MACHINE LEARNING FORECAST MODEL

IDENTIFYING LUXURY VEHICLE FLEET DEMAND

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DATA SCIENCE INTENSIVE CAPSTONE PROJECT

JUNE 30, 2021 COHORT

Springboard

The Data

Data Cleaning

Feature Removal

- private identifiers about customers
- no relevance to scope of project
- duplicate information
- high null value count

Maintaining Unknowns

- assigned string value “Not Applicable” to features with useful null observations

Categorical Features

- consulted dealership to get context on appropriate input values
- compared relevant features for context
- external web search for input values

Exploratory Data Analysis

Question 1

What are my target variables and what can be gathered about their distribution?

Target Variables

	ContractYearMonth	TotalSales
0	2004-06	53
1	2004-07	53
2	2004-08	79
3	2004-09	64
4	2004-10	81
...	...	...
149	2016-11	37
150	2016-12	52
151	2017-01	36
152	2017-02	33
153	2017-03	45

154 rows × 2 columns

Q1 Results:

The feature ***ContractYearMonth*** contains the timestamp of vehicle sales by month and year.

The feature ***TotalSales*** contains the sum of sales for each of these respective timestamps.

A distribution of 154 months across 14 years was observed

Question 2

Does the time series show any consistent pattern?

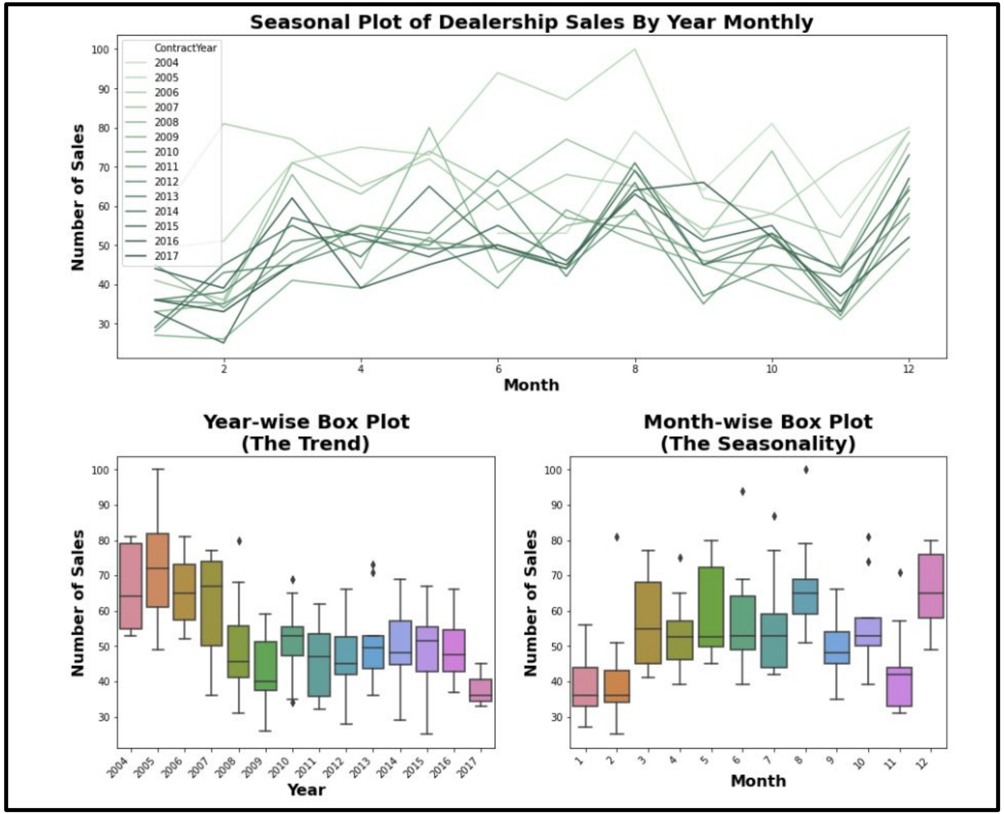
Conversion & Time Plots

- ➔ Strong seasonality within each year
- ➔ Strong cyclic behavior over a period of 2–4 years
- ➔ Downward trend beginning mid to late 2007
- ➔ 2005 appears to have outliers and values which need to be explained
- ➔ Missing observations from January to May of 2004 and April of 2017 and onward
- ➔ Clear decreasing fluctuation in 2008, which is also during the last year of the financial crisis of 2007-2008, and again in 2014

Question 3

Is there seasonality or a significant trend?

Seasonal Plots

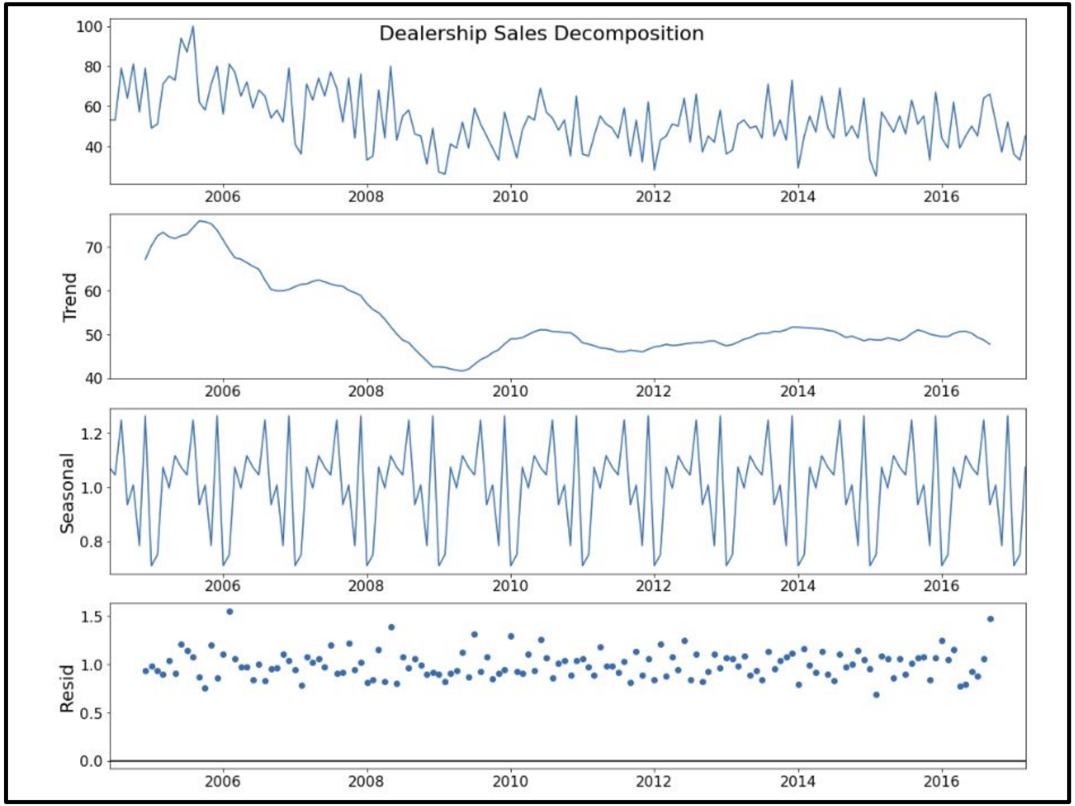


- ➔ Clear pattern of seasonal trend occurring every two months
- ➔ March, August, and December are typically in increasing fluctuation
- ➔ February, September, and November are always in decreasing fluctuation
- ➔ In the year-wise trend box plot clear outliers can be seen in 2008, 2010, and 2013
- ➔ In the month-wise seasonality box plot there are outliers in February(2), April(4), June(6), July(7), August(8), October(10), and November(11)
- ➔ clear downward trend yearly beginning in 2006 and a clear increasing fluctuation seasonally throughout the first two quarters of the year

Question 4

Since there is increasing and decreasing fluctuation over time in the data, what kind of model is appropriate for this time series?

Time Series Decomposition



➔ Downward trend beginning in late 2005 through 2009

➔ A climbing and dropping frequency that occurs every two years between 2010 through 2016, with 2010 having an increasing fluctuation

➔ Seasonal plot shows there is a pattern that occurs every two years

➔ Residual plot shows high variance in the early and late years of this time series.

Question 5

Is there any association between the years available and the number of units sold yearly?

Statistical Inference

<u>Hypothesis Test</u>

Ho:

every year = same average number of sales

Ha:

every year != same average number of sales

	TotalSales
ContractYear	
2004	66.571429
2005	72.583333
2006	65.500000
2007	61.833333
2008	48.916667
2009	42.333333
2010	51.333333
2011	46.333333
2012	47.583333
2013	50.500000
2014	50.500000
2015	48.666667
2016	49.583333
2017	38.000000

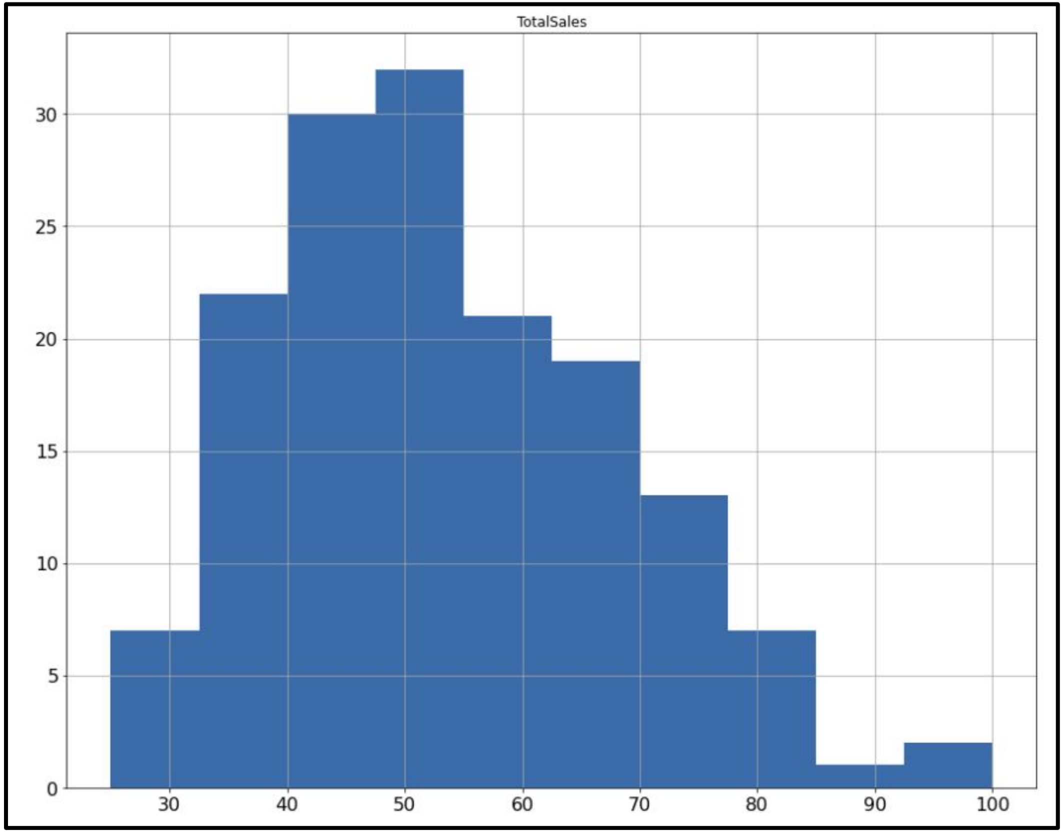
One-Way ANOVA F-test

	df	sum_sq	mean_sq	F	PR(>F)
ContractYear	13.0	12363.545455	951.041958	6.556096	1.197142e-09
Residual	140.0	20308.714286	145.062245	NaN	NaN

p-value = 0.000000001197142 **< 0.05**

Therefore, we reject the null hypothesis and accept the alternative hypothesis

Distribution of Observations



We can see from the histogram that the shape of the distribution of ***TotalSales*** observations yearly appears to be a right-skewed distribution. That is to say the mean is to the right of the median.

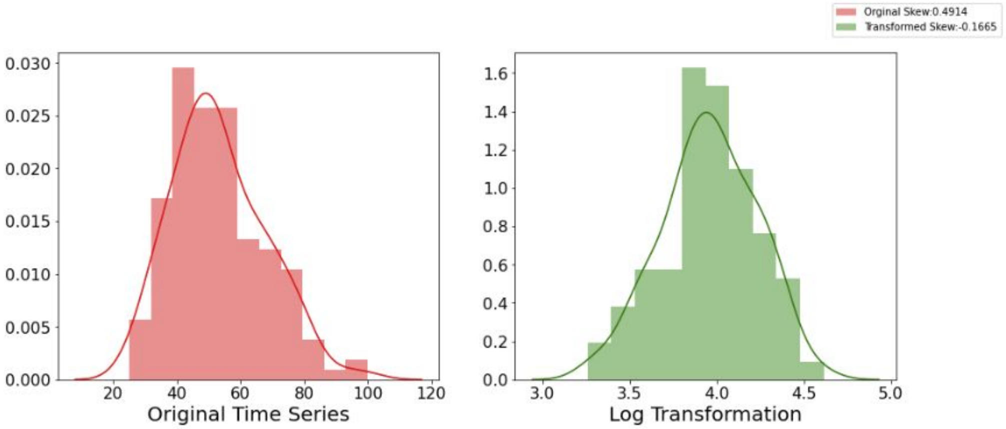
Therefore, we will need to transform the distribution of observations closer to a normal distribution.

To do so, we will use two methods and compare their results.

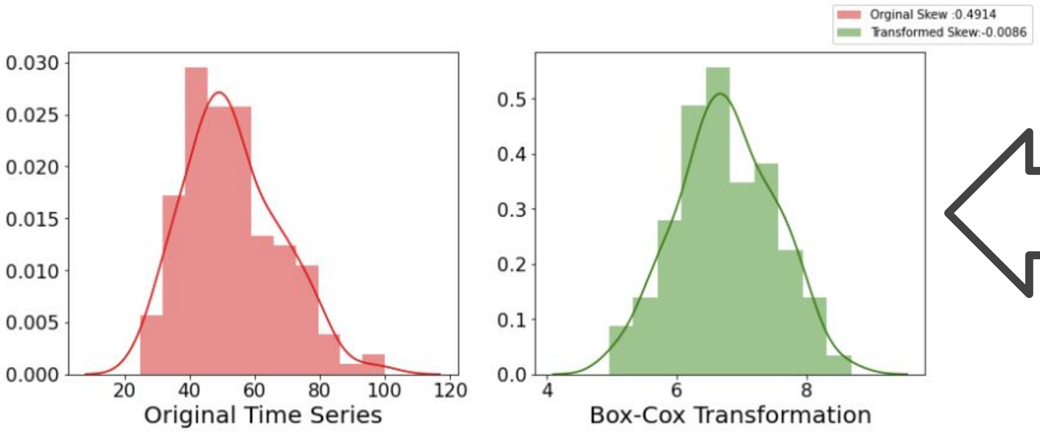
Transformations

Log Transformation reduced skewness from 0.4914 to -0.1665

* Note, the best skew value should be nearly zero




```
The best lambda is 0.2519673728602007
```



Box-Cox Transformation reduced skewness from 0.4914 to -0.0086

The box-cox transformation has proven to have the best results and will be used for the post-hoc test

Year vs. Year

Tukey's Honestly Significant Difference Test

Ho = no significant difference observed between the years

Ha = a significant difference has been observed between the years

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
2004	2005	0.2359	0.9	-0.783	1.2548	False
2004	2006	-0.0352	0.9	-1.0541	0.9837	False
2004	2007	-0.2389	0.9	-1.2578	0.78	False
2004	2008	-0.895	0.1514	-1.9139	0.1239	False
2004	2009	-1.2583	0.0034	-2.2771	-0.2394	True
2004	2010	-0.7303	0.4565	-1.7492	0.2886	False
2004	2011	-1.0076	0.0559	-2.0265	0.0113	False
2004	2012	-0.9426	0.1016	-1.9615	0.0763	False
2004	2013	-0.7783	0.3465	-1.7972	0.2406	False
2004	2014	-0.7816	0.3393	-1.8005	0.2373	False
2004	2015	-0.9043	0.1401	-1.9232	0.1146	False

As a result, we can now statistically confirm **2009** has the most statistically significant difference (negatively) in sales performance in comparison to **2004 through 2007**.

Also, **2017** has a notable statistically significant difference (negatively) in sales performance in comparison to **2004 through 2006** (whom have the highest sales performance, especially **2005**).

Lastly, **2013 and 2014** are the most statistically similar with -0.0033 mean difference. As well as, **2008 and 2015** with -0.0093 mean difference.

Preprocessing & Training

Augmented Dickey Fuller (ADF) Test

```
ADF Statistic: -2.586742
p-value: 0.095768
Critical Values:
        1%: -3.478
        5%: -2.882
        10%: -2.578
```

p-value 0.095768 **> 0.05**

Therefore, null hypothesis cannot be rejected and the time series appears **non-stationary**

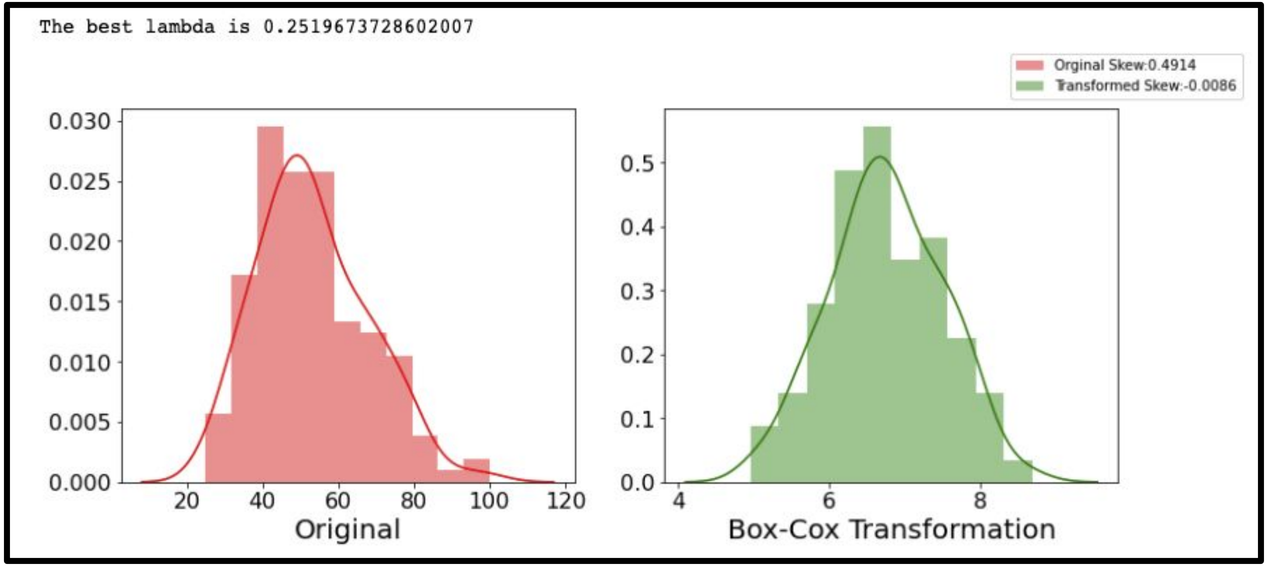
Kwiatkowski-Phillips - Schmidt-Shin (KPSS) Test

```
Results of KPSS Test:
Test Statistic              1.007066
p-value                     0.010000
Lags Used                   7.000000
Critical Value (10%)        0.347000
Critical Value (5%)         0.463000
Critical Value (2.5%)       0.574000
Critical Value (1%)         0.739000
```

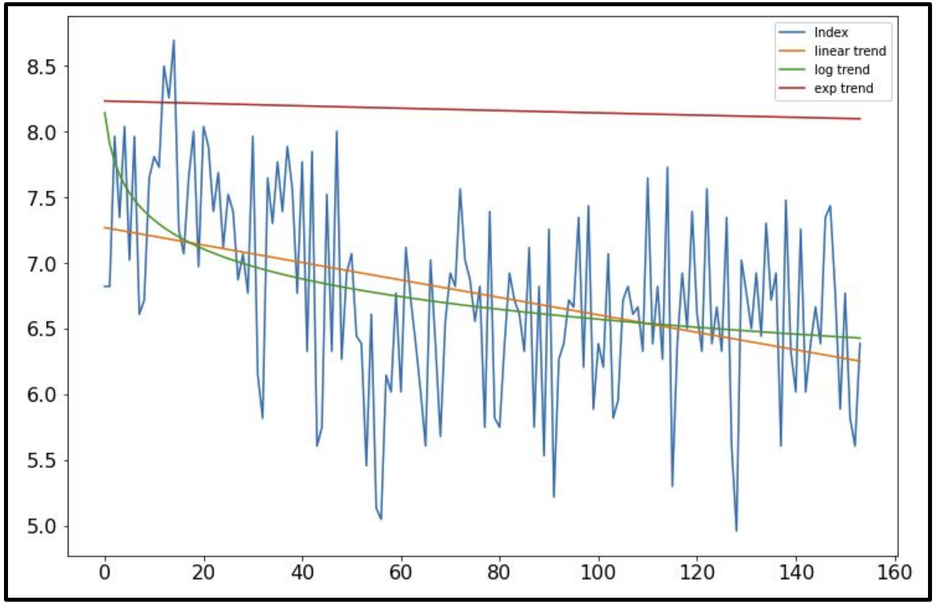
p-value 0.095768 **> 0.05**

Therefore, null hypothesis cannot be rejected and the time series appears **non-stationary**

Box-Cox Transformation

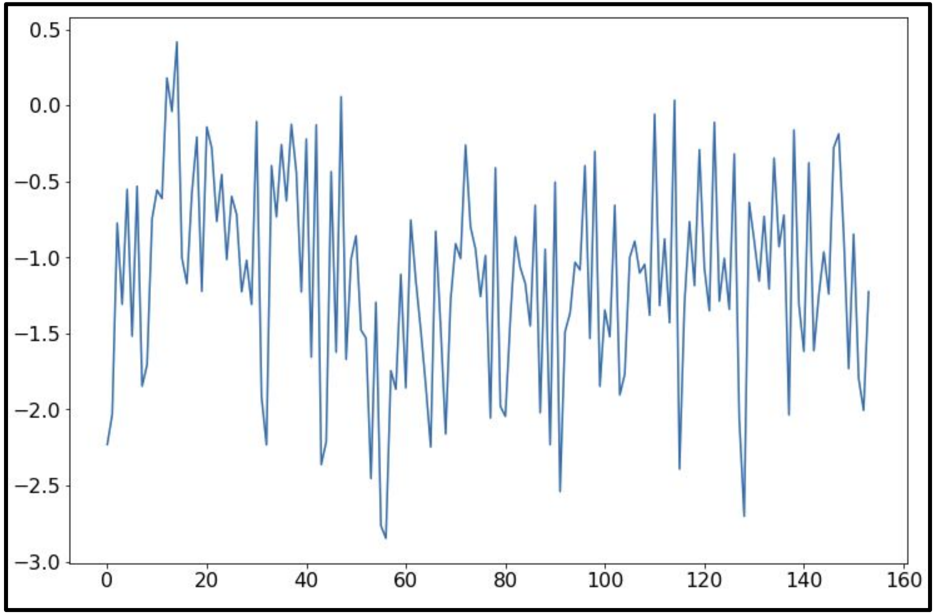


Trend Analysis



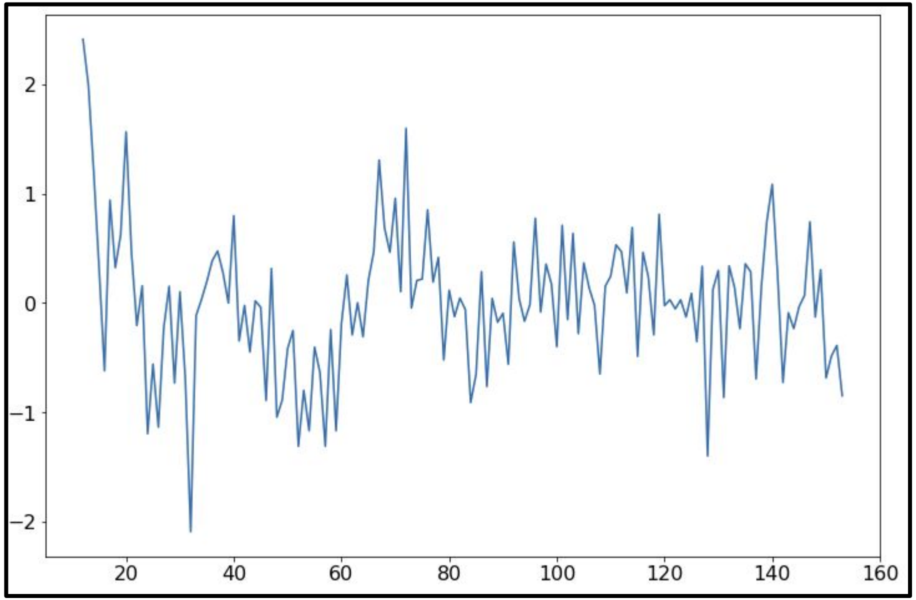
logarithmic trend is the best fit

logarithmic trend removed from data



Seasonality: difference transformation

```
#convert array to series for dealership(d)
d_series = pd.Series(d)
#applying difference transformation
plt.figure(figsize=(12,8))
plt.plot(d_series - d_series.shift(12))
plt.show()
```



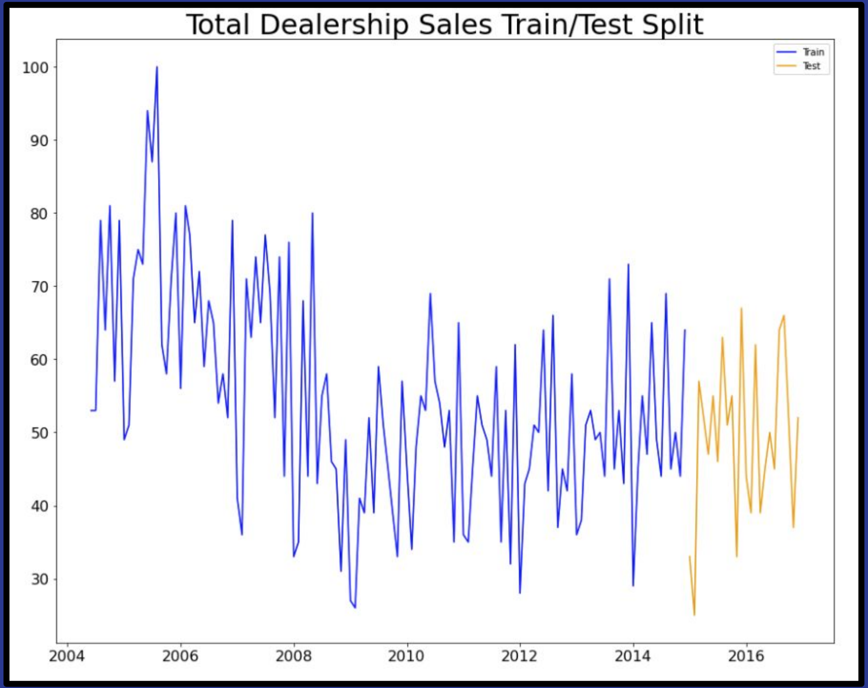

```
ADF Statistic: -4.258796
p-value: 0.000523
Critical Values:
        1%: -3.483
        5%: -2.884
        10%: -2.579
```

p-value 0.000523 **< 0.05**

Therefore, null hypothesis can be rejected and the time series **accepted as stationary**

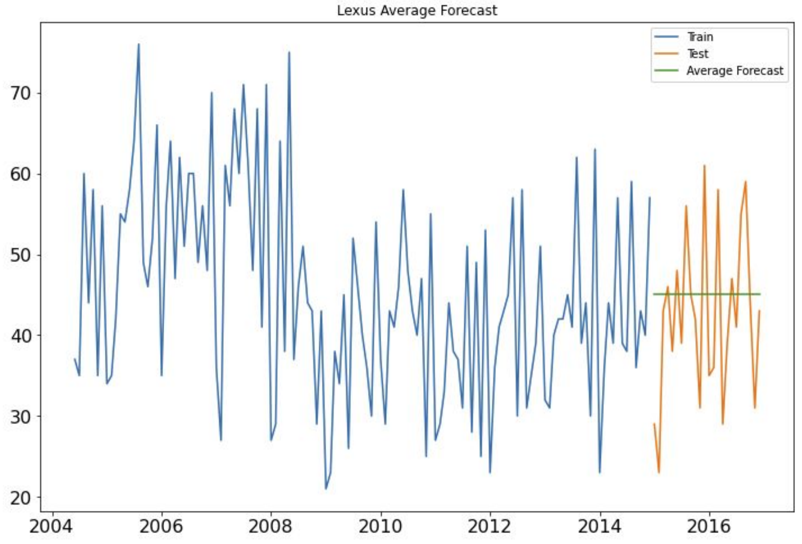
Train/Test Split

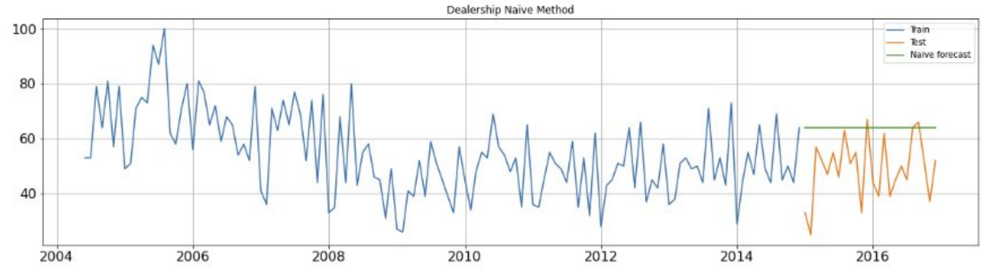
```
train = ts_dt['2004':'2014']
test = ts_dt['2015':'2016']
```



Baseline Models: Simple Average & Naive Methods

	Method	RMSE	MAPE
0	Simple Average	10.38	22.993712





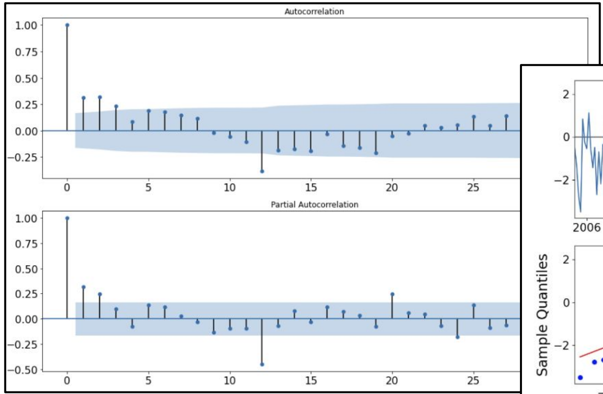
	Method	RMSE	MAPE
0	Simple Average	12.17	24.471189
0	Naive	18.47	38.762770

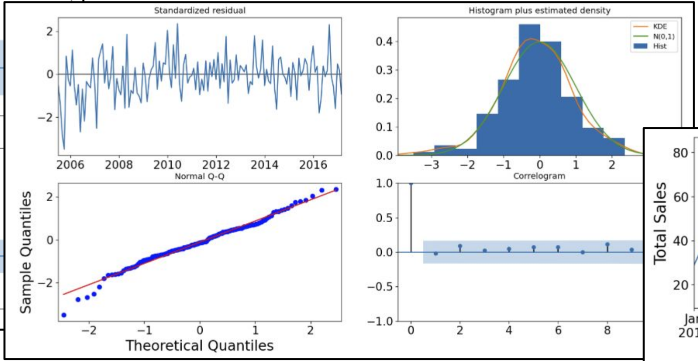
the **Naive** method is an estimating technique in which the last period's actuals are used as this period's forecast, without adjusting them or attempting to establish causal factors.

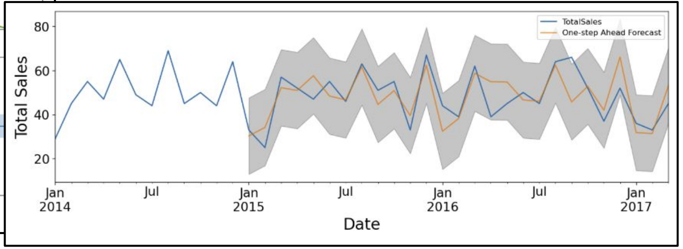
the **Simple Average** method forecasts of all future values are equal to the average (or “mean”) of the historical data

Benchmark is **Simple Average at 75.5%**

Building Models: SARIMAX





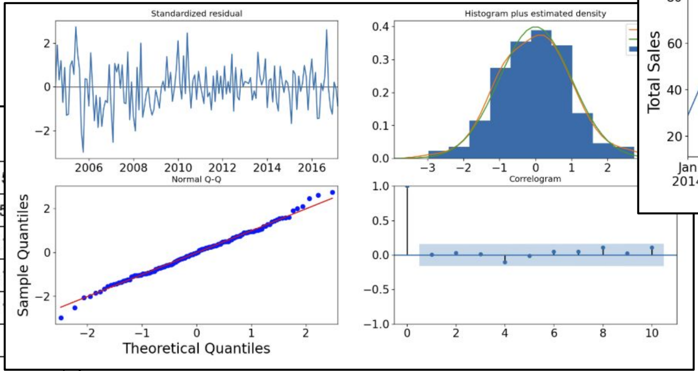


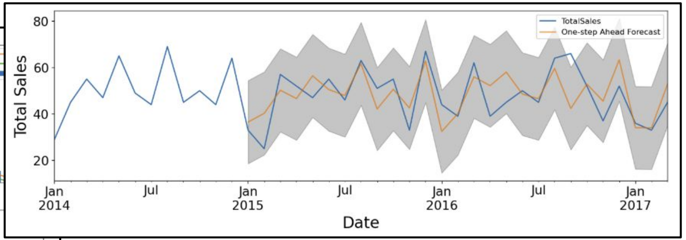
ACF / PACF parameters approach

ACF/PACF ARIMA: (2,1,3),(1,1,1)[12]

```
Best model:  ARIMA(2,1,1)(3,0,1)[12] intercept
Total fit time: 69.159 seconds
```

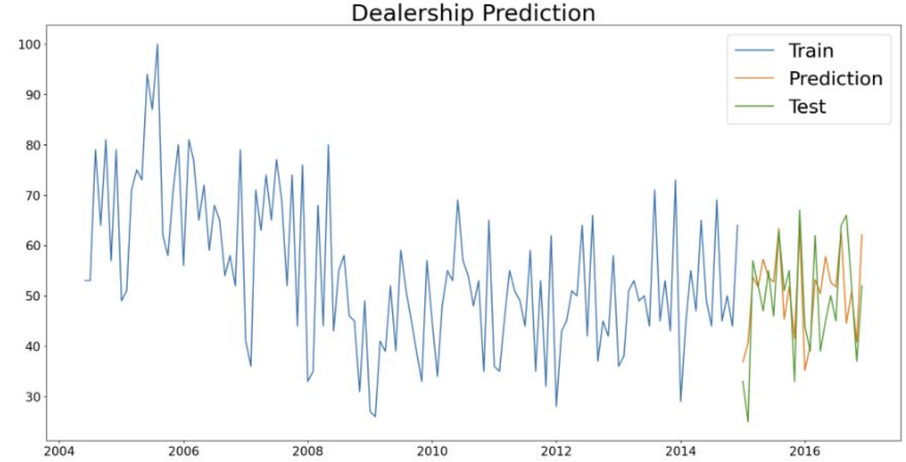
Dep. Variable:	y	**No. Observations:**	1
Model:	SARIMAX(2, 1, 1)x(3, 0, 1, 12)	**Log Likelihood**	-5
Date:	Sun, 27 Jun 2021	**AIC**	1
Time:	14:45:32	**BIC**	1
Sample:	0	**HQIC**	1
	- 154		
Covariance Type:	opg		



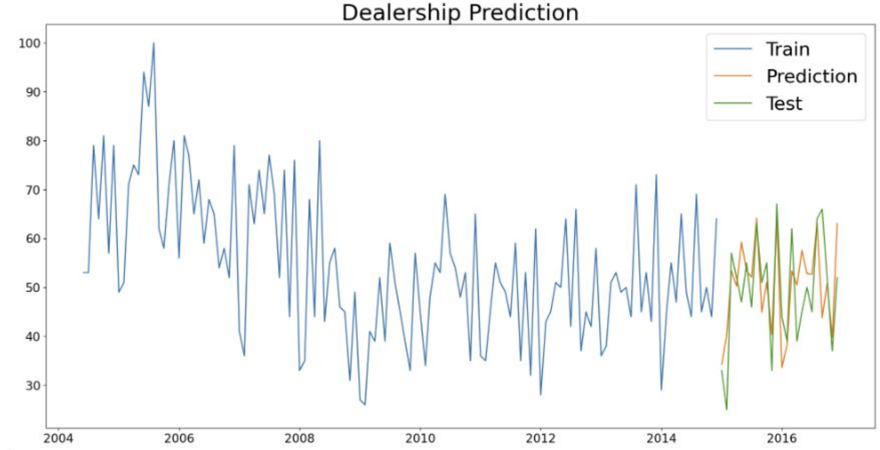


Grid Search parameters approach

Building Models: SARIMAX (Continued)



	Method	RMSE	MAPE
0	Simple Average	12.170000	24.471189
0	Naive	18.470000	38.762770
0	SARIMAX	8.241263	14.562545



	Method	RMSE	MAPE
0	Simple Average	12.170000	24.471189
0	Naive	18.470000	38.762770
0	SARIMAX	8.241263	14.562545
0	SARIMAX_autoc	8.455708	14.561804

Grid Search parameter estimation approach suggested a SARIMAX model with the ordered parameters of (2,1,1)(3,0,1)[12]

ACF & PACF parameter estimation approach suggested a SARIMAX model with the ordered parameters of (3,1,3),(1,1,1)[12]

Building Models: Holt-Winter's Method

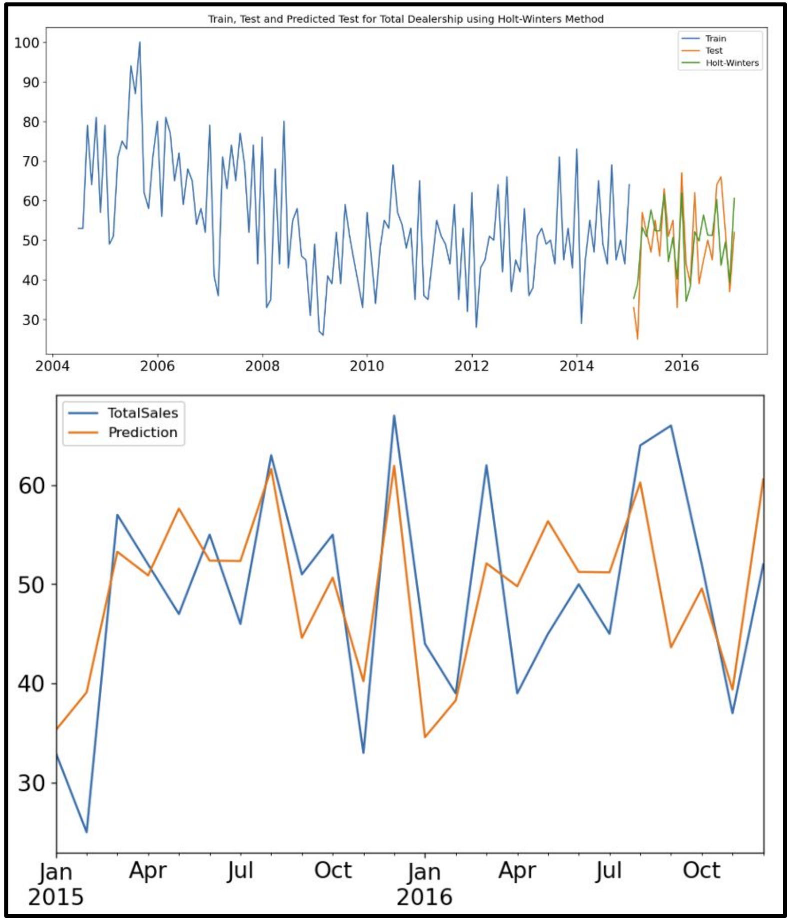
Grid Search Best Results

Trend: Multiplicative
Damped: False
Seasonal: Multiplicative
Seasonal Periods: 12
Box-Cox Transform: True
Remove Bias: False

*RMSE ~ 8.220 degrees

Validating Holt-Winter's Predictions

Method	RMSE	MAPE
Holt-Winters	8.140466	14.206432



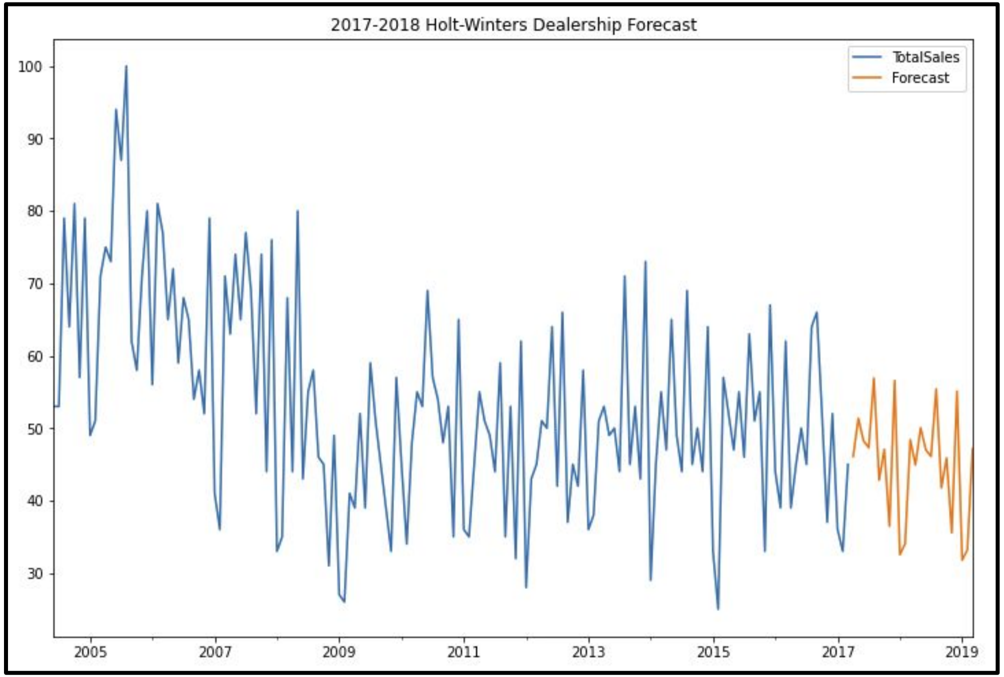
Model Evaluation

Out of the four methods explored the **Holt-Winter's model performed the best with 85.8% accuracy** in predicting the test set observations

	Method	RMSE	MAPE
0	Simple Average	12.170000	24.471189
0	Naive	18.470000	38.762770
0	SARIMAX	8.241263	14.562545
0	SARIMAX_autoc	8.455708	14.561804
0	Holt-Winters	8.140466	14.206432

Machine Learning Model Forecast

Final Model Forecast: Holt-Winter's Method



2017-04-30	46.088141
2017-05-31	51.359114
2017-06-30	48.248633
2017-07-31	47.295832
2017-08-31	56.911114
2017-09-30	42.822225
2017-10-31	47.078531
2017-11-30	36.453334
2017-12-31	56.581796
2018-01-31	32.543081
2018-02-28	34.030010
2018-03-31	48.395210
2018-04-30	44.925273
2018-05-31	50.041999
2018-06-30	47.022739
2018-07-31	46.097768
2018-08-31	55.429885
2018-09-30	41.754070
2018-10-31	45.886807
2018-11-30	35.567699
2018-12-31	55.110345
2019-01-31	31.767856
2019-02-28	33.212963
2019-03-31	47.165030

A deeper look at the forecasted sales from **April 2017 through March 2019**

24 months forecast of all vehicle sales for Lexus of Mishawaka

Project Suggestions

To improve the accuracy of this forecasting model the following constraints should be explored for solutions:

1. The dataset contains only sold vehicle information. Therefore, no vehicle information about the inventory sent to auction is available at this time.

2. All non-electronic data recorded should transcribed and be moved to the cloud

3. Due the number of inconsistencies in how sales information was recorded within this data due to turnover and changes in technology overtime, a recording standard should be established