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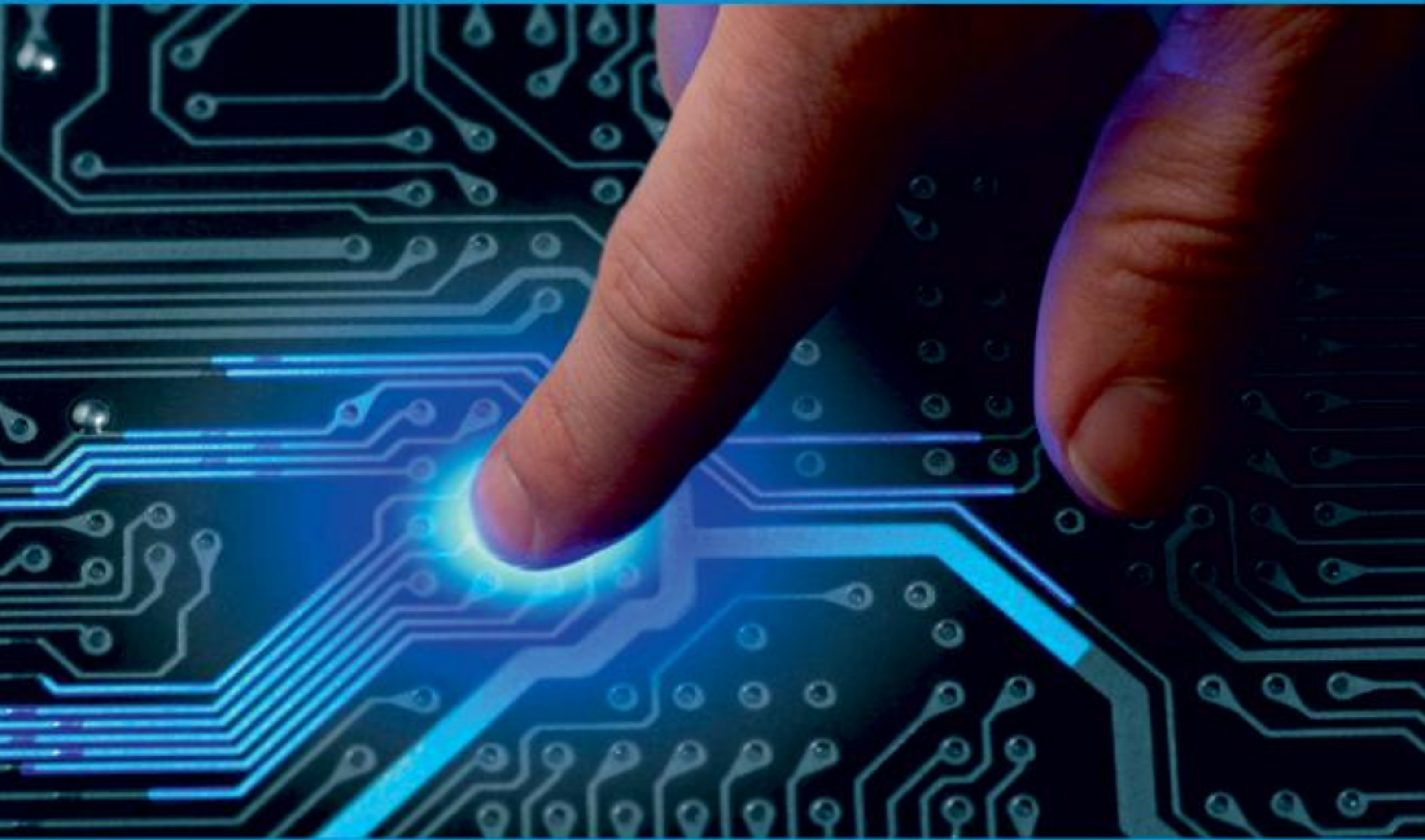

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Food Demand Forecasting for Food Delivery Companies

Dr.B. Sai Jyothi[1], Nalamalapu Chandini[2], Nayudu Lakshmi Priya[3], Malineni Anjali[4]

[1]Professor, Department of IT, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Andhra Pradesh, India

[2 ,3,4,5] UG Student, Department of IT, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, Andhra Pradesh, India

ABSTRACT: Predicting future food demand is a critical step for formulating the agricultural, Economic and conservation policies required to feed over 9 billion people by 2050 while doing minimal harm to the environment. However, published future food demand estimates range substantially, making it difficult to determine optimal policies. Here we present a systematic review of the food demand literature—including a meta-analysis of papers reporting average global food demand predictions—and test the effect of model complexity on predictions. We show that while estimates of future global kilocalorie demand have a broad range, they are not consistently dependent on model complexity or form. Indeed, time-series and simple income-based models often make similar predictions to integrated assessments (e.g., with expert opinions, future prices or climate influencing forecasts), despite having different underlying assumptions and mechanisms. However, reporting of model accuracy and uncertainty was uncommon, leading to difficulties in making evidence-based decisions about which forecasts to trust. We argue for improved model reporting and transparency to reduce this problem and improve the pace of development in this field.

I. INTRODUCTION

Demand forecasting is a barebone of every retailer's business: it is essential formanaging supply chain, planning sales, and shaping customer loyalty. However, getting accurate and timely forecast is no easy task, with errors costing retailers billions of dollars. According to IHL Group, out-of-stocks account for $634 billion in lost sales worldwide each year, while overstocks result in $472 billion in lost revenues due to markdown.

When it comes to fresh food forecasting, things get even more complicated. Fresh food is perishable and thus requires daily forecasting and daily replenishment. With fresh products accounting for up to 40 percent of grocers' revenue and shelf life of 1 to 7 days, perishables pose a forecasting challenge to every planning department.

For decades traditional planning and forecasting systems relied on a rule-based approach. This well-established technique proved to be useful when dealing with stable and predictable systems. Contemporary retailers' routine is anything but stable, however. Demand for fresh and ultra-fresh food fluctuates daily influenced by a wealth of internal and external parameters: advertising, price changes and promotions, product placement, public holidays, and even weather. In other words, historical sales data central to the rule-based approach are no longer enough to produce accurate demand forecasts for fresh food.

It is not only about the parameters. The classical approach also doesn't consider that overstocks and out-of-stocks affect business differently. In other words, the cost of forecasting error equal to 10 wholesale packages of milk is not the same for stockouts and overstocks. While the former results in lost sales, the latter consists of storage costs, cost of capital, and write-offs. For fresh-food assortments accounting for one-third of the cost of goods sold, this difference can be game-changing.

In a pursuit to overcome the limitations of the rule-based approach, retailers addressed the experience of other industries. Once the exclusive domain of internet giants, machine learning (ML) has spread far beyond the walls of IT companies to production lines, bank offices, warehouses, and even crop fields. Leading retailers also have adopted these smart predictive algorithms that analyze huge volumes of data. Unlike rule-based planning systems, ML algorithms can "learn" from data and make predictions based not only on historical sales

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records but a variety of parameters: from promotions and advertising to public holidays and weather.

Fresh food is different though. Items with short shelf life, such as dairy, meat and produce are more difficult to forecast than basic stock items and thus require vastly different forecasting solutions. The good news is, machine learning is a set of various approaches that allow solving an exact pre-defined problem.

In highly competitive retail industry, timely and reliable demand forecasting is essential. Order too little, and you lose sales; order too much, and you accumulate overstock and wastage. Bayesian methods for machine learning, however, give a fresh perspective on how to strike a balance between the two. Applied correctly, machine learning can help retailers reach new heights of operational efficiency, deepen customer loyalty and win a competitive advantage over industry rivals.

MOTIVATION:

Demand forecasting is a key component to every growing online business. Without proper demand forecasting processes in place, it can be nearly impossible to have the right amount of stock on hand at any given time. A food delivery service has to deal with a lot of perishable raw materials which makes it all the more important for such a company to accurately daily and week demand. To much inventory in the warehouse means more risk of wastage, and not enough could lead to out-of-stocks and push customers to seek solutions from your competitors.

II.LITERATURE REVIEW

The supply chain activities planning and control depends of accurate estimates of the volumes of products and services to be processed and the estimates come as forecasts (Ballou, 2007). One of the biggest challenges of food and beverage manufacturers is adjust the production and the stocks to minimize the loss of products due to its short perishability. Time series analysis is very important in a wide range of applications, especially when it comes to forecasting, and it encloses many different forecasting models.

However, it is necessary to determine which model best suits each situation (de Oliveira Silva et al. 2014). There are countless models to develop forecasts presented in the bibliography. From market research to the most complex methods computational. The reference (Ballou, 2007) presents the three main groups of these methods, they are: qualitative, historical projections and causal. Depending on the series and the desired time to be forecasted it is possible to choose a technique that best fits. Besides choosing the best technique, the forecasting to be generated by the model chosen should be as close to real as possible (Junior and Filho, 2012). In other words, the errors of forecasting should be minimized, so the production managers plan the production inattention to the market and minimizing the costs.

The demand forecasting methods can be based in mathematical models that use historical data or in qualitative methods, planned according to the administrative experience and customers reviews. They can also be based in a combination of both quantitative and qualitative methods (Lewis, 1997). This study aims to analyze and forecast the sales demand in order to improve the short to medium term production planning. For minimize the group of analysis, an ABC ranking was utilized to determine that products have bigger importance in demand and in sales. Exponential Smoothing Models The exponential smoothing models are based on smoothing the past data of a time series to predict the future. Among the main advantages of this model are the simplicity and the low cost of application. They are recommended, mainly, when the time horizon is short.

Exponential methods have also been applied in other fields, as in the investigation of exponential random geometric graphs (RGGs) process models. The RGGs characterizes

many randomly deployed networks, such as wireless sensor networks (Shang, 2009). In the following, the main exponential smoothing methods will be presented: The simple exponential smoothing method, the Holt's method and the Holt Winters method.

Simple Exponential Smoothing According to (Krajewski et al. 2012), the simple exponential smoothing is a sophisticated method of weighted moving average. In this method, each new forecast is

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gotten from the previous forecast, increased by the error in the previous forecast which is corrected by a smoothing

coefficient. This method can be applied in forecasting stable demand series, those who oscillate around a constant basis. According to (Krajewski et al. 2012), the smoothing coefficient ( ) balances the forecast sensitivity to the demand changes and the forecast stability. This coefficient has to be contained in the interval [0;1]. The greater is the value of , the faster the model will react to variations in the real demand, because the adjustment will be more aggressive compared to the forecast error made in the previous period. Otherwise, the smaller is the value of , the less aggressive the adjustment will be, in other words, the forecasts will be more smoothed by the previous forecasts and the model will take more time to assume the changes in the time series data pattern.
Holt's Method - Exponential Smoothing with Trend Adjustment The exponential smoothing with trend adjustment sometimes referred as double exponential smoothing or Holt's Method, is a variation of the simple exponential smoothing method and is used to treat seasonal demand with trend (Alexandrov et al. 2012). This method uses two smoothing coefficients, and (with values between 0 and 1) and consists in making the forecast based in two factors: the forecast of the average using the exponential smoothing and a trend exponential estimative. Holt-Winters Method –Exponential Smoothing with Trend and Seasonal Adjustment According to (Giacon and Mesquita, 2011), the Holt Winters method incorporates not only trend, but also a seasonal component. The seasonal demand data are characterized by the occurrence of cyclic patterns of variation that repeat in constant time intervals (Tratar, 2015).
The Holt-Winters method is based in three smoothing equations that are associated to each one of the series pattern components: level, trend and seasonality (Christo et al. 2013). For series where the range of the seasonal cycle keeps constant over time (additive seasonality), the forecast can be calculated through Eq. 1 to 4 (Hyndman et al. 2005): (1) (2) (3) (4) Dt = demand for the period t; Mt = forecast of the level for the period t; Tt= forecast of the trend for the period t; St = seasonal index for the period t; = smoothing coefficient for mean (0 <<1); =smoothing coefficient for trend (0 < < 1); = smoothing coefficient for seasonality (0
< 1); s = a complete seasonal period (Ex: s = 12 when having monthly data and annual seasonality); t= demand forecasting for the next k periods ahead. For series where the range of the seasonal cycle varies over time (multiplicative seasonality), the forecast can be calculated through Eq. 5 to 8: (5) (6) (7) (8) Dt = demand for the period t; Mt = forecast of the level for the period t; Tt= forecast of the trend for the period t; St = seasonal index for the period t; = smoothing coefficient for mean (0 << 1); = smoothing coefficient for trend (0 << 1);=smoothing coefficient for seasonality (0 << 1); s = a complete seasonal period (Ex: s = 12 when having monthly data and annual seasonality); = demand forecasting for the next k periods ahead.The index values for level, trend and seasonality can be calculated through Eq. 9 to 11:(9) (10) (11) ABC Analysis The ABC analysis is based on the Pareto's Principle, defined by the Italian economist Vilfredo Pareto, who says that the majoritarian values (80% of its value) of a particular group comes from a relatively short portion of its components (20 % of its quantity). The most applied method to aggregate products is the ABC ranking that determines the importance of the product, relating demand and sales (Krajewskietal. 2012).
In this case, the products can be grouped into three categories: A Items – Represents 80% of the company sales and about 20% of the products sold. The demand forecast is made individually for each product from this category, however, it maybe manager interest the stratification of the time series according to the region, costumer or sealer; B Items - Represents 15% of the company sales and about 30% of products

sold. As for the A category, the forecasting is made individually for each product from this category, however, it does not need stratification. If any stratification is made over the series correspondent to the A category, the statistical treatment of the series are the same. C Items– Represents 5% of the company sales and about 50% of the products sold. The demand forecast is made in an aggregated way for the products of this category.

II. EXISTING SYSTEM

A food delivery service has to deal with a lot of perishable raw materials which makes it all, the most important factor for such a company is to accurately forecast daily and weekly demand. Too much

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inventory in the warehouse means more risk of wastage, and not enough could lead to out-of-stocks and push customers to seek solutions from your competitors. There is no prediction of future food demands, so let's find the food demands in the coming model.

III. PROPOSED MODEL

The main aim of this project is to create an appropriate machine learning model to forecast the raw materials used for next week. To achieve this, we should know the information about of fulfilment centers like area, city etc., and meal information like category of food sub category of food price of the food or discount and also should have the information about number of orders of a particular category in a particular week. So based on the above information we can predict the number of orders and we can store the raw materials based on the requirement. So there is no problem of wastage of raw materials and lack of raw materials.

IV. METHODOLOGY

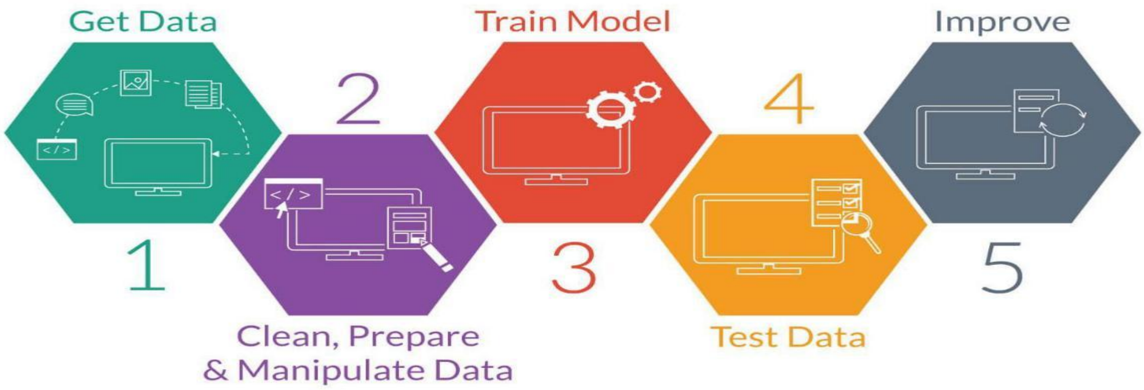

Fig 4.1: An overview of Life Cycle Management in ML

Decision Tree is one of the most commonly used, practical approaches for supervised learning. It can be used to solve both Regression and Classification tasks with the latter being put more into practical application.

It is a tree-structured classifier with three types of nodes. The ***Root Node*** is the initial node which represents the entire sample and may get split further into further nodes. The ***Interior Nodes*** represent the features of a data set and the branches represent the decision rules. Finally, the ***Leaf Nodes*** represent the outcome. This algorithm is very useful for solving decision-related problems.

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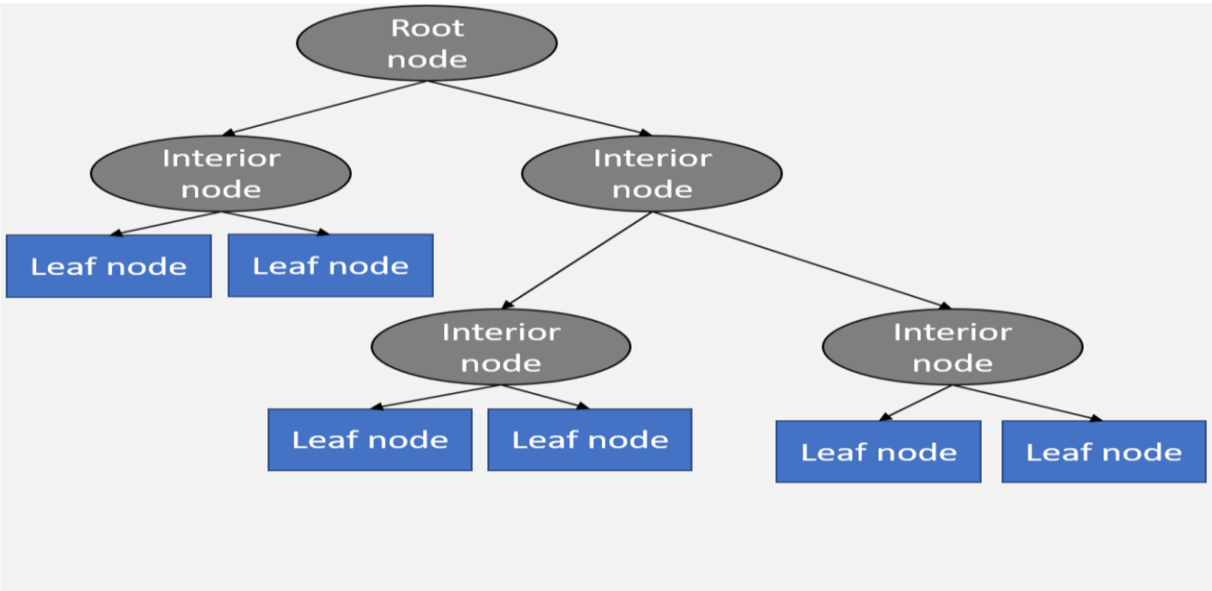

Fig 4.2:Decision Tree Structure

With a particular data point, it is run completely through the entirely tree by answering *True/False* questions till it reaches the leaf node. The final prediction is the average of the value of the dependent variable in that particular leaf node. Through multiple iterations, the Tree is able to predict a proper value for the data point.

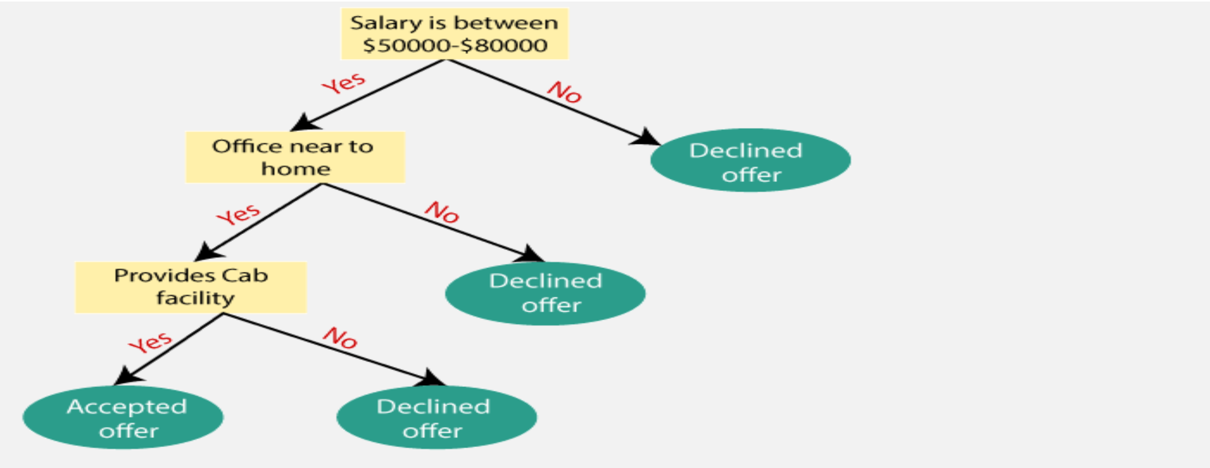

Fig 4.3: An Example of decision tree model

The above diagram is a representation for the implementation of a Decision Tree algorithm. Decision trees have an advantage that it is easy to understand, lesser data cleaning is required, non-linearity does not affect the model's performance and the number of hyper parameters to be tuned is almost null. However, it may have an over-fitting problem, which can be resolved using the ***Random Forest*** algorithm.

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VI. CONCLUSION

Demand forecasts is, with no doubt, the basis for developing an efficient supply chain. The supply chain planning and control depends of accurate estimates of the volumes of products and services to be processed to satisfy customer's needs. It can be concluded that the Holt-Winters method, which was applied in the time series analyzed in this work, showed its effectiveness for forecasting demand of products that presents trend and seasonality patterns in sales history. The use of the tool Solver of Excel made it possible to obtain smoothing coefficients in a simple way, working as an effective alternative for obtaining them even though when the access to robust computational packages is not possible. The method applied in this work showed its simplicity and accessibility due to the low cost and easiness of application. By having these characteristics, this method can be used by small and medium-sized companies, where is not possible to make huge investments in planning their operations. The food products have a factor that limits the maintenance of stocks, the short perishability. These products have a period in which they keep their characteristics and should be consumed before being considered unsuitable for consuming. Thus, it is suggested for future works that the short perishability of products must be taken into account when evaluating the results obtained by the quantitative methods. To make possible not only plan the production to satisfy the forecasted demand, but also contribute to minimize the loss of products due to its short perishability and consequently, improving the profitability of the company.

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