Divvy Bike Usage Patterns

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CHAPTERS

1. INTRODUCTION

2. DATA

3. EDA

4. MODEL

5. FUTURE WORK

Introduction

Project Overview

Divvy

A bike-sharing program that operates in Chicago, Illinois, United States.

Objective

Predicting the number of trips for Divvy bikes on a monthly basis

Expected Outcome

1. **Resource Optimization**: Strategically allocate bikes and docking stations to high-demand areas, reducing instances of unavailability or overcrowding.

2. **Expansion and Infrastructure Planning**: Installing additional docking stations or expanding Divvy’s bike fleet during months with high demand.

Data

Data

Our original dataset consists of approximately 4GB of data with Divvy bike trips between 2013 and 2023, with 9 features.

Due to the large size, which may cause the kernel to crash, we have finalized our data for modeling to include 3 main features, which are:

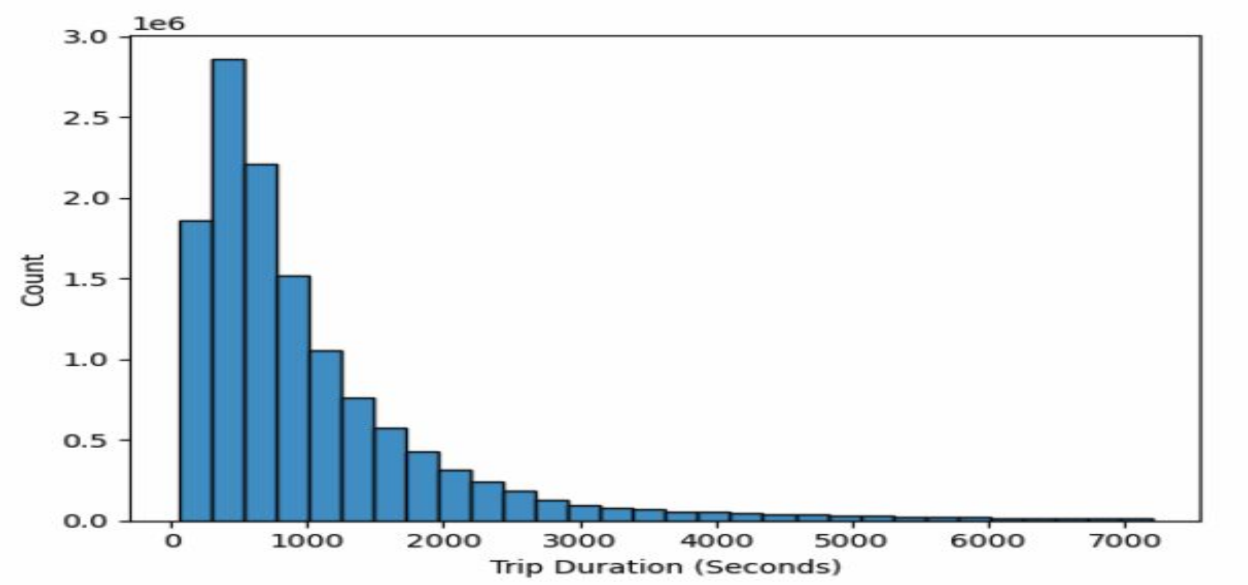
1. Year_month: from 06/2013 and 04/2023
2. Monthly Trip Count: number of trips in each month (in thousands)
3. Average Monthly Duration: average length of time for each trip in minutes (formula = total duration/total trip*60)

Train period = July 2013 - Dec 2021 & Test period = Jan 2022 - Apr 2023

EDA

EDA

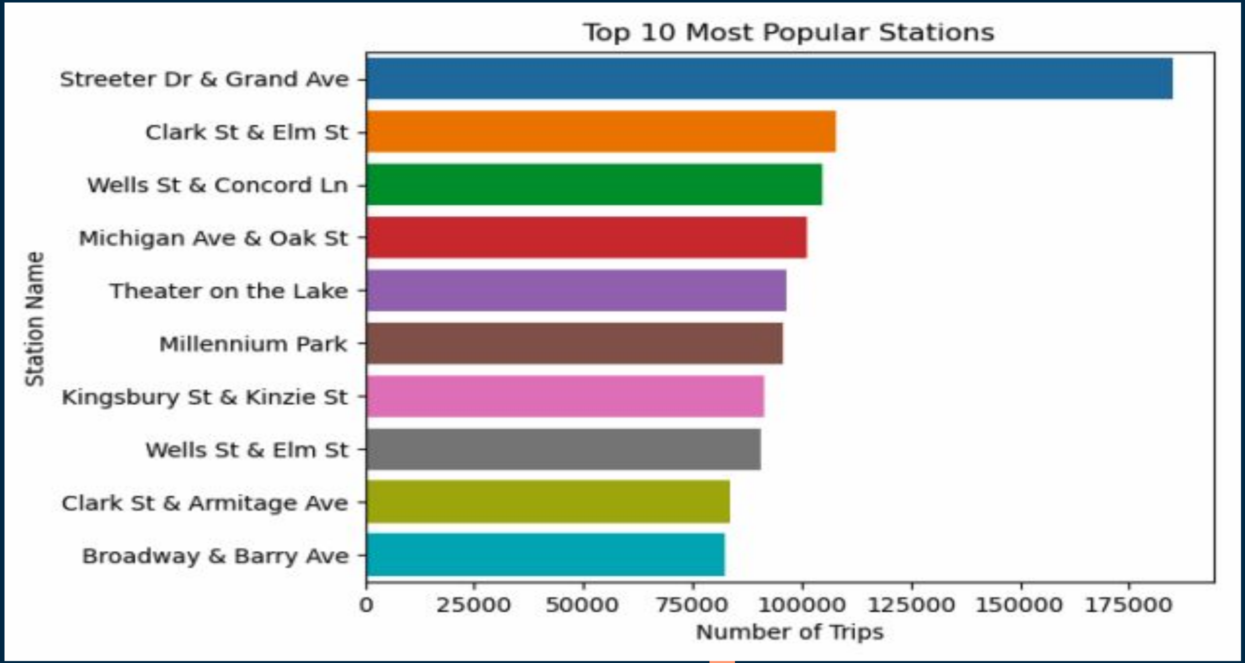
Trip Duration



The users tend to use divvy bikes only for short durations.

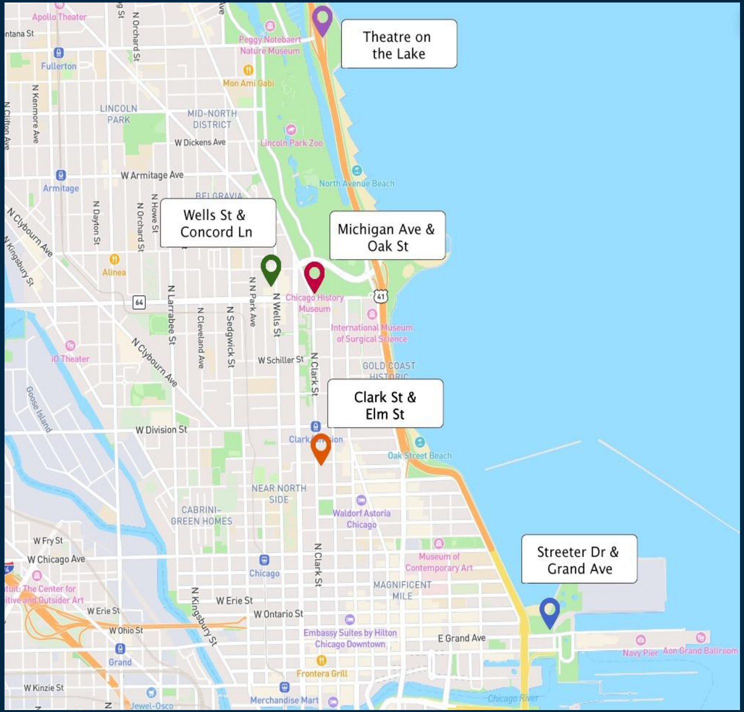
EDA

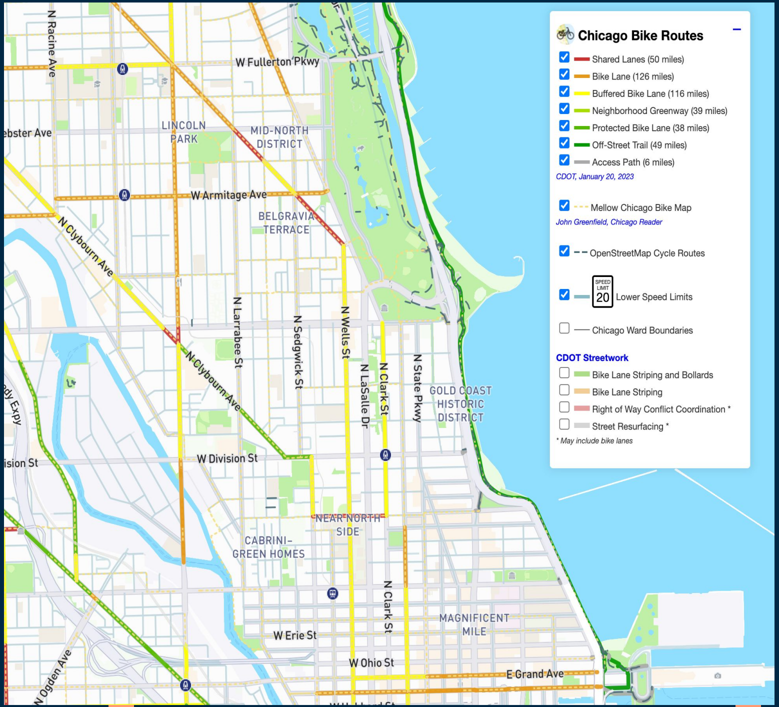
Most Popular Stations



EDA

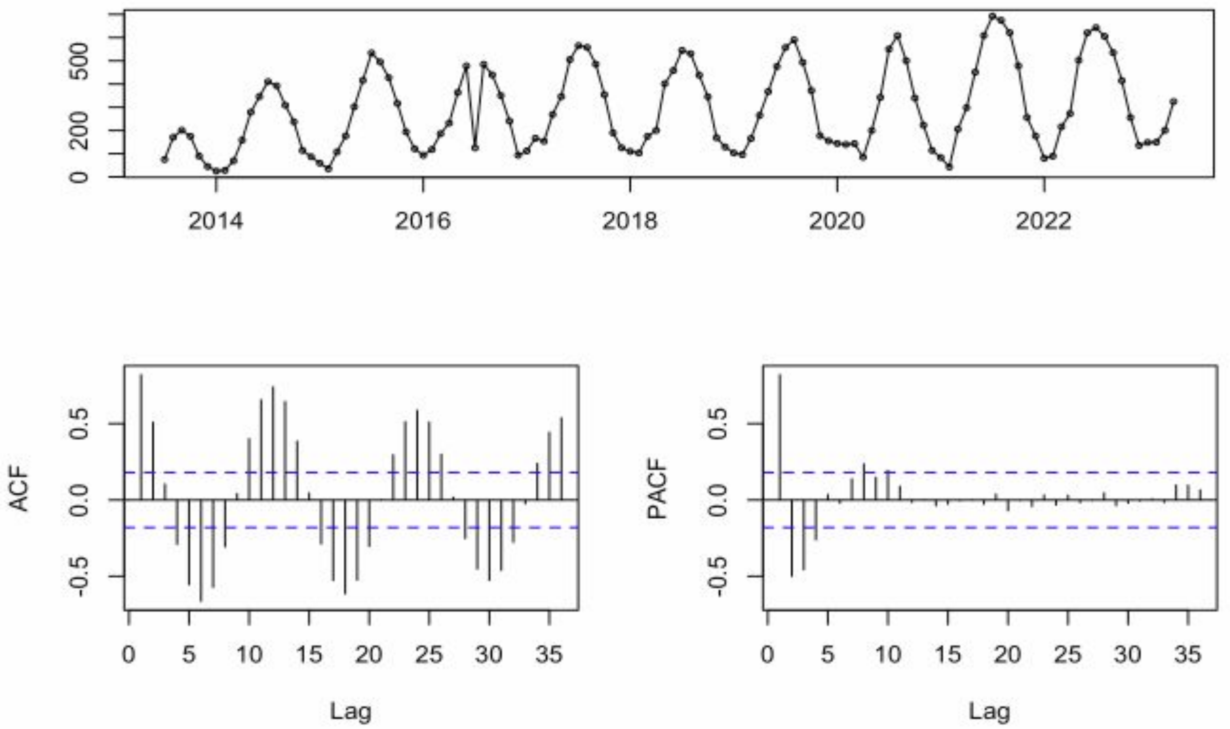
Most Popular Stations





Model

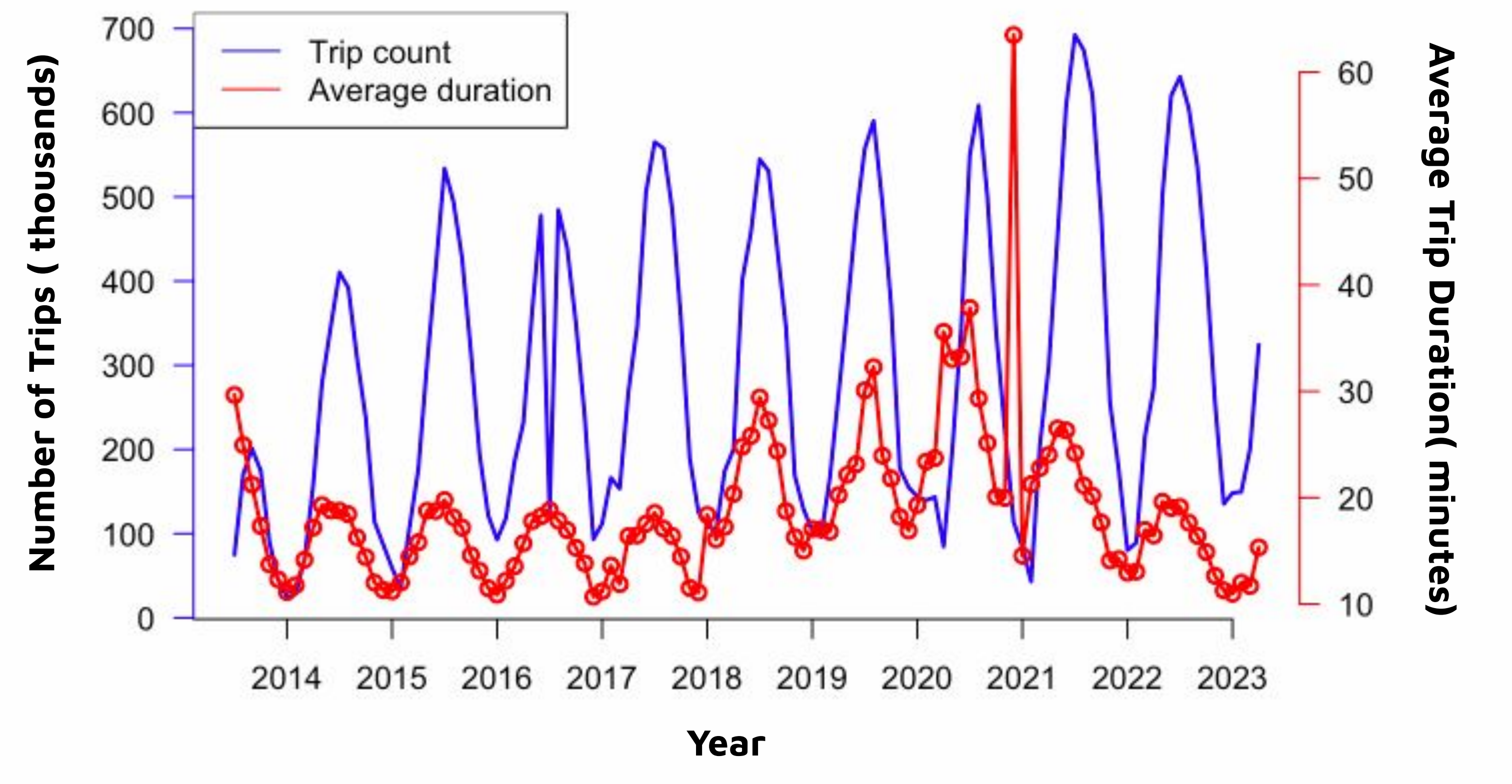
Yearly Divvy Rides in Chicago



- **Trend**: Slightly Increasing
- **Seasonal** patterns occurring on an annual basis
- **KPSS Test** : stationary time series

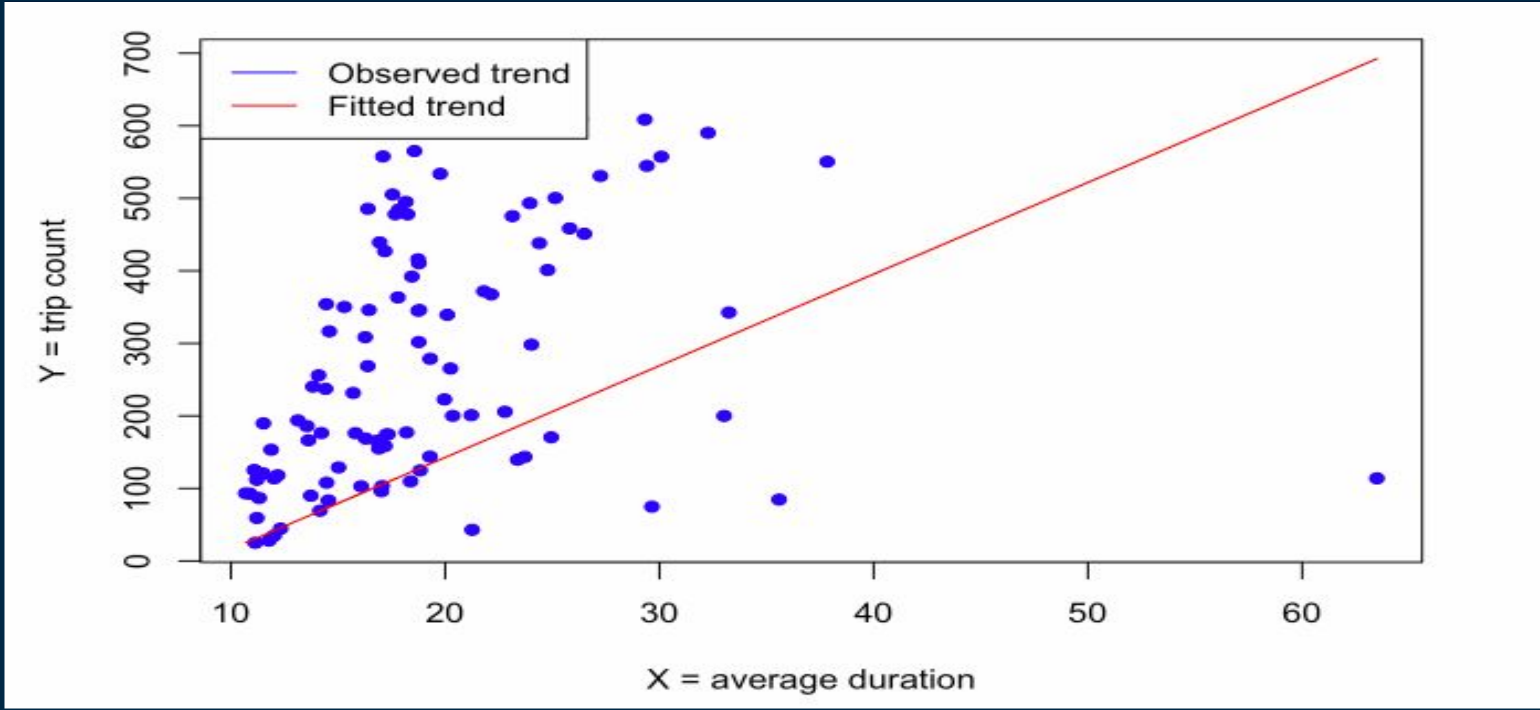
Regression

r = 0.342



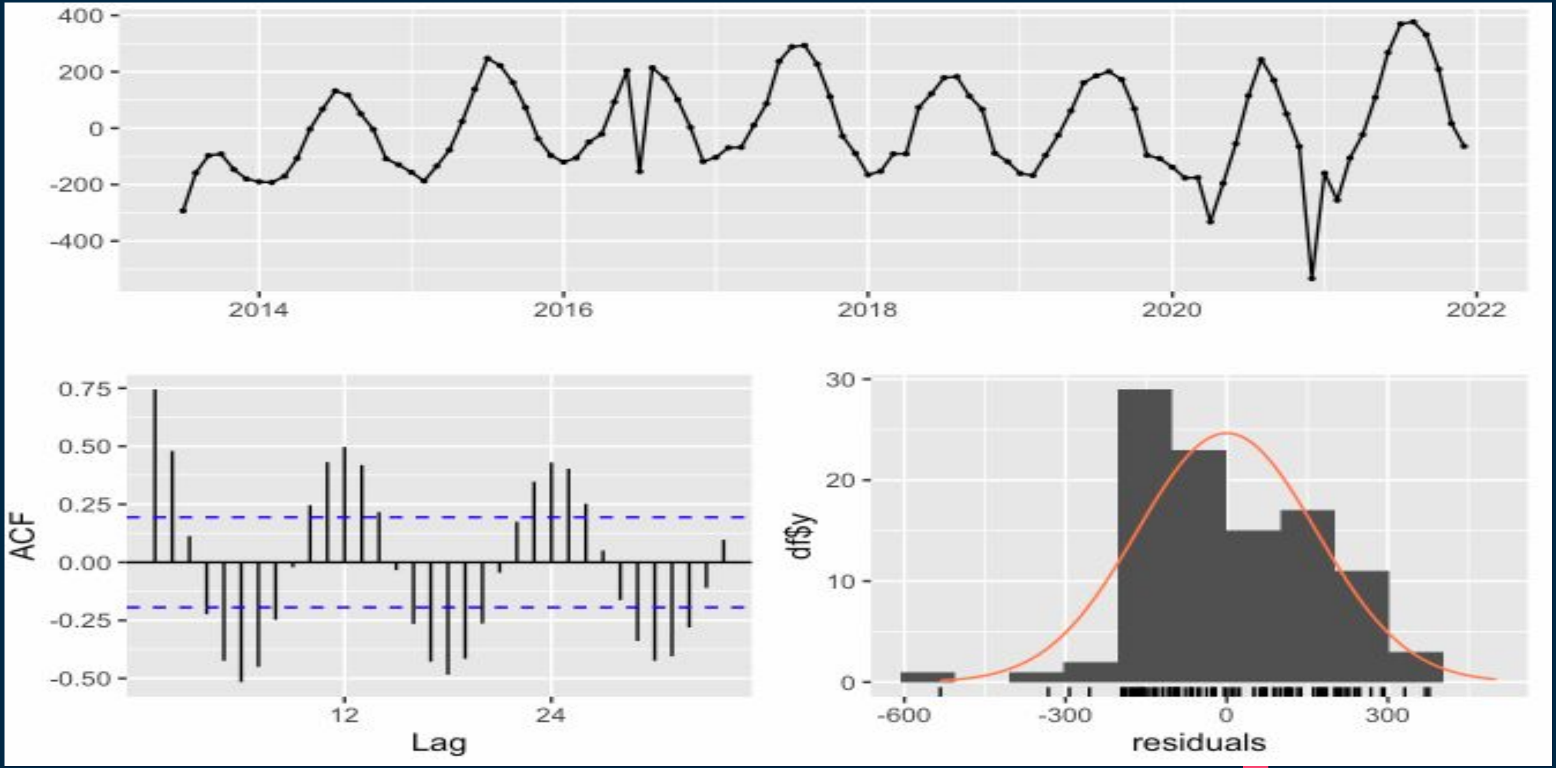
Regression

Observed Vs Fitted Trend



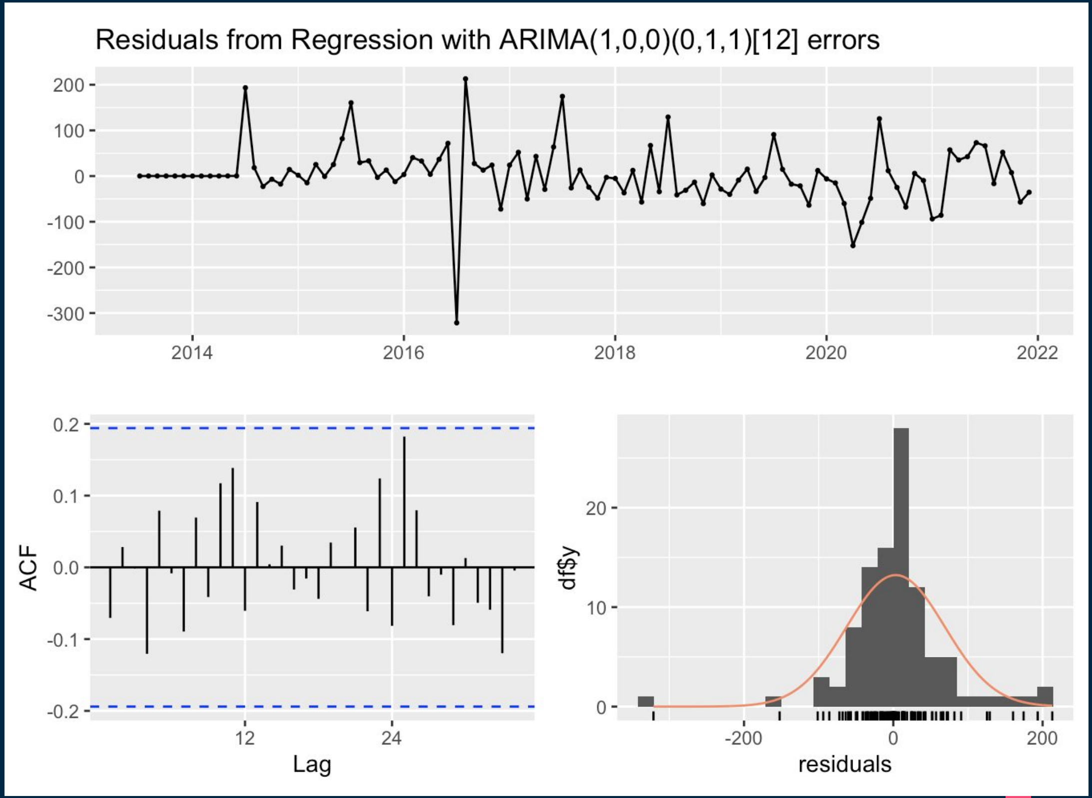
Setting up for Regression with ARIMA error

Residuals



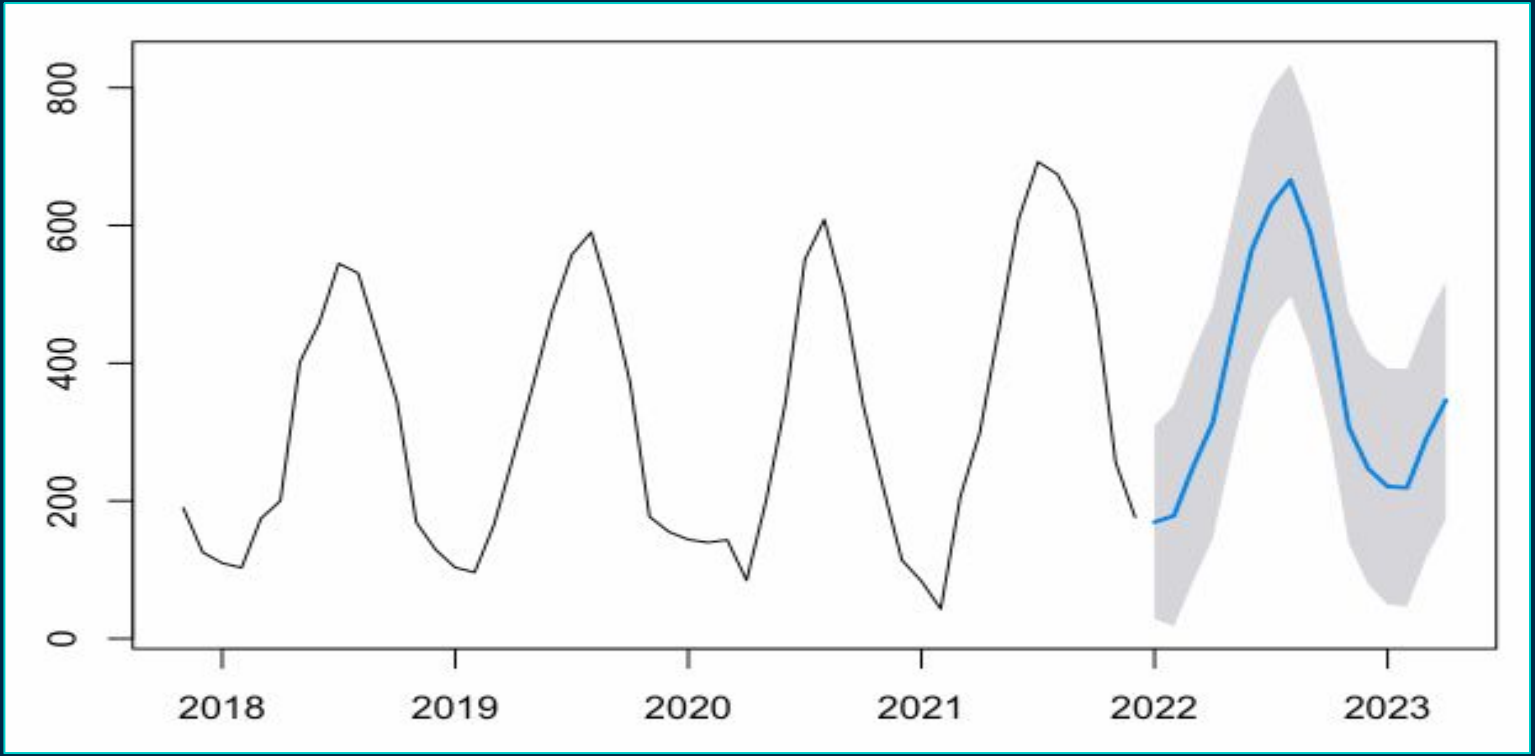
Regression with ARIMA error

ARIMA(1,0,0)(0,1,1)[12]



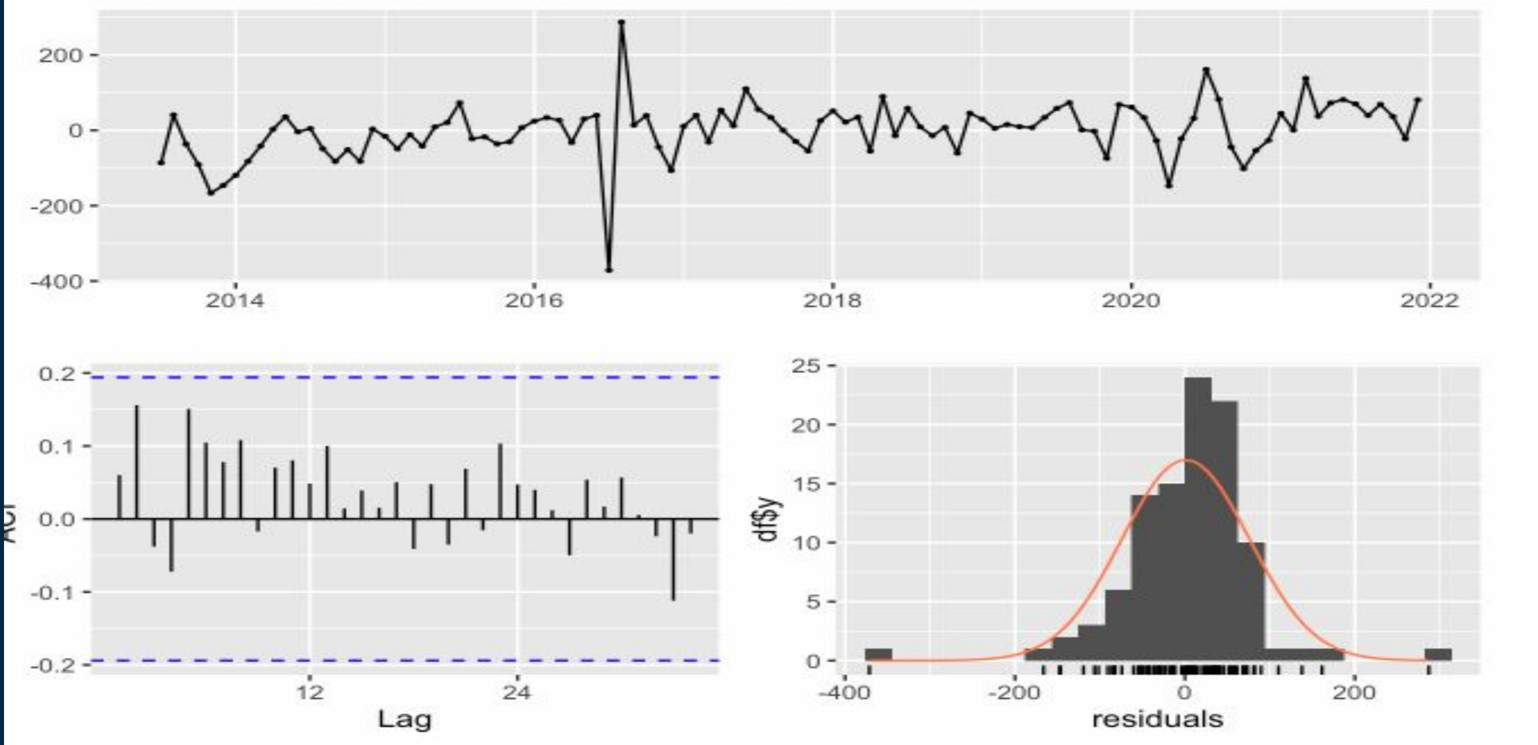
Regression & Regression with ARIMA Error

Forecast



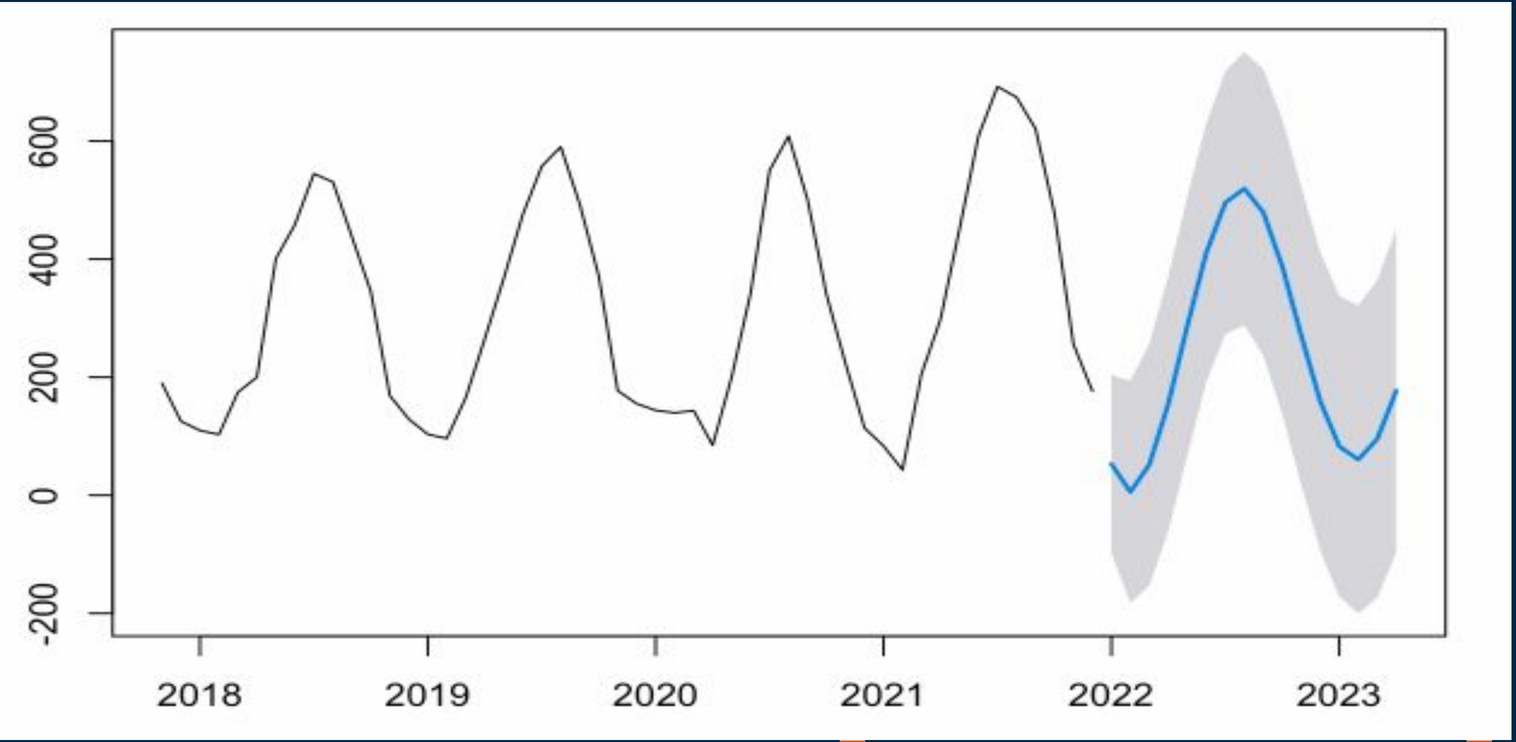
ARIMA Model

ARIMA(2,0,3) with non-zero mean



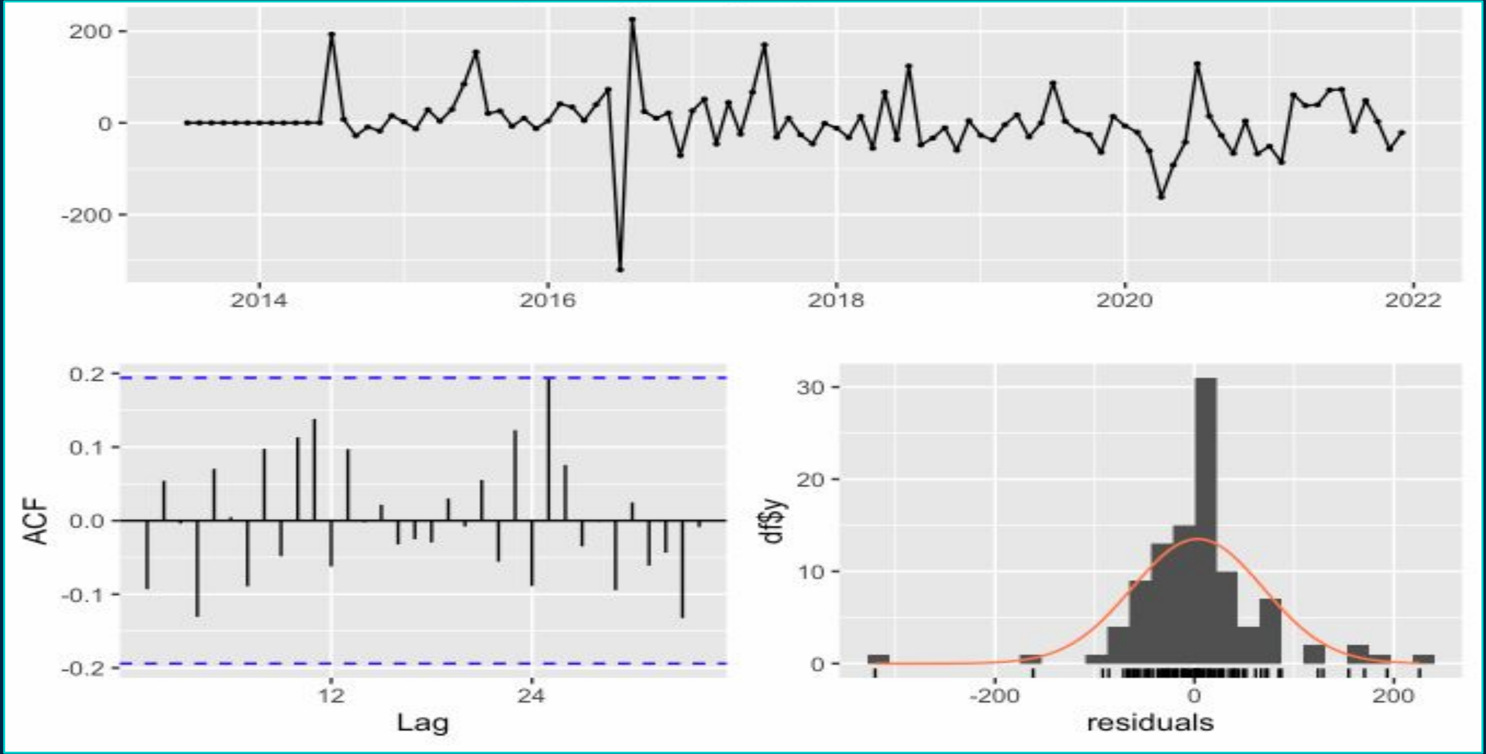
ARIMA (2,0,3) Model

Forecast



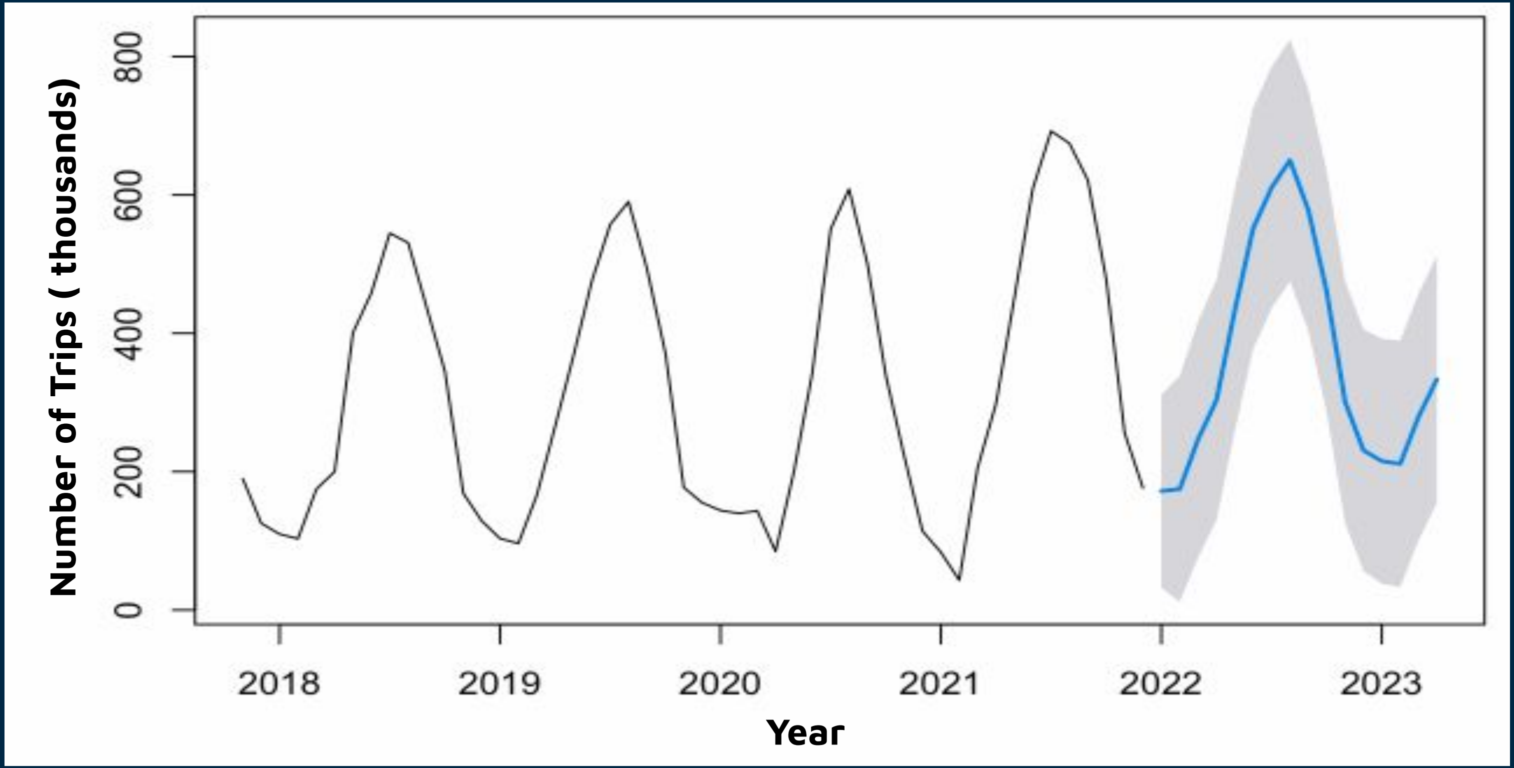
SARIMA Model

ARIMA (1,0,0)(0,1,1)[12] with drift



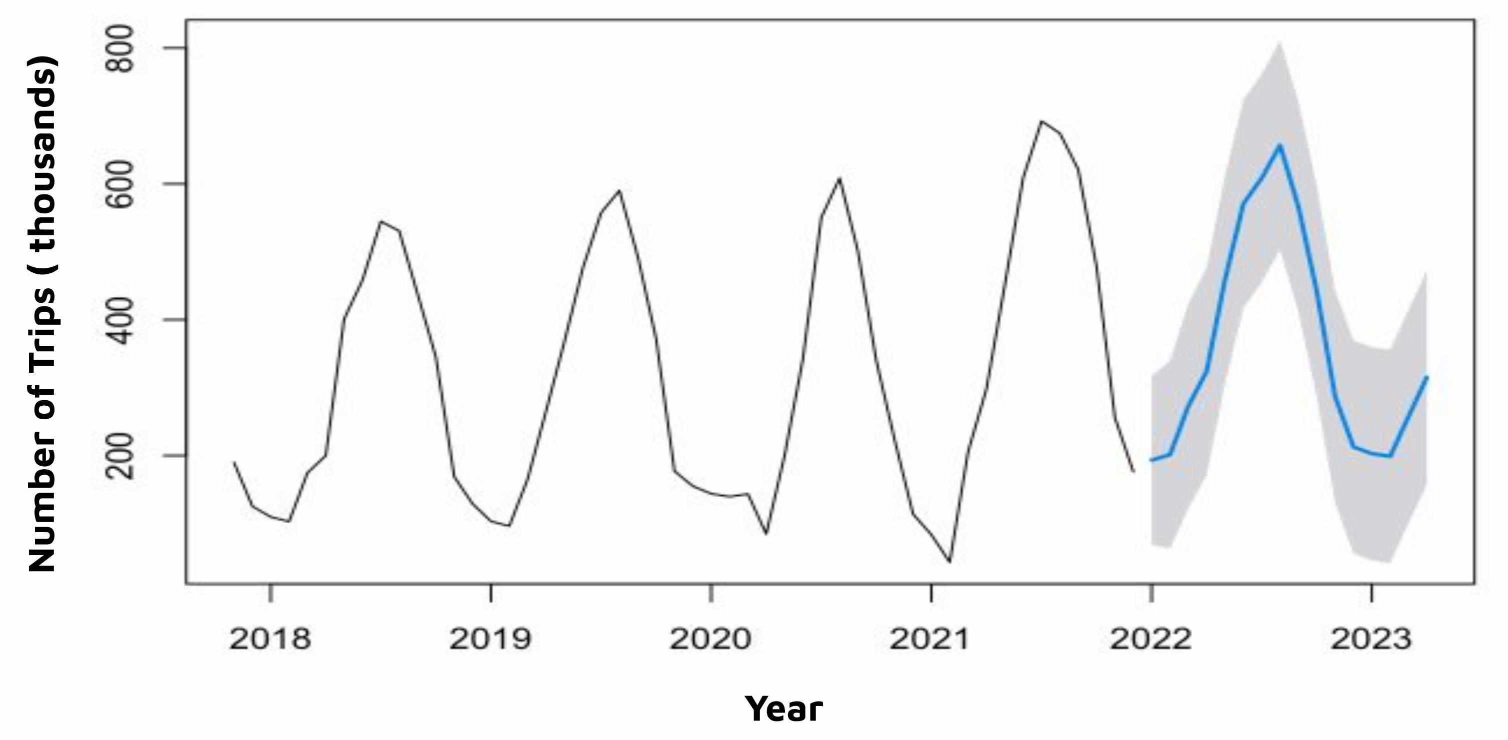
SARIMA (1,0,0)(0,1,1)[12] Model

Forecast



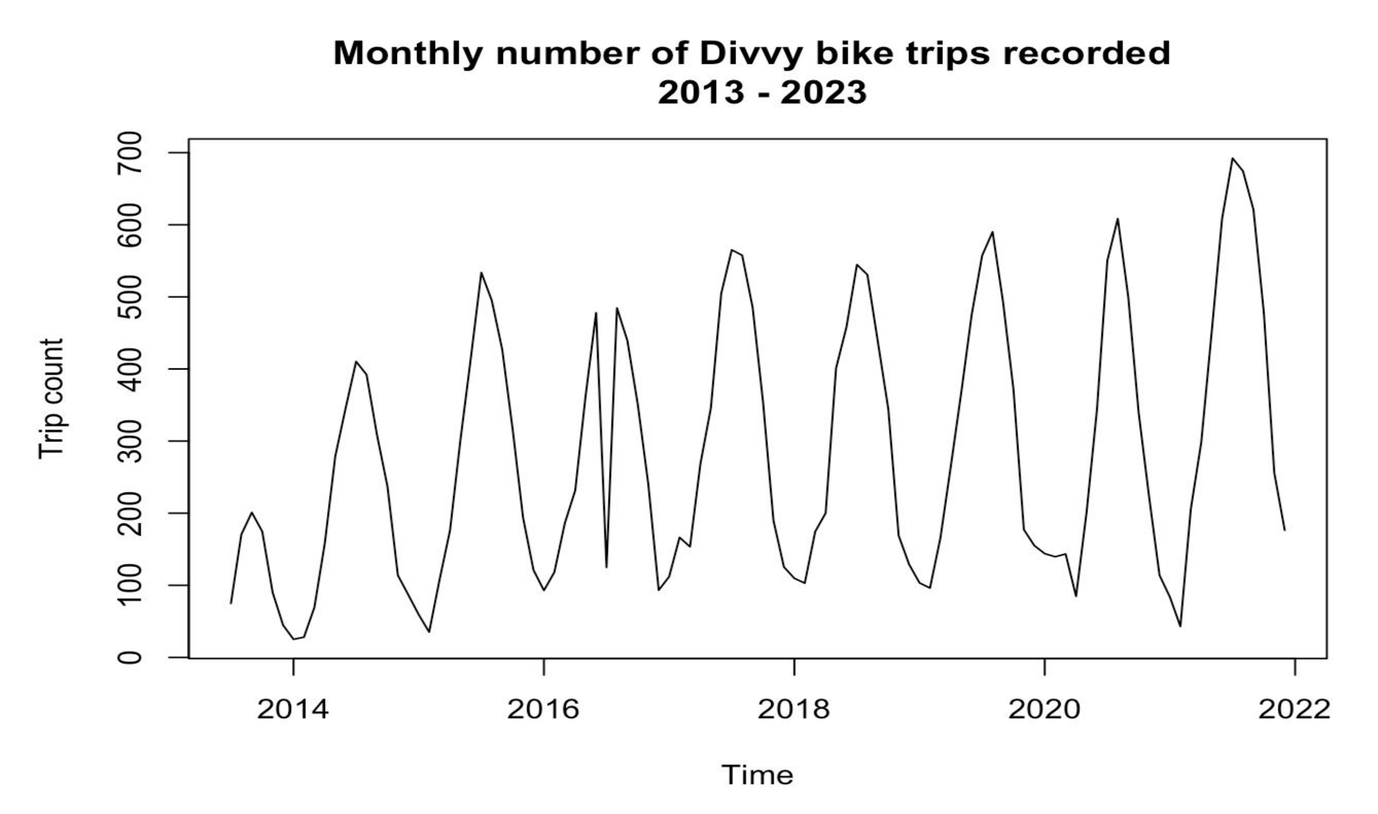
VAR (10) Model

Forecast



Seasonal Holt-Winters Model

Multiplicative vs. Additive



Seasonal Holt-Winters Model

Accuracy comparison

- Additive without damping

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
-1.368893	65.85313	43.22621	-5.772363	26.12261	0.624781	0.0763598

- Multiplicative without damping

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
-4.53528	62.63694	40.20102	-12.49822	24.29647	0.5810557	0.1876421

- Additive with damping

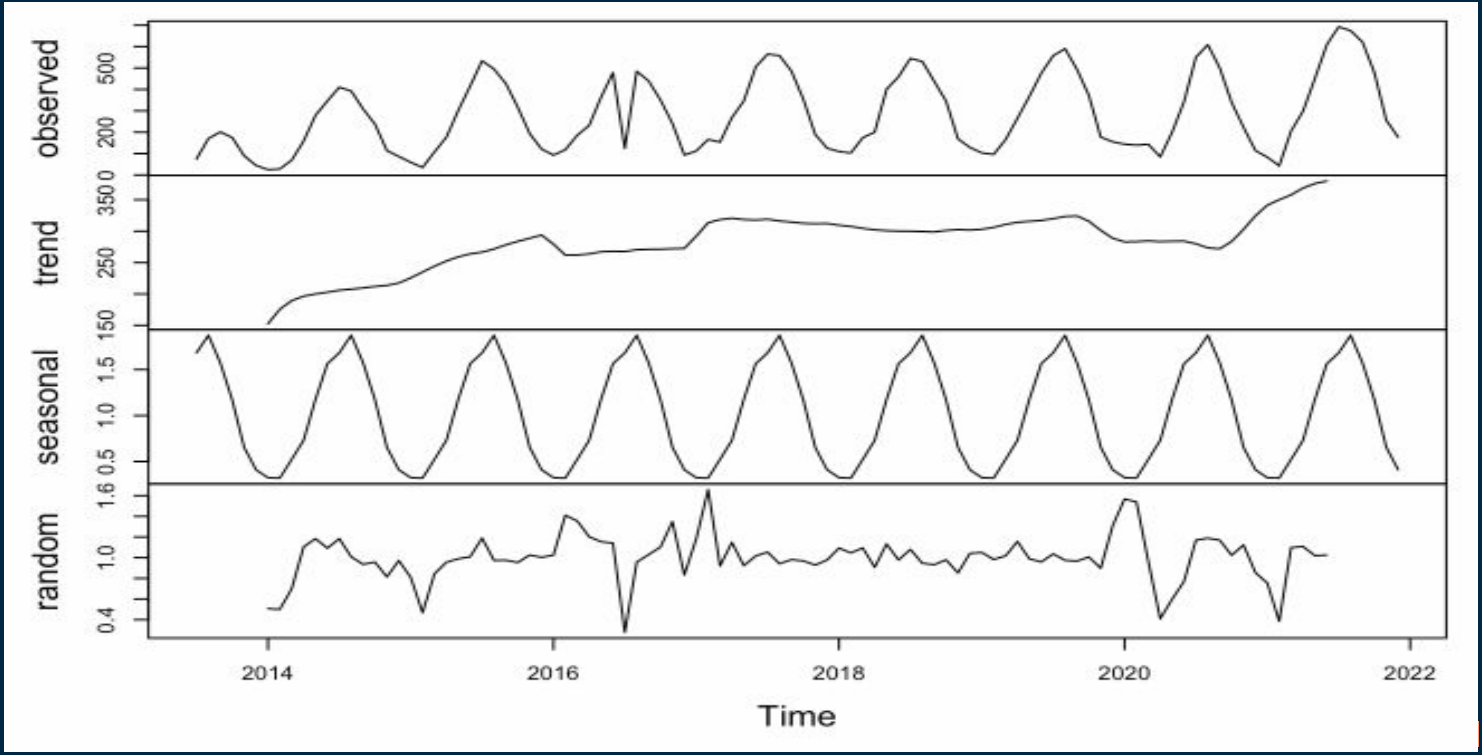
ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
2.804036	62.78255	39.91608	-8.187681	23.32441	0.5769372	0.1316823

- Multiplicative with damping

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
2.804036	62.78255	39.91608	-8.187681	23.32441	0.5769372	0.1316823

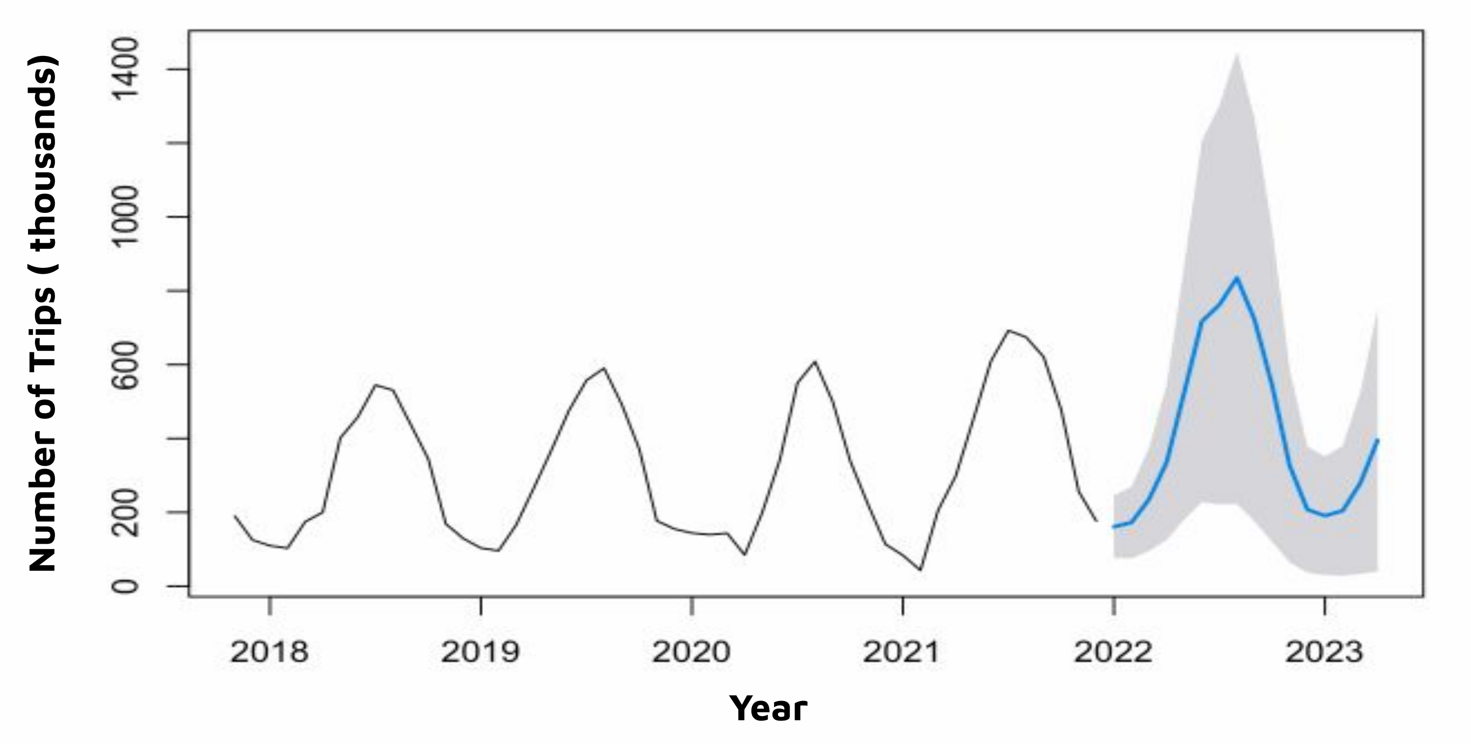
Seasonal Holt-Winters Model

Decomposition of multiplicative Time Series



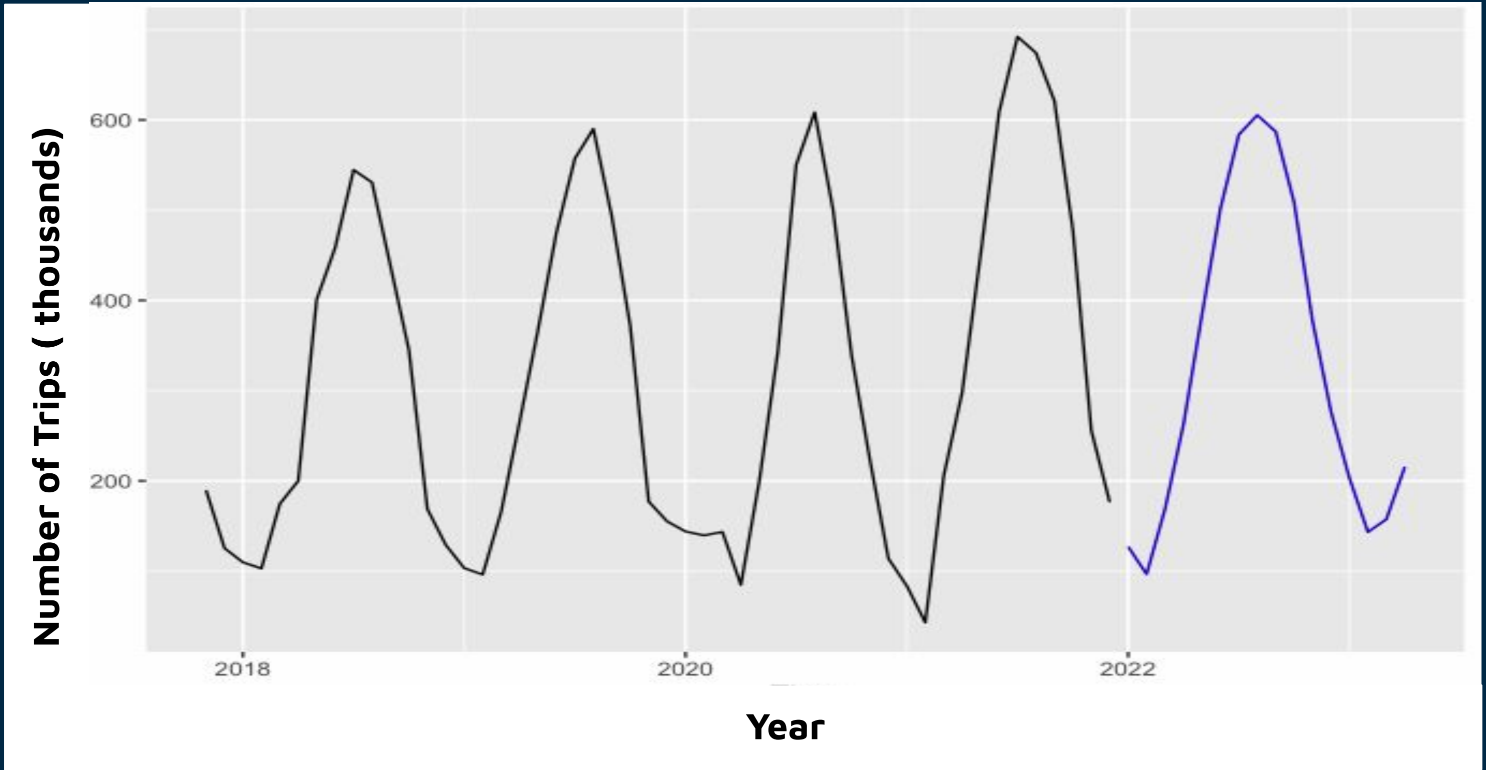
Seasonal Holt-Winters Model

Forecast



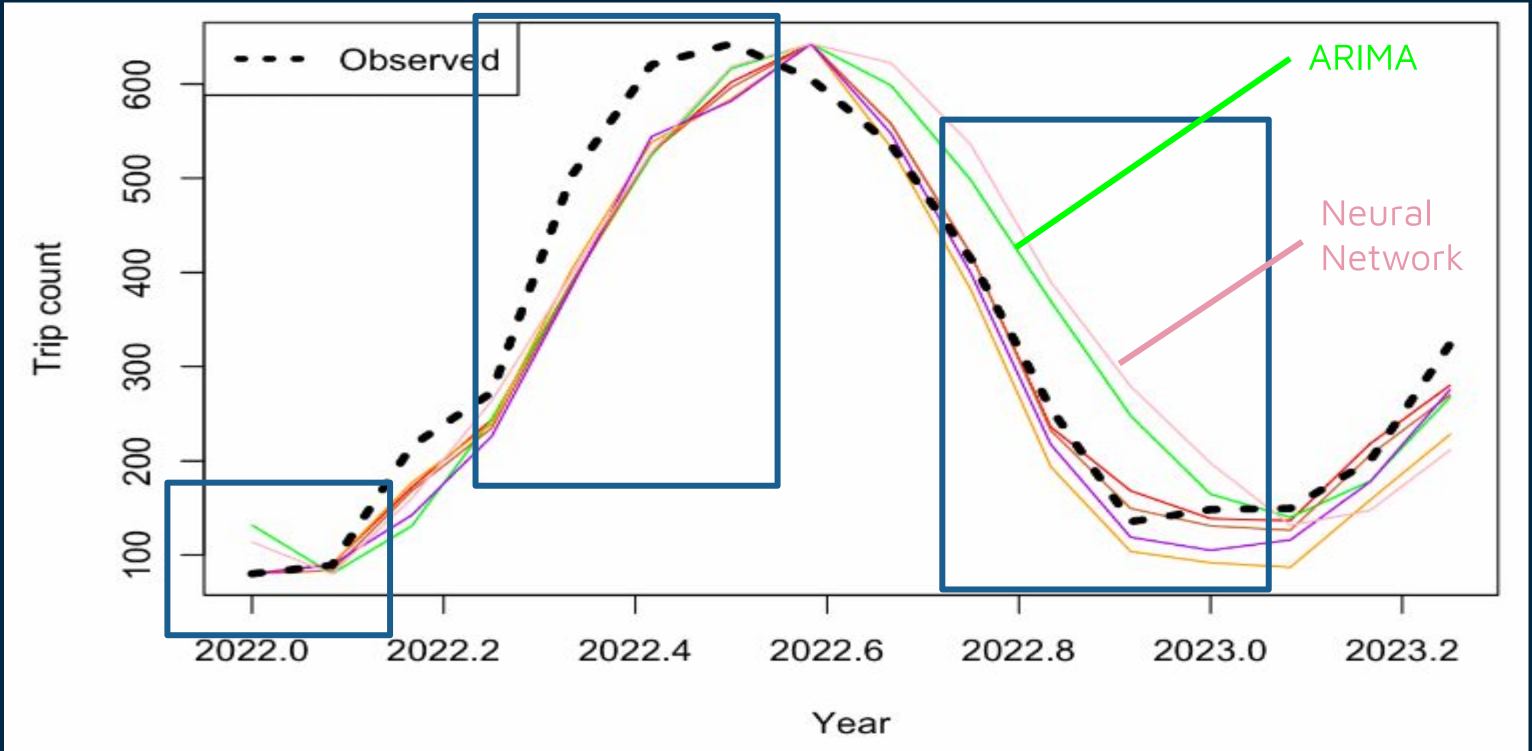
Neural Network Autoregression(1,1,2) [12] Model

Forecast



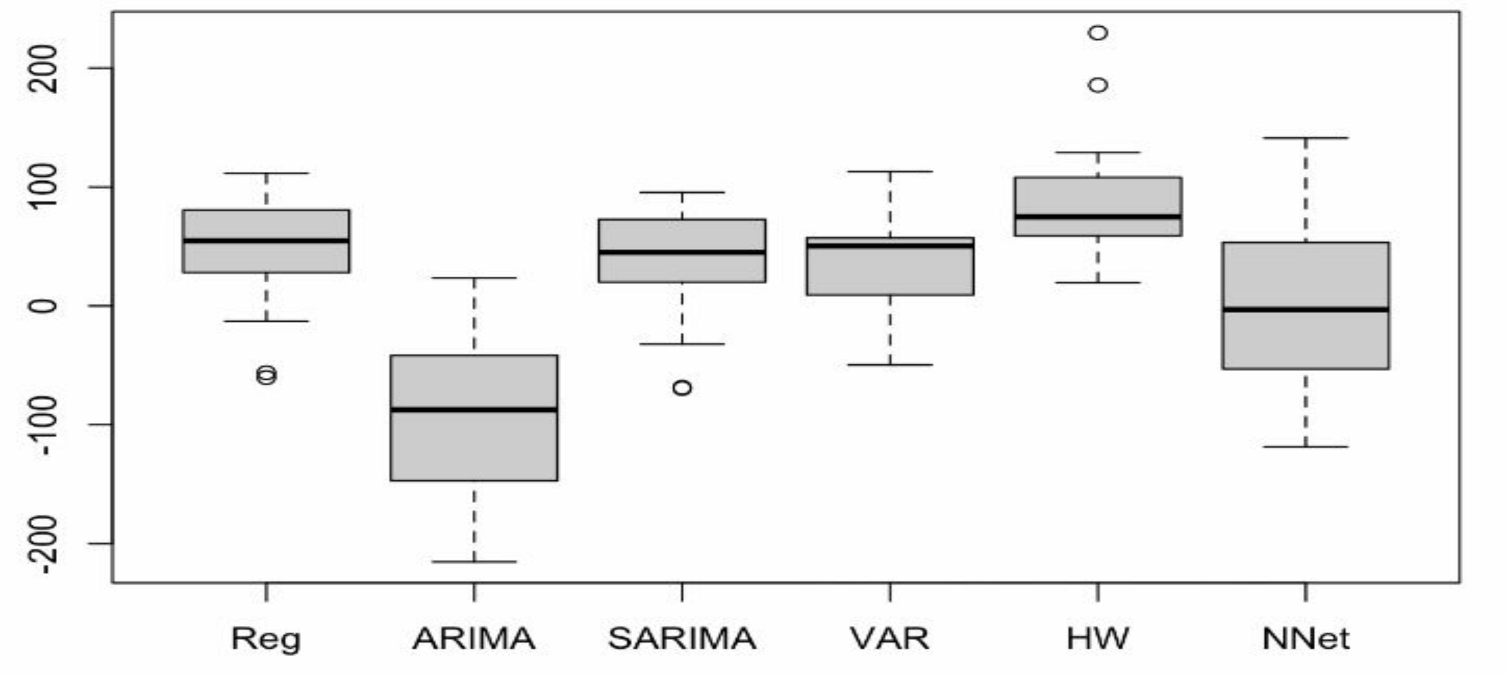
Model Selection

Comparing Forecast Residuals in a box plot



Model Selection

Observed Vs Predicted trip count values for test period Jan 2022 - April 2023



RMSE :	**65.76**	**116.40**	**61.19**	**65.76**	**103.65**	**78.66**

Future Work

Future Work

Model

- Can apply expanding and sliding window to validate prediction (currently using only one time period to test prediction)
- Extend testing period to more than one year to see if the models can factor in seasonality for longer forecast period

Business Indication

- Fine Grained Temporal Analysis : Explore granular time intervals such as weekly, daily, or even hourly, helping Divvy optimize resources on a smaller time scale.

- Incorporating External Factors: Expand the predictive model by incorporating external factors that may influence trip counts

- User Behavior Analysis: Analyze user behavior and preferences from trip count data to inform marketing, infrastructure, and service improvements

THANK YOU!