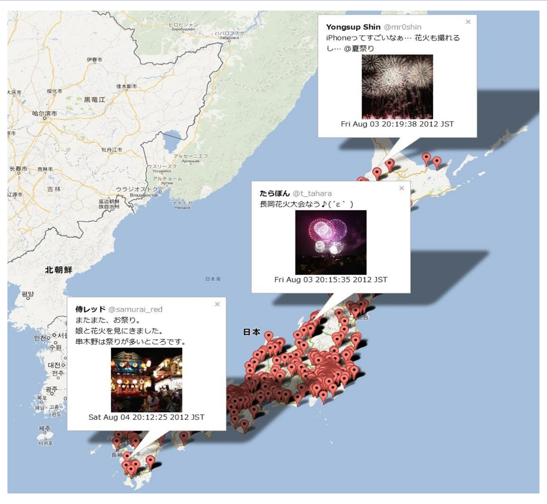
Visual Event Mining from the Twitter Stream

The University of Electro-Communications, Tokyo, Japan

Takamu Kaneko and Keiji Yanai

Background

- Spread of smart phones (camera & GPS)
  - easy to obtain photos and geotags
- Spread of Twitter
  - Real-time posting of event-related tweets



A lot of "geotags" or "photos" on Twitter. However, the number of geotagged photo tweets are limited (2-3%).

Objective

- Detect event photos with location info. from Twitter
  - helpful to understand events intuitively
- Use not only geotagged photo tweets but also geotagged non-photo tweets and non-geotagged photo tweets for event photo detection

Main contribution of this work

Proposed method

1. **Event burst detection** (text-based analysis with geotagged tweets)

Event geotagged photos

2. **Location estimation of non-geotagged photo tweets** (geotag and visual feature based analysis)

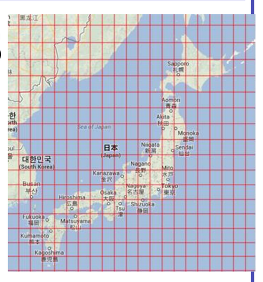
Augmented event geotagged photos

3. **Event photo clustering and representative photo selection**

4. **Visualizing events on the map**

Event detection on words and areas

- Divide target area into sub-regions
  - Grids by 0.5 degree latitude and longitude



- Build N-gram (N≦5) of all the geo-tweet texts regarding # of unique users within each grid in each unit time (1day)
  - e.g. "I'm in Japan Rock Festival."
    ⇒ Japan, Rock, Festival , Japan Rock, Rock Festival, Japan Rock Festival
- Burst detection
  - compare each 1-day 1-gird N-gram with 1-year average: their ratio = burst score

Adjusting weight

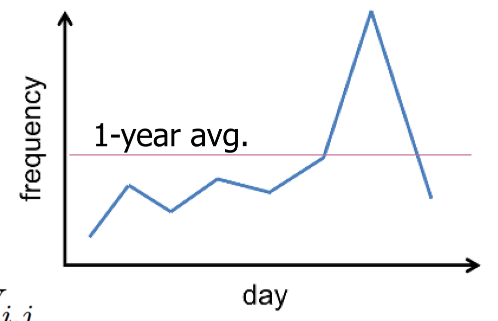
$$W_{i,j} = \frac{\#users_{\max} + s}{\#users_{i,j} + s}$$

Commonness score

$$Com(w) = \sum_{i,j} \frac{E(\#users_{w,i,j})^2}{V(\#users_{w,i,j}) + 1} W_{i,j}$$

Burst score

$$S_{w,i,j} = \frac{\#users_{w,i,j}}{Com(w)} W_{i,j}$$



Burst score $\geq th(=200)$

Event word candidates

Evaluation of "event-ness" of non-geo photos

- Location estimation of non-geo photo tweets containing event words by combining both texts and image features
  - text: Naïve Bayes (NB)
  - image: Naïve Bayes Nearest Neighbor (NBNN)
- Binary classification (if given photo is related to events or not)

Evaluating "event-ness" in given area

$$\hat{c} = \arg\max_{c} P(c) \underbrace{\prod_{i=1}^{n} P(x_i \mid c)}_{\text{text}} \underbrace{\sum_{j=1}^{v} \frac{d_j \cdot NN_c}{\|d_j\| \|NN_c\|}}_{\text{image}} \quad c \in \{event\ photo,\ non\text{-}event\ photo\}$$

Event Photo Clustering

- Image features
  - DCNN activation features (4096 dim)
    (DCNN: Deep Convolutional Neural Network)
    (Alexnet pretrained with ImageNet1000)
- Photo clustering: Ward method
  - a hierarchical clustering method
- Representative photo selection
  - a photo which is the closest to the center of the largest cluster

Experimental Results

Data collected via Twitter Streaming API

- Tweets within Japan on August. *(Many festivals in August.)*

	2012 whole (training for geo. estimation)	Aug. 2012 (for evaluation)
Geo-photo tweets	2,645,709	255,455
Only-geo tweets	24,715,962	2,102,151
Only-photo tweets		3,367,169

Comparison with the baseline (= using only geo-photo tweets)

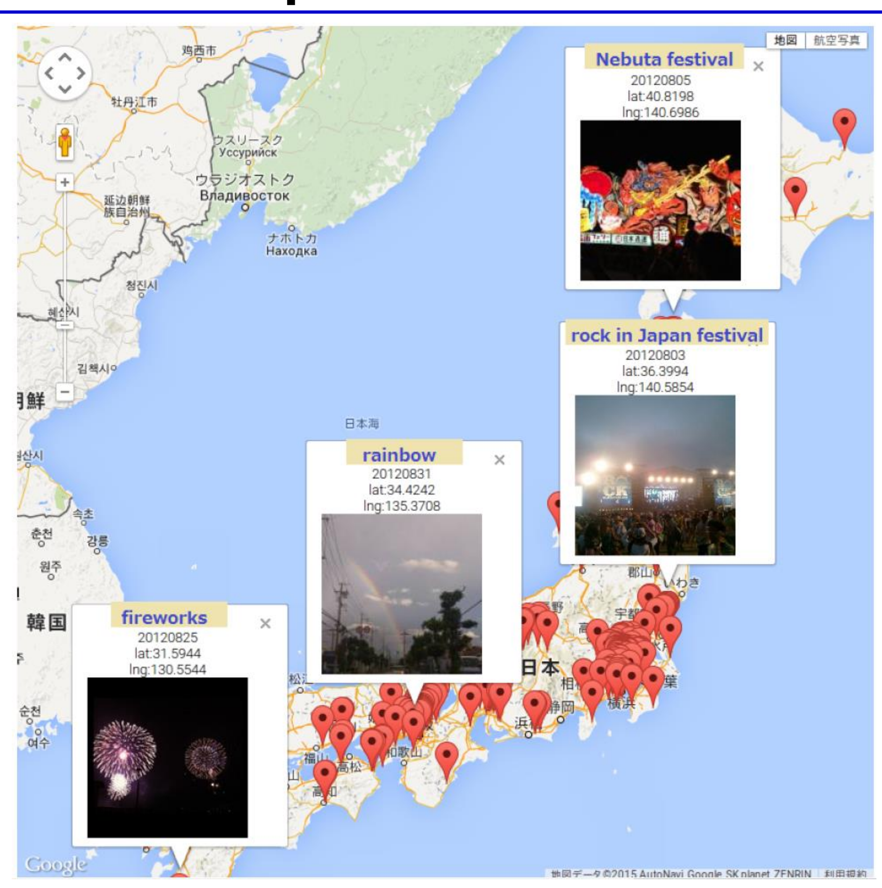
	proposed	baseline	
# events	310	35	↑ *increased*
Event precision (%)	81.3	77.1	↑ *improved*
Photo precision (%)	88.7	65.5	↑ *improved*

Examples of detected keywords

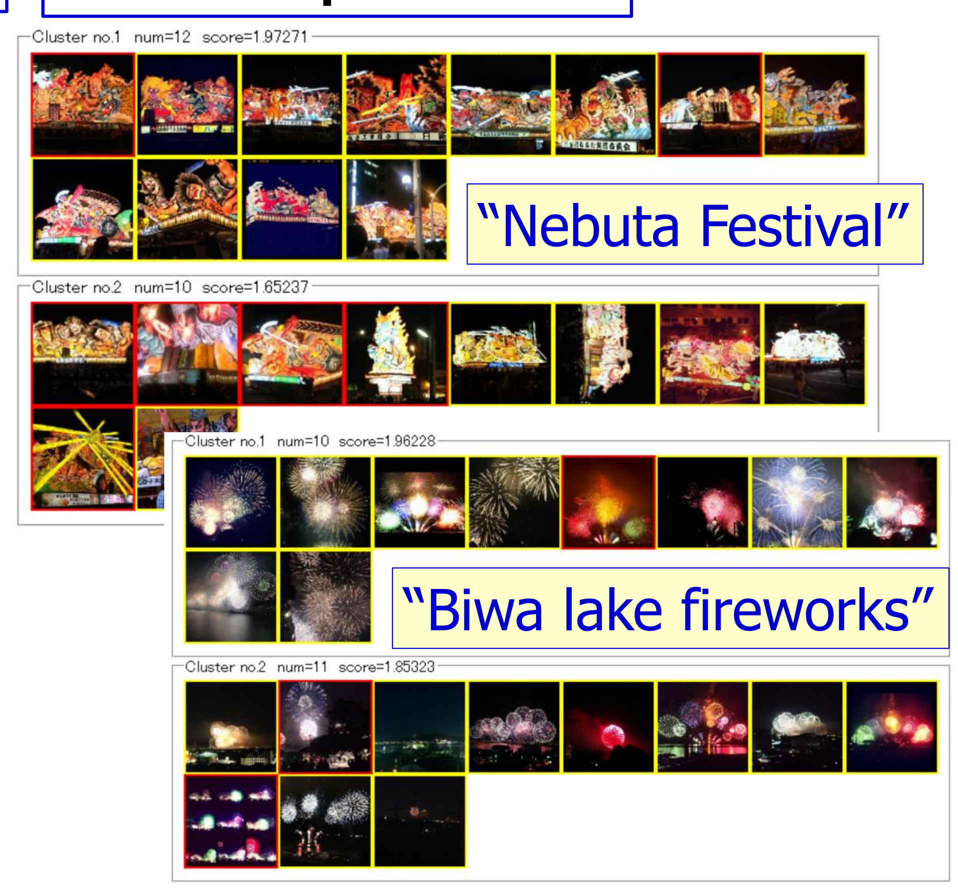
Event word	date	Loc. (lat,lng)	Burst score
Firework	20120801	33.0, 129.5	297.7
rainbow	20120801	34.0, 134.5	229.1
ROCK IN JAPAN	20120803	36.0, 140.0	430.3
Ayu Festical	20120804	34.5, 135.5	265.1
Nebuta Festival	20120806	40.5, 140.0	255.7
Awa Festival	20120814	34.0, 134.0	589.8
Thunder storm	20120818	34.0, 135.0	367.5
Blue moon	20120831	34.5, 136.0	269.7

More event photos can be seen at
http://mm.cs.uec.ac.jp/kaneko-t/tw/adv/

Event map with representative photos



Event photos



Conclusion

- A new method on Twitter event photo detection using geo-photo/only-geo/only-photo tweets with location estimation of non-geo photos
- Outperformed the baseline regarding # and prec.

Future Work

- Variable grid size and time unit for event detection
- More large-scale experiments with various languages
  - Building **world-wide event photo database** (regular, accidental)
- Real-time event photo detection