Final Project Progress Report

Definitions

Team name: ***Behind AI Artist***

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Note: Once one person uploads the report to Gradescope, please add all other team members to the submission within the Gradescope interface (top right on your submission).

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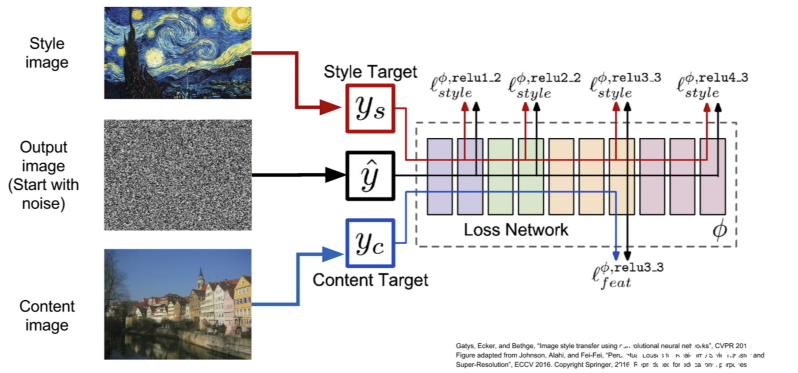
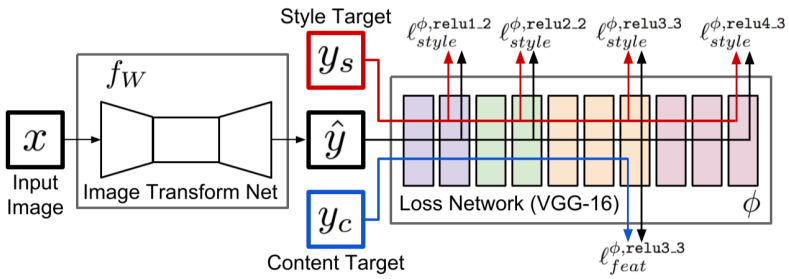
Progress Report 1

Neural style transfer (NST) is a method that we could apply the style from the style image to the content image. Ever since the seminal work of Gatys et al., different improvements have been proposed in the following years. In our project, we have selected several typical NST models to compare with each other on results generated from the same content and style:

- **Basic optimization-based model** (A Neural Algorithm of Artistic Style): proposed by Gatys et al. It only requires one content image and one style image as input for style transfer. With a pretrained VGG16 as backbone whose parameters are frozen, it calculates the content loss as well as style loss from feature maps and use back-propagation to update the output image. The biggest weakness for this method is slowness as 200-300 iterations are required before reaching some good result.

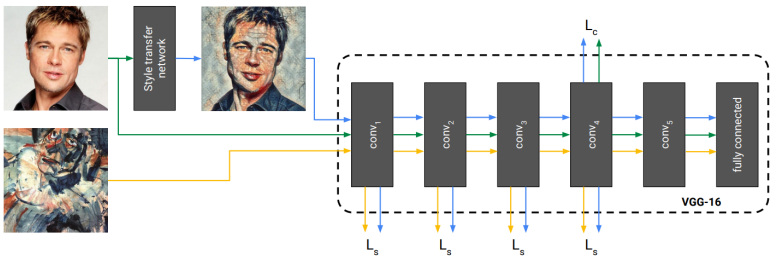


- **Fast style transfer** (Perceptual Losses for Real-Time Style Transfer and Super-Resolution): proposed by Johnson et al. Based upon the model of Gatys et al., they added an feed-forward net to fit the process of style transfer. After training, the

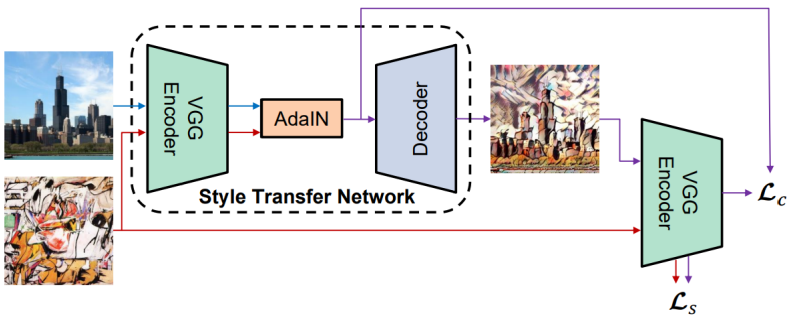


content image can be stylized easily using a single forward pass. It performs 1000 times faster than Gatys et al. in the style transfer process. However, for every style, a new model has to be trained.

- **One network with multiple styles** (A Learned Representation for Artistic Style): proposed by Dumoulin et al. They introduce a *conditional instance normalization*, which allows the model to learn multiple styles. Basically, the model reduces each style image into a point in an embedding space while for convolutional layers the parameters are kept fixed through training.



- **Arbitrary style in one model** (Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization): proposed by Huang et al. They introduce *adaptive instance normalization* that aligns the mean and variance of the content features with those of the style features, which enables arbitrary style transfer in real-time with a single model.



Results and Discussion

For test purpose, we choose Starry Night by Vincent Van Gogh, The Scream by Edvard Munch and Head of Clown by Georges Rouault as our style images. An beautiful image taken at the main green acts as our content image. Below are stylized images using different model respectively.

Figure 1: *Top Left*: a image taken at Main Green serving as the content image; *Top Right*: Starry Night by Vincent Van Gogh as Style 1 image; *Bottom-Left*: The Scream by Edvard Munch as Style 2 image; *Bottom Right*: Head of Clown by Georges Rouault as Style 3 image.

Figure 2: Results for Style 1 (Starry Night). *Top Left*: basic optimization-based; *Top Right*: fast-style-transfer; *Bottom-Left*: One network, multiple styles: image-stylization; *Bottom Right*: AdaIN

Figure 3: Results for Style 2 (Scream). *Top Left*: basic optimization-based; *Top Right*: fast-style-transfer; *Bottom-Left*: One network, multiple styles: image-stylization; *Bottom Right*: AdaIN

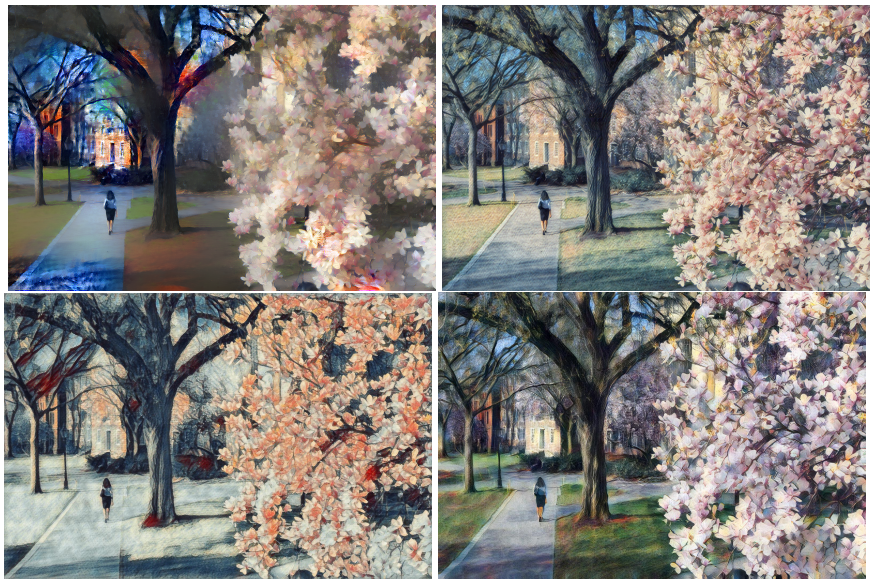


Figure 4: Results for Style 3 (Head of a Clown). *Top Left*: basic optimization-based; *Top Right*: fast-style-transfer; *Bottom-Left*: One network, multiple styles: image-stylization; *Bottom Right*: AdaIN

Future Directions

Since we have the comparison results from different models, we want to implement corresponding applications if time permits, such as website deployment or an iOS application. We would also appreciate it if TAs can give us any suggestions for improvements.