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YANG, Xiaopeng; ZHANG, Yongdong; YAO, Ting; ZHA, Zheng-Jun; and NGO, Chong-Wah. Click-boosting random walk for image search reranking. (2013). *Proceedings of the 5th International Conference on Internet Multimedia Computing and Service, ICIMCS 2013, Huangshan, Anhui, China, August 17-19*. 1-6. Available at: https://ink.library.smu.edu.sg/sis_research/6643

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Click-boosting Random Walk for Image Search Reranking

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ABSTRACT

Image reranking is an effective way for improving the retrieval performance of keyword-based image search engines. A fundamental issue underlying the success of existing image reranking approaches is the ability in identifying potentially useful recurrent patterns or relevant training examples from the initial search results. Ideally, these patterns and examples can be leveraged to upgrade the ranks of visually similar images, which are also likely to be relevant. The challenge, nevertheless, originates from the fact that keyword-based queries are used to be ambiguous, resulting in difficulty in predicting the search intention. Mining useful patterns and examples without understanding query is risky, and may lead to incorrect judgment in reranking. This paper explores the use of click-through data, which can be viewed as the footprints of user searching behavior, as an effective means of understanding query, for providing the basis on identifying the recurrent patterns that are potentially helpful for reranking. A new algorithm, named click-boosting random walk, is proposed. The algorithm utilizes clicked images to locate similar images that are not clicked, and reranks them by random walk. This simple idea is shown to outperform several existing approaches on a real-world image dataset collected from a commercial search engine with click-through data.

Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]: Retrieval models

General Terms

Algorithms, Experimentation, Performance

Keywords

Image search, search reranking, click-boosting, random walk

1. INTRODUCTION

The emergence of Web 2.0 has brought a new era of information production. Large amount of community-contributed media contents, such as images and videos, are generated and shared on

social media communities such as Flickr and YouTube. Due to the success of information retrieval, most search engines employ text-based search techniques for multimedia search by leveraging surrounding textual information. However, as textual information is sometimes noisy and even unavailable, it cannot always accurately and comprehensively describe the media content.

To improve the text-based search performance, visual search reranking has attracted extensive attention in both academia and industry in recent years. The existing visual reranking methods can be grouped into three categories according to how external knowledge is exploited [20]: self-reranking [7, 8, 17], example-based reranking [13, 18], and crowd-reranking [12]. The first category focuses on detecting recurrent patterns in the initial search results, and then uses the recurrent patterns to perform reranking. Hsu *et al.* propose an Information Bottleneck (IB) reranking method, which finds the optimal clustering of images as the recurrent patterns that preserves the maximal mutual information between the search relevance and visual features [7]. In [8], they further formulate reranking as a random walk problem along the context graph, where video stories are represented as nodes and the edges between them are weighted by multimodal contextual similarities. Compared with the first category which is purely based on the initial ranked list, example-based reranking mainly relies on the query examples provided by users. For example, Yan *et al.* propose to train a reranking classifier learned with the pseudo-relevance feedback (PRF) [18]. They treat the query examples as pseudo-positives and choose the bottom-ranked initial results as pseudo-negatives. Similar to self-reranking, the objective of crowd-reranking is to find relevant visual patterns through crowd sourced knowledge, e.g., multiple initial ranked results from various search engines [12]. Even though the above reranking methods have been proved effective, these methods ignore the significant effects of user feedback which is an explicit indication of relevance.

However, it is not easy to obtain sufficient and explicit user feedbacks as users are often reluctant to provide enough feedbacks to search engines. On the other hand, search engines may have large amounts of user click-through data, e.g., the queries issued by users and the corresponding clicked images, which represent a kind of “implicit” user feedback. Although the clicked images, along with their corresponding queries, cannot reflect the explicit user preference on the relevance of particular query-image pairs, they statistically indicate the implicit relationship between individual images in the ranked list and the given query. Therefore, we can regard click-through data as implicit user feedback based on the assumption that most of the clicked images are relevant to the given query. Compared with obtained explicit user feedback through human labeling, for example by relevance feedback mechanism [15, 22] which requests users to provide relevance scores for images, click-through

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ICIMCS '13, Aug. 17-19, 2013, Huangshan, Anhui, China.

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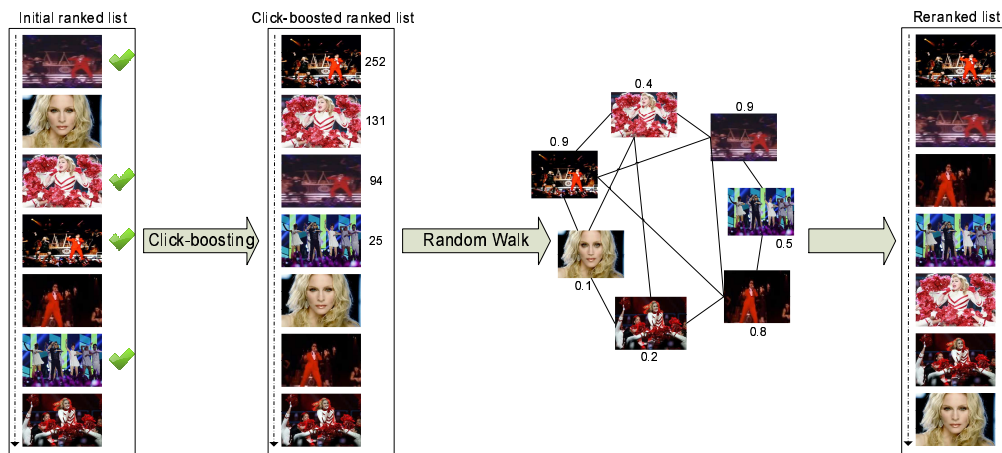


Figure 1: The overview of the proposed click-boosting random walk for image search reranking.

data is more readily available and freely accessible by search engines.

Click-through data have been widely used in the information retrieval area [2, 5, 4, 6, 11]. For example, Joachims *et al.* use eye tracking to analyze the relationship between the click-through data and the relevance of query web pages in web search [11]. They prove that click-through data can be used to obtain relative relevance judgments. Since click-through data are informative but biased, many researchers devote to building models for predicting unbiased click-through data for web search ranking. Dupret *et al.* propose a model based on user browsing behavior, which can estimate the probability that a document is seen, and thereby provide an unbiased estimate of document relevance [5]. They further use the document relevance as a feature for a “Learning to Rank” machine learning algorithm [4]. Chapelle *et al.* introduce the notion of satisfaction to separately model the relevance of the landing page and perceived relevance at the search result page, and build a Dynamic Bayesian Network (DBN) to provide the relevance from the click logs [3].

In image search, users browse image thumbnails before selecting the images to click. The decision to click is likely dependent on the relevance of an image. Thus, intuitively click-through data can serve as a reliable feedback potentially useful for search reranking. Nevertheless, to the best of our knowledge, there are very few attempts leveraging click-through data for image reranking. Based on the hypothesis that images clicked in response to a given query are mostly relevant to the query, Jain *et al.* employ Gaussian Process regression to predict the normalized click count for each image, and combine it with the original ranking score for reranking [9]. It is inspiring to bring click-through data for image search reranking. However, it is worth noticing that clicked data is likely, but not absolutely, relevant. Furthermore, an unclicked data is not necessarily irrelevant. Solely using clicked data may over (under) estimate the importance of clicked (unclicked) data.

In this paper, we focus on image search reranking using click-through data. To improve the performance of initial ranked results from search engines and avoid the biased case produced by merely using click data, we propose to combine click-through data with visual feature to conduct reranking. We propose a novel reranking method, named click-boosting random walk (CBRW), to improve the performance of text-based image search. CBRW consists of two major steps. It first boosts the initial ranked results by re-ordering images according to their click number. Then, it performs

random walk on an image graph [16] based on the click-boosted ranked results to rank the unclicked relevant images higher and the clicked irrelevant images lower. Thus, through click-boosting random walk, the reranking results are boosted by click-through data and improved by visual recurrent patterns. We applied the proposed method to perform image search reranking and conducted experiments over 40 image queries collected from a commercial image search engine. Experimental results show that the proposed click-boosting random walk reranking outperforms several existing methods.

This paper makes three major contributions:

- We leverage the click-through data and image visual feature simultaneously to perform image search reranking. In other words, we not only rerank images according to the images’ click data, but also rerank the unclicked images higher which are in close visual proximity with the clicked images. To the best of our knowledge, this is the first attempt in the domain of image search reranking.
- We propose an effective novel image search reranking method, named click-boosting random walk, which performs random walk on an image graph constructed using the ranked list boosted by click-through data.
- The algorithm is demonstrated on a real-world data consisting of 115,792,480 image URLs collected from a commercial search engine.

The rest of this paper is organized as follows. We introduce the proposed algorithm click-boosting random walk in Section 2. In Section 3, we analyze the click-through data generated from large-scale query logs. Experimental results are reported in Section 4 followed by the conclusions in Section 5.

2. CLICK-BOOSTING RANDOM WALK

There are two major steps in click-boosting random walk reranking. First, it boosts the initial ranked results according to the images’ click number since click-through data can implicitly reflect the relevance feedback of users to images. Second, it performs random walk on an image graph based on the click-boosted ranked results, where nodes in the graph represent images and edges between them are weighted by visual similarities. With this, the unclicked relevant images will be promoted if they are in close proximity

with the clicked relevant images, and the clicked irrelevant images will be ranked lower due to the dissimilarity of relevant ones. The overview of the proposed click-boosting random walk for image search reranking is shown in Figure 1.

Given a query, an initial ranked list of images is obtained by search engine based on the text-based search technique. The initial ranked list of query “madonna gangnam style” is shown as the first column of Figure 1 where images with checkmarks represent that they have been clicked by users according to the query log.

As mentioned above, we first rank the initial list in descending order according to the click number of each image as shown in the second column of Figure 1. The numbers on the right side of the top four images are the click number of the corresponding images. Based on the rule of click-boosting, the most clicked image with 252 clicks is reranked to the top and the unclicked images are r-ranked to the bottom of the list. However, we can clearly see that the 2th image with 131 clicks and the 4th image with 25 clicks are just partially relevant to the query “madonna gangnam style.” Beyond that, the 6th image is quite relevant to the given query, but gets a low position in the click-boosted ranked list. This situation is just the so called biased case produced by using click-through data solely. To improve the performance of ranked list based on click-boosting, we conduct random walk over the image graph as shown in Figure 1, where images are represented as nodes and the edges between them are weighted by visual similarities. During random walk, by iterative propagation of visual edge weights on the graph, similar recurrent patterns will get closer to each other. When random walk converges, each image will get a static probability as its reranked score (shown in Figure 1), and then a new reranked list can be generated by re-ordering the images in descending order according to their visual scores. As the third column in Figure 1 displays, after random walk, images with the same visual recurrent patterns are ranked closer to each other. Consequently, the unclicked relevant images can be promoted to higher rank; meanwhile the clicked irrelevant images may drop down to the bottom of the reranked list.

2.1 Formulation

For a given query, suppose we have an image set χ with N images to be reranked from the search engine where $\chi = \{I_1, I_2, \dots, I_N\}$ and $I_i (i \in \{1, 2, \dots, N\})$ denotes the i^{th} image of the initial ranked list. The ranked list can be recorded as $R = \{r_1, r_2, \dots, r_N\}$ where $r_i (i \in \{1, 2, \dots, N\})$ is the ranking of I_i and the initial ranked list can be represented as $R = \{r_i | r_i = i, i = 1, 2, \dots, N\}$.

Because the search engines can record the click number of each image, then we have a click-through data set C of the image set χ where $C = \{c_1, c_2, \dots, c_N\}$ and $c_i (i \in \{1, 2, \dots, N\})$ denotes the click number of I_i .

Click-boosting random walk is first formulated as a ranking problem according to the click number of images. Thus, we use quick-sort algorithm to rank the click-through data set C in descending order, and record r_{c_i} as the new ranking index of c_i . Then, the ranking r_i of image i is updated as r_{c_i} .

After click-boosting the initial image results, we get a new image ranked list $R' = \{r_i | r_i = r_{c_i}, i = 1, 2, \dots, N\}$. And then click-boosting random walk is formulated as a random walk problem [8, 21] on an image graph in Eq. (1) where images are represented as nodes and the edges between them are weighted by visual similarities.

$$x_j^{(t)} = \omega \sum_{i \in B_j} x_j^{(t-1)} p_{ij} + (1 - \omega) a_j, \quad (1)$$

where $x_j^{(t)}$ is the stationary probability of I_j at the iteration t , B_j is the set of images similar to I_j and p_{ij} is the transition probabilities

from image i to image j . The second term a_j is the score of image j obtained by click-boosting. ω is a weighting parameter which linearly weights the above two terms, and $\omega \in [0, 1]$.

When the process of random walk converges at the iteration ∞ , $x_j^{(\infty)}$ is not only the stationary probability of image I_j but also the indicator of the final reranked score of I_j . Naturally, we have $\sum_j x_j^{(\infty)} = 1$.

2.2 Solution

In this section, we will show the computation of the transition probability p_{ij} , the image score a_j in Eq. (1) and then discuss the solution.

To compute the transition probabilities p_{ij} of image j , we need the visual similarities matrix $S \equiv [s_{ij}]_{N \times N}$, where s_{ij} is the visual similarity between I_i and I_j and we use cosine distance to compute it. Noting that in order to ensure that each row of transition probability matrix $P \equiv [p_{ij}]_{N \times N}$ sums to 1, p_{ij} should be normalized as Eq. (2).

$$p_{ij} = \frac{s_{ij}}{\sum_{k=1}^N s_{ik}}. \quad (2)$$

The score a_j of random walk is calculated based on the updated ranking r_{c_j} of I_j after the step of click-boosting, and the formula can be represented as Eq. (3). Then we directly use the click-boosting ranking score and form a row vector $A \equiv [a_j]_{1 \times N}$.

$$a_j = 1 - r_{c_j} / N. \quad (3)$$

The state probability at the iteration t of the image graph can be written as a row vector $X^{(t)} \equiv [x_i^{(t)}]_{1 \times N}$. We re-write Eq. (1) in a following matrix form:

$$X^{(t)} = \omega X^{(t-1)} P + (1 - \omega) A. \quad (4)$$

As follows, we prove that the iteration of $X^{(t)}$ can converge to a fix point $X^{(\infty)}$.

Proof:

$$\begin{aligned} X^{(t)} &= \omega X^{(t-1)} P + (1 - \omega) A \\ &= \omega (\omega X^{(t-2)} P + (1 - \omega) A) P + (1 - \omega) A \\ &= \omega^2 X^{(t-2)} P^2 + \omega (1 - \omega) A P + (1 - \omega) A \\ &= \dots \\ &= \omega^t X^{(0)} P^t + \omega (1 - \omega) A ((\omega P)^{t-1} + (\omega P)^{t-2} + \dots + \omega P + U) \end{aligned}$$

where U is an identity matrix with P which diagonal elements are all 1 and the others are 0. According to Eq. (2), the sum of each row of matrix P is normalized to 1. For $0 \leq \omega \leq 1$, we can derive that

$$X^{(\infty)} = (1 - \omega) A (U - \omega P)^{-1}. \quad (5)$$

Eq. (5) is the unique solution. \square

3. CLICK-THROUGH DATA ANALYSIS

We have collected query logs from a commercial image search engine in Nov. 2012. The query logs are represented as plain text files that contain a line for each HTTP request satisfied by the Web server. For each record, the following fields are used in our data collection:

`<Query, ClickedURL, ClickCount, Thumbnail>`

where the *ClickedURL* and *ClickCount* represent the URL and the number of clicks on this URL when user submit the *Query*, respectively. *Thumbnail* denotes the corresponding image information on the *ClickedURL*.

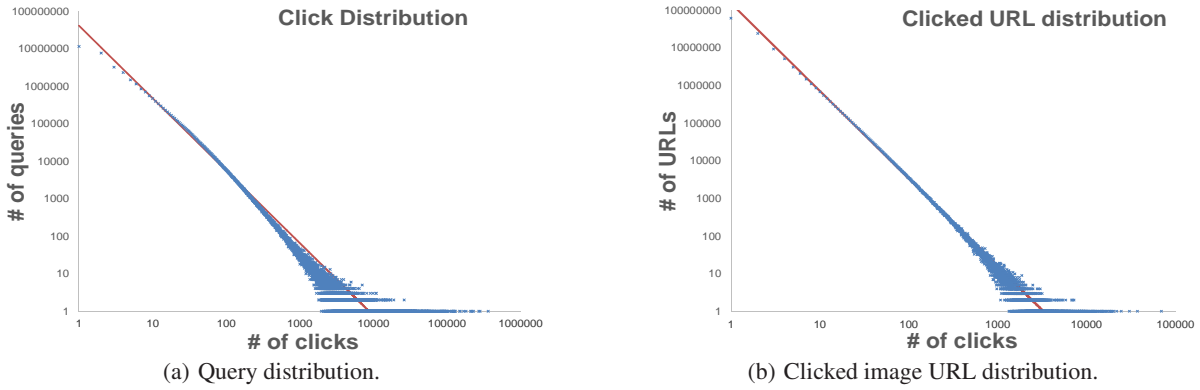


Figure 2: Query and clicked image URL distribution for the click-through data. Red lines denote the fitting power law curves.

For analyzing the click-through bipartite graph, we used all the queries in the log with at least one click. There are 34,783,188 queries and 115,792,480 image URLs on the bipartite graph. Figure 2 shows the main characteristics of the query and URL distribution. The left plot of Figure 2 shows the query click distribution. Each point represents the number of queries (y axis) with a given number of clicks (x axis). The plot on the right hand shows the clicked image URL distribution. Each point denotes the number of URLs with a given number of clicks. We can see that these two distributions clearly follow power laws. The observation is similar to [1], which also states that user search behavior follows a power law. Figure 2 shows the associated law. According to the statistics, each query has on average 11.59 clicked URLs and each URL was clicked by 3.48 times on average.

4. EXPERIMENTS

To facilitate evaluation and compare our proposed method with other methods, we randomly selected 40 queries¹ (as Figure 3 shows) from the queries mentioned in Section 3 as test samples. Since the images after the top 500 results are typically irrelevant, we used the top 500 images from the initial search results to perform reranking. We employed scale-invariant feature transform (SIFT) descriptor [14] with a Difference of Gaussian (DoG) interest point detector for extracting visual patterns of images. Then, we further used K-means to cluster the similar patches into “visual words,” and used Bag-of-Word (BoW) to represent each image as it has been successfully applied in information retrieval and computer vision [12, 19, 20]. Empirically, the number of visual words is set to 2,000.

4.1 Methodologies

We adopt Normalized Discounted Cumulative Gain (NDCG) [10] to measure the performance, which is widely used in information retrieval when there are more than two relevance levels. Given a

¹The queries include: (1) 3d wallpaper, (2) 15 party dresses, (3) 100 round ak, (4) awesome tattoo, (5) baby shower, (6) back tattoos, (7) backslash ideas, (8) beautiful tattoo, (9) boston fire hazmat, (10) bouncy castles, (11) cute baby, (12) deadmau5, (13) fall decorating ideas, (14) funny spongebob pictures, (15) gingerbread man, (16) girl teen bedrooms, (17) graffiti drawings, (18) green lantern, (19) greta garbo, (20) guitar factory, (21) gymnastics pictures, (22) hawaii, (23) hurricane sandy, (24) hurricane sandy jersey shore, (25) jennifer lopez, (26) kristen stewart, (27) lady gaga, (28) ledge stone hearth, (29) love tumblr quotes, (30) madonna gangnam style, (31) marianas trench, (32) mermaids, (33) monster high pictures, (34) murano glass, (35) siberian tiger, (36) skull, (37) tattoo drawing phoenix birds, (38) vintage christmas prints, (39) water fountains, (40) winter coloring pages.

ranked list, the NDCG score at the depth d is defined as

$$\text{NDCG}@d = Z_d \sum_{j=1}^d \frac{2^{r^j} - 1}{\log(1 + j)}, \quad (6)$$

where r^j is relevance score of the j^{th} image, and Z_d is a normalization constant to guarantee that a perfect ranking’s NDCG@ d is equal to 1. In our experiments, the relevance of each image was labeled manually with three levels: “irrelevant,” “fair,” and “relevant.”

To demonstrate the effectiveness of our proposed method click-boosting random walk (CBRW), we compare it with the following three reranking methods, where the parameters are optimized to achieve the best performance.

- Pseudo-relevance feedback (PRF)[18]. A typical example-based reranking method which assumes that top-ranked results are more relevant to the bottom-ranked results and performs reranking as a classification problem .
- Random walk (RW)[8]. A representative self-reranking method which conducts random walk on an image graph where nodes are images and edges are weighted by image visual similarities.
- Click-boosting solely (CBs). Compared to our proposed CBRW, CBs perform reranking by leveraging click-through data only.

4.2 Evaluations

4.2.1 Evaluation of reranking performance

For the proposed reranking method click-boosting random walk (CBRW), we conducted experiments to find out the most suitable weighting parameter ω in Eq. (4) for the 40 queries. Based on the experiment results, we set the weighting parameter $\omega = 0.3$ since it achieves the best performance.

Figure 4 shows the overall performance of different methods. Overall, our proposed click-boosting random walk reranking outperforms other methods, and the improvements are consistent and stable at different depths of NDCG. The click-boosting solely reranking (CBs) performs mostly better than the baseline, PRF and RW, which indicates that click-through data can provide much helpful information of user feedback for image reranking. Furthermore, the superiority of the proposed CBRW to CBs demonstrates that by means of finding images’ visual recurrent patterns we can

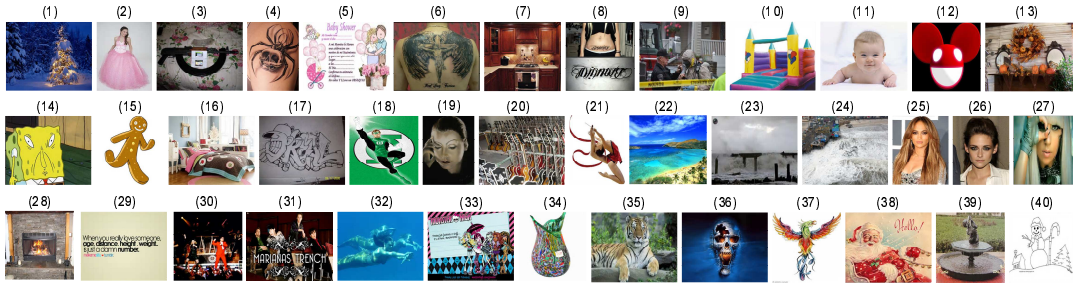


Figure 3: The exemplary relevant image thumbnails for the 40 queries in our dataset.

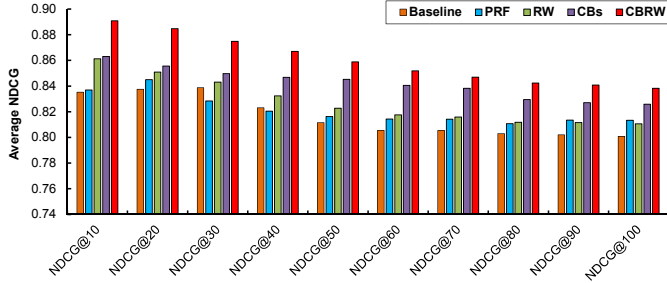


Figure 4: Comparison of reranking approaches in terms of NDCG.

solve the biased problem of click-through data to some extent. Accordingly, the unclicked relevant images can be recommended to be ranked higher and the clicked irrelevant images can be ranked lower and even excluded from the top ranked list.

Figure 5 shows the top 12 images of different reranking approaches for the query “water fountains.” We can clearly find that the most satisfying results can be obtained using our proposed method.

4.2.2 Evaluation of different queries

Figure 6 displays the NDCG performance at depth 50 across different queries. The NDCG values are normalized with respect to the maximum value and the minimum value. As we can see from Figure 6, our proposed method achieves the best performance in 22 out of 40 queries. It is worth noting that some of these queries obtain the perfect NDCG@50, for example NDCG values of query “graffiti drawings” and query “kristen stewart” are all increased to 1. Moreover, among the 22 queries which exhibit better NDCG using click-boosting random walk, there are four queries remaining the same NDCG value from using CBs to CBRW. This is mainly because that the NDCG values of those queries have already been upgraded to 1 by CBs, such as “awesome tattoo” and “deadmau5.”

However, for the queries such as “3d wallpaper” and “winter coloring pages,” the performance of CBRW is worse than CBs’. These cases are understandable because of the selection of parameter ω in Eq. (4) which determines the effects of CBRW. Due to the fact that we set parameter $\omega = 0.3$ which obtains the best performance on average, it is unavoidable that some individual queries perform worse using CBRW than CBs.

In the extreme cases, because click-boosting is an important priority of our proposed method, when click-through data are not helpful and even reduce the NDCG value of the initial ranked results, for instance, the query of “green lantern,” “greta garbo” and “siberian tiger,” unfortunately, our proposed method may fail. The possible reason is that these queries are so general that many kinds

of associated images are annotated as relevant. Therefore, it is difficult to improve the performance of initial ranked results using click-through data based on such a high baseline.

5. CONCLUSIONS

In this paper, we demonstrate the effects of the combination of using click-through data and detecting visual recurrent patterns for image search reranking. From our formulation, the initial ranked list is first boosted based on the images’ corresponding click data, and then promoted through random walk which produces the reranked result iteratively based on the image graph and the click-boosted reranked list. This can not only promote the position of relevant images according to the number of clicks, but also rank the unclicked relevant images higher owing to random walk. Our experimental results have demonstrated that the proposed click-boosting random walk reranking method outperforms several state-of-the-art approaches. Future work includes the study on feature fusion using click-through data for image reranking and also the deeper influence of click-through data on reranking according to different kinds of queries.

6. ACKNOWLEDGMENTS

This work is supported by National Nature Science Foundation of China (61172153), National Key Technology Research and Development Program of China (2012BAH39B02).

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Figure 5: Reranked lists from different methods of query “water fountains” [best viewed in color].

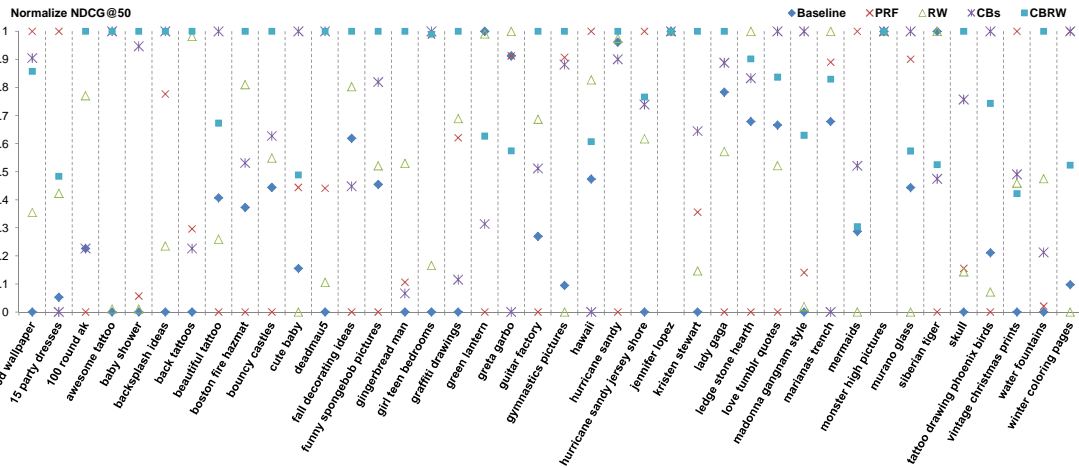


Figure 6: Normalized NDCG@50 of different methods across 40 queries. Note that NDCG is scaled with *max-min* normalization.

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