

Visual-Semantic Graphs: Using Queries to Reduce the Semantic Gap

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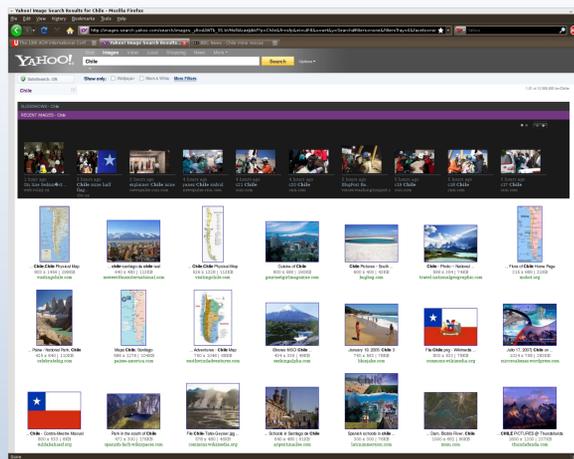
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ABSTRACT

We explore the application of a graph representation to model similarity relationships that exist among images found on the Web. The resulting similarity-induced graph allows us to model in a unified way different types of content-based similarities, as well as semantic relationships. Content-based similarities include different image descriptors, and semantic similarities can include relevance user feedback from search engines. The goal of our representation is to provide an experimental framework for combining apparently unrelated metrics into a unique graph structure, which allows us to enhance the results of Web image retrieval. We evaluate our approach by re-ranking Web image search results.

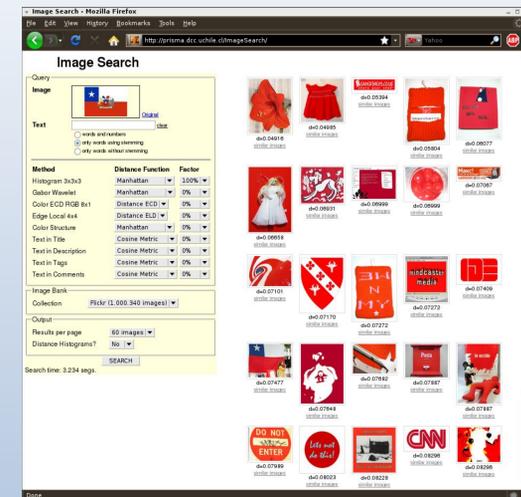
Keywords: Web Image Search, Web Image Re-ranking, Query Log Analysis, Content-based Image Features

Web Image Retrieval



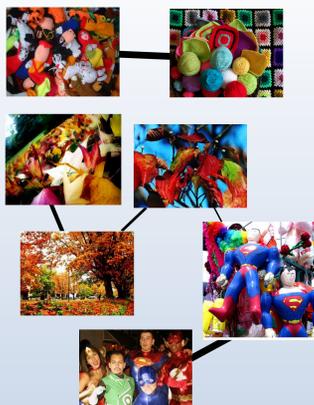
mostly explicit semantic (or textual) features are used to retrieve images, using a textual

Content-Based Image Retrieval



content-based image similarity is used to retrieve similar images, using an image query.

Visual Similarity Graph (V)

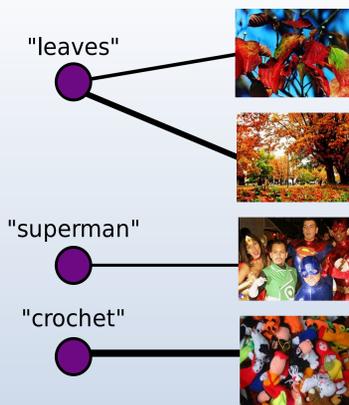


Undirected graph that represents content-based similarity relationships among images. The nodes correspond to images, and the edges connect images that are similar (given an image descriptor and a similarity measure). Each edge has an associated weight: the larger this weight, the more similar the connected images are.

$$P_V = \alpha N_V + (1 - \alpha) \mathbf{1}$$

P_V random-walk transition probability matrix
 N_V row-normalized adjacency matrix of V
 α dumping factor
 $\mathbf{1}$ teleportation matrix

Semantic Similarity Graph (S)

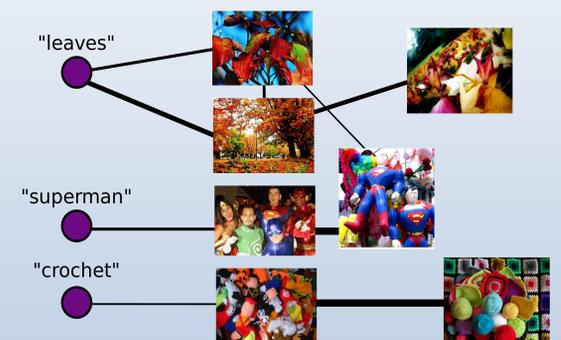


Undirected bipartite graph that represents semantic-based similarity relationships between term-sets and images. The edges in this graph connect term-sets with images that have a semantic relationship with them. Each edge has a weight associated to it which is a measure of the relevance of the term-set to the connected image.

$$P_S = \alpha N_S + (1 - \alpha) \mathbf{1}$$

Visual-Semantic Graph

Union of the visual and semantic similarity graphs. There is an undirected weighted edge between two images if both images are similar according to the visual similarity graph. There is an undirected weighted edge between a term-set and an image if there is a user defined semantic relationship between them.



$$P_{VS} = \alpha (\beta N_S + (1 - \beta) N_V) + (1 - \alpha) \mathbf{1}$$

β probability of choosing a text-based image retrieval system, as opposed to a content-based system.

Evaluation

To evaluate, we re-rank Web image retrieval results, by using the rank induced by the stationary distribution scores of the visual-semantic graph.

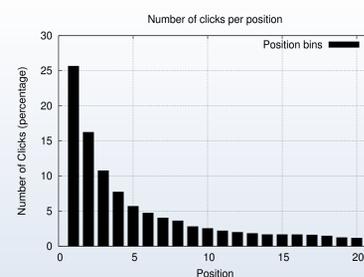
We used the Yahoo! Image Search query log over 2 weeks, first week was used to build the graphs and second week for evaluation. Each week contained over 7 million unique image clicks. Queries which were repeated in the first and second week were used for evaluation of re-ranking (2.7 million queries).

3 visual similarity graphs were computed using **EHD**, **HSV** and **OMD** content-based descriptors.

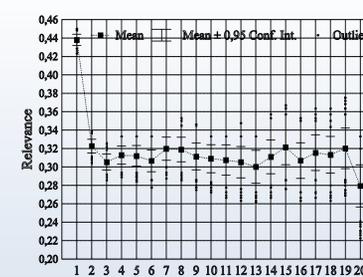
1 semantic similarity graph was computed, using the query log **click-graph**.

| β | 0 | 0.25 | 0.5 | 0.75 | 1 |
|---------|-------|-------|--------------|-------|-------|
| rank | EHD | | | | |
| 1 | 0.235 | 0.539 | 0.545 | 0.541 | 0.540 |
| 2 | 0.310 | 0.616 | 0.623 | 0.617 | 0.616 |
| 3 | 0.388 | 0.687 | 0.692 | 0.687 | 0.687 |
| 4 | 0.481 | 0.760 | 0.766 | 0.761 | 0.760 |
| 5 | 0.595 | 0.842 | 0.847 | 0.842 | 0.841 |
| rank | HSV | | | | |
| 1 | 0.326 | 0.544 | 0.549 | 0.542 | 0.540 |
| 2 | 0.362 | 0.619 | 0.624 | 0.618 | 0.616 |
| 3 | 0.430 | 0.689 | 0.694 | 0.688 | 0.687 |
| 4 | 0.518 | 0.762 | 0.767 | 0.761 | 0.760 |
| 5 | 0.630 | 0.843 | 0.848 | 0.842 | 0.841 |
| rank | OMD | | | | |
| 1 | 0.398 | 0.548 | 0.610 | 0.546 | 0.540 |
| 2 | 0.409 | 0.622 | 0.676 | 0.621 | 0.616 |
| 3 | 0.467 | 0.691 | 0.733 | 0.691 | 0.687 |
| 4 | 0.551 | 0.763 | 0.797 | 0.763 | 0.760 |
| 5 | 0.662 | 0.844 | 0.875 | 0.844 | 0.841 |

NDCG results for combination of the visual-semantic graphs.



Clicks per position in the original query log (click-bias)



Relevance distribution per position after re-ranking (top-20 results)

We have presented a new type of graph that combines visual and semantic features that are useful for Web image retrieval. Performing a random walk process over this graph and using the steady state probability distribution as scores for image re-ranking, our experiments show that it is possible to improve over 5% the baseline. We have also shown that not all combinations of visual features are useful: in this case, only one is recommended, OMD.

References

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