Research Paper Engineering

Customized Concept Learning in Image Search from Photo Sharing Websites

*Ch. priyanka **Dr P.Govardhan

* M.Tech (C.S.E) VCE (AICTE), Hyderabad, India

** Prof. IT, VCE (AICTE), Hyderabad India

ABSTRACT

The social media sites, such as Flickr and delicious, allow users to upload content and annotate it with descriptive labels known as tags, join special-interest groups, etc. Search personalization and diversification are often seen as opposing alternatives to cope with query uncertainty, where, given an ambiguous query, it is either preferable to adapt the search results to a specific aspect that may interest of the user (personalization) or to regard multiple aspects in order to maximize the probability that some query aspect is relevant to the user (diversification). In this paper, we exploit the social annotations and propose a novel bag-of-objects retrieval model for image search re-ranking of object queries. Firstly, we employ a common object discovery algorithm to discover query-relevant objects from the search results returned by text-based image search engine. Then, the query and its result images are represented as language model on the query-relevant object vocabulary, based on which the ranking function can be derived.

Keywords: Image Search Re-Ranking, Information filtering, Bag-Of-objects, Social Annotation.

1. INTRODUCTION

The rise of the Social Web underscores a fundamental transformation of the Web. Rather than simply searching for, and passively consuming, information, users of blogs, wikis and social media sites like delicious Flickr and dig, are creating, evaluating, and distributing information. In the process of using these sites, users are generating not only content that could be of interest to other users, but also a large quantity of metadata in the form of tags and ratings, which can be used to improve Web search and personalization.

The assumption is that different users may mean slightly different things by the same query expression. The Queries are in general short and non-specific. The Query "IR" has the interpretation of both information retrieval and infra-red. Users may have different intentions for the same query, e.g., searching for "jaguar" by a car fan has a completely different meaning from searching by an animal specialist. One solution to address these problems is personalized search, where user-specific information is considered to distinguish the exact intentions of the user queries and re-rank the list results.

Figure 1: A re-ranking example for query "Eiffel Tower".

The upper row is the result from a text-based search engine. The lower row is the re-ranking result by PRF assumption where the first image is regarded as positive sample. In this case, two irrelevant images are boosted to the top, because image F and D have high visual similarity to image A. For the above example, we may achieve a better performance if the re-ranking algorithm is performed.

Hence, we propose a bag-of-objects retrieval model to represent the query and its result images. To make the models focus more on the query-relevant objects we represent the image and query language models on a query-relevant object vocabulary. Since the text-based initial ranking can provide useful information on which image is more relevant than the others, we utilize this to improve the algorithm by considering the text-based ranking as a prior in Page Rank to differentiate the images at different rank positions.To estimate the relevance and condense of discovered objects to the query, we compute a set of attribute scores based on the position, size, and visual density of objects. Then these attributes are integrated into the retrieval model so that a linear weighted ranking function is derived. The proposed approaches are evaluated on two subsets of the publicly available Web Queries dataset. One comprises named person queries and the other comprises the other object queries.The results show that the bag-of objects retrieval model out performs all the other re-ranking methods.

2. ALGORITHM REVIEW

We first detect 30 ROIs with the highest saliency on each image using saliency object detection method proposed in, which are regarded as the hypothesis for query-relevant objects. Our method is composed of two steps. In the first step, we select the qualified hypotheses that are highly confident to be query-relevant objects. The second step is to cluster the selected ROIs and use the clusters as query-relevant object vocabulary. In the ROI selection step, the algorithm iteratively refines query-relevant ROI set until it becomes stable. In each iteration, the algorithm first recommends several representative ROIs which are considered to be the most query-relevant. These ROIs are called "hubs". Then, an ROI refinement procedure is applied on each image, where those ROIs with the highest similarity to the hubs are taken as query-relevant ROIs. The query-relevant ROIs selected by the second procedure are taken as the input of the next iteration.

2.1 ROI SELECTION

In iteration t, the "hubs" are obtained using link analysis technique of Page Rank [2]. Different from the hub-seeking procedure adopted in [15], the hubs selected in our method should not only be representative to an object, but also relevant enough to the query. To achieve this, we construct an augmented bipartite graph G (t) between S(t1) and C, where S(t1)={s(t1)i} denotes the ROIs selected in the last iteration, and C is the image ranking list of the current query returned by the search engine. The Page Rank algorithm calculates the ranking score for each vertex in G (t) where the ranking score on the vertex of an ROI intuitively shows the object condense and query relevance. The augmented bipartite graph G (t) is written as follows:

G (t) = [Gs (1) GdGTd 0] …….......... (1)

Where Gs is a k-nearest neighbor (k-NN) self-similarity graph constructed on S (t1). Gd is a bipartite graph constructed between S (t1) and the ranking list C, where each image document is linked to all its containing ROIs appeared in S (t1) with edge weight set to 1. In our experiment we set 0:8 For Page Rank algorithms.

I is the vector for priori probabilities I=[IkId] and the normalization term M=∑jCji1 log (i+1). The variable i indicates the ranking position of the image. Vector Id is set in this way because we assume images with higher ranking from text-based search engine are more likely to be relevant to the query. In each iteration, the text-based ranking score of each image is propagated to all its linked ROIs through the bipartite graph Gd. After Page Rank converges, we follow the hub-seeking method in to find the ROIs which are diverse.

2.2 ROI CLUSTERING

Since the "hubs" are regarded as typical for query-relevant objects, we treat each selected hub in the last iteration as the representation of a query-relevant object. Then, each selected ROI is assigned to its nearest hub if the distance is less than a threshold as the instance of the query-relevant object. We argue that the ROI's distance to the hub is not accurate enough in measuring its confidence of a query-relevant object. Thus, we re-estimate this confidence by Page Rank.

2.3 BAG OF OBJECTS RETRIEVAL MODEL

Given the discovered query-relevant object vocabulary in the above, we can represent the images and the query as a bag-of-objects .The ranking objective of an image d is related to the risk of returning it for a given query q, which can be defined on the query and document language.

2.4 MODELS

Here, a = d means the action of returning the document d for the query q, and G is the document collection in the database, r is the query-document relevance. Q and D are the language models for the query and the document, which are also called query model and document model respectively. L is the loss function which can usually be modeled by Kullback-Leibler divergence (KL divergence) between the query model and document model written as follows:

(Q; D) =∑MKi =1p (ki│Q) log p(ki│Q) p(ki│ D). .... (2)

Then, based on some derivations we can obtain the following ranking function:

R (d; q) α - ∑MKi= 1 P (ki│Q) logp (ki│ D) + q ……….......... (3)

Where Q and D are the maximum a posteriori estimation of the query and document models, and q is a constant which can be ignored for ranking. By sorting the image list with respect to the ranking function in Equation (3), we can get the re-ranked results.

In this paper, we calculate the object relevance S(ki; C) based on the attributes from each object. These attributes are proposed below to indicate the object relevance to the query. As the below attributes are extracted on each containing instance of the object, we calculate the score of each object based on the expectation and variance of the comprising instances attributes score, such that each attributecan capture not only the average information but also the variance of the instances. To reduce the impact of noisy ROIs, the score of each instance is weighted by its belonging confidence S(Ki; k)

Initial ranking: As stated in PRF based methods, the initial ranking of each image is critical to its relevance. Motivated by this, we assume that if an object has a set of instance whose parent images are all highly ranked by text-based search engine, the object can be regarded as query-relevant with a high probability. On the contrary, if all the instance of the object is ranked at the bottom of the ranking list, the object is probably irrelevant to the query. In this paper, we calculate the ranking score of each image with respect to its ranking position as follows:

IR(x) = 1log(R(x) + 1);

Where R(x) stands for the ranking position of image x.

Initial ranking of neighbourhood: The information from the visual neighbourhood can be propagated to improve the robustness of the estimation. Hence, we propose to use the initial neighbourhood.

Object size: Intuitively, if an ROI region occupies a big part of an image, it is probably the topic of the image. On the contrary, if an ROI is small, it is likely to be a background object which is the irrelevant to the topic of the image and so to the query.

Object location: An ROI locating on the center of the image intuitively tells that the photographer is taking a shot directly towards the object. In this paper, we adopt the shift of the ROI to the image center along X and Y axis, as well as the Euclidean distance of the ROI to the center.

Saliency: We use the average saliency scores of an ROI as one dimensional attribute score.

3. CONCLUSION AND FUTURE WORK

In this paper we argue that there is no single method for all queries and the research on image search re-ranking requires a new methodology. We propose a novel bag of objects retrieval model for re-ranking images for object queries. In this paper, we envision the following works. First, we will systematically classify queries into different domains regarding the possibility of image search re-ranking, and then develop algorithms to solve them respectively. Second, motivated by the object rank image representation; we may combine the object vocabulary discovered for the query and the objects from the collection to seek a more comprehensive representation of images and queries. Third, we hope to identify and address the system challenges so as to most efficiently integrate this algorithm into a real world image search engine.

REFERENCES

1. E. Oomoto and K.Tanaka. Ovid: Design and implementation of a video-object database system. IEEE Trans. On KDE, 5(4):629-643, 1993. | 2. E. Parzen. On estimation of a probability density function and mode. | 3. C. Rother, T. Minka, A.Blake, and V. Kolmogorov.Cosegmentation of image pairs by histogram matching-incorporating a global constraint. | 4. Interactive experiments in object- based retrieval. Image and video retrieval, pages 1-10, 2006. | 5. S. Sav, H. Lee, A. Smeaton, N. O'Connor, and N. Murphy.Using vid3eo objects and relevance feedback in video retrieval. 6015:353-364, 2005. | 6. F. Schroff, A. Criminisi, and A. Zisserman.Harvesting image databases from the web. In ICCV, pages 1-8, 2007. | 7. X. Tian, Y. Lu, L. Yang, and Q. Tian.Learning to judge image search results. In ACM Multimedia, pages 363-372, 2011.