Improvising Generative Adversarial Networks

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1 Problem Description

Generative Adversarial Networks have become well known recently for their capability of generating real world images. It is a class of algorithm where two neural networks work against each other to generate images close to original images. The Goal of GANs is to train generator network to produce images from a given distribution transformed by noise. And, the discriminator neural network on the other hand is trained to assign higher probability to real data and lower probability to generated data. GANs have shown remarkable achievements in synthesizing images in recent applications[1].

However, training GAN is quite difficult due Mode Collapse problem and Nash Equilibrium problem. Extensive research has been going in fields solving these problems. We plan upon a detailed analysis of these problems and thereby proposing techniques to improve training methods of GANs.

2 Literature Survey

One of the main problem in training a GAN is of model collapse. Model collapse is a phenomenon where large volume of probability for GAN tends to collapse towards a particular distribution of data. This eventually results in gradient of discriminator pointing in similar directions for similar points [2]. Due to which generator starts producing all images from the small distribution that discriminator believes is highly realistic. After, collapse discriminator realize the sample coming from generator but gradient descent algorithm becomes inefficient of separating identical outputs [2]. Hence, training such GAN ends up producing same image again and again and fails to attain equilibrium. Many approaches have been proposed in recent work to solve mode collapse problem [2]. Similarly, we plan to work upon one such technique improving training method of GANs.

Another main problem of training GANs is deciding convergence criteria of the model. In GAN, the generator and discriminator requires finding a Nash equilibrium which means they tries to reach a state where they cannot improve further which is called equilibrium state. But as GANs are generally trained using gradient descent where our aim becomes to obtain minimum error rate. Hence, in case of non convex objective function in high dimensional space and the continuous parameters it ends up in an oscillating process [3]. So, here it seems that initialization of model and parameters is the most crucial part. Bad initialization may lead to non equilibrium state. To solve this equilibrium problem, we are planning to take the following approach. We are planning to introduce modified objective function for the generator which will help to prevent overtraining on current discriminator. So, instead of blindly maximizing the discriminator, we are planning to design the objective function for the generator such that it matches the statistics of the real data[2]. We can also work upon some way of reformulating model in such a way that gradient descent with lower learning rate can actually find equilibrium. Also we are planning to train discriminator in such a manner that it propagates the knowledge of most discriminative (fake) feature of the synthesized data compared to real data to the generator.

Also, from the literature, it is indicated that most of the times the generator's learning rate is lower than that of discriminator. That means discriminator loss reaches to very small value after some iterations that it stops gradient flow and so the generators cannot be trained further effectively. Having the number of weights at a ratio of 0.5 might solve this hurdle but that may increase training period. So we are planning to implement some of techniques on GAN, which can help generator to learn faster. So that learning rate can be balanced for generator and discriminator without affecting the training period.

We are also planning to work upon changing different architecture of GANs such as instead of using gaussian distribution of input we will try different distributions such as categorical distribution and analyze that whether generator learns to disentangle certain semantic property and attribute them to such categorical distribution. Also, as GANs lack 3D composition in generated images. We plan to work on that problem if time permits.

3 Timeline

We have divided overall project work in following tasks:

- 2/25 - 3/5 : Implementing basic GAN with existing architectures on various datasets. (Kshama)
- 3/6 - 3/13 : Analyzing problems faced while training above GAN architectures. (Nishi)
- 3/14 - 4/1 : Implementing and testing techniques to improve training model of GAN. (Kshama)
- 4/2 - 4/25 : Working on implementing proposed techniques to solve mode collapse and nash equilibrium problem. (Kshama and Nishi)
- 4/16 - 4/30 : Analyze above implemented approaches from the observed output and make a report. (Kshama and Nishi)

References

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