DATA EMBEDDING AND MAPPING IN CROSS-DOMAIN RECOMMENDATION USING GRAPH NEURAL NETWORK

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ABSTRACT *– This paper studies the use of Graph Neural Networks (GNNs) in Cross-Domain Recommendation (CDR), focusing on challenges related to knowledge transfer and domain disentanglement. GNNs' capability to capture complex relationships within user-item domains is further studied and explored. This study evaluates different GNN approaches and discusses potential future research directions. This exploration contributes to the deeper understanding and potential developments in Cross-Domain Recommendation*

Keywords: Cross-domain recommendation, Graph Neural Network, knowledge transfer, domain disentanglement, embeddings, mapping

1 INTRODUCTION

Cross-domain recommendation (CDR) is a technique that addresses two common challenges in traditional recommender systems: data sparsity and the cold-start problem, which refers to the difficulty of making recommendations with limited user-item interaction data [1]. CDR enhances recommendation systems by leveraging insights from various domains. However, implementing CDR presents its challenges. One major challenge is domain disentanglement, which involves effectively separating domain-invariant (common across domains) and domain-specific (unique to each domain) representations in the data [2]. Another challenge is dealing with biases that may arise during cross-domain mapping. These biases, often favoring co-users or certain interaction patterns, can overpower learned embeddings and negatively impact predictions across other domains [3].

To address challenges on CDR, this project aims to utilize Graph Neural Networks (GNNs), a member of neural networks specifically engineered to function on graph data structures, to enhance the representation of complex user-item transitions and interactions, thereby improving information propagation across different domains [4]. Additionally, GNNs' ability to efficiently learn and represent data structures can lead to improved feature engineering of domains [5,6]. This, in turn, can help address the challenge of domain disentanglement in CDR.

2 METHODOLOGY

2.1 Cross-Domain Recommendation Framework – This section delves into the details of how GNNs and their various types perform in embedding, mapping, and evaluation. A general cross-domain framework is presented as illustrated in [5, Figure 1], and the application of this framework to other GNN models.

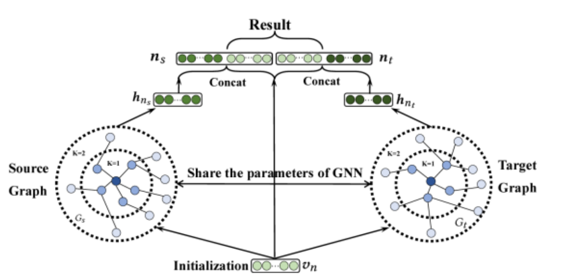

Fig. 1. A general cross-domain framework adapted from the study of Lin et al. (2021).

This framework uses a GNN to process two graphs (source and target) and outputs a result that represents predicted relationships between data points.

2.1.1 Data Preprocessing: Preparing the data in tabular format, having rows and columns, and graph format where nodes represent users and items, and edges represent interactions between users and items. Since there are two domains, two separate tables and graphs are created.

2.1.2 Graph Embedding: Using GNN to learn embeddings for the nodes in the graph. The GNN captures the topological structure of the graph and the features of the nodes. The GNN types include Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), GraphSAGE, Graph Isomorphism Networks (GIN), ChebNet, and ARMANet. These architectures are selected based on their suitability for capturing different aspects of the complex cross-domain connections present in the datasets.

2.1.3 Adversarial Training: Adversarial training is incorporated to enhance the robustness of the learned embeddings. A Contrastive Loss function is utilized, which optimizes the quality of embeddings by increasing the distance between positive samples and decreasing the distance between positive and negative samples. This adversarial training strategy encourages the model to create more discriminative embeddings, enhancing its ability to capture subtle domain-specific features.

2.1.4 Cross-Domain Mapping: A mapping function is learned to translate the embeddings from the source domain to the target domain. This function is optimized to minimize the distance between mapped embeddings and corresponding embeddings in the target domain.

2.1.5 Visualization. The study adopted a comprehensive visualization strategy to interpret and validate the learned embeddings. Visual inspection involved plotting the mapped source and target embeddings and color-coding them based on their Euclidean distances. This approach provides a qualitative assessment of the effectiveness of the cross-domain mapping.

2.1.6 Evaluation: The performance metrics involve computing the average Euclidean distance as a measure of how close, on average, the mapped source embeddings are to the target embeddings. Other metrics such as Cosine Similarity and Pearson Correlation are considered. Smaller distances and higher similarities indicate better mapping, hence potentially more accurate recommendations.

3 RESULTS AND DISCUSSION

3.1 Dataset

This study has utilized publicly accessible datasets from Amazon across two distinct domains. Each dataset featured essential components such as user IDs, item IDs, and implicit feedback information, incorporating contextual reviews. To streamline processing and maintain simplicity, a subset of 5000 records from each dataset was selected. The records underwent processing in both tabular and graph data structures, tailored to the specific demands of diverse machine-learning techniques.

3.2 Case Scenario

The task at hand was to deduce recommendations predicated on user reviews, contingent upon the quality of cross-domain mapping. This task sought to establish a connection based on implicit review information drawn from both the source and target datasets.

The simulation framework encompassed stages focused on data preprocessing, embedding learning, and cross-domain mapping. This approach furnished a holistic perspective on Cross-Domain Recommendation (CDR) performance drawing from empirical results to assess the quality of embedding and cross-domain mapping as it is an indicator for effective recommendation systems.

3.3 Performance Comparison

3.3.1 Traditional ML vs Feed-forward Neural Network vs Graph Neural Network

This research investigates three distinct approaches PCA + Linear Regression, Feed-forward Neural Network (NN), and Graph Neural Network (GNN). In the implementation, the GNN approach employs a Graph Autoencoder with GCN for cross-domain embedding and reconstruction, optimizing contrastive loss and MSE. It introduced a dedicated model for source-to-target mapping, providing qualitative and quantitative insights through visualizations. In contrast, PCA + Linear Regression simplifies mapping using PCA for feature extraction and linear regression for a straightforward source-to-target mapping with an evaluative focus on average Euclidean distance. The Feed-forward NN approach introduces non-linearity, using MSE loss and the Adam optimizer for iterative refinement, striking a balance between complexity and adaptability in cross-domain connections.

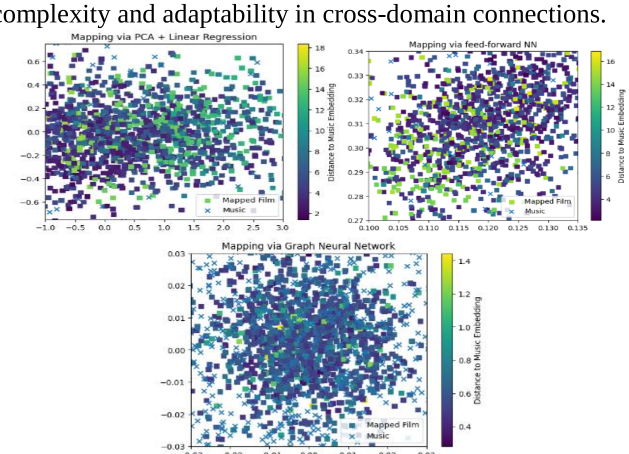

Fig. 2 Visual Inspection for embedding and mapping from different techniques

Figure 2 shows a visual inspection of each approach as part of the preliminary result in the simulation with their respective embedding learning and cross-domain mapping. In individual plots, each square represents a mapped source embedding, colored based on its Euclidean distance to the corresponding target embedding (represented by crosses). Blue squares indicate proximity, an indicator of effective mapping.

The GNN approach shows a higher concentration of blue squares, indicating superior performance in cross-domain mapping. This inferred better quality of cross-domain mapping, and potentially more accurate recommendations.

The simulation revealed that graph-structured data aligns with data representation as well as the architecture of Graph Neural Networks (GNNs). This effectively led to improved performance in both embedding and cross-domain mapping.

During experiments, the task of capturing interactions and relations across different domains posed a challenge. A thorough analysis of what kind of formatting on data structure from different domains is essential for effective data representation because it can affect both embedding and cross-domain mapping.

3.3.2 Graph Neural Network and its Types. A comparative analysis of six types of Graph Neural Network (GNN) models is presented in Table 1, demonstrating varying degrees of performance in cross-domain mapping. This performance is quantified by three key metrics: average Euclidean distance, cosine similarity, and Pearson correlation between the mapped source embeddings and their corresponding target embeddings.

Table 1. Performance of different GNN models

Model	Average Euclidean Distance	Cosine Similarity	Pearson Correlation
GCN	1.001498	0.511066	0.600095
GAT	0.826638	0.474022	0.574186
GraphSAGE	0.385798	0.323938	0.683932
GIN	0.010900	0.015322	0.984300
ChebNet	0.821228	0.499568	0.551848
ARMANet	0.013439	1.000206	-0.004150

The Average Euclidean Distance measures the average spatial separation between mapped source embeddings and their corresponding target embeddings with lower values indicating better quality of cross-domain mapping. A higher cosine similarity indicates that the mapped source embeddings and target embeddings are more similar. Moreover, a Pearson correlation close to zero between the mapped source embeddings and target embeddings indicates that there's no linear relationship between them, suggesting that the model has successfully learned to generate domain-agnostic embeddings.

The models GIN and ARMANet outperform others as shown in Table 1, indicating their superior ability to learn robust and informative embeddings that can be effectively mapped across domains. The models GraphSAGE, GAT, ChebNet, and GCN also exhibit reasonable performance, but they may encounter limitations such as over-smoothing, attention sparsity, spectral filtering, or convolutional complexity.

3.3.3 Adversarial Training. In this section, an adversarial training approach is applied to a GNN model, comprising an autoencoder and a domain classifier, aiming to enhance the quality of cross-domain mapping. Adversarial examples are crafted with the intent to mislead the model, causing it to make errors in predictions. This training strategy aims to enhance the robustness and generalization of the model by exposing it to challenging scenarios.

The autoencoder learns the input graph data representation, while the domain classifier differentiates between embeddings from various domains. The adversarial loss encourages the generation of domain-agnostic embeddings, facilitating cross-domain mapping. Table 2 presents the performance metrics of the GNN-GCN model before and after adversarial training.

Table 2. Performance of GNN-GCN model

Model	**Average Euclidean Distance**	**Cosine Similarity**	**Pearson Correlation**
without adversarial training	1.001498	0.511066	0.600095
with adversarial training	0.016179	1.000102	-0.001795

With the same performance metric, the result yields better than a model with adversarial training having a lower average distance, higher similarity, and no linear relationship indication. This suggests that adversarial training successfully produces non-domain-specific embeddings, enhancing generalizability across different domains.

4.4 Summary of results and key findings

This study contributes to the research space by demonstrating the application of Graph Neural Networks (GNNs) in Cross-Domain Recommendation (CDR). The key findings of this research include the ability of GNNs to leverage graph structure, learn robust embeddings, apply these in a cross-domain context, and disentangle domain-specific and domain-independent information making them a powerful tool for improving recommendation performance.

The most significant key finding of this study is its focus on the quality of data embedding and mapping in CDR. By using GNNs, this research has shown that it's possible to create high-quality embeddings that capture both domain-specific and domain-independent information. These embeddings can then be effectively mapped across domains, leading to improved recommendation performance. Although Graph Neural Networks (GNNs) have been in existence for some time and have demonstrated their effectiveness across diverse domains, this research opens up new paths for future exploration, particularly in the context of Cross-Domain Recommendation (CDR) scenarios. It holds the potential to substantially enhance the efficiency and quality of recommendations.

4 CONCLUSION AND RECOMMENDATIONS

The research conducted in this study has shed light on the effectiveness of Graph Neural Networks (GNNs) in cross-domain recommendation (CDR), particularly in learning embeddings and mapping across domains. The challenges and limitations of cross-domain recommendation systems, such as data sparsity, cold-start problem, domain bias, and domain disentanglement, can be addressed by leveraging the graph structure of user-item interactions across domains, learning domain-invariant and domain-specific embeddings, and propagating information effectively through graph convolution and attention mechanisms.

The performance of different GNN model types in CDR implementation varies depending on the graph construction, the message passing scheme, the loss function, and the pre-training and fine-tuning strategies. The adversarial training approach applied to a GNN model in this study has shown promising results in producing non-domain-specific embeddings, making them more generalizable across different domains.

Looking forward, future research on cross-domain recommendation using GNNs might explore more complex and realistic cross-domain settings, such as multiple source domains, heterogeneous graphs, dynamic graphs, and noisy or incomplete data. New issues and trends might arise in terms of explainability, fairness, privacy, and robustness of GNN-based CDR models. These future directions will further contribute to the broader understanding and development of cross-domain recommendation systems using GNNs.

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