IMAGE RETREIVAL AND RE-ORDERING BY USING CLICK-THROUGH DATA

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ABSTRACT: In image Retrieval and re-ordering there is difference between user query specification and actual search intention of the user which is known as intent gap which is becoming an issue in image retrieval. To resolve this issue in this paper, implicit feedback from the users is used which is known as click-through data. To obtain better search results image similarity and level of relevance typicality are very important factors. This system finds the similarity between images by considering different image features. Then this paper use re-ranking approach named Spectral Clustering re-ranking with click-based similarity and typicality (SCCST). Clustering technique is used to re-group the similar images in identical clusters. Final re-ordered list is obtained by calculating click-based cluster typicality and within cluster typicality in reverse order.

Index Terms: Image Retrieval, Click-through data, Image similarity, Image Relevance

I.INTRODUCTION

Due to use of social media and internet we have to deal with images on very large scale. So building a good image retrieval system is must [1]. Most of the search engines still use text based search technique for image retrieval. Most of the existing systems use visual information in unsupervised manner. In existing systems there is gap between user's query specification and actual intention of search which is known as intent gap.

User's real intent of search is not easy until active participation and feedback from the user. Most of the times users are not willing to give their feedback to the system; but search engines can record the queries issued by the users and corresponding response. Clicked images can indicate the relationship between individual images in ranking list. In image search new user browse image thumbnails before selecting which image to click and decision to click an image depends upon relevance of images. Here click-through data is known as implicit feedback which is easily available and accessible.

We have to assume that visually similar images are kept closer in the rankings i.e. images with more relevance are ranked higher than other images. So image similarity and level of relevance become important factors to obtain better search results. For measuring image similarity we compare features of the images like color, texture. Euclidean distance and cosine distance are commonly used due to the success in the bag-of-words models for text. We adopt multiple kernel learning technique for integrating multiple visual modalities into a single and unified similarity space. After that, spectral clustering is executed to categorize visually and semantically similar images into single unit.

The final re-ranked list is obtained by computing the within-clusters images typicality, which is determined by the click-based initial image confidence and local density.

II. LITERATURE SURVEY

Literature survey is the overview of work that has been carried out in the area of image retrieval. Following section shows the work that has been carried out over the years as follows:-

Tao Mei Yongdong Zhang. [2] Proposed that in image search there is semantic gap, intent gap which is gap between representation of user's demand/query and real search intent of the user who want to retrieve an image. To bring manual effort down while retrieving an image implicit acknowledgment can be used as feedback mechanism from users to help overcome the gap between query specification and actual intention behind retrieving particular image and hence improve the accuracy of retrieving images. But, when calculating image significance, systems only consider visual content information and initial ranking of images while overlooking the impact of data generated through implicit acknowledgments from previous users. Then based on trained similarity metric procedure of clustering is conducted to separate most significant images in a unit and get final list of images which is properly ordered.

Yongdong Zhang, Xiaopeng Yang, and Tao Mei [3] proposed that to improve the quality of image retrieval and to reduce the gap between query specification and the contents which get actually retrieved initial ranking order is adjusted by mining the visual content. Relevance feedback mechanism is used which asks users to provide relevance scores to images which is used to guess the significance of an image.

Vidit Jain, Manik Verma. [4] Discovered that to improve the quality of keyword based search engines by re-ranking their original results based on user click-data.

Jun Yu, Yong Rui and Dacheng Tao [5] worked on "Click Prediction for Image Re-ranking Using Sparse Coding" and he proposed to evaluate the issue of prediction of image retrieval using sparse coding technique clicks and new image without any click sparse coding which uses a set of images and images which are previously clicked by users which are associated with original image is used to retrieve the least possible images.

Anjali Barde, Prof. K.V.Warkar. [6]. In the paper "Image Search Re-ranking with Click based Similarity Using Color Features Algorithm" proposed that spectral clustering technique makes the use of the similarity matrix to perform dimensionality reduction. Similarity matrix is given as input which contains analysis of significance of each pair of significant instances in the set of training images.

III. PROPOSED SYSTEM ARCHITECTURE

Figure 1 Shows proposed system architecture. This section covers overall workflow of the system. Here we have large set of images which is already stored in the system. We maintain the record called click through data for the convenience of the new user who wish to search for an image through our system. When a user search for an image there is comparison made with already existing images in the system. This comparison is made by using different features of image like color, texture.

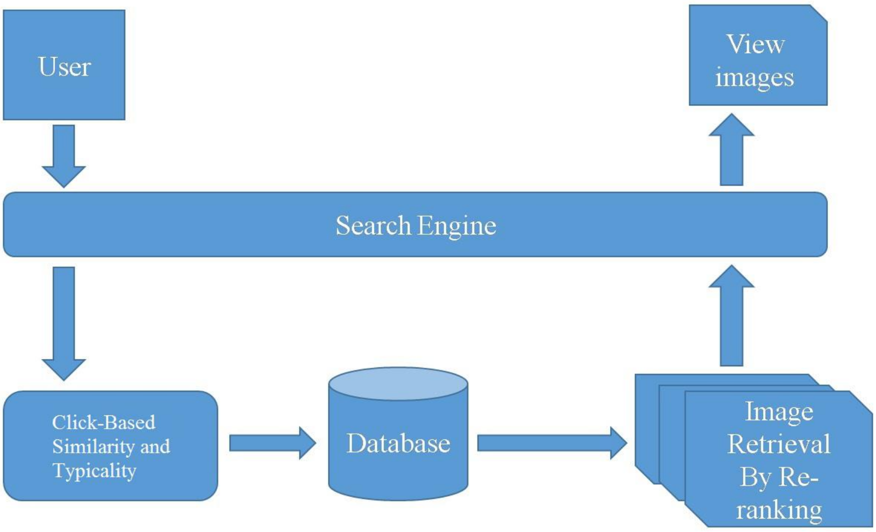

Figure 1;- Image retrieval using click-through data.

For measuring similarity between two images we use click-based similarity learning (CMSL) technique. Then we have to decide whether an image is significant to the user's query or not. For that purpose we use spectral clustering technique. We implement spectral clustering with the help of spectral clustering algorithm. By using this algorithm similar images are collected in a group. After finding significant images with user's query we have to arrange them in such a way that top ranked images are the most relevant in the list. For that purpose we use sorting technique. By sorting similar and relevant images we are able to display most relevant results. And finally we view images according to its category. I.e. if user searches an image for query "apple" our system can categorize search results as apple fruit, apple laptops, apple logo etc.

IV. ALGORITHM

We use an algorithm called spectral clustering for click-based similarity and typicality (SCCST). Which works as follows:-

Input:

For a given query q, top n initial ranked list with click information $\mathcal{X} = \{x_i | c_i \geq 0, i = 1, 2, ..., n\}$ and m different visual modalities.

1: Select clicked-clicked pairs $\mathcal{J} \triangleq \{(i, j) |\ 0 \leq c_i - c_j \leq \delta\}$:
2: **if** $|\mathcal{J}| > \tau$ **then**
3: Sort click-click pairs based on $(c_i - c_j)$ in an ascending order, and choose the top τ pairs.
4: **end if**
5: Select click-based triplets $\mathcal{S}$ based on the updated $\mathcal{J}$: $\mathcal{S} \triangleq \{(i, j, k) |\ (c_i - c_j) \in \mathcal{J}, c_k = 0\}$.
6: Assign basic kernel $K^p (p = 1, 2, .., m)$ to each feature.
7: Conduct click-based multi-feature similarity learning algorithm following Eqn. (6).
8: Execute spectral clustering based on the learnt W^p, and obtain v clusters (v is the number of clusters previously assigned).
9: Calculate click-based cluster typicality $CT(u)$ $(u = 1, 2, ..., v)$, and sort clusters based on $CT(u)$ in descending order.
10: Calculate click-based local typicality within each cluster $CT(x_j^i | u^i)$ $(1 \leq j \leq |u^i|)$, and sort images based on $CT(x_j^i | u^i)$ in descending order.

Output:

Re-ranked list for query q

Algorithm1- Spectral clustering re-ranking for click-based similarity and typicality (SCCST) algorithm

In a nutshell, to obtain the final re-ranked list, we first reorder clusters based on the calculated cluster typicality in descending order, and then re-rank images within clusters based on local typicality.

V. RESULTS AND DISCUSSION

This section has a brief overview of results that we achieve by implementation of our system. Images used to test the performance of web image re-ranking method and the images considered for reference purpose were gathered from different resources at different times. If the query keyword as an apple is searched on our web image re-ranking framework then it returns the 100 images of the apple from the database. For any given query keyword, normally 100-150 images are retrieved from our web image re-ranking approach. To collect the images for creating the dataset, we needed the internet connection. The images in all the datasets cover broad categories such as food, scenery, nature, event, animal, plant, different places.

Web image re-ranking framework is used for searching the multiple images related to search query image. For re-ranking methodology, we manually labeled all testing images. Images of reference classes which are large in quantity are not labeled. For manual labeling each query keyword with its training images are considered according to their visual semantic meaning. Image categories are carefully defined by different labelers by inspecting all the training images under the query keyword. Images that are irrelevant to the query keyword are labeled as outliers. In some cases reference class for images have same semantic meaning and their training have similar visual features. Finally we applied clustering on labeled image and got re-rank images that we consider as final output for our framework.

Offline stages of our web image re-ranking approach consists of four stages such as add images, view images, remove images and search images as shown in fig. 5.2. When we click on add button we will get add images window, so that we can add the images to the dataset covering diverse topics such as people, animals, places, food, events, object, scene, etc. Images are collected from the Google and Bing image search at different times. There are two ways of adding images to dataset. First, we can add images to dataset directly from the web, but for that we require the internet connection. Second, we can add images to dataset directly from folders.

Figure 5.1: Offline Stages of Web Image Re-ranking Approach

As shown in figure 5.1 above are the various stages in image re-ranking offline stage. We can also call it as a training stage.

Figure 5.2 add new images to dataset

As shown in figure we have added image labeled camera to our training data set.

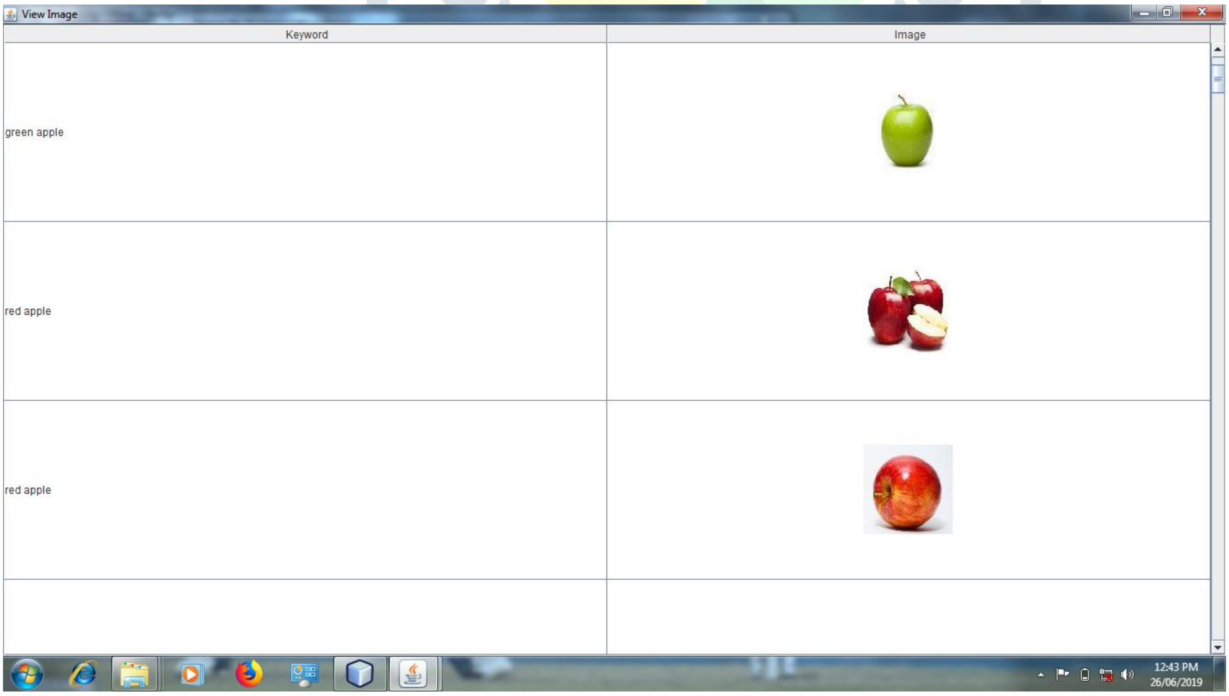

Figure 5.3 View images from dataset

As shown in figure 5.3 we can view different images like green apple, red apple from dataset.

Figure 5.4: Image Search using Query Keyword

The fig. 5.4 is showing text based image search result using apple as query keyword. When we enter query keyword as apple on search image textbox and then click on the search button, we get pool of images which contains images that may be from different categories such as apple tree, green apple, apple iPhone, apple MacBook. Images are having apple as text in their names or keywords, those images are drawn from the dataset. In above figure we are getting images of apple category which are diverse in nature. In this way, we do the image search using the various keywords from different categories.

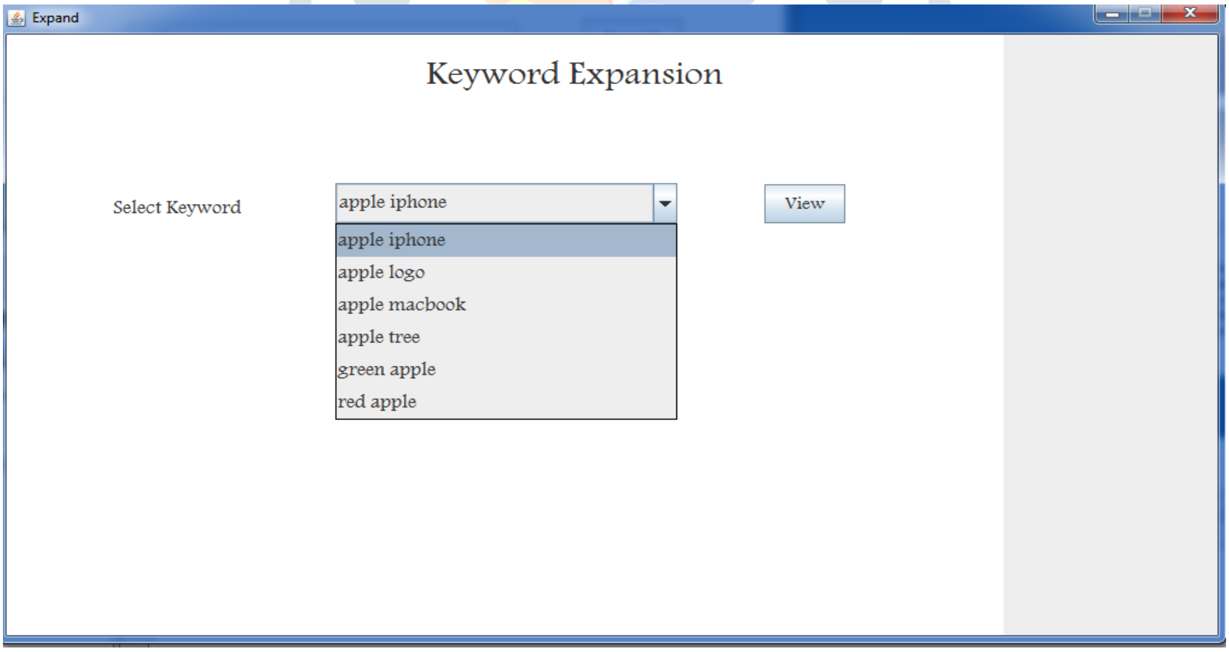

Figure 5.5:- Keyword Expansions for apple keyword

As shown in figure 5.5 there are different expansions for apple keyword such as apple iphone, apple logo, apple macbook, apple tree, green apple, red apple. From the above expansions user will choose which one to view.

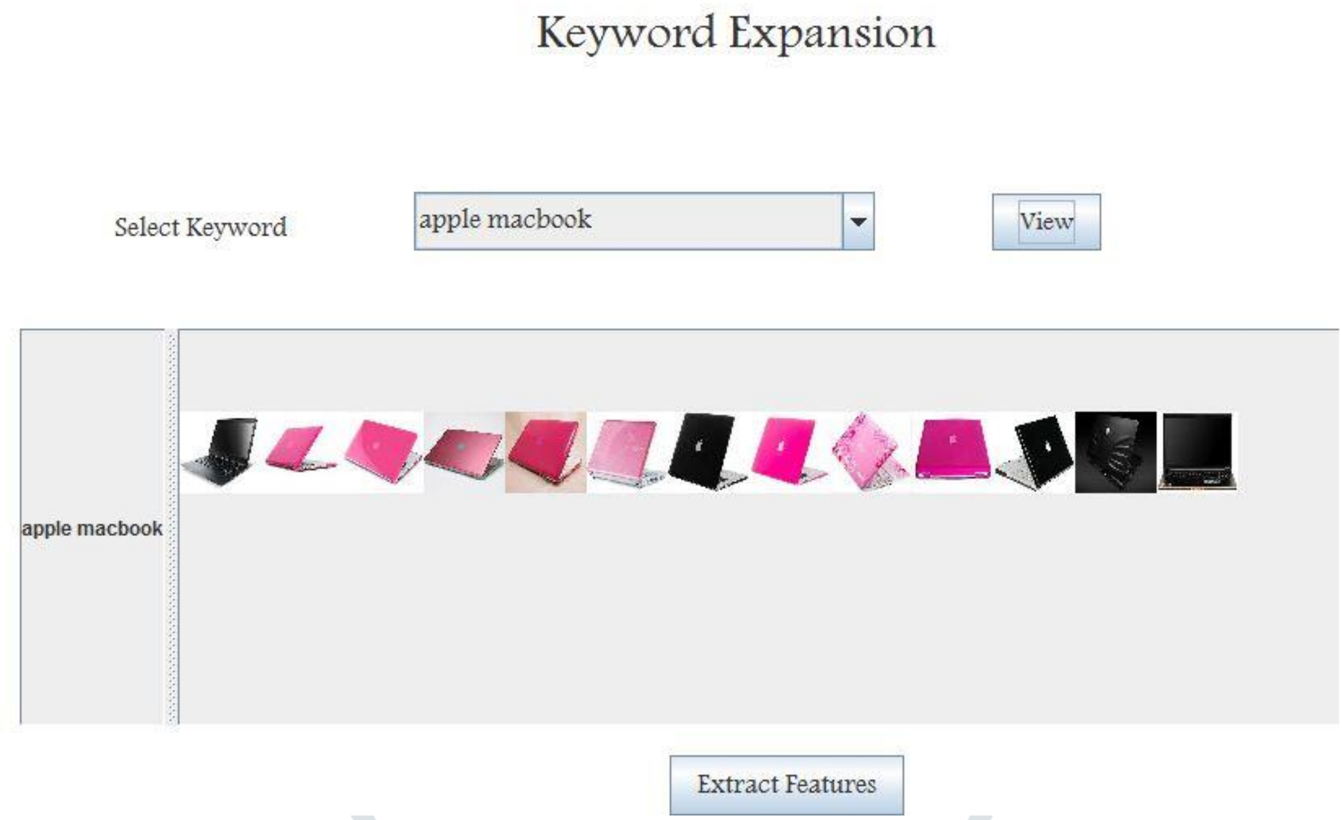

Figure 5.6:- Keyword Expansion

As shown in figure 5.6 we expand query keyword given by the user. Here user gives apple as a query. Then user clicks on apple MacBook to retrieve images of apple MacBook. Following figure shows re-ranking results after clicking particular image.

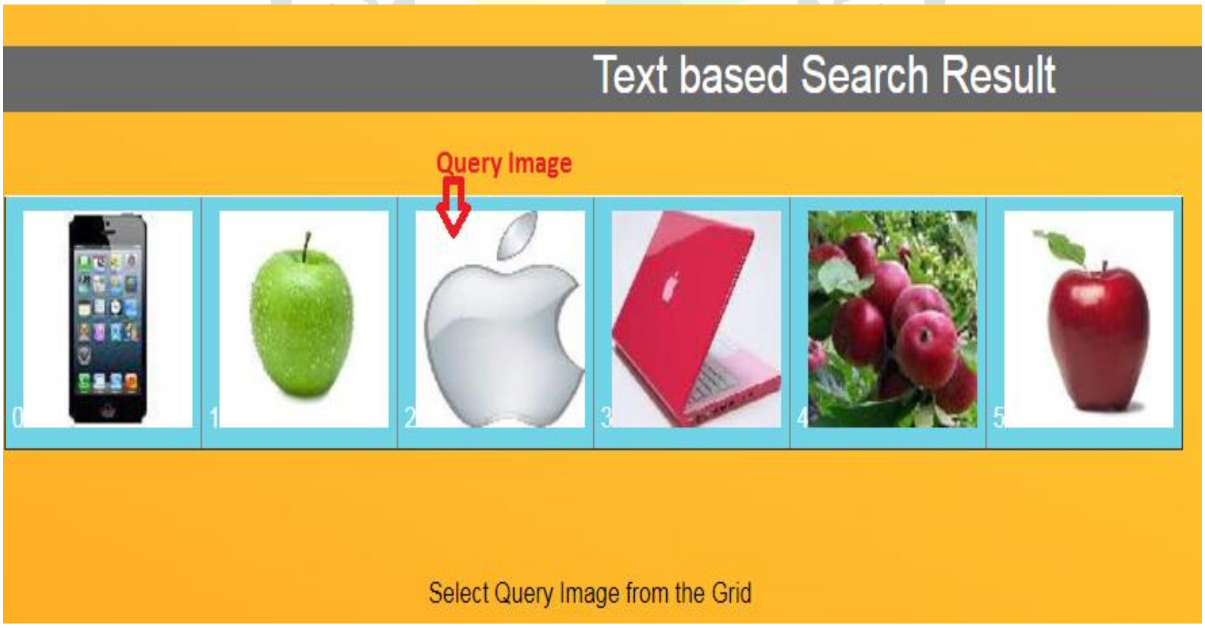

Figure 5.7: Text Based Search Result of apple as query keyword

After getting the text based image search result, we wanted apple logo images which are silver in color with white background. So we clicked on the apple logo which is considered as the query image. The query image is also called as reference image which represent user's intention. So after clicking on apple logo image as query image, we will get re-ranked images of apple logo. The re-ranking of images is done using similarity distance. We are comparing similarity distances of other images with similarity distance of query image. Finally, we got re-ranked images of apple logo category as shown in fig. 5.8. In this way, we got the re-ranked images for apple as query keyword.

Figure 5.8: Re-ranking Result of apple logo images

5.1 RE-RANKING PRECISIONS

We considered evaluation criteria as averaged top n precision. It is defined as proportion of relevant images among top n re-ranked images. Relevant images are those similar to query image in the same category. The precision is defined as,

$$\textbf{Precision} = \frac{\textit{number of relevant images in the returned images}}{\textit{total number of returned images}}$$

Precision is number of relevant images in the returned images divided by total number of returned images is called as precision.

For approach implemented by us, two different ways of computing semantic signatures are compared which are as shown below.

1) Query Specific Visual Semantic Space Using Single Signatures (QSVSS Single):

For an image, a single semantic signature is computed from one SVM classifier trained by combining all types of visual features.

2) Query Specific Visual Semantic Space Using Multiple Signatures (QSVSS Multiple):

For an image, multiple semantic signatures are computed from multiple SVM classifiers, each of which is trained on one type of visual features separately.

X-axis	Y-axis		
Keyword	**QSVSS Multiple**	**Adaptive Weighting**	**Improvements of Averaged Top 10 Precision**
Airplanes	0.6	0.424	18%
Beach	0.8	0.727	7%
Paris	0.73	0.502	22%
Car	0.75	0.492	26%
Dolphin	0.7	0.646	5%
Guitar	0.75	0.513	23%
Rice	0.725	0.656	7%

Table 1:-Improvements of averaged top 10 precisions of 7 keywords comparing QSVSS Multiple with Adaptive Weighting.

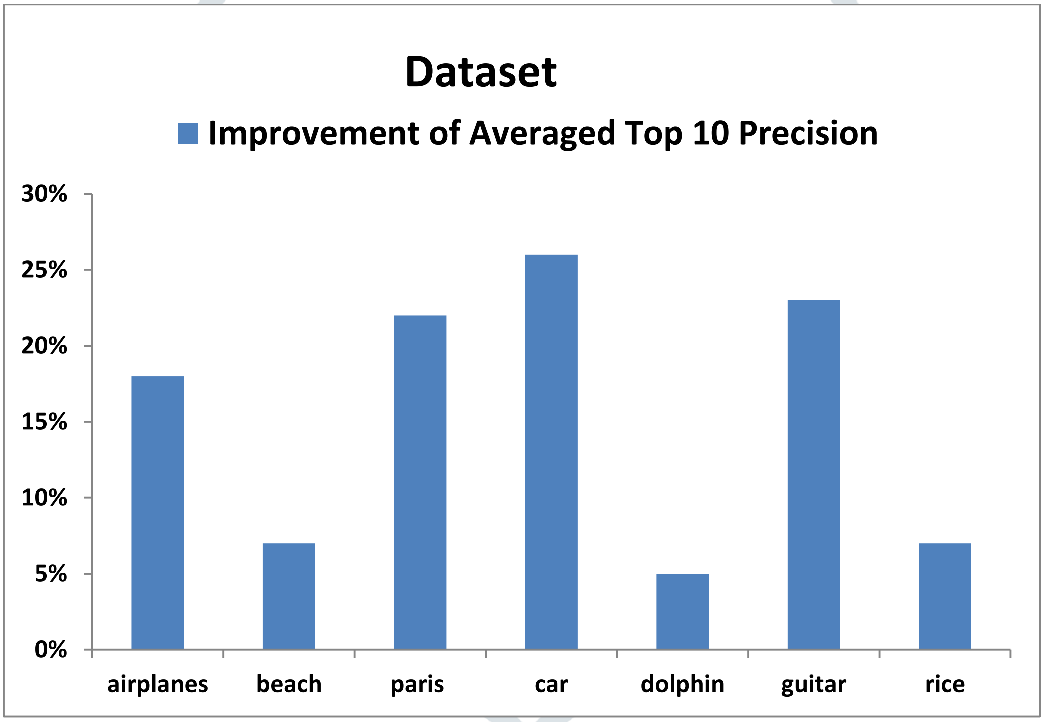

Figure 5.9: Improvements of averaged top 10 precisions of 7 keywords comparing QSVSS_Multiple with Adaptive Weighting

As shown in Table 1, we plot improvements of averaged top 10 precision with the query keywords. On x-axis we are taking values of query keywords as airplanes, beach, Paris, car, dolphin, guitar, rice and on y-axis we are taking values of averaged top 10 precision are 18%, 7%, 22%, 26%, 5%, 23% and 7% respectively. The graph is shown in the fig. 5.9 There are seven keywords considered for comparing our method with adaptive weighting method with the help of averaged top 10 precisions. The improvements of averaged top 10 precisions for 7 keywords are shown in fig. 5.9, where we compare QSVSS multiple with the adaptive weighting method.

ACKNOWLEDGEMENT:-

I am very thankful to prof. M.B. Vaidya for their valuable guidance and motivation through the course of this paper work.

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