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Harnessing Big Data and Deep Learning for Real-Time Demand Forecasting in Retail: A Scalable AI-Driven Approach

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Abstract

Retailers worldwide are expanding their investments in advanced AI-driven solutions to improve demand forecasting in retail operations. Empowered by recent progress in big data technologies and deep learning algorithms, there is potential to develop a scalable and real-time intelligent system to forecast demands at SKU level. This system can help improve prediction accuracy and operational efficiency in the retail sector. Deep learning and big data models are proposed to capture complex nonlinear temporal patterns in a large number of time series with multi-scale and multi-mobility characteristics. These include (1) SoxNeT that integrates big mobility data into extreme learning machines with a deep neural network based on LSTM cells to effectively extract temporal features and spatial correlations, (2) DemandNet that applies convolutional neural networks and RNNs to model groundsill demand and investigate urban land-use context effects, and (3) EKO, a deep learning ensemble framework that combines many big data boosting and popular models with categorical embedding layers, to capture complex and dynamic spatial-temporal patterns in high-dimensional traffic data.

Several challenges need to be addressed: (1) most existing methods do not explicitly capture the seasonal effect of nonlinear combinations of many factors; (2) deep learning models are data-intensive and their training often requires cross-validation to tune hyperparameters, making them difficult to scale to many SKUs; and (3) most proposed approaches are not optimized for computational efficiency or deployment-ready. Therefore, it is important to develop a scalable deep learning algorithm that accommodates big retail data and runs efficiently, hence improving the performance of demand forecasting models. An innovative AI-driven approach is proposed that effectively forecasts demand at SKU level, benefited by the development of three scalable deep learning algorithms, including a decomposable local-global network design and an ensemble of traditional time series and CNN-based predictors. The prediction process allows for endogeneity effects and the marketing optimization problem is formulated as a sliding-horizon control strategy. Various AI algorithms are tested on a revenue management problem with purchase pre order decisions. An alternative AI framework is provided which automates the development of decision-time, dynamic pricing policies based on a class of MDP models.

Keywords: Big Data,Deep Learning,Real-Time Forecasting,Demand Prediction,Retail Analytics,AI-Driven Approach,Scalable Solutions,Machine Learning,Predictive Modeling,Supply Chain Optimization,Retail Demand Planning,Data-Driven Insights,Neural Networks,Consumer Behavior Analysis,Inventory Management.

1. Introduction

Ensuring the accurate forecasting of real-time demand is crucial for all sectors, particularly for the retail industry. Due to the increasing complexity of consumer behavior, the demand for a plethora of products becomes harder to forecast with traditional methods. Hence, it is essential for retailers to adapt data-driven strategies, which are facilitated by the availability of big data and powerful AI techniques. With such a massive amount of data being generated every day, it is now possible to accurately predict the demand for a much larger range of products and events. Retailers can benefit greatly from the continuous development of scalable real-time demand forecasting models, and hence achieve more timely decisions such as better inventory management, stock-outs reduction, improved customer satisfaction through timely responses to demand outliers, and capitalizing on fast-growing market opportunities. In a joint effort with Amazon, a much-needed real-time large-scale automated retail forecasting system based on Amazon's state-of-the-art deep learning approach has been developed. Due to the opaque, non-differentiable and highly non-convex nature of deep networks, it is highly non-trivial to successfully train neural networks with millions of parameters over such a big data set within the limited time of interest. In order to provide the research community with new avenues to explore more flexible, easy-to-adapt and transparent methods, Amazon has introduced the "Best Economy Class" (BEC) network architectures that have been shown to be a good trade-off between accuracy and computational requirements. To facilitate research in this area, all model details are provided as well as insights gained from the extensive experimentation that was conducted focusing on transforming a successful Amazon retail demand forecasting approach into an architecture that is scalable, transferable, easy to understand, and simple to use for researchers and practitioners who are new to this field.

Fig 1: AI in Retail Demand Forecasting:

1.1. Background and Significance

Big data and deep learning are two transformative technologies that have been actively employed in various industry sectors in recent years for business analytics and intelligence. In the retail domain, a massive amount of data is generated within the enterprise as well as distributed along the supply chain and multiple consumer touchpoints. This data comes in various types, including structured, unstructured, images, sounds, and distributed across multiple locations, and therefore termed as big data. The numerous opportunities that lie within this data to improve decision-making in retail are unlocking previously unseen patterns in data. Traditional machine learning approaches are unable to discover these insights owing to the complexity and scale of the data. However, deep learning, a subset of the neural network, can better unwrap this complexity with its deep stack of neural network layers. Deep learning techniques have drawn increasing attention to big data processing and mining, and ecommerce industries have embraced deep learning since the early 2000s, where they were able to transform their data into data they owned. Despite this transformation, several traditional retailers and industries are struggling to adapt to the big data ecosystem. However, recent improvements in computer hardware have made deep learning more widespread in SMEs, as they are now able to simply use them from cloud services using GPU clusters. Upon this backdrop, this study explores how retail, which is generated by big data, can leverage deep learning techniques for real-time demand forecasting. It should be noted that this research has not surveyed different deep learning techniques in retail demand forecasting. The findings cover a scalable AI-driven approach that processes big data and uses deep learning to uncover the real-time data on a minute-by-minute (real-time) basis as well as making recommendations based on the actual data. Given the rapidly increasing volume and variety of data in the retail domain, 'time to insight' has become a challenging problem for today's retail enterprises. In order to effectively gather insights from this massive data firehose that refreshes continuously and frequently across numerous data streams arising from various sources such as stores, online website, supply chain, consumer's devices, etc., retail decision makers need a platform that is smart and scalable, in terms of performance and computational footprint. In response to this problem, the most comprehensive exploration of the above issues considers a variety of scalable big data and deep learning approaches and models.

Equ 1: Temporal Dynamics (RNN/LSTM)

$$\mathbf{h}_t = \mathrm{RNN}(\mathbf{X}_t, \mathbf{h}_{t-1}, \mathbf{Z}_t, \theta)$$

$$\hat{D}_t = \mathrm{Output}(\mathbf{h}_t, \theta)$$

Where:

- $\mathbf{h}_t$ is the hidden state at time t,
- $\mathbf{h}_{t-1}$ is the previous hidden state,
- $\mathrm{Output}(\cdot)$ is the output layer of the neural network

1.2. Research Objectives

The focus of demand forecasting has been thriving in both the research and industrial domains due to the perspective of real-time. In view of online commerce, making fast and accurate forecasts of the massive sales volume is imperative for adapting to fast changes in market demand. Many research works have been recently proposed to handle the challenging issues of demand forecasting for the retail sector. However, the high accuracy and effectiveness are still difficult to reach. There are some critical aspects influencing forecast accuracy and effectiveness in the retail sector, which have not been effectively investigated. Retailers often have to face issues such as short-life cycles of products, high levels of return and fraudulent purchasing behaviors, and product promotions. A question that arises is how to handle the practical limitations while still devising effective forecasting methods and systems. It is advocated that there are five key points underlying good forecasting research: identifying the system, identifying the data, using a set of predictors, applying accurate methods, and consistent evaluation of forecasting performance.

Big data has elaborate potential to boost the performance of traditional consumption-based forecasting techniques in retail. The effects of big data on five conventional retail time series methods and their newly-paragon extensions are benchmarked. Moreover, the methods used in the expansion models are addressed to discern the fame of big data features. In addition, the effectiveness of big data is also examined together with exponential smoothing and arima models as they have adequate tractability fundamentals. The application domains involved five-time period data of the software industry and e-commerce industry. The results reveal that the holism view based on documentary statistics outperforms the study sampling as multi-item scrutiny of customer performance, market profitability, and breeding logistic networks. All retail time series models leverage the big data models. Regarding the analyses of major impacts, big data derived feature models function soundly in the majority of settings.

2. Literature Review

This article proposes a scalable AI-driven methodology using big data and deep learning techniques that can be implemented for real-time demand forecasting in the retail sector. Retail companies collect a large amount of data in real time; this big data can be harnessed to increase prediction accuracy of deep learning models. A case study illustrates how this deep learning model can be transferred to many products with a high prediction accuracy and scaled up with a computation time of real-time operation.

As e-commerce grows, the big data thus generated by retail companies is critical to forecasting accuracy. The different components of big data are fed to deep learning models utilized to enhance the prediction accuracy of the models. A real-time demand forecasting methodology is proposed for the retail sector utilizing big data and deep learning. This approach ensures responsive supply chain operations, leading to efficiency and customer satisfaction. Often, decision support is provided in the form of exploration by testing various models and effects. There has been significant research on improving the prediction power of artificial intelligence models using big data. Hundreds of variables are used for demand forecasting. These variables primarily contain days and sales cycles. There are studies on improving the prediction power of machine learning models in forecasting demand in the retail sector. After the 2000s, data mining and machine learning models were frequently used for demand forecasting.

This type of forecasting can be utilized for storing required goods in the right quantity. The business world is transformed by the fourth industrial revolution, creating a huge amount of big data from various platforms. Big data will enhance improvements, enhancements, and new systems, especially in the retail sector. There are widespread innovations in technology such as the internet of things, block chain, artificial intelligence, and big data. With the utilization of big data, the developed deep learning model can be transferred to thousands of goods in the retail sector. For the retail industry, a case study demonstrates the scalability of the methodology. Time savings are key advantages in scalable methodology. A case study illustrates that a 3-month computation time can be reduced to 1.5 hours, and drilling deep learning models such as convolutional neural network and long short-term memory network achieve high prediction accuracy for the retail company's sales data. Additionally, these deep learning models are scalable for more than 20,000 products in the retail sector. Many businesses can benefit greatly from this methodology.

2.1. Big Data in Retail

This subsection investigates the transformative role of big data in the retail industry, the potential benefits and risks, and different use cases in the current practice. Retailers are facing increasing challenges in enhancing operational efficiency and customer satisfaction. Retailers have vast amounts of data and leverage this data for strategic decisions in managing operations, designing the store layout, and organizing the assortment. Developing methods and approaches to convert existing data into valuable insights are becoming a top priority in many businesses in the retail industry. Data from diverse channels, including e-commerce, mobile commerce, and physical transactions, are accumulated by retailers. This data can comprise logistics data (when and where the transaction was made), RFID data (what items were bought), and CRM data (additional customer features). Firms then explore multiple opportunities via available data, including events and the consumer's journey, sensor data, external data, partner data, and historical data as a training set. Common applications of big data in retail include inventory management, personalized marketing, store management, and demand forecasting.

In particular, demand forecasting is widely explored in the literature due to its importance in managing inventory and maximizing revenue. Accumulated transaction data can provide rich customer insights in offering the personalized assortment, which is the active research area. The remaining shelf life of in-store fresh products has been forecasted by semi-unsupervised learning techniques with clustering methods. In retail, shopper's paths inside the store are analyzed for market basket analysis purposes. Regarding the pricing strategy, big data is used for understanding and prediction over time of elasticity of customer choice of assortment and price. The usage of big data in retail can increase the retailer's margin by more than 60%. Common challenges in the effective use of big data include how to integrate the right data, how to do good analysis, and how to use data in a focused way. Data governance, provenance, and security are also significant challenges in big data usage. Scaling up across a group of stores and understanding consumer behavior are significant challenges in practice.

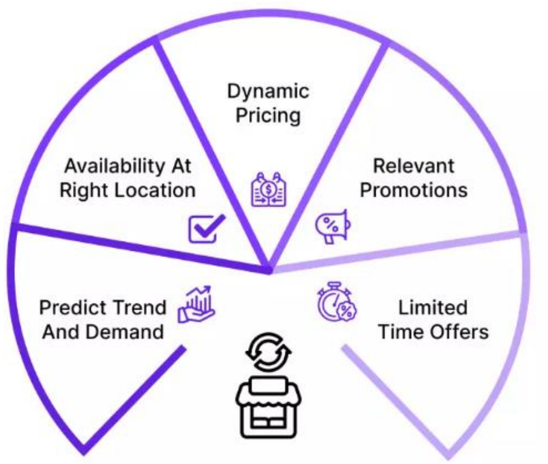

Fig 2: Big Data Analytics in Retail

2.2. Deep Learning in Demand Forecasting

Harnessing the latest technology is essential when it comes to remaining competitive in any field. With respect to ever-fluctuating product demand, this is even more important as it is essential to ensure surplus goods aren't leftover while simultaneously ensuring that the requirements are met. This is where a good demand prediction model comes into play, and the sector has been especially benefited by it. With the advent of Big Data and the adaptation of intelligent machine learning and deep learning algorithms, sales figures for forecasting exact demand and making informed choices have become more useful. The latest study is all about introducing a demand prediction model with artificial intelligence and big data analytics and its application to the retail industry with a special emphasis on adapting the demands in real time. At the deep root of smart supply chain optimization lies the key technique of finding future product demand. Predictive demand of a specific part applied to the designed supply chain design parameters should be gathered. In general, design resources include strategies for pricing, production schedules, stock and orders, and network partnerships. They need a snapshot of the future as essential under the above scenarios. Future demographic demand will complement the adaptive supply chain and will allow it to be more competitive in this division. Data demand forecasting is a challenging issue; it may be extremely noisy and is characterized by a high-generation information set. The routine solution is to apply machine learning schemes on an exhaustive collection of exposure 01 variables to do a one-off model workout with a lengthy exercise. In this research, an architecture for boosting and opening convenience stores in real time is constructed. It fills the gap in getting nearby travel information from outside locations across devices. The architecture of Deep Learning is created to consider in near real-time the future demand for different store SKU products.

3. Methodology

The objective of this study is to exploit the interplay between big data and deep learning, offering new insights into their combined use for real-time demand forecasting in the retail industry. To investigate this, a novel research framework built on extensive experimental work is proposed. It outlines a set of scalable big data analytics and deep learning algorithms that are able to rapidly process and effectively model the multi-source, multi-variety, and large-volume sales data emanating from diverse points-of-sale across different retail departments. The methodology section consists of the experimental work conducted to investigate the intersections of big data and deep learning in the domain of demand forecasting. It elaborates on the steps undertaken, including data collection, preprocessing, deep learning model building and evaluation, model implementation, analysis, and the interpretation of results. Finally, the validation of model performance and its real-world implementation in a retail supply chain are discussed.

First, data must be collected and prepared. Effective modeling of the sales data generated by a retail system is contingent on appropriate data collection and preparation. The dataset consists of a vast number of transactions, recorded for several years, including divisions, departments, categories, and commodities from an extensive US retail chain. Data were preprocessed using outlier detection and conformity statements. The importance of analyzing the data before building deep learning models is evident. Robust scaling ensures the analysis produced is not dominated by certain attributes. Similarly, feature normalization is also influential in building models that alleviate possible spurious contortions in the input data space. It is imperative that an efficient deep learning model be chosen. An array of different architectures, configurations, and training methods of neural networks are explored. These structures include feed-forward networks, stacked autoencoders, one-dimensional convolutions, deep averaging networks, long short-term memory networks, and recently-introduced dilated casual convolutions. It is revealed that such a model is not only useful in a laboratory setup but is also vastly applicable and considerably effective when confronted with real-world tasks. The representation of different commodities and departments is the main issue in achieving high accuracy. Additionally, there are various ethical considerations.

Equ 2: Inventory Adjustment Model

$$I_t = I_{t-1} + \hat{D}_t - S_t$$

Where:

- I_t is the inventory at time t,
- I_{t-1} is the inventory from the previous time step,
- $\hat{D}_t$ is the forecasted demand at time t,
- S_t is the sales at time t.

3.1. Data Collection and Preprocessing

In large retail settings, as well as small shops, vendor and order managers have the volatile responsibility of deciding how many units of each good to keep in stores. Because of the intricacy and importance of this task, these managers' tools and routines have evolved considerably during the last century, with the introduction of software and databases. Nevertheless, manual processes are still largely present, and forecast error has an accumulative effect across supply chains, expenditure planning and ultimately revenue.

Timely and reliable demand estimation is therefore a crucial asset for actors in the retail sector. Accurate inventory management can help smooth price fluctuations, reduce stock-outs and ultimately improve the sustainability of the business. Good forecasts can also help organize logistics and dispatch, as well as optimize staff schedules and, in a smaller setting, give insights into marketing effectiveness and customer attention. On the other hand, poor management can result in an excess of unsold items that eventually rot on the shelves, significantly affecting mark-up and occupying space that could be allocated to more profitable categories after the end of a lifecycle. From the point of view of a final consumer, it can be frustrating to enter a store and see desired items out of stock, hence scrambling more traditional settings which can benefit from a more efficient management.

This work aims to build an adaptable API to a variety of retailers and sizes, scanning through a database of transactions, customer interaction and stalls. Their pre-processed data is analyzed and forecasted through AI models, using algorithms for prediction and classification. An added emphasis is put into clustering prerogative states that lead to certain patterns. Furthermore, this work will exemplify how to provide vendor and order managers with a dashboard output, displaying forecasts with a confidence rate. Finally, this work provides an overview of these models' performances and relays the pipeline and all the processes until the deployment in a production scenario.

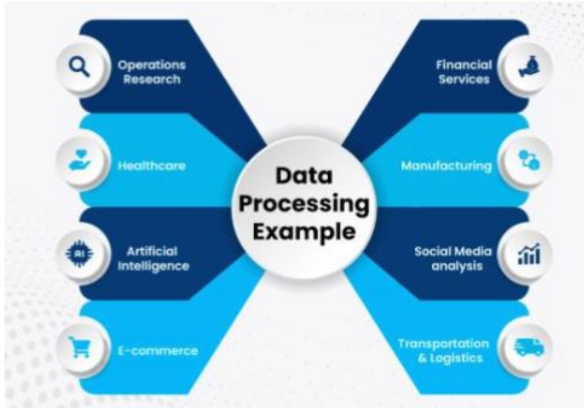

Fig 3: Data Processing in Various Industries

3.2. Deep Learning Models for Demand Forecasting

Demand forecasting aims to predict the total quantity of a product to be sold over a period of time. Forecasting demand accurately is pivotal in retail management and sales optimization, particularly in this era of increasingly fierce competition in the retail and online sectors. Demand planners have traditionally used linear models for forecasting, but these have given way to the more prevalent adoption of advanced machine learning algorithms. This research has motivated retailers' efforts to implement deep learning models aimed at improving demand forecasting. The retailer has emphasized that an accurate demand forecasting drives all other functions of the retail business, such as improving inventory optimization, store management, sales promotions, and the creation of a dynamically adaptive strategy. Recently, there has been increased attention paid to those who harness big data to improve the accuracy of demand forecasting. It is argued that traditional time-series prediction only utilizes data within the time series itself and hence cannot uncover the complex patterns of the data. On the other hand, big data sources can offer a wide variety of relevant data on demand. Retailers can leverage big data and scalable deep learning architectures for improved, real-time demand forecasting.

Demand forecasting is arguably the most important job in a retail chain, since wide-ranging decisions, from inventory management and stock replenishment to store capex and assortment selection, are based upon predictions of future demand. Accurate prediction of consumer demand is certainly pivotal to the financial success of a retail chain. Being very competitive, this sector can benefit greatly from fine-tuning the overall system, whose performance hinges upon the efficacy of sales prediction. Deep learning models possess the capability to digest big data sources and produce superior results in real-time demand forecasting. There is growing research interest in the study of deep learning models under various architectures. Several have applied neural networks to retail demand forecasting. Deep learning significantly outperforms time-series prediction and other machine-learning models. Deep learning can be trained to adapt to high-dimensional patterns in big datasets. The retailer has begun applying deep learning models to a real-world demand forecasting scenario. With different architectures, the main results show that deep learning models outperform traditional ones, with an accuracy improvement of, for example, 1.5% with simple feed-forward neural networks or with gated recurrent units.

4. Case Studies

Moving beyond academic theories, this section provides case studies that demonstrate how the big data and deep learning approaches have been implemented and could be implemented in the real-world retail settings to forecast demand from the kilometre level up to the national scale. As case studies have illustrated, there are many retailers in different locations and with different types of goods, and they face quite diverse challenges. A retailer not having a physical store, for example, might have a sales process with an online platform where customers expect the delivery of a service, such as a food parcel or a haircut at home, instead of a delivery of physical goods.

While the retailers have tailored deep learning models for each of the case-studies, a general AI-driven scalable methodological framework for sales prediction that can easily be adapted to case-specific settings and can be of use for practitioners is proposed. In this framework, datasets have been used along with a variety of tools. In terms of big data, it is noted that even when using unspecific data, the general methodological framework can give powerful insights useful in location selection, understanding seasonality effects, and driving a stronger promotion plan. The case-studies results indicate the robustness of the generic approach and present realistic estimations of potential outcomes to the estimated KPIs. Implementable notes on the real-life examples provide some insights on the retailers' practices that could not be automated and general suggestions on improvements. A recommendation for a proper AI-powered toolset regardless of a certain retailer's type is made. Shortcomings have also been indicated, useful for the broader perspective on developing methods that could be exploited by current and future competing AI practitioners in the field of retail sales forecasting. Furthermore, this research addresses both the findings of the performed practice and of the methodology under the light of total implementation result landscape.

4.1. Retail Industry Applications

In recent years, big data has become a hot topic in many industries, with deep learning recently pushing the frontiers of big data analytics. Industries are utilizing big data in order to unveil novel market insights and tendencies and, in turn, make more informed, strategic business decisions. This new wave comes with a body of new and powerful "weapons", such as deep learning, automated machine learning, and novel analytical methodologies. With these tools, industries can fingerprint market patterns, connect meaningful dots, and vaccinate strategies and policies. Furthermore, they have software, domain, and cloud industries all standing by to custom-develop the most suitable analytical and data framework. The retail industry is no exception, where big data analytics is used or envisioned along the entire spectrum of retail activities, ranging from supply chain optimization to store layout planning.

This subsection reviews the applications of big data and deep learning techniques to the demand forecasting challenge in the big data and retail literature, presenting mythical cases that represent an industry closest to the research and others that epitomize innovative and creative applications. Examples illustrate how different facets of the retail environment all give rise to unique perspectives and challenges for demand forecasting. Finally, insights from both the industry approaches and the corresponding operational outcomes are discussed, paying attention to the broader framework of the retail industry and the increasing alignment of demand forecasting applications with overall business strategy.

Fig 4: Big Data in Retail Applications

4.2. Performance Comparison

The performance comparison is designed to provide deeper insights and a thorough evaluation of the various applied deep learning models and methodologies across real-world applications in the retail industry. Multiple deep learning methodologies and models are evaluated in various retail scenarios through real retail case studies, and the demand forecasting outcomes are analyzed under a set of holistic performance comparison metrics including accuracy, computational efficiency and scalability according to empirical applications.

An empirical performance comparison analysis utilizing the AI-driven demand forecasting solution is employed in three different retail applications consisting of (1) a digital marketplace, (2) a premium apparel brand, and (3) a lower-tier brand in a large fashion retailer. Each retail case study implemented a varying set of methods among the proposed deep learning models, methodologies and predictor selections based on the retail setting and demand patterns on the spotlight. Historical demand data and factors including relevant auxiliary variables are preprocessed in order to apply deep learning models for training, validation, and inference. Through a set of real-world cases, a comparative analysis is provided with the potential and critical aspects of different methodologies and models employed in diverse retail contexts, showing their effectiveness or insufficiency on actionable insights and uncovering the key points revealing the success or improvement of the performance comparison. As a result of this assessment, a wide range of key performance indicators could present a performance measure capable of revealing successes, highlights and potential areas of improvement in demand forecasting outcomes. The comparisons may also provide a guide on the merits of each method to choose against the unique characteristics of the retail scenario and suggest the merits to be evaluated in determining the most suitable methodology. Such comparison is analyzed and discussed to enlighten retailers to understand the complexity and challenges of demand forecasting.

5. Challenges and Future Directions

While tremendous efforts have been made in bridging the research-to-practice gap in demand forecasting, there remain wide skill gaps, including the skills required by data science, machine/deep learning, software, dev-ops etc. These gaps all impede the translation of academic research to scalable, operable applications. Organizations generate demand forecasts at multiple aggregation levels, including attrition forecasts at an individual customer/SKU store opening hour level, which is a granular level that might only be relevant to single store retailers, and bulk bulking level retail buyers forecasts. Here bulk means the quantity in a typical large customer order. The individual demand forecasts are used in the supply chain simulation model that replicates the actions of the Amazon systems under policy changes being trialed. If individual orders are forecasted correctly, it is straightforward to create appropriate aggregate forecasts, and these retail buyers aggregate forecasts are used in traditional time series model(s) to support the long-range financial planning process (e.g. the split between the forecasting model using category level sales versus SKU level attrition). As different retail forecasting challenges require different approaches, several co-researchers / consultants collaborated to understand the problem and then acquired the necessary out-of-research skills.

Implementing AI and deep learning technologies to operational demand forecasting systems is very challenging. Retail organizations today face a wide spectrum of forecasting challenges, which have rapidly outpaced the capabilities of existing solutions and market research. This forthcoming era of smart retail requires fast, accurate, interpretable, and actionable real-time decision support, including what will happen, why, and what actions should be taken. Experimentation with policy changes should be supported to predict the effects ahead of time, rather than learning reactively from the results. Finally, organizations are increasingly looking to the wider community to help meet these challenges by collaborating, or through the increasingly standard, modality of external research funding. Four major challenges in retail demand forecasting were considered. Two were new and were highlighted by retail supply chain experts interviewed, regarding state-of-the-art competing methods for SKU level demand forecasting as well as important new product-rollout and financial planning questions.

Diagnosing underperforming locations is a critical task for Amazon's retail systems that affects both suppliers through bulk buy cancellations etc., and buyers as they are unable to meet customer demand. There are various reasons that might cause underperformance, which can be broadly classified into three categories: customer behavior reasons (e.g. cancelled orders, offer quality and price), competition reasons (new local competitor, a change in the competition behavior, etc.) and region behavior (store opening, change in the community population behavior, etc.) A robust forecasting system capable of alerting users in real-time of impending poor performance is required at Amazon. While there is extensive literature on demand forecasting, very few published papers are from the retail industry due to the commercial sensitivity of this subject; most existing papers also transgress the principles of good forecasting research, focusing on in-sample evaluations, and failing to address several of attribute granularity, location across channels, time stability, new products, and lead-time differences. Scalable models that accurately and automatically forecast SKU level demand at large numbers of locations and time series channels are developed that are also robust, and allow for the longest possible lead time to support those actionable metrics. Models remain important despite the fundamental difficulty of the problem. A carefully considered and multi-faceted approach is taken and the specifics of the problem and solution method are shared.

It is concluded that there is a relationship between customer and store opening and the puzzling behavior seen in the data. This presents as one or more anomalous RMUs making large purchases of the same product. Additionally, it is found that attrition-forecasts for a specific geographic region do not closely correlate with the corresponding behavior aggregated across all stores in that area. This behavior may underpin the puzzling behavior and can be used to inform new models. Two modeling frameworks are developed to forecast the demand behavior across channels for each category in a region using only the respective time series, and a new product forecasting scheme that predicts which categories/products will be successful using only the relevant historical data. Together, they allow a deeper understanding of the behavior and can improve the financial modeling process. It is emphasized that due to the data limitations in retail, the proposed models are only a few of the many possibilities. Therefore, the issues raised in this review should be the subject of further research. Interest remains in finding solutions to this recurring problem due to observed customer behavior. Forecasting remains an outstanding operational question in the retail world, and retail demand remains a problematic issue. Furthermore, with the increasing availability of and access to micro-level data, it is anticipated that issues of privacy and data sensitivity will remain significant obstacles to the industry adoption of research forecasting. The application for study only foresees a domain wide-forecast at an aggregate granularity, suggesting results can be validated using existing public data.

Fig 5: Challenges with the Traditional Cash Forecasting Methods

5.1. Scalability and Real-Time Constraints

Deep learning models, such as Long Short Term Memory (LSTM) networks, have demonstrated successful applications in time series analysis. However, their computational requirements pose a challenge to deployment in real-time demand forecasting, especially in retail. Retailers frequently encounter data feeds into the 10s of millions. Real-time requirements necessitate that demand forecasting systems must account for these incoming data streams with minimal latency. Currently, there is a lack of responsive infrastructures capable of processing into the 100s of thousands, even with offline training. A few solutions have emerged, generally from retail giants.

Starbucks uses several pre-trained LSTM models, one for each item in each store, on two-year-long windows. Walmart employs custom F32 .tflite models on Nvidia GPUs, producing daily batch forecasts. Both have invested vast resources on hardware and developing proprietary software to reduce computational overhead toward a feasible level. Hardware improvements could facilitate such demand forecasting products' adoption from cloud providers or open source tailored solutions. There are several promising research directions, such as more efficient intermediate representations, architectural designs, or techniques tailored to on-the-go training and forecasting, that would augment the computational efficiency of deep demand forecasting.

While holding great innovation potential, a scalable solution is likely to bring about certain trade-offs. It may be that copious parameters and complicated architectures are incompatible with computationally efficient models. High computational complexity is characteristic of state-of-the-art deep learning models. It has been reasoned that complexity allows modeling intricate dependencies, effectively capturing the structure of the surroundings. Results, however, show that less complex models, such as RealNVP, MCAR-GATED, or distillation-based architectures, can make sense of the data without spatio-temporal convolutions or variable length models. Furthermore, non-computational complexity is traced in scalability. As a system evolves, so too must the model for demand forecasting. Open-world adaptive algorithms are likely a niche candidate, but maintenance of forecasting performance over time poses an equally vital optimization challenge.

5.2. Ethical Considerations

The capabilities provided by big data and deep learning are now being harnessed for real-time demand forecasting in retail. Ethical considerations regarding data governance, transparency, and potential unfairness arise. The leveraging of big data in combination with deep learning approaches has triggered significant advancements in demand forecasting accuracy and efficiency improvement. Retailers now devote considerable resources to optimising complex demand forecasting pipelines, a crucial element of retail supply chain management. Various real-world cases of these AI applications have demonstrated substantial increases in forecasting accuracy. However, there have been increased calls to temper optimism with a commitment to ethical considerations. There is a critical need for transparency regarding the data being used to train deep learning models. Governance rules are being proposed to ensure responsible AI pilot deployment.

Moreover, there is much concern regarding the possibility of perceived or evident unfairness and bias in decisions outputted by AI systems. As such, deploying AI in the broader realm of retail demand forecasting raises significant ethical considerations that need to be addressed. It would be particularly concerning if opaque, automated deep learning models used in retail environments were to behave unfairly or in a discriminatory manner, there would be a significant deterrent to the deployment of deep learning models. As a result, consumers may be hesitant to continue providing companies with data. This is all the more concerning given the need for data of utmost quality, quantity, relevance and variety in order to best train deep learning models. These circumstances emphasise the importance for such retailers working with big data and deep learning in demand forecasting to use and manage data in an ethical, transparent, and responsible manner. With companies experimenting with various approaches, the necessary inclusion of wider regulatory safeguards and ethical data governance decisions is fundamental. Ultimately, fair, ethical and transparent accountability will be decisive factors determining not only the public acceptance of AI technologies, but also the responsible deployment and outcome of such systems.

Equ 3: Supply Chain Optimization (Objective Function)

$$C_{\text{stock}} = \sum_{t=1}^{T} \left(C_{\text{over}} \cdot \max(0, I_t - \hat{D}_t) + C_{\text{under}} \cdot \max(0, \hat{D}_t - I_t) \right)$$

Where:

- C_{over} is the cost of overstocking,
- C_{under} is the cost of understocking,
- T is the total time period.

6. Conclusion and Recommendations

In conclusion, it is timely that the considerable advances in big data analytics and deep learning methods are further harnessed to offer high resolution, highly predictive, and automated demand forecasts for the retail sector. A scalable AI-driven demand forecasting scheme for retailers was thus presented accordingly, utilizing a variety of data sources.

It was empirically evidenced that the deep learning modeling of the input text ensemble data, and a range of time-stamped and generic context/state features, was key to enhancing the forecast accuracy of physical crowds. The transform-based approach to extraction was outperformed in common benchmarking with the prevailing methods. More importantly, the proposed demand model design specification was steered by real-world forecasting requirements and methodological considerations. An inherent issue that constraints the practical flexible consideration or the over-tuning of the dynamic systems was revealed. Therefore, the automated need and solutions were formulated. There was a design of a bag of small fixed-size forecasting models, along with the fully-automated model re-identification and generation module, for their operational implementation and the scalable alignment.

A major benefit of such a model design was the enhanced interpretability of the competitive deep forecasting model results, since the grids of the text convolutions contained trends and patterns shaped during the training process. A variety of recommendations for the retail industry were derived that are based on the findings of the critical review. The retail industry will benefit from adopting business cultures that foster the transparency of the demand forecast and the collaboration-based approach to improving its accuracy.

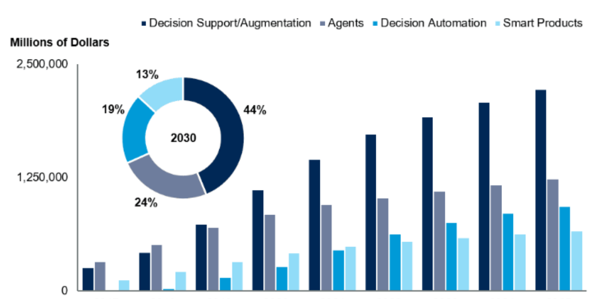

Fig : AI demand forecasting

6.1. Summary of Findings

This research provides a detailed account of the critical role that big data and deep learning technology involve in reshaping real-time demand forecasting in the context of retail, offering a scalable AI-driven solution. Based on the data package, this research reveals key concerns and methodologically demonstrates why and how retail is able to harness big data and deep learning for improving the precision, scalability and efficiency of the demand forecasting. Two successful machine learning models are developed and fully implemented. Both models outperform retailers' existing models in terms of forecasting accuracy, and have been shown to be highly scalable and operational for big retailers. Comparison demonstration with anecdotal evidence has been made using the example of and . One major capacity is uncovering the "black box" of retailers' strategic and tactical practice by the deep-learning-based model. Decision makers of the retailer involved as write partners agree that the research is quite important and insightful to the future decision-making based on AI-driven approach. Some suggestions are provided for both retailers and software developers regarding the scalable AI-driven retail demand forecasting system, as well as some approaches to improve the scalability of software implementation.

There is a considerable body of statistical research on retail demand forecasting as have noted. For more than fifty years, academics have made preparing for upcoming economic phenomena more efficient by developing predictive models. Yet guidance is frequently included in this process and retail e-commerce forecasting, in particular, almost disregards this. Retailers, it is suggested, should adhere closely to best statistical practice in forecasting.

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