

A VISUAL ANALYSIS ON RECOGNIZABILITY AND DISCRIMINABILITY OF ONOMATOPOEIA WORDS WITH DCNN FEATURES

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Summary

Objective: Examine the relation between onomatopoeia words and images using a large number of tagged images.

Approach: [1] Evaluate “recognizability” of onomatopoeia concepts by noise separation
[2] Evaluate “discriminability” of onomatopoeia concepts within the same nouns

1 “Onomatopoeia” images

Onomatopoeia words in English
→ Source of the sound that it describes such as “tic tac” and “quack”

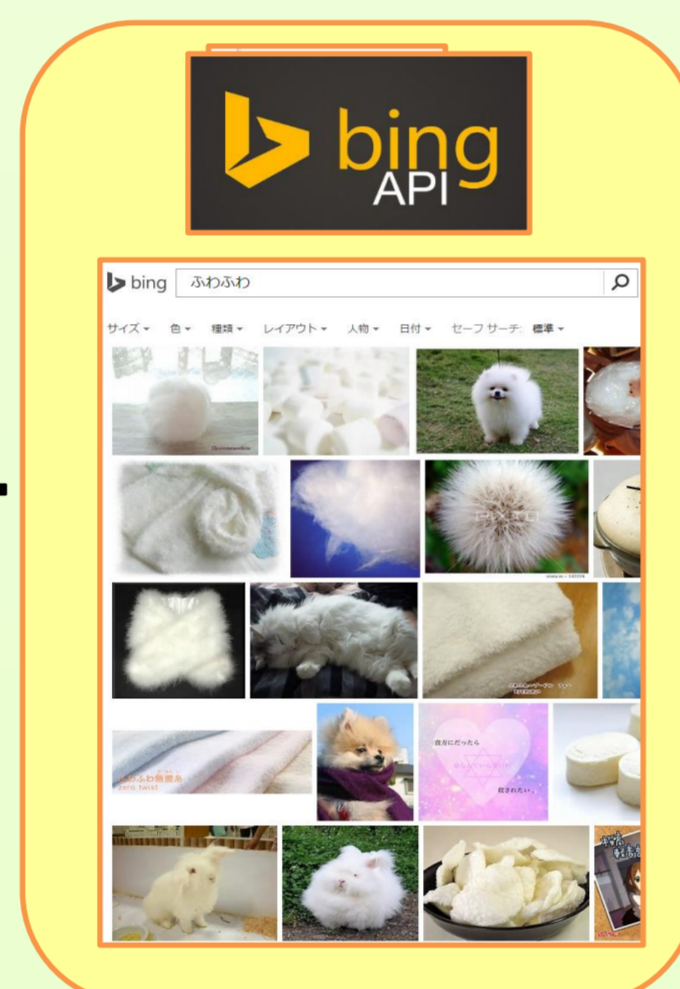


Fuwa-fuwa means being very softy like very soft cotton

Onomatopoeia words in Japanese
→ Expressing feeling of visual appearance or touch of objects or materials.

2 Collecting images from Web

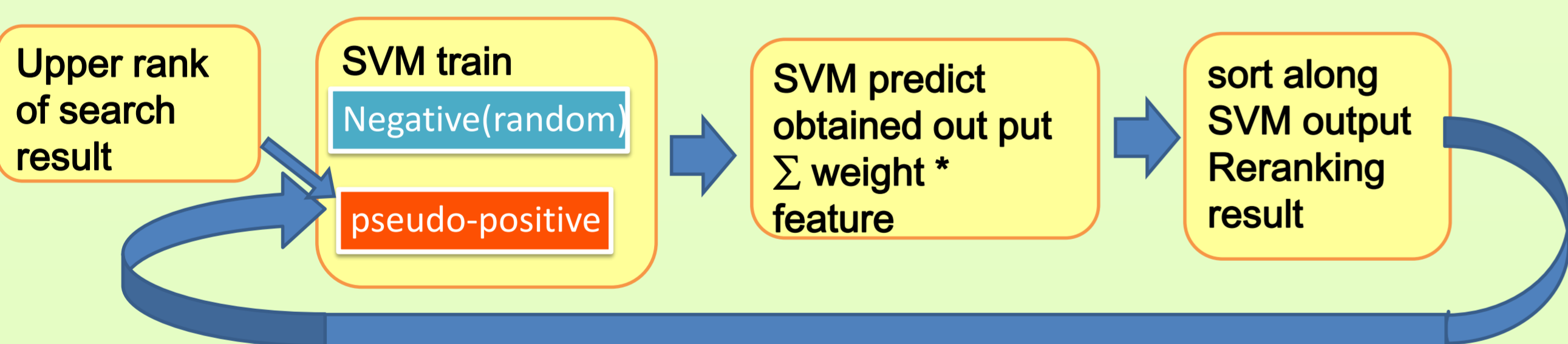
- Use Bing Image Search API
- Upper-ranked images can be regarded corresponding to the given onomatopoeia.
- There are some noisy images.



3 Re-ranking method

- Semantic annotation is a hard task due to ambiguous definition.
- Mine similar images to upper ranked images by recognition.

- Train SVM to the images in the original search results
- Sort images in the descending order of the SVM output values
- If needed, we can improve result by repeating re-ranking loop



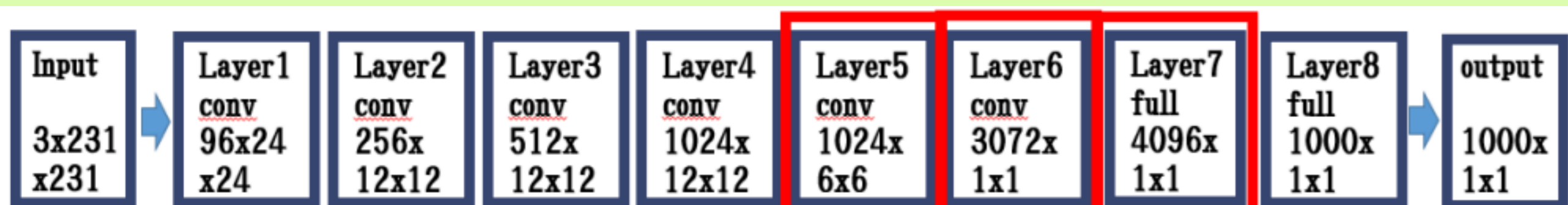
Re-ranking flow



Iterative re-ranking

4 Image features

- Improved fisher vector (IFV)
SURF 64 dim(128 to 64 by PCA), GMM = 256
Feature 2*64*256 dim
- Deep Convolutional Neural Network (DCNN) (Over feat)
Pretrained with ImageNet of 1000 class (1,000,000 images)
Use activation from layer 5,6,7 (36864, 3072 and 4096 dim)



5 Exp.(1) : Automatic building of dataset

- Collected Web images regarding twenty kinds of onomatopoeia words
- Achieved the average precision(AP) on the top 50 imgs were **89.6%** (layer 6)

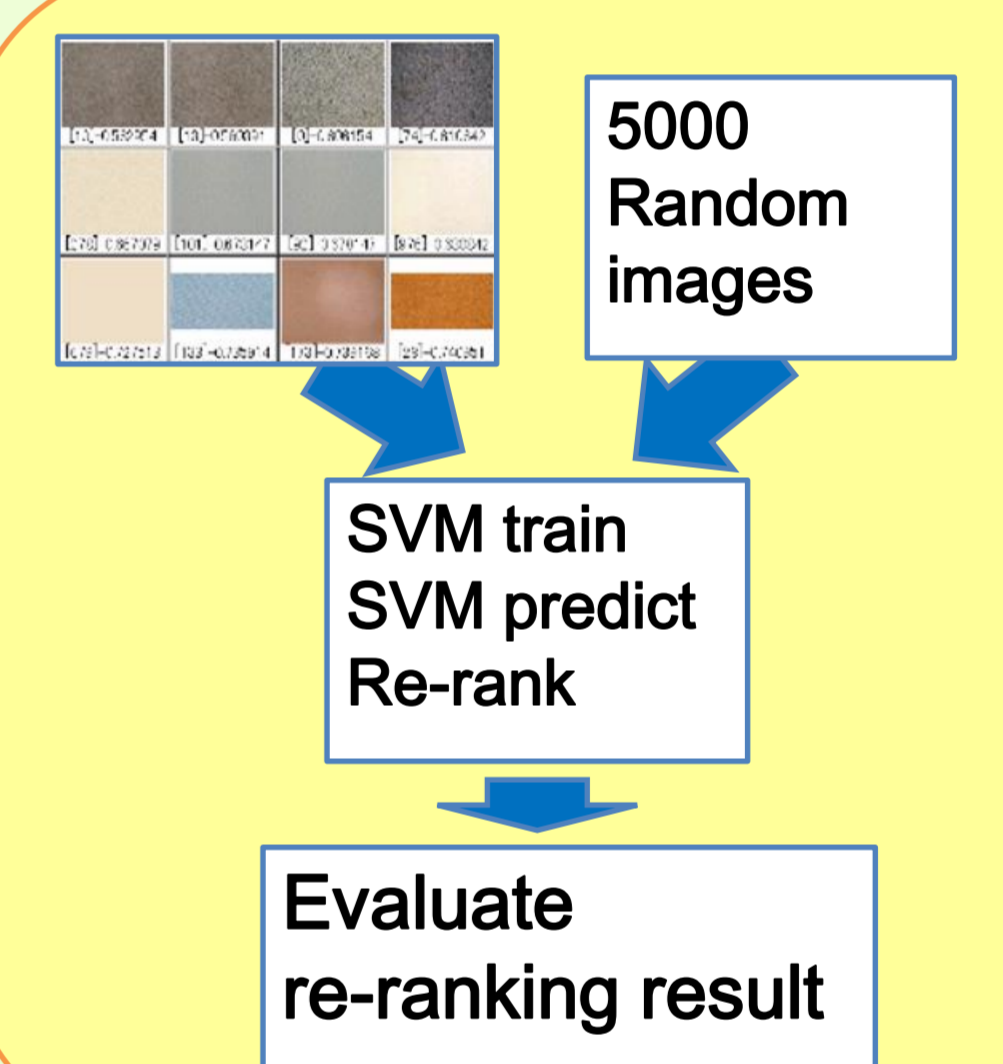
DNN features outperformed IFV clearly at image retrieval

| onomatopoeia | meaning | onomatopoeia | meaning |
|--------------|-------------------------------|--------------|-----------------------------|
| pika-pika | shining gold | mofu-mofu | softly |
| basha-basha | splashing water | mock-mock | mountainous smoke or clouds |
| fuwa-fuwa | softly; spongy | kara-kara | hanging many metals |
| nyoki-nyoki | shooting up one after another | bou-bou | overgrown |
| kira-kira | shining stars | fuwa-fuwa | well-roasted |
| gune-gune | winding | shiwa-shiwa | wrinkled; crumpled |
| toge-toge | thorny; prickly | zara-zara | sandy; gritty |
| butsu-butsu | a rash | kari-kari | crispy; crunch |
| puru-puru | fresh and juicy | guru-guru | whirling |
| gotsu-gotsu | rugged; angular; hard; stiff | giza-giza | notched; corrugated |

| Feature | IFV | Layer5(DCNN) | Layer6(DCNN) | Layer7(DCNN) |
|---------|------|--------------|--------------|--------------|
| mAP(%) | 60.4 | 85.2 | 89.6 | 85.1 |

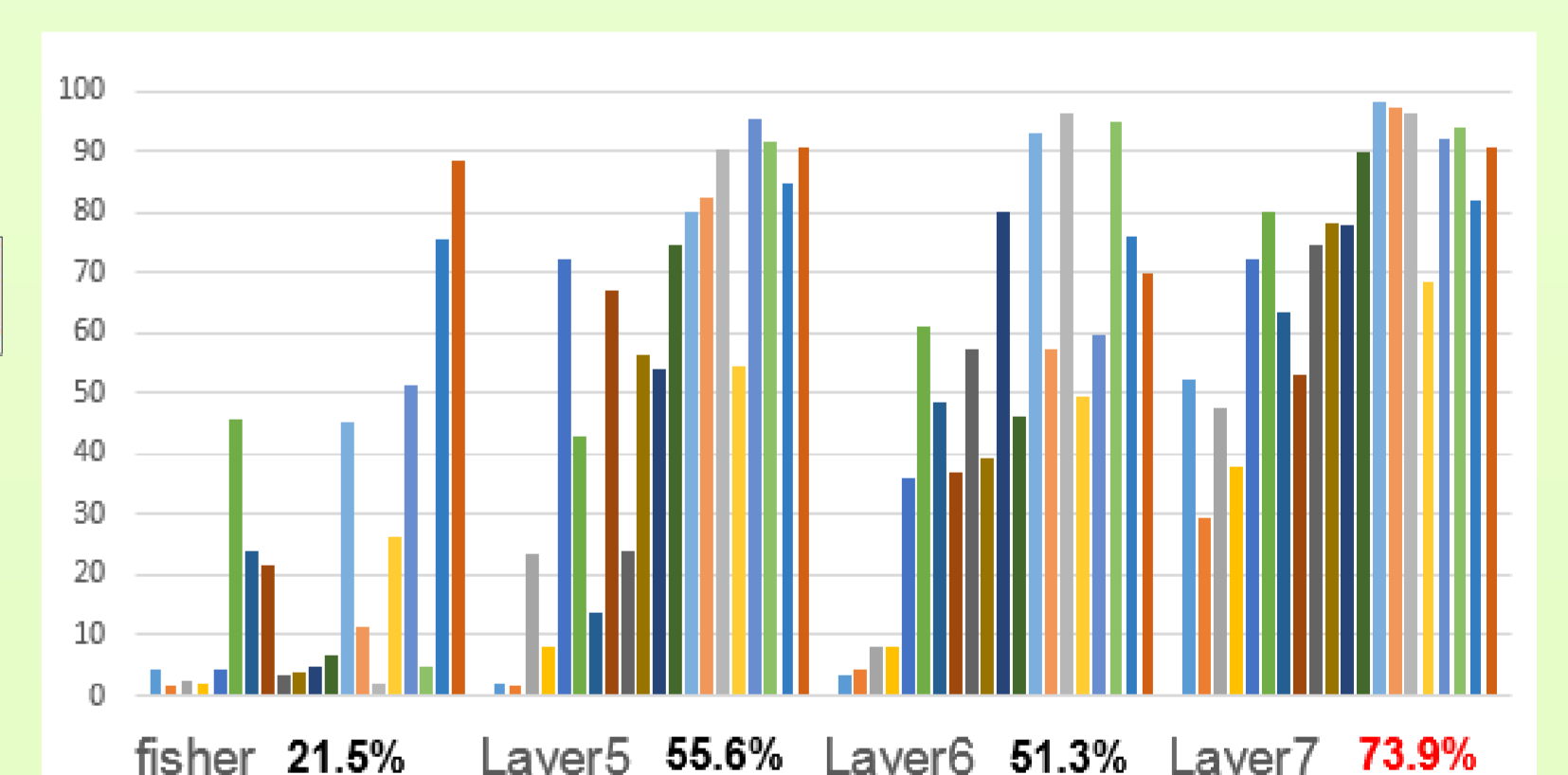
6 Exp.(2): “Recognizability”

- Discriminate onomatopoeia images from noise imgs
- Mix onomatopoeia 50 images and random 5000 noise images
- Re-rank 5050 mixed images and evaluate mAP



DCNN features has high ability to express visual onomatopoeia elements in images

| | | |
|-----------|---------------------|--|
| fuwa-fuwa | Fisher 2.8% | |
| layer7 | 47.4% | |
| zara-zara | Fisher 51.4% | |
| layer7 | 92.4% | |
| juwa-juwa | Fisher 2.1% | |
| layer7 | 96.6% | |



| Feature | IFV | Layer5(DCNN) | Layer6(DCNN) | Layer7(DCNN) |
|---------|------|--------------|--------------|--------------|
| mAP(%) | 21.5 | 55.6 | 51.3 | 73.9 |

7 Exp.(3): “Discriminability” : Fixed nouns and the different onomatopoeia words

- Some onomatopoeia words are strongly related to specific kinds of objects
- Examine visual discriminability of onomatopoeia words with images associated with noun/onomatopoeia(adjective) pairs
- 4 nouns: “dog”, “shoes”, “cake” and “flower”
- Pair words are selected based on text co-occurrence counts in Bing Img Search

| Noun | #class | Rate(%) |
|--------|--------|---------|
| dog | 8 | 52.5 |
| shoes | 6 | 85.7 |
| cake | 7 | 72.3 |
| flower | 7 | 84.6 |

Onomatopoeia words have visual characteristics which can be discriminated even within the same object category

| | | confusion matrix | | | | | | | |
|------------------|--|------------------|------|------|------|------|------|------|------|
| “goro-goro” cake | | 31 | 3 | 10 | 2 | 3 | 1 | 0 | 62.0 |
| “pasa-pasa” cake | | 3 | 26 | 3 | 7 | 5 | 6 | 0 | 52.0 |
| “saku-saku” cake | | 8 | 4 | 24 | 8 | 2 | 3 | 1 | 48.0 |
| “fuwa-fuwa” cake | | 1 | 2 | 2 | 42 | 3 | 0 | 0 | 84.0 |
| smooth cake | | 3 | 2 | 3 | 3 | 37 | 2 | 0 | 74.0 |
| deep cake | | 1 | 0 | 2 | 1 | 0 | 46 | 0 | 92.0 |
| light cake | | 0 | 0 | 0 | 0 | 3 | 0 | 47 | 94.0 |
| | | 66.0 | 70.3 | 54.5 | 66.7 | 69.8 | 79.3 | 97.9 | 72.3 |

| | | confusion matrix | | | | | | | |
|--------------------|--|------------------|------|------|------|------|-------|------|-------|
| “pon-pon” flower | | 35 | 3 | 2 | 2 | 4 | 0 | 4 | 70.0 |
| “fuwa-fuwa” flower | | 7 | 36 | 2 | 3 | 2 | 0 | 0 | 72.0 |
| fresh flower | | 2 | 1 | 38 | 7 | 1 | 0 | 1 | 76.0 |
| main flower | | 0 | 2 | 3 | 44 | 1 | 0 | 0 | 88.0 |
| blue flower | | 1 | 0 | 0 | 0 | 49 | 0 | 0 | 98.0 |
| yellow flower | | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 100.0 |
| red flower | | 3 | 0 | 0 | 0 | 3 | 0 | 44 | 88.0 |
| | | 72.9 | 85.7 | 84.4 | 78.6 | 81.7 | 100.0 | 89.8 | 84.6 |