Analyzing and Predicting : CTA Transportation

By **Python Demons** (Team - Akshat Pancholi, Faezehossadat Khademi, Kasturi Joshi, Piyush Agrawal and Vipul Dhariwal.)

Introduction

Chicago Transit Authority (CTA) is a mass transit operator in Chicago that provides bus and train services. We all use CTA on a daily basis. We noticed that sometimes the buses and trains that are a little crowded run at a low frequency, while some buses and trains which are almost empty run at a high frequency. Thus, we decided to explore trends in CTA commuter patterns and found out ways to predict ridership per stop so that we, as commuters, could face the least inconvenience and CTA can use these suggestions to optimize their transportation.

Dataset

We used publicly available dataset in CSV format from portal of City of Chicago.The CTA datasets we used were - Bus monthly ridership, Bus daily ridership, Train monthly ridership, Train daily ridership, Overall CTA ridership. They ranged from 2001 to 2019. Link for Dataset (http://www.shorturl.at/fpSX1)

In [7]:
```
# Importing all bus files
import bus_hypo as bh; import bus_clean_vis as bcv; import bus_all_ml as bam
import bus_nuke_ml as bnm; import pandas as pd; import bar_race as br
import numpy as np; import matplotlib.pyplot as plt; import baseline_bus as bb
import Kasturi_J as Kasturi
import ARIMA
import Piyush
import pandas as pd
```

Data Cleaning

Apart from the usual data cleaning procedures like: Deleting NaN entries,solving multiple entries,converting string to int, deriving columns like year and month; we also cleaned data to make our data more prepared to derive insights. 1. We normalized the yearly and Feburary month ridership for leap years (*365/366) 2. We deleted the routes that were added by CTA temporarily and does not represent regular routes 3. Seperated routes if their name is changed.

In [8]:
```
monthly = pd.read_csv("./data/Bus_monthly(weekday,weekend,total).csv")
gas = pd.read_csv('./data/gas.csv')
py_data=pd.read_csv("./data/CTA_-_Ridership_-__L__Station_Entries_-_Daily_Totals.csv")
data_days=pd.read_csv('./data/CTA_-_Ridership_-_Bus_Routes_-_Daily_Totals_by_Route.csv
monthly = bcv.clean(monthly) #Cleaned Bus Dataset
py_data = Kasturi.data_cleaning(py_data) #Cleaning the train dataset
monthly = bcv.clean(monthly) #Cleaned Bus Dataset
data_days=Piyush.data_preparation(data_days)
```

Exploratory Data Analysis

1. Granularity- The data is grained in monthly fashion for both the bus as well as train datasets. Data is divided for each bus and each train.

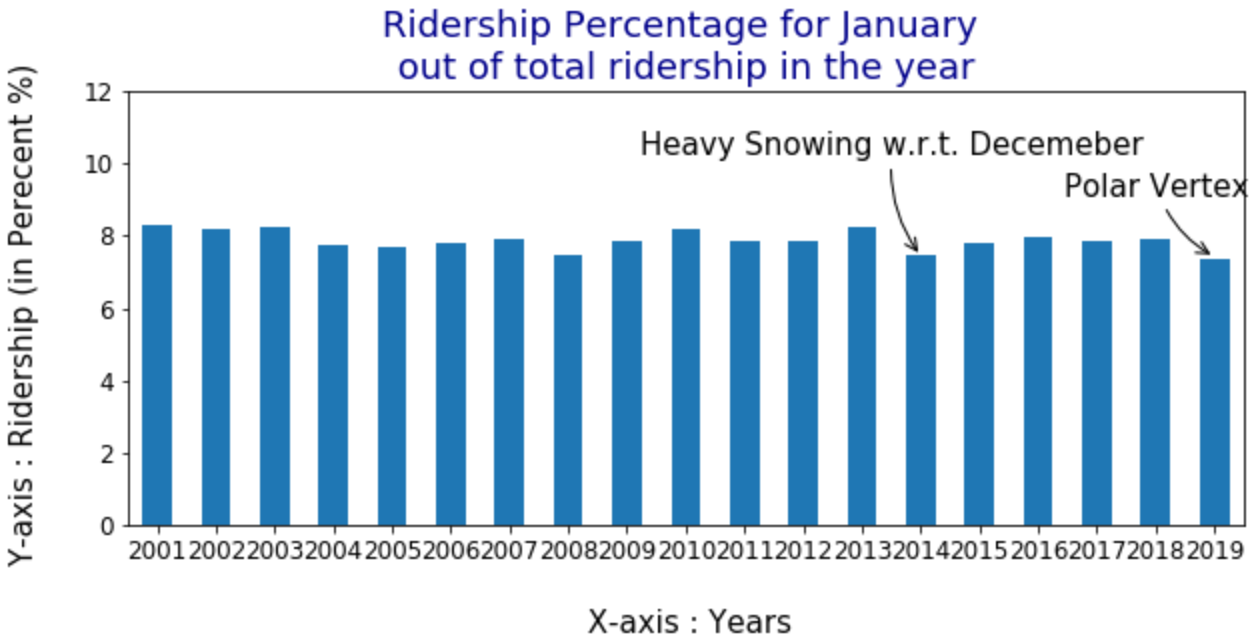
2. Structure- **Tabular form** : The data is in the form of CSV files
3. Temporality- The data we have collected ranges from **1st January 2001 to 1st December 2019**
4. Scope- We have **complete data** with respect to scope.Coverage remains the same after filtering some of the columns from both the datasets.
5. Faithfulness- Though our data is accurate and gives the idea about ridership, it does not capture the reality completely. The ridership is counted while boarding, not unboarding. Assumption: Passenger travelling rides the entire journey of the bus/ train. For trains, count is increased at the station entries. Reality is not captured when a person changes the line internally within a station

Visualizations and Insights

In [3]:
```
## Insight 1 : Percentage Drop in bus ridership in January Riderhsip due to Polar Verte
bcv.polar_vertex(monthly)
```

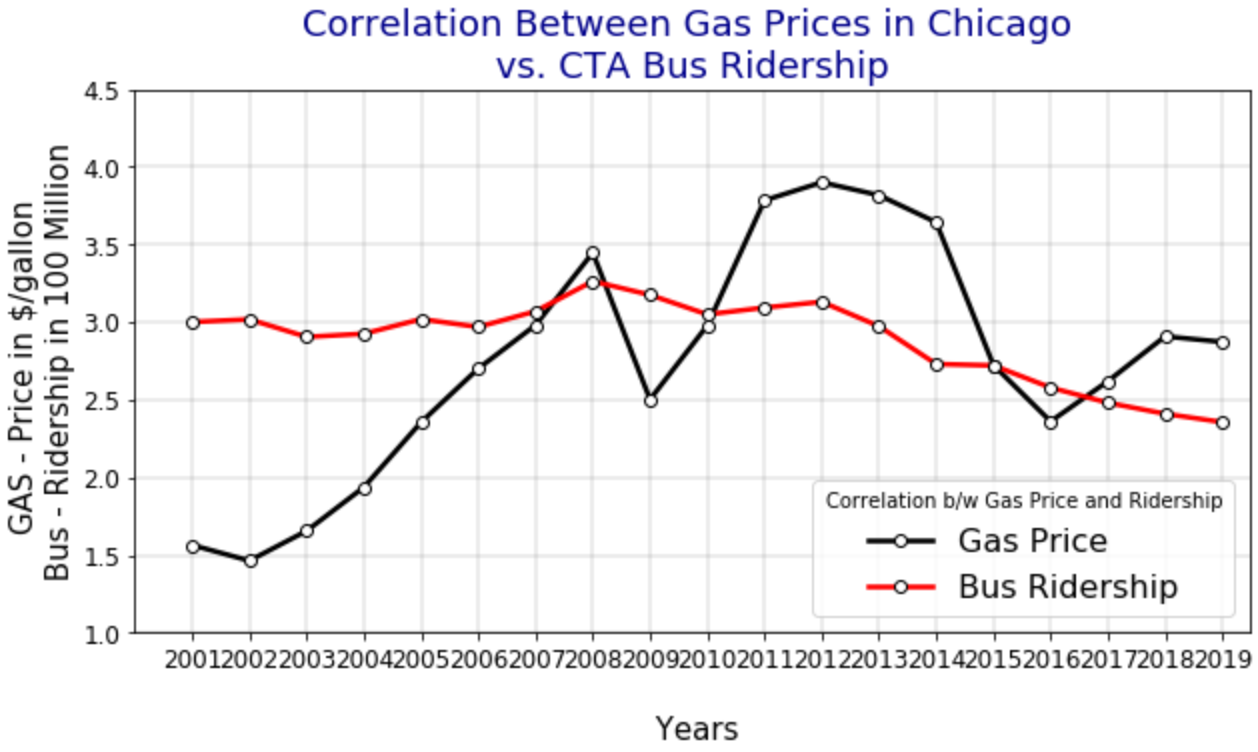
```
7.209120829161296
```

Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7f072cdb1e90>



In [4]:
```
#Insight 2 : Hypothesis-CTA claimed that the Ridership Decreases as the Gas Price Decre
bh.gasvsbus(gas,monthly)
# Result- The decline in ridership is not correlated to gas price reduction, as the cor
```

```
Correlation between Gas prices and Bus Ridership is  0.09493865538035208
```

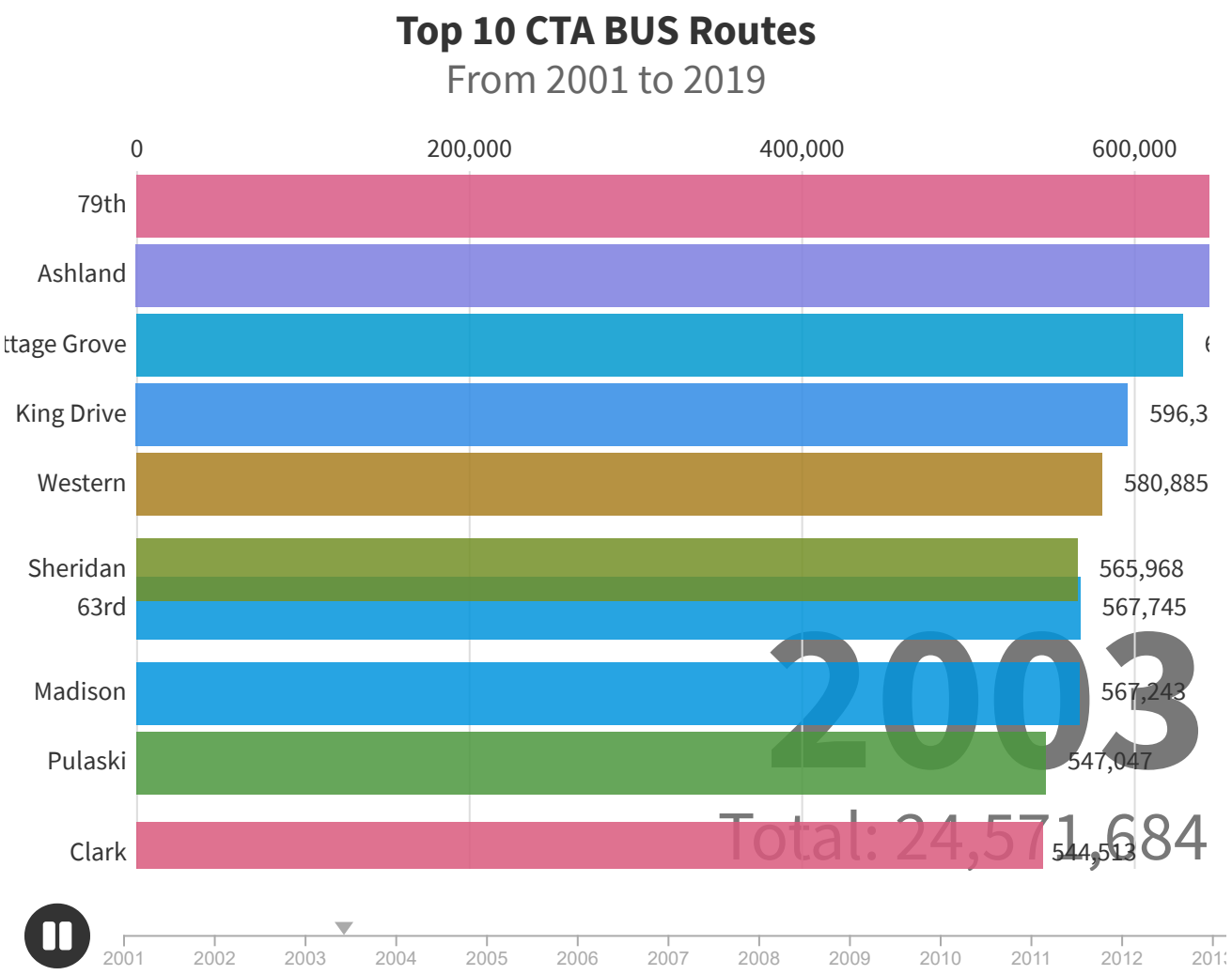


Out[4]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f072a4d5ad0>
```

In [5]:
```
# Insight 3 : Most popular bus routes from 2001 to 2019
df = br.bar_race(monthly)
```

In [1]:
```
from IPython.display import HTML
HTML("""<div class="flourish-embed flourish-bar-chart-race" data-src="visualisation/218
```

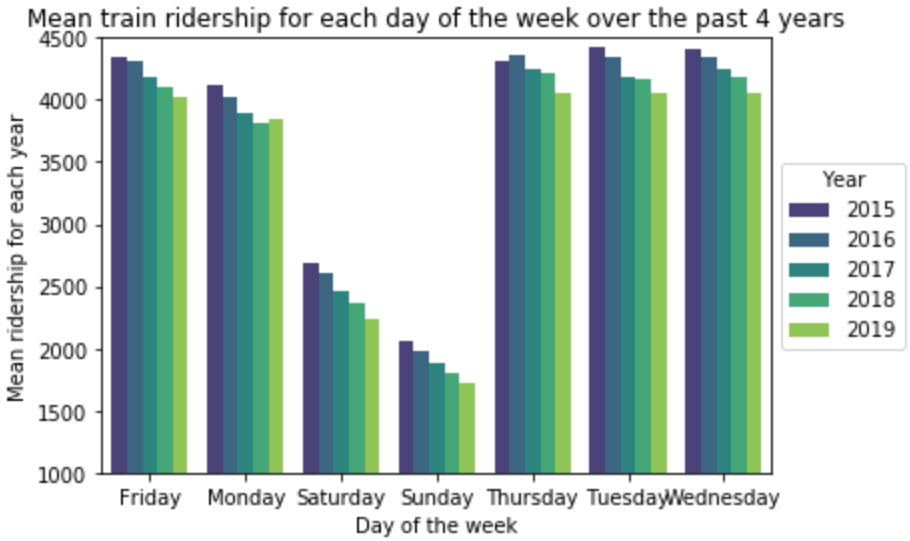
Out[1]:



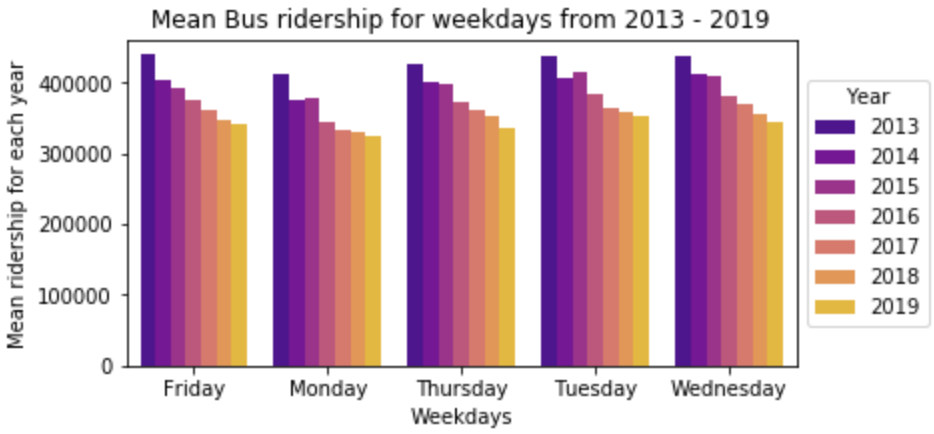
Numbers indicate passengers travelled

A Flourish data visualisation (https://public.flourish.studio/visualisation/2187019/?utm_source=showcase&utm_campaign=visualisation/2187019)

In [8]:
```
# Insight 4: The train ridership has been declining on all days of the week since the p
py_data_pivot = Kasturi.perform_eda(py_data)
Kasturi.day_of_week(py_data_pivot)
```



In [9]:
```
# Insight 5: Trend in bus ridership for weekdays from 2013 - 2019. It shows that riders
data_d = Piyush.createplot(data_days)
```



Predictions and Machine Learning

Predicting the ridership for 2019 using Long short-term memory (LSTM) and Auto-Regressive Integrated Moving Average(ARIMA) model. We can distinctly observe a pattern in the data, e.g. Ridership increase and peeks around the month of March and September, and then gradually decreases. We first predict an actual value of this variable for a future month and then categorize it with respect to the previous data whether the prediction states a 'Heavy Increase', 'Slight Increase', 'Almost Same', 'Slight Decrease' or a 'Heavy Decrease'.

- We used LSTM to predict the ridership over the years. We used 18 layers of LAG and 100 Epoche to find the prediction for the Ridership of Bus. This provides a prediction accuracy of ~ 93%
- Using Autoregressive integrated moving average (ARIMA), we were able to accurately predict the average monthly ridership for each month of the year 2019 by upto ~ 95% accuracy.
- Rolling Predictions - Using this trained model, we predict the average ridership for the month of January, 2019. We then add this predicted value to the data and re-train the model, to predict the value for the month of February, and so on till the month of December.

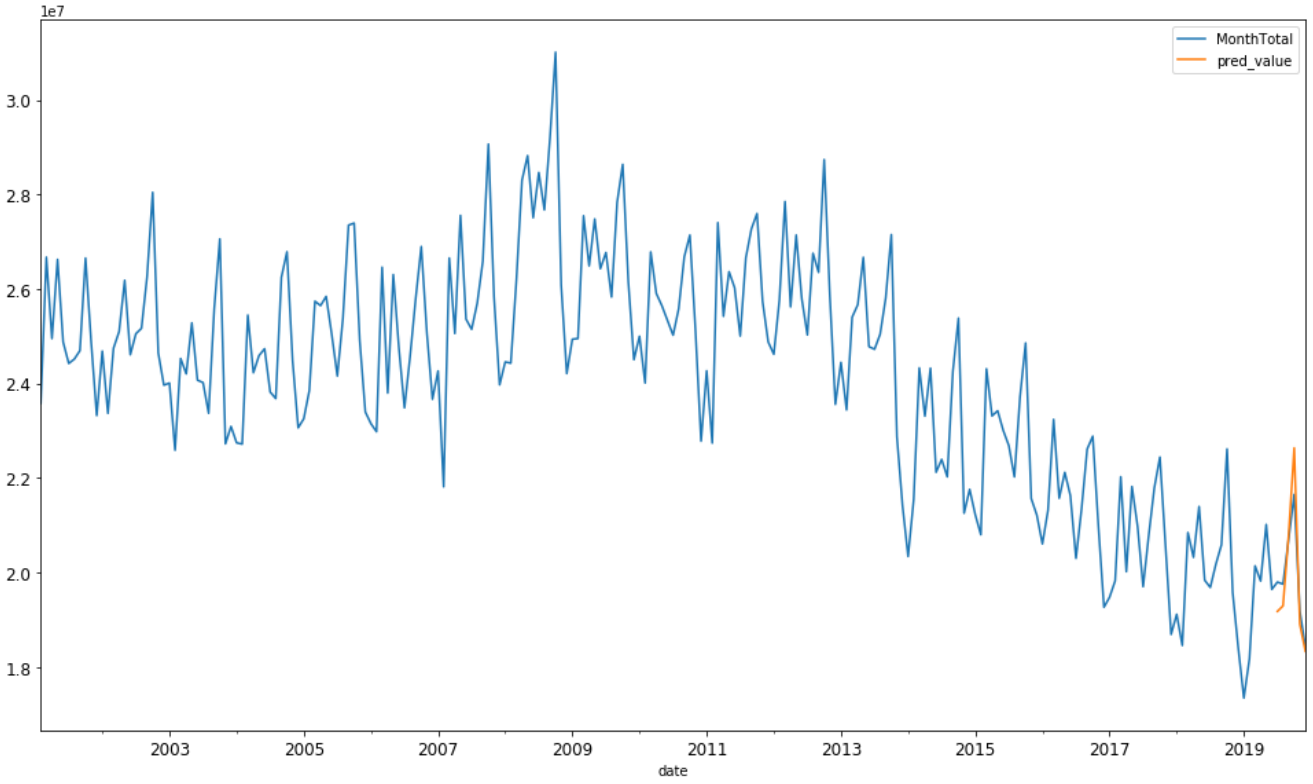
In [9]:
```
#Baseline Regression average accuracy. Method : Mean.
bb.baseline(monthly)
```

```
The accuracy for baseline model of mean is: 63.08%
```

In [ ]:
```
#Making a stable graph, adding 18 lags, running for Then we apply 100 epochs to reduce
month_sum, df_result = bam.all_monthly_ml(monthly)
```

In [10]:
```
#Testing the model to predict total Ridership of CTA Buses for 2019.
bam.graph_all_bus(month_sum , df_result)
```

Out[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcb10022310>
```



In [ ]:
```
#Predicting the Ridership values for each route each month for 2019 and classifying the
# Heavy Increase, Slight Increase, Almost Same, Slight Decrease and Heavy Decrease
# Final result in a csv file uploaded on Github
final = bnm.route_prediction(monthly)
```

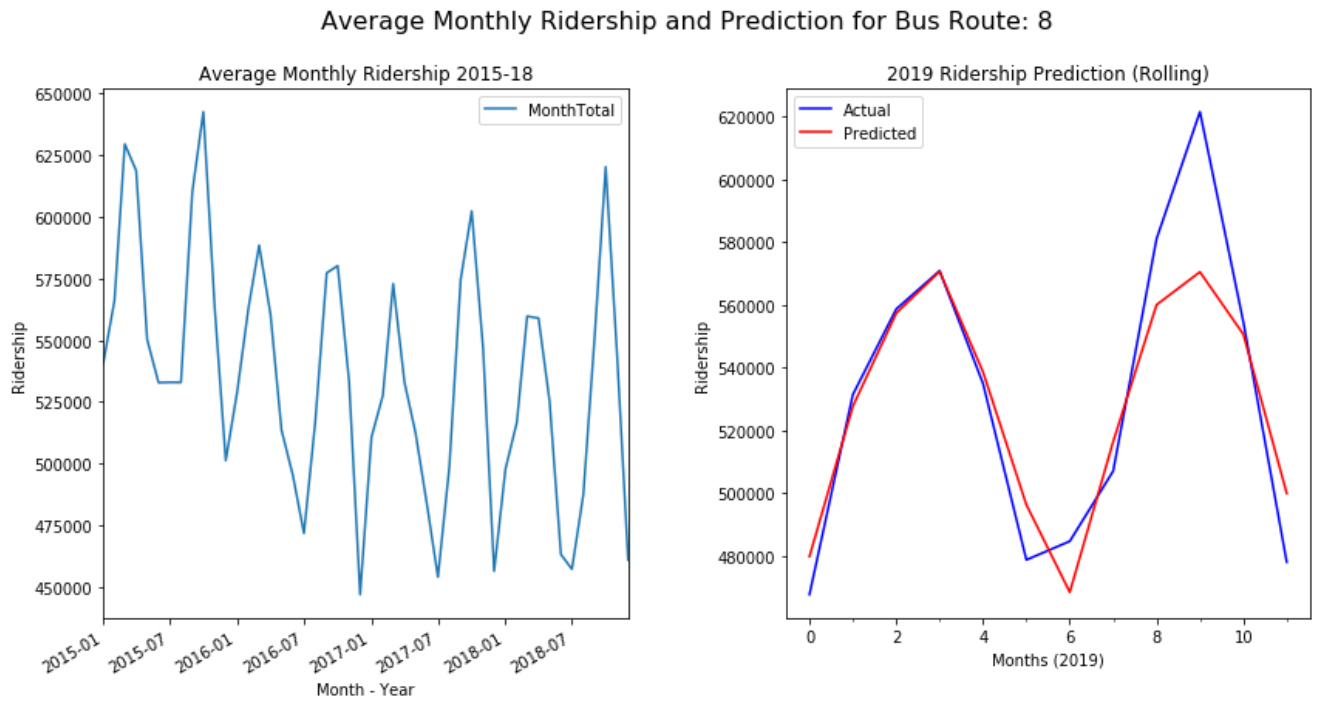
In [5]:
```
display(final)
```

	Month	route	Predicted_Ridership_2019	Ridership_2018	Classification	Accuracy_of_Prediction
0	July	3	440332	438230	Almost Same	98.023761
1	August	3	426639	425307	Almost Same	98.590945
2	September	3	437412	448073	Almost Same	97.997463
3	Ocotber	3	461374	490167	Almost Same	98.194521
4	November	3	406057	418467	Almost Same	97.216856
...	...	...	...	...	...	...
235	August	204	28801	26747	Almost Same	94.591184
236	September	204	29260	29765	Almost Same	94.494294
237	Ocotber	204	28039	31949	Slight Decrease	94.084359
238	November	204	27932	32453	Slight Decrease	93.809379
239	December	204	19352	28978	Heavy Decrease	87.558068

240 rows × 6 columns

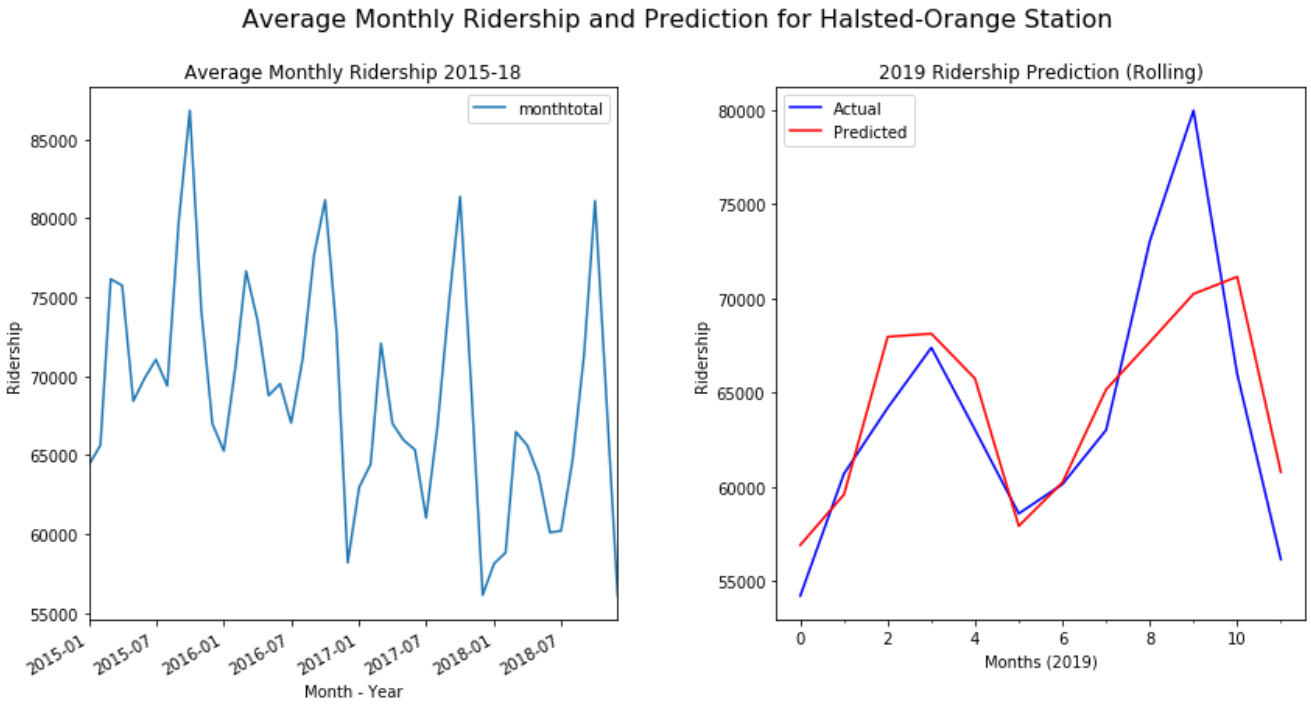
In [2]:
```
ARIMA.list_bus_routes() # Provides a list of active bus routes
ARIMA.bus_prediction(route_number = '8') # Predicts the BUS RIDERSHIP for a particular
```

```
Prediction: Slight Decrease [Prediction Accuracy: 99.97]
```



In [3]:
```
ARIMA.list_train_stations() # Provides a list of active train stations
ARIMA.train_prediction(station_name = "Halsted-Orange") #Predicts the TRAIN STATION RI
```

```
Prediction: No significant change [Prediction Accuracy: 99.95]
```



It should be noted that, as we continue to predict values for much further in the future, the predictions become less accurate. Obviously, it is easier to predict the average ridership for the upcoming month, compared to 6 months from now. Regardless, the model performs quite well.

Conclusions

We gained insights on the reasons behind the **decline in bus and train ridership** and which bus and train stations were **more popular**. We also **predicted the ridership** values for each bus route and train station with about **95% accuracy** and **classified** each bus and train station into **5 categories**. Looking at these insights, CTA can find out which routes are more popular and looking at the predictions, they can see where ridership would grow in the future. According to this, CTA can manage their bus and train services to make their transportation efficient, meet with the needs of commuters and manage their finances well.