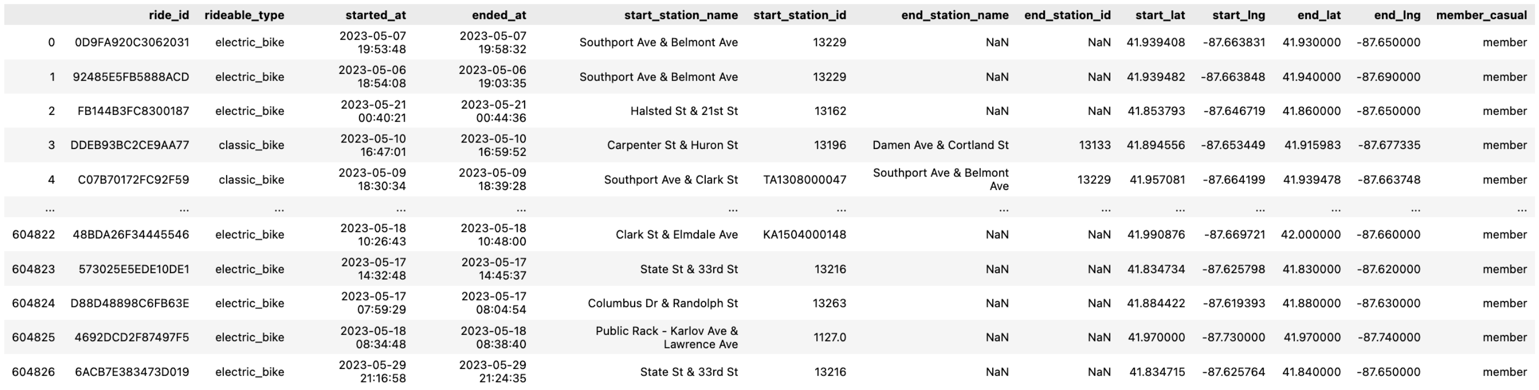
Bike-Share Case Study

This report provides the results as well as the step-by-step explanation of the data analysis performed for a bike sharing case-study. The data belongs to a bike-sharing company that has two kinds of users: annual members and casual riders. The goal of the case-study was to identify how annual members and casual riders use the bikes differently in order to help the stake-holders decide whether or not to target converting casual riders into annual members in the next marketing campaign. The data used in this case-study was between January-November 2023, each month was stored in a csv file, and was downloaded from https://divvy-tripdata.s3.amazonaws.com/index.html.

Data-Set exploration & cleaning:

The code that was used to perform the data exploration can be found in the Jupyter Notebook cleaning.ipynb. Below are the main functions:

- *read_data*:
  Here the csv file for the bike rides of each month is read and stored into a dictionary called "data". Each element in the dictionary has a key (the name of the month) and a value (the panada dataframe that holds the csv entries). This simplifies the access of the entries for each corresponding month, by using the month as the key (e.g. data["February"] retrieves the dataframe that holds the entries from February). Below we can see the first and last 5 entries of bike rides from May (a couple of NaN values already show up).



	ride_id	rideable_type	started_at	ended_at	start_station_name	start_station_id	end_station_name	end_station_id	start_lat	start_lng	end_lat	end_lng	member_casual
0	0D9FA920C3062031	electric_bike	2023-05-07 19:53:48	2023-05-07 19:58:32	Southport Ave & Belmont Ave	13229	NaN	NaN	41.939408	-87.663831	41.930000	-87.650000	member
1	92485E5FB5888ACD	electric_bike	2023-05-06 18:54:08	2023-05-06 19:03:35	Southport Ave & Belmont Ave	13229	NaN	NaN	41.939482	-87.663848	41.940000	-87.690000	member
2	FB144B3FC8300187	electric_bike	2023-05-21 00:40:21	2023-05-21 00:44:36	Halsted St & 21st St	13162	NaN	NaN	41.853793	-87.646719	41.860000	-87.650000	member
3	DDEB93BC2CE9AA77	classic_bike	2023-05-10 16:47:01	2023-05-10 16:59:52	Carpenter St & Huron St	13196	Damen Ave & Cortland St	13133	41.894556	-87.653449	41.915983	-87.677335	member
4	C07B70172FC92F59	classic_bike	2023-05-09 18:30:34	2023-05-09 18:39:28	Southport Ave & Clark St	TA1308000047	Southport Ave & Belmont Ave	13229	41.957081	-87.664199	41.939478	-87.663748	member
...	...	...	...	...	...	...	...	...	...	...	...	...	...
604822	48BDA26F34445546	electric_bike	2023-05-18 10:26:43	2023-05-18 10:48:00	Clark St & Elmdale Ave	KA1504000148	NaN	NaN	41.990876	-87.669721	42.000000	-87.660000	member
604823	573025E5EDE10DE1	electric_bike	2023-05-17 14:32:48	2023-05-17 14:45:37	State St & 33rd St	13216	NaN	NaN	41.834734	-87.625798	41.830000	-87.620000	member
604824	D88D48898C6FB63E	electric_bike	2023-05-17 07:59:29	2023-05-17 08:04:54	Columbus Dr & Randolph St	13263	NaN	NaN	41.884422	-87.619393	41.880000	-87.630000	member
604825	4692DCD2F87497F5	electric_bike	2023-05-18 08:34:48	2023-05-18 08:38:40	Public Rack - Karlov Ave & Lawrence Ave	1127.0	NaN	NaN	41.970000	-87.730000	41.970000	-87.740000	member
604826	6ACB7E383473D019	electric_bike	2023-05-29 21:16:58	2023-05-29 21:24:35	State St & 33rd St	13216	NaN	NaN	41.834715	-87.625764	41.840000	-87.650000	member

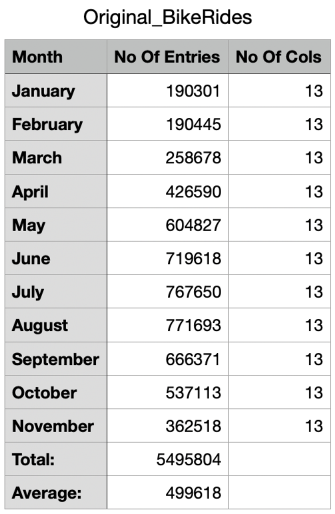
From the entries of data[“May”], we can see that the data for May consists of 13 columns: a ride id, the type of bike, date and time for the start and end of the ride, the name, id, latitude and longitude of the start and end stations, and finally whether the user was a casual rider or a member. In order to explore the dataset a bit further, the method *nunique()* is used to return the number of unique values for each column. The output is shown below.

```
Column Name:          NUnique
ride_id               604827
rideable_type              3
started_at            503683
ended_at              505259
start_station_name      1287
start_station_id        1250
end_station_name        1254
end_station_id          1210
start_lat             188591
start_lng             185410
end_lat                 4759
end_lng                 4762
member_casual              2
```

Looking at the number of unique values, it seems that only the columns *rideable_type* and *member_casual* have unique values. The method *unique()* is then be used to find these values:

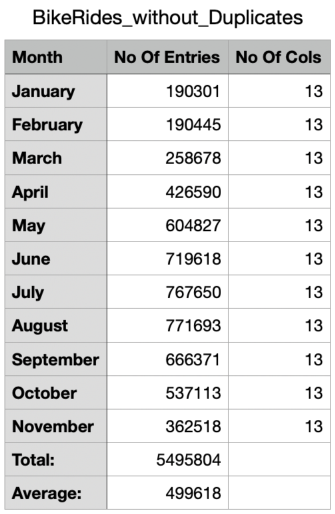
- *rideable_type*: [electric_bike, classic_bike, docked_bike]
- *member_casual*: [member, casual]

• *count_entries*:
This method collects further information about the dataset. It finds the number of entries per file as well as the number of columns. This is done in order to validate the consistency of data across the different files. From these values the method then calculates the total number of bike rides in the entire dataset. There is an option within the method to remove duplicates. Therefore, the method is first called with the remove duplicates option deactivated, in order to get a preliminary feel of the dataset, how big it is, how the entires varies across the months. And then the method is called again with the remove duplicates option activated. The results are then written to output files which are shown below.



Original_BikeRides

Month	No Of Entries	No Of Cols
January	190301	13
February	190445	13
March	258678	13
April	426590	13
May	604827	13
June	719618	13
July	767650	13
August	771693	13
September	666371	13
October	537113	13
November	362518	13
Total:	5495804	
Average:	499618	

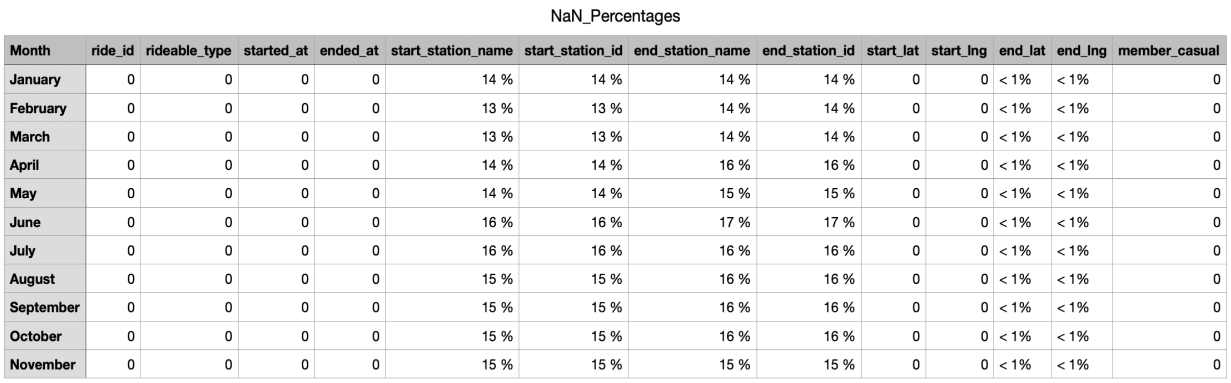


BikeRides_without_Duplicates

Month	No Of Entries	No Of Cols
January	190301	13
February	190445	13
March	258678	13
April	426590	13
May	604827	13
June	719618	13
July	767650	13
August	771693	13
September	666371	13
October	537113	13
November	362518	13
Total:	5495804	
Average:	499618	

On the left is the result of running the method without removing duplicates, and on the right is the result after removing duplicates. We can see that all the files have the same number of columns, which is a good preliminary indicator of the consistency of data across the months. In total the dataset contains almost 5.5 Million entries, with an average of approximately 500,000 entries per month. The number of entries before and after removing duplicates is identical, therefore the original dataset did not have any duplicates.

- *check_NAN*:
  Given that a brief look at the entries from May already showed a couple of NaN values, this method calculates the percentage of NaN values using the pandas function *isna()*. The number of null values for each column is calculated for each month and the results are shown below. As we can see the columns *start_station_name*, *start_station_id*, *end_station_name*, *end_station_id* in every month have around 13-17% null values. The columns *end_lat* and *end_long* have less than 1% null values.



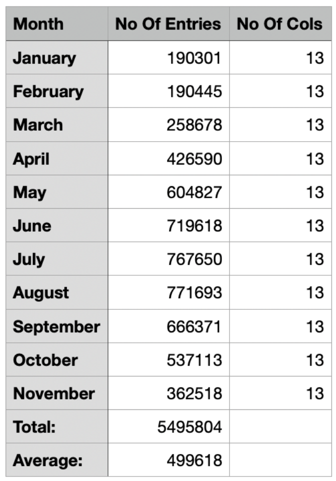
NaN_Percentages

Month	ride_id	rideable_type	started_at	ended_at	start_station_name	start_station_id	end_station_name	end_station_id	start_lat	start_lng	end_lat	end_lng	member_casual
January	0	0	0	0	14 %	14 %	14 %	14 %	0	0	< 1%	< 1%	0
February	0	0	0	0	13 %	13 %	14 %	14 %	0	0	< 1%	< 1%	0
March	0	0	0	0	13 %	13 %	14 %	14 %	0	0	< 1%	< 1%	0
April	0	0	0	0	14 %	14 %	16 %	16 %	0	0	< 1%	< 1%	0
May	0	0	0	0	14 %	14 %	15 %	15 %	0	0	< 1%	< 1%	0
June	0	0	0	0	16 %	16 %	17 %	17 %	0	0	< 1%	< 1%	0
July	0	0	0	0	16 %	16 %	16 %	16 %	0	0	< 1%	< 1%	0
August	0	0	0	0	15 %	15 %	16 %	16 %	0	0	< 1%	< 1%	0
September	0	0	0	0	15 %	15 %	16 %	16 %	0	0	< 1%	< 1%	0
October	0	0	0	0	15 %	15 %	16 %	16 %	0	0	< 1%	< 1%	0
November	0	0	0	0	15 %	15 %	15 %	15 %	0	0	< 1%	< 1%	0

- *drop_NANs*:
  Now that the percentage of null values has been identified, the next step is to determine

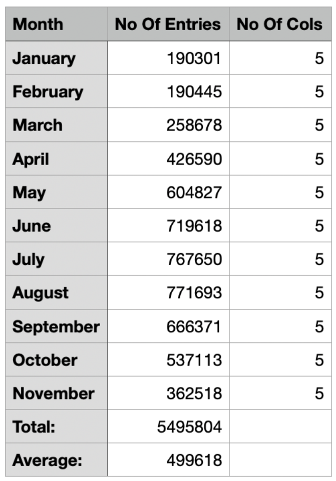
how to deal with these null values. As previously mentioned, the goal of the analysis is to find out how casual riders differ from members. After exploring the dataset, it is clear that this information can be obtained by looking at how the ride lengths vary as well as the type of bikes used. The ride length can be determined either by looking at the time or the distance. Since the information related to the distance contains a lot of null values, it is safer to rely on the time. Therefore, the relevant columns from which this information can be extracted are the: *ride_id*, *rideable_type*, *started_at*, *ended_at*, *member_casual*. Which means that we can drop all the other columns which contain the null values. Therefore, the method *drop_NANs* drops the columns related to start and end stations. After dropping the start and end stations, we can call the method *count_entries* once again and compare the new dataset shape to the original one:

Original_BikeRides



Month	No Of Entries	No Of Cols
January	190301	13
February	190445	13
March	258678	13
April	426590	13
May	604827	13
June	719618	13
July	767650	13
August	771693	13
September	666371	13
October	537113	13
November	362518	13
Total:	5495804	
Average:	499618	

BikeRides_NaNsRemoved



Month	No Of Entries	No Of Cols
January	190301	5
February	190445	5
March	258678	5
April	426590	5
May	604827	5
June	719618	5
July	767650	5
August	771693	5
September	666371	5
October	537113	5
November	362518	5
Total:	5495804	
Average:	499618	

As expected only the number of columns has changed, and the number of entries remains the same as the original.