QUERY RECONSTRUCTION IN IMAGE SEARCHING FOR OPTIMUM OUTCOME

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ABSTRACT

Image search engines suffer from a radical variance in retrieval performance over different queries. It is need to identify those difficult queries in order to handle them properly. Query difficulty estimation is an attempt to predict the performance of the search results returned by an image search system. Most existing methods for query difficulty estimation focus on investigating statistical characteristics of the returned images only, while neglecting very important information, the query and its relationship with returned images. To reduce human effects, in this paper, we use image click-through data, which can be viewed as the implicit feedback from users, to overcome the intention gap, and further improve the image search performance.

In this we propose a query difficulty estimation method with query reconstruction error with similarity and typicality. This method is proposed based on the semantic gap and the intent gap simultaneously, we propose to integrate multiple visual sense and click-through data with learning image similarity and typicality, and presenting better searching through Reranking approach, named spectral clustering re-ranking We begin query reconstruction through click based multi feature similarity and typicality(RCFST).first we propose multi feature similarity learning algorithm Then based on the learnt click-based image similarity measure, we conduct spectral clustering to group visually and semantically similar images into same clusters, and get the final re-rank list by calculating click-based clusters typicality and within clusters click-based image typicality in descending order. Showing the annotation to the resultant images for better understanding.

Keyword:-*image search, re-ranking, click based, multi feature, similarity, typicality.*

1. Introduction

Thousands of images are uploaded to the Internet with the explosive growth of on-line social media and the popularity of capture devices, thus, building a satisfying image retrieval system is the key to better user search experience. Due to the success of information recover, most commercial search engines used text-based search techniques for image search by using associated textual information, such as file name, surrounding text, image ,logo,URL, etc.. Even though text-based search techniques have achieved great success in document retrieval, text information is frequently deafening and even unavailable. In order to improve search performance, image search re-ranking, which adjusts the original ranking orders by removal visual content or leveraging some secondary knowledge, is proposed, and has been the focus of attention in both academia and industry in recent years. Most of the existing re-ranking methods make use of the visual information in an unverified and passive manner to overcome the “semantic gap” the gap between the low-level features and high-level semantics. Although multiple visual modalities have been used to further mine useful visual information, they can only achieve limited performance improvements. This is because these re-ranking approaches ignore the “intent gap” gap between the representation of users’ query demand and the real intent of the users.

User real search intent is hard to measure and capture without user involvement and response. Some researchers, attempt to integrate users interaction with the search process .It is not easy to obtain sufficient and explicit user feedback since users are often not like to provide enough response to search engines. Search engines can record queries issued by users and the corresponding clicked images. Clicked images, along with their corresponding queries, cannot reflect the clear user preference on relevance of particular query image pairs, they statistically indicate the understood relationship between individual images in the ranked list and the given query. Click-through data have been most used in the information retrieval area, users browse image thumbnails before selecting the images to click and the decision to click is likely dependent on the relevance of an image. Hence, we can view click through data as reliable “understood” user response hypothesizing that most clicked images are relevant to the given query. As the footprints of user search behaviour, click-through data is not only useful for providing understood relevance feedback from users but also is readily available and freely accessible by search engines .visually similar images should be close in a ranking list, and images with higher relevance should be ranked higher than others. Therefore, image similarity and image typicality become determinate factors correspondingly to obtain satisfying re-ranking results. Image similarity measure through, Euclidean distance and cosine distance are commonly used due to the success in the bag-of-words models for text. While image content is extracted and expressed in various kinds of features, in order to mine useful information from image content as much as possible, it would be better to leverage multiple visual modalities. However, when dealing with multiple visual modalities, there is often no obvious choice of similarity measure. Different kinds of features may lead to different forms of similarity. Beyond that, most of the existing re-ranking approaches only care whether an image is relevant (+ve) or irrelevant (-ve) to the given query without considering typicality.

Image search engines suffer from retrieval performance over different queries. It is need to identify those difficult queries in order to handle them properly. Query difficulty estimation is an attempt to expect the performance of the search results returned by an image search system. Most existing methods for query difficulty estimation focus on investigating statistical characteristics of the returned images only, while neglecting very important information, the query and its relationship with returned images. This relationship plays a fundamental role in query difficulty estimation and should be explored further.

In this we propose a query difficulty estimation method with query reconstruction error, given the images returned for an unknown query, easily visualize what the query is from those images if the search results are high quality otherwise, it is difficult to deduce the original query. Therefore, we propose to predict the query difficulty by measuring to what extent the original query can be recovered from the image search results. Explicitly, first reconstruct a visual query from the returned images to review their visual theme, and then use the reconstruction error, i.e., the distance between the original textual query and the reconstructed visual query, to estimate the query difficulty.

2. Literature Survey

1. Xinmei Tian, Qianghuai Jia, and Tao Mei. Presents Query Difficulty Estimation for Image Search With Query Reconstruction Error on which the image search engines suffer from a full contrast in retrieval performance over different queries. Existing methods for query difficulty estimation work on predicting statistical characteristics of the returned images only, while avoiding useful information. It uses Query Reconstruction Error-Based Query Difficulty Estimation (QRECE) algorithm [1].

2. The semantic gap between low-level visual features and high level semantics has been investigated for decades but still remains a big challenge in multimedia. When \search" became one of the most frequently used applications, \intent gap", the gap between query expressions and users' search intents, emerged. Researchers have been focusing on three approaches to bridge the semantic and intent gaps: 1) developing more representative features, 2) exploiting better learning approaches or statistical models to represent the semantics, and 3) collecting more training data with better quality. However, it remains a challenge to close the gaps [2].

3. Images clicked in response to a query are mostly relevant to the query. Therefore re-rank the original search results so as to promoted images that are likely to be clicked to the top of the ranked list. In this paper re-ranking algorithm employs Gaussian Process regression to predict the normalized click count for each image, and combines it with the original ranking score [3].

3. Problem Statement

To implement a efficient image search system which can perform following functions:-

After the input we present image search re-ranking, named spectral clustering re-ranking with click-based similarity and typicality.

4.Objective

1) User can give the image as input.
2) To overcome drawbacks of the drawbacks of exiting system and to improve the search performance, through the re-ranking which neglect the intent gap.
3) Feature extraction is the process of generating feature use for image selection and classification.
4) Cluster-based Reranking using click-through data.
5) Strategy for re-ranking respectively, i.e., visually similar images should close in rank list and also images which has higher relevance should be ranked higher than other images.

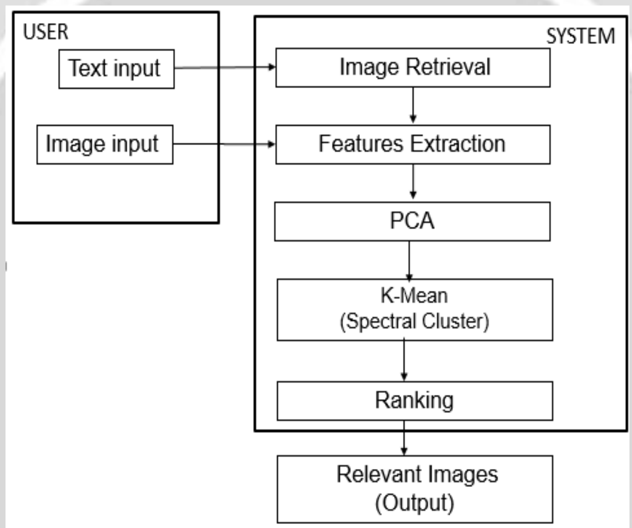

Fig -1: Proposed System Architecture

5. System Feature

In order to overbear the semantic gap and the intent gap simultaneously, we propose to integrate multiple visual sense and click-through data with learning image similarity and typicality, and presenting better searching through Reranking approach, named spectral clustering re-ranking We begin query reconstruction through click based multi feature similarity and typicality(RCFST). We elaborate the proposed multi-feature similarity learning algorithm (MSA), image typicality learning including cluster typicality and native typicality learning, and analyze the time complexity of RCFST finally.

5.1query reconstruction through click based multi feature similarity and typicality(RCFST)

To understanding the user feedback, it represent the data which is click by user. for reducing intent gap , we develop two click based acceptance and by combining them, with third acceptance as follows:

1) Images with more clicks has more typicality than relatively less or no clicks.

2) Images are more similar with each other which has at least clicked once than unclicked image.

3) Visually correlative images should be near in ranking list.

Based on the above assumptions and the commonly used strategy images with higher relevance should be ranked higher than others, we propose a novel image search re-ranking approach, named spectral clustering re-ranking with click based similarity and typicality. There are two major steps in RCFST. First, it performs click-based multi-feature image similarity learning algorithm, which leverages click through data as side information and integrates multi-feature metric learning into a unified scheme via multiple kernel l earning, to detect the appropriate image similarity metric for different features. Second, it conducts spectral clustering based on the jointly learnt image similarity measure for grouping visually and semantically similar images into clusters, and reorder search results based on the calculated click-based cluster typicality and within-clusters click-based image typicality to get the final re-ranked list. Given a query, an initial ranked list of images is obtained by the search engine based on the text-based search technique.

we first extract different kinds of visual modalities from images, and then transform multiple visual modalities into the same dimension by mapping them to their corresponding kernel space. Suppose m features are extracted in total, we adopt our proposed click based multi-feature similarity learning algorithm (detailed in the next section) to jointly learn similarity metrics for multiple features via click-based triplets detection and multiple kernel learning. After the process of click based similarity learning, feature_p (p = 1; 2; :::;m) obtains a unique image similarity metric_p accordingly. Based on these learnt multi-feature image similarity metrics, we performs spectral clustering to group similar images into same clusters. After conducting spectral clustering, in the process of learning click-based typicality, we first calculate cluster typicality based on the click-based cluster confidence and relative cluster similarity, and then re-order image clusters by the cluster typicality in descending order. Finally, based on the click-based image confidence and image local density, we compute each image's local typicality, and re-order search images within clusters to get the final re-ranked list. Compared with existing re-ranking approaches, can not only capture image visual and semantic similarity by click based multi-feature similarity learning, but also detect recurrent relevant patterns via spectral clustering using the jointly learnt metrics to further boost image search performance. We will show that this cluster-based re-ranking approach can significantly improve image search performance.

5.2 Learning Click-based Multi-feature Similarity

Encouraging by the idea of Similarity information in the form of organic or specific comparisons and multiple kernel partial order embedding (MKPOE) merging mixed data into a single and unified similarity space. We offer unusual image similarity learning algorithm integrating click based triplet's detection and multiple kernel learning into metric learning, as click based multi-feature similarity learning (CMSL) which provides relative similarity comparisons.

To be specific, since image click-through data represent users unexpressed feedback, and clicked (unclicked) images can be viewed as pseudo-labeled relevant (irrelevant) images to the given query. Thus, we capitalize click-based triplets consisting of two clicked images and an unclicked one as side information to drive the metric learning algorithm. Suppose we have two clicked image x^0i and x^0j and one unclicked image k, then the similarity side-information can be represented as "x^0i is more similar to x^0j than to xk." Besides using click-through data as images semantic guidance, to measure images at distinct visual aspects, we use multiple visual modalities, such as color, texture, and shape, in CMSL, and learn Mahalanobis distances accordingly by integrating them via multiple kernel embedding into a unified similarity space.The Mahalanobis distance between two images xi and xj can be defined as follows[4].

$$d_A(x_i, x_j) = \|x_i, x_j\|_A = \sqrt{(x_i - x_j)^{\mathrm{T}} A (x_i - x_j)}$$

5.3 Click Based Typicality.

After the process of click based similarity learning, we obtain feature_p (p = 1; 2; :::;m)and measuring image similarity.To detect similar recurrent patterns, based on the learnt similarity metrics, we conduct spectral clustering to group visually and semantically similar images into same clusters. Spectral clustering is done by using k-means which requires original data, spectral clustering only needs the pair-wise similarities between original instances. in this paper we can easily construct the pairwise-affinity matrix from the data based on the learnt image similarity metrics, and then performing spectral clustering.

Generally similar images have different level of relevance, for that we use typicality to measure the degree of relevance to certain query. For users' search intent we combine click counts of each image. So we will present cluster typicality and local typicality

1) In cluster typicality, it is click based and typicality specified by initial cluster and relative similar cluster. Define the initial cluster as a combination of initial score and click count.
2) In local typicality, determined by the initial image and local density. Local density of image measure the probability of image which appear in dataset.

To obtain the final re-ranked list. First re-rank the cluster using cluster typicality and then re-rank image using local typicality within clusters.

6. Conclusion

In this paper we have proposed system in which to improve the current image search system. Reducing the intent gap of image search. This explores relationship between the textual query and returns images. Click through data to reduce the intent gap of image. We propose a novel image search re-ranking approach, named spectral clustering re-ranking approach, named spectral clustering re-ranking with click-based similarity and typicality (RCFST). The final re-rank list is obtained by calculate cluster typicality and image typicality within cluster. Results conducted in this paper showing better performance than other existing system.

7. REFERENCES

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