PRISM: Concept-preserving Summarization of Top-K Social Image Search Results

Boon Siew Seah
School of Computer Engineering
Nanyang Technological University
Singapore
hunting.bearz@outlook.com

Sourav S Bhowmick
School of Computer Engineering
Nanyang Technological University
Singapore
assourav@ntu.edu.sg

Aixin Sun
School of Computer Engineering
Nanyang Technological University
Singapore
axsun@ntu.edu.sg

ABSTRACT

Most existing tag-based social image search engines present search results as a ranked list of images, which cannot be consumed by users in a natural and intuitive manner. In this demonstration, we present a novel *concept-preserving* image search results summarization system called PRISM. PRISM exploits both visual features and tags of the search results to generate high quality *summary*, which not only breaks the results into *visually* and *semantically coherent* clusters but it also maximizes the *coverage* of the original top-*k* search results. It first constructs a *visual similarity graph* where the nodes are images in the top-*k* search results and the edges represent *visual similarities* between pairs of images. This graph is *optimally decomposed* and *compressed* into a set of *concept-preserving subgraphs* based on a set of *summarization criteria*. One or more exemplar images from each subgraph is selected to form the *exemplar summary* of the result set. We demonstrate various innovative features of PRISM and the promise of superior quality summary construction of social image search results.

1. INTRODUCTION

The rising prominence of image sharing platforms like `Flickr` and `Instagram` in the last decade has led to an explosion of social images. Consequently, the need for superior social image search engines to support efficient and effective *tag-based* image retrieval (TAGIR) has become increasingly pertinent. Similar to traditional search engines, queries in a tag-based social image search engine are often short and ambiguous. As a result, search engines often diversify the search results to match all possible aspects of a query in order to minimize the risk of completely missing out a user's search intent. An immediate aftermath of such results diversification strategy is that often the search results are not semantically or visually coherent. For example, the results of a search query "fly" (Figure 1) may contain a medley of visually and semantically distinct objects and scenes (hereafter collectively referred to as *concepts*) such as parachutes, aeroplanes, insects, birds, and even the act of jumping.

Proceedings of the VLDB Endowment, Vol. 8, No. 12
Copyright 2015 VLDB Endowment 2150-8097/15/08.

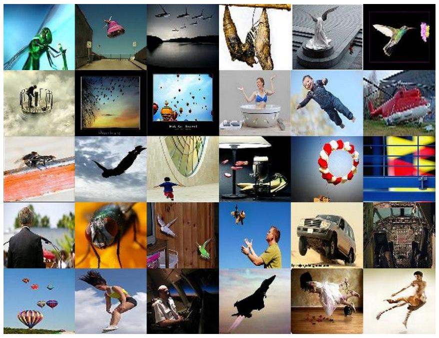


Figure 1: [Best viewed in color] Sample query results.

Image search results are typically presented as a ranked list of images often in the form of thumbnails (*e.g.,* Figure 1). Such thumbnail view of ranked images enables end users to quickly glance through a set of images without browsing through them iteratively. However, it suffers from two key limitations. First, it fails to provide a view of common visual objects or scenes *collectively*. For example, the result images of "fly" query can be clustered by visual objects (*e.g.,* aeroplane, insect) and activities (*e.g.,* jump). Such organized image search results will naturally enable a user to quickly identify and zoom into a subset of results that is most relevant to her query intent. Second, a thumbnail view fails to provide a bird eye view of different concepts present in a query results. For instance, reconsider Figure 1. It will be beneficial to users if a suitable exemplar image from each type of concept can be selected to create a "summary" of the search results. This will enable a user to get a bird eye view of various key concepts associated with the results.

An appealing way to organize social image search results of a search query is to generate a set of *image clusters* from them such that images in each cluster are *semantically and visually coherent* and the clusters *maximally cover* the entire result set. Subsequently, at least one exemplar image from each cluster can be selected to generate an *exemplar summary* of the entire result set to give a bird eye view of different concepts in it. We advocate that such image clusters must satisfy the following desirable features.

- *Concept-preserving*. Each cluster should be annotated by a *minimal* set of tags generated from the images within to semantically[1] describe *all* images in the cluster. Users therefore can easily associate the tag(s) with the images in a cluster at a glance. We refer to such a cluster as *concept-preserving*

[1] We assume that the tags are high-level semantic concepts assigned by image uploaders or annotators.

where a set of images shares at least one concept (tag)[2]. For instance, in a concept-preserving "helicopter" cluster, a single "helicopter" tag is sufficient to represent all images in it and describe them semantically.

- *Visual coherence*. Images in a cluster must be visually coherent. Visually similar images must be clustered together and dissimilar images must be separated in different clusters.
- *Coverage*. The image clusters should cover as much of the result set as possible in order to maximize incorporation of all possible query intent. In other words, image clusters should represent majority of the original result images.

In this demonstration, we present a system called PRISM[3] (concept-**PR**eserving social **I**mage **S**earch su**M**marization) [7] that constructs high quality summary of top-k social image search results based on concept-preserving and visually coherent clusters which maximally cover the result set. Figure 2 depicts subsets of clusters constructed by PRISM for the query "fly". Each cluster is represented by *minimal* tag(s) shared by *all* images in it. Due to the concept-preserving nature, the images in a cluster form an equivalence class with respect to the tags. Consequently, any image in each cluster can be selected as an exemplar without loss of accuracy to facilitate generation of high quality exemplar summary of the result set. For instance, consider the "insect" cluster. Any image can be chosen as an exemplar to represent the "insect" concept.

Any query-specific image search results summarization presents several non-trivial challenges. The set of images to be summarized is not predetermined. Hence, the summarization method does not have the luxury of preprocessing the underlying images *apriori*. Additionally, simply leveraging traditional image clustering techniques may not generate high-quality summary due to the requirement that any summary must be concept-preserving and cover as many images as possible in the result set. To address these challenges, PRISM explores the concept space (*i.e.,* tag space) to seek for visually coherent cluster of images. Specifically, it first constructs a *visual similarity graph* G where the nodes are images in the search results and the edges represent visual similarities between pairs of images. Then it *optimally* decompose G into a set of *concept-preserving subgraphs* based on the aforementioned desired features of image clusters. Particularly, images in each subgraph represents a concept-preserving cluster. Following that, PRISM performs a series of image set *compression* to simplify the subgraphs to form the final set of concept-preserving subgraphs. Lastly, one or more exemplar images from each subgraph is selected to form the *exemplar summary*.

2. RELATED SYSTEMS AND NOVELTY

One strategy to summarize image search results is by clustering tagged social images based on both visual and textual features as advocated by *early fusion* [6,9] and *late fusion* [5] approaches. The former exploits the tags and visual content of the images jointly whereas the latter considers them independently. However, these techniques do not ensure that the generated summaries are concept-preserving and maximally covers the image results. Furthermore, unlike PRISM, most of these techniques do not associate each cluster with a tag concept for user interpretation and visualization. As such, one has to associate tag(s) to each image cluster as a post-processing step.

Another approach of image summarization is to find a set of exemplars that summarize the image set. In [3], a set of exemplars is identified using a sparse *Affinity Propagation* (AP) approach. Xu *et al.* [9] evaluates visual and textual information jointly to identify exemplar images. It extends the AP algorithm to support heterogeneous messages from visual and textual feature spaces. In contrast to PRISM, these approaches do not attempt to ensure that all other images can be properly clustered by their exemplars (and their tags) in a concept-preserving manner. Additionally, they do not ensure that the exemplars maximally cover the image set. Note that even for query-specific image categorization techniques provided by Web image search engines (*e.g., Google Images* (`images.google.com`)), where data associated with images are not as sparse as social images, there is little evidence whether they maximally cover the results. For example, consider the image categories generated by *Google Images* (Figure 3) for the query ``fly''[4]. Despite having significantly larger datasets and richer set of web text annotations, these search engines still construct relatively limited variety of concepts. The concepts suggested by *Google Images* are mostly restricted to insects and cliparts, missing out other fly-related concepts such as the act of jumping, planes, helicopter, and birds.

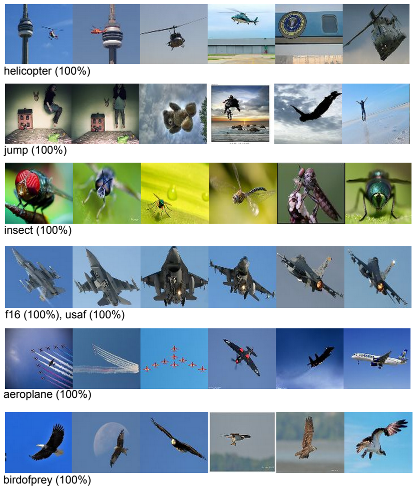


Figure 2: [Best viewed in color] Concept-preserving image clusters generated by PRISM for the query "fly".

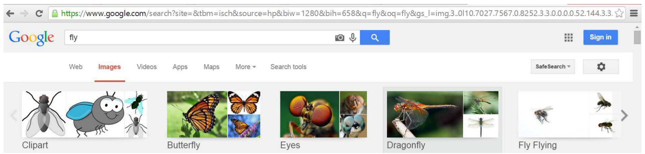

https://www.google.com/search?site=&tbm=isch&source=hp&biw=1280&bih=658&q=fly&oq=fly&gs_l=img.3..0l10.7027.7567.0.8252.3.3.0.0.0.0.52.144.3.3.
Google
fly
Sign in
Web
Images
Videos
Apps
Maps
More
Search tools
SafeSearch
Clipart
Butterfly
Eyes
Dragonfly
Fly Flying

Figure 3: *Google Images* results ("fly").

3. SYSTEM OVERVIEW

PRISM [7] is implemented using Java and Scala using the Play 2.0 framework (`www.playframework.com`). Figure 4 shows the system architecture of PRISM comprising of the following modules.

The Indexer Module. This module extracts query-independent tag features (*e.g., tag relatedness*, *tag frequency*, *tag co-occurrence*, etc.) from the underlying collection of social images $\mathcal{D}$. The *relatedness* between a tag t and its annotated image d is measured using neighborhood voting as described in [4]. *Tag frequency* of a tag t is the number of images annotated with t. *Tag co-frequency* between two tags t_1 and t_2 is the number of images annotated by both t_1 and t_2. These two features are used to compute *tag co-occurrences*

[2] In the sequel, we use *tag* and *concept* interchangeably.

[3] A prism can be used to break a beam of light up into its constituent spectral colors (the colors of the rainbow). Similarly, the PRISM system breaks the result image set into distinct image clusters.

[4] All results related to Google Images are last accessed on June 14th, 2015.

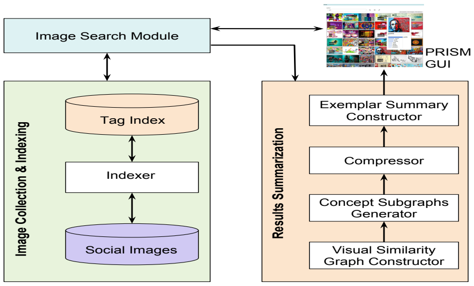


Image Search Module
PRISM GUI
Image Collection & Indexing
Tag Index
Indexer
Social Images
Results Summarization
Exemplar Summary Constructor
Compressor
Concept Subgraphs Generator
Visual Similarity Graph Constructor

Figure 4: The architecture of PRISM.

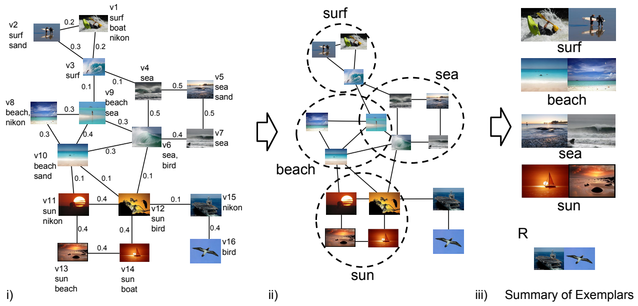


Figure 5: [Best viewed in color] An example.

using different measures (*e.g.,* Jaccard coefficient, Pointwise Mutual Information, Pointwise KL divergence). The extracted data are then stored in a RDBMS.

The Image Search Module. This module encapsulates a standard TagIR search engine. Given a keyword query Q, it leverages the *Index Module* to retrieve the top-k images that best match Q where k is a user-specified number of desired images. Each image i in the result set comprises of a d-dimensional visual feature vector representing visual content of the image and a set of tags T_i representing concepts associated with the image by users. Note that the image retrieval algorithm is implemented on top of Lucene (`lucene.apache.org`) and is orthogonal to PRISM. In fact, any superior social image retrieval technique can be adopted for PRISM. Here, we adopt the framework in [8] for multi-tag queries.

The Visual Similarity Graph Constructor Module. Given the top-k result images of a query Q, this module constructs a *visual similarity graph* based on pair-wise visual similarity between images where each node in the graph is an image. To this end, we adopt cosine similarity to measure the visual similarity between any two images as follows: $Sim = L^{-1/2}A^TAL^{-1/2}$ where A is the $n \times d$ matrix of image set visual features, A^TA encodes the inner-product of the image feature vectors, and $L^{-1/2}$ is a $n \times n$ diagonal matrix that encodes normalization of each feature vector. Given the similarity matrix, the visual similarity graph $G = (V, E)$ is constructed as follows. Let V be the set of images. We add an edge in E between two images i and j if $Sim_{ij} > \delta$ where the weight of this edge is Sim_{ij} and δ is the *edge density threshold*. Figure 5(i) illustrates a visual similarity graph.

The Concept Subgraphs Generator Module. Intuitively, PRISM formulates the summarization problem as the *optimal* decomposition of a visual similarity graph G into a set of *concept subgraphs* from which exemplar images are drawn to create the summary. Given a set of tags T, a *concept-preserving subgraph* (*concept subgraph* for brevity), denoted by $C_T = (V_T, E_T, T)$, is a subgraph of G induced by $V_T \subseteq V$. Every image in the subgraph shares the set of tags T, *i.e.,* $T \subseteq T_i \ \forall \ i \in V_T$. We use concept subgraphs to model a set of images that preserves a set of concepts represented by T. That is, images in each concept subgraph represent a *concept-preserving cluster*. We can represent it in G concisely by an *exemplar node* labeled with T. Figure 5(ii) depicts a set of exemplar nodes (represented by dashed circles) with labels (T) "surf", "beach", "sea", and "sun". These nodes represent the concept subgraphs induced by $\{v1, v2, v3\}$, $\{v8, v9, v10\}$, $\{v4, v5, v6, v7, v9\}$, and $\{v11, v12, v13, v14\}$, respectively.

This module's goal is to *optimally* decompose G into concept subgraphs so that it can facilitate high quality summary construction. Specifically, a *decomposition* of G generates a set of concept subgraphs $\mathcal{S} = \{C_{T^1}, C_{T^2}, \ldots C_{T^m}\}$ and a *remainder* subgraph R, such that the image set in G is union of all images in $\mathcal{S}$ and R. Each $C_{T^i} \in \mathcal{S}$ can be represented by an exemplar node; the remainder subgraph R represents the region of G not covered by $\mathcal{S}$ (*i.e.,* R is the subgraph induced by the set $V \setminus \bigcup_{C_T \in \mathcal{S}} V_T$). For example, the visual similarity graph in Figure 5(i) is decomposed into $\{C_{surf}, C_{beach}, C_{sea}, C_{sun}\}$ and R where C_{surf}, C_{beach}, C_{sea}, and C_{sun} are represented by exemplar nodes "surf", "beach", "sea", and "sun", respectively, and $R = \{v15, v16\}$. Our decomposition allows overlap among subgraphs in $\mathcal{S}$ (*e.g.,* overlap between C_{beach} and C_{sea}) and is guided by the following *summarization objectives*.

- *Visual coherence.* The *visual coherence* of $\mathcal{S}$ is defined as:

$$coherence(\mathcal{S}) = \frac{1}{|\mathcal{S}|} \sum_{C_T \in \mathcal{S}} \frac{\sum_{e \in E_T} w(e)}{|E_T|} \tag{1}$$

  The $coherence(\mathcal{S})$ value reflects the average weight of visually similar images in each $C_T \in \mathcal{S}$. Higher visual coherence means the images are more visually similar to each other.

- *Distinctiveness.* Intuitively, a pair of exemplar nodes that represent two disjoint subgraphs is more informative that a pair that represent identical subgraphs. We quantify this objective with the *distinctiveness* measure as follows.

$$distinctiveness(\mathcal{S}) = \frac{\left|\bigcup_{C_T \in \mathcal{S}} V_T\right|}{\sum_{C_T \in \mathcal{S}} |V_T|} \tag{2}$$

- *Coverage.* A set of concept subgraphs $\mathcal{S}$ that well represents G is preferable. We use the notion of *coverage* to measure this. Intuitively, it quantifies how many images from the image set V appears in $\mathcal{S}$. Formally, it is defined as:

$$coverage(\mathcal{S}) = \frac{\left|\bigcup_{C_T \in \mathcal{S}} V_T\right|}{|V|} \tag{3}$$

  Note that $coverage(\mathcal{S})$ is 1 if all images in V are selected in $\mathcal{S}$.

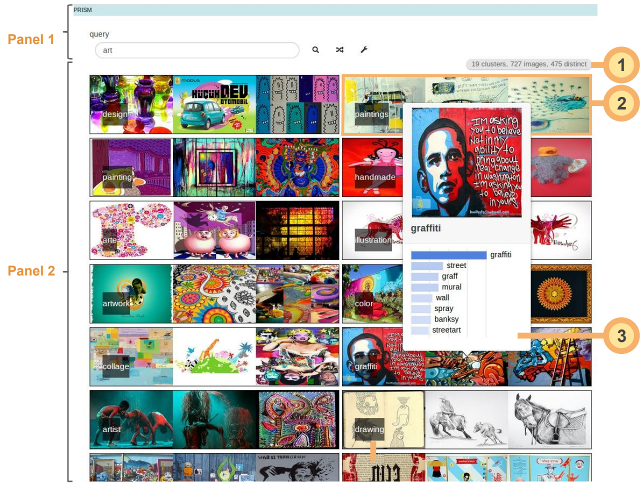
This module implements a weighted minimum k-set cover-based strategy [2] to find an optimal set of concept subgraphs $\mathcal{S}$ such that $coherence(\mathcal{S})$, $coverage(\mathcal{S})$ and $distinctiveness(\mathcal{S})$ are maximized. Since the problem is NP-hard, a H_k-approximation greedy algorithm, where $H_k = \sum_{i=1}^{k} \frac{1}{i}$ is adopted towards this goal [2]. It includes a cost model that incurs a weight (*i.e.,* cost) every time a subgraph is added as concept subgraph or as remainder subgraph. For each concept subgraph, it incurs a *visual incoherence cost*, the inverse of visual coherence of a concept subgraph, for choosing visually incoherent images (maximize $coherence(\mathcal{S})$). For each remainder subgraph, it incurs a *remainder penalty* cost for choosing large remainder subgraphs (maximize $coverage(\mathcal{S})$). Given the cost model, it finds the minimum weight (cost) of subgraphs needed to cover V, penalizing redundant subgraphs that add little to the summary since every subgraph added incurs a cost (controlling $distinctiveness(\mathcal{S})$). Note that state-of-the-art graph clustering techniques (*e.g.,* [6]) cannot be directly leveraged by this module to identify these concept subgraphs as they do not preserves concepts, typically generate non-overlapping clusters, and do not maximally cover the entire graph.

The Compressor Module. The preceding module generates an optimal collection of concept-preserving clusters *without* constraining each cluster size. This is beneficial as it enables us to select the "best" combination of clusters with highest visual coherence. On the other hand, there is a lack of control over the *summary granularity* if each concept subgraph in the constructed $\mathcal{S}$ is used for creating the exemplar summary (detailed in the *Exemplar Summary Constructor Module*) as $\mathcal{S}$ may contain too finely-grained clusters for presentation to users. We assume that a user expects a summary at a particular summary granularity. For instance, if a user wants a broad overview of the search result, then a summary of 5 exemplars may be preferable to a summary of 50 exemplars. On the other hand, if a user prefers a detailed summary, then the summary with 50 exemplars is better.

The *Compressor* module addresses this issue by *aggregating* concept subgraphs iteratively to build a *multilevel compression* scheme at varying summary granularity. Given the initial $\mathcal{S}$, it constructs a list $[\mathcal{S}, \mathcal{S}^1, \mathcal{S}^2, \ldots, \mathcal{S}^d]$ such that $\forall i, j$, $|\mathcal{S}^i| > |\mathcal{S}^j|$ if $i < j$. Each $\mathcal{S}^i$ is called a *compressed concept subgraph set* of $\mathcal{S}$. Each successive set $\mathcal{S}^{i+1}$ is a compressed representation of its predecessors ($\mathcal{S}^i$) and is constructed by *contracting* pairs of concept subgraphs. The contraction of pairs C_{T^1} and C_{T^2} removes both subgraphs from the set and replaces them with $C_{T^1 \cup T^2} = (V_{T^1} \cup V_{T^2}, E_{T^1} \cup E_{T^2})$. Note that only those pairs that share a non-empty set of concepts (*i.e.,* all images have at least one common concept) are contracted as they share conceptual similarity. For example, assume that $\mathcal{S}$ contains two subgraphs with $T^1 = \{boat, sail, rock\}$ and $T^2 = \{rock, cliff\}$. Then these two subgraphs can contracted into a larger subgraph sharing the $\{rock\}$ concept. Observe that if a user wants a detailed summary of the search result, then $\mathcal{S}$ is most appropriate for generating exemplar summaries. If a broader overview is desired, then a compressed set provides more concise view of the result set. In PRISM, by default we use $\mathcal{S}^d$ to create the exemplar summary.

The Exemplar Summary Constructor Module. This module selects one or more exemplar images (by default we chose three images) from each summarized concept subgraph to form the exemplar summary (Figure 5(iii)). Note that since the set of images in each concept-preserving cluster forms an equivalence class with respect to its concept set, any image in the set can be selected as an exemplar to associate with the concept.

The PRISM GUI Module. Figure 6 depicts the user interface of PRISM using the query `"art"`. It consists of two panels. A user issues a tag query by keying keyword(s) in Panel 1. Clicking on the "Spanner" icon in Panel 1 will invoke the *configuration dialog box* to set various parameters (*e.g.,* desired number of k images, edge density threshold, summary granularity, etc.). Once the query is processed, the top-k images are displayed as a visual summary in Panel 2. *Item 1* in this panel provides an overview of the statistics related to the summary. For example, it shows the number of images represented by the exemplar summary, the number of concept-preserving clusters retrieved, and the number of unique images represented by the summary. PRISM displays the exemplar summary as horizontal blocks of images where each block is labeled with T_i and represents the exemplar images of a concept-preserving cluster C_{T^i}. For instance, *Item 2* points to the exemplar images of the `painting` cluster. A user may click on a block to reveal a popup (*Item 3*) describing various statistics pertaining to the images within the cluster such as (a) number of images within a cluster and (b) top ranked tags most closely associated with the cluster. Additionally, the user has the option to view, in a separate pane, all images within the cluster by following a link.


query: art

19 clusters, 727 images, 475 distinct

Figure 6: [Best viewed in color] The PRISM GUI.

4. DEMONSTRATION OVERVIEW

Our demonstration will be loaded with the NUS-WIDE dataset [1] containing 269,648 images from Flickr[5]. We aim to showcase the functionality and effectiveness of the PRISM system in summarizing top-k query results. Example queries will be presented. Users can also write their own ad-hoc queries through our GUI. A video of PRISM is available at `https://www.youtube.com/watch?v=dhiAoYZCR3I&feature=youtu.be`.

One of the key objectives of the demonstration is to enable the audience to interactively experience the proposed search results summarization framework in real-time. Through our GUI, the user will be able to formulate search queries (Panel 1) and browse the exemplar summary of the top-k results (k can be specified by the user) generated by PRISM (Panel 2). Going a step further, the user may click on the exemplar images of any concept-preserving cluster which will allow her to view immediately all images in the cluster as well as information about relevant tags. Additionally, by setting different values for k and varying summary granularity, she can view changes to the exemplar summaries.

Acknowledgements: Boon Siew Seah and Aixin Sun were supported by Singapore MOE AcRF Tier-1 Grant RG13/10.

5. REFERENCES

[1] T-S. Chua, J. Tang, R. Hong, H. Li, Z. Luo, Y. Zheng. NUS-WIDE: a real-world web image database from National University of Singapore. In *ACM CIVR*, 2009.

[2] V. Chvatal. A Greedy Heuristic for the Set-Covering Problem. *Mathematics of Operations Research*, 4(3):233–235, 1979.

[3] Y. Jia, J. Wang, C. Zhang, X.-S. Hua. Finding image exemplars using fast sparse affinity propagation. In *ACM MM*, 639–642, 2008.

[4] X. Li, C. G. M. Snoek, M. Worring. Learning Social Tag Relevance by Neighbor Voting, *IEEE Trans. Multimedia*, 11(7), 1310–1322, 2009.

[5] P.-A. Moëllic, J. Haugeard, G. Pitel. Image clustering based on a shared nearest neighbors approach for tagged collections. In *ACM CIVR*, 269–278, 2008.

[6] M. Rege, M. Dong, J. Hua. Graph theoretical framework for simultaneously integrating visual and textual features for efficient web image clustering. In *ACM WWW*, 317–326, 2008.

[7] B. S. Seah, S. S. Bhowmick, A. Sun. PRISM: Concept-preserving social image search results summarization. In *ACM SIGIR*, 737–746, 2014.

[8] A. Sun, S. S. Bhowmick, K. T. N. Nguyen, G. Bai. Tag-based social image retrieval: An empirical evaluation, *JASIST*, 62(12), 2364–2381, 2011.

[9] H. Xu, J. Wang, X.-S. Hua, S. Li. Hybrid image summarization. In *ACM MM*,1217–1220, 2011.

[5] Note that we use the popular NUS-WIDE dataset instead of any other larger social image collection because its size does not impact the performance of PRISM as the focus here is to summarize top-k results regardless of the image retrieval process.