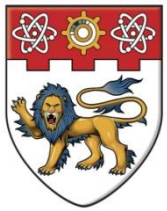

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User Profile Enhanced Geolocation Suggestion for Social Images

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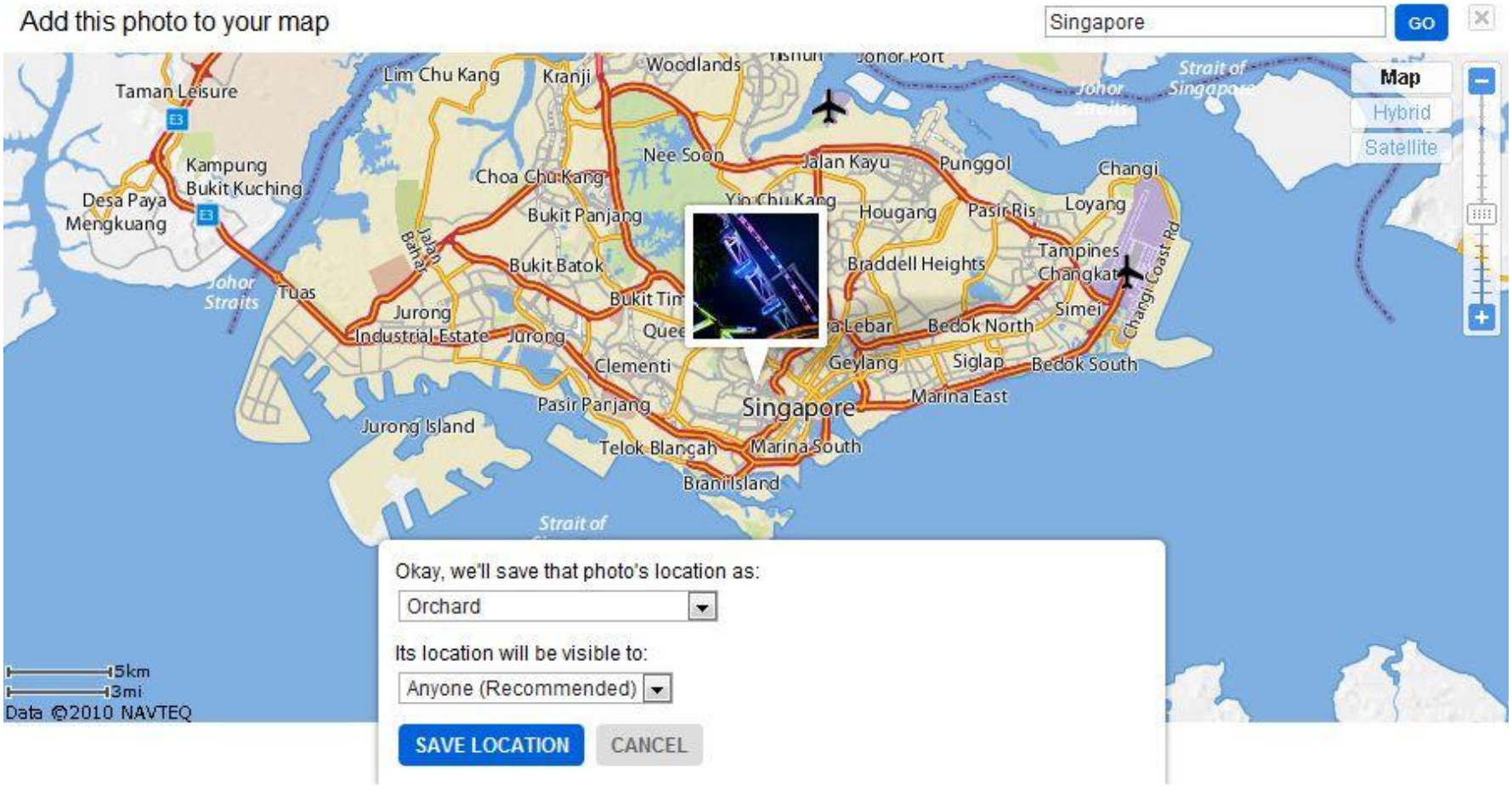
Outlines

- Motivation & Objective
- Related Work
- Geotagging Behavior For Social Images
- Proposed Method
- Experiments & Results
- Conclusion

Motivations & Objectives

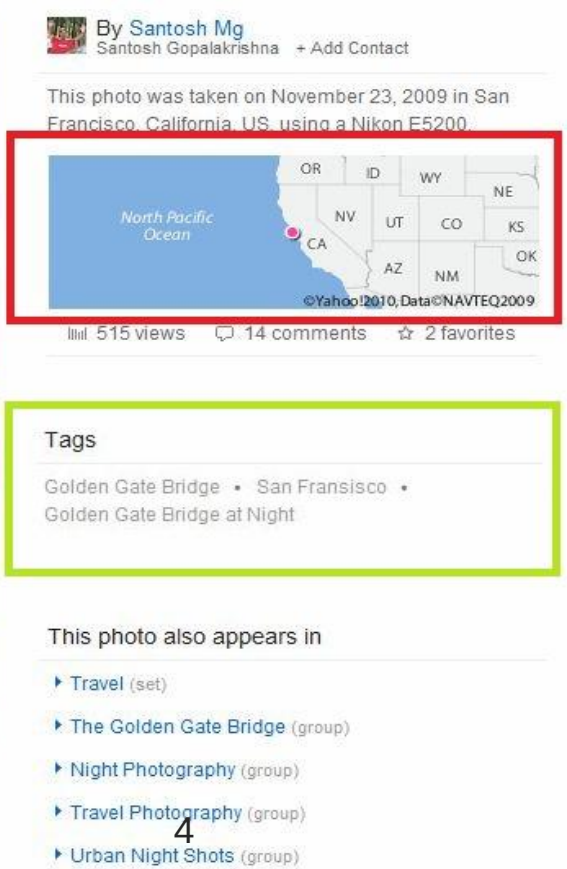


Motivations & Objectives

- Develop an effective and efficient method to suggest geolocations for images using textual tags.

Golden Gate Bridge

This is the Golden Gate Bridge in San Fransisco CA



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"innovation through collaboration"

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Related Work

- Geolocation Suggestion for Images
  - IM2GPS: estimating geographic information from a single image, J. Hyas, et al, CVPR 2008
    - Visual features, time-comsuming.
  - Placing flickr photos on a map, P. Serdyukov et al. SIGIR'09
    - Textual tags, many images have no tag.
  - Mapping the world's photos, D. Crandall et al. WWW'09
    - Textual & visual features, difficult to scale
- Geolocation Suggestion for Other Contents
  - You are where you tweet: a content-based approach to geo-locating twitter users, Z. Cheng et al. CIKM'10
    - For users
  - Spatial variation in search engine queries, L. Backstrom, WWW'08
    - For queries
  - Geolocating blogs from their textual content, C. Fink et al. AAAI'09
    - For blogs

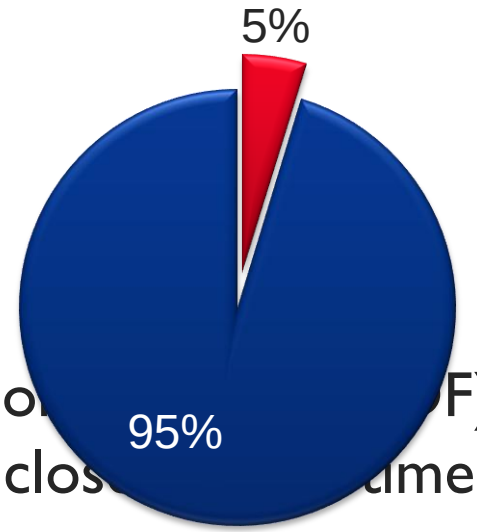
Geotagging Behavior - Dataset

- Collect a dataset of Flickr images uploaded by a set of randomly selected users

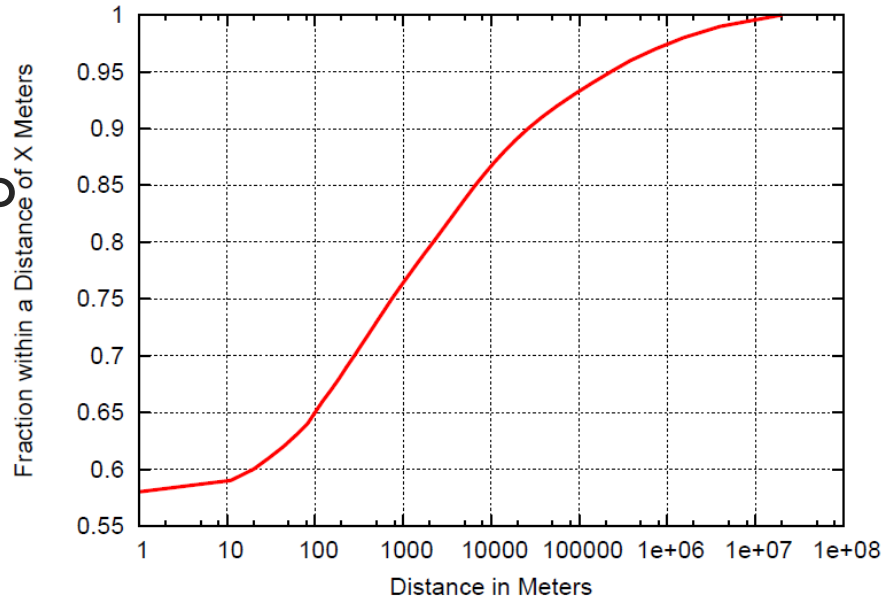
	Total	Textual Tagged	Geotagged	Both Tagged
Images	221,801,183	99,649,530 (44.9%)	17,355,876 (7.8%)	13,268,992 (5.9%)
Users	2,252,758	468,555 (20.7%)	106,289 (4.7%)	97,061 (4.3%)

- More than half of the images have no tag
- A small number of users have geotagged images

Geotagging Behavior



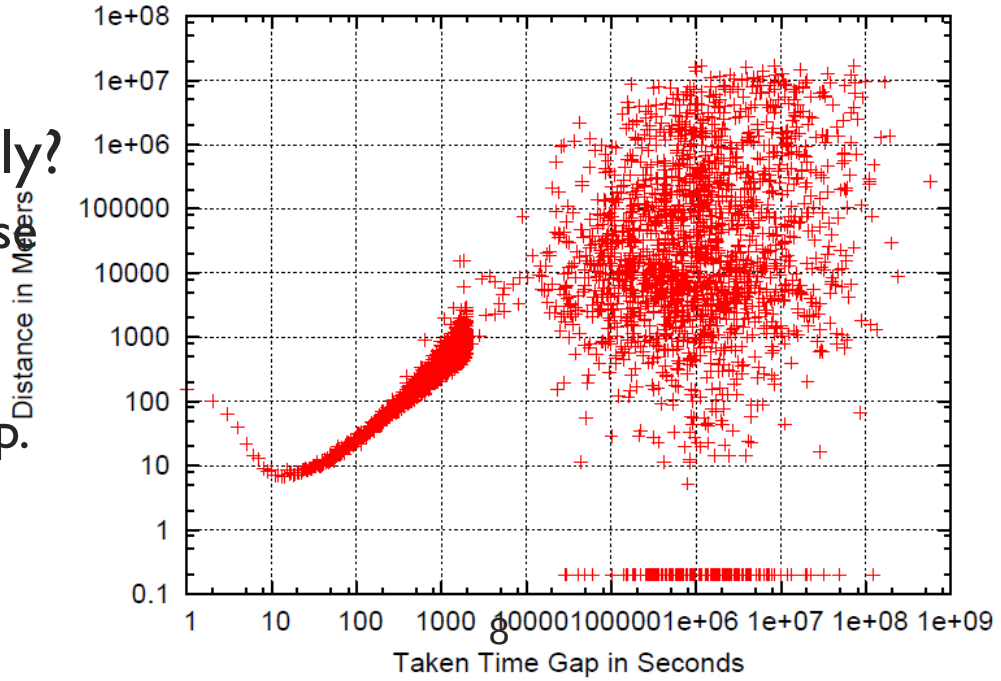
- We analyze the Cumulative Distributio F) of distance between two images with clos ime by the same user.
- Most images are close to the preceding ones.
- The geolocation of the preceding image can be used to geotag the new image.
- However…



Geotagging Behavior

- Turn to textual tags
- Generate user profile using the tags of historical images
  - Close locations share similar tags
  - Most images are spatially close to preceding image
  - Query image is likely to be taken within locations represented by user profile.

- Treat historical tags equally?
  - Close in taken time →Close in space
  - Analyze relation between distance and taken time gap.
  - Tags of recent images are more valuable.



Proposed Method
—Location Representation

- Place a grid over the world map, and define a location as a cell on it.
- Different granularity: 1, 10, 100km over latitude.
- Map the photos to the corresponding cells.

Proposed Method —Using Image Tags

- k-Nearest Neighbors Method (kNN)
  - Each image is represented by a vector on tags. Predict location of an image using k nearest neighbors.
- Language Model Based Method (LM)
  - The textual tags of photos are used to derive a language model that represents a location.

$$P(l \mid T) = \frac{P(T \mid l)P(l)}{P(T)} \propto P(T \mid l) = \prod_{t \in T} P(t \mid l) \qquad P(t \mid l) = \frac{|l|}{|l| + \lambda} P(t \mid l)_{ML} + \frac{\lambda}{|l| + \lambda} P(t \mid G)_{ML}$$

- Naïve Bayes Method (NB, NB+RT, NB+CT)
  - Expand a query image's tag set by adding with its owner's history tags until |T|=K.

$$P(l \mid T) = \frac{P(T \mid l)P(l)}{P(T)} \propto P(T \mid l)P(l) = \prod_{t \in T} P(t \mid l)P(l)$$

Proposed Method
—Example of Language Model

$$P(l \mid T) = \frac{P(T \mid l)P(l)}{P(T)} \propto P(T \mid l) = \prod_{t \in T} P(t \mid l) \quad P(t \mid l) = \frac{|l|}{|l|+\lambda} P(t \mid l)_{ML} + \frac{\lambda}{|l|+\lambda} P(t \mid G)_{ML}$$

Term Frequency

tag	L	G
NTU	3	3
SG	1	2
UK	0	3

Maximum Likelihood

tag	L	G
NTU	0.75	0.375
SG	0.25	0.25
UK	0	0.375

$\lambda = 2$

Smoothed

tag	L
NTU	0.5625
SG	0.25
UK	0.1875

Testing Image

tag	L
NTU	2
SG	1
UK	0

$$P(l \mid T) = 0.5625^2 \times 0.25 \times 0.1875 \approx 0.015$$

Proposed Method —Using User Profile

- Model User Profile (P, WP)
  - Treat the set of entire historical tags used by a user as her profile, and build a language model U to model it.
  - Two choices:
    - Equal weight for every tag (P)
    - Different weight for different tag based on taken time of an image (WP)
- Measure similarity between the user profile and each location
  - Use KL divergence

$$D_{KL}(U \parallel L) = \sum_i U(i) \log \frac{U(i)}{L(i)}$$

Proposed Method
—Combining Image Tags and User Profile

- Unified Framework (NB+P, NB+WP)
  - Combine the evidence of image tags and user profile

$$S = (1 - b^{-n}) S_{tag} + b^{-n} S_{user}$$

$$S_{user} = S_{D_{KL}(U\|L)} = 1 - \frac{D_{KL}(U \parallel L) - \min D_{KL}}{\max D_{KL} - \min D_{KL}}$$

$$S_{tag} = S_{P(l|T)} = \frac{P(l \mid T) - \min P}{\max P - \min P}$$

Experiments

- Dataset:
  - Training set: 3,491,429 images uploaded before March 1st 2011
  - Tuning set: 10,000 images uploaded after March 1st 2011
  - Testing set: 10,000 images uploaded after March 1st 2011
- Metric:
  - Accuracy (Acc)
  - Fraction of images predicted correctly within k-cell distance(Acc@k)
  - Fraction of images predicted correcly among top-k locations (Top-k)

Experiment Results

	Acc	Acc@1	Acc@2	Acc@3	Top-2	Top-3	Top-4
			$1KM$				
kNN	0.0521	0.0848	0.1054	0.1194	0.0733	0.0852	0.0922
LM	0.0576	0.0958	0.1173	0.1297	0.0815	0.0935	0.1029
NB	0.0598	0.0989	0.1217	0.1354	0.0811	0.0947	01033
NB+RT	0.0572	0.0946	0.1197	0.1351	0.0771	0.0906	0.0995
NB+CT	0.0634	0.1065	**0.1352**	0.1521	**0.0866**	**0.1011**	0.1123
P	0.0121	0.0270	0.0438	0.0599	0.0187	0.0236	0.0286
WP	0.0389	0.0737	0.0960	0.1178	0.565	0.696	0.775
NB+P	0.0577	0.0968	0.1230	0.1430	0.0800	0.0934	0.1046
NB+WP	**0.0637 (+22.3%)**	**0.1067**	0.1334	**0.1546**	0.0858	0.1007	**0.1138**
			$10KM$				
kNN	0.1420	0.1809	0.1953	0.2032	0.1774	0.1904	0.1997
LM	0.1550	0.2014	0.2187	0.2263	0.1996	0.2135	0.2228
NB	0.1581	0.2058	0.2245	0.2312	0.2010	0.2218	0.2368
NB+RT	0.1602	0.1941	0.1985	0.2005	0.2084	0.2311	0.2447
NB+CT	0.1794	0.2145	0.2193	0.2212	**0.2323**	**0.2575**	**0.2722**
P	0.0710	0.1214	0.1557	0.1697	0.1004	0.1164	0.1280
WP	0.1309	0.1982	0.2328	0.2493	0.1734	0.1996	0.2132
NB+P	0.1685	0.2301	0.2589	0.2717	0.2138	0.2365	0.2503
NB+WP	**0.1811 (+27.5%)**	**0.2442**	**0.2721**	**0.2851**	0.2285	0.2515	0.2669
			$100KM$				
kNN	0.2101	0.2362	0.2510	0.2609	0.2437	0.2565	0.2634
LM	0.2442	0.2766	0.2976	0.3081	0.2758	0.2898	0.3006
NB	0.2463	0.2818	0.3056	0.3231	0.2977	0.3300	0.3490
NB+RT	0.2839	0.3349	0.3644	0.3849	0.3399	0.3685	0.3854
NB+CT	0.3056	0.3585	0.3912	0.4151	0.3596	0.3870	0.4068
P	0.2196	0.2828	0.3209	0.3456	0.2729	0.3044	0.3311
WP	0.2978	0.3643	0.4020	0.4283	0.3560	0.3893	0.4185
NB+P	0.3023	0.3633	0.3973	0.4189	0.3640	0.3967	0.4214
NB+WP	**0.3277 (+56.0%)**	**0.3899**	**0.4254**	**0.4491**	**0.3856**	**0.4193**	**0.4439**

- Combining image tags and user profile together is able to achieve much better result
- The taken time stamps of historical images play an important role in user profile

Conclusion

- We focus on the problem of suggesting geolocations for social images.
- For the first time we analyze the user uploading patterns, geotagging behaviors and the relationship between taken-time gap of two images and their distance.
- We proposed a unified framework for geolocation suggestion.
- Experimental results show the effectiveness of the proposed method.

Q & A

Thanks!
Any questions?