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A Review of E-commerce Sales Forecasting Based on Deep Learning: Methods, Advances, and Challenges

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Abstract. Sales forecasting is becoming critical in the optimization of operations and competitiveness in the fast growing e-commerce sector. Due to the nonlinear and complex nature of e-commerce data, traditional time-series models and machine learning approaches face inherent limitations, making deep learning a compelling alternative. Deep learning models can retrieve the nonlinear relationship and the long-term dependencies successfully and thus enhance the accuracy of a forecast. The present paper will be a review of how deep learning models are applied in sales forecasting in e-commerce. It reviews the base deep learning baseline models that are common to this field which include DNNs, RNNs, CNNs, Transformers and associated hybrid models. It continues by discussing superior multimodal fusion models that incorporate multidimensional sources of data (like textual and visual information) to enable even higher precision in prediction. Lastly, as a reaction to e-commerce forecasting to the business-specific challenges, the paper reviews the available solutions to the cold-start problem. Furthermore, this paper evaluates the difficulties and drawbacks of deep learning application to e-commerce sales prediction based on three aspects: data, model, and business aspects. It also explains the direction of future research, which includes recent paradigms including generative AI, explainable AI, federated learning, and self-supervised learning and outlines the vast potential of deep learning with regard to sales prediction in e-commerce.

Keywords: E-commerce Sales Forecasting, Deep Learning, Multimodal Fusion

1. Introduction

E-commerce as a significant part of the modern business environment has experienced a boom in recent years with the mass adoption of internet technologies and mobile payment systems and made e-commerce an essential segment of the new business setting [1]. On e-commerce platforms, huge transactions volumes of user transaction activities are produced at every single moment giving rise to a huge and highly heterogeneous data stream. The information may include not just the structured traditional data (sales history, prices, and simple user profiles) but large amounts of unstructured and semi-structured multiform data, like a product image, the textual descriptions, user-reviews, and intricate behavioral profiles, like the number of clicks on products or the browsing history. Such data are characterized by high dimensionality, dynamic behavior, nonlinearity and substantial amounts of

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noise, which provide large opportunities to extract business value in addition to giving significant challenge to the traditional methods of data analysis [2].

It is against this backdrop that precise sales forecasting is of utmost importance to e-commerce organizations that are aimed at maximizing operational plans, and improving their fundamental competitiveness. At the micro level, precise sales projections are the basis of inventory control, logistics, purchase, and financial budgeting which help firms save on warehousing expenses and such swings as stockouts or overstocks [3,4]. At the macro strategic level, sales forecasting offers quantitative projections in terms of planning of marketing campaigns, aids in accurate advertisement placement and provides personalized approaches to the recommendation strategy, which eventually result in an optimal allocation of resources and maximization of profits [5]. Consequently, operational efficiency and profitability greatly rely on the precision of sales forecasting, which is why it becomes one of the most precious research subjects in the e-commerce field.

Until the emergence of deep learning, e-commerce sales forecasting was mainly based on classical models of time-series analysis and classical methods of machine learning. Time-series models, like the Autoregressive Integrated Moving Average (ARIMA) model can be used successfully to predict linear trends and seasonal variations in the data. As an example, Zhang et al. built a model predicting cigarette sales, with a seasonal decomposition model and the ARIMA model [6]. Yet, however, they are not designed to work with the complex nonlinear relationships that usually arise when working with e-commerce data, which makes them inappropriate in unstable or nonlinear conditions [7-9].

This was followed by the introduction of machine learning platforms like Support Vector Machines (SVM) and Random Forests. As an example, in the work by Zhang et al., such an approach as XGBoost was also used to predict sales to avoid manual work [10]. Although these models may be able to capture some nonlinear trends, they are dependent on feature engineering set by experts, and demands a lot of preprocessing. In addition, they are inadequate for handling high-dimensional sparse representations, long-term correlations in a sequence of data [11]. More to the point, traditional machine learning approaches have little to no ready facilities to actively incorporate and leverage the rich multimodal data, i.e. text and images, ubiquitous in the context of e-commerce, and as a result, the bottleneck in the performance can be observed as the forecasting conditions become more and more complicated. Deep learning-based models on sales forecasting have been proposed to address the shortcomings of the conventional techniques and maximize the value of extensive data of e-commerce [12].

The purpose of the review is to review and analyze the current development of the research in the field of deep learning methodically. To begin with, it revisits the evolution of development of baseline deep learning models involved in sales prediction, working our way back to early models, including Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, to contemporary models that are built on Transformers. Second, it examines the new trend of multimodal data integration to sales prediction and how visual, text, and time data can be used together to increase the accuracy of prediction. Moreover, it addresses a practical issue that is critical and important, namely, the cold-start problem that can affect newly listed products or new users and lists the strategies that are currently employed to address it. Lastly, the paper presents the general issues of this area and mentions the future research that is promising.

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2. Literature review

Figure 1 presents the bibliometric results obtained from Google Scholar using the search terms “E-commerce,” “Sales Forecasting,” and “Deep Learning.” The statistics show a continuous and substantial increase in the annual number of publications on this topic from 2010 to 2024. This trend clearly indicates that leveraging deep learning techniques for e-commerce sales forecasting has become an important and increasingly prominent research focus within the academic community.

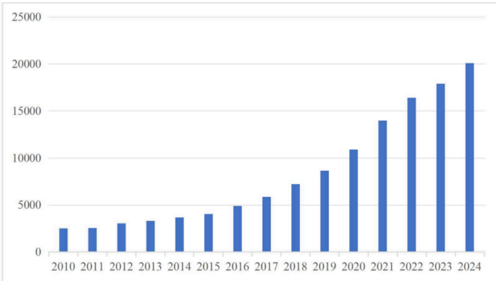

Figure 1. Annual number of publications retrieved using the search terms “e-commerce,” “sales forecasting,” and “deep learning”

3. Applications of deep learning in e-commerce sales forecasting

3.1. Evolution of baseline models for e-commerce sales forecasting

The core contribution of the Deep Neural Network (DNN) lies in its strong capability for nonlinear function approximation [13]. Loureiro et al. employed DNNs to forecast sales in the fashion retail market and demonstrated that, even on relatively small datasets, DNNs outperform most statistical and machine learning approaches [14]. However, DNNs treat data points as independent observations and thus fail to capture the dynamic dependencies inherent in time-series data. This fundamental limitation motivated the subsequent development of sequence-based models.

Recurrent Neural Networks (RNNs) have been proposed to overcome the drawbacks of DNNs in the analysis of time-related dependencies. RNNs possess a form of memory by exploiting their repeated structure and can accept varied length sequences, and in practice, it can learn longer-term dependencies using time-series data [15]. Nevertheless, typical RNNs have the vanishing and exploding gradient issue, which prevents their learning long-range dependencies in practice [16]. To address these problems, RNNs with gating, also known as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are now the central options that are used in practice. As an example, Jiang utilized LSTM as an offensive sales model to forecast agricultural products and the prediction accuracy of over 90% was obtained, which is suitable to solve agricultural sales problems [17].

Unlike the sequential nature of RNNs processing, Convolutional Neural networks (CNNs) employ a one-dimensional convolutional kernels which slide over time, which allows simultaneous and effective local pattern extraction in sequences. As an illustration, Ma and Fildes introduced a CNN-based meta-learner, which was able to automatically derive features and significant variables of the sales time-series data and apply them to make predictions, and its performance was better than most of the baseline models [18].

Even though RNNs and CNNs have recorded significant success in sequence models, sequential execution of RNNs constrain the possibility of parallelization, whereas CNNs are still inadequate at

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describing absolute long-term associations. The development of the Transformer architecture has revolutionized this field by introducing the self-attention mechanism. Existence of self-attention facilitates immediate calculating links among any two-time stages in a sequence, which is the achievement of actual global dependency modeling [19]. Li and Yu also used a Transformer-based model, on which they carried out experiments with the forecasting of the sales dataset of a grocery retailer and discovered that it was much better than other baseline models [20].

Although the baseline models proved to have great potential, scholars quickly recognized the limitations of using only one architecture and began exploring methods to enhance and hybridize these architectures to help enhance performance by further increasing the levels of forecasting [21,22]. This represents a transition of the general-purpose models to the more specialized domain models. By way of illustration, Chen et al. suggested a hybrid solution of GRU and LightGBM to solve the problem of erratic predictions aided by a solitary GRU model. The first layer, in this context, is a GRU model that is cross-validated five times to produce five prediction outputs , which exhibit some variation.The second layer employs LightGBM to integrate these outputs, smoothing out potential overfitting and anomalous predictions from individual GRU models and enhancing overall stability and generalization capability [23]. Mansur et al. proposed a CNN-LSTM hybrid model to simultaneously address the dual issues in e-commerce sales data, namely local and temporal variations which occur short-term and long-term, respectively. The one-dimensional CNN component and the LSTM component in this design act as a local pattern and sequence modeler, respectively, effectively learned short-term sales dynamics and event-based dynamics, respectively. This hierarchical model of multi-scale representation allows learning more expressive features and provides sales forecasting with very high precision [24].

3.2. Multimodal data fusion for deep learning–based sales forecasting

In the recent years, multimodal deep learning algorithms have shown great promise by incorporating data contained in different sources, such as text, image, video, and consumer interactions, to come up with richer, stronger, and more precise models than those who were based on any single modality individually [25,26]. Available literature suggests that the integration of the various types of data will give a more holistic projection of consumer demand hence leading to better precision in sales forecasting [27]. The main difficulty of multimodal deep learning is the alignment, supplementation, and integration of the information in various modalities.

A straightforward approach to multimodal fusion is to concatenate data from different modalities and feed them jointly as input features into a deep learning model. For example, Shan et al. proposed a sales forecasting method that integrates text mining with deep learning by combining bag-of-words representations of product descriptions with historical sales data and employing a WaveNet neural network for multimodal prediction [28]. Although such models are simple and easy to implement, their ability to capture complex cross-modal interactions remains limited.

To more effectively identify and model the interactions among features from different modalities, a range of fusion methods—such as tensor fusion strategies and Spatial Feature Fusion (SFF) techniques—have been developed [29]. These approaches aim to capture synergistic information that goes beyond individual modalities, thereby achieving a “1 + 1 > 2” effect. For instance, Li employed a multimodal feature clustering approach combined with an SFF strategy, in which historical order data and product review sentiment data were fused through weighted additive or multiplicative operations. By integrating these fused features into a cascaded hybrid neural network composed of BiLSTM and BiGRU layers, the method significantly improved the accuracy and efficiency of product demand forecasting [30].

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One of the strongest and most versatile ways has become the interaction based on attention, where one of the modalities actively pays attention to the most significant elements of the other, without causing any damage. Wu et al. built a heterogeneous graph to represent the consumer preferences and added multi-head self-attention mechanism to combine the consumer preferences with the time-series demand characteristics to enhance the predictive accuracy of multi-channel retail sales [31].

Transformer-based fusion is a logical next step and extension of attention mechanisms. Xu et al. offered the multimodal system of fusion wherein textual, visual, audio and numerical data were initially combined within each entity (e.g., streamers, products and live-streaming rooms). They would then apply a QuadTransformer and a multi-entity Transformer architecture to the intra and inter entity relationships respectively. Lastly, the deep neural network was used to come up with the forecasts of sales [32].

3.3. Deep learning–based solutions for the cold-start problem

In e-commerce platforms, the cold-start problem typically refers to the introduction of new users or new products for which insufficient historical data and interaction information are available. This scarcity of data makes it difficult for recommendation systems to generate accurate sales forecasts or personalized recommendations. The cold-start issue not only undermines the effectiveness of personalized recommendation strategies but also poses significant challenges to market exposure and sales prediction for newly launched products [33,34]. The core challenge in addressing cold-start sales forecasting lies in determining how to effectively incorporate existing “prior knowledge” into the system when little to no data are available, enabling the generation of informed and meaningful predictions.

One approach focuses on extracting as much information as possible directly from the product itself and then applying multimodal models for prediction. However, in most cold-start scenarios, such product-centric methods still fail to obtain sufficient data for reliable forecasting.

Another approach involves identifying products or environments that are similar to the cold-start item and leveraging their sales data to make predictions. This strategy has become the mainstream solution for addressing the cold-start problem [35]. For example, Chaube et al. employed an EfficientNet-based deep learning model that combines product attributes with image embeddings to predict a product’s potential score without relying on historical sales data [36]. Similarly, Lv et al. integrated DTW K-means clustering with a CNN–LSTM–attention architecture by clustering products with similar sales patterns and using deep neural networks for forecasting. This method effectively addresses cold-start scenarios and is particularly suitable for sales prediction involving new products and emerging markets [37].

4. Challenges and limitations

In the research and application of e-commerce sales forecasting, Deep learning has finally achieved impressive success in the research and implementation of e-commerce sales forecasting, but there are still a number of challenges based on the data, model creation, and business deployment dimensions. In terms of data, e-commerce datasets are often faced with sample sparsity, heavy noise as well as demands of high data security and privacy. There is also the limitation of new products or new users that have no historical data hence reducing the effectiveness of model training. Modeling wise, the deep learning models can easily overfit, and they generally cannot extrapolate high dimensionality and complicated features. In addition, they are black box by nature thus not

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interpretable enough thus compromising the confidence of business stakeholders on the predictions. As a business, there is a significant operating cost and large amount of computation resources on projecting the deep learning models. Moreover, the fast changing electronic commerce setting demands models that are capable of facilitating real time Adaptations and prompt responses, which are positions that most of the current models have not been able to exploit. Consequently, data quality, model quality and interpretability, deployment efficiency and real-time flexibility should be further enhanced in future research to further address the need of complex and dynamic e-commerce situations.

5. Future directions

As the technologies related to the artificially intelligent development have been evolving, sales prediction in e-commerce is shifting to a more intelligent and efficient state. Since emerging technologies can keep evolving, most of the limitations present in deep learning models will be solved in a process, thus more accurate, real-time and adaptive forecasting will be made. An example of this is that to deal with issues revolving around data security, federated learning may be applied where the model will be trained on more than one source of data without violating data privacy and confidentiality. Generative AI can be used to counter the problem of data sparsity and noise by generating realistic sales data in the past to facilitate and augment prediction tasks. Explainable AI may be useful to enhance the interpretability of deep learning models, to enable businesses to have a better understanding and confidence in the forecasting process. Besides, self-supervised learning provides more robust generalization and increases model resilience and adaptability, which proves to be stronger when applied in order to address actionable business issues and use unlabeled data.

In the future, further studies in the field of deep learning and e-commerce sales forecasting must fully account for the characteristics of e-commerce data, including high dimensionality, nonlinearity, sparsity, the reality of real-time processing, etc. and develop specific solutions. It is recommended to focus on enhancing the flexibility of models, responsiveness in real time, and readability, thus making more in-depth discovery of underlying trends and creating more commercial value.

6. Conclusion

Deep learning has emerged as a key force behind the development and improvement in e-commerce sales forecasting, showing significant benefits in terms of managing high dimensions, nonlinearity, and multimodality of e-commerce data. Deep learning has allowed replacing older forecasting methodologies with the implementation of more intelligent and finer-grained forecasting approaches through the gradual process of evolving baseline models, the constant innovations within the realm of multimodal data fusion algorithm, and various means of coping with practical business issues, like cold-start problem. Nevertheless, certain challenges remain to restrict the widespread application of deep learning models in practical e-commerce settings, including the lack of data, noisy data, low model interpretability and the need for real-time e-commerce sales forecasting, which is likely to continue to develop as more new technologies continue to emerge, including, but not limited to generative AI, explainable AI, federated learning, and self-supervised learning. In a far more macro sense, deep learning will be even more instrumental in driving significant improvements in efficiency in forecasting and better business decision-making and the latent commercial worth, thereby better equipping e-commerce ventures to navigate an increasingly dynamic and competitive market environment.

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