EXPERIMENT REPORT - Forecasting Model

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Project Name	Assignment 2 Forecasting Model
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Deliverables	Notebook Name: karki_ronik-24886412-forecasting_prophet.ipynb Github Repo: https://github.com/ronik999/Machine_learning_as_a_service/tree/master API URL: https://mla-at2-e0654ce6deb8.herokuapp.com/

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1. EXPERIMENT BACKGROUND	
1.a. Business Objective	The main goal of this project is to predict the total revenue of the US Retailer. By observing the trend, seasonality, and other aspects, the machine learning model created for this model would predict the revenue in future dates which would help the retailer to look at how much revenue the business will be making in the future and can work on improving areas if it doesn't meet the expected revenue as the retailer wants. As the problem is to predict the revenue, this problem requires a regression model for prediction. Therefore the good metrics for this problem would be having low Root Mean Squared Error(RMSE) and Mean Absolute Error(MAE). Furthermore, R-squared metrics would also be good to analyze how well the model would be able to explain the variance. If there is a high RMSE and MAE score then the model won't be able to predict the revenue properly. It defines the range(either higher or lower) than the real value which gives the estimation of errors the model made at the time of prediction. Therefore, a good model should be able to minimize both errors in creating a reliable model.
1.b. Hypothesis	The forecasting model will have the ability to preserve the trend and seasonal values for predicting future events. Therefore the hypothesis is that there will be an impact on the model performance due to the exploratory variables like holidays etc.

1.c. Experiment Objective	The expectation from this experiment is that a forecasting time series model like the Prophet model will have the ability to get insights of the time series values and predict with less MAE and RMSE scores which is also the main objective of this project.

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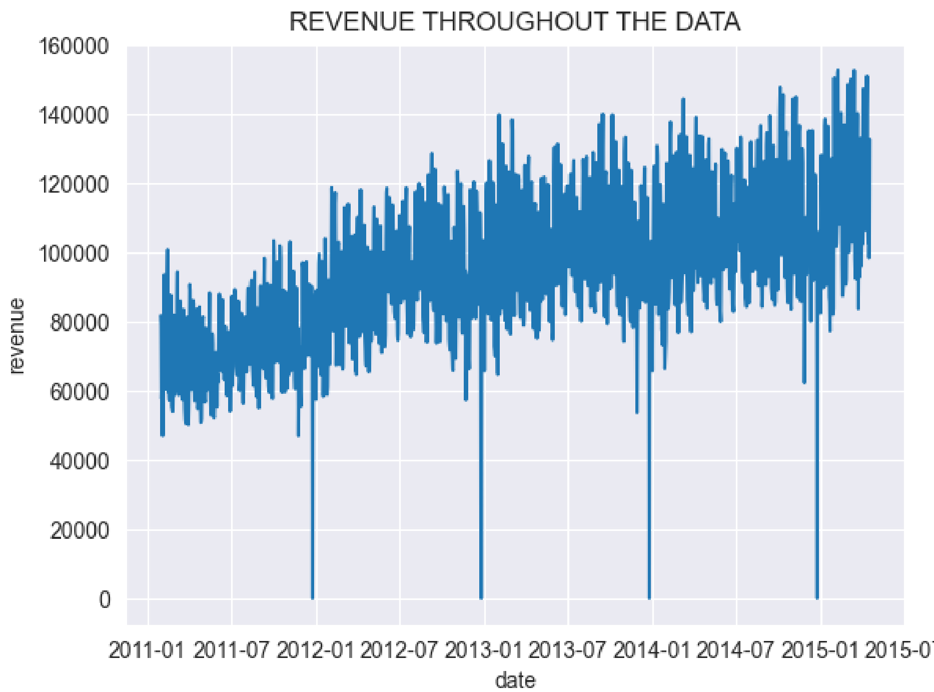
2. EXPERIMENT DETAILS	
2.a. Data Preparation	For the data preparation part, the saved pandas data frame table was imported which already had cleaned and ordinal encoded values which were then removed, and only date and revenue were selected. Furthermore, as the prediction is to be done for the total number of sales per date, the data was further grouped according to date and all of the revenues were added. This created the dataset to have 1541 dates with each date containing their relevant total revenue.
2.b. Feature Engineering	For this experiment, there was no feature engineering applied. However, there was some observation which was observed from the data and was applied for the modeling of the forecasting model.  Fig 1: Line plot of revenue for all the dates available in the data From the graph(i.e. Fig 1), it can be seen that there has been a significant drop in revenue four times in four years. To observe this in a more detailed way a table was created to find the dates where those significant drops were observed:

	date	revenue
330	2011-12-25	23.68
696	2012-12-25	24.73
1061	2013-12-25	34.32
1426	2014-12-25	37.86

Table 1: Dates of revenue below $1000

It can be seen from Table 1 that the revenue dropped on the 25th of December. It might be due to the Christmas Day holiday. Keeping this in mind, other holidays might also have an impact on revenue so these holidays were fitted on the time series model for improving the model performance.

2.c. Modelling

For the time series forecasting model, the dataset was split into two halves. The train set had the data where the date was before '2015-04-12' and the Test set had information after this date. The test set consists of only 7 days of information and the model is required to predict for the next seven days from the input date.

For the prediction, A famous time series Prophet model was used, which was fitted with the list of holiday dates as it was important for the model to observe these dates as explained in 2b. Section of this report. For the list of holidays, the model was trained on US holidays as the data is based on US retailers.

The robustness of the model was checked by performing a cross-validation on the train split for training the data for up to 1460 days and it was continuously tested for the remaining days on the 7-day interval to get the approximate error scores.

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3. EXPERIMENT RESULTS

3.a. Technical Performance

The prophet model was compared with the naive model scores. The following cross-validation scores were observed for each day as shown in Table 2 below

	horizon	mse	rmse	mae
0	1 days	1.659194e+08	12880.972103	10410.758810
1	2 days	5.043421e+07	7101.704590	6569.514600
2	3 days	8.659557e+07	9305.674033	8244.825064
3	4 days	6.636171e+07	8146.269856	6782.718133
4	5 days	7.466325e+07	8640.789939	7707.785482
5	6 days	9.120189e+07	9549.968207	7037.876172
6	7 days	1.066112e+08	10325.271067	8120.651987

Table 2: Cross Validation Scores for each day's

The model performance shows that the RMSE and MAE scores across 7 days have somewhere between 7k or 8k errors, which means that the model has decent performance as the total revenue are somewhere near 100k each day.

Fig 2: Holiday observation in model

From Fig 2, we can see that the model observed the holiday impacts and it noticed the impact of 4 holidays from the list of US holidays on the dataset. These 4 days are:

1. Christmas Day
2. New Year's Day
3. Veterans Day
4. Independence Day

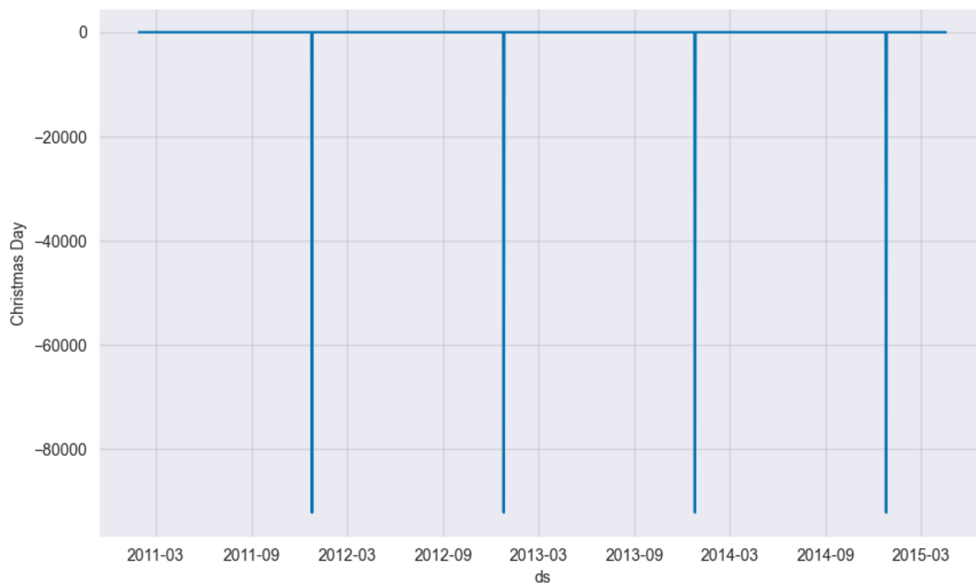


Fig 3: Christmas Day Observation by model

It also proved that the model learned especially the revenue-dropping performance observed on Christmas Day as shown in Fig 3.

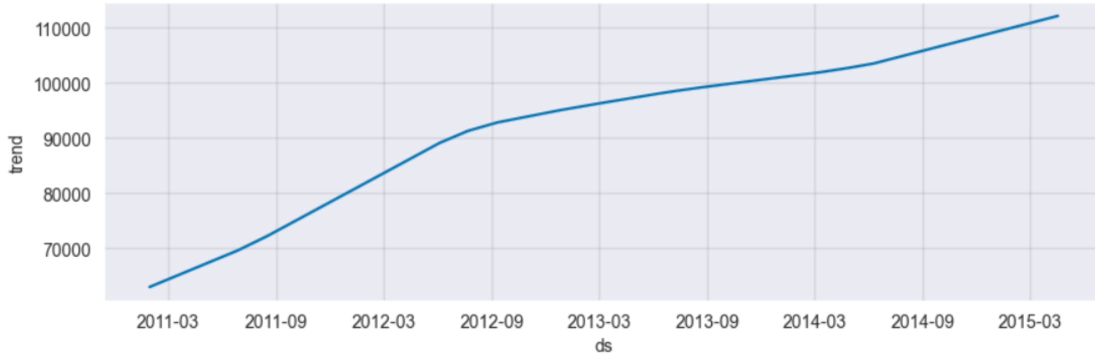


Fig 4: Trend in the data

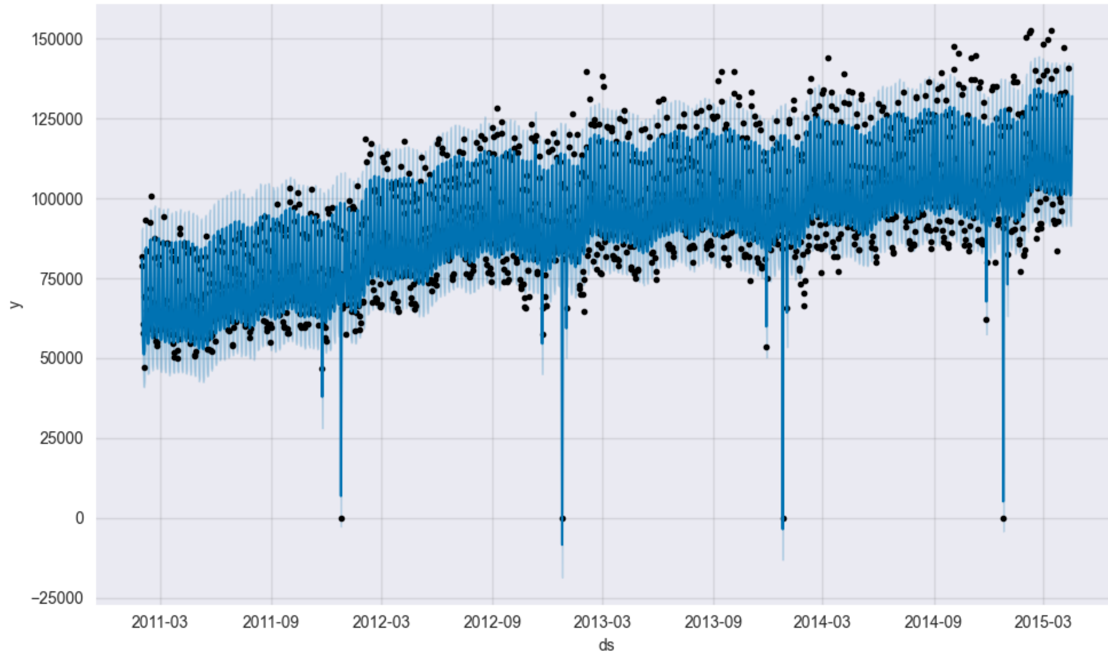
As expected from the time series model, the model was able to observe the trend of the revenue across the different dates as shown in Fig 4.

The following scores were observed in the test set:

Model	Metrics	Testing Scores
Naive Model	MAE	15444.83224
	RMSE	18020.6735
	R2	0.0
Prophet Model	MAE	5451.2427
	RMSE	8111.2247
	R2	0.79740

Table 3: Model Performance on Test Set

It can be seen that the Prophet model outperformed naive model by a lot of improvement on the scores. The prophet model significantly reduced the MAE, RMSE, and R2 scores compared to the Naive model. It is because the model was able to observe all the trends, seasonality, and holidays that impacted the revenue across different dates.

3. b. Business Impact	 Fig 5: Actual Vs Predicted Values for Prophet model MAE score which indicates that the model's predictions are closer to the actual values on average was reduced to 5451.24 and the RMSE which indicates that the model's predictions are closer to the actual values, and are sensitive to larger errors was 8111.227. R2 score of 0.797 shows that it does have a good ability to explain variance. From the figure(i.e. Fig 5) we can see that the model does have some ability to predict and has learned from the dataset. In terms of business, the model is far better than the naive model, This model can be used for estimations as it follows and shows the proper trend. The predicted value can capture significant dates as well. Therefore, the business can use this model to get the expected revenue in the future. Although the model might have errors up to $5000 it would be considerable to figure out the total sales per day in the future.

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4. FUTURE EXPERIMENT	
4.a. Key Learning	Time series model can predict future dates more accurately than the regression model as it absorbs trends and other significant date information and has higher chances to work better if date features are available.

4.b. Suggestions / Recommendations	This model can be improved if more exogenous features like economic indicators, demographic data about the customers, etc were present as they would give more information which would lead the model to get more accurate predictions.