“Time Series Analysis & Forecasting”

“India’s Overall & Sectorial GDP Growth analysis & Forecasting”

Final Project Report

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1. Problem Statement:

The problem statement for this project is to conduct time series analysis and forecasting of the overall Gross Domestic Product (GDP) of India, as well as a sectorial analysis of the various sectors contributing to the country's GDP. This project aims to identify patterns, trends, and relationships within the historical GDP data, and use this information to predict future values for both the overall GDP and individual sectors. The insights generated from this analysis can be used to inform policy decisions and investment strategies, as well as provide valuable insights into the health and growth of the Indian economy.

2. Data Source:

- National Statistical Office: The National Statistical Office (NSO) is responsible for collecting and publishing data on various economic indicators, including GDP, sector-wise performance, and other economic indicators.
- Reserve Bank of India: The Reserve Bank of India (RBI) is the country's central bank and provides valuable data on key economic indicators such as inflation, interest rates, and foreign exchange reserves.
- Ministry of Finance: The Ministry of Finance is responsible for formulating and implementing policies related to fiscal management, including taxation, budgeting, and government spending.
- International Monetary Fund: The International Monetary Fund (IMF) provides global economic data and forecasts, including country-specific data on GDP, inflation, and other macroeconomic indicators.
- World Bank: The World Bank provides a wealth of data on various economic indicators, including GDP, poverty rates, infrastructure, and other socio-economic factors. Their data covers both national and regional levels, providing a broad perspective on economic trends and patterns.

3. Theoretical Aspect (GDP & Sectorial analysis):

GDP as an economic concept:
Gross Domestic Product (GDP) is a widely-used macroeconomic indicator that measures the total value of goods and services produced within a country's borders during a specific period, typically a year. It serves as a crucial metric for assessing a country's economic well-being and provides valuable insights into the overall growth of the economy.

To calculate GDP, there are three commonly used methods: the expenditure approach, the production approach, and the income approach. The expenditure approach measures GDP by adding up the total spending by households, businesses, governments, and net exports (exports minus imports). The production approach calculates GDP by adding up the total value of goods and services produced in different sectors of the economy. Finally, the income approach measures GDP by adding up the total income earned by individuals and businesses in the economy.

Sectorial & Sub sectorial analysis of GDP:

Sectoral analysis of GDP involves breaking down the total GDP into different sectors, including agriculture, industry, and services. Agriculture includes activities related to crop production, animal husbandry, and forestry. Industry includes activities related to manufacturing, mining, and construction. Services include activities related to trade, transportation, finance, healthcare, education, and other services. Each sector comprises several subsectors, which provide further insight into the types of goods and services produced in each sector. For example:

- Agriculture, Forestry, and Fishing: subsectors include crops, livestock, forestry, and fishing and aquaculture.
- Mining and Quarrying: subsectors include coal and lignite mining, oil and gas extraction, metal ore mining, and non-metallic mineral mining and quarrying.
- Manufacturing: subsectors include food and beverage, textiles and clothing, wood and paper products, chemicals, pharmaceuticals, machinery and equipment, and more.
- Electricity, Gas, Water Supply, and Waste Management: subsectors include the production and distribution of electricity, gas supply, water collection, treatment and supply, and waste collection, treatment, and disposal.
- Construction: subsectors include the construction of buildings and civil engineering works.
- Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles: subsectors include wholesale and retail trade, repair of motor vehicles, and the sale of automotive parts.
- Transportation and Storage: subsectors include land, air, and water transportation, as well as warehousing and storage activities.
- Accommodation and Food Service Activities: subsectors include the provision of accommodation, food and beverage services, and catering services.
- Information and Communication: subsectors include telecommunications, computer programming, and information service activities.
- Financial and Insurance Activities: subsectors include banking, insurance, and other financial services.
- Real Estate Activities: subsectors include the buying, selling, and renting of real estate.
- Professional, Scientific, and Technical Activities: subsectors include legal services, accounting, research and development, and advertising.
- Administrative and Support Service Activities: subsectors include office administrative and support services, and building and landscape maintenance services.

- Public Administration and Defence: subsectors include government administration and defense activities.
- Education: subsectors include pre-primary, primary, secondary, and higher education.
- Human Health and Social Work Activities: subsectors include medical and dental services, nursing and residential care facilities, and social work activities.
- Arts, Entertainment, and Recreation: subsectors include the performing arts, museums, and sports and recreational activities.
- Other Service Activities: subsectors include religious, membership, and civic organizations, and personal services such as laundry, hairdressing, and funeral services.

GDP considering it's time series aspect:

Forecasting GDP and its growth over time can be done using time series analysis. Time series analysis involves analyzing historical data to identify trends and patterns, which can then be used to predict future values.

To forecast GDP using time series analysis, historical GDP data is collected and analyzed to identify any trends, seasonal patterns, and cycles. Once these patterns are identified, a statistical model is developed to forecast future GDP values.

Similarly, to forecast GDP growth, historical GDP growth rates are analyzed to identify any trends or patterns. The statistical model developed for forecasting GDP can also be used to forecast GDP growth rates.

4. Practical Aspect:

Library initialization:

```
library(astsa)
library(forecast)

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

##
## Attaching package: 'forecast'

## The following object is masked from 'package:astsa':
##
##     gas

library(ggplot2)
library(urca)
library(tseries)
```

We have used the above libraries for retrieving the functionalities for the forcast.

1. Astsa - Contains data sets and scripts for analyzing time series in both the frequency and time domains including state space modeling as well as supporting the texts Time Series Analysis and Its Applications.
2. forecast - Methods and tools for displaying and analysing univariate time series forecasts including exponential smoothing via state space models and automatic ARIMA modelling.
3. ggplot2 - ggplot2 is a system for declaratively creating graphics, based on The Grammar of Graphics. You provide the data, tell ggplot2 how to map variables to aesthetics.
4. urca - facilitate the application of unit root testing as well as the conduct of co-integration analysis.
5. tseries - Time series analysis and computational finance.

Data import:

```
data<- read.csv("C:/Users/bigtapp/Downloads/GDP_1961.csv")
head(data)

class(data)

## [1] "data.frame"
```

As we can see, the GDP data is dated from 1960 and it is of type data frame with variables like Country name, country code, year and GDP value.

Conversion to time series:

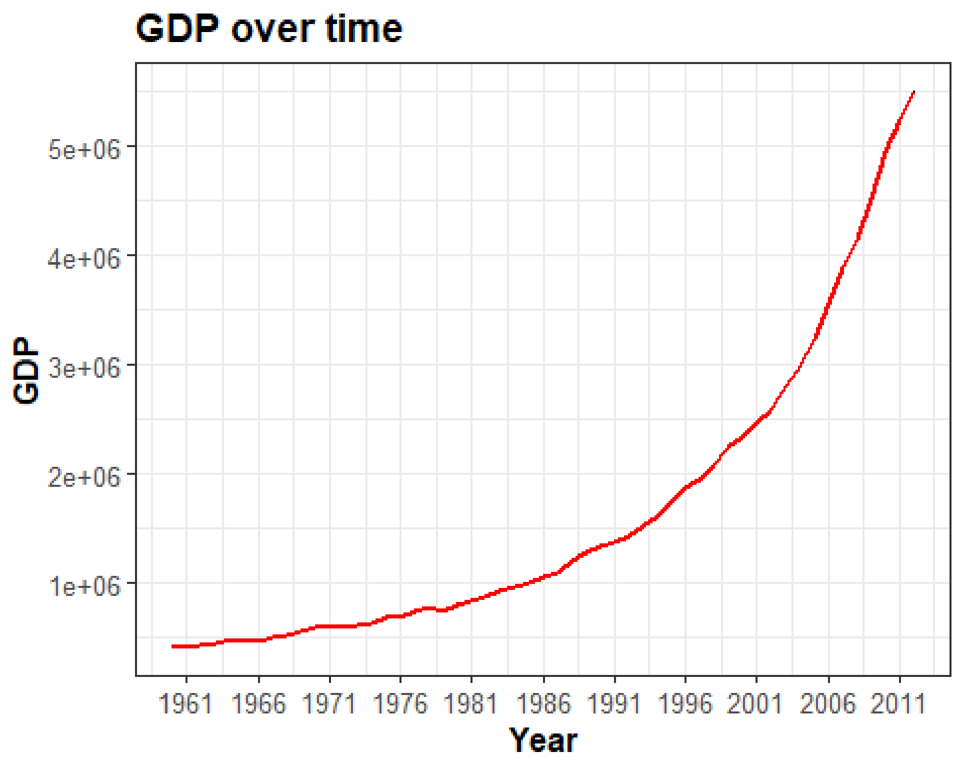
```
data_ts_gross <- ts(data$Gross.Domestic.Product..in.Rs..Cr..at.2004.05.Prices
,start = 1960,frequency = 1)
data_ts_agriculture<-ts(data$Agriculture...Allied.Services..in.Rs..Cr...at.20
04.05.Prices,start = 1960,frequency = 1)
data_ts_industry<-ts(data$Industry..in.Rs..Cr...at.2004.05.Prices,start = 196
0,frequency = 1)
data_ts_services<-ts(data$Services..in.Rs..Cr...at.2004.05.Prices,start = 196
0,frequency = 1)
```

We have considered GDP data from 1961 to 2012 and converted to time series. As the data is yearly, we have used the frequency=1. After the conversion the data is defined as We have segregated the data based on the Overall GDP, GDP contribution from different sectors like Agriculture, Industry and Services

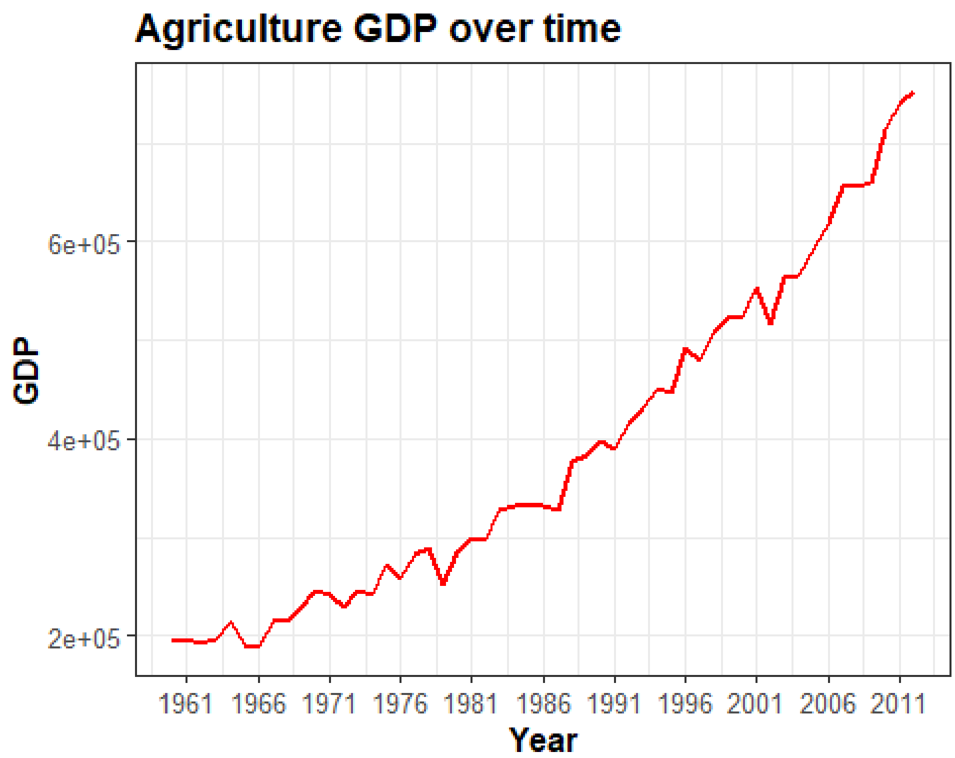
Data Exploration:

We plot the time series data and check the pattern of data in the below code chunk

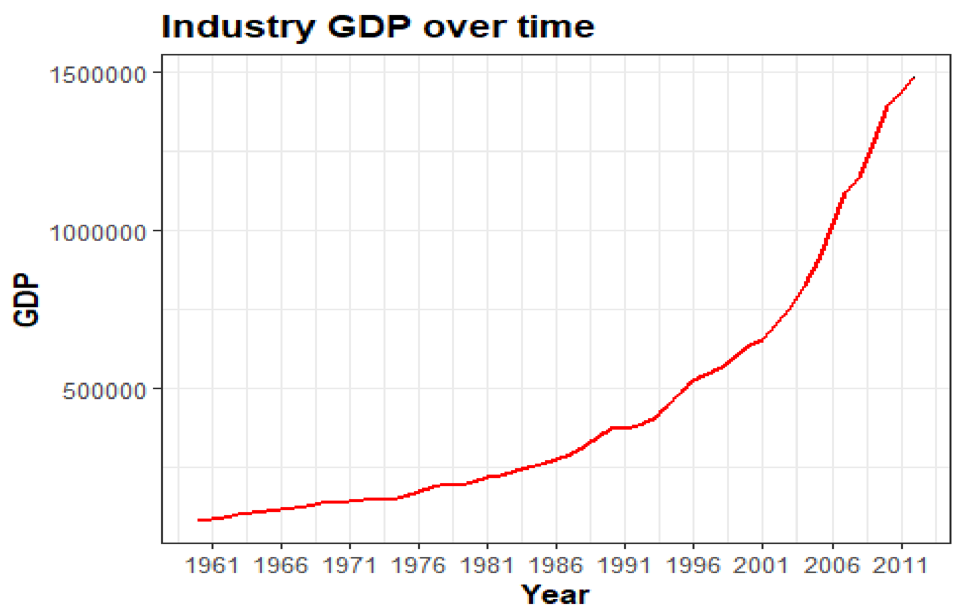
```
autoplot(data_ts_gross) +
  ggtitle("GDP over time") +
  ylab("GDP") +
  xlab("Year") +
  scale_x_continuous(breaks = seq(1961, 2012, 5)) +
  theme_bw() +
  theme(plot.title = element_text(face = "bold", size = 14),
        axis.title = element_text(face = "bold", size = 12),
        axis.text = element_text(size = 10),
        legend.position = "none") +
  geom_line(color = "red", size = 1)

## Scale for x is already present.
## Adding another scale for x, which will replace the existing scale.

## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## ℹ Please use `linewidth` instead.
```



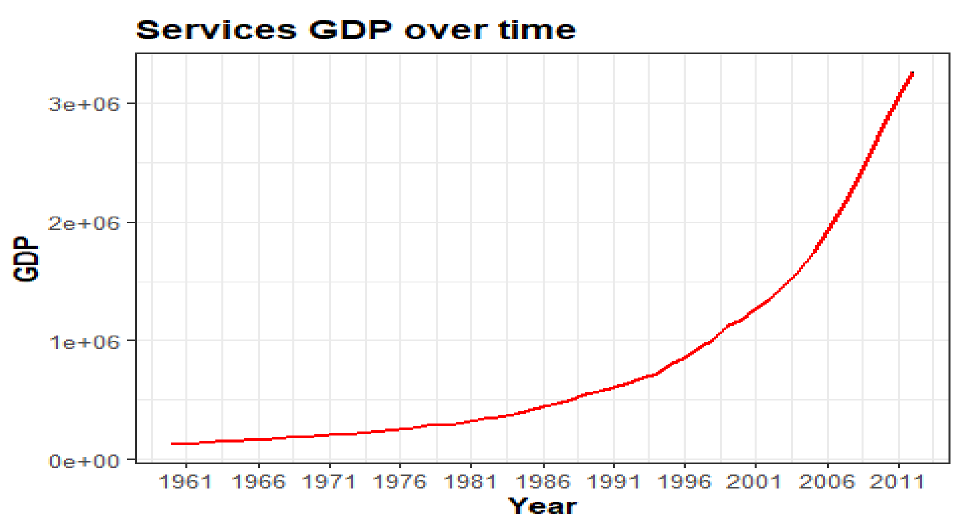

```
autoplot(data_ts_agriculture) +
  ggtitle("Agriculture GDP over time") +
  ylab("GDP") +
  xlab("Year") +
  scale_x_continuous(breaks = seq(1961, 2012, 5)) +
  theme_bw() +
  theme(plot.title = element_text(face = "bold", size = 14),
        axis.title = element_text(face = "bold", size = 12),
        axis.text = element_text(size = 10),
        legend.position = "none") +
  geom_line(color = "red", size = 1)

## Scale for x is already present.
## Adding another scale for x, which will replace the existing scale.
```




```
autoplot(data_ts_industry) +
  ggtitle("Industry GDP over time") +
  ylab("GDP") +
  xlab("Year") +
  scale_x_continuous(breaks = seq(1961, 2012, 5)) +
  theme_bw() +
  theme(plot.title = element_text(face = "bold", size = 14),
        axis.title = element_text(face = "bold", size = 12),
        axis.text = element_text(size = 10),
        legend.position = "none") +
  geom_line(color = "red", size = 1)

## Scale for x is already present.
## Adding another scale for x, which will replace the existing scale.
```




```
autoplot(data_ts_services) +
  ggtitle("Services GDP over time") +
  ylab("GDP") +
  xlab("Year") +
  scale_x_continuous(breaks = seq(1961, 2012, 5)) +
  theme_bw() +
  theme(plot.title = element_text(face = "bold", size = 14),
        axis.title = element_text(face = "bold", size = 12),
        axis.text = element_text(size = 10),
        legend.position = "none") +
  geom_line(color = "red", size = 1)

## Scale for x is already present.
## Adding another scale for x, which will replace the existing scale.
```



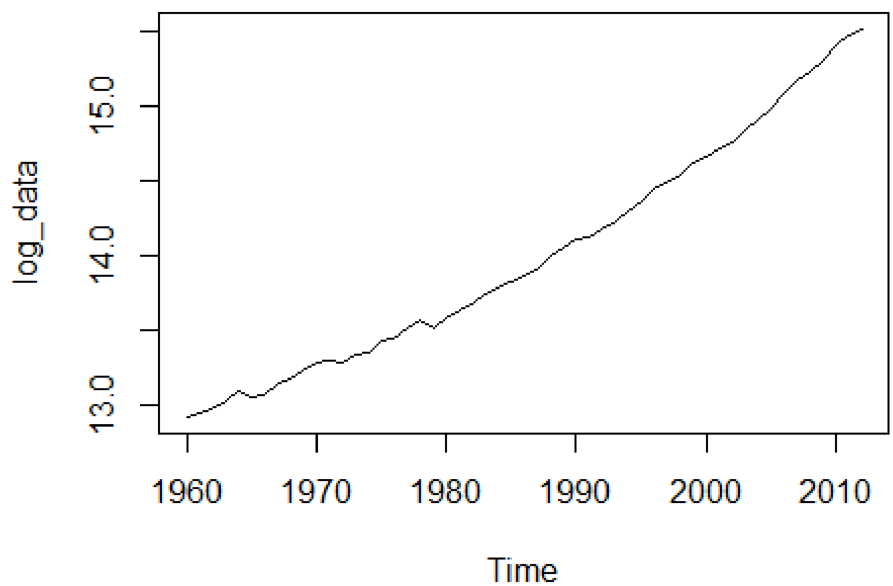
Model Application

Check for stationarity of Data

To continue building the model, it is import to check the stationarity of model. We perform Augmented Dicky-fuller test as well as inspect the ACF and PACF plots to confirm the stationary of the data.

Gross GDP Data

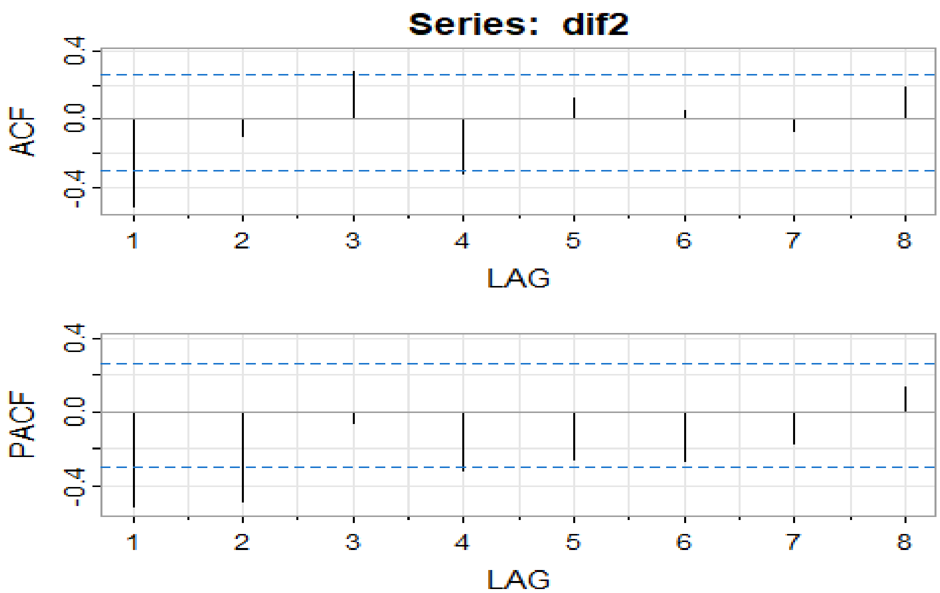
```
log_data<-log(data_ts_gross)
plot(log_data)
```




```
summary(ur.kpss(log_data))

dif1<-log_data%>%diff()
summary(ur.kpss(dif1))

dif2<-dif1%>%diff()
summary(ur.kpss(dif2))

##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 3 lags.
##
## Value of test-statistic is: 0.0372
```

```
##
## Critical value for a significance level of:
##                  10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

```
acf2(dif2)#1,11
```




```
##       [,1]  [,2]  [,3]  [,4]  [,5]  [,6]  [,7] [,8]
## ACF  -0.51 -0.09  0.28 -0.32  0.13  0.05 -0.07 0.19
## PACF -0.51 -0.48 -0.06 -0.32 -0.25 -0.26 -0.17 0.14
```

```
#auto.arima(dif2,trace=TRUE)
```

As we can observe from the above results, that Augmented Dicky-fuller test clearly shows that there is non-stationary component in the data. As P-value is greater than 0.05, we cannot reject null hypothesis. proving that data is non stationary. From the ACF and PACF plots, we see that p values can be 1,2 or 4 and values of q are 1,3 or 4.

Model selection

We check all possibilities of the parameters and select the model paramters with low AIC values.

```
AIC(arima(data_ts_gross,c(1,2,1)))
```

```
## [1] 1241.061
```

```
AIC(arima(data_ts_gross,c(1,2,0)))
```

```
## [1] 1240.712
```

```
AIC(arima(data_ts_gross,c(2,2,2)))
```

```
## [1] 1242.632
```

```
AIC(arima(data_ts_gross,c(0,2,1)))
```

```
## [1] 1239.064
```

```
AIC(arima(data_ts_gross,c(2,2,1)))
```

```
## [1] 1242.227
```

```
AIC(arima(data_ts_gross,c(4,2,1)))
```

```
## [1] 1245.348
```

```
auto.arima(data_ts_gross,trace=TRUE)
```

```
##
##  ARIMA(2,2,2)                    : 1243.966
##  ARIMA(0,2,0)                    : 1244.484
##  ARIMA(1,2,0)                    : 1240.962
##  ARIMA(0,2,1)                    : 1239.314
##  ARIMA(1,2,1)                    : 1241.571
##  ARIMA(0,2,2)                    : 1241.568
##  ARIMA(1,2,2)                    : Inf
##
##  Best model: ARIMA(0,2,1)
```

```
## Series: data_ts_gross
## ARIMA(0,2,1)
##
## Coefficients:
##           ma1
##       -0.3988
## s.e.   0.1235
##
## sigma^2 = 1.959e+09:  log likelihood = -617.53
## AIC=1239.06   AICc=1239.31   BIC=1242.93
```

After trying different combinations and checking AIC values we get th best model as ARIMA(0,2,1)

Fit the model

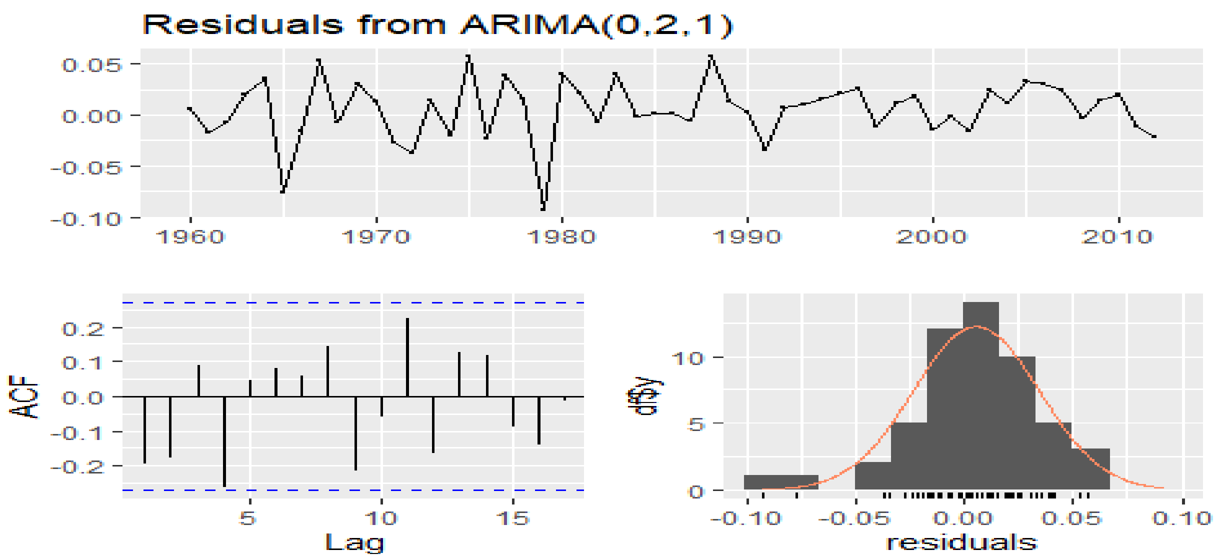
In the below code we will be applying Arima model to our data.

```
gross_model<-arima(log_data,c(0,2,1))
```

Model validation

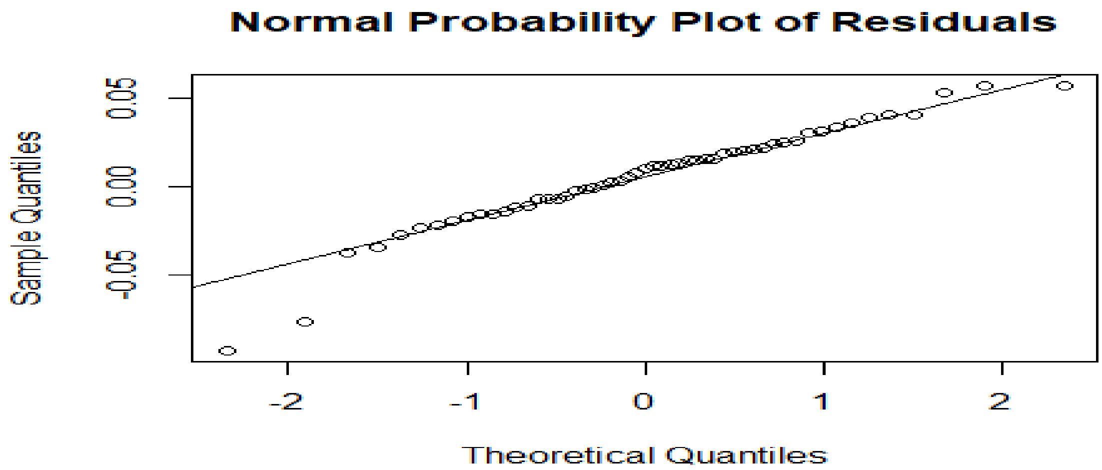
We check the residuals and forecast accuracy of the model to know the reliability on the model.

```
checkresiduals(gross_model)
```

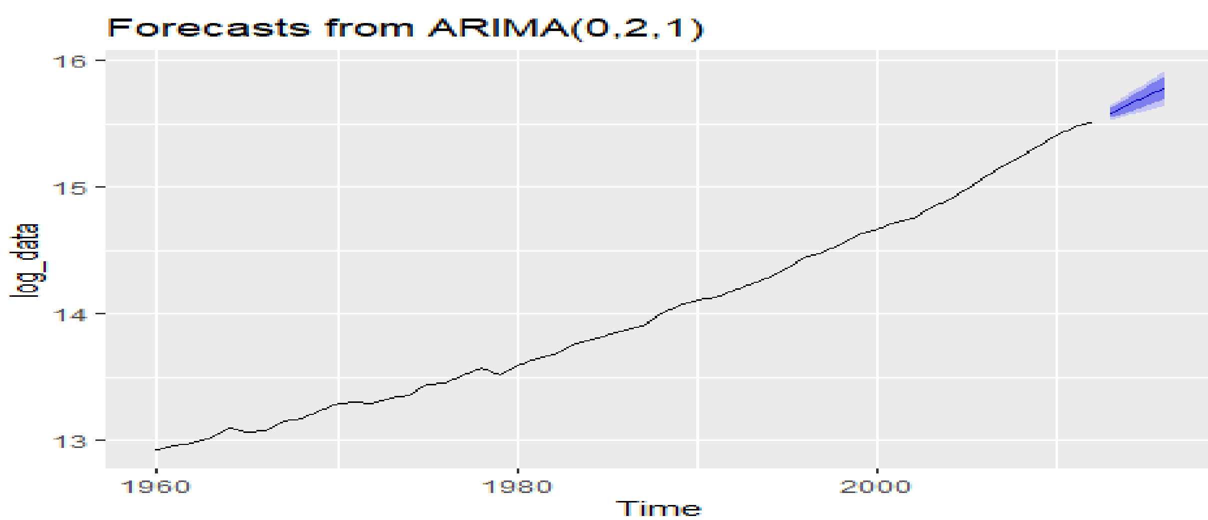



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,2,1)
## Q* = 13.853, df = 9, p-value = 0.1277
##
## Model df: 1.   Total lags used: 10
```

```
qqnorm(residuals(gross_model), main = "Normal Probability Plot of Residuals")
qqline(residuals(gross_model))
```




```
f<-forecast(gross_model,h=4)
autoplot(f)
```




```
accuracy(f)

##                       ME       RMSE        MAE       MPE      MAPE      MA
SE
## Training set 0.005403517 0.02913817 0.02242837 0.0373646 0.1622743 0.41892
38
##                    ACF1
## Training set -0.1940061
```

Observation: As we check the residual plots, we can see that all the lags lie within the limits in ACF plot and residuals follow a normal distribution which is also confirmed by qqplot. Accuracy shows that there is not much error considering the MAPE which is close to zero.

```
exp(f$mean)

## Time Series:
## Start = 2013
## End = 2016
## Frequency = 1
## [1] 5888275 6299980 6740471 7211760
```

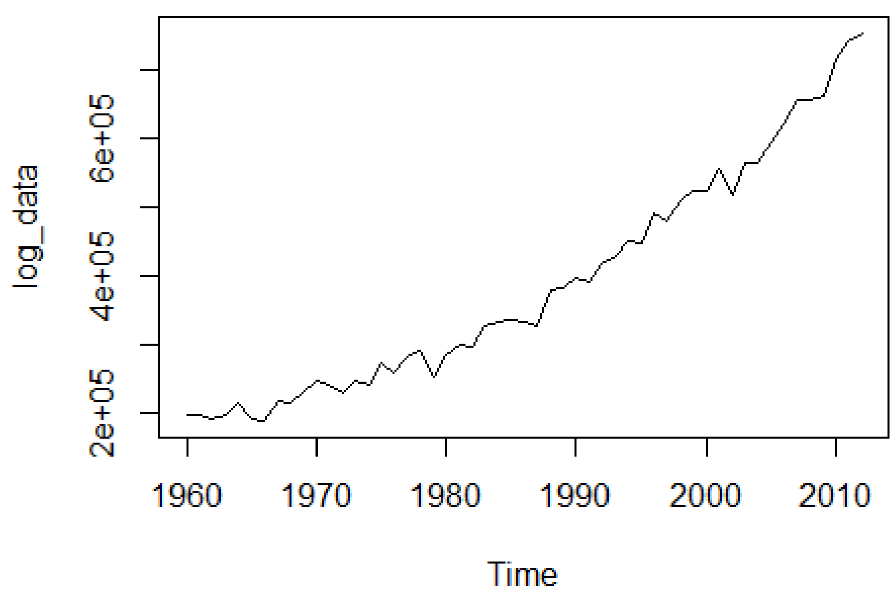
We have the delogged data of GDP for the forecasted data.

5. Sectorial Time series Analysis & Forecasting:

Agriculture Data Sector

Considering the above procedure for agriculture GDP contribution

```
log_data<-data_ts_agriculture
plot(log_data)
```




```
summary(ur.kpss(log_data))
```

```
dif1<-log_data%>%diff()
summary(ur.kpss(dif1))

dif2<-dif1%>%diff()
summary(ur.kpss(dif2))
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 3 lags.
##
## Value of test-statistic is: 0.0371
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

```
acf2(dif2)#1,11
```


```
##       [,1]  [,2]  [,3]  [,4]  [,5]  [,6]  [,7]  [,8]
## ACF  -0.69  0.21  0.00 -0.10  0.12 -0.13  0.11  0.02
## PACF -0.69 -0.49 -0.28 -0.32 -0.22 -0.32 -0.31 -0.05
```

We have the p value possibilities as 1,2,4 and q values are 0,1. We will take different combinations to select the best model.

Model Building

Now all the preprocessing checks on the data have been completed. We build our model with the best parameters on the original data.

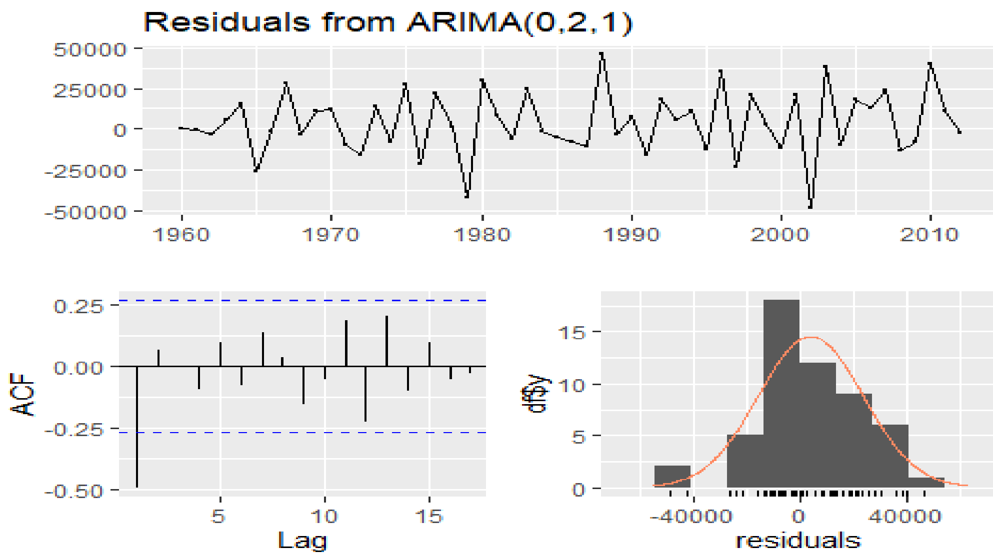
```
AIC(arima(log_data,c(1,2,1)))
```

```
## [1] 1152.445

AIC(arima(dif1,c(1,2,0)))

## [1] 1204.71

AIC(arima(dif1,c(0,2,1)))

## [1] 1191.82

AIC(arima(dif1,c(0,2,0)))

## [1] 1246.655

AIC(arima(dif1,c(0,2,2)))

## [1] 1146.379

auto.arima(data_ts_agriculture,trace=TRUE)

##
##  ARIMA(2,2,2)                    : 1153.476
##  ARIMA(0,2,0)                    : 1208.641
##  ARIMA(1,2,0)                    : 1178.694
##  ARIMA(0,2,1)                    : 1162.266
##  ARIMA(1,2,2)                    : 1151.201
##  ARIMA(0,2,2)                    : 1148.851
##  ARIMA(0,2,3)                    : 1151.202
##  ARIMA(1,2,1)                    : 1152.955
##  ARIMA(1,2,3)                    : Inf
##
##  Best model: ARIMA(0,2,2)

## Series: data_ts_agriculture
## ARIMA(0,2,2)
##
## Coefficients:
##           ma1     ma2
##       -1.5020  0.6079
## s.e.   0.1172  0.1188
##
## sigma^2 = 3.07e+08:  log likelihood = -571.17
## AIC=1148.34   AICc=1148.85   BIC=1154.14
```

We select model with paramters Arima(0,2,2) as it has less AIC value.

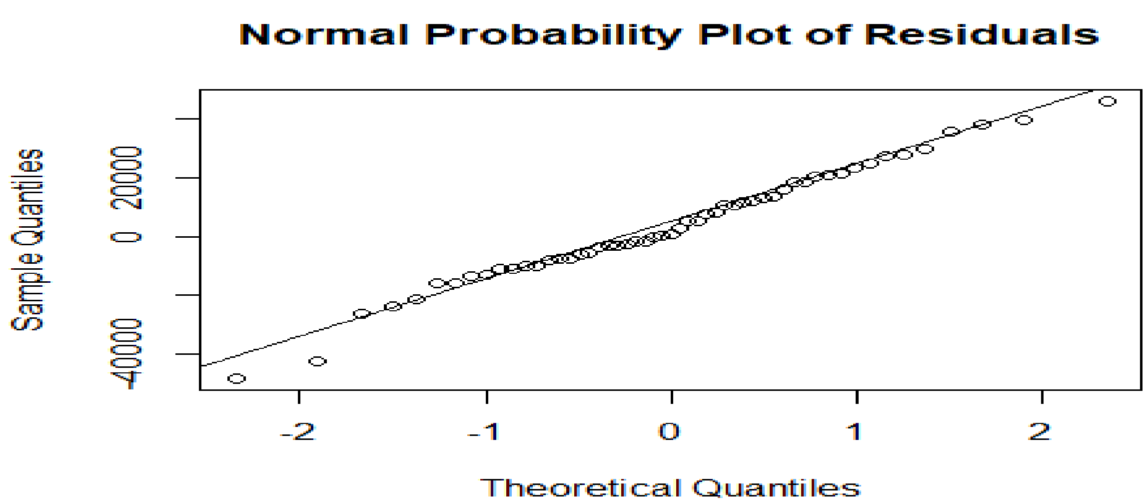
Model Fitting:

```
agri_model<-arima(log_data,c(0,2,1))
checkresiduals(agri_model)
```

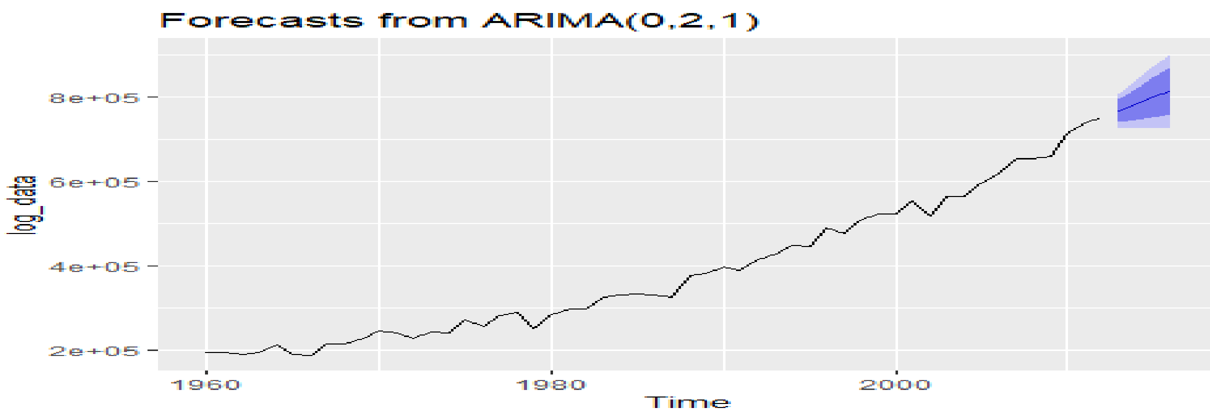



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,2,1)
## Q* = 18.55, df = 9, p-value = 0.0293
##
## Model df: 1.   Total lags used: 10
```

```
qqnorm(residuals(agri_model), main = "Normal Probability Plot of Residuals")
qqline(residuals(agri_model))
```



```
f<-forecast(agri_model,h=4)
autoplot(f)
```



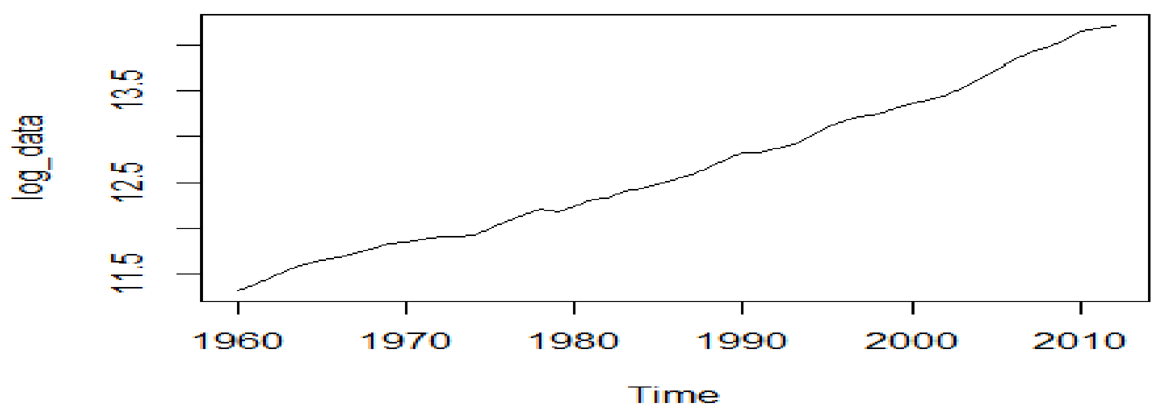

```
accuracy(f)

##                    ME     RMSE      MAE       MPE     MAPE      MASE
ACF1
## Training set 3747.943 19824.41 15565.44 0.7756106 4.425093 0.8993139 -0.49
39049
```

As we can see from the residual check, 1. In ACF plot all the values lie within the limits. 2. Residuals are normally distributed confirmed with qq plot.
Macro Reasons for Agriculture sector the growth:

- Favorable climate and fertile land: India is blessed with diverse agro-climatic zones, which provide favorable conditions for growing a wide range of crops. The country has vast fertile land, making it suitable for agriculture.
- Government policies and initiatives: The Indian government has implemented several policies and initiatives to support the growth of the agriculture sector. These include minimum support price (MSP) schemes, subsidies, and various rural development programs.
- Technological advancements: Technological advancements in the agriculture sector have significantly improved agricultural practices, increasing crop yields and overall productivity. Technologies such as precision agriculture, crop rotation, and use of genetically modified crops have contributed to the growth of the agriculture sector.
- Increasing demand for agricultural products: The growing population and changing dietary habits have led to an increasing demand for agricultural products, such as fruits, vegetables, and animal products.
- Export opportunities: The agriculture sector in India has great potential for export, and the government has been taking steps to boost agricultural exports. This has led to increased production and investments in the sector.

Industry GDP Data

```
log_data<-log(data_ts_industry)
plot(log_data)
```




```
summary(ur.kpss(log_data))

dif1<-log_data%>%diff()
summary(ur.kpss(dif1))

##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 3 lags.
##
## Value of test-statistic is: 0.3463
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739

acf2(dif1)#1,1
```


```
##      [,1] [,2] [,3]  [,4] [,5]  [,6] [,7]  [,8]
## ACF   0.3  0.0 0.01 -0.12 0.10  0.11 0.05 -0.02
## PACF  0.3 -0.1 0.05 -0.15 0.21 -0.02 0.06 -0.10
```

```
AIC(arima(log_data,c(0,2,2)))
```

```
## [1] -211.0385
```

```
AIC(arima(dif1,c(1,2,3)))
```

```
## [1] -196.9223
```

```
AIC(arima(dif1,c(0,2,3)))
```

```
## [1] -196.6928
```

```
AIC(arima(dif1,c(0,2,0)))
```

```
## [1] -143.7531
```

```
AIC(arima(dif1,c(0,2,1)))
```

```
## [1] -185.0367
```

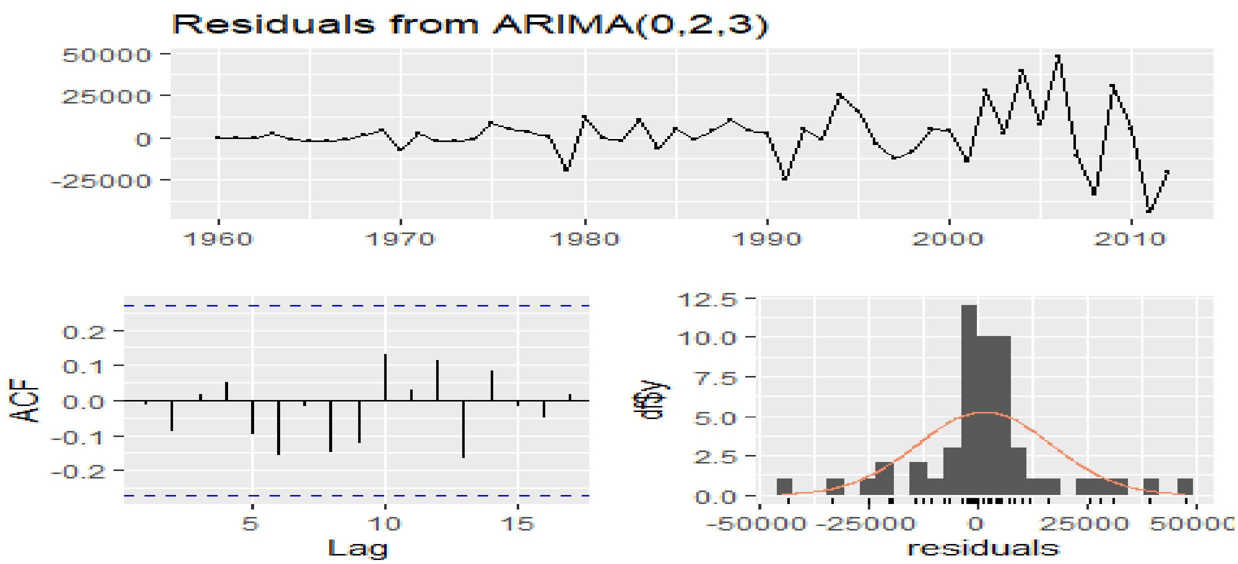
```
auto.arima(data_ts_industry,trace=TRUE)
```

```
## 
##  ARIMA(2,2,2)                          : Inf
##  ARIMA(0,2,0)                          : 1146.9
##  ARIMA(1,2,0)                          : 1147.464
##  ARIMA(0,2,1)                          : 1144.183
##  ARIMA(1,2,1)                          : 1144.658
##  ARIMA(0,2,2)                          : 1139.631
##  ARIMA(1,2,2)                          : 1139.653
##  ARIMA(0,2,3)                          : 1138.597
##  ARIMA(1,2,3)                          : 1141.059
##  ARIMA(0,2,4)                          : 1141.056
```

```
##  ARIMA(1,2,4)                    : 1141.952
##
##  Best model: ARIMA(0,2,3)
```

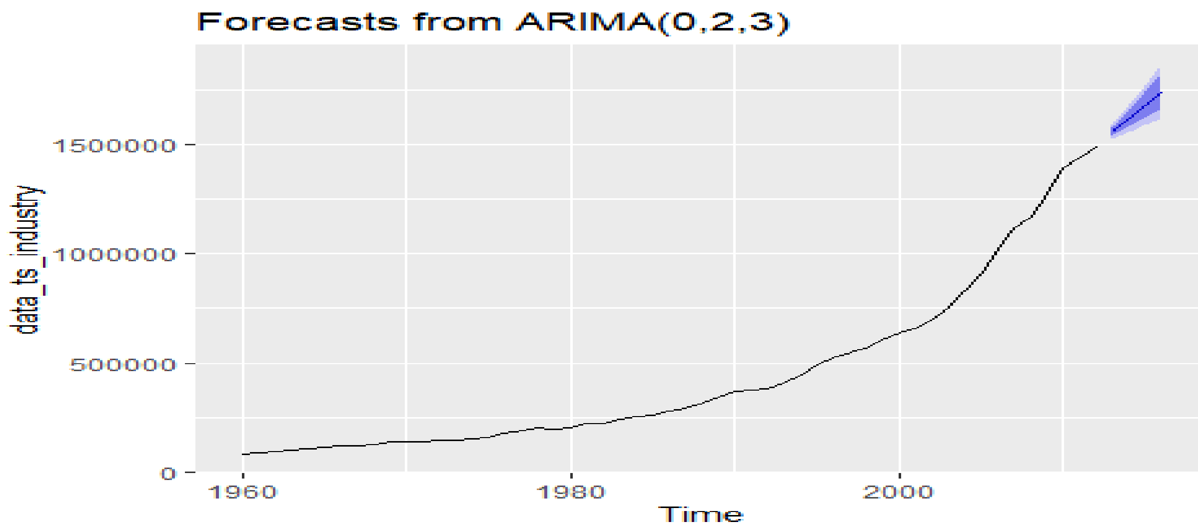
```
## Series: data_ts_industry
## ARIMA(0,2,3)
##
## Coefficients:
##           ma1      ma2     ma3
##       -0.2124  -0.4299  0.3085
## s.e.   0.1309   0.1672  0.1957
##
## sigma^2 = 256081999:  log likelihood = -564.86
## AIC=1137.73   AICc=1138.6   BIC=1145.45
```

```
industry_model<-arima(data_ts_industry,c(0,2,3))
checkresiduals(industry_model)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,2,3)
## Q* = 6.3444, df = 7, p-value = 0.5002
##
## Model df: 3.   Total lags used: 10
```

```
f<-forecast(industry_model,h=4)
autoplot(f)
```




```
accuracy(f)

##                      ME     RMSE      MAE      MPE     MAPE      MASE
ACF1
## Training set 1499.456 15229.03 9701.376 0.362757 2.184882 0.3558047 -0.014
01435
```

We can see the residual plots satisfy the conditions to fit the data well and the MAPE is also close to one.

Macro Reasons for the Industrial sector growth:

- Government initiatives: The Indian government has launched several initiatives like Make in India, Invest India, and Atmanirbhar Bharat to promote the growth of the manufacturing sector. These initiatives aim to create a favorable business environment and attract foreign investment to the country.
- Demographic advantage: India has a large population and a relatively young workforce. This demographic advantage provides a large pool of labor for the manufacturing sector. This, combined with the increasing skill levels of the workforce, has made India an attractive destination for manufacturing investments.
- Rising domestic demand: India has a growing middle class, which is driving demand for a range of consumer goods, including automobiles, electronics, and appliances. This growing domestic demand provides a significant market for the manufacturing sector.
- Access to technology: India has made significant progress in developing its technological capabilities. The country has a large pool of skilled workers in the technology sector and has made significant investments in research and development. This has helped Indian manufacturers to develop high-quality, technologically advanced products that can compete globally.
- Infrastructure development: India has been investing heavily in infrastructure development, including transportation, power, and telecommunications. These

investments have made it easier and more cost-effective for manufacturers to transport goods and communicate with customers and suppliers. This has helped to reduce production costs and improve supply chain efficiency, making Indian manufacturing more competitive globally.

6. **Conclusion**:

This project aimed to conduct time series analysis and forecasting of India's Gross Domestic Product (GDP) and sector-wise performance, with the aim of identifying patterns, trends, and relationships within the historical GDP data and using this information to predict future values for both the overall GDP and individual sectors. The project utilized data from the National Statistical Office and the Reserve Bank of India, which were both valuable sources of information for analyzing key economic indicators such as inflation, interest rates, and foreign exchange reserves. The theoretical aspect of the project focused on understanding GDP as an economic concept and conducting sectorial and sub-sectorial analysis. The time series aspect of GDP was also explored in detail, with the goal of identifying any patterns or trends in the data that could be used for forecasting.

The practical aspect of the project involved initializing the necessary libraries, importing and exploring the data, and considering all three sectors to identify potential models for forecasting. Model selection, fitting, and validation were also conducted to ensure that the chosen model was accurate and reliable. The project predicted specific sectors such as agriculture and industry, which provided insights into the health and growth of these individual sectors. This project provides valuable insights into the Indian economy and can be used to inform policy decisions and investment strategies. The results can also serve as a starting point for further research and analysis of the country's economic performance.

As we know the GDP depends on various parameter both micro and macro economic conditions. We were able to project the trend from the historic data of 1961 to 2012 and forecasting for thr next 4 years. the original values lie within the 95% confidence interval of the forecast. We can see there is a linear increasing trend of GDP in India.