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Session click sentiment behavior aware personalized recommendations system

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ABSTRACT

Session-based recommendations use short-term behavior of users to provide personalized suggestions to consumers in ecommerce platform. However, cold start, considering newly joined users and sparsity issues, where not enough short-term behavior is available, and the performance of traditional session-based recommendations is significantly impacted. Deep learning (DL) like recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and graph neural networks (GNNs) have been employed to capture session-clicks and enhance product recommendation accuracy. However, the current method is significantly affected due to the gradient descent problem in meeting convergence for top-K product recommendation. Further, the current method failed to capture product sentiment for session-clicks between inter-session and intra-session clicks. In addressing the research problems, the current research work introduced a session click sentiment behavior aware (SCSBA) personalized recommendation system using novel inter and intra session (IIS)-LSTM model. Finally, the objective function to recommend top K items to users is done using optimized Bayesian personalized ranking (OBPR) algorithm. Experiment outcome shows the SCSBA model achieves much better performance than state of art model, considering standard Tmall dataset.

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1. INTRODUCTION

Session-based recommendation systems have emerged as pivotal components in modern e-commerce platforms, offering personalized item suggestions by analyzing short-term user interactions [1]. Unlike traditional recommendation systems that rely on extensive historical data, session-based systems focus on transient user behaviors captured within a session, thereby enabling effective personalization even for anonymous or newly registered users. The increasing importance of these systems spans across various industries, with a notable impact in e-commerce, where they drive engagement and improve conversion rates through real-time decision-making [2], [3]. Despite their potential, session-based recommender systems face two primary challenges: the cold-start problem, where the system has limited data for new users, and data sparsity, which arises when available session data lacks the depth required for robust inference [4], [5]. Traditional machine learning methods, while effective to a certain extent, struggle with these limitations due to their inability to fully exploit the complex temporal dynamics and contextual cues in session data [6], [7].

To overcome these constraints, the adoption of deep learning (DL) techniques has been widely explored [8]. Models such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and graph neural networks (GNNs) have demonstrated success in capturing sequential patterns and contextual transitions in user behavior [9], [10]. These DL models enable the learning of rich representations from session-click sequences, facilitating more accurate and relevant product recommendations. Nevertheless, the application of DL in this context introduces its own set of challenges. A critical issue lies in the gradient descent optimization process [11], where convergence difficulties, particularly the vanishing gradient problem can impair the model's ability to learn from long or sparse sequences [12], [13]. Moreover, the presence of highly imbalanced interaction data, where certain items dominate user engagement, often leads to biased recommendations that fail to represent niche or underrepresented products fairly [14]. In addition, existing models largely overlook the sentiment dimension of user clicks, ignoring the valuable emotional cues embedded in session interactions. Particularly, the distinction between intra-session (within a single session) and inter-session (across multiple sessions) user behaviors remains underexplored, despite their potential to reflect different contextual preferences and affective states [15], [16].

To address these gaps, this research proposes the session click sentiment behavior aware (SCSBA) personalized recommendation system. Central to this framework is a novel inter and intra session (IIS)-LSTM model, which is designed to capture both temporal dependencies and sentiment-aware signals across and within sessions. To further enhance recommendation precision and stability, the model employs an optimized Bayesian personalized ranking (OBPR) objective function, aimed at resolving convergence issues and improving the top-K recommendation performance [17]. The proposed model is evaluated on the Tmall dataset, a standard benchmark in e-commerce recommendation research. Experimental results demonstrate the superior performance of the SCSBA model over state-of-the-art methods, confirming the efficacy of integrating sentiment analysis, session structure modelling, and optimization-aware learning for improved personalized recommendations. The contribution of this work is as follows:

– The paper introduced a novel LSTM model that can effectively capture user-item and its sentiment behavior more efficiently by adoption of effective fusion process.
– The model introduced a novel OBPR to enhance the personalized recommendation.
– The IIS-LSTM trained with Bayesian personalized ranking (BPR) is very efficient in improving hit rate (HR) and mean reciprocal rank (MRR) for Tmall dataset in comparison with recent recommendation methodologies.

The manuscript organization is as follows: section 2, introduces many recent methodologies of session-based recommendation to capture user-item behavior. Section 3 introduces a novel session-based personalized recommendation by effectively capturing user-item sentiment behavior through novel IIS-LSTM and BPR model. Section 4 presents a performance efficiency of proposed and other existing recommendation model in terms of HR and MRR using widely used publicly available Tmall dataset. The last section concludes the performance enhancement in recommendation in terms of percentage and future work to be carried out to enhance the performance considering more diverse features.

2. LITERATURE SURVEY

In this various existing session recommendation model to understand users' sentiment and behavior pattern with respect to items/product. A session-based recommendation system is designed employing context-aware and gated graph neural networks (CA-GGNNs) was proposed in [18]. the model initially constructed graph structure to represent session-clicks; later, the gated graph neural network (GGNN) was utilized to obtain the embedding vector representation of different produce within the session graph. With feedback contextual features like holidays, time, and location acquired within the session and periodic contextual features like amount of time spent on each product, the gated recurrent unit (GRU) in GGNN has been widened to substitute the structure of inputs and the current condition matrices in the traditional GRU. After gathering the likes and dislikes of consumers through a soft-attention method, a list of recommendations was provided. Session-clicks streams, and contextual feature were incorporated in the CA-GGNN model. The performance is validated using Yoochoose with precision of 0.708 and MRR of 0.3183 for top 20K recommendation and Diginetica datasets with precision of 0.5112 and MRR of 0.1848 for top 20K recommendation.

A session-click recommendation system namely session-based recommendation with graph and time-aware memory networks (SR-GTM) leveraging GNN and time-based memory networks in [19]. The system combined collective knowledge across comparable peer experiences alongside session-specific data to acquire what the consumer liked about a product. In particular, the internal feature optimization (IFO) and external feature optimization (EFO) are the two key components of SR-GTM. While EFO extracts collaboration knowledge from a memory network that has visit session statistics stored, IFO employs a GNN to acquire session characteristics according to product sequencing. Lastly, to get the recommendation rating for every potential product, SR-GTM combines IFO and EFO using the gating process and then uses a SoftMax layer for decoding the result. The performance is validated using Yoochoose with precision of 0.718 and MRR of 0.3253 for top 20K recommendation and RetailRocket datasets with precision of 0.6364 and MRR of 0.3741 for top 20K recommendation. Yang *et al.* [20] introduced a new algorithm namely logit averaging (LA) by leveraging local-global information using intra-session product association. The model is validated using various standard datasets such as Tmall, Yoochoose, RetailRocket, and Diginetica.

Session-based recommendation model is constructed using various publicly available machine algorithms [21]; the result shows k-nearest neighbor and its variant produced much better outcome than other ML-based methodologies. Wu *et al.* [22] introduced a contextual feature into session-based recommendation using RNN. A time-aware neural attention network (TNAN) was presented [23] to represent evolving consumer choices in session-based recommendation tasks. To gain insight into product embedding, a GNN was trained on every instance, resulting in a global session graph. Subsequently, an RNN was employed to enhance the product embedding and identify consumer's overall preferences according to present sentiment's context. Next, a brand-new TNAN was put forth and employed to simulate the consumer's primary goal for the period. Lastly, a combination of the consumer's primary goals and common pursuits produced dynamic consumer sentiments that were used to create suggestions aiding in improving better recommendation. Salampasis *et al*. [24] showed LSTM-based recommendation system outperforms other RNN-based recommendation system considering different datasets due to lesser requirements of parameter fine-tunning. Similarly, GNN [25] can provide a good trade-off between accuracy and efficiency for understanding consumer sentiments. The hybrid method combining LSTM and GRU produced accuracy of 97.6%.

Dong *et al.* [26] introduced an enhanced GNN model namely graph positional attention network (GPAN) to capture both low and high importance features with respect to user sessions-clicks. Finally, consumer long-term and short-term preference fused to provide session-based recommendation using three standard datasets. Similarly, hybrid time-centric prediction (HTCP) model is introduced in [27] to capture consumer short and long-term behavior. The performance is validated using Tmall and Yoochoose challenge dataset. Wang *et al*. [28] introduced session-based recommendation system [29] using repeat-aware neural network by effectively learning consumer behavior employing GNN to identify pair-wise product similarities and establish group-based consumer product sentiments. The model performance is studied using Nowplaying, Yoochoose, and Diginetica dataset. Gao *et al.* [30] developed a session-aware recommendation using multi-layer augmented aggregation with contrastive learning (SR-MACL); the model adds additional noise into the embedding layer to solve contextual behavior modelling issues of traditional GNN session-based recommendation system by effectively eliminating irrelevant products. Experiment is conducted using Nowplaying, Tmall, and Diginetica dataset with good recommendation performance; however, the model failed to extract sentiment behavior within the session clicks on respective due to poor understanding of inter and intra-session learning. This paper introduces a novel recommendation model SCSBA that effectively captures user session sentiment behavior employing novel IIS-LSTM-based model in next section.

3. METHOD

This work introduces a novel recommendation system namely SCSBA using session-aware feature and sentiment-aware behavior features. The proposed SCBSA personalized recommender system introduces a new IIS-LSTM model that captures session-aware hidden features and session-click sentiment behavior features by fusing them to obtain better understanding of user-item relationship. Finally, in building predictive model to perform personalized recommendation, the work introduce optimized version of BPR algorithm.

3.1. Problem definition and session click sentiment behavior feature

Let $V = \{v_1, \dots, v_{|V|}\}$, represent the set of users and $J = \{j_1, \dots, j_{|J|}\}$ denote the set of available products in an e-commerce system. For each user $v \in V$, we define the sequence $J^v = (j_1^v, \dots, j_{|J^v|}^v)$ as the chronological list of products interacted with or purchased by the user. The objective is to leverage the historical behavior of users j^v to generate accurate product recommendations for each v. Item representations incorporate both observable and latent sentiment-aware features. The latent feature of an item is encoded as a dense vector as in (1).

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

To model the session-level dynamics, intra-session and inter-session behavioral characteristics are represented as h and g, respectively. These are transformed into embedded spaces using two distinct matrices W and F as in (2) and (3).

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

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

To mitigate the cold-start problem typically faced by sequential recommender systems, we employ a feature fusion strategy as in (4).

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

The decoding process reconstructs session-aware features using reverse-mapping matrices F^U and W^U as in (5).

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

The reconstruction error is minimized using (6).

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

Here, $|e_g|$and $|e_h|$ are the dimensionalities of inter- and intra-session features respectively.

3.2. Inter-intra session click sentiment behavior long short-term memory model

This section presents an IIS-LST by employing dual-layer LSTM model to capture sequential dependencies across user interactions considering IISs as in (7) to (12).

$$g^u = \sigma(V_1 y^u + X_1 i^{u-1} + c_1) \tag{7}$$

$$a^u = \sigma(V_2 y^u + X_2 i^{u-1} + c_2) \tag{8}$$

$$h^u = tanh(V_3 y^u + X_3 i^{u-1} + c_3) \tag{9}$$

$$d^u = g^u \odot c^{u-1} + a^u \odot h^u \tag{10}$$

$$p^u = \sigma(V_4 y^u + V_4 i^{u-1} + c_4) \tag{11}$$

$$i^u = p^u \odot tanh(d^u) \tag{12}$$

Where $\odot$ denotes element-wise multiplication, u defines session aware features, $y^u \in S^e$ defines the SCSBA input feature, and $V_{1-4} \in S^{e\times e}$ defines the transitional matrices of the present input. The recurrent relationships denoted as $X_{1-4} \in S^{e\times e}$ play a crucial role in delivering sequential data. The terms $b_{1-4} \in S^e$can be identified as bias variable in the context of the research being conducted. The forget-gate (g^u), input-gate (a^u), update-gate (h^u), cell (d^u), output-gate (p^u), and hidden-state (i^u) are fundamental components in the context of a RNN or a variant such as a LSTM network. These elements play crucial roles in information flow and memory management within the network architecture. Specifically, the forget-gate (g^u) determines the extent to which the previous cell-state is retained or discarded. The input-gate (a^u) regulates the amount of new information that is incorporated into the current cell-states. The update-gate (h^u) controls the blending of the previous and current cell-states. The cell (d^u) represents the memory component of the network, storing and propagating information over time. The output-gate (p^u) governs the amount of information that is exposed from the current cell-state. Finally, the hidden-state (i^u) encapsulates the network's internal representation. In the present study, the LSTM approach is employed to replace the initial equation as described in (7) to (12), then, the full input is then processed using (13).

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

In (13) V composed of 4 matrices denoted as V_{1-4}. Similarly, the matrices X and c also contain four matrices each. A two-layer architecture is used. The first LSTM layer i_y^u captures latent session click features (14).

$$i_y^u = Lstm\left(V_y j_y^u, X_y i_y^{u-1}, c_y\right), i_y^u \in S^e \tag{14}$$

The second layer models session sentiment-aware features (15).

$$i_n^u = Lstm(V_n j_n^u, X_n i_n^{u-1}, c_n), i_y^u \in S^e \tag{15}$$

Where V_y is composed of four matrices defined by $V_{y1-4} \in S^{e \times e}$ and X_y, c_x, V_n, X_n, and c_n are set of matrices considering y hidden characteristics of user session clicks and n concatenated session click sentiment behavior. Therefore, the joint hidden state representation for recommendation is formed by concatenating outputs as in (16).

$$i^u = [j_y^u; j_n^u],\ i^u \in S^{2e} \tag{16}$$

Where j_y^u represent the product clicks sessions hidden information and j_n^u represent the corelated features of session click sentiment behavior of distinct products considering user's universal interest i^u. This concatenated representation serves as a comprehensive encoding of the user’s behavioral and sentiment-based preferences. The final joint LSTM is trained as in (17).

$$i^u = Lstm\left(V[j_y^u; j_n^u]Xi^{u-1}, c\right),\ i^u \in S^{2e} \tag{17}$$

The variable i^u denotes every single property of consumer likings, instead of merging of several likings as defined in (17). In this work, the parameter V, which consist of factors $V_1, V_2, V_3, V_4 \in \mathcal{R}^{2e}$ which is persuaded with availability of parameters j_y^u and j_n^u.

3.3. Personalized Bayesian personalized based learning

To generate personalized recommendations, we adopt the BPR framework. The original BPR method [27] suffers from inefficiencies due to large negative sampling spaces. The work address this by applying a constrained negative sampling w' scheme that enhances computational efficiency as presented in Algorithm 1.

Algorithm 1: Optimized BPR sampling strategy
Input: User set $\mathcal{V}$, item set $\mathcal{U}$, interaction history $\mathcal{T}$, optimization rate γ
Output: Trained parameters $\ominus$
1: For each user $v \in \mathcal{V}$:
  Estimate negative sampling distribution
  Select reduced negative item space S_v ←sample $(\mathcal{V}, \mathcal{U}, \gamma)$
2: While convergence is not met:
  Randomly sample $(v, j, k) \in \mathcal{T}(v, j, k)$ with $j \in \mathcal{T}$ and $k \in S_v$
  Compute gradients using (20)
  Update parameters $\ominus$

The pairwise preference probability is defined as in (18).

$$p(v, \ell + 1, c, w > w') = h\left(z_{v,\ell+1,c,w} - z_{v,\ell+1,c,w'}\right) \tag{18}$$

Where the non-linear function $h(y)$ is given by the logistic sigmoid as in (19).

$$h(y) = \frac{1}{1+e^{-y}} \tag{19}$$

The corresponding objective function becomes (20).

$$\mathcal{K}_1 = \sum \log\left(1 + e^{-\left(z_{v,\ell+1,c,w} - z_{v,\ell+1,c,w'}\right)}\right) + \frac{\mu}{2}\|\ominus_1\|^2 \tag{20}$$

The parameter μ regulates regularization, while $\ominus$ includes all model parameters such as $\mathcal{V}$, $\mathcal{S}$, $\mathcal{X}$, $\mathcal{U}$, and $\mathcal{N}$. In proposed optimized BPR sampling strategy presented in Algorithm 1, the constrained BPR strategy restricts negative item pool S_v to a reduced subset, thereby minimizing sampling space and enhancing model convergence. This results in improved performance in terms of ranking, quality and training efficiency.

4. RESULTS AND DISCUSSION

The section presents the performance evaluation of the proposed SCSBA model in comparison with existing state-of-the-art recommendation techniques, namely GPAN [26], HTCP [27], and SR-MACL [30]. The experiments are conducted using the Tmall dataset [31], which has also been utilized in the b aseline studies [26], [27] to ensure consistency in performance comparison. Table 1 outlines the key features and statistics of the Tmall dataset employed in this study. The dataset comprises anonymized user interactions with various products and contains session-level clickstream information necessary for modeling sentiment-aware behavior.

The SCSBA model is implemented in Python using the Anaconda framework. All experiments are executed on a system equipped with an Intel Core i7 processor, 16 GB RAM, and running the Windows 11 operating system. To assess the quality of recommendations, two widely adopted metrics are used: HR (HR@K): measures the frequency at which the recommended items appear in the user's true interaction list. MRR (MRR@K): captures the rank position of the first relevant item in the recommendation list, offering insight into how early correct items are retrieved. The experimental results demonstrate that the proposed SCSBA model consistently outperforms the comparative approaches across different values of K, highlighting its effectiveness in capturing session-specific sentiment behaviors and enhancing recommendation precision.

Table 1. Attributes present inside Tmall dataset

Features	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"

4.1. Hit-rate performance

To quantify recommendation accuracy, the HR is calculated using (21).

$$HR = \frac{TP}{TP+FN} \tag{21}$$

A higher HR indicates a greater proportion of relevant items correctly predicted by the model within the top-K recommendation list. HR@10K analysis: the comparative evaluation of HR@10K on the Tmall dataset is illustrated in Figure 1. The results demonstrate that the proposed SCSBA model outperforms existing methods with a notable margin. Specifically, the HR values for GPAN and HTCP are reported as 0.230 and 0.457, respectively, whereas the proposed SCSBA achieves a significantly higher HR of 0.568. This corresponds to an improvement of approximately 19.54% over the best-performing baseline (HTCP). The substantial gain in HR reflects the SCSBA model's ability to more effectively capture users' click sentiment behavior within sessions. Its robust performance underscores the model's potential to generate more accurate and personalized top-10K product recommendations, thereby enhancing user satisfaction in e-commerce environments.

HR@20K analysis: the HR@20K results, shown in Figure 2, further validate the performance advantage of the SCSBA model. In this setting, GPAN and HTCP achieve HR values of 0.280 and 0.534, respectively. The SCSBA model attains a higher HR of 0.645, yielding a relative improvement of 12.74% over HTCP. This enhancement reinforces the effectiveness of incorporating session-level sentiment and behavioral cues into the recommendation process. By leveraging both intra- and inter-session information, the SCSBA framework demonstrates superior competence in predicting relevant items among the top-20K candidates. These findings highlight the practical utility of the proposed model for improving recommendation precision and driving user engagement in real-world e-commerce platforms.

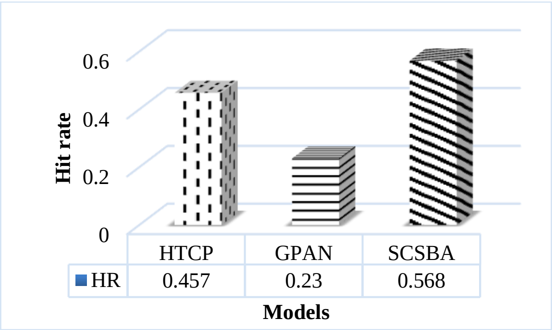

Figure 1. HR for recommending top 10 K item

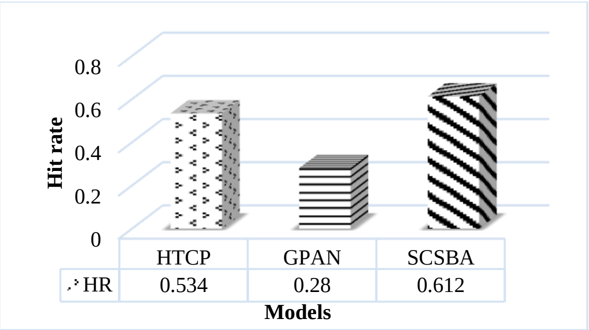

Figure 2. HR for recommending top20K items

4.2. Mean reciprocal rank performance

The MRR serves as a key metric for assessing the effectiveness of ranked retrieval in recommendation systems. It is defined as the mean of the reciprocal ranks [26] of the first relevant item in the top-N list for a set of queries Q, and is calculated using (22).

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i} \tag{22}$$

Where $rank_i$ denotes the position of the first relevant item for the i-th query. Higher MRR values indicate that relevant items are appearing closer to the top of the recommendation list, reflecting better ranking precision. MRR@10K analysis: as illustrated in Figure 3, the evaluation of MRR@10K on the Tmall dataset highlights a significant improvement delivered by the proposed SCSBA model compared to the baseline methods. The MRR values recorded for GPAN and HTCP are 0.135 and 0.197, respectively. In contrast, SCSBA achieves a substantially higher MRR of 0.359, corresponding to an improvement of 45.12% over the best-performing baseline, HTCP. This result demonstrates the SCSBA model's strength in ranking relevant items higher in the recommendation list. The improvement suggests that the integration of session-aware click sentiment behavior enables SCSBA to more accurately prioritize user-relevant products, thus offering improved personalization and utility in real-world e-commerce scenarios.

MRR@20K analysis: the performance of the proposed model on MRR@20K is presented in Figure 4. In this setting, the MRR values for GPAN, SR-MACL, and HTCP are 0.138, 0.181, and 0.298, respectively. The SCSBA model outperforms all baselines with an MRR of 0.456, indicating a 34.64% improvement over HTCP. These results further confirm the ability of SCSBA to not only retrieve relevant items but also ensure their presence at higher positions within the recommendation list. This ranking efficiency contributes to an improved user experience by reducing search effort and increasing the perceived relevance of recommendations. Consequently, the findings validate the robustness of the SCSBA framework in enhancing ranked recommendation quality on large-scale datasets such as Tmall.

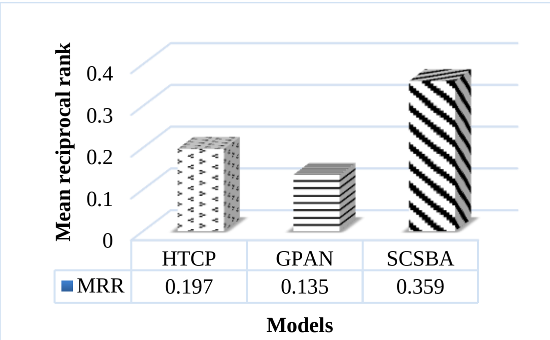

Figure 3. MRR for recommending top 10K item

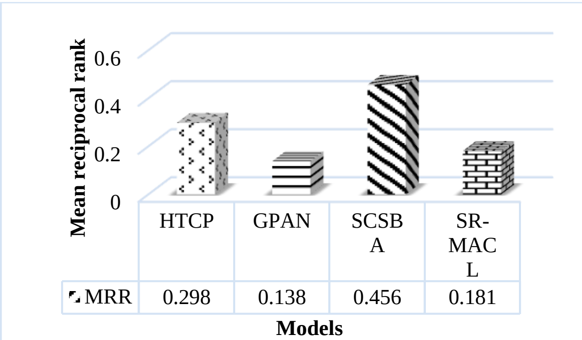

Figure 4. MRR for recommending top 20K item

5. CONCLUSION

Recommendation systems play a pivotal role across a range of application domains by delivering personalized suggestions through advanced algorithmic and data-driven methodologies. DL models such as RNNs and LSTM networks have demonstrated considerable effectiveness in modelling sequential user interactions. However, session-based recommendation systems continue to face challenges related to optimization instabilities particularly gradient descent issues and the complex task of extracting inter- and intra-session sentiment behaviors. To address these limitations, this study proposed a novel DL-based recommendation framework, referred to as SCSBA, specifically designed for dynamic and large-scale e-commerce platforms. The proposed model captures temporal dependencies within user sessions and integrates sentiment-aware behavioral signals to enhance the contextual understanding of user preferences. The architecture encompasses key modules including inter- and intra-session sentiment fusion, optimized BPR, and attention mechanisms to refine the quality of recommendations. Experimental evaluation using the Tmall dataset demonstrates the effectiveness of the proposed model. Specifically, SCSBA achieves significant improvements in HR outperforming the HTCP model by 19.54% and 12.74% for the top 10K and top 20K recommendations, respectively. Additionally, the model improves MRR by 45.12% and 34.64% for the respective recommendation levels. These results affirm the robustness of the SCSBA framework in delivering more accurate and contextually relevant product suggestions, thereby enhancing user engagement in e-commerce environments. Future research will focus on extending the SCSBA framework to incorporate predictive modelling for next-item recommendation by leveraging user-generated sentiment and review data, further enriching the personalization capability of the system.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

No financial institute has any financial competing interest from the research work. On behalf of all authors, the corresponding author states that there is no conflict of interest.

ETHICAL APPROVAL

No humans or animals have been used in this research study.

DATA AVAILABILITY

All tools and data used for experimenting will be made available to the author on genuine request through mail which must be cited properly.

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