STOCK MARKET PRICE FORECASTING

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Introduction

The project focuses on forecasting stock market prices, specifically for the Bank Nifty index, using advanced machine learning and time series analysis techniques. Accurate stock market predictions are crucial for investors, traders, and financial analysts, enabling informed decision-making and strategy development. This project involves data preprocessing, normalization, and the application of the Long Short-Term Memory (LSTM) model, a type of recurrent neural network (RNN) well-suited for time series prediction due to its ability to capture long-term dependencies. Additionally, the project includes exploratory data analysis (EDA) and visualization using tools like ggplot2 and plotly to gain insights and identify patterns in the historical stock prices. The final model aims to predict future prices, providing a valuable tool for financial forecasting and investment strategy. The results are visualized through interactive plots, enhancing the interpretability and usability of the predictions.

Loading the libraries

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(ggplot2)
library(tidyquant)
```

```
## Loading required package: lubridate
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union

## Loading required package: PerformanceAnalytics

## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

##
## ######################### Warning from 'xts' package ##########################
## #                                                                             #
## # The dplyr lag() function breaks how base R's lag() function is supposed to  #
## # work, which breaks lag(my_xts). Calls to lag(my_xts) that you type or       #
## # source() into this session won't work correctly.                            #
## #                                                                             #
## # Use stats::lag() to make sure you're not using dplyr::lag(), or you can add #
## # conflictRules('dplyr', exclude = 'lag') to your .Rprofile to stop           #
## # dplyr from breaking base R's lag() function.                                #
## #                                                                             #
## # Code in packages is not affected. It's protected by R's namespace mechanism #
## # Set `options(xts.warn_dplyr_breaks_lag = FALSE)` to suppress this warning.  #
## #                                                                             #
## ###############################################################################

##
## Attaching package: 'xts'

## The following objects are masked from 'package:dplyr':
##
##     first, last

##
## Attaching package: 'PerformanceAnalytics'

## The following object is masked from 'package:graphics':
##
##     legend

## Loading required package: quantmod
```

```
## Loading required package: TTR

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

```r
library(quantmod)
library(forecast)
library(tseries)
library(scales)
library(tidyr)
library(xts)
```

Reading the data

```r
file_path <- "C://Users//chinn//Downloads//bankNifty_12thApr.csv"

data <- read.csv(file_path)
```

```r
print(dim(data))
```

```
## [1] 4090    7
```

```r
print(nrow(data))
```

```
## [1] 4090
```

```r
print(ncol(data))
```

```
## [1] 7
```

Preprocessing

P1. Converting all columns to numeric datatype

```r
numeric_cols <- c('Open', 'High', 'Low', 'Close', 'Adj.Close', 'Volume')

data[numeric_cols] <- lapply(data[numeric_cols], as.numeric)
```

```r
str(data)
```

```
## 'data.frame':    4090 obs. of  7 variables:
##  $ Date     : chr  "2007-09-17" "2007-09-18" "2007-09-19" "2007-09-20" ...
##  $ Open     : num  6898 6921 7111 7405 7378 ...
##  $ High     : num  6977 7079 7419 7463 7506 ...
##  $ Low      : num  6843 6884 7111 7344 7367 ...
##  $ Close    : num  6897 7060 7402 7390 7464 ...
##  $ Adj.Close: num  6897 7060 7402 7390 7464 ...
##  $ Volume   : num  0 0 0 0 0 0 0 0 0 0 ...
```

```r
print(head(data))
```

```
##         Date    Open    High     Low   Close Adj.Close Volume
## 1 2007-09-17 6898.00 6977.20 6843.00 6897.10  6897.020      0
## 2 2007-09-18 6921.15 7078.95 6883.60 7059.65  7059.568      0
## 3 2007-09-19 7111.00 7419.35 7111.00 7401.85  7401.764      0
## 4 2007-09-20 7404.95 7462.90 7343.60 7390.15  7390.064      0
## 5 2007-09-21 7378.30 7506.35 7367.15 7464.50  7464.413      0
## 6 2007-09-24 7514.40 7661.05 7514.40 7650.90  7650.811      0
```

Summary of data

```r
summary(data)
```

```
##      Date                Open            High            Low       
##  Length:4090        Min.   : 3385   Min.   : 3447   Min.   : 3315  
##  Class :character   1st Qu.:10308   1st Qu.:10414   1st Qu.:10180  
##  Mode  :character   Median :18386   Median :18539   Median :18227  
##                     Mean   :20869   Mean   :21033   Mean   :20676  
##                     3rd Qu.:30228   3rd Qu.:30480   3rd Qu.:29960  
##                     Max.   :48880   Max.   :49057   Max.   :48669  
##                     NA's   :303     NA's   :303     NA's   :303    
##      Close         Adj.Close         Volume         
##  Min.   : 3340   Min.   : 3340   Min.   :0.000e+00  
##  1st Qu.:10289   1st Qu.:10289   1st Qu.:0.000e+00  
##  Median :18373   Median :18372   Median :0.000e+00  
##  Mean   :20856   Mean   :20856   Mean   :6.583e+05  
##  3rd Qu.:30216   3rd Qu.:30215   3rd Qu.:4.165e+04  
##  Max.   :48987   Max.   :48987   Max.   :1.798e+09  
##  NA's   :303     NA's   :303     NA's   :303        
```

P3. Counting missing values

```r
na_counts <- colSums(is.na(data))
print(na_counts)
```

```
##      Date      Open      High       Low     Close Adj.Close    Volume 
##         0       303       303       303       303       303       303 
```

P4. Imputing missing values with moving averages

```r
impute_local_mean <- function(x, range = 35) {
  imputed_values <- numeric(length(x))
  # Iterate over each element in the vector
  for (i in seq_along(x)) {
    if (is.na(x[i])) {
```

```r
      # Calculate the local mean within the specified range
      lower_bound <- max(1, i - range)
      upper_bound <- min(length(x), i + range)
      local_values <- x[lower_bound:upper_bound]
      imputed_values[i] <- mean(local_values, na.rm = TRUE)
    } else {
      # Keep the original value if it's not NA
      imputed_values[i] <- x[i]
    }
  }

  return(imputed_values)
}
# Apply the custom imputation function to each column of the dataframe
clean_data <- as.data.frame(lapply(data, impute_local_mean))
# Note: Replace 'data' with the name of your dataframe containing NA values
head(clean_data)
```

```
##         Date    Open    High     Low   Close Adj.Close Volume
## 1 2007-09-17 6898.00 6977.20 6843.00 6897.10  6897.020      0
## 2 2007-09-18 6921.15 7078.95 6883.60 7059.65  7059.568      0
## 3 2007-09-19 7111.00 7419.35 7111.00 7401.85  7401.764      0
## 4 2007-09-20 7404.95 7462.90 7343.60 7390.15  7390.064      0
## 5 2007-09-21 7378.30 7506.35 7367.15 7464.50  7464.413      0
## 6 2007-09-24 7514.40 7661.05 7514.40 7650.90  7650.811      0
```

Re-counting missing values

```r
na_counts <- colSums(is.na(clean_data))
print(na_counts)
```

```
##      Date      Open      High       Low     Close Adj.Close    Volume
##         0         0         0         0         0         0         0
```

P5. Replacing "0" values in Volume column

```r
# Set seed for reproducibility (optional)
set.seed(123)

# Identify zero values in the volume column
zero_indices <- which(clean_data$Volume == 0)

# Calculate the number of zero values
num_zeros <- length(zero_indices)

# Generate random integers between 200,000 and 300,000
random_numbers <- sample(200000:500000, size = num_zeros, replace = TRUE)

# Replace zero values in the volume column with random numbers
```

```r
clean_data$Volume[zero_indices] <- random_numbers

# Convert the volume column to integer type
clean_data$Volume <- as.integer(clean_data$Volume)


# Display the updated dataset
print(head(clean_data))
```

```
##         Date    Open    High     Low   Close Adj.Close Volume
## 1 2007-09-17 6898.00 6977.20 6843.00 6897.10  6897.020 388941
## 2 2007-09-18 6921.15 7078.95 6883.60 7059.65  7059.568 334057
## 3 2007-09-19 7111.00 7419.35 7111.00 7401.85  7401.764 324021
## 4 2007-09-20 7404.95 7462.90 7343.60 7390.15  7390.064 360996
## 5 2007-09-21 7378.30 7506.35 7367.15 7464.50  7464.413 426317
## 6 2007-09-24 7514.40 7661.05 7514.40 7650.90  7650.811 324506
```

P6. Feature Engineering

Adding column "Today's Opening Price and Closing Price Difference"

```r
# Add a new column 'difference' to calculate the price difference
clean_data$Today_point_difference <- clean_data$Close - clean_data$Open

# Display the updated dataset with the new 'difference' column
print(head(clean_data))
```

```
##         Date    Open    High     Low   Close Adj.Close Volume
## 1 2007-09-17 6898.00 6977.20 6843.00 6897.10  6897.020 388941
## 2 2007-09-18 6921.15 7078.95 6883.60 7059.65  7059.568 334057
## 3 2007-09-19 7111.00 7419.35 7111.00 7401.85  7401.764 324021
## 4 2007-09-20 7404.95 7462.90 7343.60 7390.15  7390.064 360996
## 5 2007-09-21 7378.30 7506.35 7367.15 7464.50  7464.413 426317
## 6 2007-09-24 7514.40 7661.05 7514.40 7650.90  7650.811 324506
##   Today_point_difference
## 1              -0.899902
## 2             138.500000
## 3             290.850098
## 4             -14.800293
## 5              86.200195
## 6             136.500000
```

Adding column "Closing (Prev.) and Opening (Curr.) Difference

```r
# Assuming 'data' is your dataframe containing stock market data with columns: date, open_price, high_p
# Sort the dataframe by date (if not already sorted)
clean_data <- clean_data[order(clean_data$Date), ]
```

```r
# Calculate the difference between yesterday's close and today's open
clean_data <- clean_data %>%
  mutate(yesterday_close = lag(Close, default = first(Close)),  # Get yesterday's closing price
         today_open = Open,  # Today's opening price
         price_difference =  yesterday_close - today_open )  # Calculate the price difference

# Rename the new column for clarity
colnames(clean_data)[which(names(clean_data) == "price_difference")] <- "closing_opening_difference"

# Display the updated dataframe
print(head(clean_data))
```

```
##         Date    Open    High     Low   Close Adj.Close Volume
## 1 2007-09-17 6898.00 6977.20 6843.00 6897.10  6897.020 388941
## 2 2007-09-18 6921.15 7078.95 6883.60 7059.65  7059.568 334057
## 3 2007-09-19 7111.00 7419.35 7111.00 7401.85  7401.764 324021
## 4 2007-09-20 7404.95 7462.90 7343.60 7390.15  7390.064 360996
## 5 2007-09-21 7378.30 7506.35 7367.15 7464.50  7464.413 426317
## 6 2007-09-24 7514.40 7661.05 7514.40 7650.90  7650.811 324506
##   Today_point_difference yesterday_close today_open closing_opening_difference
## 1              -0.899902         6897.10    6898.00                  -0.899902
## 2             138.500000         6897.10    6921.15                 -24.049804
## 3             290.850098         7059.65    7111.00                 -51.350098
## 4             -14.800293         7401.85    7404.95                  -3.100097
## 5              86.200195         7390.15    7378.30                  11.850097
## 6             136.500000         7464.50    7514.40                 -49.899902
```

P7. Downloading the modified dataset

```r
# Assuming 'clean_data' is your DataFrame and 'clean_data.csv' is the desired filename
clean_data <- data.frame(clean_data)  # Ensure clean_data is in the correct format
csv_file_path <- "clean_data.csv"

# Save the DataFrame as a CSV file
write.csv(clean_data, file = csv_file_path, row.names = FALSE)
```

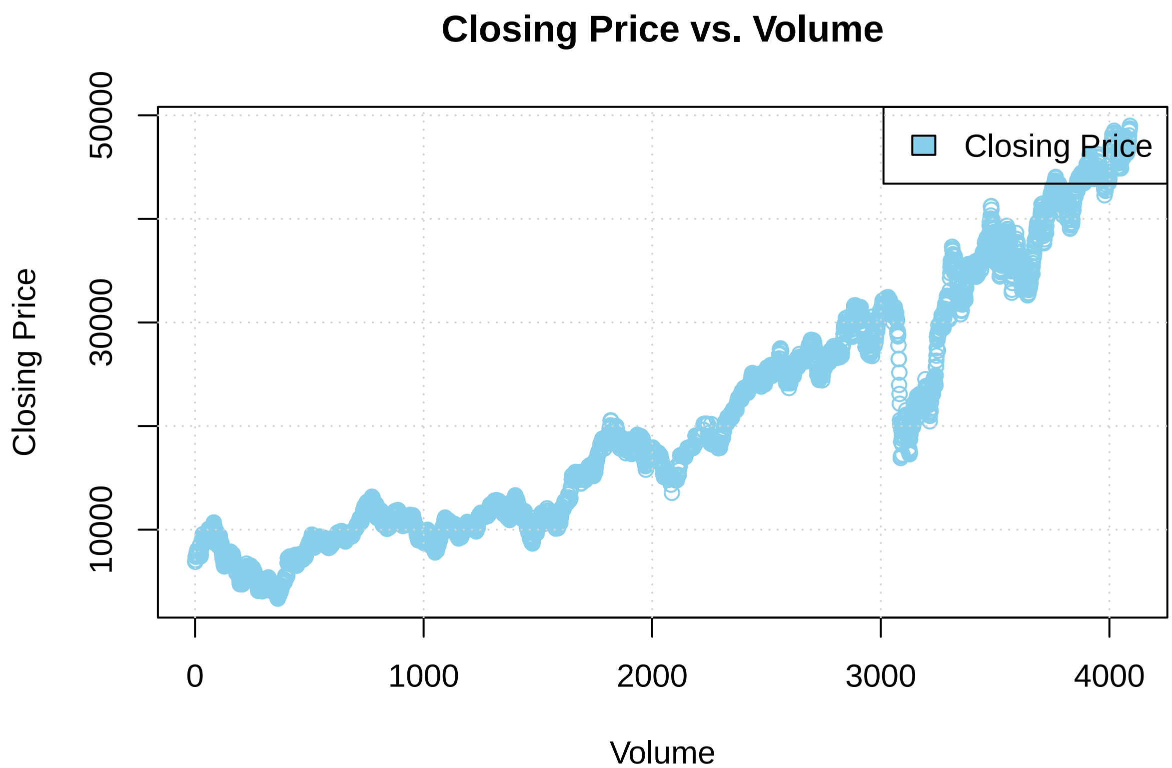
```r
clean_data = read.csv("C://Users//chinn//Downloads//clean_data.csv")
```

Data Analysis

D1. Closing Price vs Volume

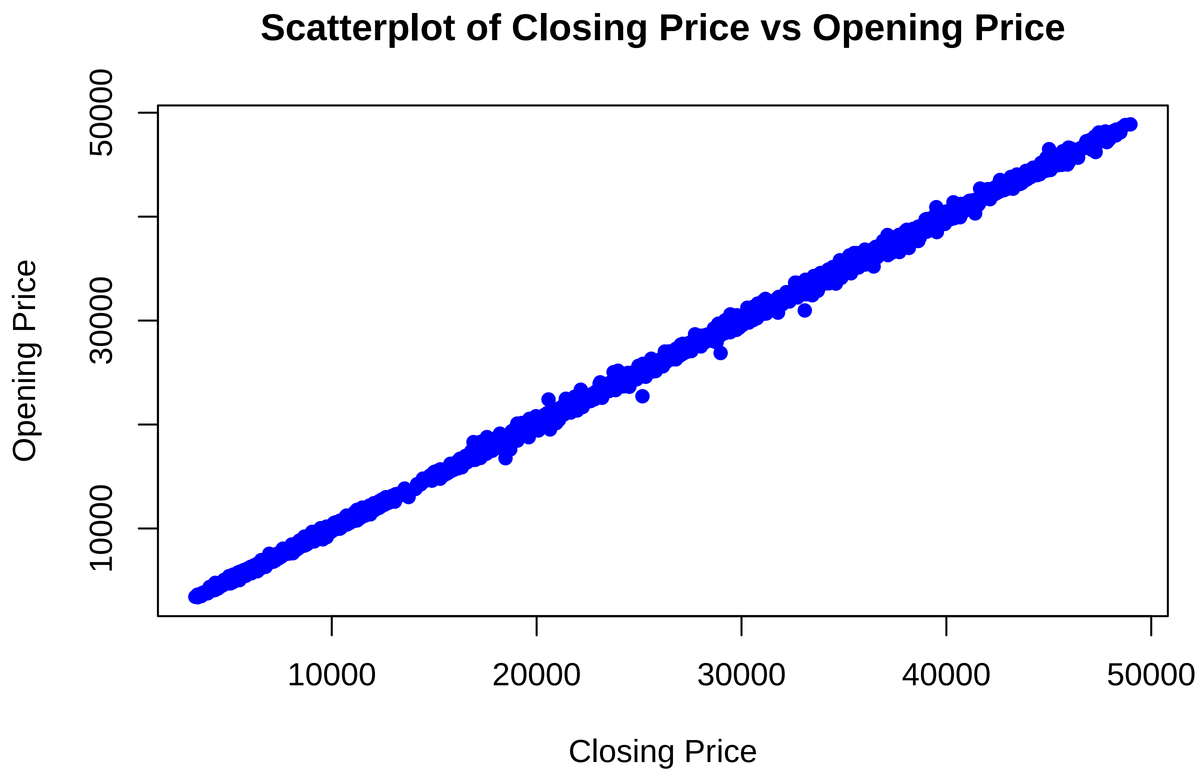
```r
plot(clean_data$Close, names.arg = clean_data$Volume, xlab = "Volume", ylab = "Closing Price",
        main = "Closing Price vs. Volume", col = "skyblue", border = "black",
        space = 0.5)

# Adding a legend
legend("topright", legend = "Closing Price", fill = "skyblue")
```

```r
# Adding gridlines for clarity (optional)
grid()
```



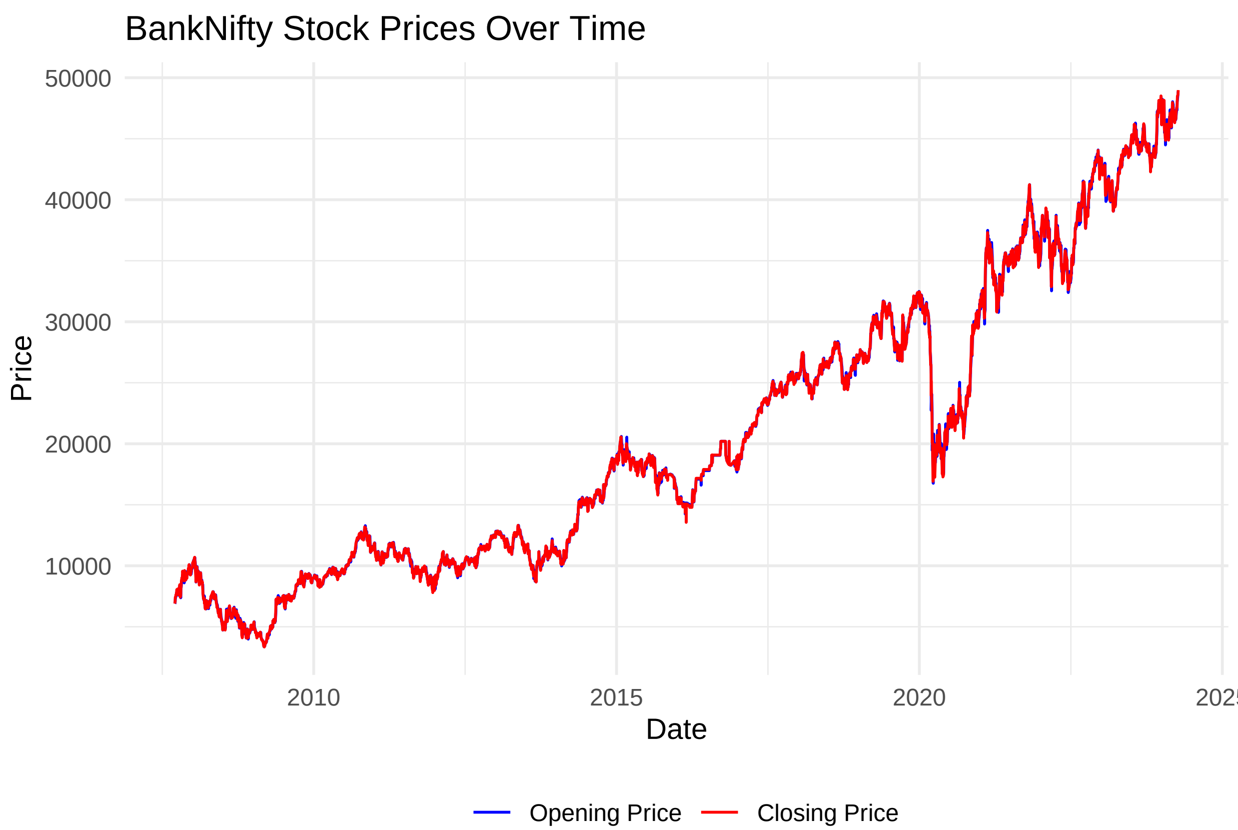
D2. Opening Price vs Closing Price

```r
# Customized scatterplot
plot(clean_data$Close, clean_data$Open,
     col = "blue",   # Change point color
     pch = 16,       # Use solid circles for points
     xlab = "Closing Price",
     ylab = "Opening Price",
     main = "Scatterplot of Closing Price vs Opening Price")
```



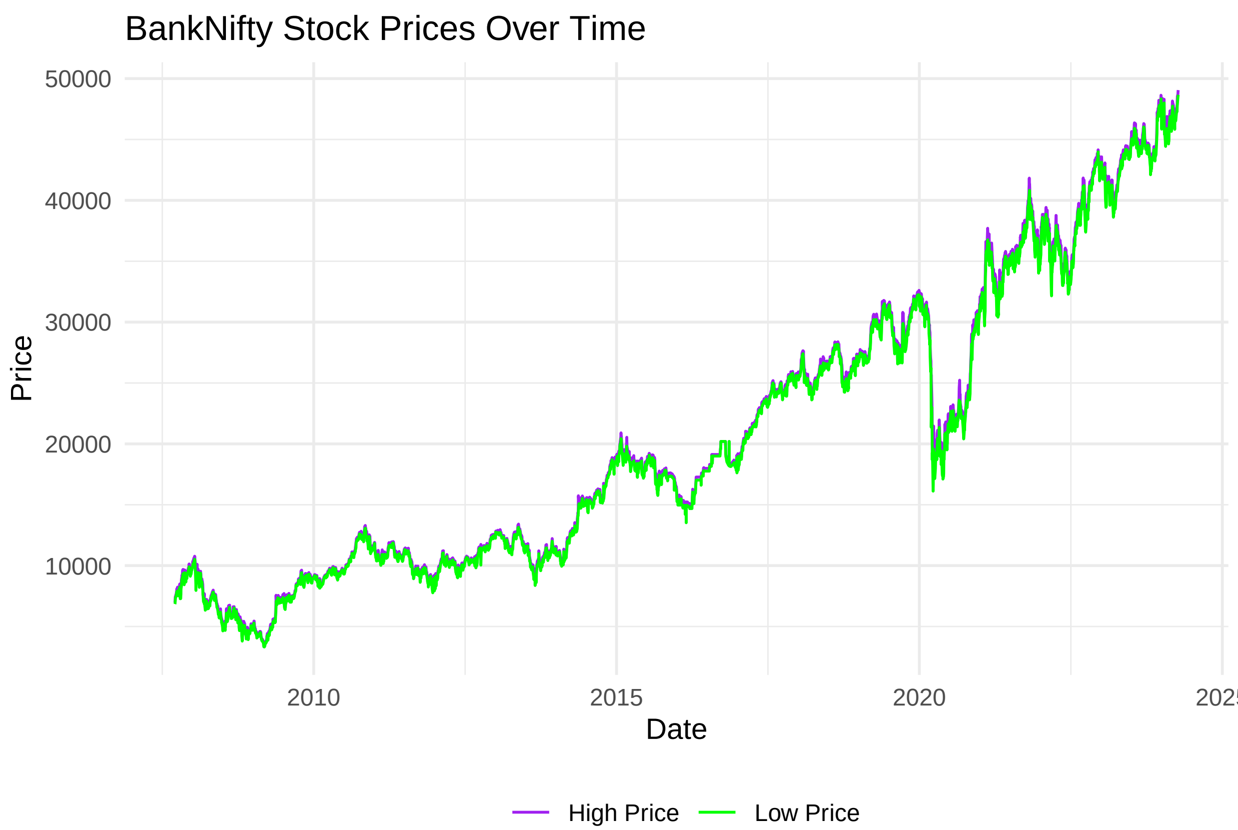
D3. Date vs Closing, Opening Price

```
# Convert 'Date' to Date format
clean_data$Date <- as.Date(clean_data$Date, format="%Y-%m-%d")

# Plotting the prices
ggplot(clean_data, aes(x = Date)) +
  geom_line(aes(y = Open, color = "Opening Price")) +
  geom_line(aes(y = Close, color = "Closing Price")) +
  labs(title = "BankNifty Stock Prices Over Time", x = "Date", y = "Price") +
  scale_color_manual("",
                     breaks = c("Opening Price", "Closing Price"),
                     values = c("blue", "red")) +
  theme_minimal() +
  theme(legend.position = "bottom")
```



D4. Date vs High, Low Price

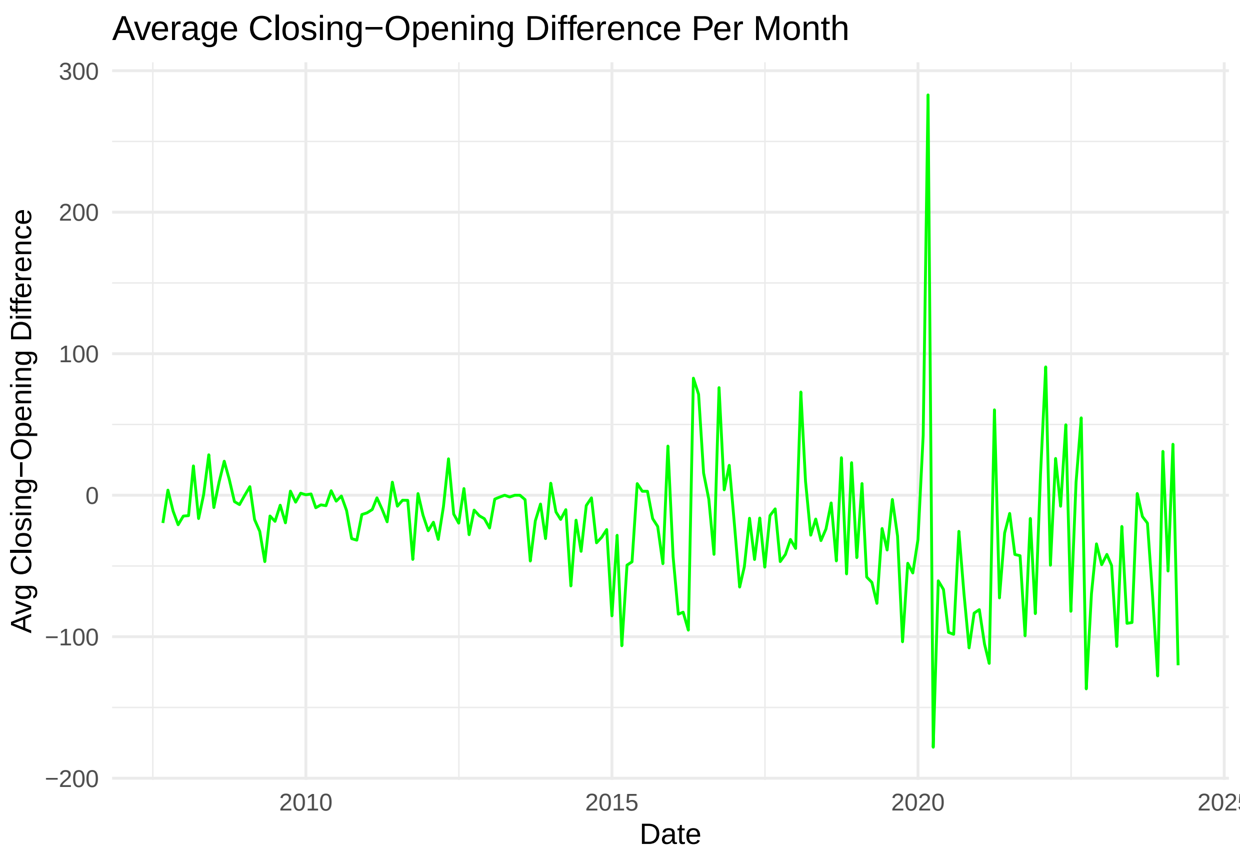
```
# Convert 'Date' to Date format
clean_data$Date <- as.Date(clean_data$Date, format="%Y-%m-%d")

# Plotting the prices
ggplot(clean_data, aes(x = Date)) +
  geom_line(aes(y = High, color = "High Price")) +
  geom_line(aes(y = Low, color = "Low Price")) +
  labs(title = "BankNifty Stock Prices Over Time", x = "Date", y = "Price") +
  scale_color_manual("",
                     breaks = c("High Price", "Low Price"),
                     values = c("purple", "green")) +
  theme_minimal()+
  theme(legend.position = "bottom")
```



We can observe the overall trend of the stock prices (opening, closing, high, and low) over time.Any sharp spikes or drops may indicate significant market events or reactions to news.

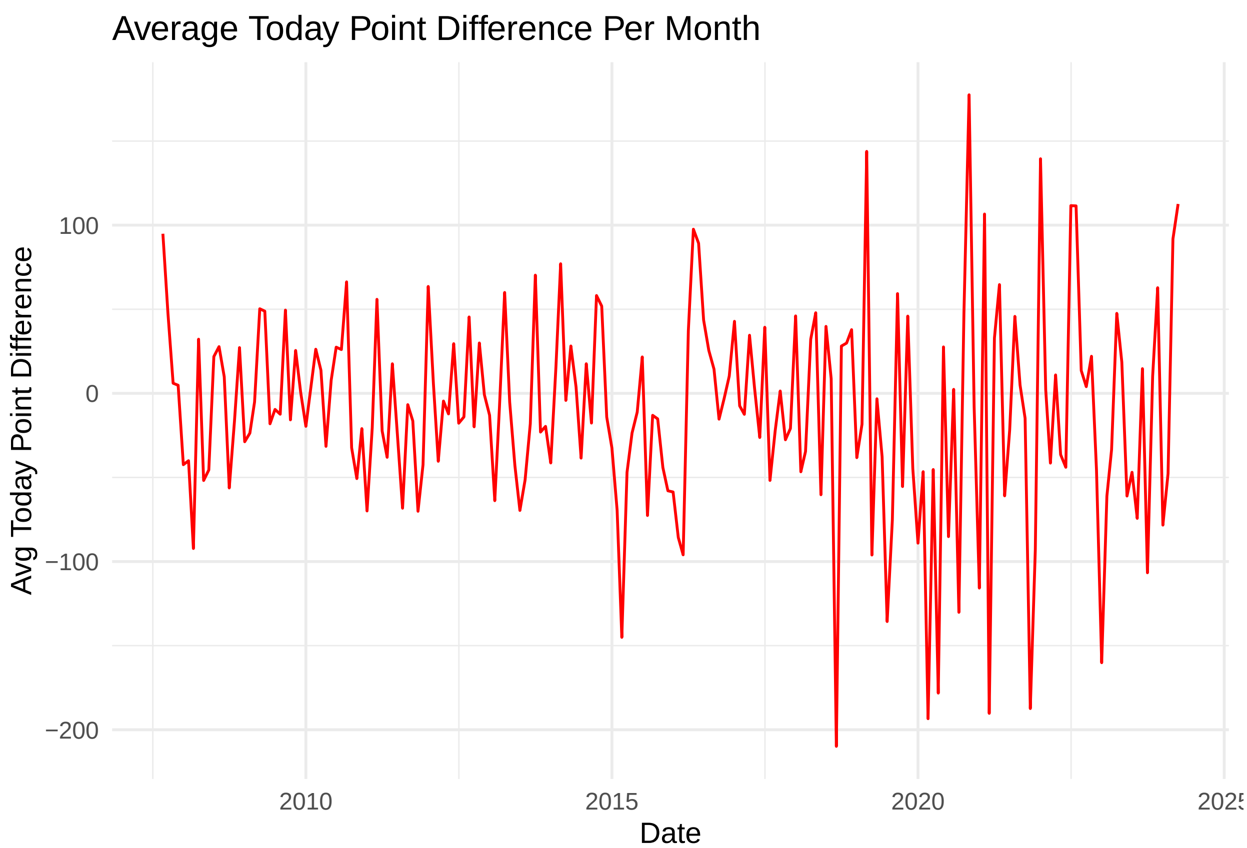
D5. Avg-Closing-Opening Difference Per Month Over time

```
clean_data$Date <- as.Date(clean_data$Date)

# Aggregate the data by month and calculate the average closing_opening_difference
monthly_data <- clean_data %>%
  mutate(Month = format(Date, "%Y-%m")) %>% # Extract year-month
  group_by(Month) %>%
  summarize(avg_closing_opening_difference = mean(closing_opening_difference, na.rm = TRUE))

# Convert Month back to Date type for proper plotting
# Convert Month to Date type for proper plotting
monthly_data$Month <- as.Date(paste(monthly_data$Month, "-01", sep=""))

# Plot the average closing_opening_difference per month
ggplot(monthly_data, aes(x = Month, y = avg_closing_opening_difference)) +
  geom_line(color = "green") +
  labs(title = "Average Closing-Opening Difference Per Month",
       x = "Date",
       y = "Avg Closing-Opening Difference") +
  theme_minimal()
```



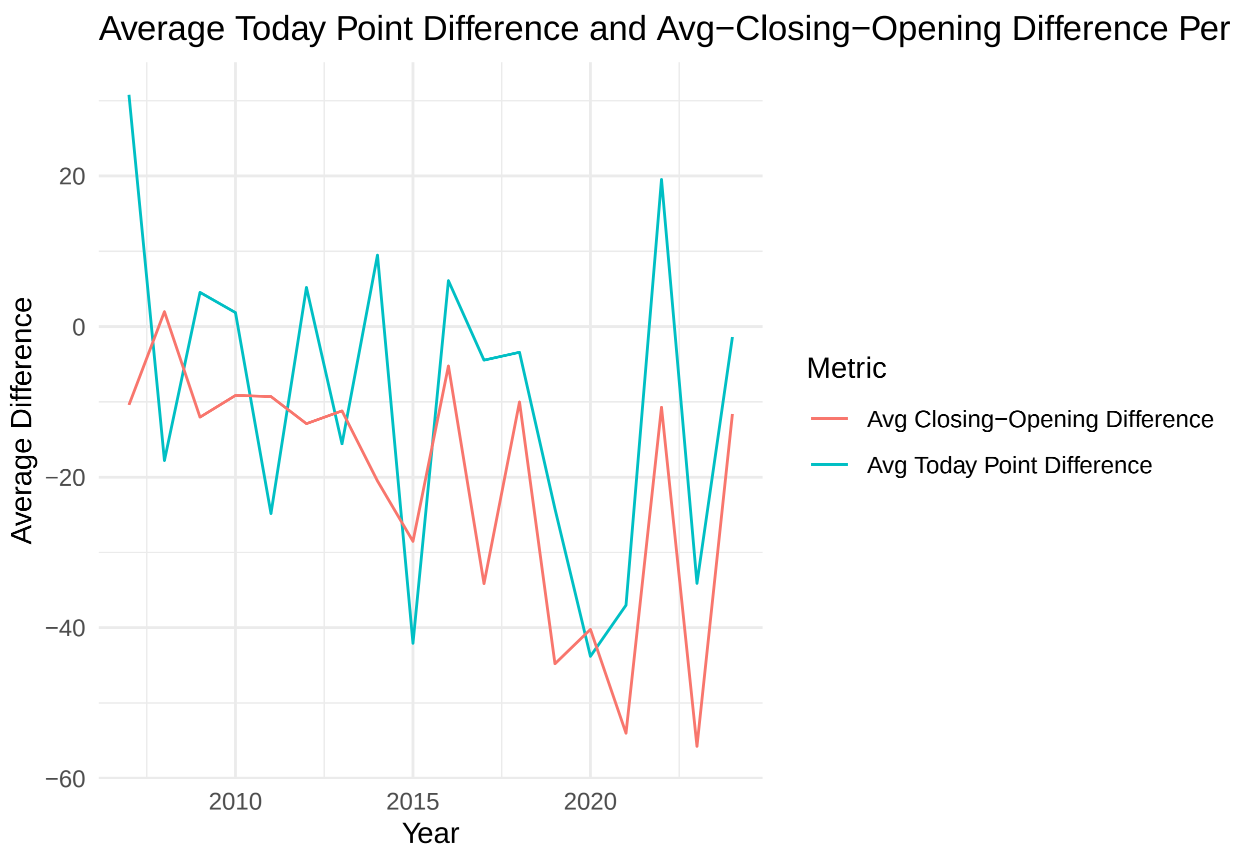
D6 .Average Today Point Difference Per Month Over Time

```
clean_data$Date <- as.Date(clean_data$Date)

# Aggregate the data by month and calculate the average today_point_difference
monthly_data <- clean_data %>%
  mutate(Month = format(Date, "%Y-%m")) %>% # Extract year-month
  group_by(Month) %>%
  summarize(avg_today_point_difference = mean(Today_point_difference, na.rm = TRUE))

# Convert Month back to Date type for proper plotting
monthly_data$Month <- as.Date(paste(monthly_data$Month, "-01", sep=""))

# Plot the average today_point_difference per month with date on x-axis
ggplot(monthly_data, aes(x = Month, y = avg_today_point_difference)) +
  geom_line(color = "red") +
  labs(title = "Average Today Point Difference Per Month",
       x = "Date",
       y = "Avg Today Point Difference") +
  theme_minimal()
```



D7. Average-Today-Point Difference and Avg-Closing-Opening Difference Per Year

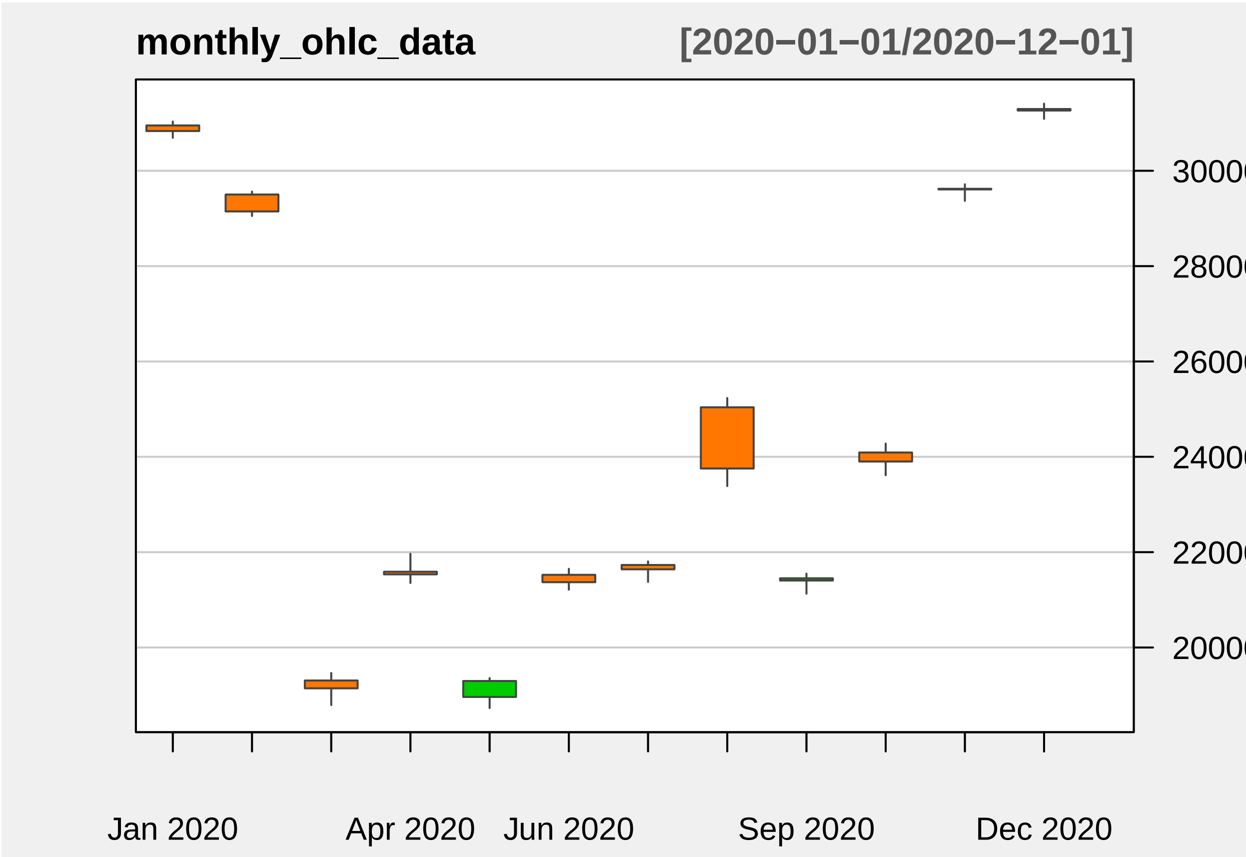
```
# Aggregate the data by year and calculate the average Today_point_difference and closing_opening_diffe
yearly_data <- clean_data %>%
  mutate(Year = format(Date, "%Y")) %>% # Extract year
  group_by(Year) %>%
  summarize(
    avg_Today_point_difference = mean(Today_point_difference, na.rm = TRUE),
    avg_closing_opening_difference = mean(closing_opening_difference, na.rm = TRUE)
  )

# Convert Year back to Date type for proper plotting
yearly_data$Year <- as.Date(paste(yearly_data$Year, "-01-01", sep=""))

# Plot the average Today_point_difference and avg_closing_opening_difference per year
ggplot(yearly_data) +
  geom_line(aes(x = Year, y = avg_Today_point_difference, color = "Avg Today Point Difference")) +
  geom_line(aes(x = Year, y = avg_closing_opening_difference, color = "Avg Closing-Opening Difference")
  labs(title = "Average Today Point Difference and Avg-Closing-Opening Difference Per Year",
       x = "Year",
       y = "Average Difference",
       color = "Metric") +
  theme_minimal()
```



D8. Year 2020 (Month wise)

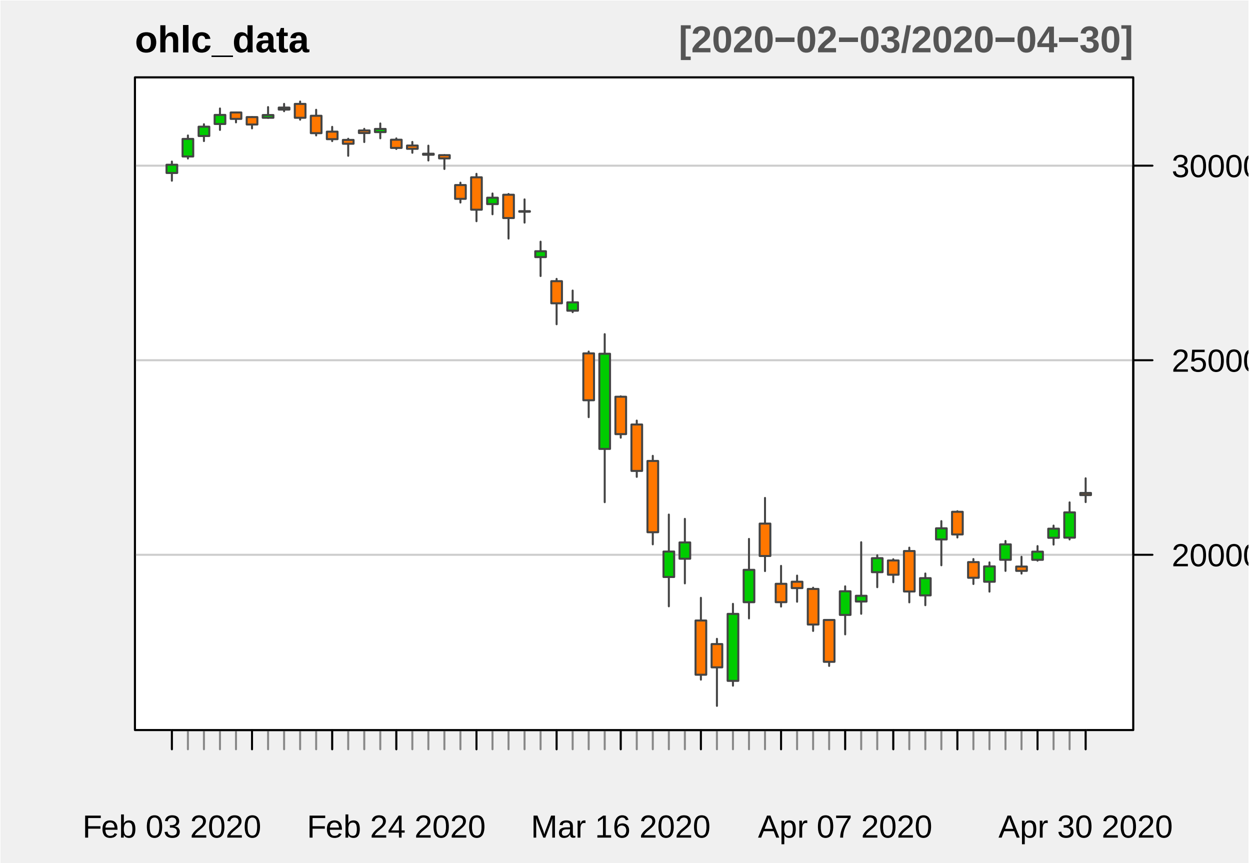
```
# Load the Bank Nifty dataset
clean_data <- read.csv("C://Users//chinn//Downloads//clean_data.csv")
clean_data$Date <- as.Date(clean_data$Date)

# Filter data for the year 2020
clean_data_2020 <- clean_data[format(clean_data$Date, "%Y") == "2020", ]

# Ensure columns are named correctly for quantmod
ohlc_data <- xts(
  x = clean_data_2020[, c("Open", "High", "Low", "Close")],
  order.by = clean_data_2020$Date
)

# Rename columns to standard OHLC names (Open, High, Low, Close)
colnames(ohlc_data) <- c("Open", "High", "Low", "Close")


# Aggregate data by month using the aggregate function

monthly_ohlc_data <- aggregate(ohlc_data, by = as.Date(format(index(ohlc_data), "%Y-%m-01")), FUN = las
```

```r
# Plot the candlestick chart
candleChart(monthly_ohlc_data, theme = "white", TA = NULL)
```



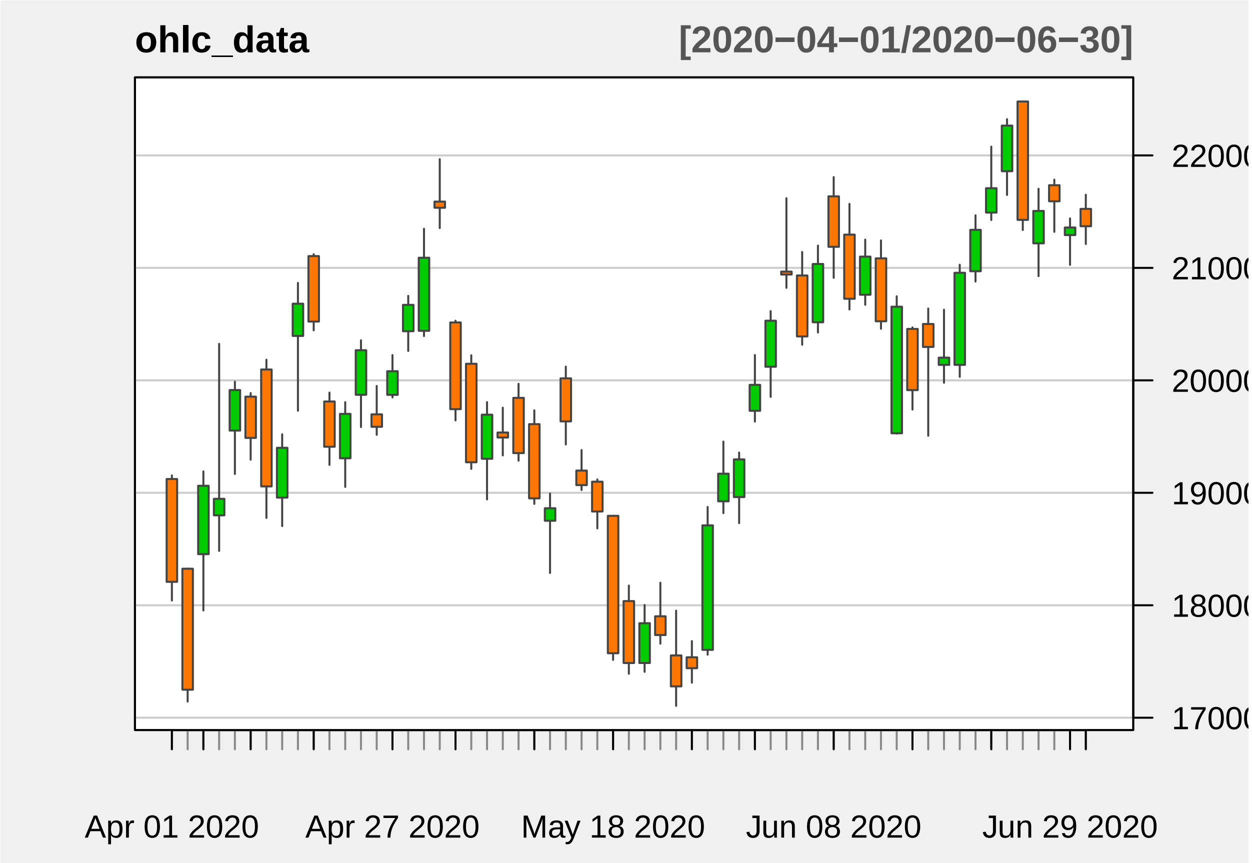
D9. Year 2020(Feb - Apr)

```r
clean_data$Date <- as.Date(clean_data$Date)

# Filter data for the year 2020 and months April to June
clean_data_2020 <- clean_data[format(clean_data$Date, "%Y") == "2020" &
                              format(clean_data$Date, "%m") %in% c("02", "03", "04"), ]

# Ensure columns are named correctly for quantmod
ohlc_data <- xts(
  x = clean_data_2020[, c("Open", "High", "Low", "Close")],
  order.by = clean_data_2020$Date
)

# Rename columns to standard OHLC names (Open, High, Low, Close)
colnames(ohlc_data) <- c("Open", "High", "Low", "Close")

# Plot the candlestick chart
candleChart(ohlc_data, theme = "white", TA = NULL)
```



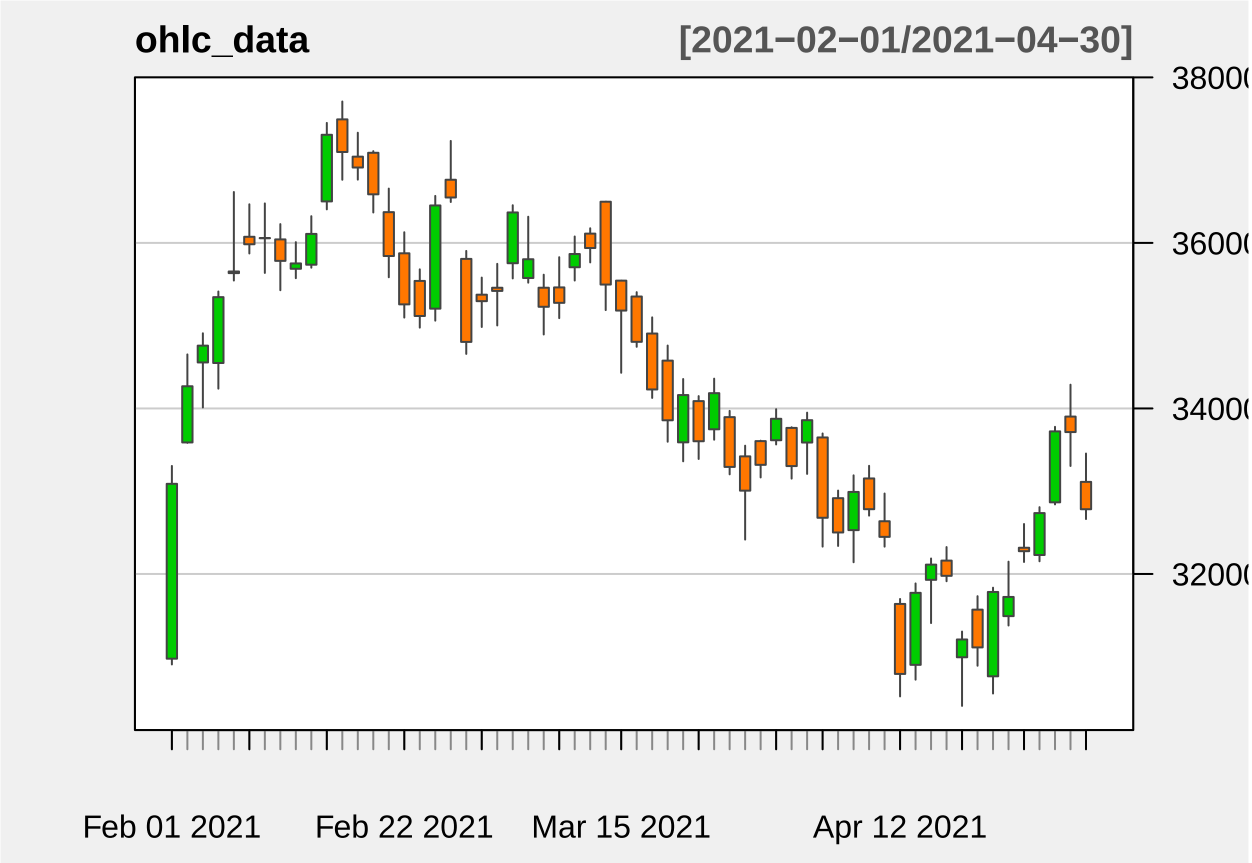
D10. Year 2020 (Apr - June)

```
clean_data$Date <- as.Date(clean_data$Date)

# Filter data for the year 2020 and months April to June
clean_data_2020 <- clean_data[format(clean_data$Date, "%Y") == "2020" &
                              format(clean_data$Date, "%m") %in% c("04", "05", "06"), ]

# Ensure columns are named correctly for quantmod
ohlc_data <- xts(
  x = clean_data_2020[, c("Open", "High", "Low", "Close")],
  order.by = clean_data_2020$Date
)

# Rename columns to standard OHLC names (Open, High, Low, Close)
colnames(ohlc_data) <- c("Open", "High", "Low", "Close")

# Plot the candlestick chart
candleChart(ohlc_data, theme = "white", TA = NULL)
```



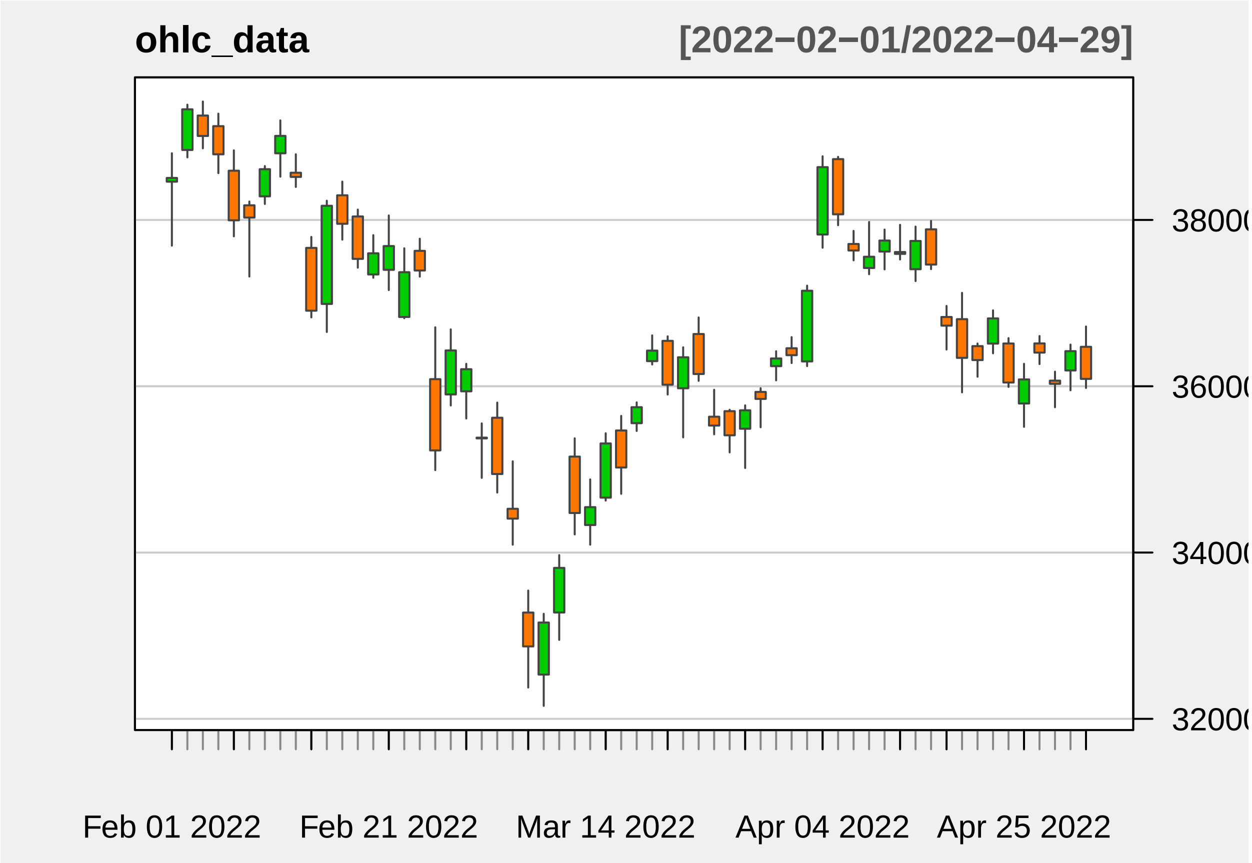
D11. Year 2021(Feb - Apr)

```
clean_data$Date <- as.Date(clean_data$Date)

# Filter data for the year 2020 and months April to June
clean_data_2020 <- clean_data[format(clean_data$Date, "%Y") == "2021" &
                              format(clean_data$Date, "%m") %in% c("02", "03", "04"), ]

# Ensure columns are named correctly for quantmod
ohlc_data <- xts(
  x = clean_data_2020[, c("Open", "High", "Low", "Close")],
  order.by = clean_data_2020$Date
)

# Rename columns to standard OHLC names (Open, High, Low, Close)
colnames(ohlc_data) <- c("Open", "High", "Low", "Close")

# Plot the candlestick chart
candleChart(ohlc_data, theme = "white", TA = NULL)
```



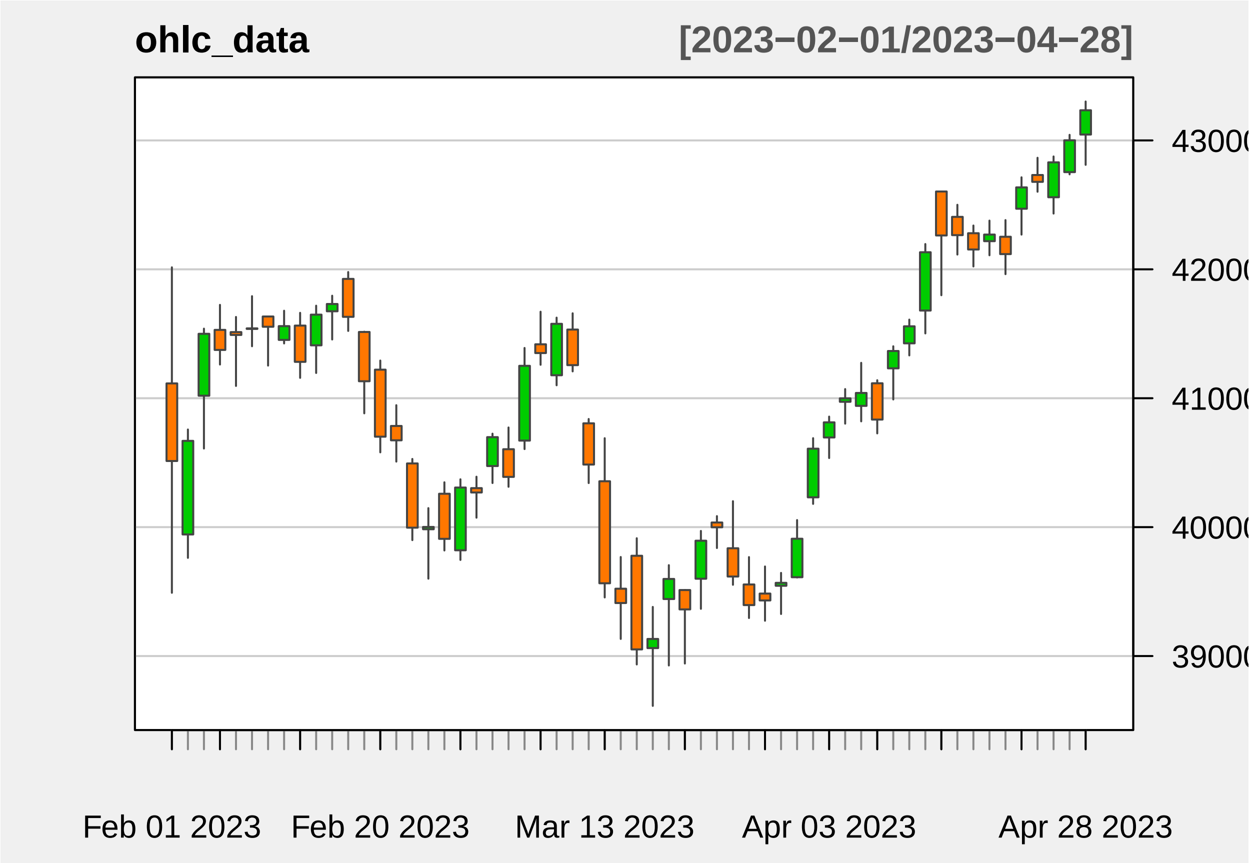
D12. Year 2022(Feb - Apr)

```
clean_data$Date <- as.Date(clean_data$Date)

# Filter data for the year 2020 and months April to June
clean_data_2020 <- clean_data[format(clean_data$Date, "%Y") == "2022" &
                              format(clean_data$Date, "%m") %in% c("02", "03", "04"), ]

# Ensure columns are named correctly for quantmod
ohlc_data <- xts(
  x = clean_data_2020[, c("Open", "High", "Low", "Close")],
  order.by = clean_data_2020$Date
)

# Rename columns to standard OHLC names (Open, High, Low, Close)
colnames(ohlc_data) <- c("Open", "High", "Low", "Close")

# Plot the candlestick chart
candleChart(ohlc_data, theme = "white", TA = NULL)
```



D13. Year 2023(Feb - Apr)

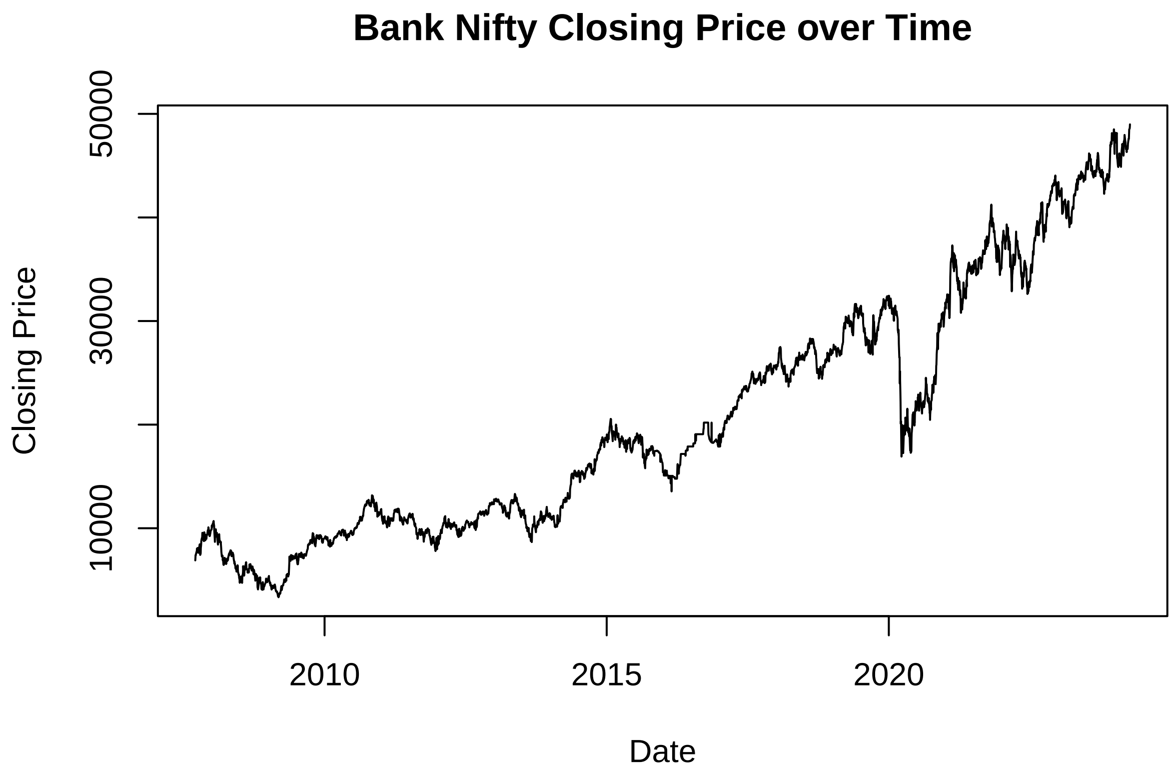
```
clean_data$Date <- as.Date(clean_data$Date)

# Filter data for the year 2023 and months April to June
clean_data_2023 <- clean_data[format(clean_data$Date, "%Y") == "2023" &
                              format(clean_data$Date, "%m") %in% c("02", "03", "04"), ]

# Ensure columns are named correctly for quantmod
ohlc_data <- xts(
  x = clean_data_2023[, c("Open", "High", "Low", "Close")],
  order.by = clean_data_2023$Date
)

# Rename columns to standard OHLC names (Open, High, Low, Close)
colnames(ohlc_data) <- c("Open", "High", "Low", "Close")

# Plot the candlestick chart
candleChart(ohlc_data, theme = "white", TA = NULL)
```



Modeling

M1. ARIMA

```
data <- read.csv("C://Users//chinn//Downloads//clean_data.csv")
data$Date <- as.Date(data$Date)

# Plot the time series data
plot(data$Date, data$Close, type='l', xlab='Date', ylab='Closing Price',
     main='Bank Nifty Closing Price over Time')
```




```r
# Check for stationarity using the Augmented Dickey-Fuller test
# If the p-value is greater than 0.05, the series is non-stationary and needs differencing
# Plot ACF and PACF to determine ARIMA parameters
```

```r
adf_test_result <- adf.test(clean_data$Close)
print(adf_test_result)
```

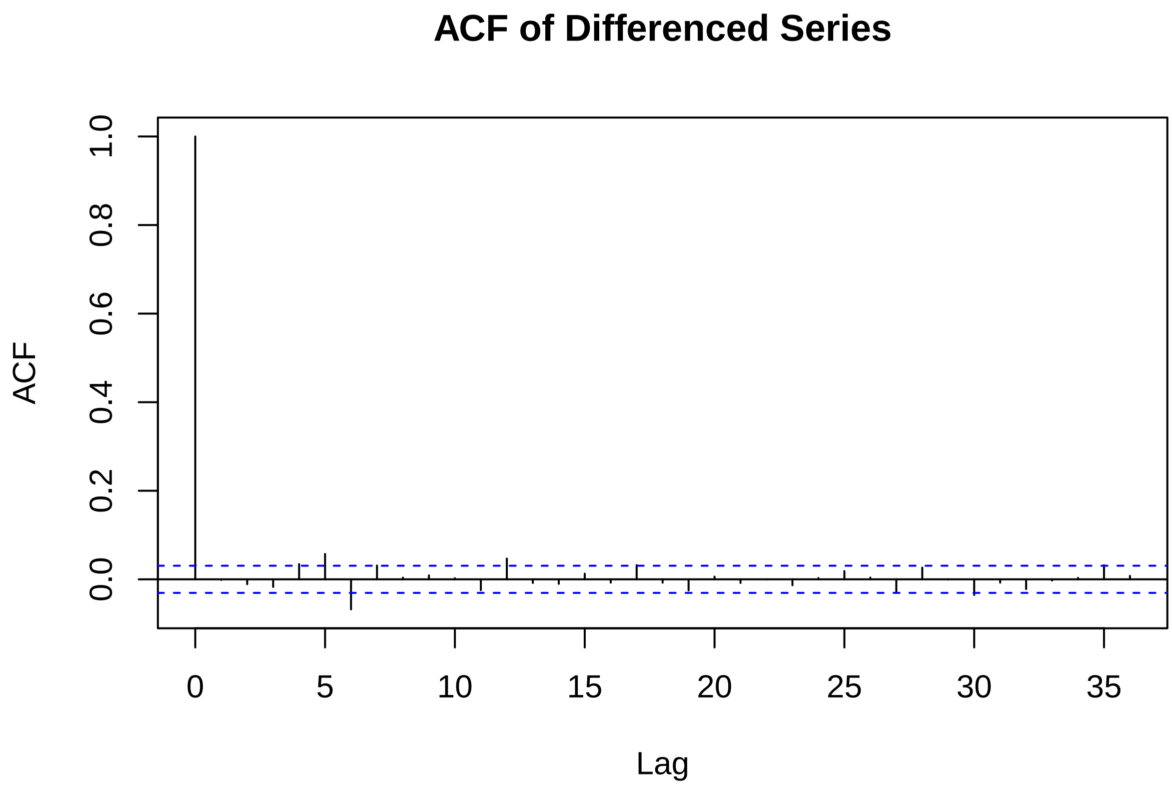
```
##
##  Augmented Dickey-Fuller Test
##
## data:  clean_data$Close
## Dickey-Fuller = -2.7608, Lag order = 15, p-value = 0.2562
## alternative hypothesis: stationary
```

```r
# If the p-value is greater than 0.05, the series is non-stationary and needs differencing
if (adf_test_result$p.value > 0.05) {
  data_diff <- diff(data$Close)
  adf_test_diff_result <- adf.test(data_diff)
  print(adf_test_diff_result)
} else {
  data_diff <- data$Close
}
```

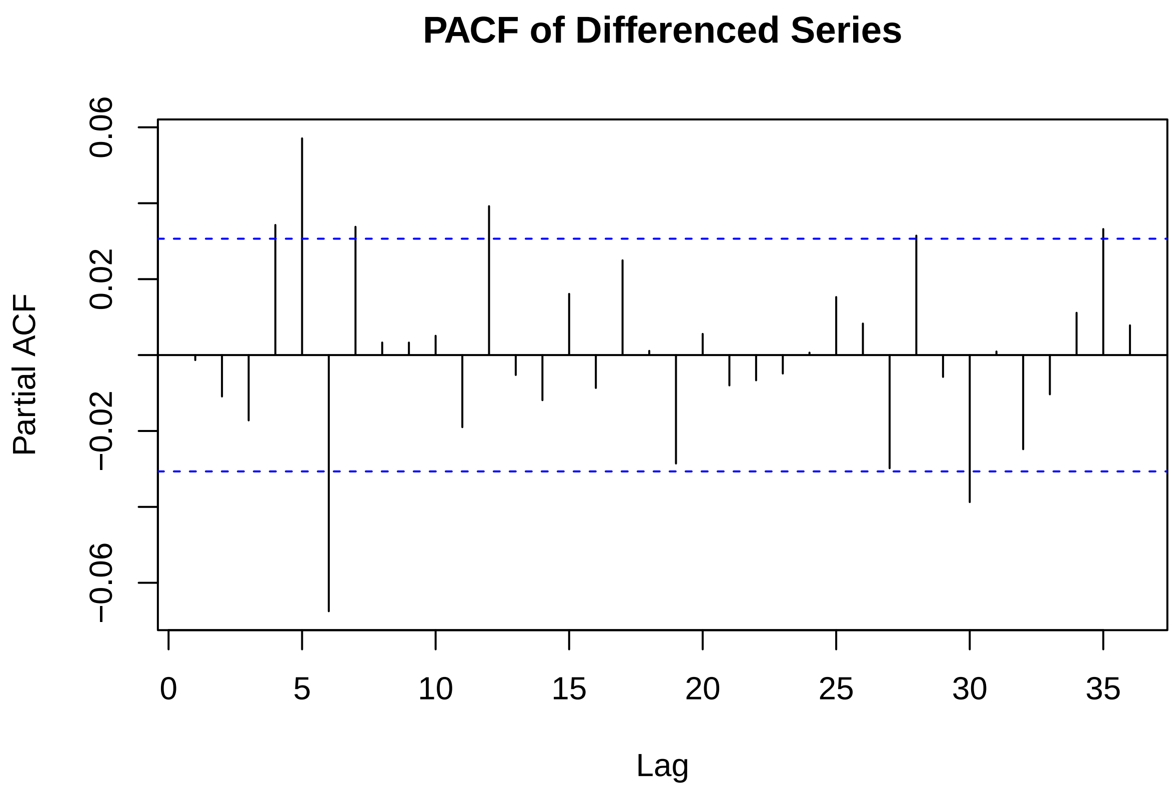
```
##
```

```
##  Augmented Dickey-Fuller Test
##
## data:  data_diff
## Dickey-Fuller = -15.495, Lag order = 15, p-value = 0.01
## alternative hypothesis: stationary
```

```r
# Plot ACF and PACF to determine ARIMA parameters
acf(data_diff, main='ACF of Differenced Series')
```




```r
pacf(data_diff, main='PACF of Differenced Series')
```

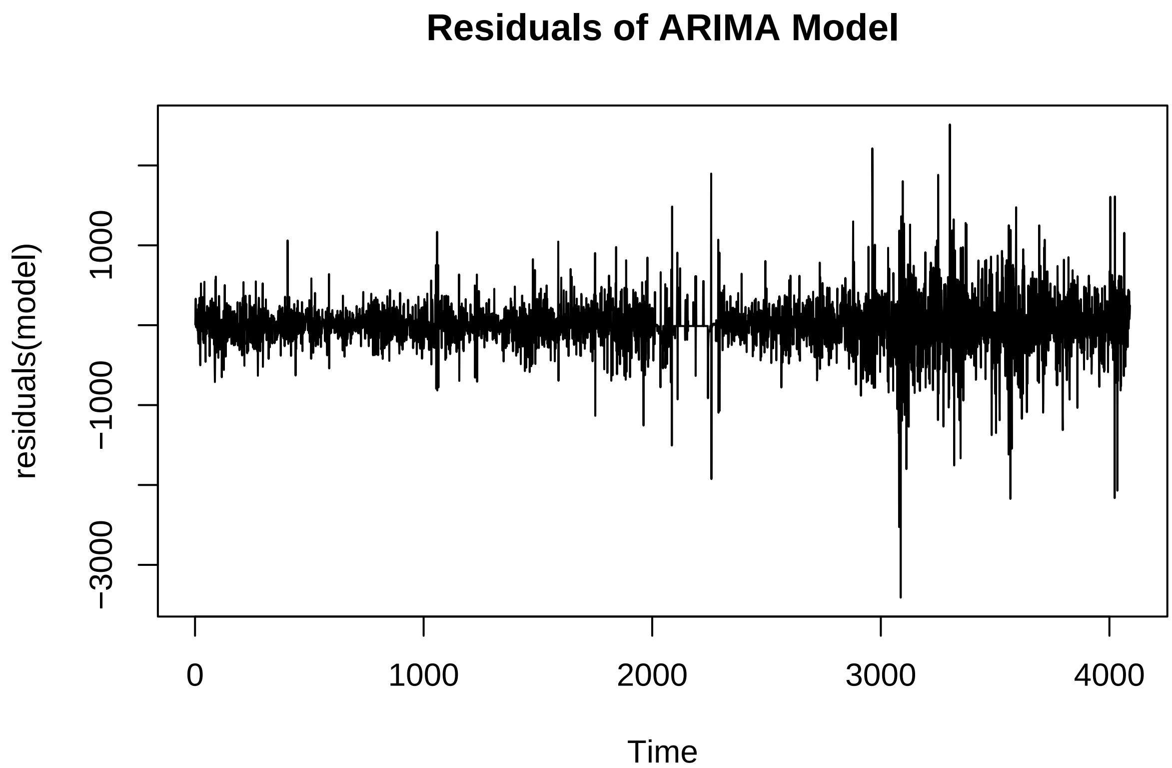



```r
model <- auto.arima(data$Close, seasonal = FALSE)
```

```r
print(summary(model))
```

```
## Series: data$Close
## ARIMA(0,1,0) with drift
##
## Coefficients:
##         drift
##       10.2933
## s.e.   5.1242
##
## sigma^2 = 107394:  log likelihood = -29485.56
## AIC=58975.13   AICc=58975.13   BIC=58987.76
##
## Training set error measures:
##                       ME     RMSE      MAE         MPE     MAPE    MASE
## Training set 0.001683815 327.6305 211.9983 -0.04297945 1.250734 1.00044
##                     ACF1
## Training set -0.00131814
```

```r
plot(residuals(model),main='Residuals of ARIMA Model')
```




```
forecast_result <- forecast::forecast(model, h=5)
print(forecast_result)
```

```
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 4091       48996.89 48576.92 49416.87 48354.59 49639.20
## 4092       49007.19 48413.25 49601.13 48098.84 49915.54
## 4093       49017.48 48290.06 49744.90 47904.98 50129.98
## 4094       49027.77 48187.82 49867.73 47743.17 50312.38
## 4095       49038.07 48098.97 49977.17 47601.84 50474.30
```

```
# Print forecasted values
cat("Forecasted closing prices for the next 5 days:\n")
```

```
## Forecasted closing prices for the next 5 days:
```

```
print(forecast_result$mean)
```

```
## Time Series:
## Start = 4091
## End = 4095
## Frequency = 1
## [1] 48996.89 49007.19 49017.48 49027.77 49038.07
```

Model Evaluation

```r
actual_values <- c(47773, 47484, 47069,47574,47924)  # Replace with actual values

# Predicted values
predicted_values <- as.numeric(forecast_result$mean)

# Calculate evaluation metrics
mae <- mean(abs(actual_values - predicted_values))
mse <- mean((actual_values - predicted_values)^2)
rmse <- sqrt(mse)
mape <- mean(abs((actual_values - predicted_values) / actual_values)) * 100

# Print evaluation metrics
cat("Mean Absolute Error (MAE): ", mae, "\n")
```

```
## Mean Absolute Error (MAE):  1452.682
```

```r
cat("Mean Squared Error (MSE): ", mse, "\n")
```

```
## Mean Squared Error (MSE):  2193842
```

```r
cat("Root Mean Squared Error (RMSE): ", rmse, "\n")
```

```
## Root Mean Squared Error (RMSE):  1481.162
```

```r
cat("Mean Absolute Percentage Error (MAPE): ", mape, "\n")
```

```
## Mean Absolute Percentage Error (MAPE):  3.057958
```

M2. LSTM

Long Short-Term Memory Networks is a deep learning, sequential neural network that allows information to persist. It is a special type of Recurrent Neural Network which is capable of handling the vanishing gradient problem faced by RNN. The shortcoming of RNN is they cannot remember long-term dependencies due to vanishing gradient. LSTMs are explicitly designed to avoid long-term dependency problems.The LSTM network architecture consists of three parts, Input gate, Forget gate and output gate

```r
#data <- read.csv()
#data$Date <- as.Date(data$Date)
# Data preprocessing
# Normalize the data
#min_value <- min(data$Close)
#max_value <- max(data$Close)
#scaled_data <- (data$Close - min_value) / (max_value - min_value)

# Define a function to create sequences of data for LSTM
#create_sequences <- function(data, time_steps) {
#sequences <- matrix(NA, nrow = length(data) - time_steps + 1, ncol = time_steps)
```

```
# for (i in 1:(length(data) - time_steps + 1)) {
#     sequences[i, ] <- data[i:(i + time_steps - 1)]  # Adjust the indices to include the current time s
#  }
#   #return(sequences)
# }
#
# # Define time steps
# #time_steps <- 5
#
# # Create sequences of data for LSTM
# #sequences <- create_sequences(scaled_data, time_steps)
#
# # Split data into training and testing sets
# train_size <- floor(0.8 * nrow(sequences))
# train_data <- sequences[1:train_size, ]
# test_data <- sequences[(train_size + 1):nrow(sequences), ]
#
# # Prepare input and output variables
# x_train <- train_data[, -time_steps, drop = FALSE]
# y_train <- train_data[, time_steps, drop = FALSE]
# x_test <- test_data[, -time_steps, drop = FALSE]
# y_test <- test_data[, time_steps, drop = FALSE]
#
# # Reshape input data for LSTM
# dim(x_train) <- c(dim(x_train), 1)
# dim(x_test) <- c(dim(x_test), 1)
#
# # Build the LSTM model
# model <- keras_model_sequential()
# model %>%
#   layer_lstm(units = 50, input_shape = c(time_steps - 1, 1)) %>%  # Change the input shape to match th
#   layer_dense(units = 1)
# # Compile the model
# model %>% compile(
#   optimizer = 'adam',
#   loss = 'mean_squared_error'
# )
#  Train the model
# history <- model %>% fit(
#   x_train, y_train,
#   epochs = 100,
#   batch_size = 32,
#   validation_split = 0.1
# )
#
# # Plot training history
# plot(history)
#Evaluate the model

# evaluation <- model %>% evaluate(x_test, y_test)
# print(evaluation)
# Make predictions
# predictions <- model %>% predict(x_test)
```

```
# print(predictions)
# Denormalize predictions
# denormalized_predictions <- predictions * (max_value - min_value) + min_value
# print(denormalized_predictions)
# length(denormalized_predictions)
# plot(clean_data$Date[1:818], denormalized_predictions, type = 'l', col = 'blue',
#      xlab = 'Date', ylab = 'Closing Price', main = 'Bank Nifty Closing Price Predicted Values')
# plot(clean_data$Date[1:818],clean_data$Close[1:818] , col = 'red', type='l',
#      xlab = 'Date', ylab = 'Closing Price', main = 'Bank Nifty Closing Price Actual Values')
# legend('topright', legend = c('Predicted', 'Actual'), col = c('blue', 'red'), lty = 1)
#  Get the last sequence from the test data
# last_sequence <- x_test[nrow(x_test), , , drop = FALSE]
#
# # Initialize an empty vector to store the predictions
# future_predictions <- numeric(5)
#
# # Iteratively predict the next 5 days
# for (i in 1:5) {
#   # Predict the next value
#   next_value <- model %>% predict(last_sequence)
#
#   # Store the predicted value
#   future_predictions[i] <- next_value
#
#   # Update the sequence: remove the first value and append the predicted value
#   last_sequence <- array(c(last_sequence[1, 2:(time_steps - 1), 1], next_value), dim = c(1, time_step
# }
#
# # Denormalize the predicted values
# denormalized_future_predictions <- future_predictions * (max_value - min_value) + min_value
#
# # Print the forecasted values
# cat("Forecasted closing prices for the next 5 days:\n", denormalized_future_predictions, "\n")
# actual_values <- c(47773, 47484, 47069,47574,47924)  # Replace with actual values
#
# # Predicted values
# predicted_values <- as.numeric(denormalized_future_predictions)
#
# # Calculate evaluation metrics
# mae <- mean(abs(actual_values - predicted_values))
# mse <- mean((actual_values - predicted_values)^2)
# rmse <- sqrt(mse)
# mape <- mean(abs((actual_values - predicted_values) / actual_values)) * 100
#
# # Print evaluation metrics
# cat("Mean Absolute Error (MAE): ", mae, "\n")
# cat("Mean Squared Error (MSE): ", mse, "\n")
# cat("Root Mean Squared Error (RMSE): ", rmse, "\n")
# cat("Mean Absolute Percentage Error (MAPE): ", mape, "\n")
```

Model Evaluation

Mean Absolute Error (MAE): 1691.7

Mean Squared Error (MSE): 2978181

Root Mean Squared Error (RMSE): 1725.741

Mean Absolute Percentage Error (MAPE): 3.559951