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Recommender systems based on generative adversarial networks: A problem-driven perspective

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A B S T R A C T

Recommender systems (RS) now play a very important role in the online lives of people as they serve as personalized filters for users to find relevant items from a sea of options. Owing to their effectiveness, RS have been widely employed in our daily life. However, despite their empirical successes, these systems still suffer from two limitations: data noise and data sparsity. In recent years, generative adversarial networks (GANs) have garnered increased interest in many fields due to their strong capacity to learn complex real data distributions. Their abilities to enhance RS by tackling the above challenges have also been demonstrated in numerous studies. In general, two lines of research have been conducted, and their common ideas can be summarized as follows: (1) for the data noise issue, adversarial perturbations and adversarial sampling-based training often serve as a solution; (2) for the data sparsity issue, data augmentation—implemented by capturing the distribution of real data under the minimax framework—is the primary coping strategy. To gain a comprehensive understanding of these research efforts, we review the corresponding studies and models, organizing them from a problem-driven perspective. More specifically, we propose a taxonomy of these models, along with their detailed descriptions and advantages. Finally, we elaborate on several open issues and current trends in GAN-based RS.

1. Introduction

Owing to the rapid development of Internet-based technologies, the quantities of data on the Internet are growing exponentially; as a result, Internet users are persistently inundated with excessive amounts of information [42,14]. In particular, when it comes to online shopping, people struggle to make choices when a vast range of options are presented. As an effective tool to tackle such information overloads, recommender systems (RS) have been widely used in various online scenarios, such as E-commerce (e.g., Amazon and Taobao), music playback (e.g., Pandora and Spotify), movie recommendation (e.g., Netflix and iQiyi), and news recommendation (e.g., BBC News and Headlines).

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Despite their pervasiveness and strong performances, RS still suffer from two main problems: data noise and data sparsity. As an extrinsic problem, data noise stems from the casual, malicious, and uninformative feedback in the training data [11,14]. More specifically, users occasionally select products outside their interests, and this casual feedback is also collected and indiscriminately used for RS model training. Moreover, during training, it is also common for the randomly selected negative samples to become uninformative and mislead the recommendation models. Besides, because of the openness of RS, some profit-driven attackers may inject a number of malicious profiles or feedback into the RS, to manipulate recommendation results. Failure to identify these data may result in security problems. Compared with the data noise problem, data sparsity is an intrinsic problem, it occurs because each user generally only consumes a small proportion of the available items. Existing RS typically rely on the historical interactive information between users and items when capturing the interests of users. When a vast quantity of the data are missing, the RS commonly fails to satisfy users, by making inaccurate recommendations [42]. Without coping mechanisms, these problems often cause the RS to fail, leading to an inferior user experience.

Numerous researchers are aware of the negative effects of these two problems and have attempted to minimize the adverse factors. For the data noise problem, a number of solutions have been proposed [45,2,41,8]. Among them, Zhang et al. [45] applied a hidden Markov model to analyze preference sequences; subsequently, they utilized hierarchical clustering to distinguish attack users from rating behaviors. Bag et al. [2] proposed a method that corrects casual noise using the Bhattacharya coefficient and concept of self-contradiction. To distinguish more informative items from unobserved ones, Yu et al. [41] identified more informative users by modeling all training data as a heterogeneous information network, to obtain the embedding representation. To obtain informative negative items, several researchers adopted popularity biased sampling strategies [8]. Although using these methods, it was found that conventional RS models are susceptible to noise in the training data, they can only prevent conspicuous noises from a specific perspective, and they cannot continuously update their ability to manage unobserved patterns of noise. For the data sparsity problem, numerous methods have been developed to integrate a wealth of auxiliary information into the RS. Such data comprise the side information of users and items, as well as the relationships between them [10,37]. For example, Cheng et al. [10] used textual review information to model user preferences and item features and tackle the problems of data sparsity. Wang et al. [37] extracted auxiliary information from a knowledge graph to enhance recommendations. Although the integration of auxiliary information is useful, these methods still struggle to obtain a satisfactory result, owing to inconsistent data distributions or patterns and large computational costs.

Recently, generative adversarial networks (GANs) have led to rapid developments in deep learning fields [1,21]. The principle of GANs is to play an adversarial minimax game between a generator and a discriminator. The generator focuses on capturing the distribution of real observed data, to generate pseudo samples to fool the discriminator; meanwhile, the discriminator attempts to distinguish whether the input is from the generator or not. This adversarial process continues until the two components reach the Nash equilibrium.

Significant successes realized by applying GANs to deep learning fields have set good examples for RS, and GAN-based RS have been introduced in several existing studies [30,19,46]. In this study, we identified relevant papers from DBLP using the following keywords: generative adversarial network, GAN, and adversarial. According to the statistics retrieved from top-level conferences related to RS in the past three years, the number of GAN-based recommendation models is increasing yearly, as shown in Table 1. Meanwhile, in a seminar on GAN-based information retrieval (IR) models presented at the SIGIR in 2018, researchers [46] suggested that GAN-based RS will become immensely popular in the field of RS research. This is because the GAN concept provides new opportunities to mitigate data noise and data sparsity. Several existing studies have verified the effectiveness of introducing adversarial perturbations and the minimax game into the objective function, to reduce data noise. Other studies have attempted to use the discriminator to recognize informative examples in an adversarial manner. Meanwhile, to address the data sparsity issue, a separate line of research has investigated the capabilities of GANs to generate user profiles by augmenting user-item interaction and auxiliary information.

To the best of our knowledge, only a small number of systematic reviews have sufficiently analyzed existing studies and the current progress of GAN-based recommendation models. To this end, we investigate and review various GAN-based RS from a problem-driven perspective. More specifically, we classify the existing studies into two categories: the first reviews models designed to reduce the adverse effects of data noise; the second focuses on the models designed to mitigate the data sparsity problem. We hope that this review will lay the foundation for subsequent research on GAN-based RS. The primary contributions of this review are summarized as follows:

- To gain a comprehensive understanding of the state-of-the-art GAN-based recommendation models, we provide a retrospective survey of these studies and organize them from a problem-driven perspective.
- We systematically analyze and investigate the capabilities of GAN-based models to mitigate data noise issues arising from two different sources: (1) models to mitigate casual and malicious noise, and (2) models to distinguish informative samples from unobserved items.
- We conduct a systematic review of recommendation models that implement GANs to alleviate data sparsity issues arising from two different sources: (1) models for generating user preferences through augmentation with interactive information, and (2) models for synthesizing user preferences through augmentation with auxiliary information.
- We elaborate on several open issues and current trends in GAN-based RS.

Table 1
Statistics of papers describing GAN-based recommendation models.

Meeting|Year	**2017**	**2018**	**2019**
AAAI	0	1	1
CIKM	0	2	2
ICML	0	0	1
IJCAI	0	1	3
KDD	0	1	3
RecSys	0	2	3
SIGIR	1	4	4
Total	1	11	17

The remainder of this paper is organized as follows. The development process of GANs is described in Section 2. In Sections 3 and 4, up-to-date GAN-based recommendation models are introduced in a problem-driven way, highlighting the efforts devoted to mitigating the problems of data noise and data sparsity, respectively. In Section 5, we discuss prominent challenges and research directions. In the final section, we present the conclusions of our work.

2. The Foundations of generative adversarial networks

In this section, we first summarize some common notations in GANs, to simplify the subsequent GAN-related content. Subsequently, we present some classical GANs.

2.1. Notations

Throughout this paper, G denotes the generator of a GAN, whilst D denotes its discriminator. $\mathbb{E}$ indicates the expectation calculation. P represents the data distribution. L denotes the loss function of the introduced model. These notations are summarized in Table 2.

2.2. Typical model

The GAN, which is an unsupervised model proposed by Goodfellow et al. in 2014 [12], has attracted widespread attention from both academia and industry. It features two components: a generator and a discriminator. The former learns to generate data that conform to the distribution of real data as much as possible; the latter must distinguish between the real data and those generated by the generator. The two components compete against each other and optimize themselves via feedback loops. The process is shown in Fig. 1.

In Fig. 1, z denotes the random noise, and x denotes the real data. The loss function is

$$\min_G \max_D L(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(x)}[\log(1-D(G(z)))], \tag{1}$$

where p_{data} is defined as the probability distribution function, and $p_z(x)$ is the probability distribution of the generated data. This model, the so-called "vanilla GANs", exhibits several shortcomings. It cannot indicate the training process of their loss functions and lack diversity in their generated samples. Martin et al. [1] have investigated the causes of these flaws; they found that when the distributions of real and generated data are non-overlapping, the function tends to be constant, which leads to the disappearance of the gradient. Then, they [1] proposed Wasserstein GAN (WGAN), which uses the Wasserstein distance instead of the original Jensen-Shannon divergence. f_w is the function that calculates the Wasserstein distance. The loss function of a WGAN is

$$L^D = \mathbb{E}_{z\sim P_z}[f_w(G(z))] - \mathbb{E}_{x\sim P_r}[f_w(x)]. \tag{2}$$

Although WGAN can theoretically mitigate the problems caused by training difficulties, they still suffer from their own problems: the generated samples are of low quality, and the training process fails to converge owing to the Lipschitz constraint on the discriminator. Consequently, Ishaan et al. [13] regularized the Lipschitz constraints and proposed a gradient penalty WGAN model (WGAN-GP). The Lipschitz constraint was approximated by assigning the constraint to the penalty term of the objective function. The loss function is

$$L = \mathbb{E}_{\tilde{x}\sim P_g}[D(\tilde{x})] - \mathbb{E}_{x\sim P_r}[D(x)] + \omega\mathbb{E}_{\hat{x}\sim P_{\hat{x}}}\left[\left(\|\nabla_{\hat{x}}D(\hat{x})\|_2 - 1\right)^2\right], \tag{3}$$

where P_r is the data distribution and P_g is the generator distribution. As shown in Eq. 3, the larger the parameter x, the smoother the log loss function, and the smaller the gradient; this leads to almost no improvement in the generator.

In addition to modifying the loss function to improve the performance of GANs, several studies [25,21] have focused on the network structure of the discriminator and generator. The structures of vanilla GAN are realized using a multi-layer per-

Table 2
Notations used throughout this paper.

Notation	Description
G	The generator
D	The discriminator
$\mathbb{E}$	The exception value
L	The loss function
P	The distribution

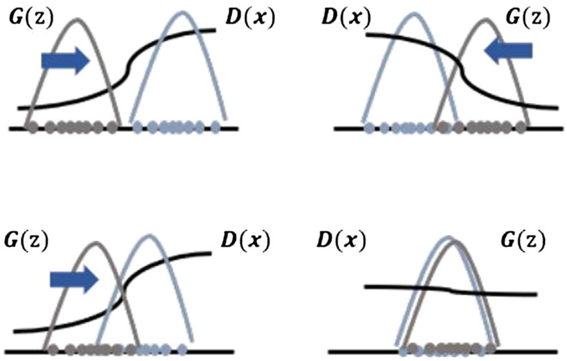

Fig. 1. Basic GAN concept.

ceptron (MLP), which makes parameter tuning difficult. To solve this problem, Alec et al. [25] proposed a deep convolutional GAN (DCGAN), because convolutional neural networks (CNNs) exhibit superior capacities for fitting and representing compared to MLPs. DCGAN dramatically enhanced the quality of data generation and provided a reference on neural network structures for subsequent research into GANs. The framework of the DCGAN is shown in Fig. 2.

Although GANs have received considerable attention as unsupervised models, the GAN generator can only generate data based on random noise, which renders the generated data unusable. Therefore, Mirza and Osindero [21] proposed the conditional GAN (CGAN). By adding conditional constraints to the model, the CGAN generator was able to generate condition-related data. CGAN can be seen as an enhanced model that converts an unsupervised GAN into a supervised one. This improvement has been proven effective and guided subsequent related work.

After considering the current progress of GANs in detail, we find that many advanced models [34,11,14] have been specifically proposed in the fields of computer vision and natural language processing. These models do have some reference value for mitigating the data noise and sparsity problems of RS. We introduce GAN-based recommendation models in the next two sections.

3. GAN-based recommendation models for mitigating the data noise issue

In RS research, the problem of data noise is attracting increasing amounts of attention. It affects not only the accuracy of RS but also their robustness. In this section, we review the state-of-the-art GAN-based models designed to identify casual and malicious noise and uninformative feedback. We categorize the GAN-based models into two categories, in terms of the sources of data noise described in the introduction: (1) models for mitigating casual and malicious noise, and (2) models for distinguishing informative samples from unobserved items.

3.1. Models for mitigating casual and malicious noise

[**APR**] Applying adversarial learning to the construction processes of recommendation models is a common method of mitigating the problem of data noise, which includes casual and malicious noise. He et al. [14] were the first to verify the effectiveness of adding adversarial perturbations into RS, and they proposed an adversarial personalized ranking (APR) model to enhance model generalizability. Furthermore, the purpose of adversarial perturbations is to help the model preemptively consider the bias caused by noise. Specifically, the loss function of the APR model contains two parts: one adds perturbations to the parameters of the bayesian personalized ranking model (BPR) and makes the performance as low as possible; the other, without adversarial perturbations, makes the recommendation performance as high as possible. The loss function of the APR model is composed of these two parts, as shown in Eq. 4:

$$L_{APR}(D|\Theta) = L_{BPR}(D|\Theta) + \omega L_{BPR}(D|\Theta + \Delta_{adv}), \tag{4}$$

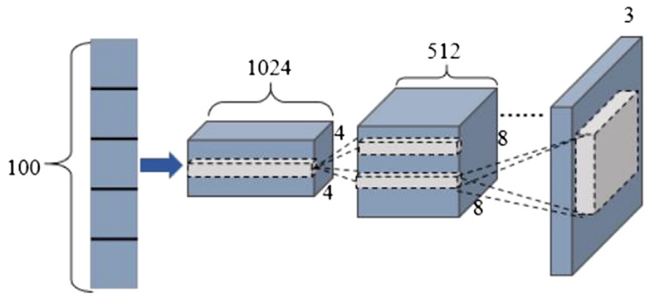

Fig. 2. DCGAN framework [25].

$$\Delta_{adv} = arg \max_{\Delta, \|\Delta \leqslant \epsilon\|} L_{BPR}\left(D|\hat{\Theta} + \Delta_{adv}\right), \tag{5}$$

where Δ represents the disturbance of the model parameters, $0 \leqslant \epsilon$ controls the magnitude of the disturbance, $\hat{\Theta}$ represents the parameters of the existing model, and ω is the equilibrium coefficient that controls the strength of the regularization term $L_{BPR}(D|\Theta + \Delta_{adv})$. In contrast to BPR, APR performs adversarial training using the fast gradient method, finding the optimal perturbations and parameters to alleviate the data noise problem.

This is an innovative idea, because it uses adversarial perturbations to simulate malicious noise and thereby improve the robustness of the BPR model; this demonstrates the competitive results that can be obtained by applying adversarial training to BPR. In ranking tasks, APR models have achieved better recommendation performances than deep neural network (DNN)-based RS [14], and they have subsequently inspired many research works.

[**AMR**] By extending APR, Tang et al. [29] devised an adversarial multimedia recommendation (AMR) model for image RS. AMR adds adversarial perturbations to the low-dimensional features of images extracted by a CNN, to learn robust image embeddings. The framework of the AMR is shown in Fig. 3. The loss function of AMR is

$$\theta^*, \Delta^* = arg\min_{\theta}\max_{\Delta}\left(L_{BPR}(\theta) + \omega L'_{BPR}(\theta, \Delta)\right), \tag{6}$$

$$\hat{y}'_{ui} = p_u^T(q_i + E \cdot (c_i + \Delta_i)), \tag{7}$$

$$\Delta^* = argmax_{\Delta} = \sum_{(u,i) \in D} - ln\sigma\left(\hat{y}'_{ui} - \hat{y}'_{uj}\right), \tag{8}$$

where Δ_i represents the adversarial perturbations and the optimal perturbation is obtained by maximizing the loss function in the training data. θ represents the parameters in AMR.

[**CollaGAN**] Tong et al. [30] proposed a collaborative GAN (CollaGAN) to mitigate the adverse impacts of noise and improve the robustness of RS. More specifically, CollaGAN uses a variational auto-encoder [17] as a generator, and its input is the rating vector for each item. After encoding, the generator learns the data distribution from the training data and generates fake samples through the embedding layer. The discriminator focuses on maximizing the likelihood of distinguishing generated item samples from real item vectors. The loss functions of the generator and discriminator are

$$L^G = -\mathbb{E}_{i \sim P_\theta(i|u)}[D(v|u)], \tag{9}$$

$$L^D = -\mathbb{E}_{v \sim P_r(v|u)}[D(v|u)] + \mathbb{E}_{x \sim P_\theta(v|u)}[D(v|u)] + \omega \mathbb{E}_{j \sim P_{\hat{p}}(\hat{v}|u)}\left[\left(\|\nabla_{\hat{v}} D(\hat{v}|u)\|_2 - 1\right)^2\right], \tag{10}$$

respectively. Here, u and v represent the low-dimensional vectors of the user and item, respectively. In addition, the authors also developed the vanilla GAN into a WGAN and WGAN-GP, to exploit the faster training speeds and superior performances of these models. Compared with other models such as IRGAN [34], the performance of CollaGAN was significantly enhanced for two movie-recommendation datasets. Moreover, CollaGAN adopts a conventional point-wise loss function instead of a pair-wise one. The performance of the entire model can be further improved if the optimization component is designed to be more elegant.

[**ACAE** & **FG-ACAE**] Yuan et al. [43] proposed a general adversarial training framework, referred to as an adversarial collaborative autoencoder (ACAE). They implemented it with a collaborative auto-encoder to strike a balance between accuracy and robustness by adding perturbations at different parameter levels. The framework of the ACAE is shown in Fig. 4. The experimental results confirmed that adding perturbations has a more significant impact on the original model, where the effect of adding perturbations to the decoder weights is higher than those of the encoder. The effects of adding perturbations to user-embedding vectors and hidden layers are negligible. To control the perturbations more precisely, they [44] used different coefficients to separately control noise terms and obtain further benefits from the adversarial training.

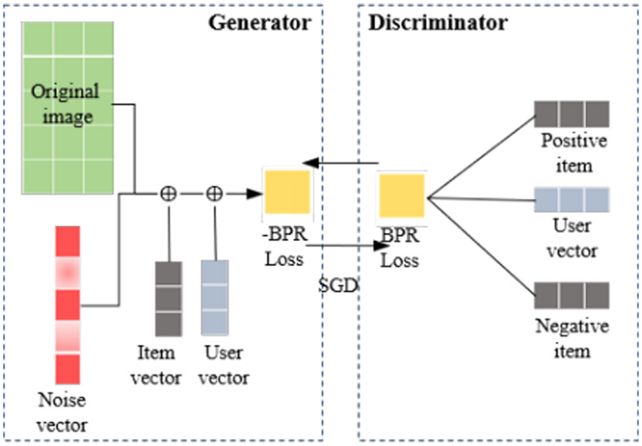

Fig. 3. AMR framework [29].

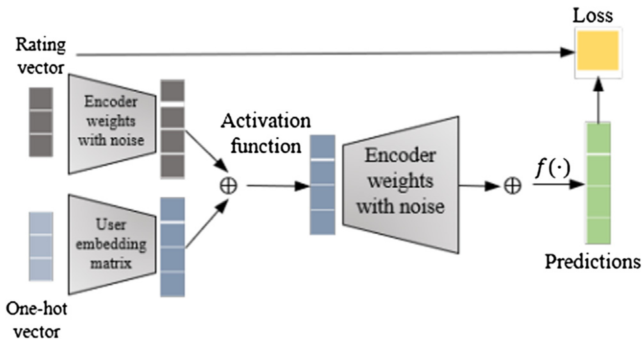

Fig. 4. ACAE framework [43].

[**SACRA**] Because of the vulnerabilities of neural networks, the adoption of adversarial training frameworks has gradually increased in related research. Li et al. [18] adopted the idea of adversarial perturbations at the embedding level; they proposed a self-attentive prospective customer recommendation model, referred to as SACRA. The model implements the fast gradient method to estimate adversarial perturbations.

[**ATF**] In addition, adversarial tensor factorization (ATF) was proposed by Chen et al. [7]; it is considered to be the first attempt to integrate adversarial perturbations into models based on tensor factorization. ATF outperformed state-of-the-art tensor-based RS. This work can incorporate more contextual data, including location, time, and social information.

3.2. Models for distinguishing informative samples from unobserved items

It is difficult for RSs to extract informative data from large quantities of unobserved data. More specifically, when models optimize their pair-wise objective functions, the negative sampling technique often provides more informative samples. Hence, it is crucial to provide informative negative samples dynamically.

[**IRGAN**] The first GANs designed to mitigate this problem was IRGAN, proposed by Wang et al. [34]. IRGAN unifies the generative retrieval and discriminative models; the former predicts relevant documents for a given query and the latter predicts the relevancy in each query document pair. The generative model is used as the generator; it selects informative items for a given user by fitting the real relevance distribution over items. The discriminative retrieval model, employed as the discriminator, distinguishes between relevant and selected items. Then, the discriminator feeds the result into the generator, to select more informative items. The generated items are inputted into the discriminator to mislead it. The loss function of IRGAN is

$$L^{G,D} = \min_{\theta}\max_{\phi}\sum_{n=1}^{N}\left(\mathbb{E}_{i\sim P_{true}(i|u_n,r)}[\log D(i|u_n)] + \mathbb{E}_{i\sim P_{\theta}(i|u_n,r)}[\log(1 - D(i|u_n))]\right), \tag{11}$$

where $D(i|u) = \frac{\exp(f_\phi(i,u))}{1+\exp(f_\phi(i,u))}, f_\phi(i,u) = b_i + v_u^T v_i$. r denotes relationships between users and items. $P_{true}(i|u_n, r)$ is the real item distribution for user u_n with relationship r, $P_\theta(i|u_n, r)$ is the distribution of generated data, and $f_\phi(i,u)$ indicates the relationship between users and items. Because the sampling of i is discrete, it can be optimized using reinforcement learning based on a policy gradient method [39], instead of the gradient descent method used in the vanilla GAN formulation. However, IRGAN [34] selects discrete samples from the training data, which causes some intractable problems. The generator of IRGAN produces a separate item ID or an ID list based on the probability calculated by the policy gradient. Under the guidance of the discriminator, the generator may be confused by the items that are simultaneously marked as both "real" and "fake", resulting in a degradation of the performance of the model.

[**AdvIR**] Unlike IRGAN, which uses GANs to sample negative documents, AdvIR [22] focuses on selecting more informative negative samples using implicit interactions. This model applies adversarial training to capture more informative positive/negative samples. Besides, the proposed model works for both discrete and continuous inputs. The experimental results were found satisfactory for three tasks relating to ad hoc retrieval.

[**CoFiGAN** & **ABinCF**] Collaborative filtering GAN (CoFiGAN) is an extension of IRGAN [19], in which G generates more desirable items using a pair-wise loss, and D differentiates the generated items from the true ones. CoFiGAN has been experimentally shown to deliver enhanced performance and greater robustness compared to other state-of-the-art models. Another relevant extension of IRGAN is adversarial binary collaborative filtering (ABinCF) [33], which adopts the concept of IRGAN for fast RS.

[**DASO**] Fan et al. [11] proposed a GAN-based social recommendation model, referred to as deep adversarial social recommendation (DASO); it uses the minimax game to dynamically guide the informative negative sampling process. For the interactive information, the generator is used to select items based on priori probabilities and output the user-item pairs as fake samples, whilst the discriminator identifies whether each interaction pair is real or not.

$$\min_{\theta_G^I}\max_{\phi_D^L} L^I\left(G^I, D^I\right) = \sum_{i=1}^{N}\left(\mathbb{E}_{v\sim p_{real}^I(\cdot|u_i)}\left[\log D^I(u_i, v; \phi_D^I)\right] + \mathbb{E}_{v\sim G^I\left(\cdot|u_i;\theta_G^I\right)}\left[\log\left(1 - D^I(u_i, v; \phi_D^I)\right)\right]\right). \tag{12}$$

For social information, the generator is used to select the most relevant friends as informative samples and output fake user-friend pairs, whilst the discriminator identifies the generated user-friend pairs and actual relevant pairs.

$$\min_{\theta_C^S}\max_{\phi_D^S} L^S\left(G^S, D^S\right) = \sum_{i=1}^{N}\left(\mathbb{E}_{u\sim p_{real}^S(\cdot|u_i)}\left[\log D^S(u_i, v; \phi_D^S)\right] + \mathbb{E}_{u\sim G^S\left(\cdot|u_i;\theta_G^S\right)}\left[\log\left(1 - D^S(u_i, u; \phi_D^S)\right)\right]\right). \tag{13}$$

In this way, the user representations are considered using both social and interactive information. In comparisons with other recommendation models [47,34], the authors found that DASO outperforms the DNN-based social recommendation models [47]. Because of the inefficient calculation of the softmax function of the generator during gradient descent, the authors replaced softmax with hierarchical softmax, to speed up calculations.

[**GAN–HBNR**] Cai et al. [4] proposed a GAN based on heterogeneous bibliographic network representation (GAN–HBNR) for citation recommendation; it uses GANs to integrate the heterogeneous bibliographic network structure and vertex content information into a unified framework. It implements a denoising auto-encoder (DAE) [31] to generate negative samples, because this produces better representations than a standard auto-encoder. By extracting each continuous vector and concatenating it with the corresponding content vector as the input, GAN–HBNR can learn the optimal representations of content and structure simultaneously, to improve the efficiency of the citation recommendation procedure.

[**NMRN-GAN**] To capture and store long-term stable interests and short-term dynamic interests, a neural memory streaming GAN (NMRN-GAN) [35] based on a key-value memory network was proposed for streaming recommendation. It also used the concepts of GANs in negative sampling. More specifically, the generator focused on encouraging the generation of plausible samples to confuse the discriminator. The goal of the discriminator was to separate real items from fake ones produced by the generator. Experiments with optimal hyper-parameters demonstrated that NMRN-GAN significantly outperformed the other comparison models. However, under the guidance of the discriminator, the generator may become confused by the items simultaneously marked as both "real" and "fake", resulting in a degradation of the performance of the model. The framework of the NMRN-GAN is shown in Fig. 5.

3.3. Quantitative analysis

After introducing the aforementioned GAN-based models designed to mitigate the data noise issue, we summarize and analyze their evaluation metrics, the datasets used in their experiments, and the domains of these datasets. As shown in Table 3, normalized discounted cumulative gain (NDCG) is the most frequently used evaluation metric, and its usage proportion exceeds two-thirds. In terms of the domains of the datasets, the movie dataset is the most popular. Furthermore, we collect the experimental results of several well-established models, for the Movielens dataset, to analyze the differences in their recommendation performance.

In the interest of fairness and accuracy, we extracted three studies (FG-ACAE[44], CollaGAN[30], and CoFiGAN[19]), all of which conducted experiments on the Movielens-1 M dataset. Furthermore, we present their performance comparison in terms of the three most frequently used evaluation metrics. Table 4 shows that IRGAN is the most commonly used baseline

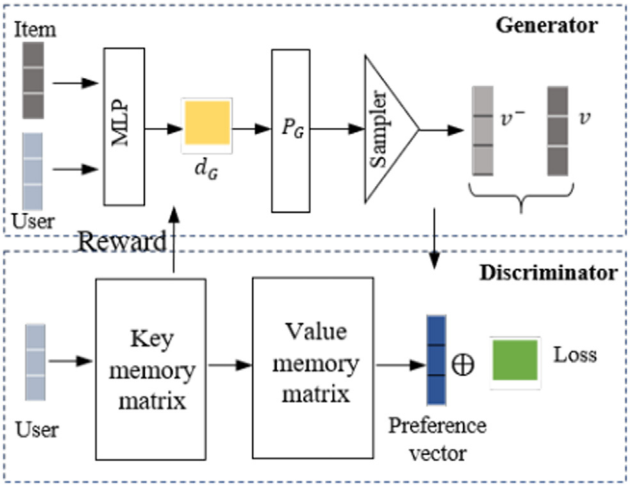

Fig. 5. NMRN-GAN framework [35].

Table 3
Evaluation and domain comparison of GAN-based models for mitigating the data noise issue. (ML: Movielens, PT: Pinterest, GW: Gowalla, AM: Amazon, NF: Netflix, FS: Foursquare, LS: Last.fm, BS: Business, IM: Image, MV: Movie, MS: Music, SO: Social, PP: Paper, BK: Book).

Category	Model Name	Evaluation Metric						Domain	Datasets
		NDCG	HR	MAP	F1	Pre	Recall		
Models for mitigating casual and malicious noise	APR [14]	✓	✓					BS, IM	Yelp, PT, GW
	AMR [29]	✓	✓					IM	PT, AM
	CollaGAN [30]	✓				✓		MV	ML, NF
	ACAE/ FG-ACAE [44]	✓	✓					MV	ML, Ciao
	SACRA [18]			✓				BS	Yelp, FS
	ATF [7]				✓			MV, MS	ML, LS
Models for distinguishing the uninformative samples from unobserved items	IRGAN [34]	✓				✓		MV	ML, NF
	DASO [11]	✓				✓		SO	Ciao, Epinion
	GAN–HBNR [4]			✓			✓	PP	AAN, DBLP
	NMRN-GAN [35]	✓	✓					MV	ML, NF
	ABinCF [33]	✓				✓		MV, BK, BS	ML, AM, Yelp
	CoFiGAN [19]	✓				✓		MV	ML, NF
	AdvIR [22]					✓		MV	ML

Table 4
Performance comparison of GAN-based models for mitigating the data noise problem, tested on the Movielens-1 M datasets (results for FG-ACAE [44], CollaGAN [30], and CoFiGAN [19]).

Source	Model	Evaluation Metric					
		HR@5	HR@10	Pre@5	Pre@10	NDCG@5	NDCG@10
FG-ACAE [44]	NeuMF	0.5832	0.7250	/	/	0.4304	0.4727
	APR	0.5875	0.7263	/	/	0.4314	0.4763
	ACAE	0.5988	0.7379	/	/	0.4446	0.4905
	FG-ACAE	0.6186	0.7507	/	/	0.4586	0.5136
CollaGAN [30]	NeuMF	/	/	0.394	0.363	0.402	0.447
	IRGAN	/	/	0.375	0.351	0.382	0.415
	CollaGAN	/	/	0.428	0.398	0.417	0.458
CoFiGAN [19]	NeuMF	/	/	0.3993	0.3584	0.4133	0.3844
	IRGAN	/	/	0.3098	0.2927	0.3159	0.3047
	CoFiGAN	/	/	0.4484	0.4007	0.4641	0.4300

model, and most of the baselines are based on neural networks. Specifically, FG-ACAE consistently outperforms ACAE, owing to the increased quantity of adversarial noise. Both FG-ACAE and ACAE outperform APR (the first adversarial learning model) on the three chosen metrics. CGAN outperforms NeuMF, which indicates that adversarial training can boost the accuracy of the recommendation models. However, NeuMF performs significantly better than IRGAN, demonstrating that neural networks can extract better latent features than conventional models based on matrix factorization (MF). A similar pattern also appears in CoFiGAN's experiment. To summarize, adversarial training can improve model performances, especially in neural network-based models.

3.4. Qualitative analysis

To more clearly elucidate the specific designs of the aforementioned models, we demonstrate their particular designs and analyze their advantages, as shown in Table 5.

4. GAN-based recommendation models for mitigating the data sparsity issue

Alongside data noise, data sparsity is another severe problem in RS. In this section, we highlight some typical models, to identify the most notable and promising advancements of recent years. We divide them into two categories: (1) models for generating user preferences by augmenting interactive information, and (2) models for synthesizing user preferences by augmenting them with auxiliary information.

4.1. Models for generating user preferences by augmenting with interactive information

Several productive approaches have enabled GAN-based architectures to improve the utility of RSs, by augmenting them with missing interactive information and thereby mitigating the data sparsity issue; these include CFGAN [6], AugCF [36], PLASTIC [48], and more.

[**CFGAN** & **RAGAN**] CFGAN [6] was the first model to generate the purchase vectors of users rather than item IDs; it was inspired by the CGAN concept [21]. The framework of CFGAN is shown in Fig. 6. The loss function of G is

$$L^G = \sum_u \log\left(1 - \left(D\left(\widehat{r}_u \cdot e_u\right)|c_u\right)\right), \tag{14}$$

where the input of G is the combination of a purchase vector c_u for user u and the random noise z. The G generates a low-dimensional user preference vector $\hat{r_u}$ using a multi-layer neural network. The D distinguishes generated preference vectors from real purchase vectors. Its loss function is

Table 5
A schematic representation of GAN-based RS for mitigating the data noise issue.

Category	Model	Generator	Discriminator	Advantage
Models for mitigating casual and malicious noise	APR [14]	maximize the BPR loss function to learn adversarial noise.	minimize the BPR loss function to improve robustness of the model.	The first one adds adversarial perturbations to the model parameters.
	AMR [29]	maximize the VBPR loss function.	minimize the VBPR loss function to improve the robustness of the model.	The first one applies adversarial noise to the images RS.
	CollaGAN [30]	apply the variational autoencoder as the generator.	maximizing the probability of generated item samples.	The first one applies GANs to the CF.
	ACAE [43]	add adversarial noise at different locations of the model.	identify the rating vectors.	The one points out how to find a balance between accuracy and robustness.
	ATF [7]	maximize the BPR loss function	minimize the BPR loss function	The first one combines tensor factorization and GANs
Models for distinguishing the uninformative samples from unovserved items	IRGAN [34]	selects items from the set of existing items.	determine the relationship pairs is real or generated.	The first one uses GANs to informative retrieval.
	CoFiGAN [19]	minimize the distance between generated samples and real.	Like the discriminator in IRGAN.	a extension of IRGAN.
	DASO [11]	apply two generators for social and interactive information.	identify whether each interaction pair is real.	generate valuable negative samples to learn better representations.
	GAN–HBNR [4]	apply DAE to integrate the content and structure of the heterogeneous network.	an energy function.	The network structure and vertex content are integrated into a unified framework.
	NMRN-GAN [35]	generate more recognizable negative samples.	identify negative samples is from the real data.	apply GAN in the process of negative sampling for stream recommendation model.

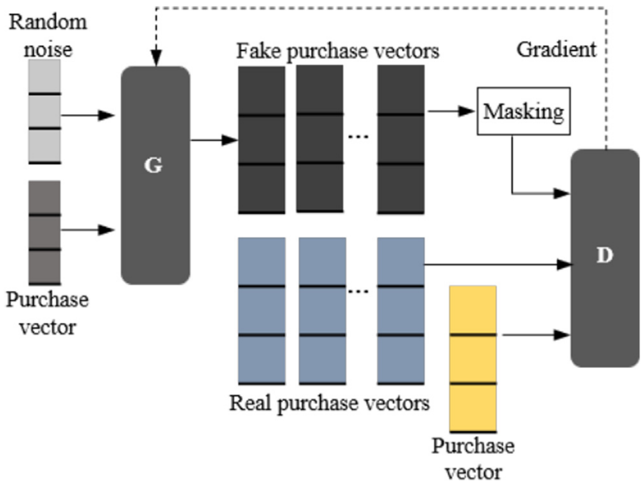

Fig. 6. CFGAN framework [6].

$$L^D = -\mathbb{E}_{x\sim P_{data}}[\log D(x|c)] - \mathbb{E}_{\hat{x}\sim P_\phi}[\log(1 - D(\hat{x}|c))] = -\sum_u \left(\log D(r_u|c_u) + \log(1 - D((\widehat{r_u} \cdot e_u)|c_u))\right), \tag{15}$$

where P_{data} represents the real data distribution, P_ϕ is the data distribution generated by the generator, $\cdot$ represents the multiplication of the elements, and e_u is an indicator vector specifying whether or not u has purchased item i. To better simulate the preferences of users, this model uses e_u as the masking mechanism.

In terms of accuracy, CFGAN has outperformed other state-of-the-art models (including IRGAN [34]) by at least a 2.8% enhancement for three different datasets: Ciao, Watcha, and Movielens. This is a new direction in vector-wise adversarial training for GAN-based recommendation tasks; it prevents D from being misled. Several state-of-the-art GANs have achieved better stability than CFGAN and can be applied thereto, to further improve the recommendation accuracy. Besides this, Chae et al. [5] proposed a rating augmentation model based on GANs, referred to as RAGAN. It uses the observed data to learn initial parameters and then generate plausible data via its generator. Finally, the augmented data are used to train conventional collaborative filtering (CF) models.

[**UGAN**] Inspired by the advances of CFGAN (in terms of generating vectors instead of item lists), Wang et al. [38] proposed a unified GAN (UGAN) to alleviate the data sparsity problem. The main idea of the UGAN is to generate user profiles with rating information, by capturing the input data distribution. The discriminator uses the Wasserstein distance to distinguish the generated samples from the real ones. The authors evaluated its recommendation performance on two public datasets. The experimental results show that the UGAN achieves significant improvement.

[**AugCF**] AugCF [36] is another GAN-based CF model designed to generate interactive information. It generates interactions for different recommendation tasks under different auxiliary information conditions. It features two training stages: (1) The generator generates the most preferred item for the user in the interaction category. The generated tuple (user, item, and interaction category) can be considered as a valid and realistic sample of the original dataset. The discriminator is only used to determine whether the generated data tuple is real. (2) The generator is fixed and used only to generate data. Then, the discriminator is used to determine whether the user likes the items or not. The framework of the AugCF is shown in Fig. 7.

The loss function of AugCF is defined as Eq. 16. The discriminator and generator compete on the category label c and user u. To perform the different roles in the two phases of the discriminator model, AugCF expands the first two relationship categories (like or dislike) into four ones: true & like, true & dislike, false & like, and false & dislike. Its loss function is

$$L^{G,D} = \min_\theta \max_\phi \left(\mathbb{E}_{(u,v,y)\sim P_C(v|u,c)} \log[D_\phi(v,y|u,c)] + \mathbb{E}_{(u,v,y)\sim P_{G_\theta}(v|u,c)} \log[D_\phi(v,y|u,c)]\right), \tag{16}$$

where $P_{G_\theta}(v|u,c)$ and $P_c(v|u,c)$ represent the distributions of the generated and real data, respectively. The models were experimentally investigated using user reviews as auxiliary information; the results show that AugCF outperformed the baselines and state-of-the-art models. The AugCF provides a new method for alleviating the data sparsity problem; however, this problem remains a long-standing research topic in the field of RSs.

[**APL**] Besides this, Sun et al. [28] proposed adversarial pairwise learning (APL), which is a general GAN-based pair-wise learning framework. APL combines the generator and discriminator via adversarial pair-wise learning, based on the assumption that users prefer items that have already been consumed. Under this framework, the generator g_θ attempts to generate items that approximate the real distribution for each user. The discriminator f_ϕ learns the ranking function between two

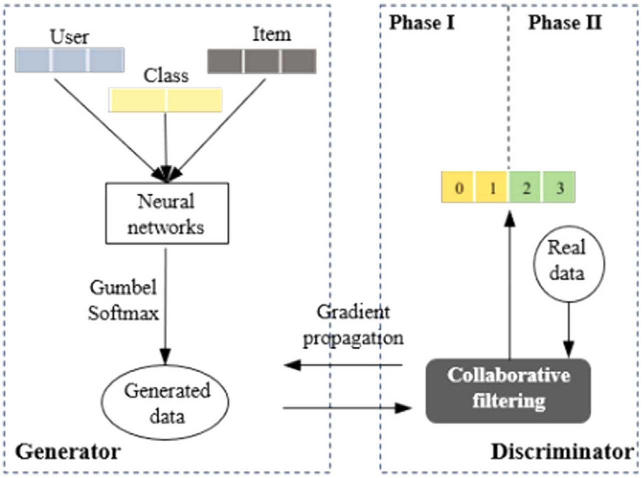

Fig. 7. AugCF framework [36].

pairs of items and determines the preference of each user. Expressed otherwise, for each pair of items i and j, the discriminator must identify which is more in line with user preferences. The framework of the APL is shown in Fig. 8. APL directly uses pair-wise ranking as the loss function, instead of a function based on the probability distribution; The loss function of APL is defined as follows:

$$L(g_\theta, f_\phi) = \max_\theta \min_\phi \sum_{u=1}^{m} \mathbb{E}_{i\sim P_{real}(i|u)}^{j\sim P_\theta(j|u)} L(f_\phi(i|u) - f_\phi(j|u)). \tag{17}$$

Here, $L(x)$ is the pair-wise ranking loss function, which differs from the loss function of GANs. If the discriminant loss function is specifically designed to maximize the difference in ranking scores between the observed and generated items, then the original objective function is equivalent to that of WGAN [1], as shown in Eq. 18.

$$\begin{aligned} L(g_\theta, f_\phi) &= \max_\theta \min_\phi \sum_{u=1}^{m} -\mathbb{E}_{i\sim P_{real}(i|u)}^{j\sim P_\theta(j|u)} L(f_\phi(i|u) - f_\phi(j|u)) \\ &= \min_\theta \max_\phi \sum_{u=1}^{m} \left[\mathbb{E}_{i\sim P_\theta(i|u)} f_\phi(i|u) - \mathbb{E}_{j\sim P_\theta(j|u)} f_\phi(j|u)\right]. \end{aligned} \tag{18}$$

This model manages the problem of gradient vanishing by utilizing the pair-wise loss function and the Gumbel-Softmax technique [15]. Extensive experiments have demonstrated its effectiveness and stability. APL is a general adversarial training recommendation framework that can be used for future RS in various fields.

[**PLASTIC**] GANs have also been applied in numerous other recommendation fields, to generate interactions and mitigate data sparsity. For example, PLASTIC [48] was proposed for sequence recommendation; it combines MF, recurrent neural networks (RNNs), and GANs. Its framework is shown in Fig. 9.

In the adversarial training process, the generator, like that of the CGAN [21], takes users and times as inputs, to directly predict the recommendation list of the user. For the discriminator, PLASTIC integrates long-term and short-term ranking models through a Siamese network, to correctly distinguish real samples from generated ones. Extensive experiments have shown that it achieves better performance than other models [34].

[**RecGAN**] Recurrent GAN (RecGAN) combines recurrent recommender networks and GANs to learn temporal features of users and items [3]. In RecGAN, the generator predicts a sequence of items for a user, by fitting the distribution of items. The discriminator determines whether the sampled items are from the distribution of the user's real preferences. In experiments, RecGAN outperformed up-to-date baseline models, such as recurrent recommender networks on Movielens datasets. This work lacks an in-depth study of the feasibility and impacts of gated recurrent unit (GRU) modifications in reflecting different granularities of temporal patterns.

[**APOIR**] Zhou et al. [50] proposed adversarial point-of-interest recommendation (APOIR), to learn the potential preferences of users in point-of-interest (POI) recommendations. The generator selects a set of POIs using the policy gradient and tries to match the real distribution. Then, the discriminator distinguishes the generated POIs from the actual browsing behaviors of the user. The proposed model uses geographical features and the social relationships of users to optimize the generator. The loss function of APOIR is

$$L^{G,D} = \min_\theta \max_\phi \sum_{u_i} \left(\mathbb{E}_{l^+}\left[\log D_\phi(u_i, l^+)\right] + \mathbb{E}_{l^R\sim R_\theta(l^R|u_i)}\left[\log\left(1 - D_\phi\left(u_i, l^R\right)\right)\right]\right), \tag{19}$$

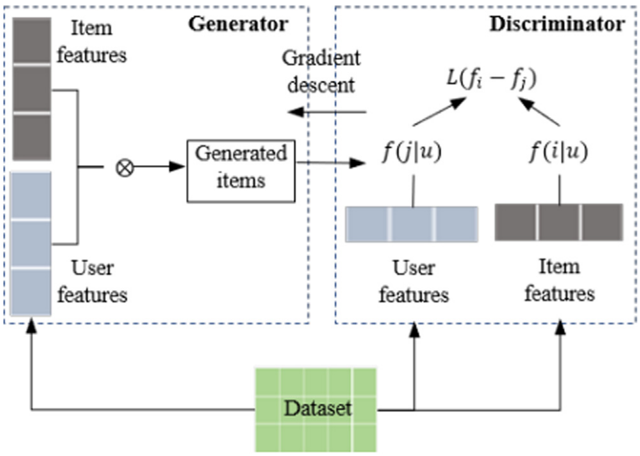

Fig. 8. APL framework [28].

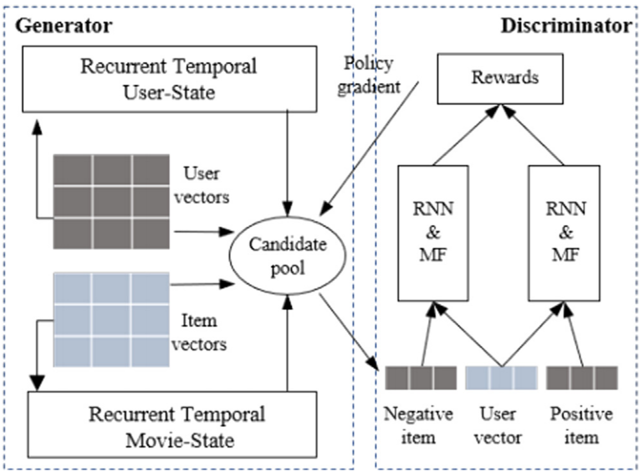

Fig. 9. PLASTIC framework [48].

where l^+ represents the POIs already visited, and $D_\phi\left(u_i, l^R\right)$ evaluates the probability that user u_i has preferentially visited POI l^R. Once the confrontation between the generator and discriminator has been balanced, the recommender (generator) $R_\theta\left(l^R|u_i\right)$ recommends high-quality POIs for the user.

[**Geo-ALM**] Liu et al. [20] proposed a geographical information-based adversarial learning model (Geo-ALM), to combine geographical information and GANs for making POI recommendations. In the model, the *G* generates unvisited POIs that match user preferences as much as possible, and the *D* focuses on distinguishing the visited POIs from unvisited ones as accurately as possible. The authors verified the superiority of Geo-ALM on two public datasets: Foursquare and Gowalla.

4.2. Models for synthesizing user preferences by augmenting with auxiliary information

In addition to augmenting models with interactive information to directly generate user preferences, several studies have tried to use the generators of GAN-based architectures to augment models with auxiliary information [5,42,40,23,32].

[**RSGAN**] Reliable social RS based on GAN (RSGAN) [42] was proposed to augment social recommenders with more reliable friends and alleviate the problem of data sparsity. It consists of two components: *G* and *D*. *G* is responsible for generating reliable friends and the items consumed by these friends. The model first constructs a heterogeneous network, to identify seed friends with higher reliability. The model collects seed users for each user and encodes them into binary vectors as the incomplete social preferences of the user. Then, the probability distributions of friends with high likelihoods are sampled through Gumbel-Softmax [15]. This strategy is also used to simulate the sampling of items. To rank the candidate items, RSGAN adopts the idea of social BPR [47] in its *D*. It sorts the candidates and recommends an item list for each user. If the items consumed by the generated friends are not useful, the D punishes them and returns the gradient to the G, to reduce the likelihood of generating such friends. The loss function of RSGAN is

$$L^{D,G} = \min_{D}\max_{G} - \mathbb{E}\left(\left(\log\sigma(x_{ui} - x_{uz}) + \log\sigma\left(x_{uz} - x_{uj}\right)\right)\right). \tag{20}$$

The designers of RSGAN conducted experiments with three models: conventional social recommendation models [47] and other GAN-based ones [34,6]. The experimental results show that RSGAN outperforms all other methods in ranking prediction. The possible reason for this is that RSGAN builds a dynamic framework to generate friend relationships and thereby alleviate the data sparsity problem. Its framework is shown in Fig. 10.

[**KTGAN**] KTGAN [40] was proposed to augment data and alleviate the problem of data sparsity by importing external information. The model consists of two phases: (1) extracting feature embeddings using auxiliary and interactions information, to construct the initial representations of users and items; and (2) putting these vectors into an IRGAN-based generator and discriminator for adversarial training. The discriminator attempts to identify whether the user-item pair is generated or real. The loss function of KTGAN is

$$L^{D,G} = \min_{D}\max_{G}\sum_{n=1}^{N}\left(\mathbb{E}_{m\sim p_{true}(m|u_n,r)}[\log P(m|u_n)] + \mathbb{E}_{m\sim p_{\theta}(m|u_n,r)}[\log(1 - P(m|u_n))]\right), \tag{21}$$

where $P(m|u_n)$ estimates the probability that user u_n prioritizes item m. The parameter r represents the relationship between a user and an item. The experiments show that it achieves a better accuracy and NDCG than other methods [34]. In particular, if the generator can generate a more accurate low-dimensional vector at the start of training, it can train a better-optimized discriminator and improve the performance of the model.

[**CnGAN**] Perera et al. [23] proposed CnGAN to learn the mapping encoding between the target and source domains for non-overlapped users in different domains. The framework is shown in Fig. 11. E is the neural network encoder that converts the distribution of inputs into a vector; the generator G uses the target encoding as an input, to generate the mapping encoding E_{sn} of the source domain for non-overlapping users. Moreover, G makes the generated preference domain correspond as much as possible to the real source domain, to deceive the discriminator. The loss function is

$$\min_{G} L^{G} = \mathbb{E}_{tn_u^t\sim p_{data}(tn)} L_{fake}\left(E_{tn}\left(tn_u^t\right), G\left(E_{tn}\left(tn_u^t\right)\right)\right) + \mathbb{E}_{tn_u^t, sn_u^t\sim p_{data}(tn,sn)} L_{content}\left(E_{sn}\left(sn_u^t\right), G\left(E_{tn}\left(tn_u^t\right)\right)\right). \tag{22}$$

D distinguishes the real source-domain encoding from the generated one. In particular, the mismatching source- and target-domain encodings are used as the input of G. The overlap between the user's real target- and source-domain embeddings is taken as the actual mapping. Formally, the loss function of D is

$$\begin{aligned} &\max_{E_{tn},E_{sn},D} L(E_{tn}, E_{sn}, D) \\ &= \mathbb{E}_{tn_u^t, sn_u^t\sim p_{data}(tn,sn)} L_{real}\left(E_{tn}\left(tn_u^t\right), E_{sn}\left(sn_u^t\right)\right) \\ &+ \mathbb{E}_{tn_u^t\sim p_{data}(tn)} L_{fake}\left(E_{tn}\left(tn_u^t\right), G\left(E_{tn}\left(tn_u^t\right)\right)\right) \\ &+ \mathbb{E}_{tn_u^t, \overline{sn}_u^t\sim \bar{p}_{data}\left(tn,\overline{sn}\right)} L_{mismatch}\left(E_{tn}\left(tn_u^t\right), E_{sn}\left(\overline{sn}_u^t\right)\right), \end{aligned} \tag{23}$$

where $P_{data}(tn, sn)$ is a matching pair with a mapping relationship, $\overline{P}_{data}(tn, \overline{sn})$ is a matching pair with no mapping relationship, $P_{data}(tn)$ is the local distribution of the target domain, and $G(x)$ is the matching source-domain encoding, generated for a given target domain. CnGAN employs a new approach to alleviate the data sparsity issue. It represents the first attempt to

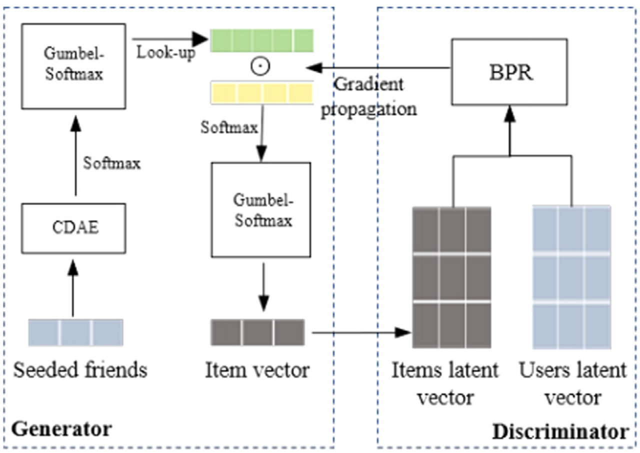

Fig. 10. RSGAN framework [42].

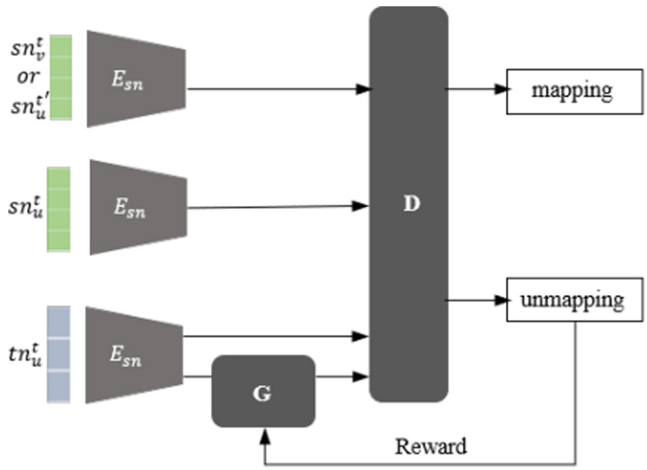

Fig. 11. CnGAN framework [23].

use GANs to generate missing source-domain preferences for non-overlapping users, by generating mapping relationships between the source and target domains.

[**RecSys-DAN** & **AB-GAN**] RecSys-DAN, proposed by Wang et al. [32], is similar to CnGAN [23]. It also uses an adversarial approach to transfer the potential representations of users and items from different domains to the target domain. Besides this, Zhang et al. [49] designed and implemented a virtual try on GAN model, referred to as AB-GAN, in which the generator G generates images for the modeling of 2D images. Given four features (the user-image feature, desired-posture feature, new-clothing feature, and body shape mask), an image of the user wearing new clothing is generated. The G can synthesize an original image of a person and ensure that the data distribution is similar to that of the real image. AB-GAN is superior to other advanced methods, according to qualitative analysis and quantitative experiments.

[**ATR** & **DVBPR**] In the adversarial training for review-based recommendation (ATR) model, Rafailidis et al. [26] used GANs to generate reviews likely to be relevant to the user's preferences. The discriminator focuses on distinguishing between the generated reviews and those written by users. Similar to generating user-related reviews, the generator also generates items-related reviews. After obtaining review information through adversarial training, this model predicts user preferences through the joint factorization of rating information. Furthermore, to synthesize images that are highly consistent with users' preferences in fashion recommendation, Kang et al. [16] proposed deep visually aware BPR (DVBPR), in which the generator generates appropriate images that look realistic, and the discriminator tries to distinguish generated images from the real ones using a Siamese-CNN framework. DVBPR is the first model to exploit the generative power of GANs in fashion recommendations. The same ideas can also be applied to non-visual content.

[**LARA**] Sun et al. [27] proposed the end-to-end adversarial framework LARA; it uses multiple generators to generate user profiles from various item attributes. In LARA, every single attribute of each item is input into a unique generator. The outputs of all generators are integrated through a neural network, to obtain the final representation vector. The discriminator distinguishes the real item-user pair from the three interaction pairs, which include the item-generated user, item-interested real user, and item-uninterested real user. The architecture of LARA is shown in Fig. 12. Formally, the objective function of LARA is

$$\begin{aligned}\mathcal{L}^{G^*,D^*} &= \min_{\theta}\max_{\phi}\sum_{n=1}^{N}\left(\mathbb{E}_{\mathbf{u}^+\sim p_{true}(\mathbf{u}^+|I_n)}[\log(D(\mathbf{u}^+|I_n))]\right.\\ &+\mathbb{E}_{\mathbf{u}^c\sim p_{\theta}(\mathbf{u}^c|I_n)}[\log(1-D(\mathbf{u}^c|I_n))]\\ &\left.+\mathbb{E}_{\mathbf{u}^-\sim p_{false}(\mathbf{u}^-|I_n)}[\log(1-D(\mathbf{u}^-|I_n))]\right).\end{aligned} \tag{24}$$

Experiments on two datasets show the effectiveness of LARA through comparisons against other state-of-the-art baselines. The same idea can be used to solve the user cold-start problem. Despite its successes, the method can still be optimized by drawing on the concept of WGAN.

[**TagRec:**] Quintanilla et al. [24] proposed an end-to-end adversarial training framework called TagRec, to make tag recommendation. TagRec features a generator G that takes image embeddings as an input and generates image tags; a discriminator D is used to distinguish the generated tags from the real ones. TagRec achieved an excellent performance on two large-scale datasets. The image content and user history records involved in TagRec are applied in parallel. If the authors had attempted to design multiple generators and put both sets of information into the generator, the performance would have been enhanced.

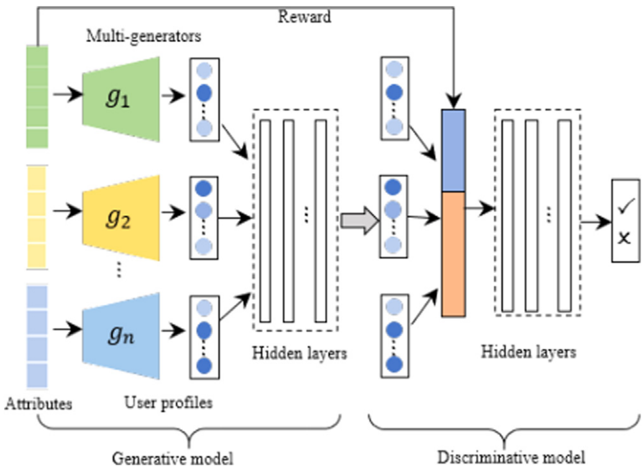

Fig. 12. LARA framework [27].

[**RRGAN:**] Similarly, Chen et al. [9] RRGAN, to generate user profiles and item representations. RRGAN takes the representations learned from reviews as the input of *G*. *G* predicts the item ratings for a given user. In contrast, *D* attempts to distinguish the predicted representations from real ones. Furthermore, the authors plan to unify explicit and implicit feedback, using adversarial training.

Table 6
Evaluation and domain comparison of GAN-based models for mitigating data sparsity issue. (ML: Movielens, PT: Pinterest, GW: Gowalla, AM: Amazon, NF: Netflix, FS: Foursquare, LS: Last.fm, BS: Business, IM: Image, MV: Movie, MS: Music, SO: Social, PP: Paper, BK: Book).

		Evaluation Metric									
Category	Model	NDCG	HR	Recall	MAE	RMSE	Pre	MAP	AUC	Domain	Datasets
Models for generating user preferences by augmenting with interactive information	CFGAN [6]			✓			✓	✓		MV	Ciao, WT, ML
	RAGAN [5]						✓			MV	Ciao, WT, ML
	AugCF [36]		✓							MV	ML, FP
	APL [28]	✓		✓			✓	✓		IM, BS, MS	GW, Yelp, PT, YH
	PLASTIC [48]	✓					✓			MV	ML, NF
	RecGAN [3]	✓						✓		MV	MFP, NF
	APOIR [50]	✓		✓			✓	✓		POI	GW, Yelp, FS
	Geo-ALM [20]			✓			✓			POI	GW, FS
	UGAN [38]			✓	✓	✓	✓	✓		MV	ML, DB
Models for synthesizing user preferences by augmenting with auxiliary information	RSGAN [42]	✓		✓			✓			SO	LF, DB, EP
	KTGAN [40]	✓					✓			MV	ML, DB
	CnGAN [23]	✓	✓							SO, MS	YT, TW
	RecSys-DAN [32]				✓					MS	AM
	ATR [26]					✓				RW	AM
	DVBPR [16]								✓	RW, IM	AM
	LARA [27]	✓			✓		✓			MV, BS	ML, Inzone
	TagRec [24]			✓	✓		✓			IM	Nus-WIDE, YFCC
	LSIC [11]	✓					✓	✓		MV	ML, NF
	RRGAN [9]	✓		✓						BS	Watches, patio, Kindle

4.3. Quantitative analysis

We provide an overview of the aforementioned models in Table 6, to summarize the evaluation metrics, experimental data, and dataset domains involved in the studies. Precision is the most widely adopted metric, followed by NDCG, with a partial overlap with the GAN-based models for mitigating the data sparsity issue. In terms of the dataset domains, movies are the most-used domain, owing to the popularity of Movielens. The following section presents a performance analysis of three prominent models.

We only collected the experimental results from three studies when making our comparison, because results are displayed in different forms across different studies. In the interest of fairness and accuracy, we summarized the data sparsity and dataset information by employing a similar sparsity in our comparison (Ciao and Yahoo). We found that CFGAN outperformed IRGAN and GraphGAN on the Movielens and Ciao datasets, as shown in Table 7. Furthermore, we can observe that almost all studies regard IRGAN as the baseline model. The overall performances of the three models are better than that of IRGAN.

4.4. Qualitative analysis

To better highlight the differences between the aforementioned models in term of their generators and discriminators, we list their specific designs and respective advantages in Table 8.

5. Open issues and future research directions

5.1. Open issues

5.1.1. The position of adversarial training

DNN-based recommendation models have recently been extensively researched, because they can learn more abstract representations of users and items and can grasp the nonlinear structural features of interactive information. However, these networks feature complex structures and a wide variety of parameters. Hence, choosing a suitable adversarial training position has become a significant challenge, requiring more in-depth knowledge and broader exploration.

5.1.2. Model parameter optimization stability problem for discrete training data

GANs were initially designed for the image domain, where data are continuous and gradients are applied for differentiable values. However, the interactive records in RS are discrete. The generation of recommendation lists is a sampling operation. Thus, the gradients derived from the objective functions of the original GANs cannot be directly used to optimize the generator via gradient descent. This problem prevents the model parameters from converging during training. Several researchers have tried to train the model, using a policy gradient [39] and Gumbel-Softmax [15]; however, the stability of the parameter optimization in the GAN-based recommendation model is still an open research problem.

5.1.3. Model size and time complexity

The scale and time complexities of the existing GAN-based RS are relatively high, because GANs include two components, with each part consisting of multiple layers of neural networks. This problem becomes more serious when the model contains multiple generators and discriminators, and it hinders the application of GAN-based recommendation models to real systems. Besides this, the training process is confrontational and mutually promoting, which can be considered as a minimax game. We must ensure high-quality feedback between the two modules to enhance the model performance. If one of the two models is under-fitting, it will cause the overall model to collapse.

Table 7
Performance comparison of GAN-based models for mitigating data sparsity, for three datasets(results from CFGAN [6], PLASTIC [48], and APL [28]).

Dataset	Source	Model	Evaluation Metric					
			Pre@5	Pre@10	Pre@20	NDCG@5	NDCG@10	NDCG@20
Movielens −100 K (93.69%)	CFGAN [6]	IRGAN	0.312	/	0.221	0.342	/	0.368
		GraphGAN	0.212	/	0.151	0.183	/	0.183
		CFGAN	0.444	/	0.294	0.476	/	0.433
	PLASTIC [48]	IRGAN	0.2885	/	/	0.3032	/	/
		PLASTIC	0.3115	/	/	0.3312	/	/
Ciao (98.72%)	CFGAN [6]	IRGAN	0.035	/	0.023	0.046	/	0.066
		GraphGAN	0.026	/	0.017	0.041	/	0.058
		CFGAN	0.072	/	0.045	0.092	/	0.124
Yahoo (99.22%)	APL [28]	IRGAN	/	10.960	/	/	11.900	/
		APL	/	11.513	/	/	12.661	/

Table 8
Schematic representation of GAN-based RS designed to mitigate the data sparsity issue.

Category	Model	Generator	Discriminator	Advantage
Models for generating user preferences by augmenting with interactive information	CFGAN [6]	Apply user purchase vectors to generate purchase vectors	Identify whether the purchase vectors meet the users' preferences	Using vector-wise training in RS
	AugCF [36]	Apply interactive categories as condition label to generate items	Two stages: (1) determine the relationships between users and items, and (2) identify the relationship labels	Design the discriminator to identify true/false data and like/dislike categories
	APL [28]	Generate the items to approximate the actual distribution	Apply the pair-wise ranking function to determine	Apply adversarial learning to the implicit feedback
	PLASTIC [48]	Apply time to generate a list of items	Capture long-term and short-term preferences of users to select the exact high-scoring items	Apply adversarial learning to combine MF and RNN
	APOIR [50]	Select POIs to fit the real data distribution	Determine whether user's POIs are real or generated	Apply adversarial learning to optimize POI RS
	RecGAN [3]	Predict a sequence of items consumed by user	A GRU that determines the probability of items sequences	Combine GRU and GANs to capture temporal profiles
	Geo-ALM [20]	Generate high-quality unvisited POIs for a given user	Distinguish between visited POIs and unvisited POIs	Combine geographic features and GANs
	UGAN [38]	Simulate user rating information	Distinguish between generated and real data	Use wGAN and CGAN to forge users
Models for synthesizing user preferences by augmenting with auxiliary information	RSGAN [42]	Generate reliable friends and their consumed items using Gumbel-Softmax	Apply the positive, negative, and generated items to sort the candidate items	Apply GANs to social recommendation
	KTGAN [40]	Apply the auxiliary information to generate relationships between users and items	Distinguish whether the relationship pair is from a real dataset	Integrate auxiliary information and IRGAN to alleviate data sparsity
	CnGAN [23]	Generate the mapping encoding of the source network for the non-overlapping users	Determine whether the mapping relationship of the overlapping users is real or generated	Apply GANs to the cross-domain RS
	RecSys-DAN [32]	Learn the vectors from different domains to learn the transfer mapping	Determine whether the relationships between users and items in different fields are genuine or not	Learn how to represent users, items, and their interactions in different domains
	ATR [26]	Use the encoder-decoder to generate reviews	Estimate the probability that the review is true	An adversarial model for review-based recommendations
	LARA [27]	Generate the profiles of the user from different attributes	Distinguish the well-matched user-item pairs from ill-matched ones	A GAN-based model that uses multi-generators
	TagRec [24]	Generate (predict) personalized tags	Distinguish the generated tags from real ones	Use GANs to predict tags resembling truth tags
	RRGAN [9]	Generate vectors of users and items based on reviews	Distinguish the predicted ratings from real ones	Predict the ratings based on reviews

5.2. Future research directions

Although studies on GAN-based recommendation models have established a solid foundation for alleviating the data noise and data sparsity issues, several open issues remain. In this section, we put forward the more promising areas of interest in GAN-based RS research and introduce the following future research directions.

5.2.1. GAN-based explanations for recommendation models

The generators and discriminators in GAN-based recommendation models are predominately constructed using DNNs, which are categorized as black-box models. In other words, we are only aware of their inputs and outputs, and the underlying principle is difficult to understand. Existing models that improve the interpretability of RS primarily give explanations following a recommendation [37], and the content of the explanation is often unrelated to the results. A beneficial development would be to use GANs to explain the results and generate a recommendation list. In this framework, the discriminator not only judges the accuracy of the generated recommendation but also the interpretation of this recommendation. Thus, the generator and discriminator can compete with each other, to improve model explainability.

5.2.2. Cross-domain recommendation based on GANs

Cross-domain models, which assist in the representation of the target domain using the knowledge learned from source domains, are a promising option for tackling the data sparsity issue. One of the most widely studied topics in cross-domain recommendation is transfer learning. This aims to improve the learning ability in one target domain by using the knowledge transferred from other domains. However, unifying the information from different domains into the same representation space remains a challenging problem. Adversarial training can continuously learn and optimize the mapping process from the source domain to the target one, thereby enriching the training data of the recommendation model. A small number of models [23,32] have employed the advantages of GANs in learning the mapping relationship between different fields of information, and their effectiveness has been verified through experiments. This is a promising but mostly under-explored area, where more studies are expected.

5.2.3. Scalability of GAN-based recommendation models

Scalability is critical for recommendation models, because the ever-increasing volumes of data make the time complexity a principal consideration. GANs have been applied to some commercial products; however, due to the continuous improvement of GPU computing power, further research on GAN-based RS is required in three areas: (1) incremental learning of non-stationary and streaming data, such as the case in which large numbers of interactions take place between users and items; (2) accurate calculation of high-dimensional tensors and multimedia data sources; (3) balancing model complexity and scalability under the exponential growth of parameters. Knowledge distillation is an ideal candidate method to manage these areas; it utilizes a small student model that receives knowledge from a teacher model. Because short training times are essential for real-time applications, scalability is another promising direction that deserves further study.

6. Conclusion

In this paper, we provided a retrospective review of the up-to-date GAN-based recommendation models, demonstrating their ability to reduce the adverse effects of data noise and alleviate the data sparsity problem. We discussed the development history of GANs and clarified their feasibility for RS. In terms of the efforts devoted to tackling data noise, we introduced existing models from two perspectives: (1) models for mitigating malicious noise; and (2) models for distinguishing informative samples from unobserved items. In terms of the studies focusing on mitigating the data sparsity problem, we grouped the models into two categories: (1) models for generating user preferences through augmentation with interactive information; and (2) models for synthesizing user preferences through augmentation with auxiliary information. After the review, we discussed some of the most significant open problems and highlighted several promising future directions. We hope this survey will help shape the ideas of researchers and provide some practical guidelines for this new discipline.

CRediT authorship contribution statement

Min Gao: Conceptualization, Validation, Writing - review & editing. **Junwei Zhang:** Investigation, Writing - original draft, Writing - review & editing. **Junliang Yu:** Validation, Resources, Writing - review & editing. **Jundong Li:** Validation, Writing - review & editing. **Junhao Wen:** Project administration, Funding acquisition. **Qingyu Xiong:** Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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