COCO dataset and Deeper Deep Architectures

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http://mscoco.org

Microsoft COCO
Common Objects in Context

Why a new dataset?

Continue our field's momentum:

IMAGENET

PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

Caltech Pedestrian Detection Benchmark

http://mscoco.org

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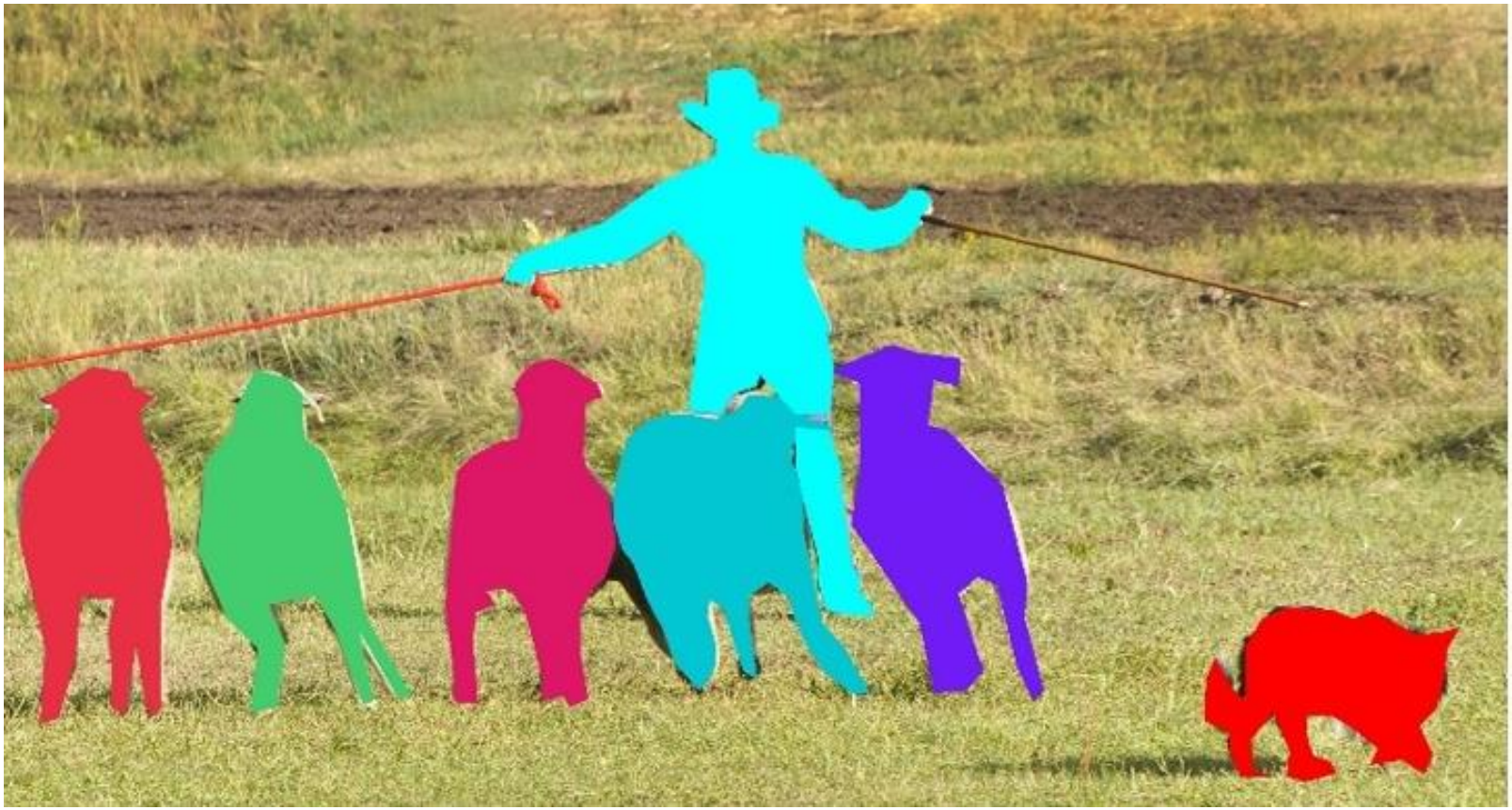
- ✓ Instance segmentation
- ✓ Non-iconic Images



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Iconic object images

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Iconic scene images

http://mscoco.org

Non-iconic images

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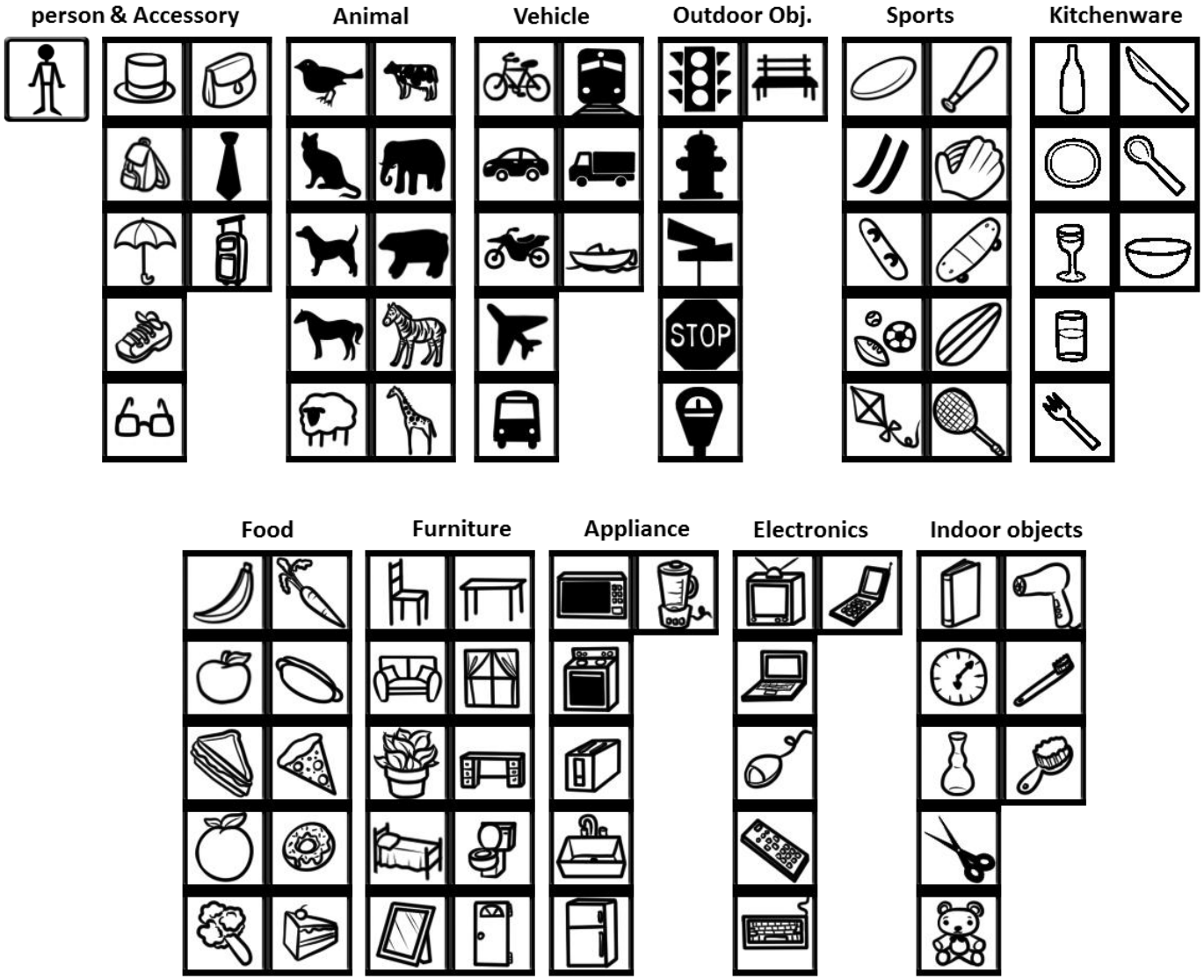
Object categories (things not stuff)



http://mscoco.org

flickr

(All creative commons)

330,000 images

http://mscoco.org

“Dog”



http://mscoco.org

“Dog + Car”

Im2Text: Describing Images Using 1 Million Captioned Photographs, V. Ordonez, G. Kulkarni, T. L. Berg NIPS’11

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Annotation pipeline

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Divide and Conquer

1. Category Labeling

dog, bottle

2. Instance spotting

3. Instance segmentation

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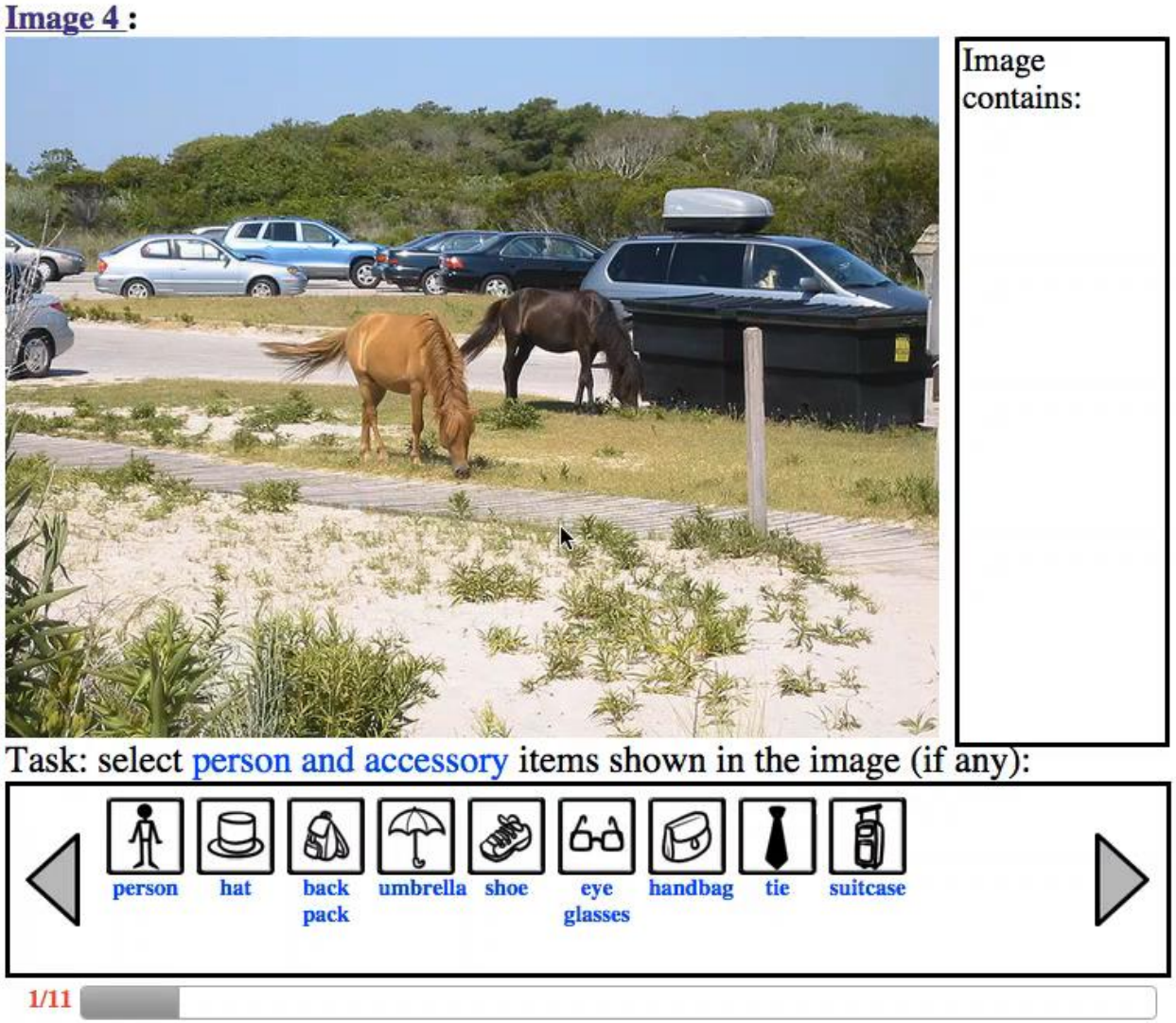
1. Category Labeling



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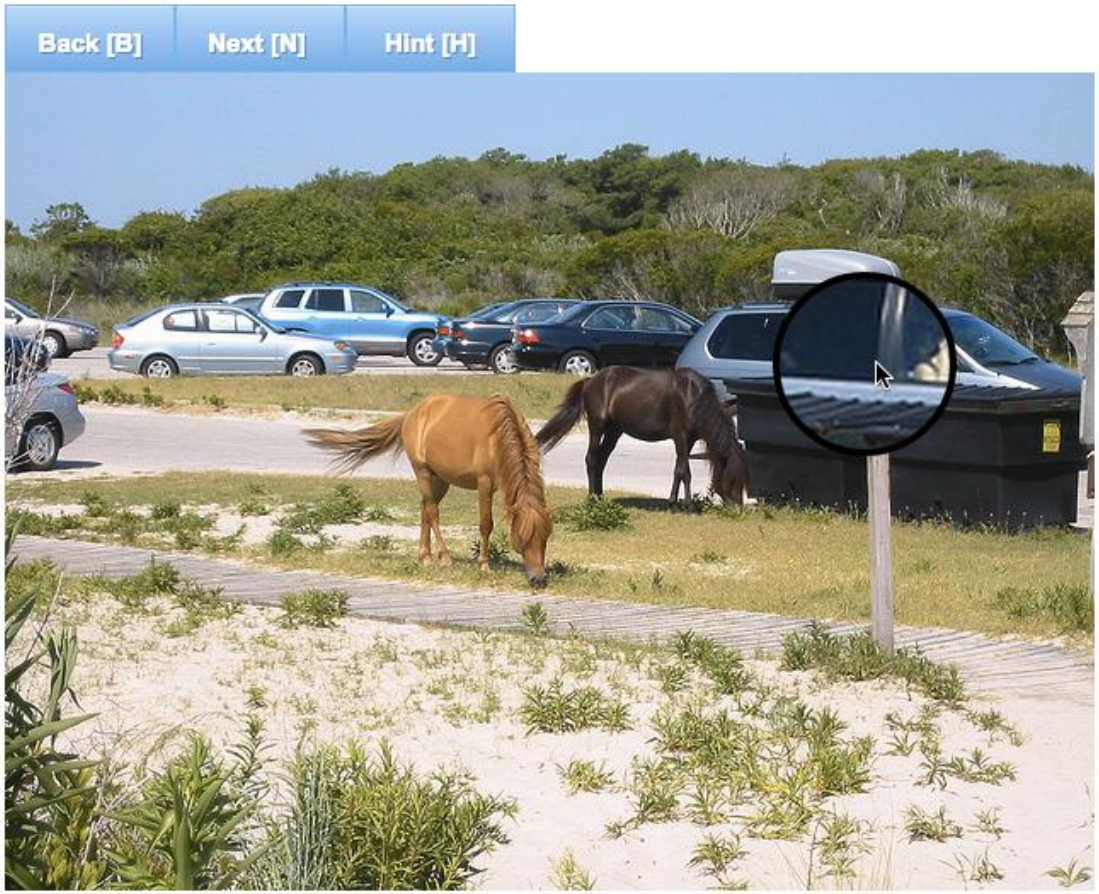
2. Instance Spotting

car

0 car(s) found in this image.



http://mscoco.org

3. Instance Segmentation

http://opensurfaces.cs.cornell.edu/

Sean Bell, Paul Upchurch, Noah Snavely, Kavita Bala, Cornell University.

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TAIZE
TURF


1

After training

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Properties

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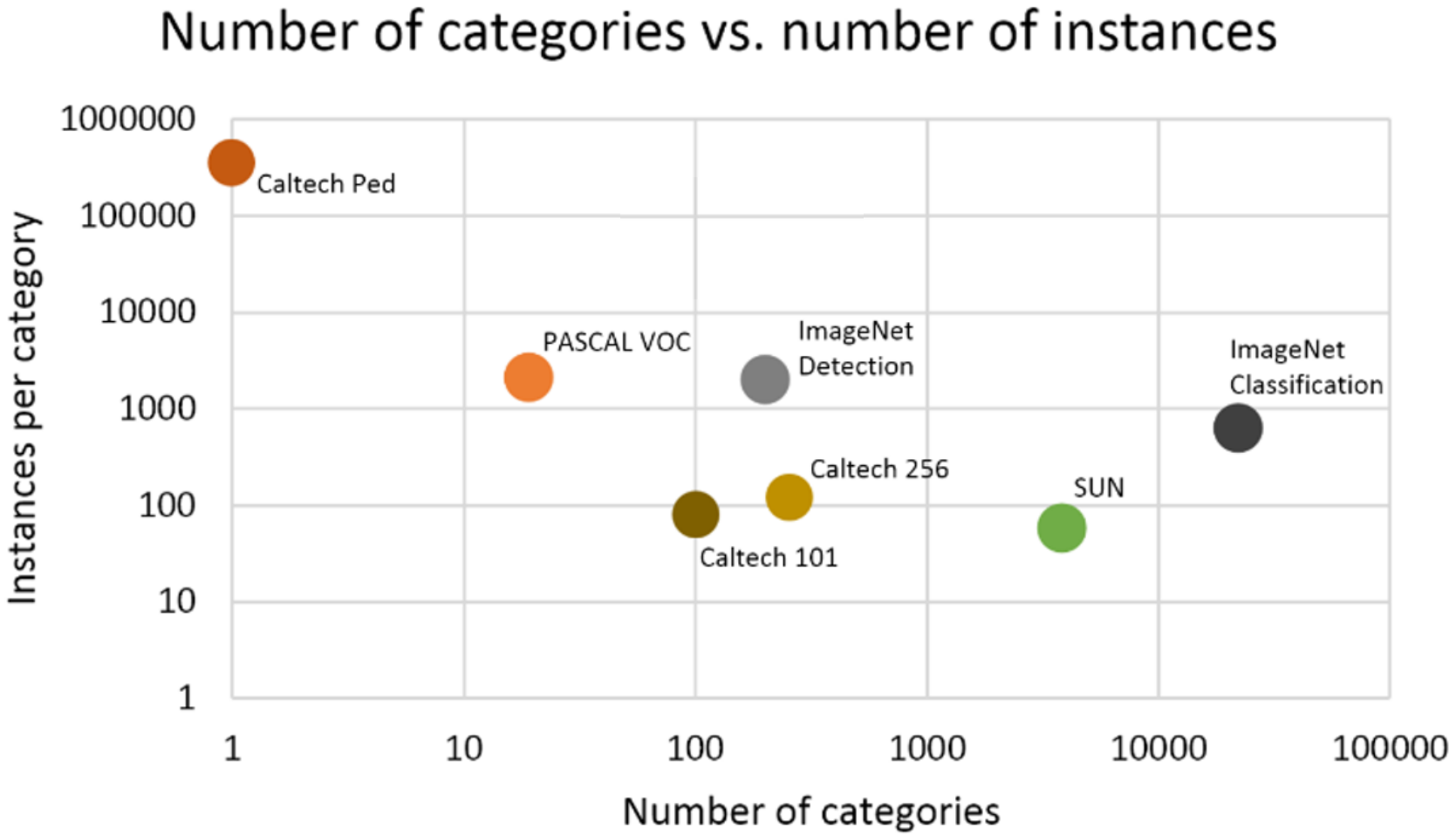
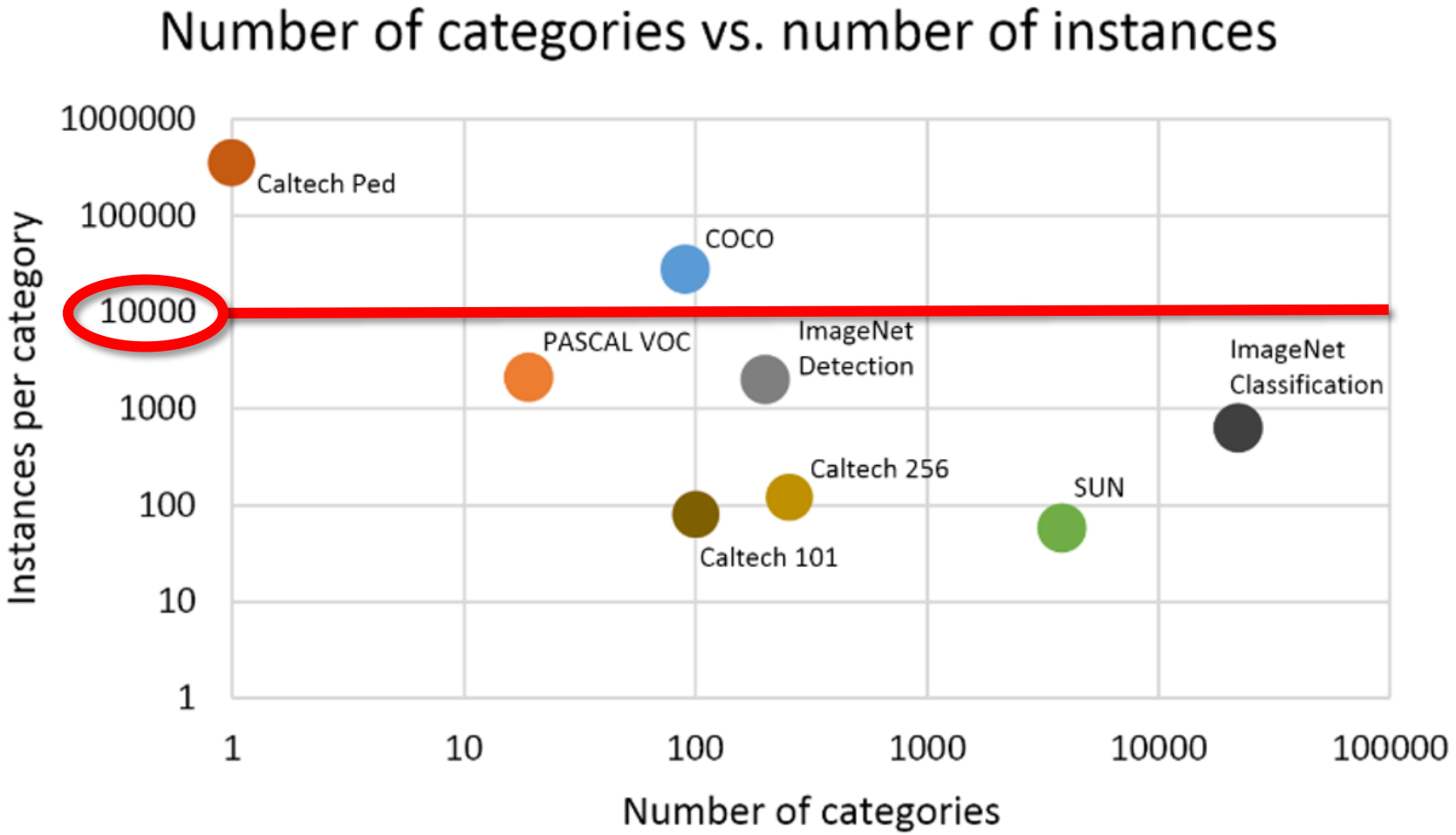
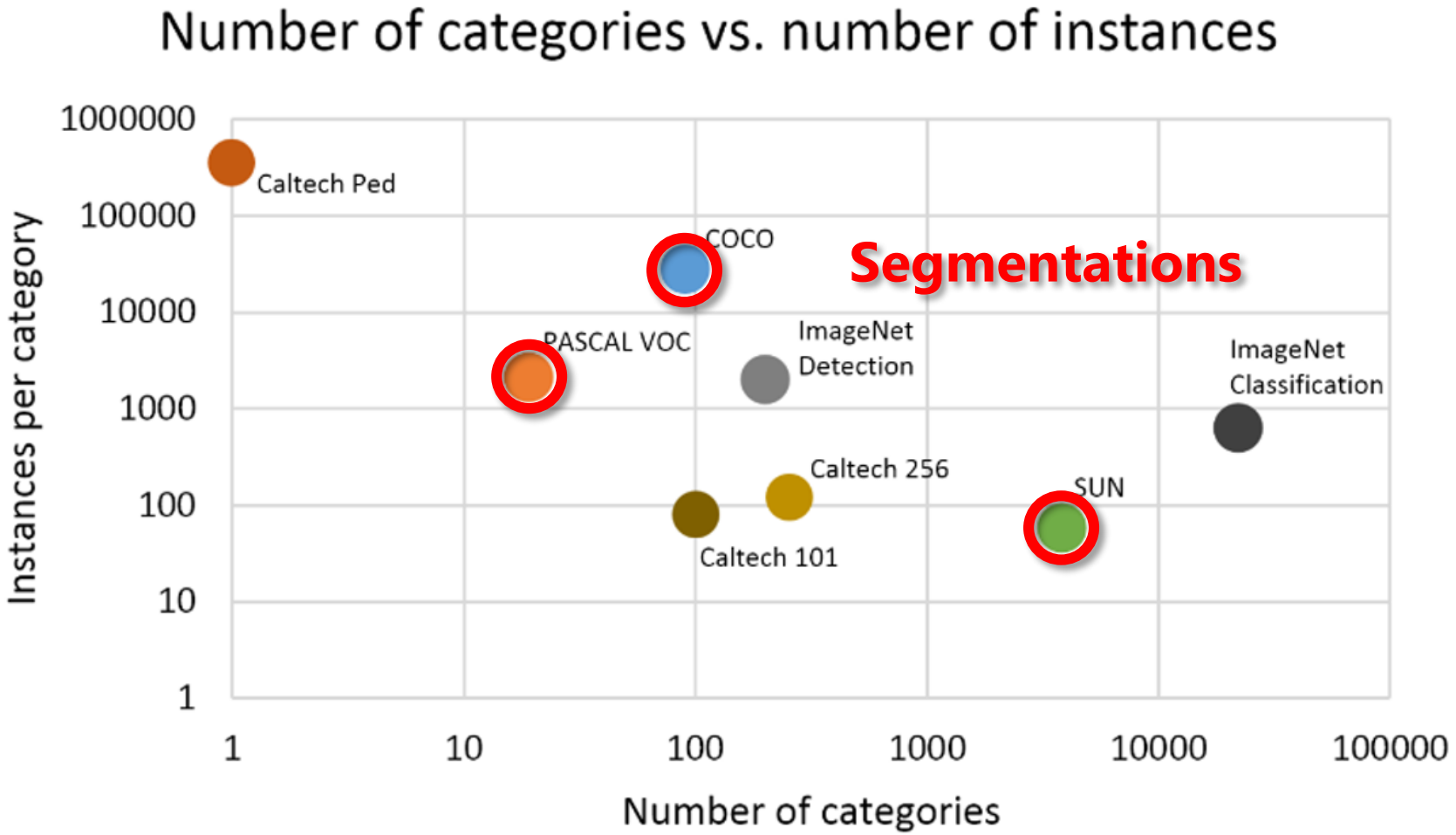


http://mscoco.org



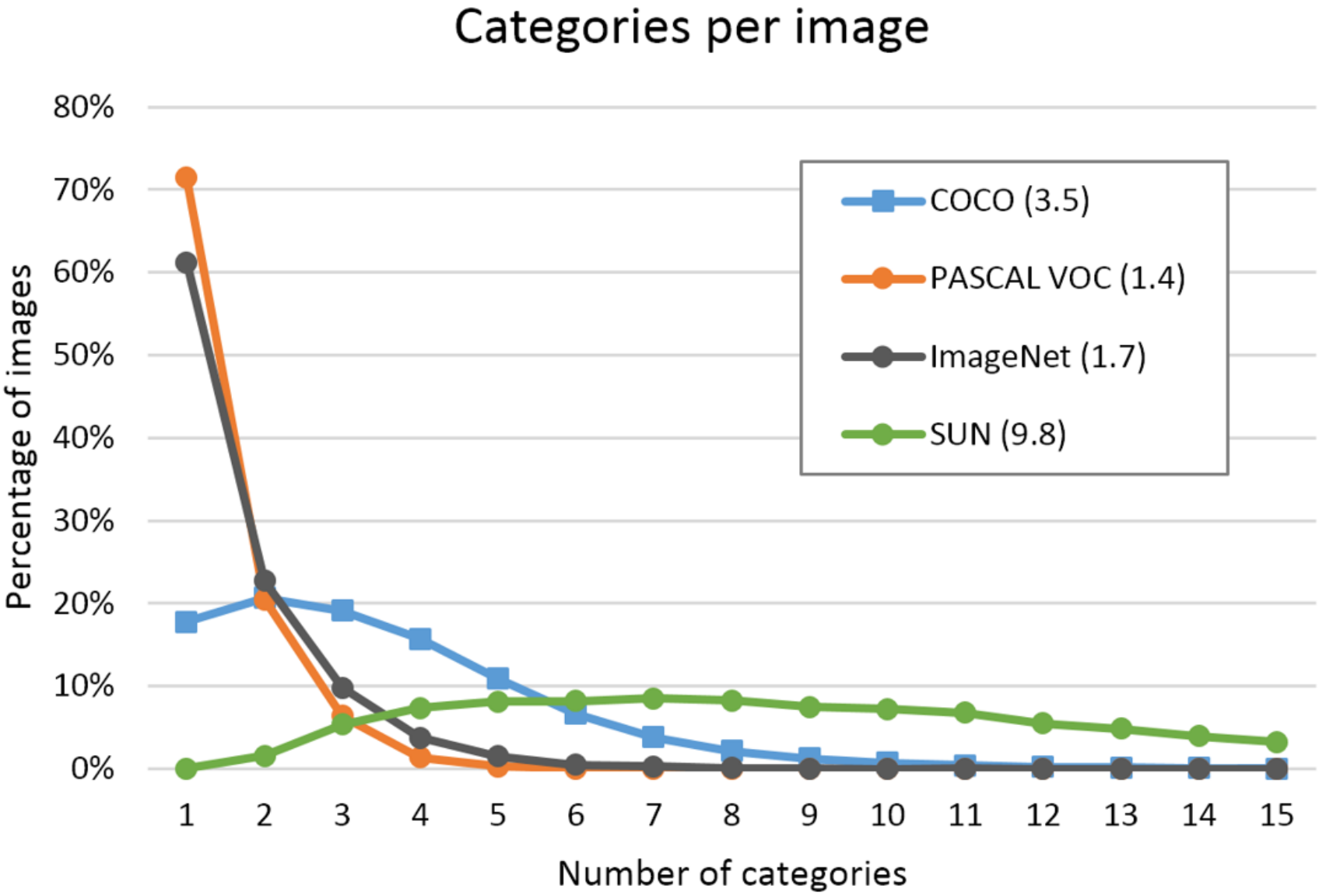
http://mscoco.org



http://mscoco.org

- 330,000 images
- >2 million instances (700k people)
- Every instance is segmented
- 7.7 instances per image (3.5 categories)

http://mscoco.org



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Detection Performance

(DPM V5)

	Person (mAP)	Average (mAP)
PASCAL VOC	41.3	29.6
MS COCO	17.5	16.9

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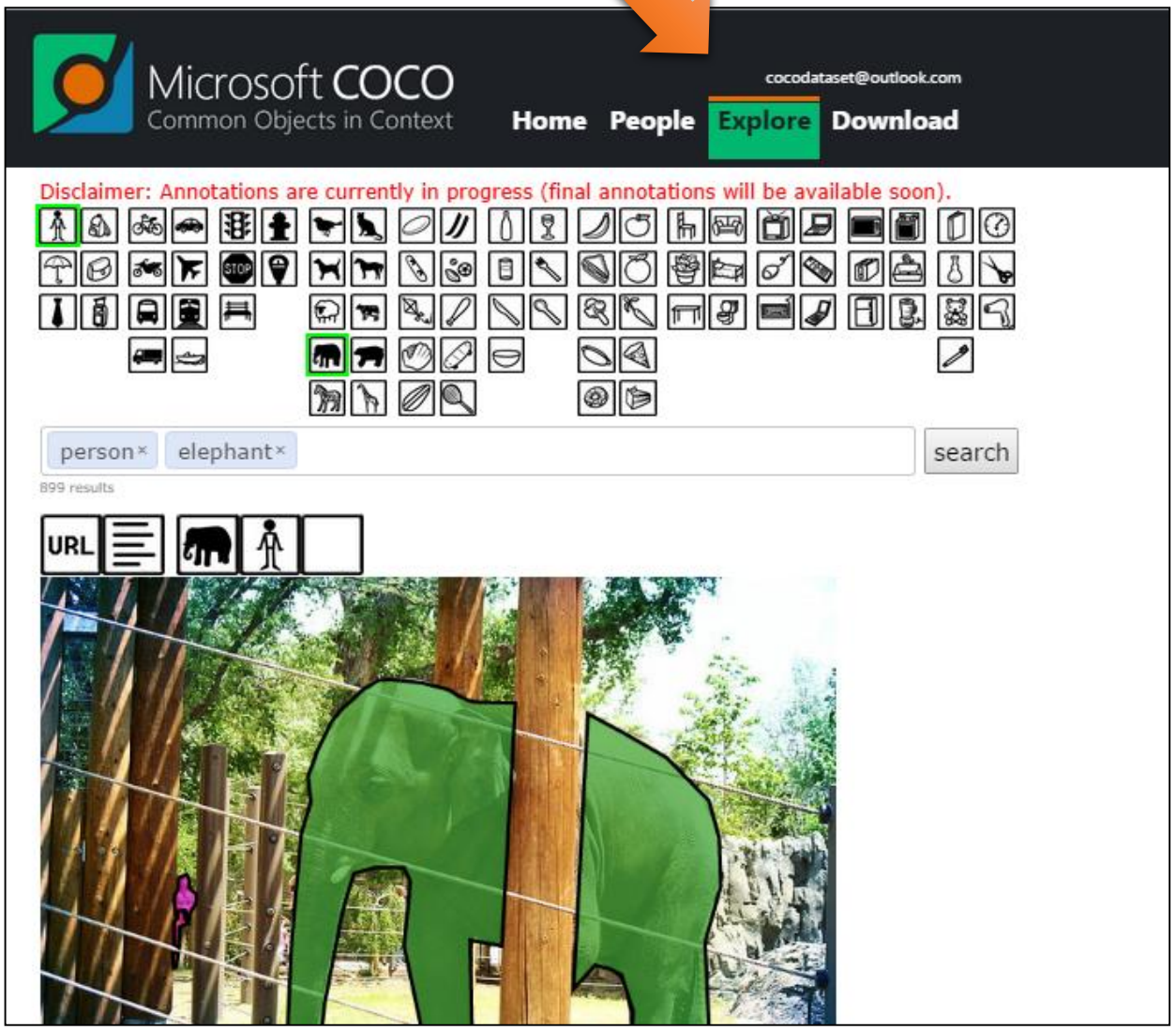

Microsoft COCO
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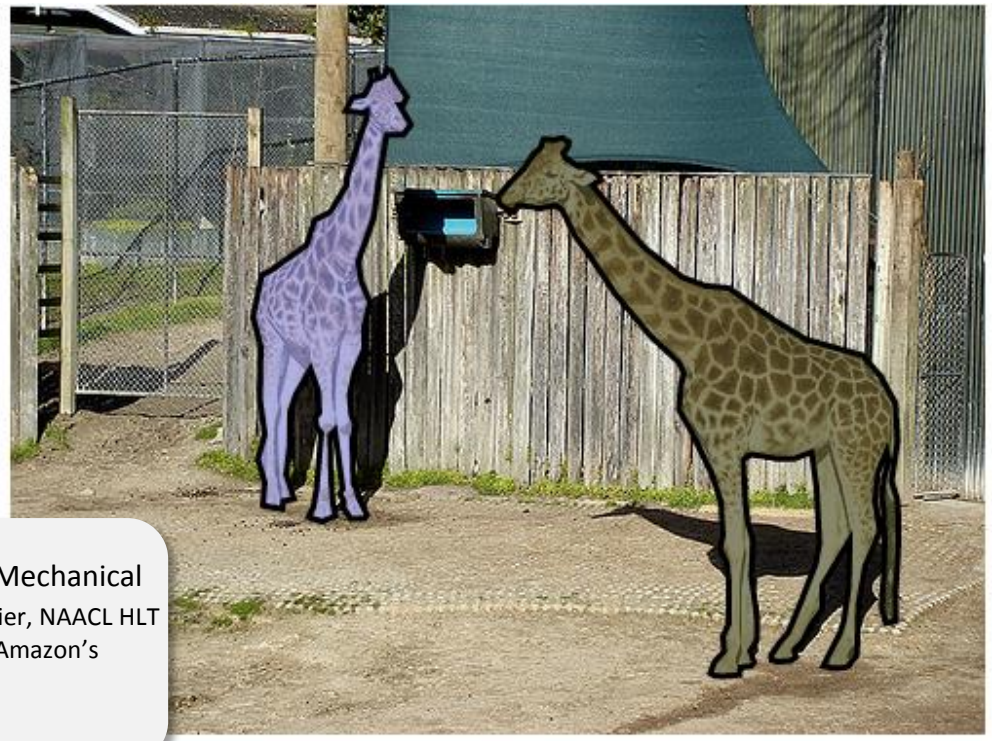
Beyond detection

http://mscoco.org

Beyond detection

- ✓ Sentences

two giraffe standing next to each other in front of a wooden fence.
two giraffes standing in the dirt near a gate.
two giraffes stand by a food box awaiting the goods.
two giraffes are standing next to a wooden fence.
two giraffes standing alone by a picket fence.

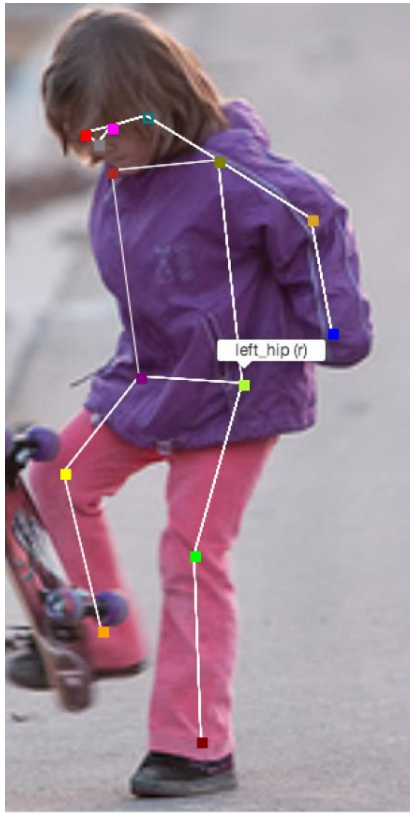


Collecting Image Annotations Using Amazon's Mechanical Turk, C. Rashtchian, P. Young, M. Hodosh, J. Hockenmaier, NAACL HLT Workshop on Creating Speech and Language Data with Amazon's Mechanical Turk, 2010

http://mscoco.org

Beyond detection

- ✓ Keypoints
  (provided by Facebook)



http://mscoco.org

Beyond detection

✓ Attributes

dog | jumping, catching, happy, exercising, floating, enjoying, hairy, playing, athletic, socializing, competitive

giraffe | eating, grazing, bending, peaceful, spotted, wild

person | traveling, bending, riding, moving, driving, adult, athletic, male, public

dog | thinking, leaning, smelling / sniffing, watching, tame, loving, curious, family-friendly

Genevieve Patterson, James Hays.
COCO Attributes: Attributes for People, Animals, and Objects.
ECCV 2016.

http://mscoco.org

Beyond AlexNet

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

Karen Simonyan & Andrew Zisserman 2015

These are the "VGG" networks.
Including what you use in Project 6

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224×224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: **Number of parameters** (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

Table 4: **ConvNet performance at multiple test scales.**

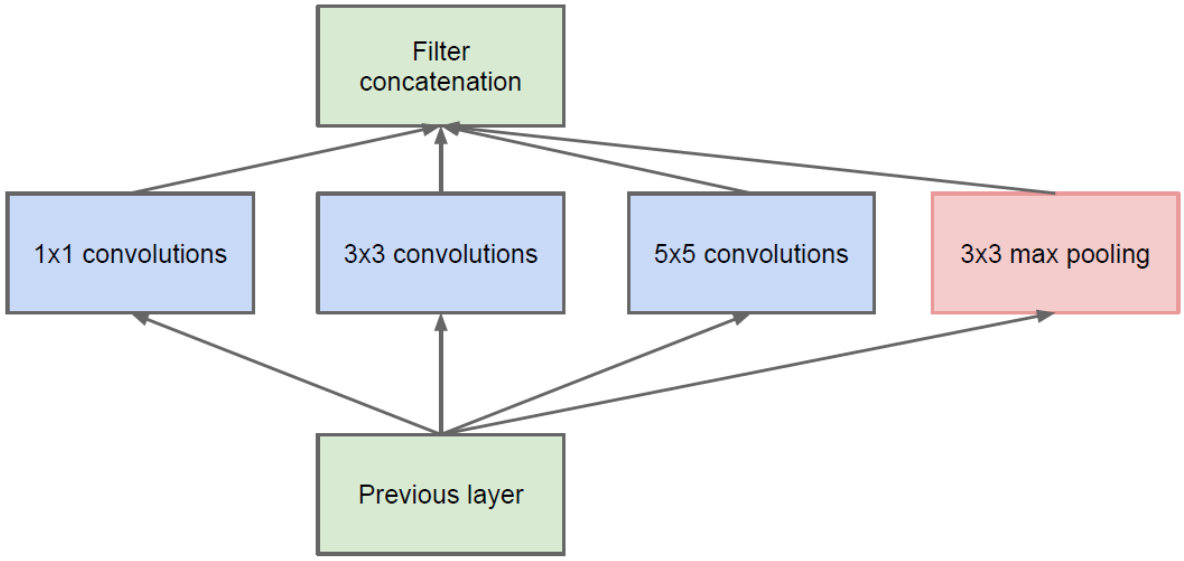
ConvNet config. (Table 1)	smallest image side		top-1 val. error (%)	top-5 val. error (%)
	train (S)	test (Q)		
B	256	224,256,288	28.2	9.6
C	256	224,256,288	27.7	9.2
	384	352,384,416	27.8	9.2
	[256; 512]	256,384,512	26.3	8.2
D	256	224,256,288	26.6	8.6
	384	352,384,416	26.5	8.6
	[256; 512]	256,384,512	**24.8**	**7.5**
E	256	224,256,288	26.9	8.7
	384	352,384,416	26.7	8.6
	[256; 512]	256,384,512	**24.8**	**7.5**

Going Deeper with Convolutions

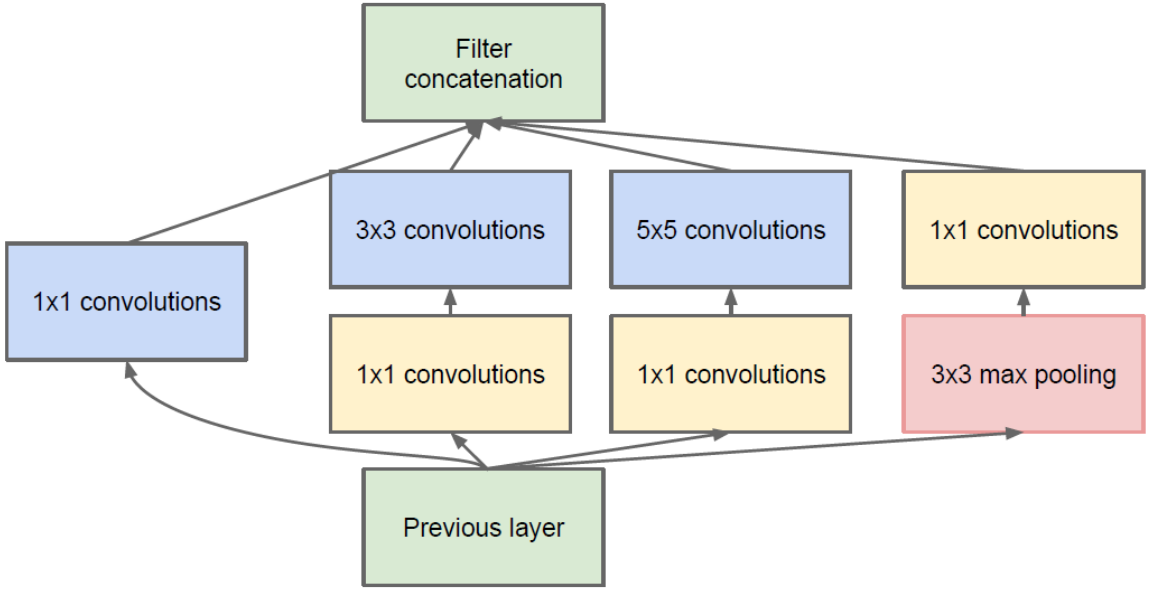
Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich
2015

This is the “Inception” architecture or “GoogLeNet”

***The architecture blocks are called “Inception” modules and the collection of them into a particular net is “GoogLeNet”**



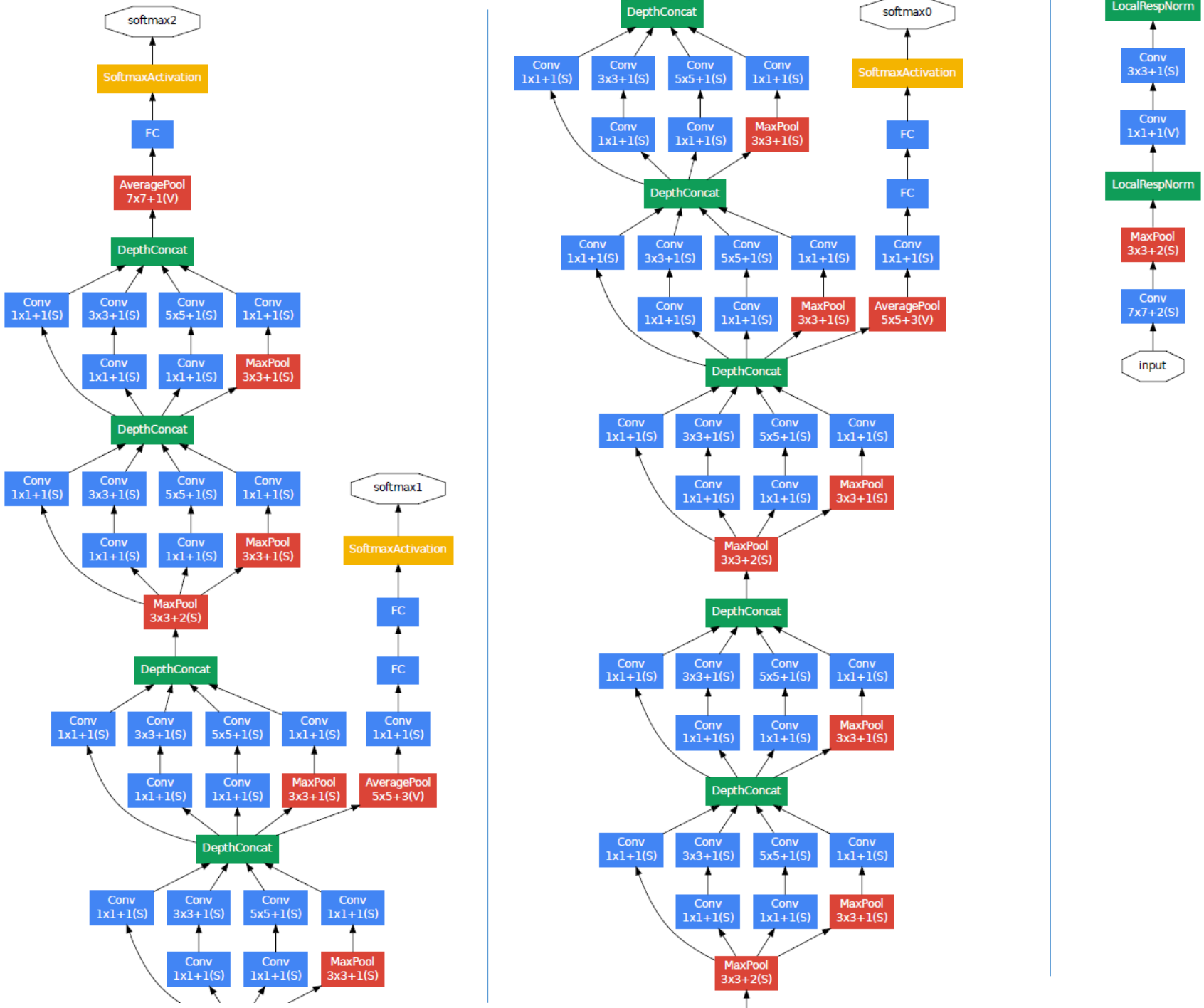
(a) Inception module, naïve version



(b) Inception module with dimensionality reduction

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Only 6.8 million parameters. AlexNet ~60 million, VGG up to 138 million


softmax2
SoftmaxActivation
FC
AveragePool 7x7+1(V)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
MaxPool 3x3+2(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
softmax1
SoftmaxActivation
FC
FC
Conv 1x1+1(S)
AveragePool 5x5+3(V)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
softmax0
SoftmaxActivation
FC
FC
Conv 1x1+1(S)
AveragePool 5x5+3(V)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
MaxPool 3x3+2(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
MaxPool 3x3+1(S)
MaxPool 3x3+2(S)
LocalRespNorm
Conv 3x3+1(S)
Conv 1x1+1(V)
LocalRespNorm
MaxPool 3x3+2(S)
Conv 7x7+2(S)
input

Team	Year	Place	Error (top-5)	Uses external data
SuperVision	2012	1st	16.4%	no
SuperVision	2012	1st	15.3%	Imagenet 22k
Clarifai	2013	1st	11.7%	no
Clarifai	2013	1st	11.2%	Imagenet 22k
MSRA	2014	3rd	7.35%	no
VGG	2014	2nd	7.32%	no
GoogLeNet	2014	1st	6.67%	no

Table 2: Classification performance.

Number of models	Number of Crops	Cost	Top-5 error	compared to base
1	1	1	10.07%	base
1	10	10	9.15%	-0.92%
1	144	144	7.89%	-2.18%
7	1	7	8.09%	-1.98%
7	10	70	7.62%	-2.45%
7	144	1008	6.67%	-3.45%

Surely it would be ridiculous to go any deeper…

- ResNet

Surely it would be ridiculous to go any deeper…

- ResNet
- See the following slides: http://kaiminghe.com/cvpr16resnet/cvpr2016_deep_residual_learning_kaiminghe.pdf