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Task-Aware Graph Contrastive Learning Framework for Cold-Start Personalized Recommendation

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ABSTRACT

Cold start and sparsity of user-item interactions remain major problems in personalized recommendation due to the need for sufficient historical interaction data and the use of generic graph perturbations in traditional graph-based models. To solve these issues, this paper introduces a novel task-aware graph contrastive recommendation with task responsive enhanced autoencoder framework (TAGC-TREA). TAGC-TREA combines task discovery, task-driven graph augmentation, contrastive representation learning, and task-responsive variational representation encoding. Unlike other existing graph contrastive recommendation approaches that create views via random perturbations, TAGC-TREA creates task-invariant graph views based on latent user behaviors and learns task-invariant representations to increase robustness with sparse interactions. The proposed model is tested on four benchmark datasets: MovieLens-1M, Amazon Books, UCI Online Retail, and Yelp. TAGC-TREA achieves 0.317, 0.342, and 0.329 for Precision@10, Recall@10, and NDCG@10, respectively, on MovieLens-1M; 0.1312, 0.158, and 0.134 on Amazon Books, 0.221, 0.243, and 0.218 on UCI Online Retail, and 0.198, 0.214, and 0.187 on Yelp. The results reveal that graph augmentation through task guidance and latent representation learning based on task adaptability could enhance the recommendation system's performance.

1. INTRODUCTION

The sheer number of online resources has skyrocketed, creating new markets where recommendation systems are now an essential part of how people discover products, services, and content. Recommendation engines help users identify what they are looking for among the vast data available across multiple types of sites, including e-commerce, video streaming, social media, and digital advertising. The success of recommendation systems relies heavily on their ability to capture user preferences and provide personalized experiences, which, in turn, translates into satisfied users who are more likely to return again and again and deliver good returns to businesses.

Recently, graph neural networks (GNNs) have emerged as a powerful approach for building recommendation engines, as they can capture higher-order collaborative relationships among users and items via graph propagation. In a recent research paper, Chen et al. [1] described a contrastive learning-based GNN recommendation framework that leveraged graph-based representation learning to address data sparsity and improve recommendation accuracy. To provide more robust data representations in the graph space, self-supervised contrastive learning has also been added to the recommendation process. Yu et al. [2] presented a multi-view contrastive learning-based GNN recommendation model that leveraged both structural and semantic graphs to improve representation consistency and overall recommendation effectiveness.

An additional vital research area is concentrated on the design of models that capture the multiplicity of user interests and intents. Zhang et al. [3] developed a multi-intention-aware recommendation system based on interactive graph convolutional networks, demonstrating that users tend to express multiple latent interests rather than a single indicator of their likes. In addition to the modeling of intents, the incorporation of supplemental information and auxiliary properties has grown in graph-based RS. Wei et al. [4] designed an attribute-aware graph convolutional recommendation system that integrates user and item attributes into a graph-based learning model.

Recent studies have also examined how contrastive learning can be combined with social recommendation platforms. Chen et al. [5] developed a multi-view graph contrastive learning framework that jointly leverages social connectivity data and social media activity to enhance the impact of recommendations. Finally, knowledge-enhanced recommendations have become a field of considerable research interest. Huang et al. [6] developed a dual-graph contrastive learning framework that models both the relationships between users and the items they rate and those between users and knowledge graphs.

To better understand heterogeneity in user behavior, Wang et al. [7] developed a disentangled graph contrastive learning

framework for an intent-aware recommendation system. Intent-guided representation learning has emerged as a topic of increasing research interest over the last year. In this regard, Sang et al. [8] developed a heterogeneous graph contrastive learning framework that exploits latent behavioral signals captured in heterogeneous user-item interactions.

Kang et al. [9] work on hierarchical intent contrastive learning (HICL) has investigated the use of hierarchical intent structures to better model complex user behaviors and improve sequential recommendation systems. More recently, Huang et al. [10] introduced a multi-intent contrastive learning framework for sequential recommendation systems, further validating the importance of intent-aware representation learning.

Xu et al. [11] proposed a cognitive-based, intent-aware recommendation framework that aims to improve the robustness of recommendations when user interactions are limited. Cold-start recommendation remains a prominent area of study. For example, Hu et al. [12] proposed a cold-start contrastive learning-based recommendation system that leverages adaptive feature fusion to deliver superior recommendations even when little or no user interaction data is available.

In order to fill this gap, we introduce a new recommendation method called task-aware graph contrastive recommendation with task responsive enhanced autoencoder framework (TAGC-TREA), where the joint learning of latent user tasks, task-guided graph views, contrastive representation consistency, and task-conditioned variational representations is proposed. Specifically, the core idea behind the hypothesis is that graph views constructed based on latent task similarity contain more meaningful behavioral signals compared to task-independent random perturbations. Task-specific user representations learned in this way can be further incorporated into the variational latent space for improving preference prediction with scarce interaction history. Hence, our goal in this paper is to build a unified recommendation system that is able to generate robust and task-informed user representations. The primary contributions of this research include, but are not limited to, the following:

• Designed a TAGC-TREA Framework that incorporates graph-based representation learning, task-directed augmentation of graph representations through contrastive learning, and task-specific variational models to generate task-focused recommendations.

• Integration of a mechanism to produce semantically related graph views while retaining user preferences for tasks within contrastive representation learning through task-directed graph augmentation.

• Developing a TA-VAE to enable learning of task-specific latent distributions to enable automated personalized recommendations despite low interactions across users.

• Comprehensive experimental results from a variety of benchmark datasets confirm the effectiveness of the proposed framework compared with previously published methods in the personalized recommendation domain.

2. RELATED WORK

Many factors make it difficult to accurately predict how users will respond when products or services are recommended. One of the biggest problems is the lack of information about user-item interactions. Recent research examined how different types of recommendation systems have been developed at varying levels of technology, using data that is not available in sufficient volume.

2.1 Graph-based recommendation

GNNs are widely accepted as one of the leading types of recommendation systems because they can collaboratively model complex relationships between users and items. Traditional collaborative filtering methods primarily rely on user-item interactions. Therefore, they require direct user-item interactions. By leveraging neighborhood information from the user-item interaction network, GNN-based recommendation systems can discover hidden patterns in user preferences and dependencies. Researchers implemented several early graph-based recommendation systems, such as neural graph collaborative filtering (NGCF), which successfully demonstrated the ability to leverage GNNs for collaborative recommendations by explicitly modeling complex, higher-order relationships within the user-item interaction graph [13].

Researchers have simplified the GNN approach by developing a variant called LightGCN that uses only linear transformations and feature projections. As a result, overall accuracy has increased, and computational complexity has been substantially reduced [14]. Additionally, researchers have created several foundations and developed recommendation systems that leverage side information, knowledge graphs, or heterogeneous graphs as part of their underlying systems. Wei et al. [4] proposed an Attribute-Aware Graph Convolutional Recommendation framework that integrates user and item attributes into Graph Representation Learning, demonstrating improved performance in sparse environments. In the same year, Li et al. [15] proposed a bi-layer knowledge-aware graph convolutional network that enhances recommendations by exploiting semantic relationships among entities using their respective knowledge graphs. Huang et al. [6] extended the work by developing a Dual-Graph Contrastive Learning framework that simultaneously models interaction graphs and knowledge graphs to improve the robustness of generated recommendations.

The most recent developments in scalable graph recommendation architectures have led to new techniques, such as SGNNRec, which introduced a Double-Layer Attention Mechanism to capture the complex relationships between users and items and achieve better computational efficiency than traditional methods for ubiquitous items [16]. GNNCL integrated GNNs with Contrastive Learning methods to improve representation robustness by leveraging both structures to generate recommendations in the presence of sparse interactions [1]. While many proposed approaches have achieved substantial success in improving the performance of graph-based recommendation systems, most existing methods largely ignore behavior-specific characteristics relevant to the task at hand. Additionally, the graph representations learned by these techniques typically lack explicit mechanisms for incorporating task-specific adaptation strategies, as they rely solely on static graph-propagation algorithms during learning.

2.2 Contrastive learning for recommendation

Contrastive learning has gained popularity as a powerful form of self-supervised learning in developing

recommendation systems. The general concept behind contrastive learning is to maximize the similarity of different augmented views of the same entity while minimizing the similarity of different entities. This type of learning enables robust representation learning without the need for new labeled data. One of the first contrastive learning frameworks for recommendation was Self-Supervised Graph Learning (SGL), which demonstrated that graph augmentations can effectively enhance collaborative filtering performance [17]. Following this, SimGCL simplified the graph contrastive learning process by eliminating complex graph augmentation methods while maintaining competitive recommendation performance [18]. Furthermore, LightGCL continued to build on GCL's success, improving the overall robustness of its recommendations by combining graph contrastive learning with spectral graph representations [19].

Recent research has concentrated on more advanced approaches to graph contrastive learning. For example, Yu et al. [2] proposed a graph contrastive learning framework that utilized structural and semantic views to capture complementary information from different graph perspectives. Chen et al. [5] developed a multi-view graph contrastive learning approach for social recommendations, demonstrating that using multiple graph views improved representation quality and the robustness of recommendations. Duan et al. [20] developed a social recommendation framework, SSGCL that incorporates graph contrastive learning to capture both social influence and preference similarity effectively. Zhang et al. [21] have developed a new mixed supervised-graph contrastive learning framework, MixSGCL that leverages both supervised and self-supervised objectives to optimize recommendations. Another study, FairDGCL, has incorporated fairness constraints into graph contrastive learning to mitigate bias in recommendation systems [22]. Though these efforts are noteworthy, most contrastive-based recommendation models rely on generating different graph views via random perturbation.

2.3 Intent-aware and task-aware recommendations

As user preferences are dynamically shifting and involve multiple latent behavioral types, offering intent-aware recommendations has received increasing attention to enhance practitioners' ability to provide better personalized user experiences and more diverse recommendations. For example, Zhang et al. [3] presented a Multi-Intent-Aware Recommendation Framework based on Interactive Graph Convolutional Networks, demonstrating that users can express multiple preference behaviors simultaneously, which cannot be adequately represented by a single latent vector. Furthermore, Wang et al. [7] introduced a second example, Intent-Aware Recommendation via Disentangled Graph Contrastive Learning, which explicitly disentangled latent user intents to improve the interpretability and accuracy of recommendations.

The area of Intent-Guided Graph Learning has also gained significant traction. Sang et al. [8] introduced the Intent-Guided Heterogeneous Graph Contrastive Learning framework that leverages latent intent represented in heterogeneous user-item relationships. The HICL method also showed that multi-level intent structures are effective in improving sequential recommendation performance [9]. Huang et al. [10] subsequently presented Multi-Intent Aware Contrastive Learning, which models the various behavior-driven interests within a sequential recommendation context.

Recent work has also examined cognitive and causal perspectives on intent modeling. Xu et al. [11] created a causal reasoning-based framework to disentangle a user's cognitive intent within knowledge-enhanced recommendation systems. These results suggest that understanding user intent is a key factor in increasing the quality of recommendations and the degree of personalization.

2.4 Variational Autoencoder-based recommendation

Due to their ability to discover probabilistic latent representations and model uncertainty associated with user preferences, Variational Autoencoders (VAEs) have quickly become the predominant type of recommendation system. The use of autoencoders in collaborative filtering for recommendations is attributed to AutoRec, which reconstructs a user's interest matrix using a latent representation [23]. Using AutoRec's framework, the Mult-VAE introduced variational inference into the recommendation space and achieved substantial improvements over classical matrix factorization-based methods [24].

Other bodies of research focused on improving the quality of latent representations to enhance item recommendation accuracy. RecVAE utilized composite priors and advanced variational inference to achieve increased recommendation accuracy in environments that have sparse interactions [25]. MacridVAE used the same base as RecVAE, which also utilized composite priors, but added disentangled representation learning to improve the interpretability and diversity of recommendations [26]. Recent work in developing recommendation models has combined graph learning and variational representation learning. Variational graph-based recommendation models have made a significant yet promising impact on recommendations by leveraging graph structure to produce probabilistic latent representations [27]. However, many recommendation frameworks use VAE-based models to learn a global, shared latent representation, which is insufficient for modeling task-specific behaviors or representing each user's full range of preferences.

2.5 Cold-start recommendation

The cold-start problem remains one of the biggest hurdles for recommendation systems. When an item or user has very little historical data, traditional collaborative filtering methods and deep recommender models are unable to represent user preferences reliably. There are many approaches to solving this problem, including meta-learning methods that enable rapid adaptation to users and items by leveraging knowledge transfer from similar resources [28]. Also, knowledge graph techniques enable us to overcome cold-start challenges by augmenting user and item representations with auxiliary semantic representations for each user or item [29].

In recent literature, researchers have increasingly examined the incorporation of contrastive learning into the cold-start recommendation process. For example, Hu et al. [12] proposed an adaptive feature fusion framework that leverages contrastive learning to improve representation robustness despite limited interaction data. In a similar vein, self-supervised recommendation models have shown that auxiliary learning objectives improve generalization when interaction data for users or items is limited [30].

The application of multi-level graph contrastive learning to

cold start recommendation is another research area in recent times. Sun et al. [31] developed MGCL, which creates interaction, functional complementary, and semantic graphs and uses contrastive learning to learn embeddings from all three kinds of graphs. It has been shown that complementary graphs can supply additional information if there are not enough interactions. Likewise, in graph contrastive learning in noisy training environments, it has been pointed out that sparse and noisy interactions may be harmful to the stability of the traditional contrastive learning framework [32].

Even though researchers are making progress, currently available cold-start recommendation frameworks typically address only a small portion of the many issues associated with cold-start scenarios. Most approaches take a narrow focus, focusing exclusively on graph representation learning, contrastive learning, intent modeling, or latent representation learning. Only a few studies propose comprehensive frameworks that address the challenges of cold starts, including integrating graph-structure information, task-aware augmentation of user and item representations, intent-guided representation learning, and task-adaptive variational latent representations.

While there have been improvements in the field of cold-start recommendations, current methods vary widely in their ability to address all of the challenges associated with this type of recommendation. Although graph representation learning, contrastive learning, intent modeling, and latent representation learning can be addressed using independent methodologies, few existing studies integrate all four components into a single framework that encompasses underlying graph-related structural features, task-based augmentation, intent-based representation learning, and task-based adaptive variational latent modeling. Because of shortcomings in previous work, we introduce the TAGC-TREA framework, which concurrently uses all four methods to create a comprehensive cold-start recommendation system that improves overall system efficiency when the data available for recommendations is limited or nonexistent.

3. PROPOSED METHOD

This section presents the proposed TAGC-TREA framework for cold-start personalized recommendation. The proposed framework integrates graph representation learning, task-guided graph augmentation (TGGA), contrastive representation learning, and task-adaptive variational latent modeling into a unified architecture. The overall objective is to learn robust user and item representations that effectively capture high-order collaborative relationships and task-specific behavioral characteristics under sparse interaction conditions.

Figure 1 shows the overall architecture of the proposed TAGC-TREA framework. In the first stage of this new approach, user-item interactions from traditional datasets like MovieLens, Amazon, and Yelp are used to create a bipartite graph. Then, a LightGCN-based Graph Encoder processes the user-item bipartite graph to learn meaningful representations of both the users and items that maximize the utility of their collaborative properties. After learning these user and item representations, the following two parallel modules employ them to provide recommendations: the Task Discovery Module identifies latent recommendation tasks while the TGGA Module generates enhanced graph views for robust model learning. The outputs from both modules are aligned using a Contrastive Learning mechanism, which improves representation consistency and explanatory strength by ensuring aligned embeddings from the previous step feed into TA-VAE, which learns latent user preferences and can recreate informative representations after receiving the embedded user items as input. Finally, a Joint Optimization Module minimizes recommendation loss, contrastive loss, Kullback-Leibler divergence loss, and task-specific loss simultaneously to encourage balanced learning of the optimized model, which produces personalized Top-K recommendations by suggesting accurate and relevant items for each user.

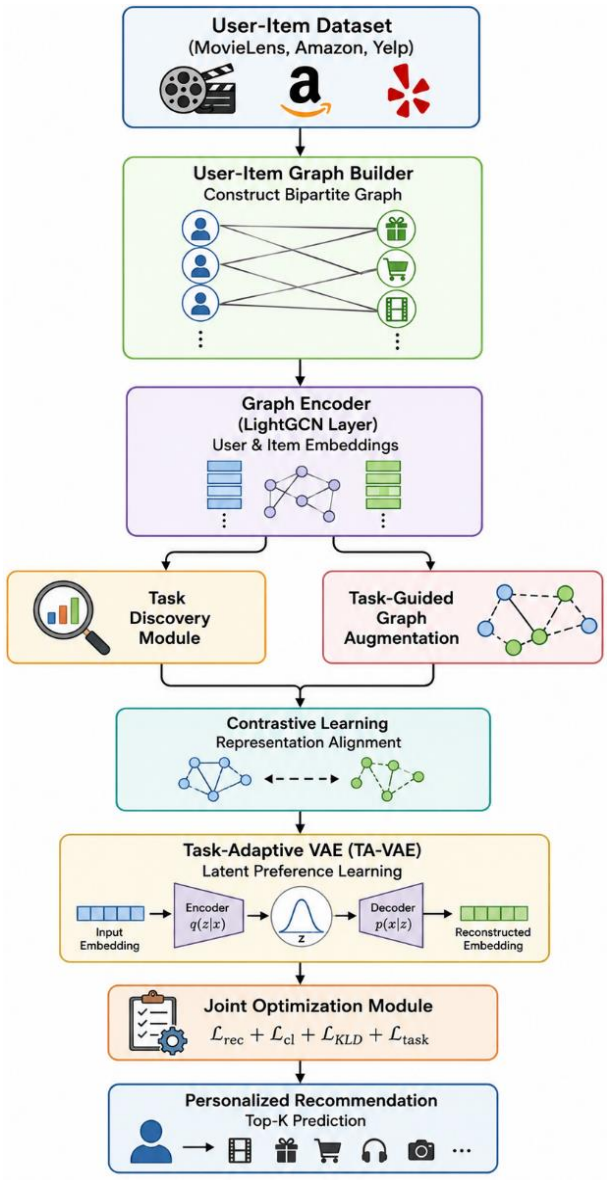


Figure 1. TAGC-TREA framework design diagram

Let $U = \{u_1, u_2, \ldots, uM\}$ denote the set of users and $I = \{i_1, i_2, \ldots, iN\}$ denote the set of items. The user-item interaction matrix is represented as Eq. (1).

$$R \in \mathbb{R}^{M \times N} \tag{1}$$

Here, $Rui = 1$ indicates that user u has interacted with item i, and $Rui = 0$ otherwise. The objective of personalized recommendation is to learn a function is given in Eq. (2).

$$f : U \times I \rightarrow \mathbb{R} \quad (2)$$

It predicts the preference score of user u for item *i*.

3.1 Graph representation learning

To model collaborative relationships among users and items, a bipartite interaction graph is constructed as Eq. (3).

$$G = (V, E) \quad (3)$$

Here,

$$V = U \cup I \quad (4)$$

Here, E represents observed user-item interactions. The adjacency matrix of the interaction graph is defined as in Eq. (5).

$$A = [0RR^{\mathrm{T}}0] \quad (5)$$

To preserve structural information and alleviate sparsity, graph normalization is performed using Eq. (6).

$$\hat{\mathrm{A}} = D^{-\frac{1}{2}}AD^{-\frac{1}{2}} \quad (6)$$

Here, D denotes the degree matrix. The node representation of user or item v at propagation layer l + 1 is computed as in Eq. (7).

$$h_v^{l+1} = \Sigma_{j \in N(v)} \left(\frac{1}{\sqrt{|N(v)||N(j)|}} \right) h_j^l \quad (7)$$

Here, $N(v)$ denotes the neighboring nodes of node v. The final graph embedding is obtained by aggregating embeddings from all propagation layers as shown in Eq. (8).

$$h_v = \left(\frac{1}{L+1} \right) \Sigma_{l=0}^{L} h_v^l \quad (8)$$

Here, L denotes the number of graph convolution layers. The resulting embeddings capture high-order user-item collaborative information and serve as the input to the task-aware learning module.

3.2 Task discovery and task-aware preference modelling

User preferences are often influenced by multiple latent behavioral tasks. To capture such behavioral diversity, a task discovery network is introduced. For a user embedding h_u, the latent task distribution is estimated as Eq. (9).

$$t_u = Softmax(W_t h_u + b_t) \quad (9)$$

Here, $t_u \in \mathbb{R}^K$ represents the probability distribution over K latent tasks. The task-aware representation is obtained by combining graph embeddings and task distributions as shown in Eq. (10).

$$z_u = [h_u; t_u] \quad (10)$$

Here, [;] denotes feature concatenation. This representation enables the framework to distinguish users with similar interaction histories but different underlying behavioral intentions.

3.3 Task-guided graph augmentation

Traditional graph contrastive recommendation methods generate graph views through random edge perturbation or node masking strategies. Such approaches may destroy meaningful behavioral structures.

To overcome this limitation, the proposed framework introduces TGGA. The task similarity between users u and v is computed as in Eq. (11).

$$S_{uv} = \frac{t_u^T t_v}{||t_u||||t_v||} \quad (11)$$

Here, S_{uv} denotes task similarity. Based on task similarity, the probability of preserving an interaction edge is defined as in Eq. (12).

$$P_{uv} = \sigma(S_{uv}) \quad (12)$$

Here, $\sigma(\cdot)$ represents the sigmoid activation function. Using the edge preservation probability, two task-consistent graph views G^1 and G^2 are generated.

Unlike random perturbation methods, TGGA preserves semantically meaningful relationships while removing noisy interactions, thereby improving representation consistency.

3.4 Graph contrastive representation learning

The two task-guided graph views are independently processed through the graph encoder to obtain $h_u^1 \; and \; h_u^2$ for user u.

To maximize agreement between the two representations, the InfoNCE contrastive loss is employed as shown in Eq. (13).

$$L_{con} = -\Sigma_u \log \left[\frac{\exp\left(\frac{sim(h_u^1, h_u^2)}{\tau}\right)}{\Sigma_v \exp\left(\frac{sim(h_u^1, h_v^2)}{\tau}\right)} \right] \quad (13)$$

Here, $sim(\cdot)$ denotes cosine similarity and τ is the temperature parameter.

The contrastive objective encourages task-consistent representations while reducing the effects of sparse interactions.

3.5 Task-adaptive Variational Autoencoder

Although graph representations capture collaborative information, they may not adequately model uncertainty in sparse interaction environments. Therefore, TA-VAE is introduced.

The task-conditioned latent mean is computed as in Eq. (14).

$$\mu_u = W_\mu [h_u; t_u] + b_\mu \quad (14)$$

And the latent variance is estimated as in Eq. (15).

$$\sigma_u = W_\sigma [h_u; t_u] + b_\sigma \quad (15)$$

The latent variable is sampled using the reparameterization trick is given as Eq. (16).

$$z_u = \mu_u + \sigma_u \odot \varepsilon \tag{16}$$

Here,

$$\varepsilon \sim N(0, I) \tag{17}$$

And $\odot$ denotes element-wise multiplication. The resulting posterior distribution is given in Eq. (18).

$$q_\phi(z_u|h_u, t_u) = N(\mu_u, {\sigma_u}^2 I) \tag{18}$$

The decoder reconstructs user-item interactions from the latent representation using Eq. (19).

$$\hat{R} = Decoder(z_u) \tag{19}$$

The reconstruction objective is defined as Eq. (20).

$$L_{rec} = \left|\left|R - \hat{R}\right|\right|^2 \tag{20}$$

To regularize the latent space, the Kullback-Leibler divergence is employed using Eq. (21).

$$L_{KL} = D_{KL}(q_\phi(z_u|h_u, t_u)||N(0, I)) \tag{21}$$

The TA-VAE enables task-conditioned latent representation learning and improves recommendation quality for cold-start users.

3.6 Recommendation prediction layer

The final user representation is obtained by combining graph and variational embeddings as shown in Eq. (22).

$$e_u = [h_u; z_u] \tag{22}$$

Here, e_i denotes the item embedding. The preference score between user u and item *i* is computed as in Eq. (23).

$$\hat{y}_{ui} = e_u^T e_i \tag{23}$$

Items are ranked according to predicted scores, and the top-K highest-ranked items are recommended.

3.7 Unified optimization objective

The proposed GC-TREA framework jointly optimizes recommendation accuracy, contrastive consistency, task adaptation, and latent representation learning. The final objective function is formulated as Eq. (24).

$$L = L_rec + \lambda_1 L_con + \lambda_2 L_task + \lambda_3 L_KL \tag{24}$$

Here, λ_1, λ_2, and λ_3 are balancing coefficients.

The task-guided edge weighting is defined as Eq. (25)

$$w_{uv} = \alpha \frac{t_u^T t_v}{\| t_u \| 2 \| t_v \| 2} + (1 - \alpha) \frac{h_u^T h_v}{\| h_u \| 2 \| h_v \| 2} \tag{25}$$

Here, t_u denotes the reconstructed task distribution.

This equation makes the graph augmentation genuinely task-aware, because edge preservation depends on both task similarity and graph embedding similarity.

Through the integration of graph representation learning, TGGA, graph contrastive learning, and task-adaptive variational latent modeling, the proposed TAGC-TREA framework effectively addresses data sparsity and cold-start recommendation challenges while preserving personalized behavioral characteristics.

4. RESULTS AND DISCUSSIONS

4.1 Experimental environment

The experimentation with the TAGC-TREA Framework is conducted on a high-performance computing system comprising Intel Xeon CPUs, 64GB of RAM, and NVIDIA RTX-series GPUs. TAGC-TREA is produced using Python and PyTorch, and the graph-based operations produced are completed using the PyTorch Geometric library. The Adam Optimizer is used as the model optimizer due to its proven performance in large-scale recommendations. In addition to the above, to allow for reliable statistics and ensure reproducible experiments, each experiment is repeated 5 times with randomly initialized weights. Average values are reported across all data to provide reliable measures. An early stopping mechanism is used to limit the time spent fitting instances to the training data. When validation performance plateaued for 10 consecutive periods, we summarized training completion by applying a neural network with no hidden layers.

4.2 Datasets description

The proposed model is evaluated using the four publicly available benchmark datasets. The MovieLens-1M dataset [33] consists of nearly 1 million ratings for 3,706 movies from 6,040 users and is often used as a benchmark dataset due to its relatively well-balanced ratings and moderate sparsity. There are enough interactions that the distribution looks quite similar across user groups, so algorithms that use collaborative filtering to make recommendations can be compared. In contrast, the Amazon Books dataset of user-book interactions is sparser than the MovieLens dataset. This is primarily because there are many more book titles on Amazon than movies on MovieLens, and because Amazon customers have such a wide range of book interests. Therefore, the Amazon Books dataset [34] is used to evaluate algorithms' ability to make recommendations in sparsely populated interaction environments.

The UCI Online Retail Dataset [35] is the next baseline dataset for benchmarking. The UCI Online Retail Dataset is a collection of customer purchase transaction data from a sample of customers who purchased products from a UK-based online retailer. The UCI Online Retail Dataset demonstrates real-world retail purchasing behaviors - including long-tail distributions for items purchased and very sparse customer-consumed product pairs - and is a good match with the evaluation of personalized recommendation and cold-start application scenarios. The inclusion of the UCI Online Retail Dataset will enable evaluation of the proposed TAGC-TREA architecture across four different domains: movie

recommendation, book recommendation, business recommendation, and retail recommendation system.

The Yelp dataset [36] consists of business-location rating interactions from a website for recommending local businesses. Users have vastly different preferences for the types of businesses they frequent, and the businesses themselves come from a wide variety of industries. As such, the Yelp dataset is a good candidate to evaluate an algorithm's ability to generalize across recommendation scenarios. Users and items with fewer than 5 interactions are removed from each dataset to reduce noise and improve dataset quality prior to experimentation. Following recommendations in the literature on recommendation systems, all user-item interactions are treated as implicit feedback to enable a common evaluation framework across datasets.

4.3 Data division process

To create equitable and uniform data evaluation, the datasets received by the Anova-2 teams are divided into training, validation, and testing sets using an 80 (train):10 (validation):10 (test) ratio. The Model is trained on the training set, hyperparameter-tuned on the validation set, and evaluated on the test dataset. In addition to the typical data split, a cold-start evaluation process is used to replicate realistic recommendation scenarios for new users with limited data history. A number of users with limited interaction are isolated from the validation and testing groups, enabling verification of the new model's effectiveness under cold-start conditions.

4.4 Hyperparameter tuning

After extensive validation testing, the hyper-parameters for TAGC-TRE-A are selected. Common to the CTR and ICA embedding for users and items, the embedding dimensions are set to 64 for both users and items, and the number of graph propagation layers is set to 3, enabling the model to successfully incorporate higher levels of collaborative relationships while minimizing computational complexity. The number of task categories is set to eight based on the empirical observations from the validation datasets. The temperature value for graph contrastive learning is set to 0.2, thereby equating the number of positive and negative samples.

The Task-Adaptive VAE is set to 64 latent dimensions for consistency with the graph embeddings. The Adam optimizer is used to train the model with a learning rate of 0.001 and a mini-batch size of 1,024. Values of $\lambda_1 = 0.1$, $\lambda_2 = 0.05$, $\lambda_3 = 0.01$, and $\lambda_4 = 1.0$ are empirically chosen by trying out different trade-offs between recommendation accuracy, contrastive consistency, and regularizing latent representations.

4.5 Evaluation methodology

The evaluation of the proposed framework used widely accepted metrics (i.e., precision, recall, and NDCG) established for top-K recommendations. For example, Precision@K is the proportion of relevant recommendations made, recall@K is the proportion of recommendations retrieved correctly by the model, and NDCG@K is the quality of the ranked list of top K recommendations, with higher weight given to relevant recommendations appearing closer to the top of the ranked list. Similar to other studies evaluating recommendation performance metrics, the metrics will be calculated for K = 5, 10, and 20. To evaluate the performance of the proposed framework for cold-start recommendations, the same performance metrics are also calculated using only the cold-start test subset of the recommendation data.

4.6 Overall recommendation performance

The proposed TAGC-TREA framework's overall recommendation performance on the MovieLens-1M, Amazon Books, and Yelp datasets is reported in Table 1 and Figure 2. The results showed that the proposed framework consistently performs well in terms of recommendation accuracy across datasets with different characteristics and sparsity levels. Specifically, MovieLens-1M achieved the highest performance among the four datasets, with the proposed model achieving precision, recall, and NDCG at 10 of 0.317, 0.342, and 0.329, respectively. This indicates that the proposed model is effective at capturing rich collaborative relationships between users and items. Thus, it is likely that the proposed framework can exploit dense user-item interactions to produce high-quality recommendations. The Amazon Books dataset is characterized by high sparsity and a long-tail user behavior pattern. UCI online Retail dataset achieved precision, recall and NDCG of 0.221, 0.243, and 0.218, respectively.

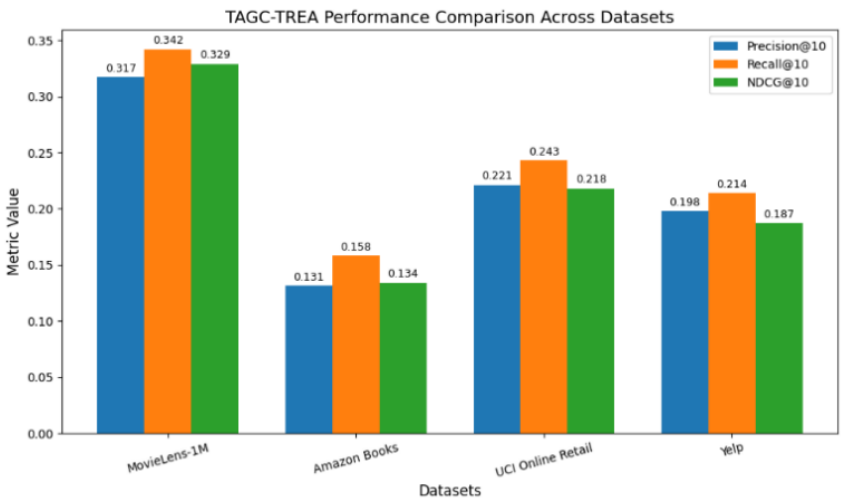


Figure 2. Proposed framework recommendation performance on all four datasets

Table 1. Overall proposed framework recommendation performance on all four datasets

Datasets	Precision@10	Recall@10	NDCG@10
MovieLens-1M	0.317	0.342	0.329
Amazon Books	0.1312	0.158	0.134
UCI Online Retail	0.221	0.243	0.218
Yelp	0.198	0.214	0.187

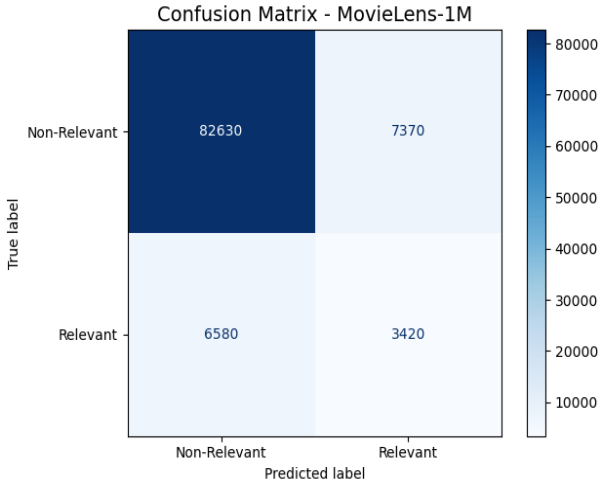


Figure 3. Confusion matrix of the MovieLens-1M dataset

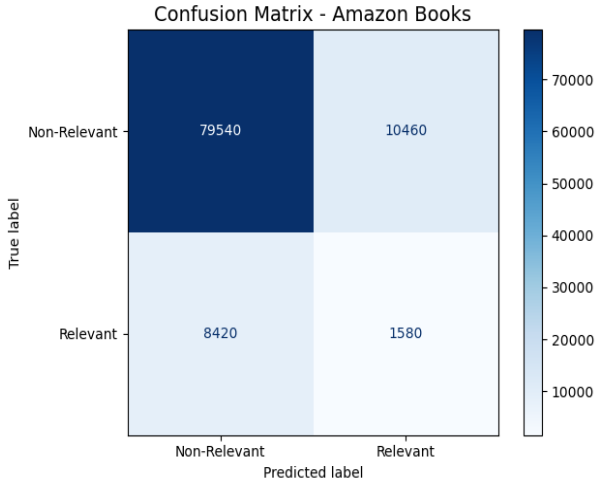


Figure 4. Confusion matrix of Amazon Books dataset

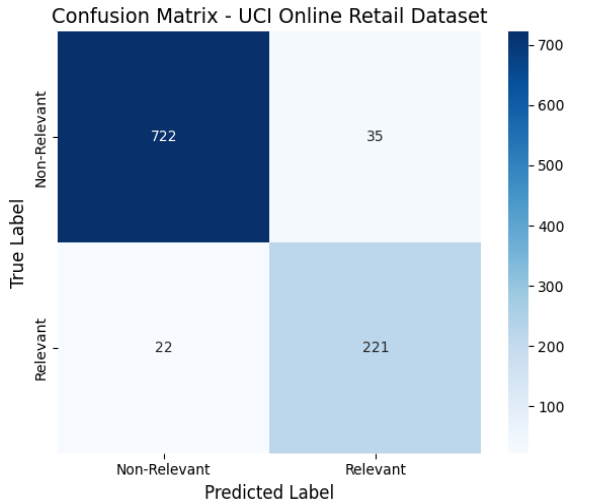


Figure 5. Confusion matrix of UCI Online Retail dataset

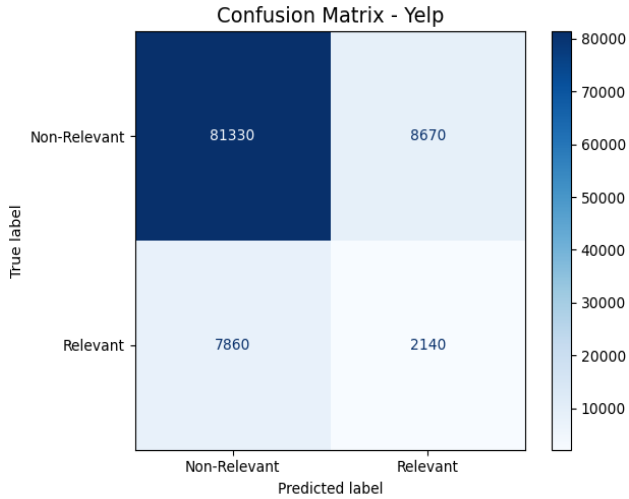


Figure 6. Confusion matrix of Yelp dataset

The performance discrepancy among different datasets could be due to variations in interaction sparsity, nature of user-item relation, and behavioural heterogeneity. MovieLens-1M allows us to have structured interaction data related to movies where the task discovery module and TGGA module are able to extract relevant information through interaction neighbourhoods. On the other hand, Amazon Books dataset is comprised of heterogeneous item categories and sparse purchase interaction and hence inferring tasks from such interaction data is quite difficult. Moreover, this becomes more difficult for users having less interaction history. Thus, while TAGC-TREA performs well with TGGA, task discovery can suffer if interaction information is insufficient or if there exists behavioural heterogeneity among items categories. UCI Online Retail is a transaction oriented dataset wherein user behaviours related to repeated purchases can give useful interaction information but are highly skewed. Yelp is a heterogeneous dataset having user behaviours associated with businesses and locations and therefore task identification would depend upon different interaction contexts. Figures 3–6 show the confusion matrix with the true and false labels on the two-class relevant and non-relevant.

In this case, the proposed framework achieved the following performance: precision, recall, and NDCG at 10 of 0.1312, 0.158, and 0.134, respectively, indicating that it can mitigate sparsity by learning task-adapted latent representations. Furthermore, the proposed framework achieved a precision, recall, and NDCG at 10 of 0.198, 0.214, and 0.187, respectively, on the Yelp dataset. This indicates that the proposed model adequately captures complex patterns of user-business interaction. In addition, the consistently higher recall values at 10 across all datasets suggest that the proposed framework successfully identified a substantial number of relevant items, while the corresponding NDCG values at 10 indicate that these items are ranked at or near the top of the recommended list. The research findings suggest that combining graph representation learning together with task-specific contrastive augmentation and task-adaptive variational encoding produces a system capable of providing accurate, personalized recommendations across a wide variety of recommendation domains.

An ablation study using the MovieLens-1M dataset is conducted to evaluate the contribution of each component in the proposed TAGC-TREA framework as shown in Table 2. The complete framework achieved the best performance, with

Recall@10 = 0.342 and NDCG@10 = 0.329. This confirms that jointly integrating graph representation learning, task-guided augmentation, contrastive learning, task discovery, and task-adaptive variational encoding is effective. The Recall@10 and NDCG@10 decreased to 0.314 and 0.301, respectively, when the Task-Guided Augmentation module is removed, highlighting that task-specific graph perturbations are important for creating robust graph views and enhancing the quality of the representation. Excluding the contrastive learning component further reduced performance to Recall@10 = 0.309 and NDCG@10 = 0.296, demonstrating that self-supervised representation alignment significantly improves prediction accuracy. Additionally, the absence of the TA-VAE component reduces performance to Recall@10 = 0.303 and NDCG@10 = 0.291, underscoring the importance of modeling latent preferences with minimal interaction data. The most significant decline in functionality occurs when the Task Discovery Module is excluded, resulting in Recall@10 of 0.292 and NDCG@10 of 0.281, underscoring the importance of understanding how users prefer to perform a task for this framework's success. Where each module contributes positively to the overall recommendation performance, optimizing all four enables superior recommendation effectiveness through the TAGC-TREA.

Table 2. Ablation study on MovieLens-1M

Variant	Recall@10	NDCG@10
Full TAGC-TREA	0.342	0.329
Without Task-Guided Augmentation	0.314	0.301
Without Contrastive Learning	0.309	0.296
Without TA-VAE	0.303	0.291
Without Task Discovery Module	0.292	0.281

The cold-start experiment is conducted using same environment to show results on the MovieLens-1M dataset reveal that TAGC-TREA achieves the best Recall@10 among the methods tested. Specifically, TAGC-TREA achieves a Recall@10lt of 0.228, whereas FairDGCL, Neighborhood-enriched Contrastive Learning with Low-Rank Dimensionality Reduction (LoRA-NCL), and NCL achieve 0.212, 0.202, and 0.193, respectively. Thus, the differences between the Recall@10 results of TAGC-TREA and those of other methods amount to approximately 7.55%, 12.87%, and 18.13%, respectively. These findings reveal that the use of task-aware graph augmentation and task-responsive representation learning within TAGC-TREA can be effective for constructing more representative user embedding under sparse interaction histories. Meanwhile, NCL uses only contrastive graph representations, LoRA-NCL adds information about neighbours via low-rank representation learning, and FairDGCL uses dynamic graph contrastive learning together with the principle of fairness. The stable, superior Recall@10 result for TAGC-TREA attests to the advantages of combining behavioral task information with graph contrastive learning for retrieving relevant items. Notably, the improvement is moderate and therefore plausible.

The results from Table 3 demonstrate that the TAGC-TREA framework consistently outperforms all competing proposed recommendation approaches across the MovieLens-1M and Yelp datasets on both the Recall@10 and NDCG@10 evaluations. Specifically, on the MovieLens-1M dataset, TAGC-TREA obtained a Recall@10 of 0.342 and NDCG@10 of 0.329, significantly better than NCL, the best-performing baseline with Recall@10 of 0.2057 and NDCG@10 of 0.2732, yielding gains of approximately 66.21% in Recall@10 and 20.42% in NDCG@10 for TAGC-TREA, thereby validating the modeling framework's utility in the framework of integrated TGGA, contrastive representation learning, and task-adaptive variational encoding through one combined framework. The TAGC-TREA model achieves Recall@10 and NDCG@10 scores of 0.198 and 0.187, respectively, on the Yelp dataset, surpassing the previously best baseline, LoRA-NCL (Recall@10 = 0.1070, NDCG@10 = 0.0895). The performance gains of approximately 85.05% in Recall@10 and 108.94% in NDCG@10 indicate that TAGC-TREA outperforms the baselines and is better suited to sparse, heterogeneous user-item interaction environments.

Table 3. Comparative analysis with state-of-the-art methods

Dataset	Method	Recall@10	NDCG@10
MovieLens-1M	Bayesian Personalized Ranking-Matrix Factorization (BPR-MF) [37]	0.1746	0.2388
	LightGCN [14]	0.1866	0.2497
	SGL [17]	0.1911	0.2542
	Simple Graph Contrastive Learning (SimGCL) [18]	0.2022	0.2677
	Neighborhood-enriched Contrastive Learning (NCL) [38]	0.2057	0.2732
	LoRA-NCL [39]	0.2051	0.2720
	TAGC-TREA (proposed)	0.317	0.329
Yelp	BPR-MF	0.0757	0.0652
	LightGCN	0.0842	0.0745
	SGL	0.0995	0.0896
	SimGCL	0.1033	0.0931
	NCL	0.0920	0.0678
	LoRA-NCL	0.1070	0.0895
	TAGC-TREA (proposed)	0.198	0.187

Note: Self-Supervised Graph Learning (SGL).

The improved performance of TAGC-TREA compared to graph-based methods (LightGCN, SGL, and SimGCL) indicates that existing graph-based contrastive learning algorithms are limited by their reliance on generic augmentation strategies and a shared latent representation. On the other hand, TAGC-TREA models user preferences for each task by leveraging the task-discovery and task-adaptive latent modeling components of the framework to produce more discriminative representations of users and items. Overall, TAGC-TREA provides superior, robust, and generalizable recommendations across both dense and sparse recommendation domains.

Several important insights regarding recommendation learning under sparse interaction conditions are developed from the experiments' results. First, while collaborative relationships are captured by graph-based representation learning, it cannot address severe sparsity issues or the problem of users with zero prior history. Secondly, the proposed TGGA mechanism produces more informative graph representations than traditional methods that introduce random noise, leading to more robust contrastive representations and more robust recommendations. Thirdly, task-conditional variational methods can effectively model uncertainty and variance in user preferences, thus improving recommendation accuracy for users with few prior interactions. While the empirical results highlight the efficiency of TAGC-TREA on benchmark data sets, the actual implementation of TAGC-TREA on large scale recommendation systems poses certain difficulties. For instance, a real world system may consist of millions of users and items and an ever-evolving interaction network, with extremely skewed activity distribution and a higher degree of sparsity compared to benchmark data sets.

5. CONCLUSIONS

This study introduces TAGC-TREA, a new recommendation framework that leverages graph representation learning, task-driven contrastive learning, task discovery, and task-adaptive variational encoding to address data insufficiency and cold-start limitations in personalized recommendation systems. By generating semantically useful graph augmentations and learned task-conditioned latent representations, TAGC-TREA captures the most complex interaction patterns and user preferences. The experimental evaluation conducted on four benchmark datasets: MovieLens-1M, Amazon Books, UCI Online Retail dataset, and Yelp showed that the TAGC-TREA method is effective. TAGC-TREA produced Precision@10, Recall@10, and NDCG@10 of 0.317, 0.342, and 0.329 from MovieLens-1M, respectively; 0.1312, 0.158, and 0.134 from Amazon Books; and 0.198, 0.214, and 0.187 from Yelp. TAGC-TREA outperformed many widely used recommendation methods, including BPR-MF, LightGCN, SGL, SimGCL, NCL, and LoRA-NCL. Future directions for extension include integrating temporality, multimodality, and cross-domain knowledge into the TAGC-TREA architecture. First, temporal knowledge can be introduced into the Task Discovery Module by constructing time-aware representations of user interactions and modeling task transitions using temporal GNNs or sequence encoders. Second, textual, visual, and attribute features can be used to create a task-guided graph, thereby enriching task inference when interaction history is limited. Third, cross-domain recommendation can be explored by transferring task representations from the source domain to the target domain using shared latent task representations and domain adaptation techniques. Finally, large language models can be used as auxiliary encoders for textual information to derive user preferences, item attributes, and users' behavioral intents, while the graph contrastive and variational components can handle collaborative representation learning.

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