Advanced Analytics and Application - SS 2020
Geospatial analysis of bike rental data
Bonn - 2019

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Köln, den 31.07.2020

Executive Summary

Urban micro-mobility solutions such as bike and scooter-sharing services have experienced a significant surge in popularity in recent years. With it, they have created a growing, yet increasingly competitive market which has become an attractive strategic focus for mobility incumbents and start-ups alike. Nevertheless, players entering this space – particularly those from adjacent industries - often lack the know-how required to effectively compete in this market, and struggle to assimilate their existing offerings to it. Success in this sector is contingent upon utilizing the ever-increasing hordes of usage and environmental data to better understand users and optimize operations.

With the aim of doing just that, this project leverages temporal and location data provided by a leading bike-sharing operator. The data, which consist of the stationary locations of every bike (when they are not rented) in the German city of Bonn in 2019, is further complemented by corresponding meteorological data from the German Weather Service (DWD), land-use data from *Copernicus* and bus and train network data from the *Verkehrsverbund Rhein Sieg GmbH (VRS)*. It is worth noting that bike-sharing data were opted for as a substitute for e-scooter-sharing data which were unavailable. This should not prove problematic as there is little reason to presume substantial differences between bike and scooter sharing usage patterns.

The analyses presented shed light on several key aspects of the micro-mobility model and seek to reliably predict future usage patterns. More specifically, they reveal patterns regarding the availability and demand for vehicles, identify potential customer segments and predict hot spots for vehicle availability and demand in a spatio-temporal resolution.

The insights drawn from our analyses imply two actionable recommendations for players entering the micro-mobility market: 1) in order to combat the natural accumulation of vehicles in low-demand areas (e.g. the outskirts of the city), operators must establish a mechanism that reliably reallocates them to areas of high demand (e.g. the city center), and 2) because students and leisurely riders seem to be two of the most common user groups, special attention should be given to them in order to ensure that their needs are met through targeted marketing and operational efforts.

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1 Problem Description

The increasingly competitive micro-mobility market has instigated a race to the bottom with regards to the optimization of virtually all business aspects. Naturally, given the growing abundance of usage and other data, effective competition in this space requires the full utilization of these data using state of the art analysis and modelling methods.
In this project the vehicle data generated by a leading operator's users in Bonn in 2019 will be used to pursue the following two goals:
First, the *business goal* of this analysis is to analyze the operator's data in such a way that the following aspects can be predicted and identified as accurately as possible:
The models provided in this report enable the prediction of the demand and availability of vehicles for a certain period and area in Bonn. This tool will allow operators to optimize the supply of bikes and avoid surpluses and shortages of vehicles in certain areas. Furthermore, clustering analyses are used to identify trip or user types in order to provide a data-driven market segmentation, which is an invaluable tool for operator's marketing and competitive strategies.
Second, there are two major goals of this project concerning the Data Mining process. The first aim is to describe the bicycle rental data by finding clusters of customer and trip types as well as rental hot spots. The second Data Mining goal is to predict the demand and vehicle availability per different temporal and spatial resolutions of Bonn. For both tasks a support vector regression and a neural network are implemented.

2 Data Collection and Preparation

The provided data set contains the separate start and end information of registered bike rides in 2019 - such as the location and date time - as well as information on each bike's first and last location.
Following, two separate data frames are created, one containing the processed trip data and the other the availability of bikes.

2.1 Data Preprocessing of Trip Data

In order to obtain information about whole trips for the demand analysis, the data needs to be rearranged. There are four different values in the trip column: *first, last, start* and *end*. Each row contains information about the location and time of a bike's availability. Consequently, two trip types are needed to represent

a whole trip; in this case the rows with the trip values *start* and *end*.
After removing the rows that do not form a whole trip, those with *start* and *end* in the trip column are then divided into two data frames, and later merged into one data set representing an entire trip in each of its rows. Rows corresponding to *first* or *last* values for the ***trip*** column merely represent the automatic daily transmissions of bikes' locations, and are hence considered redundant and removed. Similarly, trips that do not start within the city boundaries of Bonn are also dropped.
Subsequently, new features are added to the final trip data frame. This involves the dissection of the *datetime_start* column into its respective periodical features and the addition of a new 'weekend' column containing boolean values. The trips' durations are also calculated and added as new column. Meteorological data such as temperature and precipitation for each trip are also added to the trips data frame. For this, data provided by *Deutscher Wetterdienst* for the weather station closest to Bonn *Königswinter-Heiderhof* were used.
Another useful data source added is land-use data. Copernicus – Europe's eyes on Earth provides land-use data for the continent, describing the land use within a polygon-shaped area. By matching these polygons with the starting point of each trip, the land use at the starting location of each trip is determined.
The third external data is the bus and train network of Bonn, which are provided here. Containing geo-coordinates of train and bus stations, this information is used to calculate the distance from a trip's start location to the closest of such stations. The presumption being that demand for vehicles may be higher in the vicinity of train stations.

	Time basket
from 5.00 to 10.59 (Morning)	0
from 11.00 to 12.59 (Noon)	1
from 13.00 to 17.59 (Afternoon)	2
from 18.00 to 22.59 (Evening)	3
from 23.00 to 4.59 (Night)	4

Table 1: First division into a time basket

Finally, Bonn is divided into Hexagons with a resolution of 7, meaning that each trip is assigned to a unique Hexagon ID. Then, a time basket as in Table 1 is defined.

Next, the trip data is aggregated in order to predict the demand per hexagon on a daily and hourly resolution. This is calculated by summing up the trips per hexagon within each time period. While the feature mean is used for weather and distance to the next bus or train station, the most common land-use feature per hexagon is derived using the mode.
After setting up the final data frame, which contains the bike rental demand data, more features for the later prediction are generated. The hexagon ID cannot be used in the models due to its datatype. Decoding the hexagon ID also proved to be impractical, as it would only be assigned ascending numbers. That is the reason why the center coordinates of each hexagons are calculated and used in the later prediction models. Additionally, the distances from the center of each hexagon to the Central Station of Bonn and to the University are added as these two locations might be hot spots regarding the bike demand.

2.2 Data Preprocessing of Availability Data

The approach for the availability data is initially quite similar to the data preparation for the trip data. Again, features that describe the date time, land-use, weather and bus and train network are used in this approach.
Afterwards, an initial hexagonal discretization with a resolution of 7 is implemented, so that the available bikes per hexagon can be calculated as follows.
Since the first and last information of the trip column do not represent the driving behaviour of the users and are also very inconsistent, the rows containing the trip starts and trip ends are filtered. For the preparation of the availability data the initial stock of bikes is also of interest, as well as new bikes that will be added during the year. This information is obtained by filtering the first occurrence of each bike in 2019.
After removing inconsistent data, that means all trip starts with no corresponding end and all trip ends with no corresponding start, the first occurrence data frame is concatenated with the start/end data.
Then, in a new *available bikes* column, 1 is written for each row matching an arriving trip (*trip* == 'end') and for each row describing the first occurrence of the respective bike (*trip* == 'first'). So 1 represents that a new bike is added in the hexagon at that time. For each row describing a bike that is starting (*trip* == 'start'), -1 is written, as this means one less bike is available in the hexagon at that time.
Because the available bikes per hexagon and time basket are needed, the data frame is grouped by hexagon, month, day and hour, summing up the *available bike* column for each group. Thus, the number of bicycles coming from or going

to each hexagon for each hour is obtained.
Because thus far, only the hourly increase and decrease of available bikes per hexagon has been determined, the values must be accumulated. Therefore, the data is grouped by hexagon and sorted by date to sum up the column *available bikes* cumulatively per group using the function *cumsum*.
Thus, the result is a data set indicating the available bikes per hexagon for each month, day and hour, based on consumer behaviour. Large positive values in the *available bikes* column indicate that there is a surplus of bikes, whereas negative values show that there is a lack of bikes in the respective hexagon. This suggests that the operator should transport bikes from hexagons where more bikes than needed are available to hexagons where demand is high. Consequently, this crucial information can be used to optimize the supply of bikes.
Finally, for adding the remaining features the same approach is used as in the preparation of the trip data, so that, for instance, the same time basket as defined in Table 1 is applied.

3 Descriptive Analytics

This section focuses on the descriptive analysis of rental demand and bike availability regarding different aspects. In particular, the change in patterns associated with a temporal and spatial resolution will be examined. Please note that the relevant Choropleth maps provide interactive representations of the exact values per hexagon. Unfortunately, because this cannot be shown in this report, numerous .html files are attached for a more detailed viewing.

3.1 Descriptive Analytics of the Trip Data

This section outlines some of our preliminary analyses regarding various aspects relating directly to trips.

3.1.1 Start Time

As Figure 1 shows, most trips start in the afternoon between 2 and 5pm.
For further analyses it is most appropriate to examine the mode of the start time in a spatio-temporal resolution as this describes which start time is observed most often in which areas of Bonn.

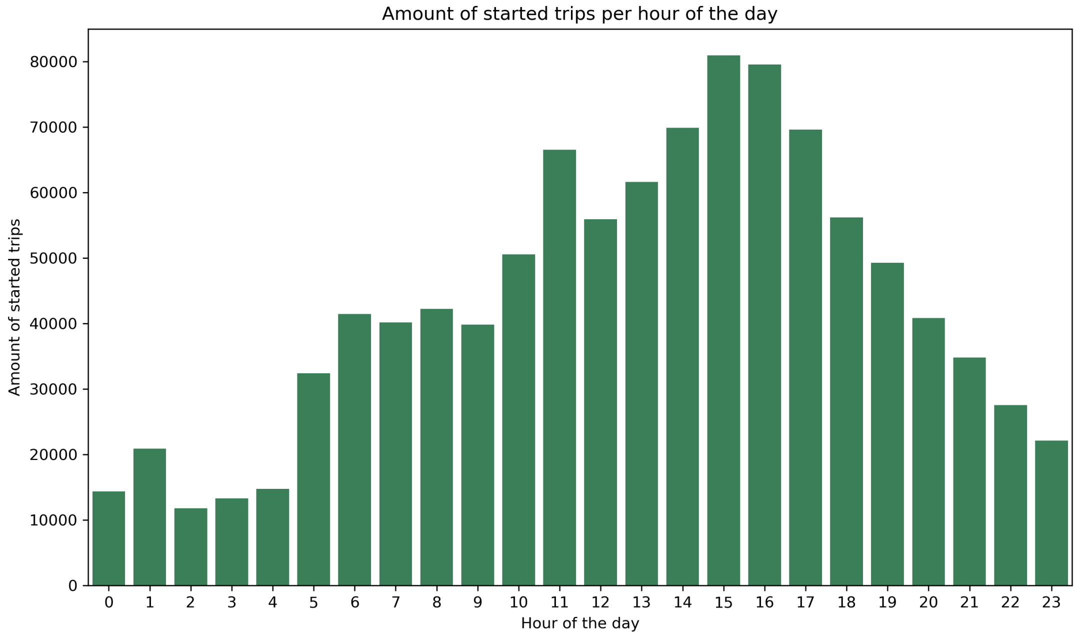

Figure 1: Amount of started trips per hour of the day

Figure 2 visualizes the mode of the start time per different hexagon resolutions, and reveals that trips in the city center tend to start slightly later than in the outer areas of Bonn. This could be attributed to commuters who use bikes as a means of commuting to and from work/university in the city center.

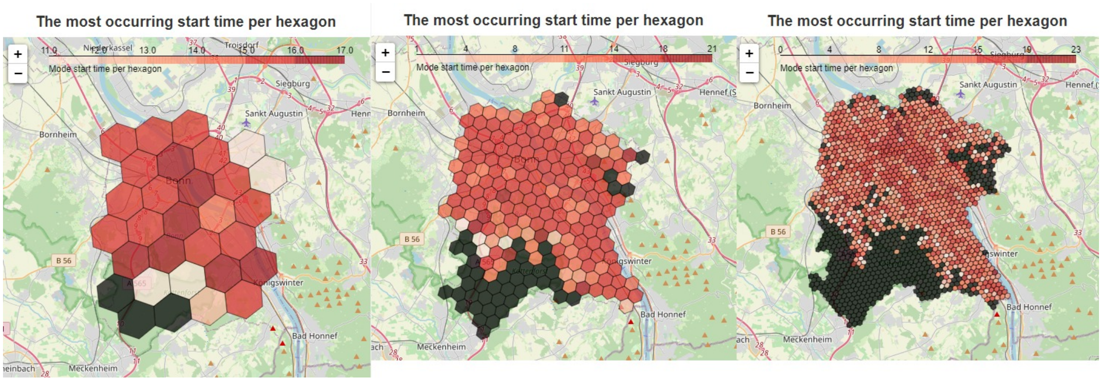

Figure 2: Most ocurring start time per different sized hexagons (*Start_ time_ hexagon7.html, Start_ time_ hexagon8.html and Start_ time_ hexagon9.html*)

3.1.2 Trip Duration

Figure 12 compares the trip durations on Mondays in July and December to those on Saturdays in July and December, and reveals that trip duration on Mondays is shorter than on Saturdays, and as one would expect, the average trip duration in July is longer than in December.

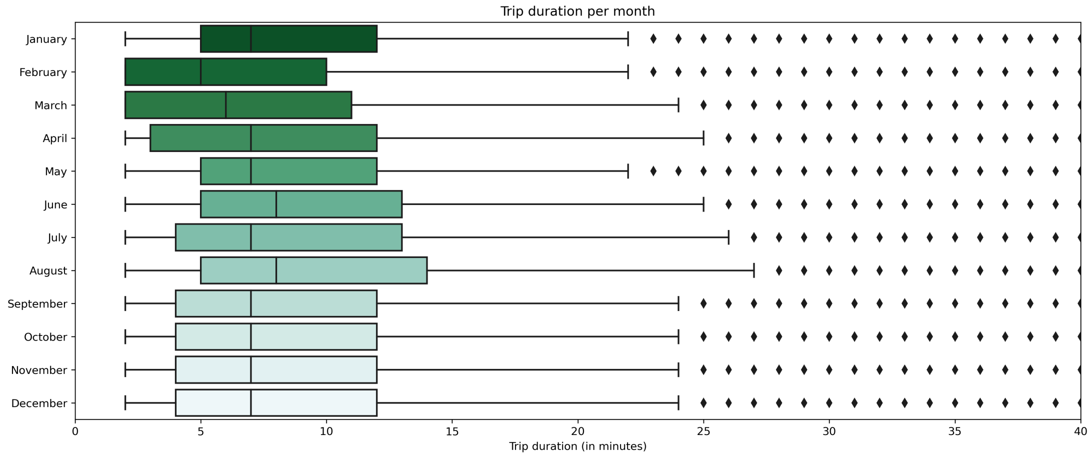

Figure 3: Trip duration per month

These findings are also observed in Figure 3, which illustrates that the trip duration during the summer months is longer, and Figure 4, which shows that longer trips are taken on weekends than on workdays.

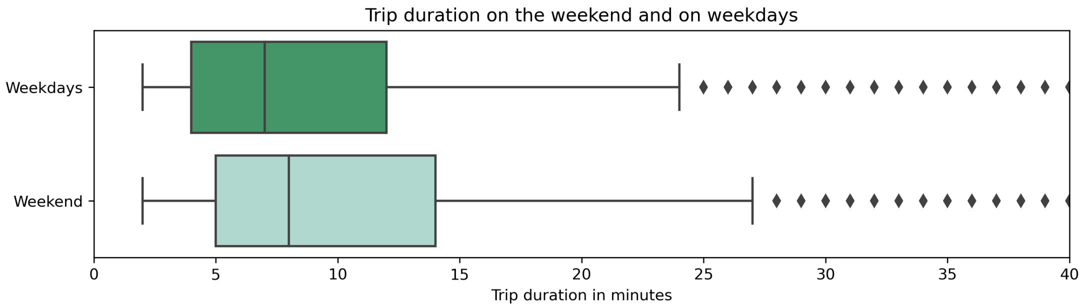

Figure 4: Trip duration on weekdays and on the weekend

Figure 12 suggests that trips starting in the outer districts of Bonn are often longer than those starting in the city center - presumably due to people in suburban areas using the bikes to reach the city center.

3.1.3 Idle Time between Trips

Figure 5 illustrates that the average idle times in the summer months are shorter than in the winter months.

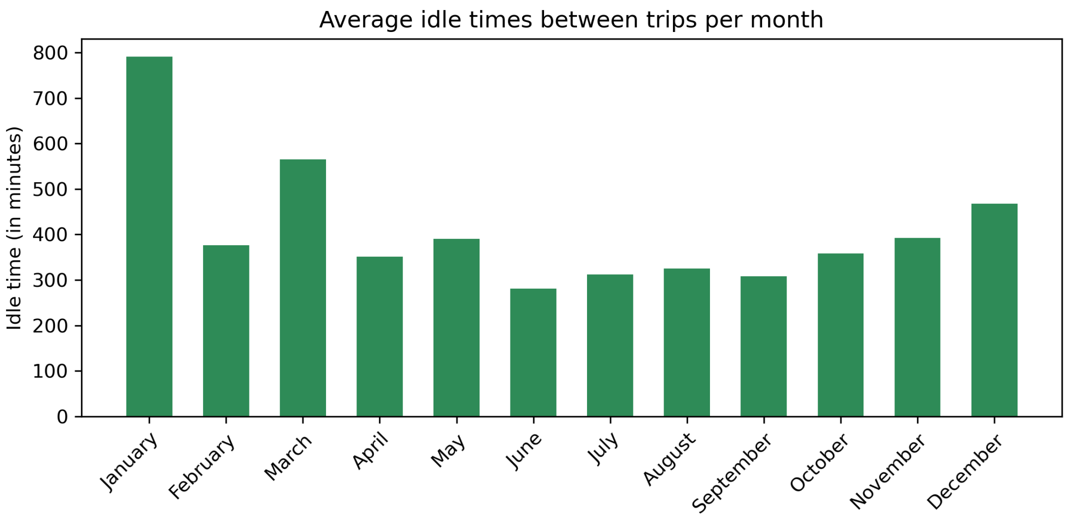

Figure 5: Average Idle Times between trips per month

This can also be explained by the higher demand during the summer as illustrated in Figure 13. It is worth noting that the extremely high idle times in January are due to the fact that the provided data set only contains data starting from the 20th of January, which increases the relative impact of outliers on this month's figures.

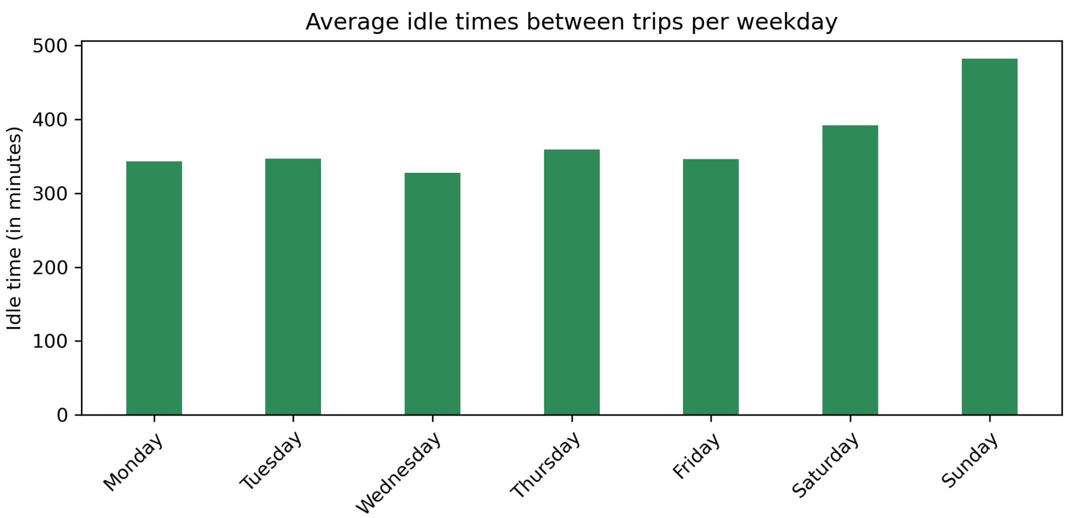

Figure 6: Average Idle Times between trips per day of the week

Regarding the average idle times on the different days of the week, Figure 6 shows that the average idle time on workdays is shorter than on weekends. This indicates higher demand and movement on workdays, which is further supported by Figure 14.

Figure 15 clearly shows that the idle times in the city center are on average shorter than in the outer areas. This means that the further bikes are parked from the city center, the longer they are unused on average.

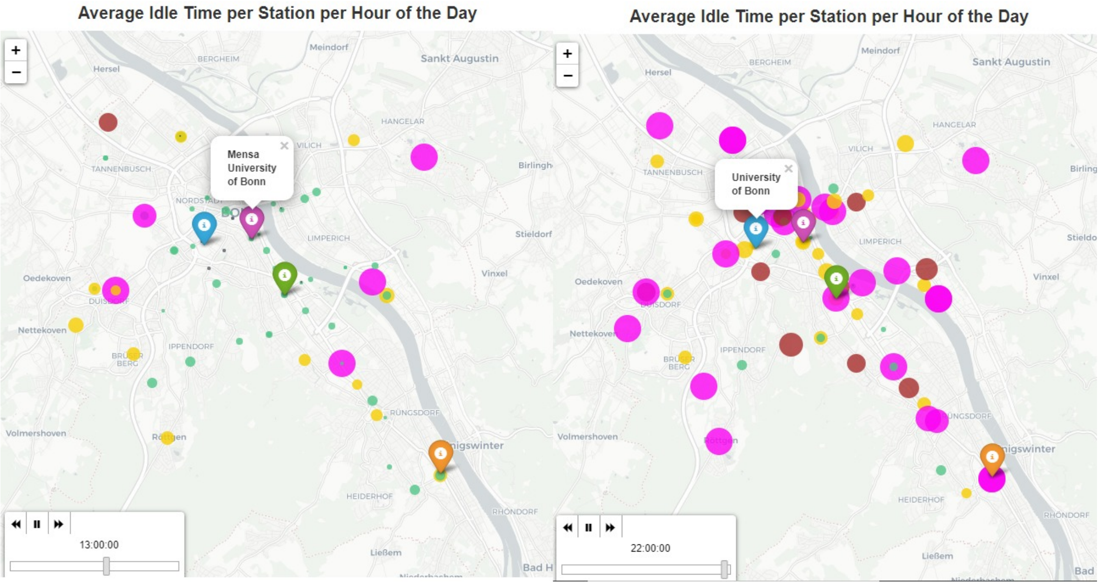

Figure 7: Average Idle Times at fixed Stations at 1PM and 10PM (*Idle_time_station_hour.html*)

Additionally, the interactive map in Figure 7 illustrates the average idle time per fixed station over the course of a day. With larger circles denoting longer average idle times, it is observed that at 1pm the idle times between trips are generally shorter than at 10pm (this is particularly salient in the city center) and at 10pm the idle times increase throughout the city. Please note that the outer circles have been intentionally reduced in size, as they would otherwise obscure the entire map at certain times.

3.1.4 Start and End Locations

The apparent similarities between Figures 16 and 17, indicates that most trips begin and end in the city center. The blue markers represent the University of Bonn and the green markers show the location of the central station. Both places seem to be hot spots regarding the start and destination of trips.

3.2 Descriptive Analytics of the Availability Data

With the goal of identifying any spatio-temporal patterns in vehicle availability, the number of available bikes for different hexagonal resolutions are visualized in Figures 18 and 19.

In Figure 18 the 21st of January exhibits the highest number of available bikes in the center of Bonn. Interestingly, a significant negative number is recorded in the same region later in the year, while the norther/northeastern regions constantly exhibit the highest positive values. The excess supply in the north/north-east and excess demand in the city center calls for a constant redistribution of vehicles in order to meet the high demand in the city center. Figure 19 supports this observation and provides a more detailed perspective.

4 Clustering

Because the clustering task required to look at the availability data with respect to the spatial distribution of bikes, we started the task with a simple Quadrat Analysis as seen in Figure 8. Applying a chi-squared test, it is determined that the process is not CSR (completely spatial random) and thereby implies that the spatial data can be used for identifying clusters.

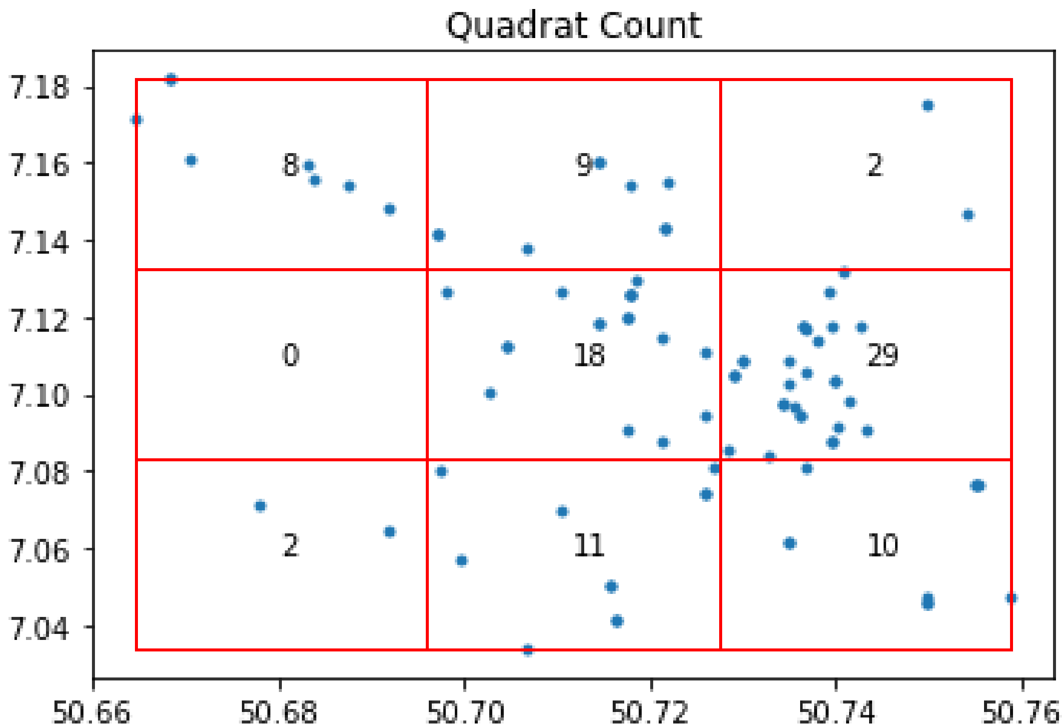

Figure 8: Quadrat Analysis

The original data table was restructured into a pivot table that counts the number of available bikes for each station in a 5 minutes interval. Next, the table was changed into an hourly profile to show fluctuations in the number of available bikes throughout the day. The optimal number of clusters was then defined by calculating the BIC and AIC or the Silhouette Coefficient.

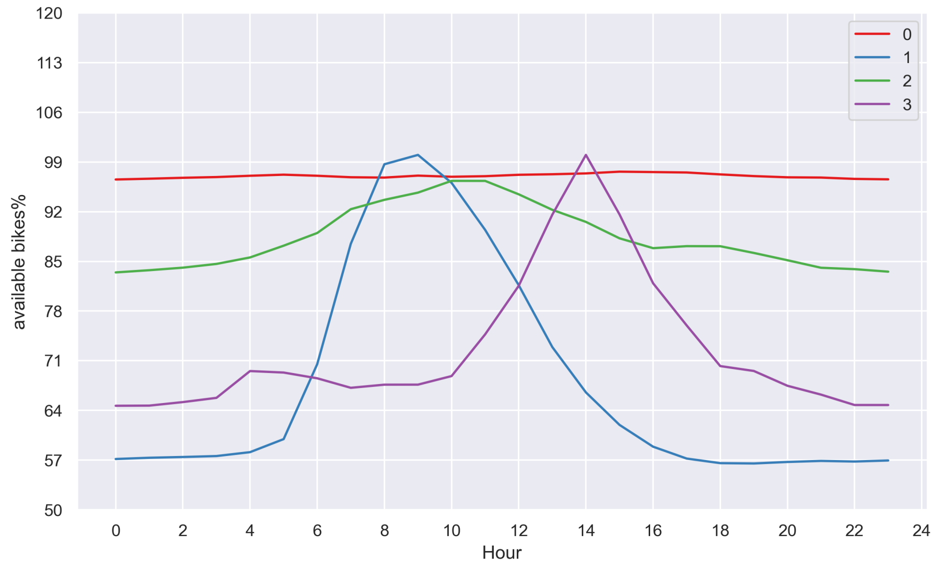

Figure 9: KMeans Available Bikes over the day

KMeans identified 4 clusters among which one (cluster 0) has a constant number of available bikes, another (cluster 1) has an almost constant number that slightly rises over the course of the day, another (cluster 2) shows a rising number of available bikes from 6am to 12am, and another (cluster 3) exhibits a rising figure from 12am to 6pm (Figure 9).

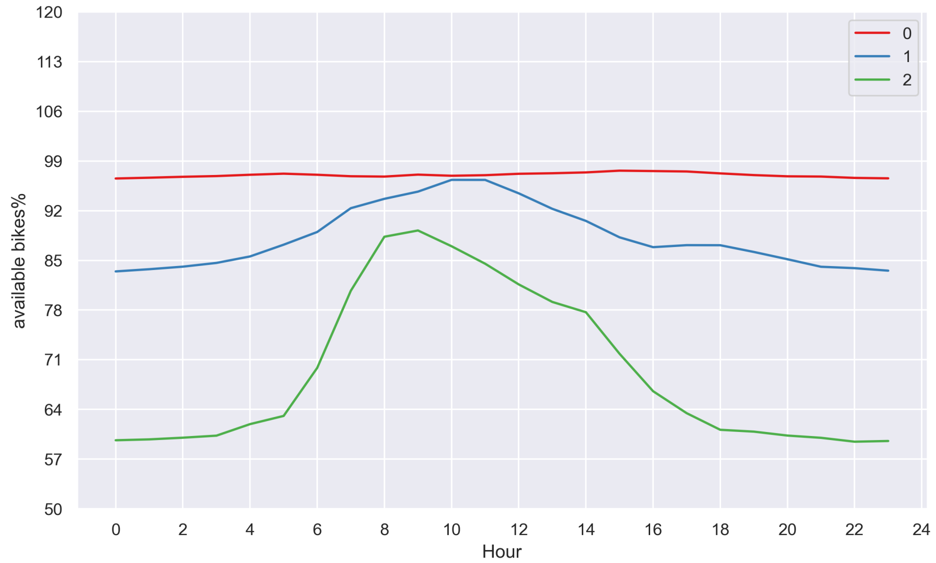

Figure 10: GMM Available Bikes over the day

A look at the assigned maps shows that all stations with a fluctuating number of available bikes are located in areas that belong to the university. Nevertheless, while most stations belong to the cluster with the constant amount of available bikes, the one with slightly fluctuating values consists entirely of stations that are located close to the Rhine.

The Gaussian Mixture model (GMM) shows less extreme fluctuations than the KMeans Clustering model, and based on the Silhouette Coefficient had only 3 optimal clusters (Figure 10). However, the three stations belonging to the university are part of one cluster and, once again, a cluster is located relatively close to the Rhine. These spatial clusters can be seen in Figure 11 with the KMeans on the right and GMM on the left.

These observations suggest that students form a specific user segment, with trip types that go to the university in the morning and afternoon. Similarly, trips taking place close to the Rhine could possibly be considered leisure trips by riders that use the bikes for sport or leisure.

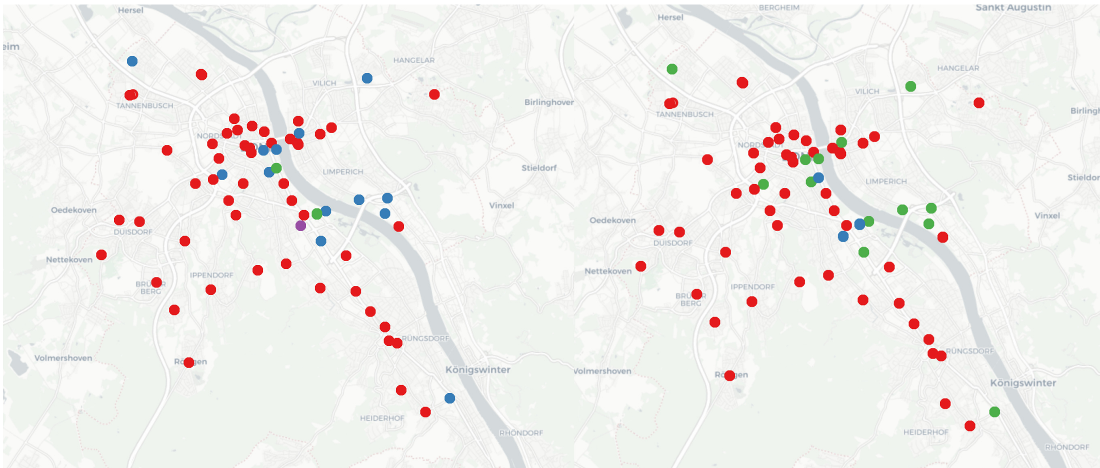

Figure 11: KMeans and Gaussian Mixture Clusters on Map

Further created clusters were formed from general information regarding duration, distance and temperature. A distribution of many short trips/less long trips both in regards to duration and distance occurs. Also, many trips during average temperatures and less trips during the more extreme temperatures are shown. This could respectively provide information about certain trips or customer types, e.g. extreme riders/comfortable riders or sporty riders/hurried riders.

5 Support Vector Machines

The objective of the fourth task is to predict the bike rental demand and the bike availability using Support Vector Regression. For this, the prediction should be based on different hexagon resolutions and time periods.

5.1 SVR for the Demand of bikes

To better grasp the correlations between features and demand, a correlation matrix is created. Based on this, the features in Table 2 are selected for the Support Vector Machines.

feature	**meaning**
time_basket	period in which the trips are summarized
month	1: January - 12: December
day	day of month
weekend	1: Weekend 0: Weekday
weekday	0: Monday - 6:Sunday
temperature	average temperature in the time_basket
distanceToCentralStation	distance from the hexagon's center to Central Station
distanceToUniversity	distance from the hexagon's center to University
distance_next_station	average distance from start location of trips to the next station within one hexagon
center_x	latitude of the hexagon's center
center_y	longitude of the hexagon's center
urban_fabric	land-use feature within hexagon
industry_commercial	land-use feature within hexagon
green_urban_area	land-use feature within hexagon

Table 2: Meanings of the selected features

The first attempt at running a simple SVR returns a R2 score of 0.41 and a Mean Absolute Error (MAE) of about 14.85. With a mean of 24.88 for the demand, the metrics are not satisfying. For a better final SVR model the data is based on a hexagon resolution of 7 and the time periods described in Table 1. To achieve a better MAE hyperparameters are optimized using Grid Search. The best results are achieved with a RBF kernel and the identified hyperparameters. As such, the R2 score increases to 0.63 and the MAE decreases to 14.13.
Table 3 shows the results of the R2 score with the final SVR on varied hexagon resolutions and time periods. Here, the R2 score is used as a metric for comparing the results. It would not be meaningful if the RMSE or the MAE were displayed in the table because, due to the fact that the data is aggregated differently, these metrics are not comparable between the hexagon resolutions and time periods .
It is clearly shown that the prediction deteriorate for smaller hexagon areas with the R2 score even going into the negative. This clarifies that the accuracy is higher in longer time periods, which also makes intuitive sense.

Hexagon resolution (Hexagon Area km^2)	**Period length (h)**			
	1	**2**	**6**	**24**
5 (252.9)	0.32	0.42	0.56	0.37
6 (36.1)	0.46	0.59	0.62	0.53
7 (5.1)	-0.06	0.45	0.64	0.69
8 (0.7)	-8.30	-1.98	0.22	0.57
9 (0.1)	-87.63	-39.19	-6.84	-0.58

Table 3: R2 score of the SVR predicting the demand using different hexagon and time resolutions

5.2 SVR for the Availability of Bikes

Next, another SVR model is developed in order to predict the availability of bikes. As per the correlation matrix and different combinations that were experimented manually, the following features are chosen for use in the final model: *time_basket, month, center_x, center_y, weekend, distance_next_station, distanceToUniversity.* The meanings of these features are outlined in Table 2.
Initially, several basic SVRs with different kernels were implemented, with the time baskets from Table 1 and hexagon resolution 7. Some of the hyperparameters were optimized for each kernel. The final model has a RBF kernel, since it returns the best metrics. The R2 score of the final model has increased from 0.29 to 0.56 through Grid Search and the RMSE has dropped from 175.50 to 137.31, which is a significant improvement. The performance of the model has become quite acceptable due to the hyperparameter optimization, but it could probably be improved by optimizing further hyperparameters. However, this option was not considered because training an SVR model with RBF kernel has a very long run-time. The same applies for the SVR predicting demand.
Finally, the final SVR model for the availability was applied to different hexagon resolutions and time periods to detect possible performance variances. Table 4 shows their corresponding R2 scores. Similar to the demand prediction, it can be clearly seen that the R2 scores decrease with higher hexagon resolutions. While predictions for the hexagon resolution 5 are nearly perfect, performance is worse for longer time periods.

Hexagon resolution (Hexagon Area km^2)	Period length (h)			
	1	**2**	**6**	**24**
5 (252.9)	0.96	0.97	0.97	0.96
6 (36.1)	0.90	0.82	0.56	0.38
7 (5.1)	0.78	0.68	0.53	0.37
8 (0.7)	0.22	0.18	0.14	0.09
9 (0.1)	0.04	0.01	-0.01	-0.00

Table 4: R2 score of the SVR predicting the availability using different hexagon and time resolutions

6 Deep Learning

This section deals with Deep Neural Networks and their usage in predicting the demand and availability of rental vehicles.

6.1 Deep Learning for the Demand of bikes

In this section we describe our final selected deep learning model for demand prediction, for which the optimizer, the number of epochs and batch size were optimized using Grid Search.
The network has one input layer with a shape that corresponds to the number of features used for prediction, and three hidden layers. The hidden layers have 64, 32 and 16 nodes respectively, and all use a Rectified Linear Unit (ReLU) as their activation functions. The network is completed with one output unit and no activation function due to the regressive nature of the task.
Furthermore, the network uses an "Adam" optimizer and the Mean Squared Error (MSE) as the loss function. The evaluation metrics used are MAE and MSE.
Table 5 shows the network's R2 scores based on the different hexagon resolutions and time periods. In comparison to the SVR it returns a higher R2 score for each combination of hexagon resolutions and time periods. Moreover, other metrics such as RMSE and MAE decrease with the neural network. This makes it possible to better predict the demand for a higher hexagon resolution compared to the previous approach. However, it still applies that the metrics are better for larger

areas and longer time periods and worse for the smallest area and the shortest time period.

Hexagon resolution (Hexagon Area km^2)	Period length (h)			
	1	**2**	**6**	**24**
5 (252.9)	0.55	0.58	0.73	0.68
6 (36.1)	0.59	0.66	0.74	0.88
7 (5.1)	0.50	0.61	0.70	0.83
8 (0.7)	0.38	0.59	0.68	0.74
9 (0.1)	0.34	0.42	0.53	0.65

Table 5: R2 score of the Neural Network predicting the demand using different hexagon and time resolutions

6.2 Deep Learning for Predicting Vehicle Availability

In this section another deep learning model is developed for predicting the availability of vehicles. A Grid Search is once again applied in order to optimize hyperparameters.

Hexagon resolution (Hexagon Area km^2)	Period length (h)			
	1	**2**	**6**	**24**
5 (252.9)	0.98	0.98	0.98	0.99
6 (36.1)	0.99	0.99	0.99	0.99
7 (5.1)	0.99	0.99	0.99	0.99
8 (0.7)	0.99	0.99	0.97	0.97
9 (0.1)	0.99	0.99	0.96	0.88

Table 6: R2 score of the Neural Network predicting the availability using different hexagon and time resolutions

Table 6 shows the different R2 scores according to hexagon resolution and time period. The results indicate that for hexagon resolution 6 to 9 the deep learning model performs significantly better than the SVR model. It is interesting to note

that the R2 score is 0.99 even for the largest hexagon resolution and the smallest time period. This is in contrast to the other models which perform worse for larger hexagon resolutions and smaller time periods - especially for demand prediction. Furthermore, the MAE and the MSE of this network are better than those of the SVR model. Because the results show that the availability of vehicles is predictable, the data seems to convey clear patterns of riding behaviour. This means that there are probably fixed places where more trips start, end and vice versa.
In addition to superior results and more accurate predictions on both tasks, our neural networks benefit from having a shorter run time. Moreover, easily implementable Deep Learning libraries such as Keras further support the use of this approach over SVRs for these tasks.

7 Conclusion

Players seeking to establish a solid foothold in the micro-mobility industry can look to the realities faced by existing operators to better understand the dynamics that dictate this sector. In doing so, they must tap into the copious amounts of usage data that is constantly being generated in order to best inform their marketing, operational and competitive strategies. Through meticulous analyses of such data provided by a global bike-sharing operator, this report has uncovered several actionable insights into the workings of micro-mobility models.
In addition to confirming some of our intuitive hypotheses (e.g. the expectation that users embark on longer trips during warmer months and weekends, and that the city center is the most common starting point and destination), our findings imply that operators should:
1) devise a means of consistently redistributing vehicles from areas of low demand to high-demand districts,
2) focus on catering to the mobility needs of students and leisurely riders who constitute two of its broadest user groups, and
Finally, with regards to modeling users' behaviours, operators and future researchers both stand to gain from a more direct approach to collecting and analyzing user data. At the very least, this would allow for a more reliable segmentation of users and eliminates much of the guesswork that is otherwise required to attribute certain patterns to a unique group of users.

A Appendix

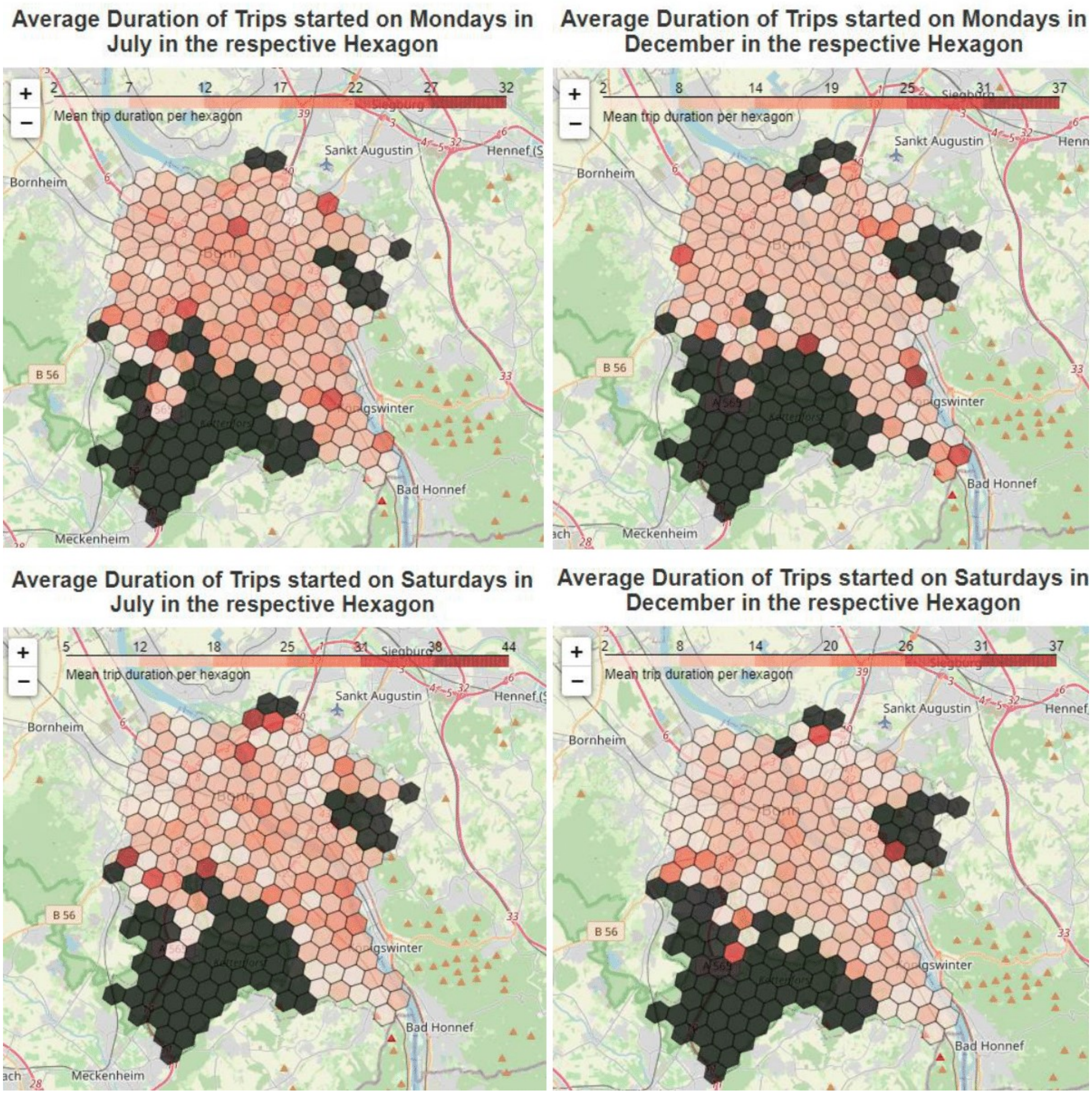

Figure 12: Trip durations Summer vs. Winter and Weekday vs. Weekend (*Trip_duration_July_Monday_hexagon8.html, Trip_duration_July_Saturday_hexag n8.html, Trip_duration_December _Monday_hexagon8.html, Trip_duration_December_Saturday_hexagon8.html*)

Figure 13: Amount of Bookings per month

Figure 14: Amount of Bookings per day of the week

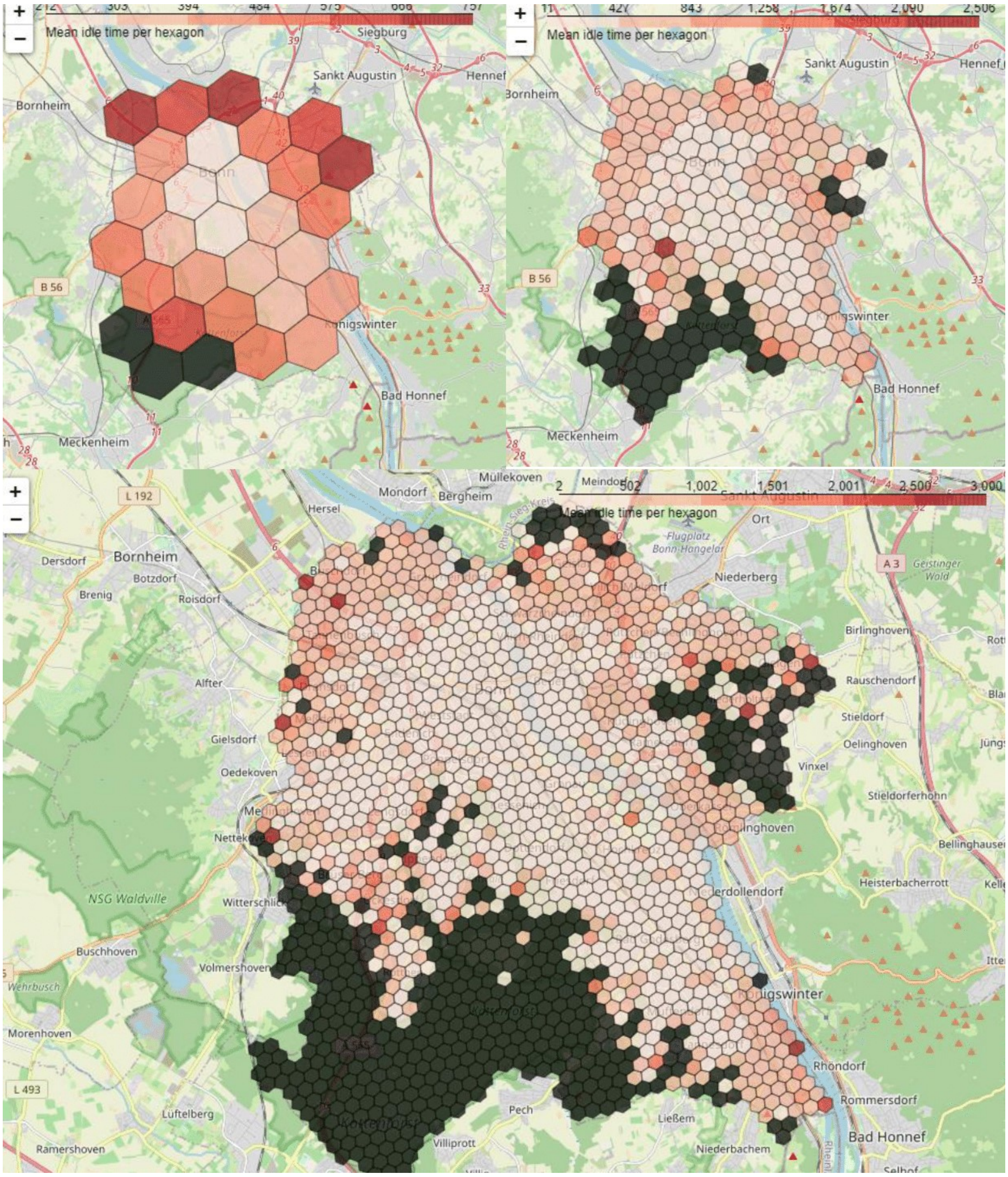

Figure 15: Average Idle Times between trips per different sized hexagons (*Idle_time_hexagon7.html*, *Idle_time_hexagon8.html*, *Idle_time_hexagon9.html*)

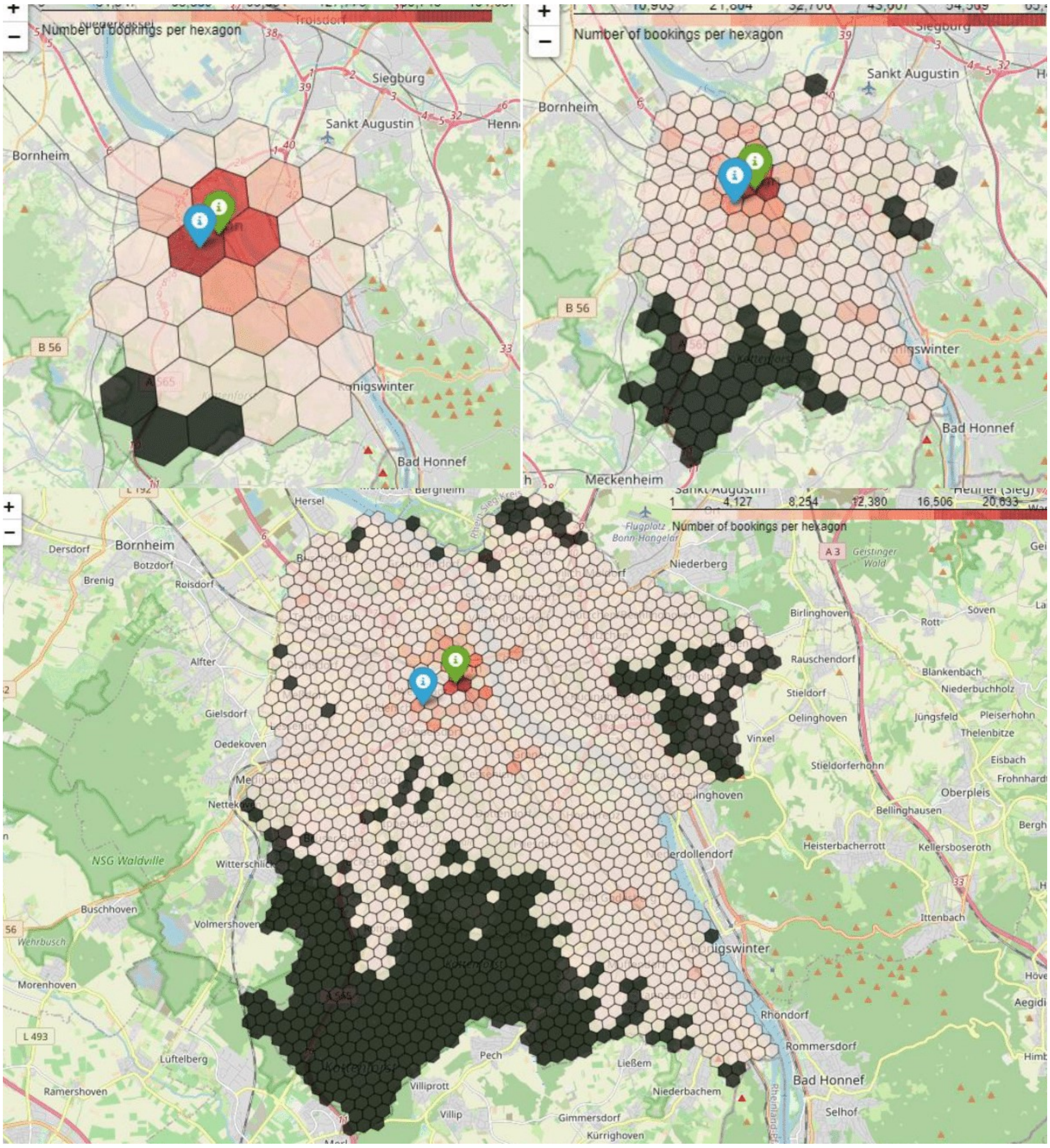

Figure 16: Amount of started Trips per different sized Hexagons (*Started_trips_hexagon7.html*, *Started_trips_hexagon8.html*, *Started_trips_hexagon9.html*)

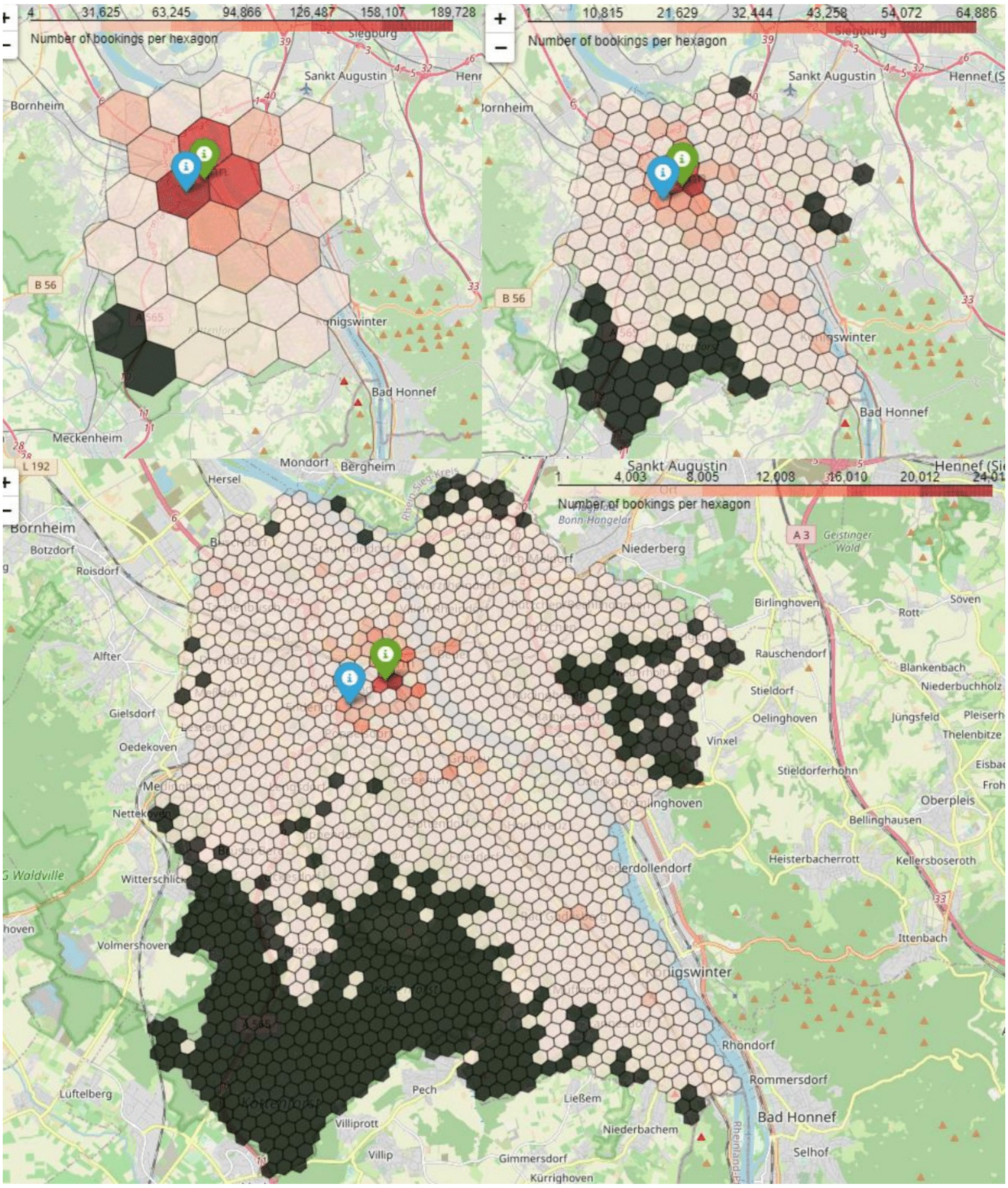

Figure 17: Amount of ended Trips per different sized Hexagons (*Ended_trips_hexagon7.html, Ended_trips_hexagon8.html,Ended_trips_hexagon9.html*)

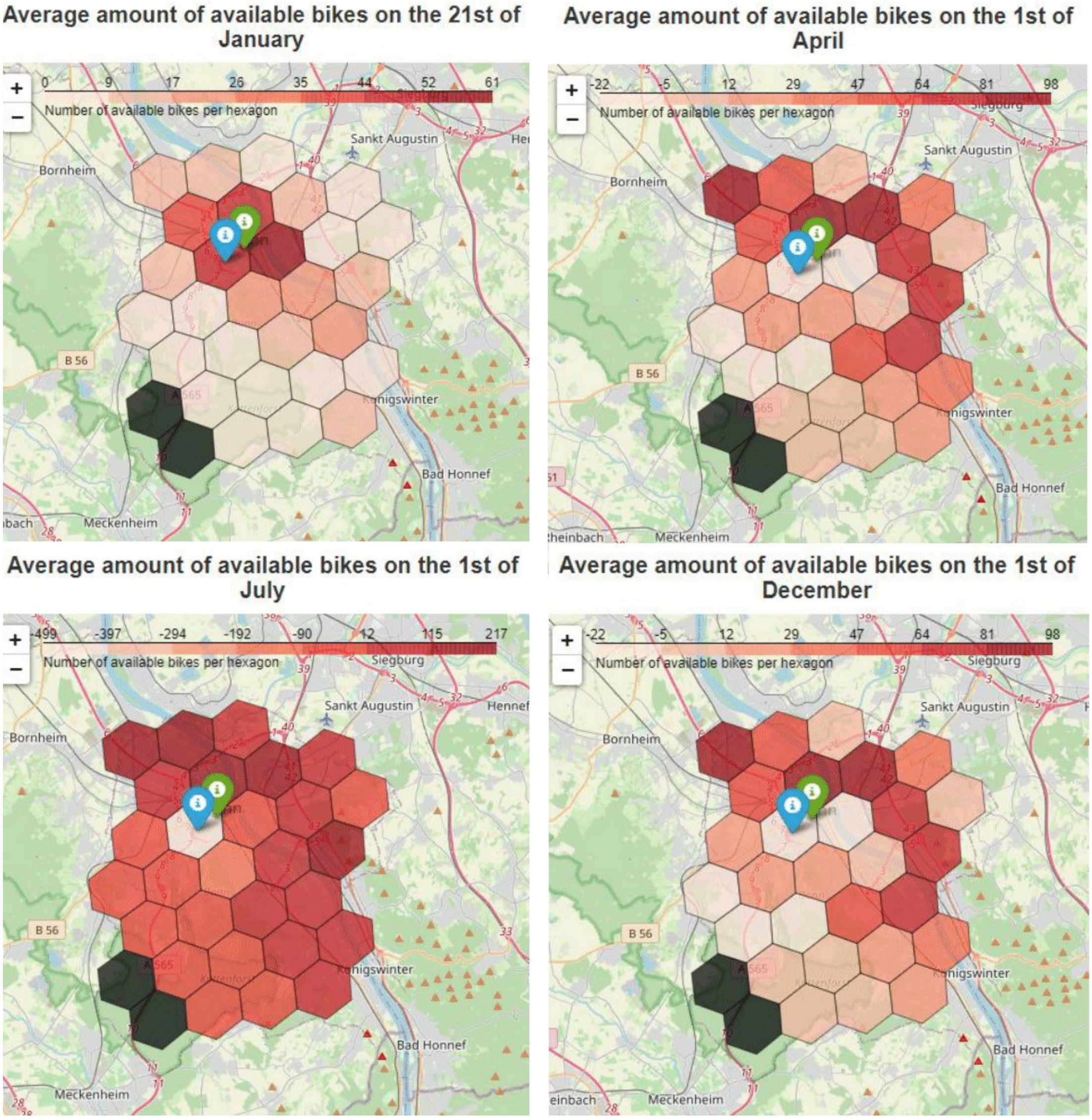

Figure 18: Development of the amount of available bikes with Hexagon resolution 7 (*available_bikes_hexagon7_01_21.html*, *available_bikes_hexagon7_04_01.html*, *available_bikes_hexagon7_07_01.html*, *available_bikes_hexagon7_12_01.html*)

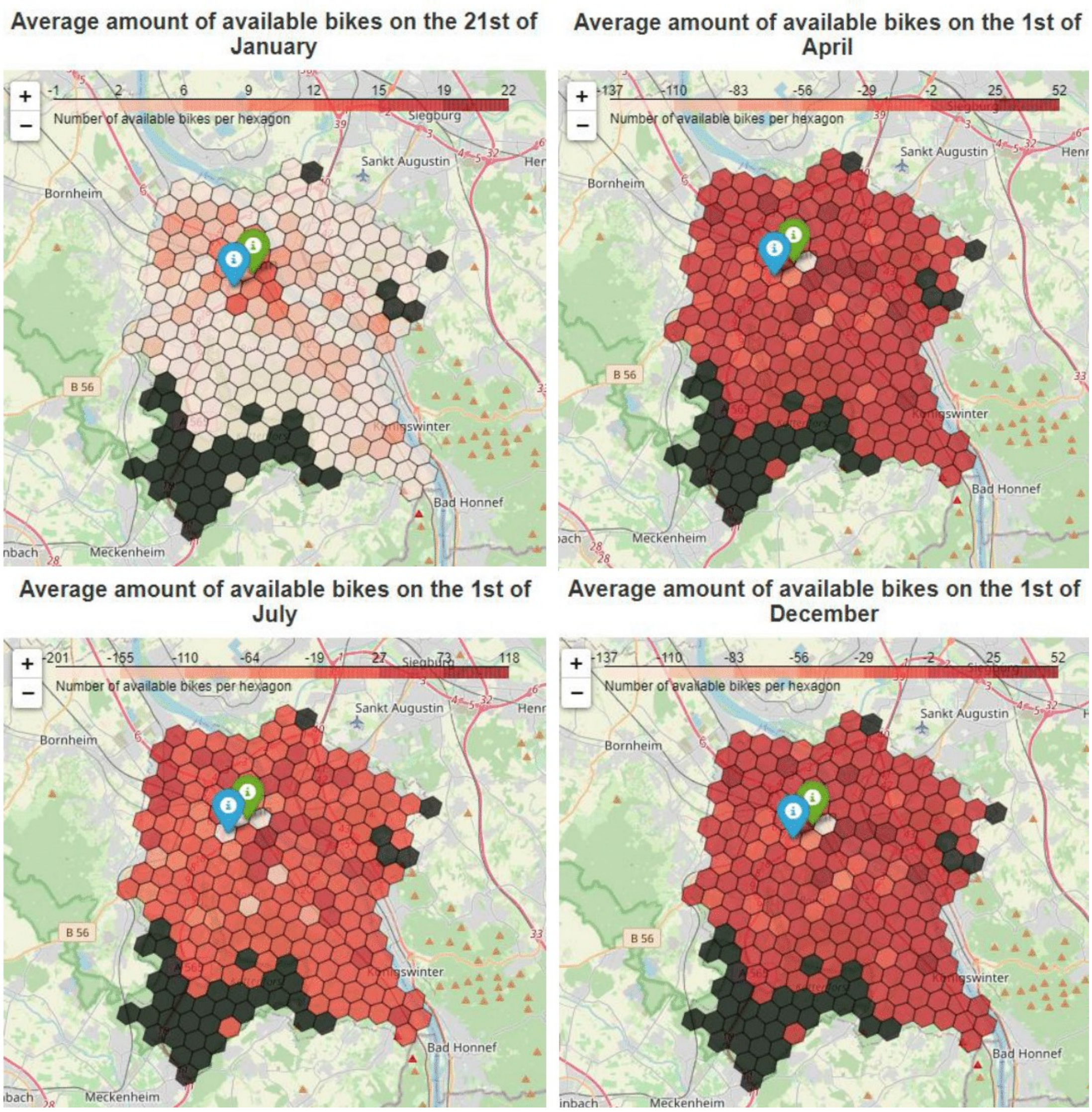

Figure 19: Development of the amount of available bikes with Hexagon resolution 8 (*available_bikes_hexagon8_01_21.html*, *available_bikes_hexagon8_04_01.html*, *available_bikes_hexagon8_07_01.html*, *available_bikes_hexagon8_12_01.html*)