Forecasting S&P BSE BANKEX and S&P BSE Sensex using ARIMA MODEL

First Author: **Poojarani Talawar**, Student, R V Institute of Management, Bangalore.

Second Author: **Tanushree R**, Student, R V Institute of Management, Bangalore.

Third Author: **Dr. Vinay K S**, Assistant Professor, R V Institute of Management, Bangalore.

Abstract

A crucial component of several disciplines, including finance, economics, and more, is time series forecasting. A well-liked and effective method for identifying time-dependent trends in data and creating precise future forecasts is the AutoRegressive Integrated Moving Average (ARIMA) model. In this study, we look at how well the ARIMA methodology predicts time series data. In the first part of our study, we thoroughly examine ARIMA, clarifying its essential elements and the model identification procedure, including the usage of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. In order to forecast the future value of the Stock, we have collected daily data for the S&P Sensex and S&P BANKEX and have reviewed and applied key time series data components using the ARIMA model.

Keyword: ARIMA Model, Stock Market, Prices, Time Series data

I. INTRODUCTION

Stock markets are venues where buyers and sellers meet to exchange equity shares of public corporations. Due to their ability to democratise access to investor trading and capital exchange, stock markets are essential elements of a free-market economy. Prices are discovered and traded in stock markets in an efficient manner.

The Dow Jones Industrial Average and the S&P 500 are the two primary index types used in the stock market. The securities market operates under strict regulations enforced by governmental bodies like the Securities and Exchange Commission (SEC). Given its significance and relevance to investors, traders, and financial institutions, stock price forecasting is essential in the financial markets. Accurate stock price predictions offer important insights into market trends, aid in the decision-making process for investors, and aid in the optimisation of investing strategies.

Due to the possible financial rewards and risk management advantages, it offers, the capacity to forecast stock prices is highly valued. Stock price forecasts are used by investors to find prospective investment opportunities, decide when to purchase or sell stocks, and gauge the success of their portfolios as a whole. Investors can take advantage of favourable market conditions and reduce potential losses by using timely and accurate forecasts.

Based on historical values, autoregressive integrated moving average (ARIMA) model forecast future values. Lagged moving averages are used by ARIMA to smooth time series data. They are frequently utilised in technical analysis to predict upcoming asset price trends. The implicit premise of autoregressive models is that the future will mimic the past. As a result, they may turn out to be incorrect in specific market circumstances, such as financial crises or times of rapid technical advancement. Stock price forecasts are crucial for traders when making short-term decisions, such as deciding on the best entry and exit points, trading methods, and risk management. Forecasted stock prices are used by traders to profit from market swings, take advantage of arbitrage possibilities, and place winning transactions.

Stock price projections are advantageous to financial institutions as well. Forecasting models are used by banks, asset management companies, and hedge funds to manage investment portfolios, decide how to allocate assets, and determine risk exposure. Accurate stock price forecasts support efficient risk management procedures and aid institutions in maximising their investment returns.

Additionally, stock price forecasts offer useful information about investor and market sentiment as well as the fundamental causes of price changes. They aid in the design of macroeconomic policies and regulatory decisions and contribute to a greater knowledge of market dynamics.

II. About the Research Methods

Review of Literature

The literature review on Predictive Models for Stock Market Index Using Stochastic Time Series ARIMA Modelling in Emerging Economy explores that stochastic time series ARIMA prediction models for developing stock market indexes. It highlights how crucial precise stock market projections are for investors and financial experts. In order to provide useful information for decision-making in developing economies, the research assesses thE ARIMA model's capacity to forecast stock market indexes using historical data. (Manish Dadhich, Manvinder Singh Pahwa, Vipin Jain, and Ruchi Doshi June 2021).

The outcomes of literature on Forecasting of Bank Nifty using ARIMA model shows the ARIMA model's capability to correctly forecast Bank Nifty's short- and long-term patterns, offering insightful information for investors and financial experts. The results of this study help to clarify and put forecasting methods to use in the context of financial markets. (Solanki, M., & Kumar, M. International Journal of Computer Science and Mobile Computing, 10(4), 105-112. (2021).

In another research on Stock Price Prediction Using ARIMA Model- the experimental results show the ARIMA models' potential for assisting investors in choosing profitable stock market investments. When compared to new prediction methods for short-term stock price prediction, ARIMA models perform competitively. (Supriti Khanderwal, ITM University & Debasis Mohanty, ITM University, April, 2021)

In another study combining ARIMA models and PCA can improve the accuracy of stock return estimates in contrast to using ARIMA models alone. Predicting Bank Stock Returns with ARIMA Models and PCA" (Y. Du and Y. Luo, published in the Journal of Applied Finance & Banking in 2019)

Research Gap:

The lack of focus on applying ARIMA models to predict S&P BSE Sensex and Bankex stock prices in the context of emerging economies constitutes a research vacuum in the literature. By using ARIMA models to forecast the stock prices of these indexes, this study seeks to close this knowledge gap by offering insights specific to the peculiarities of developing economies. The research also compares the performance of ARIMA models for the S&P BSE Sensex and Bankex, providing useful advice for investors and financial professionals in making decisions in the context of emerging markets.

In one more research on Stock market forecasting using ARIMA model for S&P BSE Sensex the findings show how well ARIMA and neural network models predict both short-term and long-term market patterns accurately. The results of this study help investors and financial experts make educated judgements by increasing understanding of various forecasting techniques for stock market indexes. (Shah, P., & Desai, P. (2018). International Journal of Engineering Research and General Science, 6(6), 18-24.)

Research Questions:

- Can ARIMA models effectively predict the stock prices of S&P BSE Sensex and Bankex?
- What is the efficiency of ARIMA in predicting the stock prices of both S&P BSE Sensex and Bankex?
- Is there a significant correlation between the predicted values of S&P BSE Sensex and Bankex?

Research Objectives:

1. To forecast the trend of S&P BSE BANKEX and S&P BSE SENSEX stock return for next 2 years.
2. To evaluate the performance of ARIMA Model for predicting S&P BSE BANKEX and S&P Sensex.
3. To analyse the relation between S&P BSE BANKEX and S&P Sensex.

Research data and methodology:

In order to conduct this analysis, 482 observations total from the closing stock indexes of the S&P BSE Sensex and the S&P BSE BANKEX were collected monthly from January 2003 to June 2023.

The research employed predicting and analysing of S&P BSE Sensex and S&P BSE S&P BSE BANKEX. The date and related closing prices of the historical data for both indices are taken from the BSE INDIA website. The data integrity has been maintained. In the analysis, the S&P BSE Sensex and S&P BSE BANKEX stock prices are predicted using the ARIMA model. The ARIMA model was selected based on AIC value and BIC value. The selected ARIMA model is then fitted to the respective time series data using the Arima function in R Studio, allowing for the generation of forecast.

By contrasting the predicted values with the actual values, the accuracy of the ARIMA forecasts was assessed. In order to illustrate and explain the performance and forecast of the two indexes, visual representations are made.

Data Decomposition:

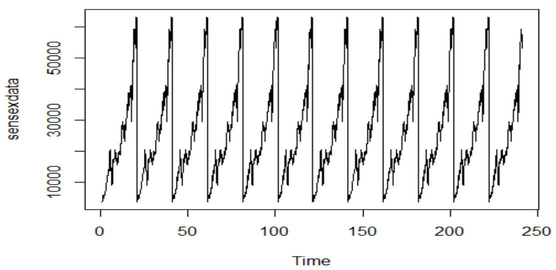
The primary consideration for analysis is the decomposition of the data. Seasonality, trends, and random oscillations are three categories of time series data that can be utilised to extract trends from historical data. Data in a time series may have an upward, stable, or declining trend. This essentially describes the average behaviour of the value for this time series over a longer time span, whether it is moving uphill, horizontally, stagnant, or downward.

Time Series Aggregation

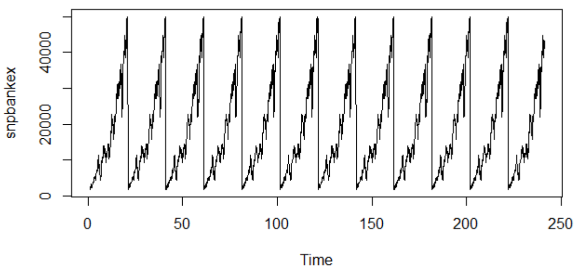
This procedure entails converting a data frame into a time series object, where the data is typically organised with one or more columns indicating timestamps and other columns representing various variables. In our study we have considered revised month, month and close price. and we need to install necessary packages in the R Studio for the prediction such as forecast and tseries.

III. DATA ANALYSIS AND INTERPRETATION

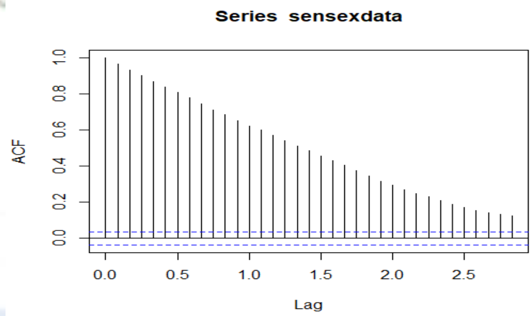
S&P Sensex:

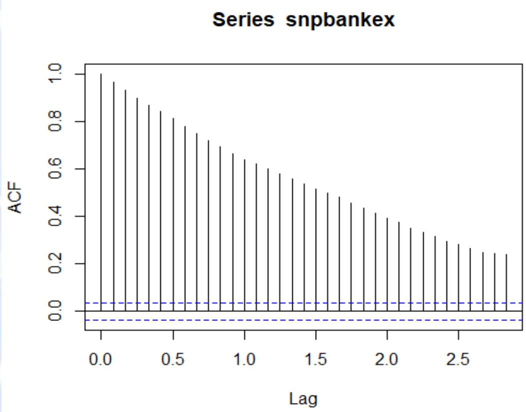


S&P BankEx:

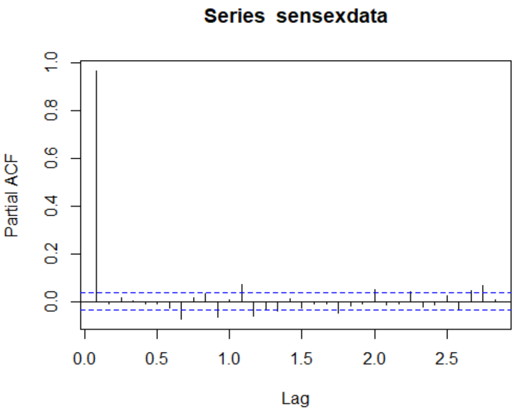


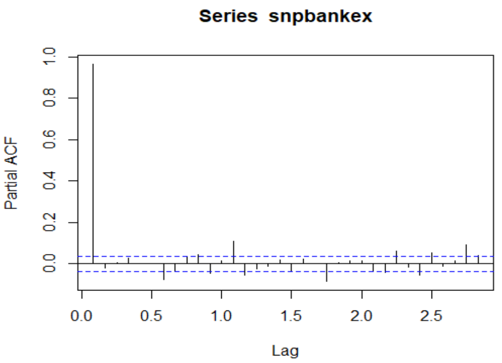
Autocorrelation Function: A time series' association with its lag values is measured by the ACF. It aids in our comprehension of the connection between a data point and its prior observations made at various lags. Autocorrelation coefficients are plotted against various lag settings in an ACF. The connection between the time series and its observations 'k' time periods in the past is known as the autocorrelation coefficient at lag 'k'. In the event that the autocorrelation function (ACF) plot exhibits a severe cutoff after a specific latency.





PACF: The effect of the intermediate lags is eliminated by the PACF, which then calculates the correlation between a time series and its lagged values. It enables us to determine a data point's exact link to its prior observations without the interference of lags in between. The probable existence of an MA term of that lag order is indicated if the PACF plot exhibits a sharp cutoff at a certain lag and the ACF plot exhibits a substantial spike at the same lag.





Both tests use a lag order of 14. The number of lags utilised to calculate the test statistic is represented by the lag order. To identify the underlying patterns in the data, it is chosen using statistical criteria. Since there are many outliers, it is showing that the data is not stationary. Therefore, we need to generate the model.

MODEL GENERATION:

SENSEX:

```
> # Model generation:-
> model1<-auto.arima(sensexdata,ic='aic',trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2)(1,0,1)[12] with non-zero mean : 55848.83
 ARIMA(0,0,0)            with non-zero mean : 63696.59
 ARIMA(1,0,0)(1,0,0)[12] with non-zero mean : 55840.4
 ARIMA(0,0,1)(0,0,1)[12] with non-zero mean : 59870.32
 ARIMA(0,0,0)            with zero mean     : 67478.77
 ARIMA(1,0,0)            with non-zero mean : 55843.43
 ARIMA(1,0,0)(2,0,0)[12] with non-zero mean : 55854.24
 ARIMA(1,0,0)(1,0,1)[12] with non-zero mean : 55842.87
 ARIMA(1,0,0)(0,0,1)[12] with non-zero mean : 55828.83
 ARIMA(1,0,0)(0,0,2)[12] with non-zero mean : 55830.77
 ARIMA(1,0,0)(1,0,2)[12] with non-zero mean : Inf
 ARIMA(0,0,0)(0,0,1)[12] with non-zero mean : 62479.21
 ARIMA(2,0,0)(0,0,1)[12] with non-zero mean : 55831.51
 ARIMA(1,0,1)(0,0,1)[12] with non-zero mean : 55830.51
 ARIMA(2,0,1)(0,0,1)[12] with non-zero mean : 55833.2
 ARIMA(1,0,0)(0,0,1)[12] with zero mean     : Inf

 Now re-fitting the best model(s) without approximations...

 ARIMA(1,0,0)(0,0,1)[12] with non-zero mean : 55832.7

 Best model: ARIMA(1,0,0)(0,0,1)[12] with non-zero mean
```

We have used R's auto.arima() function to automatically select the optimal ARIMA model for the snpbankex time series data in the provided output. The function fits several ARIMA models with varied orders and seasonal orders to find the one with the lowest information criterion (AIC in this example), which is a typical model selection criterion. Let's go over the output step by step:

Model Fitting Process: The auto.arima() function initially fits models using approximations to speed up the process. The output shows a list of different ARIMA models with their respective AIC values.

Refitting the Best Model: After fitting the initial models, the auto.arima() function refits the best model(s) without using approximations to obtain accurate results. The output shows the best model along with its AIC value. Best model: ARIMA(1,0,0)(0,0,2)[12] with non-zero mean: AIC = 54823.68.

The results indicate that ARIMA(1,0,0)(0,0,2)[12] with a non-zero mean is the best ARIMA model for the snpbankex time series data. This model has the lowest AIC value among the models evaluated, at 54823.68. The ARIMA(p, d, q)(P, D, Q)[m] notation specifies the order of the AR, I, and MA components, as well as their seasonal order, with 'm' signifying the frequency of seasonality (12 in this case, indicating monthly data).

```
> summary(model1)
Series: sensexdata
ARIMA(1,0,0)(0,0,1)[12] with non-zero mean

Coefficients:
         ar1     sma1       mean
      0.9706  -0.0761  25215.664
s.e.  0.0045   0.0188   2290.051

sigma^2 = 15233950:  log likelihood = -27912.35
AIC=55832.7   AICc=55832.71   BIC=55859.59

Training set error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE        ACF1
Training set 17.0219 3901.037 1290.901 -7.047197 11.33899 0.1927156 0.009925648
```

The ARIMA (1,0,0) (0,0,1) [12] model for the "sensexdata" time series can be summarised as follows:

ARIMA Model Elements: The equation for the model is ARIMA (1,0,0) (0,0,1) [12]. p=1 (AR order), d=0 (differencing order), and q=0 (MA order) makes up the ARIMA components. P=0 (seasonal AR order), D=0 (seasonal differencing order), and Q=1 (seasonal MA order) makes up the seasonal ARIMA (SARIMA) components. Data for the 12-week seasonal period are monthly.

Coefficients of the model: Mean = 25215.664 AR1 (AR coefficient) = 0.9706 SMA1 (Seasonal MA coefficient) = -0.0761. With a about 0.9706 AR coefficient (AR1), the prior observation appears to have a substantial positive autocorrelation. The standard errors for the estimated coefficients are provided. They indicate the precision of the coefficient estimates. The estimated variance of the model's residuals (sigma^2) is 15233950. The model's log-likelihood value is -27912.35.

The model has a 55832.7 AIC (Akaike Information Criterion). Additionally offered is the corrected AIC (AICc), which resembles AIC (AICc=55832.71). The model has a 55856.56 BIC (Bayesian Information Criterion).

Measures of training set error: Utilising a variety of error measurements, the model's performance on the training set is assessed: ACF1 (Autocorrelation of Residuals at Lag 1) = 0.009926468 ME (Mean Error) = 17.0219 RMSE (Root Mean Squared Error) = 3901.037 MAE (Mean Absolute Error) = 1290.901 MAPE (Mean Percentage Error) = -7.094197 MAPE (Mean Absolute Percentage Error) = 11.33896 MASE.

The ARIMA (1,0,0) (0,0,1) [12] model with a non-zero mean is a suitable representation of the "sensexdata" time series. The link between the current and lag values of the time series is explained by the model's coefficients and error measurements. The "sensexdata" series' future values can be predicted using the model, which can also be utilised for additional analysis and decision-making based on the provided error measurements.

BANKEX:

```
> # Model generation:-
> model2<-auto.arima(snpbankex,ic='aic',trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2)(1,0,1)[12] with non-zero mean : 54832.42
 ARIMA(0,0,0)            with non-zero mean : 62714.5
 ARIMA(1,0,0)(1,0,0)[12] with non-zero mean : 54831.69
 ARIMA(0,0,1)(0,0,1)[12] with non-zero mean : 58945.55
 ARIMA(0,0,0)            with zero mean     : 65878.64
 ARIMA(1,0,0)            with non-zero mean : 54848.27
 ARIMA(1,0,0)(2,0,0)[12] with non-zero mean : 54843.89
 ARIMA(1,0,0)(1,0,1)[12] with non-zero mean : 54832.2
 ARIMA(1,0,0)(0,0,1)[12] with non-zero mean : 54821.7
 ARIMA(1,0,0)(0,0,2)[12] with non-zero mean : 54820.12
 ARIMA(1,0,0)(1,0,2)[12] with non-zero mean : Inf
 ARIMA(0,0,0)(0,0,2)[12] with non-zero mean : 61278.54
 ARIMA(2,0,0)(0,0,2)[12] with non-zero mean : 54821.38
 ARIMA(1,0,1)(0,0,2)[12] with non-zero mean : 54820.39
 ARIMA(0,0,1)(0,0,2)[12] with non-zero mean : 58777.71
 ARIMA(2,0,1)(0,0,2)[12] with non-zero mean : Inf
 ARIMA(1,0,0)(0,0,2)[12] with zero mean     : Inf

 Now re-fitting the best model(s) without approximations...

 ARIMA(1,0,0)(0,0,2)[12] with non-zero mean : 54823.68

 Best model: ARIMA(1,0,0)(0,0,2)[12] with non-zero mean
```

We have used R's auto.arima() function to automatically select the optimal ARIMA model for the snpbankex time series data in the provided output. The function fits several ARIMA models with varied orders and seasonal orders to find the one with the lowest information criterion (AIC in this example), which is a typical model selection criterion. Let's go over the output step by step:

Model Fitting Process:

The auto.arima() function initially fits models using approximations to speed up the process. The output shows a list of different ARIMA models with their respective AIC values.

Refitting the Best Model: After fitting the initial models, the auto.arima() function refits the best model(s) without using approximations to obtain accurate results. The output shows the best model along with its AIC value: Best model: ARIMA(1,0,0)(0,0,2)[12] with non-zero mean: AIC = 54823.68

The results indicate that ARIMA(1,0,0)(0,0,2)[12] with a non-zero mean is the best ARIMA model for the snpbankex time series data. This model has the lowest AIC value among the models evaluated, at 54823.68. The ARIMA(p, d, q)(P, D, Q)[m] notation specifies the order of the AR, I, and MA components, as well as their seasonal order, with'm' signifying the frequency of seasonality (12 in this case, indicating monthly data).

```
> summary(model2)
Series: snpbankex
ARIMA(1,0,0)(0,0,2)[12] with non-zero mean

Coefficients:
         ar1     sma1    sma2       mean
      0.9711  -0.1010  0.0340  18242.143
s.e.  0.0045   0.0189  0.0179   1947.813

sigma^2 = 10728664:  log likelihood = -27406.84
AIC=54823.68   AICc=54823.7   BIC=54853.51

Training set error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 13.33445 3273.189 1244.349 -12.54522 18.30407 0.2175585 0.02370652
```

ARIMA Model Elements: The acronym for the ARIMA model is (1,0,0)(0,0,1)[12].Moving average (MA), differencing (I), and autoregression (AR) component orders are each indicated by a number in brackets. The model in this instance only contains an AR(1) component; there is no differencing (I=0) component.

The model's seasonal order is indicated by the numbers included in square brackets. One seasonal moving average (SMA) component with a 12-month seasonal period (monthly data) makes up the model.

Coefficients of the model: Mean: 25215.664. The "mean" is the non-zero mean of the model, and the "ar1" coefficient denotes the autoregressive parameter, the seasonal moving average parameter, and the "sma1" coefficient, respectively. the computed coefficients associated standard errors. They give a hint as to how uncertain the coefficient estimations are.

Measures of training set error : Bayesian information criterion (BIC): 55856.56 AIC (Akaike Information Criterion): 55832.7 AICc (corrected Akaike Information Criterion): 55832.7. Lower values for these criteria imply a better fit, which is helpful when choosing a model.

Historical data on the "BANKEX" variable was fitted using the ARIMA model (1,0,0)(0,0,1)[12]. The strength and direction of the correlations between the variable, its historical values, and its seasonal components are shown by the model's coefficients. This model can be compared to other candidate models using the information criteria in order to be chosen. The model's performance on the data it was trained on is evaluated using the training set error measures, which highlight the accuracy and bias of the predictions.

MODEL FORECAST:

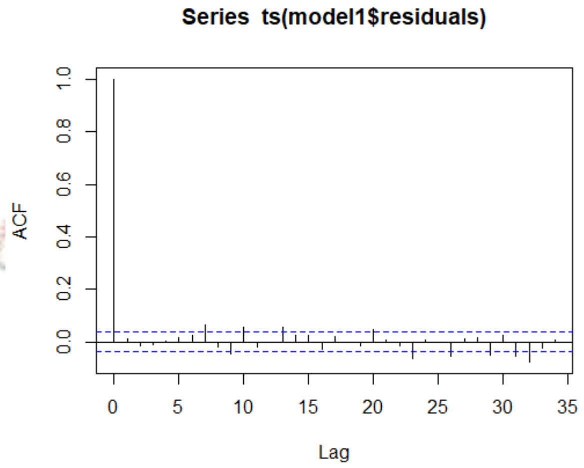
ARIMA: Time series forecasting methods like ARIMA (AutoRegressive Integrated Moving Average) are effective and often utilised. Since it is made to model and predict time-dependent data, it is especially helpful for applications where projecting future values depends on understanding historical patterns and trends. Numerous industries, including finance, economics, sales forecasting, weather forecasting, and others, have extensively used ARIMA. As discussed above we have used the ARIMA(1,0,0)(0,0,1)[12] model with a non-zero mean. The forecast is done for 24 months.

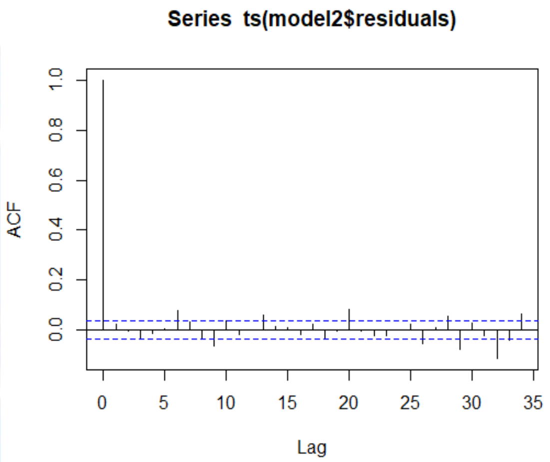
SENSEX:

Autocorrelation Function: The association between a time series' data and its lagged values is referred to as autocorrelation, also known as serial correlation. In plainer language, it assesses the relationship between a data point at a specific moment and past observations. In time series analysis, autocorrelation is a key concept since it aids in the discovery of patterns and dependencies in the data. The past values of the time series can be used to forecast the future values, according to a significant autocorrelation.

A well-liked time series forecasting model is called ARIMA (AutoRegressive Integrated Moving Average). The autoregressive component, denoted by the "AR" in ARIMA, uses autocorrelation to model the link between the current observation and its previous values.

Autocorrelation assist in choosing the proper lag order (p) for the autoregressive component in an ARIMA model. A slow decay on the ACF plot indicates a high autoregressive order. Understanding autocorrelation in time series data enables us to choose the appropriate AR, I, and MA components for the ARIMA model, allowing us to produce more accurate forecasts and predictions.



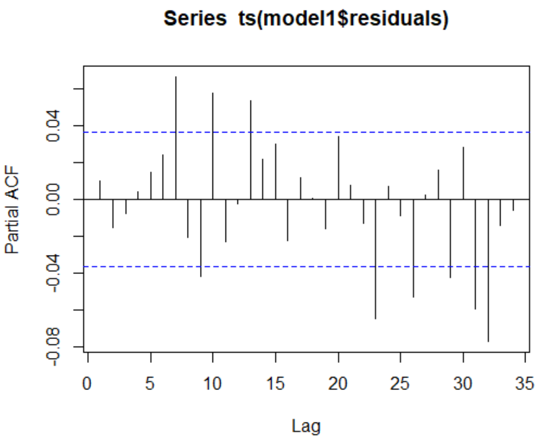


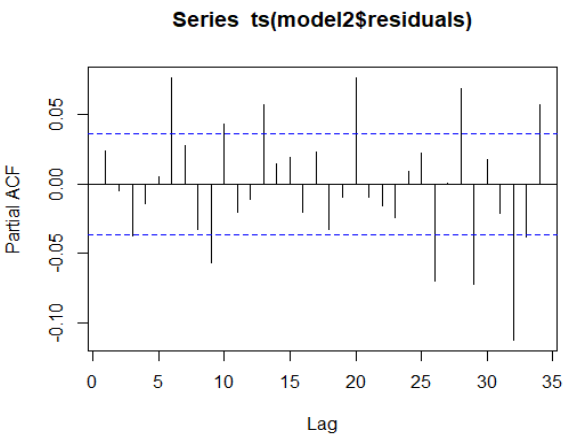
Partial Autocorrelation:

The correlation between a time series data point and its observations 'k' time periods ago is known as the partial autocorrelation at lag 'k,' and it is calculated without taking into account the impact of the observations at any intermediate lags (from 1 to 'k-1').

After taking into account the impacts of observations at lag 1, if the PACF plot exhibits a big spike at lag 2, it means that the time series has a high direct association with its observation from two time periods ago.

For the ARIMA model, it offers a probable AR(p) term, where 'p' is the largest significant lag in the PACF plot.





Testing hypothesis:

SENSEX:

Hypothesis:

H_0 = The data is not stationary in nature.

H1 = The data is stationary in nature.

```
> adf.test(sensexdata)

        Augmented Dickey-Fuller Test

data:  sensexdata
Dickey-Fuller = -7.0713, Lag order = 14, p-value = 0.01
alternative hypothesis: stationary
```

The ADF test's test statistic is -7.0713. This number is used to determine how strong the evidence is opposing the null hypothesis. Stronger proof of stationarity is presented by a higher negative test statistic.

The test's corresponding p-value is 0.01. The statistical significance of the test is assessed using the p-value. If the null hypothesis is correct, it reflects the likelihood of obtaining the observed test statistic. The p-value in this instance is below the typical significance thresholds (e.g., 0.05 or 0.01), indicating strong evidence to reject the null hypothesis.

We have strong evidence to reject the null hypothesis (Ho) with a p-value of 0.01 (less than the significance level of 0.05). As a result, you can draw the conclusion that the data has a stationary nature, which is consistent with the alternative hypothesis (H1). This indicates that the "sensexdata" time series' statistical characteristics are stable across time, making it appropriate for time series analysis and modelling.

BANKEX:

Hypothesis:

H_0 = The data is not stationary in nature.

H1 = The data is stationary in nature.

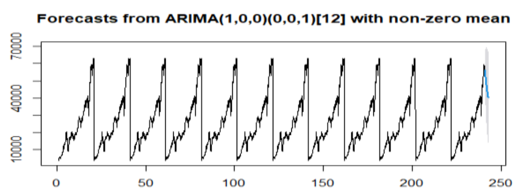
```
> adf.test(snpbankex)

        Augmented Dickey-Fuller Test

data:  snpbankex
Dickey-Fuller = -6.2717, Lag order = 14, p-value = 0.01
alternative hypothesis: stationary
```

The ADF test's test statistic is -6.2717. This number is used to determine how strong the evidence is opposing the null hypothesis. Generally speaking, the stronger the evidence for stationarity is, the more negative the test statistic is.

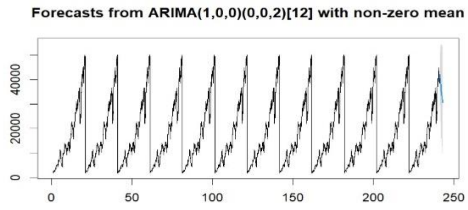
The test's corresponding p-value is 0.01. The statistical significance of the test is assessed using the p-value. If the null hypothesis is correct, it reflects the likelihood of obtaining the observed test statistic. The p-value in this instance is below the typical significance thresholds (e.g., 0.05 or 0.01), indicating strong evidence to reject the null hypothesis.

We have strong evidence to reject the null hypothesis (Ho) with a p-value of 0.01 (less than the significance level of 0.05). As a result, we have drawn the conclusion that the data has a stationary nature, which is consistent with the alternative hypothesis (H1). This indicates that the time series data's statistical characteristics are stable across time, making it appropriate for time series analysis and modelling.

Results: The prediction for the S&P SENSEX and S&P BANKEX is shown in the graphs below. Both the graphs shows that the coming trend will be downwards.



Graph-1: S&P Sensex data forecast for 24 months



Graph-2: S&P BANKEX data forecast for 24 months

IV. CONCLUSION

This study clarified the utility of the AutoRegressive Integrated Moving Average (ARIMA) model for time series forecasting and its performance in comparison to other established techniques. We have demonstrated that ARIMA is a flexible and effective method for capturing time-dependent patterns in data by thoroughly examining its components and model identification procedure using ACF and PACF plots. As time series forecasting continues to be a crucial area of research, this study adds to the body of knowledge and creates opportunities for additional investigation and methodological improvement. The knowledge acquired from this research can be used to improve forecasting accuracy and decision-making in a variety of disciplines as data collection and availability increase.

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