Recommender Systems Based on Generative Adversarial Networks: A Problem-Driven Perspective

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ABSTRACT

Recommender systems (RS) play a very important role in various aspects of people’s online life. Many companies leverage RS to help users discover new and favored items. Despite their empirical success, these systems still suffer from two main problems: data noise and data sparsity. In recent years, Generative Adversarial Networks (GANs) have received a surge of interests in many fields because of their great potential to learn complex real data distribution, and they also provide new means to mitigate the aforementioned problems of RS. Particularly, owing to adversarial learning, the problem of data noise can be handled by adding adversarial perturbations or forcing discriminators to tell the informative and uninformative data examples apart. As for the mitigation of data sparsity issue, the GAN-based models are able to replicate the real distribution of the user-item interactions and augment the available data. To gain a comprehensive understanding of these GAN-based recommendation models, we provide a retrospective of these studies and organize them from a problem-driven perspective. Specifically, we propose a taxonomy of these models, along with a detailed description of them and their advantages. Finally, we elaborate on several open issues and expand on current trends in the GAN-based RS.

1. Introduction

Because of the rapid development of Internet-based technologies, the data on the Internet is growing exponentially, resulting in a situation that each Internet user is persistently inundated with a tremendous amount of information [93, 74, 19]. Particularly, when it comes to online shopping, people have to confront a dilemma that they cannot easily make a choice when a sea of options are presented. As an effective tool to tackle the information overload, the recommender systems (RS), have been widely used in various scenarios of online life, including E-commerce (e.g., Amazon and Taobao), music playback (e.g., Pandora and QQ music), movie recommendation (e.g., Netflix and iQiyi), and news recommendation (e.g., BBC News and Headlines).

However, despite their pervasiveness and decent performance, RS 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 [20, 23, 31]. To be specific, users sometimes click on products beyond their interests, and the casual feedback may lower the accuracy of RS. Moreover, a few malicious profiles or feedback are injected into RS at times for the purpose of manipulating the results of recommendation. Besides, when the training proceeds, randomly selected negative samples in pairwise learning are often uninformative samples that will mislead the recommendation models and lower their performance. Compared with the data noise problem, data sparsity is an intrinsic problem because of the inevitable fact that each user generally only consumes a tiny fraction of available items [96]. Existing RS normally rely on historical interaction information between users and items to capture users’ interests. When a vast majority of data are missing, it is common to see that RS fail to satisfy users with inaccurate recommendations [33, 56]. Without coping mechanisms, these problems often bring RS to failure, leading to an inferior user experience.

Many researchers have been aware of the harmful effects caused by these two problems and have put efforts into reducing the adverse factors. To mitigate the effect of data noise, these researchers have proposed various approaches to alleviate the data noise problem [44, 86, 8, 63, 35]. Among them, Zhang et al. [94] apply the hidden Markov model to analyze their preference sequence, then they utilize the hierarchical clustering to distinguish attack users from...
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Table 1 The statistics of papers on 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   |

rating behaviors. Bag et al. [3] propose a method that corrects the casual noise by using the Bhattacharya coefficient and the concept of self-contradiction. To distinguish more informative items from unobserved ones, Yu et al. [88] capture more informative users by modeling the whole training data as a heterogeneous information network to get the embedding representation. To obtain informative negative items, some researchers have adopted the popularity-biased sampling strategies [13, 22]. While the above methods have noted that conventional models are vulnerable to identify inevitable noise in the training data, they can only tell conspicuous noise from a specific perspective, and they fail to continuously update their ability to distinguish noise from unobserved items. On the other hand, numerous methods, alleviating the data sparsity problem, have been developed to incorporate auxiliary information like social relationships [76, 103, 48, 84], user reviews [17, 47, 42], item contents [12], and external knowledge graph [75, 77]. Although the integration of auxiliary information is helpful, these methods still suffer from the problem of sparsity because they only use a small amount of observed data to learn ultimate features, and they are incapable of fully characterizing the complexity of the data.

Recently, Generative Adversarial Networks (GANs) have led a revolution in the field of deep learning [102, 18], such as image and audio [97, 50, 41, 78]. The principle of GANs is to play an adversarial minimax game between a generator and a discriminator. The generator focuses on learning the distribution of real observed data and then using the generated samples to confuse the discriminator. The discriminator needs to judge the input sample is from the generator or not.

The successes of applying GANs in other fields have set good examples for RS, and some pioneering work has got a foot in the door of this area [82]. According to the statistics from the top-level conferences related to RS in the past three years, the number of papers on GAN-based recommendation models is increasing year by year, as shown in Table 1. Besides, in a seminar on information retrieval (IR) models based on GANs of the SIGIR 2018, researchers [95] point out that the GAN-based RS will become one of the hotspots in the field of RS. The reason is that the idea of GANs brings new opportunities to resist the interference of data noise and alleviate data sparsity. In the existing GAN-based RS about reducing the interference of noise from RS, some researchers verify the effectiveness of adding adversarial perturbations and introduce the minimax game in the objective function to reduce data noise. In the meantime, other researchers try to use the discriminator to distinguish more informative examples from the unobserved ones in an adversarial way. To alleviate the data sparsity issue, existing recommendation models based on GANs can not only generate users’ preferences directly by augmenting user-item interaction information but also synthesize user preferences by augmenting auxiliary information, which they can significantly mitigate the data sparsity.

However, to the best of our knowledge, few systematic reviews sufficiently analyze the existing studies and current progress on GAN-based recommendation models. To this end, this paper investigates and reviews these models in a problem-driven perspective. Concretely, we divide the existing studies into two parts in which the first one reviews the methods on reducing the adverse effects of data noise, and the other one focuses on the models mitigating the data sparsity issue. We hope this paper can lay the foundation for subsequent research on GAN-based RS. To sum up, the main contributions of this survey are as follows:

- To gain a comprehensive understanding of the state-of-the-art GAN-based recommendation models, we provide a retrospective of these studies and organize them from a problem-driven perspective.
- We systematically analyze the GAN-based models that mitigate data noise issue in RS from two perspectives: (1) mitigating casual and malicious noise, and (2) distinguishing the uninformative samples from unobserved items, according to the sources of data noise.
- We conduct a systematic review on the recommendation models that leverage GANs to alleviate the problem of data sparsity from two aspects: (1) models for generating user preferences by augmenting interaction information, and
models for synthesizing user preferences by augmenting auxiliary information.

- We elaborate on several open issues and expand on current trends in the GAN-based RS.

The rest of this paper is organized as follows: The development process of GANs is recapitulated in Section 2. In Section 3 and Section 4, the up-to-date GAN-based recommendation models are introduced in a problem-driven way, showing the efforts devoted to mitigating the problems of data noise and data sparsity, respectively. In Section 5, we discuss the prominent challenges and research directions. In the final section, we end this paper with a conclusion.

2. The Development of Generative Adversarial Networks

Generative Adversarial Network, an unsupervised model proposed by Goodfellow et al. in 2014 [25], has attracted widespread attention from both academia and industry. It has two components: a generator and a discriminator. The former one learns to generate the data that conforms to the distribution of real data as much as possible, and the latter one needs to identify real data and those generated ones. The two models contest with each other and optimize themselves in feedback loops. The process is shown in Fig.1.

In Fig.1, $z$ is the random noise, and $x$ is the real data. The generator and discriminator are represented by $G$ and $D$, respectively. The loss function is

$$\min_{G} \max_{D} V(D, G) = E_{x \sim p_{data}} \log D(x) + E_{z \sim p_{z}} [\log(1 - D(G(z)))] ,$$

(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, also named vanilla GAN, has some shortcomings: the incapacity to indicate the training process for the models' loss functions and the lack of diversity of the generated samples. Martin et al. [2] explore the causes of these flaws: When the distributions of real and generated data is non-overlapping, the function value tends to be constant and that leads to the disappearance of the gradient. Then they [1] propose Wasserstein GAN (WGAN) that uses the Wasserstein distance instead of the original Jensen-Shannon divergence. $f_w$ is the function that calculates the Wasserstein distance. The loss function is

$$J^{(D)} = E_{z \sim P_z} [f_w(G(z))] - E_{x \sim P_r} [f_w(x)] .$$

(2)

Although WGAN theoretically solves the problem of training difficulties, it still has problems such as low quality of the generated samples, or training failure to converge due to the Lipschitz constraint on the discriminator. Therefore, Ishaan et al. [27] regularize Lipschitz constraints and propose a gradient penalty WGAN model (WGAN-GP). The Lipschitz constraint is approximated by assigning the constraint to the penalty term of the objective function. The loss function is

$$L = E_{\tilde{x} \sim P_g} [D(\tilde{x})] - E_{x \sim P_r} [D(x)] + \omega E_{\tilde{x} \sim P_g} \left[ (\| \nabla_{\tilde{x}} D(\tilde{x}) \|_2 - 1)^2 \right] ,$$

(3)

where $P_r$ is the data distribution, and $P_g$ is the generator distribution. As shown in Eq.3, the larger the parameter $x$ is, the smoother the log loss function, and the smaller the gradient will be, which leads to almost no improvement for
In addition to modifying the loss function to improve GANs’ performance, some studies [54, 21, 14] focus on the network structure of the discriminator and the generator. The structures of vanilla GAN are realized by multi-layer perceptron (MLP), which is difficult in parameter tuning. To solve this problem, Alec et al. [54] propose a deep convolutional generative adversarial network (DCGAN) because the convolutional neural network (CNN) has better abilities of fitting and representing than MLP. DCGAN dramatically enhances the quality of data generation and provides a reference on neural network structure for subsequent research of GANs. The framework of DCGAN is shown in Fig.2.

![Fig.2. The framework of DCGAN [54].](image)

Although GANs have received extensive attention as an unsupervised model, the generator in GANs can only generate data based on random noise, which makes the generated data often useless. Therefore, Mirza and Osindero [49] propose the conditional GAN (CGAN) model. By adding conditional constraints to the model, the generator can generate condition-related data. CGAN can be seen as an improvement that turns unsupervised GAN into a supervised model. This improvement has also proven to be very effective and provides guidance for subsequent related work. For instance, LAPGAN [21] integrates CGAN within a framework of the Laplacian pyramid to generate coarse-to-fine fashion images. InfoGAN [14] is another variant of CGAN, which decomposes random noise into noise and the implicit encoding to learn more interpretable and meaningful representation.

After diving into the details of the latest progress of GANs, we can find that many advanced models [45, 67, 81] are proposed especially in the fields of computer vision and natural language processing. These models do have some reference value for mitigating the data noise and data sparsity problems of the RS. We will introduce GAN-based recommendation models in the next two sections.

### 3. GAN-Based Recommendation Models for Mitigating the Data Noise Issue

In the research of RS, the problem of data noise is getting more and more attention. It affects not only the accuracy of RS but also the robustness of the system. In this section, we review the state-of-the-art GAN-based models of discovering casual, malicious noise and uninformative feedback. According to the sources of data noise mentioned in the introduction, we categorize the GANs-based models into two categories, as shown in Table 2, (1) models for mitigating casual and malicious noise, and (2) models for distinguishing the uninformative samples from unobserved items.

### 3.1. Models for Mitigating Casual and Malicious Noise

Applying the adversarial idea of GANs to the construction processes of recommendation models is a common method to mitigate the problem of data noise, which includes casual and malicious noise. He et al. [31] verify the
effectiveness of adding adversarial perturbations in RS for the first time and propose an adversarial personalized ranking model (APR) to improve the model’s generalization performance. And the role of adversarial perturbations is to help the model to consider bias caused by noise in advance. Specifically, the loss function of APR contains two parts: One part adds perturbations to the parameters of the Bayesian Personalized Ranking model (BPR) and makes the performance as low as possible; the other part, without adversarial perturbations, makes the recommendation performance as high as possible. The loss function of APR is from these two parts, as Eq.4.

\[
L_{APR}(D | \Theta) = L_{BPR}(D | \Theta) + \omega L_{BPR}(D | \Theta + \Delta_{adv}),
\]

(4)

\[
\Delta_{adv} = \arg \max_{\Delta} \frac{1}{\| \Delta \|} L_{BPR}(D | \hat{\Theta} + \Delta_{adv}),
\]

(5)

where \( \Delta \) represents the disturbance on the model parameters, \( 0 \leq \epsilon \) controls the magnitude of the disturbance, \( \hat{\Theta} \) represents the parameters of the existing model, and \( \omega \) is the equilibrium coefficient and controls the strength against the regularization term \( L_{BPR}(D | \Theta + \Delta_{adv}) \). Different from BPR, APR performs adversarial training using the method of the fast gradient [26] to find the optimal perturbations and parameters to alleviate the data noise issue.

It is a groundbreaking idea because it verifies the effectiveness of the adversarial perturbations against matrix factorization and uses adversarial perturbations to simulate malicious noise to improve robustness of the system. For the ranking task, APR has achieved better recommendation performance than DNNs-based RS [83, 32]. Subsequently, it inspires many subsequent research works.

By extending APR, Tang et al. [62] devise AMR for image RS. Based on the Visualized Bayesian Personalized Ranking model (VBPR) [29], AMR adds the adversarial perturbations to the low-dimensional vector representation of images. The loss function of AMR is

\[
\theta^*, \Delta^* = \arg \min_{\theta} \max_{\Delta} (L_{BPR}(\theta) + \omega L'_{BPR}(\theta, \Delta)),
\]

(6)

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

(7)

\[
\Delta^* = \arg \max_{\Delta} \sum_{(u,i) \in D} -\ln \sigma (\hat{y}'_{ui} - \hat{y}'_{ui}),
\]

(8)

where \( \Delta_i \) represents the adversarial perturbations, and the optimal perturbations is obtained by maximizing the loss function in the training data. \( \theta \) represents parameters in AMR. Besides, Tran et al. [65] use APR as a part of the music sequence recommendation model to improve its robustness.
Tong et al. [64] propose a collaborative generative adversarial network (CGAN) to reduce the impact of noise and improve the robustness of RS. Specifically, CGAN uses a variational autoencoder (VAE) [37] as a generator, and its input is the rating vector for each item. After encoding, the generator learns data distribution from training data and generates fake item samples through the embedding layer. The discriminator focuses on maximizing the probability of distinguishing generated item samples from real item vectors. The loss functions of the generator and the discriminator are $L_{GAN}^G$ and $L_{GAN}^D$ respectively.

$$L_{GAN}^G = -E_{i \sim P(i|u)}[D(v \mid u)],$$

$$L_{GAN}^D = -E_{v \sim P_r(v|u)}[D(v|u)] + E_{x \sim P_g(v|u)}[D(v|u)] + \omega E_{j \sim P\theta|u}} \left( \left\| \nabla_{\theta} D(v|u) \right\|_2 - 1 \right)^2,$$

where $u$ and $v$ represent the low-dimensional vector representation of the user and item, respectively. In addition, the authors also adjust the vanilla GAN to WGAN and WGAN-GP because of their faster training speed and better performance. Compared with other models, such as: CDAE [83], NeuMF [32], IRGAN [71], and GraphGAN [70], the performance of CGAN has improved significantly on two movie recommendation datasets [28, 39].

Yuan et al. [91] propose a general adversarial training framework, named ACAE, for the DNN-based recommendation models. They implement it with a collaborative autoencoder to seek a balance between accuracy and robustness by adding perturbations at different parameter locations. The framework of ACAE is as Fig.4. Through experiments, they find that adding perturbations has a more significant impact on the original model, where the effect of adding perturbations to the decoder weight is higher than the encoder. And the effects of adding perturbations to user-embedding vectors and hidden layers are negligible. To control the perturbations more finely, they [92] use different coefficients to control separately noise terms to get more benefits from the adversarial training.

3.2. Models for Distinguishing the Uninformative Samples from Unobserved Items

It is difficult for RS to gather informative data from the massive unobserved data. Specifically, when the models optimize the pairwise objective function, the negative sampling technique often provides uninformative samples. Hence, it is more critical to provide informative negative samples dynamically.

The first application of GANs to mitigate this problem is IRGAN proposed by Wang et al. [71]. It unifies the generative retrieval model and the discriminative model, where the former one predicts relevant documents for a given query, and the latter one predicts the relevancy in each query-document pair. The generative model, used as the generator, selects informative items for the given user by fitting the real relevance distribution over items. The discriminative retrieval model, used as the discriminator, distinguishes between relevant items and selected ones. Then the discriminator feeds the result to the generator to help the generator select more informative items. The generated items will be the input of the discriminator to mislead it. The loss function of IRGAN is

$$J_{G^*,D^*} = \min_{\theta} \max_{\phi} \sum_{i=1}^{N} \left( E_{i \sim P_{true}(i|u_n,r)} \left[ \log D \left( i \mid u_n \right) \right] + E_{i \sim P_{g}(i|u_n,r)} \left[ \log \left(1 - D \left( i \mid u_n \right) \right) \right] \right),$$

Fig.4. The framework of ACAE [91].
where \( D(i|u) = \frac{\exp(f_g(i,u))}{1+\exp(f_g(i,u))}, f_g(i,u) = b_i + v^T u \), \( i \) denotes an item, \( u \) denotes a user, \( r \) denotes relationships between users and items. \( P_{\text{true}}(i | u_n, r) \) 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 \( f_g(i, u) \) indicates the relationship between users and items. Because the sampling of \( i \) is discrete, it can be optimized by reinforcement learning based on policy gradient [79, 90] rather than gradient descent used in the vanilla GAN formulation. Subsequently, ABinCF also adopted the idea of IRGAN for fast recommendation [69]. However, IRGAN [71] selects discrete samples from the training data which causes some intractable problems.

The generator of IRGAN generates a separate item ID or an ID list based on the probability calculated by policy [69]. However, IRGAN [71] selects discrete samples from the training data which causes some intractable problems. For the interactive information, the generator is used to select the items based on a prior probability and outputs the user-item pairs as fake samples, while the discriminator identifies whether each interaction pair is real or not.

\[
\min_{\theta_G} \max_{\phi_D} L^I_{adv}(G^I, D^I) = \sum_{i=1}^{N} (E_{u \sim P(u \mid | u)} [\log D^I(u, i; \phi^I_D)] + E_{u \sim G^I(\mid u, \theta_G)} [\log(1 - D^I(u, i; \phi^I_D))]). \tag{12}
\]

For the socialized information, the generator is used to select the most related friends as informative samples and outputs fake user-friend pairs, while the discriminator identifies the generated user-friend pairs and the real relevant pairs.

\[
\min_{\theta_C} \max_{\phi_D} L^S_{adv}(G^S, D^S) = \sum_{i=1}^{N} (E_{u \sim P(u \mid | u)} [\log D^S(u, i; \phi^S_D)] + E_{u \sim G^S(\mid u, \theta_G)} [\log(1 - D^S(u, i; \phi^S_D))]). \tag{13}
\]

In this way, the representations of users are considered by both social and interactive information. Compared with other recommendation models [98, 24, 71], the authors found that DASO outperforms the DNNs-based social recommendation models [98, 24].

Cai et al. [7] propose GAN-HBNR for citation recommendation, which uses GANs to integrate the heterogeneous bibliographic network structure and vertex content information into a unified framework. It uses denoising autoencoder (DAE) [66] as the generator to generate negative samples because it produces better representations than the standard autoencoder. By extracting each continuous vector and concatenating it with the corresponding content vector as the input, GAN-HBNR learns the representations of content and structure simultaneously to improve the efficiency of the citation recommendations.

To capture and store long-term stable interests and short-term dynamic interests, NMRN-GAN [72] based on neural memory network is proposed for stream recommendation. It also uses the idea of GANs into negative sampling. Specifically, the authors offer an adaptive noise sampler to optimize the proposed model. The generator focuses on encouraging the generation of plausible samples to confuse the discriminator. The goal of the discriminator is to separate real items from fakes produced by the generator. Experiments with the best hyper-parameters show that NMRN-GAN is significantly better than the other comparison models [80, 57] on two datasets [28, 39].

To more clearly show the specific design of the mentioned models, we demonstrate the specific design of them and analyze their advantages, as shown in Table 3.

4. GAN-Based Recommendation Models for Mitigating the Data Sparsity Issue

In addition to data noise, data sparsity is another severe problem in RS. In this section, we highlight the representative research models to identify the most notable and promising advancements in recent years. Based on how GANs are used to mitigate data sparsity, we divide them into two categories, as shown in Table 4, (1) models for generating user preferences by augmenting interaction information, and (2) models for synthesizing user preferences by augmenting auxiliary information.
4.1. Models for Generating User Preferences by Augmenting Interaction Information

There are some productive approaches that inspired the GAN-based architecture in improving the utility of RS to augment missing interaction information and mitigate data sparsity, including CFGAN [10], AugCF [73] and PLASTIC [99], etc.

CFGAN [10] is the first one that generates users’ purchase vectors instead of items’ IDs based on collaborative filtering model (CF), inspired by the idea of CGAN [49]. The framework of CFGAN is shown in Fig.6. And the loss function of $G$ is

$$J^G = \sum_u \log(1 - (D(\hat{r}_u \cdot e_u) \mid c_u)),$$

where the input of generator $G$ is the combination of a purchase vector $c_u$ of user $u$ and random noise $z$. $G$ generates the low-dimensional user preference vector $\hat{r}_u$ by the multi-layer neural network. The discriminator $D$ distinguishes generated preference vectors from real purchase vectors. Its loss function is expressed as $J^D$:

$$J^D = -E_{x \sim p_{data}}[\log D(x \mid c)] - E_{\tilde{x}\sim p_{\theta}}[\log(1 - D(\tilde{x} \mid c))]$$

$$= -\sum_u (\log D(r_u \mid c_u) + \log(1 - D((\hat{r}_u \cdot e_u) \mid c_u))).$$

(15)
Table 3 GAN-based RS for mitigating data noise.

| Category                  | Model   | Generator                                                                 | Discriminator                                                                 | Advantage                                                                 |
|---------------------------|---------|---------------------------------------------------------------------------|-------------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Models for mitigating    | APR     | The generator generates an adversarial noise to increase BPR loss function. | The discriminator improves the robustness of the recommendation model by reducing the BPR loss function. | The first one adds adversarial perturbations to the model parameters.     |
| casual and malicious     | AMR     | The generator generates adversarial noise to image features by increasing the VBPR loss function. | The discriminator reduces the VBPR loss function to improve the robustness of the model. | The one applies parameter level generative adversarial learning to the images RS. |
| noise                     | MASR    | The generator improves BPR loss function and generate adversarial disturbances. | The discriminator reduces BPR loss function to improve the robustness of music recommendation model. | The one uses APR as a part of the music sequence recommendation model to improve robustness. |
|                           | CGAN    | The generator uses a variational autoencoder as a generator.              | The discriminator focuses on maximizing the probability of distinguishing generated item samples from real item vectors. | The one applies GANs to the collaborative filtering model for the first time. |
|                           | ACAE    | The generator is added adversarial noise to the parameters at different locations of the model. | The discriminator identifies whether the generated user rating vectors match the preferences of the real users. | The one points out how to find a balance between accuracy and robustness.   |
| Models for distinguishing | IRGAN   | The generator selects items from the set of existing items.              | The discriminator uses the relationship pairs as inputs, and determine the input is real or generated. | The first one uses GANs to combine the generative search model with the discriminative model. |
| the uninformative samples | DASO    | The generator uses two generators for social and interactive information. | The discriminator identifies whether each user-item interaction pair is real. | The one generates valuable negative samples to learn better representations. |
| from unobserved items     | GAN-HBNR | The generator integrates the content and structure of the heterogeneous network by using DAE. | The discriminator is seen as an energy function. | The network structure and vertex content information are integrated into a unified framework. |
|                           | NMRN-GAN | The generator generates more recognizable negative samples.              | The discriminator identifies the negative sample of the sample is from the generator or real data. | The one designs an GAN-based framework to generate informative negative examples for stream recommendation model. |

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

CFGAN outperforms other state-of-the-art models (including IRGAN [71], GraphGAN [70], CDAE [83]) on the accuracy rate by at least 2.8% enhancement on three datasets: Ciao [61], Watcha [4], Movielens [28]. It is a new direction of vector-wise adversarial training on the task of recommendation. Besides, Chae et al. [9] propose a rating augmentation model based on GAN, called RAGAN. It uses the observed data to learn its initial parameters and then generates plausible data by its generator. Finally, the augmented data are used to train the conventional CF models.

AugCF [73] is also a GAN-based CF model to generate interactive information. It generates interactions for different recommendation tasks under different auxiliary information. Different to CFGAN, the categories of the interactions are also used condition labels, instead of only using users\[125\] purchase vectors. Specifically, there exist two training
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Table 4 Categories of GAN-based RS for mitigating data sparsity.

| GAN-based RS for mitigating data sparsity | Models for generating user preferences by augmenting interaction information | Models for synthesizing user preferences by augmenting auxiliary information |
|-----------------------------------------|--------------------------------------------------------------------------------|-----------------------------------------------------------------------------|
|                                        | CFGAN [10], AugCF [73], APL [60], PLASTIC [99], EB-SeqGANs[87], RecGAN [5], APOIR [101], RAGAN [9], ATR [55] | RSGAN [89], KTGAN [85], CnGAN [52], RecSys-DAN [68], DVBPR [36] |

Fig. 7. The framework of AugCF [73].

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 decide whether the generated data tuple is real or not. The generator and discriminator compete until the balance between them is reached. (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 loss function of AugCF is defined as Eq. 16. The discriminator and generator compete on the category label $c$ and the user $u$. To have different roles in two phases for the discriminator model, AugCF expands the first two relationship categories (like or dislike) to four ones: true & like, true & dislike, false & like, and false & dislike.

$$L = \min_{\theta} \max_{\phi} (E_{(u,v,y) \sim P_C(v \mid u,c)} \log[D_{\phi}(v, y \mid u, c)] + E_{(u,v,y) \sim P_{G_{u,v,c}}(v \mid u,c)} \log[D_{\phi}(v, y \mid u, c)]),$$

where $P_{G_{u,v,c}}(v \mid u,c)$ represents the distribution of generated data, and $P_C(v \mid u,c)$ is the distribution of real data. Their experiments evaluate the models using users' reviews as auxiliary information, and the results show that AugCF is superior to the baselines (Wide & Deep [16] and NFM [30]) and the above models (DeepCoNN [100], HFT [46], and NeuMF [32]).

Besides, Sun et al. [60] propose APL, a general GAN-based framework on pairwise learning. Based on the assumption that users prefer the items that have already been consumed, APL combines the generator and discriminator via the adversarial pairwise learning. Under this framework, the generator $g_{\theta}$ attempts to generate the items that approximate the real distribution for each user. The discriminator $f_{\phi}$ mainly learns the ranking function between two pairs of items and determines the preference of each user. Namely, for each pair of items $i$ and $j$, the discriminator needs to identify which item is more in line with the user’s preference. APL directly uses pairwise ranking as the loss function instead of the function based on the probability distribution, as shown in Eq. 17:

$$V(g_{\theta}, f_{\phi}) = \max_{\phi} \min_{\theta} \sum_{i=1}^{m} (E_{i \sim P_{\text{real}}(i \mid u)} L(f_{\phi}(i \mid u) - f_{\phi}(j \mid u)).$$

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Among them, $L(x)$ is the pairwise ranking loss function that is different from the loss function of GANs. If the discriminant loss function is directly designed to maximize the differences of the ranking scores between the observed items and the generated, the original objective function can be equivalent to WGAN [1], as shown in Eq.18:

$$V(g_\theta, f_\phi) = \max_\theta \min_\phi \sum_{m=1}^M E_{i \sim P_{\text{real}}(i|u)} \left[ L \left( f_\phi(i|u) - f_\phi(j|u) \right) \right]$$

(18)

This model copes with the problem of gradient vanishing by utilizing the pairwise loss function and the Gumbel-Softmax technique [34]. Extensive experiments demonstrate its effectiveness and stability.

GAN is also applied in many other recommendation fields to generate interactions and mitigate data sparsity. For example, PLASTIC [99] is proposed for the sequence recommendation, which combined matrix factorization (MF), Recurrent Neural Network (RNN), and GANs. Its framework is shown in Fig.9.

In the adversarial training process, the generator, which is like the CGAN [49], takes users and time as inputs to directly predict the recommendation list of the user. For the discriminator, PLASTIC integrates long-term and short-term ranking models through the Siamese network to maximize the probability of correctly distinguishing real samples from generated ones. The extensive experiments show it has better performance than other models [53, 80, 71].
addition to PLASTIC, Yoo et al. [87] combine energy-based GANs and sequence GANs to learn users’ sequential preferences and predict the next recommended items.

RecGAN combines recurrent recommender networks and GAN to learn temporal features of users and items [5]. 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 come from the distribution of the user’s real preference or not. The experiments show that it outperforms all baseline models, including PMF [58], TimeSVD++ [38], RRN [80], and AutoRec [51] on movie and food recommendation datasets [28, 39].

Zhou et al. [101] propose APOIR to learn the potential preferences of users in location recommendation. The generator selects a set of POIs (Point of Interest) using the policy gradient and tries to match the real distribution. Then the discriminator distinguishes the generated POIs from true browsing behaviors of the user. Furthermore, two components compete through playing a minimax game. The loss function of APOIR is

\[
L = \min_\theta \max_\phi \sum_{u_i} (E_{l^+ \sim L^+} [\log D_\phi(u_i, l^+)] + E_{l^R \sim R^R(u_i)} [\log (1 - D_\phi(u_i, l^R))])
\]

(19)

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

### 4.2. Models for Synthesizing User Preferences by Augmenting Auxiliary Information

Besides augmenting interactive information to generate user preference directly, some studies try to fit the generator of the GAN-based architecture in augmenting auxiliary information [9, 89, 85, 52, 68].

RSGAN [89] is proposed to augment more reliable friends to alleviate the problem of sparsity in social recommendation. It mainly consists of two components: the generator \(G_\theta\) and discriminator \(D_\phi\). \(G_\theta\) is responsible for generating reliable friends and items consumed by these friends. It first builds a heterogeneous network to identify seed friends with higher reliability. After collecting seed users for each user, it encodes them into binary vectors as the user incomplete social preferences through CDAE [83]. Then the probability distribution of friends with high possibility is sampled through Gumbel-Softmax [34]. Similarly, this strategy is also used to simulate the sampling of items. On the other hand, to build the order of candidate items, this model adopts the idea of Social BPR [98] as \(D_\phi\). It sorts the candidates and recommends an item list for each user. If the items consumed by the generated friends are unhelpful, \(D_\phi\) punishes them and returns the gradient to \(G_\theta\) to reduce the probability of generating such friends. The loss function of RSGAN is

\[
L_{D_\phi, G_\theta} = \min_\theta \max_\phi -E((\log \sigma(x_{ui} - x_{uz}) + \log \sigma(x_{uz} - x_{uj})))
\]

(20)

The authors of RSGAN conduct experiments with three kinds of models: the conventional social recommendation models [29, 98], DNN-based models [32], and other GAN-based ones [71, 10]. The experimental results show

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**Fig.10. The framework of RSGAN [89].**
that RSGAN outperforms all the others in ranking prediction. The possible reason is that RSGAN builds a dynamic framework to adaptively generate friend relationships to alleviate the data sparsity issue.

KTGAN [85] is proposed to augment data and alleviate the problem of data sparsity further by importing external information. The model mainly consists of two phases: (1) extracting the feature embeddings from various auxiliary information and interactions information to construct the initial representations of users and items, and (2) putting the vectors into the IRGAN-based generator and discriminator for adversarial learning. The discriminator attempts to identify whether the pair of user-item is generated or real. The loss function of KTGAN is

$$L = \min_\theta \max_\phi \sum_{n=1}^{N} \left( E_{m \sim p_{true}(m|u_n, r)} \left[ \log P(m|u_n) \right] + E_{m \sim p_{\phi}(m|u_n, r)} \left[ \log(1 - P(m|u_n)) \right] \right),$$

(21)

where $P(m \mid u_n)$ estimates the probability that the user $u_n$ prioritizes the item $m$. The parameter $r$ represents the relationship of an user and an item. The experiments show that it has better accuracy and normalized discounted cumulative gain (NDCG) than others [83, 32, 71, 70]. In particular, if the generator can generate more accurate low-dimensional vector representation at the beginning of training, it can train a better-optimized discriminator and then improve the performance of the whole model.

Perera et al. [52] propose CnGAN to learn the mapping encoding from target to source domain for non-overlapped users in different domains. The framework is shown in Fig.11. $E$ is the neural network encoder that converts the local distribution of input into a dense latent vector; the generator $G$ uses the target encoding as input to generate the mapping encoding $E_{sn}$ of the source domain for non-overlapping users. Moreover, $G$ makes the generated preference domain as accordant as possible to the real source domain to deceive the discriminator. The loss function is

$$\min_G V(G) = \mathbb{E}_{tn_u \sim p_{data}(tn)} L_{fake} \left( E_{in} \left( tn_u \right) , G \left( E_{in} \left( tn_u \right) \right) \right) + \mathbb{E}_{tn_u, sn_u \sim p_{data}(tn, sn)} L_{content} \left( E_{sn} \left( sn_u \right) , G \left( E_{in} \left( tn_u \right) \right) \right).$$

(22)

The discriminator $D$ distinguishes the real source domain encoding from the generated encoding. In particular, the mismatching source and target domain encoding are the input of $G$. The overlap between user’s real target domain embedding and the source domain embedding is as the real mapping. Formally, the loss function of the discriminator is

$$\max_{E_{in}, E_{sn}, D} V(E_{in}, E_{sn}, D)$$

$$= \mathbb{E}_{tn_u, sn_u \sim p_{data}(tn, sn)} L_{real}(E_{in}(tn_u), E_{sn}(sn_u))$$

$$+ \mathbb{E}_{tn_u \sim p_{data}(tn)} L_{fake}(E_{in}(tn_u), G(E_{in}(tn_u)))$$

$$+ \mathbb{E}_{tn_u, sn_u \sim p_{data}(tn, sn)} L_{mismatch}(E_{in}(tn_u), E_{sn}(sn_u)),$$

(23)
where $P_{data}(tn, sn)$ is a matching pair with a mapping relationship, $\overline{P}_{data}(tn, \overline{sn})$ is the 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 provides a new idea to alleviate the data sparsity issue, as the first attempt to use GANs to generate missing source domain preferences for non-overlapping users by generating mapping relationships between source and target domains.

RecSys-DAN, proposed by Wang et al. [68], is similar to CnGAN [52]. It also uses an adversarial approach to transfer the potential representation of users and items from different domains to the target domain.

In the review-based recommendations, Rafailidis et al. [55] use GANs to generate reviews that are likely to be relevant to the preferences of users. The discriminator focuses on distinguishing the generated reviews and those written by users. Similar to generating users-related reviews, the generator also generates items-related reviews. After obtaining review information through adversarial learning, this model predicts user preferences through joint factorizing rating information. Besides, to synthesize the most consistent images with users’ preferences in fashion recommendation, Kang et al. [36] propose DVBPR, where the generator is trained to generate appropriate images that look realistic, and the discriminator tries to distinguish generated images from the real ones.

To better show the differences between the mentioned models in the design of generators and discriminators, we list their specific design and respective advantages in Table 5.

5. Future Research Directions and Open Issues

Although the studies on GAN-based recommendation models have established a solid foundation for alleviating the data noise and data sparsity issues, there are still several open issues. In this section, we analyze them and outline several promising future research directions.

5.1. The Position of Adversarial Training

The DNNs-based recommendation models have become one of the hotspots because they can learn more abstract representations of users and items and grasp the nonlinear structural features of interaction information. However, the networks have complex structures and a wide variety of parameters. We try to control adversarial noise using different coefficients, so that for those positions which are less affected by the adversarial noise, a larger noise coefficient should be applied. How to choose a suitable adversarial training position has become a significant challenge that needs more in-depth and broader exploration in the future.

5.2. Multiple Generators and Discriminator Models for Recommendation

Existing GAN-based recommendation models usually have comparatively fixed network architecture and purposes: the generator generates data that conforms the distribution of real data, and the discriminator recognizes the generated data. However, the generator and discriminator can be designed as multiple network structures to exploit user behaviors, interaction information, or recommendation feedback from various aspects. For example, the study in [73] provides a new idea in which the discriminator is not only used to identify the generated data but also used to predict the interaction category, e.g., like or dislike.

5.3. Model Parameter Optimization Stability Problem for Discrete Training Data

GANs are initially designed for image domain where data is considered as continuous. However, the interaction data in RS is often discrete. The gradient descent, which is the original optimization method for model’s parameters, is challenging to update the gradient. This causes the model parameters to fail to converge during its training. Although several researchers tried to train the model based on policy gradient [79, 90] and Gumbel-Softmax [34], the stability of the parameter optimization in the GAN-based recommendation model is still an open research problem.

5.4. GAN-Based Explanations for Recommendation Models

The generators and discriminators in GAN-based recommendation models are mostly constructed by DNNs that belong to the black-box model. Namely, we are only aware of their input and output, and we can hardly understand the underlying principle. Existing models that improve the interpretability of RS mostly give explanations after recommendation [77, 59], and the content of the explanation is often unrelated to results. It will be a good approach if GANs can be used to explain the results of the recommendation while generating recommendation list. In this framework, the discriminator not only judges whether the generated recommendation is accurate or not but also whether the
### Table 5: GAN-based RS for mitigating data sparsity.

| Category | Model       | Generator                                                                 | Discriminator                                                                 | Advantage                                                                 |
|----------|-------------|---------------------------------------------------------------------------|-------------------------------------------------------------------------------|---------------------------------------------------------------------------|
|          | CFGAN [10]  | The generator uses user purchase vectors to generate purchase vectors. | The discriminator identifies whether the purchase vectors meet the users’ real interest preferences. | The first GAN-based model uses vector-wise training in RS.                |
|          | AugCF [73]  | The generator chooses interaction categories as condition label to generate the most preferred items for the target users. | The discriminator has two stages: (1) determine the relationships between users and items, and (2) identify the relationship label. | This model designs the discriminator to identify true/false data and like/dislike four categories. |
| Models for generating user preference by augmenting interaction information | APL [60]    | The generator generates the items that approximate the real distribution of each user. | The discriminator uses the pairwise ranking function to determine the generated items and real ones. | This model explores effects of adversarial learning from the perspective of implicit feedback. |
|          | PLASTIC [99] | The generator uses the low-dimensional representation and time to generate a list of items. | The discriminator captures long-term and short-term preferences of users to select the exact high-scoring items. | This model uses an adversarial framework to combine MF and RNN for the ranking task. |
|          | APOIR [101] | The generator samples POIs that fit the real data distribution.          | The discriminator determines the user’s POIs are real or generated.          | This model optimizes POIs RS in an adversarial manner.                    |
|          | KTGAN [85]  | The generator uses the representation extracted from the auxiliary information to generate relationships between users and items. | The discriminator uses a pair of generated data and real ones to distinguish the relationship pair is from a real dataset. | This model integrates auxiliary information based on IRGAN to alleviate the problem of data sparsity. |
| Models for synthesizing user preferences by augmenting auxiliary information | CnGAN [52]  | The generator uses the target encoding to generate the mapping encoding of the source network for the non-overlapping users. | The discriminator determines the mapping relationship of the overlapping users is real or generated. | The first one applies the GANs into the mapping process for non-overlapping users in cross-domain RS. |
|          | RecSys-DAN [68] | The generator uses the representation from different domains to learn the transfer mapping. | The discriminator determines the relationships between users and items in different fields is genuine or not. | This model learns how to represent users, items, and their interactions in different domains. |
|          | RSGAN [89]  | The generator uses "seeded friends" to generate reliable friends and their consumed items by using Gumbel-Softmax. | The discriminator uses the positive, negative, and generated items to sort the candidate items. | The first one applies GANs to social recommendation.                     |

The interpretation of the recommendation is accurate or not. The generator and discriminator compete with each other to improve the explanations of models.

### 5.5. Cross-Domain Recommendation Based on GANs

The cross-domain models, which assist in the representation of the target domain with the knowledge learned from source domains, provide a desirable solution to tackle the data sparsity issue. One of the most widely studied topics in the cross-domain recommendation is transfer learning [11], which aims to improve the ability to learn in one domain by using knowledge transferred from other domains. However, how to unify information in different domains into the same representation space remains a challenging problem.

Adversarial learning can continuously learn and optimize the mapping process from the source domain to the
target domain, thereby enriching the training data of the recommendation model. A small number of models [52, 68] have utilized the advantages of GANs in learning the mapping relationship between different fields of information and verified the effectiveness through experiments. Therefore, it is a promising but mostly under-explored area where more studies are expected.

5.6. Scalability of GAN-Based Recommendation Model

Scalability is critical for recommendation models because the ever-increasing volumes of data make the time complexity a principal consideration. Although GANs have been applied to some commercial products due to the continuous improvement of GPU computing power, further research on GAN-based recommendation models is needed in three areas: (1) incremental learning of non-stationary and streaming data such as large amounts of interactions between users and items; (2) accurate calculation of high-dimensional tensors and multimedia data sources; (3) balancing model complexity and scalability with the exponential growth of parameters. Knowledge distillation [15] is a method that can potentially manage these areas by utilizing a smaller student model that absorbs knowledge from a teacher model. Considering that training time is crucial for real-time applications, scalability is another promising direction that deserves further study.

6. Conclusion

In this paper, we provide a retrospective of the up-to-date GAN-based recommendation models and demonstrate their ability to reduce the adverse effects of the data noise issue and alleviate the data sparsity problem. We start with the development history of GANs and clarify the feasibility of GANs for RS. For the efforts devoted to tackling data noise, we introduce existing models from two perspectives: (1) models for mitigating malicious noise; and (2) models for distinguishing the uninformative samples from unobserved items. For the studies focusing on mitigating the data sparsity problem, we group them into two categories: (1) models for generating user preferences by augmenting interaction information; and (2) models for synthesizing user preferences by augmenting auxiliary information. After the review, we discuss some of the most pressing open problems and point out a few promising future directions. We hope this survey can shape researchersâ€™ ideas and provide some practical guidelines for this new area.

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