# Photo Aesthetic/Quality Evaluation and Editing

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## 1 Introduction

In this document, we address the problem of evaluation and editing of photos based on aesthetics or quality. We first introduce the problem, then we provide a brief survey on existing methods. Finally we introduce our implemented baseline and proposed method, with quantitative and qualitative results shown.

### 1.1 Photo aesthetic/photo quality

The problems of photo aesthetic and photo quality are similar, but not exactly the same. In photo aesthetic assessment, we seek photos that looks beautiful to people. The aesthetic score of a photo can be affected by the photo's color tone, composition, layout, and etc. In photo quality assessment, we seek photos that are in high quality. The quality score of a photo can be affected by shake, blur, exposition level, and etc.
Compared to photo quality, photo aesthetic is more subjective and abstract. Thus, photo aesthetic is a higher level concept than photo quality. The difference between the two concepts can be better explained by examples. Figure 1 shows examples of photo aesthetic assessment, Figure 2 shows examples of photo quality assessment.

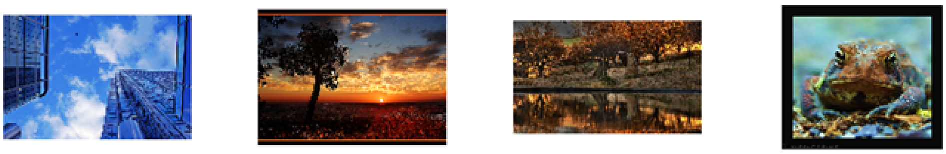

Figure 1: Example photos used in photo aesthetic assessment.

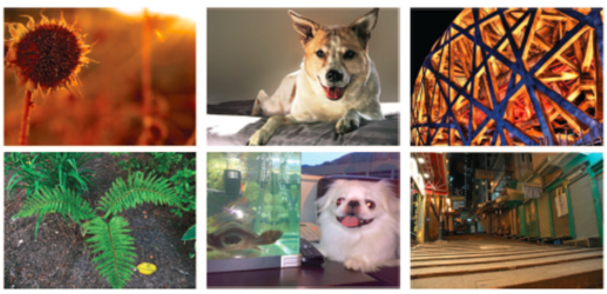

Figure 2: Example photos used in photo quality assessment.

### 1.2 Photo evaluation/photo editing

We deal with two types of photo evaluation: binary evaluation and score-based evaluation. In binary evaluation, the task is equivalent to a two-class classification problem. A photo is classified either as

good (high quality/beautiful) or bad (low quality/not beautiful). In score-based evaluation, the task is equivalent to a regression problem. A photo will be given a score related to its aesthetic/quality value. A common choice for the score range is 0-10. In our implemented methods, the baseline algorithm deals with binary evaluation, the proposed algorithm deals with score-based evaluation.
There are many types of photo editing. In here we only focus in spatial editing, i.e. image cropping. We seek a rectangular subregion of the original image, that produces the optimal aesthetic value. Figure 3 shows an example.

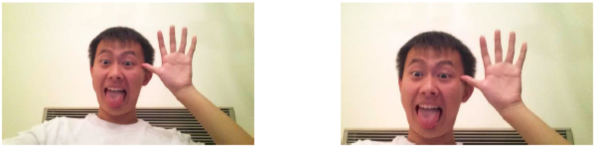

Figure 3: An example of photo cropping. Left: original image. Right: cropped image that has optimal aesthetic value.

## 2 Related work

Various methods have been proposed for photo aesthetic/quality evaluation and editing. Lo et al. [1] propose a method with highly efficient aesthetic features, it is shown to produce decent results in both photo aesthetic and photo quality assessments. This is chosen as our baseline algorithm.
In the work of Marchesotti et al. [2], a photo aesthetic assessing method using generic image descriptors is proposed. This method has the advantage of not relying on manually craft features. In a following work of Murray et al. [3], an ultra-large scale image database along with the algorithm that deals with large-scale evaluation problem are presented. Other aesthetic evaluation methods such as using high level attributes in [4] are also proposed.
In the work of Luo et al. [5], a content-based photo quality assessment algorithm has been proposed. This work also contributes a large-scale labeled photo quality database.
In multiple papers of Li et al. [6,7] from our group, aesthetic evaluation related methods have been proposed. However, [7] focuses on assessing aesthetic values of paintings and [6] focuses on assessing personal images (images with human faces), which limit the generality of both algorithms. Based on these two previous work, we propose a new objectness-based algorithm for aesthetic evaluation and cropping editing. The proposed algorithm is general and can be applied to all types of photos.

## 3 Algorithm overview

### 3.1 Baseline algorithm

The baseline algorithm uses features including:

- **Color Palette** Main color factors of all image pixels are found by clustering, which represent the color palette of the image. It should be noted that instead of using colors as features, this method first finds $k$ nearest neighbors in the database in terms of color palette, and uses the number of good and bad images as features.
- **Layout Composition, Edge Composition, Global Texture** Templates for an average good image and an average bad image are computed in color channels, edge maps or texture images. Distance between input and templates are then used to compute features.
- **General Features** This includes a set of generally adopted features in aesthetic assessment, such as blur, dark channel, contrasts, and HSV counts.

A standard SVM model is trained and used as the final classifier. For more details please refer to [1].

### 3.2 Proposed algorithm

#### 3.2.1 Evaluation

To evaluate the aesthetic score of an input photo, we first compute a set of bounding boxes that possibly contains objects using the objectness detection algorithm in [8]. Then for each of those bounding boxes, we compute color, lighting, and composition features following the method in [6]. Sparse regression [9] is used to compute coefficients from features to the final score in a sparsity-embedded manner.
The proposed algorithm has two advantages. First it is able to generate an aesthetic score, rather than just a binary label. This enables wider range of potential applications. Second comparing to [6], it is not limited to just face images.

#### 3.2.2 Editing

To crop the input image into the sub-image that has better aesthetic value, we consider 3 types of features: the visual balance feature, the Rule of Thirds feature, and the relative size between object boxes and the cropping bounding box. Particle Swarm Optimization [10] is used to compute the final cropping bounding box. The major steps basically follows the method in [6], except that we skip the page-rank step and use objectness scores as box weights.

## 4 Experimental results

We tested the baseline and proposed algorithms on the dataset from [6] and part of the AVA dataset [3]. Table 1 shows a comparison in average error in scores. It should be noted that as the baseline algorithm can do only binary classification, we use 7.5 and 2.5 as scores produced by the baseline algorithm with good and bad labels.

Table 1: Quantitative comparison between baseline and proposed algorithms.

| | baseline | proposed |
|---|---|---|
| Dataset from [6] $RMSE_{score}$ | 2.20 | 1.56 |
| AVA dataset [3] $RMSE_{score}$ | 2.24 | 0.68 |

In Figure 4 we show some qualitative results.

Figure 4: Examples of photo cropping, with the cropping bounding box shown in blue.

## 5 Future work

The current framework can be further improved in two aspects. First, the current framework uses a constant number of object bounding boxes, which is not robust to image collections that contains images with various object numbers. An object number estimator can be added to the current framework to improve the performance. Second, we have tested our method on two datasets [3,6], but those two datasets are heavily biased. A relatively large percent of images have scores around 5-6, which leads the regressor tending to produce similar scores and ignore images with very high or very low scores. Thus to improve the performance of current method, a non-biased dataset or a regression procedure that stresses rare samples can be utilized.

# 6 References

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