

# Deep Learning for Images

## The Problem: Semantic Gap

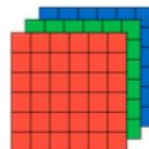


```
[[105 112 100 111 104 99 106 99 96 103 112 119 104 97 93 87]
 [ 91 98 102 106 104 79 98 103 99 105 123 136 110 105 94 85]
 [ 76 85 90 105 120 105 87 96 95 99 115 112 106 103 99 85]
 [ 99 81 81 93 120 131 127 100 95 98 102 99 96 93 101 94]
 [106 91 61 64 69 91 88 85 101 107 109 98 75 84 96 95]
 [114 100 85 55 55 69 64 54 64 87 112 129 98 74 84 91]
 [133 137 147 103 65 81 80 65 52 54 74 84 102 93 85 82]
 [128 137 144 140 109 95 86 70 62 65 63 63 60 73 86 101]
 [125 133 148 137 119 121 117 94 65 79 80 65 54 64 72 98]
 [127 125 131 147 133 127 126 131 111 96 89 75 61 64 72 84]
 [115 114 109 123 150 140 131 110 113 109 100 92 74 65 72 70]
 [ 89 93 90 97 100 147 131 110 113 114 113 109 106 95 77 80]
 [ 63 77 86 81 77 79 102 123 117 115 117 125 125 130 115 87]
 [ 62 65 82 89 78 71 80 101 124 126 119 101 107 114 131 119]
 [ 63 65 75 88 89 71 62 81 120 130 135 105 81 90 110 110]
 [ 87 65 71 87 106 95 69 45 76 130 126 107 92 94 105 112]
 [118 97 82 86 117 123 116 66 41 51 95 93 89 95 102 107]
 [164 146 112 80 82 120 124 104 76 48 45 66 88 101 102 109]
 [157 170 157 120 93 86 114 132 112 97 69 55 70 82 99 94]
 [130 120 134 161 139 100 109 110 121 134 114 87 65 53 69 86]
 [120 112 96 117 150 144 120 115 104 107 102 93 87 81 72 79]
 [123 107 96 86 83 112 153 149 122 109 104 75 80 107 112 99]
 [122 121 102 80 82 86 94 117 145 140 153 102 58 78 92 107]
 [122 164 140 103 71 56 70 83 93 103 119 139 102 61 69 84]]
```

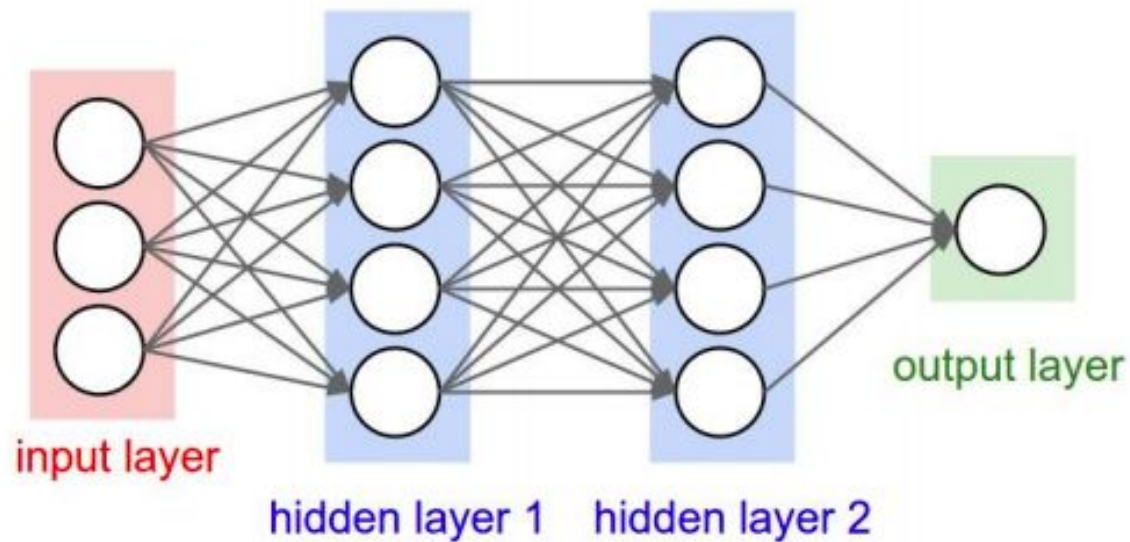
What the computer sees

An image is just a big grid of numbers between [0, 255]:

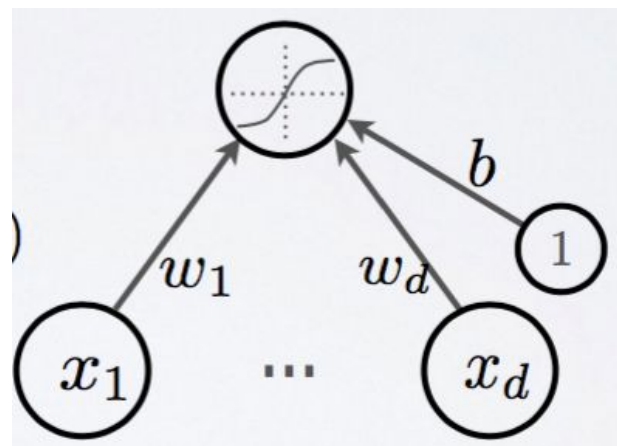
Example:  
800 x 600 x 3  
(3 channels RGB)



h  
x  
w  
x  
3



“3-layer Neural Net”, or  
“2-hidden-layer Neural Net”



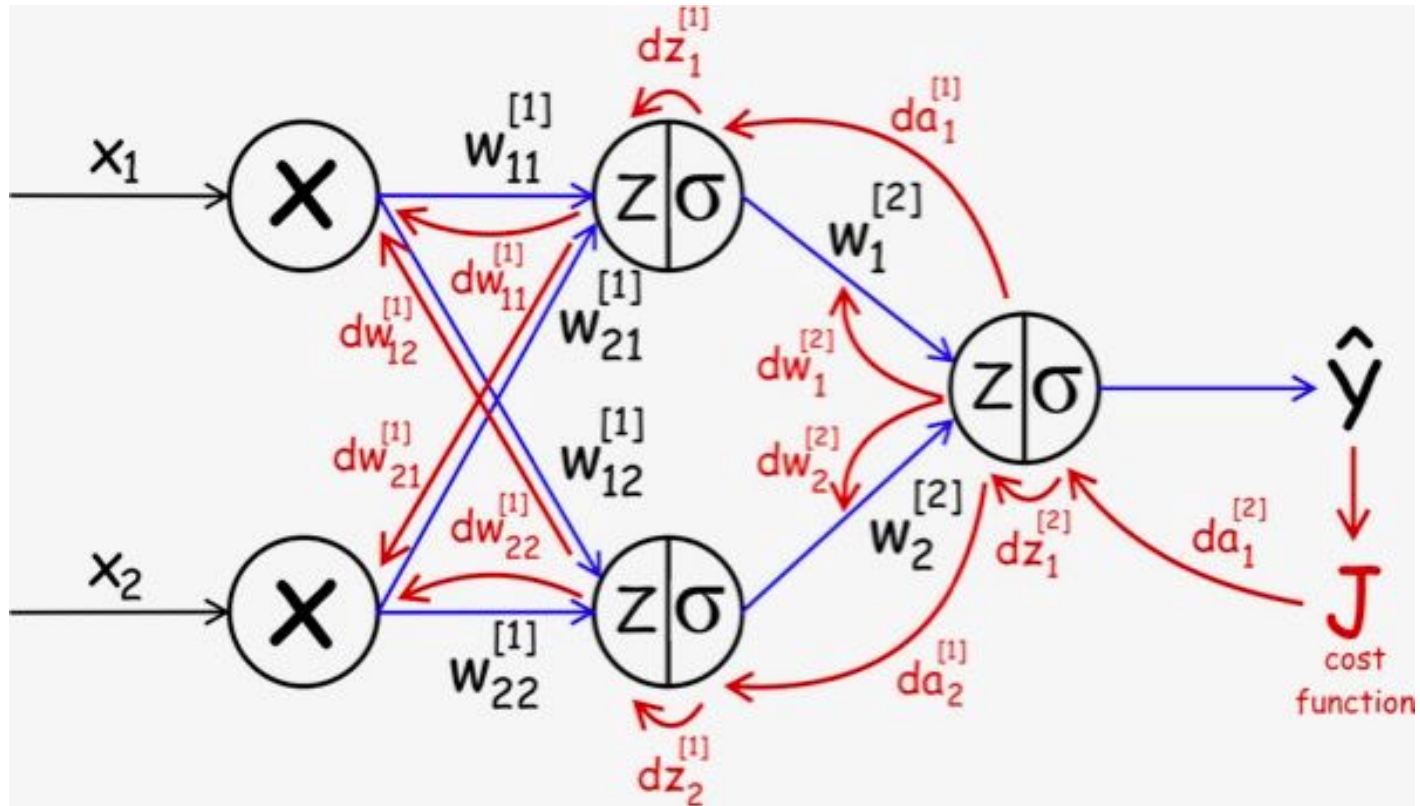
$$a(\mathbf{x}) = b + \sum_i w_i x_i$$

Suppose: 3 training examples, 3 classes.  
With some  $W$  the scores  $f(x, W) = Wx$  are:



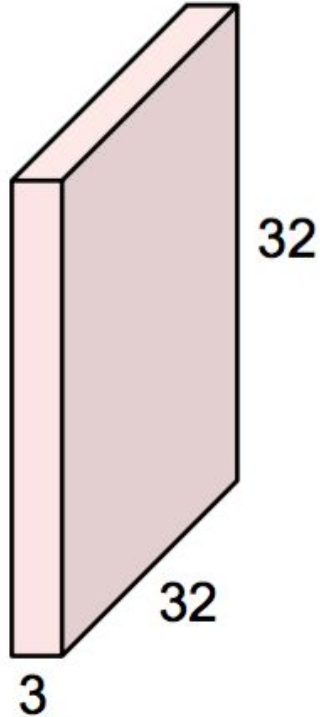
cat	<b>3.2</b>	1.3	2.2
car	5.1	<b>4.9</b>	2.5
frog	-1.7	2.0	<b>-3.1</b>
Losses:	2.9	0	12.9

# Backpropagation Algorithm



# Convolution

32x32x3 image

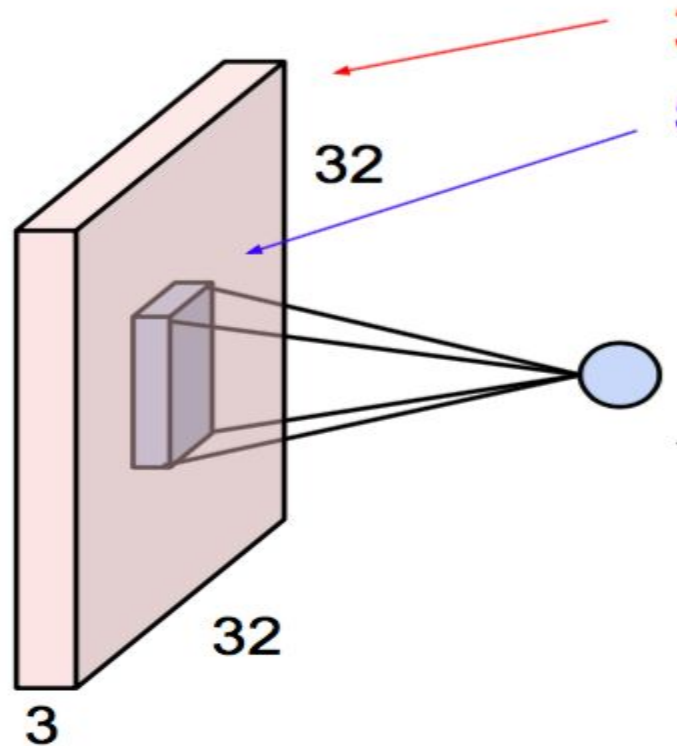


5x5x3 filter

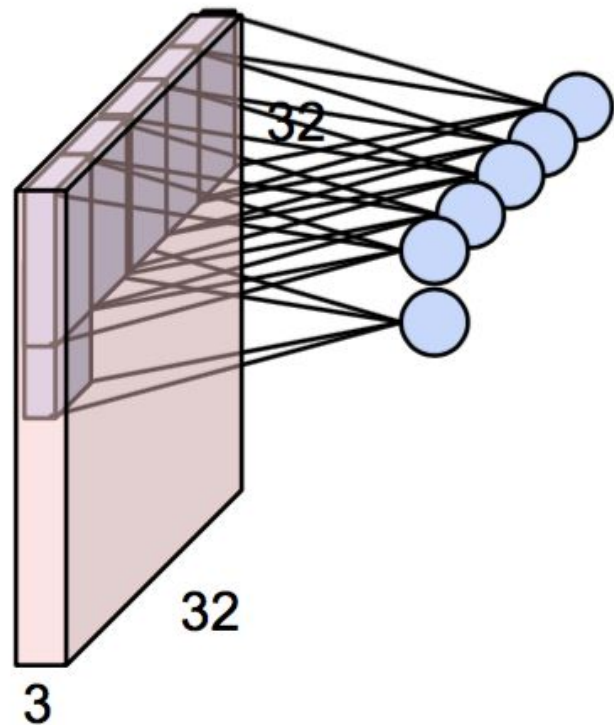


**Cc**  
i.e.  
col

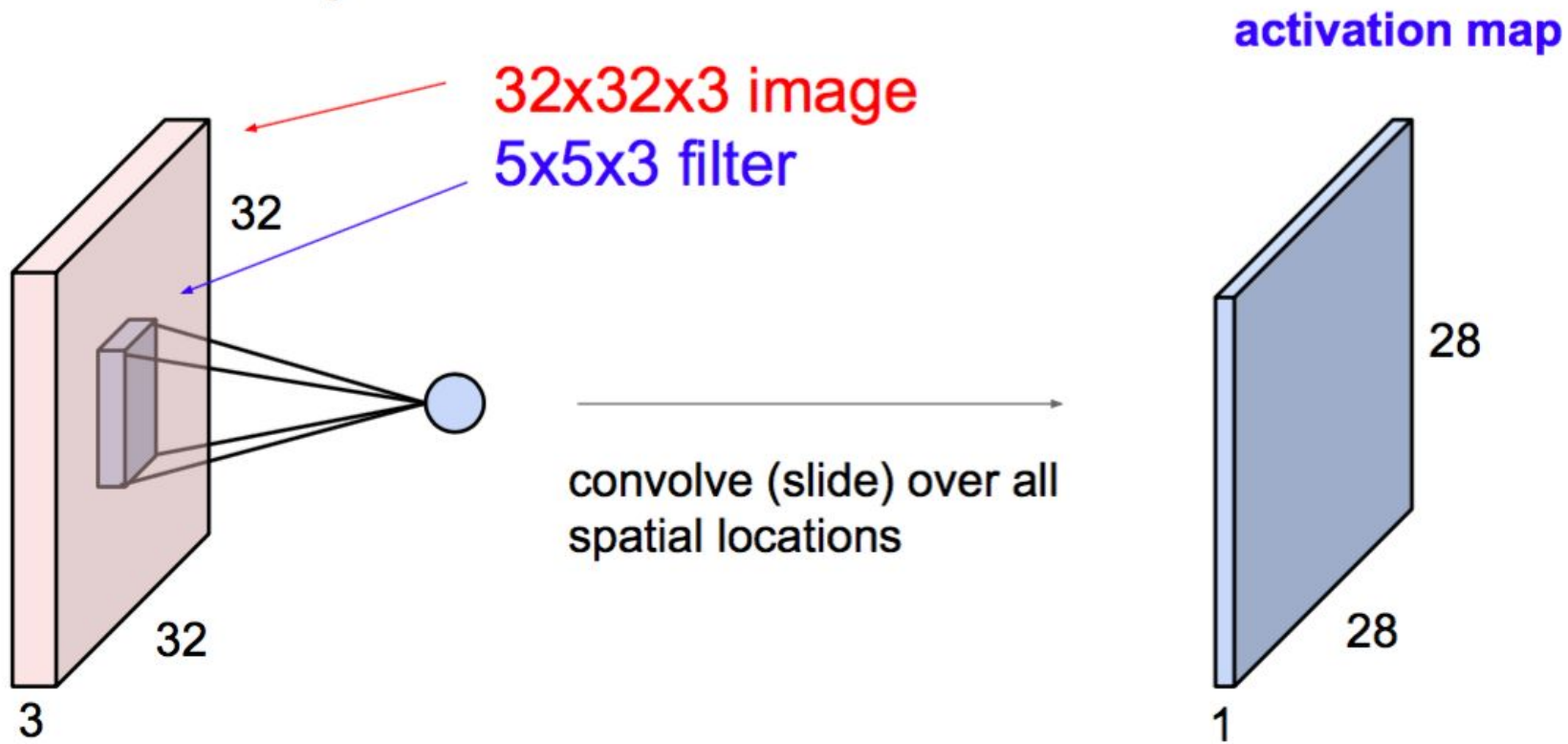
# Convolution Layer

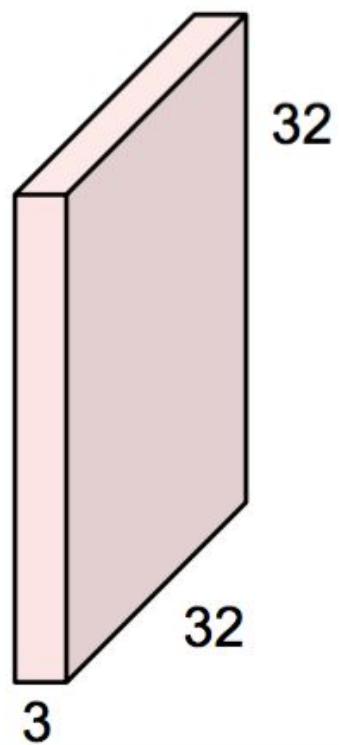


$$w^T x + b$$

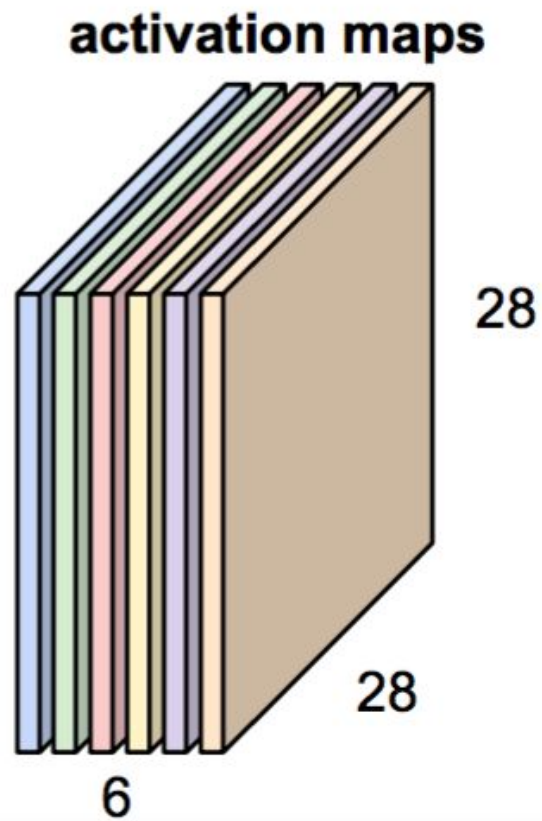




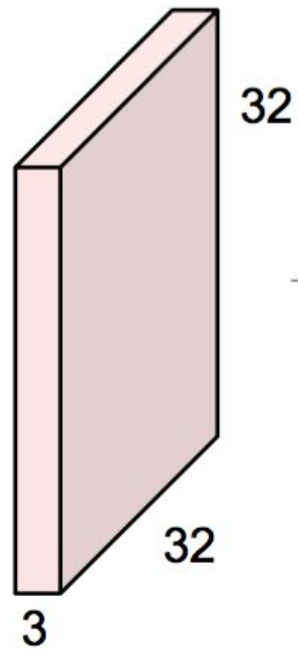




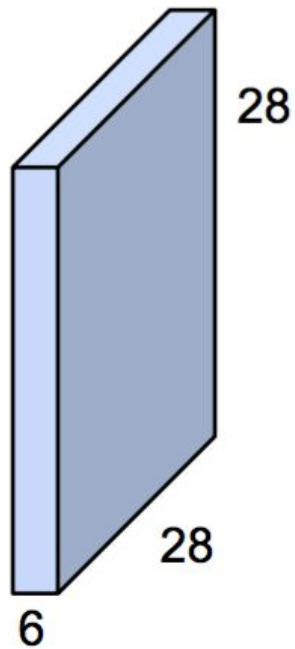
→  
Convolution Layer



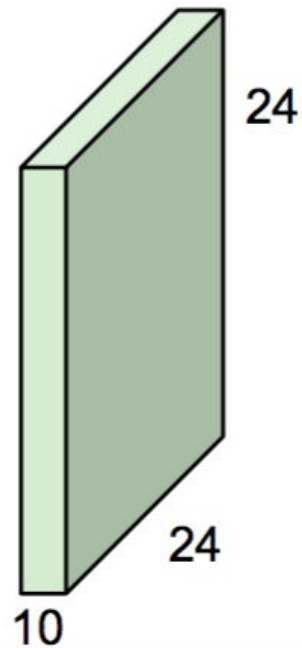




CONV,  
ReLU  
e.g. 6  
5x5x3  
filters

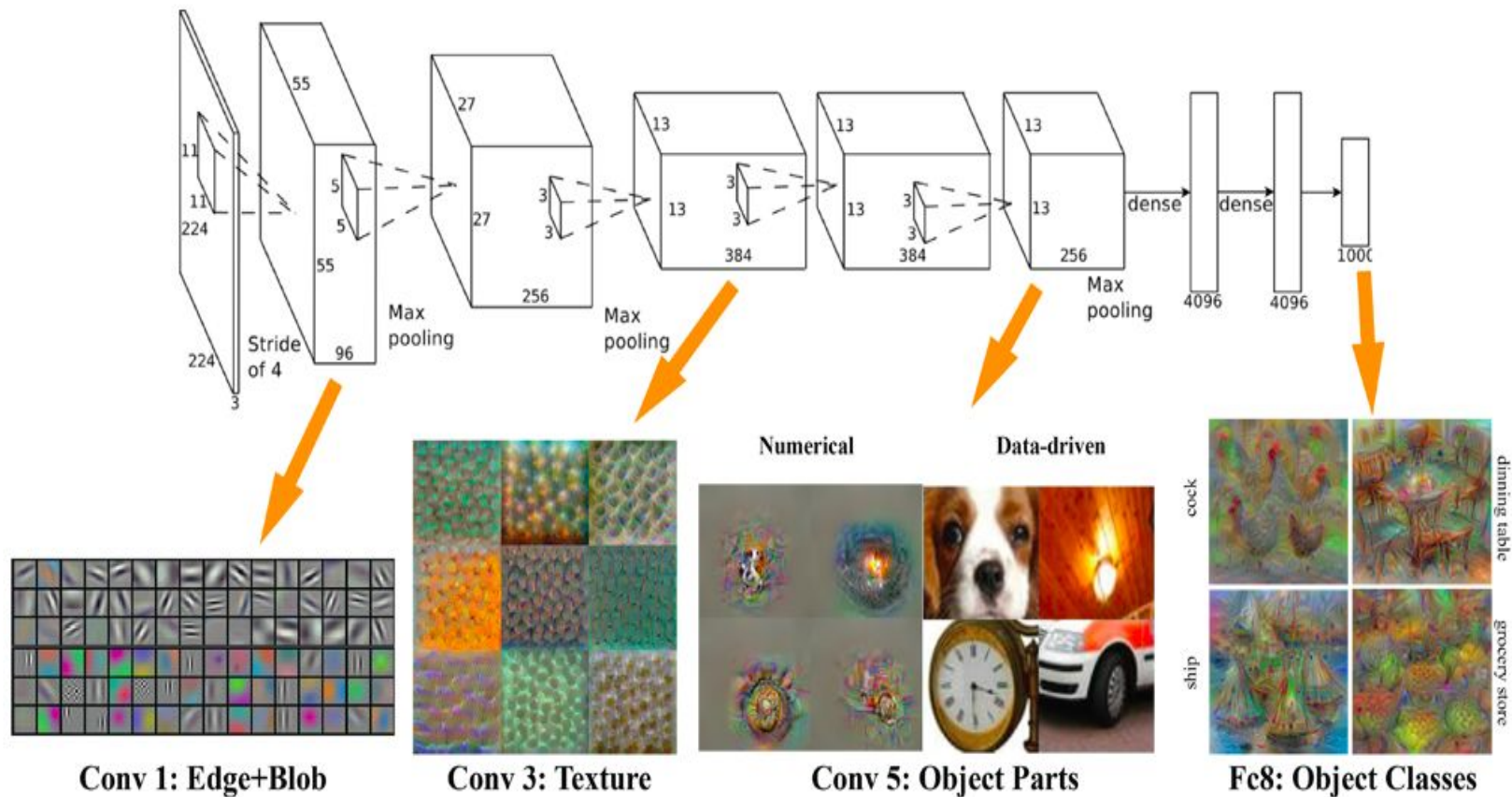


CONV,  
ReLU  
e.g. 10  
5x5x6  
filters



CONV,  
ReLU

....



AlexNet / VGG-F network visualized by **mNeuron**.

# Preview

[Zeiler and Fergus 2013]

Visualization of VGG-16 by Lane McIntosh. VGG-16 architecture from [Simonyan and Zisserman 2014].

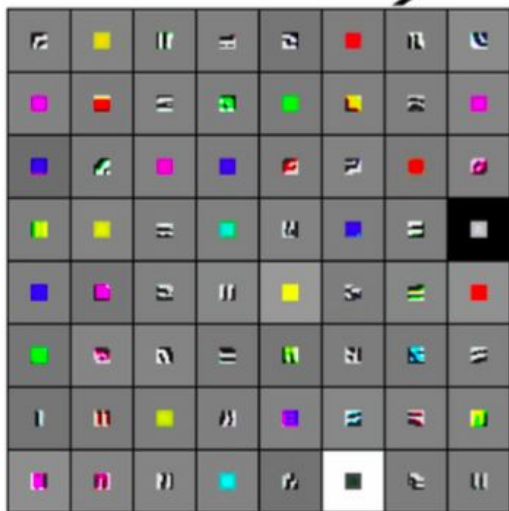


Low-level  
features

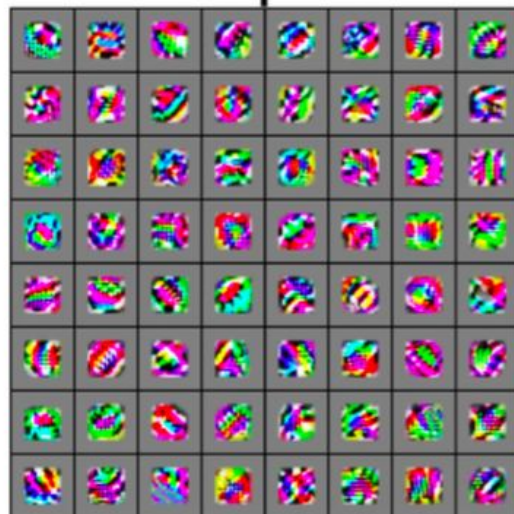
Mid-level  
features

High-level  
features

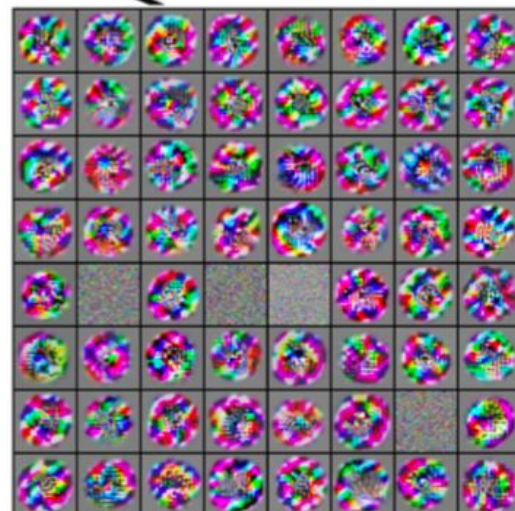
Linearly  
separable  
classifier



VGG-16 Conv1\_1



VGG-16 Conv3\_2



VGG-16 Conv5\_3

# Deep Learning Consists of two characteristics

1. End to End Training due to Backpropagation Algorithm.
2. Hierarchical Learning of Features.

Deep Learning become popular recently due to three reasons :-

1. More Data
2. More Computational Power due to GPU(Parallel Processing)
3. Better Algorithms





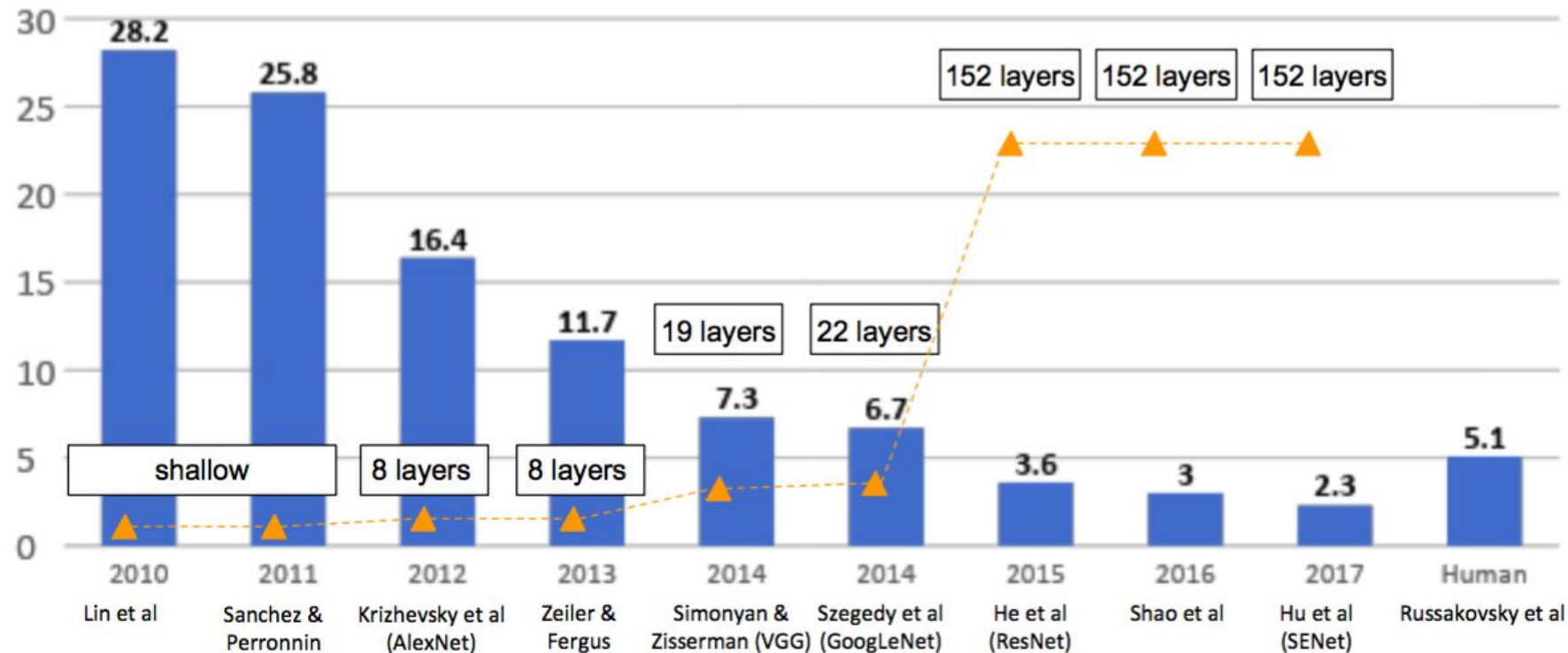
mammal → placental → carnivore → canine → dog → working dog → husky



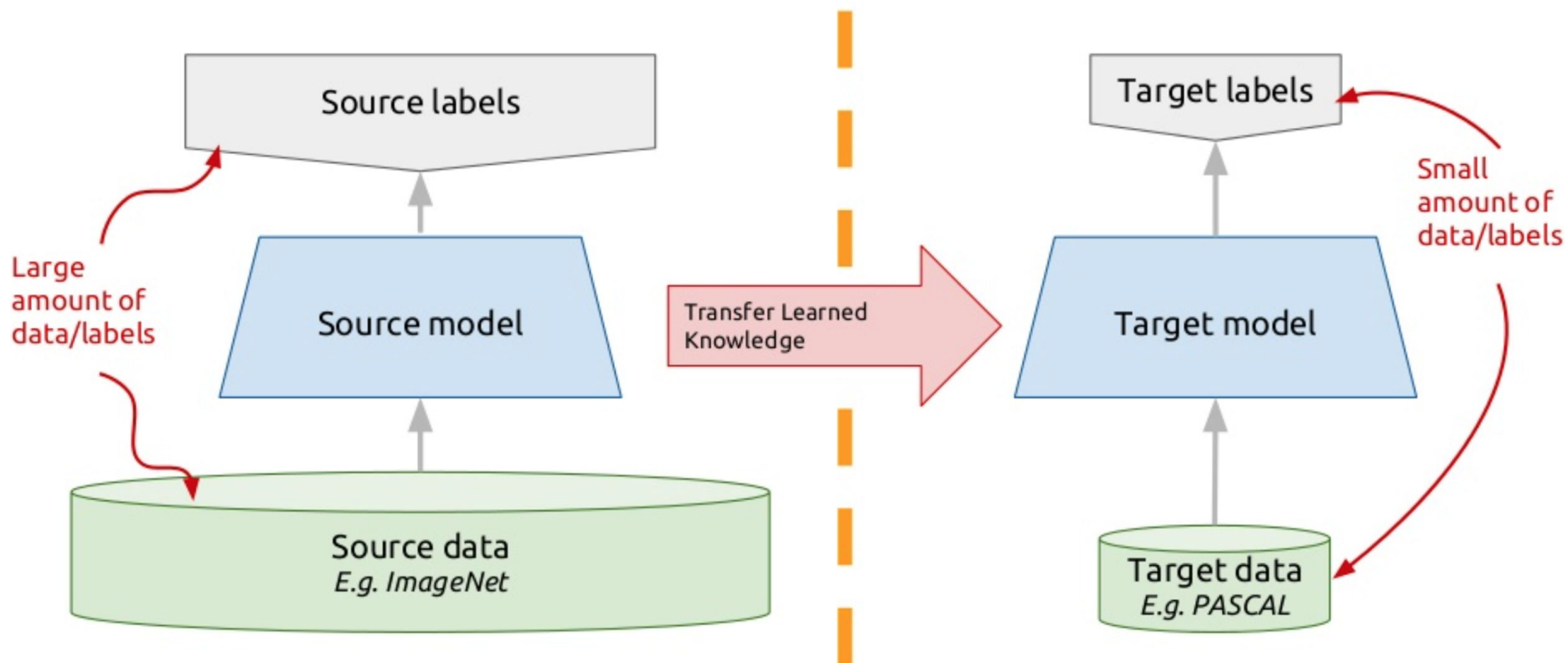
vehicle → craft → watercraft → sailing vessel → sailboat → trimaran

Imagenet Challenge(Dataset)- 1.2 million images and 1000 categories

# ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

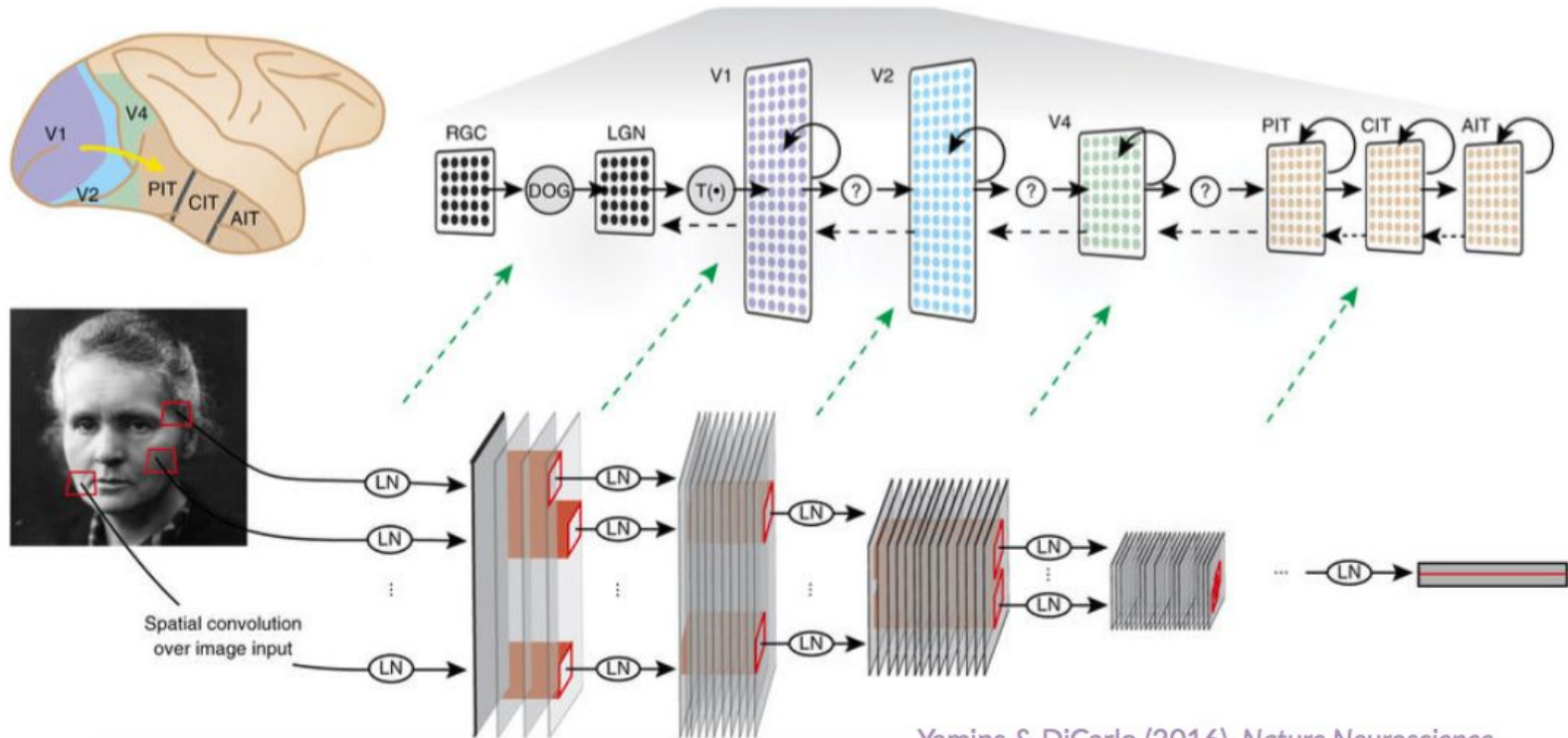


# Transfer learning: idea





At an abstract level, deep neural networks operate with some similar principals to the real brain (though there are some important differences!)



# Computer Vision Tasks

## Classification



**CAT**

No spatial extent

## Semantic Segmentation



**GRASS, CAT,  
TREE, SKY**

No objects, just pixels

## Object Detection



**DOG, DOG, CAT**

## Instance Segmentation

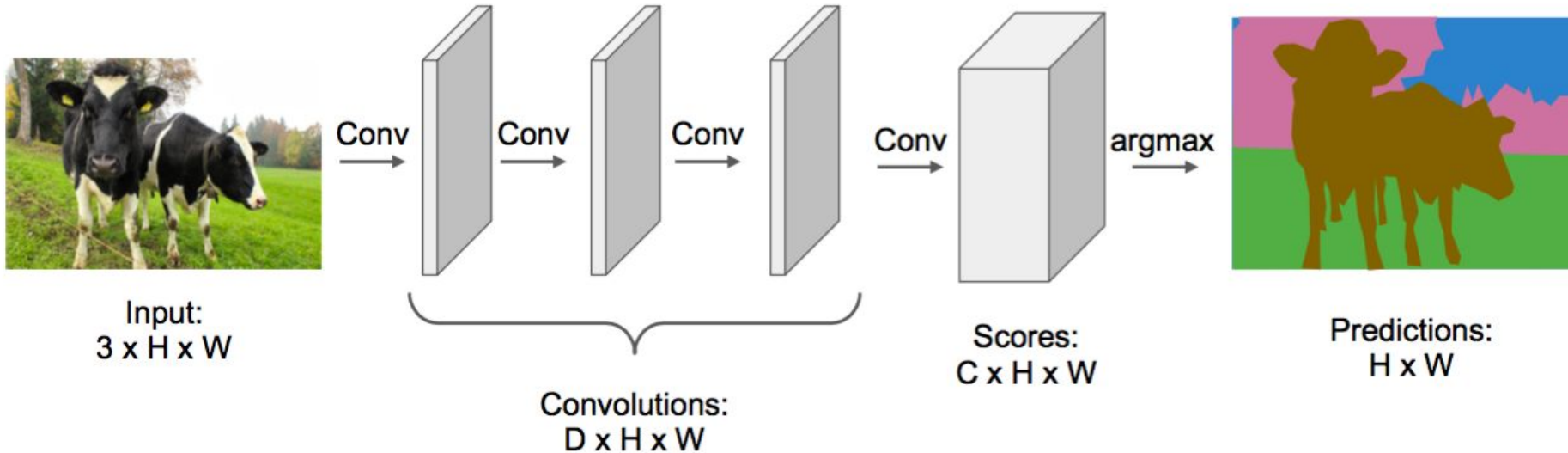


**DOG, DOG, CAT**

Multiple Object

[This image is CC0 public domain](#)

# Image Segmentation

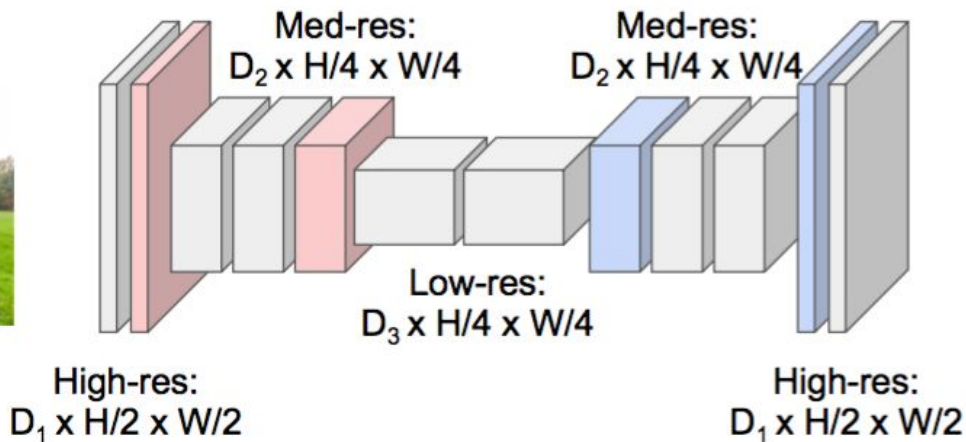


**Downsampling:**  
Pooling, strided  
convolution



Input:  
 $3 \times H \times W$

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



**Upsampling:**  
???



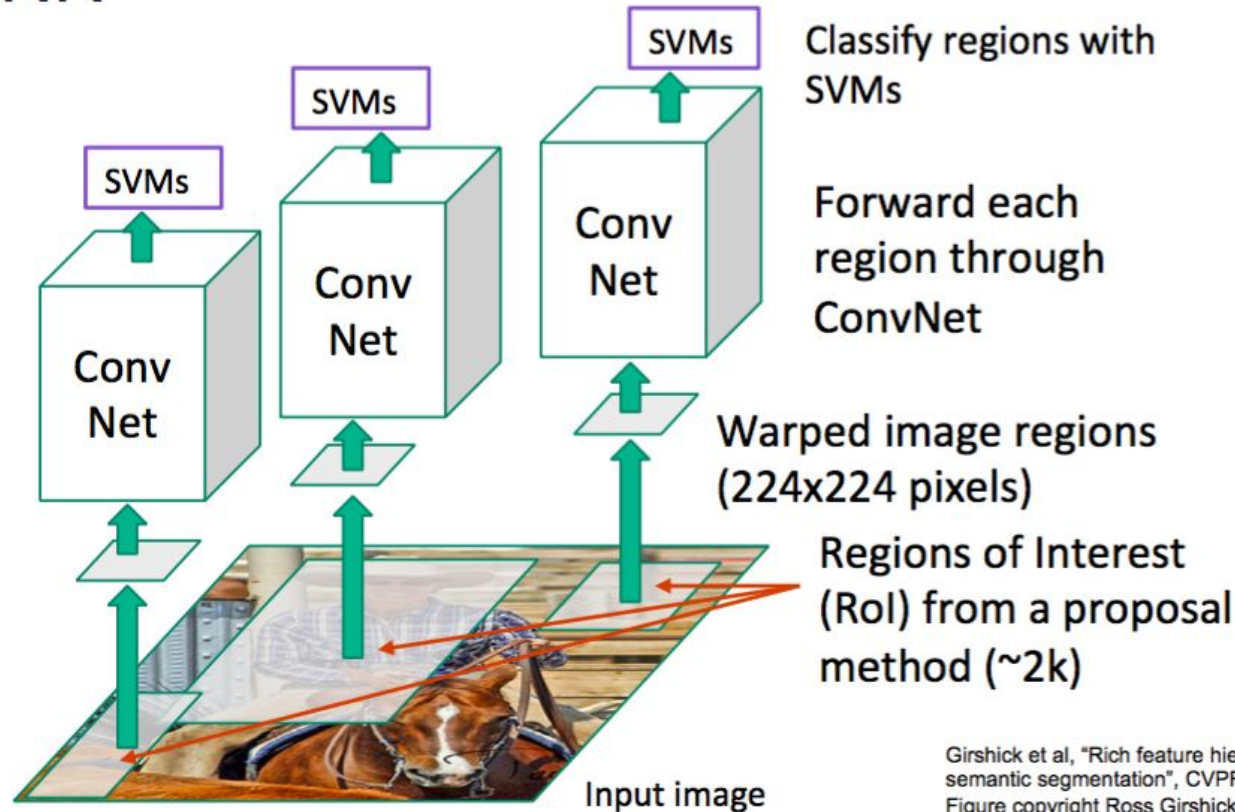
Predictions:  
 $H \times W$

# Object Detection



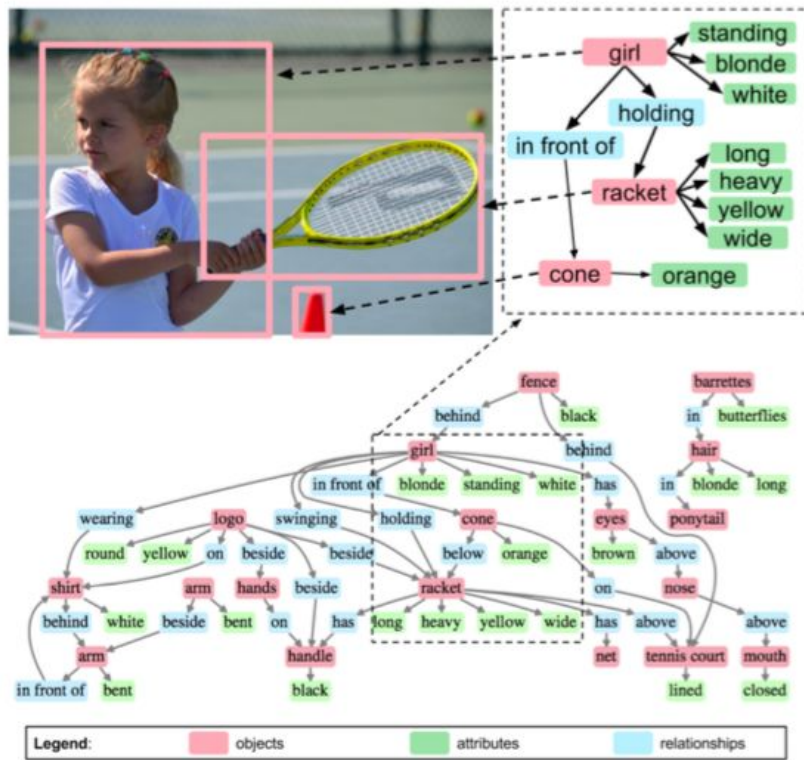


# R-CNN



Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.  
Figure copyright Ross Girshick, 2015; [source](#). Reproduced with permission.

# Objects + Relationships = Scene Graphs



108,077 Images

## 5.4 Million Region Descriptions

## 1.7 Million Visual Question Answers

### 3.8 Million Object Instances

## 2.8 Million Attributes

## 2.3 Million Relationships

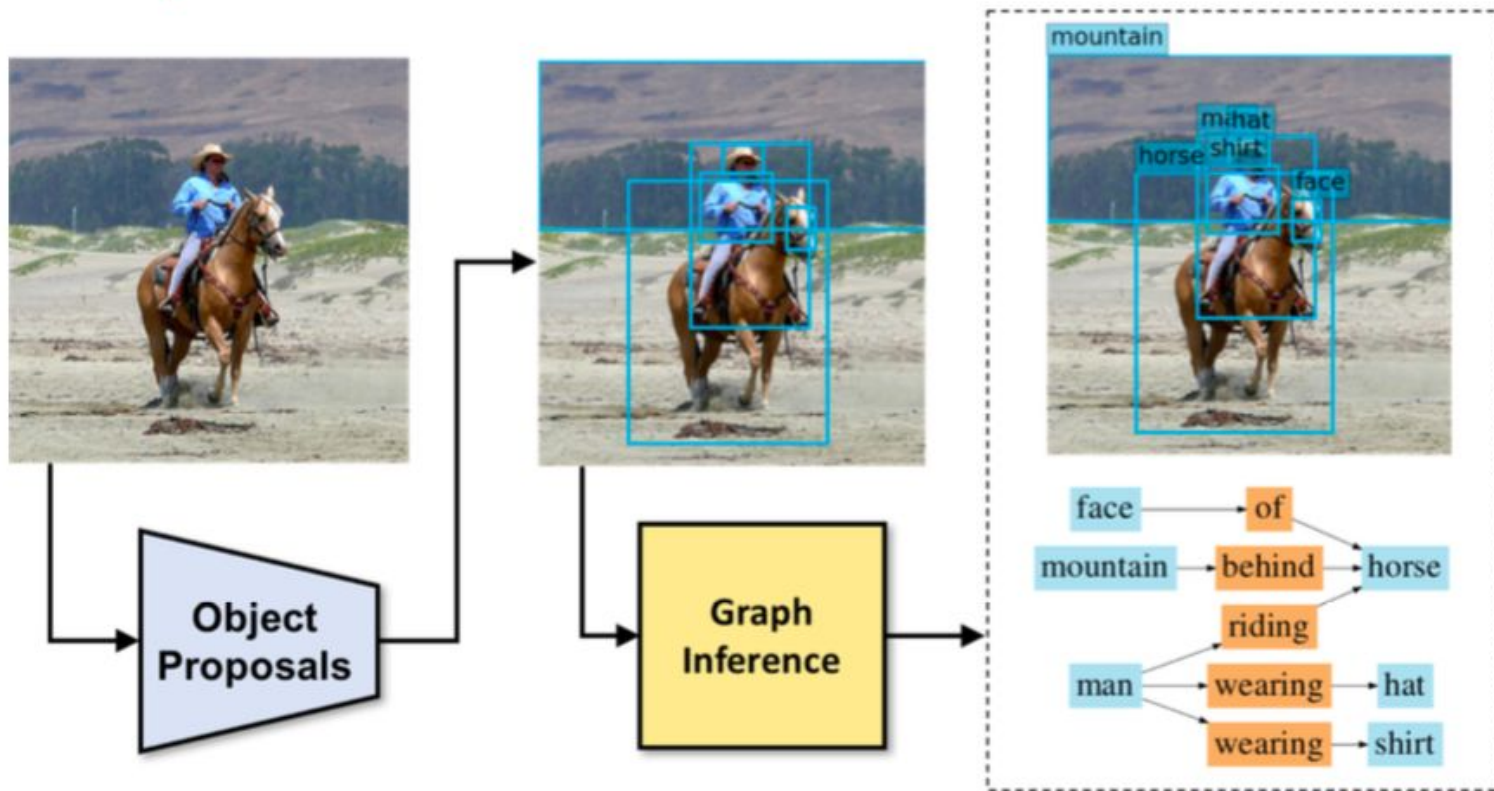
## Everything Mapped to Wordnet Synsets



Krishna, Ranjay, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "Visual genome: Connecting language and vision using crowdsourced dense image annotations." *International Journal of Computer Vision* 123, no. 1 (2017): 32-73.



# Scene Graph Prediction



# Language and vision

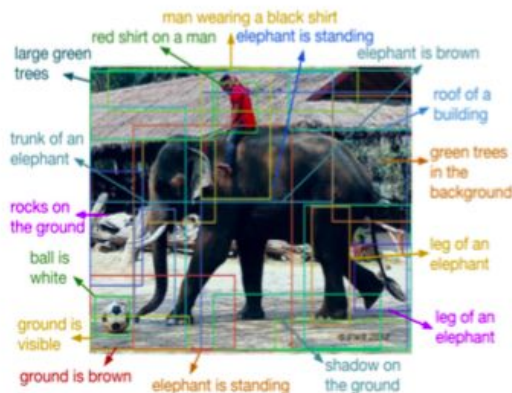
## Captioning



"man in black shirt is playing guitar."

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

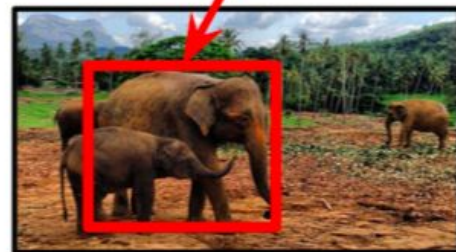
## Dense Captioning



Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

## Referring Expressions

*largest elephant standing behind baby elephant.*



Zhang, Liu, and Chang, "Grounding Referring Expressions in Images by Variational Context", CVPR 2018

# Visual Question Answering (VQA)

## VQA



What color are her eyes?  
What is the mustache made of?



How many slices of pizza are there?  
Is this a vegetarian pizza?



Is this person expecting company?  
What is just under the tree?



Does it appear to be true?  
Does this person have 20/20 vision?

- Understanding of visual input
  - Understanding of language
  - World knowledge
  - Reasoning
- 
- Can ask about anything
  - Easier to evaluate (at least for multiple choice)

"VQA: Visual Question Answering"  
[Agrawal et al, ICCV 2015]



# Visual Question Answering (VQA)

## VQA

Who is wearing glasses?

man

woman



Is the umbrella upside down?

yes

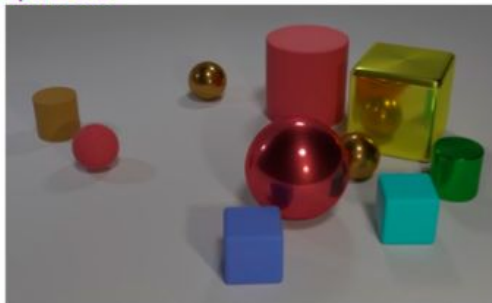
no



"Making the V in VQA Matter: Elevating the Role of Image Understanding in Visual Question Answering"  
[Goyal et al, CVPR 2017]

## CLEVR

Questions in CLEVR test various aspects of visual reasoning including **attribute identification**, **counting**, **comparison**, **spatial relationships**, and **logical operations**.



Q: Are there an **equal number** of **large things** and **metal spheres**?

Q: **What size** is the **cylinder** that is **left of** the **brown metal** thing that is **left of** the **big sphere**?

Q: There is a **sphere** with the **same size as** the **metal cube**; is it **made of the same material as** the **small red sphere**?

Q: **How many** objects are **either small cylinders** or **red things**?

"CLEVR: A Diagnostic Dataset for Compositional Language and Elementary Visual Reasoning"  
[Johnson et al, CVPR 2017]

## GQA



*Is the **bowl** to the right of the **green apple**?*

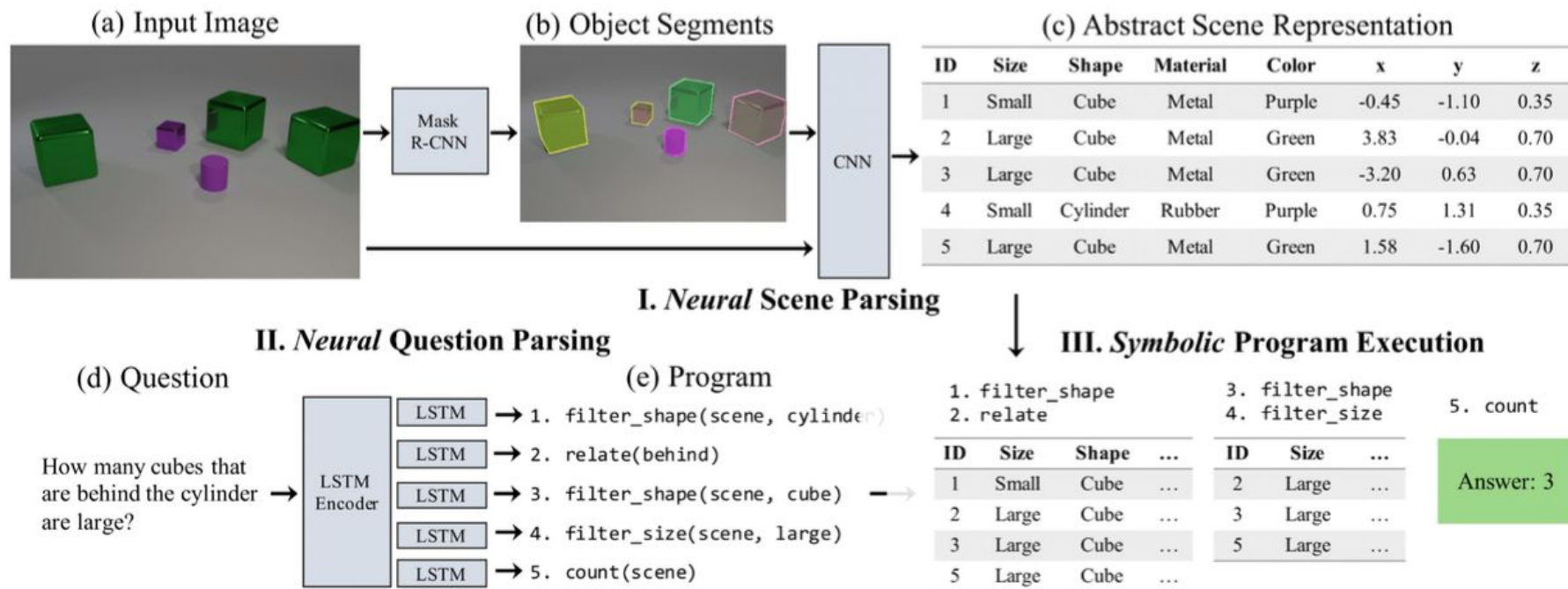
*What type of **fruit** in the image is **round**?*

*What color is the **fruit** on the right side, red or green?*

*Is there any **milk** in the **bowl** to the left of the **apple**?*

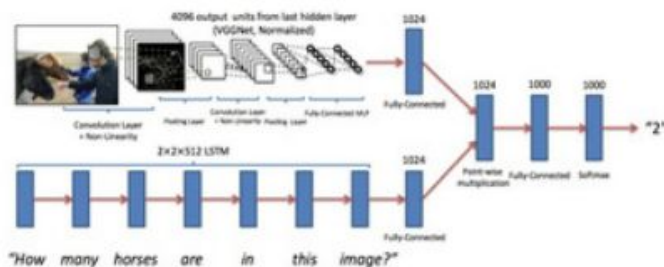
"GQA: A New Dataset for Real-World Visual Reasoning and Compositional Question Answering"  
[Hudson and Manning, CVPR 2019]

# Reasoning



“Neural-Symbolic VQA: Disentangling Reasoning from Vision and Language Understanding”  
[Yi, Wu, Gan, Torralba, Kohli, and Tenenbaum, NeurIPS 2018]

# Task- and dataset-specific models



Visual Question Answering [Antol et. al. 2015]

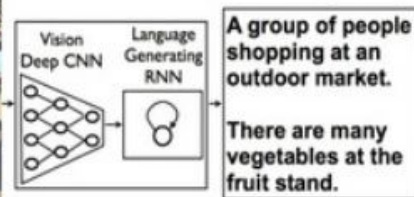
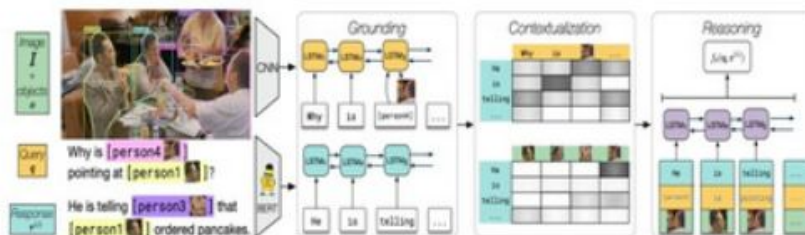
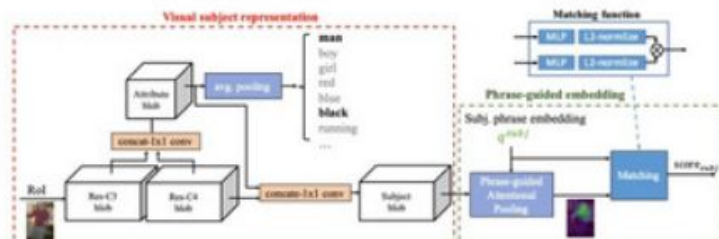


Image Captioning [Vinyals et. al. 2015]

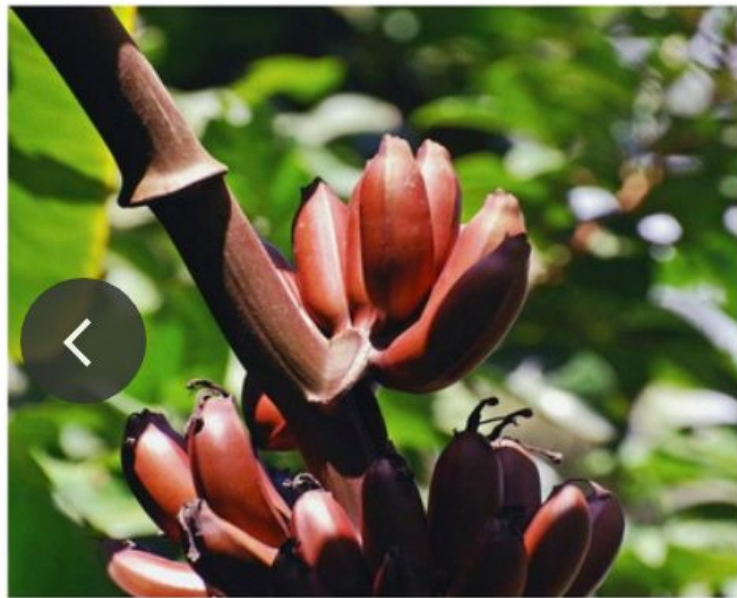


Visual Commonsense Reasoning [Zellers et. al. 2018]



Refer Expression [Yu et. al 2018]

# Task- and dataset-specific models



VQA model:

Q: What type of plant is this?

A: [Banana](#)

Captioning model:

A bunch of red and yellow **flowers** on a branch.

[Common](#) model for [visual grounding](#)

Leverage for a variety of vision-and-language tasks





# ViLBERT Multi-Task [CVPR 2020]

1 model for 12 tasks!

Higher performance, 1/12<sup>th</sup> the model size!

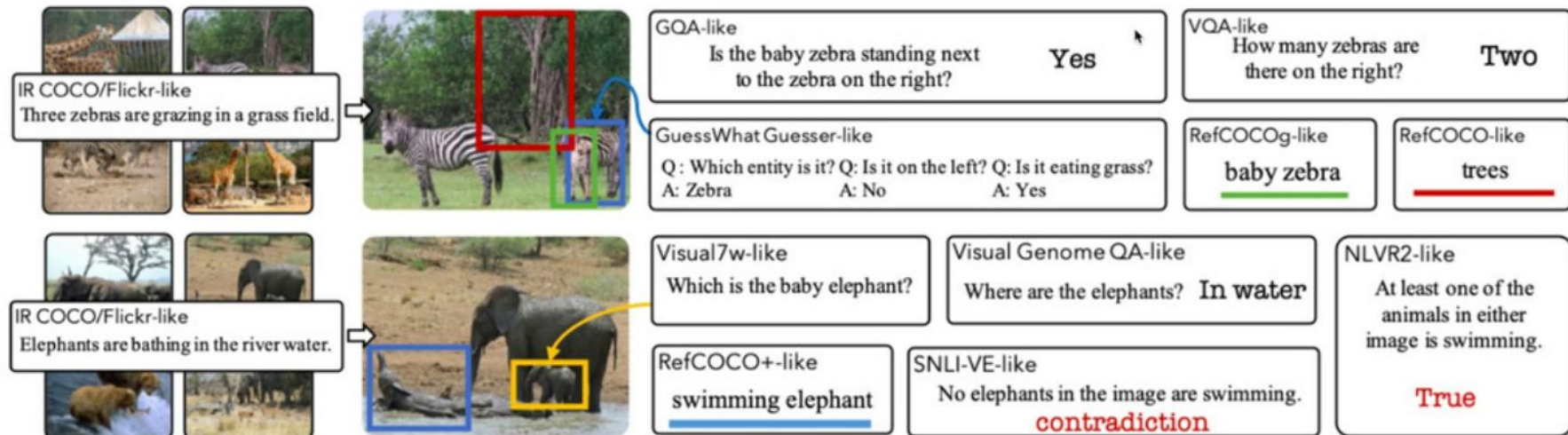
SOTA on 7 after fine-tuning



Jiasen Lu



Vedanuj Goswami



# Extending to 3D

## Classification



**Apartment**

Single label

## Semantic Segmentation



**Table, Bed, Couch, Cabinet**

No objects

## Object Detection



**Bed, Couch, Cabinet, Cabinet**

Multiple Object

## Instance Segmentation

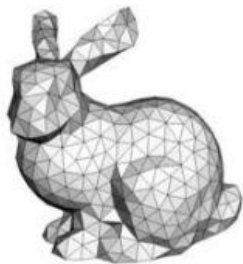


**Bed, Couch, Cabinet, Desk**

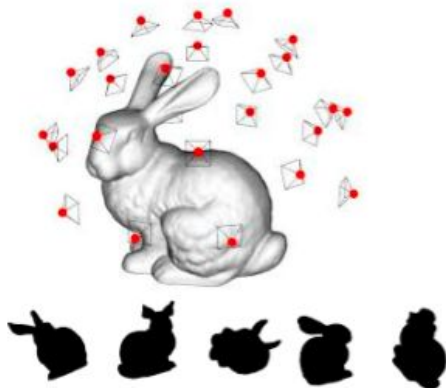
“ScanNet: Richly-annotated 3D Reconstructions of Indoor Scenes”  
[Dai et al, CVPR 2017]

# Extending to 3D - Representation

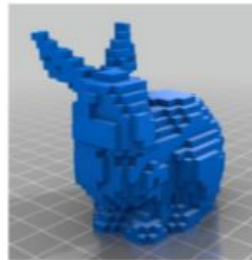
**Surface:**  
Triangle Mesh



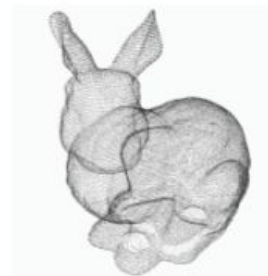
**Multi-View:**  
Set of Images



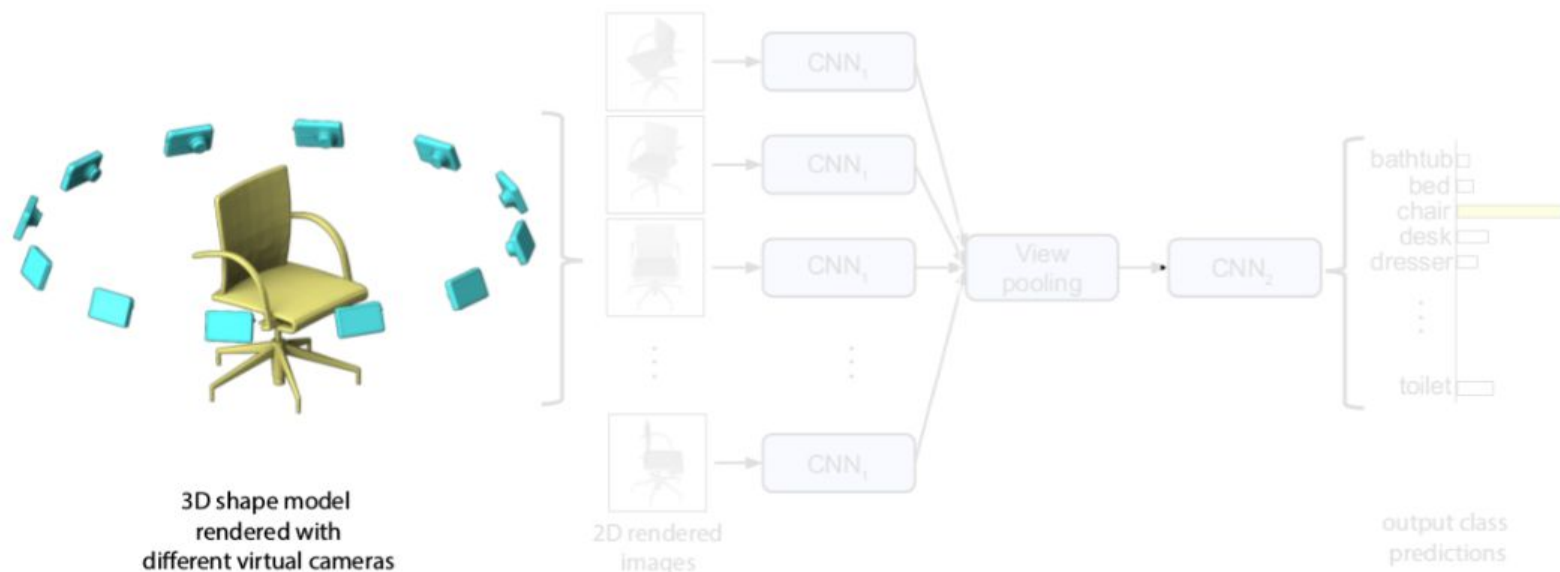
**Volumetric:**  
Voxels



**Pointcloud:**  
Set of points



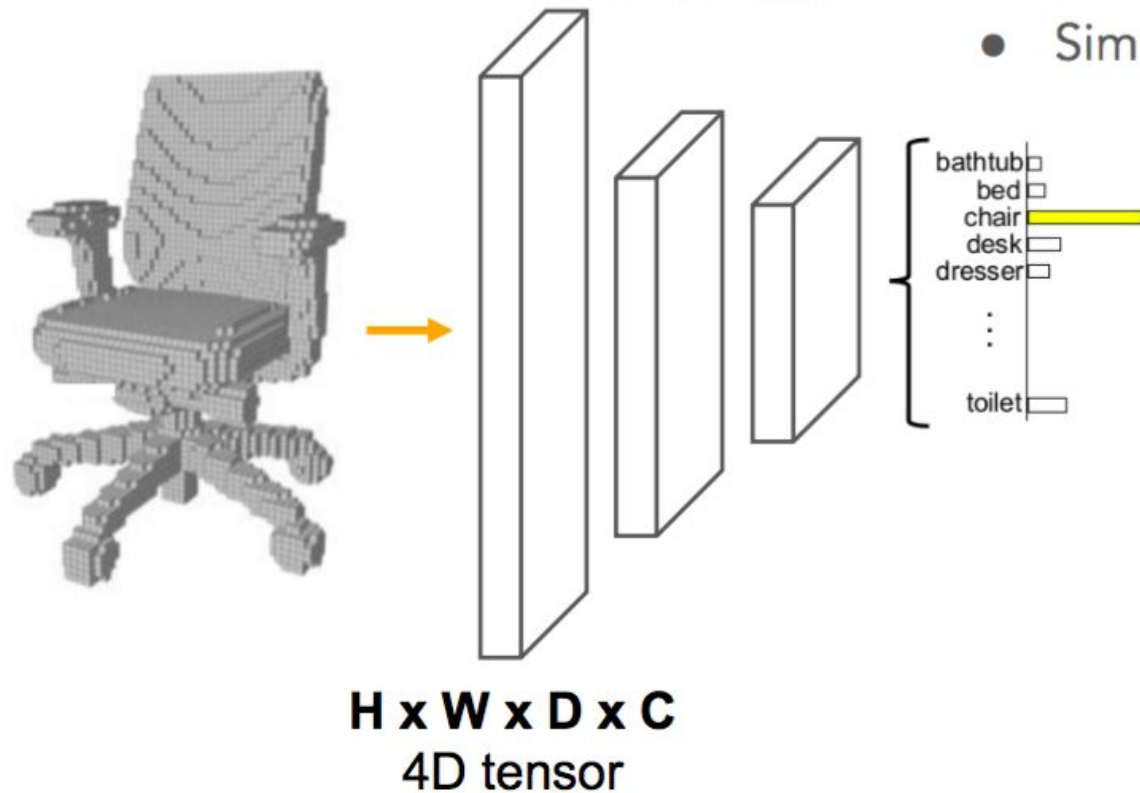
# Multiview



“Multi-view Convolutional Neural Networks for 3D Shape Recognition”  
[Su, Maji, Kalogerakis, Learned-Miller, ICCV 2015]

# Voxels

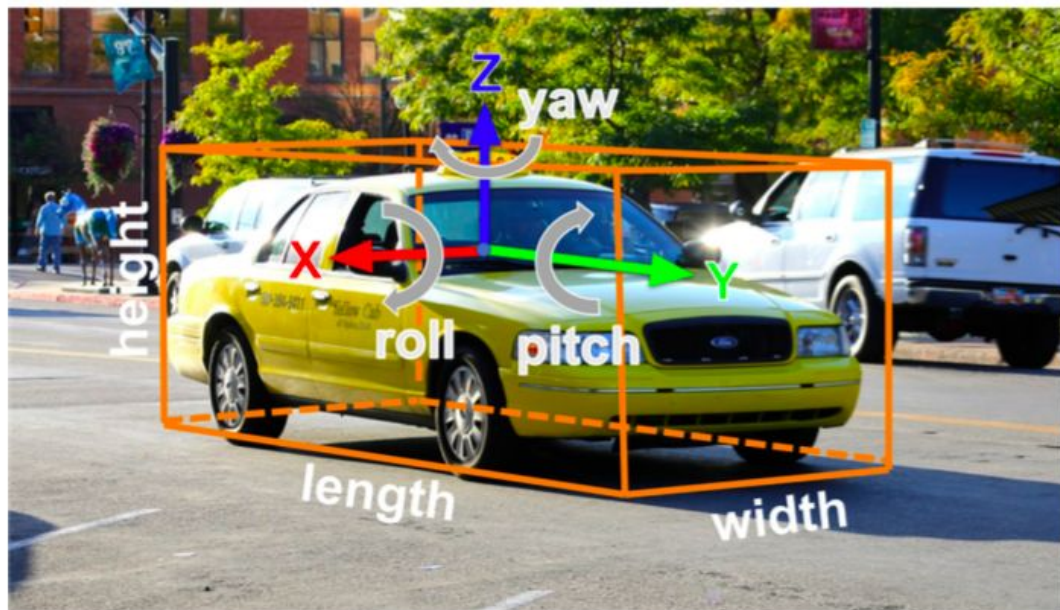
Convolve as before!



- Simple extension of pixel



# 3D Object Detection



2D Object Detection:

2D bounding box

$(x, y, w, h)$

3D Object Detection:

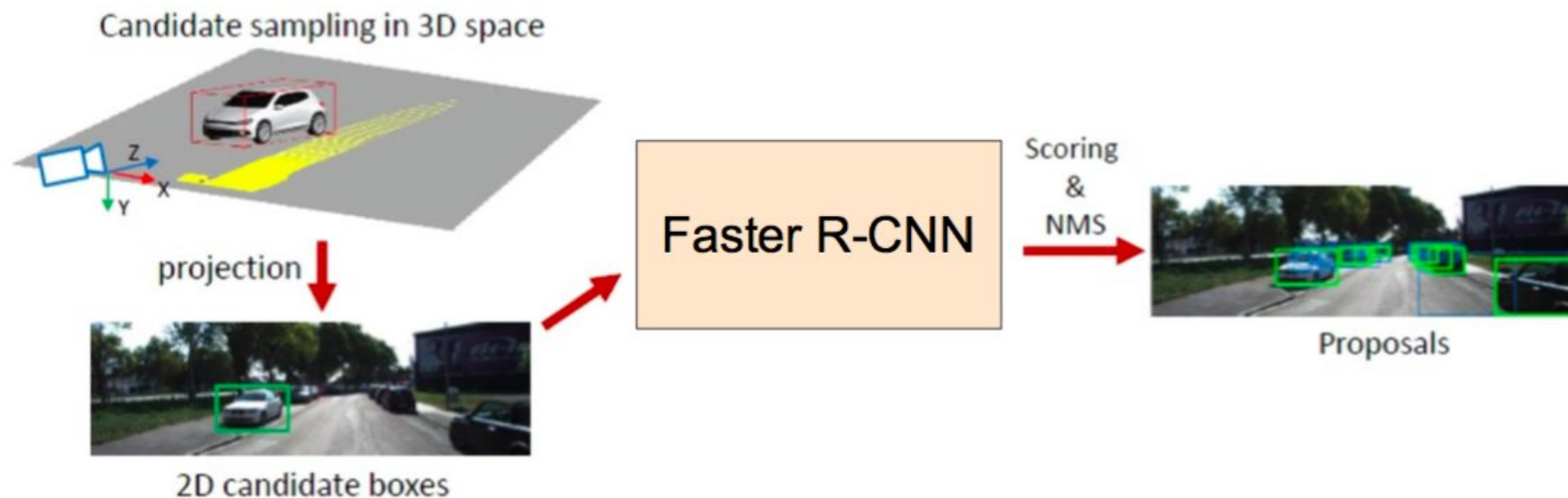
3D oriented bounding box

$(x, y, z, w, h, l, r, p, y)$

Simplified bbox: no roll & pitch

Much harder problem than 2D object detection!

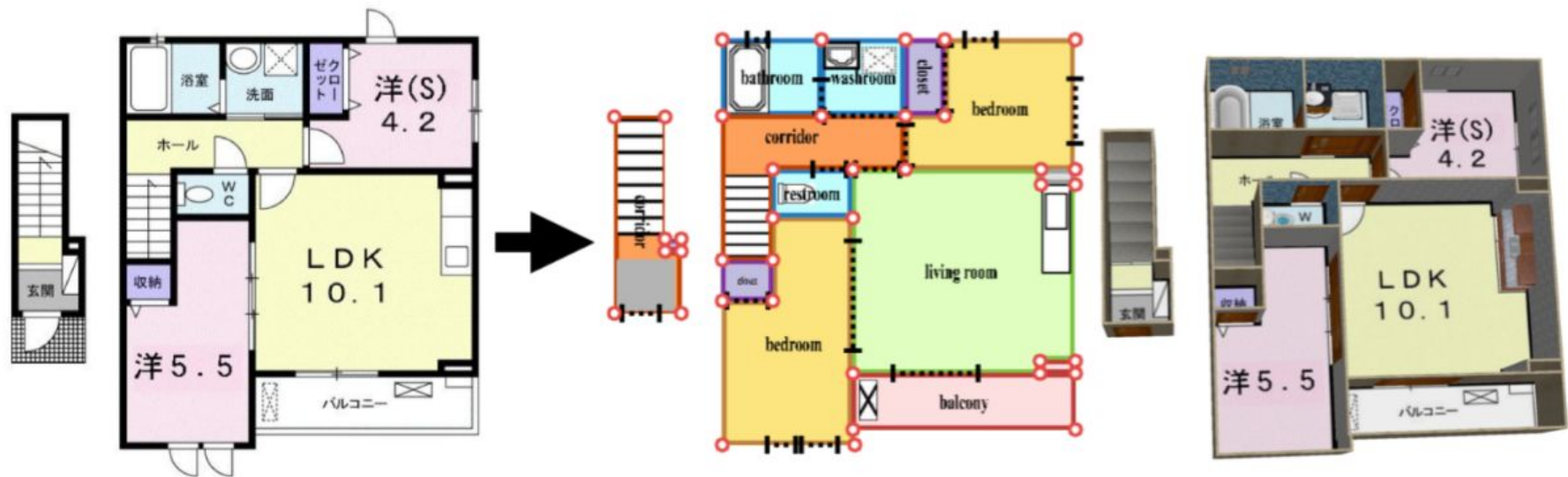
# 3D Object Detection: Monocular Camera



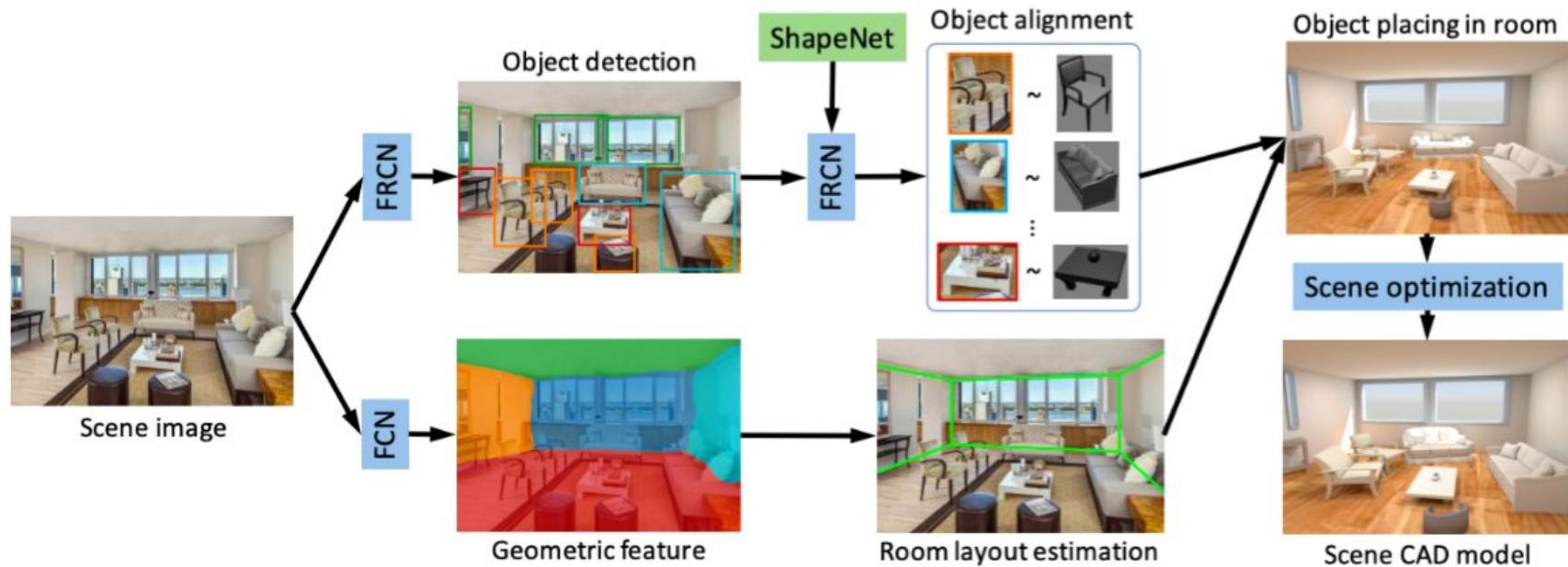
- Same idea as Faster RCNN, but proposals are in 3D
- 3D bounding box proposal, regress 3D box parameters + class score



# 2D floorplan to 3D model



“Raster-to-Vector: Revisiting Floorplan Transformation”  
[Liu, Wu, Kohli, Furukawa, ICCV 2017]



# Can we generate 3D scenes from (almost) scratch?

Empty Room



Select and arrange  
3D models



Nicely arranged  
Living Room



3D model database

