



# C14200: FROM ZERO TO ONE - DEEP LEARNING WITH PYTORCH

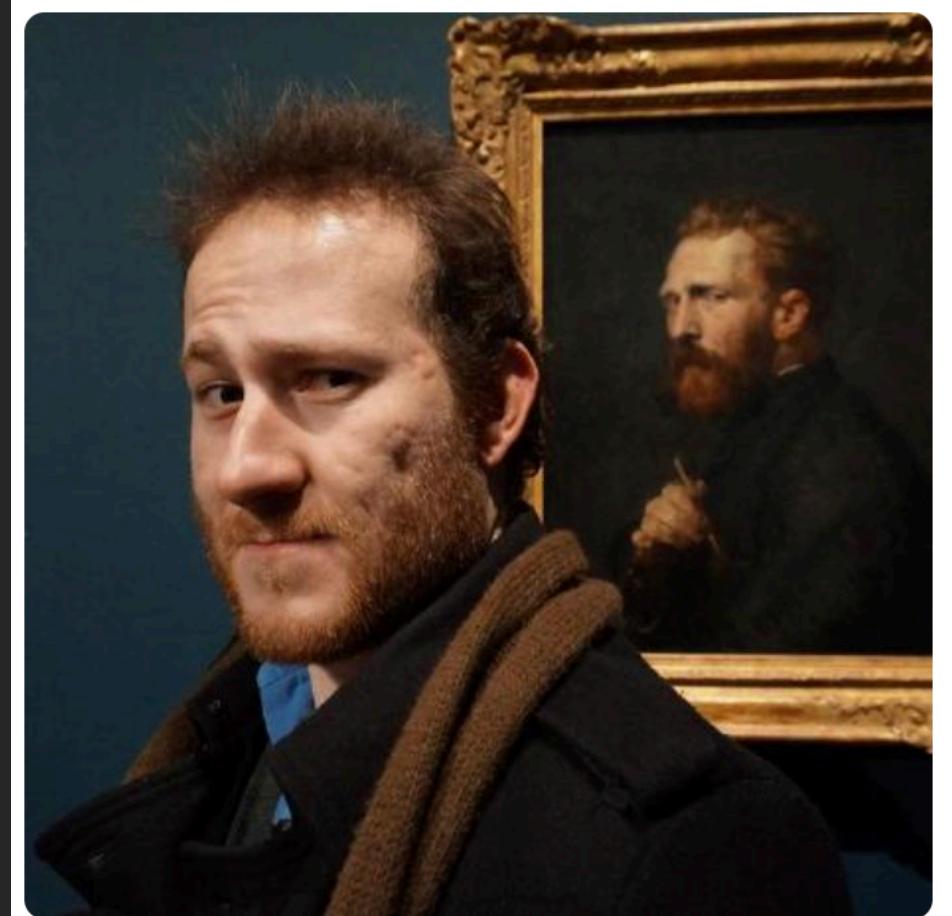
JOE SPISAK  
PRODUCT MANAGER

FRANCISCO MASSA  
RESEARCH ENGINEER





WHO AM I?



**Francisco Massa**  
fmassa

CURRENT: RESEARCH ENGINEER - PYTORCH

PREVIOUS:

- COMPUTER VISION RESEARCH ENGINEER  
@TWITTER
- PHD STUDENT AT ECOLE DES PONTS -  
FRANCE

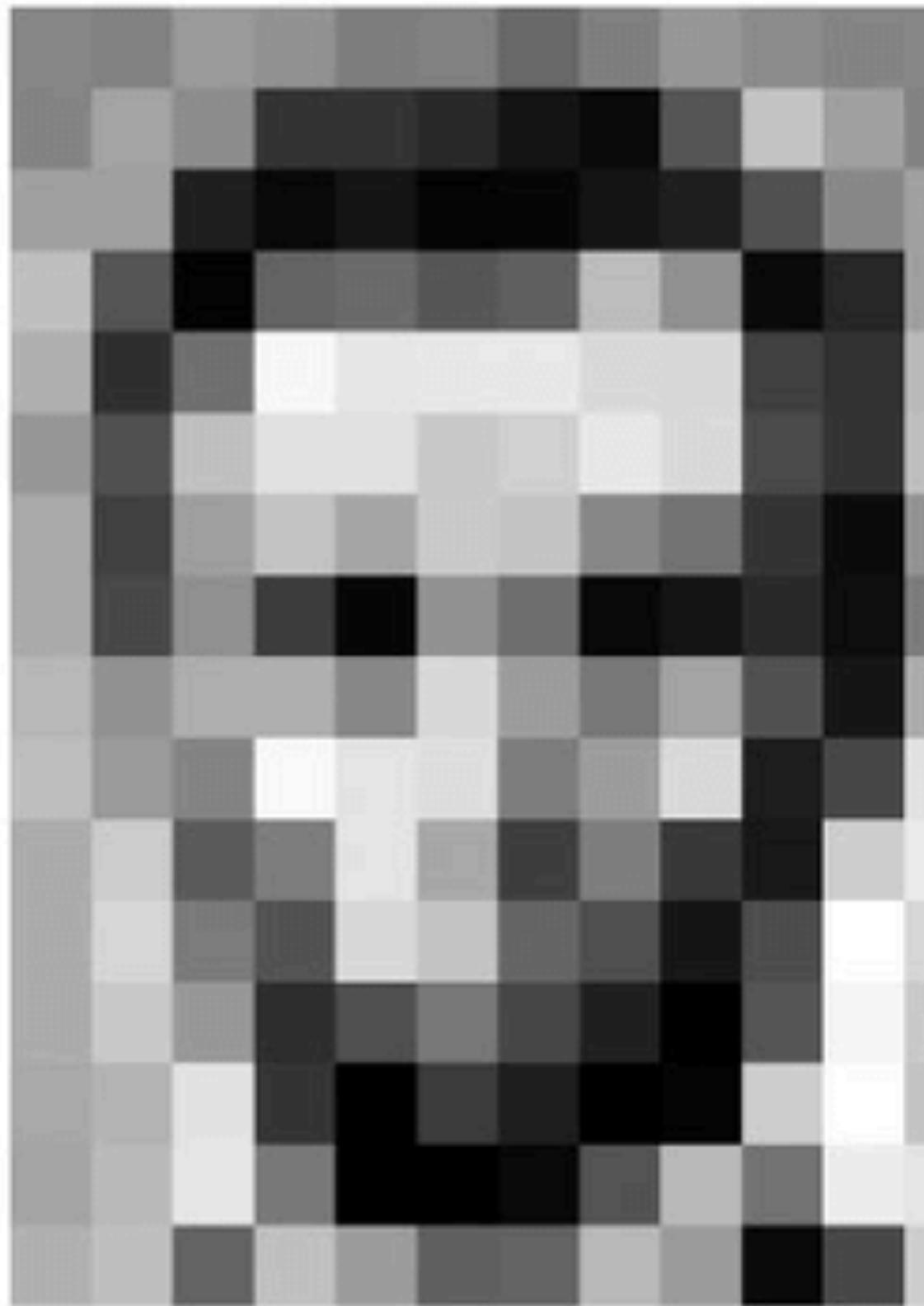




# PRIMER ON COMPUTER VISION



# HOW ARE IMAGES REPRESENTED IN A COMPUTER



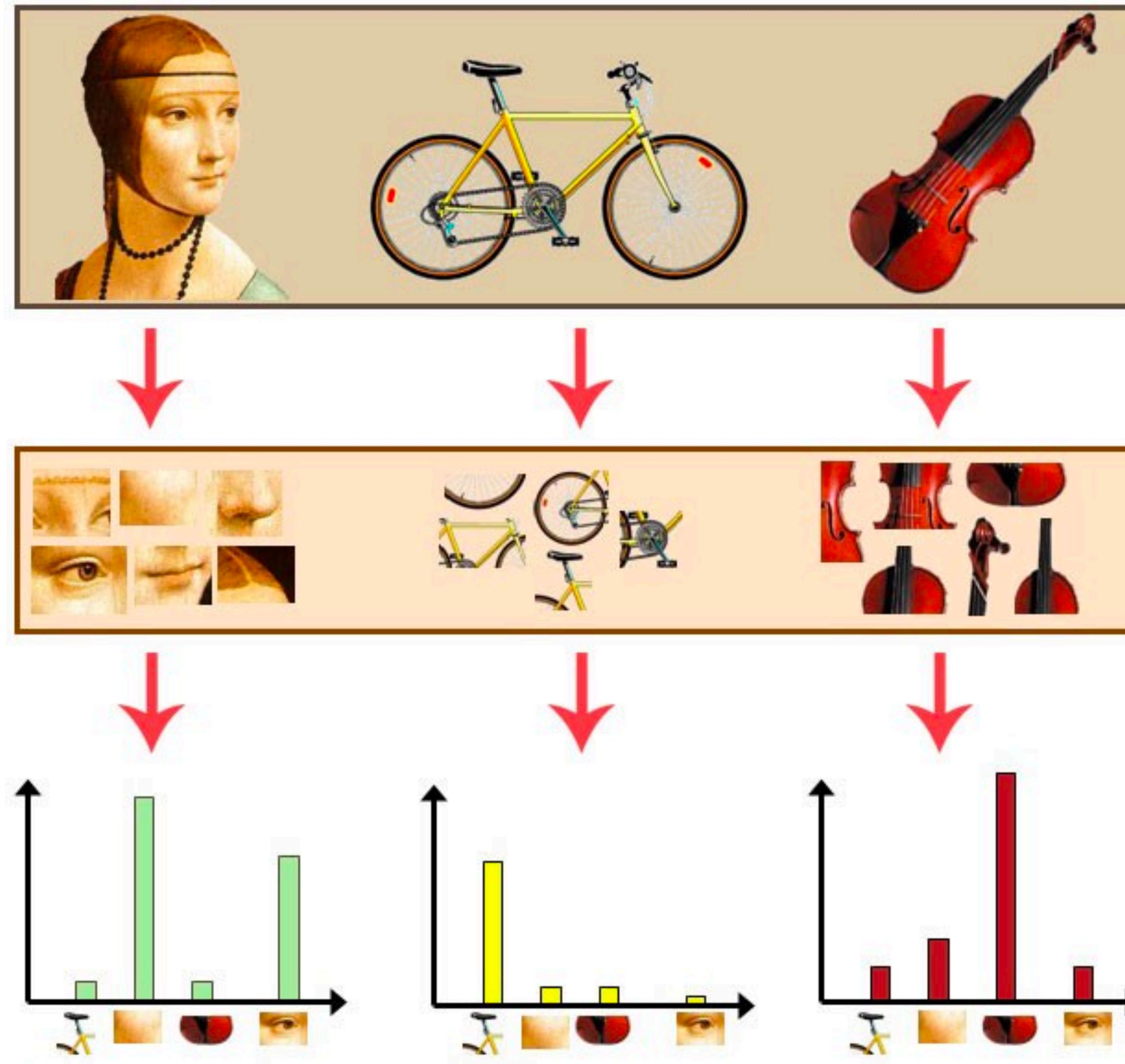
167	163	174	168	160	162	129	151	172	161	165	156
165	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	94	6	10	93	46	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	299	299	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	85	150	79	36	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

157	163	174	168	160	162	129	151	172	161	165	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	85	150	79	36	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

How can we make the computer understand what is in the image?



# OBJECTS AS A BAG OF VISUAL WORDS



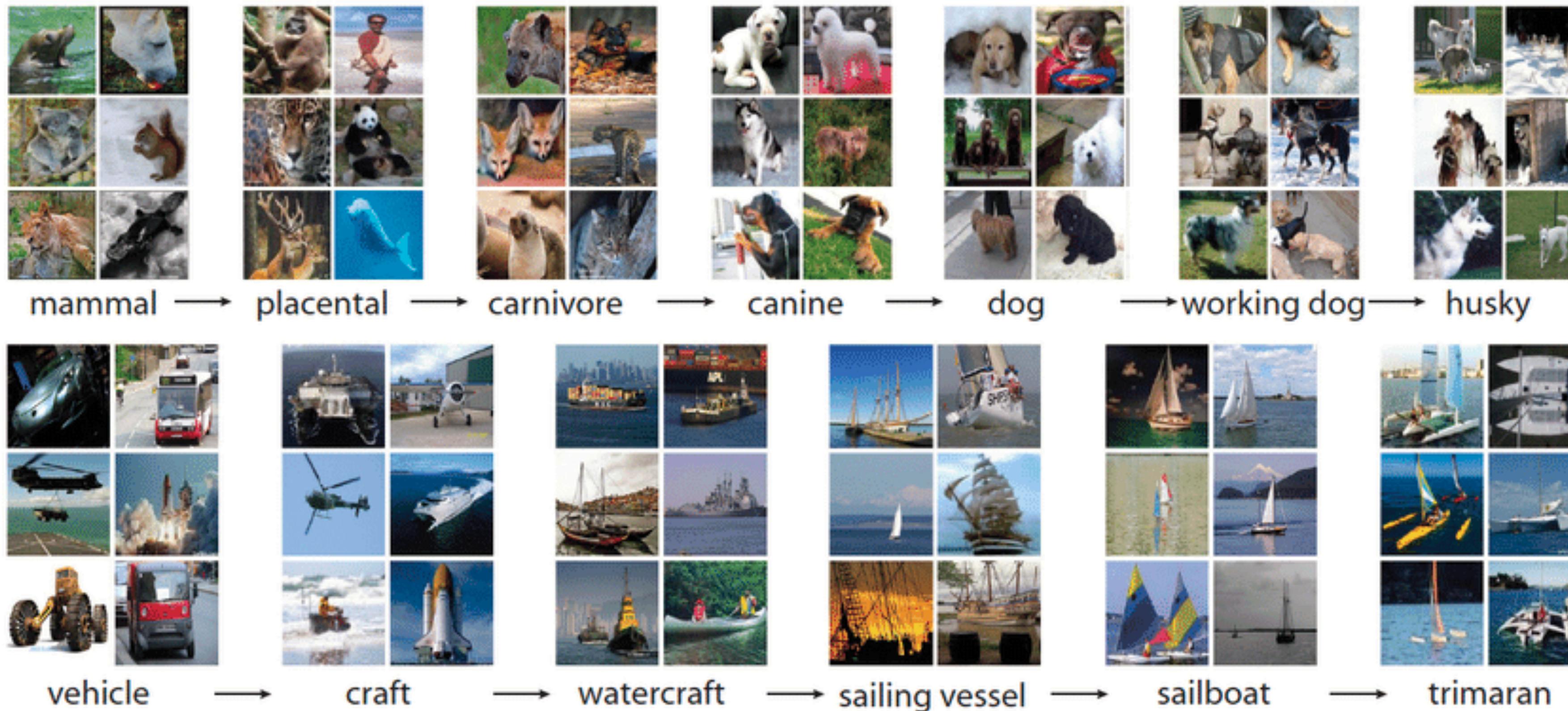
Prototype patches  
(visual words)

Histogram of  
visual words



# ALEXNET - A REVOLUTION IN COMPUTER VISION

## ImageNet Image Classification Challenge



1M Images

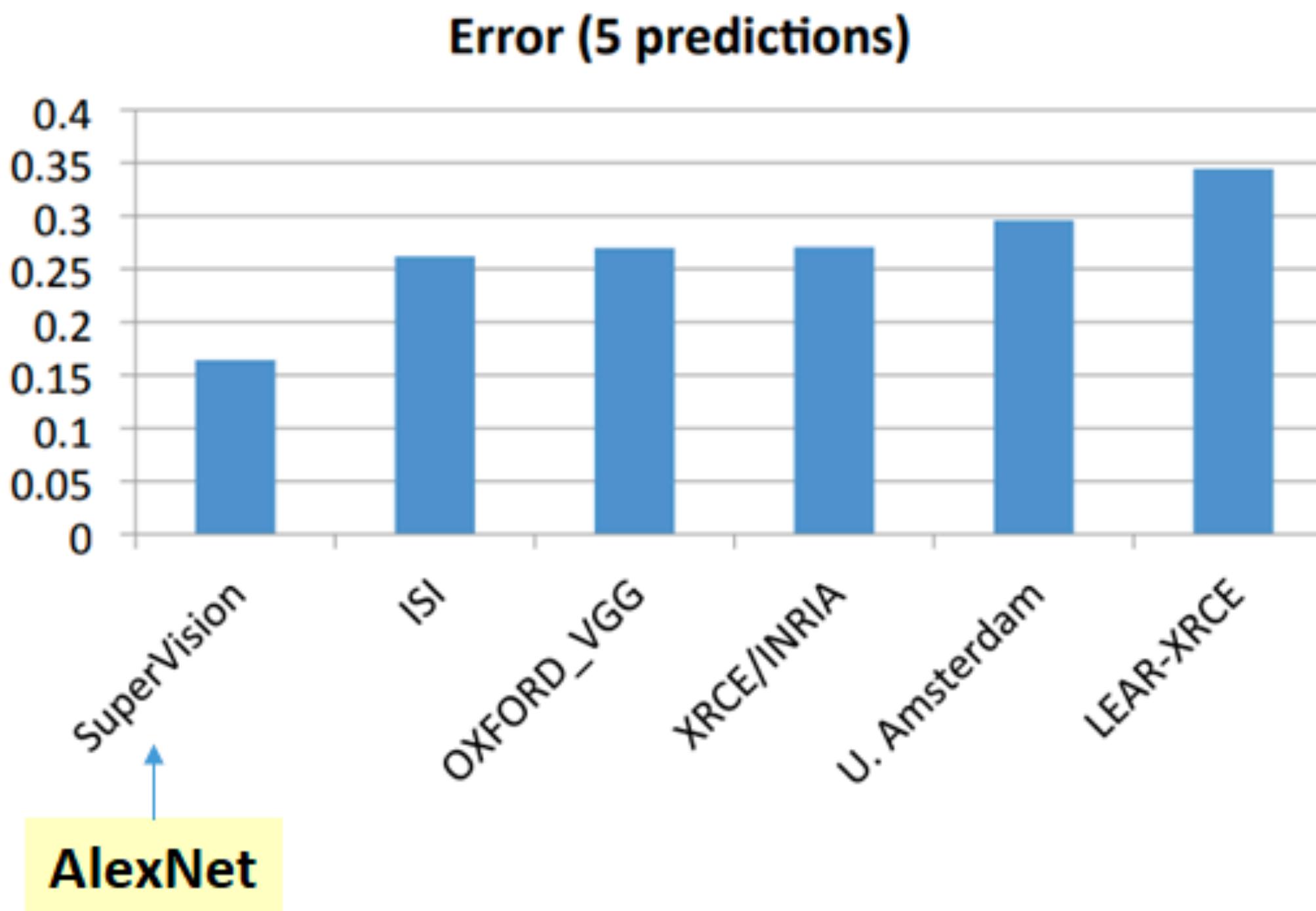
1000 categories



# ALEXNET - A REVOLUTION IN COMPUTER VISION

## ImageNet Image Classification Challenge

Ranking of the best results from each team



### Key ingredients:

- Deep Convolutional Neural Networks
- Lot's of training data
- ReLU and dropout
- GPUs



# CONVOLUTIONAL NEURAL NETWORKS

## What is a convolution?

$$\begin{array}{|c|c|c|c|c|} \hline 7 & 2 & 3 & 3 & 8 \\ \hline 4 & 5 & 3 & 8 & 4 \\ \hline 3 & 3 & 2 & 8 & 4 \\ \hline 2 & 8 & 7 & 2 & 7 \\ \hline 5 & 4 & 4 & 5 & 4 \\ \hline \end{array} * \begin{array}{|c|c|c|} \hline 1 & 0 & -1 \\ \hline 1 & 0 & -1 \\ \hline 1 & 0 & -1 \\ \hline \end{array} = \begin{array}{|c|c|c|} \hline 6 & & \\ \hline & & \\ \hline & & \\ \hline \end{array}$$

7x1+4x1+3x1+  
2x0+5x0+3x0+  
3x-1+3x-1+2x-1  
= 6



# CONVOLUTIONAL NEURAL NETWORKS

Neural networks that uses the convolution operator

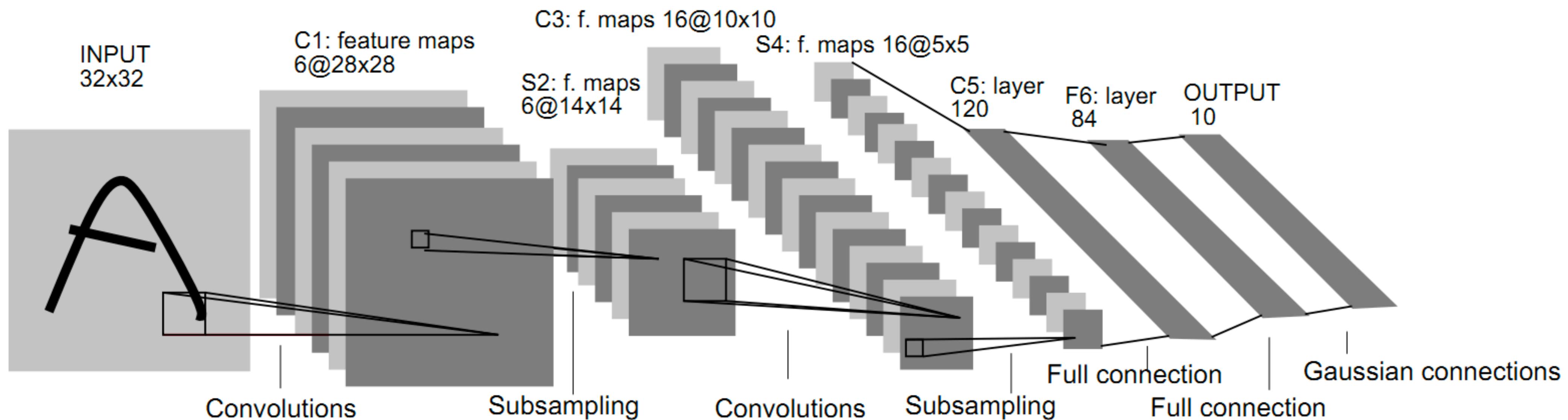


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.



# CONVOLUTIONAL NEURAL NETWORKS TODAY

More layers work better

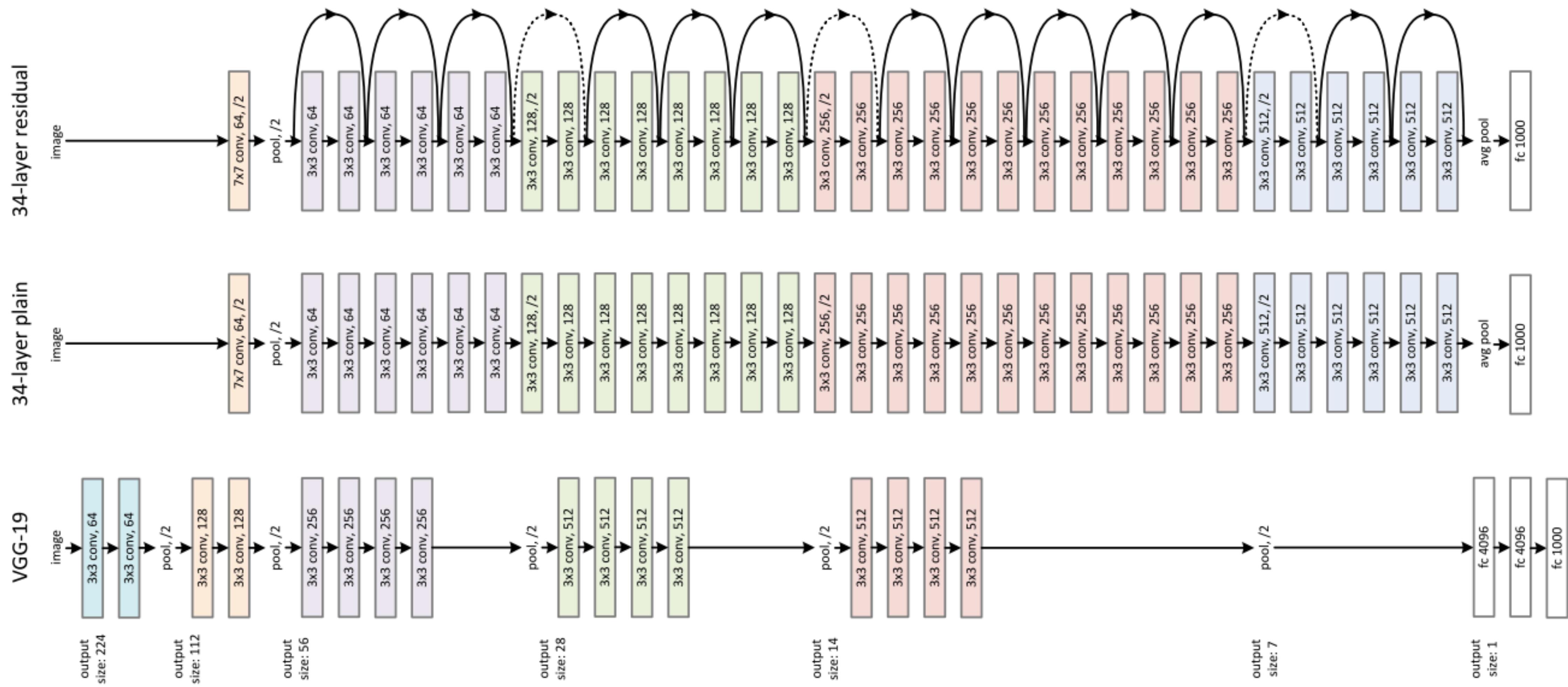


Image from [https://medium.com/@pierre\\_guillou/understand-how-works-resnet-without-talking-about-residual-64698f157e0c](https://medium.com/@pierre_guillou/understand-how-works-resnet-without-talking-about-residual-64698f157e0c)



# GOING BEYOND IMAGE CLASSIFICATION



# WHAT IS IN THE IMAGE, AND WHERE?

## Classification



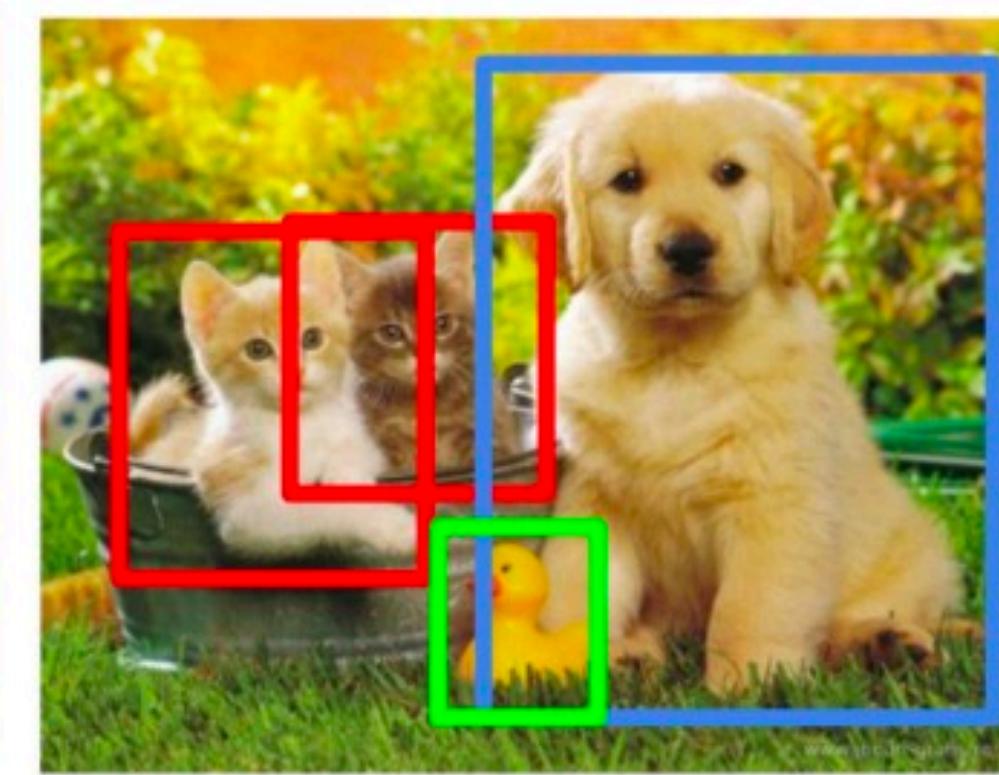
CAT

## Classification + Localization



CAT

## Object Detection



CAT, DOG, DUCK

## Instance Segmentation



CAT, DOG, DUCK

## Semantic Segmentation



GRASS, CAT,  
TREE, SKY

Single object

Multiple objects

No objects, just pixels



# CNN OVER REGIONS (R-CNN)



Image from <https://www.halifaxhumane.org/20-Little-Known-Facts-About-Cats-and-Dogs-1-38.html>



# COMPUTER VISION WITH TORCHVISION



# WHAT IS TORCHVISION?

**A library built to facilitate research and  
experimentation in the field of Computer Vision**



## DATASETS

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COMMON DATASETS

## OPS

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EFFICIENT OPERATORS

## IO

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EFFICIENT VIDEO READER

## MODELS

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PRE-TRAINED MODELS

## TRANSFORMS

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DATA TRANSFORMATION

## REFERENCES

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TRAINING SCRIPTS

DATASETS

TRANSFORMS

MODELS

OPS

IO



IMAGENET 64X64

## DATASETS

## TRANSFORMS

## MODELS

## OPS

## IO

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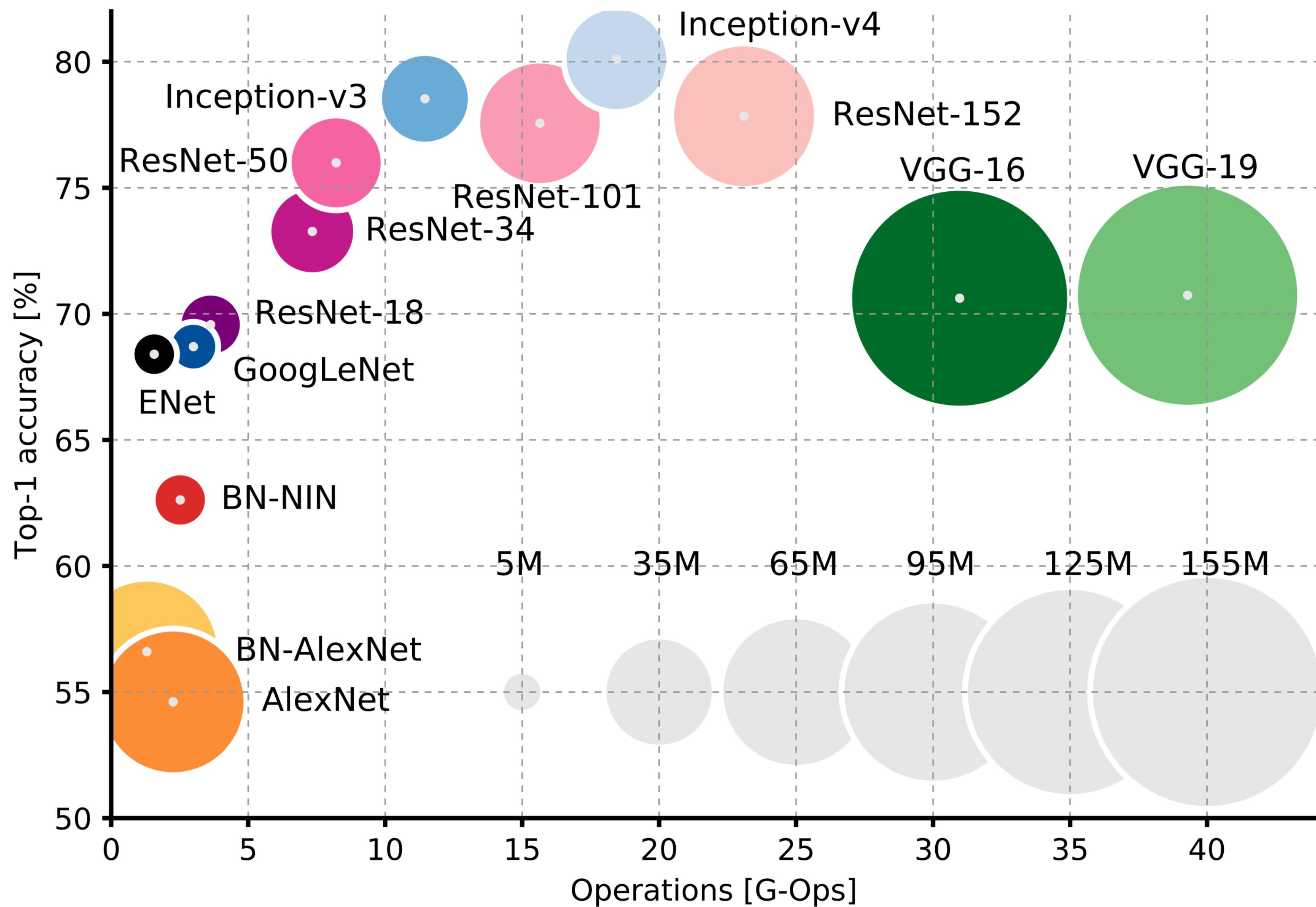
DATASETS

TRANSFORMS

MODELS

OPS

IO



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DATASETS

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TRANSFORMS

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MODELS

---

OPS

---

IO

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```
import torchvision.ops  
  
torchvision.ops.box_iou(...)  
torchvision.ops.roi_align(...)  
torchvision.ops.nms(...)  
torchvision.ops.roi_pool(...)
```

---

## DATASETS

---

## TRANSFORMS

---

## MODELS

---

## OPS

---

## IO

---

```
import torchvision.io  
  
torchvision.io.read_video(filename,  
                           start_pts=0,  
                           end_pts=None)  
  
torchvision.io.read_video_timestamps(filename)  
  
torchvision.io.write_video(filename,  
                           video_array,  
                           fps,  
                           video_codec='libx264',  
                           options=None)
```



# PRE-TRAINED MODELS



# KeypointRCNN



# MaskRCNN



# DeepLabV3





# USING TORCHVISION MODELS

```
import torchvision

model = torchvision.models.detection.maskrcnn_resnet50_fpn(pretrained=True)
# set it to evaluation mode, as the model behaves differently
# during training and evaluation
model.eval()

image = PIL.Image.open('/path/to/an/image.jpg')
image_tensor = torchvision.transforms.functional.to_tensor(image)

# pass a list of (potentially different sized) tensors
# to the model, in 0-1 range. The model will take care of
# batching them together and normalizing
output = model([image_tensor])
# output is a list of dict, containing the post processed predictions
```



# HANDS ON WITH TORCHVISION