Generative Adversarial Networks for Galaxies Images Generation

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Abstract**—** Many industries, including the arts, graphics, and machine learning, use image synthesis. Humanity has always been inspired by space travel, and owing to contemporary telescopes, it is now feasible to study celestial bodies thousands of light-years away. Now days Utilizing contemporary Deep Learning architectures like Generative Adversarial Networks and the increasing quantity of real and imagined images of space that are available on the web, Creating new representations of space is now conceivable. In our new framework, we simultaneously train two models—a generative model G that reflects the data distribution and a discriminative model D that calculates the likelihood that a sample originated from the training data rather than G—in an adversarial process. There is just one solution in the space of random functions G and D, where G recovers the training data distribution and D is equal to 1/2 everywhere. Backpropagation can be used to train the entire system when G and D are represented by multilayer perceptrons.

I. INTRODUCTION

Recently, Generative Adversarial Networks (GANs) [5] have produced figures that are challenging to identify from genuine ones in a variety of circumstances on numerous picture production tasks.. The Hubble telescope, or the first-ever image of a black hole captured in 2019, both of which were able to capture an image of a region of the universe via the merging of several separate photographs, are just two examples of how space exploration has allowed us to observe the universe with increasing clarity and detail. As a result of advancing technology, billionaires and regular people alike are taking space journeys, creating so-called space tourism. All of this is encouraging businesses to advance in this field at an ever-increasing rate and enthralling younger generations with the wonders of the cosmos [1]. As a result, there is currently a very significant enthusiasm for space exploration and a greater than ever level of curiosity about the wonders of the universe. In this study, we use generative adversarial networks to create fresh heavenly body images (planets, stars, galaxies, nebulae, etc.) image of the universe that were truly taken or online works of art. Then, in a similar manner to the Hubble image processing pipeline, we will make use of the Galaxy Zoo dataset[8], which has hundreds of thousands of images of actual galaxies, to create new image and merge them into a broad perspective of the cosmos.

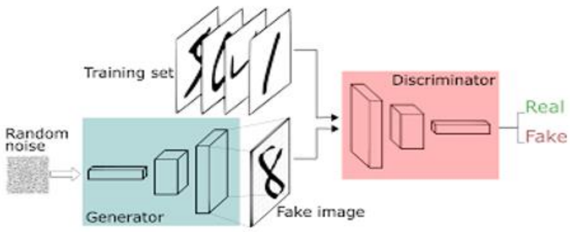


Figure 1: Generative Adversarial Network

II. RELATED WORKES

A. Generative Adversarial Network

GANs were first introduced by Ian Goodfellow and his colleagues in June 2014 [5], and They immediately achieved enormous success, which is regarded as one of the greatest advancements in AI history. GANs use two separate networks. A effective kind of neural networks used for unsupervised learning is the generative adversarial network. The core structure of gans is a system of two neural network models that compete with one another in order to assess, capture, and copy the variations present in a dataset. The network that actually creates fresh pictures in a convincing enough manner to trick its counterpart and the discriminator, the entity that must be able to determine if an image is false or not. This method made it feasible to produce original artwork [2], enhance the sharpness of previously taken pictures [5], and even produce deeply convincing deepfake images and videos [4]. Using a training collection of photos and StyleGAN2 ADA, you can teach a neural network to produce high-resolution images. The most well-known instance of this are the invented faces produced by StyleGAN2 [8]. The authors suggested a specific data augmentation strategy that considerably stabilises training under regimes of limited data, reducing the likelihood of discriminator overfitting and the ensuing divergence of the training process. This is a significant advancement because the new structure enables the achievement of great results even with insufficient data. The Lightweight GAN was used as a supplementary alternative for dealing in scenarios with minimal data [1],a more condensed version of this model that can still produce effective results but requires less time to train. The design combines a self-supervised discriminator that has been trained as a feature-encoder with a skip-layer channel-wise excitation module to achieve this.

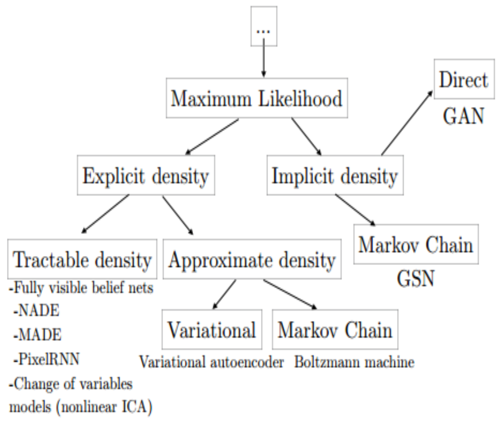
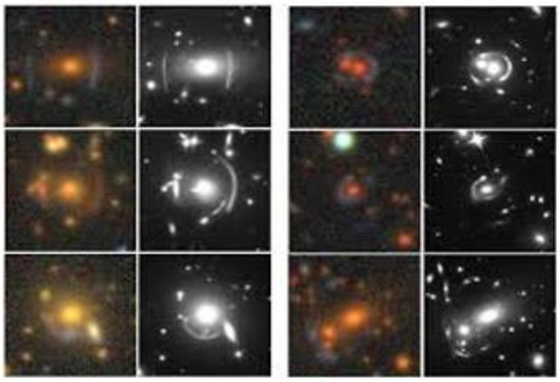


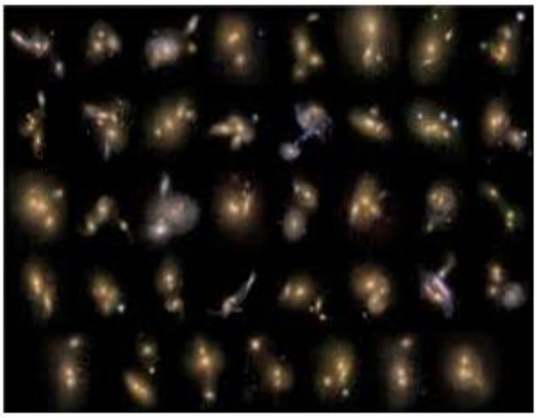
Figure 2: Taxonomy of Generative Models (Ian Goodfellow's NIPS tutorial, (2016))

B. Previous applications of GANs in Astronomy

Astronomers have used the so-called GalaxyGAN before to identify features in astronomical images of galaxies [9]. In order to increase the quality of these data, deconvolution techniques have historically been utilised, but they are quite limited. Astrophysical images are frequently disrupted by noise. With the use of GANs, missing features can be recovered, resulting in more accurate and dependable outcomes. Some applications of GAN are: The epistemic oscillation of scientific imges, Going beyond the deconvolution limit with Pix2Pix. In [13], the authors used GANs, in particular Spatial-GANs [7], to generate views of space and, consequently, of multiple celestial bodies congregated in one location, drawing inspiration from data gathered by the Hubble Space Telescope. The authors achieved surprisingly realistic results. A GAN's input in its most basic configuration is random noise. After that, the generator turns this noise into a useful output. We may cause the GAN to generate a wide range of data by adding noise, sampling from various locations throughout the target distribution. ExoGAN [6] is a model that can perform this work at a cheaper computing cost than traditional ones and is able to distinguish chemical characteristics, atmospheric trace-gas abundances, and planetary parameters. GANs in this field have also been helpful for atmospheric retrievals on exoplanets.



(a) collected dataset images



(b) Images of Galaxy Zoo Dataset

Figure 3: Examples of images in the dataset

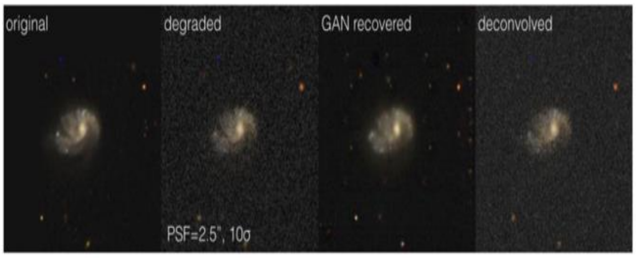


Fig. 4: Denoising of galaxy images

III. METHODOLOGIES

A sizable and diverse dataset must be produced in order in order to train the network how to produce celestial bodies. To do this, we gathered genuine space photographs as well as imaginative depictions of the universe using the Flickr Scraper library and some web to obtain images from the internet. GANs have two neural networks in them. There is a Discriminator D and a Generator G(x) (x). They engage in competitive play. By creating data that are identical to those in the training set, the generator hopes to trick the discriminator. By distinguishing between fake and authentic data, the discriminator will attempt to avoid being duped. To learn and train complicated data, such as audio, video, or image files, they both work simultaneously.

Since the photographs from the web collection were all of various sizes, they were then squarely centred cropped to prevent image distortion during resizing. At the end of this procedure, we had a dataset of 283 squared, high-quality, coherent pictures. To conduct more testing and obtain real galaxy photos to be combined into a single wide view, we also took advantage of the Galaxy Zoo Dataset [4], a sizable collection containing hundreds of thousands of space photographs gathered by observatories.

The Generative Adversarial Network used in the trials is called a Lightweight GAN [8], which is extremely comparable to the cutting-edge StyleGAN2 but is smaller and simpler to train. In fact, it has been shown that this network can converge with a few hundred training samples and a single GPU in a short period of time while producing results of exceptional quality. It is the architecture that is more suited to our situation for these reasons.

In contrast to autoregressive models in general and completely visible belief networks like WaveNet and PixelRNN, GANs may create a whole sample in a single pass as opposed to numerous network passes.

There is no constraint on the kind of function the network may utilise, unlike Boltzmann machines and nonlinear ICA.

Since neural networks are universal approximators, GANs are asymptotically consistent. Variational autoencoders might be universal approximators, but it is not proven as of 2017.

IV. MATHEMATICS

GAN's are generative models that try to learn the model to generate the input distribution as realistic as possible. Gan's end goal is to predict features given a label, Instead of predicting a label given features.

(x, y) → (features, labels) / (inputs, targets)

A. Discriminative

Given inputs we want to build a model that can classify the inputs to the corresponding targets as correct as possible.

B. Generative

Given inputs we want to build a model that can understand the inputs to generate similar inputs and it’s labels from the targets **.**

At Discriminator D

$$Dloss_{real} = \log(D(x))$$

$$Dloss_{fake} = \log(1\text{-}D(G(z)))$$

$$Dloss = Dloss_{real} + Dloss_{fake}$$

$$\log(D(x)) + \log(1\text{-}D(G(z)))$$

The total cost is

$$\frac{1}{m}\sum_{i=1}^{m} \log(D(x^i)) + \log(1 - D(G(z^i)))$$

At Generator G

$$Gloss = \log(1\text{-}D(G(z))) \text{ or } -\log(D(G(z)))$$

The total cost is

$$\frac{1}{m}\sum_{i=1}^{m} \log(1 - D(G(z^i)))$$

or

$$\frac{1}{m}\sum_{i=1}^{m} -\log(D(G(z^i)))$$

Ch 14: GAN's, DeepMathMachineLearning.ai

Figure 5: Equations for Discriminative

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

$$\max_D V(D) = \underbrace{\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})]}_{\text{recognize real images better}} + \underbrace{\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]}_{\text{recognize generated images better}}$$

$$\min_G V(G) = \underbrace{\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]}$$

Optimize G that can fool the discriminator the most.

Figure 6: Equations for Generative

V. Experiments

Using both the Galaxy Zoo Dataset and our own acquired data, we trained two separate Lightweight GAN instances. The only data augmentation method used in both instances was to randomly change the hue of the input photos with a chance of 25%.

Figure 7 : Example of images created by a lightwe GAN trained on web-scraped images

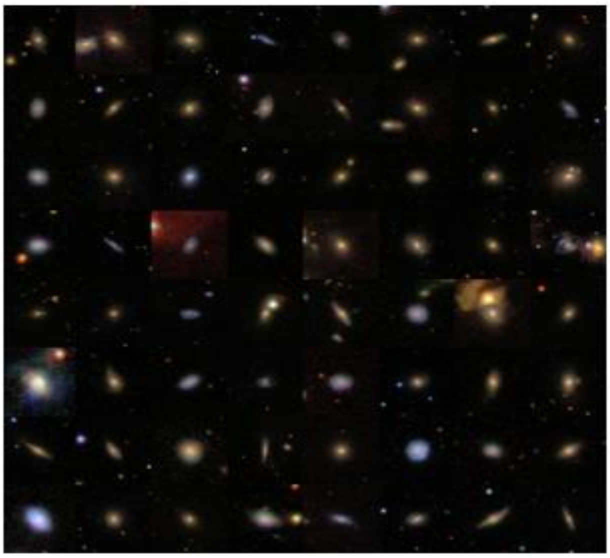


Figure 8: Example of generated images from Lightweight on Galaxy Zoo Dataset

VI. Training

The "skill level" of the two neural networks must be comparable. It takes a while to train GANs. GAN might take hours on a single GPU and more than a day on a single CPU. Although challenging to tune and hence use, GANs have sparked a lot of intriguing study and literature. Make a random noise first, then use that noise to make an image. Defining parameters such as the batch size, sample size, and epoch. Describe how to generate sample images. After training Generator, Train Discriminator will produce images. First, the 283 web-gathered photos were used to train a Lightweight GAN. Another instance of the network was subsequently trained using a subset of the Galaxy Zoo Dataset, which contained 61636 images. In both instances, we employed a 3 batch size, an Adam optimizer, and a 2e-4 learning rate. To make the network's training process easier with such a small number of input images, the generated images for the first dataset are 128x128 pixels, while for the second dataset, where we have more images available, the generated images are 256x265 pixels.

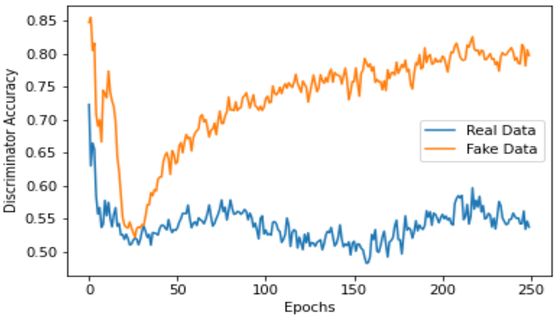


Figure 9: Accuracy of data

VII. RESULT

After training on a single Tesla T4 GPU, the lightweight GAN created some great and extremely credible images of planets, nebulae, and galaxies with a style that was very similar to that provided as input, as seen in Figure 5a. Then training in the same environment, On the Galaxy Zoo Dataset, we got some extremely reliable pictures. The trained network was able to create outputs in this example that were hardly recognisable from the original ones due to the simplicity and abundance of the input images, as shown in Figure 8. Lastly, We created a broad representation of the universe using the Lightweight GAN trained on the Galaxy Zoo dataset. This work was motivated by scientists' efforts in 2019, who merged 7500 Hubble telescope pictures to produce a mosaic showing the universe from a broad perspective.

Figure 10: wide image of the universe produced by a lightweight GAN

We first downloaded 3000 galaxies from the network, and 10 more were chosen as blank space since they were so plain and nearly entirely black. The required wide perspective, shown in Figure 7, was created by rotating, resizing, and randomly combining these photos to create a mosaic of 25000 images. Even while the produced galaxies might appear to the naked eye to be extremely similar to the original ones, To get a more quantitative evaluation, we decided to conduct a second experiment with a pre-trained detector trained on Galaxy Zoo.

As shown in Figure 11, By utilizing as input the wide-view formed by the combination of galaxies received from our GAN, the detector can recognize many of the bigger galaxies in the image.

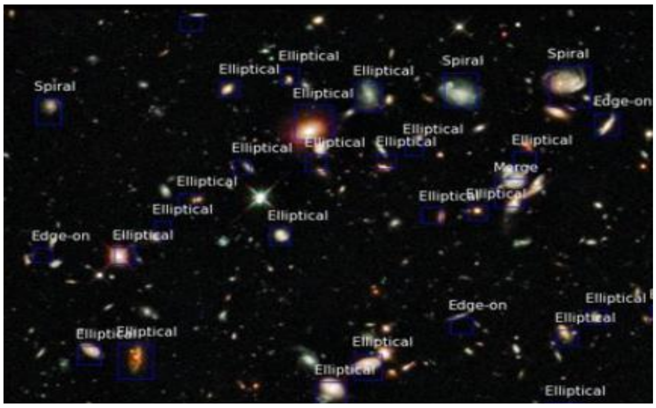


Figure 11: Galaxies detection on the entire image

The Fréchet Inception Distance (FID) was utilised to give a numerical assessment of the GAN's image quality [6]. This rating is a commonly used metric to evaluate how well a GAN performs. It provides a rating based on the variety of images produced as well as their credibility while taking into account the distribution of classes from the training set.
The problem noted in [11] is that a GAN memorising the samples provided to it during training could produce a FID value that is so near to zero and thus so good. We conducted a similarity search between all the images in the training set and 40 images that were randomly selected from the GAN-generated images in order to rule out this option. By computing the SSIM, a widely used index of similarity between two photos, each image pair—real and fake—was compared. As seen in Figure 5, it was never determined that an image from the training set was exactly similar to one that was generated; nonetheless, it is frequently rather obvious that the image is entirely new.

VIII. Conclusion

In this study, we showed that a Lightweight GAN can produce results that are incredibly credible even with little data and in a context that hasn't been studied very much. As a result of combining the photographs we created, we were able to construct a stunning wide-view of a section of the universe as well as a large number of believable images of various specific celestial bodies and galaxies. The effectiveness of the results has been verified in several methods, including (a) using pre-trained networks for purely aesthetic evaluations and detection approaches, and (b) evaluating the objective measures and criteria that are typically applied inside the Generative Adversarial Networks paradigm. The network may thus be used to generate visuals useful in the realms of art and graphics as well as a tool for data augmentation in the categorization of planets or galaxies, proving the worth and effectiveness of generative adversarial networks once more.

IX. References

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