Global Journal of Engineering and Technology Advances
eISSN: 2582-5003
Cross Ref DOI: 10.30574/gjeta
Journal homepage: https://gjeta.com/

(REVIEW ARTICLE)

Check for updates

Enhancing generative adversarial network

Rajbeer Kaur *, Amanpreet Kaur and Kirandeep Kaur

Department of Computer Application, Global Group of Institutes, Amritsar, India.

Global Journal of Engineering and Technology Advances, 2024, 19(01), 068–073

Publication history: Received on 24 February 2024; revised on 01 April 2024; accepted on 04 April 2024

Article DOI: https://doi.org/10.30574/gjeta.2024.19.1.0057

Abstract

The paper provides a comprehensive review of various GAN methods from the perspectives of theory, and applications. GAN algorithms' mathematical representations, and structures are detailed. The commonalities and differences among these GANs methods are compared. Theoretical issues related to GANs are explored, and typical applications in various fields are showcased. Future scope of research problems for GANs are also discussed in the paper.

Keywords: introduction of Generative adversarial network; Working of GAN; Structure of Generative adversarial network; Steps to improve generative adversarial network

1. Introduction

Generative modeling, an unsupervised learning task in machine learning, involves the automatic discovery and learning of patterns in input data to generate new examples. GANs introduce a clever approach to training generative models, where the problem is framed as a supervised learning task with two sub-models: the generator model, which is trained to generate new data, and the discriminator model, which is trained to distinguish between real and generated data examples, and the discriminator model, which classifies examples as real or fake. GANs, a rapidly evolving field, are delivering on the promise of generative models by generating realistic examples in various domains, notably in image-to-image translation tasks [1].

Generative Adversarial Networks (GANs) are comprised of three parts:

- **Generative:** Describing how data is generated through a probabilistic model.
- **Adversarial:** Where a model is trained within an adversarial framework
- **Networks:** Deep neural networks can be used as artificial intelligence (AI) algorithms for training purposes.

The desired end output is identified and an initial training dataset is gathered based on those parameters. This data is then randomized and input into the generator until basic accuracy is achieved in producing output [2].

2. Use cases of Generative adversarial network

- Generating images: GANs produce lifelike images with high resolution.
- Super Resolution: Enhancing image resolution is a key application.
- Image Modification: GANs modify images, including resizing and other alterations.
- Photos of real people: GANs generate realistic photos of individuals, relevant in practical domains.

* Corresponding author: Rajbeer Kaur

- The Generative Adversarial Network (GAN) is utilized for various applications: GANs create realistic visualizations from textual descriptions.
- Image-to-image synthesis: GANs transform images by changing themes, altering lighting conditions (e.g., day to night), converting between real and drawn images, and adjusting creative styles [3].

3. Working of GANs

In the adversarial game of GANs, two neural networks are involved: the Generator, denoted as G(x), and the Discriminator, denoted as D(x). They engage in a competitive process where the Generator strives to generate data resembling the training set to deceive the Discriminator, while the Discriminator endeavors to distinguish between real and fake data. Both networks operate concurrently, undergoing training to effectively handle complex data types such as audio, video, or images, with the aim of being converted into passive form.

A fake sample of data is generated by the Generator network from an input sample. The Generator is trained to cause an increase in the probability of mistakes being made by the Discriminator network.

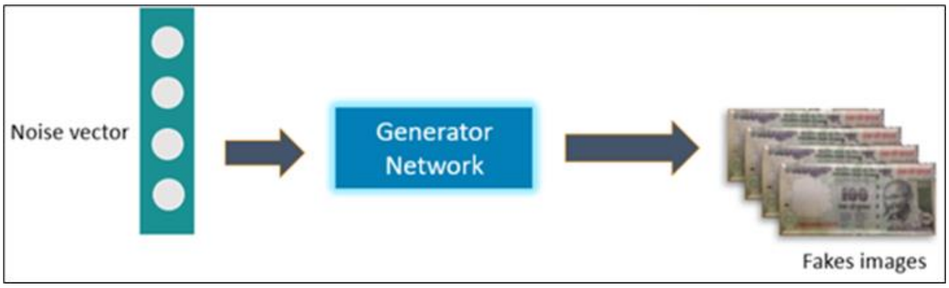

Figure 1 Working of Generator Network

First, a noise vector or input vector is fed to the Generator network, which then generates fake 100-rupee notes. The Discriminator receives real images of 100-rupee notes stored in a database, as well as images of fake notes. The notes are then classified by the Discriminator as either real or fake.

The model is trained, and the loss function is calculated at the end of the Discriminator network. The loss is then backpropagated into both the Discriminator and Generator models.

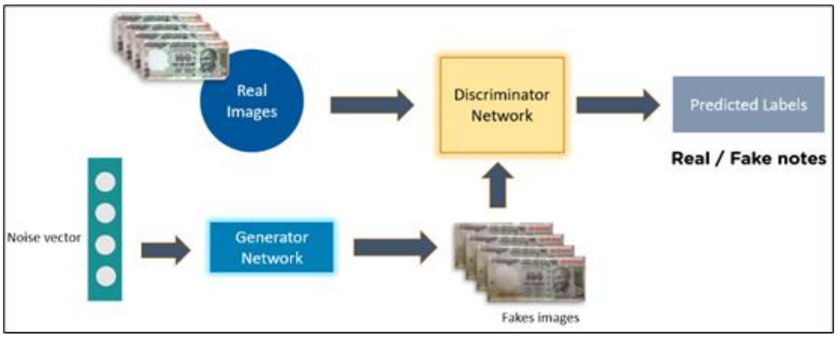

Figure 2 Discriminator and Generator models

3.1. Mathematical Equation

The mathematical equation for training a GAN can be represented as:

Here, G = Generator

D = Discriminator
P data(x) = distribution of real data
p(z) = distribution of generator
x = sample from P data(x)

z = sample from P(z)
D(x) = Discriminator network
G(z) = Generator network [4].

4. Structure of generative adversarial network

Plausible data is learned to be generated by the generator, and the generated instances are turned into negative training examples for the discriminator.

The generator produces obviously fake data when training begins, and it is quickly learned by the discriminator to tell that it's fake. The generator is then penalized by the discriminator for producing implausible results.

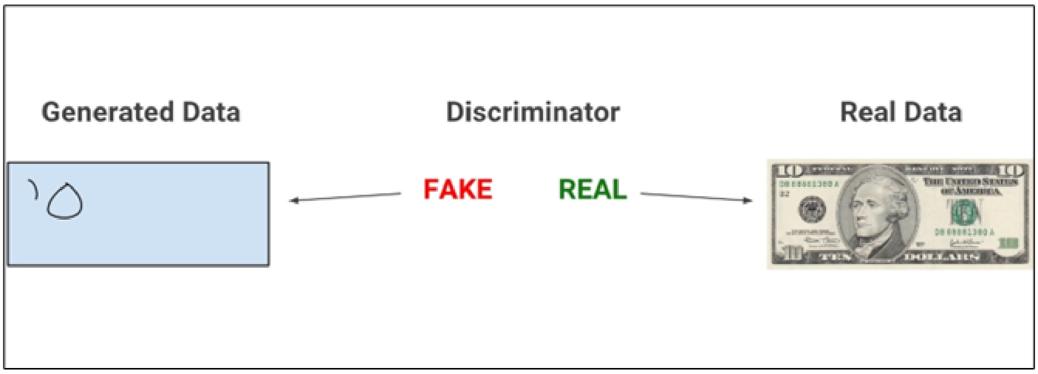

Figure 3 Training example of the Discriminatior

As training progresses, the generator gets closer to producing output that can be fooled by the discriminator.

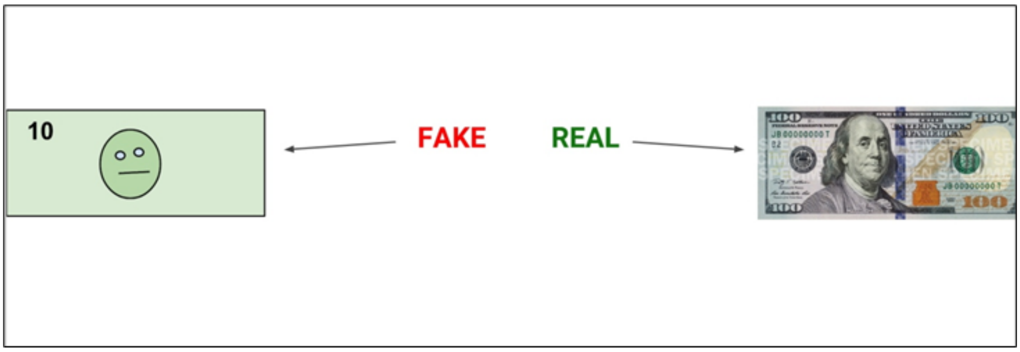

Figure 4 Telling the difference between real and fake

Finally, if generator training goes well, the discriminator starts to get worse at telling the difference between real and fake.

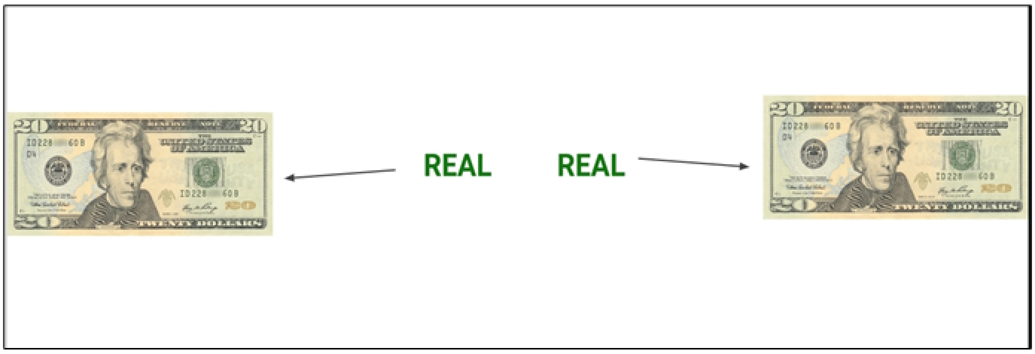

Figure 5 Classified the real data

The neural networks for both the generator and the discriminator are used. The generator's output is connected directly to the input of the discriminator. Through backpropagation, the classification by the discriminator provides a signal that is utilized by the generator to update its weights[5].

5. The discriminator

In a GAN, the discriminator is essentially a classifier tasked with distinguishing real data from generated data. It can utilize any network architecture suitable for the type of data being classified.

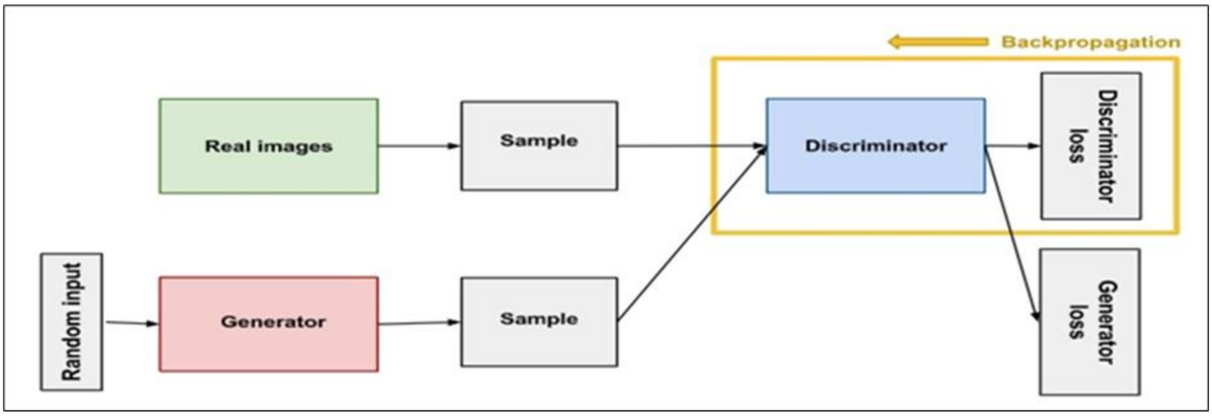

Figure 6 Backpropagation in discriminator training

6. The discriminator

Two loss functions are connected to the discriminator. During discriminator training, the generator loss is ignored, and only the discriminator loss is utilized. The generator loss is employed during generator training, as detailed in the subsequent section.

6.1. During discriminator training

- Both real data and fake data from the generator are classified by the discriminator.
- The discriminator loss is responsible for penalizing the discriminator if a real instance is misclassified as fake or if a fake instance is misclassified as real.
- The weights of the discriminator are updated through backpropagation from the discriminator loss across the discriminator network.

6.2. The Generator

The generator part of a GAN is taught to generate fake data by receiving feedback from the discriminator. It is trained to produce outputs that the discriminator identifies as real. Generator training necessitates a closer connection between the generator and the discriminator compared to what is needed for discriminator training. The portion of the GAN that trains the generator includes:

Random input
Generator network, which transforms the random input into a data instance
Discriminator network, which classifies the generated data
Discriminator output [6].

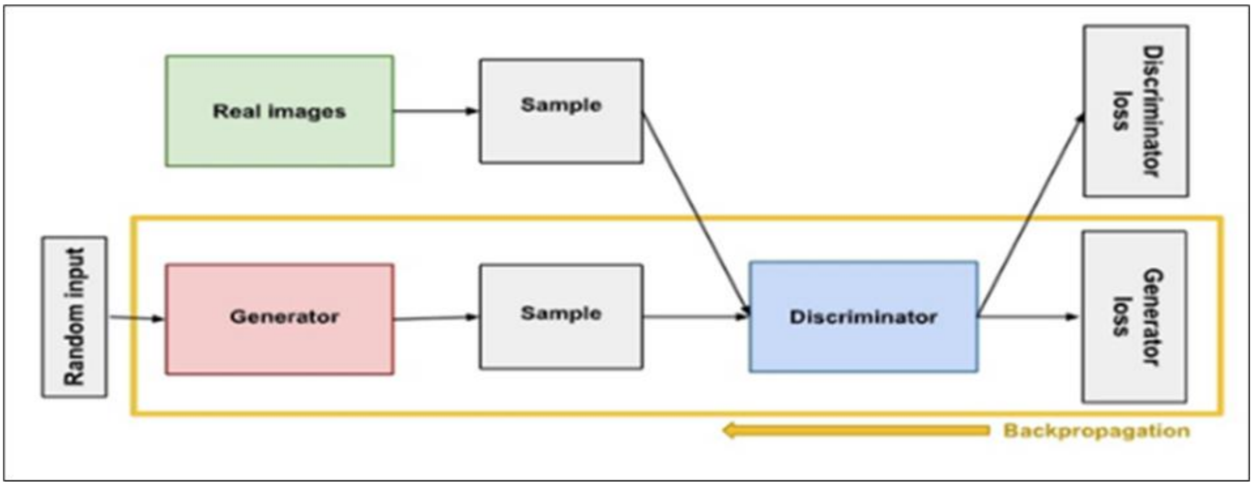

Figure 7 Backpropagation in generator training

7. Alternating back-propagation

The method for learning the factor analysis model is based on the Rubin-Thayer EM algorithm, first outlined by Rubin and Thayer in 1982 and previously introduced by Dempster, Laird, and Rubin in 1977.In this algorithm, both the E-step and the M-step rely on multivariate linear regression. Drawing inspiration from this approach, an alternating back-propagation algorithm is proposed for training the generator network, which involves iterating through the following two steps:

- **Inferential back-propagation**: For each training example, infer the continuous latent factors by Langevin dynamics or gradient descent.
- **Learning back-propagation:** Update the parameters given the inferred latent factors by gradient descent[7].

8. Steps to Improve GAN'S

- Generator should be fed with more parameters to improve the comparison.
- Previous examples or data sets should be stored in the database to improve the results of discriminator.
- Improved Algorithms which can analyses the small details should be used at the back end in order to get accurate results.
- Continuous Improvement of data sources should be there.
- Better prediction capability of GAN'S will enable the accurate outputs.
- Back Propagation process should be made less time consuming by implementing better comparison algorithms at the discriminator level [8].

9. Conclusions

Generative adversarial networks (GANs) are a class of machine learning frameworks where two neural networks, a generator and a discriminator, are trained together. The generator tries to produce data (e.g., images, text) that is indistinguishable from real data, while the discriminator tries to distinguish between real and fake data. High-Quality Data Generation(GANs have shown remarkable success in generating high-quality synthetic data, especially in image and text generation tasks.) Above paragraph shortlists the suggestions to improve GAN'S. Researchers are continually advancing GANs with techniques to improve stability, generate higher quality outputs, and address ethical concerns.

Future work

Researchers are actively working on addressing stability issues during training, such as mode collapse and convergence problems. Future advancements may lead to more robust and reliable GAN architectures. GANs become more powerful, addressing ethical concerns surrounding their misuse, such as deepfakes and privacy violations, will be crucial. Future developments may focus on mitigating these risks.Overall, the future of GANs is likely to involve a convergence of advancements in model architectures, training techniques, and applications across diverse domains, driving innovation and progress in artificial intelligence.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] ANKAN DASH, JUNYI YE, and GUILING WANG, Department of Computer Science, New Jersey Institute of Technology, USA,A review of Generative Adversarial Networks (GANs) and its applications in a wide variety of disciplines - From Medical to Remote Sensing,arXiv:2110.01442v1 [cs.LG] 1 Oct 2021 https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/.

[2] Gui Jie , Zhenan Sun, Yonggang Wen, Dacheng Tao, Jieping Ye A Review on Generative Adversarial Networks: Algorithms, Theory, and Applications JOURNAL OF LATEX CLASS FILES, VOL. 14, NO. 8, AUGUST 2015,https://www.techtarget.com/searchenterpriseai/definition/generative-adversarial-network-GAN.

[3] Alankrita Aggarwal ,Mamta Mittal , Gopi Battineni,Generative adversarial network: An overview of theory and applications,International Journal of Information Management Data Insights,https://www.javatpoint.com/.

[4] Liang Gonog, Yimin Zhou, generative adversarial networks, 2019 14th IEEE conference on industrial electronics and applications (ICIEA), 505-510, 2019,https://www.geeksforgeeks.org/generative-adversarial-network-gan/.

[5] Zhijie Deng, Hao Zhang, Xiaodan Liang, Luona Yang, Shizhen Xu, Jun Zhu, Eric P Xing,Structured generative adversarial networks, Advances in neural information processing systems 30, 2017, https://aws.amazon.com/.

[6] Xuanqing Liu, Cho-Jui Hsieh,Rob-gan: Generator, discriminator, and adversarial attacker,Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 11234-11243, 2019,https://developers.google.com/.

[7] Alternating Back-Propagation for Generator Network Tian Han ,† Yang Lu,† Song-Chun Zhu, Ying Nian Wu Department of Statistics University of California Los Angeles, USA Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17).

[8] Yi-Lin Tuan, Hung-Yi Lee,Improving conditional sequence generative adversarial networks by stepwise evaluation,IEEE/ACM Transactions on Audio, Speech, and Language Processing 27 (4), 788-798, 2019.