OPARS: Objective Photo Aesthetics Ranking System

Huang Xiao, Han Xiao, and Claudia Eckert

Institute of Informatics
Technische Universität München, Germany
{xiaohu,xiaoh}@in.tum.de
claudia.eckert@sec.in.tum.de

Abstract. As the perception of beauty is subjective across individuals, evaluating the objective aesthetic value of an image is a challenging task in image retrieval system. Unlike current online photo sharing services that take the average rating as the aesthetic score, our system integrates various ratings from different users by jointly modeling images and users' expertise in a regression framework. In the front-end, users are asked to rate images selected by an active learning process. A multi-observer regression model is employed in the back-end to integrate these ratings for predicting the aesthetic value of images. Moreover, the system can be incorporated into current photo sharing services as complement by providing more accurate ratings.

1 Introduction

In recent years, computational image aesthetics evaluation has drawn a lot of interests from researchers due to its various applications, such as content-based image retrieval and quality-based image management. The main challenge of objective aesthetics assessment is raised up by the scarcity of the image rating data set. Most online photo sharing services (e.g., Flickr, Photo.net, Photobucket) only provide the average rating of an image. Even though previous work based on such data sets have gained appreciable success[1,2], they overlook the expertise of individuals which makes their algorithms subjective.

Objective **P**hoto **A**esthetics **R**anking **S**ystem[1] (OPARS) is a web service for collecting image ratings from different users and computing the objective aesthetic score by virtue of a multi-observer regression model. Unlike conventional image rating systems, OPARS collects continuous scores instead of discrete ones.

2 System Architecture

OPARS follows the browser-server architecture. The front-end establishes a user-friendly web interface facilitating the process of image browsing and rating. The back-end contains a set of functional components including the database access and storage procedure, user authentication, score predicting and so on. The design of the architecture is depicted in Figure 1.

[1] http://ml.sec.in.tum.de/opars

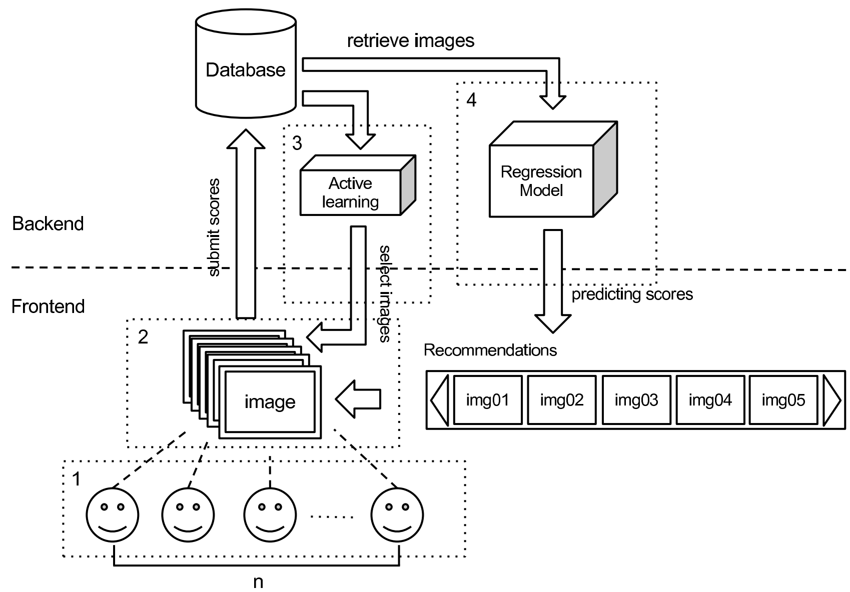


Fig. 1. System architecture of the OPARS. It follows the browser-server architecture. Main system modules are framed in dotted lines. They are 1) User authentication module 2) Continuous-valued rating module 3) Active image retrieval module 4) Image recommendation module.

3 System Details

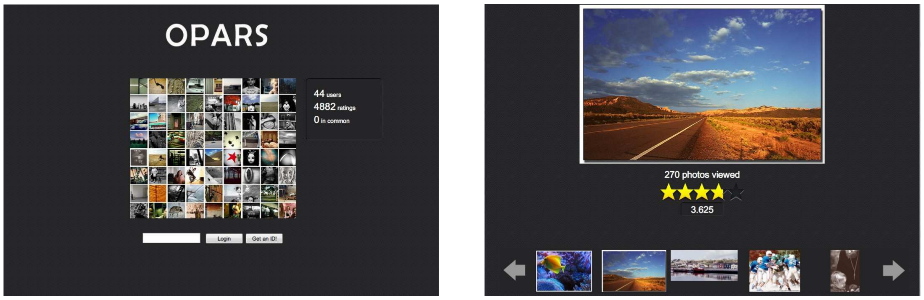
We describe the system details in a decomposition of main functional modules: 1) User authentication module 2) Continuous-valued rating module 3) Active image retrieval module and 4) Image recommendation module.

3.1 User Authentication Module

A password-based authentication protocol is adopted for convenient access control, see Figure 2 (a). In addition, users will be prompted to provide individual demographic information for research purpose, which serves as prior knowledge in our regression model.

3.2 Continuous-valued Rating Module

Authenticated users are able to browse the image gallery and response with their ratings against the images. Instead of conventional discrete image ratings, OPARS enables a continuous rating metric (ranging from 0 to 5). Additionally, it also records users' response time in milliseconds in the background.



(a) Home view (b) Main view

Fig. 2. (a) The home view of the OPARS. The right panel displays fundamental statistics of current system. (b) The main view where user can browse image gallery by pressing arrow keys. Users' response time and ratings are recorded when they click on the rating bar. At the bottom, five images with highest objective aesthetic scores are recommended by the system.

3.3 Active Image Retrieval Module

One key contribution of OPARS is that the images presented to users are not selected randomly but in an active learning process. Recently, active learning [4] has gained significant attention in machine learning community. By introducing active learning in image rating system, the underlying predicting model provides more efficient and accurate results by only rating a small portion of images. In OPARS, we adopt Gaussian process for active learning, where the unrated images with highest variances are selected for the next round evaluation. For the computational reasons, we call the active learning routine on every 10 rated images.

3.4 Image Recommendation Module

Another main contribution of OPARS is the image recommendation module, a multi-observer regression model [3] is developed for learning the objective ratings from multiple users.

Note that conventional image rating systems take an average of ratings of an image as its objective score. In this way, individual expertise is totally ignored for evaluating the aesthetics of an image objectively. In our system, the underlying regression model is capable of integrating users' expertise as prior knowledge and can successfully recover an objective score of an image, even when some users are malicious or severely biased.

We depict the graphical model in Figure 3. Assume that each instance x_n (e.g., an image) is associated with an unknown objective aesthetic score z_n, in the meantime, a user's response $y_{n,m}$ conditionally depends on both x_n and the z_n. There are M users in total. Intuitively, user's response of an image is determined by his own perception of the image and the unknown objectivity of the image. To solve this multi-response regression problem, we formulate the generative processes of $p(\mathbf{Z} \,|\, \mathbf{X})$ and $p(\mathbf{Y} \,|\, \mathbf{Z}, \mathbf{X})$ both in Gaussian process and maximize the likelihood to estimate the parameters. More technical details of the regression model can be found in [3].

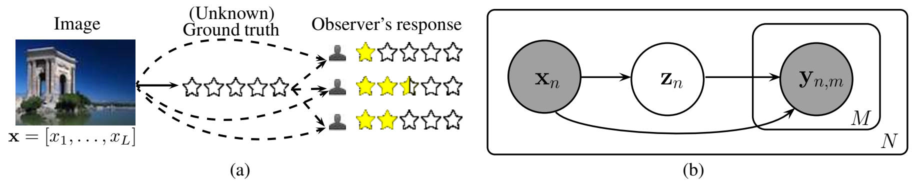


Fig. 3. (a) Generative process of subjective aesthetics scores. **(b)** Graphical model of instances $\mathbf{X}$, unknown objective aesthetics scores $\mathbf{Z}$ and responses $\mathbf{Y}$ from M different users. Only the shaded variables are observed.

Note that images with highest predicted objective scores are recommended by the system. In favor of the multi-observer regression model, the image recommendations are more resilient to variant user expertise.

4 Demo Statistics

This work is currently only distributed within an academic group for research interest. In total, we have received 42 registered users and 4839 ratings on images. Among these contributors, over 28 users have rated over 100 images, and 10 of them even reach a line of 200 images. A data set is released online from our system.

5 Future work

In future, our system will be maintained and updated constantly. Specifically, it will be improved in aspects. First, the active learning algorithm and the regression model will be refined as more efficient and accurate. Second, the system will enable the upload function of users' custom photos which are then stored and shared in our system. At last, we will provide user a personalized report, where a well formulated and virtualized summary of the user's evaluation on images will be generated, such as user's preference on image features, correlation between user's ratings and predicted objective aesthetic scores, and so on.

References

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