DARPA PPAML Challenge Problem #6: Image Labeling

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# Summary

Multimedia data such as video and pictures are being produced and shared at an unprecedented and accelerating pace in recent years. For example, on YouTube, video data is currently being uploaded at the rate of approximately 30 million hours a year. This drives a strong need to develop automated tools to help users understand, organize, and retrieve images and videos from very large collections.

The goal of the proposed challenge problem is to assign labels (e.g. "tree", "people", or "baby") to images based on relationships found in a rich social multimedia database containing visual features and metadata such as user information (e.g. username, location, network of contacts), comments, user image gallery, uploader defined groups, and links between shared content. When all this information is used collectively in a suitable fashion, it may be able to advance the state-of-the-art in image labeling.

|  |  |
| --- | --- |
| Tags: [empty]  Labels: plant\_life, sky, structures, tree | Tags: Paris, Ile-de-France, France, Act Up-Paris  Labels: female, people, plant\_life, sky, structures, tree |
| Tags: Dashboard, steering, wheel, Knox Cruise Night  Labels: car, night, structures, transport | Tags: Tuscon, flower, Om  Labels: people, plant\_life |

#### Sample images, first four associated user-supplied tags, and ground-truth labels, from [Huiskes2008].

# Problem Specification

## Overview

The problem of multimedia retrieval is to develop the scientific methodology to understand and discover images/videos with particular content from a complex, large, and growing collection of multimedia. Real-world multimedia, especially as shared on the Internet, can be challenging to retrieve using only visual information, due to complex content, partial occlusion, and diverse styles and quality. The most common solution to this problem is to annotate media with keywords that describe the content and then perform keyword search against these annotations. The problem of annotating images consists of inferring content labels, *L*, conditioned on an image, *I*, and other related metadata information, *M*, e.g. *P(L|I,M)*.

In Challenge Problem 6 (CP6), we will solve the task of automatic image annotation or labeling by exploiting the metadata, *M*, in addition to the visual information, *I*. Some types of metadata (i.e. EXIF tags) are generated by the camera when the image is taken; others (i.e. user-provided tags, comments from viewers) are generated after the image is uploaded to an image-sharing service such as Flickr. We will use a subset of the MIRFLICKR [Huiskes2008] dataset to supply the ground-truth image labels, image features, and related metadata. The MIRFLICKR data is available under Creative Commons licenses. The subset is the one used by [McAuley2012], which we will henceforth refer to as the MIR14k dataset.

Within the PPAML taxonomy of challenge problems, this CP is related to the Intelligence Analysis domain; the data structures are a hybrid of discrete (categorical) and continuous (features and feature distances) presented in both relational and vector forms. The basic parametric probabilistic model is an undirected graphical model over a fixed model structure with latent variables. Queries are formulated as marginal *maximum a posteriori* MAP for individual images, or joint MAP for the entire graph. The query timing is one-shot with slow tempo and stationary parameters.

## Problem Statement

Some definitions:

* A set of labels is a set of strings representing the "ground truth" of concepts present in an image. MIR14k provides 24 labels, such as "river", "dog", and "baby". For the purposes of CP6, is fixed and independent of any particular set of images (although we assume is relevant to whatever set of images we are considering.)
* An image is a matrix of pixel values. The raw images will be made available; however, instead of requiring the teams to work with raw images, we will summarize the images in terms of various image features such as histograms, texture measures, bag-of-word descriptors, and other standard descriptors, as well as more specialized features such the output of detectors tuned to specific real-world objects such as cars or people.
* Each image is associated with metadata , which may be divided into two type**s: intrinsic**, based on the EXIF data collected from the camera, a**nd relational**, describing the context of the image on Flickr. The following list is provided as guidance; precise file formats may be found in the "Solution I/O Specification" section. The following fields will be provided when present on the original image:
  + Date and time the picture was taken
  + Whether or not the flash fired
  + Focal length
  + Geo-location (uncommon)

Relational metadata includes:

* + The Flickr user ID of the photo's owner
  + Photo title (a string)
  + The free-form text tags associated with the image, and who provided the tag. These text tags are unrelated to the labels in the label set .
  + The Flickr **groups** to which the photo belongs. A group may contain photos belonging both to the group's owner and other Flickr users. In the context of this dataset, groups provide information via the title of the group. For example, a photo of a palm tree may be in two groups, one titled "Vacation photos" and another titled "Hawaii". Other photos in the group will not generally be available.
  + The Flickr **galleries** to which the photo belongs. A gallery may only contain photos belonging to other Flickr users.. Galleries provide both a title and a description, as ancillary information such as the number of photos in the gallery, the number of times it has been viewed, etc.

Not every photo will have every item of metadata.

Given these definitions, the problem can be stated as follows:

**Given:**

* A database of images
* Metadata for those images
* Labels for a subset of those images (the training set)

**Find:**

* The labels of all other images in the database

The following sections describe the baseline model, data package and formats, and evaluation methodology.

## Baseline Model

Many models can capture relational dependencies. Some are probabilistic, while others use potential functions or max-margin optimization [McAuley2012]. These models can jointly learn relationships between the image labels, the image features, and the metadata. As described above, the metadata can include time-of-day, tags, user information, and groups and galleries to which the images belong. We will implement a Conditional Random Field (CRF) as one of the baseline models due to its natural ability to model dependencies between pairs of labels while being conditioned on the input image, *I*, and metadata, *M*, . The work in [McAuley2012] can serve as another baseline model. That paper also provides results for non-probabilistic models applied to the same dataset we are using here.

Conditional Random Field as Baseline P(L|I,M) Model:

The CRF will capture both unary dependencies between image labels, , and the input features (e.g. image features and metadata), as well as the pairwise dependencies between pairs of labels and the input features to produce the conditional probability , where and are features derived from the image set, . The observed input features can include data from three sources:

* raw image features
* outputs from specific object detectors or classifiers
* metadata

The raw image features, , include low-level descriptors such as histogram of oriented gradients and color histograms. The classifier outputs,, are posterior probabilities or scores that represent how well the data matches a set of class models, which have been previously trained using image featuresThese classifiers characterize classes such as scene categories (building, grass, road), object categories (person, bicycle, vehicle), and image type (birthday party, nature, dancing). The metadata, *M*, is a binary indicator vector that indicates the occurrence of *words* (derived from titles, descriptions, and comments), *groups,* and *tags* for a single image.

The metadata is also used to define the cliques in the CRF prior to the parameter learning process. The cliques represent collections of labels that are dependent on each other based on having common properties (i.e. assigned to the same gallery or group).

The image labels, for each of the *N* images are binary values indicating the image has this class label, , or not, . The labels are treated as binary hidden nodes in the CRF and the image features, , classifier outputs, , and metadata, , are used in the observation nodes. The conditional probability of the CRF is:

, (1)

where is the normalization constant that depends on , , and , while and are the unary and pairwise potential functions, and is the clique neighborhood. The unary potentials are single image potentials, while the pairwise potentials are between pairs of images. For simplicity, a separate binary CRF model can be learned for each label (e.g., airplane).

The implementation of the CRF can follow the approach used in [Kumar2006, Domke13], where a fixed feature function is used to calculate the unary potential, *A*:

, (2)

where

, (3)

and is the classifier output feature vector, but can include the image features, and metadata, while *w* is a vector of learned weights. The feature vector can be normalized for faster convergence and possibly more accurate results.

The pairwise potential, B, from equation (1) can be modeled using a discriminative model similar to equation (2):

(4)

where is the parameter to be learned for the pairwise potential.. The pairwise potential for image *n* and *m* is denoted as for simplicity, but refers to the features that co-exist for the two images, i.e. , which can be concatenated image features and/or classifier outputs from the two images. The relational metadata can also be added to the pairwise potential by calculating common properties between the two images. These include:

* Number of common tags
* Flag indicating if both images were taken by the same user
* Temporal separation between two images

Kitware will provide the input features and metatdata that will be used as observations in the CRF as well as correct labels for each image in the training set as part of a data package.

## Data Source

CP6 will use a subset of the MIRFLICKR dataset [Huiskes2008] as defined by McAuley [McAuley2012], which contains 14,460 images uploaded to Flickr and licensed under a Creative Commons license. Various logistical constraints for CP6 reduce this to 12,690 images. See "Solution I/O specification" for file format details.

Each image has:

1. One or more label annotations for each image drawn from a vocabulary of 24 concepts. See Figure 1 for label frequency and per-image co-occurrence data.
2. The photo's title, description, and location (any or all may be empty)
3. The owner's user ID
4. EXIF metadata, providing the time the photo was taken, whether the flash was used, etc. when these were present on the original image.
5. Text tags associated with the photo (supplied by the owner or other Flickr users)
6. Information on the Flickr group and galleries the photo belongs to.
7. The comments associated with the photo

(Note that not every image will have all of 5, 6, or 7.)

Additionally, Kitware will provide a suite of features for all the images. The precise set of features is still being developed, but it will include standard features such as bag-of-words, color and edge histograms, and/or wavelet textures. Regardless of the precise feature set, all of these features will be presented as a vector of integers or floats together with a distance metric such as inner product or chi-squared distance. We will also provide more specialized classifier outputs as described above for specific object detections or scene classifications. These will be provided as a per-image vector of likelihoods, one for each classifier type.

|  |  |
| --- | --- |
| figure_2.png | figure_1.png |

Figure 1; Left, label frequency histogram; right: per-image label co-occurrence heatmap.

The dataset will scale in size from Round 1 to Round 2. The intent is that each round will define training (available) and testing (sequestered) subsets of the MIR14k data, scheduled as follows:

* Round 1 (introduced July 2015, evaluated January 2016): This data drop will focus on images which do **not** include the label "structures", which results in a set of 7269 images.
* Round 2 (introduced January 2016, evaluated July 2016): This data drop will add in the 5421 images with the label "structures".
* For both rounds, data will be partitioned into test and train sets based on EXIF timestamps: data taken before December 2007 will be training, data after December 2007 will be test. Data with no EXIF timestamp (approximately 2000 images) will be split evenly between testing and training. Figure 2 shows the distribution of Round 1 and Round 2 data versus timestamp.

|  |
| --- |
| round1-round2.png |

Figure 2; EXIF-timestamp distribution of round 1 and round 2 data

## Evaluation

The performance of the image label classifiers will be determined using the test data, which represents about half of the overall dataset. The performance will be measured using both Mean Average Precision (mAP) and Balanced Error Rate [McAuley2012].

The mAP is a single value metric that summarizes the quality of a ranked list of classified images based on their associated classifier probability/score. More precisely, the average precision (AP) is the average of the precision values that are calculated at all true positives in a descending ranked list. The AP is calculated for each class (i.e. label) and then averaged over all label experiments to obtain the mAP.

The Balanced Error Rate is designed to assign equal importance to false positives and negatives, which McAuley et al. believe more accurately represents the performance when simultaneously making binary label predictions for the entire dataset. The balanced error rate is calculated as follows:

(5)

where is the set of images with positive predicted labels, is theset of images with negative predicted labels, and and are the sets of correct positive and negative images, respectively.

# Solution I/O Specification

This section first describes the text files which contain the training and test data, then how input and output files are formatted.

## Dataset Overview

The dataset will be provided as a set of "flat" text files. Lines are space-separated sequences of values. Strings are UTF-8 encoded, enclosed in double-quotes. Any double-quotes in the string are replaced by spaces.

Many values are communicated via attribute indicator strings, which are of the form , where indicates the attribute state of the i'th element; typically '0' indicates the attribute is not present, '1' indicates that it is present, and '.' indicates that the state of the attribute was not observed.

## Label Table

This file contains 24 lines, one line per label; the fields are:

**label\_id label\_string**

|  |  |  |
| --- | --- | --- |
| label\_id | unsigned | The ordinal of this label (range 0-23). |
| label\_string | string | The text of the label. |

The labels are the 24 identifiers associated to the MIRFLICKR image set by the MIRFLICKR team.

## Image Table

This file contains one line per image; the fields are:

**index image\_id owner\_id title description label\_vector**

|  |  |  |
| --- | --- | --- |
| image\_id | unsigned | The ordinal of this image in the dataset. |
| image\_id | string | The Flickr ID of the image. |
| owner\_id | string | The Flickr ID of the owner. |
| title | string | The title of the image. |
| description | string | The description of the image. |
| exif\_date | date string | The EXIF date ("YYYY:MM:DD"), or "none" if not available. |
| exif\_time | time string | The EXIF time ("hh:mm:ss"), or "none" if not available. |
| exif\_flash | string | "Y" if the flash fired, "N" if not, "U" if not known. |
| flickr\_locality | string | Locality string returned by flickr API, or "none" if not available. |
| label\_vector | vector of double | A 24-element vector of doubles; the i'th element indicates the likelihood that label i applies to the image. See below for special values. |

It is intended that the image\_id is unique and stable across test and train datasets for both rounds.

Valid entries for the label\_vector are shown below:

|  |  |  |
| --- | --- | --- |
| [0..1] | testing / training | Values from [0..1] indicate the likelihood that the label applies to the image. |
| -1 | testing / training | Indicates that the label does not apply (for example, the label is not being used in this round.) In training, indicates that no examples of this label will be found in the entire dataset. In testing, indicates that this label should not be estimated. |
| -2 | testing only | Indicates that this label likelihood is to be estimated as part of testing. |

A label\_vector containing only -1 or -2 values is said to be "empty".

## Image Feature Table

Each image feature type (edge density histogram, color histogram, etc. ) will generate a table of fixed-length vector of floats for each image. The length of the vector will vary with each feature, but all image feature tables will have one line per image:

**image\_id N feature\_vector**

|  |  |  |
| --- | --- | --- |
| image\_id | unsigned | The ID of the image to which this feature vector refers. |
| N | unsigned | The dimensionality of this feature vector. (Fixed across each file.) |
| feature\_vector | N x double | An N-long vector of doubles representing the image feature. |

## Image Detector Table

In addition to image features, a bank of specialized object detectors (person, vehicle, etc.) will be run against each image. Each detector returns a likelihood that the image contains the object. The image detector file format has a header line (highlighted in blue) followed by one output line per image:

**N-detectors detector-label-1 detector-label-2 ... detector-label-N**

**image\_id detector-output-1 detector-output-1 ... detector-output-N**

|  |  |  |
| --- | --- | --- |
| N-detectors | unsigned | (header line) Number of detector outputs per line. |
| detector-label-*i* | string | (header line) The label of the target of the i'th detector. |
| image\_id | unsigned | The ID of the image to which this feature vector refers. |
| detector-output-*i* | double | The likelikehood output of the i'th detector on this image |

## Image Indicator Lookup Table

This defines the "dictionary", used by McAuley's baseline solution, which identifies "the 1000 most popular words, groups, and tags across the entire dataset, as well as any words, groups, and tags that occur at least twice as frequently in positively labeled images compared to the overall rate." [McAuley, section 5]. He further states "As word features we use text from the image's title, description, and its comment thread, after eliminating stopwords." McAuley does not use gallery information, probably because shared galleries are much less common than shared groups. The file format has a header line (highlighted in blue) followed by one entry per line.

**N-groups N-words**

**entry\_id group-or-word entry-string**

|  |  |  |
| --- | --- | --- |
| N-groups | unsigned | (header line) Number of groups |
| N-words | unsigned | (header line) Number of words |
| entry\_id | unsigned | The ordinal of the entry. Groups and Words are independently numbered (i.e. there is both a group 0 and a word 0.) |
| group-or-word | string | The entry is a "G" (group) or "W" (word) |
| entry-string | string | Either a Flickr Group ID or a word from the word sources as described above. |

## Image Indicator Table

This table lists how the groups, tags, and text associated with each image are represented in the Image Indicator Lookup Table. There is one line per image of the format:

**image\_id group\_indicator word\_indicator**

|  |  |  |
| --- | --- | --- |
| image\_id | unsigned | ID of the image. |
| group\_indicator | indicator string | Indicator string of length *N-groups* from the Image Indicator Lookup Table, indicating which groups this image belongs to. |
| word\_indicator | indicator string | Indicator string of length *N-words* indicating which words are associated with this image. |

## Edge Table

This table indicates the shared properties between any two images *A* and *B*. When two images share no properties, the edge is omitted. Edges are non-directional and the assignment of images to *A* or *B* is arbitrary. There is one line per edge with the following format (broken across multiple lines for legibility):

**image\_A\_id image\_B\_id**

**N\_shared\_groups N\_shared\_words**

**shared\_group\_id\_vector shared\_word\_id\_vector**

**same\_user\_flag same\_location\_flag shared\_contact\_flag**

|  |  |  |
| --- | --- | --- |
| image\_A\_id | unsigned | ID of image A. |
| image\_B\_id | unsigned | ID of image B. |
| N\_shared\_groups | unsigned | Number of shared groups |
| N\_shared\_words | unsigned | Number of shared words |
| shared\_group\_id\_vector | N\_shared\_groups x unsigned | entry\_id of shared groups |
| shared\_word\_id\_vector | N\_shared\_words x unsigned | entry\_id of shared words |
| same\_user\_flag | string | '1' if the same user took images A and B, '0' if different users took the images, or '.' if unknown |
| same\_location\_flag | string | '1' if images A and B share a "locality" (as defined by Flickr), '0' if different localities are specified, or '.' if one or both images has no locality |
| shared\_contact\_flag | string | '1' if images A and B are taken by users who share a contact, '0' if it is determined that they share no contacts, or '.' if no determination can be made |

## Training vs. Testing data

For each round, the training data will be supplied as a set of tables described above. Testing data will be the same tables augmented with the test images in the Image Table (with empty label\_vectors); the other tables will be modified as appropriate to indicate connections to the training data.

## Test Input format

The test input will be an instance of the data tables, set as above for testing; test images may be detected by their empty label\_vectors in the Image Table (those containing only -1 or -2 values).

## Test Output format

The output shall be a copy of the Image Table with the test image's label\_vectors filled in (i.e. all values of -2 have been replaced with label likelihoods.)

# References

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