

# PLSA ON LARGE SCALE IMAGE DATABASES

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## ABSTRACT

*The web and image repositories such as Flickr™ are the largest image databases in the world. There are billions of images on the web, and hundreds of million high-quality images in image repositories. Currently, these images are indexed based on manually-entered tags and individual and group usage patterns. In this work we are exploring a third information dimension: image features. We are exploring probabilistic latent semantic analysis in order to infer which visual patterns describe each object. We wish to build models that connect words and image features, and use content features and tags to better find similar images.*

**Index Terms**— large scale image retrieval, probabilistic semantic analysis.

## 1. INTRODUCTION

ATTENTION: THIS IS A DUMMY SUBMISSION. The final paper will be submitted to Shih-Fu Chang before the internal deadline of Oct.- 31<sup>st</sup>. On the last page there is a rough outline the final paper will be about.

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List and number all bibliographical references at the end of the paper. The references can be numbered in alphabetic order or in order of appearance in the document. When referring to them in the text, type the corresponding reference number in square brackets as shown at the end of this sentence [1].

[1] A.B. Smith, C.D. Jones, and E.F. Roberts, "Article Title," *Journal*, Publisher, Location, pp. 1-10, Date.

[2] Jones, C.D., A.B. Smith, and E.F. Roberts, *Book Title*, Publisher, Location, Date.

**What is the starting point?**

We have a database in size only few people have at their disposal, and we want to exploit this fact. In addition, we want to exploit that the database is partially tagged. However, we must use a technique that can tolerate a large fraction of noise/incorrect labels since based on visual similarity these tags might by large look incorrect.

[I have browsed through images with the same tags such as “Christmas”. Less than 5% of the images have anything to do with Christmas. I have identified a few tags where the associated images show a common theme. They are in the table at the end. And, yes, I agree that ‘Christmas’ just specifies the time, when the images were shot, not their visual content.]

**Premise:**

pLSA is a very promising technique to identify concepts in data. So far -- in the image domain -- pLSA has only been applied to small data sets up to a few thousand images. We expect that some aspects that are ignored on small image databases such as the derivation of representative visual words might become important on large image sets. Also, some findings and proposed algorithms for small image data sets will not hold on large database sets. In this paper we present our initial findings on a database with more than a million images.

We focus exclusively on improving image retrieval based on image similarity as perceived by humans. Thus we will employ the following query paradigm and evaluation scheme:

**Query paradigm & Evaluation / Performance metric:**

First we select 12 distinct categories from our database (see table below). In each category we selected “randomly” 5 representative queries images (60 in total)

| #  | OR list of tags                                  | # of image       |
|----|--------------------------------------------------|------------------|
| 1  | wildlife animal animals cat cats                 | 30477            |
| 2  | dog dogs                                         | 26119            |
| 3  | bird birds                                       | 21284            |
| 4  | flower flowers                                   | 28819            |
| 5  | graffiti                                         | 23318            |
| 6  | sign signs<br>(graffiti sign signs)              | 14489<br>(36628) |
| 7  | surf surfing                                     | 30001            |
| 8  | Night                                            | 34001            |
| 9  | food                                             |                  |
| 10 | Building buildings                               | 17303            |
| 11 | Goldengate goldengatebridge<br>(+bridge bridges) | 24364<br>(35637) |
| 12 | baseball                                         | 12390            |
|    | <b>TOTAL SUM</b>                                 | <b>188476</b>    |

We use different techniques to return the top 20 most similar images. Similarity is purely judges by humans. No rules about what constitutes visual similarity are given to the subjects. 20 test people have to rank the results of the various techniques. In other words, each test subject gets the printouts of the top 20 most similar images (tiled 5 by 4 on one sheet of paper) for each retrieval method and must bring the retrieval results (i.e., the

printouts) into an order from best to worst. We compute one combined score over all test queries (60 in total) to assign a single performance number to each algorithm: the average rank position.

As baseline technique we use (a) the tags + random selection and (b) color coherence vectors (CCVs). This is compared to plain vanilla pLSA and pLSA with active learning.

Exp. 1 – Visual Words

**Given:**  $C_N = \#$  of categories;  $C = \{c_i\}$  = set of categories (currently 12 categories);  $W_N = \#$  of visual words

**Goal:** Derive set  $W = \{w_j\}$  = set of visual words;  $|W| = W_N$

**Approaches:**

$W_N$  visual words are needed. We investigate three ways to determine visual words:

- (a) Derive  $(W_N/C_N)$  visual words by means of K-means clustering within each category using KN sample features → result:  $W_N = C_N * (W_N/C_N)$  visual words in total
- (b) Select  $C_N$  times randomly KN sample features from the set of all features. Apply K-means clustering to each set of KN samples to derive  $(W_N/C_N)$  visual words → result:  $W_N = C_N * (W_N/C_N)$  visual words in total.
- (c) Select randomly  $W_N$  sample features from the set of all features → result:  $W_N$  visual words in total.

Based on the result of the performance metric between (a) and (b) we can decide whether tags provide useful information for deriving visual words. Based on (c) compared to (a) and (b) we can decide whether K-means clustering is really worth the effort. We use pLSA as the retrieval technique in all three experiments.

Reasoning behind experiments (c):

Is K-means clustering on large databases necessary? At the extreme we can postulate that as the size of the database grows, the feature vectors will be uniformly distributed. Thus, if 1 million samples are randomly selected from a uniform distribution and then clustered into e.g., 1K clusters, the result should statistically not differ from selecting directly randomly 1K feature vectors as cluster centers (= visual words).

This is something we can test and is very important in practices. Clustering is the slowest part in the learning algorithm.

Intuitively, I believe that there is still some structure because images created by humans are biased and thus the features should not be totally uniformly distributed. In that sense first selecting a larger set and cluster them should help to find common visual words and avoid using two visual words for the same thing. Thus, with the same number of words, a larger diversity is captured through clustering. But how many are need if W visual words are requested? Do I need 10 \* W or 100 \* W or only 5\*W feature vectors.

→ Create graph where # of input features for clustering vs. performance is plotted.

Using the tags:

Does performance improve if the visual words are chosen not by just randomly sampling the features space, but by extracting them

from labeled subset of images? For instance, if a total of 2400 visual words are required, 200 for each distinct category could be generated and combined to form the 2400 visual words.

By how much does it improve? If this works it shows that even largely incorrect labels/tags carry information and thus improves results.

#### Exp. 2 – pLSA

**Given:**  $W_N = \#$  of visual words;  $W = \{w_j\}$  = set of visual words =  $\{W^c\} = \{w_j^c\}$

**Goal:** Perform visual similarity retrieval using  $P(z|d)$  to compute similarity score (= select images with the most similar concept distribution)

#### **Approaches:**

- (a) Create term-document matrix based on  $W$ ; learn pLSA; retrieve similar documents based on  $P(z|d)$  similarity (plain vanilla pLSA) (Euclidian or cosine similarity metric?)
- (b) Compare pLSA to using  $p(w|d)$  directly. Is there a performance difference? (Euclidian or cosine similarity metric?)
- (c) Interpret  $P(z|d)$  as a feature vector and apply active learning with support vector machine. Allow 3 rounds of feedback with just 20 images (5x4) each. Then evaluate the result.
- (d) Baseline methods: tags + randomly selected images
- (e) Baseline methods: use color coherence vectors (CCVs)

The active learning approach will be very simple to add since we have the code for it. It should significantly improve retrieval. Something users are interested in.