A Survey on Research Progress of Generative Adversarial Networks

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Abstract— **Purpose Since the birth of Generative Adversarial Networks (GANs), it has become a research hotspot in the field of machine learning and artificial intelligence. GAN uses the principle of adversarial training between the generator and the discriminator to solve many problems that are difficult to solve by traditional models. Based on the advantages of GAN, more and more people have begun to conduct in-depth research on it, resulting in many variants of GAN. With the continuous improvement of GAN, it has played a surprising role in some application fields, such as the visual field, image field, audio field, natural language processing field and various other fields. This article first introduces the GAN model and its basic principles, then introduces the popular variant models of GAN, and finally summarizes the application status and research progress of GAN in various fields.**

Index Terms— **GAN, CGAN, DCGAN, SeqGAN**

I. INTRODUCTION

In 1943, research methods based on deep learning were first proposed. Limited by the backwardness of technological development, this research method has not become popular [1]. It was not until 2012 that deep learning returned to people's field of vision. In 2014, Goodfellow proposed GAN [2]. The network consists of two parts, one is the generative model, and the other is the discriminative model. The generative model and the discriminant model can choose traditional algorithms or various neural network models. In the training process, the goal of generative network is try to generate real samples to deceive the discriminating network. The goal of the discriminant network is try to distinguish the samples generated by the generative model from the real samples. In this way, the generative network and the discriminant network constitute a dynamic game process. A good GAN model needs a good training method, otherwise the output result may be unsatisfactory due to the freedom of the neural network model.

In recent years, many variant models derived from GAN have achieved quite good results in various fields. This article will summarize the research progress of GAN in recent years.

II. THE BASIC PRINCIPLE OF GAN

The basic model of GAN is shown in Fig. 1.
GAN trains a generator and a discriminator at the same time. During the training process, the generator inputs a random noise variable z that obeys the prior probability distribution, and the output data is G(z). Then we input G(z) and the real sample into the discriminator, which has to determine whether the input data is real data or generated data G(z). The parameter optimization of the generator is based on the back propagation of the discriminator. The discriminator improves its ability to discriminate through continuous training, and the generator improves its ability to generate real data through continuous learning.

In the above training process, the generator and discriminator constitute a dynamic game process, and the two are continuously optimized in the iterative process. When the discriminator cannot distinguish between real data and generated data, we can consider the GAN model to be optimal. As an unsupervised learning model, GAN is characterized by the ability to learn from completely random raw data.

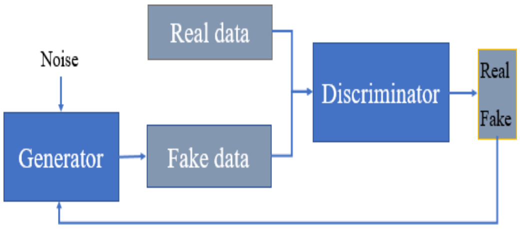

Fig.1 GAN model structure flow chart

III. THE LATEST RESEARCH PROGRESS OF GAN

The original GAN has some shortcomings, its generation results are relatively free and the convergence is unstable. The generator and discriminator need to be well balanced during training. GAN also has advantages. GAN can be combined with deep neural networks such as Convolutional Neural Network (CNN) [3], Recurrent Neural Network (RNN) [4] and Long Short-Term Memory [5]. Based on the advantages of GAN, many researchers have optimized and improved GAN. Hundreds of GAN-related models have been derived from this, and they have been widely used in image processing, natural language processing, computer vision and other fields. This chapter will introduce several representative models.

A. Conditional GAN

Aiming at the problem that the GAN model is too free and uncontrollable, Mirza and Osindero [6] proposed a model that adds constraints to GAN, called Conditional Generative Adversarial Network (CGAN).
CGAN can incorporate condition variables in its generator and discriminator. Using these condition variables to add constraints to the model can guide the data generation process. If the input constraint variable is a category label, we can think of CGAN as an improvement to transform GAN into a supervised model. By changing the label, we can get the generation results we need, or use the same generation

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network to generate different targets. Although the idea of this improvement is simple, the effect of the model has proved to be very effective [7].

B. Deep Convolutional GAN

Based on the idea of GAN, Radford [8] in 2015 proposed an architecture that combines the deep convolutional neural network CNN in supervised learning and GAN in unsupervised learning, and named it Deep Convolutional GAN (DCGAN). DCGAN is an improved structure that is widely used. DCGAN uses a convolutional layer to replace the original fully connected layer. In addition, DCGAN uses stepped convolution in the generator instead of up-sampling. These improvements have greatly improved the stability of GAN training and optimized the quality of the generated results. DCGAN build a bridge between CNN supervised learning and unsupervised learning.

C. Sequence GAN

In [9], the author proposed SeqGAN. The author's starting point is the difficulty that GAN will encounter when dealing with discrete data. This difficulty is mainly reflected in two aspects: the generator is difficult to update through the gradient, and the discriminator is difficult to evaluate incomplete sequences. For the first difficulty, the author regards the entire GAN as a Reinforcement Learning system and uses the Policy Gradient [10] algorithm to update the parameters of the Generator. For the second difficulty, the author draws on the idea of Monte Carlo Tree Search in order to evaluate incomplete sequences at any time.

IV. SUMMARY OF GAN

Since the birth of GAN, it has been widely used in images, text, audio, video and other fields, and it is still expanding. As a new type of generative model, GAN avoids some of the difficulties of other traditional generative models in practical applications, which is its biggest innovation. In view of the various problems generated by GAN, researchers continue to conduct research and analysis, improve and integrate GAN with various technologies, and thus train many effective models. However, the current GAN still has shortcomings, which need to be solved by researchers.

At present, GAN is still in the development stage, and more and more academics have joined the research, and it will be applied to a wider range of fields in the next few years.

REFERENCES

[1]Goodfellow I,Bengio Y,Courville A. Deep Learning ［M］. Cambridge, UK: MIT Press,2016.

[2]Goodfellow I, Pouget－Abadie J, Mirza M, et al. Generative adversarial nets[C] ‖ Advances in neural information processing systems. 2014.

[3]Gu, Jiuxiang, Wang, et al. Recent advances in convolutional neural networks[J]. Pattern Recognition, 2018.

[4]Lipton Z C , Berkowitz J , Elkan C . A Critical Review of Recurrent Neural Networks for Sequence Learning[J]. Computer ence, 2015.

[5]HOCHREITERS, SCHMIDHUBER J. Long short-term memory [J] . Neural Computation,1997.

[6]Mirza M, Osindero S. Conditional generative adversarial nets[J]. 2014.

[7]Odena A , Olah C , Shlens J . Conditional Image Synthesis With Auxiliary Classifier GANs[J]. 2016.

[8]Radford A, Metz L, Chintala S. Unsupervised representation learning with deep convolutional generative adversarial networks[J]. 2015.

[9]Yu L , Zhang W , Wang J , et al. SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient[J]. 2016.

[10]Sutton R S , Mcallester D , Singh S , et al. Policy Gradient Methods for Reinforcement Learning with Function Approximation[J]. Submitted to Advances in Neural Information Processing Systems, 1999.

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