RHProphet: An Enhanced Sales Forecasting Model

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Abstract

Precise and long-range business forecasting can drastically improve the performance of any organization which results in high turnover in business and consequently increase the profit. Henceforth a consistent business forecasting model is inevitable for any business organization for their growth. Forecasting of the business involves lot of issues like present trend, error handling, seasonal and holiday effects etc. In present day customer feedback or customer satisfaction is one of the most important features for analyzing the business. One of the common ways to analyze the customer satisfaction is review-score by which customer can express their view about any particular product. Maintaining a healthy review score generally increase sales, whereas unhealthy review score is detrimental. Many methods have been applied for the forecasting. In this research work we choose a new forecasting model named Prophet that is designed mainly for social network analysis. It can be successful in the area of sales forecasting too if it considers customer-satisfaction as another parameter. We propose a modified Prophet model that emphasizes more upon customer satisfaction to perform the trend analysis. Experimental results reveal that the performance of the proposed methodology is better than the other standard models in practice.

Key Words: Forecasting, prediction, prophet, data analysis, business intelligence

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1 Introduction

The goal of almost every business organization is to maximize their profit with minimum investment of resources. Therefore, proper accordance is required between production and market demand in order to result in continuous improvement of profit and high market share. Hence, business forecasting [2, 11, 23, 25] becomes an essential task for almost every organization across all the sectors. An accurate business forecasting [18, 24] model can reduce risk factors, incorporate proper production, manages supply chain, manpower and capacity planning. A good business forecasting model is one of the major concerns for every organization. A company could succeed further with a suitable forecasting model whereas another company may not excel due to the absence of a good forecasting model.

Business forecasting often employs time series [17, 26, 30] data analysis which requires close monitoring of data set's correlation over the time and therefore involves lot of data exploration. Business forecasting trend analysis initially starts with some easy statistical models like sample mean, linear trend forecasting, drift [18] etc. Nowadays, the size of data grows exponentially [17] for the huge increase of transactions and the nature of data get complex due to the introduction of different parameters [17]. A simple analysis tool is not capable to handle all these issues. Thus, a forecasting model is required that could work with different parameters, various types and patterns of data to consolidate the business intelligence [6-8, 25] to drive the future growth. But, producing finest long-range business forecast involves lot of varying factors and hence is not an easy task to perform. Hence, for more accurate business forecasting different artificial neural-network based algorithms [16, 22] have been proposed over the time.

Some powerful forecasting models like ARIMA (Auto-Regressive Integrated Moving Average) [5, 15], Prophet [26] is proposed over the time in order to perform long range forecasting. These models use series own history [9, 26] as an explanatory variable and hence produce better results. ARIMA [8] is a popular and powerful statistical method for time series forecasting but have some flaws in case of long-range business forecasting especially when specification change noticed between training data and forecasted data. Prophet is an additive model [26] which is capable of fitting non-linear trends with seasonal and holiday effects. The Prophet model is also capable of handling missing data and robust to any trend changes by selecting automatically the change-points in data. Also, it can handle outliers well enough. But, the trend function of a specific product's sales not only depends upon present trend but is also affected by the present performance of that particular product. For example, consider the trend of a particular cell-phone is moderately low due to some reason, but if it receives good review-score, then of course in future sales will be higher than calculated. But, Prophet [26] forecasting model does not consider any user feedback for trend calculation. In order to apply Prophet in sales forecasting [28] of a particular product some modifications are required. Further, in business the growth could be upward or downward however in case of negative business growth Prophet generates erroneous results. Henceforth it is a challenge to modify Prophet to forecast all type of business scenario. In this paper we have proposed a modified Prophet model to fit it for sales forecasting of a particular product.

The paper is organized in the following sections. Related work is described in Section 2. A brief discussion of prophet model is given in Section 3. Proposed methodology in Section 4. Case study and experimental results are demonstrated in Section 5. Finally, in Section 6 we conclude.

2 Related Work

Several business forecasting models [2, 11-12, 26] are proposed over the time to mitigate the gap between actual and predicted business progress. Time series forecasting models like Drift and Particle Swarm Optimization [18] use the basic concept of self-similarity and change detections in data, which emerges in application domains periodically or seasonally. These models are basically batch learning forecasting technique that snoop business trend continuously in the background and try to generate an optimized future forecasting for the organization. But, when any concept drift occurs in the previous trend, the learned established model becomes erroneous and pointless for delineating data behavior. Error monitoring [15, 23] is one of the solutions for proper drift detection. The major limitation of these methods is that they generally monitor error of a particular forecasting model and if it was built using some poor training data set, the overall error detection becomes in vain. In order to overcome this problem, a modified algorithm is proposed that drew on error supervision using multiple forecasting models based upon self-adaptive swarm intelligence [18]. Some modified algorithms like ETS (Error, Trend, Seasonal), seasonal naive are proposed to incorporate other factors that may affect trend prediction [14]. Among these, "ETS" [10] is basically a weather forecasting model and not very powerful for sales forecasting overtime series data. The main goal of "Seasonal naïve" [20] is to set forecasts closely to the last perceived value from the same season of previous years. A four layered probabilistic neural-network [16] based algorithm was proposed for more accurate business forecasting. It assigns some pre-defined tasks to each individual neurons at every layer. The same concept is used in an enhanced way for load forecasting in power system planning by an artificial neural-network [22].

Further, an advanced business forecasting model ARIMA [5, 9] was proposed that summarizes regression error as a linear combination of drift errors that occurred coevally at several times before. It is a univariant model that generates autocorrelation among data set and runs satisfactorily on short range forecasting. ARIMA does not consider exponent variables and hence likely to be unstable for observation changes in training data. It is also very wobbly for any changes in the model specification. Several modified techniques [3, 11, 19] over time series data are proposed for enhanced long-range forecasting. SARIMA (Seasonal auto regressive integrated moving average) [19, 290] was proposed by modifying ARIMA for the time series data having too much compulsion in different seasons and hence not suitable for all types of data. The concept of long-short term memory (LSTM) [3, 21] is used for long-range business forecasting. Further, it is established in study that improved algorithms are also capable of long-range forecasting by limited historical dataset [11]. Several comparative studies [23, 30] are also performed over time among these established forecasting models. A comprehensive forecasting model named as Prophet [26] was designed by Facebook to forecast their social networking progress. But Prophet doesn't consider customer reviews [8, 13] in the trend analysis and hence is not suitable for sales forecasting of a particular product. Prophet can be successful for long-range sales forecasting of a particular product if it employs customers' satisfaction metric for trend calculation.

3 Prophet Model for Forecasting

A fast and reliable model Prophet [4, 26] was proposed by the famous social networking company Facebook for their time series data forecasting. The additive Prophet [26] model is capable of fitting non-linear trends with seasonal and holiday effects. The model [26] is as follows:

$$y(t) = \mathrm{g(t)} + \mathrm{s(t)} + \mathrm{h(t)} + \varepsilon_t \qquad (1)$$

Where, g(t) represents trend function that is capable to handle non-periodic changes in time series data, s(t) is the function that represent periodic changes like yearly or weekly seasonality, function h(t) represents the holiday effects and ε_t represents the error term responsible for idiosyncratic changes.

Prophet model calculates trend function g(t) as following two ways:

a) For Nonlinear and saturating growth, it [26] uses the formula

$$g(t) = \frac{C(t)}{1+\exp\left(-\left(k + a(t)^T \delta\right)\left(t-\left(m+a(t)^T \gamma\right)\right)\right)} \quad (2)$$

b) For Linear trend with change points, it [26] uses the formula

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T \gamma) \quad (3)$$

Where, C(t) = Time-varying capacity, k = Growth rate, m = Offset parameter, δ = Change in rate, γ = Adjustment factor, a(t) = Vector, such that $a(t) \in \{0,1\}^S$, S = Change points.

Prophet basically uses a Bayesian curve fitting method in order to forecast the time series data. Unlike ARIMA, regular quantifications of data are not needed in Prophet [4, 26]. Moreover, in Prophet, missing value interpolation and removing outliers is not required. It automatically finds seasonality of the data sets and has easy to understand parameters. As a consequence, Prophet doesn't require much prior knowledge or experience of forecasting time series data. Therefore, any naive user can use Prophet without having prior knowledge about data or statistics. Prophet works satisfactorily for social-networking type of business forecasting but have low success rate for sales prediction of a particular product. Especially in case of negative business growth, it is not recommended for sales forecasting.

4 Proposed Methodology

Product review plays a vital role in the sales forecasting of a specific product, but a Prophet forecasting model does not deal with any kind of customer feedback. Prophet was mainly developed for social-networking business progress where customer feedback is irrelevant. Hence it is not very suitable for sales forecasting or review forecasting. In this research work the Prophet model is applied in different instances of sales forecasting by incorporating another parameter "Customer-satisfaction". Customer-satisfaction can be represented in different ways in different systems and here the Customer-satisfaction is incorporated as review-score. In this research work review-scores and it's helpfulness has been incorporated for a particular product and integrates these with trend function to predict the sales forecasting accurately over existing methods.

Overall customer reviews can be further judged in a subtle way as a cumulative sum of review-score and its helpfulness to others. Hence in our proposed methodology, we compute trend function g'(t) as:

$$g'(t) = g(t) \times \sum_{i=1}^{n}(r_i \times h_i) \quad (4)$$

Where, g(t) represents the Prophet trend function, n is number of reviews of that particular product, r_i and h_i represents each review-ranking and its corresponding helpfulness respectively.

The modified model is named as RHProphet (Review-Helpfulness Prophet) and can be represented as follows:

$$y'(t) = g'(t) + s(t) + h(t) + \varepsilon_t \quad (5)$$

Where, $g'(t) = g(t) \times \sum_{i=1}^{n}(r_i \times h_i)$ and the other terms g(t), r, h, s(t), h(t) and ε_t have the same meanings as in equation (1).

The next goal is to identify the weight of "r" and "h" in the trend functions. Here "r" represents the review-score and generally in most of the system customer review falls in the range of 1 to 5. In the proposed algorithm the trend model is a multiplicative model, hence we consider the average review-score (i.e., 3) as 1 and rank the other review scores accordingly. For example, consider the following review scores and there ranking as shown in Table 1.

The factor "h" is calculated as the percentage of helpfulness of that particular review. Consider an example about a particular review of a product where the review-score is 4 and it receives total 50 likes and 20 dislikes then the percentage of helpfulness h= (50/70)=0.714. Therefore, the overall "RH" value for that particular review can be calculated as RH= (2 × 0.714)=1.428. Therefore, in order to get final trend function, the $\sum_{i=1}^{n}(r_i \times h_i)$ is finally multiplied by g(t), where g(t) represents trend function of Prophet and 'n' represents the total number of reviews.

The overall process flow diagram of proposed methodology is shown in Figure 1.

5 Case Study & Performance Analysis

We have applied our proposed methodology on the real-life data set to illustrate our method and compare it with other methods. The experimental set up is described below:

Hardware: Experiments are accomplished on an Intel Core i5 processor having 16 GB RAM along with 50 GB SSD which is also used as RAM.

Software: Different Software required for this experimental environment are Python 3.6.9, scikit-learn 0.21.3 used for machine learning, Matplotlib 3.1.2 used for data visualization and pandas 0.25.3 used for large data manipulation.

Data set: We applied our proposed methodology on Amazon review data [1], available in "https://nijianmo.github.io/amazon/index.html".

We sub-divide this time-series data as training and test data. In all the cases, the last one-year data is treated as test data. We compared our proposed forecasting model with Prophet, ARIMA and SARIMA. Finally, we measure the errors using MAPE [3, 15, 22-23, 27] (Mean Absolute Percentage Error), MSE [12, 23] (Mean Squared Error) and MSLE [12, 23] (Mean Squared Logarithmic Error) and shows that the proposed method is performing better than the existing forecasting models.

In order to check the efficiency of the proposed method, we select two different datasets. The first one having positive business growth and that of second is negative. Further, we do not normalize the data and applied algorithms upon this raw data set.

5.1 Case Study-1

We have chosen "Electronics" data set from the above-mentioned Amazon data [1] sources as our first case study. The original time series data is shown in Figure 2 (Blue Line: Training data, Green Line: Test data).

In order to forecast test data with the help of training data, we applied Prophet, ARIMA, SARIMA and proposed forecasting algorithm RHProphet upon it. Results are shown in Figure 3(a), 3(b), 3(c) and 3(d), respectively.

Table 1: Review ranking scores

Review Score	**1**	**1.5**	**2**	**2.5**	**3**	**3.5**	**4**	**4.5**	**5**
Review Ranking	**-3**	**-2.5**	**-2**	**-1.5**	**1**	**1.5**	**2**	**2.5**	**3**

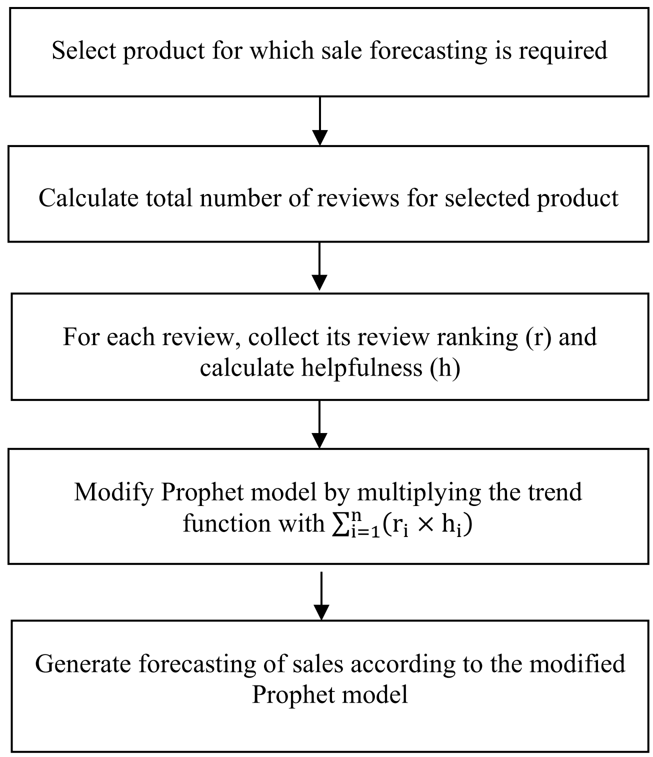

Figure 1: Process flow diagram

Algorithm

/* **Input:** Training data.
Purpose: Forecast business progress with the help of training data.
Output: Forecasted result of business progress. */
Step 1: Start
Step 2: n=number-Of-Review
Step 3: RH=0
Step 4: Loop for i=1 to n
r= i^{th} Review score
/* Total likes and dislikes of i^{th} review is fetched from the system and store it in l and d variable respectively. */
l= Total-Like
d= Total-Dislike
$\mathrm{RH} = RH + r \times \frac{l}{(d+l)}$
End Loop
Step 5: $g'(t) = g(t) \times RH$
Step 6: $y'(t) = g'(t) + s(t) + h(t) + \varepsilon_t$
Step 7: Generate forecasted result according to y'(t)
Step 8: Stop

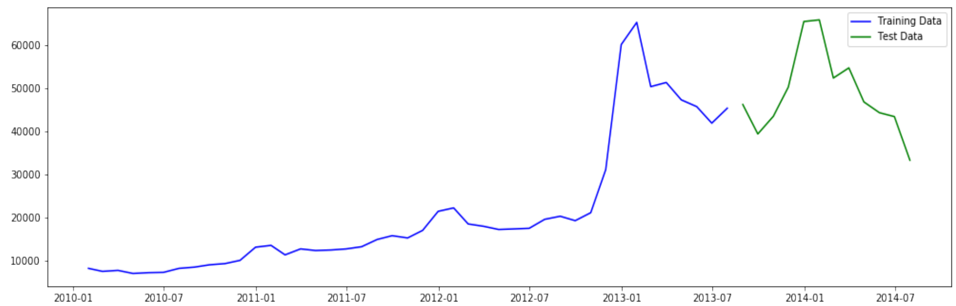

Figure 2: Original data (divided into training and test data), case study-1

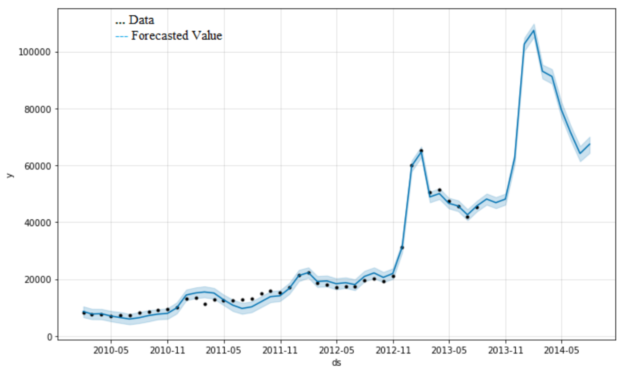

Figure 3(a): Forecasting using Prophet (case study-1)

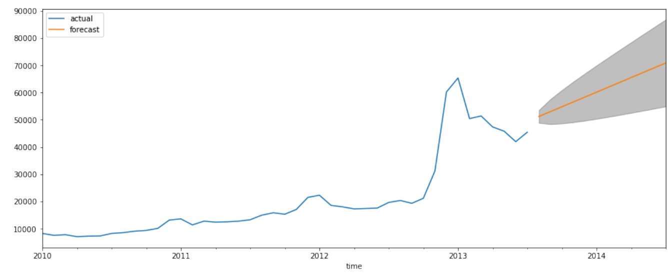

Figure 3(c): Forecasting using SARIMA (Order: 1,2,1 with seasonality 12) (case study-1)

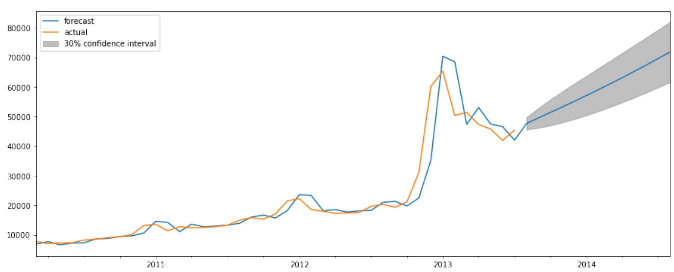

Figure 3(b): Forecasting using ARIMA (Order: 1,2,1) (case study-1)

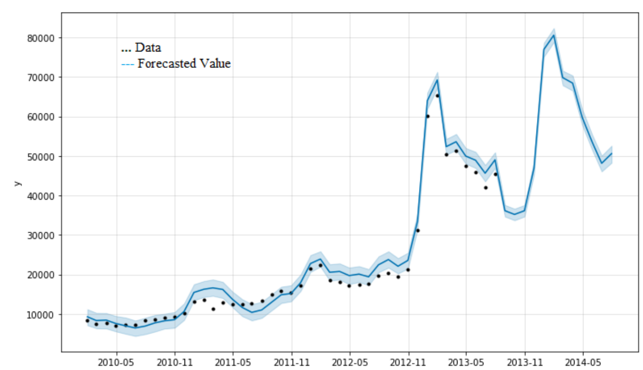

Figure 3(d): Forecasting using RHProphet (case study-1)

Figure 3: Forecasting results (case study-1)

Next, the goal is to detect the percentage of error among applied methodologies. In Table 2, we have shown a comparative result using standard error measuring techniques MAPE [12, 23], MSE [12, 23] and MSLE [12, 23] in order to validate our claim.

Table 2 clearly shows that in all the cases, the forecasting error is less in RHProphet (proposed) methodology.

Table 2: Error values (case study-1)

Forecasting Model	MAPE	MSE	MSLE
Prophet	58.00	232.52	0.23
ARIMA	29.30	105.64	0.09
SARIMA	33.32	138.28	0.11
RHProphet	25.82	88.64	0.07

5.2 Case Study-2

We chose another data set “Cell_Phone_&_Accessories” from the Amazon data [1] sources as our second case study which comprises of negative business progress. The original time series data is shown in Figure 4 (Blue Line: Training data, Green Line: Test data).

We chose this dataset as the business progress is decaying over time and we need to check whether our proposed methodology is effective in this type of business forecast or not.

In the same way, we applied Prophet, ARIMA, SARIMA and RHProphet upon training data in order to forecast test data. Results are shown in Figure 5(a), 5(b), 5(c) and 5(d), respectively.

In Table 3, we have shown a comparative result using error measuring techniques MAPE [12, 23], MSE [12, 23] and MSLE [2, 23] in order to validate our claim in this case also.

Table 3 shows that, although in case of negative business growth, error terms are more but still in all the cases RHProphet methodology produce better result than other standard models.

Hence, for both positive and negative business growth, proposed methodology (RHProphet model) produces better forecasting than other standard models.

5.3 Result Analysis and Discussions

In this section the result sets are analyzed as the outcomes of the case studies and this proves the improvement over existing methodologies.

For increasing business growth (Case study-1), a statistical comparison of forecasting errors (Reference Table 2) with other models is shown in Figure 6.

Depending upon different error measuring techniques, it is being observed that the proposed methodology produces 56% to70% less errors than the Prophet model. It’s improvement over ARIMA is 12% to 22% and that of SARIMA is 23% to 36% respectively. Hence for positive business growth, we can conclude that RHProphet model achieves 12% to 22% more accuracy than its nearest competitor (for example, in this case the nearest competitor is ARIMA model).

For negative business growth (case study-2), we have performed the same comparative analysis. The result is shown in Figure 7.

In negative business growth, it is being observed that the proposed methodology produces 36% to 91% less errors than the Prophet model. Its improvement over ARIMA is 12% to 26% and that of SARIMA is 31% to 82% respectively. Hence for negative business growth, we can conclude that RHProphet model achieves between 12% to 26% more accuracy than its nearest competitor.

6 Conclusion and Future Works

As a consequence of missing customer-review in trend calculation, Facebook’s Prophet is more prone to errors for sales forecasting of a particular type. This research paper performs a novel modification upon Prophet for forecasting sales by incorporating review-score and its helpfulness to others. The newly proposed model has been tested over real-life Amazon data with both cases of positive and negative business growth. In both of the cases, it is being noticed that the proposed model performs better than other well-known forecasting models. This model is also applicable to any type of sales forecasting provided that the data set contains the information of customer satisfaction/customer feedback.

The proposed methodology is applicable if the customer feedback is available in numerical format only. If the feedback is given in text format it is beyond the scope of this work. This could be considered as the future scope where the text data can be processed to apply in our model. Natural Language Processing (NLP) can be applied to integrate the proposed model to work with feedback in both numeric and textual form. Moreover, using customers’ review analysis, their buying pattern forecasting may be another extension of this research work. This forecasting will also help to develop the different stages of supply chain management of the organization including logistic management.

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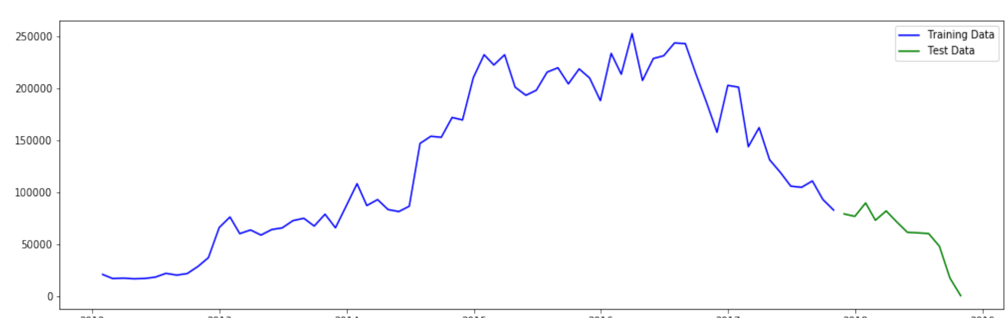

Figure 4: Original data (divided into training and test data), case study-2

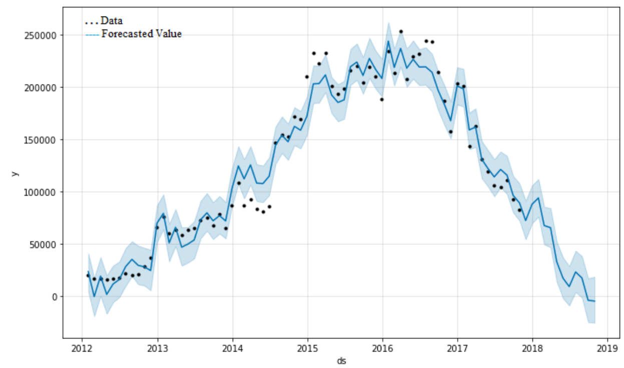

Figure 5(a): Forecasting using Prophet (case study-2)

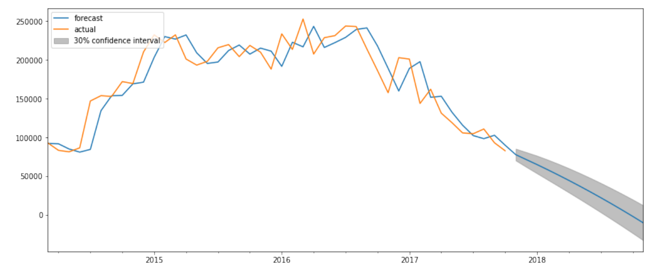

Figure 5(b): Forecasting using ARIMA (Order: 1,2,1) (case study-2)

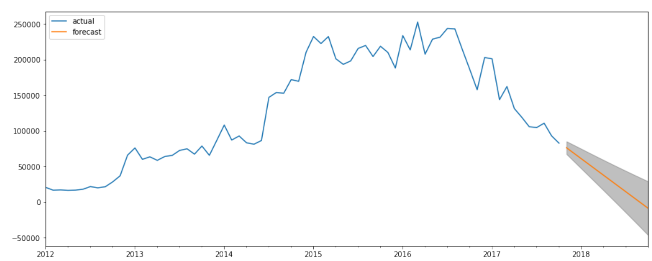

Figure 5(c): Forecasting using SARIMA (Order: 1,2,1 with seasonality 12) (case study-2)

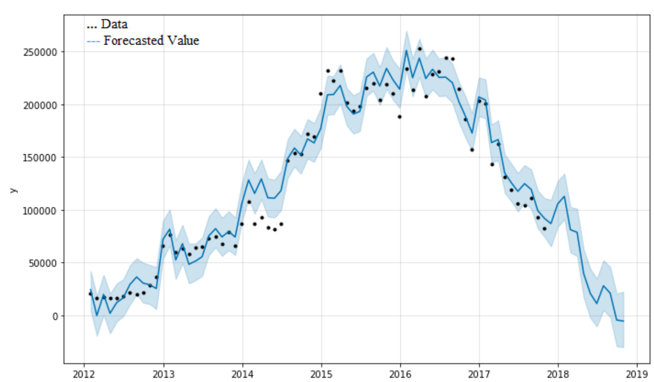

Figure 5(d): Forecasting using RHProphet (case study-2)

Figure 5: Forecasting Results (Case study-2)

Table 3: Error values (case study-2)

Forecasting Model	**MAPE**	**MSE**	**MSLE**
Prophet	57.27	274.52	21.33
ARIMA	43.38	186.24	2.73
SARIMA	53.51	220.58	10.96
RHProphet	36.05	152.66	2.02

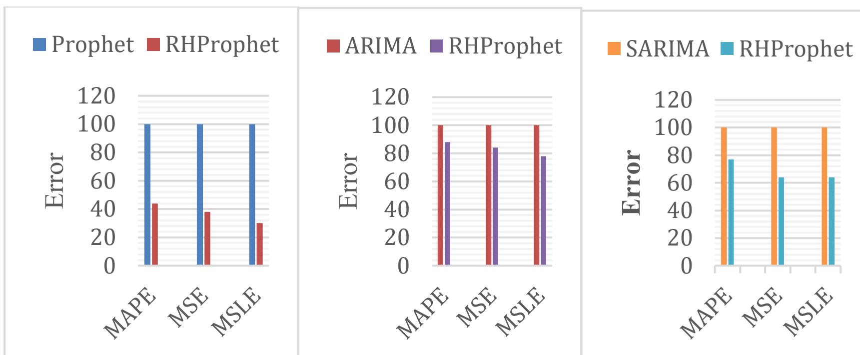

Figure 6(a): Comparison with Prophet, Figure 6(b): Comparison with ARIMA, and Figure 6(c): Comparison with SARIMA

Figure 6: Statistical comparison with other established models for positive business growth (Case study-1)

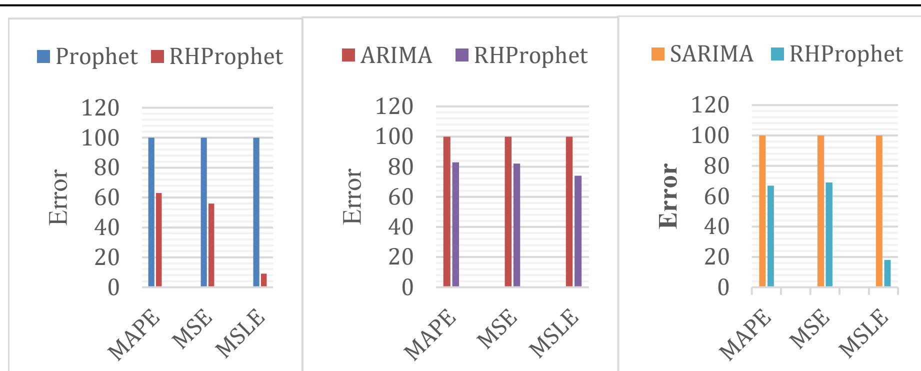

Figure 7(a): Comparison with Prophet, Figure 7(b): Comparison with ARIMA, Figure 7(c): Comparison with SARIMA

Figure 7: Statistical comparison with other established models for negative business growth (case study-2)

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