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Is there any best practice principles to estimate bus alighting passengers from incomplete smart card transactions?

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Abstract

Promoting the accuracy and coverage of the alighting of passengers in public transport is essential to support route planning and policy decisions aiming to sustainable mobility. Although previous studies place several principles for alighting estimation from incomplete smart card data, most remain dispersed and address one single mode. These gaps hinder a comprehensive comparison of the success rates of existing alighting algorithms. To address the above challenges, this work assesses side-by-side state-of-the-art principles for alight stop inference using smart card data from multimodal transport networks. To our best knowledge, this research is the first incrementally measuring the impact of each principle present in the literature. It further discusses uncertainty factors and proposes a confidence metric on the estimated alighted stops.
Keywords: sustainable urban mobility; data science; alighting stop inference; smart card data analysis; public transport; multimodal transport

1. Introduction

Public transport operators, whose automatic fare system (AFC) only records passenger ticket transactions on the vehicle boarding, depend on reliable solutions to infer the alighting information to assess traffic dynamics. End-to-end traffic dynamics are essential for the diagnosis of vulnerabilities (e.g., capacity, walking needs on transfer) to properly support an inclusive transport planning and policy-making (Gavriilidis et al., 2020; Cerqueira et al., 2021; Sobral et al., 2021). In this context, previous studies have contributed with trip-chaining algorithms for the alighting stop and timestamp inference (Farzin, 2008; Trepanier and Chapleau, 2006; Zhao et al., 2007; Nassir et al., 2011; Munizaga et al., 2014). Most of the proposed algorithms are heuristic, relying on principles that describe the prevailing passenger's mobility, e.g. a passenger boards near the alighted stop in the previous trip. Over the last two decades, novel methodologies and principles have been proposed, claiming higher percentage of successfully estimated trip transactions. Despite the relevance of these previous studies, mostly concern to the assessment of the algorithm success rather than critically assessing the impact of each underlying principle against the set of alternative principles. Briefly, the principles that have been applied so far are dispersed by various modes and their effectiveness has been assessed on single transportation modes, preventing a robust comparison of success rates between state-of-the-art principles and their methodologies.

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To address the above mentioned issues, this research aims to assess, side by side, the impact of state-of-the-art principles on alighting stop inference in a multimodal transportation network. In addition, this work contributes with a SWOT analysis on the existing principles, mainly exploring its weaknesses and providing a novel statistic that assigns a confidence score to each alighting stop inferred. The city of Lisbon is used as the study case, with the target smart card data corresponding to all transactions from October 2019 in the primary public operators: bus-and-tram operator, CARRIS, and subway operator, METRO.

The paper has the following organization: section 2 describes the state-of-the-art principles for alighting inference and validation methods; section 3 proposes six heuristic models to measure the impact of the principles; section 4 gathers the results obtained from each model using integrative AFC data from Lisbon's multimodal transport network, discussing the principles' fallacies; and finally, section 5 provides major concluding remarks.

2. Related work

Since the first alighting inference approach proposed by Barry et al. (2002), several studies suggested additional principles to explain the passengers' mobility dynamics. Usually, the principles are shaped into heuristics, which guide a trip-chaining algorithm. In this scope, previous studies generally rely on two baseline assumptions: a) the passengers tend to board next to the location where they alighted in the previous trip (Barry et al., 2002); and b) the passengers tend to return to the location where they boarded at the beginning of the day (Trepanier and Chapleau, 2006). Since then, the literature empirically proposed more complex assumptions, to progressively increment the effectiveness of models. Summarizing, the following list presents the main principles regarding the location and time alighting information, ordered chronologically:

1. The passenger boards next to the location where alighted in the previous trip (Barry et al., 2002);
2. The passenger returns to the same location where it boarded at the beginning of day (Barry et al., 2002);
3. It is not possible to estimate the alighting stop of an isolated trip within a day (Barry et al., 2002);
4. The alight stop cannot be inferred if the consecutive alight stop occurs in the same location (Barry et al., 2002);
5. If the first and last boarding of the day occur at the same stop/station, the alighting stop of last transaction cannot be inferred (Barry et al. 2002);
6. After boarding, the passenger can only alight in the following stops of the boarding route (Trepanier and Chapleau, 2006);
7. The walking distance, between an alighting stop and consecutive boarding (of the next trip), it must be less than given threshold (Trepanier and Chapleau, 2006);
8. For the last trip of the day, the alighting stop must be next to the place where boarded at the beginning of the day, at a distance less than a given threshold (Trepanier and Chapleau, 2006);
9. For the last trip of the day, if the alighting stop is not estimated, the model estimates the alighting stop that it is next to the place of the first boarding stop of the following day (Trepanier and Chapleau, 2006);
10. Given a trip set with alighting information and also with symmetric pattern (such as RB and BR, where R and B are boarding), a transaction with no alighting stop can be estimated, if it belongs to a similar symmetric pattern (Zhao et al., 2007);
11. Between consecutive trip segments there is no private transportation modes (Zhao et al., 2007);
12. The estimated alighting timestamp must occur before the boarding timestamp of the next trip segment (Nassir et al., 2011);
13. If the model does not infer an alighting stop with success, the model can relax assumptions by searching for an alight stop among the stops in the opposite direction route (Nassir et al., 2011);
14. The chaining period of 24 hours begins when the network operator has the lowest activity, for instance, 3:50 AM until the next day at 4:00 AM (Munizaga et al., 2014).

Table 1 shows principles, validation methods and the reported accuracies of the previous studies on alighting inference with trip-chaining methodology. For simplicity, the principles are cited through the order number from previous list. Overall, the reported accuracy shows that alighting inference with multimodal transportation has a positive impact on alighting inference, with an average rate percentage over the 80% (Alsger et al., 2016; Munizaga et al., 2014; Hora et al., 2017). Nevertheless, a comparative analysis on success rates is not trivial, since methodologies and validation are in a contradiction between studies. In most research, the ground-truth data are not available to test the inference results, and for this reason, the validation is based on two major options: i) sensitive analysis, by ranging the algorithm parameterization, or ii) comparative analysis with external sources, such as surveys.

Table 1 shows that most of the previous studies set a specific threshold range to limit the transactions' percentage within the alighting stops inferred. Usually, it is the walking distance or the time spent between transactions. This threshold analysis must be taken into account, because shorting the walking distance/time cutoff, increases the probability of rejecting true positives, and, otherwise, increasing the overfitting susceptibility (accepting false positives). Indeed, a detailed sensitive analysis and validation is essential to avoid jeopardizing operators decision-making based on these results or following exploratory analysis, such as transfer detection, and origin-destination matrices (Alsger et al., 2015; Sanchez-Martínez, 2017; Kumar et al., 2018; Li et al., 2011; Hussain et al., 2021).

Reference	**Mode**	**Model Principles**	**Accuracy**	**Validation and placed thresholds**
Trepanier and Chapleau (2006)	Bus	1, 3, 6, 7, 8, 9	66%	Walking distance threshold of 2 km.
Zhao et al. (2007)	Rail	1, 3, 8, 10, 11	71,2%	Statistical tests on the OD matrices.
Nassir et al. (2011)	Bus	1, 8, 11, 12, 13	51 273 of 84 413 transactions 60,74%	Average walking speed of 3mph (4.8 km/h) threshold.
Wang et al. (2011)	Bus	1, 8	62,8%-78,5%	Validation of specific routes against surveys/questionnaires.
Munizaga and Palma (2012)	Bus and Metro	1, 8	80,77% and 83,01%	Validation on two datasets, with walking distance threshold of 1 kilometer.
Munizaga et al. (2014)	Bus and Metro	1, 8, 14	85 %	Endogenous analysis through the sensitive analysis over the distance function f_d. Exogenous analysis by comparing the inferred results with the reported trips made by 53 volunteers.
Nunes et al. (2015)	Bus	1, 6, 8	62,4%	Walking distance range between 400 to 1000 meters.
Alsger et al. (2016)	Bus, Metro, Ferry	-	76%-84%	Walking distance range between 400 to 1000 meters.
Hora et al. (2017)	Bus and Metro	1, 8, 14	80%	Walking distance at 403 meters.
Lee et al. (2021)	Bus and Metro	1,8	41%-65%	Walking distance between 500 and 1500 meters

Table 1: Previous studies summary, including accuracy percentage, principles, inference results, validation and placed thresholds on the alighting inference with trip-chaining algorithms.

3. Methodology for Alighting Stop Inference

3.1. Principles for a baseline architecture

Principles 3, 4, 5, 6, 7, 8, 12 and 14 mentioned in the previous section 2 were selected to assemble a solid baseline model for bus alighting inference. Principles 1, 2, 10 and 11 are discarded in this study because are outdated for the problem scope. In summary, according to the chosen principles, the alighting stop of a given transaction is inferred, if the boarding stop of next transaction is at a distance lower than a given threshold and if the boarding stops of both transactions do not correspond to the same location. Inferring the alighting stop for the last transaction of the day, undertakes the mentioned restrictions but the sequent transaction is the first of the day. It is considered a day, a period of 24 hours, whose activity starts at 3:59 AM until the next day at 4:00 AM. Finally, the estimated alighting timestamp must occur before the boarding timestamp of next trip transaction. From the SWOT analysis point of view, the suggested principles present strengths on the simulation of general behavior of passengers. Besides, the addition of multimodality is considered an opportunity to improve the success rate (according to previous works). Yet, the next sections will discuss the weakness of some of the previous principles in the inference, due to unexpected passenger behavior (considered threats for the model).

3.2. Extended principles and remarks

Beyond considering multimodal behaviours, we further extend the baseline architecture to undertake less-trivial passenger behaviour throughout the networks. In this context, it is implemented the principles called β_1 and β_2. Principle β_1 assumes: if the passenger boards at the route's terminal, the alighting stop must be sought in the opposite direction. This new rule forks from principle 13 (mentioned in the related work), restricting the probability of inference errors (Nassir et al., 2011). It is considered a threat (external factor), triggering the search for the alighting stop on the opposite route, whatever the boarding stop may be. On the other hand, when passengers board at the terminal, it is

certain that they intend to travel in the opposite direction. So, this novel principle gives an opportunity to undertake this situation, without compromising the algorithm robustness.
Principle β_2 it is triggered when the last alighting stop of the day is not inferred, because it is far from the location of first boarding of the day. Then, the principle selects an alighting stop that is near to the first stop of the following day(s). β2 aims to cover the weakness of principle 9 (Trepanier and Chapleau, 2006), because it assumes that the passenger remains on the same spot for long period (e.g., passenger leaves the city temporarily or stays overnight in a different place from their usual). Even so, this novel principle may raise inference errors by letting a linkage between two transactions with same or close boarding.

In fact, to the best of our knowledge, the impact of this possibility, informally described in principle 9, was not yet assessed. For better understating, Figure 1 illustrates this likely situation, with the following aspects: a) at the day 5, the boarding of the last transaction occurred at the location L1 and the next boarding (another day) occurs at the location l2; b) distance between L1 and L2 is lower than 500 meters. In this scenario, the principle admits a travel from L1 to L2, although, given the short distance it is more likely a trip from L1 to a location far from L2. For this reason, this principle is only valid when the boardings of both transactions (the last transaction of the day and the first of the next days) are at distance greater than a defined threshold. For simplification, this constraint is termed Cross-Day Chaining.

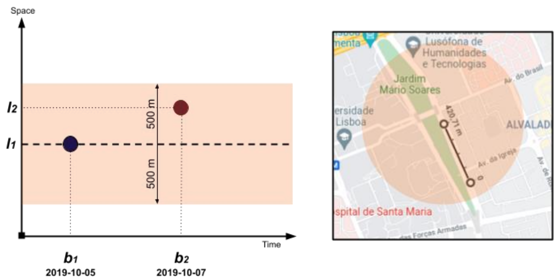

Figure 1: Consecutive unique transactions made by a passenger from same origin: potential chaining error caused by principle β2.

3.3. *Definition of Alighting Models Architecture*

Grounded on the aforementioned alighting inference possibilities, six different methods are defined and empirically assessed. The comparative analysis between these methods aims at measuring each principle's impact side-by-side in the alighting inference task. Table 2 summarizes the six models: i) models I, II, and III only receive as input bus transactions, meanwhile model IV, V, and VI receive as input transactions from bus and metro operators; ii) the models I and IV are trained with a baseline architecture, and the remaining models are trained with baseline architecture plus with extended principles (described in sections 3.1 and 3.2).

	Baseline Principle	Baseline Principle + β_1	Baseline Principle+ β_1 and β_2
Unimodal	Model I	Model II	Model III
Multimodal	Model IV	Model V	Model VI

Table 2: Summary of proposed models to measure each principle's impact.

3.4. *Core chaining trip algorithm*

The trip-chaining algorithm is the main structure to train each model. By default, the algorithm trains Model I (baseline architecture, with only input bus transactions). The algorithm receives, as input, a set of *n* transactions $\{T_1, T_2, \cdots, T_n\}$ of a passenger *s*, ordered by boarding date. Figure 2 describes the algorithm for alighting estimation. In accordance:

1. Collect a new transaction T_n from passenger *s*, on set $\{T_1, T_2, \cdots, T_n\}$, where *n* is the transaction index.
2. If T_n has alighting stop, skip for step 1, to collect a new transaction. Otherwise, skip for step 3.
3. If T_n is the sole transaction in 24 hours, then skip for step 8, otherwise continue to step 4.
4. If the boarding stop of T_n is a terminal and principle β_1 is enabled, skip for step 5. Otherwise, step 6.

5. Invert route direction. The alighting stop is searched on the opposite route direction. Continue for step 7.
6. If T_n is the last transaction, in 24 hours, then skip for step 9, otherwise continue to step 7.
7. Estimate an alighting stop for T_n nearest to the boarding of T_{n+1} . Then continue to step 11.
8. If β_2 is enabled, then skip for step 7. Otherwise, continue to step 11 (alighting stop is not estimated).
9. Estimate the alighting stop of T_n nearest to the boarding of T_f, where *f* is the index of the first transaction of the day. Continue to step 10. The distance is calculated based on the roadmap or approximated using Manhattan distance between coordinates.
10. If it was assigned an alighting stop to T_n, then continue to step 11, otherwise skip for step 8.
11. If there are more transactions, continue to step 1, otherwise the algorithm ends.

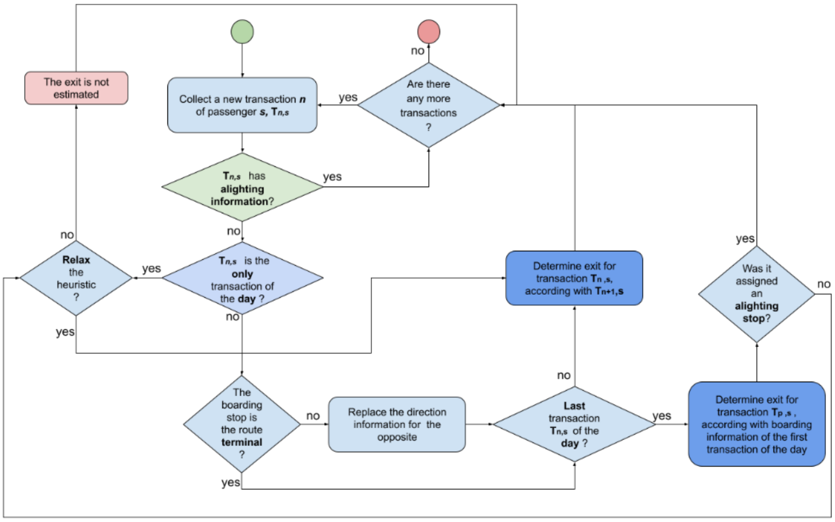

Figure 2: Flowchart explaining the alighting inference algorithm.

3.5. Validation

Validating the model outcome becomes an impractical task when there isn't available labeled dataset with ground-truth or an external dataset to compare. Therefore, the solution holds on success indicators. Since the major principles for trip chaining are based on the proximity between consecutive transactions, the most reasonable indicator is the transactions' percentage with a distance to the next transaction lower than a given threshold. For simplification, this threshold will be called Walking Distance. As mentioned in section 3.2.2, Model III and VI must be meticulously assessed, and for this reason, Section 4 will also address the impact of the Cross-Day Chaining threshold. Ultimately, this work proposes a novel and robust statistic that assigns a confidence score to each alight stop. This score is explored on the most accurate model. This score considers both indicators, the Walking Distance (*w*) and the Cross-Day Chaining (*b*) in accordance with the following equation:

$$s(w,b) = \begin{cases} 1, & if\ w \le minWd\ and\ b \ge maxCD \\ \frac{maxWD-w}{maxWD-minWD}, & if\ b \ge maxCD\ and\ minWD < w \le maxWD \\ 0.5\left(\frac{maxWD-w}{maxWD-minWD} + \frac{b-minCD}{maxCD-minCD}\right), & if\ minWD < w \le maxWD\ and\ minCD \le b < maxCD \\ 0, & otherwise \end{cases} \quad (1)$$

where [minWD , maxWD] and [minCD , maxCD] are the adopted ranges for the walking distance and Cross-Day Chaining values in order to assign a score between 0 and 1, where high values indicate that the alight stop was inferred with high confidence, and lower values otherwise. Grounded on previously collected empirical evidence (Nunes et al. 2015, Alsger et al. 2016, Hora et al. 2017, Lee et al. 2021), we assign the default values of 200 and 1000 meters for minWD and maxWD variables respectively, and 500 and 2000 meters for minCD and maxCD variables respectively.

3.6. Data acquisition and consolidation

The research counts with public traffic data from Lisbon city, from the principal public bus network and subway, called CARRIS and METRO, respectively. Both datasets were gathered by the city council in close cooperation with public operators: 44 million public traffic transactions, from October 2019, whose 33 million are from the subway operator, and 11 million are from the bus operator. The principles herein in the study are applied over the bus transactions, whose alighting information is missing. Strategically, it is used a portion of the subway dataset (about 19 million transactions), comprising only users that traveled in bus and metro operators. Employing the remaining data would be useless and add processing time and space into the algorithm. The dataset with metro smart card data includes route description, boarding and alighting features such the locations and timestamp. Meanwhile, the bus dataset has boarding information and complete route description specifying the code, orientation and route variant. Besides, we suggest other optimization measures that were implemented under python language conventions. Firstly, the stops and routes features are kept in a dictionary object, which is the most efficient data structure for retrieving. Secondly, the model avoids intense SQL calls to the database. Third, it is built, iteratively, a dictionary for each card identifier, storing the respective traffic transactions, ordered chronologically by boarding timestamp.

4. Results

All available smart card transactions, i.e. 11 360 894 bus transactions, are considered for the target imputation of alighting information. The first models I, II, III required 60 to 80 minutes to conclude the inference task, meanwhile the remaining took each 100 to 120 minutes. As a measure to read the accuracy of each model, it is considered the percentage of trips that fulfil the constraint criteria. Table 3 summarizes the results of each model against the walking distance constraint (ranging from 500 to 1500 meters) and Table 4 shows the results of Model VI considering the Cross-Day Chaining threshold. The last row on both tables show the absolute amount and percentage of sole trips made on 24 hour period, without alighting information. Ultimately, Figure 3 shows the distribution of confidence score (assigned to each alighting stop estimated), on the outcome of best model and parameterization from previous results (Model VI).

4.2. Sensitive Analysis on the walking distance constraint

Table 3 shows evidence that the accuracy is higher when the walking distance threshold and model complexity increases. Specifically, by comparing the baseline architectures (models I and IV), it is clear that the multimodal model outperforms the unimodal, with a higher increase of 11.06 pp (when the threshold constraint is marked on the 1000 meters). Additionally, Model IV halves the percentage of unique transactions without alighting information. Indeed, the overall results show that the integration of other modes boosts the models' performance. This event is explained by the algorithm's dependence on the traceability of the passenger's path.

		Unimodal			**Multimodal**		
Walking Distance	**Model description**	**Model I**	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**
	Data amount	11 360 894 input transaction without alighting stop					
≤ 500	Absolute amount	6 534 101	6 807 503	7 499 145	7 687 683	8 011 982	8 501 078
	Accuracy %	**57.51%**	**59.92%**	**66.00%**	**67.76%**	**70.52%**	**74.83%**
≤ 1000	Absolute amount	7 131 522	7 425 289	8 254 418	8 387 749	8 737 664	9 326 987
	Accuracy %	**62.77%**	**65.36%**	**72.65%**	**73.83%**	**76.91%**	**82.10%**
≤ 1500	Absolute amount	7 435 603	7 739 820	9 602 666	8 668 542	9 029 649	9 622 791
	Accuracy %	**65.47%**	**68.15%**	**75.72%**	**76.31%**	**79.51%**	**84.70%**
Sole transactions on the day without alighting information		2 400 676 21.13%	2 400 676 21.13%	1 752 377 15.42%	1 268 153 11.16%	1 268 153 11.16%	871 684 7.67%

Table 3: Results from sensitive analysis on the Walking Distance threshold.

The inclusion of both β1 and β2 principles yield a notable positive impact in both categories, unimodal and multimodal. Observing Table 3 and fixing the row with a threshold mark at 1000 meters, model IV guarantees a 73.83% accuracy and the following model V outperform it with 3.1pp. Considering walking distance $\leq 1000m$, model VI is the one with highest performance, increasing 5.19pp against model V. Additionally, the percentage of unique trip decreases between model V and VI, because principle β2 infers an alight stop by chaining with next transaction of the following days (augmented chaining window).

4.3. Sensitive Analysis on the Cross-Day Chaining *constraint*

As mentioned in Section 3, Cross-Day Chaining constraint avoids consecutive boarding within a distance lower than a given threshold. Table 4 ranges the Cross-Day Chaining threshold against the model VI. As expected, by augmenting the threshold, the model accuracy decreases. When the walking distance threshold is lower than 1000 meters and the Cross-Day Chaining is higher than 500 meters, the accuracy achieves 82.10%, meanwhile when the Cross-Day Chaining constraint increases to 2000 meters, then the accuracy reaches the lower value of 79.23%. Choosing a conservative parameterization reduces the error margin of mislabeling and consequently, lowers the accuracy. However, even with these conditions, the accuracy percentage is still higher than the previous models. For instance, if the Cross-Day Chaining threshold is settled at 2000 meters and the walking distance threshold at 1000 meters, the accuracy is 79.23%, outperforming the previous model V (76.91% accuracy at same walking distance). For this reason, it is suggested to be conservative on the parameterization in order to avoid jeopardizing operator's planning based on mislabeled alighting data.

		Model VI			
Walking Distance threshold	**Cross-Day Chaining threshold**	**CD > 500**	**CD > 1000**	**CD > 1500**	**CD > 2000**
≤ 500	Absolute amount	8 501 078	8 388 644	8 305 949	8 244 601
	Accuracy %	**74.83%**	**73.84%**	**73.11%**	**72.57%**
≤ 1000	Absolute amount	9 326 987	9 173 588	9 072 809	9 001 236
	Accuracy %	**82.10%**	**80.74%**	**79.86%**	**79.23%**
≤ 1500	Absolute amount	9 622 791	9 463 974	9 080 762	9 010 325
	Accuracy %	**84.70%**	**83.30%**	**79.93%**	**79.31%**
Sole transactions on the day without alighting information		1 268 153 11.16%	979 335 8.62%	1 044 066 9.19%	1 090 645 9.6%

Table 4: Results from sensitive analysis on Cross-Day (CD) Chaining threshold and Walking Distance threshold.

Finally, Figure 3 plots the distribution of confidence scores assigned to the inferring alighting stops by model VI, assigned using equation 1 (Validation section). These results are valuable information to indicate the overall performance of the model. Around 10 million transactions were assigned to an alighting stop, and the majority (71,56% of transactions) have a confidence score higher than 80%.

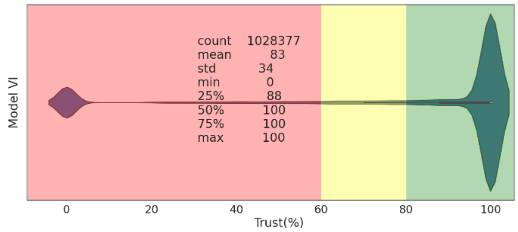

Figure 3: Distribution of confidence score on model VI

5. Concluding remarks

The gathered research outcomes shed light on pivotal issues to the alighting stop inference task, necessary for public transport planning and travel behaviour analysis in the presence of incomplete AFC systems. In particular, this work provides a critical point of view on the state-of-the-art principles; tailors models in the presence of multimodal traffic data; improves the success rate considering the specifics of situational and contextual data; and suggests practical optimization on the data processing to handle large amounts of data. The SWOT analysis and the measured impact assessment of each state-of-the-art principles revealed important weaknesses on the existing methods to handle less-trivial passenger behaviour. For this reason, new principles were suggested, including a novel parameterization in order to avoid inference errors. Moreover, to the best of our knowledge, this is the former research study with cross-modal comparisons of OD estimation principles, as well as the first comprehensive study of the alight stop predictability in the Lisbon public transport system. We expect to extend the research and conducted analysis to transport systems in other European cities. Amongst other ends, the highlighted contributions are essential to improve the quality of (multimodal) OD matrix inference, a pivotal task to respond to the ongoing traffic demand changes along time, particularly important throughout the current pandemic times.

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