Quick Graph Conversion for Robust Recommendation

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Abstract
Implicit feedback plays a huge role in recommender systems, but its high noise characteristic seriously reduces its effect. To denoise implicit feedback, some efforts have been devoted to graph data augmentation (GDA) methods. Although the bi-level optimization thought of GDA guarantees better recommendation performance theoretically, it also leads to expensive time costs and severe space explosion problems. Specifically, bi-level optimization involves repeated traversal of all positive and negative instances after each optimization of the recommendation model.

In this paper, we propose a new denoising paradigm, i.e., Quick Graph Conversion (QGrace), to effectively transform the original interaction graph into a purified (for positive instances) and densified (for negative instances) interest graph during the recommendation model training process. In QGrace, we leverage the gradient matching scheme based on elaborated generative models to fulfill the conversion and generation of an interest graph, elegantly overcoming the high time and space cost problems. To enable recommendation models to run on interest graphs that lack implicit feedback data, we provide a fine-grained objective function from the perspective of alignment and uniformity. The experimental results on three benchmark datasets demonstrate that the QGrace outperforms the state-of-the-art GDA methods and recommendation models in effectiveness and robustness.

CCS Concepts: • Information systems → Recommender Systems.

Keywords: Recommender System; Graph Data Augmentation; Robust Learning; Graph Conversion

1 INTRODUCTION
Recommender systems [6, 31] have been widely applied in many domains, and most of them use implicit feedback (e.g., view, click, and purchase) to develop machine learning models [7, 10, 23, 30]. Specifically, these methods view user-item observed interactions as positive instances, while other unobserved interactions are viewed as negative instances. However, existing recommendation models based on implicit feedback suffer from two shortcomings. (1) Noisy positive instances: a user may interact with an item by mistake, yet that user presents a negative preference for this item [1, 18]. (2) Noisy negative instances: users lack interaction with most items. Simply viewing the missing interactions as negative instances misestimates the user’s preferences [7, 27].

Some researchers represent the user-item interaction as a graph, and attempt to alleviate the noisy implicit feedback problem by various means, all of which can be generalized from a graph data augmentation (GDA) perspective. These GDA approaches can be divided into two categories. (1) Model-independent approaches [3, 5, 19, 28, 33] augment the graph using a sampler, i.e., removing noisy positive instances and transforming noisy negative instances into positive ones according to a certain sampling probability. The main problem with this type of method is the lack of knowledge related to the recommendation model, which has a limited effect on improving the accuracy of recommendations. (2) Model-dependent approaches [11, 25, 26] adaptively couple the recommendation model’s training process and the graph’s augmentation process, which can be defined as a bi-level optimization problem [2, 7]. Benefiting from the bi-level optimization framework, the adaptive process of GDA can guarantee better performance theoretically.
Figure 1. The comparison between existing GDA methods and QGrace. (a) shows model-independent GDA that trains a sampler model without model training. (b) shows model-dependent GDA from the perspective of bi-level optimization that dynamically modifies observed interactions. (c) shows that, unlike other existing model-dependent GDA methods, QGrace considers all interactions and transforms them into interests.

However, in contrast to the lightweight model-independent approaches, model-dependent ones need to repeatedly traverse and optimize million or billion graph structure parameters (the size of which is the number of users multiplied by the number of items) after each optimization of the recommendation model. It will lead to expensive time costs and severe space explosion problems. To avoid intensive computational problems caused by the overwhelming number of negative instances, existing model-dependent methods \[7, 15, 25\] often denoise noisy positive instances in observed data while neglecting noisy negative instances that hide abundant user real interests.

To account for both positive and negative instances in the model-dependent GDA, in this paper, we propose the Quick Graph Conversion (QGrace) denoising task that aims to effectively purify and densify the user-item unweighted graph to a complete weighted graph. In this manner, QGrace treats all user-item interactions (including unobserved ones) as positive instances, with the weight indicating the strength. For simplicity, the unweighted graph before QGrace reflects the interactions between users and items, called interaction graph, while the weighted graph after QGrace reflects the real interests, called interest graph. Figure 1 shows an example to present the difference between QGrace and existing GDA methods.

To elegantly fulfill the graph conversion process, we propose a framework that leverages the gradient matching scheme \[12, 36\] to simplify and expedite the process of QGrace. The gradient matching scheme is a deformation of bi-level optimization, which can be divided into inner and outer optimization. In the inner optimization, the recommendation model tries to find two optimal parameters trained on the interest graph and interaction graph, respectively. In the meantime, outer optimization optimizes the interest graph structure parameters to pull the two acquired recommendation model parameters close to each other. In detail, we bring each gradient of the recommendation model’s two optimizations closer in every iteration training, which can achieve the purpose of making the two recommendation model parameters closer \[36\].

Considering that the gradient matching process requires explicitly recording and updating the interest graph structure parameters, it easily causes the expensive time cost and space explosion problem. To deal with the problem, we design crafted generative models to generate interest graph structure parameters instead of perturbing them directly, thereby reducing both time and space costs.

Meanwhile, there is a new barrier to recommendation models in the process of gradient matching, which requires recommendation models to be trained on both interaction
Quick Graph Conversion for Robust Recommendation

2 PRELIMINARIES

2.1 Implicit Feedback based Recommendation in GDA Task

Given a user-item interaction graph $G_A = \{U, I, A\}$ and a user-item interest graph $G_R = \{U, I, R\}$, where $U \in \mathbb{R}^M$ denotes the set of user nodes, $I \in \mathbb{R}^N$ denotes the set of item nodes, $A \in \mathbb{R}^{M \times N}$ denotes the set of unweighted edges that stand for user-item interactions, and $R \in \mathbb{R}^{M \times N}$ denotes the set of weighted edges that stand for user-item interests. $A_{u,i} = \{0, 1\}$ indicates whether a user $u$ has interacted with an item $i$, $R_{u,i} \in \{0, 1\}$ indicates a user $u$’s level of interest in an item $i$. In general, recommendation methods based on implicit feedback are trained on interaction graph $A$, and attain optimal user representations $Z_U \in \mathbb{R}^{M \times d}$ and item representations $Z_I \in \mathbb{R}^{N \times d}$ ($d$ is the dimension of the latent space) by learning the model $f$ with parameters $\theta$.

The purpose of model-independent GDA methods [4, 5, 19, 28, 33] is to denoise the interaction graph from $A$ to $\hat{A}$, to enhance data quality for the model training. The formulation of the recommendation model trained on model-independent GDA is as follows:

$$\theta^* = \arg \min_{\theta} L(f_0(\hat{A})),$$

where $L$ is the recommendation loss, and $\theta^*$ is the optimal parameters. Recently, some studies [2, 7] focus on model-dependent GDA, and we will introduce the relation between model-independent and model-dependent GDA from the perspective of bi-level optimization in Section 3.1.

2.2 Alignment and Uniformity

Recent studies [24] have proved alignment and uniformity of representations are related to prediction performance in representation learning, which is also applicable to the recommendation model [22, 32]. The alignment is defined as the expected distance between normalized embeddings of positive pairs, and on the other hand, the uniformity is defined as the logarithm of the average pairwise Gaussian potential. AU (Alignment and Uniformity) loss [22] quantified alignment and uniformity in recommendation as follows:

$$L_{rec} = L_{alignment} + \alpha L_{uniformity},$$

$$L_{alignment} = \mathbb{E}_{(z_u, z_i) \sim \rho_{pos}} \|z_u - z_i\|^2,$$

Additionally, QGrace can be applied well to different recommendation models, which shows its transferity.
where $P_{\text{GDA}}$ as a bi-level optimization problem \cite{15,38}, and the cause they are more effective boost recommendation models. Recently, model-dependent GDA methods \cite{7,11,25,26} grad-
parameter matching process to gradient matching process, the Equation 6 can be rewritten as follow:

$$\min_{\mathcal{R}} \sum_{t=0}^{T-1} D(\nabla_{\mathbf{g}_t^A} L(f_0(A)), \nabla_{\mathbf{g}_t^B} L(f_0(R))).$$  
(8)

Here, the definition of $D(\cdot; \cdot)$ refers to [12] as follows:

$$D(G^A, G^B) = \sum_{c=1}^{d_1} \left( \frac{1}{\|G^A_c\| \|G^B_c\|} \right),$$  
(9)

where $G^A \in \mathbb{R}^{d_1 \times d_2}$ and $G^B \in \mathbb{R}^{d_1 \times d_2}$ are gradients at a specific layer, which are optimized on interaction and interest graph ($d_1$, $d_2$ are the number of rows and columns of the gradient matrices). $G^A_c$ and $G^B_c$ are the c-th column vectors of the gradient matrices.

Compared with the process of traditional bi-level optimization in Equation 5, we can find two advantages of the gradient matching scheme in QGrace: (1) The traditional bi-level optimization dynamically changes the graph structure, which may lose some informative interactions. On the contrary, QGrace preserves the original interaction graph structure all the time. Based on the interaction graph, the outer optimization of QGrace can perturb the interest graph structure with parameters matching scheme, preventing structure perturbations in the wrong direction. Thus, the purified and densified graph generated by QGrace shows better robustness than that generated by traditional bi-level optimization, thereby improving the performance of the recommendation. (2) The traditional bi-level optimization uses the optimal recommendation model for prediction in the outer optimization, which will take much computational time. Conversely, gradient matching merely needs the recommendation model’s gradients that have been calculated in the inner optimization. The difference will save additional computational time in outer optimization to accelerate the process of bi-level optimization.

### 3.2.2 Generative Models

In Equation 8, the efficiency of optimizing graph structure parameters $\mathcal{R} \in \mathbb{R}^{M \times N}$ is affected by the number of users $U \in \mathbb{R}^M$ and items $I \in \mathbb{R}^N$, which will cause expensive time costs and space explosion problems. To deal with it, we propose three crafted generative models to generate structure parameters of the interest graph. After using the generative model, the parameters that need to be updated change from the entire graph graph to a small number of generative model parameters. The generative models can all be formulated by Equation 10 as follows:

$$\mathcal{R} = f_{\text{gen}}(X),$$  
(10)

where $X$ is input vectors and $f_{\text{gen}}$ is the function of generative models. Then we introduce three types of generative models, including MF-based, MLP-based and VAE-based generative models.

**MF-based Generative Model.** Inspired by matrix factorization, we design a simple generative model that uses additional user embeddings $E_u \in \mathbb{R}^{M \times d_u}$ and item embeddings $E_i \in \mathbb{R}^{N \times d_i}$ to generate interests in users items:

$$\mathcal{R} = \text{normalize}(E_u^T E_i).$$  
(11)

**MLP-based Generative Model.** The MF-based generative model lacks learning ability, so we design a generative model that incorporates two-layer MLP (Multi-Layer Perceptron):

$$R_{u,i} = f_{c_2}(f_{c_1}(\text{concat}(z_u, z_i))),$$  
(12)

where $f_{c_1}$ and $f_{c_2}$ are fully connected layers.

**VAE-based Generative Model.** We also design a generative model based on VAE (Variational AutoEncoder) [14], which has proved its practicability in many domains. The VAE-based generative model has three components, including an encoder, a re-parameterized sampling layer for Gaussian distribution and a decoder:

$$\mu, \sigma = f_{e_{\text{en}}}(\text{concat}(z_u, z_i)),$$

$$z = f_{e_{\text{sample}}}(\mu, \sigma),$$

$$R_{u,i} = f_{c_{de}}(z),$$

where $f_{e_{\text{en}}}, f_{e_{\text{sample}}, f_{c_{de)}}$ are fully connected layers for the above three components.

### 3.3 Weighted Alignment and Uniformity in Gradient Matching

There is a new challenge for the gradient matching scheme used in the recommendation. Due to the limitation of implicit feedback, previous studies often use binary cross-entropy and BPR loss as objective functions. However, these loss functions can not be directly used for model training on the interest graph, so we can not get $\nabla_{\mathbf{g}_t^B}$ in Equation 8.

Some state-of-the-art methods [22, 32] proved that the quality of embeddings in alignment and uniformity is correlated with recommendation performance. Inspired by this foundation, we attempt to use the interest value as the degree of instances alignment and refine AU loss to WAU (Weighted Alignment and Uniformity) loss. The Equation 3 can be rewritten as follows:

$$L_{\text{alignment}} = \mathbb{E}_{(z_u, z_i) \sim \text{P}_{\text{data}}} W_{u,i} ||z_u - z_i||^2,$$

where $W_{u,i} = \begin{cases} A_{u,i} & \text{if interaction graph.} \\ R_{u,i} & \text{if interest graph.} \end{cases}$

Here, $P_{\text{data}}(\cdot; \cdot)$ is the distribution of all embeddings, and $R_{u,i}$ can be obtained from Equation 10. We consider $A_{u,i} \in \{0, 1\}$ as the weights when model training on interaction graph, while $R_{u,i} \in \{0, 1\}$ as the weights when model training on interest graph. We hold an opinion that WAU loss is more appropriate than AU loss in the recommendation for two reasons: (1) Since WAU has different pulling forces according to
the interest values, rather than AU rudely pulling all positive instances closer with the same forces. (2) WAU additionally considers the alignment of uninteracted instances’ potential interests. Note that we do not need to iterate over all instances in the inner recommendation model optimization, and we use a point-wise scheme based on negative sampling to train recommendation models, which randomly choose a certain number of negative instances for each positive instance.

On the basis of previous studies [22], we further prove the relation between BPR and WAU, which can be seen in Appendix A.

4 EXPERIMENTS

We conduct valid experiments to demonstrate the effectiveness of our proposed QGrace. We aim to answer the following questions:

- RQ1: How about the performance and robustness of QGrace, compared with the state-of-the-art GDA methods and robust recommendation models?
- RQ2: How does each component of QGrace affect QGrace?
- RQ3: Can QGrace be used to improve the performance of existing recommender methods except for basic recommendation encoders?
- RQ4: How about the time complexity of QGrace?

4.1 Experimental Settings

Datasets. Three public benchmark datasets: Beauty1 [22], Alibaba-iFashion2 [28], and Yelp20183 [10] are used in our experiments. More dataset statistics are shown in Table 5.

Evaluation Metrics. We split the datasets into three parts (training set, validation set, and test set) with a ratio of 7:1:2. Two common evaluation metrics: Recall@K and NDCG@K. We set K=10 and K=20. Each metric is conducted 10 times, and we then report the average results.

Baselines. We select two recommendation methods as base encoder f of QGrace:

- GMF [9] is a generalized version of matrix factorization based recommendation model.
- LightGCN [10] is a state-of-the-art graph model, which discards the nonlinear feature transformations to simplify the design of GCN for the recommendation.

We train the two base models with different GDA methods:

- WBPR [5] is a sample selection method, which considers the popular but uninteracted items.
- DeCA [26] can be seen as a model-dependent GDA method, which combines predictions of two different models to consider the disagreement of noisy samples.
- SGDL [7] can also be seen as a model-dependent GDA method, which collects clean interactions in the initial training stages, and uses them to distinguish noisy instances based on the similarity of collected clean instances.

In addition, we also compare QGrace with the state-of-the-art robust graph-based methods to further confirm the effectiveness of our model:

- BUIR [15] leverages a two-branch architecture, in which a target network and an online network learn from each other.
- SGL [28] applies edge dropout to modify discrete graph structure randomly and trains different graphs based on contrastive learning to enhance the representation of nodes.
- SimGCL [32] simplifies the contrastive loss and optimizes representations’ uniformity.

Parameter Settings. We implement QGrace in Pytorch and have released our implementations (codes, parameter settings) to facilitate reproducibility. If not stressed, we use recommended parameter settings for all models, in which batch size, learning rate, embedding size and the number of LightGCN layers are 128, 0.001, 64 and 2, respectively. For BUIR and SGL, the edge dropout rate is set to 0.1. We optimize them with Adam [13] optimizer and use the Xavier initializer [8] to initialize the model parameters.

4.2 Performance and Robustness Comparison (RQ1)

4.2.1 Performance Comparison. We first compare QGrace with existing GDA methods and robust recommendation methods on three different datasets. The VAE-based model is used in QGrace because it is superior to other generative models during the generative process. More details about the alternatives to generative models are shown in Section 4.3. Table 1 shows the results, where figures in bold represent the best performing indices, and the runner-ups are presented with underlines. According to Table 1, we can draw the following observations and conclusions:

- The proposed QGrace can effectively improve the performance of two base models and show the best/second performance in all cases. We attribute these improvements to the adaptive denoising process and the consideration of all positive and negative instances: (1) In the adaptive denoising process, QGrace dynamically generates an interest graph to assign more suitable weights for each instance. (2) Benefiting from considering all instances, QGrace can dig out potential interests from unobserved interactions. However, other model-dependent GDA baselines (e.g., DeCA and SGDL) are insufficient to provide weights for negative instances because of the expensive time and space costs.
- All model-dependent GDA approaches have better results than normal training, which indicates the need to adaptively denoise implicit feedback in recommendations. The results are consistent with prior studies [7, 26].

1https://jmcauley.ucsd.edu/data/amazon/links.html
2https://github.com/wenyuer/POG
3https://www.yelp.com/dataset
• The improvement on Yelp2018 dataset is less significant than that on other datasets. One possible reason is that Yelp2018 dataset has a higher density than the others. Thus there are enough pure informative interactions for identifying user behaviour, compensating for the effect of the noisy negative instances.

4.2.2 Robustness Comparison. We also conduct experiments to check QGrace’s robustness. Following previous work [28], we add a certain proportion of adversarial examples (i.e., 5%, 10%, 15%, 20% negative user-item interactions) into the training set, while keeping the testing set unchanged. Figure 3 shows the experimental results on Beauty dataset. We can see the results of QGrace maintain the best in all cases, despite performances reduced as noise data adding. Besides, the trend of QGrace’s drop percent curve keeps the minor change except for the noise ratio is 0.05, which illustrates that QGrace is the least affected by noise. This suggests that the adaptive process of QGrace can better figure out useful patterns under noisy conditions.

![Figure 3. Model performance w.r.t. noise ratio.](image)

4.3 Study of QGrace (RQ2)

As gradient matching scheme, WAU loss and generative models are the core of QGrace, we discuss the three parts of QGrace in greater depth on Beauty and Yelp2018 datasets. First, we directly train GMF and LightGCN without denoising on the interaction graph, in which WAU is the original AU loss. Then we add the traditional bi-level optimization scheme into recommendation model training with AU loss, optimizing graph structure parameters with gumbel-softmax optimizer. In this process, we only optimize positive instances and an equal number of random negative instances; otherwise, the model training will take more than a few days. Finally, we use three generative models in QGrace with WAU loss to compare their performances. It is worth reminding that we hardly execute QGrace without generative models due to the expensive space cost (“out of memory” will be displayed). As Table 2 shows, we observe that WAU loss with gradient matching outperforms AU loss with traditional bi-level optimization in most cases. This is because gradient matching guides the graph structure parameters to a better perturbation direction, and WAU considers the closeness of alignment for each instance. In the meantime, the VAE-based generative model works best compared with the two others, and we attribute its excellent generation ability of graph structure diversification. We also demonstrate this conclusion from the generated data distribution perspective, which is shown in Appendix D.3.

4.4 Transferity Analysis (RQ3)

Here we show that QGrace can be coupled with state-of-the-art recommendation methods well. For simplicity, we incorporate QGrace with SGL and SimGCL, which have been used in previous experiments. As Fig. 4 shows, we find that the QGrace successfully enhances SGL and SimGCL, and surprisingly their performances are up to a similar level to that of LightGCN. A possible explanation is that the data augmentation effects of SGL and SimGCL are duplicated with that of QGrace, which proves the effectiveness of QGrace in data augmentation.

![Figure 4. The transferity of QGrace to SGL and SimGCL.](image)

4.5 Time Complexity Analysis (RQ4)

In this part, we set LightGCN as the basic encoder and report the real running time of compared methods for one epoch. The results in Table 3 are collected on an Intel(R) Core(TM) i9-10900X CPU and a GeForce RTX 3090Ti GPU. QGrace can merely train recommendation models based on WAU loss, so we train compared methods based on BPR and WAU loss, respectively, to show the time consumption gap between BPR and WAU. As shown in Table 3, we can see the running time increases with the volume of the datasets, and the running speed of WAU is close to that of BPR. Besides, the running speed of QGrace is much quicker than model-dependent GDA methods (DeCA and SGDL), even though both of them only deal with positive instances. Furthermore, SGL and SimGCL do not need additional time on denoising training, but the time cost of QGrace is still less than those of SGL and SimGCL, which proves that gradient matching can save much time from the computation.

5 RELATED WORK

Researchers attempt to denoise implicit feedback through many avenues, and we classify these methods into three types from the graph data augmentation (GDA) perspective, including model-independent GDA, model-dependent GDA and other directions.
**Table 1.** Performance comparison of different denoising methods on the robust recommendation. The highest scores are in bold and the second best are with underlines. R and N refer to Recall and NDCG, respectively.

| Dataset   | Method       | Beauty   | Alibaba-iFashion | Yelp2018 |
|-----------|--------------|----------|------------------|----------|
|           | R@10 | R@20 | N@10 | N@20 | R@10 | R@20 | N@10 | N@20 | R@10 | R@20 | N@10 | N@20 |
| Base Model |      |      |      |      |      |      |      |      |      |      |      |      |
| GMF       |      |      |      |      |      |      |      |      |      |      |      |      |
|           | Normal | 0.0639 | 0.0922 | 0.0429 | 0.0518 | 0.0286 | 0.0462 | 0.0157 | 0.0205 | 0.0290 | 0.0500 | 0.0331 | 0.0411 |
|           | WBPR   | 0.0640 | 0.0919 | 0.0430 | 0.0516 | 0.0284 | 0.0461 | 0.0158 | 0.0205 | 0.0289 | 0.0498 | 0.0330 | 0.0409 |
|           | DeCA   | 0.0767 | 0.1081 | 0.0535 | 0.0669 | 0.0426 | 0.0626 | 0.0234 | 0.0297 | 0.0298 | 0.0532 | 0.0340 | 0.0429 |
|           | SGLD   | 0.0834 | 0.1181 | 0.0546 | 0.0885 | 0.0435 | 0.0646 | 0.0226 | 0.0289 | 0.0302 | 0.0541 | 0.0351 | 0.0436 |
|           | QGA    | 0.0860 | 0.1233 | 0.0594 | 0.0709 | 0.0460 | 0.0692 | 0.0250 | 0.0312 | 0.0307 | 0.0564 | 0.0356 | 0.0455 |
| LightGCN  |      |      |      |      |      |      |      |      |      |      |      |      |
|           | normal | 0.0855 | 0.1221 | 0.0561 | 0.0675 | 0.0429 | 0.0661 | 0.0247 | 0.0310 | 0.0308 | 0.0532 | 0.0361 | 0.0445 |
|           | WBPR   | 0.0864 | 0.1261 | 0.0588 | 0.0685 | 0.0431 | 0.0662 | 0.0253 | 0.0316 | 0.0317 | 0.0529 | 0.0365 | 0.0448 |
|           | DeCA   | 0.0967 | 0.1345 | 0.0665 | 0.0754 | 0.0540 | 0.0865 | 0.0354 | 0.0435 | 0.0337 | 0.0511 | 0.0432 | 0.0524 |
|           | SGLD   | 0.0946 | 0.1365 | 0.0677 | 0.0769 | 0.0591 | 0.0908 | 0.0342 | 0.0415 | 0.0339 | 0.0541 | 0.0441 | 0.0585 |
|           | BUIR   | 0.0991 | 0.1254 | 0.0626 | 0.0736 | 0.0446 | 0.0794 | 0.0294 | 0.0369 | 0.0348 | 0.0544 | 0.0388 | 0.0486 |
|           | SGL    | 0.1005 | 0.1422 | 0.0692 | 0.0821 | 0.0665 | 0.0973 | 0.0392 | 0.0473 | 0.0357 | 0.0639 | 0.0436 | 0.0534 |
|           | SimGCL | 0.0960 | 0.1316 | 0.0671 | 0.0781 | 0.0666 | 0.0940 | 0.0399 | 0.0472 | 0.0414 | 0.0711 | 0.0485 | 0.0593 |
|           | QGA    | 0.1107 | 0.1552 | 0.0759 | 0.0895 | 0.0802 | 0.1173 | 0.0472 | 0.0571 | 0.0416 | 0.0700 | 0.0490 | 0.0586 |

**Table 2.** Component analysis. Bi-level refers to the traditional bi-level optimization scheme.

| Dataset   | Method       | Beauty   | Yelp2018 |
|-----------|--------------|----------|----------|
|           | R@20 | N@20 | R@20 | N@20 |
| Base Model |      |      |      |      |
| GMF       |      |      |      |      |
|           | AU   | 0.1031 | 0.0611 | 0.0397 | 0.0312 |
|           | AU   | 0.0966 | 0.0556 | 0.0508 | 0.0405 |
|           | AU   | 0.1233 | 0.0709 | 0.0564 | 0.0455 |
| LightGCN  |      |      |      |      |
|           | AU   | 0.1452 | 0.0829 | 0.0576 | 0.0685 |
|           | AU   | 0.1489 | 0.0836 | 0.0634 | 0.0503 |
|           | AU   | 0.1389 | 0.0819 | 0.0676 | 0.0568 |
|           | AU   | 0.1539 | 0.0885 | 0.0685 | 0.0578 |
|           | AU   | 0.1552 | 0.0895 | 0.0700 | 0.0586 |

**Table 3.** Running time in seconds for per epoch.

| Method       | Beauty   | iFashion | Yelp2018 |
|--------------|----------|----------|----------|
| Base Model   | R@20 | N@20 | R@20 | N@20 |
| GMF          |      |      |      |      |
|           | AU   | 0.1031 | 0.0611 | 0.0397 | 0.0312 |
|           | AU   | 0.0966 | 0.0556 | 0.0508 | 0.0405 |
|           | AU   | 0.1233 | 0.0709 | 0.0564 | 0.0455 |
| LightGCN    |      |      |      |      |
|           | AU   | 0.1452 | 0.0829 | 0.0576 | 0.0685 |
|           | AU   | 0.1489 | 0.0836 | 0.0634 | 0.0503 |
|           | AU   | 0.1389 | 0.0819 | 0.0676 | 0.0568 |
|           | AU   | 0.1539 | 0.0885 | 0.0685 | 0.0578 |
|           | AU   | 0.1552 | 0.0895 | 0.0700 | 0.0586 |

**Model-independent GDA.** These methods [3, 5, 19, 33] focus on training a sampler model to select clean instances. For example, WBPR [5] notices that popular items are more likely real negative instances if they have missing actions, and then samples popular items with higher probabilities. These methods achieve promising results to some extent but overlook the potential relation of the model training process.

**Model-dependent GDA.** These methods [7, 11, 25, 26] adaptively optimize graph structure during recommendation model training. For example, DeCA [26] assumes that different models make relatively similar predictions on clean examples, so it incorporates the training process of two recommendation models and distinguishes clean examples from positive instances based on two different predictions. SGDL [7] finds that models tend to dig out clean instances in the initial training stages, and then adaptively assign weights for positive instances based on the similarity of collected clean instances.

**Other Directions.** There are also some robust recommendation methods that do not belong to the above GDA methods. For example, SGL [28] creates two additional views of graphs by adding and dropping edges and leverages contrastive learning to distinguish hard noisy instances. Recently, several works have considered augmentation from the perspective of embeddings. For example, SimGCL [32] considers embeddings distribution, and thus trains models to force the distribution of embeddings to fit uniformity.

It should be noted that previous research often uses additional information (attribute features [35], social information [31], etc.) to process graph structures. This paper discusses GDA tasks in extreme situations where only implicit feedback information can be obtained, so we do not introduce some GDA methods with extra information [21, 29].

6 CONCLUSION AND FUTURE WORK

In this paper, we propose a new denoising paradigm, called QGrace, which aims to transfer the original interaction graph
to a purified and densified interest graph during the bi-
optimization process of increasing recommendation perfor-
mance. The gradient matching scheme and the design of
generative models are introduced for graph conversion and
generation, to avoid expensive time costs and space explo-
sion problems. Besides, we creatively use WAU objective
function to train recommendation models on interaction and
interest graphs simultaneously. Extensive experiments on
three real-world datasets demonstrate the superiority, robust-
ness and transferity of QGrace. In the future, we will explore
more complex graph conversions, considering complicated
emotions like love, neutral and hate.
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Appendices

A PROOF

On the basis of [22], we further prove the relationship between BPR and WAU. The proof is as follows:

\[ \min L_{BPR} = \min \mathbb{E}_{(u,i) \sim p_{pos}, (u,i') \sim p_{neg}} \left( -\log \left( \frac{e^{z_u^T z_{i'}}}{e^{z_u^T z_{i'}} + e^{z_u^T z_{i'}}} \right) \right) \]

\[ \begin{align*}
&= \min \mathbb{E}_{(u,i) \sim p_{pos}, (u,i') \sim p_{neg}} \left[ -z_u^T z_{i'} + \log(e^{z_u^T z_{i'}} + e^{z_u^T z_{i'}}) \right]
\end{align*} \tag{17}
\]

The \( z_u^T z_{i'} \) can be viewed as alignment, if an instance meets perfect alignment:

\[ z_u^T z_{i'} = R_{u,i}, \tag{18} \]

and if we only think about perfect alignment, the lower boundary of BPR is:

\[ \begin{align*}
&\geq \mathbb{E}_{(u,i) \sim p_{pos}, (u,i') \sim p_{neg}} \left[ -R_{u,i} \right] + \mathbb{E}_{(u,i) \sim p_{pos}, (u,i') \sim p_{neg}} \left( \log(e^{R_{u,i}} + e^{R_{uj}}) \right).
\end{align*} \tag{19} \]

The \( \log(e^{z_u^T z_{i'}} + e^{z_u^T z_{i'}}) \) can be viewed as uniformity, if instances meet perfect uniformity:

\[ \begin{align*}
&\geq \mathbb{E}_{(u,i) \sim p_{pos}, (u,i') \sim p_{neg}} \log(e^{z_u^T z_{i'}}) + \mathbb{E}_{(u,i) \sim p_{neg}} \log(e^{z_u^T z_{i'}})
\end{align*} \tag{20} \]

\[ = 2 \int_{S^{d-1}} \int_{S^{d-1}} \log \left( e^{x^T y} \right) d\sigma_{d-1}(x) d\sigma_{d-1}(y), \]

here, \( S^{d-1} = \{ x \in \mathbb{R}^d : ||x|| = 1 \} \) is the surface of the \( d \)-dimensional unit ball, and if we only think about perfect uniformity, the lower boundary of BPR is:

\[ \begin{align*}
&\geq -1 + 2 \int_{S^{d-1}} \int_{S^{d-1}} \log \left( e^{x^T y} \right) d\sigma_{d-1}(x) d\sigma_{d-1}(y).
\end{align*} \tag{21} \]

Considering the above analysis, we can see that BPR is optimized for lower alignment and uniformity, as well as a balance of alignment and uniformity.

B ALGORITHM

Algorithm 1 shows the learning algorithm of QGrace.

Algorithm 1 The proposed QGrace algorithm

**Input:** user-item interactions data \( A \); recommendation encoder network \( f \); generative model network \( f_{gen} \); iterations of inner optimization \( iter_{in} \); iterations of outer optimization \( out \).

1: Randomly initialize all parameters.
2: while not converged do
3: for \( i = 0, \ldots, iter_{out} \) do
4: for \( i = 0, \ldots, iter_{in} \) do
5: \text{"Inner optimization:"
6: calculate WAU loss,
7: optimize \( f_{th} \) on \( A \) and \( R \),
8: record the gradients \( G_A \) and \( G_R \),
9: end for
10: \text{"Outer optimization:"
11: calculate matching distance loss,
12: optimize generative model parameters \( f_{gen} \),
13: end for
14: end while

**Output:** The optimal recommendation network \( f_{th} \) trained on \( R \).

C MODEL ANALYSIS

We summarize the model size and time complexity of QGrace in Table 4.

**Model Size.** The parameters of QGrace come from two parts: (1) the parameters of recommendation models, which we assume is \( P \); and (2) the parameters of generative models. For MF-based generative models, we need additional parameters for user embeddings \( F_U \in \mathbb{R}^{n \times d_{pu}} \) and item embeddings \( F_I \in \mathbb{R}^{n \times d_{pi}} \). For MLP-based generative models, we need additional parameters \( FC_1 \in \mathbb{R}^{2d \times d_{f_{c1}}} \) and \( FC_2 \in \mathbb{R}^{d_{f_{c2}} \times d_{f_{c2}}} \). For VAE-based generative models, we need additional parameters for the encoder layer \( EN \in \mathbb{R}^{2d \times (d_{in} + d_{cu})} \), the re-parameterized sampling layer \( \mu \in \mathbb{R}^{d_{in} \times d_{in}}, \sigma \in \mathbb{R}^{d_{in} \times d_{in}} \), and the decoder layer \( DE \in \mathbb{R}^{d_{cin} \times d_{cin}} \). Overall, the additional cost of QGrace is negligible, compared with the tremendous parameters of graph structure \( R \in \mathbb{R}^{M \times N} \).

**Time Complexity.** The complexity of QGrace consists of two parts: (1) the update of recommendation model parameters, which we assume is \( O(M) \); and (2) the update of graph structure parameters. We assume the iteration of outer optimization is \( n \). If we use the MF-based generative model, the computational complexity of user embeddings and item embeddings update is \( O(n(|U|d_{pu} + |I|d_{pi})) \). If we use the MLP-based generative model, two fully connected layers are updated, and the corresponding time complexity is \( O(n(2d_{f_{c1}} + d_{f_{c1}}d_{f_{c2}})) \). If we use the VAE-based generative model, the time complexity of the encoder layer, the sampling layer and the decoder layer are \( O(2nd_{c1} + d_{c1}d_{c2}) \) and \( O(n(d_{cin}d_{cin})) \), respectively. It is
We try to explain why the VAE-based generative model outperforms the others from the generated data distribution perspective. We randomly choose 1000 users and 1000 items from Beauty dataset, and draw their corresponding interactions and interests. As Fig. 5 shows, the interaction graph has a few white dots, which means high sparsity of interactions. The MF-based generated interest graph spreads similar red dots, and we hardly distinguish their differences, which means the values of generated interests are mostly close to 0.5. In contrast, interest graphs of MLP-based and VAE-based generative models have dots with different depths of color, so they can outperform the MF-based one. While there are many obvious horizontal and vertical lines in the MLP-based one, which indicates that a user/item has similar interests of many obvious horizontal and vertical lines in the MLP-based one, which indicates that a user/item has similar interests of

Figure 5. The distributions of interaction and interest graphs in Beauty (1000users and 1000 items). A row of dots represents a user’s interests in 1000 items and a column of dots represents the interests of 1000 users in an item. The color of the dot represents the interest level, and the closer to white the higher the level of interest, and vice versa.

Table 4. Model analysis of the base model, model-dependent GDA and QGrace.

| Model                | Model Size | Time Complexity                                      |
|----------------------|------------|------------------------------------------------------|
| Base Model           | $P$        | $O(M)$                                               |
| Model-dependent GDA  | $P + R$    | $O(Mn|\mathcal{U}||I|)$                             |
| QGrace$_{direct}$    | $P + R$    | $O(2M + n(\mathcal{U}|d_{in} + |I|d_{I}))$          |
| QGrace$_{MF}$        | $P + E_{in} + E_{I}$ | $O(2M + n(2d_{in} + d_{I})$ |
| QGrace$_{MLP}$       | $P + FC_{i} + FC_{I}$ | $O(2M + n(2d_{in} + d_{I})$ |
| QGrace$_{VAE}$       | $P + EN + \mu + \sigma + DE$ | $O(2M + n(2d_{in} + d_{I})$ |

D.1 Dataset

Table 5. Statistics of datasets.

| Dataset | #Users | #Items | #Interactions | Density |
|---------|--------|--------|---------------|---------|
| Beauty  | 22,363 | 12,099 | 198,503       | 0.073%  |
| Alibaba-fashion | 300,000 | 81,614 | 1,607,813 | 0.006% |
| Yelp2018 | 31,668 | 38,048 | 1,561,406 | 0.130% |

D.2 Parameters Sensitivity Analysis

We investigate the model’s sensitivity to the hyperparameters $\alpha$. We try different values of $\alpha$ with the set $\{0.2, 0.5, 1, 2, 5, 10\}$. As shown in Fig. 6, we can observe a similar trend in performance that increases first and then decreases on all the datasets. QGrace reaches its best performance when $\alpha$ is in $[0.5, 1, 2]$, which suggests that the weights of alignment and uniformity should be balanced at the same level.

D.3 Visualization of Interaction and Interest Graph

We try to explain why the VAE-based generative model outperforms the others from the generated data distribution