

# Artistic style classification and style transfer

## Deep Learning Project Proposal

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### ABSTRACT

Our goal is to be able to classify an artistic style of a classical painting (e.g. cubism), and then apply style transfer and measure the tradeoff between the preservation of the artistic style and the cohesion of the original image, e.g. are the objects in the content image still recognizable?

## 1 INTRODUCTION

Neural style transfer [3] was introduced by Gatys et al. and studied in class and in a course assignment. Gatys et al. mentioned that one way to recognize artistic style is to use Gram matrices of the convolution layers.

Gram matrices are proven to be useful in the calculation of cost function for the style transfer, however, are they also useful in the *classification* of the style? How does one use a neural network in order to classify an artistic style? We plan to research and experiment on that topic in phase 1 of our project.

Next we plan to use the technique found in phase 1 in order to develop a style transfer hyper parameter tuning technique. When applying style transfer one needs to tune the weights of the each loss function, the style loss and the content loss. There is a tradeoff between the two, if too much style is preserved, objects in the content photo may not be recognizable. If too much content is preserved, the style will not be noticeable. Is there an automated way of tuning these two weights such that for a given pair of content and style photos a non expert would be able to tune these in an intuitive way? We plan to research and develop such hyper tuning technique in phase 2 of our project.

## 2 RELATED WORK

Multiple ways had been suggested to classify an artistic style.

Johnson in [5] suggested to use a neural network to classify an artistic style using Gram matrices by extracting features from the matrices and classifying then

using either a Linear Classifier or a Random Forest classifier.

Bar et al. in [1], which predates Gatys et al. developed PiCodes, a sophisticated method for feature extraction from images using both classic computer vision techniques as well as deep CNNs.

Karayev et al. in [6] compare multiple techniques of style recognition (of photos) to come up with a conclusion that Deep CNNs typically result in the best results.

## 3 METHOD

We plan to start phase 1 by utilizing a pre-trained CNN on object detection, we will test several such available pre-trained networks, such as VGG16 [7], or ResNet50 [4] and from them extract Gram matrices from each layer to be used as features for classification. We will use a simple MLP classifier. Using these matrices and the artistic style classification from WikiArt <sup>1</sup> we will evaluate the performance and continue to phase 2 if good enough or improve the classifier if not. We consider 0.75 as good enough for the top 1 accuracy.

As a stretch goal we would also like to try to use the same technique to classify the artist, not just the style; after some research we've made this seems to be a more challenging task.

Next we will move to phase 2 in which we systematically apply style transfer to a pair of content and style images and measure the tradeoff between the preservation of the artistic style and the cohesion of the original image. We measure the preservation of the style using the method from phase 1, e.g. is the style image still correctly classified? And we will use classification accuracy before application of style and after application of style transfer in order to test the preservation of the content.

Eventually we will display a curve, similar to AUC curve, which for any given pair of content and style images presenting the tradeoff between the preservation of the artistic style and content cohesion.

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<sup>1</sup><https://www.wikiart.org/>

## 4 DATASET

For the artistic style classification we will use the WikiArt dataset. We will use images from the same dataset for style transfer. A ready to download version of the dataset is available at <https://www.kaggle.com/c/painter-by-numbers/data> as well as at <https://archive.org/details/wikiart-dataset> and we will test and decide which source is better.

For the content images of phase 2 we will test several available sources, we would like for this dataset to be of high enough resolution (so ImageNet may not be a good choice), one option is to use Animal Faces-HQ, produced by [2].

## 5 CONCLUSION

We look forward to starting to work on this project and discover ways to classify artistic style and then use this result in order to automatically tune the weights parameters of the style transfer algorithm.

## REFERENCES

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