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Unlocking Inventory Efficiency: Harnessing Machine Learning for Sales Surge Prediction

Kavitha Seethapathy

Software Design Engineer in Retail Supply Chain

https://orcid.org/0009-0003-8972-8427

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Abstract

Purpose: Sales forecasting plays a crucial role in inventory optimization for retail stores, especially during special events such as promotions, advertisements, holiday season, weather, social and economic situations etc. These events drive significant changes in customer buying patterns. Some of these events are captured in the current forecasting models as part of trend, seasonality, and cyclicality. But many times, unexpected local events such as extreme weather conditions, riots, and regional events such as marathons, concerts have a significant impact on sales surges which are usually not captured in the sales forecast. This leads to inventory being out of stock and store managers placing last-minute manual orders. By accurately predicting these sales pattern changes, retailers can make informed decisions, ensuring optimal inventory levels and maximizing profits.

Methodology: In this paper, a data-driven solution was discussed that leverages machine learning models to predict sales pattern changes and surges during local events in a specific geographical location. Web scraping can be used to gather data on local events from a range of online sources, including Google News, local news channels, and social media platforms. By extracting pertinent details about upcoming events, it is possible to compile a thorough database of local happenings.

Findings: Data Analysis of historical sales data mapped to its local events can provide insights on key department-categories where there is a surge in sales. Machine learning models can be used to analyze, experiment and train historical sales data in conjunction with the events data.

Unique contribution to theory, practice and policy: Machine learning models would be trained to capture the complex relationships between different local events and their impact on sales. Therefore the study recommends using the machine learning approaches specified to consider various factors, such as event type, location, duration, and historical sales patterns, our models can effectively predict sales fluctuations during specific events.

Keywords: *Retail, Sales Forecasting, Inventory Forecasting, Omni-Channel, Web Scraping, Data-Driven, Machine Learning Models, Generative AI.*

Introduction

1. Why Sales Forecasting?

Sales forecasting is critical for retail stores and their distribution centers to optimize inventory levels and maximize profits, particularly during special events like promotions, holidays, and unforeseen circumstances such as extreme weather or local events. However, existing forecasting models often fail to incorporate the impact of localized events, leading to inventory mismanagement and lost revenue opportunities. This gap highlights the need for a solution that accurately predicts sales pattern changes during such events, enabling proactive inventory management and informed decision-making (Van Steenbergen, R. M., & Mes, M. R. (2020). Forecasting demand profiles of new products. Decision support systems, 139, 113401.).

In the constantly changing supply chain system and retail industry, maintaining the right inventory levels is crucial for meeting customer demand and maximizing profitability. Failure to accurately forecast sales, especially during local events, can result in stockouts, overstocking, increased costs, and dissatisfied customers. Additionally, the need for manual intervention to address inventory shortages during such events adds operational complexity and reduces efficiency. Therefore, developing a solution that integrates local events data into sales forecasting is essential for retail stores to stay competitive and optimize their operations.

2. Introduction on the existing forecasting models

Retail stores heavily rely on accurate sales forecasting for inventory optimization, especially during special events like promotions, holidays, and other external factors like weather or social situations. However, existing forecasting models often fail to account for the impact of localized events such as extreme weather conditions, or regional events like marathons and concerts, leading to inventory mismanagement and last-minute manual orders. This results in lost revenue opportunities, increased costs, and dissatisfied customers due to stockouts. It's a problem that directly affects profitability and customer experience, making it crucial for retailers to address (Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. International Journal of Forecasting, 38(4), 1283-1318.).

Traditional forecasting models primarily focus on trend, seasonality, and cyclicality, neglecting the influence of localized events on sales patterns. This oversight necessitates the development of a new solution that integrates local events data into the forecasting process to capture the nuanced dynamics affecting sales fluctuations. Some of the existing predictive models are as discussed (Mitra, A., Jain, A., Kishore, A., & Kumar, P. (2022, September). A comparative study of demand forecasting models for a multi-channel retail company: a novel hybrid machine learning approach. In *Operations research forum* (Vol. 3, No. 4, p. 58). Cham: Springer International Publishing.).

The Time Series Models use historical data to forecast future demand. Examples of time series models include simple moving average, exponential smoothing, and autoregressive integrated moving average (ARIMA). Seasonal Models: These models are used when there is a specific pattern or seasonality in the demand. Seasonal models include seasonal exponential smoothing and seasonal ARIMA. Regression models use historical demand data along with other relevant variables such as price, promotions, and marketing efforts to forecast future demand. Samples for this include linear regression and multiple regression. Neural Network models use artificial neural networks to forecast future demand. They can capture complex relationships and patterns in the data but require a large amount of historical data for training. Judgmental models incorporate the opinions and expertise of domain experts or sales representatives to forecast demand. They can be used when historical data is limited or unreliable. Simulation models use mathematical algorithms to simulate different scenarios and predict future demand based on these scenarios. They can be useful in situations where there are multiple variables and uncertainties.

Existing solutions often lack the sophistication needed to effectively predict the impact of diverse local events on sales behavior, thus warranting the exploration of innovative approaches.

A data-driven approach using machine learning models is suggested to predict changes in sales patterns during local events. By using web scraping techniques to gather data from news channels and social media platforms, a comprehensive database of local events is created. Historical sales data is then correlated with these events to identify department-categories that experience sales surges. Machine learning models, trained on this data, analyze the complex relationships between local events and sales fluctuations, considering factors such as event type, location, and historical sales patterns.

The suggested approach brings numerous advantages to retail stores. It allows for proactive inventory management by providing precise sales forecasts during local events, preventing issues like understocking or overstocking. As a result, customer satisfaction is improved, and costs are reduced. Furthermore, it assists retailers in optimizing marketing strategies and effectively allocating resources based on predicted sales patterns.

3. Proposed Implementation technique for predictive modeling

The proposed solution addresses the challenge of sales forecasting during local events by integrating machine learning models with local events data scraped from various online sources. The solution aims to accurately predict sales pattern changes during specific events, enabling proactive inventory management and informed decision-making for retail stores. Like any machine learning model, the adapted method is going to follow CRISP DM (Cross Industry Standard Process for Data Mining) approach for this project as well which follows the below steps:

Data Acquisition: Employ web scraping methods to collect data from various online sources like news channels, social media platforms, and event calendars. Capture pertinent details regarding upcoming local events, encompassing event category, venue, duration, and any other variables that could influence sales.

Data Integration and Analysis: Merge the gathered local events data with past sales data, aligning events with their corresponding sales timeframes. Evaluate the historical sales data alongside the local events data to unveil trends and connections between events and sales fluctuations. This enables us to pinpoint specific department-category combinations that are heavily influenced by local events. These combinations will be used in the proposed forecasting going forward.

Machine Learning Modeling: Utilize a range of machine learning models, including linear/logistic regression, XGBoost, Support Vector Machines (SVM), Time series models like FBProphet, and Ensemble models (Bagging, Boosting, Stacking), to train on the merged dataset. These models will grasp the intricate connections between various local events and their influence on sales, taking into account factors like event type, location, and historical sales patterns.

Prediction and Forecasting: Employ the trained machine learning models to anticipate shifts in sales patterns during specific local events. Generate sales forecasts for upcoming events by leveraging the learned patterns and historical data. These forecasts will equip retailers with practical insights for effective inventory management.

Engage in a discussion with Store Managers: After generating sales forecasts that incorporate the projected impact of local events, we will validate the results by comparing them with historical sales data from past events. Once the forecasts demonstrate accuracy, we will share the findings with store managers. This approach is not limited to store usage, but can be used for micro-fulfillment centers and with the right parameters for huge distribution centers as well. This way, they can proactively manage their inventory to effectively meet the demands of upcoming events.

4. Predictive Methodology Approaches

Obtaining and connecting local event information to historical data is the most significant obstacle in achieving the sales surge effect caused by local events. Some approaches that can be used for this are:

1. Generative AI: When applied to predictive methodologies, generative AI can enhance the accuracy and efficiency of predictions by generating new data points or scenarios that align with historical patterns. Generative AI introduces a new dimension by enabling the creation of synthetic data that expands the available dataset and allows for more comprehensive analysis. Generative AI can augment the existing dataset by generating additional data points that are consistent with the patterns observed in the historical data. This expanded dataset can enhance the accuracy of predictions and provide a more comprehensive understanding of future trends. Second, generative AI can help identify previously unseen patterns or trends that may not be evident in the original dataset. By generating synthetic data points, it can reveal hidden relationships or correlations that were not initially apparent, leading to more accurate and insightful predictions. Furthermore, generative AI can assist in scenario planning and risk assessment. By generating multiple future scenarios, organizations can evaluate the potential outcomes and associated risks, enabling them to make more informed decisions and develop robust strategies. However, it is important to note that the use of generative AI in predictive methodologies also presents challenges. Ensuring the quality and reliability of the generated data is crucial, as inaccurate or biased synthetic data can lead to flawed predictions. Additionally, the ethical implications of using generative AI, such as potential biases or

unintended consequences, need to be carefully addressed (García-Peñalvo, F., & Vázquez-Ingelmo, A. (2023). What do we mean by GenAI? A systematic mapping of the evolution, trends, and techniques involved in Generative AI.). In summary, the integration of generative AI into predictive methodologies offers the potential to enhance accuracy, uncover hidden patterns, and facilitate scenario planning. As this technology continues to advance, organizations can leverage generative AI to gain a competitive edge and make more informed decisions in an increasingly complex and dynamic business environment.

2. Beautiful Soup package in Python: This is one of the techniques that can be used for web-scraping. Though this is not specifically designed for predictive analysis, it can be used as a part of the data collection and preprocessing steps in the predictive analysis workflow. This allows to extract data from HTML and XML files by parsing the HTML or XML content and providing a simple API for accessing and manipulating the data. Depending on the requirements of the predictive analysis task, there may be a need to preprocess the extracted data. This could involve cleaning the text, handling missing values, converting data types, etc. Once you have the preprocessed data, you can use any suitable predictive modeling technique or library to analyze and make predictions based on the data.

These tools will aid in the analysis of events that have already occurred in a specific market, allowing for the identification of the impact of local events on sales. To show that the model can be used in retail omni-channel, the below sales specific case studies were considered, to identify how it can be leveraged to inventory management.

1. Amazon: Amazon uses predictive analysis to personalize their recommendations for each customer. By analyzing customers' browsing and purchase history, as well as their demographic information, they can predict which products are most likely to be of interest to each individual customer. This helps to increase sales by providing a more tailored shopping experience.
2. Target: Target uses predictive analysis to identify customers who are likely to become pregnant based on their purchasing patterns. By analyzing historical sales data, they can identify patterns that indicate a customer might be pregnant, such as purchasing unscented lotions, supplements, and certain vitamins. Target then sends targeted coupons and advertisements to these customers, increasing the likelihood that they will shop at Target for their baby-related needs.
3. Starbucks: Starbucks uses predictive analysis to optimize their store locations and menu offerings. By analyzing data on local demographics, foot traffic patterns, and competitor locations, they can predict the potential success of opening a new store in a particular location. They can also use predictive analysis to determine which menu items are likely to be popular in different regions, helping them tailor their offerings to local preferences.
4. Nordstrom: Nordstrom uses predictive analysis to optimize their pricing and markdown strategies. By analyzing historical sales data, competitor pricing, and customer behavior, they can predict optimal price points for their products. They can also predict which products are likely to go on sale and when, helping them maximize revenue while minimizing excess inventory.

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To begin with the solution, let's look past events that have taken place within a particular market. By doing so, it will determine the influence of local events on sales and, more importantly, identify the specific department-category combinations that have experienced a significant impact. The overall framework for this forecasting process is depicted in Fig 1.

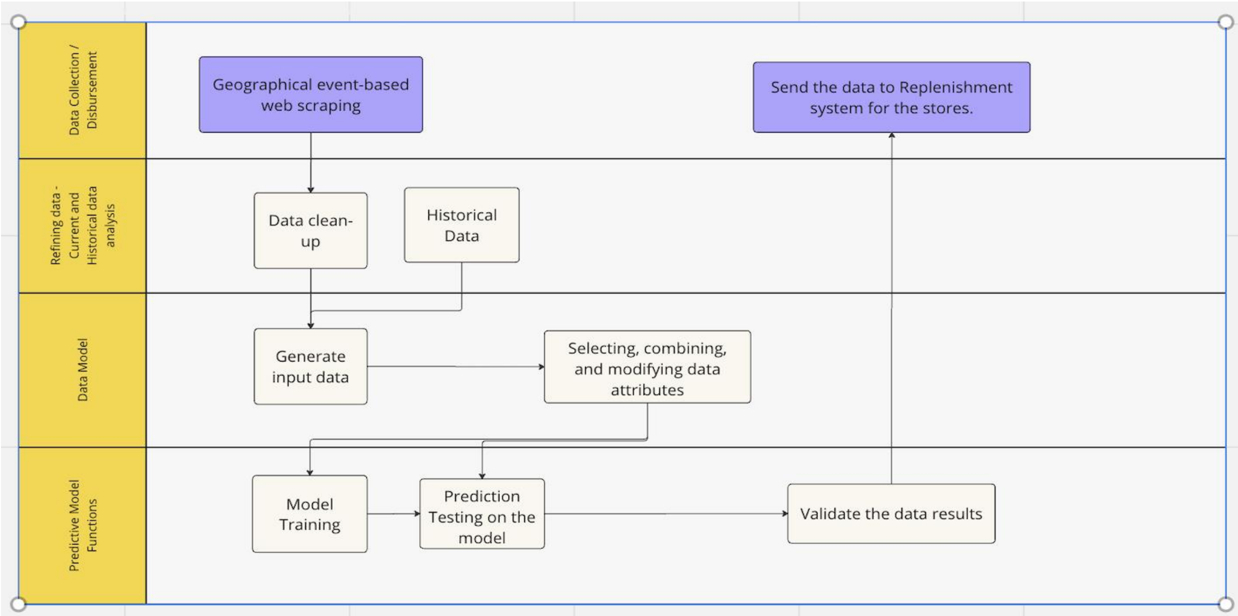

Fig. 1: Forecasting framework model.

After the collection of local events data, the next step is to clean and prepare the data. This involves ensuring that the data is in a format that can be easily used and eliminating any inconsistencies or errors. Additionally, it is necessary to map the historical events to the historical sales data so that the impact of local events on sales can be analyzed. Models like XGBoost require feature engineering, which entails creating additional features based on time, holidays, etc. By incorporating these additional features into the model training process, a more accurate analysis can be conducted. Once the data is prepared for model training, the impact of historical events can be tested using a back testing methodology. Once the local events data has been collected, the next step is to clean and prepare it for analysis. This involves ensuring that the data is in a format that can be easily used and removing any inconsistencies or errors. Additionally, it is necessary to align the historical events with the historical sales data in order to analyze the impact of local events on sales. To make use of models like XGBoost, feature engineering is required. This entails creating additional features based on factors such as time and holidays. By incorporating these additional features into the model training process, a more accurate analysis can be conducted. After preparing the data for model training, the impact of historical events can be tested using a back testing methodology. Back testing involves validating a predictive model using historical data. This process involves moving through the historical data in a step-by-step manner and testing the model's predictions against the actual outcomes. By doing so, we can assess the model's accuracy and evaluate the impact of local events on sales. Back testing methodologies involve moving backward in time, step-by-step, to evaluate the performance of a model if it had been used to make predictions during that specific time period. Some of the back testing methodologies that have been considered are the below:

1. Expanding window methodology:

   The expanding window methodology is one of the back testing methodologies used to evaluate the performance of a model. In this approach, the training data set gradually expands over time, starting from an initial period and progressively including more recent data points. The methodology involves training the model with the initial set of historical data and then making predictions for the next time period. In this approach, the historical data is divided into chunks for training the models. As additional test data is introduced, the training data set expands correspondingly. This expanding window methodology allows for the incremental inclusion of more recent data points during the model's training and evaluation process. The model's performance is evaluated by comparing these predictions to the actual outcomes for that period. Afterwards, the training data set is expanded to include the next time period, and the model is retrained using the updated data. The process is repeated iteratively, with the training data set expanding in each iteration and the model's performance evaluated for each subsequent time period (Ma, S., & Fildes, R. (2021). Retail sales forecasting with meta-learning. *European Journal of Operational Research*, *288*(1),111-128.). This methodology provides insights into how well the model performs as more recent data is incorporated into the training process, allowing for an assessment of the model's ability to adapt to changing patterns or trends over time. This methodology allows for the evaluation of the model's performance over time and the assessment of its ability to adapt to changing conditions.

   2. Sliding window methodology: The sliding window methodology is a technique used in computer science and data processing to solve problems that involve analyzing a sequence of data elements in a fixed-size window. In this methodology, a window of a fixed size is moved or "slides" through the sequence of data elements, processing and analyzing the data within the window at each step. The sliding window technique is often used in problems that require analyzing subsets or subarrays of a larger array or sequence. By sliding the window through the data, the algorithm can efficiently process the data elements within the window and update the results as the window moves. The sliding window methodology is particularly useful in problems that involve finding patterns, searching for specific elements, or computing aggregated values within a fixed-size window. It can also be used to optimize algorithms by avoiding redundant computations.

      The steps involved in the sliding window methodology typically include:

      a) Initialize the window: Set the initial position and size of the window.

      b) Process the initial window: Analyze the data elements within the window and compute the initial results.

      c) Slide the window: Move the window to the next position in the sequence.

d) Update the results: Modify the results based on the new data elements within the window.

e) Repeat steps 3 and 4 until the window reaches the end of the sequence.

The sliding window methodology can be implemented using various data structures and algorithms, depending on the specific problem. Common techniques include using arrays, linked lists, or queues to store the data elements within the window, and using efficient algorithms such as two pointers or dynamic programming to update the results. Overall, the sliding window methodology provides an efficient way to process and analyze a sequence of data elements by using a fixed-size window that moves through the data. It is widely used in various domains, including image processing, text processing, signal processing, and algorithm design. In this approach, the dataset is divided into chunks, treating each chunk as a training dataset. With each iteration, the chunk slides, and the model's training data is updated with the new chunk. This methodology enables the assessment of the model's performance under varying conditions and offers valuable insights into its adaptability.

By employing these back testing methodologies, it becomes possible to effectively analyze and comprehend the influence of local events on sales. This knowledge can subsequently be utilized to optimize sales strategies and enhance the accuracy of forecasting.

In the context of sales forecasting for an upcoming event, the back testing module plays a crucial role in identifying the best model out of all the models that have been trained. The purpose of the back testing module is to evaluate the performance and accuracy of these models using historical data.

In the realm of sales forecasting for an upcoming event, the back testing module assumes a vital role in identifying the most optimal model among those that have been trained. The primary objective of the back testing module is to assess the performance and precision of these models by utilizing historical data.

Through the comparison of predictions made by each model with past sales data, the back testing module can ascertain the model that exhibits the highest level of accuracy. This enables us to select the most dependable model for predicting sales during the upcoming weeks of the event. Alongside selecting the best model, an ensemble model is employed to further enhance the accuracy of the sales forecast. The ensemble model computes the average of sales forecasts generated by the top-performing models, reducing variance, and improving the reliability of the final sales forecast.

After obtaining the revised sales forecast, it is crucial to analyze the outcomes and compare them with historical events and the sales forecast that did not incorporate local events as features. This examination assists in identifying any impact these events may have on the sales forecast. Understanding the influence of these events on sales empowers more informed decisions regarding inventory planning.

Following the validation process, the revised sales forecast is subsequently shared with store managers. This enables them to plan for the event more efficiently by making necessary adjustments to their inventory levels. By equipping store managers with precise and current sales forecasts, they can make informed decisions and optimize their inventory management strategies.

5. Benefits of the forecasting model:

In the past, forecasting platforms utilized by retailers primarily depended on historical sales data, trends, seasonality, holidays, and promotions in specific markets to generate sales forecasts. However, these platforms overlooked the influence of local events, such as regional marathons, disputes, revolutions, strikes, concerts, sudden weather changes, and others. This omission is noteworthy because these events can significantly affect the performance of local stores.

Unpredicted local events often lead to a sudden increase in demand or cause specific items to go out of stock. Consequently, store managers are compelled to manually adjust their orders to meet the surge in demand or restock depleted inventory. However, this manual intervention is inefficient, time-consuming, and can result in inconsistencies in inventory management.

By integrating the influence of local events into the sales forecast, retailers can provide store replenishment with a more comprehensive and precise framework for efficient planning. This increased visibility enables managers to anticipate and proactively order high-demand items ahead of upcoming events. As a result, this approach mitigates the risks of inadequate or excess inventory, ensuring that the appropriate products are readily accessible to meet customer demands during local events.

In the end, this enhanced forecasting capability not only allows retailers to optimize inventory management but also enhances its ability to effectively serve customers. By accurately predicting and fulfilling customer needs during local events, retailers can increase customer satisfaction and loyalty, ultimately strengthening its competitive position in the market.

6. Conclusion

The main focus of this research is carrying out a proof of concept aimed at evaluating how a historical event affects sales forecasts. This evaluation will be done using a sample of sales data. The ultimate objective is to expand and automate this process. This expansion involves identifying and establishing correlations between future events and historical data, all while keeping the existing framework modules intact. By successfully achieving this, we will be able to generate sales forecasts that are not only up-to-date but also take into account any upcoming events. The scalability and automation of this procedure will significantly improve our ability to predict sales accurately, thereby empowering us to make well-informed business decisions.

Referees

Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. International Journal of Forecasting, 38(4), 1283-1318.

García-Peñalvo, F., & Vázquez-Ingelmo, A. (2023). What do we mean by GenAI? A systematic mapping of the evolution, trends, and techniques involved in Generative AI.

Ma, S., & Fildes, R. (2021). Retail sales forecasting with meta-learning. *European Journal of Operational Research*, *288*(1), 111-128.

Mitra, A., Jain, A., Kishore, A., & Kumar, P. (2022, September). A comparative study of demand forecasting models for a multi-channel retail company: a novel hybrid machine learning approach. In *Operations research forum* (Vol. 3, No. 4, p. 58). Cham: Springer International Publishing.

Van Steenbergen, R. M., & Mes, M. R. (2020). Forecasting demand profiles of new products. Decision support systems, 139, 113401.