Retail Motor Gasoline and On-Highway Diesel Fuel Prices Analysis

By: Cristi Darley Guevara

1 Executive Summary

This report provides technical analysis and description of the Facebook Prophet forecast modeling for the fuel price data provided in the February 2018 monthly report by the U.S. Energy Information Administration. Methods of analysis include seasonality, trends, and error "optimization" to identify the best-fitted model.

After observing the data abrupt changes, reflecting on possible causes, and exploring with the Facebook Prophet package, a "good" forecasting model was found. It included a multiplicative seasonal series, the documented U.S. economic recessions, and the U.S. official holidays as variable. The limitations of the model include the number predicted points and the percentage of points taken to identify the trend changes.

Finally, the jupyter notebook containing my work is called :
forecasting_take_home_Cristi_Guevara.ipynb

2 Data

The analysis was performed on the January 1992 - January 2018 monthly regular motor gasoline retail prices, most likely average prices. All the 313 values were included.

2.1 Exploratory Data Analysis

The graphs of the Months vs. Prices is shown in Figure 1. Overall, the prices tended to increase except for the periods between June 2008 to January 2009, May 2014 to February 2015 and June 2015-February 2016 where the prices plunged. Additionally, the prices are usually periodic, i.e., they increase from January reaching their maximum between April to September and they most-likely decrease from September to December (see Figure 1(a)). Further, the amplitude of the periods or season changed as the years passed, which suggests that the series is of multiplicative seasonality type.

3 Facebook Prophet Modeling

All the modeling was done under the assumption of predicting about a year of the fuel prices. Thus, the initial training set had 300 data point and test split had 12 points (see Figure 2.)

Since I had never heard about the Facebook Prophet package before I ran the below models; in each case the forecasted values were saved on the XXX_fcst data frame and XXX was the corresponding data to compare, i.e. test_fcst corresponds to the forecast for the test data.

- Basic Model. The simplest model was ran but turning off both weekly and daily seasonality, since the original data include neither. From the graph of the comparison of the forecast and data (Figure 4.), one can see that the basic model is under-fitting the training data and predicts all the test points within the confidence interval. It fitted 79.73% of the training points. Overall it is under-fitted.

```
model_Basic = Prophet(weekly_seasonality=False,
                daily_seasonality=False)
```

- Additive Changing Trend (ACT). Even though the data suggest a multiplicative seasonality type, I ran this model to see how the changes of trend were captured and also to see how the "abrupt changes" were captured. The model that "best" capture both was when changepoint_range equals to 0.95 and changepoint_prior_scale equal to 1 (see Figure 5a), however it did not capture the amplitude change of the seasons(periods). Additionally, it predicted 84.39% of the training data and 58.3% of the test data.

  Figure 5b. shows changepoint_range equals to 0.95 and changepoint_prior_scale equal to 0.3 which it is a worse model.

```
model_ACT = Prophet(weekly_seasonality=False,
                daily_seasonality=False,
               changepoint_prior_scale=1,
                changepoint_range=.95)
```

- Multiplicative Changing Trend (MCT): since the ACT model did not capture the season amplitude changes. I added the season multiplicative mode (See Figure 6). Although it did not improve the number of points within the confidence interval, the mean square error and mean absolute error slightly improve (see Table 1. and Table 2.)

```
model_MCT= Prophet(weekly_seasonality=False,
                daily_seasonality=False,
               changepoint_prior_scale=1,
               seasonality_mode='multiplicative',
                changepoint_range=.95 )
```

- Recession Multiplicative Changing Trend (RMCT). Observing that the abrupt changes of price (outlier) coincided with the Great Recession (Dec 2007-June 2009). I added the documented Wikipedia U.S. recessions [1] , that is, the early 2000's (March - November 2001) and Great Recession (Dec 2007-June 2009) and take the upper window equal to 1. Graphically, the model seemed to perform similarly to MCT. But in fact, the errors increased a bit.

```
model_RMCT= Prophet(weekly_seasonality=False,
                 daily_seasonality=False,
                changepoint_prior_scale=1,
                seasonality_mode='multiplicative',
                 changepoint_range=.95,
                 holidays= holidays)
```

- Holidays Recession Multiplicative Changing Trend (HRMCT): The U.S. holidays were included, since during the spring and summer holidays people tend to travel more and during fall and winter holidays people are most likely to travel less, affecting the economic activity and thus the fuel prices. Graphically, the model seems similar to RMCT and MCT. However, it predicted 83% of the training data and 75% of the testing data. It improved the prediction errors in both sets.

```
model_MCT= Prophet(weekly_seasonality=False,
                 daily_seasonality=False,
                changepoint_prior_scale=1,
                seasonality_mode='multiplicative',
                 changepoint_range=.95,
                 holidays= holidays)
model_HRMCT.add_country_holidays(country_name='US')
```

- Outliers Holidays Recession Multiplicative Changing Trend (OHRMCT). A final consideration is related to the abrupt change during June 2015 – Feb 2016. Thus, I removed the prices between November 2015 to April 2016 to treat it as an outlier. This model did better, predicted 252 training points and 10 testing points within the confidence interval, that is about the 83% of both sets and produced smaller training and testing errors (see Tables 1 and 2.)

```
model_MCT= Prophet(weekly_seasonality=False,
                 daily_seasonality=False,
                changepoint_prior_scale=1,
                seasonality_mode='multiplicative',
                 changepoint_range=.95,
                 holidays= holidays)
model_HRMCT.add_country_holidays(country_name='US')
```

3.1 Errors Metrics

When running the model, the mean absolute error (MAE), mean absolute percentage error (MAPE), and the mean squared error (MSE) were computed and presented in the following tables:

1. Training Errors

	MSE	MAE	MAPE
ACT	0.037956	0.138561	7.063923
MCT	0.032266	0.124747	6.027949
RACT	0.037956	0.138561	77.063923
RMCT	0.032611	0.127129	6.122381
HRMCT	0.028894	0.120836	5.739874
OHRMCT	0.027752	0.111796	5.511663

Table 1. Training errors

2. Testing errors

	MSE	MAE	MAPE
Basic	0.115685	0.259889	12.793006
Basic	0.044136	0.195253	8.291727
ACT	0.094243	0.249526	10.350409
MCT	0.087631	0.230471	9.530656
RACT	0.094243	0.249526	10.350409
RMCT	0.092312	0.238065	9.852019
HRMCT	0.051724	0.181873	7.543832
OHRMCT	0.020308	0.123465	5.306895

Table 2. Testing errors

4 Conclusion

The Outlier Holidays Recession Multiplicative Changing Trend model was the best performing model that I ran. It predicts 10 out 12 data prices within the confidence interval and its MAE for both test and train data is the smallest. I wonder how well it would to predict the prices for 2018 and 2019, and whether or not the predictions remain the same if the daily or the weekly historical prices are included.

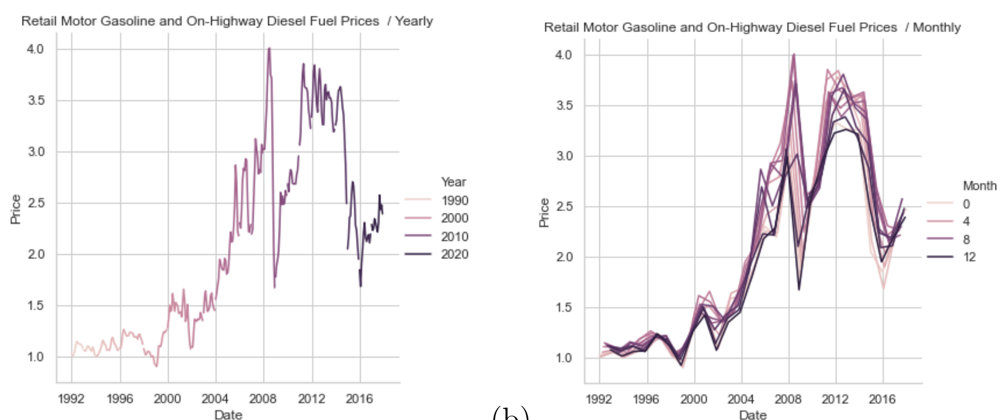
Notice that for larger test sets the model overfit, for example in the case of 295-18 split training-test, none of the models performed well, Figure 9. shows the OHRMCT model. It might be due to the *change_range* and changepoint_prior_scale parameters that force the model to the training data. Perhaps in future experimentations, one could add some simulated noise to the data and see if that improves the forecasting when the *change_range* and changepoint_prior_scale parameters are less flexible.

Finally, the facebook Prophet library gives a "pretty good" prediction on the given data and given split. In particular, since the series is a random walk, [1] an ARIMA model would not fit well and produce larger errors.

5 Bibliography

[1] *https://en.wikipedia.org/wiki/List_of_recessions_in_the_United_States*

6 Appendix: Figures



(a) (b)

Figure 1: Retail Motor Gasoline and On-Highway Fuel Prices.

[1]AdFuller test for the given data yields a p-value of 0.56 -it cannot reject the hypothesis that the series is a random walk- and the autocorrelations and partial autocorrelations of the data, and the first and second difference confirms it Figure 10.

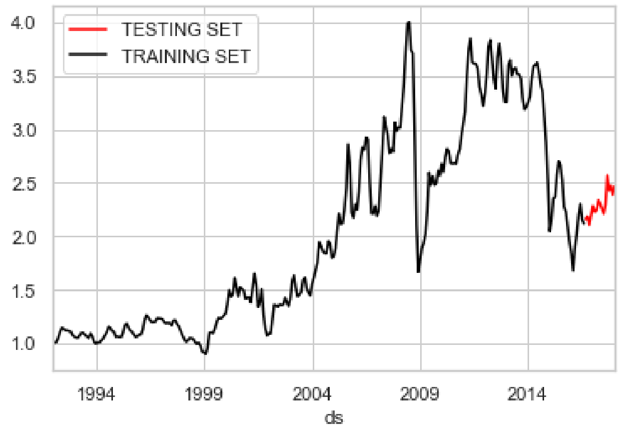


Figure 2: Training and Testing sets

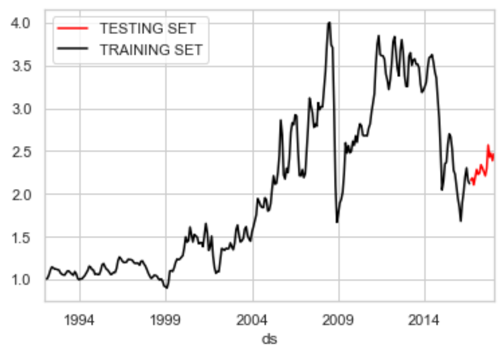


Figure 3: Training and Testing sets

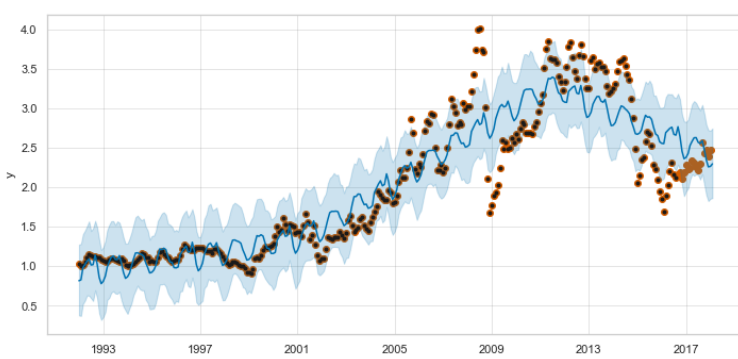


Figure 4: Basic model

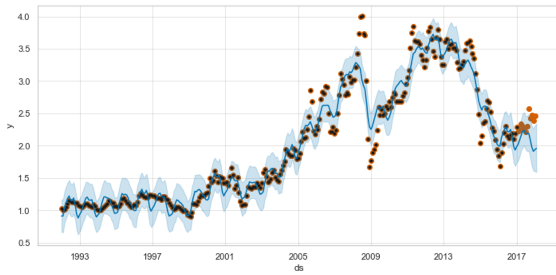
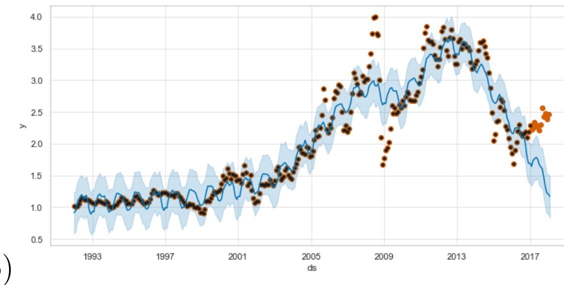
(a) 
(b) 

Figure 5: Additive Changing Trend. (a)changepoint_range=0.95, and changepoint_prior_scale=1 (b) changepoint_range =0.95 and changepoint_prior_scale=0.3

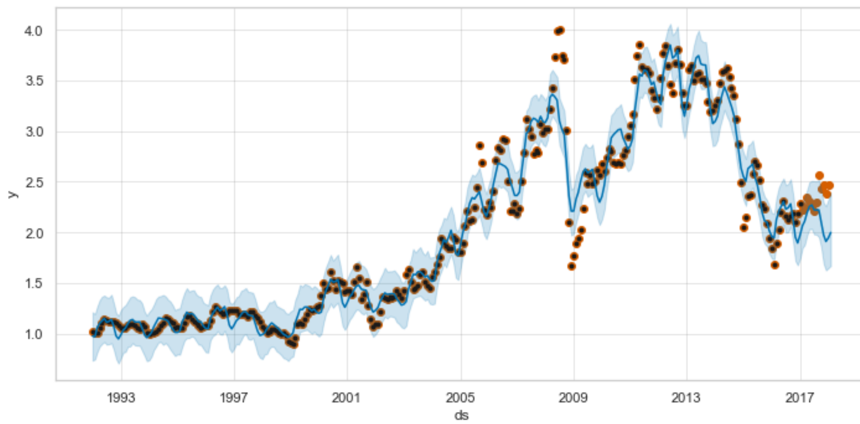


Figure 6: Multiplicative Changing Trend with changepoint_range=0.95, and changepoint_prior_scale=1

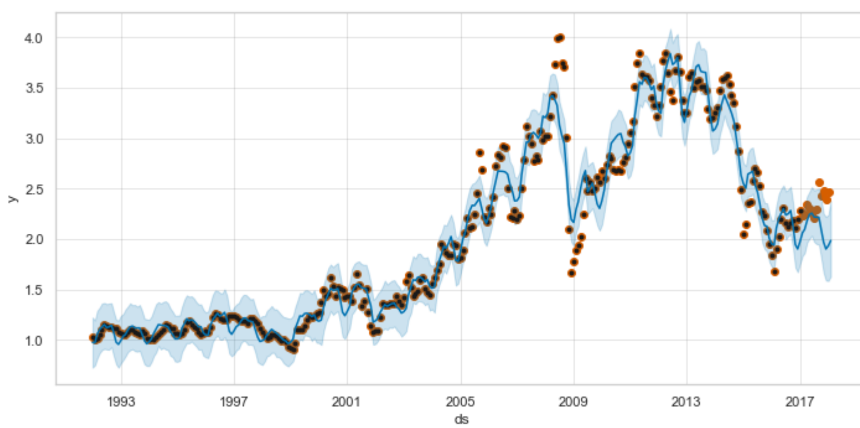


Figure 7: Multiplicative Changing Trend with changepoint_range=0.95, and changepoint_prior_scale=1, including the U.S. recession periods.

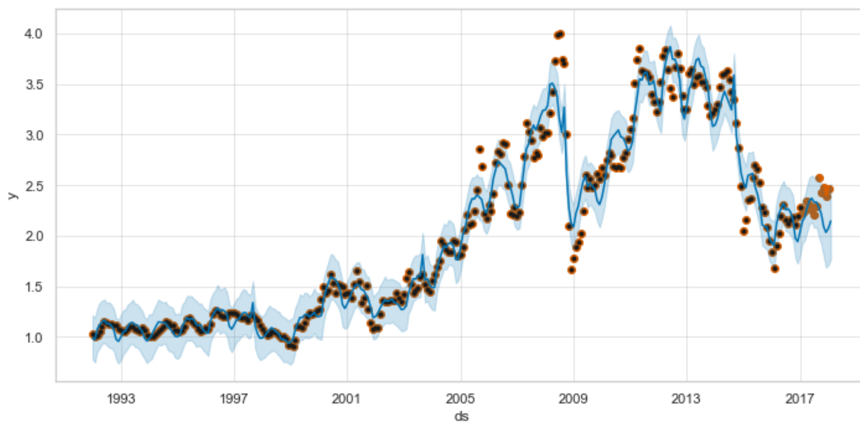


Figure 8: Multiplicative Changing Trend with changepoint_range=0.95, and changepoint_prior_scale=1, including the U.S. recession periods and U.S. official holidays

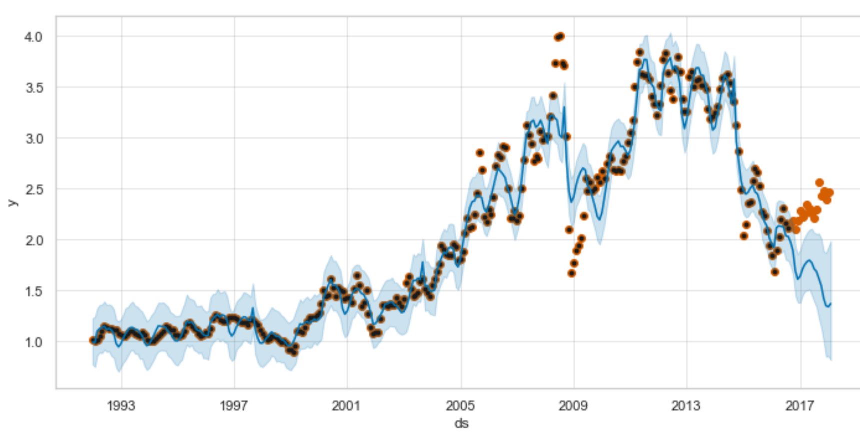


Figure 9: Multiplicative Changing Trend with changepoint_range=0.95, and changepoint_prior_scale=1, including the U.S. recession periods and U.S. official holidays, with train-test: 295-18 data point respectively

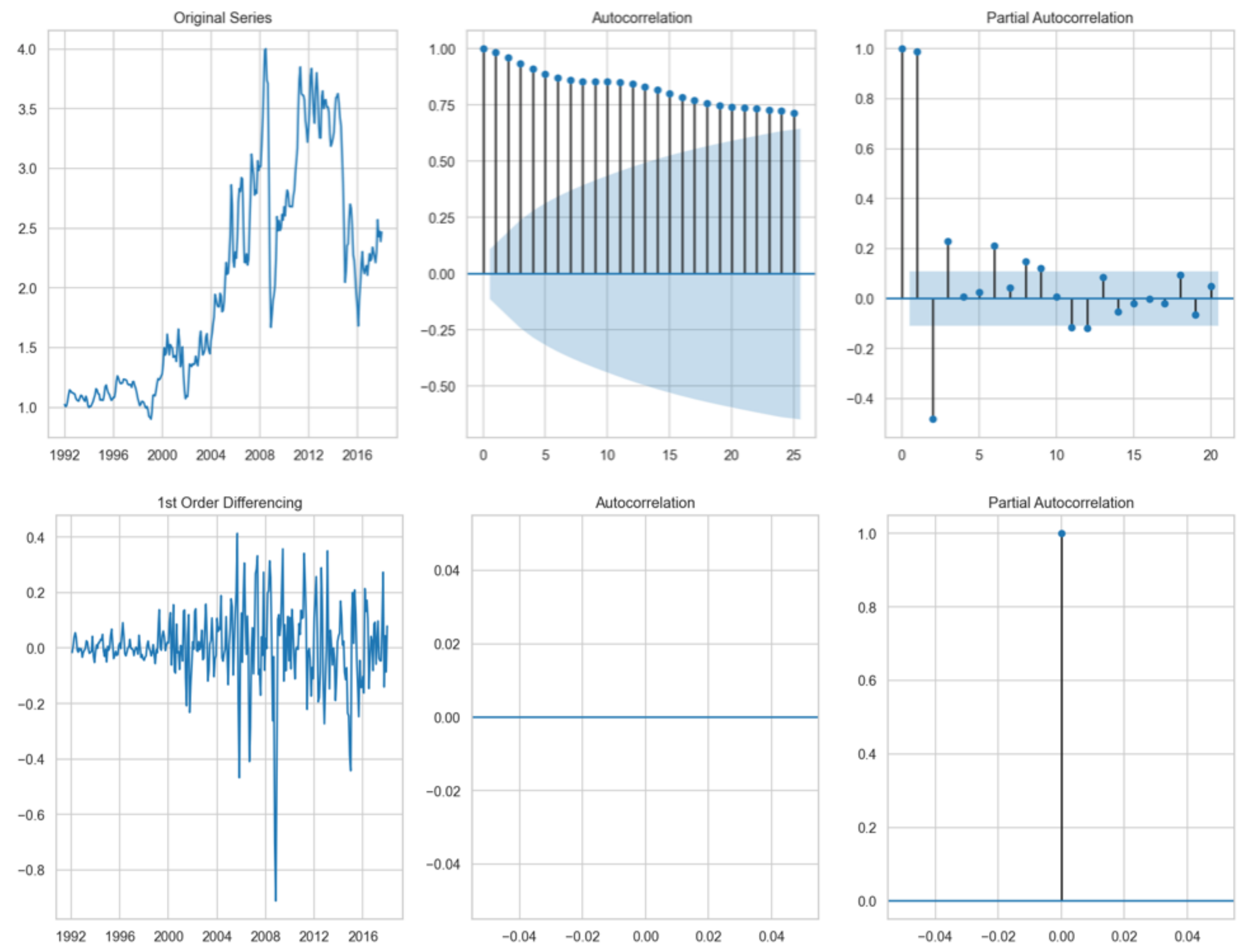


Figure 10: Autocorrelation and Partial autocorrelation graphs