MMGCN: Multi-modal Graph Convolution Network for Personalized Recommendation of Micro-video

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ABSTRACT

Personalized recommendation plays a central role in many online content sharing platforms. To provide quality micro-video recommendation service, it is of crucial importance to consider the interactions between users and items (*i.e.,* micro-videos) as well as the item contents from various modalities (*e.g.,* visual, acoustic, and textual). Existing works on multimedia recommendation largely exploit multi-modal contents to enrich item representations, while less effort is made to leverage information interchange between users and items to enhance user representations and further capture user's fine-grained preferences on different modalities.

In this paper, we propose to exploit user-item interactions to guide the representation learning in each modality, and further personalized micro-video recommendation. We design a Multi-modal Graph Convolution Network (MMGCN) framework built upon the message-passing idea of graph neural networks, which can yield modal-specific representations of users and micro-videos to better capture user preferences. Specifically, we construct a user-item bipartite graph in each modality, and enrich the representation of each node with the topological structure and features of its neighbors. Through extensive experiments on three publicly available datasets, Tiktok, Kwai, and MovieLens, we demonstrate that our proposed model is able to significantly outperform state-of-the-art multi-modal recommendation methods.

CCS CONCEPTS

• **Engaging users with multimedia → Multimedia Search and Recommendation**.

KEYWORDS

Graph Convolution Network, Multi-modal Recommendation, Micro-video Understanding

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1 INTRODUCTION

Personalized recommendation has become a core component in many online content sharing services, spanning from image, blog to music recommendation. Recent success of micro-video sharing platforms, such as Tiktok and Kwai, bring increasing attentions to micro-video recommendation. Distinct from these item contents (*e.g.,* image, music) that are solely from a single modality, micro-videos contain rich multimedia information — frames, sound tracks, and descriptions — that involve multiple modalities of visual, acoustic, and textual ones [24, 25, 28].

Incorporating such multi-modal information into historical interactions between users and micro-videos help establish an in-depth understanding of user preferences:

- There is a semantic gap between different modalities. Take Figure 1 as an example, while having visually similar frames, micro-videos i_1 and i_2 have dissimilar textural representations due to different topic words. In such cases, ignoring such modality difference would mislead the modeling of item representations.
- A user may have different tastes on modalities of a micro-video. For example, a user is attracted by the frames, but may turn out to be disappointed with its poor sound tracks. Multiple modalities, hence, have varying contributions to user preferences.
- Different modalities serve as different channels to explore user interests. In Figure 1, if user u_1 cares more about frames, i_2 is more suitable to be recommended; whereas, u_1 might click i_3 due to interest in textural descriptions.

Therefore, it is of crucial importance to distinguish and consider modal-specific user preferences.

However, existing works on multimedia recommendation [8, 17] mainly treat multi-modal information as a whole and incorporate them into a collaborative filtering (CF) framework, while lacking

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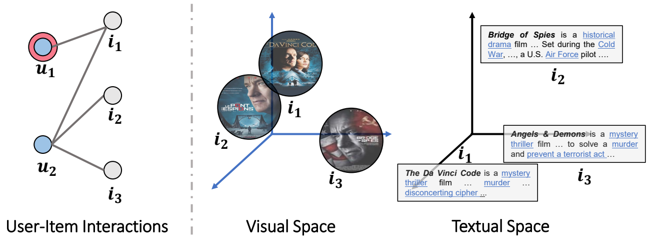


u_1
i_1
i_2
u_2
i_3
User-Item Interactions
i_1
i_2
i_3
Visual Space
Bridge of Spies is a historical drama film … Set during the Cold War, …, a U.S. Air Force pilot ….
i_2
Angels & Demons is a mystery thriller film … to solve a murder and prevent a terrorist act …
i_1
The Da Vinci Code is a mystery thriller film … murder … disconcerting cipher …
i_3
Textual Space

Figure 1: An illustration of modal-specific user preferences.

the modeling of modal-specific user preferences. Specifically, multi-modal features of each item are unified as a single representation, reflecting their content similarity; thereafter, such representations are incorporated with user and item representations derived from CF framework, such as MF [30]. For instance, VBPR [17] leverages visual features to enrich ID embeddings of items; ACF [8] employs the attention mechanism on a user's history to encode two-level personal tastes on historical items and item contents into user representations. Such signals can be summarized as the paths connecting the target user and item based on historical interactions [38, 41]. For example, given two paths $p_1 := u_1 \rightarrow i_1 \rightarrow u_2 \rightarrow i_2$ and $p_2 := u_1 \rightarrow i_1 \rightarrow u_2 \rightarrow i_3$; this would suggest that i_2 and i_3 are likely to be of interest to u_1. However, we argue that these signals are not sufficient to draw such conclusion. The key reason is that they ignore the differences and user preferences among modalities.

To address the limitations, we focus on information interchange between users and items in multiple modalities. Inspired by the recent success of graph convolution networks (GCNs) [14, 22], we use the information-propagation mechanism to encode high-order connectivity between users and micro-videos in each modality, so as to capture user preference on modal-specific contents. Towards this end, we propose a *Multi-modal Graph Convolution Network* (MMGCN). Specifically, we construct a user-item bipartite graph on each modality. Intuitively, the historical behaviors of users reflect personal interests; meanwhile, the user groups can also profile items [38, 41]. Hence, in each modality (*e.g.,* visual), we aggregate signals from the corresponding contents (*e.g.,* frames) of interacted items and incorporate them into user representations; meanwhile, we boost the representation of an item with its user group. By performing such aggregation and combination operators recursively, we can enforce the user and item representations to capture the signals from multi-hop neighbors, such that a user's modal-specific preference is represented well in his/her representation. Ultimately, the prediction of an unseen interaction can be calculated as similarities between the user and micro-video representations. We validate our framework over three publicly accessible datasets — Tiktok, Kwai, and Movielens. Experimental results show that our model can yield promising performance. Furthermore, we visualize user preference on different modalities, which clearly shows the differences in modal-specific preferences by different users.

The main contributions of this work are threefold:

- We explore how information interchange on various modalities reflects user preferences and affects recommendation performance.
- We develop a new method MMGCN, which employs information propagation on the modality-aware bipartite user-item graph, to obtain better user representations based on item content information.
- We perform extensive experiments on three public datasets to demonstrate that our proposed model outperforms several state-of-the-art recommendation methods. In addition, we released our codes, parameters, and the baselines to facilitate further researchers by others[1].

2 MODEL FRAMEWORK

In this section, we elaborate our framework. As illustrated in Figure 2, our framework consists of three components — aggregation layers, combination layers, and prediction layer. By stacking multiple aggregation and combination layers, we encode the information interchange of users and items into the representation learning in each modality. Lastly, we fuse multi-modal representations to predict the interaction between each user and each micro-video in the prediction layer. In what follows, we detail each component.

2.1 Modality-aware User-Item Graphs

Instead of unifying multi-modal information, we treat each modality individually. Particularly, we have historical interactions (*e.g.,* view, browse, or click) between users and micro-videos. Here we represent the interaction data as a bipartite user-item graph $\mathcal{G} = \{(u,i)|u \in \mathcal{U}, i \in \mathcal{I}\}$, where $\mathcal{U}$ and $\mathcal{I}$ separately denote the user and micro-video sets. An edge $y_{ui} = 1$ indicates an observed interaction between user u and micro-video i; otherwise $y_{ui} = 0$.

Beyond the interactions, we have multiple modalities for each micro-video — visual, acoustic, and textual features. For simplicity, we use $m \in \mathcal{M} = \{v, a, t\}$ as the modality indicator, where v, a, and t represent the visual, acoustic, and textual modalities, respectively. To accurately capture the users' preferences on a particular modality m, we split the bipartite graph $\mathcal{G}_m$ from $\mathcal{G}$ by keeping only the features for modality m.

2.2 Aggregation Layer

Intuitively, we can utilize the interaction data to enrich the representations of users and items. To be more specific, historical interactions of a user can describe user's interest and capture the behavior similarity with other users. Meanwhile, the user group of a micro-video can provide complementary data to its multi-modal contents. We hence incorporate the information interchange into the representation learning.

Inspired by the message-passing mechanism of GCN, for a user (or micro-video) node in the bipartite graph $\mathcal{G}_m$, we employ an aggregation function $f(\cdot)$ to quantify the influence (*i.e.,* the representation being propagated) from its neighbors and output a representation as follows:

$$\mathbf{h}_m = f(\mathcal{N}_u), \tag{1}$$

where $\mathcal{N}_u = \{j|(u,j) \in \mathcal{G}_m\}$ denotes the neighbors of user u, *i.e.,* interacted micro-videos. We implement $f(\cdot)$ via:

[1] https://github.com/weiyinwei/MMGCN.

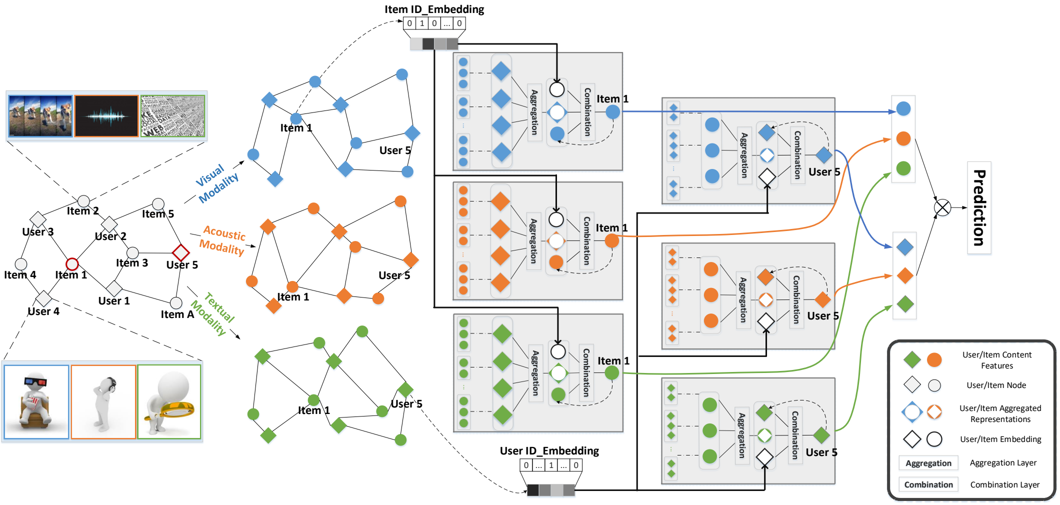


Figure 2: Schematic illustration of our proposed MMGCN model. It constructs the user-microvideo bipartite graph for each modality to capture the modal-specific user preference for the personalized recommendation of micro-video.

- **Mean Aggregation** employs the average pooling operation on the modal-specific features, and applies a nonlinear transformation, as follows:

$$f_{\text{avg}}(\mathcal{N}_u) = \text{LeakyReLU}\Big(\frac{1}{|\mathcal{N}_u|}\sum_{j\in\mathcal{N}_u}\mathbf{W}_{1,m}\mathbf{j}_m\Big), \tag{2}$$

  where $\mathbf{j}_m \in \mathbb{R}^{d_m}$ is the d_m-dimension representation of micro-video j in modality m; $\mathbf{W}_{1,m} \in \mathbb{R}^{d'_m \times d_m}$ is the trainable transformation matrix to distill useful knowledge, where d'_m is the transformation size; and we select LeakyReLU$(\cdot)$ as the nonlinear activation function [38, 41]. Such aggregation method assumes that different neighbors would have the same contributions to the representation of user u, namely, user u is influenced equally by his/her neighbors.
- **Max Aggregation** leverages the max pooling operation to perform dimension-aware feature selection, as follows:

$$f_{\max}(\mathcal{N}_u) = \text{LeakyReLU}\Big(\max_{j\in\mathcal{N}_u}\mathbf{W}_{1,m}\mathbf{j}_m\Big), \tag{3}$$

  where each dimension of $\mathbf{h}_m$ is set as the max-num of the corresponding neighbor values. As such, different neighbors have varying contributions to the output representations.

Hence, the aggregation layer is capable of encoding the structural information and distribution of neighbors into the representation of the ego user; analogously, we can update the representations for item nodes.

2.3 Combination Layer

While containing the information being propagated from the neighbors, such representations forgo user u's own feature and the interaction among different modalities. However, existing GNN efforts (*e.g.,* GCN [22], GraphSage [14], GAT [33]) only consider homogeneous features from one data source. Hence, directly applying their combination operations fails to capture the interactions between different modalities.

In this section, we present a new combination layer, which integrates the structural information $\mathbf{h}_m$, the intrinsic information $\mathbf{u}_m$, and the modality connection $\mathbf{u}_{id}$ into a unified representation, which is formulated as:

$$\mathbf{u}_m^{(1)} = g(\mathbf{h}_m, \mathbf{u}_m, \mathbf{u}_{id}), \tag{4}$$

where $\mathbf{u}_m \in \mathbb{R}^{d_m}$ is the representation of user u in modality m; and $\mathbf{u}_{id} \in \mathbb{R}^d$ is the d-dimension embedding of user ID, remaining invariant and serves as the connection across modalities.

Inspired by prior work [3] on multi-modal representation, we first apply the idea of coordinated fashion, namely, separately projecting $\mathbf{u}_m, \forall m \in \mathcal{M}$ into the latent space that is the same as $\mathbf{u}_{id}$:

$$\hat{\mathbf{u}}_m = \text{LeakyReLU}(\mathbf{W}_{2,m}\mathbf{u}_m) + \mathbf{u}_{id}, \tag{5}$$

where $\mathbf{W}_{2,m} \in \mathbb{R}^{d \times d_m}$ is the trainable weight matrix to transfer $\mathbf{u}_m$ into the ID embedding space. As such, the representations from different modalities are comparable in the same hyperplane. Meanwhile, the ID embedding $\mathbf{u}_{id}$ essentially bridges the gap between modal-specific representations, and propagates information across modalities during the gradient back-propagation process. In this work, we implement the combination function $g(\cdot)$ via the following two methods:

- **Concatenation Combination** which concatenates the two representations, using a nonlinear transformation:

$$g_{\text{co}}(\mathbf{h}_m, \mathbf{u}_m, \mathbf{u}_{id}) = \text{LeakyReLU}\Big(\mathbf{W}_{3,m}(\mathbf{h}_m \| \hat{\mathbf{u}}_m)\Big), \tag{6}$$

  where $\|$ is the concatenation operation, and $\mathbf{W}_{3,m} \in \mathbb{R}^{d'_m \times (d'_m + d)}$ is the trainable model parameters.
- **Element-wise Combination** that considers the element-wise feature interaction between two representations:

$$g_{\text{ele}}(\mathbf{h}_m, \mathbf{u}_m, \mathbf{u}_{id}) = \text{LeakyReLU}\Big(\mathbf{W}_{3,m}\mathbf{h}_m + \hat{\mathbf{u}}_m\Big), \tag{7}$$

  where $\mathbf{W}_{3,m} \in \mathbb{R}^{d \times d'_m}$ denotes a weight matrix to transfer the current representations into the common space. In the element-wise combination, the interactions between two representations are taken into consideration, while two representations are assumed to be independent in Concatenation Combination.

2.4 Model Prediction

By stacking more aggregation and combination layers, we explore the higher-order connectivity inherent in the user-item graphs. As such, we can gather the information propagated from the l-hop neighbors in modality m, mimicking the exploration process of users. Formally, the representation from l-hop neighbors of user u and the output of l-th multi-modal combination layer are recursively formulated as:

$$\mathbf{h}_m^{(l)} = f(\mathcal{N}_u) \quad \text{and} \quad \mathbf{u}_m^{(l)} = g(\mathbf{h}_m^{(l)}, \mathbf{u}_m^{(l-1)}, \mathbf{u}_{id}), \tag{8}$$

where $\mathbf{u}_m^{(l-1)}$ is the representation generated from the previous layer, memorizing the information from its $(l-1)$-hop neighbors. $\mathbf{u}_m^{(0)}$ is set as $\mathbf{u}_m$ at the initial iteration. Wherein, user u is associated with trainable vectors $\mathbf{u}_m, \forall m \in \mathcal{M}$, which are randomly initialized; whereas, item i is associated with the pre-extracted features $\mathbf{i}_m, \forall m \in \mathcal{M}$. As a result, $\mathbf{u}_m^{(l-1)}$ characterizes the user preferences on item features in modality m, and considers the influence of modality interactions that reflect the underlying relationships between modalities.

After stacking L single-modal aggregation and multi-modal combination layers, we obtain the final representations for user u and micro-video i via the linear combination of multi-modal representations, as:

$$\mathbf{u}^* = \sum_{m \in \mathcal{M}} \mathbf{u}_m^{(L)} \quad \text{and} \quad \mathbf{i}^* = \sum_{m \in \mathcal{M}} \mathbf{i}_m^{(L)} \tag{9}$$

2.5 Optimization

To predict the interaction between the users and micro-videos, we fuse their modal-specific representations and apply Bayesian Personalized Ranking (BPR) [30], which is a well-known pairwise ranking optimization framework, as the learning model. In particular, we model a triplet of one user and two micro-videos, in which one of the micro-videos is observed and the other one is not, formally as,

$$\mathcal{R} = \{(u, i, i') | (u, i) \in \mathcal{G}, (u, i') \notin \mathcal{G}\}, \tag{10}$$

where $\mathcal{N}(u)$ consists of all micro-videos associated with u, and $\mathcal{R}$ is a set of triples for training. Further, it is assumed that the user prefers the observed micro-video rather than the unobserved one. Hence, the objective function can be formulated as,

$$\mathcal{L} = \sum_{(u,i,i') \in \mathcal{R}} -\ln \mu(\mathbf{u}^{*\top}\mathbf{i}^* - \mathbf{u}^{*\top}\mathbf{i}'^*) + \lambda \, \|\Theta\|_2^2, \tag{11}$$

where $\mu(\cdot)$ is the sigmoid function; λ and Θ represent the regularization weight and the parameters of the model, respectively.

3 EXPERIMENTS

In this section, we conduct experiments on three publicly available datasets, aiming to answer the following research questions:

- **RQ1**: How does MMGCN perform compared with the state-of-the-art multi-modal recommendation systems and other GNN-based methods on our task?
- **RQ2**: How do different designs (*e.g.,* number of modalities, number of layers, selection of combination layer) influence the performance of MMGCN?
- **RQ3**: Can MMGCN capture the inconsistent preference of users on different modalities?

Table 1: Statistics of the evaluation dataset. (V, A, and T denote the dimensions of visual, acoustic, and textual modalities, respectively.)

Dataset	#Interactions	#Items	#Users	Sparsity	V	A	T
Tiktok	726,065	76,085	36,656	99.99%	128	128	128
Kwai	1,664,305	329,510	22,611	99.98%	2,048	-	128
MovieLens	1,239,508	5,986	55,485	99.63%	2,048	128	100

In what follows, we first present the experimental settings (*i.e.,* datasets, baselines, evaluation protocols, and parameter settings), followed by answering the above three questions.

3.1 Experimental Settings

Datasets. To evaluate our model, we experimented with three publicly available datasets: Tiktok, Kwai, and MovieLens. The characteristics of these datasets are summarized in Table 1.

- **Tiktok[2]:** It is published by Tiktok, a micro-video sharing platform that allows users to create and share micro-videos with duration of 3-15 seconds. It consists of users, micro-videos and their interactions (*e.g.,* click). The micro-video features in each modality are extracted and published without providing the raw data. In particular, the textual features are extracted from the micro-video captions given by users.
- **Kwai[3]:** As a popular micro-video service provider, Kwai has constructed a large-scale micro-video dataset. Similar with the Tiktok dataset, it contains the privacy-preserving user information, content features of micro-videos, and the interaction data. However, the acoustic information of micro-videos is missing.
- **MovieLens[4]:** This dataset has been widely used to evaluate recommendations. To construct the dataset, we collected the titles and descriptions of movies from the MoiveLens-10M dataset and crawled the corresponding trailers instead of the full-length videos from Youtube[5]. We use the pre-trained ResNet50 [16] models to extract the visual features from key frames extracted from micro-video. In terms of acoustic modality, we separate audio tracks with FFmpeg[6] and adopt VGGish [20] to learn the acoustic deep learning features. For textual modality, we use Sentence2Vector [1] to derive the textual features from micro-videos' descriptions.

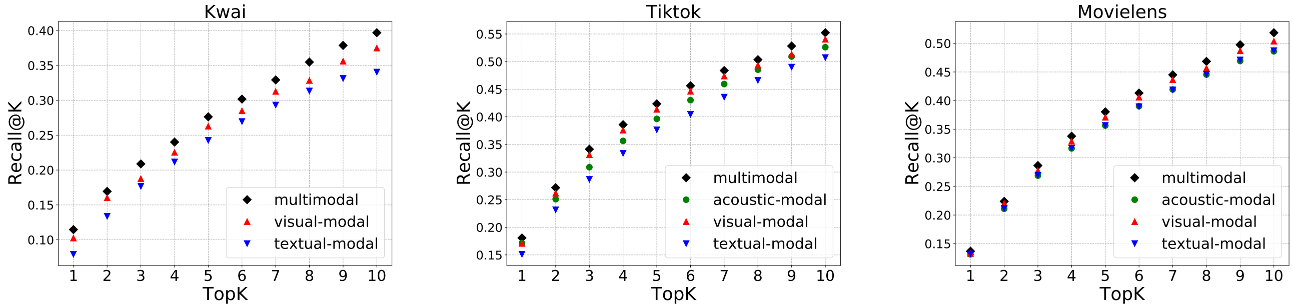
Baselines. To evaluate the effectiveness of our model, we compare MMGCN with the following state-of-the-art baselines. The baselines can be grouped into two categories: CF-based (VBPR and ACF) and GCN-based (NGCF and GraphSAGE) methods.

- **VBPR** [17]. Such model integrates the content features and ID embeddings of each item as its representation, and uses the

[2] http://ai-lab-challenge.bytedance.com/tce/vc/.
[3] https://www.kuaishou.com/activity/uimc.
[4] https://grouplens.org/datasets/movielens/.
[5] https://www.youtube.com/.
[6] http://ffmpeg.org/.

Table 2: Performance comparison between our model and the baselines.

Model	Kwai			Tiktok			MovieLens		
	Precision	Recall	NDCG	Precision	Recall	NDCG	Precision	Recall	NDCG
VBPR	0.2673	0.3386	0.1988	0.0972	0.4878	0.3136	**0.1172**	**0.4724**	**0.2852**
ACF	0.2559	0.3248	0.1874	0.8734	0.4429	0.2867	0.1078	0.4304	0.2589
GraphSAGE	0.2718	0.3412	0.2013	0.1028	0.4972	0.3210	0.1132	0.4532	0.2647
NGCF	**0.2789**	**0.3463**	**0.2058**	**0.1065**	**0.5008**	**0.3226**	0.1156	0.4626	0.2732
MMGCN	**0.3057***	**0.3996***	**0.2298***	**0.1164***	**0.5520***	**0.3423***	**0.1215***	**0.5138***	**0.3062***
%Improv.	**9.61%**	**15.59%**	**11.66%**	**9.03%**	**10.23%**	**6.11%**	**3.67%**	**8.76%**	**7.36%**



(a) Kwai

(b) Tiktok

(c) MovieLens

Figure 3: Performance in terms of Recall@K w.r.t. different modalities on the three datasets.

matrix factorization (MF) framework to reconstruct the historical interactions between users and items. In the experiments, we use the concatenation of multi-modal features as the content information to predict the interactions between users and micro-videos.

- **ACF** [8]. This is the first framework that is designed to tackle the implicit feedback in multimedia recommendation. It introduces two attention modules to address the item-level and component-level implicit feedbacks. To explore the modal-specific user preference and micro-video characteristic, we treat each modality as one component of the micro-video, which is consistent with the idea of standard ACF.
- **GraphSAGE** [14]. Such model is based on the general inductive framework that leverages node feature information to update node representations for the previously unseen data. In particular, it considers the structure information as well as the distribution of node features in the neighborhood. For a fair comparison, we integrate multi-modal features as the node features to learn the representation of each node.
- **NGCF** [41]. This method represent a novel recommendation framework to integrate the user-item interactions into the embedding process. By exploiting the higher-order connectivity from user-item interactions, the modal encodes the collaborative filtering signal into the representation. For a fair comparison, we regard the multi-modal features of micro-video as side information and feed them into the framework to predict the interactions between the users and items.

Evaluation Protocols and Parameter Settings. We randomly split the dataset into training, validation, and testing sets with 8:1:1 ratio, and create the training triples based on random negative sampling. For the testing set, we pair each observed user-item pair with 1000 unobserved micro-videos that the user has not interacted before. We use the widely-used protocols [8, 19]: Precision@K, Recall@K, and NDCG@K to evaluate the performance of top-K recommendation. Here we set $K = 10$ and report the average scores in testing set. To train our proposed model, we randomly initialize model parameters with a Gaussian distribution and use the LeakyReLU as the activation function, and optimizing the model with stochastic gradient descent (SGD). We search the batch size in $\{128, 256, 512\}$, the latent feature dimension in $\{32, 64, 128\}$, the learning rate in $\{0.0001, 0.0005, 0.001.0.005, 0.01\}$ and the regularizer in $\{0, 0.00001, 0.0001, 0.001, 0.01, 0.1\}$. As the findings are consistent across the dimensions of latent vectors, if not otherwise specified, we only show the result of 64, a relatively large number that returns good accuracy.

3.2 Performance Comparison (RQ1)

The comparative results are summarized in Table 2. From this table, we have the following observations:

- MMGCN substantially outperforms all the other baselines in most cases, verifying the effectiveness of our model. In particular, MMGCN improves the strongest baselines *w.r.t.* Recall by 15.59%, 10.23%, and 8.76%, on the three datasets respectively. We attribute such significant improvements to the learning of modal-specific representations, so as to capture users' preference effectively.
- The GNN-based model outperforms the CF-based model on Kwai and Tiktok. The improvements are attributed to the graph convolution layers. Such operations not only capture the local structure information but also learn the distribution of neighbors' features for each ego node, thus boosting the expressiveness of representations.

Table 3: Performance of MMGCN with different aggregation and combination layers.

Variant	Kwai			Tiktok			MovieLens		
	Precision	Recall	NDCG	Precision	Recall	NDCG	Precision	Recall	NDCG
g_{co-id}	0.2812	0.3689	0.2146	0.1056	0.5289	0.3143	0.1034	0.4632	0.2702
g_{co}	0.2927	0.3841	0.2188	0.1132	0.5482	0.3372	0.1209	0.5090	0.3001
g_{ele-id}	0.2840	0.3729	0.2172	0.1071	0.5312	0.3186	0.1064	0.4704	0.2743
g_{ele}	**0.3057**	**0.3996**	**0.2298**	**0.1164**	**0.5520**	**0.3423**	**0.1215**	**0.5138**	**0.3062**

Table 4: Performance of MMGCN w.r.t. the number of layers.

Layer	Kwai			Tiktok			MovieLens		
	Precision	Recall	NDCG	Precision	Recall	NDCG	Precision	Recall	NDCG
One	0.2814	0.3728	0.2123	0.1084	0.5371	0.3263	0.1174	0.5017	0.2950
Two	**0.3057**	**0.3996**	**0.2298**	**0.1164**	**0.5520**	**0.3423**	**0.1215**	**0.5138**	**0.3062**
Three	0.2983	0.3910	0.2216	0.1103	0.5431	0.3361	0.1181	0.5032	0.2957

- Generally speaking, NGCF achieves better performance than other baselines over three datasets in most cases. It is reasonable since NGCF are easily generalized to leverage the content information to characterize the users and micro-videos.
- Unexpectedly, ACF performs poorly on all datasets. The reason of this may be due to the modification that we did during the implementation of ACF model, in which we replaced the component-level features modeling by the modal-specific information for a fair comparison.

3.3 Study of MMGCN (RQ2)

3.3.1 *Effects of Modalities.*

To explore the effects of different modalities, we compare the results on different modalities over the three datasets, as shown in Figure 3. It shows the performance of top-K recommendation lists where K ranges from 1 to 10. From Figure 3, we have the following observations:

- As expected, the method with multi-modal features outperforms those with single-modal features in MMGCN, on all three datasets. It demonstrates that representing users with multi-modal information achieves higher accuracy. It further demonstrates that user representations are closely related to the content of items. Moreover, it shows that our model could capture the user's modal-specific preference from content information.
- The visual modality is the most effective among the three modalities. It makes sense since as, when a user chooses what to play, one usually pays more attention to the visual information than other modality information.
- The acoustic modality provides more important information for recommendation, compared with the textual features. In particular, for Tiktok dataset, the acoustic information even has comparable expressiveness to that of the visual modality.
- Textual modality is the least descriptive for interaction prediction, particularly on Kwai and Tiktok datasets. This is reasonable since we find the texts are of low quality, that is, the descriptions are noisy, incomplete, and even irrelevant to the micro-video content on these two datasets. However, this modality offers important cues on the MovieLens dataset. Because the textual description is the storyline of the video, which highly relates to the content, and some users may play the video according to the storyline. This phenomenon is consistent with our argument that the user preference are closely related to the content information.
- As K increases, Recall@K of MMGCN is consistently higher than the variants. It shows that user preference representations based on each modality are closer to the real preferences of users, which contribute to the prediction of user-item interactions. Modeling with user preferences on a variety of modalities can lead to quality multi-modal personalized recommendation.

3.3.2 *Effect of Combination Layers.*

In our model, we design a novel combination layer to integrate the local structure information with the node's features, facilitating the multiple modal-specific representation fusion. Wherein, the combination function can be implemented with two different way (*cf.* Equations (6) and (7)). Here we compare these different implementations and evaluate the effectiveness of the proposed combination layer, in which g_{co-id} and g_{ele-id} represent two type of implements without id embedding, respectively. As illustrated in Table 3, we have the following findings:

- In terms the three metrics, the g_{ele} achieves the best performance on the three datasets. This may be due to that the combination layer retains the modal-specific features to represent the users and micro-videos. It demonstrate the effectiveness of our combination layers.
- Comparing these methods, we found that the methods with id embedding significantly outperforms the others. This agains demonstrates the effectiveness of our novel combination layers. Besides, we suggest that the shared id embedding connects the different modalities by propagating the shared information during backpropagation.
- Comparing the two implementations, we observed that the element-wise one is better than the concatenate one. We conjecture that the concatenate one with fully connected layer is more difficult to train, especially on the spare datasets, like Kwai.

3.3.3 *Effect of Model Depth.*

To evaluate the effectiveness of layers stack, we conduct experiments on the three different layers, as shown in Table 4. From the results, we observed that:

- In terms three metrics, the two-layer model achieves better results, which show that increasing of layers does not lead to better results. This seems to indicate that the discrimination of the nodes is decreasing as the number of layers increases. We suggest

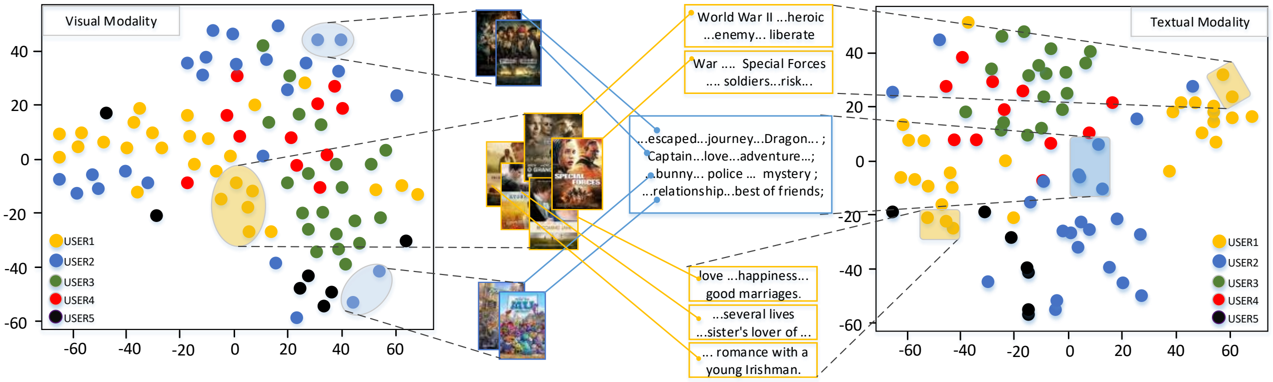


Figure 4: Visualization of users' played micro-videos distribution in different modalities, where each color indicates a user.

that the increasing layers makes the neighbors of nodes more similar, and further makes node representations more similar.

- Compared the one-layer model with the two-layer model, the improvement of the results on Tiktok and Kwai are more obvious, while that on MovieLens are not significantly improved. It demonstrates that integrating the local structure information can enhance the node representation.
- Compared the two-layer model with the three-layer model, the later model achieved worse results than the former one. This may be caused by overfitting due to the sparsity of data.
- Compared the single layer model with the three-layer model, we observed that the results of single layer model are slightly inferior to those of the three-layer model. We suppose the insufficient local structure information of the single layer model results in the low quality of node representation. This again demonstrates the effectiveness of content information in the node representations.

3.4 Case Study (RQ3)

We conducted experiments to visualize our modal-specific representations. In particular, we randomly sampled 5 users and collected the micro-videos they have played. To verify our assumption that the user preferences on different modalities are different, we visualized these representations using t-Distributed Stochastic Neighbor Embedding (t-SNE) in 2-dimension, as illustrated in Figure 4.

The coordinate graphs from left to right represent the visual and textual modality, respectively. The points in the graphs represent the videos that the users have played, and their colors represent different users. Because the acoustic modality is hard to be visualized, we only analyze the results on visual and textual modalities.

- In visual modality, the points of user1 are dispersive and some of them are mixed with the points of user2, user3, and user4. On the other hand, the points from user1 form two concentrated regions in the textual modality, and they are far apart from each other. The distribution of the points means that users have two distinct preferred themes in textual modality. While he/she has no particular preference on visual modality. The points of user2 clustered in three regions in the visual modality; while in the textual modality, they are diffuse and mixed with the points of other users. The distribution pattern of user2 shows that his/her has three preferred themes in the visual modality. The points of user3 are obviously well clustered distribution in the two modalities, which indicates that user has particular preference in each modality. The distribution of the points of user4 and user5 are scattered and mixed with other points of users.
- It is still abstract to use the distribution of points for analysis. The multi-modal information of videos represented by each point is displayed on the graph for further explanation. Take the example of user1 and user2, the visual and textual modality of some of their preferred videos are displayed in Figure 4, which are represented by video posters and storylines. We observed that the videos played by user1 have no obvious themes visually, because the posters he/she preferred cover many different varieties. However, the storylines or textual modality of these videos cover just two themes: war and romance. From user2, we observed that his/her preference on visual modality are clearly divided into animation and classicism, while he/she has no distinct preference on storylines. These phenomena supports our assumption that the users have different preference in different modalities.

4 RELATED WORK

In this section, we introduce some works that are related to our research, including multi-modal personalized recommendation, multi-modal fusion and graph convolution network.

4.1 Multi-modal Personalized Recommendation

Due to the success of CF method in recommendation systems, early multi-modal recommendation algorithms mainly based on CF models [6, 18, 38–40]. CF-based models leverage users' feedbacks (e.g. implicit feedback and explicit feedback) to predict the interactions between users and items. Although these approaches work well for items with sufficient feedbacks, they are less applicable to those with few feedbacks, which cause the low-quality recommendations. Therefore, the CF-based methods are limited by the sparsity of the data.

To remedy the disadvantage of CF-based model, researchers have developed hybrid approaches which incorporate the items' content information and the collaborative filtering effects for recommendation. For instance, Chen *et al.* [7] constructed a user-video-query tripartite graph and performed graph propagation to combine the content and feedback information between users and videos. Recently, Chen *et al.* [8] explored the fine-grained user preference on the items and introduced a novel attention mechanism to address the challenging item- and component-level feedback in multimedia recommendation. In this method, the user is characterized by both collaborative filtering effect and the attended items' content information. Although this method has learned the two levels of the user preference, it fails to model the user preferences on different modalities, which is the key in multi-modal recommendation as mentioned in Section 1. To fill the void in modal-specific features representation, our model constructs the graph in each modality and represents the model-specific features using GCN techniques, which integrates the local structure information and distribution of content information in neighborhood.

4.2 Multi-modal Representation

The multi-modal representation is one of the most important problem in multi-modal applications [27]. However, there are few prior works that focus on multi-modal representation in the area of multi-modal personalized recommendations.

Existing multi-modal representations can be grouped into two categories: joint representations and coordinated representations [3]. Joint representations usually combine the various single-modal information into a single representation and project it into the same representation space. The simplest implementation of the joint representation is the concatenation of single-modal features. Recently, with its success in computer vision [2, 15, 23] and natural language processing [9, 32], neural networks are increasingly used in the multi-modal domain, especially on multi-modal representations [10, 11, 35–37, 43]. Using neural networks, the function fusing the different modalities information into a joint representation can be learned. Besides, the probabilistic graphical models [4, 13] are another way to construct a joint representation for multi-modal information using the latent random variable. Although these methods learn a joint representation to model the multi-modal data, they are suited for situations when all of the modalities are present during inference, which is hardly guaranteed in social platforms.

Different from joint representations, the coordinated ones learn separate representations for each modality but coordinate them with constraints. To represent the multi-modal information, Frome *et al.* [12] proposed a deep visual-semantic embedding model which projects the visual information and semantic information into a common space constrained by distance between the visual embedding and the corresponding word embedding. Similarly, Wang *et al.* [34] constructed a coordinated space which enforces images with similar meanings to be closer to each other. However, since the modal-specific information is the factor causing the difference in each modality signals, the model-specific features are inevitably discarded via those similar constrains.

In contrast, in our model, we introduced a novel representation, which respectively models the common part and specific part of features, to resolve the abovementioned problem.

4.3 Graph Convolution Network

As mentioned above, our proposed model uses the GCN techniques to represent the users and micro-videos, which is widespread in recommendation systems [21, 22, 26, 29]. Towards video recommendation, Hamilton *et al.* [14] proposed a general inductive framework which leverages the content information to generate node representation for unseen data. Based on this method, Ying *et al.* [42] developed and deployed a large-scale deep recommendation engine at Pinterest for image recommendation. In this model, the graph convolutions and random walks are combined to generate the representations of nodes. Concurrently, Berg *et al.* [5] treated the recommender systems as the view of link prediction on graphs and proposed a graph auto-encoder framework based on message passing on the bipartite interaction graph. Moreover, the side information can be integrated into the node representation via a separate processing channel. However, as can be seen, these methods fail to capture the modal-specific representation for each node in the multi-modal recommendation, which is the major concern of our work.

5 CONCLUSION AND FUTURE WORK

In this paper, we explicitly modeled modal-specific user preferences to enhance micro-video recommendation. We devised a novel GCN-based framework, termed MMGCN, to leverage information interchange between users and micro-videos in multiple modalities, refine their modal-specific representations, and further model users' fine-grained preferences on micro-videos. Experimental results on three publicly available micro-video datasets well validated our model. In addition, we visualized some samples to illustrate the modal-specific user preferences.

This work investigates how the information exchange in different modalities influences user preference. This is an initial attempt to encode modality-aware structural information into representation learning. It is a promising solution to understand user behaviors and provide more accurate, diverse, and explainable recommendation. In future, we will extend MMGCN in several directions. First, we would construct multi-modal knowledge graph to present objects and relations between them in micro-videos [31], and then use it into MMGCN to model finer-grained content analysis. It will be used to explore user interests in a more fine-grained manner, and offer an in-depth understanding of user intents. It can also provide more accurate, diverse, and explainable recommendation. Second, we would explore how social leaders influence the recommendation, that is, integrating social network with user-item graphs. We would also like to incorporate multimedia recommendation into dialogue systems towards more intelligent conversational recommendations.

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