CPSC 8430
DEEP LEARNING
HW REPORT – 4

Submitted by
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Introduction:

A generator and a discriminator neural network make up the deep learning model known as generative adversarial networks (GANs). The discriminator learns to tell the difference between genuine and false data samples, while the generator learns to produce new data samples that are comparable to a given training dataset. The generator creates fresh data samples that aim to deceive the discriminator into identifying them as real by using random noise as input. On the other hand, the discriminator learns to tell the difference between actual data samples from the training dataset and fictitious data samples created by the generator.

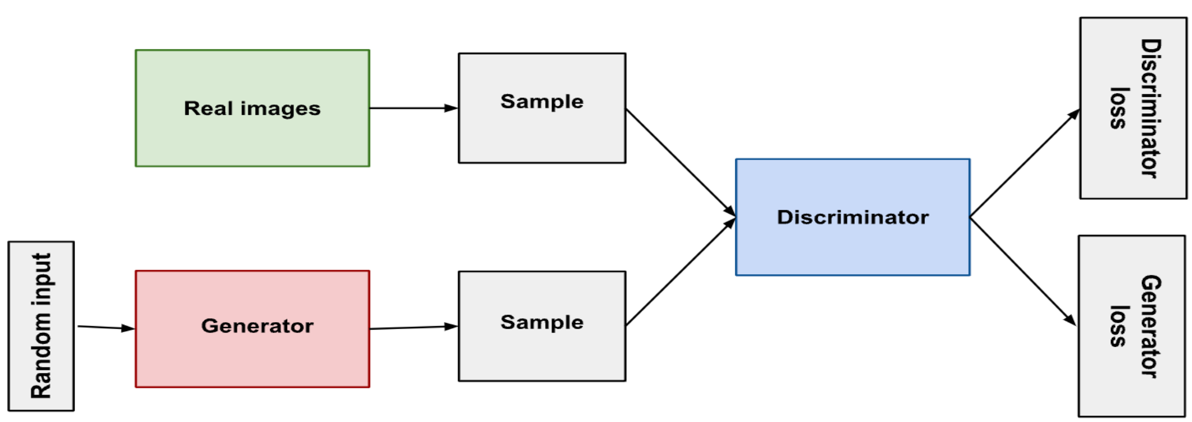

Fig 1. GAN system

This assignment includes implementation of DCGAN, WGAN and ACGAN networks with Pytorch library. The number of epochs used in this process is limited to 10 because a greater number of epochs is tending to take very high amounts of time.

Dataset:

The dataset used for this task is the CIFAR 10 dataset which consists of 60000 color images out of which 50000 images are for the training purpose and 10000 images are for testing purpose. The same CIFAR 10 dataset is used for all the three networks of DCGAN, WGAN, ACGAN.

DCGAN:

DCGAN, or Deep Convolutional Generative Adversarial Networks, is a type of neural network used for image synthesis, style transfer, and picture-to-image translation. It is characterized by convolutional layers in the discriminator and transposed convolutional layers in the generator. The discriminator classifies whether an input image is real or fake, while the generator takes a noise vector as input and produces an image. DCGANs are known for generating high-quality images that are difficult to distinguish from real ones.
The images produced by the DCGAN network is given below in the fig 2. One of the main observation in implementation of the DCGAN network is the high amounts of fluctuations in the loss which prove the network to be the most unstable network. In addition, as compared to WGAN and ACGAN, DCGAN's images are the least realistic. DCGAN network produced images that resembled actual pictures from the CIFAR10 dataset the least. They are neither translucent nor colorful.

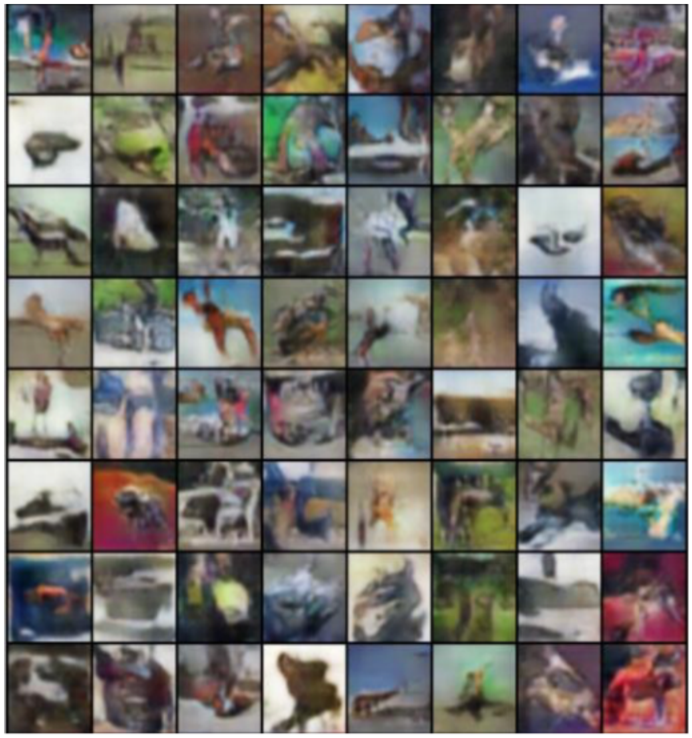

Fig 2. DCGAN output images

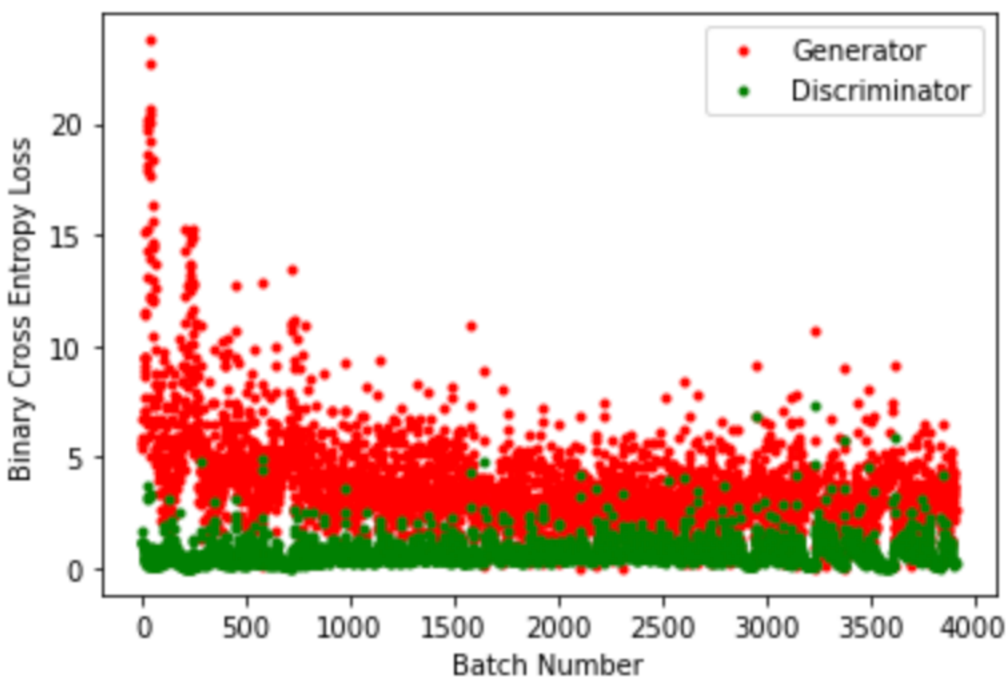

Fig 3. DCGAN Loss of Discriminator and Generator

WGAN:

Wasserstein GAN (WGAN) is a type of Generative Adversarial Network (GAN) that uses the Wasserstein distance metric to estimate the difference between actual and generated distributions. Unlike traditional GANs, WGANs use a critic network instead of a discriminator to estimate the Wasserstein distance, and the generator is trained to minimize this distance instead of maximizing a conventional GAN objective function. WGANs are more stable, have better convergence, and can be used for various tasks like image synthesis, super resolution, and style transfer. In WGAN, the activation function used is linear activation instead of the regular sigmoid function

We can also observe WGAN to be more stable that the regular GAN networks. Also, the output image of the WGAN have more clarity than the DCGAN images.

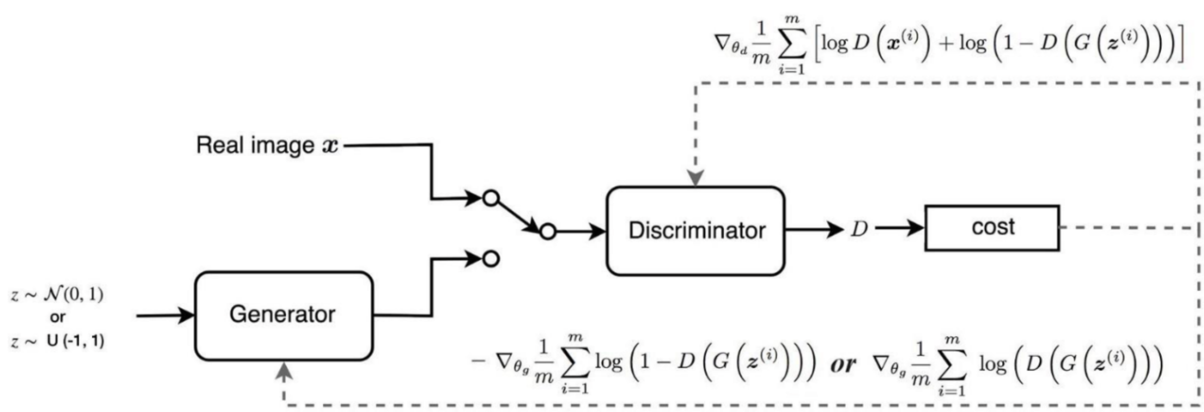

Fig 4. WGAN system

Fig 5. Output images of WGAN

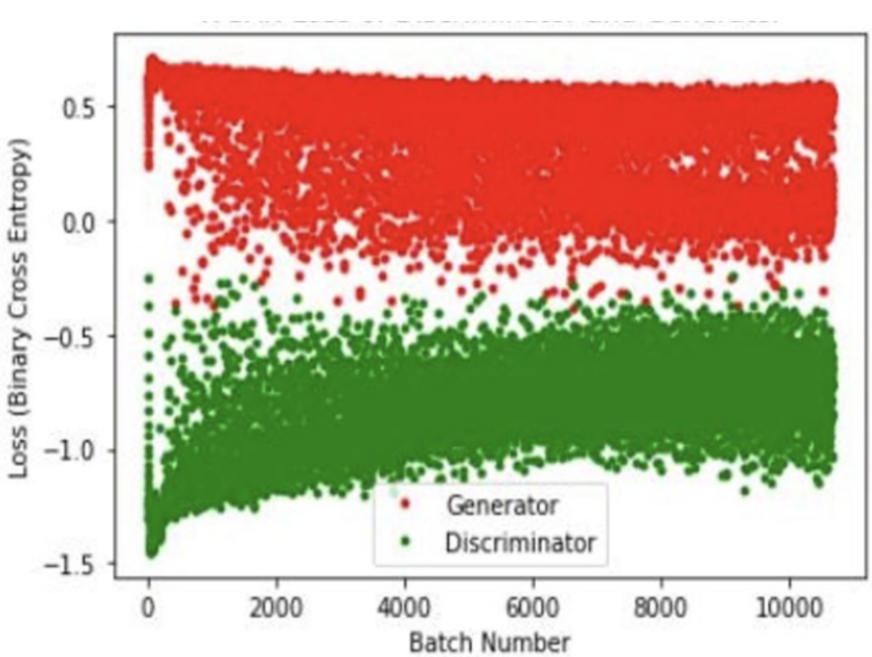

Fig 6. WGAN Loss of Discriminator and Generator

ACGAN:

ACGANs, or Auxiliary Classifier Generative Adversarial Networks, include an additional classifier in the generator and discriminator architectures. This extra classifier introduces a conditional element to the model by classifying the generated images into multiple classes, making the generated images more specific and controllable. ACGANs are more flexible than regular GANs and can produce more diverse and realistic images for various applications such as image synthesis and style transfer.

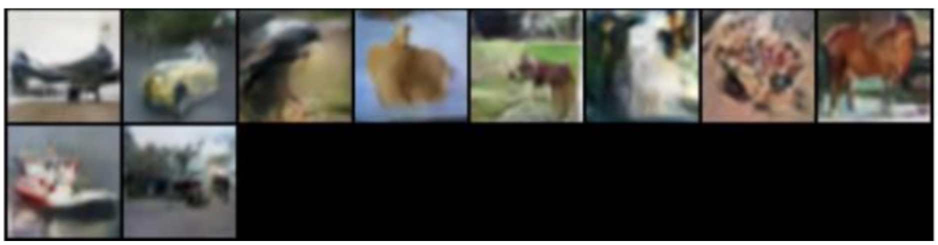

Fig 7. Output images of ACGAN

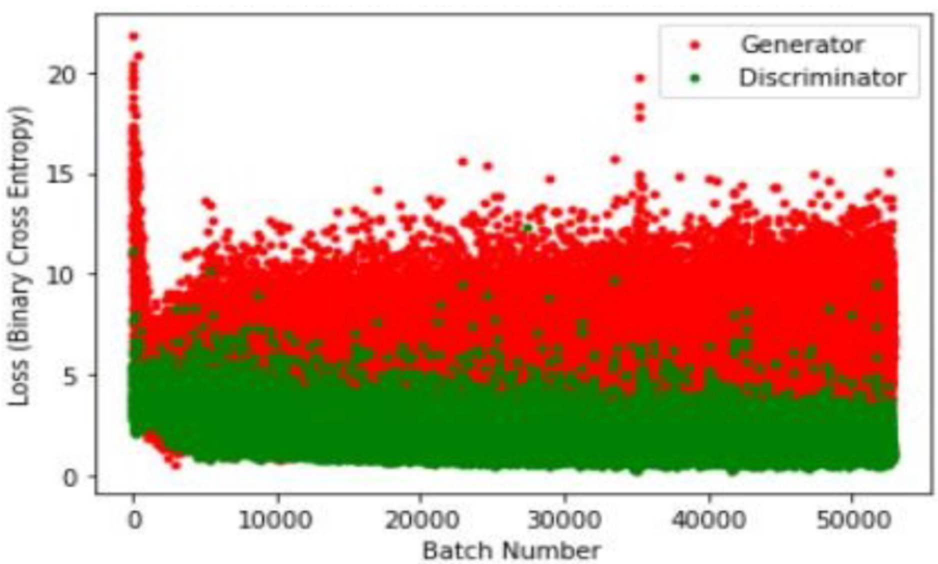

Fig 8. ACGAN Loss of Discriminator and Generator