TagPandr: Tag expansion for flickr images

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Abstract

We present an automatic method to suggest tags based on the existing tags provided by users. We use co occurrence statistics and wordnet to suggest tags in addition to the existing tags, and use visual features to maintain the relevance of the suggested tags to the image under consideration. We learn the visual features for tags from Flickr image corpus. Experimental results show that better tags are suggested especially when the quality of original tags are low.

1 Introduction

A large number of photos are now available online, especially with photo sharing sites like Flickr and Picassa. Annotation of images with relevant tags is a very useful feature especially for image search, categorization and organization. While there has been advances in content based analysis of images, scaling image data to web scale is a challenge.

In Flickr, tags are assigned by people who upload the photos. Tags irrelevant to the tasks of image search and categorization happen to exist in the image tags. For eg: 2011 (the year) is generally a tag associated with a photo taken on the new year of 2011. Similarly, model of camera is yet another tag which is very specific to an image and not relevant to the content of it. Apart from this, bulk upload of photo brings along with it the problem of bulk tagging. Especially for such uploads, we find that a group of photos are tagged with the same set of tags. Such tagging, although makes sense for the photo group as a whole, turns out to be irrelevant for many images in the group. Poorly tagged images and under tagged images are other issues with community tagging.

In this work, we present a method to automatically expand the given tags using text features and rank the expanded tags with the visual features to highly score those tags which are relevant to the given image. We present multiple statistics about the suggested tags and also perform human evaluation to compute the human perceived goodness of the suggested tags.

2 Related Work

Tag suggestion as a problem for text has been studied well and is also present in leading bookmarking sites such as del.icio.us and in certain blogging sites such as blogger. Techniques for generating personalized tag recommendations for users of social book-marking sites such as del.icio.us are formulated by Jhke et al. (2008) and works of Byde et al. (2007). Tag suggestion is an easier problem for text compared to tag suggestion for images. Tag expansion and ranking has also been a popular research topic in last few years. With the explosion of images online on Flickr, Picasa, and Google Images etc., it became necessary to devise means to organize and manage images more effectively. Research in contextual analysis of images Carneiro and Vasconcelos (2005), Lavrenko et al. (2003) has served as a motivation to apply those techniques in conjunction with textual analysis of existing tags to suggest high quality relevant tags. The combined intelligence of visual notion of an image is expressed in the form of tags that are associated with images on such photo sharing. Such tags tend to represent contextual information about the image. For instance, a cat in an image would be tagged by the name of the cat and also the tag *cat*.

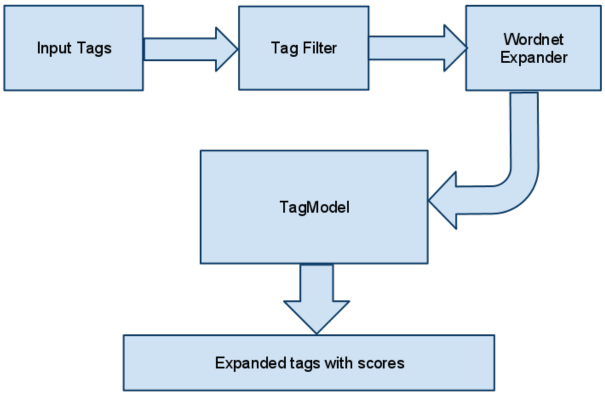
Our work is similar to the work of Liu et al. (2009) who have introduced an approach to rank tags using initial relevance scores based on probability density estimation. They tune these score based on a random walk model which models transition probabilities. This approach requires large training set to compute the probability density function and the random walk model. Sevil et al. (2010) also have proposed a methodology for tag expansion which requires user to assign initial tags. Initial tags are used to target images using similarity of tags. A list of tags is constructed based on the similar images which are weighted according to the similarity with the target image. The highest rank tags are used to expand the tags of target image. This approach uses both visual and textual similarities for expansion of tags. Their approach assign tags when the photo is uploaded. This method relies heavily on the visual similarity of images and thus, would mainly work for very similar images.

Our method aims to expand and rank tags simultaneously using tag co-occurrence and visual features. In contrast to Sevil et al. (2010) approach, our method uses co-occurrence to find similar tags. We believe, tag co-occurence will help us to tag images with such related tags and thus, improve image search results. This approach is more robust than using visual cues to get similar images. In addition, the similarity of visual features can be used to find more related tags.

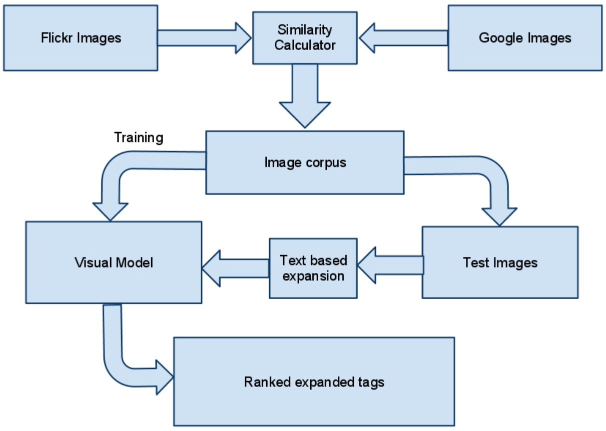
3 Implementation

We used James Hays' matlab code to query and download the meta-data for images in eight categories. We used this meta-data to extract the URLs, and the actual image download was done on a hadoop cluster to reduce the amount of time required to download all the images.

The tags we found at flickr are not of very high quality. Consequently, even searches on flickr for any particular category were not of very relevant either. To provide our implementation with a good training set, we decided to use an independent source of images for the chosen categories. For each category, we performed a Google search to get canonical images for those categories. We found that for any given keyword, the results returned by Google were consistently more representative of that category. We used the most similar Flickr images (based on Euclidean distance of the gist vectors) for training. This helped us filter flickr images to hopefully more relevant set of images.



We trained two models, a tag model and a visual model trained on the visual features of the images. We filtered the tags such that any word containing numbers was not considered for training the data. We calculated tag cooccurence for every pair of tags in the training set, assuming independence between the pairs. The probability of a given tag a tag 'tag2' depends on the number of times they co occur with the prior tags. We build a Bayes model



to calculate the probability of seeing a tag given a set of prior tags. We also extend the list of tags using wordnet Miller and Fellbaum (1998), where we choose synonyms to augment the original set. Since the text expansion was based entirely on the prior co-occurrence and wordnet synonyms, we expect this to give us a very high number of mostly relevant tags. However, some of the words might be redundant, or even irrelevant – the visual features are expected to constrain this set to certain degree of relevance.

We used two visual features, gist vectors and spatial pyramid based on Lazebnik et al. (2006) method. Gist was expected to help with global features such as color and environment. The method of spatial pyramid works by partitioning the image into increasingly ne sub-regions and computing histograms of local features found inside each sub-region. The resulting "spatial pyramid" is a simple and computationally efficient extension of an orderless bag-of-features image representation, and it shows significantly improved performance on challenging scene categorization tasks. We trained multiple classifiers on the visual features by using Weka's Hall et al. (2009) implementation of structure learning of Bayesian networks using various hill climbing (K2, B, etc) and general purpose (simulated annealing, tabu search) algorithms.

In spite of the fact that we had a lot of data, unfortunately the machine learning algorithms themselves were quite slow. Memory and time constraints prevented us from training using all the data we had, and thus we performed our evaluation on a much smaller set.

4 Experimental Evaluation

We performed experiments on flickr data set. Tags and images were separately downloaded using flickr apis. We downloaded about 500,000 images from flickr belonging to categories: cat, dog, train, aircraft, car, bus, places, crocodile, harley etc. We obtained 311,000 unique tags corresponding to these images. Like mentioned before we filtered tags which contained numbers and special characters. We found that such tags were not of much relevance to the images.

Evaluation of the tags would require some quantitative way of analyzing quality. We evaluate the tag quality automatically by two methods. Apart from these automatic methods, we also perform human evaluation to score the tag quality.

4.1 Original tag recall in top 5 suggested tags

In this evaluation, we compute the number of tags in the original image tags that we suggest in the top five tags automatically suggested by our method. The intuition behind this evaluation is to make sure that the best tags we suggest have a good coverage of the original tags. Although this method seems like a good measure of quality, the poor tags present in the original image will cause this measure to degrade. Our method will fail to suggest original tags if there is very less relevance with the given image. We calculate this measure of quality for tags generated with text only features, visual only features and visual + text features. Table 4.1 tabulates the experimental results.

From the table its clear that text features alone have better overlap with the given tags. This is because, the original

Table 1: Number of tags in the top 5 predicted tags, present in the original

Category	Text	Visual	Text + Visual	Total
aircraft	83	41	55	90
bus	40	13	15	55
car	205	124	111	480
cat	198	59	64	280
crocodile	89	51	38	100
dog	110	31	43	145

tags will also be suggested as part of the text co-occurrence model. We see a decline in the scores with visual only attributes and text+visual attributes. We attribute this to the fact that for visual features, the ranking of tags comes purely from the gist or spatial pyramid features and hence the overlap with the original tags will be lesser. For text+visual features, the ranking of tags push better tags to the top, which has lower overlap with the original tags compared to text only features.

4.2 Prediction of original tags removed from test images

For this evaluation, we randomly remove 30 percent of the original tags from the test images. We then pass these images through our pipeline and compute the number of tags suggested from the removed original tags in the top 20 of our suggested tags. The intuition behind this measure of quality is to understand how well our models are able to simulate the quality of tags possessed by original tags. This measure also has problems like mentioned before, but is a better measure of quality because we look for the existence of the removed original tags in the suggested tag set as a whole. We calculate this measure of quality for tags generated with text only features, visual only features and visual + text only features. Table 4.2 tabulates the experimental results.

4.3 Evaluation of classifier One Vs Rest

For this experimental setup, we trained a classifier one for each unique tag appearing at least 10 times in a particular category. We experimented the one vs rest classifier with support vector machines to learn the visual features for individual tags. It turns out that the performance of this classifier is worse when compared with a single classifier with multi-class prediction.

4.4 Human Evaluation

The above mentioned statistics would provide a notion of quality of the tags suggested. But we cannot compare it with the quality of the original tags. For this reason, we perform human evaluation of the input tags for the given image. Human evaluation is performed for each of the output tag and the original tags. A score from 1 to 4 is assigned to each of the tag, 1 being lowest on relevance scale and 4 being highest on relevance scale. During evaluation, tags which were about places and not obvious in the image as part of content were scored as 1. For meta images, (ie) images which are photos of the writings, visual features will be of very little use. But text features would prove to be good. Human evaluation was performed for tags expanded with text only features, visual only features and text+visual features. We also performed human evaluation of the original tags so that we could compare the scores of the original tags with the suggested tags. Table 4.2 tabulates the results of the human

Table 2: Fraction of excluded tags successfully predicted

Category	Text	Visual	Text + Visual
aircraft	0.87	1	0.70
bus	0.33	0.67	0.29
car	0.34	0.87	0.27
cat	0.32	0.95	0.27
crocodile	0.36	1	0.34
dog	0.29	0.89	0.22

Table 3: Human evaluation

Category	Text	Visual	Text + Visual	Total
aircraft	2.05	2.07	1.95	2.13
bus	2.52	2.47	2.65	2.39
car	2.26	1.80	2.41	2.43
dogs	2.64	2.13	2.57	2.53
cats	3.09	2.49	3.14	2.57
crocodile	2.79	2.08	2.36	2.59

evaluation.

We also found that when the number of tags in the image were less and those ones were very relevant, the quality of tags expanded tended to be lesser. On the other hand when the original tags were bad, we were able to suggest better quality tags. We studied the score pattern of original tags with respect to the suggested tag. Figure 4.4 shows scores from text-only, visual-only and text+visual features in comparison to increasing original tag scores. The graph shows that text+visual and text-only have higher quality than original tags. Visual-only features, by themselves, although produce lower quality tags than the original ones, we find that using them in conjunction with text features gives us better quality than original tags. We can find that text+visual features perform only marginally better than text only features. We attribute this to the fact that visual model has to learn many classes (tags). Though the class probabilities from visual classifier are weak representations, it helps in ranking the text based expanded tags.

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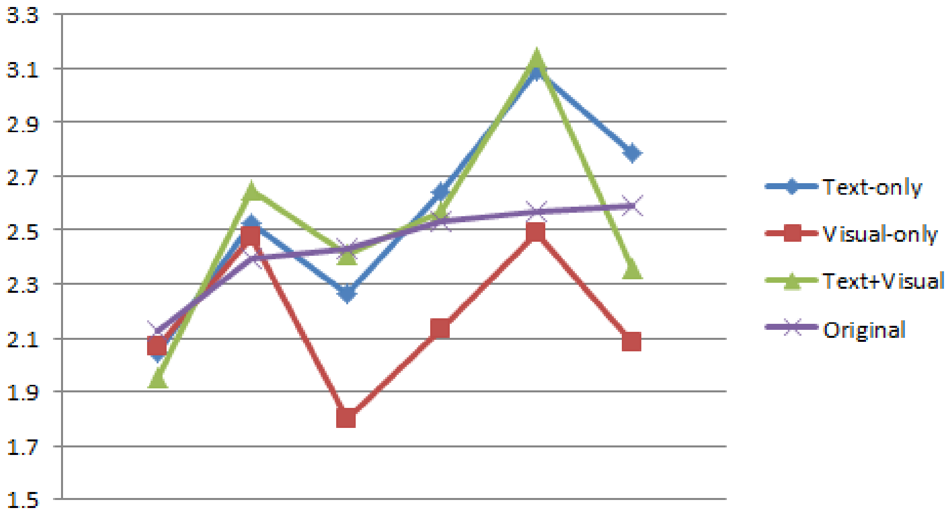
Figure 1: Human evaluation scores



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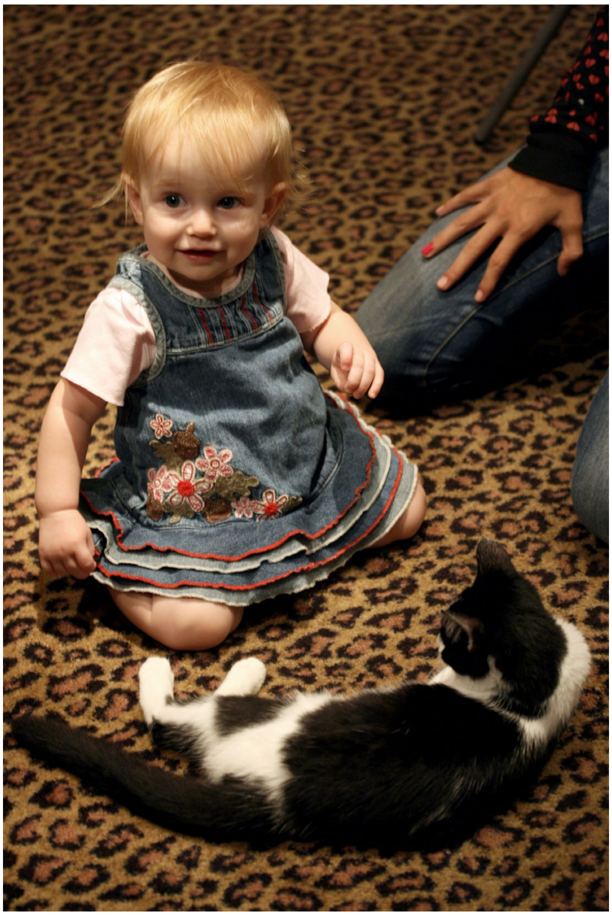
5 Examples of generated tags

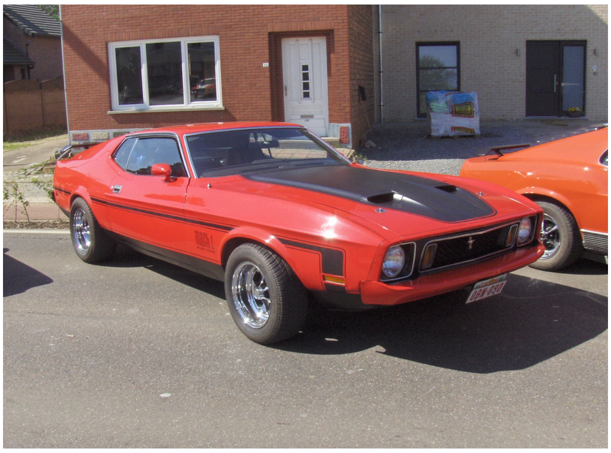


Original *cats, baby, cat, person, toddler, sitting, meetup, candid, next, hershey, bpal, willcall, ecwc, nailpolishetc*

Text-only *cats, cat, meetup, hershey, bpal,* *ecwc, nailpolishetc, willcall, candid, dog, baby, kitty, black, blackness, inkiness, pet, sitting, kitten, cute, pool*

Visual-only *cat, cats, pet, cute, kitten, kitty, animal, pets, home, garden, animals, nature, canon, flowers, family, green, city, dog, flower, car*

Text+Visual *fauna, felid, dogs, girl, baby, black, white, people, street, house, feline, dog, animals, kitty, animal, kitten, cute, pet, cats, cat*

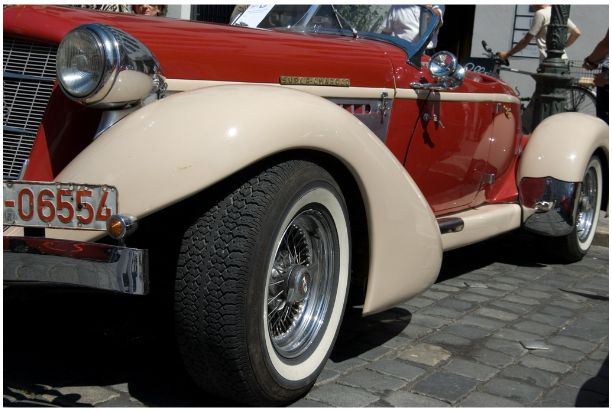


Original *ford, car, muscle, pony, american, mustang, fever, mustangpassion*

Text-only *car, auto, automobile, machine, motorcar, ford, mustang, muscle, american, pony, mustangpassion, fever, cars, classic, america, us, usa, musculus, carshow, show*

Visual-only *car, show, cars, carshow, auto, truck, club, ford, mustang, race, road, custom, cobra, classic, acctc, alabama, alabamacustomcarandtruckclub, street, chicago, museum*

Text+Visual *muscle, red, american, vintage, blue, racing, automobile, california, usa, street, classic, mustang, race, ford, auto, truck, carshow, cars, show, car*



Original *auto, cars, car, raw, nef, oldtimer, oldcars, augsburg, oldtimershow, muttertag, motherday, maximilianstrasse, moritzplatz, augschburger, borisott, adobelightroom, alteautos, autoschau*

Text-only *cars, oldtimer, car, auto, automobile, machine, motorcar, veteran, stager, warhorse, raw, augsburg, augschburger, borisott, maximilianstrasse, moritzplatz, motherday, muttertag, nef, oldcars*

Visual-only *car, show, cars, carshow, auto, truck, club, ford, mustang, race, road, custom, cobra, classic, acctc, alabama, alabamacustomcarandtruckclub, street, chicago, museum*

Text+Visual *volkswagen, autos, vw, oldtimer, oldcars, red, vintage, antique, mercedes, automobile, street, classic, ford, auto, carshow, cars, car*