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

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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 comprehenduser 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 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	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 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.

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<td>SocialGCN: An Efficient Graph Convolutional Network based Model for Social Recommendation - Le Wu, Peijie Sun, Richang Hong, Yanjie Fu, Xiting Wang, Meng Wang (2019)</td>
<td>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.</td>
<td>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.</td>
<td>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.</td>
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<tr>
<td>Relevance-Aware Anomalous Users Detection in Social Network via Graph Neural Network - Yangyang Li et al. (2021)</td>
<td>Goal: Create a Relevance Aware Anomalous Users Detection Model.
Purpose: Distinguish between benign and malignant users.
Outcome: Fine-grained detection.</td>
<td>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 based on GAT and GCN.</td>
<td>Overfitting issue and inferior outcome caused by the model when the no. of layers was set to 3.
GATs are sensitive to the selection of hyper parameters like the number of attention heads and hidden layers.
Model does not hold for changing parameters.</td>
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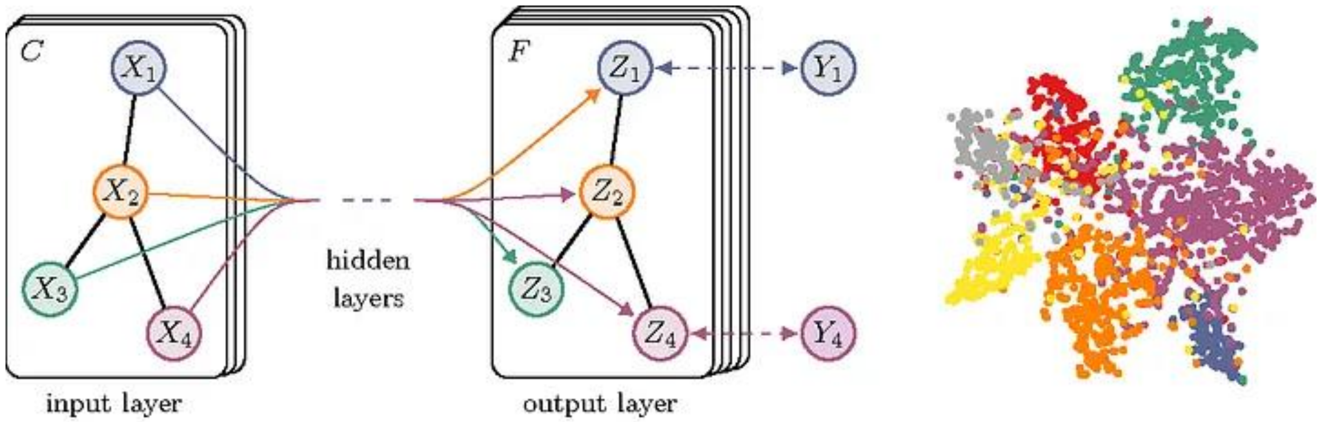
BERT4GCN: Using BERT Intermediate Layers to Augment GCN for Aspect-based Sentiment Classification - Zeguan Xia , Jiarun Wu, Qingliang Chen, Congjian Deng (2021)	**Goal:** To Construct the BERT4GCN model. • BERT4GCN combines syntactic info. from dependency graphs & grammatical sequential elements from BERT. • Aspect-based sentiment classification is the goal. Objective of aspect-based sentiment classification to identify 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)	**Goals** • 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.	• Study 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. (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. • 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)	• 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 RMS Prop 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.

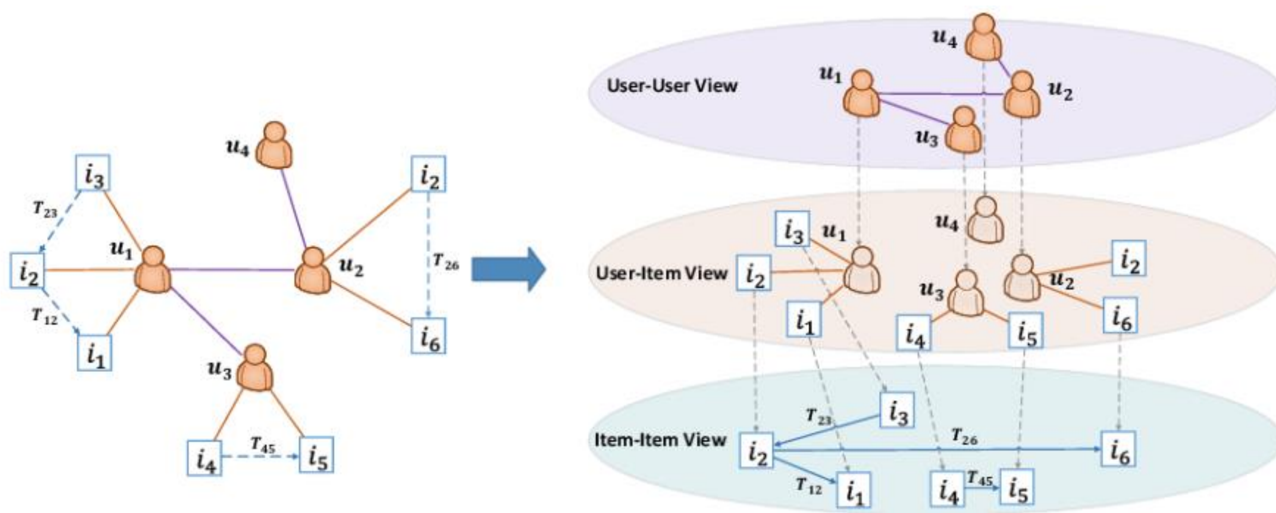
Graph Convolutional Neural Network - Overview



(a) Graph Convolutional Network (b) Hidden layer activations

In the above figure, the left side shows a GCN while right side shows hidden layer activations. The need to move on to GCN is that CNN can not handle Non-Euclidean Structure data: the number of neighbours of each node is not a constant, where we cannot directly apply the convolutional kernel

The below figure indicates the illustration of a temporal enhanced graph. We map user-user, user-item, and item-item relations into three views.



DELIVERABLES

- 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 Precision, Recall and perform 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 study.

- 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

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