# Transfer Learning - Creating Art with Deep Neural Networks

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## 1. Project goal

In our project, we will look at modelling style transfer from one set of images to another image by modeling the problem as an optimization problem. Style transfer is the process by which a target image is recomposed in the style of a reference image. We will look at how different CNNs and optimization methods fare in performing image style transfer.

## 2. Data set

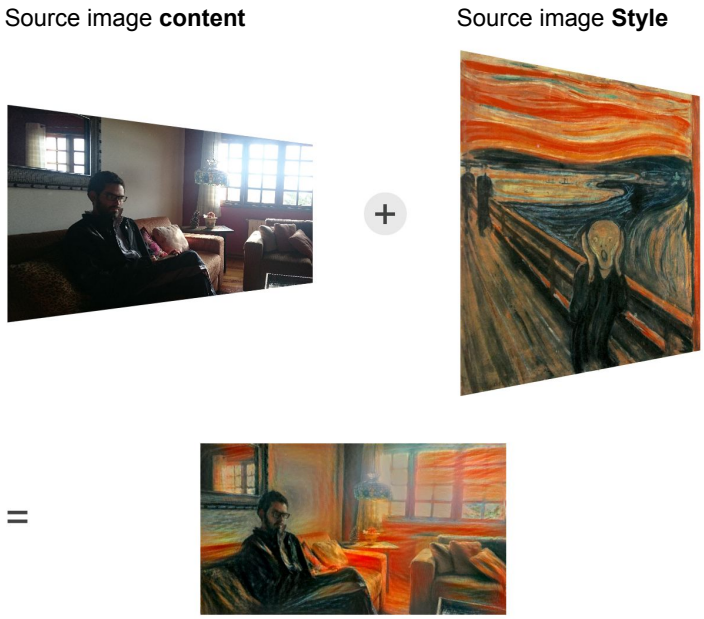
We will use a variety of classical paintings for our reference images - a subset of the Stanford Mobile Visual Search dataset and images of other famous paintings. We will generate / search for the base images for style transfer using Google Image Search.

## 3. Background

Transfer learning is a sub-field of machine learning where knowledge learned from solving one specific problem is stored and later on that knowledge is used to solve some other problem. For example, using CNN knowledge to learn to predict the cars can also be used to predict trucks. The power of CNNs to generalize visual traits comes from its ability to learn information hierarchically - each layer within a CNN focuses only at a specific level of detail.

In the field of arts, transfer learning has been used nowadays to transform pictures into piece of art. Similar to the use of filters, these machine learning algorithms uses deep neural networks to extract hierarchical features from the images. The extracted features are then transformed to obtain the content and style of the image.

*Fig 1: Image representation of transfer learning for images*[1]




Style transfer then becomes an optimization problem where the goal is minimize the stylistic differences while keeping content loss to a minimum [1]. The approach is to use a loss function which penalizes the extreme effects of style and content. Basically, the cost function imposes large penalties if the synthesized image content is different from the original image content or if the the styles of the reference image and the synthesized image are too different.

## 4. Methodology

We will be working with different loss functions and different combinations of style and content factors to come up with multiple version of our synthesized images.

## 5. Project Timeline/Plan

| | **March 16-31** | **April 1-15** | **April 16-Finish** |
|---|---|---|---|
| **Rishab** | Data Cleaning/ Aggregation and transformations<br>Hands on with TensorFlow and Keras | Feature extraction with different prebuilt CNNs<br>Extensions from one reference image to collection of images | Testing / Report<br>Bug fixing |
| **Vineeth** | Literature review<br>Hands on with TensorFlow and Keras | Optimization parameter tuning<br>Extensions from one reference image to collection of images | Testing / Report<br>Bug fixing |

[1] https://blog.paperspace.com/art-with-neural-networks/

## 6. References

[1] Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "A neural algorithm of artistic style." *arXiv preprint arXiv:1508.06576* (2015).