

# Transfer Learning

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What makes ImageNet good for transfer learning?

# ImageNet Large Scale Visual Recognition Challenge

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## IMAGENET Large Scale Visual Recognition Challenge 2017 (ILSVRC2017)

### 1000 synsets for Object classification/localization

[kit fox, \*Vulpes macrotis\*](#)

[English setter](#)

[Australian terrier](#)

[grey whale, gray whale, devilfish, \*Eschrichtius gibbosus\*, \*Eschrichtius robustus\*](#)

[lesser panda, red panda, panda, bear cat, cat bear, \*Ailurus fulgens\*](#)

[Egyptian cat](#)

[ibex, \*Capra ibex\*](#)

[Persian cat](#)

[cougar, puma, catamount, mountain lion, painter, panther, \*Felis concolor\*](#)

[gazelle](#)

[porcupine, hedgehog](#)

[sea lion](#)

[badger](#)

[Great Dane](#)

[Scottish deerhound, deerhound](#)

[killer whale, killer, orca, grampus, sea wolf, \*Orcinus orca\*](#)

[mink](#)

[African elephant, \*Loxodonta africana\*](#)

**1.2 million images**

# Synsets

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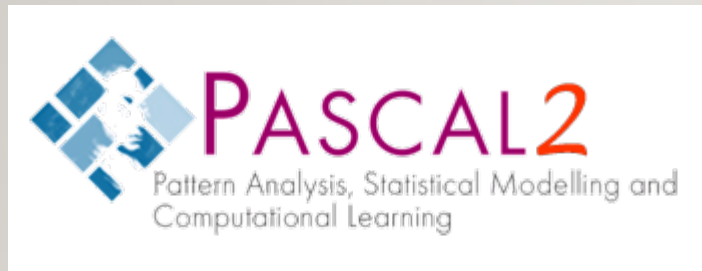


mammal → placental → carnivore → canine → dog → working dog → husky

# Target Datasets

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- PASCAL VOC - 27,450 detection objects; 11,530 images; 20 different classes



**Table 1** The VOC classes

Vehicles	Household	Animals	Other
Aeroplane	Bottle	Bird	Person
Bicycle	Chair	Cat	
Boat	Dining table	Cow	
Bus	Potted plant	Dog	
Car	Sofa	Horse	
Motorbike	TV/Monitor	Sheep	
Train			

- SUN database: 397 scene categories; 108K images



# PASCAL vs ImageNet Large Scale Visual Recognition Competition

	PASCAL	ILSVRC				
birds	 bird	 flamingo	 cock	 ruffed grouse	 quail	 partridge ...
cats	 cat	 Egyptian cat	 Persian cat	 Siamese cat	 tabby	 lynx ...
dogs	 dog	 dalmatian	 keeshond	 miniature schnauzer	 standard schnauzer	 giant schnauzer ...

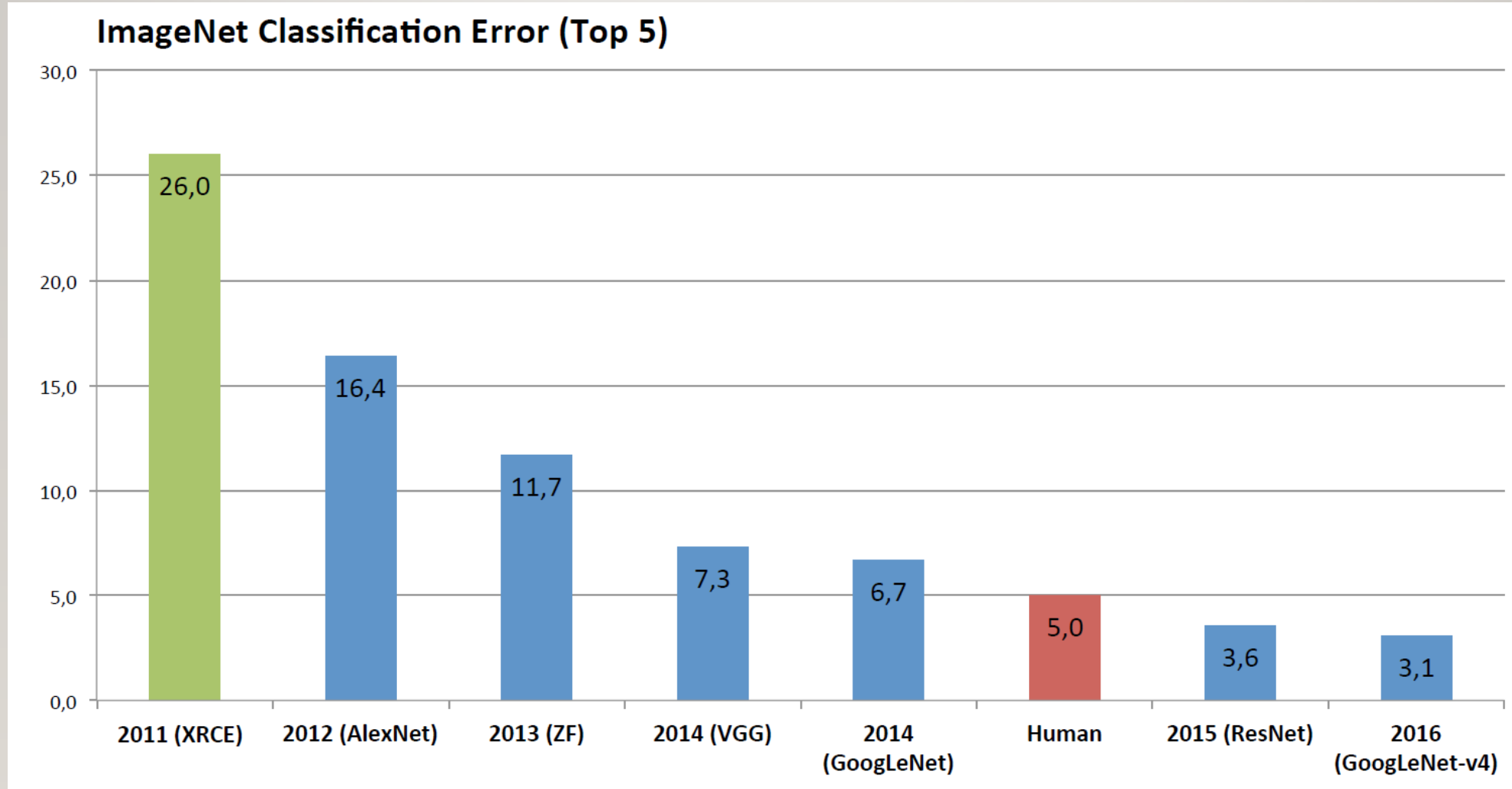
# Various architectures for transfer learning (trained on ImageNet)

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- VGG16
- InceptionV3
- ResNet
- MobileNet
- Xception
- InceptionResNetV2

# Performance of various architectures on ImageNet

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# What makes ImageNet good for transfer learning?

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# Experimental Approach

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- Pre-training – on ImageNet
- Finetuning – on Target datasets

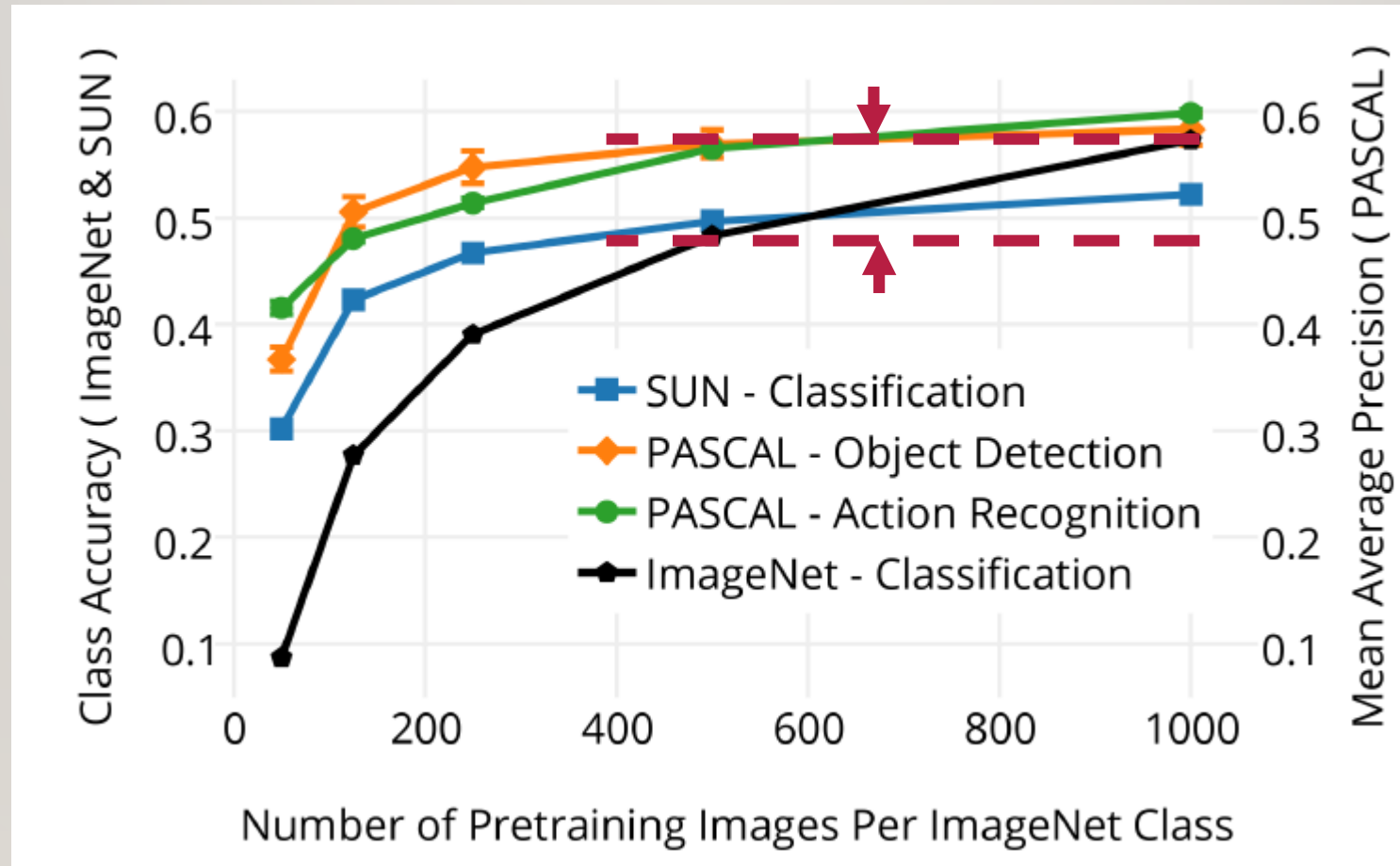
# How does the amount of pre-training data affect transfer performance?

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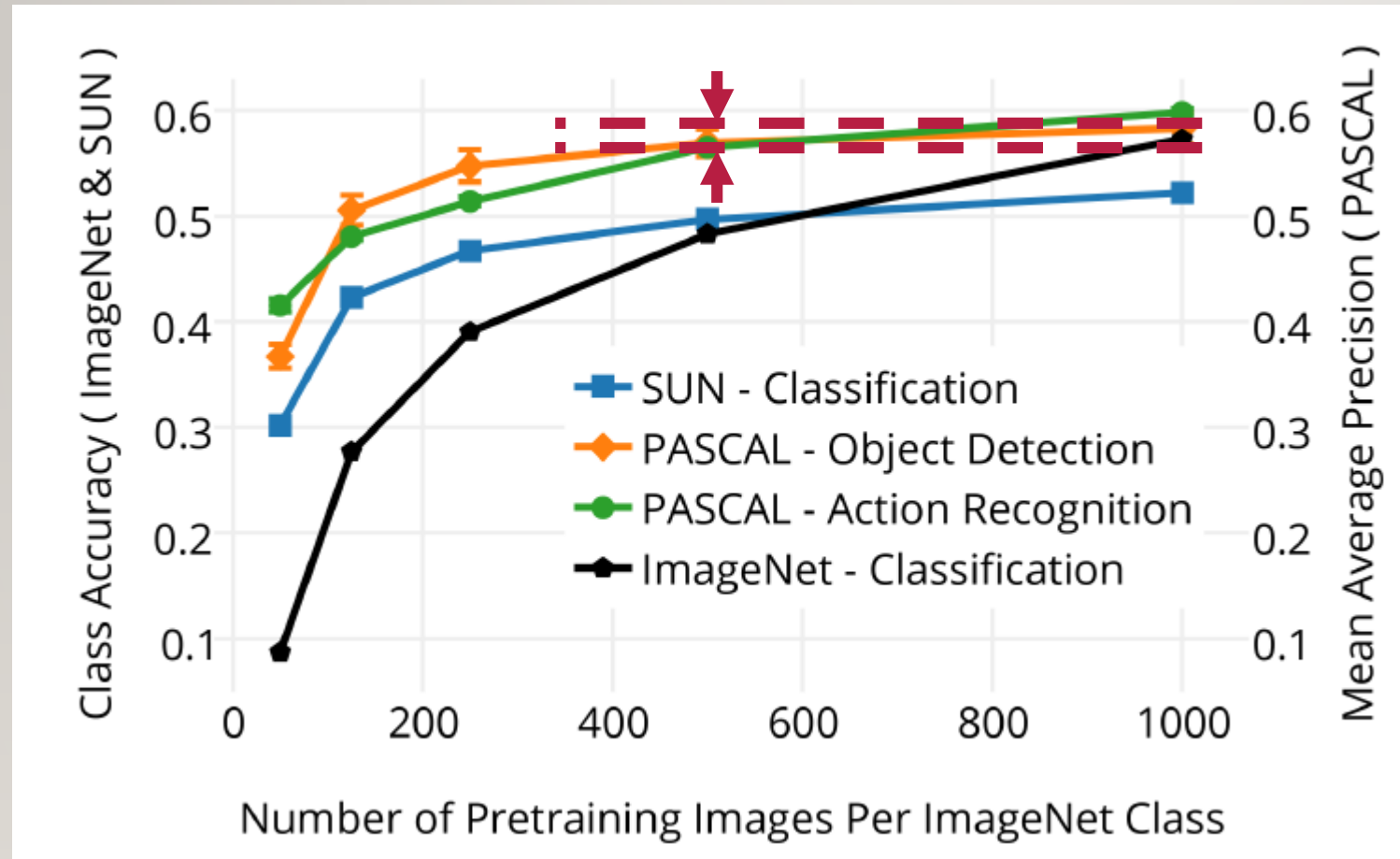
- 5 Models
- 50, 125, 250, 500 and 1000 images  
per each of the 1000 ImageNet classes

# How does the amount of pre-training data affect transfer performance?

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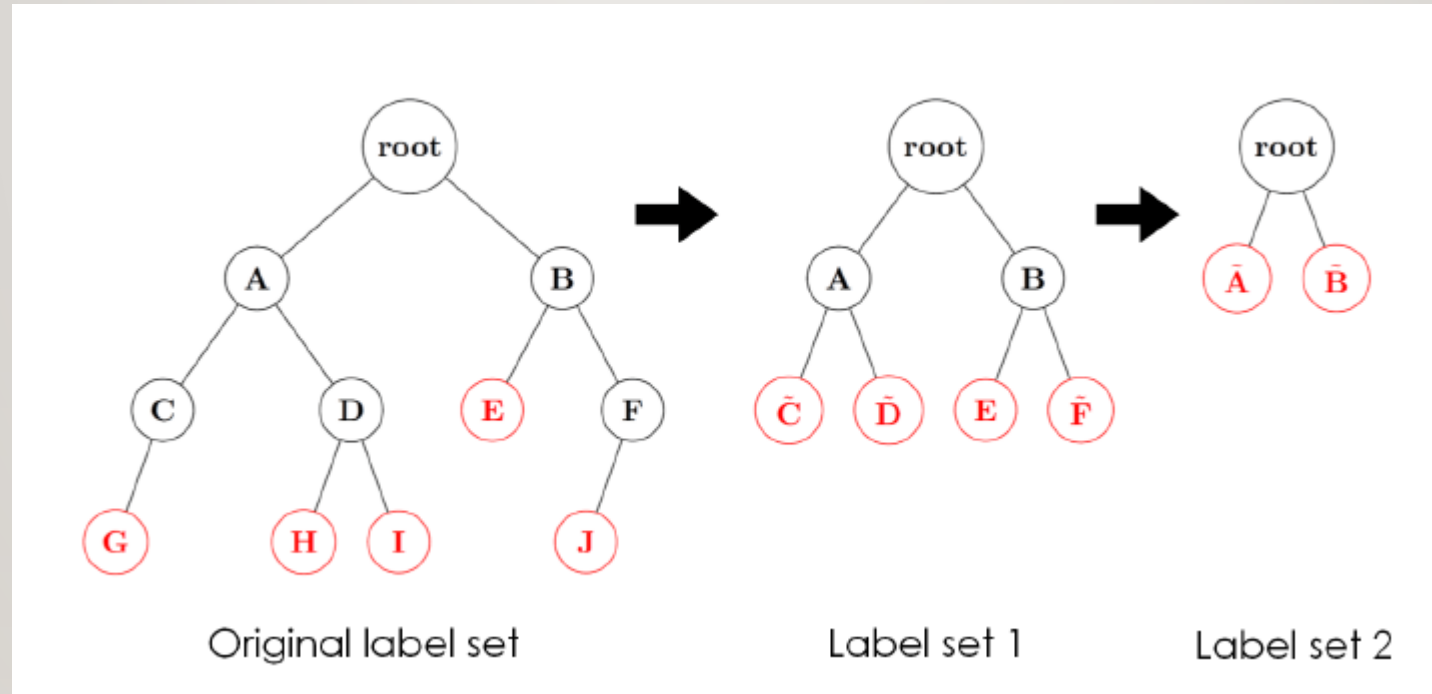


PASCAL-DET

No. of Images	Accuracy
1000	58.3
500	57.0
250	54.6

# The effect of number of pretraining classes on transfer performance

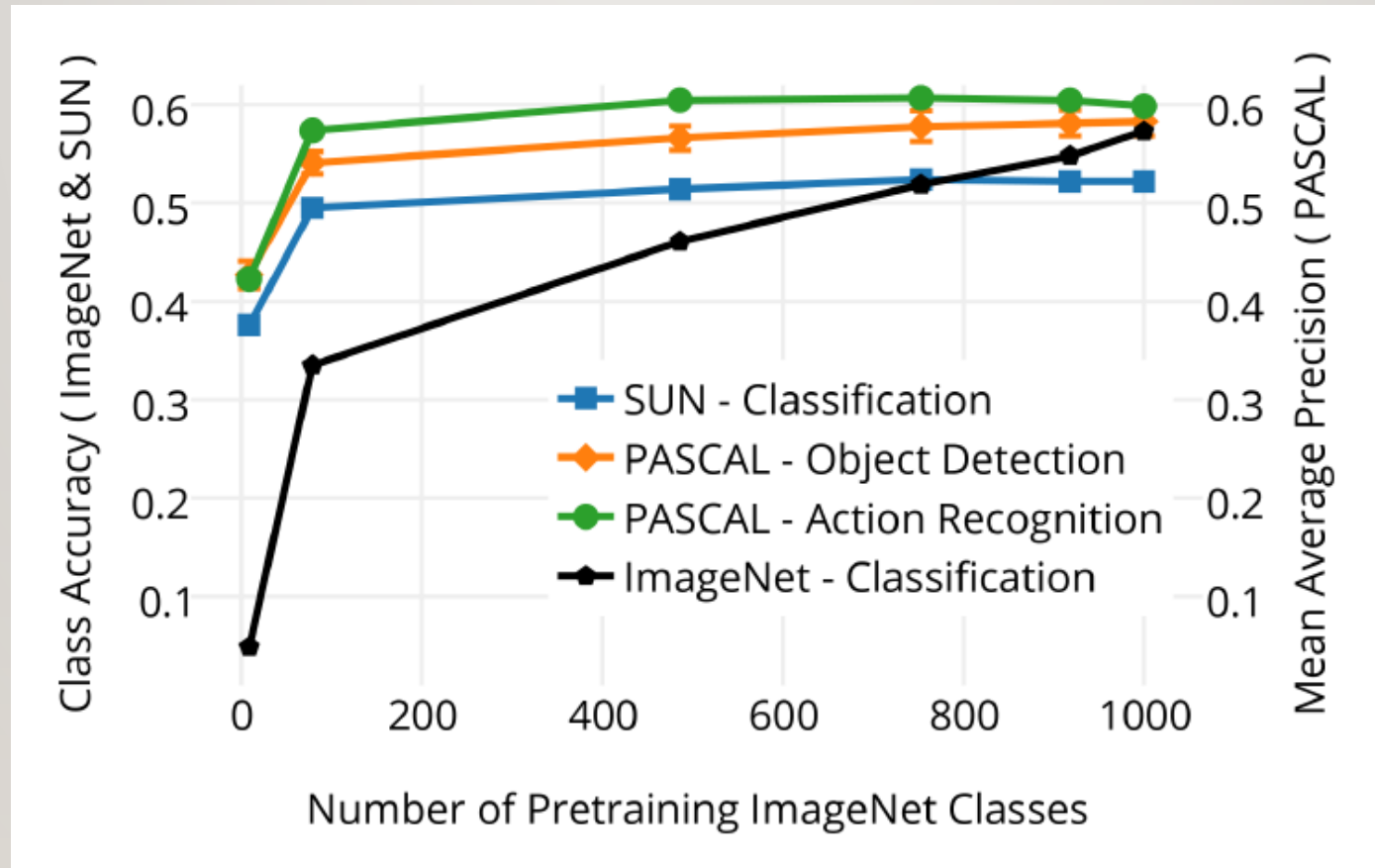
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5 sets of labels constituting 918, 753, 486, 79, and 9 classes

# The effect of number of pretraining classes on transfer performance

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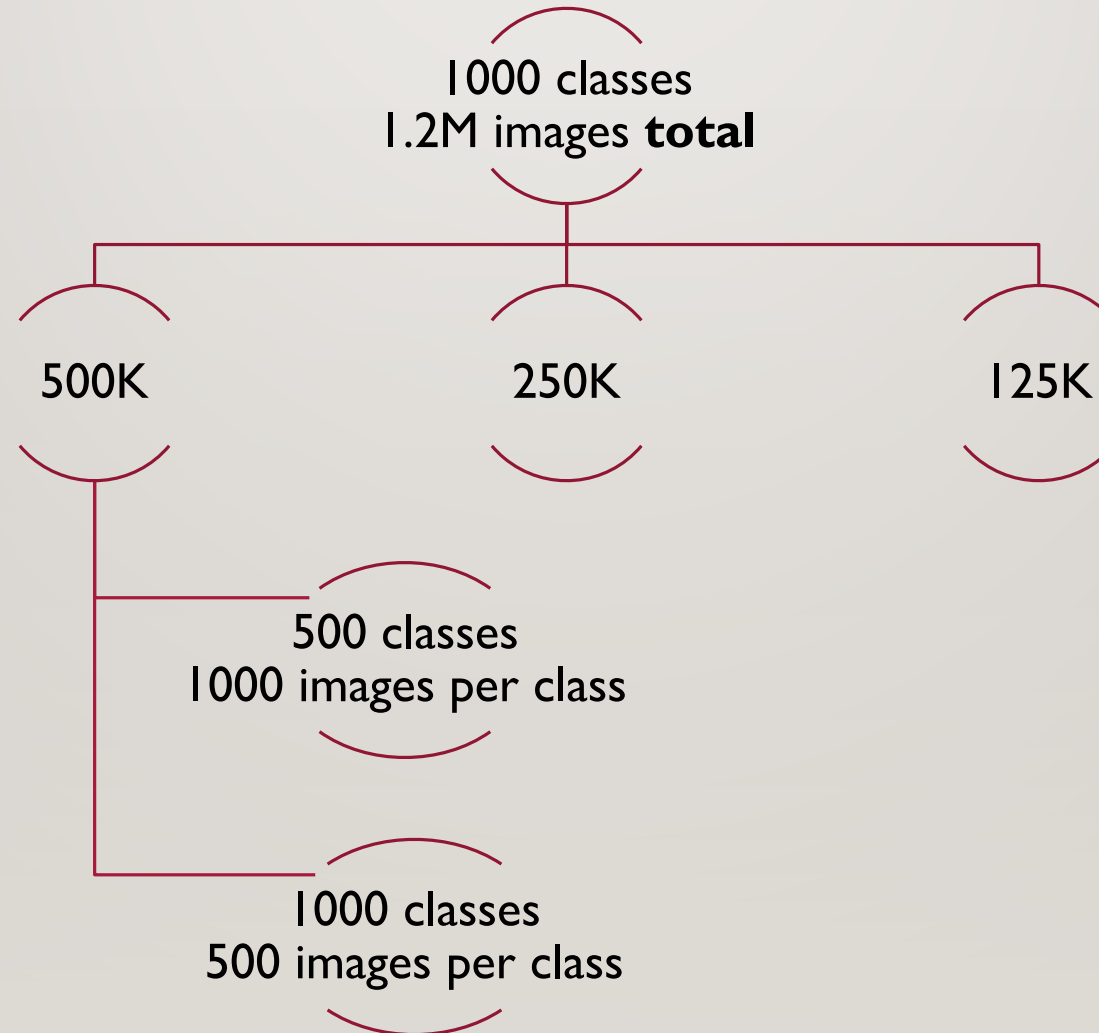


Making the ImageNet classes finer will not help improve transfer performance



# More Classes or More Examples Per Class?

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# More Classes or More Examples Per Class?

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Dataset	PASCAL			SUN		
Data size	500K	250K	125K	500K	250K	125K
More examples/class	57.1	54.8	50.6	50.6	45.7	42.2
More classes	57.0	52.5	49.8	49.7	46.7	42.3

# How important is to pretrain on classes that are also present in a target task?

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- PASCAL – 20 classes
- ImageNet minus PASCAL 20 – 771 classes

Pre-trained Dataset	PASCAL
ImageNet	$58.3 \pm 0.3$
Pascal removed ImageNet	$57.8 \pm 0.1$

# Conclusion

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- CNN training may not be as data-hungry as thought
- Tested only on AlexNet
- PASCAL and SUN may be too similar to ImageNet to test the generalization of learned features