Overview of Generative Adversarial Network in Noise Removal

***Dr. D. M. Annie Brighty Christilin**
Assistant Professor of Computer Science, Sadakathullah Appa College,
Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli-11,
anibrighty@gmail.com

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Abstract

A generative model such as Generative Adversarial Network (GAN) has achieved awesome success in the region of image classification, signal processing, etc. GANs models are used to provide the new samples which have same data representation for the training dataset. The process of GAN will be introduced in this article, followed by the various types of GANs will be explained and also its comparative details will be represented. After that, the applications of GANs will be discussed in this article.

Keywords: GAN, Discriminator, Generator, Recurrent, Laplacian, NLP, Wasserstein, SAGAN, ChemGAN

1. INTRODUCTION:

In Artificial Intelligence (AI), the ability of machine to heal the human nature increases exponentially. But the researchers of Artificial general Intelligence (AGI) wants to provide the forth-coming new machine learning algorithms which has a well performance task. One of them such as Generative Adversarial Network was introduced by Goodfellow et al. [1]. The basic principle of GAN is looked like two-player zero-sum game, in which the total gains of two players are zero, and each player's gain or loss of utility is exactly balanced by the loss or gain of the utility of another player [2]. In Fig.1 GAN consists of two model such as Generator (G) and Discriminator (D). Some of the noise data (Z) is added to the d dimensional data sample. The Generator creates a fake image G (Z). The Discriminator checks whether the real and fake image is matched or not. It is predicted as a label as 0 or 1. 0 is represented as fake value. 1 is represented as real value. And also it is estimated the probability of sample data that received from the training data not for the generator. The GANs are formulated as a minimax game [3], where the Discriminator is trying to minimize its remuneration and the Generator is trying to minimize the Discriminator's remuneration or maximize its loss. So, the discriminator wants a low error rate and the generator wants a high error rate. Thus, the optimization goal is to reach a Nash equilibrium [4]. Moreover, there is a trade-off between the learning rate of both the models. There must be separate learning rates for discriminator and generator so that neither generator nor discriminator becomes way better than the other.

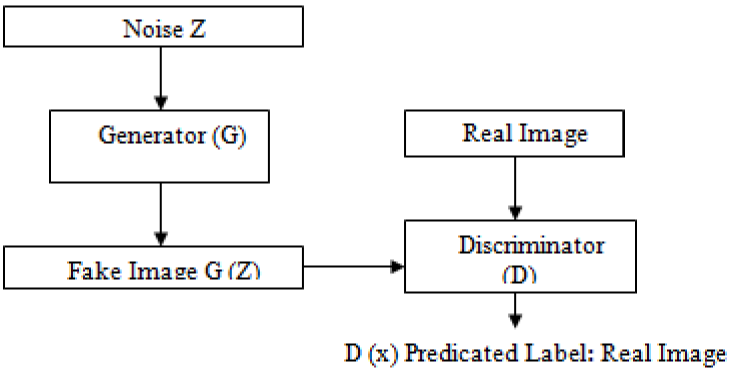


Fig 1. Process of GAN

2. CLASSIFICATIONS OF GAN

2.1. Conditional GAN (CGAN)

Fig.2 is a type of supervised learning GAN, which can be extended to a conditional model. However, both the discriminator and generator are conditioned to some additional auxiliary information y. In the generator the prior input noise pz(z), and y are combined in joint hidden representation, and the adversarial training framework works in this composition of hidden representation for considerable flexibility [5]. This result consists of class labels or data from other modalities. This architecture is multilayer perceptron (MLP). It aims to minimax the game under the condition of extra information.

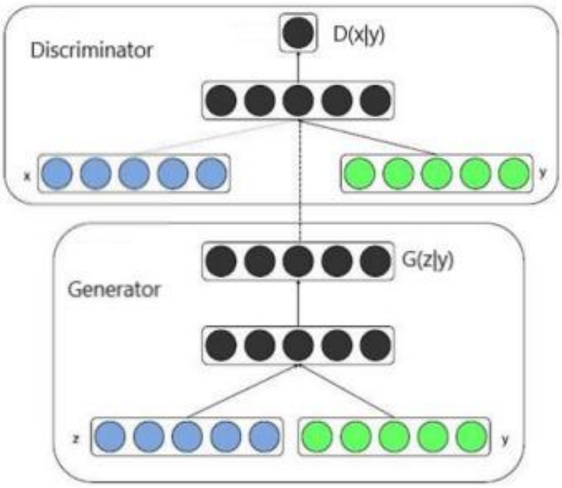


Fig 2 Conditional GAN (CGAN)

2.2. Deep Convolutional GAN (DCGAN)

This network is utilized for unsupervised learning. In this type of GAN, Convolutional Neural Networks (CNN) are used instead of MLP with some additional constraints. In DCGAN, the gap between the success of CNNs for supervised and unsupervised learning have been suppressed [6].

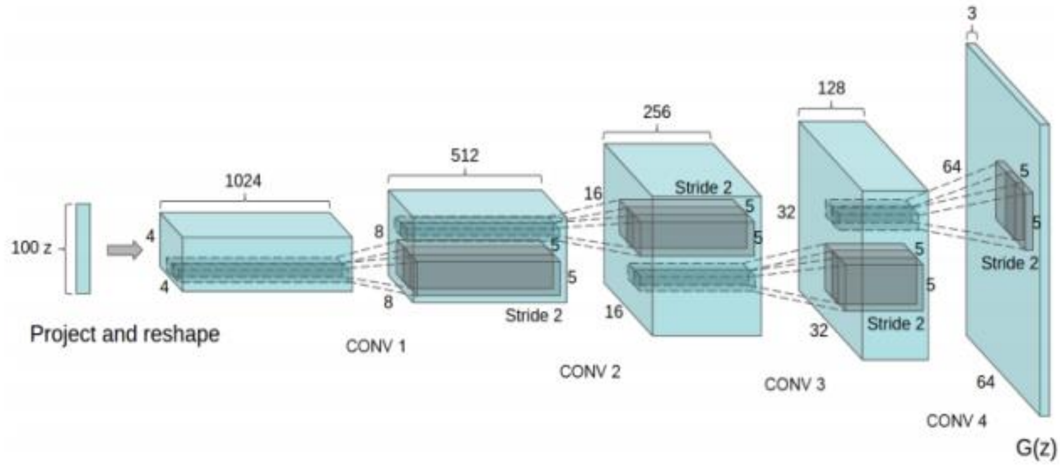
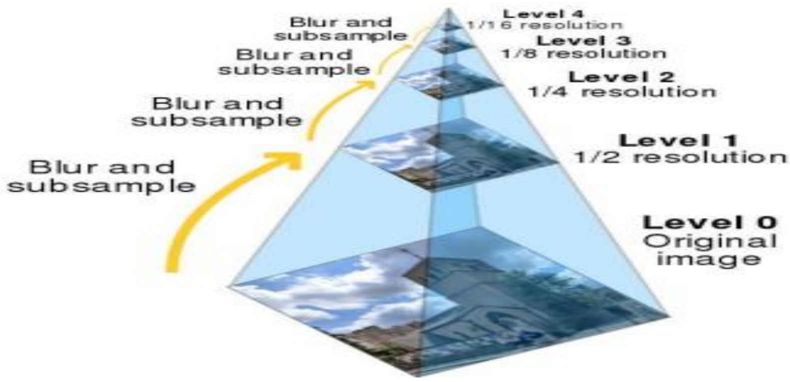


Fig. 3 Deep Convolutional GAN (DCGAN)

Generally, discriminator is mostly opposite to that of the generator, i.e., it takes an image and produces 2 numbers (i.e., the probabilities of the image which is fake or not). In every layer of the discriminator, the forward process consists of the Conv Transpose or Deconv operation [7].

2.3. Laplacian Pyramid GAN (LAPGAN)

Denton et al. (2015) proposed the Laplacian pyramid framework [8] for the creation of images in a rough-to-well approach. It is utilized for unsupervised learning. The multiple Generator-Discriminator networks used at various levels. This pyramid is constructed from a Gaussian pyramid using up-sampling and down-sampling [9].



The basic principle function of LAPGAN is that the image is first downscaled at each layer of the pyramid until it reaches the last level. The backward process executed through this pyramid for noise which is produced by DCGAN at each level. The image size is rebuilt using up-sampling. Furthermore, this method creates image samples in a sequential process. The authors evaluated the performance of the LAPGAN model on three datasets such as CIFAR10, STL10 and LSUN datasets.

2.4. Generative Recurrent Adversarial Networks (GRAN)

Im et al. (2016) proposed the recurrent generative model which shows that unrolling the gradient based on optimization which yields a recurrent computation that creates images by incrementally adding to a visual "canvas" [10]. In this architecture, the encoder extracts the images of the current canvas along with the reference image which is fed into the decoder. Then the decoder decides to change the canvas or not.

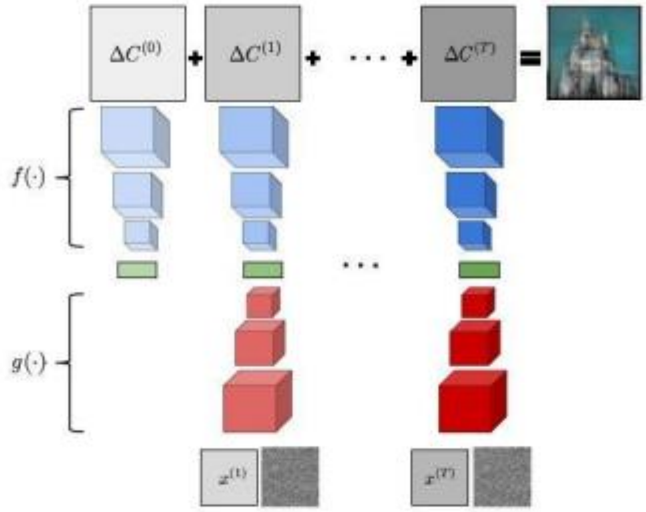


Fig.4 Generative Recurrent Adversarial Networks (GRAN)

Some other types of GANs are:

1. Photo-Realistic Single Image Super-Resolution GAN (SRGAN)
2. Information maximizing GAN (InfoGAN)
3. Bidirectional Generative Adversarial Networks (BiGAN)
4. Wasserstein GAN (WGAN)
5. Cross-domain GAN (DiscoGAN)
6. Generative Adversarial Autoencoders Networks (GAAN)
7. Self-Attention Generative Adversarial Networks (SAGAN)

3. APPLICATIONS OF GAN

The most widely used applications of GANs arise from improving the efficiency of the machine by feeding it with more virtually feeding machine more amount of data by adding noise to the existing dataset which aid to deceive a machine into thinking the data is unfamiliar and treats it as distinguished data, thereby increasing the size of the training data. As the knowledge of GANs has spread across researchers and students, many of them have proposed their own version of GANs which include: adversarial autoencoder[11] which can be used in applications such as semi-supervised classification, disentangling style and content of images, unsupervised clustering, dimensionality reduction and data visualization; image generation and sketch retrieval which can be used to improve translation, rotation and scale[12] Adversarial Feature Learning which help projecting data back into the latent space[13]. Also using GANs is getting popular for image blending, image inpainting, image translation, semantic segmentation, and video prediction and generation. As GANs will get more researched various new applications shall spring out which can extend the potential of the neural network.

4. FUTURE WORK AND RESEARCH FRONTIERS

GANs were first proposed only recently in 2014 which indicates that there are still a lot of areas which are unexplored where GANs can contribute. Though it has significantly contributed to the development of generative models, there are a lot of areas where GANs fails. In a Reddit thread, Ian Goodfellow [14] addressed to why GANs are still not applied in Natural Language Processing (NLP). GANs only work where the computed gradients have small yet continuous value. They fail to produce relevant results where the applications are based on discrete values such as NLP. A recent introduction to other types of GANs such as Wasserstein GANs has made progress on text-related applications which still requires a lot of research. Another important problem in computer vision is image synthesis. The CGAN have been successful in this field. But it struggles to capture geometric or structural patterns that occur consistently in images (for example, dogs are often drawn with realistic fur texture but without clearly defined separate feet) [15]. Hence a new type of GAN known as SelfAttention Generative Network (SAGAN) was introduced in May 2018, which allows attention-driven, long-range dependency modeling for image generation tasks. The paper [15] also mentions that, with the help of SAGAN s, an increase in ~43% Inception Scores and reduction in ~32% Fréchet Inception distance, from the previous best-published scores, was observed on ImageNet dataset. The combinations of GANs with different architectural models can also be used for text-to-image synthesis. Moreover, GANs are still mostly used only in computer vision related problems but they can also be extended to the field of audio and video domains. GANs have also started to show its presence in drug discovery for healthcare using ChemGAN [16]. The increasing domains of applications leads to challenging problems which are quite complex, thus demanding active research work and developments in generative models.

5. CONCLUSIONS

In this paper, we study and review about a developing and popular network, Generative Adversarial Networks. We also investigate about the various types of GANs, their applications, and current future developments in the field. In our opinion, GANs could be one of the highly potential field in the niche area of neural networks, which is still left unexplored and has not reached to full potential in research development. It could emerge out to be one of the most powerful generative models available.

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