# Item Enhanced Diversification in the Recommendation System Using Graph Neural Network

Naina Yadav[1,3], Ramakant kumar[2,3], and Anil Kumar Singh[3]

[1] SCSET Bennett University Greater Noida Uttar Pradesh
[2] GLA University Mathura Uttar Pradesh
[3] Indian Institute of Technology (BHU) Varanasi

**Abstract.** A recommendation system is a set of programs that utilize different methodologies for relevant item selection for the user. Graph neural networks have been extensively used in recent years to improve the quality of recommendations across all domains. A general recommendation system's main goal is to recommend items to the user accurately, and it frequently prioritizes items that are well-liked or mainstream. If the model concentrates only on one specific item category from the users' past preferences, then recommendations for the target user will become too obvious. To address this problem, diversity in the recommendation system is introduced. The model IG-DivRS (Item-Enhanced Graph Neural Network for a Diversified Recommendation System) is proposed. Our proposed model uses a Graph Neural Network (GNN) with the user's interacted and non-interacted item history for diversified recommendation generation. The novelty of our proposed model is to explore the effect of non-interacted items on the target user for diversified recommendation generation. Instead of selecting random non-interacted items for the target user, we apply the DPP(Determinantal Point Process) algorithm to select the non-interacted item appropriately. The detailed experimental analysis shows that our model ID-DivRS outperforms the state-of-the-art model in accuracy and diversity.

**Keywords:** Diverse Recommendation, Graph Neural Network, Determinantal Point Process, Accuracy-Diversity Trade-off

## 1 Introduction

With the rapid development of information over the internet, selecting information is a tedious task, which is also called the information overload problem. With the aid of a recommendation system, it is possible to select from a large collection of information and recommend only the most pertinent and useful information to the user. The recommendation system is now used in numerous fields, including E-commerce, music, movies, healthcare, etc. Collaborative filtering (CF) is one of the most popular recommendation system techniques. The fundamental CF-based technique models users' preferences from their historical interactions and then models them to predict the effective recommendation [2]. Graph Neural Networks (GNNs) in recommendation systems have recently evolved rapidly, and numerous innovative methods have been developed for efficient recommendation generation [22, ?]. A strong strategy for recommendations is the use of GNN. GNN can leverage the relationships and interactions between users, items, and other relevant entities [7]. A fundamental groundwork for analyzing relationships in various social contexts, GNN also offers an effective method of dealing with abstract concepts like relationships and interactions. In general, the main objective of traditional recommendation techniques is to generate constructive recommendations based on users' past interaction history. Generating recommendations that consider their prior preferences is the main goal of these techniques. Sometimes, these recommendations are not helpful for users who prefer diversity in their preferences because the repetition of similar items in the recommendation

David C. Wyld et al. (Eds): NET, DNLP, MLIOB -2024
pp. 31-40, 2024. CS & IT - CSCP 2024 DOI: 10.5121/csit.2024.140303

list will monotonize the system. The primary objective of introducing diversity is to generate user recommendation models that include diverse and relevant recommendations for the target user [23]. Diverse recommendations are generated at the beginning of the technique using different re-ranking-based methodologies [15]. These techniques function as post-processing techniques where the model first generates recommendations, and then the recommendation list is shuffled by the diverse item list using dissimilarity and user preferences. Due to the accuracy-diversity trade-off, adding diversity to models will impact the model's accuracy. Later, this trade-off between accuracy and diversity will give rise to a fresh avenue of exploration into recommendation systems [26, **?**,**?**]. In the two-stage diversity approach, reshuffling only rearranges items according to their dissimilarity, which limits item coverage to the recommendation list. Instead of adopting the two-stage model for the diversified recommendation, we adopted the GNN representation technique for effective recommendation generation for the target user, which are diverse and accurate. Exploring GNN for the effective representation of the target node, including diverse and relevant neighbourhood information, is one challenging issue. Apart from node representation, over-smoothing is a major challenge in GNN while including large neighbourhood information in GNN node representation. To keep these issues in consideration, we proposed a model based on GNN and Determinantal Point Processes (DPP) for effective node representation of the target user. In this proposed model, we investigate how Graph Neural Networks (GNN) and Determinantal Point Processes (DPP) might be used to enhance the accuracy-diversity trade-off for recommender systems. The distinctive aspect of the proposed model can be observed in the selection of diverse items for the target user. The diverse item selection for each target user is achieved using the DPP algorithm for the non-integrated items list for the target user. The DPP is a probabilistic machine learning-based model best used for negative correlation sampling. In the recommendation system earlier, DPP is used as a post-processing approach to model diverse subsets for the generated recommendation list. In our proposed model, we use DPP to pre-process each user's non-interacted items list for the subset selection and use these subsets with users' interacted item history for effective representation. Apart from this, we also explored the significance of both interacted and non-interacted items in diverse recommendation generations in our proposed model. The key contributions of the model we propose are addressed below -

- We proposed a GNN and DPP-based recommendation model to maintain the accuracy-diversity tradeoff.
- We investigated both the users' past interactions and non-interacted items' history.
- To verify the effectiveness of our model, we run extensive experiments on the MovieLens-100K dataset.

## 2 Related Work

Earlier, many retrieval and mining algorithms were proposed for recommendation generation, which only considers the most relevant and top-rated items for a recommendation from a large set of items. For instance, suggesting highly rated movies to users, the most listened to songs for the user and the most visited news article for the recommendation [24]. Various ranking methodologies are proposed for diversity in these systems, which re-rank items for diversification in the recommendation list [19, 5, 1]. Re-ranking approaches are the most usual way of including diversity in the recommendation system. This is a two-step approach in which a recommendation list is first retrieved. Then the re-ranking algorithm is run on that list to generate the diverse recommended list by optimising the objective function, which explicitly trade-off between relevance and diversity. Apart from the greedy re-ranking algorithm, intent-Aware Diversification is used in recommendation systems to re-rank the recommendation list using various aspects of users. These aspects can be defined explicitly or implicitly. Implicit aspects can be derived from the user's history, like latent factors and explicit aspects are a set of features used to describe items and users. These are some machine learning-based approaches. Apart from these, some deep learning approaches are also used for diversity awareness in the recommender system. Esmeli et al. [6] proposed a session-based personalization for diverse recommendations. Diversity was included in the recommendation list by adding items that depended on the diversity level of the last interacted item of the session. Similarly, Hu et al. [10] also proposed a deep learning model for a session-based recommender system that uses context information for personalized diversity. This approach is also a rearranging approach that re-ranks the recommendation list using users' relevance to the item based on some given context. Apart from single context consideration in RS, many authors incorporated multiple aspects in improving diversity in the recommendation. Oliveira et al. proposed a multiobjective method for diversity and accuracy consideration, which includes content information like contemporaneity, gender, genre, and locality. The multiobjective optimization is achieved using Pareto optimality [17].

### 2.1 Accuracy-Diversity Trade-off in Recommendation System

Recent works have used the traditional approach for a recommender system while addressing the accuracy-diversity tradeoff. Su et al. [18] propose a set-oriented framework for diversity using a matrix-factorization method based on users' context information explicitly for acquiring personalized diversity. Wang et al. [20] included personalized diversity using the similarity network for better user influence on the recommender system. This approach uses a similarity network to connect the similarity function and bipartite graph to improve the resource-allocation process. Chen et al. [4] proposed a deep learning approach for diversification. They used a sequential recommendation model with intent mining for diversity enhancement. The method uses an implicit intent mining approach to mine user intent automatically. Another concept introduced in the recommendation system for diversity using a machine learning algorithm is called DPP (Determinantal Point Process). DPP is a complementary and encouraging approach used as a probabilistic model for negative correlation, sampling, conditioning, marginalization, and many other inference tasks. Wilhelm et al.[21] included the DPP process in their work for YouTube video recommendation.

The accuracy-diversity tradeoff is one of the major problems with the recommendation system. The tradeoff occurs while increasing the diversity of the recommendation model, where a slight increase in the diversity of the recommendation list leads to a significant drop in the model's accuracy. Many models have proposed considerable solutions to overcome a tradeoff between accuracy and diversity. Liang et al. proposed a method IDF-NCF for accuracy-diversity tradeoff balance using individual users' diversity preferences. They proposed a model that includes pre-training for each user's diverse items using the TransH knowledge graph-based embedding model [16]. Another model is proposed by Isufi et al. [11]. They proposed a model using a Graph convolution neural network where they consider similar as well as dissimilar users for the neighbourhood. The proposed model relies on the joint representation of the nearest and farthest users for the ranking and rating prediction model. Kim et al. proposed a model based on the matrix factorization technique called DivMF. The model is trained for diverse recommendation generation using two separate regularizers for coverage and skewness. The author also proposed an unmasking mechanism and mini-bath learning technique to accurately and quickly learn DivMF [13]. Yang et al. proposed a model DGRec for the diversified recommendation, which includes three modules, including a submodular function for neighbour selection, followed by layer attention to handle the over-smoothing problem at the last loss function, which reweights popular items to reduce the long-tail problem [25].

## 3 Problem Formulation

Let $U = \{u_1, u_2, \ldots u_M\}$ are set of users and $I = \{i_1, i_2 \ldots i_N\}$ are set of items where $M$ and $N$ denotes the total number of users and items respectively. The rating matrix of these users and items are denoted as $R = \mathcal{R}^{M \times N}$. Let $V_u$ denote the items list rated by the user $u$ and $C_u$ denote the item set which is not rated by the user $u$. So for the target user $K_u = n - C_u$ where $n$ is the total items rated by the target user $u$. From $K_u$ we need to select $\mathcal{K}_u$ as a candidate item list for diverse item selection for the target user $u$.

## 4 Proposed Model

This Section describes our proposed model (IG-DivRS), which targets accuracy and diversity in top-N recommendation generation. Our proposed model IG-DivRS is divided into three sections. The general recommendation system (RS) utilises the use of users' prior interaction history, and this information plays an important role in generating effective recommendations. The non-interacted items are certainly ignored in the earlier recommendation model. In contrast, exploring non-interacted items will give considerable information regarding users' diverse nature in item selection. In our proposed model, we utilize these items' information to model diverse item embedding generation. It is neither sufficient nor at all accurate to take into account all non-interacted items for the target user. Therefore, we must choose items for each target user that are effective for the diversified recommendation generation. In contrast, we use the DPP algorithm to choose a wide variety of item sets for the target user. DPP is used as a post-processing model for the recommendation list in the earlier model that was defined for the diverse recommendation generation. We also choose non-interacted items for the low-dimensional representation of the user and item using DPP as a pre-processing technique. We utilised the Deepwalk GNN-based approach for embedding generation. The flow chart of our proposed approach is shown in Figure 1.

### 4.1 Determinantal Point Process

A determinantal point process (DPP) is a probabilistic model that is employed in recommendation systems to choose a diverse and representative subset of items from an extensive set. The model includes relevance and diversity to provide personalized recommendations. The first applications of DPP are the probabilistic models introduced in random matrix theory and quantum physics. DPP provides accurate and effective algorithms for inference tasks such as conditioning, marginalization, and sampling. Our proposed model uses DPP as a pre-processing technique to choose a candidate item set from the user's $u$ non-interacted item list. The data representation, in which items are encoded into a vector set, serves as the foundation of the mathematical model for DPP. The probability model chooses the distribution of the item set $I$ over the candidate set $Y$ in the kernel matrix representation where $Y \subseteq 2^V$. The item's affinity or similarity to other items in set $Y$ is

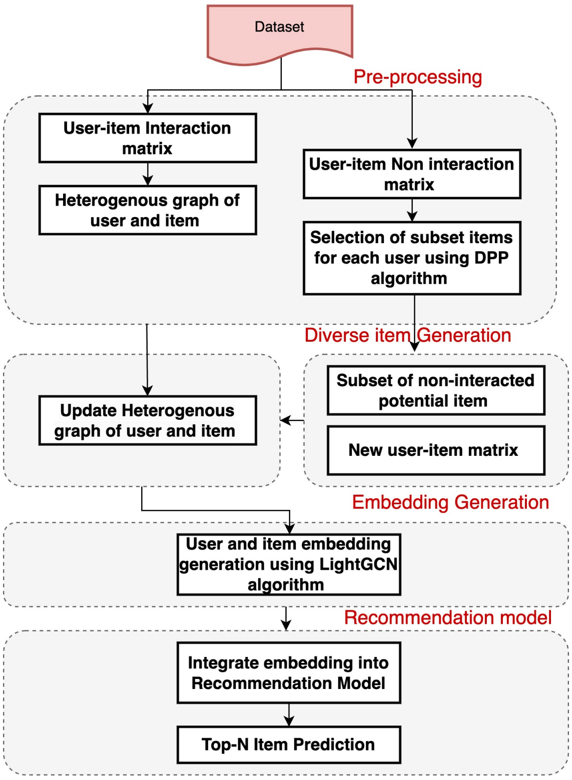



Fig. 1: Flow diagram of our proposed model.

included in the kernel matrix $L$. Using the cosine similarity measure, the similarity between the items is determined. In our proposed model, we model the user behaviour using DPP and probability distribution in the following manner: -

$$Y = \mathcal{P}_u \tag{1}$$

Using DPP, we define a probability distribution over an exponential number of item sets $2^V$, and it can be parameterized using a kernel matrix $L$. In general probability of DPP can be written as -

$$\mathcal{Y} = \frac{det(L_y)}{\sum_{y \subseteq S} det(L_y{}')} \tag{2}$$

In equation (2), kernel matrix $L$ includes rows and columns, which are indexed by subset $Y$, and the denominator in (2) is a normalizing term. The reason behind using DPP is that it includes items in the subset which are negatively correlated [14].

$$\sum_{y \subseteq S} det(L_y) = det(L + I) \tag{3}$$

In equation (3) $I$ is the identity matrix. For sampling, we use MAP inference [3].

### 4.2 Diverse Embedding Representation for Recommendation

This section includes a thorough analysis of the diverse embedding representations of the user and item, including diverse items for each user embedding representation. In our proposed model, we use the original graph structure of the user-item interaction graph, and then we update the graph, which includes the non-interacted items for users. The non-interaction items for each user are selected based on the DPP algorithm. The reason for including the DPP algorithm in the item selection algorithm is that a set of potential items will be included in the updated graph. Non-interacted items will be selected for the target user as a candidate item set using the DPP method, which is used for diversified neighbour selection. These candidate item sets are divided into several $q$ subsets, ensuring that the initial pool of candidate item sets already includes a broad range of recommendation item sets. Initially, we fixed the threshold for the candidate item selection to 0.7. Using the interacted and non-interacted item sets for the recommendation system can potentially improve the relevance and diversity of the recommendations generated for the target user. Once we updated the graph structure, we applied the LightGCN algorithm for the recommendation generation [8]. The basic idea in the LightGCN algorithm is to learn the representation of user and item nodes by smoothing features over the user-item interacted graph. The advantage of using the LightGCN algorithm in our proposed model is computational efficiency. The target node representation in the LightGCN model is done using the aggregation of neighbourhood information.

$$e_u^{(k+1)} = AGG(e_u^{(k)}, e_i^{(k)} : i\epsilon\mathcal{N}_u) \tag{4}$$

In equation (4) $AGG$ is the aggregation function which includes $k^{th}$ layer representation of the target node and neighbour node. The graph convolution in the LightGCN model is defined as follows-

$$e_u^{(k+1)} = \sum_{i\epsilon\mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_i|}.\sqrt{|\mathcal{N}_u|}} e_i^k \tag{5}$$

$$e_i^{(k+1)} = \sum_{u\epsilon\mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i|}.\sqrt{|\mathcal{N}_u|}} e_u^k \tag{6}$$

To train our model, we combined $L_2$ regularization with an objective function based on Bayesian Personalized Ranking (BPR Loss), which motivates observed user-item predictions to increase values over unobserved ones.

$$L_{BPR} = -\sum_{u=1}^{M} \sum_{i\epsilon N_u} \sum_{j\notin N_u} ln\sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \lambda \left\| E^{(0)} \right\|^2 \tag{7}$$

In equation (7) $E^{(0)}$ is a matrix of $0^{th}$ layer embeddings to learn.

## 5 Results and Analysis

### 5.1 Experimental Settings

**Dataset-** We analyse the performance of our proposed model using the MovieLens-100k dataset [4] and the MovieLens 1M dataset [5]. MovieLens-100k is a benchmark dataset with 100,000 user ratings on 1,682 movies, ranging from 1 to 5, provided by 943 users. The MovieLens-1M dataset includes 6040 MovieLens users who joined MovieLens in 2000, which includes 1,000,209 interactions of 6040 users with 3,900 distinct movies. Another dataset is the Yelp business dataset [6] of 16239 users, and 14282 business and 198397 ratings are available. Statistics of the datasets used in our proposed model are described in table 1.

[4] https://grouplens.org/datasets/movielens/100k/
[5] https://files.grouplens.org/datasets/movielens/ml-1m.zip
[6] https://www.yelp.com/dataset

Table 1: Dataset statistics

| Dataset | Users | Items | Ratings |
|---|---|---|---|
| MovieLens-100k | 943 | 1,682 | 1,00,000 |
| MovieLens-1M | 6,040 | 3,900 | 7,92,026 |
| Yelp | 16,239 | 14,282 | 1,98,397 |

To implement our model, we use the Microsoft library recommenders [7]. To implement our model, we start with a pre-process dataset for the user-item interaction matrix, represented using a heterogenous graph where two types of nodes (user and item) are present. Following our model's description, we extract negative items (items not rated by the users). Then, we apply the DPP algorithm to select more suitable non-rated items for the target users as negative neighbour item nodes for the target user. This idea is beyond the typical collaborative filtering methods, providing a more nuanced and diverse selection. Further extended user-item interaction graph is used for the recommendation generation using the typical LightGCN model. We applied DPP, where the hyper-parameter for DPP relevance and diversity threshold value ($\lambda$) is 0.5. The $\lambda$ value controls the relevance and diversity tradeoff in subset selection for the target user. In the DPP algorithm, we use the spectral sampling procedure. Spectral sampling requires an eigendecomposition of the correlation kernel $L$. We efficiently use the eigenvalues and eigenvectors of the kernel matrix connected to the DPP to produce a broad range of representative subsets of items for spectral sampling. It is an iterative process that initializes an empty set S and further calculates the probabilities of items based on their eigenvectors.
After applying DPP to a non-interacted item history, we get sets of relevant items for the users. We update our original graph of user-item interaction with sets of non-interacted items history for each user. Then, we will apply the LightGCN method for recommendation generation. We adopted the same settings as in [8] for the hyperparameter setting. We fixed the embedding size for the model to 64, and all embedding parameters are initialized randomly following the Xavier method. We use the default minibatch size of 1024 and use Adam optimization with a learning rate of 0.001. We train our model for 50 epochs.

### 5.2 Baseline Methods

This section analyses the proposed model's effectiveness using other state-of-the-art models. The details of these methods are discussed below-

- **LightGCN** [8]- It uses the collaborative filtering concept using the graph convolution operation and it is more effective in terms of complexity and efficiency of the recommendation generation.
- **Div2vec** [12] The method includes an embedding technique for node representation for diverse recommendation generation. The div2vec method is based on sampling nodes with probability inversely proportional to its degree so that in the random walk, every node will appear adequately.
- **Neural Collaborative Filtering** [9]- NCF is an efficient algorithm that uses the concept of collaborative filtering and overcomes the drawback of deep neural networks for learning the interaction from the user-item interaction data.

Table 2 shows our model's (IG-DivRS) performance comparison with other state-of-the-art models. With regard to accuracy and diversity taken into account at the same

[7] https://github.com/recommenders-team/recommenders

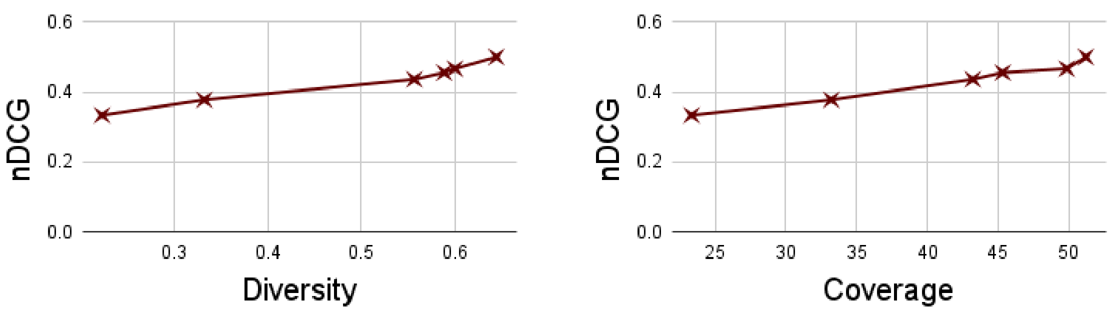
time, our proposed model, IG-DivRS, consistently outperforms other baseline methods. We compared our model's performance on two benchmark datasets of Movielens. When we attempt to increase the diversity of our model, we run into a significant issue with the recommendation system. Due to the accuracy-diversity trade-off, model accuracy will decrease as recommendation system diversity increases. We attempted to balance the accuracy-diversity trade-off in our proposed model. In the proposed model, IG-DivRS accuracy is improving in terms of nDCG and MAP for top-k recommendations, as well as model diversity in terms of ILD (intra-list diversity) for the top-k recommendation list. We evaluated all metrics for the top-10 recommendation list.

Table 2: Comparative analysis of our proposed IG-DivRS model for MAP (higher value is better), NDCG, Precision, Recall (higher value is better) diversity, and coverage

| **Datasets** | **Baseline Model** | **Map@10** | **nDCG@10** | **Precision@10** | **Rrecall@10** | **ILD@10** | **Coverage@10** |
|---|---|---|---|---|---|---|---|
| ML-100k | **LightGCN** | 0.1292 | 0.4362 | 0.3818 | 0.2058 | 0.5567 | 43.22 |
| ML-100k | **Div2Vec** | 0.0987 | 0.3002 | 0.3435 | 0.1987 | 0.7522 | 65.44 |
| ML-100k | **NCF** | 0.1057 | 0.3876 | 0.3421 | 0.1745 | 0.4112 | 39.66 |
| ML-100k | **IG-DivRS** | 0.1211 | 0.3994 | 0.3533 | 0.1922 | 0.4223 | 42.13 |
| ML-1M | **LightGCN** | 0.075 | 0.3775 | 0.3456 | 0.128 | 0.3221 | 27.66 |
| ML-1M | **Div2Vec** | 0.0655 | 0.3221 | 0.3221 | 0.1143 | 0.4332 | 33.99 |
| ML-1M | **NCF** | 0.0628 | 0.3487 | 0.3206 | 0.1081 | 0.3348 | 27.88 |
| ML-1M | **IG-DivRS** | 0.1002 | 0.3662 | 0.3321 | 0.1211 | 0.3655 | 31.11 |
| Yelp | **LightGCN** | 0.1442 | 0.2554 | 0.2113 | 0.2887 | 0.4452 | 23.19 |
| Yelp | **Div2Vec** | 0.1109 | 0.2239 | 0.2593 | 0.3233 | 0.5922 | 42.91 |
| Yelp | **NCF** | 0.1233 | 0.24472 | 0.2359 | 0.2014 | 0.511 | 33.25 |
| Yelp | **IG-DivRS** | 0.1556 | 0.2665 | 0.2554 | 0.2991 | 0.6112 | 54.23 |

## 5.3 Relevance and Diversity Comparison

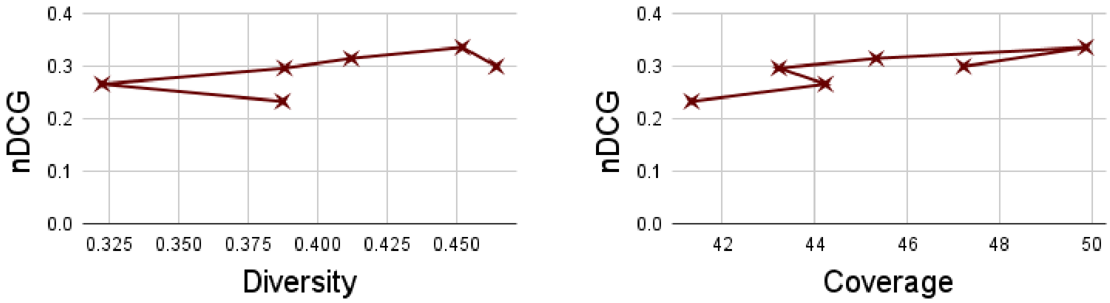
While increasing diversity in the model, it suffers from the accuracy-diversity tradeoff. For our proposed model IG-DivRS, we also demonstrated the accuracy-diversity tradeoff in the context of nDCG vs. diversity and nDCG vs. Item coverage in Figure 2, 3, 4. The tradeoff has been learned for the rating prediction model of IG-DivRS for the dataset ML-100k, ML-1M and Yelp. Our proposed model outperforms state of the art model in terms of relevance and diversity.




(a) Diversity Graph

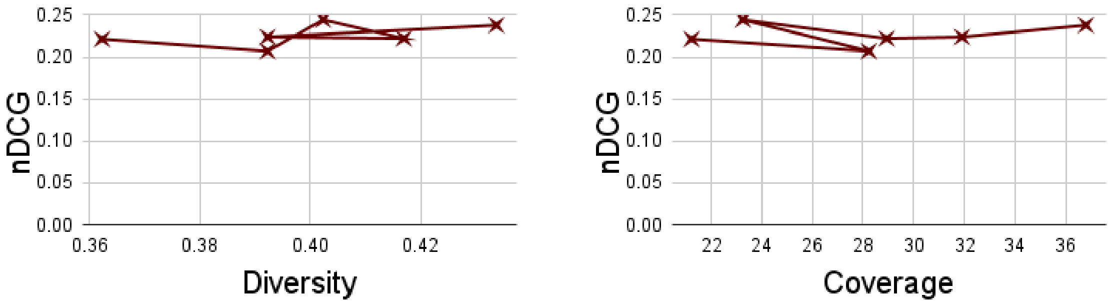
(b) Coverage Graph

Fig. 2: A demonstration for top-k diversity and coverage analysis for ML-100k dataset for baseline and our proposed IG-DivRec Model




(a) Diversity Graph (b) Coverage Graph

Fig. 3: A demonstration for top-k diversity and coverage analysis for ML-1M dataset for baseline and our proposed IG-DivRec Model




(a) Diversity Graph (b) Coverage Graph

Fig. 4: A demonstration for top-k diversity and coverage analysis for Yelp dataset for baseline and our proposed IG-DivRec Model

## 6 Conclusion

This paper proposes a model IG-DivRS for a diversified recommendation system using DPP and GNN. The non-interacted item history of each user was used in this model to attempt to strike a balance between accuracy and diversity. Instead of selecting complete non-interacted items, we obtained a subset of non-interacted items for the target user using the DPP algorithm. The subset selection for the target user for non-interacted items will be included in the past-interaction history. After that, the final heterogeneous graph of user-item interaction will be used for a diversified recommendation system. Further, we use the GNN-based method lightGCN for the embedding representation for the user and item embedding representation and final recommendation generation.

## References

1. G. Adomavicius and Y. Kwon. Improving aggregate recommendation diversity using ranking-based techniques. *IEEE Transactions on Knowledge and Data Engineering*, 24(5):896–911, 2011.
2. J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez. Recommender systems survey. *Knowledge-based systems*, 46:109–132, 2013.

3. L. Chen, G. Zhang, and E. Zhou. Fast greedy map inference for determinantal point process to improve recommendation diversity. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc., 2018.
4. W. Chen, P. Ren, F. Cai, F. Sun, and M. de Rijke. Improving end-to-end sequential recommendations with intent-aware diversification. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, pages 175–184, 2020.
5. T. Di Noia, J. Rosati, P. Tomeo, and E. Di Sciascio. Adaptive multi-attribute diversity for recommender systems. *Information Sciences*, 382:234–253, 2017.
6. R. Esmeli, M. Bader-El-Den, and H. Abdullahi. Improving session based recommendation by diversity awareness. In *UK Workshop on computational intelligence*, pages 319–330. Springer, 2019.
7. C. Gao, X. Wang, X. He, and Y. Li. Graph neural networks for recommender system. In *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining*, pages 1623–1625, 2022.
8. X. He, K. Deng, X. Wang, Y. Li, Y. Zhang, and M. Wang. Lightgcn: Simplifying and powering graph convolution network for recommendation. In *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval*, pages 639–648, 2020.
9. X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T.-S. Chua. Neural collaborative filtering. In *Proceedings of the 26th international conference on world wide web*, pages 173–182, 2017.
10. L. Hu, L. Cao, S. Wang, G. Xu, J. Cao, and Z. Gu. Diversifying personalized recommendation with user-session context. In *IJCAI*, pages 1858–1864, 2017.
11. E. Isufi, M. Pocchiari, and A. Hanjalic. Accuracy-diversity trade-off in recommender systems via graph convolutions. *Information Processing & Management*, 58(2):102459, 2021.
12. J. Jeong, J.-M. Yun, H. Keam, Y.-J. Park, Z. Park, and J. Cho. div2vec: diversity-emphasized node embedding. *arXiv preprint arXiv:2009.09588*, 2020.
13. J. Kim, H. Jeon, J. Lee, and U. Kang. Diversely regularized matrix factorization for accurate and aggregately diversified recommendation. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 361–373. Springer, 2023.
14. A. Kulesza and B. Taskar. Determinantal point processes for machine learning. *Foundations and Trends® in Machine Learning*, 5(2–3):123–286, 2012.
15. M. Kunaver and T. Požrl. Diversity in recommender systems–a survey. *Knowledge-based systems*, 123:154–162, 2017.
16. G. Liang, J. Wen, and W. Zhou. Individual diversity preference aware neural collaborative filtering. *Knowledge-Based Systems*, 258:109730, 2022.
17. R. S. Oliveira, C. Nóbrega, L. B. Marinho, and N. Andrade. A multiobjective music recommendation approach for aspect-based diversification. In *ISMIR*, pages 414–420, 2017.
18. R. Su, L. Yin, K. Chen, and Y. Yu. Set-oriented personalized ranking for diversified top-n recommendation. In *Proceedings of the 7th ACM Conference on Recommender Systems*, pages 415–418, 2013.
19. S. Vargas, P. Castells, and D. Vallet. Intent-oriented diversity in recommender systems. In *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*, pages 1211–1212, 2011.
20. X. Wang, Y. Liu, and F. Xiong. Improved personalized recommendation based on a similarity network. *Physica A: Statistical Mechanics and its Applications*, 456:271–280, 2016.
21. M. Wilhelm, A. Ramanathan, A. Bonomo, S. Jain, E. H. Chi, and J. Gillenwater. Practical diversified recommendations on youtube with determinantal point processes. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pages 2165–2173, 2018.
22. S. Wu, F. Sun, W. Zhang, X. Xie, and B. Cui. Graph neural networks in recommender systems: a survey. *ACM Computing Surveys*, 55(5):1–37, 2022.
23. N. Yadav, R. K. Mundotiya, A. K. Singh, and S. Pal. Diversity in recommendation system: A cluster based approach. In *Hybrid Intelligent Systems: 19th International Conference on Hybrid Intelligent Systems (HIS 2019) held in Bhopal, India, December 10-12, 2019 19*, pages 113–122. Springer, 2021.
24. N. Yadav and A. K. Singh. Bi-directional encoder representation of transformer model for sequential music recommender system. In *Proceedings of the 12th Annual Meeting of the Forum for Information Retrieval Evaluation*, pages 49–53, 2020.
25. L. Yang, S. Wang, Y. Tao, J. Sun, X. Liu, P. S. Yu, and T. Wang. Dgrec: Graph neural network for recommendation with diversified embedding generation. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining*, pages 661–669, 2023.
26. T. Zhou, Z. Kuscsik, J.-G. Liu, M. Medo, J. R. Wakeling, and Y.-C. Zhang. Solving the apparent diversity-accuracy dilemma of recommender systems. *Proceedings of the National Academy of Sciences*, 107(10):4511–4515, 2010.