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Literature Review & Methodology Paper

Abstract:
Undergraduate economics studies made me realize the importance of time series analysis and forecasting, whether at the macroeconomic level with government and central bank economic policies or at the microeconomic level.
During my Master's, my data science professor introduced the class to the Prophet package and required us to complete a project based on a toy problem. Playing with the package made me appreciate its power and simplicity, and it whet my appetite to learn more about it. I started reading articles and watching videos online to learn about all the framework's features. I quickly realized that the daily sales data collected by the company for which I work could be used to train a model and produce accurate business forecasts.

1/ Introduction and literature review
Forecasting is not a new endeavor. Back in 1971, it was estimated that most decision-makers used forecasts to assist them in making decisions. [1]
As the world's demand for accurate forecasts has grown and evolved, new forecasting techniques have emerged. Moving averages and exponential smoothing, ARIMA, ARCH/GARCH, and, more recently, Neural Networks and packages such as Prophet are some of the most used techniques. [2]. There are flaws in all forecasting techniques that subsequent forecasting techniques attempted to address. Prophet was developed by Facebook's core data science team to address the issue of growing demand for accurate business forecasts outpacing analysts' ability to produce them. [3]
Before devoting time and effort to implementing the package for my company's sales data, I began researching what had been done with Prophet on real-world retail sales data. The study by Žunić, Emir, et al showed promising results: using the package, approximately 70% of their study's product portfolio sales could be predicted in a quarterly forecast with a MAPE lass than 30%. 40% of the products forecasted with a MAPE less than 15% are best-sellers, accounting for 80% of the company's revenue. [4].
A study by Papacharalampous, Georgia A., and Hristos Tyralis [5] benchmarked 3 variations of Prophet, random forest, naïve, and linear model, on streamflow data. Prophet models had a higher RMSE than other models in many of their experiments. One concern I have with their study is that they did not mention tuning Prophet's hyperparameters, for example, using Grid Search, which leads me to believe they did not tune Prophet's hyperparameters to optimize Prophet for RMSE.
Many studies have been conducted using Prophet to forecast covid-19 cases in various countries. [6,7,8]. I have not found a study that optimized Prohet's hyperparameter for any performance metric after skimming through all of these studies. Most of these studies concentrated solely on the forecast, and a few of them made use of the package's seasonality plots. While the generation of forecast and seasonality plots are arguably the most important and second most important features of the Prophet package, there are many other very useful

features that could be used to supplement one's analysis. I believe that the existing Prophet literature does not highlight all of the package's features. This paper seeks to fill such a void in the literature. The methodology section will cover most of Prophet's useful features.

2/ Methodology

2.1 Obtaining and pre-processing data

The retail sales data is stored in the company's database. I created a query to retrieve them. There is the full price of the item at the time of sale as well as the actual sales price to infer the discount rate on the sale, if applicable, in the results. The model will be fed the rate passed discount rate rolled up by day later. Salesforce stores e commerce sales data. While e commerce sales do not include the full price of an item at the time of sale, I can retrieve the item's SKU and use it to retrieve the full price of the item at the time of sale and add this information to the e commerce sales data so that the discount rate, if applicable, can be calculated.

2.2 Implementing the prophet package

I implemented the package Prophet in Python. The daily sales volumes are the predicted variable y. The sales data has been rolled up by day using count function across all north American stores. As per the FP&A team, I have removed the period from March 2020 to April 2021 so that the model does not learn anything from this out-of-the-ordinary time.

Other regressors have been added, including the daily actual discount rate, the number of stores open daily, the average maximum temperature, and the average rainfall for the day across all store locations. Adding average maximum temperature and average rainfall to the mix may introduce multicollinearity, but Prophet is quite resistant to it [2].

2.3 Performing data analytics

Prophet really shines when it comes to analytics. The framework includes numerous features for analyzing the data from various perspectives. The main insight that FP&A is interested in is the linear relationship between discount rate and sales volume. The package can model the relationship between the predicted variable y and additional regressors linearly. The coefficients can be printed using the regressor_coefficients function. The coefficient represents the percentage increase in the predicted variable caused by a one-unit increase in the regressor. In the case of the actual discount rate, a one-unit increase in the regressor (here discount percent) may be profitable if it increases sales by more than 1%; otherwise, it is not. The framework also includes ways for analyzing the impact of calendar events, such as Black Fridays, on the predicted variable. Understanding the impact on sales volume by examining the results of extra regressors, calendar events, seasonality in sales volume, and long-term trend will greatly improve the leadership team's decision-making process.

2.4 Evaluating results and optimizing – performance metrics

Prophet’s diagnostic package offers 7 different metrics for model evaluation. [9] After reviewing Rafferty’s chapter on Prophet’s performance metrics [2] I decided that the metric which made the most sense to optimize the model for was the RMSE.

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \check{y}_i)^2$$

Figure 1 – Mean squared error

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \check{y}_i)^2}$$

Figure 2 – Root mean squared error

For a few key reasons, I believe that MSE, and especially RMSE, make the most sense for the scope of my project. It can be proven that optimizing for (minimizing) MSE can reduce both bias and variance [2]. Furthermore, MSE gives more weight to outliers, which is desirable in the context of my project. Indeed, demand for high-end fashion items is quite price-elastic. A 10% discount, for example, may result in a greater than 10% increase in sales volume. In other words, a large portion of annual sales volume is generated during a small window of time, which is why accurately forecasting these short time windows is critical.

One limitation of MSE is that the number it returns cannot be interpreted on its own. This is addressed by squaring the results, which gives RMSE. RMSE has the same properties as MSE and produces interpretable results because it is scaled to the same unit as the data.

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