# EECE 7370 Final Project Proposal

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**Proposed Title: GAN-based image style migration**

**Background:**
Recently, learning-based style transfer methods have become the common image-to-image translation methods. These methods can copy the style of the reference image (style image) into the input image(content image) to generate a new image which combines the content of the content image with the style of the style image. These methods primarily use the correlation between deep features and an optimization-based method to encode the visual style of an image.

A generative adversarial network is a class of machine learning frameworks. Given a training set, this technique learns to generate new data with the same statistics as the training set. Generative adversarial networks (GANs) have been applied for style transfer and achieved great results. Many researchers have proposed many GAN-based style transfer methods. So we decided to exploit GANs on style transfer and elevate its performance.

**Motivation:**
Transforming photos of real-world scenes into other style images, such as anime, is a meaningful and challenging task in terms of computer vision and artistic style transfer. Recently, generative adversarial networks (GANs) have emerged as an effective approach in style transfer by adversarial training the generator to synthesize convincing counterfeits. We propose the combination of neural style transfer and generative adversarial network (GAN) to accomplish this task. Specifically, we provide a reference style image and convert any other style of arbitrary images to it as well as keeping the content of the images.

**Objectives:**

- Comparing the model training speed of 10 typical GAN methods
- Comparing the model training result of 10 typical GAN methods
- Proposing a new GAN framework
- Forecasting the application prospects of GAN

**Methods:**

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

Training models are based on the function above. D is the discriminator network and G is the generator network. On one hand, the generator network uses the discriminator as a loss function and updates its parameters to generate more realistic data. On the other hand, the discriminator network updates its parameters to identify fake data from real data. The same training process is applied to different GAN models. Eventually, we use the FID evaluation coefficient as an evaluation metric for our results. The FID is computed by calculating the Fréchet distance between the two Gaussians fitted to the Inception network feature representation. The formula is as follows:

$$FID = \left\|\mu_r - \mu_g\right\|^2 + Tr(\Sigma_r + \Sigma_g) - 2(\Sigma_r\Sigma_g)^{1/2}$$

**Dataset:**

We will use images from Kaggle and CycleGAN to train and test the neural networks.

- Kaggle I'm Something of a Painter Myself
  (https://www.kaggle.com/competitions/gan-getting-started/data)
- CycleGAN
  (https://github.com/junyanz/CycleGAN)

**Experimental Environment:**

- Google Cloud

**Reference:**


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