Semi-Supervised Learning Using GAN

Experiments of Data Deficient Training

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Abstract

Moden machine learning is data intensive in nature. However, not all applications are appropriate enough to supply sufficient data. This study compares the performance of Generative Adversarial Network (GAN) against different dataset by setting the number of real input data as a control variable. In addition, based on the result the study trains the generator with feature matching. This forces the discriminator to learn features of the labeled set which match with the features of the generated samples, thereby reducing overfitting to labeled set.

Introduction

Since the era Artificial Neural Network gains its popularity in machine learning, researches have been utilizing the superior speed of computers to process the large of data following by relative simple algorithm. Hoping the machine can be "trained" and produce intelligent results. However, some questions can not be solved by this approach naturally due to the limited amount of data can be acquired. For example, analysis of world-famous artworks, diagnosis of rare lethal cancers, restoration of unique historical artifacts. Hence, this study analyzed the current implementations of GAN [1] with the focus of reducing its data-intensive requirement [2]. Hopefully, the research can set a guideline of how well the GAN react to the limited amount of training data and propose a few improvements.

Objectives

- To classify accuracy loss of the GAN, discriminator particularly, when gradually reduce the number of real training examples
- To improve the accuracy of the discriminator given the limited amount of data

Materials and Methods

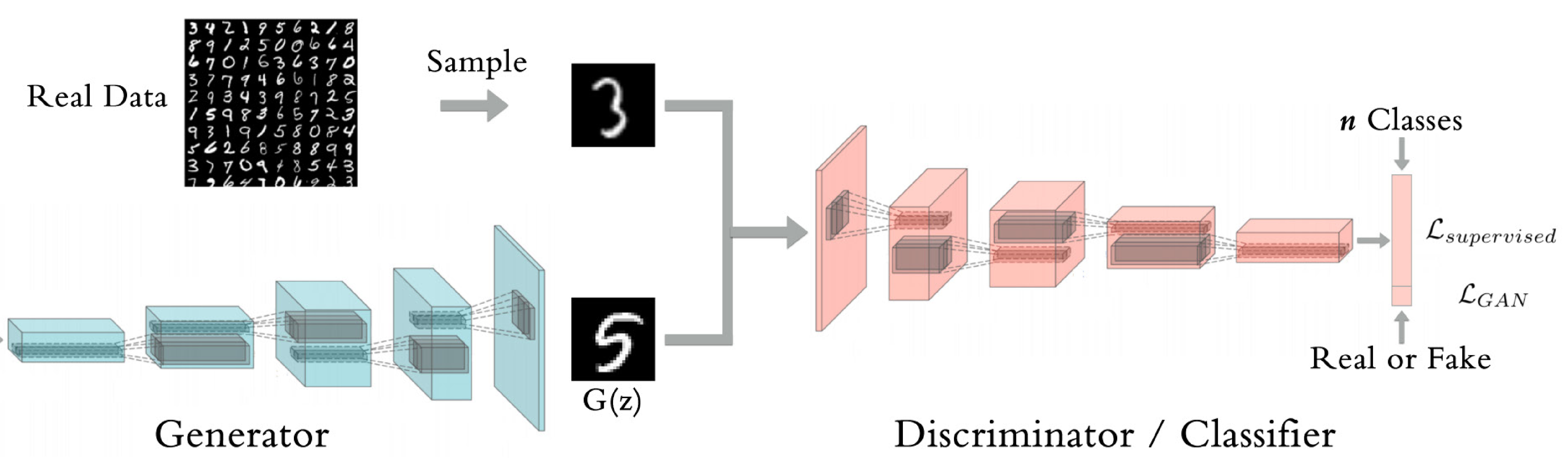

Figure 1: Generative Adversarial Network [1]

A vanilla GAN is constructed based on Mehta's work [1]. It consists of two major part: Generator who generates fake images based on seeded random noise and Discriminator who receive images and output 1.) if the image is fake; 2.) what class is the image belongs to. The vanilla GAN is used for accuracy benchmark and comparison against our proposed improvements later.

The study analyzed the MNIST, SVHN, and CIFAR10 datasets. For reduced sample experiments, each dataset is shuffled based on a seeded random variable. After normalization, the top number of needed samples are acquired from the dataset. Later, they are passed to default data loader with transformation and normalization process to augment the samples.

Instead of the standard convolution pipeline, The discriminator network uses a series of fully connected layers with linear weight normalization, ReLU activation and adding seeded random noise in each layer of the network. The generator network is also a series of fully connected networks with softplus activation and batch normalization in each layer.

Generator network is trained on discriminator loss between the fake images produced by the generator and un-labeled images used for training. This technique is called as feature matching. The idea behind feature matching is rather simple - similar representations have similar statistics. Feature matching is an alternative objective that forces the generator to produce fake images that in the discriminator have representations similar to the ones of real images. The images generated by this generator are unrealistic fake samples around the high-density region. As per [2], this generator is called as complement generator which implies that the generator is a function of the perfect generator (produces fake realistic images, where the generated image distribution perfectly matches the true data distribution).

The supervised loss is calculated as the cross-entropy loss between predicted and ground-truth labels. According to Ming et al. [4], the unsupervised loss is regularised using entropy loss between predicted outputs from un-labeled and generated images. This regularisation reduces the entropy and encourages the classifier to assign a definitive label to the input.

Results

Figure 2: Artificial sample from GAN

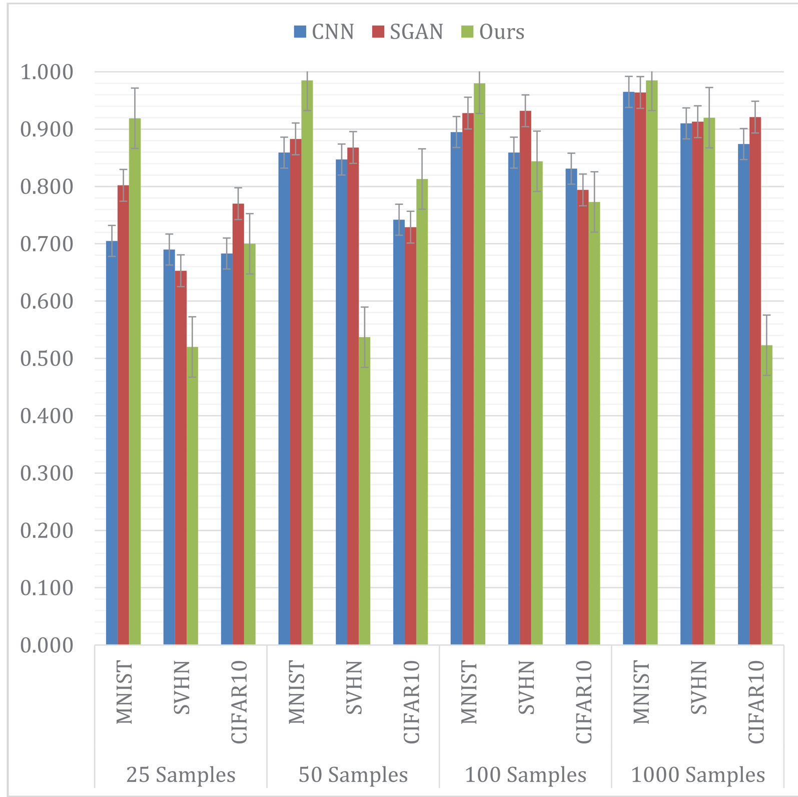

Figure 3: Benchmarks

The study confirmed the GAN is generating meaningful results first. Above images show that the synthesized images from later iteration (right) are improved from earlier iteration (left) for MNIST and CIFAR10 accordingly. Note that the objects generated on the CIFAR10 do improve visually with more clearly defined contour separated from background rather than a blob of colors. However, the details are still lacking for a human to classify the objects.

Table 1: Classifier accuracy for MNIST

Examples	CNN	SGAN	Ours
1000	0.965	0.964	0.985
100	0.895	0.928	0.980
50	0.859	0.883	0.985
25	0.750	0.802	0.919

Our works based on previous research [2] achieved higher classifier accuracy, especially for fewer samples. We also validated the results from Mehta's work [1] in the second column of the table.

The above figure shows the relationship of GAN discriminator accuracy vs a number of real samples passed to the network. Following the same configuration, the comparison is also made between different datasets and different augmentations. The trend shows the accuracy is going down while the number of real samples is reduced. However, with the help of various improvements the study introduced, the accuracy significantly increased when the number of real samples reduced to around 1000. The study also discovered that more complex dataset, say CIFAR10, is less sensitive to the improvement. The reason is that with or without the improvement, discriminator of the dataset cannot reach a threshold to produce results good enough. I.e. the synthesized data is improving but still too few of them passed the discriminator to be considered "real" samples. Thus, the later augmentation has no data to work on along the pipeline.

Conclusions

The study successfully confirmed the efficiency results from Mehta's research while expanded the improvement from Dai et al. [2] to the more complicated dataset. The information acquired here forms a foundation for future study to answer a question how much performance drop is expected for a specific number of data available quantitively. In addition, few guideline-temptations are made to improve the efficiency when available data are insufficient.

For future study, related problems for more complicated dataset should be focused. The study also suggests a more direct way to measure the performance of the generator can help to resolve the issues. Currently, the generator performance can be reflected by the discriminator accuracy. However, the discriminator is not a ground truth checker and it cannot be applied to more general cases.

References

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