

A Comprehensive Survey on Self-Supervised Learning for Recommendation

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Recommender systems play a crucial role in tackling the challenge of information overload by delivering personalized recommendations based on individual user preferences. Deep learning techniques, such as RNNs, GNNs, and Transformer architectures, have significantly propelled the advancement of recommender systems by enhancing their comprehension of user behaviors and preferences. However, supervised learning methods encounter challenges in real-life scenarios due to data sparsity, resulting in limitations in their ability to learn representations effectively. To address this, self-supervised learning (SSL) techniques have emerged as a solution, leveraging inherent data structures to generate supervision signals without relying solely on labeled data. By leveraging unlabeled data and extracting meaningful representations, recommender systems utilizing SSL can make accurate predictions and recommendations even when confronted with data sparsity. In this paper, we provide a comprehensive review of self-supervised learning frameworks designed for recommender systems, encompassing a thorough analysis of over 170 papers. We conduct an exploration of nine distinct scenarios, enabling a comprehensive understanding of SSL-enhanced recommenders in different contexts. For each domain, we elaborate on different self-supervised learning paradigms, namely contrastive learning, generative learning, and adversarial learning, so as to present technical details of how SSL enhances recommender systems in various contexts. We consistently maintain the related open-source materials at <https://github.com/HKUDS/Awesome-SSLRec-Papers>.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Information systems** → **Recommender systems**.

Additional Key Words and Phrases: Recommendation, Self-Supervised Learning

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1 INTRODUCTION

Recommender systems play a vital role in addressing the challenge of information overload by providing personalized recommendations to individual users based on their unique preferences [211]. These systems are designed to enhance the overall user experience by presenting users with recommendations that are not only relevant but also closely aligned with their interests. This tailored approach makes the user experience more engaging, efficient, and ultimately more satisfying. At the core of recommender systems lies the fundamental principle of understanding users' preferences for a

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diverse range of items [56, 94]. This understanding is achieved through a meticulous analysis of users’ past interactions, which encompass activities such as clicks and purchases. By examining these interactions, recommender systems gain valuable insights into users’ behavior, enabling them to identify patterns and uncover individual preferences.

The field of recommender systems has undergone a revolutionary transformation, thanks to the strong representation capabilities of deep learning techniques. Neural network architectures have played a pivotal role in this paradigm shift. By harnessing the power of deep learning models, such as Recurrent Neural Networks (RNNs) [29, 44], Graph Neural Networks (GNNs) [145, 190], and Transformer architectures [119, 157], recommender systems have achieved an unprecedented level of understanding of user preferences and behaviors. Consequently, this deep understanding has paved the way for precise and personalized recommendations that cater to individual user needs and preferences.

Existing supervised learning methods heavily depend on having abundant labeled data for effective training. However, practical recommender systems often encounter the problem of data sparsity [163]. This means that real-life recommendation scenarios often suffer from a limited amount of available data or an insufficient number of labeled examples. Consequently, supervised learning methods encounter significant difficulties in effectively generalizing and accurately learning representations of user preferences in such scenarios. Fortunately, taking inspiration from the accomplishments of self-supervised learning (SSL) [78], SSL techniques has proven to be beneficial for recommender systems in addressing the issue of data sparsity [110, 163]. Generally speaking, the key idea of SSL lies in leveraging the inherent structures or patterns within the data itself to create supervision signals for learning, without relying solely on externally labeled data. This allows recommender systems to utilize unlabeled data and extract meaningful representations, enabling them to make accurate predictions and recommendations even in the presence of data sparsity.

Our paper provides a comprehensive review of the latest advancements in self-supervised learning frameworks tailored specifically for recommendation systems. It aims to serve as a valuable resource for researchers from diverse disciplines, extending beyond the realms of computer science and machine learning, who wish to explore this rapidly evolving field. In this context, our paper presents several significant contributions, which are summarized as follows:

Comprehensive Collection of Papers. We have conducted a thorough review of over 170 papers that investigate the application of self-supervised learning in the field of recommendation. Our search was carried out using reputable academic databases such as Google Scholar and DBLP, utilizing specific keywords including “self-supervised”, “contrastive”, “generative”, “adversarial”, “variational”, “diffusion” and “masked autoencoder” in conjunction with “recommendation” and “recommender systems”. The surveyed papers were meticulously sourced from esteemed conferences and journals such as KDD, SIGIR, WWW, ICLR, WSDM, CIKM, ICDE, AAAI, IJCAI, RecSys, TOIS, TKDE. To ensure the inclusion of state-of-the-art research, we also explored citation networks and incorporated relevant preprints from arXiv.

Supported with Open-source Library. Our team has developed SSLRec [109], a robust framework for self-supervised learning. This user-friendly framework encompasses popular datasets, standardized code scripts for data processing, training, testing, evaluation, and cutting-edge recommender models for self-supervised learning.

Relationship with Previous Surveys. i) **Extensive Collection of SSL Research.** Our survey provides a significantly broader collection of self-supervised learning (SSL) works in the context of recommendation, encompassing over 170 papers, surpassing the previous surveys which covered approximately 80 papers [49, 198]. In addition, we incorporate generative methods (e.g., mask autoencoding, denoised diffusion) and adversarial learning, which were not previously covered but have gained prominence according to [78]. ii) **Comprehensive Taxonomy Design.** Our taxonomy refines previous classifications of contrastive learning (Yu et al., 2023; Jing et al., 2023) and proposes a view-centric taxonomy

approach. We also survey generative and adversarial learning methods based on their learning paradigms and targets. iii) **Exploration of Distinct Scenarios.** Distinguishing ourselves from earlier works [49, 198], which did not differentiate SSL-enhanced recommenders across different scenarios, we conducted an extensive exploration of nine scenarios individually. By surveying research works within diverse scenarios, we provide researchers with a more comprehensive understanding of the context-specific to each scenario and the corresponding challenges they present.

Organization of the Survey: The structure of the survey is as follows: Section 2 provides a comprehensive overview of recommendation systems and self-supervised learning, establishing the necessary background knowledge. In Section 3, we present our proposed taxonomy for understanding self-supervised learning within the context of recommendation systems. The main content of the survey is covered in Section 4, where we conduct separate reviews of the three self-supervised learning paradigms across various recommendation scenarios. Moving forward, Section 5 delves into open problems and future directions in this field. Lastly, we conclude the survey with Section 6.

2 PRELIMINARIES AND DEFINITION

In this section, we provide a concise introduction to the essential background knowledge relevant to our survey on self-supervised for learning recommendation. We begin by briefly outlining the preliminaries of the tasks in recommender systems. Subsequently, we describe the definition of self-supervised learning and introduce prominent learning paradigms: contrastive, generative, and adversarial approaches.

2.1 Recommender Systems

The research on recommendation encompasses a wide range of tasks in diverse scenarios, such as collaborative filtering, sequential recommendation, and multi-behavior recommendation. These tasks exhibit distinct data paradigms and objectives. Here, we begin by providing a general definition without delving into specific variations across diverse recommendation tasks. In recommender systems, there are two primary sets: the set of users, denoted as $\mathcal{U} = \{u_1, \dots, u_i, \dots, u_{|\mathcal{U}|}\}$, and the set of items, denoted as $\mathcal{V} = \{v_1, \dots, v_j, \dots, v_{|\mathcal{V}|}\}$. Then, an interaction matrix $\mathcal{A} \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{V}|}$ is utilized to represent the recorded interactions between users and items. In this matrix, an entry $\mathcal{A}_{i,j}$ is assigned a value of 1 if user u_i has interacted with item v_j , and 0 otherwise. The definition of interaction is adaptable to various scenarios and datasets (e.g., watching a movie, clicking or making purchases on an e-commerce website). Furthermore, in various recommendation tasks, there are distinct auxiliary observed data denoted as \mathcal{X} . For instance, in knowledge graph-enhanced recommendation, \mathcal{X} incorporates a knowledge graph comprising external item attributes with different entity types and corresponding relationships. While in social recommendation, \mathcal{X} encompasses user-level relationships, such as friendships. With the above definition, a recommendation model optimizes a prediction function $f(\cdot)$ that aims to accurately estimate the preference score between any user u and item v :

$$y_{u,v} = f(\mathcal{A}, \mathcal{X}, u, v). \quad (1)$$

The preference score $y_{u,v}$ represents the likelihood of user u interacting with item v . Based on this score, the recommender system can provide recommendations of uninteracted items to each user by presenting a ranking list of items according to the estimated preference scores. In Section 4, we will delve into the data formulation of $(\mathcal{A}, \mathcal{X})$ under different recommendation scenarios, complementing the demonstration of self-supervised learning in recommendation.

2.2 Self-supervised Learning in Recommendation

Over the past years, deep neural networks have demonstrated outstanding performance with supervised learning in various fields, including computer vision [132], natural language processing [21] and recommender systems [211]. However, due to the heavy reliance on labeled data, supervised learning faces challenges when dealing with label sparsity, which is also a common issue in recommendation systems [156, 198]. To address this limitation, self-supervised learning has emerged as a promising approach, leveraging the data itself as labels for learning. In this section, we introduce three fundamental self-supervised learning methodologies: contrastive, generative, and adversarial.

2.2.1 Contrastive Learning. To fully leverage the inherent information within the data itself as supervision signals, contrastive learning has emerged as a prominent self-supervised learning approach [43]. The primary objective of contrastive learning is to maximize the agreement between different views augmented from the data. Formally, in contrastive learning for the recommendation, the objective is to minimize the following loss function [158, 173]:

$$\min_{\mathcal{E}_1, \mathcal{E}_2} \mathcal{L}_{con}(\mathcal{E}_1 \circ \omega_1(\mathcal{A}, \mathcal{X}), \mathcal{E}_2 \circ \omega_2(\mathcal{A}, \mathcal{X})). \quad (2)$$

Here $\mathcal{E}_* \circ \omega_*$ represents the view creation operations, which can vary across different contrastive learning-based recommenders. Each operation consists of data permutation processes, $\omega_1(\cdot)$ and $\omega_2(\cdot)$, which may involve dropping nodes/edges in graphs, as well as embedding encoding processes, \mathcal{E}_1 and \mathcal{E}_2 . The objective of minimizing \mathcal{L}_{con} is to obtain robust encoding functions that maximize the agreement between the views. This cross-view agreement can be achieved through methods such as mutual information maximization or instance discrimination.

2.2.2 Generative Learning. Generative learning seeks to understand data structures and patterns to learn meaningful representations. It optimizes a deep encoder-decoder model that reconstructs missing or corrupted input data. The encoder, $\mathcal{E}(\cdot)$, creates latent representations from the input, while the decoder, $\mathcal{D}(\cdot)$, reconstructs the original data from the encoder output. The goal is to minimize the discrepancy between reconstructed and original data [79] as follows:

$$\min_{\mathcal{D}, \mathcal{E}} \mathcal{L}_{gen}(\mathcal{D} \circ \mathcal{E}(\omega(\mathcal{A}, \mathcal{X})), (\mathcal{A}, \mathcal{X})). \quad (3)$$

Here, ω represents an operation like masking or perturbation. $\mathcal{D} \circ \mathcal{E}$ denotes the process of encoding and decoding to reconstruct output. Recent studies have introduced a decoder-only architecture that effectively reconstructs data without an encoder-decoder setup. This approach uses a single model (e.g., Transformer [130]) for reconstruction, and is commonly applied in sequential recommendation with generative learning [119]. The loss function \mathcal{L}_{gen} format depends on the data type, with mean square loss for continuous data and cross-entropy loss for categorical data.

2.2.3 Adversarial Learning. Adversarial learning is a training method used to generate high-quality outputs, using a generator $\mathcal{G}(\cdot)$. What sets adversarial learning apart from generative learning is the inclusion of a discriminator $\Omega(\cdot)$, which determines whether a given sample is real or generated [27, 42]. In adversarial learning, the generator aims to enhance the quality of its generated outputs in order to deceive the discriminator. Consequently, the learning objective of adversarial learning can be defined as follows:

$$\min_{\mathcal{G}} \max_{\Omega} \{\mathbb{E}_{x \sim P(\mathcal{A}, \mathcal{X})} [\log \Omega(x)] + \mathbb{E}_{\hat{x} \sim P(\mathcal{G}(\mathcal{A}, \mathcal{X}))} [\log (1 - \Omega(\hat{x}))]\}. \quad (4)$$

Here, the variable x represents a real sample obtained from the underlying data distribution, while \hat{x} represents a synthetic sample generated by the generator $\mathcal{G}(\cdot)$. During the training process, both the generator and discriminator enhance their capabilities through a competitive interplay. Ultimately, the generator strives to generate high-quality

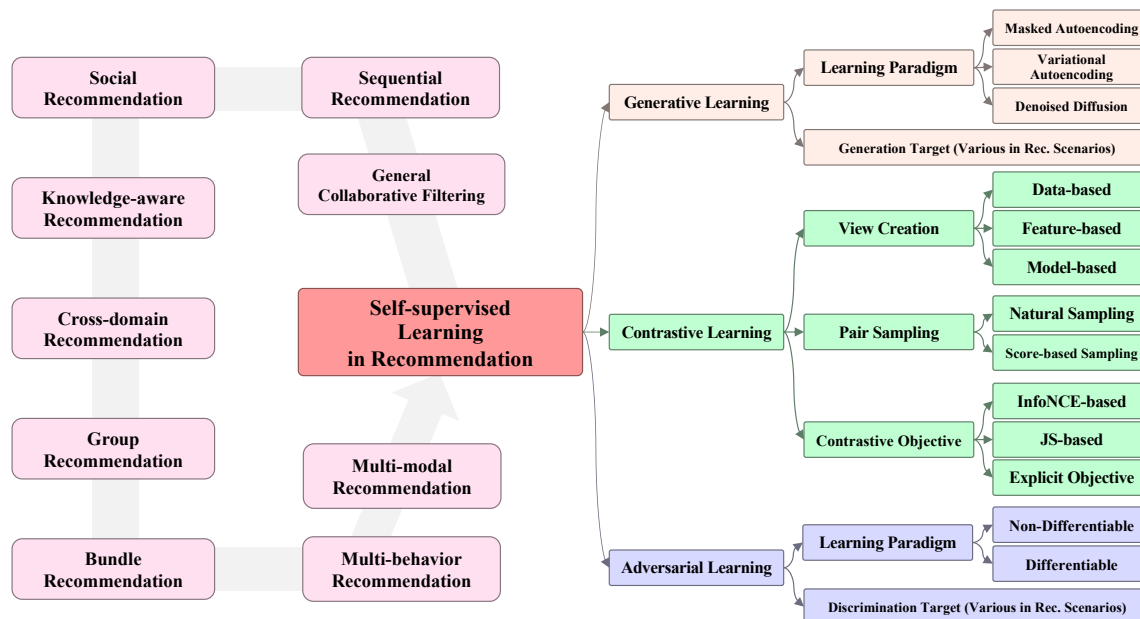


Fig. 1. The proposed taxonomy of self-supervised learning in recommender systems.

outputs that can be advantageous for downstream tasks. This training approach is commonly employed in various domains, including sequential recommendation, to enhance performance.

3 TAXONOMY

In this section, we present our comprehensive taxonomy of self-supervised learning in recommender systems. As previously mentioned, the self-supervised learning paradigm can be categorized into contrastive learning, generative learning, and adversarial learning. Therefore, our taxonomy is built upon these three categories, providing more detailed insights into each. Our overall taxonomy is shown in Figure 1.

3.1 Contrastive Learning in Recommendation

The fundamental principle of contrastive learning (CL) involves maximizing the agreement between different views. Hence, we propose a view-centric taxonomy, which contains three key components to consider when applying contrastive learning: creating the views, pairing the views to maximize agreement, and optimizing the agreement.

3.1.1 View Creation. The created view emphasizes various data aspects for the model. It can incorporate global collaborative information to improve the recommender’s handling of global relationships [163] or introduce random noise to enhance model robustness [197]. We regard augmentation on input data (*e.g.*, graphs, sequences, input features) [49, 198] as data-perspective view creation, and hidden feature augmentation during inference as feature-level view creation. Additionally, the model-based contrastive paradigm [198] serves as model-level view generation. Thus, we propose a hierarchical taxonomy encompassing view-creation techniques from basic data-level to neural model-level.

- **Data-based view creation:** In the realm of contrastive learning-based recommenders, diverse views are created by augmenting input data. These augmented data points are subsequently processed through deep neural recommenders. The resulting output embeddings from different views are then paired and utilized for contrastive

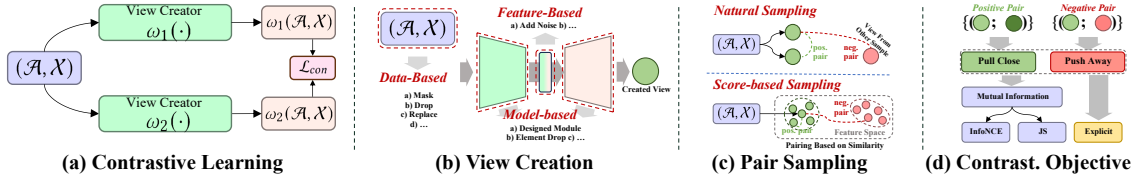


Fig. 2. Taxonomy of Contrastive Learning in Recommender Systems.

learning. The augmentation methods for the original data vary depending on the recommendation scenario. For instance, graph-based data may employ techniques such as node/edge dropout or the addition of noisy edges [156, 219], while item sequences may make use of masking, cropping, and replacing [119, 218].

- **Feature-based view creation:** In addition to generating views directly from the data, some methods consider conducting augmentation based on the hidden feature encoded during the models’ forward process. These representations can include node embedding during graph-based message passing or token vectors in the Transformer, for example. By applying various augmentation techniques or introducing random perturbations to the representations multiple times [156, 193], the model’s final output can be considered as different views. One commonly used practice is to add random noise to the representations [174].
- **Model-based view creation:** Both data-based and feature-based augmentation are non-adaptive since they are non-parametric. Consequently, various sophisticated methods have emerged to generate different views using neural modules. These views contain specific information based on the model design. For example, intent disentanglement neural modules can capture user intents [110, 159], while hyperparagraph graph modules can capture global relationships [163]. In contrast, model-based view creation involves learnable parameters within the view generator that are adaptive to the learning objective and optimized during the learning process.

3.1.2 Pair Sampling. The view creation process generates at least two distinct views for each sample in the data using appropriate view creation methods. The crux of contrastive learning lies in maximally aligning certain views (*i.e.*, pulling them close) while pushing others apart. To achieve this, it’s crucial to determine the positive pair of views that should be pulled close and identify other views that form negative pairs to be pushed away. This strategy is known as pair sampling, and it primarily consists of two main pair-sampling approaches in CL-based recommendation:

- **Natural Sampling:** One common approach to pair sampling is straightforward and non-heuristic, which we refer to as natural sampling. Positive pairs are formed by different views generated from the same data sample, while negative pairs are formed by views from different data samples. In cases where a central view exists for all samples, such as a global view derived from the entire graph, the local-global relationship also forms positive pairs. This approach is widely applied in most contrastive learning recommenders.
- **Score-based Sampling:** Another approach to pair sampling is score-based sampling. In this approach, a module calculates scores of pairs to determine positive or negative pairs. For instance, one relevant score is the distance between two views, which can be used to form pairs [103, 164]. Alternatively, clustering can be applied on views, where positive pairs are those within the same cluster, and negative pairs are those in different clusters [96].

For an anchor view, once the positive pairs are determined, the remaining views can naturally be considered as negative views, which can be paired with the given view to create negative pairs, allowing for pushing away. Therefore, in the subsequent discussion on different methods of pair sampling, we primarily focus on the construction of positive pairs.

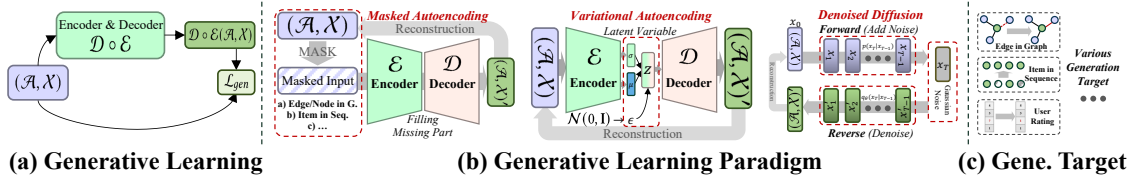


Fig. 3. Taxonomy of Generative Learning in Recommender Systems.

3.1.3 Contrastive Objective. The learning objective in contrastive learning is to maximize the mutual information between positive views, which, in turn, leads to improved performance in learning recommender models. Since directly calculating mutual information is not feasible, a tractable lower bound is commonly used as the learning objective in contrastive learning [2]. However, there are also explicit objectives that directly pull positive views closer together.

- **InfoNCE-based Objective:** InfoNCE [97], a variant of Noise Contrastive Estimation [32], has gained wide adoption as a learning objective in the field of contrastive learning for recommendation systems. The mathematical formulation of InfoNCE can be expressed as follows:

$$\mathcal{L} = \mathbb{E} \left[-\log \frac{\exp(f(\omega'_i, \omega''_i))}{\sum_{\forall i, j} \exp(f(\omega'_i, \omega''_j))} \right] \quad (5)$$

Here, $f(\cdot)$ represents a critic function that calculates a score indicating the similarity between two views. The term $f(\omega'_i, \omega''_i)$ corresponds to the score of positive pairs, while the term $\sum \exp(f(\omega'_i, \omega''_j))$ encompasses both the numerator and the scores of all negative pairs. By optimizing this, the $f(\cdot)$ will learn to assign higher values to positive pairs. This process aims to bring the positive pairs closer together and push the negative pairs apart.

- **JS-based Objective:** In addition to using InfoNCE estimation for mutual information, the lower bound can also be estimated using the Jensen-Shannon (JS) divergence [37, 49]. The derived learning objective is akin to combining InfoNCE with a standard binary cross-entropy loss [167], applied to positive pairs and negative pairs:

$$\mathcal{L} = \mathbb{E}[-\log \sigma(f(\omega'_i, \omega''_i))] - \mathbb{E}[\log(1 - \sigma(f(\omega'_i, \omega''_j)))] \quad (6)$$

Here, σ represents the sigmoid function used to normalize the output of the critic function. The main idea behind this optimization is to assign the label 1 to positive pairs and 0 to negative pairs, thereby increasing the predicted value for positive pairs and enhancing the similarity between them.

- **Explicit Objective:** Both InfoNCE-based and JS-based objectives maximize the estimated lower bound of mutual information to maximize mutual information itself, which is theoretically guaranteed. Additionally, there are explicit objectives, such as minimizing Mean Square Error or maximizing cosine similarity between samples within a positive pair, that directly align positive pairs. These objectives are referred to as explicit objectives.

3.2 Generative Learning in Recommendation

In generative self-supervised learning (GL), the primary objective is to maximize the likelihood estimation of the real data distribution. This allows the learned meaningful representations to capture the underlying structure and patterns in the data, which can then be utilized for downstream tasks. In our taxonomy, we consider two aspects to differentiate various recommendation methods with GL: generative learning paradigm and generation target.

3.2.1 Learning Paradigm. In the context of recommendation, self-supervised methods employing generative learning can be classified into three paradigms: Masked Autoencoding, Variational Autoencoding and Denoised Diffusion.

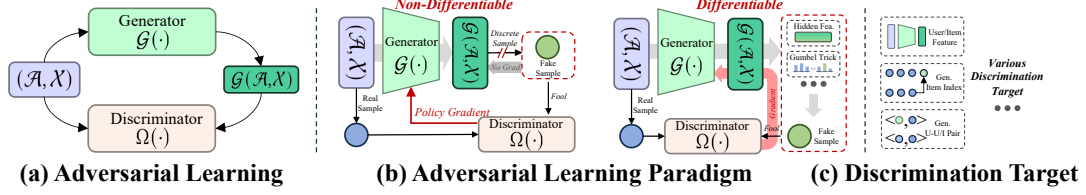


Fig. 4. Taxonomy of Adversarial Learning in Recommender Systems.

- Masked Autoencoding:** In masked autoencoders, the learning process follows a mask-reconstruction approach, where the model reconstructs complete data from partial observations [35]. In recommender systems, data can be in item sequences or user-item interaction graphs, each requiring specific masking techniques. For item sequences, certain items are randomly masked and fed into a transformer model to encode representations and reconstruct masked item features [119]. For graph data, masking occurs at the edge or node level. In GraphMAE [38], node features are masked for reconstruction, while in MaskGAE [63], edges are masked. This masking practice is common in generative self-supervised learning recommender models.
- Variational Autoencoding:** The variational autoencoder [51] is another generative approach that maximizes the likelihood estimation with theoretical guarantees. Typically, it involves mapping the input data to latent factors that follow a normal Gaussian distribution. Subsequently, the model reconstructs the input data based on sampled latent factors. Naturally, during the optimization process of VAE-based models, the learned latent factors are regularized using KL-divergence to enforce them to follow a Gaussian distribution. In self-supervised learning methods employing variational autoencoders, the latent factors may further be regulated through additional approaches, such as enhancing distinguishability through adversarial learning or contrastive learning [146].
- Denoised Diffusion:** Denoising Diffusion is a generative model that generates new data samples by reversing a noising process. In the forward process, Gaussian noise is added to the original data in multiple steps, creating a sequence of noisy versions. In the reverse process, the model learns to remove the noise from the noisy versions, recovering the original data step by step. The model is trained to denoise the data at each step, learning to capture minor changes in the complex generation process. The diffusion model has recently been introduced into the recommendation for processing data like graphs [48] or user interactions [144].

3.2.2 **Generation Target.** What pattern of the data will be considered as the label for generation in generative learning is yet another thing that needs to be considered to bring meaningful auxiliary self-supervised signals. In general, the generation target can vary for different methods and also in different recommendation scenarios. For instance, in sequential recommendation, the generation target can be the item in the sequence [113, 119], in order to model the relationships within the item sequence. For recommendation with interaction graph, the generation target can be the node/edge in the graph [61, 162], in order to capture high-level topological relevance in the graph.

3.3 Adversarial Learning in Recommendation

In the context of adversarial learning (AL) in recommender systems, the discriminator plays a crucial role in distinguishing between generated fake samples and real samples. Similar to generative learning, we propose our taxonomy that encompasses AL in recommender systems from both the learning paradigm and discrimination target perspectives:

3.3.1 **Learning Paradigm.** In recommender systems, AL consists of two different paradigms, depending on whether the discriminative loss from the discriminator can be backpropagated to the generator in a differentiable way.

- **Differentiable AL** The first approach involves objects represented as features in continuous space, where the gradient from the discriminator can naturally backpropagate to the generator for optimization. This method is known as differentiable adversarial learning. Here, the optimization loss aligns directly with the general learning objective in Equation (4) using a neural network-based discriminator. The discriminated objects vary depending on the method, such as latent representations from a variational autoencoder’s forward process, output features from a Transformer model, or generated user-item interaction matrices. As the quality of the generated content improves, the recommender system’s performance is simultaneously enhanced.
- **Non-differentiable AL** Another approach involves discriminating the output of the recommender system, specifically the recommended items. However, since the recommended results are discrete, back-propagation becomes challenging, creating a non-differentiable situation where the gradient of the discriminator cannot be directly propagated to the generator [138, 215]. To address this, reinforcement learning with policy gradient is incorporated [121]. In this scenario, the generator acts as an agent that interacts with the environment by predicting the next item based on previously interacted items. The discriminator serves as the reward function, providing a reward signal to guide the generator’s learning. The rewards from the discriminator are defined to emphasize different factors influencing recommendation quality, and it is optimized to assign higher rewards to true samples over generated ones, guiding the generator to produce high-quality recommendations.

3.3.2 **Discrimination Target.** Different recommendation algorithms lead to the generation of different inputs by the generator, which are then fed to the discriminator for discrimination. This process aims to enhance the generator’s ability to generate high-quality content, thereby approaching the ground truth. The specific discrimination objectives are designed based on the particular recommendation task. For instance, in the sequential recommendation, the discriminator may be employed to discriminate generated next-items [88] or the entire sequence. In other domains, the discriminator may supervise the quality of generated data or optimize the hidden features of the model [118, 209].

4 SELF-SUPERVISED LEARNING FOR RECOMMENDATION

The study of recommendation algorithms encompasses a variety of scenarios. In this paper, we conducted a survey specifically addressing ten scenarios utilizing self-supervised learning: General Collaborative Filtering, Sequential Recommendation, Social Recommendation, Knowledge-aware Recommendation, Cross-domain Recommendation, Group Recommendation, Bundle Recommendation, Multi-behavior Recommendation, and Multi-modal Recommendation.

4.1 General Collaborative Filtering

4.1.1 **Task Formulation.** In General Collaborative Filtering (CF), there is no additional observed data \mathcal{X} , in which the model solely relies on user-item interactions \mathcal{A} to generate personalized recommendations for uninteracted items.

4.1.2 **Contrastive Learning in CF.** Contrastive learning, as highlighted in Table 1, encompasses various SSL-based methods in collaborative filtering. These methods intelligently leverage user-item interaction data to generate diverse contrast views, facilitating effective learning in the recommendation system.

- **View Creation** in CL-based collaborative filtering covers diverse paradigms. (i) *Data-based View Creation.* Existing works employ different augmentation techniques to create views of the data for contrastive learning. For example, Liu *et al.*[84] and methods like SGL[156] and SelfCF [219] use edge/node dropout to augment the user-item graph. RGCF [127] incorporates graph structure learning to generate two different graph views, such

Table 1. A summary of SSL recommendation methods in **General Collaborative Filtering** (Part 1). For alphabets in "Category", CL means Contrastive Learning; GL means Generative Learning; AL means Adversarial Learning

General Collaborative Filtering (CF)						
Category	Method Information			Self-supervised Learning Paradigm		
	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
CL	Liu <i>et al.</i> [84]	2021	arXiv	Data-based	Natural	InfoNCE-based
	SimpleX [94]	2021	CIKM	Model-based	Natural	Explicit-based
	EGLN [183]	2021	SIGIR	Data & Model-based	Natural	JS-based
	SGL [156]	2021	SIGIR	Data-based	Natural	InfoNCE-based
	BiGI [8]	2021	WSDM	Data & Model-based	Natural	JS-based
	GDCL [208]	2022	DASFAA	Model-based	Natural	InfoNCE-based
	DirectAU [135]	2022	KDD	Model-based	Natural	Explicit
	SHT [164]	2022	KDD	Model-based	Score-based	Explicit
	HCCF [163]	2022	SIGIR	Model-based	Natural	InfoNCE-based
	RGCF [127]	2022	SIGIR	Data-based	Natural	InfoNCE-based
	SimGCL [197]	2022	SIGIR	Feature-based	Natural	InfoNCE-based
	NCL [73]	2022	WWW	Model-based	Natural	InfoNCE-based
	LightGCL [6]	2023	ICLR	Data-based	Natural	InfoNCE-based
	AdaGCL [47]	2023	KDD	Data-based	Natural	InfoNCE-based
	AdvInfoNCE [202]	2023	NeurIPS	Model-based	Natural	InfoNCE-based
	AdaMCL [221]	2023	SIGIR	Data-based	Natural	InfoNCE-based
	CGCL [36]	2023	SIGIR	Model-based	Natural	InfoNCE-based
	DCCF [110]	2023	SIGIR	Model-based	Natural	InfoNCE-based
	uCTRL [57]	2023	SIGIR	Model-based	Natural	Explicit
	VGCL [184]	2023	SIGIR	Data-based	Natural & Score-based	InfoNCE-based
	XSimGCL [193]	2023	TKDE	Feature-based	Natural	InfoNCE-based
	RocSE [186]	2023	TOIS	Data-based	Natural	InfoNCE-based
	SelfCF [219]	2023	TORS	Data & Feature-based	Natural	Explicit
	DENS [56]	2023	WSDM	Model-based	Natural	Explicit
SGCCL [59]	2023	WSDM	Data-based	Natural	InfoNCE-based	
RecDCL [204]	2024	WWW	Data & Model-based	Natural	Explicit	

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as a denoised graph and a diversity graph. Similar ideas are also utilized in EGLN [183]. AdaMCL [221] and SGCCL [59] create user-user and item-item graphs based on the data and then encode views for users and items. LightGCL [6] created another user-item graph based on SVD decomposition that captures global relationship modeling. Recently, RecDCL [204] interpolates historical and current embeddings to obtain augmented views for batch contrastive learning (ii) *Feature-based View Creation*. In collaborative filtering, various feature-based augmentations involve adding noise to node features during model inference. Methods such as SimGCL [197] and XSimGCL [193] introduce controllable random noise to node embeddings during message passing, thereby creating noised views of nodes. Another approach, RocSE [186], employs embedding perturbation techniques inspired by adversarial attacks to generate different embedding views. (iii) *Model-based View Creation*. Different methods also employ various neural modules to create views. On one hand, SimpleX [94], DirectAU [135], RecDCL-FCL [204], CGCL [36], AdvInfoNCE [203], uCTRL [57] and XSimGCL [193] directly utilize the encoded user/item embeddings from models as views. On the other hand, some methods incorporate carefully designed neural modules to encode views from different perspectives. For example, EGLN [183] and BiGI [8] focus on global representation fusion. GDCL [208] approximates diffusion models on graphs. HCCF [163] and SHT [164] employ hypergraph global encoding. DCCF [110] explores intent disentanglement. NCL [73] and CGCL [36]

Table 2. A summary of SSL recommendation methods in **General Collaborative Filtering** (Part 2).

General Collaborative Filtering (CF)					
Category	Method Information			Self-supervised Learning Paradigm	
	Method	Venue	Year	Generative Learning Paradigm	Generation Target
GL	CVAE [68]	2017	KDD	Variational Autoencoding	User Rating & Item Content
	Mult-VAE [71]	2018	WWW	Variational Autoencoding	User Rating to Items
	MacridVAE [89]	2019	NeurIPS	Variational Autoencoding	User Rating to Items
	RecVAE [116]	2020	WSDM	Variational Autoencoding	User Rating to Items
	BiVAE [129]	2021	WSDM	Variational Autoencoding	User-Item Interactions
	FastVAE [13]	2022	WWW	Variational Autoencoding	User Rating to Items
	MD-CVAE [222]	2022	WWW	Variational Autoencoding	User Rating & Item Content
	SE-VAE [19]	2022	WWW	Variational Autoencoding	User Rating to Items
	CaD-VAE [142]	2023	SIGIR	Variational Autoencoding	User Rating to Items
	DiffRec [144]	2023	SIGIR	Denosing Diffusion	User Rating to Items
	GFormer [61]	2023	SIGIR	Masked Autoencoding	Edge in User-Item Graph
	AutoCF [162]	2023	WWW	Masked Autoencoding	Edge in User-Item Graph
	Method	Year	Venue	Adversarial Learning Paradigm	Discrimination Target
AL	IRGAN [138]	2017	SIGIR	Non-differentiable	Item Index
	CFGAN [11]	2018	CIKM	Differentiable	User Purchase Vector
	Krishnan <i>et al.</i> [55]	2018	CIKM	Non-differentiable	Popular-niche Item Pair
	ABinCF [136]	2019	AAAI	Differentiable	Item Index
	AugCF [141]	2019	KDD	Differentiable	User-Item-Rating Tuple
	RAGAN [10]	2019	WWW	Differentiable	User Purchase Vector
	Conv-GCF [200]	2020	CIKM	Differentiable	Latent Interaction Map

incorporate diverse neighbor view discovery. VGCL [184] utilizes variational latent space sampling. DENS [56] incorporates item factor encoding. Recently, AdaGCL [47] designed a graph generative model and a graph denoising model to create adaptive contrastive views.

- **Pair Sampling** in this scenario includes both natural sampling and also score-based sampling. (i) *Natural Sampling*. Most of the works in collaborative filtering follow natural sampling of positive samples for the anchor views to create positive pairs. There are three common situations for natural sampling in CF. Firstly, when the model encodes multiple views for one user/item, any two of these views can form a pair [6, 110, 156, 163, 197]. Secondly, the views from the interacted user and item can form a pair [57, 135, 203]. Lastly, by considering the relevant/irrelevant factor relationship with user-item interaction, pairs of views can be naturally formed [56]. (ii) *Score-based Sampling*. SHT calculates edge solidity scores and samples pairs of edges for learning. VGCL clusters users/items based on embedding similarity and pairs users from the same cluster.
- **Contrastive Objective** utilizes InfoNCE-based or JS-based objectives to optimize mutual information. Notably, AdvInfoNCE improves the weighting of negative pairs in InfoNCE by incorporating hardness scores learned through a min-max game. Some methods explicitly design loss functions to enhance the similarity between positive pairs. This can be achieved through cosine similarity optimization [56, 94, 219], alignment/uniformity regularization [57, 135, 204], or by explicitly regulating the score difference between pairs [164].

4.1.3 Generative Learning in CF. In collaborative filtering, certain self-supervised learning (SSL) methods leverage generative learning techniques (as indicated in Table 2) to reconstruct user-item interactions. This approach allows them to obtain self-supervised signals that aid in the learning process of the model.

- **Generative Learning Paradigm** in self-supervised learning CF has evolved from variational autoencoding to masked autoencoding and denoised diffusion. (i) *Variational Autoencoding*. Different VAE-based methods in self-supervised learning CF adopt various perspectives to improve the model. For instance, CVAE [68] and MD-CVAE [222] incorporate item content information to regulate the collaborative latent variable modeling. RecVAE [116] follows the general paradigm in Mult-VAE [71] but introduces a novel composite prior distribution and a new approach to setting hyperparameters. MacridVAE [89] and CaD-VAE [142] focus on modeling the latent factor behind interactions to capture the latent variable distribution. BiVAE [129] extends the VAE paradigm to symmetrically generate user-item interactions. FastVAE [13] enhances model efficiency with inverted multi-index. SE-VAE [19] extends latent variable modeling with multi-experts and stochastic expert selection. (ii) *Masked Autoencoding*. Both AutoCF [162] and GFormer [61] adopt the mask-reconstruction paradigm, where they automatically identify valuable edges (user-item interactions) in the graph and reconstruct them using the learned user/item representations. (iii) *Denoised Diffusion*. DiffRec [144] has introduced the diffusion model into collaborative filtering. This method leverages diffusion to denoise perturbed user ratings or latent variables, which helps mitigate the high resource costs associated with large-scale item prediction.
- **Generation Target**. Both VAE-based methods [13, 19, 71, 89, 116, 142] and diffusion-based methods [144] share a similar auto-encoding architecture. In these methods, the user ratings to items, typically represented as vectors, serve as the generation target for the model. However, some VAE-based methods like CVAE and MD-CAE also generate item content to achieve hybrid generation. BiVAE adopts a symmetric approach by modeling the user and item latent variables, with user-item interactions as the generation target. On the other hand, in graph-based methods [61, 162], valuable edges in the graph are masked and then reconstructed.

4.1.4 **Adversarial Learning in CF**. Collaborative filtering methods also leverage adversarial learning (as shown in Table 2) to improve recommendation indices, user ratings, or even perform data augmentation. These methods optimize the model with discriminator and enhance the overall performance of collaborative filtering systems.

- **Adversarial Learning Paradigm** in collaborative filtering encompasses both non-differentiable and differentiable training approaches. IRGAN [138] introduced the idea of GANs into recommendation systems, sampling item indices from the generator for discrimination. However, the discrete nature of these item indices prevents the gradient from the discriminator from propagating to the generator for optimization. To overcome this issue, IRGAN employs policy gradient techniques, which are also adopted by Krishnan *et al.* [55]. In the context of differentiable adversarial training, several methods such as CFGAN [11], RAGAN [10], and Conv-GCF [200] feed the generated continuous real-valued variables into the discriminator. On the other hand, ABinCF [136] and AugCF [141] use the Gumbel trick to approximate sampling, enabling end-to-end adversarial training.
- **Discrimination Target** varies across different methods in collaborative filtering. IRGAN samples the indices of items relevant to a given user for discrimination and ABinCF follows the similar paradigm but makes the parameters of generator binary codes for efficiency. Additionally, CFGAN improves IRGAN by enabling gradient back-propagation through discriminating the user purchase vector generated by the generator. RAGAN extends this further by incorporating low ratings for items in the user purchase vector to address biased predictions. Krishnan *et al.* [55] leverage popular-niche item pairs for discrimination to improve long-tail recommendation. AugCF treats each user-item-rating tuple as a sample for the discriminator, while Conv-GCF encodes the latent interaction map of a user-item pair using a convolutional neural network for further discrimination. These methods employ different approaches to enhance recommendation performance in collaborative filtering.

Table 3. A summary of SSL recommendation methods in **Sequential Recommendation** (Part 1).

Sequential Recommendation (SeqRec)						
Category	Method Information			Self-supervised Learning Paradigm		
	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
CL	S3-Rec [218]	2020	CIKM	Data-based	Natural	InfoNCE-based
	Ma <i>et al.</i> [90]	2020	KDD	Data & Model-based	Natural	InfoNCE-based
	DHCN [167]	2021	AAAI	Model-based	Natural	JS-based
	CoSeRec [82]	2021	ArXiv	Data-based	Natural	InfoNCE-based
	CCL [3]	2021	CIKM	Data-based	Natural	InfoNCE-based
	COTREC [166]	2021	CIKM	Model-based	Score-based	InfoNCE-based
	H2SeqRec [70]	2021	CIKM	Data-based	Natural & Score-based	InfoNCE-based
	CLUE [18]	2021	ICDM	Data & Model-based	Natural	Explicit
	MMInfoRec [102]	2021	ICDM	Model-based	Natural	InfoNCE-based
	SSI [201]	2021	IJCAI	Data-based	Natural	InfoNCE-based
	ACVAE [174]	2021	WWW	Feature-based	Natural	JS-based
	CBiT [22]	2022	CIKM	Data-based	Natural	InfoNCE-based
	ContrastVAE [146]	2022	CIKM	Model-based	Natural	InfoNCE-based
	EC4SRec [139]	2022	CIKM	Data-based	Natural	InfoNCE-based
	MCLSR [147]	2022	CIKM	Model-based	Natural	InfoNCE-based
	MIC [96]	2022	CIKM	Data & Feature-based	Score-based	InfoNCE-based
	TCPSRec [126]	2022	CIKM	Data-based	Natural	InfoNCE-based
	CL4SRec [172]	2022	ICDE	Data-based	Natural	InfoNCE-based
	DCAN-PSSL [140]	2022	ICDE	Model-based	Natural	Explicit
	MISS [30]	2022	ICDE	Model-based	Score-based	InfoNCE-based
	GCL4SR [212]	2022	IJCAI	Data & Model-based	Natural	InfoNCE-based
	DCN [72]	2022	SIGIR	Data-based	Natural	Explicit
	DuoRec [103]	2022	WSDM	Model-based	Score-based	InfoNCE-based
	ICLRec [16]	2022	WWW	Data & Model-based	Natural	InfoNCE-based
	TiCoSeRec [20]	2023	AAAI	Data-based	Natural	InfoNCE-based
	ECCGAN-Rec [95]	2023	IPM	Data & Model-based	Natural	Explicit
	FDSA_CL [33]	2023	TKDE	Model-based	Natural	InfoNCE-based
	ContraRec [134]	2023	TOIS	Data-based	Natural	InfoNCE-based
	MrTransformer [91]	2023	TOIS	Model-based	Score-based	Explicit
	IOCREC [69]	2023	WSDM	Data & Model-based	Natural	InfoNCE-based
DCRec [181]	2023	WWW	Model-based	Natural	InfoNCE-based	
Meta-SGCL [34]	2024	ICDE	Model-based	Natural	InfoNCE-based	
Liu <i>et al.</i> [81]	2024	SIGIR	Model-based	Natural	Explicit	
ICSRec [101]	2024	WSDM	Model-based	Natural	InfoNCE-based	

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4.2 Sequential Recommendation

4.2.1 Task Formulation. In sequential recommendation (SeqRec), user-item interactions are recorded with timestamps, establishing a temporal order. Each user has a specific temporal sequence of engaged items denoted as $s_u = (v_1, v_2, \dots, v_T)$, where T represents the sequence length. The objective is to predict the next item (v_{T+1}) based on the past item sequence. In anonymous user scenarios, only item sequences are available, known as session recommendation.

4.2.2 Contrastive Learning in SeqRec. Contrastive learning sequential recommendation comprises the majority of self-supervised SeqRec methods (as indicated in Table 3). These methods leverage the sequential data to generate diverse views through techniques such as augmentation or neural modules.

Table 4. A summary of SSL recommendation methods in **Sequential Recommendation** (Part 2).

Sequential Recommendation (SeqRec)					
Category	Method Information			Self-supervised Learning Paradigm	
	Method	Venue	Year	Generative Learning Paradigm	Generation Target
GL	BERT4Rec [119]	2019	CIKM	Masked Autoencoding	Item in Sequence
	SVAE [113]	2019	CIKM	Variational Autoencoding	Item in Sequence
	PTUM [154]	2020	EMNLP	Masked Autoencoding	Behavior in Sequence
	PeterRec [199]	2020	SIGIR	Masked Autoencoding	Item in Sequence
	U-BERT [104]	2021	AAAI	Masked Autoencoding	Words in Review
	BiCAT [46]	2021	arXiv	Masked Autoencoding	Item in Sequence
	ShopperBERT [117]	2021	arXiv	Masked Autoencoding	Item in Sequence
	UPRec [168]	2021	arXiv	Masked Autoencoding	Item in Sequence
	VSAN [214]	2021	ICDE	Variational Autoencoding	Item in Sequence
	ASReP [83]	2021	SIGIR	Masked Autoencoding	Item in Sequence
	CBiT [22]	2022	CIKM	Masked Autoencoding	Item in Sequence
	ContrastVAE [146]	2022	CIKM	Variational Autoencoding	Item in Sequence
	DiffuASR [75]	2023	CIKM	Denoised Diffusion	Augmented Item Sequence
	Diff4Rec [161]	2023	MM	Denoised Diffusion	User-Item Interaction
	MAERec [187]	2023	SIGIR	Masked Autoencoding	Edge in Graph
	Method	Year	Venue	Adversarial Learning Paradigm	Discrimination Target
AL	AOS4Rec [215]	2020	IJCAI	Non-differentiable	Item
	MFGAN [107]	2020	SIGIR	Non-differentiable	Feature of Sequence
	SAO [93]	2020	SIGIR	Differentiable	Feature of Sequence
	SRecGAN [87]	2021	DASFAA	Differentiable	Ranking Score
	SSRGAN [88]	2021	DASFAA	Differentiable	Item
	ACVAE [174]	2021	WWW	Differentiable	Feature of Sequence
	ECGAN-Rec [95]	2023	IPM	Differentiable	Feature of Sequence

- **View Creation** in SeqRec includes data-based, feature-based, and model-based methods. (i) *Data-based View Creation*. Given that the input data is in a sequential format, numerous methods employ sequence augmentation techniques to generate diverse views of the input item sequence. In general, early works [70, 82, 117, 172, 218] propose non-heuristic and random augmentation methods including Crop, Mask, Reorder, Shuffle, Substitute, and Insert to obtain different input sequences as different views. TiCoSeRec [20] goes a step further by incorporating temporal information and introducing five operators (e.g., Ti-Crop and Ti-Reorder). These operators are designed to transform the input sequence into a uniform representation while taking into account the variations in time intervals. In EC4SRec [139], importance scores are calculated for each item in a sequence, which is then utilized to guide heuristic and explanation-driven operations for generating informative views. In addition to these methods, several data-based approaches consider constructing additional data resources such as item-item transition graphs [181, 212], item co-interaction [181], and user sequences for each item [72] to obtain diverse viewpoints. (ii) *Feature-based View Creation*. Feature-based methods employ various augmentation on the encoded features for view creation. For instance, ACVAE [174] utilizes variational auto-encoders to encode latent features of item sequences. It then shuffles these latent features to generate different negative views of the sequence. Additionally, MIC [96] applies random dropout on the encoded features, resulting in two distinct views of user/item representation for contrastive learning. (iii) *Model-based View Creation*. Model-based view creation in SeqRec encompasses two distinct approaches. The first approach involves constructing specific neural modules to encode views of interest, such as intent-aware representation [16, 90, 101], hypergraph representation [167], item

attributes representation [33], variational Transformer [34], long-short term representations [81] and utilizing graph neural networks and to encode embeddings from auxiliary graphs [72, 147, 181]. The second approach involves applying techniques such as random dropout [18, 102, 103, 146] on the model parameters to generate different outputs as distinct views.

- **Pair Sampling** in SeqRec has both natural sampling and score-based heuristic sampling. (i) *Natural Sampling*. In most cases in SeqRec, natural sampling methods [3, 22, 82, 139, 172, 212, 218] naturally considering the generated views from the same item sequences as positive views and otherwise negative views. In addition, there are other natural pairing relations utilized in SeqRec. For instance, methods like SSI [201], TCPSRec [126], and DCRec [181] construct positive pairs using various combinations, such as pairing a single item or a sub-sequence with the whole sequence it belongs to. Besides, ICSRec [101] uses clustering to generate intent prototypes and aligns the intent view with related prototypes for fine-grained intent CL. (ii) *Score-based Sampling*. Compared to natural sampling, score-based sampling utilizes necessary calculate to determine the positive pair. COTREC [166] combines the last-clicked item with the predicted next item to form a positive pair. H2SeqRec [70], DuoRec [103], and MrTransformer [91] employ sequence overlap as a metric to determine positive pairs. MIC [96] first applies k-means clustering to group samples, and then samples within the same group form positive pairs. Similarly, MISS [30] employs item embedding distance as a metric to sample positive pairs with varying probabilities.
- **Contrastive Objective** in SeqRec typically adopts an InfoNCE-based objective to maximize the mutual information between positive pairs. However, in methods such as DHCN [167] and ACVAE [174], a JS-based objective is utilized for optimization. Furthermore, several algorithms incorporate explicit loss functions to contrast data samples. The fundamental concept behind these methods is to encourage the proximity of samples within positive pairs. CLUE [18] leverages cosine similarity to minimize the distance between embeddings within a positive pair. DCAN-PSSL [140] and ECGAN-Rec [95] aim to minimize the estimated probability distribution of the next item. DCAN-PSSL uses KL/JS-divergence minimization, while ECGAN-Rec minimizes the numerical differences between the distributions. DCN [72] and MrTransformer [91] both minimize the squared error between two embeddings within a positive pair for optimization purposes. Liu *et al.* [81] explicitly align the pairwise likelihood difference scores of two edges' long- and short-term node embeddings for denoising.

4.2.3 **Generative Learning in SeqRec.** Generative learning plays a significant role in sequential recommendation (as demonstrated in Table 4). These methods primarily focus on generating sequence item data or user-item graphs to provide auxiliary signals, effectively enhancing the recommendation process.

- **Generative Learning Paradigm** in SeqRec predominantly follows the approach of mask-autoencoding. For instance, BERT4Rec [119] initially attempts to randomly mask an item within the item sequence. Then, it proceeds with the encoding process using a transformer and aims to reconstruct the masked item. Given that using transformers for modeling item sequence data [50] in SeqRec is a prevalent choice, the natural approach of mask-autoencoding with transformers has become a primary form in subsequent works [22, 46, 83, 117, 154, 168, 199]. Furthermore, MAERec [187] adopts the concept of mask-autoencoding from graph data [39, 64] to enhance the representation learning of items. Another notable approach in generative modeling is seen in SVAE [113], which leverages variational auto-encoding as a backbone. This method utilizes recurrent neural network to encode sequential records into latent variables that follow the normal distribution and subsequently generate the next-item with a re-parametrization trick [52]. This line of work is further extended by methods like VSAN [214] and ContrastVAE [146] by incorporating self-attention modules or contrastive learning on latent variables.

Recently, denoised diffusion has emerged as a promising paradigm in sequential recommendation (SeqRec) due to its strong generation capabilities. Both DiffuASR [75] and Diff4Rec [161] leverage diffusion generation to create high-quality data, which in turn enhances the training of recommendation models through data augmentation.

- **Generation Target** in SeqRec with generative learning exhibits a diverse range of approaches. In general, several works [22, 46, 83, 113, 117, 146, 168, 199, 214] follow the initial step of BERT4Rec, which involves masking and reconstructing the items within the sequence. PTUM considers the behavior sequence of users as the target for generation, aiming to effectively model user behavior patterns for recommendation purposes. On the other hand, U-BERT focuses on generating user reviews for items to capture user behaviors and enhance recommendations, particularly in content-insufficient domains. Recently, MAERec has incorporated the concept of mask-autoencoding from the graph domain. It utilizes this approach to generate paths in the item transition graph, effectively pre-training item embeddings for improved sequential recommendation performance. For diffusion-based methods, DiffuASR generates augmented item sequences to enrich sparse data for model training, while Diff4Rec pre-trains a diffusion model by corrupting and reconstructing user-item interactions in the latent space, which are then used to produce diverse augmentations for sparse user-item interactions.

4.2.4 Adversarial Learning in SeqRec. Adversarial learning in SeqRec (as shown in Table 4) employs various strategies, leveraging encoded features, ranking scores, and historical data to train discriminators in distinguishing between real and generated item sequences, while optimizing generators to produce realistic recommendations.

- **Adversarial Learning Paradigm** in SeqRec encompasses differential and non-differential methods. Differential methods, such as SAO [93], SRecGAN [87], ACVAE [174], and ECGAN-Rec [95], utilize continuous operations for gradient propagation and avoid discrete sampling. SSRGAN [88] employs Gumble-Softmax for differentiable sampling to overcome gradient blocking. In non-differential methods, reinforcement learning optimizes the generator’s parameters after generating items through non-differentiable sampling and feeding them to the discriminator. AOS4Rec [215] employs the WGAN [1] concept for simultaneous optimization and the actor-critic algorithm [53] for stable training, while MFGAN [107] uses policy gradients to improve generator predictions using the discriminator’s score as a reward.
- **Discrimination Target** exhibits a wide range of diversity within SeqRec when employing adversarial learning. Various approaches, such as MFGAN, SAO, ACVAE, and ECGAN-Rec, employ encoded features derived from the item sequence, which are then fed into the discriminator. The discriminator’s role is to determine whether the item sequence is real or generated by the generator. Besides, the discrimination target in SRecGAN is the ranking score of items, where the score difference between positive and negative items generated by the generator deceives the discriminator. The discriminator is also optimized using ground truth data with an ideal score difference, aiming to force the generator to assign higher values to positive pairs. In AOS4Rec, the discriminator calculates the score by considering the history item along with the sampled next-item. It assigns a higher value to the real item sequence. A similar concept is demonstrated in SSRGAN, but it utilizes differential sampling to circumvent the involvement of reinforcement learning.

4.3 Social Recommendation

4.3.1 Task Formulation. In social recommendation (SocRec), recommender systems are enhanced with side information that unveils the social relationships among users. The auxiliary observed data \mathcal{X} in social recommendation is commonly represented as a user-user interaction graph \mathcal{G}_{soc} . In this graph, each interaction indicates the existence of

Table 5. A summary of SSL recommendation methods in **Social Recommendation** and **Knowledge-aware Recommendation**.

Social Recommendation (SocRec)						
Category	Method Information			Self-supervised Learning Paradigm		
	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
CL	KCGN [41]	2021	AAAI	Model-based	Natural	JS-based
	SMIN [86]	2021	CIKM	Model-based	Natural	JS-based
	SEPT [194]	2021	KDD	Data-based	Score-based	InfoNCE-based
	MHCN [196]	2021	WWW	Data-based	Natural	Explicit
	DeRec [155]	2022	CIKM	Data-based	Natural	InfoNCE-based
	SDCRec [23]	2022	SIGIR	Model-based	Score-based	InfoNCE-based
	DUAL [124]	2022	TCSS	Data-based	Score-based	InfoNCE-based
	DSL [143]	2023	IJCAI	Model-based	Natural	Explicit
	ReACL [45]	2023	Inf. Sci.	Data-based	Score-based	InfoNCE-based
	HGCL [14]	2023	WSDM	Model-based	Natural	InfoNCE-based
	Method	Venue	Year	Adversarial Learning Paradigm		Discrimination Target
AL	Adit <i>et al.</i> [54]	2019	CIKM	Non-differentiable		Sampled User-User Pair
	RSGAN [192]	2019	ICDM	Differentiable		Generated Item
	DASO [24]	2019	IJCAI	Non-differentiable		Sampled User-User/Item Pair
	ESRF [195]	2022	TKDE	Differentiable		Sampled Neighbor Users
Knowledge-aware Recommendation (KnoRec)						
Category	Method Information			Self-supervised Learning Paradigm		
	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
CL	CKER [98]	2022	Mathematics	Model-based	Natural	InfoNCE-based
	KGIC [224]	2022	CIKM	Data-based	Score-based	InfoNCE-based
	KGCL [182]	2022	SIGIR	Data-based	Natural	InfoNCE-based
	MCCLK [223]	2022	SIGIR	Model-based	Natural	InfoNCE-based
	KRec-C2 [99]	2023	DASFAA	Model-based	Natural	InfoNCE-based
	ML-KGCL [12]	2023	DASFAA	Model-based	Natural	InfoNCE-based
	HiCON [153]	2023	ICME	Data-based	Natural	InfoNCE-based
	KACL [137]	2023	WSDM	Model-based	Natural	InfoNCE-based
	Method	Venue	Year	Generative Learning Paradigm		Generation Target
GL	KGRec [180]	2023	KDD	Maksed Autoencoding		Triplets in the KG
	DiffKG [48]	2024	WSDM	Denosing Diffusion		Triplets in the KG

a social relationship (e.g., friendship) between two users. The objective in SocRec is similar to general collaborative filtering: to recommend unexplored items to users by considering both collaborative and social information.

4.3.2 Contrastive Learning in SocRec. Contrastive learning has become a significant approach in social recommendation, as demonstrated in Table 5. By leveraging social relationship data, various contrastive views are generated, and mutual information is optimized through carefully designed pair-sampling strategies and objective functions.

- **View Creation** in SocRec with CL can be categorized as data-based or model-based. The model-based approach emphasizes designing neural modules to encode features from social and collaborative data for contrastive views. Examples include KCGN [41] using behavior and temporal-aware networks, and SMIN [86] and SDCRec [23] employing heterogeneous GNNs while considering social relationships. DSL [143] utilizes GNNs for encoding distinct social-aware and collaborative-aware user embeddings. Conversely, data-based methods augment original graphs to generate diverse context-specific data. SEPT [194] creates three graph views (preference, friend, and

sharing) from user-item and user-user graphs, while MHCN [196] generates hypergraphs among users using triangle motifs and applies hypergraph convolution. DcRec [155] diversifies views through edge addition and node/edge dropout, and ReACL [45] constructs additional graphs using relationship-aware augmentation. In HGCL [14], a personalized knowledge transfer meta network encodes enhanced user and item representations for one view, while a lightweight GCN encodes another view for users/items.

- **Pair Sampling** in SocRec is designed based on the encoded nature of the created views. In natural sampling methods, a user or item may have multiple views. For instance, KCGN and MHCN pair node embeddings with their encoded sub-graph or hypergraph embeddings, considering the local-global relationship. Furthermore, several methods [14, 86, 143, 155] encode multiple views for each node using graph augmentation or neural model design, treating the views of the same node as positive pairs. For score-based sampling, SEPT, SDCRec and ReACL label positive pairs by considering the representation similarly, and DUAL pre-computed a link-score for each edge in the graph based on the degree of the node, which is then utilized to choose positive pairs.
- **Contrastive Objective** in these methods commonly relies on InfoNCE-based [14, 23, 45, 124, 155, 194] or JS-based objectives [41, 86]. Notably, ReACL [45] introduces an Aug-InfoNCE contrastive loss, leveraging an expanded set of positive samples to improve consistency among similar nodes and enhance the framework’s generalization capability. In explicit optimization methods, MHCN employs a pair-wise ranking loss to maximize the mutual information between representations within a pair. On the other hand, DSL utilizes hinge loss to optimize the pair score, which proves beneficial in reducing the negative influence caused by noisy edges.

4.3.3 Adversarial Learning in SocRec. Adversarial learning in social recommendation, as demonstrated in Table 5, is frequently utilized to extract clean and representative social relations from the user-user graph in SocRec.

- **Adversarial Learning Paradigm.** Adit *et al.* [54] proposed a modular adversarial approach to prevent model collapse in recommender systems with user-level social links. Their method utilized generative adversarial learning and a discriminator to differentiate sampled user pairs from both the interest and social domains. The optimization of parameters involved policy gradient due to the non-differentiable sampling operation. Similarly, DASO [24] leveraged the sampled user-user or user-item pairs from the generator and utilized policy gradient to optimize the parameters. RSGAN [192] uses the Gumbel-softmax technique for differentiable sampling and generates items based on social links. The discriminator in RSGAN aims to assign higher scores to both ground truth and socially aware items compared to negative items, following the social BPR optimization. In ESRF [195], a concrete selector layer is utilized to avoid non-differentiable sampling for neighbor users for discrimination.
- **Discrimination Target.** In social recommendation with adversarial learning, the discrimination target aims to combine social information and collaborative information in a regularized manner. Adit *et al.* [54], RSGAN [192], and ESRF [195] all adopt a similar approach of obtaining user-user/item pairs through sampling from the generator. They then utilize the discriminator to enhance the quality of the generated samples. Notably, RSGAN [192] employs the generated items for discrimination, thereby improving the generator’s ability to generate more accurate items based on the observed ground truth items.

4.4 Knowledge-aware Recommendation

4.4.1 Task Formulation. Items in reality have diverse attributes and labels, which can form a knowledge graph (KG) when connected to corresponding items. Knowledge-aware recommendation (KnoRec) leverages this external knowledge to enhance recommendations, represented as $\mathcal{G}_k = (h, r, t)$, where h and t are knowledge entities, and r is

their semantic relationship (e.g., *book, is written by, author*). The knowledge graph \mathcal{G}_k serves as external information to improve collaborative filtering performance, similar to social recommendation.

4.4.2 Contrastive Learning in KnoRec. Contrastive learning in knowledge-aware recommendation, as shown in Table 5 merges knowledge graphs with user-item graphs, employing various encoding, graph construction, and augmentation techniques to generate diverse perspectives for improved performance.

- **View Creation** in KnoRec involves the exploration of leveraging KGs in conjunction with the existing user-item graph to construct diverse perspectives. CKER [98] employs light-weight graph convolution and relation-aware convolution to encode interaction-aware and knowledge-aware item representations as two distinct views. KGIC [224] utilizes the user-item interaction graph and KG to construct local and non-local graphs, encoding different views for nodes based on these two graphs. KGCL [182] and ML-KGCL [12] both employ graph augmentation, such as edge dropout, twice to create contrastive views. MCCLK [223] first builds an item-item graph as the semantic view using relation-aware GNN, and then encodes collaborative and semantic representations for each node for contrastive learning. KRec-C2 [99] incorporates a category-level aggregation representation layer to obtain category-level signal features, which are contrasted with the original category features derived from the embedding function. HiCON [153] leverages meta-paths to construct a high-order graph that encodes representations of users and items, contrasting them with representations obtained from the original interaction graph. KACL [137] encodes the interaction view using an augmented user-item graph and KG-aware item representations based on the KG, providing another view for contrastive learning.
- **Pair Sampling.** Generally, in these methods, multiple views are created for each user and item node in the graph using various techniques [137, 182, 224]. These views naturally form positive pairs for contrastive learning. In KGIC [224], the distance between nodes on the local/non-local graph is used to select positive node pairs, enabling inter-graph and intra-graph interactive contrastive learning.
- **Contrastive Objective.** In all the mentioned methods, the contrastive objective is to optimize the mutual information between different views using the InfoNCE-based lower bound.

4.4.3 Generative Learning in KnoRec. Generative learning also emerges as a novel SSL paradigm to further enhance the performance of KnoRec (Table 5). The intrinsic idea behind generative learning is to discover valuable knowledge triplets through generative tasks while mitigating the negative impact [77, 169] caused by noisy or irrelevant knowledge.

- **Generative Learning Paradigm** in KnoRec encompasses both masked autoencoding and denoising diffusion approaches. In KGRec [180], a criterion score is initially computed for each knowledge triplet to identify the most valuable rationale triplets. Subsequently, the masking-and-reconstructing paradigm is employed to reconstruct these important triplets using node embeddings in the KG. This enables the encoding of information brought by these crucial triplets into the node representation, thereby enhancing recommendation performance. DiffKG [48] employs the concept of denoising diffusion by adding Gaussian noise to the triplets in the KG and subsequently removing it. This approach effectively eliminates the inherent noise present in the knowledge graph, providing a cleaner and augmented KG that can be utilized for inference and recommendation purposes.
- **Generation Target** in both KGRec and DiffKG encompasses all the triplets present in the knowledge graph. This is because the original interactions within the KG may contain significant amounts of noise and redundant information that are irrelevant for recommendation [182]. The generative learning process effectively generates valuable interactions within the KG through self-supervised learning, thereby achieving denoising.

Table 6. A summary of SSL recommendation methods in **Cross-domain Recommendation**.

Cross-domain Recommendation (CroRec)						
Category	Method Information			Self-supervised Learning Paradigm		
	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
CL	PCRec [133]	2021	CogMI	Data-based	Natural	InfoNCE-based
	C2DSR [7]	2022	CIKM	Data-based	Natural	JS-based
	SASS [213]	2022	CIKM	Model-based	Natural	InfoNCE-based
	CDRIB [9]	2022	ICDE	Model-based	Natural	JS-based
	CLCDR [17]	2022	ICONIP	Data-based	Natural	InfoNCE-based
	CCDR [171]	2022	KDD	Data & Model-based	Natural	InfoNCE-based
	SITN [120]	2023	AAAI	Model-based	Natural	InfoNCE-based
	CATCL [170]	2023	DASFAA	Feature-based	Natural	InfoNCE-based
	DCCDR [210]	2023	DASFAA	Model-based	Natural	InfoNCE-based
	DR-MTCDD [31]	2023	TOIS	Data-based	Natural	InfoNCE-based
GL	Method	Venue	Year	Generative Learning Paradigm		Generation Target
	RA/SA-VAE [114]	2021	RecSys	Variational Autoencoding		User Rating to Items
	VDEA [76]	2022	SIGIR	Variational Autoencoding		User Rating to Items
	DiffCDR [178]	2024	arXiv	Denosing Diffusion		User Feature
AL	Method	Venue	Year	Adversarial Learning Paradigm		Discrimination Target
	Su <i>et al.</i> [118]	2022	CIKM	Differentiable		Domain Item Feature
	RecGURU [62]	2022	WSDM	Differentiable		Domain User Feature
	ACLCDR [40]	2023	TKDD	Non-Differentiable		Augmented Interaction Matrix
	DA-CDR [209]	2023	TKDE	Differentiable		Domain User/Item Feature
	DA-DAN [28]	2023	TOIS	Differentiable		Domain User Feature

4.5 Cross-domain Recommendation

4.5.1 Task Formulation. Cross-domain recommendation (CroRec) transfers learned user preferences from a source domain to improve recommendations in a target domain, each containing different items based on domain-specific criteria. The items are divided into source domain set \mathcal{V}_s and target domain set \mathcal{V}_t , with interaction matrices $\mathcal{A}_s \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{V}_s|}$ and $\mathcal{A}_t \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{V}_t|}$, where $|\mathcal{U}|$ represents user count. Recommendations for users with uninteracted items ($v \in \mathcal{V}_t$) are made using a function f that calculates preference scores $(y_{u,v})$ based on collaborative information across domains. CroRec can also involve multiple domains and be enhanced by incorporating sequential information [7, 120].

4.5.2 Contrastive Learning in CroRec. Contrastive learning is crucial in SSL for cross-domain recommendation methods (Table 6), as it enables knowledge transfer from the target to the source domain by treating user interaction outcomes from different domains as distinct views. This section investigates diverse contrastive view creation methods using data from different domains and techniques for pair sampling and optimization in contrastive learning.

- **View Creation.** For data-based methods, PCRec [133] generates two distinct views using random walks on the source domain graph and encodes representations for contrastive pre-training. C2DSR [7] creates single-domain and cross-domain sequences, pooling their prototype embeddings to form two positive views for contrastive learning. CLCDR [17] replaces the BPR loss with a contrastive loss, creating views and positive pairs based on interaction data. DR-MTCDD [31] employs node/edge dropping for graph augmentation, while CCDR [171] uses a sub-graph-based data augmentation technique for view creation in its intra-domain CL. For model-based view creation, several methods consider representations learned by neural modules as distinct views. SASS [213] and CDRIB [9] leverage contrastive loss to maximize differences between views of the

same node, while CCDR [171] uses neural-encoded representations of the same nodes from different domain data for inter-domain CL. SITN [120] encodes two user-specific sequences from source and target domains as distinct views and employs a clustering technique for an additional view. DCCDR [210] projects original representations into domain-specific and domain-invariant representations, maximizing mutual information between domain-invariant representations of users from two domains. For feature-based methods, CATCL [170] adopts a feature-based view creation approach, similar to SimGCL, by adding noise to the node features during inference. This noise addition process generates diverse views that can be utilized for learning purposes.

- **Pair Sampling** relies on natural sampling in these works, where multiple views are created for each data object. Positive pairs are formed by two views of the same object, while views from other objects serve as negative samples. Encoded representations from multiple views for the same user/item node can be paired, originating from different domains [9, 171, 213] or generated through data augmentation techniques [133, 170]. Additionally, these representations can be encoded by specifically designed neural modules [133, 210].
- **Contrastive Objective** within CL-based cross-domain recommendation methods typically employs the InfoNCE-based objective to optimize the mutual information between positive views [17, 31, 120, 133, 170, 171, 210, 213]. Additionally, some methods utilize the JS-based lower bound for optimization. For instance, C2DSR [7] corrupts the prototype representation to generate negative views, while CDRIB [9] derives the JS-based contrastive term based on the information bottleneck regularization theory.

4.5.3 Generative Learning in CroRec. In CroRec, generative learning (as shown in Table 6) employs variational autoencoding and diffusion models to align and transfer knowledge between the source and target domains. The core idea is to facilitate knowledge sharing and adaptation across domains.

- **Generative Learning Paradigm** in CroRec begins by employing deep generative latent variable models (*i.e.*, variational auto-encoders) to encode the latent space of user preferences. Subsequently, it transitions to the denoising diffusion model to facilitate knowledge transfer across domains. Salah *et al.* propose RA/SA-VAE [114] to simultaneously fit the target observations and align the hidden space encoded by VAE with the source latent space. They introduce both rigid alignment and soft alignment techniques with varying degrees of user preference alignment. Furthermore, VDEA [76] extends the alignment of latent spaces using variational autoencoding at both local and global levels, allowing for the exploitation of domain-invariant features across different domains, including both overlapped and non-overlapped users. Recently, DiffCDR [178] leveraged denoising probabilistic models (DPMs) to process noisy data and generate denoised results, effectively transferring data between domains.
- **Generation Target.** RA/SA-VAE and VDEA both adopt the user rating reconstruction paradigm to optimize the variational model. In these models, the generation target is the user ratings for items, represented as vectors in the model. The generated ratings include ratings for uninteracted items, which are subsequently used for ranking and recommendation. On the other hand, DiffCDR focuses on generating user features in the target domain by reversing the diffusion process conditioned on the corresponding user's information in the source domain. These generated user features in the target domain are then utilized for recommendation purposes.

4.5.4 Adversarial Learning in CroRec. Adversarial learning in Table 6 employs adversarial domain adaptation to generate domain-independent features, encoding domain-invariant user interaction preferences for effective knowledge transfer. Some methods also utilize adversarial samples to improve model learning.

Table 7. A summary of SSL recommendation methods in **Bundle Recommendation** and **Group Recommendation**.

Bundle Recommendation (BunRec)						
Category	Method Information			Self-supervised Learning Paradigm		
CL	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
	MIDGN [216]	2022	AAAI	Model-based	Natural	InfoNCE-based
	CrossCBR [92]	2022	KDD	Data & Feature-based	Natural	InfoNCE-based
GL	Method	Venue	Year	Generative Learning Paradigm		Generation Target
	DGMAE [111]	2023	SIGIR	Maksed Autoencoding		Edge in User-Item Graph
Group Recommendation (GroRec)						
Category	Method Information			Self-supervised Learning Paradigm		
CL	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
	GroupIM [115]	2020	SIGIR	Model-based	Natural	JS-based
	HHGR [205]	2021	CIKM	Data-based	Natural	JS-based
	CubeRec [15]	2022	SIGIR	Model-based	Score-based	Explicit
	SGGCF [65]	2023	WSDM	Model-based	Natural	InfoNCE-based

- Adversarial Learning Paradigm.** Several methods employ adversarial learning for cross-domain recommendation. For instance, Su *et al.* [118] use a discriminator to identify domain-specific features, with gradients propagating to optimize the feature generator. Similarly, RecGURU [62] feeds encoded user representations from both domains into a discriminator for classification, enabling differentiable adversarial learning. Moreover, ACLCDR [40] utilizes Deep Q-Learning to design a generator that enhances the interaction matrix with fake interactions, optimizing it using reward signals from downstream tasks. In addition, DA-CDR [209] encodes domain features of users and items to fool the discriminator, ensuring effective domain knowledge transfer through adversarial learning using a gradient reversal layer (GRL) for differentiable training. Furthermore, DA-DAN [28] incorporates adversarial domain adaptation into unsupervised non-overlapping CroRec, with the discriminator classifying the domain of encoded user features for overall differentiable training.
- Discrimination Target.** Su *et al.* [118]’s domain adaptation method uses features from source and target domains to discriminate between them, forcing the generator to encode domain-invariant user preferences, thereby confusing the discriminator. RecGURU adopts a similar approach, discriminating encoded user representations from both domains to generalize user representation learning across domains. In ACLCDR, the augmented interaction matrix from DQN is used for inference in subsequent models, with the recommendation model acting as an implicit discriminator. DA-CDR employs a discriminator to classify domain features of users/items, encouraging the generator to encode additional domain-shared information for cross-domain recommendation. Lastly, DA-DAN encodes user-specific item sequence representations as domain features for the discriminator’s classification task, enabling the learning of domain-invariant features for recommendation.

4.6 Bundle Recommendation

4.6.1 Task Formulation. In Bundle Recommendation (BunRec), the auxiliary observed data \mathcal{X} includes the item-bundle affiliation, where a bundle $b \in \mathcal{B}$ represents a set of items for recommendation. Therefore, we have two interaction matrices: the user-bundle interaction matrix $\mathcal{A}_{U-B} \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{B}|}$ and the user-item interaction matrix $\mathcal{A}_{U-I} \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{I}|}$. Additionally, we use the matrix $\mathcal{A}_{I-B} \in \mathbb{R}^{|\mathcal{V}| \times |\mathcal{B}|}$ to record the item-bundle affiliation. The overall objective is to recommend uninteracted bundles to each user by predicting their preference scores $y_{u,b}$.

4.6.2 Contrastive Learning in BunRec. In bundle recommendation with contrastive learning (Table 7), the relationship between items and bundles, along with user-item interactions, is utilized to form user-bundle relationships. Various methods are then designed to create views based on these relationships.

- **View Creation.** MIDGN [216] employs neural models to encode distinct representations for each user and bundle, treating them as separate views. It incorporates a graph disentangle module to encode intent-aware representations and utilizes a user-bundle graph to encode cross-view representations with LightGCN. Additionally, CrossCBR [92] initially builds the user-bundle graph by leveraging the user-item and bundle-item graphs. Subsequently, it encodes user and bundle representations using graph augmentation and embedding augmentation techniques in the bundle and item views. As a result, each user and bundle node possesses two views for contrastive learning, similar to the approach adopted in MIDGN.
- **Pair Sampling.** Both MIDGN and CrossCBR encode two distinct views for each user and bundle in the dataset. As a result, the two views of a specific user/bundle node naturally form the positive pair, while other views from different nodes serve as negative samples for contrast comparison.
- **Contrastive Objective.** MIDGN and CrossCBR both utilize the InfoNCE-based objective to optimize their models through self-supervised learning signals.

4.6.3 Generative Learning in BunRec. In BunRec, generative learning (Table 7) has adopted the concept of a graph-masked auto-encoder. The approach (*i.e.*, DGMAE [111]) is illustrated as follows.

- **Generative Learning Paradigm.** In DGMAE, a teacher GNN model is first trained using user-bundle interactions, and then its knowledge is distilled into a student graph-masked auto-encoder model. This learning paradigm in DGMAE follows the principles of mask autoencoding.
- **Generation Target.** DGMAE employs an adaptive masking strategy on the prominent edges within the user-item graph for the purpose of reconstruction. Specifically, edges with lower sparsity scores are prioritized for masking in DGMAE, increasing the reconstruction challenge and improving the model’s robustness against sparsity.

4.7 Group Recommendation

4.7.1 Task Formulation. The goal of Group Recommendation (GroRec) is to recommend items to a group denoted as $o \in \mathcal{O}$, which represents a set of users. In addition to user-item interactions, there are also group-item interactions represented by $\mathcal{A}_{\mathcal{O}-I} \in \mathbb{R}^{|\mathcal{O}| \times |\mathcal{I}|}$ and group-user affiliations represented by $\mathcal{A}_{\mathcal{O}-U} \in \mathbb{R}^{|\mathcal{O}| \times |\mathcal{U}|}$. The recommender model will predict a score $y_{o,v}$ for each group-item pair (o, v) for recommendation.

4.7.2 Contrastive Learning in GroRec. In GroRec, contrastive learning is vital in SSL methods (Table 7), utilizing diverse user-item and user-group relationships to create multiple views for each node, enabling effective training.

- **View Creation.** GroupIM [115] pioneers the use of mutual information maximization, encoding user preference and group representations as views for contrastive learning. Meanwhile, HHGR [205] constructs fine- and coarse-grained user-level hypergraphs, encoding augmented views of user nodes at different granularities. Moreover, CubeRec [15] transforms the recommendation scenario using a hypercube framework, encoding user and item representations with LightGCN and treating each user representation as a view for pairing and learning. Lastly, SGGCF [65] adopts a data-based view creation approach, constructing a group-user-item graph, augmenting it with node/edge dropout, and encoding diverse views for each node.

- **Pair Sampling.** In BunRec, users are linked with user groups, forming positive pairs between user and group representations. GroupIM maximizes mutual information (MI) between these representations. In HHGR and SGGCF, each graph node has multiple augmented views, which are naturally treated as positive pairs, while views of other nodes are considered negative samples. CubeRec constructs a group hypercube based on user representations, identifying the intersection between two group hypercubes. Each overlapping user is paired with the hypercube as a positive pair, and other users are considered negative samples. The distance between each user and the hypercube is then calculated for contrastive optimization.
- **Contrastive Objective.** GroupIM utilizes a noise-contrastive objective with a binary cross-entropy loss, specifically a JS-based objective which maximizes the mutual information (MI) between positive pairs. On a related note, HHGR also employs a similar JS-based optimization approach. In CubeRec, an explicit margin loss is utilized to ensure that the distance-to-hypercube of positive pairs is smaller than that of negative pairs. For SGGCF, it adopts the InfoNCE-based objective to achieve the contrastive learning process.

4.8 Multi-behavior Recommendation

4.8.1 Task Formulation. In Multi-behavior Recommendation (MbeRec), the user-item interaction is extended to incorporate behavior heterogeneity, resulting in a 3D tensor denoted as $\mathcal{A} \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{I}| \times |\mathcal{B}|}$, where $\mathcal{B} = \{b_1, \dots, b_K\}$ depicts the set of different types of behaviors (e.g., page view, add-to-cart). The MbeRec aims to provide item recommendations for the target behavior (e.g., purchase) by leveraging the diverse behavior information.

4.8.2 Contrastive Learning in MbeRec. In MbeRec, contrastive learning leverages multi-behavior user-item interactions to create diverse behavior-specific views for each data sample. These views, which differ among various methods, are ideal for contrastive learning. The methods are listed in Table 8.

- **View Creation.** Various methods employ model-based view creation and data-level view augmentation. HMG-CR [179] uses hyper meta-paths to construct multiple hyper meta-graphs, encoding diverse behavior embeddings as views for each user node using distinct graph encoders. S-MBRec [26] partitions the multi-behavior graph into sub-graphs, encoding multiple GCN embeddings for each user/item as views. MMCLR [160] encodes sequence and graph views for each user under different behaviors, obtaining a fusion view by combining these representations. CML [148] and IICL [67] leverage a behavior-aware graph neural network to encode user embeddings for each behavior, treating each behavior type as a separate view. MixMBR [100] encodes behavior-specific embeddings and views through behavior message passing and model-parameter mixup. TMCL [176] utilizes temporal information to encode diverse behavior embeddings as distinct views through temporal-aware global learning. RCL [152] encodes behavior-specific short-term and long-term interest embeddings as separate views, combining them to create a multi-behavior pattern view. MBSSL [175] employs behavior-aware GNNs to encode views for inter-behavior contrastive learning, and utilizes edge dropout to obtain augmented views for intra-behavior contrastive learning. KMCLR [177] encodes behavior-specific views and employs knowledge-based data augmentation to obtain KG-aware views for each item for pairing.
- **Pair Sampling.** In HMG-CR, user behavior embeddings form positive pairs, with embeddings from other graphs being negative pairs. S-MBRec calculates similarity scores based on interaction nodes to determine positive user/item pairs. MMCLR, CML, MixMBR, TMCL, MBSSL and KMCLR treat different behavior views of the same node as positive pairs, and others as negative samples. In MBSSL, user similarity scores are computed to detect false negative samples and filter negative pairs. Moreover, KMCLR also pairs two knowledge-augmented views of

Table 8. A summary of SSL recommendation methods in **Multi-behavior Recommendation** and **Multi-modal Recommendation**.

Multi-behavior Recommendation (MbeRec)						
Category	Method Information			Self-supervised Learning Paradigm		
	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
CL	HMG-CR [179]	2021	ICDM	Data & Model-based	Natural	InfoNCE-based
	S-MBRec [26]	2021	ICDM	Model-based	Score-based	InfoNCE-based
	MMCLR [160]	2022	DASFAA	Model-based	Natural	Explicit
	CML [148]	2022	WSDM	Model-based	Natural	InfoNCE-based
	IICL [67]	2023	DASFAA	Model-based	Natural & Score-based	InfoNCE-based
	MixMBR [100]	2023	DASFAA	Model-based	Natural	InfoNCE-based
	TMCL [176]	2023	DASFAA	Model-based	Natural	InfoNCE-based
	RCL [152]	2023	RecSys	Model-based	Natural	InfoNCE-based
	MBSSL [175]	2023	SIGIR	Data & Model-based	Natural	InfoNCE-based
KMCLR [177]	2023	WSDM	Data & Model-based	Natural	InfoNCE-based	
GL	Method	Venue	Year	Generative Learning Paradigm		Generation Target
	VCGAE [80]	2023	ICDM	Variational Autoencoding		Target Behavior Graph
	BVAE [106]	2023	RecSys	Variational Autoencoding		User Interaction Vector
Multi-modal Recommendation (MmoRec)						
Category	Method Information			Self-supervised Learning Paradigm		
	Method	Year	Venue	View Creation	Pair Sampling	Contrastive Objective
CL	Liu <i>et al.</i> [85]	2022	ICMR	Model-based	Natural	JS-based
	CMI [60]	2022	SIGIR	Data-based	Natural	InfoNCE-based
	MMGCL [189]	2022	SIGIR	Data-based	Natural	InfoNCE-based
	SLMRec [125]	2022	TMM	Data-based	Natural	InfoNCE-based
	MICRO [207]	2023	TKDE	Model-based	Natural	InfoNCE-based
	BM3 [220]	2023	WWW	Feature-based	Natural	Explicit
	MMSSL [149]	2023	WWW	Model-based	Natural	InfoNCE-based
GL	Method	Venue	Year	Generative Learning Paradigm		Generation Target
	MVGAE [188]	2022	TMM	Variational Autoencoding		Edge in Graph
AL	Method	Venue	Year	Adversarial Learning Paradigm		Discrimination Target
	MMSSL [149]	2023	WWW	Differentiable		User Interaction to Items

the same item for knowledge-aware contrastive learning. IICL uses intra- and inter-behavior contrastive learning, where even-layered embeddings are positive pairs in intra-behavior CL, and different behaviors for the same user are positive pairs in inter-behavior CL. Lastly, in RCL, the fused multi-behavior view is paired with other behavior-specific views as positive pairs for the same user, while considering other users as negative samples.

- **Contrastive Objective.** Most of the methods [26, 67, 100, 148, 152, 176, 177, 179] in MbeRec utilize the InfoNCE objective to optimize contrastive learning. In MMCLR, it explicitly pulls the positive pairs closer together while pushing away negative pairs by ensuring that the similarity score of the former is larger than that of the latter.

4.8.3 Generative Learning in MbeRec. Generative learning in MbeRec (Table 8) adopts the variational autoencoding paradigm to reconstruct behavior interactions, thereby providing informative auxiliary learning signals.

- **Generative Learning Paradigm.** Both VCGAE [80] and BVAE [106] adopt the variational auto-encoding generative paradigm for modeling behavior heterogeneity. In VCGAE, a variation graph autoencoder is designed. It utilizes auxiliary behavior fusion to obtain the variance vector and a behavior transfer network to obtain the

mean vector, which together form the distribution of latent factors. BVAE uses a behavior-aware semi-encoder to encode the variance vector based on users’ historical interactions. It learns the mean vector through a global feature filtering network, resulting in behavior-aware latent representations of users.

- **Generation Target.** In the VAE paradigm, the latent representations obtained are fed into the decoder for generation. In VCGAE, the generation target is the edge in the user-item graph of the target behavior (e.g., purchase). Besides, BVAE focuses on generating the user interaction vector across different behaviors.

4.9 Multi-modal Recommendation

4.9.1 Task Formulation. In the context of Multi-modal Recommendation (MmoRec), auxiliary observed data \mathcal{X} contains item multi-modal information. Typically, an item can possess auxiliary features such as text descriptions, images, or acoustic data. Each item is associated with modality-specific features e_m , where $m \in \mathcal{M}$ represents modalities. MmoRec aims to utilize this multi-modal information to improve recommendation accuracy.

4.9.2 Contrastive Learning in MmoRec. Contrastive learning in MmoRec (Table 8) cleverly leverages the multi-modal information of items to construct different contrastive views. This enables effective fusion of multi-modal information and promotes the learning of recommenders.

- **View Creation.** In data-based view creation methods, CMI [60] conducts data-level item sequence augmentation and encodes user interest embeddings to generate contrastive views. MMGCL [189] employs modality masking and edge dropout techniques to create augmented data views for each node in the multi-modal graph. Additionally, SLMRec [125] utilizes data-level augmentation techniques such as feature dropout and masking to obtain two views for each node. In contrast, model-based methods like Liu *et al.* [85] leverage a text/image encoder to encode two views for each item, which are then used for contrastive learning. Furthermore, MICRO [207] mines the latent graph structure of items and utilizes graph neural networks to encode modality-specific views and generate a fused view for each item. Meanwhile, MMSSL [149] employs adversarial learning to obtain a modality-aware user-item graph and encodes modality-fused user embeddings as one view and another user’s view based on collaborative information. For feature-based view creation, BM3 [220] encodes modality embeddings, applies feature-level embedding dropout for augmented views, and includes an ID-based view from ID embeddings.
- **Pair Sampling.** All the methods follow natural sampling. In [85], positive pairs are formed by two views from different modalities of the same item, and negative pairs consist of views from different items. CMI creates positive pairs from two augmented interest-based views for the same user. MMGCL forms positive pairs from randomly augmented views and challenging negatives obtained by replacing modality data. SLMRec forms positive pairs with two data-augmented views of each node and ID-modality and other modality representations. MICRO maximizes agreement between item representations under individual modalities and fused multi-modal representations, forming positive pairs with modality-view and fused view of the same item and negative pairs with views from other items. BM3 aligns inter-modality by pairing augmented modality-views with the ID-based view and intra-modality by pairing modality-views of the same item. MMSSL forms positive pairs with the fused modality-view and collaborative-aware view of the same user, and negative pairs with views from other users.
- **Contrastive Objective.** Most of the CL-based works utilize either InfoNCE-based [60, 125, 149, 189, 207] or JS-based [85] loss functions as the loss function. Besides, BM3 directly aligns the views with cosine similarity.

4.9.3 **Generative Learning in MmoRec.** Generative learning, as recently shown by MVGAE [188] (Table 8), employs the graph VAE to transform modality data into a latent space and utilizes generation tasks to guide the learning process.

- **Generative Learning Paradigm.** MVGAE utilizes a multi-modal variational graph auto-encoder to assign mean and variance vectors to each node in the user-item graph and employs the product-of-experts approach to fuse modality-specific latent representations for generation.
- **Generation Target.** In MVGAE, the latent representations obtained from encoder are utilized to generate (reconstruct) the interaction edges in the user-item graph using an inner product decoder and BPR loss.

4.9.4 **Adversarial Learning in MmoRec.** In MmoRec, adversarial learning is recently used in MMSSL [149] (Table 8) to perform structure learning based on multi-modal information, revealing modality-aware user-item interactions.

- **Adversarial Learning Paradigm.** MMSSL generates a modality-aware user-item graph structure using a neural generator with item multi-modal features. Then, the user-specific interaction vector undergoes adversarial learning in a discriminator. The differentiable pipeline enables multi-modal adversarial user-item relation learning.
- **Discrimination Target.** The user-item graph structure learned in MMSSL is split into user-specific interaction vectors, which are used for discrimination. The objective is to make these interaction vectors similar to real user interaction records in order to deceive the discriminator.

5 DISCUSSIONS AND FUTURE DIRECTIONS

In this section, we aim to delve into several open problems and potential future directions in the field of self-supervised learning for recommendation systems. By exploring and analyzing these challenges and opportunities, we aim to stimulate and encourage further research, development, and innovation in this rapidly advancing field of study.

5.1 Towards Foundation Recommender Models

Foundation model [4], trained on massive datasets and exhibiting remarkable generalization capabilities to handle a wide range of downstream tasks, has garnered significant attention from researchers across various domains [5, 105, 122, 165]. In recommender systems, current models using SSL techniques have shown significant performance, but they are limited by evaluation settings focused on a single dataset. Recent research in CV and NLP has improved models' generalization abilities through self-supervised learning using contrastive learning [105] or generative learning [128] on large amounts of data. A promising future direction is to design foundation recommender models that leverage SSL to learn user-item interaction patterns from massive data and achieve zero-shot cross-data reasoning and recommendation.

5.2 Unleashing the Potential of Denoised Diffusion Models

Denoised diffusion models have demonstrated remarkable proficiency in generating diverse types of data, including images, text, and even structured data. This new and popular generative learning paradigm has been effectively applied in various domains, as evidenced by recent studies such as [25, 112], and [131]. Recent studies in recommendation with generative self-supervised learning have started leveraging diffusion models either to generate augmented data [75] or as the backbone model for inference [144]. We believe that the impressive generation capabilities demonstrated by diffusion models will bring new insights and fascinating models to the generative learning-enhanced recommendation in the near future, making it a promising research line.

5.3 Self-Supervised Integration of Large Language Models

Large language models (LLMs) have gained significant attention due to their exceptional performance in various domains [74, 123, 217]. In recommender systems, LLMs can generate user/item profiles [108, 150], explain user-item interactions [66], and serve as the backbone for recommendation with instruction tuning [206]. The integration of large language models has brought about an unprecedented abundance of diverse, rich, and high-quality textual modality data. However, the challenge of effectively harnessing this textual capability remains an open research question. Recent works have employed self-supervised learning techniques, such as contrastive learning [108] and mask-reconstruction [150], to align the knowledge of LLMs with recommenders. As we look to the future, self-supervised learning techniques are poised to play a crucial role in enhancing recommenders with the incorporation of LLMs.

5.4 Self-Supervised Learning for Dynamic Recommendation Adaptation

Current recommendation research often assumes a fixed number of users and items, making it challenging for methods to adapt to continuous new data. In practice, models are deployed in dynamic environments with continuously generated user-item interactions and new users/items [191]. To address this, prompt tuning [58, 151] is utilized to efficiently update pre-trained models on new data [185]. Nevertheless, new data sparsity hinders effective supervision signals. Thus, effectively leveraging self-supervised learning for efficient learning on dynamic data is crucial.

5.5 Theoretical Foundation of various SSL paradigm

While self-supervised learning has improved recommender systems, a comprehensive theoretical foundation for various paradigms is lacking. Some methods have provided theoretical explanations for contrastive learning [110, 156] and generative masked autoencoding in graphs [64]. However, recent paradigms like denoised diffusion still need theoretical explanations to demonstrate their benefits in recommendation. This understanding would help uncover the underlying principles and mechanisms driving self-supervised learning in recommendation systems and offer insights into the generalization and robustness properties of these algorithms.

6 CONCLUSION

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