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Lessons from a trial of MEILI, a smartphone based semi-automatic activity-travel diary collector, in Stockholm city, Sweden

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Abstract

This paper describes the lessons learned from the trial of MEILI, a smartphone based semi-automatic activity-travel diary collection system, in Stockholm city, Sweden. The design of the system, together with state-of-the-art improvements of different elements of the tool, are presented before and after the trial to better illustrate the improvements based on the lessons learned. During the trial, both MEILI and a paper-based diary captured about 65% of the total number of detected trips, but only about half of the trips were captured by both systems. The unmatchable trips are partly due to different activity declaration and system specific destination specification, i.e., a verbose specification of address in the paper-and-pencil survey and a point of interest selection / declaration in MEILI. In terms of subjective appreciation, the user experiences vary greatly between the different participants in the pilot. Presumably, this is mainly due to different level of IT-knowledge of the respondents, but also due to the occasionally non-uniform behaviour of the location collection service caused by hardware and / or software difficulties. Based on these inputs, further web and support system improvements have been implemented for future trials.

Keywords: smartphone based survey; semi-automatic travel diary collection system; activity-travel diary; destination and purpose inference; travel mode detection

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1. Introduction

The success of a transportation policy depends on an accurate description and prediction of aggregate flows as well as the disaggregate travel behaviour of individuals. In doing this, good quality of data is paramount. The traditional methods used for collecting travel data have substantial drawbacks and the public participation towards such surveys is in continuous decline, especially in Sweden (VTI, 2002; Trafa, 2015). At the same time, communication and computing technologies together with location-, orientation-, and motion sensors (e.g., GPS, Wi-Fi positioning, accelerometer) in smartphones enable the large-scale collection of movements of individuals. Consequently, there has been a surge in the number of trials and studies that investigate the potential use of these new technologies to complement and replace the standard paper-and-pencil travel survey acquisition. Whereas widely implemented household travel surveys typically depend on self-reported trips and activities, the subject temporal and spatial movement now can be tracked effortlessly, in detail (Wolf et al., 2004; Stopher et al., 2008; NCHRP, 2014; Cottrill et al., 2013).

The current mobile positioning technology, however, is not without problems (Anderson et al., 2009; Cottrill et al., 2013 NCHRP, 2014). Given the limitations of positioning technologies (e.g., no indoor GPS, low resolution / reduced availability of Wi-Fi and GSM in rural areas), and the built environment constraints (subways, tall buildings, urban canyons), a user's trace is not guaranteed to be recorded at a stable desired resolution (space and / or time). Applications using this technology are often collecting GPS traces, together with accelerometer readings, which have to be further processed to derive the needed entities, i.e., trips and triplegs, and their attributes, i.e., travel modes, and trip destination and purpose. Although positioning technology can be used to directly record accurate time and geographic information of travel (e.g., Chung and Shalaby, 2005; Gong and Chen, 2012; Feng and Timmermans, 2014; Rasouli, 2014), the participants are still needed to be heavily involved by providing / verifying the entities and their attributes. To collect information that cannot be derived from GPS data alone, various prompted recall methods may be used, including paper-based (e.g. Bachu et al., 2010), mobile-phone based (e.g. Ohmori et al., 2005), and web-based (e.g. Ali and Lui, 2011; Bourbonnais and Morency, 2013).

Recently, there have been attempts to automate some of the travel diary generation tasks (Abdulazim et al., 2013; Cottrill et al., 2013; Greaves et al., 2014, Ellison et al., 2014). The automation of the activity travel diary generation using a smartphone mobile application, as opposed to dedicated GPS tracking devices, is expected to reduce the survey cost and to minimize the cases in which the users forget to carry the tracking device. A complete review of the literature is beyond the scope of this document, but the related work sections of Prelipcean et. al 2014, 2015 and 2016 provide an in-depth review of automatic transport mode detection and activity-travel diary generation and comparison. The following paragraphs highlight the most important issues.

Although automating activity travel diary generation has been the main objective of previous research, be it academic or industrial, the main drawbacks that prevented the full automation are: 1) the lack of thorough methodology, 2) the lack of collection and annotation tools, and 3) the separation of tasks without keeping in mind the objective.

First, the lack of a thorough methodology is found in studies that compare activity-travel diaries obtained via two different ways (Brika and Bath, 2006, Forrest and Pearson, 2005, Stopher and Li, 2011, Prelipcean et al. 2015). Whereas there is an agreement regarding the definition of associating the trips recorded by both system, i.e., by using a spatio-temporal purpose-based join, the results mostly report on the percentage of the trips that were joined (Brika and Bath, 2006, Forrest and Pearson, 2005). Some authors (Stopher and Li, 2011, Prelipcean et al. 2015) also provide the rationale behind the lack of recorded trips by either system, but this type of analysis does not offer any meaningful insight regarding the question: "Is it possible to replace surveys as a way of obtaining activity-travel diaries?" This report shows that the question itself might be flawed since neither system can perfectly collect activity travel diaries, but rather the data provided by an automated activity-travel diary collection system can complement the data provided by the classical collection methods.

Second, the focus on data gathering tools has shifted from tools that collect GPS traces and process the data in the absence of user annotations (Axhausen et al., 2003, Wolf et al., 2001, 2003), to systems that allow for the user to annotate their collected trips (Prelipcean et al. 2014, Montini et al. 2013, Bohte and Maat, 2009). The change in focus also lead to new considerations for the development of such products, which are either private contractor developed products (Bohte and Maat, 2009), in-house proprietary products (Montini et al. 2013), or open-source products (Prelipcean et al. 2014). Unfortunately, there does not seem to be an agreement regarding which product is mostly used, which in turn leads to results that are not comparable due to different collection strategies and methodology.

Finally, it is common for researchers to split the activity travel diaries generation into smaller tasks such as travel mode inference, destination inference, and purpose inference. Each of these tasks have specific approaches and used data types.

Travel mode inference is approached as either a point-based classification, where each location is classified into its travel mode (Stenneth et al. 2011, Prelipcean et al. 2014), or a period-based classification, where a sequence of locations is grouped into triplegs based on heuristic rules and the triplegs are further classified into transportation modes (Chung and Shalaby, 2005, Stopher et al. 2008). Furthermore, there are different types of data used for travel mode inference, such as GPS only datasets (Stenneth et al. 2011), GPS fused with accelerometer datasets (Prelipcean et al. 2014, Reddy et al. 2010), and accelerometer only datasets (Hemminki et al. 2013, Yu et al. 2014). Furthermore, these datasets are complemented with GIS auxiliary data (Stenneth et al. 2011) to distinguish between modes that have similar movement characteristics, e.g., cars and buses. While the authors report comparable accuracy values such as: 90.8% for seven classes (Prelipcean et al. 2014), 93.6% for five classes (Reddy et al. 2010), 93.5% for five classes (Stenneth et al. 2011), or 90.6% for five classes (Yu et al. 2014), a deeper investigation into mode detection performance evaluation showed that these precisions are not comparable to one another and they over-estimate the achievable accuracy (Prelipcean et al. 2016).

Destination and purpose inference are closely intertwined since at least one of the features used in purpose inference is derived from a given destination. Most destination inferences are based on proximity to POIs, which implies the need of well-defined external points of interest (POI) dataset (Axhausen et al., 2003, Wolf et al., 2001). Bohte and Maat, 2009 identify the closest point of interest to a trip's end and, based on its type, derive the purpose of the trip, with an accuracy of 43% for 13 purposes. Oliveira et al. 2014 evaluate two methods, which rely on GIS land use and POI datasets, for purpose inference that are based on choice modelling and decision tree analysis achieving an overall accuracy above 70% for 12 categories. Wolf et al. 2001 show in their pilot study that it is feasible to derive trip purpose by combining GPS point data with a spatially accurate GIS land use database, reporting an accuracy over 90% for a small data set of 151 trips. Montini et al. 2014 use random forests to infer trip purposes for a 1 week travel survey in Switzerland, 2012, that involved 156 participants, with a varying accuracy between 80% and 85%.

While these tasks have been studied independently, they do not offer an answer regarding how well the activity-travel diary collection can be automated or complemented, which is mostly due to non-uniform error measures used by different approaches, and due to the surface study of precision, e.g., there are no methods that allows us to understand what happens when combining an 70% travel mode inference method with a 59% destination inference method and a 90% purpose inference method.

In order to fully understand the real potential and challenges of such a data collection task, MEILI – a semi-automatic activity-travel tracking application – together with a set of web-based interactive surveys were deployed, for one week, in Stockholm, Sweden. This paper aims to identify what should be improved before a major trial in terms of survey design, travel mode inference, destination and purpose inference, and user support.

The next section describes MEILI's design, the system architecture and the state-of-the-art of the tool. It is then followed by the discussion of the trial implementation and also the trial results analysis. The results from the follow up interview are also discussed. Further reflection and improvements based on the trial implementation are then described. The paper is concluded by a summary section.

2. MEILI tool design and state-of-the-art

To achieve the objective of the study, MEILI, a semi-automatic activity-travel tracking application, combined with interactive web-annotation system, was deployed, for a one week observation period (i.e. Monday, 29th of September to Sunday, 5th of October, 2014). Together with this survey, the respondents were also asked to fill a web version of traditional Swedish paper-and-pencil (PP) national travel survey. The results the smartphone app survey were then compared with the results that were collected via the PP alternative and with the ‘corrected and approved’ information that were supplied by the respondents. The criteria used to measure the performance were the number and the accuracy of reported/recorded activity-travel engagements on the given day, the spatial quality of the route recorded and other practical matters that serves the interests of transport authorities. This includes forgotten trips, estimation of distance/travel time, geographic coding of departure and destination locations and the cost and burdens for the survey respondents and administrators for different survey method. The latter is planned to be gathered via a series of deep interview with the respondents.

2.1. MEILI tool design concept

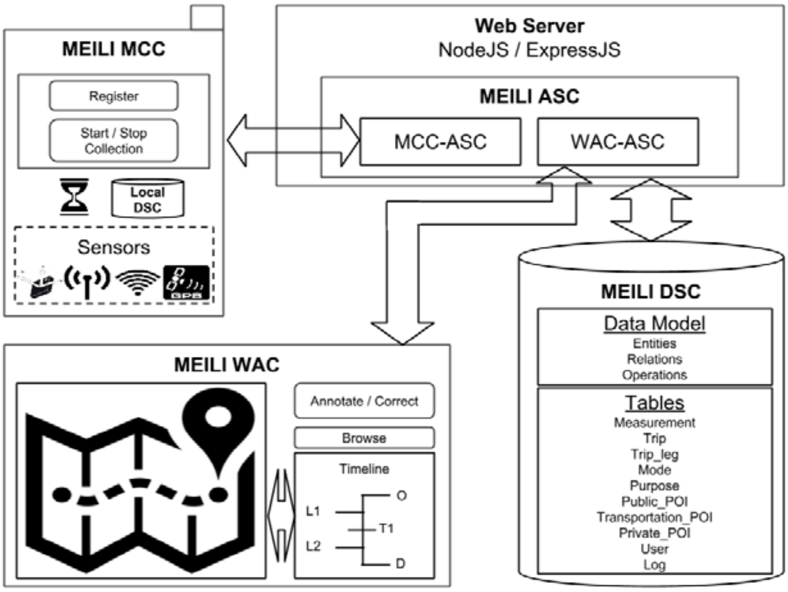
MEILI, an activity travel diary collection, annotation and automation system was developed to achieve the objective of the project. The ambitious design objective of MEILI is to develop an open-source, smartphone based software system that, in a fully automatic fashion, can effectively collect the accurate activity-travel diaries of its users using state of the art mobile computing-, communications-, and positioning and sensor technologies, auxiliary spatial information (e.g., public transport and POI datasets), and sophisticated machine learning algorithms to infer trips, trip legs, travel modes, and trip destinations and purposes. To be able to collect ground truth information for verification and machine learning algorithm training purposes, this design objective is further extended to develop an effective web based interface where users can annotate / correct / verify their activity-travel diaries.

MEILI's architecture is a typical, three-tier, Model-View-Controller (MVC) that has two types of clients: a Mobile Collection Client (MCC) and a Web Annotation Client (WAC). The primary task of the MCC is to collect movement information from a user’s smartphone in a seamless and battery efficient fashion. The primary task of the WAC is to allow users to annotate their movement information (collected by MCC) with activity-travel semantics (i.e., trips, triplegs, travel modes, trip destinations and purposes). To reduce the user’s burden, MEILI performs inferences about the activity-travel semantics, which the user can verify and, if necessary, correct. Both client components connect via a web server to an Application Server Component (ASC) that allows for the bi-directional data transfer between the clients and the Data Storage Component (DSC), i.e., a PostgreSQL/PostGIS database. The current system architecture of MEILI and the interfaces of the trialled mobile and web clients are shown in Figure 1. The architecture of this system has been continuously improved, leading to a superior data model, and a more interactive and intuitive user interface (as explained / shown later).

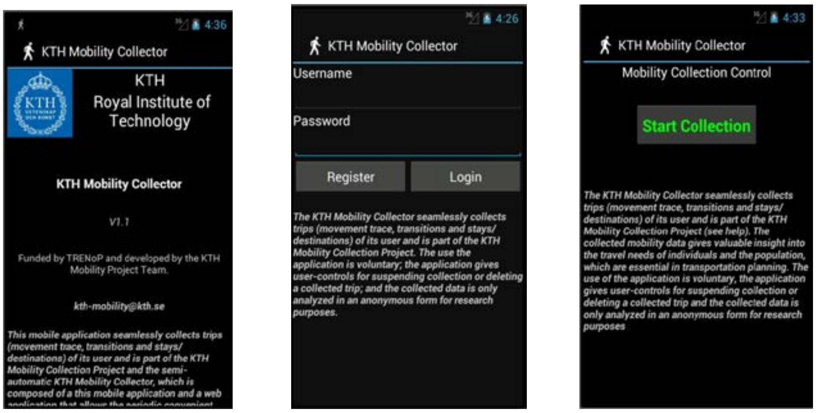
2.2. Adaptive, Equidistance, Power-conscious Sampling

Although both the Android and the iOS platforms provide functionality to track the movements of the phone user by sampling the location of the mobile unit, the default sampling strategies do not provide equidistance samples—which is desirable from a mapping and machine learning perspective, as well as from an information theoretical perspective—at an optimal power consumption (Prelipcean et al., 2014).

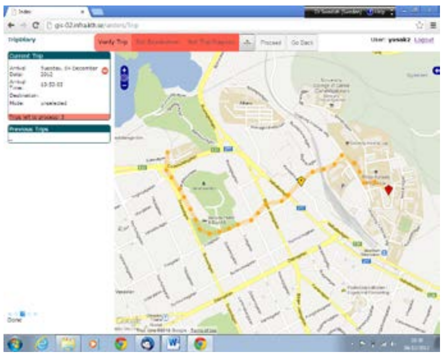
Consequently, MEILI MCC adopts an adaptive, equidistance, power-conscious sampling strategy that is motivated by the lack of adequate default sampling strategies and two observations. First, the battery consumption of a unsuccessful location request inside a building (where the user / phone is stationary, i.e., a large fraction of the time - Klepeis et al. 1996) is significantly higher than the cost of a location request outdoors (where the user moves, i.e., the relevant information that MEILI tries to capture). Second, the cost of obtaining accelerometer readings is only a fraction of the cost of obtaining a location reading. Using these observations, depending on which readings are available (location- or accelerometer readings) given the characteristics of the physical environment, MEILI MCC switches between two timer-triggered sampling loops: location sampling loop (when location readings are available) and accelerometer sampling loop (to initiate the location sampling loop when the accelerometer readings suggest movement). To provide equidistance samples given the dynamic movement characteristics of users using different transportation modes, MEILI MCC adaptively adjusts it location sampling frequency based on the distances between recently observed location samples. As a result MEILI MCC can collect equidistance location samples at a battery consumption that is significantly lower than that provided by the default sampling strategies. In particular, on current mobile phones, MEILI MCC can collect the movements of an average mobile user for a period of 30 hours. In addition to the location samples, MEILI MCC also utilizes the accelerometer readings that it collects simultaneously and derives various features (i.e., descriptive statistics of the readings and number of peaks / steps) from these readings between consecutive location samples. These features, fused together with period / sequence based features derived from location samples, are used in subsequent mobility inference tasks like trajectory segmentation and transportation mode detection.



a. Meili system architecture



b. Interface of Meili on respondents' mobile phone unit



c. interface design of the deployed Web Annotation Client in trial

Fig. 1. Meili system architecture and the interface of the mobile and web components

The detailed algorithm of this battery sampling strategy, together with the effect of each battery saving strategy, can be seen at Prelipcean et al. (2014). Field tests showed that 70% of the battery is discharged after MEILI MCC runs for 13.5 h, during which the GPS was enabled for approximately 2.5 h (with a discharge rate of 13% of battery capacity every hour for bus, and 5% of battery capacity every hour for walking) and included all the user's movement (Figure 2).

Fig. 2. Comparison between battery consumption strategies

2.3. Continuous Seamless Sampling

In order to guarantee that the sampling process, which can be manually started and stopped by the user, once started, the Mobility Collector keeps on collecting the desired location and accelerometer measurements with minimal interference with the normal use of the phone, a number of design measures were necessary. First, the sampling process had to be implemented as an independent background process without a UI component that gets automatically restarted by the system after a system restart. Additional, application logic had been implemented on both systems to detect and ask the user to confirm when the user manually tries to disable the positioning capabilities of the mobile device when the sampling process is running. Finally, to ensure that the collected data is never lost and is efficiently saved, periodically, the data collected by each MEILI MCC is replicated to the server-side Data Storage Component (DSC), MEILI has been designed to periodically upload its not-yet-uploaded data in a chunk as an automatic asynchronous task.

3. The trial implementation

The first wider public trial of MEILI was conducted in September 2014 in Stockholm city, Sweden. In this trial, only the Android version of Mobility Collector was deployed. This is part of the preparation stage of deploying MEILI in parallel with the Swedish National Travel survey in October 2015. Prior to the trial, there were several steps involved in the preparation of the survey:

1. The dissemination and recruitment of the participants via professional and personal network within the university, industries and stakeholders' involved in the beginning of summer 2014.
2. By the end of August 2014, information letters that contain more detailed information about the study and the Mobility Collector were provided.
3. One week prior to the survey (2nd week of September 2014), an email with reminder to download the Mobility Collector from Google Play and try to log in to the system was circulated.

4. A couple of days prior the survey (end of the 2nd week of September 2014), the respondents that have not downloaded the Mobility Collector were prompted to do so via an email reminder.
5. At the beginning of the first day of the survey (15 September 2014), the respondents were prompted to turn on the Mobility Collector via an email reminder.
6. At the beginning of the second day of the survey (16 September 2014), a link to the paper-and-pen survey website was sent. A link to the MEILI annotation web page for GPS data was revealed on the completion of the paper-and-pen survey. This is a prevention measure to avoid reminding users of trips that they might have forgotten to declare in the paper-and-pen survey via displaying their trajectory on a map.
7. Every evening during the survey period (from 16-21 September 2014), the respondents were prompted to log-in and annotate the GPS data via an email reminder.
8. At the end of the survey period (22 September 2014), a thank you letter and a feedback questionnaire was sent to the participants.

To support the survey, 24/7 Q&A hotline and video based tutorial to complete, edit, and confirmed the required information at the web-interface were available to the respondents in Swedish and English. An example of the tutorials that were provided to the wider public can be seen at: https://www.youtube.com/embed/CC5gcR0O6pc. The overview of the data collected from the trial can be seen on the Table 1 below.

Table 1. The Overview of the Datasets collected from the Trial

Period of trial time	29 Sept 2014 → 5 October 2014
# Participants for classic Travel Diary	42
# Participants in MEILI	30
# Participants collecting with MEILI and PP	28
# Participants providing feedback	34
Median Age	40
# Annotated GPS Points	66000
# Points	91000
# Annotated Trip-legs	1307
# Trip-legs	1762
# Annotated Trips	608
# Trips	1055

Initially, 51 persons showed interest for participating in the pilot. This number dropped to 42 participants that answered the travel diary and 39 downloaded Mobility Collector and collected data. Among the drop-outs, four people realised they had an iPhone, two had problem downloading the Mobility Collector, one person had sent his phone in service and two were on vacation. From the 39 participants, 30 managed to annotate their data and 24 persons annotated all of their data. Common problems for not managing to annotate all of their data are linked to difficulties when using the web application. In total around 1055 trips were collected and 608 of those where annotated, 102 were deleted by the users and 235 were left un-annotated. As for one day paper based diary, 116 trips of 30 travellers.

4. Matching MEILI and paper-based diary recordings of trip

On the day where both MEILI and paper-based diary (or paper-and-pencil (PP) survey method) were collected, there were 87 trips were reported by MEILI and 94 trips were reported via paper-based diary by the same group of respondents. Among these 87 and 94 trips, 43 trips were considered matched (see Table 2 below). Trips were considered matched based on temporal co-occurrence (start and stop time of a MEILI trip has to be within 30 minutes of the start and stop time of a paper-based diary trip) and has an identical trip purpose (see Prelipcean et al. 2015 for more on matching trips collected by different systems).

Table 2. Trip that were collected via MEILI vs Paper-based diary

	Number	Percentage
PP Only	51	37.0%
MEILI Only	44	31.9%
Both	43	31.2%
Total	138	100.0%

The results of further investigations into understanding why particular trips have been recorded by one system only are summarized in Table 3. The main causes for a trip's absence within the subset of trips collected by a system are:

a) Purpose difference, i.e., the trip could be matched according to the temporal constraints, but the declared purposes for a trip in PP is different than the purpose declaration in MEILI. This can be due to multiple causes, among which the most probable are forcing a multi-purpose trip into a single purpose schema, in which the user chooses differently one of the multiple purposes in each system, or the effect a trip's visualization has on a user's memory / perception of the purpose of a trip.
b) Trip chaining, i.e., a set of individually declared trips in one system is declared as a single trip in the other system. This can be due to: users unintentionally forget to declare shorter trips in PP, users intentionally ignore declaring short trips in PP because they do not fit personal definitions of what a trip is, or MEILI does not accurately detect the end of a trip, thus merging consecutive trips, and the users fail to correct for the mistake.
c) No movement, i.e., MEILI failed to record GPS locations for the duration of a PP declared trip. This can be due to: a faulty data collection caused by hardware / software difficulties, a user forgot to carry her smartphone during a trip, or an unreliable trip recollection of the user.
d) Missing declaration, i.e., PP does not contain any information about a MEILI collected trip. This is consistent with users forgetting to declare a trip in PP.
e) Other reasons, such as users falsely deleting a MEILI trip that was declared in PP, the MEILI collection was started mid-day, which means that only a subset of the PP trips could have been recorded by MEILI, or incomplete data in PP, such as missing purpose, missing destination or missing a period boundary.

Comparison of the captures of trips by MEILI and PP

On average the difference between the start and the end time of the matched recorded trip between MEILI and PP is 5 ± 5 minutes, with the maximum different is 22 minutes (see Figure 3). There is a trend that if the user overestimates the start time, he/she will likely to overestimate the end time as well. The total amount of “misreported” travel time is on average 10 ± 8 minutes; and length of trip does not seem to affect the amount of misreported time.

The summary of data collected by MEILI and PP can be seen at Table 4. In most cases (30), MEILI detects the same number of trip segments as PP. In 8 cases PP has more segments and in 5 cases PP has fewer segments. In 40 cases, MEILI identified the same main mode of transportation as PP; whilst at the rest of 3 cases, MEILI identified a different main mode of transportation as PP.

Table 3. List of common reasons of trips being recorded differently by MEILI vs Paper-based diary

	PP Only		MEILI Only	
	Number	Percentage	Number	Percentage
Purpose difference	8	15.7%	8	18.2%
Trip chaining	9	17.6%	2	4.5%
No movement / Missing	10	19.6%	29	65.9%
Other reasons	24	47.1%	5	11.4%
Total	51	100.00%	44	100.00%

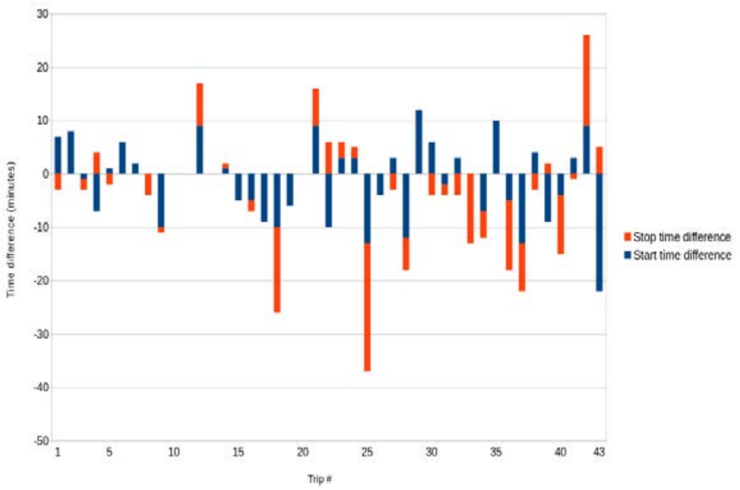


Fig. 3.The differences between start and stop times reported by MEILI and PP

Analyzing the difference between trips captured by both systems and trips captured by either system (see Table 4), it is noticeable that users forget to declare mostly short trips (median duration of 20 minutes), traveled with only one mode and with very low waiting times, which indicates that the user could be traveling via a non-public / non-shared travel mode such as walking, bike, or personal vehicle. The trips recorded only by PP are of similar duration to the trips recorded by both systems, the only main difference being the length of the trips, which are roughly 1.5 km shorter than those traveled by both systems. These might be trips during which the users did not carry their phone or during which the data collection process was not working adequately.

Table 4 also shows the useful information that can be obtained for the collected trip-legs. This can offer more insight regarding how people choose travel modes and which travel modes are considered primary. Similarly, one can compute the waiting time that is associated with each mode (very low waiting time for personal modes such as walking, bicycle, car, and taxi), and the percentage of the time spent while waiting for each mode during a trip (high percentages for public transportation modes such as bus, subway and train). This information can be further analyzed to provide insight regarding how people chain their travel modes during trips, or how people travel under different purpose assumptions.

Table 4. Summaries of Data collected by MEILI and Paper-based diary (PP)

a. Among the trips which were matched between MEILI and PP data

	PP	MEILI
Duration(mins)	23±15	24±19
Length (m)	6300±7600	6300±6000
Trip segments	1.8±1.1	1.8±1
Waiting time	-	6±10

b. Among the trips which were matched between MEILI and PP data

	Registered in both PP and MEILI	Registered in PP only	Registered in MEILI only
Duration(mins)	24±19	23±20	64±85 - median 20
Length (m)	6300±6000	4500±5000	3800±5100
Trip segments	1.8±1	1.7±1.1	1.2±0.3
Waiting time	6±10	-	1±3

c. Among the trips which were matched between MEILI and PP data

	On foot	Bicycle	Moped	Car driver	Car passenger	Taxi	Bus	Subway	Tram	Commuter train	Train
Duration(min)	6	17	14	15	13	7	6	8	45	13	73
Duration (% of trip duration)	41 %	86%	71%	88%	95%	54%	18%	29%	85%	25%	61%
Length (m)	488	2510	6624	5981	4616	3445	1389	2955	8207	11156	174082
Length (% of trip length)	31 %	91%	99%	97%	97%	59%	30%	53%	96%	51%	89%
Waiting time (min)	1	2	-	5	3	0	5	8	-	17	20
Waiting time (% of trip duration)	3%	6%	-	5%	5%	0%	13%	19%	-	27%	23%
Number of instances	414	113	6	140	32	2	63	104	3	26	6

5. MEILI vs paper and pencil vs "the ground truth"

So, does the app produce more accurate/better results? To achieve this objective, a comparison framework to compare the systems was used on with MEILI and PP datasets (Prelipcean et al., 2015). In particular, the framework was used as a comparison tool to reveal the qualitative difference in the data gathered using different collection systems. To achieve this, the framework defines: 1) a number of activity-travel diary measurement entities (trips and trip legs), entity attributes (e.g., trip purpose, origin / destination, etc.), 2) similarity functions between instances of the same entities, and 3) spatial and temporal quality indices to establish a notion of ground truth.

5.1. Creating the index to measure the accuracy of the readings

Since a person that is declaring her trips via methods that rely on her recollection of events is prone to commit error, it is difficult to establish the ground truth. To overcome this, the spatial and temporal quality indices have been introduced to describe how well, on a scale from 0% (worst case) to 100% (best case), a system captures a trip / trip-leg by analysing how far apart every two consecutive locations are in space and / or time with regards to a threshold value. A high index corresponds to a high percentage of the locations being displaced at an expected distance (spatial index) or at an expected time interval (time index). When the recordings spatial and temporal indices of a trip are close to 100%, the trip, as recorded by the system, is a candidate for ground truth. Figure 4 displays a set of three trips as captured by a system: the trip to the left has a high spatial index, which implies that the metrics based on the spatial attributes are trustworthy (this, accompanied by a high temporal index suggests the trip as a ground truth candidate), the trip in the middle has an average spatial index, which means that there are portions of the trip that have been sufficiently well recorded, and the trip to the right has a low spatial index, which suggests that there have been problems with the location recordings and not that the trip is noise.

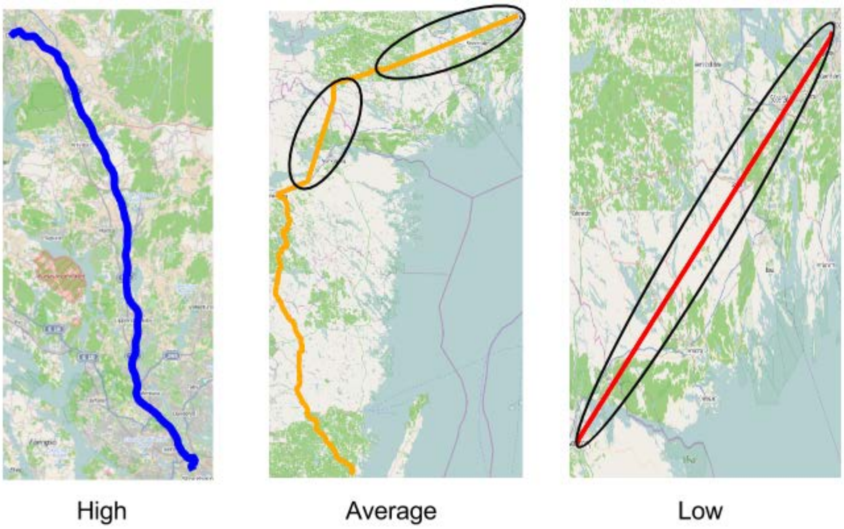


Fig. 4.Examples of trips with different level of spatial and temporal trustworthy indexes

While these measures offer a good framework for comparing two systems that build activity travel-diary based on annotated locations as recorded by devices, it is not possible to apply the spatial and temporal indices on the paper-and-pen methods that are based on user's recollection. As such, the framework was used to identify the average spatial (61% +/- 36%) and temporal (85% +- 30%) index values for the trips recorded by MEILI and to analyse the characteristics of the trips that were present only in MEILI with regards to these indicators. Based solely on the index values, a trip can be classified as: *ground truth candidate* (high spatial index and high temporal index), *noise* (low spatial index and high temporal index), *merged with another trip* (high spatial index and low temporal index) and *unreliably captured* (low spatial index and low temporal index) [†].

The spatial and temporal indices are also actively used in the development of the collection components to check in which cases the collection has to be improved. For further discussion and detail formulation of the proposed measurement, please see Prelipcean et al., (2015).

6. Follow up questionnaire results

There were 34 users that completed the feedback questionnaire that was distributed after the trial and the salient feedback is summarised as follow.

In general the participants managed to install Mobility Collector without any problems, 85 % (29 respondents) claim that they had no problem installing the app. Those who had a problem had never installed an app before or did not have a registered Google account. 95 % (32) managed to install the app without any help from other people and 85 % (29) had the app installed during the whole week.

Looking at the battery life of the phones 27 % (9) didn't notice any big difference when the app was running while 24 % (8) had to charge their phone a lot more often. The reason for these differences is hard to analyse since there are several things affecting the battery life. Some of the parameters that affect battery life are the phone model, usage time, respondent travel time.

The website used for annotation is problematic for some users. A majority answered that they thought it was difficult to understand. However, there were a number of users that found it intuitive and had no problem annotating

[†] The high and low values are subjectively determined, but in the case study a value under 60% was considered low.

their trips. Among the comments there are the following recurring issues: (1) it is difficult to get started with the annotation process, (2) deleting too many transition points (due to oversegmentation of trips) is highly problematic, (3) the website is slow, (4) it is difficult to define new destinations, i.e., declare POIs, etc. This highlights the need to improve the website interface significantly before the main data collection in October 2015.

Regarding the list with Points of Interest (POI) 47 % (14) found it difficult to find an appropriate POI and 20 % (6) would have liked a broader range of alternatives to choose from. The rest, 33 % (10) had no problem finding the right POI. Among one of the comments was that it is difficult to understand the concept of POI and its relation to the trip's purpose and destination.

On the question of whether the app had detected a trip that the respondent hadn't done 60 % (18) answered yes. Most of these trips are short trips around their home or work place.

Regarding the travel diary that the participants had to fill in for the first day of the pilot the opinions vary greatly: some people preferred the app but others preferred the travel diary. Some people claimed that it was hard to remember all the trips and the details of the trips. On the question regarding integrity (of which method was the most insulting to their integrity) 67 % (23) answered the smartphone app, 6 % (2) answered the travel diary, and the rest does not consider any different between two methods. Overall, there was an agreement that, since the user can choose whether to participate or not, the integrity is not a big issue. It is more important to state what will happen to the data after the trial in terms of how it will be used.

Even though many participants have struggled and had to put a significant amount of time and effort into annotating their data, 68 % (23) are positive to participate in the focus group discussions on how the system can be improved.

Besides these technical issues, it was also learned that it is better to collect data from Tuesday to Monday than from Monday to Sunday. If the collection starts on Tuesday, then Monday is available to help the users install the app and prepare for the collection period.

7. Lesson learned the fuel further improvements of MEILI

7.1. Web Annotation Component

It was clear from the trial results that the earlier version of MEILI needed significant improvement. Since the trial, the design of MEILI's Web Annotation Component (WAC) has undergone significant changes throughout the lifetime of MEILI. While some of these changes were technical changes that were fueled by general web technology developments, others were fueled by the need to provide user-friendly interfaces and functions interact with the collected data, i.e., annotate the collected location measurements with activity-travel diary information. While in the early versions of MEILI it was individual or sequences of location measurements that the user annotated, which then subsequently were explicitly marked as being either transition, stop and regular points with a given transportation mode, in the current version while some user annotation is supported on points (delete / alter / add a point, manually adjust / define trip start and end or transitions) most of the annotations are designed to take place on periods that are presented in the UI as elements on a timeline that are linked to corresponding map objects. The screenshot of the web annotation component can be seen at Figure 5.

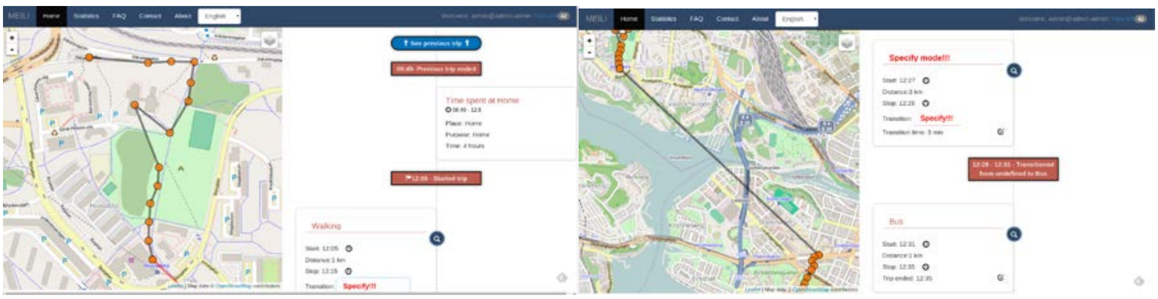


Fig. 5. The new interface of web annotation component

To deal with artefacts of the not-always-perfect data collection and activity-travel inference methods, a number of annotation tools have been implemented. First, more user friendly and intuitive interfaces and tools for deleting, altering, and adding points to deal with noisy / incorrect, inaccurate, and missing measurements have been added to the system. In particular, these extended tools were used to manually set the transportation mode of a trip leg or to delete an incorrectly identified trip that is composed of noisy location measurements or a trip that the user deems sensitive for privacy reasons. Second, although database of MEILI contains public and transportation POIs from different sources, as these datasets are neither complete nor always accurate, tools have been implemented to define spatial and non-spatial aspects of new POIs, thereby allowing the crowd-sources collection of POIs. The same tool has also been used to allow the definition of private POIs such as the home, work, and addresses of friends of the user. Notably, while geocoding, i.e., the automatic mapping of a partial address string to a geographical location) could have been used to define such POIs, due to potential errors as well the limited ability of users to remember precise addresses (even if one can be associated with a place) the designed tools allow to define POIs by dropping place marks on the map. Third, to allow the user to view his or her past trips in the context of one another, a browsing functionality has been implemented to allows the user to go back in time and review previously annotated trips. Fourth, the same trip navigation has also been used to implement the trip revision functionality that allows the user to change activity-travel annotations of a previously annotated trip. Finally, to ensure that the user annotates / verifies all of the collected data, MEILI is designed to direct the user to the first not fully annotated trip and does not allow the unconstrained browsing of not-yet-annotated trips, i.e., MEILI enforces a sequential annotation process. It is needless to state that the development and implementation of these functionalities, especially the correct maintenance of temporal relationships, have not been trivial or simple.

7.2. Data Storage Component

Like the WAC of MEILI, the Data Storage Component (DSC) of MEILI has also undergone significant design improvements. In particular, earlier versions of MEILI has had a relatively flat data model and explicitly associated much of the activity-travel information to location measurement, i.e., annotations were mainly done on locations and sequences of consecutive locations that implicitly defined periods. This early design has proven to be unsustainable, rigid, redundant, and hence error prone, and ineffective, which fueled the recent fully relational redesign of the data model that represents periods explicitly and primarily associates activity-travel annotations with periods.

Populating the public and transportation POI tables has been far from simple. Namely, different subsets of data from different data sources needed to be selected and integrated. In particular, a relevant subset of POIs from the crowd-sourced data of OpenStreetMap (OSM - https://www.openstreetmap.org/) had to be identified based on functionality-, type-, and name labels that are very liberally defined by user. The selections contained duplicates that needed to be automatically identified and eliminated by custom clustering and merging of POIs based on spatial proximity and string similarity between labels. Using a similar methodology the OSM-based transportation POIs (public transport stations with associated line information as well as parking lots) had to be additionally merged with official data sources from the local public transport authority SL (http://sl.se/), which was not as complete or accurate as one would imagine. The integration process was further complicated by the fact that information in different datasets was represented at different spatial level of detail. In particular, while in the official transportation POI datasets a stations are represented a single point, the OSM dataset contains multiple individual entrances to the same station which can be at times very far from each other. The different representation of information in the same dataset also presented initial problems that were undressed in subsequent revision. In particular, in an internal trial, while the public POI dataset contained disproportionately large number of irrelevant POIs, e.g., public benches (arguably a result of a bad selection criteria) the selected datasets did not contain a large fraction of the relevant POIs, e.g., supermarkets. The cause of these has been that initial POI selection only contained points while most of the supermarkets and other relevant POIs are represented as polygons. Finally, to aid the selection process and to establish a similarity between POIs, the POIs have been manually categorized according POI type taxonomy that has been tailor to the application and has been used in some of the activity-travel inference methods.

7.3. Inference methods

The provisioning a system for the fully automatic collection of accurate activity-travel diaries implies the need for automatic inference methods that associate activity-travel information with the collected location and associated accelerometer measurements. One general design objective for these inference methods had been from the start the inference in an online or semi-online fashion and provide almost real-time inferences, i.e., attaching the relevant semantic (such as travel mode, or whether it is part of a period between trips) to every new GPS location as it is received (or with a small delay). Another general design objective for these methods have been that if possible they can be relatively simply implemented on the mobile clients thereby offloading a major part of the work load to idling powerful mobile devices to provide a an overall system that is scalable. In the early versions of MEILI some of the inference methods have actually been implemented on the mobile clients. This design choice while optimal in an operation setting, has been inefficient in the development of these methods new methods had to be implemented on mobile clients and could easily only be evaluated on newly collected data. Therefore, in recent developments the prototyping of these methods is aided by implementing a server-side component that can sequentially replay a subset of the collected data of a user and simulate the (semi-)online execution of an inference method on the replayed data. The following subsections describe the principles behind the four activity-travel inference methods that have been developed for MEILI.

7.3.1. Trip and Trip Leg Inference

Trip and trip leg inference equivalently means the accurate identification of stop and transitions periods, respectively. This task is naturally intertwined with the task of travel mode inference of trip legs that are delimited by these periods. The intertwined tasks can in principle performed using three approaches as they are described in Prelipcean et al. (2016). In the first, a point-based transport mode classification is followed by a low-pass filtering to remove noisy classifications, which collectively results in implicit transportation mode segments. In the second, an explicit detection of segments of GPS points that have similar movement characteristics is performed and classified based on holistic segment aggregates. In the last, a consensus-based transport mode classification is performed on each point that falls within the explicitly detected segments. While it is questionable that that the previously used evaluation criteria for these different approaches are adequate from an application perspective or that the recently proposed criteria are clearly superior in aiding the selection of the most optimal method, based on the prototype implementations and evaluation of the three approaches MEILI currently adopts the explicit-consensus-based transport mode segmentation approach. In particular, with respect to trip inference, stops periods are detected by finding the longest periods during which the movement characteristics indicated by- and the accuracy of the position as well as the accelerometer suggest that the user is stationary for a period of at least 5 minutes or is indoors. With respect to trip leg inference, start and end times are detected as time instances that separate two segments of location measurements that have similar movement characteristics internally but differ from one another.

7.3.2. Travel Mode Inference

During the development of MEILI a number of different machine learning techniques as well as different general approaches for travel mode inference have been developed and tested (see Prelipcean et al. 2014; Prelipcean et al. 2015). While studying which machine learning approaches are most suitable for inferring travel mode, it became clear that the widely used performance measures for mode detection have a very limited applicability due to the idealized assumptions under which they were developed. The idealized assumptions, their effect and new methods that overcome their shortcomings are studied, discussed and proposed by Prelipcean et al. (2016). From the trialed methods, we found that random forests outperform other studied machine learning approaches (e.g., decision trees, support vector machine, etc.). However, the trial of random forests was done in a post-processing scenario and online / streaming solutions should be explored for active and personal learners.

The initial findings report a precision of 75.3% and a recall of 73.2% for 9 travel modes when using personalized random forests, i.e., one of the features used by the random forests is a user unique identifier. When disregarding the user unique identifiers, the precision drops to 43.9% and the recall drops to 43.1%. The computation of these precision and recall values is performed according to Prelipcean et al. (2016).

7.3.3. Trip Destination Inference

During the development of MEILI a number of different Trip Destination Inference (TDI) methods have been prototyped and evaluated on a small manually annotated collection. The methods can be classified into four major method types: 1) personal history based TDI methods make inferences based on the previously observed destination (POIs) of the user, 2) proximity based TDI methods make inferences based of the proximity of possible destinations to the end point of the trip, 3) conditional probability based TDI methods make inferences based on conditional probabilities of POI types that are primarily based on the time-of-day and day-of-week of the trip, and 4) spatial significance based TDI methods that make inferences based on the importance of a destination given the relative spatial distribution / clustering of different types of POIs in the vicinity end point of the trip.

As expected each of these methods have both advantages and disadvantages. In particular, personal history based TDI methods rely on the existence of a the set of POIs that the user has visited in the past, hence are only applicable only in semi-automatic systems that can actively learn this information based on initial manual annotation during a training period. However, even after the training period of a few days' worth of trips that establish the locations of frequent personal POIs such as home and work, these types of methods can only provide answers for about 80% of the trips. The other three types of methods are general in a sense that they can be applied without any information about the user in any situation. However, due to the incompleteness of POI data sets, not even these methods are applicable in all cases, i.e., the set of possible POIs within a reasonable range of the end of the trip can be empty. Internal test on small manually annotated collection have shown that the first and second highest accuracy is achieved by the personal history based TDI methods and the proximity based TDI methods, respectively. Hence to extend the applicability of the personal history based TDI methods and to provide a TDI method that in principle can make predictions even without a training period, in the current implementation of MEILI the less accurate but more applicable proximity based TDI method is combined as a fallback method to the personal history based TDI method. Due to the fact that the accuracy evaluations of the TDI methods have been performed on a small manually annotated collection, reports on the precise performance of the methods would be misleading, but in general it can be said that the above described combined TDI method after a training period of a few trips can correctly predict the destination of a user's trip with an accuracy of 41.9%. The modest performance of destination inference is caused by the absence of relevant POIs from the POI dataset, such as home and work locations. Furthermore, the accuracy of destination inference increases over time if the users have a uniform pattern for sequences of destinations.

7.3.4. Trip Purpose Inference

Similar to the TDI methods, during the development of MEILI, two types of Trip Purpose Inference (TPI) methods have been prototyped and evaluated on a small manually annotated collection: 1) personal history based TPI method that infers the most likely purpose for a given destination that the user revisits and 2) conditional probability based TPI methods make inferences based on conditional probabilities of trip purposes that are primarily based on the time-of-day and day-of-week of the trip as well as the type of the inferred POI. Although in general, on the small dataset, results have shown that the conditional probability based TPI methods have somewhat higher accuracy and applicability rate, due to the added additional work that users have to perform when defining the non-trivial type of a new POI, the current implementation of MEILI adopts the simpler personal history based TPI method complemented with the fallback prediction of a conditional probability based TPI method that determines the conditional probabilities of trip purposes only based on the time-of-day and day-of-week of the trip. Due to the fact that the accuracy evaluations of the TPI methods have been performed on a small manually annotated collection, reports on the precise performance of the methods would be misleading, but in general it can be said that the above described combined TPI method after a training period of a few trips can correctly predict the purpose of a user trip with an accuracy of 54.7%, recall of 57.9% and F1 score of 0.56. Since the purpose inference depends on the destination inference, the low precision of the destination inference acts as a ceiling for purpose inference. The purpose accuracy for correct destination usually obtains values of above 70%.

8. Summary

This paper describes the lessons that have been found from the survey designs and activity-travel mode inference semi-automation up to the trial results of MEILI. The design of the system and also state-of-the-art improvements for different elements of the smartphone-based survey have been proposed and tested.

Earlier one week pilot test with 30 public members shows promising results. The results show that both systems captured about 65% of the total number of detected trips, but only about half of the trips were captured by both systems. The unmatchable trips partly due to different definition of activities and point-of-interest that were declared by the users in paper-and-pencil, compared to the conventional ones that inferred by MEILI. Nevertheless, MEILI captured more detailed information about trip legs and the location attributes derived from the route (destinations) agrees with the user annotated data more than with the address specified in paper-and-pencil survey.

In term of subjective appreciation, the user experiences vary a lot between the different participants in the pilot. This is probably mainly because the level of IT-knowledge varies, but also because the system works better for some phone models than others. A trip that spans over several days, wrongly detected transition points and trips where only parts of the trip has been detected aggravates the annotation process, which affects the user experience. Besides seldom installation, registration and functionality problems of MEILI, the collection has worked as expected for the majority of the participants. The main problem for several users has been the annotation process and the website used for this. The main conclusion from the pilot is that this process has to be improved and simplified.

To address this problem, further system improvements have been implemented for the main trial. The main issues that should be addressed are the following:

- The segmentation of trajectories into trips should also identify short stays, which could be implemented in a personal learning scenario.
- The segmentation of trips into trip-legs is very problematic due to its sensitivity to noise. A window based filter that compares the differences in speed, duration and other relevant trip-leg metrics between every two consecutive trip-legs can potentially minimize the problem of noise sensitivity. However, this would prevent the classification to be performed in real time.
- Travel mode inference proved to be a problem more difficult to solve than initially envisioned. In the light of discovering that the widely used traditional error metrics should not be applied in real-world scenarios, future work should identify whether the number of correctly inferred trip-legs takes precedence over the accurate description of statistical aggregates per travel mode. As such, the authors advise for a deeper analysis of the implications of reported performance measures in the transportation mode detection literature.
- Any POI dataset is susceptible to being incomplete, which makes finding more robust POI datasets highly problematic. One method to overcome this would be to ask users for a list of POIs and addresses that are common for their daily activities, but that would prevent the complete automation destination inference. Although destination inference is usually treated as a moderately difficult problem in the transport science literature, the complete automation of destination inference methods, i.e., finding the place that a user visits and not the end of the sequence of GPS points collected via a given device, is an active area of research that does not have a feasible solution yet.
- Improving purpose detection can be done by either improving the destination inference, or by exploring new ways to infer the purpose of a trip that do not take into account the destination. Similarly to destination inference, there is no feasible solution that can be used as-is in automatically detecting purpose.
- The improvement of the webpage interface should be done while taking into account both user feedback and expert suggestion. However, it is important to note that the feedback received after the present case study is severely biased towards people that are affiliated with the transportation domain, be it academics or professionals. The main direction of improving the webpage interface is on presenting information to users in a clearer way and minimizing the amount of interaction a user needs for annotating a trip.
- To have access to a larger pool of respondents, it is indicated to implement the Mobility Collector component of MEILI for iOS devices as well.

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