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# **Estimating Long-Distance Travel Demand with Mobile Phone Billing Data**

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### Abstract

Analysis of long-distance travel demand has become more relevant in recent times. The reason is the growing share of traffic induced by journeys related to remote activities, which are not part of daily life. In today's mobile world, these journeys are responsible for almost 50 percent of the overall traffic. Traditionally, surveys have been used to gather data needed for the analysis of travel demand. Due to the high response burden and memory issues, respondents are known to underreport the number of journeys. The question of the real number of long-distance journeys remains unanswered without additional data sources. This paper shows how an alternative data source, mobile phone billing data, can be used to estimate long-distance travel demand. We take a sample of mobile phone billing data covering 5 months, reconstructed long-distance tours and imputed purposes. The latter was done based on a national travel survey

### Keywords

long-distance travel demand; mobile phone data; CDR; random forests

# 1 Introduction

Analysis of long-distance travel behavior has become more important in recent years since the contribution of long-distance journeys to the overall traffic is growing continuously. Therefore, its influence on planners of urban areas, highways, railroads etc. is becoming greater. Long-distance travel is usually defined by trips, which take place outside of a persons environment. In order to develop tools, which are able to provide reliable predictions, one needs data sources describing the current state of long-distance travel demand.

Data collection methods in the field of travel demand research were investigated in the past (Axhausen et al., 2002a; Armoogum and Madre, 2002). The most frequently used data sources are surveys. In case of long-distance travel the number of these is limited (the main sources are national travel surveys). However, all long-distance travel surveys are facing similar problems. On the one hand, due to the high response burden these surveys have a low number of respondents. On the other hand, it is known that number of journeys reported in surveys is too low (Madre et al., 2007; Armoogum and Madre, 2002). Both facts limit the explanatory power of studies and leave the question for the quality of the results unanswered (Kuhnimhof and Last, 2009).

To overcome these limitations alternative data sources are needed. We propose in this paper to use mobile phone billing data, so called Call Detail Records (CDRs), in order to get better estimates of long-distance travel demand. The advantage is the large number of people that can be tracked without spending a lot of effort in a survey. We analyzed 5 months of mobile phone billing data covering one third of the total French population. The data was provided by the Orange<sup>TM</sup> Labs. After reconstructing long-distance journeys from the data we used the random forest approach to impute a purpose for all long-distance tours found.

The paper is structured as follows. After a literature review we describe in detail the mobile phone data made available for our studies as well as the National Travel Survey used in this paper. In section four the tour reconstruction methodology is described. Afterwards, we present the purpose imputation algorithm. We conclude this paper with some results, a discussion and a conclusion.

In order to prevent misunderstanding take a note of the definitions, which are used in the remainder of the paper.

**Definitions:**

- User Environment: The area within a radius of 80km around the home location.
- (Home Based) Tour: A chain of activities and trips starting and ending at the home location (sometimes referred to as journey).
- Long-Distance Tour: A tour, which leaves the user environment.

## 2 Relevant Literature

Data collection has always been an important issue in the field of travel demand research. Different methods of data collection were investigated in the past (Axhausen et al., 2002a; Armoogum and Madre, 2002). The data sources mostly used are surveys, which have various forms (Dillman, 2000) to suit the diverse requirements of the researchers.

In case of long-distance travel the number of surveys is limited. Focusing on Europe, the *Mobidrive* studies are available (Zimmermann et al., 2001; Axhausen et al., 2002b; Chalasani and Axhausen, 2004). These studies focus on a six-week period, which is usually not sufficient for a deep analysis of long-distance travel behavior. Other sources are national travel surveys like the French (Armoogum et al., 2008), British (Department for Transport, 2016) or the Austrian (BMVI, 2012).

Due to the high response burden that is usually associated with long-distance surveys (Axhausen et al., 2015; Axhausen and Weis, 2010), it can be expected that the number of long-distance trips is usually underreported. The reasons are not responding frequent travellers as well as travellers claiming not to travel, while answering other questions, so called soft-refusers (Madre et al., 2007). Furthermore, there is a memory effect. Respondents tend to forget tours, which happened some time before the survey (Smith and Wood, 1977; Bradburn et al., 1987; Tourangeau, 1999). Additionally, the vehicle miles travelled are usually heavily underestimated as shown by Wolf et al. (2003).

Consequently, there is a need of alternative data sources. Nowadays, there are mainly two alternative sources available for the analysis of travel demand. Both use passive data collection. On the one hand, GPS data can be used to collect information about travel behavior (Montini et al., 2014). But the collection of GPS data is limited since the cooperation of the respondent is needed and smartphone GPS collection is battery consuming discouraging participation. On the other hand, GSM network operators produce mobile phone billing data that provides an enormous amount of data and has been already utilized in the field of transportation. One of the first applications was the analysis of travel demand induced by tourism (Ahas et al., 2008a,

2007). GSM data has been also used to estimate OD matrices (Friedrich et al., 2010; Pan et al., 2006). Altogether, GSM data is a very powerful tool for predictions of human mobility (Song et al., 2010). We will show in this paper that it is as well very useful for the analysis of long-distance travel demand.

Several studies have been carried out on data quality comparisons. These studies compared, for instance, CDR data with GPS trajectories (Iovan et al., 2013; Hoteit et al., 2014; Smoreda et al., 2013) as well as on the sociological aspects of using mobile phones like, for instance, in analysis of places relevant in transport science (Licoppe et al., 2008), concluding that CDR data forms a good proxy for overall tendencies of human mobility thanks amongst others to the large samples of persons and days involved.

## 3 Data Sources

### 3.1 Mobile Phone Billing Data

The study described in this paper is based on an anonymised CDR data set recorded by Orange<sup>TM</sup>France. It consists of CDR covering mobile phone usage of around 23 million users of the Orange<sup>TM</sup>network in France during a period of 154 consecutive days (May 13, 2007 to October 14, 2007). Given a population estimate of 63.945 million inhabitants in 2007<sup>1</sup>, that is roughly 35.9% of the French population. The numbers concord with estimates made at Orange<sup>TM</sup> about mobile phone penetration in France anno 2007: 86% (ARE, 2016) and with the supposed market share of Orange<sup>TM</sup> in that year: 43.5%.

Each CDR contains information about the action (outgoing/terminating call or sms) which took place in the network. The information needed for our purpose is the caller id, the time and duration of the action, and the antenna, which was the connection point of the mobile phone at the start of the action. In turn, the location of each antenna is known. Given location and time information for each action, a user can be traced and thus his or her movements can also be extracted. The accuracy of the movement reconstruction is dependent on the frequency of actions.

The data set has several limitations. Firstly, the action frequency is comparably low, because mobile data usage was not as intense in 2007 as it is today. Secondly, the data set does not cover a full year. Thus, any estimates for the missing time periods have to be supported with

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<sup>1</sup>This is the average of the monthly estimates for the period between Mai and October 2007 as obtained from the French National Statistics Website ([www.insee.fr](http://www.insee.fr))

complementary data sets. In addition to the temporal inaccuracy due to the low call frequency, there is also spatial inaccuracy. In case of CDR data, the spatial information is limited to the position of the mobile network antennas. For less densely populated areas of the country, the antenna can be several kilometers away from the actual position of the mobile phone. Finally, no information about phone calls made abroad is available in this data set. Even though it is known that France has one of the highest ratios of domestic trips to trips abroad within Europe (OECD, 2012; Eurostat, 2016) this circumstance limits the range for which we can make valid estimates. We will account for this limitation with respect to the special situation of a large central European nation in the validation section below.

It has been shown that mobile phone billing data should be used with caution when analyzing mobility (Ranjan et al., 2012). Nevertheless, most limitations do not have a substantial impact when focusing on long-distance travel demand. The spatial and temporal inaccuracies described above become relatively small since we are working on large spatial and temporal scales. Still, mobile phone data can provide a lower bound to the real value. When comparing with survey data, we have to account for the missing roaming data and focus on national travel, though.

We selected 62'819 customers, who left their user environment at least once and hence did at least one long-distance tour. The selection process is described in detail in Janzen and Vanhoof (2015). The selected persons lived in cities with at least 20'000 inhabitants and all big cities are covered by the selection. All CDRs for the selected persons were available for the 5 month period specified above. We describe in section 4 how CDR data can be used to identify long-distance tours.

### 3.2 Survey Data

CDR data as described above does not provide any information about travel purposes. Thus, we need an additional data source as training set for a purpose classification algorithm. We used the **Enquête Nationale Transports et Déplacements (ENTD)**, the French National Travel Survey. The ENTD is conducted every 10-15 years (1967, 1974, 1982, 1994, 2007-08). Various actors are involved in the ENTD, including the Ministry of Transport, the INSEE (French National Institute of Statistics and Economic Studies) and Ifsttar (French institute of science and technology of transport, planing and infrastructures). The last ENTD was performed from April 2007 to April 2008 (6 waves) and most parts are publicly available (IFSTTAR, 2016). Since the survey includes the time period covered by the CDR data described above we use the ENTD 2008. One of the goals of this survey was the analysis of long-distance mobility. This fact is advantageous, because it ensures that we can compare the two data sources in terms of long-distance travel behaviour.

Nevertheless, the sample size of the ENTID 2008 is much smaller than the available CDR data. In total, 20'178 households and 44'958 individuals were surveyed. Just 18'632 (representative) persons were chosen for the long-distance travel module of the survey (Armoogum et al., 2008). The latter were asked to report their long-distance travel practices within the preceding 4 weeks.. In the ENTID 2008 a long-distance journey is either a journey with the furthest destination being more than 80km away from home (crow-fly distance) or a journey, which includes at least one overnight stay (or both). We will account for the differences of the data sources in the comparisons (section 6).

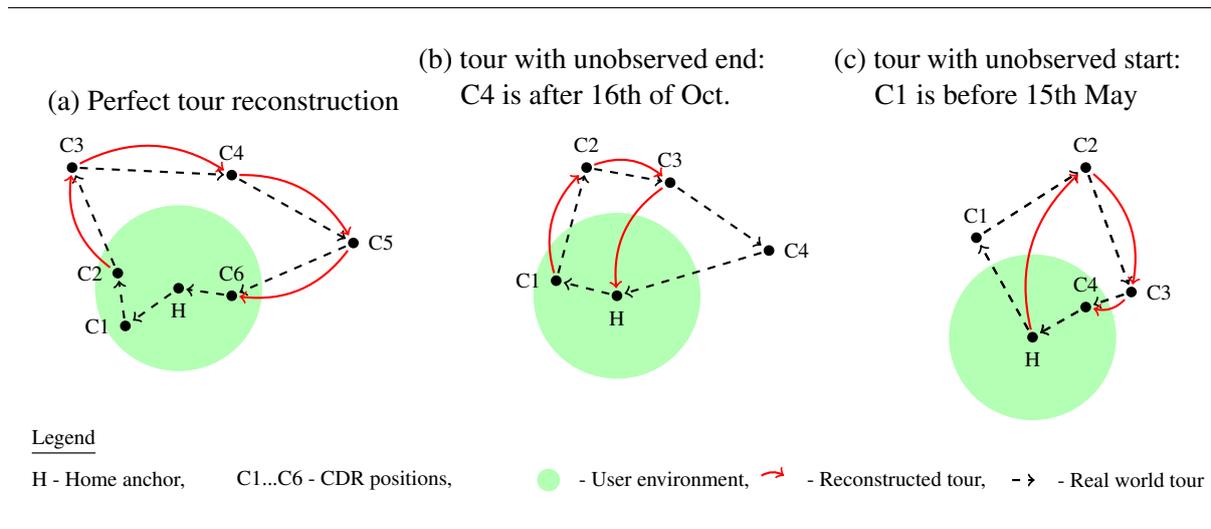
## 4 Reconstruction of Long-Distance Tours from CDR Data

Unlike surveys, mobile phone data does not provide information about tours undertaken directly. The information available is a series of time-space points. In the following, the extraction of long-distance tours is described in detail. We assume that the home location is known for each user since there are algorithms to identify the home locations from CDR data (Ahas et al., 2008b, 2010)

Scanning the CDRs of the users we suppose that a long-distance tour starts every time a CDR with a location outside the user environment occurs following a CDR located within the user environment. The tour is assumed to end with the first CDR back in the user environment. A sketch of a single construction process can be found in figure 1 (a). The initial situation consists of the home anchor (H) and the user environment (green circle). Now, the locations of CDRs are identified by C1, C2,...C6, where their sequence is given by their numbers. The black dashed arrows show an potential path of the user, while the red arrows form the reconstructed tour. In the sketch of figure 1 (a) the constructed tour fits the initial real world tour quite well. This is not always the case. A problem is the boundary of the traced time period. The tours that are not finished before the end of the observed time period have to be truncated without any information of the further duration (figure 1 (b)). Likewise, the tours started before the recording time have to be truncated (figure 1 (c)).

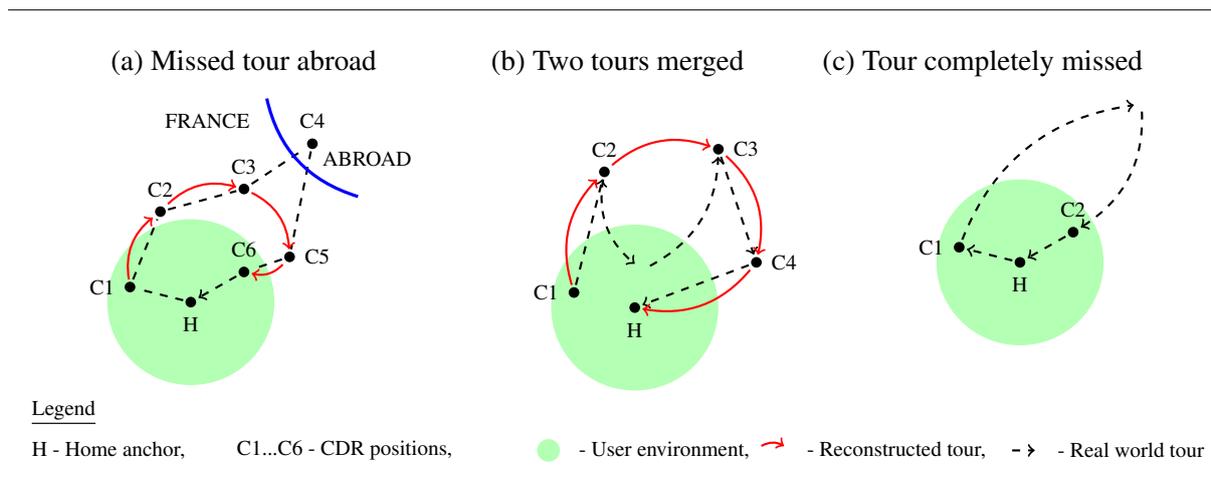
Moreover, the character of mobile phone billing data causes further limitations. Firstly, there is no information about the mobile phone usage outside of France. This lack of information induces wrong final destinations during the tour construction (figure 2(a)). Without any mobile phone activity between the user environment and the border even an around-the-world tour would be missed. Likely, this is the case for most of the international tours. Secondly, low-frequency mobile phone users might go on two distinct tours without any mobile phone activity within the user environment between the two tours. In this case the tour construction algorithm merges

Figure 1: Visualization of the tour reconstruction algorithm



the two tours due to a lack of a separation CDR (figure 2(b)). Thirdly, the worst case is a user without any CDR's that relate to his long-distance travelling. Without the CDRs indicating an exit of the user environment no tour can be reconstructed (figure 2(c)). This is the most critical and probably the most frequent case of a failed tour reconstruction. In addition, it is also possible to miss just some parts of the tour or the final destination. Note that all limitations lead to a lower number of tours in comparison to the real world. Therefore, we can assume that the number of national long-distance tours identified by the algorithm is a lower bound of the total.

Figure 2: Failed tour reconstructions



## 5 Tour Purpose Classification

There is a major limitation with the tours reconstructed from CDR data: Travel purposes are not part of the information provided. Though, travel purposes are necessary for a complete analysis of long-distance travel demand.

Thus, we have to find a technique to impute the travel purposes. The main idea is to use observed tour attributes to classify tours. We have to focus on tour attributes since socio-demographic attributes are not available (an exception is the city size of the home location). Useful tour attributes are, for example, tour distance or tour duration. A full list of used attributes can be found in table 1. All these attributes can be generated easily from the available data set.

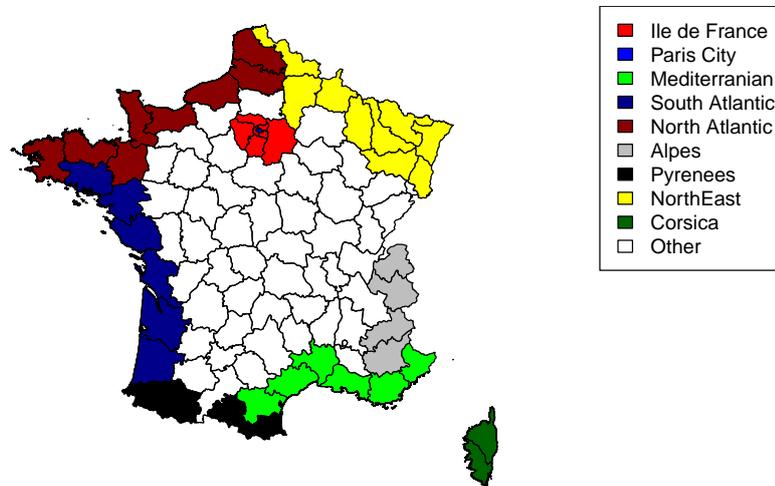
Table 1: Attributes Used for Purpose Classification

Name	Range	Description
Distance	80-1500 [km]	Distance between home location and furthest point on the tour
Duration	1-102[days]	Time between first and last CDR of the tour
Destination		see figure 3
WE-Share	0.0-100.0 [%]	Share of the tour duration that is weekend (or public holiday)
Deviation	Yes/No	Is tour distance close to average distance of that persons tours
Frequency	0.0-31.0	Average number of national long-distance tours per month
Residence	0-8	Size of the home city: rural(0), <5k(1), 5k-10k(2), 10k-20k(3), 20k-50k(4), 50k-100k(5), 100k-200k(6), 200k-800k(7), Paris(8)

There are diverse approaches to classify the purpose of the tours based on the given attributes. We used the random forest technique(Breiman, 2001), which belongs to the class of decision tree algorithms. These algorithms implement a set of rules learned by a machine and executed in a given order and were already used successfully (e.g. Griffin and Huang, 2005; Deng and Ji, 2010). There are two advantages of the random forest approach in comparison to the other decision tree methods. On the one hand, random forests do not over-fit even if more trees are added (Breiman, 2001). On the other hand, good results can be maintained even with missing data since they are estimated internally (Breiman and Cutler, 2013).

The functionality of random forests can be described as follows(Breiman and Cutler, 2013) . A random forests grows many classification trees. To classify a new object (in our case: classify the purpose) from a vector of attributes, vector is put down each of the trees in the forest. Each tree gives a classification and thus a vote for a class. The forest chooses the class having the most votes (over all the trees in the forest).

Figure 3: Destination Classes Used for Purpose Classification



If  $N$  is the size of the full training set and  $M$  the number of attributes, each tree itself is grown as follows:

1. Randomly sample around  $\frac{2}{3}N$  cases from the original data (with replacement). This sample will be the training set for growing the tree.
2. At each node  $m \ll M$  variables are selected at random and the best split on these  $m$  is used to split the node. The value of  $m$  is a parameter and is held constant during the forest growing.
3. Each tree is grown to the largest extent possible. There is no pruning.

The training set we want to use here is the ENTND 2008 as it was described in section 3.2. All the attributes shown in table 1 are accessible in this survey and thus can be used for our random forest approach. We modify the original algorithm and implement a multi stage approach. At each stage we select a single travel purpose and create a random forest to decide whether a tour is has this travel purpose or not. We want to identify five different purposes, namely commuting, business, holidays, visiting friends/parents and (other) private reasons. Therefore, we need four stages to identify all purposes. We do not use all attributes in all stages since some attributes are not important to identify some purposes, e.g. the month of the tour does not contribute to the classification of a commuting trip. The used attributes of all stages are shown in table 2. The order of the stages was determined by enumerating all possibilities and choosing the best

one. Additionally, the importance of all attributes are reported. The importance is measured by the number of classification errors, when altering a node in the decision tree that includes this attribute.

Table 2: Stages and Attributes Used including the Importance

Attribute	Stage 1 Commuting	Stage 2 Business	Stage 3 Holidays	Stage 4 Visits/Other
Distance	Average	High	Average	Average
Duration	Average		Very High	High
Destination		Average	High	Average
Month		Average	Average	Low
WE-Share	Low	Very High		Average
Deviation	Average			Low
Frequency	Very High	Very High	Average	Low
Residence		Average	Average	Low

We created 1000 multi-stage random forests and used all of these forests once to classify the tour purposes of all tours extracted from the CDR data. The results of this classification are shown in section 6. All forests consisted of 500 decision trees at each stage and  $m$ , the number of split variables, was fixed at 2. Both parameters are suggested in the literature (Breiman and Cutler, 2013).

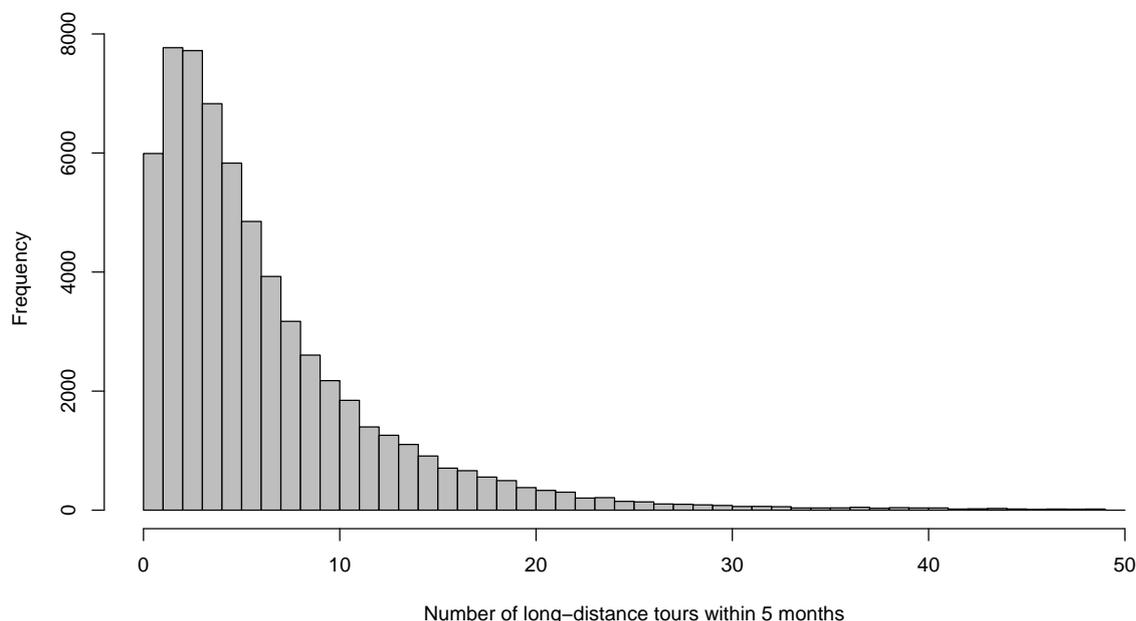
## 6 Results

All the results of the algorithms described so far and analysis of these outcomes are presented in this section. In total, 445'231 national long-distance tours were reconstructed from the CDR data for the 62'819 mobile phone users that we tracked. This results in 7.09 tours for each person. Thus, every person did on average 1.42 national long-distance tours per month since the CDR data covers 5 months.

We analyzed the frequency distribution of long-distance tours undertaken. A histogram of the frequencies can be found in figure 4. One can see that low frequencies are dominating. More than half of the tracked people did less than five tours in the observed five months. More than 80% of the people did less than 10 tours, which corresponds to two tours per month.

We also want to measure the quality of the random forests that were computed. Therefore, we

Figure 4: Histogram of the number of Long-Distance Tours within 5 months (cut at 50)



report for each stage two different error measures (see table 3). On the one hand, the out-of-bag (OOB) error reports the share of wrongly classified observations among the third of the sample that was not used to build the decision tree. On the other hand, the full data error was calculated as the share of miss-classified observations, when the purpose for the full training set is predicted by the whole random forest. One can see that the error levels are fairly low. Though, the error grows stage by stage. Consequently, the highest error rate can be found in the last stage, where we try to distinguish visits from other private tour purposes.

Table 3: Error Levels of Random Forests per Stage

	Stage 1 Commuting	Stage 2 Business	Stage 3 Holidays	Stage 4 Visits/Other
OOB Error	0.34%	7.58%	18.96 %	26.79%
Full Data Error	0.09%	0.02 %	0.07 %	0.19%

The predicted purposes for the long-distance tours extracted from the CDR data are analyzed as well. First of all, 308'071 of the 445'231 tours (69%) were classified with the same purpose by all of 1'000 generated random forests. More than 93% had the same purpose class predicted by 750 of the random forests. This shows that the prediction method is robust. We call the tours

well classified if they had at least 750 times the same predicted purpose. Table 4 shows the number of not well classified tours. The matrix describes which purpose classes could not be clearly separated from other classes in the prediction process. One can see that a clear separation between visits and other private tours is difficult. These are the two purpose classes that interfere the most during the prediction. Nevertheless, the total number of not well classified tours is relatively small.

Table 4: Number of Tours that were not well classified

	Commuting	Business	Holidays	Visits	Other
Commuting	–	466	4	15	39
Business		–	340	1'421	3'789
Holidays			–	6'506	603
Visits				–	16'248
Other					–

Finally, also the purpose classification is presented here. Table 5 shows the total number of predicted purposes, their shares and the corresponding shares from the ENTID 2008. One can see that the predicted shares fit quite good the shares from the survey.

Table 5: Predicted Purposes for the CDR data

	Commuting	Business	Holidays	Visits	Other
Total	13'108	58'774	52'854	184'412	106'005
Share	3.2%	12.8%	14.2%	44.4%	25.5%
Share in ENTID 2008	3.5%	13.8%	22.0%	38.5%	22.2%

## 7 Conclusion

This paper has shown that mobile phone billing data is a useful data source for the field of travel demand research. Especially, long-distance travel estimators can benefit from this particular data. In combination with the random forest technique used for purpose classification robust predictions for long-distance travel can be generated.

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