# NJ TRANSIT PERFORMANCE PREDICTION

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# TEAM MEMBER

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# AGENDA

## INTRODUCTION

Brielfly introduce the project and the dataset

## VISUALIZATION

We plot our data in and do some analysis.

## PREDICTION

We use different models to predict the delay minutes based on Time Series:

- Linear Regression
- ARIMA
- Facebook Prophet

# INTRODUCTION

# OVERVIEW

NJ Transit is the second largest commuter rail network in the United States by ridership; it spans New Jersey and connects the state to New York City. On the Northeast Corridor, the busiest passenger rail line in the United States, Amtrak also operates passenger rail service; together, NJ Transit and Amtrak operate nearly 750 trains across the NJ Transit rail network.

Despite serving over 300,000 riders on the average weekday, no granular, trip-level performance data is publicly available for the NJ Transit rail network or Amtrak. This datasets aims to publicly provide such data.

# CONTENT

This dataset contains monthly CSVs covering the performance of nearly every train trip on the NJ Transit rail network.

Stop-level, minute resolution data on 287,000+ train trips (248,000+ NJ Transit trips, 38,000+ Amtrak trips)

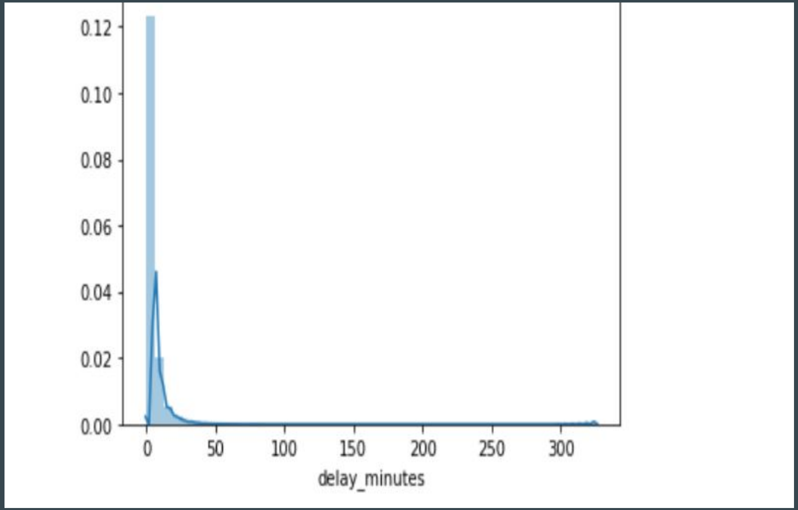
Coverage from November 1, 2018 to April 30, 2019 (updated monthly)

Transparent reporting on train trips for which data was missing/invalid, or that were scraped or parsed incorrectly (97.5% of train trips were correctly captured)

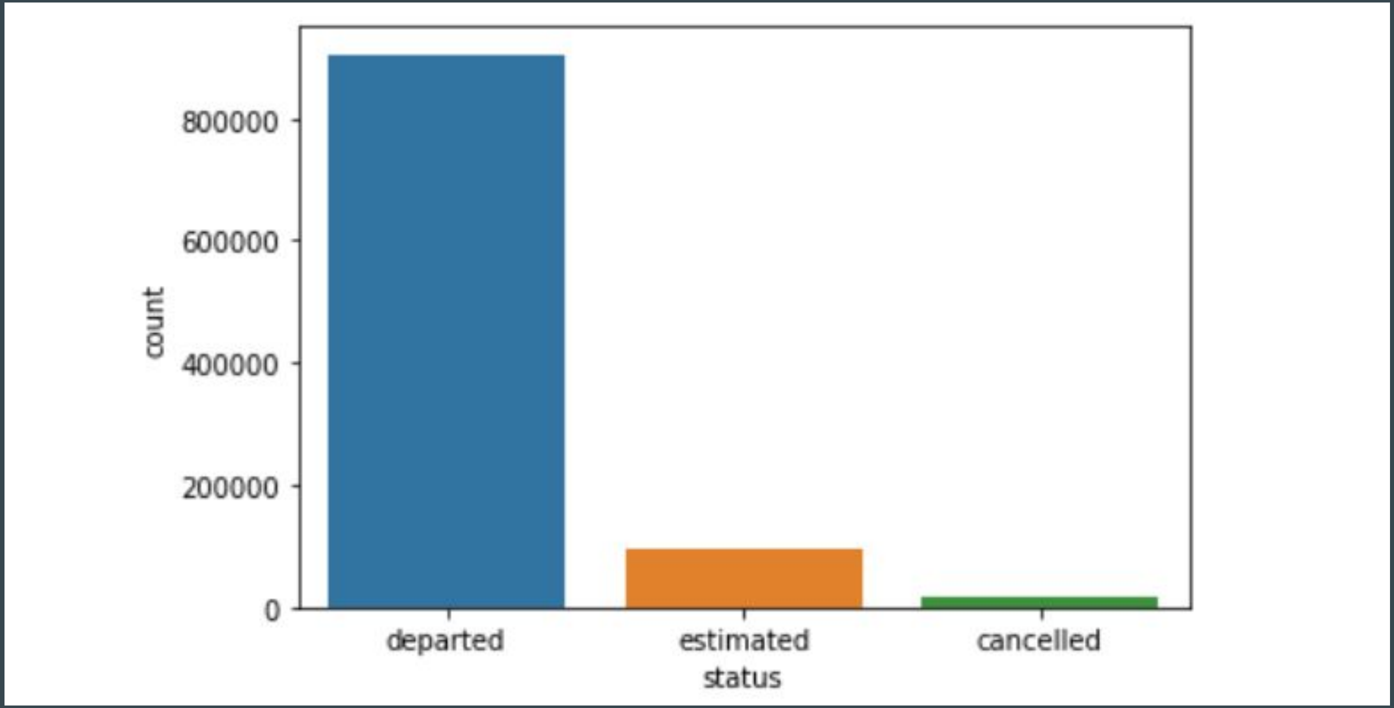
# VISUALIZATION

# Probability density Function of Delay

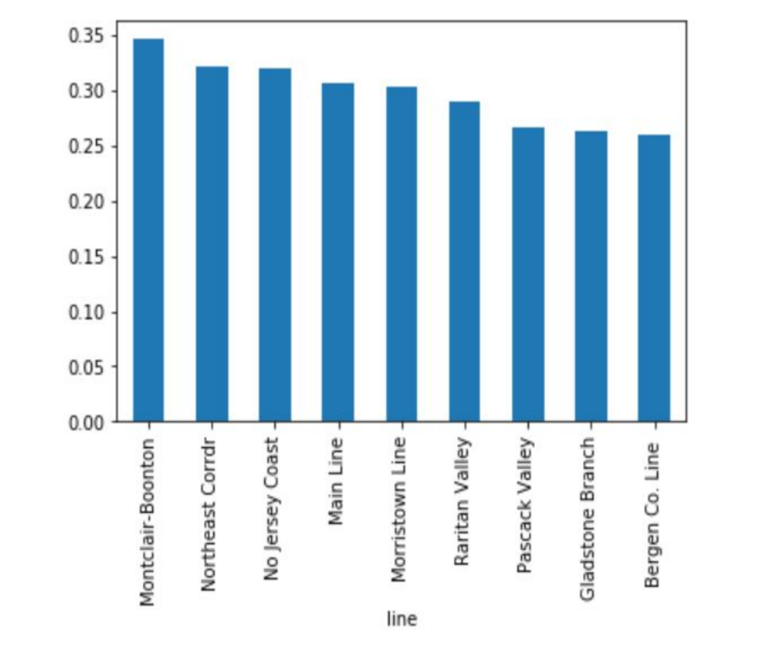
According to the histogram, we can know that there are some outliers with large delays



# Status of trains from Nov 2018 - April 2019



# Lines’ relationship with delay and cancellation




```
line
Bergen Co. Line       0.005272
Gladstone Branch      0.051631
Main Line             0.003927
Montclair-Boonton     0.018388
Morristown Line       0.019404
No Jersey Coast       0.019425
Northeast Corrdr      0.013485
Pascack Valley        0.006463
Raritan Valley        0.007298
dtype: float64
```

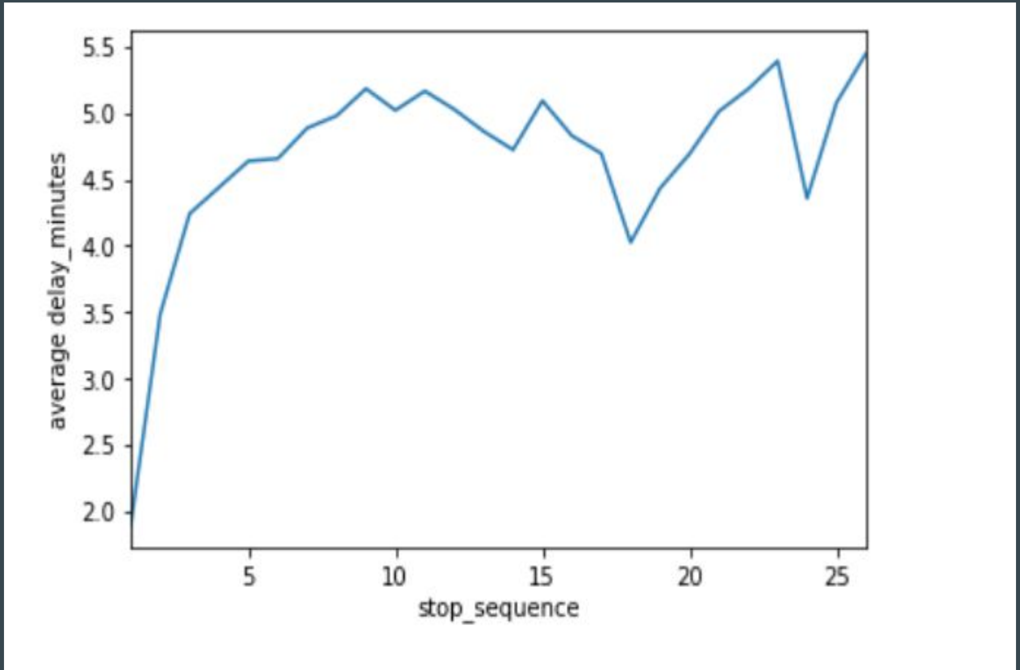
```
line
Bergen Co. Line       503
Gladstone Branch     4222
Main Line             391
Montclair-Boonton    1679
Morristown Line      3200
No Jersey Coast      2960
Northeast Corrdr     2380
Pascack Valley        451
Raritan Valley        487
Name: cancelled, dtype: int64
```

From the graph and the result we get, we can get the conclusion that all 9 lines has at least 25% of trips existing delay more than 5 minutes.

Also, we can see the delay and cancellation do not have much relation with different lines.

# Stops’ relationship with delay

From the above, we can see the stop sequence ‘s increasing will increase the delay time in some degree.



# Origins and destinations' relationship with delay

| from | |
|---|---|
| Harriman | 7.798562 |
| North Branch | 7.278237 |
| Campbell Hall | 6.885622 |
| Wayne-Route 23 | 6.577950 |
| Lincoln Park | 6.376451 |
| Mountain View | 6.160504 |
| Lebanon | 6.117999 |
| Tuxedo | 6.051452 |
| Aberdeen-Matawan | 5.849044 |
| Otisville | 5.837905 |

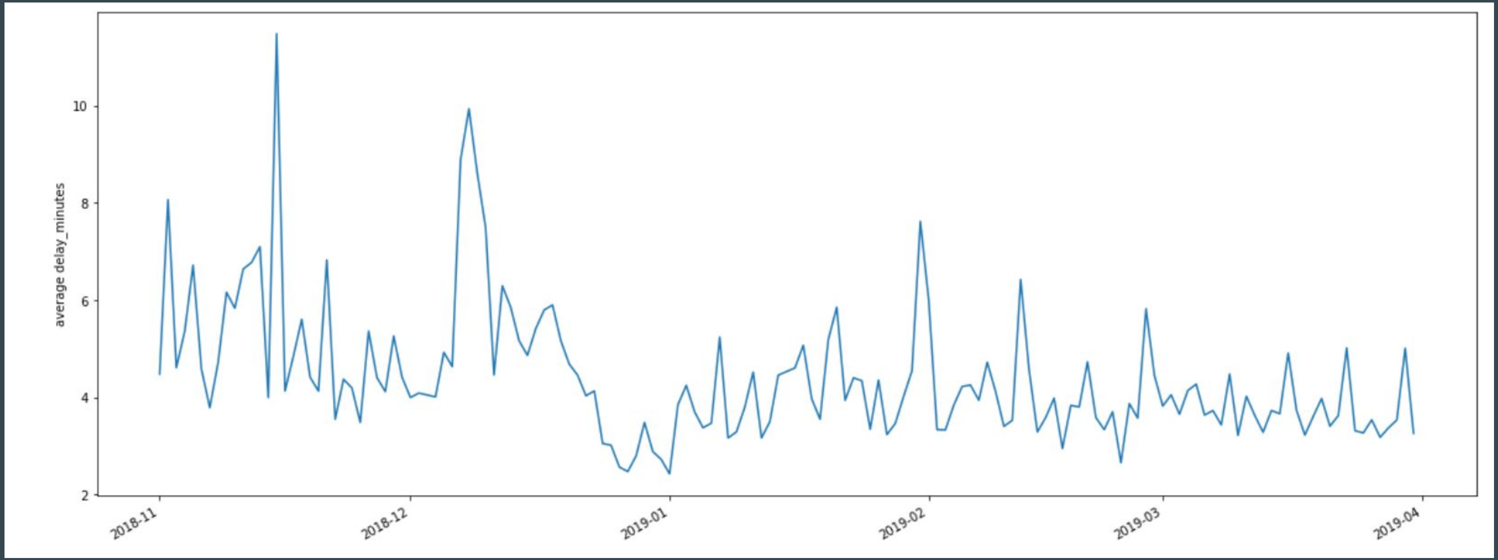
Name: delay_minutes, dtype: float64

| to | |
|---|---|
| Salisbury Mills-Cornwall | 7.990103 |
| White House | 7.192601 |
| Mountain View | 6.504376 |
| Lebanon | 6.300306 |
| Tuxedo | 6.229354 |
| North Branch | 6.175628 |
| Little Falls | 6.086691 |
| Aberdeen-Matawan | 5.943596 |
| Hazlet | 5.930178 |
| Towaco | 5.854664 |

Name: delay_minutes, dtype: float64

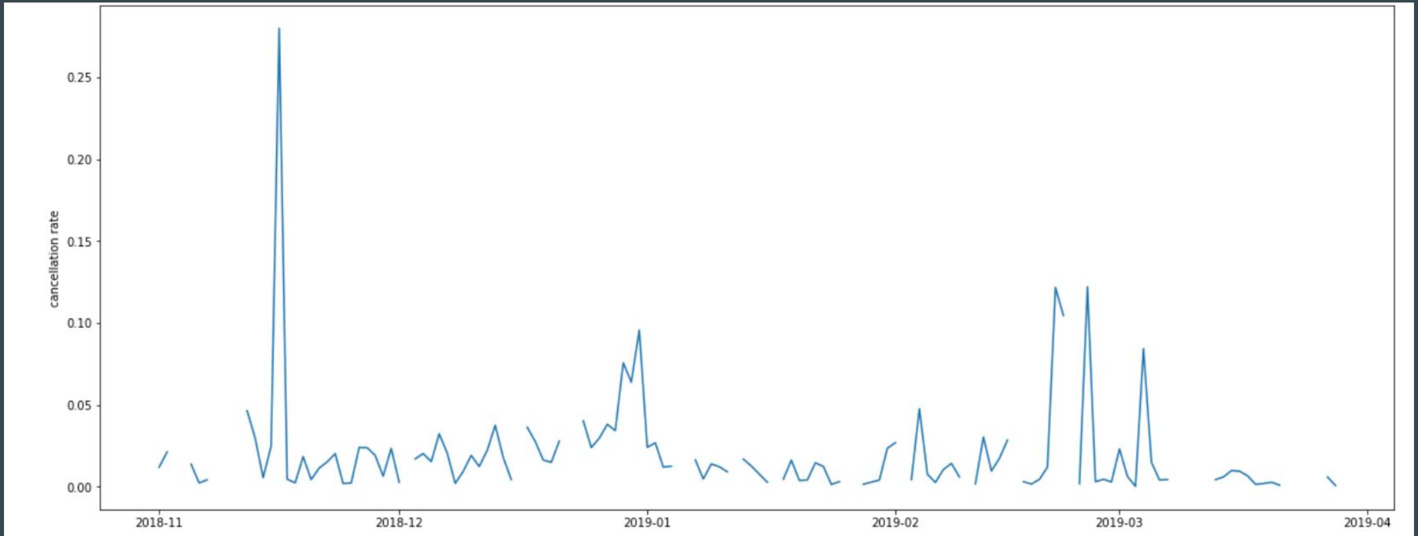
The results show that the delay time does not have relation with origins and destinations.

# Compare date with delays and cancellations to see when these delays and cancellations happen



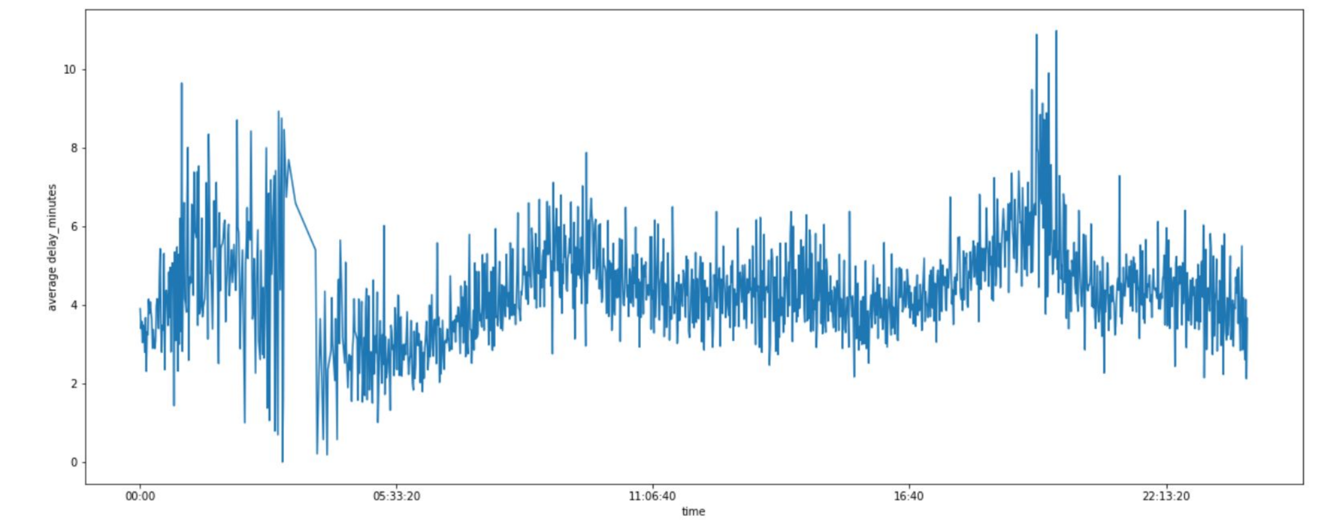

From the graph we can see that during 2018 Nov and Dec it has two times high delays. And after our investigation, we get the reason is that because of the heavy snow.

# Compare date with delays and cancellations to see when these delays and cancellations happen



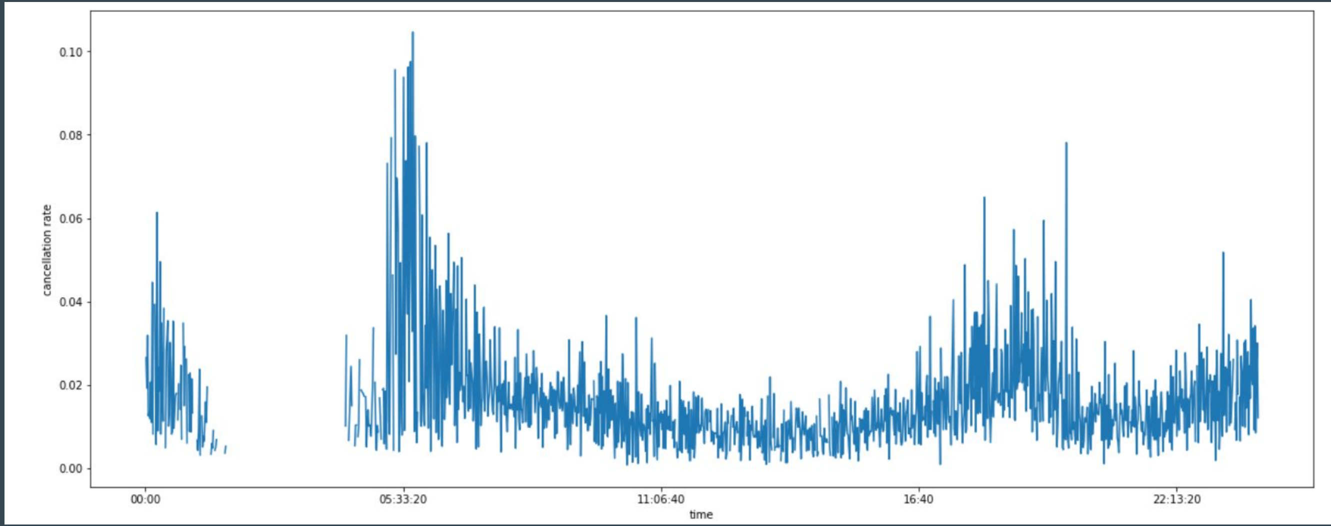

From the graph we can see that the cancellation rate is high in 2018 Nov and 2019 Feb.

# Compare time  with delays and cancellations to see when these delays and cancellations happen



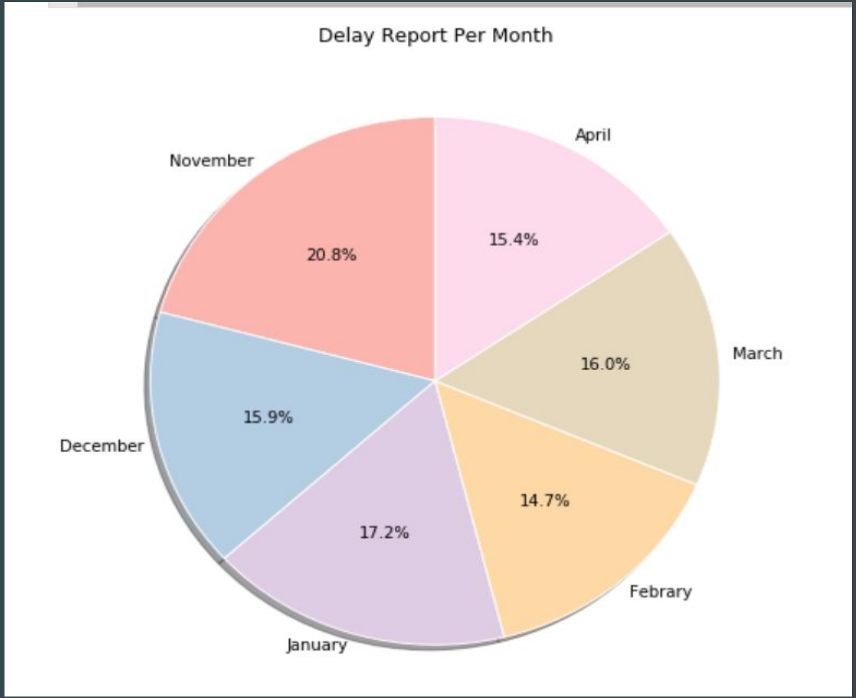

From the above we can see that the peak hour of delay is around 8pm and 1-3am.

# Compare time  with delays and cancellations to see when these delays and cancellations happen




From the above we can see that the peak hours of high cancellation is around 6am.

# Delay report per month



# PREDICTION

# PREDICTION

| | |
|---|---|
| LINEAR REGRESSION | • Implement Linear regression<br>• Predict the future value |
| ARIMA | • Make data dictionary<br>• Implement the model |
| FACEBOOK PROPHET | • Making Future Data Frames<br>• Trends and Patterns |

# Linear Regression

# LINEAR REGRESSION

## INTRODUCTION

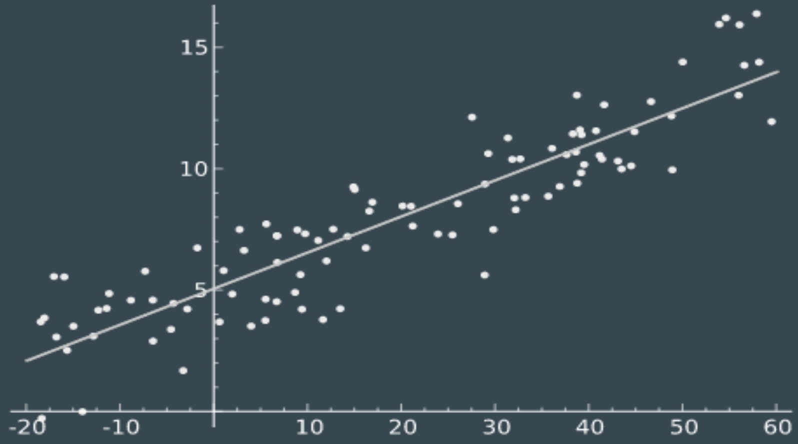
Linear regression attempts to model the relationship between two variables by **fitting a linear equation** to observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable. For example, a modeler might want to relate the weights of individuals to their heights using a linear regression model.

Before attempting to fit a linear model to observed data, a modeler should first determine whether or not there is a relationship between the variables of interest. This does not necessarily imply that one variable causes the other (for example, higher SAT scores do not cause higher college grades), but that there is some significant association between the two variables.

# LINEAR REGRESSION

## INTRODUCTION

A linear regression line has an equation of the form Y = a + bX, where X is the explanatory variable and Y is the dependent variable. The slope of the line is b, and a is the intercept (the value of y when x = 0).



# Implement Linear Regression

The Linear Regression is always the first model to come up with when we need to predict some dataset. So in this case, first we need to analyze the data types and make sure it can be implemented as a linear regression model.

| | date | train_id | stop_sequence | from | from_id | to | to_id | scheduled_time | actual_time | delay_minutes | status | line | type |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 11/1/18 | 3244 | 1 | Long Branch | 74 | Long Branch | 74 | 11/1/18 11:54 | 11/1/18 11:53 | 0.000000 | departed | No Jersey Coast | NJ Transit |
| **1** | 11/1/18 | 3244 | 2 | Long Branch | 74 | Little Silver | 73 | 11/1/18 12:02 | 11/1/18 12:02 | 0.316667 | departed | No Jersey Coast | NJ Transit |
| **2** | 11/1/18 | 3244 | 3 | Little Silver | 73 | Red Bank | 130 | 11/1/18 12:06 | 11/1/18 12:09 | 3.183333 | departed | No Jersey Coast | NJ Transit |
| **3** | 11/1/18 | 3244 | 4 | Red Bank | 130 | Middletown NJ | 85 | 11/1/18 12:12 | 11/1/18 12:13 | 1.300000 | departed | No Jersey Coast | NJ Transit |
| **4** | 11/1/18 | 3244 | 5 | Middletown NJ | 85 | Hazlet | 59 | 11/1/18 12:18 | 11/1/18 12:20 | 2.050000 | departed | No Jersey Coast | NJ Transit |

```
Data columns (total 10 columns):
train_id          1014624 non-null int64
stop_sequence     1014624 non-null int64
from_id           1014624 non-null int64
to_id             1014624 non-null int64
scheduled_time    1014624 non-null object
actual_time       1014624 non-null object
delay_minutes     1014624 non-null float64
line              1014624 non-null category
line_label        1014624 non-null int8
label             1014624 non-null float64
dtypes: category(1), float64(2), int64(4), int8(1), object(2)
```

# LINEAR REGRESSION

## INTRODUCTION

We are only using the essential columns required, which will be the features that will help us predict the outcome. Here the date time will help us in indexing the dataframe for ease of access, whereas, other columns will be predictors, that will allow us to forecast the future using the historical data we have until now.  We pick up data that can be used in this model. Meanwhile,  Line_label is also be created to distinguish the different train names.

```
df[['line']] = df["line"].astype('category')
```

```
df['line_label'] = df["line"].cat.codes
```

```
df.groupby('line')['line_label'].unique()
```

```
line
Bergen Co. Line       [0]
Gladstone Branch      [1]
Main Line             [2]
Montclair-Boonton     [3]
Morristown Line       [4]
No Jersey Coast       [5]
Northeast Corrdr      [6]
Pascack Valley        [7]
Raritan Valley        [8]
Name: line_label, dtype: object
```

Generally, you want your features in machine learning to be in a range of -1 to 1. This may do nothing, but it usually speeds up processing and can also help with accuracy. Because this range is so popularly used, it is included in the preprocessing module of Scikit-Learn. To utilize this, you can apply preprocessing.scale to your X variable.

‘

```
X = np.array(df[['train_id','stop_sequence','from_id','to_id','line_label']])
X = preprocessing.scale(X)
```

Now comes the training and testing. The way this works is you take, for example, 75% of your data, and use this to train the machine learning classifier. Then you take the remaining 25% of your data, and test the classifier. Since this is your sample data, you should have the features and known labels. Thus, if you test on the last 25% of your data, you can get a sort of accuracy and reliability, often called the confidence score.

Very bad score here, it means the dataset is definitely not linear predictable! Lets see how we can analyse the errors to understand this better.

‘

```
X = np.array(df[['train_id','stop_sequence','from_id','to_id','line_label']])
X = preprocessing.scale(X)
```

```
y = np.array(df['delay_minutes'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)
```

```
clf = LinearRegression()
results = clf.fit(X_train, y_train)
accuracy = clf.score(X_test, y_test)
print(accuracy) #means we can not use LR model to predict the delay!
```

```
0.0077642886537293565
```

We can see that the regression error is much less compared to the baseline error. It means we cannot simply use linear regression model to predict the value, we need to make some improvements.

```
output = pd.DataFrame()                    # Create a blank dataframe
output['delay_pred'] = delay_pred           # Add a column of predicted value of uber prices
output['actual'] = y_test                  # Add a column of the actual value of uber prices, we put them s
output['percent_linear_regression_error'] = abs(output['actual']-output['delay_pred'])*100/output['actual']
train_mean = np.mean(y_train)               #Baseline prediction - is the average value of dependent variab
output['baseline_error'] = abs(output['actual']-train_mean)*100/output['actual']
output.head(n=50)
```

| | delay_pred | actual | percent_linear_regression_error | baseline_error |
|---|---|---|---|---|
| 0 | 5.042728 | 4.133333 | 22.001489 | 8.761335 |
| 1 | 4.883261 | 0.000000 | inf | inf |
| 2 | 4.826120 | 0.000000 | inf | inf |
| 3 | 4.925442 | 4.000000 | 23.136039 | 12.386713 |
| 4 | 5.266116 | 10.016667 | 47.426464 | 55.120115 |
| 5 | 4.825128 | 2.483333 | 94.300459 | 81.025578 |
| 6 | 5.459495 | 1.716667 | 218.028833 | 161.871953 |
| 7 | 4.826142 | 0.000000 | inf | inf |
| 8 | 4.096158 | 0.000000 | inf | inf |
| 9 | 4.625952 | 4.150000 | 11.468733 | 8.324543 |
| 10 | 4.023822 | 5.450000 | 26.168408 | 17.514339 |
| 11 | 4.513381 | 8.283333 | 45.512500 | 45.728750 |
| 12 | 4.157110 | 4.400000 | 5.520222 | 2.169739 |
| 13 | 4.415879 | 1.166667 | 278.503949 | 285.325874 |
| 14 | 5.359149 | 9.333333 | 42.580548 | 51.834266 |
| 15 | 3.659941 | 2.066667 | 77.093931 | 117.522671 |

# Try to predict the future value

Since the prediction results do not have a strong connection with the coefficients in Linear Regression model. We tried to use Time Series to predict the future values.

In short, a time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data.

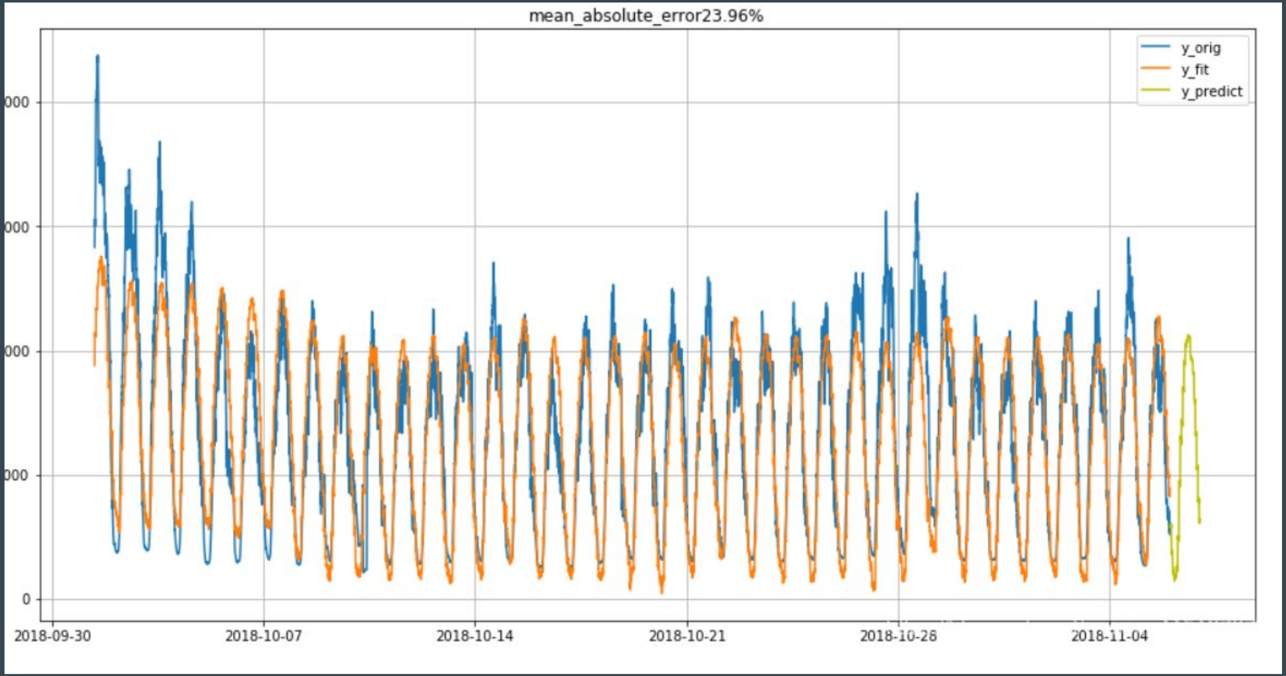
| | |
|---|---|
| day/hour/minute | day_avg/ hour_avg/ minute_agv |
| weekday/holiday | weekday_avg/ holiday_avg |

# Try to predict the future value

And we consider the shift and time variation in this dataset.

```
# make feature
def build_feature(data, lag_start, lag_end, test_size, target_encoding=False, num_day_pred=1):
    # build future data with 0
    last_date = data["date"].max()
    pred_points = int(num_day_pred * 24)
    pred_date = pd.date_range(start=last_date, periods=pred_points + 1, freq="1h")
    pred_date = pred_date[pred_date > last_date]
    future_data = pd.DataFrame({"date": pred_date, "y": np.zeros(len(pred_date))})
    # concat future data and last data
    df = pd.concat([data, future_data])
    df.set_index("date", drop=True, inplace=True)
    #print(df)
    # make feature
    for i in range(lag_start, lag_end):
        df["lag_{}".format(i)] = df.y.shift(i)
    df["diff_lag_{}".format(lag_start)] = df["lag_{}".format(lag_start)].diff(1)
    df["hour"] = df.index.hour
    # df["day"] = df.index.day
    # df["month"] = df.index.month
    df["minute"] = df.index.minute
    df["weekday"] = df.index.weekday
    df["weekend"] = df.weekday.isin([5, 6]) * 1
    df["holiday"] = 0
    df.loc["2018-11-28 00:00:00":"2018-11-29 23:00:00","holiday"] = 1
    #print(df)
    # df["holiday"]
    # average feature
    if target_encoding:
        df["weekday_avg"] = list(map(cal_mean(df[:last_date], "weekday", "y").get, df.weekday))
        df["hour_avg"] = list(map(cal_mean(df[:last_date], "hour", "y").get, df.hour))
        df["weekend_avg"] = list(map(cal_mean(df[:last_date], "weekend", "y").get, df.weekend))
        df["minute_avg"] = list(map(cal_mean(df[:last_date], "minute", "y").get, df.minute))
        df = df.drop(["hour","minute","weekday", "weekend"], axis = 1)
    #df = pd.get_dummies(df, columns = ["hour", "minute", "weekday", "weekend"])
```

Use specific build_feature method to fit the time series data according to the different kinds of data. Then scale data by using this method and train the data in Linear Regression model. We can get the result of future prediction.



# ARIMA

# Introduction

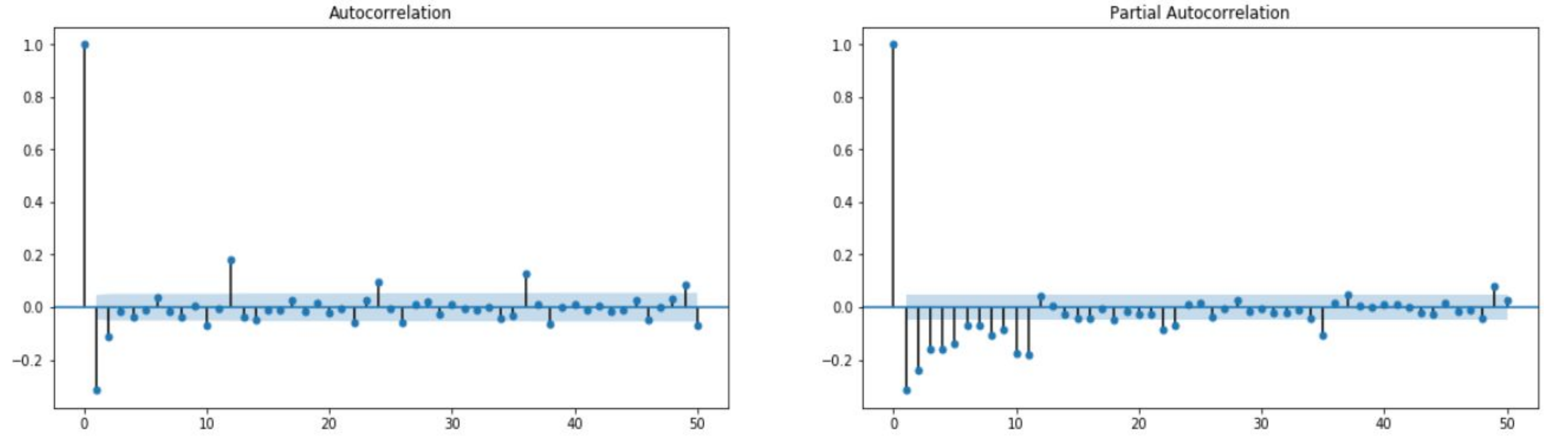
ARIMA stands for Auto-Regressive Integrated Moving Averages. The ARIMA forecasting for a stationary time series is nothing but a linear (like a linear regression) equation. The predictors depend on the parameters (p,d,q) of the ARIMA model:

Number of AR (Auto-Regressive) terms (p): AR terms are just lags of dependent variable. For instance if p is 5, the predictors for x(t) will be x(t-1)....x(t-5).

Number of MA (Moving Average) terms (q): MA terms are lagged forecast errors in prediction equation. For instance if q is 5, the predictors for x(t) will be e(t-1)....e(t-5) where e(i) is the difference between the moving average at ith instant and actual value.

Number of Differences (d): These are the number of nonseasonal differences, i.e. in this case we took the first order difference. So either we can pass that variable and put d=0 or pass the original variable and put d=1. Both will generate same results.

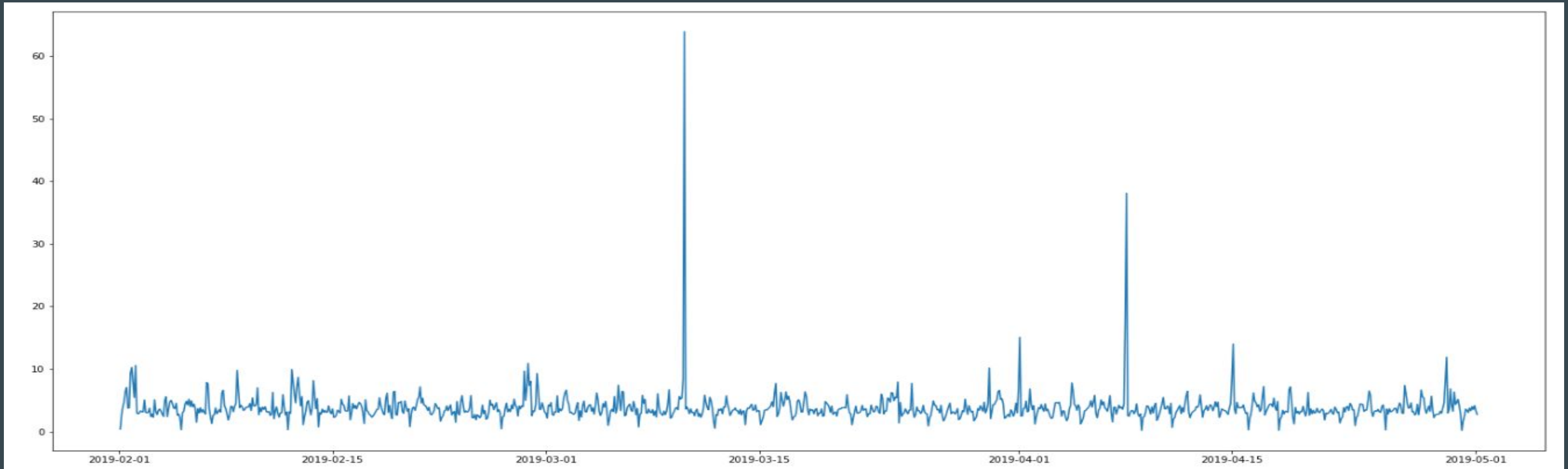
An importance concern here is how to determine the value of ‘p’ and ‘q’. We use plots of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to determine these numbers.




we use p=1, q=1 as we can see from acf and pacf above

# Make our data stationary

Although stationary assumption is taken in many TS model, most of the practical time series are not stationary. Also, the theories related to stationary series are more mature and easier to implement as compared to non-stationary series.



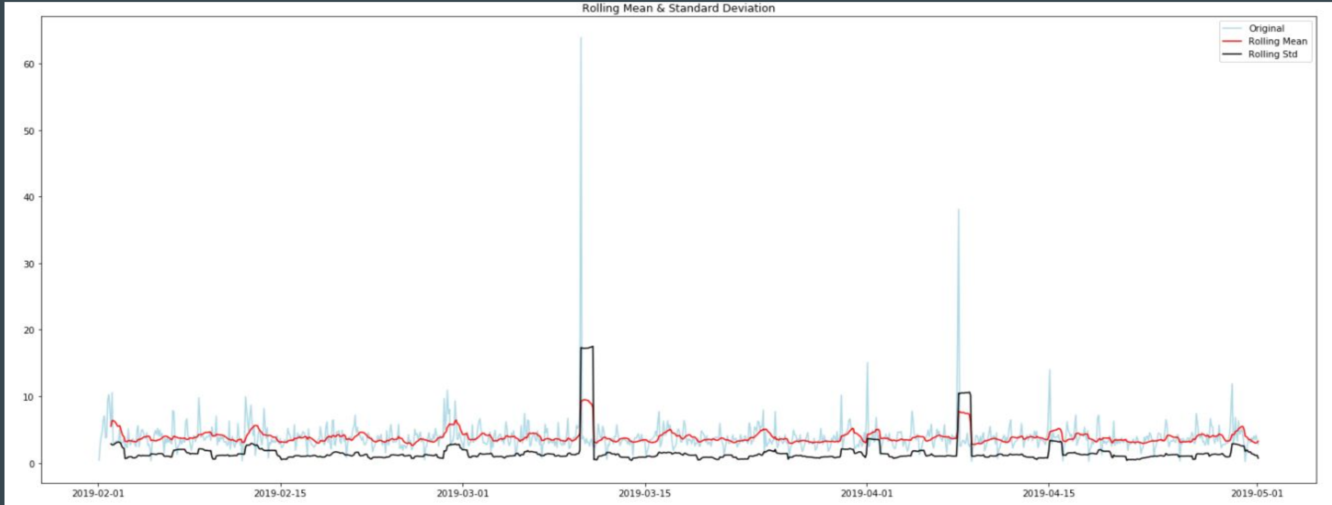

There is some period fluctuation in the plot. But we cannot say it is stationary or not. Formally, we can check stationarity using the Dickey-Fuller Test.

# Dickey-Fuller Test

Here the null hypothesis is that the TS is non-stationary. The test results comprise of a Test Statistic and some Critical Values for difference confidence levels. If the 'Test Statistic' is less than the 'Critical Value', we can reject the null hypothesis and say that the series is stationary. We plotted standard deviation instead of variance to keep the unit similar to mean.

# Dickey-Fuller Test

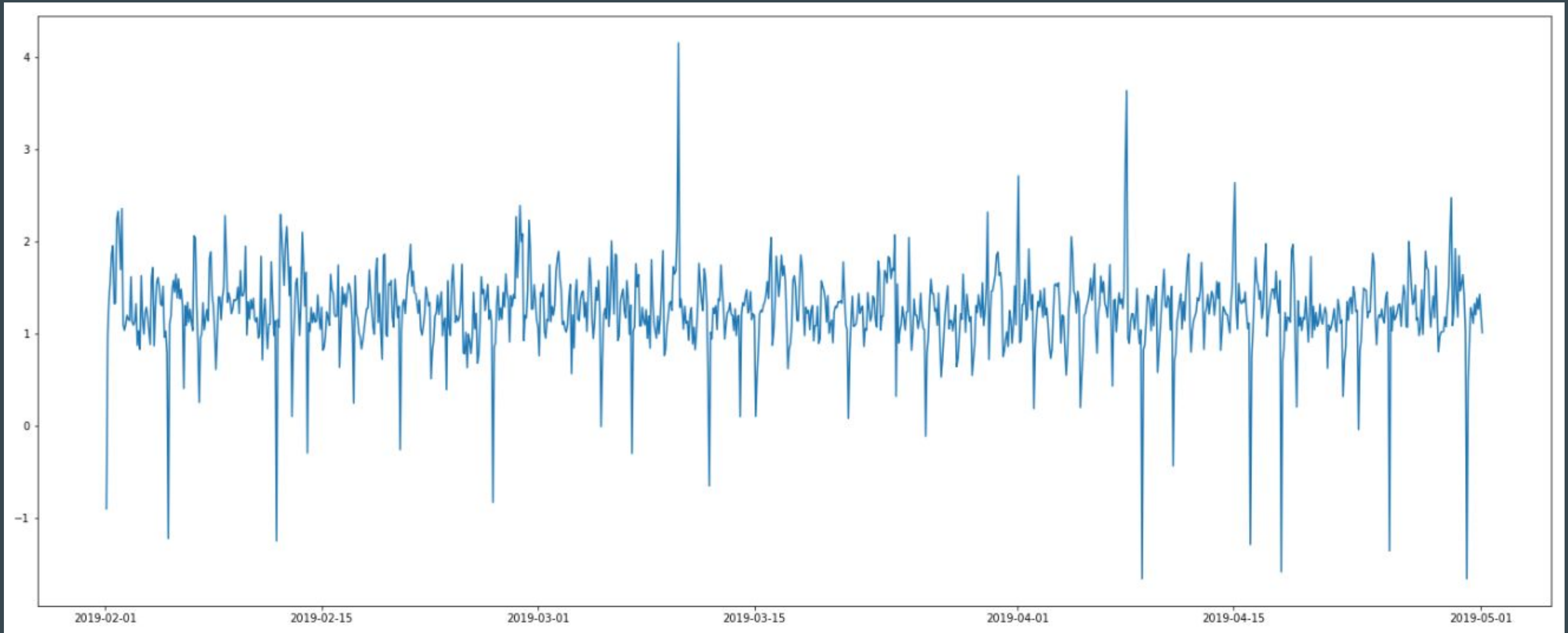
It shows us it reject the null hypothesis (H0), the data does not have a unit root and is stationary. the test statistic is less than Critical Value (1%). It means we have 99% confidence to say that the data is stationary.




```
Results of Dickey-Fuller Test:
Test Statistic                   -26.116086
p-value                            0.000000
#Lags Used                         0.000000
Number of Observations Used     1068.000000
Critical Value (1%)               -3.436488
Critical Value (5%)               -2.864250
Critical Value (10%)              -2.568213
dtype: float64
```

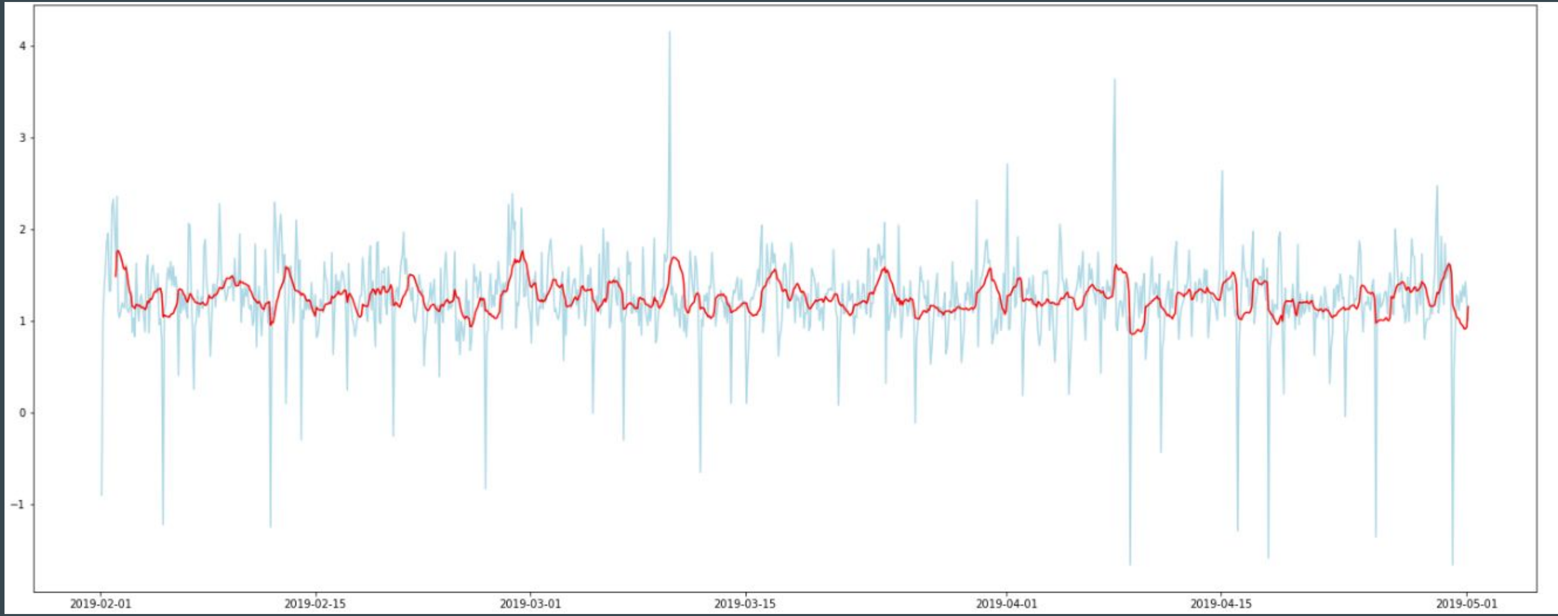
# Transforming Time Series and Moving Average

We want to reduce the fluctuation range. So we can apply Log transformation which penalize higher values more than smaller values.



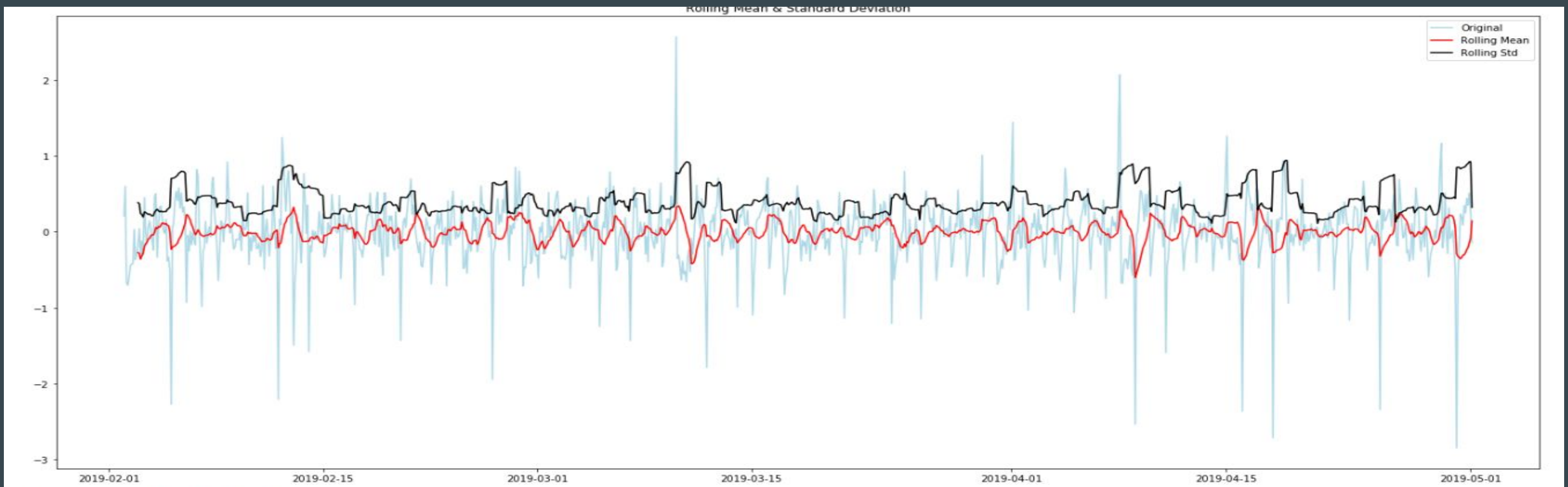
# Transforming Time Series and Moving Average

We use Moving Average Model to estimate the trend and remove it from our series. In this approach, we take average of ‘k’ consecutive values depending on the frequency of time series. As we take one day, so k is 12. Red line is the rolling mean. Since we are taking average of last 12 values, rolling mean is not defined for first 11 values. We need to drop Nan in series.



# Transforming Time Series and Moving Average

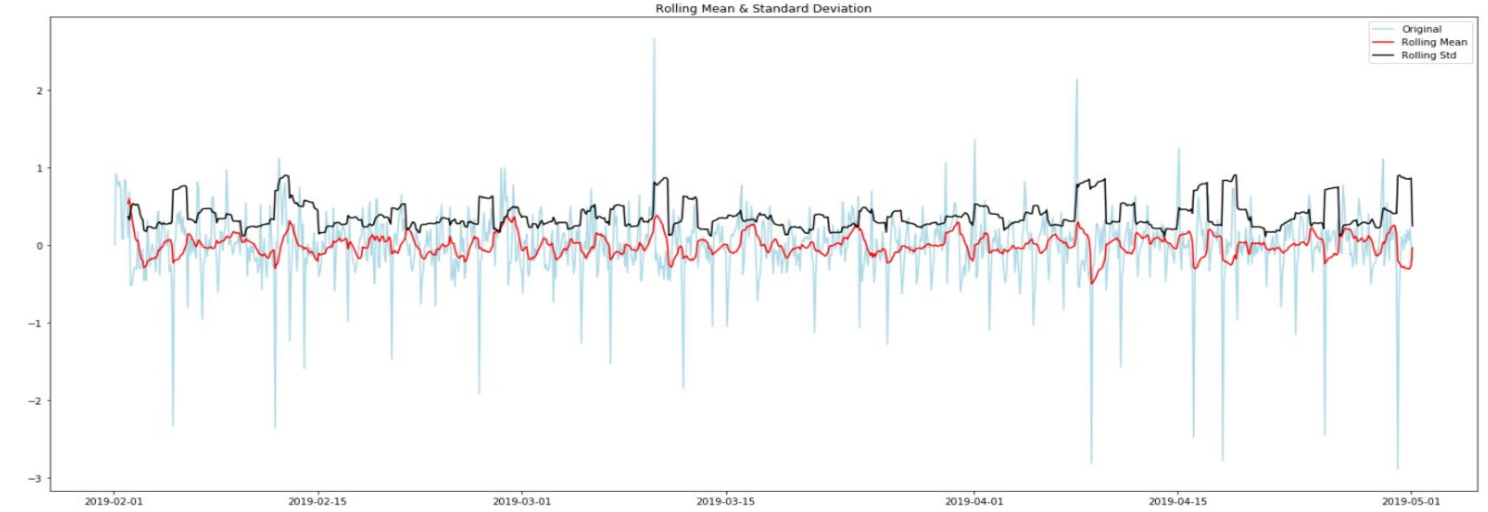
From the picture above, we can see the fluctuation range reduce and p value reduces a lot as well.




```
Results of Dickey-Fuller Test:
Test Statistic                 -1.215088e+01
p-value                         1.571369e-22
#Lags Used                      1.900000e+01
Number of Observations Used     1.038000e+03
Critical Value (1%)            -3.436666e+00
Critical Value (5%)            -2.864328e+00
Critical Value (10%)           -2.568255e+00
dtype: float64
```

# Transforming Time Series and Moving Average

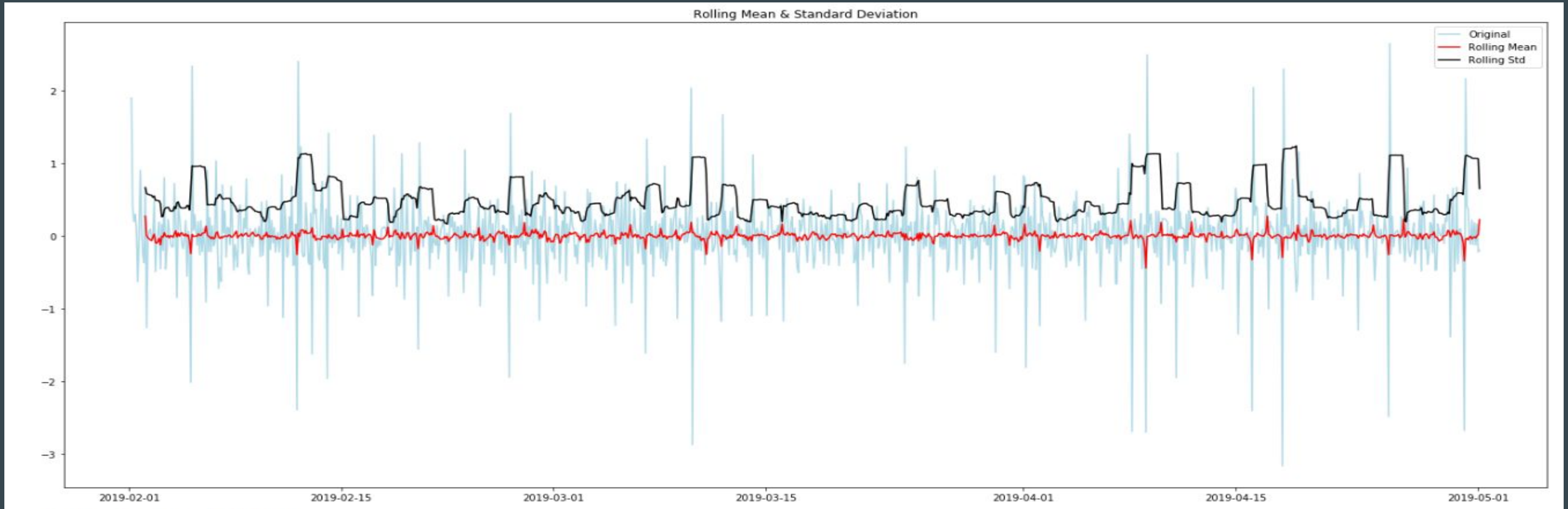
We take a Weighted Moving Average to improve it. In WMA model, it gives a higher weight for more recent value.




```
Results of Dickey-Fuller Test:
Test Statistic                -1.402241e+01
p-value                        3.551903e-26
#Lags Used                     7.000000e+00
Number of Observations Used    1.061000e+03
Critical Value (1%)           -3.436528e+00
Critical Value (5%)           -2.864268e+00
Critical Value (10%)          -2.568222e+00
dtype: float64
```

# Difference

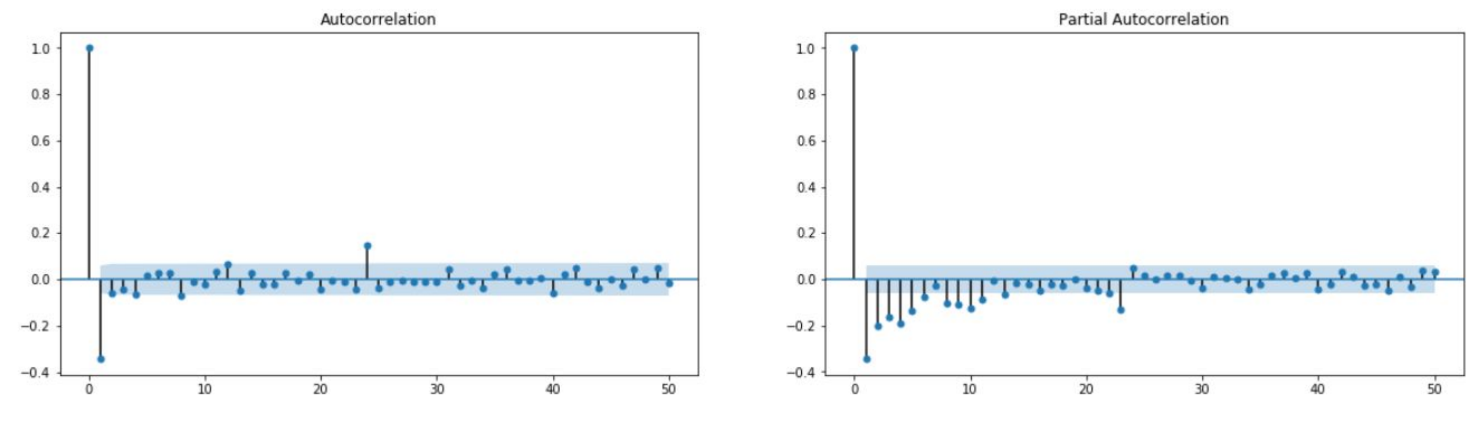
The simple trend reduction techniques discussed before don’t work in all cases, particularly the ones with high seasonality. So we implement Difference in our time series.




```
Results of Dickey-Fuller Test:
Test Statistic                 -1.390684e+01
p-value                         5.602728e-26
#Lags Used                      2.200000e+01
Number of Observations Used     1.045000e+03
Critical Value (1%)            -3.436623e+00
Critical Value (5%)            -2.864310e+00
Critical Value (10%)           -2.568245e+00
```

# Implementation

As we mentioned in the introduction of the ARIMA model. The parameter of p and q is important. We draw the picture of ACF and PACF to see the value of p and q.



# Implementation

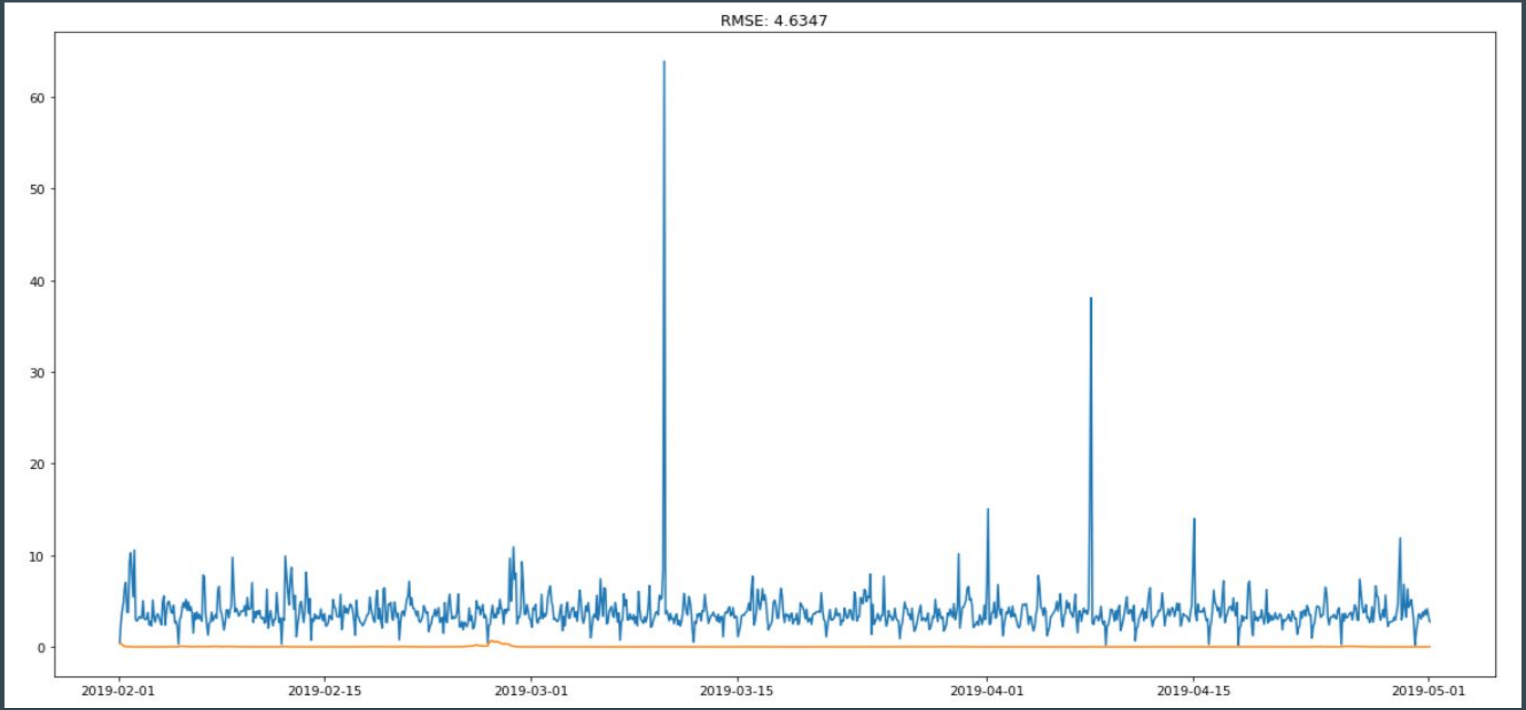
As we get the value for both p and q are 1. We implement the time series in AR, MA and ARIMA. We pick up ARIMA model at the last because it has the least RSS score.

```
print('ARIMA RSS: %.4f'% sum((ts_log_diff-results_ARIMA.fittedvalues)**2))
print('AR RSS: %.4f'% sum((results_AR.fittedvalues-ts_log_diff)**2))
print('MA RSS: %.4f'% sum((results_MA.fittedvalues-ts_log_diff)**2))
```

```
ARIMA RSS: 194.8127
AR RSS: 254.3815
MA RSS: 217.3101
```

# Implementation

The RMSE has a small value which means our model has a good result of prediction.



# FACEBOOK PROPHET

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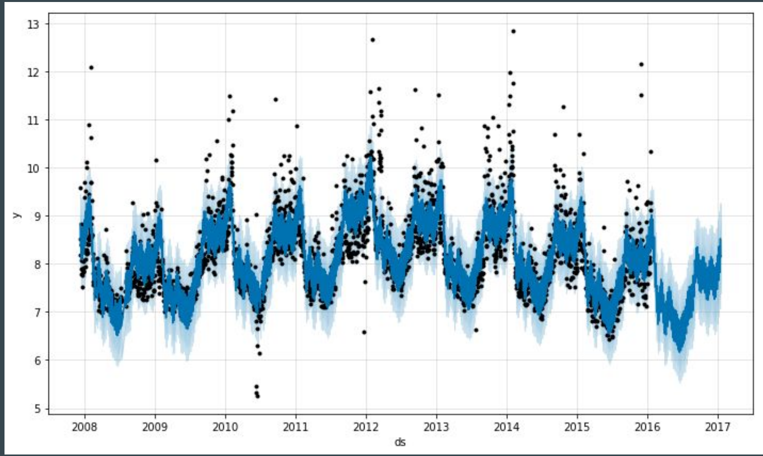
## INTRODUCTION

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with **yearly, weekly, and daily seasonality,** plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.



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## MODELING

We first import prophet and rename the columns in our data to the correct format. **The Date column must be called 'ds' and the value column we want to predict 'y'.** We then create prophet models and fit them to the data, much like a Scikit-Learn machine learning model.

| | ds | delay_minutes |
|---|---|---|
| 0 | 2018-11-01 11:54:00 | 0.000000 |
| 1 | 2018-11-01 12:02:00 | 0.316667 |
| 2 | 2018-11-01 12:06:00 | 3.183333 |
| 3 | 2018-11-01 12:12:00 | 1.300000 |
| 4 | 2018-11-01 12:18:00 | 2.050000 |

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## MODELING

We check the statistic information of the dataset and plot the data by setting 'scheduled_time' as index.

The average delay minutes is 4 minutes and 75% is 5 minutes. It's strange that we have 326 minutes as our max value. So next, we draw a plot to have a deep look of this extreme value.

| | stop_sequence | from_id | to_id | delay_minutes |
|---|---|---|---|---|
| count | 1014624.0 | 1014624.0 | 1014624.0 | 1014624.0 |
| mean | 8.0 | 4481.0 | 4470.0 | 4.0 |
| std | 5.0 | 12077.0 | 12063.0 | 6.0 |
| min | 1.0 | 3.0 | 3.0 | 0.0 |
| 25% | 4.0 | 62.0 | 61.0 | 1.0 |
| 50% | 8.0 | 105.0 | 105.0 | 3.0 |
| 75% | 12.0 | 138.0 | 138.0 | 5.0 |
| max | 26.0 | 43599.0 | 43599.0 | 326.0 |

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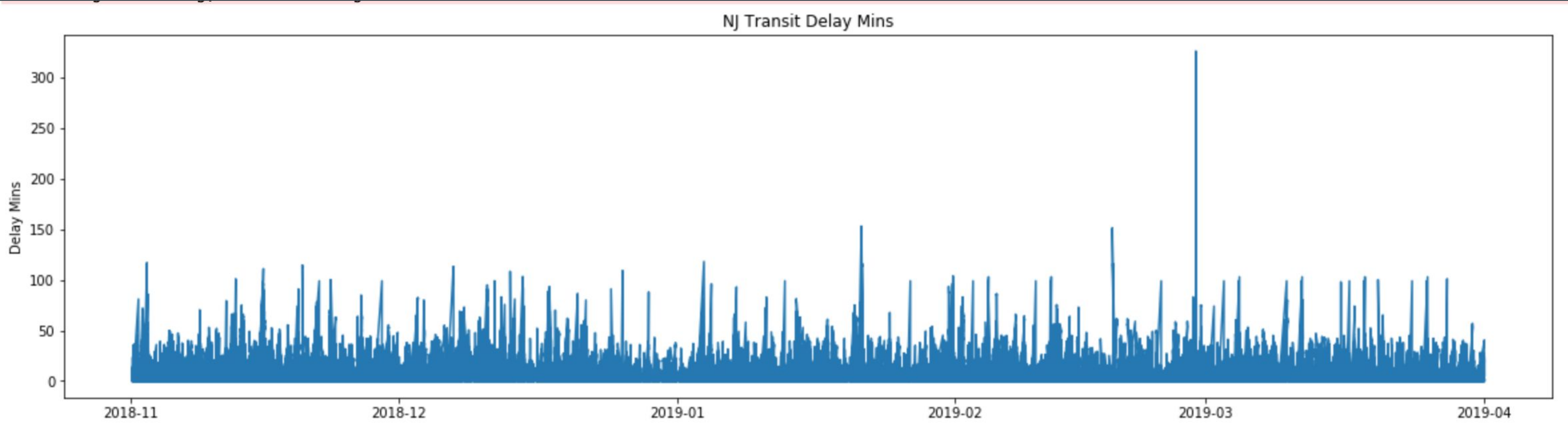


We can easily see that around the end of February, there is a high delay of NJ Transit. We then check this abnormal situation in detail.

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| | date | train_id | stop_sequence | from_id | to_id | scheduled_time | actual_time | delay_minutes |
|---|---|---|---|---|---|---|---|---|
| scheduled_time | | | | | | | | |
| 2019-02-27 21:19:00 | 2019-02-27 | 3284 | 2.0 | 74.0 | 73.0 | 2019-02-27 21:19:00 | 2019-02-28 02:44:00 | 325.0 |
| 2019-02-27 21:23:00 | 2019-02-27 | 3284 | 3.0 | 73.0 | 130.0 | 2019-02-27 21:23:00 | 2019-02-28 02:48:00 | 325.0 |
| 2019-02-27 21:28:00 | 2019-02-27 | 3284 | 4.0 | 130.0 | 85.0 | 2019-02-27 21:28:00 | 2019-02-28 02:54:00 | 326.0 |
| 2019-02-27 21:34:00 | 2019-02-27 | 3284 | 5.0 | 85.0 | 59.0 | 2019-02-27 21:34:00 | 2019-02-28 02:59:00 | 325.0 |
| 2019-02-27 21:38:00 | 2019-02-27 | 3284 | 6.0 | 59.0 | 37169.0 | 2019-02-27 21:38:00 | 2019-02-28 03:03:00 | 325.0 |
| 2019-02-27 21:47:00 | 2019-02-27 | 3284 | 7.0 | 37169.0 | 139.0 | 2019-02-27 21:47:00 | 2019-02-28 03:13:00 | 326.0 |

This delay started from Long Branch to South Amboy and the line is North Jersey Coast Line. The final station of this train is NEW YORK PENN STATION. We then find the reason of the delay. According to the Tweets from @NJTRANSIT on Feb 27, 2019.

*Rail service in and out Penn Station New York is subject to up to 30-minute delays due to a disabled NJ TRANSIT train in one of the Hudson River Tunnels.*

*— NJ TRANSIT (@NJTRANSIT) February 27, 2019*

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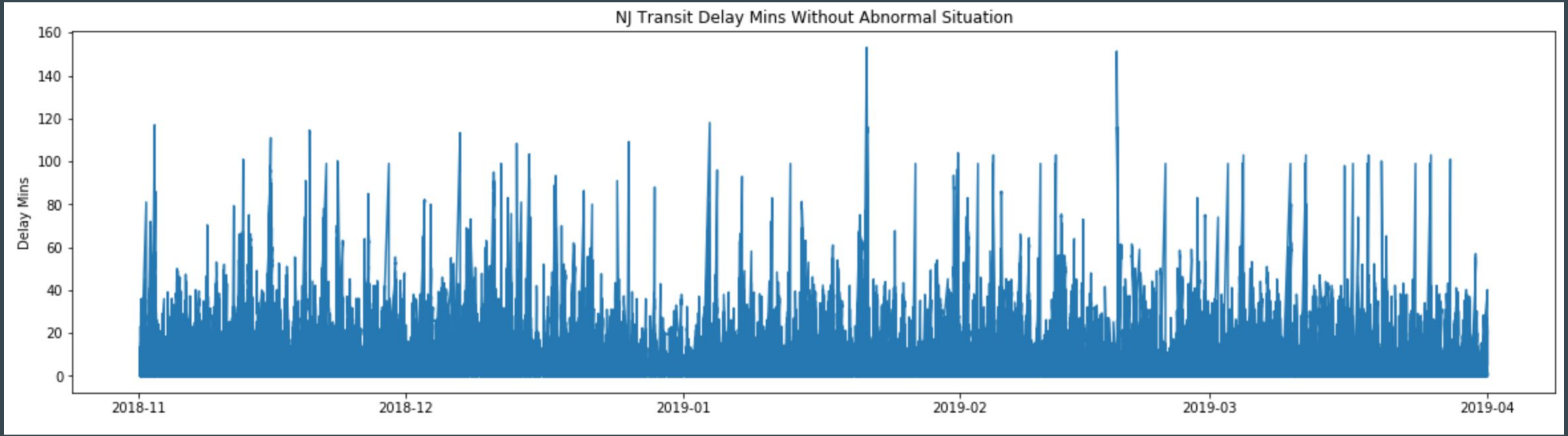


So, this delay was caused **by a disabled train which is not happened frequently,** we can remove these situations to have a better prediction.

We extract the data except these extreme values as our new dataset and check the plot again.

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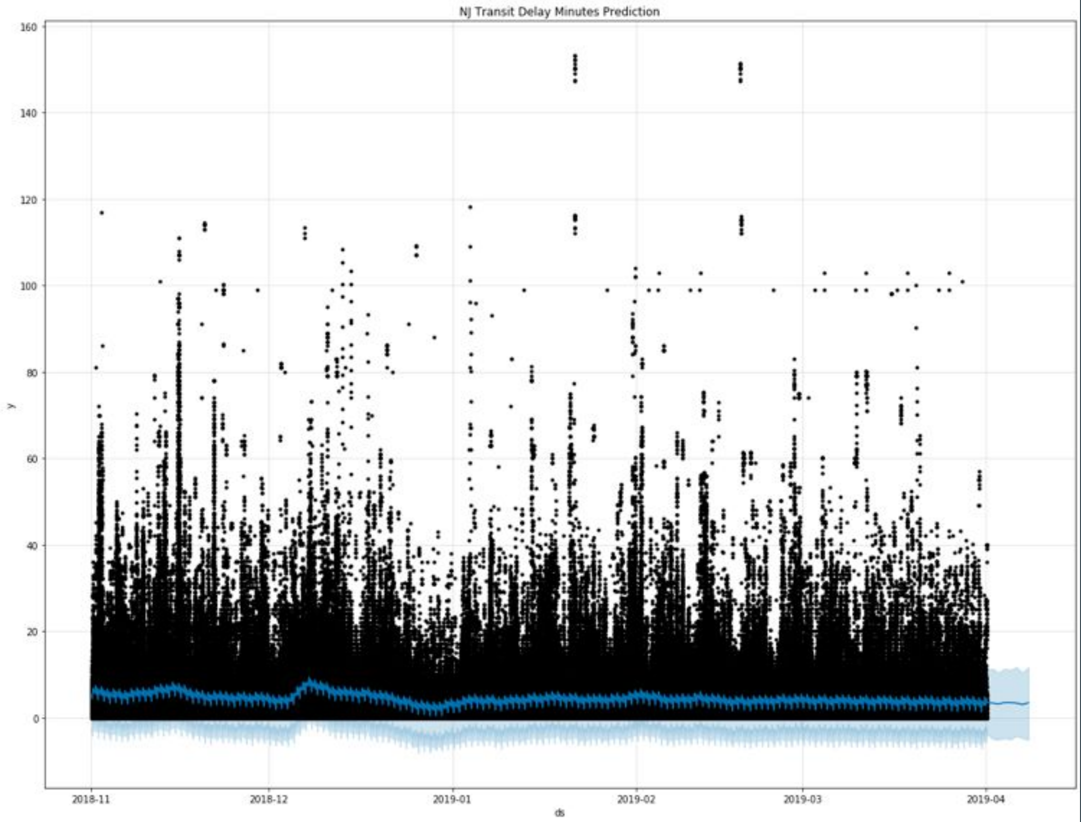
## MAKING FUTURE DF

We specify the number of **future periods to predict (one week ahead which is 7 days)** and the frequency of predictions (day). We then make predictions with the prophet model we created and the future dataframe.

Our future dataframes contain the estimated minutes and hours 7 days into the future. We can visualize predictions with the prophet plot function.



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## TRENDS AND PATTERNS

The last step of the analysis is to look at the **overall trend and patterns**. Prophet allows us to easily visualize the overall trend and the component patterns. We will split this plot into trend, yearly seasonality, and weekly seasonality of the time series.

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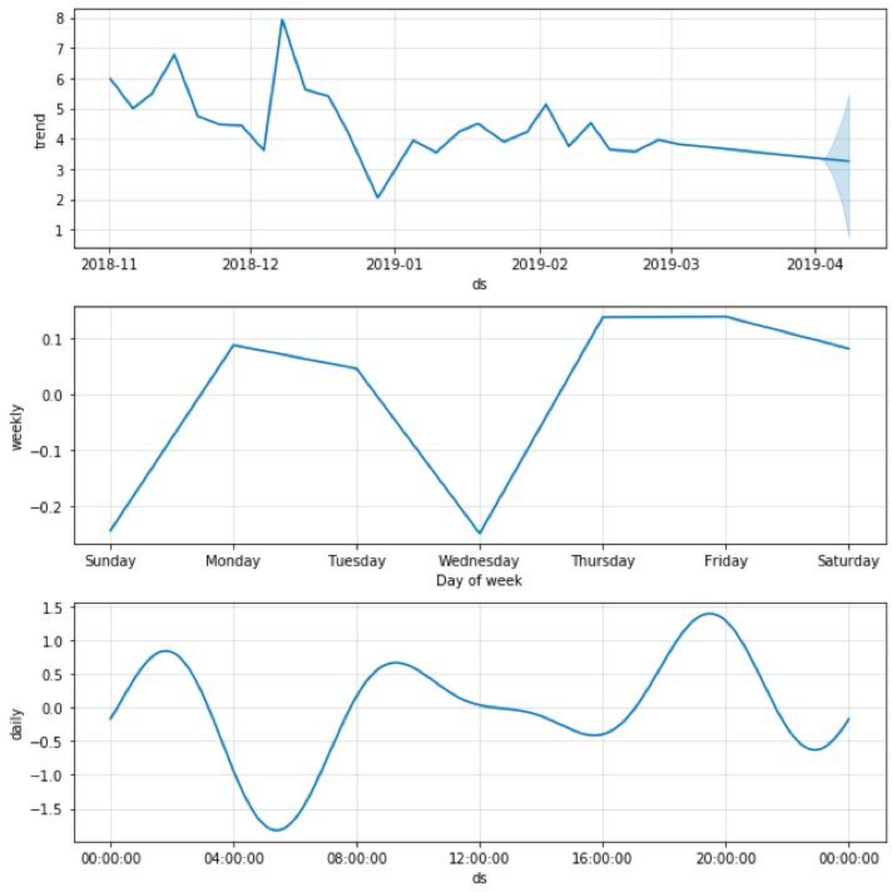
## TRENDS AND PATTERNS

The **overall trend** of delay minutes is decreasing.

During a week, **Sunday and Wednesday** are great days to take NJ Transit because they have least delay. On the opposite, trains on **Thursday** and Friday are more likely to be delayed.

During a day, **time around 9 am and 7 pm** are peak times because of the work commuters and trains also got many delays around **2 am.** This may because there are less train staff during this time.



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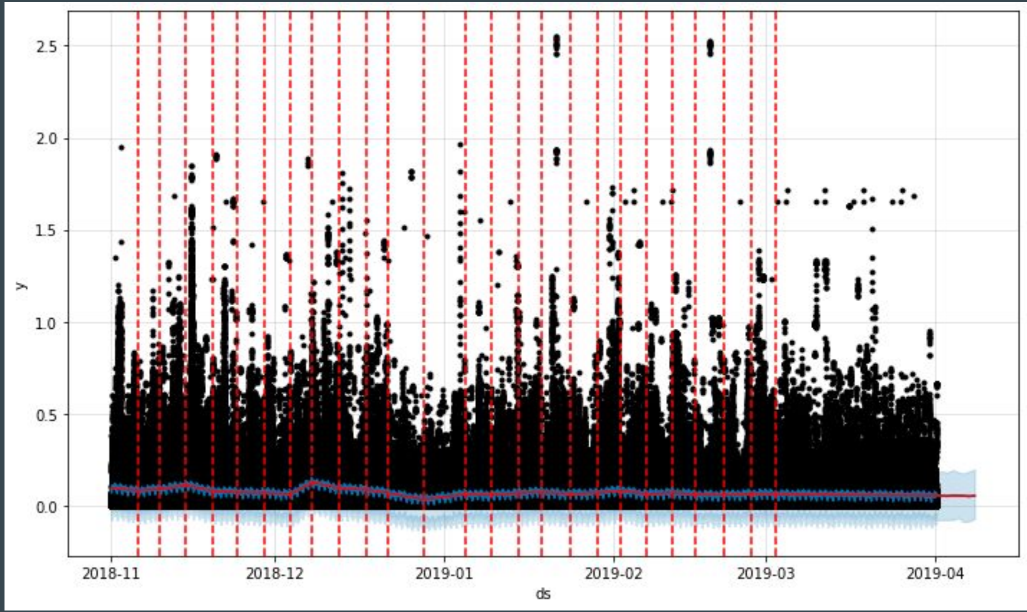
## TRENDS AND PATTERNS

Prophet also **detects changepoints** by first specifying a large number of potential changepoints at which the rate is allowed to change.

It then puts a sparse prior on the magnitudes of the rate changes (equivalent to L1 regularization)



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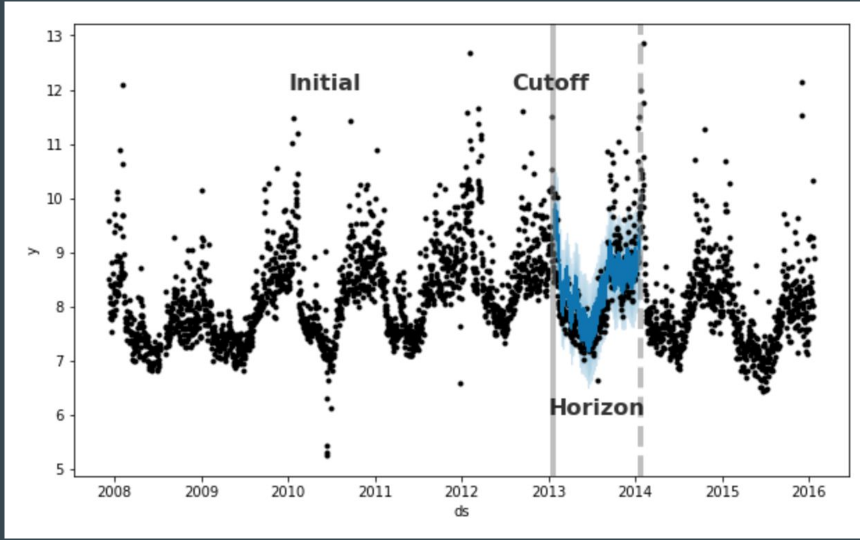
## DIAGNOSTICS

This cross validation procedure can be done automatically for a range of historical cutoffs using the **cross_validation function**.

We specify the forecast **horizon (horizon)**, and then optionally the size of the initial training **period (initial)** and the spacing between **cutoff dates (period)**. By default, the initial training period is set to three times the horizon, and cutoffs are made every half a horizon.



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## DIAGNOSTICS

The output of cross_validation is a dataframe with the **true values y** and the **out-of-sample forecast values yhat,** at each simulated forecast date and for each cutoff date.

In particular, a forecast is made for every observed point between cutoff and cutoff + horizon. This dataframe can then be used to **compute error measures of yhat vs. y.**

| | ds | yhat | yhat_lower | yhat_upper | y | cutoff |
|---|---|---|---|---|---|---|
| 0 | 2018-11-25 03:13:00 | 3.004663 | -6.679809 | 12.765498 | 1.100000 | 2018-11-25 03:10:00 |
| 1 | 2018-11-25 03:22:00 | 2.836850 | -7.195098 | 12.394706 | 0.000000 | 2018-11-25 03:10:00 |
| 2 | 2018-11-25 03:48:00 | 2.385678 | -7.318251 | 12.243165 | 9.583333 | 2018-11-25 03:10:00 |
| 3 | 2018-11-25 03:54:00 | 2.294401 | -7.659857 | 11.229298 | 3.583333 | 2018-11-25 03:10:00 |
| 4 | 2018-11-25 04:00:00 | 2.209808 | -7.301374 | 11.838781 | 2.433333 | 2018-11-25 03:10:00 |

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## DIAGNOSTICS

The metrics include mean squared error, **MSE**、 root mean squared error, **RMSE**、 mean absolute error, **MAE**、 mean absolute percent error, **MAPE** and the **estimate coverage of yhat_lower and yhat_upper.**

The estimate coverage of yhat_lower and yhat_upper is high which means our prediction covers most real data.

INFO:fbprophet:Skipping MAPE because y close to 0

| | horizon | mse | rmse | mae | coverage |
|---|---|---|---|---|---|
| 0 | 15:27:00 | 24.845259 | 4.984502 | 3.333910 | 0.941077 |
| 1 | 15:28:00 | 24.880525 | 4.988038 | 3.337846 | 0.940909 |
| 2 | 15:29:00 | 24.989466 | 4.998947 | 3.345184 | 0.940615 |
| 3 | 15:30:00 | 25.084558 | 5.008449 | 3.349188 | 0.940500 |
| 4 | 15:31:00 | 25.120285 | 5.012014 | 3.352801 | 0.940371 |

# THNAK YOU