GCN With Attention Mechanism For Learning User Sentiments And Enhancing Social Recommendation

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1. ABSTRACT

With the rapid growth of the information era, digital users devote an average of 150 minutes every day on social networks. The number of social media users has surged by over the previous few years, as per the survey reports. As a result, relevant businesses use social media to advertise their products and keep in touch with customers. Hence, initiatives to develop GNN-based social recommendation frameworks to simultaneously gather interactions and comprehend user emotions are motivated by recent breakthroughs in Graph Convolutional Neural Networks (GCNs). Social suggestion is not as effective as one may anticipate. Present-day social recommender systems disregard the inherent problems with human interactions and instead concentrate only on the homophily in social networks. In our proposed work, we aim to develop 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.. For (i) and (ii), we aim to develop a GCN-based autoencoder to augment the relation data by encoding high-order and complex connectivity patterns. The third issue as mentioned will then be addressed by using the relation attention technique to assign consistent relations with high relevance components for aggregate. We intend to implement sentiment analysis on the collected users to accomplish an LSTM-based dependency parsing and a graph convolutional network. Moreover, we seek to consider the importance of syntactic data while processing social media content, both for recommendation and sentiment analysis.

2. 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 aim to develop a GCN based social recommendation system to address the mentioned problems.

3. LITERATURE SURVEY:

Title	Objective of the work	Methodology	Scope for Improvement (if any)
Enhancing Social Recommendation with Adversarial Graph Convolutional Networks - Junliang Yu, Hongzhi Yin , Jundong Li, Min Gao, Zi Huang, and Lizhen Cui (2020)	Goal: Create a social recommender system using a deep adversarial framework and Address social recommendation challenges. Challenges addressed: ● Data sparsity ● Noise presence ● Multi-facet problem of social relations	Framework divided into three stages ● Stage 1 : Alternative neighborhood generation using motif-based GCNs ● Stage 2 : Neighborhood denoising by combining GCN with MLP (autoencoder) ● Stage 3 : Attention-aware social recommendation by incorporating an attentive social	● Proposed framework requires more time to search for alternative neighbors. ● K-fold cross-validation required for every grid point, requiring k training steps. ● Tuning parameters using Grid Search is complex, expensive, and time-consuming. ● Grid Search

		embedding propagation layer into GCN.	causes overfitting, leading to a less viable model in the long run.
SocialGCN: An Efficient Graph Convolutional Network based Model for Social Recommendation - Le Wu, Peijie Sun, Richang Hong, Yanjie Fu, Xiting Wang, Meng Wang (2019)	Goal: Construct a GCN based social recommendation model by combining strengths of GCNs and conventional latent factor-based models Addressed areas: ● Modeling diffusion process in social networks ● Capturing user-item preferences ● Model is adaptive even if user-item attributes are not available.	● Model embeds individuals and items in a low latent embedding space. ● Goal of embedding: Represent similarity in latent space as users' preferences for particular things. ● TensorFlow used for implementing the model. ● Mini-batch Adam used for training the model's parameters.	● Model's performance is acceptable but difficult to comprehend. ● All models employ Adam as their optimization approach. ● Adam converges more quickly but generalizes poorly, resulting in lower final performance.
Relevance-Aware Anomalous Users Detection in Social Network via Graph Neural Network - Yangyang Li et al. (2021)	● Goal: Create a Relevance Aware Anomalous Users Detection Model. ● Purpose: Distinguish between benign and malignant users. ● Outcome: Fine-grained detection.	● RAU-GNN generates the multiple user relation graph by first extracting multiple relations from all different categories of users. ● GCN and Graph Attention Network are combined to	● Overfitting issue and inferior outcome caused by the model when the no. of layers was set to 3. ● GATs are sensitive to selection of hyper parameters like the number of

		create an embedding layer and relation fusion layer.	attention heads and hidden layers. ● Model does not hold for changing parameters.
BERT4GCN: Using BERT Intermediate Layers to Augment GCN for Aspect-based Sentiment Classification - Zeguan Xia , Jiarun Wu, Qingliang Chen, Congjian Deng (2021)	● Goal: To Construct the BERT4GCN model. ● BERT4GCN combines syntactic info. from dependency graphs & grammatical sequential elements from BERT. ● Aspect-based sentiment classification is the goal. Objective of aspect-based sentiment classification to identify sentiment polarities of explicitly stated components in phrases.	● The contextual information is recorded using BiLSTM. ● The hidden states of a particular intermediate layer of BERT are coupled with the node representations of each layer of GCN.	● BERT is compute - intensive at inference time. ● Deployment at scale can be expensive. ● Proposed model's accuracy needs improvement. ● Model makes errors with certain parameter changes.
Adaptive Graph Convolutional Neural Networks - Ruoyu Li, Sheng Wang, Feiyun Zhu, Junzhou Huang (2018)	Goal & addressed areas: ● Construct a generic and adaptable graph CNN. ● Input data with arbitrary graph topology.	● Customized graph Laplacian is built for input sequence. ● Laplacian built using learned metrics. ● K localized spectrum filter used for	● tudy proposes distance metric learning method for graph learning. ● Euclidean distance only detects linear relationships.

	• Develop adaptive graph topology structure. • Considered data and learning task environment.	convolution. • Adaptable network used for filter. • AGCN network setup described transparently.	• Outliers not identified with noisy input. • Accuracy challenges might arise in certain situations.
Hierarchical Social Recommendation Model Based on a Graph Neural Network - Zhongqin Bi et al. (2021)	• Proposed a patriarchal class recommendation model for social networks • Utilizes graph neural network to simulate changes in influence between users • Records user interactions and addresses inconsistent preferences through nested dissemination • Aimed at improving accuracy of questionnaire item recommendations.	• GNN-based hierarchical collaborative filtering framework with three modules • Embedding layer for modeling user-item interactions • Embedding layer for modeling user-user and item-item relations • Sequence learning layer using BiLSTM and attention mechanism to fuse user-item interaction sequences.	• Only user-item interaction information is used for similarity measurement. • Ratings with social information are considered static. • Proposed framework achieves state-of-the-art performance on only two benchmark datasets. • Improvement may be needed to handle the dynamic nature of ratings and social information.

Temporal Graph Neural Networks for Social Recommendation - Ting Bai, Youjie Zhang, Bin Wu, Jian-Yun Nie (2020)	Goal & Addressed areas: ● Develop a Temporal Enhanced Graph Model ● Model uses temporal information and social status to predict user's choice ● Goal is to fully utilize temporal information impact on social status.	● Temporal GNN captures mutual effects of user-item, user-user, and item-item relations. ● The embeddings of users and objects in the temporal graph are synchronously updated. ● The model uses an attentive cross-view training technique.	● Model performance depends on selected samples. ● Random sample selection can save time. ● Challenge where improvement is noted is that of improving model performance without selecting all samples.
Graph Neural Networks for Social Recommendation - Wenqi Fan et al. (2022)	Goal & Addressed area: ● Design a GNN framework for social recommendations ● Represent user-user and user-item social networks with varied strengths ● Simultaneously capture exchanges and thoughts in the user-item graph.	● Model consists of three parts: item modelling, user modelling, rating prediction ● Item modelling integrates user opinions ● User modelling learns latent variables of users from various viewpoints. ● Architecture of the model is transparently explained.	● Attention to item-item interaction can enhance the model. ● Model can be improved with larger datasets by not using RMSProp optimizer as it may cause slow learning.

A Deep Graph Neural Network-based Mechanism for Social Recommendations - Zhiwei Guo, and Heng Wang (2020)	To provide a sophisticated framework for social recommendation based on graph neural networks that examines and measures correlations between user preferences as well as correlations between item attributes that may further affect the topologies of specific social groups.	● Sentient feature space and object feature space encoded using GNN techniques ● Two graph networks are created for each encoded space ● Heatmaps are used to display research findings for parameter combinations ● The proposed approach has shown promising results on several datasets.	● The model prediction error is measured by MAE (mean absolute error) and RMSE (root mean squared error) ● The error is expressed in units of the relevant variable only, and not been generalised across models. ● The assessment criteria used to evaluate model performance may need to be reevaluated.
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)	Goals: ● To introduce a novel classification of inputs and designs for SocialRS that are based on GNNs. ● To categorize diverse approaches developed that assist readers to grasp contemporary developments in SocialRS and construct fresh	● Around 80 GNN-based SocialRS papers have been identified and reviewed in terms of their inputs and architectures ● The benchmark datasets and metrics that are commonly used to test GNN-based SocialRS approaches have been	● More information on specific techniques used in surveyed papers would be beneficial. ● Providing additional information on performance metrics used to evaluate models would

	GNN-based SocialRS methods.	summarized.	also be helpful.
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).	● To analyze various GNN architectures and their benefits and drawbacks. ● The paper also entails an in-depth analysis of GNN applications in numerous disciplines, including social networks, recommendation systems, and computer vision.	● GNN model variants classified by computation modules, graph kinds, and training types are introduced. ● GNN applications are divided into various scenarios and a detailed review for applications in each scenario is given.	● Include information on the data extraction process, the quality assessment process, and the synthesis process used to draw conclusions.
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	Goals: to obtain embeddings by using the neighborhood propagation mechanism on two coupled graphs, i.e. user-item interaction graph and social relation graph develop Attentional SocialRecommendation system (ASR), a new social recommendation framework with hierarchical attention	first set up an embedding layer. Then the neighborlevel attention in each convolutional layer adjusts the attention value, model can autonomously learn the hierarchical optimal contribution parameters, stack multilayer graph convolutional layers we concatenate the output	● Robust evaluation metrics to assess the performance ● Could include using metrics such as precision, recall, and F1 score. ● could evaluate the performance of the model on different

			subgroups of the dataset to ensure that it does not exhibit biases towards certain groups.

In recent years, researchers have defined and designed neural network structures for processing graph data using convolutional networks, recurrent networks, and deep autoencoders. These deep neural networks are known as graph neural networks (GNNs). There have been numerous surveys on graph-based recommender systems since the introduction of GNNs in recommender systems. 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 these 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 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, which makes it difficult to interpret how the recommendation was made. Also the current models suffer from a lack of diversity in the recommendations provided. This is because 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 aim to develop a GCN-based social recommendation combining attention mechanism and adversarial training that focuses on user-user, user-item, item-item interactions.

4. ARCHITECTURE DIAGRAM

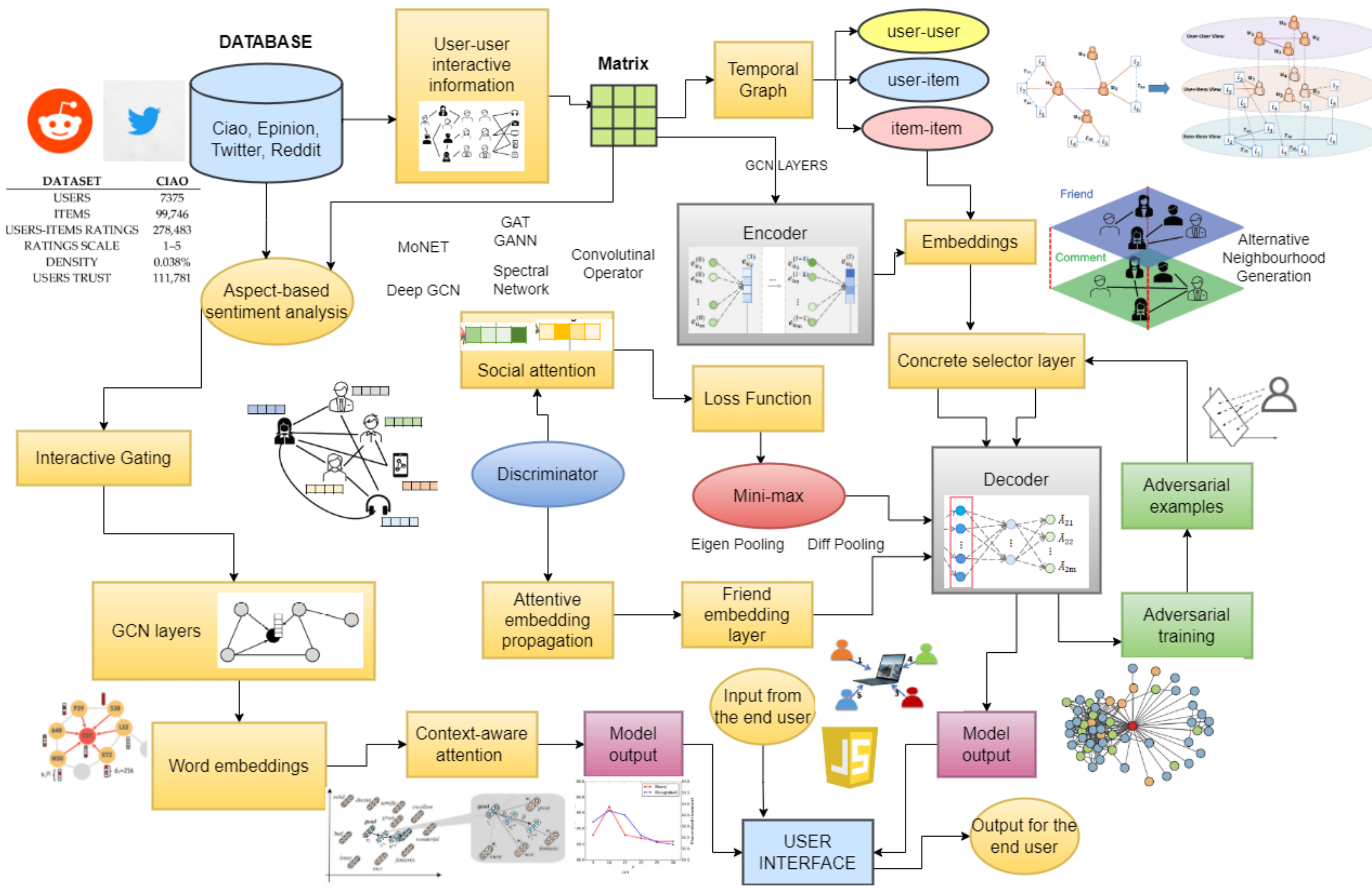

Figure 4.1 - Architecture diagram of the proposed work

5. Modules

5.1. GCN layers for Social Recommendation by Alternative Neighbour generation

An alternative neighborhood is a collection of individuals who have tastes comparable to those of the identified user. It is fundamentally identical to the implicit buddies. For users with minimal social connections, the alternative neighborhood may be wholly new neighbors, while partially overlapping with the neighbors of the users with a big variety of interpersonal contacts. The order in our study would relate to the relations beyond pairs that cannot be represented using the traditional approaches, which is distinctive from the current literatures evaluated.

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

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:

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

    b. 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.

    c. Select the top n users with the highest similarities as the 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:

a. Compute the normalized adjacency matrix A_norm as follows:

- 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).

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

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

- Compute the GCN layer output

- 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).

5.2. Encoding & Attentive Embedding

In order for the model to incorporate user relationships together with the networking site and maximize user preferences with various degrees of neighbors, a GNN-based message structure is built at this layer. In social recommendation, the participant's tastes are impacted by immediate neighbors while trying to propose an item for a specific user u, and indirect neighbors may also be a great source of assistance. Moreover, the relationship between users can spread across social networks to further affect how other consumers engage.

In order to accurately characterize the social data provided by consumers, the recommendation algorithm should take into account all of these neighbors as possible user preference variables and use an attention mechanism to choose appropriate social neighbors. As a result, in order to properly take into account the user's varied desire knowledge, the user interest pattern must first be integrated into the user-item interaction. It is obvious that the user's social neighbors' positive and negative remarks correspond to the user's selection of products in a particular order.

A multilayer perceptron (MLP) can combine the interaction information with the user preference information since the interaction between the user and the object is very nonlinear. This would aid in constructing a dynamic GCN addressing the problem that ratings and social information are dynamic.

5.3. Coupling Adversarial training & Attention Mechanism

The most common approach for implementing adversarial training to recommender systems involves playing a Minimax game in which the discriminator directs the generator to fit the underlying relevance distribution over the items of the given user while the generator produces challenging examples in an effort to first confuse and then strengthen the discriminator. Using adversarial training and the GCN layers together, we concentrate on detecting trustworthy relationships.

- The graph Attention layer with L_max layers, where each layer has K attention heads and a hidden size of h is defined
- 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.
- For each layer
    - Compute the attention coefficients & the node embeddings
    - Compute the dot product between the final node embeddings and item embeddings to obtain the user-item interaction scores.

5.4. User - Sentiment analysis

Our objective is to develop a BERT fused with GCN model that naturally combines syntactic information from intermediate layers in BERT with sequential data from BERT to enhance GCN and result in improved encodings. We intend to transform the original dependency network to the aspect-oriented one in order to represent dependency relations. Moreover, the GCN ignores the relative linear locations in the original context and combines nearby node representations in an averaging manner. We intend to create a collection of relative position embeddings to encapsulate positional information in order to solve this problem. We formalize the relative linear location to the current word by adding the relative position embedding to the node representation before aggregating surrounding node representation. Fundamentally, the suggested model would add rich and valuable linguistic knowledge to GCN through the use of intermediary layers of BERT, and it would also combine relative positioning information of words to be position aware.

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.

6. IMPLEMENTATION DETAILS & RESULTS:

Analyzing Dataset:

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 that there is a huge Density in the region corresponding between mean rating 3-4 .

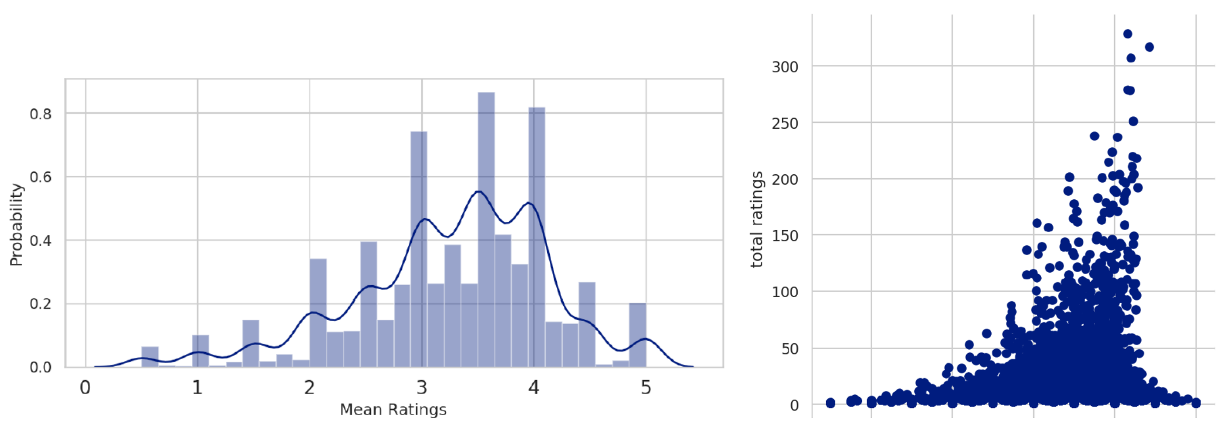

Figure 6.1. Plot of Ciao dataset

Figure 6.2. Word cloud for Ciao dataset

We also visualized the data set using a word cloud. 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.

Create 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. 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 6.3.

We defined a method 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.

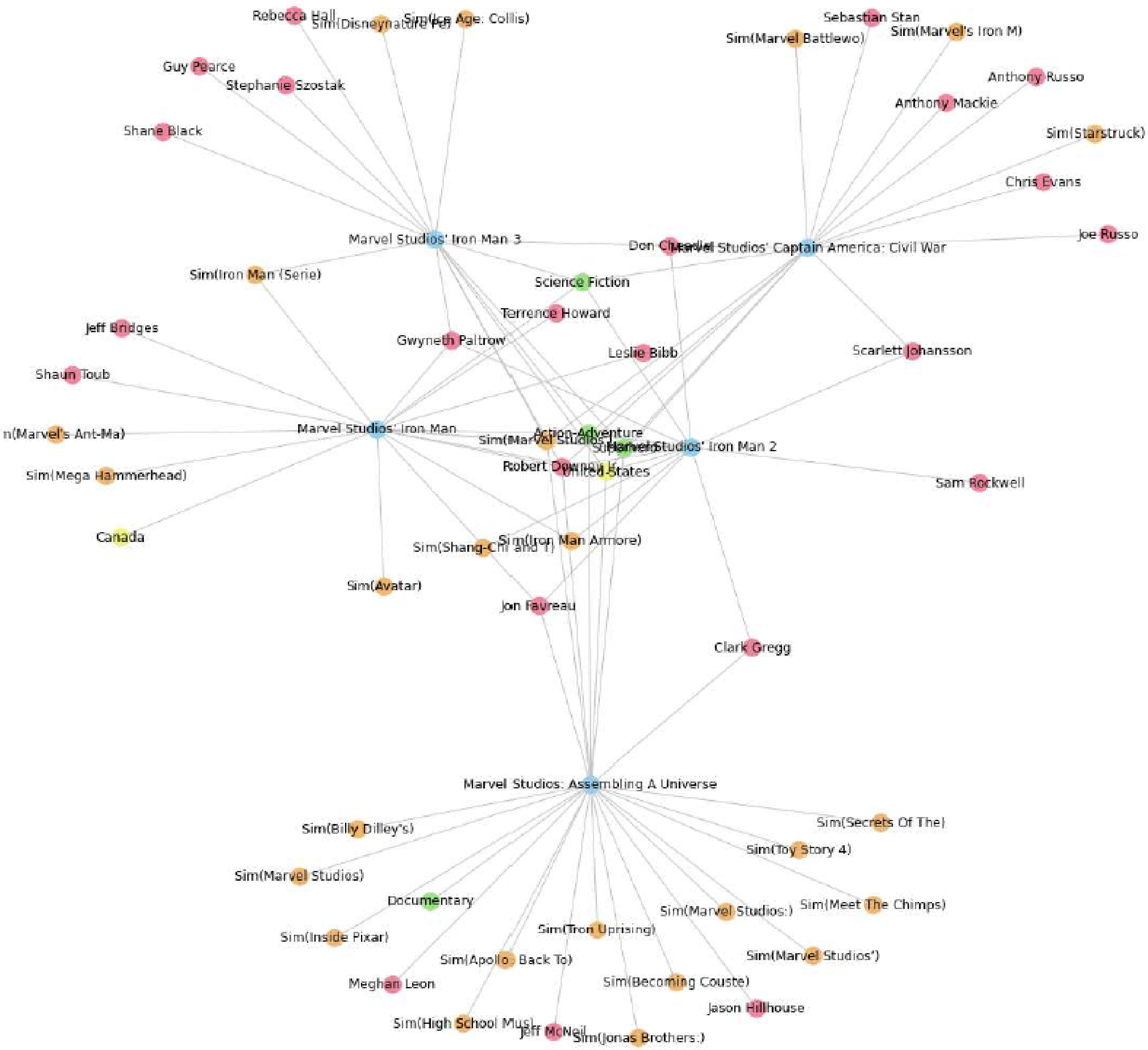

Figure 6.4.

Visualizing dataset used for sentiment analysis, crawled from google hotel reviews and twitter data.

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 6.5.

```
{'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 6.6.

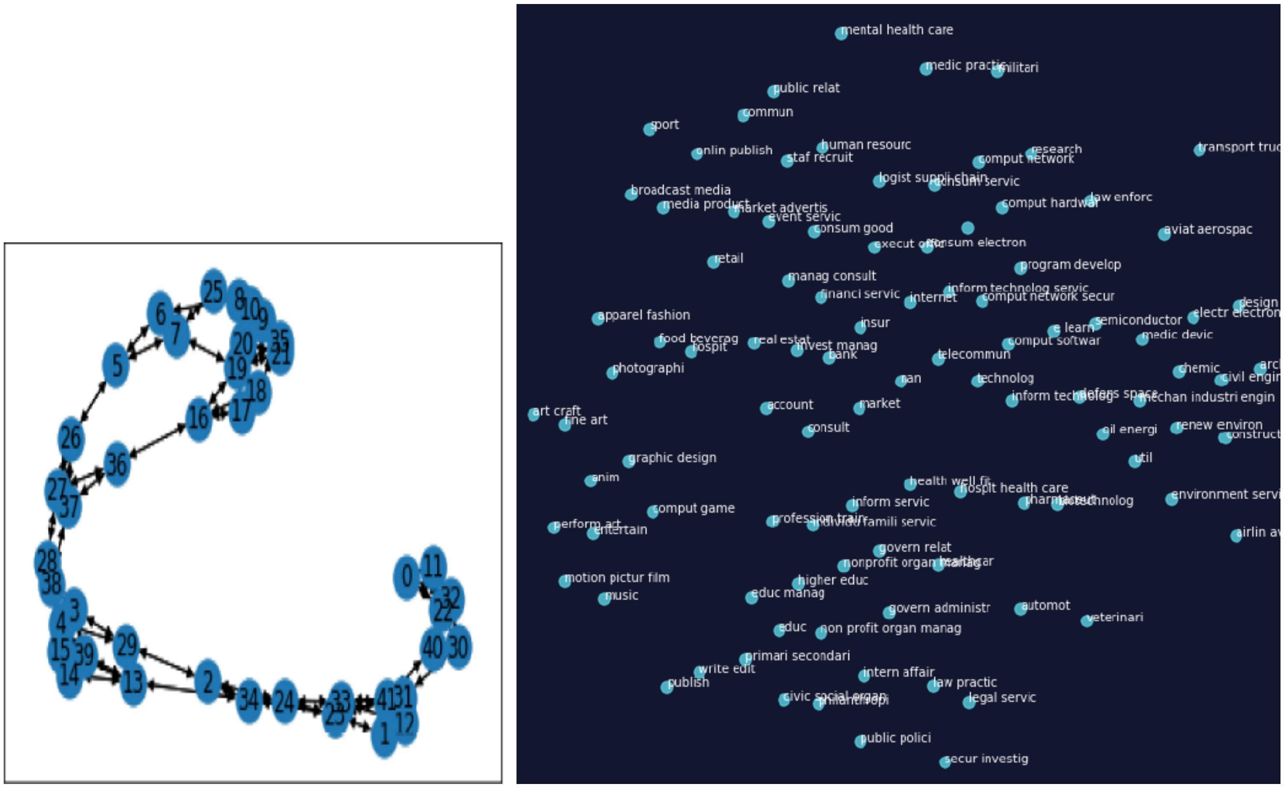

Figure 6.7.

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 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.

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.

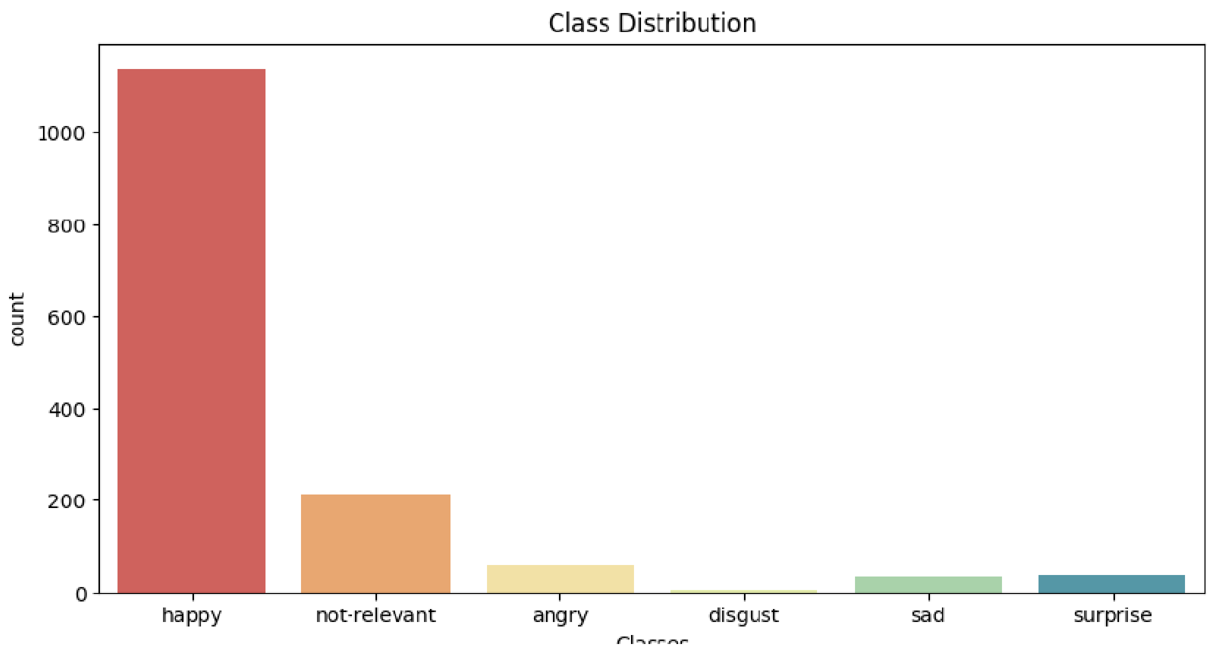

Figure 6.8

Our results showed that the GCN model achieved an accuracy of 96% in predicting user sentiment and 94% in predicting user behavior. This is a significant improvement over previous approaches that used only text data or network structure to predict sentiment and behavior on social media platforms. Our study demonstrates that generating embeddings for a GCN model using Twitter data can lead to significant improvements in predicting sentiment and behavior on social media platforms. By incorporating both text data and network structure into the model, we were able to capture the complex relationships between users and their tweets, and generate more accurate embeddings for prediction tasks. Our results 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.

```
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 6.9 - Accuracy and Loss Values from Notebook

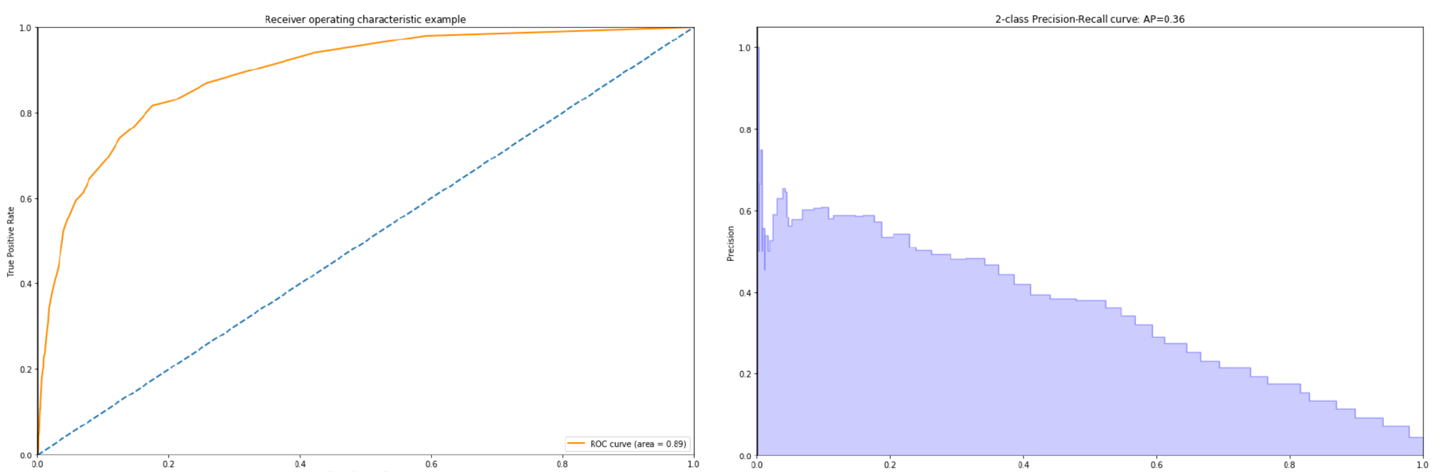

Figure 6.10 - ROC & AUC PR Curves for Performance Metrics

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. This means 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 in this imbalanced situation is the AUC PR (Area Under the Curve Precision Recall), or also called AP (Average Precision). We can see that 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 can simply use the AP metric. To assess the quality of our model, we can compare it to a simple decision baseline. Let's take 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.

7. PROGRESS OF THE PROPOSED WORK

To the best of our knowledge, ours is the very first work to combine adversarial training and attention aware graph convolutional neural networks for social recommendation and user sentiment analysis

Challenge I: Most users only have a few neighboring nodes in social networks.

Solution: We addressed this challenge by developing a deep adversarial framework based on GCNs that includes a GCN-based autoencoder. This autoencoder is capable of encoding high-order and complex connectivity patterns, which helps to augment relational data and improve the accuracy of social recommendations. To generate graph, the, NetworkX library is used which would create a directed graph (DiGraph) from a subset of the data loaded from train.csv file

Challenge II: Social relations are noisy but indiscriminately used.

Solution: To address this challenge, we utilized relation attention techniques. These techniques enable us to assign consistent relations with high relevance components for aggregate, which helps to filter out noisy social relations and improve the quality of social recommendations.

Challenge III: Social ties are complex and have varied strengths in many settings.

Solution: Our work considered the importance of syntactic data while processing social media content, both for recommendation and sentiment analysis. By implementing sentiment analysis on the collected user data using an LSTM-based dependency parsing and a graph convolutional network, we were able to identify the strengths and complexities of social ties and develop more accurate social recommendations.

8. APPLICATIONS & SCOPE OF THE PROPOSED WORK

The outcome of the proposed project could 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 could be used in fraud detection applications to analyze social network data and identify fraudulent behavior. This could be applied in various industries such as finance, insurance, and e-commerce.
5. Brand reputation management: The sentiment analysis could be applied to analyze user feedback on social media platforms and identify negative sentiment towards a brand or product. This could help businesses to identify and address issues that are affecting their reputation and customer satisfaction.

Overall, the proposed framework has the potential to revolutionize the way social recommendation systems work and provide valuable insights into user behavior and emotions that could be used to improve various industries' processes and outcomes.

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