

bikeshare-analysis

August 30, 2022

1 Case Study: How Does a Bike-Share Navigate Speedy Success?

1.1 Guiding Questions of Analysis?

1. How do annual members and casual riders use Cyclistic bikes differently?

1.2 Data Gathering

The data gathered for this analysis is sourced from the [publicly open dataset](#) which is provided by the Company **Cyclistic** under the following [Data Licence Agreement](#).

1.3 Data Cleaning

Start by Cleaning the data where there are any N/A values as well as rides that start and end at the exact coordinate values.

[3]: Rows decreased by **1.507.429** from 5.901.463 to 4.394.034.

[4]: Check for matching observations (start and end stations should have the same amount of ID's and names)

Station Type	# of ID's	# of names	DIFF
Start	1130	1253	123
End	1158	1286	128

Since there is a clear difference in the number of names to stations there seems to be some kind of irregularity, probably typos. Since we do not have an easy way to filter them out let's create a station dataframe with 1:1 id to name and only take the names with the largest number of appearances. afterwards we will replace the names in the cleaned dataframe with the stations that we found to be the most common names.

1.4 Data Preparation

- Adding formatted columns (hour of ride, weekday, month) to further slice data
- Calculating distance travelled (point-to-point)

1.4.1 Calculating the travel distane (Point-to-Point)

The haversine formula or haversine distance To calculate the distance on a sphere we can use the formula:

$$d = r * acos(sin(\Phi_1) * sin(\Phi_2) + cos(\Phi_1) * cos(\Phi_1) * cos(\Delta\lambda))$$

Where: r = radius of Sphere, Earth = ~6.371km Φ_1 = Latitude of start point Φ_2 = Latitude of end point $\Delta\lambda$ = Delta/Difference of longitude between end point and start point

Source: movable-type.co.uk

1.5 Data Analysis

Get a feel for the dataset with calculating some high-level statistics: * Average, Median, Max and Min for the ride time as well as the ride distance * most commonly observed time of day, weekday and month of ride

1.5.1 High Level Stats - 1

[12]: The high-level statistics shows the following results: Number of observations: **4.394.034** Correlation between time and distance is: $r = 0.09955$

Variable	Average	Median	Max	Min
ride length [t]	00:17:39	00:11:06	28 days 21:49:10	-1 days 21:50:55
ride distance [m]	2.221	1.667	1.189.522	0

Variable	Mode (most common)
hour of ride	17
day of ride	Saturday
month of ride	August
start station	Streeter Dr & Grand Ave
end station	Streeter Dr & Grand Ave

The data shows that there is a Min value of ride time that is negative, indicating that the end time was before the start time. The Min value of ride dist also shows 0 distance travelled (although that was supposed to be filtered out by same Lat + Long before).

Also there seems to be a stark outlier with over 1.189km travelled. On further inspection this was done with an electrik bike however the length of the bike ride was too short to make sense. Add new rule to filter out rides > 200km

Those data points are invalid and need to be filtered out before proceeding with more analysis.

1.5.2 Data Cleaning - Step 1

Filter out rows with the following conditios: * length of travel as timedelta < 0 (negative) OR * ride distane in m is <= 0 OR * ride distance in m is > 200.000

[14]: Rows drecreased by **315** from 4.394.034 to 4.393.719.

1.5.3 High Level Stats - 2

[16]: The high-level statistics shows the following results: Number of observations: 4.393.719 Correlation between time and distance is: $r = 0.10411$

Variable	Average	Median	Max	Min
ride length [t]	00:17:39	00:11:06	28 days 21:49:10	0 days 00:00:02
ride distance [m]	2.221	1.667	31.906	0

Time of ride	Mode (most common)
hour of ride	17
day of ride	Saturday
month of ride	August
start station	Streeter Dr & Grand Ave
end station	Streeter Dr & Grand Ave

Although there all rides with same start coordinates have been filtered out, there are still rides with no or very little distance travelled. Also there are rides that only last a few seconds. To get a beter understanding of “real” rides, e.g. rides that are used to travel somewhere and are not “accidentally” unlocked, a new rule will be applied: rides have to be farther than 100m and longer than 1 min.

1.5.4 Data Cleaning - Step 2

[18]: Rows drecreased by **78.917** from 4.393.719 to 4.314.802.

In total Rows decreased by **1.586.661** from original dataset.

```
C:\Users\kemke\AppData\Local\Temp\ipykernel_9028\784846940.py:10:
SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

IMPROT DF for quick restart and PURGE OBSOLETE DATA

1.5.5 High Level Stats - 3

[23]: The high-level statistics shows the following results: Number of observations: **4.314.802** Correlation between time and distance is: $r = 0.10584$

Variable	Average	Median	Max	Min
ride length [t]	00:17:38	00:11:09	28 days 21:49:10	0 days 00:01:01
ride distance [m]	2.261	1.697	31.906	100

Time of ride	Mode (most common)
hour of ride	17
day of ride	Saturday
month of ride	August
start station	Streeter Dr & Grand Ave
end station	Streeter Dr & Grand Ave

1.6 Deep Dive - Statistics via Pivot

Taking a deeper look into the cleaned data and aggregating the data into different pivots

1.6.1 Pivot - Member-Type

```
[24]:
```

	count_of_rides	r	common_hour	most_common_day	\
member_casual					
Casual	1.753.742	0.07688	17	Saturday	
Member	2.561.060	0.41390	17	Tuesday	

	most_common_month	avg_time	median_time	std_time	\
member_casual					
Casual	August	00:25:03	00:14:45	02:06:47	
Member	August	00:12:33	00:09:15	00:17:12	

	max_time	min_time	avg_dist	median_dist	std_dist	\
member_casual						
Casual	28 days 21:49:10	00:01:01	2437.0	1884.0	1934.0	
Member	1 days 00:52:55	00:01:01	2142.0	1582.0	1776.0	

	max_dist	min_dist
member_casual		
Casual	31906.0	100.0
Member	27488.0	100.0

1.6.2 Pivot - Rideable-Type

```
[25]:
```

	count_of_rides	r	common_hour	most_common_day	avg_time	\
rideable_type						
Classic Bike	2.863.190	0.29272	17	Saturday	00:16:47	
Docked Bike	184.788	0.04627	16	Saturday	00:55:20	
Electric Bike	1.266.824	0.46330	17	Thursday	00:14:03	

	median_time	std_time	max_time	min_time	avg_dist	\

rideable_type						
Classic Bike	00:11:12	00:29:30	1 days	00:59:25	00:01:01	2137.0
Docked Bike	00:25:51	06:15:34	28 days	21:49:10	00:01:10	2639.0
Electric Bike	00:10:00	00:14:44	0 days	07:59:55	00:01:01	2489.0

	median_dist	std_dist	max_dist	min_dist
rideable_type				
Classic Bike	1608.0	1739.0	30186.0	102.0
Docked Bike	1973.0	2244.0	31906.0	102.0
Electric Bike	1899.0	1987.0	28741.0	100.0

1.6.3 Pivot - Month

[26]:

	count_of_rides	r	common_hour	most_common_day	avg_time	\
month_of_ride						
August	627.257	0.09377	17	Sunday	00:19:57	
September	580.808	0.08451	17	Saturday	00:19:12	
October	449.826	0.08579	17	Saturday	00:16:58	
November	242.781	0.10864	17	Tuesday	00:13:35	
December	167.342	0.06369	17	Thursday	00:13:45	
January	76.473	0.05098	17	Thursday	00:12:36	
February	84.707	0.11718	17	Monday	00:12:35	
March	202.153	0.09013	17	Wednesday	00:16:07	
April	255.224	0.22528	17	Saturday	00:15:37	
May	462.972	0.23225	17	Monday	00:18:34	
June	573.835	0.25961	17	Thursday	00:18:12	
July	591.424	0.15218	17	Saturday	00:18:22	

	median_time	std_time		max_time	min_time	avg_dist	\
month_of_ride							
August	00:12:37	01:33:06	28 days	21:49:10	00:01:01	2357.0	
September	00:11:59	01:53:41	22 days	19:38:32	00:01:01	2331.0	
October	00:10:33	01:40:30	28 days	06:25:01	00:01:01	2190.0	
November	00:08:51	01:08:55	13 days	08:37:49	00:01:01	2002.0	
December	00:08:34	02:10:13	21 days	02:40:33	00:01:01	1976.0	
January	00:07:48	02:43:07	20 days	07:51:06	00:01:01	1780.0	
February	00:08:04	00:58:38	7 days	13:45:58	00:01:01	1855.0	
March	00:09:38	01:37:50	23 days	20:34:04	00:01:01	2134.0	
April	00:09:48	00:36:39	5 days	05:45:58	00:01:01	2148.0	
May	00:11:54	00:37:05	7 days	10:42:58	00:01:01	2343.0	
June	00:12:08	00:32:01	4 days	15:12:52	00:01:01	2370.0	
July	00:12:03	00:54:56	22 days	05:55:27	00:01:01	2381.0	

	median_dist	std_dist	max_dist	min_dist
month_of_ride				
August	1808.0	1878.0	31906.0	100.0
September	1769.0	1879.0	29389.0	100.0

October	1641.0	1792.0	28915.0	100.0
November	1492.0	1662.0	23446.0	101.0
December	1480.0	1642.0	22524.0	101.0
January	1325.0	1487.0	23263.0	102.0
February	1357.0	1579.0	24700.0	102.0
March	1581.0	1793.0	29734.0	102.0
April	1598.0	1792.0	21637.0	100.0
May	1760.0	1917.0	28036.0	101.0
June	1809.0	1897.0	30186.0	100.0
July	1802.0	1921.0	29685.0	101.0

1.6.4 Pivot - Member-Type & Month

[27]:

		count_of_rides	r	common_hour	\
member_casual	month_of_ride				
Casual	August	308.612	0.07084	17	
	September	266.430	0.06643	17	
	October	173.455	0.06243	17	
	November	64.296	0.07135	17	
	December	41.098	0.05152	16	
	January	11.539	0.04988	17	
	February	13.738	0.06506	17	
	March	59.337	0.06383	17	
	April	82.006	0.16807	17	
	May	194.465	0.17729	17	
	June	261.320	0.20812	17	
	July	277.446	0.11493	17	
Member	August	318.645	0.45973	17	
	September	314.378	0.45343	17	
	October	276.371	0.44390	17	
	November	178.485	0.38527	17	
	December	126.244	0.43902	17	
	January	64.934	0.41840	17	
	February	70.969	0.32736	17	
	March	142.816	0.30966	17	
	April	173.218	0.32382	17	
	May	268.507	0.41082	17	
	June	312.515	0.40993	17	
	July	313.978	0.45942	17	

		most_common_day	avg_time	median_time	std_time	\
member_casual	month_of_ride					
Casual	August	Saturday	00:26:39	00:15:52	02:11:25	
	September	Saturday	00:26:27	00:15:15	02:46:39	
	October	Saturday	00:24:57	00:14:01	02:40:22	
	November	Saturday	00:21:01	00:11:35	02:10:44	
	December	Friday	00:23:41	00:11:14	04:21:22	

Member	January	Saturday	00:26:08	00:09:55	06:58:20
	February	Monday	00:22:41	00:10:52	02:18:54
	March	Sunday	00:26:42	00:14:34	02:56:55
	April	Saturday	00:24:14	00:14:24	00:56:10
	May	Sunday	00:25:55	00:15:48	00:52:20
	June	Saturday	00:23:37	00:14:51	00:42:25
	July	Saturday	00:23:51	00:14:44	01:17:58
	August	Tuesday	00:13:27	00:10:08	00:15:51
	September	Thursday	00:13:03	00:09:48	00:16:10
	October	Saturday	00:11:58	00:08:54	00:15:18
	November	Tuesday	00:10:54	00:08:01	00:16:40
	December	Thursday	00:10:31	00:07:51	00:14:05
	January	Thursday	00:10:12	00:07:29	00:14:13
	February	Monday	00:10:38	00:07:37	00:18:36
	March	Wednesday	00:11:43	00:08:16	00:21:52
	April	Tuesday	00:11:33	00:08:17	00:20:51
	May	Monday	00:13:14	00:09:44	00:17:53
	June	Thursday	00:13:40	00:10:14	00:18:17
	July	Saturday	00:13:31	00:10:08	00:16:11

			max_time	min_time	avg_dist	median_dist	\
member_casual month_of_ride							
Casual	August	28 days	21:49:10	00:01:01	2483.0	1937.0	
	September	22 days	19:38:32	00:01:01	2491.0	1933.0	
	October	28 days	06:25:01	00:01:02	2390.0	1850.0	
	November	13 days	08:37:49	00:01:01	2178.0	1666.0	
	December	21 days	02:40:33	00:01:06	2116.0	1624.0	
	January	20 days	07:51:06	00:01:05	1900.0	1495.0	
	February	7 days	13:45:58	00:01:03	2083.0	1597.0	
	March	23 days	20:34:04	00:01:03	2397.0	1828.0	
	April	5 days	05:45:58	00:01:01	2419.0	1850.0	
	May	7 days	10:42:58	00:01:01	2501.0	1917.0	
	June	4 days	15:12:52	00:01:01	2457.0	1908.0	
	July	22 days	05:55:27	00:01:01	2459.0	1894.0	
Member	August	1 days	00:46:23	00:01:01	2235.0	1673.0	
	September	0 days	21:58:24	00:01:01	2196.0	1632.0	
	October	0 days	23:35:08	00:01:01	2065.0	1520.0	
	November	1 days	00:20:34	00:01:01	1939.0	1409.0	
	December	0 days	20:30:52	00:01:01	1931.0	1418.0	
	January	0 days	23:00:00	00:01:01	1758.0	1289.0	
	February	1 days	00:26:24	00:01:01	1811.0	1314.0	
	March	1 days	00:38:29	00:01:01	2024.0	1479.0	
	April	1 days	00:52:55	00:01:01	2020.0	1479.0	
	May	1 days	00:35:38	00:01:01	2229.0	1641.0	
	June	0 days	22:03:32	00:01:01	2297.0	1711.0	
	July	1 days	00:36:42	00:01:01	2312.0	1714.0	

		std_dist	max_dist	min_dist
member_casual	month_of_ride			
Casual	August	1937.0	31906.0	100.0
	September	1953.0	29389.0	102.0
	October	1883.0	28915.0	100.0
	November	1718.0	23446.0	102.0
	December	1690.0	22524.0	102.0
	January	1438.0	15667.0	102.0
	February	1707.0	24700.0	103.0
	March	1950.0	29734.0	102.0
	April	1952.0	21637.0	101.0
	May	2017.0	28036.0	101.0
	June	1941.0	30186.0	100.0
	July	1962.0	29685.0	102.0
Member	August	1810.0	26344.0	101.0
	September	1803.0	25227.0	100.0
	October	1720.0	23432.0	101.0
	November	1636.0	22073.0	101.0
	December	1624.0	20355.0	101.0
	January	1495.0	23263.0	102.0
	February	1549.0	21213.0	102.0
	March	1712.0	25216.0	102.0
	April	1696.0	21232.0	100.0
	May	1833.0	23343.0	101.0
	June	1855.0	24669.0	102.0
	July	1882.0	27488.0	101.0

1.6.5 Pivot - Member-Type & Day

[28]:

		count_of_rides	r	common_hour	avg_time	\
member_casual	day_of_ride					
Casual	Monday	202.460	0.08057	17	00:25:30	
	Tuesday	185.023	0.11569	17	00:21:31	
	Wednesday	191.032	0.07499	17	00:21:15	
	Thursday	215.972	0.06820	17	00:22:01	
	Friday	240.037	0.07902	17	00:23:26	
	Saturday	381.328	0.08328	15	00:27:47	
	Sunday	337.890	0.06255	15	00:28:54	
Member	Monday	360.537	0.42844	17	00:12:06	
	Tuesday	403.168	0.42333	17	00:11:42	
	Wednesday	401.858	0.41321	17	00:11:50	
	Thursday	397.578	0.40522	17	00:12:01	
	Friday	349.014	0.40803	17	00:12:13	
	Saturday	337.896	0.40333	12	00:14:14	
	Sunday	311.009	0.41339	15	00:14:17	
		median_time	std_time	max_time	min_time	\

member_casual	day_of_ride					
Casual	Monday	00:14:39	02:03:54	22 days	05:55:27	00:01:02
	Tuesday	00:12:40	01:15:14	10 days	18:02:58	00:01:01
	Wednesday	00:12:41	01:57:59	21 days	02:40:33	00:01:01
	Thursday	00:13:00	02:02:42	18 days	19:22:48	00:01:01
	Friday	00:13:55	01:52:18	15 days	17:09:54	00:01:01
	Saturday	00:16:55	02:12:40	28 days	06:25:01	00:01:01
	Sunday	00:17:08	02:37:23	28 days	21:49:10	00:01:02
Member	Monday	00:08:54	00:16:11	1 days	00:52:55	00:01:01
	Tuesday	00:08:45	00:16:00	1 days	00:22:02	00:01:01
	Wednesday	00:08:53	00:16:22	1 days	00:20:34	00:01:01
	Thursday	00:08:57	00:17:02	1 days	00:35:38	00:01:01
	Friday	00:09:03	00:16:52	1 days	00:15:18	00:01:01
	Saturday	00:10:28	00:19:26	0 days	23:37:03	00:01:01
	Sunday	00:10:23	00:18:39	1 days	00:46:23	00:01:01

		avg_dist	median_dist	std_dist	max_dist	min_dist
member_casual	day_of_ride					
Casual	Monday	2380.0	1828.0	1923.0	29038.0	100.0
	Tuesday	2319.0	1785.0	1843.0	28036.0	100.0
	Wednesday	2323.0	1807.0	1816.0	31906.0	100.0
	Thursday	2354.0	1827.0	1850.0	29389.0	101.0
	Friday	2359.0	1825.0	1846.0	30186.0	100.0
	Saturday	2565.0	1999.0	2019.0	29685.0	102.0
	Sunday	2561.0	1980.0	2050.0	29734.0	101.0
Member	Monday	2109.0	1538.0	1765.0	25227.0	101.0
	Tuesday	2090.0	1527.0	1752.0	23330.0	100.0
	Wednesday	2110.0	1554.0	1753.0	24669.0	101.0
	Thursday	2116.0	1555.0	1763.0	26344.0	101.0
	Friday	2092.0	1542.0	1739.0	27488.0	101.0
	Saturday	2260.0	1699.0	1827.0	25224.0	101.0
	Sunday	2253.0	1681.0	1838.0	25216.0	102.0

1.6.6 Pivot - Member-Type & Ride-Type & Month

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[29]:
```

			count_of_rides	r \
member_casual	rideable_type	month_of_ride		
Casual	Classic Bike	August	209.947	0.24366
		September	179.184	0.22760
		October	96.925	0.22574
		November	29.143	0.20890
		December	17.891	0.18177
...		
Member	Electric Bike	March	47.855	0.47299
		April	58.940	0.58292
		May	79.763	0.59476
		June	86.882	0.62357

July 107.186 0.65341

member_casual	rideable_type	month_of_ride	common_hour	avg_time	median_time	\
Casual	Classic Bike	August	17.0	00:23:29	00:15:24	
		September	17.0	00:23:06	00:14:53	
		October	17.0	00:22:36	00:14:05	
		November	15.0	00:19:50	00:12:05	
		December	14.0	00:20:52	00:11:53	
...						
Member	Electric Bike	March	17.0	00:10:31	00:07:47	
		April	17.0	00:10:27	00:07:54	
		May	17.0	00:12:08	00:09:15	
		June	17.0	00:12:13	00:09:30	
		July	17.0	00:12:00	00:09:23	

member_casual	rideable_type	month_of_ride	std_time	max_time	min_time	\
Casual	Classic Bike	August	00:36:59 1 days	00:54:07	00:01:01	
		September	00:39:39 1 days	00:57:57	00:01:01	
		October	00:41:09 1 days	00:49:22	00:01:02	
		November	00:39:43 0 days	23:14:55	00:01:01	
		December	00:46:24 1 days	00:12:59	00:01:06	
...						
Member	Electric Bike	March	00:12:45 0 days	07:58:32	00:01:01	
		April	00:10:27 0 days	07:20:46	00:01:01	
		May	00:11:08 0 days	07:45:51	00:01:01	
		June	00:11:00 0 days	05:47:04	00:01:01	
		July	00:10:26 0 days	07:05:03	00:01:01	

member_casual	rideable_type	month_of_ride	avg_dist	median_dist	std_dist	\
Casual	Classic Bike	August	2379.0	1885.0	1804.0	
		September	2375.0	1871.0	1814.0	
		October	2254.0	1747.0	1745.0	
		November	2036.0	1582.0	1593.0	
		December	1951.0	1531.0	1573.0	
...						
Member	Electric Bike	March	2276.0	1689.0	1872.0	
		April	2290.0	1714.0	1843.0	
		May	2508.0	1912.0	1996.0	
		June	2589.0	1986.0	2037.0	
		July	2550.0	1956.0	2007.0	

member_casual	rideable_type	month_of_ride	max_dist	min_dist
Casual	Classic Bike	August	28476.0	102.0

		September	29389.0	102.0
		October	28915.0	102.0
		November	21024.0	102.0
		December	22524.0	103.0
...		
Member	Electric Bike	March	25216.0	103.0
		April	18663.0	100.0
		May	23343.0	101.0
		June	24669.0	103.0
		July	26003.0	101.0

[72 rows x 13 columns]

1.6.7 Pivot - Member-Type & most used Station

```
[30]:
```

member_casual	station_id	station_name	no_of_rides
Casual	13022	Streeter Dr & Grand Ave	101345
	LF-005	DuSable Lake Shore Dr & North Blvd	50795
	13300	DuSable Lake Shore Dr & Monroe St	48169
	13008	Millennium Park	47821
	13042	Michigan Ave & Oak St	45227
Member	KA1503000043	Kingsbury St & Kinzie St	49100
	TA1308000050	Wells St & Concord Ln	43748
	TA1307000039	Clark St & Elm St	43500
	KA1504000135	Wells St & Elm St	38061
	WL-012	Clinton St & Washington Blvd	37214

1.6.8 Pivot - Member-Type & Month & most used Station

```
[31]:
```

no_of_rides	member_casual	month_of_ride	station_id	station_name
18915	Casual	August	13022	Streeter Dr & Grand Ave
11584			LF-005	DuSable Lake Shore Dr & North Blvd
15179		September	13022	Streeter Dr & Grand Ave
7954			LF-005	DuSable Lake Shore Dr & North Blvd
7980		October	13022	Streeter Dr & Grand Ave
5229			13008	Millennium Park
2746		November	13022	Streeter Dr & Grand Ave
			13300	DuSable Lake Shore Dr & Monroe St

1679	December	13022	Streeter Dr & Grand Ave
1683		13008	Millennium Park
1267	January	TA1307000039	Clark St & Elm St
216		KA1504000135	Wells St & Elm St
197	February	13022	Streeter Dr & Grand Ave
355		13008	Millennium Park
250	March	13022	Streeter Dr & Grand Ave
3674		13300	DuSable Lake Shore Dr & Monroe St
2055	April	13022	Streeter Dr & Grand Ave
5002		13300	DuSable Lake Shore Dr & Monroe St
2480	May	13022	Streeter Dr & Grand Ave
12295		13300	DuSable Lake Shore Dr & Monroe St
6312	June	13022	Streeter Dr & Grand Ave
15281		LF-005	DuSable Lake Shore Dr & North Blvd
8984	July	13022	Streeter Dr & Grand Ave
18042		LF-005	DuSable Lake Shore Dr & North Blvd
10006	August	LF-005	DuSable Lake Shore Dr & North Blvd
Member 6629		TA1308000050	Wells St & Concord Ln
6343	September	TA1308000050	Wells St & Concord Ln
5839		TA1307000039	Clark St & Elm St
5381	October	KA1503000014	Ellis Ave & 60th St
5975		TA1307000039	Clark St & Elm St
5155	November	KA1503000014	Ellis Ave & 60th St
4208			

4056		KA1503000043 Kingsbury St & Kinzie St
2922	December	KA1503000043 Kingsbury St & Kinzie St
2427		WL-012 Clinton St & Washington Blvd
1780	January	KA1503000043 Kingsbury St & Kinzie St
1382		TA1305000032 Clinton St & Madison St
2010	February	KA1503000071 University Ave & 57th St
1903		KA1503000014 Ellis Ave & 60th St
3280	March	KA1503000043 Kingsbury St & Kinzie St
2788		WL-012 Clinton St & Washington Blvd
3745	April	KA1503000043 Kingsbury St & Kinzie St
3316		WL-012 Clinton St & Washington Blvd
4925	May	KA1503000071 University Ave & 57th St
4873		KA1503000014 Ellis Ave & 60th St
5696	June	LF-005 DuSable Lake Shore Dr & North Blvd
5395		KA1503000043 Kingsbury St & Kinzie St
5760	July	LF-005 DuSable Lake Shore Dr & North Blvd
5333		KA1503000043 Kingsbury St & Kinzie St

1.6.9 Pivot - Member-Type & Day & most used Station

[32]:

no_of_rides	member_casual	day_of_ride	station_id	station_name
13005	Casual	Monday	13022	Streeter Dr & Grand Ave
6585			13008	Millennium Park
6156			LF-005	DuSable Lake Shore Dr & North Blvd
8295		Tuesday	13022	Streeter Dr & Grand Ave

5593		LF-005	DuSable Lake Shore Dr & North Blvd
4030		13008	Millennium Park
8850	Wednesday	13022	Streeter Dr & Grand Ave
5692		LF-005	DuSable Lake Shore Dr & North Blvd
3858		13042	Michigan Ave & Oak St
10072	Thursday	13022	Streeter Dr & Grand Ave
6440		LF-005	DuSable Lake Shore Dr & North Blvd
5010		13008	Millennium Park
12921	Friday	13022	Streeter Dr & Grand Ave
6440		13008	Millennium Park
5771		13300	DuSable Lake Shore Dr & Monroe St
25955	Saturday	13022	Streeter Dr & Grand Ave
13351		13300	DuSable Lake Shore Dr & Monroe St
11547		13042	Michigan Ave & Oak St
22247	Sunday	13022	Streeter Dr & Grand Ave
11497		13300	DuSable Lake Shore Dr & Monroe St
10715		LF-005	DuSable Lake Shore Dr & North Blvd
Member	Monday	KA1503000043	Kingsbury St & Kinzie St
8045		WL-012	Clinton St & Washington Blvd
6262		TA1307000039	Clark St & Elm St
6184	Tuesday	KA1503000043	Kingsbury St & Kinzie St
8751		WL-012	Clinton St & Washington Blvd
8329		TA1305000032	Clinton St & Madison St
7170	Wednesday	KA1503000043	Kingsbury St & Kinzie St

8332		WL-012	Clinton St & Washington Blvd
7960		TA1305000032	Clinton St & Madison St
6871	Thursday	KA1503000043	Kingsbury St & Kinzie St
7638		WL-012	Clinton St & Washington Blvd
7544		TA1305000032	Clinton St & Madison St
6536	Friday	KA1503000043	Kingsbury St & Kinzie St
6520		TA1308000050	Wells St & Concord Ln
5909		TA1307000039	Clark St & Elm St
5781	Saturday	TA1308000050	Wells St & Concord Ln
7331		13179	Clark St & Lincoln Ave
6156		TA1307000039	Clark St & Elm St
5863	Sunday	TA1308000050	Wells St & Concord Ln
6157		LF-005	DuSable Lake Shore Dr & North Blvd
6002		TA1308000001	Theater on the Lake
5561			

1.6.10 Pivot - Member-Type & Ride-Type & most used Station

```
[33]: no_of_rides
member_casual rideable_type station_id station_name
Casual Classic Bike 13022 Streeter Dr & Grand Ave
57559
LF-005 DuSable Lake Shore Dr & North Blvd
34245
13042 Michigan Ave & Oak St
27200
13300 DuSable Lake Shore Dr & Monroe St
27005
13008 Millennium Park
24830
Docked Bike 13022 Streeter Dr & Grand Ave
23815
13008 Millennium Park
```

11906		13300	DuSable Lake Shore Dr & Monroe St
10975		15544	Shedd Aquarium
9138		13042	Michigan Ave & Oak St
8026			
	Electric Bike	13022	Streeter Dr & Grand Ave
19971		13008	Millennium Park
11085		TA1308000050	Wells St & Concord Ln
10608		13300	DuSable Lake Shore Dr & Monroe St
10189		13042	Michigan Ave & Oak St
10001			
Member	Classic Bike	KA1503000043	Kingsbury St & Kinzie St
34308		TA1307000039	Clark St & Elm St
31554		TA1308000050	Wells St & Concord Ln
31106		KA1503000014	Ellis Ave & 60th St
30064		KA1503000071	University Ave & 57th St
29644			
	Electric Bike	KA1503000043	Kingsbury St & Kinzie St
14792		WL-012	Clinton St & Washington Blvd
13432		TA1308000050	Wells St & Concord Ln
12642		TA1307000039	Clark St & Elm St
11946		TA1305000032	Clinton St & Madison St
11636			

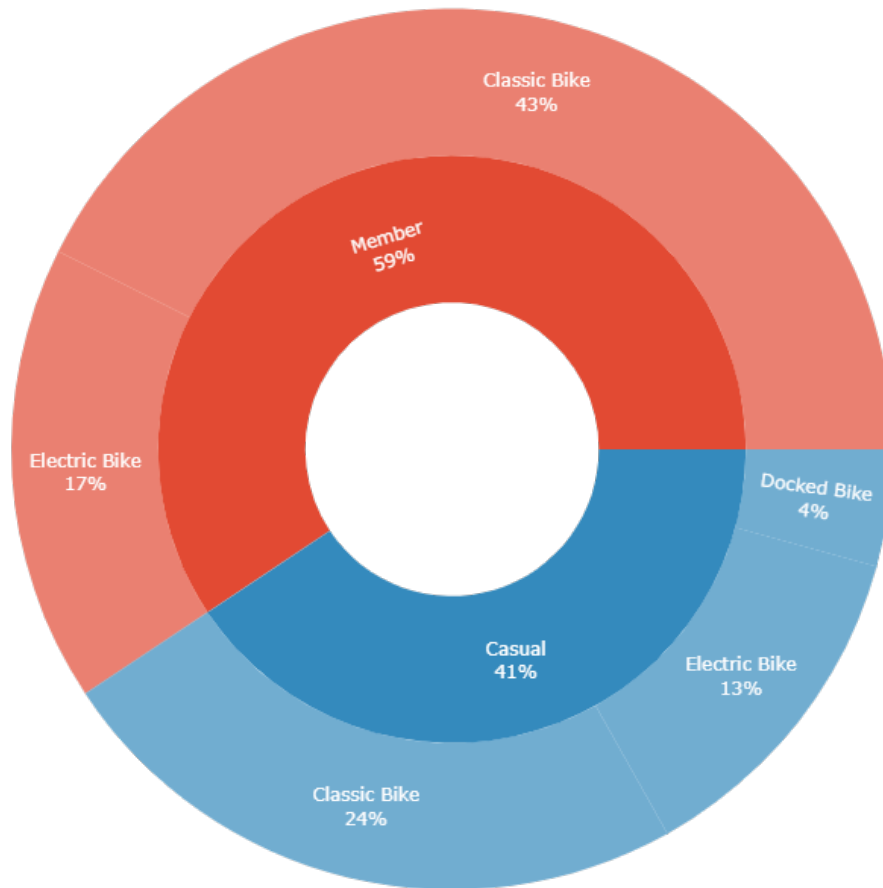
1.6.11 EXPORT PIVOTS TO EXCEL

1.7 Deep Dive - Visualization

Let's first take a look at the distribution of rides used by member and casual riders as well as what type of ride they use

1.7.1 Distribution of rides

Distribution by Ride-Type and Member



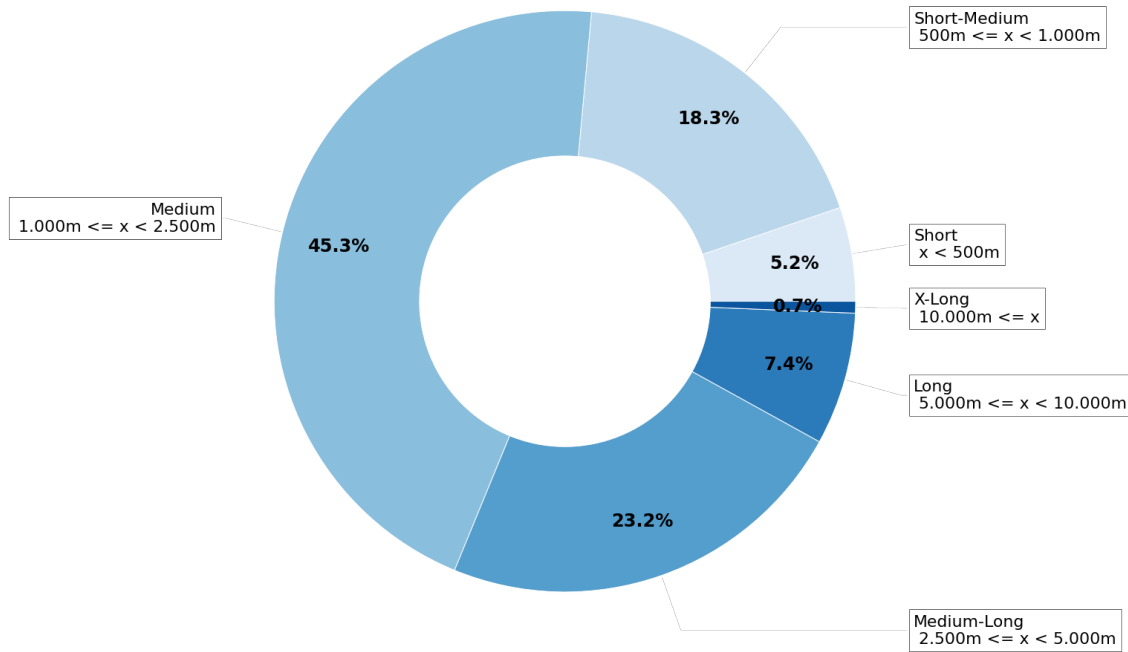
[37]: Both parties seem to have a preference for the class bike instead of an electric bike. This preference is strongest for the members who prefer to use the classic bike for 71.7% of their rides vs casual riders who use it for 58.5% of their rides.

Also casual riders are the only ones who use the option of the docked bike.

1.7.2 Ride distance

Next we will look at a quick distribution of the distance classified into 6 categories from Short to X-Long (see annotations).

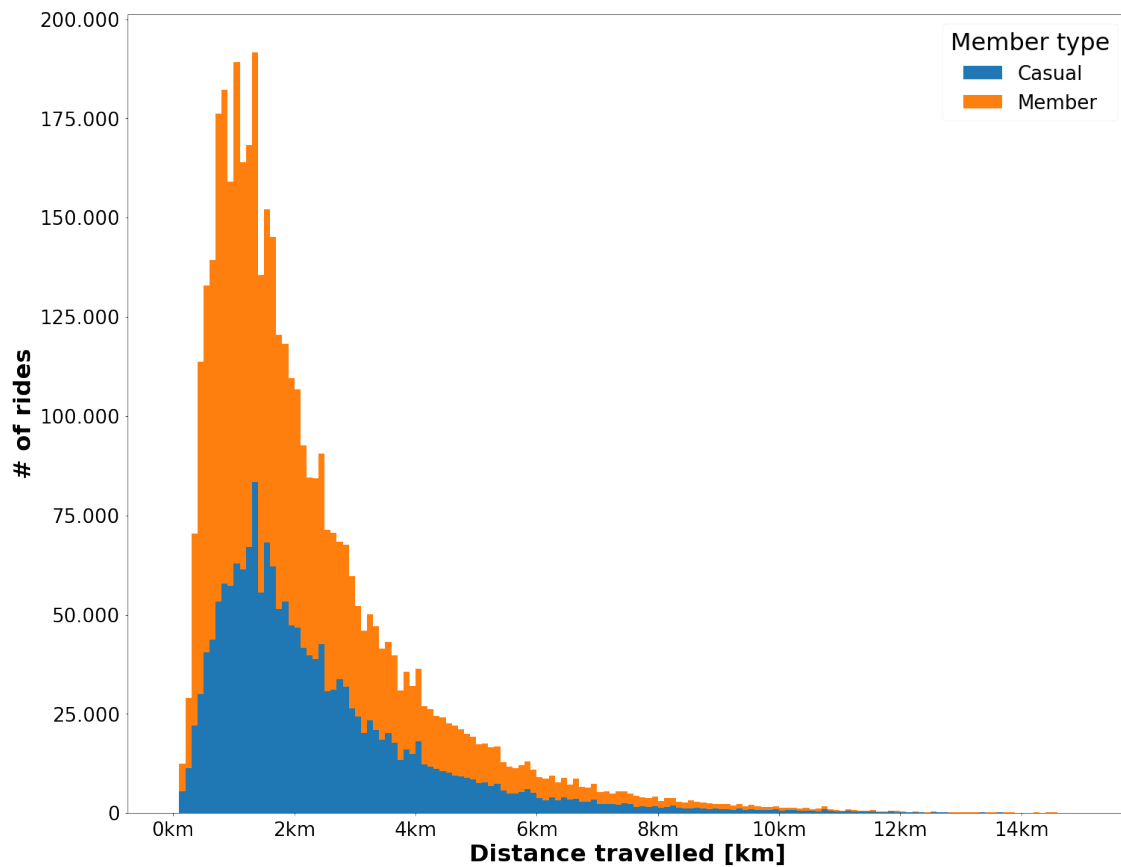
Distribution of distance travelled by classification



But is there a difference between the two groups and their ride distance?

Histogram

Histogram of rides by distance

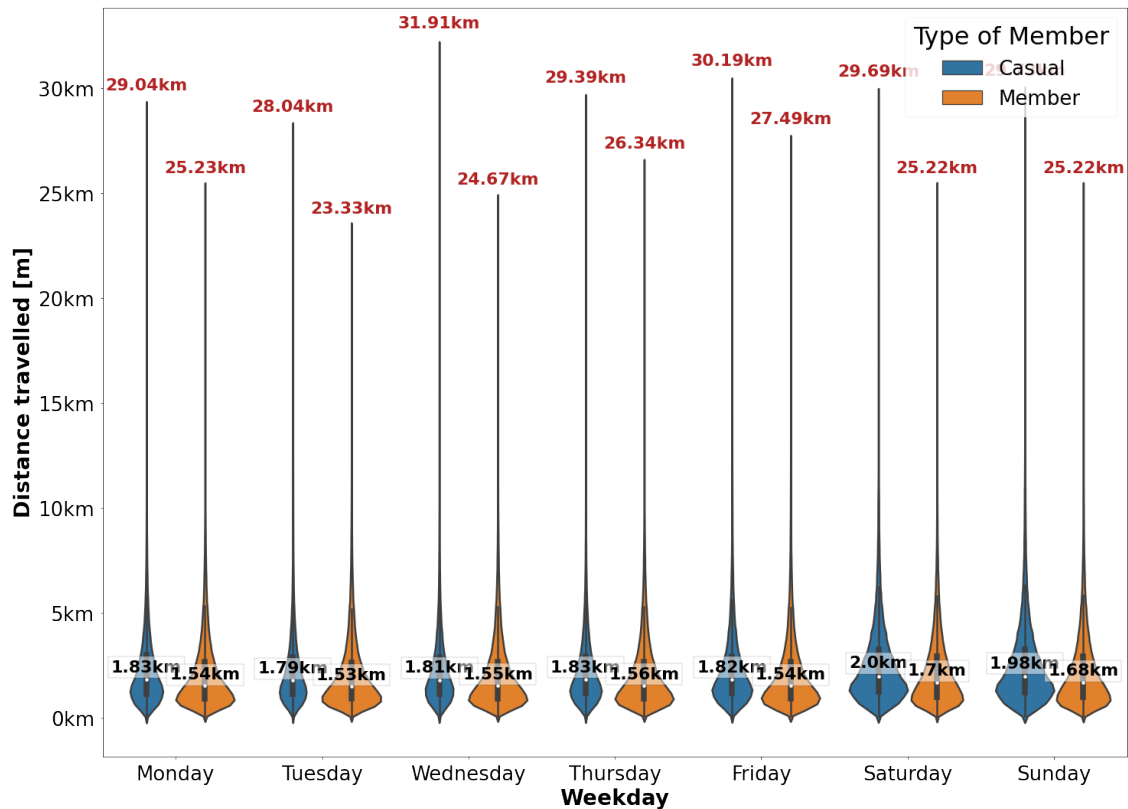


The histogram suggests that the casual riders ride slightly longer distances. Also it can be seen very well that the members use Cyclist more often.

But is there a difference in ride behaviour (number of rides, as well as distance) in the weekdays?

Violinplot for member-type and weekday

Distribution of distance travelled by Member-Type and Weekday

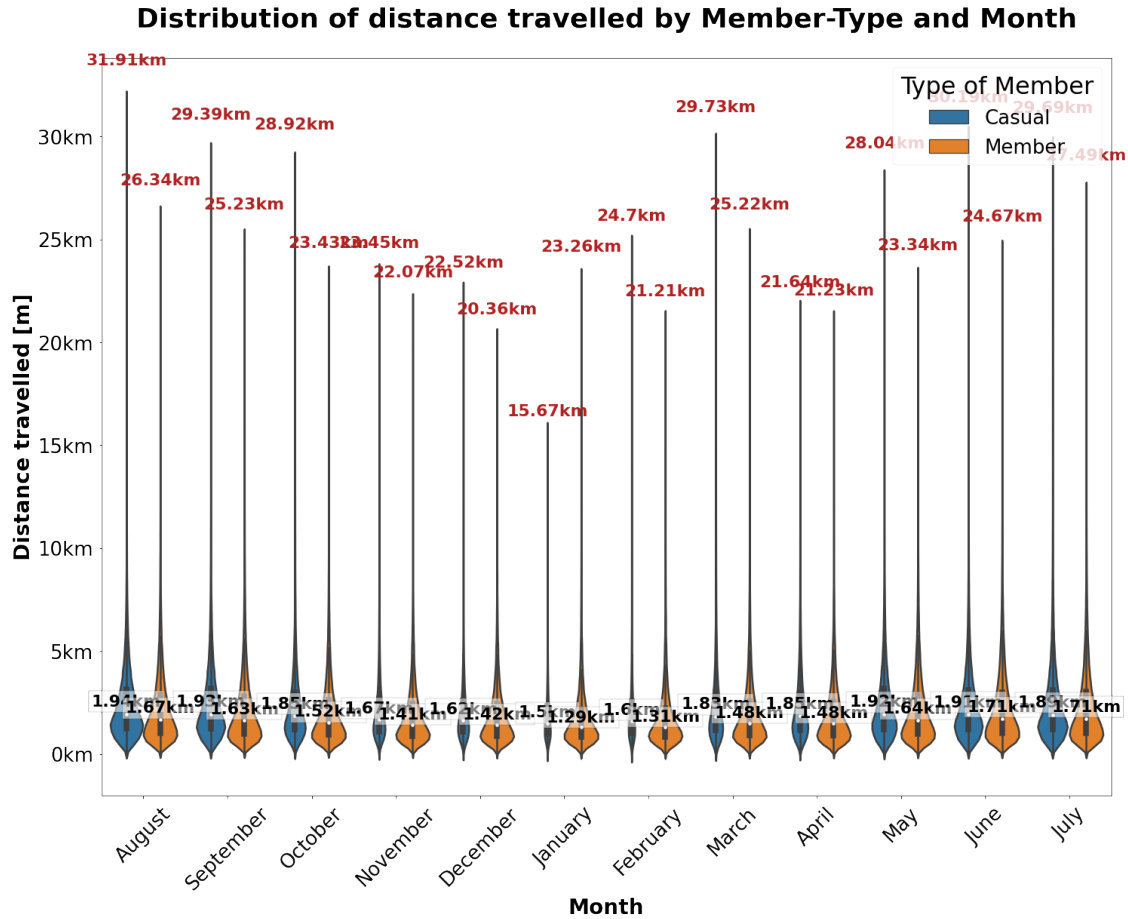


The violinplot of the ridedistance grouped by weekday and member type clearly shows that the number of rides for the casual members is significantly less in the workweek days (Mo-Fr) as shown by the slimmer widths of the violins. On weekends the casual riders even outweigh the members.

For both parties it also shows that the weekend comes with increased ride distances.

Next to the weekday is there also a difference when it comes to the months or the season?

Violinplot for member-type and month

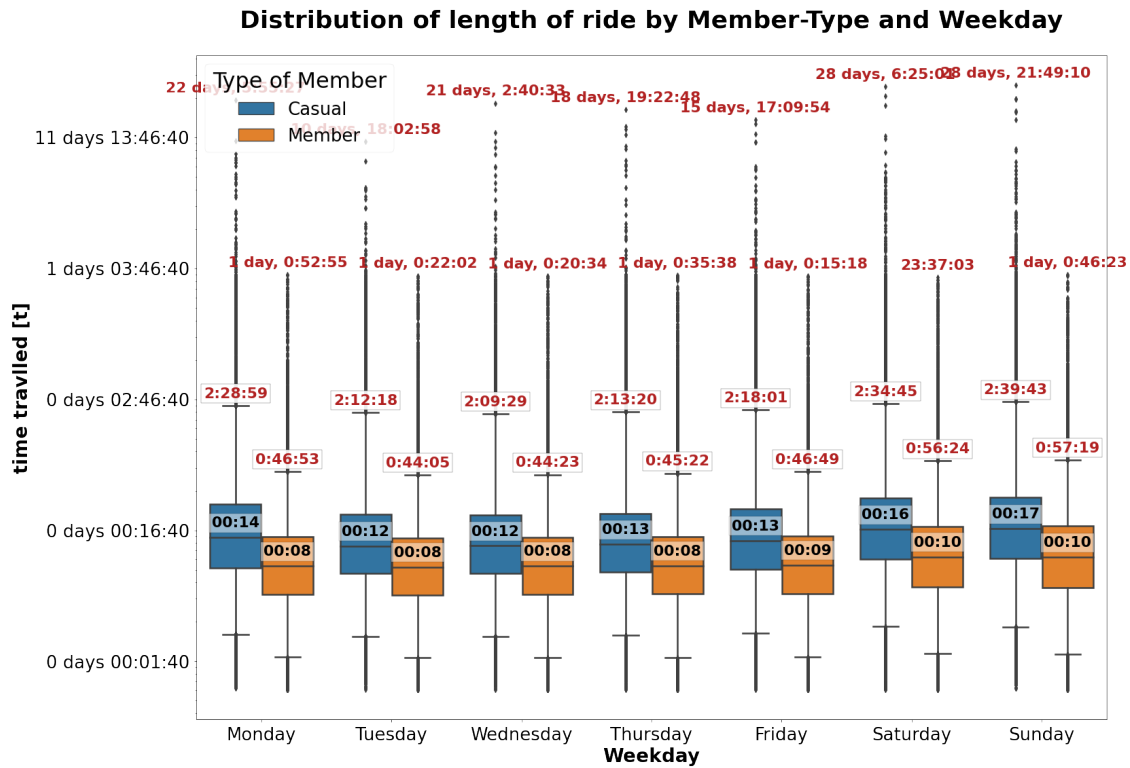


The above violinplot is similar to the one before with the only difference that the weekdays are substituted by the months. Here we also see a drastic reduction in rides (width of violin) for the cold months starting from October and stretching to March. January and February are especially low volume for the casual riders whereas the members still ride almost as much as during the summers.

Also for both parties the distance travelled is shorter during the winter months.

1.7.3 Ride length [t]

Next let's look at the difference in riding behaviour for the length of the ride.

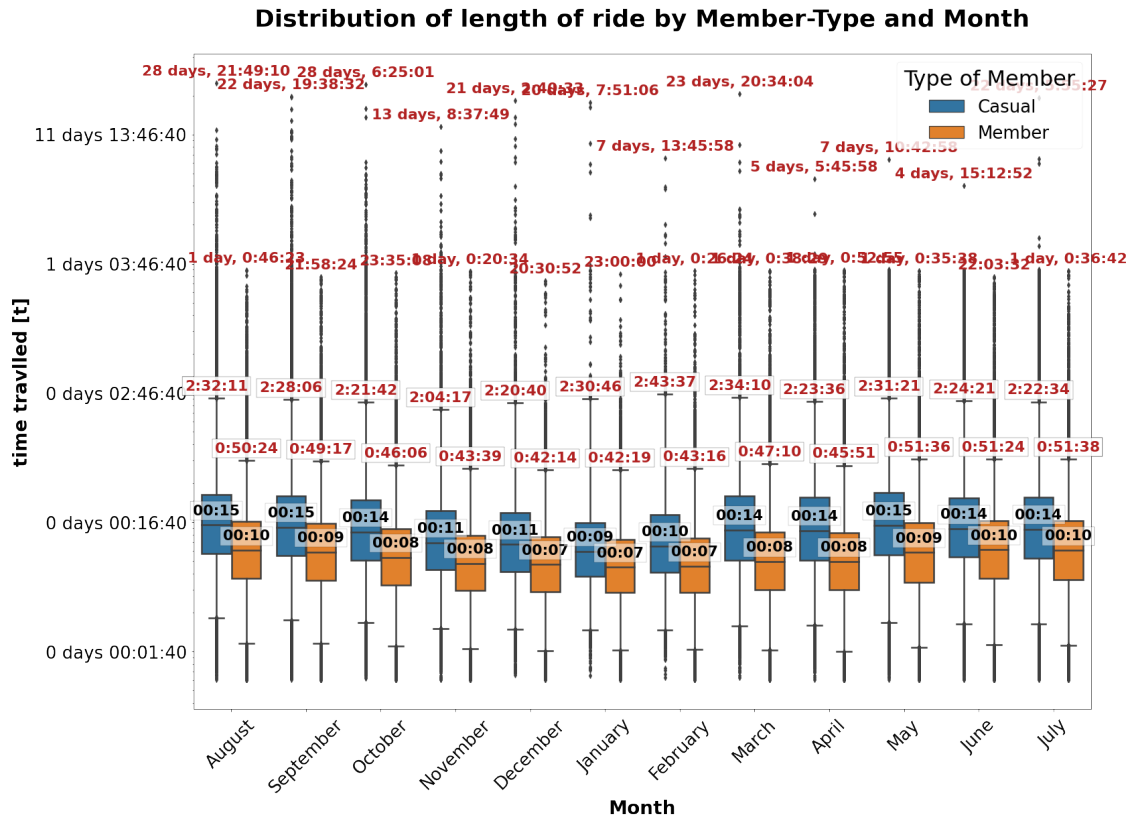


[44] : The above boxplot shows that the casual riders spent a significant time longer on the bike - by 54.4% to be exact (Casual: 00:14:25 vs Member: 00:09:20).

In the case of the ride length for Top 1% of rides (99th Percentile) this is even more drastic: Casual: 02:22:22 vs Member: 00:48:45.

So far this shows a clear difference in riding behaviour during the weekend, but is there also more differences throughout the year?

Boxplot - Ride-length by Member-Type and Month



[46]: The general difference in the ride length persisted throughout the year comparing the two groups. There is however a synchronous change in ride length throughout the year for both. During the winter months (Oct - Mar) the length of the ride drops by a significant amount (ca. 30%) for both. The drop is slightly larger for the casual riders.

This seems to be inline with the previous findings that also the distance travelled is reduced in those months - however not by 30%. During the winter months the riders seem to hurry more to get to their destination. Whereas in the summer the motto seems to be “the ride is the goal” in Winter it shifts to “the destination is the goal”.

1.7.4 Relation of distance and ride length

Now let's take a look at the relationship between the distance of the ride and the length. By now we know that the distance travelled is slightly longer for casual riders, but the time needed for this more than the distance would suggest.

If there is a correlation between the ride distance and length of the ride, I expect it to be stronger for the members who travel almost as much as the casual riders in distance, but do it in a faster manner.

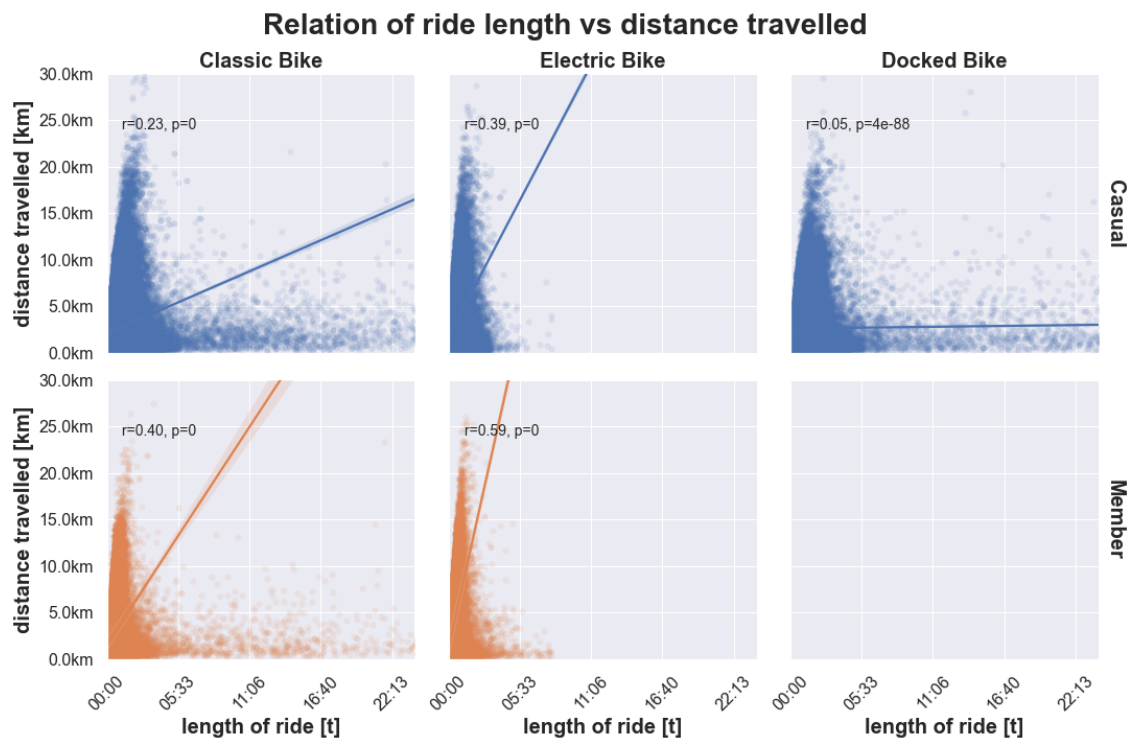
Also the docked bike has some gigantic outliers with the ride length (> 20 days). To get a good grasp let's take a look at the relationship of distance and ride length grouped by member-type and ride-type.

Linear Model of rides

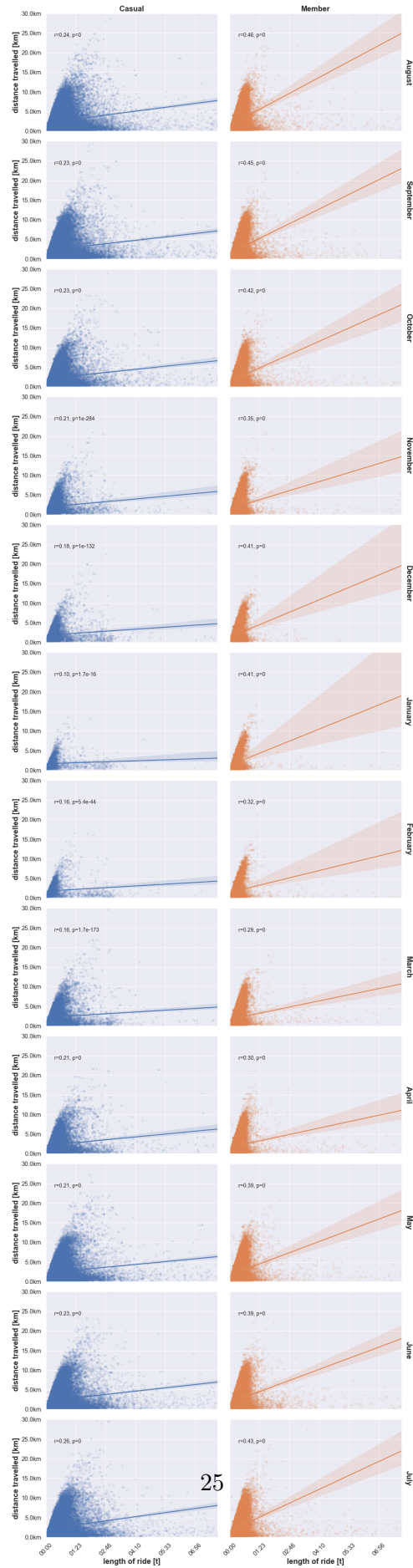
C:\Users\kemke\AppData\Local\Temp\ipykernel_9028\1318206295.py:2:
SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

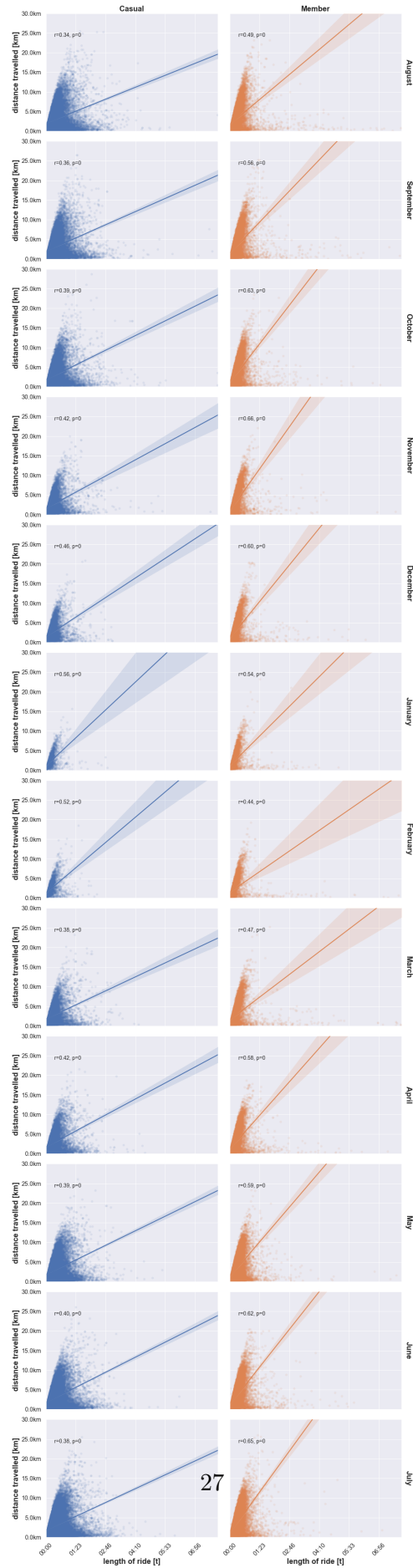
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy



Relation of ride length vs distance travelled
Classic Bike



Relation of ride length vs distance travelled
Electric Bike



1.7.5 Stations and routes used

Now let's take a look if there is a geographical difference as well. Let's look at the most used stations for this and then plot it into the map.

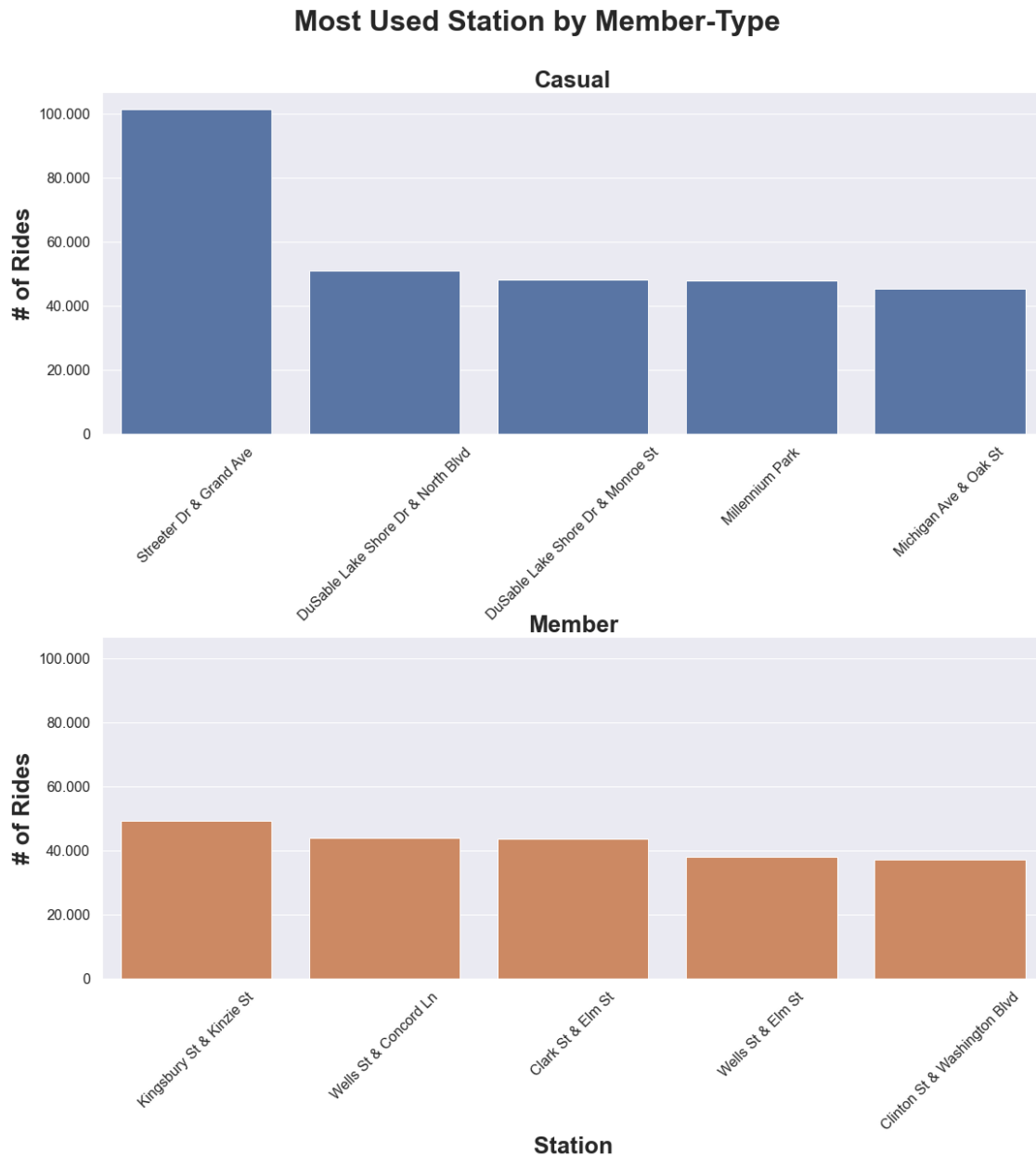
Barchart - Visited Stations

```
c:\Users\kemke\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\axisgrid.py:337: UserWarning:
```

The ``size`` parameter has been renamed to ``height``; please update your code.

```
c:\Users\kemke\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\axisgrid.py:670: UserWarning:
```

Using the `barplot` function without specifying ``order`` is likely to produce an incorrect plot.



Map Scatterplot - Visited Stations Now let's visualize the difference in used stations and plot it onto the map. The size of the marker will indicate how frequently the station is visited by each member-type.

Map Scatter- and Lineplot - Visited Stations and used routes Now let's visualize the difference in used stations and the typical routes taken by the riders. For this however the number of combinations for the routes (station to station) will be too big and the plot would end up quite confusing.

We will limit the lines plotted to visualize the routes taken therefore to the top 200 routes for each

member type.

(259344, 4)

The plot shows a clear concentration of the casual riders near the lake side and in or between the several parks.

For the members there are several little hubs or networks. One which is near downtown and a big one near the university.

1.8 Conclusion

For the members the Cyclist bike seems to be more integrated into their daily life and used for work or similar things. They ride their bike throughout the year with little change and are not wasting time when they are riding.

In contrast the casual riders show a clear tendence towards riding as a leisure activity. They ride their bikes mostly on the weekens and during the hotter months, especially in summer. While they ride mostly in the parks they seem to stroll around which is why there is also a weaker correlation between the ride time and the distance of the ride. When winter hits, this however changes and the cold temperatures seem to shift the behaviour. For the few remaining casual riders the bike becomes more of a vehicle to get from point A to B instead of a long stroll through the new cihlly cold park.