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MACHINE, OH! MACHINE, WHAT IS THE EMOTION IN THIS PAINTING? ASSESSING EMOTIONS IN ABSTRACT ARTS THROUGH MACHINE LEARNING TECHNIQUES

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Abstract

Can machines identify positive and negative emotions in abstract paintings? In order to answer this question two sets of abstract paintings (a) professional (MART) set and (b) an amateur set, conveying a wide range of emotions were rated for discrete emotions as well as arousal and valence by more than 700 raters. On the basis of the ratings, paintings were classified into three categories as conveying (a) positive emotions, (b) negative emotions and (c) indeterminate emotions. Manual content analysis of the images suggested significant dominance of certain kinds of lines and colors in positive and negative emotions. We employed Image processing techniques to identify the visual features related to (a) color content and (b) line segment trends. Logistic regression classifiers were then trained using 357 images and then validated on 154 images. Once the classifiers were trained, we were able to obtain probability measures for any given input image which we could later classify into negative, positive and mixed/ambiguous emotion images. Validation from test set reveal that we get accuracy close to 80 percent using color and line features. It is expected that this work will have implications for automated assessment of anticipated perception of images for a wide range of design contexts.

Keywords: Abstract paintings, emotions, Image processing, Machine learning

INTRODUCTION

Abstract art is the visual language that affords the maximum freedom to an artist, liberating her from the parochial concept of reality and allowing non-figurative, non-objective expression. This departure from reality confounds and perplexes the observer on multiple scales[1] but in spite of that still permits us to appropriate emotions to works of art. [2] concludes that emotion is the strongest predictor of art appreciation, independent of art styles and the expertise of people. It is no wonder that many studies show that subjects, even children, agree on the emotional and expressive nature of abstract shapes and colors [3, 4, 5]. Emotions invoked while observing the art are difficult to quantify. In this paper, we explore the idea of analyzing abstract art forms and evaluating a "machine's perspective" of the emotions resultant from the art.

Such an approach can give us some well needed insights required to formulate a theoretical approach to assessing abstract art and its emotive meaning. The paper identifies some color features which are capable of holistic representation of emotional abstract images and reports how a machine learning algorithm is trained to obtain weightages to these features. Some preliminary line features are also investigated with the hope to involve a more extensive textural feature representation. The contributions of this paper are as follows: 1) A machine learning algorithm to predict whether a given abstract painting evokes a positive or a negative emotion. 2) Determining contribution of a color combination to being positive or negative.

RELATED WORK

Fusion of aesthetics and machine learning is a relatively novel field and is barely explored. It is believed that abstract art frees our brain from the dominance of reality, enabling the brain to flow within its inner states, create new emotional and cognitive associations and activate brain-states that are otherwise harder to access[6]. Reading such metaphysical ideologies may cause a person to doubt the establishment of such a fusion. We believe, on the contrary, that a machine may provide us an unbiased and neutral perspective benchmark, which we may evolve into an extensive framework for understanding and appreciation abstract art in all its glory. Some works in this domain are briefly touched upon in this section. In [7], it was examined whether and how expertise in art history would affect the self-reported aesthetic and emotional ratings, eye-movements, and EDA during viewing of paintings. In [9] an approach was proposed to classify emotions of paintings by identifying key areas in a painting believed to be the emotional regions. A bag-of-words-visual model which largely follows [8] was trained to distinguish between positive and negative images. In [10, 11], authors aimed to identify emotional regions and relate them to perceived emotion by human viewers relying on SIFT features extracted from the painting. One possible issue with isolated emotional region search could be due to the fact that abstract works inherently have no figurative depictions. Hence trying to locate textural similarities in a large number of paintings could very well prove to be inconclusive. This was one of the major reasons we considered features dependent on color composition and content that eliminate such inductive bias.

PROPOSED METHOD

Feature identification and extraction

Abstract art aesthetics tend to be highly equivocal, sometimes with conflicting emotional elements in the same painting. We had to model the artwork in a form that machine can recognize and process. What we were looking for were descriptors or key points that are not only perceivably dominant but also contextually exhaustive for them to be capable of registering a large number of abstract images. We found the most obvious and usually overlooked characteristic of such art forms – color.

Color content and composition are a prominent contributor of the type and intensity of emotion evoked by an artwork. Artists can influence the viewers with subtle interplay between contrasting and harmonious colors, creating certain pockets which steal attention at the first glance and set the mood for the painting.

The principle advantage of using a supervised machine learning algorithm is in the fact that we do not need to dissect these intricate interactions that influence human perception. In fact, the respective weightage our algorithm assigns to particular colors and their correlations achieved for a given mood can be traced back to these “interesting areas” in the paintings. Another important feature that is tractable by machine vision techniques is the line segments encountered in abstract art forms. We performed some preliminary investigation with line features but the results proved inconclusively, prompting a further refinement in the process.

Color features:

For color features, we selected the content percentages of different colors of an image. This decision was driven by the fact that certain colors (by themselves as well as in conjunction with others) dominated certain emotional qualities. Identifying these important cues would be facilitated with the color content as a feature to be learned.

We divided the colour wheel into 10 colour bins to classify all possible pixels into a unique bin of color. HSL values for different colors can be found in Table 1. The color model we used was the cylindrical color coordinate representation HSL[14]. The reason for preferring HSL over RGB was that the identification of a color in HSL is largely determined by the hue and to some extent by lightness value[12,13]. On the other hand different shades of the same color have significantly different RGB values, causing the binning process to be more convoluted. Working example of color component segmentation can be seen in Fig 2.

Whether an image invokes a positive emotion or triggers a negative response from the user can be attributed to the presence of certain colors and color combinations. Our training algorithm gives us weights for colors against the emotion they have been annotated with. This helps us to draw conclusions about the role of a color type and its content to influence a paintings mood.

Line Features:

We investigated the use of line segments to incorporate a more extensive textural features based learning. Due to the lack of figurative forms in abstract art, line positions, intensity and acuteness contribute to the impression a painting presents.

For the features, we identified that the angular orientation of line segments is a promising avenue of investigation. We used Hough transform[15] to obtain line segments and their slopes and calculated a variance measure to serve as a feature for the learning algorithm. Working example of line detection algorithm can be seen in Fig 1. Further refinements are needed, since the results using both line and colour features were not an improvement from the results relying solely on colour features.

Learning algorithm:

Consider the training data $\{(x^1, y^1), (x^2, y^2), \ldots, (x^m, y^m)\}$, where $x = [1, x_1, x_2, \ldots\ x_k]$ is the feature vector and label $y \in \{0, 1\}$

Let $x = [1, x^1, x^2, \quad x^{k]}$ be the feature vector. Here we add a new feature '1' as bias. Logistic regression learns a parameter vector $\theta = [\theta^0, \theta^1, \theta^k]$ such that

$$0 \leq h_\theta(x) \leq 1$$

$h_\theta(Z) = g(\theta^T x)$ where 'g' is sigmoid function.

$$g(y) = \frac{1}{1+e^{-y}}$$

For example, $h_\theta(z) = 0.7$ implies 70% chance of having label '1'. We can then threshold $h_\theta(z)$ to classify the example. One such threshold could be if the probability measure exceeds 0.5, we assign it the label '1', otherwise we assign it to be '0'.

We use gradient descent to learn the parameters θ.

$$\text{Cost}\ (h_\theta(x),y) = -\log(h_\theta(x)) \qquad \text{if } y=1$$

$$\text{Cost}\ (h_\theta(x), y) = -\log(1 - h_\theta(x)) \qquad \text{if } y = 0$$

$J(\theta)=$

$$\frac{1}{m}\left[\sum_{i=1}^{m} y^i \log\left(h_\theta(x^i)\right) + (1-y^i)\log(1-h_\theta(x^i))\right]$$

Repeat { θ_j : $\theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta)$ } Till we settle down at minimum $J(\theta)$

Using the training data, logistic regression fits a model h_θ to predict the probability of label for any new test example 'z' which has its own feature vector and is tested with the learned parameters θ. .

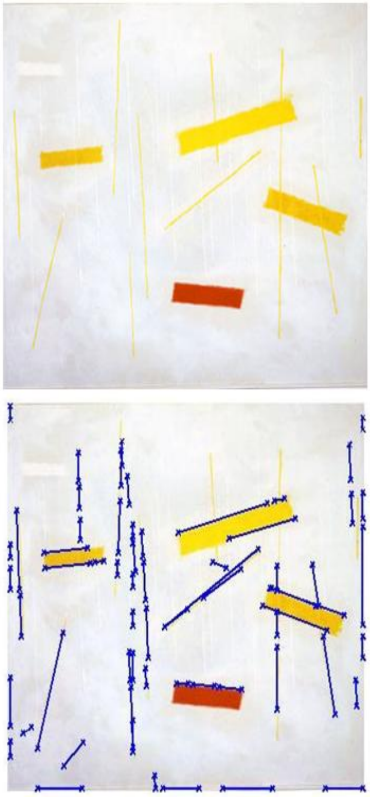

Figure 1 Image (top) and detected lines

Table 1 HSL values for color (Note: Range of Hue: (0 -360), Saturation: (0 – 1, Lightness: (0 – 1))

Color Bin	Hue	Saturation	Lightness
Red I	0-10	0.4-1.0	0.3-0.65
Red II	345-360	0.4-1.0	0.3-0.65
brown	5-35	0.4-1.0	0.05-0.3
yellow	35-85	0.4-1.0	0.3-0.65
green	85-175	0.2-1.0	0.2-0.65
blue	175-255	0.2-1.0	0.2-0.65
Purple I	255-280	0.4-1.0	0.2-0.65
Purple II	280-310	0.4-1.0	0.05-0.4
Pink	280-340	0.4-1.0	0.2-0.65
Gray	0-360	0-0.05	0.15-0.6

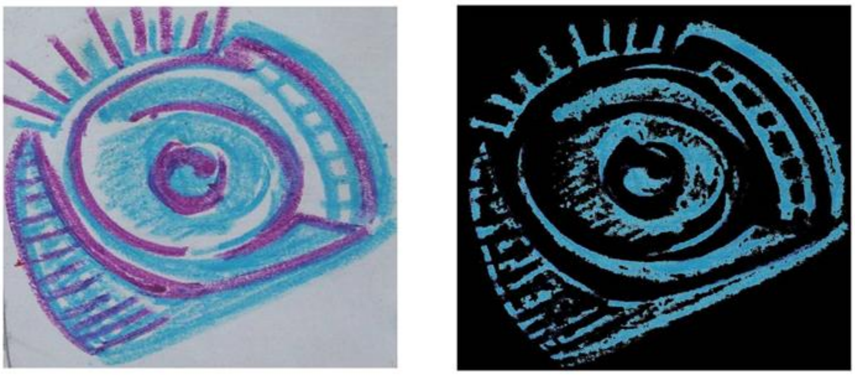

Figure 2 Image (left) and its blue color content segmented out (right)

EXPERIMENTAL DESIGN AND RESULTS

Dataset

We have used two datasets of abstract paintings. The first dataset consisted of 318 professional abstract paintings from the electronic archive of Museum of Modern and Contemporary Art of Trento and Rovereto, Italy (MART). The second dataset consisted of 193 amateur abstract paintings collected during class activities of the course Visual Communication at Indian Institute of Technology-Kharagpur. These paintings were rated by nearly 1087 students for 8 discrete emotions (Happy, Exciting, Wonder, Romance, Sad, fear, anger and disgust) as well as arousal and valence through an online survey. There were 610 male and 477 female students aged between 16 and 21. Average number of images rated by each participant is about 15. We have then classified all the paintings as positive or negative based on the ratings. Our final dataset has 511 paintings each labeled either as positive(1) or negative(0).

Evaluation

We used 357 paintings of the dataset for training and remaining 154 paintings for testing. We carried out two experiments. 1) We trained logistic regression model using 10 color features 2) We trained logistic regression model using 10 color features and one line feature. The accuracies in both cases are mentioned in table 2.

DISCUSSION

As can be seen from the accuracy results, the line features we used did not really contribute any classification information. We shall be refining these line features in future works. Instead of using one variance measure, we shall be making angular divisions and divide the variance into multiple subvariances. Another avenue worth improving is the choice of color bin boundaries. Currently we use a heuristic based approach to make the bins, but it may be beneficial to have an adaptive binning system for generating color feature vectors. We could also potentially consider non-exclusive bins such as a Gaussian mixture model for color features.

Furthermore, as suggested by the dataset, the binary classification can be developed further into 8-fold emotion based classification or a 2 dimensional arousal valence based classification.

Table 2 Accuracy of Experiments 1 and 2

Features	Accuracy
Color features	77.23%
Color + Line	77.03%

CONCLUSIONS

We observed that adding line features along with the color features did not improve the accuracy much. However, an accuracy of more than 77% is significant in classifying images into two distinctive categories in an automated manner. Line parameters need to be reexamined since they figure prominently as key features in traditional analysis of images. Future directions include achieving greater accuracy, categorizing images on the basis of discrete emotions, and exploring the application of our work in the related fields. It is indeed possible for machine to assess and classify emotions in paintings, and this may have far reaching implications for digital communication and social media.

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