Deep Spatial Pyramid Ensemble for Cultural Event Recognition

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Outline

- Background
- Deep Spatial Pyramid (DSP) and its ensemble
- Implementation details
- Experimental results

Background

Cultural Event Recognition

Deep Spatial Pyramid (DSP)

CNN:

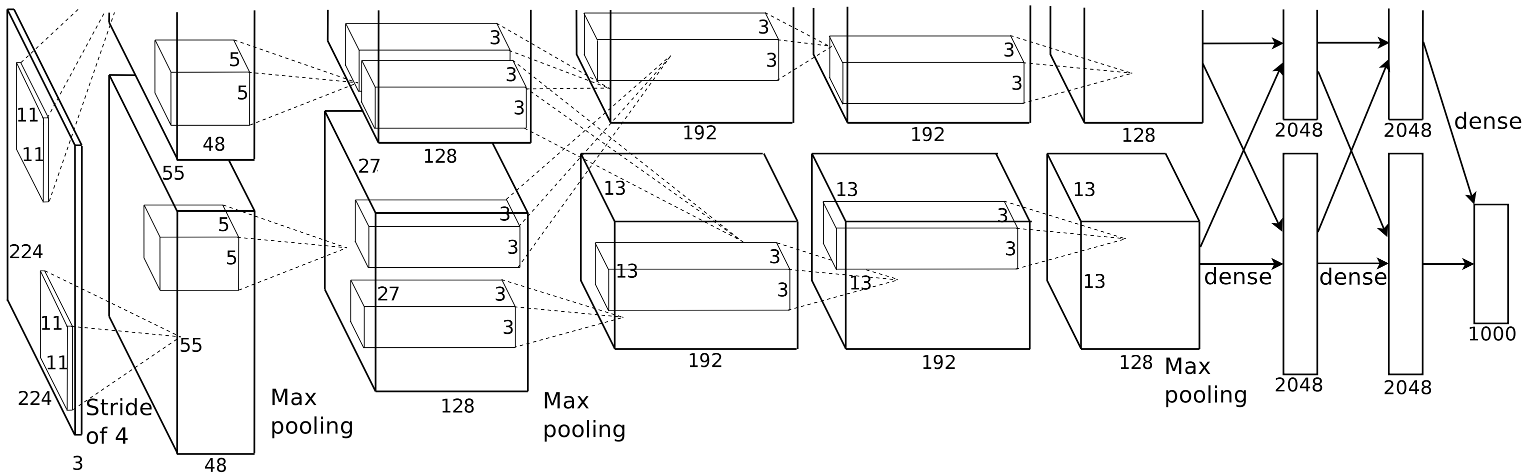

Figure courtesy of [A. Krizhevsky et al., NIPS' 12]

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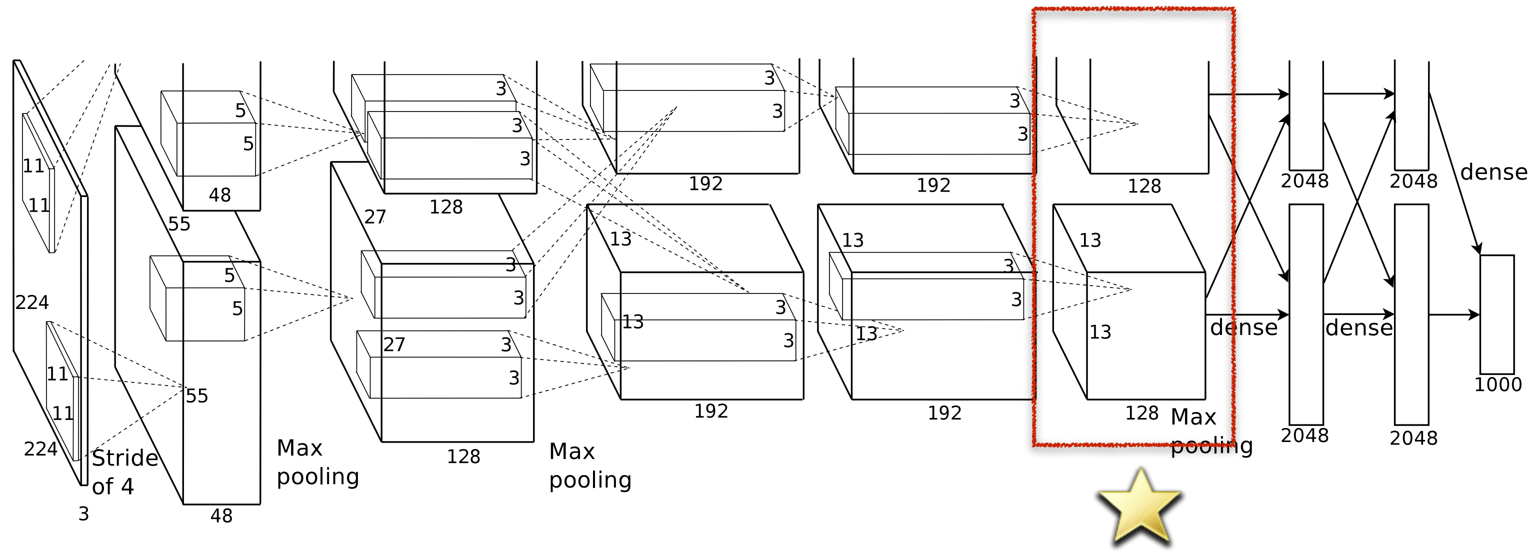

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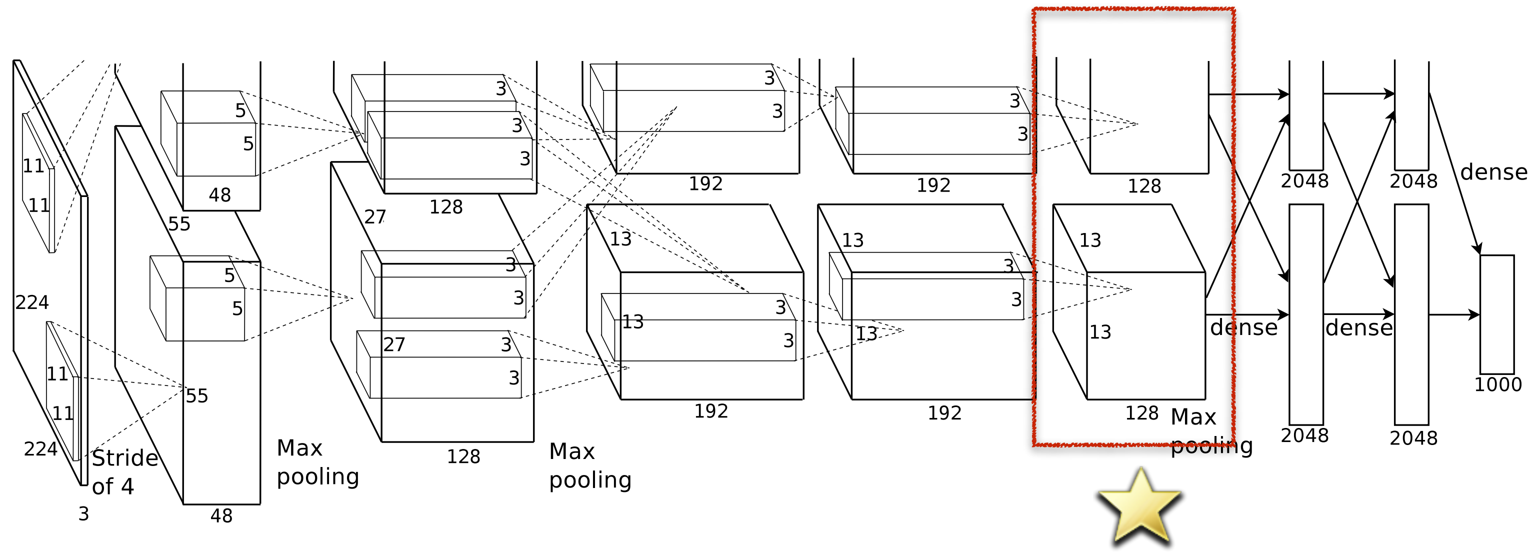
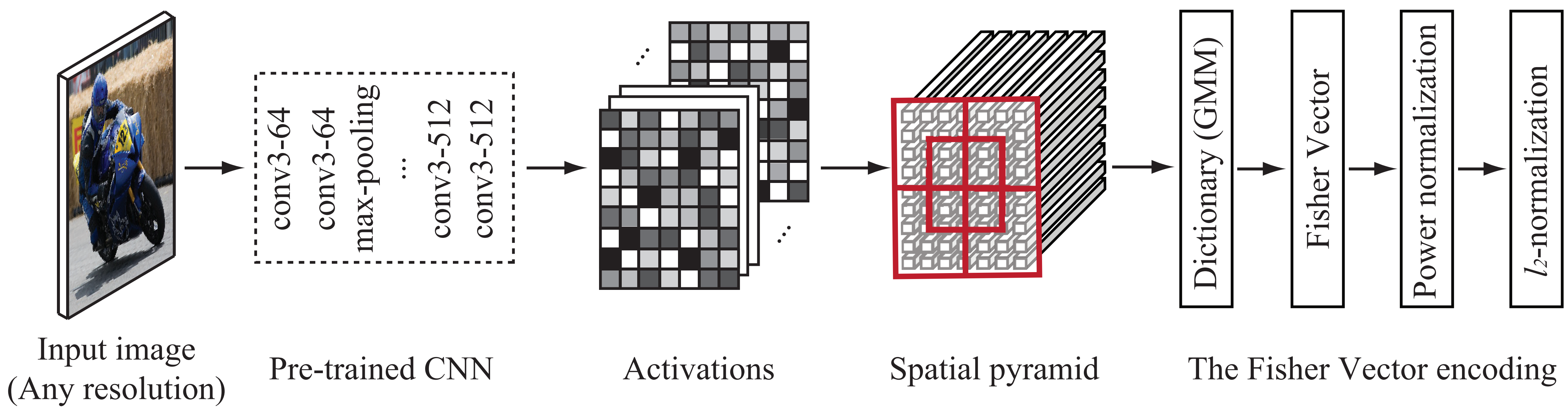


DSP:



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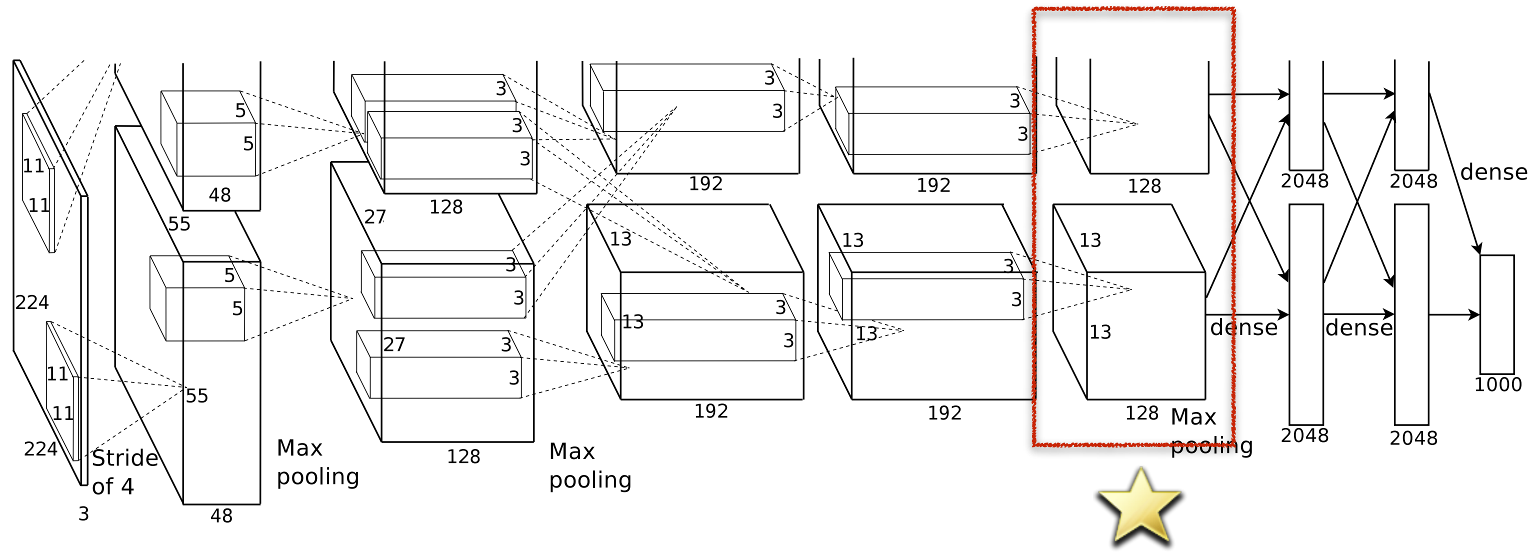

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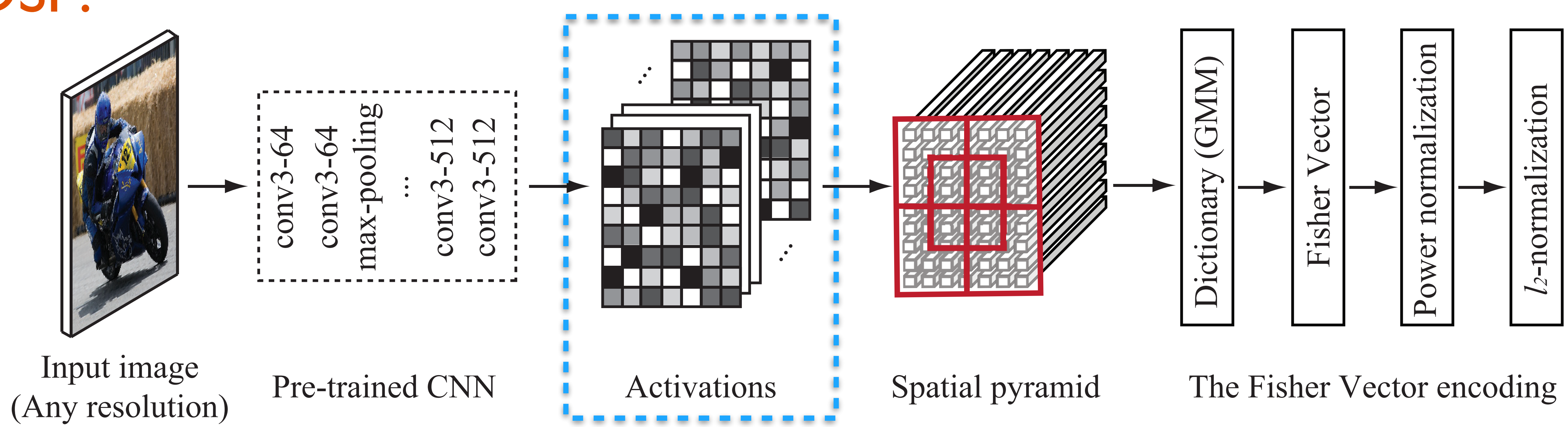

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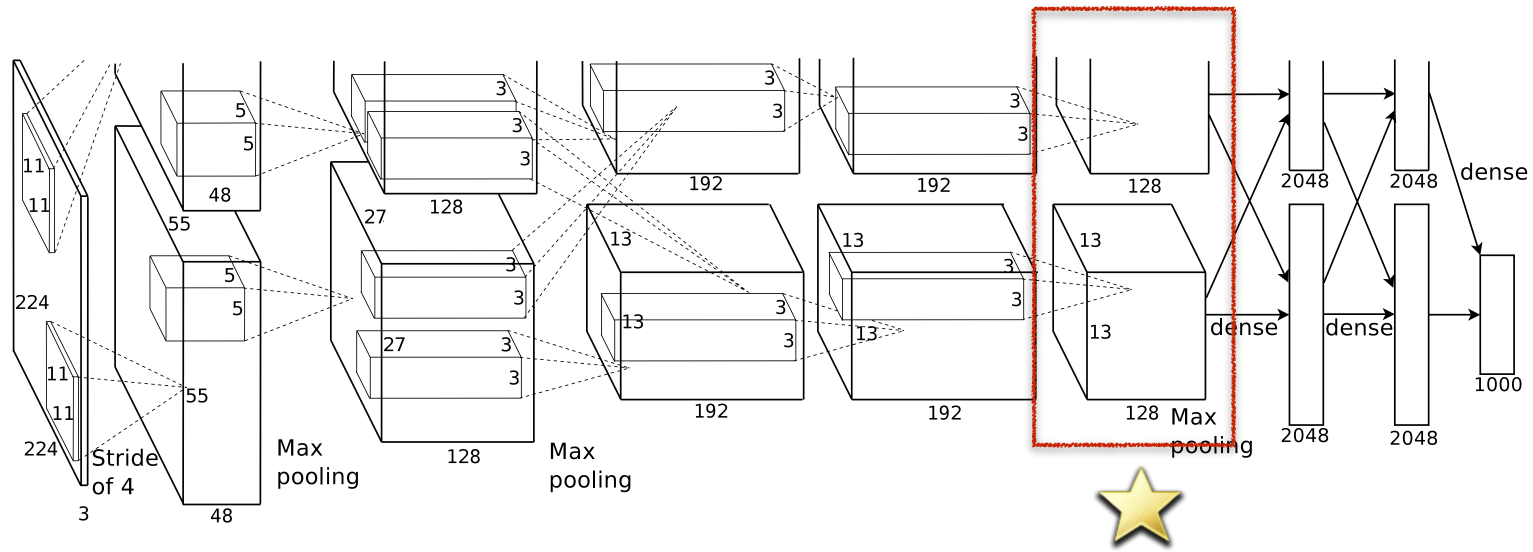

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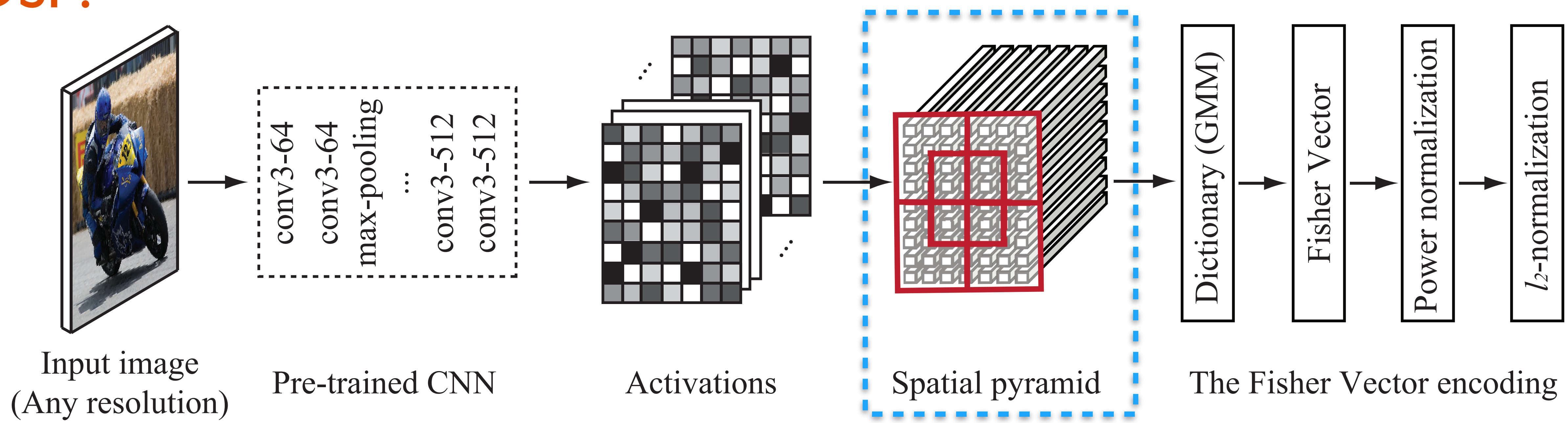

Figure courtesy of [A. Krizhevsky et al., NIPS' 12]

DSP (con't)

l_2 matrix normalization in DSP:

d-dimentional deep desctrptors

$$\boxed{\boldsymbol{x}_t} \leftarrow \boldsymbol{x}_t / \boxed{\|X\|_2}$$

matrix spectral norm

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Results of the different normalization methods:

	Caltech101	Stanford40	Scene15	Indoor67
No	90.63	74.84	90.75	71.20
ℓ_2 vector	92.02	73.41	90.92	74.03
ℓ_2 matrix	**92.56**	**78.43**	**90.99**	**74.55**
PCA+ℓ_2 matrix	91.95	75.69	90.22	71.79

DSP (con't)

Encoding deep descriptors by FV:

$$\boldsymbol{f}_{\boldsymbol{\mu}_k}(X) = \frac{1}{\sqrt{\omega_k}} \sum_{t=1}^{T} \gamma_t(k) \left(\frac{\boldsymbol{x}_t - \boldsymbol{\mu}_k}{\boldsymbol{\sigma}_k} \right) ,$$

$$\boldsymbol{f}_{\boldsymbol{\sigma}_k}(X) = \frac{1}{\sqrt{2\omega_k}} \sum_{t=1}^{T} \gamma_t(k) \left[\frac{(\boldsymbol{x}_t - \boldsymbol{\mu}_k)^2}{\boldsymbol{\sigma}_k^2} - 1 \right] .$$

DSP (con't)

Learning And Mining from DatA

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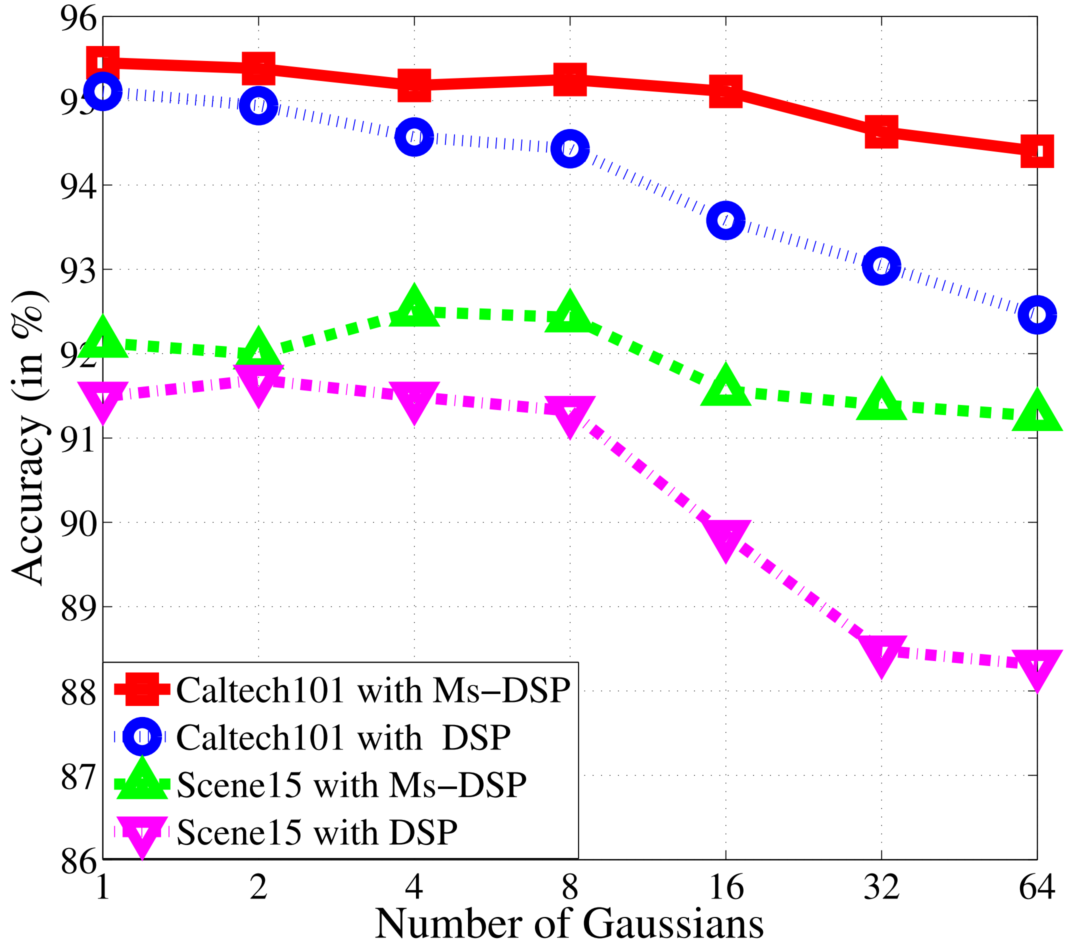
Multi-scale DSP:

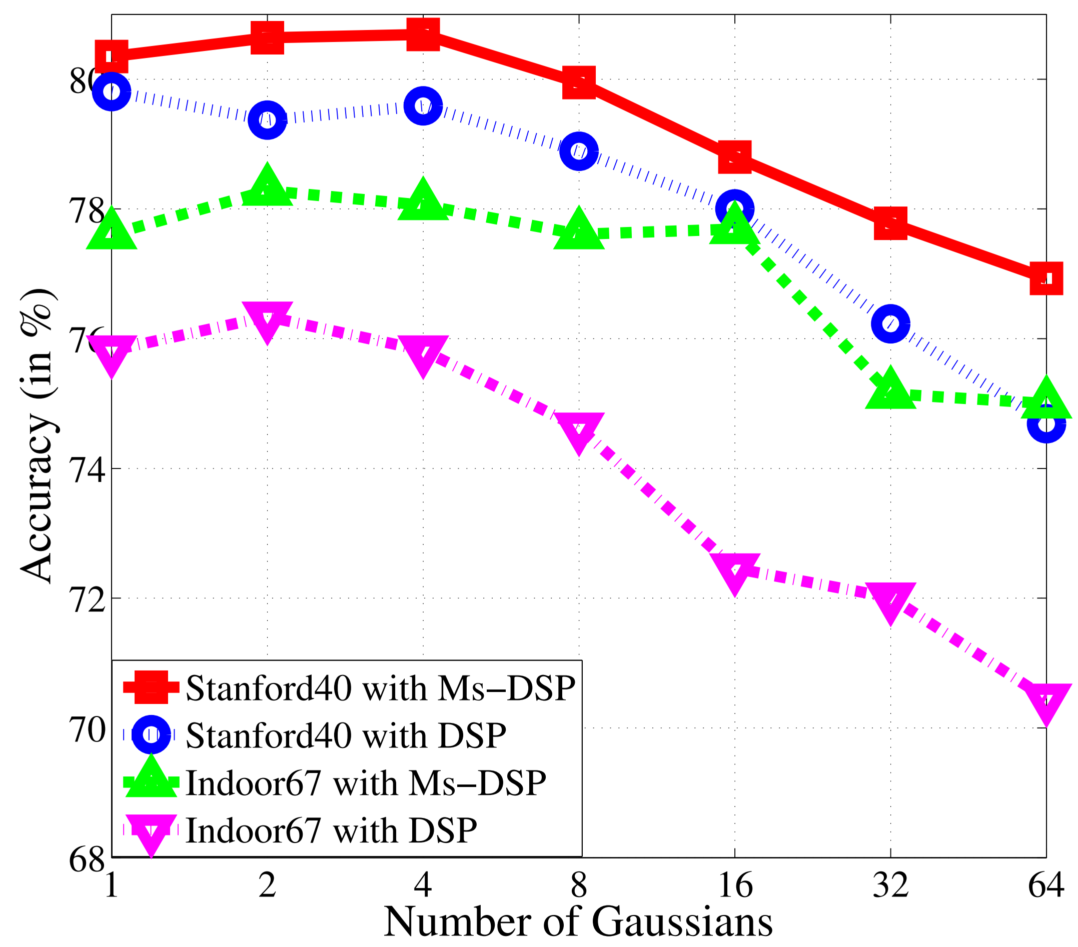
$$\boldsymbol{f}_m = \frac{1}{S} \sum_{s=1}^{S} \boldsymbol{f}_s \qquad S = \{1.4, 1.2, 1.0, 0.8\}$$

DSP (con't)

Classification performance with different *K*:



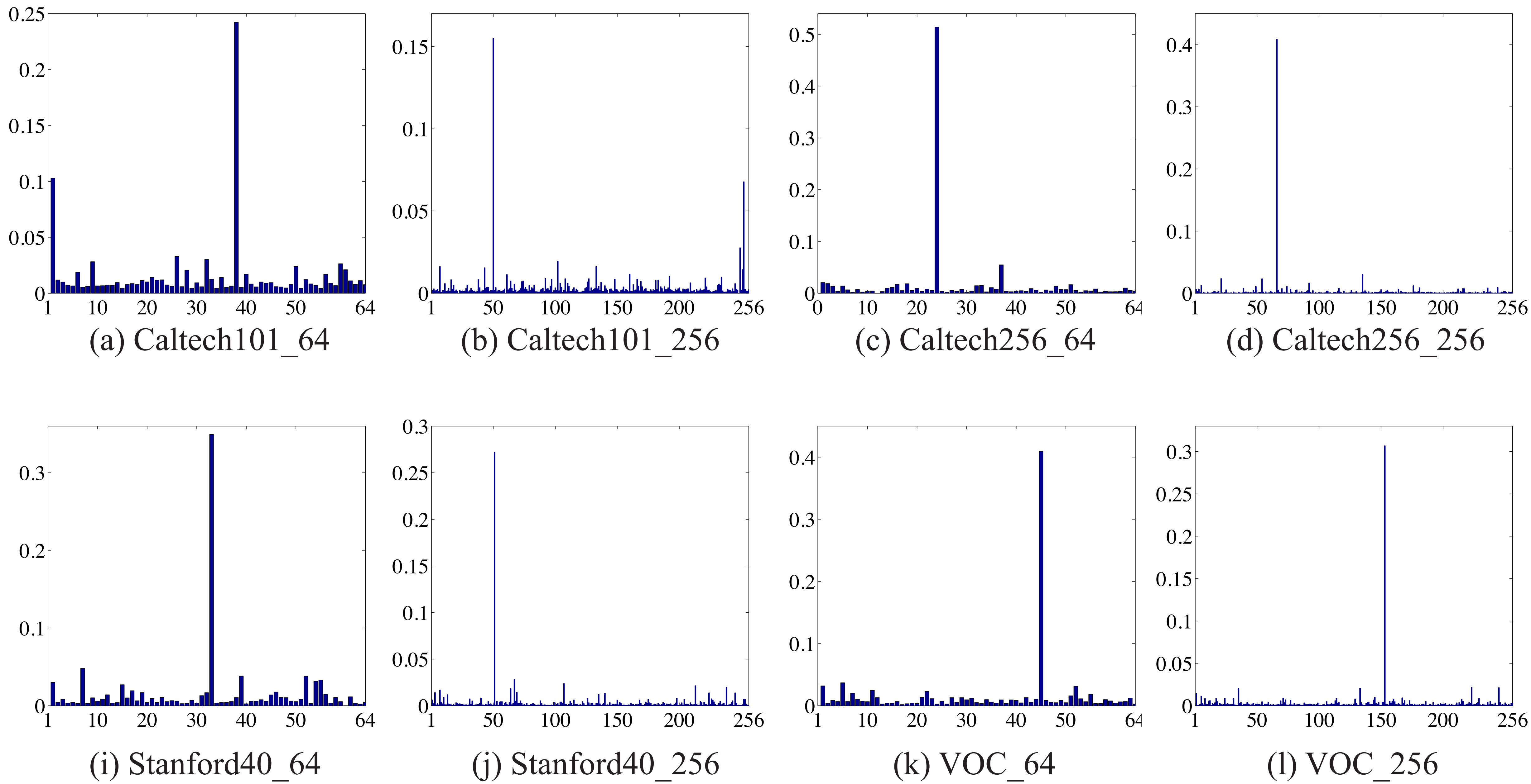
(a) *Caltech-101* and *Scene15*



(b) *Stanford40* and *Indoor67*

DSP (con't)

Plot of *w* values in DSP:



(a) Caltech101_64 (b) Caltech101_256 (c) Caltech256_64 (d) Caltech256_256

(i) Stanford40_64 (j) Stanford40_256 (k) VOC_64 (l) VOC_256

DSP (con't)

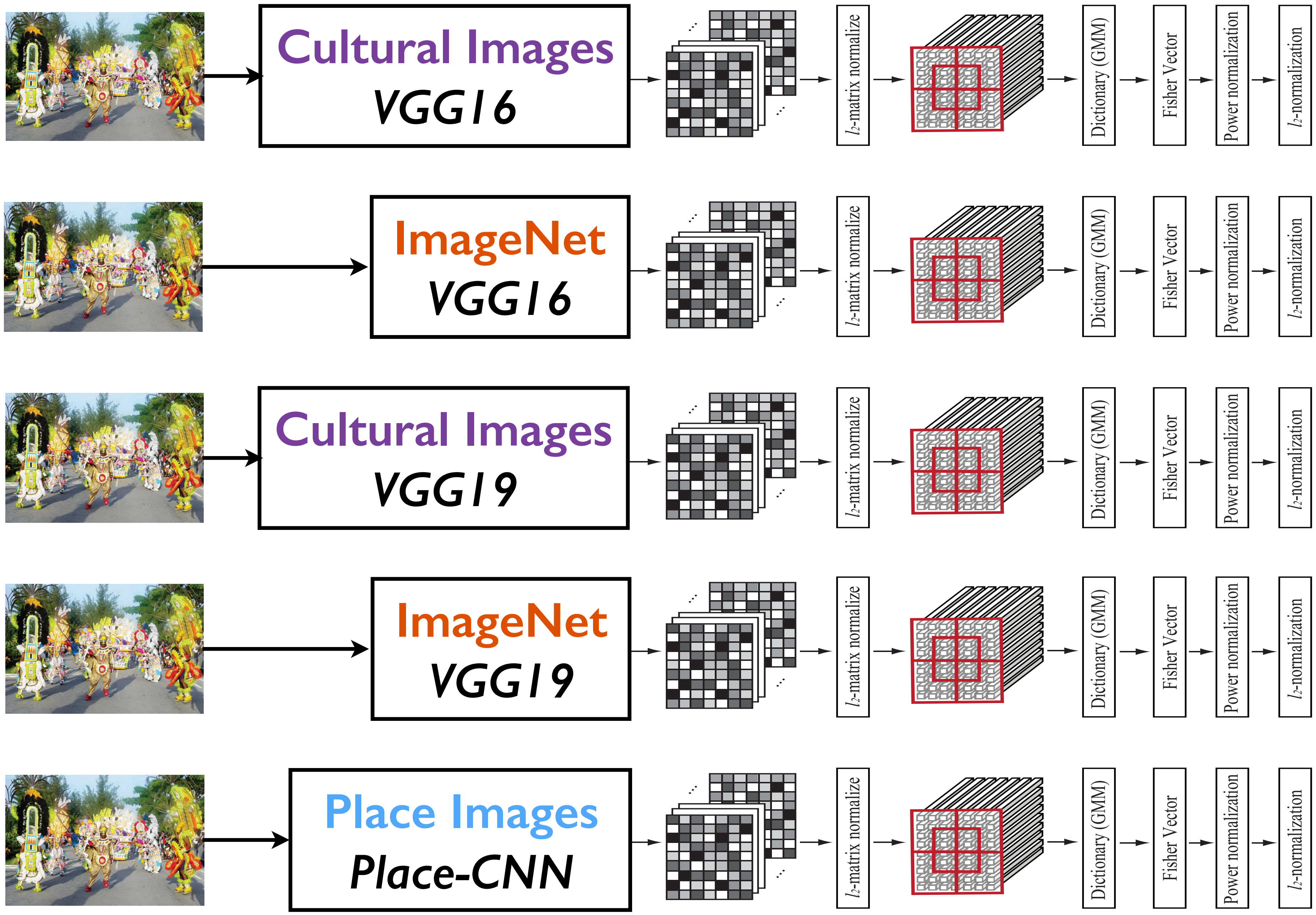
Classification accuracy/MAP comparisons:

Table 3. Recognition accuracy (or mAP) comparisons on seven datasets. The highest accuracy (mAP) of each column is marked in bold. [17]'s results were achieved using VGG Net-D and VGG Net-E, evaluation was measured by mean class recall on *Caltech-101*, *Caltech-256* instead of accuracy .

Methods	Description	Caltech-101	Caltech-256	VOC 2007	Scene15	SUN397	MIT Indoor67	Stanford40
SoA	[9]	**93.42±0.50**	-	82.44	-	-	-	-
	[7]	-	-	-	-	51.98	68.88	-
	[27]	-	-	82.13	-	-	77.56	-
	[30]	84.79±0.66	65.06±0.25	-	91.59±0.48	53.86±0.21	70.80	55.28±0.64
	[1]	88.35±0.56	77.61±0.12	82.4	-	-	-	-
	[17]	92.7±0.5 (*)	**86.2±0.3**(*)	**89.7**	-	-	-	-
Baseline	Fc_8	90.55±0.31	82.02±0.12	84.61	89.88±0.76	53.90±0.45	69.78	71.53±0.34
	$Pool_5$+FV	90.03±0.75	79.48±0.53	88.12	89.00±0.42	51.39±0.51	71.57	73.96±0.52
	DSP	94.66±0.26	84.22±0.11	88.60	91.13±0.77	57.27±0.34	76.34	79.75±0.34
Our	Ms-DSP	**95.11±0.26**	**85.47±0.14**	**89.31**	**91.78±0.22**	**59.78±0.47**	**78.28**	**80.81±0.29**

DSP Ensemble

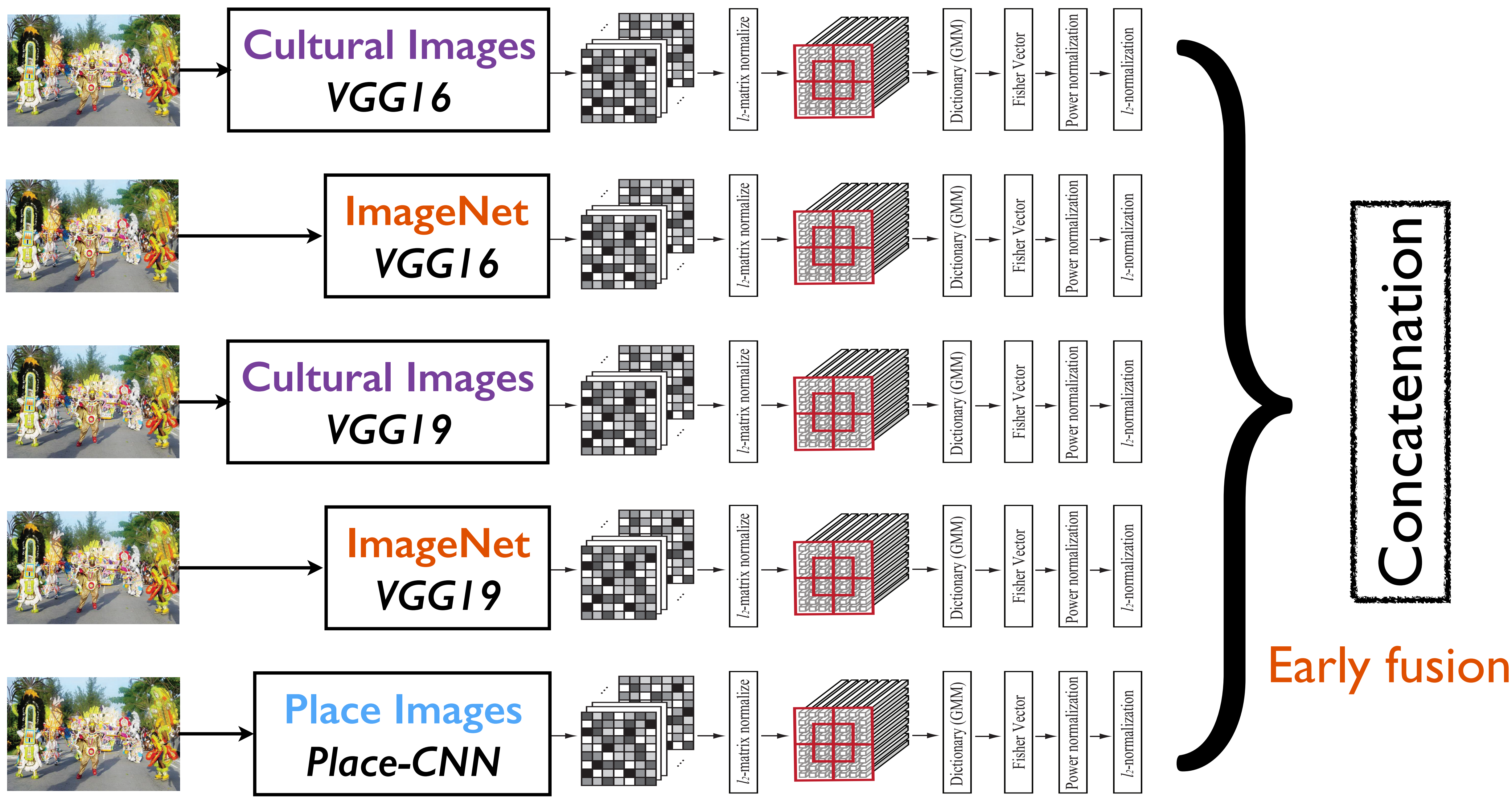
Our framework



DSP Ensemble

Learning And Mining from DatA

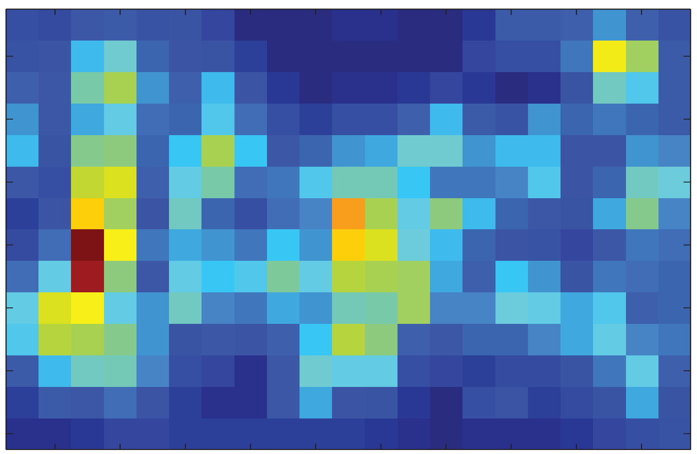
Our framework



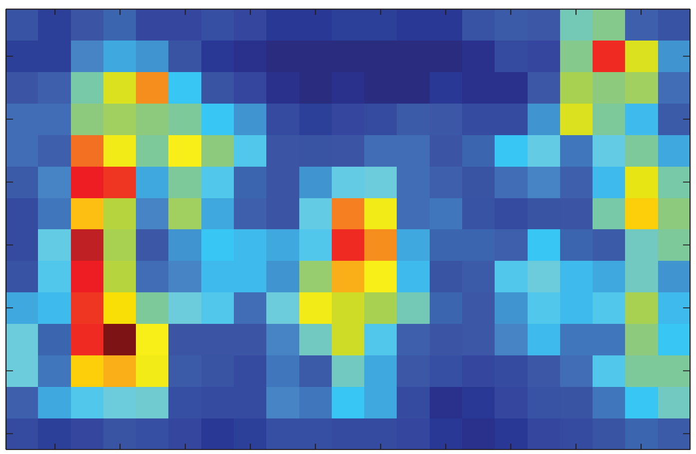
DSP Ensemble (con't)

Different feature maps from different networks:

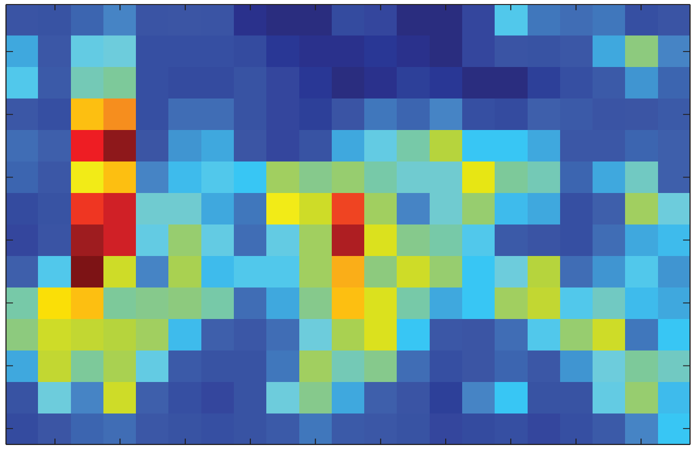
(a) The original image



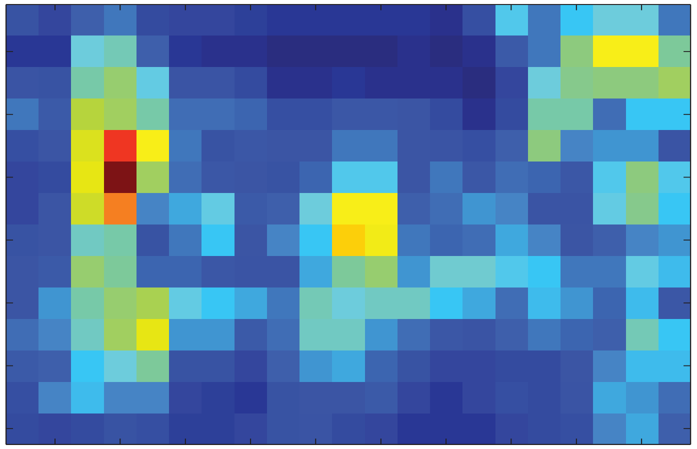
(b) Fine-tuned VGG Net-D



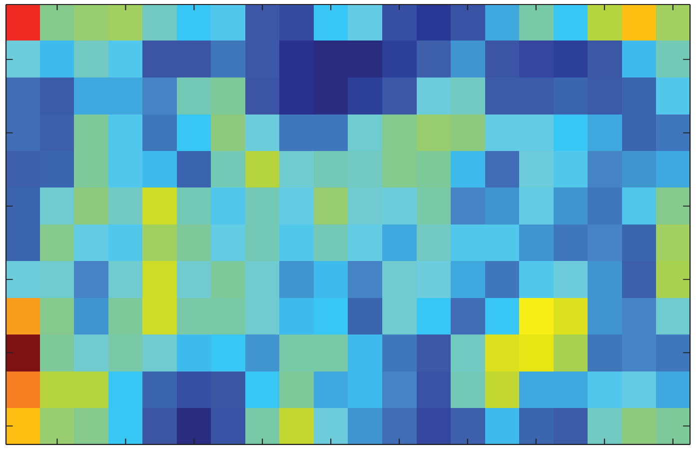
(c) VGG Net-D



(d) Fine-tuned VGG Net-E



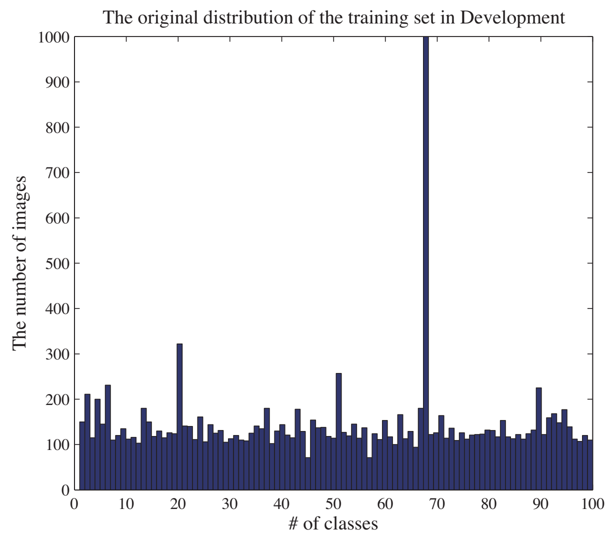
(e) VGG Net-E



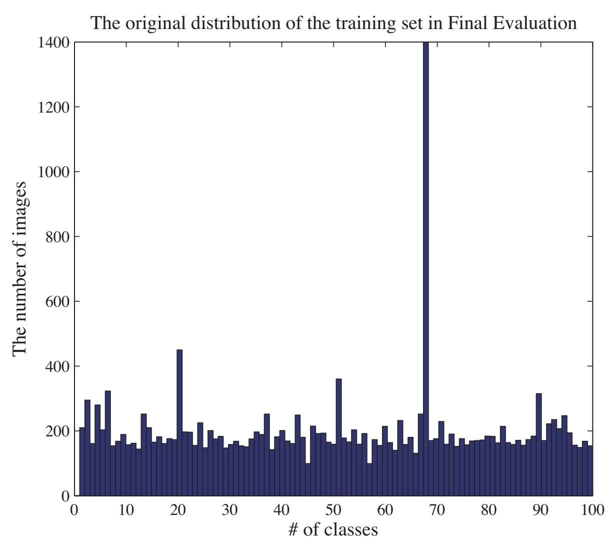
(f) Place-CNN

Implementation details

Distributions of the number of training images in Dev. and Final Evaluation:



(a)

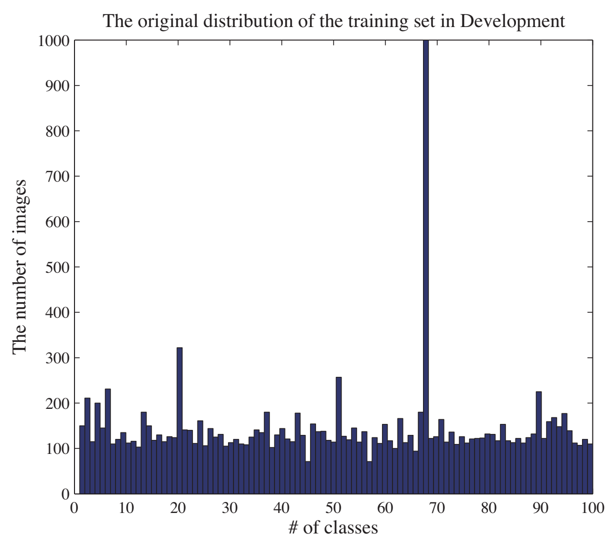


(c)

Implementation details

Learning And Mining from DatA

Distributions of the number of training images in Dev. and Final Evaluation:



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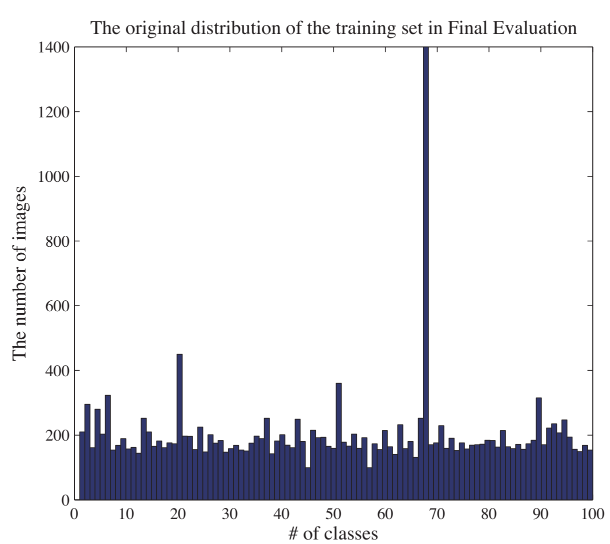
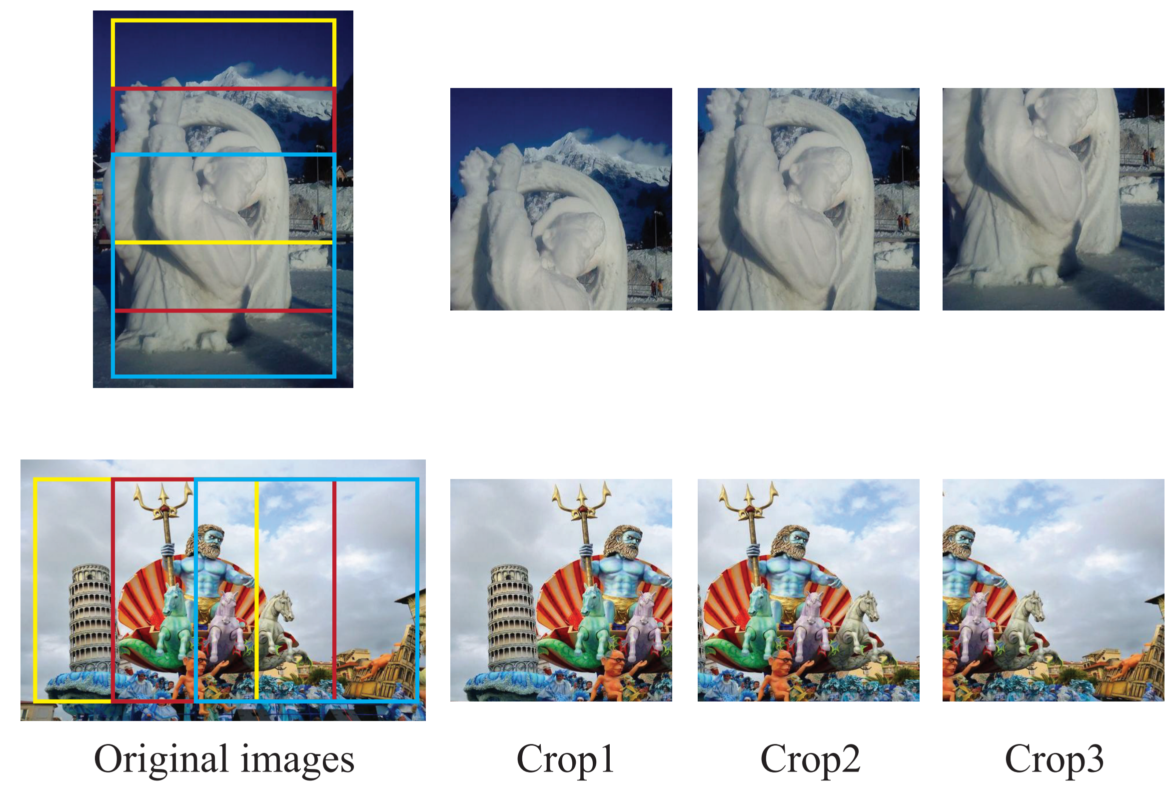


(c)



Late fusion

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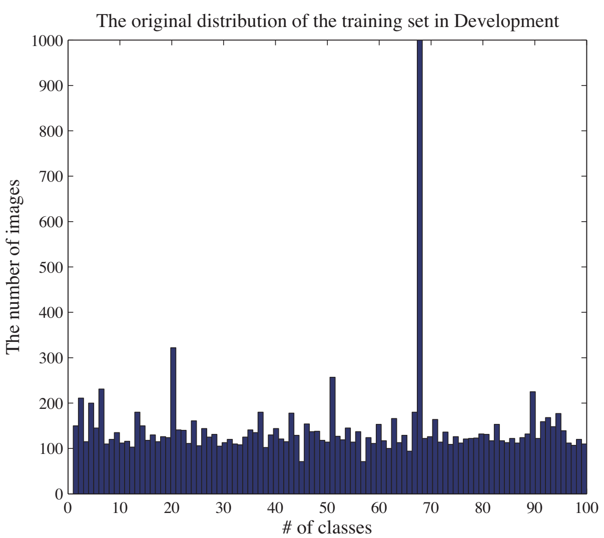

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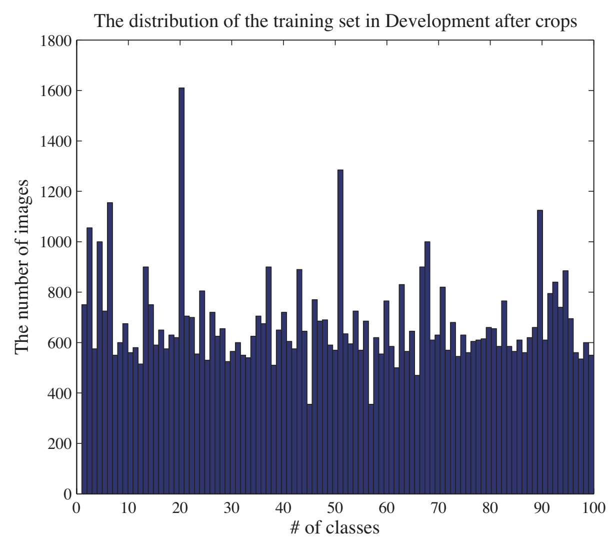
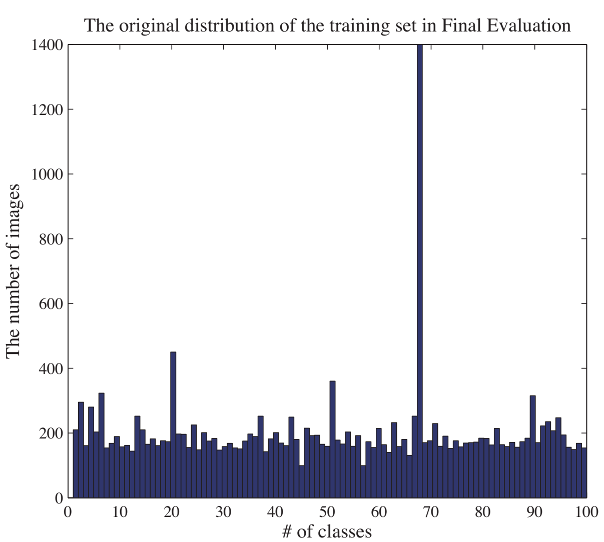


(b)



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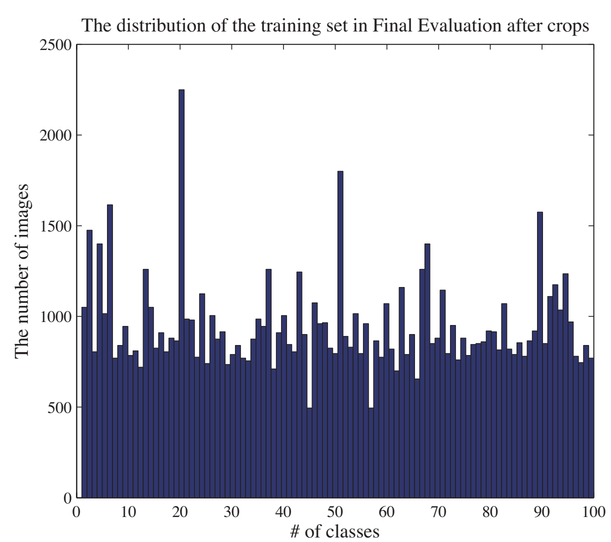
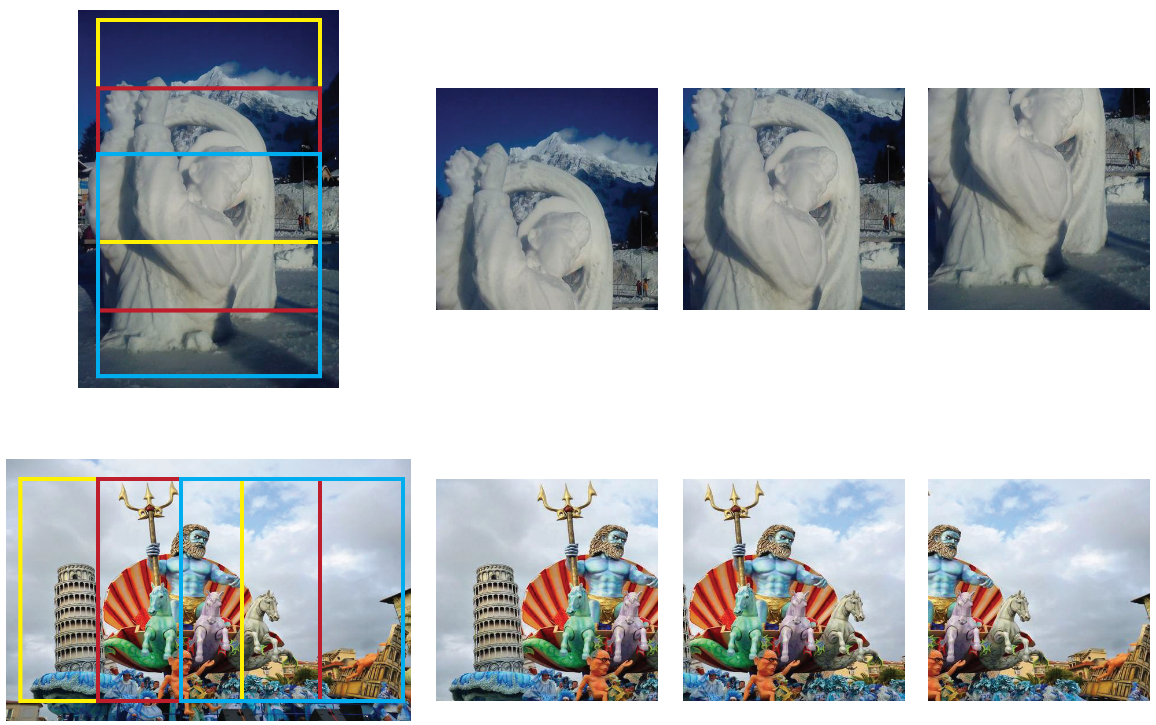


(d)


Original images　Crop1　Crop2　Crop3

Late fusion

Experimental results

Recognition mAP comparisons of the Development phase. Note that, “FT” stands for the fine-tuned deep networks; “SS” is for single scale, and “MS” is for multiple scales.

	VGG Net-D	VGG Net-E	FT VGG Net-D	FT VGG Net-E	Place-CNN
SS	0.761	0.762	–	–	–
MS	0.770	0.773	0.779	0.769	0.640
Late fusion	0.782	0.784	0.802	0.791	0.649
Ensemble	0.841				

Experimental results

LAMDA
Learning And Mining from DatA

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Rank	Team	Score
1	VIPL-ICT-CAS	0.854
2	**FV (Ours)**	0.851
3	MMLAB	0.847
4	NU&C	0.824
5	CVL_ETHZ	0.798

Thank you!