Temporal Network Approach to Explore Bike Sharing Usage Patterns

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Abstract: The bike-sharing systems have been attracting increase research attention due to their great potential in developing smart and green cities. On the other hand, the mathematical aspects of their design and operation generate a lot of interesting challenges for researchers in the field of modeling, optimization and data mining. The mathematical apparatus that can be used to study bike sharing systems is not limited only to optimization methods, space-time analysis or predictive analytics. In this paper, we use temporal network methodology to identify stable trends and patterns in the operation of the bike sharing system using one of the largest bike-sharing framework CitiBike NYC as an example.

1 INTRODUCTION

The bike-sharing systems have been attracting increase research attention due to their great potential in developing smart and green cities. On the other hand, the mathematical aspects of their design and operation generate a lot of interesting challenges for researchers in the field of modeling, optimization and data mining. In this paper, we use temporal network methodology to analyze the workload of a bike-sharing system over time. To this end, we present a bike-sharing system as a temporal network, considering stations as nodes, and trips between stations as edges. We use only two characteristics of temporal networks - centrality by degree and centrality by betweenness. We calculate each of these characteristics at two levels - at the level of individual stations and at the level of clusters, and then use them to reveal workload patterns both for stations and clusters of stations.

We use two simple but powerful tools for revealing patterns, these are heat maps and trends. Heat maps are used to visualize the average centralization of station clusters over certain time span (over hours and over weekdays). They collapse cluster centralization measurements for one hour of a certain day of the week into one value and decode it into a color cell. In order to make heat map more contrast and effective, we propose an unusual way of collapsing data, in which only the highest cluster centralization values are taken into account. In addition, we use the time series tools in order to determine whether there is a steady trend in changing the centralization values of stations in the cluster. We try to answer the question “Do the trends of different clusters differ from each other?”.

The structure of this paper is as follows: Section II outlines the background of the bike-sharing systems. Section III describes methodology of estimating temporal network centralities. Section IV describes the data and experiment results. In Section V, we summarize our present work and propose the potential directions in the future work.

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2 BACKGROUND

2.1 Bike-sharing Systems and Main Issues Related to Their Design and Use

Bike-sharing system is a system that allows people to rent a bike at one of the automated stations, go for a ride and return the bike to any other station installed in the same city. As noted in (Shaheen S.A. et.al., 2010), all bike-sharing systems work on the basis of a simple principle: people use bikes as frequently as circumstances dictate, without the expenditures and responsibilities that they would have borne if they owned these bikes. The evolution of bike-sharing systems has already spanned four generations, the systems of the last – fourth – generation present the advanced digital frameworks equipped with smart sensors that completely track all user actions in the system (Lozano A et.al., 2018). However, in the design and operation of these systems there are still certain challenges that can be conditionally divided into three large classes discussed below (Shaheen S.A. et.al., 2010).

The problems of the first class are related to the design and redesign of bike-sharing networks. Design of bike-sharing networks, including planning the layout of stations, determining their number and capacity, is a complex process that must take into account many factors, from topographic features of the city, forecasting user demand and ending with the principles of social justice (Lozano A et.al., 2018). These issues have to be addressed not only during the initial design of the network, but also during its operation, when it is necessary to make improvements to existing layout schemes.

The problems of the second class are related to incentivizing users of bike-sharing systems. Stimulating users is a necessary part of the bike rental service in conditions of busy stations (for example, when there are no bikes or free docks at the stations, while the user wants to take the bike or return it) (Raviv T. et.al., 2013). User incentives, as a rule, are based on a flexible pricing policy, depending on the current situation (time of day, weather or seasonal events, calendar events). The solution to these issues is based not only on the data generated by the bike-sharing system itself, but also on data received from external services, for example, weather data, traffic jams, repairs carried out on the city streets, etc.

The problems of the third class are related to the rebalancing of bike-sharing stations (reallocations of bikes between stations). These problems are caused by so-called commuting patterns as, for example, regular trips of citizens to work, as a result of which there are not enough bikes in the morning in the residential areas of the city, and not enough in the evening in the business areas of the city (Oppermann M. et.al., 2018; Zhou X., 2015; Papazek P. et.al., 2014). The reallocation of bikes among the stations should, on the one hand, match the predicted needs of the stations, and on the other hand, minimize the cost of managing the bike park, including the cost of transporting bikes (Raviv T. et.al., 2013).

In the next section, we will consider analytical, predictive, and optimization models and methods aimed at solving the listed three classes of problems. Despite of the fact that bike-sharing services have been deployed in hundreds of cities around the world for a long time, nevertheless, the development of such models and methods remains relevant.

2.2 Analysis, Prediction and Optimization Models to Address the Main Issues of Bike-sharing Systems

Models for designing and redesigning bike-sharing networks are offered in (Frade I. & Ribeiro A., 2015; Yuan M. et.al., 2019; Kloimüllner C. et.al., 2017; Park C. et.al., 2017; Wang J. et.al., 2016; Celebi D. et.al., 2018). The authors of (Frade I. & Ribeiro A., 2015) offer an optimization model that ensures maximum satisfaction of user demand with taking into account restrictions in the cost and maintenance of the system. The model is a target function where the input variables of which are demand, maximum and minimum throughput of stations, cost of bikes, operating costs and budget. The output of the model– the number of stations and bikes in each zone of the city, the throughput of the stations, the number of bikes movements, annual income and expenses. The model does not indicate the specific location of the stations, but determines their number in each zone. The authors of (Yuan M. et.al., 2019) argue that the disadvantage of the above model is the representation of demand as a fixed value. So they offer another model of mixed integer linear programming in which demand is a stochastic variable. Their model gives not only the number of stations at the output, but also their locations, based on the concept of subjective distance. The authors of (Kloimüllner C. et.al., 2017) also use mixed integer linear programming, but instead of separate stations consider enlarged geographical cells into which the city is divided. The authors of (Park C. et.al., 2017) solve the problem of optimal station placement in two ways: using the p-median search algorithm and the maximal covering location model. The designed stations are dispersed throughout the region in the first case (spatial equality is achieved), and they are concentrated in the center in the second case (the maximum of satisfied demand is reached). The authors conclude that the city authorities can independently choose which option is preferable for them. The authors of (Wang J. et.al., 2016) use spatial-temporal analysis to search for stations that do not march demand and then identify the most disadvantaged areas. They use retail location theory to design stations in these areas. The authors of (Celebi D. et.al., 2018) solve the problem of determining the optimal capacities of stations using the Markov decision process.

Models of incentivizing users and redistribution of user flows are considered in (Singla A. et. al., 2015; Pan L. et. al., 2019; Yang Y. et. al., 2019; Angelopoulos A. et. al., 2016). The authors of (Singla A. et. al., 2015) offer an incentive scheme that encourages users to change their behavior using micropayments. The system offers to a user an alternative nearby and a better price when he or she wants to use an overloaded station. Deep learning is used in the incentive scheme, on the basis of which the optimal price offered to users is determined. The authors of (Pan L. et. al., 2019) model this problem as a Markov decision process taking into account both spatial and temporal characteristics. The authors propose a new deep learning algorithm named Hierarchical Reinforcement Pricing to determine the optimal price. In (Yang Y. et. al., 2019), spatial statistics and graph-based approaches use to quantify changes in travel behaviours and generates previously unobtainable insights about urban flow structures. The authors of (Angelopoulos A. et. al., 2016) offer model of incentivizing users based on the priorities of moving vehicles from station to station, taking into account fluctuating demand and the time-dependent number of free docks at stations.

Models of rebalancing stations (redistribution of bikes between stations) are considered in (Alvarez-Valdes R., et. al., 2015; Liu J. et. al., 2016; Xu F. et. al., 2019; Zheng Z. et. al., 2018). The authors of (Alvarez-Valdes R., et. al., 2015; Liu J. et. al., 2016) propose a two-stage procedure consisting of predictive and optimization parts to solve the rebalancing problem. In work (Alvarez-Valdes R., et. al., 2015), the offered procedure at the first stage predicts the unsatisfied demand for free docks and bikes of each station in a given period of time in the future by changing the possible number of bikes at the beginning of the simulated period. At the second stage the procedure develops the most suitable routes for moving free bikes by combining the forecasts obtained with the current state of the system. In (Liu J. et. al., 2016), the procedure uses mixed integer non-linear programming to search for bike transportation routes at the second stage by minimizing the total covered distance. The authors of (Xu F. et. al., 2019) also solve the problem of redistributing bikes in two stages. At the first stage, they perform a cluster analysis of stations using an Affinity propagation algorithm with Adaptive Constrains that determines where the bike loader is responsible for which stations. The algorithm takes into account a complex landscape, obstacles in the form of hills and rivers, and groups the stations into clusters based on the concept of real distances. At the second stage, simulated annealing with power limitation is used to solve the routing problem of vehicles with a limited capacity. The authors of (Zheng Z. et. al., 2018) clustered neighboring stations with similar patterns of use and simulate the influence of weather conditions on the number of users. They use multivariate regression analysis to predict the number of bikes in each cluster over a period of time.

2.3 Open Data of Bike-sharing Systems

Not all existing bike-sharing systems provide their accumulated data in the public domain. At the same time such data, if it is open, quickly acquire independent value as a resource that allows researchers to hone their skills using the methods of intellectual analysis and forecasting, and developers and engineers to conduct experiments when developing new, more advanced models of the functioning of bike rental systems. One of these valuable resources is the open source CitiBike NYC bike-sharing system.

The CitiBike NYC bike-sharing system in New York opened in May 2013 and initially included 6,000 bikes and 332 stations (Kaufman S.M. et. al., 2015). As of January 2020, the number of bikes has increased to 13,000, and the number of stations to 850. Information on the use of this system is published on the Amazon cloud server (https://www.citibikenyc.com/system-data).
Understanding that open data is an additional incentive to popularize bike rental in New York and, in general, to develop the tourism industry, the system developers monthly generate reports on the use of their bikes.

Each report is a data set consisting of 15 fields:

- tripduration – trip duration (in seconds);
- starttime – start of the trip (start date and time accurate to milliseconds);
- stoptime – end of trip (date and time of the finish accurate to milliseconds);
- start station id & start station name – code and name of the station where the bike started from;
- start station latitude & start station longitude – geographic coordinates of the station where the bike started from;
- end station id & end station name – code and name of the station where the bike was finished;
- end station latitude & end station longitude – geographical coordinates of the station where the bike finished;
- bikeid – bike code;
- usertype – user type (client - 24-hour or 3-day user; subscriber - user with a subscription for a year);
- birth year – user year of birth;
- gender – user gender (0 – unknown; 1 – man; 2 – woman).

You can get answers to various questions by analyzing these data: "Where can I ride CitiBike bikes? What routes are most often used? What are the travel times? Which stations are the most popular? What days of the week do most trips take place? What type of users prevail in the morning, afternoon or evening? " As noted above, thanks to this, the CitiBike system concentrates not only users, but also developers, engineers, researchers, who can not only analyze and visualize the available information, but also carry out forecasting and carry out experiments to test new methods and models aimed at optimizing the system.

3 METHODOLOGY

3.1 Temporal Measures of Centrality for Bike-sharing Stations

In this paper, we use temporal network tools to dynamically measure the importance of nodes (stations) of a bike-sharing network. By dynamic measures we mean time-distributed estimates of the centrality. We are considering two options for estimating centrality: by degree and by betweenness. Firstly we define these options for calculating the centrality of nodes of a static network, and then extend them to the case of a dynamic one, i.e. temporal network.

The degree centrality is the simplest indicator for assessing the "importance" of a node in a static network. It is enough to know the degree of the node to calculate it, i.e. the number of its direct connections with neighboring nodes (the number of single transitions from a given node to neighboring nodes):

$$\mathrm{C_i^D} = \mathrm{deg(i)} \tag{1}$$

where i - the node for which centrality is calculated, and deg(i) - its degree. This measure is recommended for searching for strongly connected nodes. For example, in social networks, the degree of centrality is used to search for the most sociable people, i.e. people who have the most friends (contacts).

Betweenness centrality - more complex indicator, which, as noted in (Nicosia V. et. al., 2013), plays a key role in many real-world applications. To calculate it, we need to know the number of shortest paths in the network that pass through this node. Firstly, all shortest path in the network are identified and then for each node it is calculated how many times it has appeared on the shortest paths:

$$C_i^B = \sum_{j \in V} \sum_{\substack{k \in V \\ k \neq j}} \frac{\sigma_{jk}(i)}{\sigma_{jk}}, \tag{2}$$

where σ_{jk} - the number of shortest paths from node j to node k, and $\sigma_{jk}(i)$ - the number of shortest paths that pass through node i. Summation is over all nodes. It is recommended that this measure be used to search for nodes that are "bridges" or connecting links between other network nodes, thereby speeding up the flows within the network. For example, betweenness centrality is used in social networks to search for people who are intermediaries between separate unrelated communities, thanks to it the information from one community is transferred to another, where it is already spreading lightning fast.

A simple way to extend the concept of centralities to the case of a temporal network is to calculate them at each time interval (Li Y. et. al., 2015). Then formulas (1) and (2) will remain unchanged, only the method for determining direct links and shortest paths will change. They will be calculated on the basis of only those links that exist in the temporal network in a specified period of time.

Above we gave interpretations of centralities for the case of social networks. Obviously, in relation to a bike-sharing network, the temporal degree centrality indicates how many bikes have arrived at a given station and how many have traveled over a specified time period. In other words, it determines the time-distributed intensity of the incoming and outgoing bike flows at this station. At the same time, the temporal betweenness centrality indicates how intensively this station participated in the turnover of bikes between stations in a given period of time. In other words, it determines the time-distributed intensity of the exchange of bikes between stations, produced through this station.

3.2 Temporal Measures of Centrality for Clusters of Bike-sharing Stations

There are a large number of works in which the analysis or prediction of bike-sharing network traffic is preceded by the clustering of stations (Feng S. et. al., 2018; Dai P. et. al., 2018; Caggiani L. et. al., 2016; Jia W. et. al., 2018; Freeman L. 1978). The need for clustering is explained by the fact that under the influence of a large number of complex factors, the traffic of one particular station looks too chaotic to make any conclusions or predictions based on it, it also seems impossible to find any periodicity or regularity in the departure or arrival of bikes (Feng S. et. al., 2018). As most researchers note (Feng S. et. al., 2018; Dai P. et. al., 2018; Caggiani L. et. al., 2016), after grouping individual stations into a cluster, the frequency and regularity of traffic become much more obvious than in the case of individual stations, and, therefore, more predictable. The nature of the movement of bikes between individual clusters also acquires robustness.

Thus, the grouping stations into clusters will provide a smoother and less chaotic picture of traffic, but for this it is necessary to move from many separate estimates of the centrality of stations to one general estimate of the centrality of the cluster. For this purpose, the Freeman centralization measure is often used (Borgatti S.P. & Everett M.G., 2005). It reflects the degree to which a network (cluster) consists of a single node with high centralization surrounded by peripheral nodes (Borgatti S.P. & Everett M.G., 2005). This measure is the sum of the differences between the centrality of the central node of the network (cluster) and the centralities of all other nodes, divided by the maximum possible difference that can exist in the network (cluster) with this set of nodes:

$$F = \frac{\sum_{i \in V}(c_* - c_i)}{max \sum_{i \in V}(c_* - c_i)} \quad (3)$$

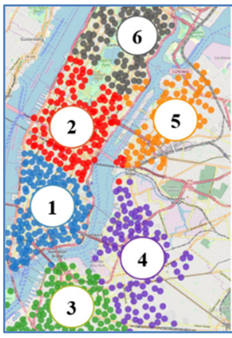
where c_* – the centrality of the most central node in the network (cluster), and c_i – the centrality of the next node i in the network (cluster).

It should be noted that not all clustering algorithms are applicable for clustering bike stations. For example, the K-means algorithm, which combines stations into clusters based on the compactness of their location, does not take into account the terrain. Meanwhile, very often the real distance between two stations is determined not by a straight line, but bypassing some obstacles, for example, a river, a hill or railway tracks (Dai P. et. al., 2018). Accordingly, the two stations are close to each other in the sense of compactness of their location on the map, are actually very far from each other, if we take into account the route between them. It is recommended to use spectral clustering algorithms instead of the K-means algorithm to eliminate such shortcomings, as well as use not only the geographical coordinates of stations for clustering, but also take into account traffic between stations.

4 EXPERIMENTS

4.1 Data

An experimental dataset has been selected from CitiBike NYC system for one month (April 2019). It consists of 1 766 094 records, describing bike trips between 791 stations. K-means algorithm has been applied to cluster these stations by their coordinates. Despite the observation in Section 3.2.2 that k-means is not appropriate for clustering urban objects, we use it for the sake of simplicity, i.e. just to split dataset into 6 more smaller fragments (see fig.1).



Cluster	Number of stations	Color on a map
1	163	Blue
2	142	Red
3	168	Green
4	115	Violet
5	83	Orange
6	120	Grey
Total	791	

Figure 1: Clustering stations by their location (latitude and longitude).

After running k-means, each cluster is represented as a temporal network with stations as nodes and trips between stations as edges. Within the each cluster, temporal centrality values for each station are calculated according to formulas (1-2). Therefore, our final data to analyze consists of 791 pairs of matrices, one pair per station. All matrices have the same dimension – 480 rows (by the number of 3-minute intervals in a day) and 30 columns (by the number of days in a month) in order to store temporal measures of the centrality for stations. For example, figs. 2-3 show betweenness centrality measures for two stations in Cluster 2, that have the highest daily totals. Measures are performed during the morning hours on Sunday and Monday (we do not present here more plots for reasons of space saving).

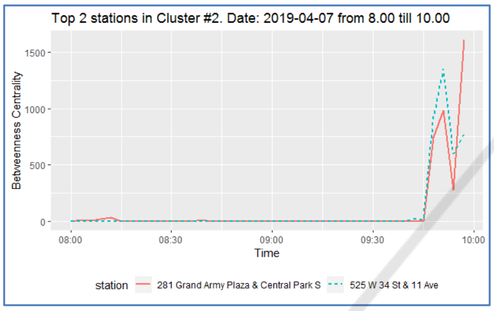


Figure 2: Selected data from Cluster 2 (Sunday).

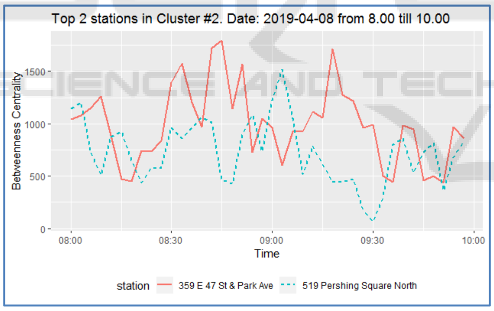


Figure 3: Selected data from Cluster 2 (Monday).

4.2 Cluster Centralizations

Once temporal measures of centrality have been calculated on the individual station level, they can be aggregated on the cluster level to find clusters centralizations in accordance with formula (3). Thereafter, we can select the highest centralization values for each cluster and use them to visualize cluster load. For example, the heat maps in figs. 4-8 represent the averaged values of the top 100 highest cluster centralizations by weekdays and hours. As it shown from the figures, all heatmaps display white spots in the lower left corner that means the intensity of bike sharing on Saturday and Sunday mornings is low for any cluster. Heat map of cluster 1 contains much less white spots than heat maps of other clusters, it means that the load on cluster 1 is more uniform. Nonetheless, the heaviest load on cluster 1 falls on morning and evening hours from Monday to Wednesday, which indicates a high turnover of bikes among stations of the cluster in these periods.

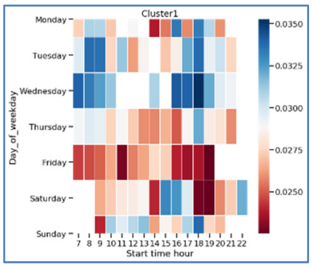


Figure 4: Heat map of intensity of betweenness centralization for Cluster no. 1.

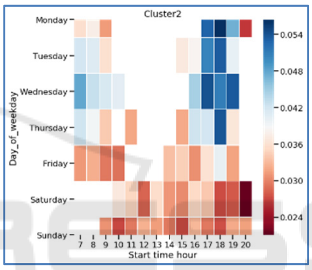


Figure 5: Heat map of intensity of betweenness centralization for Cluster no. 2.

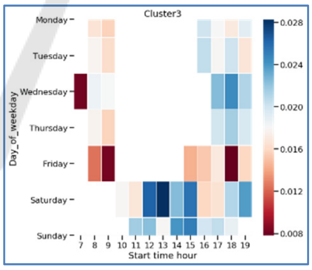


Figure 6: Heat map of intensity of betweenness centralization for Cluster no. 3.

4.3 Cluster Trends

The obtained temporal values of the centralities of the stations can be represented as time series, the comparison of which may be useful in terms of highlighting the trend. To this end, in each cluster, we took the top 10 stations with the highest average temporal centrality and built monthly trends for each of them. It turned out that the monthly trends of the top 10 stations of all clusters, except the first, retain their stable pattern inside the cluster, while the trends of the stations of the first cluster do not have a stable pattern. The graphs below show the trends of the top-4 stations in cluster 6 and cluster 5. The difference in trends is visible to the naked eye, while the trends of cluster 6 sharply decrease after April 17th and then have a peak around April 22th, then all the trends of cluster 3 after the same decline have a low peak around April 25th.

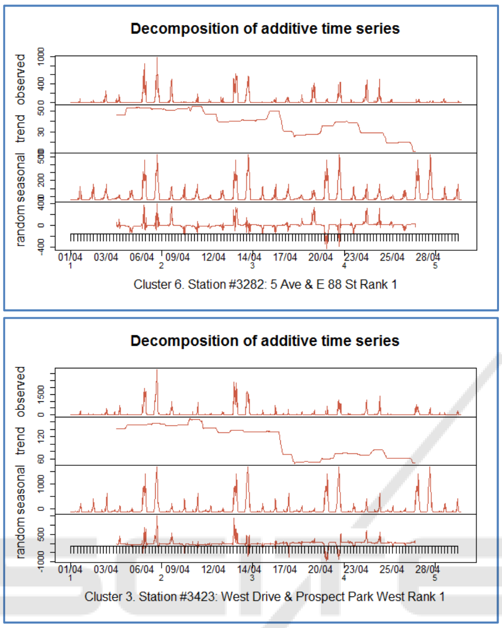


Figure 7: Trends for stations of rank 1 in Clusters no. 3 and 5.

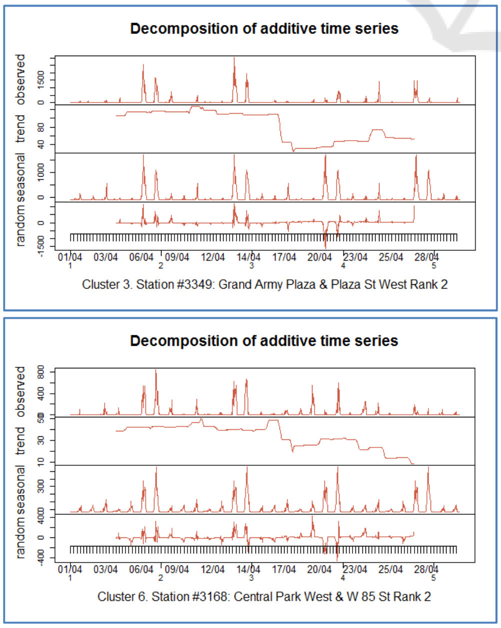


Figure 8: Trends for stations of rank 2 in Clusters no. 3 and 5.

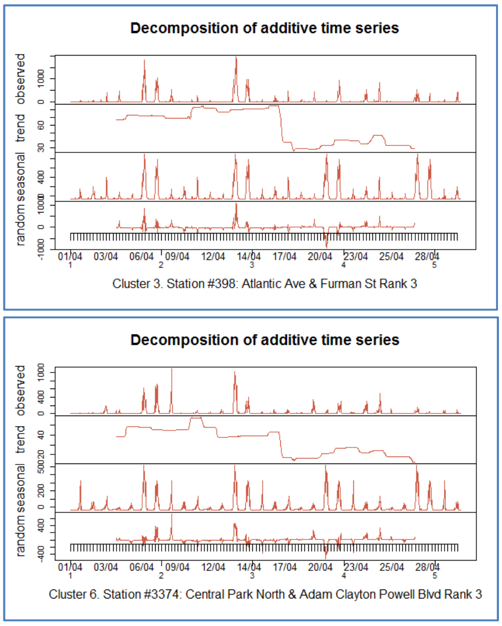


Figure 9: Trends for stations of rank 3 in Clusters no. 3 and 5.

5 CONCLUSION AND FUTURE WORK

Despite the fact that in this work we used the small dataset limited only one month, and cluster the data in a very simple manner, we believe that the goal of our work has been achieved. We have proved the applicability of the tool of temporal centralities to the identification of patterns and trends in the operation of the bike sharing system. Therefore, our future work will consist in expanding data sets, in improving clustering methods, as well as in a detailed comparison of centrality measures.

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