BGCN-PNII (Bundle recommendation on GCN with Past or Not-past Interacted Items Information)

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Abstract

Bundle recommender system aims to recommend a bundle to a user. Bundle is a powerful item that has many advantages for both users and sellers, giving a chance to users to consume many items as a whole. Good bundle recommendation model can enhance the quality of the user consumption. Existing works tried many efforts to recommend the bundle successfully, and bundle recommendation on GCN is known to work out nicely. By using GCN as our base model, we aim to incorporate the information that is crucial in bundle preference but is missing on existing works: user's past interaction with the items within a bundle. We propose a BGCN-PNII model(short for Bundle recommendation on GCN with Past or Not-past Interacted Items Information). BGCN-PNII learns the bundle representation vectors from the two levels, reflecting two different aspects. First level, UIB-propagation level, learns the representation vectors of all nodes by the propagation on all-in-one graph. Second level, PNI-incorporation level, incorporates the user's past interaction with the items within a bundle to learn the bundle representation vector specific to each user. Experiments on real-world dataset Youshu shows the performance gain of our model, which outperforms the state-of-the-art baselines by 23.47% to 26.89%. By the additional studies, we also verify the key designs of our model, discuss the results, and propose the revised version that can better model our intention.

1 INTRODUCTION

How can we nicely recommend bundled items to users? E-commerce enhanced users' accessibility for various items and also diversified business sale strategies. One of the prevailing strategy is the bundle configuration. Bundled items enhance the quality of experience for both consumers and sellers for several reasons. Users can be exposed to new item that he/she would not have interacted if the item was monotonously displayed and this can consequently broaden one's interest. Sellers can have increased business sales by expanding the order sizes.

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Bundled items have many distinguishable aspects compared to single item. Nice reflection of these aspects during recommendation is the main key for predicting user's preference and fully taking advantages of bundled items. Therefore, bundle recommendation is the important field in computer science and is being studied as the independent research field.

Most existing works for bundle recommendation concentrates on capturing users' preferences and the similarities between entities. Using graph models such as GCN, they learn the representation of users, items, and bundles during propagation, updating based on the representation vector of each neighbors. These kinds of methods are powerful for recommending bundles that contain likely preferable items for user. However, there are some aspects that are significant for bundle configuration, but are not considered in the existing models. For example, user is likely to avoid bundle that contains too many items that the user already interacted. Or, user is likely to prefer bundle that contains many items that the user already interacted. The existing model has no way to exploit the information whether the specific item in a bundle has past interaction with the user or not.

To address this limitation, we propose a solution named Bundle recommendation on Graph Convolutional Network with Past or Not-past Interacted Items Information (BGCN-PNII). Our model starts with the motivation that the user's past interaction with items within a specific bundle will affect the preference to the bundle. Utilizing the strong power of GCN in learning from higher-order connectivity, BGCN-PNII effectively incorporates past interacted items information awareness into bundle recommender mainly by learning through two levels as follows,

(1) The first level is UIB-propagation level. The representation of users, items, and bundles are learned from user-item interaction, user-bundle interaction, bundle-item affiliation information.
(2) The second level is PNI-incorporation(Past or Not-past interacted Items information incorporation) level. For learning representation of bundle, item is treated with different actions depending on whether the user has past interaction experience with it or not. To be specific, there are learnable parameters to be multiplied for each action.
(3) After the previous two levels, each bundle now has two representation vectors. By utilizing these two bundle representation vectors, we can get two scores for each user-bundle pair that contains different aspects: propagation between neighborhood entries and the past interacted information of items within a bundle. The final score is gained by the weighted sum of the scores.
(4) Lastly, recommendation score is updated via loss function with negative sampling.

The rest of the paper is organized as follows. We first define the problem formally and give the formal representation of each term. Then we organize the challenges that the bundle recommendation has, and then illustrate the methodologies in our proposed model in details. The experiments follow and in the conclusion, we discuss our model in regard to the outcomes.

2 PROBLEM DEFINITION

Let G(V, E) be a graph with nodes (V) representing users, items, and bundles and edges (E) representing interactions between them. Let U, I, B the sets of users, items and bundles. Let $\Omega_{UI} = \{(u,\ i) : user\ u\ has\ interaction\ with\ item\ i\}$, $\Omega_{UB} = \{(u,\ b) : user\ u\ has\ interaction\ with\ bundle\ b\}$, $\Omega_{BI} = \{(b,\ i) : bundle\ b\ contains\ item\ i\}$.

We define edge between each entry as

$$\gamma_{ui} = \begin{cases} 1,\ if\ (u,\ i) \in \Omega_{UI} \\ 0,\ otherwise \end{cases}$$

$$\gamma_{ub} = \begin{cases} 1,\ if\ (u,\ b) \in \Omega_{UB} \\ 0,\ otherwise \end{cases}$$

$$\gamma_{bi} = \begin{cases} 1,\ if\ (b,\ i) \in \Omega_{BI} \\ 0,\ otherwise \end{cases}$$

Based on the above definition, the problem of bundle recommendation is then formulated as follows:

Input: user-item interaction data Ω_{UI}, user-bundle interaction data Ω_{UB}, and bundle-item affiliation data Ω_{BI}.

Output: A recommendation model that estimates the score of each user-bundle pair.

3 METHODOLOGY

3.1 Overview

Successfully recommending bundled items to users has several challenges,

(1) Capturing the preference of user to certain single item or items within a bundle. Bundle that contains many items that the user prefers is more likely to be chosen by the user.
(2) Utilizing the collaborative filtering information. In other words, capturing the similarity between users, items, and bundles, respectively. Items or bundles that are similar to specific item or bundle that the user prefers are more likely to be chosen by the user.
(3) Incorporating user's past interaction information. Some users may prefer bundle that contains many new items that the user has no past interaction, while other users may prefer bundle that contains many items that the user already has past interaction and therefore familiar.

We suggest the BGCN-PNII model to overcome these challenges.

Figure 1 illustrates our proposed BGCN-PNII model which is made up of the following three parts.

- All-In-One Graph Construction: We explicitly model the interaction and affiliation between users, items, and bundles by unifying them into a graph.
- UIB-Propagation: The propagation among users, items, and bundles on the constructed graph captures the CF signal among the entries. This stage is related to challenge 1 and challenge 2.
- PNI-Incorporation: By applying the different actions depending on whether the user has past interaction with the item that the bundle contains or not, it can incorporate the affect of user's past interaction on bundle preference. This stage is related to challenge 3.

3.2 All-In-One Graph Construction and Initial Representation Vector

To explicitly model the relationship between users, items, and bundles, we first build unified all-in-one graph. The interaction and affiliation data is represented by an undirected graph G=(V, E), where nodes are V consisting of user nodes in U, item nodes in I, and bundles nodes in B, and edges are E consisting of user-item interaction edges (u, i), user-bundle interaction edges (u, b), and bundle-item affiliation edges (b, i), all with value 1.

Let the one-hot feature vector for user u, item i, and bundle b as $v_u^U,\ v_i^I,\ v_b^B \in {}^N$. Let the matrices of user embedding, item embedding, and bundle embedding as P, Q, and R.

For initial user, item, and bundle vector, we apply one-hot encoding to encode the input and compress them to dense vectors as follows,

$\mathfrak{p}_u = P^T v_u^U,\ \mathfrak{q}_i = Q^T v_i^I,\ \mathfrak{r}_b = R^T v_b^B$

3.3 UIB-Propagation

The user is more likely to prefer bundles that contain many items the user likes. Also, the user is more likely to prefer items or bundles that are similar to the item or bundle that the user likes. In addition, the user is more likely to prefer items or bundles that the other user that has similar taste with the user likes.

GCN has a strong power to capture these relationships. We construct an embedded propagation layer between users, items, and bundles. By the multi-level propagation, the representation vectors for users, items, and bundles are updated, resembling the neighbors of themselves. The embedding updating rules can be formulated as follows,

$$\mathfrak{p}_u^{(l+1)} = \sigma(^{(l)}(\mathfrak{p}_u^{(l)} + aggregate(\mathfrak{q}_i^{(l)}|i \in N_u) + aggregate(\mathfrak{r}_b^{(l)}|b \in N_u)))$$

$$\mathfrak{q}_i^{(l+1)} = \sigma(^{(l)}(\mathfrak{q}_i^{(l)} + aggregate(\mathfrak{p}_u^{(l)}|u \in N_i) + aggregate(\mathfrak{r}_b^{(l)}|b \in N_i)))$$

$$\mathfrak{r}_b^{(l+1)} = \sigma(^{(l)}(\mathfrak{r}_b^{(l)} + aggregate(\mathfrak{p}_u^{(l)}|u \in N_b) + aggregate(\mathfrak{q}_i^{(l)}|i \in N_b)))$$

3.4 PNI-Incorporation

From the UIB-propagation level, the model can reflect the similarity among users, items, and bundles and the preference for each item or bundle by past selection. However, some other important characteristic that the bundle has because of its consisted items is missing so far. Since the bundle is composed with various items, user's past interaction with the specific item can affect the preference to the bundle containing that item.

There can be two hypotheses which are entirely opposite but both make sense in real world. The user may prefer the bundle that contains many items that the user has already encountered in the past because it is familiar or closer to his or her taste. In contrast, the user may prefer the bundle that does not contain many items

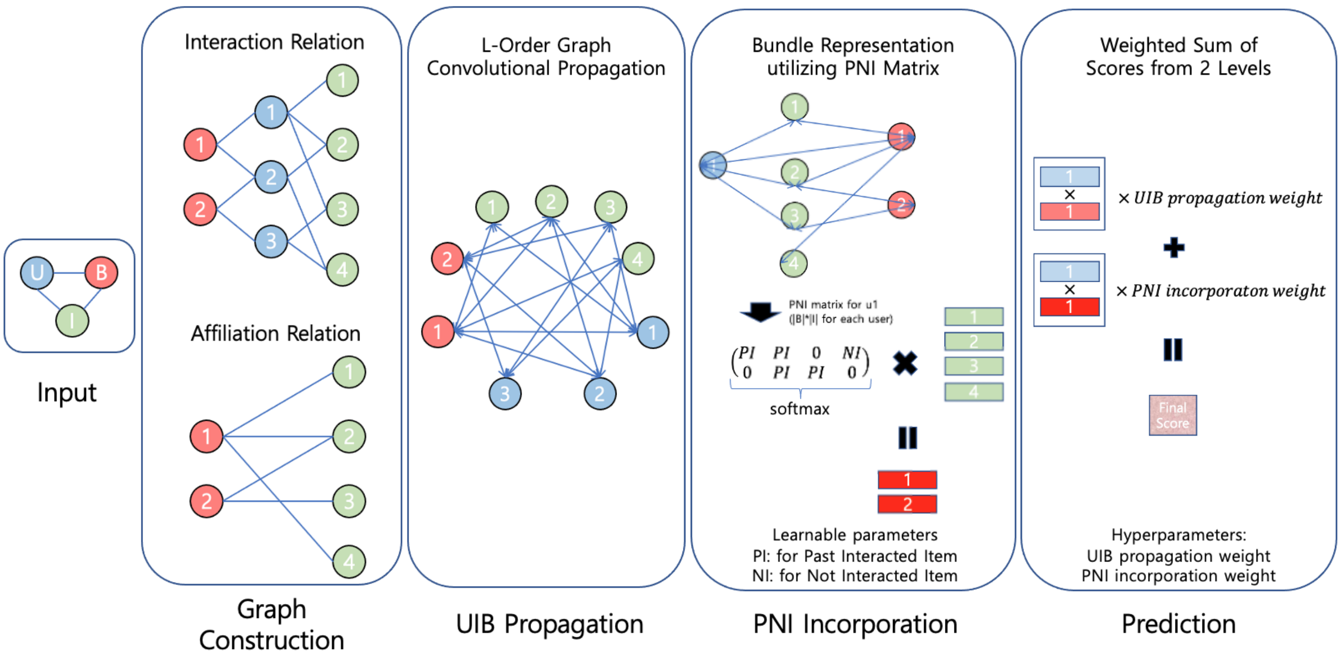

Figure 1: The illustration of BGCN-PNII model, where u1 is the target user and b1 is the target bundle.

that the user has already encountered, because he or she wants to try new items. So in our work, we are going to inquire which one is really the case. Incorporating user's past interacted items information while learning bundle vector will better reflect the user preference.

We introduce two learnable parameters, PI and NI, each for past-interacted-item and not-past-interacted-item respectively. Since the datasets in bundle recommendation research field are usually enormous, it is impossible to keep different representation for all user-bundle pairs. Therefore, unlike the UIB-propagation, in PNI-incorporation, we calculate the bundle representation only for the 'subject of interest' (u, b) pairs, that is, only the (u, b) pairs in each batch that are currently dealt with.

Let the past interaction matrix of user-items and the affiliation matrix of bundle-items as follows,

$$I_{UI} = \{(u, i) : \textit{user } u \textit{ has past interaction with item } i\}$$
$$A_{BI} = \{(b, i) : \textit{bundle } b \textit{ contains item } i\}$$

Shape for both matrices is |m|*|n|, where m is the batch size and n is the total item counts.

Applying the following equation,

$$\mathrm{F}_{(u,b)i} = NI * \mathrm{A}_{BI} + ((PI - NI) * I_{UI}) * \mathrm{A}_{BI}$$

, we can get the final PNI-info matrix F, which has the PI value in the past-interacted-item entries and the NI value in the not-past-interacted-item entries.

Finally, by doing the inner product of the softmax of PNI-info matrix F and items feature vectors gained from UIB-propagation level, we can get the bundle representation that incorporates the user's past interacted items information.

$$\mathrm{r}_b^{'} = softmax(\mathrm{F}^T_{(u,b)i})\mathrm{q}_i$$

3.5 Prediction

As the result of the previous two levels, each bundle vector has two representation r and r' that is derived from the UIB-propagation level and PNI-incorporation level respectively. We can calculate the two scalar scores of user-bundle pair by simply applying the inner product to the user vector gained from UIB-propagation level and the bundle vector each gained from UIB-propagation level and PNI-incorporation level. We get the final score by the weighted sum of these two scores. These processes can be formulated as follows,

$$\mathrm{s}_{(u,b)} = \alpha \mathrm{p}_u^T \mathrm{r}_b + \beta \mathrm{p}_u^T \mathrm{r}_b^{'}$$

To adjust the scale between two scores, we let the weight for each entry as the hyperparameter alpha and beta, and find the optimal pair.

4 EXPERIMENTS

In this section, we conduct experiments to answer the following three questions:

- Q1: How does our proposed BGCN-PNII model perform as compared with the state-of-the-art methods?
- Q2: How do the key designs in our model affect performance?
- Q3: How the learnable parameters in the model turn out to be, and what do they indicate in the real world problem?

4.1 Experimental Settings

4.1.1 Dataset. To evaluate the performance of our model, we conduct experiments on one real-world bundle recommendation dataset - Youshu. Youshu was crawled from a Chinese book review website by Cao et al. Here, users create a list of books they like under different genres.

In the dataset, users have interactions with individual items as well as bundles. Further, bundles are constructed from any subset of existing items. The statistics of the dataset are given in Table 1.

4.1.2 Evaluation Procedure. To compare the performance of the proposed model against other models, we use two widely used metrics, Recall@K and NDCG@K. Recall@K measures the ratio of test bundles that have been contained by the top-K ranking list. NDCG@K complements Recall@K by assigning higher scores to the hits at higher positions of the list.

4.1.3 Hyperparameter Settings. We implement our model using PyTorch 1.11. We tune the hyperparameter - learning rate, uib propagation weight, and pni incorporation weight. The learning rate is 3e-3 and L2 regularization term is 1e-7. We used 0.72 and 0.28 for uib propagation weight and pni incorporation weight respectively, which are the values that both considers scalability and greediness. For the other hyperparameters, we use the values that are used in [1]. We adopt BPR loss and set the negative sampling rate to 1. For the optimizer, we use Adam with the 2048-size mini-batch. We train for 48 epochs.

4.1.4 Comparison Baselines. We compare the performance of the proposed model with the following three state-of-the-art methods.

- MFBPR [2] is a matrix factorization model under a Bayesian Personalized Ranking framework, which leverages pairwise loss function during optimization.
- DAM [4] is a deep attention-based multi-task model. It models interaction between user-item and user-bundle jointly by a multi-task approach.
- BGCN [1] uses the graph convolutional network and learn the representation vectors of each entry by propagation. It is composed of item-level propagation and bundle-level propagation.

We borrow the results for MFBPR, DAM, and BGCN from [1].

4.2 Results and Discussions

4.2.1 Overall Performance Comparison. Table 2 shows the overall performance of three baseline models and our proposed model on Youshu dataset. From the results, we can derive the following analyses.

- BGCN-PNII achieves the best performance when measured with the Recall metric. This result shows that the PNI-incorporation level well captures how the user's past interaction with items within a bundle affects the preference to the bundle. Better prediction can be made by using two bundle representations each gained by UIB-propagation level and PNI-incorporation level, reflecting both aspects of bundle composition.
- BGCN-PNII performs slightly poorly than BGCN when measured with the NDCG metric. This can be interpreted by concentrating on the difference between two evaluation metrics. Whether the user has past interaction with items in a bundle or not definitely affects the user's preference to bundle, so incorporating the information acts nicely and shows better performance for Recall evaluation. However, when we concentrate on the detailed ranking itself, past interacted item information may not significantly lead to the slight changes of rankings. Among all bundles that already have high score for the user, the detailed ranking among them is likely to be affected by the user's subjective taste. For this reason, BGCN-PNII may have performed slightly poorly in terms of NDCG than the model that only utilizes the neighbor-wise propagated information.

4.2.2 Ablation Studies. We conducted two ablation studies to evaluate how the key designs contributed to the performance. The results of the studies are organized in Table 3. Two models, one only with UIB-propagation level, and the other one only with PNI-incorporation level both showed decent performance. One unexpected result is that the model only with UIB-propagation level showed better performance even than the complete BGCN-PNII model. This implies that the PNI-incorporation level was insufficient to capture all the information we intended. In this section, we mainly discuss the possible blames in PNI-incorporation level for these unexpected outcomes. We also propose the revised model that can resolve the blames.

- It takes too much time to train the learnable parameters PI and NI until convergence. After 48 epochs, PI and NI is still being updated with some tendency, so the model comes out to compute the score using not-fully-converged parameters. To successfully apply the correct parameters for past interacted items and not past interacted items, we have to train for sufficient number of epochs so that the learnable parameters can converge to the correct values.
- Bundle representation gained from PNI-incorporation level only consists of the item feature vectors, and therefore it misses information from users and bundles representation. This is the radical issue of our model. To meet this issue, we propose the model that dynamically incorporates the past interaction information in the propagation level. Instead of using two separate levels, we can apply PI and NI in the propagation level. Instead of treating all neighborhood items with equal weight in the propagation level, we can apply PI and NI weight depending on the user's past interaction, just as same as what we did in the PNI-incorporation level. The main reason we couldn't implement the model is that to incorporate the past interaction information, it is necessary to maintain PNI-info matrix for all user-bundle pairs. This occupies too much space that is not manageable for us on our training environment. Finding the way to dynamically learn from both neighborhood information and past interaction information at the same time, within the manageable space, it will be able get the desirable model that perfectly acts as we intended.

4.2.3 Learnable Parameter Analysis. Table 4 shows the learned PI and NI values in various number of training epochs. We give the initial value of 1 for both PI and NI. Although we failed to get the perfectly converged values of PI and NI, we can observe the obvious tendency of two parameters. Since we apply softmax to PNI-info matrix, the values seemingly keep increasing, but we should concentrate on the relationship between two parameters. The more epochs we train, PI increases much faster compared to

Table 1: Statistics of Youshu dataset

# Users	# Bundes	# Items	# U-B Interactions	# U-I Interactions	# B-I Interactions	Avg. Bundle Interactions	Avg. Item Interactions	Avg. Bundle size	U-I Density	U-B Density
8039	4771	32770	51377	138515	176667	6.39	17.23	37.03	0.05%	0.13%

Table 2: Overall Performance Comparison on Youshu dataset (R stands for Recall metric and N stands for NDCG metric)

	R@20	N@20	R@40	N@40	R@80	N@80
MFBPR	0.1959	0.1117	0.2735	0.1320	0.3710	0.1543
DAM	0.2082	0.1198	0.2890	0.1418	0.3915	0.1658
BGCN	0.2347	**0.1345**	0.3248	**0.1593**	0.4355	**0.1851**
BGCN-PNII	**0.2689**	0.1218	**0.3651**	0.1415	**0.4694**	0.1593

Table 3: Ablation studies of the key designs on Youshu dataset (R stands for Recall metric and N stands for NDCG metric)

Key Designs	R@20	N@20	R@40	N@40	R@80	N@80
UIB-Propagation Level	0.2749	0.1279	0.3788	0.1492	0.4944	0.1689
PNI-Incorporation Level	0.1717	0.0768	0.2543	0.0935	0.3543	0.1106

NI. In the real world situation, this tendency implies that the user tends to interact with bundle that contains the items that he or she already interacted at the past. We can now give the answer for the question we introduced at the starting point. The user tends to prefer the bundle that contains many items that he or she has already encountered in the past because the past interaction ensures his or her taste for the item. We can conclude that although the actual implementation is somehow insufficient to fully exploit the past interacted items information, the high level intuition that the user's past interaction will affect the bundle preference is worth considerable.

Table 4: PI and NI values learned from various number of training epochs.

# of training epochs	PI	NI
48	5.4123	4.6250
544	9.7367	6.7884

5 RELATED WORKS

Since bundles are widely used nowadays, there are many attempts to introduce a good model in bundle recommendation system.

Embedding Factorization Machine [2] utilizes the user's interactions with items and bundles under the BPR framework. Deep Attentive Multi-Task Model [4] jointly models user-item interactions and user-bundle interactions in a multi-task manner.

Meanwhile, GCN was introduced in the bundle recommendation field. It has a strong power when applied to bundle recommender model, learning efficiently from the interactions both interior and across the entries. By constructing graph structure and using multi-layer convolutional networks, it utilizes the adjacent information of users, items, and bundles to learn representation vectors. The most famous model among GCN based models is BGCN(Bundle Recommendation with Graph Convolutional Networks) [1]. BGCN re-constructs the two kinds of interaction and affiliation into the graph, and learns the representation vectors from two levels called item-level propagation and bundle-level propagation. Our proposed model is based on the BGCN model with upgraded UIB-propagation level and additional PNI-incorporation level.

6 CONCLUSION

In this work, we propose BGCN-PNII model for bundle recommendation task. BGCN-PNII is based on the graph convolutional network and especially aims to capture the key aspect that is important in determining user-bundle preference, but is not incorporated in the existing models. We concentrate on the user's past interaction with the items within a bundle.

Our proposed model is composed of two levels, UIB-propagation level and PNI-incorporation level. In UIB-propagation level, representation vectors of each user, item, and bundle are learned, utilizing all of the neighborhood vectors. In PNI-incorporation level, we learn the representation of bundles, specifically for each independent user, by applying different parameters for the items depending on whether the user interacted with the item in the past or not.

Experiments show that our model shows the good performance compared to baselines. However, by the ablation studies, we observed that the PNI-incorporation level may not be working well as we intended. We discussed the possible blames and also proposed the revised version to meet those issues.

Modeling the bundle recommender system requires the careful observations of the bundle characteristics. It is crucial to understand and explore the characteristics that the bundle has because of the fact that it is constructed with many single items. In this work we concentrated on the user's past interaction with the items that consist the bundle among many characteristics. By further trials with the model that dynamically exploits the information of possible aspects in the same level, we expect our proposal to contribute to the better prediction of user-bundle preference. Furthermore, we deeply realized the bright prospect of bundle recommendation system, regarding the bundle prevalence in real world and also because of its academic value in research field.

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