Time Series Forecasting Using FB-Prophet

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Abstract
In multiple problem domains, including sales, finance, the stock market, etc., predicting methods are applied. Predicting the Indian stock market is to figure out a company's future value which is listed on NSE or BSE. Accurate stock valuation predictions may result in great profits. Information about time is contained in the time-series statistics. The regression model and the logistic exponential model are just two of the many forecasting techniques available. The most recent instrument to demonstrate enhanced effectiveness in terms of forecast accuracy is the fbprophet. In comparison to traditional models, Facebook's Prophet model, developed specifically for time series prediction, has recently proved effective in precisely fitting data patterns and seasons. To accommodate both the seasonal and non-linear components of stock price data, this study analyses the Facebook Prophet model to forecast the subsequent closing price of the top-ranked bank's stock on the NSE. This study shows that fbprophet gives a lower error rate and generates improved predictions in comparison to the ARIMA model.

Keywords
ARIMA, Time series forecasting, Facebook prophet, stock market, NSE

1. Introduction

Analysing historical data to acquire relevant stats and other features is important. Future prices of stocks are greatly dependent on prediction methodology. With time-series data, the outcome is not known, thus it's very crucial how carefully the data is understood and analysed. Knowing the pattern of relevant facts and their timing is necessary to ascertain the underlying cause of a specific event. Time series' primary elements are level, trend, season-ability, and noise which means, base value, increase/decrease in cost, pattern, and variability of data respectively. Figure1 [1]shows the overview of the workflow of Prophet methodology.

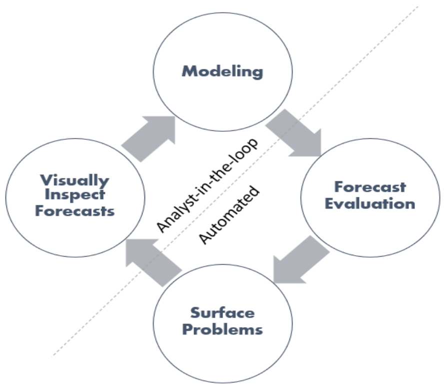

Figure 1: Workflow of Prophet methodology

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To do a forecast, Prophet is built and distributed as an open-source and works well with both python and R[2]. It takes into consideration time series data based on hour, day, week, month, year, and more. Holidays and breaks are predetermined. It also handles missing values, trends, etc.

The primary objective of this study is to use the FB Prophet methodology to perform a time series analysis of stock market data. The gathered information is examined by fitting it to the Auto-Regressive Integrated Moving Average (ARIMA) model, which has demonstrated enhanced future forecasting.

The Bayesian model's curve fitting method serves as the foundation for the FB Prophet. It contains parameters that are simple to understand and can do predictions with less amount of data as well. The approach works best when there are significant seasonal influences on the data. It also accounts for specified breaks or holidays. When it comes to missing data, changing patterns, and outlier detection, FB Prophet outperforms. It also offers libraries that are simple to use and interpret.

2. Related Work

For a variety of problem areas, the FB Prophet is used in numerous research projects for time-series prediction. Linear regression served as their base model. They have used past stock values along with hybrid parameters, which gave 0.9989 & 0.9983 as co-efficient of determination.

Thoutam et al. [3] in their work have worked with the Stock market of Indonesia. Naïve Bayes and Random Forest techniques were applied to Twitter data and tweets were then classified using sentiment analysis.

Sharma K et al.[4] have reviewed and presented the comparative study of various techniques of stock market prediction i.e., Technical and fundamental techniques, along with fundamentals of valuations: P/B ratio, P/E-ratio, PEGand dividend. It is concluded that both fundamental and technical analysis, with added features like sentiments if combined can give a good solution to this.

Nagesh P. [5] has suggested a novel pairing of the recently created Facebook Prophet model and the Attention-Based Long-Term Short-Term Memory approach to forecasting the subsequent close price of NIFTY 50 stocks from 5 sources, to account for both the seasonality and non-linear components of the stock market. This model gave MAPE 3.3 to 7.7, which is better than other undertaken models.

To create an even more reliable predictor that can manage a variety of situations wherein investing can be advantageous, Pathak et al. [6] in their research try to merge several already used methodologies. Current methods, such as sentiment analysis or neural network methods, are too limited in their application and produce incorrect results in a variety of situations. Their forecasting model offered more precise and adaptable predictions by combining the two methods. Usmani et al. [7] have attempted to forecast KSE to predict oil, silver, and gold, Foreign exchange rates, news, and social network data. Study analyses various Machine learning techniques: SMA, ARIMA, MLP, RBF, and SVM to name a few. Multi-layer perceptron gave promising results with oil rate as the prime feature amongst others.

Jing et al. [8] have developed a hybrid model for stock price prediction that blends a deep learning method with a sentiment analysis model. They have used a CNN model, the Long Short-Term Memory (LSTM) approach to analyse the technical indicators, and the sentiment analysis findings to suggest a hybrid research model. Their hybrid approach outperformed the other models (models that do not consider sentiments as part of their study).

Pathak et al. [6] have integrated sentiment analysis and NN techniques. As per their study, creating a more precise fuzzy base, enhanced scale, and duration of training data, their model can be enhanced further. The suggested approach can be used to create a trading model that calculates total returns or investments in real-time. This methodology is effective at identifying the top stocks to buy. Deniz et al. [9] in their study, used LSTM on macro-economic and technical indicator datasets. In testing utilising actual data, it was discovered that the suggested hybrid model—which incorporates two distinct LSTMs—responds pretty successfully to each of these two data sets.

Using an ensemble deep learning architecture [10], the stock price for the following day is forecasted. To get more accurate findings, the data set is improved using a variety of deep learning approaches. The approach utilizes a deep learning model to give predictions that are about 85% correct. In terms of high and low stock prices, market movements are perfectly aligned. High-frequency trading algorithms can be used to further improve efficacy.

This article [11] addresses stock prediction using machine learning as a technique to anticipate a stock's future worth. Brokers anticipate stocks, they use a lot of quantitative and technical analysis. These predictions are generally accurate, though occasionally they aren't. However, there is further potential to enhance our prediction by utilising certain machine learning models. This study uses the LR model to forecast stock prices for various financial capitalizations using assets with daily and current minute rates.

Devipriya et al. [12] to display sentiment remarks about the information in the digital trading, presented the findings of sentiments using the analytical tool Rapid Miner. They have used KNN, Decision Tree, and NB as their machine learning models.

To address the high non-linear data of the stock market Thormann et al. [13] have represented a complete guide to collecting twitter data, pre-processing that to extract sentiments out of it, and finally integrating them using technical indicators to find out the future values of AAPL. A model that serves as the basis is lagged-LSTM close price. They demonstrated that, in all situations, a combination of financial and Twitter traits can exceed the base model.

The way traders, and experts use to assess investment portfolios is imitated in Sarkar et al.[14] the study, to build a model. This involves using historical time series data is fed into an LSTM neural network & sentiment analysis to comprehend stocks' news data. It has been shown that this method produces a more generalised, clear, and accurate method that can be applied to stock market forecasting.

The least-squares LR model [15] is used where the goal of their study is to apply a machine-learning technique to estimate the close price of data in order to estimate stock values more accurately. The model is designed such that it can prove helpful as an intra-day trading manual. Their model could further be used for a variety of tasks with very minor adjustments, including analysing and forecasting students' performance, estimating the fuel usage of a car, monitoring a patient's health, and many other tasks.

3. Models and Methods

Facebook's Prophet technique is built on an addictive-regressive technique. The following elements make up the fbprophet model:

$$y(p) = g(p) + s(p) + h(p) + \in_p \quad (1)$$

Here, g(p) is the trend of the time series data, s(p) denotes its seasonal pattern, h(p) denotes its holiday influence, and Ɛp denotes the model error. The model is created using the python-based fbprophet api, and it only requires two inputs: the target variable to be forecasted which close price here, designated as "y," and timestamp, designated as "ds."

3.1. Collection of Data

Dataset is gathered using yfinance api of python for the period of 10 years containing features namely open, high, low, close, adj close, and volume. Training for the model used in this study was given on this dataset.

3.1.1. Pre-processing of data

In this step, the data is cleaned by deleting unnecessary fields and adding any missing/null data. The data was then arranged in this phase according to dates as indices. Only fields considered were close and date.

3.1.2. Analysis of data

Data is fitted to the respective algorithms to get the predictions. Data was then visualised using graphs to show the dataset as per year, which made the data easily understandable, and helped in understanding the stock market movements.

3.1.3. Accuracy Metrics

Errors are calculated in terms of mean absolute error, mean squared errors, and Root Mean Square errors of the undertaken models to check for accurate predictions.

4. Results and Discussions

The section below explains the results of the ARIMA and fbprophet models.

4.1. ARIMA Model

A Statistical prediction model, based on data differentiation minimum once to achieve stationarity level and to find the solution to the auto-correlation problem [16] and using it as input to auto-regression & average integrated equation. Three arguments namely p=5, q=1, and r=2 i.e., lag value, difference order, and moving average model respectively are provided to the Arima method. Methods fit() and predict are then used to train & predict. Figure2(A) depicts ARIMA's outlier plot. Predicted errors can be understood with fluctuations in the drawn curve(A). Figure2 (B) depicts the estimation of kernel density, whereas Figure2(C) shows the theoretical quantiles, which depict the intensity of observed & forecasted data. Figure2(D) explains the randomness in the used data. In figure3 plot is given which compares the predicted prices of the ARIMA model with the actual close price for 30 days time period.

Table 1: Results Summary of ARIMA on hdfcbank data

	Parameters					
Model	Coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-1.2214	0.054	-22.699	0	-1.327	-1.116
ar.L2	-0.7475	0.046	-16.226	0	-0.838	-0.657
ar.L3	-0.1004	0.018	-5.582	0	-0.136	-0.065
ar.L4	-0.0713	0.017	-4.08	0	-0.106	-0.037
ar.L5	0.0519	0.013	4.126	0	0.027	0.077
ma.L1	1.2649	0.053	23.89	0	1.161	1.369
ma.L2	0.73	0.047	15.469	0	0.637	0.822
sigma2	177.6506	2.057	86.383	0	173.62	181.681

4.2. FB- Prophet

API provided by python named fbprophet is used to implement the Prophet technique over the dataset. Results show that FBProphet outperforms the basic ARIMA and another same kinds of models in accuracy levels. Figure3 and figure4 show the stock price forecast based on year and day respectively. It can be derived through the plotted graphs that hdfc stock value is trending upward with the best predicting price of around 4100 and worst of around 1900. Generally, over the past 4 years, hdfc stock price experienced up and down trends during the whole year but finally ended with a higher amount in winters.

Fbprophet gave lower errors and improved fit and predictions in comparison to other state of the art models.

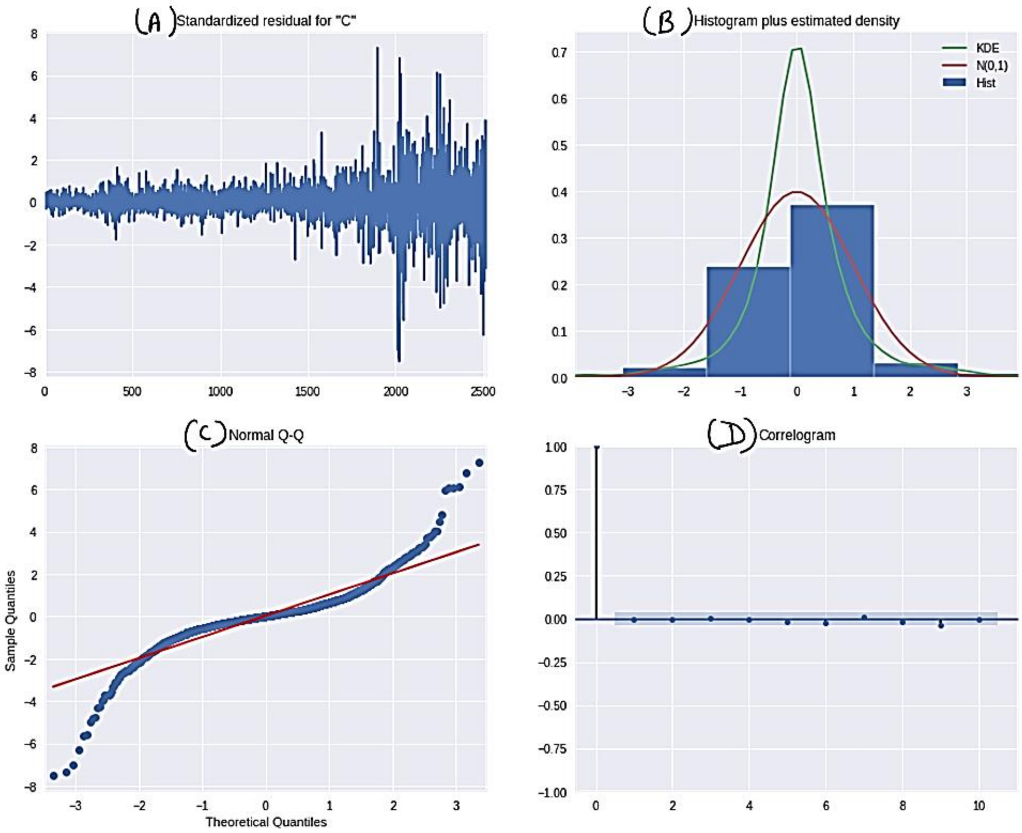

Figure 2: Diagnostic outliers' detection using ARIMA of HDFCBANK

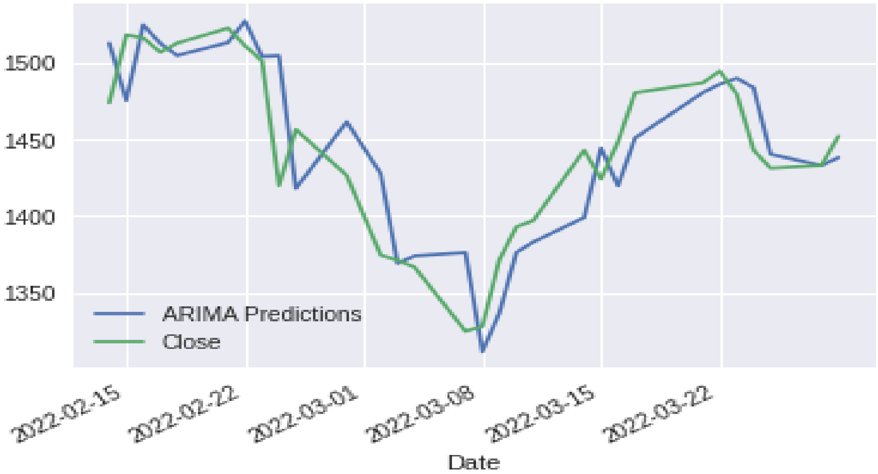

Figure 3: Graph of ARIMA Predictions vs Actual Close Price

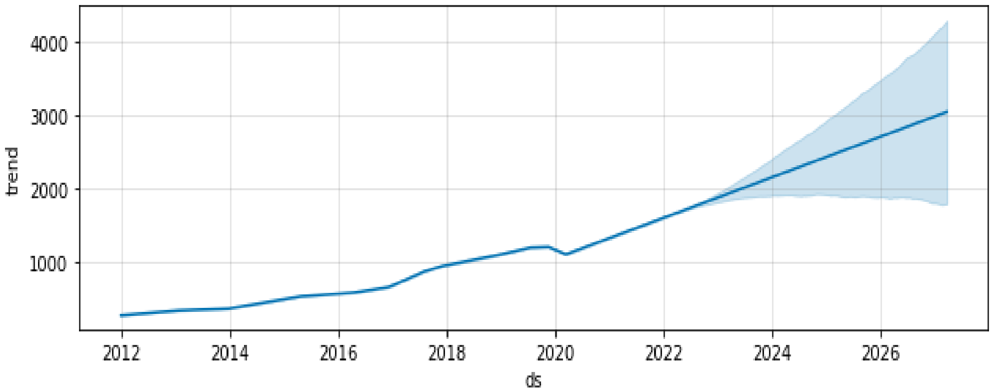

Figure 4: Yearly stock price forecast

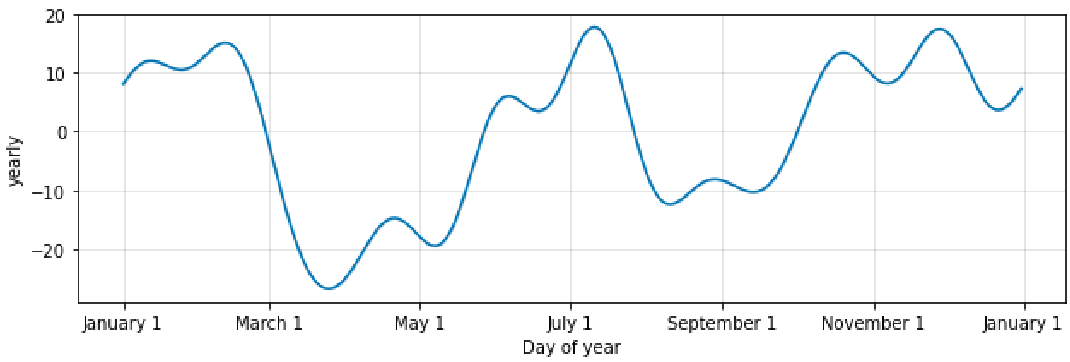

Figure 5: Daily stock price forecast

Table 2: Accuracy Matrix of ARIMA & Prophet models

Model	MSE	RMSE	MAPE
ARIMA	910.7996585	30.17945756	0.016241797
FBPROPHET	693.576886	8.1814283	0.0047011

5. Conclusion

This study analysed the Prophet technique of forecasting and compared it with the traditional ARIMA model for stock market prediction. It can be said that forecasting done using prophet is near to the real value. The proposed model is giving better prediction accuracy with lower error rate. This study has analysed ARIMA and Prophet models over hdfcbank ticker over ten years. Nevertheless, fusion methods using FB Prophet can boost performance. Another difficulty in doing a big dataset analysis can be scalability. To increase scalability and manage large datasets, FB Prophet can be used with a transfer learning methodology. The precision of real-time forecasts depends on the model that was trained and tested.

6. References

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