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Generating large scale images using GANs

Mohamed Mohsen Mahmoud Mohamed

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Mohamed Mohsen
American University in Cairo,
m.mohsen.mahmoud@aucegypt.edu

Advisor: Prof. Mohamed Moustafa

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Author

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I Abstract

Generative Adversarial Networks [1] have been used for the task of image generation and has achieved impressive results [2][3]. There is always a challenge to train networks that generate large scale images since they tend to be huge and training needs a lot of data. In this work, we tackle this problem by dividing it into two smaller parts. We first generate small scale images using GANs then use a super resolution network to enlarge the generated images resulting in large scale images. Using a super resolution network helps in adding more details to the image which results in a better quality image. This technique has been tested with a small amount of data and obtained better inception scores over the baseline GAN.

II Introduction

In modern days, the amount of data available to train machine learning algorithms is getting larger, however, the cost of labeling is expensive. Many of the machine learning approaches require annotated data for training and testing, therefore, the need for labeled data is growing. One of the solutions for this problem is to use generated data for training instead of real data.

One of the prominent approaches for image generation is using the Generative Adversarial Networks [1]. Since GANs make use of two deep networks that should be trained simultaneously, they are difficult to train. Work has been done to try and regularize the GANs training [2][3]. However, the images generated are still small in size (less than 128x128 pixels).

A different stream of work that is tackled using GANs is the image super-resolution problem [4][5]. This is where the input is a low resolution image and the output is the higher resolution version. This makes use of unlabeled data. Where a large scale image is downsized and used for the input while the large scale image is used as a reference for the output.

For this work, we will focus on the task of large scale image generation by exploring the joint training of GANs along with a super-resolution network. We explore the different ways of combining super-resolution networks with generative networks. Our proposed system achieves better results over a traditional GAN network in generating large scale images.

Section III provides a more detailed description of the problem tackled. A review of current work is presented in section IV. The approach is demonstrated in section V. Section VI describes the experiments performed and their results. The conclusion is found in section VII and possible future work is written in section VIII.

III Problem Definition

Image generation is not an easy problem. Trying to generate large scale images add complexity to the generation. Complex networks with high dimensionality inputs and outputs are not easy to train. In this work, we tackle this problem by providing a way to generate larger images. This is done by exploring the different ways to integrate a super-resolution network with a GAN to enable training with smaller sized datasets.

IV Literature Survey

IV.1 Generative Adversarial Networks (GANs)

GANs offer a technique for data generation that is based on adversarial learning [1]. This technique trains two networks simultaneously, a generator and discriminator network are trained in parallel. The goal of the generator is to fool the discriminator into thinking that a generated image is real. While the goal of the discriminator is to identify real vs fake images. As training progresses, the generator generates more real looking images and the discriminator gets better at detecting fake images [1].

Training GANs is a very challenging problem because instead of only training a single network, one has to train the generator and the discriminator networks simultaneously. Also, for the training to be successful, one has to make sure that the generator and discriminator are trained at the same speed i.e. the learning capacity of the networks is similar. If the discriminator learns faster than the generator, the whole process is affected and the generator stops learning.

The inherited difficulty and complexity of GANs make them difficult to train for generating large scale images.

IV.2 Deep Convolutional GANs (DCGANs)

Convolutional Neural Networks (CNNs) have shown remarkable results in the different image classification problems. Work has been done to scale up the learning capacity of GANs by making use of Deep Convolutional Networks [2]. The authors came up with a set of architecture guidelines for stable training of DCGANs [2]. They also suggest using the Adam optimizer [6] for the training. This approach results in plausible image generation when trained on the LSUN dataset [7].

The network uses strided convolutions as shown in figure 1. There are a total of 4 convolutional layers with a 100 dimensional input vector and a 64x64 rgb output image. This work shows the power of using deep convolutional networks in GANs however, the images generated are not high resolution images.

This approach increases the learning power of GANs and thus improves the quality of output images generated by them. However, the deeper and the more complex the network gets, the more tricky it is to train.

IV.3 Laplacian Pyramid Approach (LAPGAN)

One of the approaches to train GANs is to use a Laplacian pyramid of Adversarial Networks [3]. This means divides the training problem into smaller subproblems. As shown in figure 2, a series of Conditional Generative Adversarial Networks (CGANs) [8] are trained in sequence where each

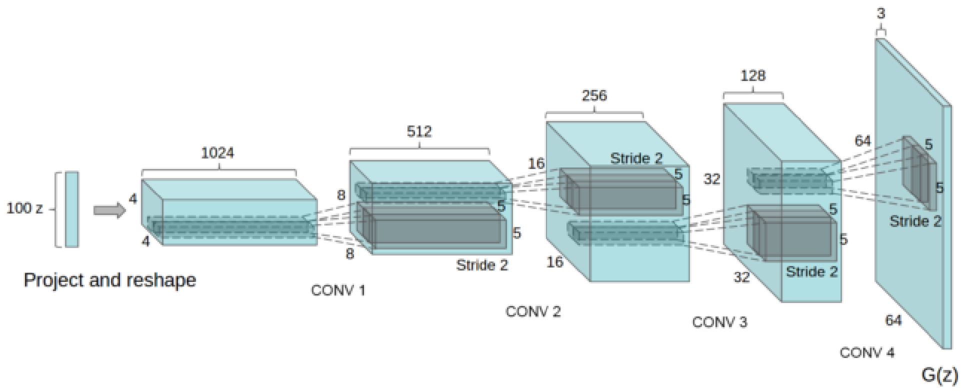


Figure 1: Deep Convolutional GAN

The architecture of the DCGAN generator network. The input is a 100 dimensional vector and the generated images are 64x64 color images. Image adopted from [2]

layer learns the differential to add to the input image for refinement. The refined image is then upscaled and moves on to the next CGAN block. The first block is a normal GAN [1] that generates a small scale image with an input of a noise vector.

This work makes use of the fact that each CGAN layer is only learning the differential to add to the input image instead of learning to generate the image from scratch. LAPGANs were tested on the CIFAR10 [9], STL10 [10] and LSUN [7] datasets and their results show an improvement over the traditional GAN approach. Human evaluation was done to come with this conclusion [3]. Images generated using this approach have a dimension of 64x64 pixels.

The success of this approach is due to the fact that it trains for the differential to improve the image quality. This decreases the amount of data the network needs to learn. Also, the layered approach makes the job of

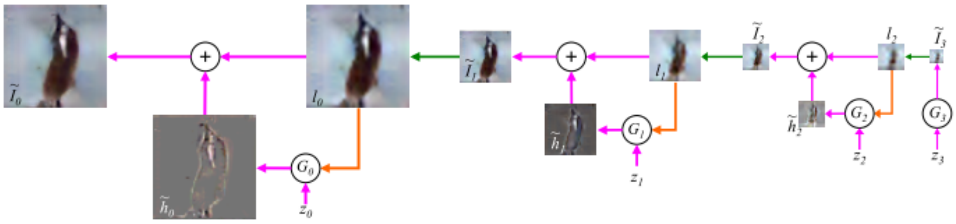


Figure 2: Laplacian Pyramid Architecture
The architecture of the LAPGAN generator network. Green arrows represent the up-sampling of the images generated at a specific stage to form the input to the next stage. Image adopted from [3]

each layer easier. All of this leads to better quality output images.

IV.4 Deep Recurrent Attention Writer (DRAW)

When drawing, we humans tend to focus on a small part of the picture at a time and then move on to the next part of the picture. This is modeled using the attention mechanism [11]. The network chooses a small part of the image to attend to at a time. A Gaussian kernel composed of a variational auto encoder is used to generate part under focus. Figure 3 demonstrates the power of this algorithm in following lines and recursively refining images generated from the MNIST data [12].

This whole operation is done in a recurrent fashion. Where the area attended to keeps getting smaller as more details are added to the image. This technique [11] is shown to work on generating MNIST [12] and SVHN [13] data. However, when generation was tested with the CIFAR10 [9] dataset, the images produced capture much of the shape structure but are blurred and not clear.

The success of this approach in generating numerical images and it's failure to generate scenery is because of the fact that it focuses on a small part of the picture at a time, this is good when it comes to tracing lines and thus generating numbers. However, scenery images do not have the same structure and thus this approach fails to generate acceptable images in this scenery images.

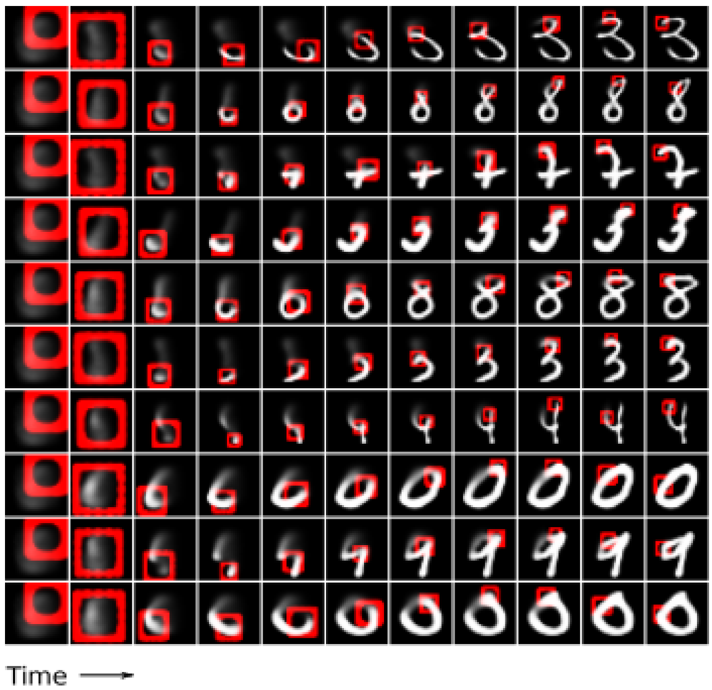


Figure 3: Deep Recurrent Attention Writer in Action

The DRAW generator in action. The red squares represent the area of attention of the algorithm. As seen, the algorithm is good at following lines and recursively refining the image. This image is adopted from [11]

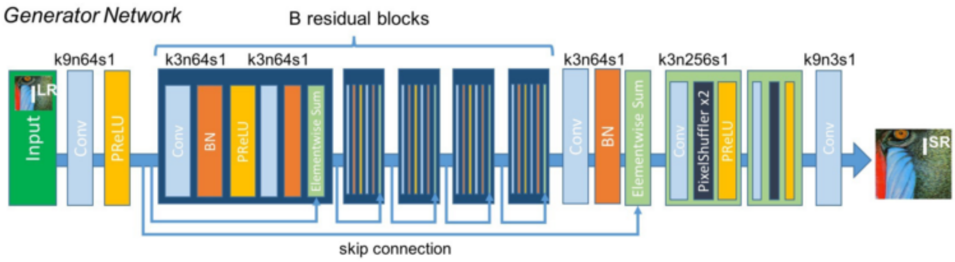


Figure 4: Super-resolution GAN Architecture
The architecture of the SRGAN generator network. As seen, the input images have a dimension of 64x64 pixels and are upscaled with a 4x factor to generate images of 256x256 pixels. Image adopted from [4]

IV.5 Super-resolution GAN (SRGAN)

The use of GANs for super-resolution is demonstrated by SRGAN [4]. This approach trains the discriminator on separating between the original and fake high-resolution images. On the other hand, the generator takes in a low-resolution image and generates the high-resolution version. Figure 4 shows the architecture of the SRGAN generator network.

In addition the output of the discriminator, the generator optimizes for the VGG [14] features loss for the generated and original high-resolution images. Using this loss function, the authors could successfully upscale images with a 4x scaling factor.

This technique produces larger scale images (256x256 pixels) than the previously described algorithms. However, it needs a low resolution image (64x64 pixels) as input.

Since this approach uses a very deep and complex super resolution network, it gets tricky to train from scratch.

Figure 5: Sample results for image hole filling
This picture shows a comparison between the use of typical convolution layer based networks vs partial convolution layers in solving the problem of hole filling. Image adopted from [15]

IV.6 Image Denoising Networks

Denoising is the problem of removing noise from images or filling in holes in the image. This problem has been tackled by various learning and non-learning techniques. In our scenario, we are more interested about the learning techniques.

The use of partial convolution layers [15] has been explored and it has shown great results in filling gaps in images. It has been testing by applying arbitrary shaped hole masks to images and then try to fill in the gaps. The partial convolution yielded far superior results when compared to the convolutional networks an example is shown in figure 5.

Another approach that focuses on noise removal is presented in [16]. They have developed a convolutional network with skip connections to eliminate the noise and improve the image quality. A sample of the output is shown in figure 6.

The use of a denoising network in the super resolution problem is shown

Figure 6: Sample results for image denoising

This picture shows sample outputs of the denoising network. The image on the left is the input image with noise and the image on the right is the corresponding enhanced version. Image adopted from [16] in [16]. The main problem is that denoising systems expect the input and output to be of the same resolution. As a workaround, the low resolution image is upscaled and then fed in the denoising network. By doing this, the overall system would be taking in a low resolution image and outputting a high resolution image.

V Proposed Solution: Combining Super Resolution with GAN

Motivated by the ability of super-resolution networks to produce 8x higher resolution images, we have explored the different ways to combine a super-resolution network along with a GAN network. Super-resolution networks need a pair or low-resolution and high-resolution images to train where the GAN only needs a random vector. Below are the different approaches to combine the two systems.

V.1 Approach 1: Separate Training

The first way to combine the systems, is by separately training the super-resolution network and the GAN on the same dataset. Where the GAN would be trained to generate low-resolution images and the super-resolution network would separately learn to enlarge low-resolution images from the same dataset. Taking the output of the GAN and feeding it in the super-resolution network should produce high-resolution images. Figure 7 shows a block diagram of this approach.

V.2 Approach 2: Joint Training

The second approach is to train the super-resolution network on the output of the GAN. Figure 8 shows the high level block diagram for this

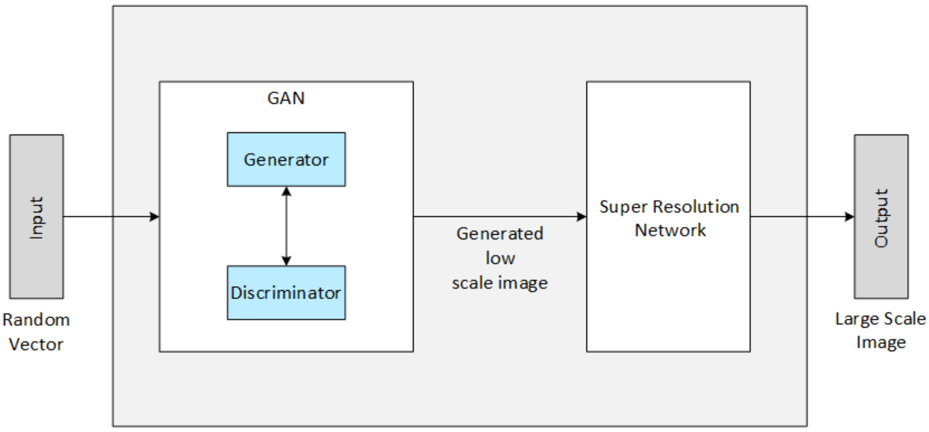


Figure 7: Block diagram for the separate training approach
The GAN and Super resolution networks are trained separately and when generating, the output of the generator network is fed in the super resolution network to obtain the large scale image.

approach. This approach aims at adapting the super-resolution network to the images generated from the GAN. The training steps are outlined below:

1. **Train the GAN to generate low-resolution images.** This steps makes use of the power of GANs in generating low-resolution images.

2. **Find the closest image from the training dataset.** Super-resolution networks need pairs of low-resolution images along with their high-resolution counterparts. The GAN already generated the low-resolution version but we still need to find the corresponding high-resolution image. Therefore, we search the training dataset to find the closest image and use its high-resolution version.

3. **Train the super-resolution network.** Making use of the generated low-resolution images along with their high-resolution counter-

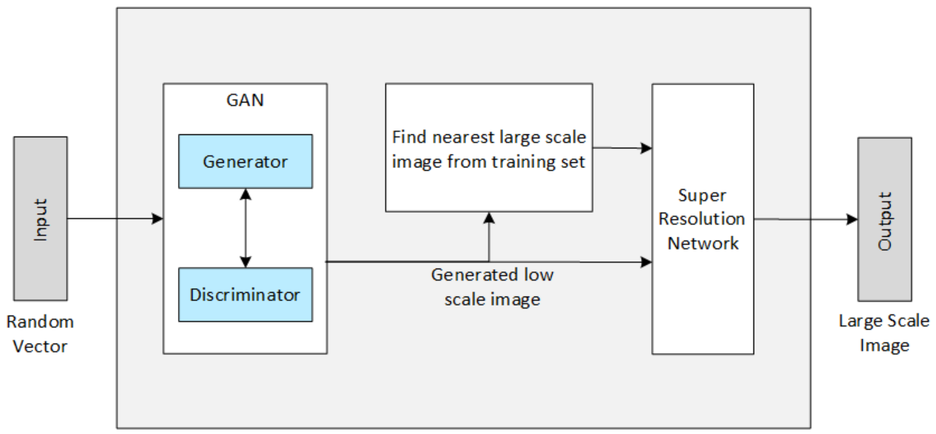


Figure 8: Block diagram for the joint training approach
After the GAN network is trained, training data for the super resolution network is created by generating random images and matching them with the nearest large scale corresponding image from the dataset.

part from the dataset, train the super-resolution network.

V.3 Approach 3: Combined Network

One further step in integrating the super-resolution network with the GAN would be to train them together. The high level block diagram is shown in figure 9. This approach makes use of the error from the super-resolution network to train the generator of the GAN. The training steps for each epoch are described below:

1. **Generate a low-resolution image.** Use the generator network from the GAN to generate an image.

2. **Find the closest image from the training dataset.** Search the dataset for the closest image to the generated one.

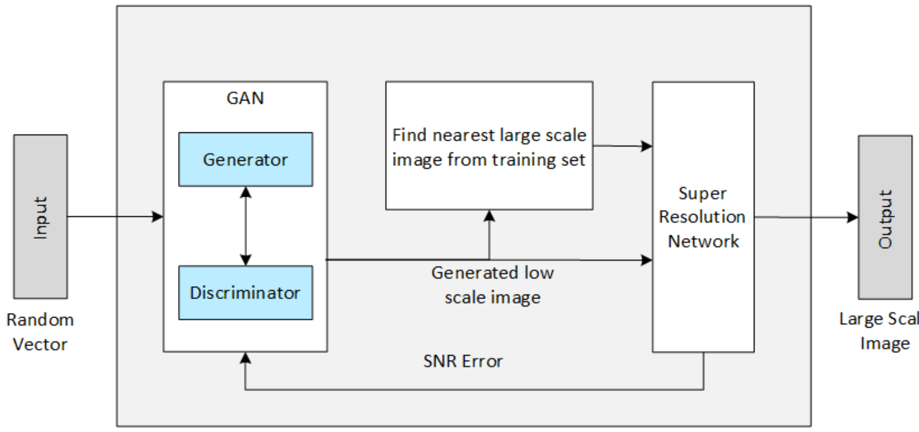


Figure 9: Block diagram for the combined network approach
The error from the super resolution network is used by the generator network to adapt.

3. **Enlarge image using super-resolution network.** Use the super resolution network to increase the image resolution.

4. **Consume the error from the super-resolution network to train the generator.** This is the key step, error from the super-resolution network should be fed back to train the generator as well as the super-resolution network.

VI Experiments

VI.1 Dataset Used

All training was done on the LSUN dataset[7] using the 'church_outdoor' category. This is the smallest category in the dataset and contains:

- 126,227 training image
- 300 validation image

The images in the dataset do not have a uniform size. All samples have their smaller dimension equal to 256 pixels or larger. The following preprocessing steps were done in order to prepare the images:

1. Crop the largest center square of each image
2. Shrink the cropped portion to the required size

VI.2 Evaluation Metrics

Inception Score

Evaluating generative models is a very difficult task since there is no ground truth to compare to. For that reason, researchers mostly rely on the human perception of the generated image quality. Recent work proposed a the inception score [17] [18] as an automated way of judging the generated image quality. It has shown to correlate well with the human perception of the image quality.

To evaluate the output of generative models, the inception score aims at measuring two things:

1. The clarity of the objects in the generated images
2. The diversity of the generated images

A classifier model is pre-trained on the imagenet dataset [19] and is used in the standard inception score calculation. This model is the core of the calculation, the clarity and diversity of the objects in the generated images are measured by measuring the output of the classifier for the different classes of the classifier.

Structural Similarity

Structural similarity [20] computes the similarity between images by using groups of pixels instead of individual pixels. It takes into consideration the luminance, contrast and image structure in the similarity computation. This is one of the metrics that we have used to find the nearest image in the training set given a generated image.

VI.3 Baseline Approach

Typically, when trying to generate large scale images using GANs, one would tend to use a very deep generator for the GAN. For the baseline of our

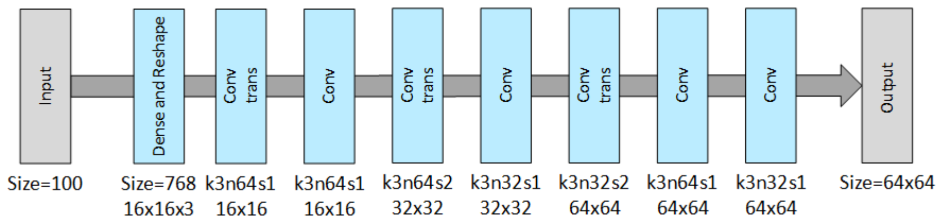


Figure 10: Baseline Generator architecture used

The architecture of the generator network for the baseline approach. As seen, the input is a random vector of size 100. Multiple convolutional layers turn that input to an image of size 64x64.

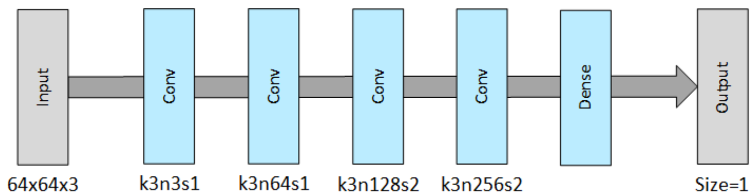


Figure 11: Baseline Discriminator architecture used

The architecture of the discriminator network for the baseline approach. As shown, the input is a 64x64 pixel image and the output is a single value that indicates if the image is authentic or fake.

work, we will use an adapted version of the deep convolutional GAN [2] to generate large scale images and compare them with the ones generated using our proposed approaches. The generator network architecture is shown in figure 10 and the discriminator network architecture is shown in figure 11.

This model is trained with a batch size of 512 images and using the Adam Optimizer[6] with learning rate of 0.0005 for 50,000 epochs. Results are quantitatively compared in subsection VI.6 with the proposed approach.

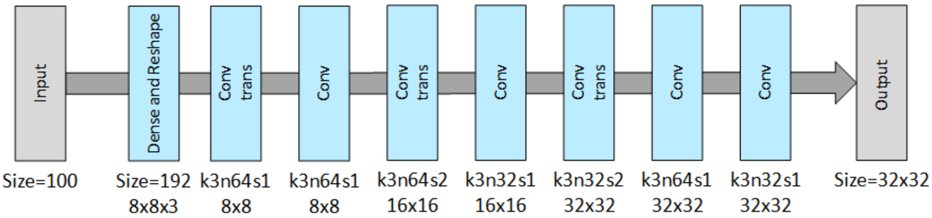


Figure 12: Generator architecture used

The architecture of the generator network used. As seen, the input is a random vector of size 100. Multiple convolutional layers turn that input to an image of size 32x32.

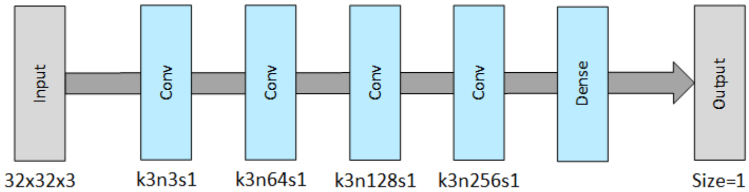


Figure 13: Discriminator architecture used

The architecture of the discriminator network used. As shown, the input is a 32x32 pixel image and the output is a single value that indicates if the image is authentic or fake.

VI.4 Approach 1: Separate Training

Generative Adversarial Network

A deep convolutional GAN is trained to generate 32x32 pixels images. The architecture of the generator network is outlined in figure 12 and the architecture of the discriminator network is outlined in figure 13.

After training various GAN models, it was noticed that the most important thing to take care of while training is that the generator and discriminator networks need to be learning with the same speed. It is quiet easy to have a powerful discriminator network that can quickly learn to discriminate

Figure 14: Samples from generator network
Those are 32x32 image samples from the generator network. As noticed, the images do indeed look like churches and some of the samples can be mistaken as real images even by a human eye.

between fake and authentic images. However, such a discriminator results in the generator not being able to keep up and thus it doesn't learn anything. Therefore, the size of the discriminator network is tweaked to maintain an accuracy of 80% to 90% for the discriminator. This is the sign of a healthy training.

The model is trained with a batch size of 512 images using the Adam Optimizer[6] with a learning rate of 0.0005 for 50,000 epochs. A sample output is shown in figure 14.

Super Resolution network

Different super resolution network architectures are tried out on the training data and the one that produced the best SNR is the Denoising Super Resolution Network[16]. The architecture used is shown in figure 15.

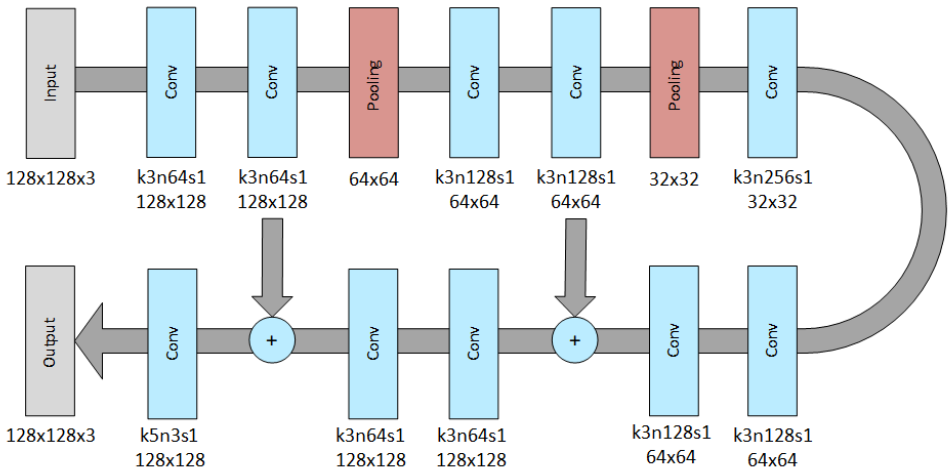


Figure 15: Super resolution architecture used
The architecture of the denoising super resolution network used. As seen, the input is a 128x128 image and the output is also a 128x128 image.

The denoising network is initially meant to remove noise from images without changing their size. To use a denoising network to enlarge images, a preprocessing step is added to stretch the image using the bilinear interpolation before feeding it to the denoising network. Therefore, the whole system would take in a 32x32 image and output the large scale image. The same idea is presented in [16].

Training is done using a batch size of 1 and the Adam optimizer[6] with a learning rate of 0.00001. The optimization function used is the mean square error. The training evaluation is shown in table 1. Examples from the network are shown in figures 17 & 16.

Figure 16: 64x64 pixel samples from the super resolution network (scaling factor 2x)

The top row is the 32x32 input image, the second row is a stretched version using bilinear interpolation for comparison. The third row is the 64x64 output of the network while the last row is the original large scale image. This network obtained a PSNR of -18.8 on the validation set.

Figure 17: 128x128 pixel samples from the super resolution network (scaling factor 4x)

The top row is the 32x32 input image, the second row is a stretched version using bilinear interpolation for comparison. The third row is the 128x128 output of the network while the last row is the original large scale image. This network obtained a PSNR of -22.24 on the validation set.

Scaling factor	Output Dimensions	PSNR
2x	64x64	-18.8
4x	128x128	-22.24

Table 1: Evaluation of super resolution network
PSNR values are calculated on the validation set.

Combined Result

Feeding the output of the generator into the super resolution networks, gives us 64x64 or 128x128 generated images depending on the super resolution network used. Figures 18 & 19 show samples of images that are generated using the combination of the GAN and the super resolution networks. The super resolution network succeeds in clearly improving the quality of the enlarged version over the bilinear interpolation by adding some missing details to the images.

VI.5 Approaches 2&3: Joint Training & Combined Network

These approaches depends on generating images and then finding similar images from the training set to train the super resolution network. We have tried out different similarity and error metrics in order to find the nearest image from the training set.

From the sample results shown in figure 20, we can notice that after the super resolution network is applied, the results are rather disappointing.

Figure 18: 64x64 pixel samples from the combined networks

The top row is the 32x32 image generated by the generator network. The second row is the stretched version using bilinear interpolation for comparison. The third row is the result of feeding the generator image to the super resolution network to generate a 64x64 version. As noticed, even tough a human eye can tell that those images are not real, they are of very good quality for machine generated images.

After some debugging, we found out that the problem is that the input and output images used to train the super resolution network are not correlated. Since we are using a very diverse training dataset, for each similarity metric a certain type of images dominate the results. Therefore, the nearest image from the training set is mostly not similar to the generated image. Example output for the different similarity metrics is shown in figure 21. Without the ability to really find the most similar image in the training set, approaches 2 and 3 cannot be trained successfully.

Figure 19: 128x128 pixel samples from the combined networks

The top row is the 32x32 image generated by the generator network. The second row is the stretched version using bilinear interpolation for comparison. The third row is the result of feeding the generator image to the super resolution network to generate a 128x128 version. As noticed, even tough a human eye can tell that those images are not real, they are of very good quality for machine generated images.

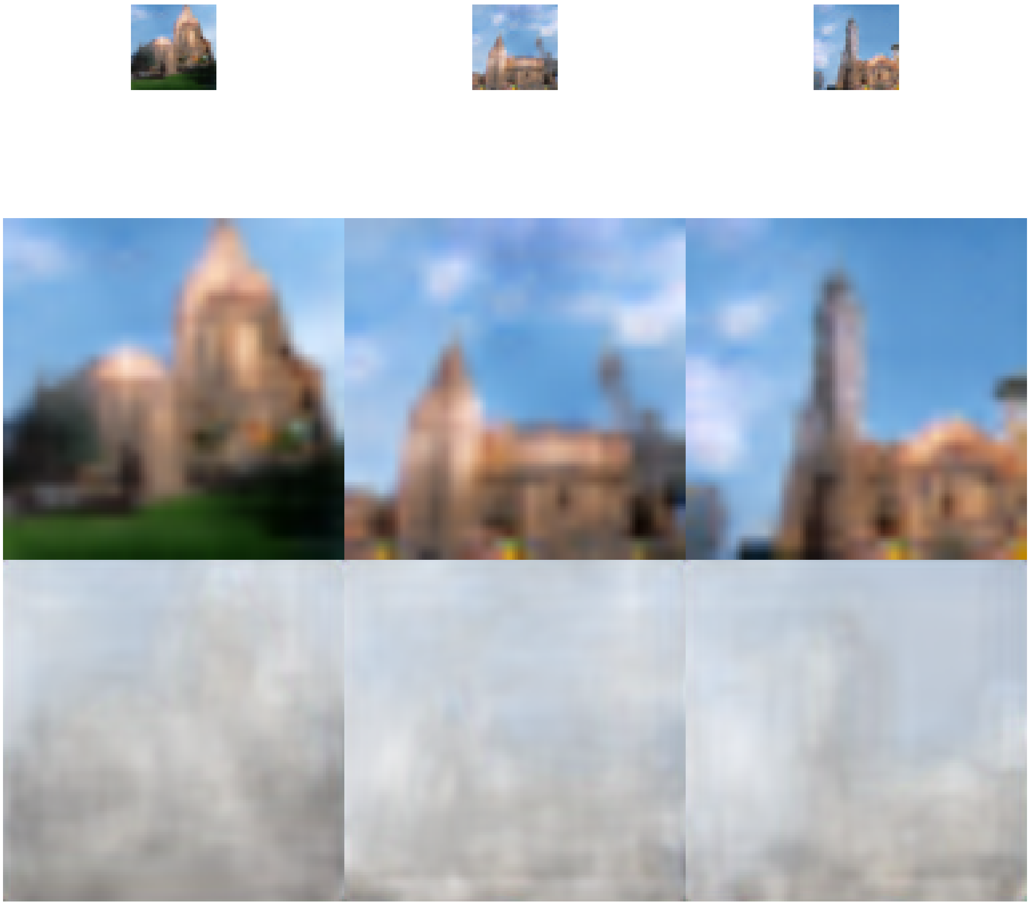
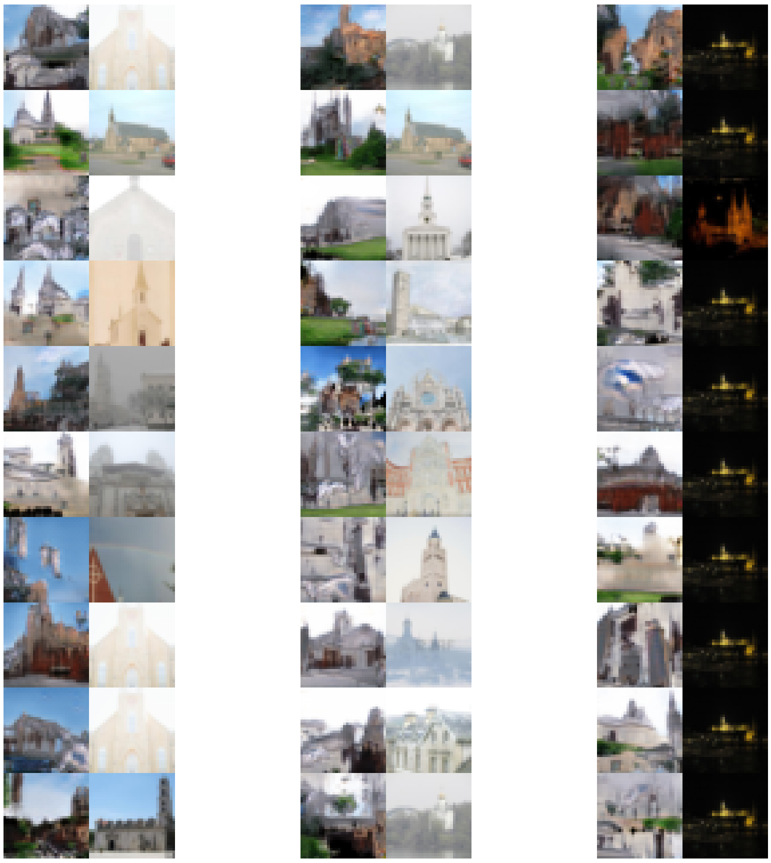


Figure 20: Sample results for the joint training approach

The top row is the 32x32 image generated by the generator network. The second row is the stretched version using bilinear interpolation for comparison. The third row is the result of feeding the generator image to the super resolution network to generate a 128x128 version. As noticed, after the super resolution network is applied, the images loose all of their details and are extremely blurred. Those samples are computed using the normalized mean square error.



(a) (b) (c)

Figure 21: Similarity between generated images and training set
In each of the sub figures shown, the image on the left is a random generated image and the image on the right is the corresponding nearest image from the training set. Each of the sub figures, represents a different similarity/error measure sub figure 21a is computed using structural similarity [20] as the similarity measure. Sub figure 21b is computed using the normalized mean squared error as the error function. While sub figure 21c is computed using PSNR as the error measure.

VI.6 Comparison to Baseline

The baseline for this work is the quality of images generated using a GAN network that is trained on the same dataset. To evaluate the baseline, a GAN network of the same architecture outlined in figures 12 & 13 is trained and the results are evaluated.

Training a network to generate 128x128 images using a single GAN is a very compute intensive process that does not fit on the GPU memory. The network will have to be stripped down for it to fit on a GPU which would lead to a weaker network and thus misleading results. Therefore, we are instead doing the comparison for 64x64 images.

For the sake of the comparison, the denoising super resolution network shown in figure 15 is retrained to generate 64x64 images. In other words, we needed to change the super resolution network scaling factor from 4x to 2x.

From the training difficulty point of view, the baseline requires a GAN to generate higher dimensionality images and is thus much more difficult to train. Using our approach, the network size is much smaller and thus the training is much easier. Moreover, bigger networks require more data to train. Therefore, our approach should work better with smaller datasets.

As noticed from table 2, our approach gives better inception score values on average than the baseline. Which shows it is indeed better than the baseline given the small dataset used.

	Inception Score	
	Mean	Standard Deviation
Baseline Convolutional GAN	3.041	0.110
Our Approach	**3.564**	**0.220**

Table 2: Comparison with the baseline

Calculated for a sample of 1024 generated image from each approach, the mean and standard deviation of the inception score are shown in the table.

VII Conclusion

Based on the results obtained on this small dataset, combining a GAN with a super resolution system proves more powerful in generating better quality images in comparison to only using GAN. This is because the proposed technique divides the problem into two smaller problems which makes it more manageable. Also, since the problem is divided into smaller problems, it is possible to use a very small training set of 126,227 images compared to the dataset size needed to train larger networks.

VIII Future Work

Although the current approach already achieved better results over the baseline, there is room for improvement. An extension to the super resolution network is to train on more data e.g. the image net dataset[19] and then adapt it to the domain. Also, noise should be added to the lower resolution images used in training the super resolution network. This would resemble the noisy images generated from the GAN which would lead to generating better quality images.

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