

# Geotagged Photo Recognition using Corresponding Aerial Photos with Multiple Kernel Learning

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## Background & Objective

◆ Geotagged Photos are easy to obtain.

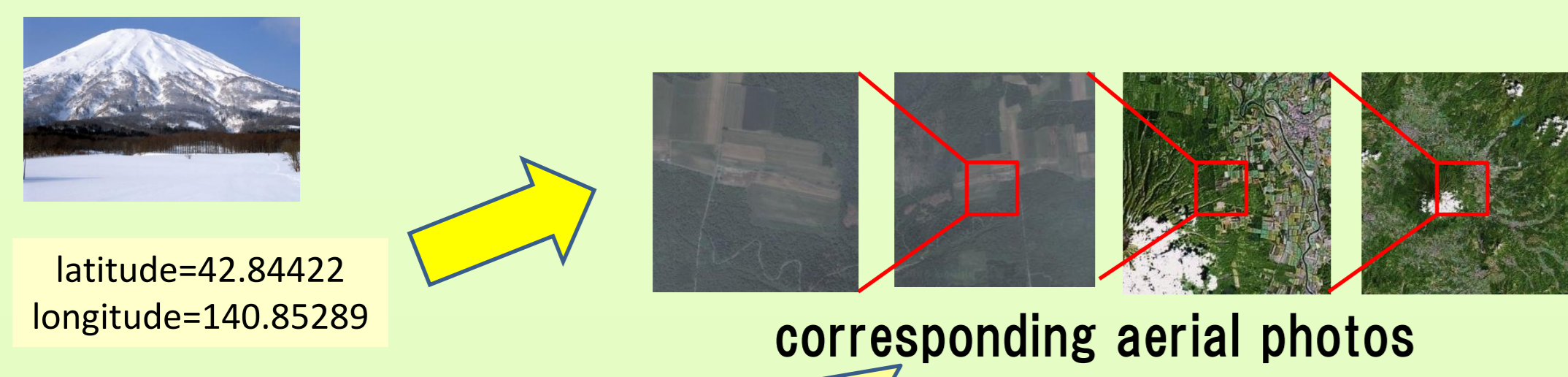


geotag = (latitude, longitude)

Can a geotag help image recognition ?

No ! when using them as 2D vectors.

Yes ! It can help image recognition by converting it into aerial photos, shown by the following two papers.



Represent geographical context

[4] J. Luo, J. Yu, D. Joshi, and W. Hao, *Event recognition: Viewing the world with a third eye*. In *Proc. of ACM International Conference Multimedia, 2008*.

Only events such as "baseball" and "on beach"

[7] K. Yaegashi and K. Yanai, *Can geotags help image recognition?* In *Proc. of Pacific-Rim Symposium on Image and Video Technology, 2009*.

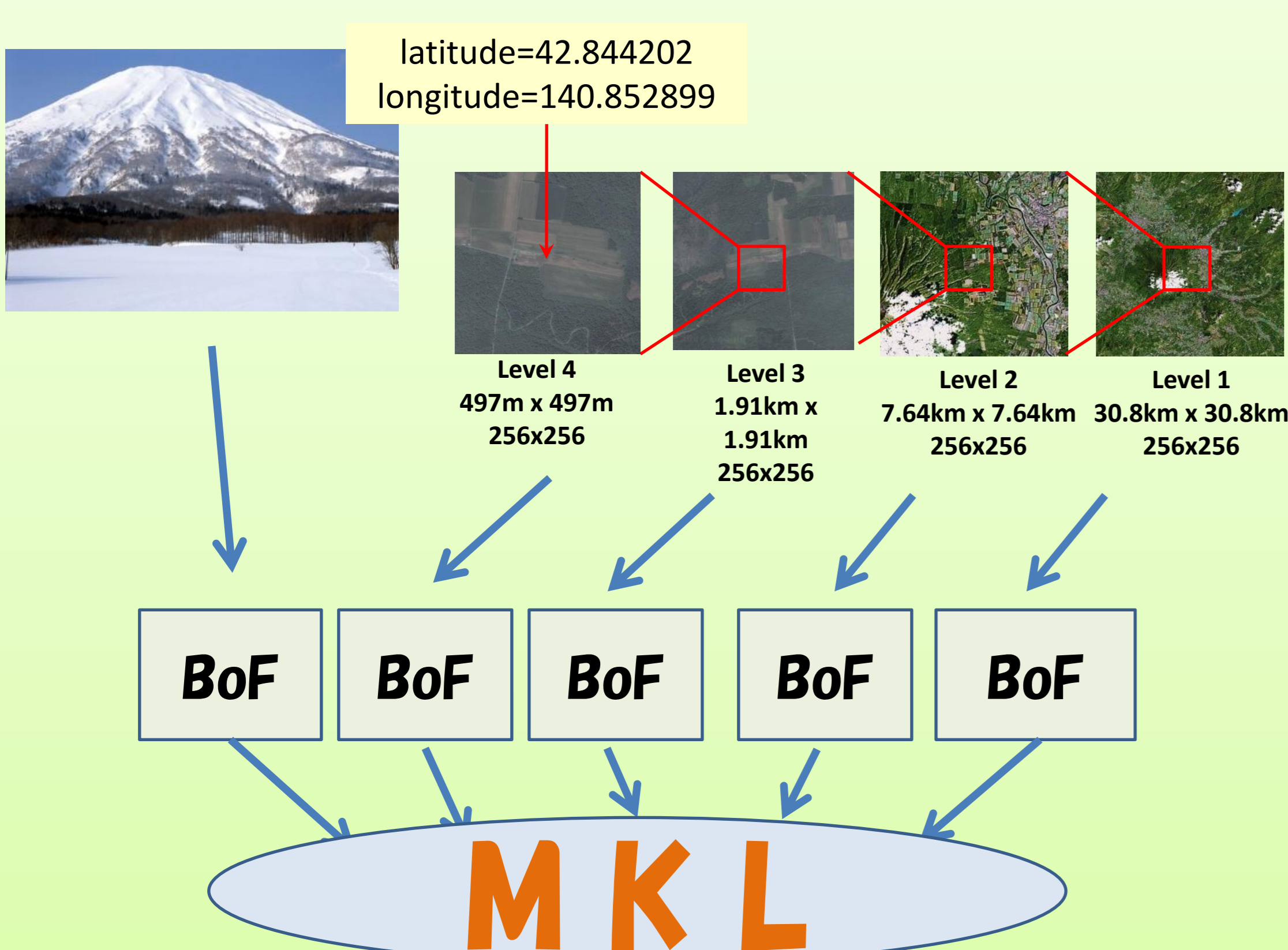
10 categories. Fusion by concatenating both feature vectors.

◆ Questions ?

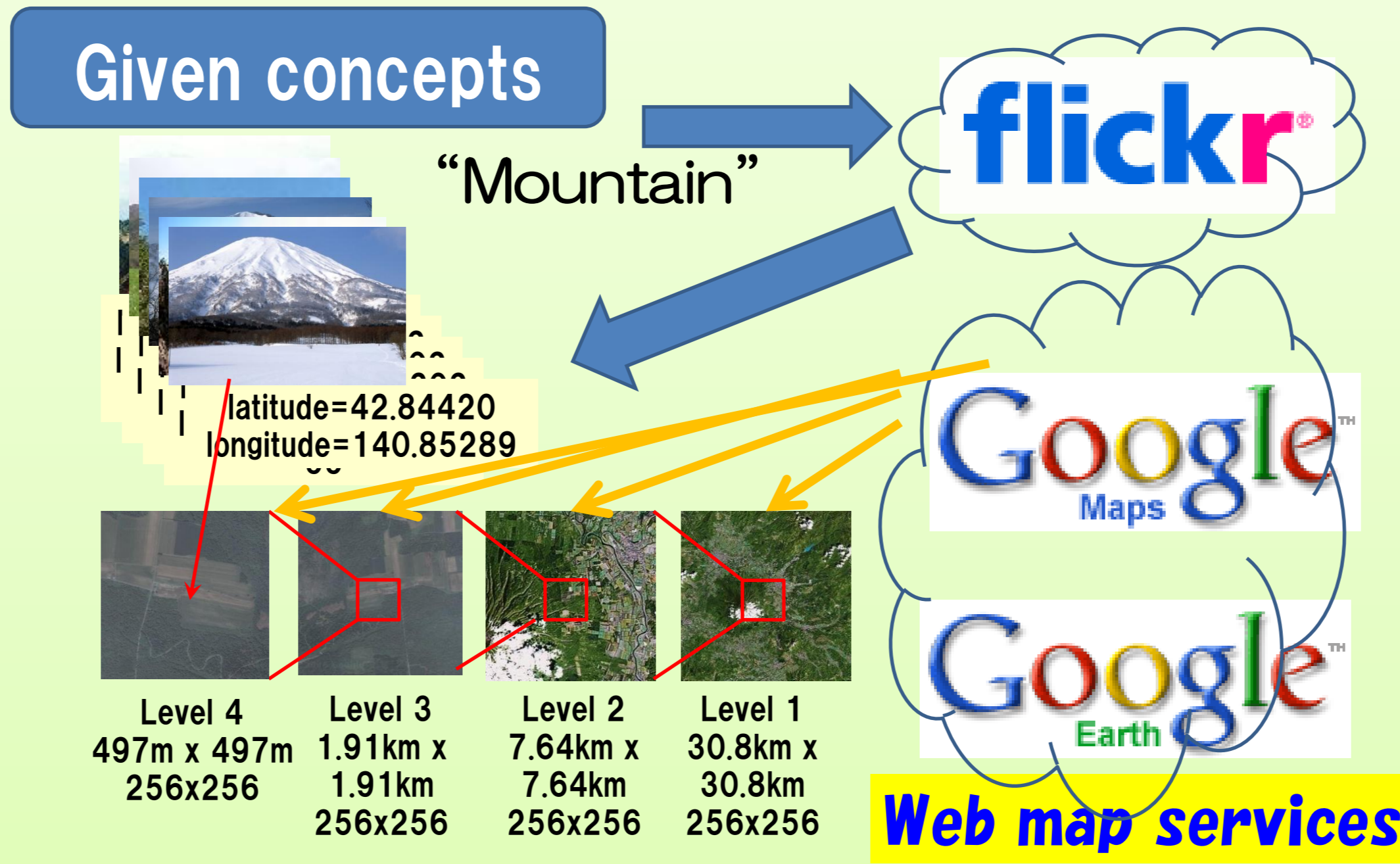
- 1) To what extent can geotags help ?
- 2) What kinds of categories are geotags effective for ?

We evaluate the contribution of aerial photos for image recognition by using Multiple Kernel Learning (MKL).

## Method

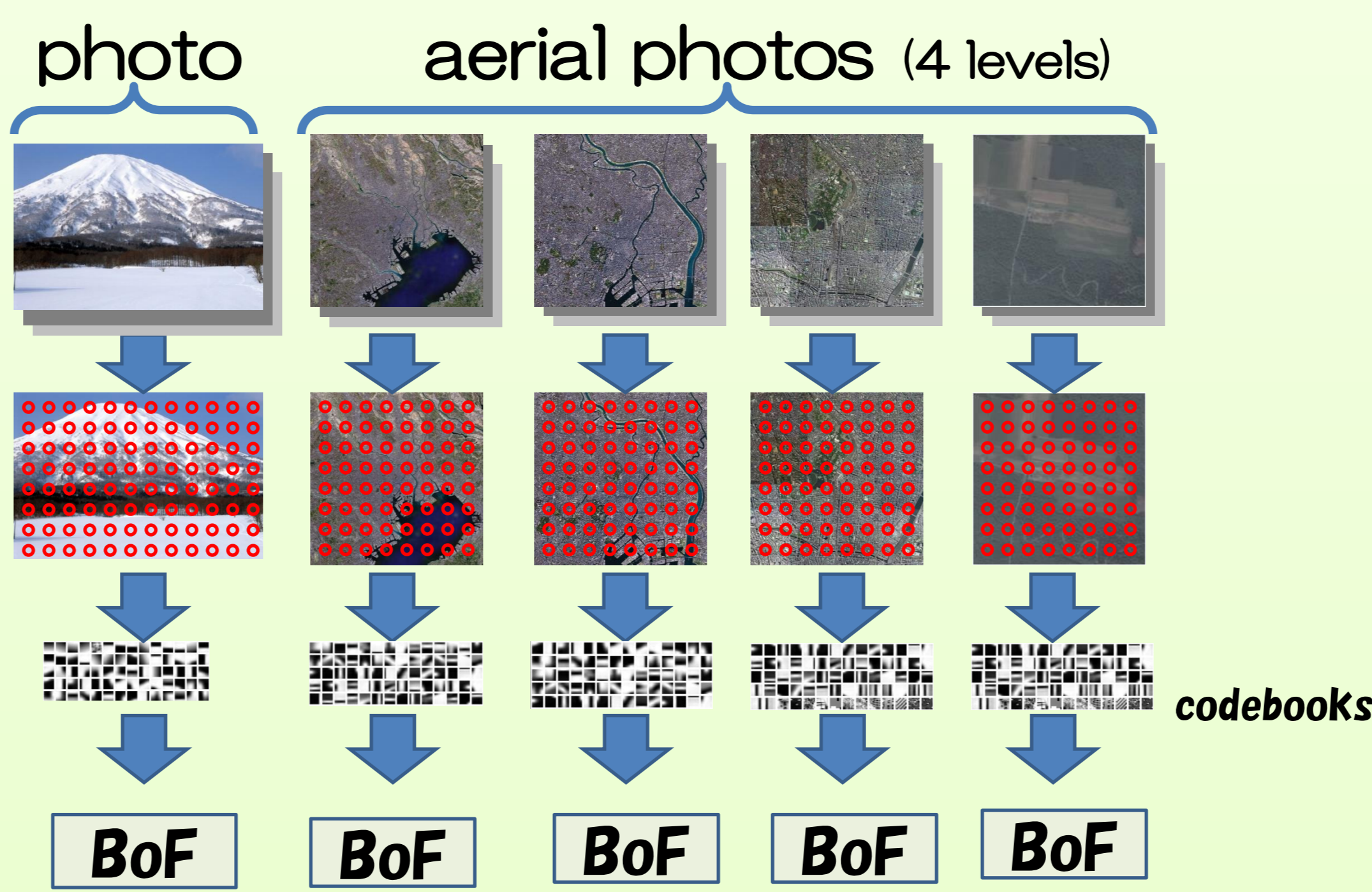


## Data Collection



◆ Gather 4 levels of aerial photos for each geotagged photo.

## Features



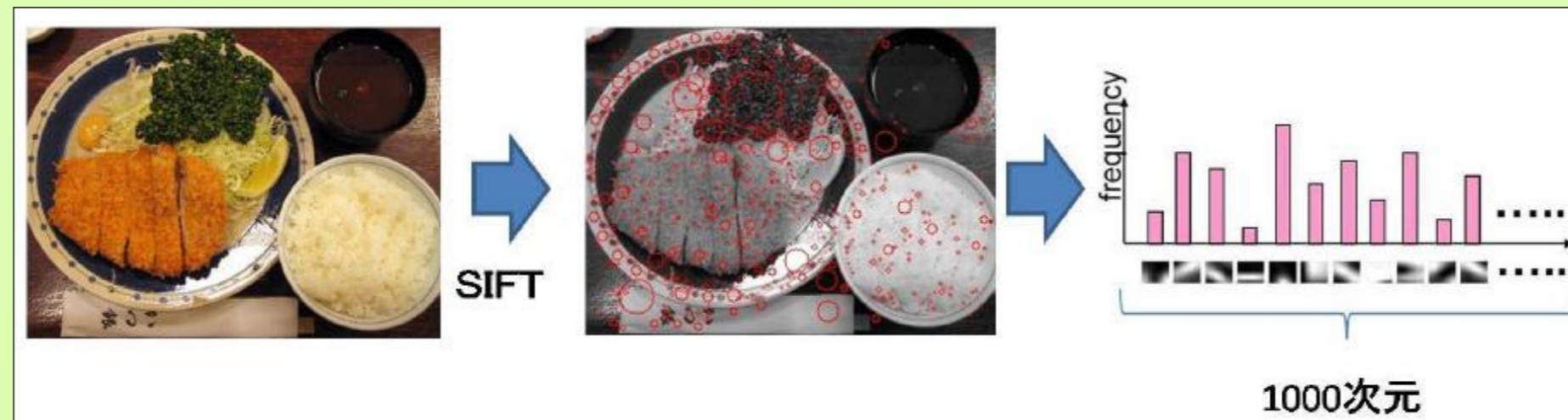
◆ Bag-of-features (BoF) (local pattern)

- (1) Sample points by grid sampling (every 10px)



Grid sampling

- (2) Describe local patterns around the sampled points with SIFT [Lowe 2004]
- (3) Generate codebooks by k-means (size of a codebook: 1000)
- (4) Convert images into BoF vectors by voting to nearest codewords



Five BoF vectors for each image

## Learning & Classifying

◆ Multiple Kernel Learning

- Is an extension of a SVM.
- Can handle "a combined kernel" which is a linear combination of kernels.
- Can estimate kernel weights and SVM model parameters simultaneously.
- Can integrate features by assigning one feature to one kernel.

Combined kernel

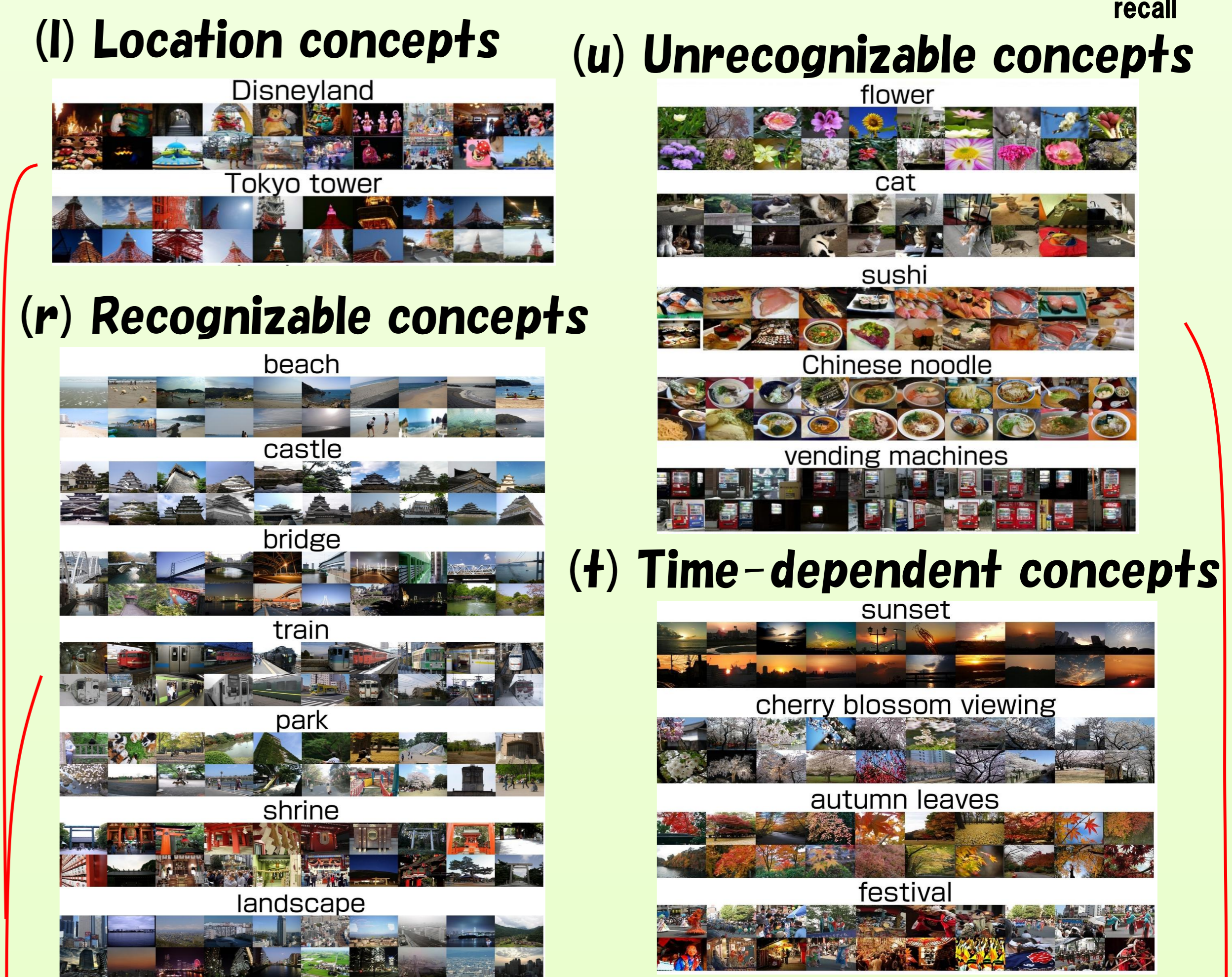
$$k(x_i, x_j) = \sum_{k=1}^K \beta_k k_k(x_i, x_j)$$

Kernel weight (to be estimated by MKL)

## Experiments

◆ 1/0 classification for 18 classes by 5-fold cross validation

- 200 positive & 200 negative images for each class
- Evaluated by average precision



• Classification results (AP, %)

(type) concept	photo	MKL	gain
(l) Disneyland	68.00	84.06	+16.06
(r) park	67.43	76.04	+8.61
(r) shrine	72.79	78.53	+5.74
(t) festival	72.32	77.75	+5.43
(r) bridge	69.51	74.89	+5.38
(r) landscape	73.71	78.37	+4.66
(r) beach	80.10	83.85	+3.75
(t) red leaves	79.18	82.45	+3.27
(l) Tokyo tower	80.84	83.84	+3.00
(r) castle	81.28	83.53	+2.23
(u) sushi	80.11	81.93	+1.82
(r) railroad	74.70	76.20	+1.50
(u) flower	77.00	78.48	+1.48
(t) cherry blossom	80.94	81.61	+0.67
(u) ramen noodle	82.34	82.70	+0.36
(u) cat	73.98	74.26	+0.28
(u) vendor machine	83.17	83.43	+0.26
(t) sunset	83.01	83.11	+0.10
AVERAGE	76.69	80.28	+3.59

• Contribution weights by MKL

(type) concept	photo	level1	level2	level3	level4
(u) ramen noodle	0.873	0.002	0.000	0.037	0.088
(u) vendor machine	0.794	0.058	0.009	0.074	0.065
(t) cherry blossom	0.774	0.038	0.006	0.093	0.090
(t) sunset	0.743	0.028	0.008	0.063	0.158
(u) cat	0.729	0.055	0.058	0.016	0.142
(u) flower	0.658	0.000	0.042	0.051	0.249
(r) railroad	0.604	0.106	0.014	0.052	0.224
(r) landscape	0.604	0.078	0.024	0.093	0.199
(u) sushi	0.596	0.062	0.015	0.062	0.266
(r) bridge	0.582	0.077	0.044	0.070	0.226
(r) red leaves	0.523	0.141	0.006	0.062	0.269
(r) castle	0.523	0.166	0.004	0.099	0.208
(t) festival	0.518	0.058	0.001	0.185	0.238
(r) shrine	0.507	0.033	0.009	0.061	0.391
(r) park	0.437	0.073	0.012	0.045	0.433
(r) beach	0.392	0.115	0.173	0.055	0.265
(l) Disneyland	0.384	0.095	0.236	0.131	0.153
(l) Tokyo tower	0.364	0.008	0.002	0.396	0.231

## Conclusions

◆ Analyzed contribution ratios of aerial images for image recognition using Multiple Kernel Learning (MKL)

- AP was improved by 3.59 % on average
- Much help to "location concepts" and "recognizable concepts"
- Less help to other kinds of concepts
- Detailed aerial photos are more helpful

◆ Future work

- More categories
- More features (e.g. color, HoG, Gabor)
- Other geo-info (e.g. geo-text: country name, area name, GIS-info: population...)