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A REVIEW ON IMAGE SEARCH RANKING CLICK BASED SIMILARITY AND TYPICALITY USING SIFT ALGORITHM

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Abstract

In image search re-ranking, besides the well-known semantic gap, intent gap, which is the gap between the representation of users' query/demand and the real intent of the users, is becoming a major problem restricting the development of image retrieval. To reduce human effects, in this paper, we use image click-through data, which can be viewed as the implicit feedback from users, to help overcome the intention gap, and further improve the image search performance. Generally, the hypothesis visually similar images should be close in a ranking list and the strategy images with higher relevance should be ranked higher than others are widely accepted. To obtain satisfying search results, thus, image similarity and the level of relevance typicality are determinate factors correspondingly. However, when measuring image similarity and typicality, conventional re-ranking approaches only consider visual information and initial ranks of images, while overlooking the influence of click-through data. This paper presents a novel re-ranking approach, named spectral clustering re-ranking with click-based similarity and typicality. First, to learn an appropriate similarity measurement, we propose click-based multi-feature similarity learning algorithm, which conducts metric learning based on click-based triplets selection, and integrates multiple features into a unified similarity space via multiple kernel learning. 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. Our experiments conducted on two real-world query-image data sets with diverse representative queries show that our proposed re-ranking approach can significantly improve initial search results, and outperform several existing re-ranking approaches.

Index Terms—Image search, search re-ranking, click-through data, multi-feature similarity, image typicality.

INTRODUCTION

Image categorization is a very active research topic which has developed researches in many important areas of computer vision. It is an important but difficult task to deal with the background information. The background is often treated as noise; nevertheless, in some cases the background provides a context, which may increase the performance of image categorization.

The influence of the background on image classification. The effect of background on image categorization varies. Only semantically important contexts, such as object co-occurrence, or particular object spatial relations are helpful for image categorization. Backgrounds which contain only clutter provide no information to support image categorization.

Hundreds of thousands of images are uploaded to the internet with the explosive growth of online social media and the popularity of capture devices , thus, building a satisfying image retrieval system is the key to improve user search experience. Due to the success of information retrieval, most commercial search engines employ text-based search techniques for image search by using associated textual information, such as file name, surrounding text, URL, etc.. Even though text-based search techniques have achieved great success in document retrieval, text information is often noisy and even unavailable. In order to improve search performance, image search re-ranking, which adjusts the initial ranking orders by mining visual content or leveraging some auxiliary 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 utilize the visual information in an unsupervised 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 neglect the “intent gap” (the gap between the representation of users’ query/demand and the real intent of the users). Users’ real search intent is hard to measure and capture without users’ participation and feedback. Some researchers, therefore, attempt to integrate users’ interaction with the search process . However, it is not easy to obtain sufficient and explicit user feedback since users are often reluctant to provide enough feedback to search engines. Fortunately, search engines can record queries issued by users and the corresponding clicked images. Although the clicked images, along with their corresponding queries, cannot reflect the explicit user preference on relevance of particular query image pairs, they statistically indicate the implicit relationship between individual images in the ranked list and the given query. Beyond the fact that click-through data have been widely used in the information retrieval area , in image search, users browse image thumbnails before selecting the images to click and the decision to click is likely dependent on the relevance of an image.

Therefore, the regard click through data as reliable “implicit” user feedback 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 implicit relevance feedback from users but also is readily available and freely accessible by search engines.

There are a widely accepted assumption and a generally applied strategy for most image search re-ranking approaches respectively, i.e., 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 (the level of image relevance) become determinate factors correspondingly to obtain satisfying re-ranking results. For image similarity measure, Euclidean distance and cosine distance are commonly used due to the success in the bag-of-words models for text. Since 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 (positive) or irrelevant (negative) to the given query without considering typicality. In fact, even for the relevant images, they still have different degrees of relevance. Typicality, then, can be viewed as a soft labeling measure of the degree of relevance to a certain query. In general, if we can properly measure the similarity and typicality of images in the initial ranked list, the image search re-ranking will be benefited from it.

LITERATURE REVIEW

Tao Mei, Yongdong Zhang in the paper ,“Web Image Search Re-Ranking With Click-Based Similarity and Typicality”,[1]Proposed in image search re-ranking, besides the well-known semantic gap, intent gap, which is the gap between the representation of users’ query/demand and the real intent of the users, is becoming a major problem restricting the development of image retrieval. To reduce human effects, image click-through data, which can be viewed as the implicit feedback from users, to help overcome the intention gap, and further improve the image search performance. Generally, the hypothesis visually similar images should be close in a ranking list and the strategy images with higher relevance should be ranked higher than others are widely accepted. To obtain satisfying search results, thus, image similarity and the level of relevance typicality are determinate factors correspondingly. However, when measuring image similarity and typicality, conventional re-ranking approaches only consider visual information and initial ranks of images, while overlooking the influence of click-through data. First, to learn an appropriate similarity measurement, we propose click-based multi-feature similarity learning algorithm, which conducts metric learning based on click-based triplets selection, and integrates multiple features into a unified similarity space via multiple kernel learning. 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.

Mr. Sandesh Keshav Pawaskar in the paper,"Visual semantic web based image re-ranking for effective search engine",[2] Proposed in visual semantic web based Image search engine is a way using that multiple images are search and matched in semantic space. This matched images we use for image reranking methodology. Image re-ranking is a method using that we improve results of web based images search. When user search any query keyword on web based search engine, then a set of images are extracted based on the textual information. User then select a required query image from the set of images and then the others images are recomputed or re-ranked based on visual occurrence of the query image. These similarities of visual features do not well match with visual semantic meanings of images which normally coordinate users search intention and it is a main problem visual semantic web image search engine. The visual semantic web image re-ranking structure, which automatically and directly offline studied different visual semantic spaces meaning for different search query keywords. Then these visual features of images are extended to their visual semantic spaces to formed visual semantic signatures.

Nikit chaudhary, Sunil jadhav in the paper ,"Web Image Re-Ranking Using Query-specific semantic signatures",[3] Proposed in image re-ranking, as an effective way to improve the results of web based image search, has been adopted by current commercial search engines. Given a query keyword, a pool of images are first retrieved by the search engine based on textual information. By asking the user to select a query image from the pool, the remaining images are re-ranked based on their visual similarities with the query image. A major challenge is that the similarities of visual features do not well correlate with images' semantic meanings which interpret users' search intention.

M Sai KumarDr. C. Nalini in the paper, "Learning Image Re-Rank: Query-Dependent Image Re-Ranking Using Semantic Signature",[4] Proposed is an effective way to improve the results of web-based image search and has been adopted by current commercial search engines such as Bing and Google. When a query keyword is given, a list of images are first retrieved based on textual information given by the user. By asking the user to select a query image from the pool of images, the remaining images are re-ranked based on their index with the query image. A major challenge is that sometimes semantic meanings may interpret user's search intention. Many people recently proposed to match images in a semantic space which used attributes or reference classes closely related to the semantic meanings of images as basis.

Ms. Smita R Patil, Mr. Gopal Prajapati in the paper, "Implimentation of re-ranking of images based on textual and visual contex",[5] Proposed in re-ranking of images which will be based on textual and visual context. In early days various web-search engines are available to adopt Image re-ranking as an effective way to improve the results of web-based image search.Two types of image search methods are available in the Internet. They are query keyword based model and content based image retrieval models. Text query are used in the textual image retrieval model. Visual re-ranking has been widely deployed to refine the quality of conventional content-based image retrieval engines. The query keyword is given as input query, a pool of images are first retrieved based on textual information. It becomes difficult for user to interpret intention only on query keywords which leads to ambiguous and noisy results which are far different from user's satisfaction. It helps user to ask to select a query image from image pool with minimum effort and images from image pool retrieved by text-based search are re-ranked based on both visual and textual content.

Keze Wang, Liang Lin, Jiangbo Lu, Member, IEEE, Chenglong Li, and Keyang Shi in the paper, "PISA: Pixelwise Image Saliency by Aggregating Complementary Appearance Contrast Measures With Edge- Preserving Coherence",[6] Proposed in driven by recent vision and graphics applications such as image segmentation and object recognition, computing pixel-accurate saliency values to uniformly highlight foreground objects becomes increasingly important. A unified framework called pixelwise image saliency aggregating (PISA) various bottom-up cues and priors. It generates spatially coherent yet detail-preserving, pixel accurate, and fine-grained saliency, and overcomes the limitations of previous methods, which use homogeneous superpixel based and color only treatment. PISA aggregates multiple saliency cues in a global context, such as complementary color and structure contrast measures, with their spatial priors in the image domain. The saliency confidence is further jointly modeled with a neighborhood consistence constraint into an energy minimization formulation, in which each pixel will be evaluated with multiple hypothetical saliency levels.

Anand Kumar Dubey, Rohin Bhat in the paper , "Web Image Re-ranking using Query Specific Semantic Signatures"[7] Proposed in image re-ranking, as an effective way to improve the results of web-based image search, has been adopted by current commercial search engines. Given a query keyword, a pool of images are first retrieved by the search enginebased on textual information. By asking the user to select a query image from the pool, the remaining images are reranked based on their visual similarities with the query image. A novel image re-ranking framework, which automatically offline learns different visual semantic spaces for different query keywords through keyword expansions. The visual features of images are projected into their related visual semantic spaces to get semantic signatures. At the online stage, images are re-ranked by comparing their semantic signatures obtained from the visual semantic space specified by the query keyword.

B. Wu, T. Mei, W.-H. Cheng, and Y. Zhang in the paper , "Unfolding temporal dynamics: Predicting social media popularity using multi-scale temporal decomposition,"[8] Proposed in a novel re-ranking approach, named spectral clustering re-ranking with click-based similarity and typicality. First, to learn an appropriate similarity measurement, we propose click-based multi-feature similarity learning algorithm, which conducts metric learning based on click-based triplets selection, and integrates multiple features into a unified similarity space via multiple kernel learning. 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. The two real-world query-image data sets with diverse representative queries show re-ranking approach can significantly improve initial search results, and outperform several existing re-ranking approaches.

J.Tang, Z. Li, M. Wang, and R. Zhao in the paper, "Neighborhood discriminant hashing for large-scale image retrieval,"[9] Proposed in the article presents an image-based application aiming at simple image classification of well-known monuments in the area of Heraklion, Crete, Greece. This classification takes place by utilizing Graph Base Visual Saliency (GBVS) and employing Scale Invariant Feature Transform (SIFT) or Speeded Up Robust Features (SURF). For this purpose, images taken at various places of interest are being compared to an existing database containing images of these places at different angles and zoom. The time required for the matching progress in such application is an important element. To this goal, the images have been previously processed according to the Graph Based Visual Saliency model in order to keep either SIFT or SURF features corresponding to the actual monuments while the background "noise" is minimized. The application is then able to classify these images, helping the user to better understand what he/she sees and in which area the image has been taken.

Gu, V. S. Sheng, K. Y. Tay, W. Romano, and S. Li in the paper, "Incremental support vector learning for ordinal regression,"[10] Proposed the First, there is no straightforward, fully automated way of going from textual queries to visual features. Image search engines therefore primarily rely on static and textual features for ranking. Visual features are mainly used for secondary tasks such as finding similar images. Second, image rankers are trained on query-image pairs labeled with relevance judgments determined by human experts. Such labels are well known to be noisy due to various factors including ambiguous queries, unknown user intent and subjectivity in human judgments. This leads to learning a sub-optimal ranker.

Sayli Baxi and S.V.Dabhade in the paper, "Re-ranking of images using Semantic Signaturse with Duplicate Removal and K-means clustering",[11] Proposed in image Search engines mostly use keywords and they rely on surrounding text for searching images. Ambiguity of query images is hard to describe accurately by using keywords.Eg:Apple is query keyword then categories can be "red apple","apple laptop" etc.Another challenge is without online training low level features may not well co-relate with high level semantic meanings. Low-level features are sometimes inconsistent with visual perception.

Miss. Namrata P. Kawtikwar, Prof. M.R. Joshi in the paper, "Re-ranking of Images using Semantic Signatures with Duplicate Images Removal & K-means clustering",[12] Proposed in Image Search engines mostly use keywords and they rely on surrounding text for searching images. Ambiguity of query images is hard to describe accurately by using keywords.Eg:Apple is query keyword then categories can be "red apple","apple laptop" etc.Another challenge is without online training low level features may not well co-relate with high level semantic meanings. Low-level features are sometimes inconsistent with visual perception. The visual and textual features of images are then projected into their related semantic spaces to get semantic signatures. In online stage images are re-ranked by comparing semantic signatures obtained from semantic space obtained from query keywords.

Sarup and Akinchan Singhai in the paper, "Image fusion techniques for accurate classification of Remote Sensing data",[13] Proposed in the Image fusion techniques are helpful in providing classification accurately. The satellite images at different spectral and spatial resolutions with the aid of image processing techniques can improve the quality of information. Especially image fusion is very helpful to extract the spatial information from two images of different spatial, spectral and temporal images of same area. An operation of image analysis such as image classification on fused images provides better results in comparison of original data. In this paper comparison of various fusion techniques have been discussed and their accuracies have been evaluated on their respected classification.

Tao Mei, Yong Rui, and Shipengli, Microsoft Research, Beijing, China Qi Tian, University of Texas at San Antonio in the paper, “Multimedia Search Reranking: A Literature Survey”,[14] Proposed in the explosive growth and widespread accessibility of community-contributed media content on the Internet have led to a surge of research activity inmultimedia search. Approaches that apply text search techniques for multimedia search have achieved limited success as they entirely ignore visual content as a ranking signal. Multimedia search reranking, which reorders visual documents based on multimodal cues to improve initial text-only searches, has received increasing attention in recent years. Such a problem is challenging because the initial search results often have a great deal of noise. Discovering knowledge or visual patterns from such a noisy ranked list to guide the reranking process is difficult. Numerous techniques have been developed for visual search re-ranking. The categorize and evaluate these algorithms. The relevant issues such as data collection, evaluation metrics, and benchmarking.

Ankush R. Deshmukh, Asst. Prof. Pushpanjali M. Chouragade in the paper, “Click Prediction For Web Image Reranking Using Multimodal Sparse Coding ”,[15] Proposed in For the improvement of the performance of a text-based image search, Image reranking is a effective method. There are two reasons for which the reranking algorithms are limited and they are: One is that the data that is associated with images is not matched with the actual visual content and the second reason is that the reextracted visual features do not accurately describe the meaningful similarities between images. The relation of retrieved images to search queries has been more precisely described by user clicks, in recent years. However, a the lack of click is the data critical problem for click-based methods, since users have clicked a small number of web images. Therefore, the solution to this problem is by predicting image clicks. A multimodal hypergraph learning-based sparse coding method is proposed for image click prediction, and apply click data that has been obtained to the reranking of images. To build a group of manifolds, a hypergraph is adopted. A hyperedge present in a hypergraph is the edge that connects a set of vertices, and preserves the constructed sparse codes. The weights of different modalities and the sparse codes are obtained by an alternating optimization procedure. Finally, to describe the predicted click as a click or no click, a voting strategy is used from the images that was corresponding to the sparse codes. Image reranking algorithms are used to improve the performance of graph-based the use of click prediction is shown by an additional image reranking experiments on real world data that is beneficial.

Sangita B. Nemade, Pratiksha R. Deshmukh in the paper, “Review of Re-Ranking Techniques for Web Based Image Search”,[16] Proposed in to retrieve image form a web, text-based image search is easy and known process in which we give image names or tags as query to search engine so that it will provide desired set of images relevant to a query from huge image collection. Web based image re-ranking is used to produce a desired way to improve the result of web based image search. Feature extraction and ranking function design are two key steps in image search re-ranking. The purpose of web based image search re-ranking is to reorder retrieved elements to get optimal rank list. However, existing re-ranking algorithms are limited for two main reasons: 1) the textual meta-data associated with images is often mismatched with their actual visual content and 2) the extracted visual features do not accurately describe the semantic similarities between images. A major challenge in re-ranking the web based image is that the similarity of visual features does not well correlate with image.

Sumit Dhotre, Sathish Kumar Penchala in the paper, “Review on Content-Based Image Retrieval Reliance on User Intention”,[17] Proposed in the search engine returns thousands of images ranked by the keywords extracted from the surrounding text. It is well known that text-based image search suffers from the ambiguity of query keywords. The keywords provided by users tend to be short. They cannot describe the content of images accurately. The search results are noisy and consist of images with quite different semantic meanings. For example, if a user wants to search for an "apple" image, he/she may request a query search using the keyword "apple" to the corresponding image search engine. The meanings of the word "apple" include apple fruit, apple computer, and apple ipod. The search results will contain different categories, such as "green apple," "apple," "apple logo," and "iphone" because of the ambiguity of the word "apple". This leads to ambiguous & noisy search results which are not satisfactory to fulfil the user query request. In order to solve the ambiguity, additional information has to be used to capture users' search intention.

S.Sangeetha, 2 Satishkumar L. Varma in the paper, "Web Image Re-ranking using User Log Data",[18] Proposed in the search engines like Google, Yahoo are used to find different type of search like text, images and videos. Normally image based search is carried out using the textual information associated with it. And the final result contains both relevant as well as irrelevant images from the user's point of view. In day today life we search text and images based on keyword. Searching by keyword is considered to be easy and capable methods to retrieve text and images. The outcome from such a system is not always 100% relevant. The reasons for irrelevant search results may be due to in appropriate query and user's wrong perception. Image reranking techniques are used to tackle the issues. Fulfillment of the user will be improved if re-ranking is used as an important factor. Image re-ranking, is an efficient way to lookup the results of web-based image search. Clustering algorithm is used to remove noisy data at offline stage. System retrieves a collection of images based on textual information of the given query keyword. The retrieved images are ranked based on text similarity. When the user opts for a query image from the collection, the left over images is re-ranked based on their shape, color and texture with the query image. The user log method maintains the keyword and query images for further reference.

A. Meiappane, S. Monesh, S. Pradeep Kumar, U. Murugan in the paper, "One Click Image Search Re-Ranking Based On User Preference",[19] Proposed in the Web-scale image search engines (For e.g. Google Image Search, Bing Image Search, Pinterest) mostly rely on surrounding text features. It is difficult for them to predict user's intention only with the query they are giving and this leads to ambiguous and noisy search results from the search engines which are far from satisfactory. A novel Internet image search approach. Which requires the user only to click on one query image with the minimum effort and images from the database retrieved by text-based search are re-ranked based on both visual and textual content. Our goal is to capture the user's search intention from this one-click query image in four steps as follows. (1) The query image which the users search for is categorized into one of the predefined adaptive weight categories, which reflect user's search intention at some level. (2) Based on the visual content of the searching image selected by the user and through image clustering mechanism, the query keywords are expanded to capture user intention by one click. (3) Expanded keywords are used to enlarge the image pool to contain more relevant images in which the user search for. (4) Expanded keywords from the above stage are also used to expand the query image to numerous positive visual.

Pallavi Yadav in the paper, "Image Quality Retrieval: Improving Web Search Engine Result Using Relevance Feedback",[20] Proposed in the Image searching is designed to find images either from database or any other sources. To perform searching, a user has to type query in text form including keywords such as image file, image link, or select something by clicking on any image etc and then system would retrieve "relevant "images to the user. System performs similarity checking by considering some points like image color, file name, metadata log data, region detection, face, no of object present in image etc. there are two popular methods available are as follows 1)Text based Image Retrieval Content based Image

Retrieval(CBIR) with Relevance Feedback. There are many commercial and popular image search engines are available who takes query from user and returns a result like Google search Engine, Bing, yahoo. One thing is common in all these search engine is giving input method to system, all engines ask user to type text keyword for searching. User type text keywords in intention to find relevant images and system returns piles of similar images ranked form.

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