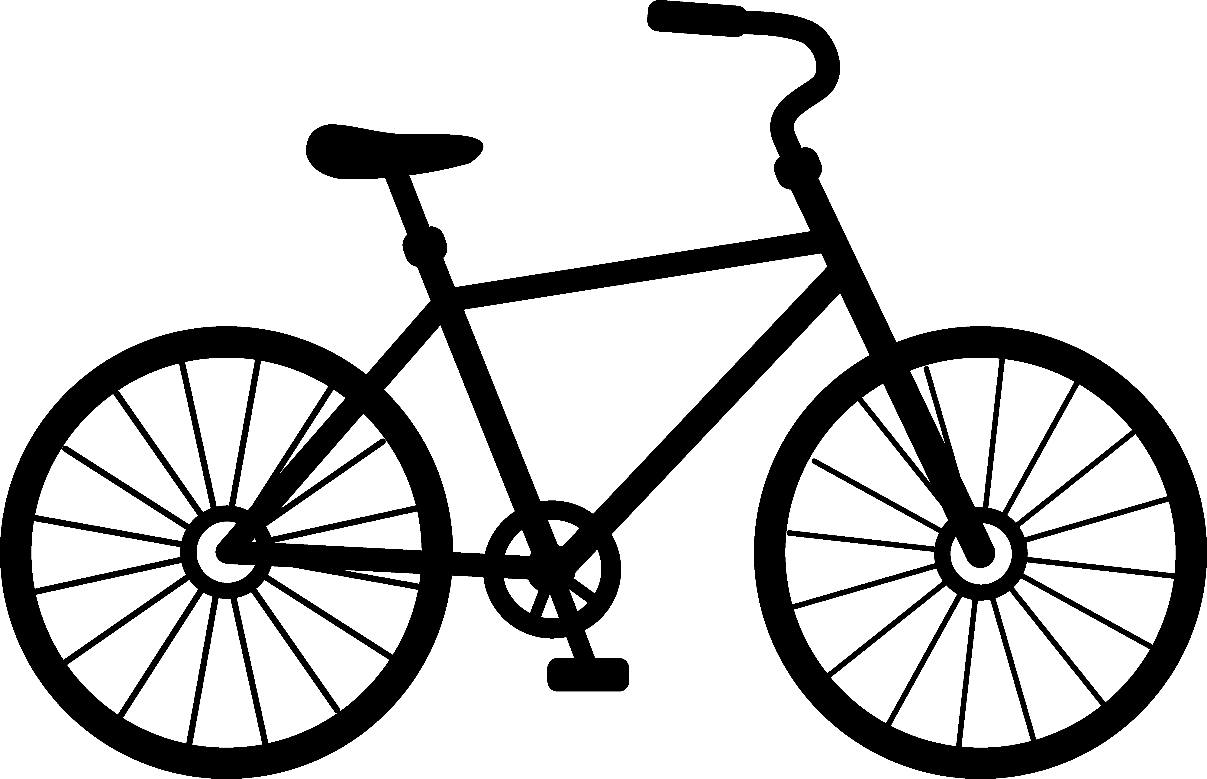
**Analysis of Casual vs. Registered Users of a Bike Share System in Washington DC**

April 13, 2023

UBC STAT 306

A report by Lab Group 2B1

|  |  |
| --- | --- |
| **Name** | **Student Number** |
| Alexander Proskiw | 27194166 |
| Youjung Kim | 38762639 |
| Mengfei Chen | 79921177 |
| Timothy Gao | 62490230 |



# Introduction

## Motivation

Bike sharing is where customers can rent a bike and return it to different places across a city, often meant to reduce vehicle dependency and extend transit capability in an urban area. Bike share services having been growing in popularity around Vancouver, with companies such as Mobi Bike Share, HOPR Bike Share, and Lime Electric Bike Sharing establishing themselves in recent years. With several cyclists in our group, we are accustomed to cycling all days of the week and in a variety of weather conditions in order to commute to school and/or work. In contrast, bicycle sharing services are often advertised as a fun and convenient way to enjoy a weekend while the weather is nice. But is this stereotype unfounded? In this report, we aim to explore the factors that influence bike share users.

## Data

The data being used for this project is [bike rental data](https://www.kaggle.com/datasets/prepinstaprime/bike-rental-data)[[1]](#footnote-1) found on Kaggle. The dataset contains information on bicycle rentals associated with bike-sharing systems in Washington, DC from 2011 to 2012. The Kaggle dataset doesn’t say where or how the data was obtained, although further research indicates it is likely from the Capital Bikeshare system.

## Variables

Response variables include:

|  |  |
| --- | --- |
| **Variable** | **Description** |
| casual | The number of non-registered users renting bikes at that time |
| registered | The number of registered users renting bikes at that time |

Explanatory variables include:

|  |  |
| --- | --- |
| **Variable** | **Description** |
| year | Categorical variable (2011, 2012) |
| time | Categorical variable representing 1-hour segments within a day (0, 1, 2, …, 23) |
| season | Categorical variable (January to March, April to June, July to September, October to December) |
| holiday | Categorical variable (not a holiday, holiday) |
| workingday | Categorical variable (weekend, weekday) |
| weather | Categorical variable (clear, mist/clouds, light rain/snow, heavy rain/snow) |
| atemp | Continuous variable representing the normalized feeling temperature (°C) |
| humidity | Continuous variable representing the humidity (normalized by 100) |
| windspeed | Continuous variable representing the wind speed (miles per hour normalized by 67) |

Several alterations were made to the raw dataset. Specifically:

* The raw dataset included a variable for datetime, representing a year-month-day-hour. We separated this into its components, and only kept year and hour as categorical variables. Month was dropped as the dataset already included a variable for season (representing a 3-month period). Day was dropped as the dataset already included a variable for weekday/weekends, which seems more applicable than whether the day is the 5th of the month vs the 17th of the month.
* The raw dataset included variables for both “temperature” and “apparent temperature”. These two variables were highly correlated (R2 = 0.985). As such, temperature was discarded in favour of apparent temperature, with the rationale being that the temperature a person “feels” would likely have a greater influence on their decision to bike.
* The raw dataset included variables for the casual, registered, and total number of users. The total number of users was not considered as our research questions focus on examining the differences between casual and registered users.

## Research Questions

One might expect that registered users use bike rentals more routinely, perhaps for commuting. In contrast, casual users might use bike rentals more regularly on weekends when the weather is nice.

We aim to use bike sharing data to investigate the difference in usage patterns between casual and registered users by exploring the following questions:

* Do casual users rent more bikes on weekends than weekdays?
* Do registered users rent more bikes at typical commuting times (such as 7-9am and 4-6pm)?
* Are the number of users that rent bikes influenced by the weather (rain, temperature, humidity)?

To answer these research questions, we will perform a combination of visualization and linear regression modelling.

# Analysis

## Visualization

To gain an understanding of the influence of each explanatory variable on the response variables, plots were made depicting the number of casual/registered users vs each explanatory variable, not accounting for any additions/interactions from other variables.

Figure 1 on the next page includes plots for the number of casual bike users, while Figure 2 on the following page includes plots for the number of registered bike users.

Figure : Effect of Different Explanatory Variables on the Number of Casual Bike Users

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  |  |  |
|  |  |  |

Figure : Effect of Different Explanatory Variables on the Number of Registered Bike Users

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  |  |  |
|  |  |  |

## Summary

Discuss observations from the above graphs, differences between casual and registered.

Registered individuals tend to rent a bike regardless of holiday, weekday/weekend, season, weather (also prefer heavy rain/snow day) than casual and registered individuals are prefer morning time than casual users but has less variation on time.

## Models

Fit different models of varying numbers of parameters

Highlight which parameters are most important. For example, the 3 parameter models include:

* For casual: Weekday, temperature, humidity
* For registered: 8am, 5pm, 6pm

Fit full models, show plots (better Rsqr, bad residual plots)

Fit Poisson models, show improvements in plots (AIC is worth, but residual looks better)

The casual and registered bike user models were fitted using different models of varying numbers of parameters. The number of parameters of forward selection model is decided by comparing adjusted R squared and value of CP. The best model for casual bike renting users using forward model selection is the model with three parameters, ‘Weekday’, ‘Temperature’, and ‘Humidity’. In comparison, three parameters from the best model for registered users using same method of model selection is ‘8am’, ‘5pm’, and ‘6pm’. Since we could not find any linearly relationship between ‘Time’ and ‘The number of users’ from the plots above, we considered the explanatory variable ‘Time’ as a categorical variable. However, the model that only includes three categories of one explanatory variable without including the explanatory variable ‘Time’ itself should not perform well.

The causal bike rider model with three parameters gives approximately 0.433 of adjusted R squared with less than 0.01 p-value and 37.632 of residual standard error. The registered bike rider user model with a parameter, ‘Time’, gives approximately 0.528 of adjusted R squared with less than 0.01 p-value and 103.773 of residual standard error. These models using forward selection show skewed Q-Q plot and tailed Q-Q plot, respectively, and are not normally distributed.

Chart, line chart

Description automatically generatedChart, line chart, histogram

Description automatically generatedFigure 3: Normal Q-Q plot of the causal bike rider model with three parameters, Weekday, Temperature, Humidity.

Figure 4: Normal Q-Q plot of the registered bike rider model with a parameter, Time.

This result leads to fitting a full linear model for the causal bike user and the registered bike user. The full model gives respectively 0.582 and 0.687 of adjusted R-squared and less than 0.01 p-value for both, which is better than the model selected using the forward selection above. However, as indicated in the figure 7 and figure 10, the full model also has a skewed Q-Q plot. The figure 5 and figure 8 also shows that residual plots exhibit heteroscedasticity with unbalanced x-axis and non-linear residual plots.

Chart, scatter chart

Description automatically generatedChart, scatter chart

Description automatically generatedChart, line chart

Description automatically generated

Figure 5: Residual vs. Fitted values of the casual bike user full model. Figure 6: Fitted values vs. Observed values of the casual bike user full model. Figure 7: Normal Q-Q plot of the casual bike user full model.Chart, scatter chart

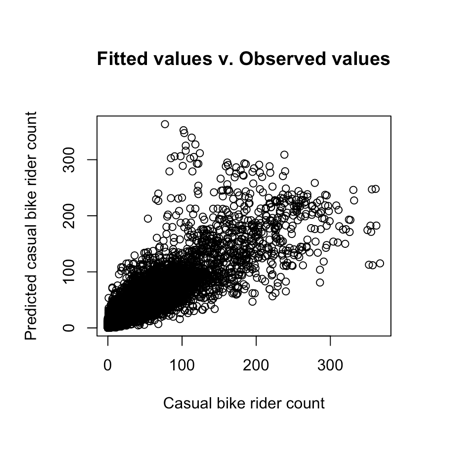
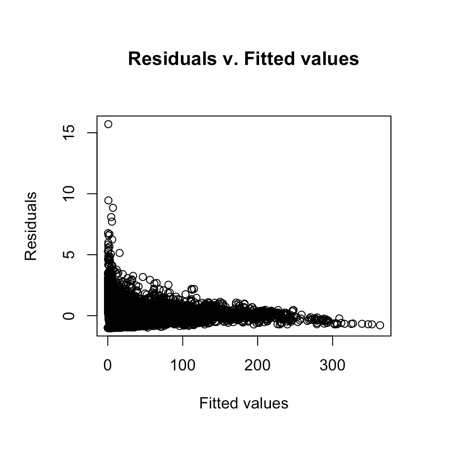
Description automatically generatedChart, histogram, scatter chart

Description automatically generatedChart, line chart, histogram

Description automatically generated

Figure 8: Residual vs. Fitted values of the registered bike user full model. Figure 9: Fitted values vs. Observed values of the registered bike user full model. Figure 10: Normal Q-Q plot of the registered bike user full model.

A poisson model is better suited to predict a dependent variable, the number of bike users, that consists of count data given independent explanatory variables. The poisson model with causal bike rider has AIC value of 146180.9486 and the registered bike rider poisson model has 348359.051 of AIC value. The residual plots for poisson model still indicate the presence of heteroscedasticity but with constant variance than the full models or the forward selected models.

Chart, line chart, histogram

Description automatically generatedFigure 9: Residual vs. Fitted values of the casual bike user poisson model. Figure 10: Fitted values vs. Observed values of the casual bike user poisson model. Figure 11: Normal Q-Q plot of the casual bike user poisson model.Chart, histogram

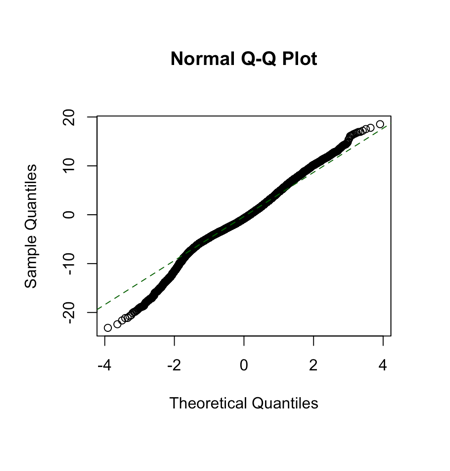
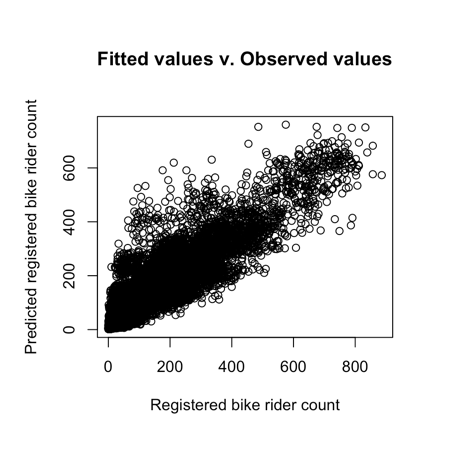
Description automatically generated

Figure 12: Residual vs. Fitted values of the registered bike user poisson model. Figure 13: Fitted values vs. Observed values of the registered bike user poisson model. Figure 14: Normal Q-Q plot of the registered bike user poisson model.

# Conclusion

## Key Findings

Use data to answer the research questions

* Do casual users rent more bikes on weekends than weekdays?
* Do registered users rent more bikes at typical commuting times (such as 7-9am and 4-6pm)?
* Are the number of users that rent bikes influenced by the weather (rain, temperature, humidity)?

## Limitations and Future Improvements

Methods of improvement include:

* Use month instead of season (e.g., 12 months vs 4 seasons)
* use day of week (Mon, Tues, etc.) rather than just weekday vs weekend

1. Dataset accessed March 15, 2023 from <https://www.kaggle.com/datasets/prepinstaprime/bike-rental-data> [↑](#footnote-ref-1)