

EXPLORING DAY-TO-DAY INDIVIDUAL ACTIVITY-TRAVEL BEHAVIOURS BASED ON A SMARTPHONE APP'S TRAVEL DIARY

Final report from the SPOT2 project

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SUMMARY

In the previous research project SPOT, the possibility to replace or complement traditional travel diary data with data from the usage of a smartphone application was examined. In the SPOT project, a large field trial was conducted with MEILI, an application for activity-travel diary. It is still unknown how much more understanding and detailed information of the traveler's behaviour and choices one-week smartphone travel diary data can reveal, than what we already know from standard one-day paper-and-pencil based travel surveys.

This project, SPOT2 (2016/13851), aims to explore the potential of the data collected in the SPOT project, particularly how this new type of data can be used to further advance in existing travel demand models. To achieve such objective, this project starts with exploring the multi-day stability and variability of individuals' day-to-day choices. This includes analysing the tendency and degree of variability and stability of their chosen travel modes and trip purposes. Then the focus of the work moves to the comparability analysis between a number of widely used assumptions and the findings based on GPS based observations. A few basic model assumptions that are adopted in SAMPERS were reanalysed and revisited through this project. Lastly, this project explored the relationships between the day-to-day variability of individuals' time space constraints (in particular on the accessibility of the individuals towards different activity locations) with their possible choice of activity participations. The later topic is an exploratory exercise in order to investigate the operational possibilities and challenges in order to integrate dynamic choice set to the existing choice behaviour models.

Consistent with previous findings and consensus within the travel behaviour research community, the findings of this project confirm that there is no such thing as a representative 'typical day'. One-day travel diary collection was found insufficient to understand the finer aspects of behaviour that transcend attributes such as average trip length, duration, travel modes, etc. It was found that while the user base, on average, perform around half of the activities in the same order, it is a larger variation in the used travel modes than in the performed activities. Only about half of the activities performed by a user are performed, on average, in the same order by any other user. The analysis found a low inter-personal similarity for most trip purposes (except for non-food shopping, restaurant and sport trips) while the intra-personal similarity was found in particular for business, leisure, sport and school trips. It was also found that it is more common for users to travel with multiple travel modes on Tuesday, Wednesday, and Friday than any other days. The travellers are more likely to using non-chainable travel modes (such as driving) when performing the activities.

In term of modelling approach, this project has introduced a new method for the study and computation of traveller similarity that focuses on the sequential aspect of travel. The method allows for the extraction of regular patterns, as well as the computation of sequential similarity measures, which complements the existing similarity measures widely used in the travel behaviour research literature. Further investigation on the potential of the multi-day data use with dynamic discrete choice model shows that introducing multi-day data with such dynamics framework has a big impact on the fitness of the model.

During the examination of the model performance, it was found that the longitudinal model is performing better than the cross-section model which is not sensitive to the temporal aspect of the process. The longitudinal ordered model performs better than both cross-section ordered logit and the multinomial logit models. At the same time, it was also found that the multinomial logit model is performing better than the cross-section ordered logit model. However, it cannot be concluded that the multinomial model would be always superior compared with the cross-section model. It can be said that according to the model statistics, the process of mode choice is, more or less, correlated with the temporal aspects of the choices made by the individual. Whether the mode choice process (except the temporal aspects) is better described by the ordered logit model or as independent choices in the multinomial set up, needs further investigations, which has not been possible in this part of the project.

Further exploration on the potential use of time space prisms in defining individual's accessibility activity locations, turned out to be unreliable because the current space time prisms analyses do not include the dynamic nature of the land use and network constraints. Relying only on potential static accessibility assumption would produce a significant oversized (or overestimate size of) 'accessible area'. More practical alternative to measure accessibility, i.e., approximating accessibility as the subset of nodes of a cost-bound shortest path tree (where the cost is the same as the accessibility budget), was provided and discussed.

SVENSK SAMMANFATTNING

I det tidigare genomförda forskningsprojektet SPOT studerades om en applikation som installeras på en smartphone kan användas som ersättare eller komplement till en traditionell resvaneundersökning. I SPOT-projektet genomfördes ett stort fältförsök med MEILL, en applikation för resedagbok. Det saknas idag kunskap om hur mycket mer förståelse och detaljerad information om resenärers beteende och val som en veckas dagbok över resaktiviteter från en smartphone kan ge, jämfört med vad vi redan vet från traditionella resvaneundersökningar som baseras på endagars-resedagbok med papper och penna. Denna rapport presenterar fortsättningsprojektet, SPOT2 (2016/13851), som syftar till att fördjupa analysen av potentialen av den resdata som samlades in i SPOT-projektet.

I SPOT2-projektet undersöks om den nya typen av resdata kan användas för att utveckla befintliga reseefterfrågemodeller. För att uppnå detta startade projektet med att undersöka variationen och stabiliteten av individers dagliga resebeslut mellan olika veckodagar. Analysen inkluderar tendenser, graden av variation och stabilitet av resenärers färdmedelsval och ärendeval. Därefter studerades jämförbarheten mellan ett antal vanligt använda antaganden och resultaten de medför baserat på GPS-observationer. Ett antal grundläggande antaganden om resandet som antas i den svenska nationella persontransportmodellen SAMPERS analyserades och granskades i projektet. Slutligen undersöktes förhållandet mellan veckodagars variation av resenärers begränsningar i tid och rum (i synnerhet individers tillgänglighet till olika aktivitetsverksamheter) med deras tillgänglighet till olika aktiviteter. Syftet med detta var att undersöka implementeringsmöjligheter och utmaningar för att möjliggöra att integrera dynamiska val i de befintliga valmodellerna.

Resultatet från projektet visar att det inte finns en representativ "typisk dag" för resor, vilket är i enlighet med tidigare forskning om resebeteende. Endast en resdag från resedagboken var inte tillräckligt för att förstå och uppskatta resenärers resebeteenden för attribut som reslängd, restid och färdmedelsval. Resultatet visade att användare i undersökningen i genomsnitt valde hälften av alla aktiviteter i samma ordning, där det valda färdmedlet till aktiviteten skiljer sig mer än själva aktiviteten som valdes. I genomsnitt valdes mindre än hälften av en användares aktiviteter i samma ordning av någon annan användare. Analysen resulterade i låga likheter mellan olika användare för de flesta ärenden (undantaget var för resor till icke-livsmedelsbutiker och restauranger, samt sportresor) medan för enskilda resenärer fanns likheter för ärenden som affärs-, fritids-, sport- och skolresor. Det visade sig dessutom att det var vanligare att användarna nyttjade flera transportmedel på tisdagar, onsdagar och fredagar jämfört med resterande veckodagar. På torsdagar var sannolikheten högre att användarna valde det färdmedel som inte krävde färdmedelsbyte (såsom bil).

Ur ett modelleringsperspektiv har projektet introducerat en ny metod för att studera och beräkna resenärers likhet, där fokus var den sekventiella aspekten av resor. Metoden möjliggör uttag av regelbundna resmönster, liksom beräkningen av sekventiella likhetsvärden. Dessa värden kompletterar de befintliga likhetsvärden som är vanligt förekommande i forskningslitteratur inom resebeteende. Ytterligare undersökning om potentialen med dataanvändning över flera veckodagar för en diskret dynamisk valmodell visar att införandet av flerdagars-data har stor inverkan på modellens lämplighet.

Undersökningen av modellers prestanda visade att den longitudinella modellen presterar bättre än tvärsnittsmodellen, som inte är känslig för processens tidsmässiga aspekt. I synnerhet presterar den longitudinellt ordnade modellen bättre än både tvärsnittsmodellerna och de multinominala logitmodellerna. Samtidigt konstaterades det att den multinominala logitmodellen presterar bättre än den ordnade tvärsnittsmodellen. Det går däremot inte att dra slutsatsen att den multinomiala modellen alltid

skulle vara överlägsen jämfört med tvärsnittsmodellen. Enligt resultaten, korrelerar processen med färdmedelsval till viss del med tidsmässiga aspekter, som vilken tid på dygnet individer väljer färdmedel. Ytterligare undersökningar behövs däremot för att kunna konstatera huruvida processen av färdmedelsval beskrivs bättre med en ordnade logitmodeller eller som oberoende val i en multinominal logitmodell.

LIST OF ABBREVIATIONS AND ACRONYMS

Table 1: List of abbreviations/acronyms

Abbreviation/Acronym	Explanation
GPS	Global Positioning System
LCS	Longest common subsequence
MEILI	A semi-automatic activity-travel diary app, developed during the SPOT-project
OSM	Open Street Map (https://www.openstreetmap.org/)
POI	Point Of Interest
SPOT project	The previous research project financed by Trafikverket which focused on trialling smartphone-based travel data collection (TRV 2014/10422)

GLOSSARY

Table 2: Explanation of frequently used terms

Term	Explanation
Paper-and-pencil	Traditional travel survey
Trip	A trip is in this context defined by a purpose. Hence, several modes can be used during the same trip and a new trip purpose initiates a new trip.
Trip leg	A trip can be divided in several trip legs. Several modes can be used during the same trip and each part of a trip using one mode is called a trip leg.
Trip destination	A trip destination is here defined by a Point of Interest where the user ends his trip. In MEILI the POI can either come from a predefined data base of POIs or be defined by the user.
Trip purpose	Categorizing trips into different purposes is very important for estimation of transport models, since there are major behavioural differences depending on trip purpose. For example, user valuation of travel time differs substantially between work trips and leisure trips.
Sampers	National transport demand model for Sweden

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1 INTRODUCTION

1.1 BACKGROUND

With the emerging mobile and GPS technologies, there has been a surge in the number of trials and studies which investigate the potential use of these new technologies to complement and replace the standard, paper-and-pencil, travel survey. As a part of this effort, there has been an effort to test the technology, funded by Trafikverket FUD project, named as SPOT project (smartphone-based travel data collection, TRV 2014/10422). During the autumn 2015, the SPOT project conducted a large field/public trial with MEILI, a semi-automatic activity-travel diary app. During the field trial, multi-day travel diaries of about 200 travellers in the Stockholm region were collected. The field trial was performed in connection with the larger (2015) travel survey in Stockholm County.

Whilst the SPOT project has proved that mobile and GPS technologies are able to be a complement (and eventually substitute) of traditional paper-and-pencil survey, it is still unknown how much more understanding and detailed information of the traveller's behaviour and choices one-week smartphone travel diary data can reveal than what is already known from standard one-day paper-and-pencil based travel surveys.

1.2 AIM

The focus of this project, SPOT2 (TRV2016/13851), is to investigate how more understanding and detailed information of travellers' behaviour one-week smartphone travel diary data can reveal. Using the data collected in the SPOT project, this project will investigate the three sub-topics below:

- The stability and variability of individuals' day-to-day choices. This includes analysing the tendency and degree of variability and stability of their chosen travel modes, activity locations, individual's time allocations and trip chaining behaviours, across different groups of travellers.
- The comparability of standard transport model indicators and assumptions with GPS-based observations. This includes comparing the individual's revealed multimodal and route choices with hypothetical shortest path and multimodal assumptions which are commonly used in urban transport modelling.
- Impacts of how the space-time accessibility factors shape and influence individual activity-travel decisions. In this sub-work, the dynamic relationships between the day-to-day variability of individuals' time space constraints (the ability and orientation of individuals to move over space in any given time) will be analysed with their choice of non-compulsory activity participation (i.e. how individuals selected the locations for their non-work activities and the amount of time spent in the destination).

1.3 METHOD

To achieve the objectives, the following steps were followed in the project:

Topic 1: Analyse patterns in data

First, an analysis of the movement patterns of individuals and groups of individuals was conducted with focus on understanding how individuals plan their daily activities. Whilst there have been a number of multi-day travel patterns studies in the past in Sweden, more in-depth analyses have been rarely done (except by Hanson and co in the beginning of 1980s), mainly due to data scarcity. Our study starts with analysing the variability of daily activity-travel choices of each user and how it differs from a typical day. The assumptions

are based on multi-day data collected via the MEILI 2015 trial. This includes identifying which sequences of activities that are stable across days of the week and which are not.

Topic 2: Test of assumptions and hypothesis in Sampers

Due to the limitation of multi-day data availability from traditional travel surveys, there have been a number of assumptions of multi-day activity travel patterns in Sampers. This includes trip chaining and route choice behaviours. At this stage, these assumptions will be compared with data from MEILI. Three different aspects of data are specifically of interest to consider in this study, i.e.: (1) spatial representation of trips, (2) temporal representation of trips, and (3) choice behavioural aspects of the model (attributes and preferences).

Topic 3: Time-space prisms exploration

Finally, the analysis of the collected trajectories from individuals allows for a deeper examination of individual's time and space constraints. The examination will provide information of how individuals define accessibilities and opportunities towards various activity locations and activity engagements on the given day. This includes testing the validity and practicality of the shortest path assumption which is widely used in transport models.

1.4 PROJECT DISSEMINATION

During the project, four meetings with the steering group of the project have been organized where the results and progress of the project have been presented and discussed. The results have also been presented at several conferences and have been published in journal papers.

Conferences

- European Transport Conference, Barcelona, 2017
- The 96th Annual Meeting of Transportation Research Board (TRB), Washington, D.C., USA, January 2017
- The 2017 annual meeting of the Association of American Geographers, Boston (AAG), USA.
- The 2017 Annual NECTAR conference, Madrid, Spain
- The 11th International Conference on Transport Survey Methods, Quebec, Canada, September 2017
- Transportforum 2018

Journal papers

- Prelipcean, A.C., Gidofalvi, G. and Susilo, Y.O. (2017) Transportation mode detection – an in-depth review of applicability and reliability. *Transport Review*, 37, pp. 442-464.
- Allström, A., Kristoffersson, I., Susilo, Y.O. (2017) Smartphone based travel diary collection: Experiences from a field trial in Stockholm. *Transportation Research Procedia* 26, pp. 32–38.
- Prelipcean, A.C., Gidofalvi, G. and Susilo, Y.O. (2018) MEILI: A Travel Diary Collection, Annotation and Automation System. *Computers, Environment and Urban Systems*, 70, pp. 24-34, doi: 10.1016/j.compenvurbsys.2018.01.011.
- Prelipcean, A.C., Susilo, Y.O., and Gidofalvi, G. (n.d.) Collecting travel diaries: Current state of the art, best practices, and future research directions. Forthcoming at *Transport Research Procedia*.
- Prelipcean, A.C., Susilo, Y.O., and Gidofalvi, G. (n.d.) Longest common subsequences: Identifying the stability of individuals' travel patterns. Submitted for publication to *Transportation*.

Big Data Workshop

- Supported by CTS, the whole project team organised, chaired sessions and presented a paper at one-day workshop on the use of big data in transport modelling and analysis, which was held at KTH on 16 October 2016 (<https://www.kth.se/en/abe/inst/tsc/workshop-on-big-data>). The summary of the event and the outputs of the workshop can be seen at the Appendix A.

1.5 OUTLINE

This report is outlined as follows. Chapter 2 covers a literature review of previous work in the area of multi-day travel analysis. This includes the methodologies employed so far and the importance to analyse the basic essence of the pattern repetition with longest common sequence method. It is followed by Chapter 3 where the MEILI data is analysed by using longest common sequence method to reveal different repetition patterns of trips and travel mode choice among the respondents. In Chapter 4 various existing Sampers assumptions were examined and further compared with patterns and behaviours found among MEILI sample. Chapter 5 explores the feasibility of implementing time-space prism concept in defining individual spatial and temporal constraints in reaching and engaging in activity locations. Chapter 6 concludes the findings from the project and briefly discusses possible future work.

2 PREVIOUS WORK

This section is split in three main parts. First, it discusses the importance of accounting day-to-day variability of individual activity-travel patterns in travel demand model. Second, it focuses on the index measures previously proposed in the transportation literature to measure travel behaviour variability. Third, it introduces applications of LCS (Longest Common Sequences) that are closely related to travel behaviour. The literature review in Sections 2.2 closely follows to the literature review presented by Prelipcean et al. (2018).

2.1 THE NEEDS FOR ANALYSING INDIVIDUAL ACTIVITY-TRAVEL PATTERNS IN MULTI-DAY CONTEXTS

Travel is an unavoidable and important part of daily life. Individuals travel to get to work, to meet friends or to pursue other activities which may be necessary or for pleasure. A well-functioning transportation system is thus important for the quality of life, and is further necessary for a well-functioning economy. However, travelling may also have negative external effects on the society; both locally through congestion, noise and emission of air pollutants; and globally through emission of greenhouse gases. A travel demand model is a tool for planners in designing and evaluating a transportation system that optimally weighs the benefit of its users against the costs incurred on the society (Västberg, 2018). To date, there have been various types of travel demand models used widely in Sweden, from Sampers, a Swedish national transport model, to experimental MATSim model for Stockholm city.

Most of these models, however, were only based on one-day observations data. Since individual needs and desires are not constant from day-to-day, an individual's travel pattern is neither totally repetitious nor new every day. Some activities (e.g., eating, sleeping) are repeated every day, while other activities such as shopping, personal business and social recreation are not necessarily repeated on a daily basis. Routine obligations, different needs on different days and changes of the travel environment transform the individual daily travel and activity pattern into a dynamic process. The dynamic process consists of learning and change on the one hand and rhythms and routines on the other (Susilo & Axhausen, 2014).

As noted in Kitamura et al. (2006), "... a need for grocery shopping does not arise when there is an adequate level of food stock at hand. [...] Likewise, a typical individual would not have the desire to go to the movie theatre everyday". Susilo and Liu (2017) show that whilst most individuals spent most of (approx. 75%) of their time to sleep and for other in-home activities. Small variations in the sleeping and in-home activity patterns are very possible to change over the course of a week. Västberg (2018) argue that accounting for this day-to-day variation may improve predictive power of a within-day model as it explicitly includes factors that otherwise must be treated as unobserved heterogeneity. Treating long term constraints as unobserved heterogeneity might further over-predict households' ability to change their behaviour due to changes that affect every day. It will under-predict their flexibility with respect to changes that only influence a single day.

2.2 MEASURING TRAVEL BEHAVIOUR VARIABILITY VIA INDEXES

The origins of travel behaviour variability research can be traced back to three research groups. Hanson et al. (Hanson & Huff 1981, 1988, Huff & Hanson 1986) studied more than 35-day long travel diaries of a sample in Uppsala, Sweden. They defined an index to measure the repetition in the travels based on a contingency table of travel-equivalence classes. Recker et al. (1985, 1987), applied data reduction techniques to derive travel-pattern profiles from features of the travel diaries of 665 individuals from the 1976 California Department of Transportation Urban and Rural Travel Survey. Finally, Pas et al (Pas 1983, 1987, Pas & Koppelman 1987), using data from the Reading Travel Survey of 1971, improved person level trip generation

models by including intra- and inter personal variation in the traditional goodness of fit of the model. The main methods for travel behaviour variability are summarized in Table 3 (Prelicpean et al. 2018).

2.2.1 Spatial, temporal and spatiotemporal variability in travel behaviour

Hanson and Huff (1981) proposed a repetition index along five dimensions:

- 1) trip purpose / activity
- 2) mode of travel
- 3) time interval of arrival
- 4) distance from last stop
- 5) location of destination.

Using combinations of dimensions 3, 4, and 5 the authors established equivalence classes and based on the frequencies in contingency tables extracted frequently occurring repetitions of trips. Subsequent research of the authors adapted the methodology to measure the similarity across all days for each person (Huff & Hanson 1986). The index was normalized using the number of trips contained in the comparison between days.

Pas (1983) established a two-level weighted schema for travel diary attributes and computed a similarity index between two days of a travel diary as a weighted match score that was normalized by the number of trips performed during the compared days.

Recker et al. (1985, 1987) applied dimensionality reduction techniques to the representation of travel diaries. To so obtained feature vectors were used to define a similarity index between two travel diaries as the Euclidean distance between the feature vectors. The metric was also used to cluster travel diaries.

Jones & Clarke (1988) defined a similarity between travel diaries as the trip- or time normalized distance between temporal activity frequencies. Minnen et al. (2015) continued this approach by including concept such as tempo (e.g., one travels daily) and regular timing (e.g., if one travels, she always travels at 6 am). Yet another approach to frequency based similarity index generation is using the Herfindahl-Hirschman index to measure the repetitiveness of identical combinations of individual's spatial-activity-travel mode choices within an observed period (Susilo & Axhausen 2014, Heinen & Chatterjee 2015).

Yet other research focused on directly embedding the variability of travel behaviour into models through: survival analysis (Schönfelder & Axhausen 2000), structural equation models (Dharmowijoyo et al. 2016), mixed logic models (Cherchi et al. 2017) or other types of models finely tuned to fit their needs (Thøgersen 2006, Zhong et al. 2015). A comparison and evaluation of some of these indexes on the same data set can be found in Schlich and Axhausen (2003).

In comparison to the aforementioned indexes that measure the spatial and / or temporal variability in travel behaviour usually based on frequencies and / or number of matched elements, which provide a good single-value overview, the LCS based index developed in this project provides insight into the sequential variability of travel behaviour, i.e., the order in which activities are performed.

Table 3: The main types of methods used for defining indexes to measure travel behaviour variability, the index definition, their disadvantage and whether they explicitly model sequences (Source: Prelipcean et al. 2016)

Method	Index definition	Disadvantages	Seq.
Equivalence classes	Frequency of equivalence classes based on contingency table	Trips aggregated per day	No
Primary-secondary attributes	Similarity of attributes of trips matched based on order	Ignores trip start time and duration.	No
Feature vector similarity	Euclidean distance between travel diaries as feature vectors	Inconsistent travel behaviour clusters	No
Herfindahl-Hirschman	Frequency of identical trip spatio-temporal attributes combinations.	Subjective matching criterion.	No
Time budget similarity	Frequency of matched labeled activities at a 15 minute granularity	Night-time stability biases the index	No
Levenshtein distance	Measures amount of difference between two trips (as strings)	Subjective penalties for operations	Yes

2.2.2 Sequential variability in travel behaviour

While the interest of researchers is primarily aimed at studying the spatial and / or temporal variability in travel behaviour (Axhausen et al. 2002, Schönfelder & Axhausen 2003, Susilo & Kitamura 2005, Kitamura et al. 2006, Buliung et al. 2008, Kang & Scott 2010, Neutens et al. 2012, Dharmowijoyo et al. 2016, Cherchi et al. 2017), a few researchers have investigated sequential variability (Wilson 1998, Joh et al. 2001b,c, Moiseeva et al. 2014, Allahviranloo et al. 2016). Sequential variability research is built on top of the ED (Edit Distance) approach. Wilson (1998) proposed the usage of ED to measure similarities between activities extracted from travel diaries. Joh et al. (2001b,c) followed on the research of Wilson (1998) and also proposed generating alphabets that embed multiple dimensions. The result used the same ED metric, which was also used by Moiseeva et al. (2014). While Wilson (1998) is more preoccupied with understanding the implications of using sequence alignments and its error measures to have a better grasp of sequential variability of individuals. The more recent studies have taken the methodology as given and focused on optimizing sequence alignment methods (Joh et al. 2001a, Kwan et al. 2014) or using a given sequence alignment method to generate coefficients that are subsequently used to cluster users (Joh et al. 2001b,c, 2002).

While the research progressed in this direction, it is worth pointing out some of the limitations of ED. Using ED is accompanied by the subjective choice of penalties for each of the ED operations, which is a sensitive operation that heavily influences the index and biases the output. Similarly, ED based indexes are non-unique, where an index value can be obtained by any combination of ED operation penalties, so there is no clear indication to what stability is, as the ED is a penalty based method.

The method adopted in this project continues the initial work of Wilson (1998) and proposes an index to measure sequential stability that is easy to understand and generate. The proposed index is based on the widely used and accepted methodology named LCS extraction, which, in this case, extracts the activities that occur in the same order in between two compared entities. E.g., comparing the activity schedules of a user for two different days, or comparing the activity schedules of two users for the same day. While ED is a penalty based method, LCS is a sequence based metric that extracts the parts that are common between sequences, which has the advantage of extracting the activities that are stable between days and not just computing penalties. A thorough discussion on the difference between ED and LCS can be further read at Prelipcean et al. (2018).

3 DATA PATTERNS

3.1 LONGEST COMMON SUBSEQUENCE (LCS)

Instead of providing inferences but rather to exemplify the use of the suggested LCS based methodology. Prelipcean et al. (2018) propose a flexible methodology to evaluate and explore inter- and intra-personal trip purpose and travel mode variability by defining various indexes based on the concept of LCS. For detailed information on the methodology and the indexes see (Prelipcean et al. 2018).

The methodology has been applied to study the sequential variability of travel behaviour using a subset of the data that was gathered using MEILI. To allow the study of intra-personal variability, from the total 2142 trips of 171 users that gathered in Stockholm, Sweden between 2nd and 9th of November 2015 (Prelipcean et al 2017). The 1250 trips collected from 51 users who collected data for at least one week were selected for the analysis. The trip purpose and travel modes schema used in the travel survey consisted of 13 trip purposes and 14 travel modes, which together with a mapping between trip purpose / travel mode and their associated alphabetic letter are shown in Table 4.

Table 4: Mapping between trip purpose and travel mode and their associated alphabets (Source: Prelipcean et al. 2018).

(a) Alphabet mapping for purposes		(b) Alphabet mapping for travel modes	
Letter	Purpose	Letter	Purpose
B	Business	B	Bicycle
F	Grocery Shopping	S	Bus
O	Hobby	D	Car as driver
H	Home	P	Car as passenger
L	Leisure	Y	Commuter train
z	Other	Z	Ferryboat
N	Other Shopping	O	Flight
P	Personal	M	Moped / Motorcycle
D	Pickup / Dropoff	T	Subway
R	Restaurant/Caf	z	Taxi
S	School	F	Train
V	Visit	X	Tram
W	Work	W	Walk

3.1.1 Inter-personal indexes

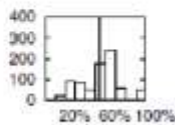
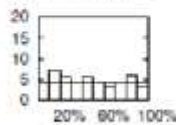
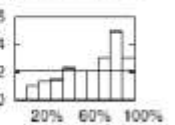
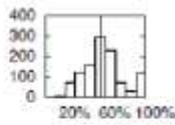
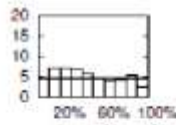
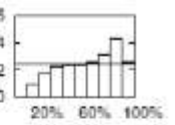
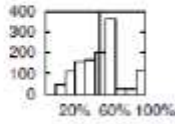
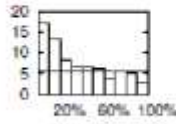
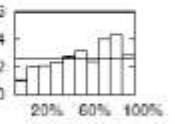
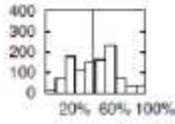
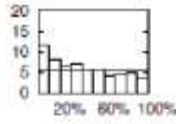
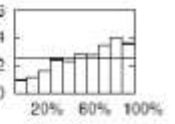
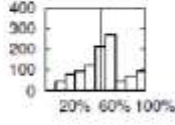
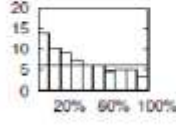
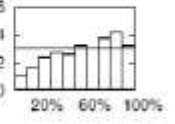
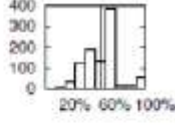
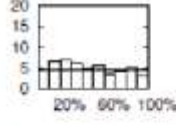
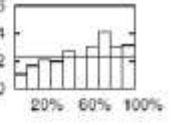
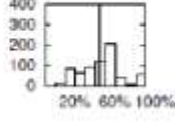
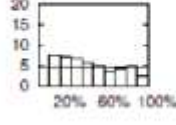
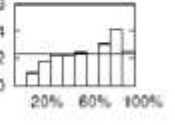
This section presents the results of the LCS based trip purpose / activity and travel mode variability analysis when it is applied to the whole user base. The method extracts the LCS values and computes the index between every two users in the user base for the same day.

3.1.1.1 Trip purpose / activity

Table 5 shows that the average degree of trip purpose sequential similarity is around 50% meaning that about half of the activities performed by one user is, on average, in the same order performed by any other user. The length values show that the average number of activities per day is between 5 and 6, while the average number of activities that are performed in the same order are between 2 and 3. In addition to these global averages, the daily averages and distributions show some variation. In particular, on Thursdays the degree of common activity ordering is lowest (47%) and has the largest spread among the users, which is in contrast with Wednesday where the average values are roughly the same but the index distribution is more peaked, i.e., has a smaller spread. The general trend is as expected: an increase in the LCS length is usually

correlated with an increase in the index value until 90%. Then there is a slight decrease from 90% to 100%, which is mostly due that the schedules that have the same activities in the same order tend to be shorter.

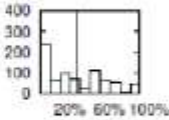
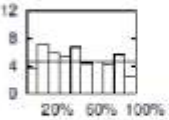
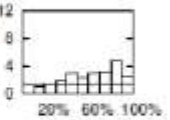
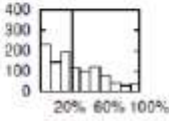
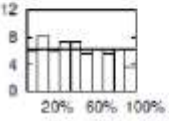
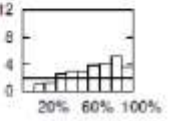
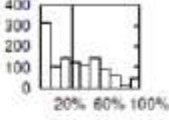
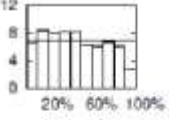
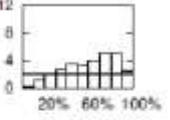
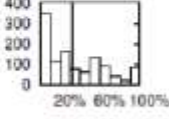
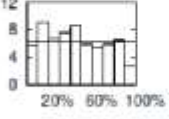
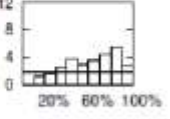
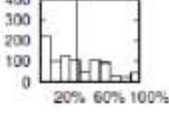
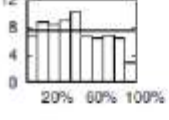
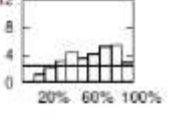
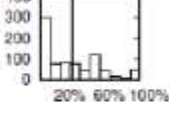
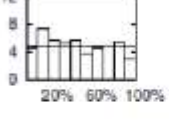
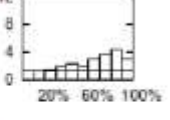
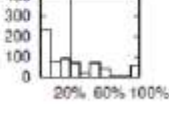
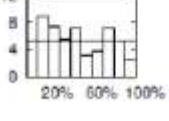
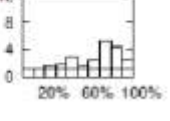
Table 5: Inter-personal trip purpose sequential variability analysis. “Idx” represents the average value of the Inter-personal trip purpose sequential variability index, and “Sch length” and “LCS length” represents average length of the activity schedule and the extracted activity LCSes for a given day, respectively. The lines in the frequency distribution charts represent the average values in the associated preceding columns (Source: Prelipcean et al. 2018).

Day	Idx	Sch length	LCS length	Idx freq	Sch length distribution	LCS length distribution
Mo.	54%	4.1	2.4			
Tu.	56%	4.8	2.1			
We.	54%	5.6	2.5			
Th.	47%	5.8	2.6			
Fr.	55%	6	2.5			
Sa.	55%	4.6	3			
Su.	54%	4.9	2.3			

3.1.1.2 Travel mode

Table 6 shows that sequential similarity in travel mode is generally lower for all the days than the sequential similarity in trip purposes / activities. This implies that while the user base performs on average around half of the activities in the same order, the used travel modes enroute to the activities differ more than the performed activities. Another interesting aspect is the length of the travel mode schedule is greater than the length of activity schedule, with Tuesday, Wednesday and Friday showing the largest differences. This implies that on those days, it is more common for users to travel with multiple travel modes while performing a trip. Another interesting finding is that while the users have a schedule on Thursday with as many activities or more than Tuesday, Wednesday and Friday, the difference between the trip purpose- and travel mode schedule's length is small. It implies that even though the users perform more activities than on average, they seldom use travel mode chains on Thursdays. This might mean that the users are more susceptible to using non-chainable travel modes (such as driving) when performing Thursday activities.

Table 6: Inter-personal travel mode sequential variability analysis. "Idx" represents the average value of the Inter-personal travel mode sequential variability index, and "Sch length" and "LCS length" represents average length of the travel mode schedule and the extracted travel mode LCSes for a given day, respectively. The lines in the frequency distribution charts represent the average values in the associated preceding columns (Source: Prelipcean et al. 2018).

Day	Idx	Sch length	LCS length	Idx freq	Sch length distribution	LCS length distribution
Mo.	36%	4.7	1.5			
Tu.	32%	6.3	1.9			
We.	33%	7	2.1			
Th.	33%	6.3	1.9			
Fr.	37%	7.4	2.4			
Sa.	32%	4.9	1.3			
Su.	31%	5.6	1.4			

3.1.2 Intra-personal indexes

This section presents the results of the LCS based trip purpose / activity and travel mode variability analysis when it is applied to study the day-to-day variability within the travels of a single user. Intra-personal index is an intrinsic metric that shows the degree of stability for the same user across different days. The method extracts the LCS values and computes the index between every two days for every user. Results are aggregated for a comprehensive analysis.

3.1.2.1 Trip purpose / activity

Table 7 shows the daily contingency table of the average intra-personal trip purpose index given by Prelipcean et al. (2018). The vertical column summarizes the ability of the day in the table header of being explained: the percentage of activities that are performed in the day in the header in the same order as in the days on the side of the table. The horizontal column summarizes the ability of the day on the side of the table of explaining other days: the percentage of activities that are performed by the days in the header of the table in the same order as in the day on the side of the table. For example, Friday can explain a high percentage of the activity sequences that occur during the other days, but no other day can explain a high percentage of the activity sequences that occur during Friday.

By analysing the table vertically, it is possible to see that across all days, users have less regular or “explainable” patterns on Wednesday and Friday. On the other hand, by analysing the table horizontally, it is possible to see that the patterns on the same days can explain the regularity on the other days. As expected, generally the explanation power of a day is directly proportional to the number of trips on the day as it is more likely the regularity in those trips captures regularity on other days: Mondays with few trips have low explanation power, while Wednesdays and Fridays with more trips have higher explanation power. A notable difference from this are Thursdays that have a relatively low explanation power compared to the number of trips. This is consistent with the finding in Section 3.1.1.2 about the use of non-chainable travel modes on Thursday, which can suggest highly specific trips that have a degree of seasonality that is longer than one week and it is not captured in the available dataset. Another interesting finding is that a high percent of the trip purpose sequence regularity on Monday can be explained by the regularity on Sunday.

Table 7: Daily contingency table of the average intra-personal trip purpose index given by Prelipcean et al. (2018) (Source: Prelipcean et al. 2018).

	Mo.	Tu.	We.	Th.	Fr.	Sa.	Su.
Mo.	N/A	54.4%	49.2%	54%	51.3%	53.8%	59.7%
Tu.	68.7%	N/A	60.4%	65.4%	53.9%	55.2%	62.9%
We.	72.1%	66.2%	N/A	67.5%	60.4%	63.4%	62.7%
Th.	65.6%	67.1%	60.9%	N/A	57.8%	53.5%	56.9%
Fr.	72.4%	65.6%	63.4%	70.7%	N/A	56.7%	63.2%
Sa.	70.1%	56%	55.3%	58.3%	49.3%	N/A	63.4%
Su.	69.7%	58%	51.4%	56.6%	50.1%	58.3%	N/A

3.1.2.2 Travel mode

Table 8 shows the daily contingency table of the average intra-personal travel mode index given by Prelipcean et al. (2018). As in the case of the inter-personal index analysis, the travel modes schedules are more irregular than the trip purpose schedules. The table also reveals a high degree of index similarity between and weekday as well as between any weekend day. Comparing corresponding values in Tables 5 and 6 one can also find examples for differences in relative explanation power for trip purposes and travel modes for some say combinations. For example, the values for Monday and Sunday suggest that even if the users might do same activities in the same order on Monday and Sunday, they travel differently when performing them.

Table 8: Daily contingency table of the average intra-personal travel mode index given by Prelipcean et al. (2018) (Source: Prelipcean et al. 2018).

	Mo.	Tu.	We.	Th.	Fr.	Sa.	Su.
Mo.	N/A	52.5%	47.3%	46.6%	46.5%	46.4%	43.7%
Tu.	58.4%	N/A	54.8%	61.4%	54%	49.6%	44%
We.	59.4%	53.7%	N/A	60.7%	51.7%	50.8%	50.6%
Th.	57.2%	56.7%	55.2%	N/A	50.4%	47%	39.9%
Fr.	58.1%	60.9%	55.7%	59.9%	N/A	55.1%	45%
Sa.	39.1%	31.6%	36.7%	37.5%	38.1%	N/A	54.2%
Su.	40.1%	41.4%	41.9%	40.1%	37.5%	56%	N/A

3.1.3 LCS advantages for sequence comparison

3.1.3.1 Trip purposes

Table 9 presents the top three (most frequent) inter and intra-personal trip purpose LCSes. As expected, intra-personal activities contain common activities such as work, home, grocery shopping and restaurants. However, for the intra-personal LCSes, new common activities are present, such as: pick-up and drop-offs of kids, school, hobbies and shopping other than groceries. This can be explained by the fact that the sequential constraints these activities impose on the schedule are not prevalent across the whole during the period of a day, but become important sequential user constraints across multiple days. This reveals a finding which can have important implications for activity modelling: the sequences of activities that occur in the same order for the entire user base are different from the sequences of activities that occur in the same order for each individual across different days.

Table 9: The three most common purpose LCSes for an LCS length of 3, 4 or more. The alphabet mapping is presented in Table 4 (Source: Prelipean et al. 2018).

Length	Inter-personal		Intra-personal	
	Sequence	#	Sequence	#
3	H→W→H	646	H→W→H	87
	H→H→H	262	H→D→H	51
	H→F→H	246	H→S→H	37
4	H→W→W→H	93	H→O→O→H	20
	H→W→R→H	91	H→R→F→H	11
	H→W→H→H	60	H→R→D→H	10
>4	H→W→R→W→H	15	H→W→D→W→H	6
	H→W→R→H→H	11	H→W→R→W→H	6
	H→W→W→R→H	10	H→R→N→F→H	4

3.1.3.2 Travel modes

Table 10 presents the top three (most frequent) inter and intra-personal travel mode LCSes. One can make several observations about the results. First, the inter- and intra-personal travel mode LCSes of length 3 and 4 are the same and are composed of walking (W), driving (D) or taking the bus (S). Second, there are no symmetrical LCSes that one might expect for users that make use of public transport, which implies that for the studied user base it was more common for travellers to come back home from work using a different sequence of travel modes than when going from home to work. Finally, the few and relatively infrequent intra-personal travel mode LCSes that include other public transport modes suggests that the studied user base contained users that travel by public transport than users traveling by car and other private modes.

Table 10: Top 3 travel mode LCSes for an LCS length of 3, 4 or more. The alphabet mapping is presented in Table 4 (Source: Prelipean et al. 2018).

Length	Inter-personal		Intra-personal	
	Sequence	#	Sequence	#
3	W→W→W	341	D→D→D	126
	D→D→D	183	W→W→W	59
	S→W→W	67	S→W→W	26
4	W→W→W→W	111	D→D→D→D	19
	W→S→W→W	36	W→S→W→W	16
	D→D→D→D	32	W→W→W→W	13
>4	W→W→W→W→W	46	D→W→W→D→D	12
	W→W→W→W→W→W	20	W→S→W→T→W→W→W	9
	W→S→W→W→W	19	S→W→W→W→W	8

3.2 COMPARING SHOPPING TRIP OD ESTIMATION BASED ON STATIC, MYOPIC, AND LONG ASSUMPTIONS

In order to further demonstrate the plausible benefit in using multi-day data in predicting individual's activity-travel schedule, MEILI data was used to explore the performance of a dynamic discrete choice model with Scaper model package (Jonsson et al., 2014), as a part of Oskar Västberg's doctorate thesis (2018), together with one-day trip data for Stockholm County 2005/2006, as a reference. In this exercise, Västberg (2018) tested a static, myopic and forward-looking version of the models. He found big improvement in the model performance when moving from a static to a dynamic model (using MEILI data), but modifying the specification of the model by allowing forward-looking (planning) ability to the agent gives a relatively small additional improvement. The idea was the following: if estimates of the single-day version could somehow be obtained, these could be used to approximate log-sums which in turn could be used when estimating the between-day model. When such log-sums are available, the day-to-day model becomes a small dynamic discrete choice model for which standard method such as the NFXP can be applied (Västberg, 2018).

The detailed of the model is not the focus of this project and can be found at Västberg (2018) and Västberg and Karlström (2017). In summary, however, in this exercise, four models were estimated:

1. Static, i.e. including the log-sum term but removing all parameters that change with the state - or in other words, the individual cannot learn and adjust to the dynamic conditions of the constraints and opportunities around.
2. Myopic, i.e. including the log-sum term but fixing $\beta = 0$ - or in other words, the individual can learn and adjust to the dynamic conditions of the constraints and opportunities around but have short sighted behaviour.
3. Long-term, i.e. including the log-sum term but fixing $\beta = 1$ - or in other words, the individual can learn and adjust to the dynamic conditions of the constraints and opportunities around and also have ability to plan a near distance.
4. Free, including the log-sum term and estimating the discount factor of β - or in other words, the individual can learn and adjust to the dynamic conditions of the constraints and opportunities around for an infinite horizon.

The estimation result for the static model as well as three alternative dynamic models are presented in Table 11. The resulting log-likelihood tell us a number of things. Firstly, introducing dynamics has a big impact on the model fit. The log-likelihood difference between the static model and the best dynamic model is 21.87 at the cost of three additional parameters. Comparing the log-likelihood between the static model with the myopic model, which performs the worst, the difference is still 18.5, so there is a large benefit in terms of model fit from introducing dynamics.

Table 11: Estimation of four different models. The largest improvement in model t comes from introducing dynamics. The additional improvement of having forward looking agents is relatively small, but significant.

Variable	Static	Myopic	Long-term	free
Shop on workday	-1.245 (-11.5)	-1.654 (-7.0)	0.488 (1.0)	0.709 (1.2)
Shop on freeday	-0.191 (-2.1)	-0.618 (-2.8)	1.281 (2.8)	1.586 (2.8)
Shop when $x_{shop} \leq 3$		0.188 (0.8)	-1.092 (-2.6)	-1.628 (-3.9)
Shop when $x_{shop} \geq 6$		2.118 (4.9)	1.6 (3.9)	2.935 (4.0)
λ	0.154 (2.4)	0.195 (2.6)	0.150 (2.5)	0.187 (2.6)
β	-	0	1	0.772 (8.8)
$\mathcal{L}\mathcal{L}$	-2442.1	-2423.7	-2422.1	-2420.2
$\mathcal{L}\mathcal{L} - \max \mathcal{L}\mathcal{L}$	-21.87	-3.496	-1.853	0

This lead to the first conclusion namely that introducing day-to-day dynamics without incorporating forward looking behaviour will give most of the model fit benefits. The difference in log-likelihood between the myopic model and the free-beta model is 3.5 so although it is significantly greater than 0. The difference in model fit might not be enough to motivate the additional model difficulties needed to consistently consider the future. It is also quite possible that a method which approximates the value of the future, like the one suggested in Arentze and Timmermans (2009), would set to obtain most of the additional benefits observed here. For the model presented here, the small difference in model fit might be because there is a single attribute which varies across individuals, namely the within-day logsum. If the difference between the expected value function between different individuals is small, constants related to when to shop will pick up most of the difference. However, these constants will not pick up how the value function changes due to policies. It is therefore possible that the myopic model will produce unrealistic forecasts.

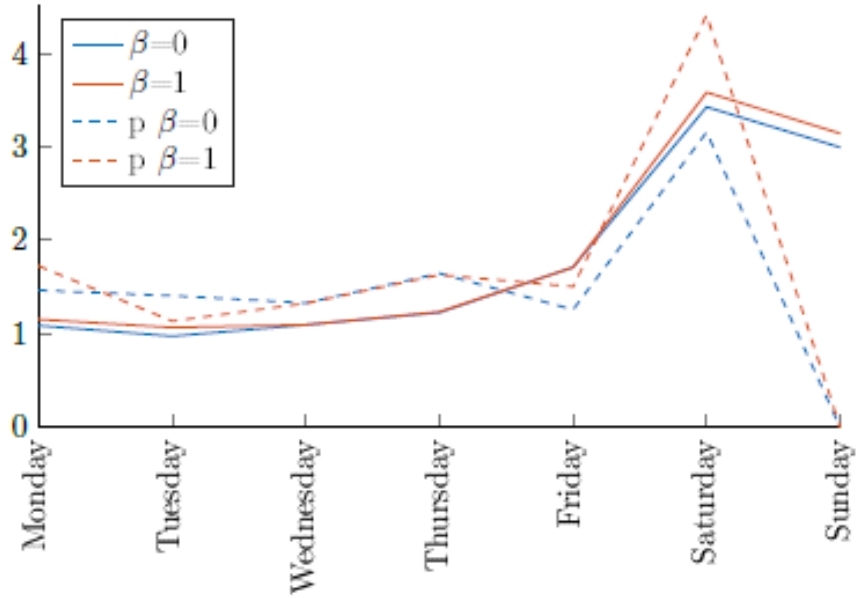
Secondly, even though the change in the model is not huge when introducing forward looking behaviour, the parameter values obtained changes drastically. For example, in the myopic model, shopping between day 1 and 3 is preferable to shopping between day 4 and 5, but the relationship is reverse in the dynamic models. This is needed in the myopic model to reproduce the correct rates of shopping, but give counter-intuitive result. In the forward-looking model, the utility to shop grows with the number of days since the last shopping trip was performed.

Policy test: grocery shopping unavailable on Sundays

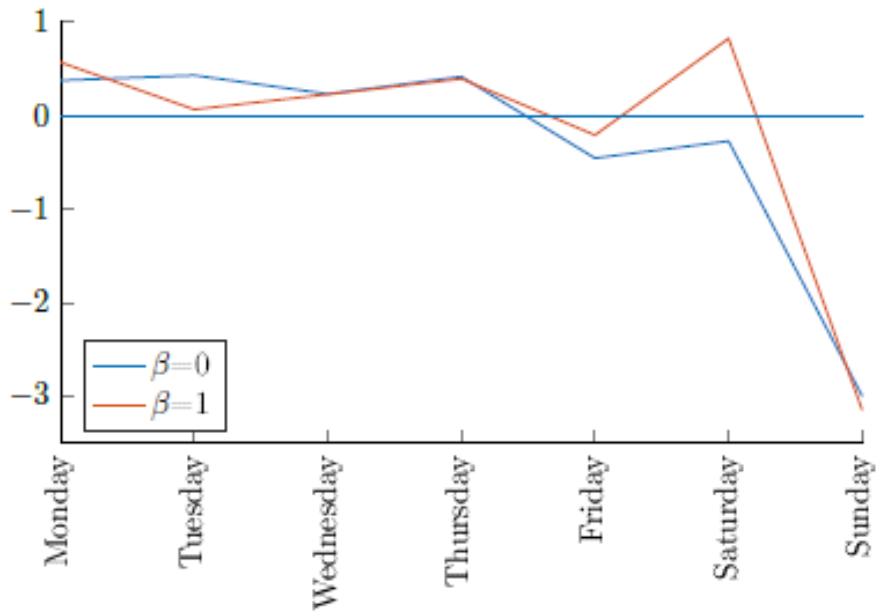
To test how the myopic model and the long-term model behave a scenario where grocery stores are closed on Sundays was implemented. This is compared to the base case where things are left unchanged. In the base case, both models will perform very similar as they are using the same data, so the change will be from the same initial levels. Observe that a purely static model would not predict changes on any other day than the day at which the policy has an effect.

The resulting change in average shopping probabilities can be observed in Figure 1. Observe that both myopic and forward-looking agents perform more shopping on the days following the Sunday (Monday-Thursday). However, myopic agents shop less on both Fridays and Saturdays. From Figure 2 it seems as if the reason for this is that since they are forced to shop in the beginning of the week, agents in general have a higher state in the end of the week and therefore have a lower need for shopping then. This produce the counter-intuitive result that they shop less on Saturdays. Forward looking agents behave more as one would expect. Since they are aware that shopping would not be possible on Sundays they compensate by shopping more on Saturdays. They also perform more shopping on Mondays-Thursdays and marginally less on Fridays. Both models further predict a decrease in shopping trips over the week but the change is almost twice as high for the myopic model. The fact that the two models have behaved so differently and the myopic model performed so counter intuitively are strong arguments for the inclusion of forward looking behaviour in day-to-day models, even though the model fit within the data set was very similar. More detailed discussions on this can be seen at Västberg and Karlström (2017)

These dynamic analyses, however, were only allowed to happen due to the availability of MEILI multi-day datasets, and such multi-day model performance triumph the performance the model formulated based only on one-day observation.



(a) Average probability of shopping trip before (solid) and after (dashed) policy change due to policy



(b) Change in probability to perform shopping trip

Figure 1: the average probability that a shopping trips is performed on specific day of the week in the base case and when shopping can no longer be performed on Sundays (dashed) (Source: Västberg and Karlström, 2017)

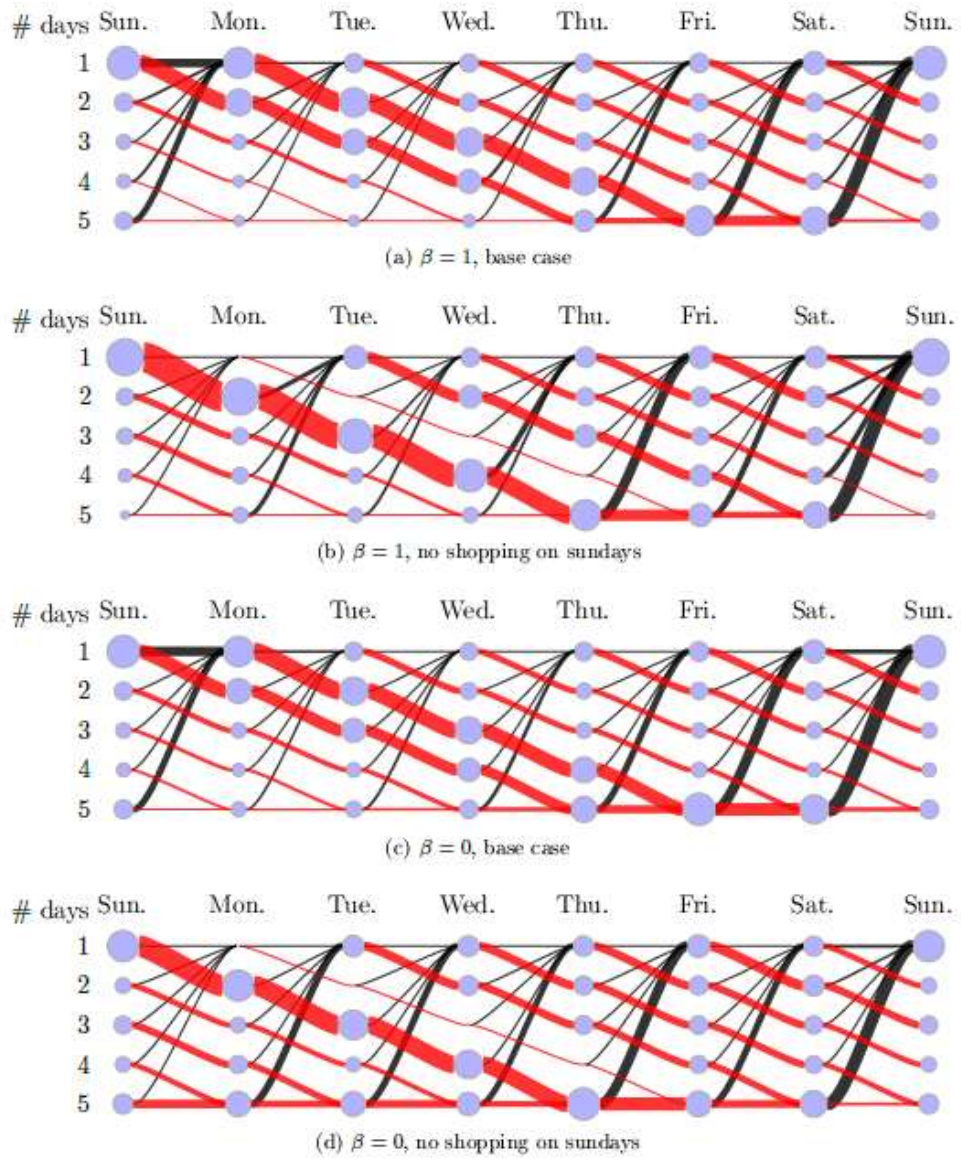


Figure 2: Stationary probabilities and transition probabilities for base and policy scenario with beta = 1 and beta = 0 respectively (Source: Västberg and Karlström, 2017)

4 COMPARISON TO CURRENT DEMAND MODELS

Trafikverket (the Swedish Transport Administration) currently uses a travel demand model, Sampers. In Sampers, several assumptions regarding the travel are made due to various reasons, such as computational time and available input data.

One of the more critical input data is the travel behaviour. In the current version as well as for the upcoming version of Sampers, the travel behaviour has been collected by traditional travel surveys made with the paper-and-pencil method. In the used travel surveys the individuals have been answering their travel behaviour for a specific day. The individuals in the survey fills in the travel diary according to their interpretation, which makes the travel diary filtered once before the modeler gets it. The interpretation can for instance be that an individual does not consider a trip as a trip, or leave some fields in the travel diary empty.

An assumption to save computational time and minimize the uncertainty in the results, is that all modelled trips are assumed to be home-based. An exception is some business trips which are modelled as workplace-based. In the data collected from the MEILI system it is shown that multiple trips are made between the stays at home. As an example, almost 30 percent of all trips are people returning home, which makes around 60 percent all trips home-based trips and around 40 percent non-home-based trips.

An important part in the Sampers model is the trip generation part, which results in a distribution of trip purposes among the trips made. The distribution from the MEILI data is similar to the results from Sampers, but the MEILI data contains a number of non-home-based trips. The non-home-based trips tends to be within the trip purpose “other”, which makes the home-based trips similar.

In Sampers there are four possible modes for regional trips

- car (driver and passenger)
- public transport
- bicycle
- walk

If public transport is used a part of a trip, public transport is the chosen mode when encoding the used travel surveys. However, in the MEILI data multiple trip legs are logged. As an example, a car trip to a train station is not modelled in Sampers, but it affects the congestion in the road network.

The route choice for cars in Sampers seems to be similar to the MEILI data. The assumption for route choice for cars in Sampers for the Stockholm region is the minimized generalized cost, which is the travel time plus the congestion charge. The MEILI data reveals that the main part of the trips by car is made along the main roads. As a main part of the workplaces are in the central part of Stockholm and the number of parallel roads into the city is few, the result is expected even though there are few data points.

4.1 OPPORTUNITIES COME WITH NEW TYPE OF DATA

Availability to detailed trip data such as MEILI data introduces a unique opportunity to progressively increase transport model systems capabilities. The richness of such data sets enables us to reconsider potential deficiencies encountered in many transport models. These potential weaknesses often are structurally enclosed in the model system in order to replicate trip decisions in accordance with observations, while lacking certain critical information.

With MEILI data, it is possible to identify and test inherent dependencies infused in the models through categorical assumption. Furthermore, it gives potential to redesign transport models in order to gain increased generality and increase their responsiveness, through reduction of debatable assumptions that have been made.

Three different aspects of data are specifically of interest to consider:

1. Spatial representation of trips
2. Temporal representation of trips
3. And choice behavioural aspects of the model (attributes and preferences)

It is crucial to remember the fact that trips are performed by individuals, based on their specific attributes and preferences, in both space and time. Therefore, any model trying to replicate trip behaviour needs to consider the three mentioned aspects in parallel, as well as in combination, demonstrated elegantly in form of space-time prisms by, for instance, Hägerstrand (1970).

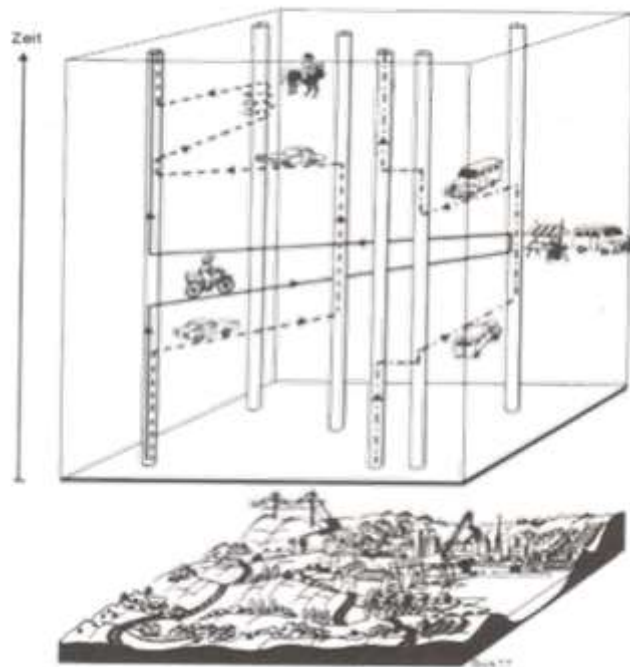


Figure 3: Hägerstrand (1970) type space-time prism

Arbia (1989) divides problems related to spatial representation of trips into two sub problems. The first is related to the effects of scale while the second corresponds to zoning problems, which is the spatial arrangement of units, also called the Modifiable Areal Unit Problem (MAUP) (Baradaran and Ramjerdi, 2003).

The zoning problems relate to the way locations are presented. Expressing locations as nodes, corresponding to urban centres requires aggregation, which means services within each zone will be aggregated with no or very little regards paid to their differences. As an example, a theatre would in most models be represented with the same attributes as a fitness centre, resulting in equal utilities in the model (see for instance Ben-Akiva and Lerman (1979)). The scale problem is related to the number of units represented in the study area. Inclusion or exclusion of units will affect the explanation by a model.

Considering for instance a Hägerstrand type space-time prism, the MAUP problem relates to destinations, vertical cylinders in Figure 3. For a specific individual, the opportunity in her destination is a fixed point in

space, for instance a shopping mall, while in the models it is assumed that opportunities are represented through the entire surface of the zone where the shopping mall is located within. As a result of this simplification, or rather aggregation, the exact location of the destination or purpose of the trip is not known. If several shopping malls are located within same zone, the model can only be sensitive for some sort of average attribute among the malls.

The availability of highly disaggregated data (also location wise) such as MEILI data means that the exact location of individual destinations and thereby the exact purpose of trips are known. However, it is difficult to gather land-use information with the required high resolution.

4.2 REVISITING CONDITIONAL AND TEMPORAL CHARACTERISTICS OF TRIP MODELS

Travel demand models are in general bounded through certain assumptions. Some of these assumptions relate to the chosen modelling framework such as assumptions about rationality or that individuals fully understand their choice options and their related costs and benefits. Other assumptions are made by modelers to be able to replicate, seemingly comparable trip choices.

For instance, choice of trip purpose on any given time (and space) is a function of a number of simultaneous factors such as:

- time budget,
- other mandatory or compulsory activities,
- mandatory or compulsory activities of other members of the household,
- availability of various trips modes and their corresponding costs,
- starting time for activities and their durations,
- and further potential factors.

Most of the models however cannot consider such complex decisions, mainly since the decision process is not standard across individuals and even if it is assumed to be standard, it is very difficult to replicate. In order to imitate the trip behaviour, modelers break down the decision process, based on certain assumptions into several simpler decision models. These are later combined using a structural framework, for instance a traditional four-step travel model. The framework should preferably combine the individual choices in the simple models so they together can imitate the complex decision process.

These simple modelling structures however are limited in many aspects. For instance, the choice of trip purpose, usually located on the highest nest of the four-step modelling structure, is assumed to be a discrete choice. This means that the activities are chosen without regards to other activities or observed frequency of the activity. Yet it is known that the choice of an activity is based on several further factors. Some activities for instance are mandatory and some are not and given individual constraints in time and cost, a choice a activity is definitely dependent on choices of other activities and individual constraints.

The study presented in this section, shows that the pattern of activities varies for an individual between days of the week. The study also shows that certain activity patterns are stable across the population while they differ between during a week. Traditional trip diaries could somehow refer to variability of choices in different days of the week since diaries are collected from many individuals and from different days. Such trip data could of course in a manner resemble the diversity across individuals and week days while they cannot replicate variations in individual choices across days of the week.

Following similar arguments, it is possible to argue that different aspects of a trip choice may not be a discrete choice but dependent on factors such as number of mandatory and compulsory activities considered by the individual as well as pattern of individual activities across days of the week. It could for

instance potentially be reasonable to model the individual trips on weekly basis. However, it is not investigated here.

If it is assumed that activities are not independent, it might be better to:

1. treat trip choices as ordinal choices, rather than discrete choices, which is generally assumed.

Furthermore, given temporally high-resolution data that has become available by the SPOT project),

2. it might be more reasonable to model trip choices, either separately or in combination with choice of trip purpose and number of trips.

The examples, 1 and 2 above, have been estimated with two types of models on the SPOT data. First, a cross-section ordinal logit model where number of trip legs has been a dependent variable, while the independent variables have been trip purpose, starting time for the trips, trip duration and demographic attributes such as age and gender.

The choice of the dependent variable might seem unusual but is motivated by the fact that the gathered data is very limited in number of observed individuals. It means it is not sufficient for modelling significant and unbiased models. However, in absence of alternative data the data is utilized, to be able to indicate the potential in the made arguments.

The second model has had the same dependent and independent variables as the ordinal logit model, while temporal aspects of the choice is replicated by construction of a longitudinal model (longitudinal ordered logit model). The model has been made responsive to the fact that time is measured in continuous space and that there could exist dependencies between activities, and their internal order.

The log-likelihood value of the panel data was significantly stronger than the cross-section model. It indicates the fact that the longitudinal model is describing the processed model better than the cross-section model which is not sensitive to the temporal aspect of the process.

This observation, despite lacking proper significant levels hints that the temporal information plays a role and contributes to a better description of the process. This could mean that neglecting of the temporal aspect of the process of interest, may probably result in biased estimates and should be avoided.

4.3 ON TEMPORAL ASPECTS OF CHOICE MODELS

In another attempt three simple mode choice models are estimated based on three different modelling approaches:

1. Multinomial logit
2. Cross-section ordered logit
3. Panel ordered logit

The idea was to investigate the choice of modelling approach and temporal aspects of the mode choice behaviour in combination. The dependent variable has been the major mode of the trip. In the data, up to five trip legs have been observed for each trip.

After studying how the choice of traveling mode is distributed across all modes and individuals, the major mode was decided as the fastest mode of the first two trip legs. For instance, if the choice is between walking and public transportation, the major mode is assumed to be public transportation. If the choice was between two fast modes, such as public transportation and car, the remaining trip legs were considered.

The mode choice models have been evaluated by the estimated values of the log likelihood, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). The evaluation shows that the longitudinal ordered model performs better than both the cross-section ordered logit and the multinomial logit models. The evaluation shows that the multinomial logit model performed better than the cross-section ordered logit model. However, it cannot be concluded that the multinomial model is superior compared with the cross-section model. The result is that the mode choice is, more or less, correlated with temporal aspects of the choices made by the individual during the day.

5 SPACE-TIME PRISMS

5.1 ACCESSIBILITY

The study of individuals' accessibility is widely used to assess how well a structure of a place (e.g., city, region) serves the needs of its inhabitants and to identify the parts of the cities where inhabitants need to incur a higher cost to perform daily activities than they would have if they lived in central parts.

The main accessibility studies build on top of concepts such as *activity spaces* (Chapin 1968), which are usually derived from the individuals' movement in an area over a period of time with a higher weight on home and work locations, and *space time prisms* (Hägerstrand 1970), which identify the space an individual can access assuming a fixed speed and different constraints (capability, coupling and authority constraints). By using the previous stated methods, the accessibility studies carry on with the extraction of possible destinations for the studied purposes that fall within the accessibility areas and propose different ways to measure opportunities based on the number and / or diversity of locations within the studied area.

One of the scopes of the current technical report is to investigate the set of potential locations (as Points of Interest – POIs) at which particular types of activities could have been performed by the users that participated in the SPOT case study. This technical report makes use of space time prisms as a measure of approximating the accessibility area that is subsequently used to extract the set of locations for selected activity types.

Before dwelling into the analysis, it is important to understand the assumptions that the authors had to make in order to analyse the potential sets of POIs for different types of activities.

5.2 ASSUMPTIONS FOR EXTRACTING POI SETS USING SPACE TIME PRISMS

As a first step, those activities whose location is not immutable, e.g., in general, has to be extracted since a user has a unique location to return home to. In the SPOT dataset, the authors have collected 13 different purposes, which are summarized in Table 12. Given the immutability of locations for a subset of the given purposes (“Home”, “Work”, “Visits”, “School”, “Pick-up / Drop-off”) and the widely generalized purposes (e.g., “Leisure”, “Hobby”, “Business”, “Personal”, “Other”, none of which has a clear association to a type of point of interest). The only activities for which potential choice sets of POIs can be extracted without making crass and unrealistic assumptions are “Restaurant / Cafe”, “Grocery Shopping” and “Other Shopping”. Even if it can be assumed that groceries activities can be performed at supermarkets, it is an oversimplification of the problem. Because it does not take into account the fact that some groceries can only be done at markets with a specific offering. Or that users might have a preference towards doing groceries at supermarkets that have ongoing special offers and discounts. Unfortunately, before being able to analyse the potential set of places at which one can perform the aforementioned activities, these assumptions are necessary.

As a second step, a modeller has to rely on a POI dataset and map activities with types of POIs at which those activities could be performed (see Table 12). This procedure makes the analysis of the potential choice set reliant on the completeness and on how up to date the dataset is. It raises the issue of both under-estimating (e.g., POIs that are available to the users are not present in the POI dataset) and over-estimating (e.g., POIs that have been closed are still present in the POI dataset) the POI set.

Table 12: Mapping between selected activity types and POI types for the data collected in the SPOT project

Purpose	Considered POI types
Work	N/A
School	N/A
Business	N/A
Restaurant/Café	Restaurant, Fast food, Cafe, Bar, Shopping mall
Leisure	N/A
Hobby	N/A
Grocery Shopping	Supermarket, Shopping Mall
Other Shopping	Clothing store, Shopping Mall
Personal	N/A
Visit	N/A
Pickup / Dropoff	N/A
Home	N/A
Other	N/A

Given these two steps, the analysis for this technical report uses POIs as obtained from OSM and that have been mapped to their activities during the case studies performed in the SPOT project. It is performed only for “Restaurant / Cafe” (with the POI types of restaurant, fast food, cafe, bar and shopping mall), “Grocery Shopping” (with POI types of supermarket and shopping mall) and “Other Shopping” (with POI types of clothing store and shopping mall), as shown in Table 12.

After establishing the activity types and the POI types for which the choice set of alternative locations, the third step is extracting each of the trips whose purpose coincides with the existing activities, and the trip that follows it. This step extracts the elements that are needed to generate a space time prism. To simplify the explanation of the elements needed to generate a space time prism, consider the following case: a user starts the first trip at 10:00 at home and travels to a coffee place at 10:45, where the user spends 20 minutes, followed by traveling to work, where the user arrives at 11:30. In this case, the elements needed to generate the space time prisms are:

- the start location – the location from which the first trip (with an activity belonging to the selected subset) starts, i.e., the user’s home
- the stop location – the location at which the subsequent activity is performed, i.e., the user’s workplace
- the time budget – the amount of time the user can spend traveling (first trip starts at 10:00 from home and the second trip starts at 11:30 at work, i.e., a duration of 1 hour and 30 minutes from which the time spent at the coffee shop, 20 minutes, is subtracted, which results in a budget of 1 hour and 10 minutes during which the user can travel to find a coffee shop and make it back in time for work)
- the speed assumption – the average speed is considered as a constant speed (see Table 13, commuter train, flight and train were disregarded in this technical report) of the fastest travel mode used in any of the trip legs belonging to the two mentioned trips

Table 13: The median speed values for the travel modes collected in the SPOT final case study. The speed values are computed as the median speed for the GPS locations belonging to trip legs annotated with the specified travel modes. Commuter train, train and flight are disregarded in the current analysis.

Travel mode	Speed m/s
Walk	1.6
Bicycle	6.0
Moped / Motorcycle	17.8
Car as driver	18.3
Car as passenger	21.0
Taxi	22.0
Bus	14.3
Subway	12.2
Tram	8.8
Commuter train*	20.5
Train*	28.6
Ferryboat	3.4
Flight*	203.7
Other	18.5

For a detailed explanation of how to generate space time prisms, see Prelipcean (2014).

The obtained space time prisms which are then used to extract the alternative POIs at which the same type of activity can be performed are shown in Figure 4. Each ellipsis represents the spatial projection of a prisms that approximates the area within which the alternative POI is extracted from. As easily noticed, the space time prisms overestimate accessibility since they do not consider any network (e.g., public network topology) or land use constraints (e.g., islands).

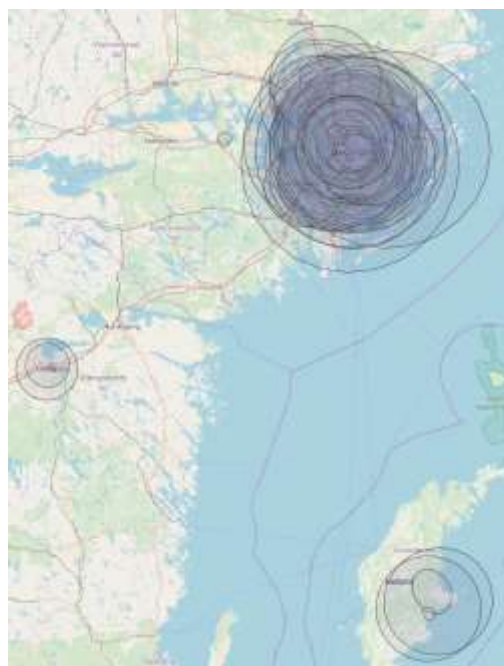


Figure 4: Map of the spatial projection of space time prisms for the subset of trips suitable for the current analysis.

Table 14: The number of possible alternative POIs, and percentage of entire relevant POI set, for the specified activities using different travel modes.

Purpose	Travel_mode	Avg #	Median #	# Instances	% POIs
Restaurant/Café	Walk	135.5	50.5	48	4.1
	Bicycle	2295.0	2295.0	2	69.0
	Moped / Motorcycle	2940.0	2940.0	1	88.4
	Car as driver	1999.0	1964.0	15	60.1
	Car as passenger	1474.5	998.5	8	44.3
	Bus	2005.5	2118.0	4	60.3
	Subway	2917.8	2919.0	5	87.7
Grocery Shopping	Walk	8.4	3.0	21	2.0
	Bicycle	115.7	124.0	3	28.2
	Car as driver	208.0	252.0	53	50.7
	Car as passenger	256.8	312.0	6	62.6
	Taxi	410.0	410.0	1	100.0
	Bus	312.3	283.0	7	76.2
	Subway	263.2	296.0	6	64.2
Other Shopping	Ferryboat	51.0	51.0	1	12.4
	Walk	50.7	59.0	3	10.6
	Car as driver	322.8	412.5	34	67.3
	Car as passenger	154.0	113.5	4	32.1
	Taxi	408.0	408.0	1	85.0
	Bus	385.3	394.0	3	80.3
	Subway	331.8	412.0	4	69.1

After extracting the POI set within each of the space time prisms, the cardinality of each set can be inspected with regards to the activity type and the fastest available travel mode. As expected, for high speed travel modes (e.g., moped, car, bus, subway), it is unreliable to use space time prisms to extract the potential POI set at which the selected activities can be performed because space time prisms do not include land use and network constraints. This is visible for high speed travel modes when inspecting the size of the potential POI set of each ellipse compared with the total size of the POI set for the given purpose. Because, on average, the potential POI set is more than 50% of the total POI set (with a corresponding type to the activity that is performed). It is however interesting to note that even when considering walking trips, the number of reachable POIs for each category is still high. However, as mentioned previously, the relatively high sets of alternative POIs for the selected activity types can be due to both data issues (both missing POIs and having inexistent POIs in the dataset) as well as the lack of network and land use constraints. It is more likely that the latter is the most problematic, since space time prisms are generally not suitable for approximating accessibility in areas that contains islands and other types of accessibility clusters. The critique of the used methodology is present in the next section.

5.3 CRITIQUE OF USING SPACE TIME PRISMS FOR EXTRACTING POI SETS

At the beginning of this section, it was mentioned that the most common ways to approximate accessibility is via activity spaces and space time prisms. The main issue with these two types of measures is that the areas they generate are not representative of the complex set of choices for people given a dynamic travel environment in which speed is not the same across different travel modes.

First, activity spaces are generated based on the observed movement on individuals so they are more representative of how people make travel choices rather than a good measure for accessibility. As such, if during the collection period individuals do not visit all places relevant for them, the result is biased towards the observed movement as opposed to the potential movement. Furthermore, this measure does not take into account the fact that people can on- and off-board public transportation vehicle only at transport station and would overestimate the accessible area in that case. This method is affected both by over- and under-estimation of accessible areas.

Second, space time prisms originate from the studies of migration and the scale of movement for which they were initially proposed and used is coarser than the study of accessibility requires. As such, even though the

constraint types significantly reduce the accessible space to reflect the effect of the constraints, it does make an assumption of constant speed, which makes it suitable for single-mode travel. As such, the questions one can usually answer using this method are of the following type: "Given 15 minutes and a set of constraints, what can I reach by walking?". This of course can be augmented to support multiple travel modes but then the assumption is that the traveller only has one travel mode per prism. Accompanying the issue of ambiguous handling of multi-modal travel also lies the overestimation of the reach since space time prisms are not dependent on transportation networks (as seen in the previous section). As such, the space time prism tends to overestimate the reachable area useful for accessibility, which is an issue for both multi-modal travel as well as for special topology networks that contain accessibility clusters (such as islands).

To counter this issue, research has pursued with the study of embedding the network effect inside the space time prisms (Miller 1991). While this was achieved with success for single-modal and static road networks, the main difficulties encountered by researchers were mostly related to the performance of algorithms used to generate network-based space time prisms. Further research has successfully embedded both multiple modes and schedules when modelling accessibility (Lei and Church 2010). Open source packages that implement variations of shortest path tree algorithms (e.g., Dijkstra, A*, etc.) for computing accessibility similar to Lei and Church, 2010 are readily available (OpenTripPlanner). Even though methods that offer a more realistic estimation of accessibility exist, they are not used in the state of the art research in transportation. This technical report documents the promising alternatives to estimating POI sets and accessibility that are more promising than space time prisms, but a comparison between space time prisms and other methods is outside of the scope of the technical report.

5.4 SPACE TIME PRISMS AND ACCESSIBILITY

As previously mentioned, the initial use of space time prisms was for studying measures similar to accessibility on a coarse scale (e.g., country-wide, continent-wide, etc.) especially under different types of constraints, i.e., capability, coupling and authority constraints (Hägerstrand 1970). Given the analysis scope and the coarse scale, using space time prisms for approximating an individual's accessibility makes two main assumptions:

- 1) the movement speed is constant
- 2) the movement is non-constrained (i.e., it makes use of Euclidean distance).

While these assumptions are of less importance on the initial scale space time prisms were used for, translating the same assumption to a city-wide scale inevitably leads to an overestimation of accessible space. This led researchers to expand the definition of space time prisms to include concept such as acceleration and deceleration to avoid the assumption of instantaneous maximal speed (Kuijpers et al. 2017). However, even the more complete space time prisms models are unsuitable for approximating accessibility because they do not take into account the movement dynamics that occurs on a street network level (Lei and Church 2010), nor do they take into account the effect of accessibility bottlenecks caused by particular geographical regions and land use (e.g., islands).

As a comparison, consider Figure 5 where the left part includes the nodes of the street network that are within the accessibility area obtained by using space time prisms and the right side contains accessibility computed estimating shortest path trees on the street network. The accessibility area for both cases is estimated using a constant speed of 3.6 km/h and an available time budget of 2 hours to arrive from the red triangle location to the blue triangle location. While the difference between shortest path tree-approximated accessibility and space time prisms-approximated accessibility would indeed be smaller on continuous surfaces (e.g., on a Manhattan network) considering low speed travel modes, this hints at the fact that space time prisms should only be used as accessibility-proxies when certain assumptions are met and should not be considered the default method for approximating accessibility.

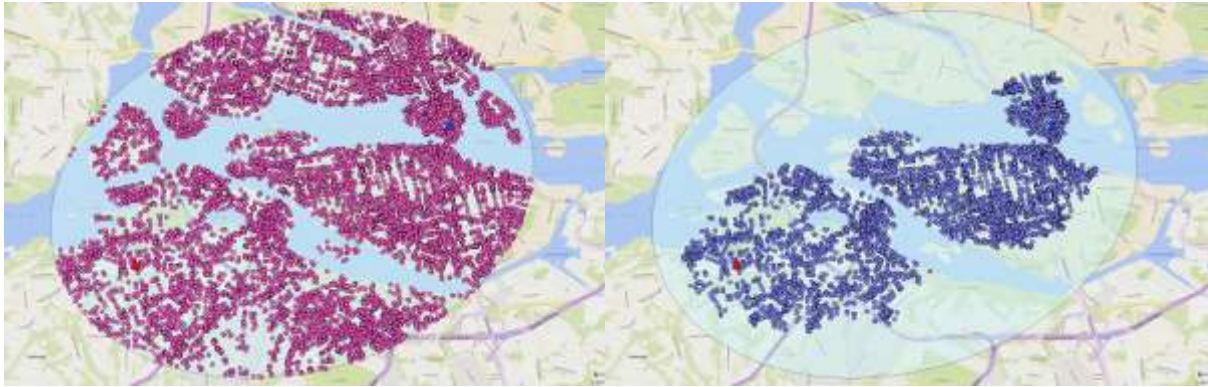


Figure 5: Network nodes for specified origin and destination and a time budget of 2 hours. (Left) All network nodes within space time prism. (Right) All network nodes within the shortest path tree.

While using shortest path trees as a method to approximate accessibility seems to be an attractive solution, this method has its own drawbacks, which are discussed more in the following section.

5.5 SHORTEST PATH TREES AND ACCESSIBILITY

The different shortest path variations (one to one, one to all, all to all) are important for navigation software, but they can also be used as a proxy for an individual's accessibility. In particular, shortest path trees, which compute the shortest path between an origin node and all the other nodes, can be used for estimating accessibility. While using shortest path trees allows for a better approximation of accessibility, this method also makes use of different assumptions:

1. the movement occurs only on a (transportation) network
2. the cost of traversing each network edge (that connects two nodes) is available.

Analysing these two assumptions reveals the vulnerabilities of using this method as a proxy for accessibility.

First, the fact that movement occurs only on a network is particularly important because the quality of the network affects the shortest path tree generation and, implicitly, the accessibility approximation. Whenever the network is missing shortcuts and paths through buildings (which are usually not present in most network datasets), it underestimates accessibility. Similarly, walking areas also cause underestimation of the accessibility since an individual can freely move within the area (e.g., shopping centre, park, etc.) without any network constraints.

The second assumption is more important because the time budget used for computing accessibility is reflected in the cost of each edge of the network. As such, the cost can be static, i.e., it takes 4 minutes to traverse the edge, or dynamic. The case when the cost is dynamic is the most interesting one, since it allows for a robust approximation of accessibility as in realistic scenarios (e.g., include waiting time and congestion), but it is also the most challenging one. As such, the dynamic cost can be dynamic with regards to:

1. *travel modes*, where the cost of traversing an edge is a function of travel mode (e.g., 4 minutes as a pedestrian, 2 minutes with a bike, 30 seconds with a car),
2. *constraints*, where an edge is only available when a constraint is satisfied (e.g., only a passenger with a travel card can traverse the public transportation network),
3. *schedule-based*, where the cost of each edge is a function of the time of arrival at the origin node of the edge (e.g., if a passenger arrives at a node 4 minutes before the bus departs, the passenger has to wait for 4 minutes), or
4. *time-based*, which is the most difficult to model, where the cost of each edge is updated based on a real-time stream of transportation data which contains traffic information regarding delays, congestions, etc.

While both static and dynamic cost implementation exist, it is worth mentioning the prerequisites in terms of data sources for each class of problem:

1. For static cost shortest path tree generation, it is sufficient to have a road network where the edges either contain travel time for the speed of the travel mode that the analysis is done for, or the distance of the edge.
2. For dynamic cost for different travel modes, one requires either a dense representation where each edge of the network contains multiple costs for different travel modes, or the cost is modelled as a function which takes as input the travel mode. Both methods yield the same result, and caching and indexing mechanisms can easily be designed for the first method. For this case, it is important to have a robust transportation network that contain realistic costs for different travel modes.
3. For dynamic cost with constraints, one can either add different (boolean) dimensions for each edge of the network to indicate whether the edge is constrained, or the cost can be modelled again as a function that takes as input a travel mode and a set of constraints. For this case, one needs either an external data source linked to the road network that contains a reference to the constraints (e.g., overlapping a public transportation network over the existing network, where the transportation network can be accessed only when a travel card is available), or manually modelled, which only functions on prohibitively small networks.
4. For dynamic cost with schedules, one needs an external data source for the schedules, which are usually available as Generalized Transit Feed Streams (GTFS) for large cities. Furthermore, these schedules need to be exactly mapped to the network at nodes that coincide with public transportation stations. Furthermore, specialized software has to be used in conjunction with the new data sources, since schedules add the extra dimension of time to the shortest path tree problem. For the algorithms used in this type of approach, the reader is directed towards Lei and Church 2010, and for software that provides this algorithm, the reader is directed towards OpenTripPlanner (OTP).
5. For dynamic cost that is time-based, i.e., the cost of each edge depends both on the time at which the origin node of the edge is reached as well as external updates to the cost, one needs multiple data sources which are well referenced to one another. It is worth mentioning that this is at least an NP-hard problem since this method has previously been used for the class of problems known as knapsack (Frieze 1976). As such, while there are heuristics that can perform well on a particular network scale, there is no algorithm that can provide a solution for this problem in polynomial time. Investigating this further is outside of the scope of the current report and it is the focus of state of the art research in computer science and operation research (Keller et al. 2004, Ishibuchi et al. 2015). The only available solutions are those that offer pseudo-time-based routing, e.g., Google Direction API, which predicts the travel time on each edge based on history and also updates the cost based on current traffic when sufficient cars are available, or Waze, which takes as input updates from users and changes the cost of each edge without taking into account any schedules or other type of temporal data. These services are only available if traveling by car.

Whenever time is added as a separate cost dimension, it is worth mentioning that one observes the following effect shown in Figure 6, i.e., the accessibility varies across time, which, albeit intuitive, it is often ignored in the state of the art research in transportation.

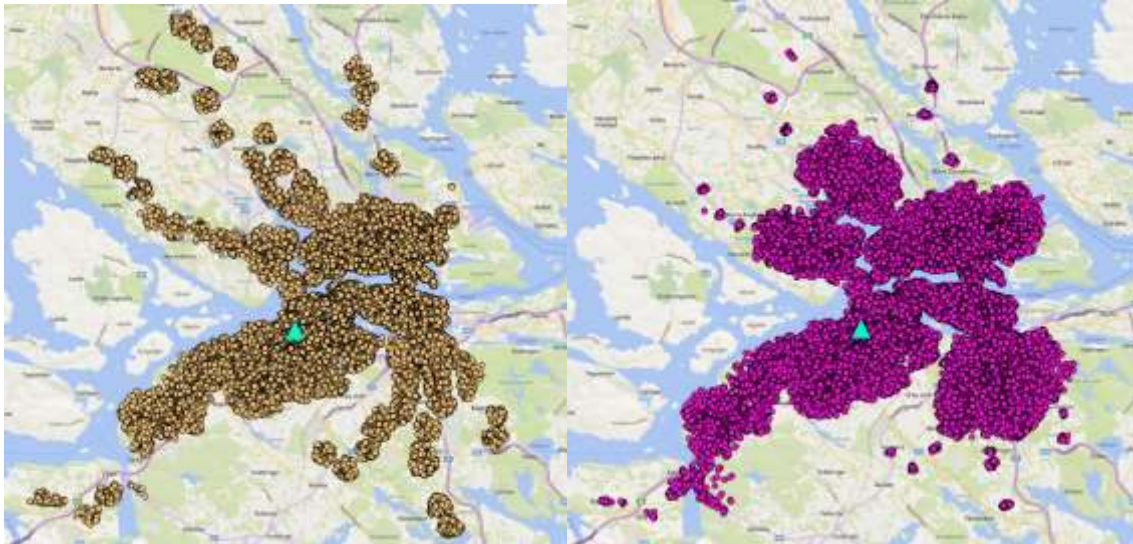


Figure 6: Effect of waiting time on accessibility for schedule-based dynamic cost networks. (Left) Shortest path tree for a low waiting time at the closest subway station. (Right) Shortest path tree for a high waiting time at the closest subway station.

While in initial stages of the technical report, the aim was to investigate with the existing SPOT dataset how it can use space time prisms as a measure of individual's accessibility. It became clear that space time prisms are not suitable for approximating accessibility for areas such as Stockholm. As such, the effort was allocating towards identifying other suitable measures for accessibility, i.e., approximating accessibility as the subset of nodes of a cost-bound shortest path tree (where the cost is the same as the accessibility budget). Furthermore, using collected data would not allow to look into accessibility, but rather into activity spaces, which although useful, are not equivalent to accessibility. A combination between accessibility, activity spaces and travel diaries would probably allow for a more detailed exploration of mental maps, but this is outside of the scope of the current paper.

6 CONCLUSIONS AND FUTURE WORK

The aim of this project was to explore the potential of the multi-day GPS-based data collected in the SPOT project, in particular to advance with multi-day travel demand analysis. The results of this project highlight the importance of having multi-day data to improve the fitness as well as the dynamic elements of the existing travel demand model. The project has shown that the nature of and the relations between intra- and inter-individual variability are unique for each activity-travel parameter and there is no such thing as a 'typical day'.

The unique method implemented in this study, longest common subsequence, enable us to identify the basic combination of different activity-travel patterns of individuals, and how this repeated over the observed period. This helps us to understand what kind of combinations that repeated most and least among the traveller groups, which complements the existing similarity measures widely used in the travel behaviour research literature.

Further investigation on the potential of the multi-day data use with a dynamic grocery scheduling model shows that introducing multi-day data with such dynamics framework has a big impact on the fitness of the model. It was also found that the longitudinal model, which was made possible with multi-day data collection, performs better than any other models currently used within the SAMPERS framework. It was further confirmed that the temporal aspects of choices made by the individuals during the day may be the ones which significantly improved the model fit.

Properly modelling the individual time space prisms dynamically proved to be challenging, in particular because of the lack of accessibility and network information that the individuals experience on the given time and space. Defining individual's accessibility activity locations based on static information turned out to be unreliable because the result will end up with over-estimating the number of locations that individuals can reach on the given time with the given travel modes. More practical alternative to measure accessibility, i.e., approximating accessibility as the subset of nodes of a cost-bound shortest path tree (where the cost is the same as the accessibility budget), was provided and discussed.

A combination between accessibility, activity spaces and individuals' mental maps would probably allow for a more detailed exploration of the use of these time-space prisms concepts in defining individual's activity and travel choice set in a more dynamic manner. This, however, would make agent based models becoming far more complex, data hungry, and computation heavy – if the whole system needed to be developed. Combining data from various secondary, real-time, sources, such as Waze or Google, may open an opportunity of integration that are not yet possible to be done today.

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8 APPENDIX A: BRIEF SUMMARY ON WORKSHOP ON BIG DATA USE IN TRANSPORT

Theme: Bringing new types of data closer into practice in transport planning and modelling

Date & Time: 16 October 2017, 9:30-17:00

Location: KTH Royal Institute of Technology, D2, Lindstedtsvägen 5, Stockholm

Number of attendees: 80 people (from 26 institutions and 7 countries)

The delivery of the event:

The event started with focusing on what we have in Sweden in term of urban and transport modelling and planning, and what kind of inputs that industries would like to have in enhancing the existing urban and transport modelling and planning. Then, the discussion continued to how now we have been using GPS and GSM data in monitoring and measuring network performance and refining and evaluating urban and transport policy in various major cities in Sweden.

Following that, we discussed various examples from various cities in the UK, Singapore, and US, on various use of smartcard and passive data (e.g. twitter and facebook) in monitoring and managing public transport operation and also in predicting/swiftly-locating and responding to various highway disruption events. Then, the discussion focused on some technologies in collecting travel diary that have been developed in Sweden and data privacy requirements that we will need to comply with according to the forthcoming 2018 EU's directive General Data Protection Regulation (GDPR) which expected to be in place by 25 May 2018.

The event is closed by a panel member discussion, which consists of relevant stakeholders (Trafika, SLL, and Trafikverket/Trafik Stockholm) and selected experts, in identifying challenges and to-do-list that need to be addressed in Swedish context.

Take home messages from the event:

Current state of the subject:

- There is a real potential to use various type of big data in practice in transport planning and modelling – and there is a serious interest of stakeholders and industries in Sweden to use big data to its maximum potential. The volume of the data collected in Sweden is enormous (and not all of them have been used to its potential) and the technical supports are relatively established.
- There have been a number of tools to analyse our big data available for everybody to (freely download/install and) use.
- There are some relatively reliable methods to redefine/identify the contexts and events of the observed trip that are available to use
- Not a single type of data that can answer everything; integration (e.g. a common shared platform) is crucial and important to develop a working, reliable, and consistent framework for everyone.

Missing puzzles that need to be addressed:

- We need an interface/dashboard system of the existing databases and tools that are accessible by the non-technical users and fit with the applied law and regulations attached to the data(bases) in concern.

- There is an absence of legal framework in enquiring and providing (buying and sharing/selling) the database and analysis results as a product.
- We need a clear, layman version, guidance of what is allowed and what is not allowed in using big data
- There is a need for data scientists, security experts, and lawyers to sit together to develop a framework that is safe, legal, and useful to serve the purposes of the stakeholders, industries and researchers.

A closing reminder:

- Given different nature of the data involve in big data analysis, more efficient and accessible analytical method is needed. That is said, this also be balanced with the local stakeholders' needs. If the old method worked, why not. Thus, it is very important for us to keep reminding ourselves whether we are asking the right question.