

STANDARDIZING PICTURE RETREIVAL VARIATION METHODS FOR WEB BASED COMMUNITIES

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ABSTRACT

Image retrieval has been an active research domain for over 30 years and historically it has focused primarily on precision as an evaluation criterion. Similar to text retrieval, where the number of indexed documents became large and many relevant documents exist, it is of high importance to highlight diversity in the search results to provide better results for the user. The Retrieving Diverse Social Images Task of the MediaEval benchmarking campaign has addressed exactly this challenge of retrieving diverse and relevant results for the past years, specifically in the social media context. Multimodal data (e.g., images, text) was made available to the participants including metadata assigned to the images, user IDs, and precomputed visual and text descriptors. Many teams have participated in the task over the years. The large number of publications employing the data and also citations of the overview articles underline the importance of this topic. In this paper, we introduce these publicly available data resources as well as the evaluation framework, and provide an in-depth analysis of the crucial aspects of social image search diversification, such as the capabilities and the evolution of existing systems. These evaluation resources will help researchers for the coming years in analyzing aspects of multimodal image retrieval and diversity of the search results.

1. INTRODUCTION

Image retrieval has been an extremely active research domain over the past 30 years [1], [2]. Starting with text based retrieval of images and then moving towards content based image retrieval and multimodal approaches, the techniques have constantly evolved to high quality of retrieval and increasingly large data sets [3], [4].

The evaluation of retrieval approaches has traditionally focused on early precision in retrieval results and on mean average precision (MAP) [5]–[7], and for specific applications, e.g., patent retrieval, on recall. With increasingly large data sets and many potentially relevant images, precision as an evaluation criterion is not sufficient anymore and requires complementary measures.

In most cases, systems aim to improve the relevance of the results assuming that the results for a query are single topic. This is not an accurate assumption anymore in the context of the current Internet, because many of the queries cover different aspects, i.e., sub-topics. For instance, objects in images show different information and have different contexts, landmarks can be captured in various conditions and angles, e.g., day-night, close-far, bicycles serve different usages conditions, e.g., city, mountain, road, vehicles are of different types, and so on. An effective retrieval system should also take into account the diversification of the results [8].

An example is provided in Figure 1. To improve the diversity of search results, one has to consider the multiple and diverse topics, contexts, intents, and interpretations of a certain query. Increasing the diversity increases also the efficiency and usefulness of the system via providing a wider selection of results and therefore, a higher chance that they address the user real needs.

A concrete example are the recommender systems, where the users' satisfaction increases with the diversification of the results. With this concept, cluster recall was introduced as a measure for diversity in image retrieval [8]. The Retrieving Diverse Social Images Task, we are introducing in this paper, has been organized under the Media Eval Benchmarking Initiative for Multimedia Evaluation and has evaluated such approaches over the past years [9]–[10].

Another important aspect of image retrieval is the availability of many input sources, e.g., not only features that represent the visual image content and textual metadata, but also information on the person posting data, tags added by other persons and possible GPS (Global Positioning System) data. Some of this information may represent what is in the image, others what the image is about but also emotional responses, for example the feeling that an image evokes and the context in which it was taken.

The Retrieving Diverse Social Images Task addressed these aspects and created a benchmark framework so that practitioners could choose from a large number of data sources. Additionally, various visual and text-based content descriptors were made available to limit the entry requirements for systems [9], [1] while focusing on diversification. The large number of publications employing the various data sets from the task and the increasing number of citations underline the importance and the high impact of the task. With the public availability of resources, we expect the impact and usage of the resources to increase strongly over the coming years, similar to other related benchmarking campaigns [3].

2. LITERATURE SURVEY

Content-based image retrieval at the end of the early years

Presents a review of 200 references in content-based image retrieval. The paper starts with discussing the working conditions of content-based retrieval: patterns of use, types of pictures, the role of semantics, and the sensory gap. Subsequent sections discuss computational steps for image retrieval systems. Step one of the review is image processing for retrieval sorted by color, texture, and local geometry. Features for retrieval are discussed next, sorted by: accumulative and global features, salient points, object and shape features, signs, and structural combinations thereof. Similarity of pictures and objects in pictures is reviewed for each of the feature types, in close connection to the types and means of feedback the user of the systems is capable of giving by interaction.

Performance evaluation in content-based image retrieval: Overview and proposals

Evaluation of retrieval performance is a crucial problem in content-based image retrieval (CBIR). Many different methods for measuring the performance of a system have been created and used by researchers.

This article discusses the advantages and shortcomings of the performance measures currently used. Problems such as defining a common image database for performance comparisons and a means of getting relevance judgments [4] (or ground truth) for queries are explained. The relationship between CBIR and information retrieval (IR) is made clear, since IR researchers have decades of experience with the evaluation problem. Many of their solutions can be used for CBIR, despite the differences between the fields. Several methods used in text retrieval are explained. Proposals for performance measures and means of developing a standard test suite for CBIR, similar to that used in IR at the annual Text REtrieval Conference (TREC), are presented.

Result Diversification in Social Image Retrieval: A Benchmarking Framework

This article addresses the diversification of image retrieval results in the context of image retrieval from social media. It proposes a benchmarking framework together with an annotated dataset and discusses the results achieved during the related task run in the MediaEval [6] 2013 benchmark. 38 multimedia diversification systems, varying from graph-based representations, re-ranking, optimization approaches, data clustering to hybrid approaches that included a human in the loop, and their results are described and analyzed in this text.

3. PROBLEM STATEMENT

The approach is based on a Random Walk scheme with restarts over a graph that models relations between images, visual features, userprovided metadata, and the information on the uploader and commentators. Radu et al. employed a crowd-sourcing approach to improve the initial results achieved by an automated visual analysis of the retrieval results for monument queries. To avoid the use of human expertise, Boteanu et al. [9] considered pseudo-relevance feedback, where user feedback is simulated by the selection of positive and negative examples from the initial query results.

3.1 LIMITATIONS OF SYSTEM

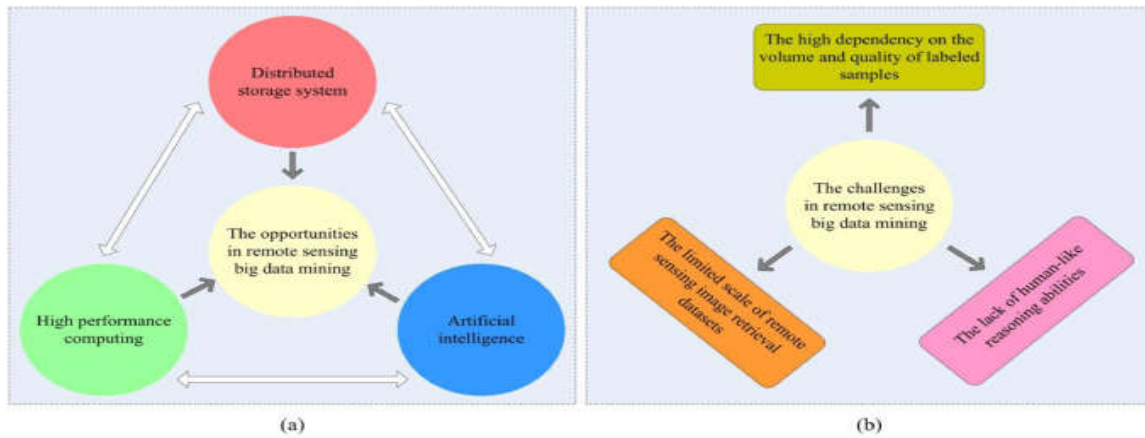
Many teams have participated in the task over the years. The large number of publications employing the data and also citations of the overview articles underline the importance of this topic. This is not an accurate assumption anymore in the context of the current Internet, because many of the queries cover different aspects, i.e., sub-topics.

4. PROPOSED SYSTEM

To explore the generalization ability of a given approach, thorough experiments on several data sets and application scenarios are required. A recent work in this direction is reported by Boato et al. [10].

The authors make use of visual saliency information for the diversification of image retrieval results and present experiments on two data sets: a self-combined collection of publicly available data sets in the context of object categorization and the Div150Creddata set [9] addressing the diversification of POI (points of interest) images retrieved from Flickr. The reported results demonstrate a notable difference in the performance on the two application scenarios, i.e., while the improvement in the diversification on the object categories is significant, the difference on the location-based data set is marginal only.

5. SYSTEM ARCHITECTURE



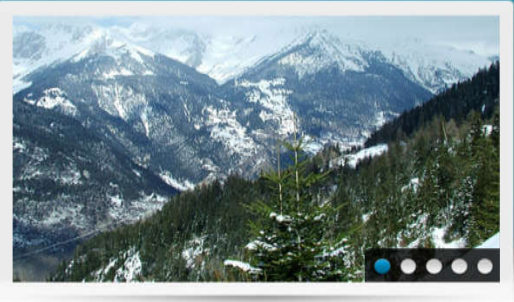
6. OUTPUT SCREENSHOTS:

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USER

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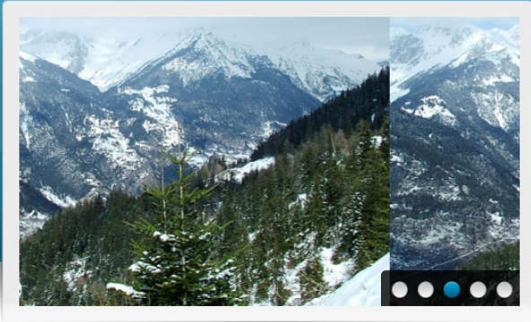
Project Abstract

“ Image retrieval has been an active research domain for over 30 years and historically it has focused primarily on precision as an evaluation criterion. Similar to text retrieval, where the number of indexed documents became large and many relevant documents exist, it is of high importance to highlight diversity in the search results to provide better results for the user. The Retrieving Diverse Social Images Task of the MediaEval benchmarking campaign has addressed exactly this challenge of retrieving diverse and relevant results for the past years, specifically in the social media context. Multimodal data (e.g., images, text) was made available to the participants including metadata assigned to the images, user IDs, and precomputed visual and text descriptors. Many teams have participated in the task over the years. The large number of publications employing the data and also citations of the overview articles underline the importance of this topic. In this paper, we introduce these publicly available data resources as well as the evaluation framework, and provide an in-depth analysis of the crucial aspects of social image search diversification, such as the capabilities and the evolution of existing systems. These evaluation resources will help researchers for the coming years in analyzing aspects of multimodal image retrieval and diversity of the search results. ”

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Name

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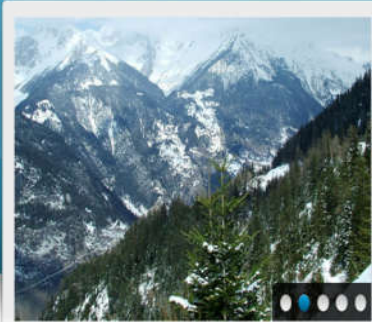
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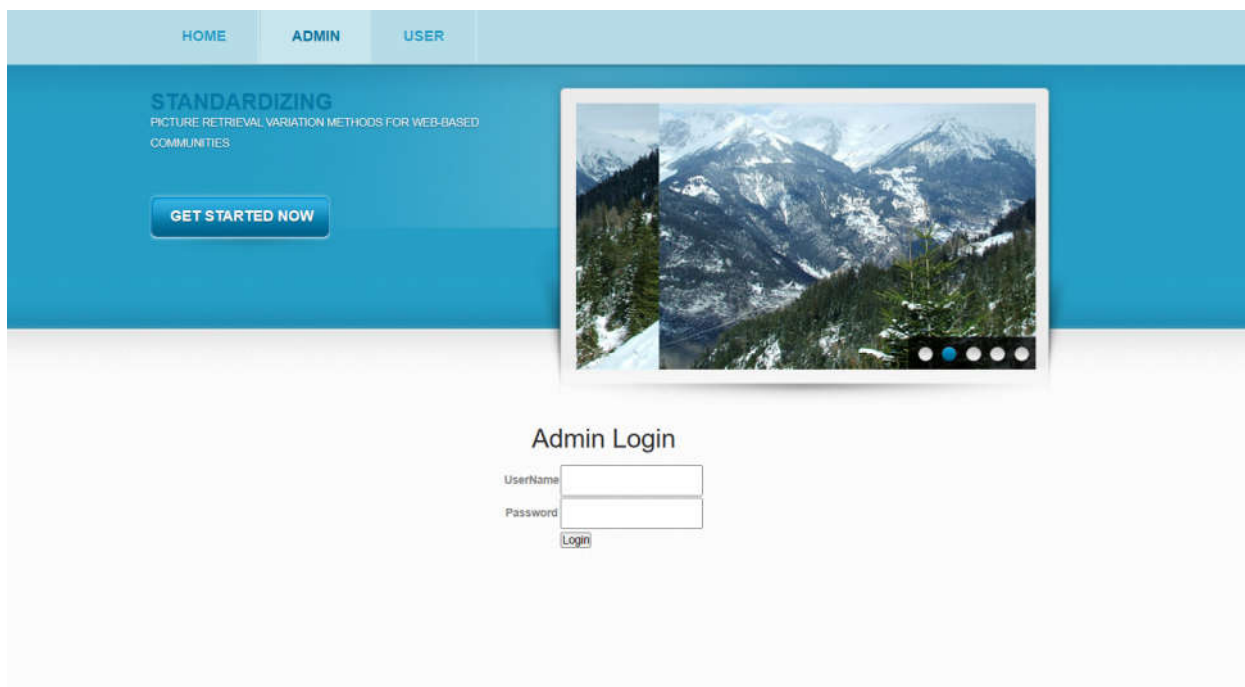
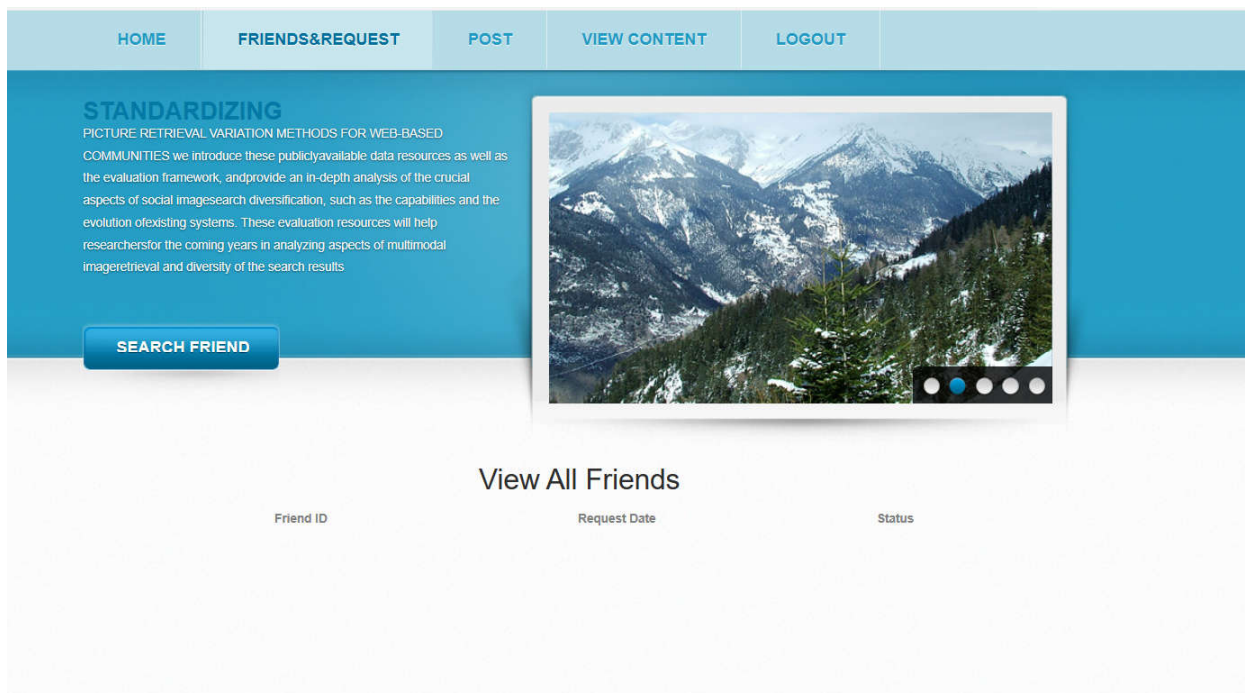


User Login Page

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7. FUTURE SCOPE:

The future scope of standardizing picture retrieval variation methods for web-based communities is vast and dynamic, driven by advancements in technology, changing user behaviors, and emerging trends. Here are some potential directions for future development:

1. Advanced AI and Machine Learning Techniques:

Integration of AI and machine learning algorithms for more intelligent image retrieval, including content-based image recognition, semantic understanding, and personalized recommendations based on user preferences and past interactions.

2. Augmented Reality (AR) and Virtual Reality (VR):

Incorporating AR and VR technologies for immersive image retrieval experiences, allowing users to interact with and explore images in virtual environments, enhancing engagement and interactivity.

3. Blockchain for Copyright and Licensing Management:

Utilizing blockchain technology to establish immutable records of image ownership, copyright status, and licensing agreements, ensuring transparency, traceability, and fair compensation for content creators.

4. Multi-modal Image Retrieval:

Expanding beyond traditional image formats to support multi-modal content retrieval, including videos, 3D models, audio clips, and interactive media, providing users with diverse and dynamic visual experiences.

5. Cross-platform Compatibility and Interoperability:

Enhancing compatibility and interoperability between different platforms and devices, enabling seamless image retrieval and sharing across web-based communities, social networks, messaging apps, and other online channels.

6. Ethical AI and Responsible Data Practices:

Integrating ethical AI principles and responsible data practices into image retrieval systems to address biases, privacy concerns, and ethical considerations, ensuring fair and transparent outcomes for all users.

7. Real-time Collaboration and Co-creation:

Facilitating real-time collaboration and co-creation of visual content within web-based communities, enabling users to collectively edit, annotate, and remix images, fostering creativity and community-driven content generation.

8. Localized and Culturally Relevant Image Retrieval:

Customizing image retrieval algorithms to account for cultural nuances, regional preferences, and linguistic diversity, ensuring that retrieved images are relevant and resonant with diverse user communities around the world.

9. Semantic Image Understanding and Contextual Relevance:

Advancing semantic image understanding techniques to infer context, intent, and emotional resonance from images, enabling more contextually relevant and emotionally engaging retrieval experiences for users.

10. Continuous Innovation and Adaptation:

Embracing a culture of continuous innovation and adaptation to stay abreast of evolving user needs, technological advancements, and market trends, iterating on image retrieval methods to deliver ever-improving experiences for web-based communities.

8. CONCLUSION

We introduced a publicly available, common image search diversification benchmark framework that focuses explicitly on social media aspects. It consists of a very rich annotated data, with over 750 single-, multi-topic and ad-hoc queries, 150k images and over 30M image links, metadata, various content descriptors for visual and text modalities. As part of the MediaEval Retrieving Diverse Social Images Task, we analyzed four years of results and more than 180 submitted systems, with the objective to provide an in-depth analysis of the crucial aspects of diversification, such as the capabilities and the evolution of existing systems.

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