ARIMA Time Series Forecasting - Python to R

Reproducible Research

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This project is a reproduction and hopefully an extension of ARIMA Time Series Forecasting - S&P 500 Stock by Yassine Sfaihi. The aim of the research is to verify whether the S&P 500 market price can be acurately forecasted using conventional time series analysis tools. In the extension of the project, the ARIMA model will be compared with a much more advanced machine learning technique - neural networks.

Introduction

Time series forecasting is a very attractive idea for researchers, especially in the context of forecasting financial asset prices. However, for centuries mathematicians and scholars who attempted such thing almost always have failed, leading many to believe that market returns are a white noise - a completely random time series.

Data

Metodology

We used the ggplot2 package to visually examine the stationarity of the time series. We plotted the prices and returns of sp500 and based on our visual analysis, we concluded that the price time series is non-stationary.

```
df <- na.omit(df)
df$Date <- as.Date(df$Date)

p1 <- ggplot(df, aes(x = Date)) +
  geom_line(aes(y = GSPC.Open, color = "Price"), size = 1) +
```

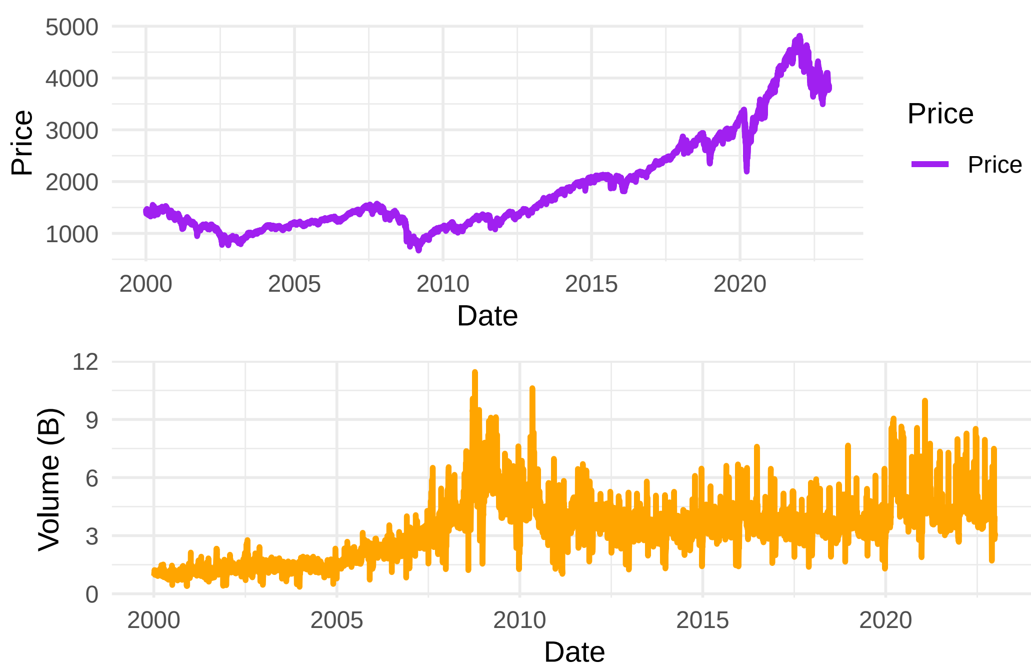
```r
  geom_line(aes(y = GSPC.High, color = "Price"), size = 1) +
  geom_line(aes(y = GSPC.Low, color = "Price"), size = 1) +
  geom_line(aes(y = GSPC.Close, color = "Price"), size = 1) +
  labs(x = "Date", y = "Price", color = "Price") +
  scale_color_manual(values = c("Price" = "purple")) +
  theme_minimal()
```

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

```r
p2 <- ggplot(df, aes(x = Date)) +
  geom_line(aes(y = GSPC.Volume/1e9), color = "orange", size = 1) +
  labs(y = "Volume (B)") +
  theme_minimal()


combined_plot <- plot_grid(p1, p2, nrow = 2, align = "v", axis = "l")

print(combined_plot)
```



Now we used the ggplot2 package to visually examine the stationarity of the returns of SP500. In addition, we also conducted an Augmented Dickey-Fuller (ADF) test to confirm the aforementioned observations. The ADF test provided further evidence supporting our conclusions, indicating that the price time series is indeed non-stationary, while the returns time series is stationary.

```
timeseries <- df$GSPC.Close

adf_result <- adf.test(timeseries)

cat("ADF Statistic:", adf_result$statistic, "\n")
```

ADF Statistic: -1.988393

```
cat("p-value:", adf_result$p.value, "\n")
```

p-value: 0.5832667

```
#Calc of returns

closing_prices <- df$GSPC.Close

returns <- diff(closing_prices) / lag(closing_prices)
```

Warning in diff(closing_prices)/lag(closing_prices): długość dłuszego obiektu
nie jest wielokrotnością długości krótszego obiektu

```
adf_result <- adf.test(returns, alternative = "stationary")
```

Warning in adf.test(returns, alternative = "stationary"): p-value smaller than
printed p-value

```
cat("ADF Statistic:", adf_result$statistic, "\n")
```

ADF Statistic: -18.47379

```
cat("p-value:", adf_result$p.value, "\n")
```

p-value: 0.01

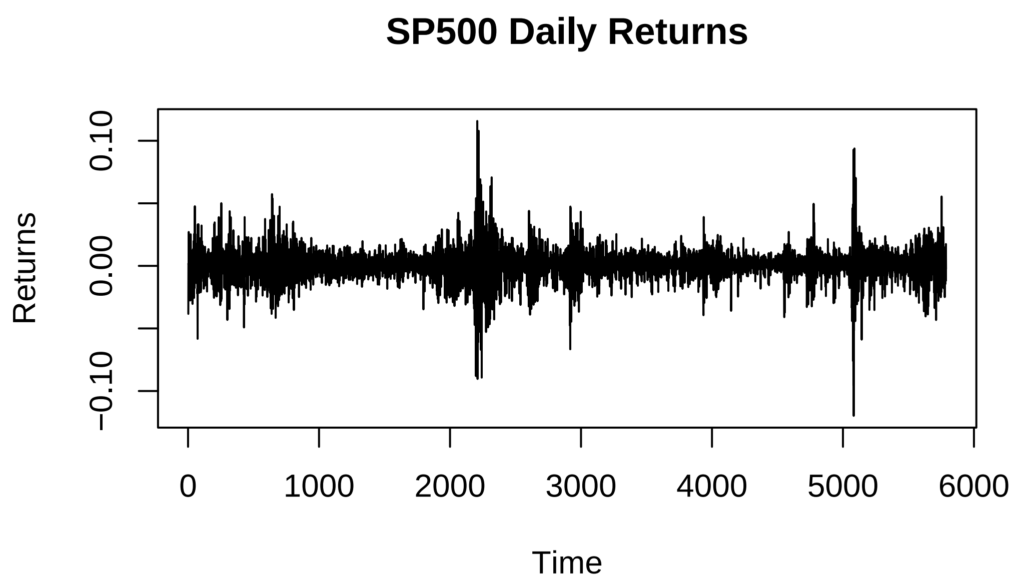
```
time_index <- time(closing_prices)[-1]

# Remove missing values from time_index and returns
complete_data <- !is.na(time_index) & !is.na(returns)
```

Warning in !is.na(time_index) & !is.na(returns): długość dłuszego obiektu nie
jest wielokrotnością długości krótszego obiektu

```
time_index <- time_index[complete_data]
returns <- returns[complete_data]

plot(time_index, returns, type = "l", xlab = "Time", ylab = "Returns", main = "SP500 Daily Returns")
```



The code below conducts a grid search to find the optimal values of p, d, and q for an ARIMA model by evaluating the AIC values for different combinations. The combination with the lowest AIC value is considered to be the best set of parameters for the model.

```
dfret <- data.frame(Date = as.Date(time_index), Returns = returns)

# Convert the Date column to a proper date format
```

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

# Remove rows with NA, NaN, or Inf in the Date or Returns columns
dfret <- dfret[complete.cases(dfret$Date, dfret$Returns), ]

# Create the xts object
xts_obj <- xts(dfret$Returns, order.by = dfret$Date)

# Rename a column in an xts object
colnames(xts_obj)[1] <- "Return"

# Define the p, d, and q parameters to take any value between 0 and 2
p <- d <- q <- 0:2

# Generate all different combinations of p, d, and q triplets
pdq <- expand.grid(p = p, d = d, q = q)

# Perform a grid search to find the optimal set of parameters that yields the best performance
best_aic <- Inf
best_pdq <- c(NA, NA, NA)

for(i in 1:nrow(pdq)) {
  model <- arima(xts_obj, order = c(pdq[i, "p"], pdq[i, "d"], pdq[i, "q"]))
  if(AIC(model) < best_aic) {
    best_aic <- AIC(model)
    best_pdq <- pdq[i, ]
  }
}

cat("Best model AIC:", best_aic,"\n")
```

Best model AIC: -34345.04

Methodology

Code below splits the data into train and test sets, fits an ARIMA model to the training data, makes predictions on the test data using the model, and plots the actual values along with the predicted values for visualization and comparison.

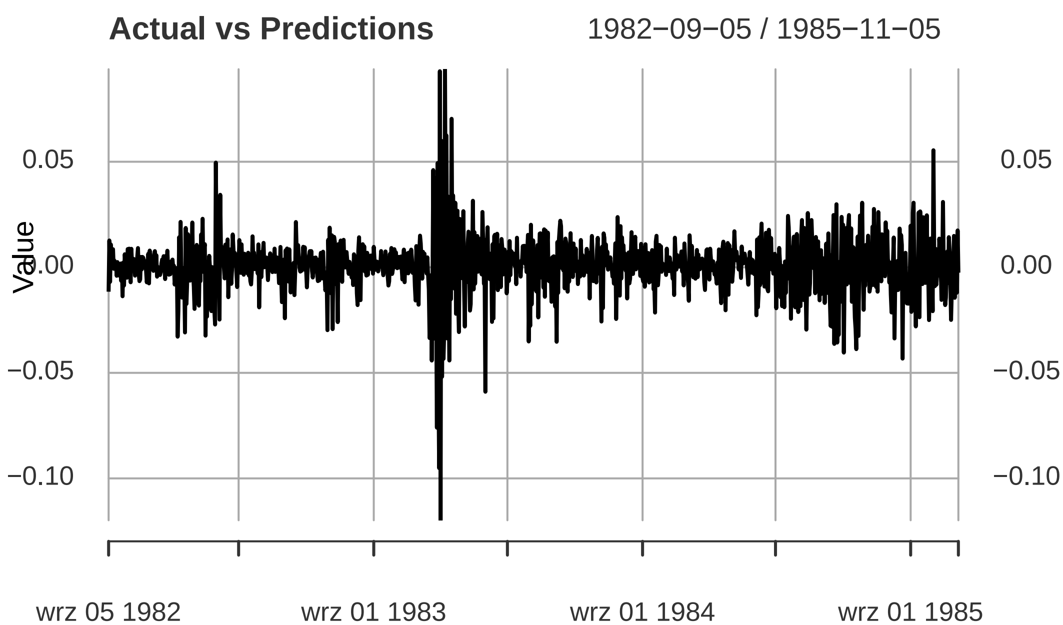
```r
# Split the data into train and test sets
train_data <- xts_obj[1:floor(length(xts_obj)*0.8)]
test_data <- xts_obj[(floor(length(xts_obj)*0.8) + 1):length(xts_obj)]

model <- arima(train_data, order = c(best_pdq[1, "p"], best_pdq[1, "d"], best_pdq[1, "q"]))

# Use the model to make predictions on the test data
predictions <- forecast(model, h = length(test_data))

# Create element for plot
dfactvspred <- data.frame(Date = index(test_data), Actual = coredata(test_data), predictions = as.numeric(predictions$

plot(test_data, main = "Actual vs Predictions", ylab = "Value")
lines(dfactvspred$predictions, col = "red")
legend("topleft", legend = c("Actual", "Predictions"), col = c("black", "red"), lty = 1)
```




```r
mse <- mean((as.numeric(predictions$mean) - as.numeric(test_data$Return))^2)
mae <- mean(abs(as.numeric(predictions$mean) - as.numeric(test_data$Return)))
rmse <- sqrt(mse)

cat("MSE: ", mse, "\n")
```

MSE: 0.0001954491

```
cat("MAE: ", mae, "\n")
```

MAE: 0.009055593

```
cat("RMSE: ", rmse)
```

RMSE: 0.01398031

Results

From the accuracy metrics above it can be observed that the best ARIMA model produced is somewhat accurate. The RMSE can be interpreted as an average daily error of 1.4%, which is not accurate enough for practical applications since the average daily return of the stock market is only around 0.04%.

Comparing ARIMA with an LSTM model

As noticed above, the ARIMA model is a good benchmark and an initial analysis tool, but it does not posses a lot of predictive power. A better alternative to the ARIMA model which is a simple machine learning model, would be the LSTM model which stands for Long Short-Term Memory and is a neural network that has shown effective in predicting time series like price data.

```
# Scale the data to values from 0 to 1
max_val <- max(df$GSPC.Adjusted)
min_val <- min(df$GSPC.Adjusted)
scaled_data <- (df$GSPC.Adjusted - min_val) / (max_val - min_val)
```

```
# Define function that will be used to generate input data sequences

data_sequence <- function(data, sl) {
  result_x = list()
  result_y = list()

  for(i in 1:(length(data)-sl)) {
    result_x[[i]] <- data[i:(i+sl-1)]
```

```
    result_y[[i]] <- data[(i+sl)]
  }

  x <- array_reshape(unlist(result_x), dim = c(length(result_x), sl, 1))
  y <- unlist(result_y)

  list("x" = x, "y" = y)
}
```

```
# Create data sequences
sequence_length <- 50

train_data <- data_sequence(scaled_data[1:round(length(scaled_data)*0.8)], sequence_length)
x_train <- train_data$x
y_train <- train_data$y

test_data <- data_sequence(scaled_data[(round(length(scaled_data)*0.8)+1):(length(scaled_data)-1)], sequence_lengt
x_test <- test_data$x
y_test <- test_data$y
```

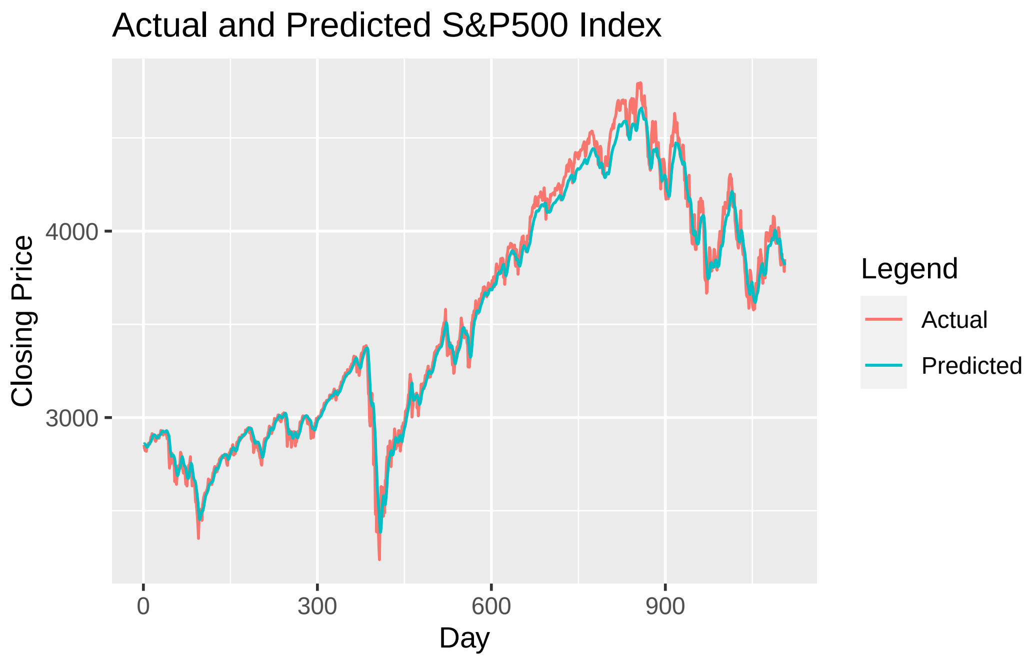
```
# Create LSTM model
model <- keras_model_sequential() %>%
  layer_lstm(units = 50, input_shape = c(sequence_length, 1), return_sequences = TRUE) %>%
  layer_dropout(rate = 0.2) %>%
  layer_lstm(units = 50, return_sequences = FALSE) %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 1)
```

```
# Compile the model
model %>% compile(
  optimizer = optimizer_adam(learning_rate = 0.001),
  loss = "mse"
)
```

Thus we have achieved a model with a MSE of 0.000555671 which is quite impressive. But let's evaluate the model's accuracy and test it's out-of-sample performance.

```
# Plot the true and predicted values
ggplot(results, aes(Day)) +
  geom_line(aes(y = Actual, colour = "Actual")) +
```

```
  geom_line(aes(y = Predicted, colour = "Predicted")) +
  labs(x = "Day", y = "Closing Price", colour = "Legend",
       title = "Actual and Predicted S&P500 Index")
```




```
# Calculate MSE and MAE
mse <- mean((results$Actual - results$Predicted)^2)
mae <- mean(abs(results$Actual - results$Predicted))
rmse <- sqrt(mse)

cat("MSE: ", mse, "\n")
```

MSE: 5423.11

```
cat("MAE: ", mae, "\n")
```

MAE: 55.11164

```
cat("RMSE: ", rmse)
```

RMSE: 73.64177

Results of the LSTM Model

The LSTM is definetely more able to capture volatility clusters in the movements of the prices as can be seen on the graph presenting its performance. The performance metrics such as the RMSE suggest that the average daily error in absolute terms is 97.12 index points which is also not very accurate since the average daily movement of the SP500 is in the range of 200 points either way. That is still better than the ARIMA model.

Conclusion

We explored the steps involved in time series forecasting using the Auto regressive Integrated Moving Average (ARIMA) model. We started with data visualization to gain insights into the time series data. Then, we conducted stationarity tests to determine the stationarity of the series.Than we performed parameter tuning by searching for the optimal values of p, d, and q using a grid search approach. We selected the best combination of parameters based on the AIC value, which measures the model's goodness of fit while penalizing complexity. After obtaining the best parameter values, we split the data into training and test sets and built an ARIMA model using the training data. We used the model to make predictions on the test data. Additionally, we calculated the root mean squared error (RMSE) to evaluate the performance of the model.

We were able to conclude that the ARIMA model was not very effective in predicting future prices, but the LSTM model proved to be more useful in predicting the price of the S&p500 index. With more polishing the LSTM model could have a real world application in a trading environment.

References

Sfaihi Y. (2023), ARIMA Time Series Forecasting - S&P 500 Stock