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Image Search Reranking with click based similarity using Color Features 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.

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-ranklist 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.*

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1. 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. 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

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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.

2. 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. 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. 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.

3. Motivation

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. For example, The query is 'shahrukh and guari's son' we want to focus only those images where the son of the 'shahrukh and guari's son' appears in images.

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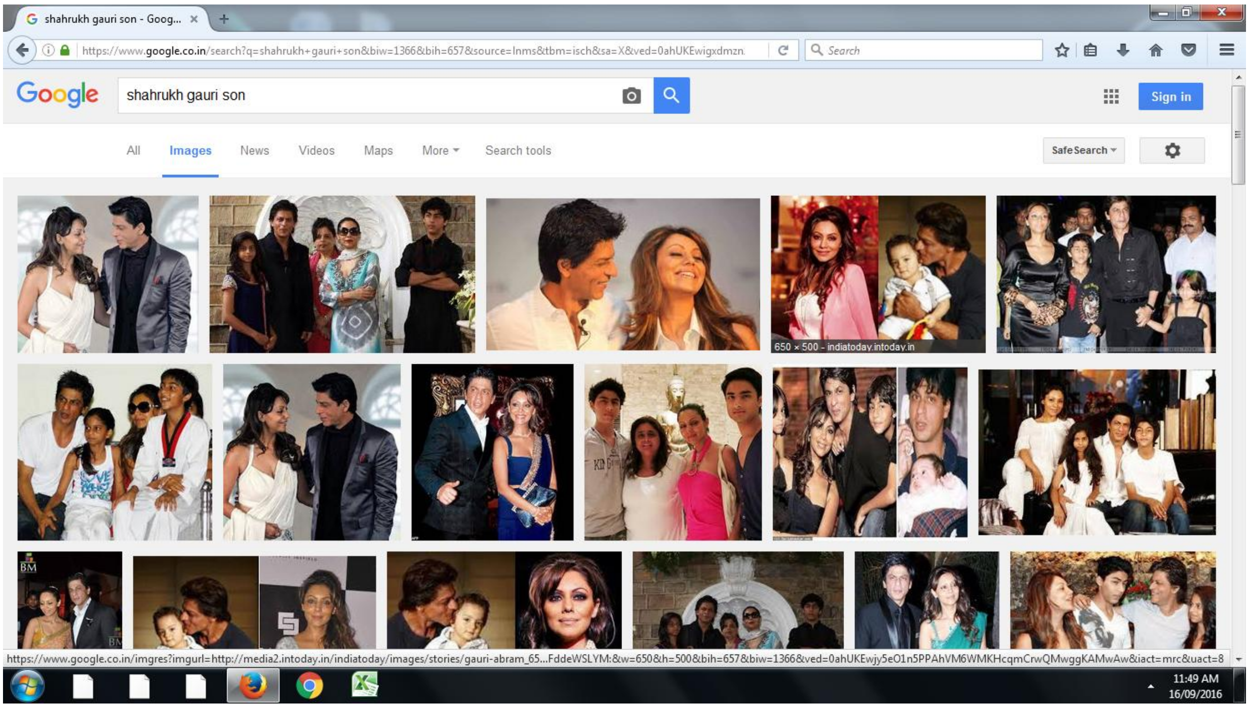

4. Problem Definition

To overcome this problem of ambiguity of keywords, text-based image search alone is not enough. Additional information has to be used to capture users search intention. As a solution to this problem, the second approach, content based image search with relevance feedback is then introduced. For this multiple relevant and irrelevant image examples are to be selected by the users. Through the online training, the visual similarity metrics are learned from them, from which re-ranking of images is performed. But a lots of user interventions is needed in this approach and hence it is very time consuming and not appropriate for commercial web-scale search engines. A combination of both above approaches is useful. But to effectively improve the search results, online image re-ranking should limit users' effort to just one-click feedback.

To overcome the above problems is 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.

Based on the learnt similarity measure, SCCST performs spectral clustering to group visually and semantically similar images into same clusters. The availability and superiority of our proposed SCCST compared with several existing re-ranking approaches. Metric adaptive fusion weights are not considered in SCCST and CMSL due to the optimization difficulty.

5. Objectives

1. To collect relevant image database for particular scenario.
2. To perform features extraction techniques to identify a particular object from the given image by using SIFT algorithm.
3. To re-rank image database according to our text base query.
4. To solve optimization problem
5. Using metric adaptive fusion weights.

6. Proposed Work

In first, take input image on query keywords and second is spectral clustering technique in multivariate statistics and clustering of dada, spectral clustering technique make use of the spectrum (eigenvalues) of the similarity matrix of the data to perform dimensionality reduction before clustering in fewer dimensions. The similarity matrix is provided as an input and consist of a quantitative assessment of the relative similarity of each pair of the point in the dataset. For example, For example, The query is 'shahrukh and guari's son' we want to focus only those images where the son of the 'shahrukh and guari's son' appears in images. The 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.

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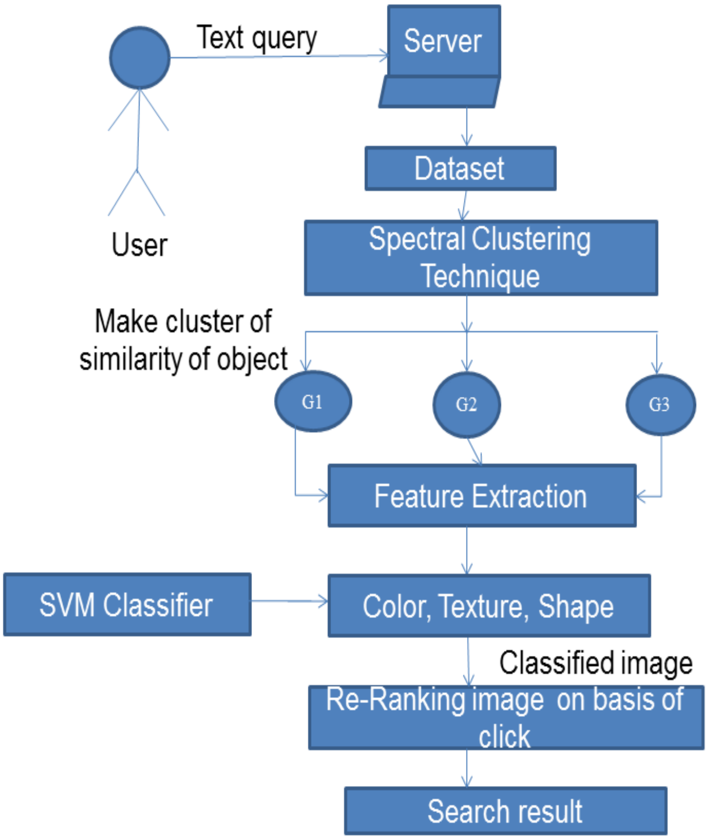


Fig: 1 System Architecture

Typicality, then, can be viewed as a soft labelling measure of the degree of relevance to a certain query. In general, if we can properly measure the similarity and typicality of image in the initial ranked list, the image search re-ranking will be benefited from it.

In order to learn appropriate image similarity and typicality measurements, meanwhile explore the effects of click-through data to reduce intent gap, a novel image search re-ranking approach, named spectral clustering re-ranking with click-based similarity and typicality (SCCST). Besides the widely accepted re-ranking assumption and strategy, we set two additional assumptions fitting click-through data, i.e., images with more clicks have higher typicality than the ones with no or relatively less clicks, and clicked images are more similar with each other than a clicked image with an unclicked one.

The 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. The following steps are:

Step:

1. ***Object detection:***

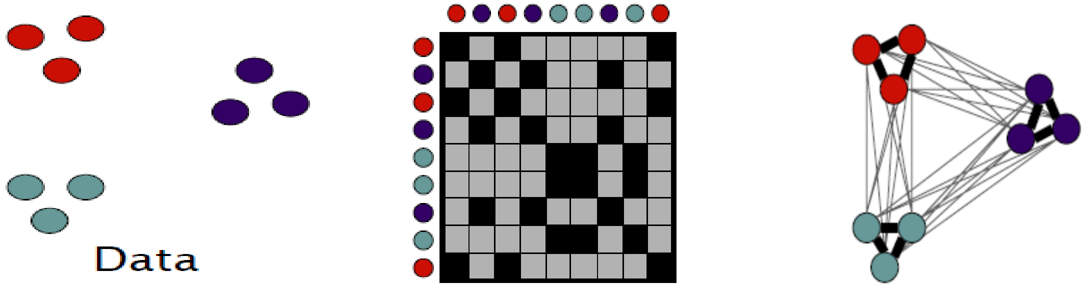
After applying saliency driven non linear diffusion filtering an image is represented as set of multi-scale images. Classify images using the saliency driven multi-scale image representation. Images whose foregrounds are clearer than their backgrounds are more likely to be correctly classified at a large scale, and images whose backgrounds are clearer are more likely to be correctly classified at a small scale. Each image is represented by its multi-scale images. In this extract image regions. Multi-scale fusion is used to combine the information which is extracted from the multi-scale images.

2. ***Spectral clustering technique:***

In spectral clustering techniques make use of the spectrum of the similarity matrix of the data to perform dimensionality reduction before clustering in fewer dimensions. The similarity matrix is provided as an input and consist of a quantitative assessment of the relative similarity of each pair of point in the dataset.

Given data points X1, …, Xn and similarities w(Xi,Xj), partition the data into groups so that points in a group are similar and points in different groups are dissimilar.

Similarity Graph: G(V,E,W)
V –Vertices (Data points)
E –Edge if similarity > 0
W -Edge weights (similarities)



Similarity Similarity graph

Partition the graph so that edges within a group have large weights and edges across groups have small weights.

3. *Feature extraction:*

During the diffusion process, the image gradients in the salient regions are increased while those in non-salient regions are decreased. Accordingly, when the scale increases, the background information gradually fades out while the foreground information is preserved and important structures in the foreground are enhanced. After applying diffusion filtering generate saliency map. It is clearly seen that the background regions are smoothed more effectively by using saliency information, while the foreground regions are preserved and extract the image feature of input image. Saliency driven nonlinear diffusion are more suitable for image classification than those produced by normal nonlinear diffusion.

4. *Image categorization:*

Information from different scales can be fused and apply classifier to acquire more accurate image classification result. Classifier categorize image then apply Re-ranking to provide the proper indexing to the images. Images will be provided on the basis of specific image.

5. *Histogram Color:*

A color histogram is a representation of the distribution of color in an image for digital image. For digital image ,a color histogram represent the number of pixels that have color in each of a pixels list of color space, the set of all possible color.

- ***Techniques used for feature extraction:***
- ➢ HSV Histogram:
- ➢ Color Autorrelogarm:
- ➢ Gabor wavelet transformation:
- ➢ Support vector machine:
- ***HSV Histogram:-***

HSV (Hue, Saturation and Value) :

- Defines a type of color space. It is similar to the modern RGB and CMYK models. The HSV color space has three components: hue, saturation and value. 'Value' is sometimes substituted with 'brightness' and then it is known as HSB.

Hue:

- In HSV, hue represents color. In this model, hue is an angle from 0 degrees to 360 degrees.

Table. 4.1 HSV color

Angle	Color
0-60	Red
60-120	Yellow
120-180	Green
180-240	Cyan
240-300	Blue
300-360	Magenta

Saturation:

- Saturation indicates the range of grey in the color space. It ranges from 0 to 100%. Sometimes the value is calculated from 0 to 1. A faded color is due to a lower saturation level.

Value:

- Value is the brightness of the color and varies with color saturation. It ranges from 0 to 100%. When the value is '0' the color space will be totally black. With the increase in the value, the color space brightness up and shows various colors.

HSV Representations:

- Hue is represented by the circle in the wheel. A separate triangle is used to represent saturation and value. The horizontal axis of the triangle indicates value and the vertical axis represents saturation.

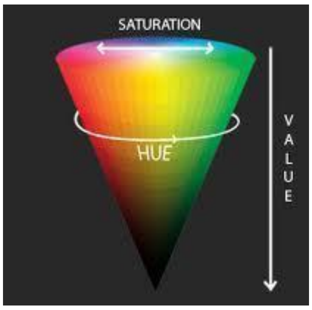


Fig. 2. HSV representation

- A color histogram is a representation of the distribution of colors in an image. For digital images, a color histogram represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color spaces, the set of all possible colors.
- The color histogram can be built for any kind of color space, although the term is more often used for three-dimensional spaces like RGB or HSV.
- A color histogram H is a vector <h1; h2; …; hi> in which each bucket hj contains the number of pixels of color j in the image. Image histogram feature is extracted for three color space Red, green and Blue. And the histogram value matrix holds no of pixels of 256 different bins
- *Image color histogram:*

  Step 1: Read the image.

  Step 2: Store the value of each red, green, blue component in three different arrays.

  Step 3: Find the image histogram of red, green, blue component by Matlab's own histogram computational method.

  Step 4: Store the histogram value of red, green, blue component in three arrays.

  Step 5: Calculate the sum of 256 different bin of red component. If there are: N no of color bin of red component then we get M (summation of each color bin) by the below said formula:

$$M = \sum_{i=1}^{N} ht$$

  Apply this method for green and blue component also.

  Step 6: Then find the mean of color historam using.

$$\overline{X} = \frac{\sum_{i=1}^{N}(t+ht)}{M}$$

  Step 7: Then find the standard deviation of color histogram using

$$\sigma = \sqrt{1/M(\sum_{i=1}^{N} ht * (t - \overline{X})^2})$$

  N = is no. of color bin of red component
  M= summation of each color bin

  Step 8: Finally store this three value- summation, mean, standard deviation in a 1D array.

  Step 9: Repeat Step 1-8 for every images in the database.

Color Auto Correlogram:

- In the analysis of the data a correlogram is an image of correlogram statistics. It generates the color auto correlogram vector for an input color image.
- Autocorrelation is a mathematical representation of the degree of similarity between a given time series and a lagged version of itself over successive time intervals. It is the same as calculating the correlation between two different time series, except that the same time series is used twice: once in its original form and once lagged one or more time periods.

Gabor wavelet transform:

- They are very similar to morlet wavelet. They are closely related to Gabor filter. Convert the image is RGB to gray.
- The important property of the wavelet is that it minimizes the product of its standard deviations in the time and frequency domain.
- A 1-D signal in time and frequency simultaneously. There is always uncertainty between the time and the frequency resolution of the window function used in this analysis since it is well know that when the time duration get larger, the bandwidth becomes smaller.
- The most common one is the multiple of the standard deviations on time and frequency domain:

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$$\sigma_t{}^2 = \frac{\int t^2|x(t)|^2 dt}{\int |\ x(t)|^2\ dt} \quad , \sigma_f{}^2 = \frac{\int f^2|x(f)|^2 dt}{\int |\ x(f)|^2\ dt}$$

$$\sigma_t \times \ \sigma_f \quad \geq \frac{1}{4\pi}$$

6. Texture:

An image texture is a set of matrix calculated in image processing designed to quantify the perceived texture of an image. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.

7. Edge Feature extraction:

Edge detection techniques includes a variety of mathematical method that aim of identifying point in a digital image at which the image brightness changes sharply or more formally, has discontinuities change sharply are typically organized into a set of curved lines segment termed edge.

Support vector machine:

- In machine learing, a support vector machine constructs a hyperplane or set of hyperplane in a high dimensional space, which can be used for classification and regression or other task.
  Step:

1) Find the goal of support vector machine.
2) Compute the margin.
3) Unconstrained minimization.
4) Convex functions.
5) Duality and lagrange multiplers.

- An SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class. The *best* hyperplane for an SVM means the one with the largest margin between the two classes.

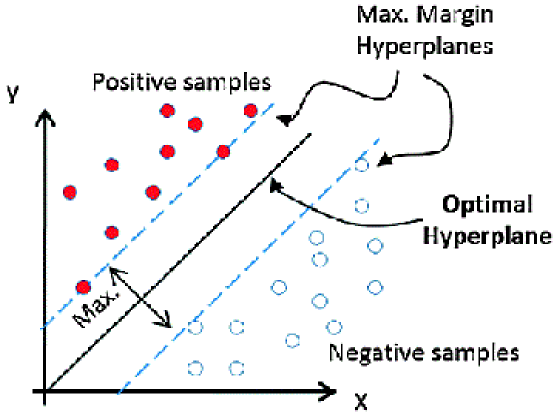


Fig. 8.1 SVM Classifier

8. SIFT:

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect and describe local features in images. Applications include object recognition, robotic mapping and navigation, image stitching, 3D modeling, gesture recognition, video tracking, individual identification of wildlife and match moving.

Given SIFT's ability to find distinctive key points that are invariant to location, scale and rotation, and robust to affine transformations (changes in scale, rotation, shear, and position) and changes in illumination, they are usable for object recognition.

The steps are given below.

- First, SIFT features are obtained from the input image using the algorithm described above.
- These features are matched to the SIFT feature database obtained from the training images. This feature matching is done through a Euclidean-distance based nearest neighbor approach.
- Although the distance ratio test described above discards many of the false matches arising from background clutter, we still have matches that belong to different objects.

For any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects. To perform reliable recognition, it is important that the features extracted from the training image be detectable even under changes in image scale, noise and illumination. Such points usually lie on high-contrast regions of the image, such as object edges.

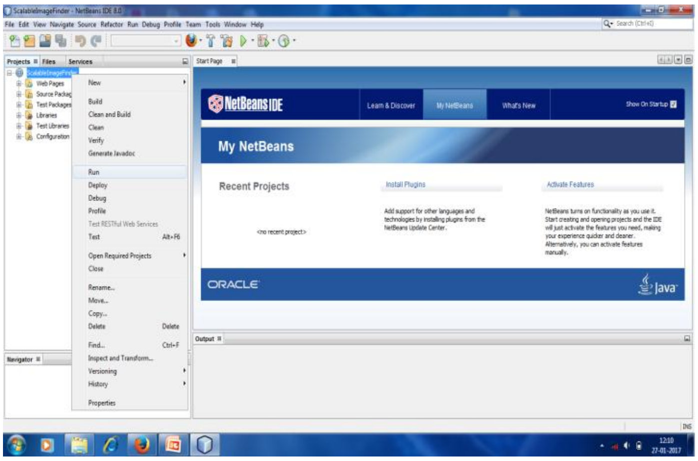
Scale Invariant Feature Transform (SIFT) features are features extracted from images to help in reliable matching between different views of the same object. SIFT is an image local feature description algorithm based on scale-space. Due to its strong matching ability, SIFT has many applications in different fields, such as image retrieval, image stitching, and machine vision. The extracted features are invariant to scale and orientation, and are highly distinctive of the image. They are extracted in four steps. The first step computes the locations of potential interest points in the image by detecting the maxima and minima of a set of Difference of Gaussian filters applied at different scales all over the image.

- ***Color Descriptor Based on SIFT***

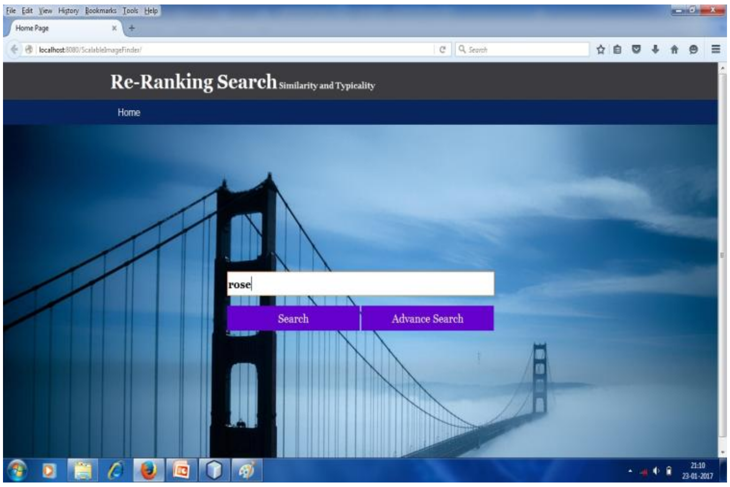
The SIFT descriptor describes the local shape of a region using edge orientation histograms. The gradient of an image is shift-invariant: taking the derivative cancels out offsets. Under light intensity changes, i.e. a scaling of the intensity channel, the gradient direction and the relative gradient magnitude remain the same. Because the SIFT descriptor is normalized, the gradient magnitude changes have no effect on the final descriptor. Light color changes have no effect on the descriptor because the input image is converted to grayscale, after which the intensity scale-invariance argument applies.

7. Screen shot

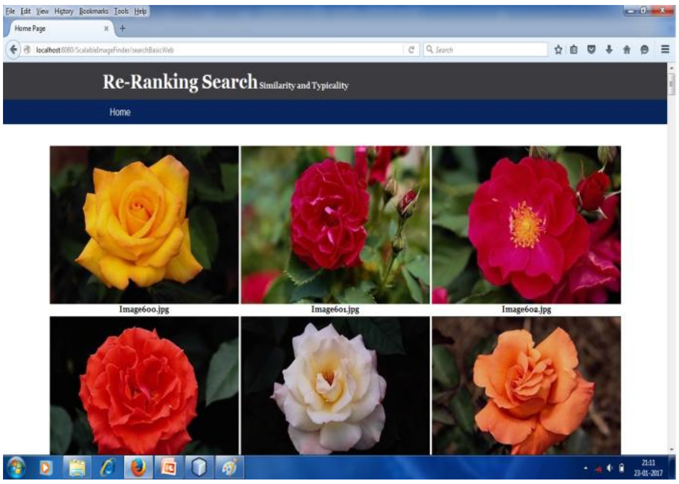
Module 1:



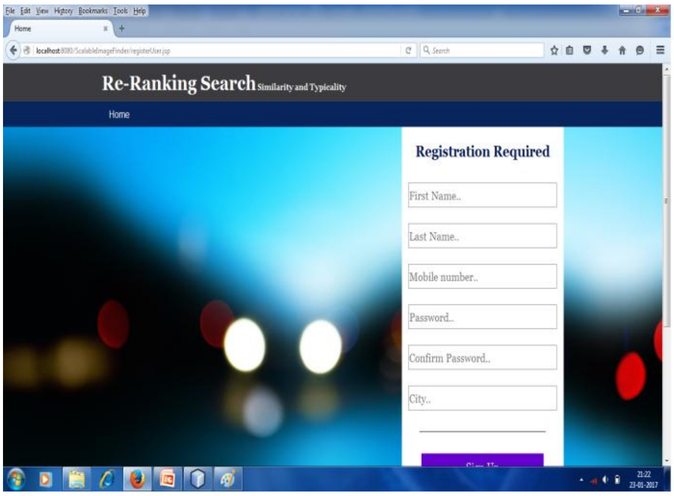
Screenshot 7.1: NetBeans IDE



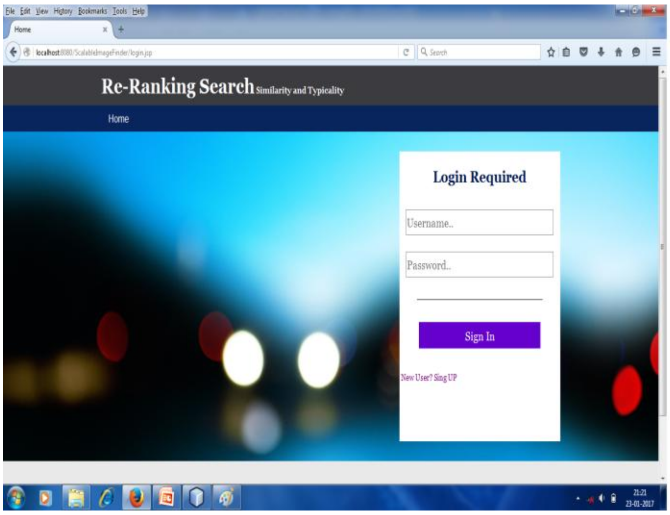
Screenshot 7.2: Search query



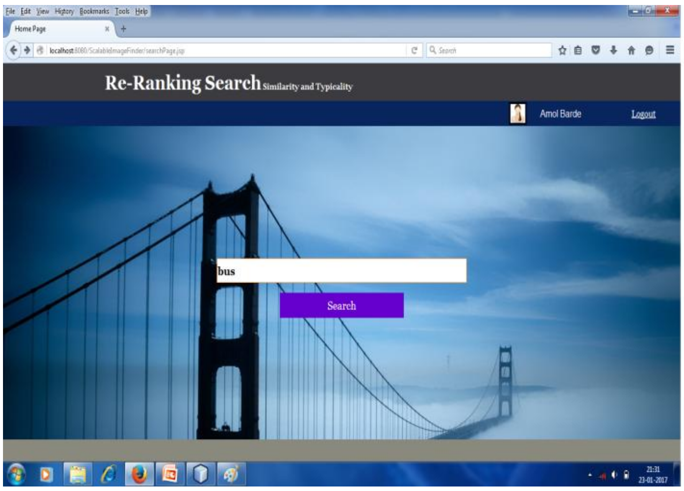
Screenshot 7.3: Basic search result



Screenshot 7.4: Registration form



Screenshot 7.5: Login page



Screenshot 7.6: Advance search

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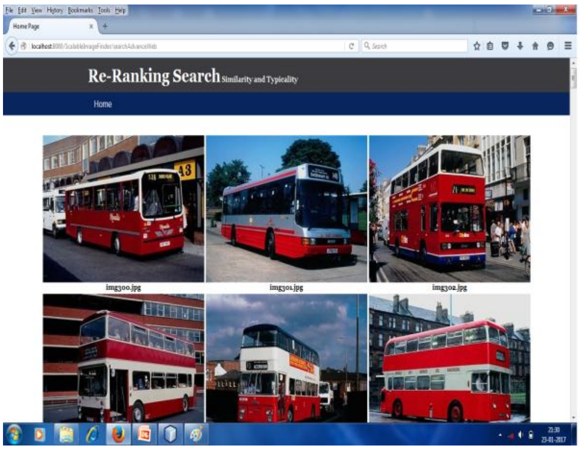
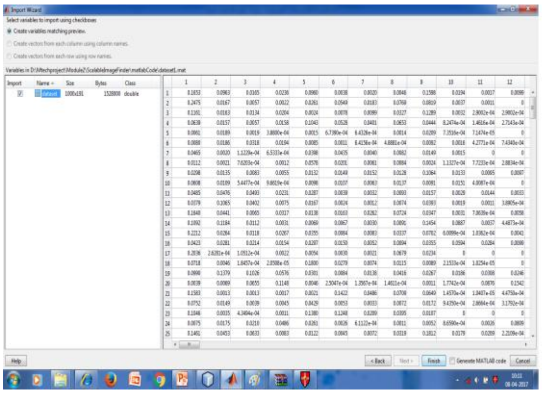
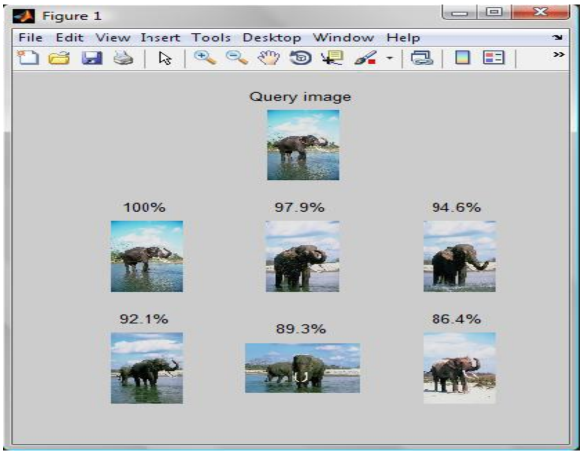


Screenshot 7.7: Advance search result



Screenshot 7.8: Dataset feature extraction



Screenshot 7.9 Most Similar image

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