Real-time Photo Mining from the Twitter Stream:
Event Photo Discovery and Food Photo Detection

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Keiji Yanai and Yoshiyuki Kawano

The Univ. of Electro-Communications, Tokyo, Japan

Background

- Various kinds of photos are posted to microblogs every minutes.
- The photos on the microblogs are uploaded with text messages.

- Microblogs such as Twitter can be regarded as another tagged photo source than Flickr.

twitter flickr™

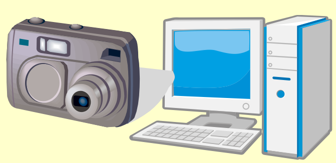
Twitter vs. Flickr as photo sources

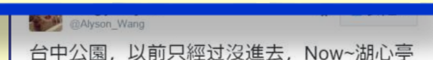
flickr™ Photo sharing

twitter Micro-blog

- Travel, special event
- w/ **keywords, description**
  - describing the contents
- **offline** uploading

- Everyday life
- w/ **tweet messages**
  - Not describing
- **instant (online)**





The biggest difference is
offline or online

Twitter photos are more helpful to understand
the current state/trend of the worlds .

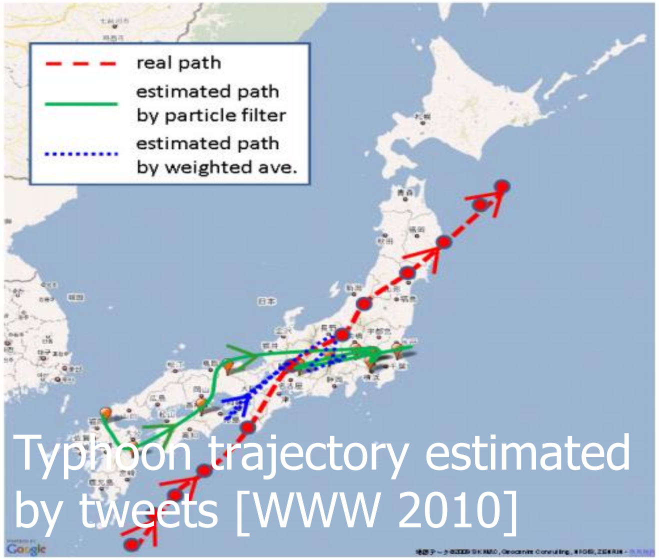
So many works with flickr™

Flickr tags are reliable, which can be regarded as "concept labels".

- Flickr Distance [ACM MM 2008]
  - Measuring concept distances
- Concept difference [CIVR 2009]
  - Detection of regional concepts
- IM2GPS [CVPR 2008]
  - Estimating photo locations with million-scale geotagged photos
- Travel Analysis [ACM MM 2010]
  - Travel trajectory analysis with geo-photos

Many text mining works with twitter

- Text analysis
  - Event detection
  - Trend mining
  - Positive/Negative reputation



Typhoon trajectory estimated by tweets [WWW 2010]

- Photo analysis ⇒ very limited
  - Evaluation of relatedness between msg. and img.
  - Brand image mining
  - Our works (event/food photo mining)

Related works on TW photos

- Classifying "visual"/"non-visual" tweets by generic methods [Chen et al. MM13]

70.5 %

Visual

陈建斌怎么看怎么还是曹操的样子啊！(No matter how I look at it, Chen Jianbing looks like Cao Cao!)

Non-visual

可恶的蚊子，我要杀了你！
(Horrible mosquitoes, I will kill you!)

- Brand image mining [Gao et al. ICMR 2014]
  - Supervised logo detector

Our works on Twitter photos

- Real-time TW geo-photo mapping system [ICMR 2012]
- Visual topic analysis on TW photos [new results]
- Event photo mining [ICME WS 2013]
- Food photo mining [PCM 2014]

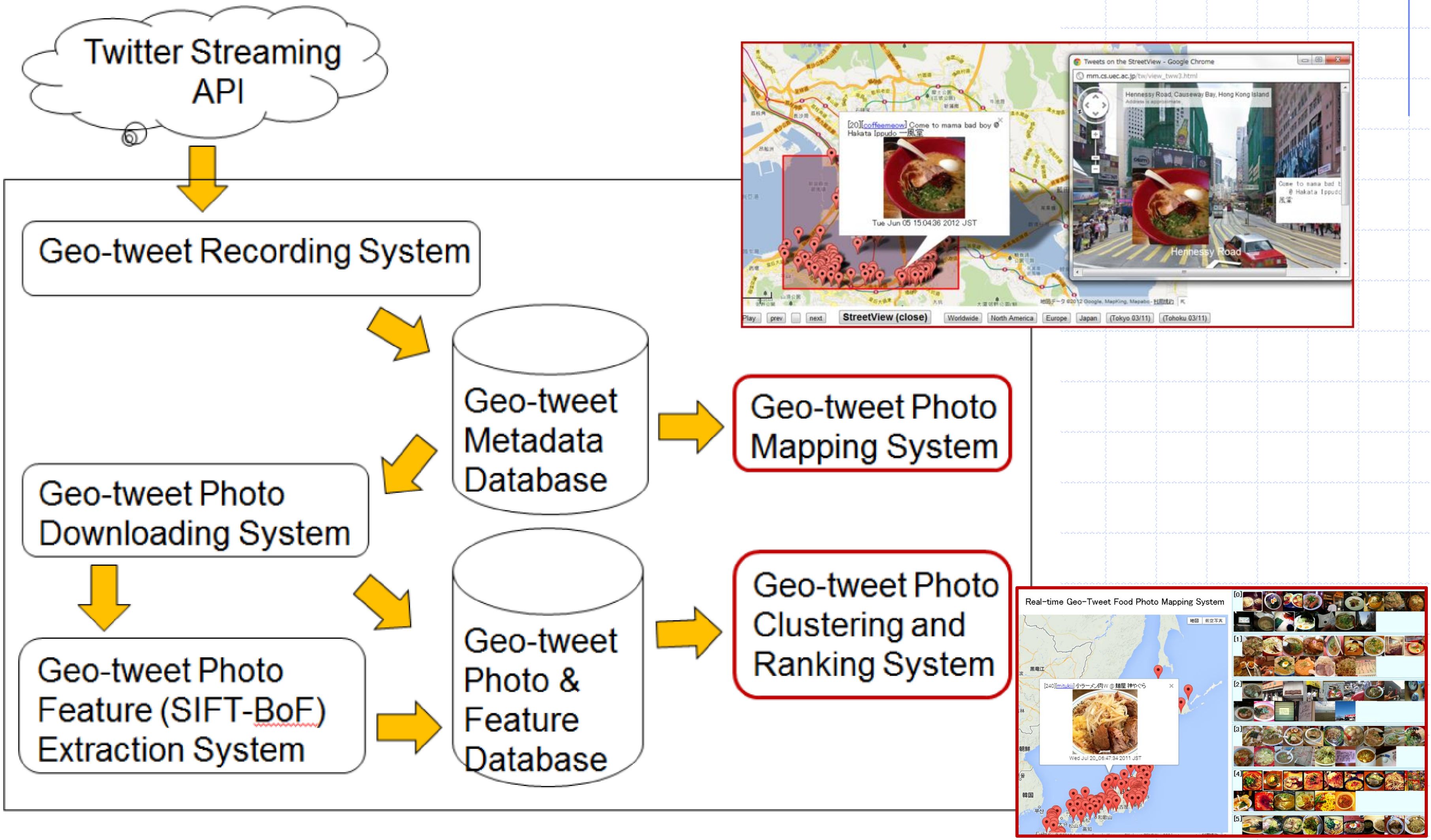
World Seer: A Real-time Geo-Tweet Photo Mapping System

ICMR 2012

World Seer: Real-time Twitter Photo Mapping System [ICMR 2012]

Build geo-photo tweet database for research

Monitoring the TW stream & Recording Geo-Photo Tweets



demo

- http://mm.cs.uec.ac.jp/tw/

Tweet photo database

- Since Feb. 2011
  - 1 billion photo tweets
  - 200 million geo-photo tweets

- We are doing several researches with this data
  - Event Photo Mining
  - Food Photo Mining
  - Visual Topic Analysis

Characteristic of the Twitter photos

- Normal condition : everday life
  - Food
  - Scene
  - People
- Something special: event photos
  - Artificial public events   sport games
  - Natural phenomena   earthquake, typhoon
  - Personal events
    - go hiking, travel, birthday

Twitter photos: special event

Special big event photos on March 11th 2011 around Tokyo area

Twitter photos: special event

Everyday-life photos on March 11th 2011 in the western part of Japan

Visual Topic Analysis of Twitter Photo Analysis

Unpublished.

demo

- http://mm.cs.uec.ac.jp/twimg/
- http://mm.cs.uec.ac.jp/twimg/dcnn.cgi

Food is one of the major topics of Twitter photos

- Visual topic analysis with half-million Twitter photos employing DCNN fea.

Mining two types of photos

- Event photo : special

- Food photo: everyday-life

Twitter Event Photo Mining

Takamu Kaneko and Keiji Yanai: **Visual Event Mining from Geo-tweet Photos**, IEEE ICME Workshop on Social Multimedia Research (SMMR), (2013).

Demo

- http://mm.cs.uec.ac.jp/kaneko-t/tw/jp/index.html
- http://mm.cs.uec.ac.jp/kaneko-t/tw/us/index.html

Twitter Event Photo Mining

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

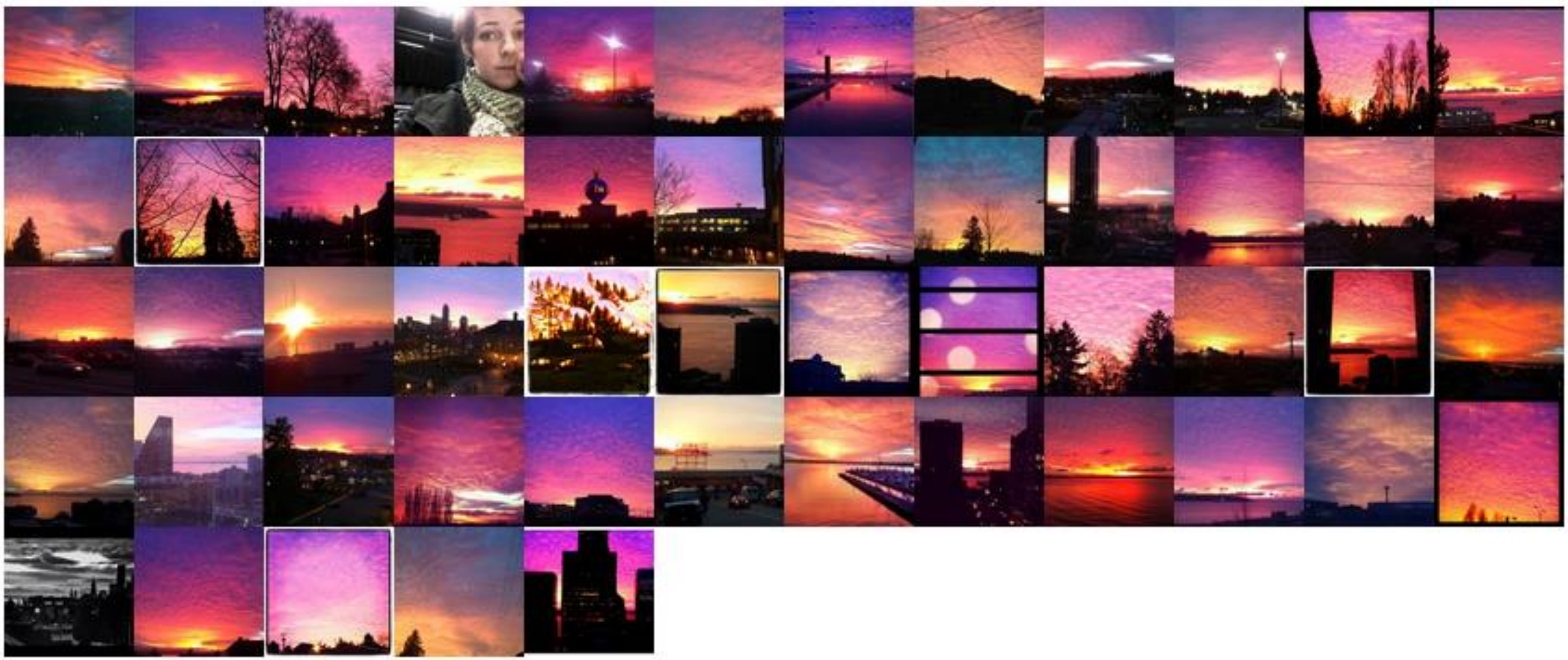
The results of detected event photos in 2012

Twitter Event Photo Mining

sunset January 13, 2012

sunset January 13, 2012

Cluster No.1 num="53" bof="156.684" color="336.837" weight="10.757" score="61.224"



Objective

- Detect events from Twitter stream
  - –Weather, natural events
  - –Festivals, sport games
- Understand events visually
  - –Select representative photo
  - –Map in a map

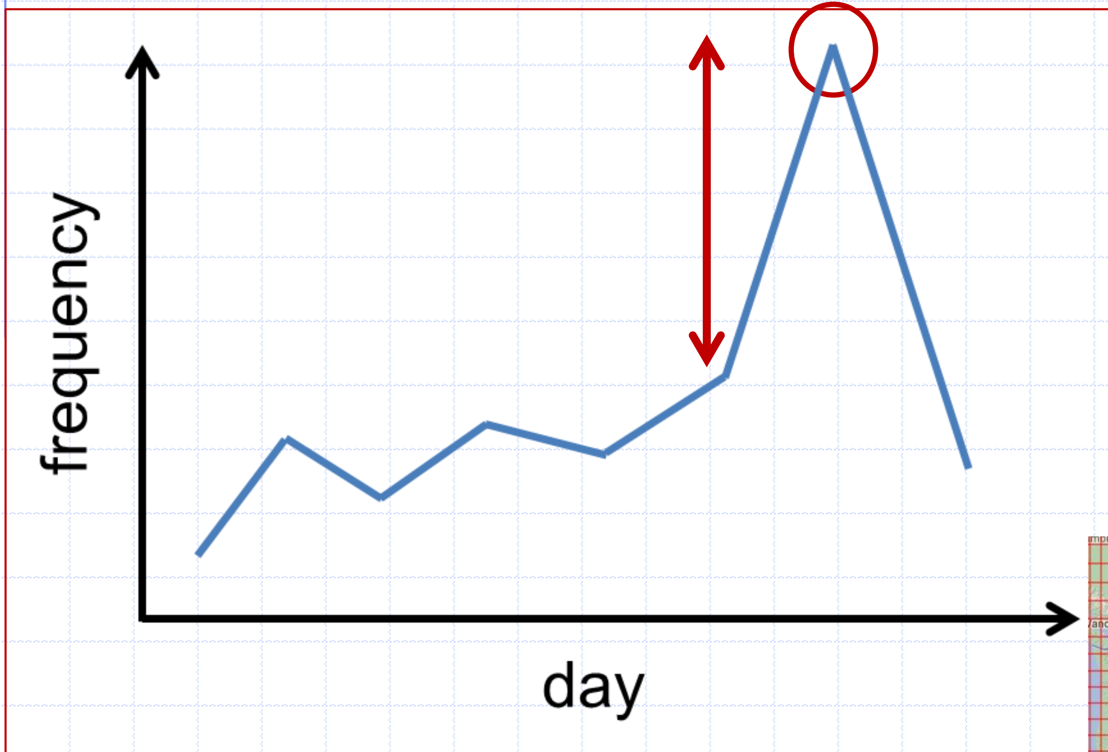
Mapping events with the photo

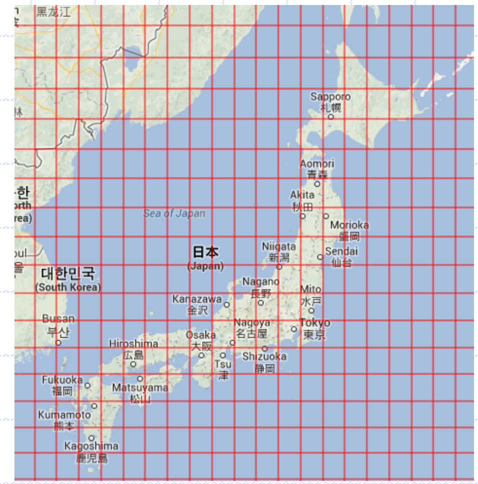
Processing flow

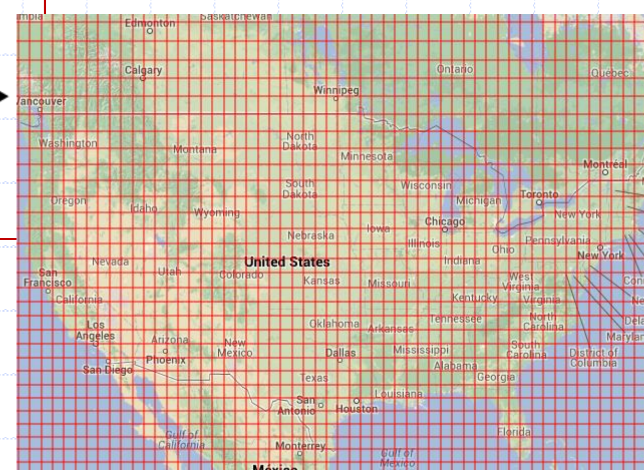
1. Event keyword detection
2. Keyword unification
3. Event photo clustering
4. Mapping event with photos

Event Keyword Burst Detection

- Examine change of daily frequency







Keyword Unification and Complement

- Unification keyword
  - more than half of the same tweets
  - “shuttle”, “Endeavor” → “shuttle”
- Complement keyword
  - more than 80% of the same word
  - b “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)

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

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)

Experiments

- Japan Dataset 1 in Japan
  - Feb 10th, 2011 to Sep 30th, 2012
  - about 3 million geo-tweet photos
- US Dataset
  - Jan 1st, 2012 to Dec 31st, 2012
  - about 17 million geo-tweet photos

Results of Keyword Detection

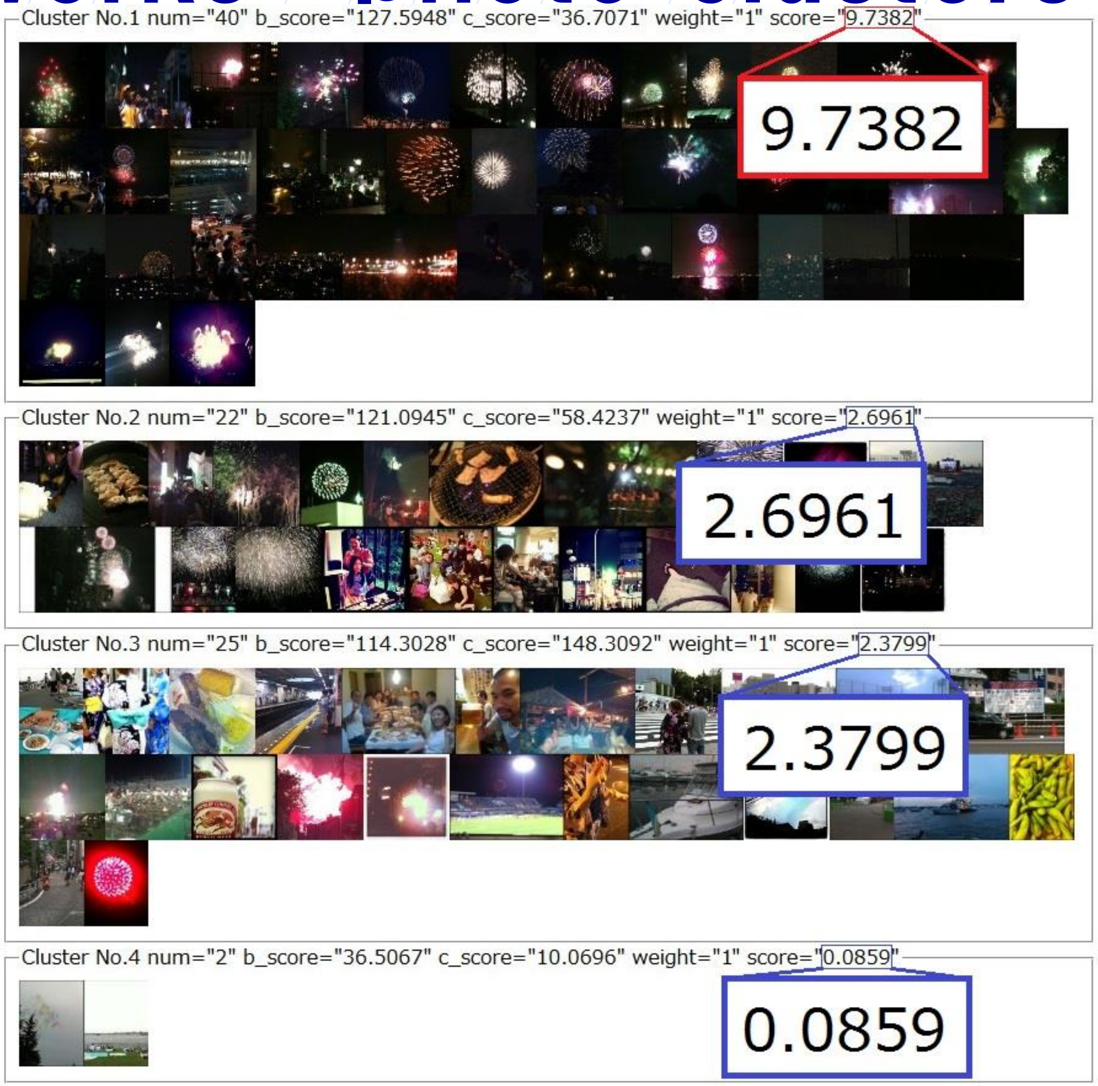
Keyword	Date
snow	11/02/2011
earthquake	11/03/2011
fireworks	06/08/2011
typhoon	21/09/2011
Mt. Fuji	24/09/2011
Apple	06/10/2011
eclipse	10/12/2011
illumination	10/12/2011
Christmas	24/12/2011
New years eve	31/12/2011
sunrise	01/01/2012
firefly	06/05/2012

Japan

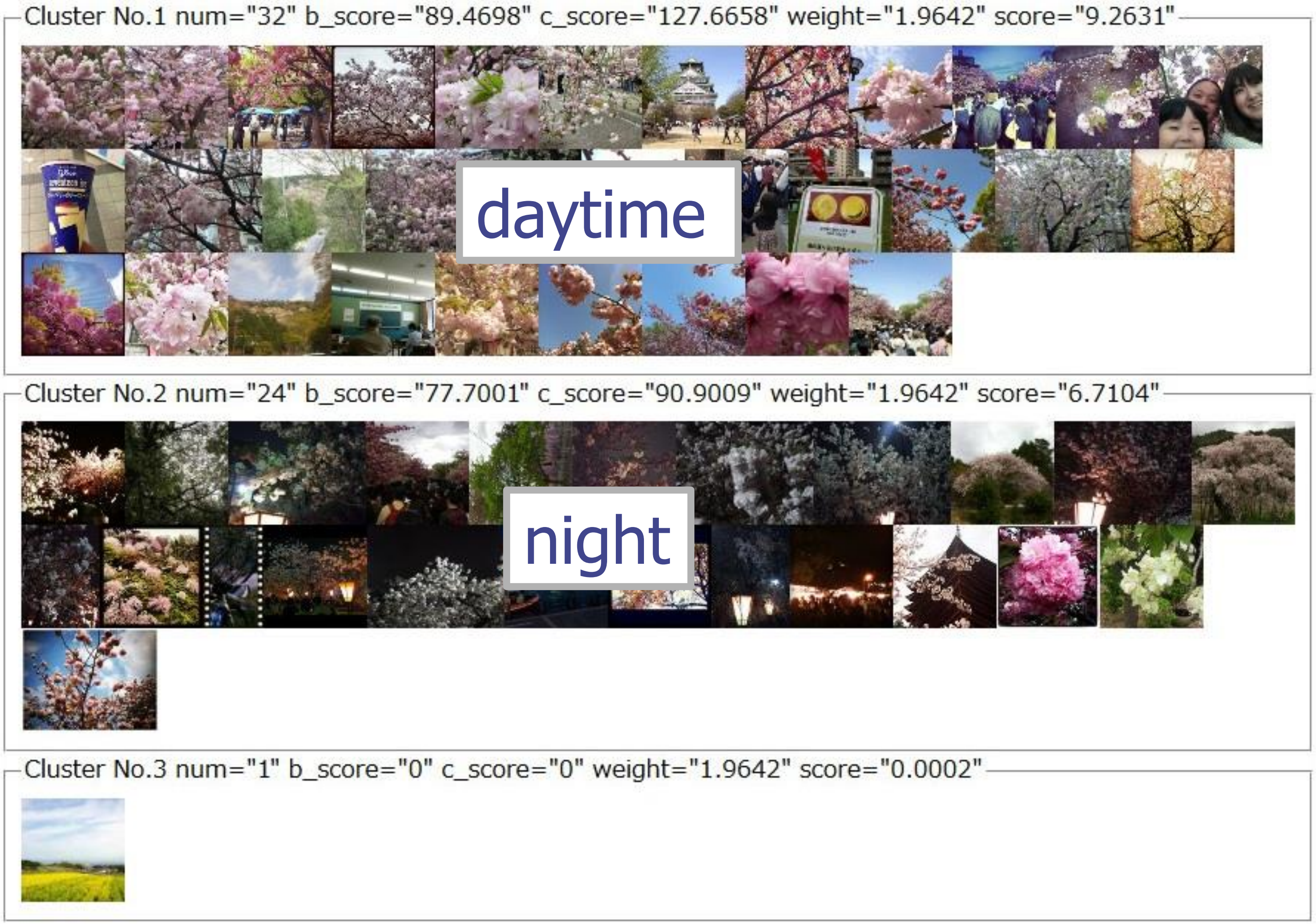
Keyword	Date
snow	09/01/2012
sunset	13/01/2012
Grammy	12/02/2012
Valentines	14/02/2012
SXSW	09/03/2012
Easter	08/04/2012
shuttle	17/04/2012
WWDC	10/06/2012
hurricane	26/08/2012
rainbow	05/09/2012
49ers	18/10/2012
NYE	31/12/2012

USA

“fireworks” photo clusters



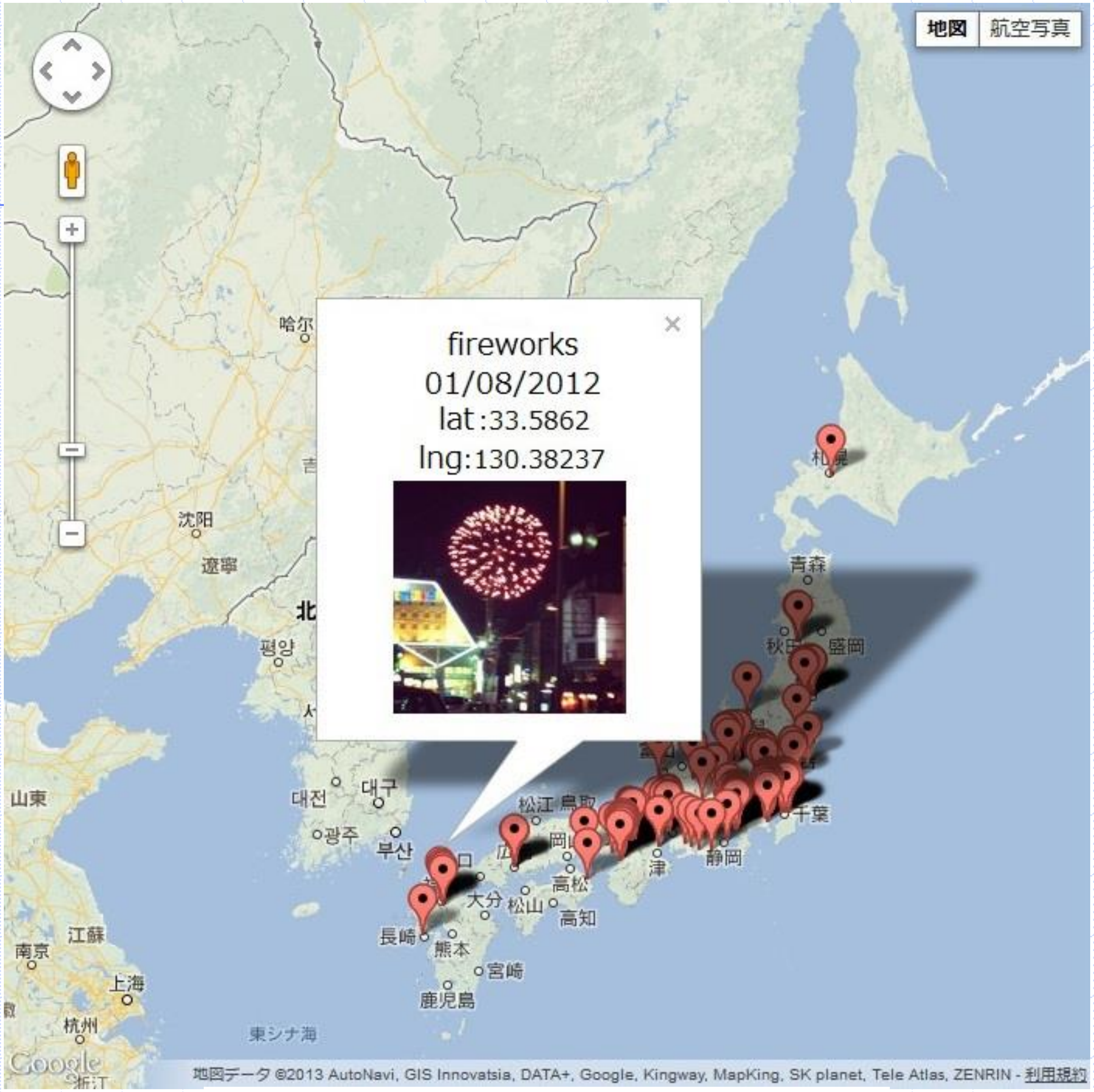
“cherry blossoms” photo clusters



Mapping Results

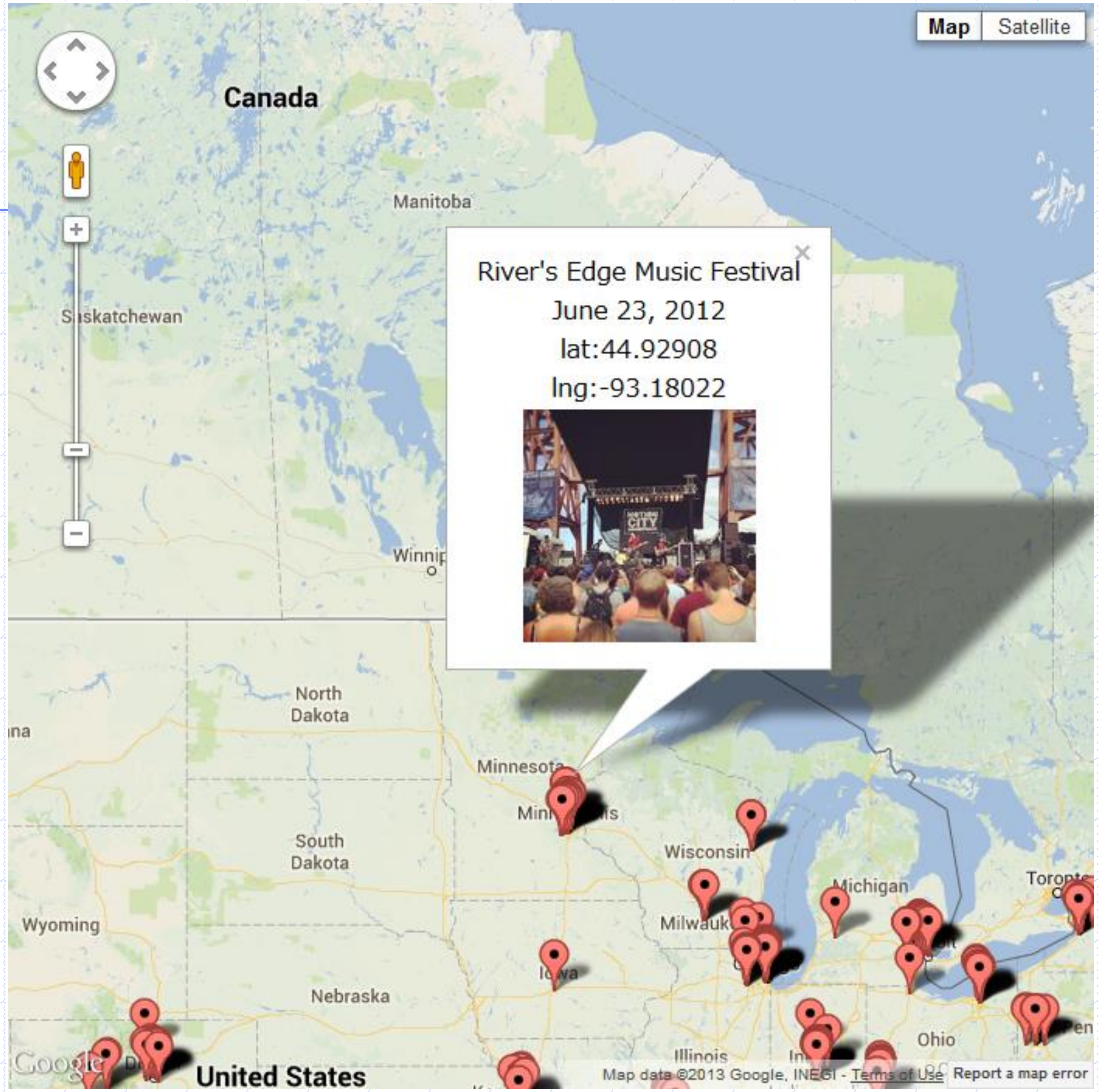
- Map event in a map
  - Calculate coordinates of event
  - Correspond information and the photo
- Summary of results

	Japan	USA
# events	258	1676
accuracy	65.5%	72.5%

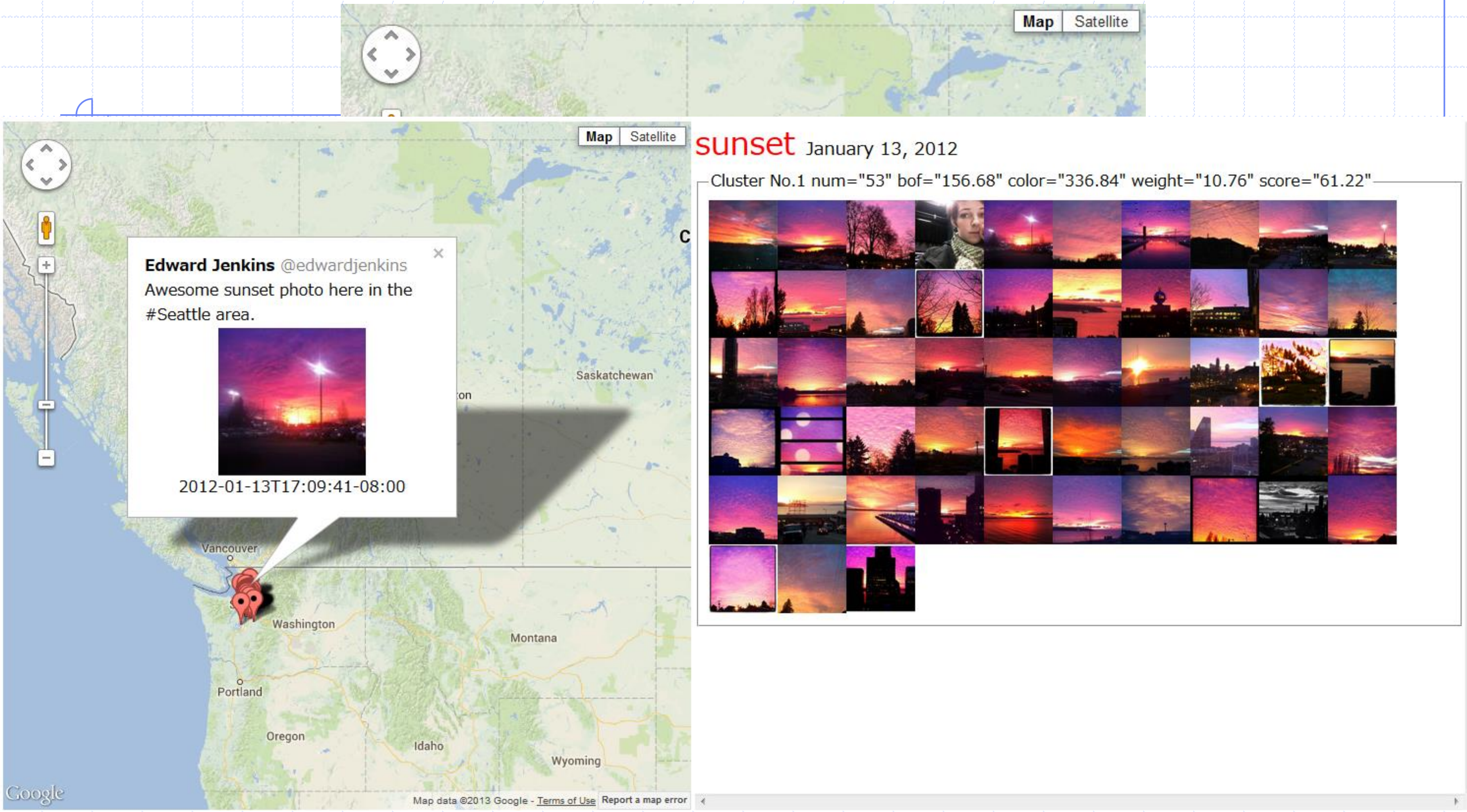


Result by photo data set

“fireworks”



“River’s Edge Music Festival”


Map
Satellite
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"

Twitter Real-time Food Photo Mining

Keiji Yanai and Yoshiyuki Kawano: Twitter Food Image Mining and Analysis for One Hundred Kinds of Foods , Pacifit-Rim Conference on Multimedia (PCM), (2014).

Yoshiyuki Kawano and Keiji Yanai, **FoodCam: A Real-time Food Recognition System on a Smartphone**, Multimedia Tools and Applications (2014). (in press) (http://dx.doi.org/10.1007/s11042-014-2000-8)

Twitter Realtime Food Photo Mining System (mm.cs.uec.ac.jp/tw/)

- What kinds of foods are being eaten in Japan ?

- Which food is the most popular in Japan?
  - "Ramen vs Curry" problem ⇒ very controversial
  - I would like to put a period to this controversy by Twitter food photo mining !!!

Approach for food photo mining

- Two-step food photo selection
  - [1] Keyword-based tweet selection
  - [2] Image-based photo selection
    - Generic food/non-food classification
    - Specific food classifiers (100 kinds)

Targets: 100 kinds of foods
in the UEC-Food100 data set

- Includes common foods in Japan
- Has more than 100 images/category

[1] Keyword-based selection

- Select the photo tweets the messages of which include any of 100 kinds of food names
  - In the experiments, we used Japanese food names.
  - We tried query expansion as well.

e.g.) I came to eat ramen noodle.
Very delicious ramen !!!
Ramen is my life.

[2] Two-step image-based selection

[2-1] Food/non-food classification

- Remove non-food photos and select only food photos

[2-2] Specific food classifiers

- Extended version of FoodCam recognition engine. 1-vs-rest 100-class classification
- Select the food photo if the corresponding food category is ranked within the top five.

I ate sushi ! → 100-class food classification → [top-5] Pizza, ramen, curry, sushi, tempra → Sushi Photo

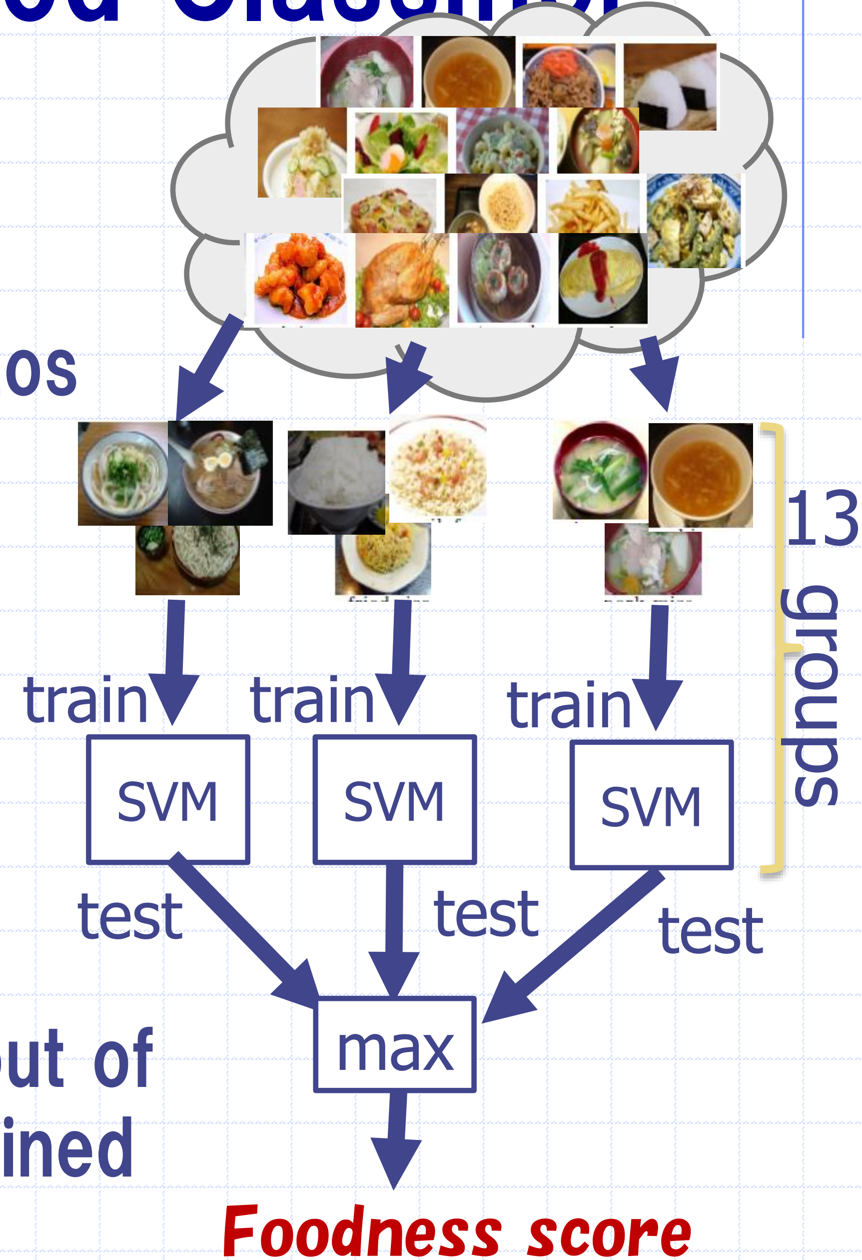
Food recognition method

- Local patch + Fisher Vector + linear SVM
  - Color patch, HOG patch
    - Color: 24 dim HOG: 32 dim
    - dense sampling
  - GMM: K=64
  - Spatial Pyramid: 1x1 + 2x2
  - Improved Fisher Vector [Perronnin et al.2010]
    - Color: 15360 dim, HOG: 20480 dim
  - Classifier
    - Linear SVM

[2-1] Food/non-food Classifier

- Train 13 linear SVMs
  - Pos.: UEC-FOOD 100
  - Neg.: typical irrelevant photos
    - Inside/outside restaurant
    - Menu, people eating, …

- Classify of food/non-food
  - The maximum value of output of 13 classifiers with pre-defined threshold values



[2-2] 100-class specific food category recognition

- 100-class food classification engine
  - Extended version of FoodCam
    [Kawano et al. MTA14]
  - Very fast (0.025 sec. / image)
    - Multi-threaded implementation optimized for quad core CPU

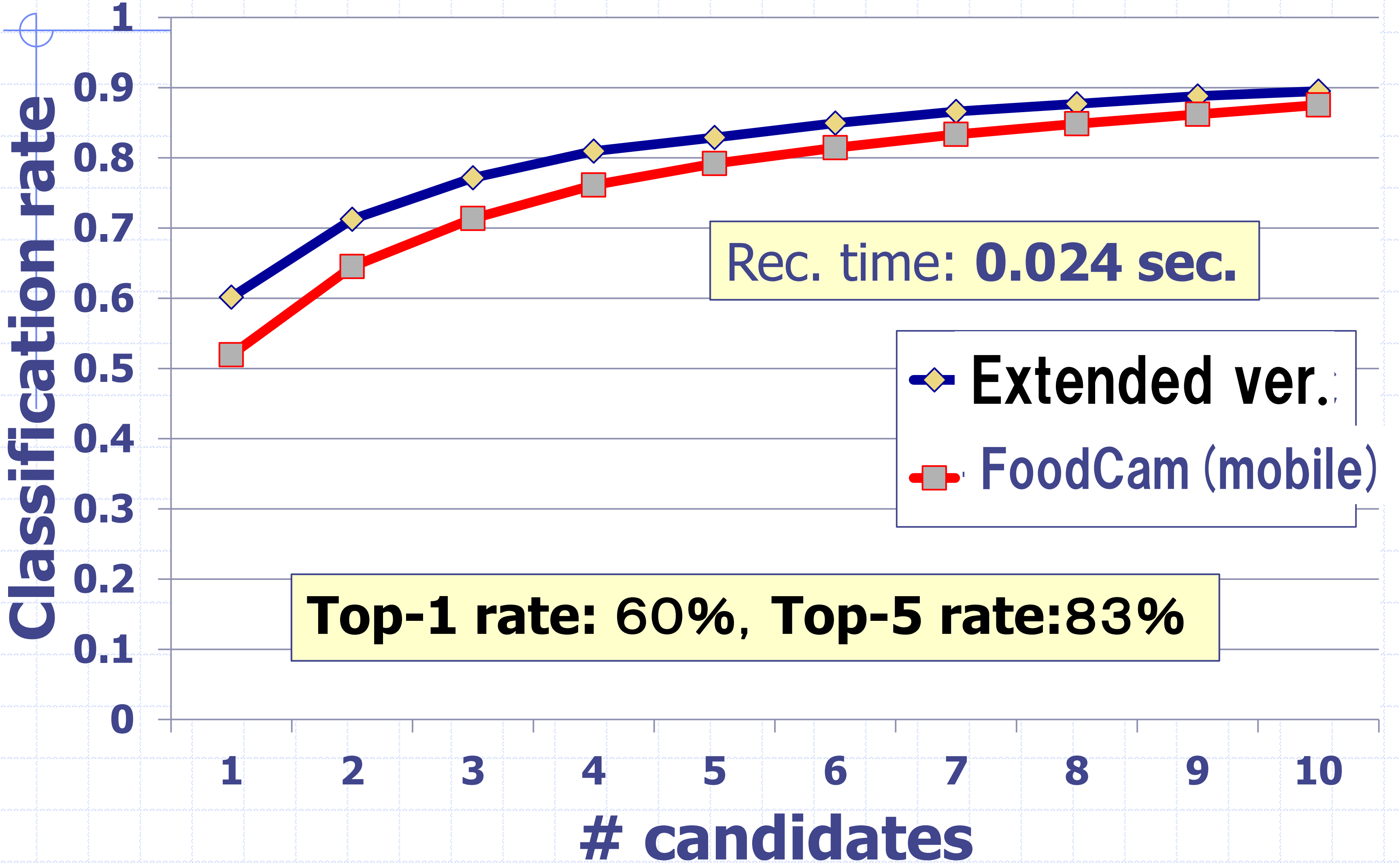
      → Suitable for big data recognition
  - HOG-FV + Color-FV + 1-vs-rest linear SVM

http://foodcam.mobi/

FoodCam : [Kawano et al. MTA13]

- Real-time mobile food recognition Android application

100-Class classification rate



Experiments

- Collect photo tweets via Twitter Streaming API
  - From 2011/5 to 2013/8
  - About one billion tweets
- Search for the tweets including any of 100-food names（in Japanese)
  - 1.7 million ⇐ Apply food image analysis
- Food/non-food classifier
  + 100-food classifier
  - 470,335 food photos

Evaluations on five kinds of representative food

- Num. of obtained food images
- Precision (random sampling of 300imgs)
  (1) Only keyword search
  (2) Keyword + food/non-food classifier
  (3) Keyword + specific food classifier
  (4) All (kw+food/non-food+specific) proposed

- Geographic analysis with geotagged photos
  - Ramen vs Curry

Twitter food photo ranking

rank	foods	#photos

Ramen noodle is the most popular food in Japan.
I have solved "ramen vs curry" problem !!!

Precision of the top 5 foods

Food	(1) KW	(2) f/n	(3) spec.	(4) ALL
ramen	275,652 **72.0%**	200,173 92.7%	84,189 95.0%	80,021 **99.7%**
curry	224,685 **75.0%**	163,047 95.0%	62,824 97.0%	59,264 **99.3%**
sushi	86,509 **69.0%**	43,536 86.0%	48,019 72.3%	25,898 **92.7%**
tsukemen	33,165 **88.7%**	24,896 96.3%	28,846 93.7%	22,158 **99.0%**
omelet	34,125 **90.0%**	28,887 96.3%	18,370 98.0%	17,520 **99.0%**

Only keyword search (Ramen noodle) (72.0%)

After applying food/non-food classifier (92.7%)

After applying 100-class food classifier (final) (99.7%)

Only keyword search (curry) (75.0%)

Final results (curry) (99.3%)

Some interesting findings

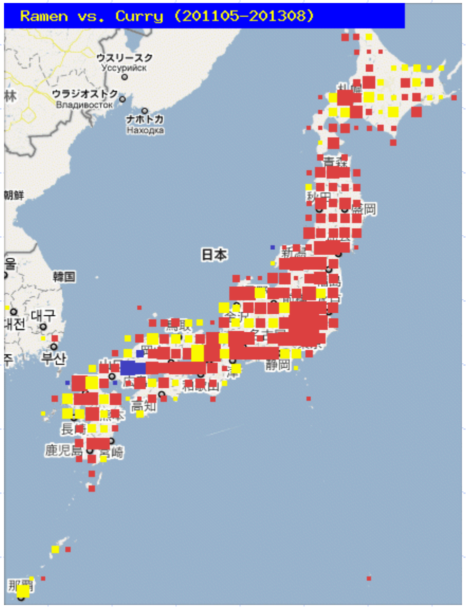
- Letters or drawings are sometimes drawn on omelets with ketchup

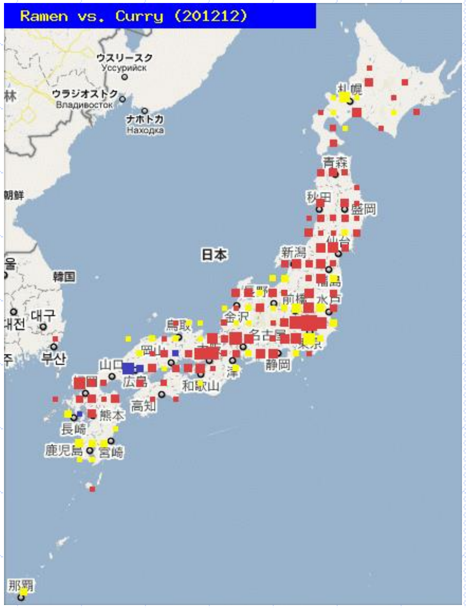
- Fast-foods such as humberger (rank 30^{th}) and beef bowl (rank 27^{th}) are ranked lower, since their appearance is always the same.

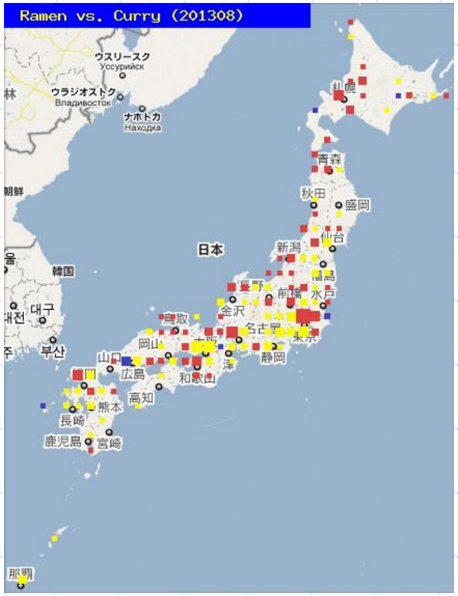
Not worth posting fastfood photos to Twitter

Geographical-Temporal analysis on ramen vs curry

12.6% of the obtained food photos have geotag.







Whole year

Dec. (winter)

Ramen is popular.

Aug. (summer)

Curry gets more popular than ramen in many areas.

Ramen Curry

Real-time Food Collection

- Monitor the Twitter stream
  - Photo Tweet
  - Text including any of 100 food names
    - 13 candidate photo tweets / minute on avg.
    - Download: 2～3sec. , recognition: ～1sec.
    - Single machine is enough！
- Recognize 20,000 photos and find 5,000 food photos from the TW stream everyday in our lab

Demo visualization system

- Map each food photo on an online map with online clustering [Yanai ICMR2012]
  - Geotagged Tweets
  - Non-geotagged Tweets for which GeoNLP can assign locations based on text msg.

- Overlay a food photo on the Streetview
  - Finding "ramen noodle shop" game !

http:/mm.cs.uec.ac.jp/tw/

Twitter Food Image Bots

- Bot who recognize food photos and return results
  - @foodimg_bot

- Bot who re-tweets food photo tweets automatically

Additional work for more Ramen Photos: Finding “Koike-san”

Koike-san is a Fujiko-Fujio comic’s character who loves “ramen noodle”.

*He is **always** eating “ramen noodle” when he appears in the comic.* (Wikipedia)

Finding "Koike-san" on Twitter
-query expansion based on user, loc & word-

- Pick up the top-*k* users who frequently post ramen photos.
  - (k=30 in the experiments)
- Apply food classifiers to all the photos "Koike-sans" posted.

raumenbot,657,0
toyamamenrui (map),128,128
oishii_bot2,107,0
Ramen___Bot,90,0
daikoubutsu_bot,88,0
shibumen,65,0
vientM535i (map),50,36
oishii_bot,45,0
kido_maru,42,0
ishikawamenrui (map),42,42
shomax96 (map),36,33
rAsAmAya (map),36,28

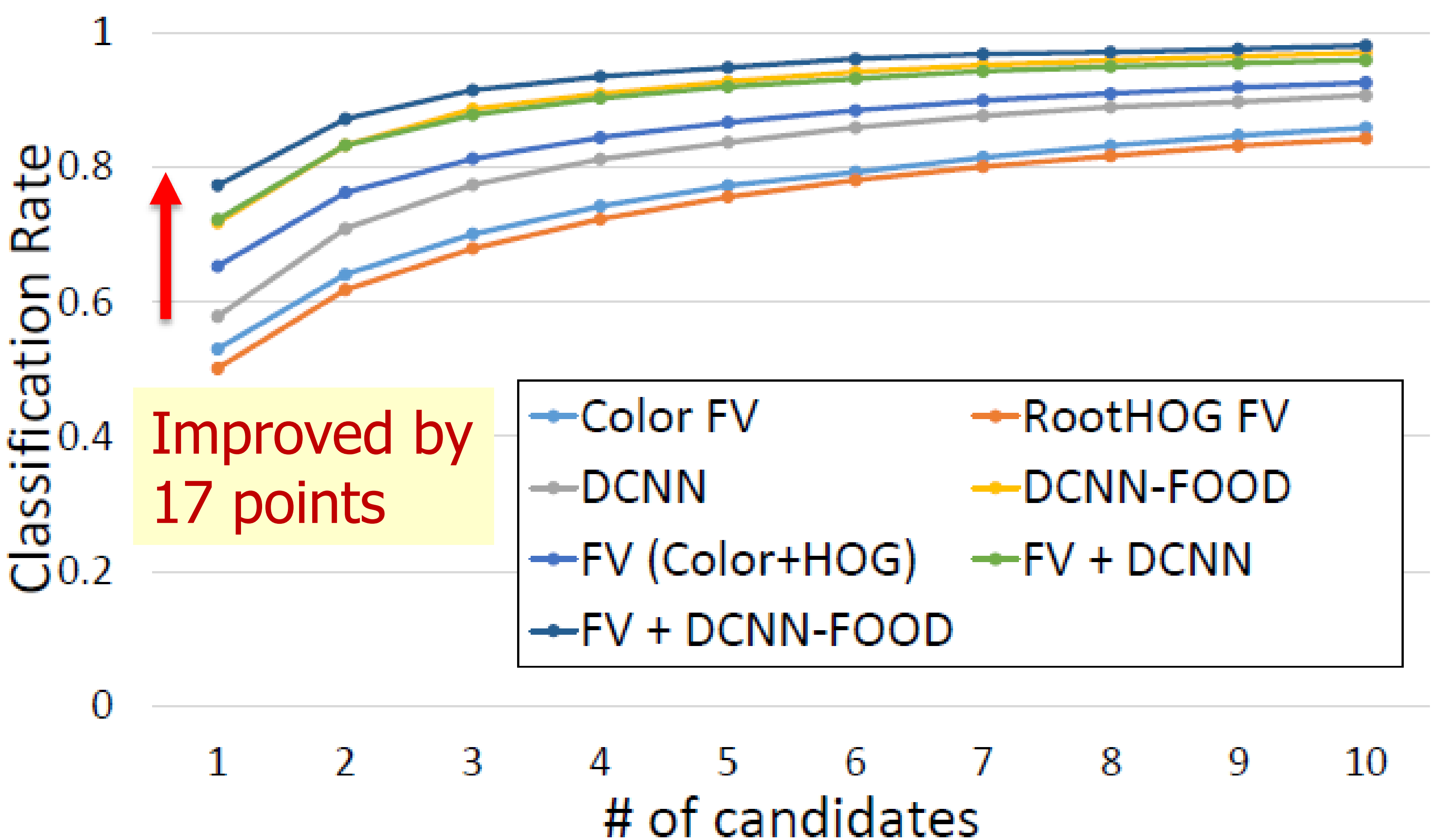
- Other methods: Finding "Koike-san" places , Finding co-occurence words

More "ramen/curry/sushi"

- Precision is not as good as the results by keyword-based candidate selection.

	Frequent user "Koike-sans"	Frequent co-occurence word	Frequent places
Ramen	6050 58.0 %	5851 68.5 %	594 44.0 %
Curry	3163 23.5 %	2806 49.0 %	313 25.5 %
Sushi	2474 13.5 %	1591 41.5 %	991 17.0 %

State-of-the-art (DCNN-based) (presented at MDBA WS)



Top-1 rate 77.4%, Top-5 rate 94.8%

Conclusions

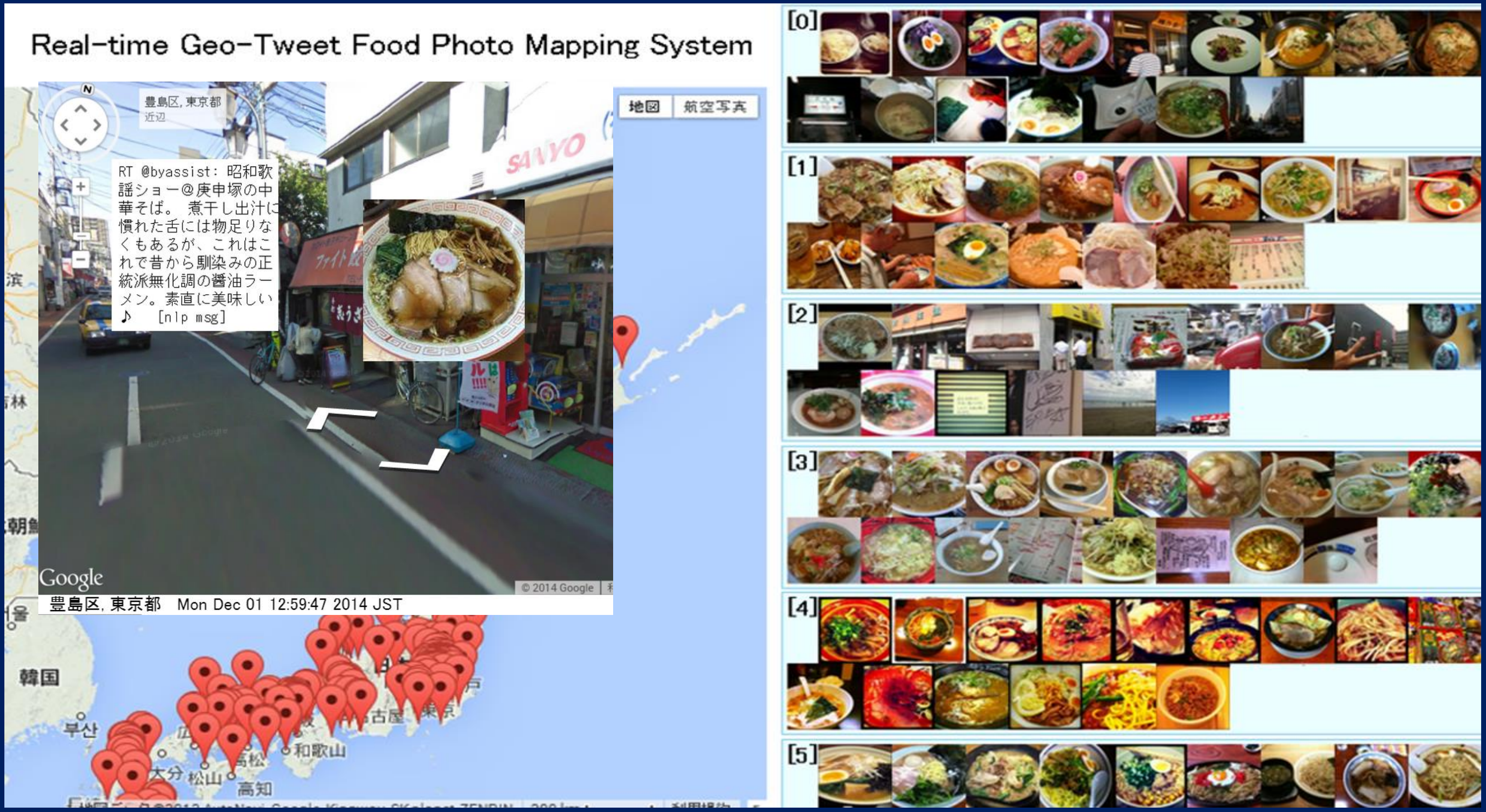
Conclusions

- Food Photo Mining from Twitter Photo data / the Twitter stream.
- Have completely solved the "ramen vs. curry" problem.
  - Note that only in summer searson, Curry becomes more popular than Ramen.
- Real-time system (demo)

Future work

- One million “ramen noodle photo dataset”
  - For all the “Ramen” fans over the world.
- Methods for collecting more Ramen !
  - Use DCNN-based classifier
  - Improve “Koike-san” methods
- Extension to World-wide foods

Thank you for your attention！



1	ramen noodle	80021
2	curry	59264
3	sushi	25898
4	dipping noodle	22158
5	omelet with fried rice	17520
6	pizza	16921
7	jiaozi	16014
8	Japanese-style pancake	15234
9	steamed rice	14264
10	sashimi	13927
11	hambarg steak	11583
12	beef stake	9503
13	takoyaki	9004
14	fried rice	8383
15	fried noodle	7905
16	oden	7453
17	toast	6350
18	cutlet curry	6339
19	tempura	5905
20	rice ball	5462
21	gratin	5223
22	croquette	4837
23	stew	4797
24	sashimi bowl	4730
25	chicken-'n'-egg on rice	4513
26	tempura bowl	4464
27	beef bowl	4285
28	spicy chili-flavored tofu	4081
29	yakitori	3829
30	hamburger	3662
31	chilled noodle	3473
32	sukiyaki	3408
33	miso soup	3295
34	fish-shaped pancake with bean jam	3281
35	pork cutlet on rice	3188
36	omelet with grilled minced meat	2592
37	bibimbap	2368
38	spaghetti	2171
39	lightly roasted fish	2162
40	seasoned beef with potatoes	2129
41	natto	2094
42	spaghetti with meat source	1994
43	steamed egg hotchpotch	1843
44	egg sunny-side up	1635
45	croissant	1579
46	udon noodle	1500
47	simmered pork	1443
48	mixed sushi	1371
49	pork miso soup	1229
50	ginger-fried pork	1158
51	potato salad	1150
52	egg omelet	1146
53	eels on rice	1071
54	egg roll	1058
55	sweet and sour pork	1049
56	fried shrimp	1049
57	sauteed vegetables	1040
58	shrimp with chill source	1003
59	cabbage roll	965
60	mixed rice	901
61	pilaf	891
62	soba noodle	880
63	potage	816
64	hot dog	795
65	chicken rice	736
66	wiener sausage	577
67	dried fish	563
68	steamed meat dumpling	561
69	french fries	561
70	beef ramen noodle	555
71	sandwiches	551
72	cold tofu	517
73	boiled chicken and vegetables	352
74	sirloin cutlet	331
75	nanbanzuke	323
76	fried chicken	314
77	stir-fried beef and peppers	312
78	roll bread	288
79	roast chicken	263
80	macaroni salad	239
81	boiled fish	228
82	kinpira-style sauteed burdock	225
83	tempura udon	213
84	raisins bread	205
85	goya chanpuru	198
86	green salad	145
87	chinese soup	141
88	Japanese tofu and vegetable chowder	137
89	salmon meuniere	96
90	grilled pacific saury	84
91	chip butty	76
92	fried fish	72
93	begitable tempura	71
94	tensin noodle	69
95	ganmodoki	34
96	grilled salmon	25
97	sauteed spinach	12
98	teriyaki grilled fish	3
99	grilled eggplant	2
100	pizza toast	0

2.1 group and some food categories

noodles	udon nooles, dipping noodles, ramen
yellow color	omlet, potage, steamed egg hotchpotch
soup	miso soup, pork miso soup, japanese tofu and vegetable chowder
fried	takoyaki, japanese-stype pancake, fried noodle
deep fried	croquette, sirloin cutlet, fried chicken
salad	green salad, sauteed vegetables, vegetable tempra
bread	sandwiches, raisin bread, roll bread
seafood	sashimi, sashimi bowl, sushi
rice	rice, pilaf, fried rice
fish	grilled salmon, grilled pacific saury, dried fish
boiled and seasoned	sesoned beef with potatoes simmered ganmodoki sesoned beef with potatoes
sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock
sauce	stew, curry, stir-fried shrimp in chili sauce

2.1 group and some food categories

noodles	udon nooles, dipping noodles, ramen
yellow color	omlet, potage, steamed egg hotchpotch
	ed salmon, grilled pacific saury, dried fish
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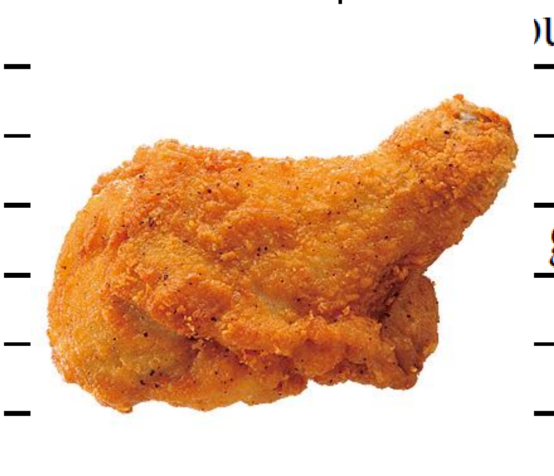
sauce	stew, curry, stir-fried shrimp in chili sauce



2.1 group and some food categories

noodles	udon nooles, dipping noodles, ramen
yellow color	omlet, potage, steamed egg hotchpotch



fish	grilled salmon, grilled pacific saury, dried fish
boiled and seasoned	sesoned beef with potatoes simmered ganmodoki sesoned beef with potatoes
sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock
sauce	stew, curry, stir-fried shrimp in chili sauce

2.1 group and some food categories

noodles	udon nooles, dipping noodles, ramen
yellow color	omlet, potage, steamed egg hotchpotch
soup	miso soup, pork miso soup, japanese tofu and vegetable chowder

fish	grilled salmon, grilled pacific saury, dried fish
boiled and seasoned	sesoned beef with potatoes simmered ganmodoki sesoned beef with potatoes
sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock
sauce	stew, curry, stir-fried shrimp in chili sauce

2.1 group and some food categories

noodles	udon nooles, dipping noodles, ramen
yellow color	omlet, potage, steamed egg hotchpotch

boiled and seasoned	sesoned beef with potatoes simmered ganmodoki sesoned beef with potatoes
sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock
sauce	stew, curry, stir-fried shrimp in chili sauce