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Deep Co-occurrence Feature Learning for Visual Object Recognition

Ya-Fang Shih*, Yang-Ming Yeh*, Yen-Yu Lin, Ming-Fang Weng, Yi-Chang Lu, Yung-Yu Chuang

*: equal contribution

Fine-grained recognition

Highly relies on discriminative parts to capture subtle inter-class variations

Part-based methods

- Appearance of parts + Spatial relationship between parts
- Robust to deformations and occlusions
- More discriminative in the case of subtle inter-class variations

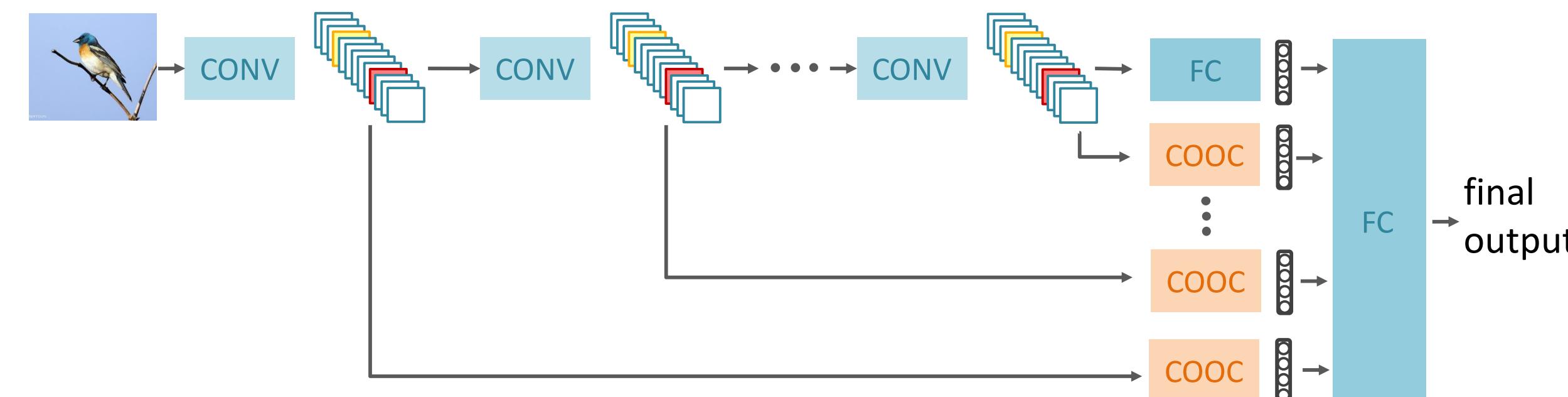
Limitations of previous work of integrating part-based representation into CNN

- Pre-defined parts and part number
- High annotation cost
- Complicated models

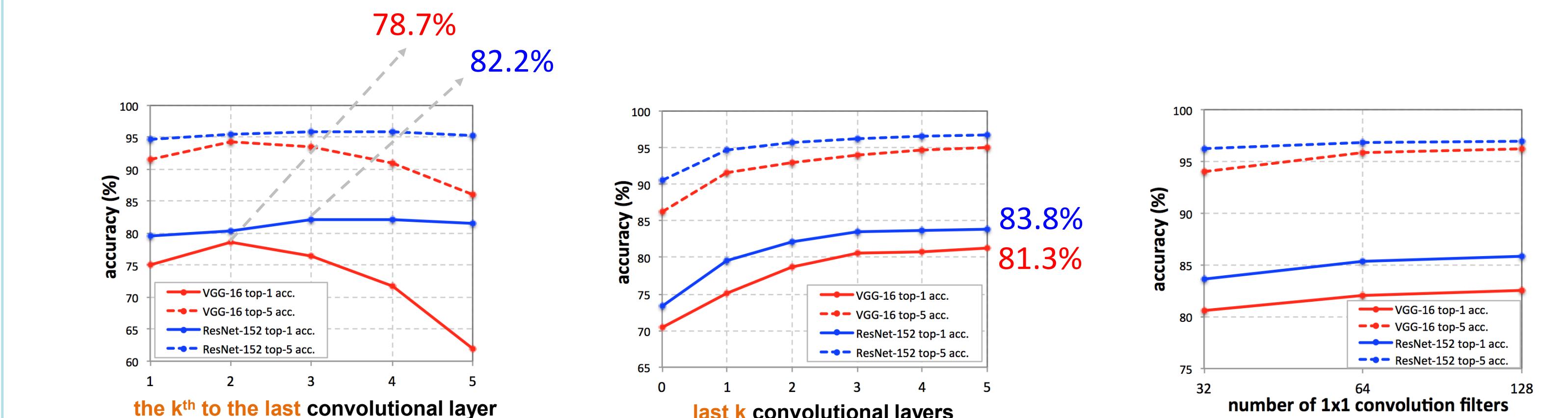
Co-occurrence layer

$$X_{ij} = \max_o \sum_p A_{p,i} A_{p+o,j}$$

A: feature maps
 $A_{p,i}$: location p (2D) on feature map i
 o : the offset (2D) with the maximal response
 X : co-occurrence vector
 X_{ij} : the co-occurrence value of feature map i and feature map j



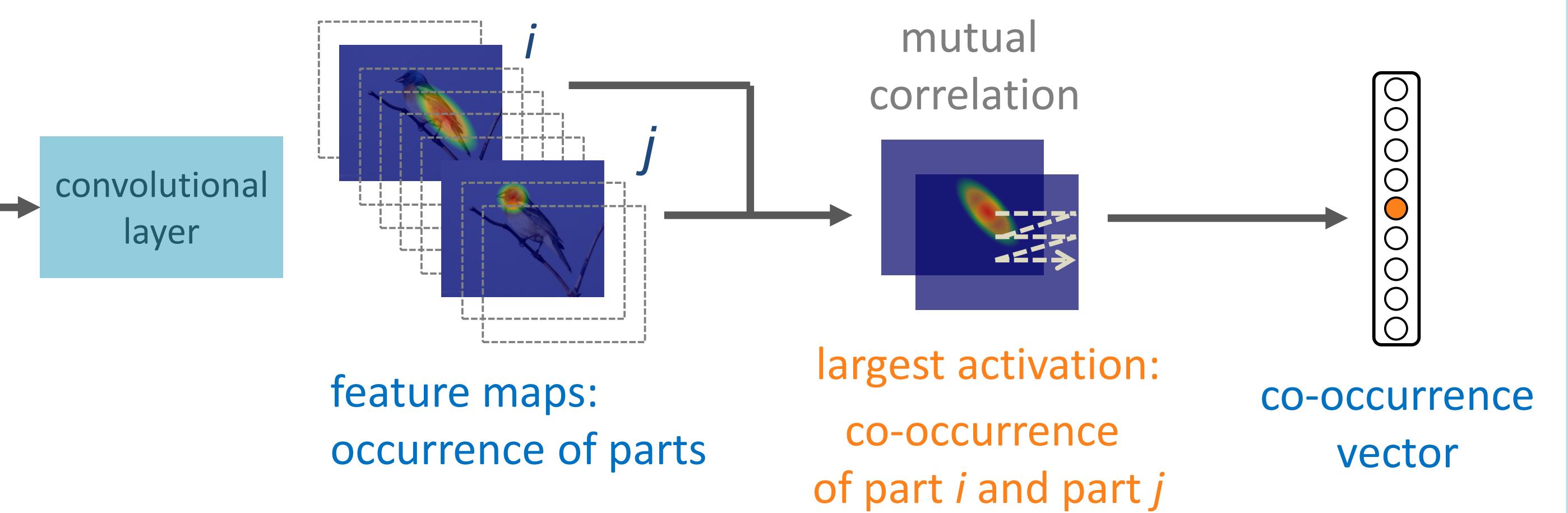
Experiments



Baseline VGG: 70.4%
 Baseline ResNet-152: 73.3%
 Co-occurrence Feature: 1024d

Complementary between layers

Apply the co-occurrence layer to the last 3 convolutional layers with 128 1x1 filters



Quantitative results

method	network	part annotation	accuracy (%)
Liu et al. [CVPR'15]	Caffe		73.5
Zhang et al. [ECCV'14]	Caffe	✓	73.9
Branson et al. [BMVC'14]	Caffe	✓	75.7
Simon et al. [ICCV'15]	VGG		81.0
Krause et al. [CVPR'15]	VGG		82.0
Huang et al. [CVPR'16]	Caffe	✓	76.6
Xiao et al. [CVPR'15]	AlexNet+VGG		77.9
Wang et al. [ICCV'15]	VGGx3		81.7
Lin et al. [ICCV'15]	VGGx2		84.1
Jaderberg et al. [NIPS'15]	Inceptionx4		84.1
Ours	VGG		83.6
Ours	ResNet-152		85.8

Visualization

The detected most influential pair of parts in each class:

- interpretable, meaningful, and consistent in a class

