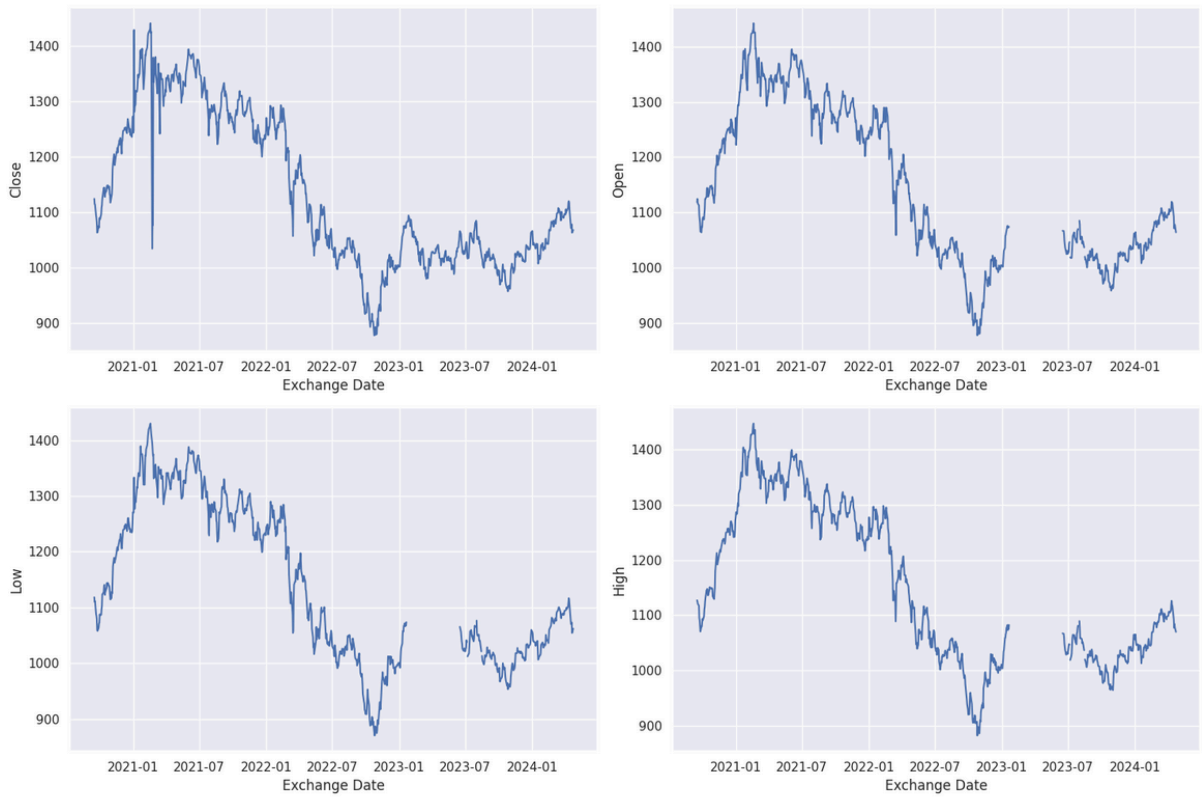
Discover the World of Quant
LSEG Challenge - ESGEM Index Price Prediction

Cretoiu Patricia-Elena, Mincu Adrian, Roșu Ana-Maria

Exploratory Data Analysis

Time series line plot for prices shows the close, open, low and high prices over time. We can see right away that there is a sudden drop in close price in 2021-02, but comparing the plots side by side, it is clear that the low value those days was actually higher, implying that there were some errors. We can also notice missing data in the 'Open', 'Low', and 'High' columns.

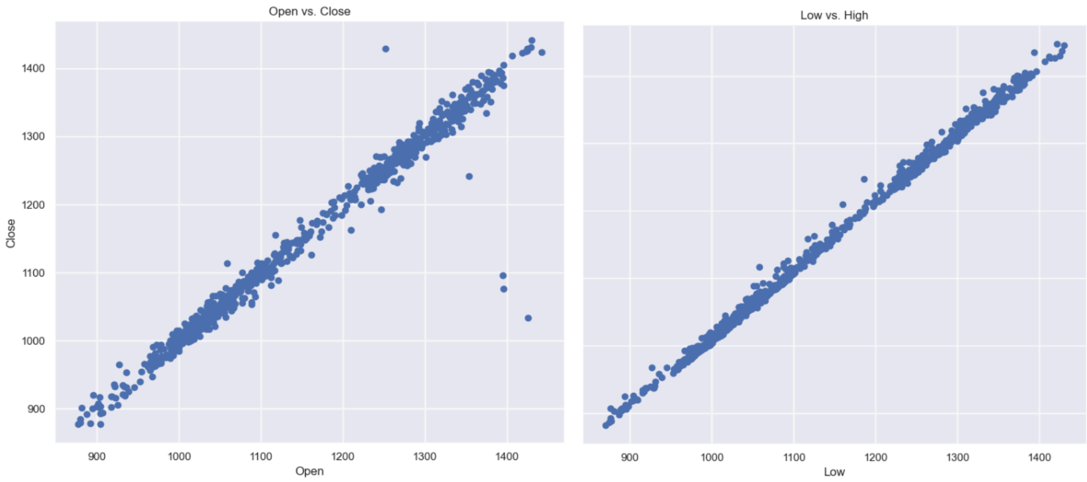


Open vs Close Price Scatter Plot

A look at the relationship between the 'Open' and 'Close' prices of the stock can give us an idea of how similar or different the prices are at the start and end of the day.We aim to understand if the prices are correlated or not, if the prices are similar or different at the start and end of the day, if the stock is volatile or not.

Low vs High Price Scatter Plot

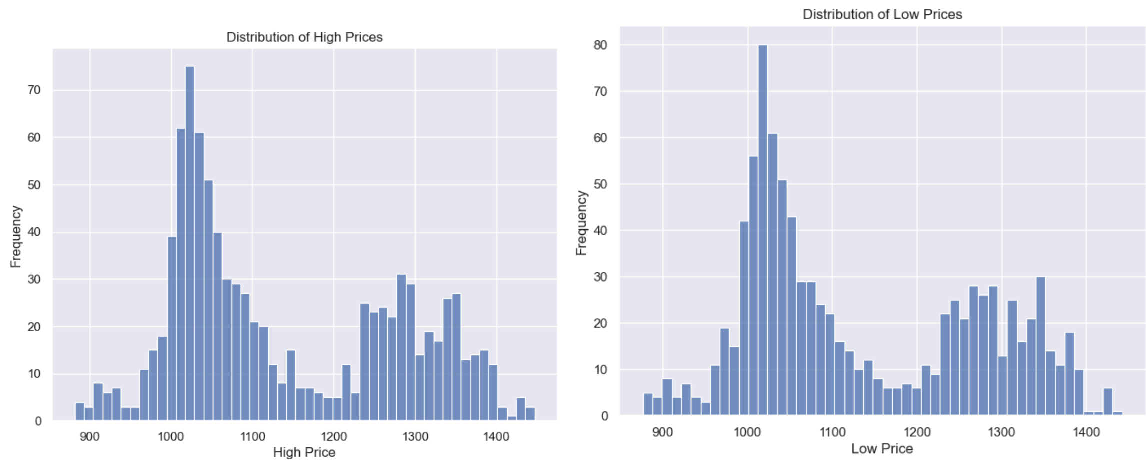
The relationship between the high and low prices of the stock gives us an idea of how similar or different the prices are at the highest and lowest points of the day to understand if the stock is volatile or not, if the prices tend to have big price swings or not.



Distribution of ‘Low’ and 'High' prices

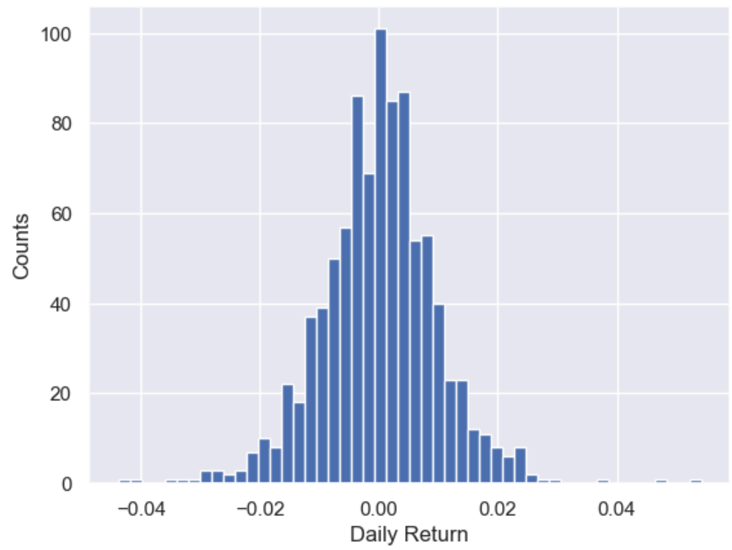
The **distribution of high** prices of the stock will give us an idea of the range of high prices that the stock has had over the time. We can identify if the stock has had any significant increase or decrease in high prices, which can indicate trends or volatility in the stock.

The **distribution of low** prices of the stock gives us an idea of the range of prices that the stock has reached at its lowest point, and how often it reaches those prices. This can give us an understanding of the volatility of the stock as well as if it tends to have big price swings or not.



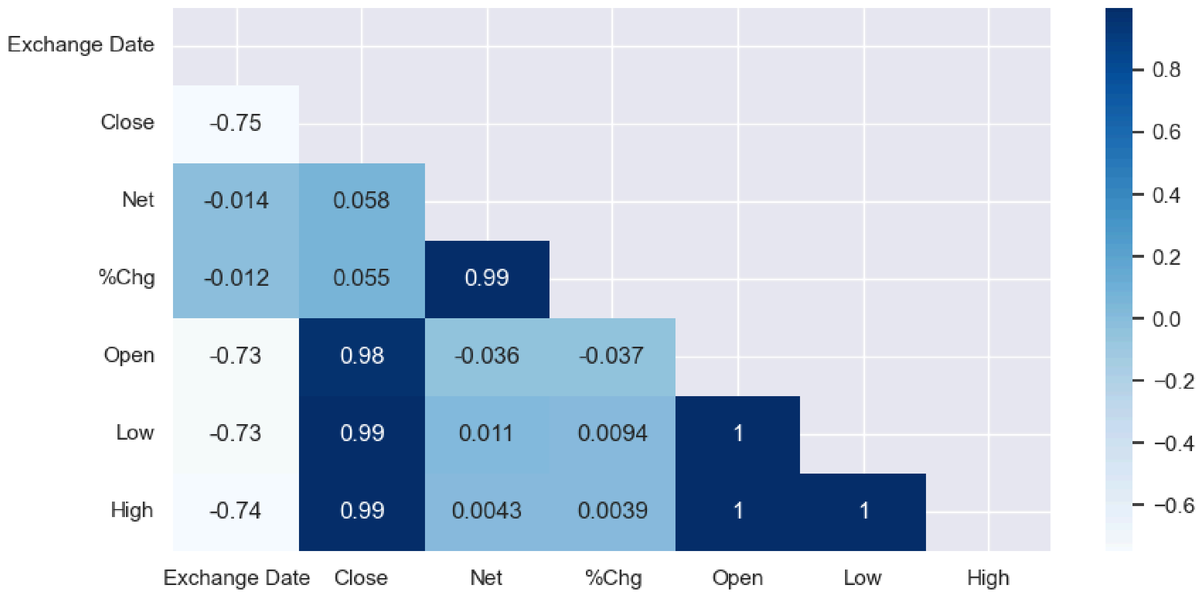
Distribution of returns

The distribution of daily returns provides valuable insights into the volatility and risk associated with the stock's performance over the analyzed period, the spread and shape of the distribution indicate the level of price fluctuation or volatility, we can observe almost a normal distribution, symmetric around its mean, implying that the probability of positive and negative returns is equal. This symmetry indicates a balanced distribution of gains and losses.



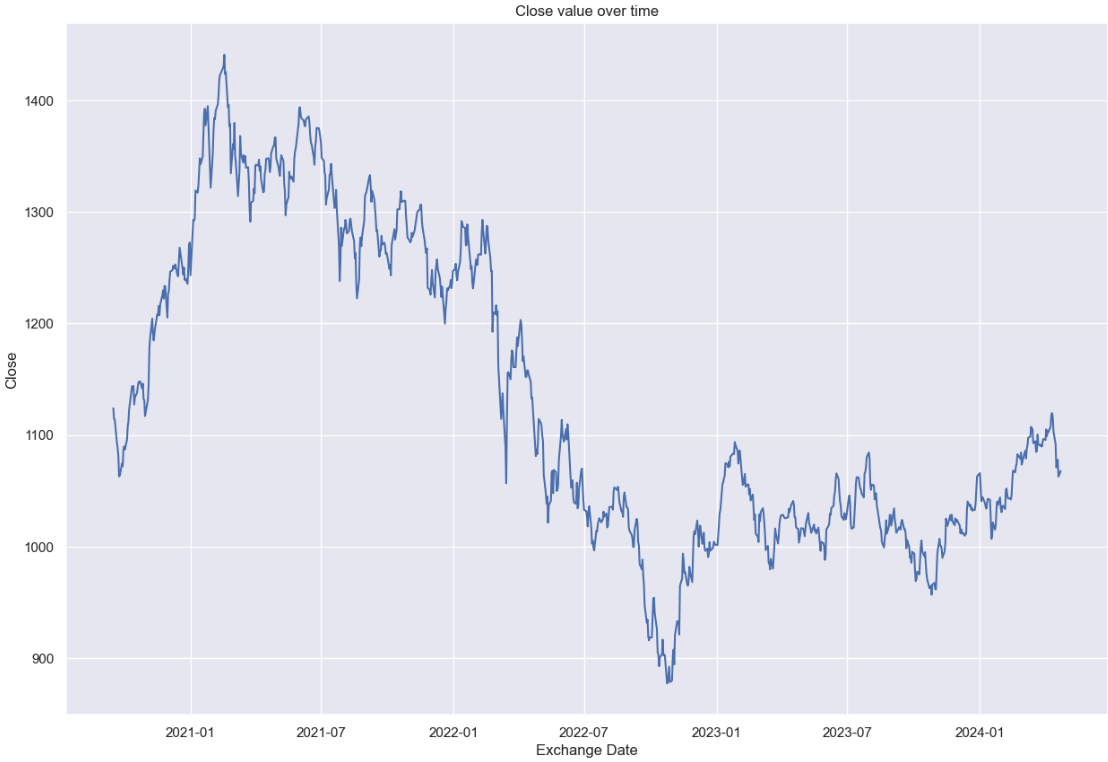
Correlation Heatmap

Shows correlation between different columns in the data. By visualizing the correlation, we can see which columns are highly correlated and which columns are not. This information can help us understand the relationship between different columns and how they affect each other.

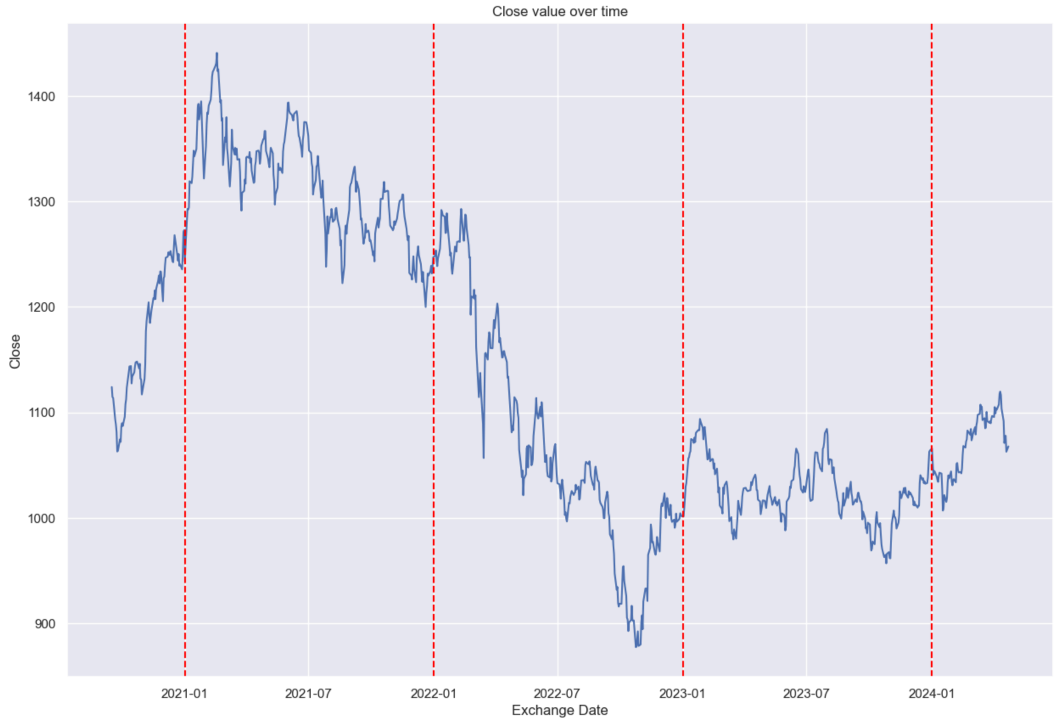


Trends and Seasonality

The original graph looks like this:

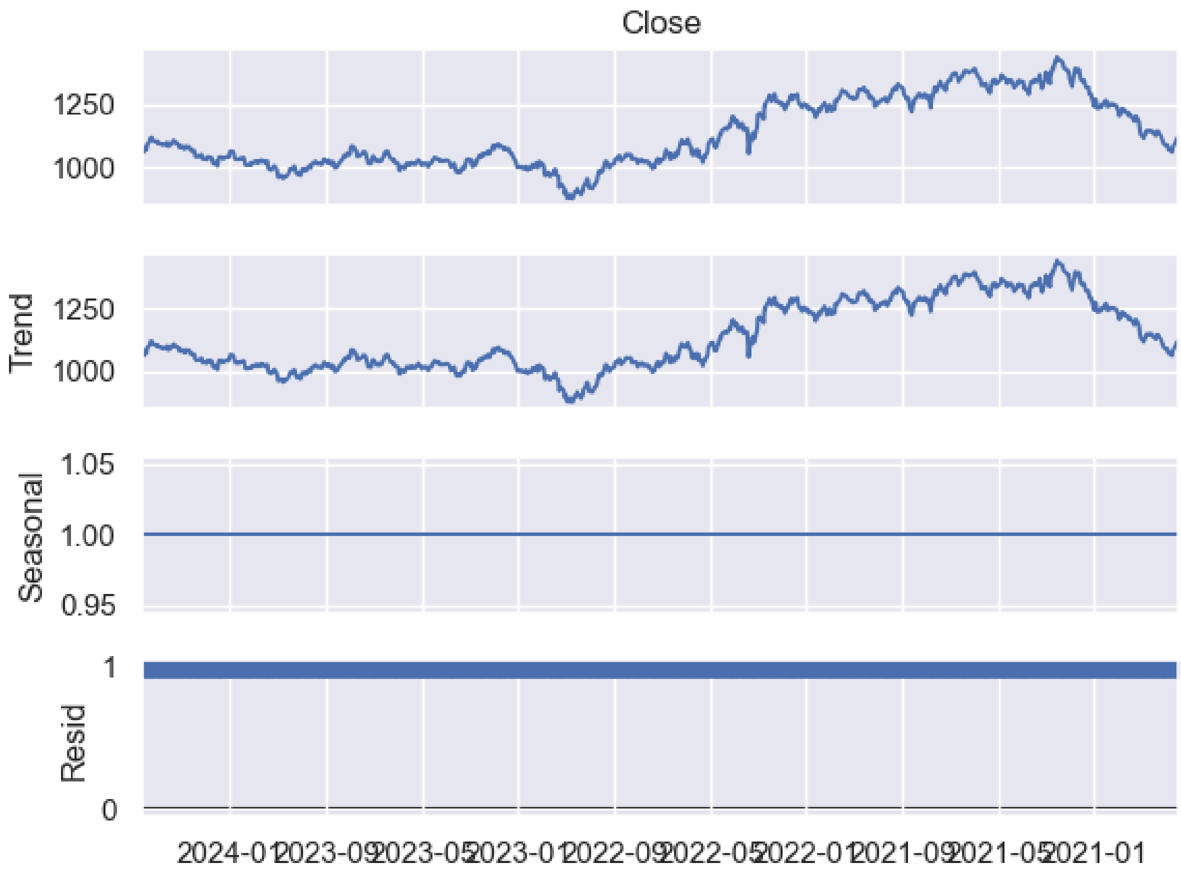


We can observe an increase in the first 6 months of 2021, a stable decline in the last 6 months and then a sudden drop in 2022 right until the beginning of 2023.
To better understand, here is the same graph but with some delimiters over the years:



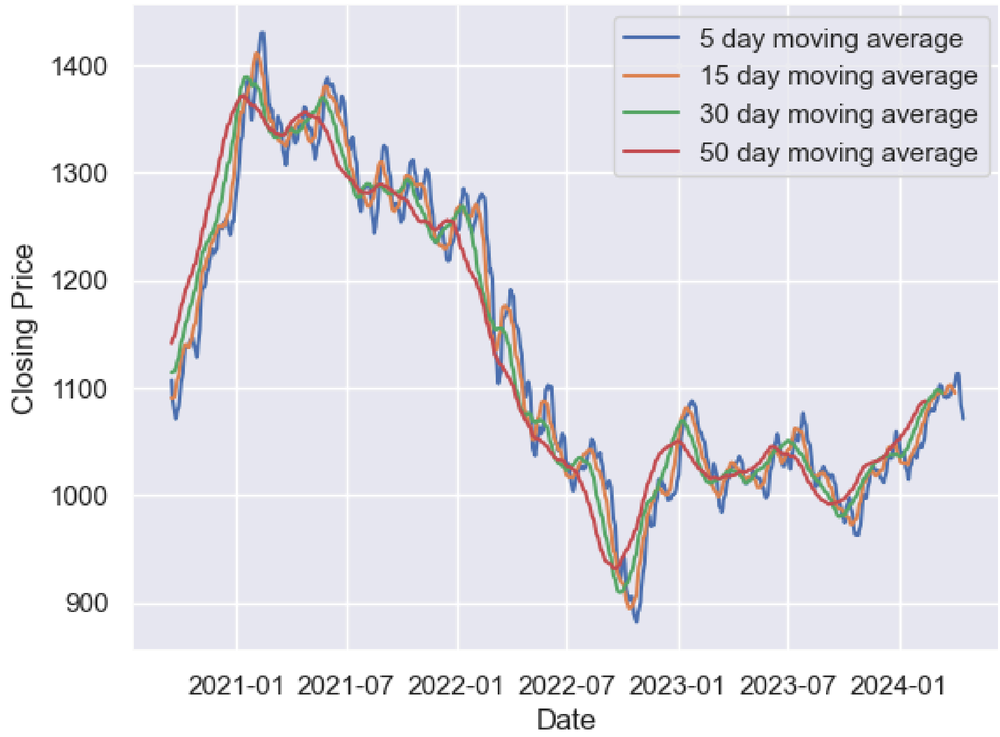
It is trivial that the information before 2023 would add a bias to our model, decreasing its performance. It is better to keep only the data from 2023 onwards.

Down below is a graph of our time series decomposition.



As for seasonal patterns, there is nothing to be observed here. The data is too small and over a span of 4 years.

In the trend pattern there can be observed a linear increase with smooth decrease. It would be better to use a mean to smooth out the graph to better see it. But a conclusion can also be drawn here. However, we cannot be fully certain, more data would be a better way to tell if it's a robust trend.



Moving averages can help identify trends in the data and can be used as a way to smooth out short-term fluctuations in the data. We can now better understand the trend behind this graphic. If we disregard all data before 2023 we can see that there is an increase, decrease, increase, decrease, much like a sinusoidal function addition with a linear ascending function.

Challenges regarding data

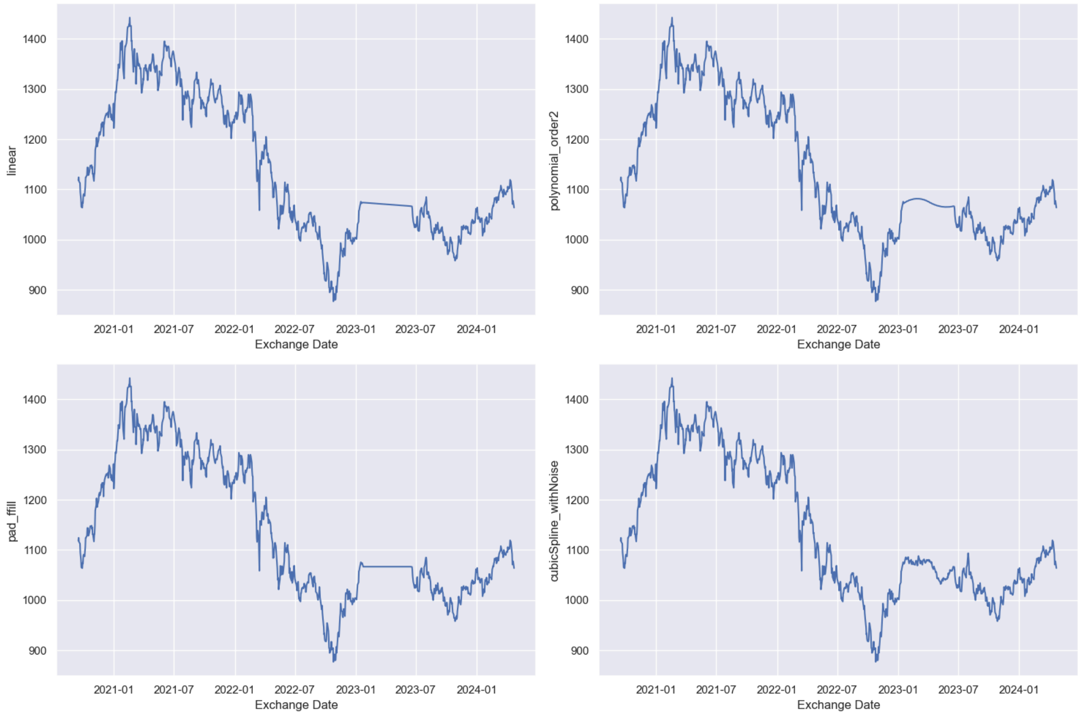
Missing Data

During our exploratory data analysis we observed the 'Open' column consists 107 continuous missing values. Not addressing these continuous missing values in the 'Open' column could significantly compromise the effectiveness of our models.

At first we wanted to take this data from an online source, like Google Finance, but unfortunately many sites or API's didn't have data up until last month. If we selected a period of time such as 1 year or 5 years, we could fetch only one datapoint per week, which was not enough since we need data every week day.

Our idea was to interpolate these missing values with different methods and keep the best one. We have tried linear interpolation, polynomial interpolation, pad interpolation and finally, the best method was a cublic spline with added noise to make the data seem more natural.

Below we can see the table with each method and the result of its interpolation.



Public Holiday

Since we have to deal with stock market data, it means that during the weekend or public holidays the market will be closed. We noticed that some days like 1 January are present in the dataset, with all the values, but we didn't know if we have to ignore them or if it's normal to have data on closed market as well.

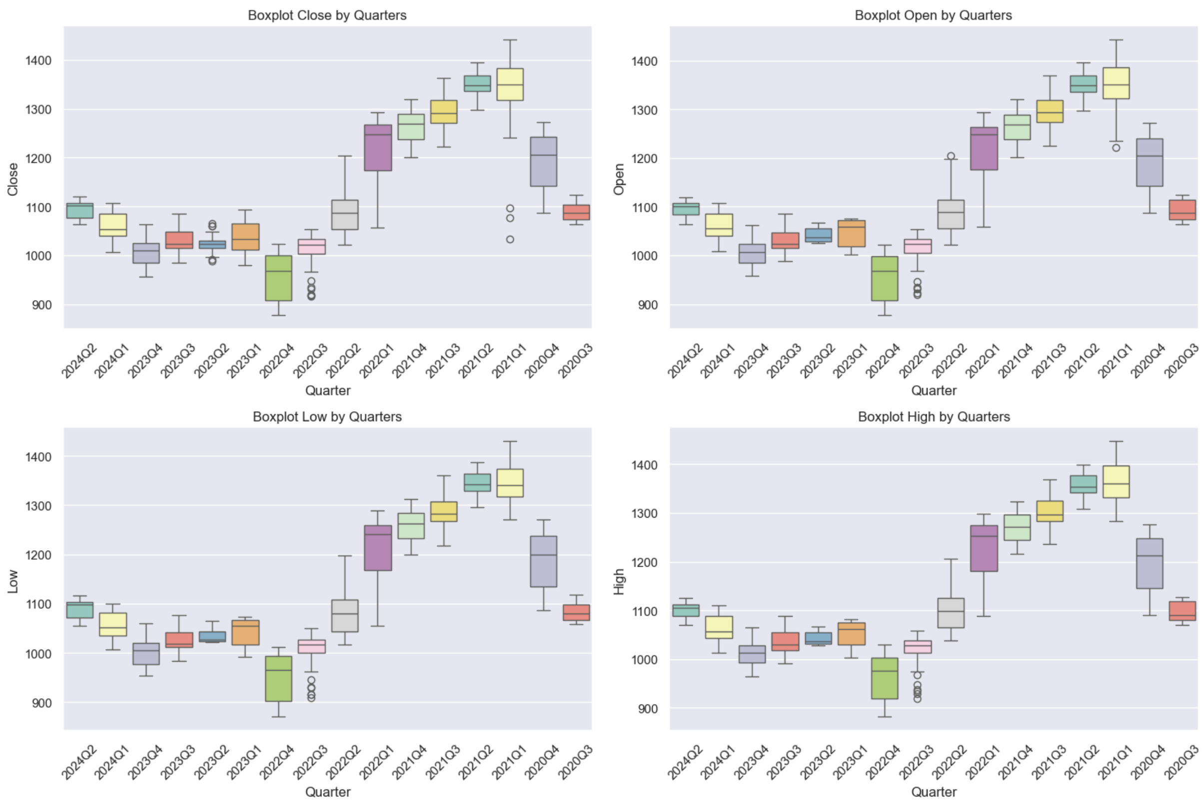
Another concern was that the public holidays differ between US and Europe, and we didn't know what market we should address. In the end, we decided to keep those days since they didn't represent any noise/outlier in our dataset.

Outliers

Outliers are data points that deviate significantly from the majority of the dataset and can have a substantial impact on machine learning models results so it's a critical step in data preprocessing.

We initiated our outlier detection process by first employing visualising techniques, starting with boxplots. Initially,we visualised the outliers for each column by year, but the results were inconclusive. We went further and plotted Close, Open, High, Low values by quarters which is more relevant to the changing trends of the stock market. This approach gave us an overview of the outlier distribution within our dataset.

To delve deeper, we explored four commonly used outlier detection techniques: Interquartile Range (IQR), Local Outlier Factor (LOF), Median Absolute Deviation (MAD) and Isolation Forest.



Data Cleaning

Since we saw during the EDA stage that there are values whose values don't match, it was needed to perform data cleaning.

Similar Rows

Another problem we have thought of is: "What if some rows have a lot of columns in common?". And so we decided to compute a difference matrix much like the one used in Hamming distance or Levenshtein distance.

A square matrix of size number_of_rows * number_of_rows where difference_matrix[i][j] represents how many columns row with index i have in common with row with index j.

This method has revealed an intriguing discovery: one row shares six columns in common with another, differing only in the exchange date; one occurring on Friday and the other sequentially on Saturday. Other rows were found with 3 and 2 similarities, and were addressed accordingly.

In the table below we can see two similar rows having 6 columns in common.

	Exchange Date	Close	Net	%Chg	Open	Low	High
339	2023-01-02	1001.45	-0.2	-0.0002	1002.88	1000.17	1003.67
340	2023-01-01	1001.45	-0.2	-0.0002	1002.88	1000.17	1003.67

Weekend days

Since we work with stock market data, we need to check if there are some issues in the dataset and it contains weekend data too. There were 3 weekend days found: 2022-01-01, 2021-01-03, 2021-01-02. We dropped their corresponding rows from the dataframe.

Missing days

In order to detect missing days, we came with a simplification to iterate through every 5 datapoints, and check if the start point and end point are monday and friday. In the end, we found 3 missing days: 2024-04-15, 2024-03-15, 2024-02-15.

Resolve obvious outliers

As we observed in the EDA section, there was a sudden drop in the 'Close' values in 2021, and by printing all the values for those lines, we observed that only the 'Close' had wrong values, by being out of range of [low, high].

The 'Net' value for those lines seemed correct. In this way, we fixed the 'Close' values by summing the 'Net' value to the 'Close' price from the previous day, starting with the day with the correct value for 'Close' (2021-02-19).

Wrong Net Values

We also have taken a look at Net values, thinking they could be wrongly calculated. After fixing the close values first, we went through the whole data and checked to see if there are some errors. And we actually found some, some Net values were not corresponding with the close values provided, we analysed more and saw that the net values were in fact the problem. We fixed this issue by calculating the correct values and replacing them in the data.

Similarly, the %Chg column also had errors, but we decided to ignore them since we dropped the column completely, being 100% correlated to the Net column.

Implemented Models

1. **ARIMA**

   Split: As we don't have a designed dataset for validation, we will use a portion of the training dataset as validation samples. A common way to set the ratio between train and validation is using 'random_state 42', which allocates 80% of the dataset to training, and the rest of 20% for validation.
   In order to prevent multiple cycles of economics and past events, which can affect the market through seasonal trends, we decided to focus on the dataset starting from 2023. After obtaining a RMSE score of ~7.55 on the splitted data, we moved to test it for our targeted five days. Five variations were tested at this point: for training data: 15, 20, 29, respectively 45 days in order to have multiple variations starting with 75%

to 90% for the training set. We then tested it on the entire temporary dataset (356 days). These variations were made to help assess the robustness of the model.

Features: Trained and predicted only the ‘Close’ column. Even though it doesn’t capture all the relevant information for accurate predictions, it seemed to be more resilient. Tried to use the ‘Open’ value too, but it obtained a worse score.

Model: ARIMA (Autoregressive Integrated Moving Average) is suitable for single time series data, since the model is univariate, in general. The abbreviation of the model comes from combining “AR”, “I” and “MA”, which comes from:

- Autoregression: it predicts future values based on a linear combination of past values
- Integrated: removes trends or seasonality and the statistical properties of a time series doesn’t change over time
- Moving Average: it helps capture short-term fluctuations or random noise

In the beginning, we fit the model without taking in consideration seasonal trends and we perform hyperparameter tuning on all variations of ‘p’ , ‘d’, ‘q’ parameters from orders.

2. XGBoost

Split: The dataset was split into multiple training sets (x_train_ndays) and corresponding target sets (y_train_ndays), with different window sizes (15, 20, 30, 45, 60, 75, 90 days) to train and evaluate the model. The primary goal is to predict stock prices for the next 5 days. Given the short-term nature of the prediction horizon, training the model on longer historical windows (e.g., 4 years) might introduce unnecessary noise and irrelevant/non-representative of current market behavior patterns and outdated trends that do not impact the short-term price movements. By using shorter training windows (e.g., 15, 20, 30 days), the model can focus on capturing recent trends and patterns that are more likely to influence prices in the immediate future. Another thing taken into consideration is that the dataset might contain unusual events (such as the significant drop in 2022) that could disproportionately influence the model's learning if included in longer training windows.

Features:
Several technical indicators and moving averages were calculated.
Moving averages help smooth out stock prices on a chart by filtering out short-term price fluctuations.

- Exponential Moving Average (EMA) - an average where greater weights are applied to recent prices - calculated with a window of 9 days.
- Simple Moving Averages (SMA) with windows of 5, 10, 15, and 30 days.

- Relative Strength Index (RSI) with a default window of 14 days, calculated using the change in closing prices. It indicates the magnitude of recent price changes and it can show that a stock is either overbought or oversold.
- Moving Average Convergence Divergence (MACD) which shows the relationship between 2 exponential moving averages and its signal line - calculated based on the 12-days and 26-days EMAs of closing prices.

Model: XGBoost (eXtreme Gradient Boosting) regression was selected for its ability to capture complex relationships in the data and handle nonlinear patterns. GridSearchCV was employed to optimize the hyperparameters of the XGBoost regressor, including n_estimators, learning_rate, max_depth, and gamma.

3. LSTM

Split: We integrated the Train-Test Split for Cross-Validation. 80% of the data was used to train the model, and the additional 20% were left to test the model performance and accuracy.

Features: In this model, we chose to predict the difference between the current close value and the next one (meaning that we predicted the Net value instead of Close). It proved to be more reliable and to not overfit as easily.

The feature chosen to work on this model where: Close and Net. We eliminated other features, as it confused the model and they were not as consistent. We also added new features like: RSI (Relative Index Strength), EMAF (Exponential Moving Average Forecasting), MACD (Moving average convergence/divergence Line) and MACDs (Moving average convergence/divergence Signal Line)

Model: LSTM's or Long Short-Term Memory models are a type of neural network that can learn long-term relationships between the selected data, useful for predicting stock prices.

They examine a sequence of data over time and predict future data, considering what they have learned so far.

LSTM's are known for being very successful in predicting next number in a sequence, predicting stock prices and where even used for natural language processing.
Why? Because this is where they shine, they can capture dependencies over time, but as the time progresses, older data becomes less relevant and doesn't impact the result as much.

Lookback period: For this model we have decided to use a lookback period approximately 1 year (start of 2023 - until the end). This choice was made regarding our data analysis done beforehand, as we have seen that in 2022, because of other events, the price took a huge dip. This phenomenon is not expected to happen in the next 5 days, which means that training the data on that time period will only make it more inaccurate.

Preparing the data: The training data was meticulously structured to optimize the model's performance. Each training vector consists of 28 curated sets of values, including metrics such as close value, net value, RSI, EMAF, MACD and MACDS.

The values within each vector were scaled to conform to the [0,1] range, a critical step in enhancing the model's comprehension and performance. By standardizing the data in this manner, the model can more effectively discern patterns and relationships, ultimately leading to more accurate predictions and analyses.
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Hyperparameter Tuning: For this model we went with 1 input layer with the same size as the train vector, 2 hidden layers: The sizes of these layers were carefully tested to best fit the data we have and improve the model's performance. Other choices, like choosing more hidden layers or making them more complex, proved to be more prone to overfitting and not generalizing well for unseen data.

The tanh activation function was deemed to be the most accurate, other tests like: sigmoid, relu, leaky_relu and linear didn't perform as good.

Other parameters like batch_size and epochs were left close to the default values, seeing as changing them would negatively affect our model.

Future Work

Data Collection and Augmentation: Given the limited time, there might have been some errors in the data provided which we probably didn't see. If we had more time, we could have dedicated more work on inspecting the data making sure it is free of anomalies, and also augment where we found problems.

Model Architecture: While all the models generated so far are pretty good, there might be other variations of the current models that would perform better, variations which we haven't got the time to test.

Feature Engineering: We would also like to dedicate more time in our feature engineering process, extracting more information from online resources, or constructing them ourselves. These could improve the models performance significantly.

Hyperparameter Tuning: We believe there is more potential for fine-tuning our hyperparameters to achieve better performance and would like to work on this topic further.

Ensemble Methods: One thing that we would love learning and applying in the future would be harnessing the potential of ensemble methods, where multiple models are combined to make predictions.