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GAN Challenges and Optimal Solutions

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Abstract - *Deep learning has received significant acceptance in the wide domain of artificial intelligence. Generative Adversarial Networks (GANs) are the deep learning models which are based on the Game theory which consists of two-players in a game. There are two multiple- layer neural networks in the model typically known as generator and discriminator which compete with each other. The objective of the model is to attain the data distribution to generate big data and realistic data using unsupervised learning. Though in demand, this model encounters the common problems during training GANs. While training GAN some of the major problems like vanishing gradients, mode collapse and non-convergence are observed which are reviewed in this paper. The optimal solutions of the GAN problems are widely surveyed and discussed as the existing research area of GAN. It gives a wider area especially for the researcher's working in the domain of artificial intelligence to obtain a stable GAN through GAN challenges.*

Key Words: **deep learning, generator, discriminator, vanishing gradients, GAN**

1. INTRODUCTION: Background

Generative adversarial networks (GANs) are continuously growing and have been improved over the years. GANs are gaining popularity and are getting recognition in the enormous real applications such as generating examples for Image datasets; generate pictures of human faces, showing face aging, translation from one image to other image and widely used in improving augmented reality. At present, GANs have been broadly used due to the extensive application prospects which include computer vision like generating lot of data, image to image translation etc. GANs are based on the min-max non-cooperative game. In this game, the players compete with each other, where one player maximizes its actions, the other player actions tries to minimize them. As per the game theory, the model converges when together the discriminator D and the generator G arrive at Nash equilibrium stage [1]. It is the stage where a player can attain the desired outcome by keeping or retaining their initial strategy. For, example if we have two players say, A and B controlling 'x' and 'y' respectively where player A takes trials to maximize the value of 'xy' and B takes trials to minimize it, then we have,

$$\min_B \max_A V(D,G) = xy$$

The Nash equilibrium stage is where $x=y=0$. The challenge is to find Nash equilibrium using the gradient descent. Thus, GANs are tough to train at actual to bring it to ideal stage. The players as shown in Figure 1 in a game are generator (Counterfeiters) which tries to trick the discriminator (Police) where the discriminator has both real and generated samples. Once the models are trained the generative model then can create new probable samples as and when required.

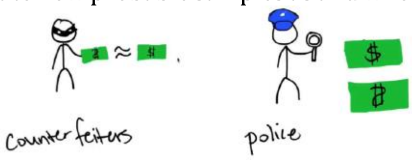

Fig -1: Generator (Counterfeiters) and discriminator (Police)

Figure 2 shows the system architecture of Generative Adversarial Networks (GANs). GANs are neural network architecture for generative modeling. Generative model generates new images that come from an distribution of samples for generating new identical images but particularly not same as dataset of existing samples. A GAN consists of a 'generator model' and a 'discriminator model' which are trained using two different multi-layer neural network models. Generative model learns to generate new images and the discriminative model learns to differentiate generated images from the real samples for determining difference between real and fake images or samples.

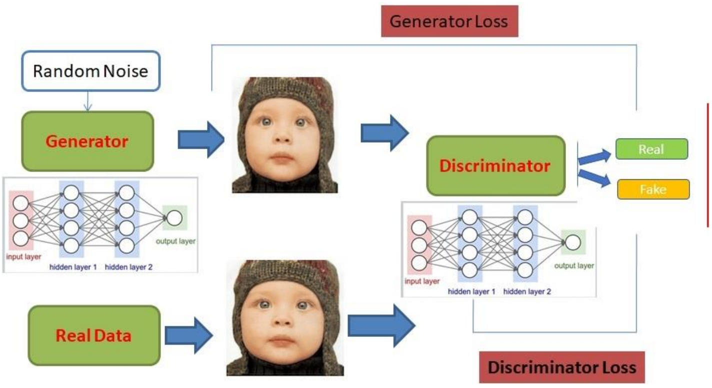

Fig -2: System Architecture of Generative Adversial Networks

The optimal stage for the min-max game is represented with the following equation with Generator and Discriminator loss [1]:

$$\min_G \max_D V(D,G) = E_{x\sim p_{data(x)}}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))]$$

Where,

x : Training Data

p_g : Generator's distribution over the data samples x

$p_z(Z)$: Input noise variable

$G(z;\theta_g)$: Mapping to data space where G is the differential function of generator with parameter

$D(x;\theta_d)$: Discriminator perceptron which outputs a scalar vector

$D(x)$: Probability that x is from the original data patterns not from p_g

As mentioned in the equation, the generator tries to minimize this function while the discriminator tries to maximize it [$\min_G \max_D V(D,G)$].

2. GAN Research Challenges and Solutions

There are some common problems that are specifically associated while training GAN. These include vanishing gradients which results in slow learning or stops learning process completely, mode collapse where the generator disperse varied inputs to the identical class at the output which results in exceedingly non-diversified examples; non-convergence occurs because of unstable, oscillatory and diverging behavior while training generator and discriminator [1] . These common problems and solutions during GAN training are discussed in this section.

2.1 GAN Problems

A. Vanishing Gradient Problem

The vanishing gradient problem occurs while training both the generator and discriminator artificial neural networks using gradient descent learning methods [1,2]. Gradients of neural networks are found using back propagation algorithms which compute the gradient of the loss function with respect to the weights of the network by chain rule moving layer by layer which begins at the final layer till the initial one to compute the derivatives of the initial layers [3]. This is shown in Figure 2.

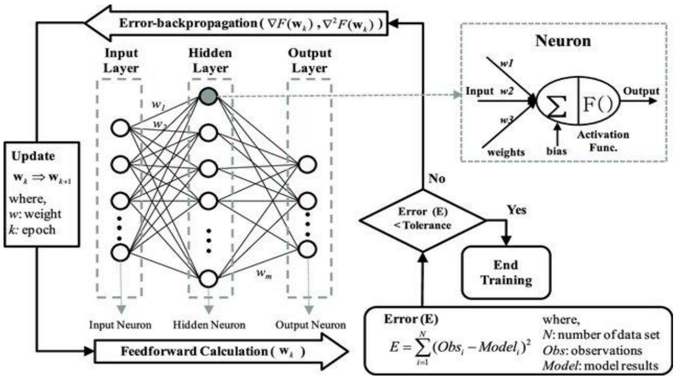

Fig-2: Schematic diagram of back propagation training algorithm (source: Sung Eun Kim, Il Won Seo, 2015 [3])

However, the problem occurs when 'n' hidden layers use activation like the sigmoid function, 'n' small derivatives are multiplied together. As a result, the gradient results in decreasing exponentially as the network propagate down towards the initial layers. When networks are trained for each session with small gradient values the parameters like the weights and biases are not updated at the initial layers effectively. Since the initial layers are critical to recognize the core essentials of the input data. This can lead to overall inaccurate training of the network and even hard to train. At times, the gradient will start vanishing efficiently preventing the weight from updating its value resulting completely stopping the neural network from getting trained further [4].

B. Non –Convergence

One of the common failures of GANs is that it frequently fails to converge. Theoretically it is observed that during GAN training it is guaranteed to converge with modification of the density functions directly, but at actual we modify sample generation function G. It results in oscillations. In this stage model can be trained for longer time, generating many diversified categories of samples with noise and blur images. Mode collapse is the most severe form of non-convergence. The GAN model parameters, generator G and discriminator D are highly non-convex parametric functions they sometimes oscillate; they are not stable and then never converge. It forms the inconsistency between the discriminator and the generator which is to be solved by balancing their training. Some regularization techniques are also used to improve GAN convergence. This was done by adding noise to discriminator inputs as discussed by Arjovsky and Bottou [4] and as suggested in paper Roth et al. [5] also by penalizing discriminator weights. When the discriminator D is trained optimally, the feedback from D is significantly close to 0, leading to the decrease of convergence rate. When the discriminator is not well trained then the gradient of the generator is not accurate. GAN can only work properly when the discriminator is well trained, but there is no indicator to show whether the discriminator is properly trained or not.

C. Mode Collapse

GAN should produce diversified outputs. The mode collapse problem occurs when the generator always produces similar output. Mode collapse is a frequent reason of failure when a generator exhibit low diversity within data and produces only explicit types of real samples. Thus, how to increase the diversity of the generated samples remains a challenging problem for the researchers. This is a common problem for GANs. This failure limits the utilization of the GAN in most computer visions applications. As shown by Jason Brownlee [6] an example of generated images that shows only a few types of figure-eight's in the image, first type- leaning left, second type- leaning right, and third type-sitting up with a blur as shown in figure .

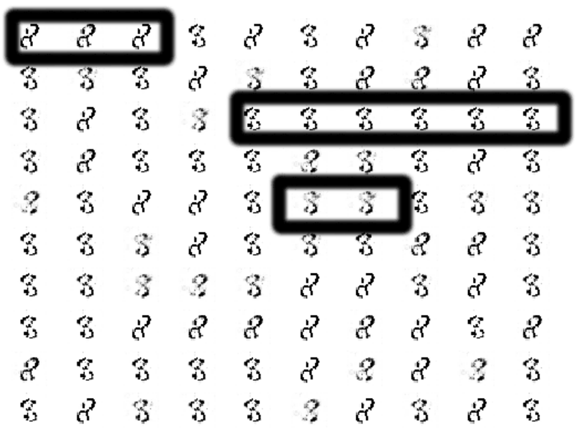

Fig 3: Sample of 100 Generated Images of a Handwritten Number 8 at Epoch 315 from a GAN that has suffered mode collapse (source, Jason Brownlee on July 8, 2019, [6])

As discussed, a mode collapse is less observed during training in DCGAN model architecture [7].

2.2 GAN Solutions

The probable solutions are for the above problems as explained below.

A. Selection of Activation Function

The vanishing gradients problems occur due to a poor choice of activation function as discussed [8]. The activation functions such as variants of ReLU or leaky ReLU functions can be recommended instead of sigmoid or tanh. The advantage of using non-saturated activation functions will solve the vanishing gradient problem. Also it will accelerate the convergence speed. The ReLU activation as discussed by Nair & Hinton [9] is used in the generator model for all layers except for the output, which uses Tanh. It was observed that using a bounded activation made the model learn rapidly to saturate the training distribution, whereas, the discriminator model used the leaky rectified activation as discussed [10] to keep it working. An extended version of GAN i.e, 'Deep Convolutional GANs' (DCGAN) as shown in Figure 4 use LeakyReLU activation in the discriminator for all layers. This model (DCGAN) is more stable than original GAN, which used the maxout activation [11].

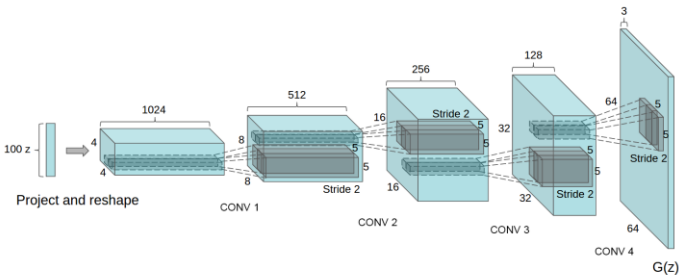

Fig 4: DCGAN

As described by authors [12] a DCGAN is a direct expansion of the GAN. It uses convolutional and convolutional-transpose layers in the discriminator and generator, respectively. The discriminator is made up of strided convolution layers, batch norm layers, and LeakyReLU activations. The generator is comprised of convolutional-transpose layers, batch norm layers, and ReLU activations.

B. Wasserstein loss- an alternate loss function

Goodfellow [13] showed that KL divergence and JS divergence under ideal conditions add to oscillating and recurring behavior of the model. This directs to the problems like non-convergence and vanishing gradients. Wasserstein GAN (WGAN) [4] proposed an alternate loss function which is outcome of Earth-Mover (EM) distance or Wasserstein metric. It gives improved gradients while training the model. It also resolves at some level the mode collapse obstruction to steady the GAN training and get better outcome. The paper Arjovsky et al. [4] discussed the fact that the since EM distance is continuous and differentiable we should train the critic till optimal level. It is said that more the critic is trained, we get stable gradient of the Wasserstein as Wasserstein is differentiable almost in all places. While using JS divergence the discriminator gets better and reliable gradients but the true gradient is 0 as the JS is locally saturated resulting in vanishing gradients.

The paper Arjovsky et al. [4] discussed that the EM distance remains constant and differentiable when the critic is trained to its optimal level. The observation is that with recurrent training reliable gradient of the Wasserstein is obtained. During experimentation both GAN discriminator and a WGAN critic is trained till it optimal level. Here, the discriminator learns instantaneously to distinguish between the real and fake samples without reliable gradient information.

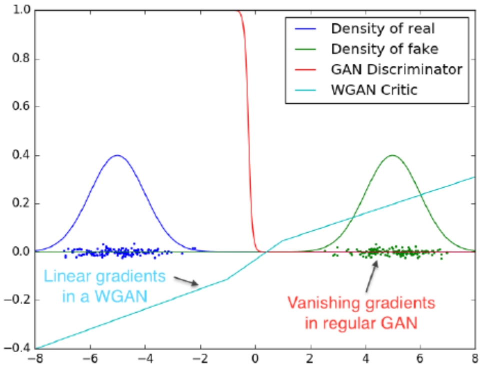

Fig 5: WGAN vs GAN

At the same time the critic does not saturate. It is observed as shown in Figure 5 it converges to a linear function with gradients.

C. Mini-Batches and Batch normalization

For mode collapse, the solution proposed is to use samples in batches. This will increase the diversity of assessment. Mini-batch discrimination (MBD) in Salimans et al. [14] proposed that multiple samples should be processed by the discriminator in mini-batches instead of processing them separately. This helps to prevent the mode collapse of the generator. The added solution is discussed in the paper Ghosh et al. [15] to use multiple generators with multiple models. Here, the samples are combined which are produced by different models to limit mode collapse. WGAN Arjovsky et al. [2017] and unrolled GAN Metz et al. [16] proposed the optimization of the objective function to overcome mode collapse. Batch normalization (BN) is a vital technique for deep network models to prevent mode collapse [17]. It works as a pre-processing stage which is applied to the hidden layers at intermediate levels to reduce the internal covariate shift which prevents the mode collapse by normalizing each mini-batch of data utilizing mean (μ) and variance (μ).

D. Balance between the discriminator and generator

The non-convergence and mode collapse is often results of an imbalance between the discriminator and the generator. The apparent solution is to balance their training which will avoid overfitting. The researchers have made few progress but few believe that this is not a feasible or desirable solution because good discriminator gives high-quality response. Some of the consideration is therefore moved on to cost functions with non-vanishing gradients instead.

3. CONCLUSION

Generative Adversarial Networks is the future generation of deep learning techniques. It is observed that training the neural networks, generator neural-network and discriminator neural-network are quite challenging to meet Nash equilibrium stage. This paper reviews the GAN model, its research challenges and discussed optimal solutions which are the research challenges of GAN. As a solution, few GAN variants are discussed which optimizes to prevail over the limitations and challenges of GAN. Researchers can seek the directions provided in this paper to provide more potential solutions to GAN challenges.

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BIOGRAPHIES

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