Forecasting Weekly Bitcoin Price

Michael Longyin Poon[a]

[a] Department of Statistics, University of California, Los Angeles, USA

Abstract

Forecasting exchange rate is an important topic to study in either the business or academic world. Conventional time series model is among the most popular method to predict future price behaviors. This research focuses not only on building a conventional time series model, but also combining information from Google Trend Index in forecasting weekly bitcoin prices. The purpose of this paper is to introduce a simplified time series model with high prediction accuracy. The result shows that Google Trend Index is a significant predictor and remarkably outperformed the traditional time series model.

Introduction

Investors often try to gain insights on trading by forecasting financial asset prices. Fundamental and technical analysis are the two most common methods. Fundamental analysis focuses on the conditions and performance of the overall economy and industry. In contrast, technical analysis studies market activities such as historical price movements and other statistics. When forecasting exchange rate for a currency, analysts often apply economic theory such as determining the underlying value and its corresponding local and global acceptance. In terms of technical analysis, time series approaches such as the autoregressive integrated moving average (ARIMA) process is commonly used to predict future price movements. This research emphasis on developing a hybrid model that takes both theories into consideration.

Bitcoin is a peer to peer version of electronic currency which allows instant transaction between parties without going through any financial institution [1]. It was created by Satoshi Nakamoto in 2009 and gained popularity in recent years. Since bitcoin is an electronic currency, we suspect its prices are highly correlated with its own public awareness and recognition. We attempted to develop an integrated time series model to forecast weekly bitcoin prices in the future. First, we fitted bitcoin historical prices into a traditional autoregressive integrated moving average (ARIMA) model. Second, we added Google Trend Index as a predictor to enhance prediction accuracy.

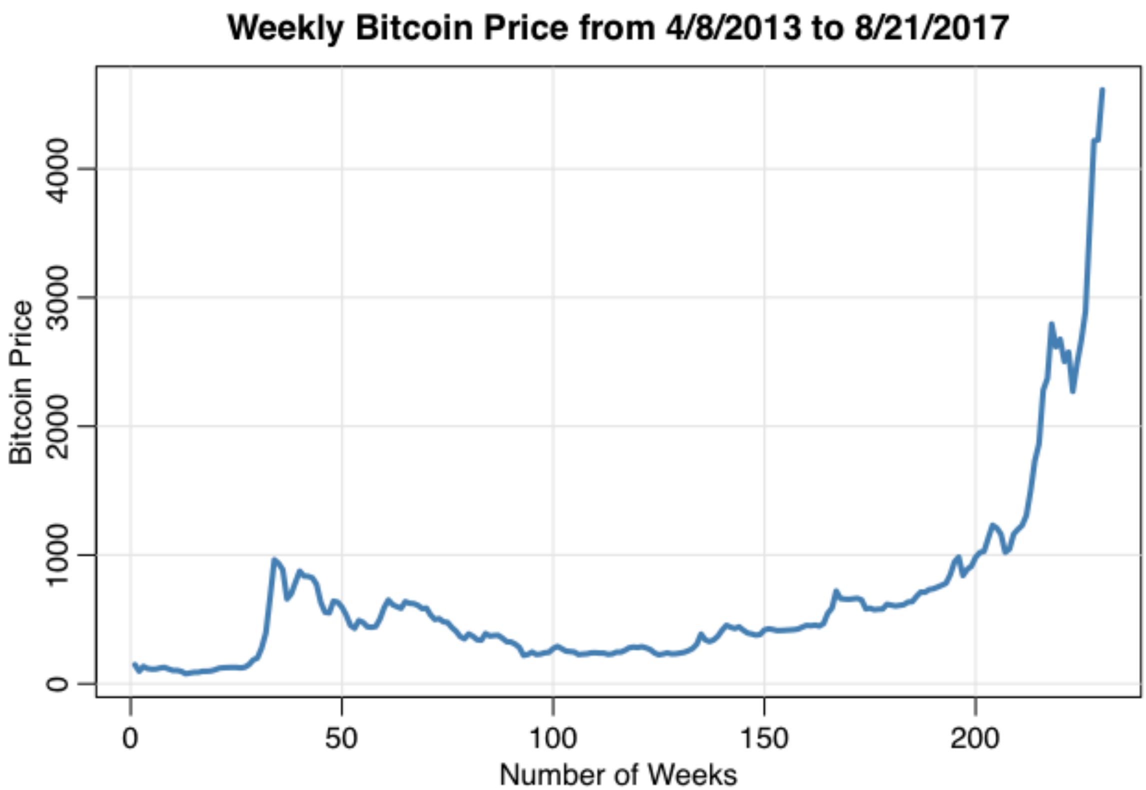
Literature Review

There exist many methods to forecast exchange rates. Quintana and West introduced a multivariate dynamic linear model to analyze international exchange rate in 1987. Their model focused on discovering principal components and prior information that determines a currency exchange rate [2]. Their study suggests a time series model along with a significant predictor would be an appropriate method in forecasting exchange rate.

There are many different approaches in time series analysis. Bagnall and Janacek discussed a clustering method with clipped data in 2004 [3]. Mercek also took the statistical, classical and fuzzy neural network approach on stock price forecasting in 2004 [4]. These studies all suggested that additional information need to be consider in addition to the traditional time series model for higher prediction accuracy.

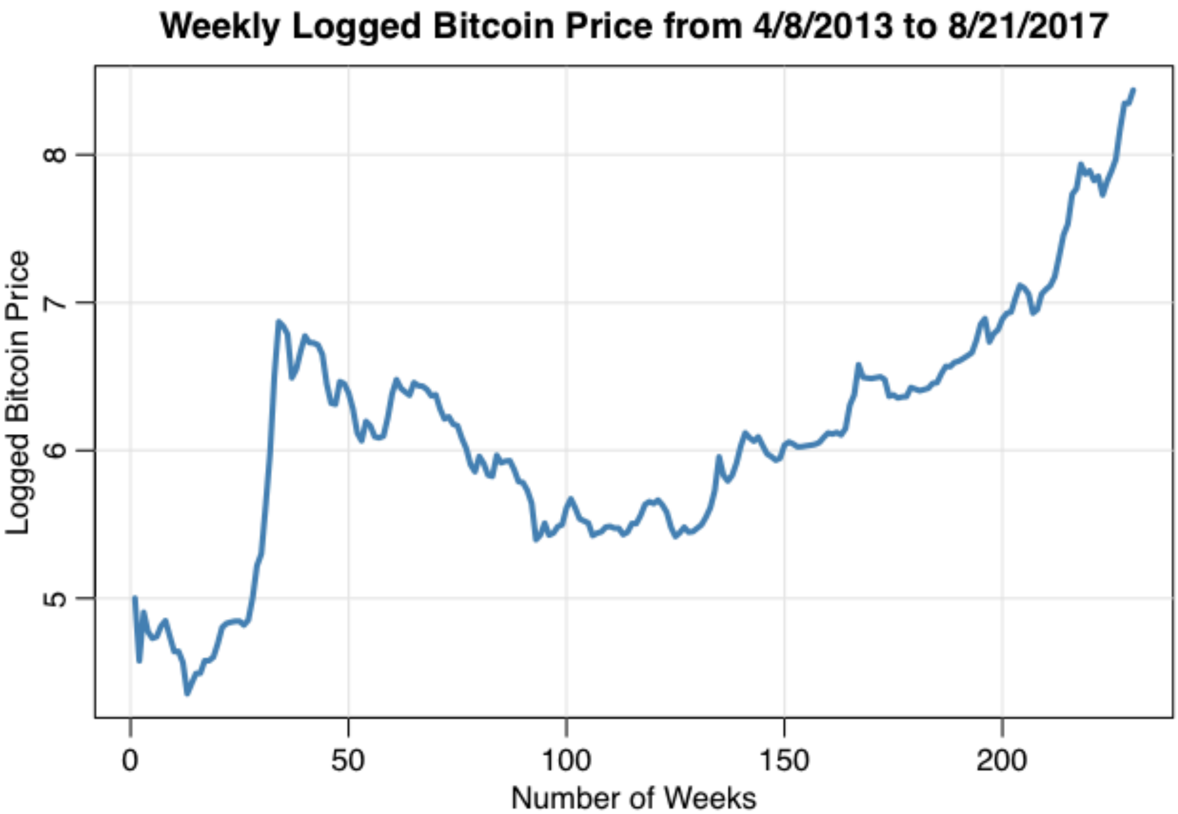
Data Analysis and Results

We used two hundred and thirty weeks of weekly bitcoin prices from April 8th 2013 to August 21st 2017 as our training data*, and thirty weeks from August 28th 2017 to March 26th 2018 as our testing data*. The first step is to perform a basic time series analysis on bitcoin historical prices. We created a plot to examine price movements.



*Data were obtained from data.bitcoinity.org

We observed bitcoin price has an increasing trend in general over the past five years. Based on the plot, it appears there is no seasonal trend over the period. Notice that variance has increased exponentially in the five years' span which violates the stationary assumption for ARIMA model. It suggests a transformation is needed prior applying an ARIMA model on our data.

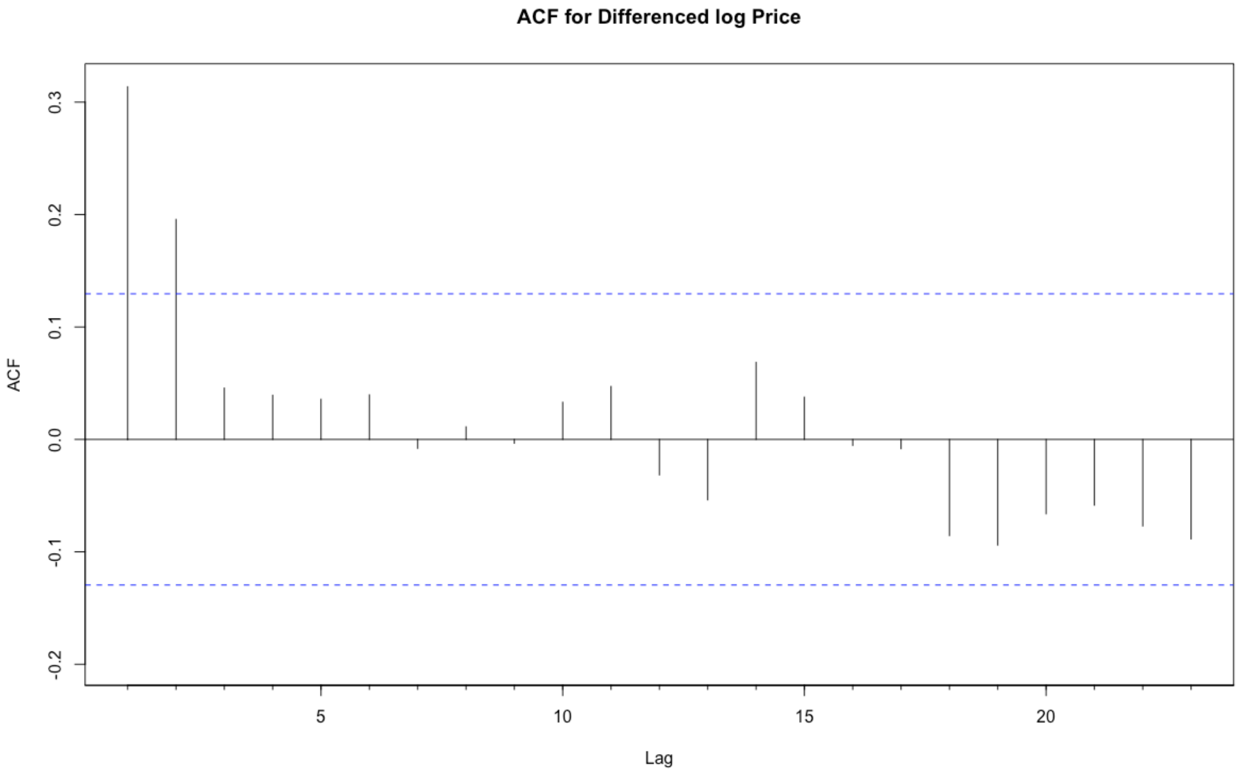


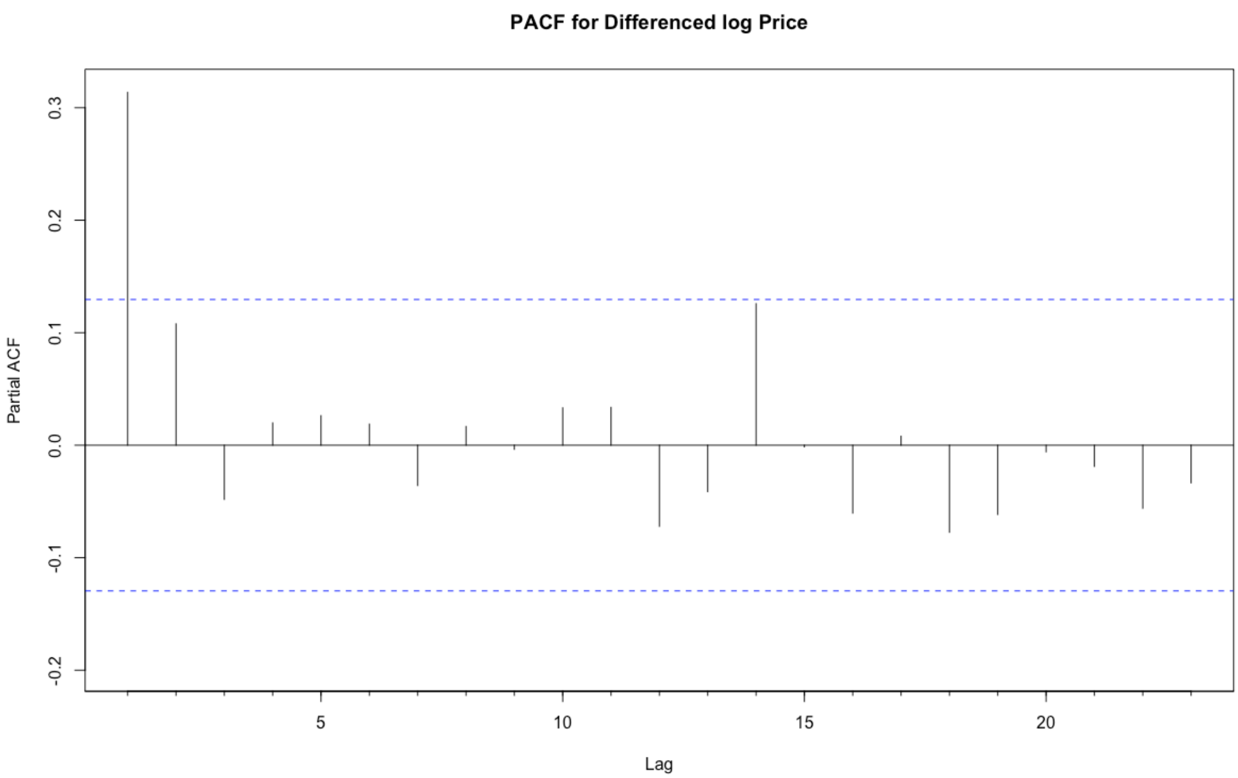
A log transformation significantly reduced the variance but a non-stationary pattern still presents. The augmented Dickey-Fuller test is used to test whether a series of data is stationary or not. The null hypothesis states that the series is non-stationary. Since the p-value of 0.8421 is much higher than benchmark of 0.05 to be statistically significant, we fail to reject the null hypothesis and concluded that the series is non-stationary. In order to solve this problem, a first order differencing on the logged bitcoin prices is considered.

```
        Augmented Dickey-Fuller Test

data:  training$log_price
Dickey-Fuller = -1.3664, Lag order = 6, p-value = 0.8421
alternative hypothesis: stationary
```

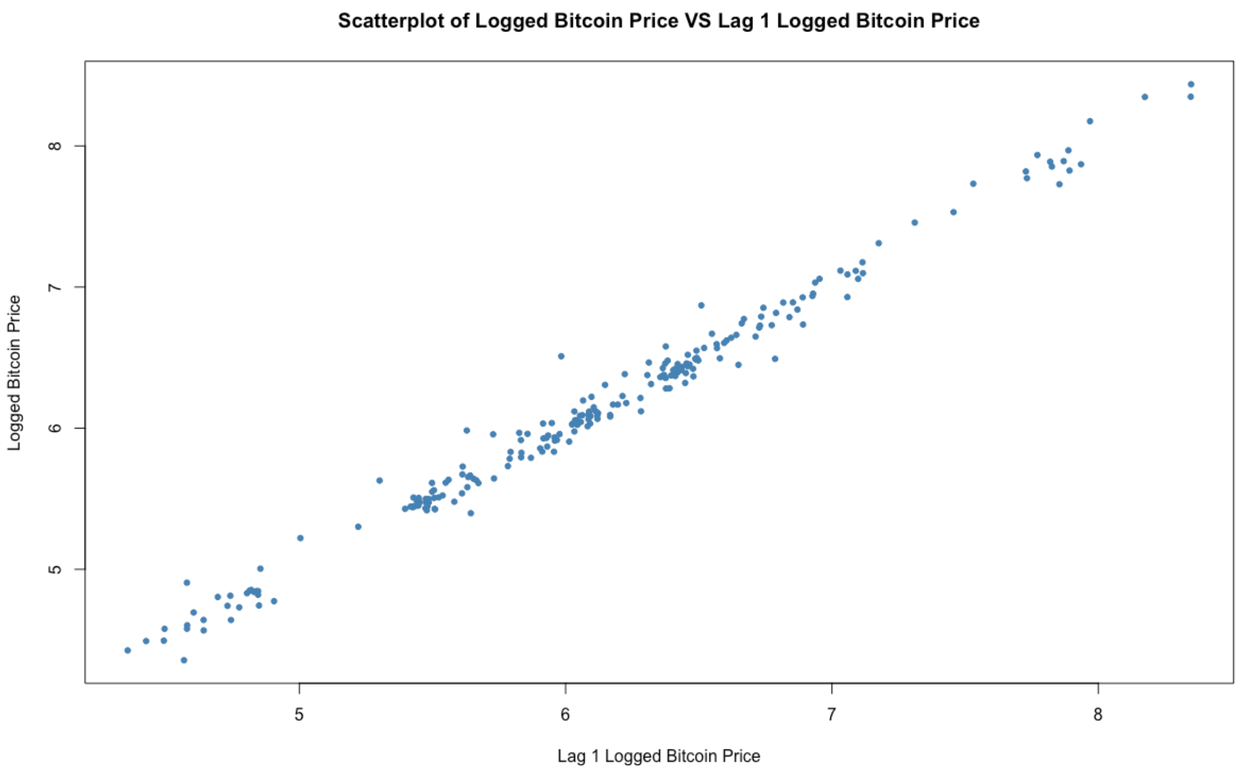
After first order differencing, the series appears to be stable over two-hundred and thirty weeks. Once again, we ran an augmented Dickey-Fuller test to solidify our observation. Since the p-value is lower than 0.01, we are confident to reject the null hypothesis. There are evidences to suggest that the series of first order differencing on logged bitcoin prices is stationary. It is now appropriate to apply ARIMA model to the transformed bitcoin prices.

The ARIMA model has three parameters (p, d, q) correspond to autoregressive (AR), differencing (d) and moving average (MA). To determine parameters p and q for our data, we need to investigate both autocorrelation function (ACF) and partial autocorrelation function (PACF) for the differenced series.


ACF for Differenced log Price
ACF
Lag
0.3
0.2
0.1
0.0
-0.1
-0.2
5
10
15
20


PACF for Differenced log Price
Partial ACF
Lag
0.3
0.2
0.1
0.0
-0.1
-0.2
5
10
15
20

There are two significant spikes at lag 1 and lag 2 in the ACF plot, so we would consider a moving average (2) model. In the PACF plot, there is only one significant spike at lag 1 but also close to significant for lag 2. We would consider either an autoregressive (1) or autoregressive (2) model to be appropriate parameter. Below is a scatterplot of logged bitcoin prices versus lag 1 logged bitcoin prices. The linear pattern suggests a first order autoregressive model is appropriate. Earlier we decided to perform first order differencing on our series so the integrated term parameter (d) equals to one. Our initial analysis suggests an ARIMA (p=1, d=1, q=2) would be suitable.



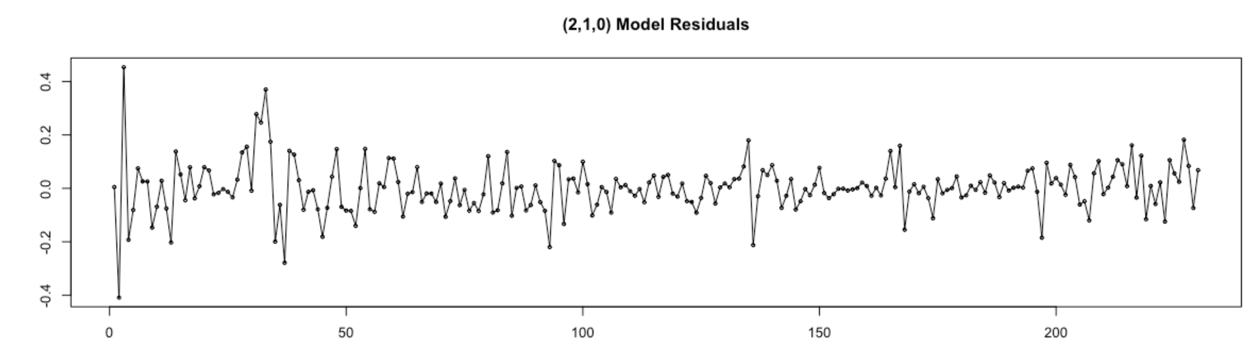
With a stationary series and pre-determined parameters, we can now fit our data into an ARIMA model. In addition, the computer can also help us to determine parameters that maximize the log likelihood as well as minimizing AIC, AICc and BIC. We will compare the two to decide the best model.

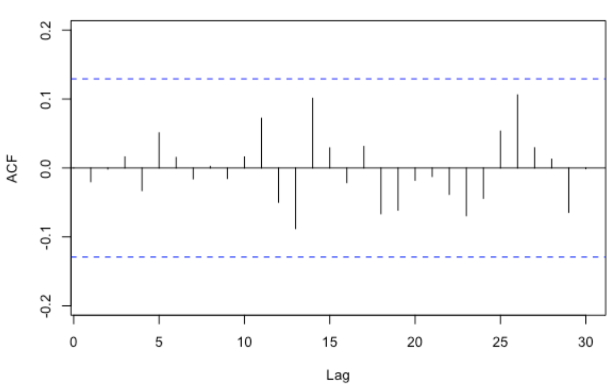
```
Series: training$log_price
ARIMA(1,1,2)

Coefficients:
         ar1     ma1     ma2
      0.1657  0.1532  0.1692
s.e.  0.4284  0.4225  0.1589

sigma^2 estimated as 0.008973:  log likelihood=216.19
AIC=-424.38   AICc=-424.2   BIC=-410.64
```

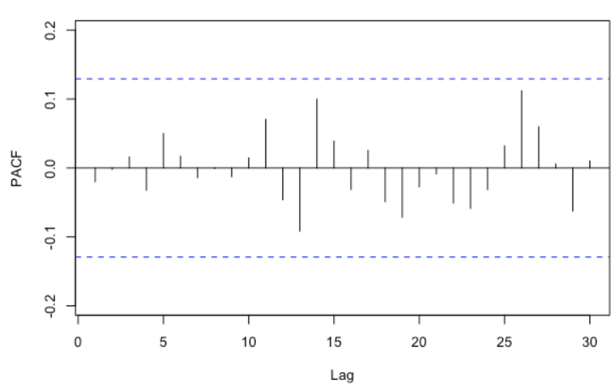
```
Series: training$log_price
ARIMA(2,1,1) with drift

Coefficients:
          ar1     ar2     ma1   drift
      -0.3461  0.3146  0.6548  0.0142
s.e.   0.4411  0.1298  0.4607  0.0099

sigma^2 estimated as 0.008916:  log likelihood=217.43
AIC=-424.85   AICc=-424.59   BIC=-407.69
```

The computer suggests an ARIMA (p=2, d=1, q=0) model. This model not only has higher log likelihood than our initial model, but also lower AIC and AICc. Therefore, we concluded the ARIMA (2,1,0) model is better than the pre-determined ARIMA (1,1,2) model.

In fact, we need to perform diagnostics to make sure the model is valid. An important part is to take a look of the residuals' pattern. It appears that residuals are somewhat randomly distributed. From the ACF and PACF plot, it is clear that there was no significant autocorrelation presented. We also performed a Box-Ljung test to test residuals' independency. The null hypothesis being the residuals are independent. The p-value we obtained was 0.7603 so we fail to reject the null hypothesis. There is enough evidence to prove the validity of an ARIMA (2,1,0) model.

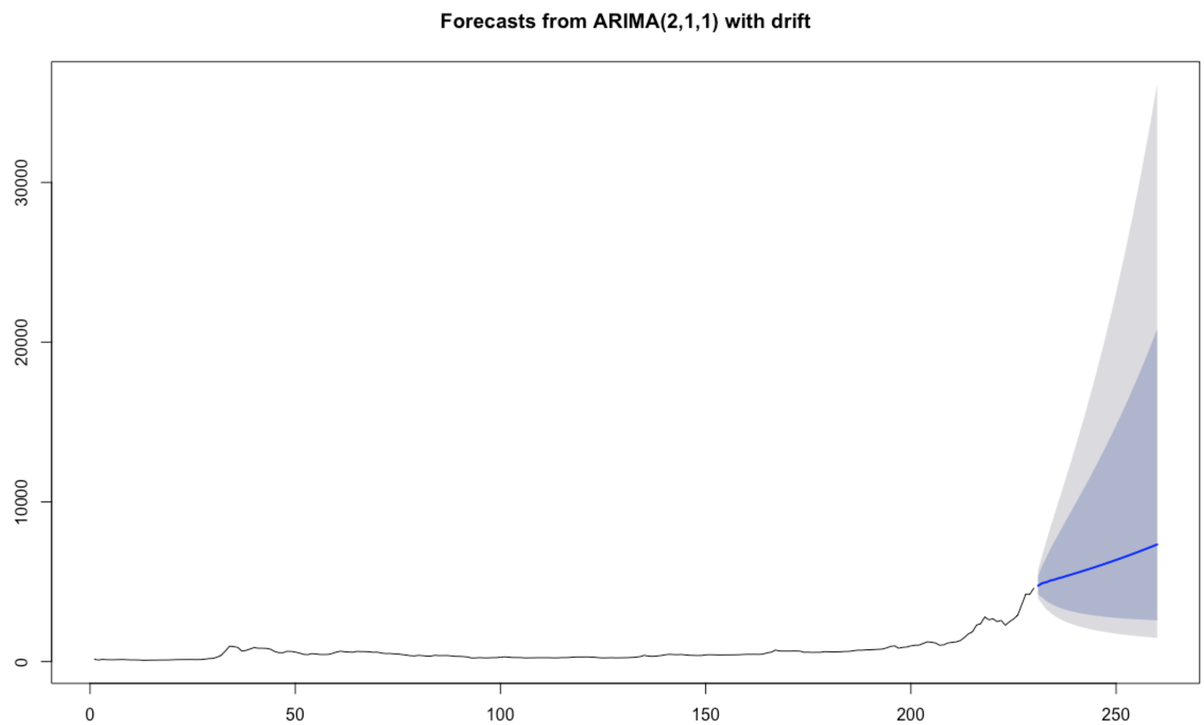




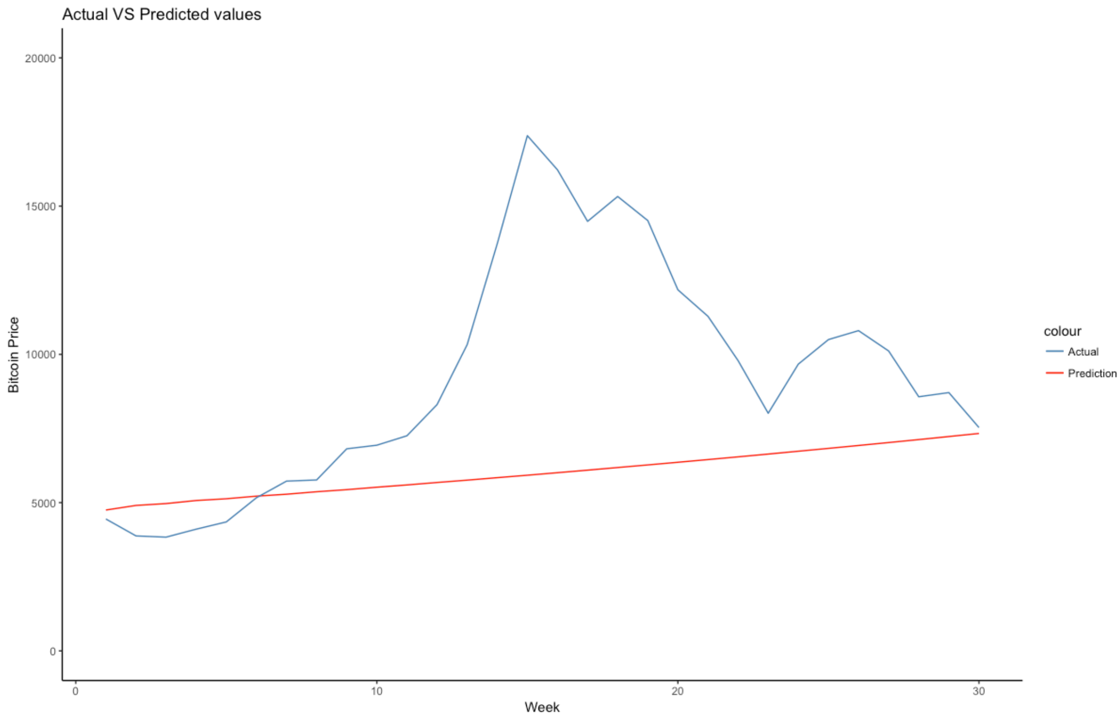


```
              Box-Ljung test

data:  res
X-squared = 0.093094, df = 1, p-value = 0.7603
```

We can now try to forecast bitcoin prices in the future by retransforming our series into its original unit. A 30 weeks forecast was performed as follow:



In order to measures the performance of our model, cross validation was performed. We compared the predicted prices with the actual bitcoin prices in the following thirty weeks. We chose thirty weeks because a rule of thumb is to use over ten percent of the training data for validation. The following plot and table give a big picture of prediction accuracy.


Actual VS Predicted values
20000
15000
10000
5000
0
Bitcoin Price
0
10
20
30
Week
colour
Actual
Prediction

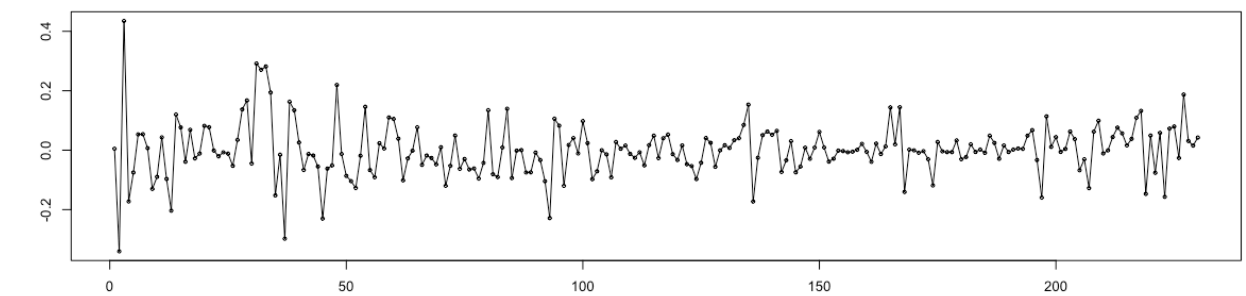
Accuracy Table:

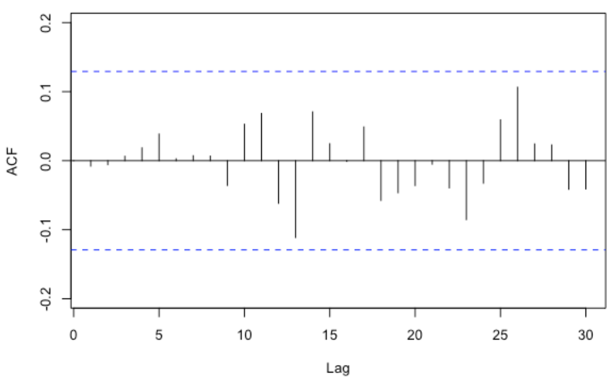
	Actual	Prediction	%Change	Week
1	4448.186	4749.975	0.06784529	1
2	3877.361	4905.766	0.26523342	2
3	3836.227	4968.332	0.29510882	3
4	4104.402	5070.842	0.23546417	4
5	4349.547	5129.876	0.17940472	5
6	5163.845	5218.222	0.01053046	6
7	5724.994	5283.266	0.07715767	7
8	5764.160	5367.087	0.06888661	8
9	6814.830	5437.888	0.20205077	9
10	6936.828	5520.471	0.20417927	10
11	7254.876	5595.853	0.22867686	11
12	8305.702	5678.743	0.31628382	12
13	10326.294	5757.848	0.44240904	13
14	13732.345	5841.911	0.57458749	14
15	17376.360	5924.226	0.65906407	15
16	16223.990	6009.992	0.62956138	16
17	14485.893	6095.232	0.57922979	17
18	15325.235	6183.044	0.59654490	18
19	14512.732	6271.070	0.56789182	19
20	12177.336	6361.160	0.47762307	20
21	11282.490	6451.919	0.42814763	21
22	9788.082	6544.454	0.33138545	22
23	8014.081	6637.945	0.17171468	23
24	9670.893	6733.058	0.30378110	24
25	10498.607	6829.314	0.34950288	25
26	10800.558	6927.115	0.35863358	26
27	10114.764	7026.186	0.30535342	27
28	8570.413	7126.775	0.16844444	28
29	8711.170	7228.726	0.17017740	29
30	7532.565	7332.195	0.02660049	30

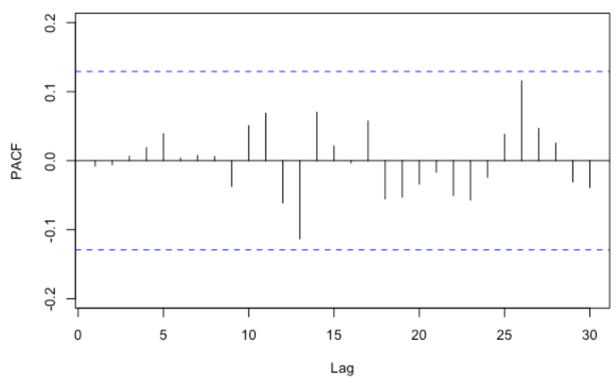
As we can see form the graph, the actual data is much more volatile than our prediction. However, we observed that the actual bitcoin prices were converging to our prediction in the long run. The margin of error is only 2.66% in week 30 and all actual prices fall within our confidence interval. One optimal choice to improve accuracy is to add predictors into our model. Google trend index measures search-volume on the internet, therefore it is a good indication on bitcoin public awareness at different points of time. We regressed weekly google trend data on differenced logged weekly bitcoin prices and allowed the computer to determine the optimal ARIMA model for us. Compare this model with all the previous model, it has the highest log likelihood and lowest AIC, AICc and BIC.

```
Series: training$log_price
Regression with ARIMA(2,1,1) errors

Coefficients:
          ar1     ar2     ma1   drift    xreg
      -0.0393  0.1705  0.2730  0.0142  0.0166
s.e.   0.7104  0.1895  0.7203  0.0088  0.0046

sigma^2 estimated as 0.008456:  log likelihood=224.04
AIC=-436.08   AICc=-435.7   BIC=-415.48
```

(1,1,1) Model Residuals

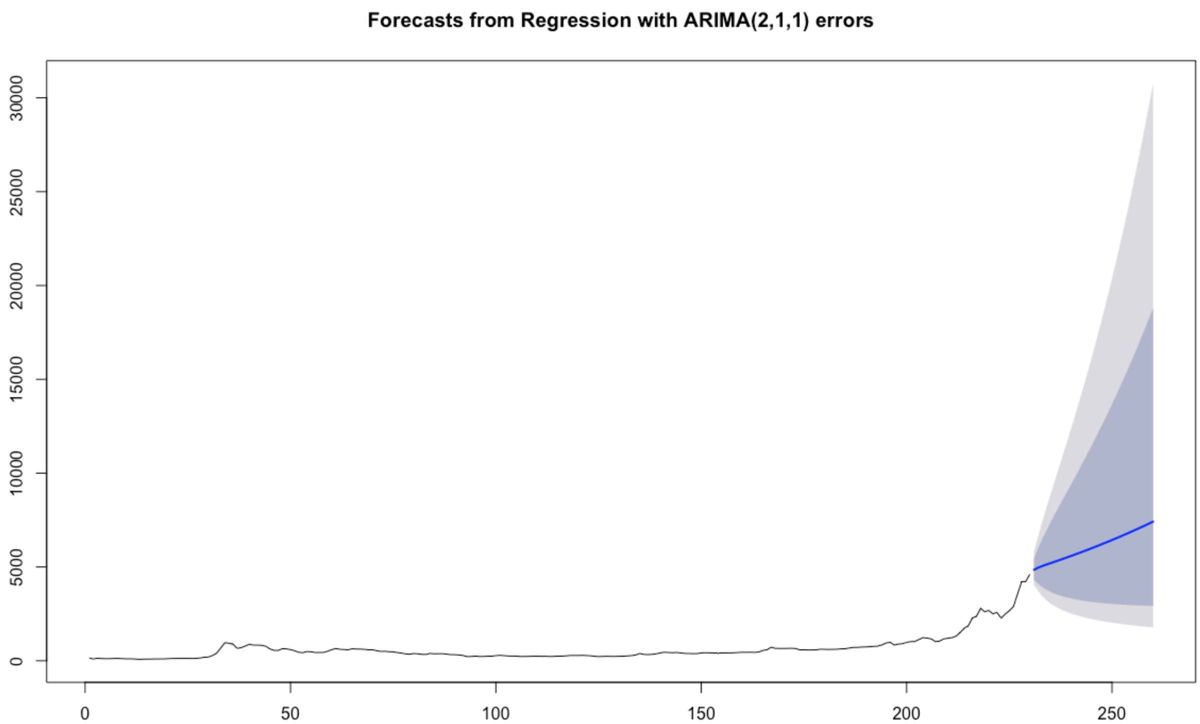


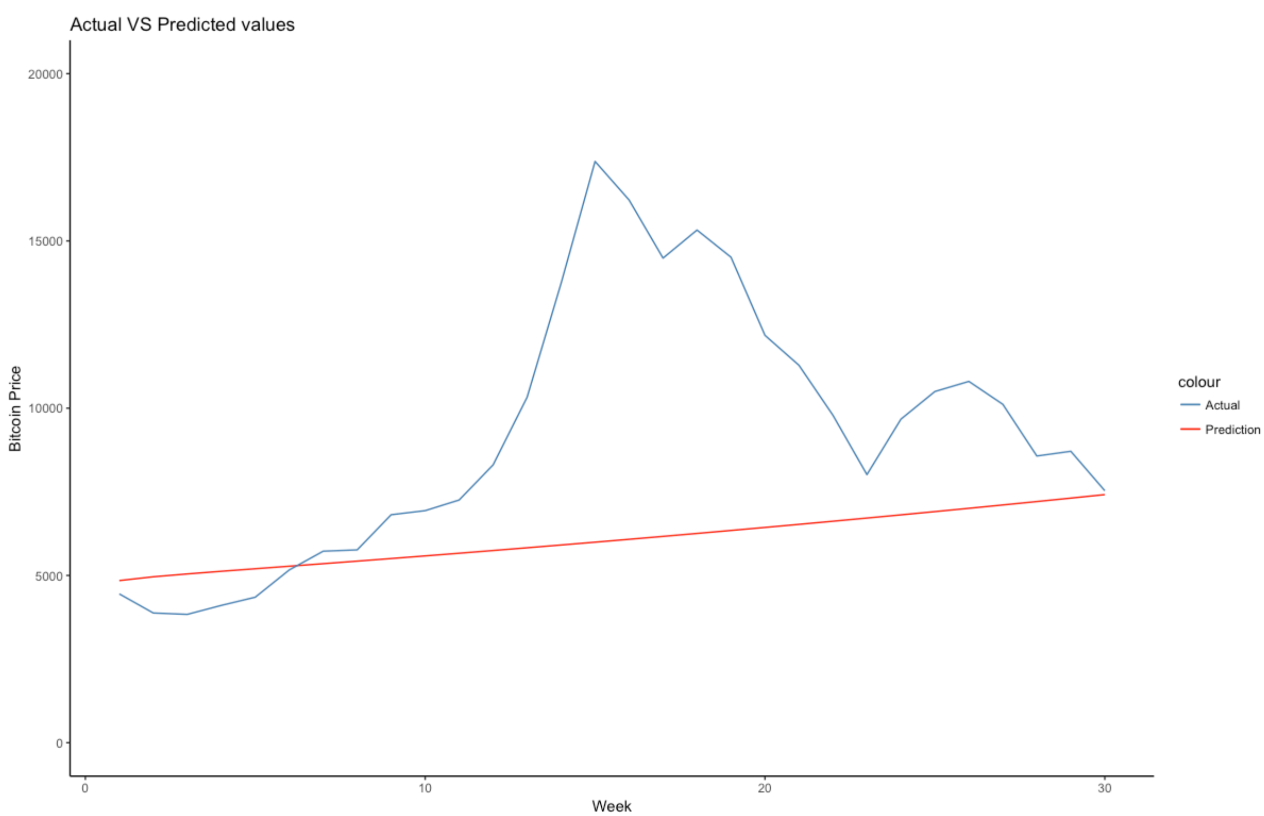





```
        Box-Ljung test

data:  res1
X-squared = 0.014416, df = 1, p-value = 0.9044
```

After we fitted a model, we need to perform diagnostics to make sure all the assumptions were met. Since residuals are independent and normally distributed and no significant autocorrelation presents, we can now forecast bitcoin prices using the ARIMA (1,1,1) model with google trend as a predictor.


Forecasts from Regression with ARIMA(2,1,1) errors
0
5000
10000
15000
20000
25000
30000
0
50
100
150
200
250


Actual VS Predicted values
Bitcoin Price
20000
15000
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0
10
20
30
Week
colour
Actual
Prediction

Accuracy Table:

	Actual	Prediction	%Change	Week
1	4448.186	4846.434	0.08953034	1
2	3877.361	4960.340	0.27930843	2
3	3836.227	5045.311	0.31517517	3
4	4104.402	5124.725	0.24859233	4
5	4349.547	5200.129	0.19555662	5
6	5163.845	5275.623	0.02164628	6
7	5724.994	5351.330	0.06526878	7
8	5764.160	5427.980	0.05832249	8
9	6814.830	5505.579	0.19211786	9
10	6936.828	5584.268	0.19498243	10
11	7254.876	5664.057	0.21927582	11
12	8305.702	5744.983	0.30830857	12
13	10326.294	5827.061	0.43570647	13
14	13732.345	5910.311	0.56960655	14
15	17376.360	5994.750	0.65500541	15
16	16223.990	6080.396	0.62522191	16
17	14485.893	6167.265	0.57425721	17
18	15325.235	6255.375	0.59182521	18
19	14512.732	6344.743	0.56281538	19
20	12177.336	6435.389	0.47152739	20
21	11282.490	6527.329	0.42146376	21
22	9788.082	6620.583	0.32360768	22
23	8014.081	6715.170	0.16207860	23
24	9670.893	6811.107	0.29571060	24
25	10498.607	6908.416	0.34196836	25
26	10800.558	7007.114	0.35122665	26
27	10114.764	7107.223	0.29734170	27
28	8570.413	7208.761	0.15887821	28
29	8711.170	7311.751	0.16064654	29
30	7532.565	7416.212	0.01544676	30

The results revealed significant improvements with much lower margin of errors throughout the thirty weeks. In particular, the margin of error is only 1.54% compared with 2.66% from the original model. We further examined model accuracy by calculating mean percentage errors, mean errors and root mean squared errors.

Model 1:

	ME	RMSE	MAE	MPE	MAPE
Test set	-3183.876	4757.224	3468.105	-50.97236	56.66672

Model 2 with Google trend:

	ME	RMSE	MAE	MPE	MAPE
Test set	-3111.502	4708.59	3423.035	-49.1853	55.34531

Model 2 with Google Trend Index as regressor gave us the lowest RMSE (Root Mean Squared Error) MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error) among all models. Results proved that adding Google Trend Index significantly enhanced the basic time series model.

Discussion

- **Conclusion**

Even though we were not able to predict the exact price, our model accurately predicted the trend and provided good approximation on bitcoin prices after thirty weeks. The actual data were more volatile than our prediction but this is common in predicting financial asset prices. Based on the performance on testing data, we are confident that our model will perform well in predicting bitcoin prices in the long run.

- **Assumptions**

When building the ARIMA model, we only extracted the Google Trend Index for the keyword “bitcoin”. We assume “bitcoin” is representative of every google user who intended to search for bitcoin. In addition, the Google Trend Index may not represents all the internet users in the world because people who live in countries like China and Vietnam have no access to Google [5]. Google is also not the primary search engine in many countries like South Korea and Russia [6]. In our research, we assume that Google Trend Index is a representative indication of bitcoin’s public awareness level. There were many debates on whether bitcoin is a legitimate currency or not. Since the primary function of bitcoin is a medium of exchange between parties, we considered bitcoin as a currency and attempted to predict its exchange rate against USD.

- **Future Improvements**

In this paper, we used five years of data to train our model and thirty weeks of data for testing. As we have more time to collect additional data and measure model performance, we can make adjustments to our model to enhance prediction accuracy. Another way to improve the model is search for significant predictor that could increase the log likelihood and decrease AIC, AICc and BIC of the ARIMA model.

References

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Appendix:

1. Bitcoin Data:

http://data.bitcoinity.org/markets/price_volume/5y/USD?r=week&t=lb&vu=curr

2. Google Trend Data:

https://trends.google.com/trends/explore?date=today%205-y&q=bitcoin