Generative Adversarial Nets

1. Introduction

This paper will introduce the component of Generatice Adversarial nets(GAN), how GAN works and how to improve the value function in GAN in order to optimize the GAN model.

2. Content

At first, this paper explains the whole adversarial nets framework with two models which are the generative model and discriminative model. In my opinion, the generative model is like a student, whose job is to create objects which would be very similar with the standard answers, but for the discriminative model, it plays a teacher role referring to students, who always judges the mark to students. The discriminative model will give marks as high as possible to those data it thinks belong to the true dataset and give a lower mark to generate data. When the discriminative model can clearly distinguish the data from the generative model and dataset, fix the discriminative model and update the generator. As a result, they give a value function V(G, D).

And then, the paper presents a theoretical analysis of adversarial nets. They optimize the equation by an algorithm and then prove the algorithm can help to gain the desired result.

At last, they trained the GAN in a range of datasets, for example, the MNIST, the Toronto Face Database (TFD), and CIFAR-10, which refers to numbers, human faces and pictures separately, and compared with some other frameworks like DBN and Deep GSN. When the generator has been trained, they show the samples drawn from it and summarize the advantages and disadvantages.

3. Innovation

Generative Adversarial Nets model, which is quite different with some model by without using the feedback loops during generation, in such case, it is better able to leverage piecewise linear unit. Then they summarize an equation to express the findings, but in practice, for the generator, this equation may not provide sufficient gradient to learn well. Because in the first period of training, when the Generator is poor, the discriminator would reject samples. In such case, training generator to maximize log D(G(z)) is a better choice rather than minimize log(1−D(G(z))). Besides, they express an algorithm to optimize the equation they raised before in a nonparametric setting that the model has infinite capacity and training time. After that, they express a global optimum for the equation that the generator's distribution over data is equal to the distribution of true data. The next section of the paper is to prove the assumption. By calculating the equation and taking x=G(z) into the equation, the equation is similar with the function y -> alog(y) + blog(1 − y). To get the maximum of such function, the variable y should be a/a+b. After such operation, the original equation can now be reformulated as:

C(G) = max V (G, D) =Ex~pdata{log [Pdata(x)/ (Pdata(x)+ pg(x))]} + Ex~pg{log[pg(x)/(pdata(x) + pg(x))]}.

Also from math theorem, the minimum of C(G) is achieved only if Pdata = Pg. At that time, the minimum of C(G) equals -log4. Because the Kullback–Leibler divergence is always non-negative and zero only when they are equal, the C(G) gets the minimum score only when Pg = Pdata, which means the generator perfectly copied the process of data generation.

4. Technical quality

This paper has a high quality as they came up with a new machine learning model with a reasonable equation. After that, they do a great job to optimize the equation and experiment the model to real data.

For the Generative Adversarial Nets model, they compared a lot with some other models like Deep generative models, restricted Boltzmann machines (RBMs), and deep Boltzmann machines (DBMs). By comparison, they claim the advantages of the GAN model, using only the highly successful backpropagation and dropout algorithms and sample from the generative model using only forward propagation, especially no approximate inference or Markov chains are necessary.

For the part of the equation and how to optimize the formula, the transformation that $x=g(z)$ plays an important role in derivation, which is also a hard part to understand. By adapting the transformation $x=g(z)$, the global Optimality pg = pdata and the Theorem that the minimum of the virtual training criterion C(G) could be calculated fluently.

At last, they do a simple experiment by using their new model and get a great job by comparing to other models.

Application and X-factor

This paper describes a real interesting model by using a confrontational way to train the model. Although the model is better than the others, from my opinion, the model has a critical problem that the generator and the discriminator are synchronous, which means when the generator works, the discriminator has to be fixed. Such a situation is a great loss of efficiency. Another problem would be that because the GAN model can directly be sampling without formulating p(x), which is one of the advantages of the GAN model, but for some big picture with a large amount of pixel, the GAN model would be easily out of control.

From my perspective, this is a good paper to spark a discussion, because this model is quite interesting and it is not very hard to understand in a short time.

Presentation

The whole structure of this paper is quite clear and introduce their work in front of the paper. However, in the middle part, it is a little hard to understand because there are a large number of proper nouns and abbreviations, which has to be googled to know what are they.

For the equation part, they do not write the whole derivation, so it is also a hard part to follow how the equation equals to the second line, especially for differential and integral calculus.

References

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