Machine Learning for the Arts
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FINAL PROJECT

True Style Transfer

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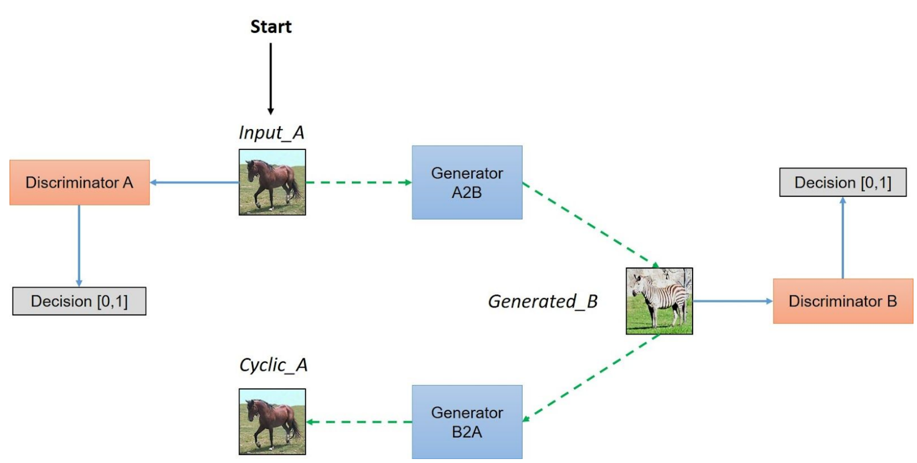
DESCRIPTION

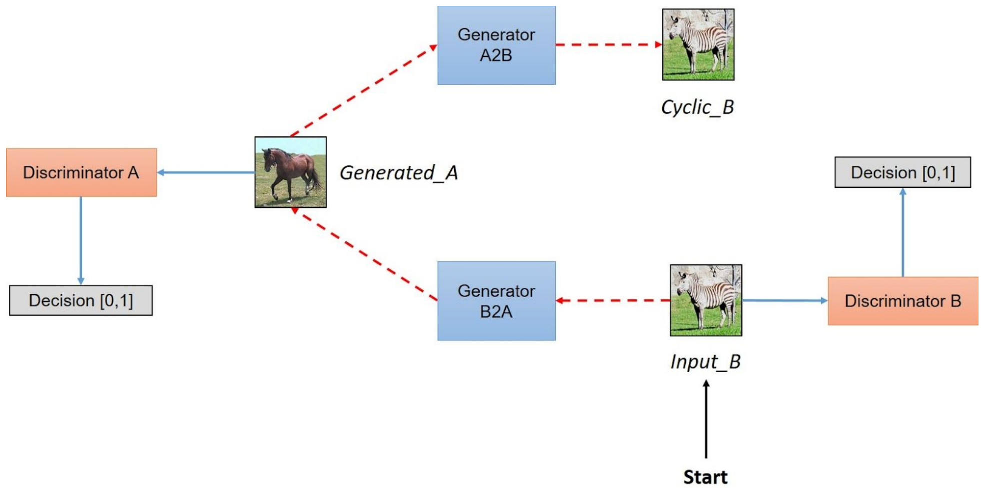
Concept: The idea of collaborating with or emulating the masters has been a dream. Of course, not everyone has the opportunity to do so. Even more so when ones favorite artist has passed. It is possible to learn an artist's style to perform a manual style transfer, but this requires a great deal of practice and dedication. Fortunately, Cycle GAN makes such a dream reachable. Inspired by the collaborations like those done between Dali and Disney[1] , we have decided to do a collaboration with Dali by using Cycle GAN on our own body of work. Using this method, we hope to perform a true style transfer, where one artist provides the subject or content and another adds their stylized artistic execution.

Originally, we tried performing a true style transfer by using cascaded CNN's and Gram Matrices. However, this method ended being ineffective as only color features ended being transferred. Even the coloring did not end up a true representation of the style as each individual CNN learned the features of one artwork. This meant that the most recent CNN would essentially overpower the previous styles of the artwork. The cascade method will be discussed further in the process section.

Cycle GANs learn from an entire selection of artworks, which is a better representation of true style transfer. We decided to choose images of similar style from one of our sketchbooks as one data set and Dali's most famous body of work from [4] as the other data set, we hope that the features from both are clear enough to generate images that may appear to be a mixture of both. The main goal is to have the sketchbook content drawn in Dali's style. This way it may be possible to perform a true style transfer and mixture between artists.

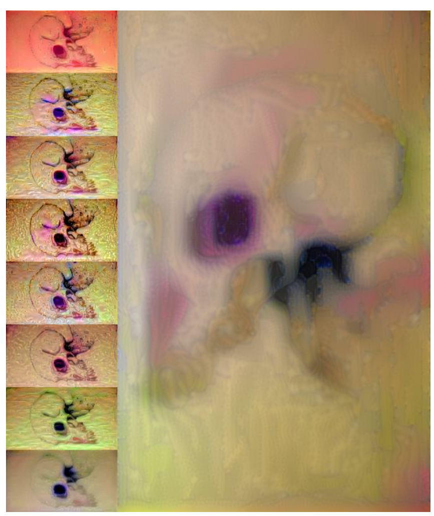
Technique: The network model in [2] is used for the true style transfer. To learn the meaningful mapping between images in our sketchbook and Dali's body of work, a generator network and a discriminator network are trained jointly on the basis of the fact that the generator learns the way to generate more likely accepted images by the discriminator while the discriminator's learning to distinguish the original and generated images. A nice view of Cycle GAN architecture from [3] is shown below:





To have a better view of the progress during training, the generated images are saved after each iteration and merged into videos to show the training over time.

Process: The initial idea was to use cascaded style transfers. We saw that the provided style transfer code can take one image's style and apply it to a content image, so we hypothesized that keeping the content constant and switching to different artworks done by the same artist should essentially transfer all those features onto the same constant, providing a more complete style transfer. However, this idea did not result in what we expected.



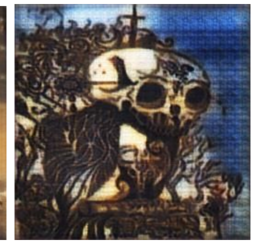
The left images show the individual style transfers and the large image shows the final result. This is definitely not representative of the style of Dali. However, it is clear from the images on the left that there are features similar in all of Dali's paintings. So, we needed to find a method to take entire bodies of work and learn on those data sets to generate art with both features.

Cycle GANs appears to cover this aspect of true style transfer. It takes two bodies of work to train on, in order to generate artwork that have features of both artists. Originally we ran the

Cycle GAN on a smaller number of epochs like 150 and 500. However, these results also had a similar problem to the cascaded style transfer. They mostly appeared to color the content image instead of completely transferring a style. In addition, the image sizes were very small. They were limited by the style dataset which have a minimum size of 400x400, while the content dataset has a minimum size of 1000x1000. Initially, the output size was 128x128, which resulted in low resolution images.

The top images are the results after 150 epochs. These have almost no features represented from Dali, instead just coloring non edges a dark color. The bottom images are the results after 500 epochs. The same problem can be seen in these. Results like these, didn't give us confidence on the effectiveness of such a system and we guessed that it would have the same problem as the cascaded style transfer with only coloring black and white content images. However, the original paper[2] showed that it is possible for a true style transfer if the net learns correctly, which is sometimes based on luck (batch randomization, random seeding). Using a higher number of epochs should result in a better chance of learning the features. In addition, the image size will be increased so that the image quality will be higher.

Result: The final results were generated after 1500 epochs with an output of 256x256. In addition there are videos showing the training over time, which highlight how the content images are formed with Dali's artistic features.

With more epochs, more of the features in Dali's paintings show on the content images. Even though Cycle GAN was essentially coloring the black and white images, it does so in an aesthetically pleasing manner. It appears that with more landscape content art, the features work better. This makes sense as Dali has an iconic landscaping style using a low horizon and stretched skyline, so it is easier to match features from an image with similar styles.

Another potential problem is the content dataset. All the images were black and white, so the majority of the features are most likely edges and shadows. This may have resulted in the coloring of the content images instead of implementing them in a Dali style, which was also seen the cascaded style transfer.

Reflection: While the idea of a true style transfer was not completely realized, the way the art was colored still looked good. The final results show that the Cycle GAN worked as well as it could with the content dataset that it was given. Some examples are the choice in colors and where the colors are used to enhance features in the content artwork.

Cycle GAN is effective, but it also has limitations. Based on the original paper and our own results, it seems that both datasets need to at least share some similar features before performing a style transfer. This technique still makes good progress into true style transfers, but we want to be able to take a content image that is completely unrelated to the style dataset and implement with that artist's style.

Even with these limitations, we have not completely exhausted all ideas with Cycle GAN. With larger datasets it is possible that the limitations can be overcome so we will continue to try by adding more content images. In the end all models are limited by data. This is especially true when trying to perform a true style transfer as artists have a limited body of work. There is only so much art someone can make with a consistent style, so in future we will need to find a model that are still effective on small datasets.

REFERENCE:

[1] Dali, Salvador. Disney. Destino. 2003. https://www.youtube.com/watch?v=rMLVqQDeY58
[2] Efros, Alexei A. Isola, Phillip. Park, Taesung. Zhu, Jun-Yan.Unpaired Image-to-Image Translation using Cycle Consistent Adversarial Networks. 2017. https://junyanz.github.io/CycleGAN/
[3] Bansal, Hardik. Rathore, Archit. Understanding and Implementing CycleGAN in TensorFlow. 2017. https://hardikbansal.github.io/CycleGANBlog/

[4] Icaro. Best Artworks of All Time: Collections of Painting of the 50 Most Influential Artists of All Time. 2019. https://www.kaggle.com/ikarus777/best-artworks-of-all-time

CODE: (This github project link)

RESULT: (Link to the online address of your results if posted somewhere like youtube, vimeo, google drive, etc. Otherwise, please just submit files through github)