Mapping the World's Photos

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ABSTRACT

We investigate how to organize a large collection of geotagged photos, working with a dataset of about 35 million images collected from Flickr. Our approach combines content analysis based on text tags and image data with structural analysis based on geospatial data. We use the spatial distribution of where people take photos to define a relational structure between the photos that are taken at popular places. We then study the interplay between this structure and the content, using classification methods for predicting such locations from visual, textual and temporal features of the photos. We find that visual and temporal features improve the ability to estimate the location of a photo, compared to using just textual features. We illustrate using these techniques to organize a large photo collection, while also revealing various interesting properties about popular cities and landmarks at a global scale.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications—*Data Mining, Image Databases, Spatial Databases and GIS*; I.4.8 [**Image Processing and Computer Vision**]: Scene Analysis

General Terms

Measurement, Theory

Keywords

Photo collections, geolocation

1. INTRODUCTION

Photo-sharing sites on the Internet contain billions of publicly-accessible images taken virtually everywhere on earth (and even some from outer space). Increasingly these images are annotated with various forms of information including geolocation, time, photographer, and a wide variety of textual tags. In this paper we address the challenge of organizing a global collection of images using all of these sources of information, together with the visual attributes of the images themselves. Perhaps the only other comparable-scale corpus is the set of pages on the Web itself, and it is in fact useful to think about analogies between organizing photo collections and organizing Web pages. Successful techniques for Web-page analysis exploit a tight interplay between *content* and *structure*, with the latter explicitly encoded in hypertext features such as hyperlinks, and providing an axis separate from content along which to analyze how pages are organized and related [17].

In analyzing large photo collections, existing work has focused primarily either on structure, such as analyses of the social network ties between photographers (e.g., [7, 12, 14, 15, 24]), or on content, such as studies of image tagging (e.g., [6, 18, 20]). In contrast our goal is to investigate the interplay between structure and content — using text tags and image features for content analysis and geospatial information for structural analysis. It is further possible to use attributes of the social network of photographers as another source of structure, but that is beyond the scope of this work (although in the conclusion we mention an interesting result along this vein).

The present work: Visual and geospatial information. The central thesis of our work is that geospatial information provides an important source of *structure* that can be directly integrated with visual and textual-tag content for organizing global-scale photo collections. Photos are inherently spatial — they are taken at specific places — and so it is natural that geospatial information should provide useful organizing principles for photo collections, including map-based interfaces to photo collections such as Flickr [4]. Our claim goes beyond such uses of spatial information, however, in postulating that geospatial data reveals important structural ties between photographs, based on social processes influencing where people take pictures. Moreover, combining this geospatial *structure* with *content* from image attributes and textual tags both reveals interesting properties of global photo collections and serves as a powerful way of organizing such collections.

Our work builds on recent results in two different research communities, both of which investigate the coupling of image and place data. In the computer vision research community there has been work on constructing rich representations from images taken by many people at a single location [22, 23], as well as identifying where a photo was taken based only on its image content [9]. In the Web and digital libraries research community there has been recent work on searching a collection of landmark images, using a combination of features including geolocation, text tags and image content [11]. While these previous investigations provide important motivation and some useful techniques for our work, they do not provide methods for automatically organizing a corpus of photos at global scale, such as the collection of approximately 35 million geotagged photos from Flickr that we consider here. As we

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see below, working at the level of all locations on earth requires robust techniques for finding peaks in highly-multimodal distributions at different levels of spatial resolution, and computer vision techniques that can capture rich image invariants while still scaling to very large image corpora.

As researchers discovered a decade ago with large-scale collections of Web pages [13], studying the connective structure of a corpus at a global level exposes a fascinating picture of what the world is *paying attention to.* In the case of global photo collections, it means that we can discover, through collective behavior, what people consider to be the most significant landmarks both in the world and within specific cities (see Table 2); which cities are most photographed (Table 1) which cities have the highest and lowest proportions of attention-drawing landmarks (Table 4); which views of these landmarks are the most characteristic (Figures 2 and 3); and how people move through cities and regions as they visit different locations within them (Figure 1). These resulting views of the data add to an emerging theme in which planetary-scale datasets provide insight into different kinds of human activity — in this case those based on images; on locales, landmarks, and focal points scattered throughout the world; and on the ways in which people are drawn to them.

Location and content. One of the central goals of this work is to study the relation between location and content in large photo collections. In particular we consider the task of estimating where a photo was taken based on its content, using both image attributes and text tags. The authors of [9] investigate a similar question, of determining GPS location using solely image content. In contrast to their work, our goal is to use location estimation as an experimental paradigm for investigating questions about the relative value of image features and text tags in estimating location. Moreover, our definition of location is hierarchical and depends on where people take photos, rather than just GPS coordinates.

We consider two spatial resolutions in defining locations: the *metropolitan-area scale* in which we resolve locations down to roughly 100 kilometers, and the *individual-landmark scale* in which we resolve locations down to roughly 100 meters. For ease of discussion we use the term *landmark* for the finer level even though not all such locations would necessarily constitute "landmarks" in the traditional sense of the term. At both scales, we determine important locations by using a *mean shift* procedure (see Section 3) to identify locations with high densities of photos; these serve as places whose locations we subsequently try to estimate by analyzing the content of the photos at that place. Mean shift is particularly applicable to the problem of finding highly photographed places, because unlike most clustering techniques that require choosing some number of clusters or making underlying distributional assumptions, mean shift is a non-parametric technique that requires only a scale of observation. We find that it is remarkably effective on this type of data and at multiple scales.

In more detail, we take n geotagged photos from each of k automatically identified popular locations. Each photo has a number of features including textual tags and image attributes (described in Section 4.1) as well as one of the k geographic locations. We separate the images into training and test sets (disjoint not only in photos but also in photographers), suppress the geographic information in the test set, and evaluate the performance of machine-learning classification techniques on estimating the (hidden) location for each photo in the test set.

For assessing the combination of visual information with textual tags, one must take into account that text-tags are the single most useful source of features for estimating hidden location values — a reflection of the fact that current techniques are considerably more effective at exploiting textual data than image data, and that photographers are generally able to provide more effective short textual descriptions than can currently be extracted from raw image data (e.g., [6, 20]).

Nonetheless, we find that at the landmark scale (100m) image information is also very effective in estimating location. In a number of locales, its performance is only a little below that of textual information (and always far above chance prediction), despite the enormous variability in photo content in the photos taken at any fixed location. Visual information also works well in combination with other features. In particular, when visual information is combined with temporal information — i.e., adding in visual features from photos taken by the same photographers within a few-minute window — it produces location estimates that are generally comparable to and sometimes above the performance of textual information. Further, the combination of textual and visual information yields significant improvements over text alone, and adding temporal information as well yields results that outperform any subset of these features.

At the metropolitan scale (100km) text tags are again highly effective for estimating location, but the image features are no longer useful; the image features alone perform at the level of chance, and adding the image features to the text features does not improve performance above the text features alone. This negative result provides further insight into the settings in which image characteristics are most effective for this type of task — specifically, in dealing with a corpus at a level of spatial resolution where there will be many different images of the same thing. It thus suggests a natural scale — at fairly short range — where the computational cost of using image-based techniques will produce the most significant payoff. It also suggests that the approach taken in [9], of using image features alone to estimate *global* location, is not the most powerful use of image content in organizing large photo collections.

Representative Images. Our second task considers the question of *what* is being photographed at a given location, by selecting representative images from a specific location. While visual information played a significant but supporting role in the first task, it becomes the dominant factor here. Selecting canonical or representative images is a problem that has a long history both in perceptual psychology and computer vision. The majority of the computational techniques are based on three-dimensional analysis of the surfaces in a scene (e.g., [5]). Recently, with the advent of Web photo collections, attention has been paid to generating canonical views of a site based on popular places to take photos of that site [22, 23]. This work again makes considerable use of three-dimensional structure of the scene to infer where photos are taken from. Our approach for this task is based heavily on this work, with the important difference that we do not make use of the three-dimensional scene constraints of that work. This results in a more lightweight, faster overall process that is capable of scaling to the global scope of our data, and yet which still produces considerably better results than randomly selecting photos from a landmark location, or even selecting photos based purely on textual tags.

Ultimately, the effectiveness of image-based features for this task — and the ability of the methods to scale to large data sizes — closes an important loop that is consistent with our overall goal and in contrast to earlier smaller-scale studies: to show the potential of applications that can provide overviews of global photo collections using absolutely no domain knowledge — no hand-selection of cities or subsets of the corpus — but instead simply employing a combination of raw usage, text, and image data available. (Fig-

ures 2 and 3 are basic examples, in which the maps, the choice of locations, the images, and the labels are all automatically inferred from the Flickr corpus.)

2. DATASET

Our dataset was collected by downloading images and photo metadata from Flickr.com using the site's public API. Our goal was to retrieve as large and unbiased a sample of geotagged photos as possible. To do this, we first sample a photo id uniformly at random from the space of Flickr photo id numbers, look up the corresponding photographer, and download all the geotagged photos (if any) of that initial user. For each photo we download metadata (textual tags, date and time taken, geolocation) and the image itself. We then crawl the graph of contacts starting from this user, downloading all the geotagged photos. We repeat the entire process for another randomly selected photo id number, keeping track of users who have already been processed so that their photos and contact lists are not re-crawled.

This crawl was performed during a six-month period in the summer and fall of 2008. In total we retrieved 60,742,971 photos taken by 490,048 Flickr users. For the work in this paper we used a subset of these photos for which the geolocation tags were accurate to within about a city block (as reported by the Flickr metadata), consisting of 33,393,835 photos by 307,448 users. The total size of the database is nearly two terabytes.

3. FINDING AND CHARACTERIZING LOCATIONS USING MEAN SHIFT

Given a large collection of geotagged photos we want to automatically find popular places at which people take photos. In measuring how popular a place is we consider the number of distinct photographers who have taken a photo there, rather than the total number of photos taken, in order to avoid pathologies associated with the wide variability in photo-taking behavior across different individuals.

Finding highly-photographed places can be viewed as a problem of clustering points in a two-dimensional feature space. For instance [11] uses k-means clustering to find popular locations in photo collections. k-means is a well-known example of a broad class of *fixed-cluster approaches* that specify a number of clusters in advance. Fixed-cluster approaches are particularly problematic for spatial data of the type we have, where extreme non-uniformity occurs at many spatial scales. As an example, in our dataset many of the largest clusters are in a few big cities such as London, biasing fixed-cluster approaches away from the entire globe and towards such areas. In their work, the authors of [11] only apply fixed-cluster methods to a manually selected metropolitan area (San Francisco); it would arguably be difficult to apply this to discovering locations at high resolution over any larger scale area.

Instead of fixed-cluster methods, we take advantage of the fact that in spatial data there is a natural parameter based on *scale of observation*. For instance, viewing a plot of photo locations at the scale of a continent one will see clusters corresponding to cities and metropolitan areas, whereas viewing the same data at the scale of a single city one will see clusters corresponding to landmarks and other points of interest. Thus we use *mean shift* clustering, because this method requires only an estimate of the scale of the data. While mean shift is often used for certain problems such as image segmentation, it appears not to be as widely used in other research areas.

Mean shift is a non-parametric technique for estimating the modes of an underlying probability distribution from a set of samples, given just an estimate of the scale of the data. In our setting, conceptually there is an underlying unobservable probability distribution of where people take photographs, with modes corresponding to interesting or important places to photograph. We are only able to observe the locations at which people take photos, from which mean shift allows us to estimate the modes of the underlying distribution. The mean shift approach is well-suited to highly multimodal probability density functions with very different mode sizes and no known functional form, such as we have here.

Mean shift operates by directly estimating the gradient of the probability density from the samples, in contrast with estimating the density itself as is done with kernel density methods such as Parzen windows. From zeroes of the gradient, local maxima of the distribution can readily be determined. In fact the mean shift calculation is an iterative procedure that uses the gradient estimate as an update, so when the gradient vector is (near) zero magnitude the procedure directly yields an estimate of the location of a local maximum of the underlying distribution.

From a given location x the mean shift vector is defined as

$$m_{h,G}(x) = \frac{\sum_{i=1}^{n} x_i g||(x - x_i)/h||^2}{\sum_{i=1}^{n} g||(x - x_i)/h||^2} - x$$

where the x_i are observed data values, g are weights for each data point corresponding to some chosen kernel function G (we use a uniform function), and h is a bandwidth parameter. The mean shift vector is simply the difference between the weighted mean, using the kernel G, and x the center of the kernel.

The mean shift procedure computes a sequence starting from some initial location $x^{(1)}$ where

$$x^{(i+1)} = x^{(i)} + m_{h,G}(x^{(i)})$$

which converges to a location that corresponds to a local maximum of the underlying distribution as the mean shift vector approaches zero. The convergence properties of mean shift are beyond the scope of this paper, but the conditions are quite broad (see [2]).

Seeding this mean shift procedure from many initial points, the trajectory from each starting point will converge to a mode of the distribution (with a given mode often being the end-result of multiple trajectories). In practice, the mean shift procedure can be made very fast, particularly for low-dimensional data such as we have here, through the use of bucketing techniques.

In our case we use the lat-long values in degrees for each photo, treating them as points in the plane because the errors in doing so are not substantial at the distances we consider. We bucket the lat-long values at the corresponding spatial scale, 1 degree for metropolitan-scale (100 km) and .001 degree for landmark-scale (100 m). At a given scale, for each photographer we sample a single photo from each bucket. We then perform the mean shift procedure at each scale separately, seeding by sampling a photo from each bucket, using a uniform disc as the kernel.

We characterize the magnitude of each peak by simply counting the number of points in the support area of the kernel centered at the peak. This is effectively the number of distinct photographers who took photos at that location (however may differ slightly as the peaks do not align with the buckets used to sample a single photo from each photographer).

Location clustering results. Table 1 presents the 15 most photographed metropolitan-scale peaks on Earth found via this mean shift procedure, ranked according to number of distinct photographers. The table also shows selected lower-ranked peaks by rank. The textual description of each cluster was generated automatically

	Top landmark	2nd landmark	3rd landmark	4th landmark	5th landmark	6th landmark	7th landmark
Earth	eiffel	trafalgarsquare	tatemodern	bigben	notredame	londoneye	empirestatebuilding
1. **newyorkcity**	empirestatebuilding	timessquare	rockefeller	grandcentralstation	applestore	columbuscircle	libertyisland
2. **london**	trafalgarsquare	tatemodern	bigben	londoneye	piccadillycircus	buckingham	towerbridge
3. **sanfrancisco**	coittower	pier39	unionsquare	ferrybuilding	prison	lombardstreet	sanfrancisco
4. **paris**	eiffel	notredame	louvre	sacrecoeur	arcdetriomphe	centrepompidou	trocadero
5. **losangeles**	disneyland	hollywood	gettymuseum	frankgehry	santamonicapier	griffithobservatory	californiaadventure
6. **chicago**	cloudgate	chicagoriver	hancock	searstower	artinstitute	wrigleyfield	buckinghamfountain
7. **washingtondc**	washingtonmonument	wwii	lincolnmemorial	capitol	jeffersonmemorial	museum	whitehouse
8. **seattle**	spaceneedle	market	seattlepubliclibrary	gasworkspark	kerrypark	downtown	fountain
9. **rome**	colosseum	vaticano	pantheon	fontanaditrevi	basilica	spanishsteps	vittoriano
10. **amsterdam**	dam	westerkerk	nieuwmarkt	amsterdam	museumplein	europe	europe
11. **boston**	fenwaypark	trinitychurch	faneuilhall	publicgarden	usa	newenglandaquarium	harvardyard
12. **barcelona**	sagradafamilia	parcguell	boqueria	cathedral	casamilà	spain	casabatlló
13. **sandiego**	balboapark	sandiegozoo	ussmidway	seals	sandiegopadres	starofindia	comiccon
14. **berlin**	brandenburgertor	reichstag	potsdamerplatz	berlinerdom	tvtower	gedächtniskirche	checkpointcharlie
15. **lasvegas**	paris	newyorknewyork	bellagio	venetian	casino	flamingo	luxor
16. **firenze**	pontevecchio	duomo	piazzadelcampo	firenze	santacroce	bridge	river
17. **toronto**	cntower	nathanphillipssquare	dundassquare	rom	eatoncentre	unionstation	hockeyhalloffame
18. **milano**	duomo	castellosforzesco	centrale	colonne	cordusio	duomo	sanbabila
19. **vancouver**	granvilleisland	vancouverartgallery	vancouveraquarium	downtown	gastown	englishbay	clock
20. **madrid**	plazamayor	puertadelsol	cibeles	cathedral	callao	metropolis	parquedelretiro
21. **venezia**	sanmarco	rialto	canal	italy	venice	venice	italia
22. **philadelphia**	libertybell	artmuseum	cityhall	logancircle	citizensbankpark	rittenhouse	centercity
23. **austin**	capital	emos	sxsw	sxsw	sxswi	tower	southcongress
24. **dublin**	oconnellstreet	bridge	dublin	dublincastle	trinity	christchurch	storehouse
25. **portland**	pioneersquare	powells	saturdaymarket	chinesegarden	japanesegarden	fountain	pdx

Table 2: The seven most photographed landmarks on Earth, and the top seven landmarks in each of the top 25 metropolitan-scale areas, found using mean-shift clustering.

Rank	Users	Photos	Most distinctive tags
1	35860	1204137	newyorkcity nyc newyork
2	29152	1122476	london england
3	25694	1115870	sanfrancisco california
4	18940	586203	paris france
5	17729	775061	losangeles california
6	12025	515884	chicago illinois
7	11834	571698	washingtondc dc washington
8	11346	535671	seattle washington
9	9839	243726	rome roma italy italia
10	9607	280549	amsterdam holland netherlands
11	9318	402658	boston massachusetts
12	9229	258926	barcelona spain
13	9132	304720	sandiego california
14	8369	236818	berlin germany
15	7652	206670	lasvegas vegas nevada
16	7438	112204	firenze florence italy italia tuscany toscana
20	6586	164454	madrid spain españa
47	3620	156693	montreal canada quebec
61	2731	131367	hongkong china
73	2312	122972	pittsburgh pennsylvania
121	1591	20319	yellowstonenationalpark yellowstone wyoming
151	1308	61971	mexicocity df mexico
202	951	27754	ithaca newyork ny
301	579	19551	iowacity iowa
374	383	9580	nassau atlantis bahamas cruise
441	291	4254	juneau glacier alaska
640	139	2411	beirut lebanon
800	85	3525	galapagos wildlife galapagosislands ecuador
933	58	709	laketiticaca southamerica titicaca uros peru puno
1000	49	608	bialystok białystok poland polska

Table 1: Clustering results at the metropolitan-scale, showing the most photographed places on Earth ranked by number of distinct photographers.

Most salient		Least salient	
58.2	agra tajmahal	6.1	desmoines iowa
49.4	córdoba cordoba	6.1	minneapolis minnesota
46.4	dubrovnik croatia	6.0	fremantle perth
45.7	salamanca españa	6.0	bern suisse
44.2	blackrockcity burningman	5.9	rochester ny
42.0	ljubljana slovenia	5.9	brisbane queensland
38.5	corpuschristi texas	5.9	frankfurt germany
34.6	montsaintmichel saintmalo	5.8	brest finistère
33.5	grandcanyon grand	5.8	amsterdam holland
32.8	deathvalley death	5.7	newcastle durham
31.8	firenze florence	5.7	taichung taiwan
31.8	kraków krakow	5.5	santiago chile
31.7	habana havana	5.4	sanfrancisco california
31.1	venezia venice	5.0	maastricht aachen
29.9	jerusalem israel	4.9	adachi arakawa
29.7	praha prague	4.7	miami florida
28.7	keywest key	4.6	connecticut ct
28.2	chattanooga tennessee	4.1	hannover deutschland
28.0	rome roma	3.7	graubünden schweiz
27.9	trogir split	3.4	taipei taiwan

Table 4: Cities ranked according to saliency of landmarks.

City	Baseline	Single photos			Temporal		
		Textual tags	Visual tags	Combined	Textual tags	Visual tags	Combined
1. newyorkcity	10.00	50.90	44.52	**66.41**	52.98	54.69	**70.28**
2. london	10.00	55.96	42.96	**67.71**	57.12	52.27	**70.38**
3. sanfrancisco	10.00	53.49	37.76	**63.96**	56.37	52.04	**70.64**
4. paris	10.00	50.30	45.34	**64.84**	51.48	56.74	**69.04**
5. losangeles	10.00	58.76	33.33	**63.10**	60.54	44.80	**65.73**
6. chicago	10.00	55.86	42.40	**66.81**	58.54	51.73	**70.36**
7. washingtondc	10.00	48.01	42.17	**61.55**	49.43	53.33	**65.28**
8. seattle	10.00	56.36	38.92	**65.11**	58.72	50.66	**69.14**
9. rome	10.00	44.73	47.56	**62.97**	45.14	58.63	**66.74**
10. amsterdam	10.00	34.96	24.00	**39.02**	36.13	28.87	**42.80**
Cities 1-10	10.00	51.67	41.63	**63.86**	53.21	52.55	**67.81**
Cities 41-50	10.00	46.91	34.15	**55.25**	48.12	42.88	**58.08**
Cities 91-100	10.00	38.87	26.58	**44.27**	39.84	30.29	**46.18**
Cities 1-100	10.00	44.57	30.59	**51.71**	45.70	37.57	**54.06**
Cities 1-10 (25-way)	4.00	44.64	23.56	**51.11**	45.90	30.11	**53.16**
Cities 1-10 (50-way)	2.00	38.16	14.40	**41.85**	39.53	20.56	**43.96**

Table 3: 10-, 25- and 50-way landmark classification performance for the 100 most photographed metropolitan-scale areas.

by finding the most distinctive of the popular tags for the photos in the peak. In particular, we discard any tags not occurring in at least 5% of the photos in the geographic cluster, and then sort the remaining tags in decreasing order according to the ratio of the number of photos in the cluster that have the tag to the total number of photos in the dataset that have the tag.

It is striking how clean the textual descriptions produced by this simple process are: for nearly all of the clusters, the first tag is a city name, with the remaining tags indicating state and/or country. This is a consequence of ordering the tags by distinctiveness: states and countries are more geographically expansive than cities, so their tags are more geographically diffuse. Thus from estimates of the largest modes of the distribution of where Flickr users take geotagged photos, we are able to reconstruct not only the locations of the most popular places but also highly accurate textual descriptions.

Analyzing peaks at both the metropolitan and landmark scales, in Table 2 we show the seven most photographed landmarks in each of the top 25 cities, as well as the seven most photographed landmarks overall on Earth. The textual tags shown were automatically selected by choosing the most distinctive tag, as described above. Most of these landmarks are well-known tourist attractions, but some surprising results do emerge. For example, one striking result is that the Apple Store in midtown Manhattan is the fifth-most photographed place in New York City — and, in fact, the 28th-most photographed place on the face of the earth! Note that repeated tags in the table indicate landmarks with multiple 100 meter-scale hotspots, such as the three distinct hotspots in Austin related to the South by Southwest festival (having tag "sxsw").

Some cities seem to have a small number of landmarks at which most photos are taken, while in other cities landmarks are less important. The magnitudes of the largest fine-scale peaks relative to the coarse-scale peak reflect this difference — in particular we consider the ratio of the sum of the ten largest fine-scale peaks to the coarse-scale peak. Table 4 shows the 20 highest-ranked and 20 lowest-ranked metropolitan-scale areas according to this criterion. Some popular tourist cities show up in the top rank such as Agra (location of the Taj Mahal), Florence, Venice, Jerusalem, Prague and Rome. However other popular tourist cities such as London, Paris and New York have large numbers of photos not taken at landmarks and thus are not ranked highly by this measure. Rural attractions such as the Grand Canyon, Death Valley and Burning Man also are ranked very highly. The bottom end of the list contains places whose lack of dominant landmarks accords with intuition, as well as a few locations where it is likely that Flickr usage is sufficiently high among the resident population as to crowd out landmarks that might otherwise be more dominant.

4. ESTIMATING LOCATION FROM VISUAL FEATURES AND TAGS

We next turn to the task of determining where a photo is taken based on both its visual features and any textual tags that are available. For these experiments we select a set of k landmarks and build a model for each of them by training a classifier using photos taken at the landmark versus those taken elsewhere. We have used approaches based on both Bayesian classifiers and linear Support Vector Machines (SVMs); the SVMs perform slightly better and so we report those results here. In particular, we train a separate SVM (using [10]) for each of the k landmarks, where the positive exemplars are the photos taken in the landmark while the negative exemplars are those taken in the $k-1$ other landmarks. To perform geolocation classification on a given test photo, we run each of the k classifiers on it and choose the landmark with the highest score (greatest positive distance from the SVM's separating hyperplane). We split our photo dataset into training and testing portions by partitioning the set of photographers, which avoids the possibility that highly similar photos by the same user appear as both test and training images.

4.1 Features

Each photo is represented by a feature vector consisting of vector-quantized SIFT features [16] capturing visual image properties and text features extracted from the textual keyword tags. In our experiments we consider using only the image features, only the text features, and both together. Image and text features have different strengths and weaknesses. For instance visual features have the advantage that they are inherent to the photo itself, whereas textual tags are only available if a human user has added them and even

then can be irrelevant to geoclassification. On the other hand, automatically finding and interpreting visual features is much more challenging than interpreting textual tags.

Visual features. Invariant interest point detection has become a popular technique for dealing with the dramatic variations in appearance of an object from one image to another. The idea is to identify salient keypoints in an image that are likely to be stable across a range of image transformations such as scaling, rotation, and perspective distortion – corners, for example. For each interest point a descriptor is also computed that characterizes the image region around an interest point in an invariant way. We use keypoints detected by SIFT [16], which is among the most popular feature point detectors in the recent computer vision literature. SIFT works by convolving an image with a bank of Laplacian of Gaussian filters at several different scales, and identifying image points that are extrema in both the spatial and scale dimensions of the filter bank response. A subsequent verification step removes points along image edges and in noisy low-contrast regions. Finally, an invariant descriptor is computed based on the response to the filter bank and an estimate of local image scale and orientation.

For a typical image, SIFT produces several hundred feature points. The SIFT descriptor for each keypoint is a 128-dimensional vector and has been found to be a highly distinctive representation of the local image data [16]. While the visual similarity of a pair of images can be measured by comparing all pairs of SIFT descriptors across the two images to find the most similar matching ones, this does not scale well (for instance, [11] does not use SIFT features for searching photo collections because of the computational cost). A more scalable approach, taken in the object category recognition literature, is to use all the SIFT features in the training set to create a "visual vocabulary" by vector quantization, generally using k-means. In our experiments we use $k = 1000$ and as in [3] we sample a fixed number of keypoints per image, so that photos with a large number of feature points are not represented disproportionately during the clustering. The result is a set of 1,000 "visual keywords" with which we can label an image. Each image is then represented by a 1000-dimensional vector indicating how many times each SIFT "keyword" occurs in the image. That is, to produce the feature vector for an image, we run the SIFT detector and then find its visual words by locating the closest cluster in our vocabulary for each of the detected interest points in the image.

We extracted the visual features from photos at Flickr's medium-scale image resolution, which is about 500 pixels on the larger dimension. We found this image size to offer a good compromise between performance and computational cost: using higher-resolution images (1000 pixels on the larger dimension) did not improve classification results significantly, while thumbnail images (100 pixels on the larger dimension) were very fast but lowered classification results by 10-20 percentage points. We also tried augmenting the local SIFT-based features with more global scene-level visual features using the Gist operator [19], but found that this did not improve our results significantly.

Textual features. We encode the textual features using a simple unweighted vector space model. Any textual tag occurring in more than 2 training exemplars is included as a dimension of the feature vector (a multi-word tag corresponds to a single dimension). Tags occurring 2 or fewer times are ignored, as they are seldom useful for geolocation. If a given image includes a given tag, then the entry in the corresponding feature vector is a 1 and otherwise it is a 0. The dimensionality of the feature vectors depends on the number of distinct tags that are found in the training set, but is typically between 500 and 3,000 in our experiments.

Geolocation results. Table 3 presents classification results for the ten most photographed landmark-scale locations in each of ten most photographed metropolitan-scale regions. In each case the task is to classify photos according to which of ten possible landmark-scale locations they were taken in. To simplify interpretation of the results, the test sets were constructed so that each of the landmarks had an equal number of photos; thus simply guessing uniformly at random achieves a baseline classification rate of 10% correct. The table shows that the correct classification rate using textual tags varies from region to region, but is typically 4-6 times better than the baseline. Using visual tags alone performs considerably worse than using textual tags, but still outperforms the baseline by a factor of about 3 or 4. That visual tags underperform textual tags is to be expected, considering that computationally extracting meaning from visual features remains a challenging problem. The classification rate differences between the baselines, visual classifier, textual classifier, and combined classifier were all statistically significant at $p < 0.00001$ according to Fisher's Sign Test.

It is somewhat surprising that, despite the power of text features alone over visual features alone, the two together outperform text features alone by a significant margin. Some of this performance gain is because some images do not have textual tags (as not all photographers add them) whereas all images by definition have visual features. For example, of the New York City photos (the first row of Table 3), 14% have no textual tags; and in fact if these photos are excluded from the test set, the performance of the textual features on the remaining photos jumps from 50.90% to 62.51%. However even on this set where all images have tags, visual features still improve performance over tags alone, increasing accuracy from 62.51% to 71.34%. This illustrates that visual features are useful even when people have added explicit textual tags to all the photos.

We conducted this 10-way landmark classification task for each of the top 100 cities, in an experiment that involved a total of over two million test and training images. The results are shown in the lower portion of Table 3. The conclusions of this experiment echo those observed above for individual cities: textual tags perform nearly 5 times better than chance, visual tags perform 3 times as well as chance, and the combination of features performs better than either does individually. As shown in the table, the performance on higher-ranked cities is generally better than on lower-ranked cities which is in part due to the greater number of training exemplars that are available in larger cities. (For example, the classification results for Amsterdam are poor because although it is the tenth-most photographed city, relatively few photos are taken in its top ten landmarks, as reflected by its low saliency score in Table 4.) However this also raises the interesting possibility that there are certain properties of the more highly photographed cities that make them more easily classifiable visually.

Table 3 also shows results for the 25- and 50-way landmark classification task for the top 10 cities. The performance of the visual classifier degrades roughly linearly as the number of landmarks increases, or about 4-6 times better than chance. Surprisingly, the textual and combined classifiers degrade quite slowly relative to the baseline; at 50 landmarks, the classifier performs more than 20 times better than chance. We do not report results for all 100 cities because most of the lower-ranked cities do not have a sufficient number of Flickr photos at their less salient landmark locations.

An analogous experiment can be performed for the top landmark-scale locations of Earth (which are listed on the first line of Table 2). For ten landmarks, the classification performance is 69.39% using

text features, 46.28% using image features and 79.59% using the two combined; for fifty landmarks, the respective correct classification rates are 52.67%, 25.43%, and 59.39% (the latter of which is nearly 30 times better than the baseline). It is perhaps not surprising that text tags are even more valuable here, as tags such as the name of a city or country are more informative when the landmarks are geographically disparate. On the other hand the visual features perform comparably on this problem as for the metropolitan-scale problems, suggesting that landmarks across the globe are not visually more distinctive than those within a given city.

Finally we consider the ability to estimate the location of more geographically disperse areas than specific landmarks. We use the same training and classification paradigm, but for clusters of photos at the metropolitan-scale rather than the landmark-scale. Textual tag features remain quite distinctive at this scale and hence perform well, giving a correct classification rate of 56.83% on the 10-way problem. Visual features, on the other hand, are not useful, performing comparably to chance (12.72%) on their own and not improving the text-only results when used in combination. This result is intuitive: there is relatively little that visually separates a typical scene in one city from a typical scene in another. These results support the use of image features for classification of spatially local landmarks rather than identifying where on the globe photos were taken.

5. ADDING TEMPORAL INFORMATION

Time provides another dimension along which photographs can be connected together. That photos are taken at the same time is not in itself a strong connection – dozens of unrelated photos are taken within seconds of one another in our dataset. However, photos taken at nearby places at nearly the same time are very likely to be related. In this section we show that temporal information can be exploited both to recover interesting facts about human behavior, and to geolocate photos more accurately.

Sequences of photos for which we know both the location and time of capture can give fascinating insight into the way that people move and interact. Geotagged and timestamped photos on Flickr create something like the output of a rudimentary GPS tracking device: every time a photo is taken, we have an observation of where a particular person is at a particular moment of time. By aggregating this data together over many people, we can reconstruct the typical pathways that people take as they move around a geospatial region. For example, Figure 1 shows such diagrams for Manhattan and the San Francisco Bay area. To produce these figures, we plotted the geolocated coordinates of sequences of images taken by the same user, sorted by time, for which consecutive photos were no more than 30 minutes apart. We also discarded outliers caused by inaccurate timestamps or geolocations. In the figure we have superimposed the resulting diagrams on city maps for ease of visualization.

The figures are striking in the amount of detail they reveal about these cities. For example, one can clearly see the grid structure of the Manhattan streets, caused by users traveling and taking photos along them. The Brooklyn Bridge, in the lower center of the figure, is clearly visible, as are the Manhattan and Williamsburg bridges just to the north. One can even see the route of the ferries that take tourists from Lower Manhattan to the Statue of Liberty.

Improving classification performance. Given the strong connection between space, time, and images, it is natural to revisit the landmark classification problem of the last section, adding temporal information in addition to the textual and visual features. We integrate temporal information directly into the classification procedure as follows. In classifying a photo, we also examine the photos taken by the same photographer within 15 minutes before and after the picture was taken. For each of these photos, we compute the classification distances for each of the k SVM classifiers, sum the scores from the different images together to produce a single k-vector, and then make the classification decision using that vector. The motivation behind this simple technique is that photos taken within a short period of time are often different shots of the same landmark. Thus the textual and visual features of contemporaneous photos are likely to be relevant in performing landmark classification.

Table 3 compares the performance on the landmark classification task with and without using this temporal information. For the classifiers that use only textual tags, the improvement is small (though statistically significant, at $p < 0.00001$): many Flickr users appear to label groups of consecutive photos with the same tags, and so tags from contemporaneous frames do not provide much additional information. For the visual tags, however, temporal information improves the results dramatically. In the case of New York City, for example, the improvement is over ten percentage points. This is also an intuitive result, though striking in the actual magnitude of the performance gain: photographers take multiple pictures of the same landmark in order to capture different viewpoints, lighting conditions, subjects, etc., and thus neighboring frames provide nonredundant visual evidence of where the photos were taken. In fact, for several of the cities including New York, Paris, Washington, and Rome, the temporal-visual features actually outperform the temporal-textual tag features. For all of the cities the best performance is achieved by using the full combination of textual, visual, and temporal information.

6. REPRESENTATIVE IMAGES

Given our ability to automatically find and generate textual descriptions of cities and landmarks, it is natural to ask whether it is possible to extract *visual* descriptions as well. That is, given a set of photos known to be taken near a landmark, we wish to automatically select a canonical image of the landmark. This problem is non-trivial because the subject of most photos taken near a landmark is actually not the landmark itself, so simple techniques like random selection do very poorly.

To choose a canonical image we once again exploit the information revealed by the collective behavior of Flickr users. People take photos because they think a subject is visually interesting, pleasing, or distinctive: it is as if photos of a landmark are votes for what the visual representation of the landmark should be. Thus we find representative images by looking for subsets of photos that are visually very similar, and choosing an image from among the most salient subset.

As in [22], we pose canonical image selection as a graph problem. We construct a graph in which each node represents a photo and between each pair of nodes is an edge with a weight indicating the degree of visual similarity between the two photos. Our goal is then to find a tightly-connected cluster of photos that are highly similar. To do this we use a spectral clustering technique [21] that partitions the nodes of the graph using the second eigenvector of the graph's Laplacian matrix. Finally, we choose as the canonical image for each cluster the one corresponding to the node with the largest weighted degree.

The main difference between our approach and that of [22] is that we are not interested in reconstructing or using detailed 3-d information about a landmark, but rather in finding canonical images for each landmark among vast amounts of data. Thus we use an image similarity technique that is less precise than their method, in that it

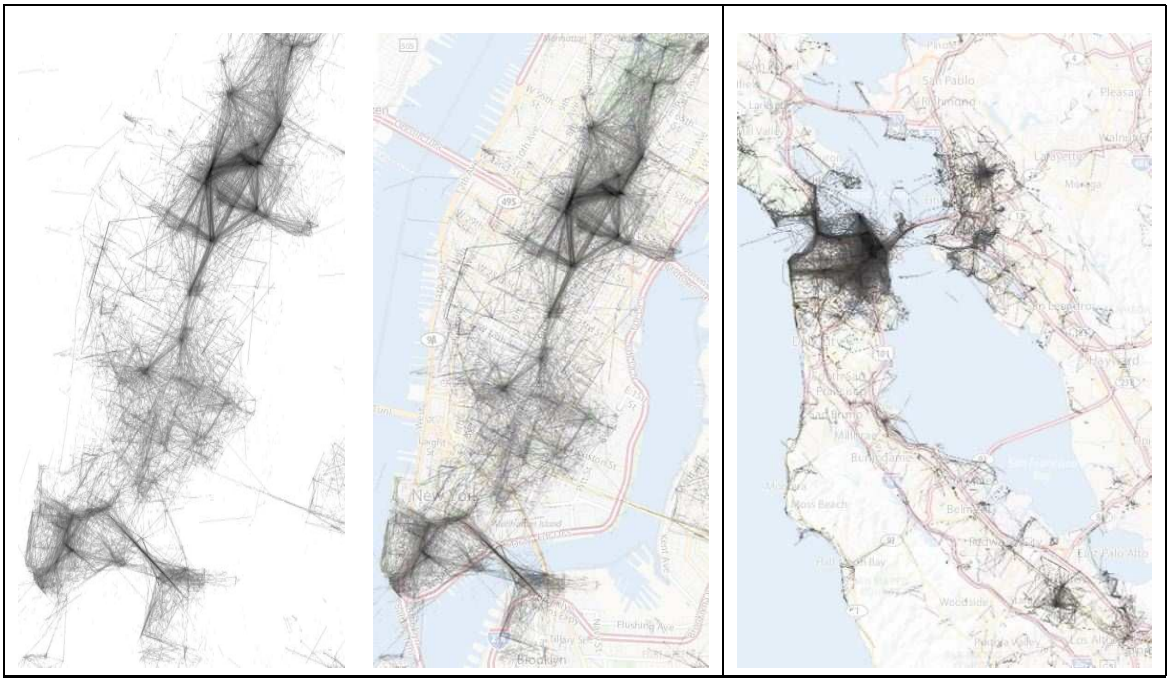

Figure 1: Visualization of photographer movement in Manhattan and the San Francisco Bay area.

does not enforce any 3d-geometric consistency, but is computationally feasible for thousands of landmarks with thousands of photos per landmark. Following [22] we extract SIFT interest points and descriptors from each image. We then simply use the number of "matching" interest points between a pair of images as a measure of similarity, where matches are determined using the Euclidean distance between SIFT descriptors.

Figures 2 and 3 present maps of representative images for the top landmark in each of the top 20 North American and European cities. All parts of the map were generated automatically using the techniques presented in this paper: the metropolitan- and landmark-sized clusters were found using the mean shift technique of Section 3, the textual descriptions were formed by concatenating the most distinctive textual tag of the landmark with that of the city, and the representative images were chosen using the method presented in this section. Even the map itself was drawn automatically, by simply plotting the raw latitudes and longitudes of all photos geotagged within North America. The result is a strikingly accurate map of the continent: land boundaries are easily recognizable (presumably due to the large number of photos taken at beaches), and one can easily see hotspots of photo activity corresponding to cities and even major transportation arteries (such as the interstate highways crossing the U.S. from east to west). Thus we see that while individual users of Flickr are simply using the site to store and share photos, their collective activity reveals a striking amount of geographic and visual information about the world.

We have generated representative images for many of the top cities and landmarks of the world; these results are available at `http://www.cs.cornell.edu/~crandall/photomap/`.

7. RELATED WORK

Our work is motivated by and builds on recent results both in the computer vision research community and in the Web and digital libraries research community (as already mentioned in the previous sections). In particular we take much of our motivation from the work of [9] and [11]; both of these papers have similar goals of combining geospatial information with content for organizing photo collections, with the former paper considering just image content and the latter considering both images and text tags. While pioneering papers, these works each have limitations that prevent them from being scaled up even to the tens of millions of images from around the globe that we consider here, much less the hundreds of millions of geotagged images on photo sharing sites.

In [9] the authors propose the challenging problem of estimating where a photo was taken based only on its image content. They create a dataset of over 6 million geotagged photos by searching photo sharing sites for tags such as names of cities and tourist sites. They then characterize each photo using a number of image features such as the gist operator [19], color and line features, and scene attributes such as surface orientations. They then manually choose a set of 237 test images taken by photographers whose photos were not included in the previous dataset. Using nearest-neighbor techniques on vectors composed of the image features, they estimate a location for each test image and measure the error compared to the (hidden) true location. They find that this results in substantial improvement compared to a random-guessing baseline, although the actual magnitudes of the spatial errors are generally quite large for any practical application to photo organization. While [9] uses a set of over 6 million images, it is difficult to conclude how general their results are because they are based only on 237 hand-selected photos, and their methods do not scale to large evaluation sets. In contrast we automatically find thousands of interesting locations, see how well each can be localized using both image properties and text properties alone and together, and report statistically significant results.

In [11] the authors address the problem of searching a collection of geolocated images, using a combination of spatial, text tag and image content features. While like our work they consider the relative value of text tags versus image attributes for localization, their

Figure 2: Representative images for the top landmark in each of the top 20 North American cities. All parts of the figure, including the representative images, textual labels, and even the map itself were produced automatically from our corpus of geo-tagged photos.

methodology is based on qualitative user assessments of just 10 locations in a single geographic area (San Francisco) and using only about 110,000 photos, again making it difficult to generalize their results. Their method also does not scale well to a global image collection, as we discussed in Section 3. There is a considerable earlier history of work in the Web and digital libraries community on organizing photo collections; however those papers in general make little or no use of image content (e.g., [1]) and again do not provide large-scale quantitative results.

8. CONCLUSIONS

In this paper we introduce techniques for analyzing a global collection of geo-referenced photographs, and evaluate them on nearly 35 million images from Flickr. We present techniques to automatically identify places that people find interesting to photograph, showing results for thousands of locations at both city and landmark scales. We develop classification methods for predicting these locations from visual, textual and temporal features. These methods reveal that both visual and temporal features improve the ability to estimate the location of a photo compared to using just textual tags. Finally we demonstrate that representative photos can be selected automatically despite the large fraction of photos at a given location that are unrelated to any particular landmark.

The techniques developed in this paper could be quite useful in photo management and organization applications. For example, the geo-classification method we propose could allow photo management systems like Flickr to automatically suggest geotags, significantly reducing the labor involved in adding geolocation annotations. Our technique for finding representative images is a practical way of summarizing large collections of images. The scalability of our methods allows for automatically mining the information latent in very large sets of images; for instance, Figures 2 and 3 raise the intriguing possibility of an online travel guidebook that could automatically identify the best sites to visit on your next vacation, as judged by the collective wisdom of the world's photographers.

In this paper we have focused on using geospatial data as a form of relational structure, and combining that with content from tags and image features. An interesting future direction is to relate this back to the explicit relational structure in the social ties between photographers. Preliminary investigation suggests that these can be quite strongly correlated — for example, we observe that if two users have taken a photo within 24 hours and 100 km of each other, on at least five occasions and at five distinct geographic locations, there is a 59.8% chance that they are Flickr contacts.

9. REFERENCES

[1] S. Ahern, M. Naaman, R. Nair, J. Yang. World explorer: visualizing aggregate data from unstructured text in geo-referenced collections, JCDL 2007.

[2] D. Comaniciu, P. Meer. Mean shift: a robust approach toward feature space analysis, *PAMI*, 24(5), 2002.

[3] G. Csurka, C. Dance, L. Fan, J. Willamowski, C. Bray.

Figure 3: Representative images for the top landmark in each of the top 20 European cities. All parts of the figure, including the representative images, textual labels, and even the map itself were produced automatically from our corpus of geo-tagged photos.

Visual categorization with bags of keypoints. Statistical Learning in Computer Vision, ECCV, 2004.

[4] http://www.flickr.com/map/

[5] W. Freeman. The generic viewpoint assumption in a framework for visual perception, *Nature*, 368(6471), 1994.

[6] S. Golder, B. Huberman. The Structure of Collaborative Tagging Systems. *Journal Information Science*, 32(2), 2006.

[7] S. Golder. Measuring Social Networks with Digital Photograph Collections. ACM Conference on Hypertext and Hypermedia, 2008.

[8] J. Hays, A. Efros. Scene completion using millions of photographs, SIGGRAPH, 2007.

[9] J. Hays, A. Efros. IM2GPS: estimating geographic information from a single image, CVPR 2008.

[10] T. Joachims. Making large-scale SVM learning practical. Advances in kernel methods - support vector learning, B. Schölkopf et al (ed), MIT-Press, 1999.

[11] L. Kennedy, M. Naaman. Generating diverse and representative image search results for landmarks, WWW 2008.

[12] R. Kumar, J. Novak, A. Tomkins. Structure and Evolution of Online Social Networks. KDD, 2006.

[13] R. Kumar, P. Raghavan, S. Rajagopalan, A. Tomkins. Trawling the web for emerging cyber-communities, *Computer Networks*, 1999.

[14] K. Lerman, L. Jones. Social Browsing on Flickr Intl. Conf. on Weblogs and Social Media, 2007.

[15] J. Leskovec, L. Backstrom, R. Kumar, A. Tomkins. Microscopic evolution of social networks. KDD, 2008.

[16] D. Lowe. Distinctive image features from scale- invariant keypoints, *Int. J. Computer Vision*, 60(2), 2004.

[17] C. Manning, P. Raghavan, H. Schütze. *Introduction to Information Retrieval.* Cambridge University Press, 2008.

[18] C. Marlow, M. Naaman, D. Boyd, M. Davis. Position Paper, Tagging, Taxonomy, Flickr, Article, ToRead, Collaborative Web Tagging Workshop (at WWW), 2006.

[19] A. Oliva, A. Torralba. Modeling the shape of the scene: a holistic representation of the spatial envelope, *Int. J. Computer Vision*, 42(3), 2001.

[20] S. Sen, S. Lam, A. Mamunur Rashid, D. Cosley, D. Frankowski, J. Osterhouse, F. Maxwell Harper, J. Riedl. Tagging, communities, vocabulary, evolution. CSCW, 2006.

[21] J. Shi, J. Malik. Normalized cuts and image segmentation, *PAMI*, 22(8), 2000.

[22] I. Simon, N. Snavely, S. Seitz. Scene summarization for online image collections, ICCV 2007.

[23] N. Snavely, S. Seitz, R. Szeliski. Photo tourism: exploring photo collections in 3d, SIGGRAPH, 2006.

[24] H.T. Welser, E. Gleave, D. Fisher, M. Smith. Visualizing the Signatures of Social Roles in Online Discussion Groups, *J. Social Structure*, 2007.