# Prediction of Bike Mobility in Cascais's Sharing System

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Abstract: Bike sharing systems offer a convenient, ecologic, and economic transport mode that has been increasingly adopted. However, the distribution of bikes is often unbalanced, which decreases user satisfaction and potential revenues. Moreover, bike sharing literature is mostly focused on the prediction of demand on large scale systems and uses simulations for the assessment of relocation operations to increase the number of utilizations. We propose prediction models based on machine learning approaches to improve the bike sharing re-balancing in a small city of Portugal. The algorithm aims to improve three metrics, namely (1) increase the number of utilizations, (2) reduce the number of stations without bikes, (3) reduce the time without available bikes in the stations. The relocation operations are validated using real data. Our findings show that (a) the estimated number of utilizations created by this system is substantially higher than the current system by 223%, (b) our model allows the correct identification of more 70%, 165%, 249% empty stations with the same or substantially higher precision than the existing approach, (c) the total time of bike unavailability reduced by the predictive model is 283% higher than the time reduced by current approach (1,394,454 vs 363,971 minutes).

## 1 INTRODUCTION

Green mobility in the urban areas is a strategic topic for the city municipalities. This subject is also enhanced by the sustainable actions promoted by the United Nations goals (UN, 2018) and is addressed by the current emerging technologies, i.e., digitalization, electric vehicles. Shared utilization of different modes of transportation (e.g., bike sharing, car sharing, ride sharing) is a common urban mobility solution. The bike is one of the most encouraged transportation mode in the cities due to its easy and economic utilization in crowded areas and positive environmental impact for the city. The city municipalities together with the stakeholders (e.g., installers, operators) work together for a smooth integration of the docked bike sharing systems into the cities, where the users play a decisive role. Data generated by the bike sharing systems is valuable to both the city municipalities and the users and it can be used for further analysis, e.g., usage patterns, bike demand, traffic analysis, environmental conditions.

Many cities have provided their bike sharing data for research. Literature about this topic applies diverse methodologies, analyzes different objectives and studies various cities. In particular, we analyze some important works and identify their main objectives, type of applied features and the corresponding cities. The summary is provided in Table 1. The majority of these studies focus on the prediction of demand. Only two papers predict related indicators such as the number of available bikes or the probability of bike unavailability. These works are performed on large scale bike sharing systems, e.g., New York, Washington, Hanghzou. The main factors that impact the bike sharing prediction are mostly related to bike usage, date, time, weather, and very few consider the events and the traffic.

In the literature, two main approaches have been considered for the redistribution of the bikes. In the first, users get incentives to park the bikes in neighboring stations to reduce the utilization of dedicated operating staff to relocate the bikes, e.g., (Haider et al., 2017). In the second, the re-balancing is done by a fleet of trucks that move around the city to relocate the bikes according to the demand. But, as reported by (ITDP, 2014), the redistribution of the bikes has a significant cost which is 30% of the total operating cost.

Bike sharing prediction is valuable for re-balancing operations. The asymmetric utilization patterns in diverse stations often create unbalanced distributions of bikes. Some stations may be empty or full, preventing many users from requesting or returning



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Table 1: Literature review for bike sharing prediction models.

| Work | Objectives | Type of Features | City |
|---|---|---|---|
| (Frade and Ribeiro, 2014) | identify informative features for demand prediction | traffic, trip characteristics, slopes | Coimbra |
| (Gast et al., 2015) | prediction of number of available bikes | date, time, bike usage | Paris |
| (Singhvi et al., 2015) | demand prediction in stations and clusters | bike and taxi usage, weather, location | New York |
| (Lin et al., 2018) | demand prediction in stations | time, bike usage, date, location | New York |
| (Datta, 2014) | demand prediction in stations | weather, time, location, date, bike usage | Seattle |
| (Yang et al., 2016) | demand prediction in stations | weather, time, location, bike usage, events | Hanghzou |
| (Chen et al., 2016) | demand prediction in clusters, probability of bike unavailability in stations | time, weather, bike usage, events, traffic, user | New York, Washington |
| (Zhang et al., 2016) | trip prediction | user, location, time, trip, events | Chicago |

bikes. Diverse works create models to optimize relocation operations (e.g., (Raviv et al., 2013), (Waserhole and Jost, 2013)). These operations depend on various factors such as the number of vehicles, the capacity of vehicles and the time available for repositioning. Additionally, these models use predictions of diverse factors (e.g., unmet demand, probability of bike unavailability or time of unavailability) to maximize the objective function. The main objectives of these approaches are the reduction of number of stations without bikes (Freund et al., 2018), (Raviv et al., 2013), (Fricker and Gast, 2016) and the increase of the number of utilizations (Waserhole and Jost, 2013).

From the previous literature, we summarize the following main insights. (1) Most works focus on the prediction of demand in stations. The improvement of critical metrics such as the increase of the number of utilizations and the reduction of the number of empty stations requires more information to obtain better decisions for relocations (e.g., probability of empty station). (2) The analyzed bike sharing systems have high utilization volumes. Thus, the assessment of the impact of application of predictive models on small scale bike sharing systems remains unclear. (3) The literature using data about performed relocation operations to validate their results is scarce. Most works about relocations use simulations to measure their impact. However, the evaluation of the number of additional utilizations created by relocations is more robust using real data. (4) The prediction of the time of bike unavailability has not been explored. These forecasts are distinct from the prediction of the probability of stations without bikes and provide more information to calculate the unmet demand.

We address these research opportunities by creating predictive models to improve three metrics: (1) increase the number of utilizations, (2) reduce the number of stations without available bikes, (3) reduce the time of bike unavailability. These predictions are used to select the stations that shall receive bikes in order to enhance these indicators. For these purposes, we create three different models to predict for each station: (i) number of check-outs (demand), (ii) time without available bikes, (iii) probability of bike unavailability. Based on the predictions of the demand and time of bike unavailability, we predict the number of additional utilizations generated by relocations.

We use data from the MobiCascais bike sharing system (MobiCascais, 2018) in Cascais, Portugal, which is a bike sharing system with small utilization volume. This system is continuously increasing its size, both in stations and number of bikes. Hence, the prediction is a challenging task and the impact of the predictive system may be more limited than in large scale systems, e.g., New York. Moreover, MobiCascais has already executed re-balancing operations to enhance bike distribution. The data is applied in this work to: (a) evaluate the prediction of the additional utilizations, and (b) calculate the improvements on each evaluation metric relatively to the current MobiCascais relocation strategy. In summary, our main contributions are:

1. Create predictive models that provide better support for decisions related to the improvement of three metrics:
   - number of utilizations,
   - number of empty stations,
   - time without available bikes.
2. Evaluate the utility of machine learning approaches to support the re-balancing operations on bike sharing systems with small utilization volume (e.g., MobiCascais).
3. Apply data of performed relocation operations to evaluate the forecasting of the number of utilizations created by relocations and measure the improvements to the existing re-balancing approach.

The rest of the work is organized as follows. Section 2 provides the data analysis, while Section 3 presents the methodology. The results are discussed in Section 4 and the work concludes with Section 5.

## 2 DATA ANALYSIS

MobiCascais is an integrated mobility system that includes bikes, buses, trains and parking services for the municipality of Cascais, Portugal. Bike sharing is an important component of this system because it permits an ecologic transportation without major time schedule constraints and provides an easy interconnection with other services. The service has started in 2016 and has been gradually increasing its activity. This work uses data from 1st of January, 2017 to 16th of November, 2018. Bike sharing data contains information about each utilization, namely: (a) identification of the user and bike associated with the utilization, (b) start and end time of the utilization, (c) identification of the start and end stations and corresponding GPS coordinates, (d) identification of the start and end docks. In addition, we collect the meteorological data from Weather Underground API (Underground, 2018) that contains information about the precipitation intensity, temperature, wind speed, visibility and cloudiness for each hour in Cascais.

Figure 1 shows the monthly number of bikes, stations, users, and utilizations. MobiCascais has been providing more bikes and stations to correspond to the increasing number of active users. Moreover, users are becoming more frequent because the number of utilizations is growing at a higher rate than the number of users. The demand for these services varies with time and geography. For instance, Figure 2 demonstrates that utilization fluctuates during each day, starting from 08:00 AM until 08:00 PM having its peak at lunch time.

Furthermore, stations present different activity patterns. Figure 3 presents the median of weekly demand for each station. Some stations have more than 20 weekly utilizations while many others have nearly none. However, this volume is insignificant when compared to big cities bike systems (e.g., New York).

Temporal patterns of utilization are also quite different between stations. Figure 4 depicts activity levels for each hour of the day of the five most active stations. The fluctuating temporal and spatial utilizations cause an unbalanced distribution of bikes that create major limitations. For instance, it is usual that some stations are empty preventing users from using bikes from their favorite station. Indeed, there are diverse situations of empty stations. The percentage of time without available bikes for each station is presented in Figure 5. Some stations are empty more than 10% of the time, including some of the most active stations. Therefore, it is obvious that a more balanced distribution could permit a higher number of utilizations.

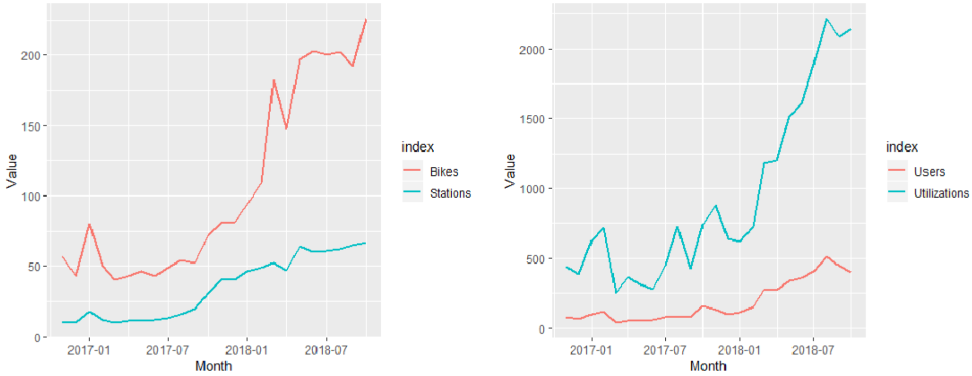
MobiCascais is already performing relocation operations to improve bike distribution. These operations are decided based on personal experience. However, predictive models may suggest more accurate real-time relocation decisions. Bikes can be used by common users or by MobiCascais maintenance staff to execute maintenance tasks. These latter situations could be related to bike repairs or just to relocate bikes between stations to obtain a better bike distribution and increase bikes availability. The number of these utilizations is shown in Figure 6. Approximately 1900 bikes are moved by maintenance services to enhance bike distribution.

## 3 METHODOLOGY

To create predictive models, we apply bike sharing data extracted from the MobiCascais system and weather data collected from the Weather Underground API. The overview of the methodology is presented in Figure 7.

### 3.1 Prediction Models

This work provides predictive models to improve three main metrics: (a) reduce the number of stations without bikes, (b) reduce time without available bikes, (c) increase the number of utilizations. Therefore, to minimize the number of empty stations, we create models that predict the probability that each station will be empty during the next period. To minimize the time without available bikes, we develop models that forecast the number of minutes without bikes in




(a) (b)

Figure 1: Number of bikes, stations, utilizations, and users during the defined period.

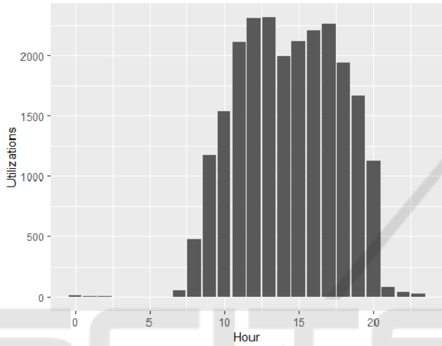



Figure 2: Hourly utilization per day.

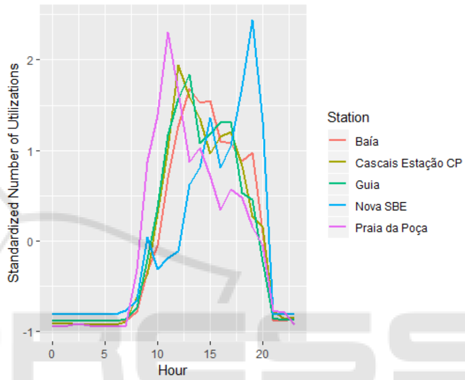



Figure 4: Hourly utilization for the five most used stations.



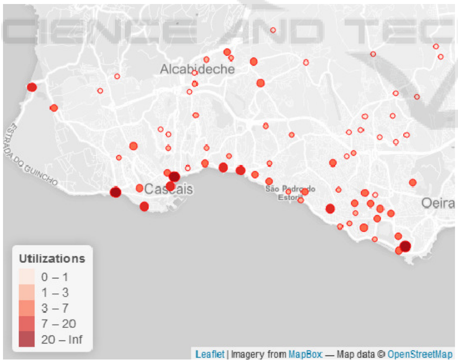



Figure 3: Median weekly pick-ups for each station.

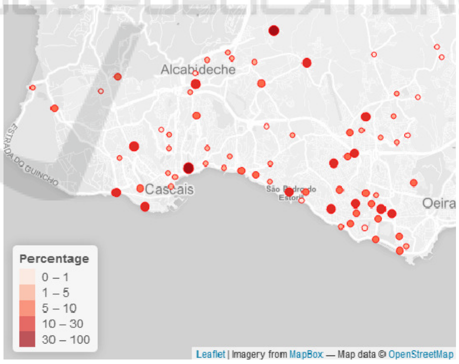



Figure 5: Time percentage w/o bikes at each station.

each station. To maximize the number of utilizations, we produce models that predict the number of utilizations created by re-balancing operations in each station. The predicted number of additional utilizations obtained by relocations is calculated based on the predicted demand and the predicted number of minutes without bikes using the following formula:

$$prediction \cdot \frac{minutes\ w/o\ bikes}{total\ minutes}.$$

The predictive models should be flexible to forecast for new stations because MobiCascais has been expanding its bike sharing system. Thus, we create predictive models able to predict for new installed stations. These models perform hourly predictions for the next 24 hours. For example, the predicted utilization for a specific station is the estimated number of bike pickups for the next 24 hours. We decided to use this approach for two main reasons: (1) hourly predictions to be able to have more solid comparisons with existing relocation tasks that are made at different hours of day, (2) predictions for 24 hour windows because the volume of utilizations is too low to use a

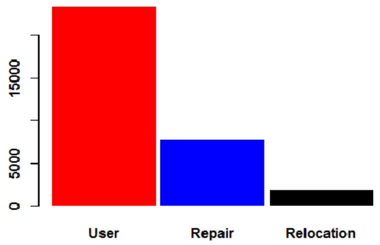



Figure 6: Number of bike utilization by each type.

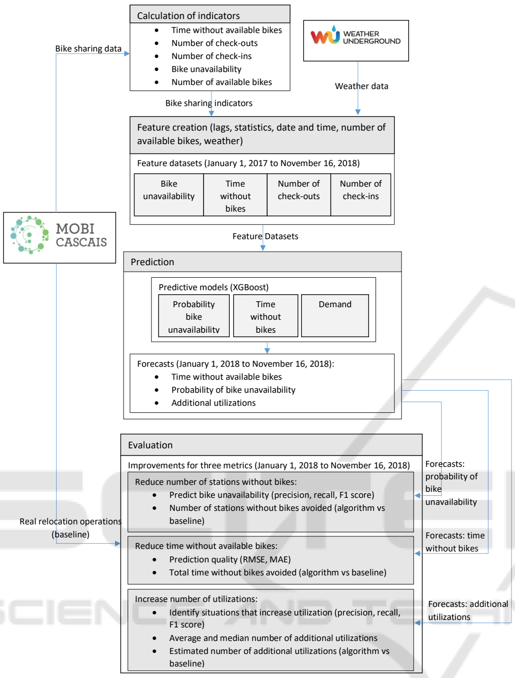



Figure 7: Overview of the methodology.

shorter time interval, e.g., one hour interval. Moreover, a longer time window permits an easier relocation planning. This scheme produces overlapping periods that are properly considered in evaluation.

Bike sharing data contains diverse relocation operations already performed by MobiCascais. However, we intend to forecast re-balancing factors based exclusively on user activity. Therefore, we minimize the maintenance influence by reducing their activity on the prediction of the probability of empty stations and time without available bikes. If we exclude all maintenance activity, some stations would have long periods with large negative number of bikes and other stations would have very large positive number of bikes, exceeding their capacity by a considerable margin. Thus, we assume the real number of bikes at the prediction moment, but we exclude all relocation tasks during the remaining period. The number of available bikes at each station is recalculated for each dataset

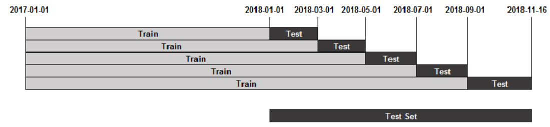



Figure 8: Data sets.

instance by subtracting relocation arrivals and adding relocation departures that occurred during the corresponding period. The identification of empty stations and the calculation of time with unavailable bikes are executed based on these recomputed values.

For the creation of each predictive model, we produce a large set of features to characterize four different time series: number of check-ins and check-outs, time of bike unavailability and minimum number of bikes at each station. The following set of features is created for each series:

- values of last 10 hours, last 6 days at the same time and last 6 weeks at the same time and day of the week,
- average values of last 7 days,
- median, maximum, minimum and standard deviation of last 6 days and 6 weeks.

The values of the last hours correspond to one hour intervals to avoid data leakage. Moreover, we add other features to each predictive model: (a) number of available bikes at the station at prediction moment, (b) hour of day, day of the week, month and holidays, (c) precipitation, intensity, temperature, wind speed, visibility, cloudiness.

A robust evaluation of time series problems requires that data splitting for training and testing should be made chronologically to avoid data leakage. Thus, test data must be posterior to all training data. This scheme also simulates real world prediction environment, in which we are restricted to data up to the present to forecast future (Tashman, 2000). The evolution of MobiCascais bike sharing system (e.g., growing number of utilizations, users and stations) makes long-term forecasts more difficult. The constant modification of the characteristics of MobiCascais time series may impact the performance of models that are trained with distant data from the prediction moment. Therefore, we implement the scheme illustrated in Figure 8 to obtain a larger forecast period that may permit a more solid evaluation. The training dataset is extended in five different moments to produce forecasts for the next time window (usually two months). Hence, we obtain and extend test dataset (more than 10 months) with acceptable accuracy levels.

This work applies the XGBoost algorithm for all predictive models. XGBoost is a gradient tree boosting algorithm known for its accuracy and efficient utilization of computational resources (Chen and Guestrin, 2016). XGBoost is the winning algorithm of many machine learning competitions, particularly for classification and regression problems using structured data. R tool (http://www.r-project.org) is applied in all processing tasks such as data collection, pre-processing, modeling and evaluation.

All predictive models apply the default XGBoost parameters, except objective function, evaluation metric and number of boosting iterations. The objective function for regressions problems (prediction of time of bike unavailability and demand) is linear regression (reg:linear), while logistic regression (binary:logistic) is applied for the classification model (prediction of the probability of empty station). The number of boosting iterations for each training model is set according to the evaluation values obtained in the validation set (last 25% of training data) using 50 early stopping rounds. For this procedure, we select Root-Mean-Squared Error (RMSE) as the evaluation metric for regression problems and area under precision-recall curve (aucpr) for the prediction of the probability of empty stations.

## 3.2 Evaluation

In this section, we will evaluate the contributions of our predictive algorithms for the test period (Jan., 2018 to Nov., 2018) by assessing three main metrics: (a) number of stations without bikes, (b) time without available bikes, (c) number of utilizations.

### 3.2.1 Number of Stations without Bikes

The contribution to reduce the number of stations without bikes is measured by analyzing the performance of the predictive model for empty stations to identify stations that will not have any available bike at some point in the next 24 hours. To avoid overlapping situations, we evaluate predictions for an unique hour of the day (00:00 AM). Moreover, we exclude stations that are already empty at the prediction moment because the output is already known. The performance of the predictive model is measured by three metrics:

- Precision: $\frac{TP}{TP+FP}$
- Recall: $\frac{TP}{TP+FN}$
- F1 Score: $2 \cdot \frac{Precision \cdot Recall}{Precision+Recall}$,

where TP is the number of true positives (empty stations correctly predicted by the model), FP is the number of false positives (stations wrongly predicted as empty), FN is the number of false negatives (stations wrongly predicted as non-empty). F1 score is useful because aggregates precision and recall into a single measure.

The precision-recall curve analyzes the trade-off between precision and recall for different threshold values and is particularly useful for imbalanced datasets like this one. The selection of the threshold value can be motivated by different business criteria. For instance, a lower budget for relocations may motivate the selection of a high precision value and a lower recall value. To quantify the potential benefits obtained by this predictive model when compared to the existing MobiCascais approach, we calculate the number of correctly identified situations by the algorithm according to three criteria: (a) select the same number of relocations made by MobiCascais services in the same period, (b) use the same precision value obtained by MobiCascais relocations, (c) apply the threshold that maximizes the F1 score. Therefore, we assess the impact that the predictive model for empty stations could have on reducing the number of empty stations relatively to the actual approach.

### 3.2.2 Time without Available Bikes

The contribution to reduce the time without available bikes is made by the predictive model of time unavailability. We apply RMSE and Mean Absolute Error (MAE) to measure the quality of predictions. These metrics are given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j^2| \tag{2}$$

where $y_j$ and $\hat{y}_j$ are the target and predicted value for the j-th situation and $n$ is the number of forecasts considered. RMSE is more sensitive to large errors than MAE. The improvements achieved by this model relatively to the current approach are measured by comparing the total number of minutes of bike unavailability avoided by both methods using the same number of relocations. The selection of situations by the predictive model is performed on the forecasts made for the same hour of the day (00:00 AM) to avoid overlapping situations.

### 3.2.3 Number of Utilizations

The contribution to increase the number of bike utilizations is ensured by the predictive algorithm for additional utilizations. The dataset about the relocation operations already performed by MobiCascais has higher value in this evaluation because the correct number of additional usages due to relocations are only available for the real executed relocations. For the remaining cases, these values are only estimates. A precision-recall curve is used to assess the predictive capability to identify situations leading to additional utilizations by applying a binary output (0 meaning zero additional utilizations, 1 meaning positive additional utilizations).

The ability to predict the number of additional utilizations is also analyzed by showing the median and average number of additional usages for different sets selected by the algorithm. These groups correspond to the top predictions sorted by decreasing order. The average number is calculated for all selected situations while the median is only calculated for the selected situations that have additional utilizations because most cases do not have additional utilizations. These values are compared with the precision, average and median number of additional utilizations obtained by MobiCascais relocations. To estimate the benefits that could be obtained by the application of the algorithm in the whole test period without the relocation data restrictions, we project the potential number of additional utilizations caused by the suggested relocations. For this purpose, we select the threshold that maximizes the F1 score in the relocation dataset and its corresponding average number of additional utilizations. The suggested relocations are the predictions made for 00:00 AM of the whole test period that are higher or equal than the threshold. The total number of additional utilizations is calculated as:

$$Tutl = Treloc \cdot Uavg \tag{3}$$

where $Treloc$ is the number of proposed relocations and $Uavg$ is the average number of additional utilizations obtained by the threshold in the relocation dataset evaluation. The potential contribution to increase the number of utilizations relatively to the current relocation strategy is the difference between $Tutl$ and the total number of additional utilizations obtained by the existing approach.

# 4 RESULTS

This section analyzes the results obtained with this work. The findings are presented and discussed according to the evaluation procedure described in the previous section.

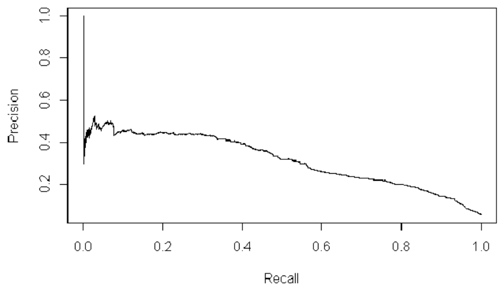



Figure 9: Precision-recall for the number of stations without bikes.

## 4.1 Impact on the Number of Stations without Bikes

The relocation operations performed by MobiCascais successfully identified 196 stations during the test period that ran out of bikes at some point in the next 24 hours. This value corresponds to 25.8% of the total number of relocations tasks executed on stations that were not empty at the time of the operation (761 relocations). Figure 9 shows the precision-recall curve for forecasts made by the predictive model for the probability of empty stations on the test set. As explained in the evaluation subsection, this assessment is performed on all predictions made at 00:00 AM in the complete test period (i.e., 19,394 forecasts).

The precision-recall curve shows that the predictive model reaches an accuracy higher than 45% for a recall score of 10% recall. Then, the precision slightly decreases until the recall score reaches 45%. The predictive model maximizes the F1 score with a precision of 36% and a recall of 46%. To measure the potential improvements, we verify the number of empty stations that are correctly identified by the algorithm using three different parameters: (1) selection of the same number of relocations executed by MobiCascais, (2) utilization of the same precision achieved by MobiCascais relocations, (3) application of the threshold that maximizes the F1 score. The selection of the same number of relocations (i.e., 761) permits the correct identification of 334 empty stations with a precision of 43.9%. This is a substantially higher precision value than the obtained by the current relocation strategy (43.9% vs 25.8%) for also a higher recall. The utilization of the same precision (i.e., 25.8%) allows the successful detection of 685 empty stations, corresponding to a recall greater than 60%. For the same precision, this strategy could identify more 489 empty stations than the current approach. The application of the threshold maximizing F1 score enables the correct identification of 519 situations with a precision of 36%. Therefore, the application of these three criteria always enables improvements when compare to the current approach. It would be possible to correctly identify more 138 (i.e., 70%), 323 (i.e., 165%) or 489 (i.e., 249%) empty stations with the same or substantially higher precision.

## 4.2 Impact on the Time without Available Bikes

The model for the time of bike unavailability predicts the number of minutes without bikes in the next 24 hours for each station. Thus, the predictions and target values range from 0 to 1,440. These forecasts obtained the following evaluation values: RMSE is 114.12 and MAE is 43.42. An example of the predicted and real number of minutes without available bikes at each station is provided in Figure 10 for a specific day, i.e., 23rd of August 2018.

To have a simple baseline for the predictive accuracy, we also evaluate the utilization of the average number of minutes without bikes for each station as the forecast for each instance. The baseline obtains the following values: RMSE is 289.14 and MAE is 135.88. The evaluation results of the model of time of bike unavailability are significantly lower than this baseline. To assess the ability of this predictive model to reduce the time of bike unavailability relatively to the current relocation approach, we compare the total number of minutes without bikes using the same number of relocations for both methods. Indeed, the utilization of the predictive model permits to reduce 1,394,454 minutes in bike unavailability while the existing approach decreases 363,971 minutes of bike unavailability, corresponding to 26% of the time reduced by the predictive model.

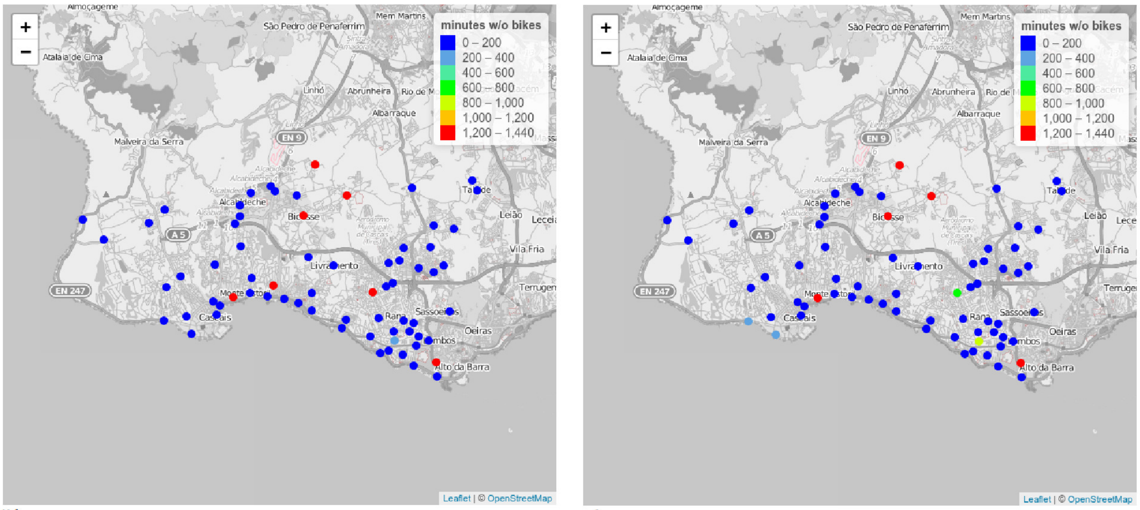
## 4.3 Impact on the Number of Utilizations

A major objective of relocation operations is to increase the number of utilizations by moving unused bikes to stations without enough bikes to satisfy their demand. Therefore, more users can pick-up a bike from their favorite station. This work suggests the application of the predictive algorithm of additional utilizations caused by relocations to improve the identification of re-balancing operations that may increase the number of utilizations. An example of the predicted and real number of check-outs for each station is provided in Figure 11 for a specific day, i.e., 23rd of August 2018. The results from the prediction model are close to the real one, as indicated by the figure.

The additional utilizations of bikes caused by relocation of the bikes from one station to another is provided in Figure 12. Approximately 17% of the relocation operations made by MobiCascais permit to increase the total number of utilizations. In these situations, there are pick-ups of bikes that would not be available without those relocations. The average number of these additional utilizations is 0.61. Figure 13 shows the median and average number of additional usages for different selections made by the algorithm. These selected sets are the top predictions sorted by decreasing order (e.g., 10% in the x-axis are the 10% highest forecasts).

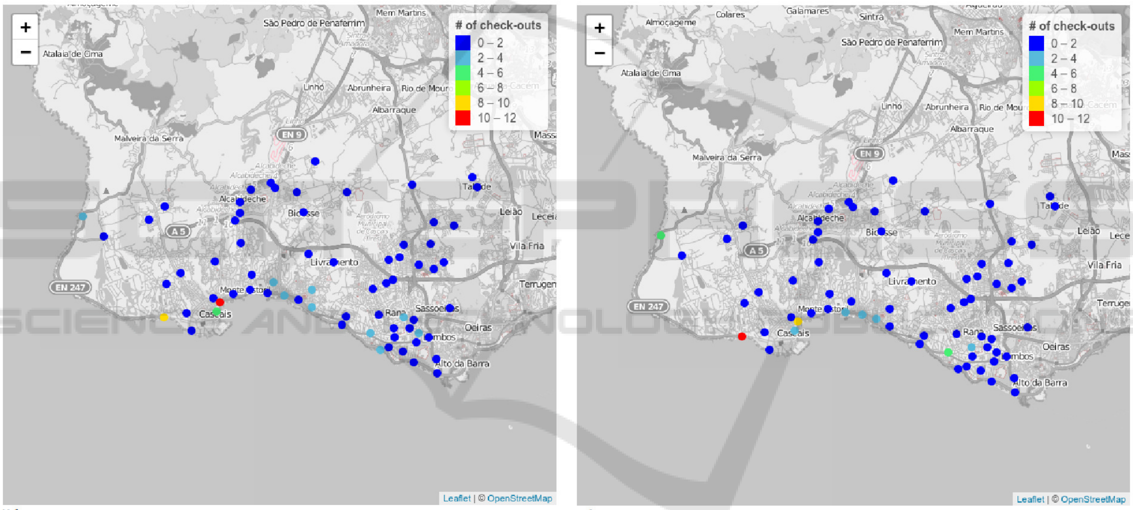
The algorithm demonstrates the capacity to identify those situations that generate more utilizations. Both median and average number of utilizations decrease as the selected number of predictions increases. Figure 14 presents the precision-recall curve for the identification of situations that may generate additional utilizations. In general, the precision of the algorithm decreases with the increase of the recall. Thus, the forecast value is correlated with the probability of additional utilizations. The highest F1 score is 48.22% corresponding to a precision of 35.44% and a recall of 75.44%. It is a precision value that is substantially higher than the obtained by the Cascais services (35.44% vs 17%) for a very high recall value. Nevertheless, it can be argued that the precision of MobiCascais services is for a larger number of relocations. Indeed, this precision-recall curve is restricted to the same relocation operations made by MobiCascais. Therefore, the algorithm will always obtain the same precision of MobiCascais for a recall score of 100% with these evaluation settings. The utilization of the relocation dataset is very important to perform a solid evaluation of predictive capacity of additional utilizations, but it limits the scope of application of the algorithm. To measure the potential improvements in the number of utilizations, it is necessary to apply the algorithm in a larger test set, without the restrictions of the performed relocations. As described in the evaluation section, we calculate the potential number of additional utilizations during the test period by using the threshold that maximizes the F1 score in the relocation dataset and its corresponding average number of additional utilizations. The utilization of this threshold allows the selection of 1,380 relocations ($Treloc$). The average number of generated utilizations for this threshold is 1.428 ($Uavg$). The estimated number of additional utilizations is 1,971 ($Tutl$), which is substantially higher (i.e., 223%) than the 610 relocations obtained by MobiCascais in the same period.

In summary, the algorithm shows predictive capacity to identify stations that shall receive bikes to increase the number of utilizations. For example, the




(a) Real (b) Predicted

Figure 10: Number of minutes w/o available bikes at each station.



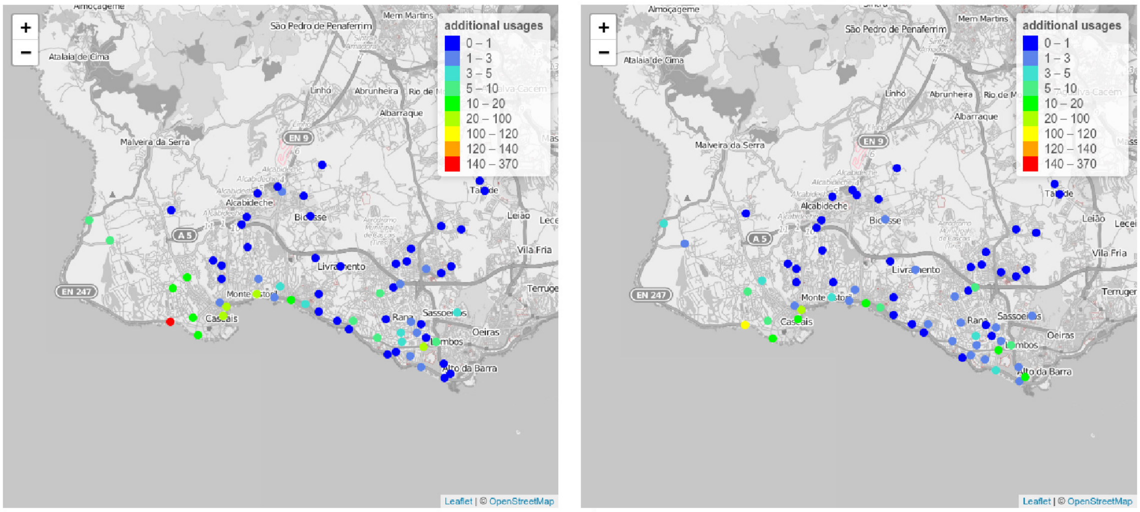

(a) Real (b) Predicted

Figure 11: Demand prediction at each station.

highest predictions permit a more accurate selection of relocations that may generate utilizations. Moreover, these top selections usually create a larger number of utilizations. This superior predictive ability is valuable because it allows to increase the number of utilizations and consequently revenues and user satisfaction. For instance, the estimated number of utilizations created by relocations suggested by the predictive algorithm in the whole test period is three times higher than the number of utilizations created by the MobiCascais operations.

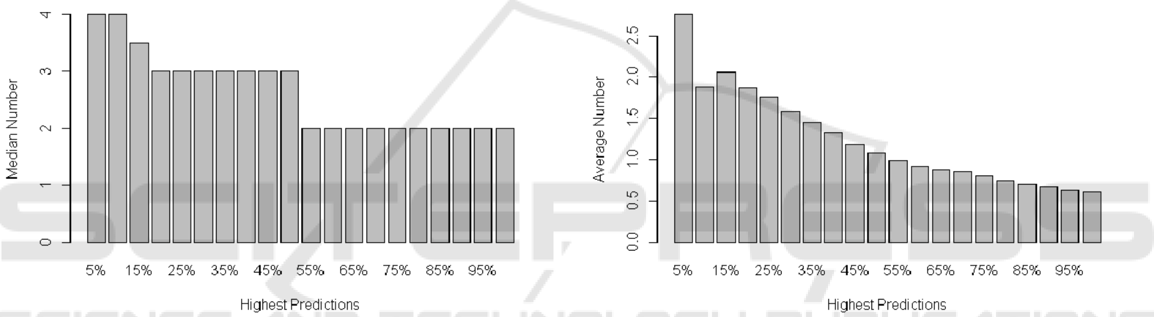
## 5 CONCLUSIONS AND FUTURE WORK

The asymmetric and fluctuating usage patterns in bike sharing systems create diverse situations of empty or full stations, preventing their users from using or returning bikes. Therefore, the unbalanced distribution of bikes has serious impact on user satisfaction and number of utilizations. Re-balancing operations permit to reduce these problematic situations. Planning these relocations requires accurate predictions of different bike sharing indicators. For instance, the selection of stations that should receive bikes may ben-




(a) Real (b) Predicted

Figure 12: Additional bike utilizations by relocation of bikes at each station.




(a) Median (b) Average

Figure 13: Median and average number of additional usages.

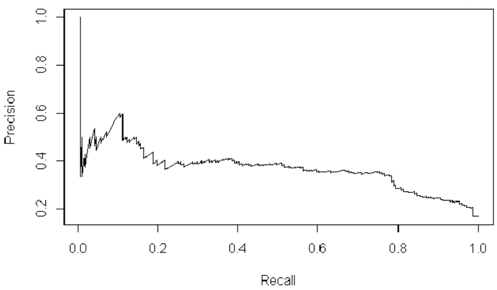



Figure 14: Precision-recall for the number of additional utilizations.

efit from the utilization of accurate forecasts of the probability of stations running out of bikes in the next hours. Literature about bike sharing prediction is mostly focused on the prediction of demand on large scale systems. However, other predictions (e.g., additional utilizations created by relocations, probability of empty stations) may improve re-balancing decisions and consequently enhance some performance metrics (e.g., number of utilizations, number of empty stations). Moreover, the assessment of the contribution of relocation operations to increase the number of utilizations has mainly used simulations. However, the application of data about real executed relocations permits a more robust evaluation of this contribution. This work analyzed the potential benefits of the utilization of a machine learning approach to support the re-balancing strategy of MobiCascais, a bike sharing system with low utilization volume. Predictive models were created to support the selection of stations that should receive bikes to improve three different metrics: (a) number of utilizations, (b) number of stations without bikes, (c) time without available bikes. Data of relocation operations already performed by MobiCascais was used to evaluate the prediction of the number of utilizations created by relocations and to measure the improvements to the current re-balancing strategy. Evaluation results indicate that the proposed machine learning approach permits to enhance relocation decisions. The predictive algorithm of the number of utilizations generated by relocations seems to have substantially higher precision to identify situations leading to additional utilizations. For instance, its predictions obtain a precision score higher than 35% for a recall score higher than 75% in the evaluation on performed relocations. Only 17% of the relocation operations made by MobiCascais increased the total number of utilizations. The estimated number of utilizations created by the relocations is also much higher than the ones obtained by the MobiCascais relocation services in the same period (1,971 vs 610).

The predictive model of the probability of stations running out of bikes in the next 24 hours allows to reduce the number of empty stations. While the existing re-balancing approach correctly identified 196 stations that became empty, our model obtained the following values: (a) 334 empty stations for the same number of relocations; (b) 685 empty stations for the same precision; (c) 519 empty stations using the threshold that maximizes the F1 score. Therefore, it allowed the correct identification of more 138, 323 or 489 empty stations with the same or substantially higher precision than the existing approach.

The predictive model of the number of minutes without bikes also improves another performance metric. The number of minutes of bike unavailability was reduced by 1,394,454, while the existing relocation strategy approach decreased 363,971 minutes (i.e., 26% of the time reduced by the predictive model).

In summary, the predictive models created in this work improve the performance of the re-balancing operations according to three different criteria. Thus, the utilization of machine learning approaches seems to be valuable even for bike sharing systems with much lower utilization than most systems studied in this topic. Hyper-parameter tuning, feature selection and the utilization of other machine learning methods may enlarge these benefits. Improvements on the efficiency of re-balancing operations may have diverse advantages such as the increase of the number of utilizations, revenues, user satisfaction, number of frequent users and the reduction of the operational costs. The predictive models created in this work answer an important question of the relocation decisions: *what stations should receive bikes?*. However, diverse questions remains unanswered and should be analyzed in future research. For instance, a complete decision support system for relocation should also suggest the number of bikes that each station should receive or provide.

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