

Automated Art Comparison Using Neural Networks

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Introduction

In the Internet Age, the presence of digitized fine art galleries has risen steadily, bringing unique masterpieces to the fingertips of everyone with a network connection. Simultaneously, machine learning has broken new ground in the realm of image classification and object recognition. Some of these techniques have been applied to online art collections in order to provide large-scale classifications of art based on style and genre [1]. However, we believe there are both features and learning techniques that have gone unexplored. Furthermore, our goal is not to classify individual art pieces; the goal of our project is to compare two paintings and determine their similarity. Ultimately, we hope to create an automated method of determining whether any two paintings share the same artist, genre, or style. This type of system can be used to determine artistic influences and relationships, as well as provide a recommendation system based on similarity.

Related Work

Saleh and Elgammal tackled the problem of predicting a painting's artist, genre, and style using a similarly labeled dataset to ours [1]. In this study, they applied metric learning to classify individual pieces of art using features obtained by unsupervised learning, and features that represented which objects were in an image. In a different study, Gatys et al. trained a convolutional neural network to perform a content invariant style transformation on an input image [2]. In other words, the neural network was trained to learn a style from one painting, and then transformed a different image to reflect the style the neural network had learned. This worked remarkably well, which demonstrates the efficacy of neural networks in more abstract feature recognition. Ivanova et al. addressed a similar art classification problem, but did not use machine learning methods [3]. The features they extracted consisted of MPEG 7 descriptors that were quantized in a tiled fashion across the image.

Data

The training and test sets for this project are labeled image datasets from the "Painter by Numbers" Kaggle competition [4]. This includes over 10 gigabytes of image files, ranging from well-known art to paintings submitted by anonymous artists. In addition, we are supplied a metadata file that includes the artist name, painting title, style, genre, and date the work was completed.

Problem

The goal of this project is to create a system that, when given two paintings, is able to determine whether the two paintings were:

1. created by the same artist,
2. painted in the same style,
3. painted of the same genre.

Specifically, the input will be a collection of image files, and a CSV file with image filename pairings. The output will be three binary vector, with each element corresponding to one

comparison of two paintings, i.e. one row in the input CSV. Additionally, we hope to return a “similarity” score for each pair, if the model allows. This would aid in a recommendation system and in uncovering relationships between artists, styles, and genres.

Methods

Preprocessing: We will first preprocess our data set to extract useful model features from the paintings. For this, we will experiment with a variety of digital image processing techniques, including L*a*b* color histogram, GIST, graph-based visual saliency, Meta-class binary features, deep convolutional neural net, content classifiers, HOG2x2, SSIM [5]. Example features include general gradients, prominence of areas with fixation potential, and image texture. Since there is a wide range of possible features to use, we plan to determine the most relevant features using principal component analysis (PCA).

Model: Because of the clear differences in the categories of artist, style, and genre, we envision our automated system will have a different model that addresses each of our three goals. From the successful work of Gatys et al. [2], we believe that a deep neural network will be a useful model for style. We also plan to test a random forest model

Baseline: For our baseline model, we reduced each image to 8 values: the mean and variance of the entire image and RGB channels individually. We then found the absolute sum of the difference between the 8 values for the images. Sums below a threshold (calculated by averaging the mean positive and negative comparisons) are categorized as by the same artist/genre/style. The results are shown in Table 1.

	<i>Genre</i>	<i>Style</i>	<i>Artist</i>
<i>Sensitivity (TPR)</i>	.618	.518	.538
<i>Specificity (TNR)</i>	.533	.557	.726
<i>Precision (PPV)</i>	.103	.042	.008

Table 1: results of baseline predictor in genre, style, and artist comparison

Oracle: The oracle for our problem would be an art aficionado with access to a database of all noteworthy art. The oracle will be able to categorize by genre and style with 100% accuracy, but won’t be perfectly accurate at identifying paintings by the same artist, since the database includes art by unknown artists.

References

- [1] Saleh, B. and Elgammal, A. “Large-scale Classification of Fine-Art Paintings: Learning The Right Metric on The Right Feature.” arXiv preprint arXiv:1505.00855v1 (2015)
- [2] Gatys, L et al. “A Neural Algorithm of Artistic Style.” arXiv preprint arXiv:1508.06576v2 (2015)
- [3] Ivanova, K. et al. “Features for Art Painting Classification based on Vector Quantization of MPEG-7 Descriptors.” ICDEM 2010. *Data Engineering and Management*, Springer (2010)
- [4] URL <https://www.kaggle.com/c/painter-by-numbers>
- [5] Karayev, Sergey, et al. “Recognizing image style.” arXiv preprint arXiv:1311.3715 (2013)