Hourly Traffic Volume Forecasting

DATS 6450: Time Series Analysis and Modeling
Term Project

Rayna Liu

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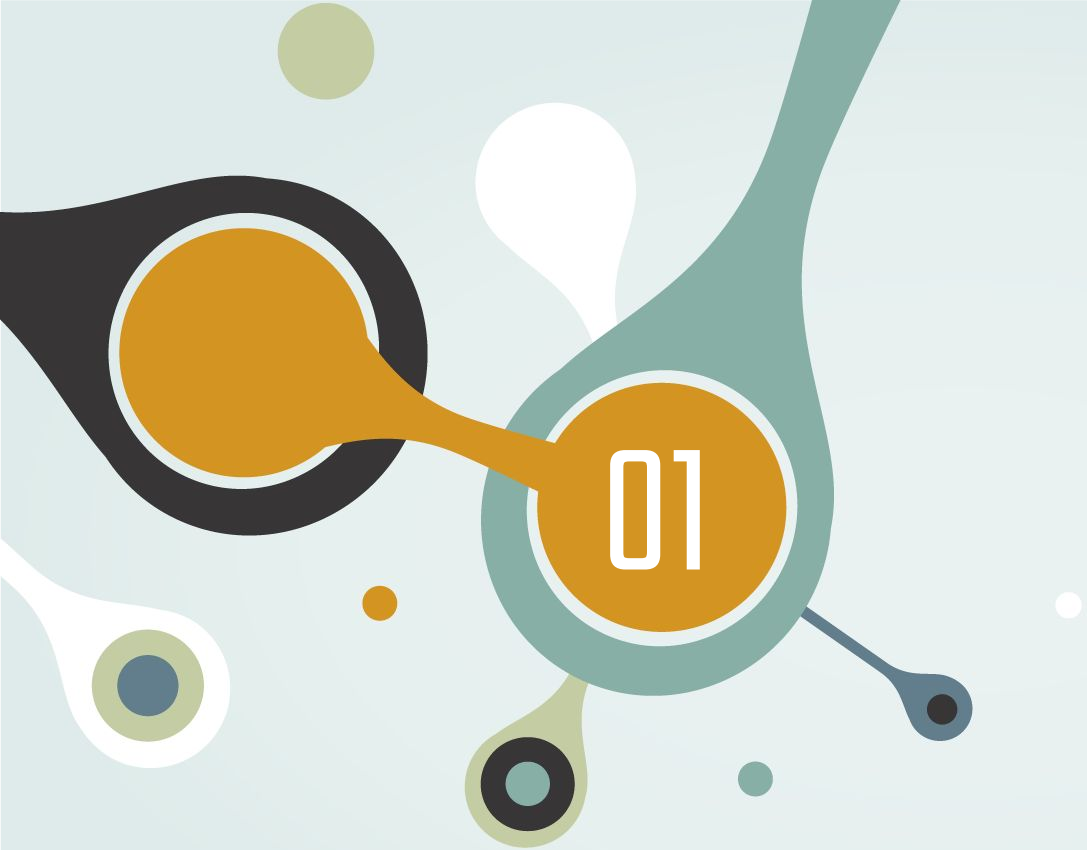


Introduction

Traffic volume forecasts are used by many transportation analysis and management systems to better characterize and react to fluctuating traffic patterns. [1]

The purpose of this term project is to find the best model to forecast the hourly traffic volume by developing, analyzing and comparing couples of model.

Description of Dataset

02

- Data Preprocessing
- Dependent Variable v.s. Time
- ACF / PACF of Dependent Variable
- Correlation Matrix

About the Dataset

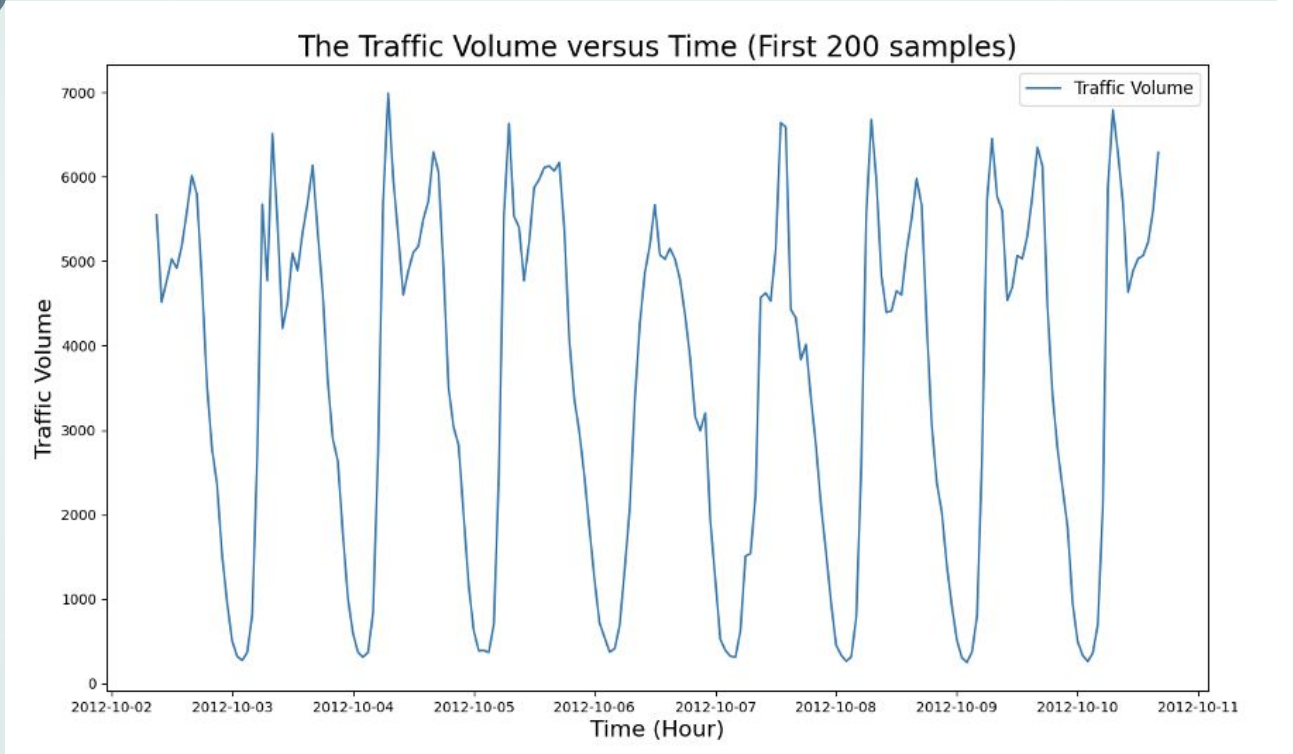
Metro Interstate Traffic Volume Dataset is about hourly Minneapolis-St Paul, MN traffic volume for westbound 1-94. It includes weather and holiday features from 2012-2018.[2] Link [Here].

- Missing data -- Replace with the mean hourly traffic volume
- 40,575 instances, 9 attributes
- DateTime range from 2012-10-02 09:00:00 to 2018-09-30 23:00:00

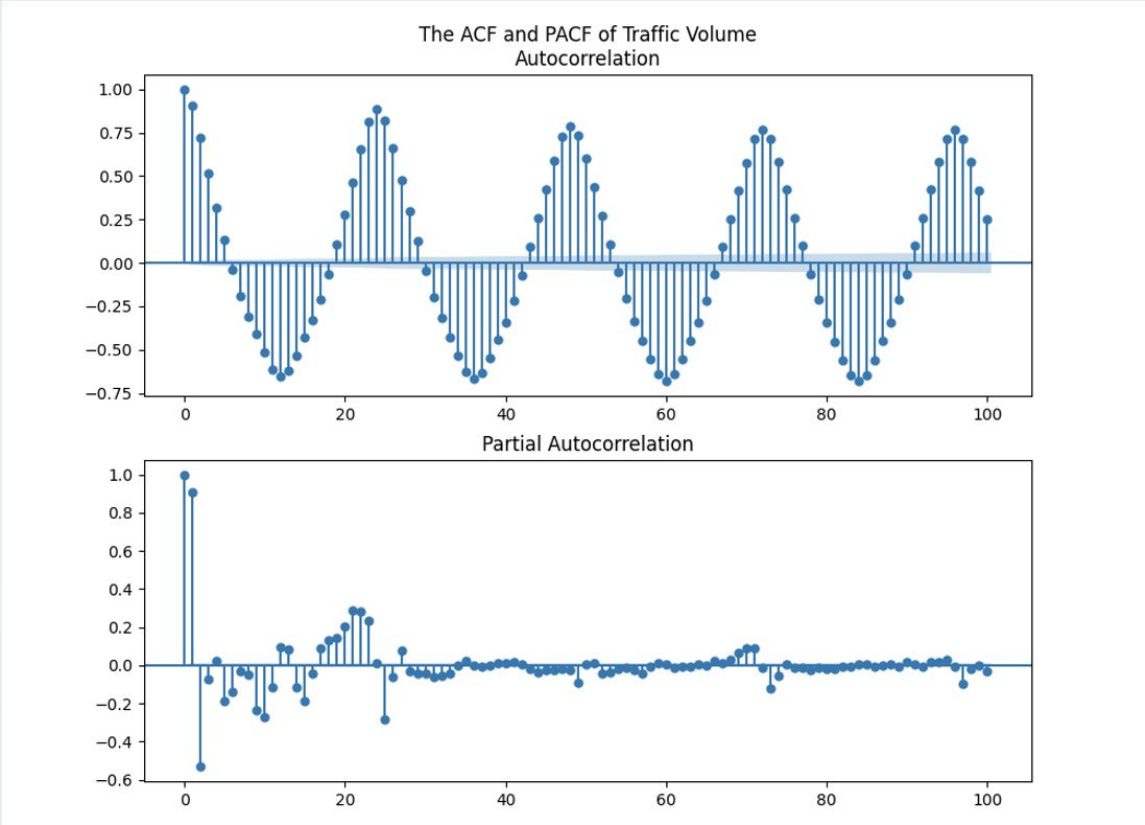
Attribute Information:

[holiday]	(Categorical) US National holidays plus regional holiday
[temp]	(Numeric) Average temperature in Kelvin
[rain_1h]	(Numeric) Amount in mm of rain that occurred in the hour
[snow_1h]	(Numeric) Amount in mm of snow that occurred in the hour
[clouds_all]	(Numeric) Percentage of cloud cover
[weather_main]	(Categorical) Short textual description of the current weather
[weather description]	(Categorical) Longer textual description of the current weather
[date_time]	(DateTime) Hour of the data collected in local CST time
[traffic_volume]	(Numeric) Hourly I-94 ATR 301 reported westbound traffic volume

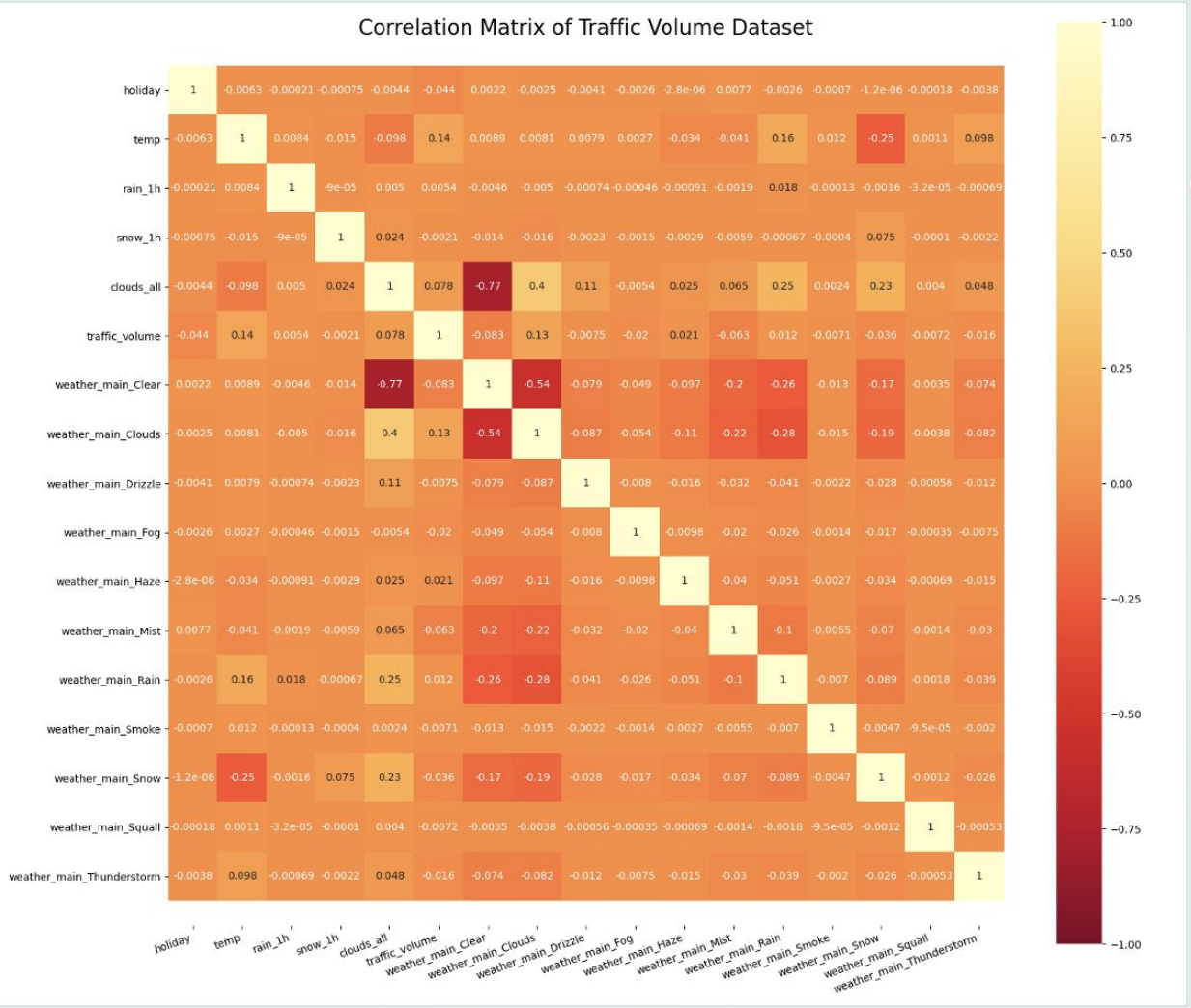
Traffic Volume over Time



ACF / PACF of Traffic Volume



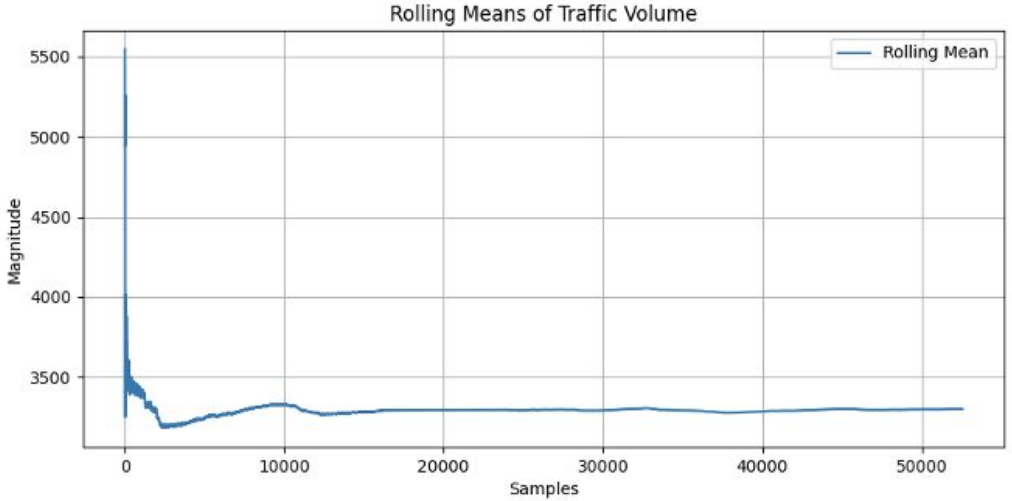
Correlation Matrix of Traffic Volume Dataset

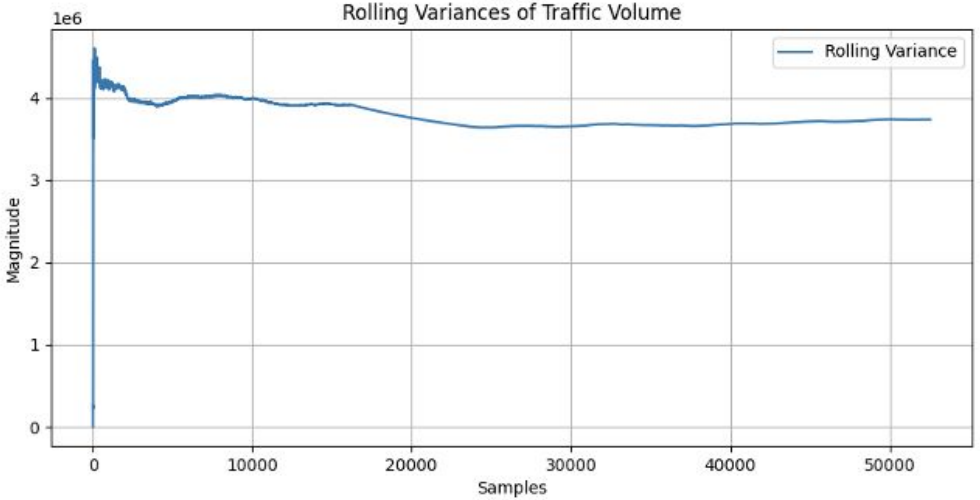


Stationary

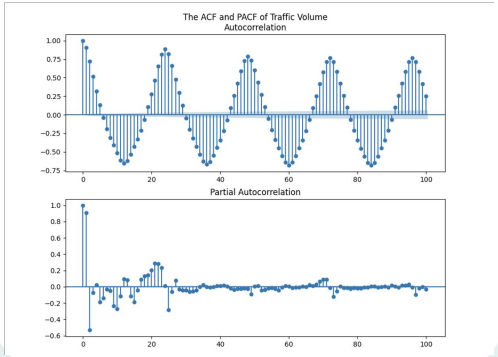
03

- ADF Test
- Plot of Rolling Mean and Variance
- Seasonal / Non-Seasonal Differencing



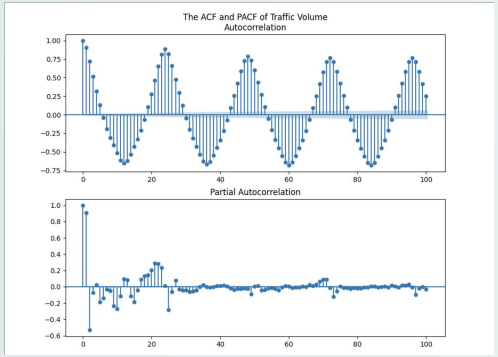



```
The ADF test of Traffic Volume:
ADF Statistic: -33.506261
p-value: 0.000000
Critical Values:
    1%: -3.430
    5%: -2.862
    10%: -2.567
```

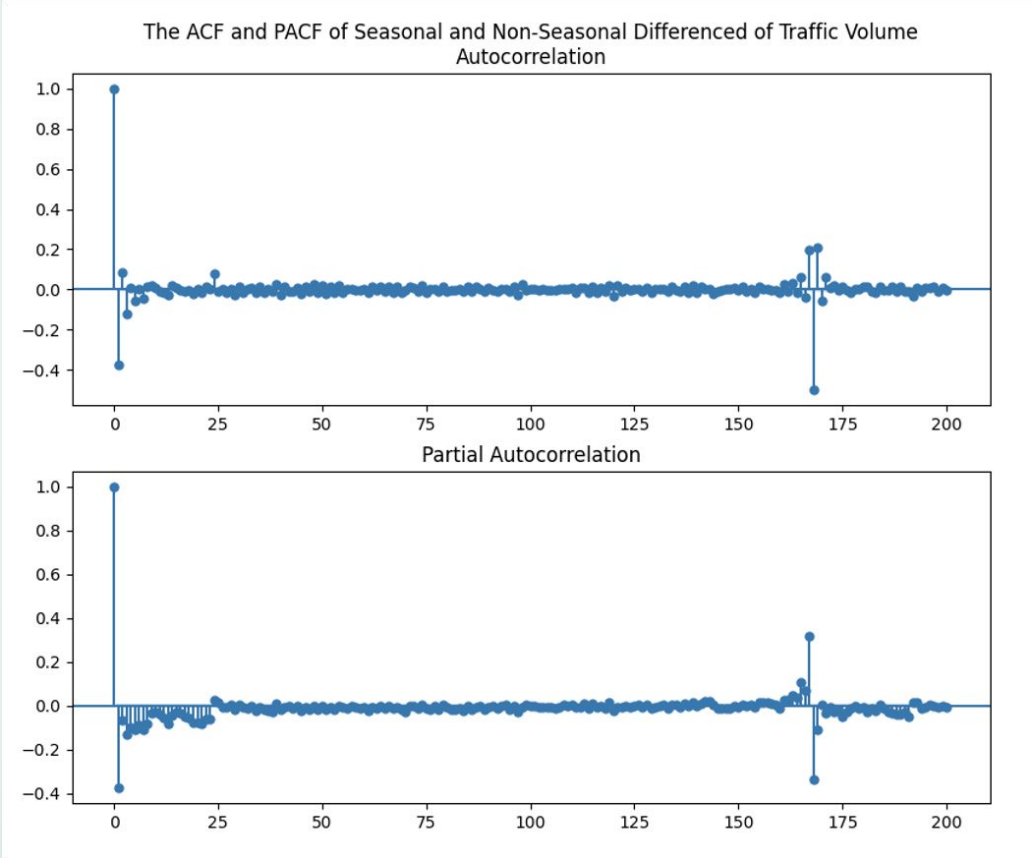


Apply Seasonal & Non-Seasonal Differencing

Before



After

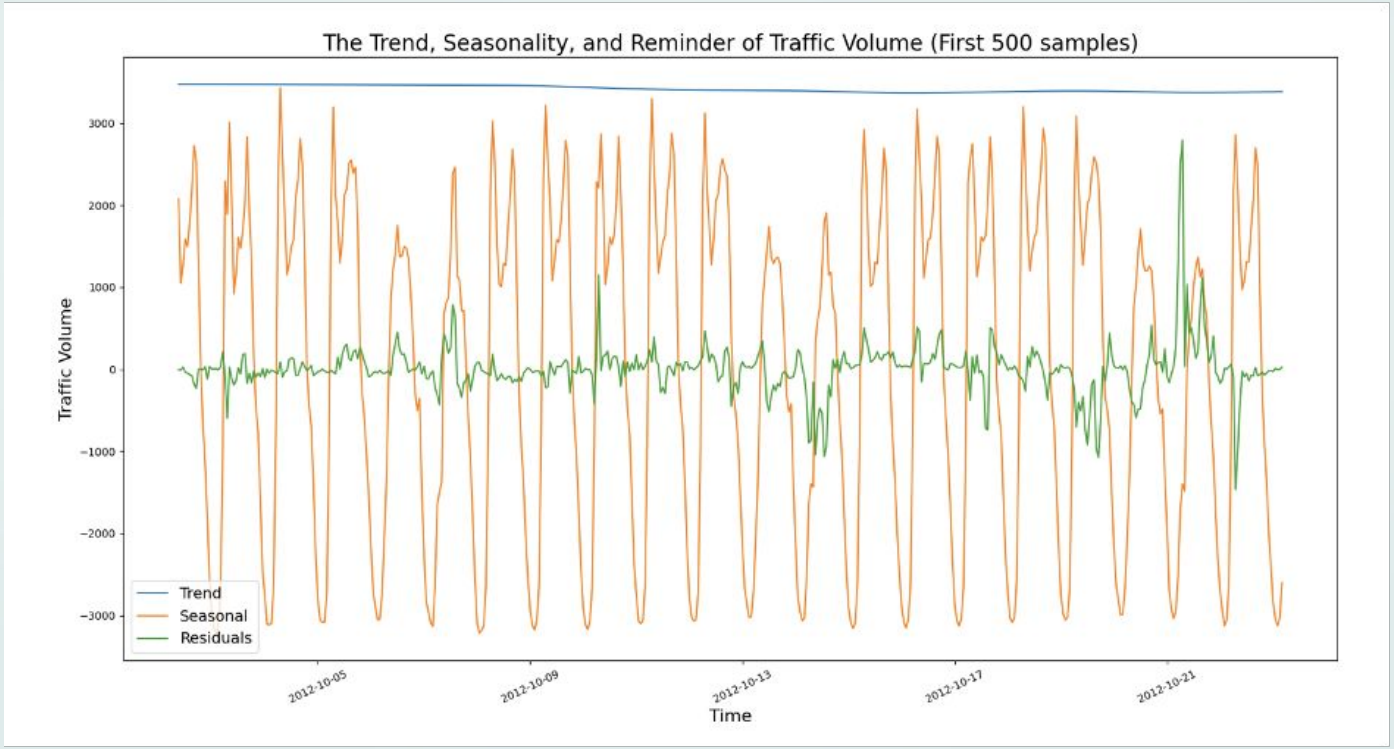


Time Series Decomposition

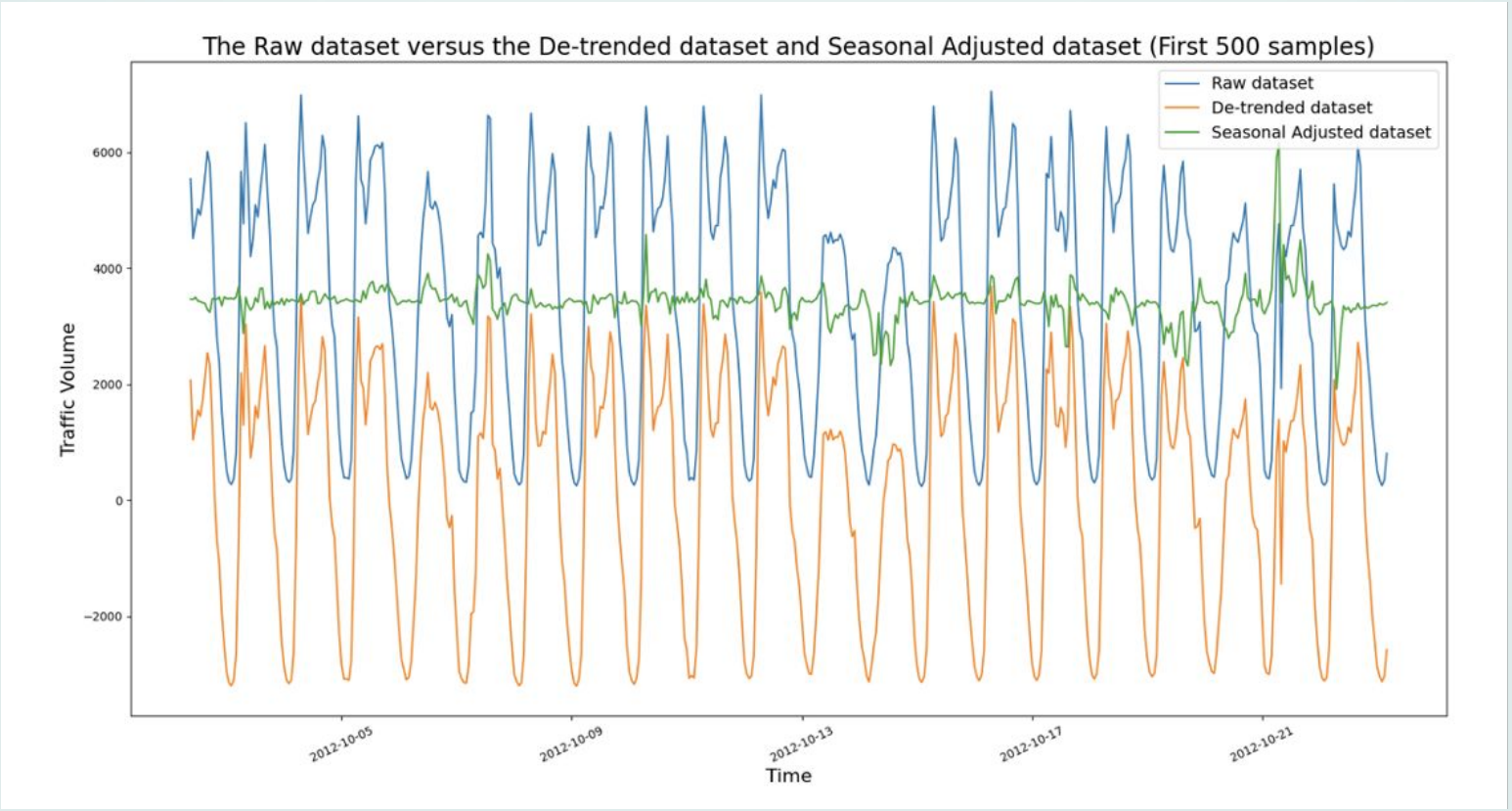
- STL Decomposition Method
- Strength of the Trend and Seasonality
- Plot of Raw Dataset v.s De-trended and Seasonally Adjusted Dataset

STL Decomposition Method

```
The strength of trend for the dataset is: 0.9999999022936712
The strength of seasonality for the dataset is: 0.9999995640033321
```



Plot of Raw Dataset v.s. the De-trended and Seasonally Adjusted Dataset

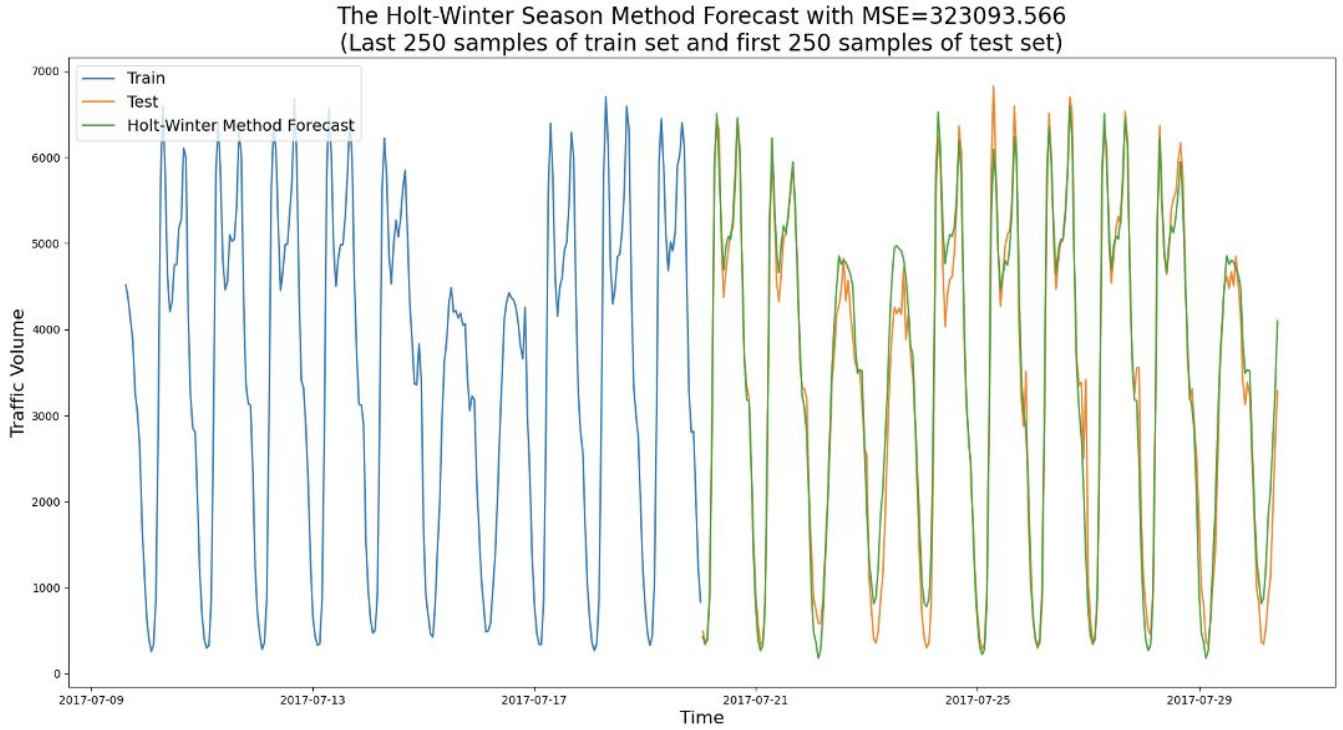


05

Holt-Winter Method

- Forecast v.s. Test set
- Forecast Analysis

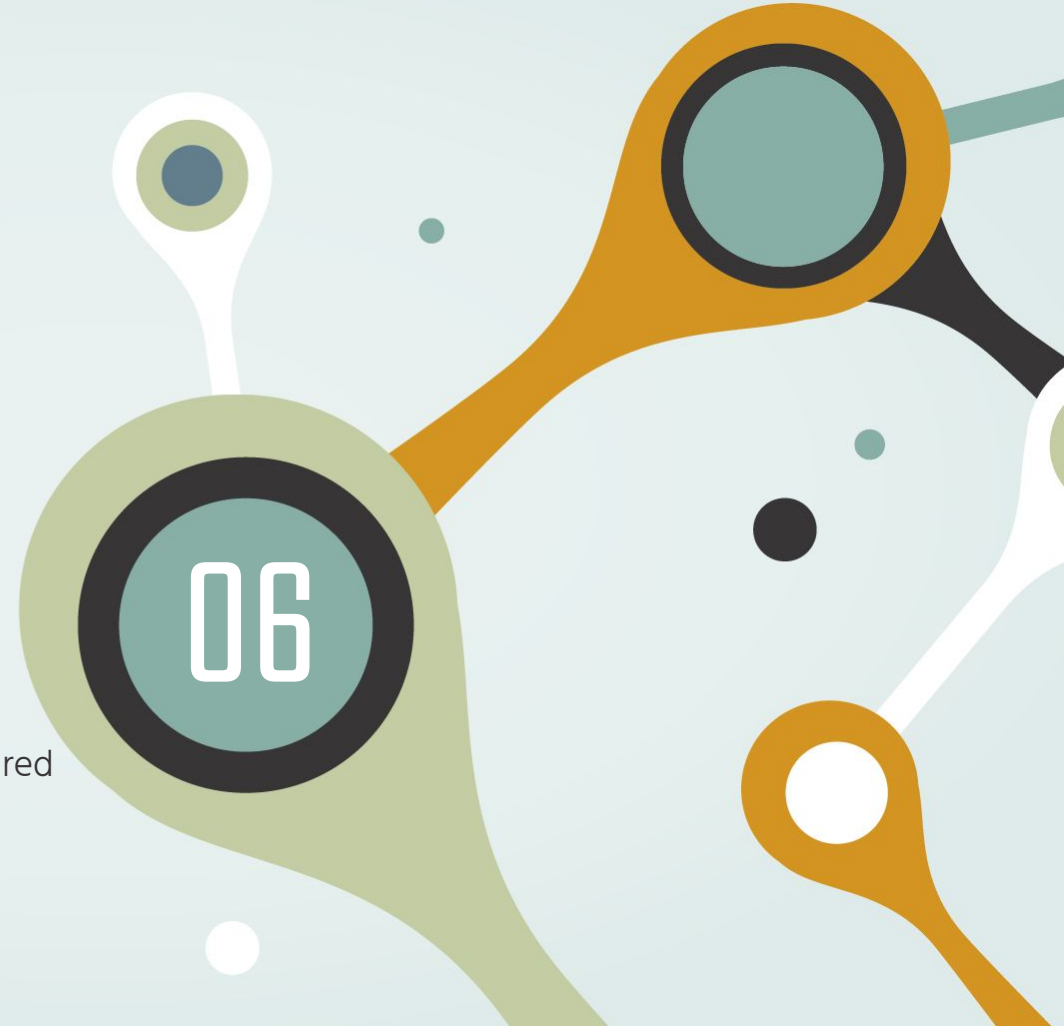
```
The mean of the forecast error of Holt-Winter Method is -173.642
The variance of the forecast error of Holt-Winter Method is 292941.916
The Q value of the forecast error of Holt-Winter Method is 42912.674
```



Multiple Linear Regression

06

- Collinearity Detection
- Feature Reduction
- Hypothesis Tests Analysis
- AIC,BIC,R-squared and Adjusted R-squared
- One-step ahead Forecast
- Residual Analysis

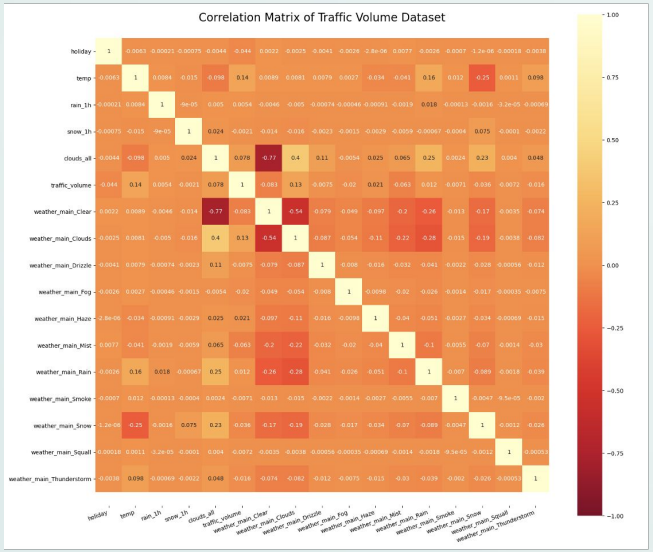


Singular Values Analysis & Condition Number

```
The Singular Values of the raw dataset is
 [3.29877152e+09 9.66769254e+07 6.00854893e+07 9.89448666e+03
 4.43254690e+03 3.63818579e+03 2.24000481e+03 9.58183058e+02
 5.96537323e+02 4.76176197e+02 2.20376316e+02 9.08586789e+01
 5.29185584e+01 1.64223293e+01 1.29977258e+00 1.08999732e+00
 2.26365803e-10]
The condition number of the raw dataset is 4.050636093231158e+17
```

Feature Reduction

Using a backward stepwise regression reduce the feature space dimension. First, generate the multiple linear regression model containing all potential predictors by using OLS function. Then, remove one predictor at a time.



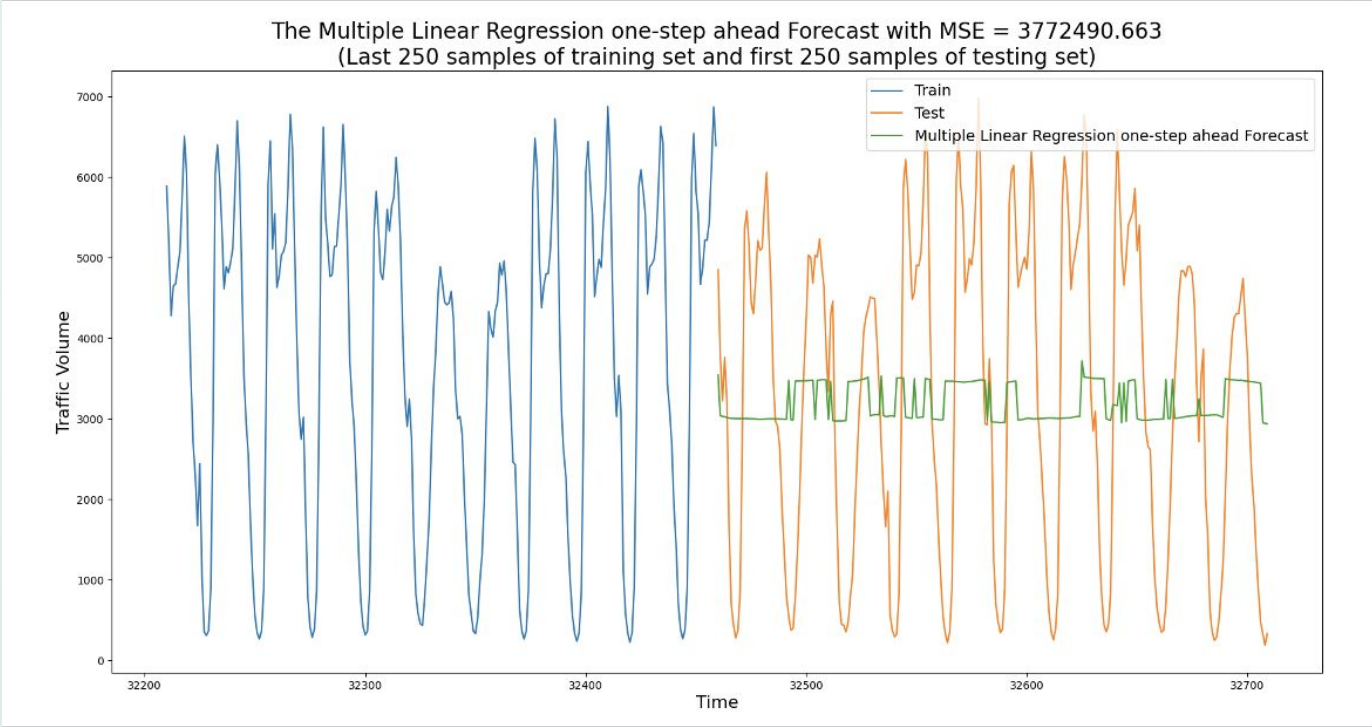

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          traffic_volume   R-squared:                       0.040
Model:                             OLS   Adj. R-squared:                  0.040
Method:                  Least Squares   F-statistic:                     90.64
Date:                 Wed, 05 May 2021   Prob (F-statistic):          6.61e-275
Time:                         19:00:28   Log-Likelihood:            -2.9193e+05
No. Observations:                32460   AIC:                         5.839e+05
Df Residuals:                    32444   BIC:                         5.840e+05
Df Model:                           15
Covariance Type:            nonrobust
================================================================================
================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const                      -3274.6339    277.321    -11.808      0.000   -3818.194   -2731.074
holiday                    -2398.9414    297.356     -8.068      0.000   -2981.770   -1816.113
temp                          22.0121      0.829     26.561      0.000      20.388      23.636
rain_1h                        0.1759      0.198      0.888      0.375      -0.213       0.564
snow_1h                      -17.1519   1711.426     -0.010      0.992   -3371.610    3337.307
clouds_all                     2.7994      0.463      6.042      0.000       1.891       3.707
weather_main_Clear           145.1102    172.954      0.839      0.401    -193.887     484.107
weather_main_Clouds          469.9697    171.551      2.740      0.006     133.724     806.215
weather_main_Drizzle         -69.9105    193.583     -0.361      0.718    -449.341     309.520
weather_main_Fog            -336.9471    218.491     -1.542      0.123    -765.198      91.304
weather_main_Haze            665.3154    185.097      3.594      0.000     302.518    1028.113
weather_main_Mist           -171.3682    174.357     -0.983      0.326    -513.114     170.378
weather_main_Rain            102.6721    173.958      0.590      0.555    -238.293     443.637
weather_main_Smoke          -956.3906    522.266     -1.831      0.067   -1980.052      67.271
weather_main_Snow            158.6635    176.159      0.901      0.368    -186.615     503.942
weather_main_Squall        -2772.9132   1786.933     -1.552      0.121   -6275.368     729.542
weather_main_Thunderstorm   -508.8354    199.626     -2.549      0.011    -900.109    -117.562
==============================================================================
Omnibus:                    23677.028   Durbin-Watson:                   0.242
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1897.051
Skew:                          -0.060   Prob(JB):                         0.00
Kurtosis:                       1.822   Cond. No.                     4.56e+17
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.27e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Final Multiple Linear Regression Model

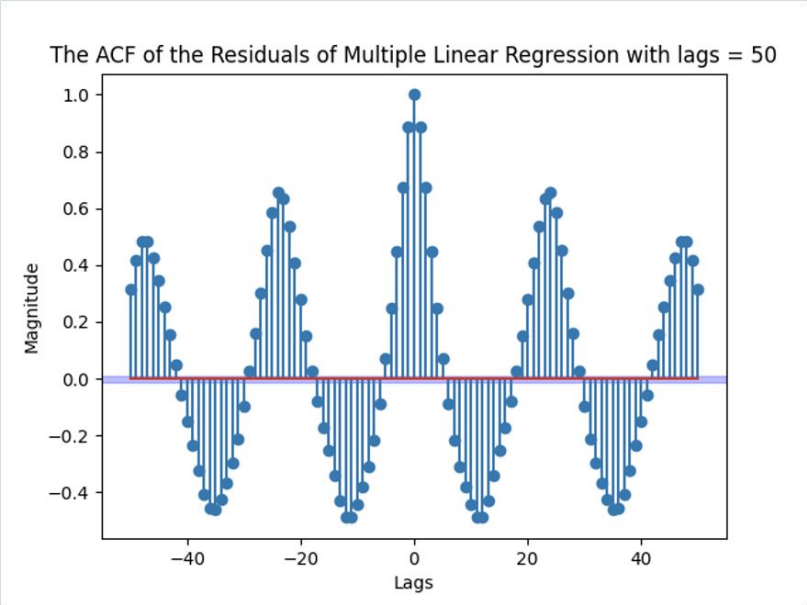
```
# ===== Final Model after Feature Selection =====
                            OLS Regression Results
==============================================================================================
Dep. Variable:         traffic_volume   R-squared (uncentered):                   0.740
Model:                            OLS   Adj. R-squared (uncentered):              0.740
Method:                 Least Squares   F-statistic:                          3.076e+04
Date:                Wed, 05 May 2021   Prob (F-statistic):                        0.00
Time:                        19:16:51   Log-Likelihood:                      -2.9211e+05
No. Observations:               32460   AIC:                                   5.842e+05
Df Residuals:                   32457   BIC:                                   5.843e+05
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------
temp                      10.9367      0.055    198.485      0.000      10.829      11.045
weather_main_Clouds      486.3230     23.353     20.825      0.000     440.551     532.095
weather_main_Rain        203.2478     35.164      5.780      0.000     134.326     272.170
==============================================================================
Omnibus:                    45793.638   Durbin-Watson:                   0.231
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2128.915
Skew:                          -0.082   Prob(JB):                         0.00
Kurtosis:                       1.756   Cond. No.                         940.
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
In[6]:
```

1-step ahead Forecast of MLR Model

```
The mean of the forecast error of MLR model is 72.238
The variance of the forecast error of MLR model is 3767272.396
The Q value of the forecast error of MLR model is 162366.193
```



ACF of Residuals

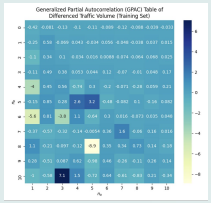



```
The mean of the residuals of MLR model is -6.133
The variance of the residuals of MLR model is 3875784.079
The Q-value of the residuals of MLR model is 363383.16
```

07

ARMA, ARIMA, SARIMA

- Order Determination
- Estimated Parameters of ARMA Model
- Diagnostic Analysis

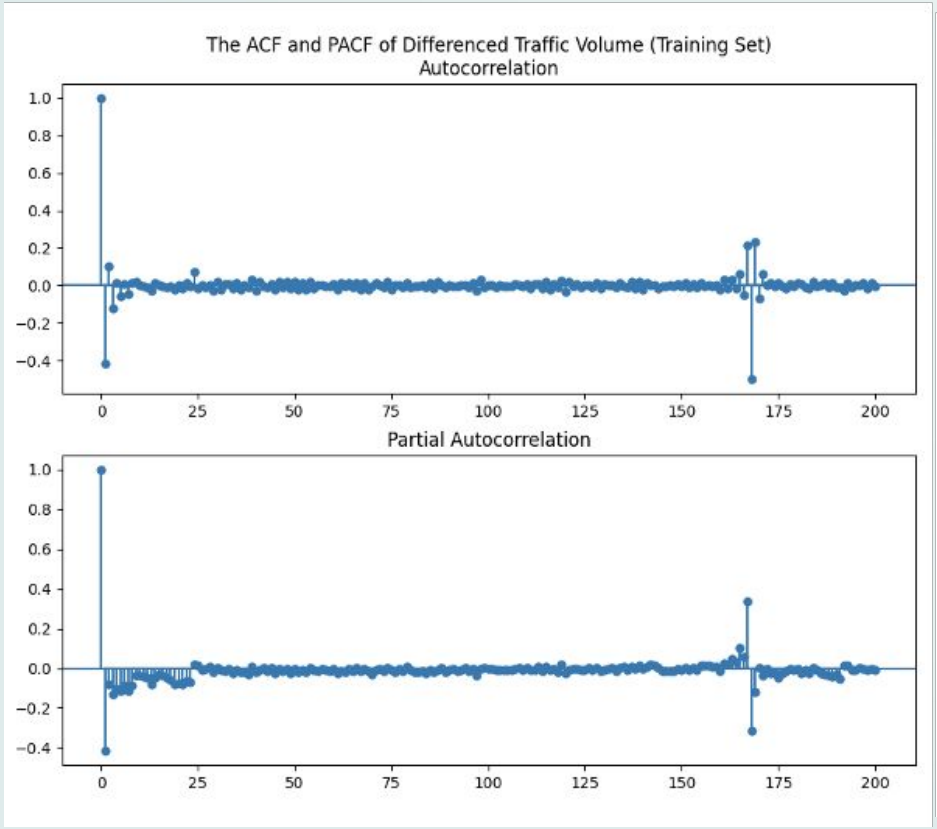


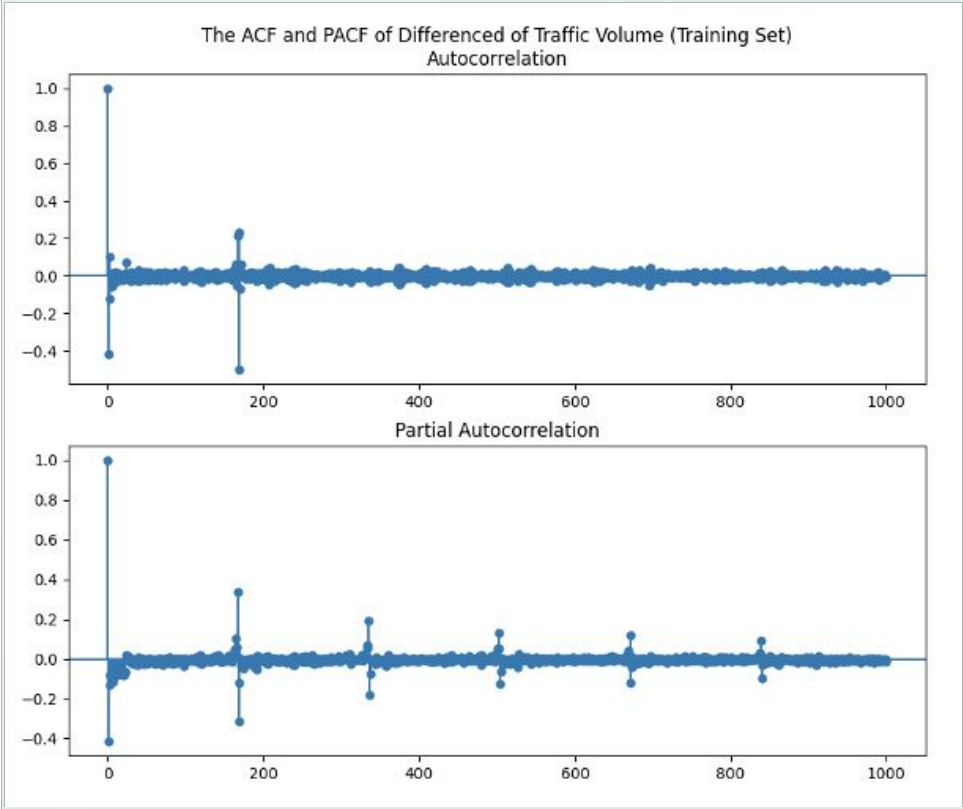
Order Determination

Estimate:

$ARIMA(0,1,3) \times ARIMA(0,1,1)_{168}$

$ARMA(0,171)$





EStimated Parameters of ARMA Model

ARMA Model Results

Dep. Variable:	y	No. Observations:	41905
Model:	ARMA(2, 2)	Log Likelihood	-318255.367
Method:	css-mle	S.D. of innovations	480.934
Date:	Wed, 05 May 2021	AIC	636520.734
Time:	09:31:33	BIC	636563.950
Sample:	0	HQIC	636534.384

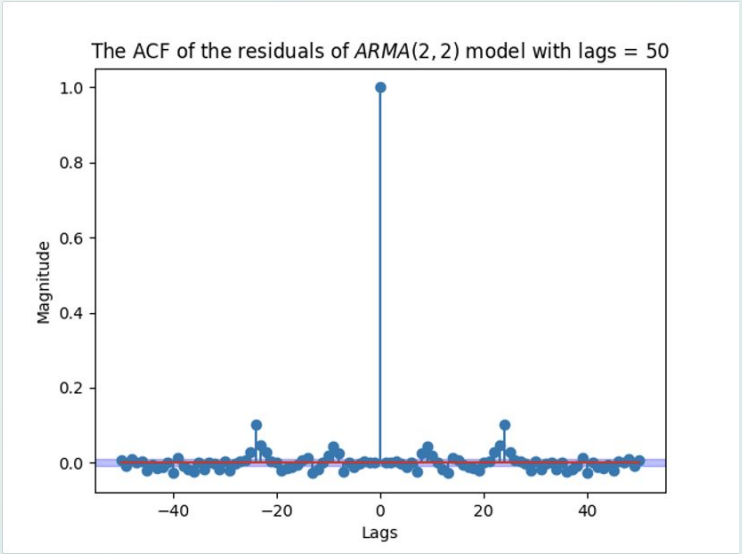
	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1.y	0.1934	0.020	9.708	0.000	0.154	0.232
ar.L2.y	0.3454	0.010	34.947	0.000	0.326	0.365
ma.L1.y	-0.7514	0.021	-35.982	0.000	-0.792	-0.710
ma.L2.y	-0.2159	0.020	-10.936	0.000	-0.255	-0.177

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	1.4445	+0.0000j	1.4445	0.0000
AR.2	-2.0045	+0.0000j	2.0045	0.5000
MA.1	1.0276	+0.0000j	1.0276	0.0000
MA.2	-4.5085	+0.0000j	4.5085	0.5000

```
The roots of numerator is
 [ 0.97323702 -0.22183702]
The roots of denominator is
 [-0.0967+0.57969743j -0.0967-0.57969743j]
```

```
The residual is NOT white
The Q value is [1258.32575539]
The chi critical is 131.141216667052
The p-value of chi square test is [1.40757232e-199]
```

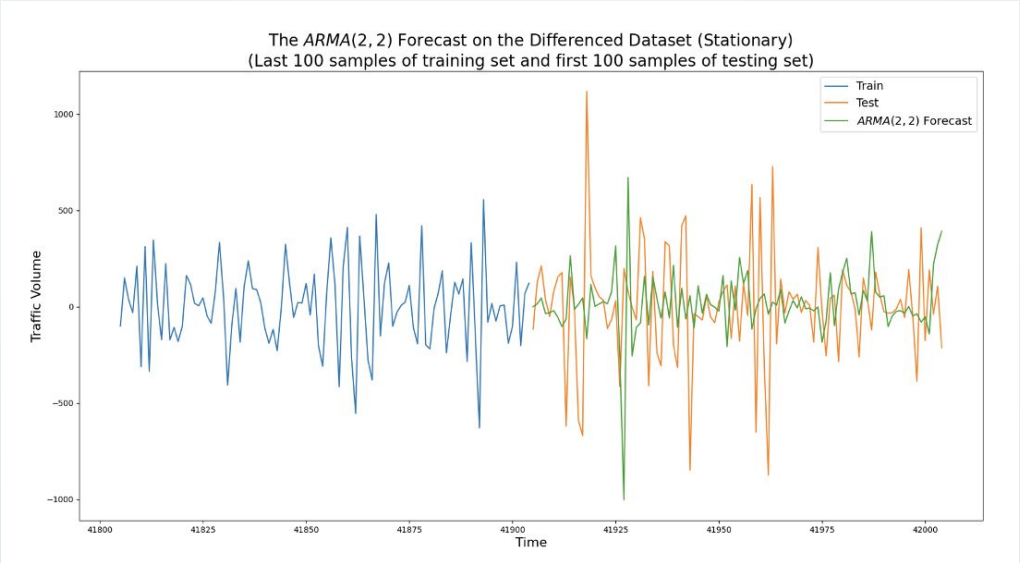


```
The estimated variance of error is 457221.63893733063
```

```
The estimated covariance of the a1 is 0.000528027316342l9
The estimated covariance of the a2 is 4.36157215150497 95e-05
The estimated covariance of the a3 is 0.0003914924749593 1077
The estimated covariance of the b1 is 0.0003750385575653475
```

```
The mean of the residual of ARMA(2,2) is -0.039
```

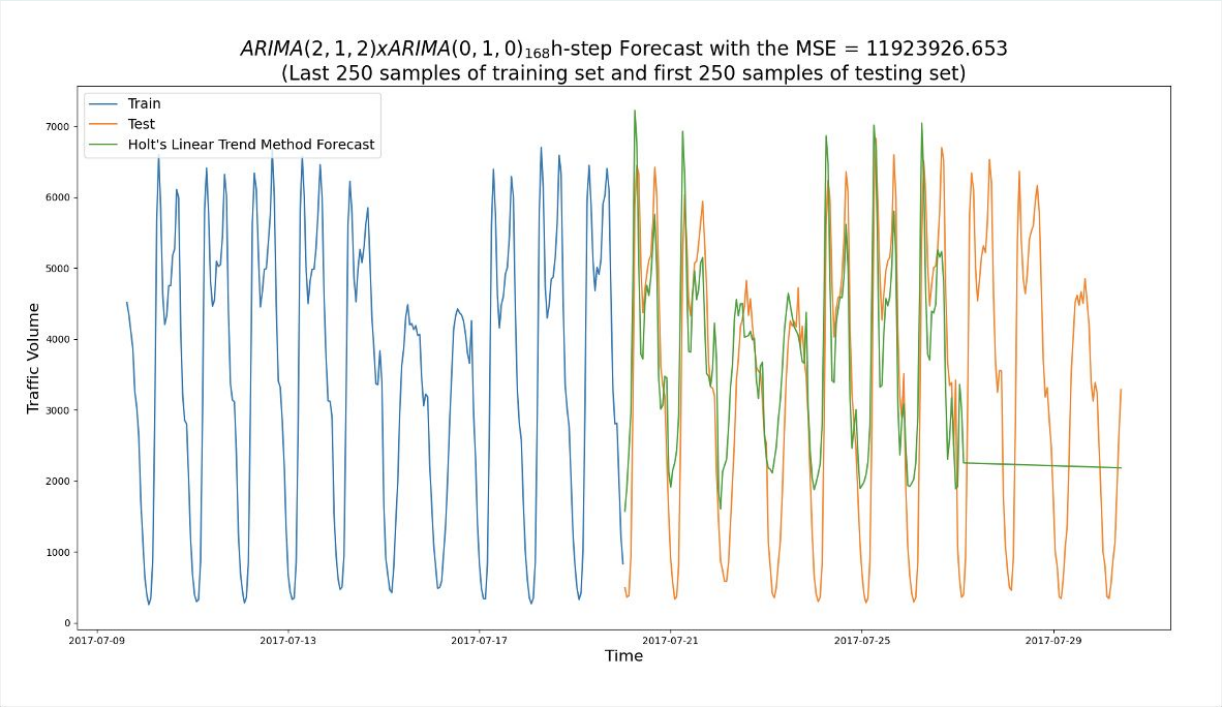
```
The variance of residual errors versus the variance of forecast errors is 0.935863574033126
```



ARMA(2,2) Forecast

ARMA(2,2) model could only forecast the differenced dataset (stationary). Convert the ARMA(2,2) process to SARIMA model, which could use for forecast the traffic volume of the raw dataset (non-stationary).

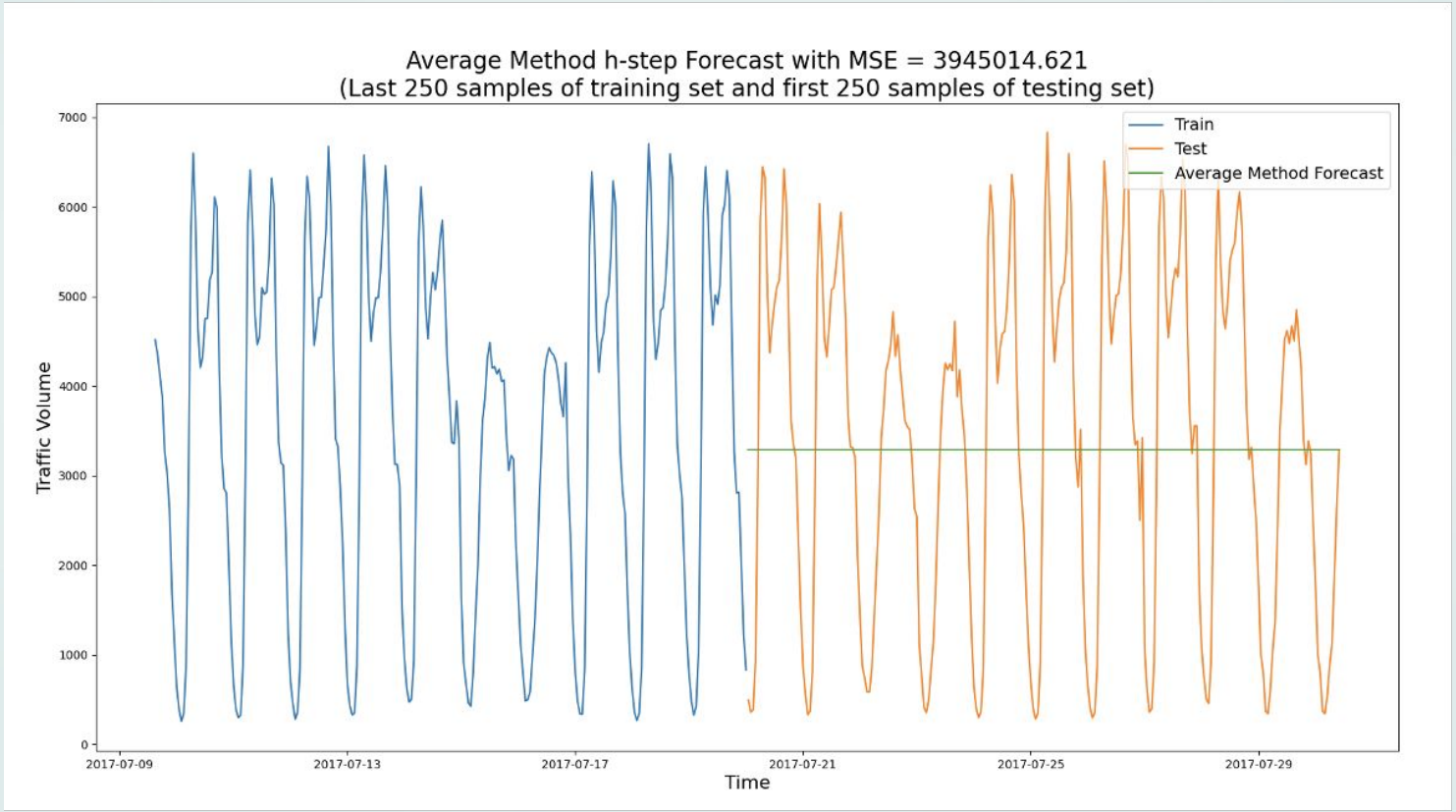
The forecast function convert from ARMA(2,2) is ARIMA(2,1,2)xARIMA$(0,1,0)_{168}$



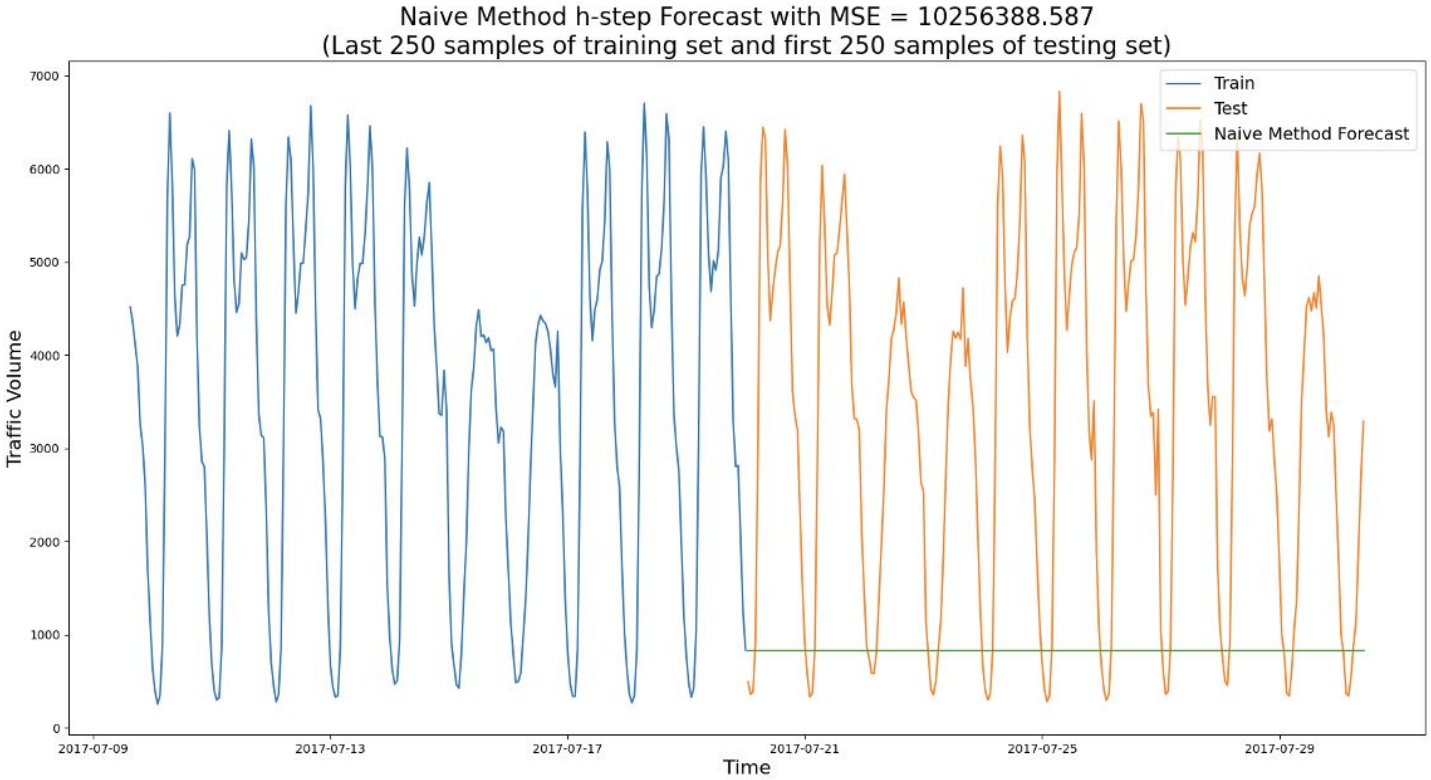
Based Models

- Average Method
- Naive Method
- Seasonal Naive Method
- Drift Method
- Simple Exponential Smoothing
- Holt’s Linear Trend Method

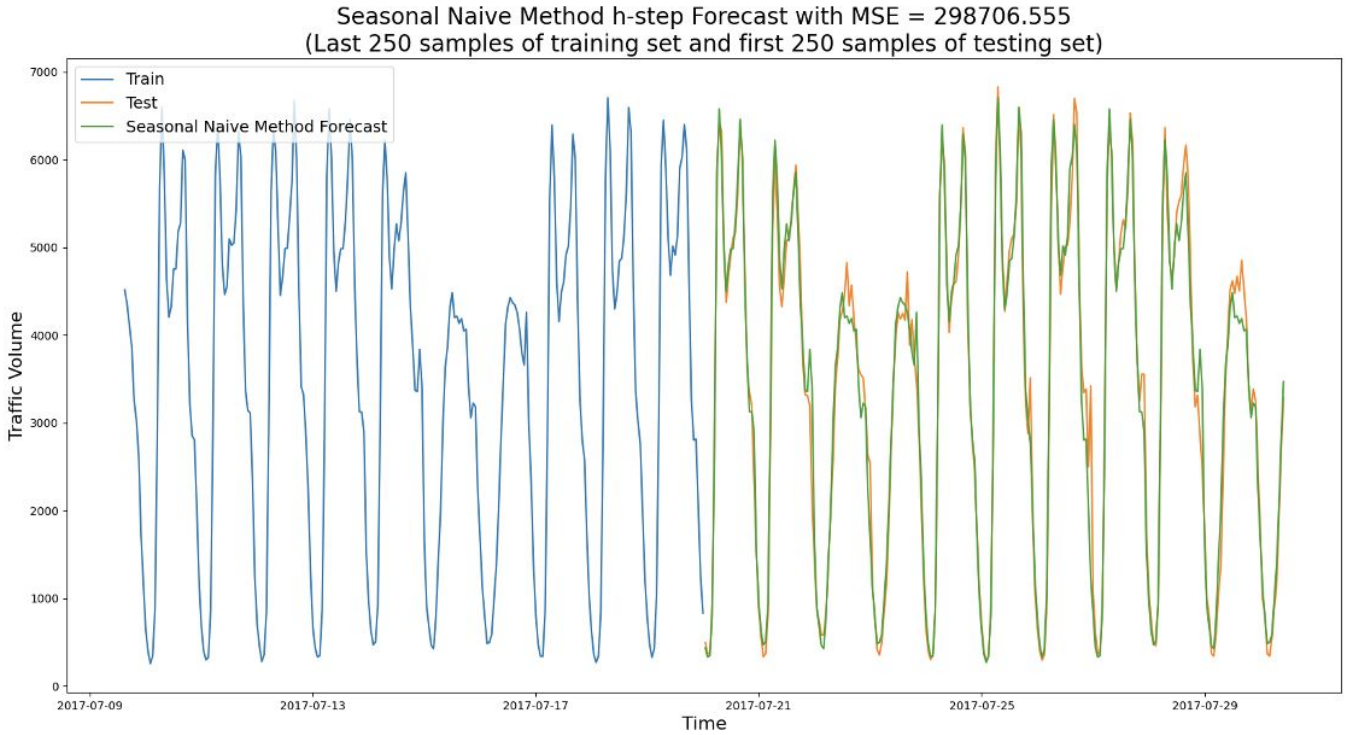
Average Method



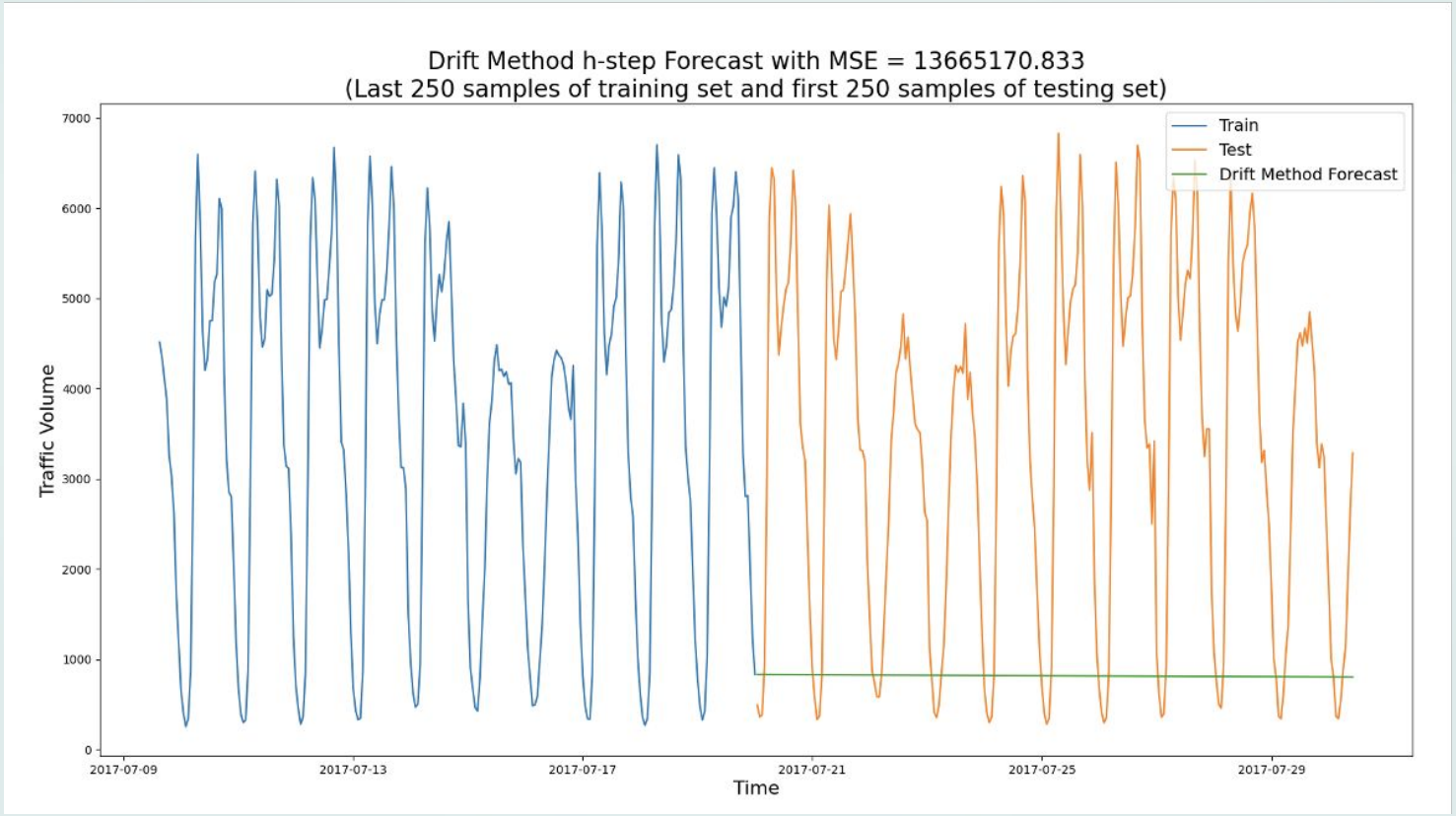
Naive Method



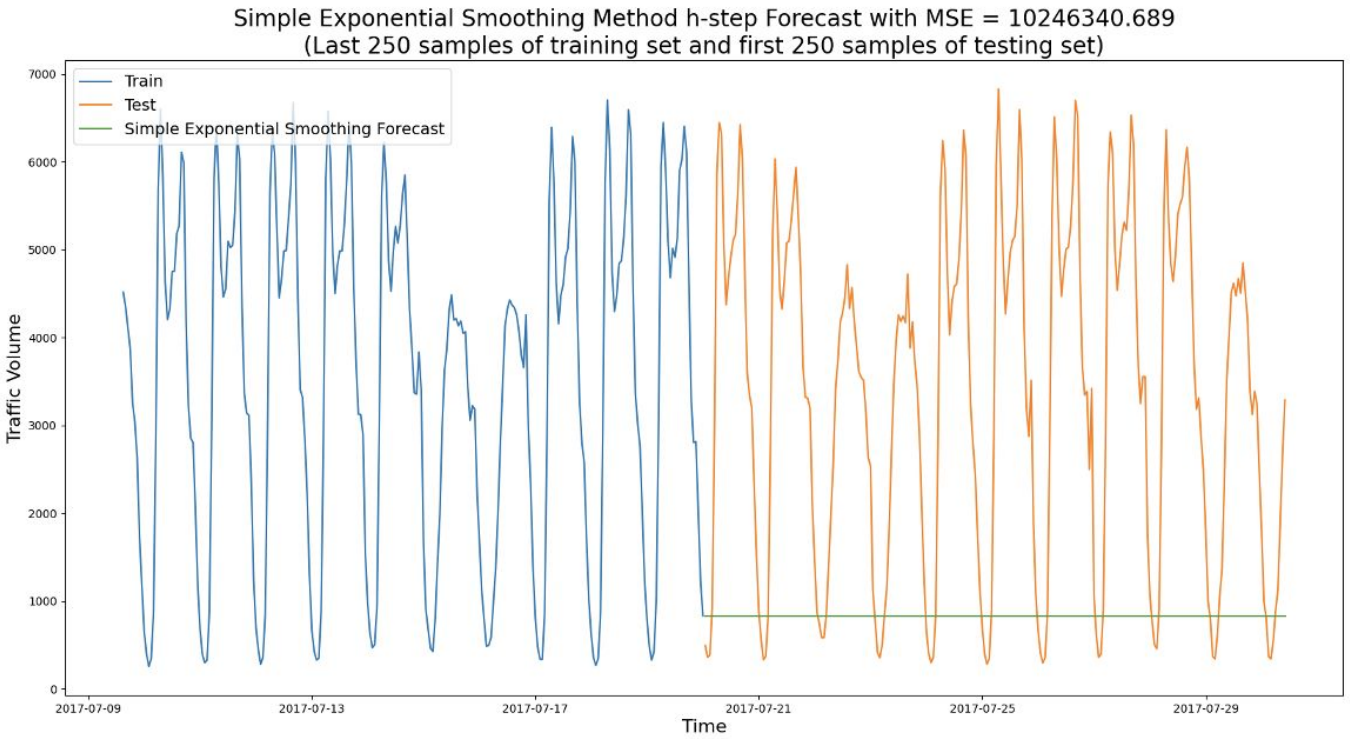
Seasonal Naive Method



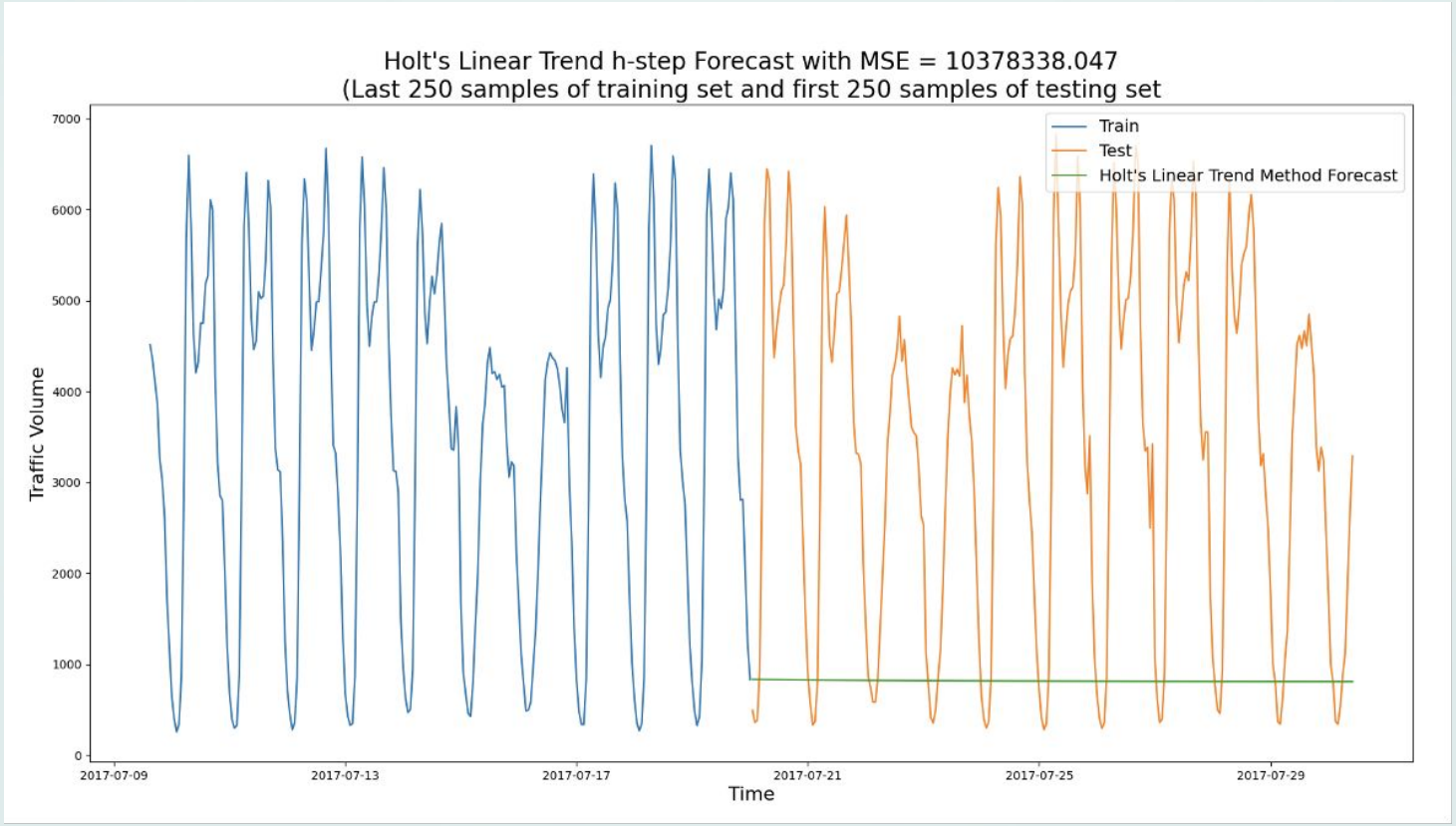
Drift Method



Simple Exponential Smoothing



Holt's Linear trend Method



09

Final Model Selection

- Forecast Function and h-step Prediction

The Comparison of 9 Forecast Method

	Method	Q value	MSE	Mean of Prediction Error	Variance of Prediction Error
0	Average Method	230379.23200	3945014.62100	53.75800	3942124.72200
1	Naive Method	230379.23200	10256388.58700	2512.82000	3942124.72200
2	Seasonal Naive Method	25900.39300	298706.55500	-96.25400	289441.66400
3	Drift Method	220901.75300	13665170.83300	3102.07100	4042326.17700
4	Simple Exponential Method	230379.23200	10246340.68900	2510.82000	3942124.72200
5	Holt's Linear Trend Method	230383.63000	10378338.04700	2536.97600	3942090.63500
6	Holt_Winter Method	42912.67400	323093.56600	-173.64200	292941.91600
7	Multiple Linear Regression	162366.19300	3772490.66300	72.23800	3767272.39600
8	ARIMA(2,1,2)xARIMA(0,1,0)_s168	200516.51300	11923926.65300	2756.97900	4322991.88800

Forecast Function and h-step ahead Prediction

In this case, I used the h-step ahead prediction function as the forecast function. For the Seasonal Naïve Method, the forecast for time $T + h$ is written as

$$\hat{y}_{T+h|T} = y_{T+h-m(k+1)}$$

where m = seasonal period, and k is the integer part of $\frac{h-1}{m}$

Summary & Conclusion

The naive seasonal method is as helpful for highly seasonal data as my traffic volume data. My final model generated by the naive seasonal method can predict future values correctly. I think the limitation of this model is its accuracy based on accurate estimation of the seasonal period. For example, the seasonal period of my dataset can be daily (s =24) or weekly(s =168). Still, if the 24 is used as the seasonal period for prediction, the effect is not as good as if the seasonal period is 168. Another limitation is that this method cannot account for week-to-week changes in level.

References

1. A Functional Data Analysis Approach to Traffic Volume Forecasting
   https://ieeexplore.ieee.org/document/7947181

2. Metro Interstate Traffic Volume Dataset
   https://archive.ics.uci.edu/ml/datasets/Metro+Interstate+Traffic+Volume#