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STGC8003 - RESEARCH METHODS AND ETHICS

Literature Survey on Neural Cellular Automata (NCA)

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Neural Cellular Automata

Abstract:

Unstable training and difficult parameter adjustment have always been the problems faced by Generative Adversarial Network (GAN). These problems lead to the instability of the image generated by GAN, often distortion, poor rendering quality or rendering into noise, andthe image is easy to lack diversity. In order to solve the above problems, in this study, we replace the generator in GAN model with Neural Cellular Automata (NCA), and combine the Variational Auto Encoder (VAE) with the generation countermeasure network to reduce the setting of parameters and improve the stability of the generator, so as to improve the quality of the generated image. The results show that the model constructed by our method is smallerand faster than the typical GAN model. Although it is better than the plain NCA, it is not significantly better than some of the original GAN models.

1. Introduction

Generative Adversarial Networks (GANs) are very popular depth generation models. Since its birth in 2014[1], the popularity of Generative Adversarial Network has only increased, and a variety of variants emerge in endlessly. Because the ability of Generative Adversarial Network in synthesizing realistic images is excellent, it is one of the most promising methods of unsupervised learning, which has always been a hot issue in academic research. GAN model is very beautiful in theory. Its vision after training is that the implicit probability distribution of the generator is completely equal to the real probability distribution of the data set, and the discriminator can not distinguish any sample point, but can only give a probabilityof 0.5. However, in fact, such a result is unlikely to be achieved.

On the contrary, many GAN models suffer the following major problems:

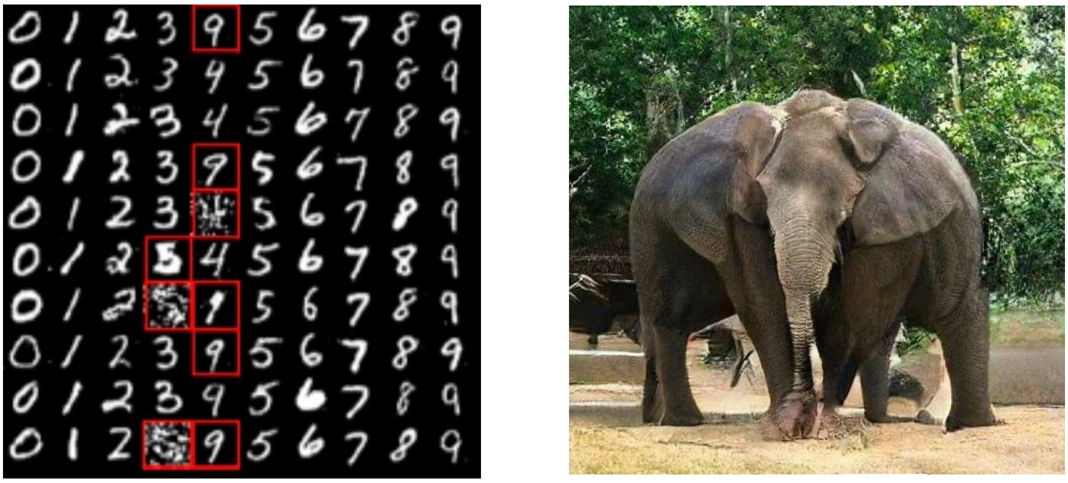
1) Non-convergence: the model parameters oscillate, destabilize and never converge,
2) Mode collapse: the generator collapses which produces limited varieties of samples,

3) Diminished gradient: the discriminator gets too successful that the generator gradientvanishes and learns nothing,

4) Unbalance between the generator and discriminator causing overfitting,

5) Highly sensitive to the hyperparameter selections.

These problems can lead to strange pictures as shown in Figure 1:



(1) (2)

Figure 1. Pictures generated by bad GANs. (1)Trained with MNIST, results are unrecognizable or wrong numbers. (2) GAN generates weird elephant image that is too fake to be easily identified.

This study focuses on the non-convergence problem, looking for a way to improve thedifficulty and instability of GAN parameter adjustment.

In view of the above problems of GAN, many scholars have conducted various studies andput forward some methods to improve GAN, especially in the following aspects:

1) Change the cost function for better optimization objectives,
2) Add additional penalties to the cost function to enforce the constraint,
3) Avoid overconfidence and overfitting,
4) Better method of optimizing model,
5) Add labels for data sets.

So far, researchers have proposed many variants of improved Gan, such as MM GAN, NS GAN, WGAN, WGAN GP, LS GAN, DRAGAN, BEGAN. Some researchers of Google conduct a neutral, multi-faceted large-scale empirical study on state-of-the art models and evaluation measures, and the results are so how upset: No evidence that any of the tested algorithms consistently outperforms the original one.

Although the results were frustrating, we were inspired by other works and found NCA andVAE may help.

In nature, the process of cellular growth and differentiation has led to an amazing diversity of organisms — algae, starfish, giant sequoia, tardigrades, and orcas are all created by the same generative process. Inspired by the incredible diversity of this biological generative process, some researchers have proposed a generative model, the Variational Neural Cellular Automata (VNCA), which is loosely inspired by the biological processes of cellular growth and differentiation. The VNCA is a proper probabilistic generative model. They find that the VNCA learns to reconstruct samples well and that despite its relatively few parameters and simple local-only communication, the VNCA can learn to generate a large variety of output from information encoded in a common vector format. While there is a significant gap to the cur- rent state-of-the-art in terms of generative modeling performance, they show that the VNCA can learn a purely self-organizing generative process of data. Additionally, the self-organizing nature bestows the VNCA with some inherent robustness against perturbations in the early stages of growth.

2. Related Works

2.1. NCA can be regarded as a neural network[2] and has the ability togenerate images[3]

Studies have shown that, Cellular automata can be seen as convolutional neural networks.In the article, authors show that deep convolutional neural networks are capable of representing arbitrary cellular automata, and they demonstrate an example network architecture that smoothly and repeatably learns an arbitrary CA using standard loss gradient- based training. Their approach takes advantage of the "mean-field limit" for large networks, for which they find that trained networks express a universal sparse representation of CA based on depth wise consolidation of similar inputs. The effective depth of this representation, however, depends on the entropy of the CA's underlying rules.

2.2. NCA with variational auto encoder can be a promising generative model [3]

Furthermore, there are researches propose a novel approach to generate images (or other artworks) by using neural cellular automatas (NCAs). Authors suggest the NCA can completely replace the up-sampling part of many image generation models. Therefore, rather than training NCAs based on single images one by one, they combined the idea with variational autoencoders(VAEs), and proved the model can be applied to image restoration and style fusion.

2.3. VAE can be a generator in GAN[4]

An appealing property of GAN is that its discriminator network implicitly has to learn a rich similarity metric for images, so as to discriminate them from “non-images”. Thus researchers propose to exploit this observation so as to transfer the properties of images learned by the discriminator into a more abstract reconstruction error for the VAE. The end result will be a method that combines the advantage of GAN as a high-quality generative model and VAE as amethod that produces an encoder of data into the latent space z.

By combining a variational autoencoder with a generative adversarial network we can use learned feature representations in the GAN discriminator as basis for the VAE reconstruction objective.

Results show that generative models trained with learned similarity measures produce betterimage samples than models trained with element-wise error measures.

2.4. NCA-GAN combination is present[5]

The Generative Adversarial Neural Cellular Automaton (GANCA)combines the adversarial training of a GAN structure with the generative capabilities of an NCA. This is very similar to a standard GAN structure, with the main difference being the generator and its input. The generator in the GANCA uses an NCA to update the input edge image step by step with only local information to produce an image. The input edge image is based on the set of real images provided for the discriminator reduced to edges. Using existing training improvements from GAN architectures, NCAs can be trained in an adversarial fashion, which drastically improve performances on out-of-distribution data

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