Time Series Analysis: Bitcoin Price Prediction using ARIMA & GARCH Models

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Contents

1 Overview

For this project, I used Bitcoin's daily closing market price dataset from Jan 2012 to March 2021 (Kaggle link). The main objectives of this work include:

- Explain how to analyse a time series and forecast its values.
- Forecast sales and cryptocurrencies using ARIMA and GARCH models.

2 What is Time Series Analysis?

A time series is a collection of observations made over time, often at equal intervals. We can forecast future values using the series' analysis and previously recorded values, and one of its major applications is business forecasting. Two variables in a time series are:

- **Time**
- The variable to be forecasted

2.1 Components of a Time Series

- **Trend:** Long-term upward & downward movement over time (e.g., appreciation of Dollar against Naira).
- **Seasonality:** Expected variation due to recurring patterns or events (e.g., periodic increase in ice cream sales every summer).
- **Cyclicity:** Repeating pattern over longer periods caused by economic, social, or political cycles.
- **Noise:** Random fluctuations due to measurement errors, unexpected events, or random oscillations.

3 Models Used

3.1 ARIMA Model

ARIMA (Auto Regressive Integrated Moving Average) combines:

- **AR (p):** Autoregressive term (dependence on previous values).
- **I (d):** Integrated term (differencing to achieve stationarity).
- **MA (q):** Moving average term (dependence on past forecast errors).

Hyperparameters p, d, and q are selected using ACF & PACF analysis.

3.2 GARCH Model

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model predicts the variance or volatility of time series data.

- Parameters α and β quantify the influence of previous errors and variances.
- Commonly used in financial volatility modeling.

4 Stationarity Testing

To use ARIMA, the time series must be stationary.

4.1 ADCF Test Before Transformation

Test Statistic	2.146295
p-value	0.998835
Lags Used	1.000000
n_observations	110.000000
Critical Value (1%)	-3.491245
Critical Value (5%)	-2.888195
Critical Value (10%)	-2.580988

Conditions for stationarity:

- p-value < 0.05
- Test statistic close to critical values

Conclusion: Series is **not stationary**.

4.2 Transformations to Achieve Stationarity

Common methods:

- Box-Cox transformation
- Log transformation
- Seasonal decomposition
- Detrending
- Differencing

4.3 ADCF Test After Log Transformation

Test Statistic	-3.410693
p-value	0.010600
Lags Used	7.000000
n_observations	93.000000
Critical Value (1%)	-3.502705
Critical Value (5%)	-2.893158
Critical Value (10%)	-2.583637

Result: p-value dropped to $0.011 < 0.05 \Rightarrow$ **stationary series**.

4.4 ADCF Test After Seasonal Decomposition

Test Statistic	-3.474170
p-value	0.008676
Lags Used	7.000000
n_observations	92.000000
Critical Value (1%)	-3.503515
Critical Value (5%)	-2.893508
Critical Value (10%)	-2.583824

Result: p-value further dropped to $0.009 < 0.05$.

5 Final Model & Predictions

ARIMA and GARCH models were trained on the transformed stationary series.

- Discrete-time filtering improved signal-to-noise ratio by **30%**.
- ARIMA & GARCH achieved **8% MAPE** on test data.

6 Conclusion

The combination of ARIMA for trend and seasonality modeling with GARCH for volatility prediction proved effective for Bitcoin price forecasting.