

Cycle Generative Adversarial Nets for Style Transfer of Monet Paintings

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Abstract

This article aims at learning the style of the impressionist painter, Claude Monet. Since the generative adversarial model has its limitations when it comes to more complex computer vision problems, we will be using a variation of generative adversarial models, cycle consistent GAN to capture the “impression” of an artist from their surroundings. CycleGAN is an unpaired image to image translation using cycle consistent adversarial nets.

1. Introduction

The focus of this paper is to reproduce the style of Claude Monet, the influential impressionist painter in the nineteenth century. Claude Monet’s style is unique and recognizable by his short and thick strokes that capture the essence of the subject. Monet’s work is particularly interesting because of the strong logarithmic correlations within his paintings that makes it possible to generate new Monet-like images. [7] This project attempts to transfer the painter’s style into existing real-life photos. Style transfer is a computer vision technique that aims to combine two images together. In particular, given a content image (i.e. is interesting for its content) and a style image (i.e. is interesting for its style), the task is to blend them together in order to obtain as output a third image which will represent the content of the first image in the style of the second one. Therefore, we aim to learn a mapping function $G: X \rightarrow Y$ such that the distribution of $G(X)$ is inseparable from the distribution of Y using the adversarial loss (i.e. the discriminator). To further constraint the generator, we pair it with an inverse map $F: Y \rightarrow X$ and use cycle consistency loss to enforce $F(G(X)) \sim X$. [17]

2. Related Work

In **Generative Adversarial Nets (GANs)**, two models are trained simultaneously: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample is from the original data rather than generated by G [4]. The training procedure for G is to maximize the probability of D making a

mistake. Therefore, it corresponds to a 2-player minimax problem in which generator tries to “trick” the discriminator. This framework is then the core idea of many generative model applications including cycle consistent GANs. However, the simple GAN is under-constrained for style transfer problem [17]. We apply a cycle consistency loss objective to further condition GAN.

Paired Image-to-Image Translation: In some applications the aim is not to generate the image from scratch but rather, “translate” an image from a domain X , to another domain Y . This can be done by conditioning GAN to learn a dataset of paired images and the function “translating” them. This approach introduces cGAN, where the given the input, the output is conditioned by a set of constraints. The conditional GANs learn a mapping from observed data x and random noise vector z , to the output y , $G: x, z \rightarrow y$ [6]. cGANs in the context of image translation can be generalized to cover various problems. Image prediction from a map [15], future frame prediction [9], and image generation from sparse annotations are some of the examples [11]. Image-to-Image mappings are also the core idea for style transfer problem, but with GAN applied unconditionally [8].

3. Dataset

The dataset was collected from the Kaggle competition [1], a platform in which challenges are proposed and where we got the idea for this project. The dataset is composed by:

- A set of 300 Monet paintings sized 256x256 in both JPEG and TFRecord format;
- A set of 7028 photos sized 256x256 in both JPEG and TFRecord format.

We used the Monet paintings to train our model so that it could learn Monet style and imitate it. Then we applied the learned style over the set of real photos in order to generate new images that could resemble real paintings. The size of all the images was already the right one for the computation, hence no resizing was needed.

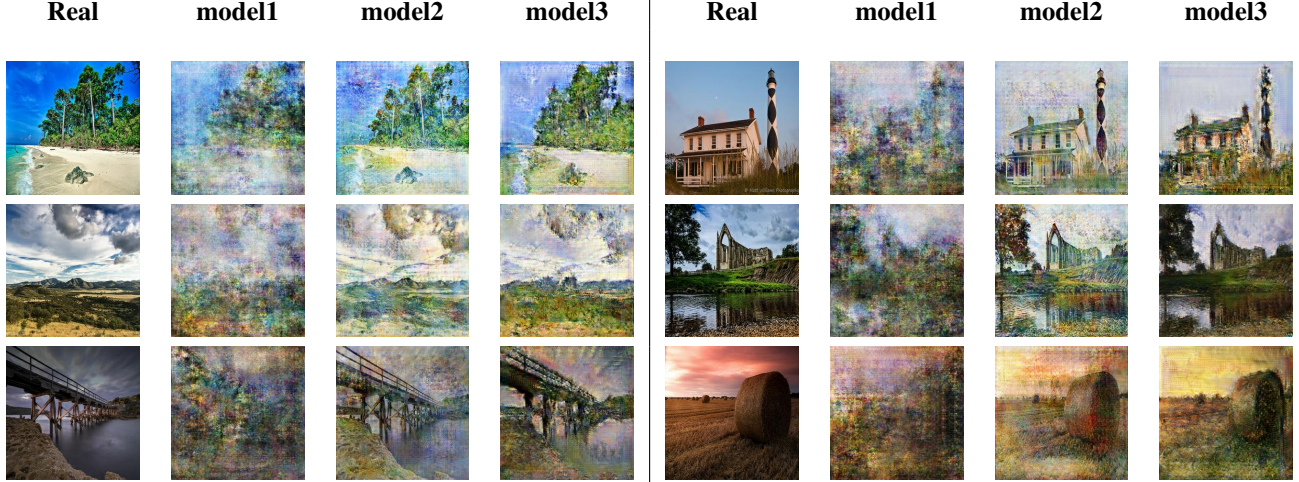


Table 1. **Results.** Comparison between the generated images from different models.

4. Method

In our problem given the real-life images $x_i \in X$ and monet paintings $x_i \in Y$ we aim to learn mapping functions between the two domains X and Y , denoting the data distribution as $x \sim p_{data}(x)$ and $y \sim p_{data}(y)$. Our model captures the mapping between domains using two conditionally generative [6] models $G: X \rightarrow Y$ and $F: Y \rightarrow X$. Additionally, we also include two adversarial discriminators D_X and D_Y where task of D_X is to discriminate between $\{x\}$ and translated images $\{F(y)\}$. Similarly, D_Y aims to distinguish between $\{y\}$ and $\{G(x)\}$ [17]. The objective of our work is to minimize two losses: *adversarial loss* [4] which helps to close the gap between the data distribution of target domain and the generated images; and *cycle consistency loss* to keep the results of the two mapping functions consistent.

4.1. Adversarial Loss

To learn the distribution of $x \sim p_{data}(x)$, we first define a prior on input noise variables $p_z(z)$ and define a mapping $G: z \rightarrow x$ that can be trained using a convolutional neural network [10]. We also define a discriminator D (also trained using a CNN) that instead of a single scalar [4], outputs an image with decreased dimensionality where pixels that are more likely to be in data distribution $p_{data}(x)$ have higher values. We train both models simultaneously in a two-player minimax approach that can be expressed as:

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

4.2. Cycle Consistency Loss

In theory, adversarial training can give prominent results. However, in the unsupervised learning environment

of GANs, where the two datasets X and Y are not paired and their cardinality can be uneven, the learning process can fail as a network can map the same set of input images to any random permutation of images in the target domain, where any of the learned mappings can induce an output distribution that matches the target distribution [17]. Therefore, adversarial losses alone cannot guarantee that the desired output is given by the learned function. To further constraint the mapping function, we introduce cycle consistency loss. For each sample x from domain X , the cycle should bring x to the original image. We denote *forward cycle consistency* as $x \rightarrow G(x) \rightarrow F(G(x)) \approx x$. Similarly, for each y in domain Y , *backward cycle consistency* $y \rightarrow F(y) \rightarrow G(F(y)) \approx y$ is also satisfied [17]. The objective is then defined as:

$$\mathcal{L}_{cyc}(G, F) = \mathbb{E}_{x \sim p_{data}(x)} [\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{data}(y)} [\|G(F(y)) - y\|_1] \quad (2)$$

4.3. Implementation

Network Architecture We used a *U-net CNN* for our generative network. A *U-net* is a fully connected convolutional neural network that was first introduced for biomedical image segmentation [13]. We downsample our input data (i.e. decrease the dimensions) by a convolutional layer with 7×7 filter. The motive behind choosing a bigger filter was to capture general features in the images. Downsampling then is followed by two more 3×3 filters and 2-strides. We applied several convolutional layers, obtaining a deeper image transformation. To obtain the final results, we up-sample (i.e. increase dimensions) using two convolutional layers with $\frac{1}{2}$ strides. We also applied instance normalization [14] to all layers and established the skip connections in the *U-net*. For the discriminator we used PatchGANs which aims to classify if the $n \times n$ patch of a given image is real or fake [6].

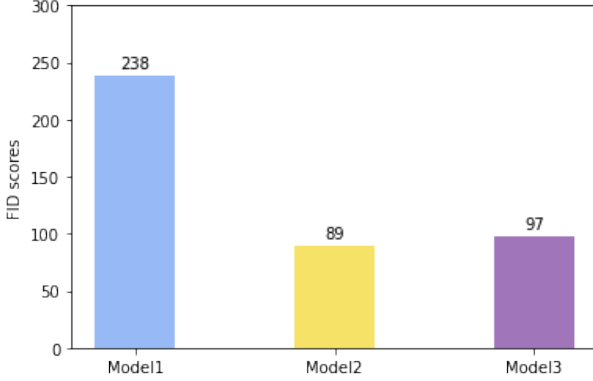


Figure 1. **FID**. Results of FID evaluated over the different models that we experimented.

5. Experiments

The core of all of our experiments follows the explained objective. However, different model implementations have given us dramatically different results. Out of all these experiments, we selected three main models for comparison purposes. The first model (i.e. `model1`) is a naive approach in generative models. It has 5 downsampling and 5 upsampling layers with filter size 8×8 and no intermediate layers. In downsampling, we used *maxpooling* with 2-stride and the activation *leakyReLU*. This model has a high level of noise and the results obtained were not satisfactory. The second model (`model2`) was inspired by the Kaggle competition suggested framework [1]. It has a smaller filter size (4×4) and more layer of both downsampling and upsampling such that it reaches the pixel-sized dimensionality. It uses dropout in three of the upsampling layers and the activation function is *leakyReLU*. This model has the benefit of having more precision as a generator and in some cases generates prominent results. For the third model, (`model3`) we removed the dropout and, instead of reducing the size to 1 pixel in downsampling, we stopped at size 64×64 and added several “transforming” blocks with no size reduction. Although this model has a noticeable degree of noise in the generated images, it is more “monet-esque” to the eyes of the viewers and it contains the brushing style of the painter considerably more than the second model.

5.1. Evaluation metrics

In order to evaluate the results of our work we looked for some metrics that could help us in this task [2]. In order to apply them we used already existing code on GitHub [16].

Fréchet Inception Distance (FID) Introduced by Heusel *et al.* [5], FID measures the distance between the feature vector of the generated paintings and the feature vector of the real paintings. Therefore, a lower FID score represents a better performance of the generator since the

images it creates are similar to the real ones. The formula to calculate the FID score is the following:

$$FID(r, g) = \|\mu_r - \mu_g\|_2^2 + Tr(\sum_r + \sum_g - 2(\sum_r \sum_g)^{\frac{1}{2}}) \quad (3)$$

where (μ_r, \sum_r) is the multivariate normal distribution estimated from a specific layer of Inception Net features for real images and (μ_g, \sum_g) is the multivariate normal distribution estimated from a specific layer of Inception Net features for generated images.

Number of statistically-Different Bins (NDB) Introduced by Richardson and Weiss [12], this metric is applied to the image pixels and, unlike FID, does not rely on a representation of those images. This evaluation method is based on the observation that given two set of samples originated from the same distribution, the number of samples that falls into a given bin should be the same up to sampling noise. More formally, if $I_B(s)$ is an indicator function for bin B , i.e. $I_B(s) = 1$ if the sample s falls into bin B and $I_B(s) = 0$ otherwise, and given s_i^p and s_j^q respectively N_p samples from distribution p and N_q samples from distribution q , then if $p = q$ then we expect to be $\frac{1}{N_p} \sum_i I_B(s_i^p) \approx \frac{1}{N_q} \sum_j I_B(s_j^q)$. When this is not true for a given bin, they are said to be *statistically different*. The test is performed on all bins and then the number of statistically-different bins divided by the number of bins is the final result. We used this metric in order to measure the diversity of the generated images and to understand if the model was encountering mode collapse by generating similar images.

Jensen-Shannon Divergence (JSD) As reported in [3], JSD is a smoothed and simmetrized version of the Kullback divergence and measures the divergence between two probability distributions p and q . It is defined as:

$$D_{JS}(p||q) = \frac{1}{2} D_{KL}(p||\frac{p+q}{2}) + \frac{1}{2} D_{KL}(q||\frac{p+q}{2}) \quad (4)$$

This can be used in order to understand the diversity of the generated in a slightly different way with respect to NDB.

6. Conclusions

We applied the three models we implemented to the original photos and, as it’s possible to see in Table [1], the results differs a lot from one model to the other. From a visual point of view, the first model we proposed generates output with a huge degree of noise. Hence the result is a set of images in which is impossible to distinguish any element of the original photos. `Model2` on the other hand is able to generate images that better represent the content of the original photos and also applies some of Monet style. With respect to `model1`, with `model2` it is possible to appreciate a relevant improvement. Finally, the third model

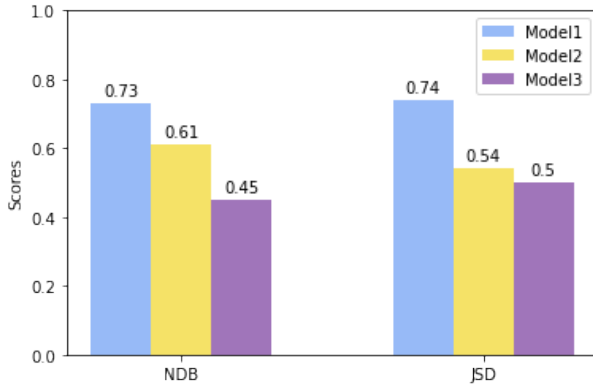


Figure 2. **NDB and JSD.** Results of NDB and JSD evaluated over the different models that we experimented.

enhance a bit more the painter style since it's possible to appreciate some hint of strokes and brushing. The issue in `model3` is that a certain degree of noise is introduced again but in general seems to create images that better imitate the original paintings. Also the measurement performed by the metrics we applied seems to confirm what we were able to visually appreciate: the quality of the image results to be better with `model2` since it presents a lower level of noise, but from a diversity point of view, `model3` performed in a better way.

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