project2

2024-03-19

```
# Install and load the quantmod package
library(quantmod)
## Loading required package: xts
## Loading required package: zoo
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
       as.Date, as.Date.numeric
##
## Loading required package: TTR
## Registered S3 method overwritten by 'quantmod':
##
     method
     as.zoo.data.frame zoo
# Specify the stock symbol and the time period
stock_symbol <- "NERV"</pre>
start_date <- "2023-12-12"
end_date <- "2024-03-12"
# Fetch the stock data
NERV_cp_trend <- getSymbols(stock_symbol, from = start_date, to = end_date)</pre>
# Plot the closing price trend
chartSeries(NERV, type = "line", theme = "white", name = "Closing Price Trend")
```



```
# Read the CSV file
NERV <- read.csv("Minerva_Stockinfo.csv")</pre>
```

Data Cleaning

```
NERV$Date <- as.Date(NERV$Date, format = "%m/%d/%y")
# Sort the data by the date column
NERV <- NERV[order(NERV$Date), ]</pre>
NERV <- na.omit(NERV)
```

Training

```
train_NERV <- subset(NERV, Date >= as.Date("2023-12-12") & Date <= as.Date("2024-02-12"))
test_NERV <- subset(NERV, !(Date >= as.Date("2023-12-12") & Date <= as.Date("2024-02-12")))
closing_prices <- xts(NERV$Close, order.by = NERV$Date)
library(tseries)

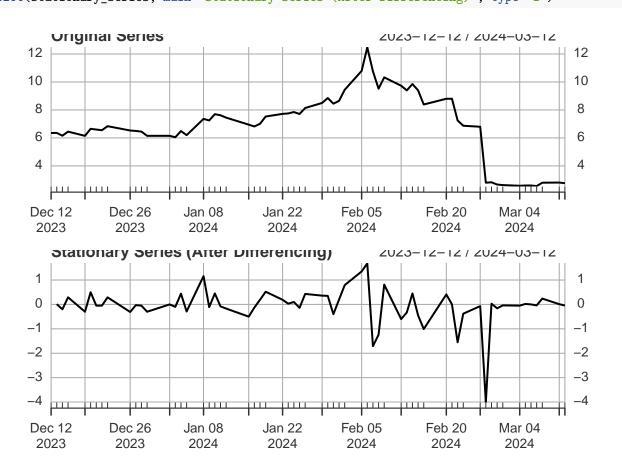
# Perform the Augmented Dickey-Fuller test
adf_result <- adf.test(closing_prices)</pre>
```

```
##
## Augmented Dickey-Fuller Test
##
## data: closing_prices
## Dickey-Fuller = -1.2546, Lag order = 3, p-value = 0.8765
## alternative hypothesis: stationary

stationary_series <- diff(closing_prices)

# Plot the original and differenced series
par(mfrow=c(2,1))
plot(closing_prices, main="Original Series", type='1')
plot(stationary_series, main="Stationary Series (After Differencing)", type='1')</pre>
```

Print the test results



```
stationary_series <- na.omit(stationary_series)

adf_result_diff <- adf.test(stationary_series)

# Print the test results
print(adf_result_diff)</pre>
```

```
##
## Augmented Dickey-Fuller Test
##
## data: stationary_series
## Dickey-Fuller = -3.438, Lag order = 3, p-value = 0.05823
## alternative hypothesis: stationary
CP_train<- xts(train_NERV$Close, order.by = train_NERV$Date)</pre>
CP_test <- xts(test_NERV$Close, order.by = test_NERV$Date)</pre>
library(forecast)
start_date <- as.Date(start_date)</pre>
time_series <- ts(data = CP_train, start = start_date, frequency = 1)</pre>
# Identify the best ARIMA model using auto.arima
arima_model <- auto.arima(time_series)</pre>
# Print the identified ARIMA model
print(arima_model)
## Series: time_series
## ARIMA(0,1,0)
## sigma^2 = 0.3573: log likelihood = -37.08
## AIC=76.16 AICc=76.26 BIC=77.87
arima_model_1 <- arima(CP_train, order = c(0,1,0))</pre>
arima_model_2 <- arima(CP_train, order = c(2,1,2))</pre>
summary(arima_model_1)
##
## Call:
## arima(x = CP_train, order = c(0, 1, 0))
##
## sigma^2 estimated as 0.3573: log likelihood = -37.08, aic = 76.16
## Training set error measures:
                                 RMSE
                                            MAE
                                                      MPE
                                                              MAPE
                                                                        MASE
                        ME
## Training set 0.08062738 0.5905978 0.4025321 0.814106 4.738915 0.9765573
## Training set 0.009387741
summary(arima_model_2)
##
## arima(x = CP_train, order = c(2, 1, 2))
## Coefficients:
##
            ar1
                     ar2
                               ma1
        0.7893 -0.4007 -0.7892 0.2398
##
```

```
## s.e. 0.8424
                  0.6920
                           0.9015 0.7741
##
## sigma^2 estimated as 0.3406: log likelihood = -36.16, aic = 82.31
##
## Training set error measures:
##
                       ME
                               RMSE
                                          MAE
                                                    MPE
                                                            MAPE
                                                                      MASE
## Training set 0.1165558 0.5766574 0.3995788 1.202237 4.721362 0.9693924
##
                      ACF1
## Training set -0.0501159
forecast_length <- nrow(test_NERV) # Number of rows to forecast</pre>
forecasted_values <- forecast(arima_model, h = forecast_length+50)</pre>
# Plot the forecast with historical data
plot(forecasted_values)
# Overlay the actual data points on the forecast plot
lines(test_NERV$Date, test_NERV$Close, col = 'red')
```

Forecasts from ARIMA(0,1,0)

