# LD4MRec: Simplifying and Powering Diffusion Model for Multimedia Recommendation

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# ABSTRACT

Multimedia recommendation aims to predict users' future behaviors based on historical behavioral data and item's multimodal information. However, noise inherent in behavioral data, arising from unintended user interactions with uninteresting items, detrimentally impacts recommendation performance. Though the issue has partly alleviated by previous studies, it still puzzles the existing recommender systems. Recently, diffusion models have achieved high-quality information generation, in which the reverse process iteratively infers future information based on the corrupted state. It meets the need of predictive tasks under noisy conditions, and inspires exploring their application to predicting user behaviors (*i.e.* generating behavioral information). Nonetheless, several challenges must be addressed: 1) Classical diffusion models require excessive computation, which does not meet the efficiency requirements of recommendation systems. 2) Existing reverse processes are mainly designed for continuous data, whereas behavioral information is discrete in nature. Therefore, an effective method is needed for the generation of discrete behavioral information.

To tackle the aforementioned issues, we propose a Light Diffusion model for Multimedia Recommendation (LD4MRec). First, to reduce computational complexity, we simplify the formula of the reverse process, enabling one-step inference instead of multi-step inference. Second, to achieve effective behavioral information generation, we propose a novel Conditional neural Network (C-Net). It maps the discrete behavior data into a continuous latent space, and generates behaviors with the guidance of collaborative signals and user multimodal preference. Additionally, considering that completely clean behavior data is inaccessible, we introduce a soft behavioral reconstruction constraint during model training,

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Figure 1: (a) Existing diffusion models generate information step by step from Gaussian noise. (b) Our proposed Light diffusion model generates information in a single step from noisy input data.

facilitating behavior prediction with noisy data. Empirical studies conducted on three public datasets demonstrate the effectiveness of LD4MRec, with notable robustness to noisy behaviors. The code will be publicly available upon acceptance.

## CCS CONCEPTS

• Information systems  $\rightarrow$  Recommender systems; Multimedia and multimodal retrieval.

## **KEYWORDS**

Multimedia recommendation, Diffusion model, Controllable generation

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## **1 INTRODUCTION**

Recommender systems have attained widespread adoption in diverse domains [4, 30]. It recommends items of interest to users by analyzing users' historical behavioral data. Recognizing that user behavior is influenced by multimodal information such as

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text and images [42, 51], recent research [2, 32, 50] has focused on how to incorporate multimodal data to enhance recommendation performance.

Early recommender research was dominated by matrix factorization methods [13] that predicted user preferences by analyzing the interaction matrix. A common approach involved deriving user multimodal preferences from textual and visual data to enhance predictions of behavioral information [8, 48]. Since user interaction data can be naturally represented as a bipartite graph, this led to the emergence of Graph Convolutional Network (GCN)-based methods in recent years [16, 39, 40, 47]. GCN-based methods are capable of capturing high-order collaborative signals within behavioral information [9, 38], enabling more effective modeling of user preferences. However, historical behavioral data often contains noise in the form of false positives and false negatives [36]. For example, a user may click an item but find it uninteresting after consuming it [41]. This results in suboptimal user preference modeling. To address this issue, several self-supervised learning (SSL) methods [33, 53] have been proposed. They introduce additional pretext task that maximize the agreement between representations under different perturbations, aiming to enhance robustness to such noise. While they have partially alleviated the problem, the inherent noise issue remains unresolved.

In recent years, diffusion models have achieved remarkable success in computer vision (CV) [22, 29] and natural language processing (NLP) [1, 14]. Diffusion models mainly consist of forward and reverse processes [10, 36]. The forward process corrupts the input data by adding noises step by step in a Markov chain. The reverse process learns to infer the future state based on the corrupted data. Since recommender models aim to infer user future behaviors based on corrupted historical interactions, the reverse process in diffusion model perfectly meets the need of recommender systems [37]. This suggests that exploring the use of diffusion models in recommendation holds great potential. However, it presents two distinct challenges. Firstly, recommender systems must handle massive volumes of data while maintaining timeliness at a high level. To make diffusion models feasible in multimedia recommendation scenarios, significant reductions in computational complexity are essential. Secondly, existing reverse processes are mainly designed for continuous data. Unlike data in CV/NLP tasks, behavioral data in recommendation systems is discrete [41]. It poses a significant challenge in effectively generating behavioral information.

To address the above challenges, we propose a Light Diffusion model for Multimedia Recommendation (LD4MRec). On the one hand, to reduce computational complexity, we simplify the reverse process to enable one-step inference instead of multi-step inference. On the other hand, we propose a novel Conditional neural Network (C-Net) to effectively generate behavior information. The design of C-Net is inspired by previous studies [31, 37] that utilize a mapping of discrete data to a continuous latent space before generation. Specifically, C-Net initially maps sparse and discrete behavioral information to a continuous latent space. It then performs denoising operations on noisy behavioral data and generates potential behaviors. To better align generated data with user interests, C-Net incorporates collaborative signals and multi-modal user preferences as guiding signals. The outputs are finally remapped to the discrete space as predicted behaviors. Additionally, considering the inaccessible of completely clean behavioral data, we introduce a soft behavioral reconstruction constraint during model training. This constraint facilitates behavior prediction in the presence of noisy data. Empirical studies conducted on three benchmark datasets demonstrate the effectiveness of LD4MRec, with notable robustness to noisy behaviors.

Our main contributions can be summarized as follows:

- We simplify and power diffusion model for multimedia recommendation, which achieves one-step inference instead of multi-step inference. To the best of our knowledge, this is the first attempt to introduce diffusion models in multimedia recommender systems.
- We develop a novel C-Net to generate user behavior information. It can effectively generation with the guidance of the collaborative signals and user multimodal preference.
- Extensive experiments on three public datasets demonstrate that the proposed LD4MRec outperforms existing multimedia models, particularly in terms of its robustness against interaction noises.

# 2 LIGHT DIFFUSION MODEL

## 2.1 **Problem Definition**

Let  $\mathcal{U}$  represent the set of users and  $\mathcal{I}$  represent the set of items. We define the modality features of items as  $\mathbf{E}_m \in \mathbb{R}^{d_m \times |\mathcal{I}|}$ , where  $d_m$  denotes the dimension of the features. Here,  $m \in \mathcal{M}$  represents the modality, and  $\mathcal{M}$  is the set of modalities. In this study, we focus primarily on two modalities: visual and textual. It is important to note that our method can be extended to accommodate multiple modalities.

Furthermore, we use  $\mathcal{R}$  to represent the historical behavior data of the users, which can be described as a matrix of size  $|\mathcal{U}| \times |\mathcal{I}|$  with entries in {0, 1}. Specifically, if user *u* has clicked on item *i*, we set  $\mathcal{R}_{u,i} = 1$ ; otherwise,  $\mathcal{R}_{u,i} = 0$ . The objective of multimedia recommendation is to accurately predict user future interaction probabilities  $\hat{y}_{ui}$  based on observed historical interactions.

## 2.2 Forward and Reverse Processes

Normally, diffusion models consist of forward and reverse processes. The forward process corrupts the input data by adding noises step by step in a Markov chain. The reverse process learns to recover the input data iteratively.

• Forward process. Given a user u and their interaction history over an item set  $r_u$ , we consider the presence of noise and define the input state  $x_{in}$  as  $r_u$  with a learnable input time representation  $t_{in}$ .  $x_0$  represents the ideal state without noise. <sup>1</sup> It is important to note that the input time behavior exhibits minimal noise, which allows us to assume that  $t_{in}$  approximates  $t_0$ . In other words, during the forward process, we can reasonably approximate the representation as  $x_{in}$  from  $t_0$  to  $t_{in}$ , while considering only the reconstruction of  $x_0$  from  $x_{in}$  in the reverse process.

During the forward process, the transition is parameterized as follows:

<sup>&</sup>lt;sup>1</sup>For brevity, we omit the subscript u in  $t_{in}$ ,  $x_0$ , and  $x_{in}$  for user u.

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$$q(\mathbf{x}_t | \mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t} \mathbf{x}_{t-1}, \beta_t \mathbf{I}), \tag{1}$$

Here,  $\mathcal{N}(x; \mu, \sigma^2)$  is a Gaussian distribution with a mean  $\mu$  and variance  $\sigma^2$ ,  $\mathbf{x}_t$  is sampled from this Gaussian,  $\beta_t$  is the noise added at the *t*-th diffusion step and  $\mathbf{I}$  is the identity matrix. The value of  $\beta_t$  is generated from a pre-defined noise schedule  $\beta$  controlling the scale of Gaussian noise added at each step *t*.

By utilizing the reparameterization trick [10] and the additivity property of two independent Gaussian noises [10, 19], we can directly obtain  $x_t$  from  $x_{in}$ . This can be formalized as:

$$q(\mathbf{x}_t | \mathbf{x}_{in}) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t} \mathbf{x}_{in}, (1 - \bar{\alpha}_t) \mathbf{I})$$
  
=  $\sqrt{\bar{\alpha}_t} \mathbf{x}_{in} + \sqrt{1 - \bar{\alpha}_t} \epsilon, \ \epsilon \sim \mathcal{N}(0, \mathbf{I}),$  (2)

where  $\alpha_t = 1 - \beta_t$ ,  $\bar{\alpha}_t = \prod_{i=1}^n \alpha_i$ .

Since  $\bar{\alpha}_t$  represents a predefined noise schedule devoid of any learnable parameters, we can effectively control  $x_t$  by establishing an appropriate  $\beta_t$ . Various noise schedules commonly employed include square-root [14], cosine [10], and linear [23]. In light of the limited availability of user behavior data in recommendation scenarios, we aim to prevent excessive degradation of behavior-related information by regulating the extent of noise introduced in  $x_{in:T}$ , as proposed by Wang [37]. To this end, a linear noise schedule is employed for  $1 - \bar{\alpha}_t$ , which can be expressed as follows:

$$1 - \bar{\alpha}_t = s \cdot \left[ \alpha_{\min} + \frac{t - 1}{T - 1} (1 - \alpha_{\min}) \right], \quad t \in 1, ..., T.$$
 (3)

Here,  $s \in [0, 1]$  serves as a hyperparameter governing the magnitude of the noise, while  $\alpha_{\min} \in (0, 1)$  is a hyperparameter indicating the minimum level of noise to be added. The variable *T* denotes the total number of diffusion steps.

• **Reverse process.** Diffusion models commonly employ an iterative approach to approximate the true representation  $x_0$  by eliminating added noises from  $x_t$  to  $x_{t-1}$ . This iterative process involves a sequence of transformations, progressing from  $x_t$  to  $x_{t-1}$  until  $x_t$  ultimately converges to  $x_0$  (*i.e.*  $x_t \rightarrow x_{t-1} \rightarrow \dots, x_{in} \rightarrow x_0$ ). To compute the subsequent denoised representation  $x_{t-1}$  given the current representation  $x_t$ , the following procedure is employed:

$$p_{\theta}(\boldsymbol{x}_{t-1}|\boldsymbol{x}_{t}) = \mathcal{N}\left(\boldsymbol{x}_{t-1}; \boldsymbol{\mu}_{\theta}(\boldsymbol{x}_{t}, t), \boldsymbol{\Sigma}_{\theta}(\boldsymbol{x}_{t}, t)\right), \quad (4)$$

where  $\mu_{\theta}(\mathbf{x}_t, t)$  and  $\Sigma_{\theta}(\mathbf{x}_t, t)$  denote the Gaussian parameters outputted by a neural network with learnable parameters  $\theta$ .

Throughout the process of training the model, the optimization of diffusion models aims to enforce the approximation of the tractable distribution  $q(\mathbf{x}_{t-1}|\mathbf{x}_t)$  by  $p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t)$  using the KL divergence. And the closed form expression of  $q(\mathbf{x}_{t-1}|\mathbf{x}_t)$  can be derived, as demonstrated in a previous study [19]:

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t) \propto \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}(\mathbf{x}_t, t), \sigma^2(t) \boldsymbol{I}), \text{ where}$$
 (5)

$$\begin{cases} \tilde{\mu}(\boldsymbol{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} (\boldsymbol{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_t), \\ \sigma^2(t) = \frac{(1 - \alpha_t)(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t}. \end{cases}$$
(6)

The mean and covariance of the distribution  $q(\mathbf{x}_{t-1}|\mathbf{x}_t)$ , denoted as  $\tilde{\mu}(\mathbf{x}_t, t)$  and  $\sigma^2(t)\mathbf{I}$  respectively. They are derived from Eq. (1) and Eq. (2) [10].

Normally, conventional diffusion models establish a neural network to estimate the noise  $\epsilon_t$  at each step, thereby predicting the initial state through multi-step inference [5, 14]. However, unlike CV and NLP tasks, sparse behavioral data contains less information, multi-step inference becomes inefficient and burdens the training of the model [37]. To address this issue, we utilize Bayes' rule to simplify the calculation of the mean, thus achieving one-step inference:

$$\boldsymbol{\mu}_{\theta}(\boldsymbol{x}_{t},t) = \frac{\sqrt{\alpha_{t}}(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_{t}}\boldsymbol{x}_{t} + \frac{\sqrt{\bar{\alpha}_{t-1}}(1-\alpha_{t})}{1-\bar{\alpha}_{t}}\hat{\boldsymbol{x}}_{\theta}(\boldsymbol{x}_{t},t). \quad (7)$$

Then we can instantiate  $\hat{x}_{\theta}(\cdot)$  via a neural network, which predicted  $x_0$  based on  $x_t$  and t. In other words, this formulation enables the one-step prediction of the state at any given time, as the diffusion process exhibits Markovian properties.

The task of recommendation is distinct from conventional generation tasks due to its primary objective of satisfying user interests. The ultimate goal of a recommender system is to predict items that meet user preference, which requires the implementation of a controllable diffusion model centered around user feedback. Consequently, we introduce modality information denoted as *m* as the control signal, which can reflect users' multimodal preferences. The ultimate expression for predicting  $x_0$  is presented below:

$$p_{\theta}(\mathbf{x}_{0}|\mathbf{x}_{t}, \mathbf{x}_{\mathrm{in}}, t, m) = \mathcal{N}(\mathbf{x}_{\mathrm{in}}; \boldsymbol{\mu}_{\theta}(\mathbf{x}_{t}, \mathbf{x}_{\mathrm{in}}, t, m), \boldsymbol{\Sigma}_{\theta}(\mathbf{x}_{t}, \mathbf{x}_{\mathrm{in}}, t, m)).$$

$$\begin{cases} \mu_{\theta}(\mathbf{x}_{t}, t, m) = \frac{\sqrt{\alpha_{t}}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_{t}} \mathbf{x}_{t} + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_{t})}{1 - \bar{\alpha}_{t}} \hat{\mathbf{x}}_{\theta}(\mathbf{x}_{t}, t, m), \\ \sigma^{2}(t) = \frac{(1 - \alpha_{t})(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_{t}}. \end{cases}$$

$$(9)$$

To effective address the discrete and interconnected nature of behavioral data, we propose and detail the C-Net in Section. 3. It is designed to fit  $\mu_{\theta}(\mathbf{x}_t, t, m)$ , allowing effective and controllable denoising.

#### 2.3 Efficient Training and Inference

• **Training.** Diffusion models undergo training using the Mean Square Error (MSE) loss, which measures the discrepancy between the sampled mean  $\mu_n$  and the predicted mean  $\mu_{\theta}$  [10].

$$\mathcal{L}_{\text{mse}} = \mathbb{E}_{q(\boldsymbol{x}_t | \boldsymbol{x}_{\text{in}})} \parallel \tilde{\boldsymbol{\mu}}(\boldsymbol{x}_t, \boldsymbol{x}_{\text{in}}, t) - \boldsymbol{\mu}_{\theta}(\boldsymbol{x}_t, t, \text{condition}) \parallel_2^2, \quad (10)$$

where  $\mu_n(x_t, x_{in})$  represents the sampled mean as defined in Eq. 6.

In light of the presence of inherent noise in the input behavior data, we have introduced a modification to the MSE loss function by drawing inspiration from soft labels [17, 21]. This modification has led to the proposal of a soft behavior reconstruction constraint denoted as  $\mathcal{L}_{rec}$ :

$$\mathcal{L}_{\text{rec}} = \mathbb{E}_{q(\boldsymbol{x}_t | f_{\text{s}}(\boldsymbol{x}_{\text{in}}))} \| \tilde{\mu}(\boldsymbol{x}_t, f_{\text{s}}(\boldsymbol{x}_{\text{in}}), t) - \mu_{\theta}(\boldsymbol{x}_t, t, \text{condition}) \|_{2^2}^2,$$
(11)

Specifically, for a given set of input behavior data  $x_{in}$ , we sample two subsets,  $S^+$  and  $S^-$ , with a probability of p. The subset  $S^+$  represents the items that have been clicked on by the user and are thus labeled as 1, while the subset  $S^-$  represents the items that

#### **Algorithm 1 Efficient Training**

Input: All users' interactions $\mathcal{R}$ , all items' modality feature
$\{\mathbf{E}_m\}_{m \in \mathcal{M}}$ and randomly initialized $\theta$ .
1: repeat
2: <b>for</b> a minibatch $\hat{\mathcal{R}} \subset \mathcal{R}$ <b>do</b>
3: Sample a diffusion step $t \sim p_t$ ,
4: Sample random Gaussian noise $\boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{I})$ ;
5: // Forward Process
6: Compute $\mathbf{x}_t$ via $q(\mathbf{x}_t   \mathbf{x}_{in})$ in Eq. 2)
7: // Reverse Process
8: Predict $x_0$ via $p_{\theta}(x_0 x_t, x_{\text{in}}, t, m)$ in Eq. 8
9: // Optimization
10: Calculate $\mathcal{L}(\mathbf{r}_u)$ via Eq. 13
11: Take gradient descent step on $\nabla_{\theta} \mathcal{L}(\mathbf{r}_u)$ to optimize
12: // Dynamic Update
13: Update the history value for $\mathcal{L}_{rec}(\mathbf{r}_u)$
14: end for
15: <b>until</b> Converged
<b>Output:</b> Optimized $\theta$ .

have not been clicked on and are labeled as 0. Then the sequential smoothing operation is performed, as shown below:

$$f_{\rm s}(x) = \begin{cases} 1 - \gamma, & x \in \mathcal{S}^+, \\ \gamma, & x \in \mathcal{S}^-, \end{cases}$$
(12)

where the hyperparameter  $\gamma$  is employed to control the intensity of the smoothing effect.

Furthermore, when the forward diffusion step t is relative small, the introduction of noise to the input representation  $x_{in}$  is minimal, allowing the model to effortlessly restore  $x_{in}$ . Conversely, as tapproaches the total diffusion step T, the denoising of  $x_t$  becomes increasingly challenging due to its similarity to Gaussian noise. It is intuitive to allocate more training steps to more difficult samples, as this enhances the denoising capability. Therefore, we utilize the technique of importance sampling [23] to incentivize the inclusion of harder samples. The weighted loss function  $\mathcal{L}(r_u)$  is defined as follows:

$$\mathcal{L}(\mathbf{r}_{u}) = \mathbb{E}_{n \sim p_{t}} \left[ \frac{\mathcal{L}_{\text{rec}}(\mathbf{r}_{u})}{p_{t}} \right], \quad p_{t} \propto \sqrt{\mathbb{E}[\mathcal{L}_{\text{rec}}(\mathbf{r}_{u})^{2}]}, \quad \sum_{t=1}^{T} p_{t} = 1,$$
(13)

where  $p_t$  represents the probability of sampling the diffusion step t. As  $\mathbb{E}[\mathcal{L}_{rec}(\mathbf{r}_u)]$  may change during training, we dynamically record the value of each  $\mathcal{L}_{rec}(\mathbf{r}_u)$  and update the record history accordingly. Before acquiring enough  $\mathcal{L}_{rec}(\mathbf{r}_u)$ , we still adopt the uniform sampling. Based on the aforementioned designs, we summarize our training strategy in Algorithm 1.

• **Inference.** Diffusion models typically employ a reverse generation process, which involves drawing random Gaussian noises [7, 28]. These noises can be guided by gradients obtained from a pre-trained classifier or other signals, such as textual queries. However, the conversion of meaningful interactions into pure noise can have a detrimental impact on the customization of user preferences in recommendation systems [37]. In order to tackle this issue, during the inference stage, we directly initiate the reverse process from the input  $x_{in}$  to reconstruct the original state  $x_0$ . This approach

Algorithm 2 Efficient Infe	rence
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np	ut:	Interaction	$r_u$	of	user	и,	all	items	' modality	features
	$\{\mathbf{E}_{t}\}$	${}_{m} \}_{m \in \mathcal{M}}$ and	trai	nec	l para	me	ters	θ.		
	Car		Ca				~	A/(A	<b>I</b> ).	

1: Sample random Gaussian noise  $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ ;

2: // Reverse Process

3: Predict  $x_0$  given  $x_{in}$  (*i.e.*  $r_u$ ) via  $p_\theta(x_0|x_t, x_{in}, t, m)$  in Eq. (8) **Output:** the interaction probabilities  $x_0$  for user u.

allows for deterministic inference by disregarding the introduction of variance, similar to the methodology employed in MultiVAE [15]. The inference procedure is summarized in Algorithm 2.

## 3 C-NET

#### 3.1 Overview

In order to promote the denoised behavioral information is close to similar users' information, we first distill collaborative signals with collaborative encoder from the global perspective. In this study, we employ the SVD [11] scheme as the encoder due to its efficient and effective capturing of collaborative signals. Additionally, similar to other multimedia recommendation approaches [47, 49], the modality features of items can be distilled using a pre-trained modality information encoder (*i.e.* VGG-16, Sentence2Vec, *etc.*). Next, the user's modality preference can be captured by weighted aggregating the modality information of clicked items through a lightweight GCN module [47]. The aggregation process can be represented as follows:

$$\mathbf{e}_{u,m} = \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}} \mathbf{e}_{i,m},\tag{14}$$

where  $\mathbf{e}_{u,m}$  denotes the *m* modality preference of user *u*,  $\mathbf{e}_{i,m}$  represents the *m* modality features of item *i*,  $\mathcal{N}_u$  indicates the set of clicked items by the user *u*, and  $\mathcal{N}_i$  denotes the set of users who clicked item *i*. And the forward diffusion step embedding  $\mathbf{z}_t \in \mathbb{R}^d (1 \le t \le T)$  is obtained by the sinusoidal function [34]:

$$z_t(2j) = \sin(n/10000^{2j/d}),$$
  

$$z_t(2j+1) = \cos(n/10000^{2j/d}), \ 0 \le j < d/2$$
(15)

where 2j and 2j + 1 represent the dimension. Meanwhile, the learnable  $z_{in}$  represents the data input time  $t_{in}$  for each user.

After the forward process, the input of noisy user behavior data  $x_t$  is fed into the C-Net, where it undergoes transformation into a continuous latent space via a fully connected layer. Subsequently, a sequence of cascaded BD-Blocks and BI-Blocks is employed to accomplish the generation of behaviors with the guidance of collaborative signals and user multimodal preference. Finally, the ultimate representation is mapped back to the original discrete behavior space using another fully connected layer. The overall framework of LD4MRec is presented in Figure 2. To maintain simplicity, we have omitted the depiction of nonlinear activation functions between the BD-Blocks and BG-Blocks.

### 3.2 Behavior Denoising Block

For the behavioral information after the forward denoising process, we proceed to denoise the behavioral information and utilize LD4MRec: Simplifying and Powering Diffusion Model for Multimedia Recommendation



Figure 2: (a) The overall framework. (b) BD-Block denoises the representations with the guidance of collaborative signals. (c) BG-Block generate behavior information under the control of user multimodal preferences.

collaborative signals to generate initial information. When the forward diffusion step is relatively small, the behavioral information incorporates little noise. Consequently, we expect the model to capture user personalized behavior information for noise removal. Conversely, a larger step size results in increased noise levels and incomplete behavioral information. In such cases, we guide the model to eliminate noise and generate possible behavioral information by incorporating collaborative signals.

Specifically, the behavioral representation is first concatenated with the representation of forward time to carry out the preliminary denoising operation:

$$\mathbf{b}'_u = \sigma(\mathbf{W}_1 \mathbf{b}_u + \mathbf{b}_1). \tag{16}$$

In the above equation,  $\mathbf{b}_u \in \mathbb{R}^d$  represents a dense representation obtained by mapping  $x_0$  through a feedforward layer. The parameters involved in this operation are  $\mathbf{W}_1 \in \mathbb{R}^{d \times d}$  and  $\mathbf{b}_1 \in \mathbb{R}^d$ , which are learnable. Here, *d* denotes the dimension of the hidden layer, and  $\sigma$  corresponds to the activation function.

Meanwhile, the collaborative signals are mapped to the same latent space through an independent feedforward neural network as supplementary information:

$$\mathbf{c}'_u = \sigma(\mathbf{W}_2 \mathbf{c}_u + \mathbf{b}_2). \tag{17}$$

In the above equation,  $\mathbf{c}_u \in \mathbb{R}^{d_{\text{svd}}}$  represents the pre-encoded collaborative representation over *u*. The parameters involved in this operation are  $\mathbf{W}_1 \in \mathbb{R}^{d \times d_{\text{svd}}}$  and  $\mathbf{b}_1 \in \mathbb{R}^d$ , which are learnable.

Then, under the control of forward diffusion time, the denoised behavioral features and collaborative information are adaptively fused:

$$\mathbf{b}_{u,d} = \mathbf{b}'_u \odot (1 - g(t_f)) + \mathbf{c}'_u \odot g(t_f)$$
(18)

$$g(t_f) = \sigma(\mathbf{W}_3 t_f + \mathbf{b}_3) \tag{19}$$

where  $g(t_f)$  is the gating function,  $\mathbf{W}_3 \in \mathbb{R}^{d \times d}$  and  $\mathbf{b}_3 \in \mathbb{R}^d$  are learnable parameters,  $\odot$  represents the element-wise product and  $\sigma$  is the sigmoid nonlinearity.  $t_f$  represents the overall forward time representation:

$$t_f = \begin{cases} t + t_{\rm in}, & if \text{ training,} \\ t_{\rm in}, & if \text{ inference,} \end{cases}$$
(20)

Under the control of time representation, BD-Block adeptly merges the information originating from two branches and effectively performs initial denoising.

## 3.3 Behavior Generating Block

Given the frequent association between user behavior and their multimodal preferences, we fuse behavior information with their multimodal preferences. To achieve this, we propose a novel Behavior Generating Block (BD-Block), which is designed to facilitate the generation of behavior that maximizes alignment with user preferences.

Table 1: Statistics of the experimental datasets

Dataset	#User	#Item	#Behavior (C)	#Behavior (N)
Baby	19,445	7,050	160,792	176,870
Sports	35,598	18,357	296,337	325,970
Electronics	192,403	63,001	1,689,188	1,858,106

More specifically, inspired by the text2image task [22, 31], we employ a sequential process to generate behavioral information, utilizing both text preference control and image preference control. Taking the generation of behavioral information controlled by text preference as an example, we first utilize two Multilayer Perceptrons (MLPs) to predict the parameters  $W_t$  for text-conditioned feature transformation and the shifting parameters **b***t* based on the user's text preference  $t_{u,t}$ , respectively:

$$\mathbf{W}_t = MLP_1(\mathbf{t}_{u,t}), \quad \mathbf{b}_t = MLP_2(\mathbf{t}_{u,t}). \tag{21}$$

Next, we perform a feature transformation operation on the given input behavior feature  $\mathbf{b}_{u,d}$  using the transformation parameter  $\mathbf{W}_t$ . Additionally, we apply the channel-wise shifting operation with the shifting parameter  $\mathbf{b}_t$ . This process can be mathematically represented as:

$$\mathbf{b}_{ud}' = \mathbf{W}_t \mathbf{b}_{ud} + \mathbf{b}_t. \tag{22}$$

The process of generating behaviors under image preference control follows a similar approach. However, the above generation process is a linear transformation process, it hinders the effectiveness of behavior generation. To address this limitation, we introduce a LeakyReLU layer between text preference-conditioned generation and image preference-conditioned generation. This inclusion introduces nonlinearity into the generation process, expanding the conditional representation space. By enlarging the representation space, we facilitate the mapping of diverse behavior information to distinct representations based on modality preference.

## **4 EXPERIMENTS**

In this section, we conduct extensive experiments to evaluate the performance of the proposed LD4MRec model on three public datasets. The following four questions can be well answered through experiment results:

• **RQ1:** How does LD4MRec perform compared to the baselines under various experimental settings?

RQ2: How do the designs of LD4MRec affect the performance? RQ3: How does different hyper-parameter settings impact the

results of the LD4MRec model?

### 4.1 Experimental Settings

4.1.1 Dataset. In line with prior studies [49, 53], we employ the Amazon review dataset for our experimental assessment. In order to facilitate the evaluation of numerous baseline approaches on extensive datasets, we select three datasets per category, namely Baby, Sports and Outdoors (referred to as Sports), and Electronics (referred to as Elec). The descriptive statistics of these datasets can be found in Table.1. Consistent with Zhou[53], we utilize the pre-extracted visual features with 4,096 dimensions and text features with 384 dimensions, which were previously published in [52].

For all datasets, we consider two different experimental settings in accordance with prior works [37, 41]. (1) **Clean training.** It first excludes user interactions with ratings < 4. Subsequently, the remaining interactions are sorted and divided into training, validation, and testing sets at a ratio of 8:1:1. (2) **Noisy training.** It employs the same testing set as the clean training. However, it introduces additional noisy interactions into the training and validation sets. These noisy interactions consist of both natural noises (*i.e.*, interactions with ratings < 4) and randomly sampled interactions.

4.1.2 *Compared Methods.* To evaluate the effectiveness of our proposed model, we compare it with several representative recommendation models. These baselines fall into two groups: General models, which only rely on interactive data for recommendation; Multimedia models, which utilize both interactive data and multi-modal features for the recommendation.

**i) General Models:** We have selected some of the most representative models as our compared methods, including MF-based methods (MF-BPR [13]), GCN-based methods (LightGCN [9]), Diffusionbased methods (DiffRec [37]) and Self-Supervised Learning (SSL)based methods (SimGCL [46]).

**ii)** Multimedia Models: To enhance the evaluation of our approach, we selected some competitive models as our compared methods. This encompasses techniques such as MF-based methods (VBPR [8]), GCN-based methods (MMGCN [40], LATTICE [49], MGCN [47]) and SSL-based methods (SLMRec [33], BM3 [53]).

4.1.3 Evaluation Protocols. To ensure a a fair comparison, we adhere to the standardized all-ranking protocol [47, 53] when assessing the performance of top-K recommendations. We calculate and present the average metrics, namely Recall@K (R@K) and NDCG@K (N@K), for all users in the test set. Our study encompasses over ten experiments, and the reported values represent their average outcomes. The statistical significance of the improvements over the best baseline is indicated by the *p*-value.

4.1.4 Implementation Details. We have implemented the proposed model and all the baseline models using the PyTorch framework [25]. To ensure a fair comparison, we have optimized all the methods using the Adam optimizer and referred to the optimal hyperparameter settings mentioned in the original baseline papers. To ensure convergence, we have employed early stopping after 20 epochs and a total of 1000 epochs. Following the approach described in [50], we have utilized Recall@20 on the validation data as the indicator for stopping the training process.

#### 4.2 Overall Performance (RQ1)

The performance comparison results are presented in Table 2 for clean training and in Table 3 for noisy training. Several key observations can be made from these tables:

(1) When trained with clean data, the diffusion model exhibits significantly improved performance compared to mainstream methods, and even outperforms the current best GCN-based method. This superior performance can be attributed to the alignment between generative modeling and real-world behavior generation procedures. Moreover, the diffusion model leverages multimodal preference information to ensure controllable generation, leading to effective personalized user behavior prediction.

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		Ba	by			Spo	orts		Electronics			
Methods	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20
MF-BPR	0.0357	0.0575	0.0192	0.0249	0.0432	0.0653	0.0241	0.0298	0.0235	0.0367	0.0127	0.0161
LightGCN	0.0479	0.0754	0.0257	0.0328	0.0569	0.0864	0.0313	0.0387	0.0363	0.0540	0.0204	0.0250
DiffRec	0.0497	0.0774	0.0263	0.0339	0.0603	0.0900	0.0331	0.0408	0.0392	0.0572	0.0224	0.0270
SimGCL	0.0498	0.0783	0.0269	0.0342	0.0624	0.0919	0.0346	0.0414	0.0409	0.0585	0.0229	0.0281
VBPR	0.0423	0.0663	0.0223	0.0284	0.0558	0.0856	0.0307	0.0384	0.0293	0.0453	0.0159	0.0202
MMGCN	0.0378	0.0615	0.0200	0.0261	0.0370	0.0605	0.0193	0.0254	0.0207	0.0331	0.0109	0.0141
SLMRec	0.0540	0.0810	0.0285	0.0357	0.0676	0.1017	0.0374	0.0462	0.0422	0.0630	0.0237	0.0291
LATTICE	0.0544	0.0848	0.0291	0.0369	0.0618	0.0947	0.0337	0.0422	-	-	-	-
BM3	0.0564	0.0883	0.0301	0.0383	0.0656	0.0980	0.0355	0.0438	0.0437	0.0648	0.0247	0.0302
MGCN	0.0620	0.0964	0.0339	0.0427	0.0729	0.1106	0.0397	0.0496	0.0442	0.0650	0.0246	0.0302
LD4MRec	0.0645	0.0981	0.0348	0.0437	0.0743	0.1115	0.0403	0.0502	0.0450	0.0662	0.0254	0.0311
p-value	6.17e-6	6.24e-6	1.81e-5	1.87e-5	4.33e-6	4.67e-6	1.67e-5	1.79e-5	6.47e-6	6.61e-6	1.80e-5	1.88e-5

Table 2: Performance Comparison of Different Recommendation Models (Clean Training)

'-' indicates the model cannot be fitted into a Tesla V100 GPU card with 32 GB memory.

Table 3: Performance Comparison of Different Recommendation Models (Noisy Training)

	Baby				Sports				Electronics			
Methods	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20
BM3	0.0500	0.0819	0.0265	0.0347	0.0562	0.0865	0.0307	0.0385	0.0383	0.0574	0.0213	0.0262
MGCN	0.0535	0.0843	0.0292	0.0365	0.0626	0.0932	0.0338	0.0418	<u>0.0397</u>	<u>0.0598</u>	0.0224	0.0267
LD4MRec	0.0602	0.0931	0.0328	0.0413	0.0709	0.1083	0.0379	0.0481	0.0418	0.0620	0.0236	0.0288



Figure 3: Performance comparison between different variants of LD4MRec. (Blue: w/o BG, Light Blue: w/o BD, Yellow: w/o SR, Orange: LD4MRec)

(2) In the presence of noisy data, diffusion models demonstrate effective resistance against noise pollution, surpassing both SSLbased and GCN-based methods. This suggests that the denoising training employed by the diffusion model enhances its representation ability, resulting in robustness. Given that practical application scenarios often involve user interactions with noise, the utilization of diffusion models for multimedia recommendation holds significant potential.

## 4.3 Ablation Study (RQ2)

In our effort to elucidate the impact of key components within LD4MRec, we established several model variants:

w/o BG: For this variant, we exclude behavior generating block and instead sequentially link the two Behavior Denoising blocks.
w/o BD: In this variant, the behavior denoising block is eliminated. Much like DiffRec [37], we concatenate behavior information and time representations directly, and then pass them through a multilayer perceptron (MLP) layer to fit the reverse process.

• w/o SR: In this variant, we have omitted the soft reconstruction loss, choosing to employ Mean Squared Error (MSE) loss for the model's training process.

Our study yielded the following findings:

(1) Upon the removal of multimodal information, there is a notable decrease in performance. This aligns with the intuitive understanding, given that user behavior is frequently influenced by item multimodal information. Guided by user multimodal preferences, LD4MRec can generate behavioral data more precisely to align with user personalized preferences.

(2) Across the three datasets, models w/o BD underperform, underscoring the substantial contribution of collaborative information to behavioral denoising. By adaptively fusing collaborative and behavior information, the model achieves a balance between focusing on similar users' information and its own information.

(3) The elimination of soft reconstruction constraint leads to a dip in performance. This can be chiefly attributed to the fact that, at the initial stage, user behavior contain a certain level of noise. Consequently, the input state deviates from the ideal zero moment, introducing some drift. It is not logical to insist that the generated behavior information fully aligns with historical behavior information, as this could misguide the model in its attempt to model user preferences. Contrarily, smoothing historical behavior

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Figure 4: Performance comparison w.r.t. different p and y.



Figure 5: Performance comparison w.r.t. different s and  $\alpha_{min}$ .

can encourage the model to extract more invariant user preferences from the noisy data.

## 4.4 Sensitivity Analysis (RQ3)

4.4.1 Analysis of soft behavior reconstruction constraint. To facilitate the effective learning of the model from noise, we devise a soft reconstruction loss. Furthermore, we perform sensitivity analysis experiments and determine that optimal outcomes are obtained when the soft probability p is set to 0.01, and the smoothing intensity  $\gamma$  is set to 0.01. Excessive values for either the soft probability or smoothing intensity can result in the loss of behavior information, leading to suboptimal results.

4.4.2 Analysis of the noise in the forward process. To investigate how the noise in the forward process affects the performance, we consider the variants of LD4MRec that use different noise scale *s* and the minimum level of noise  $\alpha_{min}$ . Figure. 5 demonstrates that the model achieves optimal performance when *s* is set to 0.01 and  $\alpha_{min}$  is set to 0.05. And we find that the efficacy of the model is closely linked to the introduction of noise during the forward process. That is to say, excessive noise may disrupt personalized behavioral information, while insufficient noise can impede the model's capability, rendering it unable to achieve satisfactory recommendation performance.

## 5 RELATED WORK

## 5.1 Multimedia Recommendation

Collaborative filtering has emerged as a prominent approach for generating top-k recommendations by leveraging behavior similarity [20, 24]. Considering that users' preferences are often influenced by multimodal information, researchers have been prompted to incorporate such information in order to enhance collaborative filtering (CF)-based approaches [42, 51]. Typically, multimodal features are extracted using pre-trained neural networks and then combined with behavior features to more effectively model user preferences. For instance, VBPR [8] utilizes convolutional neural networks (CNNs) pre-trained on ImageNet to extract deep visual features and enrich item representations. Given that user behavior data, such as clicks or purchases, can be naturally represented as a bipartite graph, recent studies have favored the adoption of Graph Convolution Networks (GCNs) as a powerful tool for extracting user behavior features [3, 45]. To handle different modalities, MMGCN [40] constructs multiple GCN modules and concatenates the resulting modality features to obtain the final representation of items. Additionally, LATTICE [49] and MGCN [47] exploit hidden associative signals using an additional item-item graph to enhance user preference modeling. Nevertheless, GCN-based methods often exhibit a heavy reliance on historical behavioral information. It leads to noise in behavioral information may mislead user preference modeling. To address this issue, several self-supervised learning (SSL) methods (SLMRec [33], BM3 [53]) have been proposed. These methods introduce additional self-supervised learning tasks that maximize the representation under two perturbations, aiming to enhance robustness. While they have partially alleviated the problem, the inherent flaw remains unresolved.

#### 5.2 Diffusion models

Diffusion models have demonstrated considerable success in the generation tasks of continuous data domains [5, 12, 22, 23], notably in image synthesis. This success has prompted a number of studies to explore the application of diffusion models to discrete data domains, such as text generation [6, 14]. Diffusion-LM [14] represents the pioneering effort in adapting continuous diffusion models for more refined control in discrete-oriented tasks. Subsequently, DiffuSeq [6] has extended the applicability of these models to accommodate a broader range of sequence-to-sequence tasks.

Despite the widespread application of diffusion models in various domains, attempts to extrapolate their potential to the field of recommendation systems have been relatively recent. Certain studies within the realm of social recommendation have explored information diffusion on social networks [43, 44]. However, these primarily concentrate on the impact of social connections on user preferences through diffusion processes [26], which is intrinsically different from the nature and application of Diffusion models. In the entire landscape of recommendation systems, CODIGEM [35] stands as the pioneer in genuinely deploying diffusion models for recommendation purposes. CODIGEM iteratively introduces noise and employs an array of distinct Autoencoders for prediction at each step. Building on this foundation, DiffRec [37] streamlines the diffusion models and utilizes a shared Multilayer Perceptron (MLP) for multi-step prediction, although it continues to predict

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the subsequent state in a step-by-step manner. Moreover, as it essentially remains an unconditional generation model, it lacks the capacity to fully generate behavioral information that aligns with user interests.

Breaking away from these previous approaches, our work seeks to simplify the diffusion model further, guiding the generation process of behavioral information via the multimodal preferences of users. We also consider the inherent connection between pieces of behavioral data during processing, thereby generating behavioral information that better aligns with user preferences.

## 6 CONCLUSION

In this paper, we have proposed a Light Diffusion model for Multimedia Recommendation (**LD4MRec**). Specifically, we greatly simplify the conventional Diffusion Models for multimedia recommendation. And we design a C-Net to fit the reverse process and effectively generate personalized behavioral information.

In our future work, we will focus on optimizing the design of the C-Net to enhance the quality of generation. Additionally, we plan to explore the diffusion of behavioral information in the hidden space, with the intention of reducing the number of parameters and computational requirements.

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