JSC370 Final Project Report

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Introduction

Bike share systems are programs that offer short term bike rentals to inhabitants of a city, providing a convenient and cheaper alternative to purchasing a bike for thousands of dollars. Bike Share Toronto, Toronto's bike share system, offers both one time bike rentals, and annual memberships for a considerably cheaper alternative to purchasing a new bike. In a city such as Toronto, where bike thefts are rampant, they also offer the security of nott having to worry about storing your bike in a secure location. Bike Share Toronto has over 600 stations across the city where you can rent and dock bikes. This program is utilized for a multitude of purposes including commute and leisure.

Toronto's Open Data repository offers monthly data on Bike Share Toronto's ridership, including variables such as the start and end time of the rental, the bike dock the rental was from, and so much more. Of particular interest in this report is the start date of the rental, which will be used to count the total number of bike rentals in a given day.

Toronto's Open Data repository also offers data on Bike Share Toronto's rental stations, including variables such as the station id, station coordinates (longitude and latitude), types of payments accepted at the station, and many more that will not be used in this report.

Canada's government website stores data on the historical weather for all weather stations in Canada. Of particular interest in this report is the historical daily weather in Toronto's weather station. Weather variables in this dataset include maximum, minimum, and average daily temperature (°C), total daily precipitation (mm), and total daily snow (cm).

This study investigates if weather conditions and temporal factors influence the number of bike share users on a given day in Toronto. This investigation will be conducted first with the total daily bike rental count for all stations, and with the daily bike rental count for each starting station. By understanding the relationship between weather factors, temporal factors, and bike share ridership, the city can understand when maintenance should be performed to avoid inconveniencing members, and when promotions would be viable.

To do this, I will collect Toronto's Open data repository data on Bike Share Toronto, and Canada's government on historical daily weather in Toronto's weather station from January 2020 to December 2022.

Note that in this report, tables or figures may be cut off. See the website for the well-formatted version of tables and figures.

Data Collection

Bike Share Toronto Ridership

From the Toronto's Open Data repository, we can obtain the data on Bike Share Toronto's ridership. On the page, there are several buttons, one for each year. We inspect the buttons for 2020, 2021, and 2022, and obtain the links to download the zipped files for each year. Each file contains twelve csv files, one for each month. Using R, download the zipped files and unzip them using the `download.file` and `unzip`, then read in the csvs. After reading in the twelve csvs for each year 2020-2022, ensure that all the variable types are consistent. Some variables such as the bike id appeared as integers in one file, and characters in another. Such variables were converted to a suitable type for consistency. In the case of bike id's, all were converted to integers. Then, combine the data for each month into one large dataframe for the bikeshare data using `bind_rows`.

Table 1, shown below, depicts the top 5 rows of the combined bikeshare data. The rows in this dataframe are sorted according to column "Start.Time", the starting time of the bike rental.

Table 1: Table 1: First Five Rows of Bike Share Toronto Ridership Data

Trip.Id	Trip..Duration	Start.Station.Id	Start.Time	Start.Station.Name	End.Station.Id	End.
7334128	648	7003	01/01/2020 00:08	Madison Ave / Bloor St W	7271	01/0
7334129	419	7007	01/01/2020 00:10	College St / Huron St	7163	01/0
7334130	566	7113	01/01/2020 00:13	Parliament St / Aberdeen Ave	7108	01/0
7334131	1274	7333	01/01/2020 00:17	King St E / Victoria St	7311	01/0
7334132	906	7009	01/01/2020 00:19	King St E / Jarvis St	7004	01/0
7334133	1098	7041	01/01/2020 00:20	Edward St / Yonge St	7134	01/0

Bike Share Toronto Station

Then we will also obtain the data on Toronto's Bikeshare stations, which contains the station ids (that correspond to the starting and ending station id's in the bike ridership data we just downloaded), the coordinates of the station, and a couple other variables that we will not be using. To obtain this data, we obtain the links for the json file, and read in the data using the `fromJSON` method.

Table 2, shown below, depicts the top 5 rows of the bike station data.

Table 2: Table 2: First Five Rows of Bike Station Data

last_updated	ttl	data.stations.station_id	data.stations.name	data.stations.physical_configuration	dat
1682362462	5	7000	Fort York Blvd / Capreol Ct	REGULAR	
1682362462	5	7001	Wellesley Station Green P	ELECTRICBIKESTATION	
1682362462	5	7002	St. George St / Bloor St W	REGULAR	
1682362462	5	7003	Madison Ave / Bloor St W	REGULAR	
1682362462	5	7004	University Ave / Elm St	REGULAR	
1682362462	5	7005	King St W / York St	REGULAR	

Toronto Weather

From the Canada government webpage, we can access the historical weather data and select Toronto's weather station. From there, we select the month and year we wish to obtain. Start with January 2020. The page has a table with the daily weather data for that month. Inspect the table and obtain the xml path for it. Then, using R's `xml2` package, we can read in the html table. We then convert that table to an R dataframe using the `rvest` package. After obtaining the dataframe for that month, note that the table does not include which month or year it was from, it only includes the day of the month. Thus, we add the month and year of the table we just scraped to the dataframe. Repeat this for all months from January 2020 to December 2022. Finally, merge all of these dataframes to obtain the combined Toronto weather data.

Table 3, shown below, shows the first five rows of the combined Toronto weather data.

Data Cleaning and Wrangling

Tables 1, 2, and 3, from the previous "Data Collection" subsection, provide us with an overview of the data we will be using to answer the question of interest. However, before that can be done, some data cleaning and data wrangling needs to be done. We will start with the bikeshare data.

Table 3: Table 3: First Five Rows of Toronto Weather Data

DAY	Max Temp Definition°C	Min Temp Definition°C	Mean Temp Definition°C	Heat Deg Days Definition	Cool
01	1.0	-1.2	-0.1	18.1	0.0
02	6.2	0.9	3.6	14.4	0.0
03	7.7	3.6	5.7	12.3	0.0
04	3.6	0.3	2.0	16.0	0.0
05	1.9	-1.2	0.3	17.7	0.0
06	2.9	-1.7	0.6	17.4	0.0

Bike Share Toronto Ridership

We are not actually using most of the variables in the bikeshare data, we only wish to obtain the number of daily bike rentals. Here we will create two counts. The number of daily bike rentals for all stations, and the number of daily bike rentals for each individual starting station. Thus we will not clean the variables in the bikeshare dataset, instead we will wrangle the data to obtain our variable of interest: daily rental count. We will use the start date of each bike rental as the day it was rented. So if a bike was rented on January 1st, and returned on January 2nd, we will count this bike in the January 1st rentals.

To do this, first convert the start date of each rental into a Date object.

Then, we will count the number of daily bike rentals grouped by the starting station and save the date, starting station id, and count in a new dataframe "count_station"

Table 4, shown below, shows the first five rows of this new dataframe. Column "n" is the number of bike rentals on that date.

Table 4: Table 4: First Five Rows of Bikeshare Daily Rental Count

Start.Station.Id	Date	n
7000	2020-01-01	4
7000	2020-01-02	18
7000	2020-01-03	17
7000	2020-01-04	16
7000	2020-01-05	12
7000	2020-01-06	19

Bike Share Toronto Stations

Now, we wrangle the data on the bike stations. For this data, we only have to remove unnecessary variables and rename them for convenience. We will only keep the station id, name, and the coordinates.

Toronto Weather

After wrangling the bikeshare and bike station data, we now clean and wrangle the weather data.

First, consider some rows of the current dataframe. Table 5 below shows the 101-105th rows of the weather dataframe, which have some problematic entries.

From Table 5, observe that in rows 101-103, the entries in column "DAY" are not actually the day of the month, but are summary statistics of that month instead. We remove all such columns in the data. Then, observe that in column "Snow on Grnd Definitioncm", there are many missing entries. Since this variable is of interest, we check the data to see why, and notice that missing entries mostly occur in the warmer months with no snow. Thus, we replace all such empty entries in the column with "0". Problematic entries in other

Table 5: Table 5: Rows 101-105 of Toronto Weather Data

	DAY	Max Temp Definition°C
101	Avg	7.4
102	Xtrm	18.4
103	Summary, average and extreme values are based on the data above.	Summary, average and extreme values are bas
104	01	9.4
105	02	14.1

columns such as "Grnd Definitioncm" are not of concern, since we are not using those variables. In fact, we will soon be dropping those unused variables from the dataframe.

Then, create a Date variable using the variables containing the month, day, and year (the "month", "DAY", and "year" columns in Table 3 and Table 5). Then unused variables (such as flags indicating status of data collection) were removed, and only the date, maximum, minimum, and average temperature, amount of precipitation, and amount of snow were kept. Rename these variables (aside from date) as "Max_temp", "Min_temp", "Mean_temp", "Precipitation", and "Snow" respectively.

Then, new temporal variables (such as the day of the week, and whether a day is on the weekend, etc.) were created for the weather dataframe using the date variable.

Data Merging

After cleaning and wrangling the bikeshare daily rental counts and weather data, we now merge the two dataframes by their dates.

Then, we merge this with the bike station information by the station ids.

Table 6 below shows the first five rows of our dataset that we will be using to answer our question of interest.

Table 6: Table 6: First Five Rows of Dataset

Station_id	Station_name	Latitude	Longitude	Date	Rental_count	Max_temp	Min_ter
7000	Fort York Blvd / Capreol Ct	43.63983	-79.39595	2022-06-30	92	25.8	15
7000	Fort York Blvd / Capreol Ct	43.63983	-79.39595	2020-09-21	71	18.9	9
7000	Fort York Blvd / Capreol Ct	43.63983	-79.39595	2020-01-13	22	2.5	-4
7000	Fort York Blvd / Capreol Ct	43.63983	-79.39595	2020-08-26	80	21.6	15
7000	Fort York Blvd / Capreol Ct	43.63983	-79.39595	2022-05-14	117	27.0	16
7000	Fort York Blvd / Capreol Ct	43.63983	-79.39595	2021-06-15	97	22.9	15

Data Exploration

Finally, now that our datasets have been cleaned, wrangled, and merged, we will begin to explore the data in greater detail.

Firstly, we will look at the distribution of bike rental counts per year for each station.

Bike Rental counts yearly for each station Figure 1, 2, and 3 showing the bike rental counts yearly for each station in 2020, 2021, and 2022 respectively can be found on the website under the Methods section.

The circles are at each bike rental station, and the colors indicate the total number of bike rentals from that station for the given year. Notice that most bike rentals occur in the downtown Toronto area, especially near the harbor front.

Summary Statistics

We will then select the most popular bike station (station with most total rentals over the three years), the median most popular bike station (station with the median number of total rentals over the three years) and the least popular bike station (station with least total rentals over the three years). After looking at some brief summary statistics, we establish below that the least popular bike station is not suitable, so only the most popular and median popular station are used. In later analysis, we will see if the relationship between the temporal and weather factors differs between the counts of the most popular, median popular, and all bike stations.

After computation, we obtain that station 7076 ("York St / Queens Quay W") is the most popular with a total of 101551 bike rentals recorded for the three years, station 7685 ("King St W / Brant St") with total 10450 bike rentals recorded for the three years is the station with median popularity, and station 7758 ("Driftwood Ave / Finch Hydro Trail") is the least popular with only 2 bike rentals recorded for the three years.

Now look at univariate summary statistics of our variables for the rental count including all stations in Table 7 below.

Table 7: Table 7: Univariate summary statistics (all stations)

Variable	Min	Q1	Median	Mean	Q3	Max
Rental Count	399	3408	8254	9508	14205	27312
Max Temperature (°C)	-13.0	4.9	14.0	14.0	24.0	36.0
Min Temperature (°C)	-20.0	-0.6	6.6	6.5	15.0	24.0
Mean Temperature (°C)	-16.0	2.2	10.0	10.0	20.0	29.0
Precipitation (mm)	0.0	0.0	0.1	2.1	1.3	55.0
Snow (cm)	0.0	0.0	0.0	1.4	0.0	32.0

[a] numerical summaries for the Date and day of the week are omitted, as it does not provide meaningful information.

From Table 7, notice that the maximum rental count in a day is 28307, which is vastly more than the minimum rental count of 425 in a day. The rental count also appears to be right skewed. Notice that variables for precipitation and snow also appear severely right skewed.

For the most popular, median popular, and least popular stations, we will only look at the summaries of rental count, as all other variables (e.g. temperature) are the same across all bike stations.

Table 8: Table 8: Univariate summary statistics (most popular)

Variable	Min	Q1	Median	Mean	Q3	Max
Rental Count	2	22	63	93	147	456

In Table 8, notice that the daily rental count for the most popular station is also right skewed, similar to the rental count for all stations.

Table 9: Table 9: Univariate summary statistics (median popular)

Variable	Min	Q1	Median	Mean	Q3	Max
Rental Count	1	9	25	28	42	108

In Table 9, notice that the daily rental count for the median popular station is also right skewed, similar to the daily rental count for all stations and most popular station.

Notice that in table 10, there are no zeros as we'd expect, since there are only a total of two rentals so there can only be two nonzero entries over the three years. It follows that the dataset we have doesn't record if

Table 10: Table 10: Univariate summary statistics (least popular)

Variable	Min	Q1	Median	Mean	Q3	Max
Rental Count	1	1	1	1	1	1

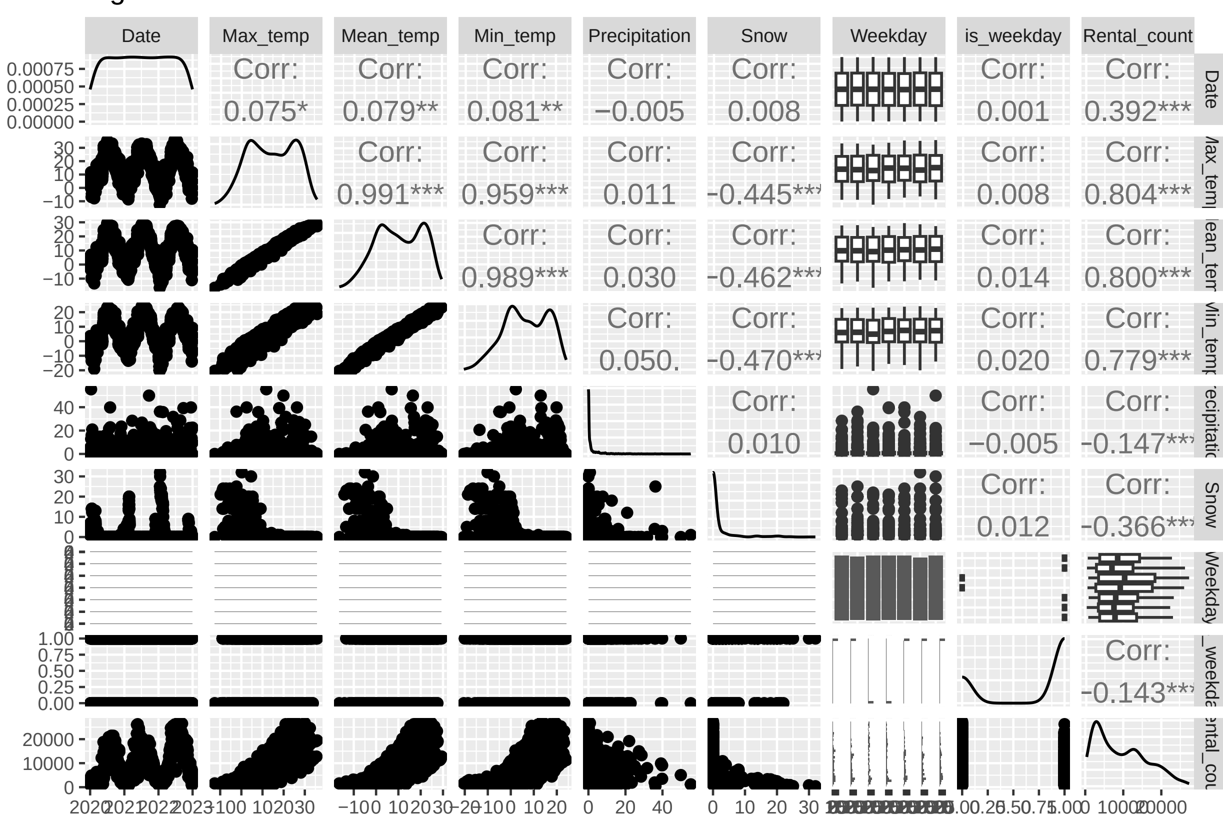
there were no bike rentals on some day. This makes sense, as we calculated count by summing up the number of rentals recorded. Thus we must take into consideration that none of the data we plot will record these zero days.

Also, only having two rentals is very strange. After taking a closer look at the information for that station, we discovered that station 7758 is not actually a station people can rent bikes from, it is instead labelled as a "VAULT", perhaps indicative of a place the bikeshare company uses to store bikes not for public use. In this case, having two rentals is still strange, and perhaps was due to internal testing. This is potentially something to look into more in the future.

Thus conclude that this station is not a good station to analyze daily bike ridership. This report will not be further analyzing this specific bike station. Therefore, in later analysis, we will only see if the relationship between the temporal and weather factors differs between the counts of the most popular, median popular, and all bike stations.

Now let us take a closer look at Figure 4 below, which is a visualization of the variables of interest in the data. These visualizations are the same for all stations because they are by date. Note that variable "Weekday_num" is omitted as "Weekday" contains the same information. Note that along the diagonal of Figure 4 is a line graph of the number of observations. The top right corner contains the Pearson correlation coefficient between each pair of variables. The more significant the correlation coefficient is, the more stars there are. For example, "*" is "slightly significant" (alpha = 0.05) while "***" is "very significant" (alpha = 0.001). The bottom left corner contains the scatter plots between each pair of variables.

Figure 4



From Figure 4, note that the “Rental_count”, “Precipitation”, and “Snow” are all severely right skewed, as noted before. Also notice significant levels of correlation between the “Rental_count” and all variables. More in depth investigation would need to be conducted to determine the exact nature of the relationship (linear, periodic, etc).

There is also significant correlation between the minimum, mean, and maximum temperatures (which is expected), so perhaps if we were to fit a model we would only want to select one of the temperature variables. Also notice the periodic relationship between temperature and date.

There is also a significant imbalance in the “is_Weekday” variable, which is expected, as there are more weekdays than weekends in a year. This is something to note as it may skew any results concerning this variable.

A further point of interest is the scatter plot between “Precipitation” and “Snow”, where we notice a few outlier points with both large amount of rain and large amounts of snow. This is interesting, as rain and snow do not usually occur together in such large amounts on the same day.

Additionally, there are so many data points that it is impossible to tell the relationship between some pairs of variables using these scatter plots. For example, between Weekday_num and Date. This is acceptable for our purposes, as we are not specifically interested in the relationship between these variables, just if there are any major issues that could affect our ability to answer the question of interest. However, in the future it may be necessary to redo the plots with perhaps a subset of the data if we desire to model these relationships.

Preliminary Results

Maximum and Minimum Rental Days

Table 11: Table 11: Summary of top five days by rental count (all stations)

Date	Rental Count	Max Temperature (°C)	Min Temperature (°C)	Mean Temperature (°C)	Precipitation (
2022-08-13	27312	25.2	13.6	19.4	
2022-08-20	26702	30.0	19.5	24.8	
2022-08-27	26557	23.1	14.0	18.6	
2022-09-10	26491	26.5	19.7	23.1	
2022-07-16	26285	29.2	18.4	23.8	

From Table 11, notice that all the days have a reasonable minimum and maximum temperature (not too cold and not too hot), no (or very little) rain, no snow, and most interestingly, all days are on a Saturday. Furthermore, all 5 days are in 2022, and there are none in 2020 and 2021. This may be due to increase in ridership over time, or the COVID situation in 2020 and 2021.

Table 12: Table 12: Summary of top five days by rental count (most popular)

Date	Rental Count	Max Temperature (°C)	Min Temperature (°C)	Mean Temperature (°C)	Precipitation (
2021-06-06	456	30.5	18.9	24.7	
2021-09-06	450	24.0	14.4	19.2	
2022-07-02	409	29.4	15.3	22.4	
2022-05-14	403	27.0	16.6	21.8	
2021-05-16	380	22.7	11.7	17.2	

From Table 12, notice that similar to Table 11, all the days have a reasonable minimum and maximum temperature (not too cold and not too hot), no (or very little) rain, no snow. One difference is that the top five days also includes Sundays, unlike Table 11, and also a Monday that is not a holiday.

In Table 13, again, similar to Table 11 and Table 12, all the days have a reasonable minimum and maximum

Table 13: Table 13: Summary of top five days by rental count (median popularity)

Date	Rental Count	Max Temperature (°C)	Min Temperature (°C)	Mean Temperature (°C)	Precipitation (
2022-08-07	108	31.4	23.2	27.3	
2022-08-13	103	25.2	13.6	19.4	
2022-07-31	95	27.4	17.7	22.6	
2022-08-06	94	30.5	21.7	26.1	
2022-08-10	91	26.6	17.3	22.0	

temperature (not too cold and not too hot), no (or very little) rain, no snow. The most major difference is that similar to Table 12, here we see a Wednesday (not a holiday or weekend) included.

Table 14: Table 14: Summary of bottom five days by rental count (all stations)

Date	Rental Count	Max Temperature (°C)	Min Temperature (°C)	Mean Temperature (°C)	Precipitation (
2022-01-18	399	0.2	-10.1	-5.0	
2022-01-17	460	-2.3	-5.0	-3.6	
2020-01-19	589	1.3	-10.4	-4.5	
2021-02-16	642	-6.4	-12.0	-9.2	
2020-12-25	664	0.2	-4.7	-2.2	

From Table 14, notice that all days are very cold, and have some snow or precipitation. The day of the week appears to have less effect here than in Table 11, as there is a wide range here. Notice that these dates also all occur in Dec-Feb winter months.

Table 15: Table 15: Summary of bottom five days by rental count (most popular)

Date	Rental Count	Max Temperature (°C)	Min Temperature (°C)	Mean Temperature (°C)	Precipitation (
2020-02-02	2	2.5	-0.1	1.2	
2020-03-23	2	3.9	0.4	2.2	
2021-02-18	2	-2.6	-6.2	-4.4	
2022-01-26	3	-8.6	-14.0	-11.3	
2020-12-25	3	0.2	-4.7	-2.2	
2020-01-12	3	2.2	-5.2	-1.5	

From Table 15, notice that the minimum daily rental counts are very small. Similar to Table 14, notice that all days are very cold, and often have some snow or precipitation. The day of the week appears to have less effect here than in Table 12, as there is a wide range here.

From Table 16, notice that the minimum daily rental counts are all ones. Recall from previous data exploration that the days with no rental counts are not included here, so it is very likely that there are many days with no rental counts that is not in this table. Aside from that, similar to Table 14 and Table 15, notice that all days are very cold, and often have some snow or precipitation. The day of the week appears to have less effect here than in Table 13, as there is a wide range here. Notice that these dates also all occur in Dec-Feb winter months.

From the above six tables, observe that the general relationship between bike share ridership and temporal and weather factors is very similar even when we consider stations separately, so there is likely no unique pattern of ridership count for each station. Thus, below, we will only consider the total daily counts of bike rentals, not the individual counts for the most popular and median popular station.

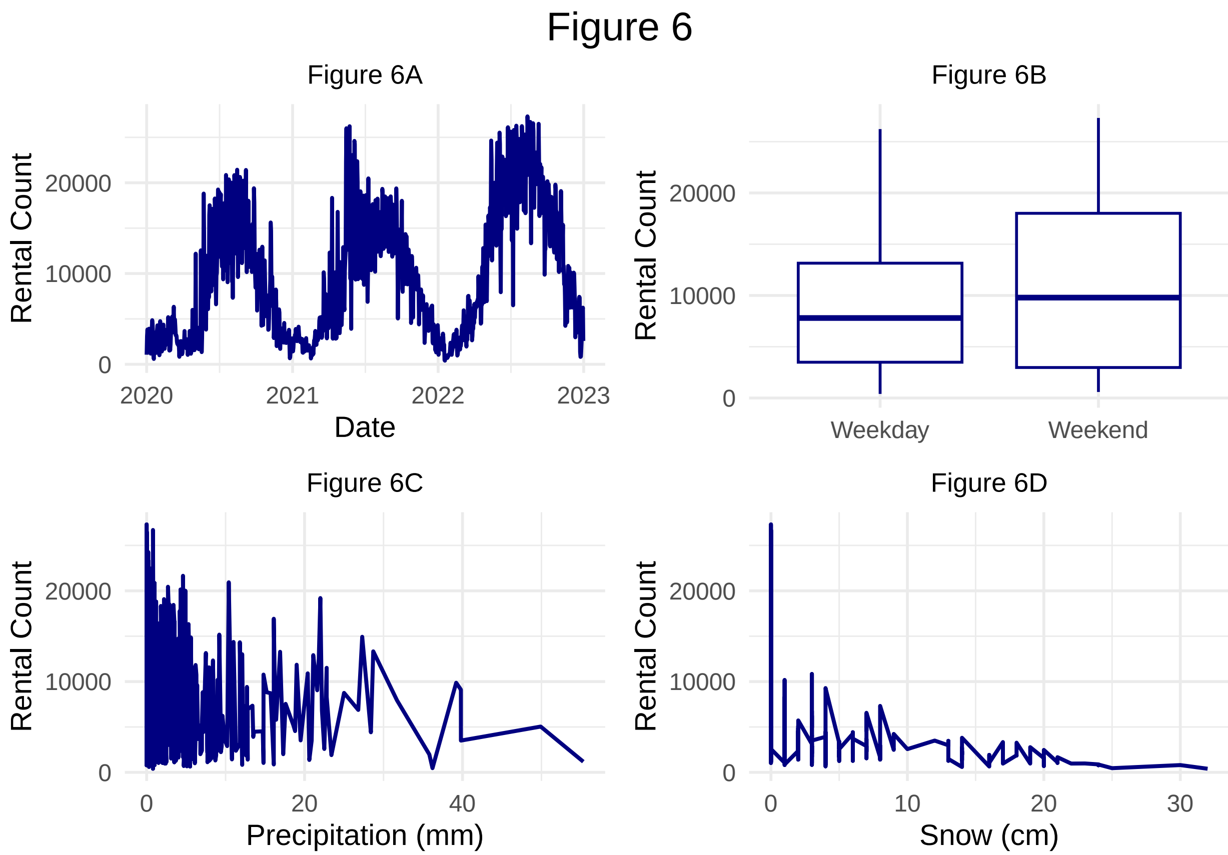
Table 16: Table 16: Summary of bottom five days by rental count (median popular)

Date	Rental Count	Max Temperature (°C)	Min Temperature (°C)	Mean Temperature (°C)	Precipitation (
2022-01-24	1	-3.8	-14.7	-9.2	
2022-12-26	1	-4.4	-8.1	-6.2	
2022-12-11	1	-0.4	-1.8	-1.1	
2022-01-22	1	-3.8	-12.4	-8.1	
2022-02-03	1	-2.1	-9.6	-5.9	
2022-01-20	1	-7.3	-16.4	-11.9	
2022-02-20	1	7.5	-8.1	-0.3	
2021-12-25	1	7.4	3.3	5.4	
2022-01-11	1	-1.7	-20.0	-10.8	
2022-02-19	1	-1.3	-9.1	-5.2	
2021-12-27	1	1.3	-5.3	-2.0	
2022-12-25	1	-3.9	-8.6	-6.2	

Rental Count Associations

Figure 5, which shows the Rental count vs Temperature, can be found on the website labelled Figure 5 in the Results section.

In Figure 5, notice that the trend appears to be relatively similar for mean, max, and min temperatures. Also notice large fluctuations in rental count as the temperature increases, indicating that much of the variation in the rental count is still not explained by the temperature. However, there is a clear trend that increase in temperature increases rental count, at least up to a certain point. Once max temperature is too high (roughly above 30°C), then the rental count starts to fall again. Also notice that as the temperature increases, the variation in rental count also increases.



In figure 6A, notice the clear trend of increasing ridership count in the summer months, then decreasing ridership count in the winter months. Also note that date and temperature are correlated, so the relationship seen here could be a reflection of the relationship seen in Figure 5. Again note the large variations in rental count across the dates. For example, in the middle of 2022, there are a few very large dips in the rental count. Also note how the variation in rental count is higher in the summer months than in winter months.

From Figure 6B, notice that the median of the rental counts for the weekday and weekend are actually relatively similar (differing by about 1500) whereas the third quantile differs greatly (by about 5000), indicating that there tends to be a higher rental count more often on the weekend. Recall from Figure 5 and 6A how when the temperature is lower (i.e. in the winter months), there is less variation in the rental counts, and there is also lower rental count. This is reflected here in Figure 6B, where being on the weekend or not has less impact on the rental count when the rental count is low. Perhaps being on the weekend or not instead explains the variation in rental counts when the temperature is high (i.e. in the summer months).

From Figure 6C, notice that when precipitation is low, there is very large variation in rental count, however when the precipitation increases, the rental count also tends to decrease somewhat. Do note that there are not many data points with more than 30 mm of precipitation, so trends seen may not be generalizeable. Also note that rain does not tend to fall in the colder winter months, where there is less bike ridership (as seen in Figure 5 and Figure 6A).

From Figure 6D, first notice that for nonzero values of snow, the variation in rental count is not very large, especially as the amount of snow increases. Do note that there is not a lot of nonzero data on snow, so this may not be generalizeable. However, from the data that we do have, even a little amount of snow appears to cap the rental count at 12000 per day. Also note that snow is correlated with temperature, in that it generally only appears in the cold winter months, where there is less bike ridership (as seen in Figure 5 and Figure 6A).

Some lingering issues with Figure 6C and Figure 6D is that the precipitation and snow is recorded for the entire day, and it is unknown whether this occurred late at night and/or for a very short amount of time, resulting in less impact on ridership for that rainfall/snowfall. To investigate this, hourly data would need to be used instead.

Rental Count Associations with Day of Week

Now, let's take a look at the variables again, this time taking into account the day of the week.

In the figures below, we will examine whether the relationship between daily bike rental counts in Toronto and other weather variables is influenced by the day of the week.

Figure 7 (Rental Count vs Mean Temp with Weekday), Figure 8 (Rental Count vs Precipitation with Weekday), Figure 9 (Rental count vs Snow with Weekday) can be found on the website under the Results section.

From Figure 8 and 9, we can observe that the day of the week doesn't seem to change the relationship between precipitation and bike ridership and snow and bike ridership. On the other hand, in Figure 7, there does appear to be a slight tendency toward more bike share ridership on weekends versus weekdays.

Effect of Weather Interactions

Now we will explore whether interactions between weather variables affects (e.g. will rain on a warm or cold day be more likely to affect rental count)

Figure 10 can be found on the website under the Results section.

In Figure 10, the larger the circle, the more precipitation there is. Looking at the size of the circles, notice that when temperature is held constant, the precipitation does decrease rental count, however having a higher mean temperature means that even if there is precipitation, the rental count is still higher than with a significantly lower mean temperature and no precipitation.

Model

Now that we have looked more closely at the individual relationships between the variables, let's try creating a model to quantify these relationships. From previous analysis, we have discovered a cyclic relationship, so the best model is likely to be a non-linear generalized additive model (GAM). Specifically, we will add a cubic spline to the Date variable, and include all other temporal and weather factors (only Mean_temp will be used for temperature, as we have already established the three temperature variables provide the same information) as the other predictors in the model.

Table 17:

Note that there is no estimate value for the spline on Date for the two models, as the spline does not provide such an estimate. Instead, only the p-value is provided next to `s(as.numeric(Date))` in the bale. After fitting the full model, we observed that the predictor for Snow is statistically insignificant, so we use the reduced model instead.

Now all the predictors are statistically significant. Our final chosen model (the reduced model) has response variable Rental_count, and predictors Mean_temp, is_weekday, Precipitation, and Date, where there is a cubic spline on Date. We obtain that the adjusted R-squared value is 0.876, indicating that about 87% of the variation in the response (Rental_count) is explained by the predictors. This is a pretty large percentage, so we can safely conclude that the total daily bike rental counts is heavily influenced by weather factors of temperature and precipitation, as well as temporal factors of the date and being a weekend.

Conclusions

The question of interest is investigation on if weather factors and temporal factors influence the number of bike share users on a given day in Toronto. From the preliminary analysis of the data, we have gained several insights.

	Full model	Reduced model
(Intercept)	8474.646	8468.749
	<0.001***	<0.001***
Mean_temp	290.769	290.631
	<0.001***	<0.001***
is_weekday	−2201.063	−2201.857
	<0.001***	<0.001***
Precipitation	−193.740	−194.146
	<0.001***	<0.001***
Snow	−6.358	
	0.761	
s(as.numeric(Date))	<0.001***	<0.001***
Num.Obs.	1088	1088
R2	0.875	0.876
AIC	19 998.4	19 991.6
BIC	20 073.2	20 061.3
RMSE	2339.65	2334.40

First, from the tables we see that days with high ridership count tend to have a comfortable temperature, be on a weekend or holiday, and have no rain or snow. On the other hand, days with low ridership count tend to be cold days (below 0°C), likely with precipitation or snow. This pattern holds true for both the total daily rental count, and the daily rental count for the most popular and median popular stations.

Then, more generally, as the temperature increases, the ridership count increases, and the variation in the ridership count also increases. Furthermore, in the summer months the ridership count increases (and has higher variation), and in the winter months the ridership count decreases (and has lower variation). Lower ridership counts appear evenly spread between weekdays and weekends, but higher ridership counts occur more often in weekends. In addition, both the occurrence of snow and/or precipitation (that is, a nonzero value), tends to decrease the ridership count.

Taking into account the day of week, we further discover that the day of the week doesn't seem to change the relationship between precipitation and bike ridership and snow and bike ridership. On the other hand, there does appear to be a slight tendency toward more bike share ridership on weekends versus weekdays.

A further observation is that when temperature is held constant, the precipitation does decrease rental count, however having a higher mean temperature means that even if there is precipitation, the rental count is still higher than with a significantly lower mean temperature and no precipitation.

Finally, after fitting a model that provided an adjusted R-squared value of 0.876, we further concluded that the total daily bike rental counts is heavily influenced by temperature, precipitation, date, and being a weekend.

In addition, notice that the relationships discussed above appear to hold true even when we consider the bike rentals for an individual station instead of the sum of all stations.

Limitations

Since the weather data used is daily weather data, this does not capture any patterns within the day. For example, there may be both large amounts of snow and a large bike rental count for some day if the snow occurs late at night, after many people have already rented bikes earlier that day. For the temperature variables, we also do not know exactly when an extreme low or high temperature is (although we can make inferences based on our own knowledge). Thus, there is an underlying assumption that the weather variables are representative of the entire day.

There is also an underlying assumption that the weather data we collected from the Toronto weather station is representative of Toronto as a whole, while that may not be the case. Bike Share Toronto has bike stations over almost 200 km^2. That is a very large area, and weather conditions within the areas may also vary.

The analysis of whether the association between the temporal and weather factors varies for each individual bike station was only conducted using two individual stations, where Bike Share Toronto actually has hundreds of stations. A more strict analysis would be to model all the stations individually, and perhaps there are some unique stations that have a different association with the temporal and weather factors. However, it was not possible to conduct such a large analysis in this report, so that is merely an idea for future exploration.