Sam Muller (sjm2221)

Da Yeon Lee (dl2950)

Project Proposal

I. Project Statement

For our final project, we are going to explore artistic style transfer and color transfer. Our goal is to create a network that can perform arbitrary artistic style transfer given some input photograph (model for content) and input painting (model for style). Once this transfer is achieved, the resulting image will have the color palette of the style input (painting). However, we are going to further manipulate this output such that the color palette more closely matches that of the original content image. In some cases, color transfer is not desirable for a stylized image–e.g. in the case where the color palette is crucial to the given style. Either way, the original stylized image and the color corrected output will be obtained for observation. For our inputs, we will use ImageNet for the content images we would like to transform and the Kaggle *Painters by Numbers* dataset for paintings to use for style. It is also possible to use the *Describable Textures Dataset* to represent “styles”.

II. Method

We will follow the method laid out in [1], that is, we will construct two neural networks– one being the style transfer network, and the other being the style predictor. The predictor will take an arbitrary style and compute a vector that represents the style (i.e. the low level features of the style image). This vector will then be passed into the style transfer network with some content image, and the result will be a new image created from minimizing content loss and style loss.

Once we compute this output image, we will use the technique explored in [2] to recalibrate the colors of the style transfer output to that of the original content image. This is done by converting the two images into CIELab color space, then separating each of the color channels. A histogram is then created for each channel of the respective images at different scales (to capture finer or coarser details) and the stylized image’s histogram is reshaped using the content image as reference. After doing this for all three channels and then converting back to RGB, the stylized image should have the same colors as the original content image.

III. Evaluation

Evaluation can be done both objectively and subjectively. Objectively, for the artistic style transfer portion of the system, we can compute the style and content loss and evaluate them. We can also evaluate the results ourselves simply by looking at the inputs and deciding if the output matches what would be expected. Similarly, for the color transfer portion a statistical analysis of the histograms can be performed and also a visual assessment of similarity between color palettes.

IV. Division of Tasks

Both partners will work together to complete the tasks, dividing work as it comes along. Because the color transfer mostly depends on the results of the style transfer, working on the two simultaneously could end up being a wasted effort on the color transfer front. Because of this, we are going to work out a schedule where we can get together to devote time to the project, helping each other with implementing each part. We will start with the style transfer network(s), then, once that is functioning satisfactorily, we will move on to the color transfer.

V. Sources

[1] Ghiasi, G., Lee H., Kudlur M., Dumoulin V., Shlens J.: Exploring the structure of a real-time, arbitrary neural artistic stylization network. Aug. 2017. https://arxiv.org/pdf/1705.06830.pdf

[2] Pouli T., Reinhard E.: Progressive color transfer for images of arbitrary dynamic range. Computers & Graphics 35, 1 (2011), 67–80. http://erikreinhard.com/papers/pouli_cag2010.pdf