	.123	.070
Other	PURP15	.396	.564	-.598	.271	.763	.017

Table 9. Standardized Canonical Discriminant Function Coefficients of Travel Distance

		Function					
Activity		**1**	**2**	**3**	**4**	**5**	**6**
Pick-up passenger	PURP1	.365	-.015	.253	-.268	-.067	.047
Drop off Passenger	PURP2	.149	.627	-.147	.331	-.295	.105
Workplace	PURP3	.414	.058	-.630	-.058	.274	-.089
Work-related Business	PURP4	.145	.080	.274	-.534	.338	.602
School/College	PURP5	.212	.215	.231	-.174	.095	-.516
Shopping	PURP6	.065	.270	.513	.031	-.124	-.352
Other Errands	PURP7	.341	.206	.010	.417	.068	.336
Eat Out	PURP8	-.156	.145	.022	.200	.391	.021
Social/Recreational	PURP9	-.269	-.050	.148	.319	-.003	.185
Medical or Dental	PURP10	.226	-.251	-.220	.064	.219	-.236
Return Home	PURP11	.213	-.527	.352	.274	-.269	.088
Religious Activities	PURP12	.310	-.306	-.043	-.125	-.621	.102
Other	PURP15	.057	-.042	.301	.272	.748	-.139

Table 10. Structure Matrix of Trip Counts

		Function					
Activity		**1**	**2**	**3**	**4**	**5**	**6**
Workplace	PURP3	.635(*)	.151	.318	-.371	.184	-.214
School/College	PURP5	.367(*)	.246	-.128	-.117	.024	.018
Religious Activities	PURP12	-.343	.614(*)	.054	-.084	.360	.197
Pick-up passenger	PURP1	.320	.374(*)	-.254	-.103	-.165	-.366
Drop off Passenger	PURP2	.249	.262(*)	.121	-.175	.110	.113
Other Errands	PURP7	.221	-.208	-.531(*)	.148	.449	-.130
Social/Recreational	PURP9	-.062	-.217	.374(*)	.216	-.188	.154
Eat Out	PURP8	.207	-.058	.251(*)	.064	.014	.071
Work Business	PURP4	.344	.389	-.168	.518(*)	-.377	.110
Return Home	PURP11	.247	.252	-.323	-.465(*)	-.010	.413
Shopping	PURP6	.010	.010	-.205	.094	.309(*)	-.042
Medical or Dental	PURP10	.308	.055	-.007	.247	.478	.573(*)
Other	PURP15	.137	-.111	-.204	.108	-.069	.402(*)

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function. (*) Largest absolute correlation between each variable and any discriminant function.

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, trip duration, and trip distance data separately (In table 10, 11, and 12).

Table 11. Structure Matrix of Travel Duration

Activity		Function 1	2	3	4	5	6
Return Home	PURP11	.645(*)	-.271	.034	.014	.056	.104
Shopping	PURP6	.509(*)	-.083	-.035	.004	-.332	.082
Workplace	PURP3	.409(*)	-.062	.138	.017	.262	-.046
Social/Recreational	PURP9	.402(*)	-.118	-.203	-.118	-.168	-.112
Other	PURP15	.319(*)	.095	-.218	-.034	.244	.217
Pick-up passenger	PURP1	.313(*)	-.025	.018	-.038	-.241	.150
Medical or Dental	PURP10	.295(*)	.012	.002	.115	.053	-.056
Eat Out	PURP8	.270(*)	-.024	-.065	-.194	-.010	.235
Religious Activities	PURP12	-.053	-.547(*)	.346	.318	.201	.065
Other Errands	PURP7	.096	.427(*)	-.199	.083	.264	.321
Drop off Passenger	PURP2	.038	.341	.587(*)	-.585	-.028	.212
School/College	PURP5	.192	.402	.353	.367	-.125	-.629(*)
Work Business	PURP4	.386	.053	.093	.338	-.439	.557(*)

Table 12. Structure Matrix of Travel Distance

Activity		Function 1	2	3	4	5	6
Workplace	PURP3	.501(*)	-.045	-.492	.014	.221	-.072
Pick-up Passenger	PURP1	.472(*)	.210	.183	-.121	-.142	.099
Medical or Dental	PURP10	.299(*)	-.219	-.180	.138	.269	-.220
Drop Off Passenger	PURP2	.272	.633(*)	-.052	.239	-.328	.175
Return Home	PURP11	.352	-.494(*)	.258	.314	-.160	.141
Religious Activity	PURP12	.317	-.360(*)	.177	.055	-.234	.019
Shopping	PURP6	.137	.230	.479(*)	.084	-.045	-.374
Other Errands	PURP7	.425	.185	.016	.490(*)	.139	.312
Social/Recreational	PURP9	-.296	-.033	.205	.432(*)	.080	.212
Eat Out	PURP8	-.158	.119	.138	.396(*)	.394	.129

Other	PURP15	.229	-.235	.312	.225	.401(*)	-.131
Work Business	PURP4	.172	.087	.286	-.525	.317	.596(*)
School/College	PURP5	.207	.221	.265	-.205	.113	-.483(*)

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. 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 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 (shown in structure matrix). Since significant tests show that only the first discriminant functions are significant (except for trip distance, even the first discriminant function is not significant), we restricted our discussion to them. Examining Table 10 for the first discriminant function (in Table 7) 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 7) 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) frequency shows not much variation within the period of one week. This conclusion is close to what we derive from the Post Hoc procedures.

Similarly, examining table 11 for the first discriminant function (in table 8) 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 8), 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.

Now, let us put our focus on trip distance. Though none of its discriminant functions is significant, we still have a look at its first one for comparison with the other two measurements--trip frequency and duration. Examining table 12 for the first discriminant function (in table 9) of trip distance, we see it is primarily the three variables -- trip with purp3 (work place, correlation = 0.501), trip with purp1 (pick up passenger, correlation = 0.472) and trip with purp10 (medical or dental, correlation = 0.299) that define the function. Then examining the standardized coefficient (table 9), we see that all these three variables are not redundant (with their coefficients above 0.2). The first discriminant function is characterized as work place -- pick up passenger -- medical or dental activity dominant. This conclusion differs a little from what we got from post hoc procedures. However, they have work place trip type in common. Therefore, we tend to revise our conclusion as the discriminant function is work-place activity dominant. Furthermore, there is no variable in table 9 with its coefficients close to zero. So there is no variable that is redundant. In other words, all of these trip-type variables contribute roughly equally (in terms of statistics) to the difference of distances traveled by the respondents across the days of the week except (go to) work-place trip type.

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 4--trip frequency, 6--trip duration, 7--trip distance shows the positions of groups for Lexington's travel survey data in the discriminant plane defined by discriminant functions 1 & 2).

From Figure 4, we can clearly see that people's activity intensity drops from weekdays to weekends. And this drop 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 of different day-of-week into classes based on Figure 4 (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). A stepped curve of activity intensity across the week is derived as illustrated in Figure 5.

Figure 4.

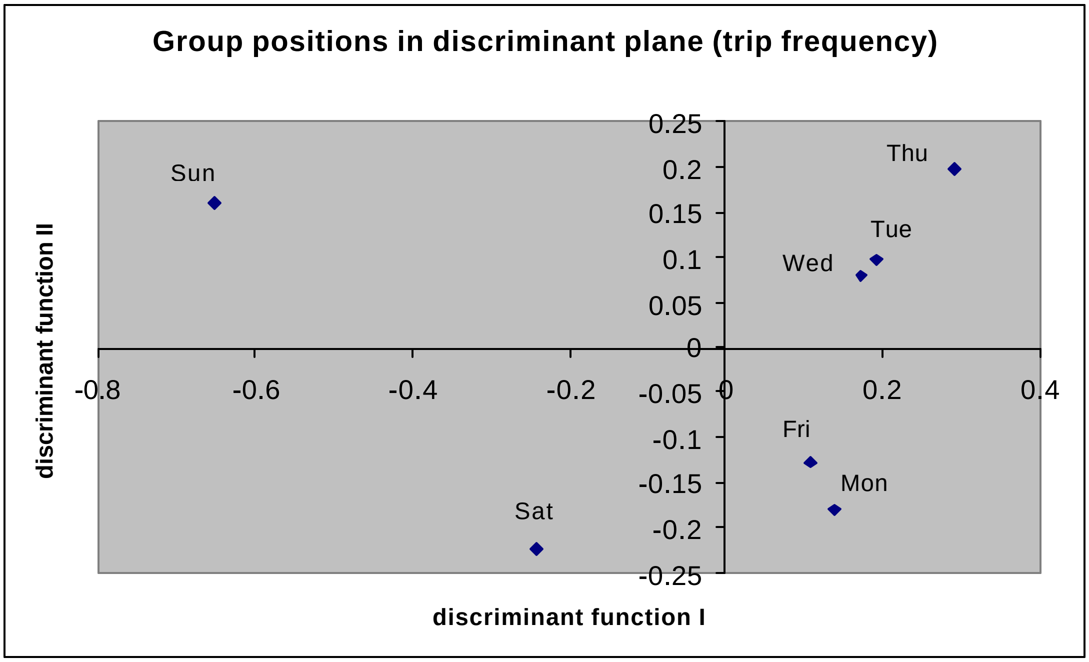


Figure 5.

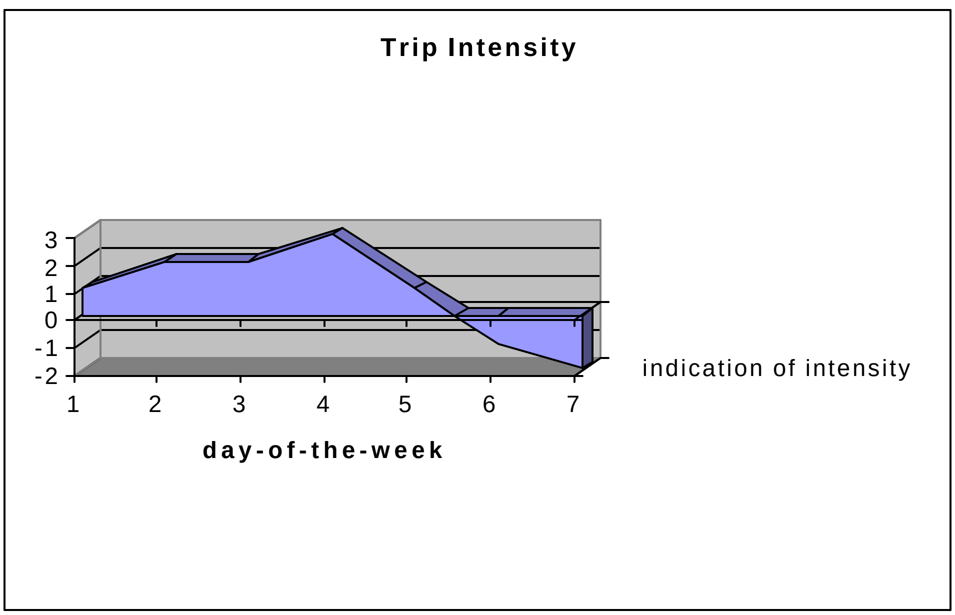
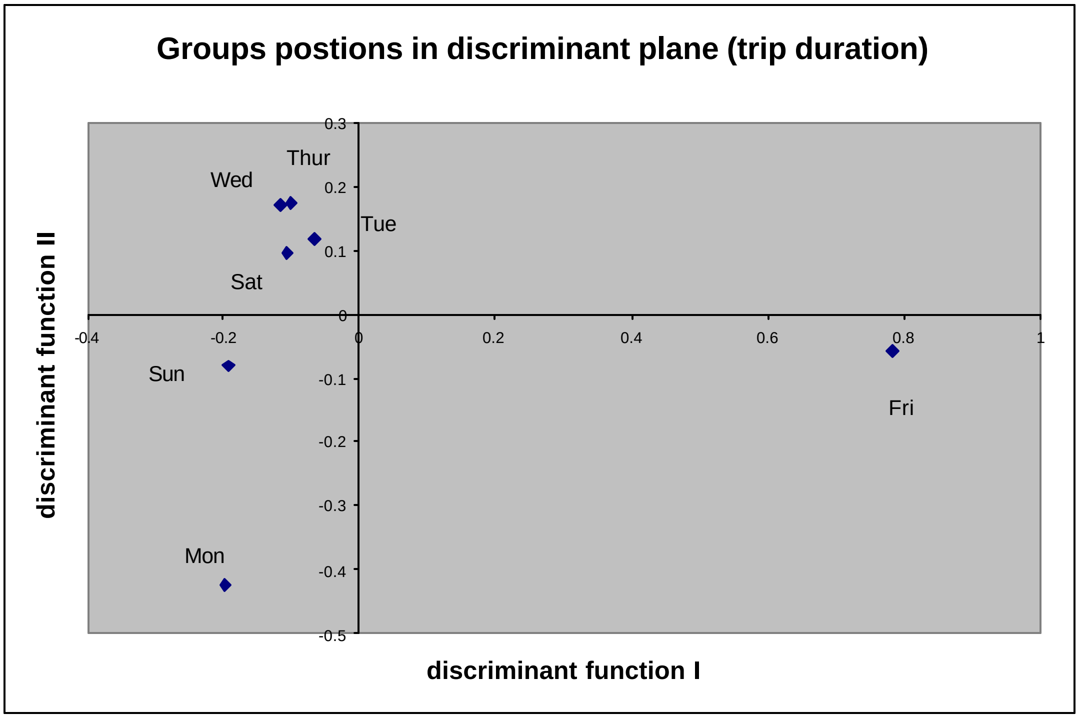


Figure 6.

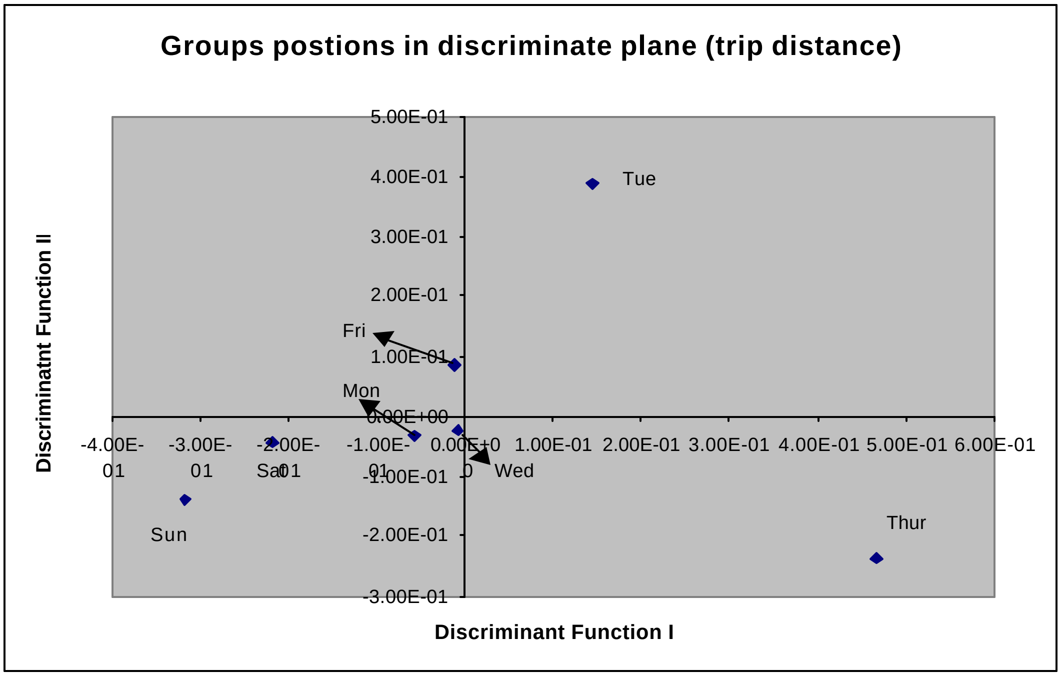


From Figure 5, we can get a picture of variation of people's activity intensity across the sample week. The activity level is depressed during the weekend. Then it starts from Monday at "warm up" level and gradually increases through Tuesday and Wednesday until reaching its peak on Thursday. Finally on Friday, it backs up to the "warm up" level.

Now, let us look at people's travel activity from the perspective of time spent (Figure 6). Note Friday is far separated from other days-of-the-week. It suggests that Friday distinguishes as 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.

Finally, we examined the difference in terms of trip distance. Different from what we saw with respect to the other two measurements, Thursday showed its significance. It implies that the respondents are traveling through longer distance on Thursday than other days. This corresponds to a high activity intensity that can be identified in Figure 4. Note on the axis of discriminant function I, we nearly have the same order for the different days-of-the-week as what appears in Figure 4, which indicates a coupled relationship between travel distance and travel frequency.

Figure 7.



To further research into how people's activity differs between any pair of days-of-the-week, we continued to apply the MONOVA technique and Post Hoc procedure to the data groups in pairs. The results are listed in the form of tables (table 13, 14 and 15).

Table 13. Pairwise Comparison of Trip Duration

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Mon-day	*	Not Significant 0.131 Purp12 Religious Activities 0.016	Significant 0.142 Purp2 Dropoff Passenger 0.049 Purp12 Religious Activities 0.012	Not Significant 0.108 Purp7 Other Errands 0.030 Purp12 Religious Activities 0.026	Significant 0.000 Purp1 Pickup Passenger 0.032 Purp3 Workplace 0.012 Purp4 Work-Related Business 0.005 Purp5 School, College University, 0.037 Purp6 Shopping 0.001 Purp9 Social or	Not Significant 0.242 Purp12 Religious Activities 0.026	Not Significant 0.599 Purp12 Religious Activity 0.029

					Recreational 0.007 Purp10 Medical or dental 0.038 Purp11 Return Home 0.000 Purp12 Religious Activities 0.033 Purp15 Other 0.009		
Tues-day	*	*	Not Significant 0.997	Not Significant 0.999	Significant 0.000 Purp1 PickupPassenger 0.033 Purp3 Workplace 0.015 Purp4 Work-Related Business 0.005 Purp6 Shopping 0.001 Purp9 Social or Recreational 0.010 Purp11 Return Home 0.000	Not Significant	Not Significant 0.941
Wednesday	*	*	*	Not Significant 0.992	Significant 0.000 Purp3 Work Place 0.007 Purp6 Shopping 0.001 Purp9 Social or Recreational 0.004 Purp10 Medical or Dental Purp11 Return Home 0.000 Purp15 Other 0.023	Not Significant 0.987	Not Significant 0.549 Purp2 Drop off Passenger 0.008
Thurs-day	*	*	*	*	Significant 0.000 Purp1 PickupPassenger	Not Significant 0.973	Not Significant 0.794

					PickupPassenger 0.039 Purp3 Workplace 0.009 Purp6 Shopping 0.001 Purp9 Social and Recreational 0.003 Purp11 Return Home 0.000		
Friday	*	*	*	*	*	Not Significant 0.992	Significant 0.000 Purp1 Pickup Passenger 0.037 Purp3 Workplace 0.002 Purp4 Work-Related Business 0.009 Purp6 Shopping 0.001 Purp9 Social or Recreational 0.020 Purp10 Medical or Dental 0.043 Purp11 Return Home 0.000 Purp15 Other 0.047
Satur-day	*	*	*	*	*	*	Not Significant 0.971
Sun-day	*	*	*	*	*	*	*

Table 14. Pairwise Comparison of Travel Distance

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday	*	Not Significant 0.23 Purp2 Dropoff Passenger 0.015	Not Significant 0.944 Purp4 Work-related business 0.042	Not Significant 0.084 Purp11 return home 0.005 Purp12 Religious Activities 0.023	Not significant 0.989	Not Significant 0.408 Purp3 work place 0.041	Not Significant 0.62 Purp3 work place 0.028
Tuesday	*	*	Not Significant 0.405	Not Significant 0.620 Purp3 Work Place 0.028	Not significant 0.575	Not Significant 0.078 purp 1 pick up passenger 0.044 purp2 Drop off passenger 0.002	Significant 0.018 Purp2 Drop off passenger 0.004 Purp7 Other Errands 0.028
Wednesday	*	*	*	Not Significant 0.161 Purp11 Return Home 0.004 Purp12 Religious Activity 0.040	Not significant 0.719	Not Significant 0.488	Not Significant 0.475 Purp4 Work related business 0.046
Thursday	*	*	*	*	Not Significant 0.081 purp11 return home 0.018	Significant 0.006 Purp1 pickup passenger 0.044 Purp3 work place 0.003 Purp11 Return Home 0.020 Purp12 Religious Activity 0.320	Significant 0.002 Purp1 pickup passenger 0.018 Purp3 work place 0.005 Purp 7 other errands 0.008 Purp10 Medical dental 0.034 purp11 return home0.013

							purp15 other 0.028
Friday	*	*	*	*	*	not Significant 0.577	Not Significant 0.508 Purp 7 Drop off Passenger 0.020
Satur-day	*	*	*	*	*	*	not significant 0.748
Sun-day	*	*	*	*	*	*	*

Table 15. Pairwise Comparison of Trip Counts

	Mon-day	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Mon-day	*	Not Significant 0.610	Not Significant 0.561 Purp4 work-related business 0.047	Not Significant 0.358 Purp4 Work Related Business 0.004	Not Significant 0.832	Not Significant 0.247 Purp3 Work Place 0.002	Significant 0.000 Purp3 Work Place 0.000 Purp7 Other Errands 0.018 Purp12 Religious Activities 0.001
Tues-day	*	*	Not Significant 0.997	Not Significant 0.797	Not Significant 0.921	Not Significant 0.065 Purp3 Workplace 0.000	Significant 0.000 Purp1 Pickup Passenger 0.049 Purp3 Work Place 0.000 Purp4 Work-related business 0.044 Purp5 School,college,uni-versity 0.038 Purp12 Religious Activities 0.010
Wedn esday	*	*	*	Not Significant 0.604	Not Significant 0.838	Not Significant 0.102 Purp3 Work	Significant 0.000 Purp3 work place 0.001 Purp10 Medical or

						Place 0.003	Dental 0.004 Purp12 Religious Activities 0.023
Thurs -day	*	*	*	*	Not Significant 0.181 Purp1 Pickup Passenger 0.039	Not Significant 0.973 Purp1 Pickup Passenger 0.007 Purp3 Work Place 0.002 Purp4 Work-related Business 0.023 Purp5 School,Col-lege, University 0.014 Purp11 Return Home 0.007	Significant 0.000 Purp1 Pickup Passenger 0.004 Purp3 Workplace 0.000 Purp4 Work-Related Busi 0.001 Purp5 School,College,Un -iversity 0.004 Purp7 Other Errands Purp10 Medical or Dental 0.039 Purp11 Return Home 0.021 Purp12 Religious Activities 0.009
Friday	*	*	*	*	*	Significant 0.000 Purp3 Work Place 0.000 Purp7 Other Errands 0.018 Purp12 Religious Activities 0.001	Significant 0.000 Purp3 Workplace 0.001 Purp12 Return Home 0.000
Satur-day	*	*	*	*	*	*	Significant 0.047 Purp7 Other Errands 0.021 Purp12 Religious Activities 0.002
Sun-day	*	*	*	*	*	*	*

In each cell of the tables, the result of the multivariate two group test (Hotelling T^2) are listed first and followed by univariate t tests -- the post hoc procedure. Hotelling T^2 will indicate whether people's activities differ significantly on the two days-of-the-week and univariate t tests will show what specific trip-type variables contribute to the activity difference.

Here is what we may reveal from the tables: Respondents' activities differ significantly on Saturday and Friday in terms of travel frequency (Table 15). The difference mainly comes from work travel, errands and religious activities. Note that travel frequency on Saturday also differs from that on Sunday significantly with respect to errands. We may draw our conclusion -- Saturday is treated as a time of taking care of "chores" (what 's left over after one week's work) by our respondents. Compared to Saturday, Sunday is special in that people's activities on Sunday differ significantly from any other days-of-the-week in terms of travel frequency. The difference mainly comes from reduced work travel or school travel, and additionally, weekend religious activity. However, this is not true in the travel distance table (Table 14). Sunday only differs significantly from Thursday and Tuesday with respect to travel distance. A tentative explanation for it is that people may travel less frequently on Sunday but travel through longer distances. In the travel time table (Table13), things change. Friday differs significantly from all the other days-of-the-week except Saturday. Shopping, social and recreational and return home appears in the contribution breakdown in common. This may suggest to us that Friday is characterized as a weekday of supplementing food, socializing, and returning home.

2.1.4 Problem with Using MONOVA and Discriminant Analysis

We didn't examine the correlation among the dependent trip-type variables, just lumped all the useful variables in a single multivariate analysis. This may not be a good idea. For example, work place trip and work-related business trip have very small differences. The inclusion of both of them may obscure a real difference(s) on some of the other variables. That is, the MONOVA detects mainly errors in the system (in the set of variables), and therefore declares no reliable overall difference.

Another issue would be the use of discriminant functions on the travel data. It implies there is a linear combination of the dependent variables (trip types) that is significantly differentiating people's travel behavior among different days-of-the-week. However, we can not guarantee that the linear combination of trip types will be a meaningful variate in terms of explaining the variation of travel behavior across the week.

2.2 Time Series Analysis

2.2.1 Outline for Time Series Analysis

A time series is a sequence of observations, usually ordered in time. The feature of time series analysis that distinguishes it from other statistical analyses is the explicit recognition of the importance of the order in which the observations are made. While in many problems the observations are statistically independent, in time series successive observations may be dependent, and the dependence may depend on the positions in the sequence. This feature is very helpful for us to recognize the interconnection of people's activities on successive days.

Generally, there are various purposes for using time series in scientific research. The objective may be the prediction of the future based on knowledge of the past; or may be the control of the process producing the series; or may be to obtain an understanding of the mechanism generating the series; or maybe simply that a succinct description of the salient features of the series is desired. In our research, we will focus the application of time series analysis only for the later two purposes. That is, try to describe and obtain an understanding of the one-week trip series of various trip types.

2.2.2 Application of Time Series Analysis on the LTS Data

2.2.2.1 *Time Series Plots*

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 the current weekend. The Data is composed of the hourly time label within one week and the number of trips made 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. The Unix Version of 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 approaches to address a series of questions related to trip frequency, trip characteristics of various trip types and schedule relationship between different trip types.

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 saw now is on a temporal scale of 168 hours rather than just a day-of-week 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 is the center of one person's activity space. The two places are the two 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. And Go-home trip must be the ending trip of a trip series with origin at home, no matter what trip types the trip series starts with and how the trip series are composed.

Figure 8. Time Series Plot of Work Place Trips

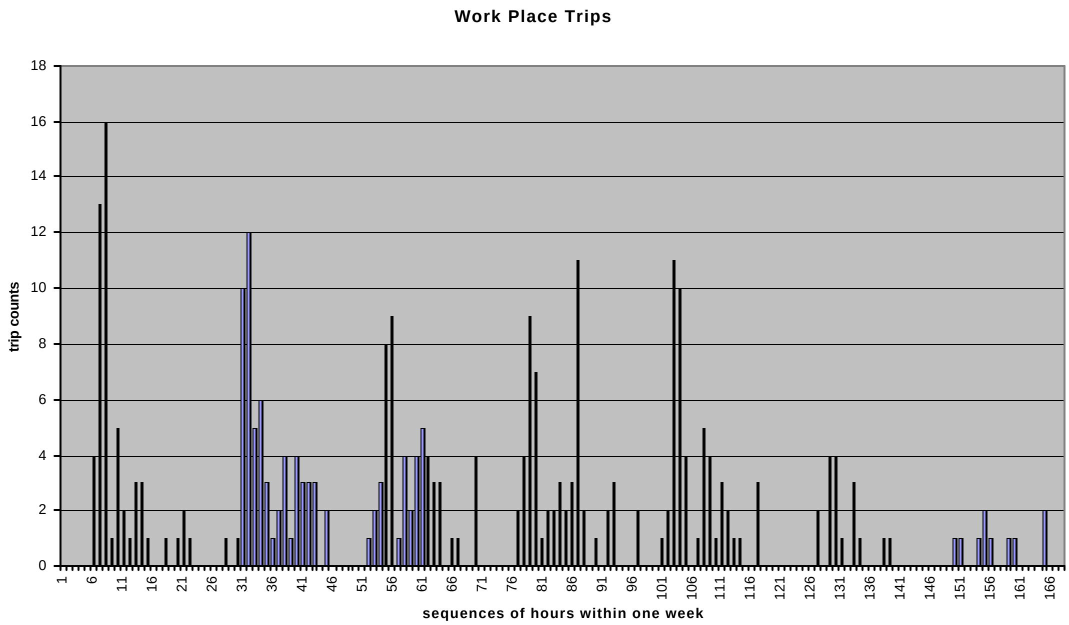


Figure 9. Time Series Plot of Eat-out Trips

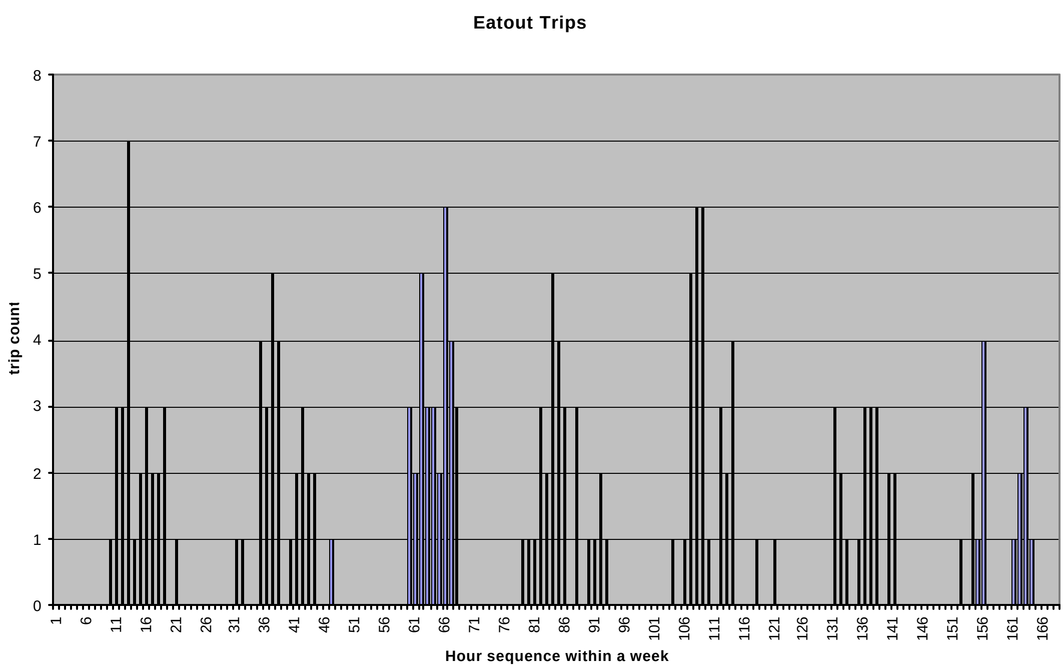


Figure 10. Time Series Plot of College Trips

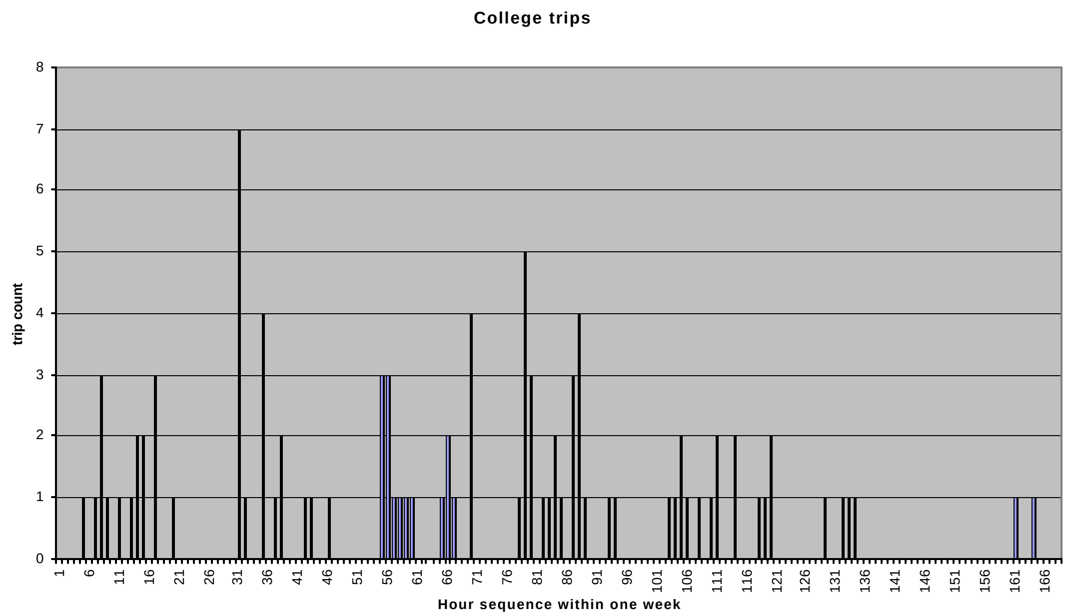


Figure 11. Time Series Plot of Social or Recreational Trips

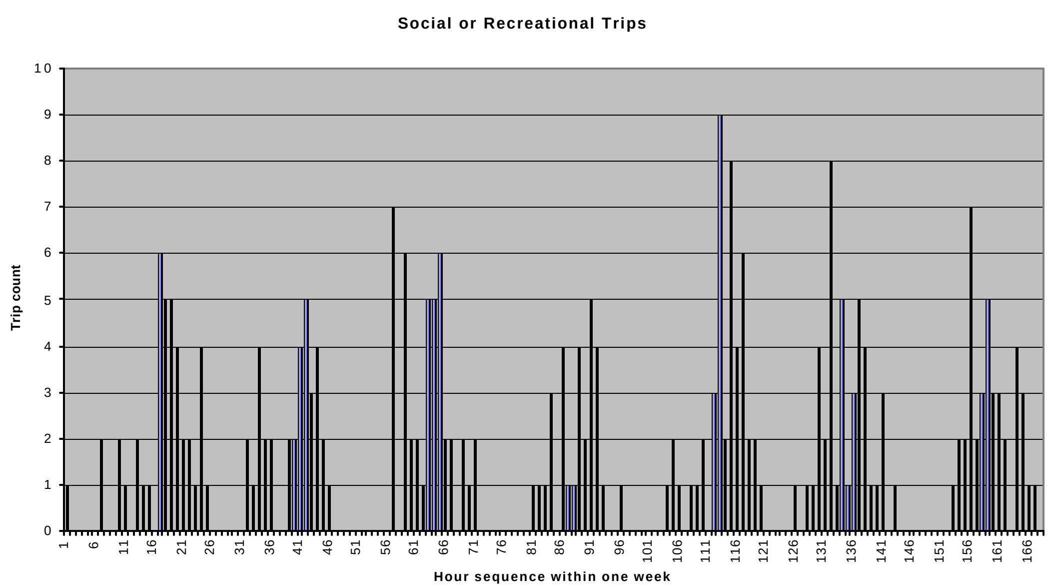


Figure 12. Time Series Plot of Medical or Dental Trips

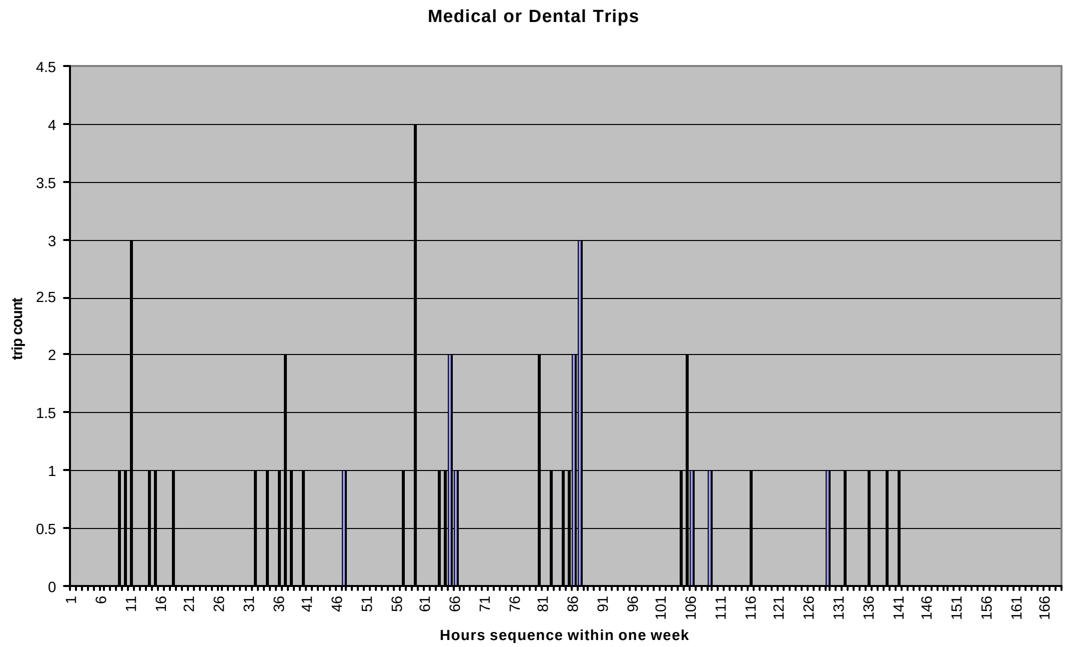


Figure 13. Time Series Plot of Religious Trips

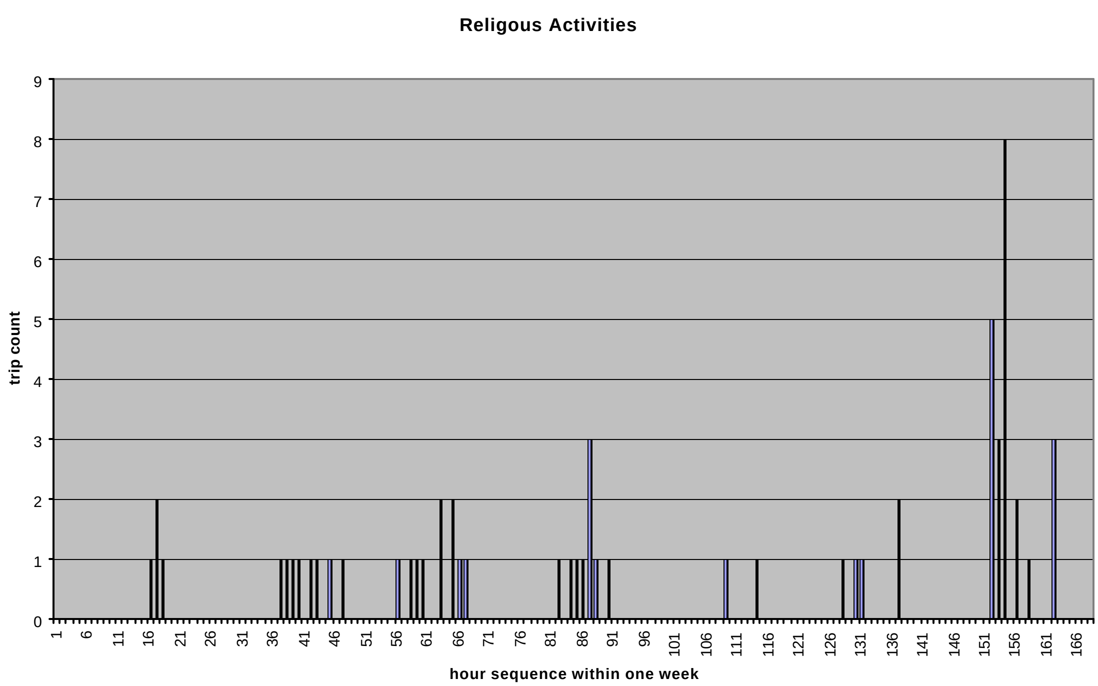


Figure 14. Times Series Plot of Shopping Trips

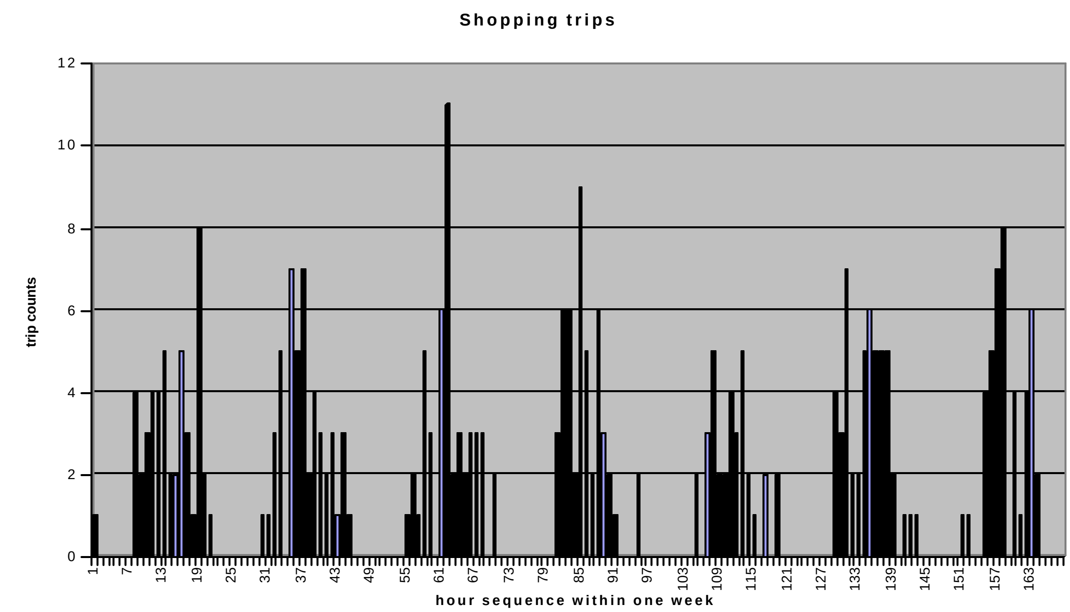
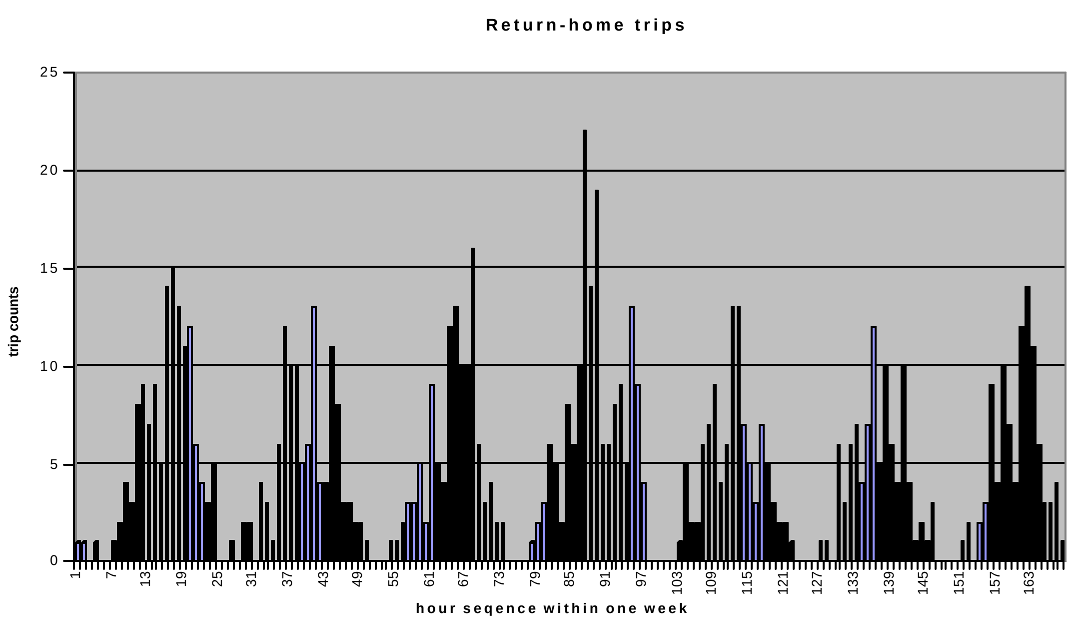


Figure 15. Time Series Plot of Return Home Trips



An insight into characteristics of different trip types can be obtained through visual examination of these plots. Go-to-work-place trips mainly happen in the morning 7, 8 or 9 o'clock. That is, the trip counts peak 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 on from Monday and bounce up again because of the approach of weekends. In other words, some psychological factors may be affecting people's go-to-work behavior. People may form their expectation for a weekly period during their life.

Eat-out trips 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 Eat-out trips belong to this type. However, it is interesting to notice that the highest peak on Wednesday occurs 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 the 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.

We saw two peaks in the college trip plot (Figure 10). One happens on Tuesday morning 7 o'clock and the other happens at 8 in Thursday morning. This may be related to the local college class schedules. More classes are scheduled on Tuesday and Thursday than on other weekdays.

Social or recreational trips mainly occur during the early night (Figure 11). 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 decreases gradually as time goes. This change indicates the relaxed time schedule on weekends.

Medical or dental trips typically happened during weekdays (Figure 12). There are no medical or dental trips that occur on Sunday. This agrees with our life experience. Dentists usually do not work on Sunday. And medical trip on Sunday would most likely be to a hospital emergency facility after a trip accident-- which is a small probability event.

Religious trips are equally distributed from Monday to Saturday (Figure 13). Most of these trips clustered on Sunday Morning when is the traditional time to go to church. Note religious trip counts are not totally blank for weekdays. Typically these trips are made by elderly or retired people.

Return-home trip distribution (Figure 15) has the widest span of all trips in terms of a single mode. Actually it could happen at any time. Typically there is a "silence" interval between any two different days-of-the-week for travel activities. With respect to return-home trips, this silence interval is shorter than any other trip types, only 4 hours long or less.

Shopping trips more or less are equally distributed among seven days of the week. The highest peaks appear at 2 o'clock Wednesday afternoon. This may be attributed to some temporary sale activity going on in a shop. Generally shopping trips have longer silence periods or inter-trip intervals than go-home trips. People's shopping activities are subject to open hours of local shops.

2.2.2.2 *Auto-correlation between Different Types of Trips*

Autocorrelation is an important tool for describing the temporal dependence structure of a univariate time series. The maximum 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 16,17). 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.
In Figure 16 and 17, the widths of sinusoidal peaks convey to us another kind of information -- the degree of flexibility associated with a certain type of trip. Go-to-work trips ACF plot has a peak width of only 2 or 3 hour interval. This indicates to 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.

Figure 16. Auto-Correlation of Work, Eat-out, College and Social or Recreational Trips

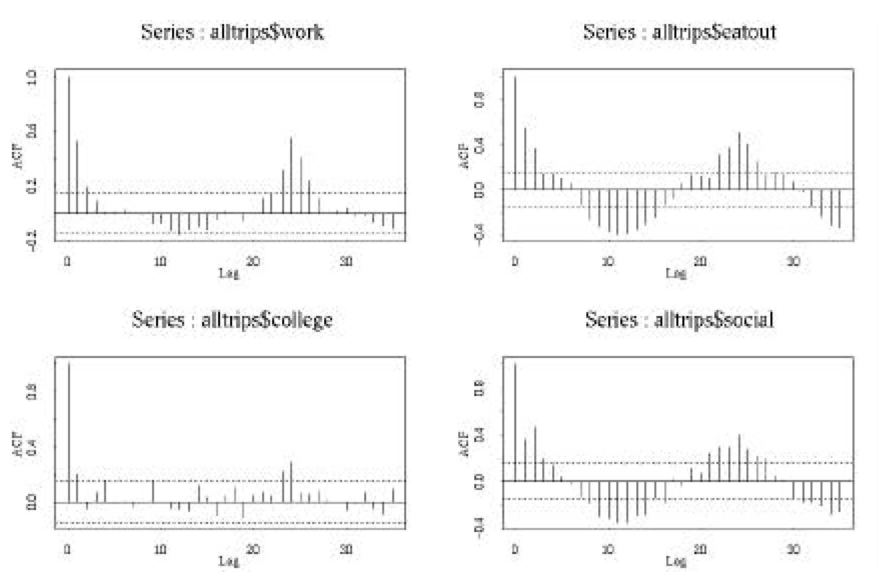
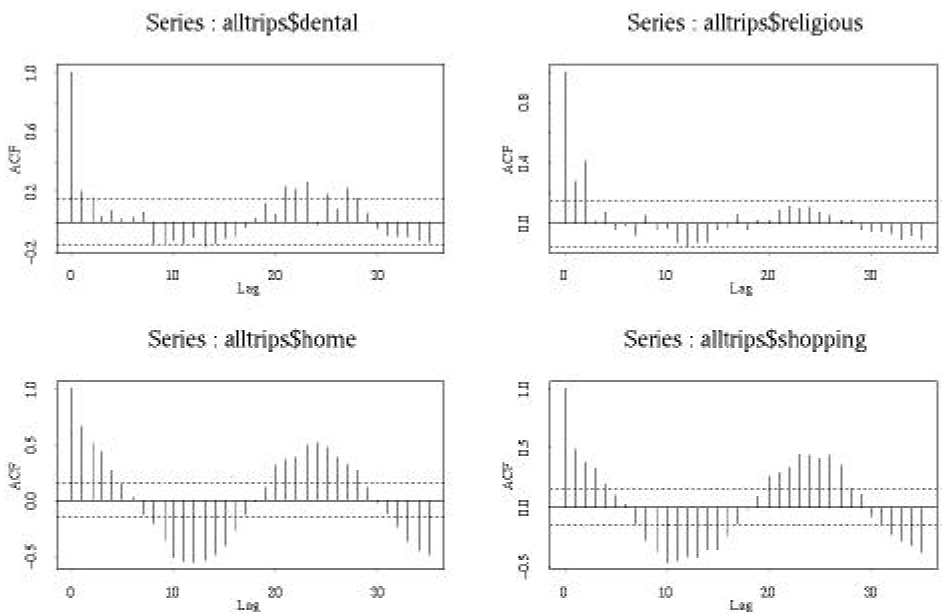


Figure 17. Auto-correlation of Medical or Dental, Religious, Return-home and Shopping Trips



2.2.2.3 *Decomposition of Trip Time Series*

Decomposition of time series plots (Figure 18, 19, 20 and 21) show us the decomposition of a time series into a cyclic component plus the residual (irregular component). Activity trends are also shown in these plots. This will help us in finding the travel pattern associated with a particular trip type.

Working trip decomposition (Figure 18) produces a daily cyclic component with a decreasing trend in peak heights as time goes from Monday to Sunday. We view this as a proof of the assumption of "work fatigue" associated with a weekly period. The bounce back of trip count on Thursday and Friday is left in residuals, which can be explained by people's expectation of the coming of weekends.

College trip decomposition (Figure 19) shows a daily cyclic component with a similar decreasing trend in peak heights as that of working trips. The bounce back on trip counts on Thursday and Friday also appears in residuals. We can also explain these with "work fatigue" and "weekend expectation".

Figure 18. Work Trip Decomposition

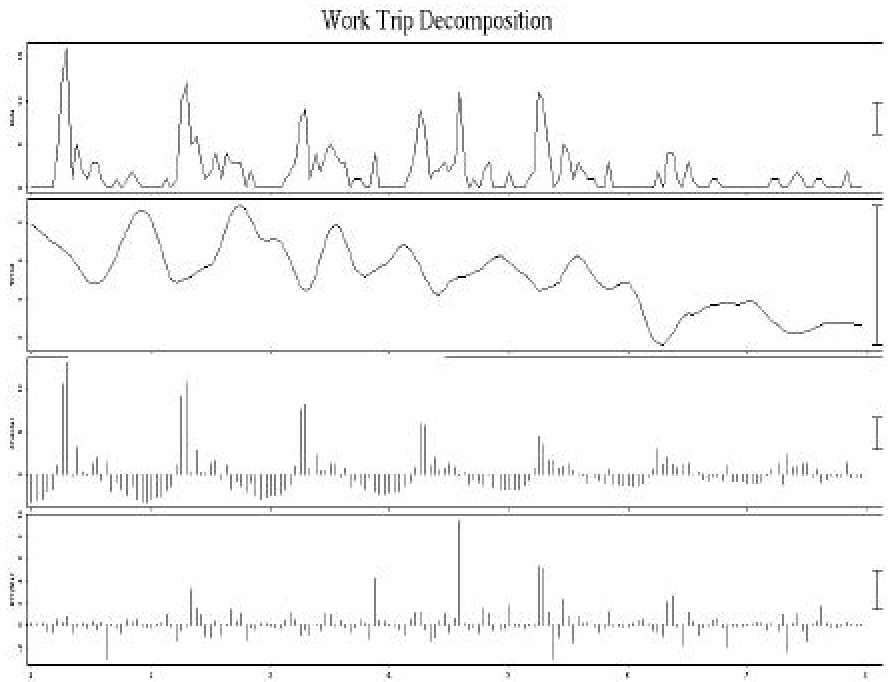
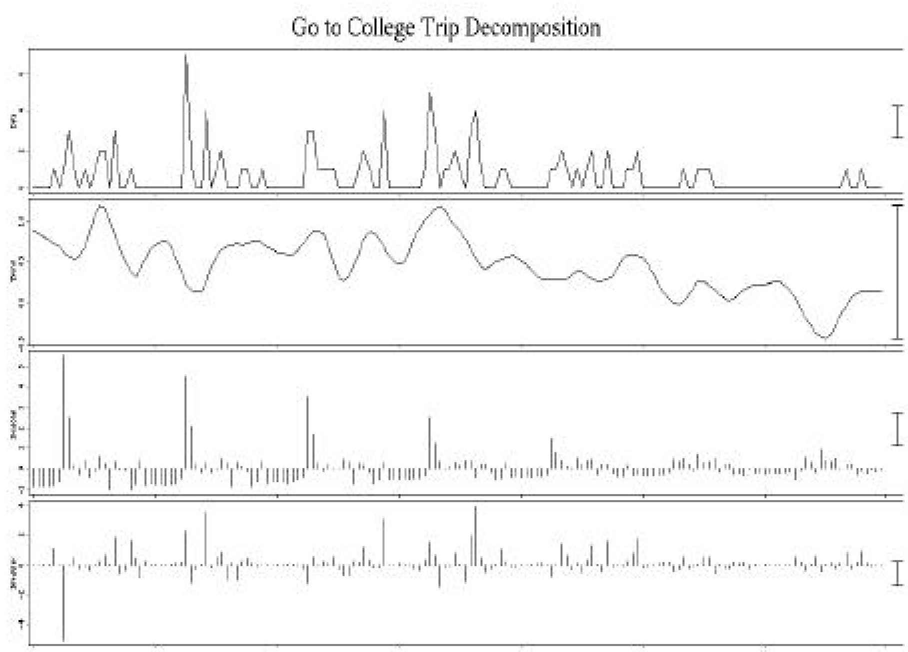


Figure 19. Go-to College Trip Decomposition



Social or recreational trip decomposition (Figure 20) shows a daily cyclic component with two peaks in one day. The lower peak is located close to noon. The relatively higher peak is located at night. As times goes from Monday to Sunday, the noon peak "grows up", and the night peaks remain constant. This shows how people shift their focused social or recreation trip time slot as the weekend is coming. Irregularity appears on Wednesday morning and Friday night. Friday night is party night. The reason for the irregularity that shows on Wednesday morning is unknown. It could be caused by an important event in the local area.

Religious trip decomposition (Figure 21) shows a daily cyclic component with peaks almost equally high. Although this daily peak mainly peaks in the afternoon from Monday to Thursday, it gets divided into two starting from Friday, one in the morning, the other in the afternoon, which indicates people get more choice to go for religious activity when weekends come. Note the scale of the cyclic component is small (1 or less) compared to that of the irregular component. It suggests that typically religious activity is not a routinely performed activity. The cluster of religious activities appears only in Sunday morning of the irregular trip component.

Figure 20. Social or Recreational Trip Decomposition

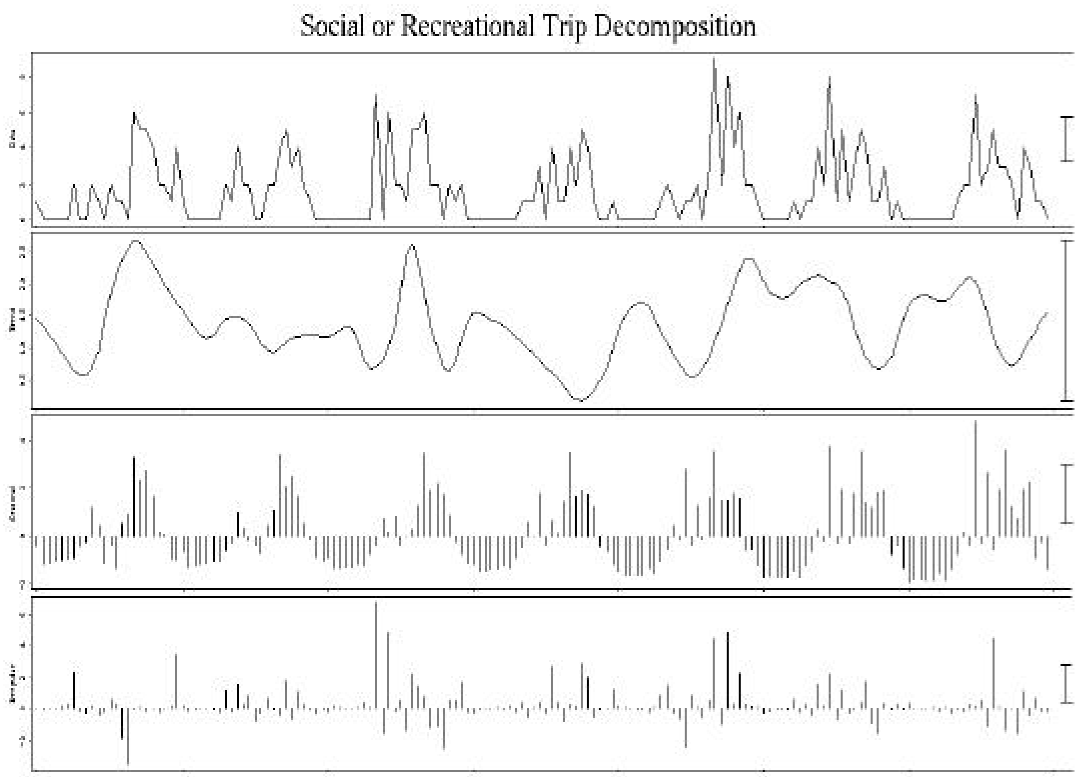
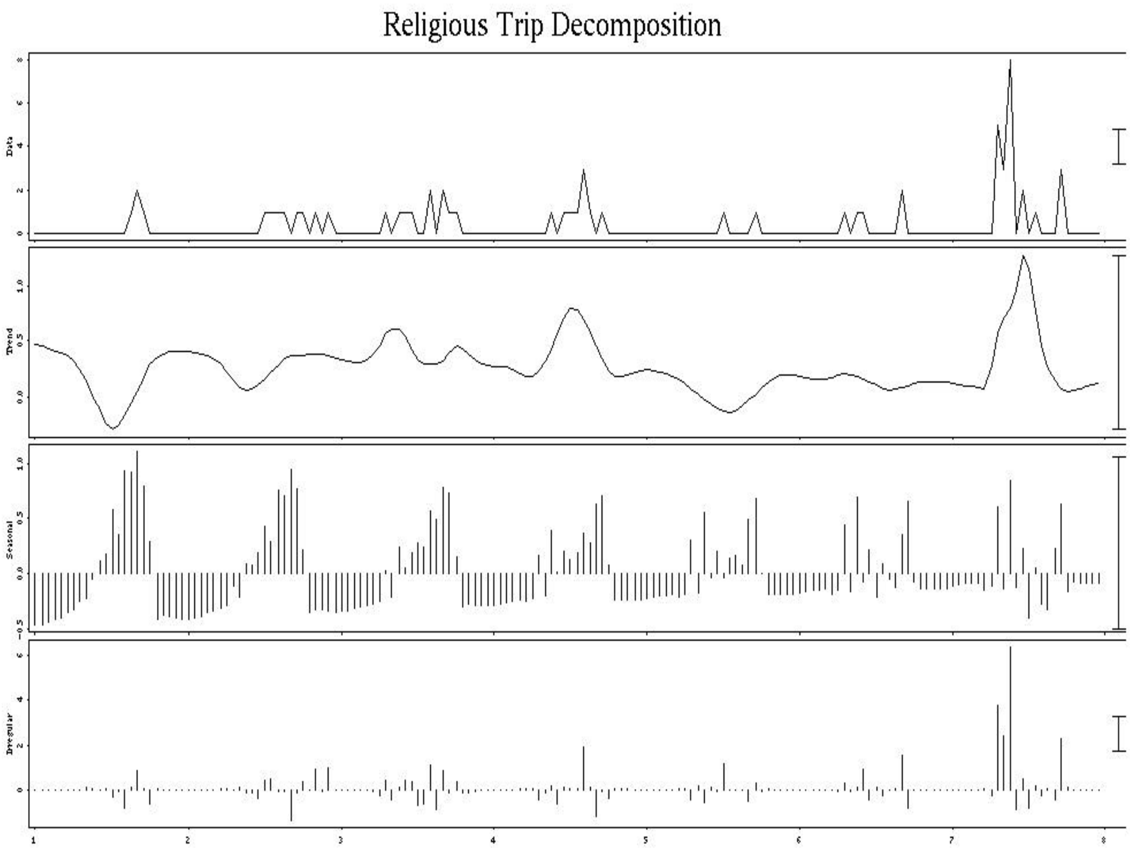


Figure 21. Religious Trip Decomposition



Shopping trip decomposition (Figure 22) shows regular daily cyclic component, with only Sunday peak a little higher (1 count more) than others, which indicates increased travels for shopping on Sundays. Note in the residual plot two peaks exist. One is on Monday evening, and the other is on Wednesday noon. We tend to interpret it as a temporary sale going on some place, which prompts the increased shopping travels.

Medical or dental trip decomposition (Figure 23) shows a weak daily cyclic component. The irregular component plot (residual) indicates that these trips happen as preferred on Monday and Wednesday.

Figure 22. Shopping Trip Decomposition

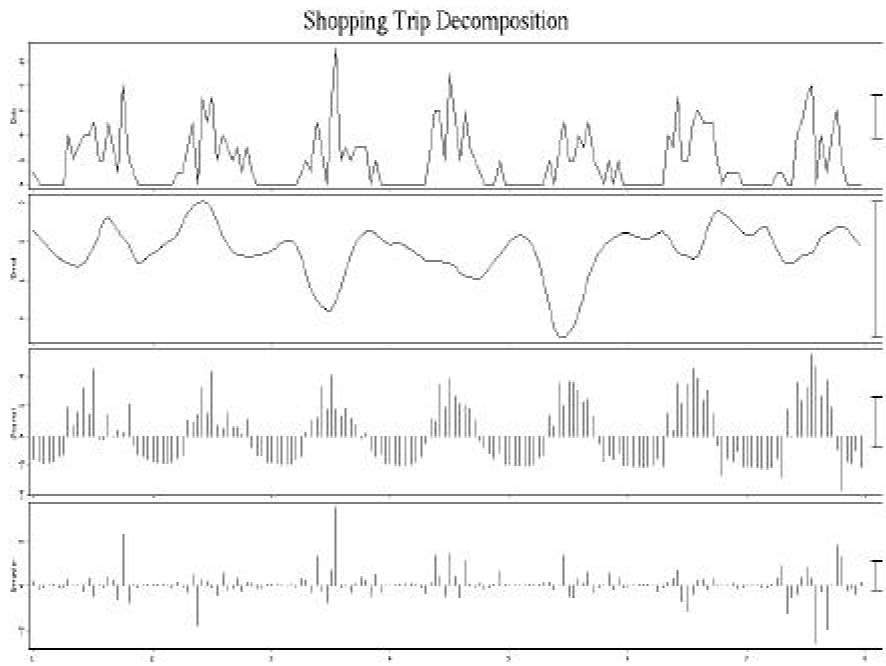


Figure 23. Medical or Dental Trip Decomposition

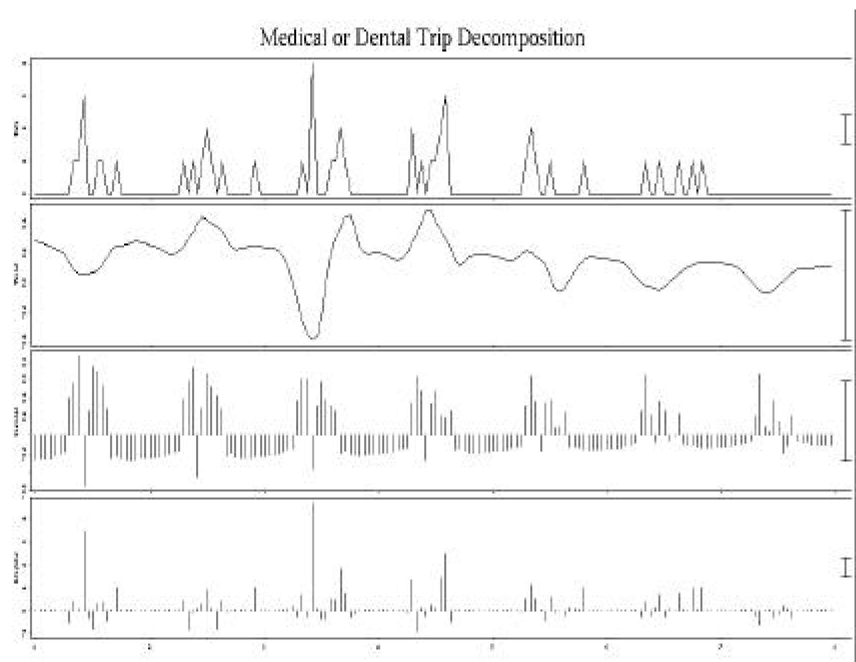


Figure 24. Eat-out Trip Decomposition

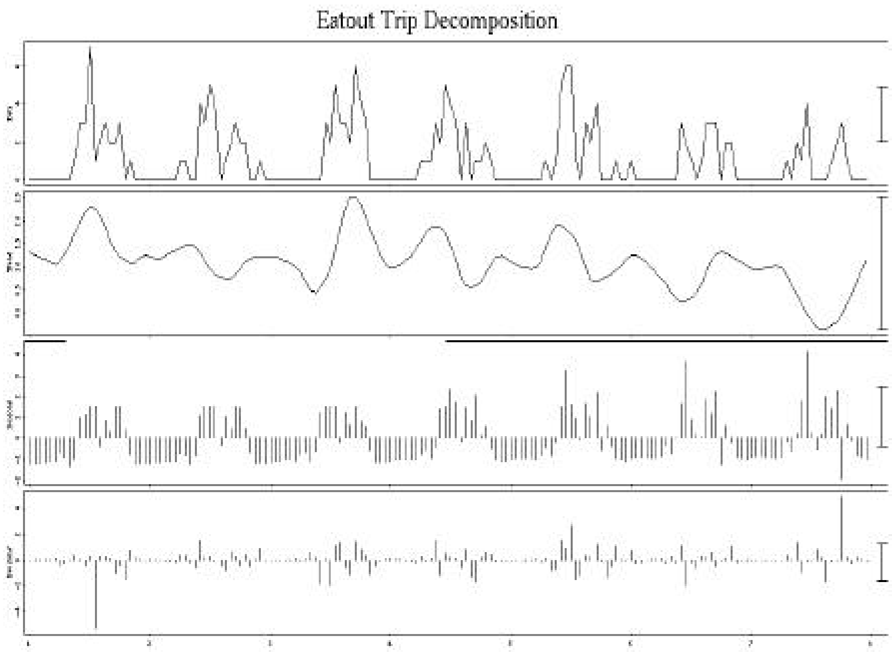
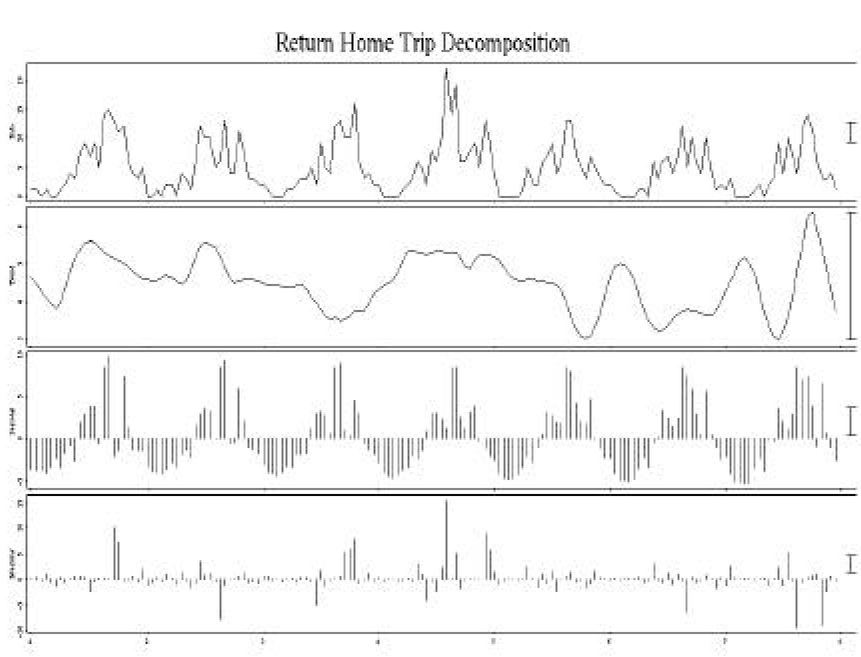


Figure 25. Return Home Trip Decomposition



Eat-out trip decomposition (Figure 24) shows relatively strong daily cycles. Each day-of-the-week has two spikes of eat-out trip occurrence. One is close to noon, namely, one or two o'clock in the afternoon and the other is in early evening-- six or seven o'clock. The irregular component shows that Sunday night is an unusual timing for a dinner-out.

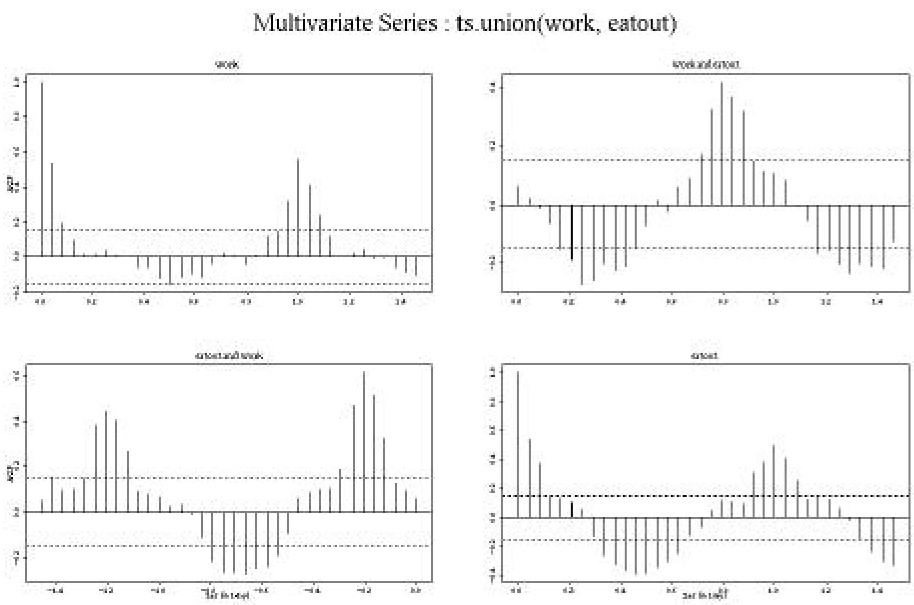
Return-home trip decomposition (Figure 25) also shows strong daily cycles. Two spikes exist in the cyclic component. One is 4 or 5 o'clock in the afternoon -- usual time to get off work, the other is 8 o'clock in the evening -- the work late time. Note one salient spike is on Thursday -- 3 o'clock in the afternoon and the scale is high (up to 15 counts). It may be caused by some specific events.

2.2.2.4 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 26, 27 and 28).

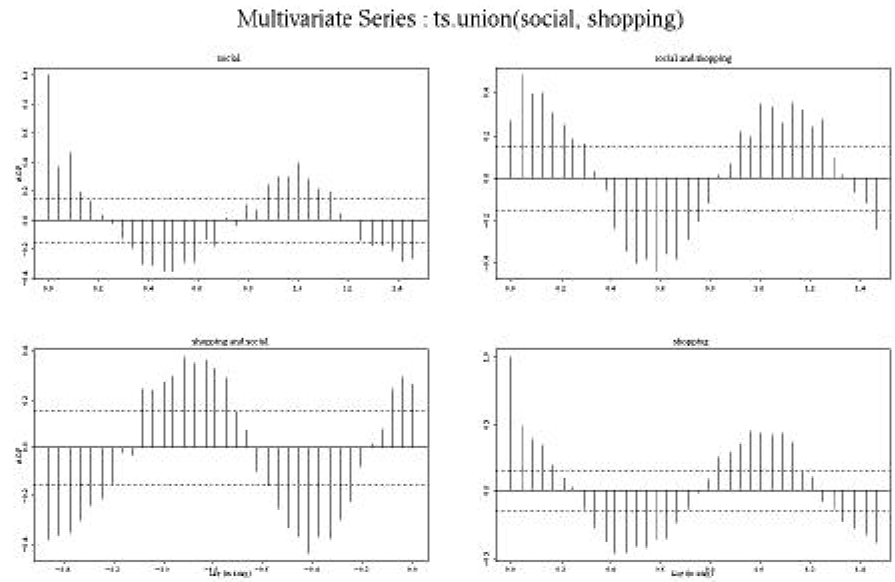
The cross-correlation plot between eat-out trips and go-work trips (Figure 26) shows that eat-out trips has the maximum correlation with go-work trips at -6 hour lag, which indicates that eat-out trips typically lags behind go-work trips by 6 hours. These "working lunch" trips usually occurs at 1 or 2 o'clock in the afternoon.

Figure 26. Cross-correlation between Go-to Work Trips and Eat-out Trips



The cross-correlation plot between social or recreational trips and shopping trips (Figure 27) 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.

Figure 27. Cross-correlation between Social and Recreational Trips and Shopping Trips



Similarly, the cross-correlation plot between return-home trips and shopping trips (Figure 28) 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 28. Cross-correlation between Return-home Trips and Shopping Trips

2.2.2.5 *Spectral Analysis*

In the last part, we used cross-correlation for studying the relationship between different types of trips. We got a relative vague picture of the "before" or "after" relations of them in terms of schedule. But it doesn't tell us how their periodicity is related. We turned to spectral approach, which is better able to separate short-term and periodic effects.

Figure 29. Coherency of Social or Recreational Trips and Shopping Trips

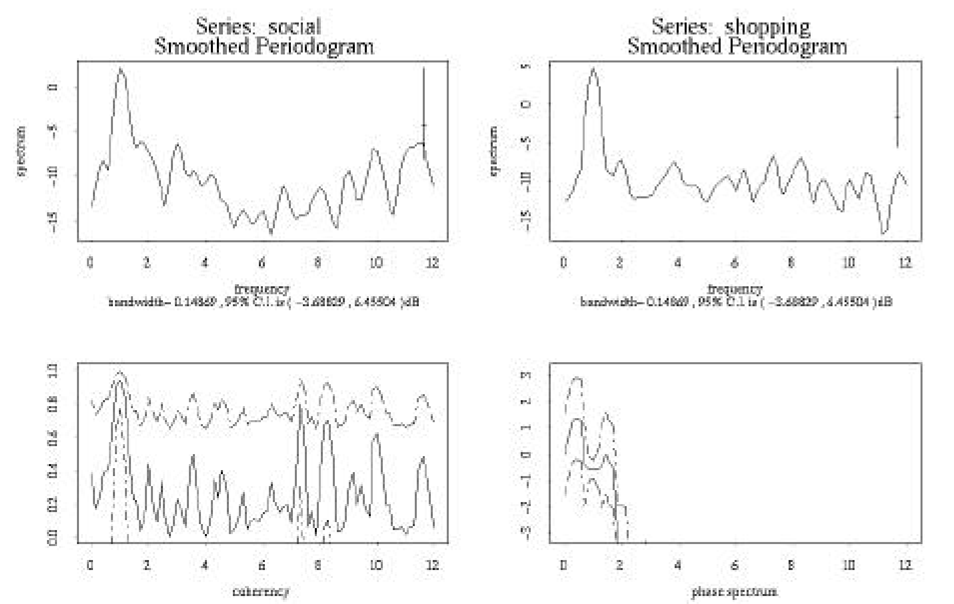


Figure 30. Coherency of Return Home Trips and Shopping Trips

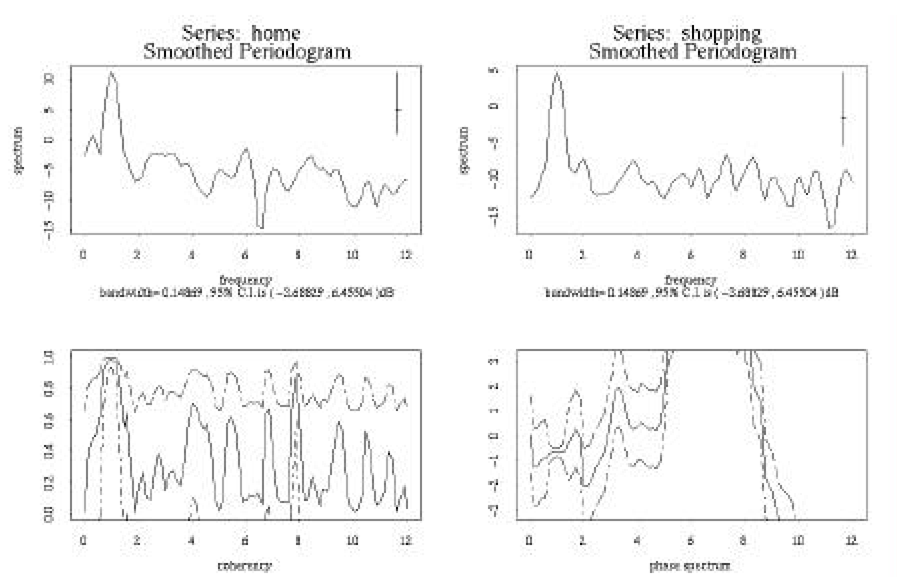


Figure 31. Coherency of Go-to Work Trips and Eat-out Trips

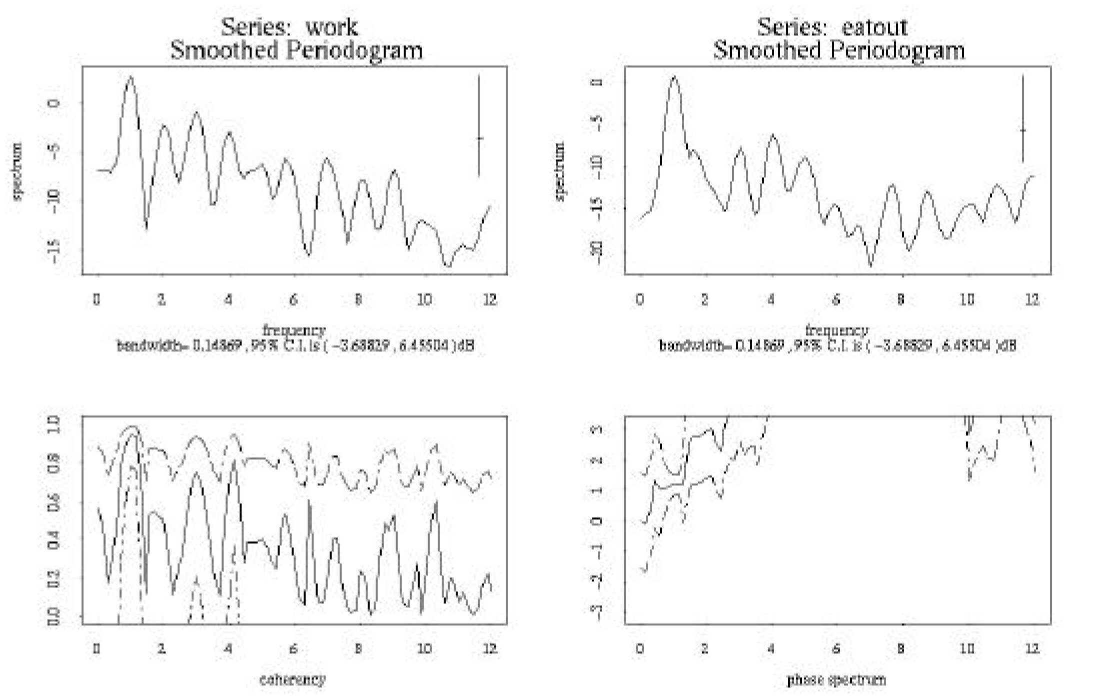


Figure 32. Coherency of Shopping Trips and Eat-out Trips

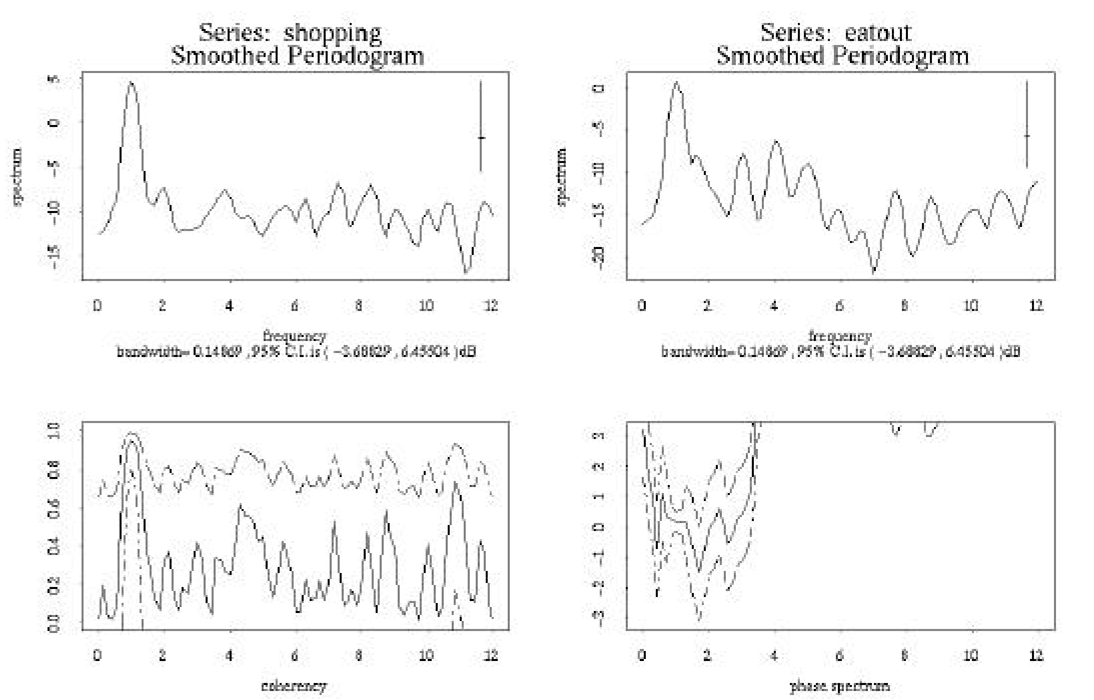


Figure 29, 30, 31 and 32 shows our results. Note for every type of trips-- return-home, go shopping, social or recreational activities, go-to work, and eat-out, the frequency 1 (one trip made per day) is within the 95 percent confidence interval. They are performed at least once a day. Work trips, compared to other types of trips, are significant (falls within confidence intervals) within more frequency slots--1, 2, 3, and 4. Eat-out trips are significant within slots 1, 3, and 4. Social or recreational trips are significant within slots 1, 2, and 3. However, return-home trips and shopping trips are only significant at frequency 1. They are performed only once a day.

When we examine the coherency plot, the results are not so exciting, as only the frequency of 1/day is a strong signal common to all of the five trip types. The coherence is high there and coherence and phase are determined very precisely (Figure 29, 31, and 33). At high frequencies there is little information, and coherence can not be fixed at all precisely. For return-home trips and go shopping trips, their frequencies do not even precisely couple at 1/day frequency (Figure 30).

2.2.3 Problem with Using Time Series Analysis

The theory of time series is based on the assumption of second-order stationarity after removing any trend. Thus second moments are particularly important in practical analysis of time series. In our time series decomposition plots, we saw the residual components are not strictly stationary. Thus it means the application of the auto-correlation, cross-correlation, and spectral analysis on our data may not be appropriate.

The second issue is that if we would like to uncover the features of people's activities across the week period using time series analysis, multiple samples of weekly activities should be needed. Unfortunately, as funding for the Lexington travel survey project was limited, there were not enough GPS-integrated devices and labors for sampling for a continuous period of more than one week. This flaw diminishes the credibility of our results.

2.3 Trip Direction Analysis

2.3.1 Outline of Trip Direction Analysis

Travel behavior is typically related to the movement of individuals from place to place, with the emphasis being upon the actual quantitative changes that take place and the natures of the localities concerned. One of the important aspects about travel trips, which are the results of people's movements in a two-dimensional space, is the physical direction of the movements (e.g. north, south, etc in terms of natural language). Once we recorded a bunch of information about the trips made by people, inherently the change of direction of the trips is available to us. With a traditional dairy keeping method, the information of travel direction inside the data is vague and unclear. We can only infer it from a paper map based on recorded place names. With GPS involved in data collection methods, travelers' paths are recorded in digital form, which are much easier to manipulate and deal with. With these data and the results derived from them, we would like to see whether the preferred travel direction exists in people's travel behavior and how it is related to the local road network.

In statistics, the kinds of data that get direction measurement involved are usually called circular data. When dealing with problems arising from circular data, we typically use some relatively unusual statistics. For example, we know that one of the inherent attributes about circular data is its periodicity. In a circular world, a simple arithmetic operation like addition does not work the same way. Suppose we have one direction, say 200 degrees from north, if we add 360 degrees to it, we do not get 560, but back to the original direction. This unusual form of addition can clearly cause problems, especially in the case where we have the individual trip orientation information of a study area and intend to collectively determine the local main traffic flow direction (the average of trip orientation). A solution for this could be taking the vector means rather than using the traditional addition operation. For the Lexington data, the trip information was collected within a period of one week. Depending on the trip types to which each trip belongs and day of week on which the trip happened, trips may be a long-distance trip (vacation trip) or short-distance trip (work, study or business related trip). By following trips and breaking the trips at that main turning point, we may divide each trip into a set of vector segments and then compute the mean orientation for the single trip. A very good representation of the final mean trip-orientation data would be a circular histogram. We expect the trip-flow-direction circular histogram for each day of the week can clearly show the main traffic flow direction for each day-of-the-week. And a Java media player can be used to dynamically link them to do a dynamic presentation on the variation of traffic flow direction of the travel data.

A variety of available circular distributions are available for us to test the circular histograms derived from trip data. The simplest distribution would be the circular uniform distribution, which describe (for circular data) cases when there is no preferred direction and all directions are equally likely. The probability density function is:

$$F(\theta) = 1/360 \,,\; 0^\circ \leq \theta < 360^\circ$$

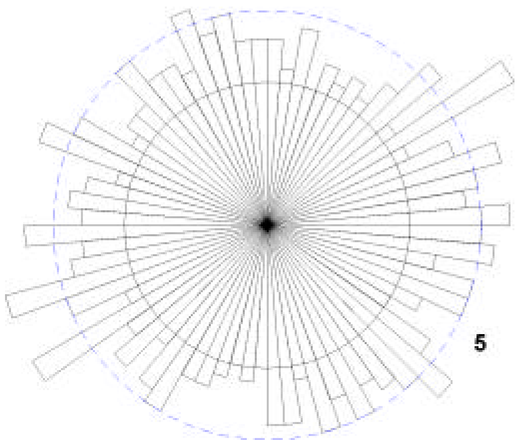
However, based on activity space-related theories in behavior science, it is very possible for individual households to present a certain degree of preference for a particular travel direction due to various reasons (sector bias). The alternate to the uniform distribution in this case would be some distribution that allows a preferred direction to exist. This distribution was suggested by Von Mises (1918). Since up to the stage we are assuming the uniformity of the distribution of travel directions of the sampled households in an aggregate way, we will focus on using the circular uniform distribution for our statistical tests.

2.3.2 <u>Application of Trip Direction Analysis</u>

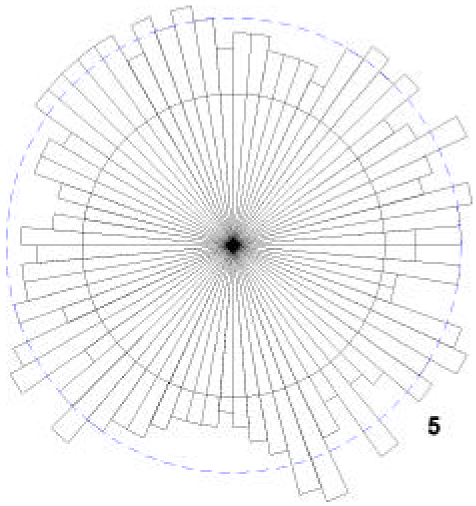
Our first step is to generate the circular histogram for the collected trip data. ARCINFO was used for this task. An AML (ARCINFO Macro Language) program was written to aggregate and generate the histograms in an automatic way (Figure 33). The trip directions are aggregated into five degrees intervals. The inner solid-line circle indicates the measurement of trip counts in the five-degree interval is 0. The outer dashed-line circle indicates the measurement of trip counts is 5.

Figure 33. Circular Histogram of the Trips made on Different Days of the Week

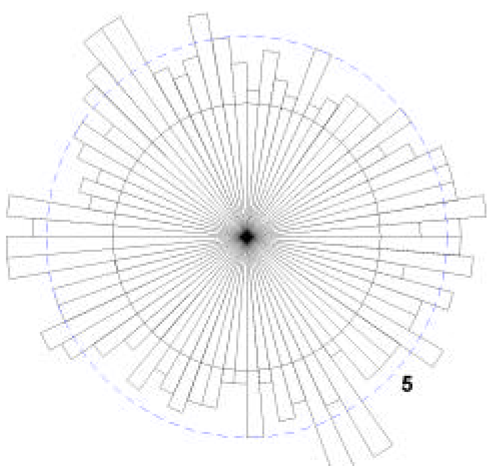
Circular Histogram of Monday Trips



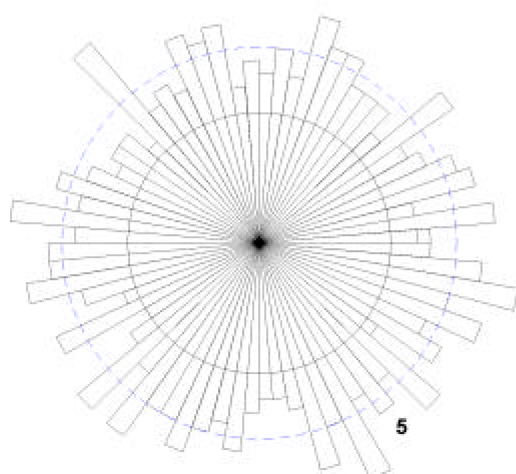
Circular Histogram of Tuesday Trips

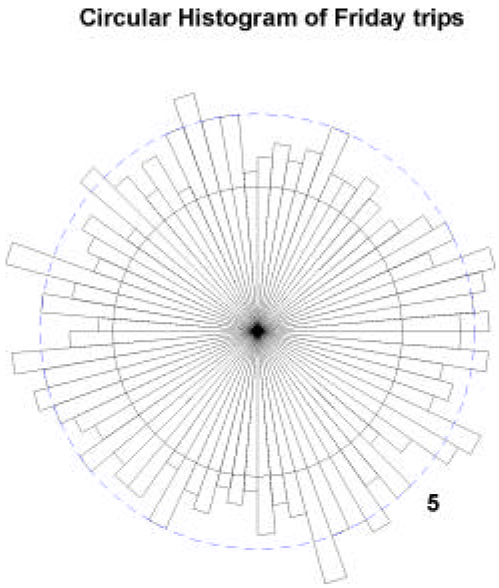


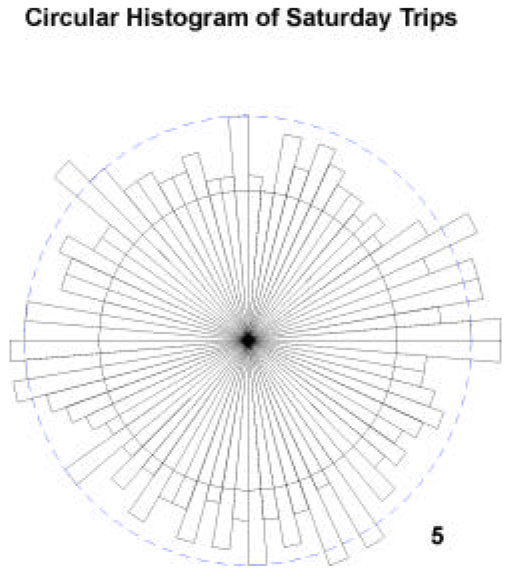
Circular Histogram of Wednesday trips

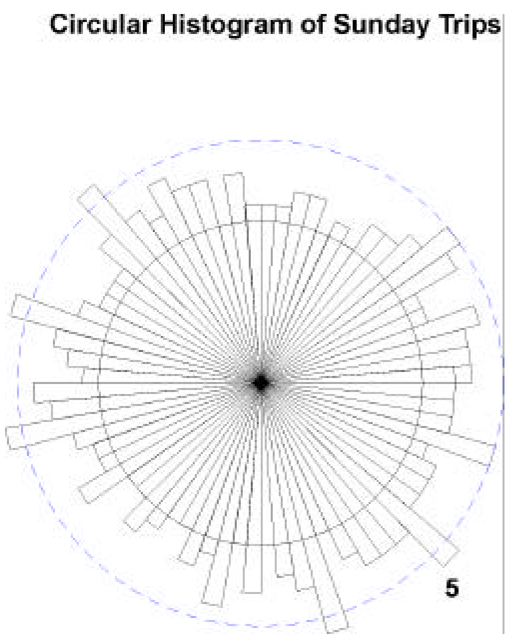


Circular Histogram of Thursday trips









Note the circular histograms show no significant trip clusters in a certain direction. And they are sort of symmetrical. Based on the concept of center-based (home-based) activity space in behavioral science, there would be a pair of go and back trips for an activity to be performed at some place other than home. There may be cases that multiple go-trips share one back-trip -- in more formal words, they consist of a multiple-purpose trip chain. We expect the mean direction of the circular histograms to indicate directions of these multiple-purpose trips.

To get the mean direction of a circular histogram, we first compute:

$$R^2 = X^2 + Y^2 = \left(\sum_1^n (C \times \cos q) \right)^2 + \left(\sum_1^n (C \times \sin q) \right)^2$$

Here, θ is the middle of five degree intervals (e.g. 0°-5° interval, θ is 2.5°). In the formula, we refer all angles to the direction of north and measured the angles in a clockwise direction from the north. C is the count of trips fall in the interval. N is the total number of trips occurring in the circular histogram. If the n observations of trips fall in one direction interval, R will be n. If there is no outstanding direction, the data will be self-canceling and R will be 0. A more formalized measure to reveal the concentration of trip directions is R/n -- the adjusted value of R. If R/n is close to 1, it suggests that the data are tightly concentrated on along the line whose orientation is estimated by

$$E(\theta) = \tan^{-1}(X / Y)$$

To test against the assumption of uniform circular distribution, we used the Rayleigh test:

$$T = 2 R^2 /n \sim \chi^2_2$$

The χ^2_2 approximation is accurate for values of n equal to 100 or more. However, in our result, we found the Rayleigh test is not sensible (due to the symmetry of the travel direction circular histogram) and that the alternative to uniformity is non-unimodal distribution. The values of R's are all close to zero, because of the opposite modes balancing each other.

Therefore, another test called the Gap test is adopted. The test does not assume the alternative to uniformity is a set of directions so clustered about a single mode and it allows for the possibility of a multi-modal distribution. In the Gap test, a series of observations are arranged in order. Then the gaps are computed as the difference of the near-by observed directions (measured in degrees). Suppose the n observations are arranged evenly around the circumference of a circle; the gap between a pair of neighbors would be 360/n degrees. Based on this idea, Rao (1969)

$$G = \sum_{i=1}^{n} | G_i - 360 / n |$$

suggested the test statistic:

By referring to a special table, we may find out whether one or more clusters in trip directions occur in the circular histogram.

Table 16. Gap Test Results of Circular Data

	Monday	Tuesday	Wednesday	Thuesday	Friday	Saturday	Sunday
trip counts	255	300	306	352	272	227	163
R	0.636	0.401	0.627	0.404	0.5811	0.59	0.652
theta	96	190	134	123	122	96	142
T	0.0031	0.001	0.0025	0.0009	0.0024	0.003	0.0052
G	295.295	263.599	277.411	284.09	289.71	269.37	283.06

Table 16 lists our results. Note none of the R values are close to 1, which indicates no significant clusters in trip directions for each day-of-the-week. The theta values (θ) --mean direction-- vary across the week, with only the values of two weekdays significantly close-- Thursday and Friday. We will need to refer to local activity sites distribution in order to explain the variation and similarity. None of the G values showed significance after referring to the statistical table. This means the distribution of trip directions shows no significant preference for a day period. Maybe further breakdown based on trip types would be needed for revealing any obvious deviation from uniform distribution. However, this requires more trip data. A one-week sample is definitely not sufficient for the analysis.

2.3.3 Problem with Using Trip Direction Analysis

To this point, we have overlooked the point that the travel behavior actually starts from scattered points over space rather than from a single point. Furthermore, people's travel over space typically follows the built road network within a certain region. This means we can not describe the travel direction in a simple fashion like with a circular histogram. Naturally occurring barriers or human built facilities may impose restrictions on the distance and direction of possible travel. Definitely variation of travel direction should be considered with other variables together in order to reveal a sensible answer for what the variation of travel directions really means to us. Fortunately, some techniques for relating circular data to other variables exist. For example, Mardia (1976) and Johnson and Wehrly (1977) suggested the idea to relate the distance traveled to the direction of travel using the relation of the linear form

$$Y_i = a + b \cos(\theta - \psi)$$

where a, b and ψ are constants. This technique could be used in our study to examine the relationship of travel distance with travel direction associated with a particular travel purpose.

Furthermore, as what has been mentioned before, a general examination of the variation of preferred travel direction across the week may not be able to give us insights into the topic. Trips and their orientations could be further examined based on trip types, the starts, or the time interval within which they happened.

3. DISCUSSION

This thesis deals with week period as a determinant of formation of travel activity patterns. The results of this study are twofold.

3.1 Regularity and Variability 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.

Different from the research conclusion of Pas (1988), even weekday travel-activity behavior was found dependent on day-of-the-week in this study. Among weekdays, when people's activities seem pretty routinized because of work or study constraints, the differences of travel-activity patterns still exist. In Pas's paper (1988), only trip generation rate was considered as a comparison measure, which represents only one perspective of the people's activity patterns. This study examined the variation of travel behavior across the week not only from the aspect of trip frequency, but also from the aspects of trip duration and trip distance. Analysis of Section 2 shows that the variability of activity patterns on weekdays mainly comes from the flexibility associated with the noon, early afternoon or the evening time slot. Activities performed in these time slots 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 prior research. 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 revealed the periodicity associated with each type of trip. A rhythmic pattern (Shapcott and Steadman, 1978) for different types of trips was established. 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).

Different from what we have assumed, the trip-direction-circular histogram is not exactly symmetrical about any arbitrary diameter of the base circle. There exists a mean vector to indicate the possible direction in which multi-purpose trips may have been undertaken. However, sensible explanation for it needs to relate the direction preference to the local activity site distribution and socio-demographic features. It is the first chance that direction data can be readily and accurately accessible to behavior and transportation researchers with the help of GPS. The attempt made in this study has proved the application of circular statistics to travel data is feasible. But more work needs to be done to make it a real worthy analysis tool in activity-related research. The statement argued by Golledge (1997) in his book that the activity spaces of people living in cities tend to have a common directional bias is yet to be proved in this study.

3.2 Defects that lie 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 sufficient 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. In cases where 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 (Table2). 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 data set in a more comprehensive way.

4. CONCLUSIONS

Concerning temporal aspects, movements to specific activity location is related to the frequency and regularity with which an individual chooses to participate an activity. Regularly scheduled activities, such as going to work and work lunch, are more likely to be made at a specific times. While others are more likely to be made at intervening times. The mixture of various activities made with different occurring frequencies, though forms patterns, appears cloudy and totally unpredictable.

In the attempts to reveal the determinants of variability of activity patterns, the earlier works by Hanson (1982) and Pas (1984) have identified their association with social-demographic and spatial or environment variables. The list of explanatory variables that potentially have influences on travel activities includes age, marital status, gender, employment status, education level, presence of young children, income, auto-ownership, residential density and the location of individual or household to potential destinations, such as shopping centers, churches, gas stations, etc. However, none of these literatures addressed the role of week period in the daily travel behavior. Kunert (1994) noticed the how various life-cycle groups show distinctively different profiles of trip-makings over the course of a week. But he considered the social constraint – week period only as a time frame for examining travel patterns instead of as an explanatory variable for them.

This study advanced our understanding of the unusual determinant (week period) of activity pattern by a breakdown analysis of its influence on travel distance, frequency, distance, direction, the type and temporal characteristics of activity pursued at an aggregate level. Kunert's finding (1994) that there is tendency of increasing trip making from Monday through Friday and relatively low trip making at the weekend was confirmed in Figure 5. As a bonus, Thursday was revealed with the highest trip intensity compared to other days of the week.

Another achievement of this study would be the evaluation of a new travel data collection method. It was the first attempt to utilize travel data collected based on GPS for travel behavior analysis. GPS involved travel data collection method has its advantages in accuracy and reliability. In addition, the overall data post-processing procedure can be automated. Up to the time that LTS data was collected, the commercially available GPS-integrated device was still bulky and uneasy to carry individually. This leads to the fact that only travel by automobiles was recorded in LTS data set, which potentially underlies any conclusion based on this data set. However, without losing generality, the research conclusions derived in this study are valid if we limit its applicability to motorized travels only.

Future work of this study is extensive in terms of extent and scope. There is a file included in LTS Data that identified some socio-demographic attributes of the households under study. These data could be used in tandem with spatial and temporal information of the trips made for analysis of the combined influence of socio-demographic factors, spatial and temporal variables on people's travel activity patterns. How to effectively incorporate spatially-defined opportunities, people's expectation to the external regimens (week period) and their socio-demographic characteristics into one research framework would be a difficult issue. Specifically, directionality of trips made will be explored in more details. Its relationship with the distribution of spatial opportunities could be examined by identifying the potential activity sites within the study area using assistant data. A second perspective will be to evaluate standard network models that define optimal routes for origin destination pairs and trip chains. Then the optimal routes could be compared with trips actually made by the sampled household. This will be followed by an evaluation (using Quadratic Assignment Procedures) of which of the models most closely reproduce the actual data set. The first perspective will provide us some hard information on the role of spatial factors and temporal factors in travel and on the extent of their importance relative to the socio-demographic variables in explaining travel-activity patterns. The second perspective follows a modeling approach. It will be valuable for us to understand the degree to which travelers are spatially rational or whether other criteria appear to be more important in choosing routes for single and multi-purpose trips.

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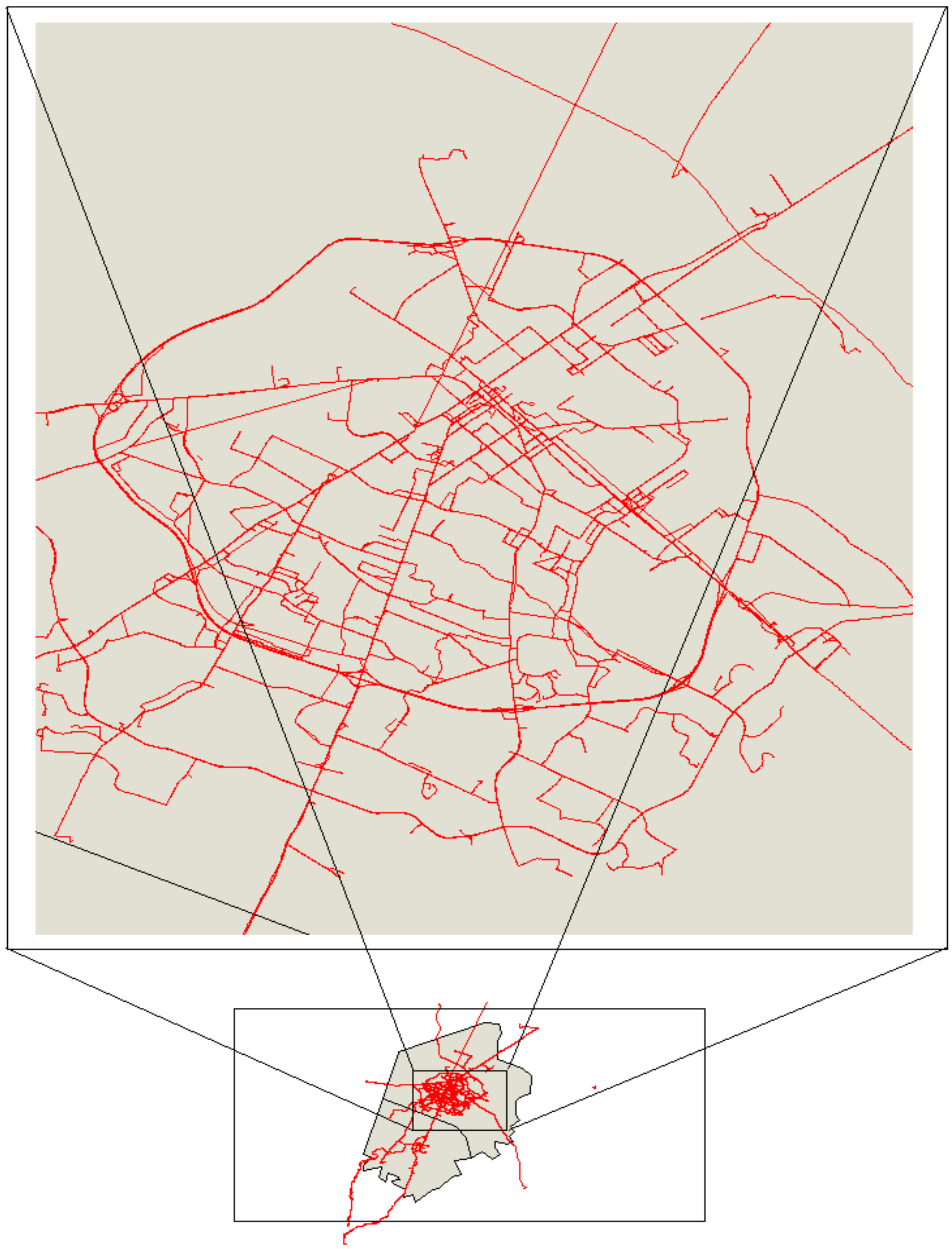
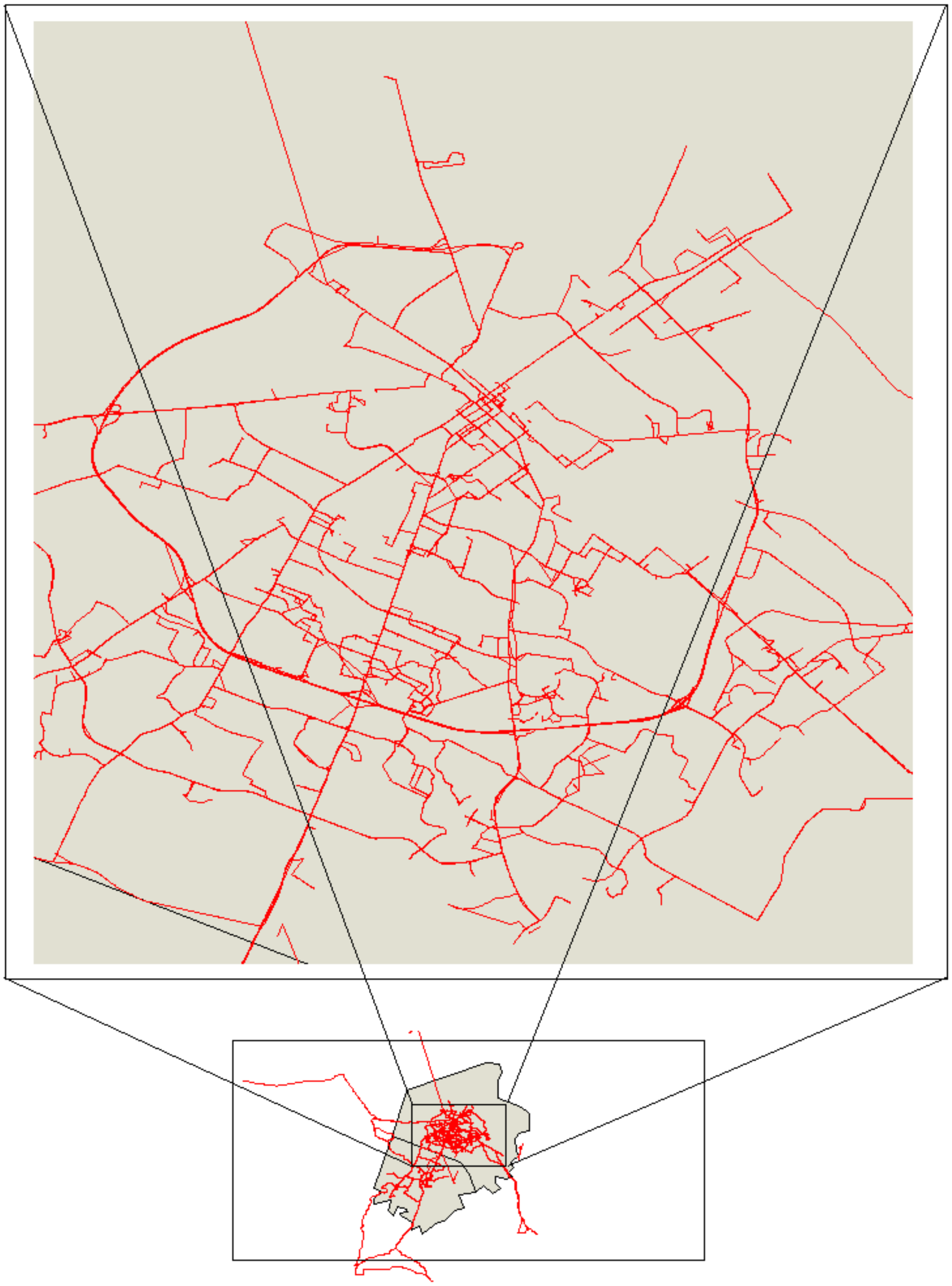
6. Appendices

--- TRAVEL ROUTES RECORDED ON DAYS-OF-THE-WEEK

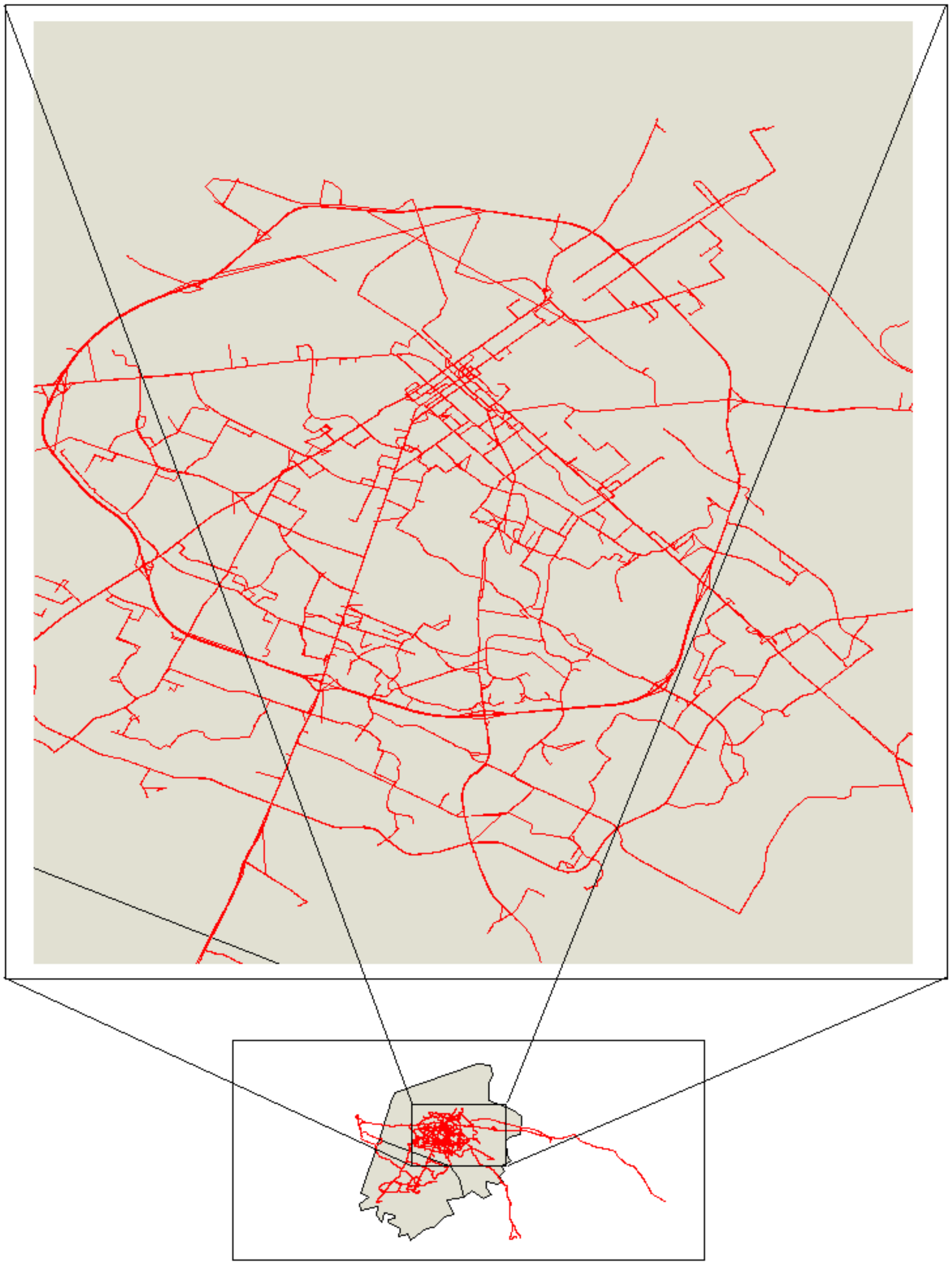
A. Travel Routes Made on Monday



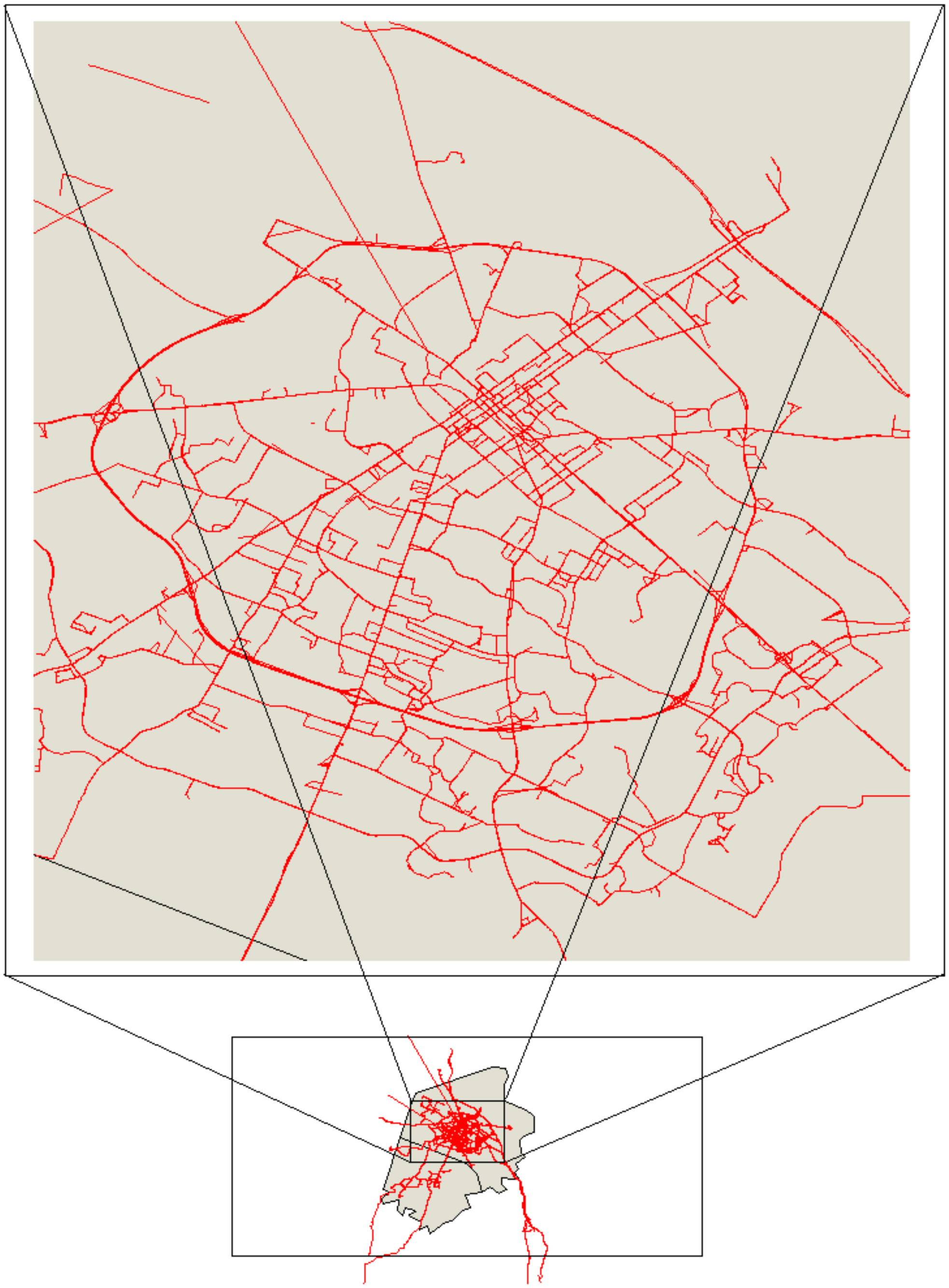
B. Travel Routes Made On Tuesday



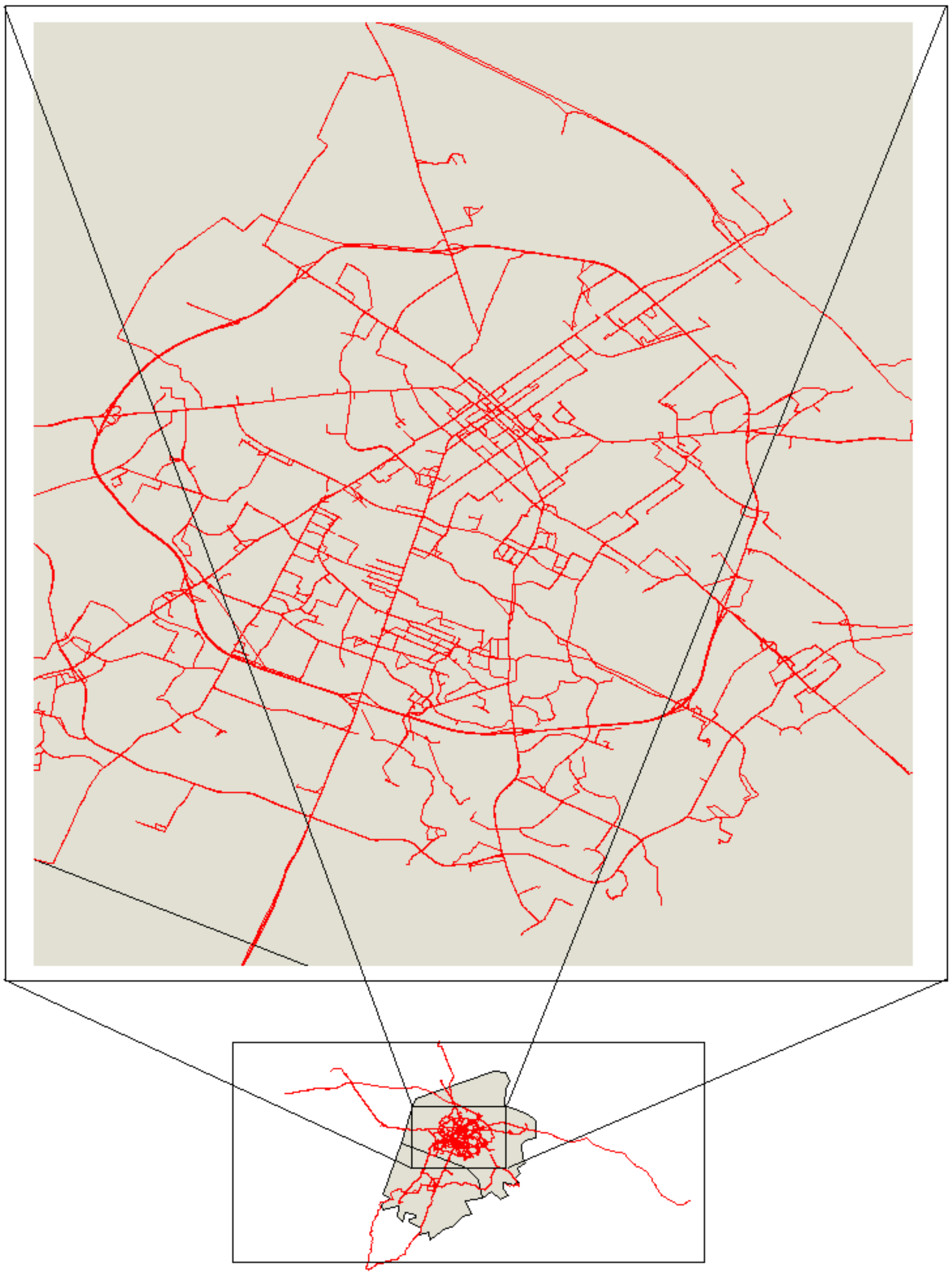
C. Travel Routes Made on Wednesday



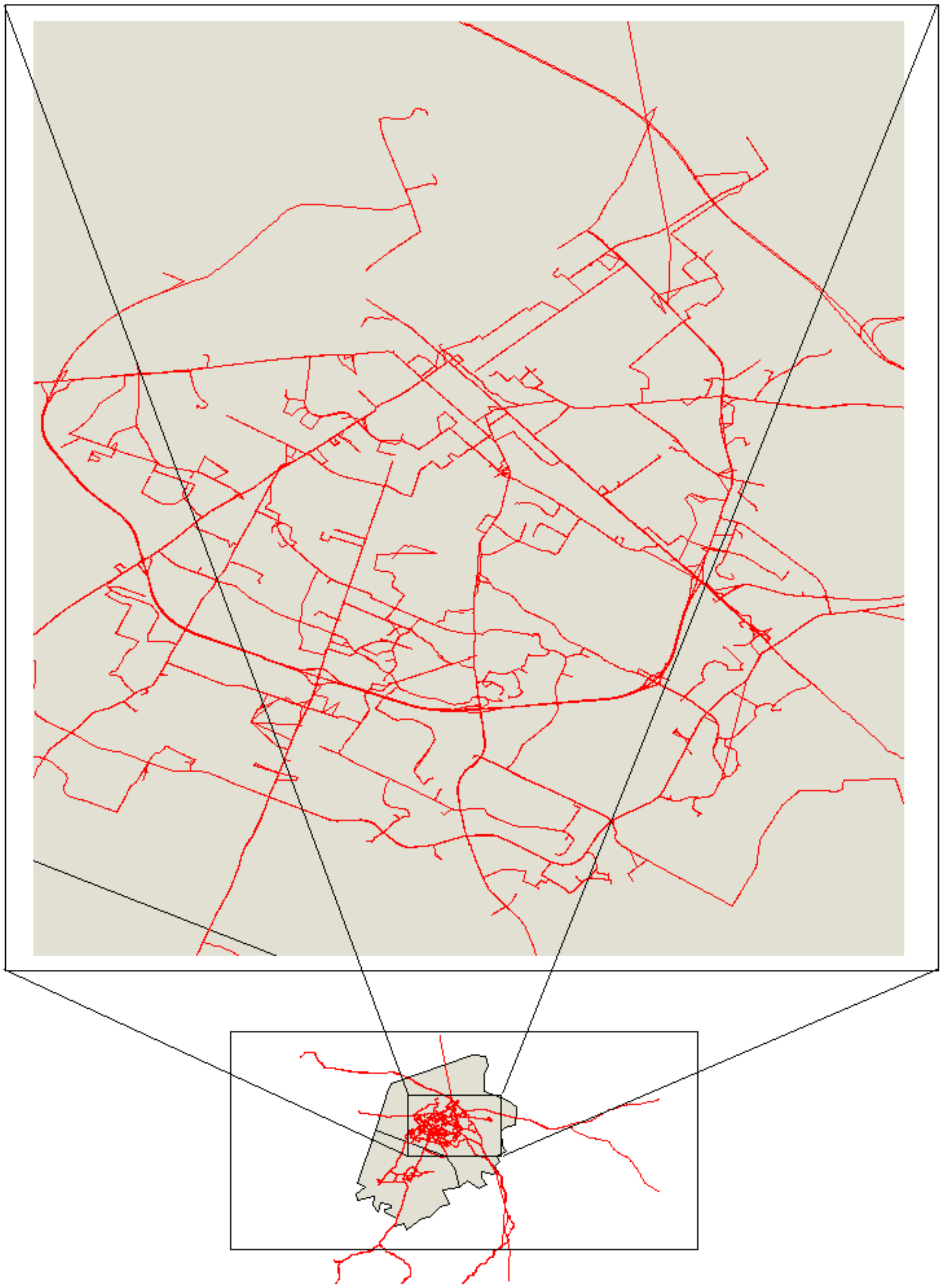
D. Travel Routes Made on Thursday



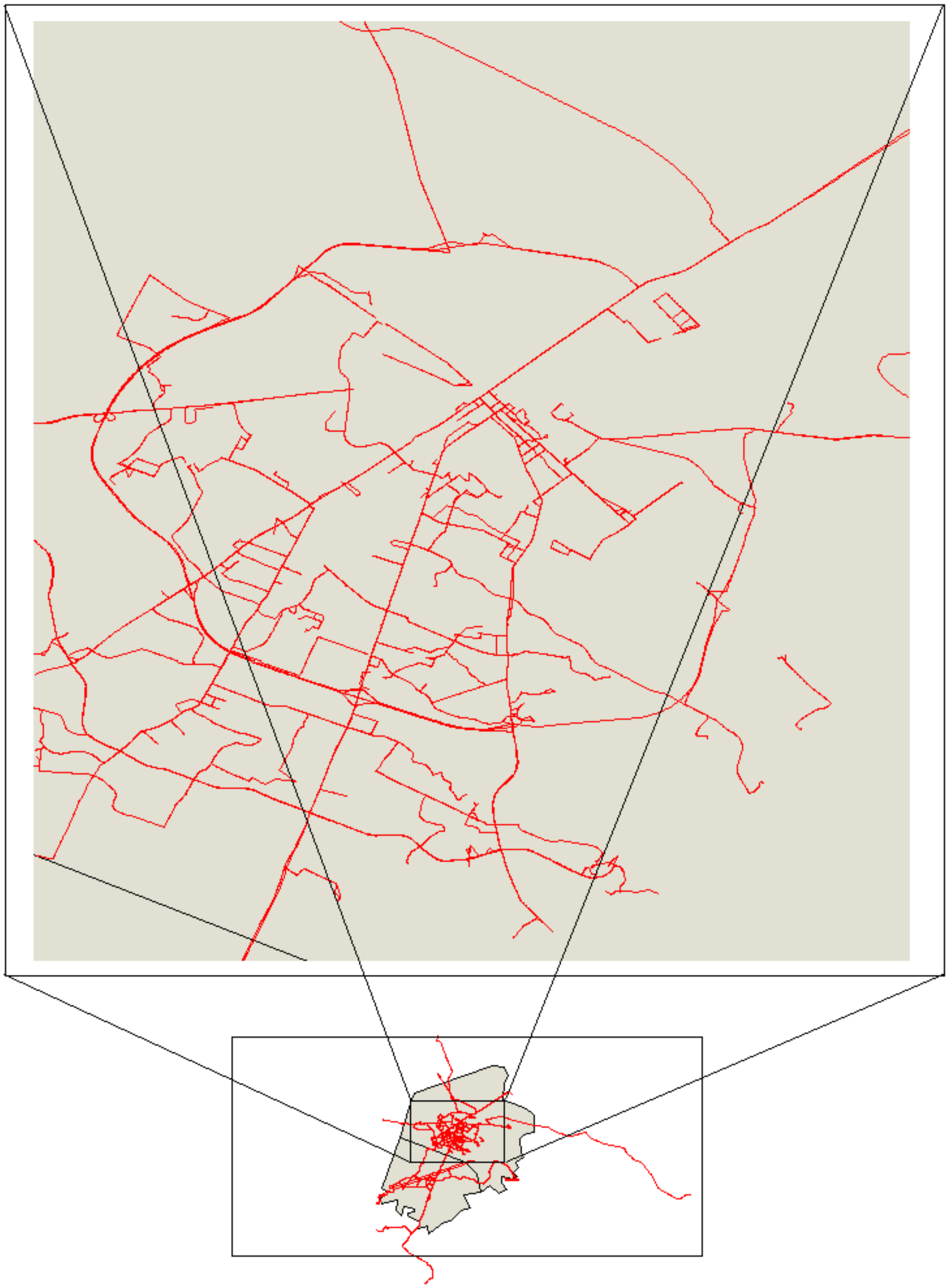
E. Travel Routes Made on Friday



F. Travel Routes Made on Saturday



G. Travel Routes Made on Sunday



A GPS-based Analysis of Household Travel Behavior

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Introduction

Goals

A major goal of Transportation Science is to enhance the effectiveness of ITS services. Recently a number of traffic management centers have been developed capable of using multimedia investigation techniques to analyze volumes and patterns of traffic flow. One area to which attention is constantly turning is that related to traffic dynamics. While there are a large number of means for observing traffic, research on traffic flow theory has still lacked that easily accessible and highly accurate geocoded database as a support for building and testing destination choice, traffic flow, and cyclical effects in traffic dynamics. Part of the successful implementation of traffic management centers depends on the adequacy and accuracy of their information services. The more we know about the actual behavior of people not just in the aggregate, but in terms of the many repetitive individual patterns that are likely to be pursued by households living in different parts of the city, the more it is likely that the effectiveness of traffic management services will be enhanced. It is anticipated that our examination of the dynamics of travel behavior as revealed in the GPS generated tracking of destination choices, will further our knowledge of several still unresearched questions on repetition behavior, path selection, multi-stop trips, cyclic travel patterns, and the relevance of single models for predicting daily travel behavior.

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. We also will try to recreate patterns of stops on single and multi-stop trips and predict what routes may have been taken using correctional network based trip allocation models.

Behavioral Geographers are concerned with where people carry out various activities: where they live, work, shop, use other services or find their recreation, and how people come to their travel-related decisions. Traditionally, considerable attention has been given to the study of locational and spatial choice aspects of human activities. It is relatively easy to study the locational attributes attached to people's activities occurring in a spatial context in GIS. But what is usually overlooked is the time label related to activities, which typically refers to a clock time or calendar time.

Typically, the study of human activities may be approached from the perspective of a spatial-temporal context. One innovative and well-known view is Hagerstrand's time geography. This approach shows that people's activities are described as trajectories or paths defined within a bounded region of time and space, from when and where an individual comes into being (birth) to the point when and where he or she ceases to live. As a constrained environment, time and space are inseparable from the intricacies of human behavior. However, using time and space as an approach is contingent upon the other constraints that operate on individuals. For example in the study of the relationship between time and people's daily travel behavior, at the individual level, it is nearly impossible to extract useful information about the influence of time on people's choice behavior, about the observable realism of movements made by individuals. Human decisions about travel seem to be random, non—optimal, and to a certain extent, non-periodic, in a temporal sense. Any appearance of intervening opportunities may shatter the seemingly reasonable behavior pattern into pieces. Real world human behavior is different from the scaled-down controlled environment intentionally formed in a lab. Human behaviors are subject to various physical, psychological, social, cultural, and other conditions.

However, It is possible for us to delve into human behavior patterns along a time axis at an aggregate level. Individual variations in the perception, conception, and measurement of space and time, variations in capability constraints, coupling constraints and authority constraints that are encountered by individuals in an environment are sometimes accounted for by averaging. 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 selected social groups, or the local social-cultural environment. Typically, trips for different purposes, such as work trips, social and recreational trips, or shopping trips, tend to exhibit quite contrasting time distributions.

Here, we would like to focus our study on variations of regularity of different kinds of trips across a week. This time scale, although relatively coarser than hour times used by other behavioral researchers, is sufficient to reveal the underlying regional travel behavioral pattern and satisfy our needs of trying to identify the change of trip frequency during the period of a week.

Research Area and Data Collection Method

Research Area: The study area of this research is located at Lexington, 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 are collected using an automatic device that collected real-time self-reported travel-related information along with automatically recording GPS position information of the vehicles in use. This new data collection method, compared to the approach of recall-interview or travel diary that has been used a lot in the past, has the advantage of accuracy. When data is entered in real-time, the chance of omitting very short trips or rounding trips times are 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 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.

Research Plan: Much research over the last two decades has paid attention to the study of locational and spatial choice aspects of human activities. The development of Geographical Information Systems (GIS) has provided an ability to produce geocoded spatial databases and has consequently assisted in the determination of relevant variables for destination choice. The temporal sequencing of activities has also received increasing attention. Access to the GPS/in-car computer data record from the Lexington study provides an opportunity to combine both real-time data input with GPS locational accuracy.

Typically the study of human activities can be approached from the perspective of a spatial-temporal context. Following the fundamental ideas expressed in Hagerstrand's "Time Geography" (1970, 1976) and those of his followers such as Lentorp (1978), and more recently the works of Miller (1991, 1999), a spatio-temporal approach to the examination of people's activities should be able to focus on the correlation between daily trajectories. Various diary surveys have concluded that on a daily basis many activities are non-periodic, and destination choices are difficult to rationalize. We plan in this study to use the GPS-based data from Lexington to look in detail at the actual time paths of individuals, to determine to what extend time-paths of individuals or groups can be best fit by simple decision making models based on criteria such as shortest path and least time. We also plan to explicitly examine trip chains and discover what regularity exists both in the periodic occurrence of similar chains and the sequences in which particular activities are performed.

Background

The past decades have seen a paradigm shift in transportation planning from the construction of new infrastructure (supply) to the more effective management of travel (demand). Part of the reason for this shift was the recognition that building new highways was only a temporary measure to relieve movement problems such as congestion. The shift to travel demand management as a significant traffic control strategy has consolidated in the last decade. Both the spatial and the temporal dimensions of travel behavior are being examined and increasing emphasis has been placed on flex-time working hours, telecommuting, and an increasing concern with the in-car dynamic reception and use of Advanced Transportation Management and Information Systems (ATMIS). These measures are designed to facilitate movement through existing systems by: a.) reducing travel demand through the suppression and selective elimination of trips; b.) targeting single occupant vehicles at peak period commuting times, and reducing traffic volume on key links in the period of peak vehicle flow; c.) reducing driver frustration and stress along with affecting traffic flow by providing timely in-car, en-route or pre-travel information about hazards such as congestion, construction, or accidents; and d.) examining in more detail the activity patterns of individuals and households to more completely understand features such as the allocation of resources (e.g. vehicles) among household members, the timing of household activities, and the significance of multipurpose and multi-stop trips (trip chaining) in the episodic activity behavior of household members. In particular, the latter trend has attempted to treat travel behavior in more realistic terms: this has required a search both for new data that is being produced either by survey and panel research, by travel simulators, by new types of travel demand models (see Mahmassani, Hatcher, and Caplice, 1996; Stopher, 1996a; Jones 1990; van Aerde, Hellinga, Baker, and Rakha, 1996), and in the future, by GPS based in-car tracking systems.

Apart from working within the idea of constrained activity spaces, this research began emphasizing behavioral changes or behavioral dynamics represented by human decision making and choice behavior when confronted with changes in the travel environment. These changes could vary from the process of switching between driving alone and carpooling to work, to the more real-time adjustment of changing destinations, changing routes, substituting destinations, changing the time scale at which activities are undertaken, deleting and delaying activities as a response to information about changing travel environments, or delaying departure times. Other travel behavior features that have come under investigation include trip chaining, scheduling of activities over a time span rather than restricting them to a single time, substituting out-of-home for in-home activities (such as might be the case with two-person-working households who begin dining out, instead of eating at home in the evenings), and an emphasis on household members' life cycle stages (Mahmassani and Herman, 1990; Stopher and Lee-Gosselin, 1997; Gärling and Hirtle, 1990; Janelle, Klinkenberg, and Goodchild, 1998).

One of the characteristics of the activity approach is that it extends interest in what is going on beyond the physical nature of the trip itself Individual cognitions (e.g., cognitive maps), person-to-person and among-household relationships, and other coupling phenomena (e.g., working out with a friend, sharing rides to a transit terminal) as well as phenomena such as variability in path selection criteria for different trip purposes, all come into play in the attempt to understand the reasons behind movement. This detailed personal and small group knowledge is often extremely difficult to obtain and to code and process (Janelle et al. 1998; Goodchild, 1998). Nevertheless, there is substantial evidence that the benefits associated with adopting the methods, the ideas, and the concerns of this general behavioral approach appear to more than compensate for those difficulties, particularly by giving increased knowledge of the nature and structure of decision and choice processes of travelers. In the spirit of these new research directions, we propose the analysis of in-car GPS and real time computer data entry procedures as represented in a novel data collection projects (The Lexington Project), with a view to searching for new insights about household travel and the evaluation of the GPS based methodology.

Driver Simulators and Computational Process Models

As the potential for ATMIS to influence driver behavior and traffic conditions in a network has become more obvious, a number of research efforts have focused on examining the impacts of real-time traffic condition information on dynamic driver behavior. Because few ATMIS systems have been implemented in the real world, much research has concentrated on using computer-based interactive simulation rather than working with real-time field studies. Driver simulation procedures differ from the more classic revealed preference studies in that, while the former require individuals to answer hypothetical questions about technologies they have yet to experience, in a driver simulator subjects are given the opportunity to experience different traffic or information scenarios such that their decision and choice processes are revealed by the consequent actions they take. Those examining driver behavior under ATMIS conditions in recent years include Bonsall and Parry (1991), Ayland and Bright (1991), Koutsopoulos, Lotan, and Yang (1994), Chen and Mahmassani (1993), Vaughn, Abdel-Aty, Kitamura, and Jovanis (1993), Adler, Recker and McNally (1992a, b, and 1993; and Hu, Rothery, and Mahmassani (1992).

Adler et al. (1992a, b, and 1993) have developed an interactive computer-based simulator named FASTCARS. Its purpose is to gather data for estimating and calibrating predictive models of driver behavior under conditions of real-time information. It was written in Turbo Pascal, and designed to run on a 386-series PC running at least 33 megahertz and equipped with VGA graphics and a voice adapter. The authors claim that it is not a pure driving simulator, but rather simulates real-time travel decision-making conditions. It presents a series of possible environments tied to the experience that a subject has with the basic environment and studies temporal and spatial factors such as perceptions of speed and volume, time lapse, network familiarity, information acquisition, and travel goal specification and evaluation. The simulator encompasses the entire driving process from pre-trip planning to arrival at the destination. During the trip, players are required to make a range of choices, including specification of goals, rerouting where necessary, changing lanes, and making decisions as to whether or not to use specific information technologies, such as in-car guidance or advisory signage. Pre-trip planning involves selection of departure time and initial route choice. In addition, travel objectives for each trip must be specified. During post-trip debriefing, subjects evaluate their success in meeting their pre-trip goals.

Researchers at MIT have also developed an interactive simulator to facilitate data collection and calibration of a route choice model. Their simulator uses fuzzy set theory, fuzzy control, and approximate reasoning (Koutsopoulos, Polydoropoulou, and Ben-Akiva, 1995) The model is loosely based on a previous study of the dynamics of driver behavior under conditions of provision of real-time information (IGOR: Interactive Guidance On Routes, Bonsall and Parry, 1991). IGOR simulates en-route travel through a network and emulates an in-vehicle navigation system to provide players with real-time route guidance so that drivers’ compliance with guidance advice can be evaluated. The quality of advice is manipulated, and the relationship between advice quality and advice acceptance was determined. The Koutsopoulos et al. (1994) model enhances the use of the interface, allows for modeling different operating conditions, improves the information provision capabilities available to the driver, and accounts for the driving task. A graphic display shows a car moving through a network and information is presented through a roadside display/broadcasting system as well as a graphical in-vehicle information window.

Chen and Mahmassani (1993) also developed a simulator that integrates a traffic simulator program and offers the capability for multiple driver participants (DYNASMART). This models pre-trip planning, en-route travel, and post-trip evaluation. Pre-trip planning involves selection of a departure time and a path. At the selected departure time, players see a display of the network with expected travel time for specific routes. An option is provided to allow departure on time or to delay the trip. The initial route is selected at the time of departure. The explicit purpose behind building this simulator was to examine the behavioral processes underlying commuter decisions on route diversions including en-route and day-to-day departure time and route choices as influenced by the provision of real-time traffic information. Three components are visually displayed by this simulator in en-route conditions: a network illustrator, a legend window for explaining color codings, and a real-time message display. Real-time updates of vehicle location are provided and where turn decisions have to be made, this information set is analyzed to determine whether the current route will be continued or an alternate path selected. The emphasis in the Texas simulator is on investigating day-to-day adjustments. It allows manipulation of departure times, offers a capability for real-time interaction with and among multiple driver participants within a traffic network, and considers both system performance as influenced by driver response to real-time traffic information and driver behavior as influenced by real-time traffic information. The Texas simulator actually simulates traffic conditions, for its engine is a traffic flow simulator and ATIS information generator that displays information consistent with the processes actually taking place in the simulated traffic system. This dynamic approach allows the researcher to investigate day-to-day evolution of individual decisions under different information strategies. Thus driver learning behavior is allowed; this provides a longer-term dimension to simulation of driver behavior than is possible with other models.

Using driver simulators then provides data that acts as a basis for the development of user response models that in turn influence simulation assignment tools and their evaluation of network performance under conditions of real-time information provision (Mahmassani, 1996). Although currently state-of-the-art in terms of the types of information that can be obtained from driver responses to changing real-time traffic conditions, the various simulation experiments are not intended to totally replace actual field demonstrations and tests, but to provide information on what conceivably may happen as different traffic condition and information flow parameters are manipulated. Solving such issues are critical to the further development of IVHS technologies.

Adler et al. (1993) and Adler (1997) suggest that real-world implementation of ATMIS will involve multiple media formats which are both auditory and visual as well as varied message contents, route guidance and traffic condition information, and information display formats. Some information may be most suited to roadside posting and be passively available to all drivers even without appropriately modified in-car vehicle guidance systems. HAR, for example, would be available to most drivers but would require active acquisition via advisory radio signals. This in turn requires a deliberate effort by drivers to tune to the advisory radio station. Yet other information will be available only to a subset of drivers who will pay extra for this service but also have to make an active decision as to when to acquire it. The cost of an in-vehicle guidance system for general consumption is still being explored and simulation experiments are still being undertaken to determine drivers' willingness to both acquire and use ATMIS of different complexity. The Adler, Recker and McNally implementation of FASTCARS

(Freeway and Arterial Street Traffic Conflict Arousal and Resolution Simulator) was specifically designed to address this question.

Multiobjective travel planning has also been examined using computational process modeling (CPM). For example, Gärling et al. (1994) and Kwan (1995) have presented related models (SCHEDULER and GISICAS) that model the scheduled trip behavior of household members over specific time periods (e.g., 24 hours). Unfortunately, their models have not fully explored the problems of using an priori scheduled set of activities, which throughout the day are influenced by changing traffic conditions such as congestion and travel delays, to explore how the initial priorities set on different trip purposes can result in adjustments such as rerouting, activity deletion, activity delay, destination substitution, and activity rescheduling.

Simulation models such as those described above still need to be evaluated against real world activities. Few have been able to do this well because of the lack of precision in available panel or diary based data sets, where criticisms of the errors induced by self report delays and recall are often mentioned as a prime limiting factor. For example, perhaps the most important part of CPM is the Sequencer module that fits together trip purpose, activity duration, activity salience, and feasible destinations. We expect that analysis of the GPS tracks of travel and destination selection in the Lexington data will contribute to obtaining information critical to the design of such trip sequencing modules.

Choice Rules and Strategies

Mahmassani (1996) has suggested that the behavior of repetitive travelers is guided by simple heuristic strategies and a limited set of mental choice rules. As such it has been necessary to depart somewhat from the formal utility maximizing paradigm, replacing this rigid constraint with the more flexible one that travelers act in a boundedly rational manner by searching for an “acceptable” outcome. In previous work, (Mahmassani and Chang, 1985, 1987) and in work by Supernak (1992) evidence is gathered from psychological and behavioral decision theory literature to show that boundedly rational processes were more realistic and reliable predictors of travel behavior than were predictions made on the basis of utility maximization. Mahmassani (1996) suggests that the first strategy concerns the willingness of a commuter to change their latest choice of route, departure time, or both, and that these choices are made conditional on each other.

A second set of influences concern the degree to which a potential traveler is familiar with route and traffic conditions, and the extent to which exogenous information is likely to be accepted. Important concepts include the traveler’s preferred arrival time at a destination which are known to be dependent on attitudes towards risk as well as conditions in the workplace itself (e.g., traffic volume, congestion, parking availability). The boundedly rational character of the decision process is operationalized via a satisficing rule. This specifies that the user does not change departure time if the schedule delay (on day I) is within a user-specified indifference band or tolerance band. The limits of this tolerance band represent the earliest acceptable arrival times. Information about trip delay and experienced congestion, influence the location of the upper and lower limits of the indifference band.

Route selection requires another set of rules. As Gärling and Hirtle (1990) have indicated, many trips may be regarded and modeled as a set of choices in which local decisions relating to route switching or selection of route segments to complete a trip chain, may result in behaviors that are other than globally optimal. For example, a traveler's schedule on a particular day may involve a trip to the workplace, a trip from workplace to another destination (e.g., lunch), a return to work trip, a trip to recreation or social activities from work, a trip from recreation/social to shopping and a trip from shopping to home in the evening. On different segments of such a trip' criteria for path selection may change from minimizing time or distance to maximizing aesthetics, maximizing use of freeway segments, or restricting travel to arterial or local streets such that signalization at intersections is minimized. The result may be a trip that is perfectly acceptable and satisfactory for the traveler but which significantly exceeds traditional time, cost or distance minimization rules. We anticipate that we should be able to do data mining on the Lexington material to investigate this hypothesis.

In general it is assumed that the purpose of providing exogenous information to travelers en route is to help them optimize route selection and overall to optimize system performance. But, what if this is not relevant for most habitual or repetitive trips? What then is the purpose of ATMIS? Experimentation with different choice rules has only recently begun (e.g., Mahmassani, 1996). There appears to be considerable potential, both in the use of driver simulators and the use of Geographical Information Systems (GIS) to explore how different decision rules, when implemented, impact features such as departure time and path selection (see Golledge and Egenhofer, 1998, for a selection of articles of these problems). As the traffic system evolves throughout the day, travel plans developed prior to initial departure, may have to be modified or altered. These changes invariably are related to the type, amount, time and reliability of information that can be accessed by the potential traveler.

En-route decisions and Information Processing

Included among the temporal and spatial factors that are involved in en-route driver decision making and information processing are those such as perception of speed, perception of traffic volume, perception of time lapse associated with completing segments of the designated route, familiarity with the network through which travel takes place, the ease and rate of information acquisition about the driving environment, travel goal specification and destination choice, evaluation of the priority of the goals associated with a specific trip, knowledge of landmarks and waypoints on and off a particular route, and perception of and familiarity with areas through which a route passes (including perceived safety, perceived areas to be traveled, and perceived feasibility for destination substitution). These factors appear to be elemental to the decision-making processes of trip making, goal specification, route choice, information search, and reaction to possible diversion. They all lend themselves to specification within experimental conditions and will be manipulated to produce participant reactions.

The information needed to allow the previously specified decision-making processes to work include knowledge of the location of the destination at which a goal can be achieved, plus information about a feasible set of possible alternative destination sites; information that will influence route segment selection and the overall configuration of the most satisfactory route for achieving goals; information about congestion and its applicability to different lanes along which traffic flows; and the availability of information technologies to provide input to each of these decision making strategies. These information technologies can be embedded in ATMIS, signalization, and radio broadcasts. Both general network information and individualized knowledge structures can be combined to provide the basic en-route scenarios that allow an individual to either conform to or change route selection criteria during a trip, or provides the opportunity for driver preferences for handling both network and traffic conditions to be expressed in the ongoing decision-making process. Since only observed trip purposes and destinations are recorded in the Lexington data, there will be little direct contribution to this segment of travel behavior modeling, but we will see if new insights may be generated that would impact variable selection for these purposes.

Over the years the California PATH institution sponsored a number of projects and a number of investigators who have conducted research on activity patterns and travel behavior (Recker, 1995; Recker, Root, and McNally, 1983; Recker, McNally, and Root, 1985; McNally, 1997, 1998; McNally and Recker, 1987; Wang, 1996). Currently there is little active work on tests of the efficacy of tracking vehicles and collecting in-car data as part of ongoing research on activity patterns, although some studies have been proposed at UC Santa Barbara (Fohi, Curtin, Goodchild, and Church, 1996), which relate to the use of GPS-based traveler information systems. Other research includes that of Farrell, Barth, Galijan, and Sinko (1998) but the latter is more concerned with GPS as an aid to INS than to providing data on recurring activity patterns.

Methodology

It is possible to delve into human behavior patterns along a time axis at both an individual and an aggregate level. Individual variations in the perception, cognition, and measurement of space and time, and variations in capability constraints, coupling constraints, and authority constraints, may be averaged to produce an aggregate constraints picture when individuals are grouped in different ways. Activity patterns are related to the frequency and regularity with which particular social groups choose to participate in those activities. A possible form that such regularities might take is to a certain extent determined by the study area itself, demographics of the local population, and the sociocultural environment. For different groups it appears that quite different patterns of work, social, recreational, and shopping trips occur (Janelle et al 1998).

In this study we plan to focus on variations or regularity of different kinds of trips across a seven day period. This time scale can reveal the underlying local patterns and help to identify changes of trip frequency and episodic intervals of trip making over the weekly period.

Our methodology is a pioneer method of data collection compared to the diary recall-interview approached often used in data collected on travel behavior. It is suggested that the GPS and real-time in-car computer recording of travel purposes will have a considerable advantage in terms of accuracy and should not suffer from misrecall, deliberate or other forms of misstatements. In particular, one of the major problems in many travel diary studies is the omittance of very short trips or the rounding of trip times to selected time intervals. GPS recording can provide more accurate locational information and can tie it more precisely into specific times.

Since time can effect people's travel choices in different ways, the first step in our methodology 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. This 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 activity in the Lexington data included trips to pick up passengers, work trips, return home trips, shopping, religion, drop off passengers, work related business, trips to school, college, or university, eating out, social or recreational, medical or dental, and other errands.

Comparing all possible combinations of two days in a week with respect to household travel behavior, may or may not yield significant differences between the two patterns (e.g. maybe Monday and Friday events will be correlated, while Sunday and Wednesday will not). Using multiple criterion measures such as the K-group multivariate analysis of variance (MANO VA) and discriminate analysis however can help determine if differences do exist.

Based on the days of the week the next step is to reformat the collected trip counts from the Lexington travel survey data into seven daily groups (Sunday through Saturday). Trip counts for each day of the week will then be further divided based on different trip purposes or trip types as dependent variables. Using the K-group MANOVA capability we can compare 13 different variables simultaneously for each of the seven working days with a null hypotheses of no significant difference between the 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 varies significantly on different days (e.g. Hanson and Huff, 1982, 1983, 1985, 1988; Timmermans and Golledge, 1990), to our knowledge no statistical testing has been put forward that explicitly measures the degree of coincidence of trips across such a seven day period. We anticipate we will reject the null hypothesis and support the general hypothesis that people's activities differ over the set of 13 trip variables and the seven week days.

Following this we will use discriminate analysis for describing major differences among the seven day groups previously used in the multiple analysis of variance. Using seven week days and 13 trip purposes the number of possible discriminate functions is six. The coefficients for each of the trip variables on the six discriminate functions will then be examined. The structure matrix will also be examined to show the correlation between each discriminate function and each of the original trip purposes. Generally it is assumed that greatest stability of the function variable correlations found in the structure matrix exist in small or medium sized samples, especially when there are high or fairly high interrelations among the variables. Also the correlations give a direct indication of which variables are most closely aligned with the unobserved trait which the cononocal variables (discriminate function) represents. We will also determine variable redundancy. A useful device for determining directional differences among the groups when two or more discriminate functions exist is in to graph them in the discriminate plane. In the horizontal direction, correspondents of the first discriminate function and lateral separation among the groups indicates how much they have been differentiated on the basis of this function. The vertical dimension corresponds to the second discriminate function and tells which groups are being differentiated in a way unrelated to the way that they were separated on the first discriminate function. We will use this graphical display method to search for other regularities among variables and groups. This should help us decide which trip purposes are related to other trip purposes on which particular day or days of the week. This explores the basic nature of multi-purpose or multi-stop trips, as well as giving insights on trip sequencing.

Finally, post-hoc procedures using Hotelling's T2 and univariate T tests will be undertaken. This is done to find out which groups and which variables are responsible for the overall association found in the discriminate analysis. Hotelling's multivariate tests (T2) and univariate T-tests determine which pair or groups differ significantly on the set of trip variables. This should highlight which days of the week are most similar to each other and which trip purposes are most frequently repeated on those days to create the patterns of similarity.

A second problem will be to compare the trips made by individuals to those suggested by various optimization network flow models. At this stage we simply plan to use path selection models found in TRANSCAD and the expanded ArcInfo Network module. Basically the study area has been geocoded and the network exists as a node-link database. Using ArcInfo functionalities we can determine distance and times from specific origins to given destinations in the geocoded network, and compare them with the actual trips and temporal intervals between origin and destination GPS-based recordings of locations. Although many conceptual criticisms have been made of standard network flow optimization models, there have been very few opportunities to compare the specific routes taken by real-world travelers with those predicted by network models.

To do model comparisons, we plan to construct origin destination matrices for both actual and different model predictions and then, using an innovative Quadratic Assignment Program (QAP) that is designed to determine which model most accurately reproduces the original data, we should be able to evaluate the accuracy of each of the different model types. The QAP method (Hubert, Golledge, and Costanzo, 1982; Hubert and Golledge, 1981, 1982; Hubert and Schultz, 1976) takes as its critical operating factors an original distance, similarities, or correlation matrix calculated on the real data, and compares via a cross-product procedure the degree of coincidence with a model-predicted database. This is done by calculating an initial cross-product statistic, then randomly commuting the rows and columns of the model matrix to create a distribution of possible outcomes. The procedure is distribution free and generates its own reference distribution. The proportion of randomly commuted matrices that give better or worse fits than the original model then define the significance level of the measured association.

We may also use Factor Analysis to examine the relations among the set of random variables observed or counted or measured, which are associated with trips. In this case, we view the trips recorded in the Lexington area as a trip group. Obviously, each trip made by a household will be an 'individual entity' within this group. The random variables of the set to be analyzed associated with trips may consist of any attributes on which the individual trips of the group differ. With transportation problems, the random variables we are most concerned with are probably trip time, trip length, and trip purpose. The contributing factors could be trip types, day of week on which the trip happened, and so on.

Travel behavior is typically related to the movement of individuals from place to place, with the emphasis being upon the actual quantitative changes that take place and the nature of the localities concerned. One important aspect of travel trips as representations of people's movements in a two dimensional space is the physical direction of the movements. Once information about the trips made by people has been recorded, inherently the change of direction of the trips are available to us. These kinds of data that get direction measurement involved are usually called circular data. When dealing with problems arising with circular data, we typically use some relatively unusual statistics.

For example, we know that one of inherent attributes about circular data is its periodicity. In a circular world, simple arithmetic operations like addition do not work. Suppose we have one direction, say 200 degrees from north; if we add 360 degrees to it, we are not getting 560, but will return to the original direction. This unusual form of addition can clearly cause problems, especially in the case where we have the individual trip orientation information of a study area and intend to collectively determine the local main traffic flow direction (the average of trip orientation). A solution for this could be taking the vector means rather than using the traditional addition operation. For the Lexington travel data, the trip information has been collected within a period of a week. Depending on the trip types to which each trip belongs and day of week on which the trip happened, trips may be long-distance or short-distance. By following trips and breaking the trips at those main turning points, we may divide each trip into a set of vector segments and then compute the mean orientation for the single trip. A very good representation of the final mean trip orientation data would be a circular histogram. Hopefully, we can show a trip flow direction circular histogram for each day of the week and dynamically link them using the Java media player. The final result would be a vivid demonstration of the variation of traffic flow direction change in the Lexington area across a week.

A Case Study: Variations in Travel by Days of the Week
Analytical Method used and Results
K-group Multivariate Analysis of Variance and Discriminant Analysis

Time might affect people’s travel choice in more then one way. An approximately complete set of activity choice may be formed to evaluate the potential influence of time on people’s activity choice. The result derived will help us understand the temporal nature of activity spaces with respect to the overall mix of activities in which people participate. For instance, if we were comparing people’s activities on the two days of a week, say, Thursday and Friday, we would obtain a more detailed and informative breakdown of the differential effects of time on people’s travel behavior if they were split into its detailed types: pick up passenger, return home, work place. etc. Comparing two days of a week on total trip counts made by a household might yield no significant difference; however, the multiple criterion measures mentioned above may make such a difference.

Based on days of the week we reformatted the collected trip counts from the Lexington Travel Survey Data into groups —Monday, Tuesday Wednesday, Thursday Friday, Saturday and Sunday. Trips counts for each day of the week were further divided based on different trip purposes or trip types as dependent variables. Table one 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 MANOVA capability provided by SPSS, we compare the 7 groups on the remaining 13 dependent variables simultaneously. Our null hypothesis for MANOVA analysis is: H_0: $\mu1=\mu2=\mu3=\mu4=\mu5=\mu6=\mu7$

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

Table 1. Activity types

-9	Unknown
1	Pick Up Passenger
2	Drop Off Passenger
3	Work Place
4	Work-Related Business
5	School, College, University
6	Shopping
7	Other Errands
8	Eat Out
9	Social or Recreational
10	Medical or Dental
11	Return Home
12	Religious Activities
13	Volunteer Work
14	Community Meetings
15	Other
16	To Day Care or Preschool
17	Go Along For The Ride
1 8	Work or School

Table 2 gives the multivariate F's from the SPSS MANOVA run on the problem. Using 0.05 as the criterion for rejection, the significance of F indicates we should reject the null hypothesis and conclude that people's activities differ overall on the set of 13 trip variables.

Table 2. Multivariate F's from SPSS MANOVA

Multivariate Tests of Significance (S = 6, M = 3, N = 390 1/2)

Test Name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	.15292	1.58530	78.00	4728.00	.001
Hotellings	.16251	1.62784	78.00	4688.00	.000
Wilks	.85421	1.60697	78.00	4323.27	.001
Roys	.08744				

Next, we use Discriminant Analysis for describing major differences among the seven day-of-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 function remains. The coefficients for each of the trip variables of the six discriminant functions are listed as follows:

Table 3: Standardized Canonical Discriminant Function Coefficients

Activity		Function 1	2	3	4	5	6
Pick-up passenger	**PURP1**	.114	.389	-.288	.049	-.227	-.392
Medical or Dental	**PURP10**	.307	.060	.083	.264	.466	.562
Return Home	**PURP11**	.007	-.095	-.485	-.816	-.391	.652
Religious Activities	**PURP12**	-.530	.699	.150	.164	.476	-.051
Other	**PURP15**	.140	-.249	-.187	.113	-.169	.274
Drop off Passenger	**PURP2**	.130	.317	.336	-.086	.052	.161
Workplace	**PURP3**	.595	-.098	.444	-.228	.325	-.348
Work-related Business	**PURP4**	.283	.415	-.108	.655	-.375	.033
School/College	**PURP5**	.259	.224	.037	.053	.003	-.070
Shopping	**PURP6**	-.057	.080	-.013	.177	.231	-.237
Other Errands	**PURP7**	.114	-.372	-.520	.268	.544	-.293
Eat Out	**PURP8**	.168	-.096	.313	.119	-.058	.032
Social/Recreational	**PURP9**	-.072	-.230	.459	.304	-.166	.130

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 variable (in this case, trip with specific purpose, e.g. PURP1).

Table 4: Structure Matrix

Activity		Function 1	2	3	4	5	6
Workplace	**PURP3**	.635(*)	.515	.318	-.371	.184	-.214
School/College	**PURP5**	.367(*)	.246	-.128	-.117	.024	.018
Religious Activities	**PURP12**	-.343	.614(*)	.054	-.084	.360	.197
Pick-up passenger	**PURP1**	.320	.374(*)	-.254	-.103	-.165	-.366
Drop off Passenger	**PURP2**	.249	.262(*)	.121	-.175	.110	.113
Other Errands	**PURP7**	.221	-.208	-.531(*)	.148	.449	-.130
Social/Recreational	**PURP9**	-.062	-.217	.374(*)	.216	-.188	.154
Eat Out	**PURP8**	.207	-.058	.251(*)	.064	.014	.071
Work-related Business	**PURP4**	.344	.389	-.168	.518(*)	-.377	.110
Return Home	**PURP11**	.247	.252	-.323	-.465(*)	-.010	.413
Shopping	**PURP6**	.010	.010	-.205	.094	.309(*)	-.042
Medical or Dental	**PURP10**	.308	.055	-.007	.247	.478	.573(*)
Other	**PURP15**	.137	-.111	-.204	.108	-.069	.402(*)

There are two methods for interpreting the discriminant functions:

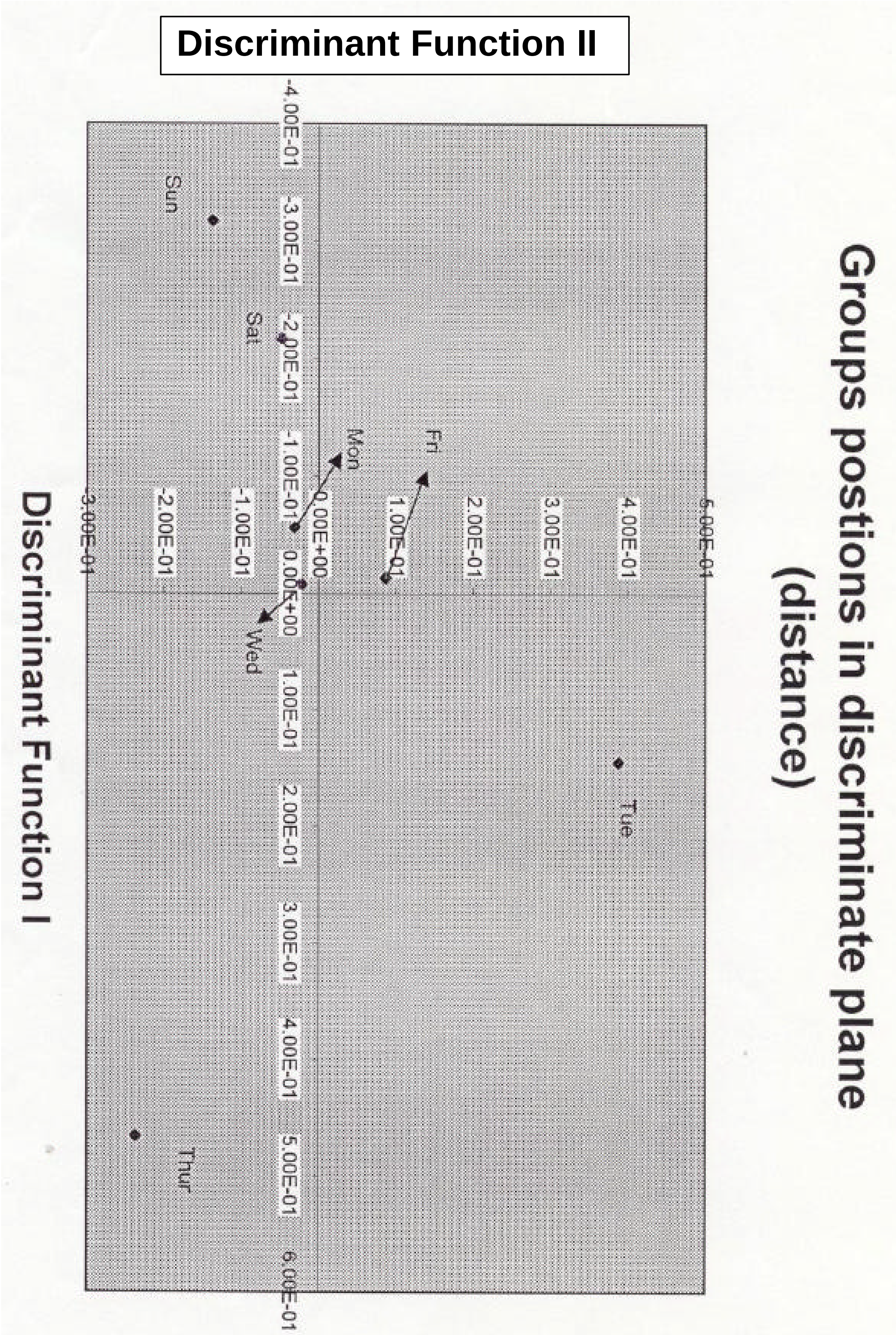
1. Examine the standardized coefficients--- these are obtained by multiplying the raw coefficient for each variable by the standard deviation for that variable.
3. Examine the discriminant function-variable correlation (structure matrix).

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 in the set.

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 shows the positions of Groups for Lexington's travel survey data in the discriminant plane defined by Function 1 & 2 and function 1 & 3).

For interpreting the first discriminant function, as mentioned earlier, we use both the standardized coefficients and the discriminant function-variable correlation. Examining Table 4 for the first discriminant function, we see that it is primarily the two variables -- trip with PURP3 (work place) and trip with PURP5 (school, college, university) that defines the function, with PURP12 and PURP4 secondarily involved. Since the correlation for PURP12 is negative, this means that the groups that have higher PURP12 trip counts scored lower on the first discriminant.

Now, examining the standardized coefficients 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 purp1, 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 is characterized as work—school—religious activity dominant. The three kinds of trips maximized the difference of people's activities among the days of a week. And on the other hand, we know that return home, shopping and social recreation trips show not much variation within the period of one week. Note, from the group centroids, it is on weekend people that live in Lexington area go to religious activities and don't go to work place or study place (school, college and university), which is obvious. We may also infer from the relative large positive coefficient of purp10 that medical or dental trips are typically made during weekdays but not on weekend.


Groups postions in discriminate plane
(distance)
Discriminant Function II
Discriminant Function I
-4.00E-01
-3.00E-01
-2.00E-01
-1.00E-01
0.00E+00
1.00E-01
2.00E-01
3.00E-01
4.00E-01
5.00E-01
6.00E-01
-3.00E-01
-2.00E-01
-1.00E-01
0.00E+00
1.00E-01
2.00E-01
3.00E-01
4.00E-01
5.00E-01
Sun
Sat
Mon
Fri
Wed
Tue
Thur

Post Hoc Procedures

Hotelling T^2's and Univariate t tests

After a significant overall multivariate result one would like to know which groups and which variables were responsible for that association, i.e., a more detailed breakdown. Pairwise multivariate tests (T^2's) and univariate t test are used to determine which pair of groups differs significantly on the set of trip variables. Here, we use a loose criterion, say, each at the .05 level for univariate t tests, to determine which kind of trips are contributing the significant pairwise difference of people's travel pattern on two different days of the week. Some interesting results are showed as follows:

Pairwise activity comparison based on groups:

Thursday - Friday Not Significant
purp1 pickup passenger Significant

Tuesday - Thursday Not Significant

Monday - Thursday Not Significant
purp4 work-related business Significant

Thursday - Saturday Significant
purp1 pickup passenger Significant
purp3 work place Significant
purp4 work-related business Significant
purp5 school, college, university Significant
purp11 return home Significant

Saturday - Sunday Significant
purp7 other errands Significant
purpl2 religious activities. Significant

Wednesday - Sunday Significant
purp3 work place Significant
purp10 medical or dental Significant
purpl2 religious activities Significant

Tuesday - Saturday Significant
purp3 work place. Significant

Monday - Tuesday Not Significant

Wednesday - Saturday Not Significant
purp3 work place Significant
purp10 medical or dental Significant

Friday - Saturday	Significant
purp3 work place	Significant
purp7 other errands	Significant
purpl2 religious activity	Significant

The major difference between activities on weekdays and weekends is whether to make work-trips. Work trips usually go from home to a specific place then back on a regular basis, and usually they occur on five days per week.

It is worth noticing that people's activity-choice on Saturday and Sunday also show contrasting difference. Saturday time typically is devoted to errands compared to that of Sunday, while Sunday's religious activity can be viewed in terms of routines. It is more or less performed on a weekly basis. Thus it is easy for us to understand why the two points that represents Saturday and Sunday on the discriminant plane are separated widely.

Ongoing Research

Following this case study, we found that some of the household data in the Lexington study was incomplete and thus we have to reduce the household set from 100 to about 80. This is still a significant number. There also appears to be some problems with the digitized basemap; a preliminary search through the CD-ROM obtained from DOT shows that only one of the two counties was thoroughly geocoded. 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. It appears that we may also have to obtain land-use maps and geocode the locations of specific urban functions such as shopping centers, educational institutions, parks and recreational areas, churches, and so on. This preliminary session on evaluating the cleanliness of the dataset and transforming it to one that we can use will be followed by a MANOVA based examination of the activity patterns, thus determining the nature of activity patterns for specific purposes on different days of the week. A second project will be to evaluate standard network models that define optimal routes for origin destination pairs and trip chains and then compare them with the trips actually made by the sample members. This will be followed by an evaluation (using Quadratic Assignment Procedures) of which of the models most closely reproduce the actual dataset. A third project is to examine the daily and weekly temporal sequencing of trips to define repetitive cycles. Two-dimensional (Spatial) Spectral Analysis will be used. A fourth project will be to examine directionality in trip making using circular statistics. We will examine the directional relation between different trip types, as well as looking for different trip patterns for a given type on different weekdays.

Ultimately, we will focus on two areas; (1) adding a final touch to the considerable volume of data on destination choice activity behavior as reconstructed in the past from whole or partial week diaries; (2) evaluating which of the set of prevailing optimizing network flow models most closely represent the actual behavior of sample members. This will provide us some hard information on the degree to which travelers are spatially rational or whether other criteria appear to be more important in choosing routes for single and multi-purpose trips.

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An Analysis of Household Travel Behavior Based on GPS

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Introduction

Goals

A major goal of Transportation Science is to enhance the effectiveness of ITS services. Recently a number of traffic management centers have been developed capable of using multimedia investigation techniques to analyze volumes and patterns of traffic flow. One area to which attention is constantly turning is that related to traffic dynamics. While there are a large number of means for observing traffic, research on traffic flow theory has still lacked that easily accessible and highly accurate geocoded database as a support for building and testing destination choice, traffic flow, and cyclical effects in traffic dynamics. Part of the successful implementation of traffic management centers depends on the adequacy and accuracy of their information services. The more we know about the actual behavior of people not just in the aggregate, but in terms of the many repetitive individual patterns that are likely to be pursued by households living in different parts of the city, the more it is likely that the effectiveness of traffic management services will be enhanced. It is anticipated that our examination of the dynamics of travel behavior as revealed in the GPS generated tracking of destination choices, will further our knowledge of several still unresearched questions on repetition behavior, path selection, multi-stop trips, cyclic travel patterns, and the relevance of single models for predicting daily travel behavior.

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. We also will try to recreate patterns of stops on single and multi-stop trips and predict what routes may have been taken using correctional network based trip allocation models.

Behavioral Geographers are concerned with where people carry out various activities: where they live, work, shop, use other services or find their recreation, and how people come to their travel-related decisions. Traditionally, considerable attention has been given to the study of locational and spatial choice aspects of human activities. It is relatively easy to study the locational attributes attached to people's activities occurring in a spatial context in GIS. But what is usually overlooked is the time label related to activities, which typically refers to a clock time or calendar time.

Typically, the study of human activities may be approached from the perspective of a spatial-temporal context. One innovative and well-known view is Hagerstrand's time geography. This approach shows that people's activities are described as trajectories or paths defined within a bounded region of time and space, from when and where an individual comes into being (birth) to the point when and where he or she ceases to live. As a constrained environment, time and space are inseparable from the intricacies of human behavior. However, using time and space as an approach is contingent upon the other constraints that operate on individuals. For example in the study of the relationship between time and people's daily travel behavior, at the individual level, it is nearly impossible to extract useful information about the influence of time on people's choice behavior, about the observable realism of movements made by individuals. Human decisions about travel seem to be random, non—optimal, and to a certain extent, non-periodic, in a temporal sense. Any appearance of intervening opportunities may shatter the seemingly reasonable behavior pattern into pieces. Real world human behavior is different from the scaled-down controlled environment intentionally formed in a lab. Human behaviors are subject to various physical, psychological, social, cultural, and other conditions.

However, It is possible for us to delve into human behavior patterns along a time axis at an aggregate level. Individual variations in the perception, conception, and measurement of space and time, variations in capability constraints, coupling constraints and authority constraints that are encountered by individuals in an environment are sometimes accounted for by averaging. 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 selected social groups, or the local social-cultural environment. Typically, trips for different purposes, such as work trips, social and recreational trips, or shopping trips, tend to exhibit quite contrasting time distributions.

Here, we would like to focus our study on variations of regularity of different kinds of trips across a week. This time scale, although relatively coarser than hour times used by other behavioral researchers, is sufficient to reveal the underlying regional travel behavioral pattern and satisfy our needs of trying to identify the change of trip frequency during the period of a week.

Research Area and Data Collection Method

Research Area: The study area of this research is located at Lexington, 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 are collected using an automatic device that collected real-time self-reported travel-related information along with automatically recording GPS position information of the vehicles in use. This new data collection method, compared to the approach of recall-interview or travel diary that has been used a lot in the past, has the advantage of accuracy. When data is entered in real-time, the chance of omitting very short trips or rounding trips times are 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 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.

Research Plan: Much research over the last two decades has paid attention to the study of locational and spatial choice aspects of human activities. The development of Geographical Information Systems (GIS) has provided an ability to produce geocoded spatial databases and has consequently assisted in the determination of relevant variables for destination choice. The temporal sequencing of activities has also received increasing attention. Access to the GPS/in-car computer data record from the Lexington study provides an opportunity to combine both real-time data input with GPS locational accuracy.

Typically the study of human activities can be approached from the perspective of a spatial-temporal context. Following the fundamental ideas expressed in Hagerstrand's "Time Geography" (1970, 1976) and those of his followers such as Lentorp (1978), and more recently the works of Miller (1991, 1999), a spatio-temporal approach to the examination of people's activities should be able to focus on the correlation between daily trajectories. Various diary surveys have concluded that on a daily basis many activities are non-periodic, and destination choices are difficult to rationalize. We plan in this study to use the GPS-based data from Lexington to look in detail at the actual time paths of individuals, to determine to what extend time-paths of individuals or groups can be best fit by simple decision making models based on criteria such as shortest path and least time. We also plan to explicitly examine trip chains and discover what regularity exists both in the periodic occurrence of similar chains and the sequences in which particular activities are performed.

Methodology

It is possible to delve into human behavior patterns along a time axis at both an individual and an aggregate level. Individual variations in the perception, cognition, and measurement of space and time, and variations in capability constraints, coupling constraints, and authority constraints, may be averaged to produce an aggregate constraints picture when individuals are grouped in different ways. Activity patterns are related to the frequency and regularity with which particular social groups choose to participate in those activities. A possible form that such regularities might take is to a certain extent determined by the study area itself, demographics of the local population, and the sociocultural environment. For different groups it appears that quite different patterns of work, social, recreational, and shopping trips occur (Janelle et al 1998).

In this study we plan to focus on variations or regularity of different kinds of trips across a seven day period. This time scale can reveal the underlying local patterns and help to identify changes of trip frequency and episodic intervals of trip making over the weekly period.

Our methodology is a pioneer method of data collection compared to the diary recall-interview approached often used in data collected on travel behavior. It is suggested that the GPS and real-time in-car computer recording of travel purposes will have a considerable advantage in terms of accuracy and should not suffer from misrecall, deliberate or other forms of misstatements. In particular, one of the major problems in many travel diary studies is the omittance of very short trips or the rounding of trip times to selected time intervals. GPS recording can provide more accurate locational information and can tie it more precisely into specific times.

Since time can effect people's travel choices in different ways, the first step in our methodology 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. This 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 activity in the Lexington data included trips to pick up passengers, work trips, return home trips, shopping, religion, drop off passengers, work related business, trips to school, college, or university, eating out, social or recreational, medical or dental, and other errands.

Comparing all possible combinations of two days in a week with respect to household travel behavior, may or may not yield significant differences between the two patterns (e.g. maybe Monday and Friday events will be correlated, while Sunday and Wednesday will not). Using multiple criterion measures such as the K-group multivariate analysis of variance (MANOVA) and discriminate analysis however can help determine if differences do exist.

Based on the days of the week the next step is to reformat the collected trip counts from the Lexington travel survey data into seven daily groups (Sunday through Saturday). Trip counts for each day of the week will then be further divided based on different trip purposes or trip types as dependent variables. Using the K-group MANOVA capability we can compare 13 different variables simultaneously for each of the seven working days with a null hypotheses of no significant difference between the 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 varies significantly on different days (e.g. Hanson and Huff, 1982, 1983, 1985, 1988; Timmermans and Golledge, 1990), to our knowledge no statistical testing has been put forward that explicitly measures the degree of coincidence of trips across such a seven day period. We anticipate we will reject the null hypothesis and support the general hypothesis that people's activities differ over the set of 13 trip variables and the seven week days.

Following this we will use discriminate analysis for describing major differences among the seven day groups previously used in the multiple analysis of variance. Using seven week days and 13 trip purposes the number of possible discriminate functions is six. The coefficients for each of the trip variables on the six discriminate functions will then be examined. The structure matrix will also be examined to show the correlation between each discriminate function and each of the original trip purposes. Generally it is assumed that greatest stability of the function variable correlations found in the structure matrix exist in small or medium sized samples, especially when there are high or fairly high interrelations among the variables. Also the correlations give a direct indication of which variables are most closely aligned with the unobserved trait which the cononocal variables (discriminate function) represents. We will also determine variable redundancy. A useful device for determining directional differences among the groups when two or more discriminate functions exist is in to graph them in the discriminate plane. In the horizontal direction, correspondents of the first discriminate function and lateral separation among the groups indicates how much they have been differentiated on the basis of this function. The vertical dimension corresponds to the second discriminate function and tells which groups are being differentiated in a way unrelated to the way that they were separated on the first discriminate function. We will use this graphical display method to search for other regularities among variables and groups. This should help us decide which trip purposes are related to other trip purposes on which particular day or days of the week. This explores the basic nature of multi-purpose or multi-stop trips, as well as giving insights on trip sequencing.

Finally, post-hoc procedures using Hotelling's T^2 and univariate T tests will be undertaken. This is done to find out which groups and which variables are responsible for the overall association found in the discriminate analysis. Hotelling's multivariate tests (T^2) and univariate T-tests determine which pair or groups differ significantly on the set of trip variables. This should highlight which days of the week are most similar to each other and which trip purposes are most frequently repeated on those days to create the patterns of similarity.

We will also use Factor Analysis to examine the relations among the set of random variables observed or counted or measured, which are associated with trips. In this case, we view the trips recorded in the Lexington area as a trip group. Obviously, each trip made by a household will be an 'individual entity' within this group. The random variables of the set to be analyzed associated with trips may consist of any attributes on which the individual trips of the group differ. With transportation problems, the random variables we are most concerned with are probably trip time, trip length, and trip purpose. The contributing factors could be trip types, day of week on which the trip happened, and so on.

A Case Study: Variations in Travel by Days of the Week

Analytical Method used and Results

K-group Multivariate Analysis of Variance and Discriminant Analysis

Time might affect people's travel choice in more then one way. An approximately complete set of activity choice may be formed to evaluate the potential influence of time on people's activity choice. The result derived will help us understand the temporal nature of activity spaces with respect to the overall mix of activities in which people participate. For instance, if we were comparing people's activities on the two days of a week, say, Thursday and Friday, we would obtain a more detailed and informative breakdown of the differential effects of time on people's travel behavior if they were split into its detailed types: pick up passenger, return home, work place. etc. Comparing two days of a week on total trip counts made by a household might yield no significant difference; however, the multiple criterion measures mentioned above may make such a difference.

Based on days of the week we reformatted the collected trip counts from the Lexington Travel Survey Data into groups —Monday, Tuesday Wednesday, Thursday Friday, Saturday and Sunday. Trips counts for each day of the week were further divided based on different trip purposes or trip types as dependent variables. Table one 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 MANOVA capability provided by SPSS, we compare the 7 groups on the remaining 13 dependent variables simultaneously. Our null hypothesis for MANOVA analysis is: H_0: $\mu1=\mu2=\mu3=\mu4=\mu5=\mu6=\mu7$
(Population mean vectors are equal. Namely, there is no difference on people's travel activities across the week.)

Table 1. Activity types

-9	Unknown
1	Pick Up Passenger
2	Drop Off Passenger
3	Work Place
4	Work-Related Business
5	School, College, University
6	Shopping
7	Other Errands
8	Eat Out
9	Social or Recreational
10	Medical or Dental
11	Return Home
12	Religious Activities
13	Volunteer Work
14	Community Meetings
15	Other
16	To Day Care or Preschool
17	Go Along For The Ride
1 8	Work or School

Table 2 gives the multivariate F's from the SPSS MANOVA run on the problem. Using 0.05 as the criterion for rejection, the significance of F indicates we should reject the null hypothesis and conclude that people's activities differs overall on the set of 13 trip variables.

Table 2. Multivariate F's from SPSS MANOVA

Multivariate Tests of Significance (S = 6, M = 3, N = 390 1/2)

Test Name	Value	Approx. F	Hypoth. DF	Error DF	Sig. of F
Pillais	.15292	1.58530	78.00	4728.00	.001
Hotellings	.16251	1.62784	78.00	4688.00	.000
Wilks	.85421	1.60697	78.00	4323.27	.001
Roys	.08744				

Next, we use Discriminant Analysis for describing major differences among the seven day-of-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 function remains. The coefficients for each of the trip variables of the six discriminant functions are listed as follows:

Table 3: Standardized Canonical Discriminant Function Coefficients

		Function					
Activity		**1**	**2**	**3**	**4**	**5**	**6**
Pick-up passenger	**PURP1**	.114	.389	-.288	.049	-.227	-.392
Medical or Dental	**PURP10**	.307	.060	.083	.264	.466	.562
Return Home	**PURP11**	.007	-.095	-.485	-.816	-.391	.652
Religious Activities	**PURP12**	-.530	.699	.150	.164	.476	-.051
Other	**PURP15**	.140	-.249	-.187	.113	-.169	.274
Drop off Passenger	**PURP2**	.130	.317	.336	-.086	.052	.161
Workplace	**PURP3**	.595	-.098	.444	-.228	.325	-.348
Work-related Business	**PURP4**	.283	.415	-.108	.655	-.375	.033
School/College	**PURP5**	.259	.224	.037	.053	.003	-.070
Shopping	**PURP6**	-.057	.080	-.013	.177	.231	-.237
Other Errands	**PURP7**	.114	-.372	-.520	.268	.544	-.293
Eat Out	**PURP8**	.168	-.096	.313	.119	-.058	.032
Social/Recreational	**PURP9**	-.072	-.230	.459	.304	-.166	.130

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 variable (in this case, trip with specific purpose, e.g. PURP1).

Table 4: Structure Matrix (Discriminant Function/Variable Correlations)

Activity		Function 1	2	3	4	5	6
Workplace	**PURP3**	.635(*)	.515	.318	-.371	.184	-.214
School/College	**PURP5**	.367(*)	.246	-.128	-.117	.024	.018
Religious Activities	**PURP12**	-.343	.614(*)	.054	-.084	.360	.197
Pick-up passenger	**PURP1**	.320	.374(*)	-.254	-.103	-.165	-.366
Drop off Passenger	**PURP2**	.249	.262(*)	.121	-.175	.110	.113
Other Errands	**PURP7**	.221	-.208	-.531(*)	.148	.449	-.130
Social/Recreational	**PURP9**	-.062	-.217	.374(*)	.216	-.188	.154
Eat Out	**PURP8**	.207	-.058	.251(*)	.064	.014	.071
Work-related Business	**PURP4**	.344	.389	-.168	.518(*)	-.377	.110
Return Home	**PURP11**	.247	.252	-.323	-.465(*)	-.010	.413
Shopping	**PURP6**	.010	.010	-.205	.094	.309(*)	-.042
Medical or Dental	**PURP10**	.308	.055	-.007	.247	.478	.573(*)
Other	**PURP15**	.137	-.111	-.204	.108	-.069	.402(*)

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).

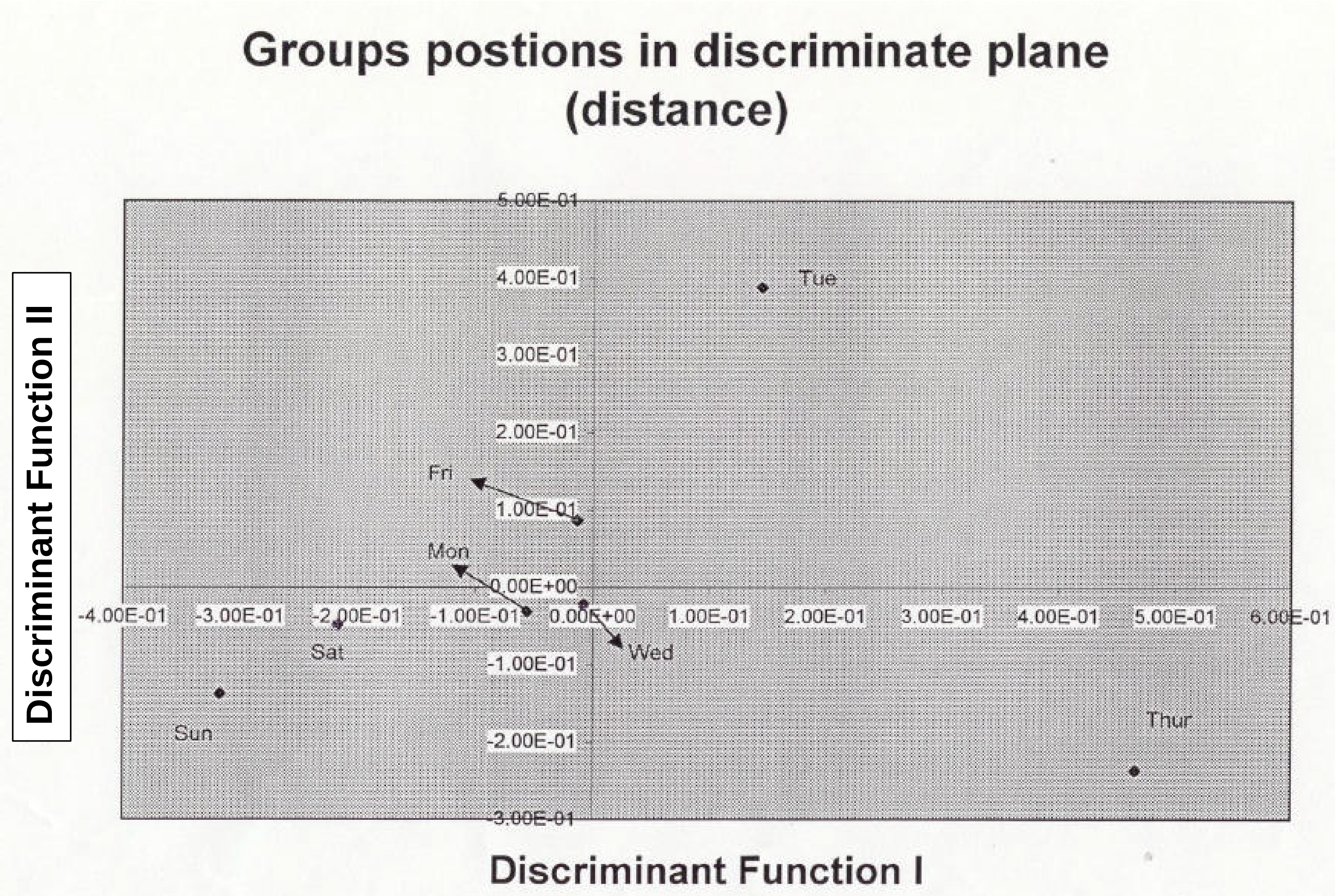
Generally, it is assumed that greater stability of the correlation exists in small or-medium sized samples, especially when there are high or fairly high interrelations among the variables. Also the correlation gives a direct indication of which variables are most closely aligned with the unobserved 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 in the set.

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 shows the positions of Groups for Lexington's travel survey data in the discriminant plane defined by Function 1 & 2 and function 1 & 3).

For interpreting the first discriminant function, as mentioned earlier, we use both the standardized coefficients and the discriminant function-variable correlation. Examining Table 4 for the first discriminant function, we see that it is primarily the two variables -- trip with PURP3 (work place) and trip with PURP5 (school, college, university) that defines the function, with PURP12 and PURP4 secondarily involved. Since the correlation for PURP12 is negative, this means that the groups that have higher PURP12 trip counts scored lower on the first discriminant.

Now, examining the standardized coefficients 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 purp1, 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 is characterized as work—school—religious activity dominant. The three kinds of trips maximized the difference of people's activities among the days of a week. And on the other hand, we know that return home, shopping and social recreation trips show not much variation within the period of one week. Note, from the group centroids, it is at the weekend that people who live in the Lexington area go to religious activities and don't go to work place or study place (school, college and university), which is obvious. We may also infer from the relative large positive coefficient of purp10 that medical or dental trips are typically made during weekdays but not on weekend.

Fig. 1


Groups postions in discriminate plane
(distance)
Discriminant Function II
Discriminant Function I
5.00E-01
4.00E-01
3.00E-01
2.00E-01
1.00E-01
0.00E+00
-1.00E-01
-2.00E-01
-3.00E-01
-4.00E-01
-3.00E-01
-2.00E-01
-1.00E-01
0.00E+00
1.00E-01
2.00E-01
3.00E-01
4.00E-01
5.00E-01
6.00E-01
Tue
Fri
Mon
Wed
Sat
Sun
Thur

Post Hoc Procedures

Hotelling T^2's and Univariate t tests

After a significant overall multivariate result one would like to know which groups and which variables were responsible for that association, i.e., a more detailed breakdown. Pairwise multivariate tests (T^2's) and univariate t test are used to determine which pair of groups differs significantly on the set of trip variables. Here, we use a loose criterion, say, each at the .05 level for univariate t tests, to determine which kind of trips are contributing the significant pairwise difference of people's travel pattern on two different days of the week. Some interesting results are showed as follows:

Pairwise activity comparison based on groups:

Thursday - Friday Not Significant
purp1 pickup passenger Significant

Tuesday - Thursday Not Significant

Monday - Thursday Not Significant
purp4 work-related business Significant

Thursday - Saturday Significant
purp1 pickup passenger Significant
purp3 work place Significant
purp4 work-related business Significant
purp5 school, college, university Significant
purp11 return home Significant

Saturday - Sunday Significant
purp7 other errands Significant
purpl2 religious activities. Significant

Wednesday - Sunday Significant
purp3 work place Significant
purp10 medical or dental Significant
purpl2 religious activities Significant

Tuesday - Saturday Significant
purp3 work place. Significant

Monday - Tuesday Not Significant

Wednesday - Saturday Not Significant
purp3 work place Significant
purp10 medical or dental Significant

Friday - Saturday Significant

purp3 work place Significant
purp7 other errands Significant
purpl2 religious activity Significant

The major difference between activities on weekdays and weekends is whether to make work-trips. Work trips usually go from home to a specific place then back on a regular basis, and usually they occur on five days per week.

It is worth noticing that people's activity-choice on Saturday and Sunday also show contrasting difference. Saturday time typically is devoted to errands compared to that of Sunday, while Sunday's religious activity can be viewed in terms of routines. It is more or less performed on a weekly basis. Thus it is easy for us to understand why the two points that represents Saturday and Sunday on the discriminant plane are separated widely.

Time Series Analysis

Application of time series analysis on the data

The original GPS recorded data were 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 S-plus is 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.

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 saw 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 trips happened least frequently on trip and go-work trips happened most frequently as home and work place is the center of one person's activity space. The two places are the two 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. And 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 (Fig. 2).

Social or recreational trips mainly occur during the early night (Figure 3). The highest peak in a week appears at 5 o'clock on Friday, and secondarily as Saturday and Sunday noon peaks. If we look at the trip distribution for each day, we may find that the tripcount 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.

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 4). 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.

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 S-plus 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 5, 6 and 7).

The cross-correlation plot between eat-out trips and go-work trips (Figure 5) 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.

Similarly, the cross-correlation plot between return-home trips and shopping trips (Figure 7) 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 (possibly shopping is usually part of a multiple purpose trip or trip chain).

Spectral Analysis

In the last part, we used cross-correlation for studying the relationship between different types of trips. We got a relative vague picture of the "before" or "after" relations of them in terms of schedule. But it doesn't tell us how their periodicity is related. We turned to spectral approach, which is better able to separate short-term and periodic effects.

Figure 8 shows an example of our results. Note for every type of trips-- return-home, go shopping, social or recreational activities, go-to work, and eat-out, the frequency 1 (one trip made per day) is within the 95 percent confidence interval. They are performed at least once a day. Work trips, compared to other types of trips, are significant (falls within confidence intervals) within more frequency slots-- 1, 2, 3, and 4. Eat-out trips are significant within slots 1, 3, and 4. Social or recreational trips are significant within slots 1, 2, and 3. However, return-home trips and shopping trips are only significant at frequency 1. They are performed only once a day.

When we examine the coherency plot, the results are not so exciting, as only the frequency of 1/day is a strong signal common to all of the five trip types. The coherence is high there and coherence and phase are determined very precisely (Figure 8, 9, 10). At high frequencies there is little information, and coherence can not be fixed at all precisely. For return-home trips and go shopping trips, their frequencies do not even precisely couple at 1/day frequency (Figure 8).

Problem with using time series analysis

The theory of time series is based on the assumption of second-order stationarity after removing any trend. Thus second moments are particularly important in practical analysis of time series. In our time series decomposition plots, we saw the residual components are not strictly stationary. Thus it means the application of the auto-correlation, cross-correlation, and spectral analysis on our data may not be appropriate.

The second issue is that if we would like to uncover the features of people's activities across the week period using time series analysis, multiple samples of weekly activities should be needed. Unfortunately, as funding for the Lexington travel survey project was limited, there were not enough GPS-integrated devices and labors for sampling for a continuous period of more than one week. The flaw detriments the credibility of our results.

Discussion and Conclusions

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 slots 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 the 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).

Defects that lie 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 sufficient 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 dataset is the classification schema for activities (Table 1). 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 this case study, we found that some of the household data in the Lexington study was incomplete and thus we have to reduce the household set from 100 to about 80. This is still a significant number. There also appears to be some problems with the digitized basemap; a preliminary search through the CD-ROM obtained from DOT shows that only one of the two counties was thoroughly geocoded. 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. It appears that we may also have to obtain land-use maps and geocode the locations of specific urban functions such as shopping centers, educational institutions, parks and recreational areas, churches, and so on. This preliminary session on evaluating the cleanliness of the dataset and transforming it to one that we can use will be followed by a MANOVA based examination of the activity patterns, thus determining the nature of activity patterns for specific purposes on different days of the week. A second project will be to evaluate standard network models that define optimal routes for origin destination pairs and trip chains and then compare them with the trips actually made by the sample members. This will be followed by an evaluation (using Quadratic Assignment Procedures) of which of the models most closely reproduce the actual dataset. A third project is to examine the daily and weekly temporal sequencing of trips to define repetitive cycles. Two-dimensional (Spatial) Spectral Analysis will be used. A fourth project will be to examine directionality in trip making using circular statistics. We will examine the directional relation between different trip types, as well as looking for different trip patterns for a given type on different weekdays.

Ultimately, we will focus on two areas; (1) adding a final touch to the considerable volume of data on destination choice activity behavior as reconstructed in the past from whole or partial week diaries; (2) evaluating which of the set of prevailing optimizing network flow models most closely represent the actual behavior of sample members. This will provide us some hard information on the degree to which travelers are spatially rational or whether other criteria appear to be more important in choosing routes for single and multi-purpose trips.

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The Sex Factor in Weekly Travel Behavior

Research Report Draft By Jianyu (Jack) Zhou

After we performed MONOVA and DISCRIMINANT analysis on the Lexington travel data as a whole without considering sex difference among the drivers in each household, we decided to take the sex factor into our consideration. The problems that interest us are: does male and females' travel behavior follow a similar pattern within a one-week period? Which kind of travel activity dominates the weekly travel pattern of male or female respondents?

The original travel survey data on the Lexington CD was partitioned and compiled into two parts. One part consists of trips made by male drivers only and the other part consists of trips made by female drivers only. For each set of compiled data, we repeat our previous analysis, i.e., we performed MONOVA and DISCRIMINANT on them respectively, and then the results were graphically illustrated on the DISCRIMINANT planes.

Two kinds of errors were involved during the data complication process. One was that we have the GPS trip information but the driver sex data are missing. The other is that driver sex data are available but the driver actually did not experience driving during the sampled period. Between the two kinds of errors, error one brings more damage to our research conclusion. As an illustration, when compiling the travel distance data, we lost 523 data records because of error I, and 26 data records because of error II. Finally, the total number of trips made by male driver is 1567 and the total number of trips made by female driver is 1179. In total, we have 2746 trips. In comparison, before we partitioned the trip data, there are 3295 trips in total.

To our surprise, when the travel survey data are analyzed based on sex, no significant travel behavior difference were found across the sample week period. None of the four multivariate tests we performed shows significance beyond 5 % for trips made by male drivers and trips made by female drivers. This indicates that in general the behavior of both male drivers and female drivers (with or without passengers in the vehicle) is pretty consistent across the week period.

As for travel frequency, we found the main travel difference across the week for male drivers mostly comes from the Go-To-Work trip, with a significance level of 0.026. But for female drivers the main difference mainly comes from the work-related business trip, with a significance level of only 0.006. This could imply the fact that the jobs performed by women in our sample more or less requires business travel or in other words, their jobs sometimes need them to make such trips. In terms of travel duration (travel time), we found the main travel difference for male simply comes from the social or recreational travels, with a significance level of 0.028. But for female, the situation is totally different. The main travel difference can only be attributed to shopping trips and return-home trips, with a significance lever of 0.043 and 0.004 respectively. In most families, males play dominant roles in bringing money to home. Social or recreational events are rare during the busy week but important to their travel pattern. In contrast, shopping shows its important role in women's travel patterns. Many of the past researches also suggested chained trips are often made by women. The chained trip could be a multipurpose trip made when work is over, in most times with shopping as one of the aims. This may explain why the significance level of return-home trips is high too. In terms of travel distance, we didn't find any type of travel activities significantly contributes to the overall travel difference across the week for both the male and the female. It indicates that the activity scopes of our respondents (either male or female) are roughly similar in magnitude for the thirteen types of travel activities.

For further analysis, we used SPSS to find out the discriminant functions of our data. The week-day groups centroids of the data were computed via the discriminant functions and plotted on the DISCRIMINANT planes. The following diagrams (Figure 1 and Figure 2) indicate our results for trips made by males and trips made by females when only trip frequency is considered. From the diagrams, we can see that both the male and the female have highest trip frequency on Thursday. Females have nearly the same low trip frequency on Monday and on Friday. But males have a higher trip frequency on Monday then on Friday.

Figure 1.

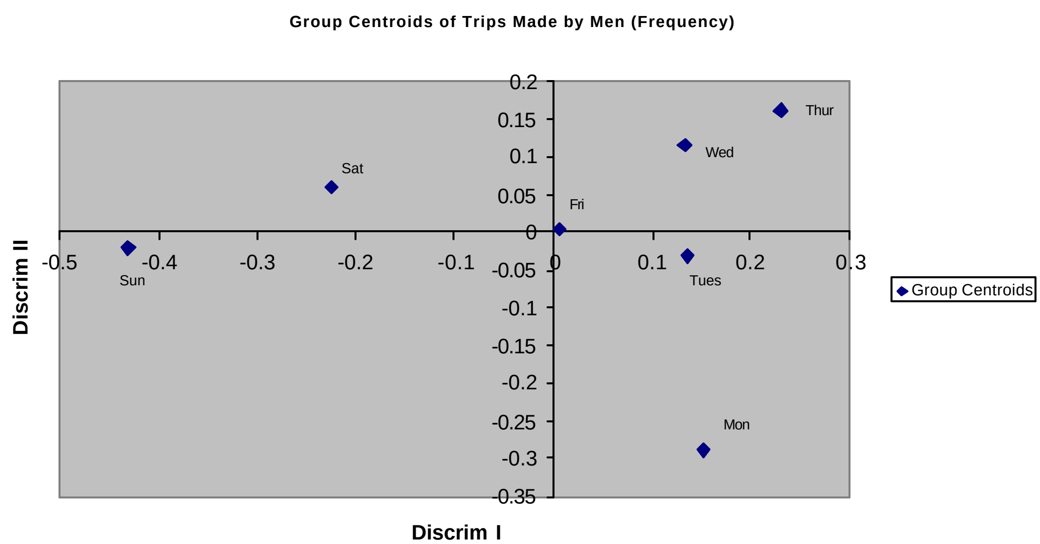


Figure 2.

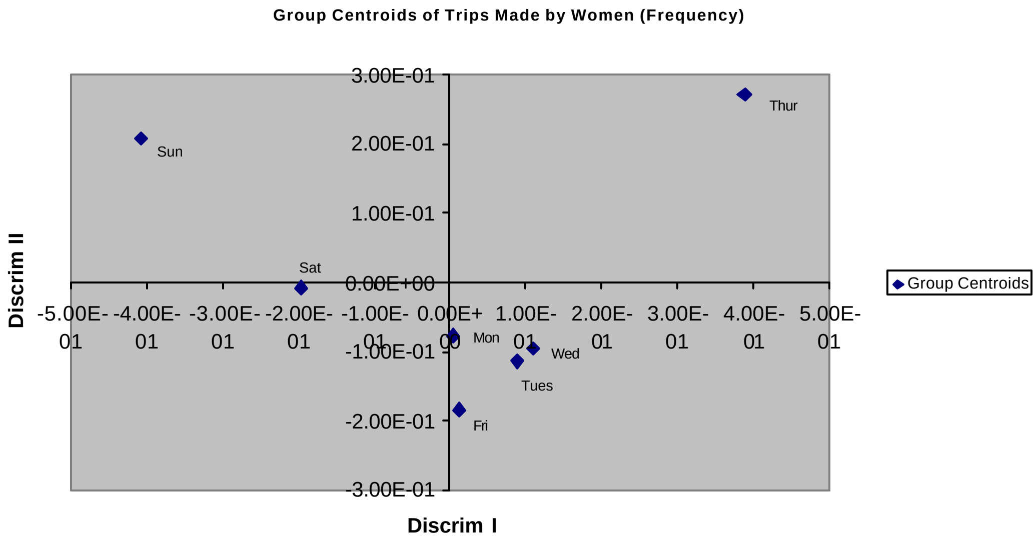


Figure 3 and Figure 4 indicate our results for trips made by males and trips made by females when travel time is considered. We can see from the diagrams that both the male and female travels more time than any other day-of-the-week.

Figure 3.

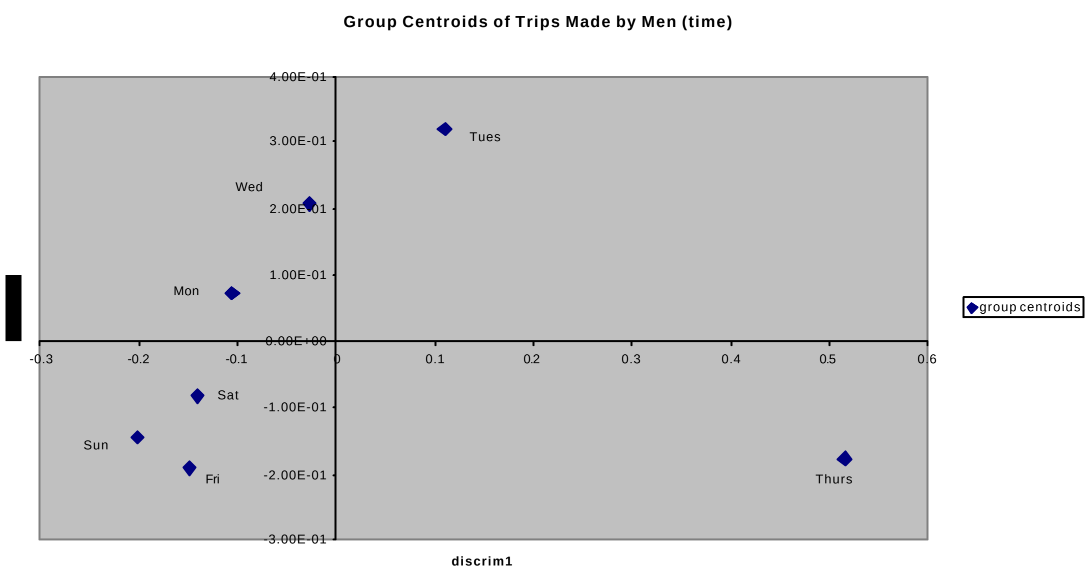


Figure 4.

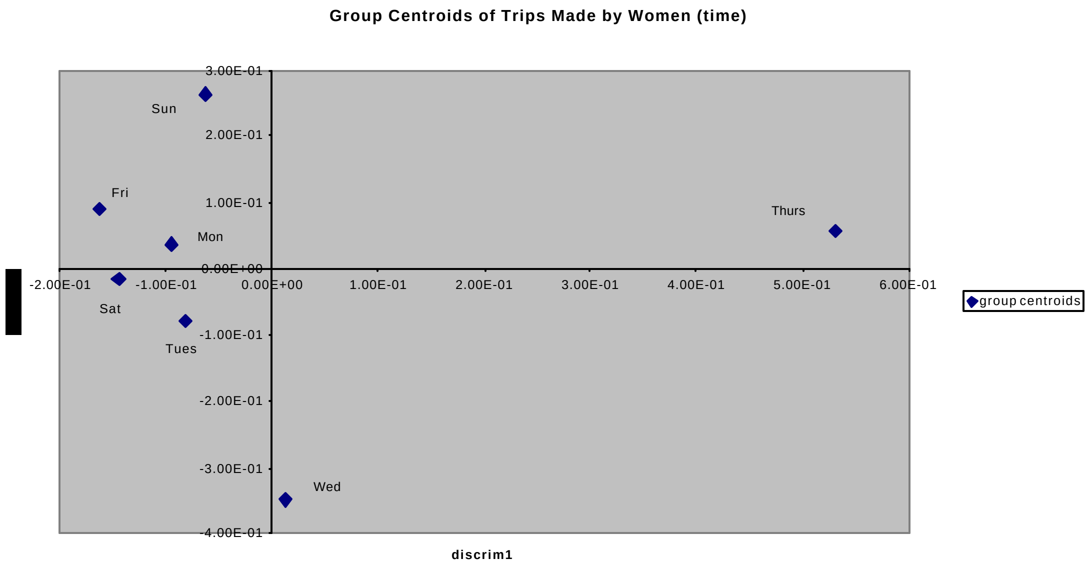


Figure 5 and Figure 6 indicate our results for trips made by males and trips made by females when travel distance is considered. The diagrams show that females travel longer distances on Thursday than any other day-of-the-week with Saturday averaging the next longest. But for males, Tuesday shows more importance in travel distance. Saturday featured with no much longer travel distance than Sunday.

Figure 5

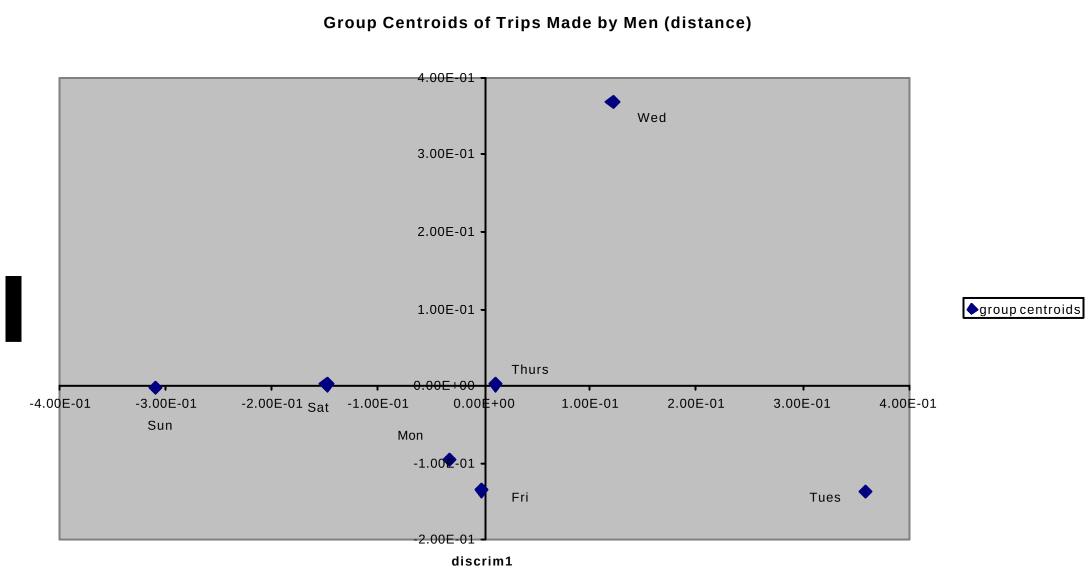
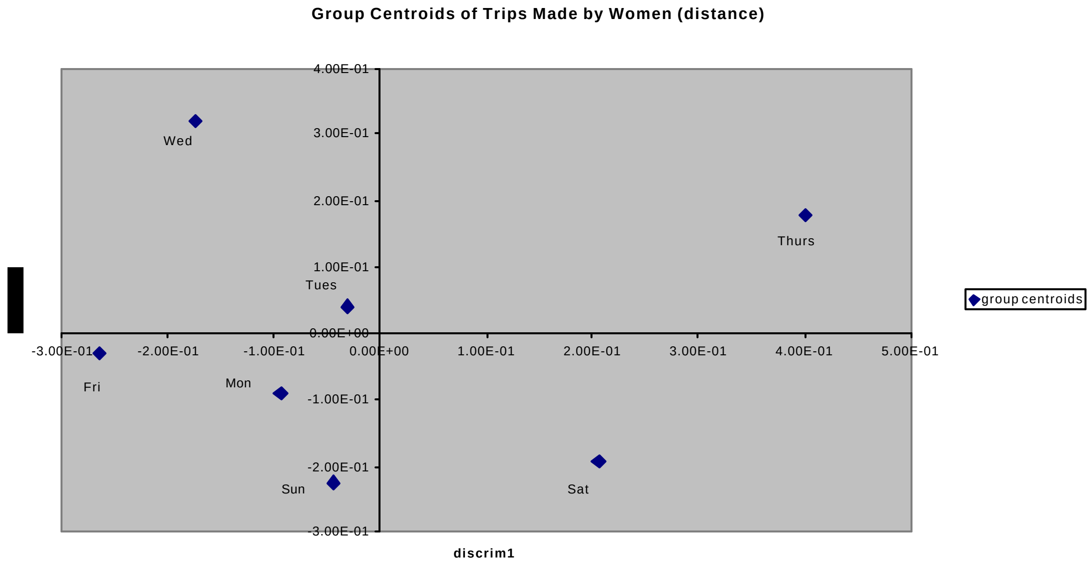


Figure 6

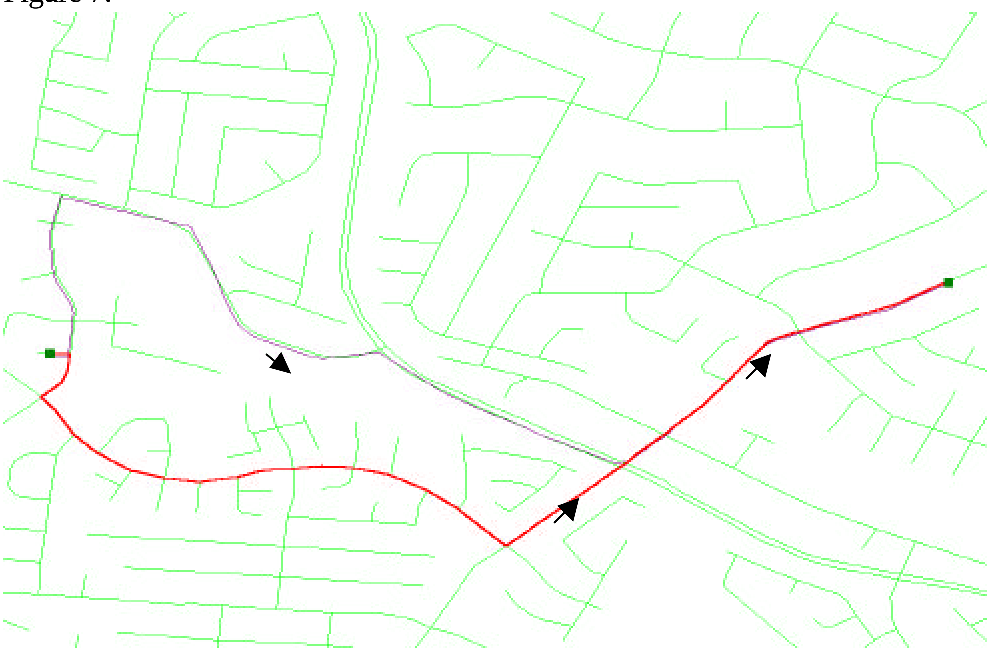


2. Route Selection in Travel --- Shortest Path?

It is not a common practice for people to take the shortest path toward their destination. A local road network typically consists of different types of roads. Highways or freeways, as the backbones of the local network, provide the most fast and efficient transportation routes for local residents. In comparison, the local major roads, though sometimes being parallel to the highways, have more traffic lights along the routes. These traffic lights are potential impendence for local residents using them as part of their travel routes, particularly if there are no highway alternatives. In the case that the destination is located on the other side of a highway, part of the highway may be used as part of the travel route. Here a highway serves two roles in the local region. First it divides the local region basically into two parts and serves as the boundary of the local sub-regions: Second it may be part of a fast transport channel between two local sub-regions it bisects. Thus when people who live in one sub-region want to travel to destinations located in another sub-region, and there is no direct major road from the origin to the destination, they usually make a zigzag routing choice. That is, at the beginning travelers take the collector road to get on the major local roads, then follows part of the highway; after exiting the highway they switch to the local major roads again, finally reaching the destinations using collectors. Using the ARCVIEW network module to compute the shortest path between the origin and the destination of a recorded path from the Lexington travel survey, the route chose by ARCVIEW includes many local road segments in the travel route. Some of the road segments even belong to the class of collectors. However, real routes taken by the sampled households obviously put emphasis on travel time. The roads of higher levels are used at a maximum along the sampled route. The number of intersections expected to be encountered along the route tends to be minimized. Actually ARCVIEW also provides multiple options for customizing its shortest path computation. It allows a user to add average speed information to each road segment in the road network database. And a turn table could also be added to provide the information about how much time it is going to take to turn from one segment of road into another segment of road or if some types of turns are prohibited at the intersection. The above additional information could be incorporated into shortest path computation in ARCVIEW to minimize the travel time rather than travel distance. Unfortunately, our database includes information only on the road types and speed limits. Therefore the distance is used as an optimization goal only when computing the shortest path computation in ARCVIEW.

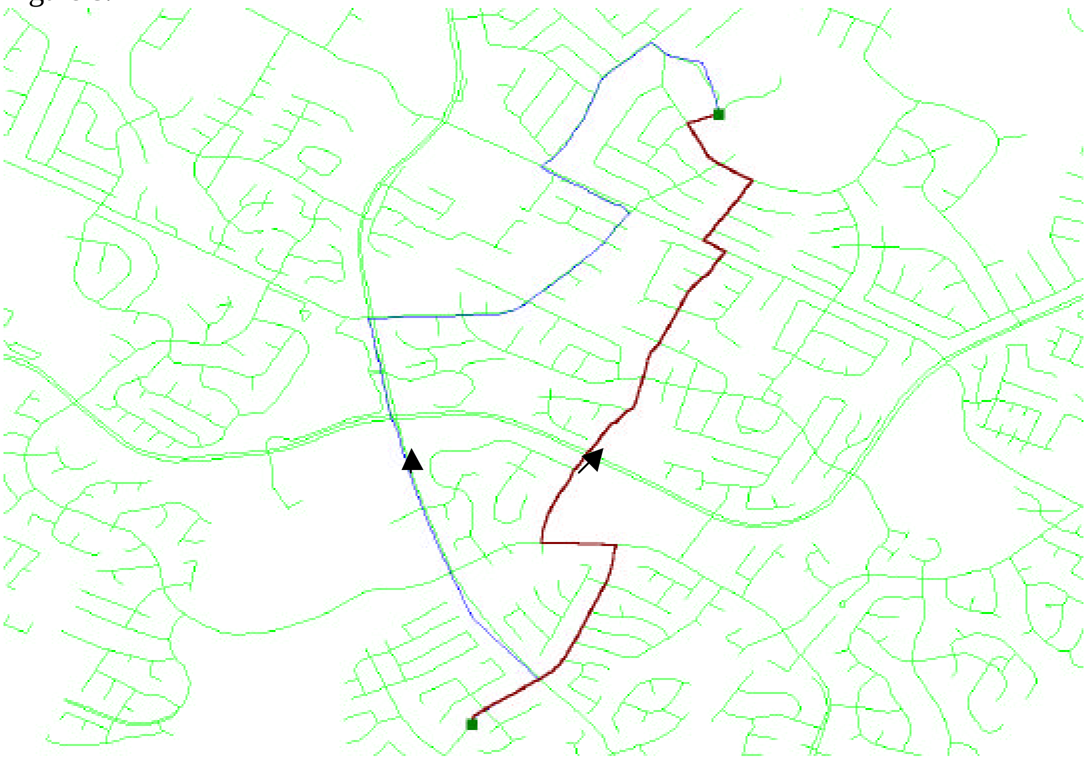
The following is one of a few typical examples that come from our research. Figure 7 shows a return-home trip. The route taken by our respondent starts from Clays Mill near Merrimac and ends at Hannibal near Clemens, as indicated by the blue lines. The red line shows the shortest path route computed by ARCVIEW network module based on travel distance. As we can see from the graph, the major difference between the real-life route and the shortest route is that real-life route takes the most of advantage out of the high levels of roads. The respondent took the nearest path for getting to a main arterial of the local road network and then traveled part of the highway before finally getting on the main arterial leading to home. In contrast, the shortest path didn't use the highway, but traveled a long way on collectors before turning into the main arterial leading to the home.

Figure 7.



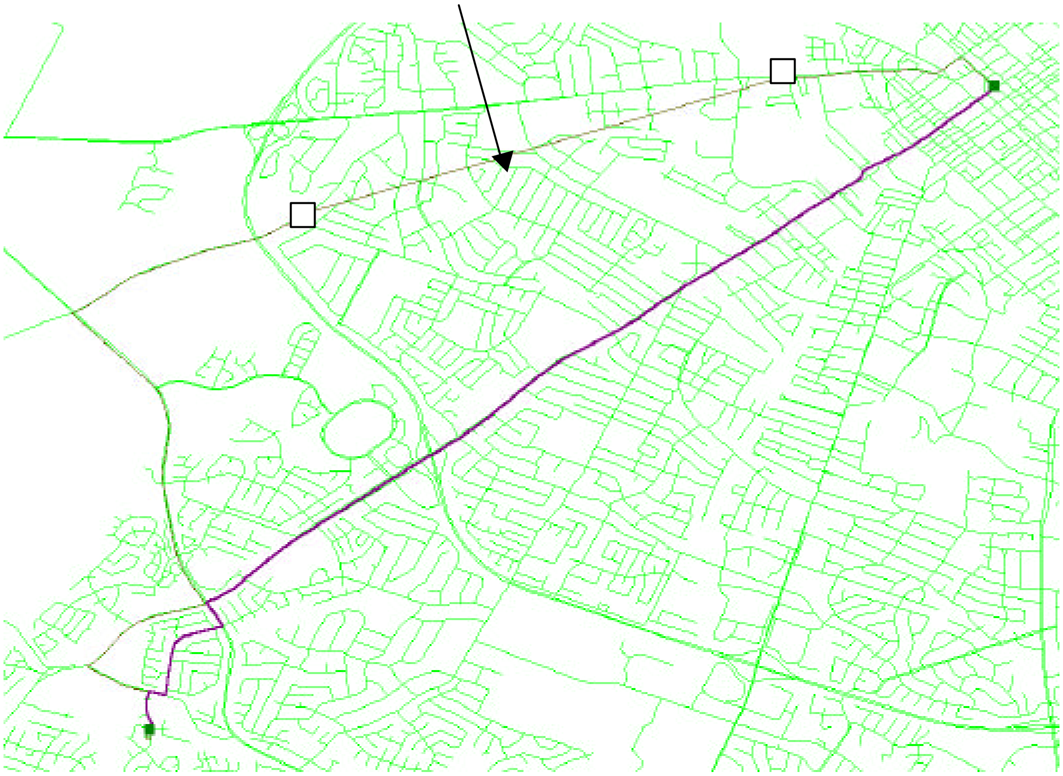
Here is another example. Figure 8 shows a Go-to-School, College or University trip. The trip starts from RockBridge near Tates Creek and ends at Tates Creek School. Again the blue line indicates the real route taken by our respondent and the red line indicates the shortest route computed by ARCVIEW. In this case, our respondent didn't exactly make the maximum use of highway along his way to Tates Creek School, but only part of the north-south highway. In contrast, the shortest route automatically computed by ARCVIEW chose mostly the local arterials and collectors.

Figure 8.



One thing that needs to be mentioned in our research is that not every route recorded by GPS exactly reflected the actual route taken by our respondents. The GPS modules used in the Lexington Travel Survey do not have the built in smoothing function enabled. When the GPS signals are temporarily lost become functional again some time later, the lost parts of the track are simply replaced by a line connecting the last valid data point before signal loss and the newly valid data point after the signal is back on. Figure 9 shows a typical example of this case. Note the segment indicated by the arrow line doesn't follow any real road in the local road network. It is simply a line segment between the last valid data point before the GPS signal is lost and the newly valid data point right after the GPS signal is back on (indicated by the squares). This line segment doesn't correspond to any part of the local road network.

Figure 9.



Bio-Sketch

PROFESSOR REGINALD G. GOLLEDGE

Professor Reginald G. Golledge is a Professor of Geography at UCSB. He is a senior professor with interests in behavioral geography, including disaggregate transportation modelling, spatial cognition, cognitive mapping, individual decision-making, household activity patterns, and the acquisition and use of spatial knowledge across the life-span. His research has included work on adults, children, teenagers, mentally retarded persons, and adventitious and congenitally blind people. He has had more than two decades of experience in designing survey instruments and collecting data in both field and laboratory situations. He has published extensively in the literature of several fields including geography, regional science, and psychology. He has considerable experience supervising post-doctoral researchers, Ph.D., and Master students, in managing large grants and contracts, and has been chair of his department.

Professor Golledge has written or edited fourteen books, sixty chapters in books, more than 100 papers published in refereed academic journals, and about 150 miscellaneous publications including technical reports, book reviews, published research notes, and so on. He has presented more than two hundred papers at local, regional, national, and international conferences in geography, regional science, planning, psychology, and statistics. He received an Association of American Geographers Academic Honors Award in 1981 and the Institute of Australian Geographers International gold medal in 1999. He was a Guggenheim Fellow in 1987-88. He is an Honorary Life-Time Member of the Institute of Australian Geographers and a Fellow of the American Association for the Advancement of Science. He has been Associate Editor and Editor of the journal *Geographical Analysis* and a Founding Editor of the journal *Urban Geography*. He has served on Editorial Boards of the *Annals of the Association of American Geographers*, *The Professional Geographer*, *Tijdschrift Voor Economische en Sociale Geografie*, *Environment and Behavior,* and *The Journal of Spatial Cognition and Computation*, and he has been a reviewer for many different journals, as well as for the National Science Foundation, the National Institute of Justice, the National Institute of Health, the Canada Council, the Australian Research Grants Council, and the European Science Foundation. Professionally, he has served on national research grants committees, on the AAG Honors Committee, and three times on the AAG Program Committee—acting as chair of that committee for the San Diego Meetings. In 1998-99 he was elected Vice President of the Association of American Geographers, and he was elected President for 1999-2000.

Professor Golledge became legally blind in 1984. He now works almost exclusively in a multi-researcher environment. Over the years he has worked with statisticians, educational psychologists, cognitive psychologists, cognitive scientists, developmental psychologists, economists, planners, and regional scientists, as well as transportation engineers. His collaborative research has taken place within the United States and in Canada, England, Sweden, The Netherlands, New Zealand, and Australia. He has also interacted extensively with the private sector, including state governments and transportation planning agencies in the states of New South Wales, Victoria, and West Australia in Australia; the National Government of The Netherlands; and with private firms in Japan, Canada, and the United States.

Bio-Sketch

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Employment and Research Experience

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Graduate Researcher, NCGIA, UCSB: (1999.1---1999.8)
Graduate Researcher, Department of Geography, UCSB (1998.9 ---present)
Graduate Researcher, NCGIA, UCSB: (1998.6---1998.9)
Programmer/Analyst, Department of Geography, UCSB
Teaching Assistant, Department of Geography, UCSB: 1997-1999
Undergraduate Student Researcher, Department of Geography, Peking University

Computer Skills

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Honors

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Outstanding Student Awards, 1994-1995, Peking University.

Publications and Presentations:

Goodchild, M. F., & Zhou, J. Finding geographic information: Collection-level metadata. *Geoinformatica, Submitted*.

Zhou, J. (2000). Analysis of variability of weekly travel behavior using GPS-recorded data. Unpublished M.A., University of California, Santa Barbara.

Zhou, J., & Golledge, R. G. (1999, August). A GPS-based Analysis of Household Travel Behavior. Paper presented at the Western Regional Science Association Annual Meeting, Kauai, HI.

Zhou, J., & Golledge, R. G. (2000, February 26-March 1). An analysis of household travel behavior based on GPS. Paper presented at the International Association of Travel Behavior Researchers Annual Meeting, Gold Coast, Australia.

Zhou, J., & Golledge, R. G. (2000, April). An analysis of variability of travel behavior within one-week period based on GPS. Paper presented at the 1st IGERT Graduate Student Research Conference, UC Davis, Davis, CA.

Papers Presented

Zhou, J. (2000). *Analysis of variability of weekly travel behavior using GPS-recorded data.* Unpublished M.A., University of California, Santa Barbara.

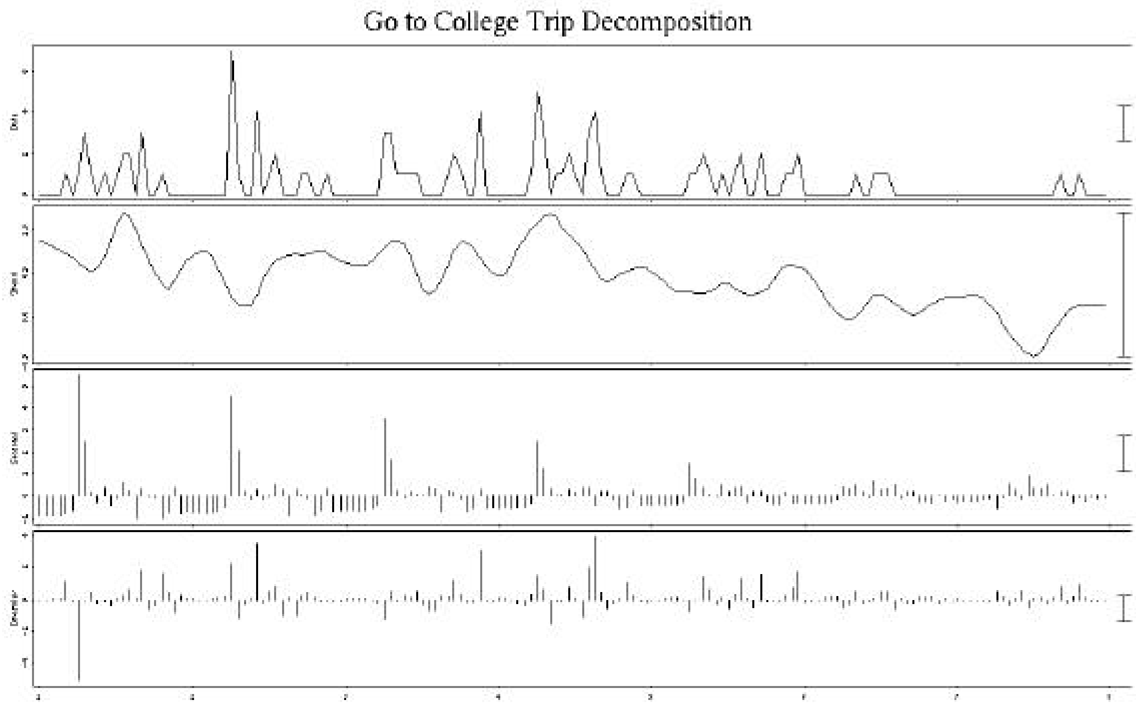
Zhou, J., & Golledge, R. G. (1999, August). *A GPS-based Analysis of Household Travel Behavior.* Paper presented at the Western Regional Science Association (WRSA) Annual Meeting, Kauai, HI.

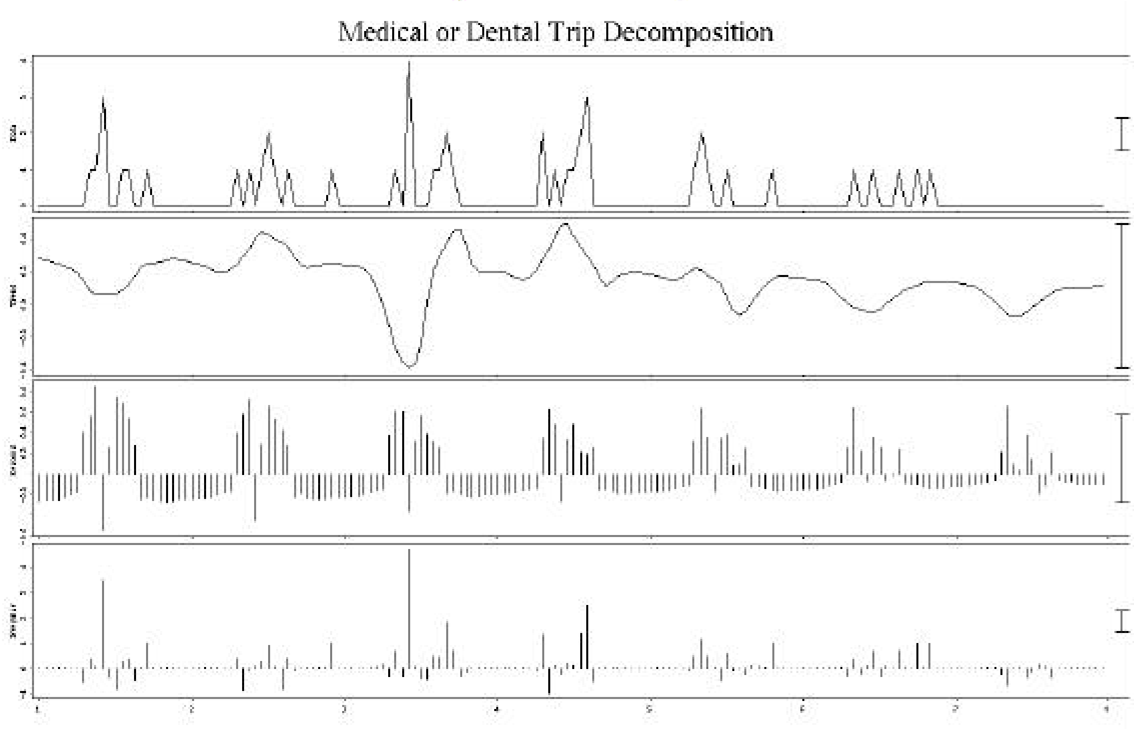
Zhou, J., & Golledge, R. G. (2000, February 26-March 1). *An analysis of household travel behavior based on GPS.* Paper presented at the International Association of Travel Behavior Researchers (IATBR) Annual Meeting, Gold Coast, Australia.

Zhou, J., & Golledge, R. G. (2000, April). An analysis of variability of travel behavior within one-week period based on GPS. Paper presented at the 1st Integrative Graduate Education and Research Traineeship Program (IGERT) Graduate Student Research Conference, UC Davis, Davis, CA.

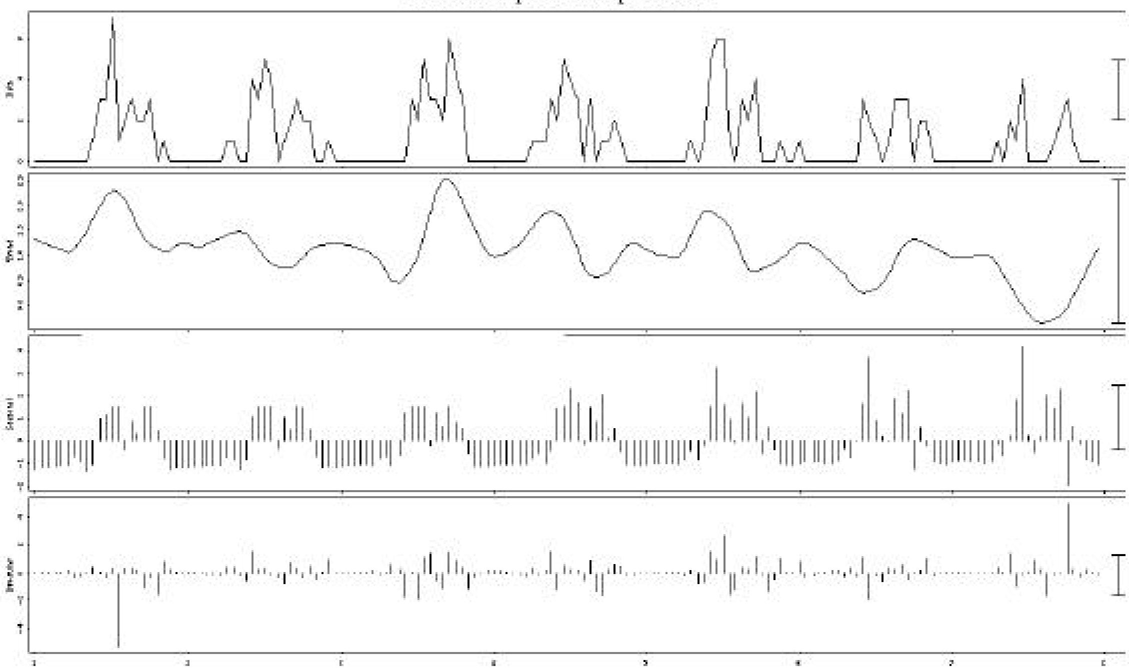
Decomposition of Trip Time Series

Decomposition plots of trip time series are generated from SPLUS, which show the decomposition of a time series into a cyclic component in addition to the residual (irregular component). Activity trends are also shown in these plots (top to bottom: Data, Trend, Seasonal, Irregular). This will help us in finding the travel pattern associated with a particular trip type.

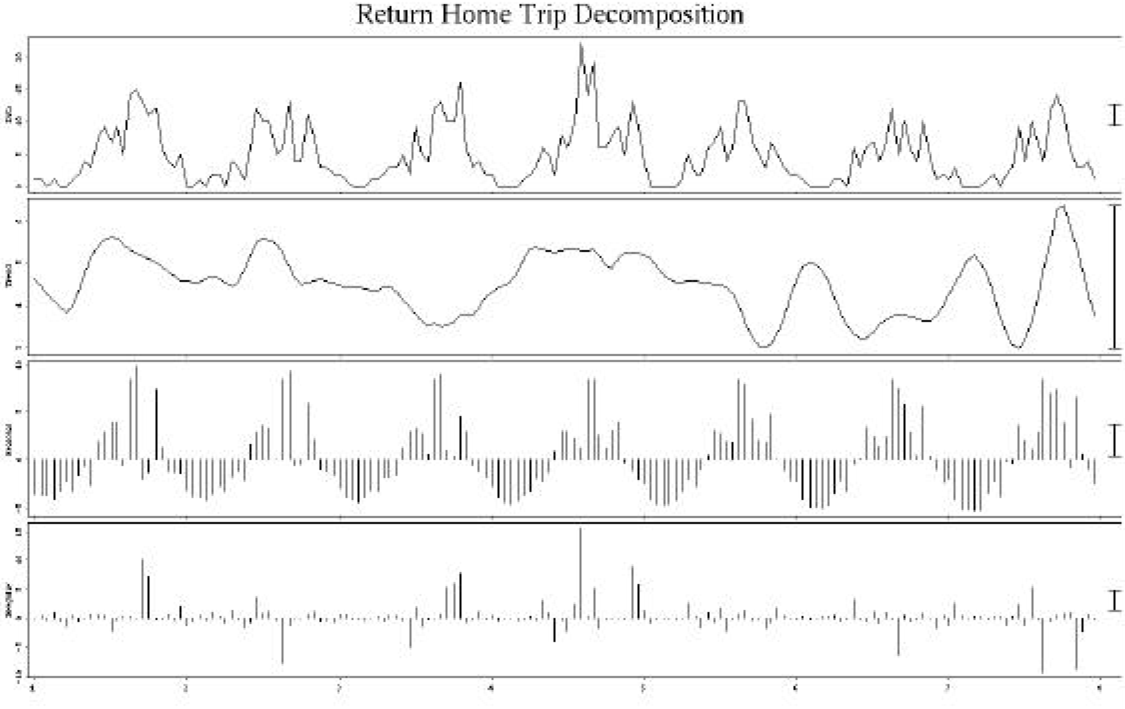




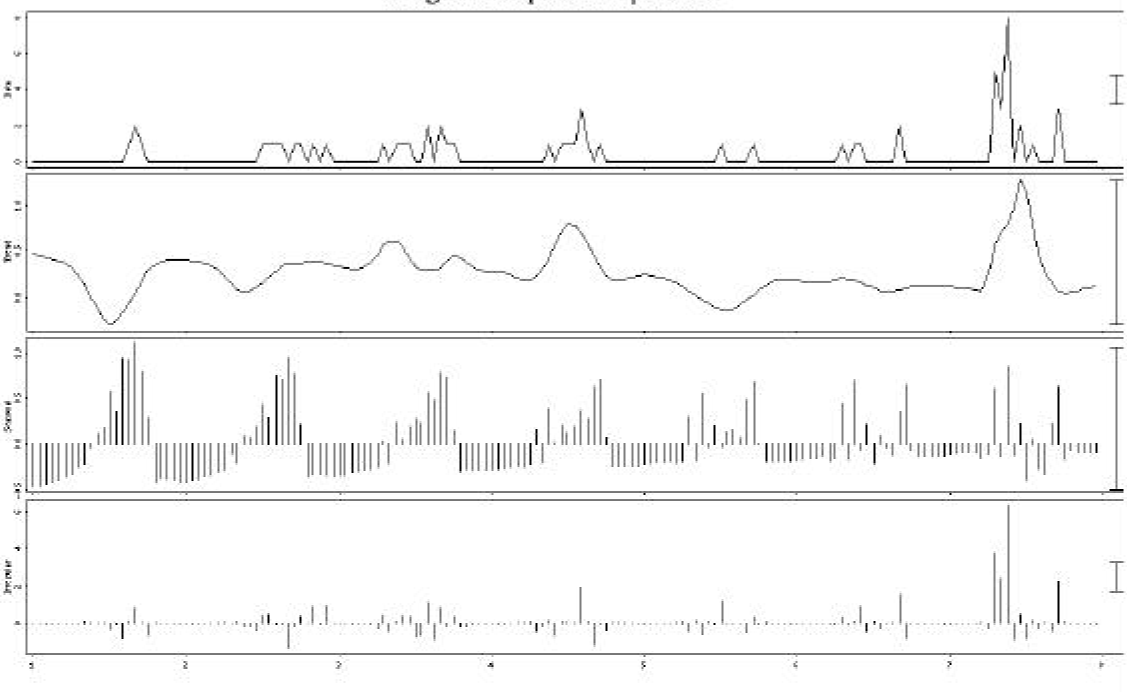
Eatout Trip Decomposition



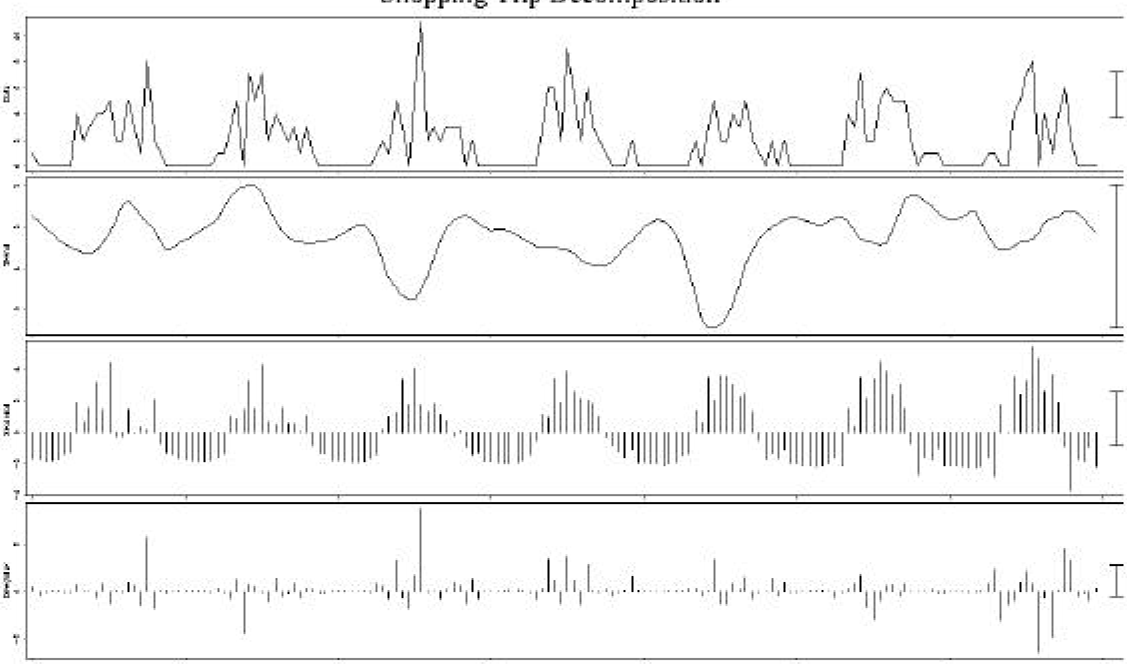
Return Home Trip Decomposition



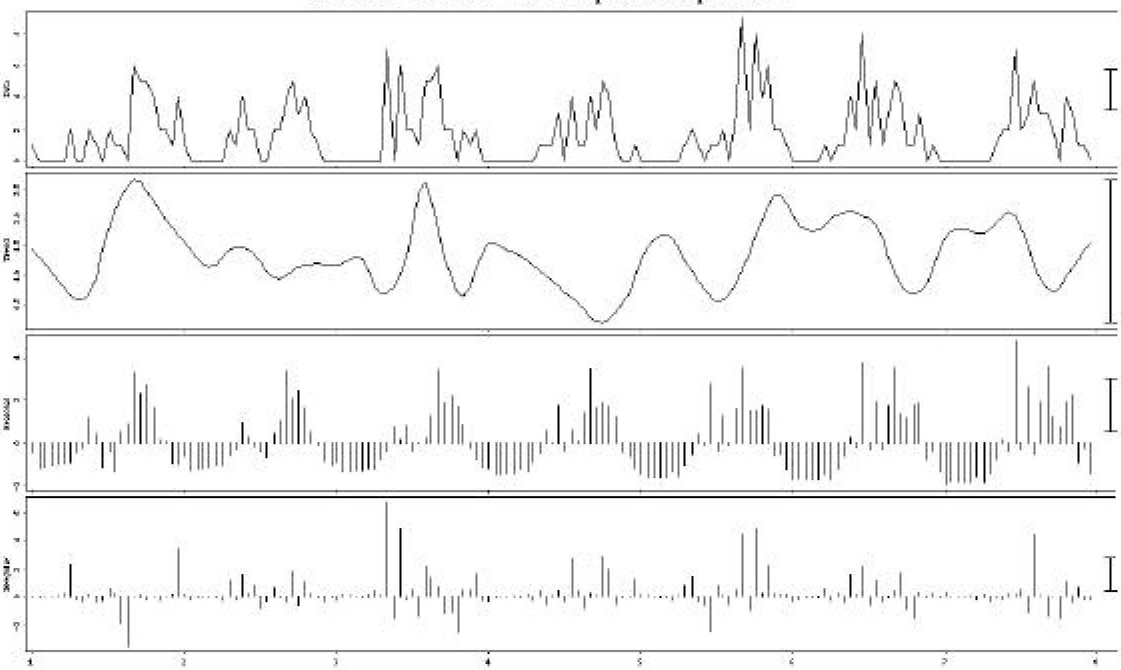
Religious Trip Decomposition



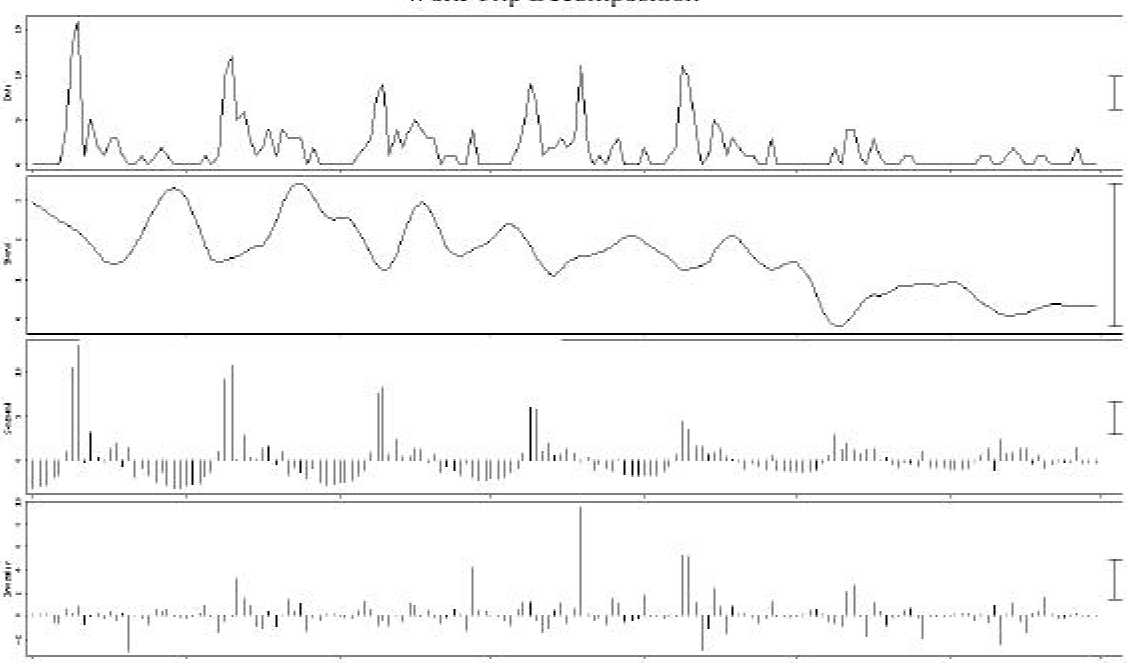
Shopping Trip Decomposition

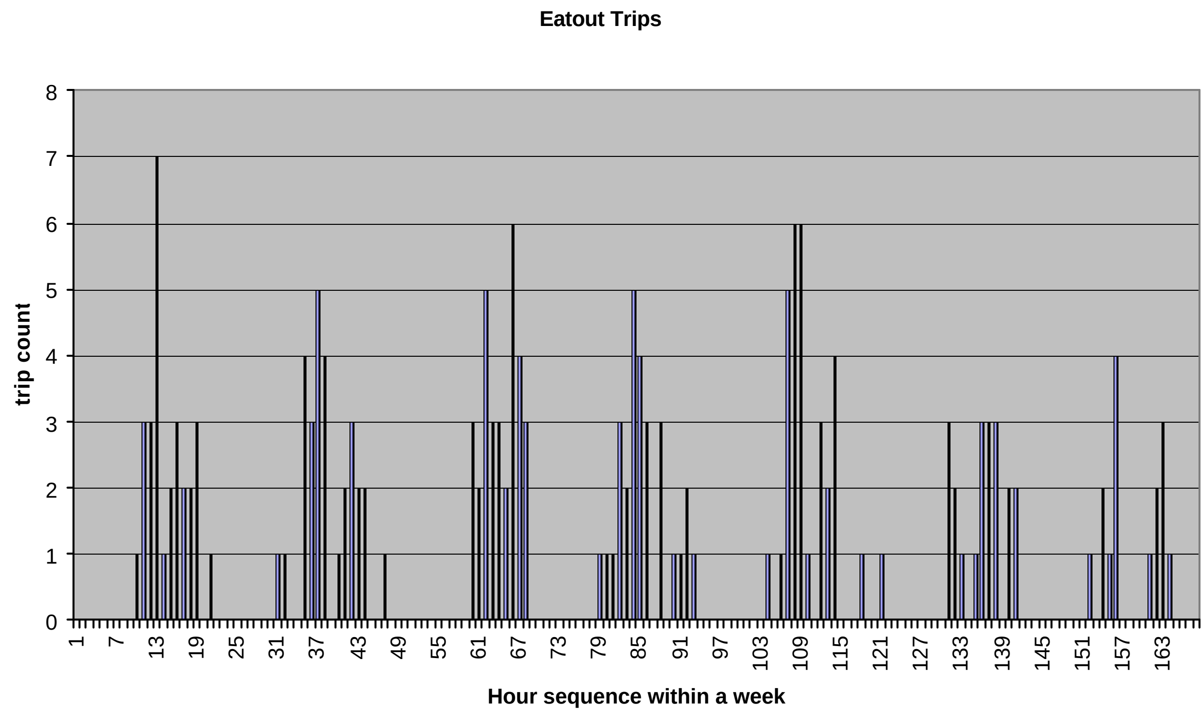


Social or Recreational Trip Decomposition



Work Trip Decomposition

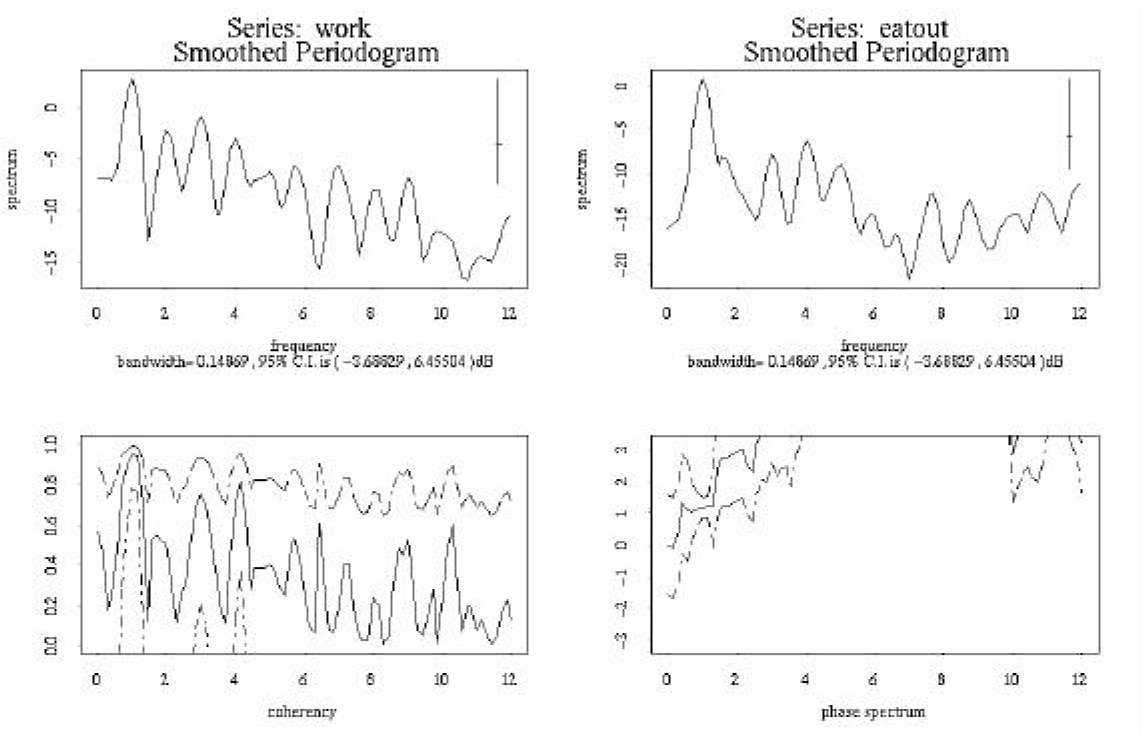


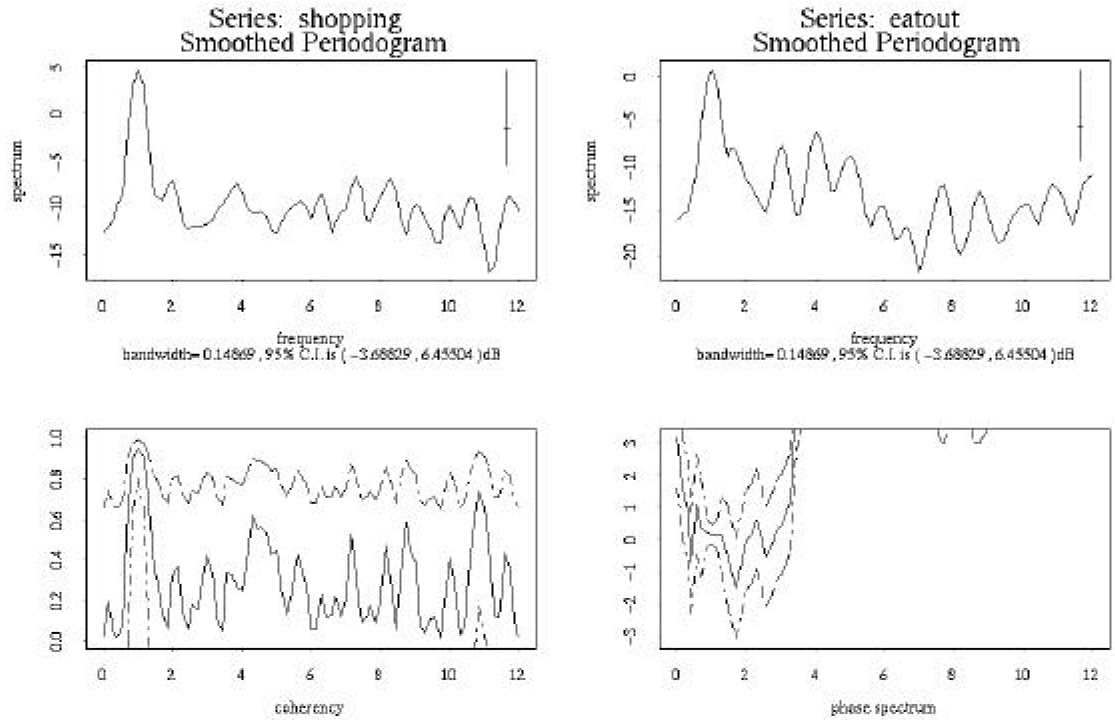

Eatout Trips
trip count
Hour sequence within a week
0
1
2
3
4
5
6
7
8
1
7
13
19
25
31
37
43
49
55
61
67
73
79
85
91
97
103
109
115
121
127
133
139
145
151
157
163

Spectral Analysis

We used cross-correlation for studying the relationship between different types of trips. We got a relative vague picture of the "before" or "after" relations of them in terms of schedule from correlation analysis of time series. But it doesn't tell us how the periodicities of different types of activities are related. We turned to spectral approach, which is better able to separate short-term and periodic effects.

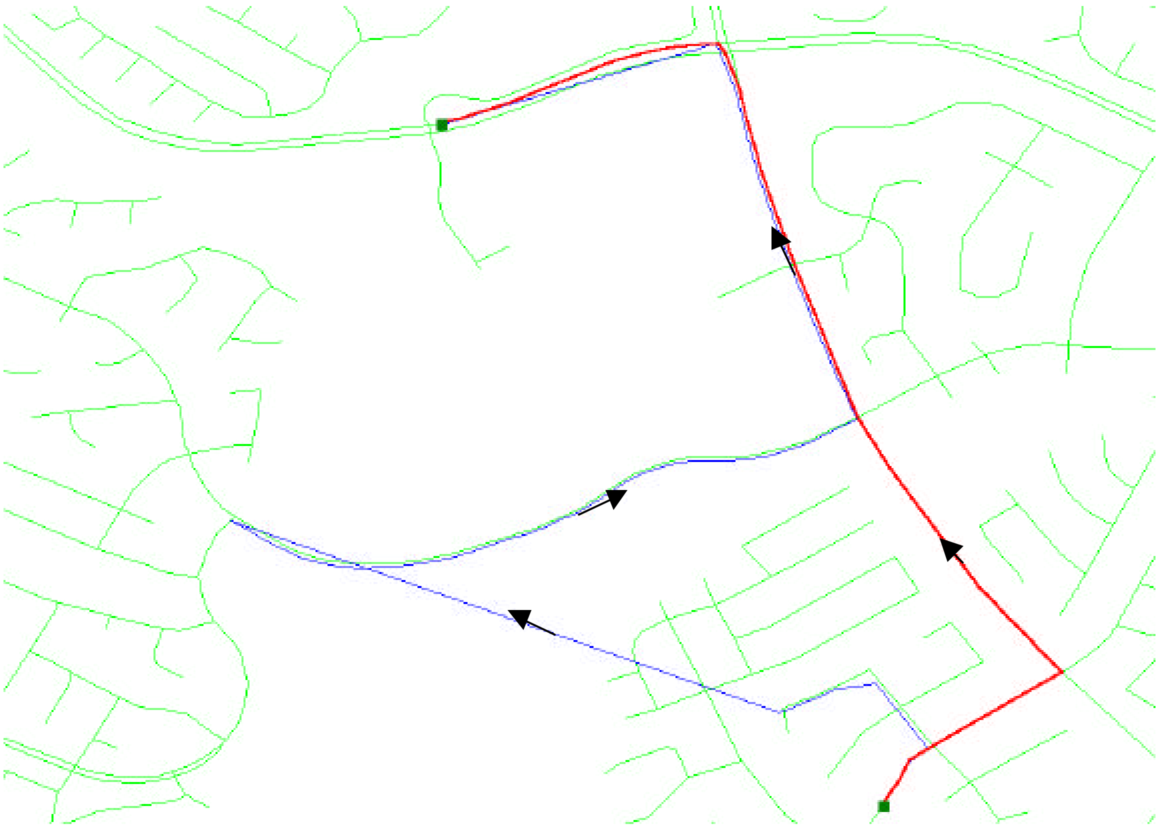
These diagrams are generated from SPLUS. The periodogram is conventionally defined as the modulus-squared of the discrete Fourier Transform. If the input time series contains periodic structure, then the periodogram can be calculated for any frequency, and displays the presence of a sinusoid near one frequency value as a distinct peak in the spectrum. Coherency plots help us to analyze if two different activity types being measured at the sampled interval have the same or closely related frequencies. We didn't use phase spectrum in our analysis. It is a byproduct when using SPLUS for spectrum analysis for time series data. It could be useful in other cases.

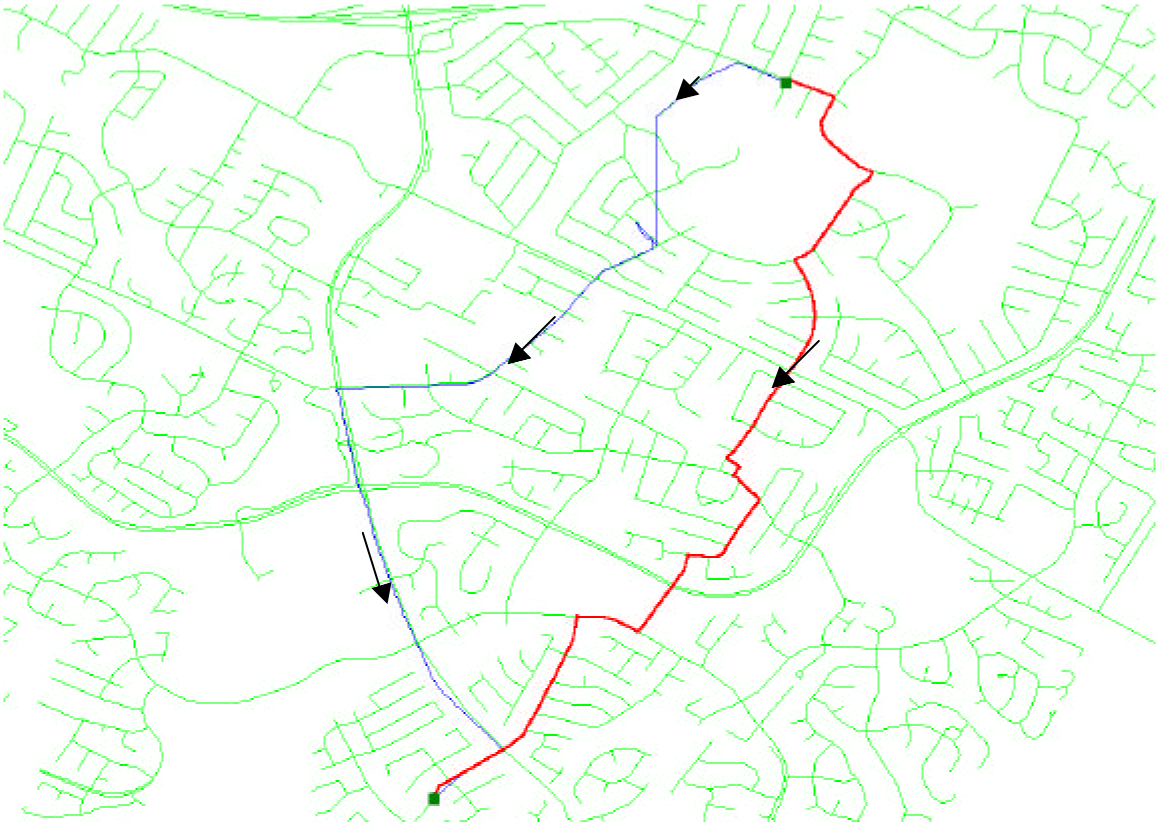


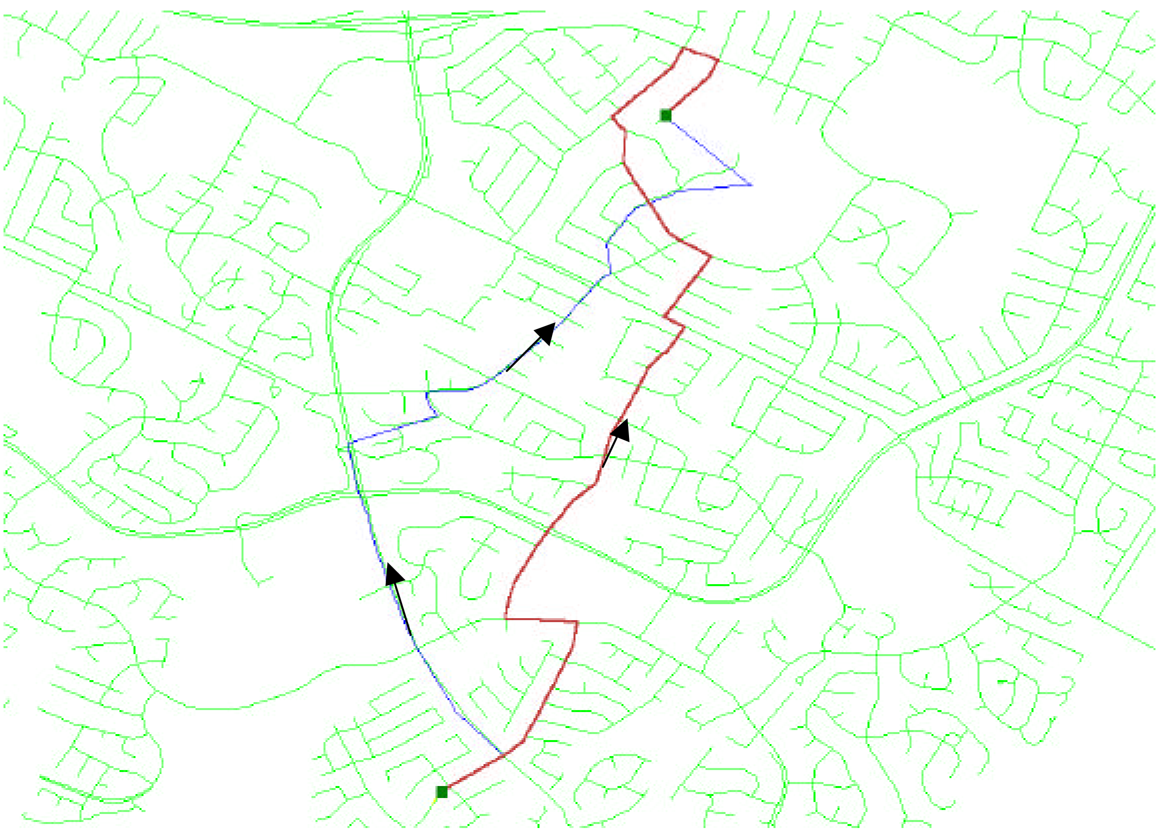

Series: shopping
Smoothed Periodogram
spectrum
frequency
bandwidth= 0.14869 , 95% C.I. is (-3.68829 , 6.45504)dB
Series: eatout
Smoothed Periodogram
spectrum
frequency
bandwidth= 0.14869 , 95% C.I. is (-3.68829 , 6.45504)dB
coherency
phase spectrum

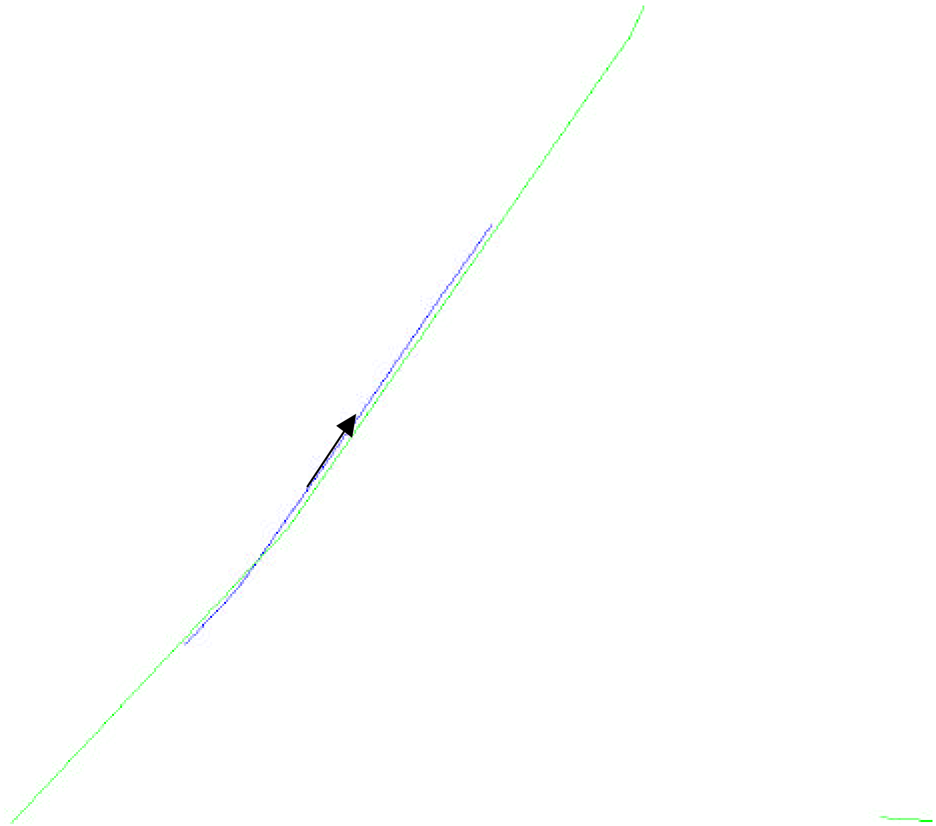
Route Selection

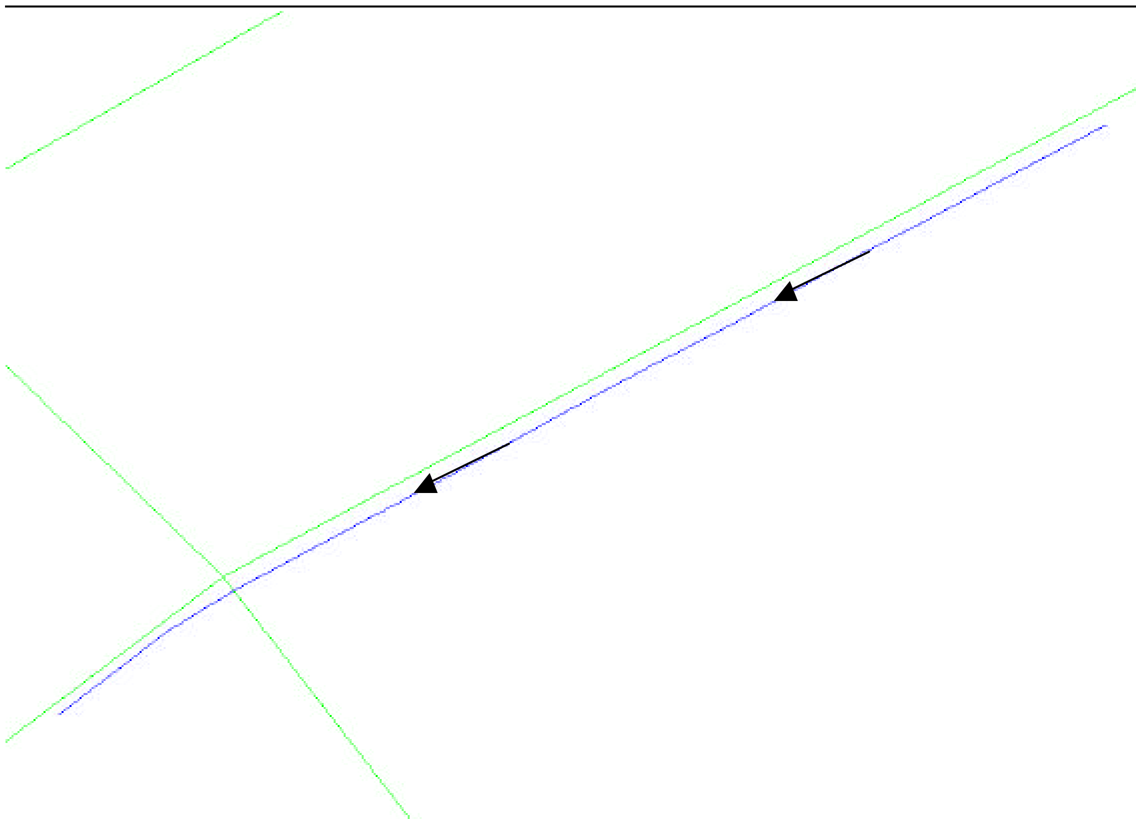
The collected travel data was analyzed on the per-trip basis for route selection study. The thin lines in these diagrams indicate the actual route taken by the respondents. And the thick lines represent the shortest path between the origin and destination computed by ARCVIEW network analysis module. The arrows on the lines indicate the travel direction. One or two diagrams show only the thin line. The reason is simply that the shortest path computed by ARCVIEW is the same as the actual route traveled.

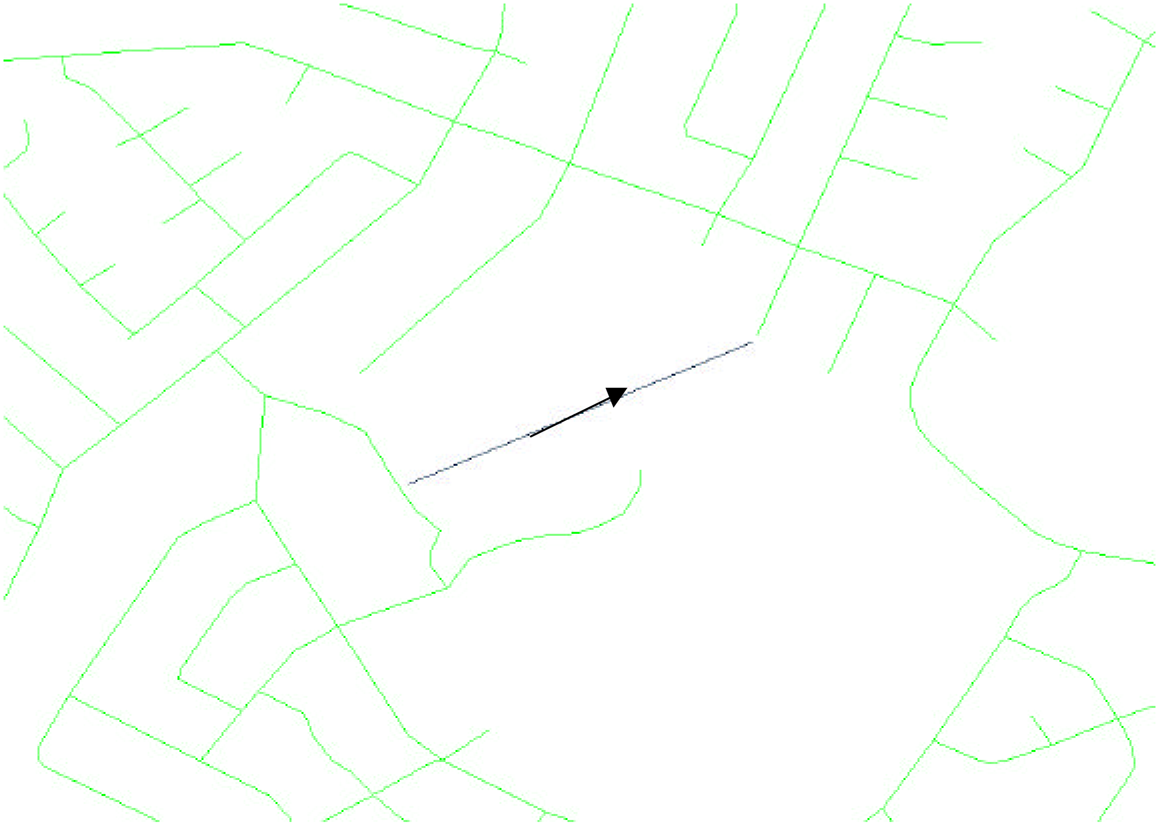


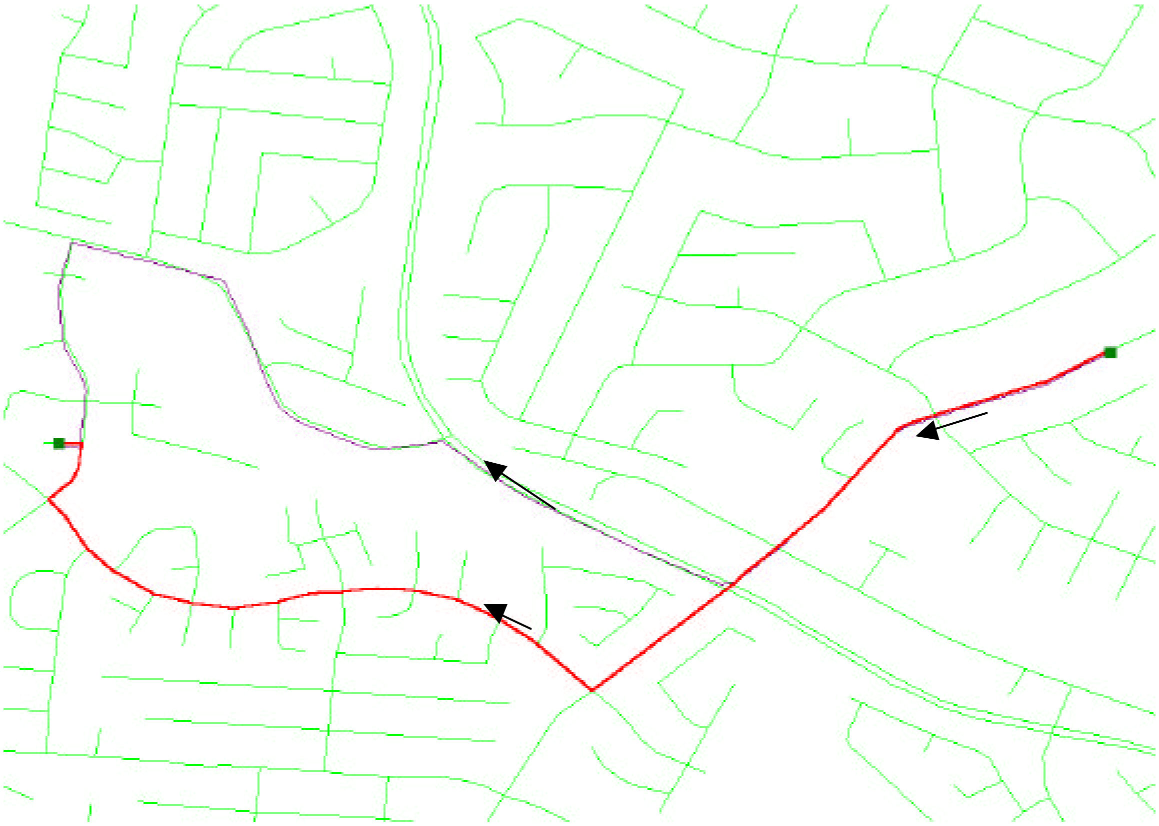


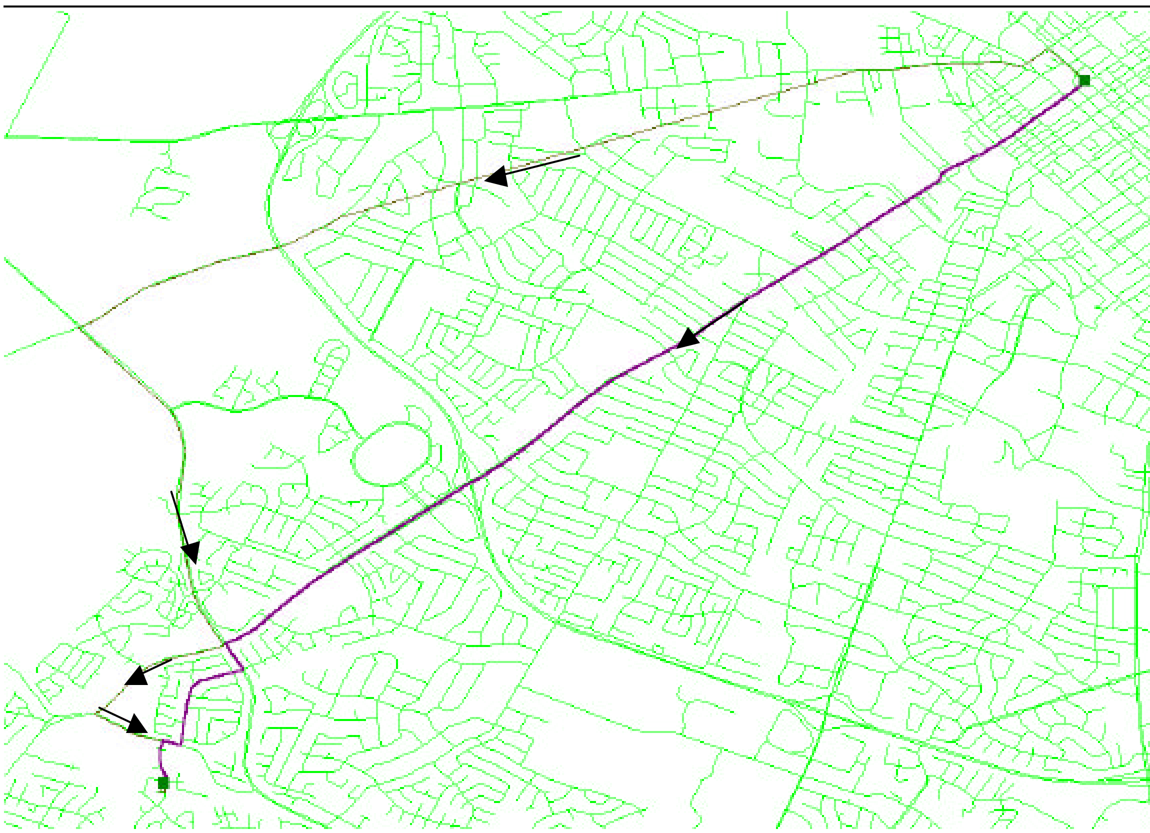




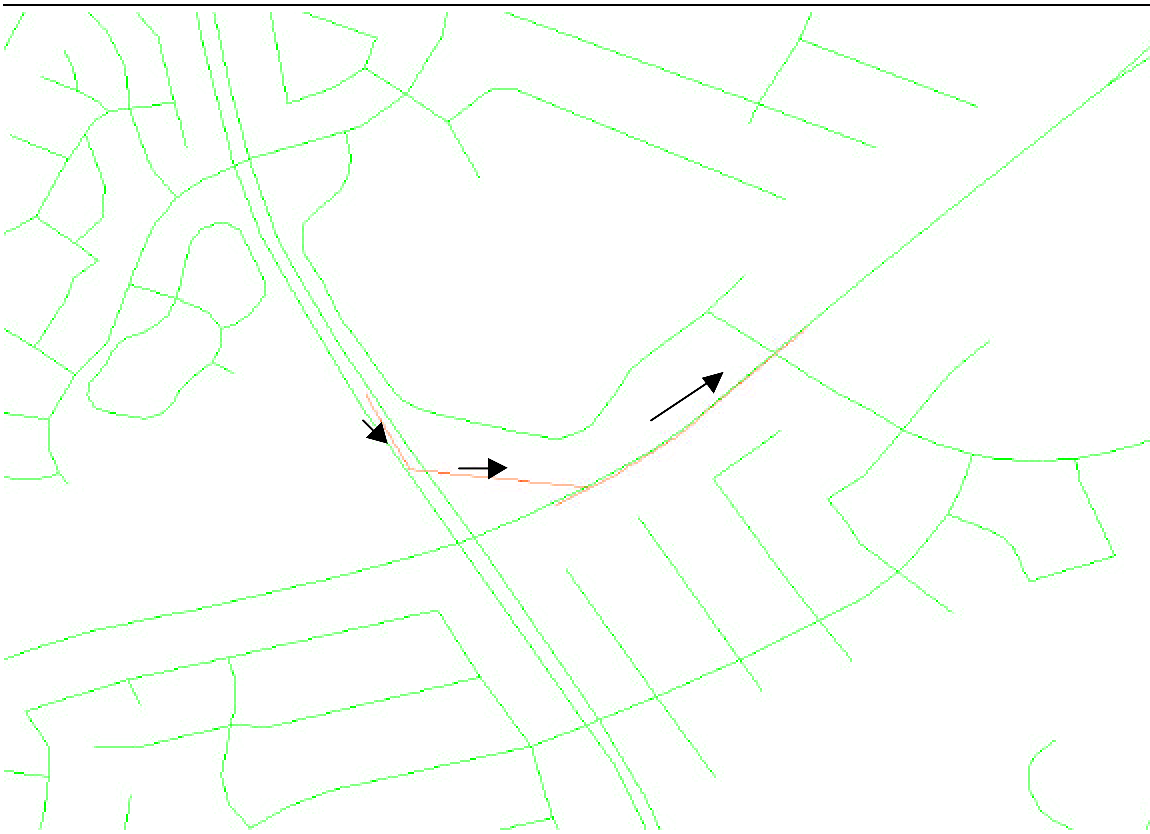








Note: This is a long trip made by our respondent. It looks like a tour around the city.



Compilation of shopping trip series across the week: autocorrelation and crosscorrelation

To compile the original data for time series analysis, we divide a day-of-week into 24 one-hour intervals in a natural way. Based on the start time of a trip, we allocate it into the one-hour intervals and accumulate the trip counts. Results were formulated into excel tables for exporting to other statistical software to do further analysis. In the attachment is the shopping trip series in the Excel table format. As indicated, the first column is the label for the valid shopping trips from 1 to 168 happened during the week. The second column shows the day of week on which trips happened. The third column is the ordered hour interval in the particular day of week. The rightmost column indicates the number of trips that falls into the time interval.

The excel table was used to generate a diagram of the variations of shopping trip count across the week directly using Excel program. Two types of such descriptive diagrams were generated: line graph and bar graph. As a supplement, we exported the data into SPLUS too. An autocorrelation diagram was also generated from SPLUS, which help us to examine the periodic characteristic of the particular type of travel activity under study. For example, the autocorrelation diagram of shopping trip time series clearly indicates the 24-hour positive correlation and 12-hour negative correlation among the trips.

Both SPSS and SPLUS were used to generate cross-correlation between different activity types. In our paper, we decide to use SPLUS to support our conclusion since it allows us more the flexibility in generating the diagram. However, SPSS output also has its advantage. As we can see, the exact cross-correlation values and the standard error at each lag step are listed right beside the cross-correlation plot. We examine the spot where the maximum cross-correlation pikes happen in the plot to identify the time relationship between different activity types.

Shopping trips

No.	day of week	hour	count
1	1	1	1
2	1	2	0
3	1	3	0
4	1	4	0
5	1	5	0
6	1	6	0
7	1	7	0
8	1	8	4
9	1	9	2
10	1	10	3
11	1	11	4
12	1	12	4
13	1	13	5
14	1	14	2
15	1	15	2
16	1	16	5
17	1	17	3

18	1	18	1
19	1	19	8
20	1	20	2
21	1	21	1
22	1	22	0
23	1	23	0
24	1	24	0
25	2	1	0
26	2	2	0
27	2	3	0
28	2	4	0
29	2	5	0
30	2	6	1
31	2	7	1
32	2	8	3
33	2	9	5
34	2	10	0
35	2	11	7
36	2	12	5
37	2	13	7
38	2	14	2
39	2	15	4
40	2	16	3
41	2	17	2
42	2	18	3
43	2	19	1
44	2	20	3
45	2	21	1
46	2	22	0
47	2	23	0
48	2	24	0
49	3	1	0
50	3	2	0
51	3	3	0
52	3	4	0
53	3	5	0
54	3	6	0
55	3	7	1
56	3	8	2
57	3	9	1
58	3	10	5
59	3	11	3
60	3	12	0
61	3	13	6
62	3	14	11
63	3	15	2

64	3	16	3
65	3	17	2
66	3	18	3
67	3	19	3
68	3	20	3
69	3	21	0
70	3	22	2
71	3	23	0
72	3	24	0
73	4	1	0
74	4	2	0
75	4	3	0
76	4	4	0
77	4	5	0
78	4	6	0
79	4	7	0
80	4	8	0
81	4	9	3
82	4	10	6
83	4	11	6
84	4	12	2
85	4	13	9
86	4	14	5
87	4	15	2
88	4	16	6
89	4	17	3
90	4	18	2
91	4	19	1
92	4	20	0
93	4	21	0
94	4	22	0
95	4	23	2
96	4	24	0
97	5	1	0
98	5	2	0
99	5	3	0
100	5	4	0
101	5	5	0
102	5	6	0
103	5	7	0
104	5	8	0
105	5	9	2
106	5	10	0
107	5	11	3
108	5	12	5
109	5	13	2

110	5	14	2
111	5	15	4
112	5	16	3
113	5	17	5
114	5	18	2
115	5	19	1
116	5	20	0
117	5	21	2
118	5	22	0
119	5	23	2
120	5	24	0
121	6	1	0
122	6	2	0
123	6	3	0
124	6	4	0
125	6	5	0
126	6	6	0
127	6	7	0
128	6	8	0
129	6	9	4
130	6	10	3
131	6	11	7
132	6	12	2
133	6	13	2
134	6	14	5
135	6	15	6
136	6	16	5
137	6	17	5
138	6	18	5
139	6	19	2
140	6	20	0
141	6	21	1
142	6	22	1
143	6	23	1
144	6	24	0
145	7	1	0
146	7	2	0
147	7	3	0
148	7	4	0
149	7	5	0
150	7	6	0
151	7	7	1
152	7	8	1
153	7	9	0
154	7	10	0
155	7	11	4

156	7	12	5
157	7	13	7
158	7	14	8
159	7	15	0
160	7	16	4
161	7	17	1
162	7	18	4
163	7	19	6
164	7	20	2
165	7	21	0
166	7	22	0
167	7	23	0
168	7	24	0

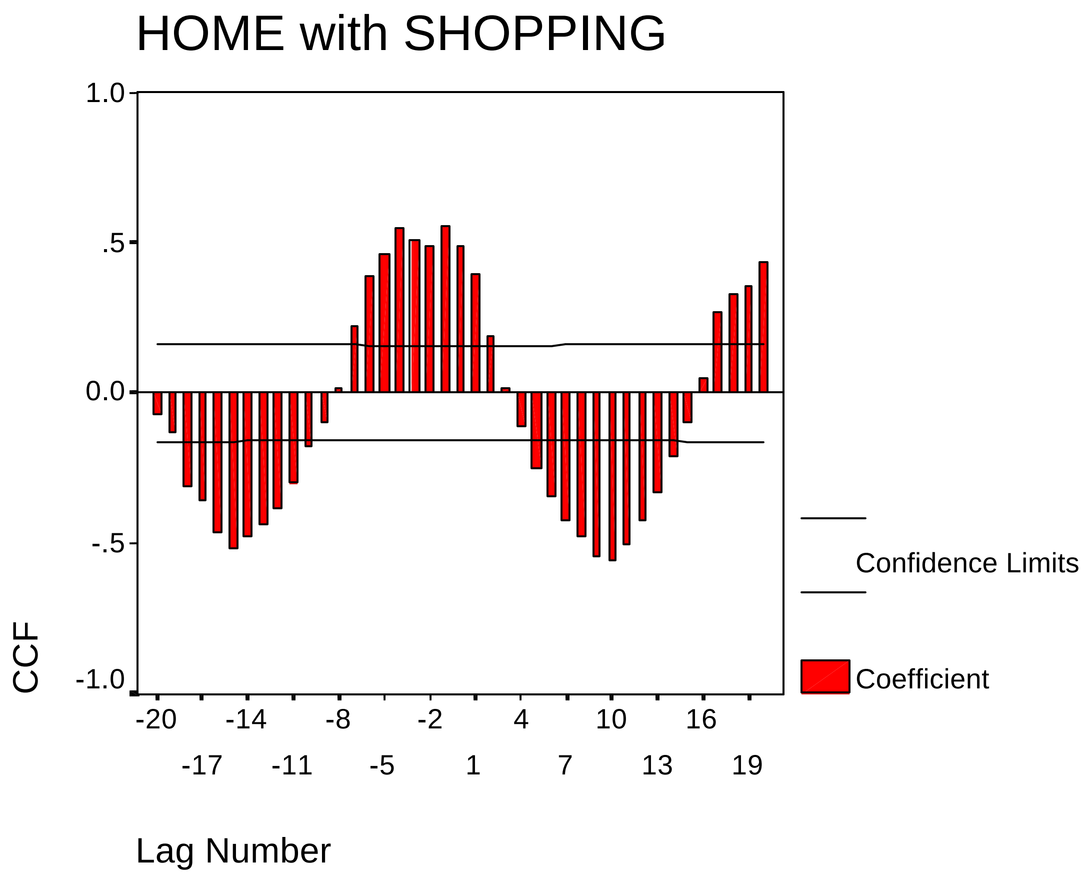
Return Home trips

No.	day of week	hour	count
1	1	1	1
2	1	2	1
3	1	3	0
4	1	4	1
5	1	5	0
6	1	6	0
7	1	7	1
8	1	8	2
9	1	9	4
10	1	10	3
11	1	11	8
12	1	12	9
13	1	13	7
14	1	14	9
15	1	15	5
16	1	16	14
17	1	17	15
18	1	18	13
19	1	19	11
20	1	20	12
21	1	21	6
22	1	22	4
23	1	23	3
24	1	24	5
25	2	1	0
26	2	2	0
27	2	3	1
28	2	4	0
29	2	5	2
30	2	6	2

31	2	7	0
32	2	8	4
33	2	9	3
34	2	10	1
35	2	11	6
36	2	12	12
37	2	13	10
38	2	14	10
39	2	15	5
40	2	16	6
41	2	17	13
42	2	18	4
43	2	19	4
44	2	20	11
45	2	21	8
46	2	22	3
47	2	23	3
48	2	24	2
49	3	1	2
50	3	2	1
51	3	3	0
52	3	4	0
53	3	5	0
54	3	6	1
55	3	7	1
56	3	8	2
57	3	9	3
58	3	10	3
59	3	11	5
60	3	12	2
61	3	13	9
62	3	14	5
63	3	15	4
64	3	16	12
65	3	17	13
66	3	18	10
67	3	19	10
68	3	20	16
69	3	21	6
70	3	22	3
71	3	23	4
72	3	24	2
73	4	1	2
74	4	2	0
75	4	3	0
76	4	4	0

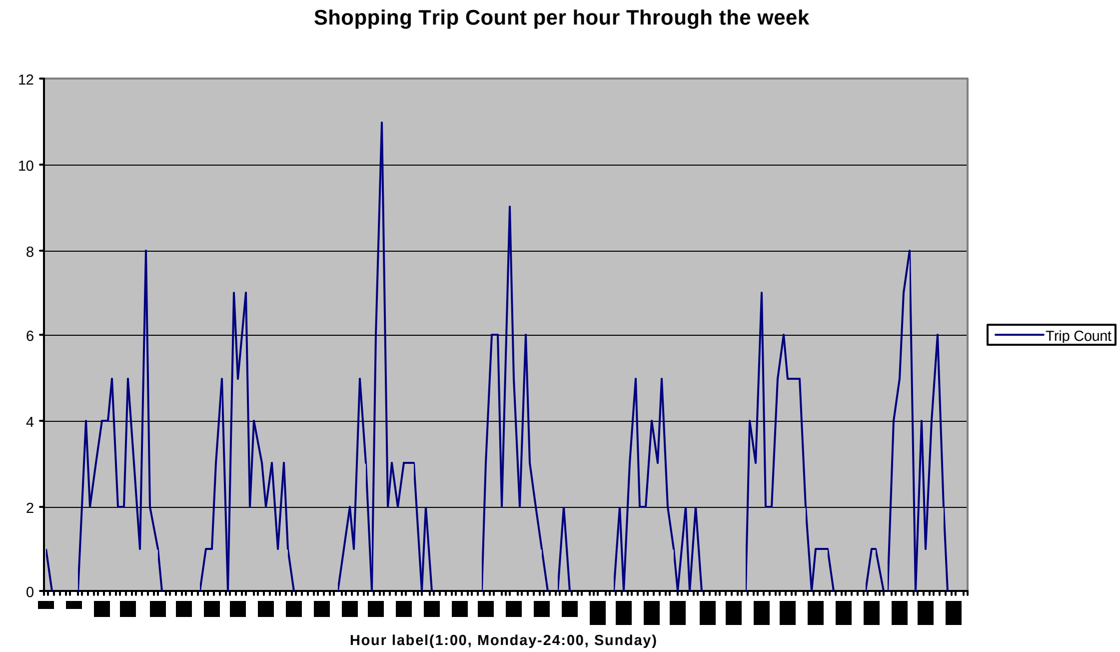
77	4	5	0
78	4	6	1
79	4	7	2
80	4	8	3
81	4	9	6
82	4	10	5
83	4	11	2
84	4	12	8
85	4	13	6
86	4	14	10
87	4	15	22
88	4	16	14
89	4	17	19
90	4	18	6
91	4	19	6
92	4	20	8
93	4	21	9
94	4	22	5
95	4	23	13
96	4	24	9
97	5	1	4
98	5	2	0
99	5	3	0
100	5	4	0
101	5	5	0
102	5	6	0
103	5	7	1
104	5	8	5
105	5	9	2
106	5	10	2
107	5	11	6
108	5	12	7
109	5	13	9
110	5	14	4
111	5	15	6
112	5	16	13
113	5	17	13
114	5	18	7
115	5	19	5
116	5	20	3
117	5	21	7
118	5	22	5
119	5	23	3
120	5	24	2
121	6	1	2
122	6	2	1

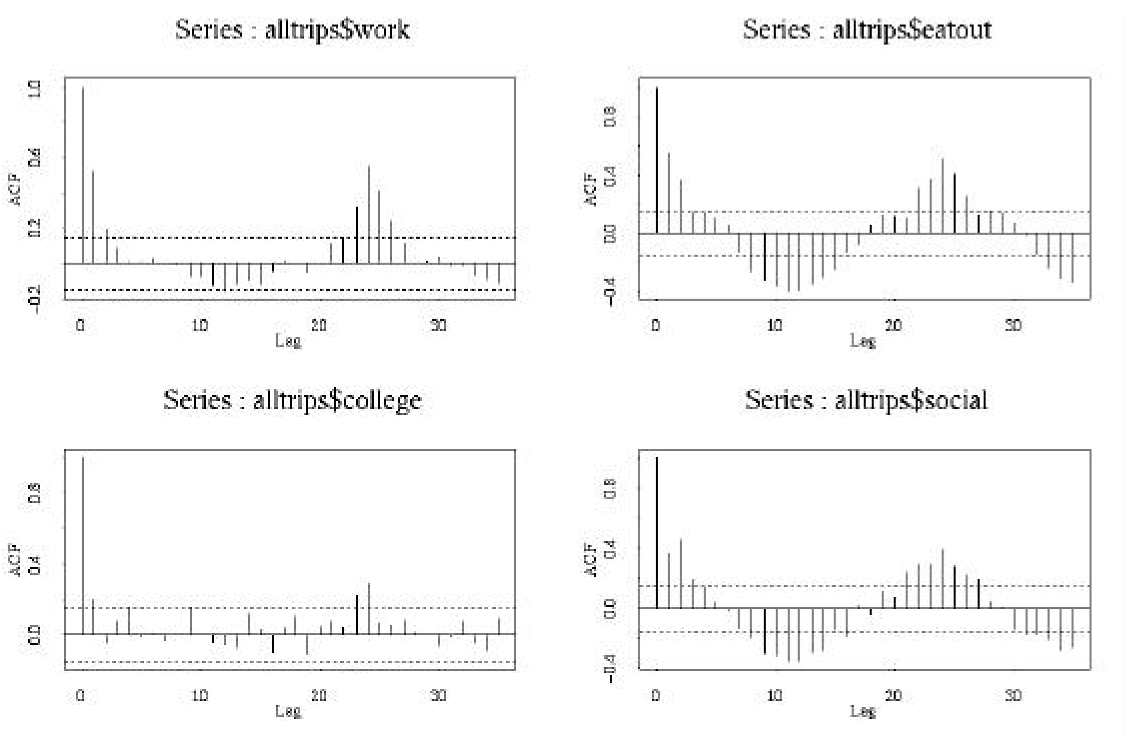
123	6	3	0
124	6	4	0
125	6	5	0
126	6	6	0
127	6	7	1
128	6	8	1
129	6	9	0
130	6	10	6
131	6	11	3
132	6	12	6
133	6	13	7
134	6	14	4
135	6	15	7
136	6	16	12
137	6	17	5
138	6	18	10
139	6	19	6
140	6	20	4
141	6	21	10
142	6	22	4
143	6	23	1
144	6	24	2
145	7	1	1
146	7	2	3
147	7	3	0
148	7	4	0
149	7	5	0
150	7	6	0
151	7	7	1
152	7	8	2
153	7	9	0
154	7	10	2
155	7	11	3
156	7	12	9
157	7	13	4
158	7	14	10
159	7	15	7
160	7	16	4
161	7	17	12
162	7	18	14
163	7	19	11
164	7	20	6
165	7	21	3
166	7	22	3
167	7	23	4
168	7	24	1

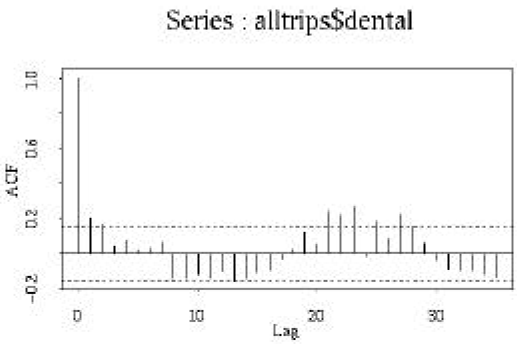

HOME with SHOPPING
1.0
.5
0.0
-.5
-1.0
CCF
-20
-14
-8
-2
4
10
16
-17
-11
-5
1
7
13
19
Lag Number
Confidence Limits
Coefficient

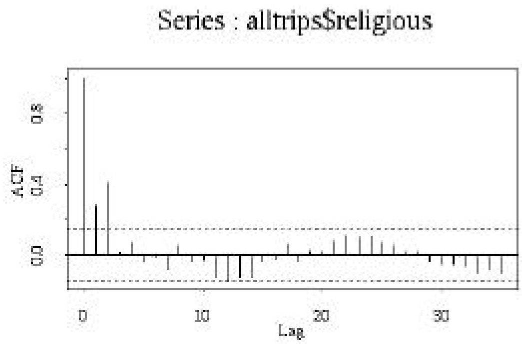
MODEL: MOD_2.

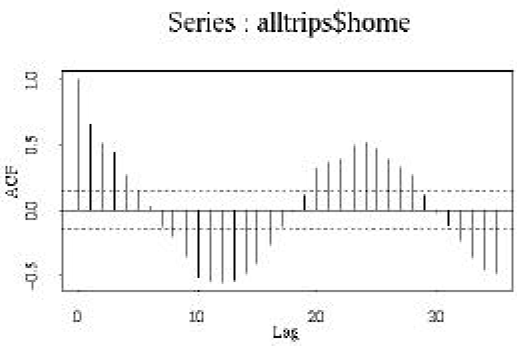
```
Cross Correlations:   HOME
                      SHOPPING

     Cross Stand.
Lag  Corr.   Err. -1  -.75  -.5 -.25   0   .25  .5   .75   1
                   +----+----+----+----+----+----+----+----+
-20  -.070   .082                    . *I  .
-19  -.132   .082                    ***I  .
-18  -.313   .082                 ***.**I  .
-17  -.358   .081                ****.**I  .
-16  -.466   .081              ******.**I  .
-15  -.519   .081             *******.**I  .
-14  -.478   .081             *******.**I  .
-13  -.437   .080              ******.**I  .
-12  -.380   .080               *****.**I  .
-11  -.303   .080                 ***.**I  .
-10  -.180   .080                   *.**I  .
 -9  -.097   .079                    .**I  .
 -8   .020   .079                    .  *  .
 -7   .224   .079                    .  I**.*
 -6   .390   .079                    .  I**.*****
 -5   .458   .078                    .  I**.******
 -4   .547   .078                    .  I**.********
 -3   .513   .078                    .  I**.*******
 -2   .489   .078                    .  I**.*******
 -1   .555   .077                    .  I**.********
  0   .491   .077                    .  I**.*******
  1   .398   .077                    .  I**.*****
  2   .189   .078                    .  I**.*
  3   .013   .078                    .  *  .
  4  -.113   .078                    .**I  .
  5  -.253   .078                  **.**I  .
  6  -.341   .079                ****.**I  .
  7  -.426   .079              ******.**I  .
  8  -.480   .079             *******.**I  .
  9  -.544   .079            ********.**I  .
 10  -.558   .080            ********.**I  .
 11  -.506   .080             *******.**I  .
 12  -.424   .080               *****.**I  .
 13  -.329   .080                ****.**I  .
 14  -.212   .081                   *.**I  .
 15  -.098   .081                    .**I  .
 16   .050   .081                    .  I* .
 17   .270   .081                    .  I**.**
 18   .325   .082                    .  I**.****
 19   .357   .082                    .  I**.****
 20   .434   .082                    .  I**.******

Plot Symbols:      Autocorrelations *     Two Standard Error Limits .

Total cases:  168     Computable 0-order correlations:  168
```

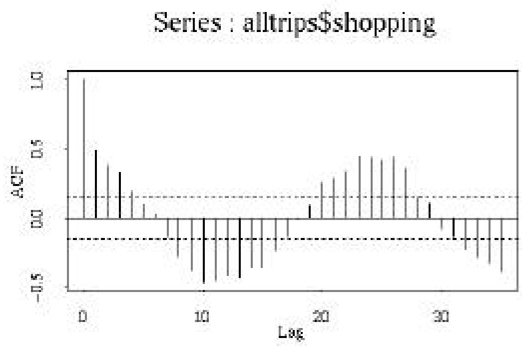

Shopping Trip Count per hour Through the week
0
2
4
6
8
10
12
Trip Count
Hour label(1:00, Monday-24:00, Sunday)

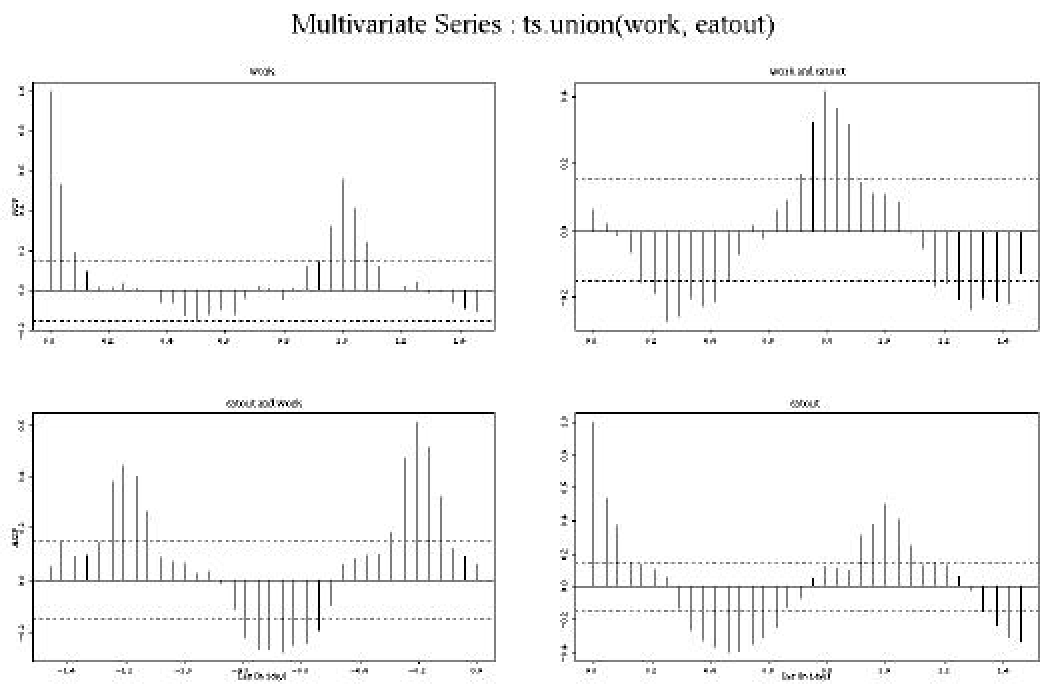

Series : alltrips$work
Series : alltrips$eatout
Series : alltrips$college
Series : alltrips$social
ACF
Lag
0
10
20
30


Series : alltrips$dental
ACF
Lag

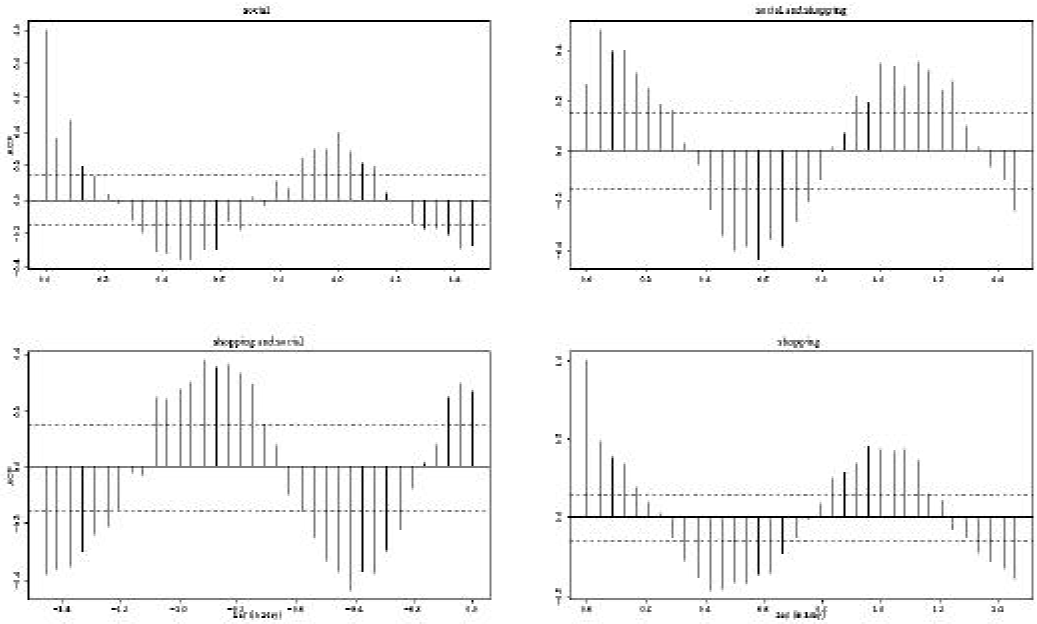

Series : alltrips$religious
ACF
Lag


Series : alltrips$home
ACF
Lag

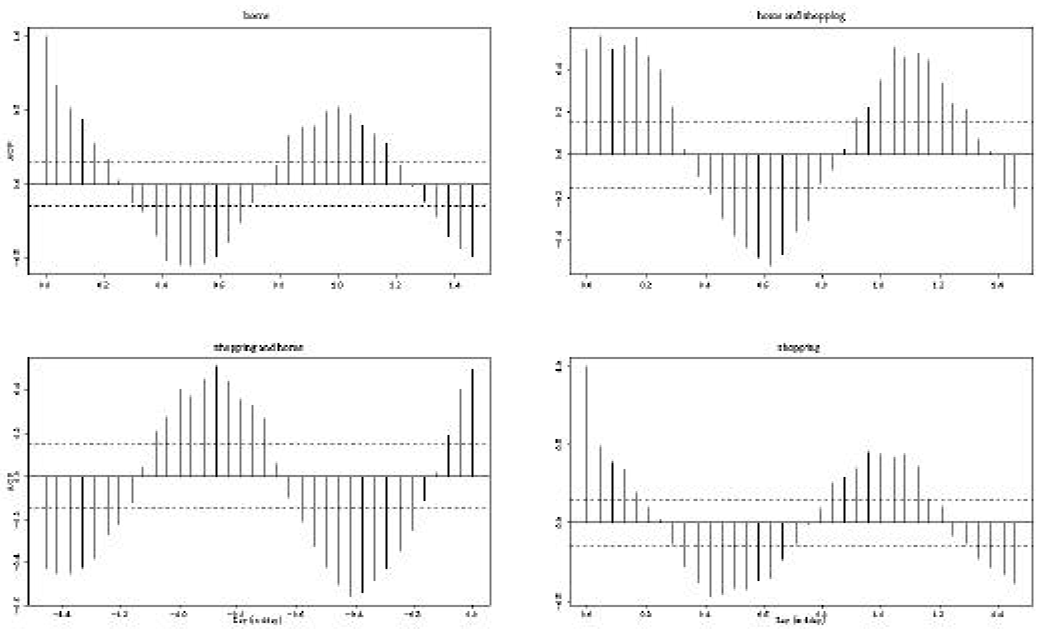

Series : alltrips$shopping
ACF
Lag

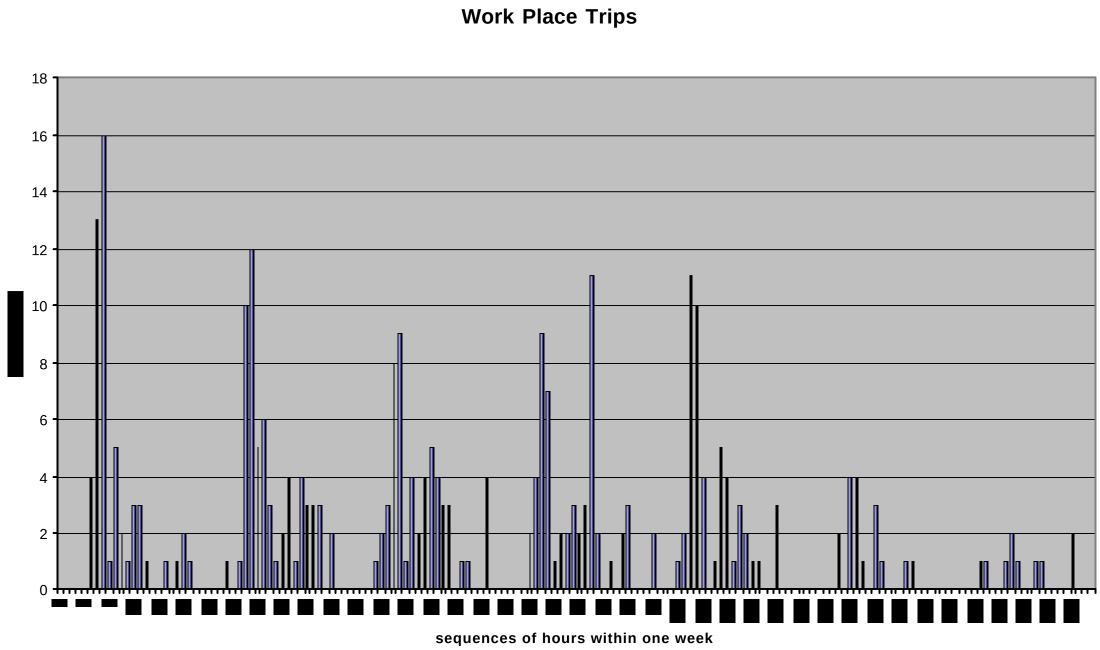

Multivariate Series : ts.union(work, eatout)
work
work and eatout
eatout and work
eatout

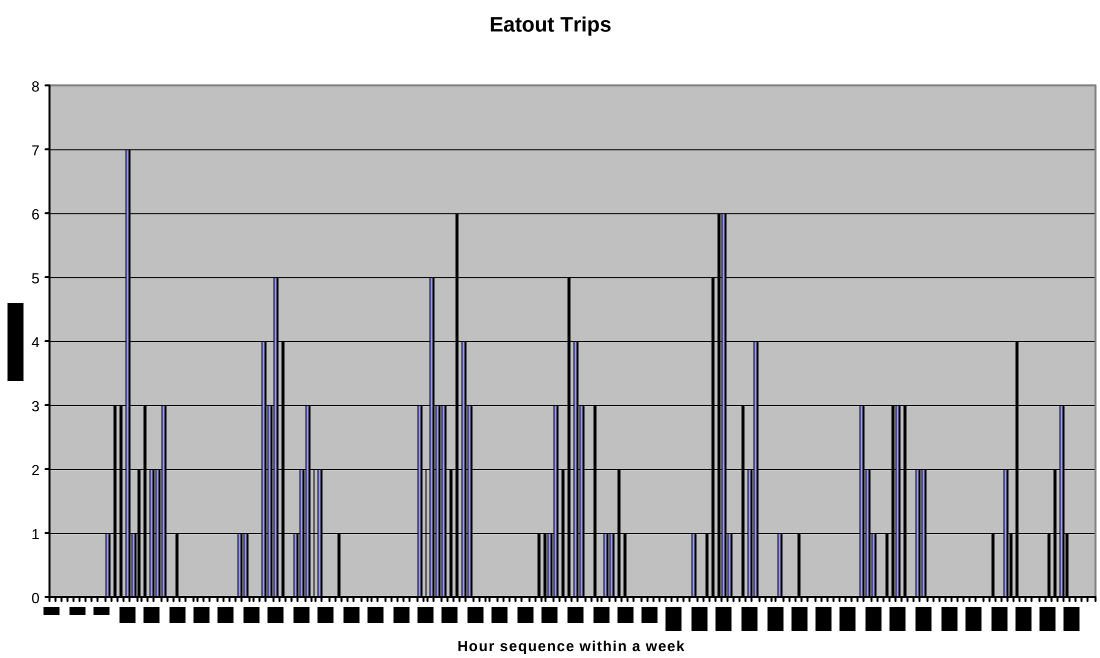
Multivariate Series : ts.union(social, shopping)



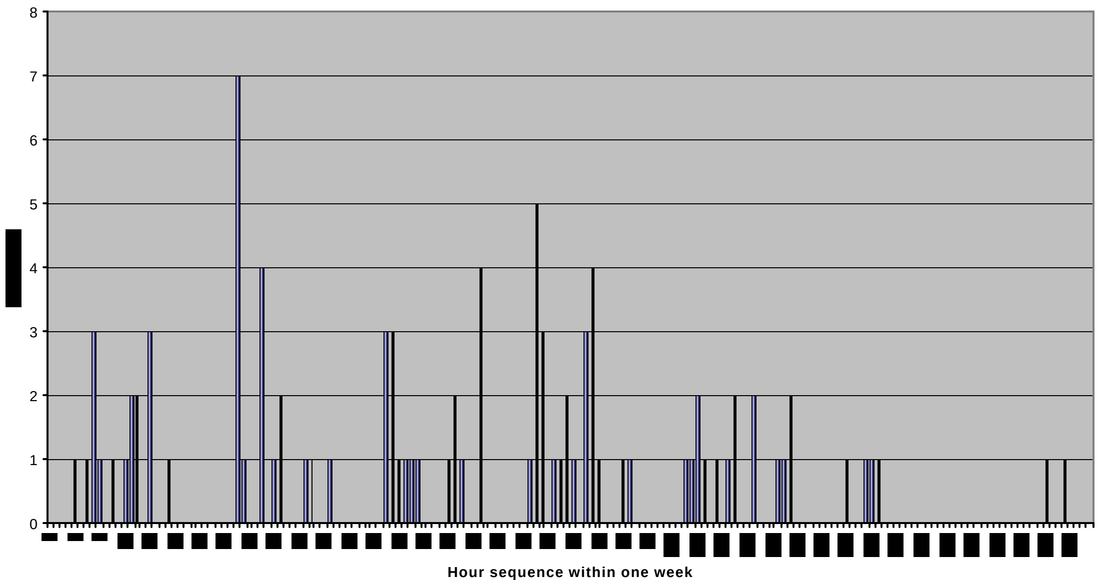
Multivariate Series : ts.union(home, shopping)



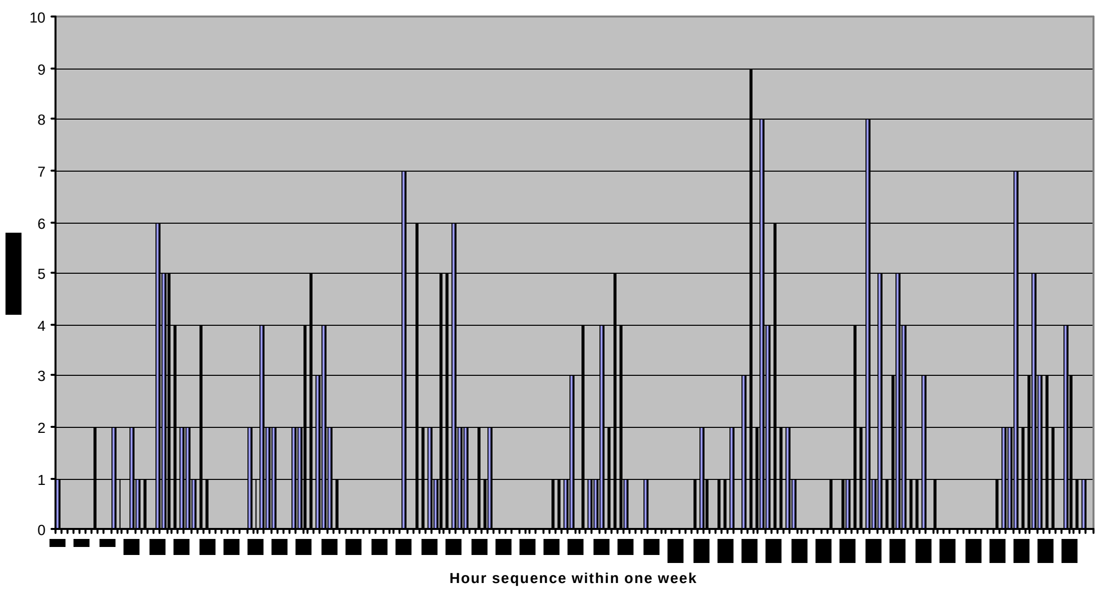

Work Place Trips
18
16
14
12
10
8
6
4
2
0
sequences of hours within one week


Eatout Trips
8
7
6
5
4
3
2
1
0
Hour sequence within a week

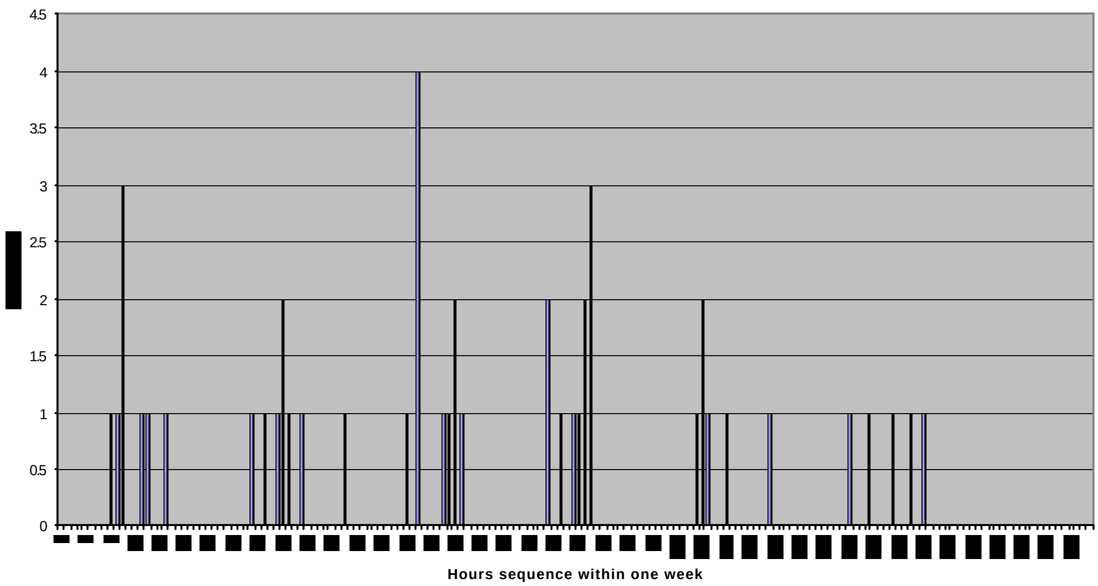
College trips



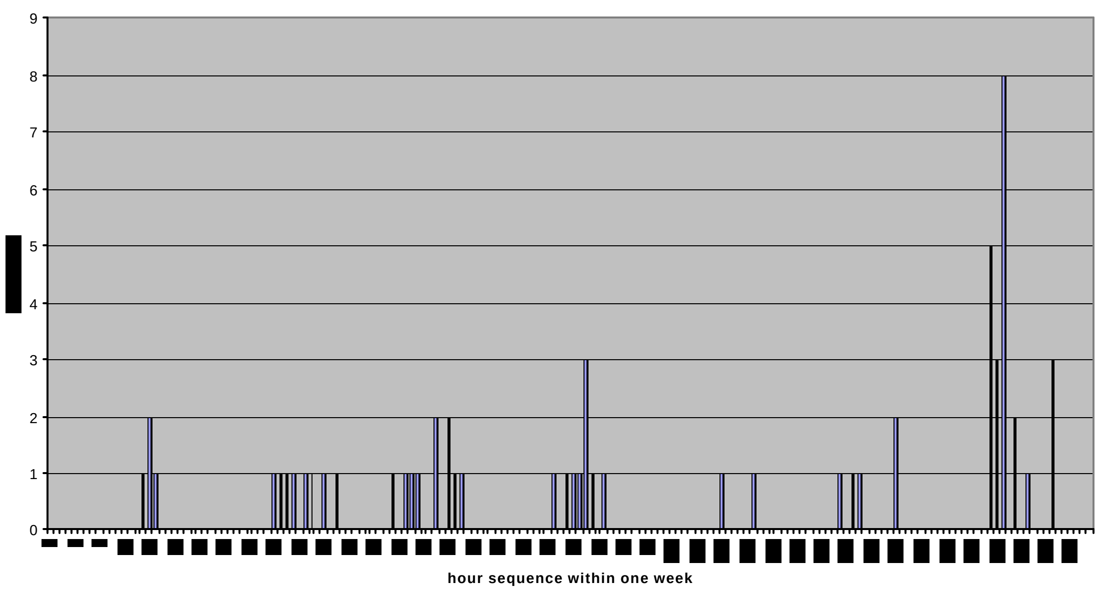
Social or Recreational Trips



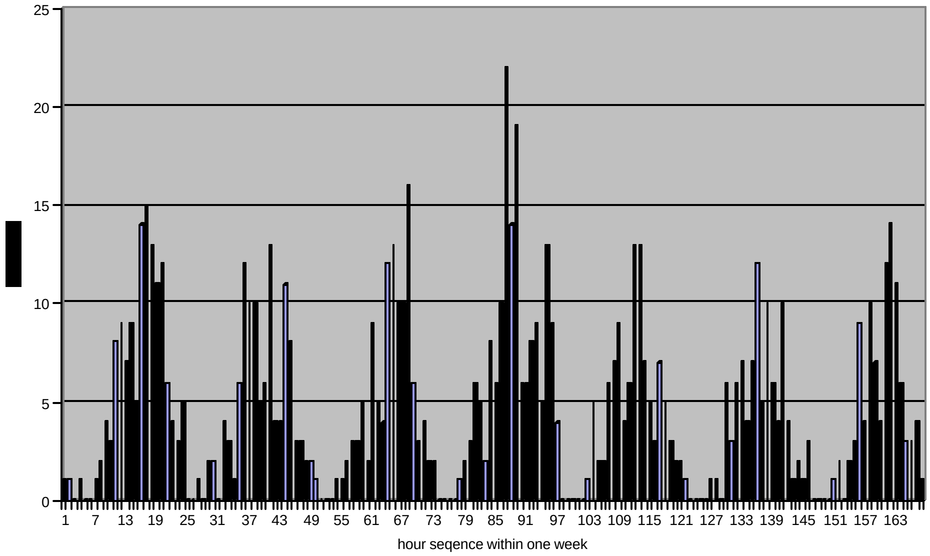
Medical or Dental Trips



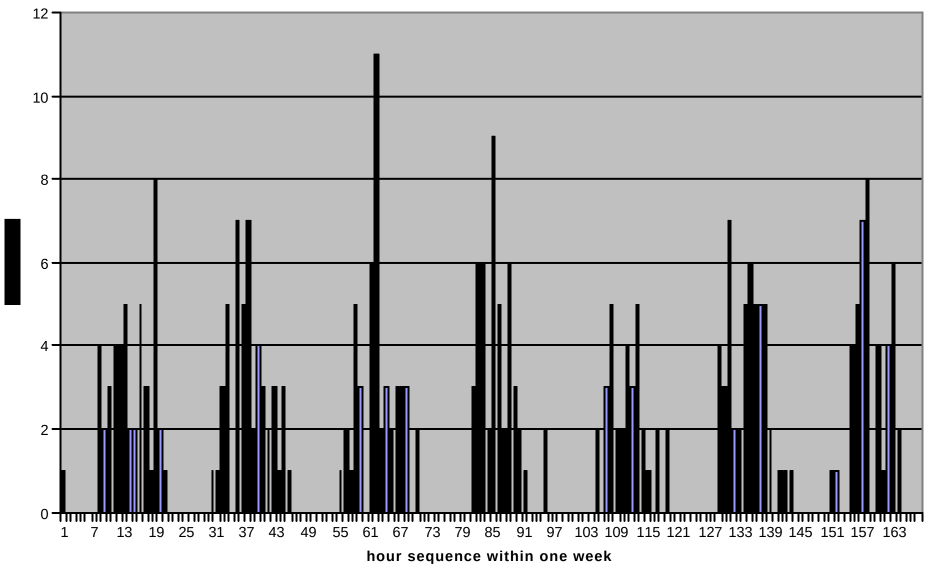
Religous Activities



Return-home Trips



Shopping trips



Loss of short trips in GPS-recorded trip distance data

The difficulty we met in trying to apply multivariate analysis to trip distance data is that the GPS-recorded trip distance data are not complete. Due to GPS signal loss under some circumstance, the time that the data collection device needs to gain fix for GPS equipment and occasional system malfunction, a lot of trips in original data file do not contains enough valid GPS points to define their trip distance. Only 1984 out of 3266 trips have distance records. Most of distance-missing trips in our dataset typically are very short trips, as what the trip duration time shows. In our analysis, we fill the distance-missing trips with distance 0. Since these trips are typically very short trips, we expect the analysis result won't be subject to big change even with more accurate data.

hh_id	drvrno	tripno	gps_dist	map_dist	drvrpurp	strtdate	stopdate
002	01	001	0	0	7	10/3/96	10/3/96
002	01	002	0	0	7	10/6/96	10/6/96
002	01	003	0.2751	0.42	6	10/6/96	10/6/96
002	01	004	7.4174	7.01	7	10/7/96	10/7/96
002	01	005	1.7134	1.75	7	10/7/96	10/7/96
002	01	006	8.3684	8.51	11	10/7/96	10/7/96
002	01	007	0	0	9	10/7/96	10/7/96
002	01	008	0	0	7	10/7/96	10/7/96
002	01	009	1.7793	1.85	11	10/7/96	10/7/96
002	01	010	0	0	9	10/8/96	10/8/96
002	01	011	0	0	11	10/8/96	10/8/96
002	01	012	0	0	7	10/8/96	10/8/96
002	01	013	0	0	11	10/8/96	10/8/96
002	01	014	0	0	8	10/8/96	10/9/96
002	01	015	0	0	7	10/9/96	10/9/96
002	01	016	0	0	7	10/9/96	10/9/96
002	01	017	0	0	11	10/9/96	10/9/96
002	01	018	0	0	6	10/9/96	10/9/96
002	01	019	0	0	11	10/9/96	10/9/96
002	01	020	0	0	7	10/10/96	10/10/96
002	01	021	0	0	7	10/10/96	10/10/96
002	01	022	0	0	11	10/10/96	10/10/96
002	01	023	0	0	9	10/10/96	10/10/96
002	01	024	0	0	9	10/11/96	10/11/96
002	01	025	0	0	9	10/11/96	10/11/96
002	01	026	0	0	11	10/11/96	10/11/96
002	01	027	0	0	7	10/12/96	10/12/96
002	01	028	0	0	7	10/12/96	10/12/96
002	01	029	0	0	11	10/12/96	10/12/96
002	02	001	0	0	-9	1/1/04	10/7/96
002	02	002	0	0	-9	10/14/96	10/14/96
003	01	001	0	0	-9	10/14/96	10/14/96
003	01	002	0	0	-9	1/1/04	10/20/96

003	01	003	0	0	-9	10/25/96	10/25/96
003	02	001	3.6251	3.37	5	10/15/96	10/15/96
003	02	002	0.1395	0.29	2	10/15/96	10/15/96
003	02	003	0.1671	0.17	2	10/15/96	10/15/96
003	02	004	0.0425	0.05	5	10/15/96	10/15/96
003	02	005	2.658	3.05	5	10/15/96	10/15/96
003	02	006	4.4366	4.17	11	10/15/96	10/15/96
003	02	007	0.0097	0.01	9	10/15/96	10/15/96
003	02	008	2.1941	2.43	3	10/15/96	10/15/96
003	02	009	0.1675	0.15	8	10/15/96	10/15/96
003	02	010	0	0	3	10/15/96	10/15/96
003	02	011	0.3217	0.23	3	10/15/96	10/15/96
003	02	012	1.4614	1.43	11	10/15/96	10/15/96
003	02	013	0.0224	0.01	1	10/16/96	10/16/96
003	02	014	2.9634	4.42	5	10/16/96	10/16/96
003	02	015	0	0	2	10/16/96	10/16/96
003	02	016	0	0	9	10/16/96	10/16/96