MEILI

Multiple Day Travel Behaviour Data Collection, Automation and Analysis

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Abstract

Researchers' pursuit for the better understanding of the dynamics of travel and travel behaviour led to a constant advance in data collection methods. One such data collection method, the travel diary, is a common proxy for travel behaviour and its use has a long history in the transportation research community. These diaries summarize information about when, where, why and how people travel by collecting information about trips, and their destination and purpose, and triplegs, and their travel mode. Whereas collecting travel diaries for short periods of time of one day was commonplace due to the high cost of conducting travel surveys, visionary researchers have tried to better understand whether travel and travel behaviour is stable or if, and how, it changes over time by collecting multiple day travel diaries from the same users. While the initial results of these researchers were promising, the high cost of travel surveys and the fill in burden of the survey participants limited the research contribution to the scientific community. Before identifying travel diary collection methods that can be used for long periods of time, an interesting phenomenon started to occur: a steady decrease in the response rate to travel diaries. This meant that the pursuit of understanding the evolution of travel behaviour over time stayed in the scientific community and did not evolve to be used by policy makers and industrial partners.

However, with the development of technologies that can collect trajectory data that describe how people travel, researchers have investigated ways to complement and replace the traditional travel diary collection methods. While the initial efforts were only partially successful because scientists had to convince people to carry devices that they were not used to, the wide adoption of smartphones opened up the possibility of wide-scale trajectory-based travel diary collection and, potentially, for long periods of time. This thesis contributes among the same direction by proposing MEILI, a travel diary collection system, and describes the trajectory collection outlet (Paper I) and the system architecture (Paper II). Furthermore, the process of transforming a trajectory into travel diaries by using machine learning is thoroughly documented (Papers III and IV), together with a robust and objective methodology for comparing different travel diary collection system (Papers V and VI). MEILI is presented in the context of current state of the art (Paper VIII) and the researchers' common interest (Paper IX), and has been used in various case studies for collecting travel diaries (Papers I, V, VI, VII). Finally, since MEILI has been successfully used for collecting travel diaries for a period of one week, a new method for understanding the stability and variability of travel patterns over time has been proposed (Paper X).

Keywords multiple day travel diary collection; trajectory segmentation; travel mode, destination and purpose inference; travel diary collection system comparison; travel pattern stability and variability over time

Sammanfattning

Forskarnas strävan efter en förbättrad förståelse av dynamiken i resande och resebeteenden har lett till ständiga framsteg i datainsamlingsmetoder. En sådan datainsamlingsmetod, resdagboken, är ett vanligt sätt att representera resebeteenden, och har en lång historia av tillämpning inom transportforskning. Dessa resdagböcker summerar information om när, var, varför och hur människor reser genom att samla in information om resor, deras destination och syfte, samt vilka delsträckor, och transportmedel som används. Till följd av den höga kostnaden av att genomföra resvaneundersökningar genom enkäter, har insamling av resdagböcker oftast gjorts för kortare perioder och enstaka dagar. Trots detta har visionära forskare försökt att bättre förstå huruvida resande och resebeteenden är stabila eller om, och hur, dessa förändras över tid, genom att samla in flerdagars-resdagböcker från samma användare. Även om de initiala resultaten från dessa forskare har varit lovande, den höga kostanden av att genomföra en resvaneundersökning samt besväret för deltagare att fylla i resvaneenkäter, har begränsat forskningsbidraget till endast vetenskapliga sammanhang. Innan utvecklingen av resdagboksinsamlingsmetoder som kunde användas under längre perioder, påbörjades ett intressant fenomen: en beständig minskning av svarsfrekvensen till resdagböcker. Detta innebar att ambitionen att förstå utvecklingen av resebeteenden över tid stannade inom vetenskapliga grupper, och utvecklades inte till att användas av politiska beslutsfattare och industriparter.

Dock, genom utvecklingen av teknologier som kan samla in trajektoriadata för att beskriva hur människor reser, har forskare undersökt sätt att komplettera och ersätta de traditionella resdagboksinsamlingsmetoderna. De inledande ansträngningarna var endast delvis framgångsrika på grund av att forskare behövde övertyga människor att bära omkring utrustning som de inte var vana vid att ha med sig. När smartmobiler började användas i större utsträckning öppnades upp nya möjligheter för trajektoria-baserad resdagboksinsamling i bred omfattning och, potentiellt, för längre tidsperioder. Denna avhandling bidrar i samma riktning genom att föreslå MEILI, ett system för att samla in resdagböcker, och beskriver medel för att samla in trajektoriedata (Paper I), och systemarkitekturen (Paper II). Processen att omvandla trajektorier till resdagböcker genom maskininlärning dokumenteras grundligt (Papers III och IV) tillsammans med en robust och objektiv metod för att jämföra olika system för resdagboksinsamling (Papers V och VI). MEILI presenteras inom kontexten av aktuell forskning inom området (Paper VIII) och forskarnas gemensamma intresse (Paper IX), och har använts i olika fallstudier för insamling av resdagböcker (Papers I, V, VI, VII). Slutligen, då MEILI har framgångsrikt använts för att samla in resdagböcker för en tidsperiod av en vecka, föreslås en ny metod för att förstå stabiliteten och variationen i resmönster över tid (Paper X).

Keywords flerdagars-resdagboksinsamling; trajektoriasegmentering; inferens av transportmedel, destination och syfte; jämförelse av resdagboksinsamlingssystem; stabilitet och variation i resmönster över tid

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List of Papers

I Prelipcean, A. C., Gidófalvi, G., and Susilo, Y.O., 2014. “Mobility Collector”. *Journal of Location Based Services*, number 4, volume 8, pages 229–255, DOI: 10.1080/17489725.2014.973917

II Prelipcean, A. C., Gidófalvi, G., and Susilo, Y.O., 2018. “MEILI: an activity travel diary collection, annotation and automation system”. *Computers, Environment and Urban Systems*, forthcoming, pages 1-11, 2018, DOI: doi.org/10.1016/j.compenvurbsys.2018.01.011.

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VII Susilo, Y. O., Prelipcean, A.C., Gidófalvi, G., Allström A., Kristoffersson, I., Widell, J., 2016. “Lessons from a trial of MEILI, a smartphone based semi-automatic activity-travel diary collector, in Stockholm city, Sweden”. *World Conference on Transport Research - WCTR 2016 Shanghai. 10-15 July 2016*

VIII Prelipcean, A. C., Susilo, Y.O., and Gidófalvi, G., 2018. “Future directions of research for automatic travel diary collection”. Proceedings of the *11th International conference on Transport Survey Methods*, forthcoming.

IX Prelipcean, A. C., and Yamamoto, T., 2018. “Workshop synthesis: New developments in travel diary collection systems based on smartphones and GPS receivers”. Proceedings of the *11th International conference on Transport Survey Methods*, forthcoming.

X Prelipcean, A. C., Gidófalvi, G., and Susilo, Y.O., 2018. “Longest common subsequences: Identifying the stability of individuals’ travel patterns”. Submitted to *Transportation.*

Chapter 1

Introduction

1.1 Introduction and theoretical points of departure

Obtaining insights on travel behaviour relies on collecting data on where, why and how people travel from representative user groups and for long periods of times. The primary and most common method to collect where, why and how people travel is via travel diaries, which collect information on trips and their destination and purpose (where and why people travel), and triplegs and their travel modes (how people travel during a trip). Traditionally, transport scientists focused on collecting travel diaries for short period of times and for large user groups that are supposed to be representative for the population of a studied region (e.g., city or country), which provides a good overview for travel behaviour during the short time frame when the diaries were collected, but do not capture the stability or variability of travel patterns over time (Axhausen et al., 2002).

Although classical studies have investigated the potential of collecting data over extended periods of times, e.g., Hanson and Huff (1981) identified similarity measures that can measure daily variability, Pas and Koppelman (1987) augmented the traditional goodness of fit measure to include inter- and intra-personal variability, the high cost for periodically or continuously collecting data over large periods of time has constrained multi-day travel diary analysis to few research groups.

Expectedly, most transport research, focused on testing hypotheses and building models according to the knowledge that could be extracted from single-day travel diaries. As such, the majority of performed analysis focuses on temporal snapshots of large groups of individuals. This analysis has provided unique insight into how people travel (Bhat, 2000; Balmer et al., 2008; Zhu et al., 2017) since the response rate during 1990 and early 2000 to travel diaries was considered to be economically rational, i.e., between 50% and 80% (Axhausen et al., 2002; Crosbie, 2006; Swedish National Travel Survey, 2012). As such, most strategies and efforts coming from researchers and policy makers could be summarized as periodic short time travel diary collection from independent user groups.

However, the response rate of individuals steadily decreased over time and the traditional travel diary collection methods failed to adapt and counter this decrease. In countries such as Norway (Norwegian National Travel Survey, 2015) and Sweden (Swedish National Travel Survey, 2012), the low response rate and a clear age bias made the traditional travel diaries unsuitable for collecting data from a representative user group.

In response to this decrease, a considerable effort in new travel diary collection methods has been undertaken by the research community. Systems such as those proposed by Guensler and Wolf (1999) and Wolf (2000), which initially collected data from cars only and then expanded to pedestrians (Draijer et al., 2000) were successful starting points that showed the feasibility of travel diary collection without asking people to answer a paper or web form. However, this was a temporary solution because it is not feasible to ask people to equip themselves and carry dedicated devices that offer them no direct and immediate benefit. Nevertheless, these initial efforts were an irreplaceable step towards modern travel diary collection systems since they have identified a promising data type that can be collected to generate travel diaries: user trajectories.

With the development of smartphones, which have a high adoption and penetration rate (Falaki et al., 2010), researchers focused on identifying the amount of time users spend on or in the poximity of their smartphones (Patel et al., 2006; Dey et al., 2011). Since people tend to spend considerable amounts of time next to their smartphone, it became obvious that researchers have a medium for collecting trajectories and other types of data (Kwok, 2009) from a large group of users. As such, the efforts have moved away from building dedicated devices and asking people to carry them for a period of time (Draijer et al., 2000) and towards building smartphone applications for collecting travel diaries (Kim et al., 2010).

The new travel diary collection methods based on smartphones can reach large user groups and collect data for large periods of time at a relatively low cost. However, this technology is still in its initial stages and considerable amounts of research still need to be allocated before travel diaries can be obtained from trajectories with a same accuracy and trustworthiness as when they are collected by asking people to fill forms. In particular, before applying and expanding the research pioneered by Hanson, Pas and their peers, a set of objective measurements for determining how good a system algorithm can transform a trajectory into travel diaries need to be determined. To achieve this, the new systems have to be comparable both with one another as well as with traditional form based travel diary declarations. After proving the potential of new travel diary collection systems, it becomes feasible to study periodical behavioral patterns of travelers such as how do people make use of their surroundings and build daily routines, how unique are those routines during different times of day, week, month, year, and how unique are the routines of each traveler in a city. This thesis contributes with a set of tools and methods that can transform a set of trajectories into travel diaries. It does so by proposing MEILI, a travel diary data collection system that continuously learns from data annotated by users to improve its performance of transforming trajectories into travel diaries.

The architectural choices, data modeling considerations and the machine learning methods applied by MEILI are presented during multiple case studies. Furthermore, a standardized methodology for comparing travel diary collection systems was developed for comparing MEILI with other travel diary collection systems. Finally, the thesis expands the existing methods on multi-day travel behaviour analysis by proposing the use of longest common sequences on activity schedules and travel modes to identify the sequential stability of the individuals travel patterns in a dataset collected with MEILI for over a week.

1.2 Research objectives

The main research objective of this thesis is to identify the prerequisites for building a travel diary collection system that allows for the investigation of the stability and variability of individual travel patterns. The following minor research objectives are addressed in this thesis:

1) Propose a way to collect trajectories from user smartphones with a low battery overhead (Paper I)
2) Design a suitable architecture that can store travel diaries, propose different machine learning and statistical modeling techniques to automatically transform trajectories into travel diaries, and identify a set of performance metrics for the aforementioned techniques (Papers II, III, IV)
3) Propose a robust methodology that can objectively compare any two travel diary collection systems (Paper V,VI)
4) Test the proposed travel diary collection system in different case studies and track its improvements over time (Papers VII,VII)
5) Identify which are the best practices for collecting travel diaries (Paper VIII)
6) Identify the state of the art of travel diary collection systems and future directions of research (Papers VIII, Paper IX)
7) Measure the stability and variability of individual travel patterns (Paper X)

1.3 Thesis structure

This thesis is organized as a collection of papers and has two parts: the overview, which summarizes the main body of work, and the papers, which constitute the main body of work. The overview contains five chapters: the first and current chapter introduces the research and contains the paper structure, the second chapter contains a relevant literature that puts the current body of work in perspective with existing research, the third chapter describes the methodological aspects of the current body of work, the fourth chapter presents the contribution and the limitations of the current research, and the fifth chapter presents the future work directions.

1.4 Declaration of contributions

Paper I – Adrian C. Prelipcean wrote the paper, proposed and implemented the algorithms, and performed the analysis for the paper. Győző Gidófalvi provided feedback to the major iterations of the paper and supervision. Yusak O. Susilo provided feedback to the final iterations of the paper and supervision.

Paper II – Adrian C. Prelipcean wrote the paper, proposed the architecture of MEILI, proposed and implemented the algorithms, and performed the analysis for the paper. Győző Gidófalvi provided feedback to the major iterations of the paper and supervision. Yusak O. Susilo provided feedback to the final iterations of the paper and supervision.

Paper III – Adrian C. Prelipcean wrote the paper, proposed the methods, proposed and implemented the algorithms, and performed the analysis for the paper. Győző Gidófalvi provided feedback to the major iterations of the paper and supervision. Yusak O. Susilo provided feedback to the final iterations of the paper and supervision.

Paper IV – Adrian C. Prelipcean wrote the paper, performed the extended literature review and summarized the findings of the paper. Győző Gidófalvi provided feedback to the major iterations of the paper and supervision. Yusak O. Susilo provided feedback to the final iterations of the paper and supervision.

Paper V – Adrian C. Prelipcean wrote the paper, proposed the methodology, and performed the analysis for the paper. Győző Gidófalvi provided feedback to the major iterations of the paper and supervision. Yusak O. Susilo provided feedback to the final iterations of the paper and supervision.

Paper VI – Adrian C. Prelipcean wrote the paper, proposed the methods, and performed the analysis for the paper. Győző Gidófalvi provided feedback to the major iterations of the paper and supervision. Yusak O. Susilo provided feedback to the final iterations of the paper and supervision.

Paper VII – Adrian C. Prelipcean performed the analysis for the paper, wrote the section describing the use of spatial and temporal indicators, coordinated the writing of sections on MEILI system design and architecture, and performed edits on the paper. Yusak O. Susilo wrote the majority of the paper. Győző Gidófalvi wrote the sections on MEILI system design and architecture. The other authors were involved in organizing and designing the field study, and offering user support during the field study.

Paper VIII – Adrian C. Prelipcean wrote the paper, proposed the methodology, and performed the study of multiple travel diary collection systems and their current status for the paper. Yusak O. Susilo provided feedback to the major iterations of the paper and supervision. Győző Gidófalvi provided feedback to the final iterations of the paper and supervision.

Paper IX – Adrian C. Prelipcean and Toshiyuki Yamamoto wrote the paper to summarize the main concerns and possible future work directions on the status of travel diary collection systems based on GPS trajectories. The paper encompasses the views of the researchers present in the workshop chaired by the authors at the 11th International Conference on Transport Survey Methods.

Paper X – Adrian C. Prelipcean wrote the paper, proposed the methods, proposed and implemented the algorithms, and performed the analysis for the paper. Győző Gidófalvi provided feedback to the major iterations of the paper and supervision. Yusak O. Susilo provided feedback to the final iterations of the paper and supervision.

Chapter 2

Literature Review

This section contains a brief literature review relevant for this thesis, with a particular focus on travel diary collection systems and the analysis of collected travel diaries.

2.1 Travel diary collection and automation

The most widely used proxy for people travel behaviour is a travel diary, which collects two main entities: *trips* with their purposes and destinations, and *triplegs* with their travel modes. Clarke et al. (1981) have shown that the order of questions that travelers respond to in travel diaries affects the response rate. There are two variations for the order of questions, that of *travel diaries*, which are centered on the concept of "trip", and that of *activity travel diaries*, which are centered on the concept of "activity". Whereas the first question for *travel diaries* is to find out the destination, i.e., where did the users travel, the first question for *activity travel diaries* is to find out the purpose (activity) of the trip. Inherently, while there is no difference in between the data collected from travel diaries and the data collected from activity travel diaries, Clarke et al. (1981) and Stopher (1992) showed that activity travel diaries have a higher response rate than travel diaries. While this is seldom mentioned in the current research, this classification is still maintained in the modern travel diary collection systems that allow users to verify and / or correct inferred and collected (activity) travel diaries. The two following subsections contain a brief description of the types of travel diary collection systems and an overview of the current efforts for automating the travel diary collection from different data sources.

2.1.1 Types of travel diary collection systems

Typically, there are five main steps that can describe the methodology behind conducting surveys to collect travel diaries:

1) *Design*, where the questions, focus (travel diary or activity travel diary) and any supplementary materials (e.g., schematics that clarify concepts) are decided on.

2) *Distribution*, where the surveys are distributed to the target user group.

3) *Fill-in procedure*, where participants fill in the surveys.

4) *Retrieval*, where the diaries are retrieved and centralized.

5) *Analysis*, where the travel diaries are summarized and analyzed.

Considering these steps, there are mainly three different implementations for travel diary collection systems: memory-based declaration, automated generation of diaries, and semi-automated generation of diaries. These variations are described in detail in Paper VIII.

First, the memory-based travel diary collection systems, also known as paper and pencil surveys, ask users to answer a list of questions (either on-line or on paper) regarding the start and end time of each trip, its purpose and destination, and, in some cases, the start and end time of each tripleg and its travel mode. These answers are collected in a standardized form, which is now known as a travel diary. Given that these questions are standardized and reusable during future surveys, the design costs are low. However, since the list of questions is sent both on-line (cheap) and on paper (expensive) to users, the distribution costs are significant. Another considerable expense for this method is the data centralization, clean-up and analysis since most non-digital surveys have to be centralized and digitized, which is difficult when users can verbosely declare addresses, which can be incomplete or hard to geocode. Furthermore, it is common to only ask users about the main travel mode instead of complete tripleg information, which is problematic because the user's route is unknown. When route information is necessary, it is common to simulate the route while relying on assumptions such as using the shortest path between origin and destination given the main travel mode, which has proven to be unrealistic (Zhu and Levinson, 2015).

Second, the automated generation of travel diaries relies on collecting trajectories of users and extract features from the trajectories and auxiliary data sources (e.g., transportation networks, social media data, accelerometer movement, etc.) that are used by different classification methods (e.g., statistical modeling, machine learning, etc.) to generate travel diaries. While the current state of the art for travel diary automation is presented in the following section, the main problem with full automation of the travel diary generation without user intervention (usually in the form of annotation and ground truth confirmation) is that the research in travel diary automation is still in its infancy. The main drawback is the lack of methods for objectively assessing the performance of such algorithms and the relatively fragmented research that focuses on independent inference tasks (e.g., trajectory segmentation, destination inference, travel mode inference, etc.) without consolidated efforts that measure how well a trajectory can be transformed in a travel diary "end to end", and not each of its entities.

Finally, the semi-automated generation of travel diaries combines the memory-based declared travel diary methods and the automated generation of travel diaries by attempting to convert a trajectory into travel diaries first, and then displaying the inferred travel diaries to its user for confirmation or corrections. This method can in theory consider the data corrected / confirmed by users as ground truth and use it as training data for continuously improving the automated classifiers. However, while this approach results in an improvement of the classified data for a current data set (Fan et al., 2015), it is not clear what is the percentage of learned features can be extrapolated to other scenarios (e.g., different users, different geographical regions, different seasons, etc.). Furthermore, when the users are accustomed to correctly inferred travel diaries, their attention to the attributes of each entity (e.g., start and stop time, travel mode, etc.) can decrease, which can result in a biased classifiers that functions well as long as the dataset maintains similar characteristics with the dataset annotated by users while paying attention. Unfortunately, to the author's knowledge, there is no research that identified and measured this trade-off.

2.1.2 Travel diary automation

Regarding the automation of travel diary collection systems, the majority of work is focused on automating parts of the travel diaries, e.g., segmenting trajectories into trips and triplegs (Zheng et al., 2008; Stenneth and Xu, 2011; Biljecki et al., 2013; Rasmussen et al., 2013; Safi et al., 2016), inferring a trip's purposes (Wolf et al., 2001; Griffin and Huang, 2005; Lu et al., 2012; Xiao et al., 2016; Ermagun et al., 2017), destinations (Ashbrook and Starner, 2003; Trépanier et al., 2007; Alvarez-Garcia et al., 2010; Nassir et al., 2015), or a tripleg's travel mode (Gonzalez et al., 2010; Gong et al., 2012; Shafique and Hato, 2016; Su et al., 2016; Mäenpää et al., 2017). However, the attempts for taking a trajectory stream and generating a travel diary have been limited (Wolf, 2000).

The most widely used method for segmenting a trajectory into trips is by using a stationarity rule, i.e., detect the locations where user spent a minimum period of time (Wolf, 2000; Doherty et al., 2001; Axhausen et al., 2003; Schüssler and Axhausen, 2009; Tsui and Shalaby, 2006; Stopher et al., 2008; Rasmussen et al., 2013). For a summary of the effect of the thresholds on trip detection see Shen and Stopher (2013). Other used methods involve spatio-temporal clustering (Das and Winter, 2016), using distance threshold (Schüssler and Axhausen, 2009) and identifying segments traveled at a low speed in the vicinity of a POI (Rasmussen et al., 2015). The widely declared accuracy for these methods is over 90%, which is computed by dividing the number of inferred trips that were matched to ground truth trips by using a temporal buffer. Paper III discusses the problem of using these types of metrics for measuring accuracy and proposes a new set of metrics as well as a new method that aligns inferred trips to ground truth trips.

Segmenting trajectories into triplegs and detecting their travel modes are two intrinsically linked tasks. There are two main approaches for this, i.e., first segmenting a trajectory into triplegs and detect the travel mode of each tripleg (Chung and Shalaby, 2005; Schüssler et al., 2011; Bohte and Maat, 2009; Rasmussen et al., 2015), and detecting the travel mode of each of the locations of the trajectory and generate triplegs from the sequence of locations with the same travel mode (Stenneth and Xu, 2011; Hemminki et al., 2013; Manzoni et al., 2010). Paper IV describes the main approaches to travel mode detection.

Both trip and tripleg segmentation are methods where the widely used accuracy measures are only focusing on the number of detected trips and triplegs as compared to the ground truth trips and triplegs. However, this approach misses the fact that trips and triplegs are in a sequence, i.e., a trip that was not detected means that its two neighboring trips (before and after) are now merged into one trip, which affects the overall temporal and spatial characteristics of the available dataset. Paper III discusses this phenomenon and its drawbacks at length.

When it comes to annotating the travel mode of each tripleg, and the purpose and destination of each trip, it is common to take the ground truth trips and triplegs and extract features that are then used by classifiers. For travel mode detection is common to use rule based heuristics (Chung and Shalaby, 2005; Zheng et al., 2010; Montini et al., 2014a; Rasmussen et al., 2015), fuzzy logic (Tsui and Shalaby, 2006; Biljecki et al., 2013), decision trees (Hemminki et al., 2013) and random forests (Stenneth and Xu, 2011), where the declared accuracies vary between 80% and 90%. Similar methods are used for inferring the purpose of each trip: rule based heuristics (Wolf et al., 2001; Bohte and Maat, 2009), decision trees (Deng and Ji, 2010) and random forests (Montini et al., 2014b), where the declared accuracies vary between 70% and 90%. Inferring the destination of a trip mostly relies on spatial or spatio-temporal clustering (Axhausen et al., 2003; Liao et al., 2007; Alvarez-Garcia et al., 2010; Chen et al., 2010; Dill and Broach, 2014) and the accuracies for such methods are seldom declared. The features used by the classifiers applied to each of these inference task have been detailed in previous work (Prelipcean, 2016), and Paper IV provides an in-depth review of the travel mode methods that are common in multiple disciplines.

It is important to note that the way user choose their activities, destinations and travel modes has a certain degree of repetition, e.g., the activities of users are concentrated at few places (Schönfelder and Axhausen, 2004), it is likely those locations are visited for the same purpose every time and the travel mode is limited by external constrains. Papers II and VII describe iterative algorithms that take advantage of this repetition by continuously learning from the annotations provided by users.

2.2 Travel diary analysis

It is important to frame the travel diary collection and automation into a suitable context, i.e., travel diaries are collected to be further analyzed. As such, this section discusses two main analysis topics for collected travel diaries that are relevant for the current work: comparing travel diaries collected from the same travelers but by using different collection methods, and making use of travel diaries collected from the same users over multiple days. While single day travel diaries have been used for various reasons such as inputs for simulation modeling, descriptive statistics for the traveler in a given region, etc., this work acknowledges the aforementioned research but does not continue it. The main focus for data analysis relevant for the current body of work is only on travel diary comparison and multiple day travel diary analysis.

2.2.1 Travel diary comparison

Comparing the travel diaries as output of different collection systems and methods gained importance with the development of new travel diary collection systems that had to be compared with one another. However, there is no widely accepted method on how to compare the travel diaries collected by different systems or via different methods.

The comparison methodology when ground truth data are available varies from subjective interpretations regarding which trips were missed by a system (Wolf, 2000) to automated matching of trips using spatio-temporal joins between the travel diary entities that have a spatial and temporal component (Stopher et al., 2007) to proprietary software (Bricka and Bhat, 2006). This results in a one-to-one matching for trips (and in some cases triplegs) collected by different systems.

Similarly, when there is no ground truth dataset, it is common to either simulate data given a-priori knowledge collected previously for a geographical region (Drchal et al., 2015) or to compare descriptive summary statistics of the population as obtained in previous travel diary collection studies with the same statistics derived from the newly collected dataset (Schüssler and Axhausen, 2009).

Paper V proposes a framework for comparing different travel diary collection systems and describes the methods needed to find the corresponding trips and triplegs between travel diaries collected from different systems and / or methods. It also gives a method to estimate which trip description should be considered as ground truth in case the representation of the same trip varies across systems.

2.2.2 Multiple day travel diary analysis

While transportation science is mostly focused on the analysis of travel diaries collected from individuals for a single day, researchers have also focused on the analysis of travel diaries collected from same individuals over multiple days. Most research in multiple day travel diary analysis can be traced back to three visionary groups: Hansson and colleagues (Hanson and Huff, 1981, 1988; Huff and Hanson, 1986), Recker and colleagues (Recker et al., 1985, 1987) and Pas and colleagues (Pas, 1983, 1987; Pas and Koppelman, 1987). These groups and the research that followed them have mostly focused on designing index values that measure similarity in between user trips or daily trips. As such, the focus is mostly on spatial and / or temporal variability of trips and triplegs either for descriptive reasons (Hanson and Huff, 1981) or modeling reasons (Pas, 1987; Schönfelder and Axhausen, 2000; Dharmowijoyo et al., 2016; Cherchi et al., 2017).

Paper X continues the research in measuring variability for travel diaries collected over multiple days with a focus on sequential variability, i.e., identifying which activity chains are stable across days and / or users to identify, within a traveler group and for a given region, what are the primary activities that are performed in the same order by travelers. The main research in the field of sequential variability focuses on computing index values based on alignment penalties, as given by the Edit Distance method (Levenshtein, 1966). The earliest attempt to measure sequential variability was made by Wilson (1998), who tried to understand the implications of using sequence alignment via Edit Distance on daily schedules of activities. Research that followed Wilson focused on expanding the dimension set that is embedded in the alphabet used for computing the Edit Distance penalties (Joh et al., 2001a,b), or on optimizing the sequence alignments methods (Kwan et al., 2014). Paper X continues the initial attempts of understanding the implications of sequence alignment for travel behaviour (Wilson, 1998) and proposes an alternative way of measuring the sequential variability / stability of travel by using longest common sequences (Hirschberg, 1975). This method identifies which activities are performed in the same order and extracts them as subsequences, which can be used to complement descriptive statistics or to postulate new hypotheses by researchers.

Chapter 3

Methodology

The chapter provides an overview of the methodological contributions of the current body of work. In particular, it focuses on the architecture and implementation considerations for MEILI, the automatic generation of travel diaries from trajectories, comparing travel diaries collected from different systems or via different methods, and measuring stability and variability of travel patterns by using Longest Common Subsequences. The remainder of this chapter offers a high level representation of the proposed methods.

3.1 Travel diary collection with MEILI

Even though MEILI underwent multiple changes and iterations, the main considerations have staid the same, i.e., MEILI is a system that allows for the semi-automated collection of travel diaries that is open source and simple to deploy.

First, MEILI should allow for the collection of travel diaries, the fact that it relies on semi-automated collection is an implementation detail that allows the system to potentially reach more users. Similarly, semi-automated travel diary collection systems can converge to fully automated when sufficient data have been collected and annotated by the users. To allow for the collection of data as seamless as possible, Paper I presents a battery saving strategy that minimizes the amount of drained battery according to physical movement as recorded by accelerometer and travel speed. Papers II and VI show that users react positively to the battery consumption, but negatively towards the data annotation interface.

Second, MEILI is released under an open source license to encourage the knowledge share between individuals working on travel diary collection systems. As such, any modifications made on the existing MEILI source code are released under the same license as MEILI.

Third, simplifying the deployment and maintenance of MEILI is a particularly challenging task because of the system's complexity. While the code base is small relative to other open source projects, the difficulty lies in acquiring the expertise

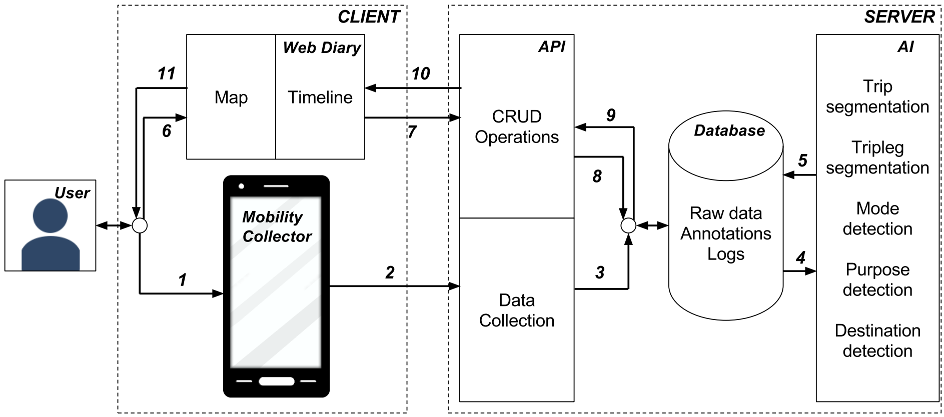


Figure 3.1: MEILI system's architecture. The two main parts of the architecture, i.e., the client and server side, are presented within dashed rectangles. The client side contains the MEILI Mobility Collector, which is the application that continuously runs in the background on a user's smartphone and the MEILI Travel Diary, which is the web page that the user can use to view and annotate her data. The server contains an API that allows the communication between the clients component and the database, a database that stores raw data, user annotations and interaction logs, and the Artificial Intelligence (AI) API that partially annotates the user's data. The flow of actions is denoted in numbered arrows and is explained in text.

needed to deploy and maintain MEILI. This is mostly due to its different components (Figure 3.1), i.e., the database (which has to be hosted on an accessible server), the API (which has to have the required security clearances to write to and read from the database), the mobile applications (which have to be compiled separately, iOS using the compilers only available on Apple Operating Systems, and Android using the compilers provided by Google). Furthermore, the machine learning logic that constitutes the semi-automated logic of MEILI has to be maintained and improved while taking into account the aforementioned architecture. Finally, to increase the machine learning accuracy and to facilitate the annotation process for the users, an underlying data source of Points of Interests (POIs) should be made available in MEILI's database, which varies on a per-project basis.

Paper II presents the architecture of MEILI together with considerations that simplify the deployment and maintenance process. Furthermore, Paper I offers a detailed analysis of the battery consumption and considerations for designing the mobile application side of Airmee. Finally, Paper VIII presents a set of best practices for running systems similar to MEILI in production, and shows how MEILI fits in the current state of the art.

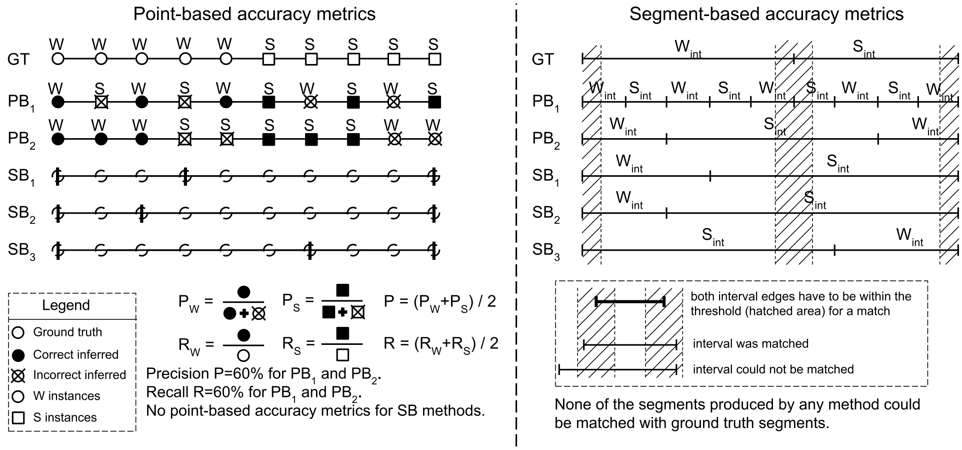


Figure 3.2: Difficulties of comparing different methods using common error metrics. On the left, two different point-based methods PB_1 and PB_2 make the same number of mistakes and misses but on different points. On the right, the segments of PB_i and of three different segment-based methods SB_i are treated as equal since none of them are matched to GT.

3.2 Travel diary entities automation

The potential of semi-automated travel diary collection systems (where users confirm and correct the predicted travel diaries) is the convergence to fully automated travel diary collection systems, where the user's involvement is minimized (e.g., only asking for predictions whose confidence level is beneath a threshold value) or eliminated (where the user only carries a data collection device). The convergence is possible when a set of trajectories can be transformed into a set of travel diaries with a high enough accuracy. The first part of this section presents the contributions of the current work to measuring the certainty and accuracy of segmentation algorithms that transform a trajectory into trips and triplegs. The second part discusses the iterative learning processes that are used by MEILI to converge from a semi-automated travel diary collection system to an automated one.

3.2.1 Trajectory segmentation

Trajectory segmentation is the process of transforming a user's trajectory into the trips and triplegs of the user's travel diary. There are two main approaches for segmenting a trajectory into trips and triplegs: 1) direct / explicit, by detecting sequences of points that have shared characteristics (e.g., speed and acceleration for triplegs, long period of idle time for trips), and 2) indirect / implicit, by detecting the travel mode of each location and, as a byproduct, the triplegs as sequences of same travel mode locations.

Both these methods have pros and cons and ultimately satisfy different technological needs, e.g., detecting travel mode in real time can be used to offer a service that makes use of this characteristics (letting a traveler know whether to hurry up to catch the bus). Papers III and IV describes this in detail. However, choosing either segmentation method is difficult, which is mostly due to the lack of objective measures for assessing the performance of either method.

Traditionally, direct methods rely on comparing inferred segments with ground truth segments and declare the performance using precision and recall by comparing the number of inferred segments to the number of ground truth segments (Zheng et al., 2010). As this method ultimately relies on counting how many times an algorithm detected a segment correctly, it does not account for the magnitude of the mistakes made by the segmentation algorithm. Figure 3.2 shows that the precision of all segmentation algorithms is the same independent of how close they are to the ground truth segments.

Similarly, indirect methods rely on computing precision and recall by investigating how many locations have a correctly inferred travel mode. This is misleading because of the high baseline accuracy of this inference task, where users tend to have low modal variability (Heinen and Chatterjee, 2015), which does not translate to a high segmentation accuracy because triplegs are missed during multi-modal trips. Conversely, if the dataset contains high modal variability, this usually results in over-segmentation because any one location with a wrongfully inferred travel mode prompts the registration of a new segment. This is an oversimplification of the issue since it is possible to apply a high-pass filter to minimize the oversegmentation, but this comes at the trade-off of missing short triplegs.

Paper III proposes new performance measures inspired by interval algebra (Allen, 1983) that objectively assess any segmentation output as compared with a given ground truth. The proposed method relies on interval alignment, which first identifies the correspondence in between inferred segments (or intervals) and ground truth segments. After identifying the segment correspondence, a set of errors based on spatial displacement, temporal displacement and cardinality penalties are computed. These errors are then summarized into five evaluation metrics that can be used to get more insight into the performance of any segmentation algorithm:

1) *precision:* the percentage of *correctly* inferred segments that are aligned to a ground truth segment.

2) *recall:* the *minimum* percentage of length / duration explained by correctly inferred segments divided by total length / duration of ground truth segments.

3) *shift-in penalty:* the penalty of moving every missed ground truth segment inside the inferred segment so that all the ground truth segments occupy the same position in the inferred sequence as in the ground truth. The shift-in penalty has a penalty in the time dimension and one in the space dimension.

4) *shift-out penalty:* the penalty of moving *each* of the incorrect segments – i.e., the segments that do not have the same value for the inferred transportation mode as the ground truth transportation mode – outside of the inferred segment when *more than one* inferred segments are aligned to one ground truth segment.

5) *oversegmentation:* the number of inferred segments a ground truth segment is split into by the tested method / algorithm.

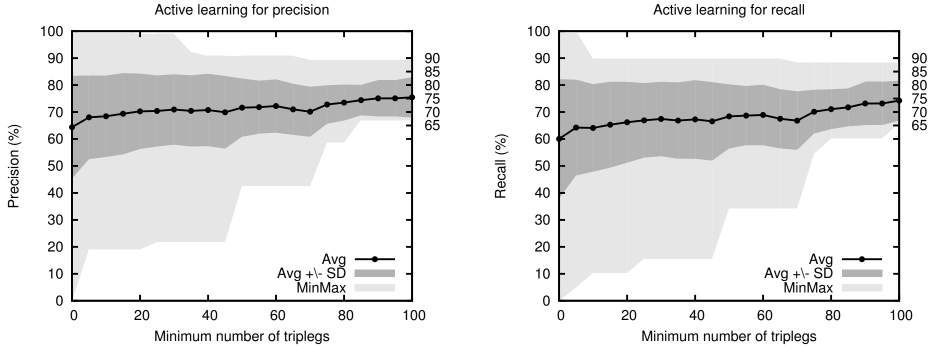
Although these five metrics are more difficult to read than traditional precision and recall values, they nevertheless offer sufficient insight as to evaluate how reliable a segmentation algorithm is given a data-set on which the evaluation is performed. Finally, an important attribute of this methodology is that, when applied to a set of triplegs (or trips), the proposed evaluation metrics show the maximum achievable performance by any travel mode detection algorithm when applied on the proposed segmentation. The same procedure can be applied on inferred triplegs with inferred travel modes since the alignment logic supports categorical values such as travel mode. This is important because it can identify if the problem is the tripleg segmentation (the metrics on the aligned triplegs without travel modes are similar to the metrics on the aligned triplegs with travel modes) or the travel mode detection (the metrics are considerably worse on the aligned triplegs with inferred travel modes). This aspect is new because in the encountered literature review on trajectory segmentation, it is common to report on the trajectory segmentation accuracy first and then report on the travel mode detection accuracy given ground truth triplegs, which is not a reliable indicator of how well the proposed algorithms can perform in real life, in a production environment. For a case study on this comparison see Prelipcean (2016). Paper III discusses in depth the alignment process and its implications, and Paper IV places this new method in the context of the state of the art in trajectory segmentation and travel mode detection.

3.2.2 Iterative learning processes

The convergence of a semi-automated travel diary collection system to a fully automated one depends on any classifier's ability to learn over time.

This would be less of a factor if the attributes based on which a schema of travel modes is inferred are stable over time. However, since travel behaviour is seasonal and mode choice during weekends is different from traveler's mode choice during weekdays (Heinen and Chatterjee, 2015), a system that can be used for collecting travel diaries over large periods of time needs to have a strategy for handling the distribution shifts of travel modes. The same observations hold for destination and purpose inference as well.

Furthermore, the problem becomes more nuanced with the introduction of new travel modes or activities for which no annotated data is available. Similarly, expanding or moving the geographic area of a case study affects the design of a travel diary collection system. It is common for travel diary collection systems to be



(a) Precision increase due to active learning (b) Recall increase due to active learning

Figure 3.3: The effect of active learning on precision and recall.

designed with a fixed travel mode schema and a fixed activity / purpose schema to avoid dealing with this complexity. Furthermore, the majority of automated and semi-automated travel diary collection systems have been trialled in single geographical regions.

With the architecture presented in the previous section, MEILI allows ad-hoc updates of the travel mode and activity schemas, as well as expanding or moving the collection into new geographical areas without needing redeployments or downtime. While this is a noteworthy architectural benefit, the learning process applied by MEILI had to be designed with this type of flexibility in mind.

Any alteration of a schema results in a learning mismatch in between the schema on which the inference methods are trained on, and the schema on which the predictions occur. This means that the inferences will not make any predictions on the newly added elements to the schema, which ultimately leads to incorrect classifications. However, MEILI is a semi-automated travel diary collection system, and users are asked to confirm the inferred travel modes, purposes and destinations. As such, when a classification schema is altered, the learning process takes into account the new schema (which includes the updates) and gradually learns from the user's annotation. This contrasts the common approaches, where any modifications of a schema results in either a redeployment of the system or in de-activating the inferences for the new elements part of the schema. The iterative learning process that MEILI adopts has poor performance initially because of the lack of annotated ground truth data that can be used when inferring the new schema elements (e.g., introducing electric vehicles as a travel mode after a week of data collection). However, this means that the schemas can be updated to reflect the needs of any travel diary collection case study without needing offline periods or compromising on the variety of travel modes or purposes inferred by the classification algorithms.

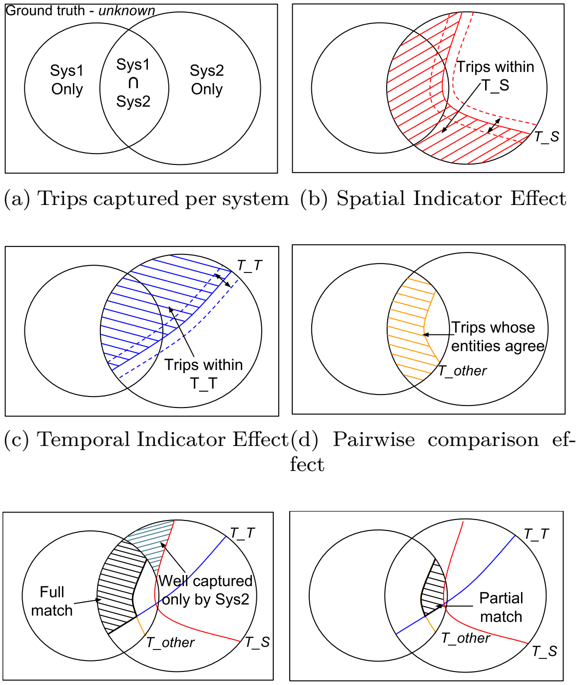
However, to allow for this flexibility MEILI's architecture has to take into account any such changes and use classification algorithms that both support iterative learning and do not require a monopolization of resources when the learning is performed. MEILI was used in different case studies with real-time iterative learning (when the learning procedure is executed on any new entry) as well as a scheduled iterative learning (when the learning procedure is executed according to a schedule, e.g., daily). The methods that were feasible to be used in production for MEILI were: cluster-based nearest neighbour classifier for travel modes, and a Naive Bayes classifiers for purposes and destinations. The methods and their performance were presented by Prelipcean (2016). Figure 3.3 shows the iterative learning for a case study that was run in Stockholm Sweden with 15 different travel modes. The itertaive learning process improves the initial precision of 65% to 75% after the annotation of 100 triplegs. The shown precision and recall methods are those proposed in the previous section and not their traditional definition.

It is important to note that while travel mode, purpose and destination inference are the output of an iterative learning process, the trajectory segmentation into trips and triplegs is based on the widely used rule-based / threshold methods. Most classification algorithms try to minimize the number of wrong inferences and maximize the number of correct inferences. However, as discussed previously, this is a problem with segmentation algorithm because these methods do not allow for any differentiation in between a sufficiently good segmentation algorithm and a considerable worse segmentation algorithm that outputs the same number of inferred segments matched to ground truth segments. To overcome this issue, new learning algorithms that try to minimize / maximize the five proposed evaluation methods should be implemented and trialled. This is also pervasive in the travel diary literature, while machine learning is used for travel mode, destination and purpose inferences, it is seldom use for trajectory segmentation. A method that can iteratively learn a better segmentation that is unaffected by a sensitive choice of thresholds has the potential to make the automated and semi-automated collection of travel diaries as a stable and reliable tool for collecting travel diaries from particular population segments.

3.3 Multiple source travel diary comparison

To begin this section, it is important to note that when comparing two different automated or semi-automated travel diary collection systems, it is sufficient to rely on the same evaluation metrics as proposed in the previous section. However, those methods are most suitable when the trajectory that underlies the travel diaries is available for analysis, which is not the case for the traditional travel diary collection methods, where people recall and declare their travel diaries in a form.

It is common, especially when evaluating the usage feasibility of a semi-automated / automated travel diary collection system, to collect data with two systems: 1) a declarative travel diary collection system that is widely used in the researchers' region, and 2) the new trialled system. Both systems collect travel diaries and the



(a) Trips captured per system (b) Spatial Indicator Effect

(c) Temporal Indicator Effect (d) Pairwise comparison effect

(e) Ground truth candidates (f) Partially matched trips

Figure 3.4: The spatial and temporal indicators can be used to propose a ground truth candidate set, and comparing the captures of trips and triplegs that both systems agree / disagree on can offer insights into which system is superior and whether a system is suitable to replace the other system.

system comparison focuses on trips and triplegs. The major problem in this case is that there is no objective ground truth since no system is guaranteed to collect the complete travel diary. As an attempt to provide a solution to this problem, Paper V introduced a framework for analyzing collected travel diaries by proposing ground truth candidates and then performing a set comparison on all trips collected by either system.

Ground truth candidates are generated by investigating indexes that describe how well a trip / tripleg is captured by either system (Figure 3.4). These indexes look at the spatial and temporal sampling characteristics of the trajectory describing each trip / tripleg. However, since the trajectory is not available in travel diaries declared via forms, the declared time intervals are used to extract the parts of the user's trajectory for each trip / tripleg in the form-declared travel diaries. Whenever there is a disagreement in the form of mismatched trip or tripleg representation in between the two systems, the representation with the higher index value is considered as ground truth. Paper V describes this methodology at length together with a case study and Paper VI expands this methodology by adding the disagreements on the representation of trips / triplegs in the forms of system penalties.

3.4 Stability and variability of travel patterns

As previously mentioned, most research that looked into multi-day data has focused on the spatial, temporal and spatio-temporal variability of users' travel patterns (Axhausen et al., 2002; Schönfelder et al., 2003; Susilo and Kitamura, 2005; Kitamura et al., 2006; Buliung et al., 2008; Kang and Scott, 2010; Neutens et al., 2012; Dharmowijoyo et al., 2016; Cherchi et al., 2017), but relatively few efforts were allocated into the sequential variability of activities or travel modes of users across days. Those few efforts that look into sequential variability use edit distance as a proxy for measuring stability. This work complements the edit distance method with a method based on longest common subsequence that has been successfully used in genetics, code versioning, etc.

A first step in investigating sequential variability is mapping a set of entities that occur in a sequence (e.g., activities, travel modes) to an alphabet that is then used when applying common methods such as edit distance and longest common subsequences on the mapped sequences of activities / travel modes. The widely used method for sequential variability is edit distance, which sums up the penalties allocated to the minimum cost edit operation set (insertion, deletion and substitution) when transforming one string into another. As such, the output of the edit distance is a number that represents how similar the two compared activity / travel mode schedules are.

Conversely, the LCS extracts the subset of activities / travel modes that occur in the same order in both compared activity / travel mode schedules. While analyzing the cardinality of the extracted subsequence as compared to the original two sequences, one can generate the similarity measures that can convey the same meaning as edit distance, the output of ED cannot be mapped back to an LCS. More importantly, by applying LCS one can extract which subsequences are most common in a travel diary dataset, both from an inter-personal (the variability for a user on a given day) and a intra-personal (the variability for a given user group on the same day) perspective. The ability to extract common subsequences in a given dataset makes the LCS more suitable for complementing the descriptive statistics that are commonly generated when first investigating the data set. Similarly, one can gain more knowledge by knowing which subsequences are common for a given dataset than by looking at an index value that is mostly meaningful when it has very large or very low values. Paper X presents the details of applying LCS to extract common travel patterns, investigates the advantages and disadvantages of using LCS as compared to ED, and explores the special cases when LCS-based indexes coincide with the ED-based indexes.

Chapter 4

Thesis contributions

This thesis contributes to the current transportation research landscape related to travel diaries in three main ways: data collection, data automation and modelling, and data analysis.

First, the main data collection contribution is the development of MEILI, a travel diary collection, annotation and automation system. The intricacies of developing a system that can collect data from large user groups are described in Paper II. The prerequisites for low battery consumption and robust trajectory data collection are shown in Mobility Collector (Paper I), which is the smartphone app used to collect trajectories fused with accelerometer readings. MEILI has been trialled during different case studies and it was continuously improved as a result, as shown in Papers VI and VII. Furthermore, Paper VIII puts MEILI in context of the state of the art research in travel diary collection and justifies the choice of using an open source license for its release. The main limitation of using MEILI is the steep learning curve that is needed for collecting data with MEILI in production. Although all components are available for public usage and the source code is open for anyone to read, it does not change the fact that the MEILI backend and API have to be hosted and that the MEILI Mobility Collector mobile applications have to be compiled and deployed. The advancement in cloud hosting infrastructure and the on-demand pricing models that come with it are a promising potential solution to this. However, for this to be materialized, a considerable effort has to be put into the deployment pipeline of MEILI to allow for a worry free hosted deployment.

Second, there are two main contributions in terms of data analysis: an objective comparison of travel diaries collected from different systems and via different means (Papers V and VI), and the proposal of new features derived from the travel pattern sequential stability / variability that can complement commonly used descriptive statistics (Paper X). The travel diary comparison methodology brings a standardized matching technique for travel diaries collected from the same users but via different systems / methods that can be readily used on any travel diary datasets. Furthermore, the methodology can be used to identify which system to

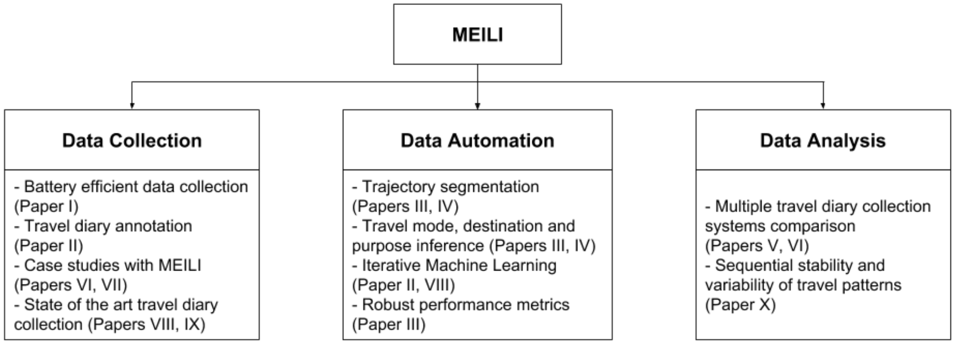


Figure 4.1: Overview of thesis contributions. The contributions of this thesis have been split into three types: data collection, data automation and modelling, and data analysis.

trust more in case of conflicting recordings for the same trips and triplegs. Finally, the set comparison of the travel diary representation of each system allows to identify which systems are more likely to collect different types of trips (e.g., GPS-based diary generation collect more short trips than form diary declaration). However, proposing a set of methods is just one step in its journey to usefulness, since the methodology has to be proven in different case studies by different research groups. As such, implementing the travel diary comparison as an analysis package and making it the available to everyone is a likely next step. Paper IX, which contains the travel diary researchers' main concerns at the moment of this writing, identified that the non-standardized development and comparison of travel diary collection system as problematic. This methodology is a likely candidate solution to that problem.

Since MEILI allows researchers to collect travel diaries from multiple users over long periods of time, a natural research effort was identifying how multi-day data from the same users can be analyzed. Paper X proposes a new method based on extracting longest common subsequences of activity schedules or sequences of travel modes that indicate the level of stability or variability of the travel patterns inside a given data set. Besides offering different ways of computing indexes that describe the stability or variability of travel patterns, the proposed method also extracts those patterns, thus enriching the previously used methods that are limited to generating indexes. Knowing which patterns are present in a travel diary dataset allows for researchers to know more about the data at hand and postulate and test new hypotheses that would be hidden without knowing the patterns.

Finally, the contributions in data automation and modelling are pertinent for the automated generation of travel diaries from trajectories. In particular, Paper III provides an in-depth analysis of trajectory segmentation and proposes a new method for modeling segmentation errors, and Paper II presents a data model that allows

MEILI to take advantage of iterative learning for travel mode, purpose and destination inferences. First, the modeling of segmentation errors allows scientists to measure the performance of any trip or tripleg detection algorithm without relying on setting subjective threshold values for matching inferred segments with ground truth segments. The method aligns any two sequences of segments, computes the alignment discrepancies in terms of duration and distance, and summarizes the segmentation performance using five different measures. This can then be reused after the travel mode detection for each tripleg is performed to also understand the travel mode inference accuracy. The method addresses an important research gap, it allows for measuring how well a set of algorithms can transform a trajectory into a travel diary, thus avoiding the common unrealistic performance for inferring the travel mode for ground truth segments.

The iterative machine learning approach that is used by MEILI shows a working implementation of a system that self-improves without needing redeployments or other types of interventions. MEILI continuously learns while it has users collecting and annotating data, which is an important landmark since most methods rely on collecting data that are annotated by the users and then train the algorithms on the full dataset. While important, the systems that rely on batch learning are not well suited for being run in a production environment that discourages downtime. The system design and improvements over time for active learning are detailed in Paper II. However, using self-improving systems brings new performance considerations to the forefront, which is why the current MEILI uses simple and easy to index classification algorithms such as nearest neighbour classifiers and Naive Bayes. For more involved tasks and for higher accuracies, new algorithms that can learn incrementally should be considered and proposed.

Chapter 5

Future work

As mentioned in previous works, it is always the case that research raises more questions than it answers. This work is not an exception. While the potential of having a travel diary collection system that is free to use and can be applied anywhere, with any schema of travel modes and activity types, is of considerable benefit, it is important to identify what stands in between the current state of MEILI and other state of the art travel diary collection systems and their potential.

First, the research in travel diary collection systems is unusually fragmented, where it is common for entire collection systems to be developed for a small group of case studies and become the legacy of the research group, which results in non-sharable systems that collect non-sharable data. Following the fragmentation trend, most research in trajectory segmentation uses unsuitable performance measures. While the proposed methodology in this work could help achieving standardized error measures and algorithms, future work should focus on proving these measures in multiple case studies and scenarios. Furthermore, when this set of measures proves to be insufficient for the research needs, new and more robust error measures should be proposed and tested. Finally, considerable effort should be invested in building a trajectory dataset annotated into travel diaries to be provided as a baseline benchmarking dataset for scientists to use and test on when developing new methods.

Second, to obtain a robust trajectory segmentation into trips and triplegs, it is important to investigate alternatives to the widely used dwell time rules. New segmentation algorithms should focus on minimizing the spatial and temporal displacements as proposed in Paper III and should also improve as more data are collected and annotated by users. This iterative learning for segmentation combined with iterative learning for travel mode, destination and purpose inferences would likely constitute the next generation of travel diary collection systems that would be widely accepted for particular demographics by the research and industrial communities. However, a word of caution is necessary here, since the automatic extraction of features for segmentation and inferences is prone to overfitting. Extra efforts should be allocated to making sure that the new developed methods perform well across datasets and different demographics and are not merely models that overfit available datasets.

Third, while developing new algorithms for transforming trajectories into travel diaries, it is important to avoid tunnel vision and keep in mind that the automated and semi-automated generation of travel diaries is just one of the options for data collection and that they are well suited for particular demographics (e.g., smartphone users) but that these methods do not replace traditional declarative travel diaries since those are aimed at different demographic groups. It is unlikely for one travel diary collection method or system to be viable for all user groups.

Finally, the new generation of scientists inherited considerable legacy from research that is mostly focused on travel diaries collected during a single day, and, as such, concepts and models that are built on that foundation need to be challenged. It is not feasible to assume that the life of people can be simplified by schedules that involve working, spending time at home and other randomly assigned activities. Furthermore, it is not feasible to assume that it is sufficient to reduce the complexity of travel patterns into indexes. The next wave of research in travel behaviour is probably going to have to spend considerable resources in identifying and correcting mistakes before moving on to discoveries. I hope that the methods and tools described in this body of work will be of use during this process.

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