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Can technologically assisted travel surveys improve mode choice modelling? Differences and improvements compared to travel conventional survey data.

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Abstract

Travel surveys often serve as the primary input for the creation of traffic simulations models, in particular as the data basis for the estimation of mode choice models. In this paper we investigate the differences of technologically assisted data (TAD) and conventional travel survey data for mode choice modelling. We describe the necessary steps to enable the use of TAD for mode choice modelling like data pre-processing, choice set generation and the adaptation of the travel times in the choice set to fit those in the TAD. Model estimation shows that TAD enables a better prediction of modal splits compared to the models estimated on the conventional survey data. Furthermore TAD offers a clear advantage when predicting walking times in the trips. Lastly, the influence of misclassification in the automated mode detection on the prediction of modal split and walking times is studied. Finally, a short overview is given on how TAD can be used for route choice modelling which is a further advantage of the new collection technology.

Keywords: Mode and Route Choice, Technologically Assisted Data Collection

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1. Introduction

Comprehensive mobility surveys often serve as an input to the modelling process for the development of traffic simulation models (see e.g. Horni and Vitins (2011)). Data from conventionally collected surveys like Österreich unterwegs (Tomschy et al. (2016)) can be used as an input to different parts of the modelling process. This includes the creation of a population (e.g. Farooq et al. (2013)) together with origin-destination-matrices and activity chains for agent based simulation models but it can also be applied as the input data for mode-choice modelling (e.g. Rudloff et al. (2015)). Due to the nature of classic mobility surveys, the collection is restricted to start and end points and the corresponding start and end times of the trips in the trip chains performed by the respondents together with the modes taken for the trips. However, for data protection reasons usually only the postal districts are stored. While this restriction still applies to technologically assisted data (TAD) acquisition, the TAD contains a much more detailed description of the trip data, since it allows to gather very detailed information like time spent in different vehicles as well as walking times and waiting times for each of the trips in the activity chain. Furthermore, due to the detailed knowledge of the trip chain it is easy to use a router to create and store similar information for alternatives to the route in different modes. As a result, it is easy to store all the data necessary for route choice modelling; the information of the chosen routes as well as the information for alternative routes without revealing too much personal information.

Despite the relative novelty of TAD, there are a number of papers that deal with the development of a smart-phone based travel survey tool (see e.g. Safi et al. (2015) or Nitsche et al. (2014)), the development of mode detection (e.g. Nitsche et al. (2012)) or activity recognition (e.g. Kim et al. (2014)). There is also some results on comparative data analysis of conventional and TAD collection methods (e.g. Khodadadi et al. (2016)) that show amongst other things that the modal share for all but private vehicles are strongly under-represented in the traditional survey compared to the TAD.

While Literature about the development of smart phone applications for the collection of TAD exists, information about the applicability of such data for the development of transportation simulation models is still sparse. In particular, this is the case since, to the authors best knowledge, there are no large scale travel surveys that were conducted with such automated collection tools as of yet. Since travel survey data from conventional travel surveys is widely available many examples exist where such data was applied for mode choice modelling (see e.g. Bhat (1997), Ewing et al. (2004), Frank et al. (2007) or Rudloff et al. (2015)). These papers answer many interesting questions like travel choices of certain groups, transportation mode choice under different weather conditions or questions of trip chain complexities or number of stops on route. However, quality of the underlying data and its applicability are usually not questioned since for a long time conventional travel surveys were the best source for large scale data.

With the rise of mobile devices it is now possible to reach a relatively representative sample of people with a smart phone based surveys, resulting in more comprehensive and more detailed data sets. One of the advantages of TAD is that under-represented multimodal trip chains might be captured better (see Clifton and Muhs (2012)), e.g. walking trips are captured at the beginning and end of a car trip.

In this paper advantages and disadvantages of the novel data source for mode and route choice modelling are studied in this paper. In the remainder of the paper we describe what steps are needed to apply data collected in a technologically assisted travel survey collection for mode choice modelling. Afterwards we compare mode choice models estimated on that data with models estimated on a data set restricted to look like conventional travel survey data. Finally we give an outlook into the possibilities of applying the new data for multi-modal route choice modelling and show strength, weaknesses as well as necessary next steps to make technologically assisted travel surveys ready for mode and route choice modelling without strongly restricting data privacy.

2. Data Collection and Data preprocessing

The data for this study was collected using the tool Smart Survey (see e.g. Nitsche et al. (2014)) that allows to collect GPS and other sensor data (e.g. accelerometer data) with a smart phone application. The data is automatically segmented into single mode stages and an automatic mode detection is applied. To ensure that the automatic trip chains and the activities are detected correctly a web based correction tool is supplied to the users where the trips and stages can be adjusted.

To be able to compare the approach used in the collection of traditional travel surveys (here the comparison was data from the Österreich unterwegs (OEÜ) project (see Tomschy et al. (2016))) with the technology assisted

approach in smart survey, a TAD set was collected from 74 respondents. The set consists of a total of 505 trips in the Vienna region.

Since all information available in the OEU data was also collected in Smart Survey, a data set comparable to the OEU data was created from the Smart Survey data set. To achieve the same level of information the geographical information from the TAD was replaced by postal districts, the detailed information of the trips and stages was aggregated such that only the travel time information for the full trip as well as the modes of the trip remained.

To enable the estimation of mode choice models, for each of the trips alternatives using different modes were calculated using the router Ariadne for routes by foot, bike and car routes (Prandstetter et al. (2013)) and the electronic timetable information system of the local public transport provider for public transport (PT) routes. In this paper, we concentrate on these four modes, since they are the main modes of transportation in the region.

Since the OED data does have only postal districts as geographical information, routes with the four modes were calculated between all centres of the census tracts of the districts. These census tracts divided the districts roughly into areas with similar population. The census tracts of for the city of Vienna can be seen in Fig. 1. The densely populated districts in the inner city have relatively small census tracts and as a result the travel times are relatively accurate, while there travel times for the outer census tracts are less reliable due to the size of the tracts.

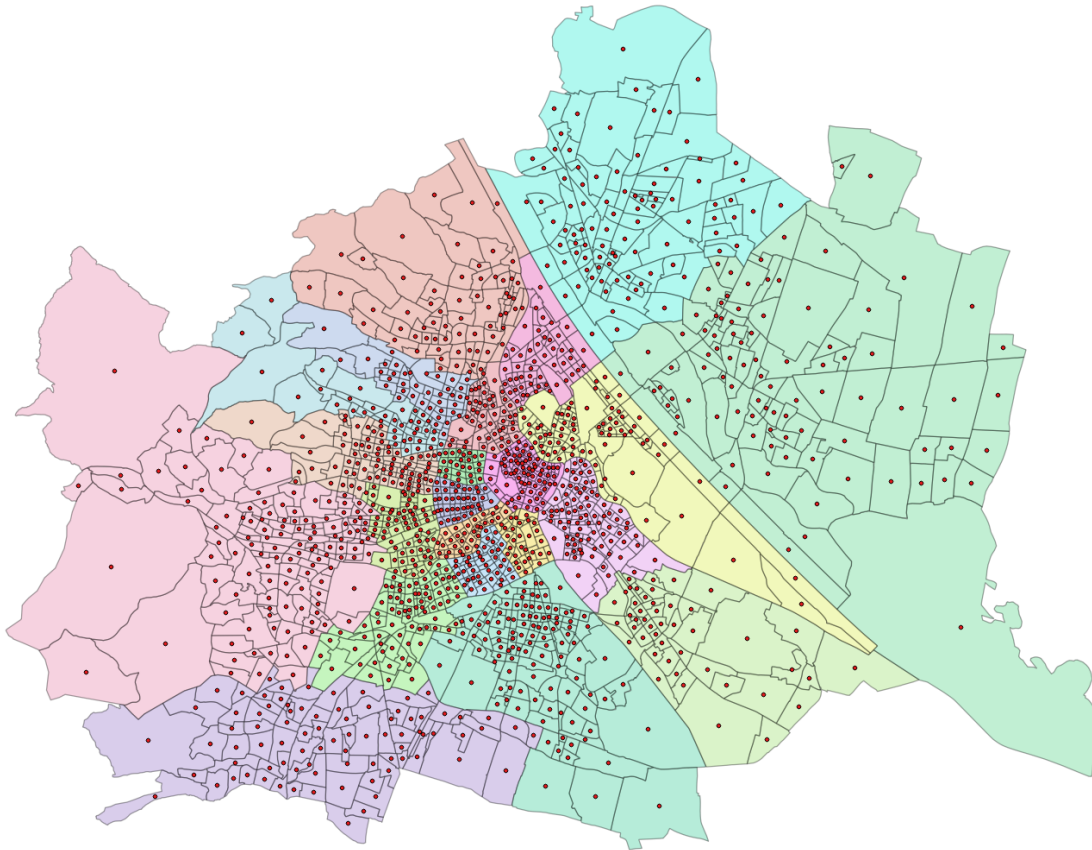


Figure 1: Census tracts for the city of Vienna. The postal districts are in different colours. The red dots are the centroids of the census tracts.

The travel times of the alternative routes in the route set might contain a systematic error due to the restricted information in the routing graph or faulty assumption on the speed of travellers. Hence, it is important to adjust the data such that the alternative routes are comparable to the measured travel times. In Fig. 2 the routed travel times are plotted versus the recorded ones together with the regression line and the line of gradient one. The slope of the regression line suggests that the travel times for PT are comparable between measured and routed travel times, whereas for the other modes the travel times for the routed alternatives are generally shorter. For walking trips there is a large number of routes, where the routed travel times is very short compared to the measured ones. This is due to mistakes by the respondents when the recording of the route was not switched

off at the end of a trip. The according travel times are manually adjusted, so the trips have a reasonable walking speed of about 3 km/h.

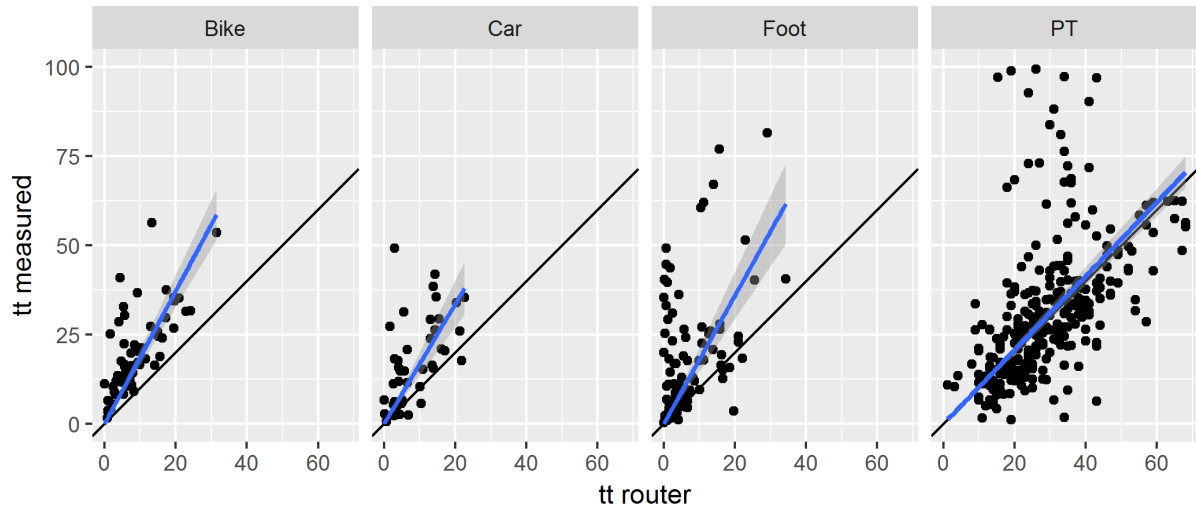


Figure 2: Differences between routed and measured travel times for the different modes for the chosen alternative. In blue a regression line is given.

In the TAD, in many cases, there is a walking stage at the end of the trips. This is the case, since in particular in cities there often is a walking stage from the car and bike parking from the starting point or the end point of a trip. They are however often not recorded in surveys like OEU. As an example, walking is only recorded as a mode of transportation for trips which have car or biker as the main mode in about 3% of the cases in OEU. In the technologically assisted collection there is walking stage recorded for 55% of bike and car trips. Since the trips for other modes often contain a walking stage at the end, the problem with ending a trip manually happens mostly in those walking stages. Hence the adjustment of travel times for the different modes should happen within the single mode stages. In Fig. 3 one can see that the data with the walking stages included has a smaller variance and the slope of the regression line is closer to one and influenced by the outliers less.

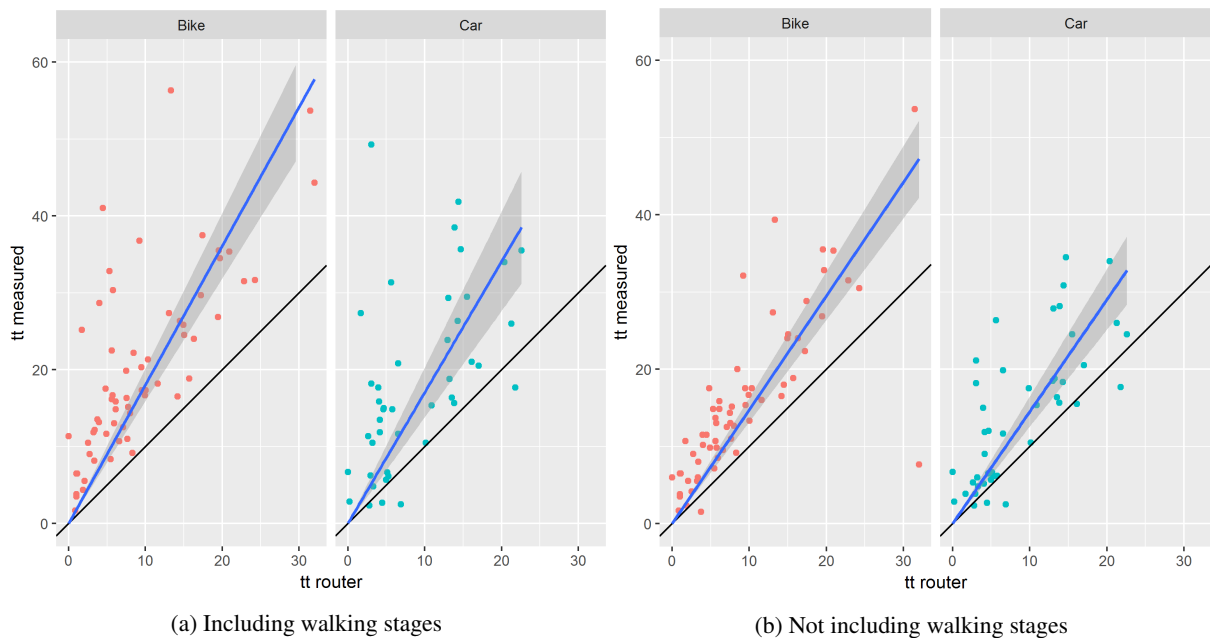


Figure 3: Comparison of measured and routed travel times of bike and car including (a) and not including (b) walking stages.

For the PT trips, Fig. 4 shows that while there is quite a variation between measured and routed travel times even with the walking stages taken out of the travel times, the slope of the regression line is close to one, i.e. routed and measured travel times match quite well on average. The large variance is partly due to the

fact that there usually several options for PT travel in the city of Vienna (some might result in longer walking stretches, some just use different modes) and mode choice within PT is influenced strongly by personal taste or physical shape (some people might simply prefer buses to trams, some might like longer walking stages from their starting point rather than more changes).

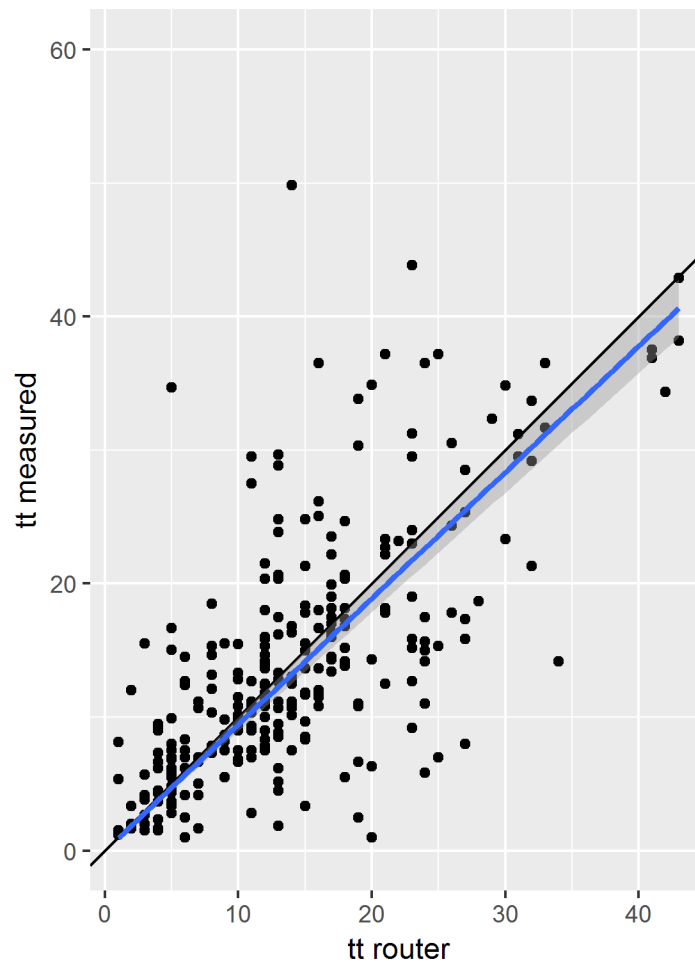


Figure 4: Measured and routed travel times for public transport trips without walking stages.

As suggested by the above figures (Fig. 2-4) a linear regression on the routed travel time should work well for modelling the measured travel time for Car, Bike and PT, in particular, when the travel times are adjusted for mistakes in the final walking stages. In Table 1 the results of the linear regression is shown together with the R^2 for those modes. One can see that modelled travel times for bike and car trips are clearly shorter on average which again shows that speeds might be overestimated while effects of traffic lights and crossings of priority routes might be underestimated in the router.

Table 1: Regression results for the different modes

	Car	Bike	PT
slope of regression line	1.38	1.45	0.94
r-squared	0.89	0.87	0.83

3. Mode Choice Modelling

To compare the results of different mode choice models for the two collection methodologies different models were estimated for the different data sets. Due to the small amount of data only simple mode choice models based on travel time and changes as well as modes used on the trips only were estimated. While the inclusion of other variables as well as the application of group based models will improve the results of forecasts (see e.g. Rudloff and Leodolter (2017) for an application of latent class mode choice models) the application of easy models is enough to show differences in the modelling and forecasting.

To test the different models a leave one user out cross validation (LOUOCV) was applied where the models were estimated for all but one user and the resulting models were applied to forecast the probabilities for the different modes for the remaining users. This procedure was repeated for all 74 respondents.

Models were estimated for five different data sets, three for the technology assisted collection data and two for the OEU style data.

The three data-sets for the technology assisted models were the set, where the alternatives were the alternatives routed in the external router (TAD 1). The second data set was created by modelling the travel times for the different modes for the routed travel times to be more similar to the measured travel times (TAD 2). For the third data set the chosen alternative was replaced by the measured travel times (TAD 3).

For the OEU style data, the alternatives were created from the routed trips between the census districts. For the first data set, the start and end location was chosen such that the travel time of the chosen alternative and the travel times for the alternative modes the corresponding travel times for that pair of points were used (OEUD 1). For the second alternative, the mean travel times between all the postal district pairs of start and end point of the trip were used (OEUD 2).

Exemplary parameter values are given for TAD2 and OEUD1 in Table 2. For TAD the travel times in each mode are known, so they are included in the variables and denoted by *tt.mode*. Furthermore, due to the detailed travel information that TAD offers, the number of transfers as well as the waiting time can be used as variables in the model. Lastly, the models include alternative specific constants (ASC) for each of the main modes in the trip.

In the OEUD model, only the modes used in the trip are known. Hence dummy variables are used when a mode is part of a trip, hence replacing the ASC. In addition the total travel time is known for each of the alternatives.

One can see that the log/likelihood indicates that the model fit of the TAD model is clearly better than that of the OEUD.

Table 2: Parameter values for two of the estimated models. The values in brackets are the t-values. Bold parameter values are significantly different from zero at a 5% level

Variable Name	TAD2	OEUD1
ASC bike	-3.3589 (-9.850)	
ASC car	-4.803 (-11.465)	
ASC PT	-1.434 (-6.592)	
tt foot	-0.134 (-9.839)	
tt car	-0.045 (-1.088)	
tt bike	-0.088 (-3.450)	
tt PT	0.0002 (0.008)	
Number of Transfers	-0.414 (-1.723)	
Waiting Time	0.033 (0.593)	
walking stage in trip		4.478 (13.0488)
bike stage in trip		2.728 (8.1555)
car stage in trip		2.353 (6.949)
commuter train stage in trip		0.863(2.058)
underground stage in trip		1.266 (5.765)
bus stage in trip		0.357 (2.374)
tram stage in trip		-0.200 (-1.179)
total tt		-0.015 (-6.584)
Log Likelihood	-394.91	-453.64

One can see that the all the parameter values significantly different to zero have the expected sign. In addition the mode dummy variables as well as the ASC suggest that there is a strong bias towards walking.

To test the models, the LOUOCV was applied. For each user U the out of sample modal split (OoS MS) was predicted by estimating the mode choice models M_U on the different data sets with the data of user U left out. The probabilities for each mode for the trips of user U were predicted with the model M_U . After repeating this for all other users, the mean probabilities for the modes can be taken as a prediction of the modal split

applying the different models. In Tab. 3 one can see that the modal split predictions of the TAD models are all very and close to the real modal split in the data set. The OoS MS for the OEUD models are further of the mark. Applying the different travel time models for the set of alternatives does not make much of a difference for the predicted modal splits of the TAD models. For the OEUD models, the prediction is better when using the travel times for the closest routed alternative. Overall, the TAD performs better than the OEUD when it comes to predicting modal splits.

Table 3: Out of Sample modal split predictions with the different models

	Foot	Bike	Car	PT
Orig. Modal Split	0.2242	0.1290	0.0873	0.5595
OoS MS TAD1	0.2244	0.1281	0.0880	0.5594
OoS MS TAD2	0.2246	0.1281	0.0879	0.5594
OoS MS TAD3	0.2245	0.1293	0.0884	0.5579
OoS MS OEUD1	0.2187	0.1298	0.0861	0.5654
OoS MS OEUD2	0.2096	0.1318	0.0926	0.5661

Since one of the advantages of the technology assisted data acquisition is that all stages are capture all the stages and hence there is a better chance to capture features like short walking stretches in the modelling process. Here we only test how long the combined walking stages in the out of sample predictions are. The results can be seen in Table 4.

For that test we multiply the probabilities for each mode for the trips of the OoS user U by the travel time that is spent walking for that alternative. These values are summed up to predict the number of minutes walked within all the trips. One can see that TAD3 performs best and that the modelling of the data to more closely resemble the measured data is necessary. One can also see, that while the modal split prediction of TAD1 is good, the prediction of the minutes walked is clearly worse than that of TAD3. Not surprisingly, the OEUD models are outperformed by all of the TAD models, since for the OEUD models. only the actual walking trips contain any walking while for TAD many alternatives have walking stages.

Table 4: Out of Sample prediction of minutes walked

	measured	TAD1	TAD2	TAD3	OEUD1	OEUD2
minutes walked	11823.05	5660.42	8745.48	11170.20	4746.84	3205.54

Since for TAD, automatic mode detection is used this adds a possibility that the modes are detected incorrectly. Of course wrong detections add the possibility that bad data worsens the accuracy of the mode choice models. To test this, the TAD data was assumed to be the ground truth. To test what the influence of wrong mode detections are, two tests were run. To perform the tests, the detected modes were changed. Three data sets were created, one where 5% of the modes were changed, one with 10% and one with 15%, where the stages were drawn at random. For each of these data sets, the LOUOCV was run and the modal split and walking times were predicted. The whole process was repeated five times.

In Table 5 the average modal splits are presented. One can see that the wrong detections do have some influence and the modal split prediction deteriorates with a growing error rate. This shows that a good mode detection algorithm is important and that good training data for that algorithm is needed since the quality of the mode choice model prediction is getting worse quickly. One can also see that at a 10% detection error rate, the modal split prediction is already worse than that of the OEUD models.

Table 5: Out of Sample modal split predictions for TAD3 with a percentage of wrong mode detections

	Foot	Bike	Car	PT
orig	22.42	12.90	8.73	55.95
5%	21.35	12.99	9.82	55.84
10%	20.39	13.69	10.77	55.15
15%	19.47	14.12	12.15	54.26

The quality of the walking time predictions deteriorates slower than that of the modal splits (see Table 6). However, the variance increases quickly, showing that the spread of walking times is getting larger with a growing error rate and hence the results become less reliable as the error rate grows.

Table 6: Out of Sample minutes walking with different error percentages in mode detection

	5%	10%	15%
mean	11256.0	11436.8	11534.5
sd	101.0	106.5	169.3

4. Route Choice Modelling

Since there is no route information in data sets collected in the traditional travel surveys, this data is not applicable for the task of route choice modelling. Data collected with the technologically assisted collection contains GPS data and is therefore a very good source for the creation of route choice models. There are still some complex steps that need to be taken before GPS data can be applied in route choice modelling, but it is accepted as a good basis to estimate route choice models. A vast body of research papers exists, where uni-modal route choice models were estimated based on revealed preference data in form of GPS-data (e.g. Bierlaire et al. (2013) for car route choice or Rudloff et al. (2017) or Broach et al. (2012) for bike trips).

There are three main steps that need to be taken care of in the process in route choice modelling:

1. **Data Preprocessing:** In case of technologically assisted data collection there is two main task that need to be taken care of. The first is that of mode detection such that the GPS trip data can be cut into single mode stages. These stages can afterwards be map matched to actually extract all the necessary information for the modelling process from the routing graph. Methodologies exist for these processes (e.g. Nitsche et al. (2014) and Koller et al. (2015)).
2. **Choice Set Creation:** To estimate route-choice models a choice set of possible routes needs to be created. It is important to create a set that has enough variance to cover a large set of possible routes without having too much overlap in the route set. A wide range of algorithms for choice set creation exist in the literature ranging from labelling methods (e.g. Broach et al. (2010)) to branch and bound techniques (e.g. Prato and Bekhor (2006)). A good overview about the different approaches can be found in Prato (2009).
3. **Route Choice Modelling:** Due to the correlation within the choice set common multinomial mixed logit methodologies need to be adjusted to deal with this problem. Again Prato (2009) gives a good overview over different methodologies like path size logit (e.g. Rudloff et al. (2017) or Broach et al. (2012)) or cross nested logit (e.g. Mai et al. (2015)).

In addition to unimodal route choice models data from technologically assisted data acquisitions could be used for a more comprehensive modelling approach combining route and mode choice. Due to the difficulties in collecting multi-modal routing data there is not much work on this topic yet. Technologically assisted data collection can overcome this gap since large amounts of data can be collected without too much user interaction.

5. Lessons learned

In this paper it was shown that due to the larger amount of information, both geographically as well as with respect to stages that are collected with technologically assisted travel survey collection, mode choice models can be improved compared to traditional travel surveys. However, for a thorough companion of TAD with conventional collection methods, it is important to guarantee that the sample compositions for the two survey types is comparable, since the reliance on technology might create a bias in the sample.

Some parts of the collection process like the mode detection or an automatic stopping mechanism need to be improved since they are essential for the estimation of reliable mode choice models, since they ensure that the length of the walking stages is not artificially inflated and the misclassification of modes is kept to a minimum. However, even with the problem of artificially long walking stages at the end of the recorded trips, some easy preprocessing stages ensure that the modelling results can be improved significantly.

In general for mode choice modelling, there needs to be a process of creating a choice set with the alternative modes. Due to the better geographic resolution of the data a more appropriate choice set can be created. Even with the restriction of data privacy, a router could be connected to the data collection tool to store all the information necessary for the mode and route choice process without actually storing the geographical data in the high resolution. Another advantage of the technologically assisted data collection is that the length of the walking stages is estimated better with that data while it is strongly underestimated when the technologically assisted data collection is not used. Hence a much more detailed modal split can be predicted for the usage in simulation models.

Finally, while route choice modelling is not possible with data collected in the conventional way technologically assisted data acquisition provides all the information to model route choice based on revealed preferences. In addition, more complex tasks like combined route and mode choice can be addressed once a large TAD is collected.

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