Social-oriented visual image search

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\begin{abstract}
Many research have been focusing on how to match the textual query with visual images and their surrounding texts or tags for Web image search. The returned results are often unsatisfactory due to their deviation from user intentions, particularly for queries with heterogeneous concepts (such as “apple”, “jaguar”) or general (non-specific) concepts (such as “landscape”, “hotel”). In this paper, we exploit social data from social media platforms to assist image search engines, aiming to improve the relevance between returned images and user intentions (i.e., social relevance). Facing the challenges of social data sparseness, the tradeoff between social relevance and visual relevance, and the complex social and visual factors, we propose a community-specific Social-Visual Ranking (SVR) algorithm to rerank the Web images returned by current image search engines. The SVR algorithm is implemented by PageRank over a hybrid image link graph, which is the combination of an image social-link graph and an image visual-link graph. By conducting extensive experiments, we demonstrated the importance of both visual factors and social factors, and the advantages of social-visual ranking algorithm for Web image search.
\end{abstract}

1. Introduction

Image search engines play the role of a bridge between user intentions and visual images. By simply representing user intentions with textual query, many existing research works have been focusing on how to match the textual query with visual images and their surrounding texts or tags. However, the returned results are often unsatisfactory due to their deviation from user intentions. Let’s take the image search case “jaguar” as an example scenario, as shown in Fig. 1. Different users have different intentions when inputting the query “jaguar”. Some are expecting leopard images, while others are expecting automobile images. This scenario is quite common, particularly for queries with heterogeneous concepts (such as “apple”, “jaguar”) or general (non-specific) concepts (such as “landscape”, “hotel”). This raises a fundamental but rarely-researched problem in Web image search: how to understand user intentions when users conducting image search?

In the past years, this problem is very difficult to resolve due to the lack of social (i.e., inter-personal and personal) data to reveal user intentions. On one hand, the user search logs, which contain rich user information, are maintained by search engine companies and kept confidential; on the other hand, the lack of ID (user identifier) information in the user search logs makes them hard to be exploited for intention representation and discovery. However, with the development of social media platforms, such as Flickr and Facebook, the way people can get social (including personal) data has been changed: users’ profiles, interests and their favorite images are exposed online and open to public, which are crucial information sources to implicitly understand user intentions.

Thus, let’s imagine a novel and interesting image search scenario: what if we know users’ Flickr ID when they conducting image search with textual queries? Can we exploit users’ social information to understand their intentions, and further improve the image search performances? In this paper, we exploit social data from social media platforms to assist image search engines, aiming to improve the relevance between returned images and user intentions (i.e., user interests), which is termed as Social Relevance.

However, the combination of social media platforms and image search engine is not easy in that:

1. Social data sparseness. With respect to image search, the most important social data is the favored images of users. However, the large volume of users and images intrinsically decide the sparseness of user-image interactions. Therefore most users only possess a small number of favored images, from which it is difficult to discover user intentions. This problem can be
alleviated by grouping users into communities, with the hypothesis that users in the same community share similar interests. Thus, a community-specific method is more practical and effective than a user-specific method.

(2) The tradeoff between social relevance and visual relevance. Although this paper aims to improve the social relevance of returned image search results, there still exists another important aspect: the Visual Relevance between the query and returned images. The visual relevance may guarantee the quality and representativeness of returned images for the query, while the social relevance may guarantee the interest of returned images for the user, both of which are necessary for good search results. Thus, both social relevance and visual relevance are needed to be addressed and subtly balanced.

(3) Complex factors. To generate the final image ranking, we need to consider the user query, returned images from current search engines, and many complex social factors (e.g. interest groups, group-user relations, group-image relations, etc.) derived from social media platforms. How to integrate these heterogeneous factors in an effective and efficient way is quite challenging. In order to deal with the above issues, in this paper, we propose a community-specific Social-Visual Ranking (SVR) algorithm to rerank Web images according to their social relevances and visual relevances. In this algorithm, complex social and visual factors are effectively and efficiently incorporated by hybrid image link graph, and more factors can be naturally enriched.

It is worthwhile to highlight our contributions as follows:

(1) We propose a novel image search scenario by combining the information in social media platforms and image search engines to address the user intention understanding problem in Web image search, which is of ample significance to improve image search performances.

(2) We propose a community-specific social-visual ranking algorithm to rerank Web images according to their social relevances and visual relevances. In this algorithm, complex social and visual factors are effectively and efficiently incorporated by hybrid image link graph, and more factors can be naturally enriched.

(3) We have conducted intensive experiments, indicated the importance of both visual factors and social factors, and demonstrated the advantages of social-visual ranking algorithms for Web image search. Except image search, our algorithm can also be straightforwardly applied in other related areas, such as product recommendation and personalized advertisement.

The rest of the paper is organized as follows. We introduce some related works in Section 2. Image link graph generation and image ranking is presented in Section 3. Section 4 presents the details and analysis of our experiments. Finally, Section 5 concludes the paper.

2. Related work

Aiming at improving the visual relevance, a series of methods are proposed based on incorporating visual factors into image ranking. The approaches can be classified into three categories: classification [1–3], clustering [4] and link graph analysis [5–7]. An essential problem in these methods is to measure the visual similarity [8], assuming that similar images should have similar ranks. Besides, many kinds of features can be selected to estimate the similarity, including global features such as color, texture, and shape [9,10], and local features such as Scale Invariant Feature Transform (SIFT) feature [11]. Although there are different
performance measurements of a reranking algorithm [12], the relevance to the query is still the most recognized measurement [13].

As an effective approach, VisualRank [5] determines the visual similarity by the number of shared SIFT features [11], which is replaced by visual words in the later works [14–17]. The similarity between two images is evaluated by the co-occurrence of shared visual words. After a similarity based image link graph was generated, an iterative computation similar to PageRank [18] is utilized to rerank the images. A latent assumption in VisualRank is, similar SIFT features represent shared user interests. Intuitively, if an image captures user's intention, the similar images also should be of user's interest. By this hypothesis, VisualRank obtains a better performance than text-based image search in the measurement of relevance for queries with homogeneous visual concepts. However, for queries with heterogeneous visual concepts, VisualRank does not work well. For the returned results often include multiple categories, it is difficult for us to estimate which one best captures user's intention. Though VisualRank can better rank the images from same category, it is still hard to determine which category is expected by the user. Thus, VisualRank is applied mainly for product search, where the queries are usually with homogeneous visual concepts.

With the development of social media platform, the concept of social image retrieval was proposed, which brings more information and challenges to us. Most of works in social image search focus on tags of social image, such as evaluating the tag relevance [19,20], and measuring the quality of the tag [21,22]. It is obvious that search result quality is very low for queries with heterogeneous visual concepts. However, for queries with heterogeneous visual concepts, VisualRank does not work well. For the returned results often include multiple categories, it is difficult for us to estimate which one best captures user's intention. Though VisualRank can better rank the images from same category, it is still hard to determine which category is expected by the user. Thus, VisualRank is applied mainly for product search, where the queries are usually with homogeneous visual concepts.

In our approach, a random walk model based on PageRank is utilized for image ranking. Although for image search there are not direct relationships as hyperlinks, we can intuitively imagine that there are some invisible links driving the user to jump from one image to another. Therefore, the essential problem is to define the weights of the links. In our model, the weight p(l, l′) of the link from image l to image l′ represents the probability that a user will jump to l′ after viewing l. This procedure can be considered in both social factor and visual factor. From the social point of view, when the user is interested in l, he will also be interested in l′’s group Gp. Then he found a group Gq which is very similar to Gp. Finally he decides to visit the images in Gq, including l′. This type of jump is driven by social relevance. From the visual point of view, a user may be attracted by some contents of l, and then decide to view l′, which also contains these contents. This jump is driven by visual similarity. As a result, these two factors will both have significant effects in image ranking. For incorporation, we define our image link graph as the linear combination of the visual-link graph and the social-link graph. I.e.,

$$P_v = \alpha \cdot P_C + (1 - \alpha) \cdot P^v$$

where $P_v$ is the adjacency matrix of the hybrid image link graph. $P_C$ is the matrix for image social-link and $P^v$ is the matrix of image visual-link graph. $\alpha$ is a parameter to balance these factors. The estimation of $\alpha$ will be discussed in Section 4. In this equation, $P_C$ and $P^v$ are relevant to the user’s membership group G. Therefore they have a subscript as ‘G’. The symbols with the subscript ‘G’ in our algorithm have the same meaning.

In the next sections, we will show how to generate image link graph for final ranking step by step.

3.2. Image social-link graph

For image social-link graph is based on the social strength, we will first generate a global group link graph based on group similarity. Then, PageRank method is utilized for this graph to evaluate the group importance. Next, we generate a local group link graph specific for group G. The edge weights of the group link graph are determined by social strength. Finally, an image social-link graph can be constructed based on the local group link graph.

3.2.1. Global group ranking

First, a global group link graph is generated in preprocessing phase of our algorithm based on group similarity. The similarity between two groups is determined by two factors: image factor and user factor. It can be assumed that an image belongs to a category of interest, a user has some interests and a group is a community where users share interests with others. Based on this hypothesis, if two groups have many users in common, it is of high probability that these two groups are of same interests. Similarity, if two groups have many images in common, they are also very probable to share the common interests. Therefore, group similarity in user interests can be measured by the overlap of user sets and data sets, which is defined as:

$$S(G_u, G_v) = \lambda \cdot \frac{\text{overlap}(M_t, M_i) + (1 - \lambda) \frac{\text{overlap}(I_u, I_v)}}$$

where $M_t$ is the member set of group $G_u$ and $I_u$ is the image set of group $G_u$. $\lambda$ is a parameter to balance the user factor and the image
factor. It will be studied by our experiments. The overlap of \( \mathcal{M}_i \) and \( \mathcal{M}_j \) can be described as Jaccard similarity:

\[
\text{overlap}(\mathcal{M}_i, \mathcal{M}_j) = \frac{\left| \mathcal{M}_i \cap \mathcal{M}_j \right|}{\left| \mathcal{M}_i \cup \mathcal{M}_j \right|}
\]  

so is the overlap of \( I_u \) and \( I_v \). We utilize overlap function rather than the number of common elements for the consideration of normalization.

After the pair-wised group similarities are computed, we define the importance of a group as its centrality in the global group link graph. Intuitively, a group similar to many other groups should be important. The iterative computation based on PageRank can be utilized to evaluate the centrality of the groups:

\[
gr = d \cdot S \cdot gr + (1 - d)e_0, \quad e_0 = \left[ \frac{1}{N_G} \right]_{N_G \times 1}
\]

where \( S \) is a column-normalized matrix constructed by \( S(G_u, G_v) \). \( N_G \) is the number of groups. \( d \) is called damping factor, which denotes the probability user stay in visiting the images along the graph links. In practice, \( d = 0.8 \) has a good performance with small variance around this value.

As illustrated in Fig. 3, PageRank over global group link graph models the random walk behavior of a user on these groups. First, he randomly accesses a group. Then, for the interests in some members or some images of this group, he visits another group which also contains these members or images. After a period of time, he is tired of visiting the images along the link of the group, then he randomly access another group again.

Global group link graph and group rank describe the global properties (similarity and importance) of groups. It is not specific for the query and the user's membership group \( G \). Therefore, \( S(G_u, G_v) \) and \( gr \) can be computed off line and updated at regular time.

### Table 1

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>( G )</td>
<td>The user membership group for image ranking</td>
</tr>
<tr>
<td>( G_u )</td>
<td>The ( u )th group in our group set</td>
</tr>
<tr>
<td>( I_i )</td>
<td>The ( i )th image in our image set</td>
</tr>
<tr>
<td>( M_u )</td>
<td>The member set of ( G_u )</td>
</tr>
<tr>
<td>( I_u )</td>
<td>The image set of ( G_u )</td>
</tr>
<tr>
<td>( p_u(I_i, I_j) )</td>
<td>The image social similarity between ( I_i ) and ( I_j ) for ( G_u )</td>
</tr>
<tr>
<td>( p_v(I_i, I_j) )</td>
<td>The visual similarity between ( I_i ) and ( I_j )</td>
</tr>
<tr>
<td>( p^v(I_i, I_j) )</td>
<td>The image visual-link graph matrix constructed by ( p_v(I_i, I_j) )</td>
</tr>
<tr>
<td>( p^s(I_i, I_j) )</td>
<td>The image social-link graph matrix constructed by ( p_u(I_i, I_j) )</td>
</tr>
<tr>
<td>( S(G_u, G_v) )</td>
<td>The similarity of ( G_u ) and ( G_v )</td>
</tr>
<tr>
<td>( T(G_u, G_v) )</td>
<td>The social strength of ( G_u ) and ( G_v )</td>
</tr>
<tr>
<td>( C(I_i, I_j) )</td>
<td>The number of co-occurrence visual words of ( I_i ) and ( I_j )</td>
</tr>
<tr>
<td>( A(I_i, G_u) )</td>
<td>The indicator function of ( I_i ) belongs to ( G_u )</td>
</tr>
</tbody>
</table>

### Fig. 2

The framework of our approach. Among the four generated graphs, global group link graph evaluates the global importance of each group. Local group link graph reflects the relationship of the groups w.r.t. the interests of the current user. Image social link graph evaluates the social similarity of the images. Image visual link graph calculates the visual similarity of the images. Our ranking method is based on the last two graphs.

### Fig. 3

An illustration of group similarity (middle layer), which is determined by images' overlap (top layer) and users' overlap (bottom layer).
3.2.2. Local group link graph

Since the global group link graph and group ranking are obtained, the local group link graph can be generated based on social strength of pairwise groups. The social strength of group \(G_u\) and group \(G_v\), which is represented as \(T_c(G_u, G_v)\), describes the correlation \(G_u\) and \(G_v\) in \(G\)'s intentions. In other words, \(T_c(G_u, G_v)\) denotes the probability that an user in \(G\) will jump to the images of \(G_v\) after viewing the images of \(G_u\).

For instance, when \(G\) is a group about animals, one group about zoos and another about birds should be of tight social strength. Meanwhile, if a user in \(G\) has viewed the images of a group about IT, they may be more probably interested in the images about cartoon production than computer hardware because he is more interested in animals. Although the group about IT and another group about hardware are similar globally, the global social strength of them for \(G\) should be very weak. For quantitative analysis, there are some basic considerations about the social strength as following:

- The group similarity \(S(G_u, G_v)\) denotes the degree that \(G_u\) recommend \(G_v\) to \(G\).
- Users in \(G\) will not accept all the recommendations for it has a specific intention. If they are interested in \(G_v\), indeed, they may decide to visit it.
- In another case, When users in \(G\) are interested in \(G_u\) and \(G_v\), recommend \(G_v\) to \(G\), \(G\) may decide to accept the recommendation to visit \(G_v\).
- If other conditions are the same, the users in \(G\) will trust the recommendation of the most important group.

Under these considerations, we can formulate the social strength \(T_c(G_u, G_v)\):

\[
T_c(G_u, G_v) = \frac{(S(G, G_u) + S(G, G_v)) \cdot S(G_u, G_v)}{f(gr(G_u))} 
\]

where \(f(gr(G_u))\) is a function of the group rank value of \(G_u\) in the rank vector calculated in Eq. (4). It denotes the weight of group importance.

It has been proved that there is a power law between the scale (importance) of the groups and the quality of the images [28]. In this paper, we consider the function \(f(x)\) in the form of power function, which is proved to be valid in previous work [15], i.e.:

\[
f(x) = x^r
\]

where \(r\) is a parameter which will be estimated by experimental study.

3.2.3. Image social-link graph

Image social-link graph can be generated based on the social strength of group. For images and groups, we first construct a basic image-group graph. The edge from an image to a group denotes the image belonging to the group, which can be formulated as:

\[
A(i, G_u) = \begin{cases} 
1 & i \text{ belongs to } G_u \\
0 & \text{otherwise} 
\end{cases}
\]

Fig. 4 is an illustration of image social similarity. Based on local group link graph and image-group graph, we can define the weight of the edge in image social-link graph as:

\[
p^c(I_i, I_j) = \frac{Z_i}{\sum_{i=1}^{N_i} A(I_i, G_u) \sum_{i=1}^{N_j} A(I_j, G_v)} 
\]

3.3. Image visual-link graph

In VisualRank [5], the visual image link is weighted as the number of common SIFT descriptors. In our approach, we improve this method by a BoW (bag of words) representation. Since the SIFT descriptors of each image are extracted, a hierarchical visual vocabulary tree [30] based on hierarchical k-means clustering is built by all the descriptors. The leaf nodes of the hierarchical vocabulary tree are defined as visual words. After visual vocabulary is generated, an image can be regarded as a documents including some words. We can efficiently count the co-occurrence of visual words in two images. Therefore, the weight of the edge in visual image link graph can be defined as:

\[
p^v(I_i, I_j) = \frac{C(I_i, I_j)}{\sum_{i=1}^{N_i} A(I_i, G_u) \sum_{i=1}^{N_j} A(I_j, G_v) \cdot T(G_u, G_v)}
\]

where \(Z_i\) is a column-normalization factor to normalize \(\sum p^c(I_i, I_j)\) to 1. \(p^v(I_i, I_j)\) denotes the probability that group \(G\) will visit \(I_j\) after viewing \(I_i\).

In traditional random-walk model such as topic-sensitive PageRank [29], there is a basic assumption that the probabilities of the user’s jump from one vertex to another is only determined by the global correlation of the vertices. However, users usually surf on the Internet with some specific intention. By assuming this, users’ random walks are usually not on a global graph but a local one for a specific intention. Therefore, it is of great significance for us to generate the image social-link graph by a local group link graph.

However, there will be some problems if we only consider social-link graph. When the value of \(p^v(I_i, I_j)\) is high, the user will be very probable to jump from \(I_i\) to \(I_j\). However, when the value is low, it just indicates that we cannot estimate the probability based on our social knowledge. In other words, low social similarity cannot represent low transition probability. An extreme case is, when the current group \(G\) has no correlation to the query at all, social image ranking will not work. For instance, if a user in an IT group wants to search some foods one day, all the values in \(P^v\) may be close to zero. This is an important reason why we incorporate the visual factor to the social factor as well as to improve visual relevance.
features and jump to an image \( I_i \) which includes similar local features. If the image's local areas are shared by many other images, it will obtain a high ranking order by VisualRank. A lot of works show the effectiveness of VisualRank in visual relevance. In this paper, we explore the effect of VisualRank in social relevance.

### 3.4. Image social-visual ranking

After two image link graphs are generated, hybrid image link graph can be constructed by Eq. \((1)\). Then, the iteration procedure based on PageRank can be formulated as:

\[
 r_G = d \cdot P_G \cdot r_G + (1 - d)e 
\]

where \( d = 0.8 \) as in Eq. \((4)\). \( e \) is a parameter to describe the probability a user jumps to another image without links when they are tired of surfing by links. In the basic implementation of PageRank, each element of \( e \) is taken an equal value, as the jump without link is expected to be random. However, for a specific user, \( e \) should be relevant to the user's interests. Therefore, in personalized PageRank [31], \( e \) is defined as the probability that user randomly access a document based on his interest. In this method, a good measurement of the user's interests of image \( I_i \) is the average similarity of the user's group \( G \) and the groups including \( I_i \). Thus we have two choices of \( e \):

\[
 e_{1}(i) = \frac{1}{N_{i}} 
\]

where \( N_{i} \) is the number of images, and

\[
 e_{G}(i) = \frac{Z_{2} \sum_{u=1}^{N_{G}} A(l_{i}, G_{u}) \cdot S(G_{u}, G)}{\sum_{u=1}^{N_{G}} A(l_{i}, G_{u})} 
\]

where \( Z_{2} \) is the factor to normalize the sum of \( \sum e_{G}(i) \) to 1. In parameter analysis of PageRank [18], \( e \) is an important parameter for personalized search. Next session we will discuss the effect of \( e \) for \( e_{1} \) and \( e_{G} \) in our algorithm.

### 4. Experiments

#### 4.1. Dataset and settings

To implement our algorithm, we conduct experiments with data including images, groups, users, group-user relations and group-image relations from Flickr.com. Thirty queries are collected and 1000 images are downloaded for each query. These selected queries cover a series of categories tightly related to our daily life, including:

1. Daily articles with no less than two different meanings, such as "apple", "jaguar" and "golf".
2. Natural scenery photos with multiple visual categories, such as "landscape", "scenery" and "hotel".
3. Living facilities with indoor and outdoor views, such as "restaurant" and "hotel".
4. Fashion products with different product types, such as "smart phone" and "dress"

Each image downloaded must belong to at least one group. Social data are collected through Flickr API. If the size of a set (both user set and image set) is larger than 1000, we just keep the first 1000 elements.

The SIFT feature is extracted by a standard implementation [11]. The hierarchical visual vocabulary tree is of 4 layers and 10 branches for each layer. Each image is of normal size in Flickr, i.e., the length of the longest edge is no more than 400 pixels. According to our statistics, each image has about 400 SIFT features in average. Therefore, there are about 400 thousand SIFT descriptors in the image set of 1000 images for the query. Besides, the number of clustered visual words is no more than 10 thousand.

In our experiment, we compare our algorithm SVR with other three rank methods: VisualRank (VR), SocialRank (SR) and Flickr search engine by relevance (FR) as baseline. Among them, VR is the special case for SVR when \( \alpha = 0 \), and SR is the special case for \( \alpha = 1 \). We evaluate our algorithm in social relevance and visual relevance respectively.

#### 4.2. Metrics

We estimate the performance of our approach by two measurements. One is the relevance of current group's intentions, i.e., social relevance. The other is image quality, which is represented by visual relevance. The target of our algorithm is to improve the social relevance as much as possible with maintaining the visual relevance.

![Fig. 5. Performance for different values of \( r \) with \( \alpha = 0.3 \), \( \lambda = 0.4 \) and \( e = e_{G} \). Best performance is obtained with \( r = 0.5 \).](image_url)

![Fig. 6. Performance for different values of \( \alpha \) with \( \lambda = 0.4 \), \( r = 0.5 \) and \( e = e_{G} \). Best performance is obtained with \( \alpha = 0.3 \).](image_url)
4.2.1. Social relevance

Defined as the relevance of user intentions, social relevance is an important measurement in our experiments. To estimate whether the results of our approach is of group G’s intention, we use MAP (Mean Average Precision) as the metric. Sharing behaviors are used as the ground truth. For a query, we randomly select n testing groups from the dataset. For each group, if an image contains the query and belongs to the group, we can believe this image is relevant to the intention of the group. After the definition of the ground truth, MAP can be calculated as:

$$MAP = \frac{1}{|Q|} \sum_{q \in Q} \frac{1}{|G_q|} \sum_{G \in G_q} AP(q, G)$$

where $Q$ is the set of queries; $G_q$ is the set of the testing groups for the query $q$; and $AP(q, G)$ is the average precision of the ranking result when group $G$ searches for query $q$. In our experiments, there are 30 queries and we select 20 testing groups for each query. Therefore, $|Q| = 30$ and $|G_q| = 20$. MAP reflects the social relevance, i.e., whether an image is relevant the interests of the group. However, we need to consider about the over-fitting problem: it is possible for a mac user to find an image about fruit apple. Therefore, we can sacrifice the performance of AR a little as a trade off to visual relevance.

4.2.2. Visual relevance

For all images in our dataset are labeled according to their relevance, Normalized Discounted Cumulative Gain (NDCG) is adopted to measure the visual relevance [13,32]. Giving a ranking list, the score NDCG@n is defined as

$$NDCG@n = Z_n \sum_{i=1}^{n} \frac{2^{r(i)} - 1}{\log(1+i)}$$

$r(i)$ is the score of the image in the ith rank. $Z_n$ is the normalization factor to normalize the perfect rank to 1. In our experiment, we set $n = 100$, which means the user usually find the target image in the first 100 results returned by the search engine.

To evaluate the visual relevance, all the images are scored with ground truth according to the relevance to the corresponding query. The scores are of four levels, 0: irrelevant, 1: so-so, 2: good, 3: excellent. The score of an image is just determined by the quality of the image. For the query with heterogeneous visual concepts, all categories will be equal. For instance, both a leopard and a Jaguar brand car will be scored 3 if they are complete and clear.

In the rest of the this session, we’ll show the effectiveness of the proposed graphs in our approach and evaluate the performance based on these two measurements.

4.3. Parameter settings

In our approach, there are four parameters: $\lambda$ in Eq. (2), $r$ in Eq. (6), $\alpha$ in Eq. (1) and $e$ in Eq. (10). In this subsection, we will investigate the effect of different parameter settings. First, we randomly
sample a region of parameters and select the best setting. Starting from this setting, we study the effectiveness of each parameter. Iteratively, we fix three other parameters as constants and adjust the other one until there is no change for all parameters. After all parameters and convergent, we draw the curves of MAP and NDCG@100 for each parameter. Testing groups are selected over the whole dataset, as a total of 600. It is observed from Figs. 5–7 that MAP and NDCG@100 usually obtain the best performance for different parameter values. Actually, our hope is to improve the MAP while maintaining higher NDCG.

4.3.1. Effectiveness of global group link graph
In the above four parameters, \( r \) denotes the importance of global group link graph. When \( r = 0 \), we do not consider this graph in our method. When \( r \) is large, the more important groups will affect the user intention more. Fig. 5 shows the performance when \( r \) obtains different values. From the figure, it can be observed that the best performance measured by NDCG@100 is obtained when \( r = 0.5 \) and \( r = 1 \) for MAP. Besides, Fig. 5 indicates that the performance varies less when \( r \) is around 0.5. To guarantee the quality of search results, i.e., visual relevance, we utilize \( r = 0.5 \) as the near optimal setting of \( r \), which means the social strength \( S(u, v) \) in Eq. (5) finally should be defined as:

\[
T_G(G_u, G_v) = (S(G_u, G_v) + S(G_v, G_u)) \cdot S(G_u, G_v) \\
\cdot \sqrt{gr(G_u) \cdot gr(G_v)}
\]  

(15)

This result shows that in our algorithm, the importance of a group does help to improve the performance of our approach. However, it is not the decisive condition especially for NDCG. In other words, the importance of groups can help us better judge the image quality of the images.

4.3.2. Trade-off between social and visual link graph
\( \alpha \) is the parameter that denotes the importance of weigh of social factor in our ranking method. When \( \alpha = 0 \), the ranking methods is purely a visual method. When \( \alpha = 1 \), the method is only determined by social factors. It can be imagined that \( \alpha \) should have correlation to the query. Therefore, we estimate the setting of \( \alpha \) for each of the four categories. Fig. 6 shows the performance of our approach when \( \alpha \) obtains different values. From the results, we can observe that:

Fig. 10. Top-10 reranking results of our approach for two different groups compared to FlickrRank and VisualRank.
• For any category, the result of our approach obtains the best performance when $\alpha$ is not zero, i.e., $\alpha$ is of great help for all the queries tested in our experiment. The hypothesis that social factor is effective in image search is proved.
• Measured by MAP, $\alpha$ close to 1 produces the best performance. Therefore, if we just consider to give a higher ranking order to the images fit for user intentions, image ranking can be mainly based on social factor.
• The curve of NDCG indicates that, as the weight of social factor growing after a critical point, more and more images with low visual relevance are ranked to the front. In most cases, the performance of social image ranking in relevance is much worse than visual image ranking.

Based on these observation, $\alpha$ is determined to be 0.3 in our approach, which can guarantee the effect of NDCG with a fairly high MAP.

4.3.3. Other parameters
In Eq. (2), we calculate the group similarity in two dimensions: user dimension and image dimension. $\lambda$ is a trade-off parameter of these two dimensions. When $\lambda = 0$, we evaluate the group similarity by the overlap of their images. When $\lambda = 1$, the similarity depends on the overlap of the images. Fig. 7 shows the performance of our approach for different $\lambda$. From the figure, it can be observed that all these two measurements can be of best performance when $\lambda = 0.4$. As a parameter representing the trade-off between the users’ overlap and the images’ overlap, $\lambda$ shows a user more likely to be interested in a group due to its images than users. With above three parameters being set, we investigate the effect of $e$ in Eq. (10). We compare the performance of $e = e_c$ to $e = e_l$ for four categories of queries. Fig. 8 shows the results by two measurements. It can be observed that the approach with $e = e_c$ is better than $e = e_l$ for all categories. Thus, $e_c$ can indeed improve the performance of our approach.

4.4. Overall performance and search results
To prove the results of SVR can really reflect the user intentions, we randomly select 4 queries in different areas, which have obvious different visual meanings: “apple” (including fruits and mac products), “jaguar” (including leopards and automobiles), “landscape” (including different categories of photos about natural scenarios) and “hotel” (including photos about location and decoration). For each query, we select 2 groups that we can obviously estimate the interests by their names. Then, we show the top 10 images ranked by our approach for the selected two groups with FR and VR as baselines. Fig. 10 shows the results. For each query, each row from top to bottom corresponds to the top 10 results of FR, VR, SVR for the first group and SVR for the second group. From these instances it can be observed that our approach really knows what the group wants and the results are mostly of high quality. For the query “apple” and “jaguar”, which has obvious different visual concepts, SVR can find the images fit for the group names fairly well. In contrast, the top-10 results of VisualRank for “jaguar” are all about leopards.

For the quantitative evaluation of the performance, we compare our approach with other three ranking methods FR, VR and SR by the measurements MAP and NDCG for each category of queries defined in Section 4.1. The parameters are set from previous section. The NDCG and MAP are calculated by our approach compared with other three methods. Fig. 9 shows the comparison results. It can be observed that our approach achieves the best performance in NDCG and has great improvement in MAP compared to VisualRank. Although SocialRank performs best on MAP, the NDCG of SocialRank is much worse than VisualRank. Under the comprehensive consideration, SVR performs best in these four ranking methods.

5. Conclusions and future work
In this paper, we propose a novel framework of community-specific social-visual image ranking for Web image search. We explore to combine the social factor and visual factor together based on image link graph to improve the performance of social relevance under the premise of visual relevance. Comprehensive experiments show effectiveness of our approach. Our proposed method is significantly better than VisualRank and Flickr search engine in social relevance as well as visual relevance. Besides, the importance of both social factor and visual factor is discussed in details. For the query with heterogeneous visual concepts and the group with clear intention, our framework can effectively conduct community-specific image search.

Future work will be carried out on taking more features in social network into our consideration and making the social weight adaptive.

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