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Class Imbalance in Generative Deep Learning: A Systematic study

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Introduction

The rapid phenomenal advancements in the field of Deep Unsupervised learning has led to a better understanding of the data, its features, distribution and other parameters. It can be linked to the continuous rise of computation processing power and economical data solutions. This has prompted researchers to solve the intricacies of real world by developing complex architectures, algorithms and AI models. One of the salient part this field can be said to be Generative deep learning.

The generative models is to be the effort put by AI to get closer to the complex human brain. To be able to generate novel dissimilar to the real one is the imagination defined.

Problem Statement

To investigate the images generated by the Generative Adversarial Networks(GAN) with respect to the original inherent data bias. The data given to these models are prone for underlying bias. This is to highly affect the Generation and decline its diversity with features from major samples being combined with the minor. To strongly determine on this generation bias of implicit GAN versus the probabilistic models. And discover other shortcoming of these models with critical analysis.

Background

- The generated samples are affected by the bias in original data to an extent that it is magnified with generation. The randomness and bias in the GAN is seemed to be higher than the probabilistic models such as Variational Autoencoder(VAE) .
- There is a major limitation of GANs which is the inability to determine its probabilities and hence failing to accurately or at the least perform better analysis of the model.
- GANs take larger amount of time, processing power and are more complex to understand the internal generation.
- GANs offer more diversity and dissimilarity from other Explicit models, as it doesn't require the probabilities of data. Only generator working to produce better fake images to be able to fool the discriminator.
- The initial batch distribution while training the GANs can lead to mode collapse as most of a features in the training data is taken into discriminator. Which makes generator to incline its generation samples to that class distribution.

Generative Deep Learning Implemented,

- Deep Convolution Generative Adversarial Network (DCGAN)
- Variational Autoencoder (VAE)

PyTorch machine learning framework with torchvision libraries and dependencies the experiment was performed. The python language has implemented throughout the research project. The images were handled as Tensors.

The Deep convolutional neural networks architectures were applied to both DCGAN and VAE.

Unlike the GANs, VAE offers strong representation learning from its latent space. Making images far closer. To understand the effect of controlled bias in such probabilistic models. It was included.

Controlled Bias Introduction

The imbalanced dataset used for the experiment is the standard MNIST Handwritten digits dataset.

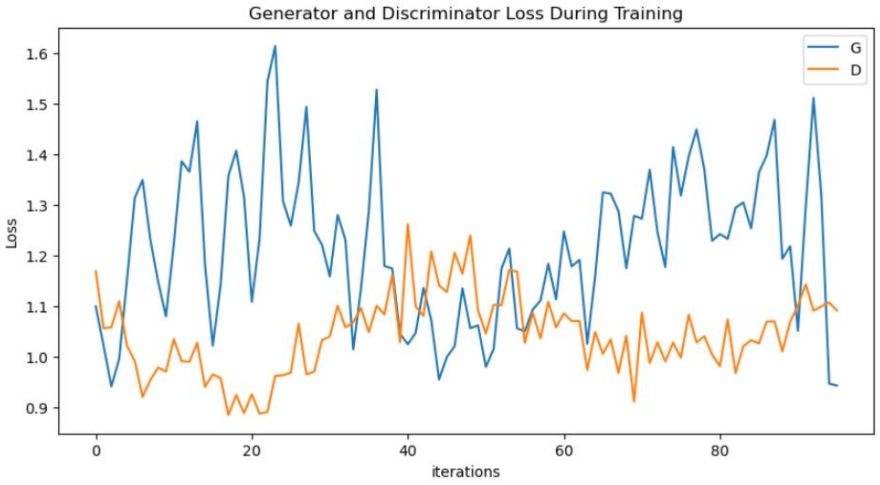
- http://yann.lecun.com/exdb/mnist/
- The complete dataset is not used for the experiment. Introduced a controlled bias technique for the training of the generative models by implementing custom dataset and data loader.
- The data imbalance is considered for three classes combined with two of them fixed batch sizes. Whereas the other being varied throughout the experiment.

Analysis of Generated Images

- The data imbalance The generated images are submitted for classification with a pre-trained classifier of high accuracy (>95%). The labels are predicted for the three classes accordingly .
- The distribution of three classes is visualized for each batch size going for 5 iterations with the mean and standard deviation.
- The generated images with original bias is critically analysed.

DEMO

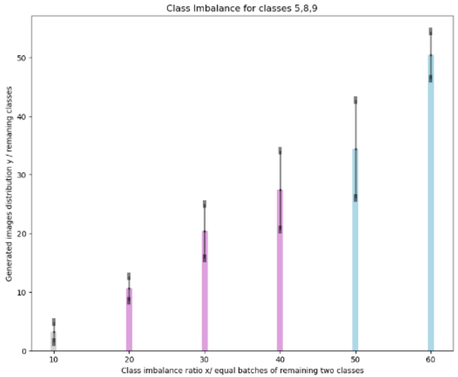
- DCGAN
- VAE
- Experimental Study

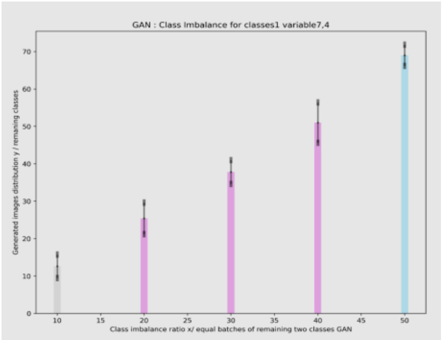


VAE offers the near imitation of generation

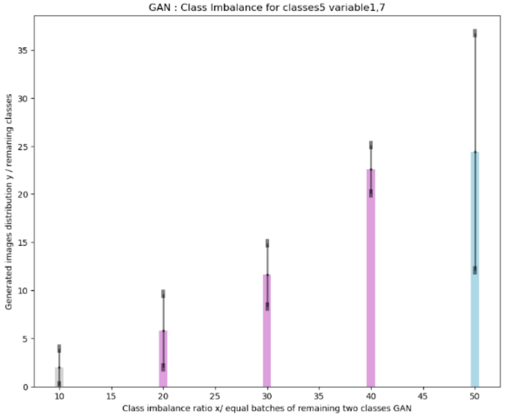
Results & Discussion

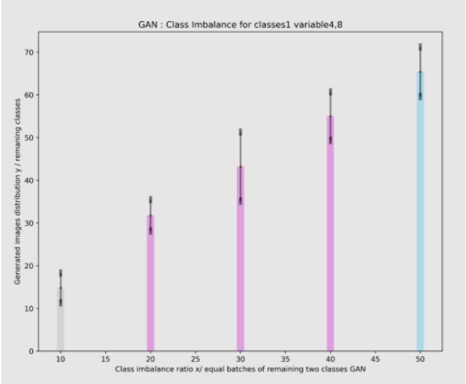
- The generation in GAN with majority classes when controlled varied has produced steady distribution.
- Like in the case of varying the number 1 has highly been proportionally steady increase and generating more than original. But not in the case of the minority class like
- The VAEs have better closer distribution, however lesser diverse and quality. Basically just a reconstruction.
- The varied batch of minority sample has produced fewer images than majority.
- The inherent original data bias is affecting the generation even after controlled bias introduction





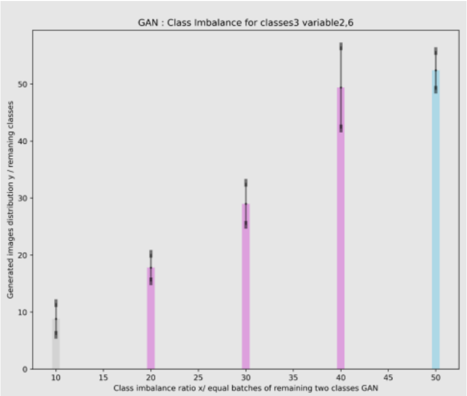
#Performing Classification of the Generated Images

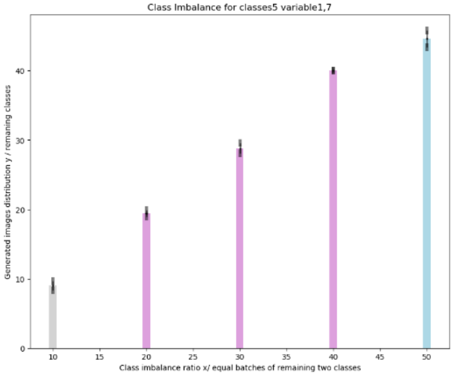




Conclusion

- The process of generating images using GANs is highly unpredictable and not uniform well distributed like in VAE as compared with various samples.
- For the generating of minority samples has higher unpredictability when combined with other distributions, can be inferred with the mode collapse.
- Explored the limitations of GANs and VAEs with each other.
- During the run of experiment there was maximum generator loss can be related to discriminator trained and noticed convergence over the minority class run.
- Gained preliminary data for developing a method to obtain controlled generation images as aa future scope.





VAEgenerated images distribution

Thank you

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