**Master Thesis: Anomaly Detection and Time Series Forecasting in the Irish Finance Market: Evaluating the Performance of the Prophet Model**

Abstract: Accurate anomaly detection and time series forecasting in financial markets are crucial for informed decision-making and risk management. This paper presents a comprehensive study of anomaly detection and time series forecasting in the Irish finance market, specifically focusing on stock prices and market trends. To achieve this, I propose an integrated approach that combines the use of Facebook's Prophet model with insights from relevant research papers. Specifically, I draw inspiration from the " Time Series Forecasting Using FB-Prophet” (Kirti Sharma et al., 2022) and "Integrating Navier-Stokes Equation and Neoteric iForest-BorutaShap-Facebook’s Prophet Framework for Stock Market Prediction: An Application in Indian Context" (Ghosh and Chaudhuri, 2022) papers.

Introduction:

**1.1 Background and Motivation**

**1.2 Research Objectives**

- Evaluate the Prophet model's effectiveness as a forecasting tool by comparing its forecasts against historical data, while also analysing its strengths and limitations to assess its overall performance in capturing the distinctive characteristics of financial data within the Irish finance market.

- Examine the Impact of detected anomalies on the accuracy and reliability of time series forecasting within the Irish finance market. By systematically analysing how identified anomalies affect the Prophet model's forecasting performance, researchers can gain insights into potential risks and opportunities associated with anomalous events.

- Validate the Proposed Approach with Real-world Data on a comprehensive dataset comprising historical financial record. Through rigorous validation, researchers can ascertain the generalizability and practicality of the developed framework and assess its potential for real-world application in financial decision-making.

**1.3 Scope and Limitations**

**1.4 Thesis Organization**

Literature Review:

2.1 Time Series Forecasting Techniques

2.1.1 Statistical Time Series Model (ARIMA, SARIMA, GARCH)

2.1.2 Time Series Decomposition and Forecasting Model (Prophet)

2.1.3 Deep learning model (LSTM, NeuralProphet,)

2.2 Anomaly Detection Approaches

2.2.1 Deep learning model (NeuralProphet, LSTM, Autoencoder)

2.2.2 Ensemble Anomaly Detection (Isolation Forest)

2.2.3 Support Vector Machine Anomaly Detection (One-Class SVM)

2.2.4 Time Series Decomposition and Forecasting Model (Prophet)

2.3 Related Studies in Finance Market Analysis

2.4 Overview of the Prophet Model

2.4.1 Traditional

2.4.2 Neural Prophet

**3. Data Collection and Preprocessing:**

**3.1 Data Sources**

**3.2 Data Description**

**3.3 Data Preprocessing Steps**

3.3.1 Data Cleaning

Now, let' s import several indexes from Finance yahoo (3 years 24/08/2020 to 22/08/2023) BEL20 (Belgium), FTSE100 (UK), CAC40 (France), ISEQ20 (Ireland), DAX40 Germany), PSI20 (Portugal), ISEQ20 to preprocess and have a comparable data.

let's compare the Irish market (ISEQ20) to most important and relevant European indexes. let's use date and close columns as it's a univariate analyse for time series and anomaly detection.

- Handle missing values

No missing values in all the datasets.

3.3.2 Outliers

Let's use z-score, because in statistics, they’re used to measure how far a data point is from the mean of a dataset in terms of standard deviation.

Z-scores are computed for the 'Close' column. These scores indicate how far each data point deviates from the column's mean in terms of standard deviations.

Identifying potential outliers by comparing the absolute Z-scores to a specified threshold value z\_threshold. If the absolute Z-score of a data point exceeds this threshold, the data point is considered an outlier.

there are three Potential Outliers in Close column 'FTSE100.xlsx, but they seem legitimate, because they are usual and true values and following same position as the rest, so I won't remove them from my dataset.

4. Time Series Forecasting:

4.1 Introduction to Time Series Forecasting Models

Time series forecasting has emerged as a prominent trend among researchers in recent years, leading to the development of diverse and interesting prediction methods and algorithms. Time is a crucial factor in time series models, making them highly relevant for various applications, such as predicting stock prices or electricity consumption. Understanding when and how prices or values may rise is of great interest in these domains.

A time series is a collection of several data points arranged in chronological order. Typically, time serves as the independent variable, and the main objective is to forecast future values.

We need to consider certain aspects when dealing with time series data (Vishwakarma, A., Singh, A., Mahadik, A., & Pradhan, R. (2020)):

a) Stationarity: Stationarity is a key characteristic of time series. If the statistical properties remain constant over time, we consider the series stationary. Stationarity implies a constant mean, variance, and covariance independent of time. However, real-world scenarios, like stock prices, often exhibit non-stationary behaviour due to trends or changing volatilities.

b) Testing Stationarity: We can test for stationarity using the Dickey-Fuller test, a statistical test that examines the presence of a unit root.

• If the test yields a p-value greater than 0, the process is considered stationary.

• Otherwise, if the p-value is 0, we reject the null hypothesis of stationarity, indicating non-stationary behaviour.

c) Seasonality: Seasonality refers to the recurring patterns or fluctuations in a time series. For instance, online sales may increase during holidays like Diwali and then decline afterward. We can identify seasonality through the autocorrelation plot, which exhibits a sinusoidal pattern, and the period in the plot reveals the season's length.

d) Autocorrelation: Autocorrelation measures the similarity between observations at different time lags. A sinusoidal shape in the autocorrelation plot suggests seasonality, and we can determine its value by finding the period in the plot.

**4.2 Implementing the Prophet Model**

The additive-based model, known as Prophet, is a powerful technique for time series forecasting. It effectively captures non-linear trends, yearly, weekly, and daily seasonality, as well as holiday effects. This model performs exceptionally well when dealing with time series data that exhibit strong seasonal patterns and have a substantial historical data span data (Vishwakarma, A., Singh, A., Mahadik, A., & Pradhan, R. (2020)).

Prophet is designed to handle missing data, trend shifts, and outliers robustly, making it a reliable choice for forecasting tasks. Developed by Facebook's Core Data Science team, Prophet is an open-source software that utilizes the stan library for complex statistical modeling, which is a prerequisite for using this tool.

Prophet follows the familiar model API of scikit-learn (sklearn). To use Prophet, an instance of the Prophet class is created, and then the fit and predict methods are called to train the model and make predictions.

In the Prophet model, the input data frame must consist of two columns: 'ds' (date stamp) and 'y'. The 'ds' column should be in a format recognized by pandas, such as YYYY-MM-DD HH:MM: SS for timestamps or YYYY-MM-DD for dates. The 'y' column should contain numeric values representing the measurement or attribute to be forecasted. By following these guidelines, analysts can leverage the power of Prophet for accurate and reliable time series forecasting.

4.2.1 Model Architecture and Configuration

**How prophet works:**

Prophet is an additive model that effectively captures the various components of a time series y(t) = g(t) + s(t) + h(t) + ϵ (Taylor & Letham, 2018):

Trend g(t): The trend component models the long-term behaviour of the time series. It captures the overall direction in which the data is changing over time, helping us understand whether the series is increasing, decreasing, or remaining stable.

Seasonality s(t): The seasonality component accounts for recurring patterns or cycles that repeat over fixed intervals, such as daily, weekly, or yearly effects. Prophet uses Fourier series to model seasonality, which enables it to handle complex seasonal patterns.

Holidays and Occasions h(t): This component considers the impact of special events or occasions on the time series. For example, it can account for the increased demand during product launches, holiday seasons like Diwali or Christmas, or any other significant events that may affect the data.

Irreducible Error ϵ: The irreducible error term represents the noise or random fluctuations in the data that cannot be explained by the model's components. It accounts for the uncertainty and unpredictability in the time series.

By decomposing the time series into these additive components, Prophet can effectively model and forecast complex time series data. The trend captures the overall behaviour, seasonality captures recurring patterns, and the occasion component accounts for specific events. The irreducible error term acknowledges that there will always be some level of uncertainty and randomness in the data, which the model cannot fully explain. This approach allows data analysts to gain a comprehensive understanding of the time series and make accurate forecasts.

4.2.2 Training Parameter

The Prophet model consists of five essential training parameters that data analysts need to consider (Vishwakarma, A., Singh, A., Mahadik, A., & Pradhan, R. (2020)):

a) Base Trend k: The base trend parameter represents the overall trend component of the time series. It captures the fundamental direction in which the data is changing over time.

b) Offset Parameter (m): The offset parameter represents the shift or offset of the overall trend. It accounts for any displacement or deviation from the base trend, allowing the model to adjust the trend line accordingly.

c) Changepoints δ={δi}: Changepoints are time points in the data where the trend experiences abrupt changes or shifts. These points allow the model to identify and adapt to different periods of the time series with varying trends.

d) Seasonal and Exogenous Parameters β={βi} Zi=0: The seasonal component is modeled using Fourier series, capturing the periodic patterns in the data, such as daily, weekly, or yearly fluctuations. Additionally, the exogenous regressors, represented by the parameters βi, account for the impact of extra features on the time series.

e) Level of Noise σ: The noise parameter σ represents the level of random fluctuations or uncertainty in the data. It allows the model to account for the inherent unpredictability in the time series.

Furthermore, for each i-th regressor, the parameters mutrain and stdtrain represent the mean and standard deviation values, respectively, calculated from the training data. These values are essential for effectively incorporating additional regressors into the model.

Understanding and tuning these parameters are crucial for training an accurate and reliable Prophet model. By appropriately setting these parameters, analysts can ensure the model captures the underlying patterns and behaviours of the time series, leading to better forecasts and insights.

**4.2.3 Hyperparameter Tuning**

**4.3 Performance Evaluation Metrics**

**4.3.1 Mean Absolute Error (MAE)**

**4.3.2 Mean squared error (MSE)**

**4.3.3 Root Mean Squared Error (RMSE)**

**4.3.4 Mean Absolute Percentage Error (MAPE)**

**4.3.5 R-squared (R2)**

**4.4 Results and Discussion**

**4.4.1 Comparing Prophet with Traditional Forecasting Methods**

**4.4.2 Analyzing Forecasting Accuracy and Robustness**

**4.5 Time Series Analysis (Code Section)**

4.5.1 Descriptive Analysis

- Summary statistics

Analyzing the provided statistics for the six stock market indices (BEL20, FTSE100, CAC40, ISEQ20, DAX40, and PSI20) in their respective 'Close' columns, we can draw the following conclusions:

Mean (Average) Value:

These indices exhibit significant differences in their mean (average) values. The DAX40 has the highest mean value at roughly 14,590, indicating a generally higher average stock price level. In contrast, the ISEQ20 has the lowest mean value at around 1,337. Standard Deviation (Volatility):

The standard deviation measures the extent of price fluctuations or volatility. A higher standard deviation suggests greater price swings. The DAX40 boasts the highest standard deviation (1173.04), indicating more significant price volatility, while BEL20 has the lowest standard deviation (287.84), implying relatively lower volatility. Minimum and Maximum Values:

The minimum and maximum values represent the lowest and highest closing prices observed during the data period. DAX40 records the highest maximum value (16,469.75), signifying the peak during the period, while BEL20 shows the lowest maximum value (4,402.32). CAC40 reports the lowest minimum value (4,569.67), indicating the least price drop, while PSI20 reflects the highest minimum value (3,863.20). Median (50th Percentile):

The median, or 50th percentile, reflects the middle value when the data is sorted in ascending order. It provides insight into the central tendency. The medians vary, with DAX40 having the highest median (14,856.48) and ISEQ20 having the lowest median (1,368.86). Percentiles (25th and 75th):

The 25th and 75th percentiles help understand the data's spread and identify the interquartile range. DAX40 reports the highest 75th percentile value (15,623.23), indicating a relatively higher upper price range, while CAC40 has the lowest 75th percentile value (7,017.20). PSI20 shows the highest 25th percentile value (5,111.13), suggesting a relatively higher lower price range, while FTSE100 displays the lowest 25th percentile value (6,963.49).

- Data distribution

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Fig 1. Distribution of close prices Iseq20

From Fig.1, The most common price range for 'Close' prices falls within the interval of (1448.704, 1496.887], with a frequency of 138. This suggests that a significant portion of the observed prices are in this range.

There is also a notable frequency in the range of (1400.521, 1448.704], with 124 data points.

The range (1207.789, 1255.972] and (1255.972, 1304.155] also have substantial frequencies, indicating that prices are relatively evenly distributed in these ranges.

The lowest frequency is in the range (1304.155, 1352.338], which suggests that fewer data points fall in this range compared to others.

Overall, the frequency distribution provides insights into the distribution of 'Close' prices and highlights the concentration of prices within certain ranges. It appears that there are more data points in the mid to higher price ranges, with fewer data points in the lower and higher extremes of the data.

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Fig 2. Box Plot Iseq 20

From Fig. 2:

Range of Prices: The 'Close' prices vary between a minimum of approximately 1063.24 and a maximum of around 1545.07. This suggests a considerable range of stock prices over the given time period.

Central Tendency: The median (Q2) of approximately 1342.58 is between the 1st quartile (Q1) and the 3rd quartile (Q3), indicating a roughly symmetrical distribution. This suggests that the central tendency of the 'Close' prices is around 1342.58.

Spread of Data: The interquartile range (IQR), which is the difference between Q3 and Q1, is approximately 218.67 (1451.91 - 1233.24). This indicates the spread of the middle 50% of the data. A larger IQR suggests a wider range of prices within this central range.

Outliers: It's worth noting that there may be outliers in the data as well. Outliers are data points that fall significantly below Q1 or above Q3 and are represented as individual points on the box plot. These outliers can potentially indicate extreme price fluctuations.

In summary, the box plot statistics provide valuable insights into the distribution and variability of the 'Close' prices. The data appears to have a somewhat symmetrical distribution with a central tendency around 1342.58, but there are also outliers suggesting occasional extreme price movements.

- Density Plot

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Fig.3 Density Plot

The density estimates provide insights into the distribution and likelihood of 'Close' prices within the dataset:

Rare Low Prices: 'Close' prices in the lower range (e.g., 1063 to 1067) have very low estimated probabilities (density values around 0.0005 to 0.0006). This suggests that observing 'Close' prices at these levels is relatively rare.

Gradual Increase: As 'Close' prices increase (e.g., 1068 and beyond), the density values also increase gradually. This indicates that there is a slightly higher likelihood of observing 'Close' prices in this range, although they are still relatively uncommon.

Variability: The density values continue to change as 'Close' prices vary, reflecting the variability in the dataset. Some price levels have slightly higher probabilities than others, but the overall distribution is not strongly skewed.

Higher Likelihood at Higher Prices: Towards the higher end of the 'Close' price range (e.g., 1540), the density values become higher (density value of 0.001195). This suggests a higher likelihood of observing 'Close' prices in this range, indicating that they are more common or probable in the dataset.

In summary, the density estimates provide a probabilistic view of 'Close' prices of the ISEQ20 dataset. They indicate that lower 'Close' prices are relatively rare, while higher prices are more commonly observed. This information can be valuable for understanding the distribution of 'Close' prices and making informed decisions related to trading or investment strategies.

4.5.2 Time Series Analysis

- Timeline plot

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Fig. 4 Timeplot Iseq20

- Autocorrelation and partial autocorrelation

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Fig. 5. ACF

The ACF values decline as the lag between data points increases. This decline suggests that the correlation between data points weakens as they become more separated in time.

The ACF value at lag 0 is always 1.0 because it represents the correlation of the time series with itself at the same time point.

The ACF values decrease gradually but do not reach zero quickly, indicating some level of correlation between nearby data points.

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Fig. 6 PACF

PACF values exhibit a more intricate pattern compared to ACF. Several PACF values significantly differ from zero.

The PACF value at lag 1 is notably high, indicating a strong correlation between the current data point and the one immediately preceding it.

There are discernible spikes in the PACF plot at specific lags, suggesting direct correlations with those lags.

Conclusion from both plots:

The time series data displays strong autocorrelation with its immediate past values, indicated by the high values at lag 1 in both the ACF and PACF plots.

The gradual decline in ACF values and the presence of significant PACF spikes hint at the possibility of an autoregressive (AR) component in the data. In AR models, the current value is influenced by its past values.

**4.6 Modeling and Optimization (Code Section)**

4.6.1 Bayesian optimization (Hyperparameter tuning)

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Fig.7 Bayesian optimization Iseq20

Hyperparameters: The chosen hyperparameters for your model indicate the prior scale for changepoints and holidays. These values have been determined through model tuning or optimization.

Model Performance:

The MAE (Mean Absolute Error) of 227.66 suggests that, on average, your model's predictions are off by approximately 227.66 units from the actual values. Lower MAE values are desirable.

The MSE (Mean Squared Error) of 62,832.77 indicates the average squared difference between predictions and actual values. It's a larger value due to squaring, and lower values are preferred.

The RMSE (Root Mean Squared Error) of 250.66 is the square root of MSE and provides a measure of the model's prediction error in the original units. Smaller RMSE values are better.

The MAPE (Mean Absolute Percentage Error) of 17.36% indicates that, on average, your model's predictions have an error of 17.36% relative to the actual values. Lower MAPE values are desirable.

The R-squared (R2) of -2.64 suggests that the model is not performing well. R-squared should ideally be close to 1, indicating a good fit. A negative R-squared indicates that the model's predictions are worse than simply using the mean of the observed values.

Overall, the model's performance, as indicated by the provided metrics, suggests that it may not be a good fit for the data. Further model refinement or alternative modeling approaches may be necessary to improve prediction accuracy. Additionally, the negative R-squared suggests that the model is performing worse than a simple mean-based model, indicating the need for significant improvement.

4.6.2 Prophet Model Forecast with Confidence Intervals (plot)

A graph showing a line

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Fig. 8 Iseq20 Prophet Model Forecast with Confidence Intervals

Original Data:

The original dataset is the ISEQ20 historical index from August 24, 2020, to August 22, 2023, with a use of 764 data points.

In this period, the index fluctuates from a low of 1132.07 to a high of 1461.70.

Forecasted Values:

The forecasted values extend beyond the original dataset, covering the period from August 24, 2020, to August 21, 2024, with a total of 1129 data points.

These forecasted values, indicated by the 'yhat' column, start at 1124.90 and show an upward trend, eventually reaching approximately 1900.27 by August 21, 2024.

This suggests that the model predicts an increase in stock prices over the forecasted period.

Upper Confidence Interval:

The upper confidence interval (CI) values, represented in the 'yhat\_upper' column, provide an upper limit for the forecasted stock prices.

Beginning at 1164.76, these upper CI values rise over time, indicating the highest potential stock price levels.

The upper CI offers insight into the possible upper boundary of stock price growth, suggesting that prices may reach as high as 1164.76 by August 24, 2020, and potentially higher in the forecasted period.

Lower Confidence Interval:

Conversely, the lower confidence interval (CI) values, shown in the 'yhat\_lower' column, provide a lower limit for forecasted stock prices.

Starting at 1083.71, these lower CI values increase over time, indicating the lowest potential stock price levels.

The lower CI helps define a range within which stock prices are likely to remain, suggesting that prices may not drop below 1083.71 by August 24, 2020, and potentially higher in the forecasted period.

Overall Conclusion:

In summary, the forecasts, along with upper and lower confidence intervals, provide valuable information regarding expected trends and the potential range of stock prices.

The forecasts point toward an upward trend in stock prices, while the confidence intervals acknowledge uncertainty and potential price variability.

Investors and stakeholders should consider these forecasts and confidence intervals when making investment decisions, weighing the upward trend against potential price fluctuations.

**4.7 Decomposition and Smoothing (Code Section)**

4.7.1 Trend analysis

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Fig. 9 Iseq 20 trend

The trend component reveals the underlying, longer-term pattern in the data. Starting from August 27, 2020, there is a noticeable upward trend in the closing prices of the ISEQ20 index, with an increase of approximately 1142.93 points. Prior to this date, the trend component is marked as "NaN," indicating that there might not have been a clear trend during that period.

4.7.2 Seasonal decomposition

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Fig. 10 Iseq 20 Seasonal decomposition

The seasonal component represents regular, repeating patterns in the data that occur at specific intervals. It exhibits a distinct pattern with fluctuations alternating between positive and negative values. This pattern implies that there are recurrent seasonal influences affecting the closing prices, with deviations of approximately ±0.93 to ±0.23 points from the trend.

4.7.3 Residual component

A graph showing a sound wave

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Fig. 11 Iseq 20 Residual component

The residual component reflects the unexplained variability or noise in the data after accounting for the trend and seasonal patterns. On August 27, 2020, there is a notable positive residual value of approximately 5.75 points, indicating an unexpected increase in the closing prices beyond what the trend and seasonal patterns explain. On August 28, 2020, there is a small negative residual value of approximately -0.08 points, suggesting a minor decrease in closing prices beyond expected patterns.

4.8 Performance Evaluation (Code Section)

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Fig. 12 ISEQ20 Performance Metrics

Mean Absolute Error (MAE):

The MAE value of approximately 224.28 indicates that, on average, the model's predictions differ from the actual values by approximately 224.28 units. This metric represents the absolute magnitude of prediction errors.

Mean Squared Error (MSE):

The MSE value of approximately 62104.87 represents the average squared difference between the model's predictions and the actual values. A higher MSE suggests a significant spread in prediction errors, potentially due to outliers or model inaccuracies.

Root Mean Squared Error (RMSE):

The RMSE value of approximately 249.21 is the square root of the MSE and provides a sense of the average magnitude of prediction errors. It is similar to the MAE but gives more weight to larger errors. In this case, the RMSE is smaller than the MAE, indicating that larger errors have less impact on the overall RMSE.

Mean Absolute Percentage Error (MAPE):

The MAPE value is expressed as a percentage and is useful for understanding the relative magnitude of errors.

i's approximately 17.11% indicates that, on average, the model's predictions deviate from the actual values by about 17.11%.

R-squared (R2):

The R-squared (R2) value of approximately -2.60 is unexpectedly negative. R-squared measures the proportion of the variance in the dependent variable that is predictable from the independent variables. A negative R2 suggests that the model is performing worse than a horizontal line (a model that predicts the mean of the dependent variable). This may indicate that the model is not capturing the underlying patterns in the data effectively.

Conclusion:

The model's performance, as indicated by the provided metrics, appears to be suboptimal. The MAE, MSE, and RMSE values, although providing insight into the magnitude of errors, suggest that the model's predictions exhibit significant discrepancies from the actual values.

The negative R-squared value is a concerning sign, indicating that the model is not explaining the variance in the data and is potentially a poor fit.

The MAPE of approximately 17.11% indicates that, on average, the model's percentage errors are moderate.

Overall, there may be room for improvement in the model's accuracy and explanatory power. Further model refinement, feature engineering, or parameter tuning may be necessary to enhance its forecasting performance.

**4.9 Model Comparison (Code Section)**

4.9.1 Prophet Model vs. Other Algorithms

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Fig. 13 Prophet Model VS other models

4.9.2 Scatter plot comparing Prophet with other algorithms

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Fig. 14 Performance Metrics Scatter plot

Mean Absolute Error (MAE):

Prophet MAE: 641.50

MAE Range: 139.80 (ARIMA) to 671.77 (NeuralProphet)

Prophet's MAE is approximately 78% higher than ARIMA, indicating that ARIMA has the lowest absolute prediction errors. However, Prophet outperforms NeuralProphet by approximately 4%.

Mean Squared Error (MSE):

Prophet MSE: 480,185.90

MSE Range: 33,089.28 (ARIMA) to 5,278,636.00 (NeuralProphet)

Prophet's MSE is approximately 93% lower than NeuralProphet, making it the superior model in terms of minimizing squared prediction errors. However, ARIMA still outperforms Prophet by approximately 93%.

Root Mean Squared Error (RMSE):

Prophet RMSE: 692.95

RMSE Range: 181.90 (ARIMA) to 1334.10 (GARCH)

Prophet's RMSE is approximately 52% lower than GARCH, which indicates that it provides better point forecasts in terms of the root mean squared error. However, ARIMA and LSTM have lower RMSE values than Prophet, outperforming it by approximately 62% and 65%, respectively.

Mean Absolute Percentage Error (MAPE):

Prophet MAPE: 49.11%

MAPE Range: 11.44% (ARIMA) to 99.20% (GARCH)

Prophet's MAPE is approximately 328% higher than ARIMA, demonstrating that ARIMA has the lowest percentage prediction errors. However, Prophet significantly outperforms GARCH, which has the highest MAPE, by approximately 102%.

R-squared (R2) Score:

Prophet R2: -26.85%

R2 Range: -0.92% (ARIMA) to -102.22% (GARCH)

Prophet's R2 score is negative, indicating that it doesn't fit the data well compared to a horizontal line. In this case, ARIMA has the highest R2 score, being closest to 0. This suggests that ARIMA fits the data better, explaining more of the variability.

In summary, when comparing Prophet to the other models:

Prophet performs better than NeuralProphet and GARCH across all metrics, with significant percentage improvements in MAE, MSE, RMSE, and MAPE.

However, Prophet is outperformed by ARIMA and LSTM in terms of MAE, MSE, RMSE, and R2 score, indicating that these models provide more accurate point forecasts and better data fit.

The choice of the best model depends on the specific requirements of your forecasting task. If minimizing absolute or percentage errors is crucial, ARIMA may be preferred. If you prioritize ease of use and interpretability, Prophet might be a suitable choice despite its slightly higher errors compared to ARIMA and LSTM.

**4.10 Index Comparison (Code Section)**

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Fig. 15 Iseq20 vs other European Indexes

Key Observations:

Initial Variability (August 2020): In August 2020, the indices exhibit variability in their Close prices. Indices such as BEL20 and FTSE100 show relative stability, while others like DAX40 and PSI20 experience fluctuations.

Market Response to Events: Throughout the dataset, significant market events and macroeconomic factors likely influenced the indices. Notable price movements may correspond to economic announcements, geopolitical events, or sector-specific news.

Pandemic Impact (Early 2020): A visible impact of the COVID-19 pandemic can be seen in early 2020, with a substantial drop in indices' Close prices followed by gradual recoveries.

Recovery and Volatility: Indices generally recover from the initial pandemic shock but continue to display volatility. Notably, DAX40 and PSI20 show relatively larger fluctuations compared to others.

Periods of Synchronization: At times, several indices move in tandem, reflecting broader market trends. These synchronized movements might be influenced by global economic indicators or sector-wide developments.

Differences in Behaviour: Despite overall similarities, individual indices exhibit unique behaviours. For instance, FTSE100 and CAC40 show relatively smoother trends, while BEL20 and PSI20 experience more pronounced oscillations.

4.10.1 Iseq20 vs. Other European Indexes

4.10.2 Scatter plot comparing Iseq20 vs. Other Indexes.

- Plot with Normalized data for comparison

A graph of a stock market

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Fig. 16 Normalized Close Prices

- Heatmap for performance comparison

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Fig. 17 Heatmap for performance comparison

In our case, the correlation coefficients are all positive, which indicates that there is a positive linear relationship between the close prices of the 6 indexes.

We can see here that the irish index has the strongest correlation in the map and with the german index (0.94), followed by uk-Portuguese indexes (0.93), and uk-French indexes correlation (0.91). this means that the Irish market is strongly influenced by the German Market. - Stacked area chart for visualizing forecasts

4.10.3 Irish Vs German Index

4.10.3.1 Scatter Plot

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Fig. 18 Irish Vs German Index

4.10.3.2

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Fig 19. Irish Vs German Index

Conclusion from both Fig. 18 and Fig. 19

Index Values:

DAX 40: The DAX 40 index represents the German stock market. It has consistently maintained higher closing values compared to the ISEQ 20 index.

ISEQ 20: The ISEQ 20 index represents the Irish stock market. While it generally has lower closing values compared to the DAX 40, it follows a similar overall trend.

Market Trends:

Overall Increase: Both indices show a general upward trend in their closing values over the observed period. This indicates overall positive performance in both the German and Irish stock markets during this time.

Volatility and Stability:

Volatility Comparison: The DAX 40 appears to exhibit higher volatility compared to the ISEQ 20, as seen in its larger price fluctuations. This suggests that the German market might be subject to more significant price swings than the Irish market.

Recent Performance:

As of August 22, 2023, the DAX 40 is at 15,705.62, while the ISEQ 20 is at 1,461.70. This reflects the pattern observed throughout the data, with the DAX 40 maintaining a significantly higher value compared to the ISEQ 20.

Market Factors:

Economic factors, corporate performance, and geopolitical events in Germany and Ireland can influence the relative performance of these indices. Economic growth, stability, and investor sentiment are key drivers.

Investment Considerations:

Diversification: Investors interested in diversifying their portfolio across different European markets may consider the performance and characteristics of both indices.

Risk and Return: The higher volatility in the DAX 40 may provide potentially higher returns but also comes with increased risk. The ISEQ 20's relatively lower volatility might offer stability but could yield lower returns.

In summary, the DAX 40 and ISEQ 20 indices exhibit differing performance and volatility characteristics, with the DAX 40 generally outperforming the ISEQ 20 in terms of closing values. Investors should consider these trends, market context, and their own investment goals when making informed decisions. Additionally, it's essential to conduct a more comprehensive analysis, including factors like historical performance, sector-specific trends, economic indicators, and external events, for a more complete investment strategy.

- Daily returns comparison

A graph showing a number of data

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Fig. 20 Daily returns comparison (german vs Irish indexes)

Closing Prices: The DAX index consistently maintains higher closing prices compared to the ISEQ20 index. This implies that, on average, the German stock market (DAX) features stocks with higher values than the Irish stock market (ISEQ20). Daily Returns:

DAX Performance: Daily returns for the DAX index fluctuate across the timeframe. Positive returns signal days when the DAX index increased in value, while negative returns denote days of decline. Overall, the DAX portrays a mix of positive and negative daily returns, indicating a combination of upward and downward market movements. ISEQ20 Performance: The ISEQ20 index also displays fluctuations in daily returns, mirroring the pattern observed in the DAX. Similar to the DAX, the ISEQ20 showcases both positive and negative daily returns over the studied period.

Comparative Analysis: Volatility: Both indices demonstrate volatility, evident from the oscillations in daily returns. Investors might note that market volatility can present opportunities for profit while simultaneously carrying heightened risk. Correlation: To delve into the relationship between these indices, one can conduct a correlation analysis on their daily returns. A positive correlation indicates that when one index rises, the other often follows suit, whereas a negative correlation suggests the opposite behavior.

Color Indicator: The "Color" column signifies whether the daily return for each index is positive (labeled as "Positive") or negative (labeled as "Negative"). This feature aids in swiftly identifying the direction of daily movements. Recent Performance:

As of August 22, 2023, the DAX index rests at 15,705.62, while the ISEQ20 index stands at 1,461.70. This mirrors the historical trend where the DAX consistently upholds a higher value than the ISEQ20. In summary, the DAX index persistently outperforms the ISEQ20 index in terms of closing prices. Both indices showcase volatility and fluctuating daily returns, rendering them susceptible to market dynamics and external influences. To make well-informed investment decisions, investors should weigh factors such as their risk tolerance, investment timeline, and portfolio diversification. Scrutinizing the correlation between these indices and monitoring their performance in the context of broader economic and geopolitical events can yield valuable insights for constructing effective investment strategies.

- Cumulative returns comparison

A graph showing the stock market

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Fig. 21 Cumulative returns comparison

**Anomaly Detection:**

**5.1 Introduction to Anomaly Detection Methods**

**A graph with red and blue lines

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Fig. 22 Iseq 20 Closing Prices with Anomalies

**A graph showing the growth of a stock market

Description automatically generated**

Fig 23 actual vs predicted

A graph with a line going up

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Fig. 24 Residuals

**5.2 Implementing Anomaly Detection Models (Code Section)**

5.2.1 Isolation Forest for Anomaly Detection

5.2.2 One-Class SVM for Anomaly Detection

5.3 Performance Evaluation Metrics for Anomaly Detection (Code Section)

5.3.1 Precision and Recall and F1-score

5.3.4 Receiver Operating Characteristic (ROC) Curve

5.3.5 Area Under the ROC Curve (AUC-ROC)

5.3.6 Precision-Recall Curve (AUC-PR)

**5.4 Results and Discussion**

5.4.1 Comparing Anomaly Detection Methods

A screenshot of a computer screen

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Fig. 25 Model Comparison in Anomaly detection

5.4.2 Analyzing the Prophet Model's Anomaly Detection Capability vs Other models

Prophet Model:

Precision: 0.562 (moderate)

Recall: 1.000 (perfect)

F1-Score: 0.719 (moderate)

AUC-ROC: 0.500 (low)

AUC-PR: 0.781 (moderate)

Key Takeaways for Prophet:

Recall: Prophet achieves a perfect recall (1.000), indicating that it effectively identifies all actual anomalies in the dataset. This suggests that it is excellent at capturing true positive cases without missing any.

Precision: The precision of Prophet is moderate (0.562), suggesting that while it has a good true positive rate, it might generate some false positives, leading to a trade-off between precision and recall.

F1-Score: The F1-Score, which balances precision and recall, is also moderate (0.719). This indicates that the model achieves a reasonable balance between correctly identifying anomalies and minimizing false alarms.

AUC-ROC: The AUC-ROC is 0.500, which is relatively low. This suggests that the model's Receiver Operating Characteristic (ROC) curve performs no better than random chance when distinguishing between anomalies and normal cases. In terms of ROC, it does not perform well.

AUC-PR: The AUC-PR is moderate at 0.781. This metric takes into account the precision-recall trade-off, and the moderate value suggests that Prophet provides a reasonable balance between precision and recall.

Comparison to Other Models:

Isolation Forest: Isolation Forest has a very high precision (1.000) and a slightly lower recall (0.977). This indicates it has a higher precision than Prophet but a slightly lower recall. However, it lacks an AUC-ROC value, making it challenging to compare in terms of ROC performance.

One-Class SVM: One-Class SVM also has perfect precision (1.000) but a lower recall (0.562) than Prophet. It shares a similar precision-recall trade-off with Prophet. However, like Isolation Forest, it lacks an AUC-ROC value.

NeuralProphet: NeuralProphet achieves perfect precision, recall, and F1-Score, suggesting it excels in both precision and recall aspects. However, it lacks an AUC-ROC value, making it challenging to compare in terms of ROC performance.

LSTM: LSTM has a moderate precision (0.555) and a perfect recall (1.000), similar to Prophet. It has a slightly lower F1-Score (0.714) than Prophet. However, like Prophet, it has a low AUC-ROC (0.500) and a moderate AUC-PR (0.778).

Summary:

Prophet excels in recall, ensuring that it identifies all actual anomalies. This makes it suitable for tasks where missing any anomalies is critical.

However, Prophet has a moderate precision, indicating a trade-off between correctly identifying anomalies and generating some false positives.

In terms of ROC performance, both Prophet and LSTM have a low AUC-ROC, suggesting that they perform no better than random chance.

The choice between Prophet and other models depends on the specific requirements of your anomaly detection task. If recall is crucial and some false positives can be tolerated, Prophet may be a good choice. However, if you need a higher precision or better ROC performance, you may need to explore other models or further optimize Prophet's parameters.

A blue rectangles on a white background

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Fig. 26 Model comparison anomaly detection

A screen shot of a graph

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Fig. 27 Model comparison anomaly detection

Integrated Analysis:

**6.1 Combining Time Series Forecasting and Anomaly Detection**

**6.2 Identifying Anomalous Market Behavior in Forecasted Data**

**6.3 Decision-Making Implications for Investors and Financial Institutions**

**Conclusion:**

**7.1 Summary of Findings**

**7.2 Contributions and Implications**

**7.3 Limitations and Future Directions**

**References:**

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Appendices:

**9.1 Detailed Model Configurations**

9.2 Additional Figures and Tables