Advancements in Recommender Systems through the Integration of Generative Adversarial Networks*

Naouel MANAA[1,*,†], Hassina SERIDI[1,†] and Mohamed Said Mehdi MENDJEL[1,†]

[1]*Department of computer Science, Laboratory of Electronic Document Management LabGED, Badji Mokhtar Annaba University, Algeria*

Abstract

Generative Adversarial Networks (GANs) have emerged as powerful tools in the realm of artificial intelligence, reshaping various domains, from image generation to text synthesis and music composition. In recent years, researchers have ventured into the realm of integrating GANs into recommendation systems, driven by the desire to elevate the quality of recommendations. This article presents an in-depth exploration of the current landscape surrounding the incorporation of GANs in recommendation systems.

Researchers have harnessed the potential of GANs to craft highly personalized recommendations by incorporating user and item features. Notably, techniques like conditional GANs have been employed to consider user demographics, browsing history, and item attributes, enabling the tailoring of recommendations to individual preferences. Nevertheless, challenges have surfaced, including issues related to training stability, mode collapse, scalability limitations, and data privacy concerns in the application of GANs to recommendation systems.

Diligent and persistent research endeavors are actively addressing these challenges with the overarching goal of not only overcoming the hurdles but also enhancing the stability and performance of GANs within recommendation systems. This article serves as a comprehensive guide to the current state of GANs in recommendation systems, offering insights into their potential and the evolving landscape of research and development in this field.

Keywords

Recommender systems, generative adversarial networks, artificial intelligence, Personalization, recommendations.

1. Introduction

In today's digital era, recommender systems have become essential tools that are changing the way we discover products, services, and information. They are now integrated into various aspects of our online lives, from e-commerce websites and streaming platforms to news aggregators and social networks. These systems are designed to provide users with personalized recommendations that match their interests and preferences. This ability to sift through vast amounts of data and offer tailored suggestions has not only transformed user experiences but also brought significant benefits to businesses, including increased customer engagement, improved conversion rates, and enhanced customer satisfaction.

At their core, recommender systems aim to address the overwhelming problem of information overload. As the number of choices available continues to grow exponentially, users often find it challenging to navigate through the sheer volume of options to discover what truly resonates with them. In this context, personalized recommendations play a vital role in simplifying decision-making, saving time, and enhancing user satisfaction.

Personalization is the key to the effectiveness of recommender systems. These systems analyze user preferences, past interactions, and contextual information to provide tailored recommendations that match individual tastes and needs. While traditional recommendation methods like collaborative filtering and content-based filtering have made significant improvements in recommendation accuracy, they still face challenges, especially in offering diverse and unexpected recommendations that go beyond users' known preferences.

Generative Adversarial Networks (GANs), a promising approach that has gained significant attention in recent years. Introduced by Goodfellow and his colleagues in 2014, GANs are a type of deep learning model known for their ability to generate realistic and novel data. While GANs were initially associated with tasks like creating images, they have piqued the interest of researchers for their potential to enhance recommender systems.

GANs have garnered attention in the field of recommender systems due to their capability to capture complex data patterns[1]. They offer a unique solution to the challenge of recommendation diversity. GANs work by using a generator and discriminator network in an adversarial manner. The generator learns to produce recommendations that resemble a user's actual preferences, while the discriminator provides feedback to help the generator create high-quality recommendations that are distinct from what the user already knows. This dynamic interaction between the generator and discriminator en-

6th International Hybrid Conference On Informatics And Applied Mathematics, December 6-7, 2023 Guelma, Algeria

*Corresponding author.
†These authors contributed equally.
naouel.manaa@univ-annaba.dz (N. MANAA); seridi@labged.net (H. SERIDI); mendjel@labged.net (M. S. M. MENDJEL)
0009-0006-6025-9374 (N. MANAA)

CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

courages the generation of diverse recommendations, introducing users to new and unexpected items.

The application of GANs in recommender systems holds immense potential for improving recommendation accuracy. By leveraging deep learning and adversarial training, GANs can push the boundaries of personalized recommendations, enabling users to discover new and relevant content that aligns with their evolving interests. However, there are challenges to overcome, such as ensuring stable training, scalability, and safeguarding data privacy, to fully harness the benefits of GANs in recommender systems.

In this review article, we delve into recent advancements, methodologies, challenges, and future possibilities in using GANs for recommender systems. We explore how GANs can be applied to generate personalized recommendations, enhance diversity, tackle the cold-start problem, and handle sparse data. By examining the strengths and limitations of GAN-based recommender systems, our goal is to shed light on the potential of GANs to revolutionize the recommendation landscape and create new opportunities for research and innovation.

2. Background on Recommender Systems

Recommender systems are tools that help users overcome information overload by suggesting items that they may be interested in based on their preferences and behaviors [2]. These systems have become increasingly important in various domains, including e-commerce, social media, news, travel, and tourism [3]. The importance of recommender systems in these domains lies in their ability to improve user experience, increase user engagement, and drive revenue. By providing personalized recommendations, these systems can help users find relevant and interesting content more easily, leading to increased satisfaction and engagement[2]. In e-commerce, recommender systems can help increase sales by suggesting products that users are more likely to purchase[2]. In tourism, these systems can help users plan their trips more efficiently by suggesting destinations, accommodations, and activities that match their preferences[3]. However, there are also challenges associated with recommender systems, such as the potential for biases and fairness concerns. To ensure that these systems provide fair outcomes for all stakeholders involved in the recommendation process, it is important to evaluate them from multiple perspectives and consider the potential impact on the environment and local communities[3]. Additionally, there is ongoing research on how to incorporate serendipity, or the discovery of unexpected and novel items, into recommender systems to broaden user preferences and improve satisfaction [4].

3. Generative Adversarial Networks (GANs)

In 2014, Goodfellow, et al.[5] introduced a groundbreaking deep-learning technique called Generative Adversarial Networks (GANs). This innovative approach harnessed the power of discriminative learners to construct a proficient generative learner, opening up new possibilities in the field of artificial intelligence.

Generative Adversarial Networks (GANs) are a class of structured probabilistic models that consist of two interconnected models engaged in an adversarial process.As shown in Fig. 1 The first model, known as the Generator (G), is responsible for capturing the data distribution and generating synthetic data. The second model, known as the Discriminator (D), aims to discriminate between real data samples and those generated by G.

The training of GANs involves a two-player minimax game, where the Generator and Discriminator compete against each other until reaching a Nash equilibrium. This equilibrium is achieved using a gradient-based optimization technique called Simultaneous Gradient Descent. During training, G learns to generate data that closely resembles samples from the true data distribution, while D strives to correctly classify whether the data is real or generated.

To update the parameters of both G and D, gradient signals are obtained from the loss incurred by comparing the distributions of real and generated data. This is typically achieved by calculating divergences between the two distributions using D as the discriminator. Through this iterative process, G and D continually improve their abilities until G is capable of generating synthetic data that is indistinguishable from real data, according to the Discriminator's perspective [6].

4. Applications of GANs in Recommender Systems

4.1. Personalization Techniques

Conditional GANs: GANs that incorporate user and item features to generate personalized recommendations. The paper [7] presents an enhanced conditional GAN model called c+GAN for generating relevant bottom item recommendations based on input top items. The c+GAN model incorporates a modified generator with both a classical mean squared error (MSE) loss and a simplified perceptual loss using discrete cosine transform (DCT) coefficients of the generated and target images. A simplified lensing technique is introduced to the discriminator to improve the stability of the generator training. The data is clustered using a simple K-Means clustering technique to enforce mode normalization across training batches.

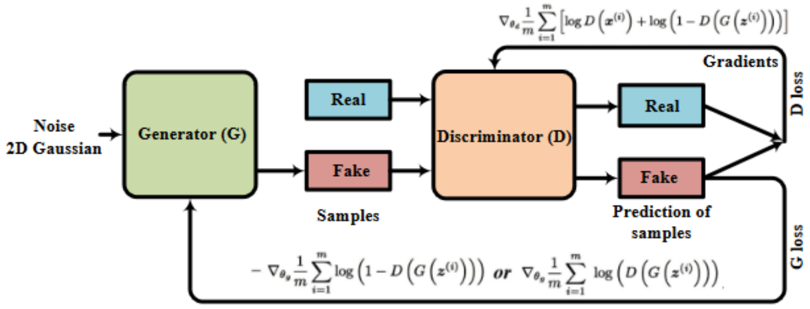

Figure 1: GAN architecture.[6]

These methods result in a powerful technique that generates meaningful fashion items, which can be utilized for searching similar products in e-commerce platforms.

4.2. Solve Imbalanced Data Problem

In this work [8] proposes a hybrid GAN approach to address the data imbalance problem and improve the performance of recommendation systems. The authors implement a conditional Wasserstein GAN with gradient penalty to generate tabular data that includes both numerical and categorical values. To tackle the data imbalance issue, an augmented auxiliary classifier loss is introduced to encourage the model to generate data from the minority class. Additionally, the discriminator architecture incorporates the concept of PacGAN, which processes multiple samples as input to overcome the mode collapse problem. The proposed model is evaluated based on the quality of the generated data and the performance of different recommendation models using the generated data compared to the original data. The study focuses on GAN, imbalanced data, and oversampling techniques.

4.3. Cold-Start Problem Solutions

a. Synthetic Data Generation: GANs that generate synthetic user-item interactions for cold-start users or items, enabling initial recommendations even with limited data. The paper [9] introduces a novel method based on Generative Adversarial Networks (GANs) for generating collaborative filtering datasets in a customizable manner. Unlike regular GANs, this method allows users to specify their desired number of users, items, samples, and stochastic variability. The proposed GAN model utilizes dense, short, and continuous embedding representations of items and users, which enables accurate and efficient learning compared to traditional approaches that rely on large and sparse input vectors.To extract the dense user and item embeddings, the authors employ a DeepMF model within the proposed architecture. Additionally, a clustering process is incorporated to convert the dense GAN-generated samples into discrete and sparse vectors, which are required for creating each synthetic dataset. The generated datasets exhibit suitable distributions, expected quality values, and follow the desired evolutions compared to the source datasets.

[10] A tourism recommendation system, which relies on technology, offers suggestions to visitors based on their preferences, previous travels, and experiences. These systems gather information from different sources such as web searches, user reviews, and travel history. However, current technologies face challenges when dealing with limited data for certain users or items, resulting in inaccurate recommendations. Another obstacle in tourism is the diversity issue, where similarities are prioritized over individual preferences. To address these challenges, this system combines GAN (Generative Adversarial Networks) and context-aware recommendation techniques.

The primary objective of the system is to provide personalized recommendations to travelers by considering various contextual factors. By utilizing GANs, the system identifies patterns and connections between different elements of a tourist's environment and their preferences. Additionally, synthetic data is generated to supplement the original dataset, enabling the system to overcome issues related to cold-start and sparsity. Furthermore, this approach contributes to the development of more scalable recommendation systems.

In this paper[11], the authors introduced the Graph Convolutional Generative Adversarial Network (GC-GAN) as a solution to address the cold start problem in recommendation systems. GCGAN combines the power of GAN and graph convolution to effectively learn domain information by propagating feature values through a graph structure. An important advantage of GCGAN is its ability to incorporate new nodes (Users) without requiring retraining, as it leverages recommended user features. By conducting experiments using the Movie-

Lens 1M dataset, we demonstrated that the proposed GCGAN significantly outperforms the compared method in terms of recommendation performance. We also explored the impact of batch size and the number of graph convolution layers on the recommendation performance and observed the integration of nodes. The proposed method is characterized by its capability to learn domain information for both users and items, eliminating the need for retraining the model when introducing new nodes. Moreover, it holds potential for application in various information recommendation services with similar conditions. Future research could focus on applying this method to such services.

4.4. Handling sparsity and scalability techniques

This paper[12] introduces a novel approach to improve user recommendations by utilizing a generative network and a discriminative network in tandem. Additionally, an adversarial training strategy is employed to train the model effectively. By leveraging the discriminative network's guidance, the generative network reaches an optimal solution, leading to enhanced recommendation performance, particularly on sparse datasets. Furthermore, we provide evidence demonstrating that our proposed method substantially enhances precision. Recommender systems face challenges in dealing with sparse interaction data and noisy data in real-world scenarios. Recently, Generative Adversarial Network (GAN)-based recommender systems have emerged as promising solutions to tackle these issues. Negative sampling methods leverage the generator to extract informative signals from abundant unlabeled data, mitigating the data sparsity problem. However, they encounter challenges in the policy gradient training process due to sparse rewards. On the other hand, vector reconstruction methods generate user-related vectors to augment the data and improve robustness but involve redundant calculations and overlook item-specific information. To overcome the limitations of these approaches, The authors [13] propose a novel framework called Personalized Recommendation with Conditional Generative Adversarial Networks (PRGAN). The framework considers both the user and the item subset as conditions, formulating the generation of conditional rating vectors as a user-item matching problem. By doing so, we can control the sparsity of conditional rating vectors, simplifying the learning task for the discriminator. In [14] the authors present a new GAN-based approach called GANMF for the top-N recommendation problem in collaborative filtering. GANMF incorporates user and item latent factors using a matrix factorization framework. Two unique issues in applying GAN to collaborative filtering are identified and addressed by using an autoencoder as the discriminator and introducing an additional loss function for the generator. The performance of GANMF is evaluated using well-known datasets in the recommender systems community, demonstrating improvements compared to traditional CF approaches and other GAN-based models. An ablation study is conducted to analyze the effects of the architectural choices in GANMF, and a qualitative evaluation of the matrix factorization performance is provided.

4.5. Improving accuracy of recommendation

Collaborative filtering for implicit feedback has seen successful applications of Generative Adversarial Networks (GANs). However, GANs encounter challenges in effectively capturing user interest distributions due to difficulties in feature characterization. To overcome this issue, this paper [15] propose a collaborative filtering model called Improved Generative Adversarial Networks (IGAN). In IGAN, we introduce an independent encoder and generator to learn feature representations during adversarial training. To further align with users' interest distributions and enhance recommendation accuracy, we incorporate the Kullback-Leibler (KL) loss and reconstruction loss as penalty terms.

As illustrated in Table 1, this table is designed to classify various techniques and approaches employed in GAN-based recommender systems based on their objectives and functionalities. It serves as a foundational resource for advancing research and development in this field, aiding in a more comprehensive understanding of the diverse applications and methodologies utilized within GAN-based recommender systems.

5. Challenges and Limitations of GANs in Recommender Systems

While Generative Adversarial Networks (GANs) offer promising opportunities for enhancing recommender systems, there are several challenges and limitations that need to be addressed. In this section, we discuss some of these challenges and their potential impact on GAN-based recommender systems. We also explore ongoing research efforts and potential solutions to overcome these limitations.

5.1. Training Instability

GANs are notorious for their training instability, where the generator and discriminator networks can enter a cycle of chasing each other without convergence. In the context of recommender systems, this instability can hinder the generation of accurate and reliable recommendations. Researchers have proposed various techniques

Table 1
Comparative Analysis of GAN-based Recommendation Systems

Paper	Challenge	Functionality
[7]	Generating relevant recommendations for bottom items	Incorporates user and item features
[8]	Data imbalance in recommendation systems	Generating tabular data with numerical and categorical values
[9]	Generating synthetic user-item interactions for cold-start users/items	Generating collaborative filtering datasets
[10]	Limited data and diversity issues in tourism recommendation	Personalized recommendations based on contextual factors
[11]	Cold start problem in recommendation systems	Learning domain information for users and items
[12]	Sparse datasets and noisy data in recommender systems	Enhanced user recommendations using adversarial training
[13]	Sparse rewards and overlooking item-specific information	Generating conditional rating vectors for recommendations
[14]	Top-N recommendation problem in collaborative filtering	Matrix factorization framework with GAN
[15]	Difficulty in capturing user interest distributions	Enhanced collaborative filtering with feature representations

to stabilize GAN training, such as adjusting the learning rate, using different architectures, employing regularization techniques, or incorporating auxiliary losses.

5.2. Mode Collapse

Mode collapse occurs when the generator fails to explore the entire item space, resulting in the generation of limited or repetitive recommendations. In recommender systems, mode collapse can lead to biased recommendations that focus only on popular or commonly selected items. Addressing mode collapse requires strategies like improving the diversity objectives, introducing regularization techniques, or utilizing advanced GAN variants such as Wasserstein GANs or InfoGANs.

5.3. Scalability

GAN-based recommender systems face scalability challenges when dealing with large-scale datasets or high-dimensional item spaces. As the size of the data increases, training GANs becomes computationally expensive and time-consuming. Various techniques have been explored to improve scalability, such as parallelization, mini-batch training, distributed computing, or model compression. These approaches enable efficient training of GANs on large-scale datasets, making them more applicable in real-world recommender systems.

5.4. Evaluation Metrics

Assessing the performance of GAN-based recommender systems poses a unique challenge due to their generative nature. Traditional evaluation metrics like accuracy or precision-recall may not capture the full picture of the generated recommendations. Researchers are actively working on developing evaluation metrics that account for diversity, novelty, coverage, or serendipity in GAN-based recommender systems. These metrics aim to provide a comprehensive assessment of the quality and effectiveness of recommendations generated by GANs.

Ongoing research efforts focus on addressing these challenges and limitations associated with GAN-based recommender systems. Techniques such as progressive training, self-supervised learning, adversarial regularization, and domain adaptation are being explored to improve the stability and performance of GANs. Furthermore, collaborations between the recommender system community and the privacy research community aim to develop privacy-preserving GAN architectures that protect user data while maintaining recommendation accuracy.

6. Conclusion

This paper has provided an exploration of the role of Generative Adversarial Networks (GANs) in revolutionizing recommender systems. We have witnessed the transformation of recommender systems from tools designed to alleviate information overload to sophisticated engines that cater to users' individual preferences and needs.

Recommender systems have become ubiquitous in our digital lives, enhancing user experiences across various domains, including e-commerce, social media, and travel. Personalization lies at the heart of their effectiveness, as these systems continuously analyze user behavior and preferences to generate tailored recommendations. However, traditional recommendation techniques still face challenges, especially in offering diverse and serendipitous recommendations.

GANs, a disruptive technology that has captured the attention of researchers and practitioners alike. Initially celebrated for their prowess in image generation, GANs have proven to be equally transformative in the realm of recommender systems. These networks, driven by a generator and discriminator, offer a dynamic interaction that fosters diversity in recommendations, introducing users to novel content.

The applications of GANs in recommender systems are vast and promising. They enable the generation of personalized recommendations, enhance diversity, tackle the cold-start problem, and address issues related to sparse data. Leveraging deep learning and adversarial training, GANs extend the boundaries of recommendation systems, empowering users to discover content that aligns with their evolving interests.

References

[1] M. Gao, J. Zhang, J. Yu, J. Li, J. Wen, Q. Xiong, Recommender systems based on generative adversarial networks: A problem-driven perspective, Information Sciences 546 (2021) 1166–1185. doi:10.1016/j.ins.2020.09.013.

[2] M. Al-Ghossein, Context-aware recommender systems for real-world applications, Ph.D. thesis, Université Paris Saclay (COmUE), 2019.

[3] A. Banerjee, P. Banik, W. Wörndl, A review on individual and multistakeholder fairness in tourism recommender systems, Front Big Data 6 (2023) 1168692. doi:10.3389/fdata.2023.1168692.

[4] D. Kotkov, J. A. Konstan, Q. Zhao, J. Veijalainen, Investigating serendipity in recommender systems based on real user feedback, in: Proceedings of the 33rd Annual ACM Symposium on Applied Computing, SAC '18, Association for Computing Machinery, New York, NY, USA, 2018, pp. 1341–1350. doi:10.1145/3167132.3167276.

[5] I. Goodfellow, et al., Generative adversarial nets, in: Advances in Neural Information Processing Systems, Curran Associates, Inc., 2014.

[6] D. Saxena, J. Cao, Generative adversarial networks (gans): Challenges, solutions, and future directions, ACM Comput. Surv. 54 (2022) 1–42. doi:10.1145/3446374.

[7] S. Kumar, M. D. Gupta, c^{+}GAN: Complementary fashion item recommendation, arXiv (2019). doi:10.48550/arXiv.1906.05596.

[8] W. Shafqat, Y.-C. Byun, A hybrid gan-based approach to solve imbalanced data problem in recommendation systems, IEEE Access 10 (2022) 11036–11047.

[9] J. Bobadilla, A. Gutiérrez, R. Yera, L. Martínez, Creating synthetic datasets for collaborative filtering recommender systems using generative adversarial networks, arXiv (2023). doi:10.48550/arXiv.2303.01297.

[10] E. E. Stephy, M. Rajeswari, Empowering tourists with context-aware recommendations using gan, in: 2023 Second International Conference on Electronics and Renewable Systems (ICEARS), 2023, pp. 1444–1449. doi:10.1109/ICEARS56392.2023.10085604.

[11] T. Sasagawa, S. Kawai, H. Nobuhara, Recommendation system based on generative adversarial network with graph convolutional layers, JACIII 25 (2021) 389–396. doi:10.20965/jaciii.2021.p0389.

[12] R. Yin, K. Li, J. Lu, G. Zhang, Rsygan: Generative adversarial network for recommender systems, in: 2019 International Joint Conference on Neural Networks (IJCNN), 2019, pp. 1–7. doi:10.1109/IJCNN.2019.8851727.

[13] J. Wen, B.-Y. Chen, C.-D. Wang, Z. Tian, Prgan: Personalized recommendation with conditional generative adversarial networks, in: 2021 IEEE International Conference on Data Mining (ICDM), 2021, pp. 729–738. doi:10.1109/ICDM51629.2021.00084.

[14] E. Dervishaj, P. Cremonesi, Gan-based matrix factorization for recommender systems, in: Proceedings of the 37th ACM/SIGAPP Symposium on Applied Computing, SAC '22, Association for Computing Machinery, New York, NY, USA, 2022, pp. 1373–1381. doi:10.1145/3477314.3507099.

[15] X. Song, J. Qin, Q. Ren, J. Zheng, Igan: A collaborative filtering model based on improved generative adversarial networks for recommendation, Engineering Applications of Artificial Intelligence 124 (2023) 106569. doi:10.1016/j.engappai.2023.106569.