Travel time estimation in public transportation using bus location data

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Abstract. The user experience of passengers using public transportation is highly sensitive to travel time. In this regard, travel time is a key input to assess the quality of service offered by a public transportation system and to compute performance and service-level metrics. Moreover, travel time is needed to evaluate the accessibility to different opportunities in the city (e.g., employment, commercial activities, education) that can be reached using public transportation. This article presents a data analysis approach to estimate in-vehicle travel time in public transportation systems. Vehicle location data, bus stops locations, bus lines routes, and timetables from the public transportation system in Montevideo, Uruguay, are considered in the case study used to evaluate the proposed approach. Results are compared against scheduled timetables and are used to compute several performance indicators of the public transportation system of the city.

Keywords: travel time, public transportation, data analysis, GPS data

1 Introduction

In urban scenarios, citizens are required to travel in order to engage in the social and economic activities of their city [3]. In this context, public transportation plays a major role, since it is the most efficient and socially-fair mean of transportation [7]. Understanding the accessibility of citizens to the public transportation service of a city is paramount in order to identify inequalities among the population and implement policies that aim at improving the quality of service offered to passengers. Several indicators may be considered to measure the accessibility offered by a transportation system, among them, travel time strikes as the most intuitive one, since it is tightly related to the perception of passengers of the quality of service of a transportation system [17].

Public transportation systems operate on predefined routes and depend on schedules that vary throughout the day. Additionally, travel speeds vary greatly due to traffic congestion, passenger demand, and road infrastructure. Thus, assuming constant speed of vehicles along routes usually results in significant travel time differences between the estimations of the model and the actual reality. A comprehensive model for travel time estimation in public transportation networks needs to account for all these factors.

This article presents a model to estimate in-vehicle travel times in public transportation systems. The proposed model applies a data analysis approach [12] incorporating real vehicle location data from on-board GPS units as well as open data regarding the public transportation lines and bus stops. The public transportation system in Montevideo, Uruguay, is used as a case study. For the studied scenario, the difference between the estimated travel times and those available in the public timetables are reported. Furthermore, relevant metrics to assess the quality of service of public transportation systems are computed. Results indicate that the proposed approach is suitable to accurately estimate in-vehicle travel times in the city. The applied methodology is also useful to detect situations that prevent users from having a good quality of experience when using the public transportation system, which should be the focus of further studies by the city administration.

The remainder of the paper is organized as follows. Section 2 gives an overview of the topic and the context for this study. Section 3 reviews works in the related literature. Section 4 outlines the proposed methodology for travel time estimation. The application to the case study is presented in Section 5 and the conclusions and future work are presented in Section 6.

2 Characterizing travel times of the public transportation system

In the context of the research project that studies the territorial, universal, and sustainable accessibility in Montevideo, Uruguay, one of the most relevant tasks is the characterization and analysis of the public transportation system. In this regard, accessibility and quality of service provided by the public transportation system is a very important issue that can significantly affect vulnerable groups in society. A proper analysis of public transportation allows conceiving and applying sustainable mobility strategies (e.g., including electric mobility options and other alternatives for non-polluting means of transportation).

For studying accessibility, it is crucial to compute relevant indicators that allow determining the impact and availability of different means of transportation. Travel time using the public transportation system is a relevant indicator that assess how long it takes [a citizen] to make a trip using the public transportation system, and it is also considered as an indicator of mobility, defined as "the ease of traveling between locations within a community" [2]. The travel time metric is not only valuable as a subjective indicator, i.e., related to the user-experience of passengers of the public transportation system, but is also meaningful to determine the quality of service of any given bus route or the system as a whole. Furthermore, travel time also allows computing comparative indicators, such as the additional travel time required over an automobile making the same trip, as defined by the Transportation Research Board [1], and other metrics of route directness. Travel time is also useful to determine the reliability of the public transportation system, defined as "the ability of the transit system to adhere to schedule or maintain regular headways and consistent travel times" [18].

In order to quantify the provision of the public transportation system, the problem studied in this article consists in estimating in-vehicle travel times at each stop along the routes of the bus lines in the system. Travel times can be estimated from the (fixed) schedules established by the city administration for the different bus lines in the city, providing a static view of mobility and accessibility. Complementing this approach, this article proposes using real GPS data of the buses from the Metropolitan Transport System of Montevideo and open data providing information about the existing infrastructure for public transportation in the city (e.g., bus stops, bus lines). These sources of data allow characterizing the mobility offered by the transportation system and its accessibility, to complement the use of fixed information that may not accurately reflect reality.

3 Related works

Lei and Church presented a short review on measuring the accessibility in public transportation systems [11]. The survey showed that several authors focus on the physical aspects of a system (e.g., distance to a bus stop) instead of focusing on the travel time between pairs of locations. Furthermore, previous works which do focus on travel times usually make assumptions which significantly impact the accuracy of their estimations, e.g., constant transfer and waiting times, average speed of vehicles, or not considering bus schedules at all. The authors propose an extended GIS data structure to account for the temporal dimension of public transportation systems which is applied to the public transportation system in Santa Barbara, California.

Salonen and Toivonen presented a comparison of different travel time measures [17]. The work covers both travel times using private vehicles and public transportation. Regarding the latter, three models are outlined and applied to a case study in the capital region of Finland: a simple model which does not include vehicle schedule information at all, an intermediate model which uses schedules only to estimate the average waiting time, and an advanced model which queries a government API with up-to-date schedules and uses its routing engine as a black-box to compute travel times. The proposed models identified travel time disparities accross modes (i.e., private vs. public transportation), with a lower effect in areas near the city center.

Previous works have addressed the public transportation system in Montevideo, Uruguay, which is used as a case study in this article. Massobrio and Nesmachnow proposed an urban data analysis approach to understand mobility in the city using different sources of urban data [12]. Origin-destination matrices, which describe mobility, were built using ticket sales data. Other studies have measured the quality of service offered by the public transportation service in Montevideo, by analyzing punctuality based on GPS bus location data [13, 14].

Hernández et al. studied accessibility to employment opportunities in Montevideo, Uruguay [8]. For this purpose, the authors built a travel time matrix using the scheduled timetables for bus lines in the city. The methodology proposed by the authors models the public transport network as a graph, to compute travel times between different zones in the city. This model allows configuring the maximum walkable distance and the maximum number of transfers within the route. The computed travel time matrix was validated against a government web application and the results from a household mobility survey.

According to the review, few previous works have applied a systematic procedure to estimate travel times of public transportation in Montevideo, Uruguay. The model proposed in this article combines several sources of information including bus location data from on-board GPS units. Thus, the proposed approach extends the static approaches that only consider fixed timetables data when computing in-vehicle travel time by incorporating real data that reflect the reality of the buses operating throughout the network.

4 Methodology

This section outlines the methodology applied for data processing and analysis.

4.1 Data sources

One week of bus GPS location data were obtained, corresponding to buses operating from Monday 5^{th} to Sunday 11^{th} of August 2019. Records in the bus location dataset correspond to measures registered with the on-board GPS unit in each bus, which are sampled every 20-30 seconds. Each record in the dataset includes a bus line identifier, a unique trip identifier (to discriminate different trips of the same bus line), the scheduled departure time for the trip, GPS coordinates, and a timestamp. For this study, we aimed to compute travel times during the morning peak, so we considered only trips with scheduled departures on working days between 7.00 am and 9.00 am (inclusive) as reported in [12]. Some trips had corrupted records, with timestamps spreading for very long periods. For this purpose, we discarded all trips that lasted more than four hours, as they are not representative of bus line lengths in the city and they are very likely outliers. After this filtering, the bus location dataset held more than 2.8 million records, corresponding to 8224 trips of 258 different bus lines.

Bus stop location data were also used for the analysis. Open data from the local government were processed to obtain, for each bus line, the ordered set of bus stops it visits, with their locations. Another source of open data used for the analysis were the timetables for each bus line. Records hold the scheduled departure of each trip and the expected arrival time at each bus stop. The same filter was applied to consider only trips within the morning peak. Open data were obtained in July 2021, thus, some discrepancies appear when combining it with bus location data from 2019. For instance, some bus lines and bus stops were modified, schedules were updated, etc. We deal with these issues throughout the data analysis process described next.

4.2 Data processing

Each trip in the dataset is processed independently to compute in-vehicle travel times. The result of this processing is an ordered list of the time it takes from the first bus stop in the journey to each of the bus stops corresponding to the bus line of the trip. Vehicle location using GPS is prone to errors from a variety of sources, so several methodologies have been proposed to cope with this phenomena [10]. To address this issue we created a buffer on bus stops of 25 meters an all directions and discarded all measures falling outside these buffers. When processing the records of a given trip, the timestamp assigned to each bus stop is set as the timestamp of the earliest record that falls within the bus stop buffer. This applies to all bus stops except the first one in the journey, where the latest timestamp is selected, as buses usually turn on their GPS device before departing, thus multiple records fall within the first stop. In some cases, drivers forget to update the on-board machine at the end of the trip. As a consequence, the trip identification is kept for more than one trip (e.g., inbound and outbound consecutive trips of the same line). This issue was mitigated by adding a validity check ensuring that the time between consecutive measures assigned to stops needs to be smaller than 30 minutes. Additionally, integrity checks are made to ensure that timestamps and bus stop identifiers are increasing monotonically and the bus line and trip identifier is unchanged. If any assertion does not hold, the process of that trip is interrupted.

As a result of the previous processing, the proposed method computes travel times (measured from the first stop of the bus line) for each of the bus stops with a valid nearby GPS record. However, some of the bus stops of the bus line being processed may still have no travel time information. For bus stops located between other bus stops that already have assigned travel times, we interpolate the values based on the distance between the stops along the bus route. For bus stops at the start or end of the bus line with no travel time assigned, we extrapolate using the travel times offered in the timetable for that bus line.

4.3 Metrics

After computing the travel times between bus stops for every line in the public transportation system, a set of relevant metrics are considered in the analysis. These metrics focus on evaluating different features of the public transportation system. The studied metrics include:

- *Difference between scheduled and real travel time*: This metric evaluates the gap between the scheduled time and the actual travel time computed from GPS records. It is a very relevant metric to assess the punctuality of buses when arriving at each stop. The ideal value for this metric is zero, for a perfectly synchronized bus system.
- *Operational speed* (OS): This metric evaluates the average speed of buses when operating a route. Operational speed is defined as the length of a bus route divided by the average travel time required to perform a trip from the

beginning to the end of the route. Larger values of the operational speed indicate a more efficient transportation system. Related to this metric, in a recent article, Deng and Yang [4] introduced an holistic metric to evaluate the dispersion of the operational times for all bus lines in a public transportation system, i.e., dispersion OS (dOS). This metric is defined by $dOS = \max(OS_l) - OS_l$.
- *On-time arrival rate* (OTAR): This metric evaluates the number of trips performed without a significant delay, considering a predefined delay threshold (the *buffer time*). OTAR is defined as the ratio of buses arriving on time at the final stop over the total number of bus trips performed. The buffer time coefficient accounts for any unexpected delay during the trip. It is computed as the ratio of the difference between the 95^{th} percentile travel time and the average travel time, and the average travel time [6].
- *Additional travel time over automobile* (ATToA): This metric evaluates the directness of a bus route, by comparing the travel time required for performing a trip on the public transportation system over the time required using private transportation (automobile) that makes the same trip. Smaller values of this metric means a more direct route; thus, a most efficient transportation system [1].

5 Results and discussion

This section reports and discusses the main results and finding of the proposed analysis of the public transportation system in Montevideo, Uruguay.

5.1 Analysis of GPS records

Fig. 1 shows an example of the data processing methodology to assign GPS records to bus stops to compute in-vehicle travel times. The example corresponds to the final stops of bus line 306 from Parque Roosevelt (located in the east side of the city, in the border with Canelones department) to Casabó (a neighborhood in the west of Montevideo). Blue dots correspond to GPS measures and gray circles correspond to the buffered stops for the bus line. Bus stops with at least one GPS measure in their vicinity (i.e., at least one blue dot within the gray area) are assigned the timestamp of the earliest of those GPS measures. Bus stops with no GPS measures in their vicinity are assigned a timestamp by interpolating the timestamps of the previous and next bus stops with matching GPS records and taking into account the distance between those stops along the route of the bus. This case is shown in yellow in the figure. Finally, the last four stops (shown in orange in the figure) have no matching GPS records. This happens on some trips when the driver turns off the on-board GPS unit prematurely, thus the end of the trip is not recorded. In this case, the travel time to reach each bus stop is extrapolated using the information available in the timetable for the bus line and the latest GPS timestamp assigned to a bus stop of the line.

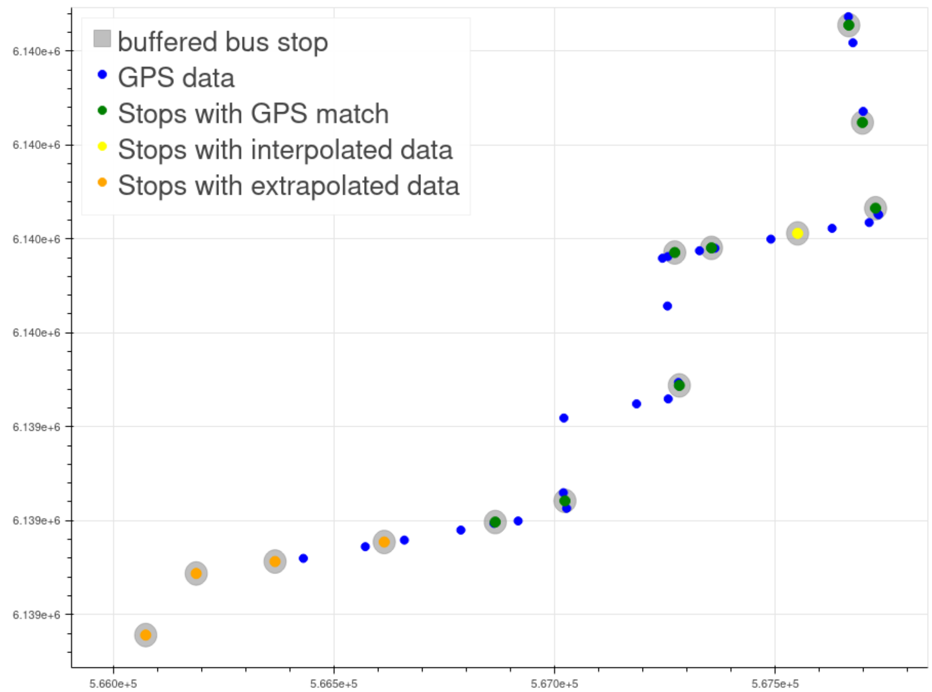


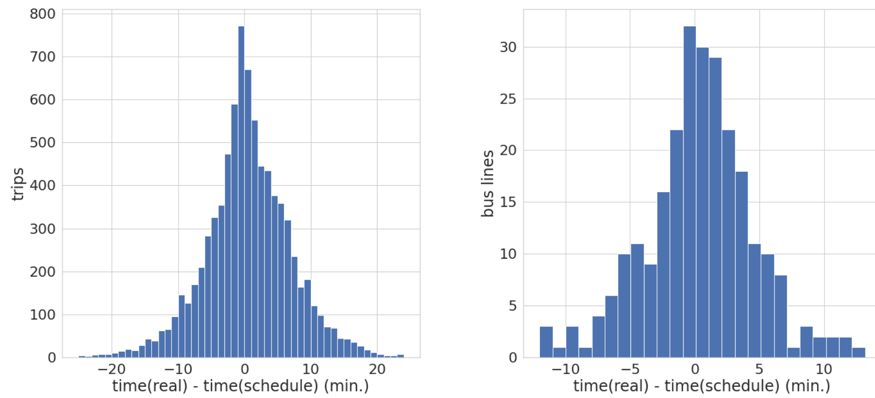
Fig. 1: Example of travel time assignment to bus stops at the end of line 306 from Parque Roosevelt to Casabó

As a result of the data processing, travel time estimations for 8 195 trips corresponding to 257 different bus lines were obtained. Overall, travel times of trips at each bus stop were estimated directly in 67.9% of the cases, when there was a matching GPS measure of the trip at the bus stop. In turn, 21.6% of travel times were interpolated based on nearby GPS measures and 10.5% were extrapolated using data from the available timetables.

5.2 Differences between scheduled and real travel times

The in-vehicle travel times estimated using bus location data can be compared against the scheduled timetables of the corresponding bus lines, to assess deviations from the scheduled times that may exist due to passenger demand, traffic congestion, and other external factors.

Fig. 2 presents histograms of the difference between the (estimated) real travel time and the scheduled travel time that appears on the timetable. Histogram in Fig. 2a corresponds to each independent trip in the studied dataset, whereas results in Fig. 2b correspond to the median difference in travel time of each bus line. Values greater than zero correspond to trips/lines where the total travel time was larger than the scheduled time whereas negative values indicate that the travel time was shorter than that indicated by the schedule.



(a) per trip (b) median value per line

Fig. 2: Histogram of difference between (estimated) real travel times and scheduled travel times

Results show that most trips adhere to their scheduled total travel time, with an average difference of half a minute with regards to the timetable. When looking at the 25^{th} and 75^{th} percentiles, the differences are of 3 an 4.4 minutes, respectively. These differences, while small, might affect passengers that may miss the bus and need to wait for a full headway for the next bus of the line and is specially significant for travelers transferring between different bus lines. Extreme values of trips arriving 30 minutes before the scheduled time and 37 minutes after the scheduled time were found, which might be useful to detect special events taking place along the route of those bus lines. When looking at the median differences of trips grouped by bus lines (Fig. 2b) it can be observed that, while most lines are consistent to their scheduled total travel time, some bus lines have significant differences with their schedules. On one extreme, line 137 from Paso de la Arena arrives to its destination in Plaza de los Treinta y Tres 12 minutes (in median) before its scheduled time. In contrast, line L1, a short local line that connects Paso de la Arena with Pajas Blancas arrives (in median) 13 minutes after its scheduled time.

Besides looking at overall differences in travel times among the trips and bus lines in the system, travel times of specific trips can be analyzed. Fig. 3 shows the difference between the estimated travel time and the scheduled travel time at each bus stop of a trip of bus line 185, a bus line that travels through several neighborhoods of Montevideo going from Casabó to Pocitos. The same information is displayed in Fig. 4 using the bus stop location and the street map of the city. Each bus stop in the figure is colored according to the absolute difference between the estimated travel time to reach the bus stop and the scheduled time.

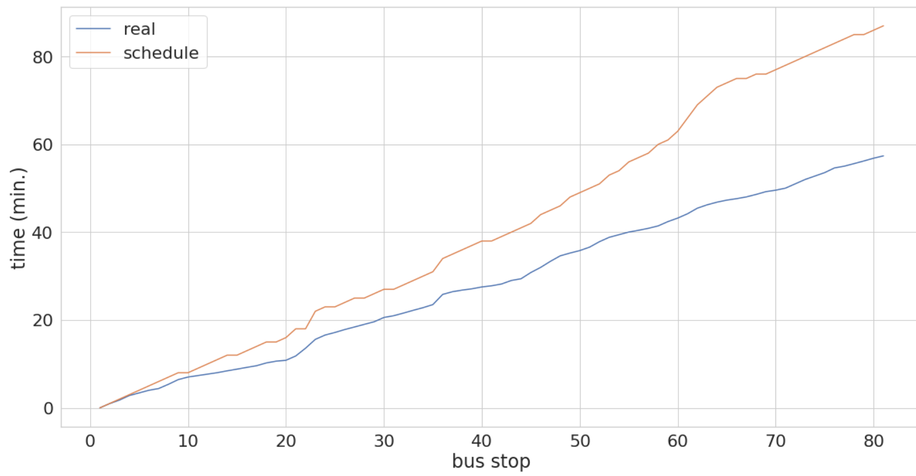


Fig. 3: Real (estimated) vs. scheduled travel time of a trip of bus line 185 from Casabó to Pocitos

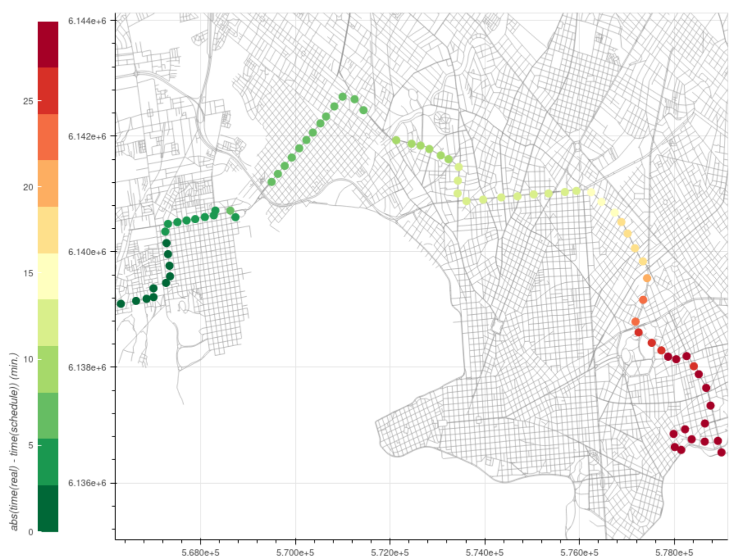


Fig. 4: Absolute difference of estimated and scheduled travel times of a trip of bus line 185 from Casabó to Pocitos

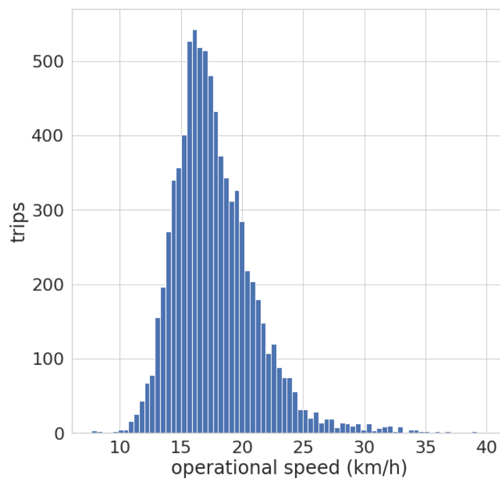
In the studied example, the trip of line 185 is, on average over all stops, 12 minutes ahead of its schedule. The difference increases along the route, reaching its maximum at the last stop, where the bus arrives nearly 30 minutes ahead of its schedule. The average headway of this bus line for the morning peak considered is 5 minutes. Thus, in this case, a severe case of bus bunching occurs, which is detrimental to the quality of service and reliability offered to citizens.

5.3 Operational speed

Several indicators can be computed using the estimated travel times as input. Among these, the operational speed is very useful to transport operators and authorities. Fig. 5 outlines the results of computing the operational speed for all trips in the studied dataset. Descriptive statistics are outlined in Fig. 5(a) and a boxplot of the operational speed is presented in Fig. 5(b). Results are expressed in km/h.

indicator	*operational speed*
count	8195.00
mean	17.77
std. deviation	3.41
minimum	7.70
25% percentile	15.54
50% percentile	17.22
75% percentile	19.54
maximum	40.06

(a) Indicators



(b) Histogram

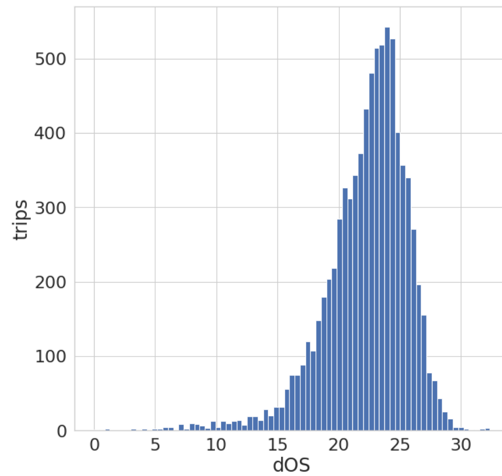
Fig. 5: Descriptive statistics of operational speed

Results in Fig. 5 show that the average operational speed for all trips in the studied dataset is 17.77 km/h. This result is consistent with performance indicators published by local authorities corresponding to the year 2018 (www.montevideo.gub.uy/observatorio-de-movilidad, October 2021). The largest operational speed (40 km/h) is achieved by a trip of line L13, which operates on the outskirts of the city. The slowest operational speed (7.7 km/h) corresponds to a trip of line L31, a short local line. This particular trip took almost 17 minutes to complete the nearly 2 km of the bus line. Short local lines have the higher dispersion regarding operational speed. The median of operational speed (17.22 km/h) corresponds to a trip of line 105 from Parque Roosevelt (in the east of the city) to Plaza Independencia in the city center. This is a very long bus line, with a total route length of over 21 kms. In this specific trip, the total length of the route was covered in nearly one hour and fifteen minutes.

In turn, the dispersion of the operational speed (dOS) is outlined in Fig. 6. Descriptive statistics are reported in Fig. 6(a) and the distribution of results is shown in the histogram of Fig. 6(b).

indicator	*dOS*
count	8195.00
mean	22.29
std. deviation	3.41
minimum	0.00
25% percentile	20.52
50% percentile	22.84
75% percentile	24.52
maximum	32.36

(a) Indicators



(b) Histogram

Fig. 6: Descriptive statistics of OS dispersion

The dOS metric results indicate that most lines have a large dispersion of OS values, with a mean of 22.29 km/h. This result is mainly conditioned by the extreme values of the OS metric for short local lines, which account for both the maximum and minimum values of OS, as reported in the previous analysis.

5.4 On-time arrival rate

The calculation of the OTAR metric requires computing the buffer time, i.e. the coefficient that defines the acceptable delay threshold for completing a trip, with respect to the scheduled time. Table 1 outlines descriptive statistics for the buffer coefficients of the bus lines of the studied scenario. According to the computed results, the average value for acceptable delay is 11%.

indicator	*buffer coefficient*
count	257.00
mean	0.11
std. deviation	0.06
minimum	0.00
25% percentile	0.08
50% percentile	0.11
75% percentile	0.15
maximum	0.38

Table 1: Descriptive statistics of buffer coefficients for on-time arrival rate

After determining the buffer coefficients, the OTAR metric was computed for each of the bus lines in the considered scenario. Results are shown in the histogram in Fig. 7.

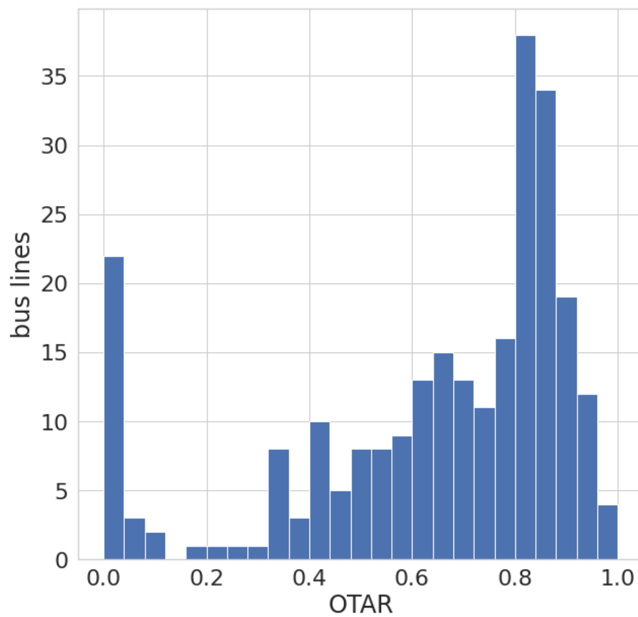


Fig. 7: Histogram of on-time arrival rate for bus lines

Results in Fig. 7 indicate that the average OTAR among all bus lines in the studied scenario is 0.64, with a standard deviation of 0.27. The histogram allows identifying a large number of bus lines with an OTAR value of 0.0. In these cases, none of the trips of a given bus line completed their journey within their scheduled time (even considering the time tolerance). In these extreme cases, authorities should review the predefined schedules and modify them to reflect the real operation times. These results confirm the usefulness of the proposed approach to detect anomalous situations in the public transportation system.

5.5 Additional travel time over automobile (ATToA)

The heatmap in Fig. 8 reports the values of the ATToA metric for bus line 185. Bus line 185 has a higher-than-average operational speed, considering all bus lines in the city. The analysis is representative of those performed for other 'fast' bus lines in the city. Results correspond to the ATToA values computed from/to 17 (regularly spaced) stops along the route. Travel times in automobile were computed using the API provided by Google Maps.

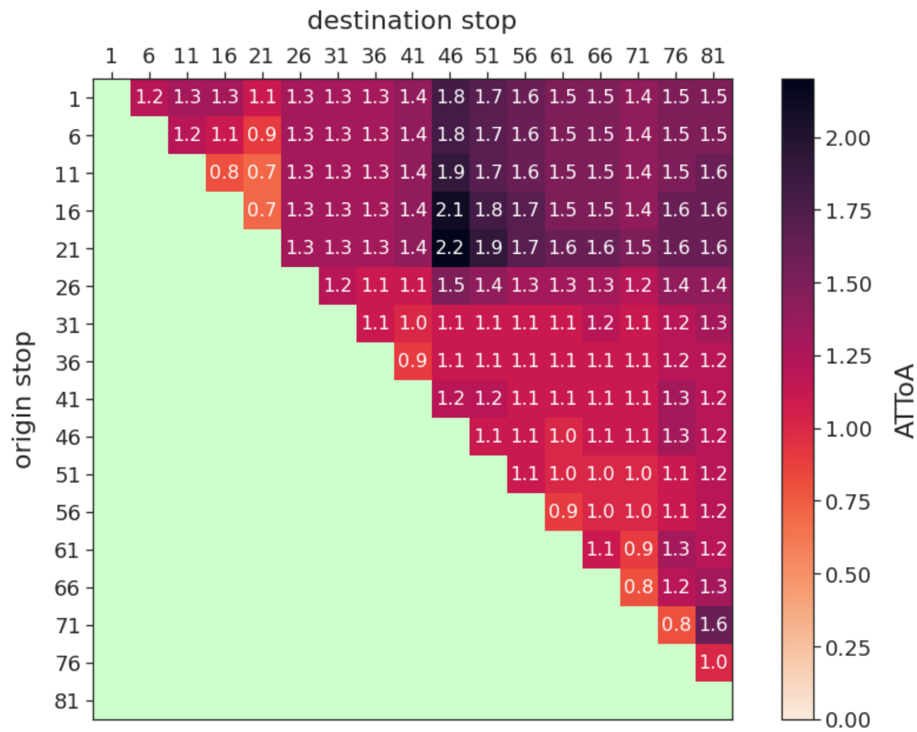


Fig. 8: Additional travel time over automobile (ATToA) of a trip of bus line 185 from Casabó to Pocitos

Results in Fig. 8 allow observing an almost regular pattern: the bus is very (time-wise) efficient for traveling between nearby stops, as demonstrated by ATToA values lower than 1.0, meaning that bus is faster than automobile in those cases. Values slightly increase for longer trips, up to reasonable 1.5× to 1.6× additional time factors. The only exceptions are for bus stop #46, for which the ATToA values are closer to 2.0 (and a worst value of 2.2 was computed for a trip with origin on stop #21). Two main reasons explain this result: between stops #21 and #46 the bus route has a big detour, which impacts on route directness, whereas the fastest way is traveling using automobile via a direct avenue (Bv. Artigas). Furthermore, bus stop #46 is located after a long red light that allows buses to turn left towards Bv. Artigas. Despite the reported delay, the bus line manages to recover a normal operational speed, as ATToA values after bus stop #46 reduce to a reasonable 1.6× additional time factor.

Overall, reported ATToA values are similar to the ones reported for other bus networks in similar cities (e.g., Stockholm, Sweden and Amsterdam, the Netherlands), and lower than values reported for larger cities such as São Paulo, Brazil and Sydney, Australia, for which average values up to 2.6× longer than driving a car have been reported [17].

6 Conclusions and future work

This article presented a data analysis approach to estimate in-vehicle travel time in public transportation systems, using GPS bus location data and several other sources of open data regarding the system infrastructure. The public transportation system in Montevideo, Uruguay, was used as a case study. A specific data analysis methodology is presented and then applied to one week of GPS bus location data comprised of over 2.8 million records corresponding to the morning peak hours. Estimated travel times were obtained for over 8 000 trips, corresponding to 257 different bus lines. These travel times were used as input to compute several relevant metrics, focused on evaluating different features of the public transportation system, including: i) differences against scheduled timetables, ii) operational speed, iii) on-time arrival rate, and iv) additional travel time over automobile. Computed metrics are a useful input for operators to evaluate the reliability of the transportation system and are relevant to policy-makers aiming to improve the quality of service offered to citizens.

The main lines of future work focus on improving the analysis and applying the computed results to solve relevant problems regarding public transportation in the case study considered. Regarding the first line, the data analysis process could be further improved by considering data from different peak and non-peak hours, as well as weekends, and by processing larger amounts of historical data. For the latter, parallel computing strategies should be devised to deal with the increased computational burden. Regarding the application of the computed travel times and indicators, several relevant lines are planned for future work, including bus timetable synchronization [15, 16], bus network redesign [5], sustainable mobility plans [9], and assessing accessibility using public transportation to different opportunities in the city. For this last application, a specific line of work is to extend the model presented in our previous work [8], which only used scheduled timetables, and incorporate the estimated (real) in-vehicle travel times to further refine the accessibility metric.

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