Comparing the interpretability of different GAN architectures

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1 Abstract

A Generative Adversarial Network (GAN) uses an adversarial process between two models which are simultaneously trained to estimate a generative model.[1] There are many variants of GAN architectures, such as COCO-GAN[2] and StyleGAN[3], which both have the ability to generate synthetic images which mimic real images.

We are exploring methods of comparing the quantitative performance of these architectures with their interpretability. Our quantitative measures include C2ST[4], image quality measures[4], Maximum Mean Discrepancy (MMD)[4], etc.

In order to analyze these networks qualitatively, we will use methods such as SmoothGrad[5], Latent Space Exploration[6] and nearest neighbour tests[4] to decipher what the networks have learned.

By combining these two forms of analysis, we hope to gain insight into the relationship between performance metrics and the generated output of the models.

2 Introduction

StyleGAN and COCO-GAN generate images using different techniques to accomplish two different goals: StyleGAN is designed such that high level features of the output image can be finely tuned and adjusted (e.g. lighting, hair colour, etc.)[3]. On the other hand, COCO-GAN generates each part of the image separately before stitching it together in order to simulate the human perception of vision[2]. As a result, we expected each model to generate images with different qualities that relate to their designed tasks.

Although we tried to analyze the models using all the metrics listed in the Abstract, there were a few challenges involved with getting the desired results.

3 Analysis Dataset Generation

Both GAN models were trained on the LSUN Bedroom dataset[7] at a resolution of 256×256. Due to time constraints, we used pretrained models to generate images for our analysis.

3.1 StyleGAN

NVIDIA Research Projects' Official TensorFlow Implementation of StyleGAN pretrained to the LSUN Bedroom dataset[8] was used to generate 5000 images for analysis. 5000 latent code vectors $\mathbf{z} \in \mathbb{R}^{512}$ drawn from a standard normal distribution which each correspond to an output image.

3.2 COCO-GAN

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4 Quantitative Analysis

4.1 C2ST

Classifier Two-Sample Tests (C2ST) is used to predict if two samples came from the same distribution[9]. In the context of evaluating GANs, we will use C2ST to quantitatively measure how well the models mimic real images. We trained a deep convolutional neural network to perform binary classification based on the recommended discriminator architecture from *Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks*[10]. The goal is to compare the margin by which each GAN model is able to trick the classifier to quantify image generation quality.

The classifier was implemented using Pytorch with Cross Entropy loss, the Adam optimizer ($\alpha = 0.1$), and the following network architecture:

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test
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To avoid introducing bias, all three datasets (training, validation, test) were equally balanced with real and generated images. The 5000 generated images were further divided in half between images from StyleGAN and COCO-GAN. Out of the combined pool of 10000 images, 5000 were allocated for training, 2500 validation, and 2500 testing.

The model was trained with a batch size of 200 for 1000 epoches. After tuning hyper parameters and performing early stopping with the validation dataset, the following results were attained:

Table 1: Real vs (StyleGAN or COCO-GAN)	
Data Set	Accuracy
Training	82.1% of 5000
Validation	66.8% of 2500
Test (Real)	58.4% of 1250
Test (StyleGAN)	62.4% of 625
Test (COCO-GAN)	86.4% of 625

The model was able to identify the origin of an image the majority of the time. This data suggests that StyleGAN is better at tricking the classifier than COCO-GAN.

To confirm this, we trained additional classifiers using the same architecture, data set distribution, and hyper-parameters but only using images from one of the GAN models. (i.e. all 5000 generated images are all from one model) The goal is to test how well the classifier performs when isolated to a specific GAN.

Table 2: Real vs StyleGAN

Data Set	Accuracy
Training	77.6% of 5000
Validation	68.1% of 2500
Test (Real)	74.6% of 1250
Test (StyleGAN)	61.4% of 1250

Table 3: Real vs COCO-GAN

Data Set	Accuracy
Training	87.9% of 5000
Validation	88.2% of 2500
Test (Real)	96.4% of 1250
Test (COCO-GAN)	76.1% of 1250

As seen here, the Real vs COCO-GAN classifier (Table 3) performed significantly better than the Real vs StyleGAN classifier (Table 2). This supports the hypothesis that StyleGAN generates better quality images than COCO-GAN.

4.2 Image Quality

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5 Qualitative Analysis

5.1 Latent Space Exploration

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5.2 Nearest Neighbours

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