Refining Graph Representation for Cross-Domain Recommendation Based on Edge Pruning in Latent Space

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ABSTRACT In this paper, we present refining graph representation for cross-domain recommendation (CDR) based on edge pruning considering feature distribution in a latent space. Conventional graph-based CDR methods have utilized all ratings and purchase histories of user's products. However, some items purchased by users are not related to the domain for recommendation, and this information becomes noise when making CDR. So, the proposed method introduces edge pruning into the latest graph-based CDR method to refine graph representation. To compare the item embedding features calculated in different domains, we construct a latent space and perform edge pruning through their correlations. Additionally, we introduce a state-of-the-art graph neural network into the graph construction of the proposed method that considers the interactions between users and items thereby obtaining effective embedding features in a domain. This makes it possible to consider domain-specific user preferences and estimate embedding features with high-expressive power. Furthermore, to compare the embedding features of items in the two domains, we construct their latent spaces and project them. Edge pruning is performed using the correlation of items between the two domains on the latent space. We obtain cross domain specific graph representation through edge pruning, which improves the performance by considering the relationship between both items across domains. To the best of our knowledge, no study in the CDR field focuses on eliminating unnecessary node information. We have demonstrated the effectiveness of the proposed method by comparing several graph-based state-of-the-art methods.

INDEX TERMS Edge pruning, cross-domain recommendation, latent space graph convolutional networks.

I. INTRODUCTION

Recently, the number of e-commerce services has increased rapidly providing a variety of services. As the number of items increases, it has become difficult for users to find their favorite items in these services (e.g., Amazon,[1] eBay,[2] and Tmall[3]). So, e-commerce services have introduced a recommendation system [1]–[5] on their backends

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[1]https://www.amazon.com/
[2]https://www.ebay.com/
[3]https://www.tmall.com/

to recommend items while predicting potential relationships between the users and the items. Thus, these services make an effort to achieve personalized item recommendations. General link prediction tasks [6]–[9] have a data sparsity problem, which happens when many items do not have links between users and items. As the main cause of this problem, many users only evaluate very few items. Consequently, a large number of items in the long tail are only evaluated a few times. Note that long tail is a way of selling products on the Internet. This sparsity problem is known as the cold-start problem [10]–[12], and it becomes increasingly serious for new users and items.
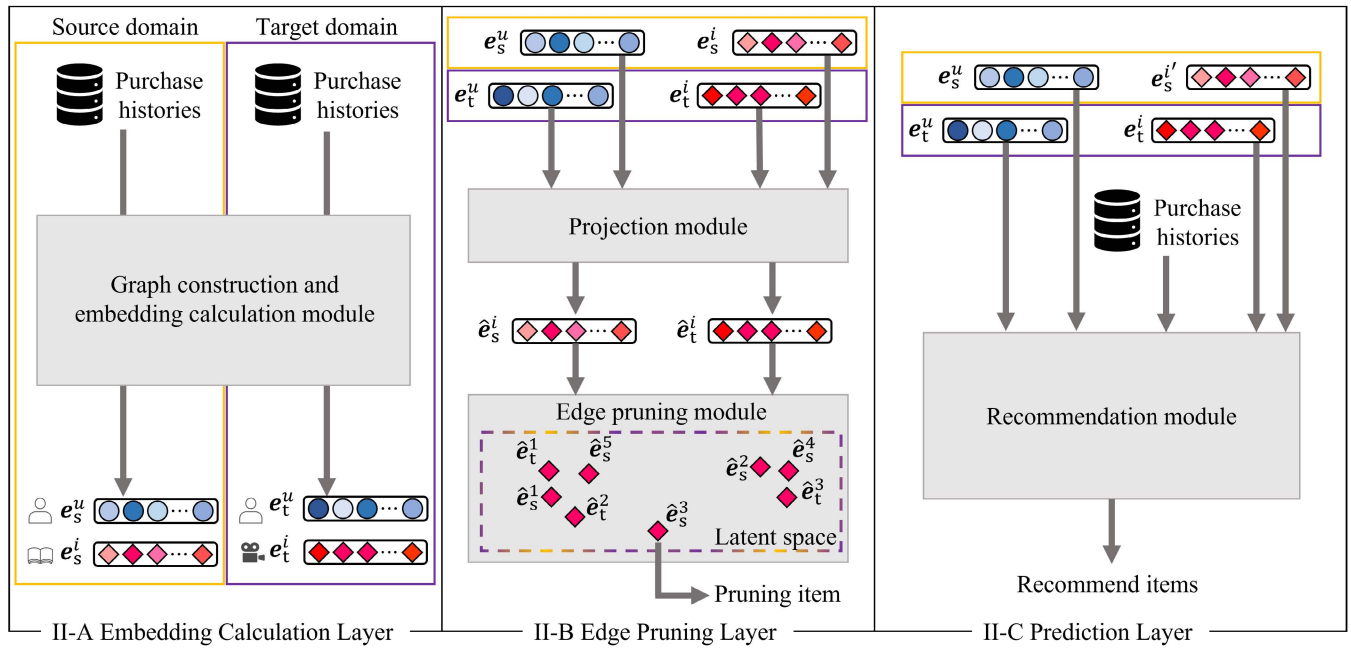
FIGURE 1. Framework of the proposed method. We calculate the embedding features of users and items for each domain using the purchase history. We project the embedding features to the latent space via canonical correlation analysis (CCA) to directly compare features across domains. Furthermore, we perform edge pruning via the distance of items in the latent space. Finally, we construct the recommendation module using the graph on the latent space constructed after edge pruning.

The cross-domain recommendation (CDR) has been studied [13]–[20] to solve the cold-start problem. CDR is a method of item recommendation that complements the information in the target domain by utilizing the information in the source domain with enough information. In the previous methods, domains were regarded as product categories (e.g., books, movies, music, and clothing). The CDR methods can be classified into semantic, factorial, tag, and graph-based methods. Among them, various graph-based methods have attracted significant attention. In these methods, users and items are defined as nodes. The relationships between the users and the items are defined as edges, and their interactions can be considered to improve the recommendation accuracy.

Although previous graph-based methods use the information of all the items for which interactions exist in the source domain, some of those items have nothing to do with the target domain. It means that there is a possibility that the users' embedding features were calculated using the information of those items that contain noise. Thus, they cannot deal with information on items in the source domain that have little relationship with those in the target domain which is a fundamental problem. Therefore, to conduct accurate item recommendations considering the characteristics of the domain, it is necessary to eliminate the influence of items in the source domain that are not related to item recommendations in the target domain when embedding features are calculated. Thus, it is expected that pruning the edges of items in the source domain that are irrelevant for item recommendation in the target domain improves the performance of the CDR. To the

best of our knowledge, no study in the CDR field focuses on eliminating unnecessary node information.

In this paper, we propose a refining graph representation for CDR based on edge pruning considering feature distribution in a latent space. By employing the proposed method, we can efficiently use information from the source domain in the target domain by minimizing the influence of the items in the source domain that are not needed in the target domain. First, we construct the graphs for each domain using users' purchase histories with LightGCN [21], i.e., a state-of-the-art method. Then, we project the item embedding features of the source and the target domains into the latent space using the simplest method, canonical correlation analysis (CCA) [22] and analyze within a domain correlation of item embedding features. We prune the edges of items in the source domain that have a low correlation with those in the target domain using the local outlier factor (LOF) [23], which is a method for anomaly detection. The proposed CDR method enables item recommendations that are not affected by noisy items. We conduct experiments with representative real-world datasets. We confirmed the effectiveness of the proposed method by reducing the influence of unnecessary information in several experiments. Note that this paper is an extension of [24].

II. PROPOSED METHOD

This section presents refining graph representation for CDR with edge pruning. Figure 1 shows a framework of the proposed method. We introduce edge pruning into the new

graph-based CDR method for refining graph representation. First, we train graph representation through the relationship between domains using user-item interactions. Next, we calculate the embedding features with high representation ability for users and items (**II-A**). Then, we project the item embedding features of the source and the target domains into the latent space and prune the edges of useless source domain items via relations in the latent space (**II-B**). This is the main contribution of this paper. Furthermore, we train a recommendation module based on preference propagation graphnet (PPGN) [14], which is a state-of-the-art graph-based CDR method, by utilizing the graph after edge pruning in the latent space (**II-C**). Finally, we use the embedding features of the target user to determine the recommended items (**II-D**). It is only then, that we can estimate user preferences based only on information about items that are useful for recommendations in the target domain.

A. REPRESENTATION BASED ON RELATIONSHIP WITHIN THE DOMAIN

We train graph representation through the relationship between domains. In the proposed method, we construct graphs using the user-item interactions in both domains, respectively. To illustrate this method, we show the graph construction in a domain. The purpose of the graph construction is to calculate the user and item embedding features using the user-item interaction. Figure 2 shows a framework of the construction of the graph. Given, user $u \in \{1, 2, \cdots, U\}$, U is the number of users and item $i \in \{1, 2, \cdots, I\}$, and I is the number of items, we define user and item embedding features as $e^u \in \mathbb{R}^d$ and $e^i \in \mathbb{R}^d$, respectively. Particularly, d denotes the dimension of the embedding features. Then, we adopt LightGCN [21], which is one of the latest graph neural networks. The embedding features of the users and the items are estimated using only the interaction between the users and the items in the domain. The user and item embedding features e^u and e^i are calculated from linear combinations of their h-th hop embedding features, respectively. Additionally, $h (= 0, 1, \cdots, H)$ denotes the number of hops from user u or item i.

We can calculate $e^u_{(h+1)}$ and $e^i_{(h+1)}$ to capture the relationship between the users and the items within a domain as follows:

$$e^u_{(h+1)} = \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}} e^i_h, \tag{1}$$

$$e^i_{(h+1)} = \sum_{u \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i||\mathcal{N}_u|}} e^u_h, \tag{2}$$

where $\mathcal{N}_u$ and $\mathcal{N}_i$ denote the set of items interacted by the user u and the set of users who interact with the item i, respectively. The symmetric normalization term $\frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}}$ is defined based on the standard graph convolution networks [25] and avoids the scale-up of the embedding features related to graph convolution operations. Given e^u_0 and e^i_0, the user-item embedding
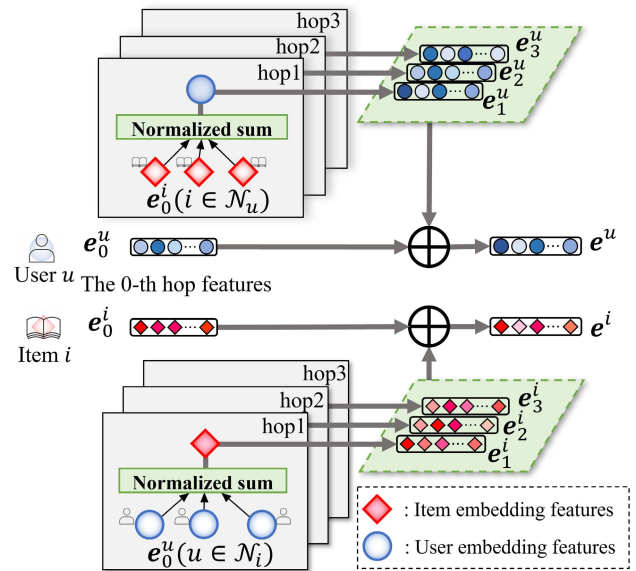

FIGURE 2. Framework of the graph construction in one domain. The constructed graph provides effective representation through the relationship between the users and the items.

features at higher hops can be repeatedly calculated using Eqs. (1) and (2). These embedding features obtained at each hop are combined with the final embedding features of user u and item i as follows:

$$e^u = \sum_{h=0}^{H} \alpha_h e^u_h, \tag{3}$$

$$e^i = \sum_{h=0}^{H} \alpha_h e^i_h. \tag{4}$$

Here, $\alpha_h \geq 0$ represents the importance of the h-th neighborhood embedding feature that produce the final embedding features. The trainable parameters for our graph construction are only the 0-th hop embedding feature matrix $E^{(0)} \in \mathbb{R}^{(U+I) \times d}$. Then, we train a model that can introduce the interactions using the Bayesian personalized ranking (BPR) loss [2] as follows:

$$L_{\text{BPR}} = -\sum_{u=1}^{U} \sum_{i \in \mathcal{N}_u} \sum_{j \notin \mathcal{N}_u} \ln \sigma(y_{(u,i)} - y_{(u,j)}) + \varepsilon ||E^{(0)}||_F^2. \tag{5}$$

Here, $\sigma(\cdot)$ represents a nonlinear activation function, which is a sigmoid function, and ε controls the strength of the L_2 regularization. We can estimate user u's preferences $y_{(u,i)}$ and $y_{(u,j)}$, which are the criteria for determining whether the item i or j are user u's preferences. Thus, we calculate $y_{(u,i)}$ and $y_{(u,j)}$ using the embedding features as follows:

$$y_{(u,i)} = e^{u\mathsf{T}} e^i, \quad y_{(u,j)} = e^{u\mathsf{T}} e^j, \tag{6}$$

where $j (= 1, 2, \ldots, J)$ denotes an unfavorable item for user u. We can calculate the users' embedding features via user-item interactions that consider the user's preferences by

minimizing L_{BPR}. Consequently, we obtain the embedding features with high embedding expressiveness that considers the relationships within the domain.

B. EDGE PRUNING MODULE

We prune the edges of not closely related items using the embedding features of users and items in the source and target domains calculated in Section II-A. Therefore, to project these features to the latent space, we obtain projection matrices $\boldsymbol{\Psi}_s \in \mathbb{R}^{d_s \times d_{cca}}$ and $\boldsymbol{\Psi}_t \in \mathbb{R}^{d_t \times d_{cca}}$ by applying CCA to the user embedding features $\boldsymbol{E}_{u_s} = [\boldsymbol{e}_s^1, \boldsymbol{e}_s^2, \dots, \boldsymbol{e}_s^U] \in \mathbb{R}^{d_s \times U}$ and $\boldsymbol{E}_{u_t} = [\boldsymbol{e}_t^1, \boldsymbol{e}_t^2, \dots, \boldsymbol{e}_t^U] \in \mathbb{R}^{d_t \times U}$. Specifically, we maximize the following objective function:

$$(\hat{\boldsymbol{\psi}}_s, \hat{\boldsymbol{\psi}}_t) = \arg \max_{\boldsymbol{\psi}_s, \boldsymbol{\psi}_t} \frac{\boldsymbol{\psi}_s^\top C_{E_{u_s} E_{u_t}} \boldsymbol{\psi}_t}{\sqrt{\boldsymbol{\psi}_s^\top C_{E_{u_s} E_{u_s}} \boldsymbol{\psi}_s} \sqrt{\boldsymbol{\psi}_t^\top C_{E_{u_t} E_{u_t}} \boldsymbol{\psi}_t}}. \tag{7}$$

Here, $\boldsymbol{\psi}_s$ and $\boldsymbol{\psi}_t$ are the projection vectors, and $\boldsymbol{\Psi}_s \in \mathbb{R}^{d_s \times d_{cca}}$ and $\boldsymbol{\Psi}_t \in \mathbb{R}^{d_t \times d_{cca}}$ include these vectors. The projection vectors are calculated by maximizing Eq. (7) by solving the eigenvalue problems to obtain $\boldsymbol{\Psi}_s \in \mathbb{R}^{d_s \times d_{cca}}$ and $\boldsymbol{\Psi}_t \in \mathbb{R}^{d_t \times d_{cca}}$. Therefore, we obtain the projected features $\hat{\boldsymbol{e}}_s^i \in \mathbb{R}^{d_{cca}}$ and $\hat{\boldsymbol{e}}_t^i \in \mathbb{R}^{d_{cca}}$ that considers their relationships as follows:

$$\hat{\boldsymbol{e}}_s^i = \boldsymbol{\Psi}_s^\top \boldsymbol{e}_s^i, \tag{8}$$

$$\hat{\boldsymbol{e}}_t^i = \boldsymbol{\Psi}_t^\top \boldsymbol{e}_t^i. \tag{9}$$

Thus, we can compare items in the source and target domains in the latent space. It is worth noting that items with high correlation will be closer to each other in the latent space, whereas the items with low correlation will be farther away. Therefore, if there are few items in the neighborhood, we can regard them as those whose edges should be pruned. We calculate the anomaly of items in the source domain using local density on the latent space and prune the edges of highly-anomalous items with LOF [23]. Thus, we express how the local density of item i_s differs from the local density of neighbor item o in terms of outlier scores as an anomaly. First, $\text{lrd}(i_s)$ for the local density of i_s is calculated as follows:

$$\text{lrd}(i_s) = 1 \Big/ \left(\frac{\sum_{o \in N_v(i_s)} \text{reach-dist}_v(i_s, o)}{|N_v(i_s)|} \right), \tag{10}$$

where $N_v(i_s)$ is the set of v neighbor items of i_s; $\text{lrd}(i_s)$ is the inverse of the average reachability distance through the v nearest neighbors of i_s. Furthermore, $\text{reach-dist}(i_s, o)$ for the reachability distance of i_s from o is calculated as follows:

$$\text{reach-dist}_v(i_s, o) = \max(v\text{-dist}(i_s), \text{d}(i_s, o)), \tag{11}$$

where $v\text{-dist}(i_s)$ is the distance of i_s to the v-th neighborhoods; $\text{d}(i_s, o)$ is the distance between i_s and o. If the outlier score $\text{lrd}(i_s)$ is an indicator that measures distance between i_s and the item set, then the outlier score as local reachability density of a i_s, $\text{lof}(i_s)$, is calculated as follows:

$$\text{lof}(i_s) = \frac{\sum_{o \in N_v(i_s)} \frac{\text{lrd}(o)}{\text{lrd}(i_s)}}{|N_v(i_s)|}. \tag{12}$$

The value $\text{lof}(i_s)$ captures the degree to which we regard i_s as an outlier. It is the average of the ratio of the local reachability density of i_s and those of i_s âs v-nearest neighbors. Finally, we obtain the embedding features $\hat{\boldsymbol{e}}_{i_s}^{i'} \in \mathbb{R}^{d_{cca}}$ of the item by pruning the edges of the item determined based on the outlier. Note that $i' \in \{1, 2, \cdots, I'\}$ and I' are the number of items after edge pruning. In this way, edge pruning based on outlier detection is achieved.

C. TRAINING STRATEGIES OF RECOMMENDATION MODULE

We train the recommendation module using PPGN [14]. The knowledge of the recommendation module flows along with the observed user-item interactions. Thus, we can capture the higher-order user-item relationships across domains on a superimposed graph. We can recommend items based on the graphs of the two domains in the latent space using PPGN. After obtaining the potential embedding features of users (e.g., $\hat{\boldsymbol{e}}^u$) and items (e.g., $\hat{\boldsymbol{e}}_s^{i'}$ and $\hat{\boldsymbol{e}}_t^i$) calculated in the previous section (II-B), the tuples of ($\hat{\boldsymbol{e}}_s^{i'}$, $\hat{\boldsymbol{e}}^u$ and $\hat{\boldsymbol{e}}_t^i$) are fed into multilayer perceptions (MLPs). Here $\hat{\boldsymbol{e}}_s^{i'}$ is the embedding feature of the items in the source domain after edge pruning. Specifically, $\hat{\boldsymbol{e}}_s^{i'}$, $\hat{\boldsymbol{e}}_t^u$, and $\hat{\boldsymbol{e}}_t^i$ can be combined as inputs of two MLPs to obtain recommendation predictions for the training samples, i.e., $\hat{x}_s$ and $\hat{x}_t$ between the users and the items in both domains as follows:

$$\hat{\boldsymbol{e}}_s^{u,0} = [\hat{\boldsymbol{e}}_s^{i'}, \hat{\boldsymbol{e}}^u], \quad \hat{\boldsymbol{e}}_t^{u,0} = [\hat{\boldsymbol{e}}_t^i, \hat{\boldsymbol{e}}^u],$$

$$\hat{\boldsymbol{e}}_s^{u,1} = \sigma(\boldsymbol{W}_s^{1\top} \hat{\boldsymbol{e}}_s^{u,0} + \boldsymbol{b}_s^1), \quad \hat{\boldsymbol{e}}_t^{u,1} = \sigma(\boldsymbol{W}_t^{1\top} \hat{\boldsymbol{e}}_t^{u,0} + \boldsymbol{b}_t^1),$$

$$\vdots$$

$$\hat{\boldsymbol{e}}_s^{u,L} = \sigma(\boldsymbol{W}_s^{L\top} \hat{\boldsymbol{e}}_s^{u,L-1} + \boldsymbol{b}_s^L), \quad \hat{\boldsymbol{e}}_t^{u,L} = \sigma(\boldsymbol{W}_t^{L\top} \hat{\boldsymbol{e}}_t^{u,L-1} + \boldsymbol{b}_t^L),$$

$$\hat{x}_s = \phi_s(\hat{\boldsymbol{e}}_s^{u,L}), \quad \hat{x}_t = \phi_t(\hat{\boldsymbol{e}}_t^{u,L}). \tag{13}$$

Here, $\boldsymbol{W}_s^L$ and $\boldsymbol{W}_t^L$ are the trainable transformation matrices; $\boldsymbol{b}_s$ and $\boldsymbol{b}_t$ are the trainable transformation biases; L is the total number of MLP layers. ϕ_s and ϕ_t are the two MLPs to map $\hat{\boldsymbol{e}}_s^{u,L}$ and $\hat{\boldsymbol{e}}_t^{u,L}$ to the two scalars $\hat{x}_s$ and $\hat{x}_t$. The proposed method aims to improve the prediction performance on both domains using refined graph representation for CDR. The loss function $\mathcal{L}$ of PPGN is constructed via a joint cross-entropy loss from the recommendation prediction of both domains: $\mathcal{L}_{u_s}$ and $\mathcal{L}_{u_t}$ and a regularization term $\mathcal{L}_{\text{reg}}$ as follows:

$$\mathcal{L} = \mathcal{L}_{u_s} + \mathcal{L}_{u_t} + \mathcal{L}_{\text{reg}}, \tag{14}$$

$$\mathcal{L}_{u_s} = -\sum_{(i_s, u, i_t) \in T} x_s \log \hat{x}_s + (1 - x_s) \log(1 - \hat{x}_s), \tag{15}$$

$$\mathcal{L}_{u_t} = -\sum_{(i_s, u, i_t) \in T} x_t \log \hat{x}_t + (1 - x_t) \log(1 - \hat{x}_t), \tag{16}$$

$$\mathcal{L}_{\text{reg}} = -\varepsilon \sum |\Theta|. \tag{17}$$

Here, T is the training dataset with positive and negative samples; x_s and x_t are the corresponding labels; ε is the

regularization coefficient; Θ is a set of trainable parameters. We adopted Adam [26] as the optimizer for the parameter update.

TABLE 1. Details of the items used for the experiment dataset.

Domain	#users	#items	#edges
Books	37,388	269,301	1,254,288
Movies and TV	37,388	49,273	792,319

TABLE 2. Number of pruned edges and their ratios.

v	pruned edge	ratio
3	13,021	4.85%
5	9,552	3.55%
20	4,508	1.67%
100	3,105	1.15%

D. ITEM RECOMMENDATION

We determine the recommended items using PPGN learned in the previous subsection (II-C). Specifically, we predict the existence of an edge for user u'. The recommendation module consists of multiple MLPs, which can estimate the users' preferences $\hat{x}_{u'}^{i_\mathrm{t}}$ using embedding features of the users and the items as follows:

$$\hat{x}_{u'}^{i_\mathrm{t}} = \phi_\mathrm{t}(\hat{e}_\mathrm{t}^{u',L}). \tag{18}$$

Here, items with high users' preference $\hat{x}_{u'}^{i_\mathrm{t}}$ are more likely to have an edge. Finally, we recommend items in order of user u''s preference $\hat{x}_{u'}^{i_\mathrm{t}}$ for item i_t as predicted using PPGN.

III. EXPERIMENTAL RESULTS

This section evaluates the proposed method to verify its effectiveness using the real-world dataset. First, we explain the experimental setting (III-A). Then, we analyze and discuss the experimental results qualitatively and quantitatively in (III-B), respectively.

A. EXPERIMENTAL SETTING

In this experiment, we verify the effectiveness of the proposed method. We used the dataset constructed according to the Amazon review dataset[4] [27]. The five-core dataset,[5] which is the original dataset is available for download. The five-core dataset contains 75.26 million reviews, and all users and items have at least five reviews. In this experiment, we set the domain as the product category of Amazon.com. We set the source and target domains to ''Books'' and ''Movies and TV,'' respectively. From the five-core dataset, we collected 37,388 users who are mutual users between the source and the target

[4]https://jmcauley.ucsd.edu/data/amazon/
[5]http://deepyeti.ucsd.edu/jianmo/amazon/categoryFiles/All_Amazon_Review_5.json.gz

domain. Specifically, 269,301 items in the source domain and 49,273 items in the target domain were rated by those users, respectively. The details of the dataset are presented in Table 1. Table 2 presents the number of pruned edges and their ratios. The number of items to be pruned depends on the number of neighboring items of the target item.

In this experiment, we split the training and test users in a ratio of 8:2. We adopted the widely used hit ratio (HR@k), mean reciprocal rank (MRR@k), and normalized discounted cumulative gain (NDCG@k) [28] as the performance evaluation of all methods following [29]. Here, k was 5, 10, and 20. Additionally, as a comparison with the baseline, we set LightGCN, which is one of the latest graph recommendation methods, as a comparison method. We adopted the original PPGN, which is a state-of-the-art method in the CDR field and the proposed method without edge pruning as the comparative methods. The effectiveness of the proposed method was verified by comparing the proposed methods ($v = 3, 5, 20$, and 100) with the comparative methods. In the following subsection, we will show the actual recommendation results and discuss the effectiveness of the proposed method.

B. PERFORMANCE EVALUATION

Table 3 presents the overall experimental results. Consequently, we have the following observations. First, the proposed method significantly outperforms LightGCN. It also accurately captures the user's preferences and generates high-quality recommendations. These results confirm the effectiveness of the CDR by calculating the embedding features for each domain. Second, the proposed method produces higher quality recommendations than the method without edge pruning. The proposed method without edge pruning generates higher quality recommendations than PPGN. As shown in Table 3, we achieve the best recommendation at $v = 5$. The proposed method prunes 4.85% ($v = 3$) and 3.55% ($v = 5$) of the edges in the source domain. The results show that the recommendation accuracy is highest at $v = 5$, followed by $v = 3$. Here, the recommendation accuracy is higher than the proposed method without edge pruning. This indicates that edge pruning improves the recommendation accuracy in the CDR task. Therefore, the recommendation accuracy at $v = 3$ is lower than that at $v = 5$. This may be due to the effect of pruning too much information in the source domain, suggesting that there was 3%-4% noise in the source domain data in this experiment. Therefore, the effectiveness of calculating the embedding features for each domain and using them for CDR is confirmed.

Figure 3 shows the qualitative experimental results of the top five items purchased by a user (Books) and the top five recommended items (Movies and TV). Figure 3 shows that while a user is interested in action and mystery, they like items about a person's life, such as (c), (g), (h), and (i). Then, we focus on the recommendation results of LightGCN and the proposed method. First, the recommendation results of LightGCN are biased toward action and mystery, which is attributed to roughly capturing user preferences in the source

TABLE 3. Details of the experimental results. The best results are highlighted in bold.

|	k	LightGCN	PPGN	PM without edge pruning	PM (v=3)	PM (v=5)	PM (v=20)	PM (v=100)
	5	0.010	0.578	0.594	0.592	**0.600**	0.584	0.589
HR@k	10	0.010	0.723	0.742	0.741	**0.749**	0.735	0.735
	20	0.010	0.846	0.846	0.856	**0.858**	0.855	0.857
	5	0.020	0.361	0.363	**0.373**	**0.373**	0.366	0.369
MRR@k	10	0.020	0.372	0.379	0.387	**0.399**	0.383	0.383
	20	0.030	0.386	0.388	0.400	**0.403**	0.399	0.401
	5	0.015	0.415	0.421	**0.428**	0.427	0.420	0.424
NDCG@k	10	0.018	0.455	0.466	0.471	**0.483**	0.467	0.467
	20	0.023	0.491	0.492	0.504	**0.507**	0.503	0.505
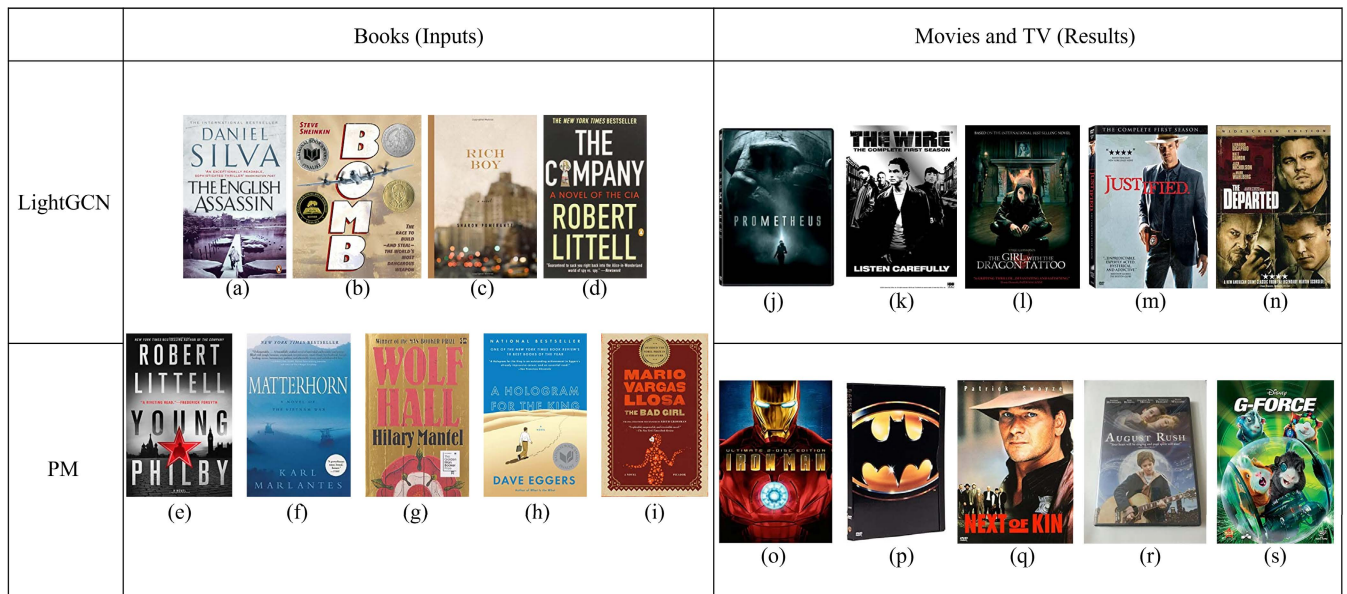
FIGURE 3. Qualitative evaluation results. This figure shows the items (Books) purchased by the user and the recommendation results (Movies and TV). It also shows that while the users are interested in action and mystery, they like items about a person's life, such as (c), (g), (h), and (i). The recommendation results of LightGCN are biased toward action and mystery. In contrast, the proposed method includes the items of not only action and mystery but also the main character's life, such as (r).

domain. In contrast, the proposed method includes the items of not only action and mystery but also the main character's life, such as (r). Consequently, the proposed method can more clearly grasp the user's preference in the source domain and recommend items based on it, confirming its effectiveness.

IV. CONCLUSION

This study proposed refining graph representation for CDR with edge pruning considering feature distribution in the latent space. Extensive experiments validated our motivation to make better recommendations in CDR by removing unnecessary information in the source domain. We observed that the proposed method outperforms the comparative methods, including the state-of-the-art methods.

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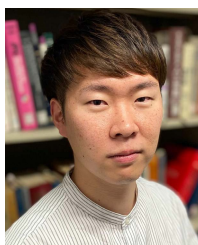
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