

Masked Diffusion for Generative Recommendation

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Abstract

Generative recommendation (GR) with semantic IDs (SIDs) has emerged as a promising alternative to traditional recommendation approaches due to its performance gains, capitalization on semantic information provided through language model embeddings, and inference and storage efficiency [RMS⁺²³, DWC⁺²⁵]. Existing GR with SIDs works frame the probability of a sequence of SIDs corresponding to a user’s interaction history using autoregressive modeling. While this has led to impressive next item prediction performances in certain settings, these autoregressive GR with SIDs models suffer from expensive inference due to sequential token-wise decoding, potentially inefficient use of training data and bias towards learning short-context relationships among tokens. Inspired by recent breakthroughs in NLP [SAS⁺²⁵, SHW⁺²⁴, ONX⁺²⁴], we propose to instead model and learn the probability of a user’s sequence of SIDs using masked diffusion. Masked diffusion employs discrete masking noise to facilitate learning the sequence distribution, and models the probability of masked tokens as conditionally independent given the unmasked tokens, allowing for parallel decoding of the masked tokens. We demonstrate through thorough experiments that our proposed method consistently outperforms autoregressive modeling. This performance gap is especially pronounced in data-constrained settings and in terms of coarse-grained recall, consistent with our intuitions. Moreover, our approach allows the flexibility of predicting multiple SIDs in parallel during inference while maintaining superior performance to autoregressive modeling. Our code is available at <https://github.com/snap-research/MADRec>.

1 Introduction

Generative Recommendation (GR) is a rapidly growing paradigm in Recommendation Systems (RecSys) that aims to leverage generative models to recommend items to users based on users’ historical interaction sequences. Among GR paradigms, GR with semantic IDs (SIDs) [RMS⁺²³, HHMZ23] has garnered widespread interest and usage, including successful industrial applications in long [SVM⁺²⁴] and short [DWC⁺²⁵, ZHC⁺²⁵] video recommendation, music recommendation [PDDN⁺²⁵], and online retail [LCS⁺²⁴, MZZ⁺²⁵].

The GR with SIDs framework has led to such successes in large part by offering a means to incorporate both semantic and collaborative signals in item representations that use an exponentially smaller vocabulary size than traditional sparse IDs [RMS⁺²³, YPH⁺²⁴]. These representations are learned by first executing *item SID assignment*: assigning tuples of tokens, known as SIDs, to items based on a residual clustering of their text and/or visual feature embeddings extracted from a pretrained language and/or vision model. Then, in the *user sequence modeling* phase, embeddings

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of these tokens are trained in concert with a sequential model to learn the probability distribution of the sequences of SIDs corresponding to users’ interaction histories [RMS⁺23, JCN⁺25].

Despite tremendous interest in GR with SIDs, the majority of studies focus on design choices around item SID assignment [XWW⁺25, HXGZ23, QFZL25, WBL⁺24, WXH⁺24, LZL⁺24, TXH⁺24, JZW⁺23, ZJL⁺24, KCW⁺24, HNH⁺], adopting the default autoregressive (AR) modeling from [RMS⁺23] for the user sequence modeling stage. AR modeling has long been the dominant paradigm in Natural Language Processing (NLP) [RZ85, BDVJ03, SVL14], leading to countless breakthroughs in the development of LLMs [VSP⁺17, RNS⁺18, RWC⁺19, BMR⁺20]. This makes it a reasonable starting point for modeling SID sequences, and indeed, existing results verify that AR modeling’s efficacy for modeling text sequences translates to modeling users’ SID sequences. However, since AR models model the probability of all future tokens as dependent on all preceding tokens, they must generate tokens sequentially, leading to fundamental upper bounds on inference speed and planning. Moreover, in practice, by training on next token prediction, AR models tend to under-index on global relationships among tokens [KHQJ18, HKK⁺20, BDDR23].

Diffusion modeling in NLP alleviates these issues by modeling the probability of future tokens as independent conditioned on the context tokens, allowing for parallel token generation. Early approaches to diffusion language modeling applied continuous, i.e. Gaussian, diffusion over token embeddings [LTG⁺22, GLF⁺22b, YYT⁺22, ZLKE23], mimicking the continuous diffusion protocol that has a long track record of success in image generation [SDWMG15, HJA20, DN21, RBL⁺22, HS22], but failed to match the performance of AR models on language modeling benchmarks [LME24, GAZ⁺24]. However, more recent advancements have shown that an alternative diffusion paradigm – *masked diffusion* – can compete with AR language modeling on standard benchmarks [AJH⁺21, LME24, SAS⁺25, SHW⁺24, ONX⁺24]. The key innovation is the use of discrete masking noise rather than Gaussian noise, which empirically leads to improved learning of discrete token sequence distributions.

This masked diffusion framework is especially promising for GR over discrete SID sequences for several reasons. First, by employing random masking with all possible masking rates, masked diffusion uses exponentially many training samples per raw sequence in the raw sequence length, whereas AR modeling uses only linearly many. In NLP, this more aggressive augmentation strategy tends to extract more signal out of limited training data [PWZ⁺25, Ntt25], which is appealing for recommendation scenarios that typically have sparse interactions between users and items. Second, masked diffusion may better capture global relationships among tokens, by virtue of being trained to unmask throughout the sequence rather than continually predict the next token. Third, masked diffusion allows for simultaneously decoding multiple tokens in one forward pass of the model. This is critical for GR with SIDs since decoding an item requires decoding multiple SID tokens, and inference latency is often a bottleneck for practical deployment [HPJ⁺14].

In this work, we realize these advantages for GR with SIDs by developing **MADRec**: MAsked Diffusion over SIDs for Generative **R**ecommendation. To the best of our knowledge, MADRec is the first application of masked diffusion for GR with SIDs, and as such, MADRec prioritizes simplicity and generality in its design. This allows us to make a number of foundational empirical observations regarding the effectiveness of masked diffusion for GR with SIDs:

- **Overall performance.** MADRec consistently outperforms standard AR modeling with SIDs (i.e. TIGER [RMS⁺23]) as well as other GR baselines on several benchmark sequential recommendation datasets. The performance improvement is especially large for coarse-grained recall, suggesting masked diffusion’s strength at learning global item relationships.
- **Data efficiency.** Up until a point at which the data becomes too sparse, the performance gap between MADRec and TIGER grows as we shrink the dataset size, supporting the hypothesis

that masked diffusion makes better use of limited data.

- **Inference efficiency and flexibility.** MADRec can decode multiple tokens in parallel, which allows for flexibly trading off inference performance and efficiency by choosing the number of forward passes (function evaluations) to execute. MADRec already outperforms TIGER with fewer function evaluations, and its performance improves with additional evaluations.
- **Extensibility.** MADRec is compatible with auxiliary methods for improving performance in GR. Here we focus on incorporating dense retrieval, motivated by the impressive performance of fusing TIGER with dense retrieval [YPH⁺24, YJL⁺25].

Reproducibility. Our code is available at the following link: <https://github.com/snap-research/MADRec>.

2 Generative Recommendation with Semantic IDs

In this section we formally introduce the Generative Recommendation with Semantic IDs framework. We start by discussing the Generative Recommendation (GR) task it aims to solve.

Generative Recommendation. Let \mathcal{U} be a set of users interacting with a set of items \mathcal{I} . For each user $u \in \mathcal{U}$, we are given their interaction sequence of length n_u , denoted by $(i_1, \dots, i_{n_u}) \in \mathcal{I}^{n_u}$. Our goal is to predict the next item i_{n_u+1} that user u will interact with, given their past interactions. The GR framework addresses this task by modeling the probability distribution over interaction sequences and then outputting the most likely item according to $p(i_{n_u+1} | i_1, \dots, i_{n_u})$.

Generative Recommendation with Semantic IDs. The GR with Semantic ID (GR with SIDs) paradigm represents items with tuples of SIDs derived from item semantic features, and models the probability of user sequences over SIDs, rather than directly over item IDs. More specifically, GR with SIDs consists of two steps: *item SID assignment* and *user sequence modeling* [RMS⁺23, DWC⁺25, HLS⁺25].

Item SID assignment. The goal of *item SID assignment* is to represent items based on their rich semantic features, such as text and/or visual features, in a concise, scalable way. To do this, we first obtain a semantic embedding h_{i_j} for each item $i_j \in \mathcal{I}$ by feeding the item's semantic features through a pre-trained semantic encoder, such as a large language or vision model. Then, we execute a multi-layer clustering algorithm, such as Residual K-Means (RK-means) [LCS⁺24, DWC⁺25], Residual Quantized Variational Autoencoder (RQ-VAE) [ZLO⁺21, RMS⁺23], or product quantization [GHKS14, JDS11, HHMZ23], on the set $\{h_{i_j}\}_{j \in \mathcal{I}}$ of all items' semantic embeddings. Suppose that we have m clustering layers, then the cluster assignments $(s_{i_j}^1, s_{i_j}^2, \dots, s_{i_j}^m)$ for each item i_j form a semantically meaningful tuple. We treat the assignments at different layers as distinct tokens, i.e. if we have c clusters per layer, then $s_{i_j}^1 \in \{1, \dots, c\}, s_{i_j}^2 \in \{c + 1, \dots, 2c\}$ and so on. In this way, $(s_{i_j}^1, s_{i_j}^2, \dots, s_{i_j}^m)$ forms the SID tuple for item i_j .

User sequence modeling. The goal of *user sequence modeling* is to model the probability of each user's interaction sequence over the SIDs. In particular, for an interaction history (i_1, \dots, i_{n_u}) , GR with SIDs models the probability of the sequence

$$S^u := (s_1^1, \dots, s_1^m, s_2^1, \dots, s_2^m, \dots, s_{n_u}^1, \dots, s_{n_u}^m)$$

corresponding to the sequence of SIDs of the items interacted with by user u .

Existing methods primarily rely on autoregressive modeling, factorizing the probability either by each SID (eq.(1)) or by each item’s full SID sequence (eq.(2)):

$$p(S^u) = \prod_{i=1}^{n_u} \prod_{j=1}^m p(s_i^j | s_1^1, \dots, s_{i-1}^m, s_i^{<j}) \quad (1)$$

$$p(S^u) = \prod_{i=1}^{n_u} p(s_i^1, \dots, s_i^m | s_1^1, \dots, s_{i-1}^m) \quad (2)$$

Factorizing by each SID (eq.(1)) is the typical approach used in GR with SIDs methods [RMS⁺²³, DWC⁺²⁵, JCN⁺²⁵]. It is typically paired with encoder-decoder or decoder-only transformer architecture and a next-token prediction loss, making no assumptions on conditional independence of the tokens. On the other hand, [HLS⁺²⁵] proposed eq.(2) along with a method to embed the sequence using a decoder transformer and predict all SIDs of the next item jointly, assuming that the SIDs for the next item are conditionally independent given the previous SIDs. These methods require sequential inference of unseen SIDs, or in the case of [HLS⁺²⁵], unseen items, since they model the probability of unseen SIDs or items as dependent on all previous SIDs or items, including other unseen ones. Further, the number of training targets is limited by the number of SIDs or items in the sequence (i.e. the number of factors in equations (1) and (2), respectively). To overcome these limitations, we propose to instead model the probability of SID sequences using masked diffusion.

3 Proposed Method: MADRec

Recent works have demonstrated the power of masked diffusion models for modeling complex discrete distributions in NLP as well as protein design [LME24, SAS⁺²⁵, SHW⁺²⁴, ONX⁺²⁴]. Motivated by these results and the limitations of AR modeling, we propose **M**Aked **D**iffusion over SIDs for Generative **R**ecommendation, i.e. **MADRec**, a framework that models the probability distribution of SID sequences through masked diffusion.

Similar to prior works on GR with SIDs, we first generate a semantically meaningful SID tuple for each item and represent a user’s interaction history by converting the item ID sequence (i_1, \dots, i_{n_u}) into the corresponding SID sequence: $S^u := (s_1^1, \dots, s_1^m, s_2^1, \dots, s_2^m, \dots, s_{n_u}^1, \dots, s_{n_u}^m)$. To introduce the masked diffusion framework over SIDs, we consider $n_u = n$ for all users $u \in \mathcal{U}$.

3.1 MADRec Training

We model the probability of the SID sequence S^u using discrete diffusion models with the masking noise framework [LME24, SAS⁺²⁵, SHW⁺²⁴, ONX⁺²⁴]. Before explaining the framework, we start with notations. Let $[M]$ denote the special mask token, S_t^u denote the corrupted SID sequence at noise level $t \in [0, 1]$, and $S_t^u(i)$ be its i^{th} element.

Forward Process. The forward process corrupts the original sequence, $S_0^u = S^u$, by independently applying masking noise to each of its SID tokens. Specifically, each token in S_0^u is replaced with the $[M]$ token with probability t , resulting in the noisy sequence S_t^u . Formally, the transition probability from the clean sequence S_0^u to the noisy sequence S_t^u is defined as:

$$p(S_t^u | S_0^u) = \prod_{i=1}^{mn} p(S_t^u(i) | S_0^u(i)),$$

$$\text{where } p(S_t^u(i) | S_0^u(i)) = \text{Cat}((1-t)e_{S_0^u(i)} + te_{[M]}),$$

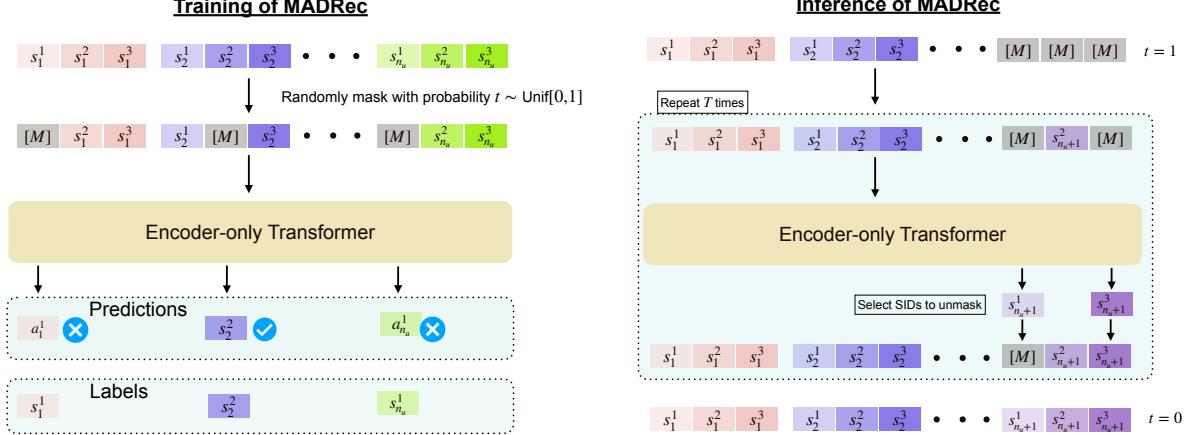


Figure 1: Overview of training and inference of MADRec. During training, MADRec randomly masks each SID in the SID sequence with a probability $t \sim \text{Unif}[0, 1]$ and feeds the masked sequence into an encoder-only transformer. The model is then optimized to reconstruct the original values of the masked SIDs using a cross-entropy loss applied at the masked positions (see Eq. (3)). During inference, MADRec begins with all SIDs of the last item replaced by masks. At each inference step, the partially masked sequence is passed through the network to predict values for all masked positions. The model then selectively unmasks a subset of these positions by retaining their predicted values while keeping the remaining positions masked. This iterative process continues until all SIDs are unmasked.

where $\text{Cat}(\cdot)$ denotes the categorical distribution over $mc + 1$ possible tokens, and e_x represents the one-hot vector corresponding to token x . Recall that m denotes the number of SIDs per item and c is the codebook size of each SID.

Reverse Process. To derive the denoising direction, we first compute the posterior $p(S_\ell^u | S_t^u, S_0^u)$ for some noise scale $\ell < t$. Since the forward process is coordinate-wise independent, the posterior can be coordinate-wise decomposed into

$$p(S_\ell^u | S_t^u, S_0^u) = \prod_{i=1}^{mn} p(S_\ell^u(i) | S_t^u, S_0^u)$$

where the posterior for each coordinate is given by

$$p(S_\ell^u(i) | S_t^u, S_0^u) = \begin{cases} \text{Cat}(e_{S_t^u(i)}) & \text{if } S_t^u(i) \neq [\text{M}] \\ \text{Cat}(\frac{\ell}{t} e_{[\text{M}]} + (1 - \frac{\ell}{t}) e_{S_0^u(i)}) & \text{if } S_t^u(i) = [\text{M}] \end{cases}.$$

We approximate the above denoising posterior probability by approximating $e_{S_0^u(i)}$ with $f_\theta(\cdot | S_t^u) : \{1, \dots, mc, [\text{M}]\}^n \rightarrow \mathcal{P}^{mc}$, where \mathcal{P}^{mc} is the probability simplex over mc discrete elements. Specifically, the model f_θ takes an SID sequence S_t^u —in which some SIDs are masked—and outputs the predicted probability distribution over mc elements for the possible values at each of those masked positions. In practice, f_θ is a neural network, typically a transformer encoder, with parameters θ .

Training Objective. The model parameters θ are trained by maximizing the evidence lower bound (ELBO) on the likelihood, which simplifies to a cross-entropy loss over the masked tokens:

$$L = \mathbb{E}_{\substack{t \sim \text{Unif}[0,1], \\ S_0^u \sim p_{\text{SID}}, S_t^u \sim p(S_t^u | S_0^u)}} \left[-\frac{1}{t} \sum_{i=1}^{mn} \mathbb{I}[S_t^u(i) = [\text{M}]] \log p_\theta(S_0^u(i) | S_t^u) \right], \quad (3)$$

where p_{SID} denotes the distribution over SID sequences, and the indicator function $\mathbb{I}[S_t^u(i) = [\text{M}]]$ ensures the loss is computed only for masked SIDs.

This training objective randomly masks a subset of SIDs from the sequence according to the transition probability $p(S_t^u | S_0^u)$ and predicts the original values of the masked SIDs. This formulation is reminiscent of BERT4Rec [SLW⁺19], which randomly masks a fixed proportion of item IDs and learns to reconstruct them. In contrast, our approach follows the transition-based masking process, is mathematically grounded, and provably samples from the underlying probability distribution of the SID sequence [LME24].

After training, MADRec learns the conditional distribution of each masked SID given the remaining sequence. The next section describes the inference procedure and beam search for MADRec.

3.2 MADRec Inference and Beam Search

To describe MADRec inference, consider a user interaction history of item IDs (i_1, \dots, i_{n-1}) with the corresponding SID sequence $Q = (s_1^1, \dots, s_{n-1}^m)$, and assume we want to predict the next item i_n . To generate a sample using the learned denoising distribution $p_\theta(S_0^u(i) | S_t^u)$, MADRec begins by masking the SIDs of the n th item, forming $\tilde{S}_1 = (Q, A_1)$ where $A_1 = ([\text{M}], \dots, [\text{M}])$. To transition from $\tilde{S}_t = (Q, A_t)$ to $\tilde{S}_r = (Q, A_r)$ for a lower noise scale $r < t$, the model iteratively unmarks a selected subset of masked tokens, sampling their values from the learned distribution $p_\theta(\tilde{S}_r(i) | \tilde{S}_t)$.

In standard masked diffusion inference, each masked token is unmasked independently with probability $1 - (r/t)$. However, recent works [ZYYK23, KSK⁺25, BHGS⁺25] demonstrate that performance can be substantially improved by selecting tokens to unmask based on the model’s prediction uncertainty at the masked positions. This unmasking process is repeated until all SIDs are unmasked.

The masked diffusion inference results in a *sample* of an item from the probability conditioned on Q . In contrast, GR methods typically *deterministically* output the most probable items given the interaction history by using beam search to find the most probable items.

Beam Search in MADRec. Unlike AR models, which decode tokens in a fixed left-to-right order, MADRec can generate SIDs in any order. Therefore, to understand the beam-search, suppose the tokens of the next item are unmasked following a specific order (k_1, \dots, k_m) . Beam search in MADRec aims to maximize the probability of the generated item by computing

$$p_\theta(s_n^1, \dots, s_n^m | Q) = \prod_{i=1}^m p_\theta(s_n^{k_i} | Q, s_n^{k_1}, \dots, s_n^{k_{i-1}}). \quad (4)$$

Notably, the generation order does not need to be predetermined; it can be dynamically adjusted during inference. In our experiments, we evaluate three generation strategies: (1) random order as in vanilla masked diffusion models, (2) uncertainty-based order that prioritizes tokens with lower prediction uncertainty, and (3) left-to-right order. Please see Section 4.5 for more details.

Beam Search in MADRec with Multi-Token Prediction. The MADRec framework also supports predicting multiple tokens simultaneously, enabling the generation of the full m -length SID sequence with fewer than m sequential function evaluations. Since MADRec models only the conditional probabilities of masked tokens and not the joint probability among the masked tokens, i.e. it assumes the masked tokens are conditionally independent given the unmasked tokens, it *approximates* the probability of the generated item $p_\theta(Q, s_n^{k_1}, \dots, s_n^{k_m})$ during beam search.

To generate the m -length SID tuple of the next item, consider that $T < m$ model evaluations are used and in the i th step, α_i SIDs at positions $(k_1^i, \dots, k_{\alpha_i}^i)$ are unmasked. For simplicity, assume the sequence of unmasking counts $(\alpha_1, \dots, \alpha_T)$ are predetermined. In this case, we approximate the probability of the item as follows:

$$p_\theta(s_n^1, \dots, s_n^m | Q) = \prod_{j=1}^T \prod_{i=1}^{\alpha_j} p_\theta(s_n^{k_i^j} | Q, s_n^{k_1^1}, \dots, s_n^{k_{\alpha_{j-1}}^{j-1}}).$$

In other words, we approximate the joint probability of all SIDs $(k_1^i, \dots, k_{\alpha_i}^i)$ being unmasked at step i by the product of their conditional probabilities. We use this approximation to guide the beam search inference in MADRec while predicting multiple SIDs. Empirically, we find that decoding multiple tokens simultaneously outperforms AR models despite this conditional independence assumption; please see Section 4.4 for more details. In the following section, we demonstrate how to extend MADRec to incorporate an auxiliary method, namely fusing dense and generative retrieval, that was originally developed for AR-based SID modeling.

3.3 Extending MADRec with Dense Retrieval

AR modeling is a dominant paradigm to model the SID sequences in GR. Several prior works have extended it, for instance, by combining SID generation with dense retrieval [YPH⁺24, YJL⁺25], incorporating user preferences [PYL⁺24], or developing methods for long SID generation [HLS⁺25]. MADRec presents a novel approach to modeling the probability distribution of SID sequences. We believe that, in principle, MADRec can be integrated with these existing AR extensions. To demonstrate this potential, we integrate MADRec with dense retrieval, inspired by the work of Yang et al. [YPH⁺24].

To unify MADRec’s SID generation capabilities with dense retrieval, we modify the framework to output a dense item embedding in addition to the sequence of SIDs. Specifically, we introduce three key modifications to the MADRec framework:

- **Input Representation:** Instead of using only SID embeddings as input to the encoder-only architecture, we combine them with the text representation of each item. Formally, for an item i with SID sequence $(\sigma_i^1, \dots, \sigma_i^m)$, the input embedding is defined as:

$$H_{\sigma_i^j} = h_{\sigma_i^j} + A_j h_i^{\text{text}},$$

where $h_{\sigma_i^j}$ is the embedding of the SID token σ_i^j , h_i^{text} is the embedding of item i ’s text features extracted from a language model, and A_j is a learnable linear transformation that projects the text embedding to the same dimension as the SID embeddings.

- **Masking Strategy:** In the original MADRec, each SID is independently masked with a probability proportional to the noise scale t . However, since the dense embedding corresponds to the item as a whole, we encourage learning at the item abstraction level by masking all SIDs of an

item jointly. Concretely, during training, with a fixed probability β , we mask all SIDs of an item together, using the same noise scale as the masking probability, and with probability $1 - \beta$, we use the masking strategy of the original MADRec. Here, β is a hyperparameter.

- **Prediction Mechanism and Loss Function:** After a fixed number η of layers in the network f_θ , we use the resulting hidden states to form the predicted dense embedding. More precisely, to predict a dense embedding of an item, we mask all its SIDs and pass the full sequence through f_θ , as described in Section 3.2. Let \tilde{h}^j denote the embedding of the j -th SID after η layers; we concatenate the predicted embeddings for all m SIDs to obtain the predicted dense embedding $\tilde{H} = \{\tilde{h}^1, \dots, \tilde{h}^m\}$. Next, we project the predicted dense embedding to the same dimension as the text item embedding with a linear or a small MLP g_θ . The dense retrieval objective encourages \tilde{E} to align with the ground-truth text embedding of the corresponding item, formulated as:

$$\mathcal{L}_{\text{dense}} = -\log \frac{\exp(g_\theta(\tilde{H})^\top h_i^{\text{text}})}{\sum_{j \in \mathcal{I}} \exp(g_\theta(\tilde{H})^\top h_j^{\text{text}})},$$

where \mathcal{I} denotes the set of all items. The dense retrieval loss is applied only to items whose SIDs are all masked.

These modifications extend MADRec to unify SID generation with dense retrieval. We now turn to experiments to examine the performance of MADRec.

4 Experiments

In this section, we empirically study the following questions:

- **Q1.** How does the *overall performance* of MADRec compare to AR modeling with SIDs and other GR baselines?
- **Q2.** How does MADRec’s perform in *data-constrained settings*?
- **Q3.** How does MADRec *trade off inference efficiency and performance*?
- **Q4.** How does MADRec depend on its *components*?
- **Q5.** Does *extending MADRec with dense retrieval* improve its performance?

4.1 Experimental Setup

We first describe the experimental settings. Please see Appendix A.1 for more details.

Implementation details. We use an 8-layer encoder-only transformer model with a 128-dimensional embedding and rotary position embedding. The model includes 8 attention heads and a multi-layer perceptron (MLP) with a hidden layer size of 3072. The total number of parameters in our model is 7M. Following [JCN⁺25], we assign SIDs by first extract 4096-dimensional text embeddings from item metadata with Flan-T5-XXL [CHL⁺24], then apply residual k-means clustering with four layers, each having a codebook size of 256. We append de-duplication token to distinguish items with identical SID tuples as in [RMS⁺23]. Unless specified otherwise, the number of inference steps is equal to the number of SIDs per item. We use a greedy inference strategy to choose the set of tokens to unmask based on their prediction uncertainty, measured as the difference between the probabilities of the first and second most likely assignment at each masked SID position – please see Section 4.5 for more details.

Evaluation. We evaluate all methods using Recall@K and NDCG@K metrics, with $K \in \{5, 10\}$. We use the standard leave-one-out evaluation protocol, where the last item of each user’s sequence is used for testing, the second-to-last for validation, and the remaining items for training [KM18, ZWZ⁺20, GLF⁺22a, RMS⁺23, YPH⁺24].

Baselines. We compare the performance of MADRec against six representative baselines [KM18, SLW⁺19, YWW⁺23, CWH⁺24, RMS⁺23, YPH⁺24]:

- **Item ID-based methods:** SASRec [KM18] and BERT4Rec [SLW⁺19], two widely used sequence recommendation models that operate directly on item IDs.
- **Diffusion-based methods:** DreamRec [YWW⁺23] and CaDiRec [CWH⁺24], which apply continuous diffusion processes on item IDs for recommendation. Both methods use 1,000 inference steps.
- **Generative recommendation with SIDs:** TIGER [RMS⁺23], which autoregressively models the probability distribution over the SID sequence, and LIGER [YPH⁺24], which extends TIGER by integrating dense retrieval.

Datasets. We evaluate our method on four public benchmarks: three categories (Beauty, Sports, and Toys) from the Amazon Review dataset [MTSVDH15] and the MovieLens-1M (ML-1M) movie rating dataset [HKA16]. For the Amazon datasets we apply the standard 5-core filtering to remove users and items with fewer than 5 interactions, and use title, category, description and price as the item text features, following [RMS⁺23]. We also apply 5-core filtering to ML-1M, and use title, year and genres as the item text features. Table 6 provides statistics of the processed datasets.

4.2 Q1. Overall Performance

We begin by presenting our experimental results on the generative recommendation (GR) task, comparing MADRec’s performance with other GR methods across the four aforementioned datasets. The results, shown in Table 1, indicate that our proposed framework performs comparably or better than other GR methods.

Comparison with AR modeling. The results indicate a *significant improvement over TIGER*, with an average of a 21.9% increase in NDCG@5 across all datasets. Recall that TIGER autoregressively models the probability of the SID sequence. Our results support prior work showing that masked diffusion frameworks are more effective than autoregressive (AR) models in data-sparse settings like sequential recommendation [PWZ⁺25, Ntt25].

Moreover, we further observe in Figure 2 that the performance gap between MADRec and TIGER increases as we *increase the retrieval granularity*. Here we measure Recall@K for $K \in \{5, 10, 20, 40\}$ on the Beauty and Sports datasets, and notice MADRec’s increasing performance gains with larger K , i.e., more coarse-grained retrieval. This suggests that masked diffusion is better able to model global relationships among tokens than AR modeling, as MADRec’s rankings tend to have higher-quality depth than TIGER’s. This is consistent with prior results suggesting that AR modeling over-indexes on local relationships among tokens [KHQJ18, HKK⁺20, BDDR23], as well as our intuition that masked diffusion, by training a more diverse set of targets, is better able to model global relationships.

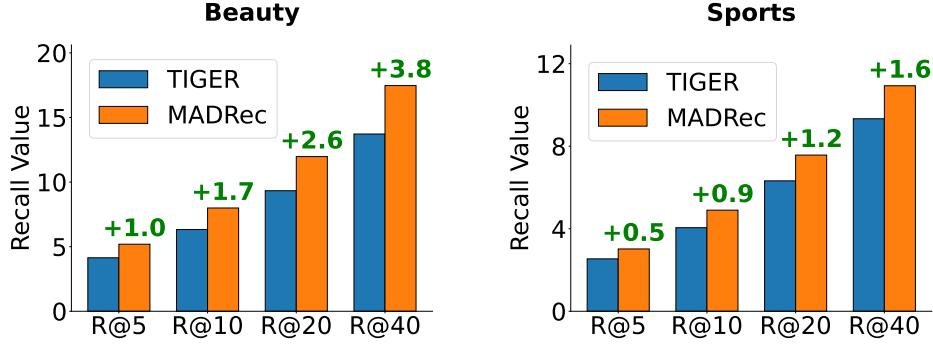


Figure 2: Improved performance gap for coarse-grained retrieval on the Beauty and Sports datasets. The gap in Recall@K between TIGER and MADRec increases as K increases.

Comparison with continuous diffusion. MADRec also *outperforms continuous diffusion-based recommendation* approaches, namely DreamRec and CaDiRec, as shown in Table 1. Importantly, both DreamRec and CaDiRec require 1000 diffusion inference steps, whereas our method uses only 5 inference steps. This further supports the conclusion of prior works that diffusion with masking noise is more effective for generation in discrete domains than diffusion with Gaussian noise [LME24, GAZ⁺24].

Table 1: Performance comparison of MADRec with other GR methods on the Beauty, Sports, Toys, and MovieLens-1M datasets. The best result for each metric is in bold and the second best is underlined.

Method	Beauty		Sports		Toys		ML-1M	
	R@5	N@5	R@5	N@5	R@5	N@5	R@5	N@5
SASRec	3.87	2.49	2.33	1.54	4.63	3.06	9.38	5.31
BERT4Rec	3.60	2.16	2.17	1.43	4.61	3.11	13.63	8.89
DreamRec	4.40	2.74	2.48	1.51	4.97	3.16	13.04	8.58
CaDiRec	<u>4.95</u>	3.14	<u>2.76</u>	<u>1.83</u>	<u>5.22</u>	<u>3.56</u>	<u>15.04</u>	<u>10.01</u>
TIGER	4.29	2.88	2.45	1.64	4.42	2.91	12.83	8.85
LIGER	4.62	<u>3.17</u>	2.61	1.67	4.66	3.01	13.73	9.12
MADRec	5.38	3.51	3.02	1.91	5.48	3.75	16.72	11.12
+ Improv %	+8.7 %	+10.7 %	+9.4 %	+4.4 %	+ 5.0 %	+5.3 %	+11.2 %	+11.1 %

4.3 Q2. Data-constrained Performance

To better understand MADRec’s effectiveness in data-constrained settings, we evaluate its and TIGER’s performance on increasingly sparsified versions of the Beauty dataset. Specifically, we drop 25%, 37.5%, 50%, 62.5%, and 75% of items from each sequence in the training set, while ensuring each sequence has at least three items. The validation and test sets remain unchanged. We then measure the retained performance by comparing the Recall@5 and NDCG@5 scores of these models with the scores of a model trained without dropping items. The results are shown in Figure 3.

As the percentage of dropped items increases, TIGER’s performance drops faster than MADRec’s.

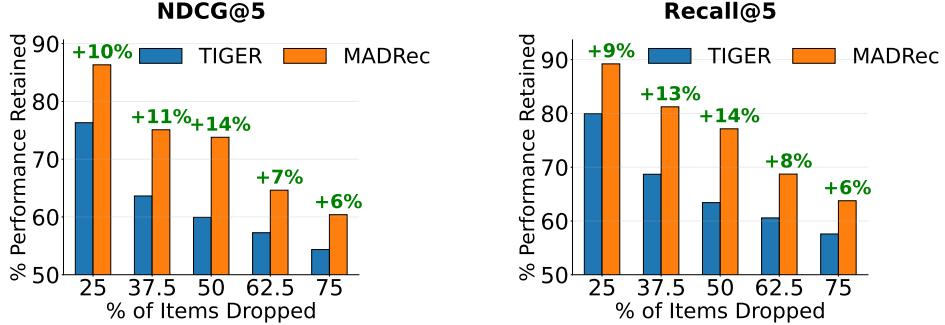


Figure 3: Comparison of data efficiency of MADRec and TIGER by dropping 25%, 37.5%, 50%, 67.5% and 75% of items from each sequence, while maintaining at least three items in each sequence.

At significantly high drop percentages (62.5% and 75% of items dropped), the performance drop for both methods becomes similar, but this is expected, as dropping close to 100% of the items would result in near-zero performance retention for any method.

4.4 Q3. Inference Performance-Efficiency Trade-off

Single-item prediction. Unlike AR methods, MADRec can decode m SIDs of an item with fewer than m sequential function evaluations, albeit with a potential drop in performance. To study the trade-off between the number of function evaluations (NFEs, denoted as T in Section 3.2) and performance, we evaluate MADRec with 2, 3, 4 and 5 NFEs on the Beauty dataset (MADRec uses 5 SIDs per item). We compare the performance using NDCG@5 with AR baselines in Figure 4. Notably, even with only 3 NFEs, MADRec surpasses the performance of TIGER by 13% and LIGER by 4.7%, which both use 4 NFEs.

Multi-item prediction. Intuitively, the benefit of MADRec’s multi-token prediction should become more apparent as the number of items to recommend grows. To evaluate this hypothesis, we adapt the standard leave-one-out evaluation protocol into a leave-two-out protocol: the last two items of each user’s sequence are used for testing, the two preceding items for validation, and the remaining sequence for training. This evaluation protocol also aligns closely with session-wise recommendation tasks [DWC⁺25].

We train and evaluate MADRec and TIGER on the ML-1M dataset using this leave-two-out protocol, choosing ML-1M because of its longer average sequence length. We fix the total number of generated beams to 10. In this setting, each beam represents a pair of items, so the number of candidate recommendations at each position is fewer than 10. After generating 10 session beams, we compute the recall for each predicted item and average the results, which we refer to as the *average session recall@10*. Figure 4 plots this metric against the number of function evaluations. We observe that MADRec achieves the same performance as TIGER with only 4 NFEs—reducing NFEs by 50% compared to TIGER’s 8.

4.5 Q4. Component-wise importance.

We next execute several ablation studies to understand the importance of key components of MADRec.

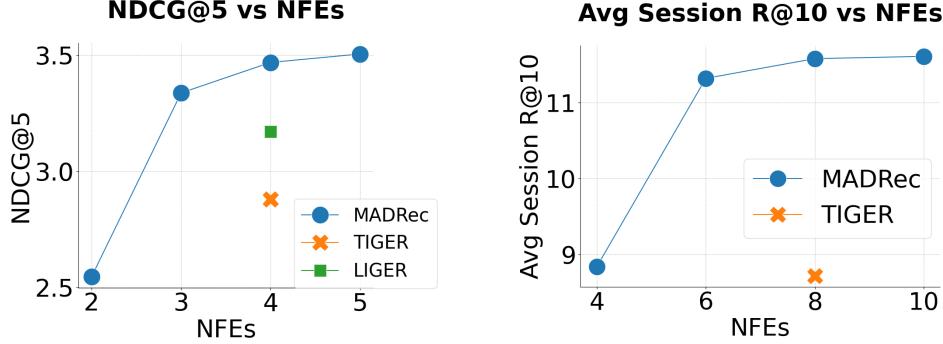


Figure 4: Next- k item prediction performance vs number of function evaluations (NFEs) during inference for (Left) $k = 1$ on Beauty and (Right) $k = 2$ on MovieLens-1M. The AR methods (TIGER and LIGER) must decode tokens sequentially, so they always execute $k \times (\# \text{ SIDS/item})$ NFEs. MADRec can decode multiple items in parallel, thereby allows trading off performance and efficiency by tuning the NFEs. Moreover, it already outperforms the AR methods with fewer NFEs.

Table 2: Comparison of Recall@K (R@K) and NDCG@K (N@K) for $K \in \{5, 10\}$ for different versions of MADRec on the Beauty dataset. Note that BERT4Rec is effectively MADRec + Item IDs with fixed masking ratio.

Method	R@5	R@10	N@5	N@10
BERT4Rec	3.60	6.01	2.16	3.08
MADRec w/ Item IDs	4.69	6.71	3.12	3.77
MADRec w/ Random SIDs	3.78	5.53	2.61	3.05
MADRec	5.38	8.15	3.51	4.41

Importance of semantic IDs. To understand MADRec’s ability to utilize semantic information from the SIDs derived from the item text embeddings, we conduct two complementary experiments on the Beauty dataset in which the provided semantic information is systematically removed. In the first experiment, instead of using SIDs generated from item embeddings, we replace them with randomly assigned tuples of tokens with the same vocabulary as the original SIDs. We refer to this method as MADRec + Random SIDs. In the second experiment, instead of modeling the probability distribution over the SID sequence as in MADRec, we directly model the probability distribution over the item IDs. More specifically, we model the item ID sequence (i_1, \dots, i_n) according to the framework of MADRec in place of the SID sequence (s_1^1, \dots, s_n^m) . We refer to this method as MADRec + Item IDs. We report and compare the performance in Table 2.

We find that replacing the true SIDs computed by residual k-means clustering of semantic item embeddings with random SIDs reduces Recall@10 from 8.15 to 5.53, a drastic reduction. Moreover, using MADRec on item IDs instead of SIDs decreases performance from 8.15 to 6.71. These results demonstrate that MADRec effectively leverages the semantic information contained in the SIDs.

Importance of dynamic masking probability. In Table 2, we also compare against BERT4Rec [SLW⁺19]. Interestingly, *MADRec trained directly on item IDs still outperforms BERT4Rec*. BERT4Rec predicts randomly masked item IDs in the interaction history but masks only a fixed fraction of items during training ($t = 0.15$), whereas MADRec + Item IDs masks all possible fractions in the interval $[0, 1]$, enabling a more effective training regime.

Dependence on the number of SIDs per item. To understand the performance of MADRec as we scale number of SIDs per item, we perform an ablation on changing number of SIDs while fixing the rest of the setting. We report our results in Table 3. We observe that the performance of MADRec improves as we increase number of SIDs from 3 to 4 but decreases as we go from 4 to 5. A plausible reason for the decrease in performance from 4 to 5 is the potential increase in invalid predicted SIDs, as the model may predict SIDs that do not correspond to a valid item. Combining MADRec with constrained beam search to prevent such invalid SIDs as we scale the number of SIDs would be an interesting future direction [HLS⁺25].

Table 3: Performance comparison on the Beauty dataset as we scale the number of SIDs per item.

Number of SIDs	R@5	R@10	N@5	N@10
3	4.96	7.93	3.24	4.20
4	5.38	8.15	3.51	4.41
5	4.86	7.53	3.26	4.11

Role of inference strategy. As MADRec training does not incorporate an inductive bias toward any particular token order – such as the left-to-right ordering used in autoregressive training – it offers greater flexibility in choosing which tokens to unmask during inference [ZYYK23, KSK⁺25]. In this section, we evaluate three strategies for selecting the tokens to unmask:

- **Random inference:** follows vanilla masked diffusion modeling inference in randomly selecting SIDs to unmask.
- **Greedy inference:** chooses the SIDs based on their prediction uncertainty, measured as the difference between the probabilities of the first and second most likely assignments at each masked SID position.
- **Left-to-right inference:** sequentially unmasks tokens from left to right, consistent with the order in which residual k-means assigns SID tokens.

Table 4 reports the results of these experiments. We find that both greedy and left-to-right inference substantially outperform random inference, with greedy inference achieving slightly better performance than the fixed left-to-right order.

Table 4: Performance of different inference strategies for MADRec. By default, MADRec uses the Greedy strategy.

Inference Method	R@5	R@10	N@5	N@10
MADRec + Random	5.01	7.54	3.27	4.09
MADRec + Left-to-right	5.31	8.09	3.46	4.37
MADRec (Greedy)	5.38	8.15	3.51	4.41

4.6 Q5. Extension via Dense Retrieval

In this section, we present the experimental results of extending MADRec with dense retrieval. The MADRec with dense retrieval unifies the MADRec’s SID generation capabilities with dense retrieval as described in Section 3.3. We use the same 4096-dimensional Flan-T5-XXL embeddings that we used for SID assignment as the items’ text embeddings. We construct the predicted dense embedding of an item by combining the output of the 4th layer of our encoder model and projecting it to 4096 dimensions (matching the text embedding size) through a one-layer MLP with a hidden dimension of 256. Since both the text and predicted embeddings are high-dimensional, MLP with full-rank weights would introduce over one million parameters per layer. Therefore, we use an MLP with low-rank weights of rank 32. During training, with a probability of $\beta = 0.2$, we mask all SIDs of an item to promote learning at the item-level abstraction. In the unified retrieval setup—where SID generation and dense retrieval are jointly leveraged—MADRec first generates 20 beams using beam search and then re-ranks them based on their dense retrieval scores to obtain the top-10 candidates.

We report our results on the Beauty dataset in Table 5. The results indicate that integrating MADRec with dense retrieval and unified retrieval both improve performance compared to the generative retrieval baseline, while the two enhanced variants perform comparably to each other. Perhaps more importantly, these observations exemplify that MADRec is general enough to be compatible with auxiliary methods developed for improving performance in AR modeling for GR.

Table 5: Performance comparison of MADRec combined with different retrieval methods. By default, MADRec uses the generative retrieval strategy outlined in Section 3.2.

Method	R@5	R@10	N@5	N@10
MADRec	5.38	8.15	3.51	4.41
MADRec + Dense Retrieval	5.41	8.50	3.53	4.45
MADRec + Unified Retrieval	5.43	8.59	3.54	4.47

5 Related work

Generative Recommendation. Advances in generative models in NLP and computer vision have inspired a number of innovations in modeling user interaction sequences in recent years. GRU4Rec [JL17] and SASRec [KM18] applied a gated recurrence unit and decoder-only transformer, respectively, to autoregressively predict the next interacted item, while BERT4Rec [SLW⁺19] trained a BERT-style encoder using masked language modeling. More recently, a plethora of works have aimed to leverage the power of Large Language Models (LLMs) for sequential recommendation. Such approaches can be categorized as either *LLM-as-Recommender* or *LLM-as-Enhancer*. The former approaches treat the LLM itself as the recommendation system, which has achieved promising results [LWL⁺23, CMY⁺24, ZHL⁺24, BZZ⁺23] but faces challenges in teaching the LLM the item corpus and collaborative signal. Conversely, LLM-as-Enhancer treats the LLM as an auxiliary source of information to aid more traditional recommendation systems. This includes using LLMs to produce embeddings to replace item embedding tables [SZZ⁺24, YYS⁺23, HMZ⁺22], distill semantic knowledge into smaller recommenders [XWL⁺24, LLY⁺24, ZXH⁺25, XLL⁺24, GSX⁺23], and generate synthetic data for training [LYD⁺24]. However, arguably the most popular LLM-as-Enhancer paradigm entails using the LLM to produce embeddings for deriving SIDs.

Generative Recommendation with SIDs. Since its introduction in VQ-REC [HJMZ23] and TIGER [RMS⁺23], much of the work in GR with SIDs has focused on improving item tokenization, via methods such as contrastive learning [ZJL⁺24], incorporating collaborative signals [XWW⁺25, HXGZ23, QFZL25, WBL⁺24, WXH⁺24, LZL⁺24], directly using LLMs [TXH⁺24, JZW⁺23] and encouraging more uniform SID distributions [KCW⁺24]. Other works have conditioned SID generation on user profiles [PYL⁺24], merged GR with dense retrieval [YPH⁺24, YJL⁺25], and employed tree-based decoding [FLL⁺22, SSC⁺24]. However, all of these works adopt the AR training strategy from [RMS⁺23]. RPG [HLS⁺25] proposes to use product-quantized SIDs to enable decoding the SID tokens for a single item in parallel, however this approach requires decoding items sequentially and needs many SIDs per item to see performance gains.

In contrast, our method allows for parallel decoding with *any* SIDs, achieving SOTA even with the standard residual-quantized SIDs. Outside of GR, [RYW⁺24] and [VMD⁺24] employ non-AR, non-diffusion generative models for reranking and information retrieval, respectively.

Diffusion for Recommendation. The successes of diffusion models in CV and NLP have spurred increasing interest in leveraging diffusion models for RecSys in recent years. Several works diffuse over the space of user interaction vectors [WXF⁺23, MXM⁺24, WZZ⁺22, YTLC23, HPS24, ZWX⁺24, WZZ⁺22] or the user-item interaction graph [ZWZX24, CFW⁺24, CHPC23], but the dimension of these spaces grows with the item cardinality, raising scalability concerns. Numerous other works apply continuous diffusion over the space of item embeddings, in both the traditional collaborative filtering [LXH⁺25] and sequential recommendation [YWW⁺23, LSL23, LHZ⁺25, WLYY24, YXC⁺25, MLL⁺25, CXJ25] contexts. [CWH⁺24] and [HYC⁺24] utilize semantic information by executing continuous diffusion over pretrained semantic embeddings. DDSR [XWZ⁺24] uses a discrete diffusion process over SIDs to predict next items, but employs this in an AR manner.

6 Conclusion

We present a novel modeling paradigm for GR with SIDs inspired by recent advancements in masked diffusion modeling in NLP. Empirically, our framework brings several advantages over standard AR modeling, including improved generalization in data-sparse settings, inference efficiency, and coarse-grained recall. Our framework is also simple and general enough to incorporate innovations from AR SID modeling, such as incorporating dense retrieval. Exploring novel design choices to combine other such auxiliary techniques with MADRec presents an interesting direction for future research. We also envision that user sequence modeling with masked diffusion can be further improved by a more sophisticated training and inference guidance strategy (e.g., classifier-free/classifier-based guidance [SSP⁺24] or error correction via remasking [WSSK25, vRFD⁺25]).

References

- [AJH⁺21] Jacob Austin, Daniel D. Johnson, Jonathan Ho, Daniel Tarlow, and Rianne van den Berg. Structured denoising diffusion models in discrete state-spaces. *NeruIPS*, 2021.
- [BDDR23] Dominique Brunato, Felice Dell’Orletta, Irene Dini, and Andrea Amelio Ravelli. Coherent or not? stressing a neural language model for discourse coherence in multiple languages. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 10690–10700, 2023.

- [BDVJ03] Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. A neural probabilistic language model. *Journal of machine learning research*, 3(Feb):1137–1155, 2003.
- [BHGS⁺25] Heli Ben-Hamu, Itai Gat, Daniel Severo, Niklas Nolte, and Brian Karrer. Accelerated sampling from masked diffusion models via entropy bounded unmasking. *arXiv preprint arXiv:2505.24857*, 2025.
- [BMR⁺20] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- [BZZ⁺23] Keqin Bao, Jizhi Zhang, Yang Zhang, Wenjie Wang, Fuli Feng, and Xiangnan He. Tallrec: An effective and efficient tuning framework to align large language model with recommendation. In *Proceedings of the 17th ACM conference on recommender systems*, pages 1007–1014, 2023.
- [CFW⁺24] Ruixin Chen, Jianping Fan, Meiqin Wu, Rui Cheng, and Jiawen Song. G-diff: A graph-based decoding network for diffusion recommender model. *IEEE Transactions on Neural Networks and Learning Systems*, 2024.
- [CHL⁺24] Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. Scaling instruction-finetuned language models. *Journal of Machine Learning Research*, 25(70):1–53, 2024.
- [CHPC23] Jeongwhan Choi, Seoyoung Hong, Noseong Park, and Sung-Bae Cho. Blurring-sharpening process models for collaborative filtering. In *Proceedings of the 46th international ACM SIGIR conference on research and development in information retrieval*, pages 1096–1106, 2023.
- [CMY⁺24] Yuwei Cao, Nikhil Mehta, Xinyang Yi, Raghunandan Keshavan, Lukasz Heldt, Lichan Hong, Ed H Chi, and Maheswaran Sathiamoorthy. Aligning large language models with recommendation knowledge. *arXiv preprint arXiv:2404.00245*, 2024.
- [CWH⁺24] Ziqiang Cui, Haolun Wu, Bowei He, Ji Cheng, and Chen Ma. Context matters: Enhancing sequential recommendation with context-aware diffusion-based contrastive learning. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, pages 404–414, 2024.
- [CXJ25] Jialei Chen, Yuanbo Xu, and Yiheng Jiang. Unlocking the power of diffusion models in sequential recommendation: A simple and effective approach. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2*, pages 155–166, 2025.
- [DN21] Prafulla Dhariwal and Alex Nichol. Diffusion models beat gans on image synthesis. *NeurIPS*, 2021.
- [DWC⁺25] Jiaxin Deng, Shiyao Wang, Kuo Cai, Lejian Ren, Qigen Hu, Weifeng Ding, Qiang Luo, and Guorui Zhou. Onerec: Unifying retrieve and rank with generative recommender and iterative preference alignment. *arXiv preprint arXiv:2502.18965*, 2025.

- [FLL⁺22] Chao Feng, Wuchao Li, Defu Lian, Zheng Liu, and Enhong Chen. Recommender forest for efficient retrieval. *Advances in Neural Information Processing Systems*, 35:38912–38924, 2022.
- [GAZ⁺24] Shansan Gong, Shivam Agarwal, Yizhe Zhang, Jiacheng Ye, Lin Zheng, Mukai Li, Chenxin An, Peilin Zhao, Wei Bi, Jiawei Han, et al. Scaling diffusion language models via adaptation from autoregressive models. *arXiv preprint arXiv:2410.17891*, 2024.
- [GHKS14] Tiezheng Ge, Kaiming He, Qifa Ke, and Jian Sun. Optimized product quantization. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 36(4):744–755, 2014.
- [GLF⁺22a] Shijie Geng, Shuchang Liu, Zuohui Fu, Yingqiang Ge, and Yongfeng Zhang. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5). In *Proceedings of the 16th ACM conference on recommender systems*, pages 299–315, 2022.
- [GLF⁺22b] Shansan Gong, Mukai Li, Jiangtao Feng, Zhiyong Wu, and LingPeng Kong. Diffuseq: Sequence to sequence text generation with diffusion models. *arXiv preprint arXiv:2210.08933*, 2022.
- [GSX⁺23] Yunfan Gao, Tao Sheng, Youlin Xiang, Yun Xiong, Haofen Wang, and Jiawei Zhang. Chat-rec: Towards interactive and explainable llms-augmented recommender system. *arXiv preprint arXiv:2303.14524*, 2023.
- [HHMZ23] Yupeng Hou, Zhankui He, Julian McAuley, and Wayne Xin Zhao. Learning vector-quantized item representation for transferable sequential recommenders. In *Proceedings of the ACM Web Conference 2023*, pages 1162–1171, 2023.
- [HJA20] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in neural information processing systems*, 33:6840–6851, 2020.
- [HKA16] F. Maxwell Harper, Joseph A. Konstan, and Joseph A. The movielens datasets: History and context. *ACM Trans. Interact. Intell. Syst.*, 5:19:1–19:19, 2016.
- [HKK⁺20] Tom Henighan, Jared Kaplan, Mor Katz, Mark Chen, Christopher Hesse, Jacob Jackson, Heewoo Jun, Tom B Brown, Prafulla Dhariwal, Scott Gray, et al. Scaling laws for autoregressive generative modeling. *arXiv preprint arXiv:2010.14701*, 2020.
- [HLS⁺25] Yupeng Hou, Jiacheng Li, Ashley Shin, Jinsung Jeon, Abhishek Santhanam, Wei Shao, Kaveh Hassani, Ning Yao, and Julian McAuley. Generating long semantic ids in parallel for recommendation. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2*, pages 956–966, 2025.
- [HMZ⁺22] Yupeng Hou, Shanlei Mu, Wayne Xin Zhao, Yaliang Li, Bolin Ding, and Ji-Rong Wen. Towards universal sequence representation learning for recommender systems. In *Proceedings of the 28th ACM SIGKDD conference on knowledge discovery and data mining*, pages 585–593, 2022.
- [HNH⁺] Yupeng Hou, Jianmo Ni, Zhankui He, Noveen Sachdeva, Wang-Cheng Kang, Ed H Chi, Julian McAuley, and Derek Zhiyuan Cheng. Actionpiece: Contextually tokenizing action sequences for generative recommendation. In *Forty-second International Conference on Machine Learning*.

- [HPJ⁺14] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Atallah, Ralf Herbrich, Stuart Bowers, et al. Practical lessons from predicting clicks on ads at facebook. In *Proceedings of the eighth international workshop on data mining for online advertising*, pages 1–9, 2014.
- [HPS24] Yu Hou, Jin-Duk Park, and Won-Yong Shin. Collaborative filtering based on diffusion models: Unveiling the potential of high-order connectivity. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1360–1369, 2024.
- [HS22] Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance. *arXiv preprint arXiv:2207.12598*, 2022.
- [HXGZ23] Wenyue Hua, Shuyuan Xu, Yingqiang Ge, and Yongfeng Zhang. How to index item ids for recommendation foundation models. In *Proceedings of the Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region*, pages 195–204, 2023.
- [HYC⁺24] Guoqing Hu, Zhengyi Yang, Zhibo Cai, An Zhang, and Xiang Wang. Generate and instantiate what you prefer: Text-guided diffusion for sequential recommendation. *arXiv preprint arXiv:2410.13428*, 2024.
- [JCN⁺25] Clark Mingxuan Ju, Liam Collins, Leonardo Neves, Bhuvesh Kumar, Louis Yufeng Wang, Tong Zhao, and Neil Shah. Generative recommendation with semantic ids: A practitioner’s handbook. In *Proceedings of the 34th ACM International Conference on Information and Knowledge Management (CIKM)*, 2025.
- [JDS11] Herve Jégou, Matthijs Douze, and Cordelia Schmid. Product quantization for nearest neighbor search. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(1):117–128, 2011.
- [JL17] Dietmar Jannach and Malte Ludewig. When recurrent neural networks meet the neighborhood for session-based recommendation. In *Proceedings of the eleventh ACM conference on recommender systems*, pages 306–310, 2017.
- [JZW⁺23] Bowen Jin, Hansi Zeng, Guoyin Wang, Xiusi Chen, Tianxin Wei, Ruirui Li, Zhengyang Wang, Zheng Li, Yang Li, Hanqing Lu, et al. Language models as semantic indexers. *arXiv preprint arXiv:2310.07815*, 2023.
- [KCW⁺24] Zhirui Kuai, Zuxu Chen, Huimu Wang, Mingming Li, Dadong Miao, Binbin Wang, Xusong Chen, Li Kuang, Yuxing Han, Jiaxing Wang, et al. Breaking the hourglass phenomenon of residual quantization: Enhancing the upper bound of generative retrieval. *arXiv preprint arXiv:2407.21488*, 2024.
- [KHQJ18] Urvashi Khandelwal, He He, Peng Qi, and Dan Jurafsky. Sharp nearby, fuzzy far away: How neural language models use context. *arXiv preprint arXiv:1805.04623*, 2018.
- [KM18] Wang-Cheng Kang and Julian McAuley. Self-attentive sequential recommendation. In *2018 IEEE international conference on data mining (ICDM)*, pages 197–206. IEEE, 2018.

- [KSK⁺25] Jaeyeon Kim, Kulin Shah, Vasilis Kontonis, Sham M. Kakade, and Sitan Chen. Train for the worst, plan for the best: Understanding token ordering in masked diffusions. In *Forty-second International Conference on Machine Learning*, 2025.
- [LCS⁺24] Xincheng Luo, Jiangxia Cao, Tianyu Sun, Jinkai Yu, Rui Huang, Wei Yuan, Hezheng Lin, Yichen Zheng, Shiya Wang, Qigen Hu, et al. Qarm: Quantitative alignment multi-modal recommendation at kuaishou. *arXiv preprint arXiv:2411.11739*, 2024.
- [LHZ⁺25] Wuchao Li, Rui Huang, Haijun Zhao, Chi Liu, Kai Zheng, Qi Liu, Na Mou, Guorui Zhou, Defu Lian, Yang Song, et al. Dimerec: a unified framework for enhanced sequential recommendation via generative diffusion models. In *Proceedings of the Eighteenth ACM International Conference on Web Search and Data Mining*, pages 726–734, 2025.
- [LLY⁺24] Jiayi Liao, Sihang Li, Zhengyi Yang, Jiancan Wu, Yancheng Yuan, Xiang Wang, and Xiangnan He. Llara: Large language-recommendation assistant. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1785–1795, 2024.
- [LME24] Aaron Lou, Chenlin Meng, and Stefano Ermon. Discrete diffusion modeling by estimating the ratios of the data distribution. *ICML*, 2024.
- [LSL23] Zihao Li, Aixin Sun, and Chenliang Li. Diffurec: A diffusion model for sequential recommendation. *ACM Transactions on Information Systems*, 42(3):1–28, 2023.
- [LTG⁺22] Xiang Li, John Thickstun, Ishaan Gulrajani, Percy S Liang, and Tatsunori B Hashimoto. Diffusion-lm improves controllable text generation. *Advances in neural information processing systems*, 35:4328–4343, 2022.
- [LWL⁺23] Jiacheng Li, Ming Wang, Jin Li, Jinmiao Fu, Xin Shen, Jingbo Shang, and Julian McAuley. Text is all you need: Learning language representations for sequential recommendation. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 1258–1267, 2023.
- [LXH⁺25] Zongwei Li, Lianghao Xia, Hua Hua, Shijie Zhang, Shuangyang Wang, and Chao Huang. Diffgraph: Heterogeneous graph diffusion model. In *Proceedings of the Eighteenth ACM International Conference on Web Search and Data Mining*, pages 40–49, 2025.
- [LYD⁺24] Dairui Liu, Boming Yang, Honghui Du, Derek Greene, Neil Hurley, Aonghus Lawlor, Ruihai Dong, and Irene Li. Recprompt: A self-tuning prompting framework for news recommendation using large language models. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, pages 3902–3906, 2024.
- [LZL⁺24] Enze Liu, Bowen Zheng, Cheng Ling, Lantao Hu, Han Li, and Wayne Xin Zhao. End-to-end learnable item tokenization for generative recommendation. *arXiv preprint arXiv:2409.05546*, 2024.
- [MLL⁺25] Wenyu Mao, Shuchang Liu, Haoyang Liu, Haozhe Liu, Xiang Li, and Lantao Hu. Distinguished quantized guidance for diffusion-based sequence recommendation. In *Proceedings of the ACM on Web Conference 2025*, pages 425–435, 2025.

- [MTSVDH15] Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton Van Den Hengel. Image-based recommendations on styles and substitutes. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*, pages 43–52, 2015.
- [MXM⁺24] Haokai Ma, Ruobing Xie, Lei Meng, Xin Chen, Xu Zhang, Leyu Lin, and Zhanhui Kang. Plug-in diffusion model for sequential recommendation. In *Proceedings of the AAAI conference on artificial intelligence*, volume 38, pages 8886–8894, 2024.
- [MZZ⁺25] Luyi Ma, Wanjia Zhang, Kai Zhao, Abhishek Kulkarni, Lalitesh Morishetti, Anjana Ganesh, Ashish Ranjan, Aashika Padmanabhan, Jianpeng Xu, Jason HD Cho, et al. Grace: Generative recommendation via journey-aware sparse attention on chain-of-thought tokenization. In *Proceedings of the Nineteenth ACM Conference on Recommender Systems*, pages 135–144, 2025.
- [Ntt25] Jinjie Ni and the team. Diffusion language models are super data learners. <https://jinjeni.notion.site/Diffusion-Language-Models-are-Super-Data-Learners-239d8f03a866800ab196e49928c019ac>, 2025. Notion Blog.
- [ONX⁺24] Jingyang Ou, Shen Nie, Kaiwen Xue, Fengqi Zhu, Jiacheng Sun, Zhenguo Li, and Chongxuan Li. Your absorbing discrete diffusion secretly models the conditional distributions of clean data. *arXiv preprint arXiv:2406.03736*, 2024.
- [PDDN⁺25] Gustavo Penha, Edoardo D’Amico, Marco De Nadai, Enrico Palumbo, Alexandre Tamborrino, Ali Vardasbi, Max Lefarov, Shawn Lin, Timothy Heath, Francesco Fabri, et al. Semantic ids for joint generative search and recommendation. In *Proceedings of the Nineteenth ACM Conference on Recommender Systems*, pages 1296–1301, 2025.
- [PWZ⁺25] Mihir Prabhudesai, Mengning Wu, Amir Zadeh, Katerina Fragkiadaki, and Deepak Pathak. Diffusion beats autoregressive in data-constrained settings. *arXiv preprint arXiv:2507.15857*, 2025.
- [PYL⁺24] Fabian Paischer, Liu Yang, Linfeng Liu, Shuai Shao, Kaveh Hassani, Jiacheng Li, Ricky Chen, Zhang Gabriel Li, Xialo Gao, Wei Shao, et al. Preference discerning with llm-enhanced generative retrieval. *arXiv preprint arXiv:2412.08604*, 2024.
- [QFZL25] Haohao Qu, Wenqi Fan, Zihuai Zhao, and Qing Li. Tokenrec: Learning to tokenize id for llm-based generative recommendations. *IEEE Transactions on Knowledge and Data Engineering*, 2025.
- [RBL⁺22] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10684–10695, 2022.
- [RMS⁺23] Shashank Rajput, Nikhil Mehta, Anima Singh, Raghunandan Hulikal Keshavan, Trung Vu, Lukasz Heldt, Lichan Hong, Yi Tay, Vinh Tran, Jonah Samost, et al. Recommender systems with generative retrieval. *Advances in Neural Information Processing Systems*, 36:10299–10315, 2023.

- [RNS⁺18] Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. 2018.
- [RWC⁺19] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.
- [RYW⁺24] Yuxin Ren, Qiya Yang, Yichun Wu, Wei Xu, Yalong Wang, and Zhiqiang Zhang. Non-autoregressive generative models for reranking recommendation. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 5625–5634, 2024.
- [RZ85] David E Rumelhart and David Zipser. Feature discovery by competitive learning. *Cognitive science*, 9(1):75–112, 1985.
- [SAS⁺25] Subham Sahoo, Marianne Arriola, Yair Schiff, Aaron Gokaslan, Edgar Marroquin, Justin Chiu, Alexander Rush, and Volodymyr Kuleshov. Simple and effective masked diffusion language models. *Advances in Neural Information Processing Systems*, 37:130136–130184, 2025.
- [SDWMG15] Jascha Sohl-Dickstein, Eric A. Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics. *ICML*, 2015.
- [SHW⁺24] Jiaxin Shi, Kehang Han, Zhe Wang, Arnaud Doucet, and Michalis K. Titsias. Simplified and generalized masked diffusion for discrete data. *NeurIPS*, 2024.
- [SLW⁺19] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. Bert4rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the 28th ACM international conference on information and knowledge management*, pages 1441–1450, 2019.
- [SSC⁺24] Zihua Si, Zhongxiang Sun, Jiale Chen, Guozhang Chen, Xiaoxue Zang, Kai Zheng, Yang Song, Xiao Zhang, Jun Xu, and Kun Gai. Generative retrieval with semantic tree-structured identifiers and contrastive learning. In *Proceedings of the 2024 Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region*, pages 154–163, 2024.
- [SSP⁺24] Yair Schiff, Subham Sekhar Sahoo, Hao Phung, Guanghan Wang, Sam Boshar, Hugo Dalla-torre, Bernardo P de Almeida, Alexander Rush, Thomas Pierrot, and Volodymyr Kuleshov. Simple guidance mechanisms for discrete diffusion models. *arXiv preprint arXiv:2412.10193*, 2024.
- [SVL14] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. *Advances in neural information processing systems*, 27, 2014.
- [SVM⁺24] Anima Singh, Trung Vu, Nikhil Mehta, Raghunandan Keshavan, Maheswaran Sathiamoorthy, Yilin Zheng, Lichan Hong, Lukasz Heldt, Li Wei, Devansh Tandon, et al. Better generalization with semantic ids: A case study in ranking for recommendations. In *Proceedings of the 18th ACM Conference on Recommender Systems*, pages 1039–1044, 2024.
- [SZZ⁺24] Leheng Sheng, An Zhang, Yi Zhang, Yuxin Chen, Xiang Wang, and Tat-Seng Chua. Language models encode collaborative signals in recommendation. 2024.

- [TXH⁺24] Juntao Tan, Shuyuan Xu, Wenyue Hua, Yingqiang Ge, Zelong Li, and Yongfeng Zhang. Idgenrec: Llm-recsys alignment with textual id learning. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 355–364, 2024.
- [VMD⁺24] Ravisri Valluri, Akash Kumar Mohankumar, Kushal Dave, Amit Singh, Jian Jiao, Manik Varma, and Gaurav Sinha. Scaling the vocabulary of non-autoregressive models for efficient generative retrieval. *arXiv preprint arXiv:2406.06739*, 2024.
- [vRFD⁺25] Dimitri von Rütte, Janis Fluri, Yuhui Ding, Antonio Orvieto, Bernhard Schölkopf, and Thomas Hofmann. Generalized interpolating discrete diffusion. *arXiv preprint arXiv:2503.04482*, 2025.
- [VSP⁺17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.
- [WBL⁺24] Wenjie Wang, Honghui Bao, Xinyu Lin, Jizhi Zhang, Yongqi Li, Fuli Feng, See-Kiong Ng, and Tat-Seng Chua. Learnable item tokenization for generative recommendation. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, pages 2400–2409, 2024.
- [WLYY24] Yu Wang, Zhiwei Liu, Liangwei Yang, and Philip S Yu. Conditional denoising diffusion for sequential recommendation. In *Pacific-Asia conference on knowledge discovery and data mining*, pages 156–169. Springer, 2024.
- [WSSK25] Guanghan Wang, Yair Schiff, Subham Sekhar Sahoo, and Volodymyr Kuleshov. Remasking discrete diffusion models with inference-time scaling. *arXiv preprint arXiv:2503.00307*, 2025.
- [WXF⁺23] Wenjie Wang, Yiyan Xu, Fuli Feng, Xinyu Lin, Xiangnan He, and Tat-Seng Chua. Diffusion recommender model. In *Proceedings of the 46th international ACM SIGIR conference on research and development in information retrieval*, pages 832–841, 2023.
- [WXH⁺24] Ye Wang, Jiahao Xun, Minjie Hong, Jieming Zhu, Tao Jin, Wang Lin, Haoyuan Li, Linjun Li, Yan Xia, Zhou Zhao, et al. Eager: Two-stream generative recommender with behavior-semantic collaboration. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 3245–3254, 2024.
- [WZZ⁺22] Joojo Walker, Ting Zhong, Fengli Zhang, Qiang Gao, and Fan Zhou. Recommendation via collaborative diffusion generative model. In *International conference on knowledge science, engineering and management*, pages 593–605. Springer, 2022.
- [XLL⁺24] Yunjia Xi, Weiwen Liu, Jianghao Lin, Xiaoling Cai, Hong Zhu, Jieming Zhu, Bo Chen, Ruiming Tang, Weinan Zhang, and Yong Yu. Towards open-world recommendation with knowledge augmentation from large language models. In *Proceedings of the 18th ACM Conference on Recommender Systems*, pages 12–22, 2024.
- [XWL⁺24] Wujiang Xu, Qitian Wu, Zujie Liang, Jiaojiao Han, Xuying Ning, Yunxiao Shi, Wenfang Lin, and Yongfeng Zhang. Slmrec: Distilling large language models into small for sequential recommendation. *arXiv preprint arXiv:2405.17890*, 2024.

- [XWW⁺25] Longtao Xiao, Haozhao Wang, Cheng Wang, Linfei Ji, Yifan Wang, Jieming Zhu, Zhenhua Dong, Rui Zhang, and Ruixuan Li. Progressive collaborative and semantic knowledge fusion for generative recommendation. *arXiv preprint arXiv:2502.06269*, 2025.
- [XWZ⁺24] Wenjia Xie, Hao Wang, Luankang Zhang, Rui Zhou, Defu Lian, and Enhong Chen. Breaking determinism: Fuzzy modeling of sequential recommendation using discrete state space diffusion model. *Advances in Neural Information Processing Systems*, 37:22720–22744, 2024.
- [YJL⁺25] Yuhao Yang, Zhi Ji, Zhaopeng Li, Yi Li, Zhonglin Mo, Yue Ding, Kai Chen, Zijian Zhang, Jie Li, Shuanglong Li, et al. Sparse meets dense: Unified generative recommendations with cascaded sparse-dense representations. *arXiv preprint arXiv:2503.02453*, 2025.
- [YPH⁺24] Liu Yang, Fabian Paischer, Kaveh Hassani, Jiacheng Li, Shuai Shao, Zhang Gabriel Li, Yun He, Xue Feng, Nima Noorshams, Sem Park, et al. Unifying generative and dense retrieval for sequential recommendation. *arXiv preprint arXiv:2411.18814*, 2024.
- [YTLB23] Penghang Yu, Zhiyi Tan, Guanming Lu, and Bing-Kun Bao. Ld4mrec: Simplifying and powering diffusion model for multimedia recommendation. *arXiv preprint arXiv:2309.15363*, 2023.
- [YWW⁺23] Zhengyi Yang, Jiancan Wu, Zhicai Wang, Xiang Wang, Yancheng Yuan, and Xiangnan He. Generate what you prefer: Reshaping sequential recommendation via guided diffusion. *Advances in Neural Information Processing Systems*, 36:24247–24261, 2023.
- [YXC⁺25] Meng Yuan, Yutian Xiao, Wei Chen, Chou Zhao, Deqing Wang, and Fuzhen Zhuang. Hyperbolic diffusion recommender model. In *Proceedings of the ACM on Web Conference 2025*, pages 1992–2006, 2025.
- [YYS⁺23] Zheng Yuan, Fajie Yuan, Yu Song, Youhua Li, Junchen Fu, Fei Yang, Yunzhu Pan, and Yongxin Ni. Where to go next for recommender systems? id-vs. modality-based recommender models revisited. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2639–2649, 2023.
- [YYT⁺22] Hongyi Yuan, Zheng Yuan, Chuanqi Tan, Fei Huang, and Songfang Huang. Seqdiffuseq: Text diffusion with encoder-decoder transformers. *arXiv preprint arXiv:2212.10325*, 2022.
- [ZHC⁺25] Guorui Zhou, Hengrui Hu, Hongtao Cheng, Huanjie Wang, Jiaxin Deng, Jinghao Zhang, Kuo Cai, Lejian Ren, Lu Ren, Liao Yu, et al. Onerec-v2 technical report. *arXiv preprint arXiv:2508.20900*, 2025.
- [ZHL⁺24] Bowen Zheng, Yupeng Hou, Hongyu Lu, Yu Chen, Wayne Xin Zhao, Ming Chen, and Ji-Rong Wen. Adapting large language models by integrating collaborative semantics for recommendation. In *2024 IEEE 40th International Conference on Data Engineering (ICDE)*, pages 1435–1448. IEEE, 2024.

- [ZJL⁺24] Jieming Zhu, Mengqun Jin, Qijiong Liu, Zexuan Qiu, Zhenhua Dong, and Xiu Li. Cost: Contrastive quantization based semantic tokenization for generative recommendation. In *Proceedings of the 18th ACM Conference on Recommender Systems*, pages 969–974, 2024.
- [ZLKE23] Linqi Zhou, Aaron Lou, Samar Khanna, and Stefano Ermon. Denoising diffusion bridge models. *arXiv preprint arXiv:2309.16948*, 2023.
- [ZLO⁺21] Neil Zeghidour, Alejandro Luebs, Ahmed Omran, Jan Skoglund, and Marco Tagliasacchi. Soundstream: An end-to-end neural audio codec. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 30:495–507, 2021.
- [ZWX⁺24] Jujia Zhao, Wang Wenjie, Yiyan Xu, Teng Sun, Fuli Feng, and Tat-Seng Chua. Denoising diffusion recommender model. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1370–1379, 2024.
- [ZWZ⁺20] Kun Zhou, Hui Wang, Wayne Xin Zhao, Yutao Zhu, Sirui Wang, Fuzheng Zhang, Zhongyuan Wang, and Ji-Rong Wen. S3-rec: Self-supervised learning for sequential recommendation with mutual information maximization. In *CIKM ’20: The 29th ACM International Conference on Information and Knowledge Management, Virtual Event, Ireland, October 19-23, 2020*, pages 1893–1902. ACM, 2020.
- [ZWZX24] Yunqin Zhu, Chao Wang, Qi Zhang, and Hui Xiong. Graph signal diffusion model for collaborative filtering. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1380–1390, 2024.
- [ZXH⁺25] Junjie Zhang, Ruobing Xie, Yupeng Hou, Xin Zhao, Leyu Lin, and Ji-Rong Wen. Recommendation as instruction following: A large language model empowered recommendation approach. *ACM Transactions on Information Systems*, 43(5):1–37, 2025.
- [ZYYK23] Lin Zheng, Jianbo Yuan, Lei Yu, and Lingpeng Kong. A reparameterized discrete diffusion model for text generation. *arXiv preprint arXiv:2302.05737*, 2023.

A Experiments

A.1 Additional Experimental Details

Dataset statistics. We summarize the detailed statistics for our datasets (Amazon Beauty, Sports, Toys, and MovieLens-1M) in Table 6.

Implementation details. Our implementation of MADRec is based on the GRID codebase presented in [JCN⁺25]. We use the AdamW optimizer with a learning rate of 0.005, a weight decay of 0.001, a batch size of 8192, and early stop all experiments using validation recall@10. We use the implementation of TIGER [RMS⁺23] provided in GRID. We use the implementation of LIGER [YPH⁺24] using the public repository released by the paper’s authors. Both TIGER and LIGER use 4 SIDs per item, including the deduplication token, consistent with their original implementations and TIGER’s optimal setting for the Amazon datasets [JCN⁺25]. All SIDs are assigned

Table 6: Dataset statistics after preprocessing.

Dataset	Beauty	Toys	Sports	ML-1M
# Users	22,363	19,412	35,598	6,040
# Items	12,101	11,924	18,357	3,416
# Interactions	198,502	167,597	296,337	999,611
# Avg. Length	8.88	8.63	8.32	165.50
Sparsity	99.93%	99.93%	99.95%	95.16%

by executing residual k -means clustering with $c = 256$ clusters per layer on mean-pooled Flan-T5-XXL embeddings. For baselines, we use SASRec results reported by Rajput et al. [RMS⁺23], and BERT4Rec, DreamRec, and CaDiRec results from Cui et al. [CWH⁺24].

We execute all experiments on nodes with four 16-GB NVIDIA V100 GPUs or four 40 GB NVIDIA A100 GPUs.

A.2 Additional Experimental Results

In Table 7 we share the NDCG@10 and Recall@10 metrics for the same experiments as in Table 1.

Table 7: Comparison of the performance of MADRec with other GR methods on multiple datasets.

Method	Beauty		Sports		Toys		ML-1m	
	R@10	N@10	R@10	N@10	R@10	N@10	R@10	N@10
SASRec	6.05	3.18	3.50	1.92	7.12	4.32	16.89	7.72
BERT4Rec	6.01	3.08	3.59	1.81	6.65	3.68	20.56	11.12
DreamRec	6.87	3.52	3.74	1.91	6.43	4.02	20.29	10.47
CaDiRec	<u>7.18</u>	<u>3.86</u>	<u>4.25</u>	<u>2.33</u>	<u>7.85</u>	<u>4.41</u>	<u>22.82</u>	<u>12.51</u>
TIGER	6.33	3.54	3.61	2.03	6.63	3.61	19.97	10.13
LIGER	<u>7.52</u>	<u>4.14</u>	<u>4.27</u>	2.30	6.25	3.52	20.58	10.81
MADRec	8.15	4.41	4.54	2.49	8.46	4.45	23.96	13.45
(+ Improv. (%))	+8.7 %	+6.5 %	+6.3 %	+6.9 %	+7.8 %	+0.9 %	+5.0 %	+7.5 %