A Survey of GANs as an Image Augmentation Technique

## Abstract

## Introduction

Generative adversarial networks (GANs) are an adversarial method to generate new data from noise by pitting a generator against a discriminator and training in a zero-sum game trying to find a Nash Equilibrium.

## Background

## GANs for Image Augmentation

### Intra-Class Imbalance

In the previous section we discussed about imbalance between difference classes in the dataset, but another common issue faced that is crucial for the network to generalize well, i.e. in particular several samples in the same class could be very diverse, an evident example is that of automatic defect detection in manufacturing environments, where the defects of different subclasses are all classified as defects, the defects themselves could be very diverse in nature. To resolve this issue Lijyun Huang et.al (2019) came up with AC-GAN (Actor-Critic Generative Adversarial Network) data augmentation technique, which efficiently improves similarity of fake data of all subclasses, by using a novel loss function that adapts to intra-class data distribution, which when used to train a neural network results in a classification model with better accuracy. The experiments made in their paper shows that the higher the heterogeneity among data in the same class, larger the improvements AC-GAN can achieve. [3]

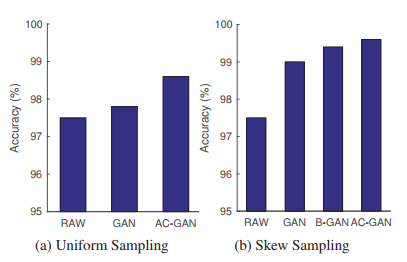


Figure 3 Performance comparison of AC-GAN

### Inter-Class Imbalance

A common problem faced during training of neural networks in real word for multi-class classification is that number of samples of some classes dominate over other classes, this leads to slower convergence of the network, and the model fails to generalize well over the dataset, medical image analysis is a good example where such problems are faced, where for example the frequency of one class like cancer can be as high as 1000 times less than another class like healthy patient.

In the case of classical Machine Learning this problem is attempted to be mitigated by operating over the data itself, one of the common methods is to applying different weights to misclassification of examples from different classes, also under-sampling and over-sampling are widely used and proven methods.[1] In the case of CNNs this issue is addressed by performing a two-stage training, in which first the network is trained on the imbalanced dataset and then further fine-tuned in the second stage.[2] Another way to deal with imbalanced datasets is to augment the dataset with classic techniques like rotations, mirroring, shearing, color space transforms, translation, noise injection.

GANs can also be used as a great augmentation tool to generate images of the minatory classes and balance the class frequency distribution. SOTA (state-of-the-art) GANs are not suitable for dealing with imbalanced datasets, BAGAN (Balancing GAN) proposed by Giovanni et.al (2018) was the first methodology to address this topic. BAGAN trains on the entire dataset, both minority and majority classes, which enables BAGAN to learn the features of the classification problem, and then applying those to generate new minority-class images.

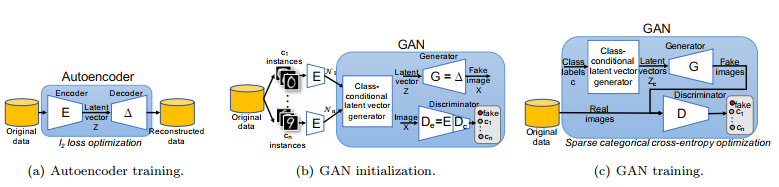


Figure Training steps involved in BAGAN methodology [4]

Unlike a traditional GAN, BAGAN has a unique training regime, autoencoder is used to initialize the GAN close to a good solution, this ensures that mode collapse does not occur. The Encoder (E) is used to initialize the first layers of Discriminator () followed by dense layer () with softmax function, the Decoder () is used to initialize the Generator (G). When the GAN modules are initialized, a class-conditional latent vector generator is setup that learns the probability distribution in the latent space of the different classes. This is then continued by fine tuning by carrying out a traditional GAN training.[4]

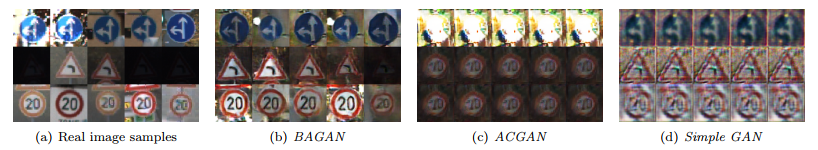


Figure Samples generated for three least represented minority classes in GT-SRB dataset [4]

From the results in the BAGAN paper we can see ACGAN fails to generate images for the minority classes and collapses, also in the second row where it was supposed to generate warning signs, ACGAN prefers to generate speed sign. Simple GAN collapses as well, although the images generated in Simple GAN are even worse.

### Medical Image Analysis

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### CycleGAN

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## Discussion

## Future Work

## Conclusion

## Acknowledgements

## Bibliography

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