



RERANKING OF WEB IMAGE PREDICTION USING MULTIMODAL SPARSE CODE

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Abstract: Image search engine, as an effective way to provide matching of images in a semantic space which used attributes or reference classes closely related to the semantic meanings of images as basis. Given a query keyword, a pool of images is first retrieved 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. We propose a multimodal hyper graph learning-based sparse coding method for image click prediction, and apply the obtained click data to the reranking of images. We adopt a hyper graph to build a group of manifolds, which explore the complementarily of different features through a group of weights. Unlike a graph that has an edge between two vertices, a hyper edge in a hyper graph connects a set of vertices, and helps preserve the local smoothness of the constructed sparse codes. An alternating optimization procedure is then performed, and the weights of different modalities and the sparse codes are simultaneously obtained. Finally, a voting strategy is used to describe the predicted click as a binary event (click or no click), from the images' corresponding sparse codes. Thorough empirical studies on a large-scale database including nearly 330K images demonstrate the effectiveness of our approach for click prediction when compared with several other methods. Additional image re-ranking experiments on real world data show the use of click prediction is beneficial to improving the performance of prominent graph-based image re-ranking algorithms.

Keywords: Image Search, Semantic Signatures, Image Re-Ranking, Keyword Expansion, Semantic Space.

I.INTRODUCTION

Due to the tremendous number of images on the web, image search technology has become an active and challenging research topic. Well-recognized image search engines, such as Bing, Yahoo and, usually Google use textual meta-data included in the surrounding text, titles, captions, and URLs, to index web images. Although the performance of text-based image retrieval for many searches is acceptable, the accuracy and efficiency of the retrieved results could still be improved significantly.

One major problem impacting performance is the mismatches between the actual content of image and the textual data on the web page. One method used to solve this problem is image re-ranking, in which both textual and visual information is combined to return improved results to the user. The ranking of images based on a text-based search is considered a reasonable baseline, albeit with noise. Extracted visual information is then used to re-rank related images to the top of the list. Most existing re-ranking methods use a tool known as pseudo-relevance feedback (PRF), where a proportion of the top-ranked images are assumed to be relevant, and subsequently used to build a model for re-ranking.

This is in contrast to relevance feedback, where users explicitly provide feedback by labeling the top results as positive or negative. In the classification-based PRF method, the top-ranked images are regarded as pseudo-positive and low-ranked images regarded as pseudo-negative examples to train a classifier, and then re-rank. Hsu et al. also adopt this pseudo-positive and pseudo-negative image method to develop a clustering-based re-ranking algorithm.

The problem with these methods is the reliability of the obtained pseudo-positive and pseudo-negative images is not guaranteed. PRF has also been used in graph-based re-ranking and Bayesian visual re-ranking. In these methods, low-rank images are promoted by receiving reinforcement from related high-rank images. However, these methods are limited by the fact that irrelevant high-rank images are not demoted. Therefore, both explicit and implicit re-ranking methods suffer from the unreliability of the original ranking list, since the textual information cannot accurately describe the semantics of the queries.

Instead of related textual information, user clicks have recently been used as a more reliable measure of the relationship between the query and retrieved objects, since



clicks have been shown to more accurately reflect the relevance. Joachims et al. conducted an eye-tracking experiment to observe the relationship between the clicked links and the relevance of the target pages, while Shokouhi et al. investigated the effect of reordering web search results based on click through search effectiveness.

In the case of image searching, clicks have proven to be very reliable; 84% of clicked images were relevant compared to 39% relevance of documents found using a general web search. Based on this fact, Jain et al. proposed a method which utilizes clicks for query-dependent image searching. However, this method only takes clicks into consideration and neglects the visual features which might improve the retrieved image relevance to the query. In another study, Jain and Varma proposed a Gaussian regression model which directly concatenates the clicks and various visual features into a long vector.

Unfortunately the diversity of multiple visual features was not taken into consideration. According to commercial search engine analysis reports, only 15% of web images are clicked by web users. This lack of clicks is a problem that makes effective click-based re-ranking challenging for both theoretical studies and real-world implementation. In order to solve this problem, we adopt sparse coding to predict click information for web images.

Sparse coding is a popular signal processing method and performs well in many applications, e.g. signal reconstruction, signal decomposition, and signal denoising. Although orthogonal bases like Fourier or Wavelets have been widely adopted, the latest trend is to adopt an over complete basis, in which the number of basis vectors is greater than the dimensionality of the input vector. A signal can be described by a set of over complete bases using a very small number of nonzero elements. This causes high sparsity in the transform domain, but many applications need this compact representation of signals. In computer vision, signals are image features, and sparse coding is adopted as an efficient technique for feature reconstruction. It has been widely used in many different applications, such as image classification, face recognition, image annotation, and image restoration.

In this paper, we formulate and solve the problem of click prediction through sparse coding. Based on a group of web images with associated clicks (known as a codebook), and a new image without any clicks, sparse coding is utilized to choose as few basic images as possible from the codebook in order to linearly reconstruct a new input image while

minimizing reconstruction errors. A voting strategy is utilized to predict the click as a binary event (click or no click) from the sparse codes of the corresponding images. The over complete characteristic of the codebook guarantees the sparsity of the reconstruction coefficients. However, in addition to sparsity, the over completeness of the codebook causes loss in the locality of the features to be represented. This results in similar web images being described by totally different sparse codes, and unstable performance in image reconstruction; clicks are thus not predicted successfully. In order to address this issue, one feasible solution is to add an additional locality preserving term to the formulation of sparse coding. Laplacian sparse coding (LSC), in which a locality-preserving Laplacian term is added to the sparse code, makes the sparse codes more discriminative while maintaining the similarity of features, and enhancing the sparse coding's robustness.

However, LSC can only handle single feature images; in practice, web images are usually described by multiple features. For instance, commercial search engines extract and preserve different features such as color histograms, edge direction histograms, and SIFTs. Two categories of methods are used to deal with multimodal data: early fusion and late fusion. They differ in the way they integrate the results from feature extraction on various modalities. In early fusion, feature vectors are reconnected from different modalities as a new vector. However, this concatenation does not make sense due to the specific characteristics of each feature. In late fusion, the results obtained by learning for each modality are integrated, but these fused results from late fusion may not be satisfactory since results for each modality might be poor, and assigning appropriate weights to different modalities is difficult.

Web - image search engines mostly use keywords as queries and rely on surrounding text to search images. They suffer from the ambiguity of query keywords, because it is hard for users to accurately describe the visual content of target images only using keywords. For example, using "apple" as a query keyword, the retrieved images belong to different categories, such as "red apple", "apple logo", and "apple laptop". In order to solve the ambiguity, content-based image retrieval[9] is widely used. It requires users to select multiple relevant and irrelevant image examples, from which visual similarity metrics are learned through online training. Images are re-ranked based on the learned visual similarities.

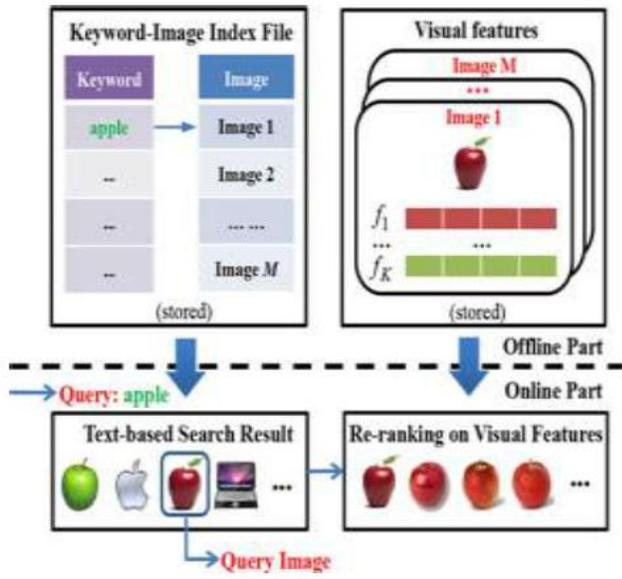


Fig. 1: The conventional image re – ranking framework.

In this paper, a novel framework is proposed for web image re-ranking. Instead of manually defining a universal concept dictionary, it learns different semantic spaces for different query keywords individually and automatically.

II.PROBLEM STATEMENT

Introduce the markov process semantic indexing (MSI), a brand new methodology for automatic annotation and annotation primarily based image retrieval. The properties of MSI create it significantly appropriate for ABIR tasks once the per image annotation information is restricted. The characteristics of the tactic create it additionally significantly applicable within the context of online image retrieval systems. The targeting is a lot of correct, compared to different systems that use external means that of non-dynamic or non-adaptive nature to outline keyword connection. MSI achieves higher retrieval ends up in sparsely annotated image knowledge sets. A comparison to LSI on (64) pictures gathered from the Google Image Search and annotated in a very clear means by the planned system, discovered sure benefits for the MSI technique, chiefly in retrieving pictures with deeper dependencies than easy keyword cooccurrence.

EXISTING SYSTEM

Most existing re-ranking methods use a tool known as pseudo-relevance feedback (PRF), where a proportion of the top-ranked images are assumed to be relevant, and subsequently used to build a model for re-ranking. This is in contrast to relevance feedback, where users explicitly provide

feedback by labelling the top results as positive or negative. In the classification-based PRF method, the top-ranked images are regarded as pseudo positive and low-ranked images regarded as pseudo-negative examples to train a classifier, and then re-rank. Hsu et al. also adopt this pseudo-positive and pseudo-negative image method to develop a clustering-based re-ranking algorithm.

Disadvantages of Existing System:

» One major problem impacting performance is the mismatches between the actual content of image and the textual data on the web page.

» The problem with these methods is the reliability of the obtained pseudo-positive and pseudo-negative images is not guaranteed

III.PROPOSED METHOD

In this paper we propose a novel method named multimodal hyper graph learning-based sparse coding for click prediction, and apply the predicted clicks to re-rank web images. Both strategies of early and late fusion of multiple features are used in this method through three main steps. We construct a web image base with associated click annotation, collected from a commercial search engine. The search engine has recorded clicks for each image. Indicate that the images with high clicks are strongly relevant to the queries, while present non-relevant images with zero clicks. These two components form the image bases.

We consider both early and late fusion in the proposed objective function. The early fusion is realized by directly concatenating multiple visual features, and is applied in the sparse coding term. Late fusion is accomplished in the manifold learning term. For web images without clicks, we implement hyper graph learning to construct a group of manifolds, which preserves local smoothness using hyper edges. Unlike a graph that has an edge between two vertices, a set of vertices are connected by the hyper edge in a hyper graph. Common graph-based learning methods usually only consider the pair wise relationship between two vertices, ignoring the higher-order relationship among three or more vertices. Using this term can help the proposed method preserve the local smoothness of the constructed sparse codes. Finally, an alternating optimization procedure is conducted to explore the complementary nature of different modalities. The weights of different modalities and the sparse codes are simultaneously obtained using this optimization strategy.

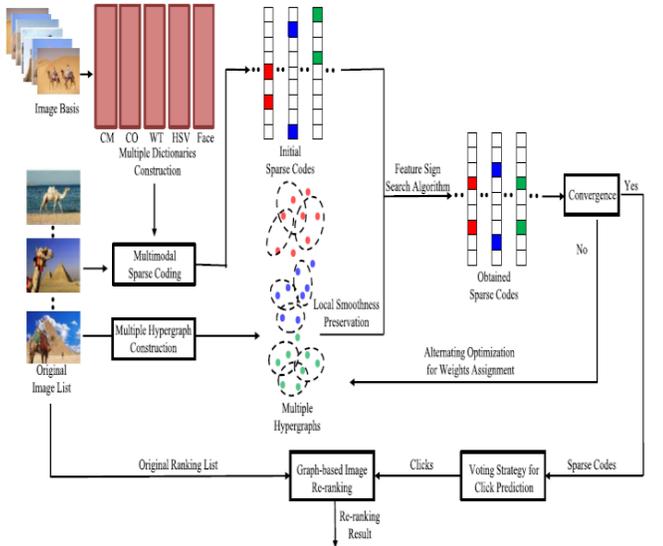


A voting strategy is then adopted to predict if an input image will be clicked or not, based on its sparse code.

Advantages of Proposed System:

- We effectively utilize search engine derived images annotated with clicks, and successfully predict the clicks for new input images without clicks. Based on the obtained clicks, we re-rank the images, a strategy which could be beneficial for improving commercial image searching.
➤ Second, we propose a novel method named multimodal hyper graph learning-based sparse coding. This method uses both early and late fusion in multimodal learning. By simultaneously learning the sparse codes and the weights of different hyper graphs, the performance of sparse coding performs significantly.

SYSTEM ARCHITECTURE



In this paper we propose a novel method named multimodal hypergraph learning-based sparse coding for click prediction, and apply the predicted clicks to re-rank web images. Both strategies of early and late fusion of multiple features are used in this method through three main steps. First, we construct a web image base with associated click annotation, collected from a commercial search engine. As shown in Fig. 1, the search engine has recorded clicks for each image. Second, we consider both early and late fusion in the proposed objective function. The early fusion is realized by directly

concatenating multiple visual features, and is applied in the sparse coding term. Late fusion is accomplished in the manifold learning term. For web images without clicks, we implement hyper graph learning to construct a group of manifolds, which preserves local smoothness using hyper edges. Unlike a graph that has an edge between two vertices, a set of vertices are connected by the hyperedge in a hypergraph. Common graph-based learning methods usually only consider the pairwise relationship between two vertices, ignoring the higher-order relationship among three or more vertices. Using this term can help the proposed method preserve the local smoothness of the constructed sparse codes.

Finally, an alternating optimization procedure is conducted to explore the complementary nature of different modalities. The weights of different modalities and the sparse codes are simultaneously obtained using this optimization strategy. A voting strategy is then adopted to predict if an input image will be clicked or not, based on its sparse code. The obtained click is then integrated within a graph-based learning framework to achieve image re-ranking. In summary, we present the important contributions of this paper:

- » First, we effectively utilize search engine derived images annotated with clicks, and successfully predict the clicks for new input images without clicks. Based on the obtained clicks, we re-rank the images, a strategy which could be beneficial for improving commercial image searching.
» Second, we propose a novel method named multimodal hypergraph learning-based sparse coding. This method uses both early and late fusion in multimodal learning. By simultaneously learning the sparse codes and the weights of different hypergraphs, the performance of sparse coding performs significantly.
» We conduct comprehensive experiments to empirically analyze the proposed method on real-world web image datasets, collected from a commercial search engine. Their corresponding clicks are collected from internet users. The experimental results demonstrate the effectiveness of the proposed method.

Markovian semantic Model :

Hidden Markovian Models for Automatic Annotation introduces a novel method for automatic annotation of images With keywords from a generic vocabulary of concepts or objects for the purpose of content based image extraction . An image, represented as continues of feature vectors characterizing low level visual features such as color, texture



or oriented-edges, is modeled as having been stochastically generated by a hidden Markovian model, whose states represent concepts. The parameters of the model are estimated from set of manually annotated (training) images. Each image in large test collection is then automatically annotated with the posteriori probability of concepts present in it. Annotation of Images Using Spatial Hidden Markovian Model is a 2D generalization of the traditional HMM in the sense that both vertical and horizontal transitions between hidden states are taken into consideration. The two most crucial problems with this approach are how to build a statistical model for each concept class, and how to propagate annotations from keywords associated with some specific classes. In this a new Spatial- HMM to describe the spatial relationships of objects and investigate the semantic structures of concepts in natural scene images.

Latent Semantic Indexing (LSI) :

Latent semantic indexing (LSI) is an indexing and retrieval method that uses a mathematical technique called singular value decomposition (SVD) to identify patterns in the relationships between the terms and concepts contained in an unstructured collection of text. LSI is based on the principle that words that are used in the same contexts tend to have similar things . A feature of LSI is its ability to extract the important matter of a body of text by establishing associations between those terms that occur in similar contexts. When Latent Semantic Indexing (LSI) is used for Image retrieval, Singular Value Decomposition (SVD) is used to decompose the term by Image matrix into three matrices a term by dimension matrix, S a singular value matrix (dimension by dimension), and D a Image by dimension matrix. After computing the SVD using the original term by document matrix, we compute term-to-term similar manner. Markovian Semantic Indexing (MSI)The Markovian Semantic Indexing (MSI), a new method for automatic annotation and annotation based image retrieval. The properties of MSI make it particularly suitable for ABIR tasks when the per image annotation data is limited one. This method make it also particularly applicable in the context of online image retrieval systems. The proposed approach (MSI) is presented in together with proximity measure (distance). In geometric interpretation and the optimal properties of the proposed distance are examined a statistical model with hybrid text/visual characteristics also based on the aspect model. The approach proposed here in, while stochastic in nature, raises the reasoning aspect of Probabilities, as it defines plain relevance relationships between keywords. Using network representations for Capturing semantics is common in AI systems.

IV.CONCLUSION

In this paper we propose new multimodal hypergraph learning based sparse coding method for the click prediction of images. The obtained sparse codes can be used for image re-ranking by integrating them with a graph-based schema. We adopt a hypergraph to build a group of manifolds, which explore the complementary characteristics of different features through a group of weights. Unlike a graph that has an edge between two vertices, a set of vertices are connected by a hyperedge in a hypergraph. This helps preserve the local smoothness of the constructed sparse codes. Then, an alternating optimization procedure is performed and the weights of different modalities and sparse codes are simultaneously obtained using this optimization strategy. Finally, a voting strategy is used to predict the click from the corresponding sparse code. Experimental results on real-world data sets have demonstrated that the proposed method is effective in determining click prediction. Additional experimental results on image re-ranking suggest that this method can improve the results returned by commercial search engines.

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