

ML Powered Analytics for Sensing Demand in Consumer Industry

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Abstract— The consumer goods industry is facing significant challenges in meeting the consumer's ever-evolving demands and preferences. The e-commerce and online delivery brought in the ease of access to purchase products, while the popularity of social media brought the social sentiment angle which are impacting customer purchases patterns. These factors are leading to a rise in influencer marketing campaigns and have enabled businesses or brands to reach consumers faster. The goal of the study is to address these challenges and to explore the use of Machine learning and big data analytic techniques to provide insights by understanding consumer purchase patterns, sales data, market and social media trends, news feed and stock levels to predict future demand for products in advance which will better enable inventory planning.

Keywords: Demand Sensing, Machine Learning(ML), Predictive Analytics, Extreme Learning Machine, Consumer Purchase Patterns, Big Data Analytics

I. INTRODUCTION

Demand sensing tracks market trends, macroeconomic factors, social media trends, promotional discounts, stock levels, shipping history, and order transactions to estimate the aggregate demand in short-term, mid-term, and long-term in advance by predicting consumer purchase orders over a period of time.

Demand sensing helps ensure the correct volume of stock of known products in inventory to determine the demand by identifying the relationship of an existing product in that market and the demand of the existing product influenced by various explanatory variables and phenomenon.

Demand sensing can help win time by instantly responding to early demand insights and providing better input supply signals to replenish stocks and determine the stock threshold for a product to avoid stock-out and optimize stock level in the inventory of the warehouse by factoring expected and refreshed demand. With granular visibility in the supply chain process, it is possible to adjust stocks in inventory when product demand drops by

taking timely decisions to eliminate excess stocks, dead stocks, or obsolete stocks.

The study will research ML methods to analyze the data from various sources of data and analyze the underlying patterns in the data and draw valuable insights to identify trends in demand, the influence of multiple demand signals, give early warning alerts by employing an ML solution to sense the demand of products to help optimize inventory keeping and replenishment planning of stocks to reach consumers faster and increase sales.

The solution focuses on building a seamless end-to-end pipeline that derives insights in demand sensing in commodity industry and helps to make the data-driven decision by publishing KPI metrics and actionable alerts in a unified dashboard. The pipeline will employ ML models in multi-stage architecture which will employ clustering algorithms to understand the underlying patterns in the data and help in feature engineering to create new significant features and then apply an ensemble of models with a final integrator model that predicts the future demand of products across regions. This will contribute to driving insights into actions and the development of best practices for using data analytics to improve operational efficiency and sales for retailers and brands.

The proposed solution is an end-to-end demand sensing analytics platform designed for the retail and consumer industry. It integrates machine learning (ML) algorithms and deep learning neural networks, leveraging the strengths of both. ML algorithms handle data pre-processing, aggregation, key factor identification, classification, and clustering, while deep learning neural networks offer advantages in learning speed, fast convergence, generalization ability, and implementation ease. The solution's modular architecture, featuring multi-stage data processing, multi-class classification, incremental and sequential learning capabilities, and the ability to combine results from different data cluster modules, sets it apart. Unique Key Performance Indicators (KPIs) associated with actionable flags provide valuable insights for enhancing or controlling demand patterns based on customer feedback.

II. LITERATURE SURVEY

Every business wants to ensure best customer satisfaction. Consumer goods industries are no exception to this. Different methods have been used to forecast or predict the demand in the retail sector. The businesses use traditional mathematical models to predict demand. However, in recent times, the customer purchase pattern is influenced by multiple demand signals and the need to maintain the stock of goods in this challenging scenario is inevitable to ensure customer satisfaction. The retail industry has been exploring various mechanisms and Machine Learning models to plan to predict the expected demand.

To mitigate the effects of the changing purchase behavior there is a need for a recommender system.[1] The success of such a system is based on the KPIs influencing the demand. Collaborative Planning, Forecasting, and Replenishment (CPFR) will result in a holistic management of stock availability. A few major conglomerates like Unilever, Del Monte, and Procter and Gamble have successfully implemented Demand Sensing to improve their supply chain processes, increase customer satisfaction, and reduce costs and demand forecasting errors by 25%. PG implemented demand sensing to achieve a more accurate forecast and realized substantial reductions in Out-of-Stock (OOS) and inventory levels, a forecast error reduction of greater than 30 percent, and a 10 percent reduction in safety stock [2].

Boosting algorithms, such as AdaBoost and Gradient Tree Boosting, are used to improve model performance. Factors impacting sales, including brand, packaging, and advertising, are considered. Accurate sales forecasting is essential to avoid inventory shortages and meet customer demands.[3]

The utilization of big data for retailers around the world is very important, which can help optimize marketing, merchandising, operations, supply chains and create new business models. [4] The McKinsey Global Institute identified 16 big data providers that can improve retail performance through significant improvements in areas such as demand forecasting, inventory management, and operational efficiency.[4]

Various factors influence a purchase decision. A study mentions seven factors that affect consumers' willingness to purchase products online using principal component analysis (PCA) and confirmatory factor analysis (CFA). The factors are price, availability, social proof, scarcity, product details, and social media activity. The research findings provide empirical evidence for the validity of these factors and can help marketers and online retailers improve their strategies to increase online sales and customer satisfaction with the adoption of demand sensing.[5]

Clustering methods like K-Means can be used to group the commodities into various purchase and demand groups before feeding it into the prediction algorithms.[6],[7]. The ensemble techniques improve the efficiency and provide better clusters when compared to standalone methods [8],[9]. The Clustered products can be fed to various algorithms including the regular TSF ARIMA, SARIMA [12] models.

The clustered data can also be fed to Neural network models such as ELM, LSTM to predict the demand.[11][13]. Various combinations of Time series forecasting methods and neural network algorithms perform well to forecast with the demand, but are computationally intensive [10][14].

LSTM and ELM models, along with appropriate feature engineering and normalization techniques, have the potential to provide valuable insights for businesses and vendors in e-commerce to better predict sales of their products [15][16].

Light GBM performs better in terms of forecasting accuracy. Leveraging machine learning algorithms and deep learning frameworks for demand forecasting provides a competitive edge to retail companies. By harnessing the power of these advanced techniques, retail companies can make more informed decisions, better allocate resources, and optimize their supply chain operations for improved business performance. [17][18]

In the pursuit of Demand sensing, time is of the essence. Many deep learning and neural network algorithms perform well in demand sensing. However, the models have to train on live and enormous data in a short duration. The learning rates, learning epochs, stopping criteria, local minima and other factors pose significant challenges in terms of cost and time. The One promising alternative is the use of Extreme Learning Machine (ELM) is a single-hidden-layer feedforward neural network. ELM selects hidden nodes randomly and analytically determines output weights, allowing for faster learning with higher generalization performance compared to traditional gradient-based algorithms. It mitigates the challenges of other algorithms and ELM's efficiency even makes it suitable for real-time applications, such as real-time control. While artificial neural networks like MLP have great learning capabilities, ELM provides faster learning with higher generalization performance, making it suitable for real-time and short turnaround time applications. [19]

III. IMPLEMENTATION

Based on our literature survey, the primary motivation for this project is to build a comprehensive E2E solution coined as Demand Sensing Analytics Platform (DSAP) which predicts the demand for a product of interest to the retailer.

Expected demand for the identified product is forecasted for short term demand sensing with ML time series forecasting technique, the Prophet Model. This forecasted demand is known as the Expected Demand. The proposed solution uses clustering algorithms (K - Means clustering) for the formation of clusters based on products, and uses Artificial Neural Networks (ANN) along with ensemble techniques to sense demand for that product cluster.

These techniques will provide insights into the demand signals for a product by analyzing demand patterns from data sources such as order transactions, consumer purchase history, stock level, shipping history, market trends, macroeconomic factors, and impact of promotion.

Based on the identified product cluster, the ML Engine will select the best model for the demand prediction. This predicted demand using the above demand signals is coined as the Refreshed demand. The expected demand and the refreshed demand are consumed and then aggregates desired features from the data points and history information from data catalog using the Glue Data Service.

The data is further processed to compute the Key Performance Indicators (KPIs) for business intelligence for the products. The KPIs and demand signals are consumed to discover actionable alerts for the retailer to make appropriate decisions to improve the demand for the product and which parameters need to be controlled based on the alert triggers suggested by the solution.

A. Ingestion:

This is the location where live data feed will reside for sensing demand which will be then processed in batch by triggering the ML pipeline. The ML pipeline will execute all the workflow steps in the ML engine and publish the KPIs and Alerts to the RADS Dashboard.

B. Pre-processing Feature Engineering layer:

Pre-processing layer will operate in 2 different modes, namely, the training mode and the inference mode. In the training mode, the pre-processing layer will perform the following steps:

- Categorical encoding is performed for categorical features.
- Standard scaling is performed to scale all the features in the data
- Feature engineering is performed to introduce insightful business dimensions.
- PCA is performed for better clustering.

In the inference mode, the data from the ML pipeline is directly fed to the pre-processing layer and the transformation of data using previously mentioned steps. During the EDA, from the primary data points, few derived data points such as customer frequency of purchase, product-wise customer spend, Shelf life of a product, obsolesce factor of the product, customer pickup rate (fast moving / slow moving) etc., are derived from the primary data points. These derived data points are very useful for KPI.

C. ML Engine:

The workflow steps are executed by the ML engine. ML Engine picks up the demand history and the previous inferences from the Data catalog which contains the trends history, seasonality history, holiday effects etc.

Aggregated data from the pre-processing layer will be fed to the K-means clustering algorithm to classify the data into different product clusters. Each cluster data is fed to the Custom LSTM-RNN Network and Custom ELM Neural Networks respectively.

A long short-term memory (LSTM) network is a modified version of a recurrent neural network that facilitates the retention of previous information. LSTM is suitable for classification, processing and forecasting of time series of unknown duration. This trains the model by multiplying the traces.

Extreme learning machine (ELM) is widely used in continuous learning, batch learning and augmentation because of its fast and efficient learning speed, good generalization ability, fast convergence, and easy implementation. ELM is a neural network, and various data-related parameters will be fed to ELM as input.

Demand predicted by the LSTM-RNN network model, (referenced as Expected demand) and demand predicted by

ELM Neural Network model (referenced as refreshed demand) are then passed to the glue data service which will aggregate information on the input data point, historical information and predicted output to the KPI computer and Alert Discovery and action trigger. Finally, the KPIs and alerts are published to the RADS dashboard.

D. ML Store:

ML store is a repository for ML models. The models used in training to sense demand are persisted in the ML store. The ML engine will look up the right-fit model in the ML store for demand sensing during inference mode.

E. Remote Analytics Demand Sensing Dashboard:

This dashboard is a ML insight UI application which showcases the KPIs, actionable alerts and visualization of performance trends of demand for each product.

IV. DATA SOURCE OVERVIEW AND ML MODELS

Data Source Overview

As mentioned in the previous section, we have performed demand prediction and forecasting for all the 118 distinct products that are sold by the retail chain. The data employed for above prediction and forecasting of demand sensing belongs to the leading retailer chain which is spread across different states in the US.

Data set is having close to 180K sales transactions which span across 4 years from 2015 to 2018. In order to prepare the data suitable for running the ML models, necessary feature engineering is performed during the data preprocessing stage. After data cleansing, training data contains 22,273 records for distinct dates of the 118 products.

We have identified below demand signals and sensitivity of external factors to sensing demand for a product, such as:

- Sales history,
- Customer segment data, purchase patterns and economic factors,
- Shipping history,
- Details on product availability such as stock levels, product visibility etc.

Listed in the table below are the 20 features that were selected for ML modeling:

TABLE I. FEATURE DESCRIPTIONS

Feature Name	Feature Description
ProductCode	Unique Identifier of the product
OrderDate	Date of purchase/sale of the product
DaysTookToShip	Days took to ship from warehouse to outlet
EstimatedShipmentInDays	Estimated days to ship from warehouse to outlet
ProductValuePerOrder	Earnings or benefit per order placed for the product
LateDeliveryRisk	Categorical variable that indicates if sending is late (1), it is not late (0).
ProductDiscount	Rate of discount provided for the product
UnitsSold	Target Variable - number of units sold on that day
Sales	Total sales of the product on that day
ProductPrice	Price of the product

ProductRating	Overall product rating of the product on that day
CurrentStockLevel	Stock level on that day for the product
LastPurchaseInDays	Last transaction in days for the product
B2B%	Percentage of Business-to-Business transactions on that day for the product to total transaction done for the day for the product.
D2C%	Percentage of Direct-to-Consumer transactions on that day for the product to total transaction done for the day for the product.
ShippingMode Standard Replenishment	1 denotes Standard Replenishment and 0 denotes Back Order shipment
GroceryStore_Item_Visibility	Max item visibility percentage for the product in Grocery Store
SuperMarket_Item_Visibility	Max item visibility percentage for the product in Supermarket
HyperMarket_Item_Visibility	Max item visibility percentage for the product in Hypermarket.
IsHoliday	1 denotes Sales Event and 0 otherwise

ML Models and Algorithms:

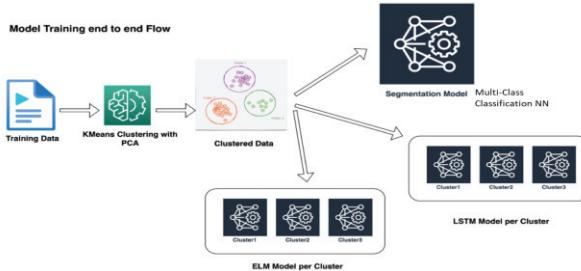


Fig. 1. High-level Architecture in Training Mode

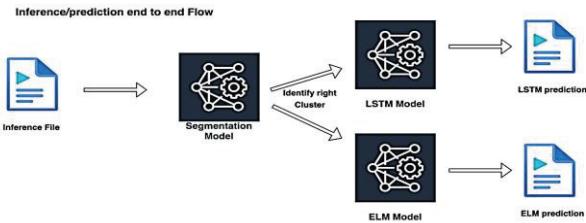


Fig. 2. High-level Architecture in Inference Mode

A. Clustering the Data:

The pre-processed data is fed to the clustering layer. We have employed a K-means clustering model to classify the data into different clusters based on their demand patterns.

K-means algorithm groups the data points based on how similar the data points are with each other. If the data points are similar, then the distance between the data points will be very minimal and they can be clustered into the same cluster. ‘Euclidean distance’ is used to measure the distance between the points and closer the distance between the data points, then they will be clustered in the same cluster. Next vital step is to find out the centroid of the cluster. Once the Centroid of the cluster is found, then each data point distance is calculated from the centroid of the cluster and the cluster is formed with the data points closer to the centroid of the cluster.

Since, initial value of k is very important to get good clustering performance, we use the Silhouette score for

identifying the optimum value of k. Based on the silhouette score and plots in the below diagram, we have concluded that the K = 3 will be the optimum number of clusters.

After applying the K-means clustering model to the PCA processed data, we categorized the data into 3 different clusters, namely Cluster 0, Cluster 1 Cluster 2. Different ELM and LSTM models are trained for each cluster for demand sensing.

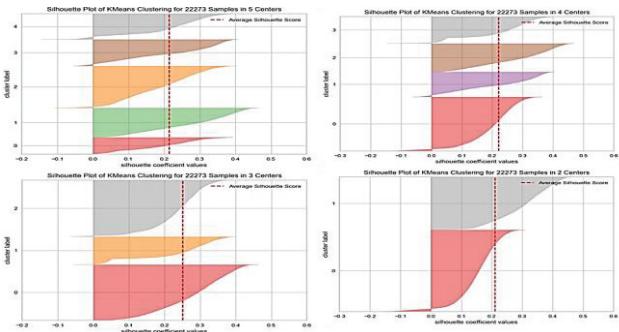


Fig. 3. Silhouette score plot for identifying optimum number of clusters

B. Classification of the clusters:

Cluster classification is performed after the formation of clusters. Here we used Multi Class Classification Neural Network (Segmentation Model) for classification of the clusters. While training the model, we consider the existing datasets which are suitable for the better model building. In the inference mode, when the model is deployed in a server etc., organization specific data will be pre-processed and fed to the model. Precision, Recall, Accuracy and F1-Score parameters are considered for comparing the models for applying the appropriate model from the ML engine.

C. Extreme Learning Machine (ELM) Neural Network layers:

Data related to each cluster is further analyzed using the Extreme learning Machines. We have employed a multi-layered structure for analyzing the customer demand pattern.

Extreme learning machine (ELM) is widely used in continuous learning, batch learning and augmentation because of its fast and efficient learning speed, good generalization ability, fast convergence, and easy implementation. ELM is a neural network, and various data-related parameters will be fed to ELM as input. With the development of the traditional ELM, lots of improved ELM algorithms have emerged over a period of time.

The ELM uses have expanded from supervised learning, to the arena of semi-supervised learning and also unsupervised learning. Traditional ELMs have their own limitations like memory-resistance, high space requirements and time complexity. Hence, traditional ELM is not able to efficiently and quickly train big data. However, a few optimization strategies have been employed for the traditional ELM to solve this problem.

Extreme Learning Machine (ELM) Neural Network layers:

Each cluster of data is modeled using a different ELM neural network. Each ELM mentioned below focuses on analyzing an aspect of the demand signals.

ELM1: Aimed at analyzing the Sales data for the products in an outlet (sales, no. of products, frequency of purchase etc.)

ELM2: Aimed at analyzing the customer profiles, likes, reviews and feedbacks

ELM3: Aimed at analyzing the customer preferred channel of purchase, shipping, delivery, payment preference etc.,

ELM4: Aimed at the stock levels, demand per outlet, customer returns, discount options, promotions etc.,

The outcome of each ELM in the previous layer will be consumed in this layer with a dense FCC regression layer and subsequent output layer arrives at a refreshed demand for the product belonging to a cluster.

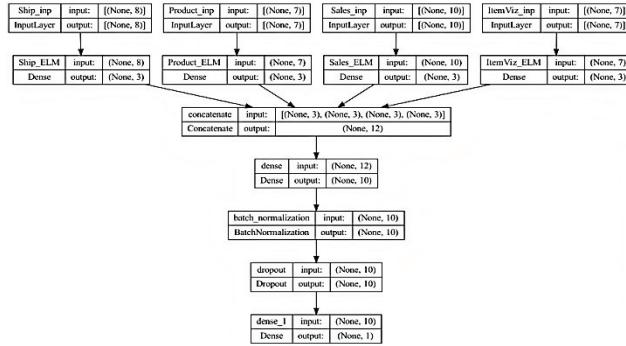


Fig. 4. ELM Neural Network Design Architecture

D. LSTM-RNN:

A long short-term memory (LSTM) network is a modified version of a recurrent neural network that facilitates the retention of previous information. RNN vanishing gradient problem is solved in LSTM. LSTM is suitable for processing time series and forecasting unknown time. It trains the model by backpropagation.

LSTM-RNNs excel in real-time data processing and short-term forecasting for retail demand sensing. These models handle non-linear patterns, adapt to new information, and incorporate external factors, enabling retailers to respond quickly to demand changes, optimize inventory, and make data-driven decisions.

LSTM networks can contribute to demand sensing in:

- Capturing complex temporal patterns
- Handling missing data
- Adapting to changing conditions
- Incorporating external factors
- Scalability

A bi-directional LSTM is employed on data for each cluster. For each of the features, say, $x_1, x_2 \dots x_{17}$, each data point contains observations from a period of 3 lags that are considered by shifting the data. X_1 is $x_1(\text{lag}1)$, $x_1(\text{lag}2)$, $x_1(\text{lag}3)$. Each lag is lagged by one day. Standard scaler is used for scaling the data. In the subsequent layer the outcome of each bi-directional LSTM in layer1 is concatenated and the final layer provides expected demand.

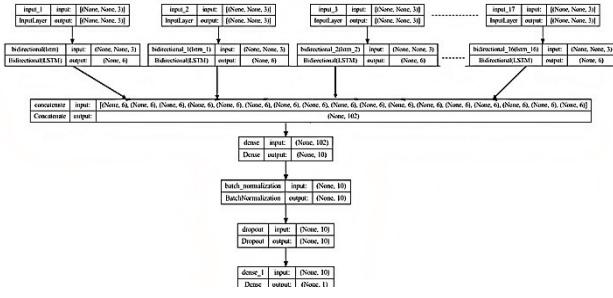


Fig. 5. LSTM Design Architecture

Loss function used for the ELM and LSTM networks is MSE (Mean-squared error).

Hyper parameters chosen are - Dropout with 0.2, early stopping with 0.1 patience, use of Adam optimizer for regularization, and batch normalization with momentum of 0.5.

V. MODEL RESULTS AND DISCUSSION

The ML models are evaluated using performance metrics MAPE and MSE.

ELM and LSTM Model performance parameters are as given below:

TABLE II. PERFORMANCE METRICS OF ELM & LSTM

Cluster	Metrics	LSTM	ELM
Cluster 0	MSE	0.0064825	0.0184362
	MAPE	0.9310715	4.2804749
Cluster 1	MSE	0.0071507	0.0097673
	MAPE	4.3226402	2.2654765
Cluster 2	MSE	0.0531553	0.0205652
	MAPE	0.8354101	0.4620012

We can observe from the Table2 that the ELM and LSTM are neither overfitting nor underfitting and are able to learn from the data progressively.

TABLE III. PERFORMANCE METRICS OF CLUSTER-LABEL CLASSIFIER NEURAL NETWORK

	Recall	Precision	F1-Score	Accuracy
Training	0.977	0.982	0.9795	0.979
Inference	0.984	0.985	0.9845	0.985

We can observe from the Table3 that the performance of the cluster label classifier neural network is neither overfitting nor underfitting and is able to efficiently classify unseen data points to the best cluster label.

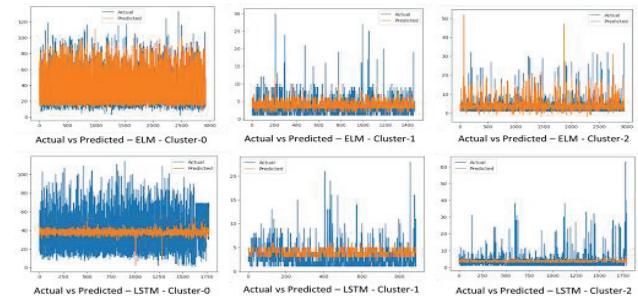


Fig. 6. ELM and LSTM Actual v/s Predicted Demand Plot

We can observe from the plots in Figure 6 that the ELM Neural Network is giving better results as it progresses with learning as it can perform well even during demand disruptions. The refreshed demand identified is a better representation of demand sensed for a product.

VI. CONCLUSION

We started our research to address the business challenges being faced by the Consumer Industry where the demand sensing is the most important step towards making the Retail Execution a reality. Towards this endeavor we have come up with a comprehensive E2E solution which is coined as Demand Sensing Analytics Platform with the help of ELM Neural Network. We identified that the demand signals had non-linear relationships and hence we explored the models LSTM and ELM Neural Networks for demand prediction of a product on a day. When we compared the learnings and performance of the two models, we understood that ELM Neural Network is giving better results as it progresses with learning as it can perform well even during demand disruptions. The refreshed demand identified is a better representation of demand sensed for a product.

The Remote Analytics Demand Sensing Dashboard which displays the Key performance Indicators (KPIs) and the Risk Alerts to the retailers so that data driven decisions can be undertaken based on the product demand variations.

In the scope of this project a nascent framework of sensing demand was developed, and we observe that to enhance and extend the current platform following use-cases can be augmented using the initial analytics, such as:

- Sensitivity of demand based on Customer and Social-Media feeds, Customer purchase pattern analysis, promotions and marketing of products in a region.
- Optimizing inventory management, dynamic pricing, and replenishment based on the demand sensing.
- Applying more enhanced and novel demand forecasting models such as Neural Prophet which could improve the predictions for expected demand.
- Better promotion and market campaigning based on demand for the product in a region.
- Personalized offering to a segment of customers based on demand sensed for a product.
- Identifying demand for a new similar product in a region.

Above mentioned are future directions in regards to the current project. Also, based on feedback from customers of this solution more real time use-cases can be explored.

The proposed solution outperforms conventional models in terms of accuracy and precision for demand predictions. Evaluation from a real-time stream computing perspective is pending, but the design suggests that segmentation models yield favorable results in classifying streamlined data. The solution demonstrates enhanced scalability due to its modular multi-stage data processing

and expandable ELM models. Usability is highlighted through a flexible KPI dashboard, enabling users to fine-tune demands, control supply, and minimize inventory costs. Future enhancements, including integration of customer feedback, sentiment analysis, and customer purchase behavior analysis, aim to further customize the solution to meet customer requirements. Acknowledging the preliminary nature of the proposed solution, there is room for improving design, real-time stream computing, and overall flexibility, which will be addressed in subsequent releases.

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