Twitter Event Photo Detection Using Geotagged Tweets and Non-geotagged Photo Tweets

Takamu Kaneko and Keiji Yanai
Department of Informatics,
The University of Electro-Communications,
Tokyo, Japan

Background

- Spread of smart phones
  - -Geotagged photos
- Spread of Twitter
  - -Real-time posting

A huge number of “geotags” and “photos” in the Twitter stream

Twitter Event Photo Mining

[ICME WS 2013]

- Mine the photos related to the events happened in the specific areas and times

The results of detected event photos in 2012

Objective of Twitter Event Photo Detection

- Detect events from Twitter stream
  - Weather, natural events
  - Festivals, sport games
- Understand events visually
  - Select representative photos
  - Visualize events on an on-line map

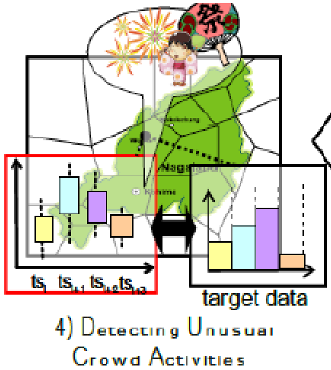
Mapping events with the photo

Related Work: Twitter Event Mining

- Many works which use only text analysis

- **Sakaki et al. [WWW 2010]**
  - -Regard Twitter users as social sensors
  - -Estimate the location of natural events

- **Lee et al. [ACM SIGSPATIAL WS 2010]**
  - -Divide target area into small sub-regions
  - -Monitor the number of tweets



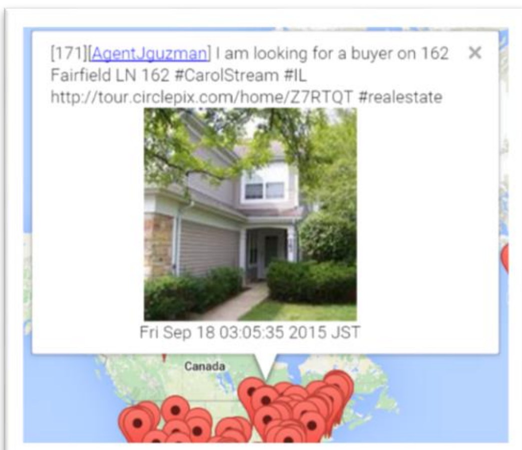
Detect events and their locations from geotagged tweets

Related Work: Twitter Photo Mining

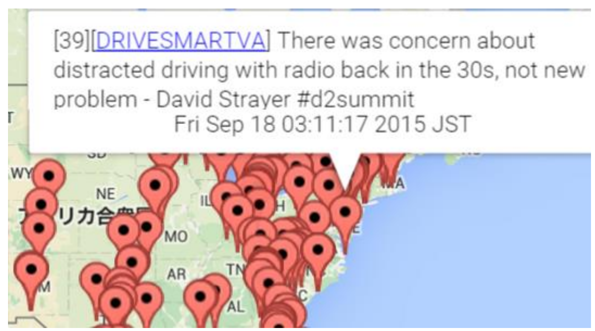
- Use geo-tweet photos
- **Nakaji et al. [ICME WS 2012]**
  - Mine representative photos for given event words
  - Compare differences of events depending on places and time
- **Our previous work [ICME WS 2013]**
  - Event keyword detection + photo clusterting
  - **Use only “geotagged photo tweets”**
    - **The number of images are limited.**
    - **About 2 or 3% of all the tweets**

Contributions of this work

- Extend the previous work so as to use not only geotagged photo tweets but also geotagged non-photo tweets and non-geotagged photo tweets



Geotagged photo tweets



Geotagged text tweets

For event word detection

Non-geotagged photo tweets

For event photo detection

Differences to the previous work

		Previous[1]	This work
Types of tweets	**Geotagged photo tweets**	○	○
	Geotagged text tweets	×	○
	Non-geotagged photo tweet	×	○
Text analysis method		Morphological analysis	N-gram
Image features		BoF + color hist.	DCNN

20 times larger volume

[1] T. Kaneko and K. Yanai. Visual event mining from geo-tweet photos. In Proc. of IEEE ICME Workshop on Social Multimedia Research (SMMR) , 2013.

Overview

1. Event keyword detection

↓

2. Location estimation of non-geotagged photo tweets

↓

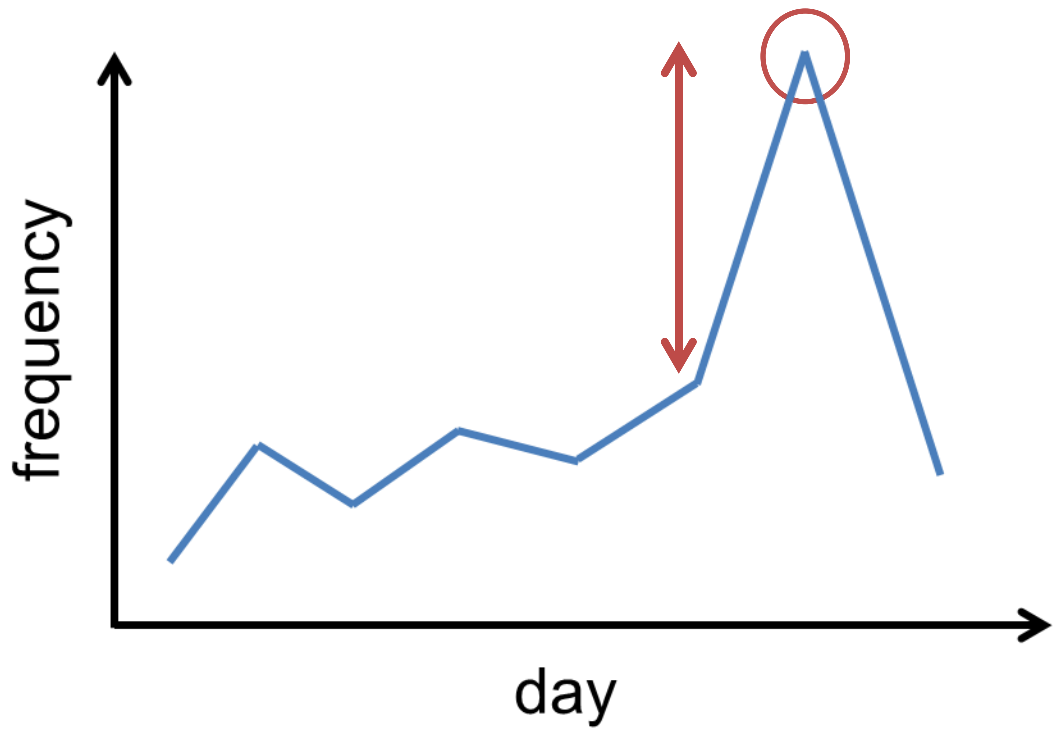
3. Event photo clustering

↓

4. Mapping event with photos

Event Keyword Detection

- Examine change of daily frequency
  ⇒ burst detection



Event Word and Region Detection

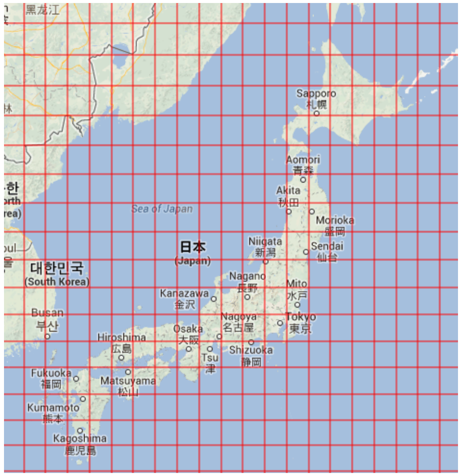
- N-gram: words by more than 5 unique users

  e.g. "I'm in Japan Rock Festival."

  ⇒ Japan, Rock, Festival , Japan Rock, Rock Festival, Japan Rock Festival

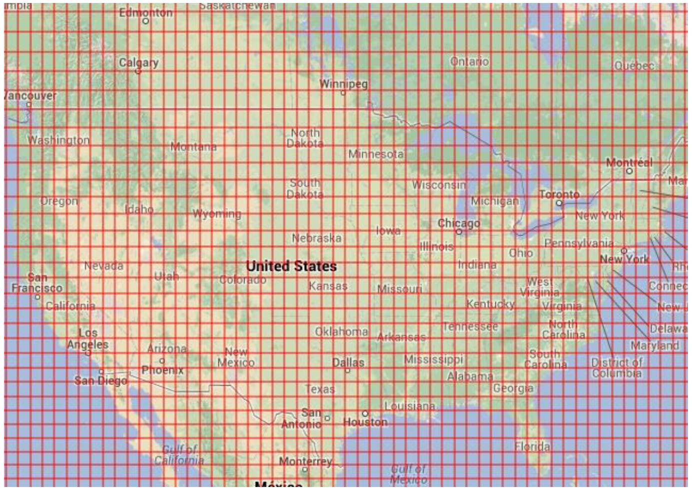
- Divide target area into sub-regions

  -Grids by 0.5 degree latitude and longitude



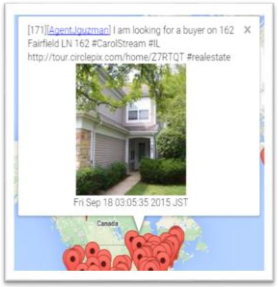
Japan

US

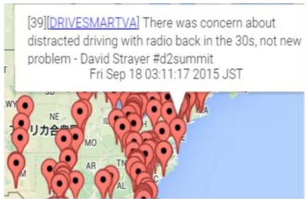


Event word detection

- Use both geotagged photo tweets and geotagged non-photo text tweets



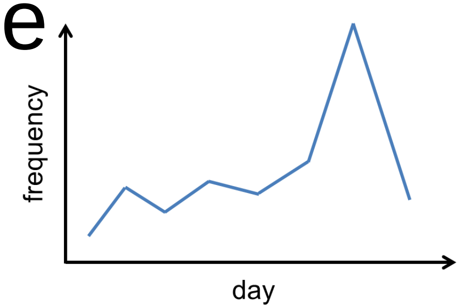
Geotagged photo tweets



Geotagged text tweets

For event word detection

1. Count unique users who tweets given word combinations within the specific region in the given day
2. Compare the user counts with the previous day's counts
   ⇒ burst detection



Estimating locations of non-geotagged photo tweets

- The number of geotagged photo tweets is very limited (2-3%) ⇒ use non-geo photo as well
- Judge if a non-geotagged photo tweet including the given event words is posted from the area of the event
  - two class classification (in area/out of area)
- Use geotagged photo tweets as training data
  - positive: event-related tweets
  - negative: tweets including event words posted from out of the area

Estimate Locations of Non-geotagged Photos using both texts and image features

- Text: Naive Bayes
- Image: Naïve Bayes Nearest Neighbour (NBNN, Boiman et al. CVPR2008)
  - Local feature(SIFT) based image classification
  - The sum of cos similarity between local features and nearest features in training sets.

$$\hat{c} = \arg\max_{c} P(c) \underbrace{\boxed{\prod_{i=1}^{n} P(x_i \mid c)}}_{\text{text}} \underbrace{\boxed{\sum_{j=1}^{v} \frac{d_j \cdot NN_c}{\|d_j\| \|NN_c\|}}}_{\text{image}}$$

$c \in \{event\ tweet, unrelated\ tweet\}$ NN_c

Event Photo Clustering

- Image features
  - DCNN activation features (4096 dim) (Alexnet pretrained with ImageNet1000)

- Photo clustering: Ward method
  - a hierarchical clustering method

$$E(C) = \sum_{x \in C}\left(\left(x_{BoF} - \overline{x_{BoF}}\right)^2 w_{BoF} + \left(x_{RGB} - \overline{x_{RGB}}\right)^2 w_{RGB}\right)$$

- Representative photo
  - A photo which is the closest to the center of the largest cluster

Expetiments

- Tweets Dataset
  - Collect via Twitter Streaming API
  - Limit Tweets posted only from Japan
  - train: Whole, 2012 (training for NB/NBNN)
  - test: August, 2012 (target for event detection)

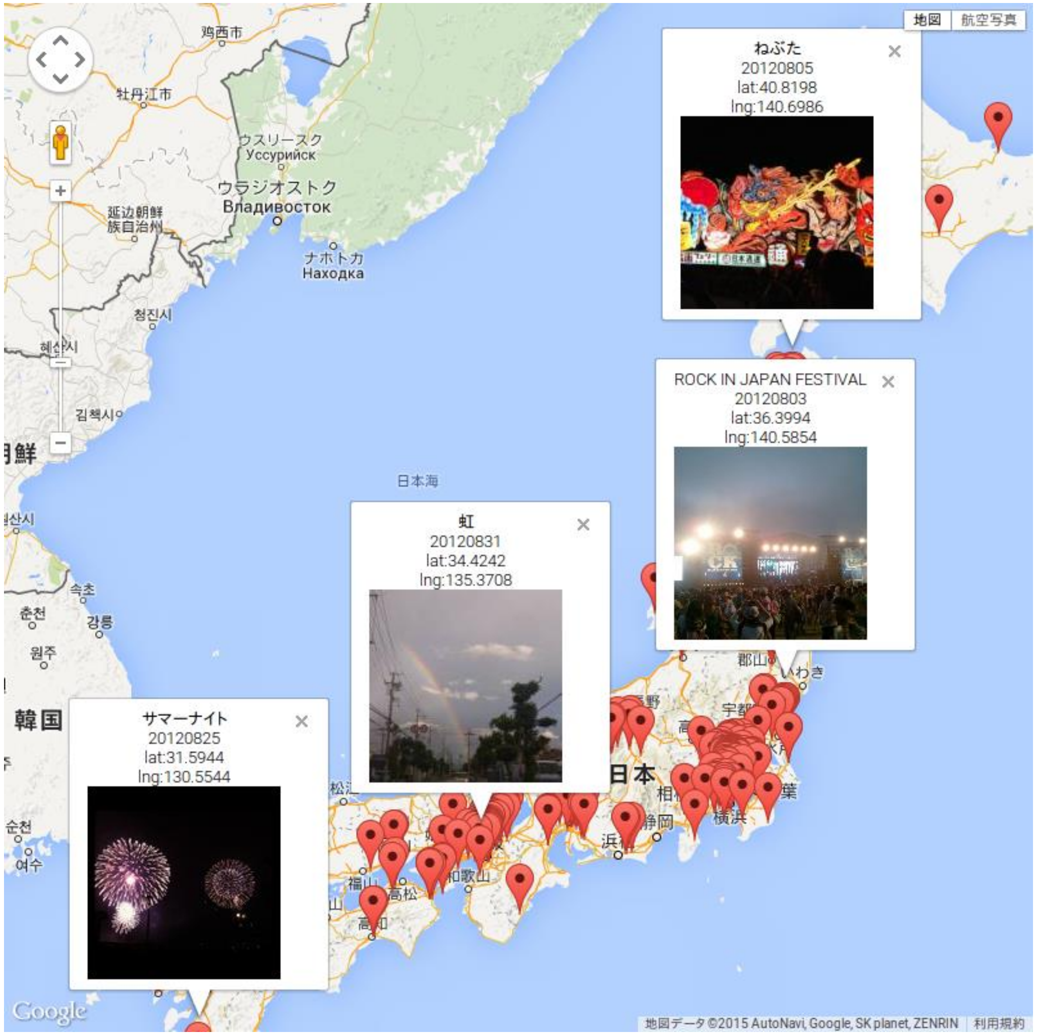
(We have many festivals in August.)

	2012 whole	Aug. 2012
Geotagged photo	2,645,709	255,455
Only Geotag	24,715,962	2,102,151
Only Photo		3,367,169

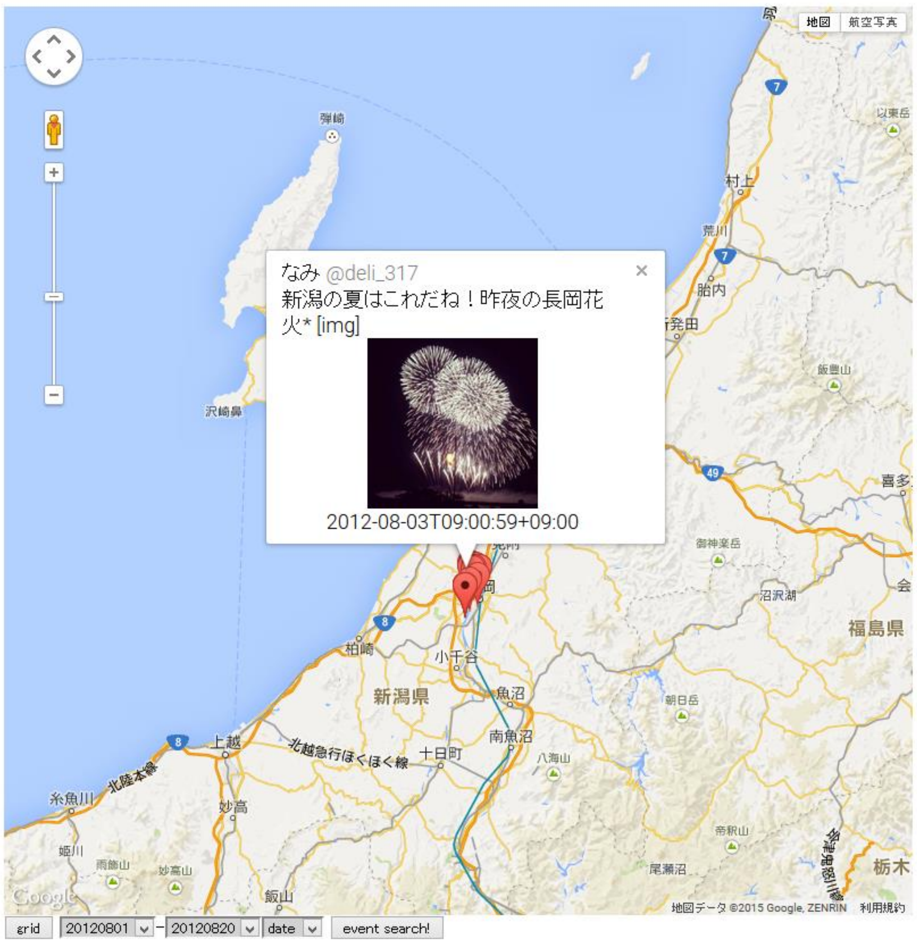
Detected Event Words (8/2012)

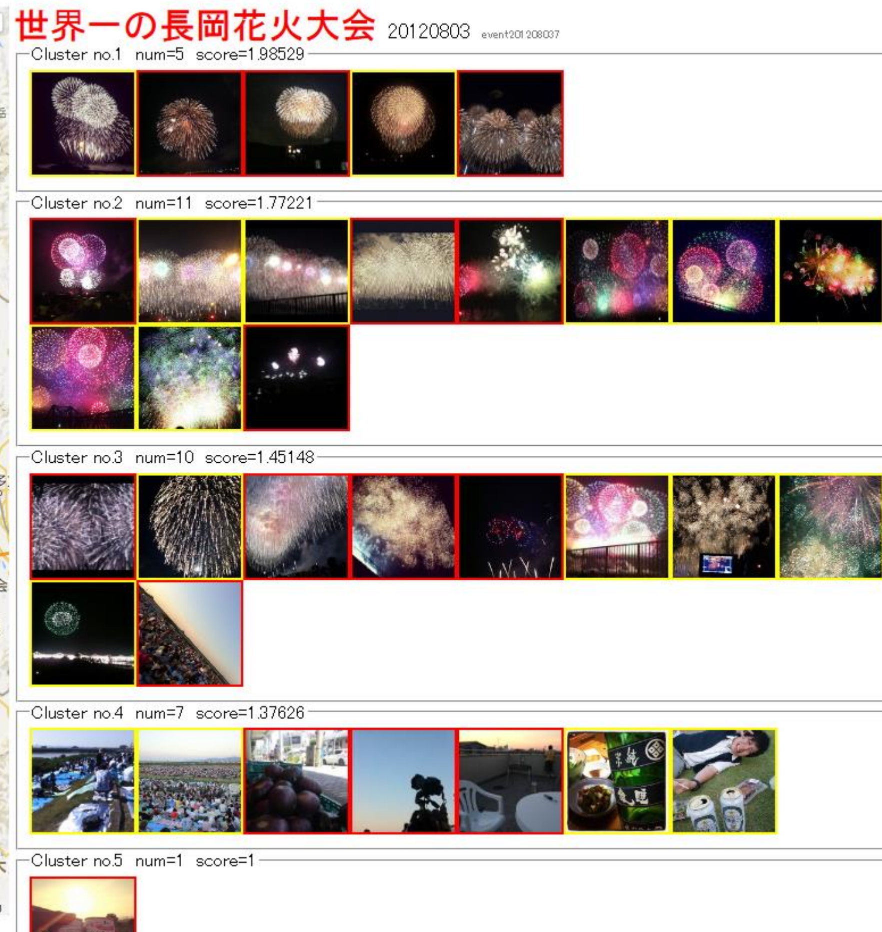
Event word	date	Locatio (lat,lng)	Eval. score
Firework	20120801	33,129.5	297.7
rainbow	20120801	34,134.5	229.1
ROCK IN JAPAN	20120803	36,140	430.3
Ayu Festical	20120804	34.5,135.5	265.1
Nebuta Festival	20120806	40.5,140	255.7
Awa Festival	20120814	34,134	589.8
Thunder storm	20120818	34,135	367.5
Blue moon	20120831	34.5,136	269.7

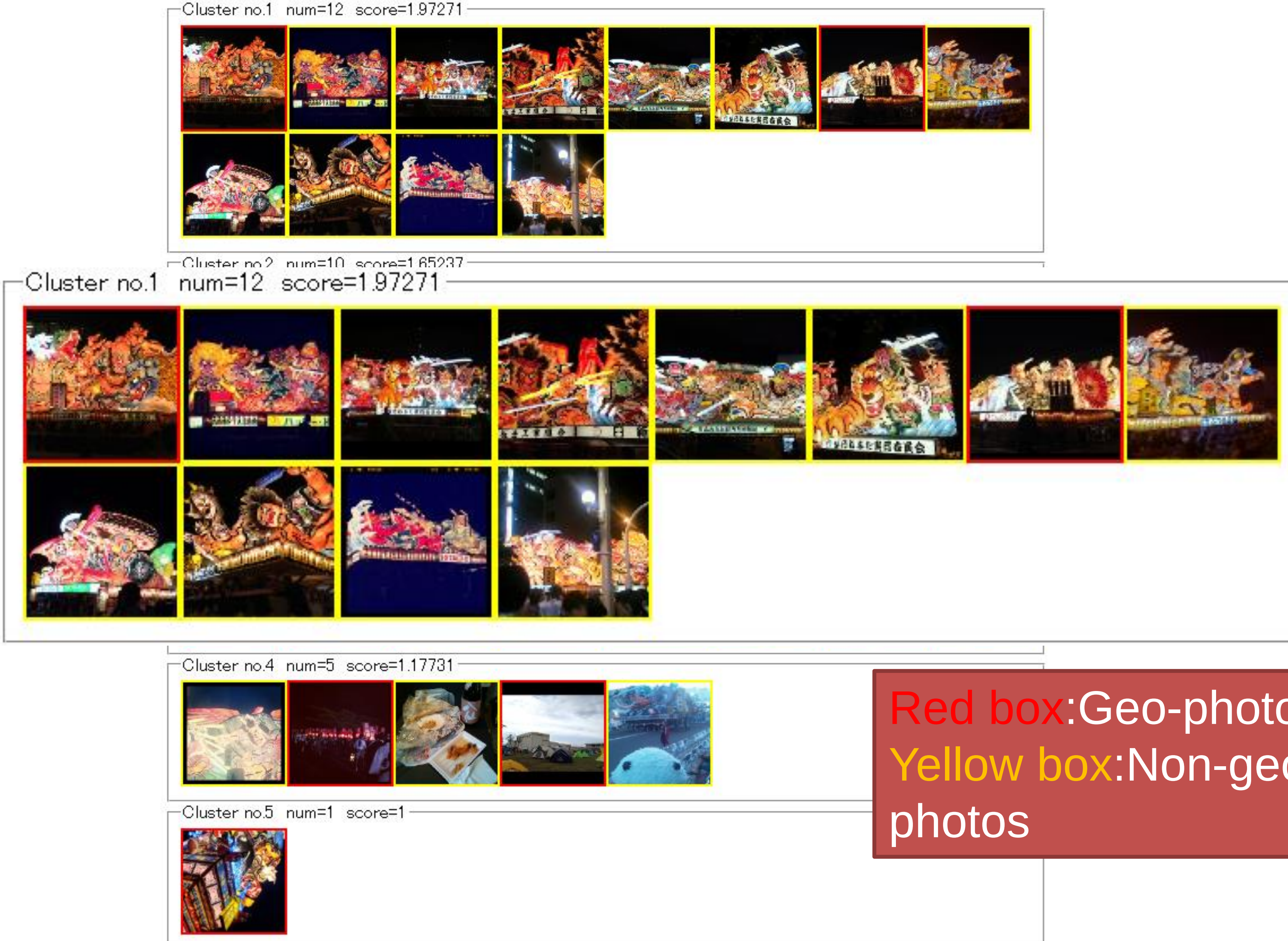
Events with representative event photos on Google Maps



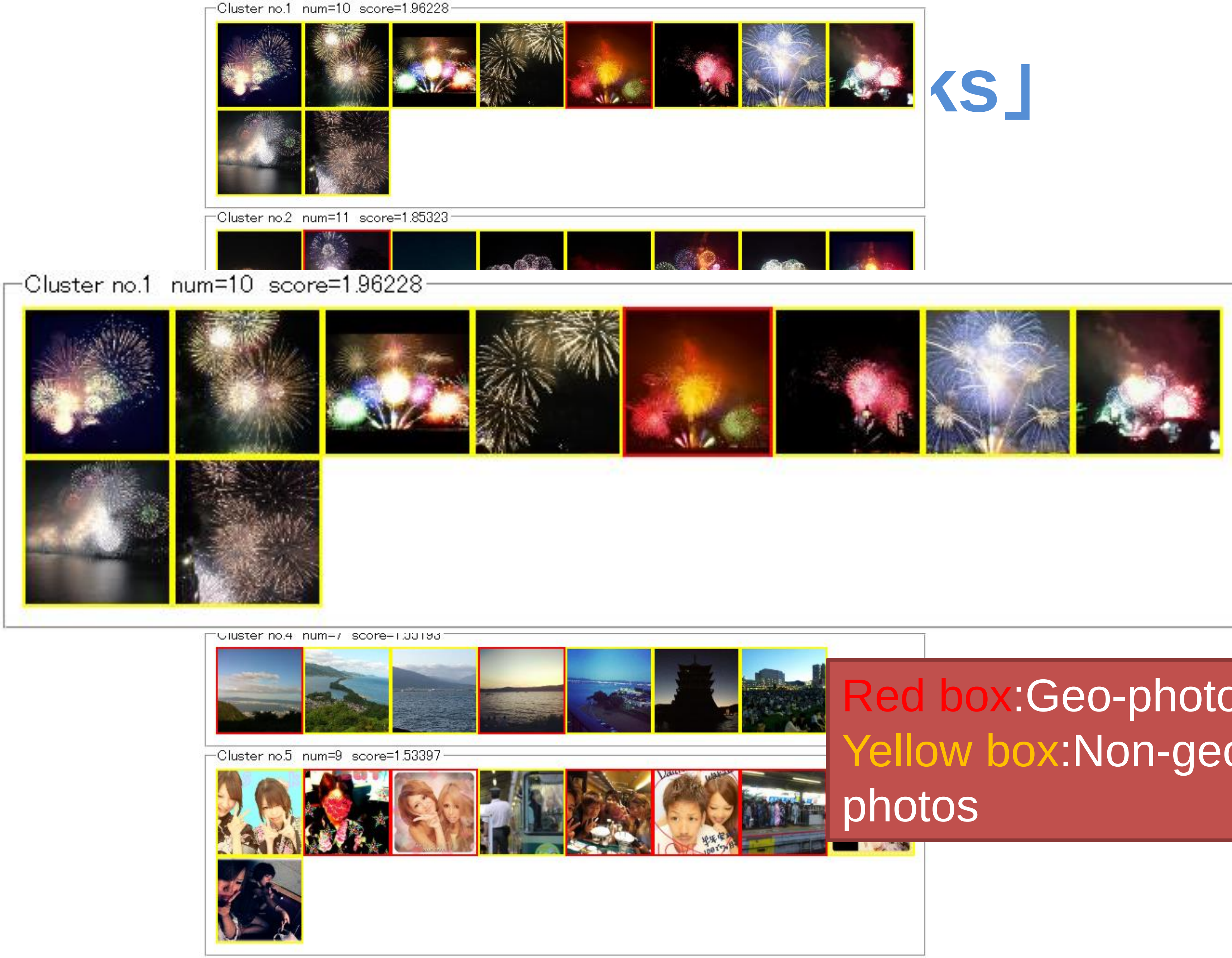
Event Photos on “Nagaoka firework festival”







Red box:Geo-photo
Yellow box:Non-geo photos



Red box:Geo-photo
Yellow box:Non-geo photos

「S… …stival」

Red box:Geo-photo
Yellow box:Non-geo photos

Summary of event detection

	This work	previous
# events	310	35
Event precision(%)	81.3	77.1
Photo precision(%)	88.7	65.5

- The num. event: 10 times
- イベントの精度は約4%向上
- 代表画像の適合率は大幅に改善

Conclusions

- Proposed a method to detect events and corresponding photos from Twitter
- Proposed a method to detect event photos from non-geotagged photos
  - Use both text and visual features with NB and NBNN
- Future work
  - Detailed evaluation
  - Realtime event detection

Unification and Complement

- Unification keyword

  -more than half of the same tweets

  -Use the highest score keyword

  “shuttle”, “Endeavor” → “shuttle”

- Complement keyword

  -more than 80% of the same word

  -before and after the keyword

  “Festival” → “Music Festival”

Event Photo Clustering

- Image features

  -Bag-of-Features with SURF

  -Color histograms

- Ward method

  -a hierarchical clustering method

  -threshold is 300(both)

$$E(C) = \sum_{x \in C}\left(\left(x_{BoF} - \overline{x_{BoF}}\right)^2 w_{BoF} + (x_{RGB} - \overline{x_{RGB}})^2 w_{RGB}\right)$$

Event Photo Selection

- Select a representative cluster

  -evaluate cluster score on representativeness

$$V_C = \frac{{\#photos_C}^2}{E(C)} W_{area}$$

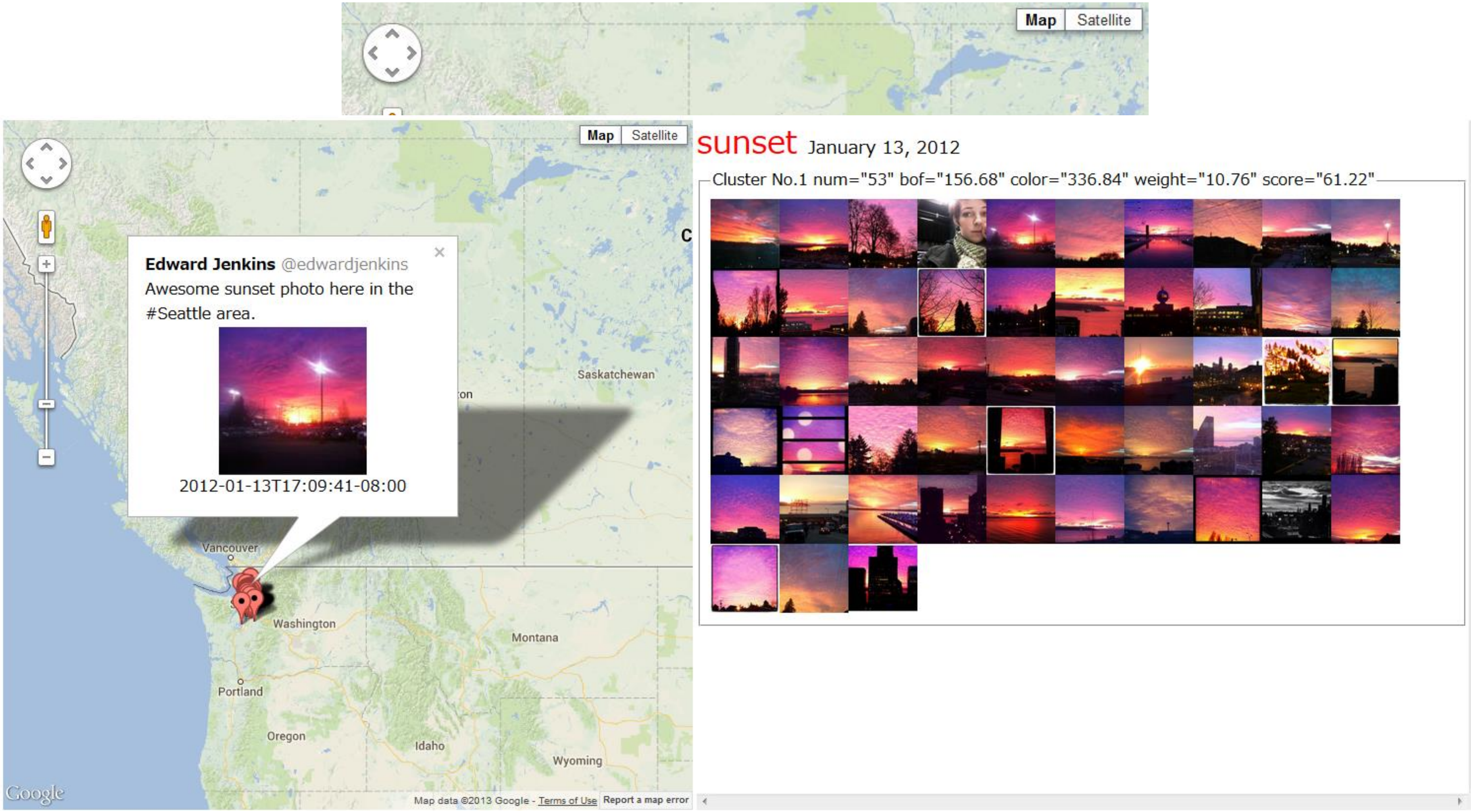
- Select a representative photo

  -from the maximum score cluster

- Eliminate lower score cluster

  -less than 5(JPN) , 20(USA)

“River's Edge Music Festival”



Map
Satellite
Edward Jenkins @edwardjenkins
Awesome sunset photo here in the #Seattle area.
2012-01-13T17:09:41-08:00
Saskatchewan
Vancouver
Washington
Montana
Portland
Oregon
Idaho
Wyoming
Google
Map data ©2013 Google - Terms of Use
Report a map error
sunset January 13, 2012
Cluster No.1 num="53" bof="156.68" color="336.84" weight="10.76" score="61.22"

“sunset”

Conclusion

- Event detection with geo-tweet photos
  - -Detection of keywords
  - -Selection of representative photos
- Detection results
  - -258 events in Japan dataset
  - -1676 events in US dataset
- Accuracy of representative photos
  - -65.5% in Japan dataset
  - -72.5% in US dataset

Future Works

- Flexible detection
  -Variable size of grid
  -Variable term for detection
- Real-time detection
- Improvement of methods for selection representative photos

More results…

- ICME demo session on July 18th