INVESTIGATING AND PREDICTING SOCIAL AND VISUAL IMAGE INTERESTINGNESS ON SOCIAL MEDIA BY CROWDSOURCING

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ABSTRACT

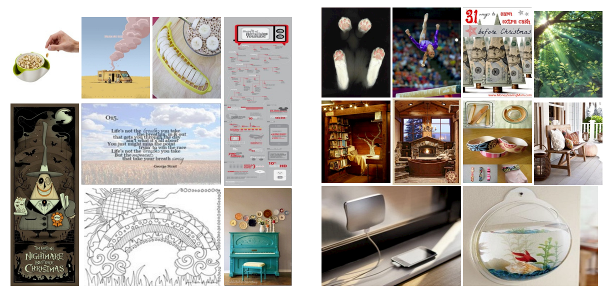
Not all images are interesting to people. People are drawn by interesting images and ignore tasteless ones. Image interestingness has the importance no less than other subjective image properties that have received significant research interest, but has not been systematically studied before. In this work we focus on visual and social aspects of image interestingness. We rely on crowdsourcing tools to survey human perceptions for these subjective properties and verify data by analyzing consistency and reliability. We show that people have an agreement when deciding if an image is interesting or not. We examine the correlation between the social, visual aspects of interestingness and aesthetics. By exploring the correlation, we find that: (1) Weak correlation between social interestingness and both of visual interestingness and image aesthetics indicates that the images frequently re-shared by people are not necessarily aesthetic or visually interesting. (2) High correlation between image aesthetics and visual interestingness implies aesthetic images are more likely to be visually interesting to people. Then we wonder what features of an image lead to social interestingness, e.g. receiving more likes and shares on social networking sites? We train classifiers to predict visual and social interestingness and investigate the contribution from different image features. We find that social and visual interestingness can be best predicted with color and texture, respectively, providing a way to manipulate social and visual liking of images with image features. Further, we investigate the correlation between social/visual image interestingness and image color. We find that colors with arousal effect show more frequently in images with higher social interestingness. That could be explained by previous studies for activation-related affect of colors and provides useful and important advice when advertising on social networking sites.

***Index Terms*—** Social image interestingness, visual image interestingness, aesthetics

1. INTRODUCTION

As Internet and digital camera users, we all sense the explosive growth of image data in recent years. However, the time available for people to consume these images has still been limited. There is an emerging need for people to be able to process images selectively, such as identifying images that will interest them the most. This observation might partly explain the success of photo sharing services like Flickr and Pinterest, where image interestingness is explicitly or implicitly used as a criterion to filter and present images.

We may have all used these emerging online photo services to browse the images interesting to us. What's not so clear is about the nature of image interestingness. What makes an image interesting to people? Is there only one type of interestingness? We consider image interestingness a multi-faceted concept. Image interestingness can involve several aspects of perception. The reason why an image is thought as interesting by a viewer may be due to its visual content or social opinions of other people, such as friends. In this work, we are interested in visual and social aspects of image interestingness.



(a) (b)

Fig. 1. (a) Set of socially interesting Pinterest images with lower visual interestingness. (b) Set of visually interesting Pinterest images with lower social interestingness. Best seen in color.

We distinguish the two aspects of image interestingness and define them as *"visual interestingness"* and *"social interestingness."* Taking images in Figure 1 as examples, we can observe the difference between two aspects of image interestingness. The images shown in Figure 1(a) are examples of Pinterest images more socially interesting to users. To operationalize social interestingness, we take the "repins" plus "likes" counts of each Pinterest image as its quantified social interestingness. Some images in Figure 1(a) are not visually attractive and have not contained interesting objects. But these images still have many people to re-share them on Pinterest. In other words, social interestingness may not be solely explained by the visual properties of an image, and is possibly more of a result of social interaction between people. When we glance at the images in Figure 1(b), we sense higher aesthetic quality. Those images are annotated as visually interesting by a group of people. It hints us that visual interestingness may relate to image aesthetics at some degree. However, few examples in Figure 1(b) can not be thought as aesthetic but are still visually attractive to people. That is to say that visual interestingness might not be completely as the same as image aesthetics.

Identification of image interestingness can be applied in many applications such as photo sharing services, advertising, cover design, etc. While image interestingness is important and has been mentioned in previous work [1], the multi-faceted feature of image interestingness has not been comprehensively investigated. Furthermore, image interestingness has been confused with image aesthetics in previous work. Among those subjective image properties that have received significant research interest in recent years such as memorability [2], attractiveness [3], aesthetics [4], sentiment [5], etc., visual interestingness is most similar to attractiveness. But to

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the best of our knowledge, no work has studied the concept of social interestingness.

This is the first work to compresentively study multiple aspects of image interestingness. In order to obtain the data of image interestingness, we use crowdsourcing service Amazon Mechanical Turk (AMT) to collect survey data. We use statistical tools such as Pearson correlation coefficient and Cronbach's α to verify the feasibility of constructing consistent and reliable dataset for image interestingness by using the crowdsourcing platform. Despite the high subjectiveness of image interestingness, the analysis results with high Pearson correlation coefficients indicate that there is an agreement to some extent between people in deciding if an image is interesting or not to them.

In this work we investigate the correlation between social, visual interestingness and image aesthetics. By exploring the correlation, we find that: (1) Weak correlation between social interestingness and both of visual interestingness and image aesthetics indicates that the images frequently re-shared by people are not necessarily aesthetic or visually interesting. (2) High correlation between image aesthetics and visual interestingness implies aesthetic images are more likely to be visually interesting to people. The results suggest useful considerations for promoting and advertising multimedia content on similar social networking sites.

Then we wonder what features of an image lead to social interestingness, e.g. receiving more likes and shares on social networking sites? We apply boosting-like learning methods and image features that approximate human view perception to predict visual and social interestingness for images. We train classifiers to predict visual and social interestingness and investigate the contribution from different image features. We find that social and visual interestingness can be best predicted with color and texture, respectively, providing a way to manipulate social and visual liking of images with image features. Further, we investigate the correlation between social/visual image interestingness and image color. We find that colors with arousal effect show more frequently in images with higher social interestingness. That finding could be explained by previous studies for activation-related affect of colors and provides useful and important advice when advertising on social networking sites.

In summary, our key contributions in this work are: (1) The first attempt to identify social and visual aspects of image interestingness and investigate their correlations. (2) Verifying the feasibility of using crowdsourcing to collect consistent and reliable data for subjective image properties. (3) Conducting experiments by investigating learning algorithm and numerous image features to predict image interestingness and compare their performance.

2. EXPLORING IMAGE INTERESTINGNESS BY CROWDSOURCING

Image interestingness may be more subjective than other image properties such as aesthetics, memorability, and photo quality. However, in most cases we thought that the images interesting to one person are more likely to be the interesting ones for somebody else. This is also the foundation of popular image social networking services such as Flickr and Pinterest. In this section, we explore the degree of consistency of image interestingness by crowdsourcing. By analyzing the consistency and reliability of collected data, we verify the feasibility of using crowdsourcing method to collect research data for subjective image property. We also investigated the correlation between visual and social image interestingness.

Correlation between Visual and Social Interestingness: We collected quantified values of "visual interestingness" by conducting user survey on crowdsourcing platform. We presented workers on AMT with an image visual interestingness survey. In the survey, workers viewed a set of images, each of which was displayed along with a question about image interestingness. Each image was displayed to 10 workers and was collected 10 assignments from these workers. The image interesting question was "Is the image interesting to you?." Workers chose their answers from 5 pre-defined options: "Very boring," "Boring," "Neutral," "Interesting," "Very interesting." Because workers were asked to give answers about image interestingness only considering the visual cue of image, we obtained visual interestingness scores of images.

	Pearson correlation coefficient	Cronbach's α
	(a) "Interestingness"	
HIT1	0.367	0.672
HIT2	0.516	0.699
HIT3	0.655	0.778
HIT4	0.707	0.777
	(b) "Aesthetics"	
HIT1	0.685	0.799
HIT2	0.618	0.768
HIT3	0.680	0.792
HIT4	0.661	0.785

Table 1. Pearson correlation coefficients and Cronbach's α values of "Interestingness" and "Aesthetics" for four HITs, respectively. Notice that images of HITs were randomly sampled in every survey. Thus the HITs with same serial number in different surveys contain different images. The results show quite consistency from human annotations.

Our dataset included social media images from Flickr and Pinterest. We randomly sampled 40 images respectively from Flickr's highest interestingness images and lowest interestingness images in 2011. We also sampled 120 user interesting images from another popular social-network site Pinterest. The total 200 images were randomly separated into 4 groups, each of which was taken to form a human intelligence task (HIT). So each HIT included 50 images and questions. We payed workers \$0.20 per HIT. Workers were not restricted to perform only one HIT. However, there was duration limitation of 30 minutes for completing a HIT. If workers can not complete a HIT in the duration, the answers for the HIT would be cancelled. A total of 23 workers from AMT (with more than 95% approval rate) completed our survey.

We can only collect quantified values of "visual interestingness" by conducting user survey. How to quantify "social interestingness" is a challenging task. Photo sharing services such as Flickr and Pinterest usually assign an interestingness score to each uploaded image. This score could be explicit or implicit to users and come from user social interaction, such as the number of users liking an image, the user comment count, or the number of users resharing an image. Thus, in our experiments, we use the scores extracted from social photo services as quantified values of "social interestingness."

Consistency and Reliability Analysis: User answers of "Interesting," "Very interesting" are classified as "Interestingness." In order to evaluate human consistency on image visual interestingness, we randomly split survey participants into two independent halves and calculated how much visual interestingness scores (i.e. "Interestingness") given by first half of the participants correlated to visual interestingness scores answered by the second half. We repeated the random splitting process 20 times and averaged the trials to calculate Pearson correlation coefficient between two sets of "Interestingness" scores for the four HITs ((a) in Table 1). Although image visual interestingness is likely to be a subjective property of images, the analysis shows human-to-human image visual interestingness con-

	Pearson correlation coefficient		
	(a) VI vs. SI	(b) SI vs. AE	(c) VI vs. AE
Flickr high	0.195	0.018	0.805
Flickr low	0.289	0.281	0.842
Pinterest	-0.015	-0.112	0.564

Table 2. Pearson correlation coefficients. Column (a): "social interestingness" and "visual interestingness." Column (b): "social interestingness" and "image aesthetics." Column (c): "visual interestingness" and "image aesthetics." We observed a high correlation in (c) that implies that aesthetic images are more likely to be visually intersting to people. The low correlation in columns (a) and (b) indicates that the images frequently re-shared by people are not necessarily aesthetic or visually interesting.

sistency can be high to some degree.

In addition to consistency, we also calcuated Cronbach's α for the four HITs ((a) in Table 1) to evaluate the reliability of visual interestingness scores. As the analysis shows, the values of Cronbach α are either very close to or higher than 0.70 that has tranditionally been used to indicate an "acceptable" level of reliability [6]. Thus, our data has sufficient reliability that it focuses on a single idea or construct.

In order to investigate the correlation between social interestingness and visual interestingness, we calculated the Pearson correlation coefficient between their quantified scores (Column (a) in Table 2) for Flickr highest interestingness (40 images), Flickr lowest interestingness (40 images), and Pinterest (120 images). The small correlation implicitly means that how much an image is visually interesting to viewers would not be strongly related to its relative intensify of social interestingness.

Correlation between Image Aesthetics and Two Kinds of Image Interestingness: As one of important image properties, image aesthetics has been well studied in previous works [4, 1] recently. However, there are no previouse studies that try to explore how image aesthetics relates to image interestingness. In other words, we wan to ask: is beautiful image more interesting to people?

We conducted a similar image aesthetics survey on AMT and analyzed the results. The human-to-human image aesthetics consistency is shown in ((b) in Table 1). Cronbach's α for the four HITs was calculated to evaluate the reliability too.

In order to answer the question: is beautiful image more interesting to people? We calculated the Pearson correlation coefficient between "social interestingness", "visual interestingness" and "image aesthetics" of images (Column (b) and (c) in Table 2). We observed a very small correlation between "social interestingness" and "image aesthetics" for Flickr highest interestingness photos. But for Flickr lowest interestingness photos, it shows more higher correlation coefficient. After examining two subsets of Flickr photos, we found that Flickr highest interestingness photos are all professional photographs and with good image quality. It is hard to tell the aesthetic difference between two such photos. Thus, for these professional photos, a lower correlation between "image aesthetics" and "social interestingness" can be expected.

We also want to know if beautiful image is more interesting to people visually? Because of their close semantics, we assumed a high correlation between these two constructs or ideas. The analysis of Pearson correlation coefficient shown in the column (c) of Table 2 has supported this assumption. However, for Pinterest, we only calculated a medium correlation coefficient. We thought that because the very social-oriented characteristic of Pinterest and its usage as a scrapbook of Internet images, this photo service includes many images that are not beautiful but convey abundant semantics in their visual content which evoke interest of people.

3. PREDICTING IMAGE INTERESTINGNESS

We have already investigated the correlation between image visual interestingness, social interestingness and aesthetics. In this section, we explore how well image interestingness can be predicted by using machine learning algorithms and visual-based image features. In order to incorporate multiple image features and explore their effectiveness in image interestingness prediction, we adopted the learning framework from our previous work [7] that utilized Adaboost as the learning method of photo aesthetic quality to combine and compare image features such as color (HSV), texture (LBP), saliency [8], and edge (HOG with bin number = 8). In this previous work we proposed to model human views in a coarse-to-fine manner by a multi-resolution grid-based decomposition.

Briefly, each of image features serves as a hypothesis (denoted as h) and has treated as a weak classifier. A total N ($N = 200$ in our experiments) features $h_n(\cdot)$ are selected and integrated with a boosting approach using Adaboost as shown in the equation $A(\Phi) = \sum_{n=1}^{N} \alpha_n \cdot h_n(\Phi)$, where Φ represents a training photo; A is the learned model that is a weighted combination of the selected discriminative features $h_n(\cdot)$ from extracted image features. Based on the learnd model A, we classify a testing photo I as interestingness or not by using the equation $H(I) = sign(A(I))$, where $H(I) = 1$ indicates that the testing photo possesses interestingness while $H(I) = -1$ means I is a photo with no interestingness.

We crawled 989 images from Pinterest along with 'repins' and 'likes' counts of images. We payed an AMT worker $2.0 for annotating visual interestingness property for at most 100 images. Each image was annotated by 10 workers. Again, the 'repins' and 'likes' counts of Pinterest images were used as image social interestingness scores. We calculated the mean value of visual interestingness and split crawled images as the sets of positive (467 images) and negative images (524 images) according to that their visual interestingness scores were higher or lower than the mean value. For social interestingness, the procedure was same and generated 183 positive images and 808 negative images. Then we trained and tested on the dataset with a 10-fold cross-validation approach by using Adaboost. The results of testing errors for different features are listed in Table 3.

For visual interestingness, texture and color feature has best and worst performance, respectively. As a rich source of visual information, texture is known to provide cues about scenic depth and surface orientation and describe the content of both natural and artificial images [9]. Since visual interestingness predominantly relates to visual content of image, it may not to be too surprised with the exhibited performance of texture feature. On the other hand, image features such as color and edge, seem to be too low level to perform well on the prediction of visual interestingness. An image can be visually interesting to people, not only because of its visual-based content, but also semantic meanings conveyed by the visual content. We thought that is why the classifiers trained using only visual-based image features had poor performance for visual interestingness prediction.

For social interestingness, in contrast, color was the best feature and texture had worst performance. As known in previous work, color is an important part of human vision and has an influence on behavioral intention [10]. In order to further investigate the relation between color and image social interestingness, we plotted these Pinterest images with their mean hue values and social interestingness scores in Figure 2. We found a relevance between mean hue val-

	Color	Edge	Texture	Saliency	All
Visual int.	*0.4558*	0.4481	**0.3829**	0.4511	0.4083
Social int.	**0.2728**	0.3043	*0.3611*	0.3280	0.2831

Table 3. Testing error of different features for predictions on visual and social interestingness. Averaged over 10-fold cross-validation.

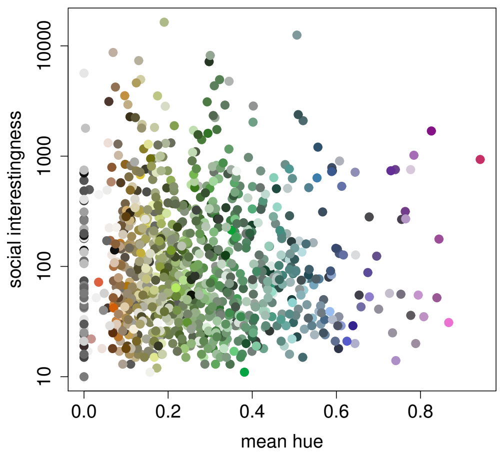

Fig. 2. Plot of image social interestingness ('repins' plus 'likes' for Pinterest image) and mean hue. The proportion of images with medium mean hue (0.2 $\sim$ 0.5) is relatively less in higher social interestingness section (c.f. Figure 3). Best seen in color.

ues of images and image social interestingness (Figure 3) which fits the U-shaped relationship between color wavelength and arousal effect [11]. As suggested by the U-shaped curve, colors with extreme wavelengths such as red and violet, can evoke greater activation-related affect (arousal). Previous studies also found that certain colors, especially red, are more physiologically and psychologically activating than other colors [12]. Thus, the correlation between social interestingness and color aspect of images exhibited by the performance of color feature, can be explained by the U-shaped curve if we assume that the re-sharing behavior leading to high social interestingness of image may need greater arousal effect to evoke it. Compared to visual interestingness, this experiment results may imply that the perception of simple visual elements (e.g., color, edge) plays more important role when people re-share images.

4. CONCLUSIONS

People always seek interesting things in their surroundings. Interesting images especially attract the sight of people. That is why so many photo services emerge on Internet today that facilitate sharing of images interesting to users. As one of the subjective properties of images, image interestingness is not a simple and single concept, but in fact involves several aspects of viewer perception. In the area of computer vision research, while there has been few previous works to study some related concepts such as image attractiveness, this multi-faceted feature of image interestingness has not been comprehensively investigated. Considering the explosive growth of the number of images produced and shared by people, combined with people's habit to seek interesting images, the importance of image interestingness is no less than other subjective properties well studied in the literatures, such as aesthetics, memorability. Image interestingness could be used in applications such as user photo service, advertising, etc.

This is the first work that attempts to comprehensively study the concept of image interestingness. Based on the surveys conducted

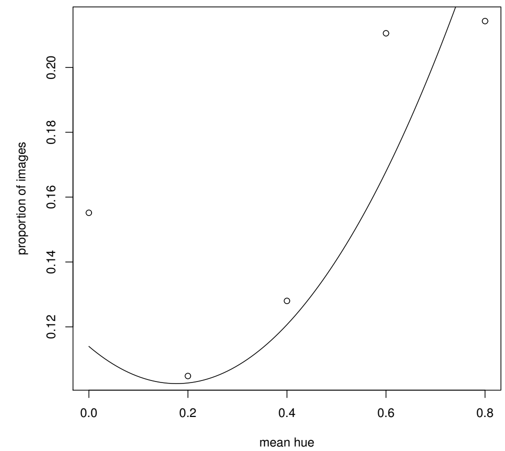

Fig. 3. Plot for the polynomial regression fitting (residual: 0.03562) between the proportion of images with higher social interestingness (i.e. more than 400) and mean hue. Notice that in higher social interestingness section, the proportion of images with medium mean hue (0.2 $\sim$ 0.5) is relatively less. In contrast, the proportion of images with extremely low and high mean hue ($<$ 0.2 and $>$ 0.5), which would evoke arousal effect, becomes greater in this section. The trend fits the U-shaped relation between color wavelength and arousal level evoked by color.

by using AMT, we investigated the difference between visual interestingness, social interestingness, and image aesthetics. Using statistical tools, it was verified that we can rely on the crowdsourcing platform to produce data with enough high consistency and reliability for those highly subjective image properties.

We found that image aesthetics is more related to visual interestingness than social interestingness. There has been only small or even no correlation between visual and social interestingness. It suggests that beautiful images are not certainly the images people would be more likely to re-share on photo service. However, compared to Flickr, for another relatively new photo service Pinterest, the correlation between visual interestingness and image aesthetics is much less. In fact, the correlation coefficients between social interestingness and other properties are all less for Pinterest. It implies that visual factor plays less importance behind frequently re-shared Pinterest images.

We found that social and visual interestingness can be best predicted with color and texture, respectively. The experiment results suggest a way to manipulate social and visual liking of images with image features. Further, we found that colors with arousal effect show more frequently in images with higher social interestingness. That finding provides useful and important advice when advertising on social networking sites. In future work we will collect more image data from more online photo services. We will investigate the correlation between image interestingness and other image features such as object semantics and human attributes.

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