Forecasting Tesla Stock Price with Time Series

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1 Introduction

This paper will provide an analysis of financial times series in R environment. First, I will discuss the stationarity and differencing of the time series. Then I will implement time series models, and look at their performance and effectiveness in modeling and forecasting the Tesla time series data.

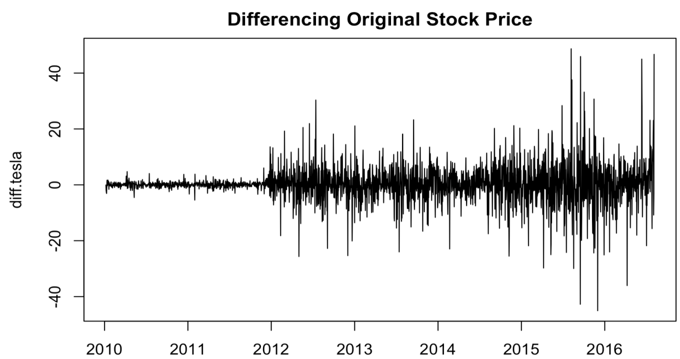
Table 1: I used the Tesla stock price which was obtained from Kaggle. The dataset includes the stock price from 2010-06-29 to 2020-02-03. The snippet below shows the first 6 rows of the dataset. I will only use the “Date” column and the “Close” column.

	Date	Open	High	Low	Close	Adj.Close	Volume
1	2010-06-29	19.00	25.00	17.54	23.89	23.89	18766300
2	2010-06-30	25.79	30.42	23.30	23.83	23.83	17187100
3	2010-07-01	25.00	25.92	20.27	21.96	21.96	8218800
4	2010-07-02	23.00	23.10	18.71	19.20	19.20	5139800
5	2010-07-06	20.00	20.00	15.83	16.11	16.11	6866900
6	2010-07-07	16.40	16.63	14.98	15.80	15.80	6921700

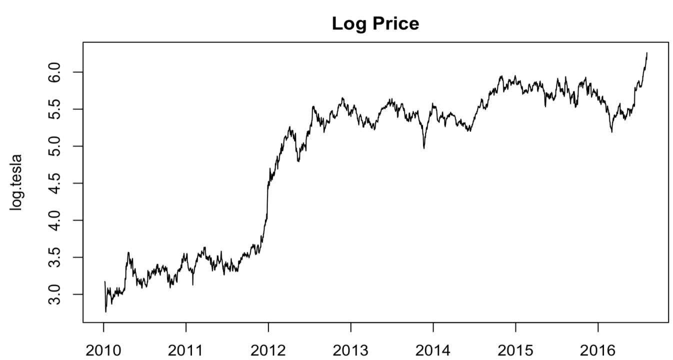
2 Stationarity and Differencing

- Figure 1: The graph below is the original time series of Tesla stock price from 2010-06-29 to 2020-02-03. The graph shows an exponential growth.

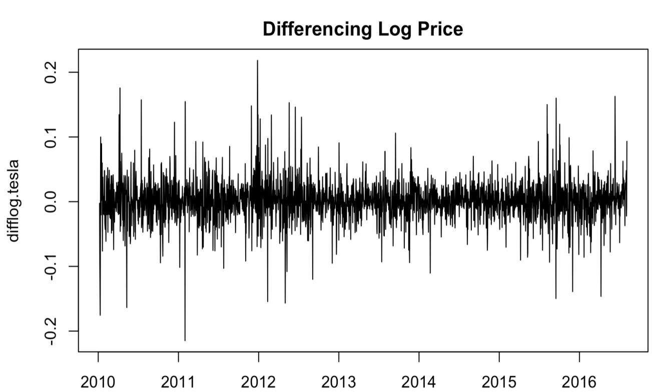
- Figure 2: The graph below shows the differences of Tesla stock prices. The variance of the series increases as the level of original series increases; thus, it is not stationary



- Figure 3: The graph below is the log price of the original time series. Logging the series makes it more linear.



- Figure 4: The graph below shows the differences of the log price. The variance of the series is constant. The augmented Dickey Fuller Test proves that this graph is stationary.



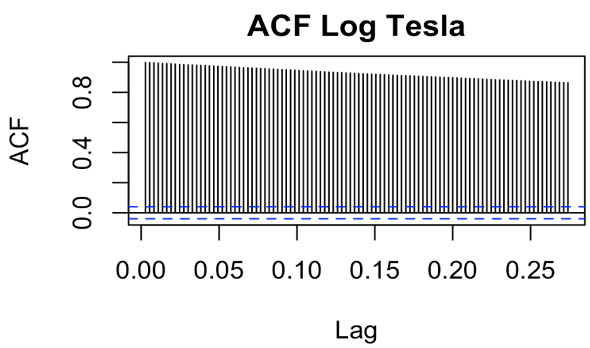

```
p-value smaller than printed p-value
        Augmented Dickey-Fuller Test

data:  diff(log(input_ts))
Dickey-Fuller = -12.867, Lag order = 13, p-value = 0.01
alternative hypothesis: stationary
```

3 Methods

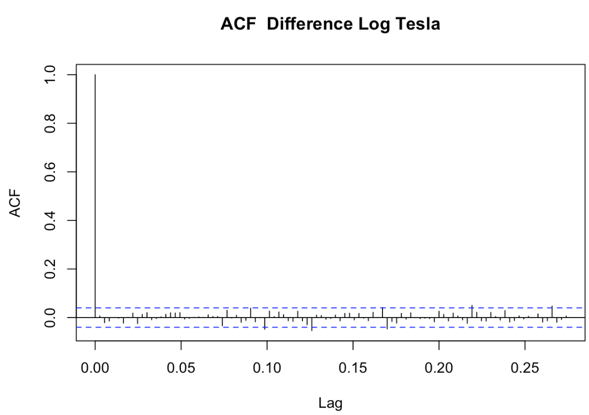
3.1 ARIMA model

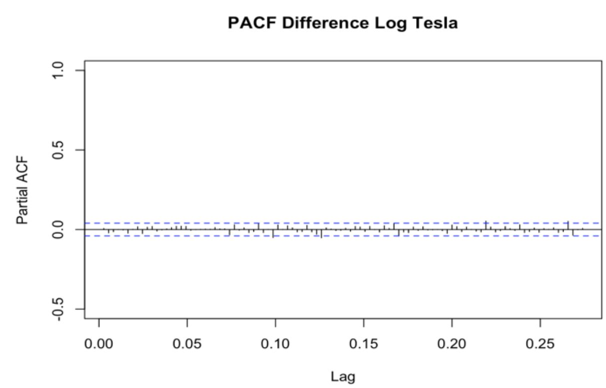
a. Model Specification

- Figure 5: The graph below shows the ACF of log Tesla stock price. The ACF slowly decreases and doesn't die down, which means the model needs to be differenced.



- Figure 6 and Figure 7: The graph on the left side shows ACF of differenced and logged Tesla price. The graph on the right side shows PACF of differenced and logged Tesla price. Both graphs don't show any significant lags.





The model for differenced log Tesla series is thus a white noise, and the original model resembles random walk model ARIMA (0,1,0).

- Table 2: Next, I found the Akaike Information Criterion (AIC) scores in the table below to find model with the lowest score. ARIMA model (0,1,0) has the lowest AIC score.

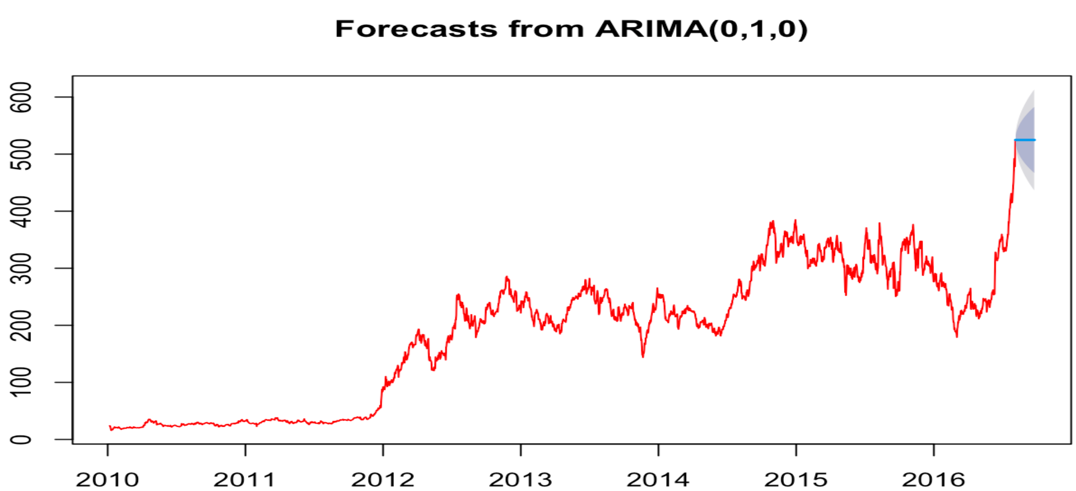
	model <chr>	AIC <dbl>
1	0 1 0	-9689.125
2	1 1 0	-9687.512
3	2 1 0	-9685.955
4	3 1 0	-9684.354
5	4 1 0	-9682.376
6	5 1 0	-9680.382
7	0 1 1	-9687.522
8	1 1 1	-9685.517
9	2 1 1	-9684.089
10	3 1 1	-9682.236

b. Model Fitting

Estimating Parameters: Following snippet shows the estimate of each element of the model. Since I'm using ARIMA (0,1,0), this won't be as useful.

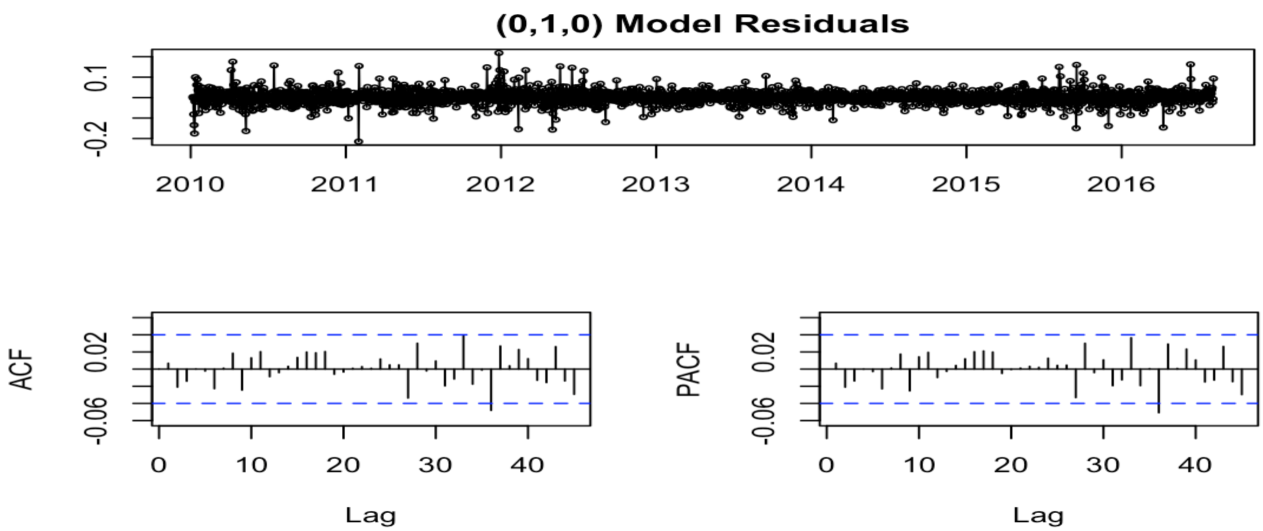
```
stats::arima(x = log(input_ts), order = c(0, 1, 0))

sigma^2 estimated as 0.001044:  log likelihood = 4834.36,  aic = -9666.73
```

Figure 8: The graph below shows the prediction for the Tesla stock for next 50 days in the grey region. There aren't any fluctuations in the blue line, and the dark grey region represents the 95% confidence interval.



c. Model Diagnostics

- Figure 9: The residual plot, ACF and PACF do not show any significant lags, therefore the selected ARIMA model is appropriate model to represent the data.



- Ljung-Box is another way to test if the model is a good fit for the data. The test has a P-value of 0.9629 greater than 0.05. So, the selected model is an appropriate model of Tesla stock price.

```
        Box-Ljung test

data:  resid(Arima_0_1_0)
X-squared = 10.277, df = 20, p-value = 0.9629
```

3.2 GARCH model

a. Model Specification

Figure 10: How do we know when to use the GARCH model? The plots below show the squared residuals plot that shows cluster of volatility at some points in time, ACF and PACF dies down. So, GARCH would be a good fit for the time series.

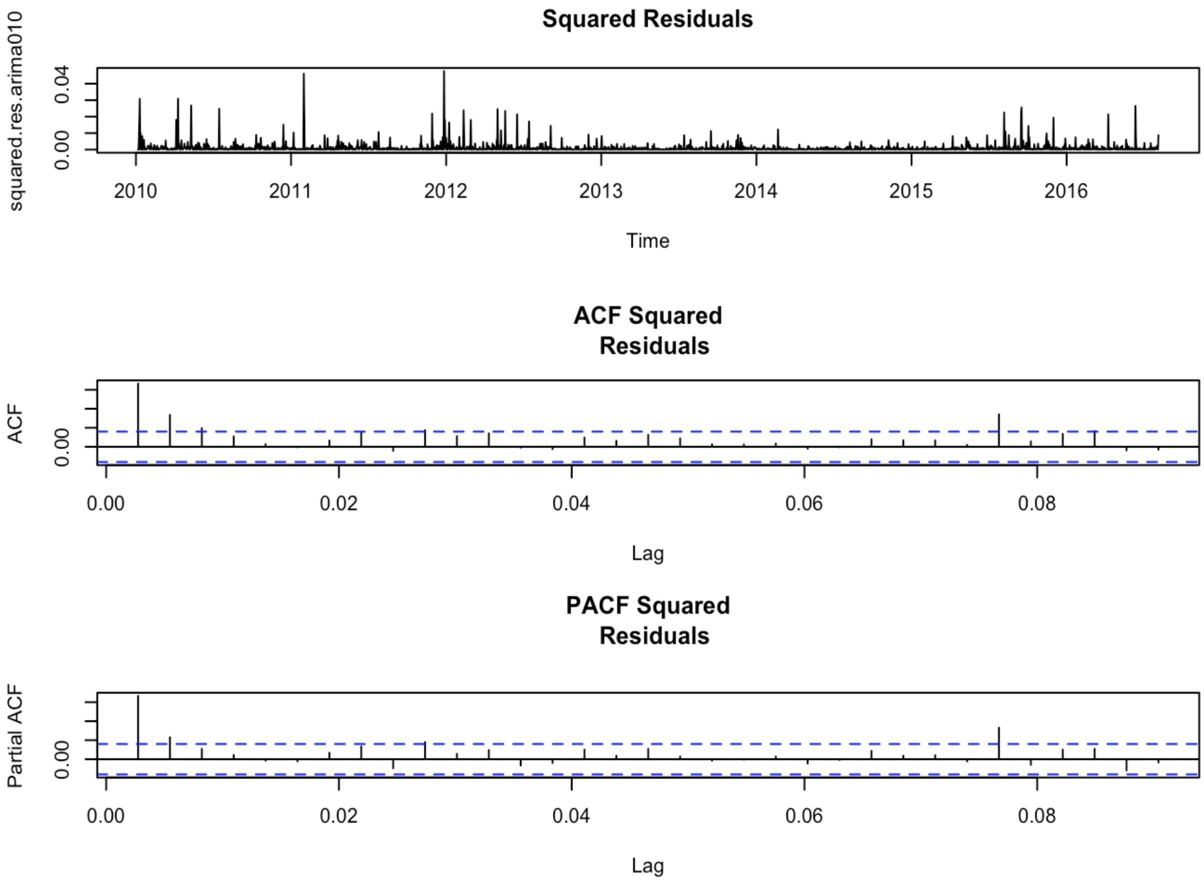


Table 3: The table below shows list of GARCH models with their respective AIC score. GARCH (4,3) has the lowest AIC score so, I picked that model.

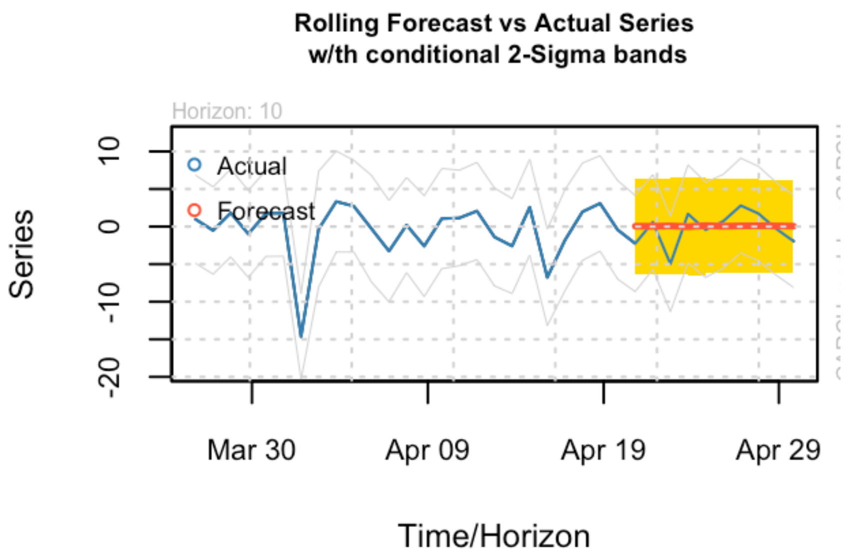
	df	AIC
m.43	8	12289.26
m.42	7	12296.83
m.33	7	12303.79
m.32	6	12311.68
m.21	4	12316.37
m.22	5	12329.59
m.31	5	12339.28

b. Model Fitting

Estimating Parameters: Following snippet shows the estimate of each parameter of the model.

```
Call:
garch(x = r.tesla, order = c(4, 3), trace = FALSE)

Coefficient(s):
       a0         a1         a2         a3         b1         b2         b3
6.776e+00  7.983e-02  7.402e-02  5.436e-02  8.898e-02  3.551e-02  5.828e-13
       b4
3.862e-03
```

Figure 11: The graph below shows the Rolling forecast for the Tesla stock price for 10 days. There aren't any fluctuations in the orange line (the forecast), and the yellow box represents the 95% confidence interval for the prediction.



c. Model Diagnostics

Ljung-Box test has a P-value of 0.403 greater than 0.05. So, the selected model is an appropriate model of Tesla stock price.

```
        Box-Ljung test

data:  Squared.Residuals
X-squared = 0.6995, df = 1, p-value = 0.403
```

4 Conclusion

ARIMA is a method to linearly model the data, it provides best linear forecast for the series, and thus plays little role in forecasting model nonlinearly. It does not reflect recent changes as new information is available. Therefore, in order to update the model volatility, ARCH/GARCH method is very helpful. ARCH/GARCH incorporates new information and analyzes the series based on conditional variances where users can forecast future values with up-to-date information.

References

[1] Bozsolik, T. (2020, February 4). Tesla stock data from 2010 to 2020. Kaggle. https://www.kaggle.com/timoboz/tesla-stock-data-from-2010-to-2020. Accessed 8 May 2021

[2] Forecasting Bitcoin Prices with using Univariate GARCH model . *RPubs*. https://rpubs.com/Naishad/forecasting-bitcoin-v1. Accessed 8 May 2021

[3] Ghalanos, A. (2020, July 15). Introduction to the rugarch package. https://cran.r-project.org/web/packages/rugarch/vignettes/Introduction_to_the_rugarch_package.pdf. Accessed 15 April 2021

[4] Package 'rugarch.' (2020, July 16). https://cran.r-project.org/web/packages/rugarch/rugarch.pdf. Accessed 19 April 2021

[5] Pedersen, J. H. ARMA(1,1)-GARCH(1,1) Estimation and forecast using rugarch 1.2-2. http://www.unstarched.net/wp-content/uploads/2013/06/an-example-in-rugarch.pdf. Accessed 10 April 2021

[6] Pham, L. Time Series Analysis with ARIMA – ARCH/GARCH model in R. https://talksonmarkets.files.wordpress.com/2012/09/time-series-analysis-with-arima-e28093-arch013.pdf. Accessed 8 April 2021