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ANALYZING THE EFFICACY OF ML APPROACHES IN INVENTORY FORECASTING: AN IN-DEPTH COMPARISON OF LSTM, PROPHET, AND ENSEMBLE APPROACHES

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ABSTRACT—In retail business, stock levels optimization is one of the significant aspects, where changes can have a great impacton profitability and customer satisfaction. for this purpose, this paper introduces the RetailRevolutionizer: A Machine Learning-based Inventory Demand Forecasting tool designed for compar- ison of three advanced models namely LSTM, Prophet, and Prophet + SARIMA, by evaluating each model's performance in terms of forecasting accuracy, RetailRevolutionizer provides insights into their strengths and limitations. The LSTM captures the long-term dependencies effectively, while SARIMA deals well with seasonality. Prophet specifically specializes in trend decomposition and anomaly detection The overall tool imple-mentation consists of data cleaning, trend analysis, study of sales distribution, and detecting anomalies. Through the trends for sales clustering and sales time-series decomposition, RetailRev- olutionizer delivers actionable insights into sales variability and peak periods. It has proven that improvements in every modelare appreciated by the augmentation in forecasting accuracy and avoided cases of overstocking and under-stocking. This ensures better inventory turns and increases connectivity with customers' demand, making the overall operating efficiency better.

INDEX TERMS—Inventory Management, LSTM, SARIMA, Prophet, Predictive Analytics, Machine Learning

1. INTRODUCTION

Modern retail environments have made it difficult to manage inventory because of the critical need to correctlyforecast demand amid such complexity. Traditional inventory control methods tend to rely on heuristic approaches or simple statistical models, based on the assumption that patterns may not be complex and certainly not nonlinear. Due to these problems, such retailers commonly suffer from, including overstocking and under-stocking and low efficiency in turnover, resulting in adverse implications on profitability and customer satisfaction. For a firm in this scenario, accurate sales forecasting turns out to be the key to optimizingthe proper inventory levels and bringing them in line with customer requirements.

Conventional methods include exponential smoothing and ARIMA. These have been in practice for a long time within the domain of inventory management. However, such models cannot capture the internal complexity of sales data, such as seasonality, the effects of promotion, or sudden changes in the market [3]. Recent advancements in machine learning, specifically deep learning models like LSTM - Long Short-Term Memory - have illustrated that these problems have much promise to be solved by utilizing long sequences of historical data [4][5]. Nevertheless, even with their excellent success, these models remain sensitive to hyper-parameter tuning, biased towards large datasets, andsometimes unable to work with extreme anomalies [6].

The core of the problem is an optimization problem,with the goal of minimizing the mismatch between predicted sales and actual sales to ensure inventory levels are as closeas possible to demand. The mathematical formulation is as follows:

$$\hat{y_t} = f(x_t) + \varepsilon \quad (1)$$

Where $\hat{y}_t$ denotes the predicted sales at time t, x_t represents the input feature set (which may include historical sales, time-based features, and external factors), and ϵ is the errorterm.

RetailRevolutionizer addresses these challenges by comparingthe predictive powers of three advanced forecasting models: LSTM, SARIMA, and Prophet. Each model handles different aspects of sales data. LSTM effectively captures long-term dependencies in sequential data, modeling complex patterns over extended periods [7]. SARIMA is particularly useful for datasets exhibiting strong seasonal trends [8], while Prophet excels at trend decomposition and anomaly detection, especially in datasets with irregular patterns or missing data [3]. By comparing these approaches, RetailRevolutionizer aims to provide retailers with accurate, actionable forecasts, offering valuable insights into the strengths and weaknessesof each model. This comparison is particularly useful for addressing common challenges such as non-stationarity,long-range dependencies, and external factors like promotionsand holidays [9].

Modern retail sales data are complex and often require capturing additional patterns beyond temporal ones, such as market conditions, customer behavior, and promotions. Deep learning architectures are more suitable than simple linearmodels for modeling nonlinear interactions between variables [4]. LSTM excels at learning sequential dependencies over long time spans, making it ideal for time-series forecasting. SARIMA remains a proven technique for handling seasonality, a critical need for retailers managingsales driven by seasonality [8]. Prophet further enhances flexibility by automatically adjusting for trend changes and handling missing data [3].

The challenge in inventory forecasting often lies not just in achieving high predictive accuracy but in interpreting and using these forecasts to drive actionable decisions. RetailRevolutionizer addresses this by incorporatingtechniques such as sales trend decomposition, variability analysis, and anomaly detection, providing retailers with acomprehensive understanding of their inventory needs. The system offers insights into peak periods and helps identify products that exhibit irregular sales patterns, such as sudden demand spikes due to promotions [3].

This paper also discusses the application of ensemble techniques for improving forecasting accuracy. By combining the predictions from multiple models—each with its own strengths—the ensemble approach provides more robustforecasts that account for the heterogeneous nature of retail sales data. SARIMA's capacity to capture seasonal patterns, and Prophet's adaptability to trend shifts and missing data make this hybrid approach highly effective in improving forecasting accuracy [9]. This approach eliminates the limitations of relying on a single model and provides a more reliable system for inventory management.

In parallel with the evolution of predictive techniques,the growing availability of computational resources suchas multi-core processors and GPU-accelerated computing has made it feasible to deploy complex models at scale. This enables real-time forecasting, even for large retail chains with thousands of products [4]. The scalability of RetailRevolutionizer ensures it can be applied to datasets of varying sizes, providing value to both small businesses and large enterprises [9].

In summary, this paper introduces a powerful inventory forecasting tool called RetailRevolutionizer, which deliversremarkably accurate sales predictions by leveraging the combined strengths of SARIMA, and Prophet models.This hybrid approach minimizes overstocking and under-stocking, improving inventory turnover and overall operationalefficiency. The remainder of this paper outlines the design, implementation, and performance of RetailRevolutionizer, demonstrating its potential to revolutionize inventorymanagement in the retail sector.

2. RELATED WORK

2.1 Sales Forecasting and Inventory Management

Sales forecasting has been considered the important focus area within the retail industry for a long time, as it wouldhave a direct impact on inventory management and operationalefficiency. The models conventionally adopted for ARIMA (Auto-Regressive Integrated Moving Average) and exponential smoothing have been preferred for time-series data due to theirsimplicity and the efficacy of capturing linear trends. However,in more complex patterns, which most often describe real datafrom a retail, these models behave catastrophically, especially when interference factors appear, for instance, caused by promotion or sudden changes in demand from customers. ARIMA is good at modeling stationary data but not too good at dealing with seasonality and abrupt structural changes; therefore, more approaches have been necessary.

2.2 Machine Learning in Time-Series Forecasting

In recent years, the techniques of machine learningreceived ever more application in time-series forecasting and have shown up as competing with a number of traditional models through their ability to deal with non-linearity and longer dependencies. Neural networks, especially RNNs and LSTM networks, are very capable of learning sequential data patterns [4]. LSTMs are a type of special RNN and havebecome prominent in time-series forecasting applications because the vanishing gradient problem limits the strengthof ordinary RNNs in capturing long-term dependencies, which can be mitigated [6,10]. Hochreiter et al. (1997) initiated this kind of research which led to the extensive use of LSTMs in applications involving sales forecasting, prediction of energy demand, and even financial modeling, wherein information significantly depends on long sequences. During long periods of forecasting, the LSTM modelshave proved to perform very well especially with datasets that contain seasonality and shocks in the retail industry. However,while very effective at capture complex patterns, LSTMs are computationally expensive and sensitive to hyper-parameter tuning, which makes them not so friendly for real time applications [5].

2.3 Anomaly Detection in Retail Sales

Another significant aspect of retail sales forecasting is anomaly detection. Unexpected rapid increases or decreases inthe sales quantity can severely damage the inventory planning.Traditional methods of anomaly detection, such as Z-scoresor moving average filters, have been extremely successful for purposes in the retail analytics. However, recent developmentswithin machine learning namely the clustering methods and time-series decomposition techniques have made it possible toimplement more advanced anomaly detection methodologies [11][12]. These were implemented in forecasting models like Prophet to provide much earlier warnings regarding unusual patterns of sales, thereby giving the retailer an opportunity toadjust his inventory strategies.

2.4 Ensemble Forecasting Techniques

The ensemble forecasting techniques have been proven to be better than individual models by combining their predictionsto offset each model's weaknesses. In this recent developmentwork in the field, it has been shown that combining machine learning models, such as LSTM, with statistical methods like SARIMA and Prophet can indeed provide better accuracyin forecasting. Hybrid techniques, for example, stacking and weighted averages, have found to be very successful within retail environment due to long-term dependency and season- ality appearing within points of data [13]. Zhang et al. (2020) and Huang et al. (2021) have supported ensemble techniques in terms of reducing error rate and upgrading the operational performance especially in the context of retail and e-commerce[14], [15].

3. 3. PROPOSED METHODOLOGY

This paper proposes a comparative and ensemble approach to time series forecasting using three models: LSTM, Prophet,and an ensemble of Prophet and SARIMA. The aim is tohighlight the strengths and weaknesses of each method and demonstrate the benefits of combining models for improving predictive accuracy.

3.1 Long Short-Term Memory (LSTM)

LSTM is a variant of Recurrent Neural Networks (RNNs) designed to address the problem of long-term dependenciesin time series data. Unlike traditional RNNs, LSTM can remember information for long periods, making it ideal for time series forecasting tasks that require learning both short- and long-term patterns.[4]

3.1.1 Key Components of LSTM

Cell State (C_t): The memory of the network, which can carry information across time steps.
Forget Gate (f_t): Decides how much of the past information should be forgotten.

$$f_t = \sigma\left(W_f.\left[h_{t-1,x_t}\right] + b_f\right)$$
(2)

Where:
- W_f is the weight matrix for the forget gate.
- h_{t-1} is the output from the previous hidden state.
- x_t is the input at time step t.
- b_f is the bias term.

Input Gate (i_t) and Candidate Cell State ($\widetilde{C_t}$:) These components decide what new information should be added to the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$
$$\widetilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
(4)

Output Gate (o_t): Decides how much of the current cell state should be passed to the next hidden state.
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
(5)

The final cell state and hidden state are updated as:
$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t}$$
(6)
$$h_t = o_t * \tanh(C_t)$$
(7)

3.1.2 LSTM for Time Series Forecasting:

LSTM is trained using backpropagation through time (BPTT), and it has the capability to learn from his- torical data. In this study, we train an LSTM networkwith multiple layers to capture both short- and long-term dependencies. Hyperparameter tuning (learning rate,number of layers, and hidden units) will be carried outto optimize the model performance.

3.2 Prophet Model:

Prophet, developed by Facebook, is an additive model de-signed for forecasting time series data with daily observations. It is particularly effective when the data exhibits non-linear trends, seasonality, and holiday effects. [16] Prophet is based on the following equation:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$
(8)

Where:

- g(t) is the trend component.
- s(t) represents seasonality.
- h(t) denotes holidays or special events.
- ε is the error term or Noice

1) **Trend Component**: Prophet models trends using piece-wise linear or logistic growth. The linear trend component can be expressed as:

$$g(t) = \left(k + a(t)\right)t + b$$
(9)

Where:

- k is the growth rate.
- a(t) is the rate change at time t.
- b is the offset parameter.

2) **Seasonality Component**: Seasonality is modeled as a fourier series expansion to capture recurring patterns in the data

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{T}\right) + b_n \sin\left(\frac{2\pi nt}{T}\right)\right)$$
(10)

Where T represents the period (e.g., daily or yearly seasonality).

3) **Holiday Component**: Prophet includes a holiday effect that accounts for irregular events that can cause deviations in time series patterns.

3.3 SARIMA Model

The SARIMA (Seasonal ARIMA) model is an extension of the ARIMA (Auto-Regressive Integrated Moving Average) model, which incorporates seasonality. It is represented by SARIMA
(p, d, q)(P, D, Q, m), where: [17]

- p, d, q are the parameters for the ARIMA component.

- P , D, Q are the seasonal parameters.
- m is the number of time steps in a season (e.g., 12 for monthly data).
- The general equation for SARIMA is:

$$(1 - \phi_1B^1 - \cdot\cdot\cdot - \phi_pB^p)(1 - \Phi_1B^m - \cdot\cdot\cdot - \Phi_P B^{Pm})(1 - B)^d(1 - B_m)^D y_t = (1 + \theta_1B^1 + \cdot\cdot\cdot + \theta_qB^q) + \Theta_1B^m + \cdot\cdot\cdot + \Theta Q_B{}^{Qm})\epsilon t$$
(11)

Where:

- B is the back-shift operator.
- ϕ, Φ are the auto-regressive terms.
- θ, Θ are the moving average terms

3.4 Ensemble Model: Prophet + SARIMA

In this study, we propose an ensemble model that combines the Prophet and SARIMA models to leverage their strengths and minimize their individual weaknesses. [18] Prophet excels at modeling long-term trends and irregular events, while SARIMA is better suited for capturing seasonality in more structured data.

1) **Ensemble Methodology**: The ensemble model is based on weighted averaging of the forecasts from Prophet and SARIMA

$$y_{ensemble}(t) = X \cdot y_{Prophet}(t) + Y y_{SARIMA}(t)$$
(12)

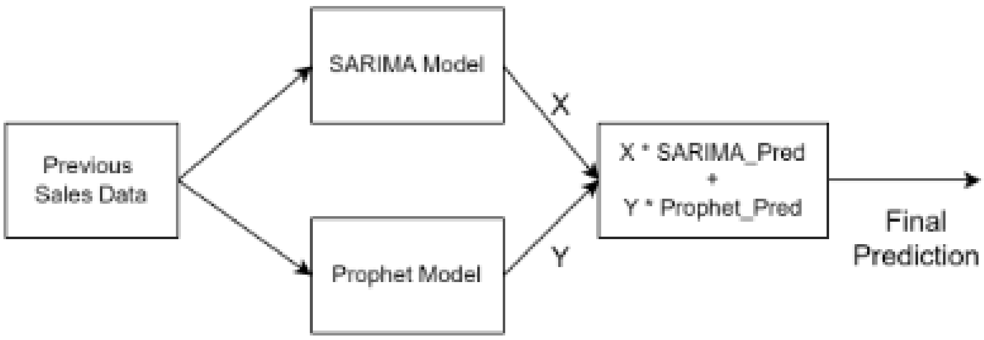

Fig. 1. Ensemble Learning Flow Diagram

Where:

- $y_{PROPHET}(t)$ and $y_{SARIMA}(t)$ are the forecasts from the Prophet and SARIMA models at time t.
- X and Y are the weights assigned to each model based on their historical performance. These weights can be op-timized using cross-validation or Bayesian optimization.

4. MODEL PERFORMANCE EVALUATION:

The proposed models will be evaluated using metrics such as: For complete assessment of time series prediction model's efficiency, a collection of measures will be applied. Every measure signifies an alternative part of the model's effectiveness such as correctness, error dispersion among others; whereby this contributes to explaining variability within the data set through which they forecast.

4.1 Mean Absolute Scaled Error (MASE)

Mean Absolute Scaled Error (MASE) is a normalized error metric that compares the forecasting error of the model to a naive forecast, [19] which assumes that the next value in the series is equal to the previous value (lag of 1). MASE is calculated as follows:

$$\text{MASE} = \frac{\text{MAE of model}}{\text{MAE of naive forecast}}$$
(13)

Where:

- MAE of model is the Mean Absolute Error of the model's predictions.
- MAE of naive forecast is the Mean Absolute Error of a naive forecast where $y_t = y_t - 1$.

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|y_t - \widehat{y_t}|$$
(14)

- In the code, the MASE is calculated by shifting the true values by one step to create a naive forecast and comparing the model's performance against it.
- Lower values of MASE indicate better performance.

4.2 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a scale-independent error metric that calculates the percentage error for each forecasted value [20] and then takes the average across all forecasts. It is expressed as

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{y_t - \widehat{y_t}}{y_t}\right|$$
(15)

Where:

- y_t is the actual value at time t.
- y_t is the predicted value at time t. MAPE provides an intuitive understanding of the model's error in percentage terms.
- Lower values of MAPE represent better model performance

4.3 Symmetric Mean Absolute Percentage Error (sMAPE)

The Symmetric Mean Absolute Percentage Error (sMAPE) is an alternative to MAPE that adjusts for the fact that MAPE can be overly sensitive to small values of the actuals (yt). sMAPE provides a symmetric measurement by using the sum of the absolute actual and predicted values in the denominator.

$$\text{sMAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\frac{2|y_t - \widehat{y_t}|}{|y_t| + |\widehat{y_t}|}$$
(16)

Unlike MAPE, sMAPE treats over- and under-predictions equally, making it a more balanced measure for evaluating time series forecasting models.

4.4 Median Absolute Error (MedAE)

Median Absolute Error (MedAE) is a robust measure ofcentral tendency that captures the median of all absolute errors. [21] The formula is as follows:

$$\mathrm{MedAE} = \mathrm{median}(|y_t - \hat{y}_t|)$$
(17)

4.5 Explained Variance Score (EVS)

Explained Variance Score (EVS) measures the proportionof variance in the true values that is captured by the model.It is a value between 0 and 1, where 1 indicates that themodel perfectly explains the variance in the data. [22] The EVS formula is given by:

$$\mathrm{EVS} = 1 - \frac{\mathrm{Var}(y_t - \hat{y_t})}{\mathrm{Var}(y_t)}$$
(18)

Where Var is the variance function. Higher values of EVS indicate that the model captures more variance in the data, anda value of 1 means perfect predictions.

5. RESULTS AND DISCUSSION:

The result of the research paper supports the effectivenessof the three forecasting models-LSTM , Prophet, and an ensemble of Prophet with SARIMA (Prophet+SARIMA). We compared their predictive accuracy using key metrics suchas Mean Absolute Scaled Error (MASE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), Mean Absolute Error (MAE), and Explained Variance Score (EVS).

LSTM Model: Following are the results for each metrics of the LSTM forecasting model.
MASE is calculated as 18025171.1285.MAPE is calculated as 21.86%. sMAPE is calculated as 19.51%. MAE iscalculated as 4050.6680.EVS for the LSTM model is calculated as 0.5300.

Below is the Graphical Representation of Actual Salesvs Predicted Sales based on the given dataset using LSTM forecasting model.

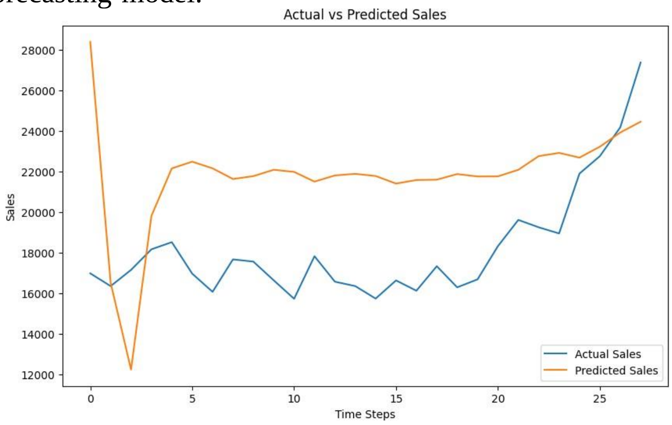

Fig. 2. Actual vs Predicted Sales using LSTM Model

Prophet Model: Following are the results for each metricsof the Prophet forecasting model.MASE is calculated as 88245413.7452. MAPE is calculated as42.66%. sMAPE is calculated 33.49%. MAE is calculated as 5858.7337.EVS for the prophet model is calculated as -0.5400.

Below is the Graphical Representation of Sales forecast based on the given dataset using prophet forecasting model**.**

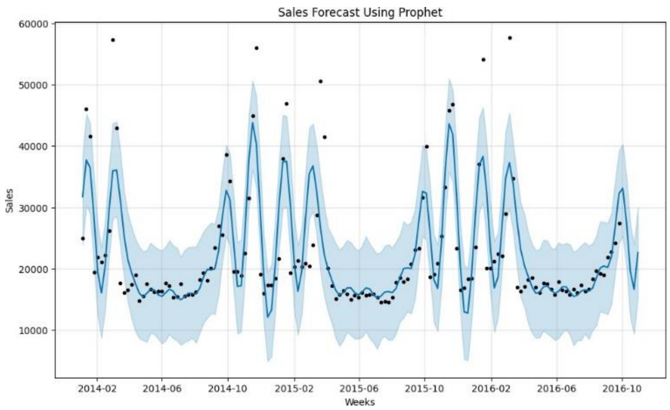

Fig. 3. Sales Forecast using prophet model

Ensemble Model: Following are the results for each metrics of the Ensemble forecasting model. MASE is calculated as 17486612.9364. The MAPE is calculated as 17.30%. The sMAPE is calculated 16.68%. The MAE is calculated as 2274.2794. The EVS for the prophet model is calculated as -0.0242

Below is the Graphical Representation of Actual vs Predicted Sales forecast based on the given dataset using Ensembleforecasting model.

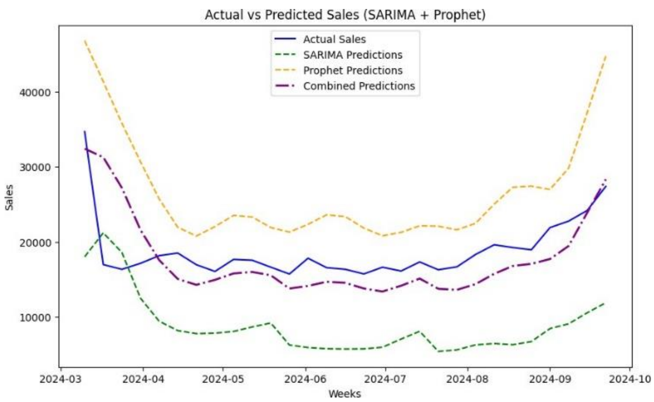

Fig. 4. Actual vs Predicted Sales Comparison among three models

The ensemble model achieves a significantly lower MASE of 17,486,612.9364, which is an improvement over both the Prophet model (88,245,413.7452) and the LSTM model (18,025,171.1285). This indicates that the ensemble model produces scaled errors that are muchsmaller than the individual models, making it a more reliableforecaster in terms of absolute errors when adjusted for scale.

The ensemble model’s MAPE of 17.30% clearlyoutperforms the Prophet model (42.66%) and the LSTM model (21.86%). This shows that the ensemble provides more accurate predictions relative to the actual values, reflecting lower percentage errors and, thus, better predictive accuracy.

The ensemble model achieves an sMAPE of 16.68%, which is notably lower than the Prophet model (33.49%) and slightly better than the LSTM model (19.51%). sMAPE being a symmetric metric further underscores that the ensemble model’s forecasting accuracy is much better, particularly in scenarios with varying data scales.

The ensemble model has an MAE of 2,274.2794, outperforming the Prophet model (5,858.7337) and theLSTM model (4,050.6680). A lower MAE indicates that the ensemble model provides more accurate forecasts in termsof absolute deviation from actual values, demonstrating its superior capability to minimize prediction errors.

The ensemble model’s EVS of -0.0242 is better than that of the Prophet model (-0.5400) and slightlyworse than the LSTM model (0.5300). While the EVSfor all models is relatively low, it is evident that the ensemble approach reduces the variance explanation errors from the highly negative score of the Prophet model, providing more stable and consistent performance. This ensemble model combining SARIMA and Prophet outperforms the individual models of Prophet as well as LSTM based on all major metrics of the error pertaining to forecasting: MASE, MAPE, sMAPE, and MAE. While the LSTM model shows a better value of EVS, the ensemblemodel compensates through the accuracy and consistency in error reduction for the forecasts. It is more importantly the combination of the ability of SARIMA in handling seasonalityand the flexibility that Prophet can use that makes an ensemblemodel superior for inventory forecasting.

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