Style Transfer Generator for Movie Posters

Theme & Genre Transfer

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ABSTRACT

This paper documents the use of a convolutional neural network, TensorFlow's Style Transfer, to create novel outputs of movie posters blended with genre-specific style images. In this paper, we will discuss the process of creating the style inputs, gathering movie posters, and what we learned while training the network (i.e., the best input and content images). We will also examine the results to see how different styles compare to the original movie posters and consider whether our approach was successful.

CCS CONCEPTS

• Network Algorithm • Arts and Humanities

KEYWORDS

Style generator, neural style transfer, neural network, machine learning

ACM Reference format:

Bryan Chao and Alison Crosby. 2021. Style Transfer Generator for Movie Posters.

1 INTRODUCTION

For this project we used a Neural Style Transfer machine learning algorithm from TensorFlow to create reimagined movie posters based on styles from various movies genres. In general, our stylizing pipeline consisted of training filter models through a pre-trained VGG16 loss network to then apply it, to content images, generating stylized movie posters. (More details discussed under section 3) The process included creating a styled reference image based on themes from movies genres (Cyberpunk, Drama, Fantasy, Horror, Sci-Fi, Superhero) and blending these filter images with content images consisting of a wide variety of movie posters.

Before using the algorithm, we first had to analyze and deeply consider the specific style and design aspects of movie posters for specific genres. Examples of these aspects include colors, saturation, layout, patterns, which were distinct across genres. By examining such genre aspects and determining which themes were consistent in films, we could adjust the aesthetics of our illustrative designs, which we trained the filter model. In turn, this allowed us to produce dedicated style filters, which could then be applied to transfer certain thematic visual elements to various existing film posters.

An example of determining thematic visual aspects that we aimed to train our filter models with is included below:

Cyberpunk movie posters have high color saturation values and contain a high amount of blue, purple, and pink colors while horror movie posters are very dark or black and white with often a bright contrast of red. These different styles also convey specific themes present in the actual movie. We extracted the details of such stylistic themes and incorporated them into the reference filter image that we illustrated to train specific genre filter models. For instance, the cyberpunk reference image for model training would, in this case, include high color saturation values, high amounts of blue, purple, and pink, etc. On the other hand, the reference filter for the horror genre had a darker and more ominous stylistic approach.

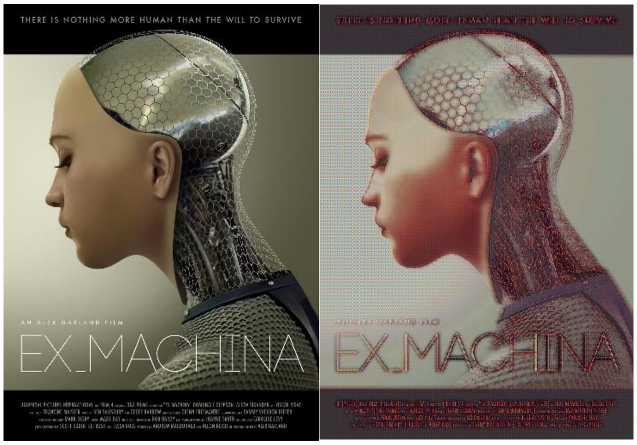

Figure 1: Before & After Filter - Thematic Contrast

Overall, we established that the success of our project would be determined by how closely the applied filter would change an observer's impression of a film poster to interpret the intended genre. Our motivation for this project developed from an interest in seeing how new styles can change the overall tone of a movie poster and whether it would change our overall expectations and interpretations of the movie. This is an important component of design as understanding what aspects (colors, saturation, etcetera) are associated with specific themes and emotions can greatly affect one's work- movie posters, video games, general user interface layouts.

2 RELATED WORK

We based our project from a fast style transfer repository found on GitHub by Qian Ge [1]. The Fast Style Transfer is a module found on the machine learning platform, TensorFlow. The module was based of the GitHub repository, magenta, Arbitrary Image Stylization code by Sayak Paul [2] as well as a paper by Ghiasi et al [3]. Ghiasi et al. purpose the model of combining Gatsy et al.'s [4] work on creating a neural algorithm "that creates artistic images of high perceptual quality" with fast style transfer networks. This allows for the real time stylization of artwork by using any content and style imaging pairs.

3 APPROACH

The process of generating stylized film posters begins with illustrating or generating a filter image to use as reference to train the filter model. After specifying in our code, the style and content weight that the following process should adhere to, this reference image proceeds into the generative pipeline. The reference image enters an image transform net that down samples the image via two convolutional layers with stride 2. It is then computed through a pretrained loss network called "VGG16" network, where it runs against a general image of the originally developer's pet cat. This training phase of the pipeline continuously iterates on applying the reference filter image.

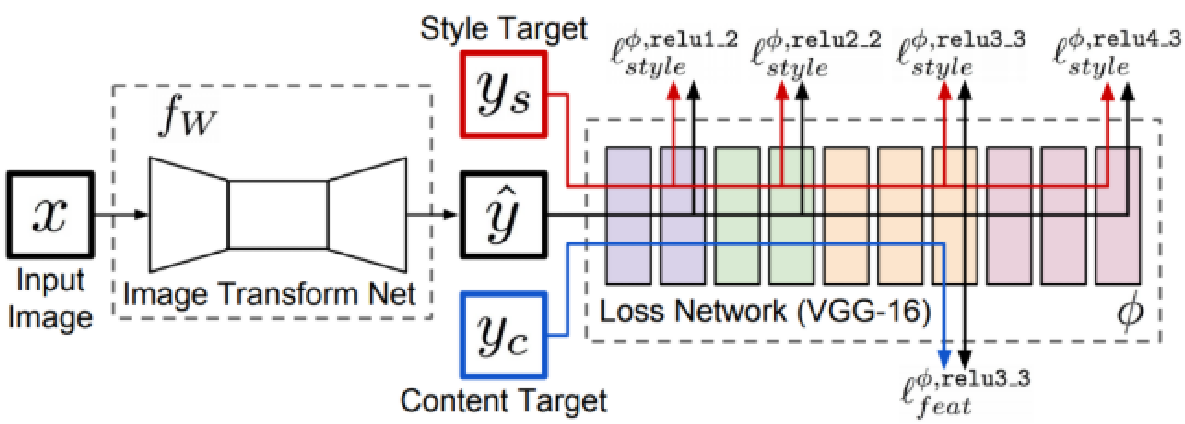

Figure 2: Illustration of the filter model training process

(style target) and the generic image (content target) to minimize the amount of data loss for both sources. With each iteration, the original input image is upsampled by two transpose convolutional layers with stride ½ and undergoes total variation regularization (de-noising).

The resulting filter model that becomes refined by the algorithm over iterations of training, is then plugged back into the code to be used in generating stylized versions of our specified film posters.

3.1 REFERENCE FILTER IMAGES FOR TRAINING

The filter image that we use as reference to train the style model consists of specific filter themes. To create filter themes, we analyzed movie posters of like genres to establish a consistent style. For one of our superhero themes, we created an image via Photoshop and Adobe Illustrator that had highly saturated bursts of colors throughout the image. This was so the superhero filter would increase the color saturation and color layout of our various non-superhero movies. As a contrast, for our horror filter image, we used a back background with red splattered blobs (blood). This Filter image increased the darkness of the movie posters and highlighted outlines as red.

As briefly mentioned in the introduction, we recognized that the cyberpunk genre aesthetic included high color saturation and dominant neon colors. See figure 3.

Figure 3: Existing cyberpunk themed film posters that we referenced in our filter designs.

Using the above existing cyberpunk film posters as reference, we designed and found reference images that shared similar aesthetics.

Regarding format compatibility and optimization, all images that we use for training must be RGB (24 color bit-depth) as HDR (32 color bit-depth) is not compatible with our code. Furthermore, filter images should generally be 500kb or less in file size, and relatively medium – small in resolution to maintain faster training speed. Larger file sized and higher resolution filter images can take exponentially longer to iterate and train.

After considering the thematic elements of a specific film genre as well as the compatibility requirements, our reference image is created. See figure 4.

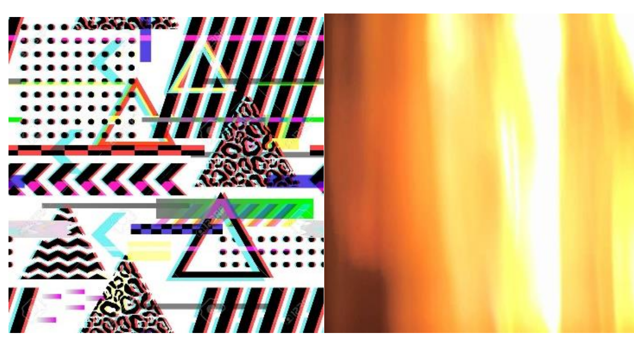

Figure 4: Example filter images

3.2 TRAINING THE FILTER MODELS & GENERATING IMAGES

As briefly mentioned in 3.0, in the training phase, the desired style weight, content weight, and compatible filter image is referenced before running "—train". These 3 variables in addition to the number of iterations we allow the model to train for are the 4 main factors that determine our outcome filter model. A higher style weight will prioritize preserving data from the reference filter image over the content image. Vice Versa.

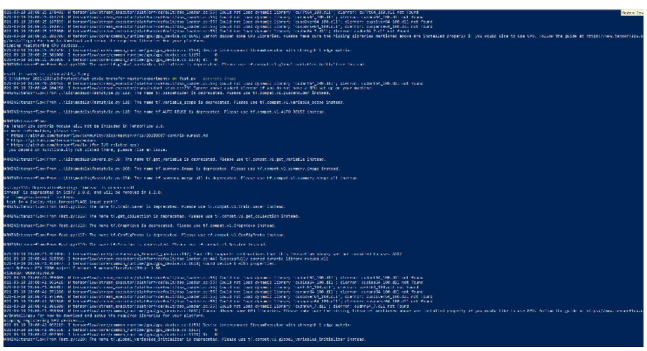

Figure 5: Example feedback in CMD of training iterations.

In the generative phase, the trained filter, which consists of three files per iteration, a .data, .meta, and .index, is referenced in the code and applied to our desired film poster. The generative aspect of the project is much faster in terms of processing time when compared to the training phase. This allows numerous posters to quickly inherit the style of the filter models that we created.

In terms of compatibility and optimization, we found that film posters with high resolution and high data size (no compression) facilitated the best outcome aesthetic. Furthermore, the color depth of the posters, like the reference filter images, needs to be at a 24-color bit-depth value and not 32.

All in all, the structure of our style transfer algorithm serves to optimize the amount of processing required per poster. By splitting up the training phase from the generative phase we only needed to train a style/ theme once, to then be able to apply it to many posters. On the other hand, if the training and generative phase were not separated, each iteration of a new poster would require a much higher processing time. Nevertheless, the main product of this project is not only the stylized poster but also the trained model that can be reused.

4 RESULTS

Overall, we found several successful style transfers that effectively changed the tone of movie posters. Particularly for the horror style transfer, we found the filter image to greatly increase the darkness of the posters and create an unsettling mood with the deep red highlights it incorporated. As we can see in Figure 6, the animated comedy, Despicable Me, turns into a terrifying landscape of zombie-like minions.

Figure 6: Despicable Me movie poster before/after with the horror-style filter image.

The effects of the filter images were very dependent on the content images. We found more success in filter images that had contrasting colors and more specifically, patterns. As we can see in Figure 7, the effects of the superhero style transfer were more subtle and did not change the overall tone as drastically. It had a variation of colorful elements but was not very contrasting nor did it have any defining patterns.

Figure 7: From left to right: Superhero filter image, original Martian content image, generated result.

This project provided us with interesting insights into how posters are designed to convey specific themes as well as a deeper understanding of how some tweaks in colors, saturations, etcetera can warp the tone of an image.

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