Inferring Modal Split from Mobile Phones

Principles, Issues and Policy Recommendations

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Roundtable

Norbert Brändle

Austrian Institute of Technology, Vienna

Discussion Paper

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Introduction

The personal mobility of a population is comprised of a mix of different travel modes such as passenger cars, buses, subway, commuter trains, walking and cycling. The share of different travel modes in a population is dynamic: modal splits do change, for example, due to control measures such as congestion charges, more efficient public transport offers and disruptive events such as a pandemic. Knowledge and data about travel modes are critical to understanding people's travel behaviour and vital for improving transportation planning, management and operations and to performing policy impact assessment. The transportation means people use when they are on the move has therefore been a key component of trip information collected during travel surveys for several decades.

Traditional travel surveys collect information about people's travel behaviour by asking survey respondents to fill out trip diaries, either paper-based, supported by telephone or online (Kagerbauer et al., 2015). The high penetration rates of mobile phones together with their built-in sensors make them useful devices to collect more extensive and dynamic data than data collected with traditional travel surveys (Wang, He, and Leung, 2018). Identifying travel modes with people's smartphones allows for the collection of detailed trip data in an unobtrusive manner. Dedicated smartphone-based travel survey solutions, for example, automatically detect trips and document travel modes of respondents, thus allowing compilations of very detailed mobility profiles and travel diaries, including carbon footprint. In addition, smartphone-based inference of travel modes can also be a part of other mobile applications such as Mobility as a Service (MaaS), gamification apps or smartphone-based implicit mobile ticketing solutions.

In contrast to active inference techniques with installed smartphone apps, mobility patterns also can be inferred passively by analysing signalling data between mobile phones (not necessarily a smartphone) and the cell towers of a telecommunications network. Passive travel mode inference in telecommunication networks is possible to some extent and has the potential of dynamically capturing very large samples of a population.

Active and passive travel mode inference from mobile phones illustrate the potential of big data to support transport planning. There are major barriers and limitations when it comes to taking full advantage of big data approaches to the domain of transport modelling. In "Leveraging Big Data in Transport Operations (LeMO)", Hong et al. (2020) describe the current barriers and limitations influencing the general uptake of big data in the transport sector. A major identified issue in LeMo concerns transport data collection, which is "often inaccessible, expensive to procure or collect, or not available in digital form" (EU Survey LeMo Project, 2020). As a contribution to data collection, this paper first introduces some basic principles and technical problem statements of collecting travel mode data with mobile phone-based techniques.

The second section of this paper describes other key challenges and most importantly the risk that mobile phone techniques might yield low-quality unreliable data with no use to transport modellers. This paper describes the risks and the reasons why quality indicators for travel mode inference might be too optimistic. The paper also addresses some aspects of representativeness of mobile phone based samples for a population, and privacy and data protection aspects.

The third section of this paper provides some policy recommendations resulting from the described issues.

Principles of travel mode inference

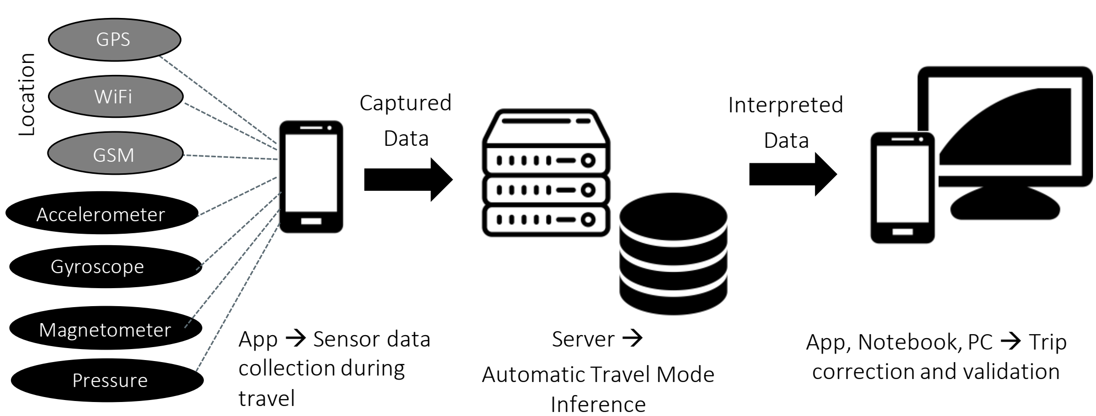
This section introduces some basic principles of active and passive travel mode inference with mobile phones and provides an idea of the range of problems to be solved.

Active travel mode inference with smartphone apps

Smartphones have become an effective tool for the unobtrusive monitoring of human travel behaviour. This is attributed to the devices' ever-growing sensing capabilities, large market penetration rate and effective distribution channels for third party applications. Smartphone devices have built-in sensors that measure motion, orientation, and various environmental conditions. Active smartphone-based travel mode inference systems are typically implemented as a server-based solution (see Figure 1). They include an app that runs on the smartphone of a person and records sensor data (e.g. accelerometer readings) along with location data (e.g. GPS). The mobile app transfers the recorded data from the smartphone to a server via available wireless data standards. The server software maps the transferred sensor data to a number of different travel modes.

Smartphone-based travel survey solutions enable trip validation, where a survey respondent can confirm or correct automatic travel mode inference results. Figure 2 shows an example of the web interface of a smartphone-based travel survey solution, where an individual's trip details are automatically captured, summarised in a travel diary and visualised on a map. The trip example in Figure 2 is composed of trip stages with different modes such as walking, bus, subway and train. Such trips with combinations of different trips are denoted as intermodal trips.

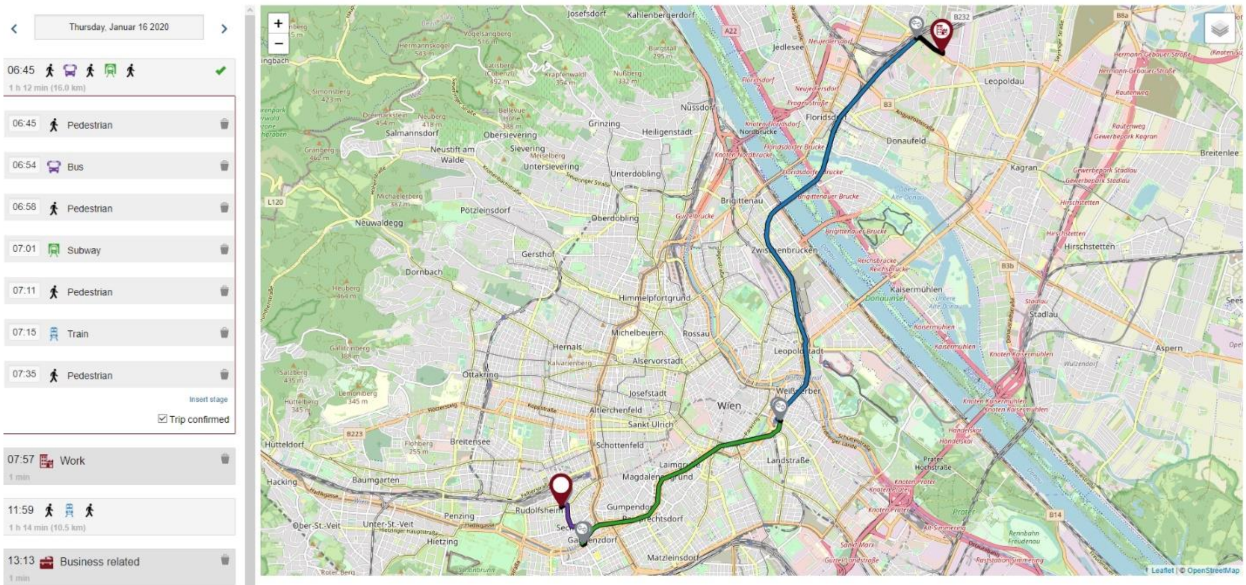
Figure 1. Concept of server-based solutions for smartphone-based data collection and travel mode inference



Respondents often forget to report trips, especially short trips on foot in traditional travel surveys. Smartphone-based travel surveys reduce the risk that respondents forget to report some trips.

Travel mode inference via smartphone apps has use cases beyond the realm of travel surveys. It can be integrated to other mobile applications such as implicit autonomous ticketing for public transport journeys, incentive schemes for behaviour change (Kultur-Token, 2020), capturing of actual travel in MaaS applications and many others.

Figure 2. Screenshot for travel diary generated with a smartphone-based travel survey app



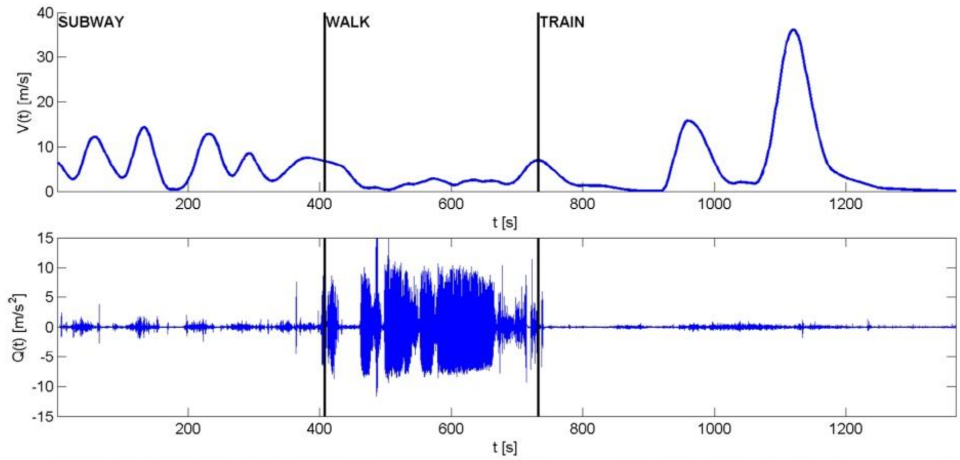
Source: Austrian Institute of Technology (Smart Survey).

The reason why today's advanced solutions perform sensor data analysis on a server rather than directly on the smartphone is because the algorithms are very complex. While it is tempting to assume that different travel modes may be recognised and distinguished with simple features such as travelling speeds, travel mode inference is in fact an extremely hard pattern classification problem. Mapping the smartphone's location and sensor data to the correct transport mode is hard because the classification algorithm must be robust against many influence factors on smartphone sensor data (besides transport mode). In addition, the classification algorithm must be robust against sparse and noisy location data. Smartphone-based travel mode inference is therefore an active research field worldwide, with scientific publications and solutions mushrooming in recent years. The following sections describe in mode details the two phenomena – multiple influence factors and sparse and noisy location data – because they are key for understanding current issues and policy recommendations.

Multiple influence factors on smartphone sensor data

The measurements of the inertial sensors of the smartphone (accelerometer and gyroscope) are important for distinguishing travel modes of a travelling person. Figure 3 shows an extract of velocity and accelerometer data recorded in the course of a trip including three trip stages – riding the subway, followed by walking and riding the train. The first row in Figure 3 shows the velocity-time series measured during the trip, with velocities oscillating between the public transport stops. The second row in Figure 3 illustrates the accelerometer measurements, i.e. the forces that impact the smartphone – not limited to accelerations derived from the velocity. The smartphone of a walking person measures accelerometer values with frequencies correlated with the individual walking pace. Sophisticated analysis of the time series is performed to separate travel modes, for example with spectral analysis.

Figure 3. Example for velocity and acceleration of an intermodal trip



Source: Austrian Institute of Technology.

Travel mode is, of course, not the only influence factor shaping curves such as the accelerometer time series in the second row of Figure 3. Table 1 lists other important other factors contributing to inertial sensor time series.

Table 1. Influence factors on smartphone sensor data apart from travel mode

Influence factor on smartphone sensor data	Travel mode
Person (driving style, walking pace, gait, ...)	all
Travel route (pavement, functional road class, ...)	Vehicles on tyres (car, bus, bike)
Traffic State	Vehicles on tyres
Type of vehicle (SUV, diesel engine, electric engine ...)	Vehicles on tyres
Device sensors (range, precision, sampling frequency, ...)	all
Carrying position of the device (pocket, bag, in the hand, smartphone holder)	all
Interactions with the device (phone calls)	all
Sitting, standing, walking in public transport	Public transport

While this multi-factor influence of inertial sensor data appears obvious, it is a key reason for erroneous and disappointing results in data collection campaigns. Active travel mode inference algorithms are essentially data-driven, meaning that they are being trained with reference datasets in a machine learning phase. Such reference datasets for travel mode inference must comprise examples of mappings between smartphone sensor time series together with the correct travel mode label. If the reference dataset does only cover a subset of influence factors of Table 1, the travel mode inference is prone to fail during travel surveys. If there are, for example, only buses with diesel engines in the reference dataset, a classification algorithm might learn highly frequent vibrations of a diesel engine as a salient feature for buses. The classification algorithm trained with diesel engines only is bound to fail when applied to data collected in a bus with an electric engine during a travel survey. On other words, the training of the classification algorithm suffered from so-called overfitting to data from diesel buses. The second section of this paper demonstrates the overfitting problem with the example of the results of an international challenge.

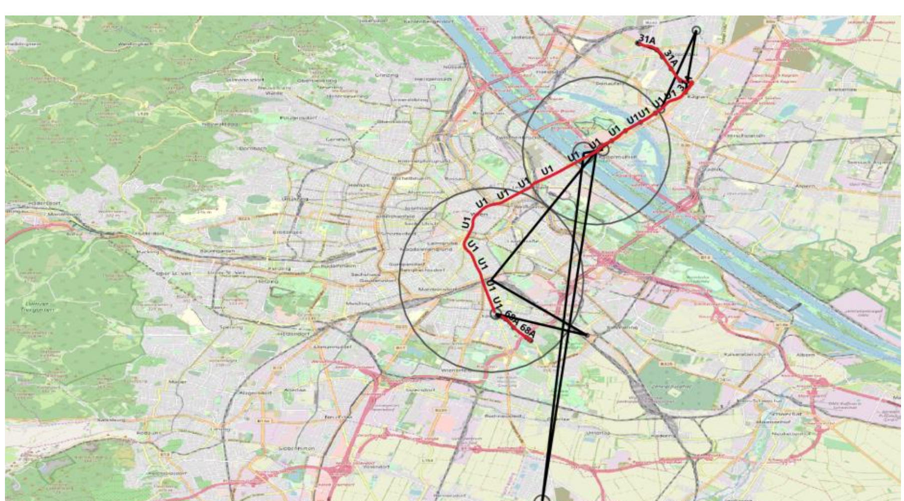
Sparse and noisy location data

Smartphone geolocation is helpful for travel mode inference, and indispensable to visualise journeys on a map, such as in Figure 2. Location tracks provide clues for distinguishing travel modes for which the time series as in Figure 3 are very similar. Public buses, for example, may be distinguished from cars by matching the location traces with public transport network information such as General Transit Feed Specification (GTFS). GTFS data provide public transport timetables, and ideally also include shapes of the public transport routes in the map: a bus ride is expected to produce location traces which are similar to the path of the bus. The technique of assigning location points to elements of a transportation network is called map matching.

In many urban regions, location measurements are far from being dense and accurate, but rather sparse and noisy: GPS locations are not available in the underground and indoors, and are inaccurate in streets which are flanked by high buildings. Alternative location techniques to GPS such as WiFi of cell network signals are sparser and more inaccurate compared to GPS, in particular cell network signals. Locations computed from different sensors including an estimation of their uncertainty are provided by the smartphone operating systems via application programming interfaces (Apple, 2020; Google, 2020a).

Figure 4 illustrates an example of sparse and noisy location measurements: the red line represents the route of an intermodal journey in Vienna including a bus line (31A), a subway line (U1), and another bus line (68A). The black circles in Figure 4 represent the spatial uncertainly of smartphone localisations during this journey. Only a few location reports with large uncertainty are measured during the subway ride, which occurs mostly in the underground. To make things worse, the reported location uncertainties are sometimes wrong: The small circle around the obviously very inaccurate location point in the lower boundary of Figure 4 – far beyond the travelled route – indicates relatively high confidence, but should definitely have a much larger radius.

Figure 4. Spare and noisy location data for an intermodal journey including a subway



Note: Black = spare and noisy location data; Red = intermodal journey including a subway.

Source: Austrian Institute of Technology.

Performing map matching with such sparse and noisy location data, and possibly wrongly estimated uncertainties as in Figure 4 is particularly challenging. Typical map matching techniques for sparse and noisy locations have probabilistic nature, meaning that they identify the most likely route through the transportation network given the measured locations (Newson and Krumm, 2009). While probabilistic approaches are straightforward in formulation, the major bottleneck here is the complexity in terms of computation time and memory requirements of the algorithm, which is prone to be prohibitively high.

Map matching of smartphone locations requires data from the transportation network where travel mode inference is applied: public transport network data such as GTFS must be available and integrated into the algorithms. Publicly available map data such as OpenStreetMap require pre-processing, and the map data may be incomplete or obsolete. An elegant solution to avoid such problems of managing transportation data is to include information from a routing engine such as Google or HERE: travel mode inference is performed on short instances of one second, for example, and the information of these instant models is matched with a set of routes obtained from the routing engine to identify the most likely journey. One must keep in mind, however, that routing engines provide dynamic real-time information: whenever datasets are analysed which were recorded in the past (e.g. for evaluation or benchmarking purposes), the routing engine might avoid routes due to changed conditions (e.g. closed subway lines due to construction works).

Passive travel mode inference in mobile phone networks

Every mobile device connecting to the mobile phone network (GSM, GPRS, UMTS or LTE) generates digital traces in the network of the mobile network operator (MNO). The analysis of such signals between mobile phones and antennas (also known as cell towers) contains valuable information that can reveal which trips people make. The analysis of these signals is passive in the sense that no particular app is required on a person's smartphone. All mobile devices with a SIM-card produce this signal, which does not limit the analysis to smartphones alone. In this way, one can also track older and simpler mobile devices or senior-friendly mobile phone models. MNO datasets in a telecommunication network include, among other items:

- a mobile device pseudonym, which usually changes every 24 hours,
- the current antenna identifier,
- a timestamp,
- the event type such as mobile phone use (call, SMS, data) or location area updates.

The role of mobile phones as a proxy for human movement and the vast amount of data generated by such devices provide much potential to analyse mobility. Mobile phone data were already used to compute origin-destination matrices and traffic volumes, identify traffic incidents and characterise land use. MNOs are integrating such mobile phone data analysis algorithms into their own big data landscapes, to offer value for new markets such as public transport, retail and other domains.

With the beginning of the COVID-19 crisis, MNO data analysis was an important data source for quantifying the relative importance of mobility in the early stages of the virus outbreak in different European countries (Iacus et al. (2020a) and measuring the impact of COVID-19 confinement measures on human mobility (Santamaria et al., 2020). Iacus et al. (2020b) describe the techniques for mapping mobility functional areas using mobile positioning data to inform COVID-19 policies.

Large scale studies such as the COVID-19 studies above rely on a set of mobility indicators derived from origin-destination matrices, but do not include analysis of travel modes of a population. Some commercial providers also promote travel mode inference in MNO data, and scientific work started to include travel mode inference, e.g. Bonnetain et al. (2019).

It is important to keep realistic expectations about which travel mode information can be extracted from such mobile phone signalling data. The major challenge was already introduced above describing the principle of active travel mode inference with smartphones (Figure 4): travel mode inference requires that the traces in a telecommunication network be matched to a transportation network (public transport line, road segments). The traces of communication signals in a mobile phone network are sparse and noisy with respect to the transportation network:

- Low spatial resolution: the left part of Figure 5 notionally illustrates a rail track with different segments (r_0, r_1, r_2) and a street network with different segments (s_0, … s_3). The green bubbles indicate positions of a moving mobile phone at times t_0 to t_{10} estimated from MNO data; the bubble radius represents the uncertainty of the location estimation. Map matching for travel mode inference must assign the uncertain location estimates either to railway segments or road segments, which is obviously challenging.
- Low temporal resolution: a mobile device generates signals only when phone usage occurs or when mobility management events occur in the mobile telecommunication system. While the temporal resolution of phone usage events with older mobile phone devices used to be particularly low (only phone calls or text messages), data traffic on smartphones has improved temporal resolution. However, neither GPS nor sensor data are available due to the passive nature of data analysis.

The low spatial and temporal location resolution together with their uncertainties implies that passive travel mode inference will only be successful in extended areas, and for a limited set of travel modes, for example public transport vs. motorised traffic. It will be, for example, very hard to distinguish between cycling and car traffic at the inner city block level, despite a higher density of antenna compared to rural areas. Dedicated indoor antenna deployed at public transport transit stations can provide additional clues.

Figure 5. Sparse and noisy mobile phone location data: Concept and real-world example

Source: Austrian Institute of Technology

The right part of Figure 5 shows a real-world example of a long car journey (in green) inferred from the sparse and noisy locations with probabilistic map matching: matching the sparse and noisy locations to the roads produced a higher likelihood than matching the locations to the public transport network. The major bottleneck is the computational complexity of the search algorithm finding the most plausible route. Complexity is even more crucial than in active travel inference techniques since the sample size is larger by orders of magnitudes compared to data collected during active smartphone-based travel surveys.

Issues with travel mode inference from mobile phone data

Active and passive travel mode inference techniques must solve difficult algorithmic tasks as described above. This section addresses some important challenges when applying such techniques for sampling the modal split of an entire population, with the aim to use the information for subsequent transportation modelling tasks.

Data quality

The reported accuracies for smartphone-based travel mode inference technique are rarely below 90%, either described as experimental results in scientific publications or in commercial folders. Developers of solutions usually collect their own reference data, and most studies are not specific about their evaluation procedure. Consequently, the meaning of reported performance indicators is often unclear, and it is virtually impossible to compare and rank different solutions based on the reported quality indicators. Only when a solution is applied to unseen data in the field, the true accuracy is revealed, which is often still disappointing. This section sheds some light on the evaluation of the data quality generated by travel mode inference solutions.

Quality indicators for travel mode inference

Quantifying the accuracy of a travel mode inference technique requires an evaluation dataset to compare the travel mode computed by the classification algorithm with the correct travel mode. Evaluation datasets are composed of pairs of input sensor data together with the correct travel mode which produced the input data of the journey. The quality indicators accuracy, precision, recall and F1-score are often used to compare actual 'true' instances of travel mode with classified instances, and can be described as follows:

- accuracy: rate of correctly classified instances vs. total number of instances
- precision of travel mode class *M*: rate of correctly classified instances of class *M* vs. total number of instances classified as class *M*.
- recall of travel mode class *M*: rate of correctly classified instances of class M vs. total number of actual instances of class *M.*
- F1-score of travel mode class *M*: combination of precision and recall to express recognition performance in a single figure.

The abstract term 'instance' in the definitions above can be specified, for example, as a duration of 60 seconds. Alternatively, an instance may also represent a distance, for example of 100 metres. Obviously, the values for the quality indicators above will change with the specification of the instance.

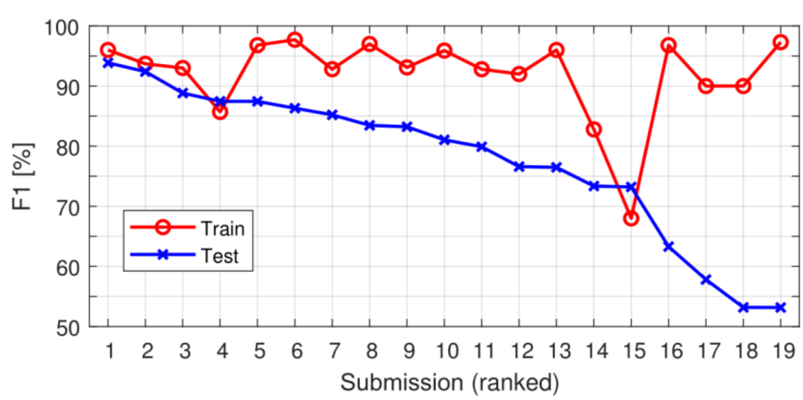
In general, tuning a classification algorithm to high precision such that it will report a travel mode *M* only when the confidence is high, tends to lead to a low recall, thus many relevant instances with *M* are overlooked and wrongly classified. Conversely, striving to achieve high recall – all instances with travel *M* should be recognised – can lead to low precision due to many wrong classifications. Both indicators are therefore relevant.

An alternative quality indicator is the Full Trip Correctness (FTC), which regards trips as correctly identified only when all stages of the intermodal trip are correctly identified. A trip stage is regarded as correctly identified only when its travel mode is correctly identified, and the start and end of the trip stage deviate no more than 60 seconds and no more than 200 metres, for example. If one trip stage is wrongly identified, the entire trip will be regarded as wrongly identified. This FTC metric is considerably stricter than the definitions above, and will thus yield lower quality indicators. However, compared to metrics based on trip stages, the FTC metric is more intuitive and more relevant for practical application such as autonomous public transport ticketing.

Overfitting and spurious correlations

Travel mode inference algorithms are trained with reference datasets in a machine learning phase. The travel mode inference learned from the available reference data should later produce accurate results when confronted with previously unseen data. Overfitting to the available data means that computed quality indicators such as F1-score are high only for the available data, but possibly much lower for new data. Data scientists, therefore, split the available reference data into a training dataset and a test dataset. Travel mode inference is then trained on the training dataset only, and the relevant quality indicators for travel mode inference are computed on the test dataset. This splitting of the reference dataset and subsequent training is usually repeated with different splits into training set and test set in order to improve the predictive quality.

Figure 6. Accuracy of 19 travel mode inference solutions, on training data vs. test data



Source: Results of the Sussex-Huawei Locomotion Challenge 2018 (Wang et al., 2018).

An illustrative example of overfitting risk in the field of active travel mode inference is the results of the Sussex-Huawei Locomotion (SHL) Challenge (Wang et al., 2018). This international initiative to make travel mode identification performance comparable provides annotated reference datasets for eight travel modes (still, walk, run, bike, car, bus, train, and subway). Three persons carried four smartphones simultaneously at four body positions while collecting intermodal trip reference data: in the hand, at the torso, in the hip pocket, in a backpack or handbag. The SHL challenge invites competitors to submit a solution for travel mode inference for a released training dataset. The organisers of the 2018 SHL challenge released a training dataset of one person, with data split into non-overlapping 60-second segments. In addition, a test dataset was provided, however, with transportation labels kept confidential until after the challenge.

Figure 6 shows the results of the 19 submissions to the 2018 challenge, ranked by the F1-score on the test dataset (blue line). The red line in Figure 6 represents F1-scores of the training dataset. What is striking is that only five submissions had a reasonably low gap between the performance on the training data and test data. The worst-performing solutions achieve only 55% – 65% accuracy on the test set, despite an accuracy of at least 90% on the training set. Roughly speaking, many approaches did not randomly shuffle the consecutive 60-second segments before training and therefore learned the spurious correlations between data of consecutive 60-second segments (Widhalm, Leodolter and Brändle, 2019). Even very sophisticated and popular approaches such as deep learning caused biased performance figures when the temporal order of the 60-second segments was not removed before training.

Lack of comprehensive reference datasets

The overfitting problem with travel mode inference techniques showed in Figure 6 was observed on data collected by a single person carrying the smartphone in the hip pocket. The entire SHL dataset – other parts of which were released for the 2019 and 2020 challenges – comprises simultaneous recordings of four smartphone carrying positions, but recorded only from three persons (Wang et al., 2018). There are certainly large differences in the way people walk and drive, and mode inference techniques should not learn the style of a particular person or person group.

Ideally, the reference data should comprise an unbiased sample covering all travel modes and the influence factors listed in Table 1. In practice, it is very difficult to cover the wide variety of these factors and to avoid spurious correlations between these factors. Evaluation will therefore strongly depend on the characteristics of the data. In addition, if training data and test data are subsets of the same data collection initiative, they often share the same spurious correlations. As a consequence, overfitting cannot be revealed. This lack of reference data is in stark contrast to other domains such as natural language or visual object recognition, where (deep) learning algorithms are trained on millions and billions of instances.

Concerning passive travel mode inference in mobile phone networks, there currently exists no publicly available reference datasets. Active travel mode inference using smartphone apps can help collect intermodal trip data and associate with the network traces of the phone.

Representativeness

The representativeness of the sample data is critical to a successful survey, especially for large-scale model-building applications and operational planning analysis. Recent years saw a steady decline in response rates: Miller, Srikukenthiran and Chung, B. (2018) provide figures for Toronto region's Transportation Tomorrow Survey, for which the response rate declined from 73.3% in 1986 to 16.3% in 2016. With a low response rate there is a risk that the results are biased. People who respond and people who do not may have different travel behaviour.

Smartphone-based travel surveys that automatically collect intermodal trip data are not free of burden for the respondent who must install a mobile application and interact with the travel diary via the smartphone application or a web interface (see Figure 1 and Figure 2). In addition, information about the trip purposes is often required but rarely automated. Ferreira et al. (2018) compared the performance of trip validation interfaces in three smartphone-based survey solutions. Mere ownership of a smartphone does not necessarily mean that, for example, a senior will run other mobile applications apart from phone calls, text messages and camera, and thus not install and run a travel survey app. On the other hand, Prelipcean and Yamamoto (2018) argue that also traditional survey instruments such as pen and paper do not capture the behaviour of individuals who cannot use the means adequately to declare their travel (e.g. individuals suffering from dyslexia, visual impairment). Prelipcean and Yamamoto (2018) therefore argue that the meaning of a representative sample should be redefined.

Since smartphone-based travel inference solutions currently do not allow representative surveys in the traditional sense, Miller, Srikukenthiran, and Chung (2018) advocate a “core-satellite” design, combining traditional surveys with smartphone-based survey apps for capturing the respondent’s trips over a multi-day time period. The core-satellite paradigm proposes a large-sample, relatively low-burden survey, which might be a conventional travel survey, and several smaller, more detailed, special-purpose satellite surveys designed to target specific sub-populations and/or behaviours, for example, bicycle usage, car ownership usage, or e-scooters.

Apart from dedicated travel surveys, intermodal trip data can be also collected with other mobile smartphone applications which have built-in a module for travel mode inference, for example, such as journey planners or MaaS. The real-time samples of traffic indicators from smartphones such as travel times for cars are a good example. Of course, only reasonably large penetration rates will provide good estimates, and informed consent of the users is key meet privacy regulations.

Passive data collection in mobile phone networks provides huge trip samples of the mobile phone subscribers. A solid analysis must account for varying trip detection rates between geographical regions, e.g. due to varying market share of the mobile operators across different regions or districts. A straightforward and simple technique for extrapolation is to link home locations to socio-demographic data of the corresponding census tract and to weight the shares accordingly. To this end, the mobile phone subscriber’s home location should be used. The billing address of the personal contact data could be anonymised by aggregation to the district level. However, the billing address need not be identical to the home address (e.g. phones provided by the company). The home location should therefore be identified from the NMO data. Arrival time and stay duration provide hints for home location, but mobile device pseudonym changes every 24 hours. In any case, personal data must be strictly kept on the servers hosted by the telecommunications provider and not released to third parties.

Privacy and data protection

Traditional travel diaries do not contain information regarding the actual route, waiting times, or any detailed trip leg information for travellers. In contrast, travel mode inference with mobile phones generates an abundance of data available for analysis. A legal framework dedicated to personal data protection is the General Data Protection Regulation (GDPR) which applies to all European Union residents (EU GDPR, 2016). Compliance of an application with the GDPR requires, for example, data minimisation (an application must collect only necessary personal data), purpose limitation (the purpose of personal data collection must be clear and limited) and transparency to the end user.

Active travel mode inference with smartphones

The GDPR protects people from being tracked without their knowledge. Therefore, the installation of mobile applications collecting and transmitting location data of people is only possible with the informed consent of the user. Large technology companies impose compliance rules for application developers to obtain spatial-temporal location data with the highest possible accuracy. Google, for example, defines "stalkerware" as "code that transmits personal information off the device without adequate notice or consent and doesn't display a persistent notification that this is happening." and defines a set of compliance rules for applications developers distributing mobile applications on the app store (Google, 2020b). It appears that access to fine-grained location data is getting increasingly difficult, which is in favour of the end users, but restricts options for smartphone application developers including travel mode identification into their applications.

Solutions for smartphone-based travel mode data collection usually adopt the concept of pseudonymisation, where all information that is directly linked to a person's identity (name, address, etc.) is replaced with an artificial identifier. Such data collection solutions, therefore, do not store personal contact data which would enable assignment of travel behaviour to people. This separation of contact data and location data is useful for smartphone-based travel surveys, where the personal contact data remain at the survey organiser. The survey organisers assign each respondent a unique identifier for the survey duration, and all data collected by the smartphone-based travel survey solution are pseudonymised.

Fiore et al. (2020) point out that pseudonymisation only provides a mild level of data protection, and describe the risks that persons can be re-identified in location tracking data. Pseudonymised fine-grained location data representing daily routines of respondents must therefore be regarded as personal data. Hence data owners providing access of such datasets of to third parties do not act in compliance with the GDPR. As in traditional travel surveys, travel data collected with smartphone-based active travel mode inference systems must be aggregated to a level that preserves privacy before being published. The aggregation level must make it impossible for people to re-identify survey respondents. The privacy problem with pseudonymised location tracking data might be a reason why there is currently a lack of comprehensive reference datasets for the development and evaluation of active travel mode identification.

Passive travel mode inference in mobile phone networks

MNO data are also pseudonymised before analysis, and the artificial identifier is regularly switched, for example, every 24 hours. Consequently, no detailed profiles can be created over multiple days, identifying frequently visited locations. Authorities in Europe therefore usually consider this regular switching of identifiers together with the limited spatial accuracy of localisation as GDPR compliant.

Nevertheless, analysing MNO data often raises privacy concerns despite regular pseudonymisation. The seminal work of de Montoye et al. (2013) demonstrated that knowledge of few random points in the spatiotemporal location tracking data of a user allows pinning him down almost certainly, even within a very large population. An attacker having observed the whereabouts of a target individual at two random moments (whose corresponding spatiotemporal points are present in the target database) during a whole year has a 50% probability of recognising his target in a dataset of millions. The percentage grows to 95% if as little as four random points are known to the attacker. Yet in practice, Fiore et al. (2020) argue that such an attack on an MNO dataset is very unlikely to happen in real life, as the adversary would have to anticipate when the user's location will be sampled by the positioning system.

Due to privacy concerns and legal privacy regulations, telecommunication providers often provide only aggregated MNO data to third parties to perform mobility studies and research. Such aggregated data do not contain traces of device signals, but only MNO data summarised in, for example, 15-minutes intervals and in a geographical region (usually a regular grid). Balzotti et al. (2018) introduce a technique to estimate flows from aggregated mobile phone data, and provide visual examples for assignments of flow data to roads, thus performing travel mode identification. As often with mobile phone data, no thorough evaluation is provided.

Policy recommendations

A number of policy recommendations in the general context of big data already exist, for example, the European strategy on data (European Commission, 2020), or the policy recommendations for big data in transport worked out in the LeMo project (Sangwan et al., 2020). These policy recommendations address data availability, imbalances in market power, data interoperability and quality, data governance, data infrastructures and technologies, empowering individuals to exercise their rights, skills and data literacy, and cybersecurity. Many of the already formulated policy recommendations for big data are certainly relevant to the new data source for travel modes inference from mobile phones. This section suggests topic-specific policy recommendations directly resulting from the issues described in this paper. The policy recommendations for travel mode inference from mobile phones concern the enabling of reproducible research and development in the spirit of Wang et al. (2019) with large datasets.

1. **Fostering the collection of comprehensive reference datasets:** there is currently a lack of comprehensive manually labelled reference datasets covering unbiased samples of multimodal transport. As shown in this paper, this lack of proper reference data may lead to biased (too optimistic) quality indicators and makes it impossible to compare and benchmark the accuracy of mobile phone-based travel mode inference techniques. Data collection campaigns should be dedicated to producing comprehensive sensor datasets together with manually labelled travel mode information. Reference data should cover all relevant travel modes, combinations of travel modes, vehicle types, device positions, device interaction, etc. (see Table 1). In order to avoid spurious correlations, coverage of all relevant transport modes and variations of other influencing factors should be controlled by data collection "scripts", instead of collecting huge amounts of data during the daily routine of volunteers. Such a scripted data collection should exclude home locations and work locations of the volunteers, such that not re-identification can be performed on the pseudonymised data.
2. **Companies** (such as *Apple* and *Google*) **developing smartphone operating systems and controlling the smartphone app marketplace must keep granting access to fine-grained smartphone location data:** the major players make it increasingly difficult for third parties to collect fine-grained location data, with the aim of protecting end users from being spied on without their consent. However, the trend towards more access restrictions should not lead to big tech players being the only stakeholders with access fine-grained location data. End users should always have the possibility to opt-in for being tracked for the purposes of trip detection and travel mode inference via third party mobile applications such as travel surveys, autonomous ticketing, incentive and gamification apps.
3. **Enabling the implementation of reference data exchange frameworks**: this includes a collection of best practices and guidelines, including specifications for data labelling and common data formats for intermodal trip data as well as tools and documentation to use them, a common open-access platform safeguarding ethical usage of test data in a transparent manner to improve cooperation across projects and stakeholders.

The list of policy recommendations can be complemented by recommendations already compiled during the International Conference of Travel Survey Methods (Miller, Srikukenthiran and Chung, 2018).

4. "Smartphone application developers need to be made much more aware of the travel survey applications of their applications, so as to ensure the usability of the data that is collected by these applications for travel analysis and modelling purposes."
5. "Transportation agencies need to improve their understanding of the technical issues and trade-offs concerning survey sample size, frequency and regularity. In particular, in many urban regions more frequent, regularly-spaced (and, often, larger-sample) surveys are needed."

References

Apple (2020), "Core Location – Obtain the geographic location and orientation of a device", https://developer.apple.com/documentation/corelocation (accessed on 05 November 2020).

Balzotti, C. et al. (2018), "Understanding Human Mobility Flows from Aggregated Mobile Phone Data", *15th IFAC Symposium on Control in Transportation Systems CTS 2018,* https://www.researchgate.net/publication/323550345_Understanding_Human_Mobility_Flows_from_Aggregated_Mobile_Phone_Data.

Bonnetain, L. et al. (2019), "Can we map-match individual cellular network signaling trajectories in urban environments?", *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2673, pp 74-88, https://doi.org/10.1177/0361198119847472.

de Montoye et al. (2013), "Unique in the crowd: The privacy bounds of human mobility", *Scientific Reports*, Vol.3, https://doi.org/10.1038/srep01376.

European Commission (2020), "A European strategy for data", https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age/european-data-strategy_en.

EU GDPR (2016), "Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)", *Official Journal of the European Union*, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679 (accessed on 18 November 2020).

EU Survey LeMo Project (2020), "Factors influencing the uptake of big data in the transport sector", *Survey of the H2020 Project Leveraging Big Data in Transport Operations (LeMO)* https://ec.europa.eu/eusurvey/pdf/survey/277186?lang=EN&unique=7487afe2-7b48-4ae5-997a-23974a8e0f55 (accessed on 05 November 2020).

Ferreira, A. et al. (2018), "Assessment of trip validation interfaces for smartphone-based travel surveys", *Transport Research Procedia,* Vol. 32, pp. 126-134, https://doi.org/10.1016/j.trpro.2018.10.025.

Fiore, M. et al. (2020), "Privacy of trajectory micro-data publishing: A survey", *arXiv:1903.12211*, https://arxiv.org/abs/1903.12211 (accessed on 05 November 2020).

Google (2020a), "Simple, battery-efficient location API for Android", https://developers.google.com/location-context/fused-location-provider (accessed on 05 November 2020).

Google (2020b), "Stalkerware – effective 1 October 2020", *Developer Programme Policy: 16 September 2020 announcement*, https://support.google.com/googleplay/android-developer/answer/10065487 (accessed on 05 November 2020).

Hong, M. et al. (2020), "Report on the characterization of the barriers and limitations", *Deliverable 4.1 of H2020 Project Leveraging Big Data in Transport Operations (LeMO),* https://lemo-h2020.eu (accessed on 05 November 2020).

Iacus, S. et al. (2020a), "How human mobility explains the initial spread of COVID-19", *Publications Office of the European Union*, Luxembourg, EUR 30292 EN, RC121300, https://doi.org/10.2760/61847.

Iacus, S. et al. (2020b), “Mapping Mobility Functional Areas (MFA) using Mobile Positioning Data to Inform COVID-19 Policies”, *Publications Office of the European Union*, Luxembourg, EUR 30291 EN, JRC121299, https://doi.org/10.2760/076318.

Kagerbauer, M. et al. (2015), “Household travel survey of intermodal trips – Approach, challenges and comparison”, *Transport Research Procedia*, Vol. 11, https://doi.org/10.1016/j.trpro.2015.12.009.

Kultur-Token (2020), “Vienna introduces Kultur-Token pilot project”, www.themayor.eu/en/a/view/vienna-introduces-kultur-token-pilot-project-4369 (accessed on 05 November 2020).

Miller, E.J., S. Srikukenthiran and B. Chung (2018) “Workshop synthesis: Household travel surveys in an era of evolving data needs for passenger travel demand”, *Transport Research Procedia*, Vol. 32, pp. 374-382, https://doi.org/10.1016/j.trpro.2018.10.067.

Newson, P. and J. Krumm (2009), “Hidden Markov Map Matching Through Noise and Sparseness”, in *Proceedings 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL GIS 2009),* www.microsoft.com/en-us/research/publication/hidden-markov-map-matching-noise-sparseness/ (accessed on 05 November 2020).

Prelipcean, A.C., Y.O. Susilo and G. Gidófalvi (2018), “Collecting travel diaries: Current state of the art, best practices, and future research directions”, *Transport Research Procedia*, Vol. 32, pp. 155-166, https://doi.org/10.1016/j.trpro.2018.10.029.

Prelipcean, A.C. and T. Yamamoto (2018), “Workshop synthesis: New developments in travel diary collection systems based on smartphones and GPS receivers”, *Transport Research Procedia*, Vol. 32, pp. 119-125, https://doi.org/10.1016/j.trpro.2018.10.023.

Sangwan, J. et al. (2020), “Roadmap-Research and Policy Recommendations for the Efficient Utilisation of Big Data in the Transport Field (Version 1)”, *Deliverable 4.3 of H2020 Project Leveraging Big Data in Transport Operations (LeMO),* https://lemo-h2020.eu (accessed on 05 November 2020).

Santamaria, C. et al. (2020), “Measuring the Impact of COVID-19 Confinement Measures on Human Mobility using Mobile Positioning Data”, EUR 30290 EN, *Publications Office of the European Union,* Luxembourg, JRC121298, https://doi.org/10.2760/913067.

Wang L. et al. (2019), “Enabling Reproducible Research in Sensor-Based Transportation Mode Recognition with the Sussex-Huawei Dataset”, *IEEE Access,* Vol.7, pp. 10870 – 10891, https://doi.org/10.1109/ACCESS.2019.2890793.

Wang L. et al. (2018), “Summary of the Sussex-Huawei Locomotion-Transportation Recognition Challenge”, in *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, pp. 1521-1530, https://doi.org/10.1145/3267305.3267519.

Wang, Z., S.Y. He and Y. Leung (2018), “Applying mobile phone data to travel behaviour research: A literature review”, *Travel Behaviour and Society*, Vol. 11, pp. 141-155, https://doi.org/10.1016/j.tbs.2017.02.005.

Widhalm, P., M. Leodolter and N. Brändle (2019), "Into the Wild – Avoiding Pitfalls in the Evaluation of Travel Activity Classifiers", *Human Activity Sensing. Corpus and Applications*, Springer, Cham, pp. 197-211, https://doi.org/10.1007/978-3-030-13001-5_13.

Inferring Modal Split from Mobile Phones

This paper describes methods to identify trip details, including the mode of transport for each trip, from smartphone app data and from mobile network data. Use cases include travel demand surveys, travel behaviour gamification, mobility-as-a-service and automated ticketing. In the context of transport planning, the paper examines solutions to protect privacy and to enhance the representativeness of mobile phone data samples. It makes recommendations to overcome the many obstacles involved, in particular the scarcity of annotated training data.

All resources from the Roundtable on Use of Big Data in Transport Models are available at:
www.itf-oecd.org/big-data-transport-models-roundtable

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