Generative Adversarial Neural Networks

April 19, 2025

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Contributions:

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Course: CS551 - Deep Learning

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1.1 Abstract

In this report, we present the implementation and evaluation of two Generative Adversarial Network (GAN) architectures. In the first part we focused on the development of a Deep Convolutional GAN (DCGAN) to generate images of grumpy cats from random noise inputs. We implemented and analyzed key components, such as data augmentation, the discriminator, the generator, and the training loop for this study. Additionally, we evaluated the impact of data augmentation strategies (basic and deluxe) on the training process, with visual comparisons of generated samples at different training stages.

In the second part, we explored the CycleGAN architecture for unpaired image-to-image translation, by transforming images between two distinct cat types: Grumpy and Russian Blue. The CycleGAN implementation includes encoding, transformation, and decoding stages in the generator, as well as the introduction of cycle consistency loss that guarantees that the translated images retain their original features. We conducted experiments to compare results with and without cycle consistency loss, highlighting its impact on training stability and image quality.

The report consolidates all results and analyses, accompanied by visualizations of training losses, generated samples, and loss curves. This work gave us practical experience in implementing and training GANs, providing insights into their capabilities and limitations in image generation and translation tasks.

1.2 Introduction

Generative Adversarial Networks (GANs) have become a powerful framework for generative modeling in deep learning, enabling us to create realistic images and data samples across various domains. In this report, we investigate two distinct GAN architectures; Deep Convolutional GAN (DCGAN) and CycleGAN to explore their capabilities in image generation and translation tasks.

At the core of GANs, lies a competitive game between two neural networks: the Generator, whose job is to produce images that appear authentic, and the Discriminator, that tries to discern real images from fake ones. This adversarial game, drives both networks to improve continuously, but also leads to the generation of more and more realistic images. In our study, the DCGAN is tasked with creating images of grumpy cats from random noise inputs, while CycleGAN is used for unpaired image-to-image translation between two distinct cat types: Grumpy and Russian Blue. CycleGAN uses a dual-generator setup and incorporates cycle consistency loss to ensure that transforming an image from one style to another, and back, preserves its original features.

In this stydy, we also examine data augmentation techniques. In particular, we compare a "basic" augmentation strategy with a more elaborate "deluxe" approach to understand how the quality and variability of the training data affect the performance and stability of both GAN models.

Our report consolidates the findings through detailed visualizations of training losses, generated samples, and loss curves, offering a comprehensive look at the strengths and limitations of GANs in creative and transformative applications.

1.3 Methodology

In this section, we describe the methodology that we used for this study, can be subdivided and described as follows:

1.3.1 Deep Convolutional GAN (DCGAN)

- **Data Preparation:**
  - The grumpy cat images dataset was preprocessed and augmented using two strategies: basic and deluxe augmentations.
- **Model Architecture:**
  - We implemented the DCGAN architecture with a generator and discriminator, designed using convolutional and deconvolutional layers.
  - We performed padding calculations to make sure that the spatial dimensions were halved at each layer of the discriminator.
- **Training:**
  - We implemented a training loop to optimize the generator and discriminator, using adversarial loss.
  - We used TensorBoard to log training metrics and visualize loss curves.
  - We conducted experiments with both basic and deluxe augmentations, to evaluate their impact on the model's performance.
- **Evaluation:**
  - We analyzed the images generated at different training iterations, to examine the quality and progression of the model.
  - We compared the loss curves for the generator and discriminator, to understand the training dynamics.

1.3.2 CycleGAN

- **Data Preparation:**
  - We used unpaired datasets of grumpy and Russian Blue cat images.
  - Preprocessing steps included resizing and normalization of the images.
- **Model Architecture:**
  - We implemented the CycleGAN architecture with two generators and two discriminators.
  - We incorporated cycle consistency loss, to ensure that translating an image to another domain and back retains its original features.
- **Training:**
  - We implemented a training loop to optimize the generators and discriminators, using adversarial and cycle consistency losses.
  - We experimented with and without cycle consistency loss, to evaluate its impact on training stability and image quality.
- **Evaluation:**
  - We analyzed the images generated at different training iterations, to assess the quality of the translations.
  - We compared the loss curves, to understand the effect of cycle consistency loss on training dynamics.

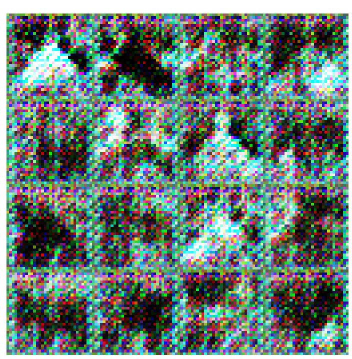
1.4 Results and Discussion

1.4.1 Results Overview

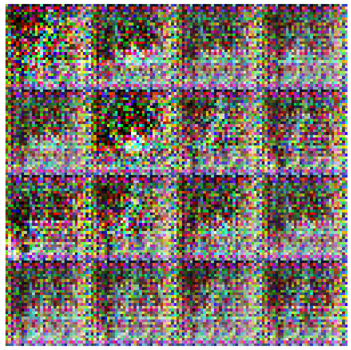
In this section, we summarize the results obtained from training the DCGAN and CycleGAN models. We analyze the generated images, loss curves, and training dynamics to provide insights into the performance of the models. Finally, we compare the results of different augmentation strategies and the impact of cycle consistency loss on CycleGAN.

1.4.2 DCGAN Results

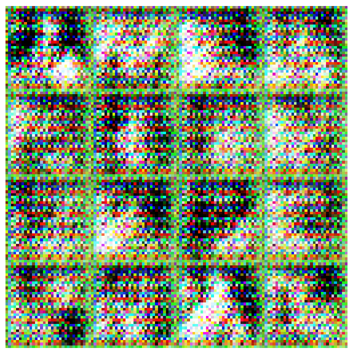
Generated Images **Basic Augmentation: - Iteration 200:** The generated images are mostly noise and lack any discernible structure resembling a grumpy cat.



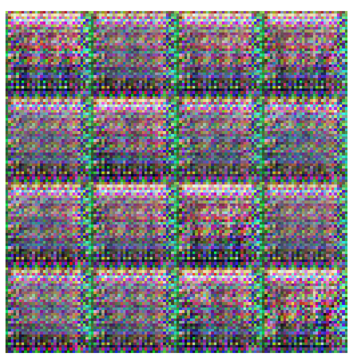
- **Iteration 1200:** The images show some improvement, with vague shapes and colors resembling cats, but they remain blurry and lack fine details.



Deluxe Augmentation: - **Iteration 200:** Similar to the basic augmentation, the images are noisy and lack structure.

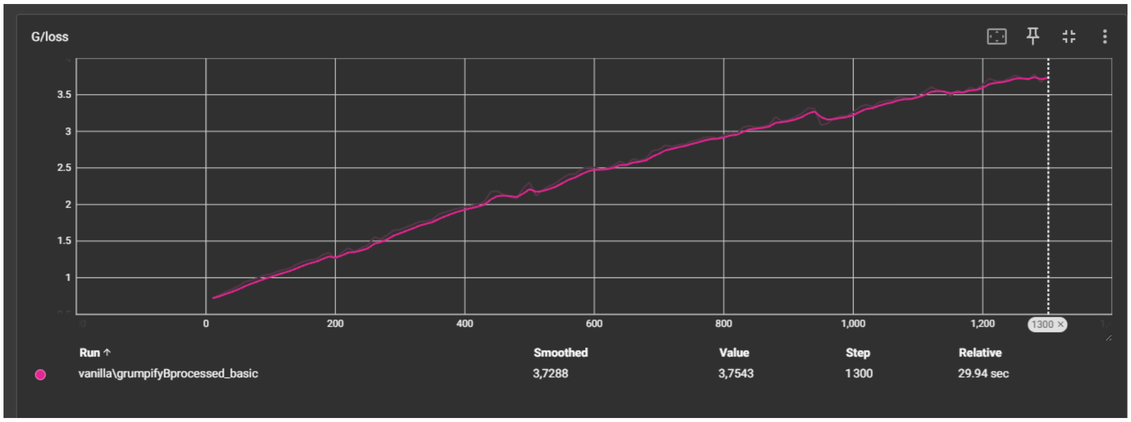


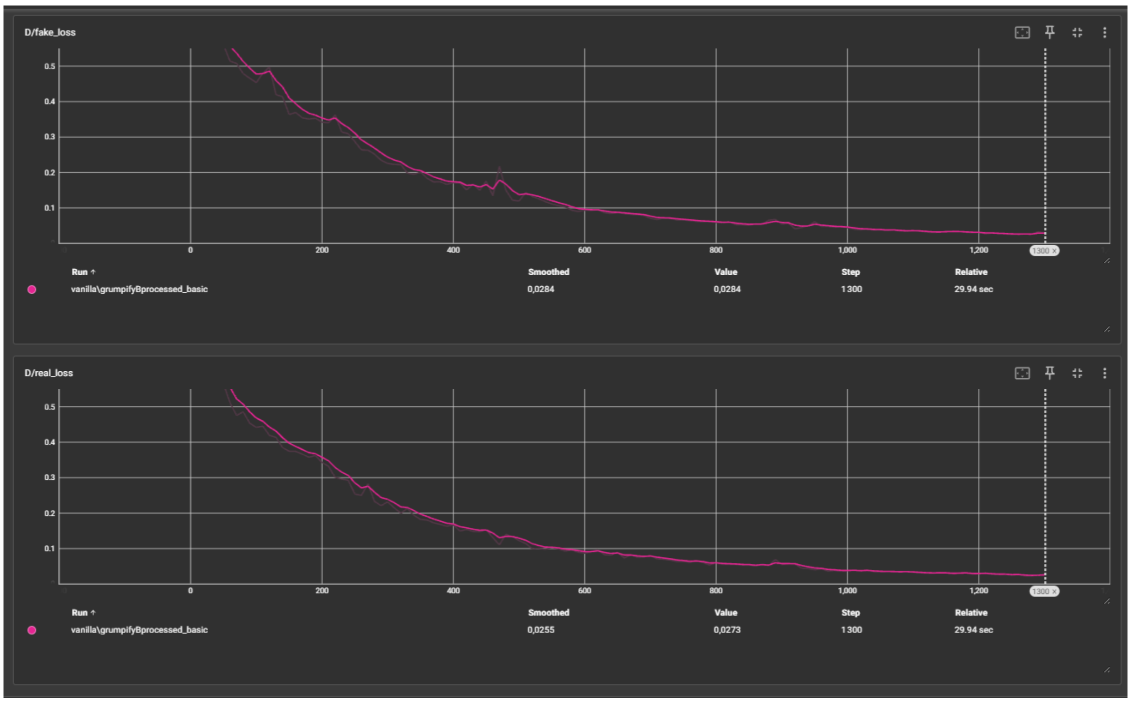
- **Iteration 1200:** The images show better quality compared to the basic augmentation, with more defined shapes and textures.



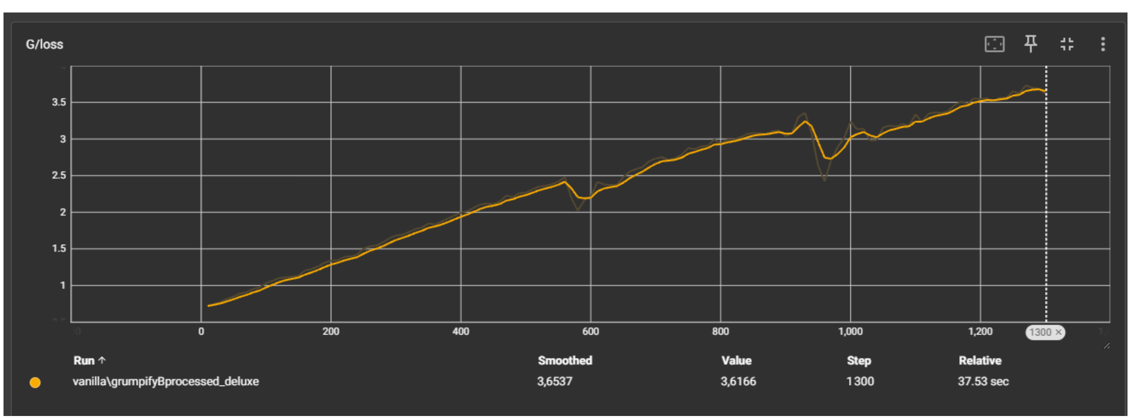
Loss Curves

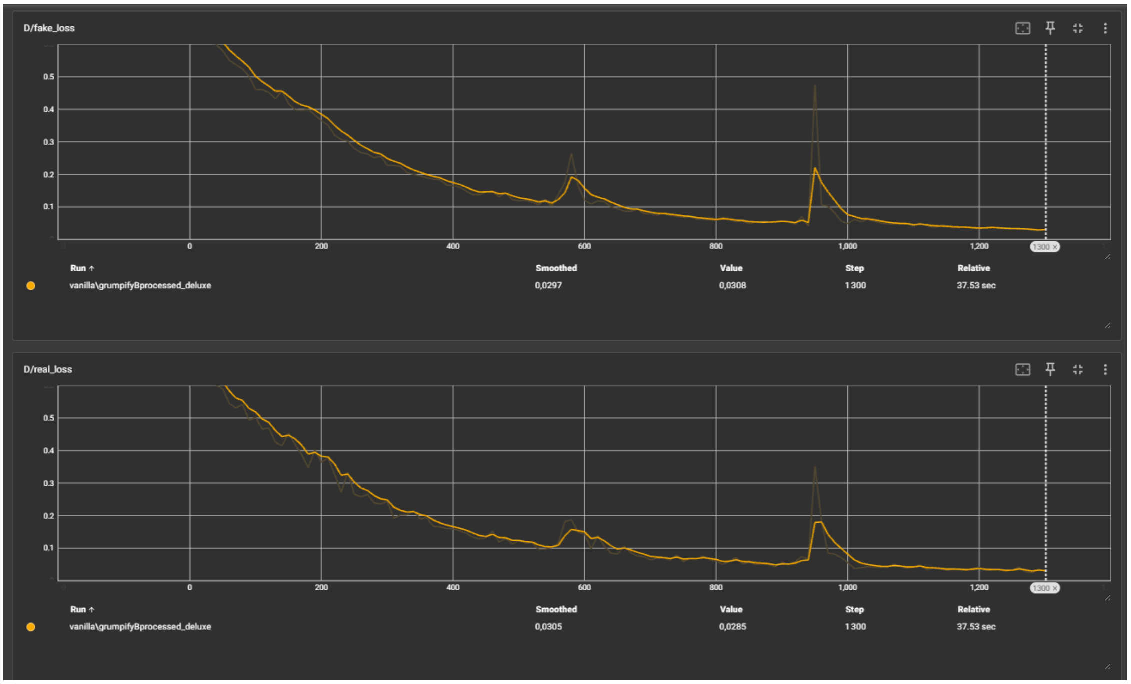
- **Basic Augmentation:** The generator loss shows an increasing trend, indicating that the discriminator is becoming better at distinguishing real from fake images. The discriminator loss decreases, suggesting that it is learning effectively.





- **Deluxe Augmentation:** The loss curves are more stable compared to the basic augmentation, indicating that the deluxe augmentation helps in stabilizing the training process.

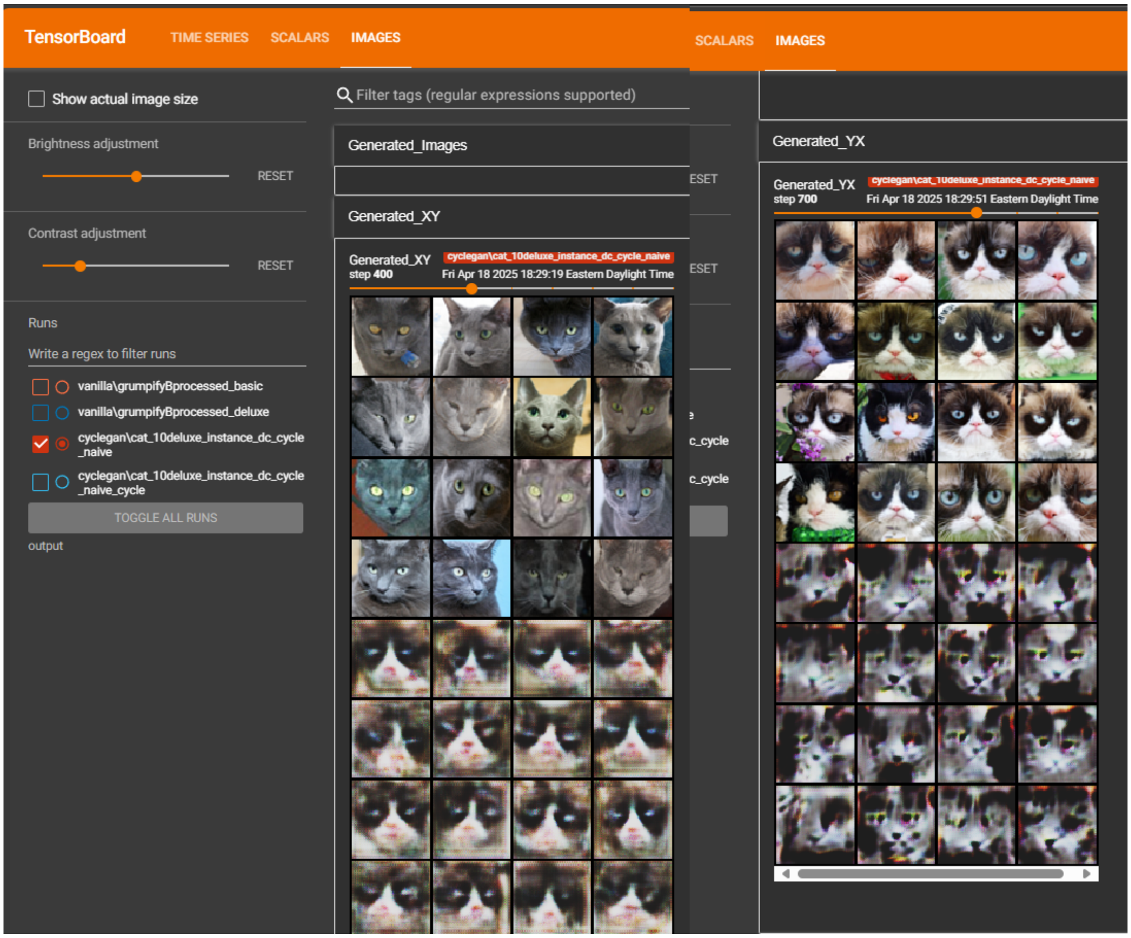


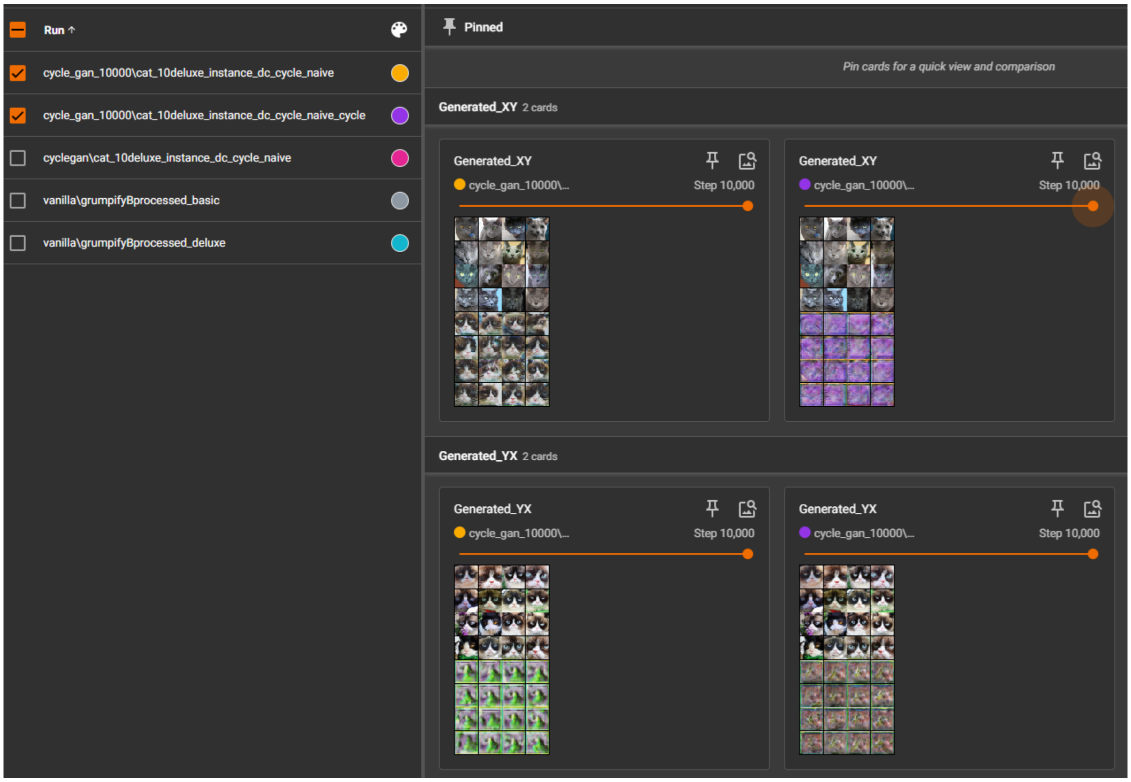


1.4.3 CycleGAN Results

Generated Images

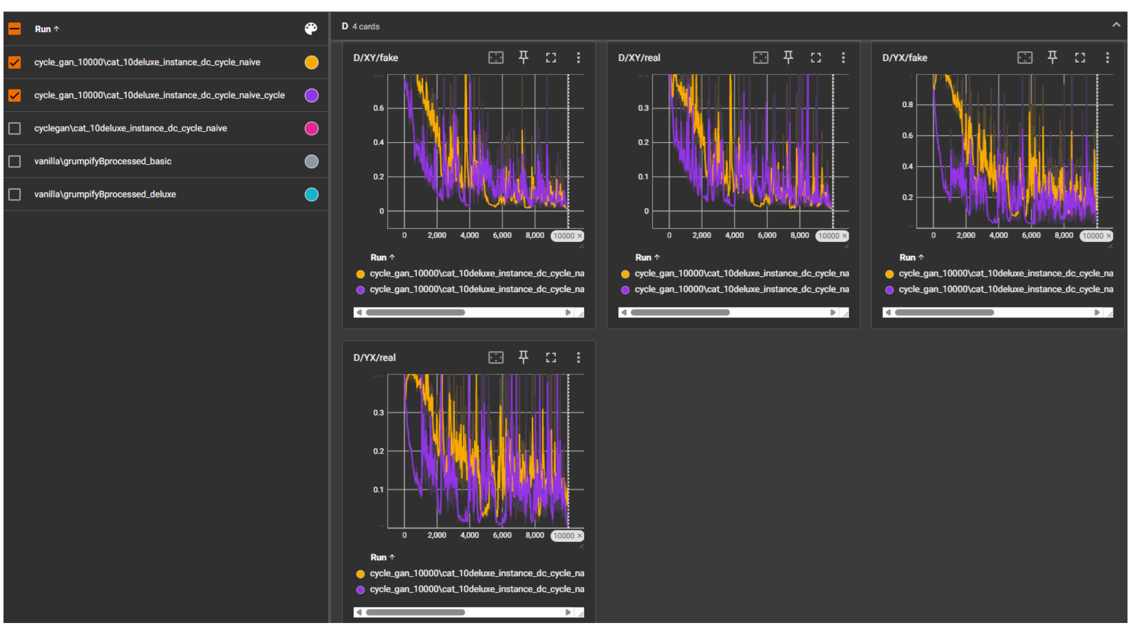
- **Without Cycle Consistency Loss:**
  - **Iteration 400:** The generated images show some resemblance to the target domain but lack fine details and consistency.
  - **Iteration 700:** The images improve slightly, but the quality remains suboptimal.
  - **Iteration 10000:** The images improve, with acceptable quality.
- **With Cycle Consistency Loss:**
  - **Iteration 400:** The images are more consistent and retain some features of the original domain.
  - **Iteration 700:** The images show noticeable improvement, with better textures and colors.
  - **Iteration 10000:** The images show substantial improvement, with even better textures and colors.


TensorBoard
TIME SERIES
SCALARS
IMAGES
Show actual image size
Brightness adjustment
RESET
Contrast adjustment
RESET
Runs
Write a regex to filter runs
vanilla\grumpifyBprocessed_basic
vanilla\grumpifyBprocessed_deluxe
cyclegan\cat_10deluxe_instance_dc_cycle_naive
cyclegan\cat_10deluxe_instance_dc_cycle_naive_cycle
TOGGLE ALL RUNS
output
Filter tags (regular expressions supported)
Generated_Images
Generated_XY
Generated_XY
step 400
cyclegan\cat_10deluxe_instance_dc_cycle_naive
Fri Apr 18 2025 18:29:19 Eastern Daylight Time
SCALARS
IMAGES
Generated_YX
Generated_YX
step 700
cyclegan\cat_10deluxe_instance_dc_cycle_naive
Fri Apr 18 2025 18:29:51 Eastern Daylight Time



Loss Curves

- **Without Cycle Consistency Loss:** The loss curves show fluctuations, indicating instability in the training process.
- **With Cycle Consistency Loss:** The loss curves are smoother and more stable, suggesting that the cycle consistency loss helps in regularizing the training.



1.4.4 Results Summary

1.5 Results Table

Model	Augmentation	Iterations	Insights	Loss Curve Insights
DCGAN	Basic Augmentation	200	No discernible structure, mostly noise.	Increasing generator loss, decreasing discriminator loss.
		1200	Vague shapes resembling cats, blurry images. (wrapped for clarity)	Stable training dynamics.
	Deluxe Augmentation	200	No discernible structure, mostly noise.	Similar to basic augmentation.
		1200	Better-defined shapes and textures compared to basic augmentation.	More stable loss curves compared to basic augmentation.
CycleGAN	Without Cycle Consistency	400	Some resemblance to the target domain, but lacks fine details.	Fluctuating loss curves, indicating instability.
		700	Slight improvement in quality, but still suboptimal. (wrapped for clarity)	Fluctuations persist.
	With Cycle Consistency	400	More consistent images, retaining features of the original domain.	Smoother and more stable loss curves.
		700	Noticeable improvement in textures and colors, better quality overall.	Stable training dynamics, indicating the effectiveness of cycle consistency loss.
		10000	Most noticeable improvement in overall quality, textures and colors.	Stable training dynamics, indicating the effectiveness of cycle consistency loss.

1.5.1 Discussion

1. **Impact of Augmentation on DCGAN:**
    - The deluxe augmentation strategy leads to better image quality and more stable training compared to the basic augmentation. This highlights the importance of diverse and enriched training data in improving GAN performance.
2. **Effectiveness of Cycle Consistency Loss:**
    - The inclusion of cycle consistency loss in CycleGAN significantly improves the stability of the training process and the quality of the generated images. This demonstrates the importance of regularization techniques in unpaired image-to-image translation tasks.

1.6 Questions and Answers

1.6.1 Padding Calculation for DCGAN Discriminator

Question: With kernel size (K=4) and stride (S=2), what padding (P) halves the spatial dimensions?

Answer: We want each layer to reduce the spatial dimensions by a factor of 2, without clipping important features. That means that we want to control the padding. So, we have the convolution output formula:

$$O = \left\lfloor \frac{I + 2P - K}{S} \right\rfloor + 1$$

Where: - (I) = input size - (O) = output size - (K = 4) (kernel size) - (S = 2) (stride) - (P) = padding

We want to obtain this:

$$\text{output\_size} = \frac{\text{input\_size}}{2}$$

So we solve as follows:

$$\left\lfloor \frac{I + 2P - 4}{2} \right\rfloor + 1 = \frac{I}{2} \Rightarrow 2P = 2 \Rightarrow P = 1$$

1.6.2 Can you account for these differences?

Answer: We can see that when we use cycle consistency, the loss curves appear more stable, as their slopes are generally gradual, without any major peaks. This could happen because the consistency loss acts as a rule that tells the networks not only to create fake images that "fool" the other network, but also to make sure that if you change an image and then change it back again, it looks like the original image you started from. This rule helps the training to be more stable and helps the networks learn in a more organized way, rather than in a disorganized way, trying to "fool" each other all the time. The generator seems to learn better when this rule applies.

1.6.3 Provide explanations as to why there might or might not be a noticeable difference between the two sets of results.

Answer: Analyzing the images, one possible explanation as to why we do not see a big difference in the images in the end, is because the two types of "grumpy cats" we are using are not that different in style. If the change we want to make is not too significant, the network can probably learn to do it right, even without the cycle consistency rule. Also, the rule has a weight (lambda), that if we do not adjust correctly, it may not help the network in its learning process. Additionally, in this case we use 1 loss, as the original paper suggested. Perhaps, if we trained longer or used larger networks, or if the difference between cat styles was more noticeable, we would see a significant improvement in the images produced, when we use the cycle coherence rule. This indicates that the rule helps the learning process to be more stable. However, for the images to look much better, we could apply further augmentations or train for longer.

1.7 Conclusion

In this report, we explored the implementation and evaluation of two Generative Adversarial Network (GAN) architectures: Deep Convolutional GAN (DCGAN) and CycleGAN. Through several experiments, we analyzed the impact of data augmentation strategies and the inclusion of cycle consistency loss on the performance and stability of these models.

For DCGAN, we can see that the deluxe augmentation strategy led to better image quality and more stable training dynamics compared to the basic augmentation. This highlights the importance of diverse and enriched training data in improving the performance of GANs. However, the generated images still lacked fine details, indicating the need for further optimization or more advanced architectures.

For CycleGAN, the inclusion of cycle consistency loss significantly improved the stability of the training process and the quality of the generated images. This demonstrates the importance of regularization techniques in unpaired image-to-image translation tasks. While the generated images showed noticeable improvements with cycle consistency loss, the differences between the two cat styles used in this study may have limited the visual impact of the results.

Overall, this study provided us with valuable insights into the capabilities and limitations of GANs in image generation and translation tasks. Future work could focus on exploring more complex architectures, longer training durations, and additional data augmentation techniques to further enhance the quality of the generated images.