Dynamic long short-term memory model for enhanced product recommendations in e-commerce

Snehal Bhogan, Vijay S. Rajpurohit, Sanjeev S. Sannakki
Department of Computer Science and Engineering, K. L. S Gogte Institute of Technology, Affiliated with Visvesvaraya Technological University, Belagavi, India

Article Info

Article history:

Received May 7, 2024
Revised Sep 2, 2024
Accepted Sep 7, 2024

Keywords:

Deep learning
Hit rate
Long short-term memory
Mean reciprocal rate
Recurrent neural network

ABSTRACT

Recommendation systems are pivotal for personalized user experiences, employing algorithms to predict and suggest items aligned with user preferences. Deep learning (DL) models, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), excel in capturing sequential dependencies, enhancing recommendation accuracy. However, challenges persist in session-based recommendation systems, particularly with gradient descent and class imbalances. Addressing these challenges, this work introduces dynamic LSTM (D-LSTM), a novel DL-based recommendation system tailored for dynamic E-commerce environments. The primary objective is to optimize recommendation accuracy by effectively capturing temporal dependencies within user sessions. The methodology involves the integration of D-LSTM with weight matrix optimization and a Bayesian personalized ranking (BPR) adaptable learning rate optimizer to enhance learning efficiency. Experimental results demonstrate the efficacy of D-LSTM, showing significant improvements over existing models. Specifically, comparisons with the hybrid time-centric prediction (HTCP) model reveal a performance enhancement of 19.4%, 17.2%, 35.41%, and 21.99% for hit-rate (HR) and mean reciprocal rank (MRR) in 10k and 20k recommendation sets using the Tmall dataset. These findings underscore the superior performance of D-LSTM, highlighting its potential to advance personalized recommendations in dynamic E-commerce settings.

Corresponding Author:

Snehal Bhogan
Department of Computer Science and Engineering, K. L. S Gogte Institute of Technology, Affiliated with Visvesvaraya Technological University
Belagavi 590018, India
Email: snehalrbhogan@gmail.com

1. INTRODUCTION

Recommendation systems play a crucial role in various domains by providing personalized suggestions to users. These systems utilize algorithms and data analysis techniques to predict and present items that users might be interested in, based on their preferences, behaviours, and interactions [1]. The significance of recommendation systems extends across diverse sectors, including entertainment, social media, education, and notably, E-commerce platforms [2]. In the realm of E-commerce, recommendation systems enhance user experience and drive sales by offering relevant product suggestions [3]. Sessions, which represent a series of user interactions within a specific timeframe, play a pivotal role in understanding user preferences and guiding the recommendation process [4]. Existing machine-learning (ML) methods [5], [6] in E-commerce often rely on session-based recommendation systems to capture temporal dynamics, and user behaviour patterns. Moreover, the traditional ML approaches have been extensively employed for recommending products based on user sessions [7]. However, researchers are increasingly turning to deep learning (DL) models due to their ability to handle complex patterns and hierarchical representations [8]. DL models, such as recurrent neural networks (RNNs) [9] and long short-term memory networks (LSTMs) [10], excel in capturing sequential dependencies in user sessions, thereby enhancing the accuracy of recommendations. Despite the advantages of DL, challenges persist in session-based recommendation systems, particularly regarding gradient descent [11], and class imbalance issues [12].

DL models, while powerful, may face challenges associated with the optimization process, such as the vanishing gradient problem [13]. Additionally, class imbalance, where certain products have significantly more interactions than others, can lead to biased recommendations [14]. Consequently, researchers are exploring ways to address these issues and enhance the performance of recommendation systems [15]. In this work, a novel model is proposed in this work to tackle the challenges of gradient-descent and class imbalance in session-based recommendation-systems (SBRS). The proposed model incorporates innovative technique to mitigate the vanishing gradient problem, ensuring the stable and efficient training of DL models. Furthermore, it addresses class imbalance by implementing strategies that prioritize the learning of underrepresented items, resulting in more equitable and unbiased recommendations. By integrating these enhancements, the model aims to push the boundaries of SBRS and deliver more accurate, diverse, and fair product suggestions to users on E-commerce platforms. The contribution of this work is as follows:

- Introduced a LSTM based approach for recommendation in E-commerce, leveraging user sessions, called as dynamic-LSTM (D-LSTM).
- Addressed key challenges in recommendation systems by presenting a weight optimization approach.
- Presented a novel adaptable learning rate optimizer which is proposed to overcome limitations associated with conventional BPR optimization.

The manuscript is structured to provide a comprehensive understanding of the research. In section 2 delves into an exploration of various existing SBRS, offering insights into the current landscape of the field. Following this, in section 3, we introduce the proposed model, detailing its architecture and innovative features. Moving forward, section 4 is dedicated to presenting and analysing the results obtained from our proposed approach. Finally, section 5 encapsulates the key findings and implications of the research, serving as a conclusive summary of the work undertaken and future work is also discussed.

2. LITERATURE SURVEY

This section delves into an exploration of various existing SBRS, offering insights into the current landscape of the field. Ye *et al.* [16] developed an LSTM-based technique for SBRS and constructed framework for music selection. This framework was constructed up of a total of four distinct components: MDM which stands for “music data-modeling”, NSP which stands for “next-song-prediction utilizing LSTM”, MLB which stands for “music-library-building”, and R4U which stands for “recommendation-for-users”. A modification of the fundamental LSTM was made possible by the presented framework through the utilization of enhanced session-parallel mini-batches along with a scoring-loss mechanism. According to the results of the study, they were able to achieve an approximate boost in ranked measures, i.e., mean-reciprocal rate (MRR) and hit-rate (HR or recall) in comparison with existing SBRSs. The MRR and HR that their method attained for N=10, 20, and 30 were respectively 0.2512, 0.3029, and 0.2405 and 0.6533, 0.6701, and 0.6392 respectively. By utilizing artificial-neural-network (ANN) and hidden-markov-model (HMM), Djellali and Adda [17] presented a DL approach for recommendation called as recurrent HMM (RHMM). For the purpose of optimizing the bias-variance tradeoffs for the predicted anticipation, a selection approach was utilized. The findings of their study demonstrated that using DL approach resulted in a substantially higher level of performance compared to benchmarked approaches. They were able to reach a level of precision, accuracy, f-measure and recall that was 93.15%, 97.24%, 88.98%, and 93.15% respectively. A SRBS was built using context-aware and gated-graph-neural-networks (CA-GGNNs) by Li and Gao [18]. The CA-GGNN approach merged data of the entire session series alongside data regarding the situation at a regular basis. It was demonstrated by the utilization of Digentica and Yoochoose datasets, CA-GNN attains a substantial enhancement in comparison to the most recent SRBS. The CA-GNN approach was able to obtain MRR of 31.83 and precision (PR) of 70.84 for 20k recommendation-set for Yoochoose1/64. Also, CA-GNN approach was able to obtain MRR of 32.91 and PR of 72.93 for 20k recommendation-set for Yoochoose1/4. For Digentica dataset, CA-GNN approach achieved MRR of 18.48 and PR of 51.12.

An SBRS incorporating time-aware memory-network along with GNN was suggested by Wen *et al.* [19]. The approach was primarily comprised of the outer-feature and inner-feature extraction-models called as OFEM and IFEM respectively. The approach used a gating system to combine IFEM and OFEM. They ran their experiments on RetailRocket, Yoochoose1/4, and Yoochoose1/64. The achieved MRR of

32.53 and PR of 71.92 for 20k recommendation-set for Yoochoose 1/64 dataset. For Yoochoose 1/4 dataset and RetailRocket, they achieved MRR of 32.57 and PR of 72.07 and MMR of 37.41 and PR of 63.64 for 20k recommendation-set respectively. Using local-level logits derived from product changes within sessions along with global-level logits derived from accumulated logits of linked sessions, a new approach named logit-averaging (LA) was presented by Yang *et al.* [20]. Comprehensive experimental evidence demonstrates that the suggested strategy improves SRBS performance with regard to diversification and correctness. Fot the Tmall dataset, the LA using the TAGNN+ with GraphMix (TAGNN+GM) achieved MRR and HR of 17.11 and 34.27 for 10k recommendation-set, whereas for 20k recommendation-set it achieved MRR and HR of 43.33 and 17.76 respectively. For Yoochoose 1/64 dataset, it achieved MRR and HR of 30.86 and 60.75 for 10k recommendation-set, whereas for 20k recommendation-set it achieved MRR of 31.59 and 71.15. Wu *et al.* [21] presented a SRBS that combined a session-based context-aware-recommendations. A RNN recommendation approach was founded using sessions which was created by combining three distinct configurations of Stack, Add, and multi-layer perceptron (MLP). Two publicly available data sets were used for the numerous studies that they carried out. The findings of the experiments demonstrated that their approach performed noticeably better than the most advanced kinds of SRBS currently available. For the purpose of evaluating the effectiveness of various approaches and evaluating their outcomes, Kumar and Kumar [22] used eight ML approaches against a variety of datasets originating from a variety of areas. In comparison to all approaches, it appeared that using SRBS using K-nearest neighbour (KNN) along with its modifications resulted in improved outcomes. This was determined using the findings that were collected.

A time-aware neural-attention network (TNN) was presented by Wang *et al.* [23] as a means of modelling dynamic customer preferences in subject-based reasoning tasks. The results of many testing demonstrated that their strategy surpassed SRBSs which were considered to be state-of-the-art in a substantial consistent manner. Salampasis *et al.* [24] examined both practical and theoretical challenges related to creating and assessing techniques for SBSR in E-commerce scenarios, particularly in circumstances in which customer profiles along with buying information was unavailable. One significant finding indicated that a “temporal-locality-principle” was in effect, suggesting that current conduct was more predictive. For further evaluation of such systems in real-world settings, various SRBS were incorporated into an E-commerce platform, along with an A/B testing approach was implemented. An accuracy of 97.6% was attained using the LSTM+gated recurrent unit (GRU) model. A SRBS called SMONE, which relied on neighbouring sessions that had comparable probability insights, was introduced by Jia *et al.* [25]. SMONE used a probabilistic framework to determine the underlying objectives of sessions and subsequently found nearby sessions that share those objectives. The efficacy along with efficiency of SMONE were demonstrated through tests conducted on real-world datasets. A GNN SRBS-based approach called GNN-position-attention (GPAN) was presented by Dong *et al.* [26]. In particular, they suggested a new high and low values order session perception which models undirected and directed networks independently to derive session-level low and high-order product presentations. The suggested GPAN approach outperformed the competition, according to the outcomes of multiple tests conducted over three actual data sets. A hybrid time-centric predicting (HTCP) approach was proposed by Sreenivasa and Nirmala [27] in order to handle researching concerns which integrates both the long and short-term behaviors of consumers. To evaluate the effectiveness of the HTCP approach, existing hybrid approaches were compared and experiments were conducted using the recsys competition dataset. The goals of these tests were to determine the MRR and HR.

3. PROPOSED METHODOLOGY OF PRODUCT RECOMMENDATION FOR ECOMMERCE ENVIRONMENT

This work presented a system for E-commerce that uses DL for recommending products. We begin by introducing the system framework that supports recommendation of products approach. This work presents a novel approach known as D-LSTM. The initial step in this research work involves the formulation of the issue at hand, i.e., problem-definition. In the subsequent analysis of the proposed methodology, we will get into distinct methodologies aimed at integrating multi-click features characteristics at the initial input stage to accurately present the recommendation item in question. This research focuses within the investigation of models that can effectively model multi-click features characteristics at their hidden states to construct a comprehensive user representation. In conclusion, it is noteworthy that the various iterations of D-LSTM can be effectively trained by leveraging the Bayesian learning optimization methods.

3.1. System framework

The system framework as presented in Figure 1 comprises essential components designed to optimize recommendation accuracy in an E-commerce context. At the core of the framework lies the dataset, serving as the foundational source of user interaction information. This dataset encapsulates user sessions, forming the basis for training and evaluating the recommendation model. The D-LSTM network represents a pivotal element in the framework, leveraging its ability to capture temporal dependencies within user sessions. To address challenges associated with training DL models, a weight matrix optimization approach is introduced. This element focuses on mitigating the gradient-descent problem and class imbalance issues, ensuring a more stable and equitable learning process. By optimizing the weight matrices, the model can adapt and generalize effectively to varying user behaviors. In addition, the framework incorporates a Bayesian personalized ranking (BPR) optimizer, a sophisticated approach designed to overcome limitations associated with traditional optimization methods. This adaptability is crucial for navigating through the complex landscape of E-commerce data, avoiding convergence issues, and facilitating the model's ability to escape local minima during the training process. Together, these components create a robust system framework that synergistically integrates the dataset, LSTM network, weight matrix optimization, and adaptable BPR learning optimizer. This holistic approach aims to enhance the accuracy and fairness of product recommendations in E-commerce platforms by addressing key challenges and leveraging advanced DL techniques.

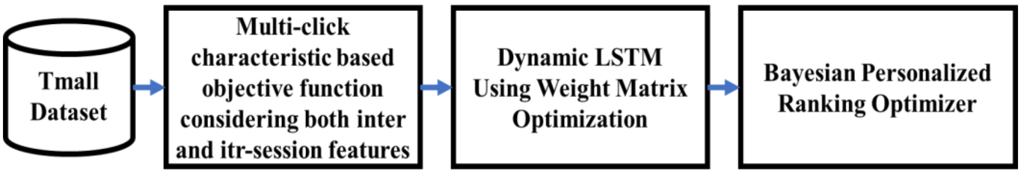

Figure 1. D-LSTM system framework

3.2. Problem definition

The acquisition of past information associated within the E-commerce environment serves as a crucial component through the process of problem description for a series prediction. The set V, denoted as $\{v_1, \dots, v_{|V|}\}$, represents the collection of customers in the domain of E-commerce. Similarly, the collection J, denoted as $\{j_1, \dots, j_{|J|}\}$, represents the related products associated with these customers. The notation $J^v = (j_1^v, \dots, j_{|J^v|}^v)$ is employed to represent the products that have been ordered by customers v in a sequential manner. Here, $j_u^v \in J$ refers to the j^{th} product ordered by customer v, where J represents the set of all available products. Based on the past information J^v related to every customer, our primary objective is to provide a set of recommendations for potential product purchases.

3.3. Multi-click characteristics

Multi-click feature characteristics of an item can be broken down into two broad categories: those that can be observed directly and observed indirectly. The hidden characteristic, also known as the first viewpoint, is a commonly employed concept in recommendation systems. The hidden characteristic of a product is characterized by a vector, as per the established definition given in the (1). The present study incorporates a combination of intra-session and inter-session characteristics, denoted as h and g, respectively, to form a multi-session aware feature. The differing value between the variables h and g necessitates the acquisition of a pair of distinct directional embedded matrices, denoted as W and F into embedded low-dimensional characteristics, represented as j_h and j_g, using (2) and (3) respectively.

$$j_y = y, \;\; j_x \in \mathcal{R}^e \tag{1}$$

$$j_h = Wg, \;\; j_h \in \mathcal{R}^e \tag{2}$$

$$j_g = Fg, \;\; j_g \in \mathcal{R}^e \tag{3}$$

The cold-start issue is a common challenge faced by sequential-recommendations systems. This issue arises because of limited availability of feedback-information, which makes it difficult to accurately understand and indicate the preferences of consumers and products. The utilization of multi-click features characteristics in modeling has been identified as a promising approach to mitigate the aforementioned issue. The establishment of aggregation approach is usually achieved through the simple execution of the addition function, without the need for any nonlinear-transformation. This is achieved using the (4). The method of encoding is mathematically described by (2) and (3), while the construction of the associated hidden-layer is modeled by (4). During the method of decoding, it is imperative to undertake the task of reconstructing the multi-modal input-characteristics. The mapping-matrix utilized in the decoding step is equivalent to the reverse from the mapping-matrix used during the encoding step using (5) In the proposed approach, the inclusion of a bias variable is deliberately omitted, and the initial characteristics of h and g are utilized as input. Therefore, the objective-function of proposed approach is derived using (6) In this work, $|e_h|$ and $|e_g|$represent the initial dimensions of inter-session and intra-session characteristics, respectively. They serve as balance variables.

$$j_n = j_g + j_h, \;\; j_n \in \mathcal{R}^e \tag{4}$$

$$\hat{g} = F^U j_n \,, \hat{h} = W^U j_n \tag{5}$$

$$\ominus^* = \underset{\ominus}{\operatorname{argmin}} \frac{1}{2n} \sum_{j=1}^{n} \left(\frac{\|g_j - \hat{g}_j\|^2}{|e_g|} + \frac{\|h_j - \hat{h}_j\|^2}{|e_h|} \right)^2 \tag{6}$$

3.4. Dynamic LSTM and bayesian personalized approach for recommendation of product

In this section, we introduce a novel LSTM approach designed to effectively tackle issues related to gradient-descent. The equation describing the LSTM's function in improving the gradient-descent over the period of time (session) is evaluated using (7) and (8). The (7) represents the cell-state defined as d_u and (8) represents the hidden-state defined as i_u. g_u, j_u, p_u, and h_u defined the gates of LSTM for the given time (session) u. Further, $\odot$ represents the product of point-wise multiplication. The different gates, i.e., h_u, g_u, j_u, and p_u are evaluated using the (9) to (12) respectively.

$$d_u = g_u \odot d_{u-1} + j_u \odot h_u \tag{7}$$

$$i_u = p_u \odot \tan h(d_u) \tag{8}$$

$$h_u = \tanh\left(V_{hi} i_{u-1} + V_{hy} y_u + c_h\right) \tag{9}$$

$$g_u = \sigma\left(V_{gi} i_{u-1} + V_{gy} y_u + c_g\right) \tag{10}$$

$$j_u = \sigma\left(V_{ji} i_{u-1} + V_{jy} y_u + c_j\right) \tag{11}$$

$$p_u = \sigma\left(V_{pi} i_{u-1} + V_{py} y_u + c_p\right) \tag{12}$$

Where σ represents the occurrence, V_{hi}, V_{gi}, V_{ji}, and V_{pi} are weighted matrix for the gates h_u, g_u, j_u, and p_u respectively. One interesting feature of LSTM approach is the utilization of recurrent relationships between the cell-states, which remains linear throughout the execution of LSTM. This linear relationship helps the flow of gradients for a longer duration. Nevertheless, the V_{hi}, V_{gi}, V_{ji}, and V_{pi} exhibit polynomial characteristics that increase as time passes. Hence, this leads to varying paths causing gradient-imbalance, particularly affecting the gradients which have linear-path whenever dealing with more weighted matrix. Due to this there is a decrease in performance of recommendation of products. To solve the above mentioned issues, this work presents a back-propagation approach for the LSTM approach. Consider, an element represented as x for the matrices V_{hi}, V_{gi}, V_{ji}, V_{pi}, V_{hy}, V_{gy}, V_{jy}, and V_{py}. Using this, a function for the LSTM gates is represented as P_u which comprises of cell-states and hidden-states which is mathematically represented using (8). The P_u comprises of various gradient-ascending paths (i.e., G_u and $\tilde{G}_u$) because of the temporal-paths (i.e., l_u and $\tilde{l}_u$) of various sessions. Further, the gradients which have residual-path (i.e., far from the linear-path) is represented using the matrix Q_u. Further, the derivative of cell-state d_u and the gate i_u is represented using a matrix represented as a_u. In the present study, the LSTM approach is employed to replace the initial equation as described in (10).

$$i^u = Lstm(Vy^u, Xi^{u-1}, c), \;\; i^u \in \mathcal{R}^e \tag{13}$$

The set V consists of four matrices denoted as V_1, V_2, V_3, and V_4. Similarly, the sets X and c also contain four matrices each. The multi-click customer feature representation is formed by concatenating the hidden-states obtained using the two recurrent units. In this study, it has been observed that the entities under investigation exhibit a strong interconnection, which persists throughout each temporal iteration of our product recommendation as (14).

$$i^u = \left[j_y^u; j_n^u\right],\ i^u \in \mathcal{R}^{2e} \tag{14}$$

Where j_y^u defines hidden information of product clicks stream and j_n^u defines the corelated features of multiple clicks of different products. The user's general interest, denoted as i^u, serves as a focal point for investigation and exploration. The suggested design demonstrates its ability to accurately represent the relationship among multi-click feature characteristics and subsequently build a unified representation of customers preferences. This integration of multi-view characteristics significantly enhances the efficiency of the system, making it more likely in achieving its objectives using (15). The variable i^u represents every aspect of customer preferences, rather than being just a concatenation of various preferences as described in (14). In our research, we utilize the variable V, which comprises elements $V_1, V_2, V_3, V_4 \in \mathcal{R}^{2e}$. This choice is motivated by the presence of variables j_y^u and j_n^u.

$$i^u = Lstm\left(V\left[j_y^u; j_n^u\right]Xi^{u-1}, c\right),\ i^u \in \mathcal{R}^{2e} \tag{15}$$

3.5. Bayesian personalized based learning

Following a comprehensive analysis and examination of the input-characteristic and hidden-state elements that make up the D-LSTM approach, we proceed with discussing the training process pertaining to the output. Regardless of the particular combination of input-characteristics or hidden-state systems, the BPR system [2] consistently proves to be applicable. The BPR approach is a robust approach for handling implicit-feedback information. The characterization is additionally predicated upon the variables i_x and i_m. The set of training data S consists of triples ðu; p; qÞ, in which u indicates the customer and q and p indicate the negative and positive products, respectively. Product p is intentionally chosen through the customer's past purchases, denoted as I_u. Conversely, product q is chosen at random through the remaining products, denoted as the intersection of the set of all products and I_u, denoted as $(I_n \cap I_u)$. In every epoch, a regenerative process occurs wherein a negative product exists for every positive product, which is represented using (16). Based upon the provided training dataset, the research methodology involves quantifying the disparity in customer preferences for negative and positive products within the output at each time-step. At the tth time-step, the computation can be performed by (17).

$$\hat{y}_{vqr}^u = \hat{y}_{vq}^u - \hat{y}_{vr}^u = (i^u)^U\left(j_q^{u+1} - j_r^{u+1}\right) \tag{16}$$

$$T = \{v, q, r | v \in V \wedge q \in J^v \wedge r \in J \backslash J^v\} \tag{17}$$

The variables j_r^{u+1} and j_q^{u+1} are used in this context to denote negative and positive inputs, respectively. The objective-function effectively integrates the BPR approach with our MCAE in a concise manner. The D-LSTM has the capability to effectively model both types of losses concurrently. The primary objective of BPR is maximizing the following equation, which encompasses various factors contributing to overall efficiency.

$$\ominus^* = \underset{\ominus}{\operatorname{argmax}} \sum_{(v,q,r)\in T} \log \sigma\left(\hat{y}_{vqr}\right) - \frac{\mu_\ominus}{2} \|\ominus\|^2 \tag{18}$$

In our research, we have successfully achieved the transformation of the given data into its minimal form. The D-LSTM loss, as denoted by (6), is further expanded in conjunction using the BPR. The symbol $\ominus$ represents a collection of variables as defined in [27]. The regularization variable, denoted as $\mu_\ominus$, is a crucial component in various research fields. Its significance lies in its ability to control the trade-off between the model's complexity. The proposed D-LSTM optimized using BPR aid in improving recommendation performance with higher hit rate and mean reciprocal rate which is experimentally shown below.

4. RESULTS AND DISCUSSION

Within this section encompassing results and discussions, a detailed presentation of the essential components necessary for executing the proposed model is provided. The system requirements, including the architectural aspects and functional requirements, are presented to offer a comprehensive understanding of the environment in which the model operates. Moving forward, a meticulous discussion ensues regarding the Tmall dataset employed in the experimental setup. Subsequently, the evaluation metrics of HR and MRR is discussed. A comparative analysis is conducted, wherein the performance of the proposed model is compared against the HTCP model [27]. This comparative assessment serves to benchmark the efficacy of the proposed approach, shedding light on its ability to generate accurate recommendations in contrast to existing state-of-the-art models. The discussion not only delves into numerical results but also interprets the implications of these metrics in the context of user satisfaction and system performance.

4.1. System requirements

In configuring the system for working with the Tmall dataset, a robust computational environment was employed, featuring an Intel Core i7 processor, 16 GB RAM, and the Windows 11 operating system. The development of this research was carried out using Python within the Anaconda framework. By using Python, especially within Anaconda, offered versatility, and popularity in coding practices.

4.2. Dataset

The Tmall dataset, accessible from [28], stands as an extensive and commonly employed resource in the realm of E-commerce research and development. Sourced from the Tmall online marketplace, this dataset encompasses a rich repository of information encompassing user behaviours (session), item specifications, and transaction records. It encapsulates diverse data points such as user clicks, purchase activities, demographic details, and comprehensive product information within the Tmall platform. This dataset serves as a cornerstone for researchers in the exploration and advancement of recommendation systems, personalized marketing strategies, and various E-commerce-related algorithms. Its widespread usage underscores its significance as a valuable asset in fostering innovations and insights within the dynamic landscape of E-commerce analytics. The attributes in Tmall dataset are given in Table 1.

Table 1. Attributes in the dataset

Field	Description
User_id	Unique user ID
Seller_id	Unique online seller ID
Item_id	Unique item ID
Category_id	Unique category ID
Online_Action_id	“0” denotes “click” while “1” for “buy”
Time_Stamp	Date of the format “yyyymmdd”

4.3. Hit-rate performance

The performance of HR is calculated utilizing (19). The results analysis for HR@10K recommendation on the Tmall dataset as presented in Figure 2 indicates a notable performance improvement achieved by the D-LSTM model over the HTCP. The HR for HTCP stands at 0.457, while D-LSTM demonstrates a substantially enhanced HR of 0.567.

$$HR = \frac{TP}{TP+FN} \tag{19}$$

This performance boost represents a remarkable 19.4% improvement in favor of D-LSTM over HTCP. The higher HR values for D-LSTM suggest its efficacy in accurately recommending items within the top 10 choices, showcasing its superior ability to understand user preferences and provide more relevant suggestions. This outcome underscores the effectiveness of the novel D-LSTM model in optimizing product recommendations on the Tmall dataset, emphasizing its potential significance in enhancing user experience and engagement within the E-commerce domain. The results analysis for HR@20K recommendation as presented in Figure 3 on the Tmall dataset reveals a significant performance improvement demonstrated by the D-LSTM model compared to the HTCP model. The HR for HTCP is reported at 0.534, whereas D-LSTM exhibits a substantial enhancement with an HR of 0.645. This shows a noteworthy improvement of 17.209% in favor of D-LSTM over HTCP for HR@20K recommendation. The higher HR values achieved by D-LSTM underscore its superior capability to provide accurate recommendations within the top 20 choices. The results reaffirm the effectiveness of the D-LSTM model in understanding user preferences and delivering more relevant suggestions, highlighting its potential to elevate the quality of product recommendations within the dynamic landscape of the Tmall dataset. This outcome reveals the practical significance of D-LSTM in optimizing user engagement and satisfaction in the E-commerce domain.

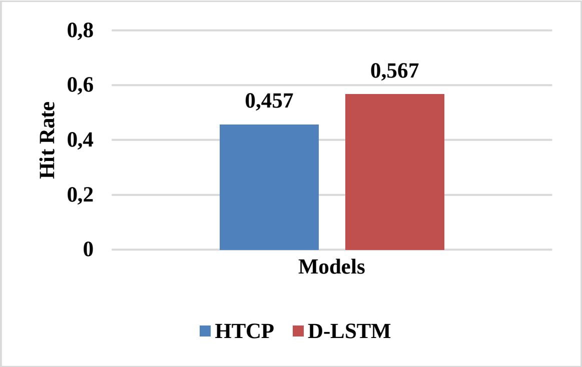

Figure 2. HR for 10k recommendation set

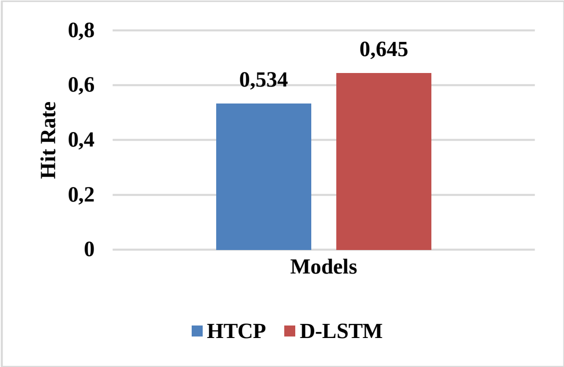

Figure 3. HR for 20k recommendation set

4.4. Mean reciprocal rate

The MRR is characterized as the average of the reciprocals of the ranking positions for the initial N recommended products [26]. The MRR is evaluated using (20). The analysis of the MRR for the Tmall dataset at the 10,000-recommendation set as presented in Figure 4 shows a substantial performance enhancement by the D-LSTM model compared to the HTCP model. The MRR for HTCP is reported at 0.197, whereas D-LSTM exhibits a notable improvement with an MRR of 0.305. This represents a significant advancement of 35.41% in favor of D-LSTM over HTCP for MRR@10K recommendation. The higher MRR values for D-LSTM signify its efficacy in not only recommending relevant items within the top 10 choices but also in improving the ranking positions of those recommendations.

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i} \tag{20}$$

This outcome underscores the superior ability of the D-LSTM model to enhance user satisfaction by providing more accurate and higher-ranked suggestions within the specified recommendation threshold on the Tmall dataset. The analysis of the MRR for the Tmall dataset at the 20,000-recommendation level as presented in Figure 5 reveals a noteworthy performance improvement by the D-LSTM model over the HTCP model. The MRR for HTCP stands at 0.298, while D-LSTM demonstrates a significant enhancement with an MRR of 0.382. This results in a substantial improvement of 21.99% in favor of D-LSTM over HTCP for MRR@20K recommendation. The higher MRR values achieved by D-LSTM indicate its effectiveness not only in recommending relevant items within the top 20,000 choices but also in improving the overall ranking positions of those recommendations. This outcome emphasizes the superior ability of the D-LSTM model to provide more accurate and better-ranked suggestions within the specified recommendation threshold on the Tmall dataset, enhancing the overall quality of user experience and engagement in the E-commerce setting.

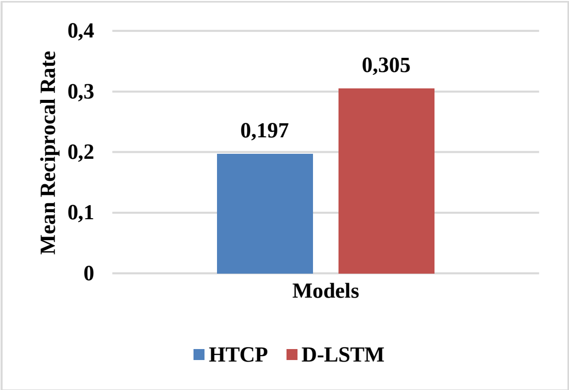

Figure 4. MRR for 10k recommendation set

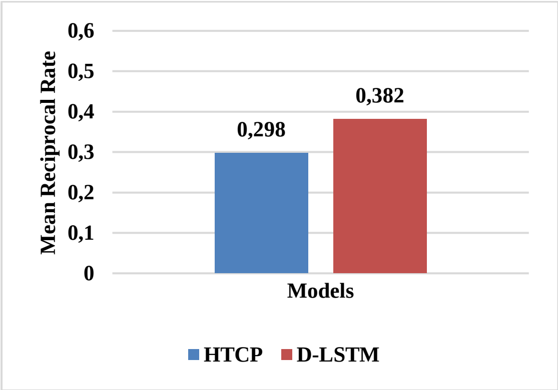

Figure 5. MRR for 20k recommendation set

5. CONCLUSION

In conclusion, recommendation systems remain indispensable across diverse domains, offering users personalized suggestions through advanced algorithms and data analysis techniques. While DL models like RNNs and LSTMs excel in capturing sequential dependencies for enhanced accuracy, challenges persist in SBRS, particularly related to gradient descent and class imbalance issues. This work addresses these challenges by introducing D-LSTM, a novel DL-based product recommendation system tailored for dynamic E-commerce environments. By using the D-LSTM approach, D-LSTM optimizes recommendation accuracy by capturing temporal dependencies within user sessions. The integrated framework incorporates key components, including D-LSTM, weight matrix optimization, and an adaptable Bayesian learning optimizer. Significantly, D-LSTM outperforms HTCP by 19.4%, 17.2%, 35.41%, and 21.99% for HR and MRR in the 10k and 20k recommendation sets, for the Tmall dataset underscoring its superior performance and potential impact on advancing recommendation systems in dynamic E-commerce platforms. For the future work, the D-LSTM model can be further integrated to predict the next product in the cart using the sentiments and reviews of the users.

REFERENCES

[1] D. Roy and M. Dutta, "A systematic review and research perspective on recommender systems," *Journal of Big Data*, vol. 9, no. 1, p. 59, 2022, doi: 10.1186/s40537-022-00592-5.

[2] Y. Feng, "Enhancing E-commerce recommendation systems through approach of buyer's self-construal: necessity, theoretical ground, synthesis of a six-step model, and research agenda," *Frontiers in Artificial Intelligence*, vol. 6, 2023, doi: 10.3389/frai.2023.1167735.

[3] F. Messaoudi and M. Loukili, "E-commerce personalized recommendations: a deep neural collaborative filtering approach," *Operations Research Forum*, vol. 5, no. 1, p. 5, 2024, doi: 10.1007/s43069-023-00286-5.

[4] Mikkili Dileep Kumar, G. V. Sivanarayana, D. N. V. S. L. S. Indira, and M. P. Raj, "Session based recommendation system using gradient descent temporal CNN for E-commerce application," *Multimedia Tools and Applications*, vol. 83, no. 22, pp. 61121–61138, 2024, doi: 10.1007/s11042-023-17907-0.

[5] S. Nagraj and B. P. Palayyan, "Personalized E-commerce based recommendation systems using deep-learning techniques," *IAES International Journal of Artificial Intelligence*, vol. 13, no. 1, pp. 610–618, Mar. 2024, doi: 10.11591/ijai.v13.i1.pp610-618.

[6] R. A. Farooqi, S. Kesarwani, M. Shakeeb, N. Sharma, and I. Bhatnagar, "Enhancing E-commerce applications with machine learning recommendation systems," *International Journal of Scientific Research in Science, Engineering and Technology*, pp. 85–90, 2022, doi: 10.32628/ijsrset122935.

[7] B. Thomas and A. K. John, "Machine learning techniques for recommender systems – a comparative case analysis," *IOP Conference Series: Materials Science and Engineering*, vol. 1085, no. 1, p. 012011, 2021, doi: 10.1088/1757-899x/1085/1/012011.

[8] X. Chen, L. Yao, J. McAuley, G. Zhou, and X. Wang, "Deep reinforcement learning in recommender systems: a survey and new perspectives," *Knowledge-Based Systems*, vol. 264, p. 110335, 2023, doi: 10.1016/j.knosys.2023.110335.

[9] J. Zhang, C. Ma, X. Mu, P. Zhao, C. Zhong, and A. Ruhan, "Recurrent convolutional neural network for session-based recommendation," *Neurocomputing*, vol. 437, pp. 157–167, 2021, doi: 10.1016/j.neucom.2021.01.041.

[10] S. T. T. Nguyen and B. D. Tran, "Long short-term memory based movie recommendation," *Science & Technology Development Journal - Engineering and Technology*, vol. 3, no. SI1, pp. SI1–SI9, 2020, doi: 10.32508/stdjet.v3isi1.540.

[11] H. Steck, L. Baltrunas, E. Elahi, D. Liang, Y. Raimond, and J. Basilico, "Deep learning for recommender systems: a Netflix case study," *AI Magazine*, vol. 42, no. 3, pp. 7–18,. 2021, doi: 10.1609/aimag.v42i3.18140.

[12] J. M. Johnson and T. M. Khoshgoftaar, "Survey on deep learning with class imbalance," *Journal of Big Data,* vol. 6, no. 1, p. 27, 2019, doi: 10.1186/s40537-019-0192-5.

[13] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, no. 1, p. 53, 2021, doi: 10.1186/s40537-021-00444-8.

[14] M. Färber, M. Coutinho, and S. Yuan, "Biases in scholarly recommender systems: impact, prevalence, and mitigation," *Scientometrics*, vol. 128, no. 5, pp. 2703–2736, 2023, doi: 10.1007/s11192-023-04636-2.

[15] H. Zhou, F. Xiong, and H. Chen, "A comprehensive survey of recommender systems based on deep learning," *Applied Sciences (Switzerland)*, vol. 13, no. 20, p. 11378, 2023, doi: 10.3390/app132011378.

[16] Y. Ye, Y. Xie, and C. Chen, "Improved session-based recommendations using recurrent neural networks for music discovery," *Journal of Physics: Conference Series*, vol. 1314, no. 1, p. 012194, Oct. 2019, doi: 10.1088/1742-6596/1314/1/012194.

[17] C. Djellali and M. Adda, "A new hybrid deep learning model based-recommender system using artificial neural network and hidden Markov model," *Procedia Computer Science*, vol. 175, pp. 214–220, 2020, doi: 10.1016/j.procs.2020.07.032.

[18] D. Li and Q. Gao, "Session recommendation model based on context-aware and gated graph neural networks," *Computational Intelligence and Neuroscience*, vol. 2021, no. 1, 2021, doi: 10.1155/2021/7266960.

[19] Y. Wen, S. Kang, Q. Zeng, H. Duan, X. Chen, and W. Li, "Session-based recommendation with GNN and time-aware memory network," *Mobile Information Systems*, vol. 2022, pp. 1–12, Apr. 2022, doi: 10.1155/2022/1879367.

[20] H. Yang, G. Kim, and J. H. Lee, "Logit averaging: capturing global relation for session-based recommendation," *Applied Sciences (Switzerland)*, vol. 12, no. 9, p. 4256, 2022, doi: 10.3390/app12094256.

[21] T. Wu, F. Sun, J. Dong, Z. Wang, and Y. Li, "Context-aware session recommendation based on recurrent neural networks," *Computers and Electrical Engineering*, vol. 100, p. 107916, 2022, doi: 10.1016/j.compeleceng.2022.107916.

[22] C. Kumar and M. Kumar, "User session interaction-based recommendation system using various machine learning techniques," *Multimedia Tools and Applications*, vol. 82, no. 14, pp. 21279–21309, 2023, doi: 10.1007/s11042-022-13993-8.

[23] R. Wang, J. Lou, and Y. Jiang, "Session-based recommendation with time-aware neural attention network," *Expert Systems with Applications*, vol. 210, p. 118395, 2022, doi: 10.1016/j.eswa.2022.118395.

[24] M. Salampasis *et al.*, "A flexible session-based recommender system for E-commerce," *Applied Sciences (Switzerland)*, vol. 13, no. 5, p. 3347, 2023, doi: 10.3390/app13053347.

[25] B. Jia *et al.*, "SMONE: a session-based recommendation model based on neighbor sessions with similar probabilistic intentions," *ACM Transactions on Knowledge Discovery from Data*, vol. 17, no. 8, pp. 1–22, 2023, doi: 10.1145/3587099.

[26] L. Dong, G. Zhu, Y. Wang, Y. Li, J. Duan, and M. Sun, "A graph positional attention network for session-based recommendation," *IEEE Access*, vol. 11, pp. 7564–7573, 2023, doi: 10.1109/ACCESS.2023.3235353.

[27] B. R. Sreenivasa and C. R. Nirmala, "Hybrid time centric recommendation model for E-commerce applications using behavioral traits of user," *Information Technology and Management*, vol. 24, no. 2, pp. 133–146, 2023, doi: 10.1007/s10799-022-00358-8.

[28] "IJCAI-16 Brick-and-mortar store recommendation Dataset_Tianchi datasets," *tianchi.aliyun.com*, 2018. https://tianchi.aliyun.com/dataset/53 (accessed Feb. 23, 2023).

BIOGRAPHIES OF AUTHORS

Snehal Bhogan is a research scholar in the KLS Gogte Institute of Technology College in Belgavi, Karnataka. Currently, working as Assistant Professor, Department of Computer Engineering at Agnel Institute of Technology and Design, Goa. She has a Bachelor's degree in Computer Engineering from Goa University, Master's degree in information Technology from Goa University. She has served in the education sector for more than 15 years at college level. Her area of interests in research are recommendation systems, deep learning, and machine learning technologies. She can be contacted at email: bhogansnehal@gmail.com.

Prof. Vijay S. Rajpurohit is a professor in the Department of Computer Science and Engineering at KLS Gogte Institute of Technology, Belgaum, Karnataka, India. He has got his B.E. in Computer Science and Engineering from Karnataka University Dharwad, M.Tech. from N.I.T.K Surathkal, and completed his Ph.D. from Manipal University in 2009. With an extensive background in image processing, cloud computing, and machine learning. Over the course of his illustrious career, he has authored more than 50 peer-reviewed journal publications, contributed to over 100 conferences, and penned few book chapters. His commitment to accessible knowledge dissemination is evident through the authorship of three online books, reflecting his dedication to sharing expertise with a global audience. He can be contacted at email: vijaysr2k@yahoo.com.

Prof. Sanjeev S. Sannakki is working as a professor in the Department of Computer Science and Engineering at KLS Gogte Institute of Technology, Belgaum, Karnataka, India. He pursued his B.E. in Electronics and Communication from Karnataka University Dharwad in 2004, M.Tech., and Ph.D. from VTU, Belagavi in 2009, and 2016 respectively. His research areas include image processing, cloud computing, computer networks, and data analytics. He has published a good number of papers in journals, international, and national conferences. He is the reviewer for a few international journals and conferences. He is also a life member of CSI, and ISTE associations. He can be contacted at email: sannakkisanjeev@yahoo.co.in.