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IMAGE SEARCH AND RE-RANKING BASED ON KEYWORDS AND IMAGE VISUAL CHARACTERISTICS

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ABSTRACT:

Web Image search re-ranking, is the best way to improve the result of web image search, which has been adopted by commercial search engines like Bing and Google, etc. When we give a query keyword, a pool of images are retrieved first based on query information. We ask the user to select a image from the pool of images, so that the remaining images are re-ranked based on their visual similarity with the selected image. A major problem is that the visual similarity features do not well coordinate with images' semantic meanings. We need to match images in a semantic space which uses reference class that are closely associated to the semantic meaning of images. In order to measure similarity FCTH(Fuzzy Color and Texture Histogram) and CEDD(Color and Edge Directivity Descriptor) are used. The proposed features are appropriate for accurately retrieving even in distortion cases such as deformation, noise and smoothing. It is tested on a large number of images selected from proprietary image databases or randomly retrieved from popular search engines. Low computational power is needed for its extraction. Image understanding is widely used in many areas like satellite images, robotic technology, sensory network, medical and biomedical imaging, intelligent transportation system, etc. But it is difficult by existing image processing.

1. INTRODUCTION:

Number of images databases on the internet is widely increasing day-by-day since internet is made available to many people in the last few decade. The major challenge is to find the right images that user wants to search. Most of the commercial web image search engines use only keywords as queries. The query keywords provided by the users tend to be short and they are not able to describe the actual visual content of the target images just by using query keywords. For example, if "apple" is entered by the user to a search engine as a query keyword, the search results may belong to different categories such as "green apple," "apple logo," "green apple," "apple iphone" and "apple laptop" because of the ambiguity of the word "apple". In order to overcome this issue of query ambiguity, text-based image extraction with relevance is commonly

examples. The visual similarity are learned from online training experience, according to which, images are re-ranked. A major challenge in re-ranking the web based image is that the similarity of visual features does not well correlate with image. The user gives input as a query keyword, according to the word-image index file, a pool of images that are relevant to the query are retrieved by the search engine. Users are asked to select the query image from the retrieved pool of images. By using this approach the remaining query images in the pool are re-ranked based on their visual appearance and similarity with the selected query image.The visual features of images are calculated before in offline and stored by the web search engine. The important computational cost of web image re-ranking is based on comparing the visual features. Efficiency is high when the visual features are short and faster in speed while

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image search approach. It requires the user to give click on a query image and images from a dataset is retrieved by text-based search and re-ranked based on their visual and textual similarities to the query image searching. [10] proposed a method in which the minimization is per-formed in a sequential manner by the fusion move algorithm that uses the QPBO min-cut algorithm. Multi-shape GCs are proven to be more beneficial than single-shape GCs. Hence, the segmentation methods are validated by calculating statistical measures. The false positive (FP) is reduced and sensitivity and specificity improved by multiple MTANN.

2. RELATED WORK:

Image search re-ranking methods usually fail to capture the user's intention when the query term is abstruse. Therefore, active re-ranking is highly demanded to improve search performance. This paper presents a structural information based sample selection strategy to target the user's intention to reduce the user's showing efforts. To select the most informative query images, the structural information based active sample selection strategy takes both the ambiguity and the denote into consideration. It proposes to use adaptive visual similarity to re-rank the text based search results.

Text-based approaches:

The search engine returns corresponding images by processing the associated textual information, such as file name, surrounding text, URL, etc., according to keywords input by users. Text-based search techniques have been verified to perform well in textual documents; they often result in mismatch when applied to the image search.

Content-based approaches:

Another technique CBIR (Content based retrieval) with relevance feedback. Users label multiple positive and negative image examples. This type of engine extracts semantic information from image content features, such as color, shape, texture, spatial location of objects in images etc. Retrieve object from the images.

Keyword Expansion:

The keywords provided by users tend to be short. They cannot describe the content of images accurately. The query keywords' meanings may be richer than user's expectations. If user can enter incorrect query or some missing words in query because of lack of user knowledge, then Keyword expansion can be used for proper search query.

Visual Query Expansion:

The goal of visual query expansion is to obtain multiple images by using visual similarity metric. To capture the user's intention only one query image is not enough. These similarity metrics reflect users' intention which gives better images.

Image Pool Expansion:

Image pool expansion shows the top ranked images from the image pool and user may select choice of his image from that image pool. The image pool is enlarged through combining the original image pool retrieved by the query keyword and an additional image pool retrieved by the expanded keywords. Images in the enlarged pool are re-ranked using the learned query specific visual and textual similarity metrics.

3. EXISTING SYSTEM:

A novel image search re-ranking, named spectral clustering re-ranking with click-based similarity and typicality (SCCST), which first use image click information to guide image similarity learning for multiple features, then conducts spectral clustering to group visually and semantically similar images into clusters, and finally obtain the re-ranking results by calculating click-based clusters typicality and within-clusters click based image typicality in descending order. To the best of our knowledge, this is the first attempt for cluster-based re-ranking using click-through data. We use click-through data and multiple visual modalities simultaneously to learn image similarity, and propose an innovative similarity learning algorithm, called click based multi-feature similarity learning (CMSL), which conducts metric learning based on click-based triplets selection, while integrating multi-feature into a unified similarity space via multiple kernel learning. We integrate click-through data with image typicality learning to mine the influence of this implicit feedback in determining the degree of image relevance to the given query, and further improve the image search performance. In order to learn appropriate image similarity and typicality measurements, meanwhile explore the effects of click-through data to reduce intent gap, we develop a novel image search re-ranking approach, named spectral clustering re-ranking with click-based similarity and typicality (SCCST).Compared with existing re-ranking approaches, SCCST 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

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image search performance. In order to overcome the semantics of same image adopting multiple kernel learning technique for integrating multiple visual modalities into a single and unified similarity space. Existing re-ranking approaches only care whether an image is relevant (positive) or irrelevant (negative) to the given query without considering typicality. During the learning process, clicked images and other clicked ones should be closer than other unclicked ones in the metric space. Even multiple features represent different aspects of image content, they potentially share the semantics of the same image, and thus the similarity measure should not go too far. Web based image search mostly use keywords as queries for searching the images and they suffer from the ambiguity of query keywords, so this becomes hard for users to accurately describe the visual content of the target images by only using keywords. The semantic gap and intend gap is more.

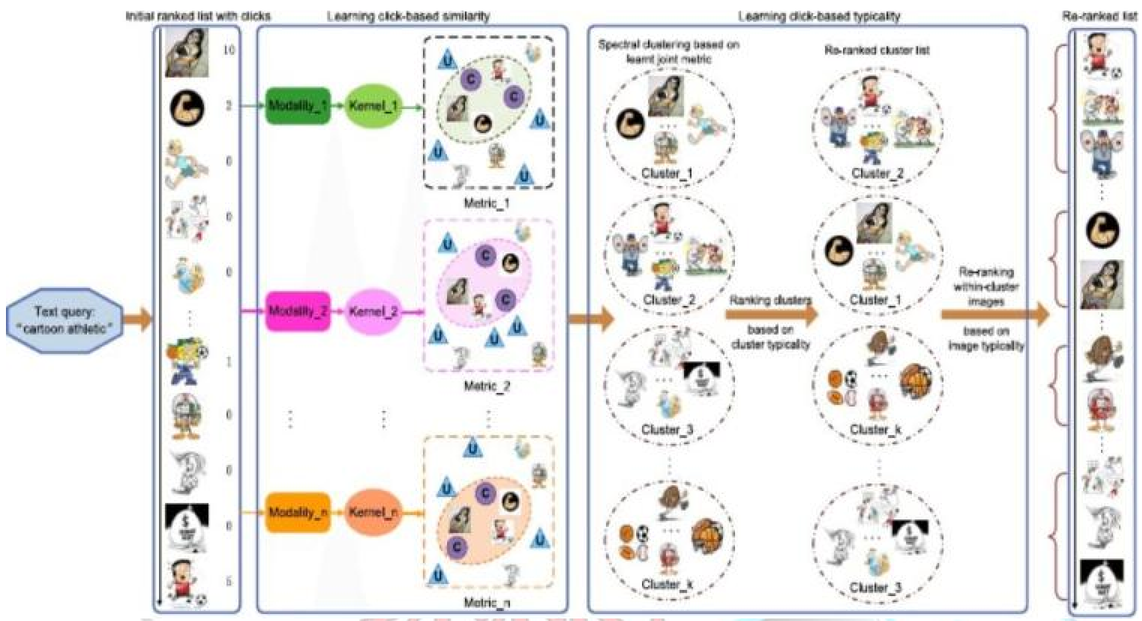

Fig3.1. The overview of the proposed image search re-ranking approach, named spectral clustering re-ranking with clicked-based similarity and typicality [best viewed in color].

4. PROBLEM DEFINITION:

Web image search engines (For e.g. Google Image Search, Bing Image Search, Pinterest) mostly depend on text features. It is very difficult for them to predict user's intention only with the query they are giving and this leads to more ambiguous and noisy based search results from the search engines which are far from satisfaction. Visual relevance cannot be just judged by text based approaches as the textual data is normally too noisy to precisely describe visual content or even not available the obtainable image search engines, rank and recovers images mostly on the base of textual information belong with an image in the organized web pages, like as the name of image and rounding text. This technique is famous but needs very precise description of the query which is too long and not always possible. Generally the process of searching image based on keyword typed. The process which occurs in the background is difficult thing.

5. PROPOSED SYSTEM:

The existing system can be improved in many ways. Proposed method requires less time and acquires less memory as compared to existing method. In the proposed method, when user gives query keyword, keyword expansion related to it can be done. After that, visual query expansion is done automatically to get multiple positive example images specific to the query image to accurately users' intention by getting more relevant results.In thisuser-specific information is considered to distinguish the exact intentions of the user queries and re-rank the list results.

IMPLEMENTATION: ALGORITHM/TECHNIQUES:

STOP WORDS FOR TEXT MINING AND RETRIEVAL:

Stop words are a set of commonly used words in any language, not just English. The reason why stop words is critical to many applications is that, if we remove the words that are very commonly used in a given language, we can focus on the important words instead.
Supervised machine learning – removing stop words from the feature space Clustering – removing stop words prior to generating clusters Information retrieval – preventing stop words from being indexed Text summarization - excluding stop words from contributing to summarization scores & removing stop words when computing rouge scores.
Determiners - Determiners tend to mark nouns where a determiner usually will be followed by a noun examples: the, a, an, another Coordinating conjunctions – Coordinating conjunctions connect words, phrases, and clauses examples: for, an, nor, but, or, yet, so Prepositions - Prepositions express temporal or spatial relations. In proposed system, this stop word for text mining and retrieval technique is used to remove unwanted words from the text query given by the user and only takes the main keywords of the user query, which makes it easier to search pool of images.

PORTER'S STEMMING ALGORITHM:

Stemming algorithms are used to transform the words in texts into their grammatical root form, and are mainly used to improve the Information Retrieval System's efficiency. Several algorithms exist with different techniques. The most widely used is the Porter Stemming algorithm. However, it still has several drawbacks, although many attempts were made to improve its structure. This paper reveals the inaccuracies encountered during the stemming process and proposes the corresponding solutions.
Porter's Stemming Algorithm was developed by Martin Porter at the University of Cambridge in 1980 and was first published in Porter, M.F., and reprinted in Sparck, Karen, and Peter .As described in the publication, "The Porter stemming algorithm (or 'Porter stemmer') is a process for removing the commoner morphological and inflexional endings from words in English. Its main use is as part of a term normalization process that is usually done when setting up Information Retrieval systems". Since then it has been very widely used and coded mainly on stemming operations that remove suffixes from words, such as gerunds (motoring Æ motor), plurals (cats Æ cat), and replacing words ending with "ator" for example with "ate" (operator Æ oper), etc….These operations are classified into rules where each of these rules deals with a specific suffix and having certain condition(s) to satisfy. A given word's suffix is checked against each rule in a sequential manner until it matches one, and consequently the conditions in the rule are tested on the stem that may result in a suffix removal or modification.

RANKED K-MEDOIDS ALGORITHM:

A fast and accurate rank-based partitioning algorithm for clustering large datasets. Clustering analysis is the process of dividing a set of objects into none-overlapping subsets. Each subset is a cluster, such that objects in the cluster are similar to one another and dissimilar to the objects in the other clusters. Most of the algorithms in partitioning approach of clustering suffer from trapping in local optimum and the sensitivity to initialization and outliers. In this paper, we introduce a novel partitioning algorithm that its initialization does not lead the algorithm to local optimum and can find all the Gaussian-shaped clusters if it has the right number of them. In this algorithm, the similarity between pairs of objects are computed once and updating the medoids in each iteration costs O(km) where k is the number of clusters and m is the number of objects needed to update medoids of the clusters. Comparison between our algorithm and two other partitioning algorithms is performed by using four well known external validation measures over seven standard datasets. The results for the larger datasets show the superiority of the proposed algorithm over two other algorithms in terms of speed and accuracy.
There are several approaches of clustering such as hierarchical , partitioning, density-based , model-based and grid-based . Xu and Wunsch provided a good survey on the clustering algorithms. In this paper our particular interest is in the partitioning approach that divides a dataset into k < N clusters (N is size of dataset) such that every cluster has a center by which other members are determined according to their similarities. By using an iterative manner and re-computing the centers, algorithms of this approach attempt to find the best partitioning which has a high degree of intra-similarity and inter-dissimilarity. They mostly report the circle-shaped or Gaussian-shaped clusters because of assigning an object in the dataset to the most similar center.
To evaluate the results of clustering methods, two types of cluster validation techniques are using: internal validation measures and external

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evaluate clusters based on the structure of the dataset; therefore, intra-clusters similarity (cohesion) and inter-cluster dissimilarity (separation) are the main factors for these measures. On the other hand, external validation measures evaluate clusters by comparing computed labels of objects with their real label. In our experiments, the clusters were evaluated by four external validation measures which are Mirkin , Purity, F-measure and Adjusted RandIndex (ARI) . In the following these measures are described briefly. To explain the external validation measures we need a matrix called association matrix. Suppose that a dataset with N objects is partitioned into C ={ c1,c2,...,cI} classes and the algorithm finds K ={k1,k2,...,kJ} clusters, then matrix A =[aij]IJ is association matrix where aij indicates number of ci's members which belong to ki.

MODULES:

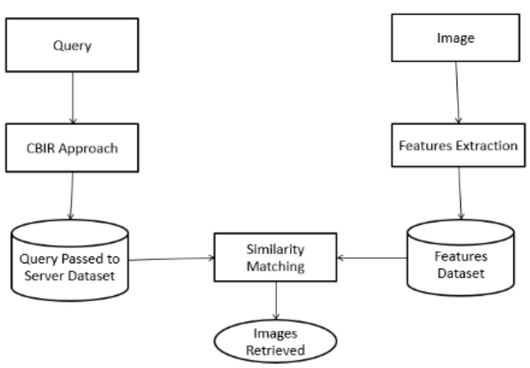

Fig5.2:Architecture of web image search re-ranking based on query keywords and image visual similarity

PROCESSING THE QUERY:

In this module, user gives the query in the search engine and the query is processed using stop words and porter's stemming algorithm.

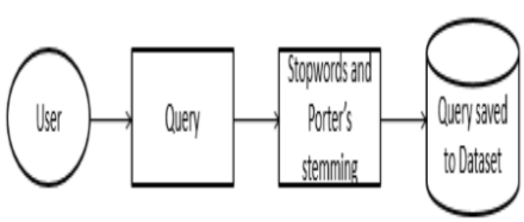

Fig5.2.1: Query Processing

ACCESSING THE IMAGES:

In this module, we select a query image from the

according to their visual similarity with the query image.

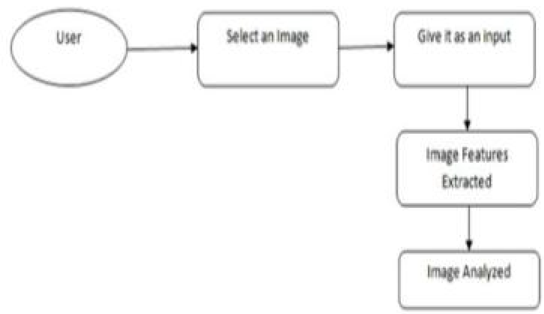

Fig5.2: Image Accessing

RETRIEVING THE RE-RANKED IMAGES:

In this module, the re-ranked images that are relevant to the query keyword is accurately retrieved from the server using Ranked k-medoids algorithm i.e fast re-ranking and clustering of large datasets.

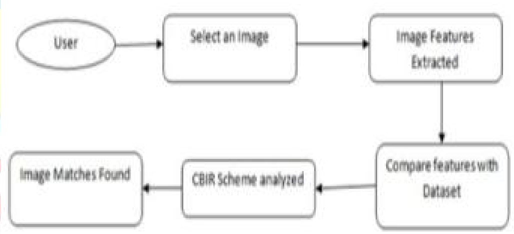

Fig5.2.3:Re-ranked images are retrieved

CLUSTERING OF IMAGES:

In this module, the retrieved images are clustered under each keywords relevant to the query keyword and are shown in tree format. This makes us easier to search a particular image uniquely and accurately without wasting much time to search the exact images.

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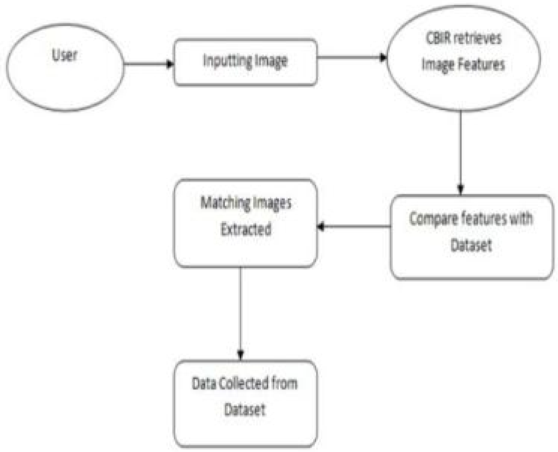

Fig5.2.4:Image clustering

5.3 ADVANTAGES OF PROPOSED SYSTEM:

The proposed features are appropriate for accurately retrieving images even in such as distraction, deformations, noise and smoothing. Searching time is less. Detect recurrent relevant patterns via spectral clustering. Improves search performance.

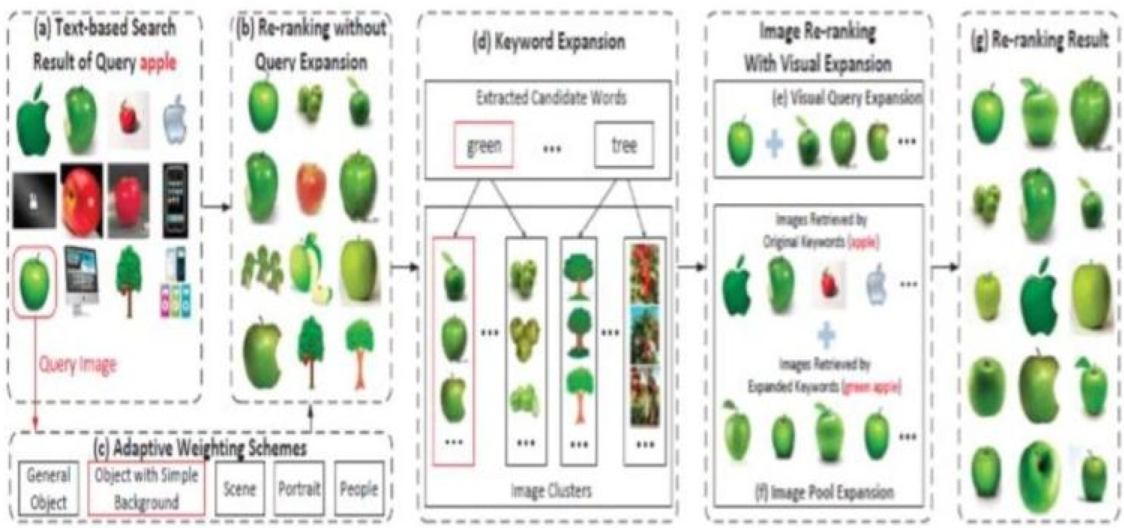

Fig5:Images after re-ranking and clustering(final)

7. EXPERIMENTAL RESULTS:

TABLE 1
AVERAGE COMPUTATION TIME ON QUERY-IMAGE 100k DATASET

ح	Time in SCCST (s)	Time in k-medoids(s)
10	0.4868	0.4728
30	0.9576	0.9481
50	1.5479	1.5384
70	2.1129	2.1024

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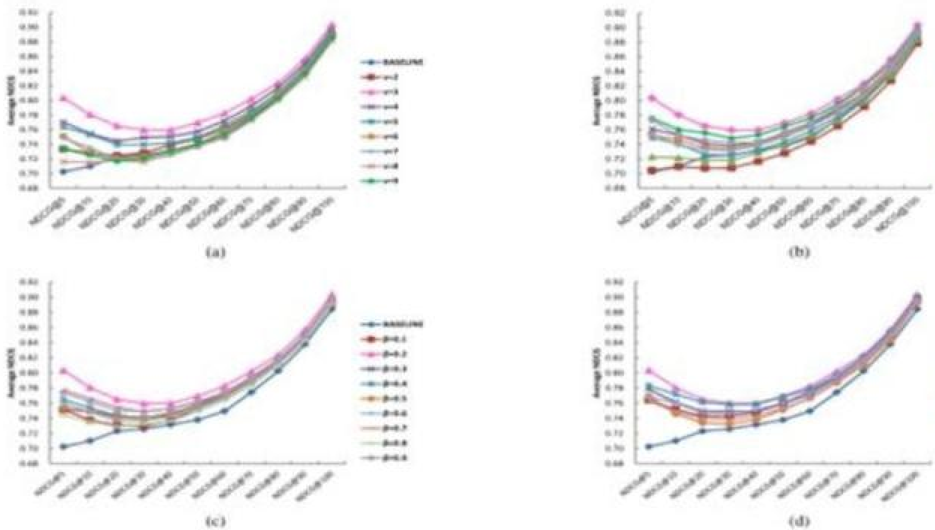

Fig7.1: The sensitivity of re-ranking parameters [best viewed in color]. (a) Re-ranking performance variation with various v. (b) Re-ranking performance variation with various γ. (c) Re-ranking performance variation with various β. (d) Re-ranking performance variation with various δ.

TABLE 2
RE-RANKING PERFORMANCE IN TERMS OF NDCG WITH VARIOUS ج on QUERY-IMAGE 100k DATASET

	ج=10	ج=30	ج=50	ج=70
NDGG@3	0.9826	0.9848	0.9844	0.9834
NDGG@5	0.9709	0.9735	0.9734	0.9729
NDGG@10	0.9520	0.9546	0.9534	0.9546
NDGG@20	0.9365	0.9383	0.9383	0.9383
NDGG@50	0.9276	0.9284	0.9284	0.9280

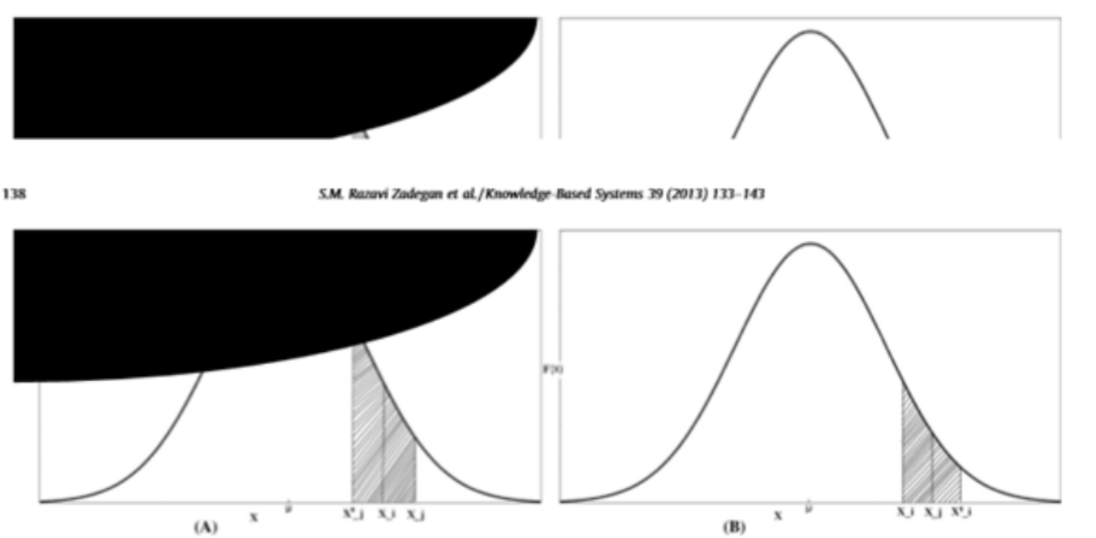

Fig7.2:The curve of Gaussian distribution with the average (l). (A) Hachured area shows the probability of a point belonging to Uij andkX0 (B) hachured area shows the probability of a point belonging to Uji

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TABLE 3
THE PARAMETER OF RUNNING RANKED k-MEDOIDS OVER DIFFERENT DATASETS

PARAMETER	A2	S3	mfeat-fac	WBC	Iris	Zoo	Wine
m	10	10	10	10	5	5	5
maxiter	100	100	50	50	50	50	50

6. CONCLUSION:

In this paper, we have studied about web image search re-ranking approach based on visual similarity and query keyword expansion. We have used three algorithms in this approach for expanding query keyword and image visuality. The proposed image re-ranking system can overcome the limitations of the previous systems and also considered to get better in both the accuracy and efficiency of the re-ranking method and can give accurate results in less time. To filter the quality of retrieved images, various postprocessing approaches have been taken after the search process like clustering into tree structure. The proposed work presents an approach to re-rank the web based images by narrow down the semantic gap and intend gap between query keywords and images. Thus the proposed approach takes very less time to answer the queries while providing more accurate information and unlimited number of irrelevant images are excluded from the search.

7. FUTURE WORK:

Metric adaptive fusion weights are not considered in this web image search re-ranking approach based on image visuality and query keywords due to the optimizing is very difficult, and we will figure this out in our future work.

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