



Computer Vision; Image Classification; Transfer Learning



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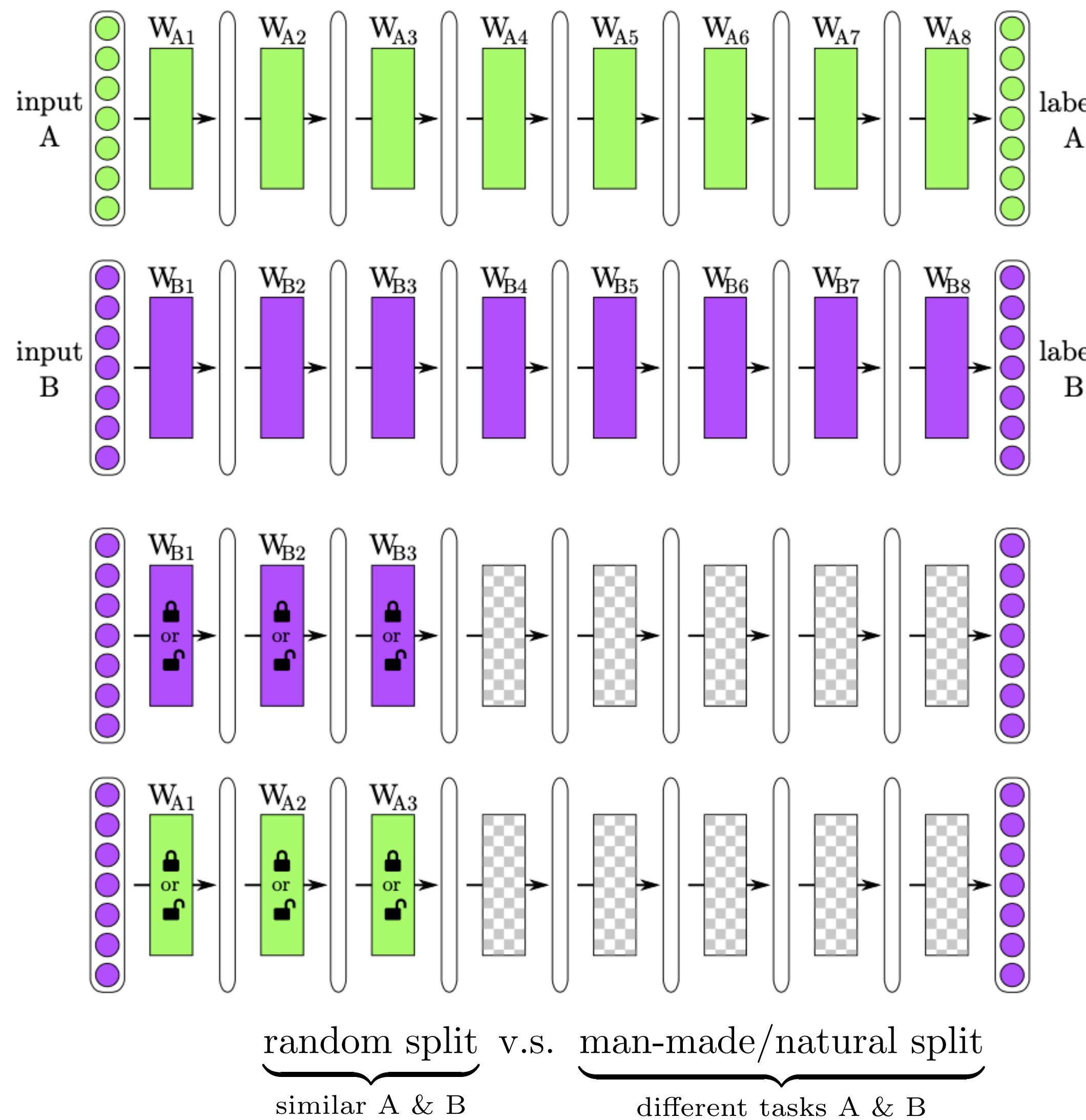


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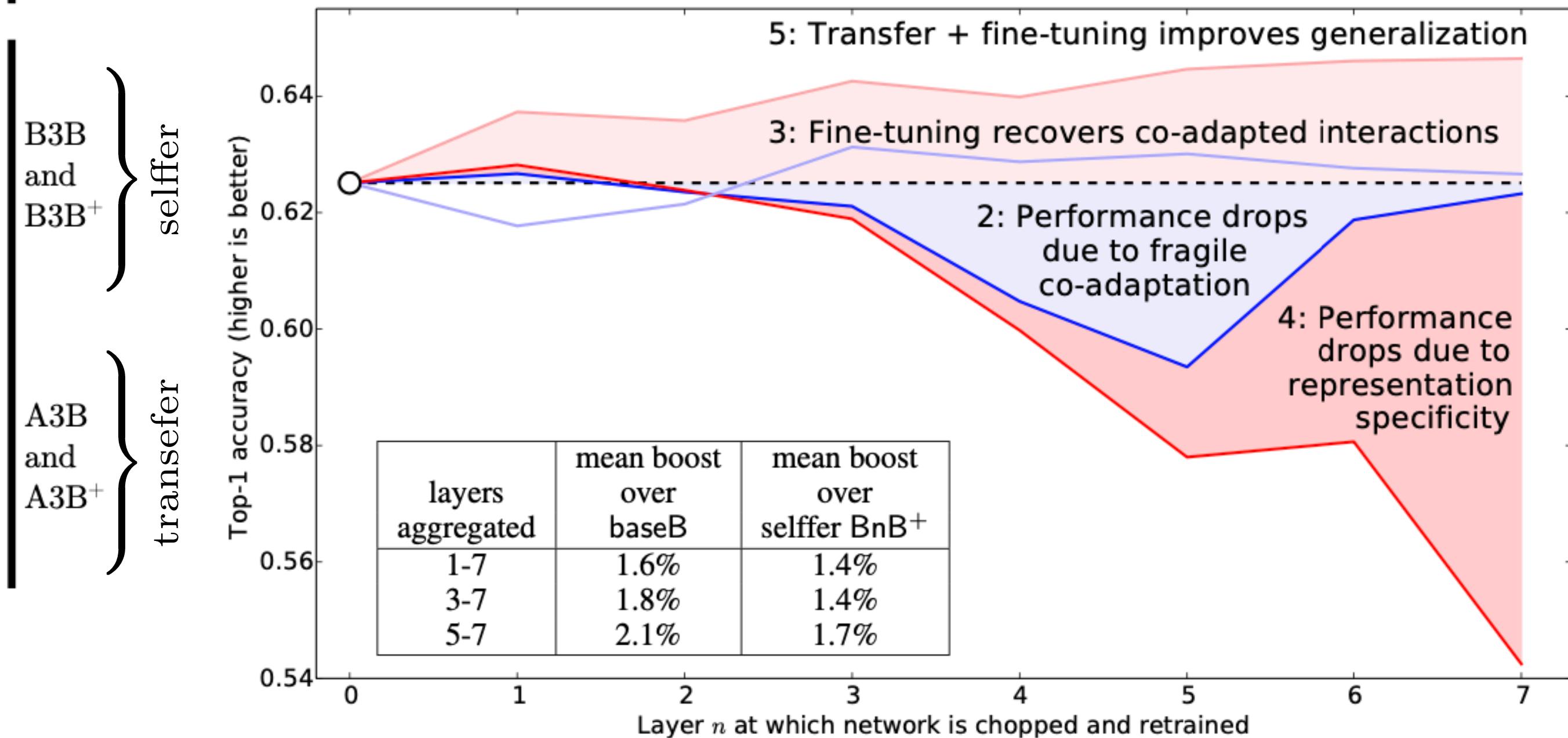
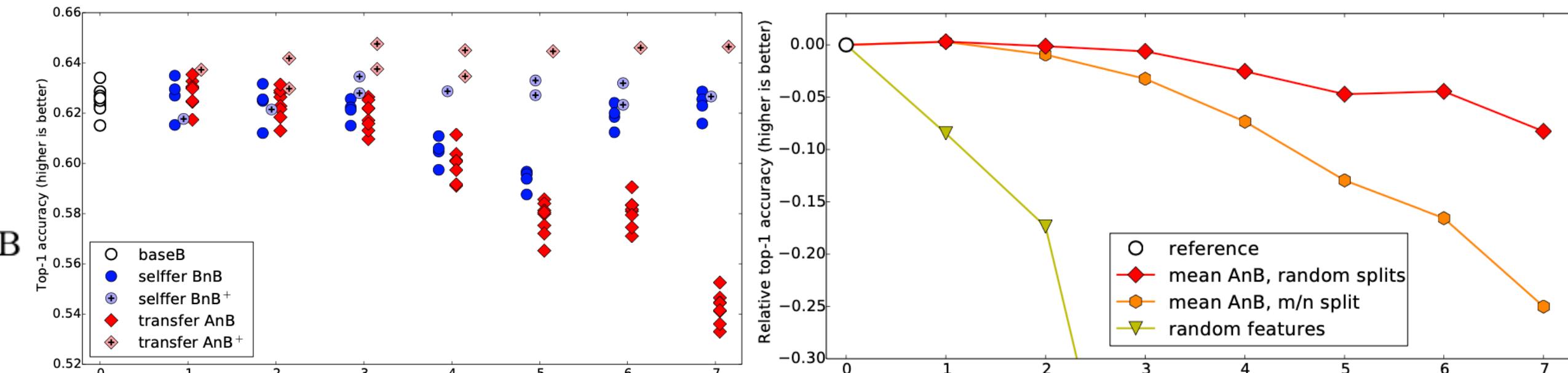


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How transferable are features in deep neural networks?



- Can we quantify the degree to which a particular layer is general or specific?
- Does the transition occur suddenly at a single layer, or is it spread out over several layers?
- Where does this transition take place: near the first, middle, or last layer of the network?

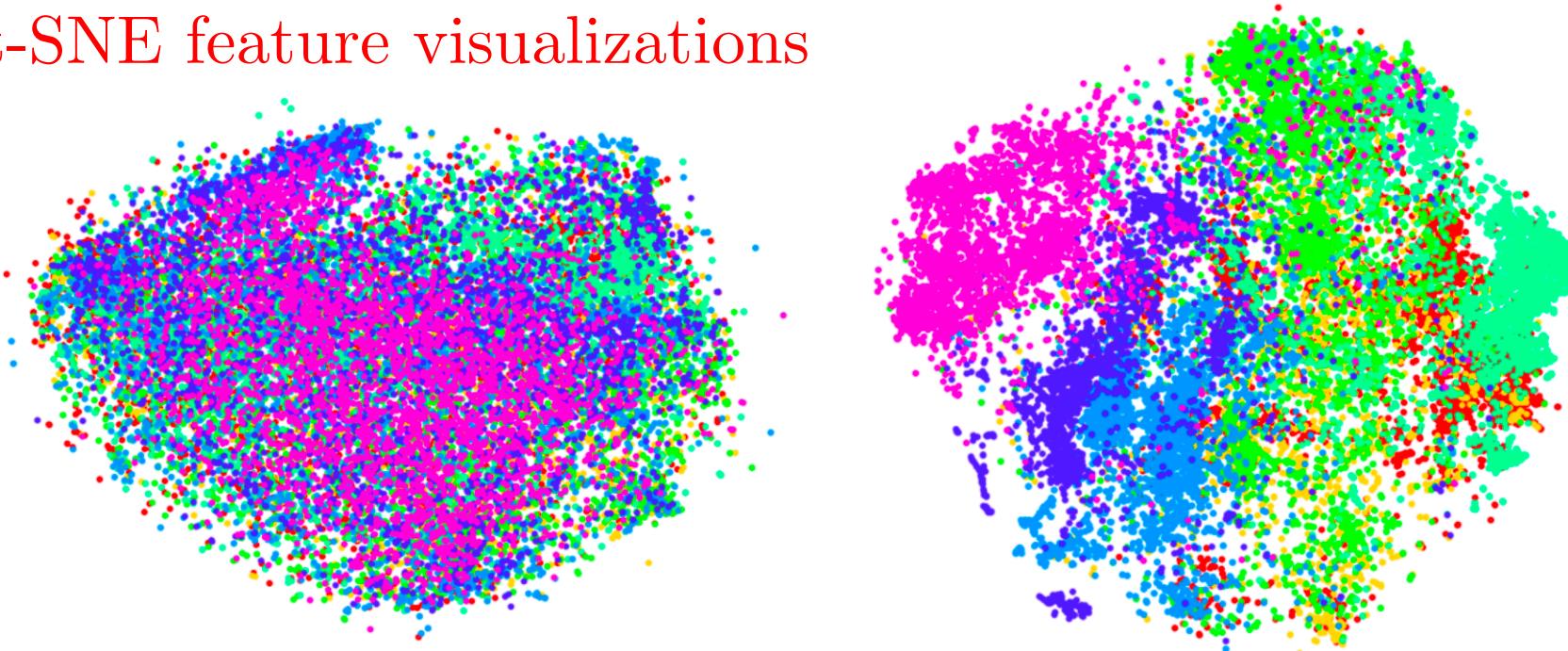




DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition


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t-SNE feature visualizations

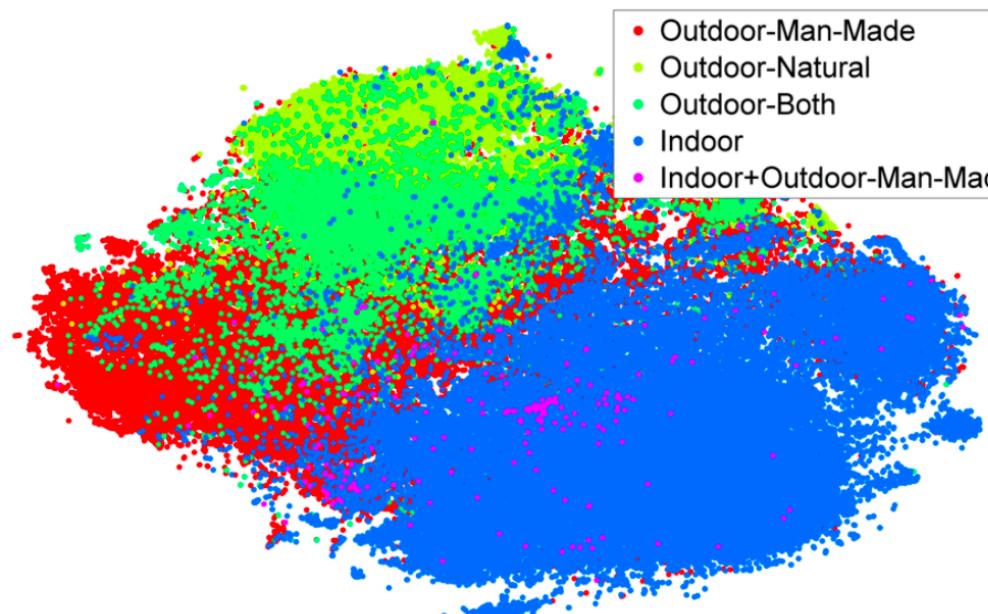


DeCAF₁
first pooling layer

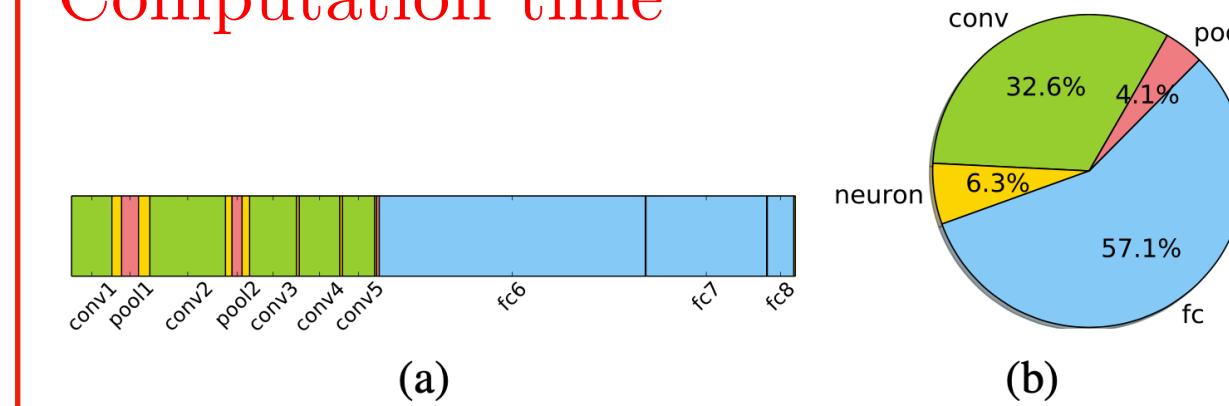
- structure, construction
- covering
- commodity, trade good, good
- conveyance, transport
- invertebrate
- bird
- hunting dog

First layers learn “low-level” features, whereas the latter layers learn semantic or “high-level” features.

Features trained on ILSVRC-2012 generalized to SUN-397

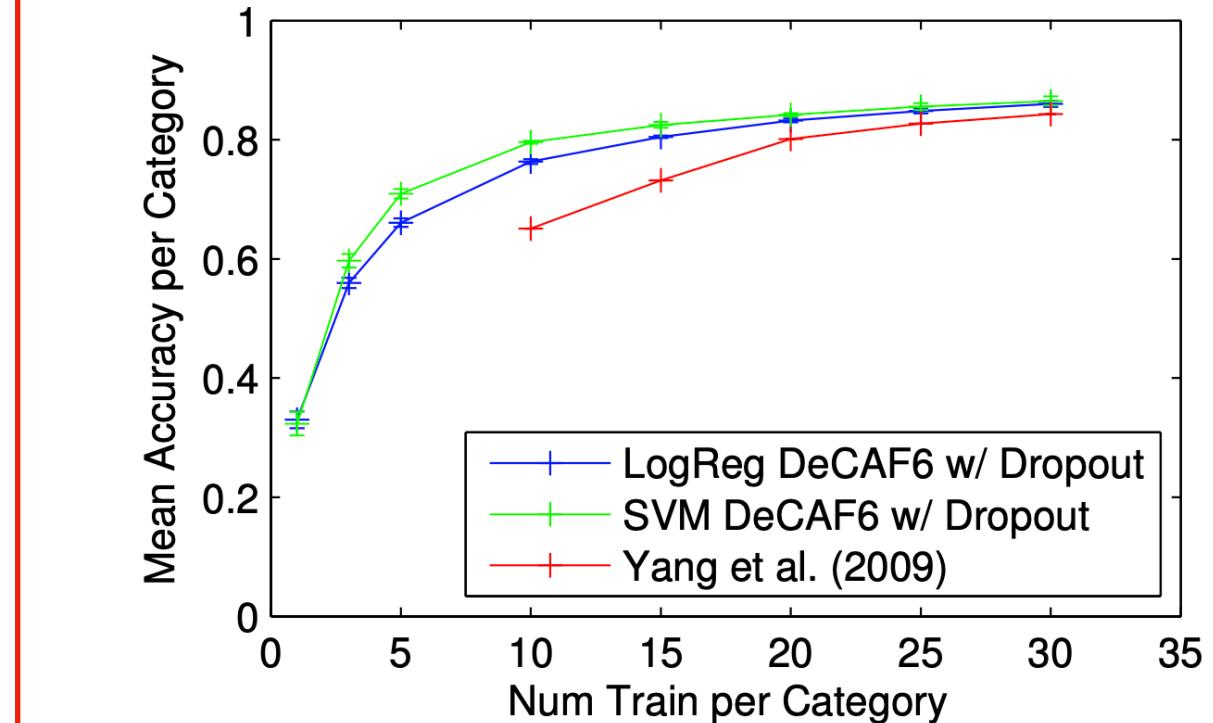


Computation time



Object recognition (Caltech-101)

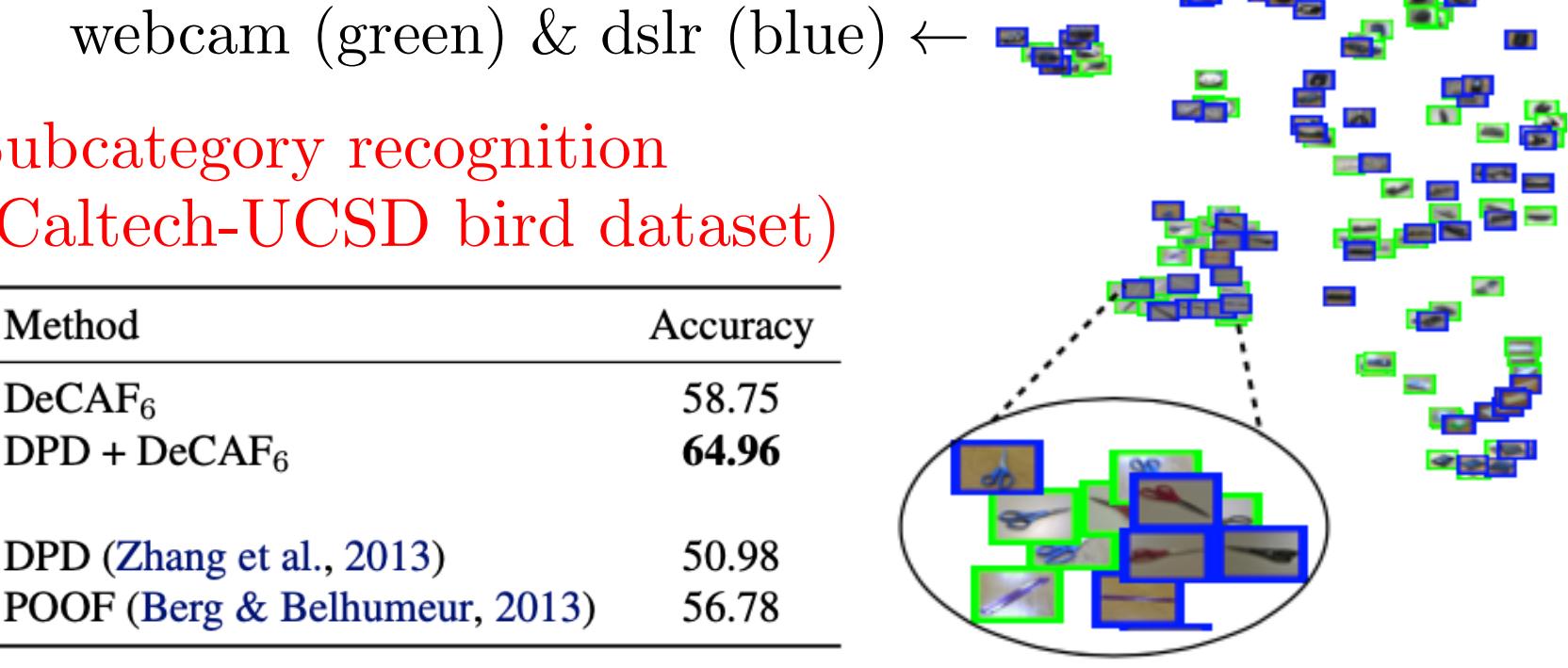
	DeCAF ₅	DeCAF ₆	DeCAF ₇
LogReg	63.29 ± 6.6	84.30 ± 1.6	84.87 ± 0.6
LogReg with Dropout	-	86.08 ± 0.8	85.68 ± 0.6
SVM	77.12 ± 1.1	84.77 ± 1.2	83.24 ± 1.2
SVM with Dropout	-	86.91 ± 0.7	85.51 ± 0.9
Yang et al. (2009)		84.3	
Jarrett et al. (2009)		65.5	



Domain adaptation (Office dataset)

The dataset contains three domains: Amazon, which consists of product images taken from amazon.com; and Webcam and Dslr, which consist of images taken in an office environment using a webcam or digital SLR camera, respectively.

	Amazon → Webcam			Dslr → Webcam		
	SURF	DeCAF ₆	DeCAF ₇	SURF	DeCAF ₆	DeCAF ₇
Logistic Reg. (S)	9.63 ± 1.4	48.58 ± 1.3	53.56 ± 1.5	24.22 ± 1.8	88.77 ± 1.2	87.38 ± 2.2
SVM (S)	11.05 ± 2.3	52.22 ± 1.7	53.90 ± 2.2	38.80 ± 0.7	91.48 ± 1.5	89.15 ± 1.7
Logistic Reg. (T)	24.33 ± 2.1	72.56 ± 2.1	74.19 ± 2.8	24.33 ± 2.1	72.56 ± 2.1	74.19 ± 2.8
SVM (T)	51.05 ± 2.0	78.26 ± 2.6	78.72 ± 2.3	51.05 ± 2.0	78.26 ± 2.6	78.72 ± 2.3
Logistic Reg. (ST)	19.89 ± 1.7	75.30 ± 2.0	76.32 ± 2.0	36.55 ± 2.2	92.88 ± 0.6	91.91 ± 2.0
SVM (ST)	23.19 ± 3.5	80.66 ± 2.3	79.12 ± 2.1	46.32 ± 1.1	94.79 ± 1.2	92.96 ± 2.0
Daume III (2007)	40.26 ± 1.1	82.14 ± 1.9	81.65 ± 2.4	55.07 ± 3.0	91.25 ± 1.1	89.52 ± 2.2
Hoffman et al. (2013)	37.66 ± 2.2	80.06 ± 2.7	80.37 ± 2.0	53.65 ± 3.3	93.25 ± 1.5	91.45 ± 1.5
Gong et al. (2012)	39.80 ± 2.3	75.21 ± 1.2	77.55 ± 1.9	39.12 ± 1.3	88.40 ± 1.0	88.66 ± 1.9
Chopra et al. (2013)		58.85				78.21



Scene recognition (SUN-397)

	DeCAF ₆	DeCAF ₇
LogReg	40.94 ± 0.3	40.84 ± 0.3
SVM	39.36 ± 0.3	40.66 ± 0.3
Xiao et al. (2010)		38.0

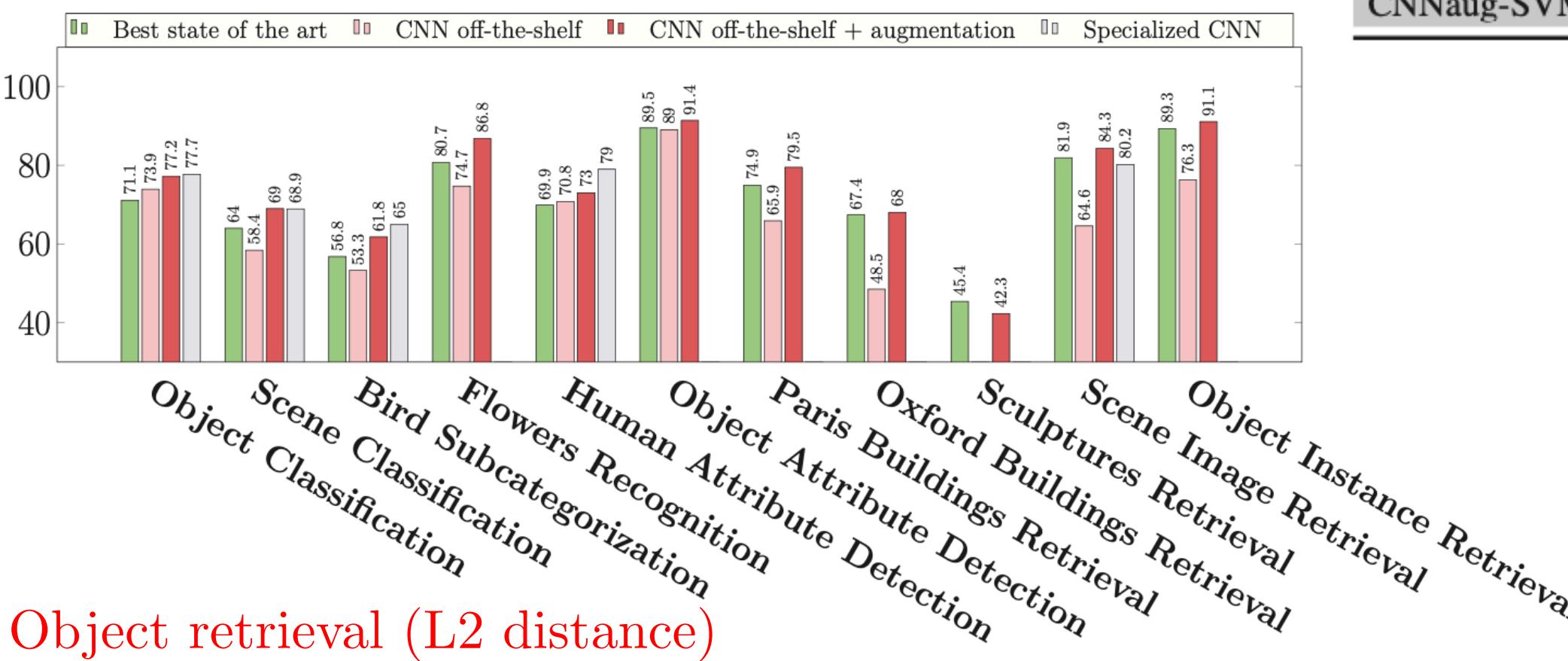
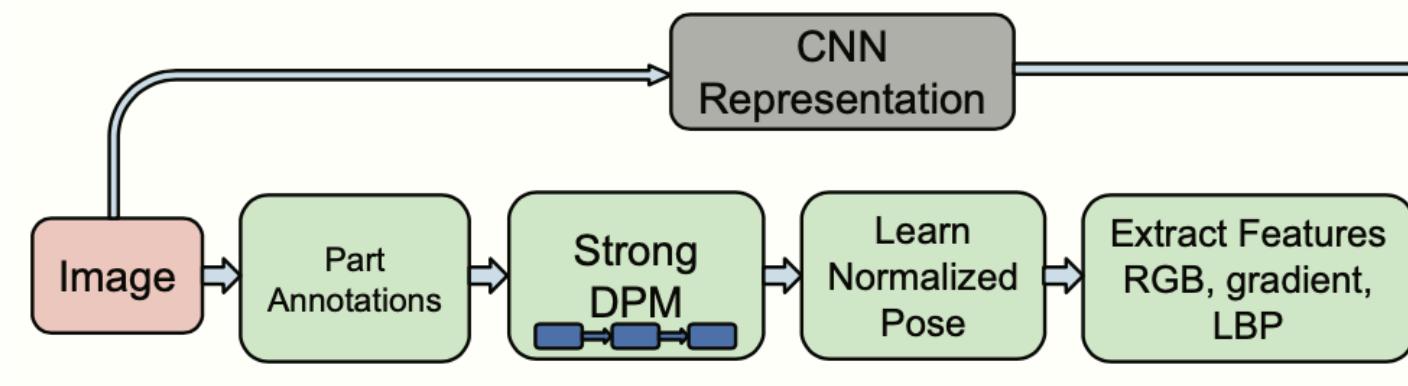


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CNN Features off-the-shelf: an Astounding Baseline for Recognition



Object retrieval (L2 distance)

	Dim	Oxford5k	Paris6k	Sculp6k	Holidays	UKBench
BoB[3]	N/A	N/A	N/A	45.4 [3]	N/A	N/A
BoW	200k	36.4[20]	46.0[35]	8.1[3]	54.0[4]	70.3[20]
IFV[33]	2k	41.8[20]	-	-	62.6[20]	83.8[20]
VLAD[4]	32k	55.5 [4]	-	-	64.6[4]	-
CVLAD[52]	64k	47.8[52]	-	-	81.9[52]	89.3[52]
HE+burst[17]	64k	64.5[42]	-	-	78.0[42]	-
AHE+burst[17]	64k	66.6[42]	-	-	79.4[42]	-
Fine vocab[26]	64k	74.2[26]	74.9[26]	-	74.9[26]	-
ASMK*+MA[42]	64k	80.4[42]	77.0[42]	-	81.0[42]	-
ASMK+MA[42]	64k	81.7 [42]	78.2[42]	-	82.2[42]	-
CNN	4k	32.2	49.5	24.1	64.2	76.0
CNN-ss	32-120k	55.6	69.7	31.1	76.9	86.9
CNNaug-ss	4-15k	68.0	79.5	42.3	84.3	91.1
CNN+BOW[16]	2k	-	-	-	80.2	-

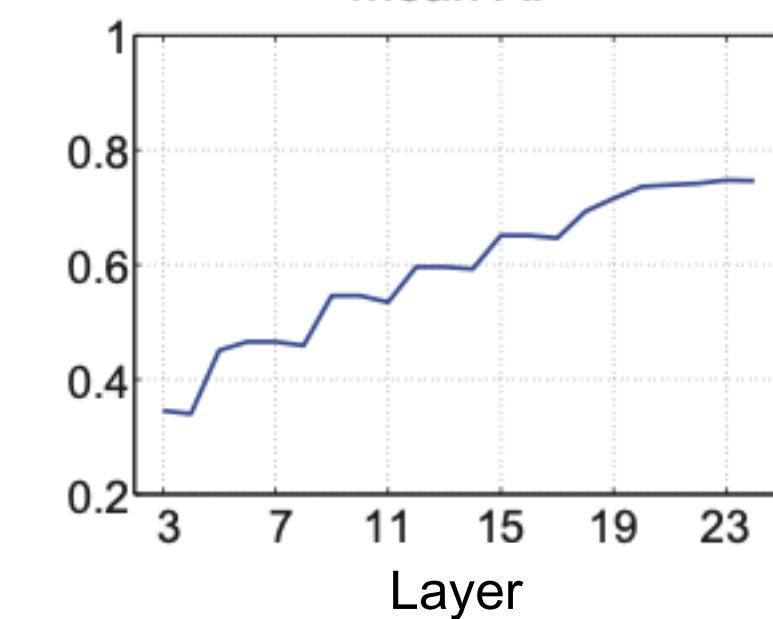
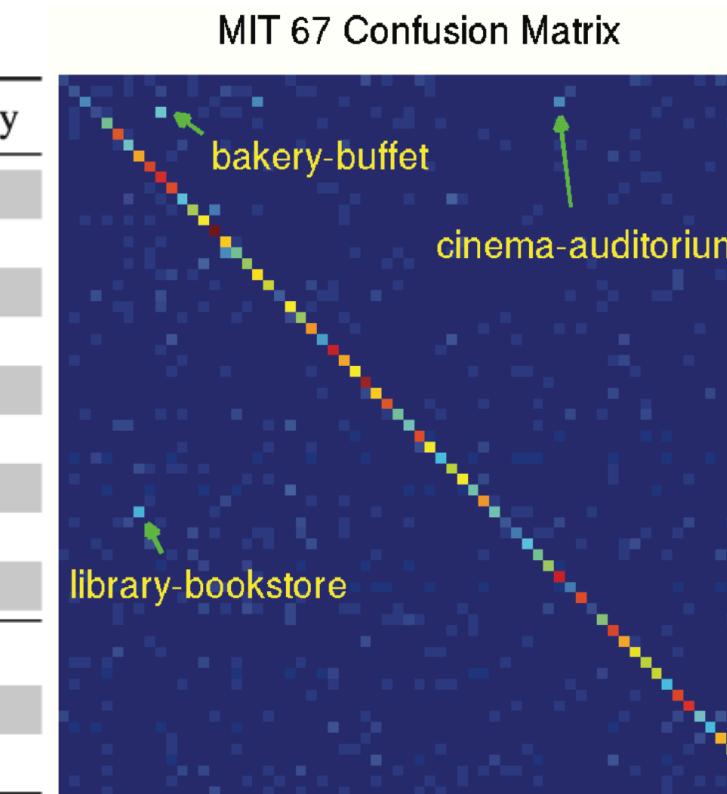
Sharif Razavian, Ali, et al. "CNN features off-the-shelf: an astounding baseline for recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*. 2014.

Pascal VOC 2007 Image Classification

	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
GHM[8]	76.7	74.7	53.8	72.1	40.4	71.7	83.6	66.5	52.5	57.5	62.8	51.1	81.4	71.5	86.5	36.4	55.3	60.6	80.6	57.8	64.7
AGS[11]	82.2	83.0	58.4	76.1	56.4	77.5	88.8	69.1	62.2	61.8	64.2	51.3	85.4	80.2	91.1	48.1	61.7	67.7	86.3	70.9	71.1
NUS[39]	82.5	79.6	64.8	73.4	54.2	75.0	77.5	79.2	46.2	62.7	41.4	74.6	85.0	76.8	91.1	53.9	61.0	67.5	83.6	70.6	70.5
CNN-SVM	88.5	81.0	83.5	82.0	42.0	72.5	85.3	81.6	59.9	58.5	66.5	77.8	81.8	78.8	90.2	54.8	71.1	62.6	87.2	71.8	73.9
CNNaug-SVM	90.1	84.4	86.5	84.1	48.4	73.4	86.7	85.4	61.3	67.6	69.6	84.0	85.4	80.0	92.0	56.9	76.7	67.3	89.1	74.9	77.2

MIT-67 indoor scenes dataset

Method	mean Accuracy
ROI + Gist[36]	26.1
DPM[30]	30.4
Object Bank[24]	37.6
RBow[31]	37.9
BoP[21]	46.1
miSVM[25]	46.4
D-Parts[40]	51.4
IFV[21]	60.8
MLrep[9]	64.0
CNN-SVM	58.4
CNNaug-SVM	69.0
CNN(AlexConvNet)+multiscale pooling [16]	68.9



CNNaug: augment the training set by adding cropped and rotated samples

CUB 200-2011 Bird dataset

Method	Part info	mean Accuracy
Sift+Color+SVM[45]	✗	17.3
Pose pooling kernel[49]	✓	28.2
RF[47]	✓	19.2
DPD[50]	✓	51.0
Poof[5]	✓	56.8
CNN-SVM	✗	53.3
CNNaug-SVM	✗	61.8
DPD+CNN(DeCaf)+LogReg[10]	✓	65.0

H3D Human Attributes dataset

Method	male	lg hair	glasses	hat	tshirt	lg slvs	shorts	jeans	lg pants	mAP
Freq[6]	59.3	30.0	22.0	16.6	23.5	49.0	17.9	33.8	74.7	36.3
SPM[6]	68.1	40.0	25.9	35.3	30.6	58.0	31.4	39.5	84.3	45.9
Poselets[6]	82.4	72.5	55.6	60.1	51.2	74.2	45.5	54.7	90.3	65.2
DPD[50]	83.7	70.0	38.1	73.4	49.8	78.1	64.1	78.1	93.5	69.9
CNN-SVM	83.0	67.6	39.7	66.8	52.6	82.2	78.2	71.7	95.2	70.8
CNNaug-SVM	84.8	71.0	42.5	66.9	57.7	84.0	79.1	75.7	95.3	73.0



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Return of the Devil in the Details: Delving Deep into Convolutional Nets

$I \rightarrow \text{image}$

$\phi \rightarrow \text{encoding function}$

$\phi(I) \in \mathbb{R}^d \rightarrow \text{vector image representation}$

Shallow Representation (IFV)

Improved Fisher Vector (IFV)

- Extract a dense collection of patches and corresponding local descriptors $x_i \in \mathbb{R}^D$

(e.g., SIFT) from the image at multiple scales

- Each descriptor x_i is then soft-quantized (i.e., clustered) using a Gaussian Mixture Model with K components.

$$u_k := \sum_{\{x_i: NN(x_i)=\mu_k\}} (x_i - \mu_k) \in \mathbb{R}^D$$

Nearest Neighbor

accumulated first order differences

$$v_k := \sum_{\{x_i: NN(x_i)=\mu_k\}} (x_i - \mu_k)^2 \in \mathbb{R}^D$$

accumulated second order differences

$$\phi_{\text{FV}}(I) = [u_1; v_1; \dots; u_K; v_K] \in \mathbb{R}^{2KD}$$

$$\phi_{\text{IFV}}(I) \leftarrow \phi_{\text{FV}}(I) \triangleright \text{sign}(\cdot) \sqrt{|\cdot|} \triangleright \ell_2 \text{ normalize}$$

Deep representation (CNN) with pre-training

$\phi_{\text{CNN}}(I) \rightarrow \text{vector activities of penultimate layer}$

Deep representation (CNN) with pre-training and fine-tuning

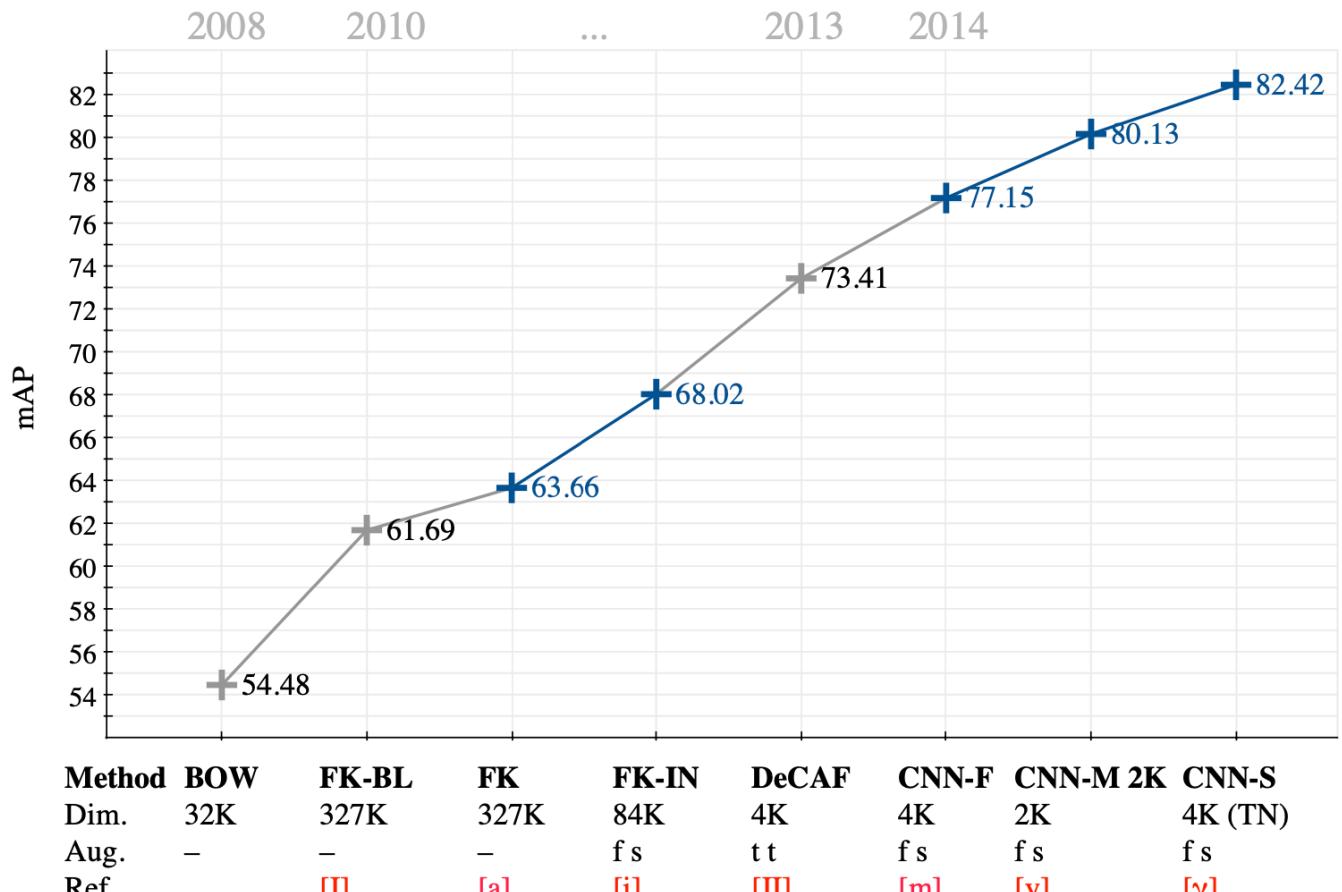
	ILSVRC-2012 (top-5 error)	VOC-2007 (mAP)	VOC-2012 (mAP)	Caltech-101 (accuracy)	Caltech-256 (accuracy)	Method	SPool	Image Aug.	Dim	mAP
(a) FK IN 512	-	68.0	-	-	-	(I) FK BL	spm	-	327K	61.69
(b) CNN F (Fast)	16.7	77.4	79.9	-	-	(II) DECAF	-	(C) t t	327K	73.41
(c) CNN M (Medium)	13.7	79.9	82.5	87.15 ± 0.80	77.03 ± 0.46	(a) FK	spm	-	327K	63.66
(d) CNN M 2048	13.5	80.1	82.4	86.64 ± 0.53	76.88 ± 0.35	(b) FK IN (Intra-normalisation)	spm	-	327K	64.18
(e) CNN S (Slow)	13.1	79.7	82.9	87.76 ± 0.66	77.61 \pm 0.12	(c) FK	(x,y)	-	42K	63.51
(f) CNN S TUNE-CLS	13.1	-	83.0	88.35 \pm 0.56	77.33 ± 0.56	(d) FK IN	(x,y)	-	42K	64.36
(g) CNN S TUNE-RNK	13.1	82.4	83.2	-	-	(e) FK IN	(x,y)	(F) f -	42K	64.35
(h) Zeiler & Fergus [19]	16.1	-	79.0	86.5 ± 0.5	74.2 ± 0.3	(f) FK IN	(x,y)	(C) f s	42K	67.17
(i) Razavian <i>et al.</i> [9], [10]	14.7	77.2	-	-	-	(g) FK IN	(x,y)	(C) s s	42K	66.68
(j) Oquab <i>et al.</i> [8]	18	77.7	78.7 (82.8*)	-	-	(h) FK IN 512	(x,y)	-	84K	65.36
(k) Oquab <i>et al.</i> [16]	-	-	86.3*	-	-	(i) FK IN 512	(x,y)	(C) f s	84K	68.02
(l) Wei <i>et al.</i> [17]	-	81.5 (85.2*)	81.7 (90.3*)	-	-	(j) FK IN COL 512	-	-	82K	52.18
(m) He <i>et al.</i> [29]	13.6	80.1	-	91.4 ± 0.7	-	(k) FK IN 512 COL+	(x,y)	-	166K	66.37
						(l) FK IN 512 COL+	(x,y)	(C) f s	166K	67.93
						(m) CNN F	-	(C) f s	4K	77.38
						(n) CNN S	-	(C) f s	4K	79.74

Pascal VOC

multi-label dataset

$I_{\text{pos}}, I_{\text{neg}} \rightarrow \text{positive, negative images for each class } c$
one-vs-rest classification hing loss

$w_c^T \phi(I_{\text{pos}}) > 1 - \xi, w_c^T \phi(I_{\text{pos}}) > -1 + \xi \rightarrow \text{slack}$
ranking hing loss $w_c^T \phi(I_{\text{pos}}) > w_c^T \phi(I_{\text{neg}}) + 1 - \xi$



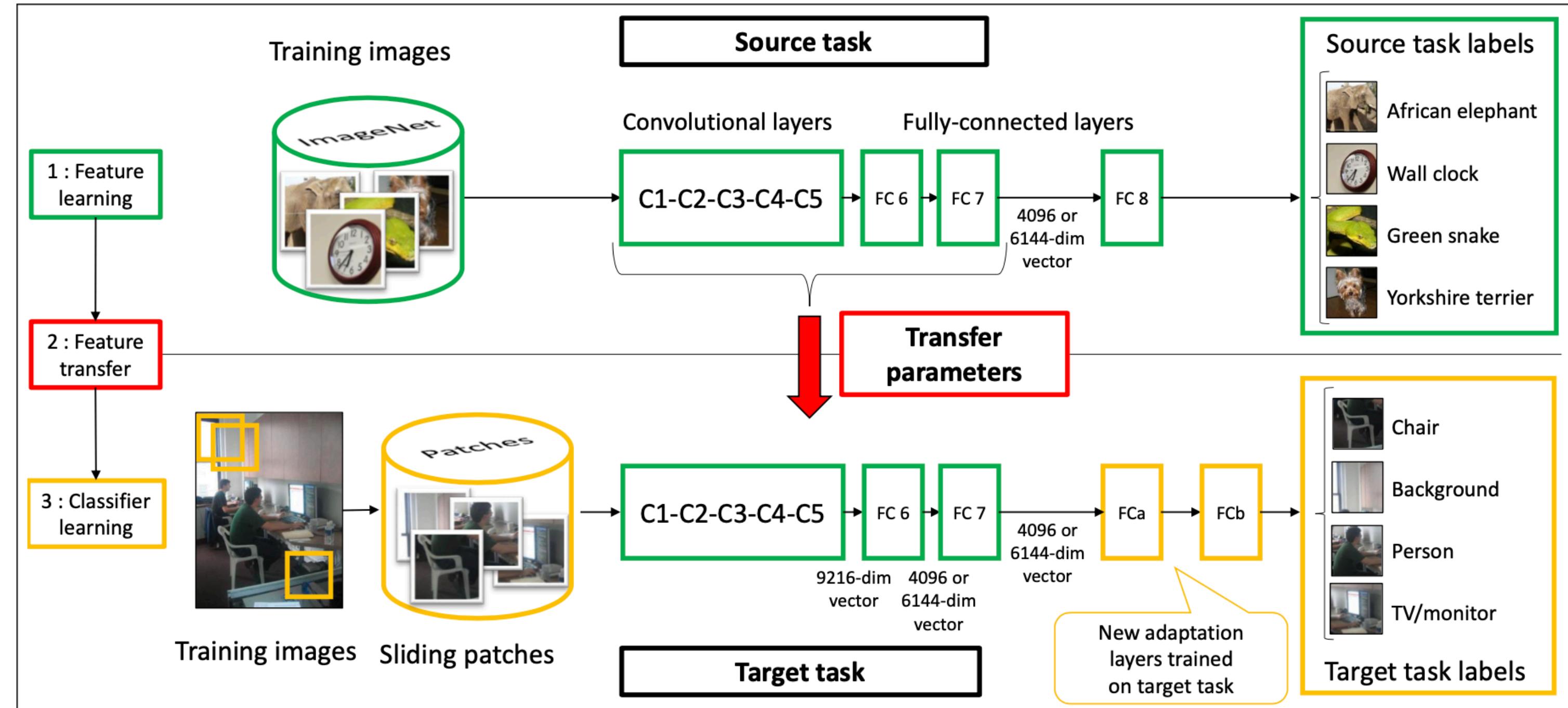
Performance of shallow representations can be significantly improved by adopting **data augmentation**, typically used in deep learning. In spite of this improvement, deep architectures still outperform the shallow methods by a large margin.

(x) CNN M 2048	-	(C) f s	2K	80.10
(y) CNN M 1024	-	(C) f s	1K	79.91
(z) CNN M 128	-	(C) f s	128	78.60
(α) FK+CNN F	(x,y)	(C) f s	88K	77.95
(β) FK+CNN M 2048	(x,y)	(C) f s	86K	80.14
(γ) CNN S TUNE-RNK	-	(C) f s	4K	82.42



Learning and Transferring Mid-Level Image Representations using Convolutional Neural Networks

Transfer: ImageNet → Pascal VOC (Limited Training Data)



ImageNet



Pascal VOC

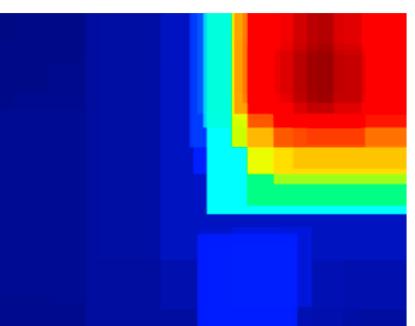
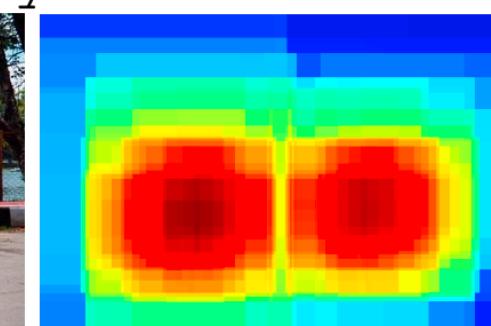


“dataset capture bias” and “negative data bias”

Inference

$$\text{score}(C_n) = \frac{1}{M} \sum_{i=1}^M y(C_n|P_i)^k$$

Output of the network for class C_n on image patch P_i
 $M \rightarrow$ number of patches in the image
 $k \geq 1$ ($k = 5$) \rightarrow higher values of k focus on highest scoring patches and attenuate the contributions of low- and mid-scoring patches



Network Architecture: AlexNet

Input: 224×224 RGB Image

Output: Distribution over the ImageNet object classes

Label Bias: ImageNet → husky dog, australian terrier, etc.

Pascal VOC → dog

Pascal VOC → reading, running, etc.

500 square patches per each image

at least 50% overlap between neighboring patches

$\lambda \in \{1, 1.3, 1.6, 2, 2.4, 2.8, 3.2, 3.6, 4\}$ \rightarrow 8 different scales

$$s = \min(w, h)/\lambda \text{ pixels}$$

width of square patches
rescale each patch to 224×224

$P \rightarrow$ bounding box of a patch

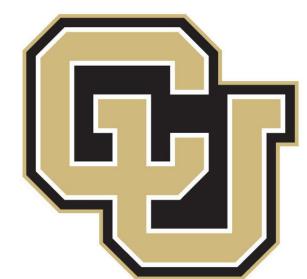
$B_o \rightarrow$ ground truth bounding box for class o

1. $|P \cap B_o| \geq 0.2|P| \rightarrow B_o$ overlaps sufficiently with the patch

2. $|P \cap B_o| \geq 0.6|B_o| \rightarrow$ the patch contains large portion of the object

3. the patch overlaps with no more than one object

\Rightarrow the patch is labeled as a positive label example for class o



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Questions?

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