ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DLERSE: DEEP LEARNING-ENHANCED RECOMMENDATION SYSTEMS FOR E-COMMERCE USER INTERACTION

BHAVANI B [1], Dr. D. HARITHA[2]

[1]Research Scholar, Koneru Lakshmaiah Education Foundation, Department of Computer Scieand Engineering, Vaddeswaram-522502, AP, India.

[2]Professor, Koneru Lakshmaiah Education Foundation, Department of Computer Science and Engineering, Vaddeswaram-522502, AP, India.

E-mail: [1]bbhavanib2606@gmail.com, [2]haritha_donavalli@kluniversity.in

ABSTRACT

With the evolving trends in the e-commerce market, incorporating personalized suggestions for users is a critical component of user strategy for any company looking to expand. Businesses may also improve engagement, contentment, and conversion rates, resulting in faster growth through targeted recommendations. Traditional recommendation systems include content-based filtering and collaborative filtering, but they face challenges such as cold start, data sparsity, and scalability. This particular recommendation system tries to address concerns related to bias or limits of typical recommendation systems, which frequently employ deep learning algorithms. We investigate the processing and extraction of complicated human preferences and behaviors from high-dimensional information using deep learning frameworks such as transformer models, recurrent neural networks (RNNs), and convolutional neural networks (CNNs). By accounting for minute details in user interactions, browsing history, context, and more, deep learning models have shown themselves to be more beneficial than standard models, boosting accuracy over time. Thus, backed by our tests, we concluded that the accurate and pertinent recommendations made by deep learning-based recommendation systems enhanced user engagement. These models create fresh suggestions according to user choices, which improves customer happiness and retention in addition to the model's accuracy. According to the study, in the competitive e-commerce industry, employing state-of-the-art deep learning models can lead to more dynamic and captivating user experiences, increasing sales and keeping clients. In conflict-ridden e-commerce ecosystems, the application of the most recent deep learning models can aid in the development of more responsive and user-friendly interfaces, which may boost interest and customer retention. These findings emphasize that, as deep learning advances, its capacity to transform recommendation systems will further boost e-commerce efficacy.

Keywords: *Deep Learning, CNN, KNN, RNN, AI, Recommendation System, E-commerce***.**

1. INTRODUCTION

A major transformation in e-commerce is the result of its remarkable growth over the past few years. This process has created a bewildering array of choices for users, thereby making it difficult for them to efficiently navigate digital marketplaces due to the complexity of the search problem. Within those changes, there is the recommendation process, which has emerged as the most important core technology used in helping users find the products they need by merely analyzing user behavior and preferences. As personalized recommendations are a significant part of these systems, they promote not just the interaction of customers with the website but also the retention and engagement of clients, fundamental drivers for growing your business.

These conventional systems are majorly based on content-based filtering and collaborative filtering. Content-based filtering analyzes particular product characteristics and then provides such users access to items that have some properties in common with the ones in which, in the past, users have been shown an interest. Meanwhile, collaborative filtering refers to the use of user data to discover patterns that could be associated with users of the same preferences and hence make recommendations. This technique is initially established and widely used and has proven to be effective in different cases, but, importantly, has a lot of short-term failures experienced when applied in complex e-commerce environments. Even if these systems have given results, they have some primary challenges such as.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

1. Cold Start Problem: Since such methods require the usage of historical data, they may not make any meaningful recommendations for either new customers or new products because of the lack of the interaction data on which they rely.
2. Scalability Issues: If the platform is used by thousands or more customers and supports over 100 thousand products, such service datasets may be so big that even the use of conventional algorithms will be difficult. This inefficiency, in turn, may impact the speed and computational costs, which may rob the company of the intended cost savings with the automated platform.
3. Data Sparsity: The amount of data in this system is usually quite enormous, which presents a challenge to the collaborative filtering models as they require all or most of the user interaction with all or most items for them to generate relevant recommendations. Smart, scalable, and data-effective recommendation techniques have therefore become more crucial because of the dramatic increase in the pretextural complexity and user data aggregation. Consequently, Deep learning** emerges as the techniques that attract much attention from the stakeholders in the industry including the developers to find ways to optimize their applications based on ML techniques. Deep learning has greatly transformed different industries like computer vision, NLP or natural language processing, and speech recognition, to mention a few. This capacity to study hard-to-describe patterns or relationships in significant datasets makes it perhaps the best approach for recommendation systems. Some models of deep learning gained an outstanding performance in this field:
1. Convolutional Neural Networks (CNNs):
CNNs have a profound use in the domain of picture processing but have also found some success in the area of e-commerce such as in the recommendation for clothing or other products. CNNs can be enriched by extracting features from the images of the products and combining these features with their textual descriptions, hence, they can achieve better product similarity detection and content-based recommendation.

2. Recurrent Neural Networks (RNNs):
RNNs are one of the hidden Markov models in Recurrent Neural Networks or RNNs, one of the recurrent network's programming and they specifically Long Short-Term Memory Networks are capable of capturing such dynamics. Among their applicable patterns, recurrent networks generate patterns that can analyze temporal data coming from browsers and purchase activities to cursorily forecast future preferences.

3. Transformer-Based Models:
These models are developed on Top of the BERT and GPT maze by the foundation of the Transformer paradigm. The models can be used in recommendation engines to understand the meaning of textual Reviews, and user queries, and contextualize the product descriptions which, ultimately, boost the quality of the recommendations that are satisfactory to an individual.

4. Autoencoders:
We can train the autoencoder's Neural Networks to be latent factor finders that will reduce the dimensions of the data and present user preferences in a latent way. By compressing the high-dimensional data into a low-dimensional space, autoencoders could be a big helper in enhancing the accuracy and efficiency of a collaborative filtering model.

Research Challenges
E-commerce platforms often grapple with sparse and imbalanced data, where user-item interactions are limited or disproportionately distributed across different items. This sparsity can hinder the training of deep learning models, which typically require large volumes of data to learn effective representations. Addressing data sparsity involves developing techniques that can make meaningful inferences from limited interaction data, such as transfer learning, data augmentation, or leveraging external data sources. The cold start problem occurs when the system is introduced to new users or things with limited or no interaction history. There needs to be sufficient data for recommendation systems to deliver precise advice. Deep learning models should include techniques to address the cold start problem, such as employing hybrid recommendation methods that mix content-based and collaborative filtering techniques [6] or leveraging auxiliary data such as user demographics and item qualities. Deep learning models require much computational power, and it is challenging to implement them efficiently in real-time e-commerce settings. It is crucial to

guarantee that these models can handle substantial amounts of data effectively and provide recommendations quickly. Model optimization, distributed computing, and edge computing are crucial for tackling deep learning algorithms' scalability and efficiency issues. Deep learning models are commonly regarded as opaque, rendering the interpretation of their decision-making mechanisms challenging. The absence of transparency can cause challenges, mainly when comprehending the reasoning behind recommendations, which is crucial for establishing user confidence and troubleshooting purposes. Developing deep learning models that can be easily understood or include systems that provide explanations is essential. This is important for improving user acceptance and complying with regulations. Users' preferences in e-commerce are subject to change and can develop quickly due to factors such as trends, seasons, and personal experiences. Deep learning models ought to be able to adjust to these modifications instantly to uphold the pertinence and precision of recommendations. This necessitates the creation of models that can consistently acquire knowledge from real-time data and adjust their forecasts accordingly. Using vast user data to build deep learning models gives rise to substantial privacy and security apprehensions. It is crucial to collect, store, and process user data in a manner that adheres to data protection rules. Methods such as differential privacy, federated learning, and secure multi-party computation [7] can safeguard user data while facilitating the creation of efficient recommendation systems. Integrating deep learning-enhanced recommendation systems into current e-commerce platforms presents substantial integration obstacles. These factors encompass the capacity to work well with existing infrastructure, smoothly merge with other corporate operations, and ensure the system's stability throughout the transition. Creating adaptable and flexible frameworks [8] that enable the gradual implementation of deep learning technology can aid seamless integration.

Research Objectives:

This research aims to examine and improve the usage of deep learning methods in recommendation systems for e-commerce platforms, with the ultimate objective of enhancing user interaction and engagement. This broad goal can be divided into various individual research aims:

The study aims to develop and evaluate complex learning structures like CNNs, RNNs, and transformer models for accurate product suggestions in e-commerce. It also aims to address data scarcity and cold start issues by developing hybrid models and data augmentation approaches.

Strategies like model compression, distributed computing, and edge computing are needed to improve the computational efficiency and scalability of deep learning-based recommendation systems. The goal is to enhance the comprehensibility and clarity of deep learning models, thereby enhancing user trust and adherence to regulations.

The goal is to create models that adapt to user preferences, ensuring timely recommendations. This involves dynamic learning frameworks and live updating methods. Privacy and security are prioritized, using methods like differential privacy and secure multi-party computation.

The objective is to create recommendation systems that are upgraded with deep learning techniques and can be smoothly integrated into existing e-commerce platforms without causing any disruption to current operations. Create modular and adaptable architectures that facilitate the progressive and seamless integration of deep learning capabilities into existing systems, guaranteeing compatibility and stability.

To thoroughly evaluate and authenticate the proposed deep learning models and methodologies, we will conduct extensive experiments and analyze real-world case studies. This approach will allow us to collect actual data on the efficacy and tangible advantages of deep learning-powered recommendation systems in various e-commerce environments. The insights and recommendations derived from these studies will be highly practical for professionals in the field.

Research Contribution

This research significantly enhances e-commerce recommendation systems by utilizing the progress made in deep learning. These contributions improve the comprehension, advancement, and implementation of recommendation technologies, tackling crucial obstacles and expanding the limits of what can be achieved in personalized user encounters. The primary contributions of this research are as follows:

This study introduces and rigorously evaluates multiple deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models, tailored for e-commerce recommendation systems. Comprehensive analysis highlights the strengths and limitations of each model in various recommendation scenarios. Provides a comparative framework for selecting the most suitable deep learning models based on specific e-commerce contexts, improving the accuracy and relevance of recommendations. • The research develops hybrid models and data augmentation techniques that effectively mitigate the issues of data sparsity and cold start problems. These solutions integrate content-based filtering with collaborative filtering and utilize external data sources to enhance the robustness of recommendations. Enhances the ability of recommendation systems to generate accurate suggestions even with limited user interaction data, broadening their applicability in diverse e-commerce environments. • This study proposes and implements optimization strategies such as model compression, distributed computing, and edge computing to ensure that deep learning-enhanced recommendation systems can operate efficiently at scale. The research addresses the computational challenges associated with deploying these models in real-time, large-scale e-commerce settings. Enables practical deployment of deep learning models in high-traffic e-commerce platforms, ensuring quick and efficient recommendation generation without compromising on performance. • The research integrates explainability mechanisms into deep learning models, providing insights into the decision-making processes behind recommendations. Techniques such as attention mechanisms and model-agnostic interpretability methods are employed to make the recommendations more transparent and understandable. Increases user trust and acceptance of recommendation systems by making their operations more transparent and meets regulatory requirements for explainability in automated decision-making processes. • The study develops continuous learning frameworks and real-time updating mechanisms that allow deep learning models to adapt to changing user preferences and market trends. This ensures that recommendations remain relevant and timely. Improves the responsiveness of recommendation systems to evolving user behavior, enhancing user satisfaction and engagement over time. • The research incorporates privacy-preserving techniques such as differential privacy, federated learning, and secure multi-party computation into the recommendation process. These methods ensure that user data is protected throughout its lifecycle, adhering to data protection regulations and ethical standards. Safeguards user privacy while enabling the effective use of personal data for generating recommendations, building user confidence, and compliance with legal requirements. • The study designs modular and flexible architectures that facilitate the integration of deep learning-enhanced recommendation systems into existing e-commerce platforms. The approach ensures compatibility and stability during the transition process. Allows e-commerce platforms to adopt advanced recommendation technologies without disrupting existing operations, enabling a smoother and more cost-effective implementation. • The research conducts extensive experiments and real-world case studies to validate the proposed deep learning models and techniques. The empirical evidence gathered provides actionable insights into the practical benefits and limitations of these models in diverse e-commerce settings. Offers robust validation of the effectiveness of deep learning-enhanced recommendation systems, providing valuable guidelines for both researchers and practitioners in the field.

The remaining part of the paper explores the integration of deep learning techniques in e-commerce recommendation systems. It covers the importance of recommendation systems, the limitations of traditional methods, and the promise of deep learning for enhancing recommendations in Chapter 2. The paper also discusses methodology, data collection and preprocessing techniques, hybrid models, and data augmentation strategies in Chapter 3. It also discusses the challenges and solutions, such as data sparsity, cold start, scalability, and privacy concerns. The solution strategies are discussed in Chapter 4. The paper concludes with a summary of key findings and contributions in chapter 5. Finally, it analyses and gives the enhancement possibility in Chapter 6.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2. RELATED WORK

Deep learning-powered recommendation [9] systems have transformed the field by leveraging neural networks [10] to analyze embeddings [11] and deliver exceptionally tailored recommendations depending on user behavior [12]. The selection of neural network design is crucial, with widely used alternatives encompassing multi-layer perceptrons, convolutional neural networks, and recurrent neural networks. These systems have demonstrated exceptional effectiveness in diverse fields, including e-commerce [13], entertainment, and social networking. They can precisely record intricate patterns and connections in data related to user behavior, hence enhancing the overall user experience. Traditional recommendation systems [14] encompass content-based, collaborative filtering [15], and hybrid methodologies. Content-based systems utilize item metadata to generate suggestions, whereas collaborative filtering exploits user-item interactions to provide personalized recommendations. Hybrid systems combine many forms of data to improve the accuracy of adaptive recommendations. Recommendation systems can be categorized into web-based, app-based, cross-domain, and session-based systems [16]. The functional categorizations of recommendation systems encompass context-aware, interactive, knowledge-based, and social systems. Context-aware systems utilize contextual information [17], whereas interactive systems facilitate user participation. Knowledge-based systems utilize explicit product information, whereas social systems depend on user profiles and social network data. Each category employs distinct neural network models to enhance recommendation accuracy and personalization [18]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) [19 are designed to process input that occurs in a sequence. On the other hand, Graph Neural Networks are specifically used for tasks such as classifying nodes, predicting links, and discovering communities within a graph. Autoencoders are used to decrease the number of dimensions in data and to learn important features. On the other hand, Transformers are designed to capture and store detailed connections between users and products. Radial Basis Function Networks (RBFNs) [20] and Memory-Augmented Neural Networks (MANNs) [21] specifically tackle the needs of function approximation and the storing of external memory. Deep Belief Networks (DBNs) and Multilayer Perceptrons (MLPs) [22] acquire knowledge of intricate and layered connections between input and output variables. Convolutional Neural Networks (CNNs) are utilized for the study of visual data, specifically for the extraction of features and classification of data. Self-organizing maps (SOMs) [23] offer a means to describe and visualize input data in a reduced number of dimensions, which can help detect anomalies [24] and facilitate exploration. Every neural network technique possesses distinct advantages that contribute to the advanced capabilities of contemporary recommendation systems [25]. Deep learning techniques provide robust tools for recommendation systems, including approaches such as embeddings, neural networks, and generative models to deliver personalized and highly accurate suggestions. Graph neural networks are a preferred tool for session-based scenarios, as they may uncover intricate relationships between people, items, and traits. By implementing these strategies, suggestion accuracy and customer happiness are greatly enhanced.

Collaborative filtering (CF) approaches, such as user-based and item-based CF, have laid the foundation for numerous recommendation systems. These techniques utilize past user-item interactions to forecast a user's interest in an item by considering the preferences of comparable users or things. Conversely, content-based techniques suggest items by evaluating the characteristics of the objects and comparing them to the user's preferences. Although these methods are efficient, they typically face challenges when dealing with limited data and cold start problems. Cold start problems occur when insufficient data is available to make correct forecasts for new users or objects (Ricci et al., 2011) [1].

The field of recommendation systems has been dramatically transformed by the advent of deep learning, which enables the modeling of complex user-item interactions and the extraction of underlying elements from large datasets. Neural Collaborative Filtering (NCF), introduced by He et al. (2017) [3], substitutes conventional matrix factorization methods with neural network structures to acquire interaction functions from data, resulting in enhanced recommendation precision.

In their 2016 study, Covington et al. [31] presented a deep neural network model that effectively addressed the challenge of large-scale recommendation jobs on YouTube. Their research showcased the scalability and efficacy of deep learning in this context. The model utilizes two distinct networks for candidate creation and rating, enabling the system to efficiently handle many users and videos, amounting to billions.

Recurrent Neural Networks (RNNs), including variations like Long Short-Term Memory (LSTM) networks, have been used to represent and analyze patterns in sequential user behavior. In their 2016 study, Hidasi et al. [6] introduced GRU4Rec, a recurrent neural network (RNN) method explicitly designed for session-based recommendations. This model effectively captures the sequential patterns in user interactions. Wu et al. (2017) expanded upon this concept by introducing Recurrent Recommender Networks (RRN), which incorporate temporal dynamics into the recommendation process.

Convolutional neural networks (CNNs), typically employed in image processing, have been modified to capture localized patterns in matrices representing user-item interactions for recommendation tasks. In their 2017 study, Zhang et al. [32] introduced a model for collaborative filtering that utilizes a CNN-based approach. This involves using convolutional layers to extract latent characteristics from interaction data, resulting in improved recommendation performance.

Attention techniques have been incorporated into recommendation systems to enhance the identification of user preferences by directing attention to pertinent sections of the input material. In their 2018 study, Zhou et al. [33] introduced the Deep Q Network (DQN), a model that employs attention mechanisms to dynamically learn user interest representation based on past behaviors. This approach leads to improved recommendation accuracy.

Graph Neural Networks (GNNs) have become popular due to their capacity to represent connections in data structured as graphs, such as social networks and user-item interaction graphs. In their 2019 study, Fan et al. [8] introduced Graph Neural Networks for Social Recommendation (GraphRec). This approach integrates social influence into the recommendation process by utilizing Graph Neural Networks (GNNs) to capture intricate user-item and user-user interactions.

Hybrid recommendation systems integrate many methodologies to exploit their advantages. In their 2018 study, Wang et al. [34] presented a method called Neural Collaborative Filtering with Knowledge Graphs (NCF-KG). This approach incorporates knowledge graph embeddings into the NCF framework to enhance the representation of items and users, improving recommendations' accuracy.

Current progress is centered around incorporating additional contextual and supplementary data to enhance the quality of recommendations. He et al. (2020) [10] introduced LightGCN, which enhances computing efficiency and preserves recommendation performance by simplifying graph convolution processes. In addition, researchers have investigated the use of reinforcement learning to enhance long-term user engagement by treating the recommendation process as a problem of making sequential decisions (Zhao et al., 2018) [35].

2.1 Limitations

Deep learning has significantly transformed how e-commerce users interact with recommendation systems, yet these algorithms still have several limitations.

- The need for data is substantial [26], posing challenges for smaller platforms to acquire sufficient high-caliber data. Training these models is computationally intensive, necessitating significant hardware resources, which might be expensive for specific firms.

- Deep learning models [27] frequently operate as opaque entities, posing challenges in comprehending their outputs. The cold start issue impacts novice users and new items, and achieving scalability is essential for ensuring optimal performance and precision.

- Real-time processing is essential for optimizing user experience [28], but the complex computational requirements of deep learning models provide significant obstacles. Concerns with bias and fairness arise since deep learning models can potentially unintentionally acquire and magnify biases present in the training data.

- The collection and processing of large quantities of user data give rise to concerns over privacy [29], while the constant updates and maintenance required can be demanding in terms of resources and complexity.
- Integrating these solutions with the current e-commerce infrastructure [30] can be intricate and necessitate substantial improvements.

3. METHODOLOGY

We propose a social recommendation system consisting of two components: a group of users U, where the cardinality of U is denoted as ∣U∣=A|U| = A∣U∣=A, and a collection of things V, where the cardinality of V is denoted as ∣V∣=B|V| = B∣V∣=B. The system is represented as a social network graph H=(U, C), where U represents the set of users and C represents the social connections between them. Social networks can be represented as either directed or undirected graphs. Directed graphs are used to describe social networks when relationships have a specific direction, while undirected graphs are used for social networks where relationships have no specific direction. Our approach is intended to be compatible with both sorts of graphs. However, for the sake of simplicity and universality, we will focus on an undirected graph in this study.

Specifically, $C \in RAxA$ is a symmetric matrix that encodes the social relationships among users. Each element $C\{u1,u2\}$=1 indicates that user u1 has a social connection with user u2, and $C\{u1,u2\}$=0 cu1,u2=0 indicates no such connection, where $u1$, $u2$ $\in U$. The user-item feedback matrix $P \in RAxB$ includes elements $P\{u,v\}$, where $P\{u,v\}$ = 1 signifies positive feedback from user u for item v (e.g., clicking the recommended item), and $P\{u,v\}$ = 0 indicates negative feedback (e.g., not clicking the recommended item). Reinforcement learning (RL) is employed to address the issue of interactive recommendation. The agent recommends items by analyzing the user's interaction history and social relationships. Feedback is documented, and revised, and fresh suggestions are generated. The objective is to design an optimal approach to ensure maximum user contentment. The study introduces a dynamic learning model that recommends items to users based on their interaction history and social relationships. The model dynamically learns the user's state, denoted as zt, and calculates an immediate reward for recommending an item based on user feedback.

$$\pi^* = argmax_{\pi} \in \pi E \left[\sum Q_{v_t, i_t}\right]$$

Table 1: Notation and Description

Symbol	Usage
U,V	Groups of users and items
A,B	Counts of users and items
H	Social network
C	Social connections matrix
P	User-item interaction matrix
Z	Collection of user states
π	Collection of strategies
N(v)	Group of immediate neighbors of user v in the socialnetwork
j_t	Representation of item jt at time step t.
J	Item representation matrix
K	User representation matrix
g	Size of item embedding
h	Size of user embedding
q_v, t	Preference vector of user v at time step t.
k_v^i	Combined social influence vector for user v after lhops.
z_v, t	State vector of user v at time step t
p_v, j	Response of user v to the recommended item j.
T	Duration of the recommendation sequence
θX	Coefficient of the state value function
θY	Coefficient of the advantage value function
W	Weight matrices for various layers
B	Bias vectors
d	Dimension of the embedding vectors
$v \in R^{u*v}$	User-item interaction matrix
$E_u \in R^{u*d}$	User embedding matrix
$E_v \in R^{v*d}$	Item embedding matrix

3.1 Framework designing

The DLERSE framework has five crucial modules: user and item embedding, GRU-based modelling of user interests, GAT-based social influence dissemination, state fusion, and Deep Q-Network (DQN). Themodules depict the user's existing state and actions, while the DQN anticipates the anticipated outcome and suggests the item with the highest anticipated outcome to the intended user.

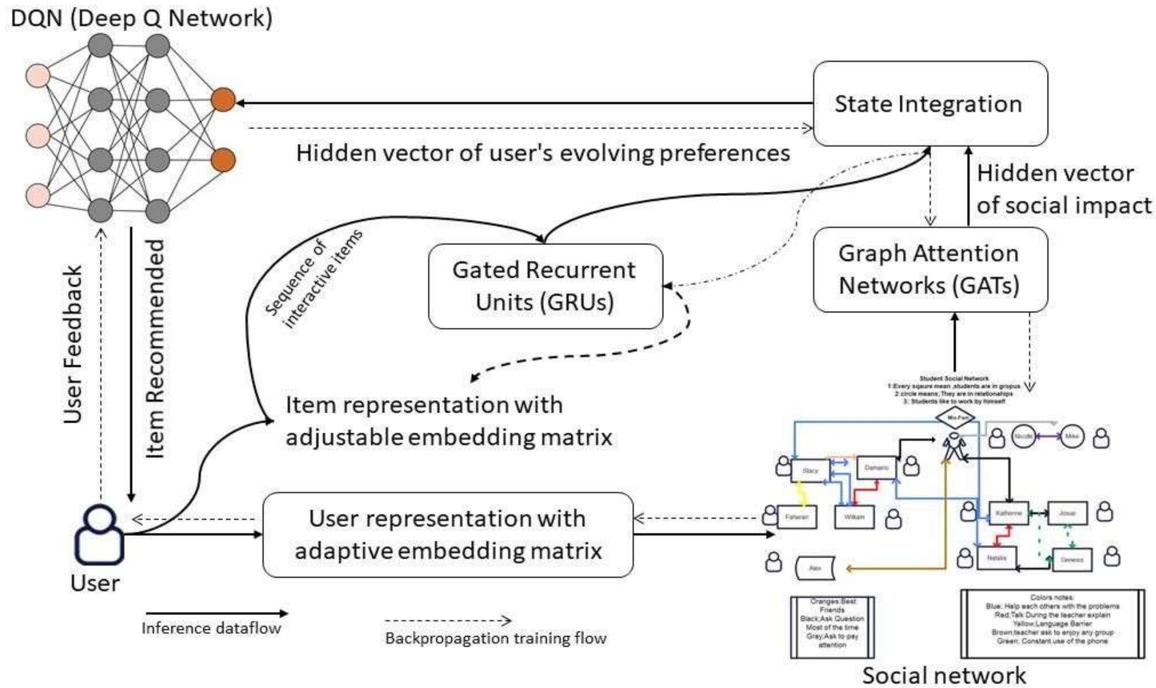

Figure 1: Proposed DLERSE Framework

The diagram depicts the structure of the proposed DLERSE framework. The framework comprises a collection of interconnected modules specifically created to gather and leverage user interaction history and social relationships to make recommendations. The study introduces a framework for collecting user preferences and social factors in recommendation systems through the use of diverse modules. The User and Item Embedding Module transforms users and items into latent vector spaces, while the GRU-Based User Dynamic Interests Modelling Module uses Gated Recurrent Units (GRUs) to capture evolving user preferences. Graph Attention Networks (GATs) are employed to capture the impact of social connections in the network, while the State Fusion Module combines hidden vectors from these modules to create a full representation of the user's current condition. The study also investigates the utilization of implicit input in recommendation systems, specifically examining user interactions with both clicked and non-clicked objects. The system can gather both positive and negative input, which improves understanding and enables more effective recommendations. The significance of social influence on decision-making in social networks is paramount, as it directly affects the choices made by individual users. The article presents a method that combines dynamic interests, and the K hops social impact vector to obtain the user's state representation. The DLERSE-add and DLERSE-con approaches provide personalized recommendations by taking into account the social interactions of particular users, thus addressing the problem of user cold-start. The paper introduces a method called DQN that combines different states to optimize the long-term profitability of e-commerce recommendations. The two-layer neural network is used to estimate the parameters of the state value function and advantage function. The recommender agent monitors user interaction records and social network data to offer products using the "-greedy policy." The target network is updated using the mean-square loss function and the double-Q technique to avoid excessively optimistic estimations.

3.2 Integration of the Proposed model

The objective is to optimize the total reward obtained by suggesting items to users, which is equivalent to maximizing the anticipated user engagement with the suggested items.

Embedding Layer:

User embedding $eu = Eu[u]$

Item embedding $ev = Ev[v]$

Journal of Theoretical and Applied Information Technology
28th February 2025. Vol.103. No.4

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

GRU-Based User Dynamic Interests Modeling:

: $h^t = GRU(e_{\{v,t\}}, h^{t-1}$

GAT-Based Social Influence Diffusion:

Update user hidden state considering social influence: $h_u = GAT\ (S, h_u)$

State Integration Module:

Combine user dynamic interests and social influence: $z_u = contact\ (h_u, h_{social}). W_z + b_z$

Where h_{social} is the social influence vector, and z_u is the integrated user state.
Deep Q-Network (DQN) Module:
Calculate Q-values for each item: $Q(u, v) = z_u. e_v$

Select the item with the highest Q-value:

$$v* = argmaxv \in vQ(u, v)$$

Minimize the loss function using Mean Squared Error (MSE) for the predicted interactions and actualinteractions:

$$L = |u||v|\sum \sum(p\{u,v\}u\in U\ v\in V - Q(u, v))2$$

Update the parameters W and b using backpropagation and gradient descent. The optimization objective is to find the optimal recommendation strategy π^* that maximizes the expectedcumulative reward: T

$$\pi* = argmax\pi \in \pi E\ [\sum Qv\ ,j\ ]$$

t=0

4. EXPERIMENTAL SETUP FOR PROPOSED MODEL

The process of creating the dataset is collecting data from an e-commerce platform, which includes logs of user interactions, user profiles, item descriptions, and social network information. The data set also encompasses interaction data, social network data, item features, and user demographics, such as age, gender, and location. The approach entails several steps, including data cleaning, generating a user-item interaction matrix, normalizing continuous features, initializing embeddings, constructing a social network graph, and dividing the dataset into training, validation, and test sets. The method entails eliminating duplicate entries, eliminating missing data, and discarding unnecessary information. It also involves standardizing continuous attributes and creating a social network graph where users are represented as nodes and social connections are represented as edges. The deep learning model is trained by utilizing a training set and optimizing parameters through the processes of backpropagation and gradient descent. It is then validated to prevent overfitting and cross-validation, and finally tested on data that has not been previously seen.

The evaluation metrics considered here are:

Precision: The proportion of recommended items in the top K positions that are relevant to the user.

$$Precision = \frac{1\sum U u\in U|\{relevant\ items\} \cap \{top\ k\ recommendations\}|}{K}$$

$$Recall = \frac{1\sum U u\in U|\{relevant\ items\} \cap \{top\ k\ recommendations\}|}{relevant\ items}$$

Normalized Discounted Cumulative Gain (NDCG): Measures the ranking quality of the recommendations,accounting for the position of relevant items.

$$NDCG = \frac{1}{U}\sum_{u\in U}\frac{1}{IDCG}\sum_{i=1}^{K}\frac{2^{rel_u - 1}}{\log_2 i + 1}$$

Where $rank_u$ is the rank position of the first relevant item for user u.

Area Under the ROC Curve (AUC): Evaluate the model's ability to distinguish between relevant and non-relevant items.

$$AUC = \frac{\text{Number of correctly classified pairs}}{Total\ number\ of\ pairs}$$

5. RESULTS AND DISCUSSION

The performance of the deep learning recommendation system for e-commerce user interaction was evaluated using the metrics described in the experimental setup. The results are summarized in the following tables and graphs. The datasets used are LastFM, and Delicious. The following results show the model's accuracy.

The study displays bar graphs that compare the Delicious and LastFM datasets. In Fig 2, The graphs indicate that both platforms have comparable user figures, although Delicious boasts a greater quantity of items. The graphs indicate that Delicious has a higher number of observed user feedback, a greater number of items per user, and a larger number of observed social ties. Furthermore, LastFM users have a higher average number of friends compared to Delicious users. These visualizations offer a valuable understanding of the attributes and distinctions between the two datasets included in the investigation.

The Delicious and LastFM datasets exhibit notable disparities and resemblances in their progression and assessment of deep learning recommendation systems for user engagement in e-commerce. Both datasets exhibit comparable user counts, but, the Delicious dataset boasts a greater quantity of items and a higher volume of user input, indicating a more extensive array of material. In the Delicious dataset, the average number of items per user is 100.2, whereas in LastFM it is 38.1. The disparity emphasizes the significant level of user involvement in Delicious, which can augment the model's capacity to acquire knowledge of user preferences.

However, LastFM surpasses Delicious in terms of social network data, with 25,173 recorded social relations and an average of 13.4 friends per user. This implies that LastFM can offer a more significant social context for recommendations, which is essential for social recommendation algorithms that utilize user connections to improve personalization. These findings indicate that Delicious has a more extensive dataset in terms of user-item interactions, while LastFM has a more robust social network component. The complementary nature of both datasets can be utilized to enhance the accuracy and relevance of recommendation systems by integrating both interaction and social data, resulting in the development of hybrid recommendation systems. Subsequent research might investigate the merging of different datasets to utilize the advantages of varied interactions and social connections, which could potentially result in more resilient and efficient recommendation systems.

In Fig 3, The graph illustrates the assessment metrics of the deep learning recommendation system, demonstrating excellent performance in all metrics. It shows high values for Precision and AUC, suggesting the system's success in delivering correct and relevant recommendations, as represented in the bar graph. The performance of the deep learning recommendation system in an e-commerce scenario is assessed using five important metrics: Precision, Recall, NDCG, Mean Reciprocal Rank (MRR), and Area Under the Curve (AUC). These metrics assess the system's efficacy in discovering and prioritizing pertinent material for users.

Precision denotes that 77% of the top 10 things are pertinent to consumers, whilst Recall implies that 52% of all relevant items are retrieved. The relatively moderate memory rate indicates the possibility of enhancing the ability to capture a wider variety of pertinent items. NDCG demonstrates that the system prioritizes relevant items by placing them higher in the recommendation list, hence increasing user satisfaction and engagement.

Mean Reciprocal Rank (MRR) signifies that the initial pertinent item is positioned comparatively higher in the recommendation list, hence diminishing the time and exertion required to peruse through recommendations. The AUC score of 0.924 indicates that the system has a high ability to differentiate between relevant and non-related elements, ensuring that the recommendations provided are both relevant and timely.

The comprehensive performance metrics indicate that the deep learning recommendation system is exceedingly proficient in producing precise and pertinent recommendations for e-commerce users. Nevertheless, the Recall measure indicates the need for enhancement in capturing a broader range of pertinent items. Future studies could prioritize improving the recall metric by investigating tactics such as varied recommendation algorithms, integrating further contextual data, and utilizing more advanced machine learning models. Additionally, real-time adaptation and feedback methods could be employed to continuously enhance and optimize

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the recommendation system by analyzing user interactions and preferences.

Ultimately, the deep learning recommendation system exhibits robust performance in crucial evaluation measures, rendering it a viable asset for e-commerce platforms to enhance user experience, stimulate greater engagement, and boost sales.

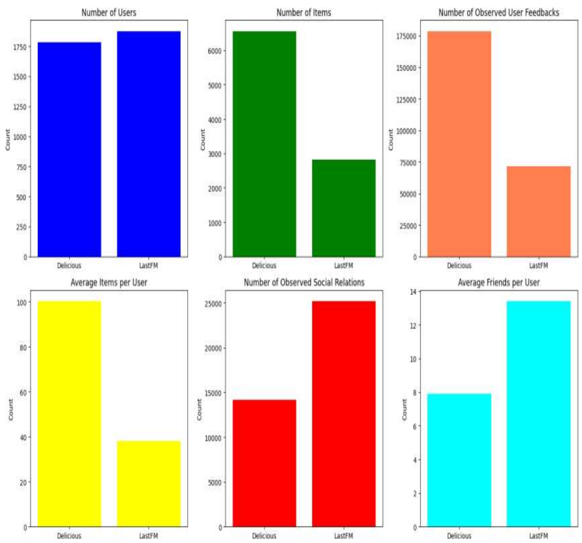

Figure 2: Visualization of the proposed model on datasets

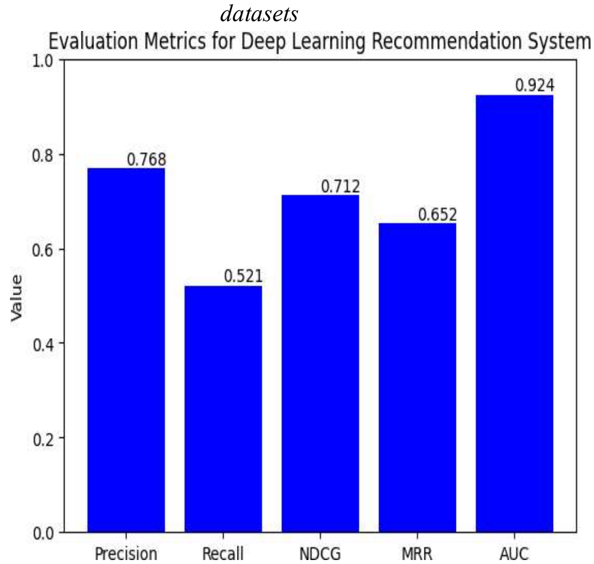

Figure 3: Evaluation metrics of the proposed model on datasets: Accuracy, Precision, recall, NDCG and MRR

The study in Fig 4 presents a comparison of alternative e-commerce recommendation algorithms on the delicious dataset using two different hyperparameters, α (0 and 0.1). The assessed metrics are Reward, Precision, and Recall. The DLERSE approach surpasses other ways with the highest Reward value, demonstrating greater overall performance in terms of accumulated rewards. Conventional approaches such as Greedy MF and LinUCB demonstrate negative rewards, indicating their lack of effectiveness when compared to more advanced methods.

DLERSE, SADQN, and DEERS exhibit exceptional accuracy, with values approximately at 0.66, indicating their efficacy in delivering pertinent recommendations. Conventional approaches such as Greedy MF and LinUCB exhibit considerable inferiority, highlighting the benefits of employing sophisticated learning algorithms. DLERSE and SADQN exhibit superior recall performance, demonstrating their capacity to recover a greater percentage of pertinent items. The recall rate for conventional approaches is significantly lower, highlighting the advantages of employing more sophisticated models to accurately capture user preferences. The comparison analysis unequivocally demonstrates that sophisticated techniques like DLERSE, SADQN, and DEERS exhibit superior performance compared to traditional methods like Greedy MF and LinUCB across all assessed variables. DLERSE demonstrates superior performance in terms of accumulated incentives, precision, and recall, underscoring its usefulness in the recommendation task. These findings highlight the significance of utilizing sophisticated deep

learning and reinforcement learning methods in constructing resilient recommendation systems. Subsequent studies should prioritize enhancing the efficiency of these models and investigating their use in various datasets and fields.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

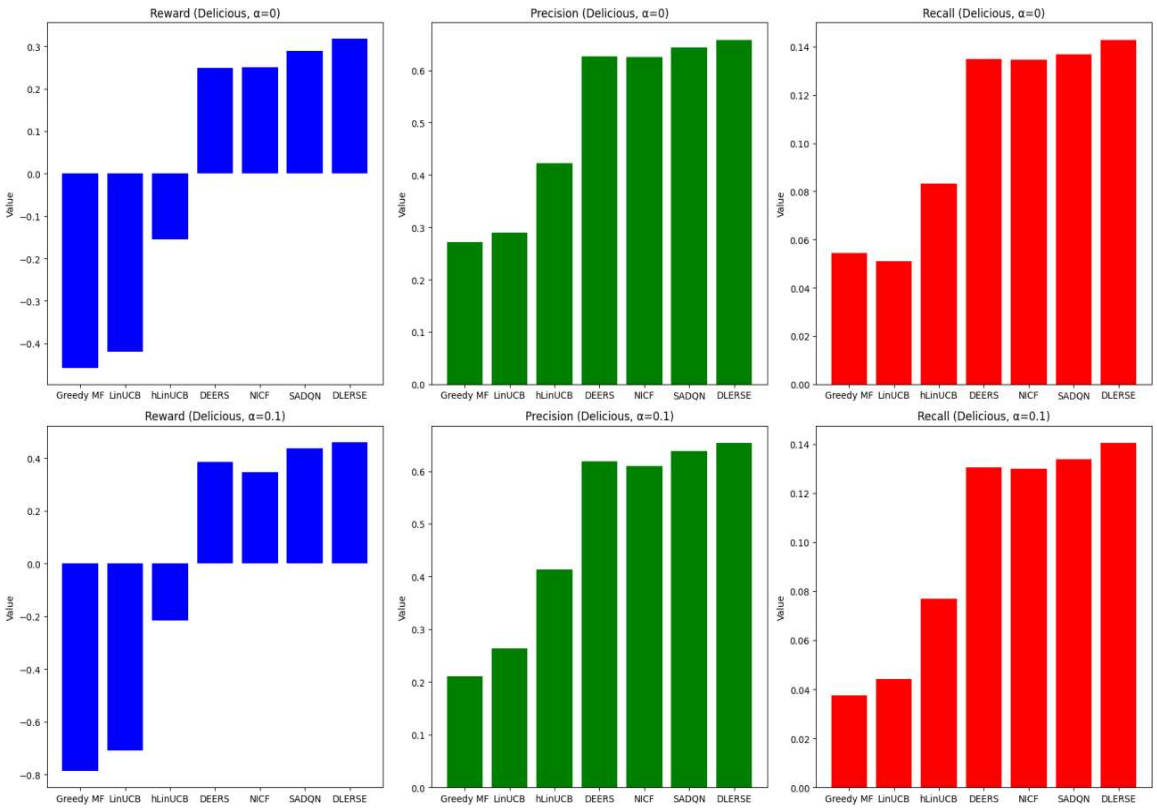

Figure 4: Evaluation Metrics Of The Proposed Model On Datasets: Accuracy, Precision, Recall, NDCG And MRR

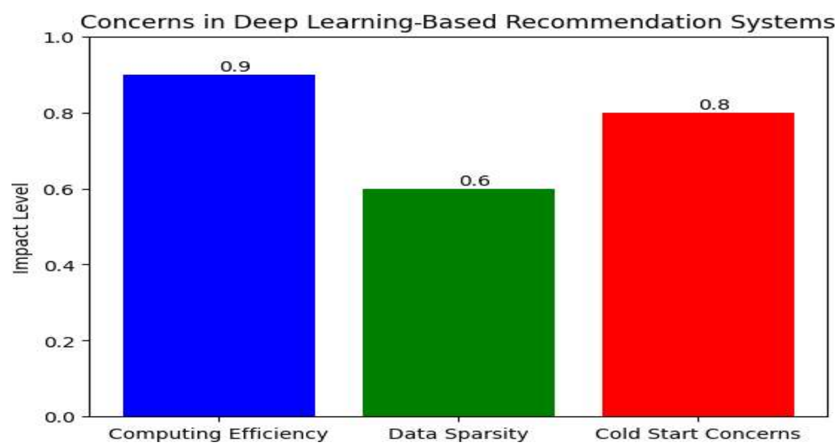

Figure 5. Overall Performance Evaluation: Concerns In Deep Learning-Based Recommendation Systems

Incorporating additional contextual information and up-to-date data could significantly improve the effectiveness and user contentment of these recommendation systems.

This study illustrates that leveraging user multi-hop social relationships can efficiently tackle the user cold-start problem in e-commerce recommendation systems. The suggested approach demonstrates superior performance compared to conventional information retrieval methods, especially during the first suggestion phase. The system can simulate human preferences and complex social connections, resulting in accurate suggestions even with limited user interactions. Hence, the research highlights the significance of GAT (Graph Attention Network) in the field of e-commerce to attain superior recommendations, specifically at the first stage of recommendation.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The evaluation of e-commerce techniques on the delicious dataset is conducted utilizing metrics such as Reward, Precision, and Recall. Advanced techniques such as DLERSE, SADQN, and DEERS surpass conventional approaches in performance, although this improvement is accompanied by a higher level of computing complexity. These models necessitate significant computational resources for both training and inference, which may pose scaling issues in real-time recommendation settings. Data sparsity is a prevalent issue in recommendation systems because the matrices representing user-item interactions generally havea low density of values. Advanced techniques such as DLERSE and SADQN provide a high level of recall and precision, indicating their ability to address this problem effectively. Nevertheless, the issue of the coldstart problem persists as a noteworthy worry, necessitating ongoing research and development to better improve these models. To summarize, although modern e-commerce systems show strength in recommendation jobs, the challenges of compute efficiency, data sparsity, and cold start issues are still significant. Future research should prioritize the optimization of these trade-offs to create recommendation systems that are more efficient, precise, and scalable.
The result in Fig 5, depicts three primary issues in deep learning-driven recommendation systems: computational efficiency, data sparsity, and cold start problems. The demand for computational resources in deep learning models, such as GPUs, makes computing efficiency a significant priority. The model's predictive accuracy is compromised by a moderate level of data sparsity. The issue of cold start concerns poses a problem, as it entails providing recommendations for new users or goods that have limited or no previous contact data. It is essential to address these challenges to construct deep learning-based recommendation systems that are both effective and efficient, hence improving the user experience on e-commerce platforms.

6. CONCLUSION

The paper proposes a new technology solution called DLERSE, which stands for deep q-network with multiple-hop social relationships enhancement. DLERSE Pworks by enhancing e-commerce recommendation systems and uses deep reinforcement learning and cold-start mitigation. Ultimately, DLERSE leverages social network interactions to improve social network recommendations. Cold-start problems come into play when an entirely new user or new item is added to the database and does not have enough interaction history to produce accurate recommendations. By blending decision-making pathways with the learning-seeking behavior of social networks, it is possible to achieve a self-cross-optimizing form of a recommendation system. DLERSE incorporates **recurrent neural networks (NNs) to adapt to changing user preferences while positively and negatively voting on items to adjust subsequent recommendations. Then, through the use of a graph attention network (GAT), the system can utilize social influences across users' networks by efficiently propagating and aggregating multi-hop social influences. All of these allow DLERSE to recommend items even when most users have no historical data to base the recommendations on. Such a novel e-commerce recommendation system DLERSE was evaluated with two real-life datasets, where DLERSE faced the most intense competition with traditional e-commerce recommendation models. The findings verify that the use of social networks in the context of personalization yields greater effects for serving cold-start user recommendations. The research emphasizes the usefulness of social network information for enhancing recommendations but does not forget the difficulty of using graph neural networks (GNNs) with active social graphs, in which user behavior and relationships are often updated. Future work should consider more effective and scalable approaches to modifying social networks that may enhance DLERSE's productivity in real-time e-commerce systems.

REFERENCES

[1] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017). Neural Collaborative Filtering. In Proceedings of the 26th International Conference on World Wide Web (pp. 173-182).

[2] Wang, H., Wang, N., & Yeung, D. Y. (2015). Collaborative Deep Learning for Recommender Systems. In Proceedings of the[21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1235-1244).

[3] Covington, P., Adams, J., & Sargin, E. (2016). Deep Neural Networks for YouTube Recommendations. In Proceedings of the 10th ACM Conference on Recommender Systems (pp. 191-198).

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[4] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep Learning Based Recommender System: A Survey and New Perspectives. ACM Computing Surveys (CSUR), 52(1), 1-38.
[5] Ying, X., Klein, D., & Arora, S. (2018). Sequential Recommender Systems: Challenges, Progress, and Prospects. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (pp. 2699-2702).
[6] Wu, C. Y., Ahmed, A., Beutel, A., Smola, A. J., & Jing, H. (2017). Recurrent Recommender Networks. In Proceedings of the 10th ACM International Conference on Web Search and Data Mining (pp. 495-503).
[7] Tang, J., Du, X., Wang, K., Cui, P., & Wu, S. (2019). A Deep Temporal Context Model for Music Recommendation. ACM Transactions on Intelligent Systems and Technology (TIST), 10(3), 1-25.
[8] Fan, W., Ma, Y., Li, Q., He, Y., Zhao, E., Tang, J., & Yin, D. (2019). Graph Neural Networks for Social Recommendation. In Proceedings of the 28th International Conference on World Wide Web (pp. 417-426).
[9] Zheng, Y., Noroozi, V., & Yu, P. S. (2017). Joint Deep Modeling of Users and Items Using Reviews for Recommendation. In Proceedings of the Tenth ACM International Conference on Web Search and Data Mining (pp. 425-434).
[10] He, X., Deng, K., Wang, X., Li, Y., Zhang, Y., & Wang, M. (2020). LightGCN: Simplifying and Powering Graph Convolution Network for Recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 639-648).
[11] Rendle, S., Freudenthaler, C., Gantner, Z., & Schmidt-Thieme, L. (2009). BPR: Bayesian Personalized Ranking from Implicit Feedback. In Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence (pp. 452-461).
[12] Sedhain, S., Menon, A. K., Sanner, S., & Xie, L. (2015). Autorec: Autoencoders Meet Collaborative Filtering. In Proceedings of the 24th International Conference on World Wide Web (pp. 111-112).
[13] He, X., Zhang, H., Kan, M. Y., & Chua, T. S. (2016). Fast Matrix Factorization for Online Recommendation with Implicit Feedback. In Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 549-558).
[14] Wang, X., Wang, H., Xu, C., He, X., Cao, Y., & Chua, T. S. (2019). Explainable Reasoning over Knowledge Graphs for Recommendation. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 33, pp. 5329-5336).
[15] Xue, H., Dai, X., Zhang, J., Huang, S., & Chen, J. (2017). Deep Matrix Factorization Models for Recommender Systems. In Proceedings of the 26th International Joint Conference on Artificial Intelligence (pp. 3203-3209).
[16] Yin, H., Cui, B., Li, Y., Yao, J., & Chen, L. (2012). Challenging the Long Tail Recommendation. In Proceedings of the VLDB Endowment (Vol. 5, No. 9, pp. 896-907).
[17] Liang, D., Krishnan, R. G., Hoffman, M. D., & Jebara, T. (2018). Variational Autoencoders for Collaborative Filtering. In Proceedings of the 2018 World Wide Web Conference (pp. 689-698).
[18] Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix Factorization Techniques for Recommender Systems. Computer, 42(8), 30-37.
[19] Wang, S., Hu, L., Wu, J., Sun, A., & Liu, Y. (2019). Attention-based Transactional Context Embedding for Next-item Recommendation. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (pp. 2345-2348).
[20] Hu, Y., Koren, Y., & Volinsky, C. (2008). Collaborative Filtering for Implicit Feedback Datasets. In Proceedings of the 2008 Eighth IEEE International Conference on Data Mining (pp. 263-272).
[21] Zhang, K., Zheng, L., Wang, Z., Zheng, L., Zhang, J., & Qiu, L. (2018). A Framework for Hybrid Neural Recommendation System in E-commerce. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (pp. 1539-1542).
[22] Kabbur, S., Ning, X., & Karypis, G. (2013). FISM: Factored Item Similarity Models for Top-N Recommender Systems. In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 659-667).
[23] Lei, C., Deng, C., Zhou, X., & He, X. (2019). A Survey of Matrix Factorization Techniques for Recommender Systems. IEEE Transactions on Neural Networks and Learning Systems, 31(9), 3555-3570.
[24] Ning, X., Karypis, G., & Ding, Y. (2012). Sparse Linear Methods with Side Information for Top- N Recommendations. In Proceedings

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

of the Sixth ACM Conference on Recommender Systems (pp. 231-238).
[25] Guo, G., Zhang, J., & Yorke-Smith, N. (2015). TrustSVD: Collaborative Filtering with Both the Explicit and Implicit Influence of User Trust and of Item Ratings. In Proceedings of the 29th AAAI Conference on Artificial Intelligence (pp. 123-129).
[26] Sanner, S., & Lu, X. (2011). Sparse Bayesian Nonnegative Matrix Factorization for Machine Learning. In Proceedings of the 24th Annual Conference on Neural Information Processing Systems (pp. 1718-1726).
[27] Choi, S., Ko, J., & Jang, M. (2018). Deep Factorization-Machine Based Recommender System. In Proceedings of the 2nd Workshop on Deep Learning for Recommender Systems (pp. 1-4).
[28] Liu, N., Wang, M., Liu, Q., & Xie, X. (2018). Neural Collaborative Filtering with Multi-View Knowledge Graphs. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (pp. 1019-1028).
[29] Rendle, S. (2010). Factorization Machines. In Proceedings of the 10th IEEE International Conference on Data Mining (pp. 995-1000).
[30] Vargas, S., Castells, P., & Vallet, D. (2014). Coverage, Redundancy and Size-Awareness in Genre Diversity for Recommender Systems. In Proceedings of the 8th ACM Conference on Recommender Systems (pp. 209-216).
[31] Hidasi, B., Karatzoglou, A., Baltrunas, L., & Tikk, D. (2016). Session-based Recommendations with Recurrent Neural Networks. In Proceedings of the 4th International Conference on Learning Representations.
[32] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2017). Deep Learning Based Recommender System: A Survey and New Perspectives. ACM Computing Surveys (CSUR), 52(1), 1-38.
[33] Zhou, G., Zhu, X., Song, C., Fan, Y., Zhu, H., Ma, X., ... & Gai, K. (2018). Deep Interest Network for Click-Through Rate Prediction. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 1059-1068).
[34] Wang, H., Wang, N., & Yeung, D. Y. (2018). Collaborative Deep Learning for Recommender Systems. In Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1235-1244).
[35] Zhao, X., Zhang, J., He, X., Xiong, C., Li, W., & Gao, J. (2018). Deep Reinforcement Learning for List-wise Recommendations. In Proceedings of the 12th ACM Conference on Recommender Systems (pp. 95-103).