Graph Convolutional Networks with Attention Mechanism for learning user sentiments and enhancing Social Recommendation

Team Members

Hemanth N (2019503519)
Paavendhan K S (2019503031)
Sai Soundharya Lakshmi B (2019503554)

Project Guide - Prof. Dr. Jayashree Padmanabhan

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.

LITERATURE SURVEY:

Title & Authors	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 IEEE Transactions on knowledge and data engineering (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 embedding propagation layer into GCN.	● 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 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 Doi: 10.48550/arXiv.1811.02815 (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. IEEE - International Joint Conference on Neural Networks (IJCNN) - 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 create an embedding layer and relation fusion layer.	● 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 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. ● 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. ● BERT4GCN combines syntactic info. from dependency graphs & grammatical sequential elements from BERT.	● 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 In Proceedings of the AAAI conference on artificial intelligence (Vol. 32, No. 1) (2018)	Goal & addressed areas: ● Construct a generic and adaptable graph CNN. ● Input data with arbitrary graph topology. ● Develop adaptive graph topology structure. ● Considered data and learning task environment.	● Customized graph Laplacian is built for input sequence. ● Laplacian built using learned metrics. ● K localized spectrum filter used for convolution. ● Adaptable network used for filter. ● AGCN network setup described transparently.	● tudy proposes distance metric learning method for graph learning. ● Euclidean distance only detects linear relationships. ● 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. IEEE - Wireless Communication. Mob. Computations. (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-art performance on only 2 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 In Proceedings of IEEE International Conference on Big Data (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 IEEE Transactions on Industrial Informatics (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 prediction error is measured by MAE (mean absolute error) and RMSE. ● The error is expressed in units of the relevant variable only, and not been generalized 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 model that assist readers to grasp contemporary developments in SocialRS and construct fresh GNN-based SocialRS methods.	● 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 summarized.	● More information on specific techniques used in surveyed papers would be beneficial. ● Providing additional information on performance metrics used to evaluate models would 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.” (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. IEEE Transactions on Network Science and Engineering, 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 Social Recommendation system (ASR), a new social recommendation framework with hierarchical attention.	● First set up an embedding layer. Then the neighbor level attention in each convolutional layer adjusts the attention value, model can autonomously learn the hierarchical optimal contribution parameters, ● Stack multilayer graph convolutional layers, proved to be rewarding. ● Finally, 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.

From the literature review undertaken, we comprehend that in recent years, researchers have defined and designed neural network structures for processing graph data using convolutional networks, recurrent networks, and deep autoencoders. 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. GCNs have also been 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 like Deep GCN, MoNET, Spectral network seem to less effective. The performance of these systems is significantly reduced when dealing with new users. So another major scope for improvement is that GCN-based social recommendation systems provide a black-box solution, which makes it difficult to interpret how the recommendation was made.

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.

ARCHITECTURE DIAGRAM

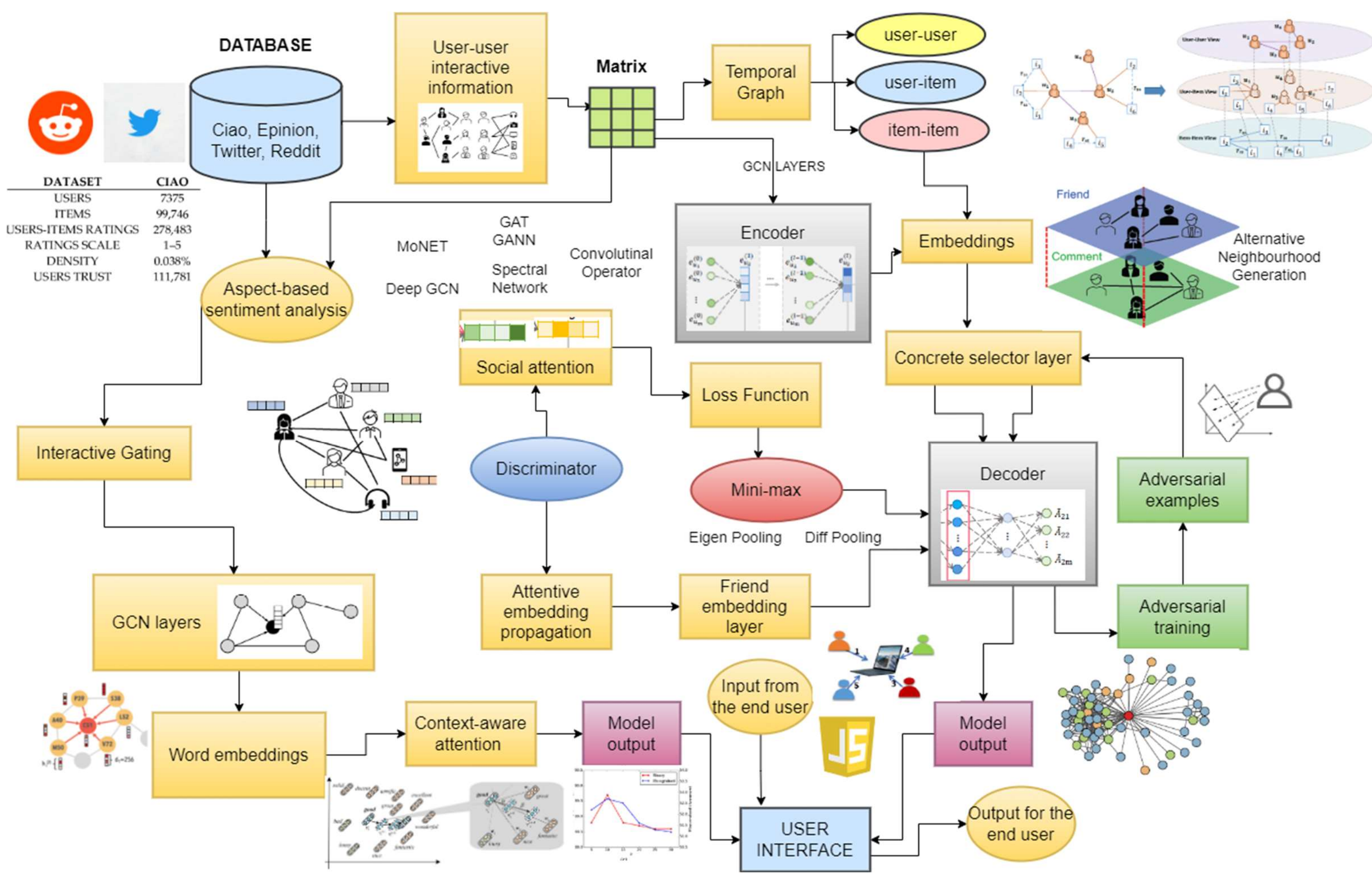

Figure 1 - Architecture diagram of the proposed work

MODULES OF OUR PROPOSED WORK:

I. GCN layers for Social Recommendation by Alternative Neighbor 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 is chosen. Algorithm for the module would have the following flow:

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 u.

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 optimization (just similar to gradient descent).

II. 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.

III. 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.

IV. 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 would 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.

The algorithm for performing user sentiment analysis from the available dataset:

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.

DELIVERABLES & OUTCOMES

- The proposed work would include components to systematically and effectively deal with the three tough problems in social recommender systems.
- Use DeepMind, GCL. Spektral to utilize the flexible framework for creating GNN and visualizing before proceeding for building the model, since GCN may be less efficient while it comes to handling sparsed order of data. Hence data may be visualized so that adaptive choosing of graph nodes may be done.
- We would conduct extensive analysis on available datasets as well as collected datasets from twitter mining and reddit data tool, to demonstrate the betterness of the proposed framework.
- Perform complexity analysis based on model size, time complexity and various other common metrics like Parameter Sensitivity Analysis, that is introducing small hyper parameter to see how the model behaves under extreme situations, basically testing high and low sparsity problems identified in the literature review.
- A model with a deep adversarial framework based on attention aware GCNs, enabling adaptive selection of graph nodes to address the challenges of social recommendation.
- An application where the user's sentiment analysis is done based on the built model, and the social recommendation is accomplished using a dependency parsing and the GCN.

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

- The proposed work aims to address the challenges of social recommendation by developing a deep adversarial framework based on GCNs. The project intends to address three main issues with social recommendation: (i) most users only have a few neighboring nodes in social networks; (ii) social relations are noisy but indiscriminately used; and (iii) social ties are complex and have varied strengths in many settings.

- To address these issues, we would develop a GCN-based autoencoder to augment relation data by encoding high-order and complex connectivity patterns. Additionally, our work will use relation attention techniques to assign consistent relations with high relevance components for aggregate.

- The work will also implement sentiment analysis on the collected users to accomplish an LSTM-based dependency parsing and a graph convolutional network. The project would consider the importance of syntactic data while processing social media content, both for recommendation and sentiment analysis.

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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