Time Series Forecasting and Modelling of Food Demand Supply Chain Based on Regressors Analysis

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Abstract:

Accurate demand forecasting has become extremely important, particularly in the food industry, because many products have a short shelf life, and improper inventory management can result in significant waste and loss for the company. Several machine learning and deep learning techniques recently showed substantial improvements when handling time-dependent data. This paper takes the ‘Food Demand Forecasting’ dataset released by Genpact, compares the effect of various factors on demand, extracts the characteristic features with possible influence, and proposes a comparative study of seven regressors to forecast the number of orders. In this study, we used Random Forest Regressor, Gradient Boosting Regressor (GBR), Light Gradient Boosting Machine Regressor (Light GBM), Extreme Gradient Boosting Regressor (Boost), Cat Boost Regressor, Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi LSTM) in particular. The results demonstrate the potential of deep learning models in forecasting and highlight the superiority of LSTM over other algorithms.

INTRODUCTION:

Due to the consumer’s varying needs and increasing levels of competitiveness among companies, most companies in today’s market are shifting their focus to demand forecasting for the effective demand-supply chain management. Demand forecasts are beyond the scope of any planning decisions, as they directly impact a company’s profitability. Inaccurate approximation of demand can either cause too much inventory, which eventually results in a high risk of wastage and high costs to pay or too little inventory, leading to out of stocks which ultimately pushes the company’s customers to seek services from its competitors. For these very reasons, the use of demand forecasting methods is one of the most the associate editor coordinating the review of this manuscript and approving it for publication was Sajid Ali. fundamental components of the strategic planning and administration of a company's logistics. Its importance becomes evident as its outcome is used by many subdivisions in the company: the financial department uses it to estimate costs, profit levels, and the required capital; the marketing department uses it to plan its course of action and analyse the impact of diverse marketing strategies on the volume of sales; the purchasing department may devise their plans of short- and long-term investments; and finally, the operations department can manage their plan of purchasing the necessary raw materials, machinery, and labour well in advance. It is, therefore, concordant that forecasts are beneficial, and their high accuracy has the potential to prove lucrative, improve demand-supply chain management, and reduce wastage. Its importance becomes evident as its outcome is used by many subdivisions in the company: the financial department 42679 S. Kumar Panda, S. N. Mohanty: Time Series Forecasting and Modeling of Food Demand Supply Chain uses it to estimate costs, profit levels, and the required capital; the marketing department uses it to plan their course of action and analyze the impact of diverse marketing strategies on the volume of sales; the purchasing department may devise their plans of short- and long-term investments; and finally, the operations department can manage their plan of purchasing the necessary raw materials, machinery, and labor well in advance. It is, therefore, concordant that forecasts are very useful, and their high accuracy has the potential to prove lucrative, improve demand-supply chain management, and reduce wastage.

A. MOTIVATION

Out of all the services, the biggest challenge faced by a meal delivery company is adjusting production and stock levels to minimize the loss of raw materials due to their short perishability, thus making the accuracy of the forecast of utmost importance

[1]. Demand forecasting involves converting the time series problem to a regression problem. Currently, numerous models are available for both linear and nonlinear approaches to quantitative demand forecasting. The models adhere to various archetypes but have the same fundamental idea. Traditionally,

forecasting models consisted of Linear Regression, Random Forest Regression, etc., suitable for short-term demand situations. But, several boosting algorithms like Gradient Boosting Regressor (GBR)

[2], Light Gradient Boosting Machine Regressor (Light GBM)

[3], Extreme Gradient Boosting Regressor (XG Boost)

[4], and Cat Boost Regressor

[5] perform better than the traditional algorithms when both numerical and categorical features are involved. Also, models like Long-Short Term Memory (LSTMs)

[6] and Bidirectional LSTMs have good portability and application scenarios, as they can internally maintain the memory of the input, thus making them well suited for solving problems involving sequential data, such as a time series, and for long-term demand situations.

B. PROBLEM DEFINITION

The client is a meal delivery service with multiple locations. In these cities, they have several fulfilment centres for delivering meal orders to customers. As there is a high chance of food going to waste, the client needs a good model to predict how many orders will come in over the next few weeks so that suitable raw materials can be stocked. Since most raw materials must be replenished on a weekly basis and are perishable, procurement planning is crucial. Second, accurate demand forecasts are very beneficial when staffing the centre. The following data will be used to forecast demand for the subsequent 10 weeks: 1) Historical data of the number of sales of a particular meal for a specific centre. 2) The meals' features include category, subcategory, current price, and discount. 3) Information about fulfilment centres, such as the region code, city code, etc.

C. NOVELTY OF THE WORK

As this is a forecasting problem, calculating lag features and Exponentially Weighted Moving Average (EWMA) for lag values play a vital role in improving prediction accuracy. Numerous experiments were carried out to determine the optimal parameters for each model. In the present article, we aim to compare 7 models: Random Forest Regressor, GBR, Light GBM, XG Boost, Cat Boost Regressor, LSTM, and Bi-LSTM, to analyse the adeptness of each of them. D. CONTRIBUTIONS The aim of this article is to predict the number of meals for the next 10 weeks using machine learning and the deep learning regressors mentioned above. Significant contributions of the work manifested in this paper include:

1) Traditional Random Forest Regressor is optimized and implemented as the baseline model.

2) Boosting algorithms like GBR, Light GBM, XG Boost and Cat Boost Regressor are applied since they are more adaptable to categorical and numerical features.

3) Only the lag and EWMA features are used with LSTMs and Bidirectional LSTMs because they are more reliable in analysing historical data and forecasting using the same.

4) The Root Mean Squared Log Error (RMSLE), Root Mean Square Error (RMSE), Mean Average Percentage Error (MAPE) and Mean-Average Error (MAE) reach values 28.18, 18.83, 6.56%, and 14.18 respectively. The rest of the article is organized as follows: in Section II, we present a literature survey of the forecasting methods used in time series analysis. In Section III, we describe and analyse the dataset and calculate the lag and EWMA features used for prediction.

Related works:

Comparison and Financial Assessment of Demand Forecasting Methodologies for Seasonal CPGs

Forecast accuracy is an ongoing challenge for made-to-stock companies. For highly seasonal fast-moving consumer packaged goods (CPGs) companies like King's Hawaiian, an improved forecast accuracy can have significant financial benefits. Traditional time series forecasting methods are quick to build and simple to run, but with the proliferation of available data and decreasing cost of computational power, time series' position as the most cost-effective demand forecasting method is now in question. Machine learning demand forecasting is increasingly offered as an improved alternative to traditional statistical techniques, but can this advanced analytical approach deliver more value than the cost to implement and maintain? To answer this question, we created a three-dimensional evaluation (cube search) across five unique models with varying pairs of hyper-parameters and eight different data sets with different features to identify the most accurate model. The selected model was then compared to the current statistical approach used at King's Hawaiian to determine not just the impact on forecast accuracy but the change in required safety stock. Our approach identified a machine learning model, trained on data that included features beyond the traditional data set, that resulted in a nearly 4% improvement in the annual forecast accuracy over the current statistical approach. The decrease in the value of the safety stock as a result of the lower forecast variation offsets the incremental costs of data and personnel required to run the more advanced model. The research demonstrates that a machine learning model can outperform traditional approaches for highly seasonal CPGs with sufficient cost savings to justify the implementation. Our research helps frame the financial implications associated with adopting advanced analytic techniques like machine learning. The benefits of this research extend beyond King's Hawaiian to companies with similar characteristics that are facing this decision.

Greedy function approximation: A gradient boosting machine.

Function estimation/approximation is viewed from the perspective of numerical optimization in function space, rather than parameter space. A connection is made between stagewise additive expansions and steepest-descent minimization. A general gradient descent "boosting" paradigm is developed for additive expansions based on any fitting criterion. Specific algorithms are presented for least-squares, least absolute deviation, and Huber-M loss functions for regression, and multiclass logistic likelihood for classification. Special enhancements are derived for the particular case where the individual additive components are regression trees, and tools for interpreting such "Tree Boost" models are presented. Gradient boosting of regression trees produces competitive, highly robust, interpretable procedures for both regression and classification, especially appropriate for mining less than clean data. Connections between this approach and the boosting methods of Freund and Shapira and Friedman, Hastie and Tulshiram are discussed.

XG Boost: A Scalable Tree Boosting System

Tree boosting is a highly effective and widely used machine learning method. In this paper, we describe a scalable end-to-end tree boosting system called XG Boost, which is used widely by data scientists to achieve state-of-the-art results on many machine learning challenges. We propose a novel sparsity-aware algorithm for sparse data and weighted quantile sketch for approximate tree learning. More importantly, we provide insights on cache access patterns, data compression and sharding to build a scalable tree boosting system. By combining these insights, XG Boost scales beyond billions of examples using far fewer resources than existing systems.

Cat Boost: gradient boosting with categorical features support

In this paper we present Cat Boost, a new open-sourced gradient boosting library that successfully handles categorical features and outperforms existing publicly available implementations of gradient boosting in terms of quality on a set of popular publicly available datasets. The library has a GPU implementation of learning algorithm and a CPU implementation of scoring algorithm, which are significantly faster than other gradient boosting libraries on ensembles of similar sizes.

LONG SHORT-TERM MEMORY

Learning to store information over extended time intervals via recurrent backpropagation takes a very long time, mostly due to insouciant, decaying error back ow. We brie y review Hochreiter's 1991 analysis of this problem, then address it by introducing a novel, scient, gradient-based method called \Long Short-Term Memory" (LSTM). Truncating the gradient where this does not do harm, LSTM can learn to bridge minimal time lags in excess of 1000 discrete time steps by enforcing constant error ow through \constant error carrousels" within special units. Multiplicative gate units learn to open and close access to the constant error ow. LSTM is local in space and time; its computational complexity per time step and weight is O (1). Our experiments with arterial data involve local, distributed, real-valued, and noisy pattern representations. In comparisons with RTRL, BPTT, Recurrent Cascade-Correlation, Elman nets, and Neural Sequence Chunking, LSTM leads to many more successful runs, and learns much faster. LSTM also solves complex, arterial long time lag tasks that have never been solved by previous recurrent network algorithms.

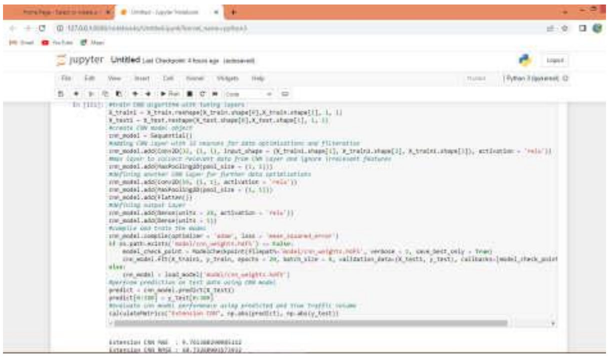
Using Internet of Things (IoT) in Agri-Food Supply Chains: A Research Framework for Social Good with Network Clustering Analysis

Agri-food supply chains (AFSCs) are critical in our society. Proper management of AFSCs is crucial for improving social welfare. Over the past years, digitization in AFSCs has emerged as a new paradigm. In this context, the Internet of Things (IoT) is a growing approach, providing a huge amount of information to manage AFSCs. Thus, the purpose of this article is to examine extensive studies on IoT-based AFSC. Our research starts with the identification of 346 articles in the relevant field from the Web of Science (Woos) database by applying rigorous filtration. Using the VOS viewer software, a network analysis has been performed. With seven identified clusters, this article recognizes the role of IoT technologies as Cluster 1: agri-food safety, traceability and sustainability; Cluster 2: AFSC sustainability; Cluster 3: AFSC performance measurement; Cluster 4: AFSC resilience in disruption; Cluster 5: AFSC integration and traceability; Cluster 6: AFSC transparency and coordination, and finally Cluster 7 identifies the barriers in IoT adoption. Thus, findings of this study offer robust guidance to link IoT technologies and AFSCs together. Based on these findings, propositions are proposed and a research framework is established. We believe the findings would help engineering managers, researchers, and government regulating bodies better plan and manage AFSCs for social good.

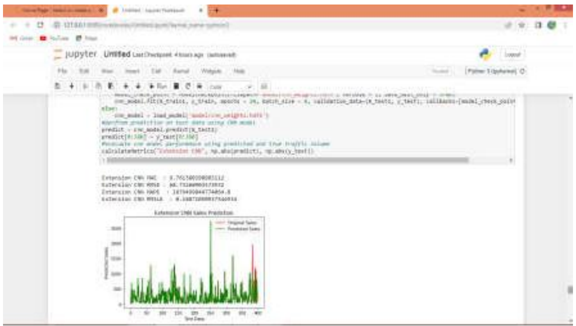
Solving stochastic online food delivery problem via iterated greedy algorithm with decomposition-based strategy

Online food delivery (OFD) service has developed rapidly due to its great convenience for customers, the enormous markets for restaurants and the abundant job openings for riders. However, OFD platforms are encountering enormous challenges, such as massive demand, inevitable uncertainty and short delivery time. This article addresses an OFD problem with stochastic food preparation time. It is a complex NP-hard problem with uncertainty, large search space, strongly coupled subproblems, and high timeliness requirements. To solve the problem, we design an iterated greedy algorithm with a decomposition-based strategy. Concretely speaking, to cope with the large search space due to massive demands, a filtration mechanism is designed by preliminarily selecting suitable riders. To reduce the risk affected by the uncertainty, we introduce a risk-measuring criterion into the objective function and employ a scenario-sampling method. For timeliness requirements caused by short delivery time, we design two time-saving strategies via mathematical analysis, i.e., an adaptive selection mechanism to choose the method with less computational effort and a fast evaluation mechanism based on the small-scale sampling and machine learning model to speed up evaluation. We also prove an upper bound of the stochastic time cost under risk measurement as one of the baseline features to improve the prediction accuracy. The experiments on real-world data sets demonstrate the effectiveness of the proposed algorithm.

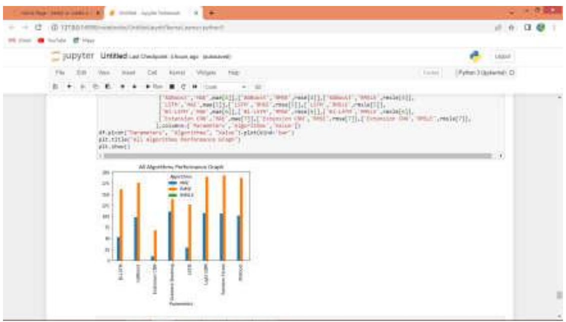
RESULTS:



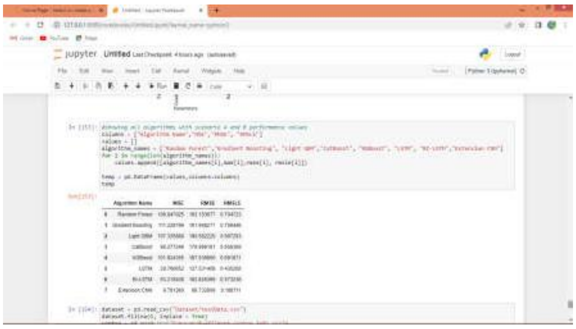
In above screen training extension CNN2d algorithm and after executing above block will get below output



In above screen extension CNN2d got only 9 as MAE



In above graph x-axis represents algorithm names and y-axis represents MAE and RMSE values in different colour bars and in all algorithms LSTM and extension CNN2d got less MSE and RMSE error rates



In above screen displaying all algorithm performance in tabular format

CONCLUSION:

The management of raw materials for a meal delivery service is significantly impacted by demand forecasting. Accurately forecasting the number of orders provides pertinent information to the concerned authority about the expected situation so that the inventory can be managed effectively without any waste. This study demonstrates the efficacy of deep learning and machine learning techniques for forecasting the volume of orders. In essence, these deep learning models are capable of identifying the time-variant characteristics and significant trends of historical data as well as predicting the future tendency of the given time-series data. On the basis of 135 weeks' worth of historical data, forecasts for the next 10 weeks are given. Each model's performance has been validated in terms of RMSLE, RMSE, MAPE, and MAE. Results and the statistical tests show that LSTM outperformed all other models in terms of forecasting performance. The dataset used in this study was restricted as it did not account for the date, month or any holidays. Without these factors, it was difficult to infer any trend or seasonality. Also, there was no mention of any event (like special discount or occasion) which may be able to explain sudden spikes of the target variable. The concept of applying transfer learning to time-series can also be explored as it may hold the key to improve the performance on smaller dataset. In future, these variables must be considered along with the limitations of the studied models to perform in depth analysis and propose a robust model.

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