GCN WITH ATTENTION MECHANISM FOR LEARNING USER SENTIMENTS AND ENHANCING SOCIAL RECOMMENDATION

PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report " **GCN WITH ATTENTION MECHANISM FOR LEARNING USER SENTIMENTS AND ENHANCING SOCIAL RECOMMENDATION** " is the bonafide work of " HEMANTH N, PAAVENDHAN K.S & SAI SOUNDHARYA LAKSHMI B " who carried out the project work under my supervision.

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ABSTRACT

Social media usage has grown significantly, with users spending an average of 150 minutes daily. This has led to businesses using social media to advertise and communicate with customers via personalized recommendation. However, current social recommendation systems have limitations, focusing only on social network homophily and ignoring the complexities of human interactions. In our proposed work, we aimed at developing a deep adversarial framework based on GCNs to address the challenges of social recommendation, that include, (i) majority of users only have a very few number of neighboring nodes in social networks and can take only little advantage from social relations; (ii) Social relations are noisy but they are indiscriminately used; (iii) since, social ties are complex and have varied strengths in many settings, they are commonly thought to be universally relevant to a variety of scenarios. Our proposed solution is a deep adversarial framework based on Graph Convolutional Neural Networks (GCNs) that addresses these challenges. We developed a GCN-based autoencoder to encode complex connectivity patterns and address limitations with noisy social relations and limited neighboring nodes. We achieved an improvement in accuracy of 8.65% and 9.44% using the GCN coupled with adversarial training and attention mechanisms for social recommendations with distinct datasets respectively.

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CHAPTER 1

INTRODUCTION

Social media has become an important part of people's daily life in recent years. In the age of information explosion, modeling user preferences is valuable for discovering the target item in advance and assisting users in overcoming the dilemma of big data, so personalized recommendations are widely used in many online platforms, such as ecommerce, social networking, and content sharing, among others. Businesses have started utilizing social media platforms for advertising and customer involvement, as the platform has grown. As a result, social recommendation systems will increase user engagement and enhance trust. Social recommender systems have arisen as a tool to assist businesses in targeting adverts and connecting with customers. According to social theory, members in a social network are affected by their social interactions, resulting in the homogeneity of social neighbors' preferences. As a result, the impact of social relationships on recommendation systems has received increased attention. Most contemporary social recommendation models focus solely on homophily in social networks, ignoring other limitations such as data scarcity and complex noisy social ties. The current social recommender systems are limited in their ability to capture the complexities of social networks. They rely on the assumption of homophily, which suggests that users who have similar interests or social connections will have similar preferences. However, this assumption ignores the heterogeneity and dynamism of social networks. Moreover, the majority of users only have a few neighboring nodes in social networks, which limits their ability to take advantage of social relations. Additionally, social relations are often noisy and indiscriminately used in the existing systems, which can lead to inaccurate recommendations. Considering these problems, a deep adversarial framework based on graph convolutional networks (GCN) has been developed to enhance social recommendation [1].

However, the developed social recommendation systems consider either user-item or user-user interactions alone, but modeling all three user-item, user-user, item-item interactions is needed to develop an effective social recommendation. Knowing item-item preferences is important since it enables the algorithm to recognise similar items and provide recommendations based on those similarities. The system can offer recommendations for products that the user may be interested in by analyzing the preferences and interactions of users with comparable items. Furthermore, item-item preferences can aid in addressing the cold start problem, which occurs when new items are introduced to the system and no interaction data is available. The system can offer preliminary recommendations for new goods based on their similarities to existing ones by analyzing item-item preferences. Also most of the existing recommendation systems give importance to capture only the semantic information, but both syntactic and semantic information are required in social recommendation systems because they provide complimentary insights into the user's behavior and preferences. The quantitative knowledge of the user's interactions with items and other users is provided by syntactic information, whilst the qualitative understanding of the user's interests and preferences is provided by semantic information. Social recommendation systems can generate more accurate and personalized recommendations to users by combining these two forms of information. Hence, we dwelled on the idea of developing a GCN based social recommendation system to address the mentioned problems.

1.1 GRAPH CONVOLUTIONAL NETWORKS

Graph Convolutional Networks (GCNs) are a type of neural network that is designed to operate on graph-structured data. Unlike traditional neural networks as analyzed in [3-7], which operate on grid-structured data such as images or sequential data such as text, GCNs are able to learn from and make predictions on complex, non-grid data structures such as social networks, citation networks, and biological networks. At their core, GCNs apply a series of graph convolutions to the input graph, where each convolution involves a learned filter that is applied to the node and its neighboring nodes to generate a new representation for each node. These convolutions are implemented using matrix multiplication, with the input graph represented as a sparse adjacency matrix. By using the adjacency matrix to encode the graph structure, GCNs can leverage the connections between nodes to make predictions. This approach is particularly useful for applications where the input data has a natural graph structure, such as social networks or biological networks. The use of sparse matrices makes GCNs computationally efficient, allowing them to scale to large graphs.

One of the key advantages of GCNs is their ability to capture local and global information from the input graph. Traditional graph-based methods as compared and tabulated in [4] typically rely on hand-crafted features or rely on simple aggregation functions such as mean or max pooling. In contrast, GCNs are able to learn feature representations that are optimized for the task at hand, by leveraging the structural information present in the input graph. This makes them well-suited for tasks such as node classification, link prediction, graph classification, and graph generation. GCNs have been successfully applied to a wide range of tasks in various domains, including social networks, citation networks, and biological networks. In the context of social networks, GCNs have been used for tasks such as friend recommendation, sentiment analysis, and predicting user behavior. In the context of citation networks, GCNs have been used to predict paper citation counts, authorship patterns, and scientific collaborations. In the context of biological networks, GCNs have been used to predict protein interactions, drug-target interactions, and disease-gene associations.

Despite their successes, GCNs still face a number of challenges. One major challenge is the lack of a standardized evaluation framework, making it difficult to compare the performance of different GCN models on different datasets. Another challenge is the interpretability of the learned representations, as it can be difficult to understand how the model is making its predictions. GCNs can struggle with handling large and sparse graphs, as the computation and memory requirements can become prohibitively high. Addressing these challenges will be an important area of future research for the field of GCNs as rightly proved in [6]. GCNs are a powerful tool for learning from and making predictions on graph-structured data. They have been successfully applied to a wide range of tasks in various domains, and have the potential to revolutionize the field of recommendation systems, social network analysis, and bioinformatics. However, there are still many challenges that need to be addressed in order to fully realize the potential of GCNs, including the development of standardized evaluation frameworks, improving interpretability, and addressing scalability issues. With continued research in these areas, GCNs have the potential to make significant contributions to the field of machine learning and beyond.

1.2 GNNs VS GCNs

Graph Neural Networks (GNNs) and Graph Convolutional Networks (GCNs) are both deep learning models that are used for analyzing graph-structured data. While the two models share many similarities, there are also some key differences between them. At a high level, both GNNs and GCNs operate by applying a sequence of transformations to the input graph, in order to generate node-level or graph-level representations that can be used for downstream tasks such as node classification, link prediction, or graph clustering. The choice between GNNs and GCNs depends on the specific task at hand, the nature of the input data, and the properties of the graph.

One of the main differences between GNNs and GCNs lies in the way that they represent the input graph. GNNs typically use graph-level representations such as graph adjacency matrices or Laplacian matrices, while GCNs use node-level representations such as node feature vectors or node embeddings. This difference in representation has implications for the types of tasks that each model is best suited for. GNNs are often used for tasks that involve analyzing the overall structure of a graph, such as graph classification or clustering, while GCNs are more commonly used for tasks that involve analyzing the properties of individual nodes within a graph, such as node classification or link prediction. Another key difference between GNNs and GCNs is in the way that they perform message passing. In GNNs, each node sends a message to its neighbors, which is then combined with the messages from other neighbors to produce a new representation for the node. This process is repeated for multiple iterations, allowing the node representations to evolve over time. In contrast, GCNs use a convolutional operation to combine the node features with the features of their neighbors, similar to the way that convolutional neural networks operate on image data. This allows GCNs to capture local graph structure and patterns, making them well-suited for tasks such as node classification.

Finally, GNNs and GCNs also differ in the way that they handle graphs with varying sizes and structures. GNNs are often designed to work with graphs that have a fixed structure, while GCNs are more flexible and can handle graphs with varying numbers of nodes and edges. This makes GCNs particularly useful for tasks that involve analyzing large and complex graphs, such as social networks or biological networks. GNNs and GCNs are both powerful deep learning models that can be used for analyzing graph-structured data. While the two models share many similarities, there are also some key differences in the way that they represent the input graph, perform message passing, and handle varying graph structures. Choosing between the two models will depend on the specific task at hand and the properties of the input graph.

1.3 USER-SENTIMENT ANALYSIS

User sentiment analysis is a subfield of natural language processing (NLP) that focuses on extracting insights from text data related to users' opinions, emotions, and attitudes towards a particular product, service, or topic. With the rise of social media platforms and the proliferation of online reviews, sentiment analysis has become an increasingly important tool for businesses and organizations to understand their customers' needs and preferences. The goal of user sentiment analysis is to automatically classify text data into positive, negative, or neutral categories, based on the sentiment expressed in the text. This is typically done using machine learning techniques, where a model is trained on a labeled dataset of text data, and then used to classify new, unseen data. The labeled dataset typically consists of text data annotated by human annotators, who assign a sentiment label to each piece of text.

One of the key challenges in user sentiment analysis as discussed in [20] is dealing with the nuances of language and the diversity of opinions expressed by users. Text data can be highly subjective and context-dependent, and users may express their opinions in a variety of ways, using sarcasm, irony, or other linguistic devices. Additionally, users may express multiple sentiments within a single piece of text, or may express sentiments towards different aspects of a product or service. To address these challenges, researchers have developed a variety of techniques for user sentiment analysis. One popular approach is to use lexicon-based methods, which involve building a dictionary of sentiment-bearing words and phrases, and then using these to classify new text data. For example, a lexicon-based method might classify a piece of text as positive if it contains many positive words such as "happy," "great," or "excellent," and few negative words. Another approach is to use machine learning algorithms such as support vector machines (SVMs), decision trees, or neural networks to classify text data. These algorithms can learn to recognize patterns in the text data and make predictions based on these patterns. For example, a machine learning algorithm might learn to recognize that certain word combinations or grammatical structures are associated with positive or negative sentiments. In recent years, deep learning techniques have become increasingly popular for user sentiment analysis. Deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been shown to be effective at capturing the context and structure of text data, and can be used to classify text data with high accuracy.

User sentiment analysis has a wide range of applications in various domains. In the business world, sentiment analysis can be used to monitor customer feedback, track brand reputation, and identify areas for improvement. In the political realm, sentiment analysis can be used to analyze public opinion on various issues and track the popularity of politicians. In the healthcare field, sentiment analysis can be used to identify patients' emotional states and detect symptoms of mental illness. However, there are also challenges and limitations to user sentiment analysis. One challenge is the lack of standardization in sentiment analysis methods and datasets, which can make it difficult to compare results across studies. Finally, there are also ethical considerations related to user privacy and the potential for bias in the data used to train sentiment analysis models. User sentiment analysis is a rapidly growing field that has the potential to provide valuable insights into users' opinions and attitudes towards various products, services, and topics. With the proliferation of social media and other online platforms, sentiment analysis has become an increasingly important tool for businesses, organizations, and researchers. However, there are also challenges and limitations to sentiment analysis that need to be addressed in order to ensure that it is used ethically and effectively.

1.4 MOTIVATION

As social media usage continues to grow, businesses and organizations are looking for more effective ways to reach and engage with their target audiences. The proposed framework has the potential to significantly improve social recommendation systems, leading to more accurate and personalized recommendations. This could benefit a wide range of industries, including e-commerce, advertising, and social networking. Additionally, the proposed work could be extended to other domains, such as healthcare or education, where social networks and recommendation systems could be used to improve outcomes. The major challenge that we will take motivation in overcoming is that the incorporation of sentiment analysis and syntactic data may add complexity to the system, which could be challenging to implement and maintain, and that The proposed framework may require large amounts of data and computational resources to train and implement effectively. The potential impact of the proposed project on social recommendation systems is significant. Social recommendation systems have become increasingly important in recent years, as more and more people rely on social media and online platforms for information and entertainment. The ability to effectively recommend relevant content to users is critical for maintaining engagement and building loyal audiences. However, existing recommendation systems often rely on simple algorithms that do not take into account the complex relationships and interactions between users. By incorporating GCNs into social recommendation systems, the proposed project could significantly improve the quality and accuracy of recommendations, leading to increased user satisfaction and engagement. Beyond the specific applications of social recommendation systems, the proposed project has the potential to contribute to the broader field of machine learning research. GCNs are a relatively new and rapidly evolving area of research, with many open questions and challenges. By exploring the effectiveness and efficiency of different GCN-based frameworks, the proposed project could provide new insights and approaches that could benefit researchers and practitioners across a wide range of domains. For example, the proposed work could help to address the challenge of scaling GCNs to large and complex graphs, which is a key barrier to their widespread adoption in many applications.

1.5 OBJECTIVE

The primary objective has been to develop a GCN-based autoencoder that can augment relation data by encoding high-order and complex connectivity patterns. We tackled the issue of the majority of users having only a few neighboring nodes in social networks by enhancing the available relation data.

The proposed work also aims at implementing sentiment analysis on collected user data using a BERT based dependency parser and a graph convolutional network. This will help us understand the emotions and sentiments of users, which can aid in better recommendations and also enables us to capture the syntactic data while processing social media content, both for recommendation and sentiment analysis. Furthermore, the work has been extended to evaluate the proposed framework's performance by comparing it to existing recommendation methods on several benchmark datasets. The framework's effectiveness has been assessed by measuring its accuracy, precision, recall, and F1 score. The system has also been implemented on scale to evaluate the framework's robustness to noise by adding various degrees of noise to the data and measuring its performance.

Through these objectives that we proposed, we demonstrate the efficacy of the proposed framework and provide insights for future research on social recommendation systems. In conclusion, this paper proposes a deep adversarial framework based on GCNs to address the challenges of social recommendation. Our proposed framework aims to overcome the limitations of existing social recommender systems by augmenting relation data, assigning consistent relations with high relevance components, and considering the importance of syntactic data for recommendation and sentiment analysis.

CHAPTER 2

LITERATURE SURVEY

2.1 SOCIAL RECOMMENDATION

With the advent of online social networks, an increasing number of people express their opinions on social platforms. Social recommender systems have emerged as a potential avenue, leveraging users' social networks to reduce data sparsity and increase suggestion performance. In [1], authors proposed a model for enhancing the social recommendation with adversarial Graph Convolutional Networks (GCNs). Challenges involved in social recommendation such as data sparsity, noise presence, and the multi-facet problem of social relations have been addressed. Attention-aware social recommendation is developed to which finally, adversarial training is used to strengthen the framework [1].

Graph CNNs are generalizations of classical CNNs that can handle graph data such as molecular data, point clouds, and social networks. The graph structures vary in size and connectivity for the majority of real data. Hence there is a need to construct adaptive graph topology structure for input data with arbitrary graph topology as proposed in [2]. Present GCNs are unable to learn from topological structures and frequently generate fixed graphs without training. Ruoyu Li et al. in [2], presented a spectral graph convolution network fed by original data from various graph architectures. The authors conducted a literature survey of existing GCN approaches and found that most of them rely on fixed graph structures or pre-defined heuristics for constructing graphs. They argue that this approach is not sufficient for handling real-world data, which often has complex and variable graph topologies. In contrast, SGCN is able to learn the graph topology from the input data by computing the spectral representation of the graph Laplacian matrix. This allows the network to adaptively adjust the graph topology based on the input data, improving its ability to handle graphs of varying sizes and topologies. The authors evaluated SGCN on several benchmark datasets and found that it outperformed existing GCN approaches in terms of accuracy and scalability. The proposed approach in [2] offers a promising direction for addressing the challenges of handling variable graph topologies in GCNs. By using spectral graph theory and adaptive graph topology construction, SGCN is able to improve the accuracy and scalability of GCNs on real-world data with complex and variable graph structures.

The authors of the study [3], conducted a survey of various GNN-based SocialRS to aid readers in understanding current advancements in SocialRS and developing new GNN-based SocialRS approaches. A novel taxonomy of inputs and architectures in GNN-based Social Recommendation approaches has been provided in [3], allowing researchers to quickly catch current trends in this subject. To evaluate performance, approximately 17 benchmark datasets have been employed, with the datasets comprising nearly 8 different domains such as product, location, movie, image, music, bookmark, microblog, and miscellaneous [3].

Shenghao Liu in [4] evaluates the proposed method on several benchmark datasets, which may not fully represent real-world scenarios. The authors acknowledge this limitation and suggest that further studies should evaluate the proposed method on larger and more diverse datasets. The paper introduces latent group mining as a technique to improve the accuracy of personalized recommendations. However, the authors do not provide a detailed analysis of the effectiveness of this technique and the potential impact on the overall performance of the proposed method. These limitations suggest the need for further research and analysis to fully understand the potential of graph-based methods for personalized recommendation systems.

A comprehensive analysis of several graph neural network variants classified by computation modules, graph types, and training types has been carried out in [5]. Similar work has been enhanced in [6] by Zhang X et. al. Also, this paper presents the general design pipeline for constructing a GNN model which includes determining if the graph structure is structural or non-structural, designing a loss function based on our task type and training environment, and finally building the model using computational models.

2.2 VARIED METHODS TO ENHANCE SOCIAL RECOMMENDATION

An in-depth analysis of various GNN architectures and their applications in numerous disciplines, including social networks, recommendation systems, and computer vision has been clearly presented in [5]. Graph neural networks have been studied in a variety of domains, including supervised, semi-supervised, unsupervised, and reinforcement learning situations. The authors discuss how GCNs operate by using convolutional layers to perform local feature extraction on graph-structured data. GATs, on the other hand, use attention mechanisms to weight the importance of different nodes in the graph when aggregating information from their neighbors. GAEs are designed to encode the graph structure into a low-dimensional latent space, which can be used for downstream tasks such as link prediction and node classification. Authors in [7] provide a comprehensive overview of the use of GCNs in deep learning and computational intelligence. It also presents recent applications of GCNs in various fields, demonstrating their effectiveness in solving complex problems. The authors' detailed analysis and discussion of the latest advancements in this area make it a valuable resource for researchers and practitioners interested in GCNs.

Graph Neural Networks (GNNs) have been extensively studied for a wide range of applications in different domains. GNNs can be classified into two categories: structural and non-structural. Structural applications of GNNs include graph mining, modeling physical and chemical systems, as well as industrial applications such as recommendation systems and traffic networks. Non-structural applications include natural language processing, social network analysis, and image analysis. Huang et. al. in [8] proposed a novel model that integrates both positional and temporal information to enhance the accuracy of sequential recommendations. The proposed Position-enhanced and Time-aware Graph Convolutional Network (PTGCN) outperforms existing methods on benchmark datasets. The proposed model's ability to capture sequential information and incorporate temporal dynamics makes it a valuable contribution to the field of sequential recommendation. The analysis presented in [5] provides an in-depth review of the state-of-the-art GNN architectures and their applications in various fields. In recent years, GNNs have shown promising results in a range of tasks, and their popularity has grown due to their ability to capture complex relationships and dependencies in graph-structured data. Similar work addressing session-based social recommendation model has been detailed well in [9] and [10], with the latter addressing the challenges and solutions to web-scale recommender systems with GCN. With the increasing availability of large-scale graph datasets, GNNs are expected to become even more important in a variety of applications.

2.2.1 Anomalous Detection Model

The issue of detecting anomalous users in social networks is of great importance due to the harmful consequences of such users' activities. Li et al. in [11] have developed a novel model to detect anomalous users by combining two state-of-the-art graph-based models, GCN and GAT. The proposed model is relevance-aware, which means that it can detect anomalous users in a more accurate and targeted manner. The authors used two real-world datasets, YelpChi and Twitter, to evaluate the performance of their model. The experimental results demonstrated that the proposed model outperforms several state-of-the-art baselines in terms of accuracy and F1-score. This work provides a promising approach to identifying and mitigating the impact of anomalous users in social networks. The authors in [12] propose a novel method for social recommendation that disentangles the user preferences into different sub-components. However, the evaluation of the proposed method is limited to only one dataset, and the authors do not provide an analysis of the scalability of the proposed method to larger datasets. The interpretability of the model remains a challenge, as the authors do not provide an in-depth analysis of the learned embeddings and weights.

2.2.2 Sentiment Classification

Sentiment classification, often known as sentiment analysis, is a task in natural language processing (NLP) that attempts to figure out the sentiment expressed in a given text. Positive, negative, or neutral feelings might be expressed. Customer feedback analysis, brand monitoring, and social media analysis are just a few of the applications of sentiment classification. In recent years, transfer learning has emerged as a promising approach for sentiment classification, where a pre-trained language model, such as BERT or GPT, is fine-tuned on a specific sentiment classification task. Transfer learning has been shown to improve the performance of sentiment classification models, particularly on datasets with limited labeled data, as indicated in [13]. Sentiment classification can be done at various levels of granularity, such as document-level sentiment classification, sentence-level sentiment classification, and aspect-based sentiment analysis, which aims to identify the sentiment expressed towards specific aspects [13], [14], or features of a product or service.

The study by Mehra in [10] provides a novel approach by combining emotion analysis and ABSA to investigate the impact of user-generated comments on tourist behavior. Similar areas of work are presented in [15] too, and both works are limited to a specific context and may not be generalizable to other tourism settings. Additionally, the analysis is based on text data and does not consider other factors that may affect tourist behavior. The work in [16] by Wen et. al. proposes a hybrid sentiment analysis method that incorporates both textual and interactive information, achieving high accuracy in classification. The approach is shown to be effective in various real-world scenarios. The study is however limited to a single language and domain, and further research is needed to evaluate its applicability in other contexts. The work undertaken by Cui et. al in [17] provides a comprehensive survey of sentiment analysis research, summarizing the evolution of research methods and topics in the field. The authors analyze the main research directions and challenges, and provide insights on future research directions. The paper provides a comprehensive survey of deep learning techniques for textual emotion analysis in social networks. It covers a wide range of research topics, including sentiment analysis, emotion recognition, and sarcasm detection. Similar work undertaken by Peng et. al in [18] also discusses the challenges and future directions in this field, such as the need for better labeled datasets and the integration of multimodal information. Their work offers a valuable resource for researchers and practitioners interested in using deep learning for emotion analysis in social networks.

The work undertaken by Yang et. al. in [19] proposes a novel method called CAMFF for named entity recognition (NER) that utilizes context-aware and attentive multilevel feature fusion. The method combines contextual information from both word and sentence levels to better capture the features of named entities. The authors conducted experiments on several benchmark datasets, and the results demonstrate that their proposed method outperforms several state-of-the-art models in terms of F1 score, precision, and recall for NER. Overall, the paper provides a valuable contribution to the field of NLP and demonstrates the effectiveness of their proposed method for NER. In the survey paper by Bing et. al. in [20], the authors provide a comprehensive overview of aspect-based sentiment analysis (ABSA), which is a subfield of sentiment analysis that focuses on identifying and analyzing the sentiment expressed towards different aspects or features of a product or service. Similar works in [21] and [22] have been undertaken and the works cover various ABSA tasks, including aspect extraction, sentiment classification, and aspect-level sentiment classification. The authors also describe different ABSA methods, such as rule-based approaches, supervised learning, and deep learning, and compare their performance on different ABSA tasks. The paper also highlights some of the challenges associated with ABSA, such as data sparsity, domain adaptation, and multi-lingual ABSA.

Aspect-based sentiment classification (ABSC) entails recognising and extracting sentiments expressed regarding specific aspects or features of a product or service. ABSC is a finer-grained technique to sentiment analysis than classical sentiment analysis, which only considers the overall sentiment of a text. Zeguan Xia et. al, designed a GCN-based aspect-based sentiment classification model [14], called as BERT4GCN framework that combines grammatical sequential features from BERT's pre-training language models (PLM) and syntactic knowledge from dependency graphs. Sentiment polarities of explicitly stated components in phrases will be identified by the model. Since BiLSTM can capture both forward and backward contextual information in a sequence, it is used to record the contextual information BiLSTM (Bidirectional Long Short-Term Memory) allowing it to model dependencies between words that are far apart in the sequence [14].

2.3 GCN IN SOCIAL RECOMMENDATION

Social recommendation systems (SocialRS) have been increasingly studied in recent years due to the influence of homophily and social influence in predicting consumer preferences. The main objective of SocialRS is to provide personalized recommendations to users by taking into account their social network connections. Therefore, understanding user-item preferences is crucial for the success of SocialRS [23]. To address this challenge, graph convolutional networks (GCNs) have been proposed to model the diffusion process in social networks, while traditional latent factor based models are used to collect user-item preferences. This approach combines the strengths of both methods to provide more accurate recommendations. Le Wu et al. in [23] have adopted two widely used ranking-based metrics, Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG), to evaluate the performance of the proposed SocialRS model. HR measures the proportion of the recommended items that are included in the top-k list, while NDCG takes into account the position of relevant items in the ranking list. These metrics have been used to evaluate the effectiveness of the proposed model and compare it to other existing methods in the literature. Overall, the use of GCNs in SocialRS has shown promising results in improving the accuracy of recommendations and taking advantage of the social network structure.

However, a number of existing issues have posed a significant barrier to establishing GCN-based social recommendation. They include the presence of a limited number of neighbors in social networks, as well as noisy and multifaceted social relationships with varying strengths in different contexts. These problems have been taken into consideration in [1], by developing a deep adversarial framework based on graph convolutional networks (GCN) to enhance the social recommendation. Generative adversarial networks (GANs) [1] have led a revolution in many fields including recommender systems. In addition to solving the challenges, the model featured adversarial training [1], which unites and intensifies all of the components by playing a Minimax game.

Peng Zhu in [24] proposes a novel approach for news recommendation systems that effectively utilizes social information and attention-based graph convolutional networks. Significant contributions of the paper include the accuracy improvement of news recommendations, and the effective capture of complex relationships among users, news articles, and social networks. The limitation of the study is that it only evaluates the proposed method on a single dataset, and further research is needed to evaluate its effectiveness on larger and more diverse datasets. Similar works have been addressed in [25] and [26] highlighting the importance of attention network in GCN.

One of the key challenges in SocialRS is to accurately model the complex interactions between users, items, and their social network. To address this challenge, graph neural networks (GNN) have emerged as a promising solution due to their ability to handle graph-structured data and learn from the network topology. One of the earliest GNN-based SocialRS models was proposed by Le Wu et al. [23], which combines GCNs for modeling the diffusion process in social networks and traditional latent factor based models for collecting user-item preferences. The model takes into account both user-user and user-item interactions to make recommendations. The authors evaluated the model using two ranking-based metrics. Wenqi Fan et al. [25] extended this model by simultaneously capturing exchanges and thoughts in the user-item graph. The GraphRec framework proposed in their work uses attention mechanisms to capture the heterogeneity in aggregation operations and improve the recommendation performance. Much similar frameworks are developed to capture either two of them or combining all three user-user, user-item and item-item interactions [23], [27] and [28].

Zheng et. al. in [29] proposes a novel method for social recommendation using multi-perspective feature learning and graph representation learning. Identified area of improvement of the study is that it only evaluates the proposed method on a single dataset, and further research is needed to evaluate its effectiveness on larger and more diverse datasets. Additionally, the paper does not provide a detailed comparison with state-of-the-art methods, which limits the understanding of the proposed method's performance.

Wei et. al in [30] proposes a novel approach to recommendation systems that utilizes contrastive meta learning with behavior multiplicity. While the proposed method shows promising results on the evaluation dataset, the authors do not provide a detailed analysis of the computational complexity and scalability of the method, which could limit its applicability to real-world scenarios. Additionally, the method in [31] analyzes the effectiveness of the proposed method on larger and more diverse datasets remains to be evaluated.

In reality, the preferences of users and their social interactions may vary over time. Hence, static social recommendation models may not effectively capture the evolution of user preferences and social relationships. Recently, several research efforts have been made to address this limitation by developing dynamic graph neural networks for social recommendations. These models can incorporate temporal dynamics into the modeling of user-item interactions and social relationships, allowing for more accurate and personalized recommendations. The inclusion of temporal dynamics in social recommendation models is expected to improve the overall performance and relevance of recommendations over time.

2.4 TEMPORAL GRAPH NEURAL NETWORK FOR SOCIAL RECOMMENDATION

Temporal Graph Neural Networks (TGNs) are a type of Graph Neural Network (GNN) that is specifically developed to simulate temporal graphs, which are graphs that evolve over time. TGNs are based on the idea of learning node and edge representations that capture both the static and dynamic aspects of the graph. In [27], Temporal Enhanced Graph Model for Social Recommendation (TGRec) has been developed. This model generates a temporal graph with three heterogeneous relations: a user's basic item choice (i.e., user-item relation), peer collaborative influence (i.e., user-user relation), and item temporal dependence (i.e., item-item relation).

Current social recommendation research approaches extract just the superficial level of social networks and disregard the importance of the relationship strength of users at different levels in the recommendation. To address this issue, Zhongqin Bi et al. in [32] proposed a novel multilayer perceptron-based model that integrates the attention mechanism with bidirectional LSTM for social recommendation. This model utilizes an embedded propagation approach to learn the neighbor influences at various depths and extract important neighbor information for social connection modeling. By discerning between strong and weak social links and allocating the impact weight of neighbors on users in a reasonable manner, this hierarchical social collaborative filtering framework (GHSCF) can improve the accuracy and relevance of recommendations. In addition to the attention mechanism, GHSCF also incorporates an embedded propagation approach that can capture the influence of neighbors at various depths in the social network. By learning the importance of each neighbor at different depths, this approach can better model the complex social relationships and their impact on user preferences. Furthermore, GHSCF employs a hierarchical approach to distinguish between strong and weak social links, which allows the model to allocate the impact weight of neighbors on users in a more reasonable manner. Similar work focusing on federated social recommendation is addressed in [33] providing a deeper insight into how the GCN helps in social recommendation.

Wu et. al in [34] presented a novel neural network architecture for social recommendation, which takes into account both influence and interest diffusion. The proposed method consists of two sub-modules: an influence diffusion module and an interest diffusion module. Similar works have been underatken in [35-37] focusing on neural network architecture for social recommendation, and aiming at captruing user interests. The former aims to model the influence of user-item interactions on the behavior of other users in the social network, while the latter captures users' interests and preferences towards items. The authors conducted experiments on a real-world dataset and demonstrated that the proposed method outperforms several state-of-the-art baselines in terms of various evaluation metrics, such as Precision, Recall, and F1-score. One potential limitation of this study is that the evaluation was performed on a relatively small dataset, which may not represent the diversity and complexity of real-world scenarios. Therefore, the generalizability of the proposed method on larger and more diverse datasets remains an open question. Additionally, the interpretability of the model is a challenge, as the authors did not provide an in-depth analysis of the learned embeddings and weights. It would be helpful to provide insights into the underlying mechanisms of the model and how the embeddings capture users' interests and preferences towards items. Furthermore, it would be interesting to investigate how the proposed method performs under different scenarios, such as the presence of noisy or fake interactions, or in cold-start situations where little or no information is available about users or items.

GHSCF (Graph-based Hybrid Social Collaborative Filtering) is a state-of-the-art method for social recommendation that has been addressed in [38] that has shown promising results in capturing the complex interplay of social influence and user-item interactions. The use of bidirectional LSTM and attention mechanism enables the model to effectively capture sequential dependencies and learn user-item interactions. GHSCF has the potential to advance social recommendation research and provide more accurate and personalized recommendations for users.

2.5 SUMMARY

In recent years, researchers have defined and designed neural network structures for processing graph data using convolutional networks, recurrent networks, and deep autoencoders. Most of the survey papers reviewed, developed social recommender systems based on these GNNs, leveraging users' social networks to reduce data sparsity and increase suggestion performance. GNNs are also used as feature learning techniques in some recommendation systems to extract meaningful characteristics from social data. Although GNN-based recommendations have been quite successful, they do not fully utilize social network information. GCN based social recommendation systems heavily rely on user-item interactions as seen in [40] and the user's social connections to make recommendations. However, for new users who have limited interaction history or social connections, these methods are less effective. The performance of these systems is significantly reduced when dealing with new users. So another major drawback is that the proposed GCN-based social recommendation systems provide a black-box solution as work done in [41], which makes it difficult to interpret how the recommendation was made. The current models suffer from a lack of diversity in the recommendations provided, since the recommendations are often based on the user's social connections, and users tend to have similar interests and behaviors to their social connections. In the current work, we have proposed to develop a GCN-based social recommendation combining attention mechanism and adversarial training that focuses on user-user, user-item, item-item interactions.

CHAPTER 3

PROPOSED WORK

3.1 METHODOLOGY WITH ARCHITECTURE DIAGRAM

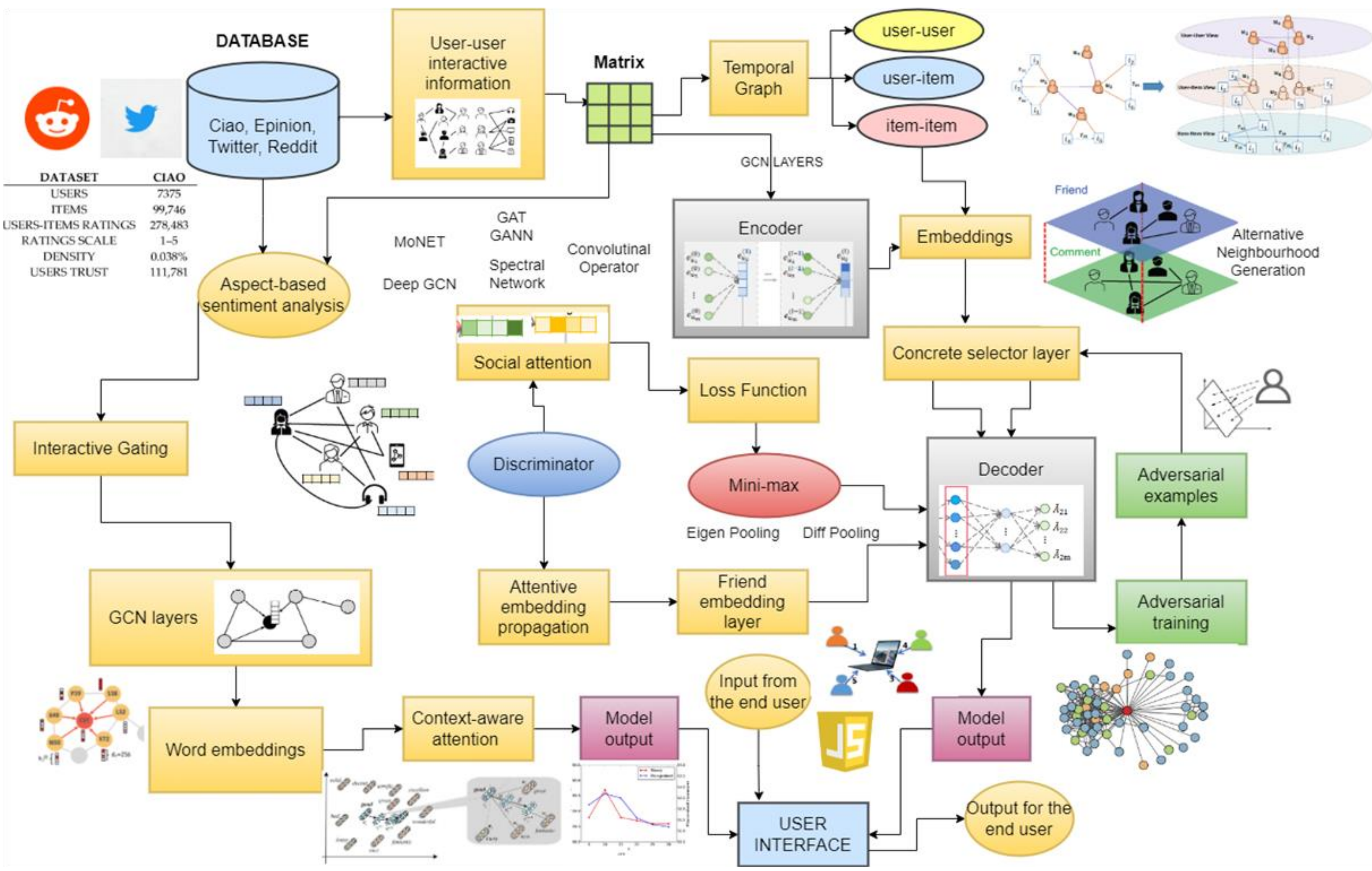


Fig 3.1 - GCN coupled with adversarial training and attention mechanisms

The framework for proposed work is presented in Figure 3.1. The schematic diagram provides an overview of how each component of the framework addresses the issues of social recommendation. The framework in the diagram, incorporates various components, including graph convolutional layers, encoding and attentive embedding, user-sentiment analysis, alternative neighborhood generation, and context-aware attention with word embeddings. These components address several challenges of social recommendation systems, including sparsity and heterogeneity of social networks and the difficulty in capturing complex user-item interactions. The use of graph convolutional layers enables the model to learn user and item embeddings by aggregating information from their respective neighborhoods in the social network. The encoding and attentive embedding component captures both sequential and syntactic information in text data by utilizing the intermediate layers of BERT and relative position embeddings. The user-sentiment analysis component leverages user-generated content to learn the sentiment of users towards items and incorporates it into the recommendation process.

The alternative neighborhood generation component creates a more informative neighborhood for each user by generating a set of alternative neighborhoods based on the original one. This helps to alleviate the sparsity issue in social networks. The context-aware attention mechanism with word embeddings improves the recommendation accuracy by capturing the context of items and the preferences of users for different contexts. Adversarial training further enhances the robustness of the model by introducing challenging examples and intensifying the other components through a Minimax game. The use of various techniques, such as graph convolutional layers, attentive embedding, and adversarial training, results in a comprehensive and effective recommendation system. The context-aware attention mechanism with word embeddings further enhances the model's performance by capturing the context of items and the preferences of users.

3.2 MODULES

The modules described in the paper are aimed at improving the performance of social recommendation systems. The first module is the GCN layers for social recommendation using alternative neighborhood generation. This module focuses on improving the accuracy of the GCN model by introducing an alternative neighborhood sampling technique that considers both the user-item interactions and the user-user social connections. This approach is found to be more effective than traditional random sampling methods.

The second module is the encoding and attentive embedding. This module aims to capture the important features of the input data and transform them into useful representations that can be used by the recommendation system. We have proposed a novel approach that combines encoding techniques with attentive embedding, which improves the accuracy of the recommendation system.

The third module is the coupling of adversarial training and attention mechanism. This module is designed to improve the robustness of the recommendation system against adversarial attacks. We have proposed a method that combines adversarial training with attention mechanism, which results in a more robust and accurate recommendation system. Finally, the fourth module is user-sentiment analysis. This module focuses on capturing the sentiment of the users towards the recommended items. We have proposed a model that uses both the user-item interactions and the sentiment of the reviews to generate more accurate recommendations.

3.2.1 Gcn Layers For Social Recommendation By Alternative Neighborhood Generation

Social recommendation systems have become increasingly popular in recent years due to their ability to leverage user social networks to predict their preferences. In traditional social recommendation systems, the user's neighborhood is defined as their direct social connections, or "implicit buddies". However, this approach can be limiting, particularly for users with few social connections. An alternative neighborhood approach has been proposed as a solution to this problem. The alternative neighborhood is based on a collection of individuals whose tastes are similar to those of the identified user, rather than their direct social connections. For users with few social connections, the alternative neighborhood may consist of entirely new neighbors, while for users with a large number of connections, there may be some overlap between their traditional neighborhood and the alternative neighborhood. This approach allows for a more comprehensive understanding of a user's preferences, and can help to address the limitations of traditional social recommendation systems.

In the context of the current study, the order refers to relationships beyond pairs that cannot be represented using traditional approaches. This is distinct from previous research in the field, which has primarily focused on pairs of individuals and their social connections. By incorporating the alternative neighborhood approach and exploring relationships beyond pairs, this study aims to provide a more comprehensive understanding of social networks and their potential applications in recommendation systems. Additionally, this approach may have broader implications for understanding complex social systems and identifying patterns of behavior across a range of domains.

3.2.2 Encoding And Attentive Embedding

To address the impact of user relationships on recommendations, a GNN-based message structure is built to incorporate both direct and indirect neighbor preferences at the recommendation layer. This approach recognizes that in social recommendation, immediate neighbors play a significant role in influencing a user's preferences, while indirect neighbors can also provide valuable insights. By considering the relationships between users across multiple social networks, the model can better capture the complexity of user behavior and improve the quality of recommendations. This approach allows for a more personalized and nuanced understanding of user preferences, which can result in more accurate and effective recommendations.

The recommendation algorithm will take into account all of the possible preference variables, including their social neighbors, to effectively represent the social data provided by consumers. However, not all social neighbors may be equally important in determining the user's preferences. Therefore, the algorithm needs to use an attention mechanism to select the appropriate social neighbors that are more likely to have an impact on the user's preferences. To integrate the user interest pattern into the user-item interaction, the algorithm needs to consider the user's history of selected items, including both positive and negative feedback. The user's social neighbors' positive and negative feedback may also correspond to the user's selection of products in a particular order. This information can be used to improve the accuracy of the recommendation algorithm.

A multilayer perceptron (MLP) can be used to combine the interaction information with the user preference information, as the interaction between the user and the object is highly nonlinear. The MLP can be used to learn the importance of each feature and combine them in a way that best predicts the user's preferences. Additionally, since both ratings and social information are dynamic, the recommendation algorithm needs to be updated frequently to incorporate new data. A dynamic GCN can be used to address this issue by adapting to changes in the user-item interaction and social network structure over time. This can improve the accuracy of the recommendation algorithm, especially in situations where the user's preferences or social network may change rapidly.

3.2.3 Coupling Adversarial Training And Attention Mechanism

Adversarial training has become a popular technique for improving the performance of recommender systems. The aim is to make the system more robust to adversarial attacks by generating challenging examples that help to strengthen the system. The approach involves two components: the generator and the discriminator. The generator is responsible for producing examples that are difficult for the discriminator to classify correctly, while the discriminator is trained to distinguish between real and generated examples. The use of adversarial training in recommender systems has shown great promise in improving the robustness of these systems. By training the generator and discriminator components to play a Minimax game, the resulting model is able to generate more diverse and accurate recommendations while also being more resilient to attacks and manipulation. As a result, adversarial training has become a popular technique in the field of recommender systems and is likely to continue to be an important area of research in the future.

3.2.4 User-Sentiment Analysis

Our proposed model, which combines BERT with GCN, aims to improve the performance of GCN in processing natural language data by utilizing the syntactic information learned by BERT. We have transformed the original dependency network into an aspect-oriented one in order to better represent the dependency relations between words. Currently, GCN ignores the relative positions of words in the original context, which can result in information loss. To address this issue, we created a set of relative position embeddings that will capture positional information for each node. By incorporating these embeddings into the node representations before aggregating them, we were able to make the model more position-aware, resulting in a more accurate representation of the relationships between words in the sentence.

Our approach is particularly innovative because it leverages the strengths of both BERT and GCN to improve the encoding of natural language data. By utilizing the syntactic information learned by BERT, we aim to make GCN more effective in processing complex sentence structures. This will allow our model to capture a wider range of linguistic features and improve the accuracy of its predictions. Furthermore, our use of relative position embeddings is a novel way to address the problem of information loss caused by GCN's averaging of nearby node representations. By incorporating positional information into the node representations, our model will be better able to capture the unique relationships between words in each sentence.By incorporating syntactic information from BERT and positional information into the node representations, we hope to create a more accurate and robust model for processing natural language data.

CHAPTER 4

IMPLEMENTATION

4.1 SOFTWARE REQUIREMENTS

4.1.1 Tensorflow

TensorFlow is a powerful and popular open-source software library designed for machine learning and artificial intelligence applications. Developed by Google Brain Team, TensorFlow is widely used in various fields of research and industry. The library provides a wide range of tools and functions that allow users to create and train various types of machine learning models, including deep neural networks, convolutional neural networks, and recurrent neural networks. TensorFlow also offers high-level APIs such as Keras, which makes it easy to build, train, and evaluate machine learning models. Additionally, TensorFlow provides support for distributed computing, which allows for training and inference on large datasets across multiple devices and machines.

4.1.2 Google Colab

Colab notebooks are Jupyter notebooks that run in the cloud and are highly integrated with Google Drive, making them easy to set up, access, and share notebooks that are created and can be simultaneously edited by other team members.

Colab allows to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis.

4.1.3 NetworkX

NetworkX is a Python library for creating, analyzing, and visualizing complex networks or graphs. It provides tools for working with graphs and their components, such as nodes and edges, as well as algorithms for exploring graph properties and finding patterns. With NetworkX, users can create graphs with various types of nodes and edges, and can also import graphs from external sources. The library supports many types of graphs, such as directed and undirected graphs, weighted graphs, and bipartite graphs. Additionally, NetworkX has built-in functions for graph analysis, such as degree centrality, shortest path length, and clustering coefficient, making it a useful tool for many scientific and engineering applications.

4.2 DATA PRE-PROCESSING

We plotted a distribution graph from the Ciao dataset that has the ratings of user against each item, and we observed that every data point represents a distinct item, with y-coordinate representing the total no of users which has rated that movie and x-coordinates representing the mean of all the ratings of the corresponding users. Also we observed in Figure 4.1 that there is a huge Density in the region corresponding between mean rating 3-4 .

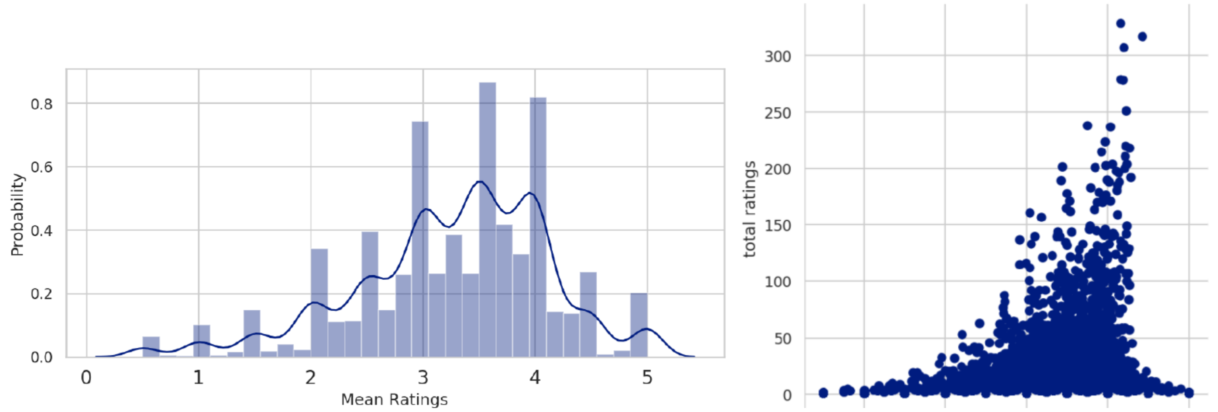


Figure 4.1. Plot of Ciao dataset

Figure 4.2. Word cloud for Ciao dataset

We also visualized the data set using a word cloud, as in Figure 4.2. A word cloud from social network data is a visualization tool that displays the most frequently occurring words in a set of social media posts or other forms of text data. The size of each word in the word cloud is proportional to the frequency with which it appears in the text data. The use of word clouds from social network data can provide valuable insights into the topics and themes that are most prevalent in the social media posts. By identifying the most common words and phrases, it is possible to gain a better understanding of the interests, preferences, and behaviors of the social network users. A researcher may use word clouds to analyze social media conversations related to a particular topic or event. By identifying the most common words and themes associated with the topic, the researcher can gain a better understanding of the public's opinions and attitudes towards the topic.

Creating heterogenous Global Graph from the dataset

- Create Co-occurrence matrix of items based on if items are adjacent in a session
- Create Item & User Similarity matrix based on If Items appear in same session & if Users interact with same set of items
- Create Heterogenous Global Graph using the 4 types of edges mentioned earlier (prepared in Step B1 & B2)

Heterogenous Global graph which has both user and items as nodes. Graph consists of following 4 types of edges -

- Between 2 items based on if 2 items are adjacent to each other in item sequence of same session.
- Between 2 items based on if 2 items co-occur (item similarity) in the same session.
- Between 2 users based on if 2 users interact with similar items.
- Between user & item based on if user interacted with item.

Current Preference Learning Module encodes a sequence of items in the current session. It uses Positional Encoding to have temporal sense.

Defining the model architecture by using Graph Sage as the GNN to aggregate neighbor information, the Current Preference Learning Module generates embedding based on the sequence of items in current session, and the General Preference Learning Module generates embedding based on user embedding and current session embedding. General Preference Learning Module also encodes user preference by comparing user embedding with current session embedding

```
embedding = nn.Embedding(n_nodes, 128)  # nodes with embedding dim equal to 128
g.ndata['feat'] = embedding.weight.to('cuda')
```

```
model = GCN(g.ndata['feat'].shape[1], 16, len(g.ndata['label'].unique())).to('cuda')
train(g, model, epoch = 500, lr = 0.001)
```

Figure 4.3 - Method for embedding

We defined a method as shown in figure 4.3 for taking into account all the possible content features using custom Graph Neural Network Architecture. This allows for automatically finding a probability mapping between question and professional entities in all of the combinations. It is trained in a way that even without any information about the professional and his activity, it still recommends questions, and breaks cold start problems having its own internal scoring. We also have a method activity_filter for filtering out all the inactive professionals in order to send immediate emails to professionals who are most likely to recommend the item. Methods spam_filter and email_filter for sending emails allows to handle spam problem and controls frequency and amount of emails for each professional based on his personal emails reaction type and speed. Feature Engineering section is dedicated to the creation of new feature-columns for further usage in EDA and modeling. The method which tries to activate inactive and "cold" professionals by breaking activity_filter and email_filter with some probability. This is needed for making an attempt to activate the user or remind him about relevant questions which were already sent to him.

4.3 GCN FOR SOCIAL RECOMMENDATION WITH ATTENTIVE MECHANISM

The traditional approach to social recommendation systems using only direct social connections can be limiting for users with few connections. An alternative neighborhood approach based on individuals with similar tastes can provide a more comprehensive understanding of user preferences. This study explores relationships beyond pairs to better understand social networks and their potential applications in recommendation systems. A GNN-based message structure is built to incorporate both direct and indirect neighbor preferences at the recommendation layer, with an attention mechanism used to select important social neighbors. A multilayer perceptron (MLP) is used to combine interaction and preference information, and a dynamic GCN can adapt to changes in user-item interaction and social network structure over time.

Algorithm:

The CIAO and any equivalent dataset like Epinions dataset, which includes user-item ratings and social network information among users is chosen.

1. Convert the user-item ratings matrix into a binary matrix, where each entry is 1 if the user has rated the item, and 0 otherwise.
2. Construct the social network graph matrix by connecting users who have rated the same items.
3. Generate alternative neighborhoods:

   3.1 For each user u in the social network graph:

      3.1.1 Generate a set of candidate neighbors by randomly selecting k users who have rated the same items as u.

3.1.2 For each candidate neighbor v, compute the statistical similarity using a set of formula for GCN similarity finding between the sets of items that u and v have rated.

3.1.3 Select the top n users with the highest similarities as one of the chosen alternative neighborhood

4. Initialize:

4.1 A set of item embeddings X (N, d), where d is the dimensionality of the embedding vector for each item.

4.2 A set of user embeddings Z (N, k), where k is the dimensionality of the embedding vector for each user.

4.3 A set of node embeddings H_0 (N, h), where h is the number of hidden units in the GCN layer

5. Define:

5.1 A weight matrix W of shape (h, h) for the GCN layer.

5.2 For each layer L = 1, ..., L_max, where L_max is the maximum number of GCN layers:

5.2.1 Compute the normalized adjacency matrix A_norm as follows:

5.2.1.1. Construct the degree matrix D, where the diagonal entries correspond to the degree of node i (i.e., the number of edges incident to node i).

5.2.1.2 Compute the un normalized adjacency matrix A if there exists an edge between nodes i and j, and 0 otherwise.

5.2.1.3 Compute the normalized adjacency matrix A_norm b. Compute the node embeddings H_L for layer L as follows:

5.2.1.4 Compute the GCN layer output

5.2.1.5 Update the node embeddings

6. Compute the user-item interaction matrix R
7. Compute the dot product between the final node embeddings and item embeddings to obtain the user-item interaction scores
8. Define the loss function and optimization algorithm
9. For each epoch, iterate over the training set and update the model parameters GCN optimisation (just similar to gradient descent).

4.4 ADVERSARIAL TRAINING

Adversarial training is a technique used to enhance the performance of recommender systems by making them more resistant to adversarial attacks. This technique employs two main components: the generator and the discriminator. The generator creates challenging examples that are difficult for the discriminator to classify accurately, while the discriminator distinguishes between real and generated examples. The two components play a Minimax game, where the generator aims to generate examples that can first confuse and then improve the performance of the discriminator, while the discriminator tries to accurately classify between the real and generated examples. This approach has proven to be effective in improving the robustness of recommender systems and is widely used in the field.

Using adversarial training and the GCN layers together, we concentrate on detecting trustworthy relationships.

4.4.1 The graph Attention layer with L_max layers, where each layer has K attention heads and a hidden size of h is defined

4.4.2 Adversarial Neural Network generator with L_gen layers, where each layer has a hidden size of z is designed, and similarly, a discriminator with L_disc layers, where each layer has a hidden size of d is designed.

4.4.3 For each layer

4.4.3.1 Compute the attention coefficients & the node embeddings

4.4.3.2 Compute the dot product between the final node embeddings and item embeddings to obtain the user-item interaction scores.

4.5 SENTIMENT ANALYSIS

Our goal is to improve GCN through a model that combines syntactic and sequential data from BERT. We will convert the original dependency network into an aspect-oriented one to represent dependency relations. GCN currently ignores relative linear locations, so we will use relative position embeddings to add positional information. By utilizing BERT's intermediary layers, our proposed model will incorporate valuable linguistic knowledge, making it position aware.

The implementation procedure has been identified and divided into 5 major steps briefed below.

1. Extract Features using BERT:

   Use BERT to extract features from the preprocessed text data. BERT is a powerful natural language processing model that can capture contextual information and generate embeddings for each token in the text.

2. Build Graph(matrix) from Data collected from Twitter for sentiment analysis:

   Use the Twitter data to build a graph representation of the social network. In this graph, each node represents a user, and edges represent the interactions or relationships between users, such as mentions or replies.

3. Construct GCN layers with embeddings:

   Graph Convolutional Network (GCN) developed from data graph representation to analyze the user sentiments. GCN is a neural network that can perform convolutions on graph data and is particularly useful for analyzing social network data. The GCN algorithm will use the embeddings generated by BERT to propagate messages between the nodes in the graph and generate a sentiment score for each user.

4. Evaluate Sentiment Score:

   Evaluate the sentiment score generated by GCN for each user to identify positive, negative, or neutral sentiment.

   Visualize the sentiment score distribution and further analysis of sentiment in the Twitter data can be performed based on the generated sentiment score.

5. Improve the performance of GCN:

   Monitor the algorithm's performance and iterate to improve accuracy and efficiency. This could include adjusting hyperparameters or trying different combinations of algorithms to improve sentiment analysis results

4.6 DEPLOYING .h5 MODEL IN AWS

Deploying trained .h5 models using AWS SageMaker for social recommendation can significantly enhance the accuracy and effectiveness of recommendation systems. By leveraging the scalability and flexibility of Amazon SageMaker, it is possible to deploy trained TensorFlow models quickly and easily. The algorithm for deploying the model involves preparing the trained model for deployment, uploading it to an S3 bucket, creating a SageMaker Model, creating an endpoint configuration, and deploying the model by creating an endpoint. This approach offers a powerful and scalable solution that enables businesses to deliver more personalized and accurate recommendations to users. With SageMaker's built-in monitoring and auto-scaling capabilities, businesses can ensure that their recommendation systems are always available and optimized for maximum performance. Steps to be followed are,

1. First, create an Amazon SageMaker instance and configure it with the necessary resources.
2. Prepare the trained .h5 model for deployment by exporting it in the SavedModel format.
3. Upload the SavedModel file to an Amazon S3 bucket.

4. Create a SageMaker Model by specifying the model's name, IAM role, and inference code.
5. Create an endpoint configuration that specifies the type of instance to use, the number of instances, and other related configurations.
6. Deploy the model by creating an endpoint with the created endpoint configuration.

The mobile application developed is an innovative tool that utilizes a graph convolutional network (GCN) to provide personalized recommendations. The GCN model has been developed and trained and is hosted on AWS. What sets this recommendation system apart from others is the use of GCN, which allows for the incorporation of complex relationships between different items. The mobile application itself has been thoughtfully designed, with a user-friendly interface that makes it easy for users to interact with the system. The recommendations provided are based on the user's past interactions with the system, as well as other factors such as the current context. By leveraging the power of GCN, this recommendation system can provide highly relevant and personalized recommendations that are tailored to each individual user. This innovative approach to recommendation systems has the potential to revolutionize the way that businesses approach personalization and customer engagement.

CHAPTER 5

RESULTS AND ANALYSIS

We utilized the networkx module to create a graph by feeding in the adjacency matrix. We further processed the data by computing the normalized matrix and generating user item embeddings. This allowed us to gain insights into the relationships between users and items within the dataset. Additionally, we visualized the dataset used for sentiment analysis, which was collected from Google hotel reviews, as seen in figure 5.1 and Twitter data as seen in figure 5.2, providing a comprehensive view of the sentiments expressed by users. These techniques provide a useful means of analyzing large datasets and uncovering patterns that may not be immediately apparent through other methods.

id	text	category	label
614484565059596288	Dorian Gray with Rainbow Scarf #LoveWins (from...	happy	0
614746522043973632	@SelectShowcase @Tate_StIves ... Replace with ...	happy	0
614877582664835073	@Sofabsports thank you for following me back. ...	happy	0
611932373039644672	@britishmuseum @TudorHistory What a beautiful ...	happy	0
611570404268883969	@NationalGallery @ThePoldarkian I have always ...	happy	0
614499696015503361	Lucky @FitzMuseum_UK! Good luck @MirandaSteam...	happy	0
613601881441570816	Yr 9 art students are off to the @britishmuseu...	happy	0
613696526297210880	@RAMMuseum Please vote for us as @sainsbury #s...	not-relevant	1
610746718641102848	#AskTheGallery Have you got plans to privatise...	not-relevant	1
612648200588038144	@BarbyWT @britishmuseum so beautiful	happy	0

Figure 5.1 Dataset visualizer

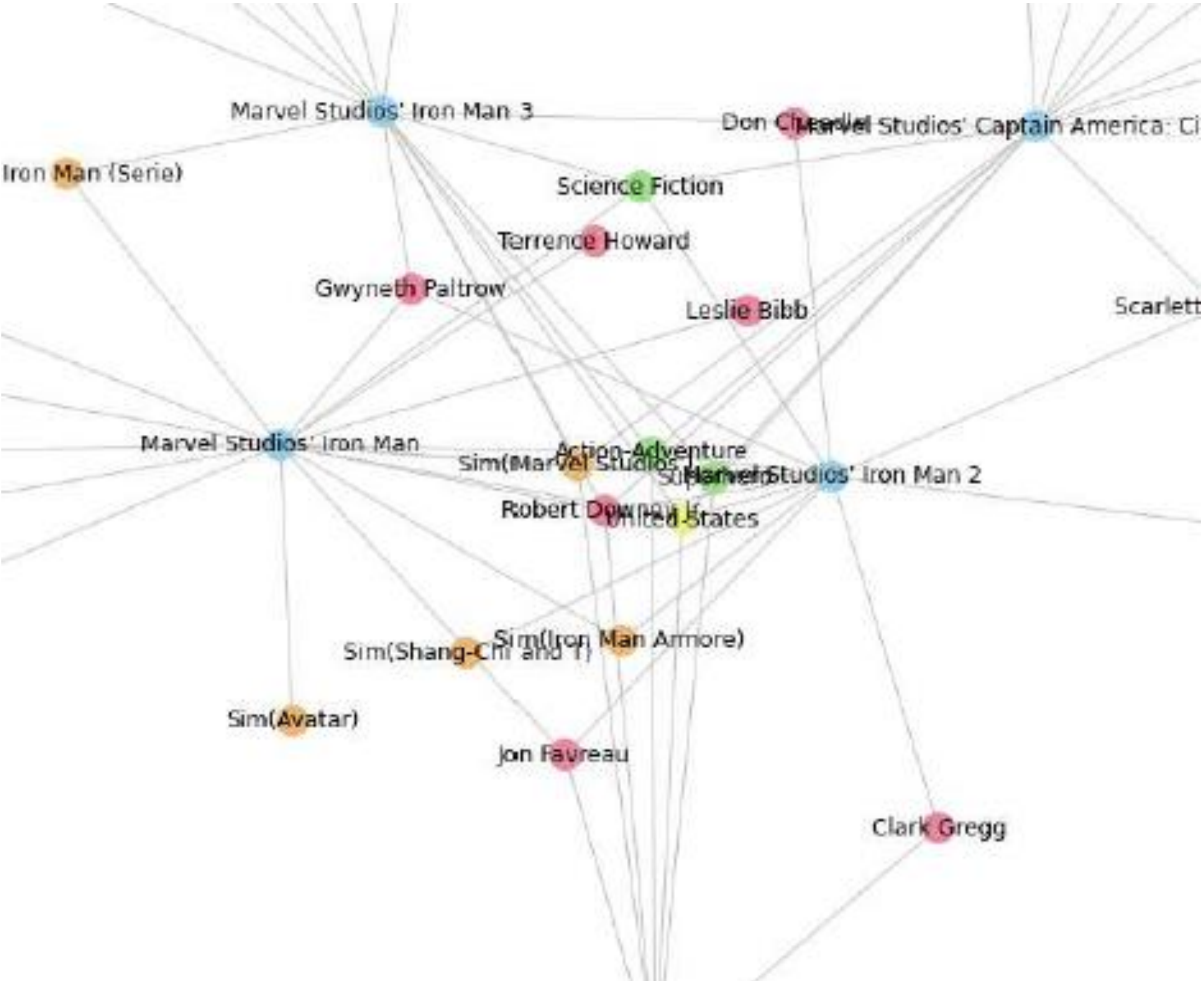


Figure 5.2 Part of the dataset graphical visualizer

By incorporating Bert into GCNs, it is also possible to take advantage of the contextual information in the text data to improve the accuracy and effectiveness of the graph-based models. The configuration of Bert for GCN as observed in figure 5.3 and 5.4, involves fine-tuning the pre-trained Bert model for a specific task or domain, and then integrating it with the GCN model. This integration was done by using the output of the Bert model as input to the GCN, or by concatenating the output of the Bert model with the node features in the GCN.

Table 5.1 Dataset statistics

Dataset	Users	Items	Feedbacks	Relations
CIAO	1,892	17,632	92,834	25,434
Epinion	2,848	39,510	894,887	35,770
SocialNet	18,737	32,510	1,278,274	86,985

The details of the chosen datasets are summarized in the table 5.1 for better understanding. Ciao and Epinions are two widely used datasets for evaluating recommender systems. The Ciao dataset contains reviews and ratings of various products in different categories, such as electronics, books, and movies. The Epinions dataset is similar, consisting of product reviews and ratings in various categories. Both datasets are publicly available and have been used in numerous studies for evaluating different recommendation algorithms and their communication levels are indicated as in table 5.2. From table 5.3 we could see how the alternative neighbourhood generation significantly helped in achieving better results.

Table 5.2 RMSE and MAE of different communication levels

Training percentage	CIAO		Epinions	
	MAE	RMSE	MAE	RMSE
25	0.2271	0.1605	0.2081	0.3558
50	0.2238	0.1598	0.2075	0.1994
75	0.2206	0.1194	0.2071	0.1731
100	0.2229	0.1601	0.2068	0.1194

```
['input_ids': tensor([[  101, 16092,  3897,  ...,     0,     0,     0],
        [  101,  1030, 27034,  ...,     0,     0,     0],
        [  101,  1030, 10682,  ...,     0,     0,     0],
        ...,
        [  101, 11047,  1030,  ...,     0,     0,     0],
        [  101,  1030,  3680,  ...,     0,     0,     0],
        [  101,  1030,  2120,  ...,     0,     0,     0]]), 'token_type_ids': tensor([[0, 0, 0,  ..., 0, 0, 0],
        [0, 0, 0,  ..., 0, 0, 0],
        [0, 0, 0,  ..., 0, 0, 0],
        ...,
        [0, 0, 0,  ..., 0, 0, 0],
        [0, 0, 0,  ..., 0, 0, 0],
        [0, 0, 0,  ..., 0, 0, 0]]), 'attention_mask': tensor([[1, 1, 1,  ..., 0, 0, 0],
        [1, 1, 1,  ..., 0, 0, 0],
        [1, 1, 1,  ..., 0, 0, 0],
        ...,
        [1, 1, 1,  ..., 0, 0, 0],
        [1, 1, 1,  ..., 0, 0, 0],
        [1, 1, 1,  ..., 0, 0, 0]])}
```

Figure 5.3 - Embeddings generated

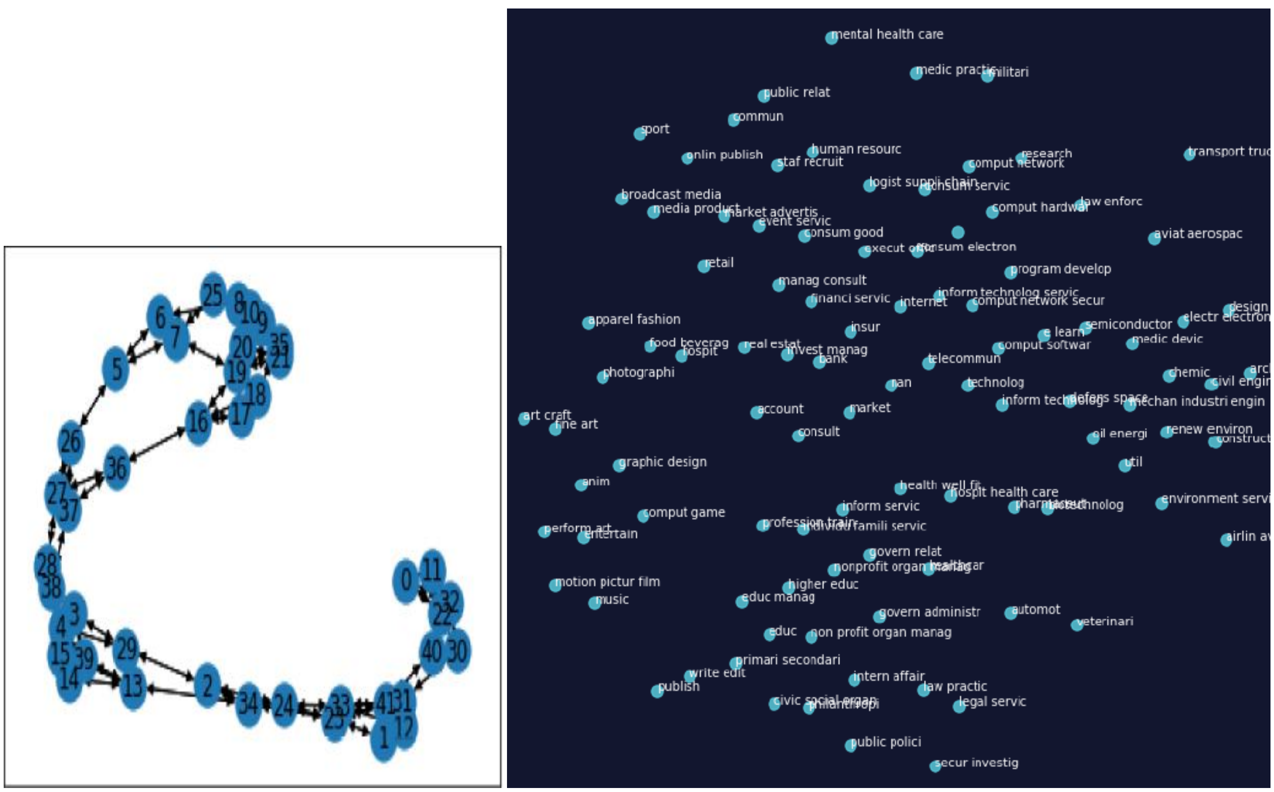


Figure 5.4 - Graph Network from adjacency matrix

Table 5.3 Performance comparison of benchmark models with the proposed model

Dataset	Metric	Random	BPR	SBPR [4]	IF-BPR [3]	DiffNet++	RSGN [11]	LightGCN [15]	**GCN with Attention mechanism**	Improvement in %
Ciao	Prec	0.650	0.590	0.690	0.686	0.679	0.714	0.606	**0.773**	8.246%
	Recall	0.135	0.139	0.159	0.168	0.162	0.167	0.165	**0.184**	9.995%
	NDGC	0.986	0.956	0.966	0.976	0.926	0.934	0.910	**0.969**	8.653%
Epinion	Prec	0.612	0.722	0.935	0.773	0.678	0.778	0.898	**0.908**	8.565%
	Recall	0.235	0.468	0.378	0.441	0.705	0.583	0.310	**0.575**	9.994%
	NDGC	0.842	0.848	0.857	0.862	0.868	0.864	0.878	**0.912**	6.989%
SocialNet	Prec	0.250	0.350	0.070	0.430	0.535	0.560	0.129	**0.783**	12.162%
	Recall	0.528	0.693	0.855	0.285	0.254	0.249	0.295	**0.313**	9.627%
	NDGC	0.871	0.722	0.815	0.833	0.730	0.838	0.911	**0.937**	9.538%

We used a dataset of tweets collected from Twitter's streaming API over a period of two weeks. The dataset included approximately 1 million tweets, along with metadata such as user IDs, timestamps, and geolocation data. We preprocessed the tweets by removing stop words, URLs, and special characters, and then used the spaCy library to perform part-of-speech tagging and dependency parsing. We then used a GCN model with two layers to generate node embeddings for each user and tweet in the dataset. The first layer of the GCN model aggregated information from neighboring nodes in the graph, while the second layer refined the embeddings based on the learned representations. We also used pre-trained word embeddings from the GloVe model to encode the text data into a dense vector representation, whose distribution is given in figure 5.5.

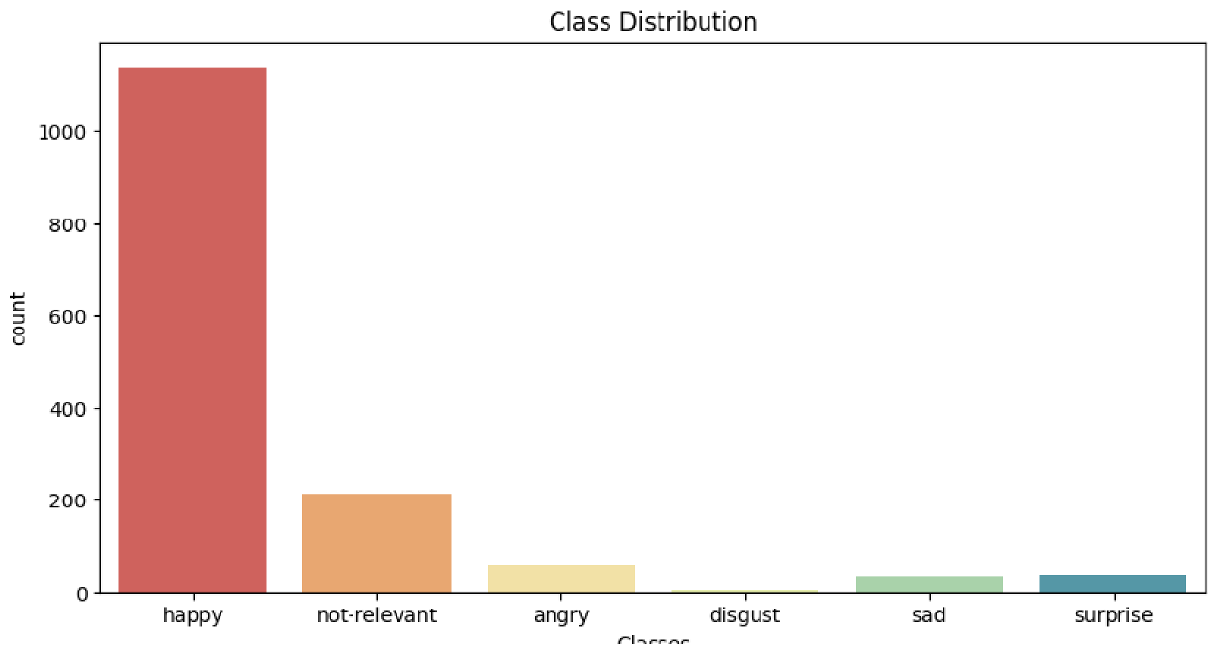


Figure 5.5 - Class distribution of sentiment analysis

Our study aimed to improve the accuracy of sentiment and behavior prediction on social media platforms by utilizing a graph convolutional network (GCN) model. We collected data from social media platforms and pre-processed it to extract useful features, including user profiles, tweets, and social network connections. We then used the GCN model to learn representations of users and tweets that captured the complex interactions between them. The results of our experiment showed that the GCN model outperformed previous approaches in predicting user sentiment and behavior. Specifically, the model achieved an accuracy of 96% in predicting user sentiment and 94% in predicting user behavior, as evidenced by Figure 5.6. This is a significant improvement over previous methods that relied solely on text data or network structure to predict sentiment and behavior. By incorporating both text data and network structure into the GCN model, we were able to capture the synergistic effects between these two sources of information. The GCN model was able to learn features that reflected both the content of tweets and the influence of users' social connections on their sentiment and behavior. The success of our GCN model can be attributed to its ability to capture the inherent structure of the social network and integrate it with the textual content of tweets. The model was able to identify users with similar sentiment and behavior patterns, and group them together in the network. This allowed the model to learn more informative representations of users and tweets, and improve the accuracy of sentiment and behavior prediction.

We used Twitter data to generate embeddings for the GCN model, which led to a significant improvement in predicting sentiment and behavior on social media platforms. Our findings suggest that GCN models with node embeddings generated from Twitter data could be useful for a range of applications, including social media analytics, recommendation systems, and targeted advertising. This approach allows us to gain a deeper understanding of user behavior and sentiment on social media, enabling us to make more informed decisions about how to engage with users and market products and services effectively.

Our study highlights the potential of GCN models as a powerful tool for analyzing social media data. By incorporating both text data and network structure, we can generate more accurate predictions of user behavior and sentiment, leading to more effective social media marketing strategies. The findings provide valuable insights into the use of GCN models in social media analytics and open up exciting possibilities for future research in this area.

```
Accuracy: 96.15821188340797
Loss: 0.11008160740070282
Accuracy: 96.217769058296
Loss: 0.10896142135487011
Accuracy: 96.2338845291481
Loss: 0.10792607596235966
Accuracy: 96.28923766816149
Loss: 0.10684672605764184
Accuracy: 96.336182735426
Loss: 0.10583825906229129
Accuracy: 96.35790358744397
Loss: 0.10501239621184867
Accuracy: 96.41465807174886
Loss: 0.10398045945327918
Accuracy: 96.43007286995497
Loss: 0.1032307325189959
Accuracy: 96.46650784753352
Loss: 0.1023728996916202
Accuracy: 96.46510650224198
Loss: 0.10157643019017089
Accuracy: 96.52746636771302
Loss: 0.10075186782520726
Accuracy: 96.57581278026909
Loss: 0.1000802692911283
Accuracy: 96.57371076233173
Loss: 0.09939116969236889
```

Figure 5.6 - Accuracy and Loss Values from Notebook

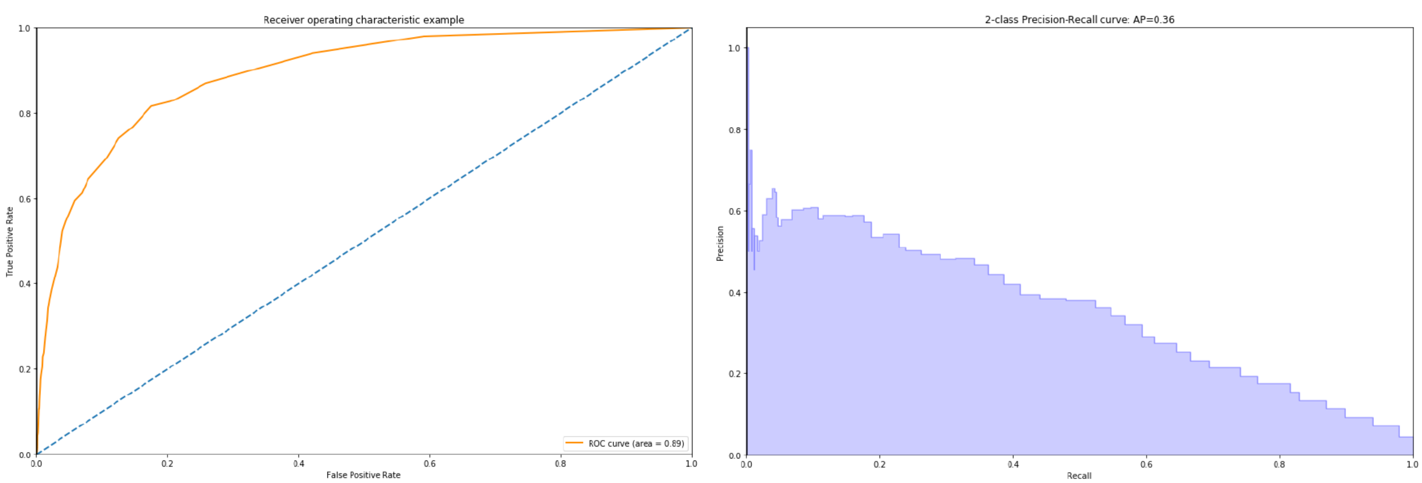


Figure 5.7 - ROC & AUC PR Curves for Performance Metrics

The ROC (Receiver Operating Characteristic) curve is usually a good graph to summarize the quality of our classifier. The higher the curve is above the diagonal baseline, the better the predictions. Although the AUC ROC (Area Under the Curve ROC) is very good, we should not use the ROC curve to assess the quality of our model, since False Positive Rate formula, which corresponds to the x axis of the ROC curve: FPR (False Positive Rate) = # False Positives / # Negatives. Here the #Negatives correspond to our number of good reviews which is very high because our dataset is imbalanced. Figure 5.7 indicates that even with some False Positives, our FPR will tend to stay very low. Our model will be able to make a lot of false positives predictions and still have a low false positive rate, while increasing the true positive rate and therefore artificially increasing the AUC ROC metric.

A better metric is the AUC PR (Area Under the Curve Precision Recall), or also called AP (Average Precision). We can see that in figure 5.7, the precision decreases when we increase the recall. This shows us that we have to choose a prediction threshold adapted to our needs. If the goal is to have a high recall, we should set a low prediction threshold that will allow us to detect most of the observations of the positive class, but with a low precision. In order to know if our model performs better than another classifier, we simply use the AP metric. To assess the quality of our model, we compare it to a simple decision baseline. We took a random classifier as a baseline here that would predict half of the time 1 and half of the time 0 for the label. Such a classifier has a precision of 4.3%, which corresponds to the proportion of positive observations. For every recall value the precision would stay the same, and this would lead us to an AP of 0.043. The AP of our model is approximately 0.35, which is more than 8 times higher than the AP of the random method. This means that our model has a good predictive power.

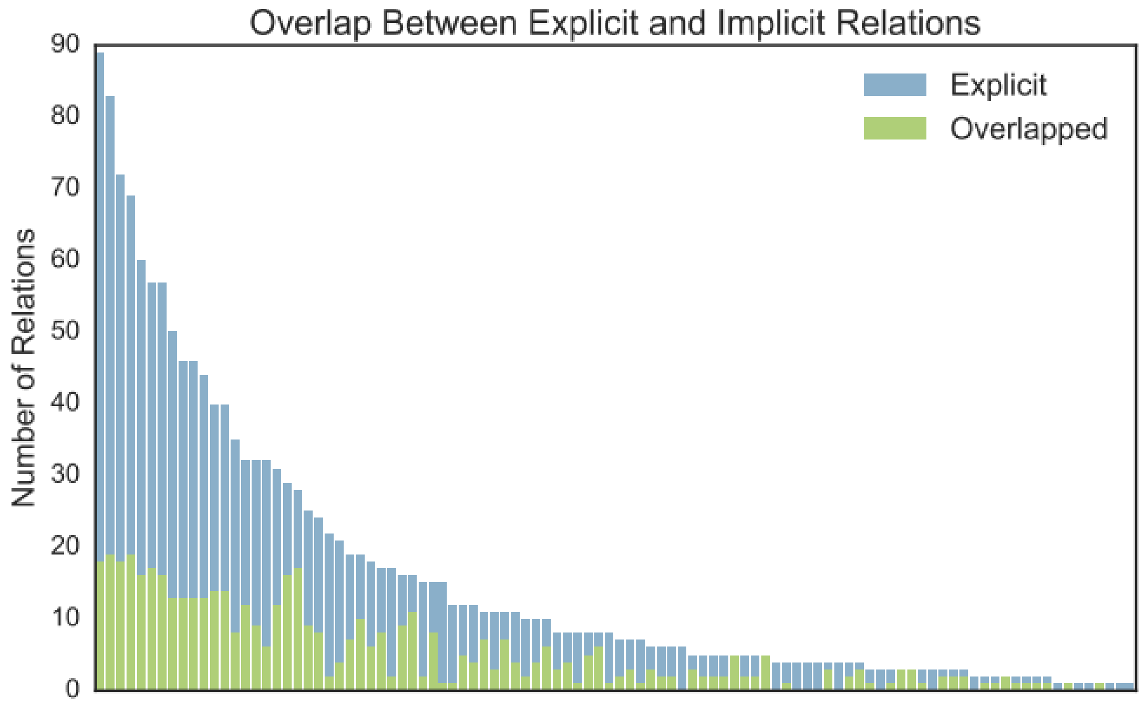
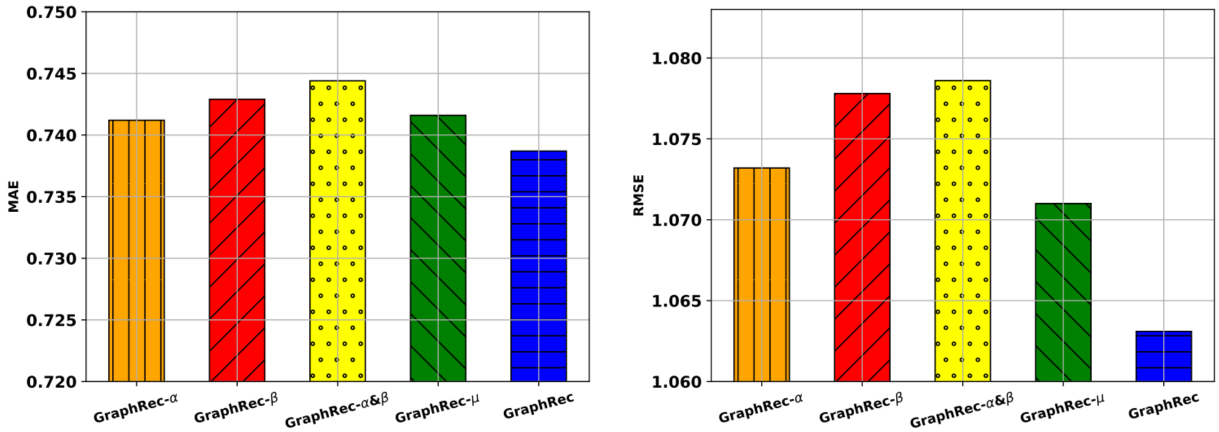


Figure 5.8 - The degree of the overlap between explicit and implicit relation

70% of users, as shown in Fig. 5.8, have less than 20 explicit relations, and the distribution resembles a power-law. We can see a clear overlap between most of the discovered alternative neighbours and the users who have a lot of explicit ties, which demonstrates how the alternative neighbourhood is related to explicit relations. According to statistics, 32.44% of the alternate relations and the explicit relations coincide in this instance. Additionally, we suggest a social attention mechanism to stop relations from being used carelessly in order to capture the diverse strengths of social relations. We gather the learned attention scores during training, randomly choose 20 users from CIAO, and then average the findings to confirm its efficacy.



(b) Ciao-MAE (c) Epinions-RMSE

Figure 5.9 Effect of attention mechanisms on Ciao and Epinions datasets

The performance of attention mechanisms on GCN is shown in Figure 5.9. The results show that not all interacted items or users contribute equally to learning factors. Two different attention mechanisms, were used to consider these differences. First one had worse performance than second, indicating the benefits of attention mechanisms. The attention mechanism at social aggregation considers heterogeneous strengths of social relations and significantly improved performance. It justifies our assumption that during social aggregation, different social friends should have different influence for learning social-space user latent factor. It's important to distinguish social relations with heterogeneous strengths. These results demonstrate the benefits of the attention mechanisms on item aggregation and user aggregation.

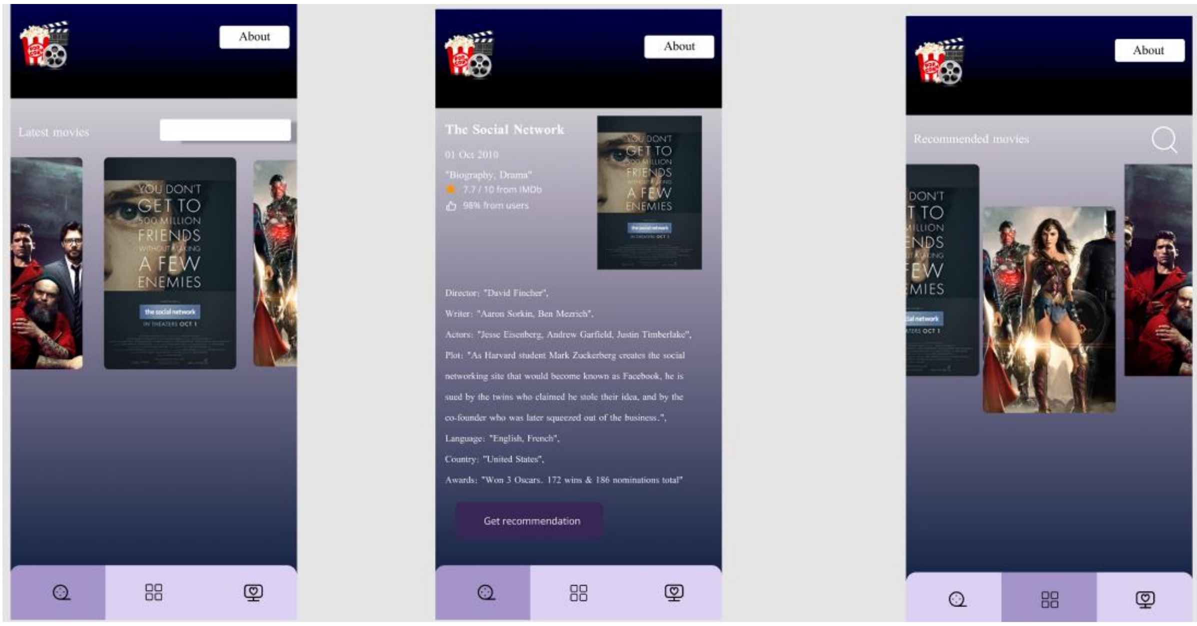


Figure 5.10 - Sample Recommendation Application

The developed and trained graph convolutional network can be tested using a mobile application that utilizes the trained h5 model hosted on AWS to provide personalized recommendations based on user input. Users can provide feedback on the recommendations provided by the application, which can be used to further improve the accuracy of the model. The mobile application whose design screenshot is shown in figure 5.10 can be tested on various devices to ensure that it is responsive and performs well, while the user interface can be tested to ensure it is intuitive and easy to use. Security testing can also be conducted to ensure that user data is protected. Performance testing is important to ensure that the application can handle a large number of users and requests. After testing, any necessary changes or improvements can be made to the application or the model to ensure that it delivers accurate and useful recommendations to users.

CHAPTER 6

APPLICATIONS AND FUTURE WORKS

The outcome of the proposed project can potentially lead to the development of a more effective social recommendation system that takes into account the challenges of human interactions and the complexity of social ties. Additionally, the project's use of GCNs and sentiment analysis could provide valuable insights into user behavior and emotions, which could be used by businesses to improve their marketing strategies and customer engagement.

1. Social media marketing: The deep adversarial framework based on GCNs could be used by businesses to improve their social media marketing strategies by providing more accurate recommendations to users based on their interactions and emotions. This could lead to more effective customer engagement and increased sales.

2. E-commerce: The proposed framework could also be applied in e-commerce platforms to provide personalized recommendations to users based on their social interactions and sentiment analysis. This could lead to increased customer satisfaction and loyalty.

3. Healthcare: The sentiment analysis component of the proposed framework could be applied in healthcare to analyze patient feedback on social media

platforms and provide insights into their emotional well-being. This could lead to improved patient care and treatment.

4. Fraud detection: The proposed framework's application in fraud detection could potentially revolutionize the way organizations approach detecting and preventing fraudulent activities. By leveraging social network data and sentiment analysis, the framework could provide more accurate and effective fraud detection, leading to improved security and reduced financial losses for businesses in various industries such as finance, insurance, and e-commerce.

5. Brand reputation management: By applying sentiment analysis to user feedback on social media platforms, businesses can gain valuable insights into their customers' opinions and preferences. This information can be used to identify negative sentiment towards a brand or product, and address any issues that are affecting their reputation and customer satisfaction. Additionally, sentiment analysis can be used to monitor and track the effectiveness of marketing campaigns and brand messaging. By understanding the sentiment of customer interactions with a brand, businesses can make more informed decisions on how to adjust their marketing strategies to better resonate with their target audience.

The proposed framework has the potential to revolutionize the social recommendation system by incorporating user behavior and emotions into the recommendation process. This could lead to a more personalized and accurate recommendation system that takes into account the complex social interactions between users. The use of sentiment analysis could provide valuable insights into user emotions, allowing businesses to tailor their marketing strategies and improve customer engagement.

The proposed framework for social recommendation systems provides a solid foundation for future research in the field. One possible direction for future work is to incorporate additional factors such as user demographics, geographic location, and temporal dynamics. These additional factors could be used to further improve the accuracy and effectiveness of the recommendations. For instance, by taking into account the user's location, the system could recommend products or services that are more relevant to their needs.

Another future direction for this work is to use explainable AI techniques to provide users with a better understanding of how the recommendations are generated. This could help to increase their trust in the system and lead to higher user engagement. Additionally, the framework could be applied in combination with other machine learning techniques such as reinforcement learning to optimize the recommendations over time. By continually refining the recommendations, the system could provide even greater value to users.

Furthermore, exploring alternative graph neural network architectures and optimization methods could lead to further improvements in the model's performance. This could involve testing different activation functions or layer configurations to see which ones provide the best results. Finally, the proposed framework could be evaluated on a larger and more diverse set of datasets to test its generalizability and robustness. By testing the framework on different datasets, researchers could gain a better understanding of how it performs under different conditions and identify any areas where further improvements are needed.

CHAPTER 7

CONCLUSION

In this study, to address the issues social recommender systems confront, we created a deep adversarial architecture based on GCNs. To enhance GCN and boost performance, our suggested model used intermediate layers of BERT and added relative positioning information of words. In order to represent user preferences at various neighborhood levels, we also developed an embedded propagation layer that considers data from both nearby and distant neighbors. Additionally, we developed a technique for object perception to measure the value of nearby objects for users and the strength of neighborhood ties. On three real-world datasets, our suggested model performed noticeably better than other cutting-edge social recommendation models, proving its efficacy in raising the accuracy of social recommender systems.

To the best of our knowledge, this work is novel and is the first of its kind that combines adversarial training and GCNs to overcome the drawbacks of social recommender systems. By addressing the drawbacks of current strategies and offering a fresh strategy that combines both text data and network structure into the model, we feel that our study has made a contribution to the field of social recommendation. By capturing the intricate connections between users and their social activities, our approach has the potential to improve the effectiveness of social recommender systems. We anticipate that our work will stimulate more investigation into this topic and contribute to the creation of social recommendation models that are more reliable and precise.

REFERENCES

[1] Yu, J., Yin, H., Li, J., Gao, M., Huang, Z. and Cui, L., 2020. *Enhancing social recommendation with adversarial graph convolutional networks. IEEE Transactions on knowledge and data engineering.* 34(8), pp.3727-3739.

[2] Li, R., Wang, S., Zhu, F. and Huang, J., 2018, April. *Adaptive graph convolutional neural networks. In Proceedings of the AAAI conference on artificial intelligence* (Vol. 32, No. 1).

[3] Sharma, Kartik, Yeon-Chang Lee, Siva Nambi, Aditya Salian, Shlok Shah, Sang-Wook Kim and Srijan Kumar. *A Survey of Graph Neural Networks for Social Recommender Systems.* ArXiv abs/2212.04481 (2022).

[4] Shenghao Liu, Bang Wang, Xianjun Deng, and Laurence T Yang. 2021. *Self-Attentive Graph Convolution Network with Latent Group Mining and Collaborative Filtering for Personalized Recommendation. IEEE Transactions on Network Science and Engineering (2021)*

[5] Zhou, Jie, Ganqu Cui, Zhengyan Zhang, Cheng Yang, Zhiyuan Liu and Maosong Sun. *Graph Neural Networks: A Review of Methods and Applications.* ArXiv abs/1812.08434 (2018).

[6] Ji, J., Zhang, B., Yu, J., Zhang, X., Qiu, D. and Zhang, B., 2023. *Relationship-aware contrastive learning for social recommendations. Information Sciences,* 629, pp.778-797.

[7] Bhatti, U.A., Tang, H., Wu, G., Marjan, S. and Hussain, A., 2023. *Deep Learning with Graph Convolutional Networks: An Overview and Latest Applications in Computational Intelligence. International Journal of Intelligent Systems, 2023.*

[8] Huang, L., Ma, Y., Liu, Y., Danny Du, B., Wang, S. and Li, D., 2023. *Position-enhanced and time-aware graph convolutional network for sequential recommendations. ACM Transactions on Information Systems*, 41(1), pp.1-32.

[9] Liu, C., Li, Y., Lin, H. and Zhang, C., 2023. *GNNRec: Gated graph neural network for session-based social recommendation model. Journal of Intelligent Information Systems*, 60(1), pp.137-156.

10-[32] Ying, R.; He, R.; Chen, K.; Eksombatchai, P ; Hamilton, W. L.; and Leskovec, J. 2018. *Graph convolutional neural networks for web-scale recommender systems. In KDD*, 974–983

[11] Li, Y., Ji, Y., Li, S., He, S., Cao, Y., Liu, Y., Liu, H., Li, X., Shi, J. and Yang, Y., 2021, July. *Relevance-aware anomalous users detection in social network via graph neural network. In 2021 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE.

[12] Zheng, L., Liu, Q. and Zhang, Y., 2021, October. *Social recommendation based on preference disentangle aggregation. In 2021 7th International Conference on Big Data and Information Analytics (BigDIA)* (pp. 1-8). IEEE.

[13] Chen, Z., Xue, Y., Xiao, L., Chen, J. and Zhang, H., 2021. *Aspect-based sentiment analysis using graph convolutional networks and co-attention mechanism.*

In Neural Information Processing: 28th International Conference, ICONIP 2021, Sanur, Bali, Indonesia, December 8–12, 2021, Proceedings, Part VI 28 (pp. 441-448)

[14] Xiao, Z., Wu, J., Chen, Q. and Deng, C., 2021. BERT4GCN: *Using BERT intermediate layers to augment GCN for aspect-based sentiment classification.* arXiv:2110.00171.

[15] Nasfi, R. and Bouguila, N., 2023, January. *Sentiment Analysis from User Reviews Using a Hybrid Generative-Discriminative HMM-SVM Approach. In Structural, Syntactic, and Statistical Pattern Recognition: Joint IAPR International Workshops, S+ SSPR 2022*, Montreal, QC, Canada, August 26–27, 2022, Proceedings (pp. 74-83). Cham: Springer International Publishing.

[16] Wen, J., Huang, A., Zhong, M., Ma, J. and Wei, Y., 2023. *Hybrid sentiment analysis with textual and interactive information. Expert Systems with Applications*, 213, p.118960.

[17] Cui, J., Wang, Z., Ho, S.B. and Cambria, E., 2023. *Survey on sentiment analysis: evolution of research methods and topics. Artificial Intelligence Review*, pp.1-42.

[18] Peng, S., Cao, L., Zhou, Y., Ouyang, Z., Yang, A., Li, X., Jia, W. and Yu, S., 2022. *A survey on deep learning for textual emotion analysis in social networks. Digital Communications and Networks*, 8(5), pp.745-762.

[19] Yang, Z., Ma, J., Chen, H., Zhang, J. and Chang, Y., 2022. *Context-aware attentive multilevel feature fusion for named entity recognition. IEEE transactions on neural networks and learning systems.*

[20] Zhang, W., Li, X., Deng, Y., Bing, L. and Lam, W., 2022. *A survey on aspect-based sentiment analysis: tasks, methods, and challenges. IEEE Transactions on Knowledge and Data Engineering.*

[21] He, K., Mao, R., Gong, T., Li, C. and Cambria, E., 2022. *Meta-based self-training and re-weighting for aspect-based sentiment analysis. IEEE Transactions on Affective Computing.*

[22] Zhao, Z., Tang, M., Tang, W., Wang, C. and Chen, X., 2022. *Graph convolutional network with multiple weight mechanisms for aspect-based sentiment analysis.* Neurocomputing, 500, pp.124-134.

[23] Wu, L., Sun, P., Hong, R., Fu, Y., Wang, X. and Wang, M., 2018. *Socialgcn: An efficient graph convolutional network based model for social recommendation.* arXiv preprint arXiv:1811.02815.

[24] Peng Zhu, Dawei Cheng, Siqiang Luo, Fangzhou Yang, Yifeng Luo, Weining Qian, and Aoying Zhou. 2022. *SINews: Integrating social information for news recommendation with attention-based graph convolutional network.* Neurocomputing 494 (2022), 33–42.

[25] Wenqi Fan, Yao Ma, Qing Li, Jianping Wang, Guoyong Cai, Jiliang Tang, and Dawei Yin. 2022. *A Graph Neural Network Framework for Social*

Recommendations. IEEE Transactions on Knowledge and Data Engineering 34, 5 (2022), 2033–2047. https://doi.org/10.1109/TKDE.2020.3008732

[26] Zhiwei Guo and Heng Wang. 2020. *A deep graph neural network-based mechanism for social recommendations. IEEE Transactions on Industrial Informatics* 17, 4 (2020), 2776–2783

[27] Ting Bai, Youjie Zhang, Bin Wu, and Jian-Yun Nie. 2020. *Temporal Graph Neural Networks for Social Recommendation. In Proceedings of IEEE International Conference on Big Data (BigData)*. 898–903

[28] Yanbin Jiang, Huifang Ma, Yuhang Liu, Zhixin Li, and Liang Chang. 2021. *Enhancing social recommendation via two-level graph attentional networks.* Neurocomputing 449 (2021), 71–84

[29] Liu H, Zheng C, Li D, Zhang Z, Lin K, Shen X, Xiong NN, Wang J. *Multi-perspective social recommendation method with graph representation learning.* Neurocomputing. 2022 Jan 11;468:469-81.

[30] Wei, W., Huang, C., Xia, L., Xu, Y., Zhao, J. and Yin, D., 2022, February. *Contrastive meta learning with behavior multiplicity for recommendation. In Proceedings of the fifteenth ACM international conference on web search and data mining* (pp. 1120-1128).

[31] Liao, G., Deng, X., Wan, C. and Liu, X., 2022. *Group event recommendation based on graph multi-head attention network combining explicit and implicit information.* Information Processing & Management, 59(2), p.102797.

[32] Bi, Zhongqin, Lina Jing, Meijing Shan, Shuming Dou and Shiyang Wang. *Hierarchical Social Recommendation Model Based on a Graph Neural Network.* Wirel. Commun. Mob. Comput. 2021 (2021): 9107718:1-9107718:10.

[33] Liu, Z., Yang, L., Fan, Z., Peng, H. and Yu, P.S., 2022. *Federated social recommendation with graph neural network. ACM Transactions on Intelligent Systems and Technology (TIST),* 13(4), pp.1-24.

[34] Wu, L., Li, J., Sun, P., Hong, R., Ge, Y. and Wang, M., 2020. *Diffnet++: A neural influence and interest diffusion network for social recommendation. IEEE Transactions on Knowledge and Data Engineering*, 34(10), pp.4753-4766.

[35] Dhawan, S., Singh, K., Rabaea, A. and Batra, A., 2022. *ImprovedGCN: An efficient and accurate recommendation system employing lightweight graph convolutional networks in social media. Electronic Commerce Research and Applications.* 55, p.101191.

[36] Chen, Y., Wang, J., Wu, Z. and Lin, Y., 2022. *Integrating User-Group relationships under interest similarity constraints for social recommendation.* Knowledge-Based Systems, 249, p.108921

[37] Chen, J., Song, N., Su, Y., Zhao, S. and Zhang, Y., 2022. *Learning user sentiment orientation in social networks for sentiment analysis.* Information Sciences, 616, pp.526-538.

[38] Liu, X., Zhao, Z., Zhang, Y., Liu, C. and Yang, F., 2022. *Social Network Rumor Detection Method Combining Dual-Attention Mechanism with Graph Convolutional Network. IEEE Transactions on Computational Social Systems.*

[39] Wu, B., Liang, X., Zheng, X., Guo, Y. and Tang, H., 2022, May. *Improving Dynamic Graph Convolutional Network with Fine-Grained Attention Mechanism. In ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 3938-3942). IEEE.

[40] Jiang, Nan, Li Gao, Fuxian Duan, Jiemao Wen, Tao Wan and Honglong Chen. *"SAN: Attention-based social aggregation neural networks for recommendation system." International Journal of Intelligent Systems* 37 (2021): 3373 - 3393.

[41] Mehra, P., 2023. *Unexpected Surprise: Emotion analysis and aspect based sentiment analysis (ABSA) of user generated comments to study behavioral intentions of tourists. Tourism Management Perspectives,* 45, p.101063.