A Solution to Forecast Demand Using Long Short-Term Memory Recurrent Neural Networks for Time Series Forecasting

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ABSTRACT

This study focuses on predicting demand based on data collected which spans across many periods. To help our client build a solution to forecast demand effectively, we developed a model using Long Short-Term Memory (LSTM) Networks, a type of Recurrent Neural Network, to estimate demand based on historical patterns. While there may be many available models for dealing with a time series problem, the LSTM model is relatively new and highly sophisticated to its counterpart. By comparing this study which works excellently for sequential learning, to the other existing models and techniques, we are now closer to solving at least one of many complications apparent across industries. The study becomes even more important for supply chain professionals, especially those in the purchase department, as they can now rely on a highly accurate model instead of basing their forecasts purely on intuition and recent customer behavior. Using data from the M3-Competition, which is a competition conducted by the International Institute of Forecasters, we develop a working framework to help our client compare their existing models (feedforward neural network and exponential smoothing model) with our LSTM model.

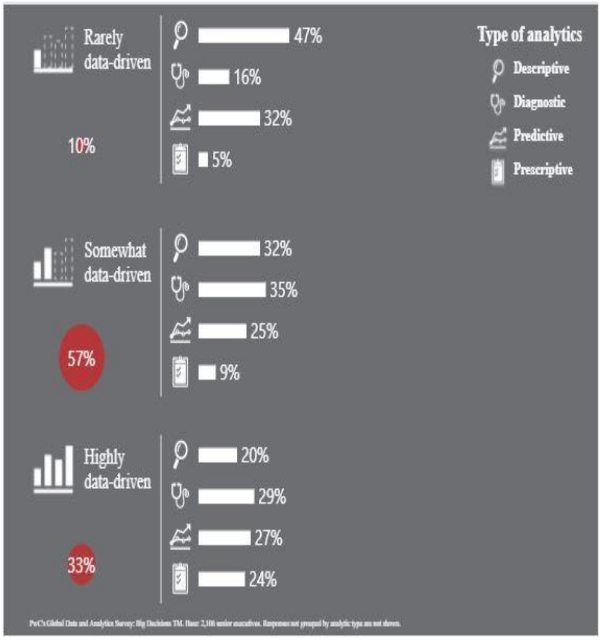
Keywords: RNN-LSTM, Demand Forecasting, Predictive Modeling, Time Series Forecasting

INTRODUCTION

“The forecast is always wrong”, is a common saying among those professional in the supply chain industry. No matter how good the predictive model is, one is never going to achieve 100 percent accuracy or even a number which is close to the figure. However, the cost savings that can be achieved by continuously predicting/ forecasting demand better is what separates an average company from the market leader. No matter how strong the company’s supplier/ distributor network is, not able to predict stock accurately, can be very costly. Whether it means losing customers by not being able to meet their demand due to understocking or incurring ridiculous amounts by overstocking and thereby blocking working capital in the process, the importance of forecasting demand cannot be underemphasized. The biggest companies in the world like Walmart, Amazon, and Apple are all investing heavily in analytics and especially supply chain analytics to get their demands and sales predictions correct.

A recent study by Gartner revealed that nearly sixty-five percent of worldwide companies are now spending a huge chunk of their budget on analytics and other big data projects. A research conducted by Retail Week revealed that Tesco achieved a 100 million Euro saving by a reduction in wastage stock. These huge savings were possible by getting experts in the retail space to work together with highly skilled data analysts to build models that help predict demand more precisely. The top management comprising of CEO’s COO’s and CFO’s are slowly but surely realizing the value of analytics in forecasting demand. A survey performed by Loudhouse for SAP, on 51 decision makers in the industry, found that almost 50 % felt that predictive analytics not only gave companies a competitive edge but also significantly improved customer satisfaction.

If hiring data scientists and other analytical professionals was not enough, the biggest of manufacturing companies and retailers also work with other big data analytics companies trying to make maximum use of the abundant data they have at their disposal. PWC’s 2016 survey revealed that companies are now looking at the big picture and are achieving tremendous success by using a combination of mind and machine as illustrated in *Fig.1.1* and *Fig 1.2*. The graphics below clearly depict the influence of analytics at the workplace.



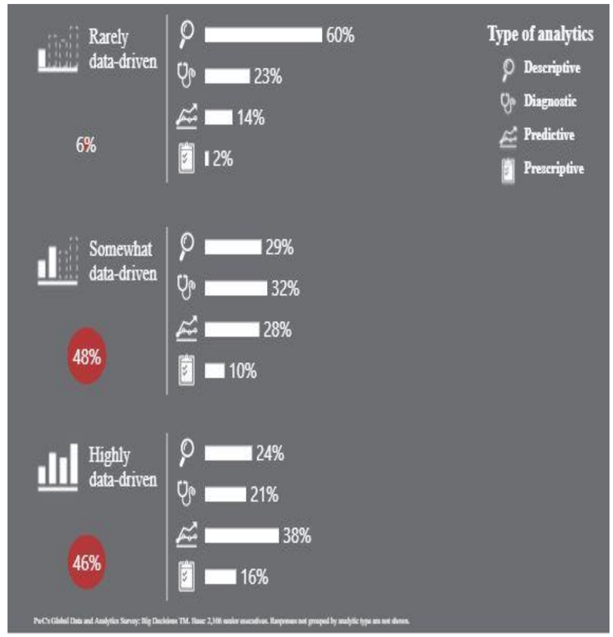


Figure 1.1 Companies in the United States Using Analytics *Figure 1.2 Companies in the Retail Space Using Analytics*
(PWC's 2016 global data and analytics' survey)

Analytics Spread Across Various Supply Chain Verticals

Figure 2. Application areas of analytics in the supply chain vertical.
(As illustrated in Cybage Blog-Supply Chain Planning on October 30, 2016)

Analytics in the supply chain is no different than analytics in any other business domain. It is practically used in every company these days to make better-informed decisions and make 'the procure to pay' business cycle, an efficient process. The image above (*Fig. 2)* shows the application of analytics to every team in the supply chain vertical. If all the research mentioned above is anything to go by, forecasting and planning can now truly be used as a competitive advantage and need not be wrong after all!

The paper is broken-down into various sections beginning with a literature review in the next section. In this section, we look at various aspects of the problem and study models/ theories already known to us and try to understand those approaches which are new, unknown but show a lot of promise for success. The literature review is then followed by a section describing the data and its origin. The methodology section is where a step by step explanation of the various stages involves in data preparation, cross-validation techniques, the performance measures etc. are determined. The model piece of the paper highlights and stresses the use of RNN-LSTM and why we believe this model is the best approach for a time series forecasting problem. Finally, we move onto the results and conclusion section where the goal is to see if the model has given a good result and that the results in the test set are similar in the test set as well. (No overfitting/ underfitting of data). To conclude, we spend a few lines talking about the implication of this approach as well as future research opportunities in the time series forecasting space for predicting demand.

LITERATURE REVIEW

Before diving into creating our RNN-LSTM model, we reviewed prior research work in time series forecasting across various industries while giving special emphasis to research papers on supply chain analytics (sales forecasting, inventory forecasting). Whenever there is a certain degree of uncertainty involving future outcomes, using a time series approach has always yielded the best results. With organizations understanding the need to anticipate future outcomes, developing forecasting techniques has been one of the top priorities over the last few years. Kevin Bonnes paper on Predictive Analytics for supply chains discusses various models and available papers for predictive analytics in the supply chain industry. As expected time series forecasting was the most popular approach for modelers with forecasting i.e. (demand/ order forecast, inventory forecasting etc.) comprising of more than 50% of research papers.

To comprehend how deep learning is especially beneficial for time series modeling, we found Martin Längkvist, Lars Karlsson, Amy Loutfi (2014) paper on unsupervised feature learning and deep learning for time-series modeling very useful. The paper offers insights into recent developments in deep learning and unsupervised feature learning for time-series problems. It also addresses the challenges present in the time series data and provides reviews of previous works which have applied this approach across a variety of forecasting problems and suggests certain modifications to these algorithms. Similarly, to understand how LSTM can be used to make predictions Thomas Fischer & Christopher Krauss's paper on Deep learning with long short-term memory networks for financial market predictions was a good starting point. Although the paper is based on the application of LSTM for financial time series predictions, it also provides insights on time series predictions in general. It offers a comparative study of LSTM and methods and shows why LSTM is a superior technique for sequence learning.

To understand the working principles of machine learning, time series decomposition, deep neural networks and sequence modeling we found two books -Rob J Hyndman, George Athanasopoulos's book on Forecasting Principles and Ian Goodfellow, Yoshua Bengio, Aaron Courville's book on Deep learning great reads to build our knowledge around the subject.

To understand how LSTM performed in comparison to other neural networks the paper by Abdelhadi Azzouni and Guy Pujolle was particularly useful. The paper aims to develop a real-time time series model that provides the flexibility of real-time monitoring. The authors have used several methods of time series prediction such as Linear Prediction, Holt-Winters Algorithm, and Neural Networks. Finally, LSTM RNN architecture was developed using Keras Library and used for prediction. It was found that the LSTM RNN was the best predicting model.

For many different time series datasets, having an idea and working knowledge of clustering in time series forecasting would help us combine datasets based on factors such as industry type, kind of market etc. Durga Toshniwal, R. C. Joshi's paper on clustering time series data gave insights to unique approaches in clustering. In this paper, to cluster, the time series cumulative weighted slopes were used for feature extraction. Slopes were calculated at corresponding points of each of the time series. The slopes computed at corresponding points of the sequences were then assigned weights depending on the location of the slope along the time axis. Weighted slopes were obtained for each of the time sequences which were then summed to obtain the cumulative weighted slope for the respective time sequence. The cumulative weighted slopes were then grouped into clusters using k-means clustering method to identify similar patterns.

Finally, running an LSTM model, without having other models to compare the results with, one would not be able to conclude whether the model performed well or not. For this reason, Zaiyong Tang, Chrys de Almeida, Paul A. Fishwick's paper on Time series forecasting using neural networks vs. Box- Jenkins methodology as well as JW Taylor's paper on Short-term electricity demand forecasting using double seasonal exponential smoothing gave us an idea on other approaches such as ARIMA modeling and exponential smoothing.

Table 1 Literature review

Author	**Studies**	**Motivation for research**	**Result of Research**
Martin Längkvist, Lars Karlsson, Amy Loutfi (2014)	A review of unsupervised feature learning and deep learning for time-series modeling	To gain an understanding of applications of deep learning in time series forecasting and challenges faced while using it.	Deep learning methods offer better representation and classification on a multitude of time-series problems compared to shallow approaches when configured and trained properly.
Thomas Fischer, Christopher Krauss	Deep learning with long short-term memory networks for financial market predictions	To gain insights into the prediction capabilities of LSTM.	LSTM networks to outperform memory-free classification methods, i.e., a random forest (RAF), a deep neural net (DNN), and a logistic regression classifier (LOG). Long short-term-memory networks exhibit highest prediction accuracy

Abdelhadi Azzouni and Guy Pujolle	A Long Short-Term Memory Recurrent Neural Network Framework for Network Traffic Matrix Prediction	To study LSTM RNN in comparison with other neural networks and methods	The study highlights how LSTM RNN outperforms traditional linear methods and Feedforward Neural Network. Also, a technique of data preprocessing and RNN feeding was suggested that was shown to achieve high prediction accuracy
Durga Toshniwal, R. C. Joshi	Using Cumulative Weighted Slopes for Clustering Time Series Data	To study a new approach for clustering time series data	Clusters are formed on the basis of this weighted sum of slopes to identify similar patterns over periods over time. The paper analyses how one can optimize the cluster size and group similar time-series.
Zaiyong Tang, Chrys de Almeida, Paul A. Fishwick	Time series forecasting using neural networks vs. Box- Jenkins methodology	To study the results of a comparative study of the performance of neural networks and conventional methods in forecasting time series.	The experiments demonstrate that for time series with a long memory, Box-Jenkins model and ANN produced comparable results. However, for series with a short memory, neural networks outperformed the Box-Jenkins model.

JW Taylor	Short-term electricity demand forecasting using double seasonal exponential smoothing	This paper considers univariate online electricity demand forecasting for lead times from a half-hour-ahead to a day ahead. A time series of demand recorded at half-hourly intervals contains more than one seasonal pattern. The multiplicative seasonal ARIMA model has been adapted for this purpose.	The resulting forecasts on half-hourly electricity demand projects that double seasonal Holt-Winters method outperformed those from standard Holt-Winters and those from a well-specified multiplicative double seasonal ARIMA model
Rob J Hyndman, George Athanasopoulos	(Book) Forecasting Principles and Practice	To comprehensively understand time series decomposition and various advanced forecasting methods	This book presents a discussion of time series models and its various components. It also compares different forecasting methods such as ARIMA, Neural Networks, and Dynamic regression models. The book uses R throughout and is a good reference to understanding modeling in R
Ian Goodfellow, Yoshua Bengio, Aaron Courville	(Book) Deep Learning	To help build a mathematical background of relevant topics like machine learning, deep neural	This book offers a conceptual understanding of linear algebra, probability theory, and machine learning. It describes in

		networks, and sequence modeling: Recurrent and Recursive nets	detail deep learning techniques used in the industry, including Sequential modeling using Recurrent and Recursive nets. It helps in building concepts of LSTM.

DATA

The data used in the study was provided by the client and comprises of just one feature which is the value (demand quantity). This was a time series forecasting problem involving predicting demand for the next few periods based on the available data for earlier periods. However, there are various batch ID's (product categories) spanning over three different frequencies or time series (monthly, quarterly and yearly).

Table 2. Data used in the study

Variable	Type	Description
Value	Numeric	Demand Quantity

Below is a monthly-sample demand listing for Batch ID-N1495:

batchID	time	value
N1495	1/1/1990	5080
N1495	2/1/1990	3690
N1495	3/1/1990	4260
N1495	4/1/1990	3920
N1495	5/1/1990	4290
N1495	6/1/1990	3840
N1495	7/1/1990	4830
N1495	8/1/1990	4120

Figure 3. Sample data from a monthly time series

METHODOLOGY

Fig. 4. below outlines the flow of our study:

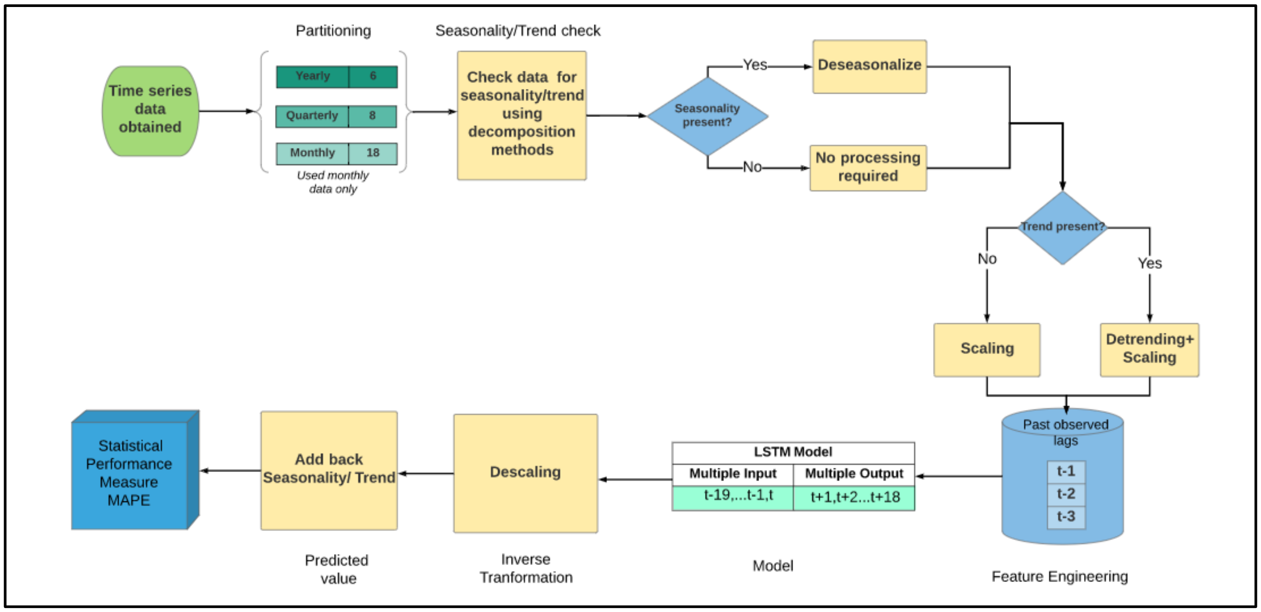


Figure 4. Methodology flow chart

Once the time series data has been obtained the following sequence of steps were followed:

- **Partitioning data:** Our data consists of yearly, quarterly and monthly frequencies. Since quarterly and yearly data have less number of data points, LSTM trains ineffectively on this set and poses the issue of overfitting. Hence, we forecast on monthly time series only, which is 18 time steps.
- **Check seasonality and Trend (Deseasonalize /Detrend if required):** LSTM or any neural network struggles when working with non-stationary data. We use STL decomposition to separate seasonal, trend and residual components and LSTM model is then applied on the residual part to learn long-term dependencies.

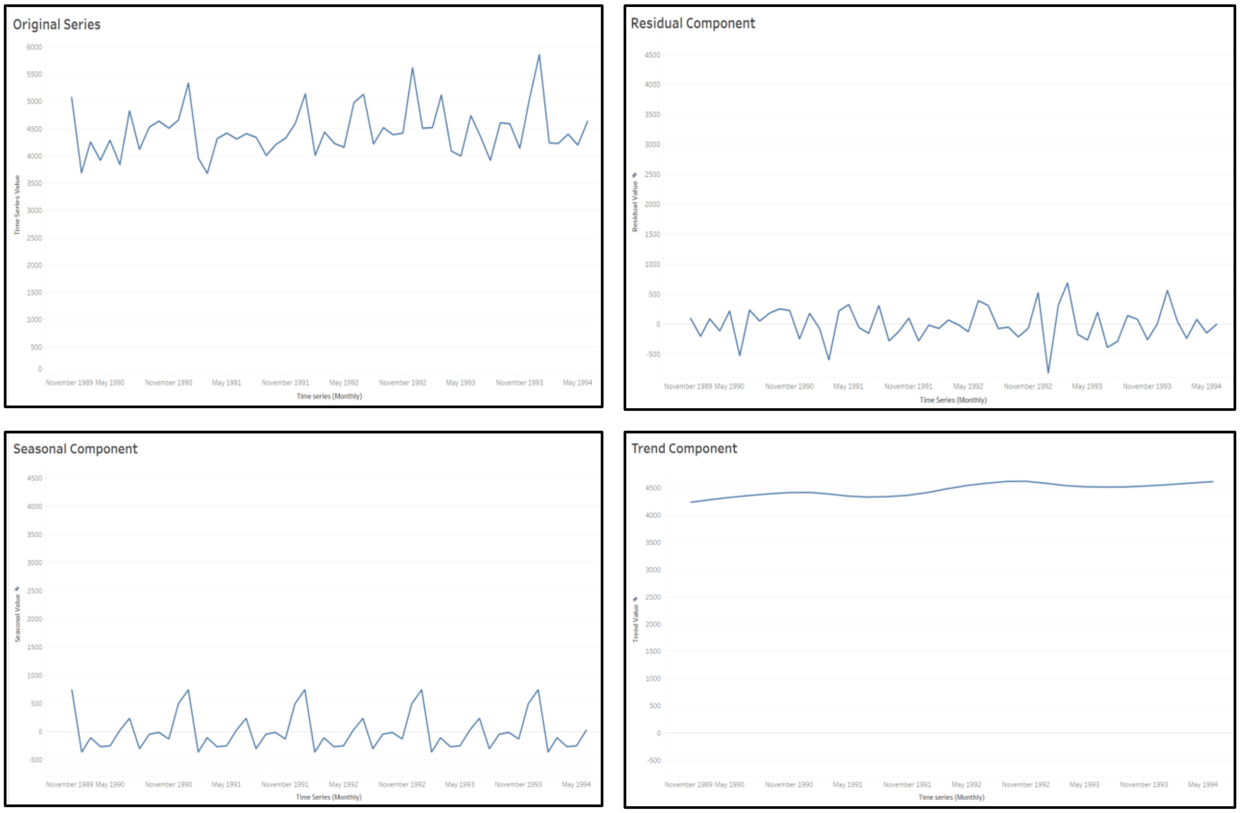


Figure 5. Splitting the time series into seasonal, trend and noise components

We used STL decompose method to split the time series into seasonal, trend and the noise components in order to convert it into a stationary time series. After removing the trend and seasonal components, the residual component is a stationary time series as indicated in the above graphs (*Fig. 5)* and would be used for further analysis.

- **Scaling:** As the data values may vary across a wide scale, we perform min-max normalization to ensure they lie within a fixed range (0 to 1) for better forecast
- **Feature Engineering:** Since we do not have parameters about the business context of the data, we only use past 20 observed lags as features to our LSTM model for forecasting.
- **LSTM Model:** Long short-term memory network is a type of recurrent neural network, specifically designed to learn long-term dependencies, overcoming the problems of vanishing and exploding gradient. The current model works on the Many-In-Many-Out mechanism, that is it predicts multiple forecast outputs using multiple inputs (lag variables).

- **Descaling:** The output of the LSTM network is inverse transformed to obtain the original range of values.
- **Adding back the seasonality and trend:** We add back the seasonal and trend components to the forecast output from the model.
- **Statistical performance measures:** The performance of the LSTM model is judged over MAPE (Mean Absolute Percentage Error) across all the monthly time series.

MODEL

We use Long-Short Term Memory (LSTM) neural network model to forecast time series. We believe LSTM will perform better than traditional and other advanced machine learning forecasting methods like ARIMA Modeling, Random Forest etc., because of its abilities to learn long-term dependencies, which is crucial in time series modeling. One disadvantage of using neural networks is that it can be very hard to train the model, especially on smaller sets of data aggregated over years, quarters or months.

LSTM was first introduced by Sepp Hochreiter and Jürgen Schmidhuber and improved in 2000 by Felix Gers' team. LSTM networks are popularly used in speech recognition, handwriting recognition etc.

Data handling and preparation is conducted in Python 3.6. Our deep learning LSTM networks were developed with Keras on TensorFlow backend. The LSTM network is trained on a CPU cluster.

LSTM networks are a type of recurrent neural networks (RNNs), i.e., neural networks where connections between units form a directed cycle. This allows them to retain memory i.e. exhibit temporary dynamic behavior. LSTM networks are capable of learning long-term dependencies and can overcome the previously inherent problems of RNNs, i.e., vanishing and exploding gradients.

LSTM networks, like dense layers, have an input layer, one or more hidden layers, and an output layer. The number of neurons in the input layer is equal to the number of explanatory variables (feature space). Neurons in the output layer reflect the output space, i.e., eighteen neuron in our case, indicating forecast of t+1 to t+18 time state. The main characteristic of the model is contained in the hidden layer(s) which consists of memory cells. Three gates in each memory cell maintain a cell state s_t: a forget gate (f_t), an input gate (i_t), and an output gate (o_t).

The structure of the memory cell is illustrated in Fig. 6 below.

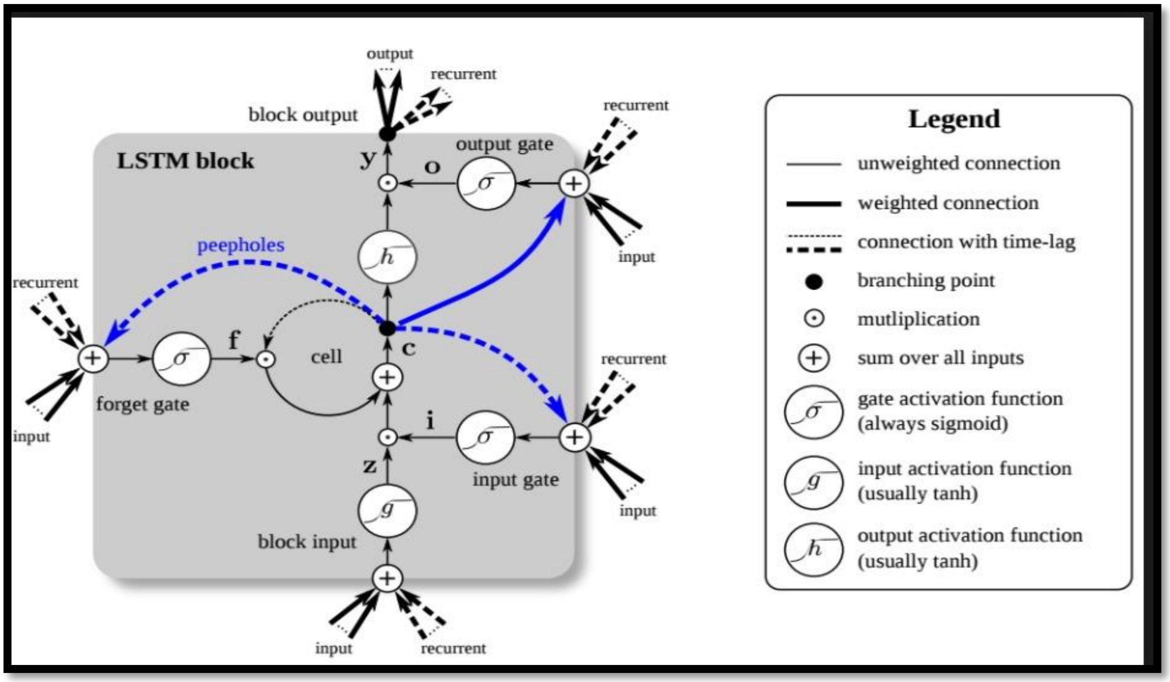


Figure 6: LSTM model's memory cell architecture
(As illustrated in NVIDIA Developer Blog-Deep Learning in a Nutshell: Sequence Learning by Tim Dettmers on March 7, 2016)

- Forget gate: Defines which information is removed from the cell state.
- Input gate: Specifies which information is added to the cell state.
- Output gate: Specifies which information from the cell state is used as output.

As illustrated in *Fig. 7* at every timestep t, each gate is presented with the current input x_t. and the output h_{t-1} of the memory cells at the previous timestep $t - 1$. Each gate has a bias vector associated with it which adds to its calculated value after every input. The working of an LSTM layer can be summarized in the following steps:

- In the first step, the LSTM layer generates activation values of its forget gates at timestep t, based on current input x_t, previous timestep output h_t and the bias term associated with the gates. This determines the information to be removed from its previous cell states s_{t-1}. An 'activation' function (sigmoid always here) finally scales all the values into a suitable normalized range which determines varying degree of forgetfulness of the input:

$$\mathbf{f_t = activation\ (W_{f,x} * x_t + W_{f,h} * h_{t-1} + b_f\ )}$$

- In the second step, the LSTM layer decides what information to be stored in the network's cell states (s_t) This has two parts: First, new candidate/subject values $\tilde{s}_t$, that could potentially be added to the cell states, are computed. Second, an activation layer called the "input gate layer" decides which values we'll update

$$\tilde{s}_t = \text{activation}\ (W_{s,\tilde{x}} * x_t + W_{s,\tilde{h}} * h_{t-1} + b_{\tilde{s}})$$

$$i_t = \text{activation}\ (W_{i,x} * x_t + W_{i,h} * h_{t-1} + b_i)$$

- In the third step, the new cell states s_t are calculated based on the results of the previous two steps with $\circ$ denoting the Hadamard product (dot product):

$$s_t = f_t \circ s_{t-1} + i_t \circ \tilde{s}_t$$

- In the last step, output of memory cell h_t can be obtained by following equations

$$o_t = \text{activation}\ (W_{o,x} * x_t + W_{o,h} * h_{t-1} + b_o)$$

$$h_t = o_t \circ \text{activation}(s_t)$$

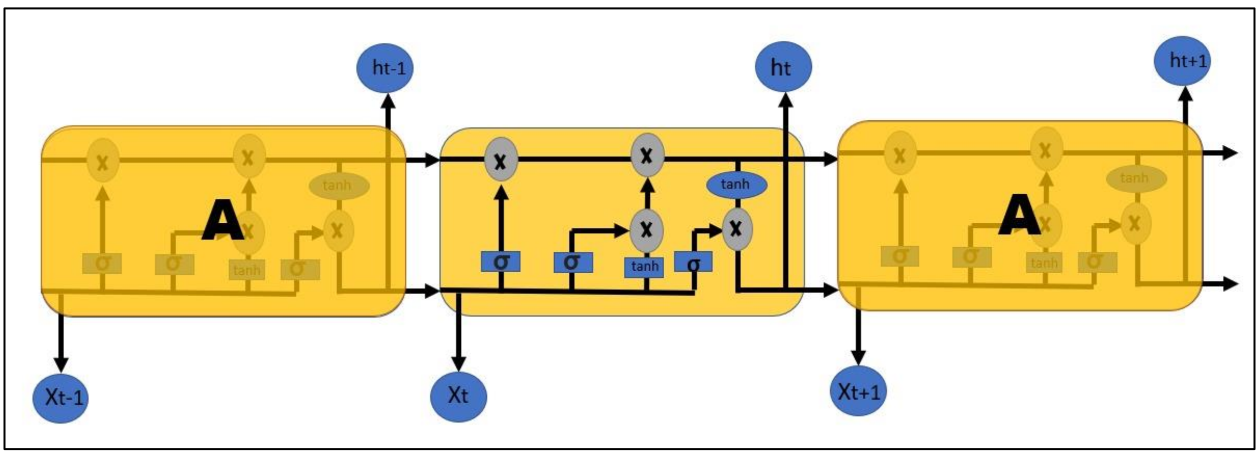


Figure 7. Processing steps in a LSTM memory cell

(As illustrated in Colah's blog Understanding LSTM Networks posted on August 27, 2015)

Training a neural network requires multiple iterations called epochs. The weights and bias vectors keep adjusting so that the loss of the specified function is minimized across the training data. Since we are dealing with a regression type problem in forecasting, we use mean-squared-error as our loss function.

In our case, we make use of Adam optimizer (commonly used), as optimizer via keras for the training of the LSTM network. The specified topology of our trained LSTM network is hence as follows:

- Input layer with one feature and six timesteps.
- LSTM layer with h = 20 hidden neurons and ‘relu’ activation function.
- Output layer (dense layer) with 18 neurons.

RESULTS

Our dataset consists of more than 1428 univariate time-series aggregated over monthly frequency level. We have built LSTM models for each time-series and forecasted values (quantity demanded) for next eighteen timesteps. However, for purpose of this paper, we present through graphical visualization few examples of time series randomly chosen from our dataset. We then contrast our LSTM model against feed-forward neural networks and theta decomposed exponential smoothing model (winner of M3 Competition).

We select MSE (Mean Squared Error) to train our networks and MAPE (Mean Absolute Percentage Error) as our performance measure against the test set. We choose MAPE because different time series have a different range of values, hence errors in percentage terms help in relative comparisons among a different set of time series. The plot of prediction on the validation dataset is shown below:

On running the LSTM model for 1428 time series, we observe most MAPE values between **4% to 35%** with the average being around **20**%.

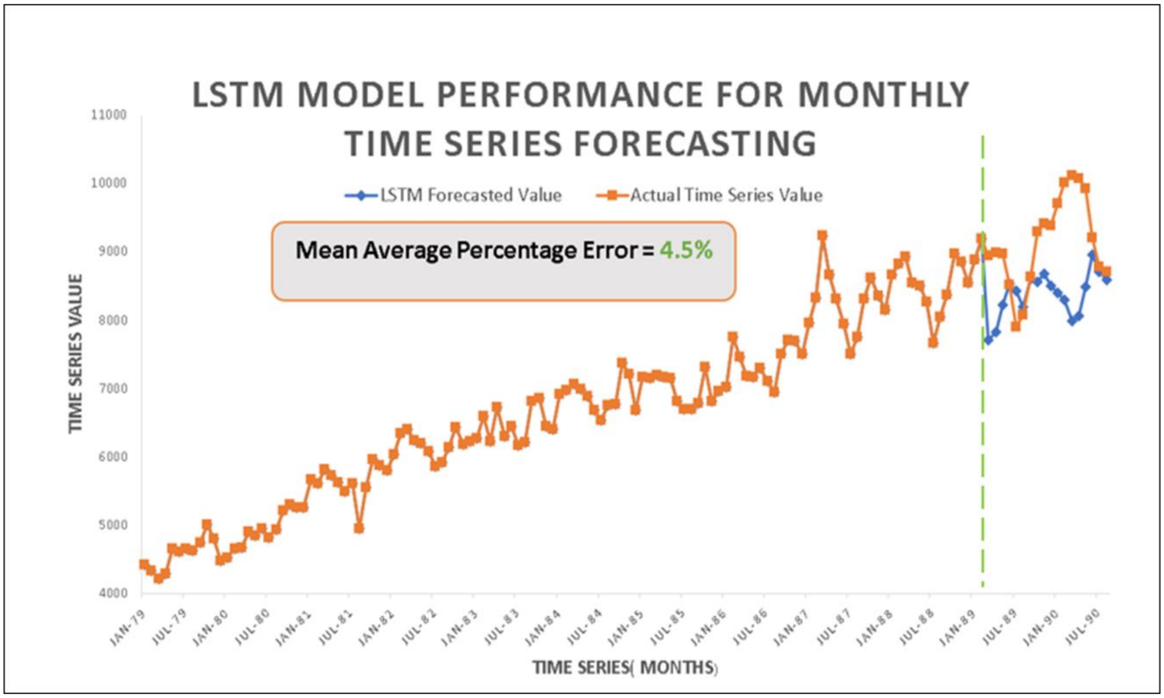


Figure 8: Plot of monthly aggregated time series and forecast

We further compared these results against other models as mentioned above. The feed-forward neural networks model gives an average of 19%, but it requires a lot of feature engineering. LSTM model performs better than traditional exponential smoothing model which gives MAPE average of about 21%. An additional advantage of LSTM model over traditional models is that it requires lot less data preprocessing and can be automated without visualizing the number of lags required to be included for prediction.

CONCLUSION

Inventory management is no longer just any task performed by those in the purchase department/ warehouse function but is now at the core of operational performance in most industries. Companies are investing heavily to ensure they get the optimum level of inventory at any point in time to minimize overhead costs and maximize revenues. However, organizations are still far from understanding to what extent descriptions, prescriptions, and predictions of these models are valid in the industry to give companies a competitive advantage.

The objective of this study was to try and develop one such model using a Recurrent Neural Network to forecast demand that offsets the disadvantages of traditional demand prediction models. The data used was from a publicly available source and represents various fields such as Finance, Economics, Demographics etc. The baseline models tested by the clients were Feed Forward Neural Network and Exponential Smoothing. In the study, Long-Short Term Memory Network was trained and tested on monthly level time series data. It was observed that LSTM Neural Network model performs better (lower MAPE) than the baseline models and requires minimal feature engineering.

We believe this study could be a valuable contribution in the area efficient demand prediction and inventory management enabling enhanced cost savings. LSTM Neural Network has the ability to take into consideration long-term dependencies and eliminates the need to visualize the number of relevant demand lags to be fed into the model. LSTM can be considered a successful decision support tool in demand forecasting in the Supply Chain and Logistics industry as well as other industries.

REFERENCES

Hochreiter Sepp, Sehmidhuber Jurgen (1997) “Long Short-Term Memory”

Gers Felix A., Sehmidhuber Jurgen, Cummins Fred (1999) “Learning to Forget: Continual Prediction with LSTM”

Patterson Josh, Gibson Adam (2017), “Deep Learning: A Practitioner’s Approach”

Abdelhadi Azzouni,Guy Pujolle (2009) “A Long Short-Term Memory Recurrent Neural Network Framework for Network Traffic Matrix Prediction”

Bonnes Kevin (2015),“Predictive Analytics for Supply Chains: A Systematic Literature Review”

C. W. J. Granger and M. J. Morris (1976),” Time Series Modelling and Interpretation”

Durga Toshniwal , R. C. Joshi(2012)“Result of Research: Using Cumulative Weighted Slopes for Clustering Time Series Data”

Fischer, Thomas Krauss Christoper (2017)“Deep learning with long short-term memory networks for financial market predictions”

Ian Goodfellow, Yoshua Bengio, Aaron Courville (2009),” Deep Learning”

James Hamilton (1995), “A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle”

Jan G. De Gooijer, Kuldeep Kumar “Some recent developments in non-linear time series modeling, testing, and forecasting”

JW Taylor (2003) “Short-term electricity demand forecasting using double seasonal exponential smoothing”

Kanad Chakroborthy, Kishan Malhotra, Chilikuri Mohan (1992), “Forecasting the behavior of multivariate time series using neural networks”

M.Langvist, L. Karlsson, A Loufti (2014) “A review of unsupervised feature learning and deep learning for time-series modeling”

Rob J Hyndman, George Athanasopoulos (2008), “Forecasting Principles and Practice”

S Makridakis, A Andersen, R Carborne, R Fildes (1982) “The accuracy of extrapolation (time series) methods: Results of a forecasting competition”

Yuehui Chen, Bo Yang, Jiwen Dong, Ajith Abraham (2005), “Time-series forecasting using flexible neural tree model”