Predicting Image Aesthetics using Objects in the Scene

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ABSTRACT

Analyzing aesthetic quality of images is a highly challenging task because of its subjectiveness. With the exponential rise of digital images in social media, it is of great demand to assess the aesthetics of images for several multimedia applications such as increasing social popularity etc. Previous approaches to address this problem have used hand-designed features or automated features extracted by deep convolutional neural network architectures. In this paper we predict the aesthetics of images by using the inferential information depending on the visual content found in an image. To the best of our knowledge, this is the first attempt to address such problem by using tags predicted. Experimental results show that our proposed method outperforms the traditional machine learning methods and demonstrate competitive performance compared to the state-of-the-art methods of image aesthetics prediction.

KEYWORDS

Image Aesthetics, Convolutional Neural Network, Image tags

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1 INTRODUCTION

In recent years, image aesthetics analysis has drawn a significant attention of the computer vision community because of its potential applications in the visual experience domain, such as image enhancement, image cropping, image retrieval, and photo management [5, 9, 13, 18, 23, 25]. Evaluating aesthetics of images using a computational algorithm is a very difficult task for computers because different people perceive beauty in different ways and rate aesthetics of images differently as seen in Figure 1. Therefore, to deal with the subjectivity of the human's aesthetic evaluation, several machine learning approaches have been proposed over the years [1, 2, 5–7, 9, 11–13, 17–19, 22, 23, 25, 26, 30]. Most of the early research works have focused on designing intuition based features ranging from low-level features such as color, hue, saturation, etc. [5] to high-level describable image attributes such as compositional, content based or illumination based attributes

[9] for image aesthetics prediction. However, it is very difficult to choose appropriate features to map the human perception of images to their aesthetic score. To tackle this problem researchers have also adopted generic features such as SIFT and Fisher Vector [19] for predicting aesthetics of images. However, over the past few years, deep convolutional neural network (CNN) based models have shown outstanding performance on various challenging visual recognition tasks [3, 10, 15, 27, 29, 31] and they have the capability of learning features automatically from image examples in a hierarchical way. Therefore, in the most recent studies researchers have exploited the automated feature learning power of deep convolutional neural network (CNN) for the image aesthetics prediction task, in order to avoid the requirement of domain-related knowledge to choose appropriate features.

(a) Average score: 8.5714

(b) Average score: 6.8824

(c) Average score: 5.9804

(d) Average score: 4.4630

Figure 1: Photos with ratings given by viewers collected from www.dpchallenge.com

In this work, we introduce a new approach of predicting image aesthetics using tags generated by the computer vision API of the Microsoft Azure Cognitive Services. The generated tags are mostly object names, but there are some context-related tags such as *indoor*, *outdoor*, etc. We use 250,000 images of the AVA dataset [21] where each of the images is associated with an aesthetic score on a

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scale ranging from 1 - 10. We also use three types of aesthetic prediction models to understand the mapping between human understandable semantic features to the aesthetic score of every image. We show that our proposed idea of using tags for aesthetics prediction can produce comparative results close to the state-of-the-art methods and that is the main finding of this paper.

The rest of the paper is organized as follows. In Section 2 we discuss more related work on this topic. Section 3 provides the details of the used dataset and the proposed prediction models. In Section 4 we present the experimental results of image aesthetics prediction and conclude this paper in Section 5.

2 RELATED WORKS

In this section, we talk about the related works where the problem of image aesthetics analysis has been formulated as a classification or a regression problem. We review the hand-designed features and generic features proposed over the years to solve this problem. We also discuss the recent studies that show that convolutional neural network can be successfully applied for image aesthetics prediction achieving state-of-the-art results.

The approaches that formulate aesthetic quality assessment as a classification problem distinguish aesthetically pleasing and displeasing images. The hand-designed features that were proposed in the literature for appropriate representation of image aesthetic characteristics are as follows: Datta et al. [5] designed 56 visual features for each image based on intuition. Apart from considering visual cues like colorfulness, brightness, saturation, hue etc. they also considered features related to wavelet-based texture, size and aspect ratio, shape convexity, low depth of field etc and trained a statistical model to automatically classify images of having good or bad aesthetic quality. Ke et al. [13] used high-level semantic features to describe the spatial distribution of the high-frequency edges, color distribution, hue count, blur etc. for the classification task. Dhar et al. [9] proposed a different type of human-perceived high-level image attributes related to image configuration, the content of the image and the natural lighting conditions of the image, to predict image aesthetics and interestingness of the image. Nishiyama et al. [22] proposed an approach based on color harmony and bags of color patterns to deal with the complex color distribution of an image. They combined the color harmony feature along with blur, edges, and saliency features of the photos to improve their aesthetic classification performance. An alternative approach of using generic image descriptors such as GIST, Bag-of-Visual-Words descriptor, Fisher vector were proposed by Marchesotti et al. [19] which being able to implicitly encode the aesthetic characteristics of an image from SIFT information [16], could outperform traditional hand-designed features. Despite the success of the prior works using handcrafted features and generic features, in recent years several deep convolutional neural networks have been proposed for image aesthetics prediction. Lu et al. [17] proposed a double column CNN to improve aesthetic categorization using style attributes and semantic attributes. Two heterogeneous inputs, i.e., global and local views of an image, were fed to both the columns of the double column deep CNN, in order to capture both global and local characteristics of images.

On the other hand, the approaches that formulate aesthetic quality assessment as a regression problem focuses on finding the aesthetic scores using several data-driven machine learning techniques. Datta et al. [5] predicted the numerical aesthetics ratings by using Linear Regression (LR) on polynomial terms of the features. Bhattacharya et al. [1] used an interactive application, based on user-guided object segmentation and inpainting for extracting aesthetic features subsequently used for training a Support Vector Regression (SVR) model. Wu et al. [30] designed a new regression algorithm called support vector distribution regression (SVDR) and two separate learning strategies (RSL and LR) to tackle the difficulties in learning of a visual quality distribution prediction model. Leveraging the success of CNN architectures, Kao et al. [19] proposed a regression model based on CNN and showed impressive results. Later, Jin et al. [11] came up with a CNN based histogram prediction model that not only predicts the aesthetic score but also is able to obtain an aesthetically pleasing crop of an input image using the same regression model. Most recently, Murray et al. [20] showed that using only one deep CNN model (trained only for the distribution prediction task), three different kinds of tasks namely aesthetic quality classification, aesthetic score regression, and aesthetic score distribution prediction, can be solved.

However, none of the previous works focused what's inside the photos. In this work, we propose a novel approach of predicting image aesthetic score using machine-generated tags based on the content of the image. This research is the first trial that use object detection in aesthetics analysis tasks. Surprisingly, only machine generated tags can achieve comparable prediction performance to the state-of-the-art results.

3 PROPOSED METHOD

In this section, we explain the details of our procedure for mapping raw RGB images to aesthetics tags. We first describe the AVA dataset [21] and how we extracted the labels from the data. We also give details of the different models we used for determination of the aesthetic scores.

We denote each image by X_i and the corresponding score by s_i . The score is usually in the range of 0 to 10. We assume that the tags obtained from all the images in the dataset belong to a set $\mathcal{T}$. A generator of tag from images $g_{tag} : \mathbb{R}^{M \times N} \mapsto \mathcal{T}$. The predicted score for each image X_i is given by y_i . The indicator function $\mathbb{1}(x)$ produces 1 if x is true else 0.

3.1 Dataset

We use the large-scale image database for Aesthetic Visual Analysis known as AVA dataset [21], which contains more than 255,000 images covering a wide variety of subjects on 1,447 challenges. These images along with a rich variety of meta-data were collected from an online community of photography amateurs such as www.dpchallenge.com [21]. We used all 255,494 images for our experimental purpose. For each image X_i , we have a distribution of user votes from score 1 to 10. We compute the weighted average for these score distribution with votes as the weights to obtain a single real values score depicting the aesthetic rating of the image.

Figure 2: Proposed architecture

3.2 Prediction model

In this paper, our main focus is to illustrate the dependence of human understandable semantic features to the aesthetics of each image. More specifically, we try to find the relationship between machine generated tags and the aesthetic score of the image. We leverage Microsoft Azure Cognitive Services framework to generate tags of each image which we use for building regressor models for the aesthetic score. We mainly illustrate three kinds of models: (i) Naive Bayes model using only tag information, (ii) Convolutional Neural network(CNN) based score regression, and (iii) Combination of CNN and sparse tag information vector for score prediction. The details of the architectures are shown in Figure 2.

3.2.1 Naive Bayes using only tags. In this approach, we considered only the machine-generated tags to find its effect on the aesthetic scores. We opted for the naive Bayes regressor, where for each tag we find the average aesthetic scores of all the images having that tag. The mathematical formulation of the same is given as follows:

$$p(y_i | t_1, t_2, \dots, t_{n_i}) = p(y) \prod_{j=1}^{n_i} p(t_j | y_i), \quad (1)$$

We assume an uninformative uniform prior on the aesthetic score distribution, and two sided exponential distribution,

$$p(t_j | y_i) = \frac{\lambda}{2} \exp(-\lambda |y_i - \mu_j|),$$

where $\mu_j = \frac{\sum_{i=1}^N s_i \mathbb{1}(t_j \in g_{tag}(X_i))}{\sum_{i=1}^N \mathbb{1}(t_j \in g_{tag}(X_i))}$ is the mean score for each tag across all images and λ is the inverse mean of the distribution. With the above assumption of two sided exponential distribution, we get the mode of the aesthetic score distribution as,

$$y^* = \frac{1}{n_i} \sum_{j=1}^{n_i} \mu_j. \quad (2)$$

This gives a closed form solution to the aesthetic score prediction model from tag information and there is no iterative learning procedure involved in this method. While being very simple and straight-forward modeling, in the experimental section, we show that, it does a very good job of modeling the relationship between high-level human understandable tag information and aesthetic

score, comparable to certain early methods in aesthetics prediction.

3.2.2 Convolutional Neural Network. It has been shown that residual networks [10] can produce state-of-the-art results in image classification tasks and the intermediate feature representations from the learned parameters of Residual Network (ResNet) can extract meaningful semantic knowledge about the content of the images. Thus these features have been used for various kinds of end-to-end image based tasks such as segmentation and depth estimation from a single image and other high-level computer vision tasks. We leverage these semantically meaningful features to extract aesthetic score from images. Although image aesthetics analysis is a highly subjective matter, our belief is that humans are aesthetically inclined to certain features in images whereas some other features decrease the attractiveness of an image. Given this, the aesthetic score prediction problem reduces to correlating features that improve or decrease aesthetic score of an image. To achieve the above mapping between semantically meaningful features and aesthetic score we deploy a multi-layer perceptron with single output depicting the real-valued score. Similar to recent works in deep models we leverage a large number of image data available from the AVA dataset [21] to learn generalizable features for the above mapping. This is obtained by simply minimizing the mean square error between the feed-forward prediction of the network and the ground-truth score while back-propagating the error gradients through the network and weight update using ADAM optimization method [14]. This method is similar to prior works but we use ResNet [10] features which are more expressive and can lead to better understanding of raw RGB to real-valued aesthetic scores. Although we have used only high-level fully connected features we believe there is room for improvement concatenating low-level, mid-level and high-level ResNet features similar to prior work; where we consider small details of the image like dots, lines, edges, gradients, pixel intensities or colours as low-level features; color histograms, texture or shape descriptors as mid-level features and features related to shapes and objects of the image as high level features. We resize each of the image in the AVA dataset [21] to $224 \times 224 \times 3$ so that it matches the Imagenet [8] dimensions and this stage is referred to as the pre-processing

Figure 3: Relationship of tag index with average cumulative aesthetic scores

stage. Then, we use the ResNet-50 architecture pretrained on Imagenet dataset [8] and extract high-level features obtained from fully connected units.

3.2.3 CNN using tag spare vectors. In this approach, we concatenate both the features extracted by CNN and a sparse feature vector obtained from the tag generator using Microsoft Azure Cognitive Services. Although prior work has shown that combination of low level, mid-level, and high-level features results in the good performance of aesthetic score prediction, neither of these features were human understandable. In this method, we combine latent feature vectors from deep models and inspect how human-understandable features like object tags influence the aesthetics of an image. This is important because it gives a hint of interpretability as to why a certain image is aesthetically more appealing to the subjective human brain.

To achieve this we fuse features obtained from ResNet explained in the previous section in two ways: (i) early fusion, where we directly fuse the sparse feature vectors obtained from one-hot representation of tags in a particular image with real-valued ResNet features of size 2048, (ii) late fusion, where we first find an intermediate real-valued representation from the one-hot representation and then fuse it with the ResNet features.

3.3 Visualizing dependence of tags on aesthetic score

Figure 3 shows the relationship between the tag index with the average cumulative score, where we can see that in the middle region, the gradient is low and the randomness is greater. Therefore these tags affect the average cumulative score very little. However, in both of the sides, the gradient is quite high and the randomness is much lower, which means that the tags in those two regions affect the average aesthetic score in a great fashion.

4 EXPERIMENTAL RESULTS

In this section, we show the experimental results reported in the literature and the results obtained from the three architectures as explained above. Table 1 shows the mean square errors for each of the methods. The top four rows in Table 1 report the results

Table 1: Mean Square Error for different methods

	MSE
GIST linear-SVR	0.5222
GIST rbf-SVR	0.5307
BoVW SIFT linear-SVR	0.5401
BoVW SIFT rbf-SVR	0.5513
Kao et al. 2015 [12]	0.4510
Jin et al. 2016 [11]	0.337
Murray et al. 2017 [20]	0.279
(i) Naive Bayes using only tags	0.512
(ii) CNN based score regression	0.3569
(iii) Combination of CNN and sparse tag information vector	0.3562

obtained by combining the generic image descriptors, GIST [24], SIFT [16] and Bag-of-Visual-Words (BoVW) [4], along with the linear and non-linear Support Vector Regression (SVR) [28]. Note that these results are reported directly from the paper. Details of these methods can be found in [19], [12]. The last three rows show the result achieved by our proposed architectures. Overall it shows that our method of aesthetic score prediction using CNN and using the combination architecture performs almost comparable with the previous methods reported in the literature. Figure 4 shows the qualitative results and the correlation between the ground truth scores (GT) and the aesthetic scores predicted (pred) by our model (iii). We can see that the model can predict aesthetic scores close to the ground-truth scores. In Figure 5, however, we show the failure cases i.e. the images for which our proposed method failed to predict the aesthetic scores correctly. The ground truth scores (GT) and predicted scores (pred) are mentioned for each of the images.

5 CONCLUSION

In this paper, we proposed a novel idea of using tags for image aesthetics prediction. We formulated the problem as a regression problem with three kinds of models: (i) Naive Bayes model using only tag information, (ii) Convolutional Neural network (CNN) based aesthetic score regression, and (iii) A combinational architecture of CNN and sparse tag information vector for aesthetic score prediction. Experimental results on the AVA dataset, which is the benchmark dataset with the rich aesthetic rating, showed that our proposed idea performed comparably with the state-of-the-art results. Although it could not outperform the previously reported results on the same dataset, it is worth mentioning that, this is the very first attempt of using inferential information to predict the aesthetic score. We showed that even simple tag based naive regressor could produce quite good results for aesthetic score prediction. We believe that using a combination of low-level deep features combined with inferential information like tags, can be used to produce state-of-the-art systems that can be used to increase the number of views/likes on Social Networking Sites.

Figure 4: The ground truth scores (GT) and predicted scores (Pred) for some images in test set. The ground truth scores are shown in blue. The predicted scores are shown in green.

Figure 5: Failure cases of our aesthetic prediction model

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