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Effective Relevance Feedback for Content Based Image Retrieval Using Mining Navigation Pattern and SEO Tools

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Abstract— with a rapid increase of images that are available in social blog and media, image annotation has evolved as an important thing due to its application in image toning and retrieval. Most studies cast image annotation into a multi label classification problem. Images with complete annotations in order to learn a reliable model for tag prediction. We address this limitation by developing a novel approach that combines the strength of tag ranking with the power of matrix recovery. Instead of having to make a decision for each tag, our approach ranks tags in the descending order of their relevance to the given image, significantly simplifying the problem. In addition, the proposed method aggregates the prediction models for different tags into a matrix, and casts tag ranking into a matrix recovery problem, so that a reliable prediction model can be learned for tag ranking even when the tag space is large and the number of training images is limited. Experiments on multiple well-known image data sets demonstrate the effectiveness of the proposed framework for tag ranking compared with the state-of-the-art approaches for image annotation and tag ranking.

Index Terms — image annotation; tag ranking; matrix recovery; low-rank;

I. INTRODUCTION

The popularity in visuals lead to an explosive growth of digital images that are available over the internet. How to accurately retrieveImages from enormous collections of digital photos has become an important research topic. Content-based image retrieval (CBIR) addresses this challenge by identifying the matched images based on their visual similarity. **Image search** is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc.

A. Image meta search - search of images based on associated metadata such as keywords, text, etc.

B. Content - based image retrieval – the application of computer vision to the image retrieval. CBIR aims at avoiding the use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colors, shapes etc.) to a user-supplied query image or user-specified image features.

C. List of CBIR Engines - list of engines which search for images based image visual content such as color, texture, shape/object, etc.

D. Image collection exploration - search of images based on the use of novel exploration paradigms.

It is crucial to understand the scope and nature of image data in order to determine the complexity of image search system design. The design is also largely influenced by factors such as the diversity of user-base and expected user traffic for a search system. Along this dimension, search data can be classified into the following categories

II. EXISTING SYSTEM

Automatic image annotation aims to find a subset of keywords/tags that describes the visual content of an image. it plays an important role in bridging the semantic gap between low-level features and high-level semantic content of images. most automatic image annotation algorithms can be classified into three categories (i) generative models that model the joint distribution between tags and visual features, (ii) discriminative models that view image annotation as a classification problem, and (iii) search based approaches. Below, we will briefly review approaches in each category. Both mixture models and topic models, two well known approaches in generative model, have been successfully applied to automatic image annotation. in a gaussian mixture model is used to model the dependence between keywords and visual features. in kernel density estimation is applied to model the distribution of visual features and to estimate the conditional probability of keyword assignments given the visual features. topic models annotate images as samples from a specific mixture of topics, which each topic is a joint distribution between image features and annotation keywords. Various topic models have been developed for image annotation, including probabilistic latent semantic analysis (plsa), latent dirichlet allocation and hierarchical dirichlet processes. since a large number of training examples are needed for estimating the joint probability distribution over both features and keywords, the generative models are unable to handle the challenge of large tag space with limited number of training images.

A. *Disadvantages of Existing System*

1) *Unable to capture the correlation among classes.*
2) *Tag ranking problem.*

III. PROPOSED SYSTEM

We have proposed a novel tag ranking scheme for automatic image annotation. The proposed scheme casts the tag ranking problem into a matrix recovery problem and introduces trace norm regularization to control the model complexity. Extensive experiments on image annotation and tag ranking have demonstrated that the proposed method significantly outperforms several state-of-the-art methods for image annotation especially when the number of training images is limited and when many of the assigned image tags are missing. We first present the proposed framework for tag ranking that is explicitly designed for a large tag space with a limited number of training images. We then discuss a computational algorithm that efficiently solves the related optimization problem. A straightforward approach for tag ranking is to search for a matrix W that minimizes the ranking error f (W). This simple approach is problematic and could lead to the over fitting of training data when the number of training images is relatively small and the number of unique tags is large. We Like most machine learning algorithms, an appropriate regularization mechanism is needed to control the model complexity and prevent over fitting the training data.

A. *Advantages of Proposed System*

1) The scheme casts the tag ranking problem into a matrix recovery problem and introduces trace norm regularization to control the model complexity.

IV. ALGORITHM

Input: A set of positive images P[i] picked up by user, a set of negative set N[i];
Output: A set of relevant images R[i];
Step 1: Generate a new query points and features $\sum$ of positive images.
Step 2: let Negative images are stored in the Negative image set N[i].
Step 3: Initialize flag=0;
for each query image belongs to P[i] do
Determine the images with the shortest distance to query image
end for
if threshold exceeds then
for each negative image belongs to N[i] do
determine the images with the shortest distance to negative images.
end for
end if
if flag=1 then
Find the set of visual query points with in the retrieved images.
end if
for i=1 to k do
find the relevant image set R[i] from the database
end for
eliminate the negative images from retrieved images.

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return the retrieved image set R[i] of top k similar images.

V. MODULES

A. User Registration

URS provides a user registration service allowing users to self-register, free of charge. The user needs to set up a profile that includes a user ID, password, and provide a small amount of additional information, including affiliation, country, and a valid e-mail address. This information is never provided to any application without a user's explicit permission.

B. User Login

A login, logging in or logging on is the entering of identifier information into a system by a user in order to access that system (e.g., a computer or a website). It is an integral part of computer security procedures. A login generally requires the user to enter two pieces of information, first a *user name* and then a *password*. This information is entered into a *login window* on a GUI (graphical user interface) or on the command line in a *console* (i.e., an all-text mode screen), depending on the system and situation. A user name, also referred to as an *account name*, is a *string* (i.e., sequence of characters) that uniquely identifies a user. User names can be the same as or related to the real names of users, or they can be completely arbitrary.

C. Memory Booster

Memory Booster is a powerful mobile Memory & RAM boosting tool specially designed for Android smartphone users. It is a handy memory optimizer tool that will keep your Android smartphone running faster and efficiently. It increases your cell phone's performance by making more memory available for both your applications and the mobile system. Memory Booster is designed to tackle the difficult but crucial problem of memory management for Android smartphone users. Memory is the most precious resource in your smartphone; when it becomes low, your cell phone will slow down severely or crash. If the mobile system cannot handle your memory properly by itself, your smartphone will slowly lose memory over time and bring you to a critical state. Memory Booster solves these problems by reclaiming lost memory for your programs. It helps your smartphone run at optimum speed by efficiently defragmenting your smartphone's memory, recovering memory leaks from poorly behaved application, flushing unused libraries temporarily out to disk and so on. By all this optimization tricks your favorite applications and games will run faster and efficiently with Memory Booster running in the background.

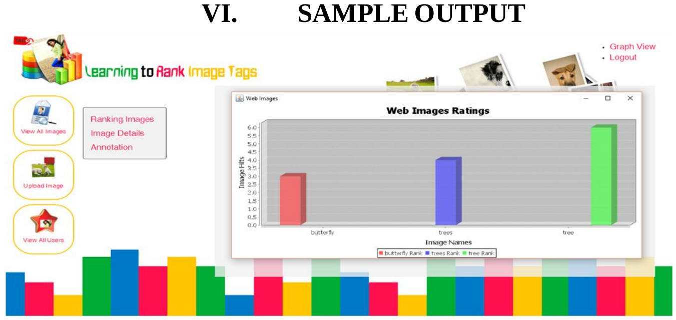
D. Battery Information

Battery Info View is a small utility for laptops and net book computers that displays the current status and information about your battery. The displayed battery information includes the battery name, manufacture name, serial number, manufacture date, power state (charging/discharging), current battery capacity, full charged capacity, voltage, charge/discharge rate, and more... Battery Info View also provides a log window, which adds a new log line containing the battery status every 30 seconds or any other time interval that you choose.

E. Scanner

The automated process of proactively identifying security of computing systems in a network in order to determine if and where a system can be exploited and/or threatened. While public servers are important for communication and data transfer over the Internet, they open the door to potential security breaches by threat agents, such as malicious hackers

VI. SAMPLE OUTPUT



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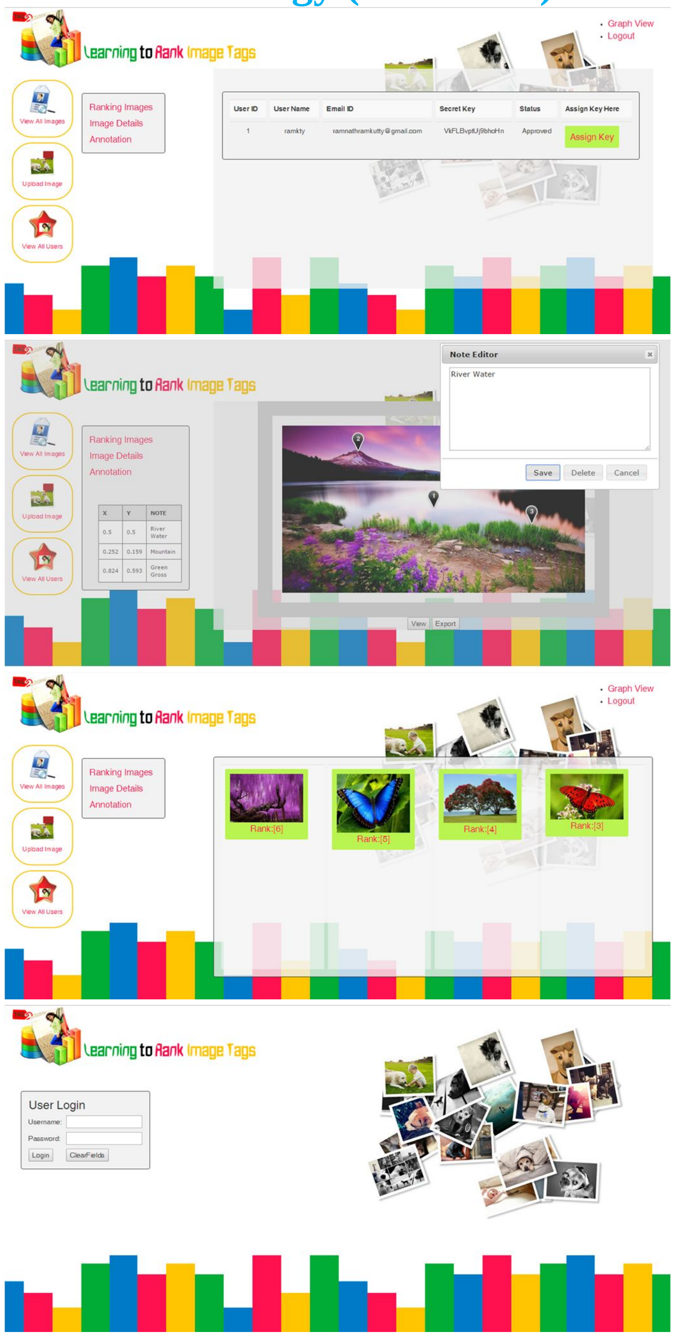

VII. CONCLUSION

In this work, we have proposed a novel tag ranking scheme for automatic image annotation. The proposed scheme casts the tag ranking problem into a matrix recovery problem and introduces trace norm regularization to control the model complexity. Extensive experiments on image annotation and tag ranking have demonstrated that the proposed method significantly outperforms several state-of-the-art methods for image annotation especially when the number of training images is limited and when many of the assigned image tags are missing. In the future, we plan to apply the proposed framework to the image annotation problem when image tags are acquired by crowd souring that tend to be noisy and incomplete.

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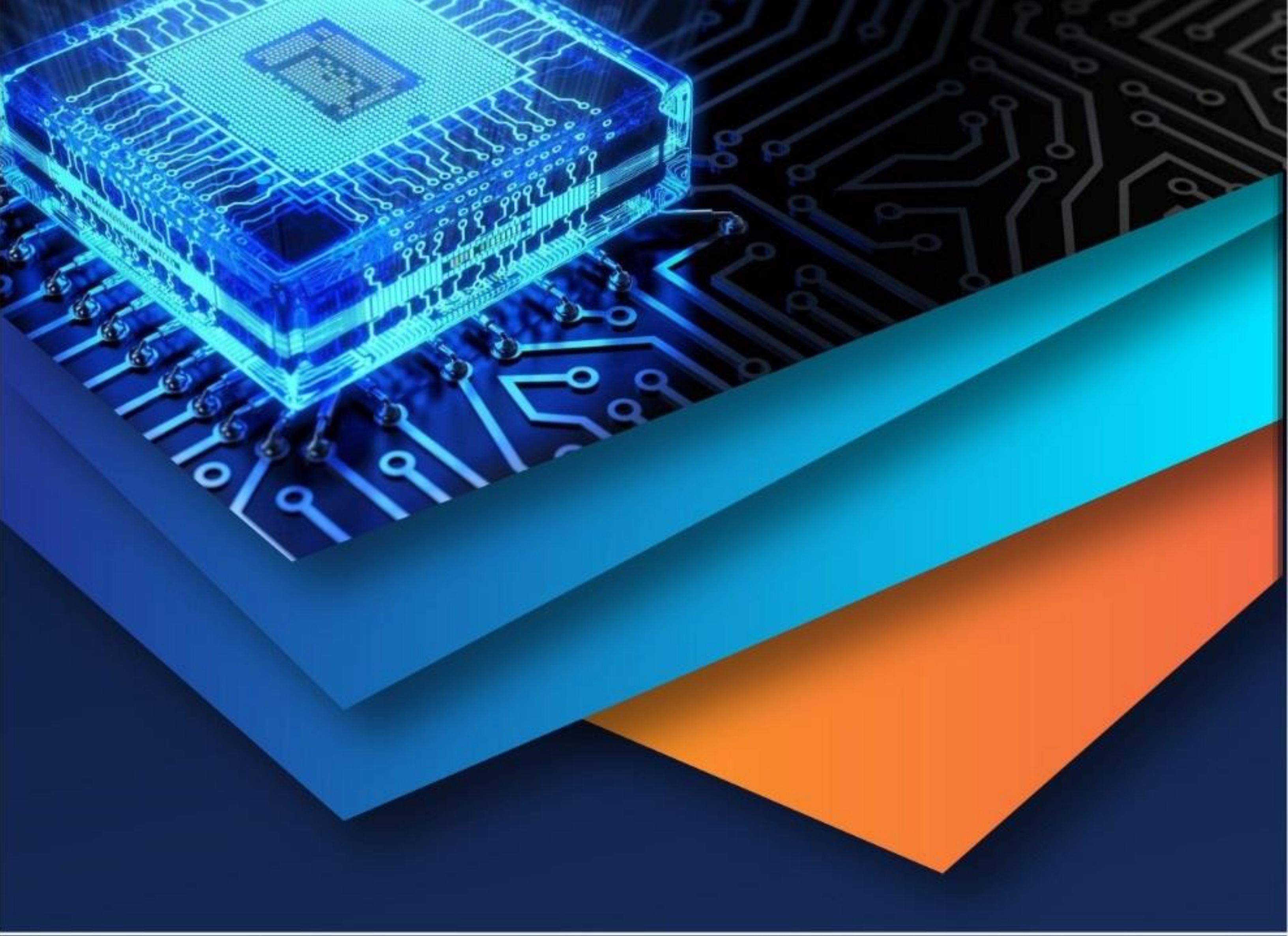

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