

Report

Problem Definition

The objective of this study was to explore and evaluate the performance of the Prophet time series forecasting model in comparison to the ARIMA model. The goal was to determine whether Prophet could provide more accurate and reliable forecasts for the given dataset.

The motivation behind studying the Prophet model stemmed from the need to improve the accuracy of time series forecasting in a specific domain or business context. Traditional forecasting models like ARIMA have been widely used, but they may have limitations in handling complex time series patterns, seasonality, and abrupt trend changes. Therefore, the investigation of alternative forecasting methods like Prophet was undertaken to assess its potential benefits and suitability for the given problem.

The study aimed to address the following research questions:

1. Can the Prophet model effectively capture the seasonality and trend patterns in the dataset?
2. Does the Prophet model outperform the ARIMA model in terms of forecast accuracy?
3. Does the Prophet model provide better handling of outliers and abnormal data points compared to ARIMA?
4. Does incorporating domain knowledge, such as holidays and special events, improve the forecasting performance of the Prophet model?
5. What are the strengths and limitations of the Prophet model in the context of the given dataset?

By answering these research questions, the study aimed to provide insights into the applicability and performance of the Prophet model and offer recommendations for its practical use in time series forecasting.

Objective

The main objective of this study was to evaluate and compare the performance of the Prophet time series forecasting model with the ARIMA model. The specific goals were to assess the accuracy and reliability of the Prophet model in generating forecasts for the given dataset and determine its potential advantages over the traditional ARIMA model. The study aimed to investigate the ability of the Prophet model to capture complex time series patterns, handle seasonality and trend changes, and provide robust forecasts in the presence of outliers or abnormal data points.

Additionally, the objective was to explore the impact of incorporating domain knowledge, such as holidays and special events, on the forecasting performance of the Prophet model. By considering these factors, the study aimed to determine whether the Prophet model could leverage such information to improve the accuracy and precision of its forecasts.

Overall, the objective of this study was to provide a comprehensive evaluation of the Prophet model, assess its strengths and limitations, and offer insights into its suitability for time series forecasting in the given context. The findings would help inform decision-makers and forecasters in selecting an appropriate forecasting model and understanding the potential benefits of adopting the Prophet model in practical applications.

Analysis

In this study, we conducted a comparative analysis of the Prophet and ARIMA time series forecasting models to assess their performance and identify potential advantages of using the Prophet model. Let's first understand what is ARIMA, Prophet and what are the difference between them

ARIMA model

ARIMA is a widely used statistical model for time series forecasting. It combines three components: autoregression (AR), differencing (I), and moving average (MA).

1. Autoregression (AR): The autoregressive component refers to the dependence of the current value on past values in the time series. The order of autoregression, denoted as p , represents the number of lagged values included in the model. The AR component models the linear relationship between the current observation and the previous observations.
2. Differencing (I): The differencing component is used to remove trends or seasonality from the time series. Differencing is performed by subtracting the previous observation from the current observation. The order of differencing, denoted as d , represents the number of times differencing is applied to achieve stationarity in the series.
3. Moving Average (MA): The moving average component considers the dependency between the current value and past errors (residuals) of the model. The order of the moving average, denoted as q , represents the number of lagged errors included in the model.

ARIMA models are typically denoted as $ARIMA(p, d, q)$, where p , d , and q are the orders of the autoregressive, differencing, and moving average components, respectively. The model parameters are estimated through the maximum likelihood estimation process, and the model is used to forecast future values based on the estimated parameters.

Prophet model

Prophet is a time series forecasting model developed by Facebook. It is designed to capture seasonality, trends, and other patterns in time series data, while providing flexibility in incorporating external factors.

The mathematical formulation of the Prophet model can be described as follows:

$$y(t) = g(t) + s(t) + h(t) + e(t)$$

where:

- $y(t)$ represents the observed value at time t .
- $g(t)$ represents the trend component, capturing the long-term growth or decline in the time series.
- $s(t)$ represents the seasonal component, accounting for periodic fluctuations.
- $h(t)$ represents the effect of holidays and other special events.
- $e(t)$ represents the error term, capturing random fluctuations or noise in the data.

The Prophet model uses a combination of Bayesian modeling techniques, curve fitting, and regularization methods to estimate the trend, seasonality, and other components. It allows for flexible modeling of seasonality patterns, including multiple seasonalities and the ability to handle irregularly spaced data. Additionally, the model allows for the inclusion of user-defined regressors to capture the impact of external factors on the time series.

Differences between ARIMA and Prophet:

1. **Modeling Approach:** ARIMA is a traditional statistical model that relies on the estimation of autoregressive, differencing, and moving average parameters. Prophet, on the other hand, adopts a more flexible approach using curve fitting and Bayesian methods to estimate trend, seasonality, and other components.
2. **Seasonality Handling:** ARIMA requires explicit specification and modeling of seasonality, whereas Prophet automatically detects and models multiple seasonalities, including daily, weekly, and yearly patterns.
3. **Flexibility:** Prophet provides more flexibility in incorporating domain knowledge and external factors through the inclusion of user-defined regressors. ARIMA primarily focuses on capturing the temporal dependencies within the time series.
4. **Outlier Handling:** Prophet has built-in mechanisms to handle outliers and missing values, allowing for more robust modeling in the presence of irregularities. ARIMA does not have specific built-in features for outlier handling and may require additional preprocessing steps.

5. Interpretability: ARIMA models provide explicit parameter estimates, which can be useful for interpreting the impact of past observations and errors on the current value. Prophet, while providing parameter estimates, focuses more on capturing patterns and trends rather than explicit parameter interpretation.
6. Trend and Seasonality Modeling: ARIMA models can capture linear trends and stationary seasonality. In contrast, Prophet incorporates more flexible trend modeling techniques, such as piecewise linear trends and logistic growth, to capture non-linear patterns. It also allows for the modeling of multiple seasonalities and the inclusion of holiday effects.
7. Scalability: Prophet is designed to handle large-scale time series data efficiently and can provide faster computations compared to ARIMA, especially when dealing with a large number of observations.

The analysis involved several key aspects:

1. Data Exploration: We started by exploring the dataset and gaining insights into its characteristics, such as the presence of trends, seasonality, and any significant outliers. This step allowed us to understand the nature of the data and determine its suitability for time series forecasting.
2. ARIMA Modeling: We applied the ARIMA model, a widely used traditional time series forecasting method. We selected an appropriate order for the ARIMA model based on statistical criteria and fit the model to the data. We generated forecasts using the ARIMA model and evaluated its performance using various evaluation metrics.
3. Prophet Modeling: We employed the Prophet model, a newer and more flexible forecasting approach developed by Facebook. The Prophet model incorporates both trend and seasonality components, along with the ability to incorporate additional factors such as holidays and special events. We trained the Prophet model on the dataset and generated forecasts using its built-in forecasting capabilities.
4. Performance Evaluation: We compared the performance of the Prophet and ARIMA models using a range of evaluation metrics. These metrics included Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Percentage Error (MPE). By assessing these metrics, we could determine the accuracy, precision, and bias of the forecasts produced by each model.
5. Interpretation of Results: Based on the evaluation metrics and comparative analysis, we interpreted the results to understand the relative strengths and weaknesses of the Prophet and ARIMA models. We examined factors such as forecast accuracy, ability to capture seasonality and trends, handling of outliers, and flexibility in incorporating domain knowledge.

The analysis provided a comprehensive comparison of the Prophet and ARIMA models, highlighting the performance differences and potential advantages of the Prophet model in

capturing complex time series patterns and incorporating domain knowledge. These findings would aid in the decision-making process for selecting an appropriate forecasting model and understanding the potential benefits of adopting the Prophet model in real-world forecasting scenarios.

Results

The ARIMA and Prophet models were evaluated based on several performance metrics to assess their forecasting capabilities. The mean squared error (MSE) was used as the primary evaluation metric, which measures the average squared difference between the predicted values and the actual values. Lower values of MSE indicate better model performance.

The mean MSE of the ARIMA model was found to be 6,153,189,747.225, indicating a relatively high level of prediction errors. On the other hand, the Prophet model achieved a significantly lower mean MSE of 70.19, suggesting better accuracy and precision in its forecasts.

Additionally, other evaluation metrics such as root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), median absolute percentage error (MdAPE), and symmetric mean absolute percentage error (SMAPE) were calculated for both models. These metrics provide further insights into the performance of the models across different forecast horizons.

The results clearly demonstrate that the Prophet model outperformed the ARIMA model in terms of forecasting accuracy. It consistently achieved lower MSE values, indicating superior predictive capabilities. The lower MSE values of the Prophet model imply that it provides more accurate and reliable forecasts compared to the ARIMA model.

These findings suggest that the Prophet model is a more suitable choice for forecasting the given dataset, as it demonstrates better performance and accuracy in capturing the underlying patterns and trends. The ability of Prophet to incorporate seasonality, trend changes, and outlier handling techniques contributes to its superior performance over the ARIMA model, which relies solely on past values and stationary assumptions.

Overall, based on the evaluation metrics, it can be concluded that the Prophet model is better suited for the forecasting task at hand, offering improved accuracy and higher-quality predictions compared to the ARIMA model.

Discussion

The results of the evaluation provide valuable insights into the performance of the ARIMA and Prophet models for forecasting the given dataset. In this discussion section, we will delve into

the implications of the results, discuss the strengths and limitations of each model, and provide possible reasons behind the observed performance differences.

The significantly lower mean squared error (MSE) achieved by the Prophet model compared to ARIMA indicates that Prophet was able to capture the underlying patterns and trends in the dataset more accurately. This is likely due to the unique characteristics and capabilities of the Prophet model, which incorporates additional features such as seasonality, trend changes, and outlier handling techniques. These factors allow Prophet to handle non-linear trends and capture complex patterns that may exist in the data, resulting in improved forecasting accuracy.

ARIMA, on the other hand, relies on the historical values of the time series and assumes stationarity, making it less flexible in capturing changing patterns and trends. This can lead to higher prediction errors, especially when the underlying data exhibits non-linear patterns or seasonality. The high mean squared error observed for ARIMA suggests that it struggled to capture the inherent complexities and dynamics of the dataset accurately.

It is worth noting that both models have their own strengths and limitations. ARIMA is a classical time series model with a solid theoretical foundation, making it suitable for capturing linear dependencies and well-behaved stationary data. It is relatively simple to implement and interpret, making it a popular choice in various forecasting applications. However, it may struggle with non-linear and complex datasets, as evidenced by the higher MSE in this study.

Prophet, on the other hand, is a more modern and advanced forecasting framework that integrates several innovative techniques. It incorporates domain-specific knowledge, handles multiple seasonality, and is robust to outliers and missing data. Prophet's flexibility and ability to adapt to various types of datasets make it a powerful tool for forecasting tasks. However, it may require more computational resources and longer training times compared to ARIMA.

In conclusion, the results of this study demonstrate that the Prophet model outperforms the ARIMA model in terms of forecasting accuracy for the given dataset. The superior performance of Prophet can be attributed to its ability to handle non-linear trends, incorporate seasonality, and adapt to changing patterns. The discussion highlights the strengths and limitations of both models and emphasizes the importance of selecting the appropriate model based on the characteristics of the dataset and the forecasting requirements.

Further research and experimentation could focus on exploring other advanced forecasting models and techniques, evaluating their performance against the Prophet model, and considering ensemble methods or hybrid approaches that combine the strengths of multiple models. Additionally, conducting sensitivity analyses and robustness checks could provide additional insights into the stability and reliability of the obtained results.

Evaluation and Reflection

Evaluation

The evaluation of the ARIMA and Prophet models involved a comprehensive analysis of their forecasting performance using various evaluation metrics. The evaluation process aimed to assess the accuracy and reliability of the models in predicting the future values of the dataset.

Both models were evaluated based on metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), median absolute percentage error (MdAPE), and symmetric mean absolute percentage error (SMAPE). These metrics provided a holistic view of the models' performance by capturing different aspects of forecast accuracy and error.

The results of the evaluation indicated that the Prophet model consistently outperformed the ARIMA model in terms of forecasting accuracy. The lower MSE values obtained for Prophet compared to ARIMA reflected the superior ability of Prophet to capture the underlying patterns and trends in the dataset. The Prophet model exhibited lower RMSE, MAE, MAPE, MdAPE, and SMAPE values, indicating better overall performance across different error metrics.

Reflection

The evaluation results highlight the strengths of the Prophet model in handling complex and non-linear patterns, incorporating seasonality, and adapting to trend changes. The superior accuracy of Prophet can be attributed to its advanced modeling techniques and the incorporation of domain-specific knowledge. On the other hand, the evaluation revealed the limitations of the ARIMA model, which struggled to capture non-linear patterns and handle seasonality effectively.

The evaluation of the ARIMA and Prophet models provided valuable insights and raised important considerations for forecasting tasks. The comparison between the two models showcased the advantages and disadvantages of each approach, shedding light on the trade-offs involved in selecting an appropriate forecasting technique.

Reflecting on the evaluation process, it is evident that accurate forecasting requires careful consideration of the dataset characteristics and the specific requirements of the task. The selection of the Prophet model for this study was justified by its ability to handle non-linear trends and seasonality, which were present in the dataset. The evaluation confirmed that this choice led to more accurate forecasts compared to the ARIMA model.

However, it is important to note that the evaluation results are specific to the dataset and the forecasting horizon considered in this study. Different datasets with varying characteristics may yield different performance outcomes for the ARIMA and Prophet models. It is crucial to thoroughly analyze the dataset, understand its underlying patterns, and consider the modeling assumptions and capabilities of different forecasting techniques before making a selection.

Furthermore, the evaluation could be enhanced by exploring additional evaluation metrics, considering longer forecasting horizons, and conducting cross-validation or out-of-sample testing to assess the models' generalization capabilities. The inclusion of uncertainty estimation techniques, such as prediction intervals or probabilistic forecasting, would provide a more comprehensive assessment of the models' reliability and confidence in their predictions.

In conclusion, the evaluation and reflection emphasize the importance of selecting the most suitable forecasting model based on the dataset characteristics, understanding the modeling assumptions and limitations, and critically evaluating the performance metrics. The results obtained from this study provide valuable insights for decision-making and highlight the potential benefits of leveraging advanced forecasting techniques like the Prophet model.