UTILIZING ARTIFICIAL NEURAL NETWORKS TO PREDICT DEMAND FOR WEATHER-SENSITIVE PRODUCTS AT RETAIL STORES

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Abstract
One key requirement for effective supply chain management is the quality of its inventory management. Various inventory management methods are typically employed for different types of products based on their demand patterns, product attributes, and supply network. In this paper, our goal is to develop robust demand prediction methods for weather sensitive products at retail stores. We employ historical datasets from Walmart, whose customers and markets are often exposed to extreme weather events which can have a huge impact on sales regarding the affected stores and products. We want to accurately predict the sales of 111 potentially weather-sensitive products around the time of major weather events at 45 of Walmart’s retail locations in the U.S. Intuitively, we may expect an uptick in the sales of umbrellas before a big thunderstorm, but it is difficult for replenishment managers to predict the level of inventory needed to avoid being out-of-stock or overstock during and after that storm. While they rely on a variety of vendor tools to predict sales around extreme weather events, they mostly employ a time-consuming process that lacks a systematic measure of effectiveness. We employ all the methods critical to any analytics project and start with data exploration. Critical features are extracted from the raw historical dataset for demand forecasting accuracy and robustness. In particular, we employ Artificial Neural Network for forecasting demand for each product sold around the time of major weather events. Finally, we evaluate our model to evaluate their accuracy and robustness.

Keywords
Supply chain, Inventory management, Big Data, Artificial Neural Networks

Introduction
Over the past few years Big Data has become the focus of IT innovation in business, science and industry. In general, Big Data means having the ability to gather, store, explore, and analyze with velocity, variety, and volume of data. Analytics refers to the ability to explore insight data by considering many known methods and techniques, such as statistics, mathematics, econometrics, simulations, and optimizations, to help business organizations and companies become lean and make a decision based on quick changes in the world. Most companies, industries, and organizations want to increase their ability to process their data (internal or external) efficiently. Some lean companies such as Walmart, eBay, Progressive Insurance, and Target have reported the ability to consider Big Data and its benefits; they store internal data such as transactions, last year’s sales, etc. in their databases automatically (Wang et al, 2016). These companies are successful in extracting new insights and obtaining new forms of value by considering Big Data analysis in their operation plans (Sanders, 2016). This literature review discusses previous research on routing and scheduling logistics as well as the optimization operational network used in inventory and labor scheduling. Recently, other Big Data analytics applications, such as segmenting suppliers, measuring and mitigating risk, forecasting demand and informing suppliers have increased especially in the area of in sourcing (Kourentzes et al, 2014). Since a key aspect of supply chain management is designing and controlling processes, operations and inventory to meet demand, then forecasting demand by considering Big Data analysis is a huge step to deal with variations to decrease shortage or overproduce.

By increasing the application of Big Data among many companies, choosing the best tools and methods to analyze them is the key issue to consider. Because of the growth of computing power and the accessibility of data, the use of Artificial Neural Networks (ANN) for forecasting concepts is now commonly applied (Kourentzes et al, 2014). ANN is a mathematical model that includes the group of connected artificial neurons, which is like the human neural network, to compute and store specific information. This method has the ability to investigate and submit the nonlinear relationships of the given information and data, so ANNs have been widely considered as one method or technique
Recent research on the use of Big Data for forecasting has been extensively discussed. However, there has been a need for the development of new methods that can handle large datasets and provide accurate predictions. In this paper, we propose a new approach to forecasting that integrates Big Data with machine learning algorithms, specifically Artificial Neural Networks (ANNs). We demonstrate the effectiveness of this approach by applying it to a real-world dataset and comparing its performance to traditional forecasting methods.

The use of Big Data in forecasting has gained significant interest due to the increasing availability of large and diverse datasets. These datasets can be utilized to capture various factors that influence demand, such as weather, economic indicators, and social media trends. By leveraging Big Data, we can improve the accuracy of our predictions and better understand the underlying patterns in the data.

## Feature Selection Method

Feature selection is a crucial step in forecasting, as it helps in identifying the most relevant features that contribute to the prediction accuracy. In this paper, we employ feature selection methods to identify the most important features in our dataset. We compare the performance of different feature selection techniques and evaluate their impact on forecasting accuracy.

## Methodology

The methodology of this paper involves the following steps:

1. Data Collection: We collect a large dataset containing historical demand information and relevant external factors such as weather, economic indicators, and social media trends.
2. Feature Selection: We apply various feature selection methods to identify the most important features that contribute to forecasting accuracy.
3. Model Building: We build different forecasting models using selected features and compare their performance.
4. Model Evaluation: We evaluate the performance of the models using standard metrics such as mean absolute error (MAE) and root mean square error (RMSE).
5. Results and Discussion: We present the results of our analysis and discuss the implications of our findings.

This approach allows us to leverage the power of Big Data and machine learning to improve the accuracy of demand forecasting, which is critical for businesses and organizations.
In addition, by applying an optimal evaluation criterion we can reduce the dimension of features compared to the number of original feature numbers, but in the selected feature subset we will obtain as much information as possible (Almuallim, H., & Dietterich, T., 1991; Hoque, N., et al., 2014). Feature selection methods can be divided into three models based on the evaluation criteria (Chen, G., & Chen, J., 2015): the wrapper model, the embedded model, and the filter model. In the wrapper model, the performance of the feature selection depends on the classifier directly, such as IWSS (Bermejo, P., et al., 2014) GA/FDA (Chiang, L., & Pell, R., 2004) and RFE (Guyon, I., Weston, J., Barnhill, S., et al., 2002). For the embedded model, we need a specific learning algorithm before conducting the feature selection in our process which can be viewed as in an intermediate method between wrappers and filters. The filter model is used to maximize the evaluation function for getting an optimal feature subset through a search strategy (Liu, J., et al., 2017).

One of the main issues in applying the feature selection is considering an appropriate method for specific problems. Each feature selection method has advantages and disadvantages, and its performance depends on the dataset. However, despite the availability of the growing number of methods, generally no specific feature selection method exists. Some knowledge of existing algorithms is generally required in order to be able to choose a method that is appropriate to the problem. One possible solution to this problem is to use an ensemble method since better results could be achieved by combining different machine learning methods to solve the same problem; thus, We used a known ensemble model, Random Forest (RF) (Seijo-Pardo, B., et al., 2017). Random Forest (RF) is a kind of supervised classifier constructed from an ensemble of classification and regression trees (CART) that use most of their constituent terminal nodes to forecast the class of a given data (Seijo-Pardo, B., et al., 2017).

Methodology

Artificial Neural Networks (ANN)

ANNs are information processing systems that simulate the behavior of the human brain (Martín del Bío & Sanz Molina, 2006). ANNs obtain the inherent information from the considered features and learn from the input data, even when our model has noise (Kasabov, 1996). ANN structure is composed of essential information processing units, which are neurons. They are defined into several layers and interconnected with each other by defining weights. Synaptic weights show the interaction between every pair of neurons (Garrido, C., et al., 2014). These structures distribute information through the neurons. The mappings of inputs and estimated output responses are calculated through combinations of different transfer functions. We can use the self-adaptive information pattern recognition methodology to analyze the training algorithms of the artificial neural networks. The most commonly used computation algorithm is the error back propagation algorithm proposed by the PDP group of Rumelhart in 1985 (Lippmann, R. P., 1987; Sharma, A., & Panigrahi, P.K., 2011).

Neural networks can be divided into single-layer perception and multilayer perception (MLP) networks. The multilayer perception network includes multiple layers of simple, two state, sigmoid transfer functions having processing neurons that interact by applying weighted connections. A typical feed-forward multilayer perception neural network consists of the input layer, the output layer, and the hidden layer as shown in Exhibit 1 (Sharma, A., & Panigrahi, P.K., 2011). The multilayer perceptron (MLP) with the back propagation learning algorithm is used in this study because numerous previous researchers used this type of ANN (Gedeon, Wong, & Harris, 1995), and it is also a general function approximator (Funahashi, 1989).

Exhibit 1. Architectural Graph of an MLP Network with Two Hidden Layers.
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Time-Delay Neural Networks
The time-delay structure (Lollia, F. et al, 2017) differs from the feedforward one because each input $t$ not only consists of the feedforward network input $y_t$ but also some of the preceding samples. The number of these preceding inputs is called taps (Lollia, F. et al, 2017). Therefore, the time-delay neural network input $t$ is shown in Equation (1):

$$y_t^{\hat{}} = (y_t, y_{t-1}, \ldots, y_{t-taps})$$

This changes both the dimension of each input vector and of each input weight vector ($R^{n \times (taps + 1)}$). The rest of the architecture remains the same.

Recurrent Neural Networks (RNN)
The Recurrent structure applied in this study forecasting as shown in Exhibit 2 (Lollia, F. et al, 2017) includes a layer connected to the hidden layers and empowers the training step using the previous output signals. In this structure, each input $t$ includes both the sample $x_t$ and hidden layer’s output defined as:

$$\bar{g}_t = (g(w_1, \hat{x}_t + b_1), g(w_2, \hat{x}_t + b_2), \ldots, g(w_N, \hat{x}_t + b_l))$$

The Recurrent architecture was introduced by Elman and Zipser (1988) to add dynamic memory to our network. Nasiri Pour et al. (2008) tested it with promising results for forecasting demand patterns.

Exhibit 2. Architectural Graph of Recurrent Neural Networks (RNN).

Bagging
When small changes in learning data occur, the decision trees become unstable. If the first cutting variables are different because of a minor change in the learning data, the entire structure of the tree may be modified. Bagging, as well as a tree-based ensemble methods, employs the fact that singular trees may produce unstable results but the correct prediction on average. Bagging trains a number of trees on a boot and applies all the constructed trees on the test set. The final prediction is the average value of the predictions resulting from each tree (Wauters, M., & Vanhoucke, M., 2016). The superiority of bagging over singular classification or regression trees was introduced by Bühlmann and Yu (2002). In that paper, the authors analyzed the reduction of variance by using bagging. For forecasting demand, We used bagging as an ensemble method in this study and compared its results with other methods.

Experimental Analysis

Data Collection
To empirically evaluate the performance of the methods described in pervious section, a daily data set collected at 45 different Walmart stores from 2012 to 2014 is used (the original data set is available at https://www.kaggle.com/c/walmart-recruiting-sales-in-stormy-weather/data). In this paper, We want to accurately predict the sales of 111 potentially weather-sensitive products (such as umbrellas, bread, and milk) around the time of major weather events at 45 of their retail locations. We used the information from 20 stations where weather features were calculated from 1/1/2012 until 10/31/2014. In applying the ANNs already emphasized in pervious section, the data set was divided into a training and a test set. the training data included the history of unit sales for
111 potentially weather-sensitive products from 1/1/2012 to 05/31/2014 (contained in 3892716 observations), and the training data set included the rest of them from 06/1/2014 to 10/31/2014 (around 721000 observations). Because the amount of unit sales for all 111 different products is wide ranging and highly fluctuating, the best method to evaluate our prediction models will be the Root Mean Squared Logarithmic Error (RMSLE), Equation (3) is shown below.

$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (\log (p_i + 1) - \log (a_i + 1))^2}$$  

(3)

To follow the Equation (3) We changed my unit sales (considered as output for my model described in section 4) to log unit sale and replaced them with the amount of unit sales in my data set. Exhibit 3 plots log unit sale for all 111 different types of products during our time line, and is obvious that some products have the same behavior during these times, so we can conclude that they may belong to the same categories; for example, products 1, 2, 3, and 4 may be sensitive to a specific season (winter or summer). In the next step for easily predicting and removing non-informative information, We excluded products at all stores whose log unit sales are zero overtime since customers might not tend to purchase these products on specific dates. Also We removed all data or information on the date 2013-12-25 since it was a holiday and all Walmart stores were closed. Therefore, my observation’s testing dataset is reduced to 235789. Finally, in my testing data, their log unit sale (unit sale) would be predicted to be zero; then, our model just focused on predicting the remaining log unit sale. After reducing my data set to informative data by removing the zero units, We defined two data sets as follows to compare whether using ANNs and a weather feature in forecasting will help us have more accurate predictions:

1. Data set 1 included input date and weather features, output log unit sale (specified by Ddate Dweather)
2. By considering that events and holidays could affect customer demands, data set 2 included input date, weather features, and holiday (or event) features obtained as in the following steps. (specified by Devent)
   2-1. weekday, is_weekend, is_holiday, is_holiday_and_weekday, is_holiday_and_weekend
   2-2. is_BlackFriday-3days, -2days, -1day, is_BlackFriday, +1day, +2days, +3days
   2-3. year, month, day

Random Forest
There were some unrelated or unimportant variables in our data sets 1 and 2; thus, as described in pervious sections, we applied Random Forest (4 models: ntry 2and 4, ntree 50 and 100) to define and identify the essential features. Exhibit 4 shows the results (MSE shows mimum square error of respective model and % Var explained(%IncMSE) are outcome of applying Random Forest) and we concluded that the Random Forest with ntry= 4 and ntree=50 has minimum error, so we chose it as our model for feature selection. Our Dweather dataset has 20 variables and Devent dataset has 31 variables (included 20 variables of Dweather and events which are described in pervious section). By comparing the value of %IncMSE (is the importance measures which shows how much MSE or Impurity will increase when that variable is randomly removed) which is one of outcome of our model, we chose and kept variables with the absolute value %IncMSE more than 1. Finally, for the Dweather dataset the number of variables decreased to 15 and...
for the Devent the number of variables decreased to 22. By reaching the optimized features for all data sets, we fitted our models to log unit sale values by using methodologies described in previous section.

**Exhibit 4. Random Forest Results.**

| Model  | MSE       | % Var explained |
|--------|-----------|-----------------|
|        | ntry:2 ntree:50 | ntry:4 ntree:50 | ntry:4 ntree:100 | ntry:2 ntree:100 | ntry:4 ntree:50 | ntry:4 ntree:100 |
| Dweather | 2.83338  | 2.876044  | 2.65173  | 2.700654  | 8.34  | 6.96  | 14.22  | 12.63 |
| Devent   | 1.40582  | 1.130887  | 0.22281  | 0.223172  | 54.52 | 63.42 | 92.79  | 92.78 |

After applying random forest to keep informative variables, We fitted different ANN models to forecast the log (unit sales) by applying bagging, timing lag, RNN and MLP. For constructing the MLPs, we defined layers ranging 2 to 4 with the number of neurons ranging from 20 to 100 that present in Exhibit 5 (column Methodology). We summarized the MLP structure by using three notations; for example, MLP-L2-N30 means this MLP has 2 layers and 30 neurons at each layer. In Exhibit 5, we compared the results of two datasets in separate columns (Devent and Dweather), for each of them we calculated MSE and time (two important factors in prediction at each layer).

**Exhibit 5. MSE Through Different MLP Models.**

| Methodology | MSE | Time (mint) | MSE | Time (mint) | Methodology | MSE | Time | MSE | Time |
|-------------|-----|-------------|-----|-------------|-------------|-----|------|-----|------|
| MLP-L2-N20  | 0.324734 | 2.6535 | 3.482135 | 2.33 | MLP-L3-N70  | 0.200235 | 7.303 | 2.195085 | 6.4 |
| MLP-L2-N30  | 0.309068 | 3.2508 | 3.314149 | 2.85 | MLP-L3-N80  | 0.2081061 | 9.9939 | 2.095009 | 8.7581 |
| MLP-L2-N40  | 0.295530 | 4.0144 | 3.168985 | 3.52 | MLP-L3-N90  | 0.21464939 | 12.3273 | 2.07501 | 10.8029 |
| MLP-L2-N50  | 0.28299 | 4.3370 | 3.034576 | 3.8 | MLP-L3-N100 | 0.21681627 | 19.1324 | 2.098464 | 16.7665 |
| MLP-L2-N60  | 0.271233 | 5.0735 | 2.731941 | 4.45 | MLP-L4-N20 | 0.310981611 | 3.2583 | 3.07141 | 2.8198 |
| MLP-L2-N70  | 0.268715 | 6.4514 | 2.881444 | 5.65 | MLP-L4-N30 | 0.2959791966 | 3.9918 | 2.923239 | 3.4546 |
| MLP-L2-N80  | 0.255970 | 8.8286 | 2.74478 | 7.74 | MLP-L4-N40 | 0.2830148888 | 4.9295 | 2.795197 | 4.2662 |
| MLP-L2-N90  | 0.264018 | 10.8899 | 2.831082 | 9.54 | MLP-L4-N50 | 0.2710111528 | 5.3256 | 2.676642 | 4.6089 |
| MLP-L2-N100 | 0.26684 | 16.9014 | 2.666583 | 14.8 | MLP-L4-N60 | 0.2597462461 | 6.23 | 2.565384 | 5.3916 |
| MLP-L3-N20  | 0.241977 | 2.7145 | 2.594735 | 2.38 | MLP-L4-N70 | 0.2573352741 | 8.766 | 2.541572 | 7.5864 |
| MLP-L3-N30  | 0.230304 | 3.3255 | 2.46956 | 2.91 | MLP-L4-N80 | 0.2451301522 | 11.9961 | 2.421028 | 10.3818 |
| MLP-L3-N40  | 0.220216 | 4.1068 | 2.29808 | 3.6 | MLP-L4-N90 | 0.2528375557 | 14.7970 | 2.49715 | 12.8057 |
| MLP-L3-N50  | 0.210876 | 4.4367 | 2.297093 | 3.89 | MLP-L4-N100 | 0.2553899442 | 22.9654 | 2.522359 | 19.8749 |

**Discussion**

For each defined MLP in Exhibit 5, our inputs were our variables and output was log unit sale values. We ran each model 25 times and calculated the average MSE (Mean Square Errors); Exhibit 5 summarizes the results. By looking through Exhibit 5 we can find that by increasing the number of layers, the MSE started to decrease, but after changing 3 layers to 4 layers, the MSE started to increase. It was proved that by increasing the number of layers after 3 layers, we did not have improvement in our model (it means we could not have lower MSE).

You can see the minimum error belongs to MLP-L3-N70 for Devent and MLP-L3-N90 for Dweather, so we can use these MLP structures to forecast our unit sales. We fixed these models (MLP- L3-N70 for Devent and MLP-
L3-N90 for Dweather) and compared their training results with others (RNN, Bagging and time lagging) to find an appropriate model.

We ran RNN and time lag model with same structure that we fixed for MLP for each Data set (3 layers and 70 Neurons for Devent and 3 Layers and 90 Neurons for Dweather). Exhibit 6 shows the results of training for RNN and timing lag. Also, we ran bagging for 10 times and saved the average of its training results in Exhibit 6 (in Exhibit 6 different type of ANN models were categorized in the first column and we compared the MSE and time of training of each data set in different columns and tables related to each models). By comparing training MSEs in Exhibit 6, the appropriate model with minim MSE is belong to MLP for both dataset. However, when we compare the computational time, we can find that acceptable error with a minimum or appropriate time is belong to the bagging. Generally, the main goal in most industries is to reach minimum error in forecasting, so we chose and applied MLP to predict two data sets (Dweather and Devent), and it is obvious their times are not so affective. In addition, Exhibit 6 presents how the timing lag and RNN with maximum errors are absolutely not an acceptable method for forecasting compared to others since our output may not be influenced by previous information and just tends to be related to features and variables.

Finally, we tested MLP (MLP-L3-N70 Devent, MLP-L3-N90 Dweather) and other methods by using the testing data to make sure to choose the appropriate model for forecasting, and their results summarize in Exhibit 6 in Test columns related to each model. The MSE of the testing data set was obtained as follows: Devent (0.198765) and Dweather (2.000165) and confirm our accuracy to use these models for forecasting. From Exhibit 6, it appears that by considering event features in addition to weather features, we have more accurate forecasts with smaller errors, but their differences are not too great. This may show that these products are affected by event more than weather features. We also used simple linear regressions for forecasting the log unit sale, and the mean square error obtained was 12.88769, which is too high to compare with MLP. Therefore, it may show that by considering weather and event features in addition applying MLP, we could have a more accurate model with minimal error.

**Exhibit 6. Compare Results of Different Model.**

| Model         | Dweather |         | Test    |         |
|---------------|----------|---------|---------|---------|
|               | MSE      | Time    | MSE     | Time    |
| MLP-L3-N90    | 2.07501  | 10.8029 | 2.00165 | 8.8764  |
| Time-Delay    | 4.44019  | 16.0045 | 4.85769 | 14.7863 |
| RNN           | 5.476349 | 20.8756 | 5.67898 | 18.9765 |
| Bagging       | 2.550736 | 3.98761 | 2.764989| 3.2145  |

| Model         | Devent   |         | Test    |         |
|---------------|----------|---------|---------|---------|
|               | MSE      | Time    | MSE     | Time    |
| MLP-L3-N70    | 0.200235 | 7.303   | 0.198765| 6.9887  |
| Time-Delay    | 0.486539816 | 19.0098 | 0.46780987 | 15.8703 |
| RNN           | 0.61287609 | 21.9873 | 0.54678295 | 19.0024 |
| Bagging       | 0.2323396 | 4.0176  | 0.2298746 | 3.7654  |

Finally, when we chose my appropriate methodology to fit a model, its output is log unit sale values. Therefore, for obtaining the unit sale of each items we must follow the below steps:

1. Predicted unit = exp(predicted_log1p*) – 1
2. Assigned zero value for: item/stores whose units are all zeros and on date 2013-12-25.

* obtain from MLP models.

Applying weather features can help retail stores predict product inventory and reduce any lack of inventory problems in the future.

**Conclusions and Future Research**

Accurate forecasts with minimal errors are essential for an efficient inventory control system. Inventory management of weather sensitive products is one example of this, whereby changing weather conditions increases or decreases product demands, so retailers and industries need to consider other features to obtain an accurate model. Another
factor which can help retailers obtain an appropriate forecast model is choosing the best methodology. The multilayer perceptron (MLP) with the back propagation learning algorithm neural network represents a promising approach; its main strength is the ability to control non-linear functions without the requirement for distribution assumptions. However, few papers investigated the forecasting accuracy for weather sensitive products, and they have not been widely applied in real world problems due to the great computational effort for training the networks. Back-propagation learning has been typically fitted into this research field. In order to improve the understanding of these predictors (MLP with the back propagation learning algorithm) in the field of forecasting to avoid the lack of inventory, this study provides a comparison between standard methods. This study shows that back-propagation has better performance, and thus should be suggested to practitioners. Conversely, timing lag, Bagging, Recurrent Neural Network (RNN) and linear regression do not have perfect performance. Our research had some limitations; for example, our data summarized a two year period, and it is better to consider a bigger data set; also our data was not collected very carefully especially weather features which were recorded at different stations and have several missing data. The main advantages and disadvantage of applying this approach (ANN) can be summarized in the following points:

1. In our study, the high capability of forecasting and its accuracy that characterizes ANNs are met in the used database, and this accuracy is much higher and more appropriate than those obtained by applying some other methods, such as bagging, regression models, and timing lag in the field of inventory management at retail stores.

2. The main disadvantage of this approach is the computational time, since a large number of ANNs must be trained and tested, and the back propagation learning algorithm determining the connection weight must be calculated as many times as ANNs are involved in the selected architecture.

For our future work, we will test larger databases to examine the performance of ANNs. Meanwhile, more information of different databases will be explored during the course of forecasting, like the distribution of the ANNs with the worst forecast results. The other future research can be manipulating or merging weather features, since in this study we applied the exact value of features but by transferring or merging weather features maybe we can obtain better results. Finally, ANNs will be widely used for forecasting problems in real-world industries to see if they are also efficient. ANNs are proposed in this research because of their numerous advantages over more traditional parametric models, but also over other non-parametric models, such as decision trees. ANNs are a better fit for the phenomenon under this study.

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