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Research Article

A Comparison Between Long Short-Term Memory And Prophet For Time Series Analysis And Forecasting Technique

Km Priyanka Saini[1*], Amit Sharma[2]

[1*]Student of M.Tech Computer Science and Engineering, SCRIET, Chaudhary Charan Singh University Campus, Meerut, India
Email: km786084@gmail.com
[2]Assistant Professor, Department of Computer Science and Engineering, SCRIET, Chaudhary Charan Singh University Campus, Meerut, India, Email: amitccsu.net@gmail.com

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ABSTRACT

Time series analysis and forecasting are vital to many industries, such as resource management, economics, and weather forecasting. The ability of deep learning approaches, especially Networks employing Long Short-Term Memory (LSTM), to capture intricate temporal correlations has made them more and more popular recently. Furthermore, because of their ease of use and interpretability, conventional statistical techniques like Prophet have gained widespread traction. In this study, the prediction and time series analysis abilities of Prophet and LSTM are examined. We assess the effectiveness of these methods using empirical data while taking precision, computing economy, and usability into consideration.

Our findings suggest that while LSTM networks excel in capturing intricate patterns and long-term dependencies, they require substantial data preprocessing and tuning.

Prophet is better suited for scenarios with large periodic components that require rapid prototyping and reporting, since it provides a more straightforward modeling approach that accounts for seasonality and holiday support.

The specifics of the forecasting problem and the resources available for model construction and training ultimately determine which of LSTM and Prophet is best.

Keywords: LSTM, Prophet, Security, Forecasting, Machine Learning, Accuracy

Introduction

There are numerous methods for analyzing temporal sequence data and projecting future patterns, and the fields of forecasting and data analysis are always growing. Long Short-Term Memory (LSTM) and Prophet are two well-liked methods.

One well-known application of recurrent neural networks (RNNs) is long-term dependence detection and processing (LSTM). Conversely, Facebook created the open-source forecasting tool Prophet with the intention of making time-series forecasting tasks easier. In order to analyze and forecast time series, we will examine the benefits and drawbacks of both approaches in this post: LSTM vs. Prophet.

LSTM

This form of long short-term memory, or LSTM, is a part of the recurrent neural network (RNN). RNNs are quite helpful when working with sequential data because of their ability to capture dependencies over time. Because LSTM can hold data for a very long time, it is highly useful for time series research and forecasting.

There are four gates.
1. Forget gate
2. Input gate
3. Input modulation gate
4. Output gate

Prior to delving into LSTM, it is crucial to comprehend the fundamental elements of a neural network.

1. Artificial Neural Network (ANN)
2. Recurrent Neural Network (RNN)

Artificial Neural Network (ANN):
Three layers are required for a neural network to function:
1. A layer of input
2. Hidden layer
3. Output layer

The demensionality or total number of nodes, in the input layer is determined by the quantity of characteristics in the data collection. [6]

Hidden layer:
These nodes and the node that formed in the buried layer are connected by structures known as synapses. To learn, neural networks just adjust the weights given to each component. [3]

Output layer:
The output layer creates a vector of probabilities for each output and then chooses the output with the lowest cast or error rate. [7]

Recurrent Neural Network (RNN)
Recurrent neural networks are a particular kind of neural network that uses the stages that have already been witnessed in the sequence to anticipate the next observational step.

How Does LSTM Work?
States, also called memory cells, are the basic building blocks of LSTM networks since they process and store data. The information flow in these cells is regulated by a few gates, including the output, forget, and input gates. [5]

The output gate regulates the information flow to the following layer or output, the forget gate chooses what data should be deleted, and the input gate chooses which data to store in the memory cells.
Long-term dependencies can be captured by LSTM networks by using this gating mechanism, which enables them to selectively keep or discard input. [5]

Application of LSTM:
1. Robot control
2. Time series prediction
3. Speech recognition
4. Music composition
5. Hand-written recognition
6. Human action recognition

Accuracy for LSTM:
LSTM & machine learning models 89% accuracy

How to improve LSTM accuracy /performance:
Increasing your dataset turning your model architecture and using regularization and stopping.

Advantage of LSTM
Because LSTM can identify long-term relationships in time series data, it is a valuable tool for trend analysis and forecasting over extended time horizons.
It is a useful tool for many purposes due to its capacity to handle complex and non-linear interactions between variables. [9]
LSTM networks can be taught to automatically learn and extract relevant properties from incoming data, hence eliminating the need for human feature engineering.

The LSTM's limitations
Large datasets can make training and optimizing LSTM networks computationally expensive. LSTM networks require a lot of training data to avoid overfitting, which might be problematic when there is a data deficit.
Interpretability can be a challenge with LSTM models, as the inner mechanisms of the network are often considered a black box.

Prophet
The Core Data Science team at Facebook has developed an open-source forecasting framework called Prophet.

It aims to provide a simplified and intuitive method for handling time series forecasting, suitable for both experts and non-experts.

How Does Prophet Work?
Prophet divides time series data into components related to seasonality, trend, and holidays. It is based on the generalized additive model (GAM). It uses a Fourier series to capture the impacts of seasonality and a logistic or piecewise linear growth curve to model the trends. Prophet also contains additional regressors, such as holidays, which could impact the time series. [1]

Where $Y(t) = g(t) + s(t) + h(t) + e(t)$

Prophet provides us with two examples.
1. Logistic Growth model
2. Piece-wise linear model

The Logistic growth Model
$G(t)=C/1+\exp(-K(t-M))$
1. C is the carrying capacity
2. K is the rate of growth
3. M is a parameter for offset.

Advantages of the Prophet
Prophet is simple to set up and needs little configuration, making it an excellent choice for beginners or those with limited data analysis experience.
It provides built-in functionality for handling missing data and outliers, reducing the amount of preprocessing required.
Prophet offers excellent visualization capabilities, allowing users to inspect and interpret the forecasted trends easily.

Prophet's limitations
Prophet's oversimplified modeling methodology might not be appropriate for intricately patterned or irregularly varying complex time series. [1].
It may not perform well on datasets with limited historical data, as it relies on past trends and patterns for accurate forecasting.
Prophet's main focus is on univariate time series forecasting, hence it might not be able to handle multivariate time series with a lot of interdependencies.

Accuracy for the Prophet
The overall forecast accuracy is a very high 94.57%.

How do you calculate the accuracy of a prophet?
Prophet has the ability to measure forecast error using past data using time series cross validation. To do this, historical cut-off points are selected, and data is used only to fit the model up to each of those cut-off points [2].

Literature review:
1."Long Short-Term Memory" by Hoch Reiter and Schmidhuber (1997)
This paper introduced the LSTM architecture, which uses a memory cell with self-connections and gating units to manage the information's flow. The output, forgets, and input gates make up the three primary parts of the LSTM model. These gates control information flow into and out of the memory cell, allowing the model to learn long-term dependencies.
2. **By Ilya Sutskever et al., "Sequence to Sequence Learning with Neural Networks" (2014)**
The sequence-to-sequence (seq2seq) model was presented in this research. It consists of two LSTM networks, a decoder and an encoder, that work together to translate an input sequence into an output sequence.Numerous tasks, including text summarization, speech recognition, and machine translation, have been effectively tackled using the seq2seq approach.
3. **A study by Alex Graves and associates, "Large-Scale Acoustic Modeling Using Long Short-Term Memory Recurrent Neural Network Architectures" (2013)**

In this study, the LSTM-RNN architecture—a variation of the LSTM architecture designed specifically for large-scale speech recognition tasks—was proposed. LSTM-RNN architecture makes use of. Several gating unit types and multiple layers of LSTM cells are used to mimic the intricate temporal connections found in voice data.
4. **" Acquiring the Memory of None: Constant Forecasting Using LSTM "** by **Felix A. Gers et al. (2000)**
This paper proposed a method for training LSTM models that enables them to acquire the ability to forget irrelevant information and remember important information for extended durations of time. The method

involves adding an additional error term to the loss function, which encourages the model to forget information that is no longer random forests. The information gathered, however, shows that Prophet surpasses the naïve technique Random forests work better for forecast horizons greater than three days overall.

5. Facebook's Core Data Science team released a forecasting algorithm called Prophet. (Taylor et al., 2017)

It modifies parameters to account for typical features of business time series without prior knowledge of the underlying model details. It comprises of a process created for time series forecasting data using an additive model that accounts for the effects of holidays as well as seasonality in nonlinear patterns that occur on a daily, monthly, and annual basis. It was used to estimate sales in earlier research (Zuni et al., 2020), and the results were provided based on the percentage error with mean absolute (MAPE) level for predicting sales of different kinds of articles. They were successful in reaching a MAPE level of less than 30% for 70% of the commodities based on a quarterly estimate. Default seasonality patterns were used in this study.

A set of contrasts between Prophet and Long Short-Term Memory, or LSTM, for prediction and time series analysis are presented here:

Parameter	LSTM (Long Short-Term Memory)	Prophet
Model Complexity	Capable of capturing complex patterns in data, the deep learning model has a sophisticated architecture.	A reduced additive regression model for seasonality and vacations based on a Fourier series basis.
Data Requirement	Requires large amounts of data for training, especially for complex patterns.	Works well with smaller datasets and can handle missing data.
Interpretability	Because it's a black-box system, it's harder to interpret and comprehend how predictions are created.	More readable projections include elements like vacations, seasonality and trends that are easy to understand.
Training Time	Longer training times, especially for large datasets and intricate structures.	Faster training compared to LSTM, suitable for quick experimentation and prototyping.
Managing Seasons	Can capture complex seasonal patterns but may require more data and tuning.	Incorporates seasonality via the Fourier series, which facilitates handling and modeling. .
Handling Trends	Capable of capturing nonlinear trends but may require careful tuning and regularization.	Automatically detects and models linear and non-linear trends, providing robust forecasts
Implementation Complexity	Requires knowledge of frameworks for deep learning and expertise in hyper parameter tuning.	Straightforward to implement with built-in functions in Python, R, and other languages

Table 1: Comparison List between Long Short-Term Memory, or LSTM, and Prophet.

Result: -

Parameter	**LSTM (Long Short-Term Memory)**	**Prophet**
Security	Time series are only an anomaly when it comes to LSTM-based recurrent neural networks, which are the best technique for learning from sequential data	One of Prophet's advantages is that its main purpose is to help businesses find trends in time series. The smallest hyper-parameter is needed.
Accuracy	89% accuracy for LSTM and machine learning models	The overall forecast accuracy is 94.57% which is extremely high.

Flexibility	High It is a more accurate model of flexibility.	Low
Robustness	Robustness against adversarial attacks may be b concern.	A simpler model might be less prone to adversarial attacks.

FUTURE WORK AND SCOPE

1. Performance Evaluation: Perform thorough performance evaluations on a range of datasets from various businesses and fields using a variety of metrics, such as mean absolute percentage error (MAPE) and root mean squared error (RMSE).
2. Model Interpretability: Examine the Prophet and LSTM Models' interpretability to learn how each one represents temporal trends and patterns. This might entail looking at Prophet's component analysis, LSTM attention processes, and feature importance.
3. Robustness Analysis: Assess the robustness of LSTM and Prophet models under different conditions such as noisy data, missing values, and irregularly sampled time series.
4. Uncertainty Estimation: Investigate techniques for estimating uncertainty in Profit Forecasts and LSTM to produce probabilistic forecasts or confidence intervals, which are essential for making decisions in the face of uncertainty.
5. Long-Term Forecasting: Examine the effectiveness of Prophet and LSTM for long-term forecasting that goes beyond the usual time frame covered by previous research. Predicting patterns over several years or decades may be required for this.
6. Real-Time Forecasting: Examine whether using LSTM and Prophet Models for real-time forecasting applications is feasible while taking latency and computational efficiency limitations into account.
7. Domain-Specific Applications: Explore specific applications in different domains such as finance, healthcare, energy, and retail to assess the suitability of LSTM and Prophet Models and identify any domain-specific challenges or requirements.
8. Model Explainability: Give an explanation of the predictions made by the LSTM and Prophet models using your understanding of the factors affecting the estimations.
9. Resource Requirements: Analyser the computational and memory requirements of LSTM and Prophet Models to understand their scalability and resource efficiency, especially for large-scale deployment scenarios.

Conclusion

Prophet and LSTM both provide distinctive methods for forecasting and time series analysis. Because of its deep learning capabilities, LSTM is a good choice for challenging jobs involving lengthy.

LSTM vs. Prophet Comparison in Forecasting and Time Series Analysis Method Overview There are various methods available in the constantly developing field of data analysis and forecasting to examine time series data and project future trends.
Prophet and Long Short-Term Memory (LSTM) are two well-liked methods. The ability of long-term dependent recurrent neural networks (RNNs) with long-term memory (LSTM) to process sequential input is widely recognized.

In contrast, Facebook created Prophet, an open-source forecasting library, to simplify the process of time series forecasting. In order to analyze and predict time series, this article will compare Prophet and LSTM. Both methods have benefits and drawbacks. LSTM: A Deep Learning Approach What is an LSTM? Extended Short-Term Memory, or LSTM for short, is an architecture type called a recurrent neural network, or RNN. Because they can capture dependencies over time, RNNs are very helpful when working with sequential data.

Time series analysis and forecasting greatly benefit from long-term memory's (LSTM) ability to retain information. What is the operation of the LSTM? LSTM networks are composed of strands of memory that store and process states. These cells have a few gates that regulate the information flow. The input (forget) gate and the output gate are two types of these gates. The input gate selects data to be stored in memory cells, the forget gate removes it, and the output gate moves it to the next layer or output.

Because of this gating mechanism, long-term dependencies can be captured by LSTM networks by allowing them to choose store or reject information. Benefits of LSTM: Because it can identify long-term dependencies in time series data, LSTM is helpful for researching and forecasting trends that span a considerable amount of time.
It is a helpful tool for many different applications because of its capacity to manage intricate and non-linear interactions between variables. It might be possible to do away with the necessity for human feature engineering by teaching LSTM networks to automatically learn and extract pertinent features from input data.

The computational expense of training and optimizing LSTM networks may rise due to the limits of large datasets.

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