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Bitcoin Price Prediction Using SARIMAX Model

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ABSTRACT: Bitcoin is one of the most widely used and most valued cryptocurrencies in the world. Bitcoin usage is growing year by year. Apart from consumers, companies also have adopted the usage of bitcoin. Bitcoin remains by far the most popular choice, followed by Ethereum and Litecoin. Bitcoin is considered an uncorrelated asset, meaning that there appears to be no link between the performance of the traditional stock and bond markets and that of Bitcoin. Bitcoin price had a steep increase in the recent years. Many attempts have been made to predict these fluctuations. There always remains a question that, is it follows a random walk process or is there any hidden patterns in it? In this paper, historical data of bitcoin price from years 2012 to 2020 is used to predict the fluctuations of price using Machine Learning algorithm. This paper also explains the efficiency of Autoregressive Integrative Moving Average (ARIMA) model for predicting bitcoin price. ARIMA is a statistical analysis model which is mainly used for time series data. In this paper, I have used SARIMAX which is the extension of ARIMA model. As cryptocurrency price prediction problem is a time series problem, this approach will be more suitable to predict the future trends.

KEYWORDS: Cryptocurrency, Bitcoin, ARIMA, SARIMAX, Machine Learning

I. INTRODUCTION

Cryptocurrency is a digital currency in which encryption techniques are used to regulate the generation of units of currency and verify the transfer of funds, operating system independently of a central bank [24]. This decentralized structure allows people to have a full control over their currency. Blockchains, which are organizational methods for ensuring the integrity of transactional data, is an essential component of many cryptocurrencies. It provides real-time access to trade documents, shipment status, etc and it boosts transparency and decreases the threat of frauds and cyber attacks. The first blockchain based cryptocurrency was Bitcoin, which still remains the most popular and most valuable. Bitcoin is private (as your name/identity is not made public), but Bitcoin transactions are public. Bitcoin can be sent from user to user on the peer-to-peer bitcoin network without the need for intermediaries. Transactions are verified by network nodes through cryptography and recorded in a blockchain. Cryptography is the method for protecting information by transforming it into a secure format.

The prediction of bitcoin price is a type of time series problem. A time series is a set of observations taken at specified times, usually at equal intervals. It can be taken as any variable that changes over time. For time series forecasting of Bitcoin price, I have used Autoregressive Integrative Moving Average (ARIMA) model. An autoregressive integrated moving average, or ARIMA, is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends. It is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables. It examines the differences between values in the series instead of through actual values to predict the fluctuations in price. ARIMA model is one of the most widely used approaches to time series forecasting, and it provides complementary approaches to the problem. This model aims to describe the autocorrelations in the data and thus it measures the relationship between a variable's current value and its past values. As bitcoin price follows a seasonal trend in the fluctuations of price over years, the Seasonal Autoregressive Integrative Moving Average with Exogenous Regressors (SARIMAX) model which is the extension of ARIMA model will be best suited. Exogenous Regressors is the factor in the model whose value is identified by factors of variables outside the model of study. As there is no such impacting factor in the model, we can think of it as a SARIMA model. It supports the direct modeling of the seasonal component of the series. It adds three new hyperparameters to specify the autoregression (AR), differencing (I) and moving average (MA) for the seasonal component of the series, as well as an additional parameter for the period of the seasonality.

The structure of the paper is as follows: Section II covers the related work that has been done in this topic. In Section III, the whole process flow for prediction of bitcoin price using SARIMAX model is explained. In Section IV, the experimental results of the model is discussed. Section V concludes the paper.

II. RELATED WORK

By the emergence of BTC with an initial value of around one dollar in the year 2009, no one predicted that in 8 years it would pass all prior records and would reach to the unbelievable value of \$18000 [12]. After 2017 there was a steep increase in the value and followed a unusual trend. There are many contributions done in this topic. Abraham et al. [1] compared the factors effective among tweet sentiments, tweet volumes and google trends for predicting value changes of cryptocurrencies and found that the google trends and tweet volumes includes a nice correlation with the value changes. The search volume index is highly correlated with cryptocurrency prices both when prices rise and when they fall, as are tweet volumes. Based on the intensity of the tweet sentiments Stenqvist et al. [2] used a naive prediction model to predict the price fluctuation accurately with a 83% accuracy. Pintelas et al. [3] used deep learning models like CNN, LSTM and BiLSTM to predict the price of cryptocurrencies like bitcoin and ethereum and concluded that advanced deep learning models such as CNNs and LSTMs are inefficient and unreliable for price prediction probably due to the fact that this problem is a very complicated one.

P. Jay et al. [4] concluded that stochastic neural network model like Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) models are superior in comparison to the deterministic models for price prediction of Bitcoin, Ethereum, and Litecoin. While comparing between MLP and LSTM, the researcher Kumar et al. [13] concluded that the LSTM model is more precise and robust for long term dependency. The two researchers named Yu Wang and Renyu Chen [5] proved that the trading price premium rate in different markets will affect the price to be predicted, and adding social media comment features can significantly improve the accuracy of the forecast. The researchers Dutta et al. [15] combined the recurrent neural network models such as LSTM and GRU which proved to be more efficient than traditional machine learning models and also concluded that shallow learning models can effectively benefit to quantitative finance in the coming years. Phaladisailoed et al. [19] concluded that these models gives better result than Theil-Sen regression and Huber regression.

Zhao et al. [6] found that support vector machines yields the most profitable trading strategies, which outperform the market on average of Bitcoin, Ethereum and Litecoin since January 2018. Valencia et al. [18] experimented neural networks (NN) like support vector machines (SVM) and random forest (RF) and concluded that the Neural Networks model outperforms the other models in predicting the cryptocurrency prices. Poogodi et al. [7] used the SVM method a got a higher accuracy (96.06%) than the LR method (85.46%). The researcher have said that accuracy of the proposed model can be increased up to 99% by adding features to the SVM method. And Mittal et al. [17] proved the multivariate linear regression method to be efficient by giving a accuracy of 99.30452 for a smaller dataset. The researchers Premarathne et al. [8] combined the Deep Learning with Data parallelism and Cloud Computing Machine learning engine as “hybrid architecture” to predict new Cryptocurrency prices. The four hybrid architecture models, namely, (i) standalone PC, (ii) Cloud computing without data parallelism (GPU-1), (iii) Cloud computing with data parallelism (GPU-4), and (iv) Cloud computing with data parallelism (GPU-8) utilized for the analysis and concluded that it can reduce computation time up to 90% with 80% of accuracy.

Two researchers named Yufang Wang and Haiyan Wang [9] proposed a partial differential equation (PDE) model to capture the influence of transaction patterns on bitcoin price over time and combined the effect of all chainlet clusters through analysis of bitcoin subgraphs and chainlets. Google Trends Index is also incorporated to the PDE model to reflect the effect of bitcoin market sentiment. The experiment resulted in a average accuracy of 0.82 for 365 consecutive days in 2017. The authors Li et al. [10] proposed the transaction graph based feature to automatically encode the patterns. By experimenting the results showed that the proposed method outperforms the most recent state-of-art method, and demonstrate the effectiveness of automatically learning the transaction patterns from multiple blockchain history periods. Xiaolei et al. [11] concluded that the LightGBM model outperforms other methods like Support Vector Machine (SVM) and Random Forest (RF), which would make it capable of forecasting the prices effectively while managing large number of features and data objects simultaneously. Ayaz et al. [12] proposed a Autoregressive Integrative Moving Average (ARIMA) model method to predict the bitcoin price and their experiment gave rise to a conclusion that the ARIMA model will be effective when the price is predicted in subperiods of timespans over which it has a unique trend.

The researchers Mehta et al. [14] proposed two machine learning approach like sentiment analysis and XG-Boost for bitcoin price prediction. The experimental results proves that the growth trend of bitcoin can be efficiently predicted using



the proposed approach. Timaul et al.[16] trained the classification models and the RMSProp optimizer and Adam Optimizer recorded better results and the SGD optimizer performed worst during training. As results were pretty close to training data, the researchers concluded that this model is more robust, and can manage to make predictions with less familiar data. The researcher Kim et al.[20] used User Comments and Replies for predicting the bitcoin price and it gave rise to a conclusion that when the time lag was six days, the predicted result proved to be highest with an accuracy of 71.823%. The negative replies section shown a very significant impact in the fluctuation in the number of transactions when the time lag was 11 to 13 days. While for a time lag of one day, the predicted fluctuation in the number of transaction yielded an accuracy of 66.129%. Researchers named Amjad and Shah[21] concluded that algorithms like Classification and directly learning the empirical conditional distribution (EC) both outperforms ARIMA model on all evaluation metrics. The researchers Germán Cheuque et al.[22] compared models fed only with recent price history versus when it is fed with a measure of the positivity or negativity of the sayings of these influencers in addition for predicting bitcoin Price and it resulted that both had almost the same predictive score. I have tried to efficiently predict the bitcoin price using ARIMA approach as there are very less contributions done using this approach.

III. METHODOLOGY

In this section, the proposed model is described. First part is Data Analysis. Dataset is taken from Kaggle website and it is up-to-date and trustworthy data. It is a csv file containing bitcoin exchanges for the time period of January 2012 to September 2020, with minute to minute updates of OHLC (Open, High, Low, Close), Volume in BTC and indicated currency, and weighted bitcoin price. Timestamps are in Unix time. Timestamps without any trades or activity have their data fields filled with NaNs. Dataset csv file is read using pandas library in python. The following Figure 1 shows the first ten rows of the dataset.

	Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
1	1325317980	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	1325318040	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	1325318100	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	1325318160	NaN	NaN	NaN	NaN	NaN	NaN	NaN
5	1325318220	NaN	NaN	NaN	NaN	NaN	NaN	NaN
6	1325318280	NaN	NaN	NaN	NaN	NaN	NaN	NaN
7	1325318340	NaN	NaN	NaN	NaN	NaN	NaN	NaN
8	1325318400	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9	1325318460	NaN	NaN	NaN	NaN	NaN	NaN	NaN
10	1325318520	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Figure 1

Before proceeding further, Timestamp which is in Unix time should be converted to normal datetime format. After converting, it has been resampled into different frequencies-daily, monthly, yearly and quarterly. The first ten rows of the dataset looks as shown in Figure 2.



Timestamp	Open	High	Low	Close	Volume_(BTC)	Volume_(Currency)	Weighted_Price
2011-12-31	4.490000	4.513333	4.490000	4.513333	31.620766	141.106779	4.498804
2012-01-01	4.806667	4.806667	4.806667	4.806667	7.200667	35.259720	4.806667
2012-01-02	5.000000	5.000000	5.000000	5.000000	19.048000	95.240000	5.000000
2012-01-03	5.252500	5.252500	5.252500	5.252500	11.004660	58.100651	5.252500
2012-01-04	5.200000	5.223333	5.200000	5.223333	11.914807	63.119577	5.208159
2012-01-05	6.281429	6.286190	6.281429	6.286190	4.514373	27.987370	6.284127
2012-01-06	6.435000	6.445000	6.435000	6.445000	2.420196	15.914659	6.438999
2012-01-07	6.800000	6.800000	6.800000	6.800000	0.295858	2.011834	6.800000
2012-01-08	6.950000	6.950000	6.950000	6.950000	2.500000	17.300000	6.950000
2012-01-09	6.584167	6.584167	6.581667	6.581667	1.857481	12.306798	6.582770

Figure 2

As shown in the four graphs in Figure 3 section, the prices of bitcoin from 2012 to 2020 is plotted. We can see in Figure 3d that from 2012 to 2017 the bitcoin price was constant, and thereafter there was an unusual fluctuation in the price. Now we have to convert this problem into time series to remove this unusual trend and effectively evaluate it.

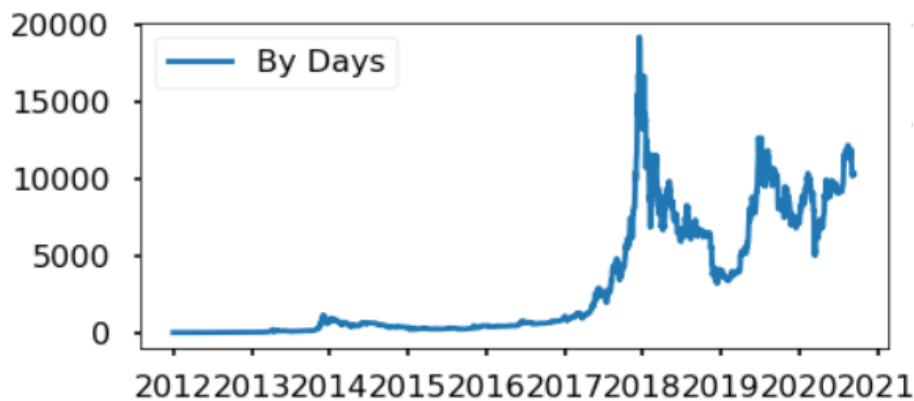


Figure 3a

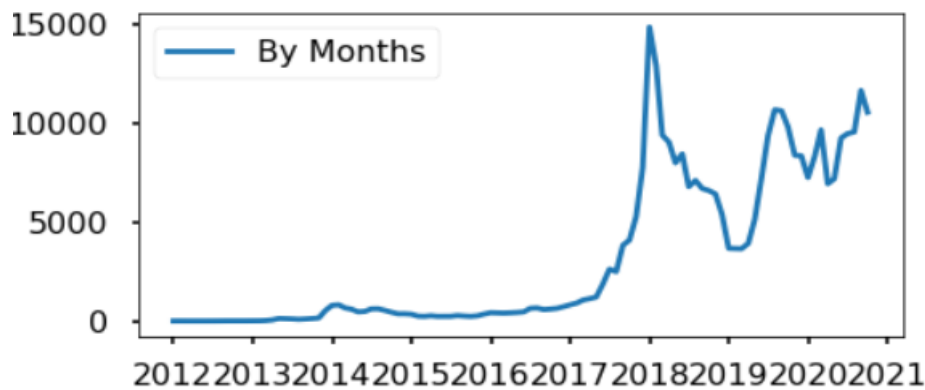


Figure 3b

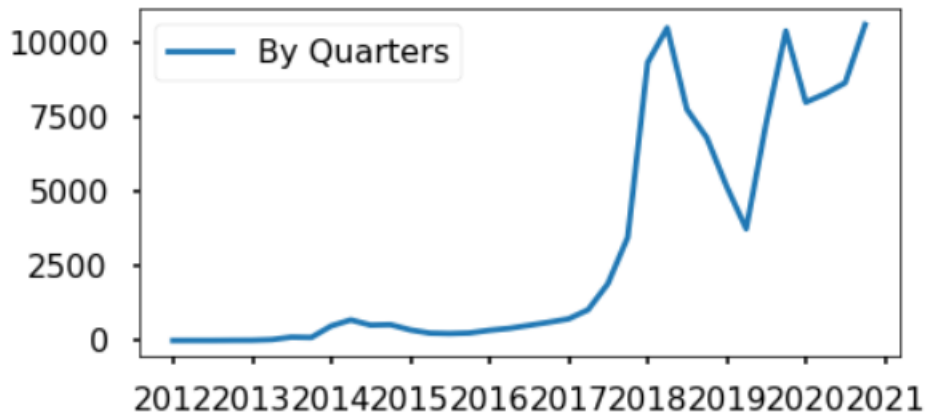


Figure 3c

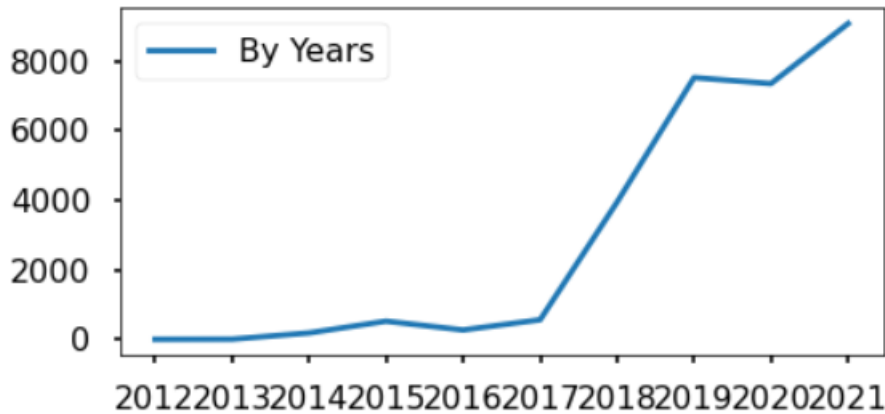


Figure 3d

Before finding out the parameters and building the model, we have to check whether the data is stationary or not. The criteria is that the p value should be less than 0.05 for the data to be stationary. Statistical test named Augmented dickey fuller test has to be done for the stationarity check of the data. As shown in the figure 4, after performing the test, the p value of original data came to be greater than 0.05 which means it is not stationary.

```
sm.tsa.seasonal_decompose(df_month.Weighted_Price).plot()
print("Dickey-Fuller test: p=%f" % sm.tsa.stattools.adfuller(df_month.Weighted_Price)[1])
```

Dickey-Fuller test: p=0.617866

Figure 4

For making the data stationary, seasonal decomposition of the data has to be performed. As shown in the figure below, after plotting the seasonal trend of the data can be seen i.e. the repeated variations that is occurring at specific intervals. This is the reason, Seasonal Autoregressive Integrative Moving Average with Exogenous Regressor (SARIMAX) model which is the extension of ARIMA model is more suitable as it supports the direct modeling of the seasonal component of the series.

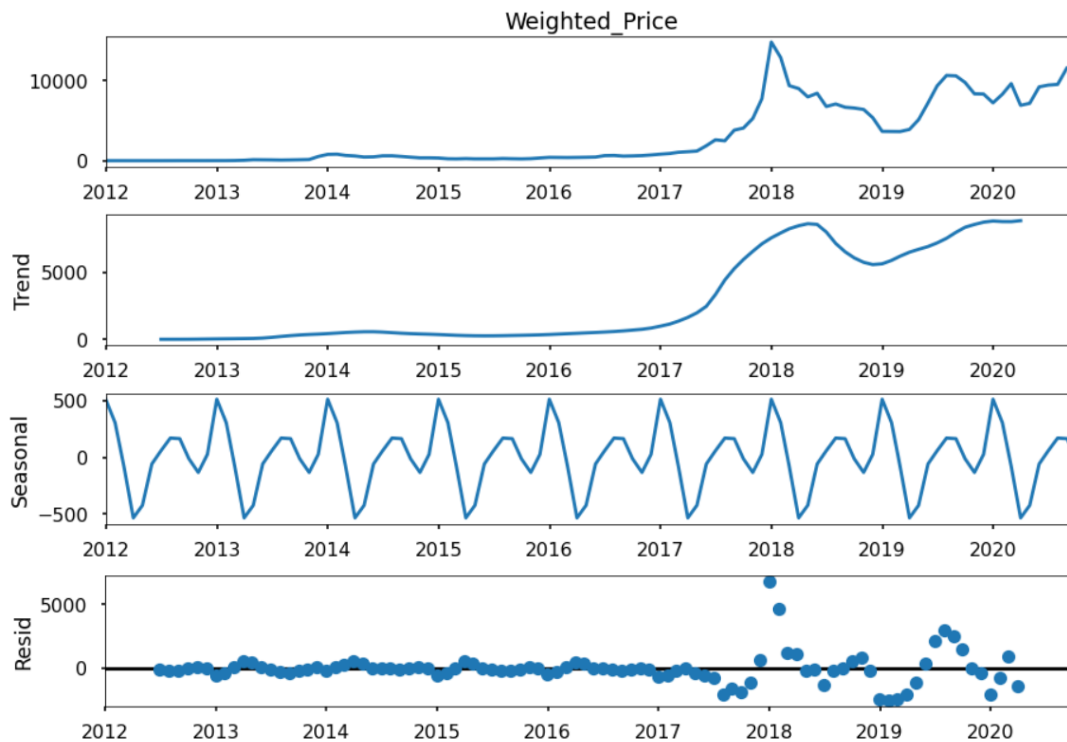


Figure 5

For converting it into stationary, we have to do differencing. The differencing process is basically taking each datapoint and subtracting it to the previous data. First of all to convert the data into normality, Box-Cox transformation is used as shown in Figure 6a. After that, performing seasonal and regular differentiation resulted in a p value less than 0.05 as shown in Figure 6b.

As shown in the Figure 6c the plot shows that the data is stationary.

```
# Box-Cox Transformations
df_month['Weighted_Price_box'], lmbda = stats.boxcox(df_month.Weighted_Price)
print("Dickey-Fuller test: p=%f" % sm.tsa.stattools.adfuller(df_month.Weighted_Price)[1])
```

Dickey-Fuller test: p=0.617866

Figure 6a

```
# Seasonal differentiation
df_month['prices_box_diff'] = df_month.Weighted_Price_box - df_month.Weighted_Price_box.shift(12)
print("Dickey-Fuller test: p=%f" % sm.tsa.stattools.adfuller(df_month.prices_box_diff[12:])[1])
```

Dickey-Fuller test: p=0.288907

```
# Regular differentiation
df_month['prices_box_diff2'] = df_month.prices_box_diff - df_month.prices_box_diff.shift(1)
plt.figure(figsize=(15,7))
```

```
# STL-decomposition
sm.tsa.seasonal_decompose(df_month.prices_box_diff2[13:]).plot()
print("Dickey-Fuller test: p=%f" % sm.tsa.stattools.adfuller(df_month.prices_box_diff2[13:])[1])
plt.show()
```

Dickey-Fuller test: p=0.000002

Figure 6b

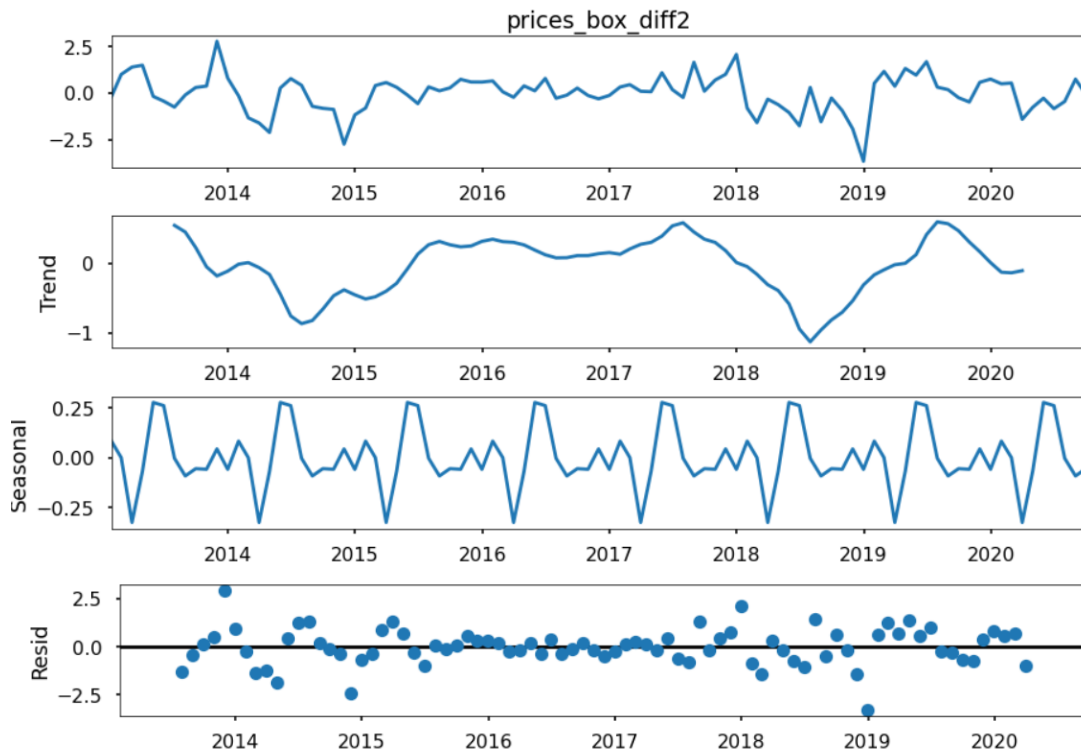


Figure 6c

Now we can proceed further to building the model. For implementing the model, we have to find out the parameters that can build the best suited model. There are three parameters p, d, q of which p is the order of AR model i.e. AR model lags, q is the order of MA model i.e. MA model lags and d is the number of differencing needed to make the data stationary. The Initial approximation of parameters can be done using Autocorrelation and Partial Autocorrelation Plots. Identification of an AR model can be done with the help of PACF. For an AR model, the theoretical PACF sudden falls past the order of the model which means if there is a sudden drop in the partial autocorrelation after the first higher autocorrelation, that point will be the AR model lags. As shown in the Fig 7b, in our case as there is no sudden decrease in the autocorrelation, the AR model lags will be 0. Identification of an q parameter i.e. MA model lags is often best done with the ACF rather than the PACF. For an MA model, there will be an exponential decay rather than sudden decrease. That point of autocorrelation will be the q parameter. As shown in the Fig 7a, the exponential decay is at the point 1 after the first higher autocorrelation. Therefore the q parameter will be 1. As the number of regular differencing needed was 1, the d parameter will be 1.

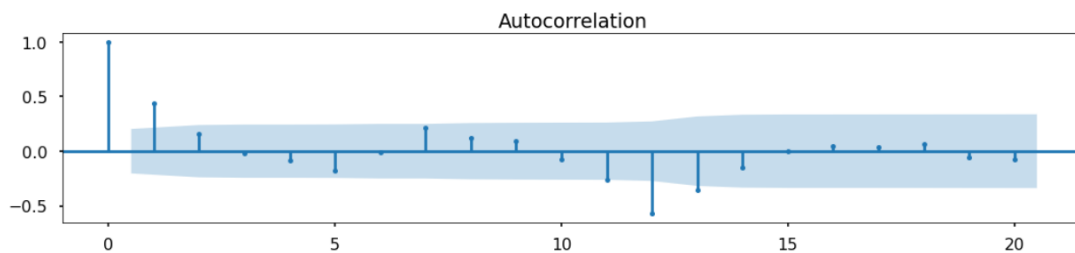


Figure 7a

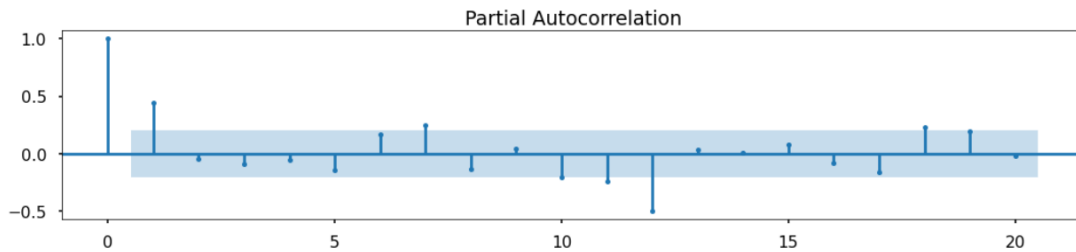


Figure 7b

After that, algorithm should be built to perform the model selection process. One of the criteria for the best model is that the AIC value should be minimum. The algorithm will choose the best suited model with parameters. Below Figure 8 shows the summary of the best model. As we approximated the p,d,q values before, the algorithm also shows the same result. This model has the minimum AIC compared to other models. As we can see in the figure below that the seasonal AR part with 12 months lag (ar.S.L12) and seasonal MA part with 12 months lag (ma.S.L12) has the minimum p value which means it is significant and it is best suited to include in the model. Apart from p,d and q parameters of regular ARIMA model, there are another three parameters P,D,Q for seasonality. As there was one seasonal differencing needed to make the data stationary, the D parameter will be 1. Therefore the best model suited is SARIMAX(0, 1, 1)x(2, 1, 1, 12) where the order p=0,d=1,q=1 and seasonal order P=2,D=1,Q=1 and 12 is the seasonal lags.

parameters	aic
11 (0, 1, 2, 1)	198.770908
23 (1, 0, 2, 1)	198.826934
19 (1, 0, 0, 1)	199.111609
21 (1, 0, 1, 1)	199.386610
7 (0, 1, 0, 1)	199.472014

SARIMAX Results			
Dep. Variable:	Weighted_Price_box	No. Observations:	106
Model:	SARIMAX(0, 1, 1)x(2, 1, 1, 12)	Log Likelihood	-94.385
Date:	Tue, 10 Nov 2020	AIC	198.771
Time:	00:30:36	BIC	211.434
Sample:	12-31-2011	HQIC	203.884
	- 09-30-2020		
Covariance Type:	opg		

	coef	std err	z	P> z	[0.025	0.975]
ma.L1	0.3521	0.105	3.344	0.001	0.146	0.559
ar.S.L12	-0.4293	0.178	-2.416	0.016	-0.778	-0.081
ar.S.L24	-0.3107	0.173	-1.793	0.073	-0.650	0.029
ma.S.L12	-0.6118	0.217	-2.825	0.005	-1.036	-0.187
sigma2	0.3702	0.050	7.354	0.000	0.272	0.469

Ljung-Box (L1) (Q):	0.02	Jarque-Bera (JB):	10.76
Prob(Q):	0.88	Prob(JB):	0.00
Heteroskedasticity (H):	1.18	Skew:	0.57
Prob(H) (two-sided):	0.64	Kurtosis:	4.22

Figure 8

As we have done the box-cox transformation before, inverse of box-cox transformation has to be done to transform the forecasted values back to their original units. After this process, we can proceed to prediction part.

IV. EXPERIMENTAL RESULTS

After fitting the model, I have predicted the bitcoin price. Figure 9a shows the last 15 original weighted price. As the original dataset contains data up to September 2020 it has future values as NaN values. Figure 9b shows the predicted values up to January 2021. As shown in the figure, the predicted values are almost close to the original values.



2020-01-31	8321.725828	2020-01-31	9047.043950
2020-02-29	9647.446186	2020-02-29	10297.187645
2020-03-31	6929.254708	2020-03-31	5998.153282
2020-04-30	7182.033733	2020-04-30	8720.904574
2020-05-31	9236.327890	2020-05-31	10768.250144
2020-06-30	9459.531635	2020-06-30	9040.961754
2020-07-31	9545.436344	2020-07-31	10766.765033
2020-08-31	11637.080012	2020-08-31	12162.258149
2020-09-30	10541.968835	2020-09-30	11107.257761
2020-10-31	NaN	2020-10-31	13604.908421
2020-11-30	NaN	2020-11-30	17550.384576
2020-12-31	NaN	2020-12-31	16638.983047
2021-01-31	NaN	2021-01-31	15057.788298

Figure 9a

Figure 9b

For understanding the result more efficiently, the figure 10 shows the visualization of the original weighted price of bitcoin and the predicted price of bitcoin. The SARIMAX model has performed very well for such a very large dataset of almost 9 years. The original weighted price has a range of 4.49880 to 14840.2604 and our predicted price resulted with a RMSE value of 546.2697 which means it has got a very good accuracy.



Figure 10

V. CONCLUSION

In this paper, I have predicted the bitcoin price using SARIMAX which is the extension of ARIMA model. I have proved that it is possible to predict this unusual trend of bitcoin price using a time series model with a very good accuracy. As Root Mean Squared Error (RMSE) value has the benefit of penalizing large errors more and as it is more suitable for such a large dataset, RMSE value metric is used to determine the accuracy level of predicted price. The RMSE value of the predicted value is 546.2697 which is much better as the range of bitcoin price is much larger. As the result suggests, there is still some room for improvement. In future, it may be worth exploring by combining two or more machine learning algorithms like LSTM and CNN and tune the parameters to find a more suitable and efficient method to predict the bitcoin price.

VI. ACKNOWLEDGEMENT

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