Efficient Use of Geographical Information Systems for Improving Transport Mode Classification

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***Abstract*—Comparison between transport mode classifiers is usually performed without considering imbalanced samples in the dataset. This problem makes performance rates, such as accuracy and precision, not enough to report the performance of a classifier because they represent a cut-off point in the classifier performance curve. Our rule-based method proposes to combine both, the network elements associated with the transport mode to identify, and the elements associated with other means of transport. We performed a comparison between our proposed method and another geospatial rule-based method, by applying a real-world representative dataset with a target class imbalance. We evaluated the performance of both methods with five experiments, using the area under the Receiver Operating Characteristic curve as metric. The results show that the tested methods achieve the same false positive rate. However, our method identifies correctly 84% of the true positive samples, i.e., the highest performance in our test data (data collected in Belgium). The proposed method can be used as a part of the post-processing chain in transport data to perform transport and traffic analytics in smart cities.**

***Keywords*–Transport mode classification; Crowdsourcing; Tracking data; Receiver operating characteristic.**

I. Introduction

Mobility surveys are carried out around the world with the purpose of discovering the behavior of citizens according to the transport mode [1]. Knowing the demand for transport services helps cities to manage and improve their transportation systems. Different strategies, such as questionnaires, interviews or space-time diaries have been used to collect travel data in the past. With the advent of smart-phones, that integrate sensors, such as Global Positioning System (GPS) receivers, crowdsourcing has come to the scene as a new tool to gather mobility data, either using a travel diary app or as a background location-aware service. Hence, automatic public-transport classification becomes the key element to capture user's activity patterns as well as to perform transport and traffic analytics.

Therefore, the identification of public transport modes has become an active research area [2]. For instance, Transmob project [3] provided users with mobility cards as a single payment method to pay bus, tram, subway and train tickets, parking at garages or streets, and shared bike rentals. M-card10 [4] is a smartphone application of De Lijn, the Flemish bus agency, in which commuters can buy up to 10 public transport tickets. The app activates a ticket when getting on a bus or a tram. These ticket-based systems provide information for automatic public transport mode detection. However, users must generate events, check-in and check-out, to identify each mode accurately. Live positioning systems [5][6] take advantage of the capabilities of Geographical Information Systems (GIS) to perform transport-mode classification on tracking data collected through cell phones. Such systems require the integration of tracking data with open access or proprietary GIS layers for generating geospatial data to discover new knowledge.

In several studies, GPS data is used because of the temporal aspects, accurate information about travels and geographical aspects when it is combined with GIS data, such as Open Street Map (OSM) transport network [5][7]–[9]. These studies are aimed to identify transport mode using a rule-based approach. A common factor among those methods is to use network elements related to the transport mode for the automatic transport mode identification, e.g., train segments will only cross railways and train stations. In this paper, we named these kind of elements as Passing Points (PP). Our approach for transport mode classification also considers traffic network elements that do not belong to the transport mode to be identified. We called these elements Non Passing Points (NPP).

Usually, researchers focus only on reporting the success rates of their proposed systems. However, when a representative dataset is used, real case scenarios, this is typically an unbalanced classification problem where it is easy to classify a sample as non-class to get a high accuracy and precision [10]. Hence, we focus on the true positive rate to report our outcomes. Our method performs transport mode classification (e.g., train) using the network elements associated with the transport mode to identify (e.g., train stations and railways), but we also consider elements associated with other means of transport (e.g., motorway junctions) to filter out false positive trip segments. In this paper, we perform a comparison between an improved version of our methodology [6] and the work described by Gong et al. [5]. We evaluated both techniques by applying them on an extensive labeled dataset collected during a mobility campaign. Results show that the probability of falsely rejecting train trips decrease when Non Passing Points are considered into the method.

The remainder of the paper is organized as follows. In Section 2, we present an overview of the works that use the transport network information, and position our approach related to the state-of-the-art. In Section 3, we describe the methodology used to compare the tested methods. In Section 4, we explain the evaluation process used to compare the tested methods. Furthermore, in Section 5, we perform experiments with the tested techniques, followed by the results and discussion at Section 6. The final section includes the concluding remarks.

II. GPS AND GIS TRANSPORT MODE CLASSIFICATION

Nowadays, mobility survey studies are carried on with GPS technology. Transport and traffic analytics require that GPS raw data are post-processed to identify transport modes. Some studies follow a fuzzy logic approach to carry on this task. The study by Schüssler et al. [11] combines GPS data as well as accelerometer data and the locations of public transport stops to derive stage start and end times and transportation modes. They report an accuracy of 92.5%. The study by Rasmussen et al. [12] implemented a three stage method which combines GIS rules and fuzzy logic. The method to identify rail trips was very efficient; however, there are two differences among our studies. First, they use a small dataset to test their method while our is bigger and follows an official statistics distribution. Finally, a dedicated GPS device was used by them during the data collection while in our case data was gathered through crowdsourcing using smartphones, so the resolution and the quality data are different [13]. The study by Biljecki et al. [14] used geographical data to calculate some indicators, such as the proximity of the trajectory to the network to perform the classification of single-mode segments. The accuracy of their method is 91.6%, however they do not report the accuracy by each transport mode.

Another alternative are the rule-based approaches where spatial operations are used for filtering out trip segments that do not correspond to the target transport mode to identify. They can achieve similar results compared to machine learning approaches [15]. The study by Stopher et al. [8] used the contextual information from the user (e.g., if the household has any bicycles), or from the transport network (e.g., most bus stops are located midway along blocks) to build a probability matrix to determine if the user is walking, biking or driving. Then, motorized vehicle trips are identified using street and public transport GIS layers using an elimination process looking for what happens before and after the trip segment analyzed (e.g., public transport trips usually are among walking trips). This study used a dedicated GPS device. Data logging was sporadic in buses or it was non-existent in trains. They classified a segment as a train segment when the starting and/or ending point was on a railway. They do not report the accuracy per transport mode however they report an overall success rate of about 95%. Bohte and Maat [9] also use a similar approach comparing the starting and ending points of a trip against the locations of train stations of the rail network however they apply more rules to these points under the assumption that a train trip take place between the two trips. They report a success rate 34% for train trip classification.

Gong et al. [5] developed a rule-based methodology to identify five transport modes (walk, subway, rail, car and bus). This study was carried in New York city, using a dedicated GPS device. They report the best success rate (35.7%) for train trip classification to the best of our knowledge. Therefore, we will perform a comparison with this method. Our studies have some similarities and differences. The study by Gong et al. was applied over a small dataset which contains data generated by 63 volunteers in one week while our was applied to a large crowdsourcing dataset; however, both dataset are made of multimodal trips. Our studies differ in the data collection method, they used a dedicated GPS device while we used cellphone devices. Regarding to the techniques, both use train station elements from a GIS layer for classifying transport mode of GPS segments likewise the previous studies mentioned, but only both use railway elements to determine alignment between GPS points and the rail network. Our technique exploits traffic network elements that belong to others transport network to improve the elimination process, i.e., those segments that cross elements, such as motorway junctions and train stations will be excluded.

III. METHODOLOGY

This paper presents a comparison among two rule-based methods that perform transport mode classification using GPS and GIS data.

Gong et al. [5] classifies four transport modes: bus, car, foot and train. However, we modified the output to focus only on train classification. This method uses five rules to identify walking segments, four rules to identify train segments, and finally four rules to classify bus and car segments. This method uses rail stations and rail links to establish whether the GPS points that belong to a trip segment follow the railway or not. The rules used to detect train trips in this study are listed as follows:

1) Distance from first point of trip segment to the nearest subway entrance <100 m or to the nearest commuter rail station <200 m; or distance from first point of trip segment to nearest subway or commuter rail link endpoint <200 m
2) Distance from last point of trip segment to nearest subway entrance <100 m or to the nearest commuter rail station <200 m; or distance from last point of trip segment to nearest subway link endpoint <200 m
3) Distance from each point of trip segment to nearest subway or commuter rail link <60 m
4) If possibly elevated train, then distance from each stopped point to nearest subway station <184 m or to the nearest commuter rail station <311m

In our work, the transport mode classification is performed based on the assumption that a train trip segment is a trip segment which along its path includes at least one train station, follows the railway and does not include other transport network elements, such as motorway junctions. We use a set of rules to filter out all those trips that do not comply with these characteristics.

First, we smoothed the segments using a speed-based filter to filtered out GPS point with high speed. We used 300 km/h as threshold due to the high-speed trains that uses part of the railway network. Second, we extracted Passing Points, such as train stations and railways, and Non-Passing Points, such as motorway junctions, from OSM. Then, Non-Passing elements that intercept with Passing elements were excluded (e.g., using a 100 meters buffer around railways, we excluded motorway junctions which were close to railways). Third, we performed spatial operations to filter out non train segments. The smoothed trip segments were intercepted with train station buffers to keep segments which cross train stations. The remaining segments were intercepted with motorway junctions, which are distant from railways, to filter out every possible car segment. Finally, a distance-based filter between the GPS points of the remaining segments and railways was applied to filter out segments that are not following the railway. The remaining trip segments correspond to the train trip segments.

We designed five experiments for testing our proposed method. In each experiment, we built a classifier following the rules of each method. We identified three parameters in common among the methods: the train station buffer radius, the amount of necessary GPS points, and the distance between GPS points and railways.

IV. Experiment Evaluation

A. Dataset

In this study, we used a labeled subset of 4,534 trip segments, which correspond to 178 devices from the dataset collected during the GPSWAL mobility survey, a crowdsourcing travel survey carried out between 2016 and 2017 by the L'Institut Wallon de l'évaluation, de la Prospective et de la Statistique (IWEPS), in Belgium. This dataset was described in our previous work [6]. Figure 1 shows a sample of GPSWAL segments.

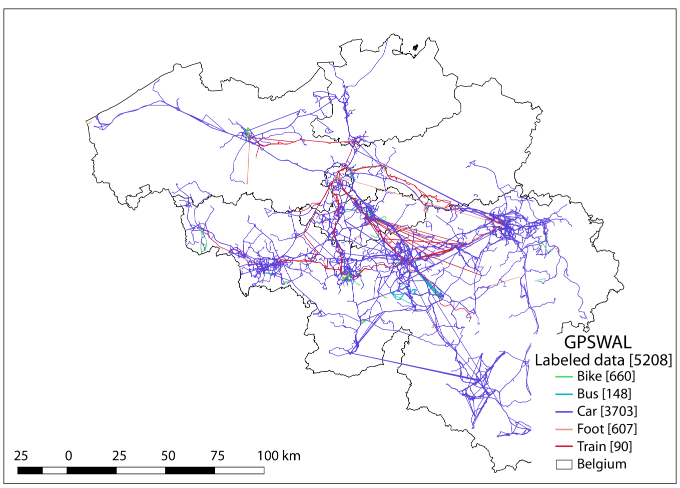


Figure 1. Subset of trip segments collected during the travel survey GPSWAL in Belgium.

The distribution of the trip segments by transport modes follows the modal split described by the Flemish Travel Behavior Survey OVG 5.1 [16] and is depicted in Table I.

TABLE I. Modal split of the trip segments

Transport mode	*OVG 5.1*	*Segments*
Bike	12.41%	660
Bus	2.78%	148
Car	69.62%	3703
Foot	11.41%	607
Train	1.69%	90

To implement both methods, we used four GIS data sources to extract transport network elements. The following layers were created and data transformation and cleaning processes were performed over them:

1) Bus stops from bus agencies: De Lijn, TEC Walloon and MIVB/STIB Brussels
2) Train stations from OpenStreetMap
3) Railways from OpenStreetMap
4) Motorway junctions from OpenStreetMap

B. Evaluation

Each experiment was repeated changing the threshold of the parameters to find the best classifier, i.e., every possible combination of the parameter values was evaluated. We computed a confusion matrix for every operating point to gather information about the classifier's performance. The following rates were calculated using the confusion matrix:

$$\mathrm{ACC} = \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{FP} + \mathrm{FN} + \mathrm{TP} + \mathrm{TN})} \tag{1}$$

$$\mathrm{PRE} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FP})} \tag{2}$$

$$\mathrm{TPR} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})} \tag{3}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{(\mathrm{FP} + \mathrm{TN})} \tag{4}$$

where TP is the True Positive, FP is the False Positive, FN is False Negative, and TN is True Negative. Here, ACC and PRE are accuracy and precision, respectively. These rates are valid only for one single operating point. Shifting the decision threshold of the classifier, we plotted values of True Positive Rate (TPR) against False Positive Rate (FPR). The resulting curve is called a Receiver Operating Characteristic (ROC) curve [17]. ROC graphs are useful tools for selecting models for classification based on their performance with respect to the false positive and true positive rates [18]. Figure 2 shows those ROC for the first experiment.

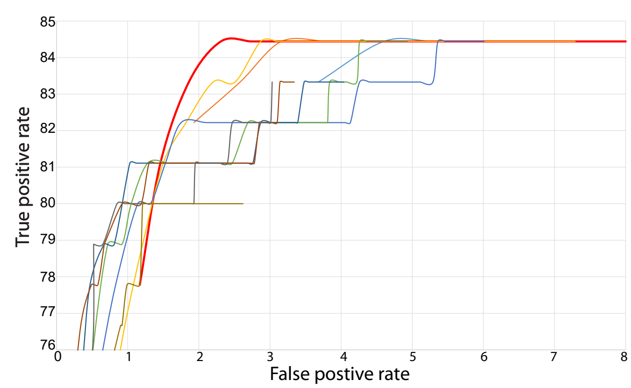


Figure 2. ROC curves for iteration of experiment 1: distance between GPS points and railways is 30 m, train station buffer is 100 m.

The optimal classifier in every experiment was selected using the ROC Area Under the Curve (ROC AUC). In general, a ROC AUC with the highest value identifies the classifier with the best performance. To identify the operating point that represents the combination of parameters with the best performance, we computed the Euclidean distance to the top-left corner of the ROC curve for each cutoff value. This is defined as follows:

$$d = \sqrt{(1 - \mathrm{TPR})^2 + \mathrm{TPR}^2} \tag{5}$$

where TPR is the true positive rate and FPR is the false positive rate. We selected the best operating point based on the lowest distances to the corner. Finally, using the ROC AUC and the Euclidean distance metrics, we perform the comparison between the five classifiers.

V. Experiments

Before performing the experiments, we determined the threshold of each parameter.

In the literature, spatial buffer size has been used in other studies to analyze public transport facilities [19], transport classification [5][14] or public transport flow analysis [20]. This parameter usually ranges from 20 to 1000 meters. Gong et al. [5] fixed the radius value in 200 m. Figure 3 shows how many train segments cross the train stations when the buffer radius increases. In our method, it was fixed in 100 m, 93.33% of the train segments cross at a distance less than or equal to this. For the benchmarking, we performed the experiments using these two values to set the buffer radius.

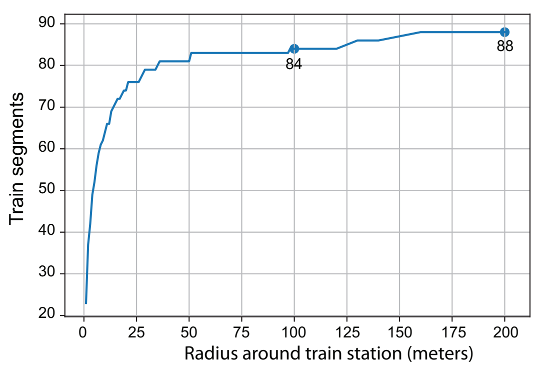


Figure 3. Number of train segments crossing around train stations.

Gong et al. [5] used the total number of GPS-point' segment for classifying, i.e., 100% of GPS points. We wondered which is the minimum amount of GPS points from a train trip segment to classify it as such. We changed this parameter in steps of 5% in each iteration, ranging from 5% to 100%.

The distance between GPS points and railways was fixed to 60 meters in the study by Gong et al. [5]. We analyzed the labeled train segments to determine the appropriated range of values to change the threshold of this parameter. We found that GPS points from train segments were in average 18.19 meters far from rail ways, while the maximum distance was 217.56 meters. Hence, the possible values of this parameter are in a range between 15 and 220 meter, we changed this parameter in steps of 5 meters in each iteration.

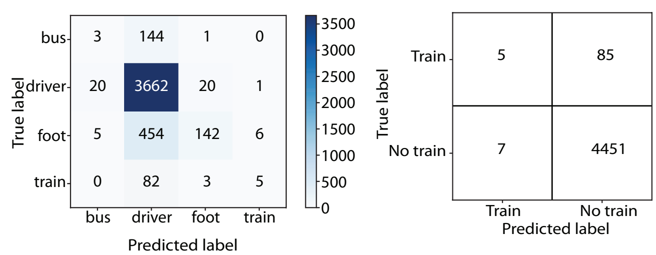
The first experiment consisted in applying our method [6] to the labeled dataset. The results have shown that there are misclassified train segments; this occurred when a segment crossed more than one train station, but it does not use railways. Another issue not handled by this version was the non-classification of train segments when they cross only one train station. We improved our method incorporating a stage to filter further non-train segments using the amount of GPS points needed per segment as well as the distance between those points and the rail ways. We compared the performance of both versions computing a confusion matrix in each case. The values of the confusion matrices are shown in Figure 4.

(a) Version I (b) Version II

Figure 4. Confusion matrix of the proposed method.

We evaluated our improved method to determine which are the best parameter values to built the classifier. The parameter values, performance rates, and metrics calculated for the best classifier of this experiment are shown in Table II.

The second experiment consisted in the implementation of the method by Gong et al. [5]. We configured the parameters according to the values established in their method. Figure 5a shows the confusion matrix computed after applying this method on the labeled dataset. Figure 5 shows the confusion matrix of the classifier modified to focus only on train classification. We evaluated the method to determine which are the best parameter values to built the best classifier. The confusion matrix for the best operation point is shown in Figure 6a.



(a) Transport mode classification. (b) Train classification.

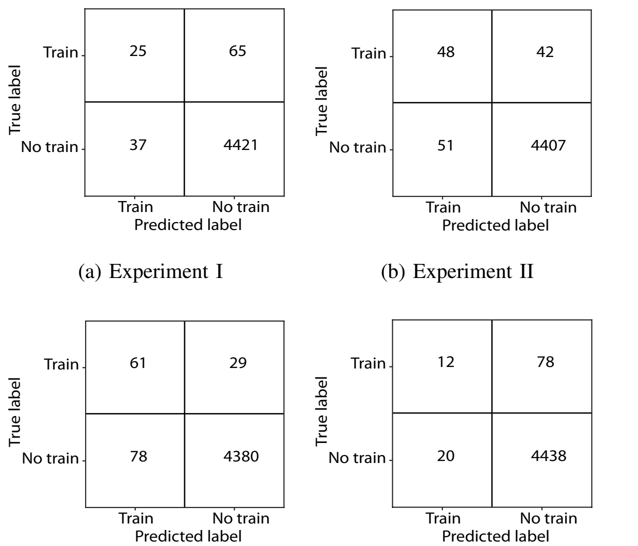
Figure 5. Confusion matrix of the Gong et al. method applied to the dataset.

We performed three additional experiments combining the rules used by Gong et al. [5] for detecting train trips. Experiment three consisted in combining rules one and three, so this experiment analyze the starting point and how far the GPS points which belong to a segment are from the railways. Experiment four combines rules two and three. In this case, ending points and how far the GPS points which belong to a segment are analyzed. The last experiment uses rules one or two combined with rule three. Hence, segments that start or end in a train station are analyzed in conjunction with how far their GPS points are from the railways.

The confusion matrices at the best operating point for each experiment performed with Gong et al. [5] method are shown in Figure 6. The parameter values, performance rates, and metrics calculated for the best classifiers are shown in Table II.

TABLE II. PARAMETER VALUES, RATES, AND METRICS FROM THE BEST CLASSIFIER OF EACH EXPERIMENT

Experiment	*ROC AUC*	*Euclidean distance*	*Train station buffer*	*Min GPS points (%)*	*Min rail distance*	*FPR*	*TPR*	*Accuracy*	*Precision*
1	0.0685	0.16	100	30	30	0.02	0.84	97.43	42.46
2	0.0004	0.87	200	20	15	0.01	0.13	97.85	37.50
3	0.0079	0.72	200	25	25	0.01	0.25	97.76	40.32
4	0.0201	0.47	200	25	20	0.01	0.53	97.96	48.49
5	0.0423	0.32	200	25	25	0.02	0.68	97.65	43.89



(a) Experiment I
(b) Experiment II
(c) Experiment III
(d) Experiment IV

Figure 6. Confusion matrix of the best operation point for each experiment with Gong et al. method.

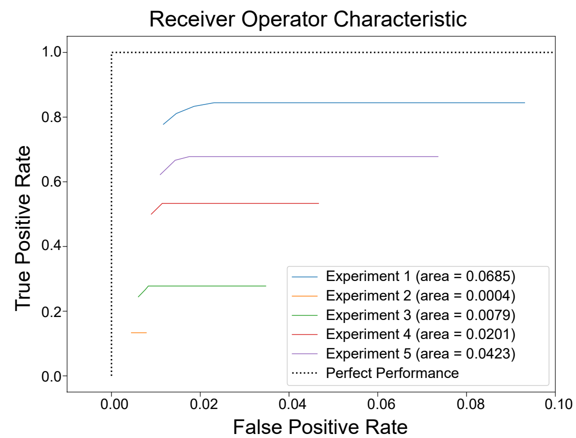


Figure 7. Benchmarking for the five experiment using the ROC AUC metric

VI. RESULTS AND DISCUSSION

This section presents the results of the performed comparisons. We have evaluated two methods through five experiments, one corresponds to our method which uses Passing and Non-Passing Points and four correspond to Gong et al. [5] method which uses only Passing Points. The dataset has an unbalanced set of classes, e.g., the target class represents only 1.69% of the data.

Before benchmarking, we performed the value choice of the three parameters in common between the methods: the train station buffer radius, the amount of necessary GPS points, and the distance between GPS points and railways. In each experiment, we selected the classifiers that maximize the relation between the true positive rate and the false positive rate instead of only considering the accuracy or precision. Figure 7 shows the benchmarking using the ROC AUC as metric. The parameter values, computed rates and metrics of each ROC curves are showed in Table II.

Results showed that the ROC AUC in experiment two had the lowest values. After analyzing this scenario, we realized that rules of the method by Gong et al. [5] were too restrictive for the used railway network and dataset quality [21]. Because of this, we performed three other experiments to test its behavior with less restrictive rules. This classifier has an accuracy of 97.85% while its true positive rate is 0.13, the lowest among the experiments. The results of experiment three showed us an improvement of the method by Gong et al. [5] in the identification of positive cases when only rules one and three are combined. In comparison with experiment two, we observed that in this experiment the true positive rate and precision are better, however the accuracy is lower. The results of experiment four showed a good performance, i.e., when only segments and end train stations are used. This experiment had the highest rate values when we applied the method by Gong et al. [5] to the dataset. Nevertheless, the ROC AUC value does not represent the best classifier with this method. Experiment five used a combination between rule number one or two with rule number three used. In this case, the results showed the best ROC AUC value using the method by Gong et al. [5] besides having the best true positive rate among experiments with this method. However, the number of false positive cases increased.

When comparing the results obtained from the benchmarking between the method by Gonzalez and the proposed method, we determined that our classifier presents a better performance in relation with the true positive rate. For instance, we classified correctly 84 trips out of every 100 train trips, while the method by Gong et al. [5] only identified 68 trips. However, both methods misclassified 2 train trips in every 100 trips.

VII. CONCLUSION AND FUTURE WORK

In this paper, we reported a comparison performed among location based methods which aim to classify transport mode. We have also presented the design, execution and results of the experiments performed with each method. Additionally, the influence of the parameters of the tested algorithms has been experimentally studied with the purpose of performing a fair comparison. Finally, we have shown the results of the best classifier according to the ROC curves.

The objective of this paper was to perform a comparison between a methodology that only uses Passing Point elements, and a methodology which uses both Passing and Non-Passing

Points, applying both on a dataset where the transport-mode classes are unbalanced. Previous works in transport mode classification only report successful rate but the results showed that in addition to calculate the accuracy and precision of a method, it is also necessary to calculate the true positive and false positive rates to evaluate the classifier performance. According to the ROC graph, the proposed method has the greatest ROC AUC value, i.e., it has a better performance in comparison with the method by Gong et al. [5]. The true positive rate of the proposed methodology is 84% in comparison with 64% obtained by the best classifier using the method by Gong et al. [5]. For future work, we plan to apply the proposed method to classify other transport modes (e.g., bus) or combining it with other kind of techniques. We also plan to explore transport classification with unbalanced classes using crowdsourcing data.

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