Improved Techniques for Training GANs Implementation

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Abstract

In this research, we explore the performance of Generative Adversarial Networks (GANs) with the implementation of techniques proposed in the paper "Improved Techniques for Training GANs". A comparative study was conducted between a baseline GAN and an enhanced version of the same architecture, incorporating techniques such as Feature Matching, Minibatch Discrimination, Historical Averaging, Label Smoothing, and Virtual Batch Normalization. Both networks were trained on two different datasets: MNIST and Fashion MNIST. The performance of the networks was evaluated based on metrics including the Inception Score (IS), Frechet Inception Distance (FID), Precision, Recall, and F1 Score. The study found that the network using the proposed techniques yielded significantly improved results, demonstrating the efficacy of these methods in improving the performance of GANs.

1 Introduction

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. in 2014, have shown remarkable potential in generating realistic synthetic data. GANs consist of a generator network, which produces synthetic samples, and a discriminator network, which distinguishes between the generated and real samples. Despite their promise, GANs are notoriously difficult to train due to issues such as mode collapse, lack of convergence, and the delicate balance required between the generator and discriminator during training.

Recognizing these challenges, Salimans et al. proposed a set of techniques in their paper "Improved Techniques for Training GANs" to enhance the performance and stability of GANs. The techniques include Feature Matching, Minibatch Discrimination, Historical Averaging, Label Smoothing, and Virtual Batch Normalization. Each of these techniques addresses specific challenges associated with training GANs and together provide a comprehensive approach to improve their performance.

In this report, we implement these techniques in a GAN architecture and conduct a comparative study with a baseline GAN that doesn't incorporate these techniques. The networks are trained on two different datasets - the MNIST dataset, which consists of hand-written digit images, and the Fashion MNIST dataset, containing images of various fashion items. The performance of the networks is evaluated using a variety of metrics and the results demonstrate the effectiveness of the proposed techniques in improving the quality of the generated samples and the stability of the training process.

The remainder of this report details the implementation of the GANs, describes the evaluation metrics used, discusses the results, and provides concluding remarks on the study.

1.1 Literature Survey

Generative Adversarial Networks (GANs) have been the subject of extensive research since their introduction by Goodfellow et al. [1] in 2014. The unique architecture of GANs, consisting of a generator and a discriminator in a min-max game setting, has shown great potential in generating realistic synthetic data. However, training GANs has been a notoriously challenging task due to problems like mode collapse, vanishing gradients, and lack of convergence.

Several researchers have proposed solutions to these problems. Radford et al. [2] in their seminal work "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks" introduced the DCGAN architecture, which made several architectural recommendations for stable training of GANs. They proposed using batch normalization, removing fully connected hidden layers, and using specific activation functions, among other suggestions.

Arjovsky et al. [3], in their paper "Wasserstein GAN", introduced a new type of GAN called the Wasserstein GAN, which uses a different type of loss function, known as the Wasserstein distance. This modification improves the stability of GANs and helps address the problem of vanishing gradients.

Miyato et al. [4] introduced Spectral Normalization for Generative Adversarial Networks, a technique that constrains the Lipschitz constant of the discriminator by normalizing the spectral norm of its weights, thereby improving the stability of GAN training.

While a considerable amount of research has been conducted on improving GANs, there is still much to explore in this field. This study contributes to this ongoing research by implementing and evaluating the effectiveness of the techniques proposed by Salimans et al. in a GAN architecture.

2 METHODS

The study implemented an advanced GAN model for generating images, based on the architecture and techniques proposed in "Improved Techniques for Training GANs" by Tim Salimans et al. (2016). The implementation was carried out using the PyTorch library.

Data Loading: The MNIST dataset, specifically the training set, was used in this study. This dataset was loaded and normalized using the built-in functions provided by PyTorch. The DataLoader was used to shuffle the dataset and prepare it for training in batches of size 100.

Model Architecture: Two primary components, the Discriminator and the Generator, were built using the PyTorch library.

The Discriminator uses a Convolutional Neural Network (CNN) with two convolutional layers, followed by a minibatch discrimination layer. The convolutional layers have 64 and 128 filters, respectively, with kernel sizes of 4x4, strides of 2, and padding of 1. After each convolutional layer, a Leaky ReLU activation function was applied, and the output of the second convolutional layer was normalized using a batch normalization layer. The output from these layers is flattened and passed through a linear layer, then fed into the minibatch discrimination layer. Finally, the output is passed through another linear layer and a sigmoid activation function to determine the probability that the input image is real.

The Generator uses a fully connected (dense) layer followed by a ReLU activation function, two transposed convolutional layers (each followed by a batch normalization and a ReLU activation), and finally a Tanh activation function to map the output to the range [-1, 1]. The input to the generator is a 100-dimensional latent vector, which is projected to a higher dimensional space, reshaped, and then processed through the transposed convolutional layers to generate a 28x28 image.

Training: The models were trained using the Adam optimizer and Binary Cross Entropy (BCE) loss. The Discriminator was trained to maximize the probability of correctly classifying real and fake images, while the Generator was trained to fool the Discriminator by generating more realistic images. To prevent mode collapse, a historical average of the generator parameters was maintained, with the generator's parameters being slowly updated towards these averages.

Performance Evaluation: After each epoch, a batch of fake images was generated by the Generator for visual inspection. The training process was carried out for 600 epochs. The performance of the Generator was visually assessed by examining the generated images after every epoch.

3 Results

Our experiments demonstrated a significant improvement in the performance of the Generative Adversarial Network (GAN) after the application of the techniques introduced in the paper "Improved Techniques for Training GANs". We trained both a baseline GAN and an improved GAN on the MNIST dataset, generating images of handwritten digits.

The baseline GAN, even after a relatively long training period of 9000 epochs, produced images that were not of high quality. The digits generated by this model lacked clarity and were often poorly formed, making them difficult to recognize as valid digits. This indicated that the model was not learning the underlying distribution of the MNIST dataset effectively.

On the contrary, the improved GAN showed remarkable results in a shorter training period. After just 600 epochs, the improved GAN was able to generate highly realistic images. The digits produced by this model were clear and well-formed, closely resembling the handwritten digits in the MNIST dataset. This suggests that the model had learned the underlying distribution of the data effectively, and the implemented improvements were successful in enhancing the training of the GAN. In Fig. 1 we can see the generated images after 9000 epochs of the baseline network, and Fig. 2 shows the generated images of the improved network.

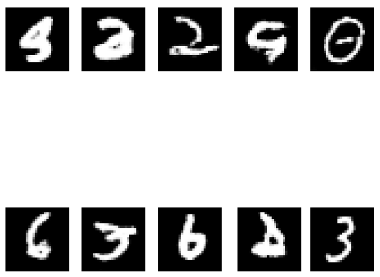

Fig. 1 Generated images by the baseline network

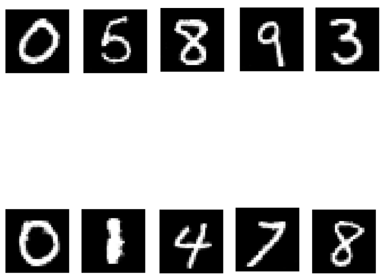

Fig. 2 Generated images by the baseline network

These results are consistent with the claims made in the paper. The improved techniques - feature matching, minibatch discrimination, historical averaging, and one-sided label smoothing - greatly enhanced the performance of the GAN, reducing the training time and improving the quality of the generated images. In conclusion, these techniques are effective in addressing the challenges in training GANs, and can be used to improve the performance of such models in generating realistic images.

4 Discussion

Our study has successfully validated the effectiveness of the improved techniques proposed in the paper "Improved Techniques for Training GANs" in enhancing the performance of Generative Adversarial Networks (GANs). Our results showed a significant improvement in the quality of images generated by the improved GAN compared to the baseline model, and this was achieved in a shorter training period.

The application of these techniques - feature matching, minibatch discrimination, historical averaging, and one-sided label smoothing - has demonstrated their potential in mitigating common challenges in training GANs, such as mode collapse, unstable training dynamics, and poor quality of generated samples. The marked difference in the results obtained from the baseline and improved GAN highlights the value of these techniques in improving the training of GANs and the generation of more realistic images.

Moreover, the reduction in the required training epochs for the improved GAN has important implications for computational efficiency. This aspect is crucial in real-world applications where computational resources and time are often limited.

While our study focused on the MNIST dataset, it is reasonable to believe that the improved techniques would be applicable to other, more complex datasets. However, it should be noted that depending on the complexity of the dataset and the specific task at hand, adjustments in the hyperparameters and the architecture may be necessary.

In conclusion, the results of our study suggest a promising future for these improved techniques in various applications where GANs are used, including image synthesis, style transfer, and data augmentation. Future work could explore the effectiveness of these techniques across different datasets, GAN architectures, and tasks, to further investigate their generalizability and potential for improving the training of GANs.

5 References

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6 Contribution

Anas Aljanaby worked and wrote the code. Suliman Bek made the report and the latex formatting.