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Development of a station-level demand prediction and visualization tool to support bike-sharing systems' operators

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Abstract

Bike-sharing systems operate in a number of cities around the world, aiming to promote sustainable urban mobility. Successful management of these systems is to a large extent linked to the optimal distribution of bicycles, which implies the accurate prediction of demand for rentals and returns at each station within the day. For this purpose, a tool for predicting bike demand for rentals and returns and visualizing the results has been developed and is presented in the present paper. Different predictive models based on machine learning regression algorithms are trained and evaluated. The tool is tested using data from the bike-sharing system that operates in the city of Thessaloniki, Greece for which the results indicate that the tested system's utilization is highly correlated to the location and spatial characteristics of a station, as well as the season of the year and time of day. The proposed machine learning algorithms use custom engineered features to learn those correlations and achieve the highest possible performance.

Keywords: bike-sharing systems; demand prediction; machine learning

1. Introduction

One of the main objectives of the European transport policy, as reflected in European Commission's White Paper on Transport 2011 (COM 144, 2011), is the promotion of sustainable modes of transport, such as cycling. The promotion of cycling is pursued due to its significant benefits in: a) health issues (Oja et al., 2011; Mulley et al., 2013), b) travelers' well-being (Friman et al., 2017; Singleton, 2018; Vaitsis et al., 2019), c) the environment (Litman, 2018), d) the economy (Blondiau et al., 2016) and e) car reduction (Woods and Masthoff, 2017). To promote cycling, it is essential to develop a comfortable, safe and extensive bicycle network (Buehler and Dill, 2015), to implement secure

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bicycle parking spaces and to give priority to bicycles at signalized intersections (Martino et al., 2010), as well as to carry out promotional activities (Urbanczyk, 2010). Also, the implementation of bike-sharing systems is an action often applied to assist the bicycle usage increase. At the same time, it seems that shared mobility solutions, which enable users to have short-term access to transportation modes on an "as-needed" basis (Shaheen et al., 2017), is constantly gaining ground. In this context it is clear that bike-sharing systems are an important part of the transport systems of modern cities and that is why more and more cities worldwide are implementing such systems (Shaheen et al., 2010).

The history of bike-sharing systems (BSS) begins in 1965, with the "white bicycle plan" in Amsterdam (DeMaio, 2009). From then until today, the way in which these systems operate has varied considerably and over the years four generations have formed (DeMaio, 2009; Shaheen et al., 2010):

- "Free Bike Systems" or "White Bikes": that are characterized by a total absence of rules
- "Coin-Deposit Systems": in this generation systems with stations, from where the bicycles can be rented with a coin deposit are introduced
- "Information Technology-Based Systems": the systems of this generation collect data about rentals and users in order to deal with phenomena of vandalism and theft
- "Demand Responsive, Multi-Modal Systems": elements of this generation's systems are the usage of GPS devices on bicycles, the usage of electric bicycles, the advanced methods for bike re-distribution, the integration with other transport modes and the usage of mobile stations or the lack of fixed stations (dockless systems).

The evolution of bike-sharing systems reveals the important role played by technology. Also, the operation of these systems, particularly those of the latter two generations, shows that their success depends on the solution of three optimization problems: a) number and location of stations, b) capacity of the stations, c) bicycles distribution. To solve these problems, it is essential to estimate the system's demand. An extensive review of the bike-sharing research published from 2010 to 2018 concludes that demand estimation is one of the most evolutionary trends in the field of bike-sharing research globally (Si et al., 2019). In the literature there are many studies which attempt to identify factors that affect stations' demand. According to the United States Department of Transportation (2012), stations' demand is correlated with: a) population density, b) employment density, c) proximity to universities, d) commercial activity density, e) available bicycle infrastructure, f) proximity to tourist attractions and recreation areas, g) available public transit, h) topography. The impact of these factors on station demand is explored further in other surveys. Zhao et al. (2015) use data from Nanjing, China and identify that the demand for bike-sharing trips is mainly generated in residential areas and is mainly attracted by rail stations. Noland et al. (2016) use Bayesian regression models and conclude that stations close to subway stations and bicycle infrastructure exhibit higher demand. Apart from the bicycle infrastructure, the presence of neighboring bike-sharing stations has significant impact on the station usage (Hyland et al., 2018). Another study highlights that demand is lower in areas with higher elevation (Faghih-Imani et al., 2017).

The factors mentioned above to affect station demand are related to the built environment, land uses and transport systems and can therefore be useful information for the optimal planning of bike-sharing systems, that is the determination of the number, the location and the capacity of the stations. However, for the proper management of the system and more specifically for the re-distribution of bicycles, it is useful to estimate the change in demand of a station, within the year, even the day. Kim (2018) identifies that demand for bike-sharing trips is approximately the same on weekends and weekdays, but lower during public holidays and during days with high temperatures. Weather variables, such as temperature, wind intensity, rainfall and humidity level, found to be important predictors also in Ashqar et al. (2019) and Corcoran et al. (2014) studies.

Recent studies apply machine learning techniques in order to develop tools for short term prediction of demand at station level (Hulot et al., 2018; Wang and Kim, 2018; Lozano et al., 2018; Lin et al., 2018). These studies mainly exploit temporal and weather data and apply methods such as random forests, gradient boosting and recurrent and graph convolutional neural networks. The aim of the present paper is to present a methodology for the development of a tool, as well as the tool itself, which consists of a demand prediction model and a web-based application visualizing the predictions. In contrast with other predictive models developed in this field, the model proposed in this paper focuses on small-medium sized systems and is intended to be easily adaptable to the needs and characteristics of different bike-sharing systems of similar size. As such, and this is also an innovation of the tool, for every system, several machine learning regression algorithms are tested and evaluated and the user (the bike-sharing system's operator) is provided with the results of the best-fitting algorithm. Such a tool could comprise a useful assistance for bike-sharing operators in order to optimize bikes' redistribution process and offer reliable services to the systems' users.

2. Methodology

The developed prediction tool is based on a data driven model that fuses data from three different sources; a static file with information and the location (coordinates) of the bike-sharing system stations, the rental records database of the system, which includes spatial and temporal data for both the start and end of each rental, and weather data for the area where the system operates as well as short term weather forecast.

Three different time intervals for model training and issuing predictions are considered, namely 1-hour, 2-hour and 3-hour. For systems with high rental density, the one- or two-hour intervals are considered more meaningful and suitable. However, when analyzing systems with sparse rental frequency, it might be the case that different stations have very few or even 0 rentals for the vast majority of short intervals. In such cases, increasing the time interval to 3 hours is a countermeasure.

After the desired time interval is selected, an efficient algorithm groups rentals' records according to trip start station and counts the rentals within each selected temporal interval, to create the dependent (target) variable for the demand predictive algorithms. A similar method is applied for the bike returns predictive model; however, the grouping is implemented with respect to the station where each trip has ended, so that the target variable is the number of bikes returned at each station for each time interval. For both models the rest of the processing steps is identical. The weather and rental datasets are resampled to matching time intervals. For each time interval sample, four weather features are extracted from the weather database: a) average temperature b) wind speed c) sky cover (ordinal numeric variable representing clear, scattered, broken, overcast and obscured conditions) and d) liquid precipitation. The final data preprocessing step is feature engineering; methods applied to raw data in order to create custom independent variables to be utilized by the model. The tool automatically extracts several such variables from the date and time of each interval. Two binary variables indicate whether the day is a holiday or a Sunday respectively, an important feature because bike demand is typically differentiated during such days. The time, weekday and month of each time interval are encoded in a cyclical fashion, considering a day, a week and a year as complete circles respectively. For example, a week circle consists of $N=7$ weekdays, represented as $n=0, 1, 2, \dots ,6$ and each of them is mapped to its corresponding angle of $\theta =(2pi*n)/7$ rad and is coded to the tuple $(\sin\theta,\cos\theta)$. Consecutive weekdays are mapped to angles with the minimum difference of (2pi)/7 rad, and thus coded to tuples with small sine and cosine numerical difference, unlike inconsecutive weekdays. Finally, an ordinal variable encodes the year and is useful for systems that operate for prolonged period of times and demand might change over the years.

Per station demand and returns of a BSS might also be affected by the number of available bikes to rent in nearby stations. In the case when a station is empty, the demand in nearby stations might increase. Furthermore, according to each BSS policy, a full station might not accept bikes. In such scenarios the number of bikes returned to nearby stations is expected to increase. In the developed predictive model, the state of nearby stations was not utilized as an independent variable due to data limitations. The historical dataset utilized for the case study consists of the rental records; data for redistributed bikes are not available, thus the number of bikes per station at any point in time is unknown.

The preprocessed historical data is utilized in order to train different predictive models, based on machine learning regression algorithms that are most suitable for the specific task, according to previous studies. Tested algorithms vary from ensemble and boosting methods like Random Forests, Gradient Boosting and XGBoosting to Artificial Intelligence methods utilizing Neural Networks. Initially, all models are constructed with their default hyperparameter values, as configured by the Python machine learning library Scikit-learn (Pedregosa et al., 2011). The neural network has an input layer of size 20, followed by two hidden layers of size 20 and 8 respectively, and an output layer of size 1. Each models' performance is evaluated with the 10-fold cross-validation method. The considered evaluation metrics are the Mean Squared Error (MSE), the Rooted MSE of the log-transformed predicted and target values, called Root Mean Squared Logarithmic Error (RMSLE), and the easier to interpret Mean Absolute Error (MAE). The coefficient of determination (R2) is also monitored, as an indicator of the percentage of variability in the dependent variable that each model was able to explain. A detailed evaluation report is automatically composed by the tool, along with the ranking of algorithms with respect to predictive performance. The user is then able to select which of the algorithms will be optimized to achieve the highest predictive performance. Optimization is achieved through a grid search cross-validation (GSCV), a procedure during which the models are trained and cross-validated with different hyperparameter value combinations to identify the optimal configuration. The GSCV is a computationally expensive procedure, as it includes training (with potentially large datasets) and testing of several models. As a result, it is implemented after the initial evaluation of model performance, and only for specific algorithms designated by the user.

The tool is implemented in Python programming language and utilizes the established libraries Pandas (McKinney, 2010) and Scikit-learn (Pedregosa et al., 2011) for data processing, transformations, analysis and machine learning. The neural networks are realized with Keras (Chollet, 2015) running on top of Tensorflow (Abadi et al., 2015). The interactive user interface is built with Dash by Plotly (Plotly Technologies Inc., 2015). The system's architecture is presented in Fig. 1.

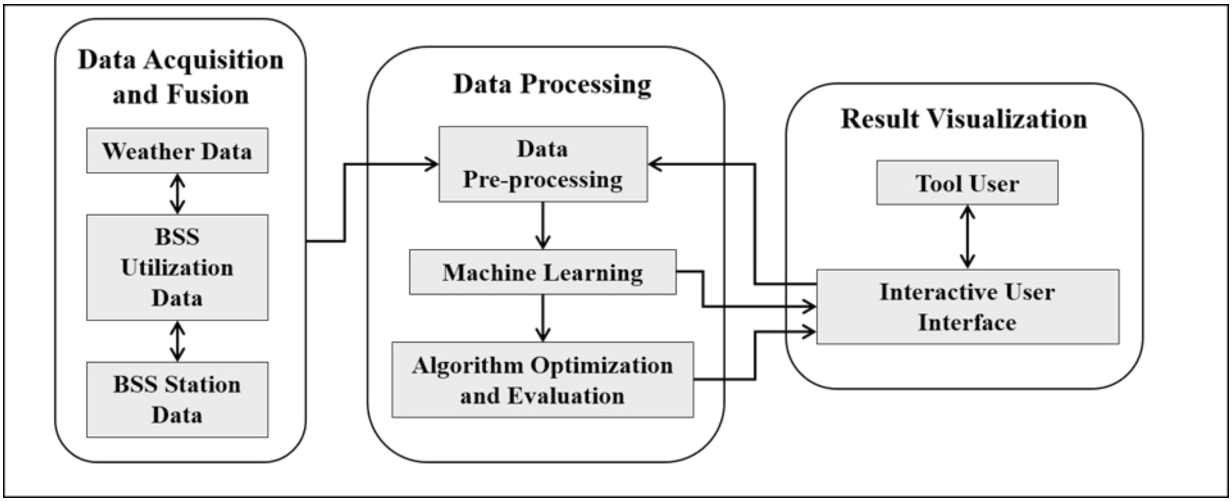

Fig. 1. The proposed tool's architecture.

3. Evaluation of the tool in Thessaloniki's bike-sharing system

3.1. Study area and bike sharing system

The proposed demand prediction and visualization tool is applied and evaluated in the city of Thessaloniki, which is the second largest city in Greece, with a population of around 1 million people. Cycling usage levels are very low in Thessaloniki (Nikiforiadis and Basbas, 2019), while the city's environment is judged by the citizens as unsafe and uncomfortable for cycling (Vaitsis et al., 2019). The bicycle lanes network currently operating in Thessaloniki has a total length of 11.73 km and does not provide sufficient accessibility to bicycle users. Nevertheless, it is estimated that this situation will change in the near future through appropriate interventions resulting from the implementation of the Sustainable Urban Mobility Plan (SUMP), which is conducted by the local authority.

In the city of Thessaloniki, a bike-sharing system, named ThessBike, operates since September 2013. From its foundation until October 2018, 16000 members have been registered and 92000 rentals have been made. In the current situation, the system operates with 200 bicycles and 8 stations, mainly located in the city center. Fig. 2 provides useful information for understanding the system usage patterns. More specifically, Fig. 2(a), shows that demand is distributed in a similar manner per month for all years of operation of the system and two peaks appear, one in May and the other in September, months in which weather conditions in the city are ideal for cycling. On Fig. 2(b) it is mainly noted that the distribution of hourly demand is differentiated according to the season; during summer demand is low during the day but peaks sharply late in the afternoon, contrary to the winter season which reveals the opposite pattern. Spring and autumn hourly demand distributions follow similar motives.

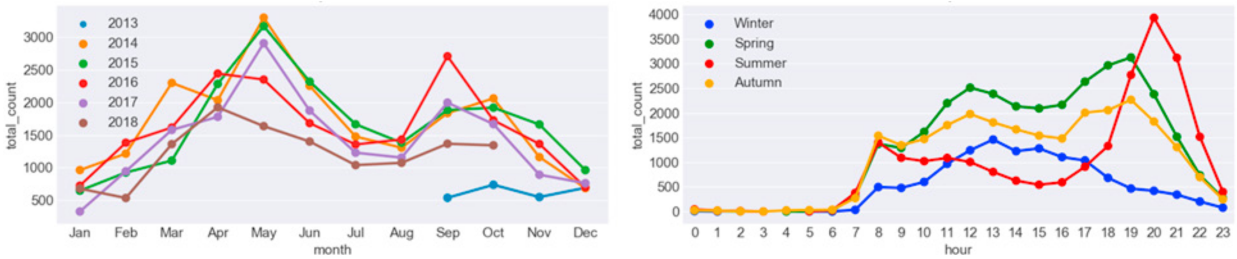

Fig. 2. (a) Distribution of rentals per month for each year of operation; (b) Distribution of rentals per hour based on the season.

Furthermore, demand is found to be higher during weekends and especially on Sundays, further indicating that the system is mainly used for recreation purposes rather than commuting.

3.2. Data description

As needed, three datasets are utilized to test the tool, two concerning information about the bike rental scheme (station locations and historical rentals) and the weather data. They are extracted from the bike-sharing system operator database and local airport weather station database in .csv format. To the best of the authors' knowledge, the airport weather station is the only local station that provides with accurate and open historical and current data. Ideally, the tool should be directly connected to the dynamic databases (weather and rentals) in order to have access to real time rentals data as well as short-term weather forecast. Such a mechanism is foreseen and developed for the tool; however, it could not be exploited in our case study, due to the proprietary nature of the bikes rental data.

The weather dataset used records the average wind speed and temperature for the previous 30 minutes, sky clearance report for the last 3 hours and precipitation levels for the last 6 and 24 hours. The precipitation values were normalized as hourly values to enable correct resampling in any of the desired temporal intervals of 1, 2 or 3 hours.

The rental dataset includes the rent and return timestamp and station for each rental. Another two variables include the user and bike ID. Analysis on this dataset reveals that almost 2.5% of rentals have a duration up to 5 minutes. According to the bike sharing operator, such trips should be considered invalid, and therefore were excluded from further analysis. Furthermore, data for 2013 were excluded from the training set because demand during this initial period of system operation was very low, as Fig. 2(a) confirms. As a final preprocessing step, each day is considered to have an 18-hour duration, from 6:00:00 a.m. to 23:59:59 p.m., because the main rental stations are not automated and only operate during this time window.

3.3. Application and evaluation of the demand prediction model

The station-level bike demand and return prediction and visualization tool, as described in section 2, was tested with data from the BSS that operates in the city of Thessaloniki. The temporal aggregation level chosen for the tests is the 3-hour interval. The 1-hour and 2-hour levels were also investigated but were considered inappropriate for the bike sharing system of Thessaloniki, as many stations produce 0 rentals for the majority of time intervals.

The application of cross-validation on the four predictive models revealed that XGBoost outperformed the rest of the models by some margin. However, the performance of all models converged when the optimized hyperparameter values obtained by the GSCV were utilized. The Random Forest and Gradient Boosting models appear to fit the train set better than the other algorithms, with lower errors and higher R^2 values, as Table 1 indicates. However, a model's predictive performance and generalization ability is more accurately assessed on a test dataset, a subset of the data that was not used during the model training. On the test set, Gradient Boosting produces marginally less errors compared to the rest of the models. A final important comment on the evaluation results is that the neural network model produces similar results on both the train and test set. It clearly has the worst fit for the train set, however, on the test set it produces errors which are just slightly larger than the other models. This indicates that the neural network is the least prone to overfitting of all tested predictive algorithms. Neural networks are commonly known for their overfitting tendency and in this study, overfitting is avoided by adopting a dropout strategy between the two hidden layers and utilizing proper training epochs and layer size for the network.

Table 1. Evaluation metrics for all predictive models after GSCV hyperparameter optimization.

	Train set metrics				Test set metrics			
Bike rentals	**MAE**	**MSE**	**RMSLE**	**R^2**	**MAE**	**MSE**	**RMSLE**	**R^2**
Gradient Boosting	0.75	1.81	0.42	0.76	0.85	2.69	0.46	0.64
XGBoost	0.76	1.91	0.43	0.74	0.85	2.71	0.46	0.63
Random Forest	0.72	1.91	0.40	0.74	0.85	2.77	0.46	0.63
Neural Network	0.89	2.66	0.49	0.64	0.91	3.00	0.49	0.6
Bike returns								
Gradient Boosting	0.74	1.80	0.42	0.75	0.85	2.69	0.46	0.63
XGBoost	0.76	1.90	0.43	0.74	0.85	2.70	0.46	0.63
Random Forest	0.71	1.90	0.40	0.74	0.84	2.76	0.46	0.62
Neural Network	0.89	2.66	0.48	0.64	0.91	3.00	0.49	0.59

The evaluation metrics are directly presented to the user, who then chooses any of the models and specific date. Bike demand and returns are estimated for any 3-hour interval or even consecutive ones, within this date. The results are visualized on a map, with which a user can interact by zooming in or out, moving to any direction and hovering over or selecting points (bike stations) for further information (see Fig. 3).

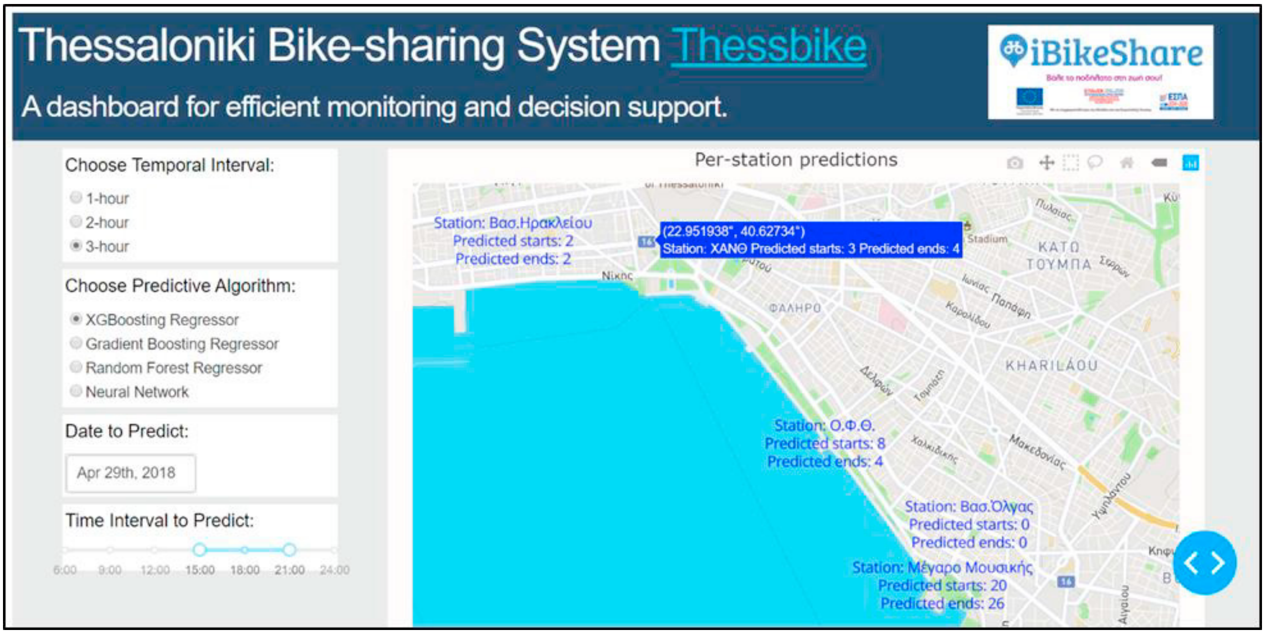

Fig. 3. The predictive tool application interface with estimations for 15:00 to 21:00 on April 29th, 2018.

4. Conclusions

In this paper, a tool for predicting the demand for rentals and returns of bikes for station-based bike sharing schemes and visualizing the results is presented. The tool facilitates a simple, intuitive interface that requires no special training or expertise and can be utilized by any bike-sharing system operator. After receiving and harvesting the historical bike rental dataset, it automatically produces the best performing algorithm for rental demand and return forecasting for all stations of the system. The level of model appropriateness is reported to the user along with a detailed report of the predictive performance of the different algorithms. After the model evaluation, the tool-user opts for the desired time interval for issuing predictions (i.e. 1, 2 or 3 hours). The produced results are visualized on an interactive, user-friendly environment in real-time, supporting the operators in decision making and data-driven management of their fleet and stations.

The developed tool empowers the management of bike-sharing systems enabling accurate, data-driven decisions to optimize the systems' operation and it can provide very useful insight for the development of strategies incentivizing users to return/rent bicycles from/to specific stations according to expected demand.

Future work will deploy the demand prediction output of this tool, to develop an optimal bicycles' redistribution tool to support bike-sharing systems' operation.

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