COMPUTATIONAL AESTHETIC EVALUATION USING CONVOLUTIONAL NEURAL NETWORKS: FILTERING GENERATIVE ART BY MODELING USER TASTES

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ABSTRACT

Recent advances in machine learning techniques have resulted in increasingly effective algorithms for discovering creative solutions to quantifiable optimization problems. In general, problems unaffected by advances in machine learning are not those involving creativity, but those whose optimization functions are difficult to quantify. To teach a computer to produce aesthetically pleasing artwork, one must first have in hand a model for aesthetic evaluation to guide the artwork generation. We performed several experiments with Convolutional Neural Networks to produce a hybrid Computational Aesthetic Evaluation model, and generate abstract art appealing to the user's tastes.

ACKNOWLEDGEMENTS

I dedicate this paper to science.

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CHAPTER 1

INTRODUCTION

Generative art is produced according a set of well-defined procedures, and establishes a cooperative relationship between these procedures and the artist. The procedures defining a piece of generative art need not be carried out by a computer. Early examples of generative art can be found in ancient pottery and religious decorations, often involving the tesselation of geometric shapes and colors. These early examples are impressive for their cerebral nature and the unusual human precision, but their scale and complexity were severely limited by the available human resources for calculation and manufacture. With the invention of modern computers, the limiting factor on the increasing prevalance and complexity of generative art has become the artist, specifically their expertise in creative decision making and aesthetic evaluation. Despite their enormous computational power, the primary use of modern computers in generative art falls into the category of rendering procedures into their realized form, rather than participating in the search for aesthetic beauty. Advances in machine learning for pattern recognition have proved useful in many different types of well-defined tasks. In this study we apply modern image classification techniques using convolutional neural networks to the problem of computational aesthetic evaluation, observing whether they are capable of learning the tastes evident in a dataset of randomly generated triangle art, labeled with aesthetic quality ratings.

CHAPTER 2

RELATED WORK

The focus of this study of computation aesthetic evaluation is composed of two parts: generative art and machine learning.

2.1 Related Work in Generative Art

Philip Galanter has done the most to rigorously define the problem of computational aesthetic evaluation. In his paper, Computational Aesthetic Evaluation: Steps Towards Machine Creativity, he lays out current difficulties with programing creativity into a computer [1].

Several others have applied genetic algorithms to optimize heuristics for aesthetic quality. For instance, a group seeking to automatically generate layouts for page content used the heuristic of minimizing wasted space as a fitness function on their population of layouts.

2.2 Related Work in Image Classification

CHAPTER 3

THEORY

3.1 Generative Art

Three factors went into the selection of the type of artwork to be used in this experiment. First, a body of art with a significant variance in subjective quality was desirable, since the experiment hinges on judging differences in quality. Next, a type of art with sufficiently simple characteristics was desirable to make the job of image classification as simple as possible without sacrificing the fundamental complexities of color scheme and composition. Last, in order to collect a large corpus of images quickly, an artform allowing for an efficient curation process was desirable. A corpus generative art lends itself nicely to these three constraints, since the randomness inherent tends to result in a variance in quality, the sophisitcation of abstract art is relatively low, and an endless pool of images can be sourced instantaneously.

I designed an extremely simple generative art method for producing our corpus of data. To produce an image, the program randomly places a random number of randomly-colored triangles on a randomly-colored background. I used a uniform random distribution in every case. I bounded the possible number of triangles, and limited the lightness of colors to a range, to boost the ratio of good results to bad results.

3.2 Compuational Aesthetic Evaluation - Convolutional Neural Network

We will use various CNN models that come with Caffe öut of the boxẗo test their efficacy, rather than attempt to customize a model to this task. The first model we will test is called GoogLeNet, which won the ImageNet Large Scale Visual Recognition Challenge in 2014.

CHAPTER 4

IMPLEMENTATION

4.1 Generative Art

I designed a web interface for recording a binary rating to 4000 generated images, each three times, to form a composite score for each image. At each training interval, the trainer is shown an image on the screen, and asked to rate its quality as g̈oodör b̈ad̈. Sometimes the trainer is shown an image they have rated before, in order to corroborate the quality of the image.

The business logic of this training interface is written in python, because Caffe supports python bindings to its functionality. The images were drawn using the p̈illowp̈ython package. I opted not to use processing because I was unaware of any processing port to python.

4.2 Compuational Aesthetic Evaluation - Convolutional Neural Network

I chose to use the Caffe framework for image recognition for its documentation and widespread adoption in the machine learning community.

We will train GoogLeNet on a random subset of the images, and test it on the rest.

CHAPTER 5

RESULTS

I put together a training corpus of 4000 images, each with 3 binary ratings.

I plan to use standard metrics for measuring the effectiveness of our classifier.

I plan to use our model to filter ugly results from our triangle art generator and showcase the quality of the CAE model on free range images.

If time allows, I plan to feed different classes of artwork into the CAE model to test its efficacy at applying aesthetic preferences learned with the abstract shapes to forms of higher complexity.

CHAPTER 6

CONCLUSION

Given the difficulty of defining art itself, it is no surprise that the criticism and reception of art itself is as nebulous. Yet despite the unclear underpinnings of aesthetic tastes, it is clear that aesthetic judgements are an integral part of everyday life. Short of machine intelligence, computerized judgements of aesthetics will likely never supercede our own, but in combination with our own, there is the potential for computers to make artists out of us all, or at least reduce the cost of aesthetically pleasing design.

The outcome of this experiment may not be clear and but the field of computational aesthetic evaluation will only gain in relevance as we strive to make our world more beautiful.

Qualitative results here

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