EXPLORATIONS ON ENGINEERING LETTERS (EEL)
VOLUME 1, ISSUE 1 (2016):PP.200-205
SANA ACADEMIC PRESS

Dynamic Image Re ranking and unused Image Removal based on user click

W.Shibi getziyal [1], B.Bhuvaneswari [2] , R.Latha [3]

[1]*Research Scholar, St.Peter's University, Chennai.*

[2]*Asst.Prof, Dept. of Computer Application, St. Peter's University, Chennai*

[3]*Prof. & Head., Dept. of Computer Science & Applications, St. Peter's University, Chennai*

shibi5joyce@gmail.com

***ABSTACT*: *Learning to rank refers to machine learning techniques for training the model in a ranking task. Learning to rank is useful for many applications in information retrieval, natural language processing, and data mining. Intensive studies have been conducted on the problem recently and significant progress has been made. Which are more reliable than textual information in justifying the relevance between a query and clicked images,are adopted in image ranking model. However the existing ranking model cannot integrate visual features, which are efficient in refining the click-based search results. A novel ranking model based on the learning to rank framework, Visual Features and click features are simultaneously utilized to obtain the ranking model. Specifically, the proposed approach is based on large margin structured output learning and the visual consistency is integrated with the click features through a hyper graph regular term. In accordance with the fast alternating linearization method, we design a novel algorithm to optimize the objective function To improve the performance of keyword based image search engines by re-ranking their original results and we remove the unused images from the image search engines and unstructural result to structural result is done.*

***Keywords**:* Click, Ranking, Removal.

I.INTRODUCTION

Ranking has recently come to be regarded as a learning problem and some machine learning algorithm have been applied to it. To measure the performance of a search engine, the discounted cumulative gain (DCG) has been widely adopted to evaluate relevance in the context of search engines. The learning to rank approach has also been widely used in image retrieval. The query dependent features for each image extract from the textual information to describe the relationship between a query and an image. The textual information sources include the title, the surrounding text, the HTML alternative texts, or the titles of the host webs. The query related features can be extracted to represent the relationship between the query and the visual contents, and the textual features can then be integrated with them.The learning to rank approach has also been widely used in image are retrieved. A classification-based method which utilizes uppermost images as pseudo-positive and undermost images as pseudo-negative examples to train a classifier and conduct re-ranking. Hsu *et al.* also adopted the pseudo-positive and pseudo-negative images to develop a clustering-based re-ranking method. However, visual re-ranking methods cannot successfully relegate irrelevant images which have originally been allocated a high rank, and suffer from an unreliable original ranking list because the textual information cannot accurately describe the semantics of the queries. Instead of textual information, user click has recently been used to measure the relationship between queries and retrieved objects.

II. EXISTING SYSTEM

In existing process many existing re-ranking methods are based on implicitly adopting pseudo-relevance feedback (PRF).Visual re-ranking methods cannot successfully relegate irrelevant images which have, originally been allocated a high rank, and suffer from an unreliable original ranking list because the textual information cannot accurately describe the semantics of the queries. Combining visual information is visual re-ranking. This combines both the text and visual information and returns visually satisfying retrieved results. The ranking list of images obtained from the text-based search can be regarded as a reasonable baseline with certain noises. The visual information of the images is then adopted to shift the related images to the top of the ranking list Combining visual information is visual re-ranking. This combines both the text and visual information and returns visually satisfying retrieved results The ranking list of images obtained from the text-based search can be regarded as a reasonable baseline with certain noises. The visual information of the images is then adopted to shift the related images to the top of the ranking list

III. PROPOSED SYSTEM:

Proposed a classification-based method which utilizes uppermost images as pseudo-positive and undermost images as pseudo-negative examples to train a classifier and conduct re-ranking. The query dependent features for each image extracted from the textual information to describe the relationship between a query and an image. Proposing a novel image ranking model. First, the ranking of images is determined according to the interactions between those images. The ranking result is a structured list, but traditional learning algorithms cannot handle the structured result. Second, unlike click features, which are extracted according to specific query, visual features are obtained from images regardless of queries. Therefore, the traditional learning to rank approaches cannot be used directly. Accordingly, we propose a new objective function for our learning to rank model under the framework of large margin structured output learning. Using the click features creates a robust and accurate ranking model, and adopting the visual features will further enhance the model’s performance. VCLTR is evaluated over a largescale and practical image search dataset, in which the click features are collected from real web users.

The experimental results suggest the effectiveness of our method. Visual and click information are simultaneously utilized in the learning process for ranking. The Accurate ranking model can be learned from this framework because the noises in click features will be removed from the visual content.

V. RELATED WORK

A. USER INTERFACE

To connect with server user must give their username and password, then only they can able to connect the server. If the user already exits directly can login into the server else user must register their details such as username, password and Email id, into the server. The Server will create the account for the entire user to maintain upload and download rate. The Name will be set as user id.

B. QUERY ANALYSIS:

VCLTR which jointly considers visual features and click features in image retrieval. A robust and accurate ranking model can be built by using the click features, and the visual features are effective in further enhancing the model's performance.

C. FILTERING AND QUERY RELAXATIONS:

In this module to design an incremental relaxation paradigm and the relaxation is triggered if no or few results are returned. To provide the search-as-you-type feature for the interactive search. If its result size is smaller than the result size threshold, different types of relaxed queries are applied incrementally. In this section, we present how a single query is processed.

D. NODE-LEVEL AND OBJECT-LEVEL FILTERS:

Filters are used at two levels: node Level Filter () and object Level Filter () to filter nodes and objects that cannot satisfy the string constraint respectively. The essence of the node-level and object-level filters is to obtain the candidate nodes and objects that appear at least a certain number of times on the given inverted lists. For the node-level filters, the lists are retrieved from the node-level inverted index using the matching (positional)q-grams. For the object-level filters, the lists are retrieved from the object-level inverted index using the matching spatial (positional) q-grams.

E.USER INTEGRATED OUTPUT:

VCLTR-Graph jointly utilizes both the click and visual information. It can be concluded that the visual consistency has positive effects in enhancing the ranking model. Results demonstrate that the utilization of both the visual features and click features will lead to the learning of a better ranking model.

V. EXPERIMENTAL ANALYSIS

The experiments are conducted on different data sources, where the dataset and the Caltech-101 dataset are treated as the target domains, and the HMDB51 dataset and some Web images indexed by Google are treated as the source domains. To obtain the source domain Web images, we select the first 20 categories out of the 101 categories, and randomly choose 20-30 images for each category among the first 100 searching results returned by Google when using category names as the key words. For both action recognition and image classification tasks, the BCDC method is evaluated on the categories which exist in both the target and source domains.

A. IMAGE CLASSIFICATION:

We adopt the dense descriptors plus the sparse coding approach for low-level and mid-level image representations. The weight a on the label constraint term and the weight b on the classification error term are set as 4 and 2 respectively. We run our method on five different partitions of the Caltech-101 dataset, where the number of 10/15/20/25/30 images are randomly chosen as the training images while the remaining images are used for testing for each partition. In order to demonstrate the effectiveness of our proposed approach, we compare with the baseline Sparse-coding Spatial Pyramid Matching Ksingular Value Decomposition , Label Consistent-Singular Value Decomposition AdaBoost, and Weakly Supervised Cross-Domain Dictionary Learning (WSCDDL) and Transfer AdaBoost (TrAdaBoost). Experimental results are reported when source domain data are applied or not applied respectively. Results on the first 20 selected image categories of the Caltech-101 dataset using five different numbers of training data are reported, and all the results are obtained by averaging 5 runs of randomly selected training and testing images to guarantee the reliability. The proposed BCDC method consistently leads to the best performance over other methods. The reported results of ScSPM, K-SVD and LC-KSVD in TABLE are obtained by simply treating the source domain data as extra training data without knowledge transfer. Note that the performance of ScSPM, K-SVD and LC-KSVD is even decreased when source domain data are used, which further validates the importance of our boosted cross-domain categorization method. Figure 3 shows the error rate comparison of the proposed method and TrAdaBoost according to the boosting iterations on the Caltech-101 dataset when using 30 training samples per category.

B. ACTION RECOGNITION:

source domain data as auxiliary training samples, the BCDC method can improve the performance of the original ScSPM and LLC, which are free of the data mismatch problem, by 2:41% and 3:53% in average, which are significant improvements over the leading results.Performance comparison between the BCDC and state-of-the-art methods on the dataset with source domain data.

C. LEARNING SEMANTIC FEATURES FOR IMAGES:

So far, we have built a connection between images and text through annotating tags. In this section, we learn the semantic features for images by exploiting the relationship between images and text from the auxiliary sources. Recall that we have a matrix of images with low-level image features Z and a relational matrix between images and annotations T. We first define a new matrix $G= Z^{T}T \in R^{d\times h}$ to denote the correlation between low-level image features and annotations which can be referred to as high-level concepts. Note that $G_{ij} = \Sigma_k z_{ik} \cdot t_{kj}$, where $z_{ik} \geq 0$ is the value of the *ith visual word* in the *kth* image, and $n(i)_j = \Sigma_k t_{kj}$ is the number of images that are annotated by the *jth* tag and whose *ith* visual word is observed at the same time. G_{ij} is large when $n(i)_j$ is large or some of the values of the *ith* visual word in the images with the *jth* tag annotation are large. This implies that if G_{ij} is large, then the *ith* image feature and the *jth* tag may have strong correlation. Motivated by the well-known Latent Semantic Analysis (LSA) (Deerwester), we proceed to extract the latent semantic features for each low-level image feature. We accomplish this by a matrix factorization that decomposesThe experiments in this paper used two benchmark PGMformat image data sets. The first comprises of a collection of face and non-face image cut-outs from the Center for Biological and Computational Learning at MIT and the second a collection of pedestrian and non-pedestrian cutouts from the Intelligent Systems Lab at the University of Amsterdam. For image features we extracted low-level pixel statistics corresponding to the mean and variance of pixel values around certain local regions within each image. These features represent overall pixel brightness/intensity and the contrast of a given region. We used two sets of local region features for each problem: generic equally-sized quadrants spread evenly around each image, and rectilinear regions placed around distinguishing regions in the image

VI. CONCLUSION

In this paper we have present Visual and click features based learning to rank (VCLTR).In this method can provide accurated image re-ranking compare than existing ranking model in this we done the unstructured images to the structured images in this the valuable images are present in the top of the image list for this we save the time now we don't want to search the un wanted images again and again noises in click features will be removed by the visual content. Remove image in click rank based image. Visual and click information are simultaneously utilized in the learning process for ranking. Accurate ranking model can be learned from this framework because the noises in click features will be removed by the visual content.

VII. FUTURE ENHANCEMENTS

In future people can share this image to their friends via share button easily It reduce the searching time,Some real time examples are face book and twitter, This method is used to improve the quality of the each image and easily share with our friends using email id.

REFERENCES

[1] H. Li, "Learning to rank for information retrieval and natural language processing," Synth. Lect. Human Lang. Technol., vol. 4, no. 1, pp. 1–113,2011.

[2] S. Robertson and S. Walker, "Some simple effective approximations tothe 2-poisson model for probabilistic weighted retrieval," in Proc. Annu.Int. ACM SIGIR Conf. Res. Dev. Inf. Retrieval, 1994, pp. 232–241.

[3] J. Xu and H. Li, "AdaRank: A boosting algorithm for information retrieval," in Proc. Int. ACM SIGIR Conf. Res. Dev. Inf. Retrieval, 2007,pp. 391–398.

[4] D. Cossock and T. Zhang, "Statistical analysis of Bayes optimal subset ranking," IEEE Trans. Inf. Theory, vol. 54, no. 11, pp. 5140–5154,Nov. 2008.

[5] T. Liu, "Learning to rank for information retrieval," Found. Trends Inf.Retrieval, vol. 3, no. 3, pp. 225–331, 2009.

[6] C. Burges, "From RankNet to Lambda Rank to LambdaMART:An overview," Microsoft Res., Tech. Rep. MSR-TR-2010-82, 2010.

[7] W. Liu, D. Tao, J. Cheng, and Y. Tang, "Multiview Hessian discriminative sparse coding for image nnotation," *Comput. Vis. Image Underst.*, vol. 118, pp. 50–60, Jan. 2014.

[8] W. Liu and D. Tao, "Multiview Hessian regularization for image annotation," *IEEE Trans. Image Process.*, vol. 22, no. 7, pp. 2676–2687, Jul. 2013.

[9] I. Tsochantaridis, T. Hofmann, T. Joachims, and Y. Altun, "Support vector machine learning for interdependent and structured output spaces," in *Proc. Int. Conf. Mach. Learn.*, Banff, AB, Canada, 2004,

[10] C. Hong and J. Zhu, "Hypergraph-based multi-example ranking with sparse representation **for** ransductive learning image retrieval," *Neurocomputing*, vol. 101, no. 4, pp. 94–103, 2013.

[11] C. Hong, J. Yu, J. Li, and X. Chen, "Multi-view hypergraph learning by patch alignment framework," *Neurocomputing*, vol. 118, pp. 79–86, Oct. 2013.

[12] Y. Gao, M. Wang, Z. Zha, and J. Shen, "Visual-textual joint relevance learning for tag-based social image search," *IEEE Trans. Image Process.*, vol. 22, no. 1, pp. 363–376, Jan. 2013.

[13] S. Zhu, C. Ngo, and Y. Jiang, "Sampling and ontologically pooling web images for visual concept learning," *IEEE Trans. Multimedia*, vol. 14, no. 4, pp. 1068–1078, Aug. 2012.

[14] W. Liu, Y. Jiang, J. Luo, and S. Chang, "Noise resistant graph ranking for improved web image search," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2011, pp. 849–856.

[15] J. Shen, D. Tao, and X. Li, "Modality mixture projections for semantic video event detection," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 18, no. 11, pp. 1587–1596, Nov. 2008.

[16] F. Zhu and L. Shao, "Weakly-supervised cross-domain dictionary learning for visual recognition," *Int. J. Comput. Vis.*, vol. 109, nos. 1–2, pp. 42–59, 2014.

[17] L. Shao, L. Liu, and X. Li, "Feature learning for image classification via multiobjective genetic programming," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 7, pp. 1359–1371, Jul. 2014.

[18] L. Zhang, X. Zhen, and L. Shao, "Learning object-to-class kernels for scene classification," *IEEE Trans. Image Process.*, vol. 23, no. 8, pp. 3241–3253, Aug. 2014.