E-commerce Recommendation System Based On GNN And LSTM

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***Abstract*—**The recommendation system is made for suggesting best products for users as per their conveniences. In this system Individual suggestions are Important for making in general future decisions this data will be useful in upcoming ages. DRL has been a good option for E-com. This system will focus on multiple hops rather than single hops. This could lead to optimal suggestions that's why Graph based neural network has been used in this system. Also, this system propagates use of LSTM. Here in this system, we are using Interactive recommendations by using LSTM which is useful for predicting long term dependencies in the system. This will lead to more interactive and speedy suggestions. Social graph neural network and LSTM is going to play huge role in this recommendation system which will suggest proper products through E-com system. LSTM will be useful for speeding the processing rate which is a part of RNN and will help system to understand past events and user preferences in product suggestions

***Keywords*—**Interactive Recommendation (IR), Long Short-Term Memory (LSTM), Graph Neural Network (GNN).

I. INTRODUCTION

Recommender systems, which are critical for business applications, are based on user experiences and interactions. Large companies such as Amazon, Netflix and Google have invested in the development of these systems, but the dynamic nature of user preferences and the complexity of the data make perfection a constant search. Despite this, these companies continue to refine and improve referral systems for customer engagement and business success. Referral systems have shaped the world of e-commerce as e-commerce platforms use referral systems to provide additional value to their customers and increase their profits. . Previous studies have shown that recommendation systems based on the entire set of articles and user interaction improve user experience and system functionality to provide accurate recommendations for current IR. So, the goal is to balance research and optimization.

II. LITERATURE SURVEY

1) IR (Interactive Recommendation System) Recommendation systems have modify the world of E-com since online suggestion system to provide their customers with proper information[1].In this literature the IR issue has been modeled as Multi-Armed bandits (MAB) also called as contextual problem which gives the proper suggestions to the customer based on the history of user, However this system useful for linear mapping models[2,3].Recently this system has attracted people's attention because it can be benefitted in long term interactive user recommendations

2) Graph Neural Network : In the field of social recommendation, several schemes use graphical neural networks (GNN) to model multi-hop social influence among socially connected users, spreading social influence among users to alleviate the user cold start problem[4, 5]. Compared to those systems that consider only one-hop social relations, these systems achieve better efficiency due to the strong representativeness of GNN. However, these GNN-based social propagation methods are used in one-step recommendation systems, and their performance in interactive recommendation systems is rarely studied [6]. Here then we are using Single step social oblivious recommnedation system by using Matrix Factorization(MF) is a very well known suggestion model[7]. The prediction rate is combines explicit and implicit use of recommendation based on SVD++ by modellinglatest user recommendations[8].Considerng different ways may have a different impact on users work,as attension based NN[9] is proposed for item based col filtering,which can differentiate the importance if different items in a user profile[10].

Data spareness is a fundamental problem in single-step social-oblivious suggestion methods and external relationships [11] have become more an effective effort to recommend right products to the user and can be easily used to spareness problem in the suggestion system. Due to the ability of modeling multiple relationships have recently achieved good results in the suggestion system [12,13], An influence NN based on (DIFFNet) is proposed, which targets information addition and integration among users in social media networks (GCN) levels [14].

Deep Q-Net based methods find wide application in IR [15] An Deep reinforcement learning interactive news recommendation scheme is proposed by BAN[16].A neural network CF is method proposed to solve the IR problem[17].Collaborative LINUCB is bandit algo that explicitly models the dependency among users[18].The ISR proposes MAB method that can adaptively learn the trust level of users and friends[19].SADQN only gives single hop social influence among users instead of multiple hop social relationships among users by GAT which brings better IR performance[20].

III. PROPOSED WORK

Traditional recommendation approaches often struggle to cope with the inherent complexities of e-commerce datasets, characterized by sparse user-item interactions, evolving user preferences, and temporal dynamics. To address these challenges, advanced machine learning techniques, such as Graph Neural Networks (GNN) and Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for modeling intricate patterns and relationships in user behavior.

The integration of GNN enables the model to effectively capture complex user-item relationships encoded in the interaction graph. GNNs excel at propagating information across graph nodes, allowing the model to leverage not only direct interactions but also indirect relationships between users and items. This holistic view of the e-commerce ecosystem facilitates more accurate and contextually relevant recommendations, even for users with sparse interaction histories.

This study proposes a novel e-commerce recommendation system that harnesses the synergies of GNN and LSTM architectures to deliver highly personalized and context-aware recommendations. By combining the graph structure of user product interactions and capturing temporal dependencies in user behavior, the hybrid model offers a comprehensive solution to the inherent challenges of recommendation in e-commerce environments.

IV. APPLICATIONS

Recommendation systems can analyze users' history which he/she bought in the past and according to the purchasing history

E-commerce recommendation systems find numerous applications across various stages of the customer journey and within different components of online retail platforms. Here are some key applications:

Product Recommendations: One of the most common applications is providing personalized product recommendations to users based on their previous buying history and their likes.

Recommendation systems can suggest related items to customers based on their purchases. This helps to increase the businesses as more people are buying the products.

Dynamic Homepage Content: E-commerce platforms often use recommendation systems to dynamically populate the homepage with personalized content tailored to each user. This could include featured products, trending items, based on previous reviews.

Personalized Email Campaigns: Recommendation systems power personalized email marketing campaigns by suggesting relevant products to individual customers. These recommendations depend on previous items bought, history, or specific interests indicated by the user.

Search Recommendations: When users search for products on an e-commerce platform, recommendation systems can enhance the search experience by suggesting relevant products or categories based on the search query and user context. This helps users discover products more efficiently.

Recommendation Widgets and Carousels: E-commerce websites often feature recommendation widgets or carousels on product pages, checkout pages, or in shopping carts. These widgets showcase related or recommended products to encourage additional purchases or provide alternative options.

Content Recommendations: In addition to product recommendations, e-commerce recommendation systems can also suggest relevant content such as blog posts, tutorials, user reviews, or customer-generated content to enhance the overall shopping experience and provide valuable information to users.

Personalized Pricing and Discounts: Some e-commerce platforms leverage recommendation systems to offer personalized pricing or discounts to individual customers based on their behavior, purchase history, or loyalty status. This helps optimize pricing strategies and improve customer retention.

Mobile App Recommendations: E-commerce recommendation systems are also integrated into mobile apps to provide personalized recommendations on-the-go. This includes features such as personalized home screens, push notifications for relevant offers, and in-app product suggestions.

These applications demonstrate the versatility and impact of e-commerce recommendation systems in enhancing user engagement, driving sales, and improving overall customer satisfaction in online retail environments.

IV. ADVANTAGES

a) This system uses sentiment analysis and collaborative filtering using the LSTM to provide product recommendations, thus improving user experience and increasing the business profits. This method improves customer satisfaction by combining the products with user emotions and preferences.

b) The system also increases customer engagement, encouraging them to explore more products and make repeat purchases. It also improves conversion rates by recommending products based on user sentiments and past behaviour. The system also efficiently uses available data, maximizing the utility of user feedback and interaction data. Overall, this system enhances customer satisfaction, engagement, and data utilization, ultimately making higher sales for the businesses.

c) Graph Neural Networks (GNNs) offer several advantages, particularly in tasks involving graph-structured data.

d) GNNs excel at capturing the complex relationships and dependencies among entities in these graphs, making them well-suited for tasks where understanding the underlying connectivity patterns is crucial.

e) Unlike traditional neural networks, which operate on vectorized or tabular data, GNNs explicitly leverage the graph structure of the data. This allows them to incorporate information from neighbouring nodes and edges, enabling richer and more context-aware representations' can learn both node-level and graph-level representations simultaneously. At the node level, GNNs can capture the features and characteristics of individual nodes based on their local neighbourhood. At the graph level, GNNs can aggregate information from all nodes in the graph to derive global graph-level representations, capturing the overall properties and dynamics of the entire graph.

f) GNNs can mitigate the effects of noisy or incomplete data and maintain stable performance in dynamic graph environments.

V. FUTURE SCOPE

Assumed that the social network among users can be obtained through an exogenous method. For e.g. mining the social network platform.in some cases it is difficult to extract the social network prior thus is important to learn social graph during recommendations. It is challenging to conduct graph neural network operations on the dynamically changed social graph and it can deeply investigate in the future.

Explainable AI techniques increase transparency and trust by providing users with insights into recommendation generation.

Personalization across multiple channels, such as mobile apps, email marketing, and social media interactions, creates a seamless shopping experience.

Future research is to develop the interactive models for clear explanations for recommendation decision.

The future scope of e-commerce recommendation systems utilizing neural networks is quite promising. Here are some potential advancements and directions:

Neural networks can enable highly personalized recommendation systems by analyzing customer interests. As neural networks continue to evolve, they can better understand complex patterns in user interactions, leading to more accurate product recommendations tailored to individual users.

Advancements in deep learning architectures, such as RNNs, can improve the understanding of product images, text descriptions, and user reviews. This can lead to better feature extraction and representation learning, resulting in more effective recommendation systems.

Sequential recommendation models based on recurrent neural networks (RNNs) or transformer architectures can capture sequential patterns in user behavior over time. By modeling the temporal dynamics of user interactions, these models can make more accurate and timely recommendations, especially in dynamic e-commerce environments.

Neural networks can effectively process and integrate information from different modalities, such as images, text, and audio, to provide richer and more engaging recommendations to users.

Federated learning techniques allow training recommendation models across distributed data sources without sharing raw data. It is important for e-commerce systems to deal with sensitive user information. Neural networks can be adapted to federated learning settings, enabling collaborative model training while preserving user privacy.

As e-commerce transactions continue to shift towards real-time interactions, there is a need for recommendation systems that can quickly adapt to changing user preferences and market trends. Neural networks optimized for low-latency inference can deliver real-time recommendations, enhancing user experience and engagement.

VI. CONCLUSION

In this proposed this multiple hop social relationship-based framework has developed which is based on LSTM, GNN which is interactive and recommends best products according to the user's previous history with maximum accuracy. It will suggest products to the customer as per his/her requirements on time. The social graph network via graph attention network which can effectively exploit the social relationships among users. As e-commerce continues to grow and diversify, the adoption of such advanced recommendation systems holds significant potential for enhancing user satisfaction, engagement, and ultimately, business profitability. By leveraging the graph structure of user-item interactions with GNN and capturing sequential patterns in user behavior with LSTM, this hybrid model can effectively address the challenges of sparsity and temporal dynamics in e-commerce datasets. In short, we modeled a system which can provides better recommendations based on user demands.

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