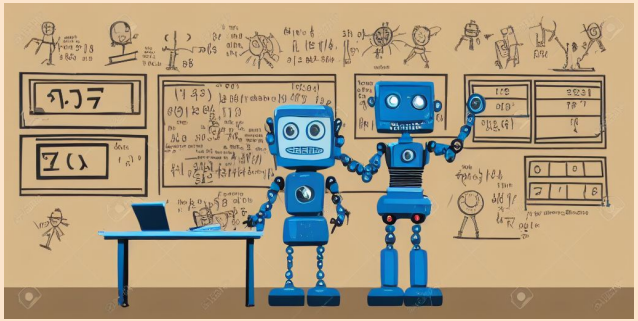


# Advanced Workshop on Machine Learning

## Lecture 2: Convolutional Neural Network



(Image by a Stable Diffusion model)

# Today’s Agenda

Part 1

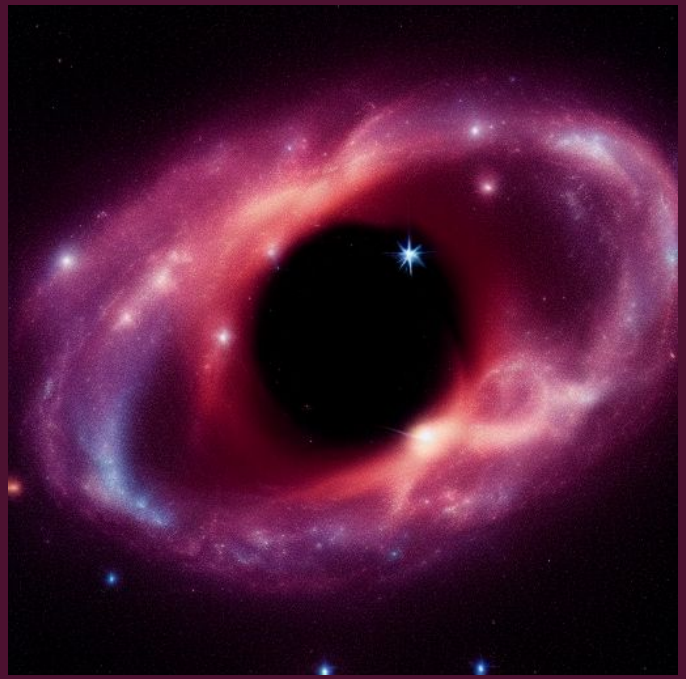
1. Convolutional Layer
2. Pooling Layer
3. Edge Detection

Part 2

1. ImageNet Models
2. COCO Models
3. Transfer Learning
4. Inference as an API

# Part 1

## Convolutions



(Image by a Stable Diffusion model)

# Image Classification Task


Model Input

| Class | Probability |
|---|---|
| Vehicle | 100% |
| Banana | 0% |
| Sheep | 0% |

Model Output

# Fully Connected Layer for Image Classification?

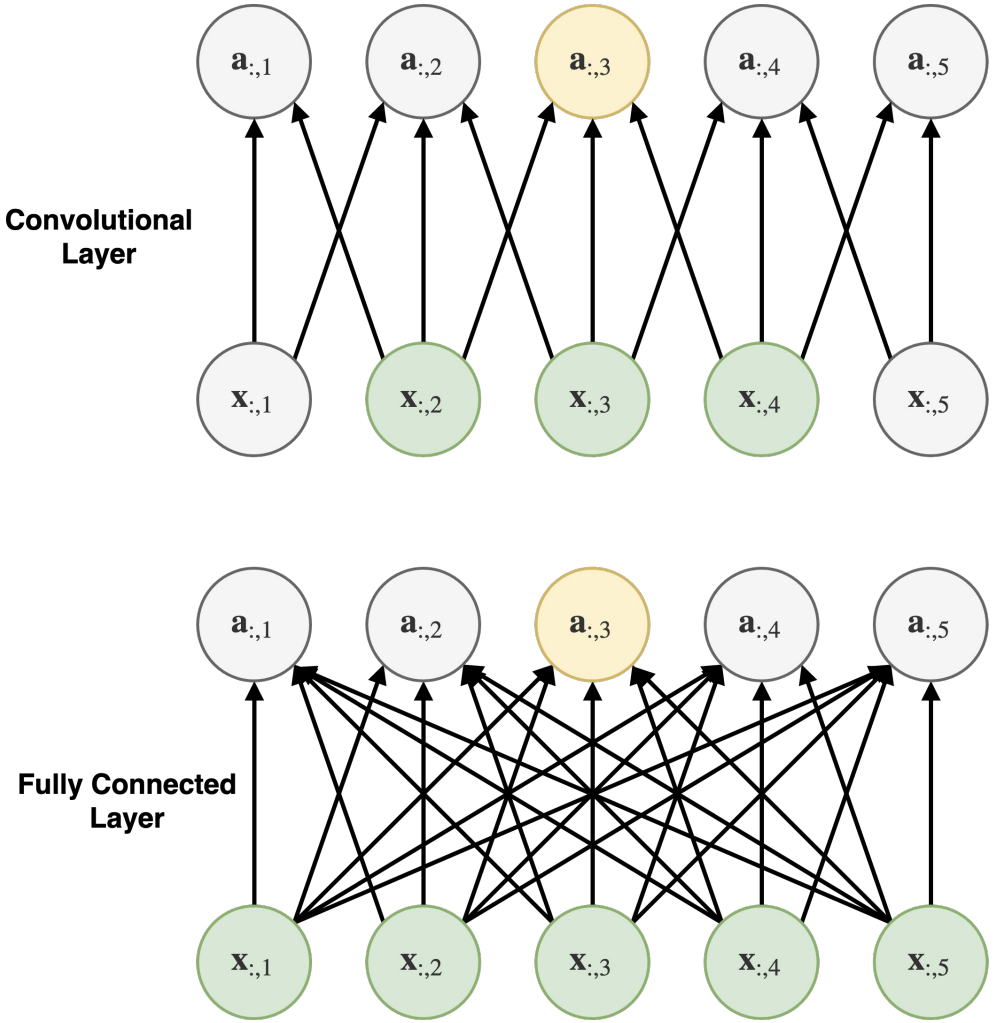
**#1: Patch Independence**
Detecting an object in one region of the image does not require any perception of other regions.

**#2: Parameter Duplication**
Detecting an object in one region of the image is the same task as in any other region.

# Sparse Connectivity

**#1: Patch Independence**
Detecting an object in one region of the image does not require any perception of other regions.

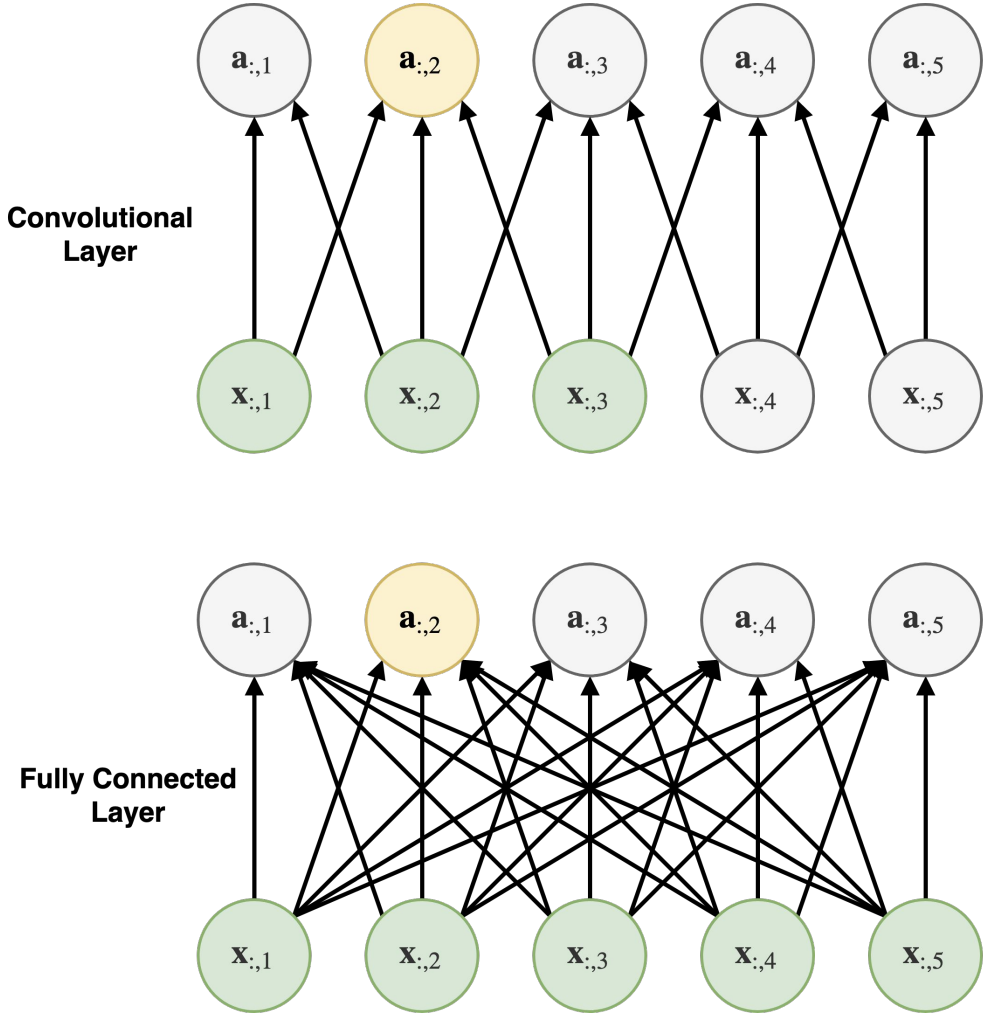
**Solution**
Connect each neuron only with a subset of the input.



# Sparse Connectivity

**#1: Patch Independence**
Detecting an object in one region of the image does not require any perception of other regions.

**Solution**
Connect each neuron only with a subset of the input.



# Sparse Connectivity

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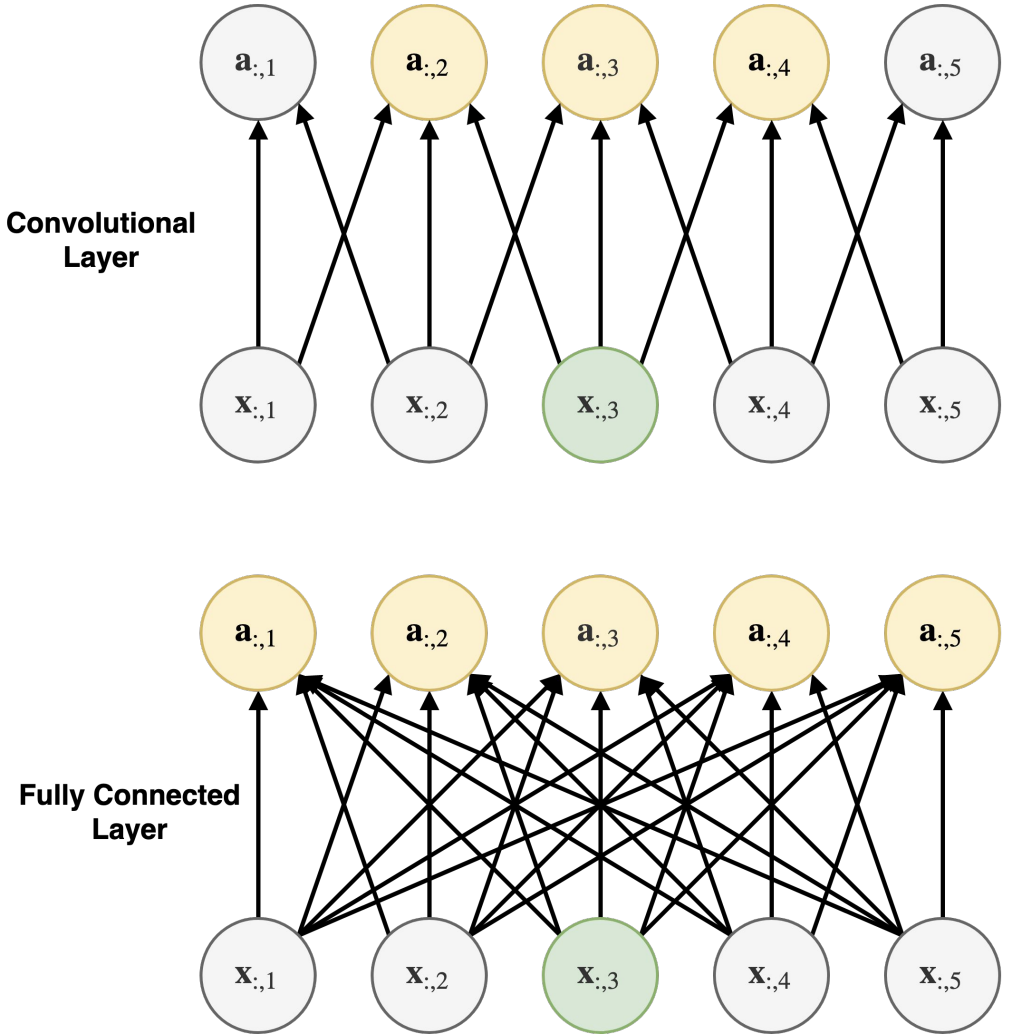

# Sparse Connectivity

**#1: Patch Independence**
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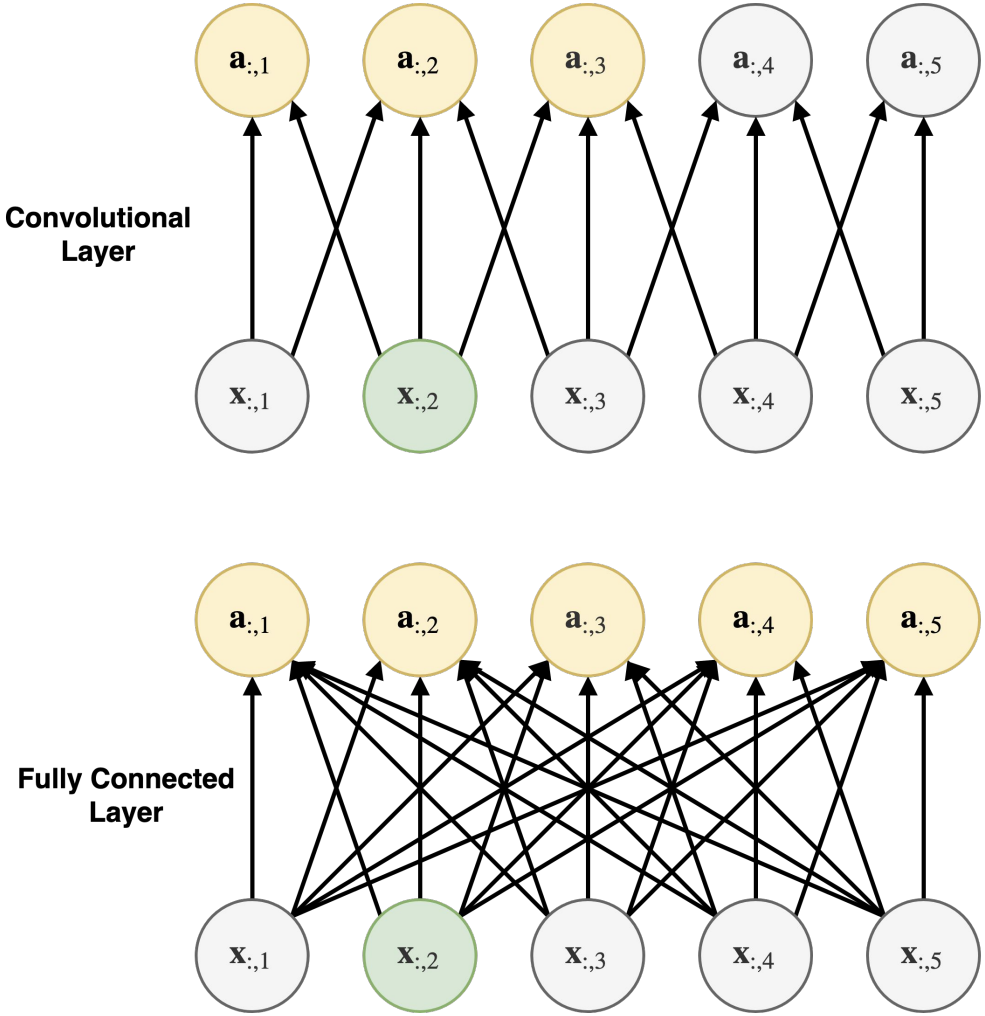
**Solution**
Connect each neuron only with a subset of the input.

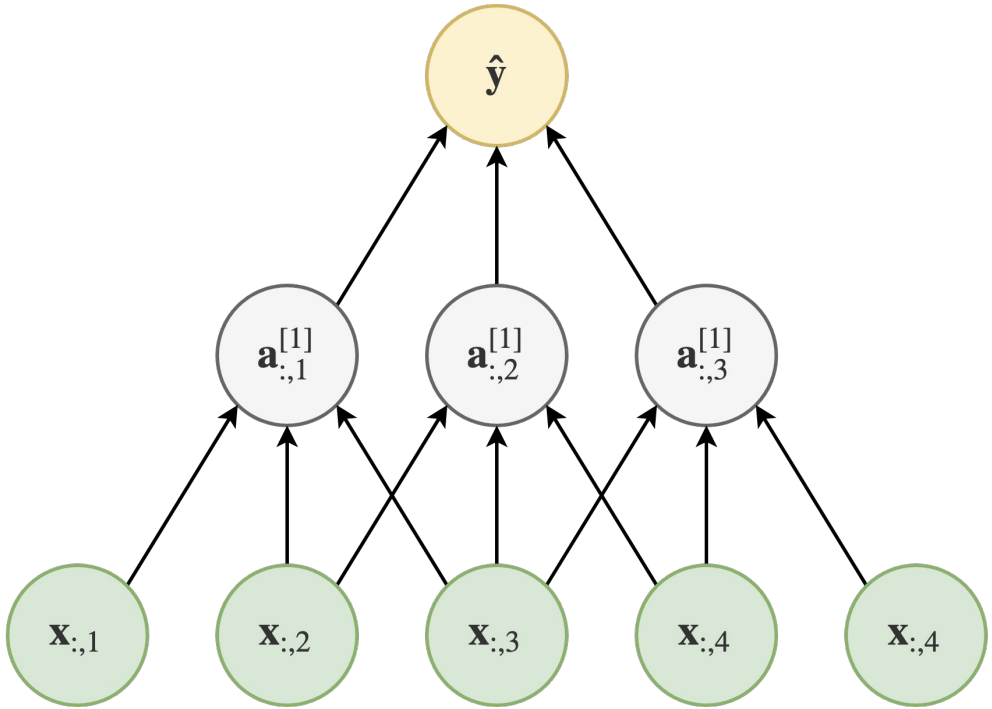


# Indirect Receptive Field

**Question**
Can a network with sparse weights see large objects?

**Answer**
Indirect receptive field is exponentially increasing with layer depth.

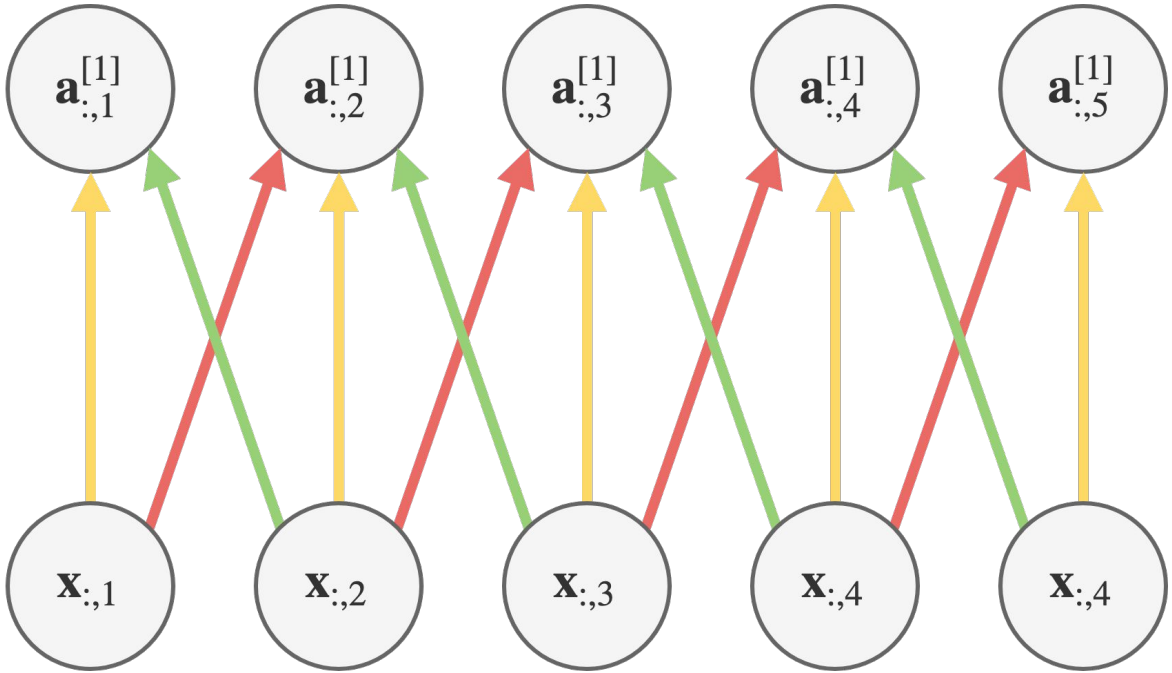
Deep enough networks have output layer connected to every unit of the input layer.



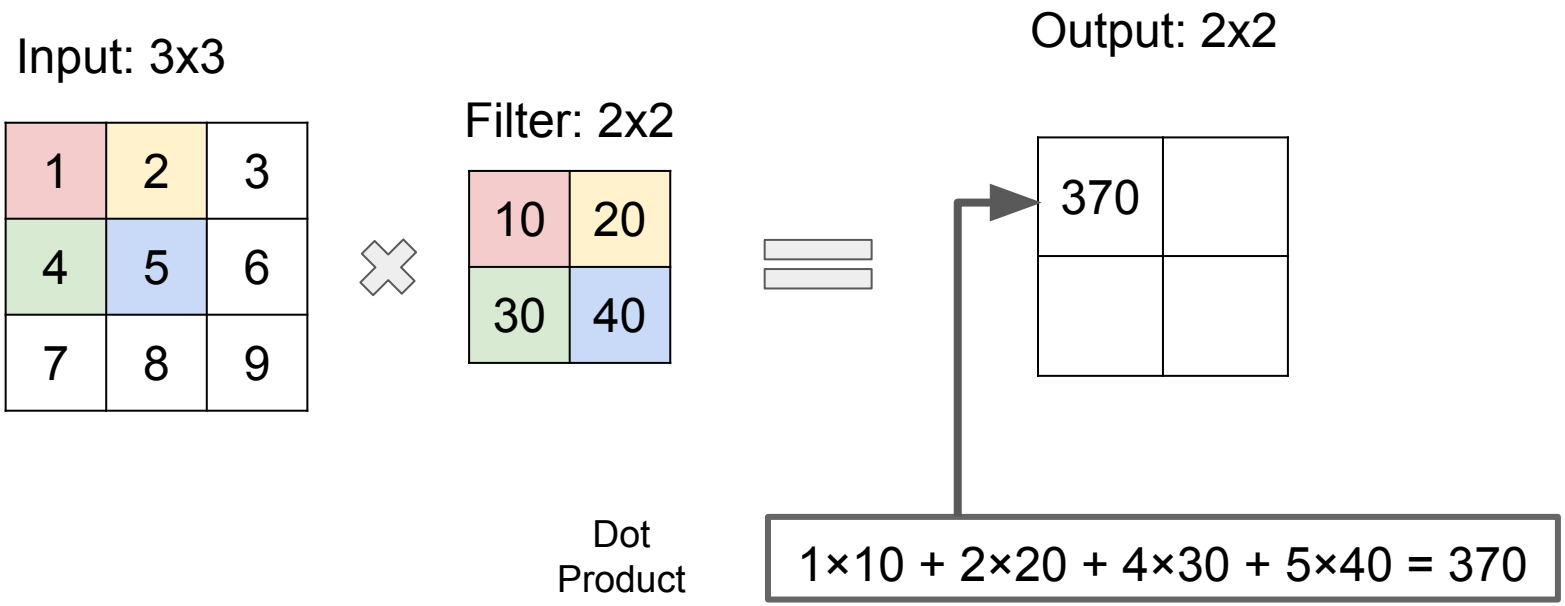
# Parameter Sharing

**#2: Parameter Duplication**
Detecting an object in one region of the image is the same task as in any other region.

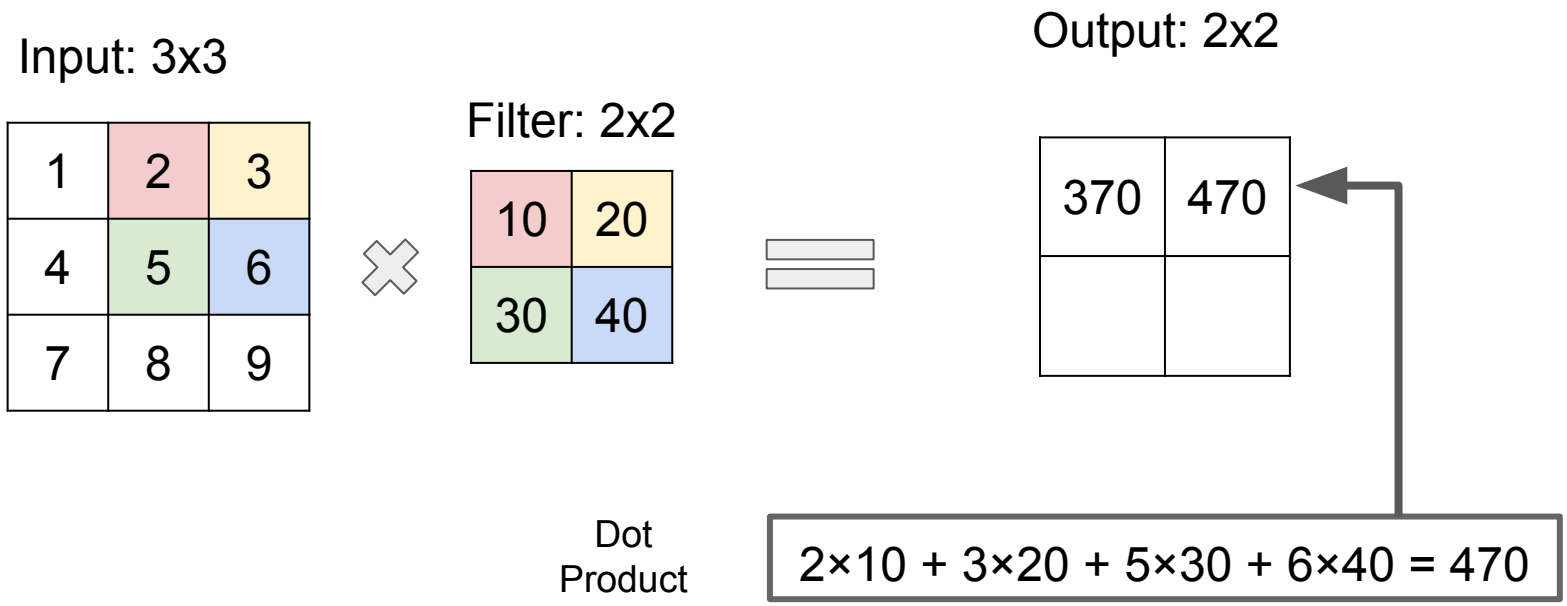
**Solution**
Parameters are shared within layer.
Equivariance to linear translation of input.



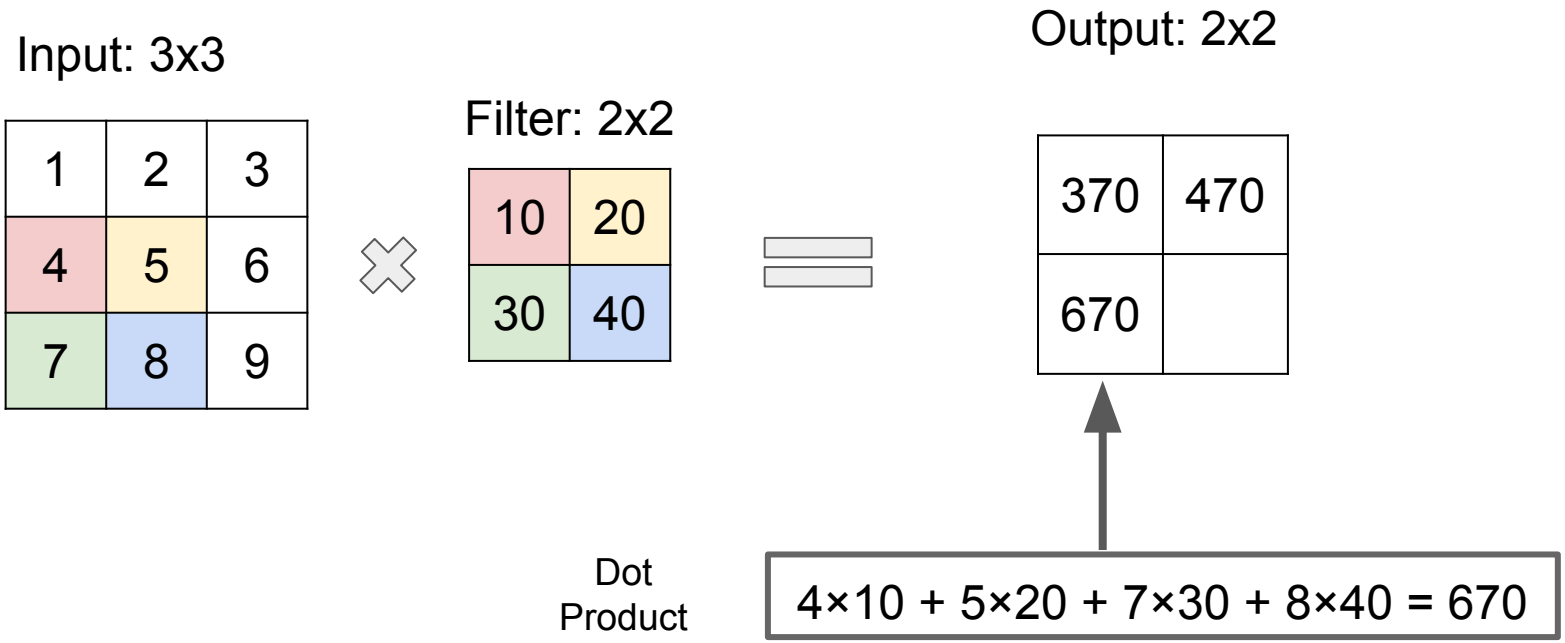
# Convolution



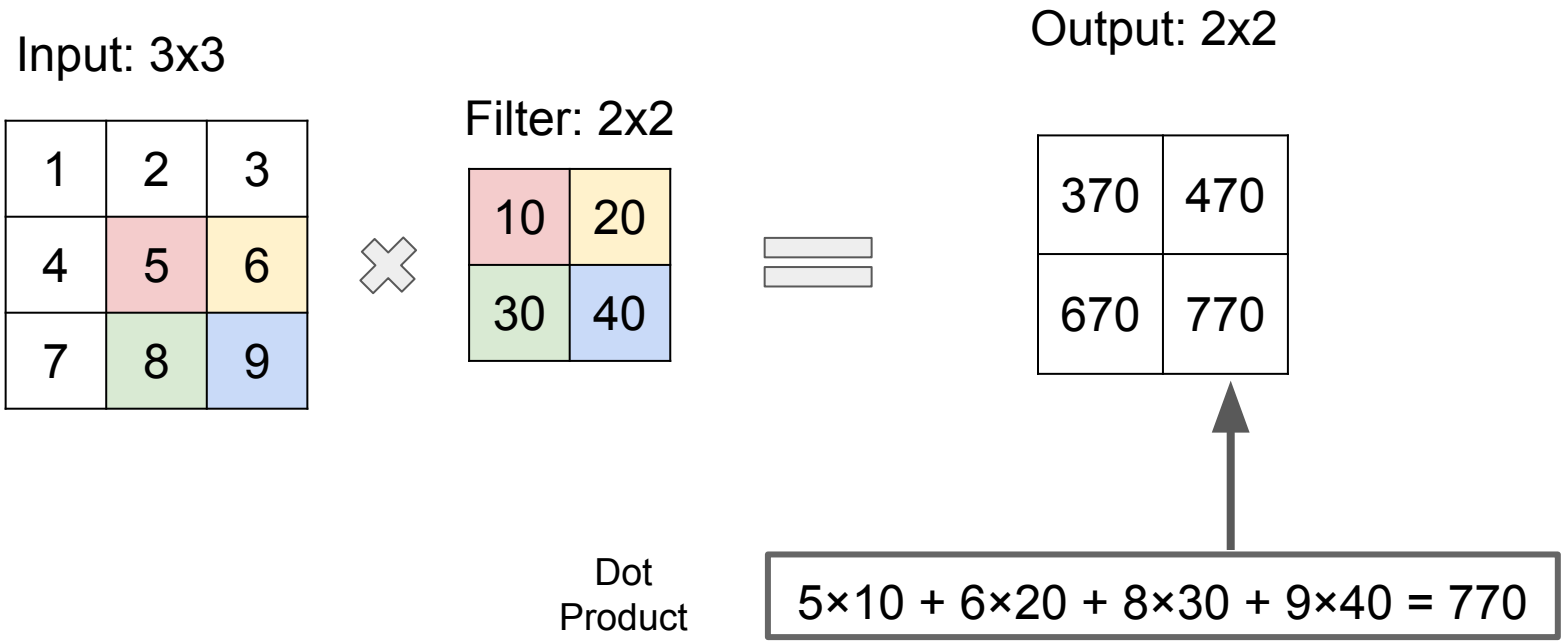
# Convolution



# Convolution



# Convolution



# Convolution

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter: 2x2

| | |
|---|---|
| 10 | 20 |
| 30 | 40 |

Output: 3x3

| | | |
|---|---|---|
| 370 | 470 | 210 |
| 670 | 770 | |
| | | |

Dot Product

3×10 + 0×20 + 6×30 + 0×40 = 210

# Convolution

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter: 2x2

| | |
|---|---|
| 10 | 20 |
| 30 | 40 |

Output: 3x3

| | | |
|---|---|---|
| 370 | 470 | 210 |
| 670 | 770 | 330 |
| | | |

Dot Product

$6 \times 10 + 0 \times 20 + 9 \times 30 + 0 \times 40 = 330$

# Convolution

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter: 2x2

| | |
|---|---|
| 10 | 20 |
| 30 | 40 |

Output: 3x3

| | | |
|---|---|---|
| 370 | 470 | 210 |
| 670 | 770 | 330 |
| | | 90 |

Dot Product

$9 \times 10 + 0 \times 20 + 0 \times 30 + 0 \times 40 = 90$

# Convolution

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter: 2x2

| | |
|---|---|
| 10 | 20 |
| 30 | 40 |

Stride: 2x2

Output: 2x2

| | |
|---|---|
| 370 | |
| | |

Dot Product

1×10 + 2×20 + 4×30 + 5×40 = 370

# Convolution

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter: 2x2

| | |
|---|---|
| 10 | 20 |
| 30 | 40 |

Stride: 2x2

Output: 2x2

| | |
|---|---|
| 370 | 210 |
| | |

Dot Product

3×10 + 0×20 + 6×30 + 0×40 = 210

# Convolution

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter: 2x2

| | |
|---|---|
| 10 | 20 |
| 30 | 40 |

Stride: 2x2

Output: 2x2

| | |
|---|---|
| 370 | 210 |
| | 90 |

Dot Product

9×10 + 0×20 + 0×30 + 0×40 = 90

# Convolution

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter: 2x2

| | |
|---|---|
| 10 | 20 |
| 30 | 40 |

Stride: 2x2

Output: 2x2

| | |
|---|---|
| 370 | 210 |
| 230 | 90 |

Dot Product

7×10 + 8×20 + 0×30 + 0×40 = 230

# Convolution (No depth)

$$\text{Convolution}\left(n_h^{[l-1]} \times n_w^{[l-1]}, f^{[l]} \times f^{[l]}\right) \rightarrow n_h^{[l]} \times n_w^{[l]}$$

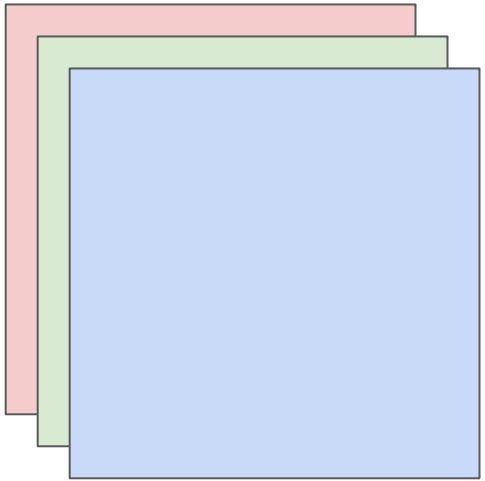
$$n_h^{[l]} = \left\lfloor \frac{n_h^{[l-1]} + p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

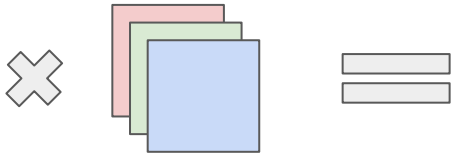
$$n_w^{[l]} = \left\lfloor \frac{n_w^{[l-1]} + p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

See ConvolutionalLayer.ipynb for details and Tensorflow implementation.

# Convolution (Depth: Many in, 1 out)

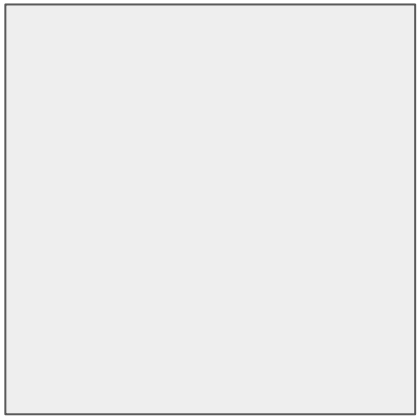
$n_h^{[l-1]} \times n_w^{[l-1]} \times n_c^{[l-1]}$





$f^{[l]} \times f^{[l]} \times n_c^{[l-1]}$

$n_h^{[l]} \times n_w^{[l]}$



# Convolution (Depth: Many in, 1 out)

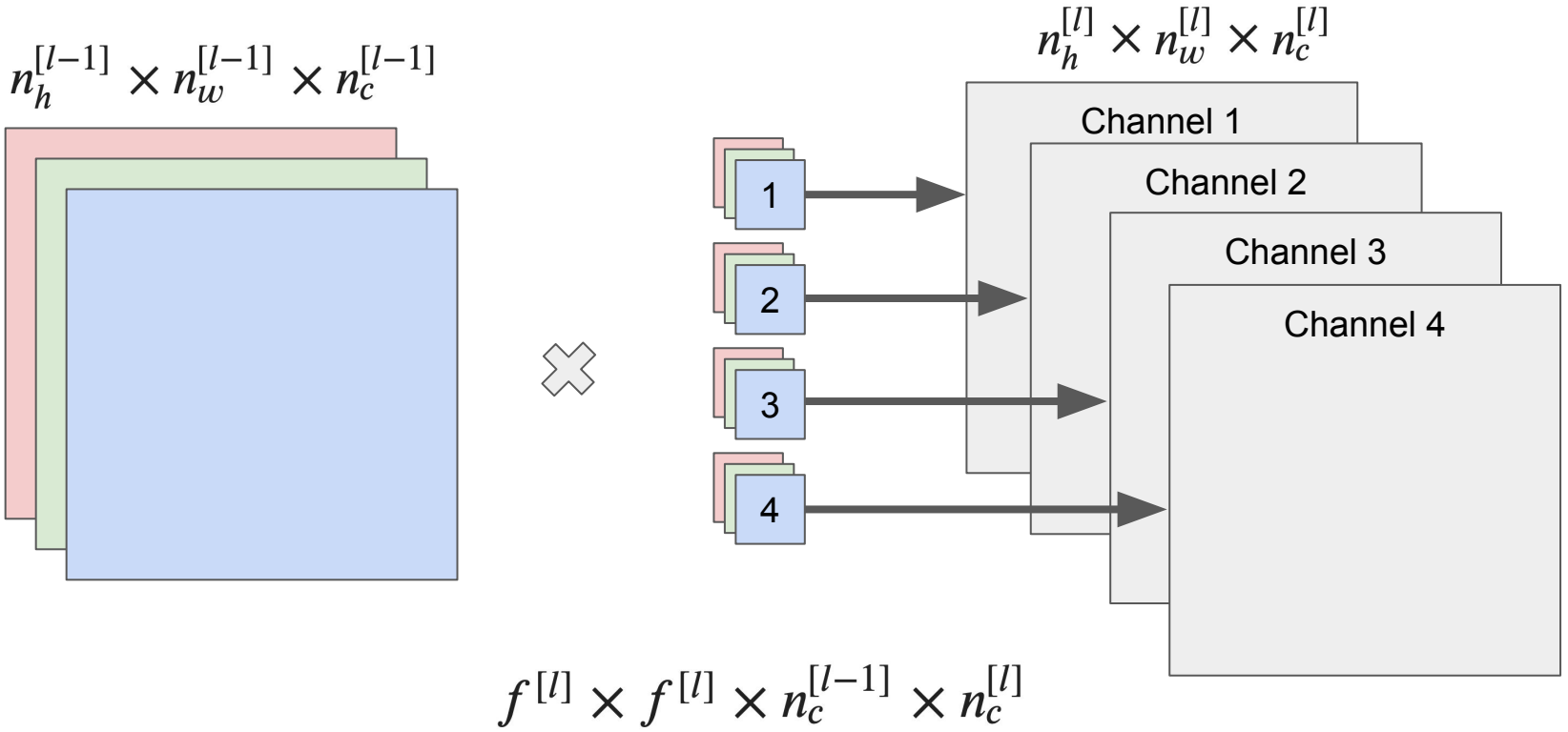
$$\text{Convolution}\left(n_h^{[l-1]} \times n_w^{[l-1]} \times n_c^{[l-1]}, f^{[l]} \times f^{[l]} \times n_c^{[l-1]}\right) \rightarrow n_h^{[l]} \times n_w^{[l]}$$

$$n_h^{[l]} = \left\lfloor \frac{n_h^{[l-1]} + p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

$$n_w^{[l]} = \left\lfloor \frac{n_w^{[l-1]} + p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

See ConvolutionalLayer.ipynb for details and Tensorflow implementation.

# Convolution (Depth: Many in, many out)



# Convolution (Depth: Many in, many out)

$$\text{Convolution}\left(n_h^{[l-1]} \times n_w^{[l-1]} \times n_c^{[l-1]}, f^{[l]} \times f^{[l]} \times n_c^{[l-1]} \times n_c^{[l]}\right) \rightarrow n_h^{[l]} \times n_w^{[l]} \times n_c^{[l]}$$

$$n_h^{[l]} = \left\lfloor \frac{n_h^{[l-1]} + p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

$$n_w^{[l]} = \left\lfloor \frac{n_w^{[l-1]} + p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

See ConvolutionalLayer.ipynb for details and Tensorflow implementation.

# Hierarchy of Visual Information

1. Pixels (RGB)
2. Edges
3. Curves
4. Shapes: circles, boxes, triangles, ...
5. Textures: checkers, gradient, monotonic, ...
6. Parts: wheels, road, windows, ...
7. Objects: cars, cats, dogs, oranges, …
8. Scenes: crowd of people, fruit garden, ...

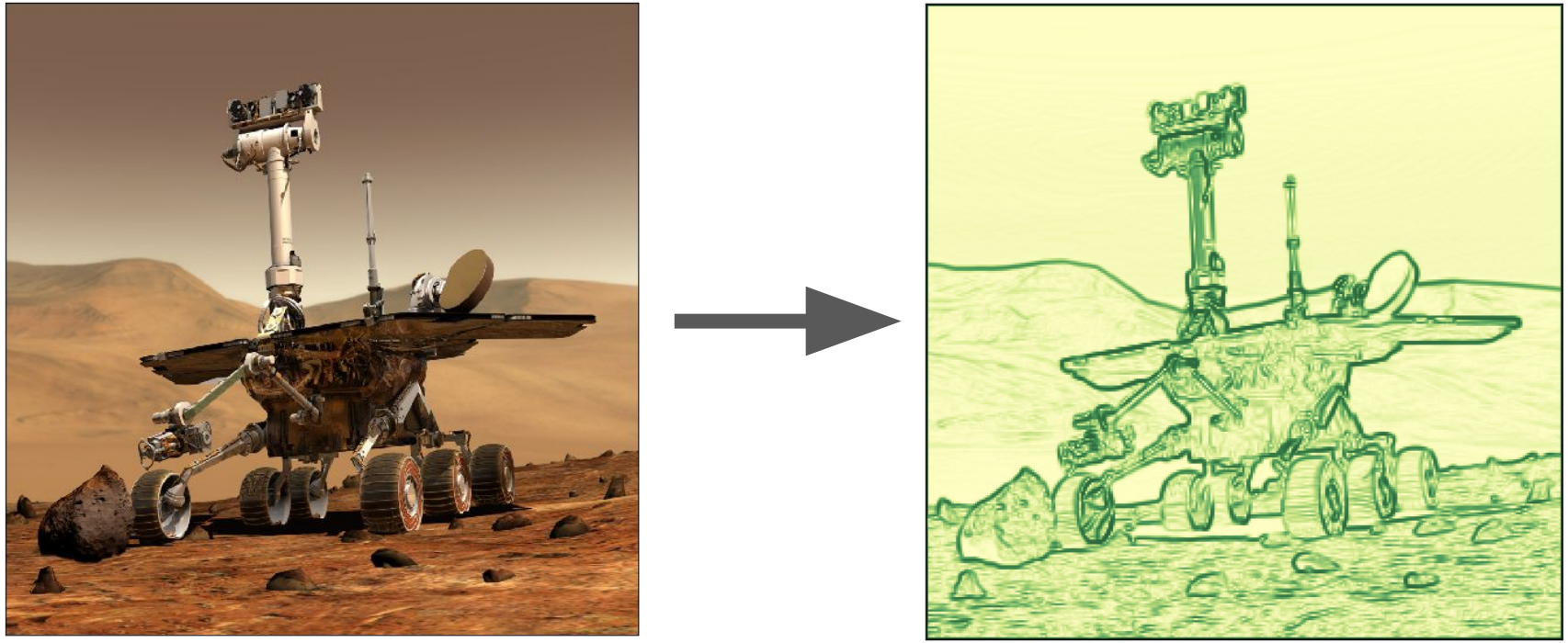
# Case Study: Edge Detection

**Image**
Artistic Rendering of Mars Exploration Rover (Spirit and Opportunity)

**Dimensions**
300 x 300 x 3 channels

**Task**
Detect all edges at various angles: horizontal, vertical, tilted, etc.

# What is edge detection?

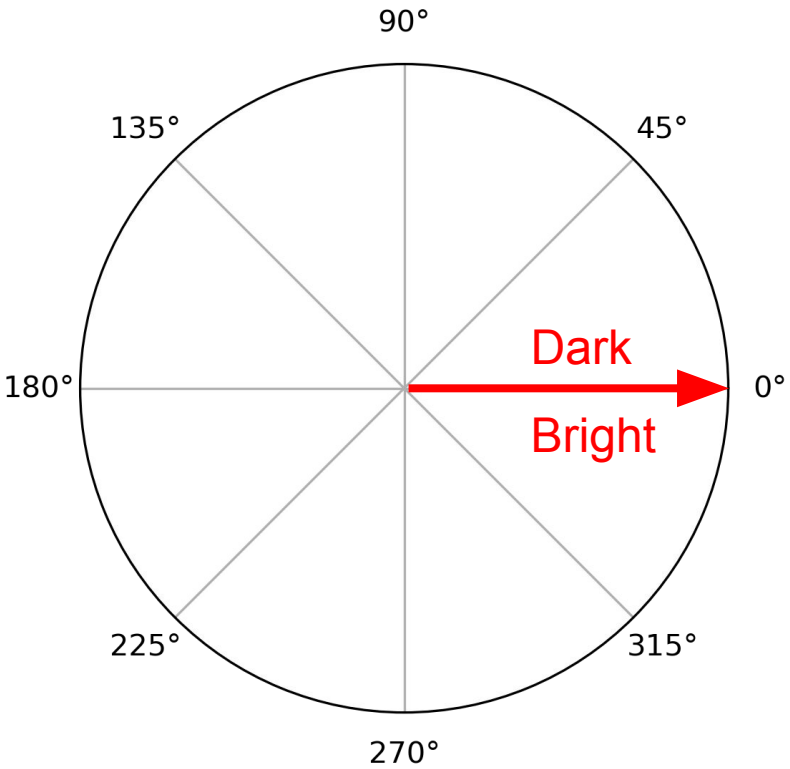


# Edge Detection

Every possible edge from 0 to 360 with 45 degree step.

- Dark side on LHS
- Bright side on RHS

Brightness averaged across RGB channels.



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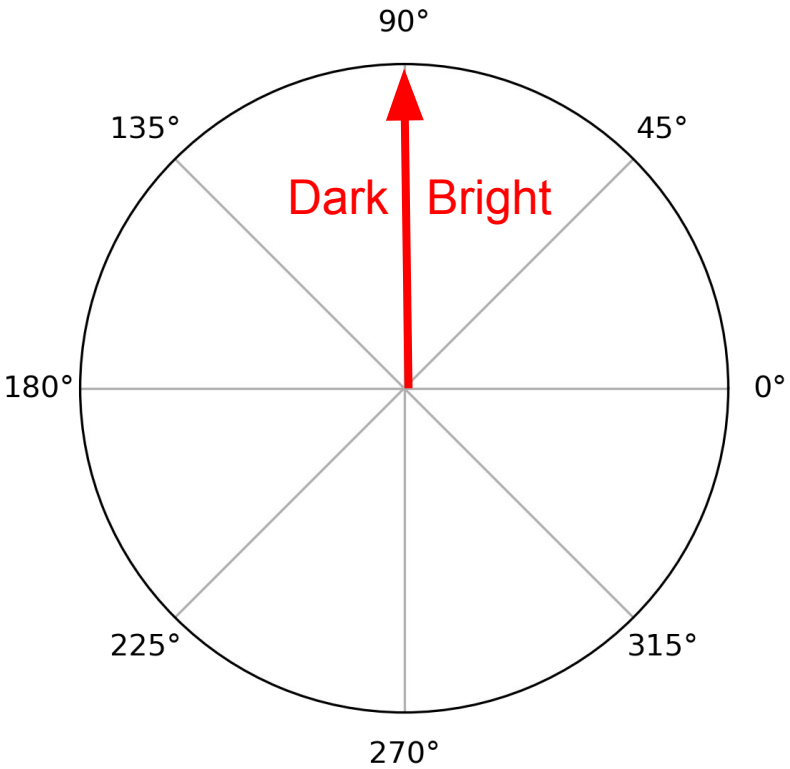

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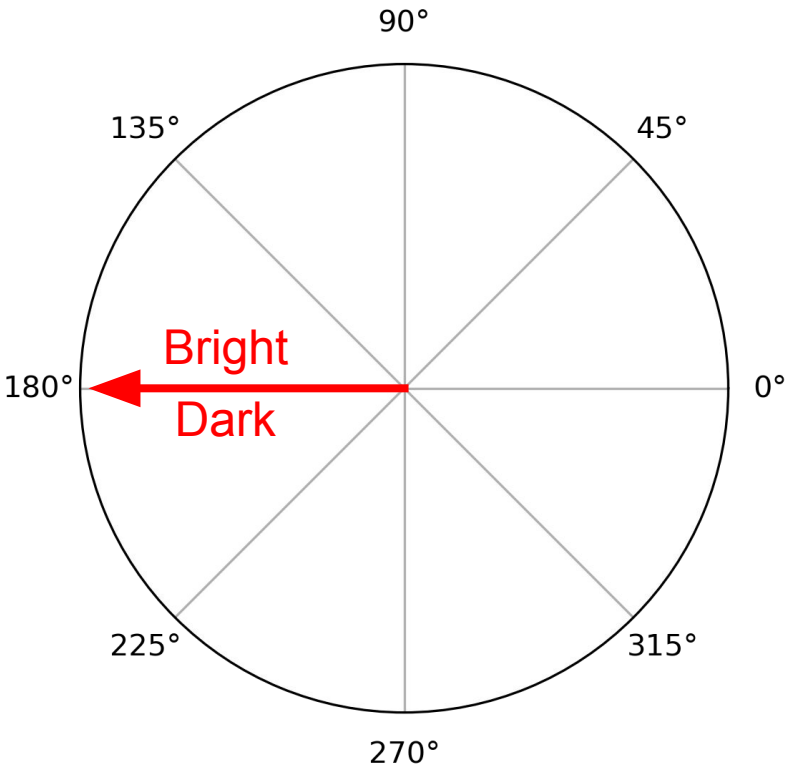
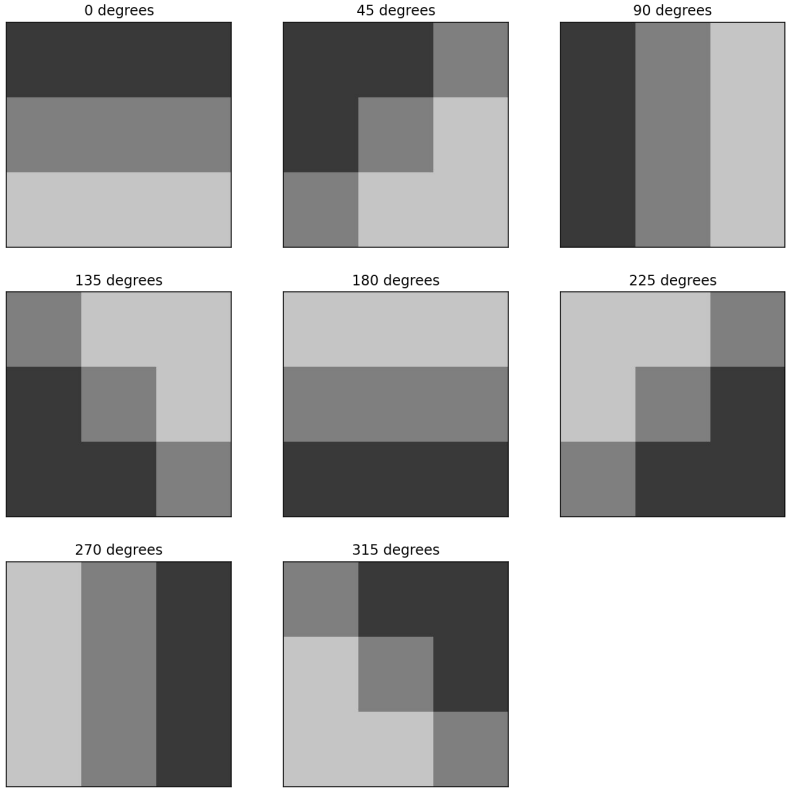
Brightness averaged across RGB channels.

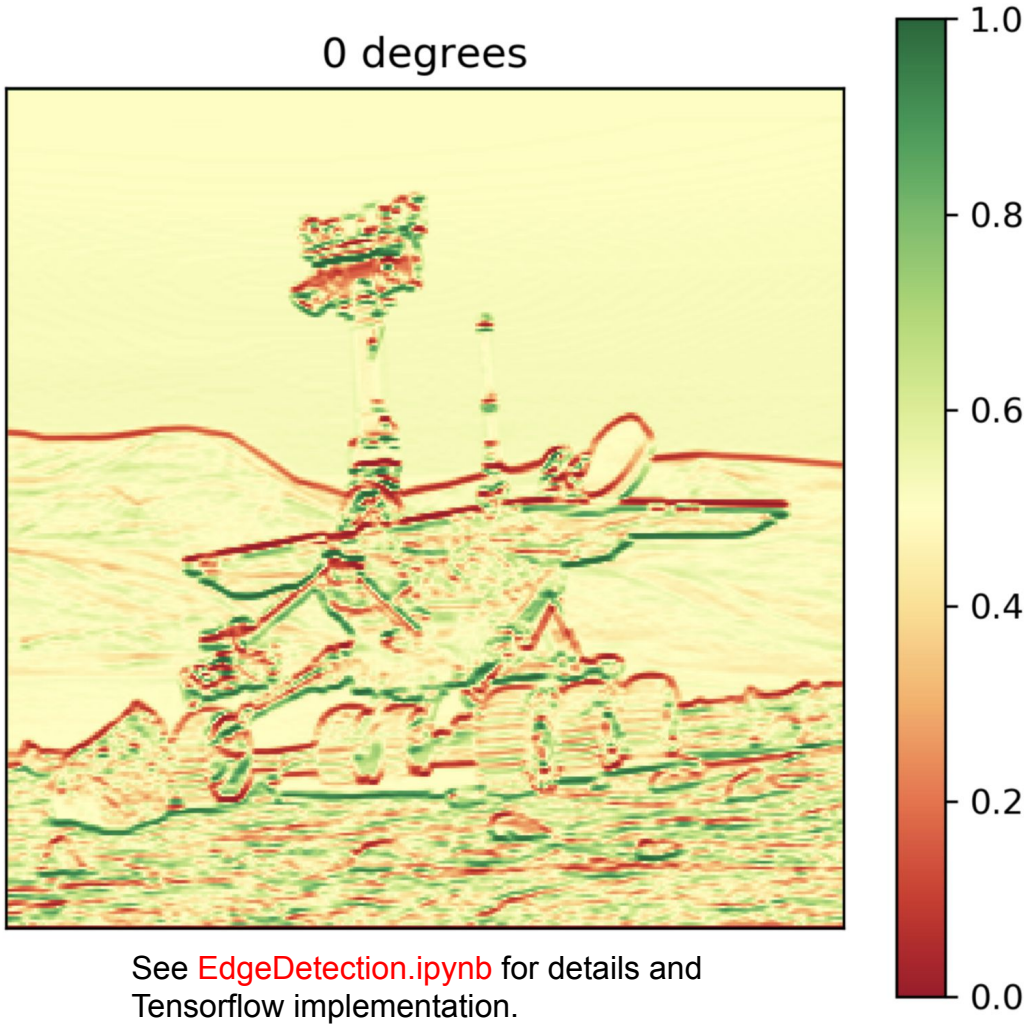


# Filter Visualization

- Manually constructed filters from Edge Detection task.
- 3 x 3 x 3 x 8
- Rescaled to std = 1 and transformed via sigmoid for visualization purposes



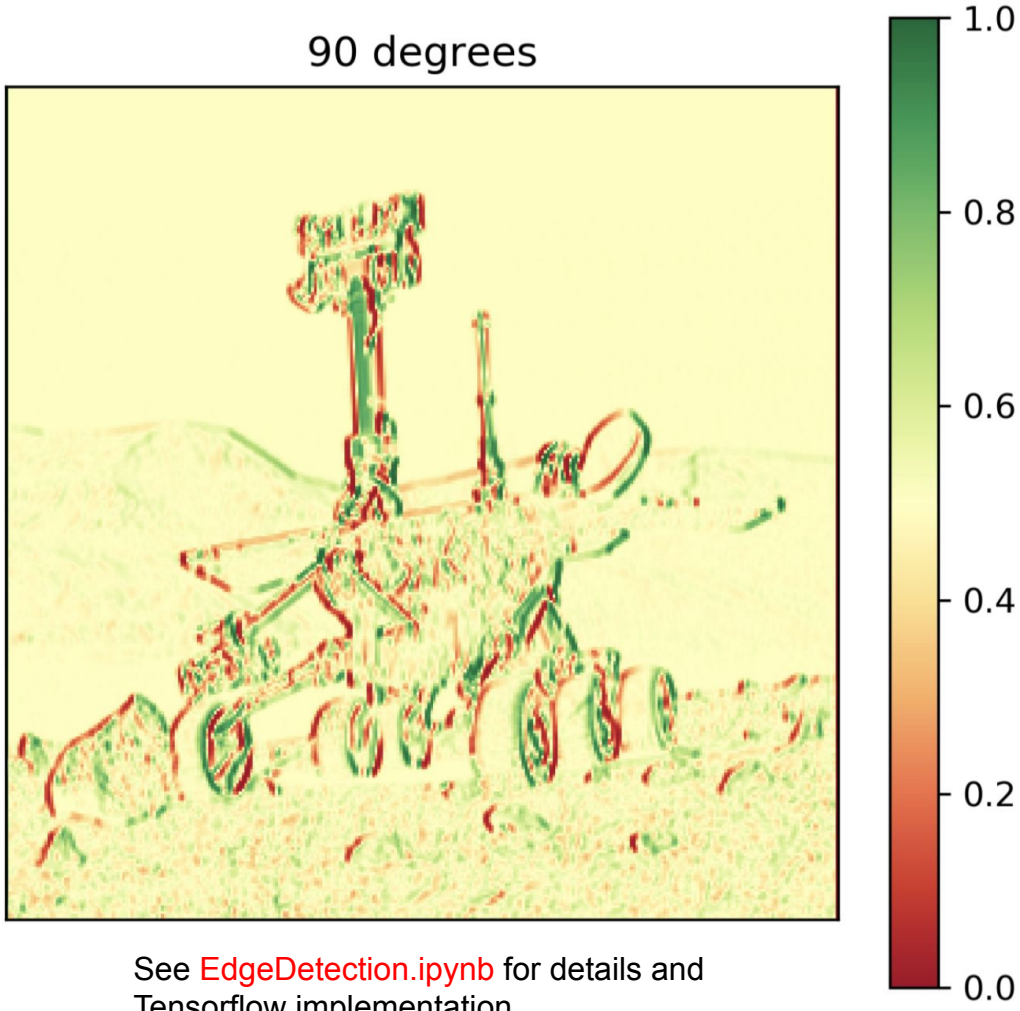

See EdgeDetection.ipynb for details and Tensorflow implementation.




See EdgeDetection.ipynb for details and Tensorflow implementation.

```
'0 degrees': [
    [-1, -1, -1],
    [ 0,  0,  0],
    [ 1,  1,  1]
],
```

- Input = 300 x 300 x 3
- Filter = 3 x 3 x 3 x 1
- Stride = 1
- Padding = same
- Output = 300 x 300 x 1
- Sigmoid activation for visualization purposes

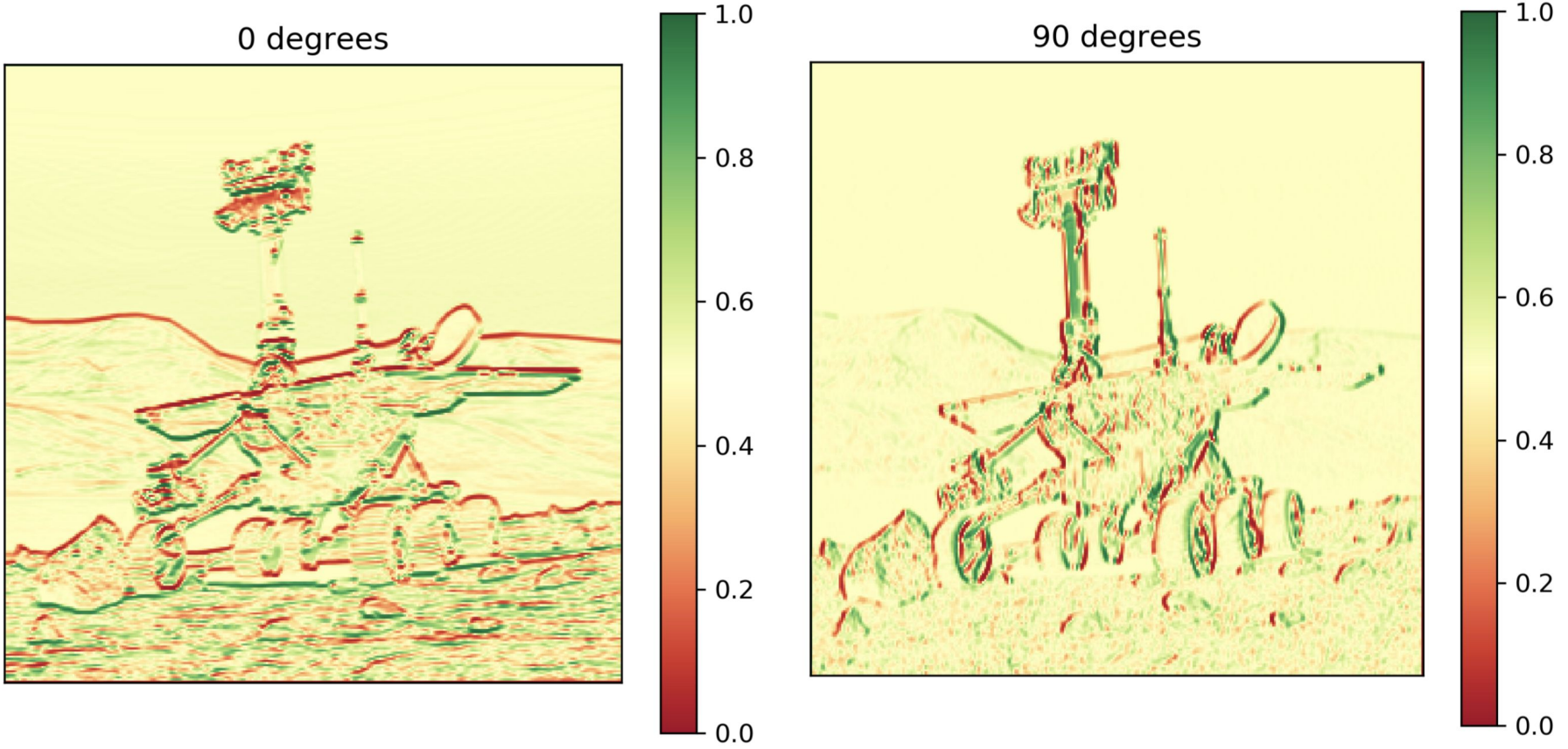



```
'90 degrees': [
    [-1, 0, 1],
    [-1, 0, 1],
    [-1, 0, 1]
],
```

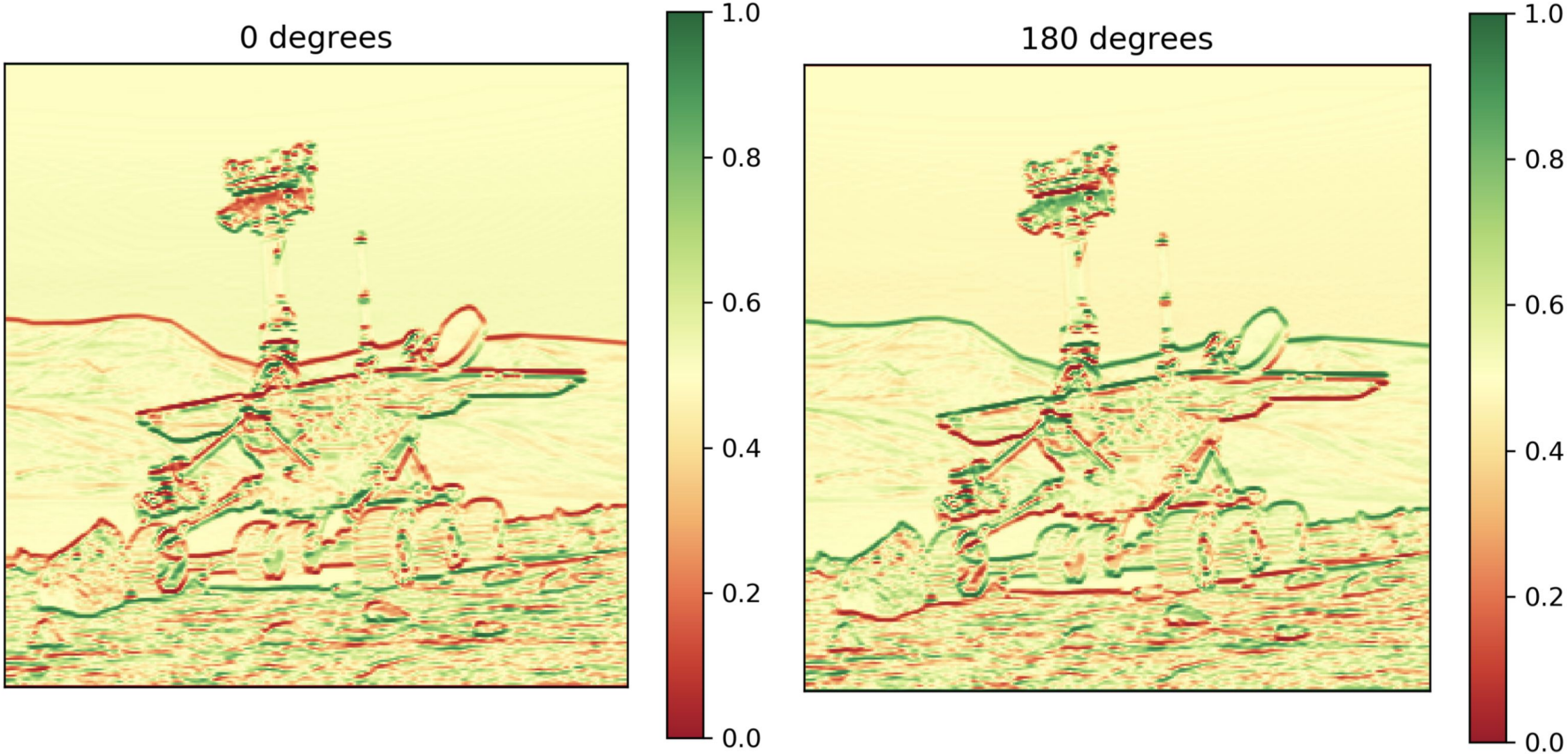
- Input = 300 x 300 x 3
- Filter = 3 x 3 x 3 x 1
- Stride = 1
- Padding = same
- Output = 300 x 300 x 1
- Sigmoid activation for visualization purposes

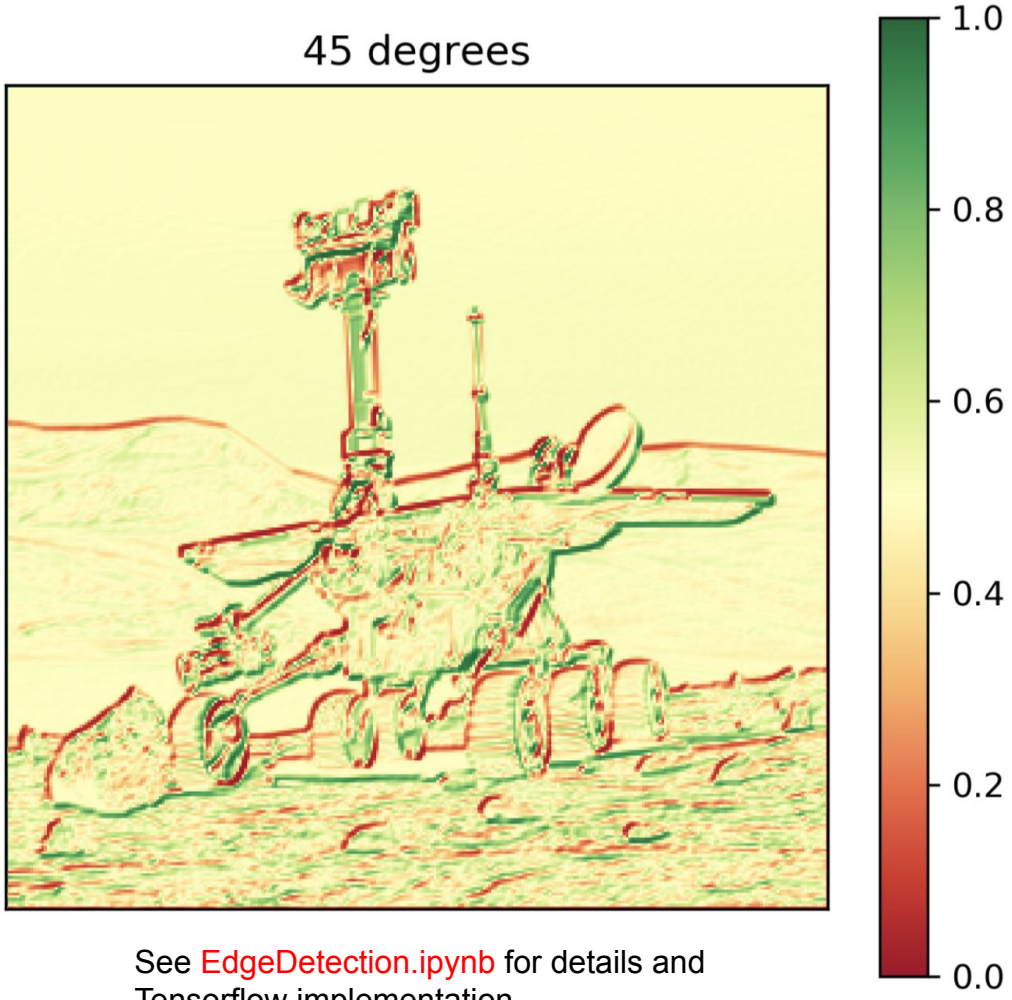
See EdgeDetection.ipynb for details and Tensorflow implementation.

# Comparison of 0- and 90-degree edges



# Comparison of 0- and 180-degree edges

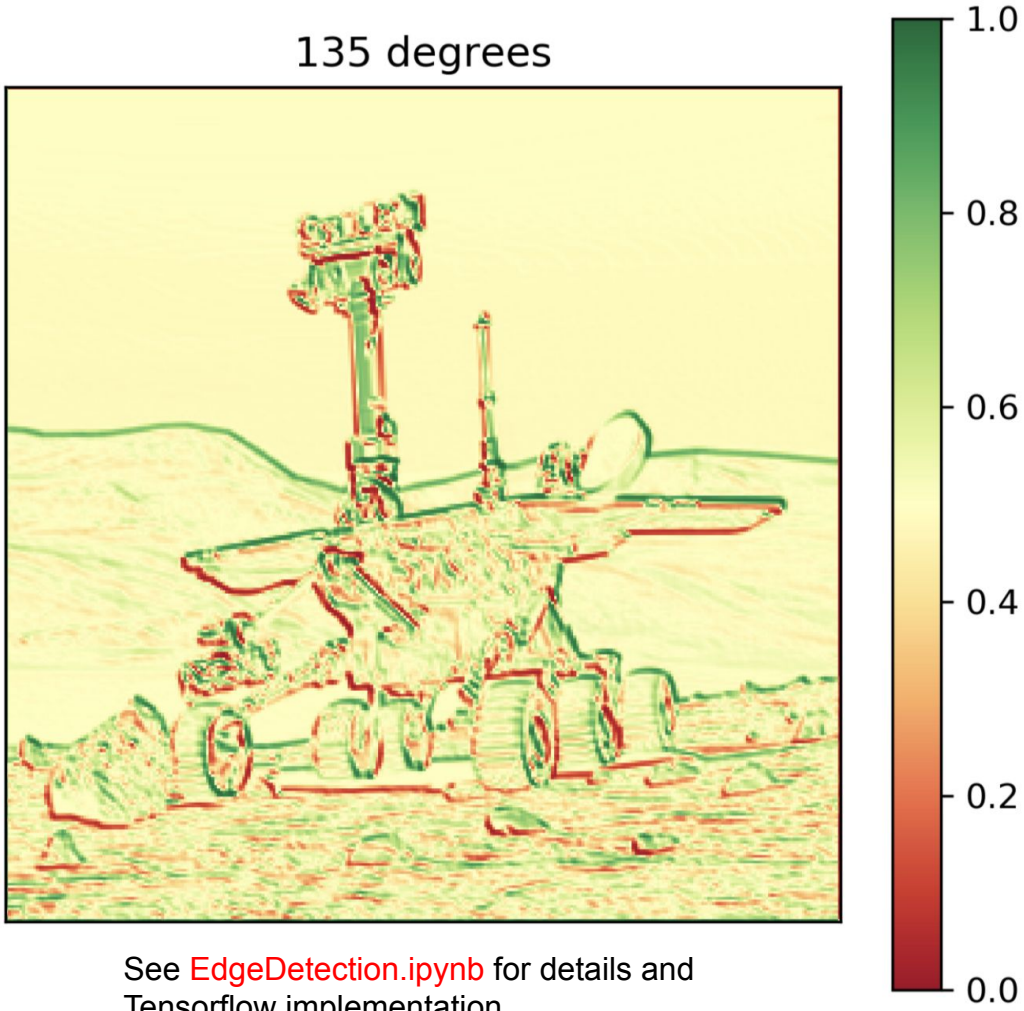





```
'45 degrees': [
    [-1, -1,  0],
    [-1,  0,  1],
    [ 0,  1,  1]
],
```

- Input = 300 x 300 x 3
- Filter = 3 x 3 x 3 x 1
- Stride = 1
- Padding = same
- Output = 300 x 300 x 1
- Sigmoid activation for visualization purposes

See EdgeDetection.ipynb for details and Tensorflow implementation.

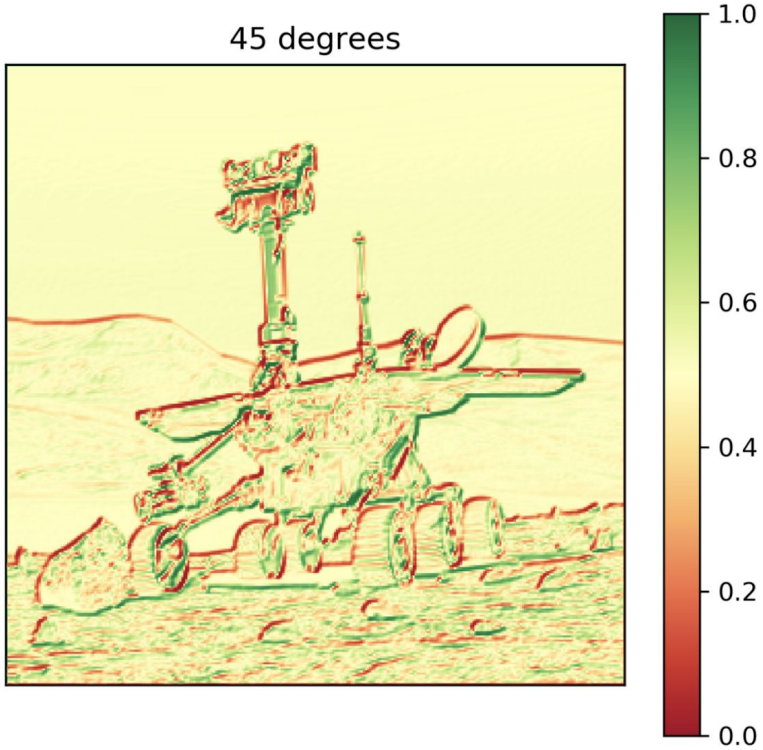


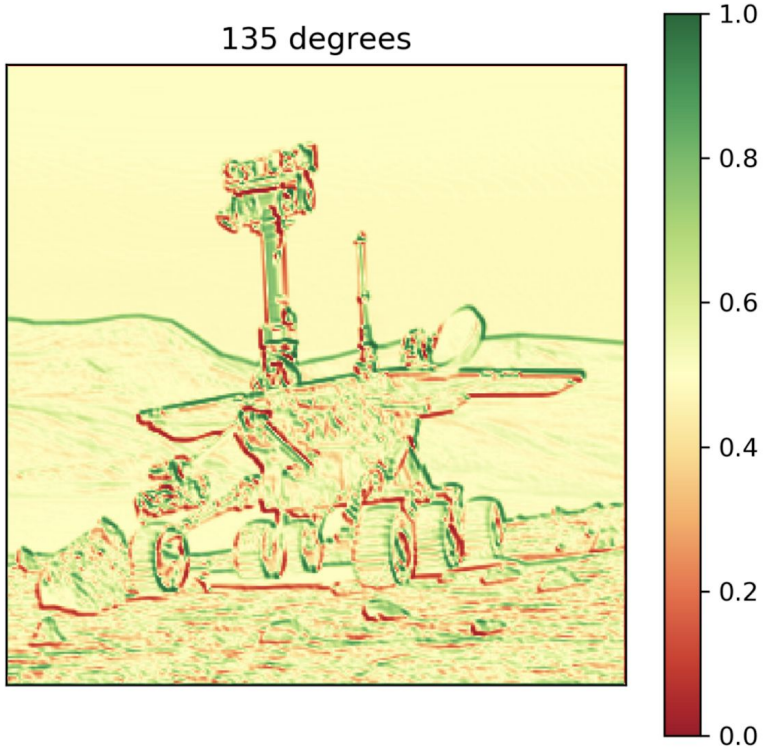

```
'135 degrees': [
    [ 0,  1, 1],
    [-1,  0, 1],
    [-1, -1, 0]
]
```

- Input = 300 x 300 x 3
- Filter = 3 x 3 x 3 x 1
- Stride = 1
- Padding = same
- Output = 300 x 300 x 1
- Sigmoid activation for visualization purposes

See EdgeDetection.ipynb for details and Tensorflow implementation.

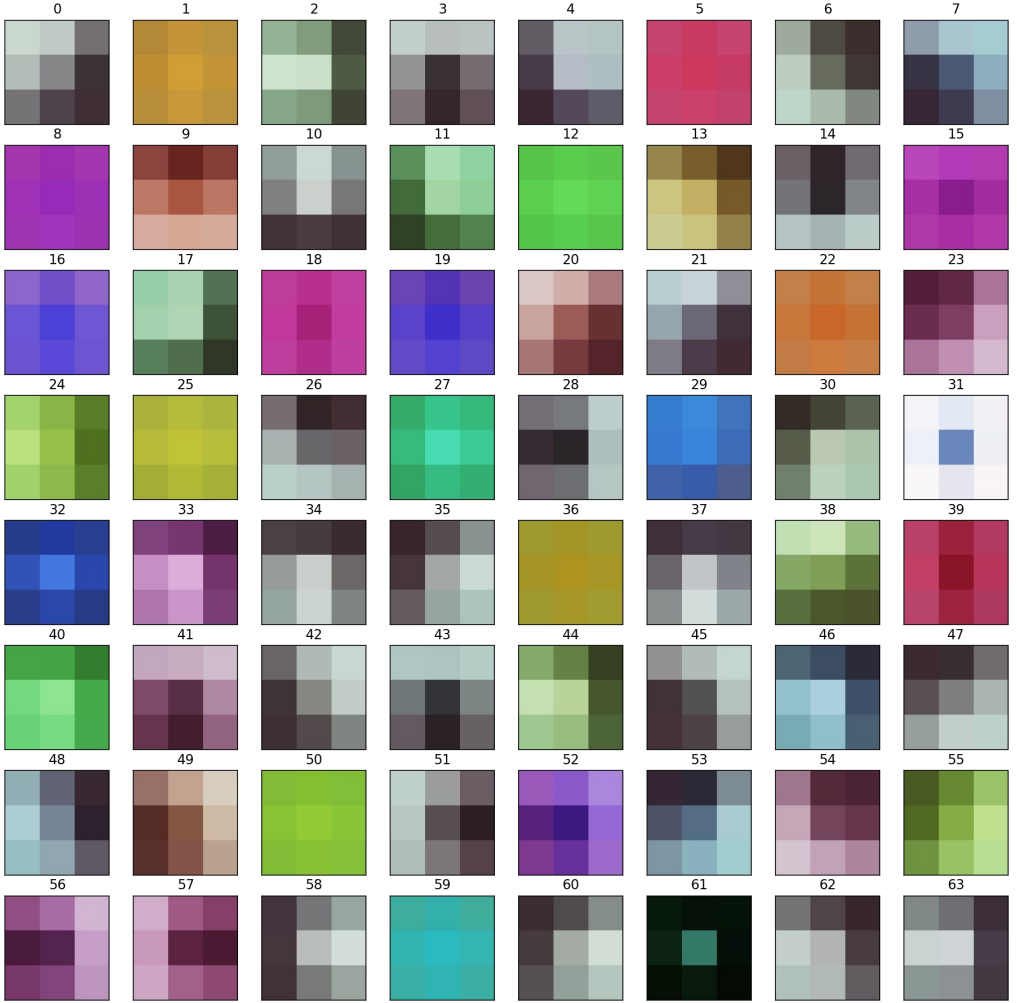
# Comparison of 45- and 135-degree edges



# Learned Filters

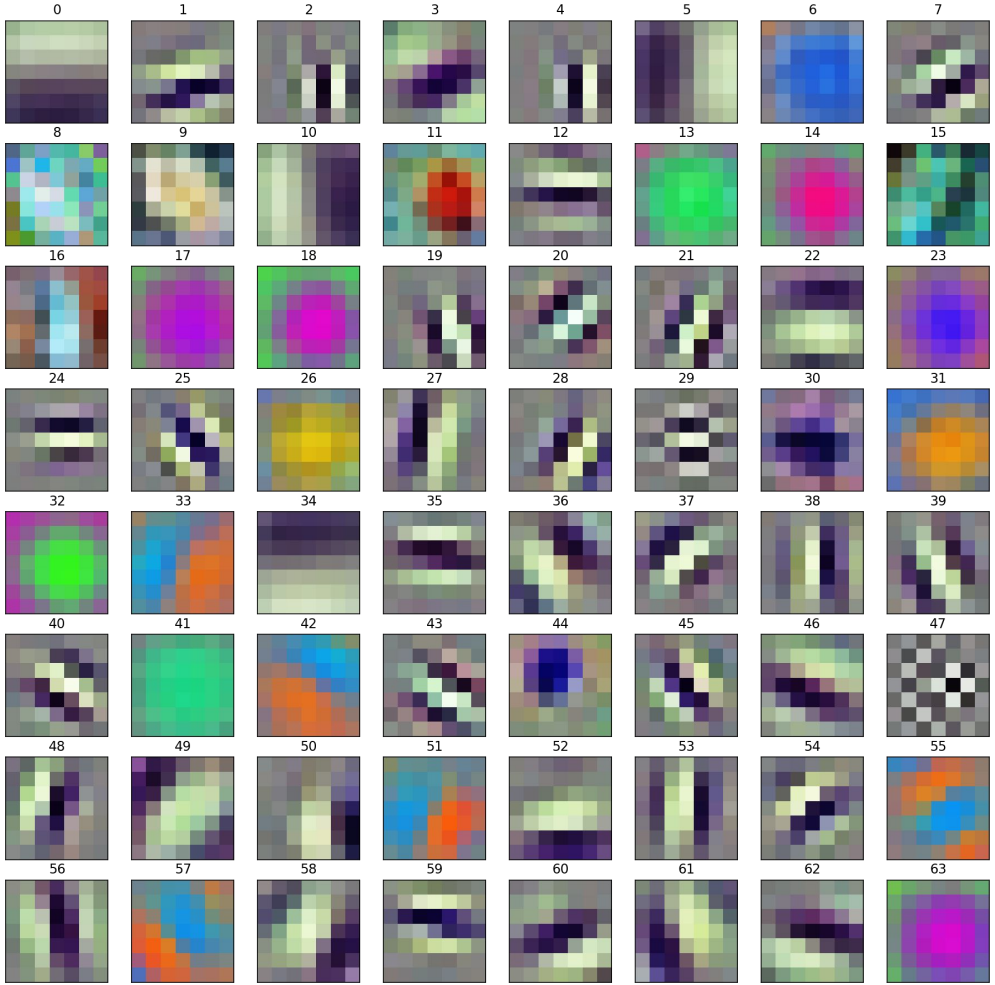
- First layer of VGGNet 16
- 3 x 3 x 3 x 64
- Trained on ImageNet
- Rescaled to std = 1 and transformed via sigmoid for visualization purposes



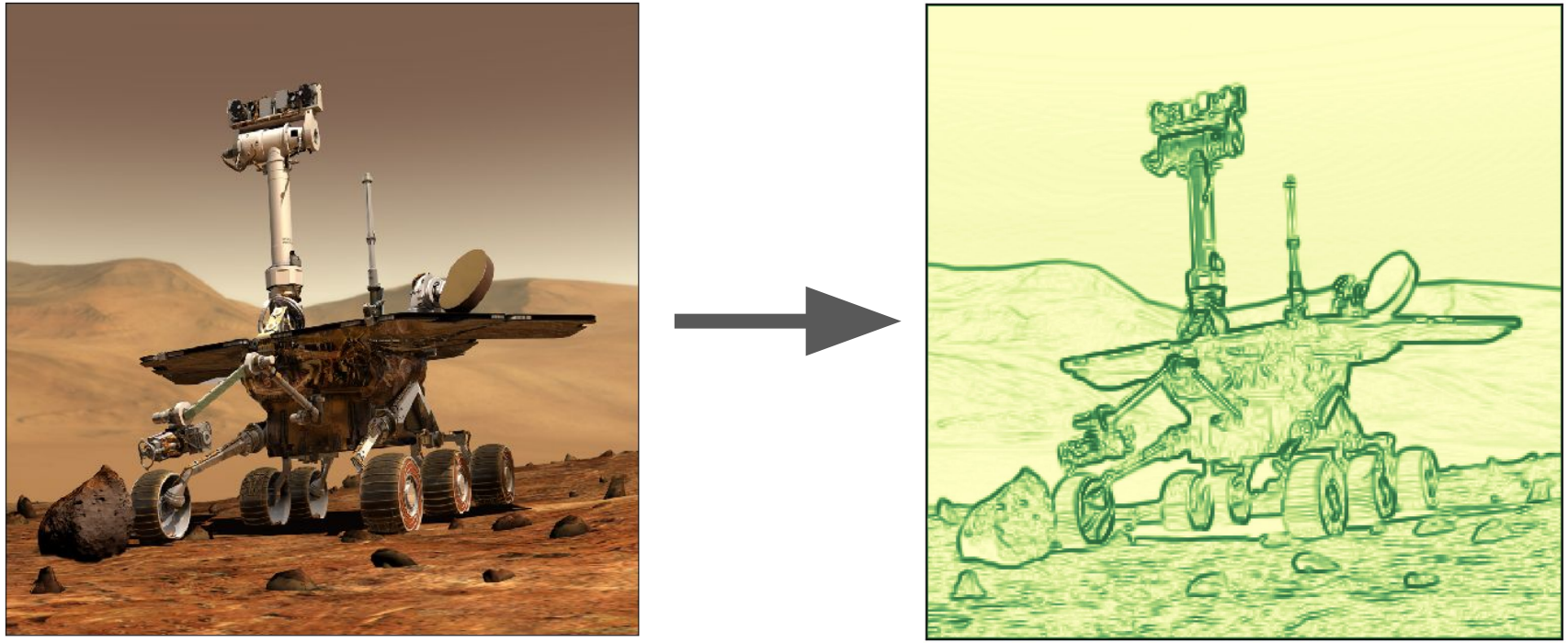

See VGGDeepDream.ipynb for details and Keras implementation.

# Learned Filters

- First layer of DenseNet201
- 7 x 7 x 3 x 64
- Trained on ImageNet
- Rescaled to std = 1 and transformed via sigmoid for visualization purposes



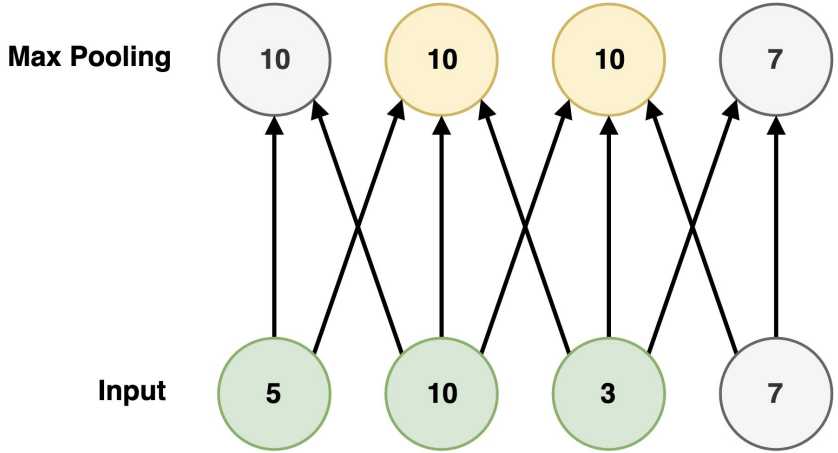
# What is edge detection?

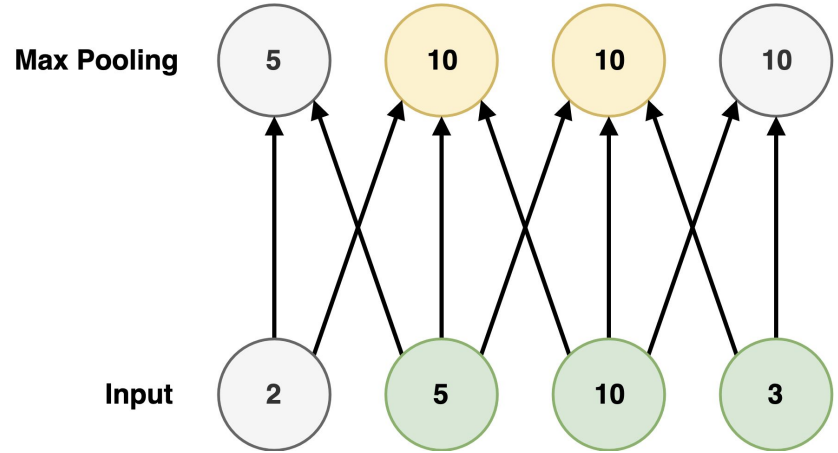


# Max Pooling

**Problem**
Convolutions are invariant with respect to linear transformations, but output is still affected.

**Solution**
Pooling over spatial positions is invariant with respect to linear translations in the input.



# Max Pooling over Space

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter
2x2

Output: 3x3

| | | |
|---|---|---|
| 5 | 6 | 6 |
| 8 | 9 | 9 |
| 8 | 9 | 9 |

# Max Pooling over Space

Input: 3x3 + 1x1 padding

| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter
2x2

Output: 3x3

| | | |
|---|---|---|
| 5 | 6 | 6 |
| 8 | 9 | 9 |
| 8 | 9 | 9 |

# Max Pooling over Space

Input: 3x3 + 1x1 padding

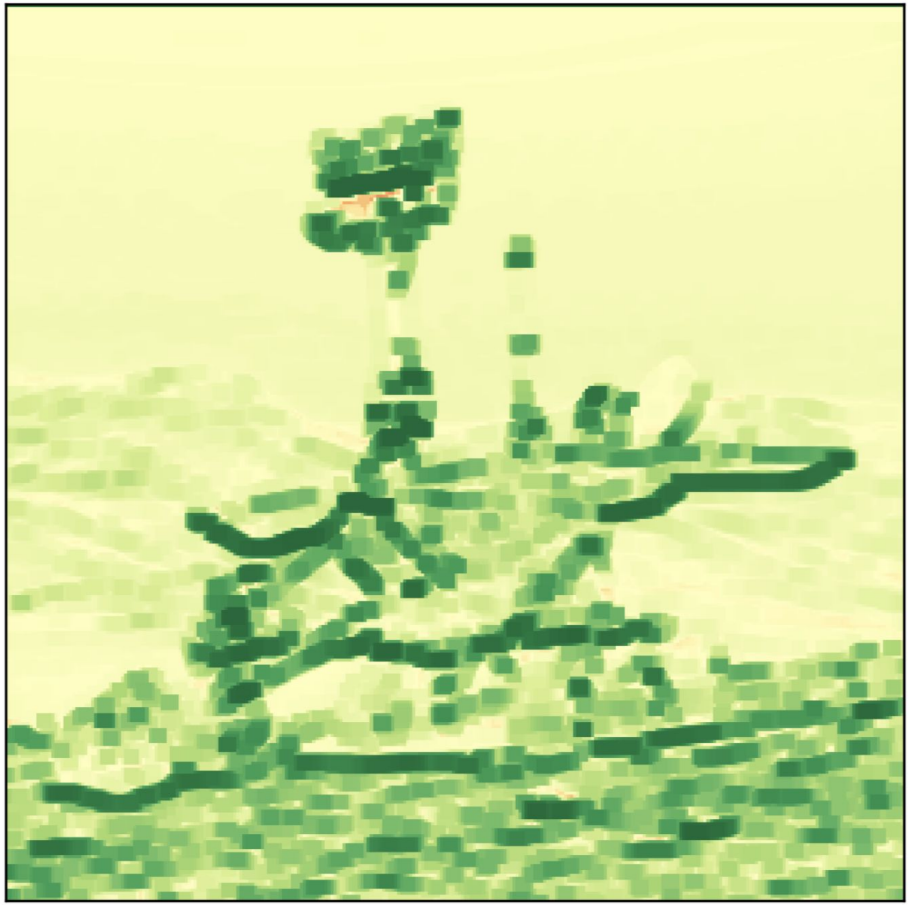
| | | | |
|---|---|---|---|
| 1 | 2 | 3 | 0 |
| 4 | 5 | 6 | 0 |
| 7 | 8 | 9 | 0 |
| 0 | 0 | 0 | 0 |

Filter
2x2

Output: 3x3

| | | |
|---|---|---|
| 5 | 6 | 6 |
| 8 | 9 | 9 |
| 8 | 9 | 9 |

Filter: 5 x 5 x 1



## Max Pooling

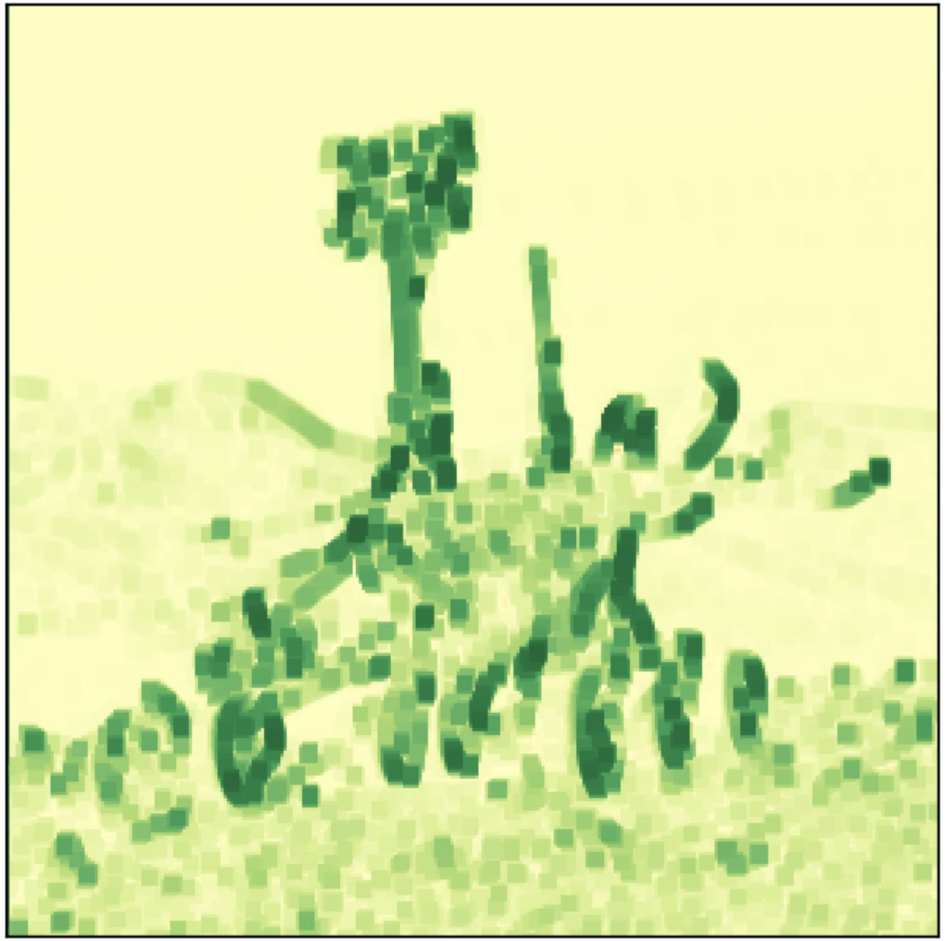
- Input: 300 x 300 x 8
  Convolution + sigmoid

- Filter = 5 x 5 x 1
- Stride = 1 x 1 x 1
- Padding = 0

- Output = 296 x 296 x 8
  Displaying the channel from the 0-degree edge activation map

See EdgeDetection.ipynb for details and Tensorflow implementation.

Filter: 5 x 5 x 1



## Max Pooling

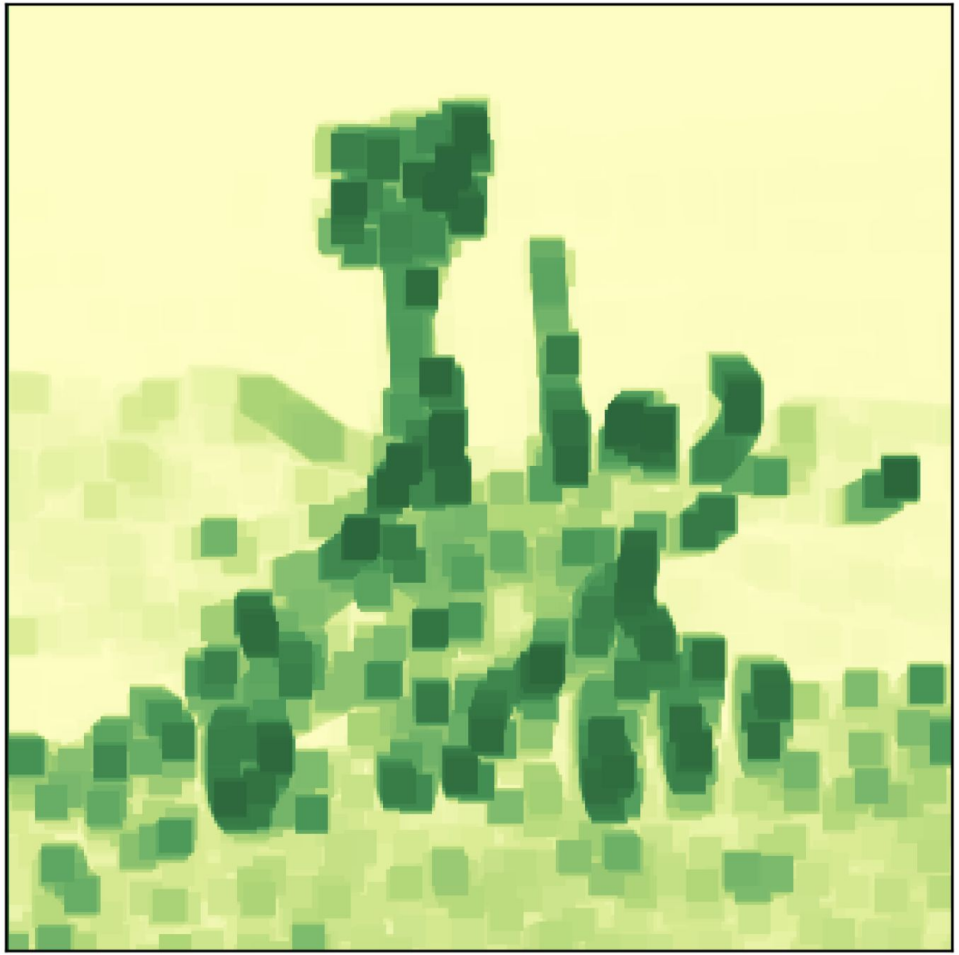
- Input: 300 x 300 x 8
  Convolution + sigmoid

- Filter = 5 x 5 x 1
- Stride = 1 x 1 x 1
- Padding = 0

- Output = 296 x 296 x 8
- Displaying the channel from the 90-degree edge activation map

See EdgeDetection.ipynb for details and Tensorflow implementation.

Filter: 10 x 10 x 1



## Max Pooling

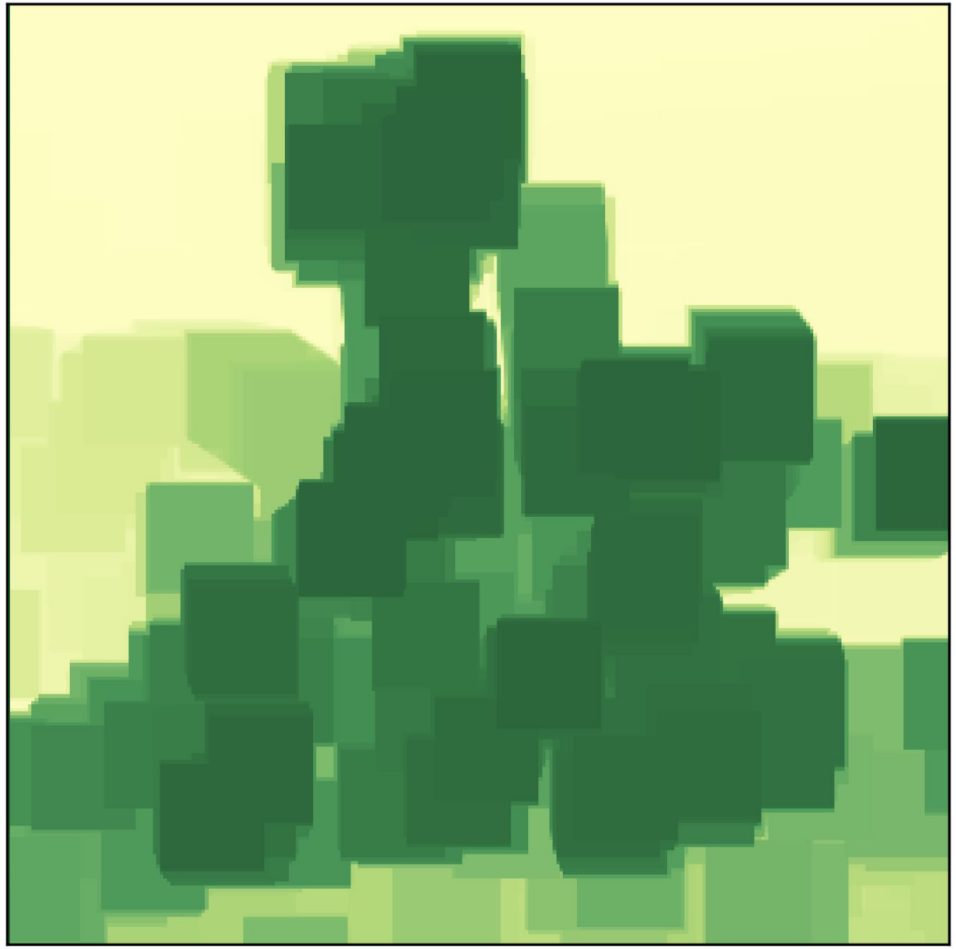
- Input: 300 x 300 x 8
  Convolution + sigmoid

- Filter = 10 x 10 x 1
- Stride = 1 x 1 x 1
- Padding = 0

- Output = 291 x 291 x 8
- Displaying the channel from the 90-degree edge activation map

See EdgeDetection.ipynb for details and Tensorflow implementation.

Filter: 30 x 30 x 1



## Max Pooling

- Input: 300 x 300 x 8
  Convolution + sigmoid

- Filter = 30 x 30 x 1
- Stride = 1 x 1 x 1
- Padding = 0

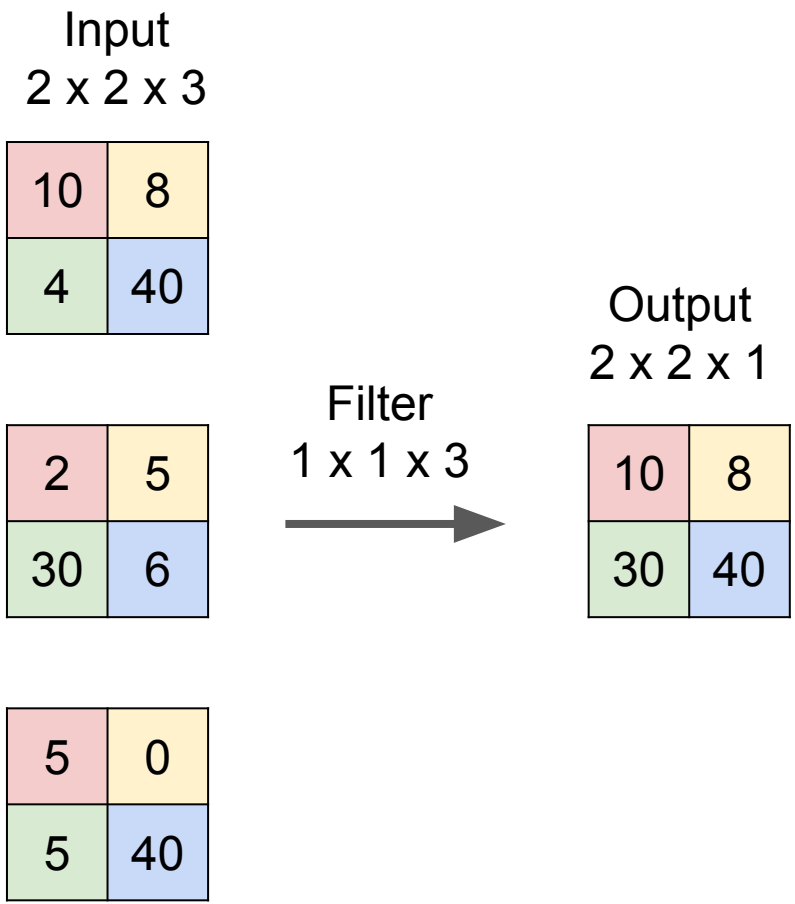
- Output = 271 x 271 x 8
- Displaying the channel from the 90-degree edge activation map

See EdgeDetection.ipynb for details and Tensorflow implementation.

# Max Pooling over Depth

**Problem**
Detect features in the same spatial location but in different channels.

**Solution**
Take a maximum of the same surface location across all channels.



Filter: 1 x 1 x 4

## Max Pooling

- Input: 300 x 300 x 8
  Convolution + sigmoid

- Filter = 1 x 1 x 8
- Stride = 1 x 1 x 8
- Padding = 0

- Output = 300 x 300 x 1

See EdgeDetection.ipynb for details and Tensorflow implementation.

# Part 2

## Datasets & Models

(Image by a Stable Diffusion model)

# Project ImageNet

**Dataset**

14M images

20K classes

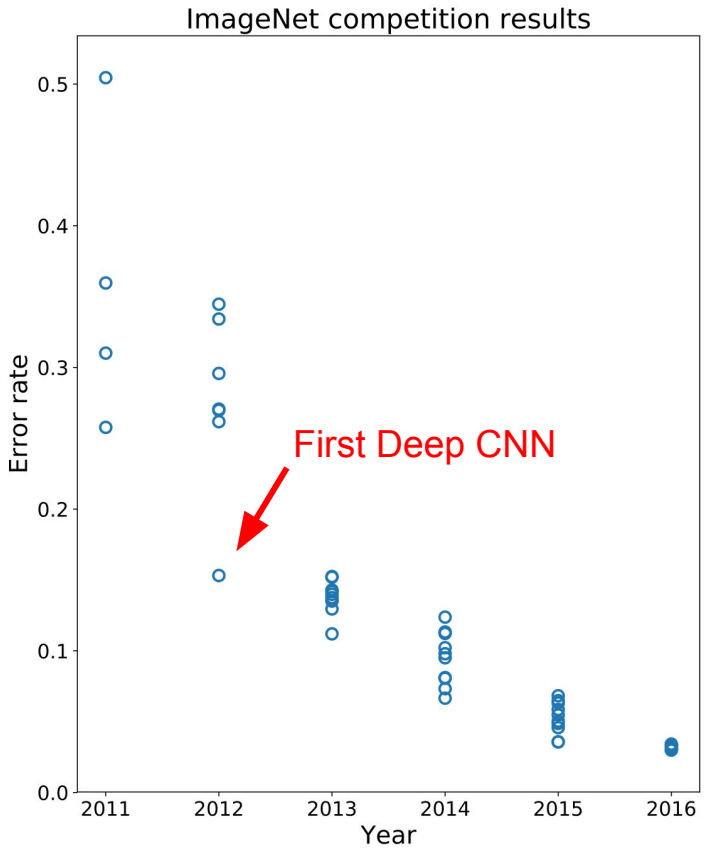
Amazon Mechanical Turk

**Competition**

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Timeline: 2010 - 2017

Subset of 1K classes

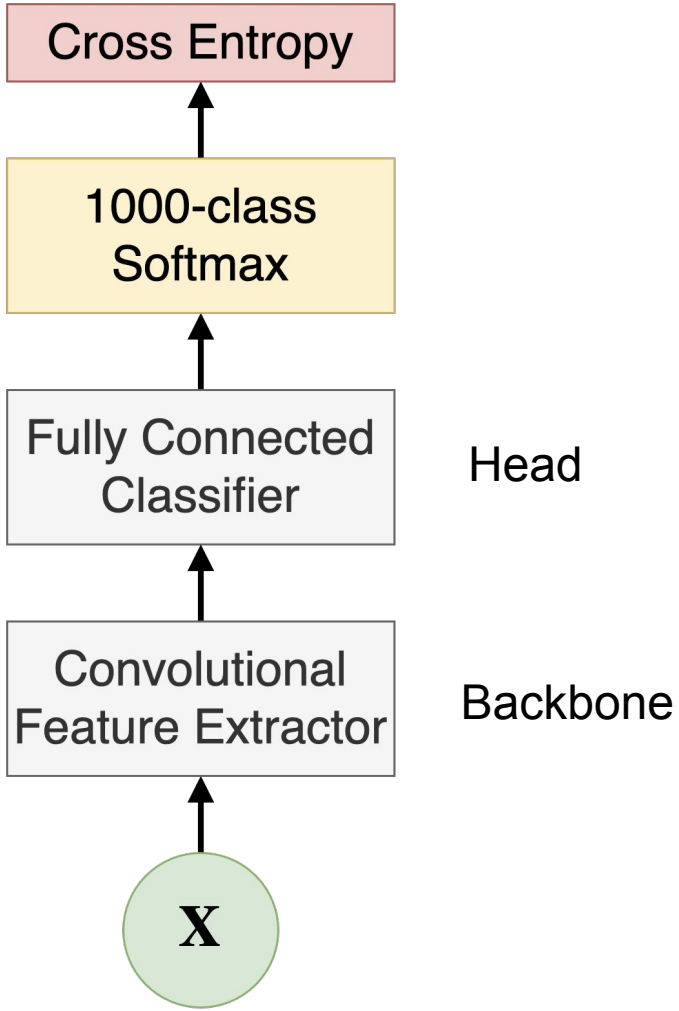


# AlexNet

**ImageNet Results**
Winner of 2012
Top-5 Error: 17.0%

First to successfully use Deep CNN approach in this competition.

**Hyperparameters**
Momentum GD
Batch size = 128
L2 Regularization

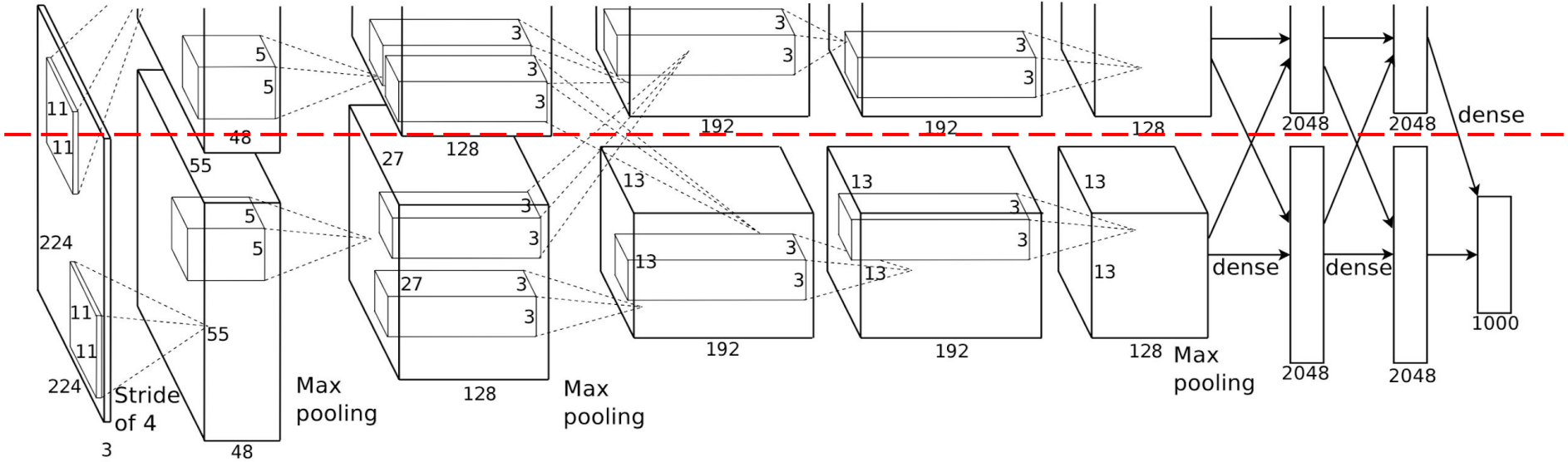



Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012)

| L | Type | Filter Shape | Padding | Stride | Activation Shape | Activation | Parameters |
|---|---|---|---|---|---|---|---|
| 0 | Input | | | | (224 + 3) x (224 + 3) | | |
| 1 | Convolution | 11 x 11 x 3 | Valid | 4 | 55 x 55 x (48 + 48) | ReLU + LRN | 34,848 |
| 2 | Max Pooling | 3 x 3 x 48 | Valid | 2 | 27 x 27 x (48 + 48) | | |
| 3 | Convolution | 5 x 5 x 48 | Same | 1 | 27 x 27 x (128 + 128) | ReLU + LRN | 307,200 |
| 4 | Max Pooling | 3 x 3 x 128 | Valid | 2 | 13 x 13 x (128 + 128) | | |
| 5 | Convolution | 3 x 3 x 128 | Same | 1 | 13 x 13 x 384 | ReLU | 442,368 |
| 6 | Convolution | 3 x 3 x 384 | Same | 1 | 13 x 13 x (192 + 192) | ReLU | 1,327,104 |
| 7 | Convolution | 3 x 3 x 192 | Same | 1 | 13 x 13 x (128 + 128) | ReLU | 442,368 |
| 8 | Max Pooling | 3 x 3 x 128 | Valid | 2 | 6 x 6 x (128 + 128) | | |
| 9 | Fully Connected | | | | 4096 | ReLU | 37,748,736 |
| 10 | Fully Connected | | | | 4096 | ReLU | 16,777,216 |
| 11 | Fully Connected | | | | 1000 | Softmax | 4,096,000 |

Source: Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012)

# AlexNet: Architecture

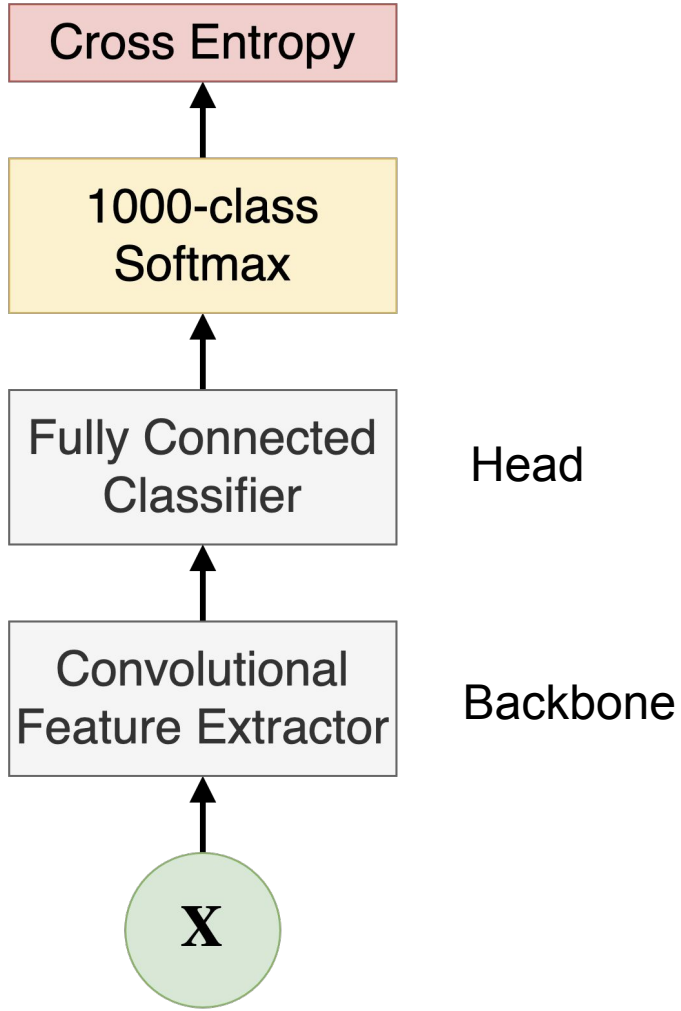



Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012)

# VGGNet

**ImageNet Results**
2nd place in 2014
Top-5 Error: 7.3%

**Architectural Insight**
Decrease convolutional filter surface area in favor of stacking several layers.




Source: Simonyan, K., and Zisserman, A. (2015)

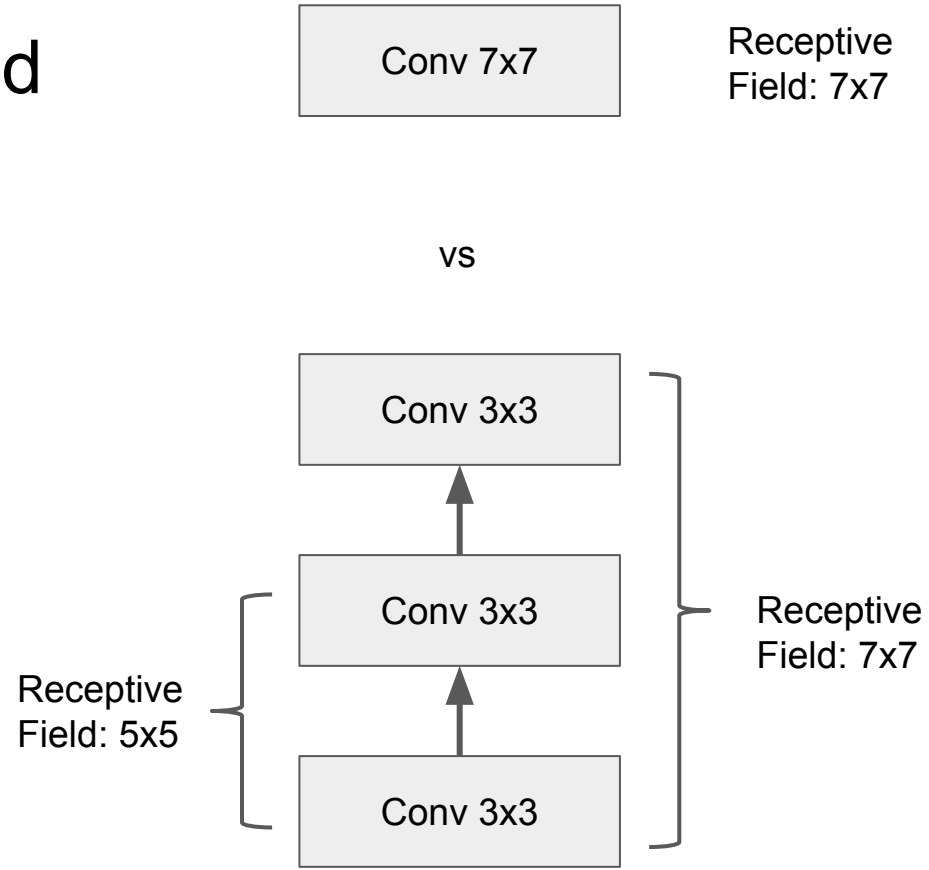
# VGGNet: Receptive Field

**Architectural Insight**

Decrease convolutional filter surface area in favor of stacking several layers.

**Advantages**

1) Can insert non-linearity between layers.
2) Fewer trainable parameters (27 vs 49).




Source: Simonyan, K., and Zisserman, A. (2015)

## VGGNet: Convolutional Feature Extractor of VGG16

| Layer | Filter Shape | Padding | Stride | Activation Shape | Activation | Parameters |
|---|---|---|---|---|---|---|
| Input | | | | 224 x 224 x 3 | | |
| Stack of 2 x Conv | 3 x 3 x ? | Same | 1 | 224 x 224 x 64 | ReLU | 38,720 |
| Max Pooling | 2 x 2 x 64 | Valid | 2 | 112 x 112 x 64 | | |
| Stack of 2 x Conv | 3 x 3 x ? | Same | 1 | 112 x 112 x 128 | ReLU | 221,440 |
| Max Pooling | 2 x 2 x 128 | Valid | 2 | 56 x 56 x 128 | | |
| Stack of 3 x Conv | 3 x 3 x ? | Same | 1 | 56 x 56 x 256 | ReLU | 1,475,328 |
| Max Pooling | 2 x 2 x 256 | Valid | 2 | 28 x 28 x 256 | | |
| Stack of 3 x Conv | 3 x 3 x ? | Same | 1 | 28 x 28 x 512 | ReLU | 5,899,776 |
| Max Pooling | 2 x 2 x 512 | Valid | 2 | 14 x 14 x 512 | | |
| Stack of 3 x Conv | 3 x 3 x ? | Same | 1 | 14 x 14 x 512 | ReLU | 7,079,424 |
| Max Pooling | 2 x 2 x 512 | Valid | 2 | 7 x 7 x 512 | | |

Source: Simonyan, K., and Zisserman, A. (2015)

# VGGNet: Classifier

Note that almost 90% of parameters are in the classifier.

Newer networks use Global Average Pooling followed directly by 1 FC with Softmax activation.

| Layer | Neurons | Activation | Parameters |
|---|---|---|---|
| FC | 4096 | ReLU | 102,764,544 |
| FC | 4096 | ReLU | 16,781,312 |
| FC | 1000 | Softmax | 4,097,000 |



Source: Simonyan, K., and Zisserman, A. (2015)

# VGGNet: 16 layers

**Architecture Stats**

16 trainable layers

138,357,544 trainable params

Initial Learning Rate = 1e−2

Update Learning Rate x 0.1 on Plateaus

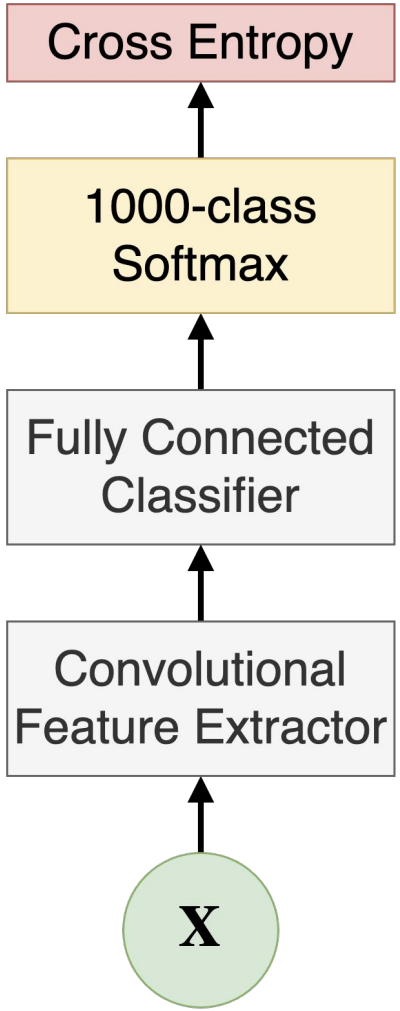
**Training Time**

74 epochs

2-3 weeks

4 NVIDIA Titan Black GPUs

With AWS prices, the cost ~$3.3K




Source: Simonyan, K., and Zisserman, A. (2015)

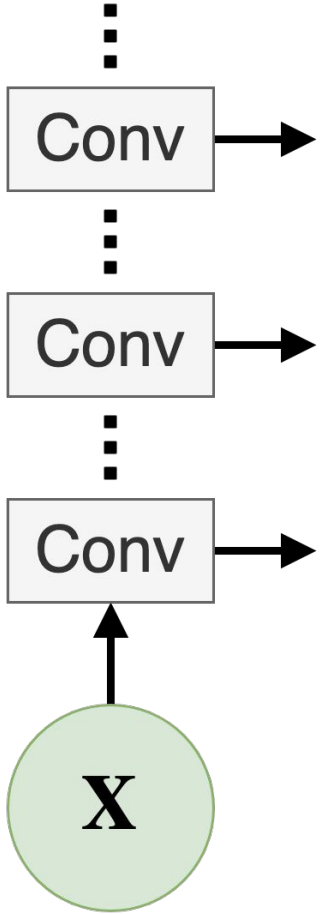
# Demo

VGGClassification.ipynb

# Visualizing Deep Activations

**Problem**
How to gain intuition about behavior of convolutional filters beyond the first layer?

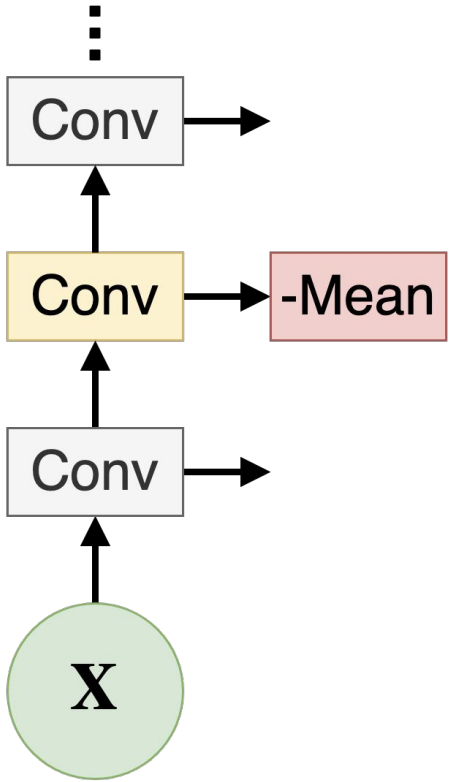
**Solution**
Feed an image through the network and plot activation maps of the deep convolutional layers.



# Optimizing Image for Deep Activation

In order to understand what a deep filter is looking for:

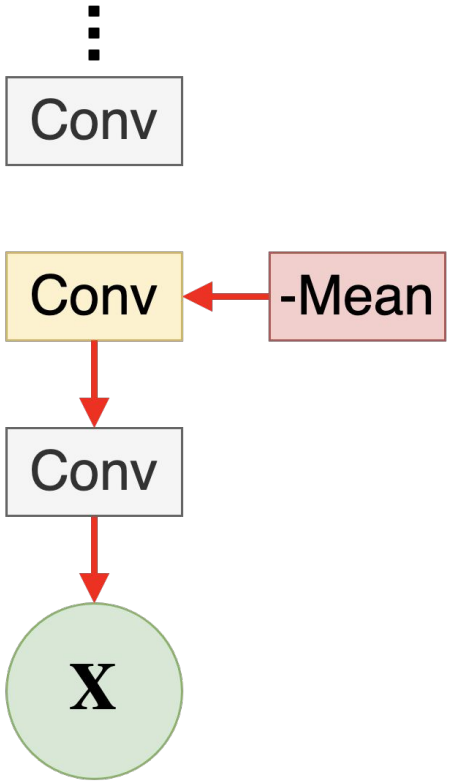
1. Take a pre-trained model, and choose a particular activation map,
2. Maximize activation map by finding gradient with respect to the image's pixels.



# Optimizing Image for Deep Activation

In order to understand what a deep filter is looking for:

1. Take a pre-trained model, and choose a particular activation map,
2. Maximize activation map by finding gradient with respect to the image's pixels.



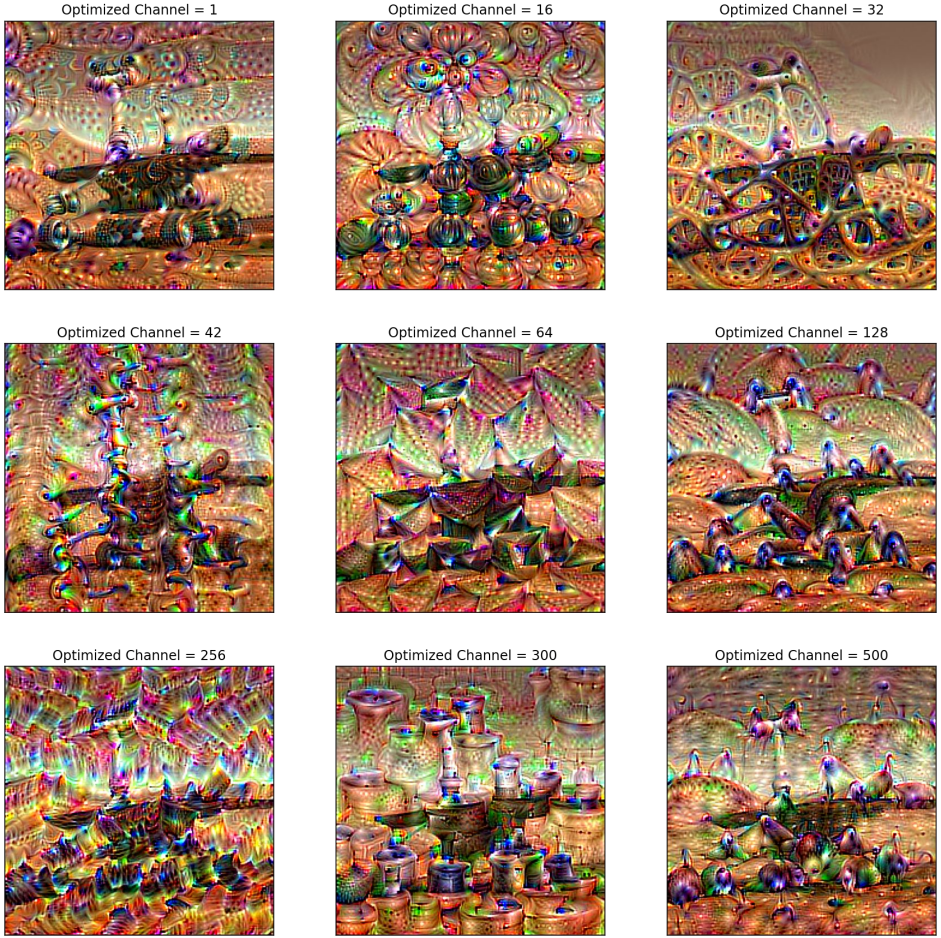
# Deep Dream with VGG16

1. Load pre-trained VGG16
2. Layer block5_conv2
3. Channel 42
4. Average Activation across H/W

1. Setup Gradient Descent to find an image that maximizes the average activation.

2. Start with the rover image
3. Iterate for 50 epochs

# Deep Dream with VGG16



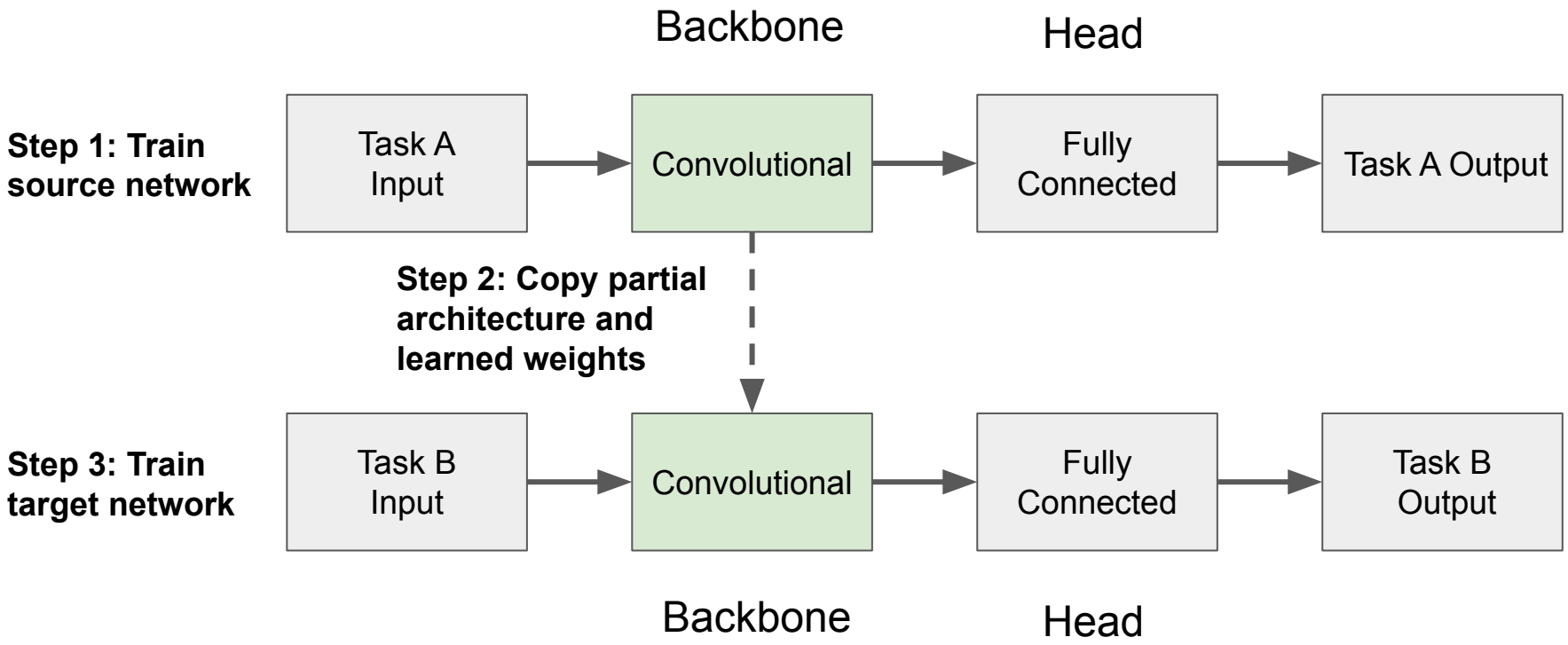
# Hierarchy of Visual Information

1. Pixels (RGB)
2. Edges
3. Curves
4. Shapes: circles, boxes, triangles, ...
5. Textures: checkers, gradient, monotonic, ...
6. Parts: wheels, road, windows, ...
7. Objects: cars, cats, dogs, oranges, ...

# References on CNN Visualizations

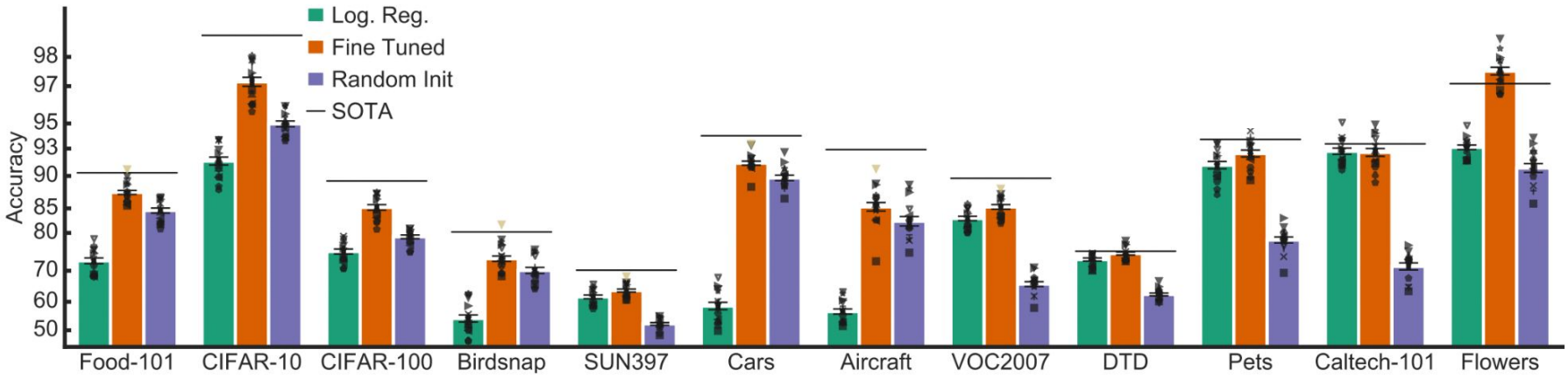
- Visualizing and Understanding Convolutional Networks
  - (Zeiler, M, and Fergus, R., 2013)
- https://github.com/yosinski/deep-visualization-toolbox
- https://distill.pub/2017/feature-visualization/
- https://distill.pub/2019/activation-atlas/

# Transfer Learning




Tan, C., et al. (2018)

# Transfer Learning from ImageNet




Source: Do Better ImageNet Models Transfer Better? (Kornblith, S, et al, 2018)

# Demo

AssignmentTemplate.ipynb

# Assignment #2

- Learning Objectives:
  - Inspecting pre-trained models
  - Transfer learning to a new task
- Deadline: EOD 10/9
- Instructions: AssignmentTemplate.ipynb
- If Accuracy @ 0.5 threshold > 60%, then
  - + 10 points flat
  - + 10 points proportionally to the rank within class
- If Accuracy @ 0.5 threshold <= 60%
  - Zero points

# Assignment Deliverables

1. Jupyter notebook and/or Python script
    a. Data preprocessing
    b. Construction and training of the final model
    c. Inference on the Score segment
2. Model definition
    a. Keras serialization in JSON format
3. Model parameters
    a. Keras serialization in H5 format
4. Probabilities of Person Label for the Score segment
    a. Shape = 20K x 1
    b. Data Type = float32 in [0, 1]
    c. File Type = Parquet

# GoogLeNet

**ImageNet Results**
Winner of 2014
Top-5 Error: 6.67%

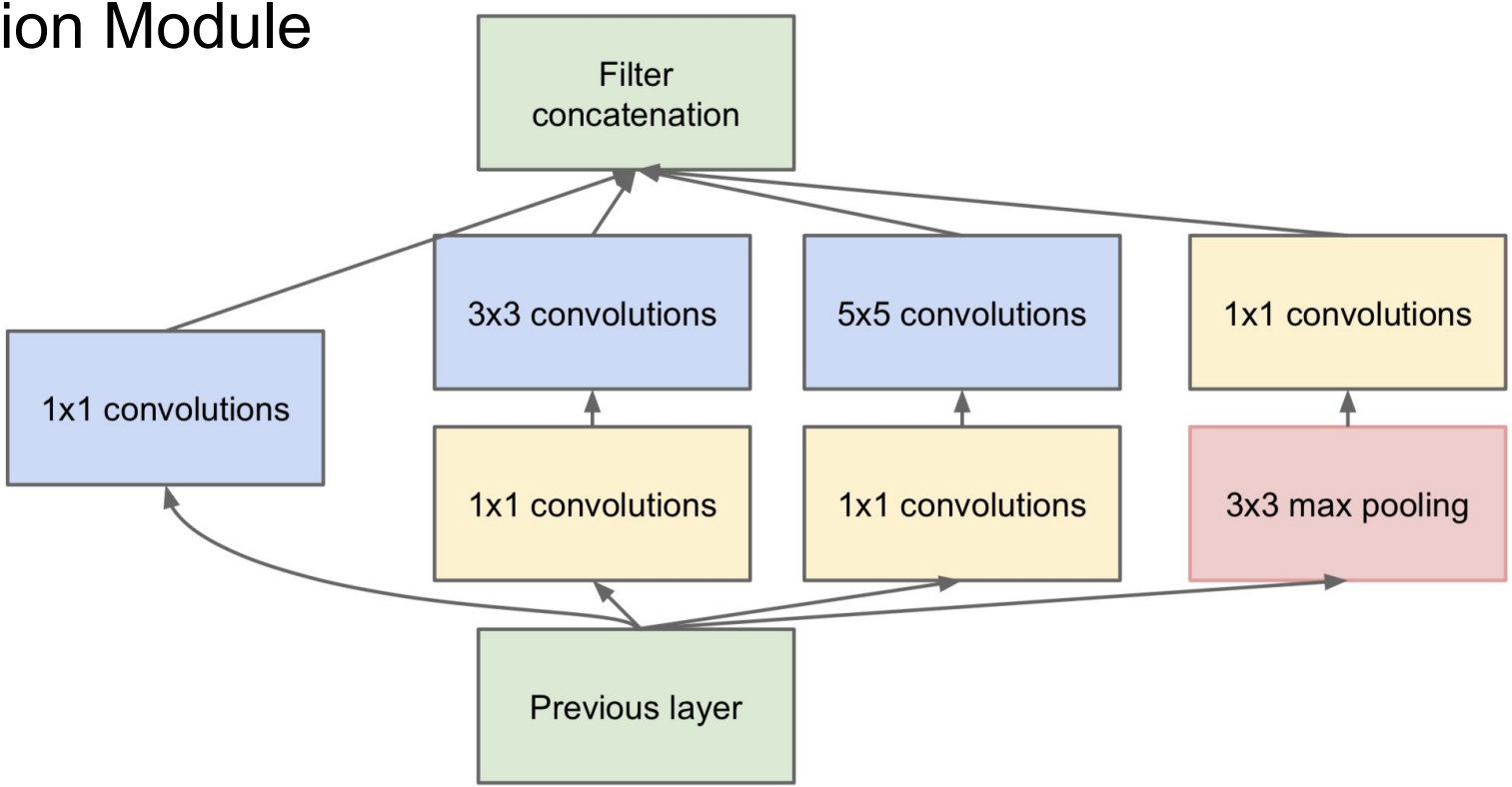
**Architecture Insight**
22 trainable layers
6M parameters
Just 1 FC layer

**Optimization**
Async GD with Momentum
LR x 0.96 every 8 epochs


Referenced in the original paper.

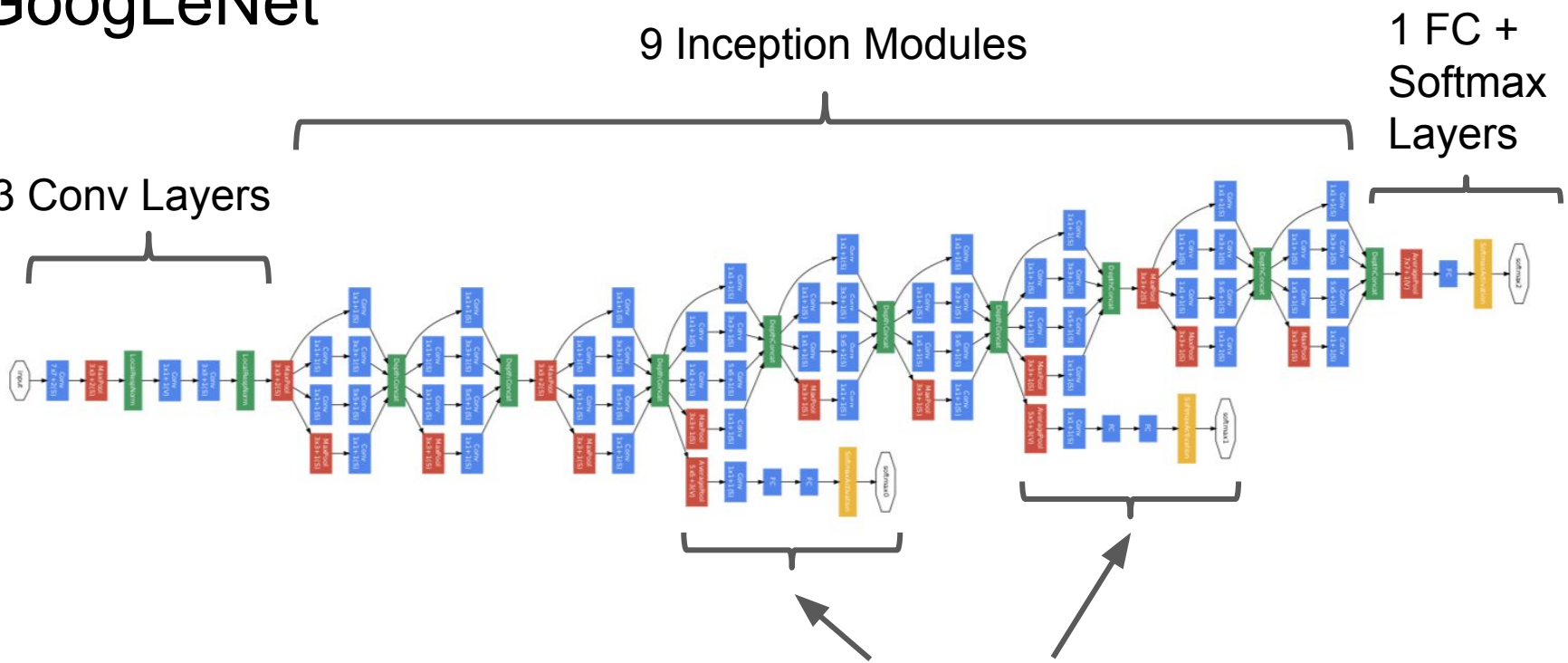
Szegedy, C., et al. (2014)

# Inception Module



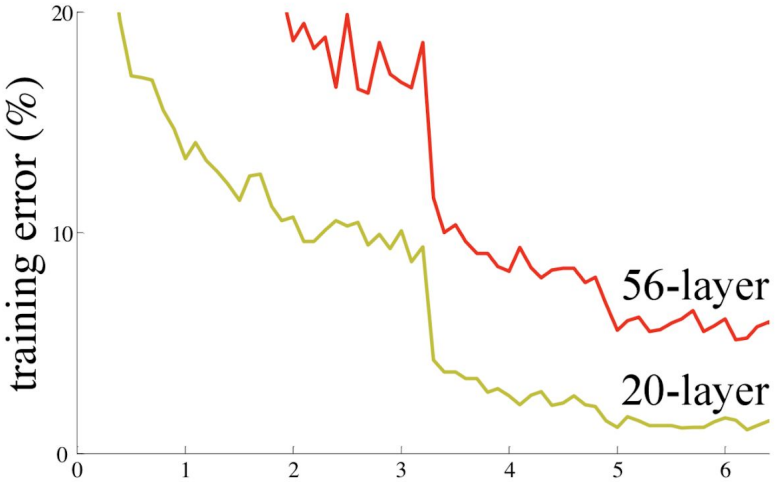

Source: Szegedy, C., et al. (2014)

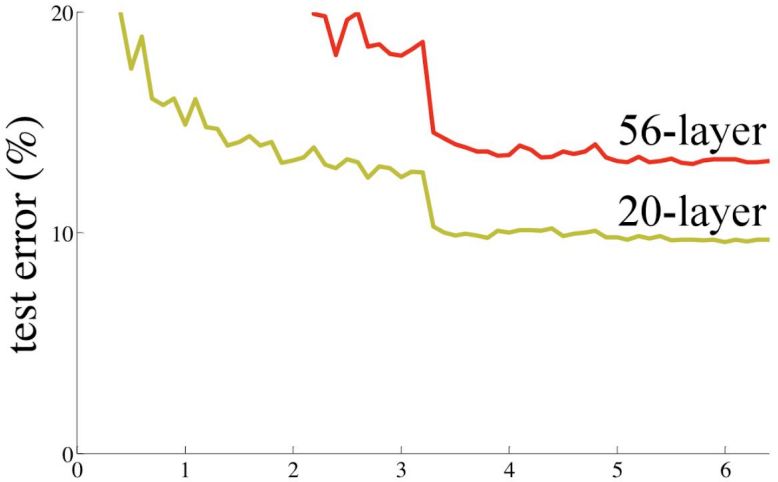
# GoogLeNet




Source: Szegedy, C., et al. (2014)

# Challenges with Deeper CNNs




Why is the network with larger capacity not overfitting the data better?

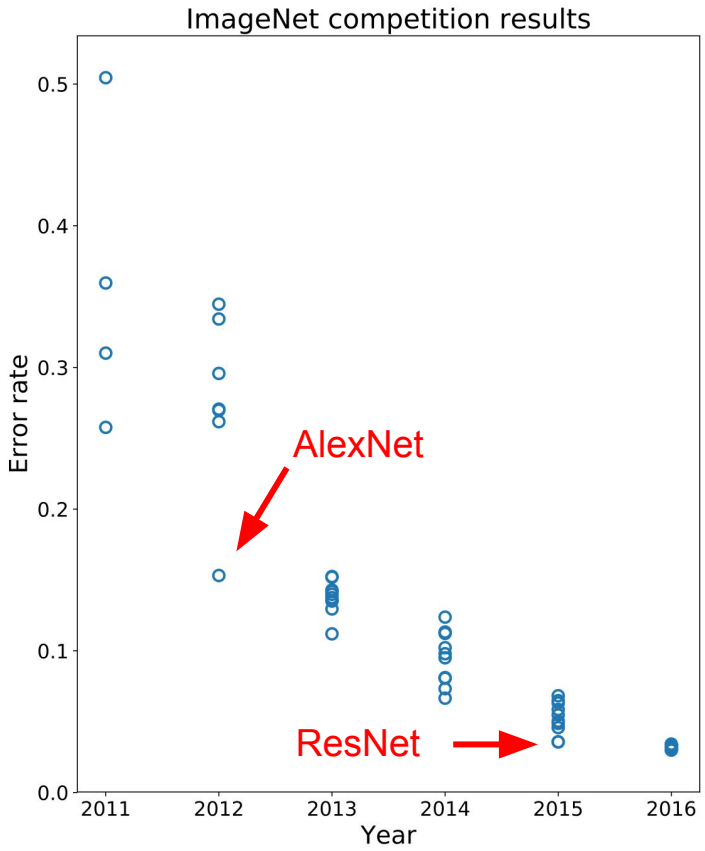
Source: He, K., et al. (2015)

# ResNet 152

**ImageNet Results**
Winner of 2015
Top-5 Error: 3.57%

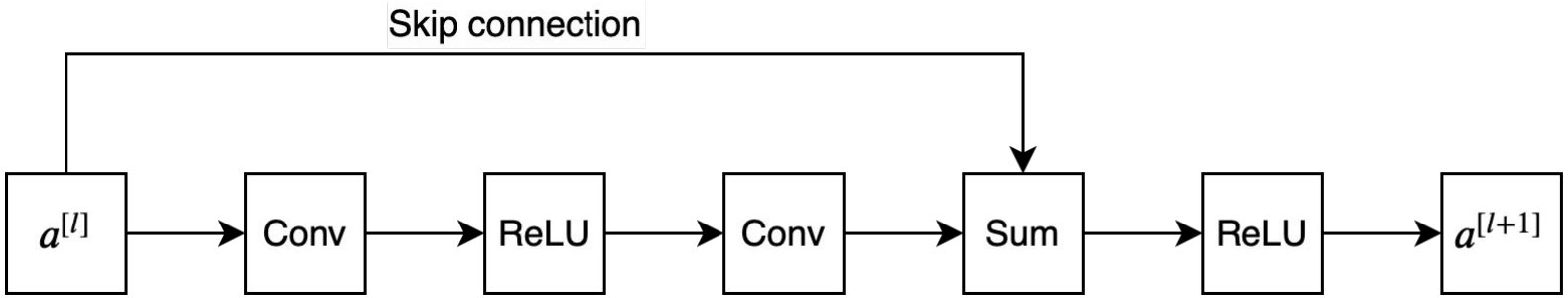
**Architecture**
152 trainable layers
25M parameters

Surpassed human performance.




Source: He, K., et al. (2015)

# Residual Block




Why is this useful?

1) Model can learn to turn-off layers
2) Reduces vanishing gradient problem

He, K., et al. (2015)

# ResNet Family

ImageNet submission

| layer name | output size | 18-layer | 34-layer | 50-layer | 101-layer | 152-layer |
|---|---|---|---|---|---|---|
| conv1 | 112×112 | 7×7, 64, stride 2 | | | | |
| conv2_x | 56×56 | 3×3 max pool, stride 2 | | | | |
| | | $\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$ |
| conv3_x | 28×28 | $\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$ | $\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$ | $\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$ | $\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$ |
| conv4_x | 14×14 | $\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$ | $\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$ | $\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$ | $\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$ |
| conv5_x | 7×7 | $\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$ | $\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$ | $\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$ |
| | 1×1 | average pool, 1000-d fc, softmax | | | | |
| FLOPs | | $1.8\times10^9$ | $3.6\times10^9$ | $3.8\times10^9$ | $7.6\times10^9$ | $11.3\times10^9$ |

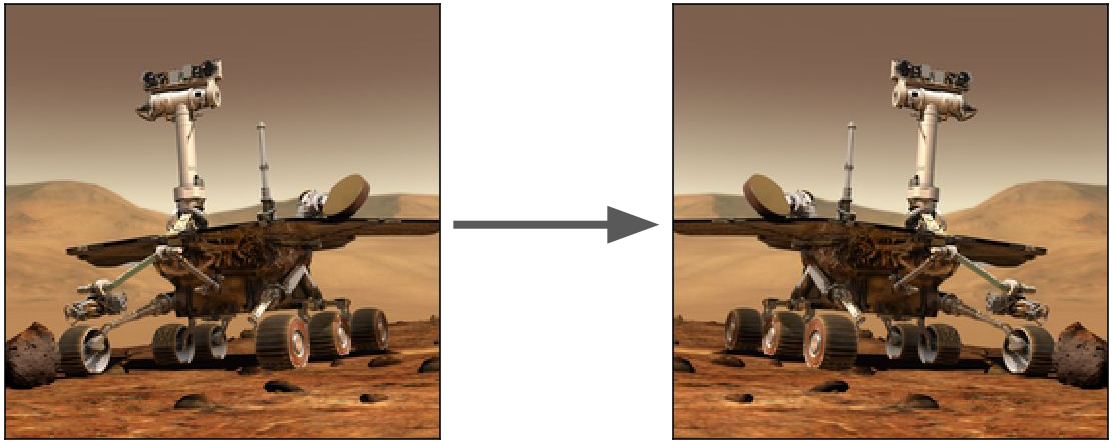
Source: He, K., et al. (2015)

# Regularization

**Data Augmentation**

Flip
Scale
Color shift
Rotate
Crop

Any change that produces a different image that has the same class.



Example: Horizontal Flip

# Notable Papers

- NASNet (Zoph, B, et al, 2018)
- Inception-ResNet (Szegedy, C., et al, 2017)
- DenseNet (Huang, G, et al, 2018)
- EfficientNet (Tan, M, et al, 2020)
- EfficientNetV2 (Tan, M, et al, 2021)

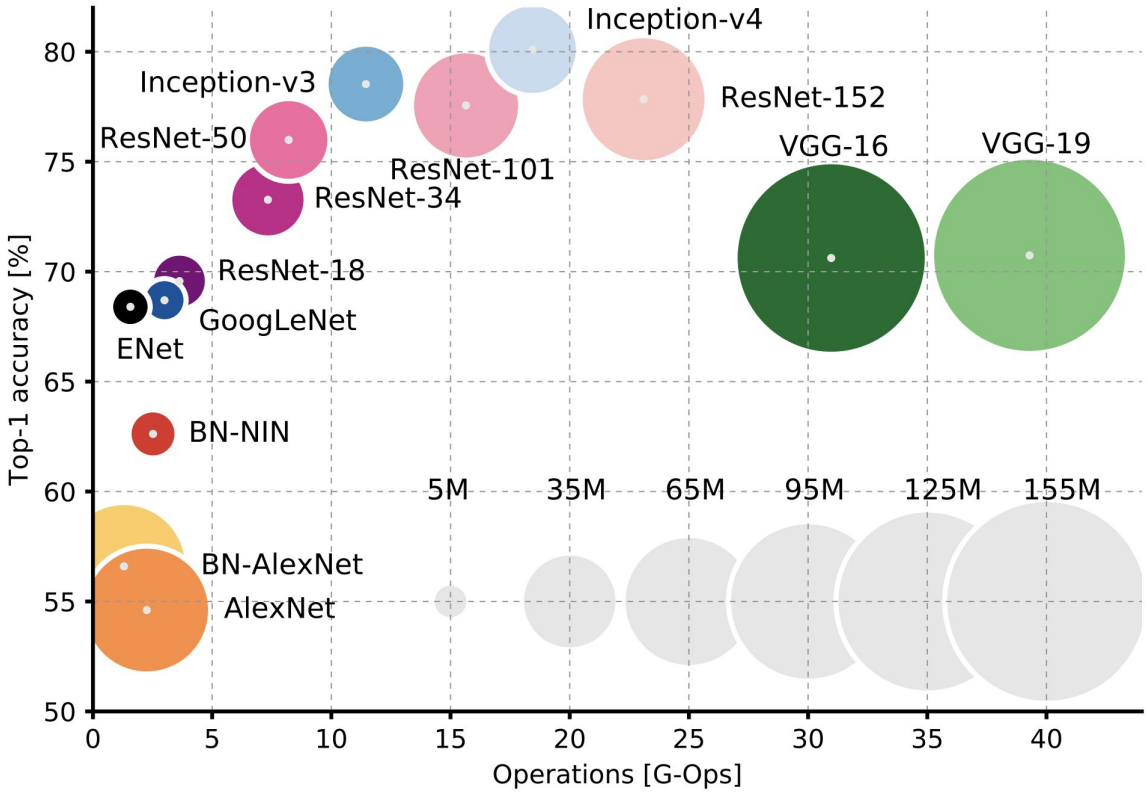
Pre-trained models available in Keras Applications.

# Model Zoo

**Trade-off Dimensions**
Inference time
Memory consumption
Accuracy

**Strong Preferences**
ResNet
Inception

Note: includes classifier parameters.




Source: Canziani, A., Culurciello, E., and Paszke, A. (2017)

# Project COCO

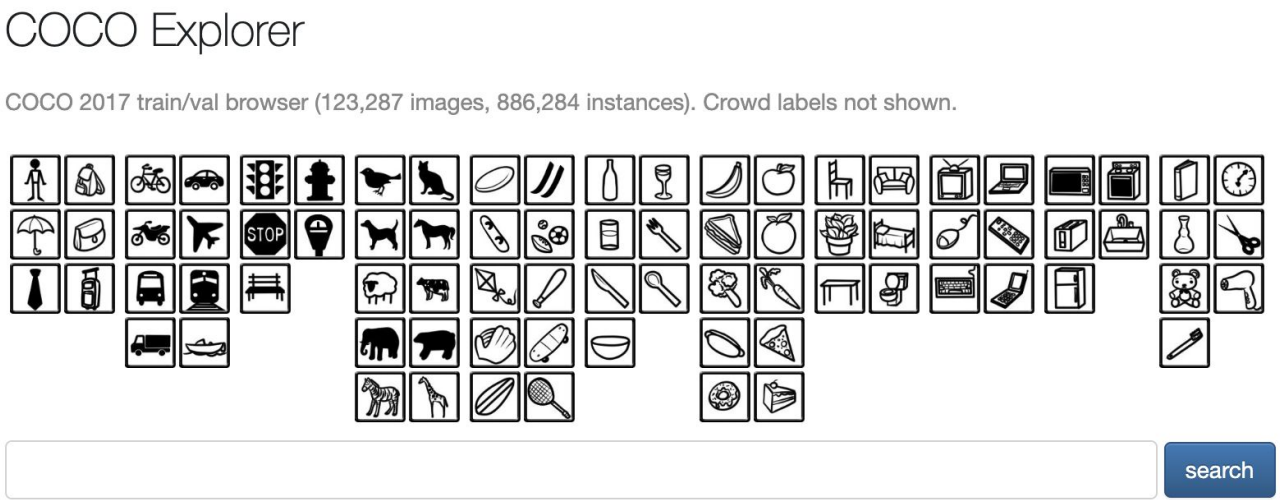
**Dataset**

200,000 images and 80 categories

Browse online! https://cocodataset.org/#explore

**Competition**

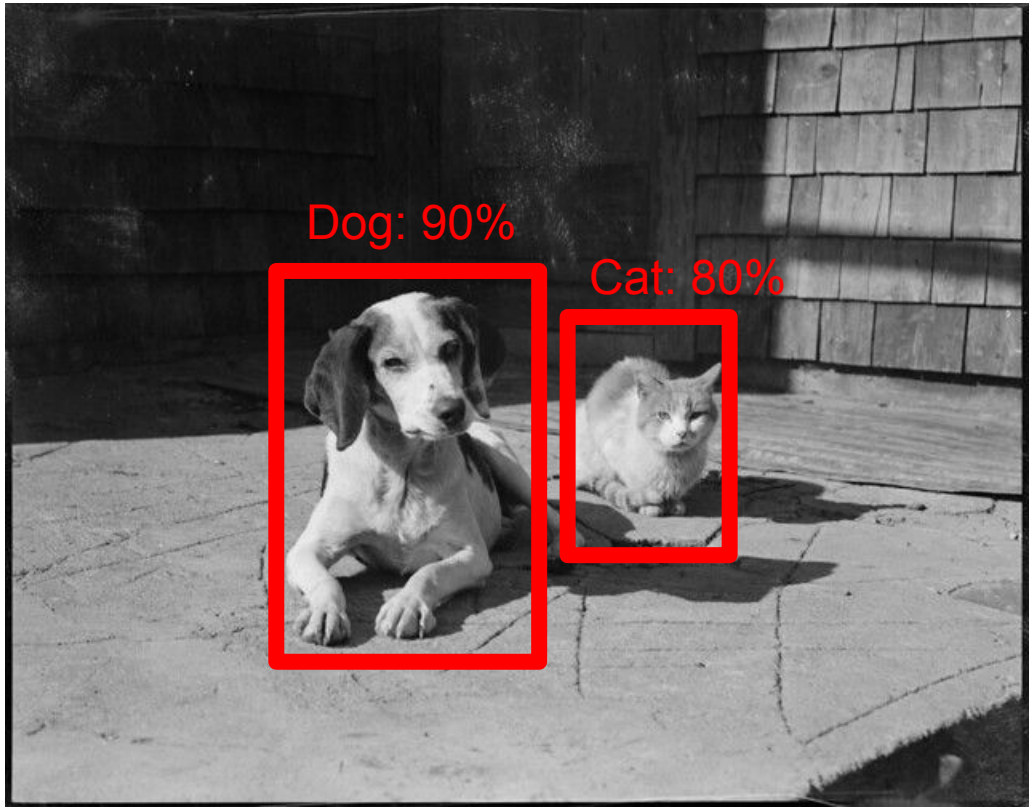
Four new and challenging tasks.




Source: COCO (CC BY 4.0)

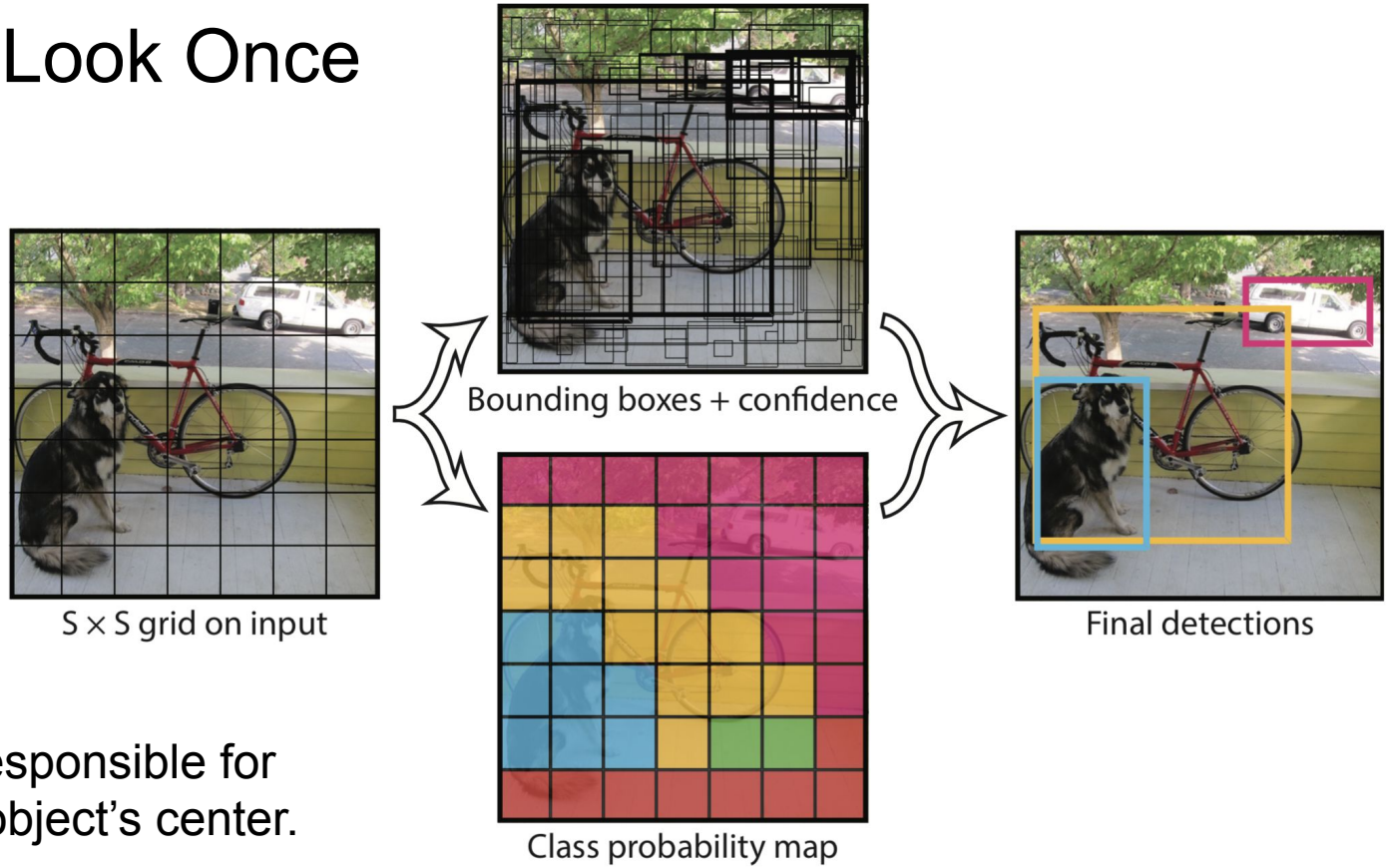
# Object Detection and Localization

**Problem**
Identify any number objects by their class probability and a bounding box providing their location on the image.




Source: Flickr / License: CC BY 4.0

# You Only Look Once




Each cell is responsible for detecting an object's center.

Source: You Only Look Once: Unified, Real-Time Object Detection
Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi (2015)

# YOLO: Model Output

Each of **SxS** cells predicts **B** boxes and a distribution over **C** classes.
Each of **B** boxes consists of:

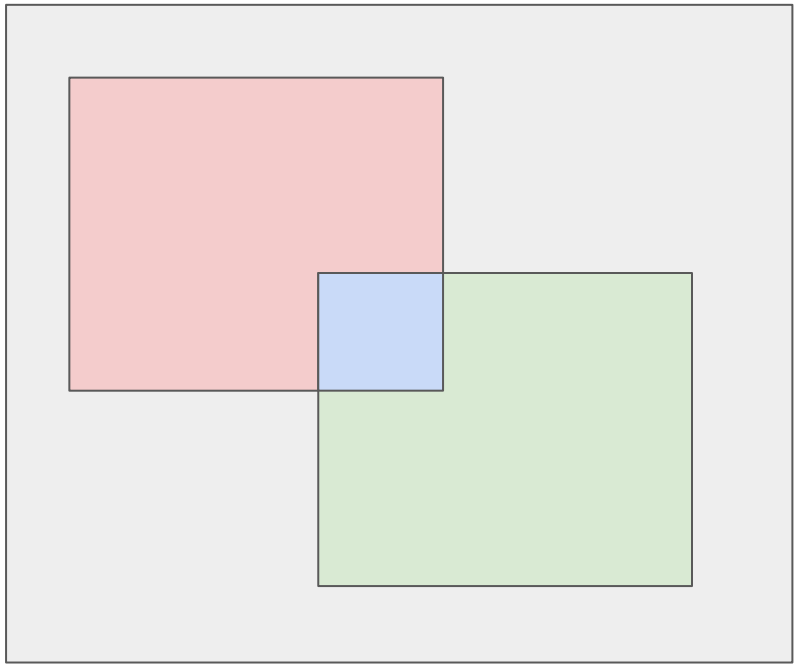
- Confidence score = Probability of object x IOU
- Location = the object's center relative to the cell's top-left corner
- Dimensions = the object's dimensions relative to the image size

The cost function is a multi-part MSE:

- If a cell contains an object, MSE of the distribution over classes
- If a box contains an object, MSE of all three box-level prediction attributes
- If a box does not contain an object, only MSE of the confidence score

Source: You Only Look Once: Unified, Real-Time Object Detection
Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi (2015)

# YOLO: Intersection over Union



IOU = Area of Intersection / Area of Union
IOU $\in$ [0, 1]

Typically, IOU > 0.5 is accepted as a correct bounding box.

Example:
IOU = Blue / (Red + Green + Blue)

# YOLO: Non-max Suppression

**Problem:** When an object is large enough, multiple cells will detect the same object. However, we only one want to detect each object once.

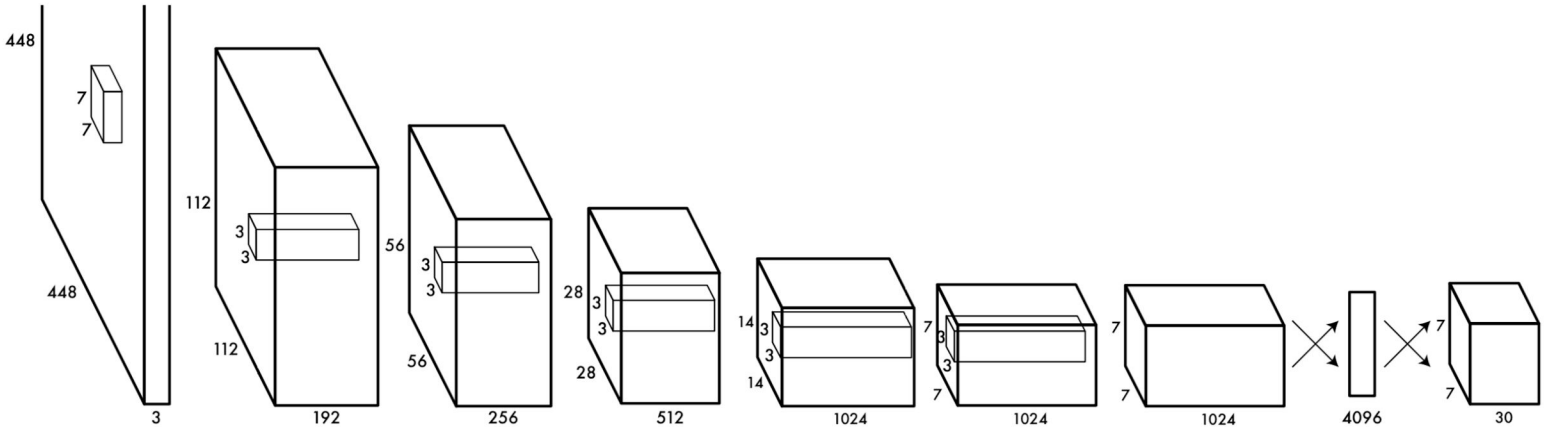
**Solution:**

1. Remove cells with probability < 0.5
2. Remove cells that **do not match both** conditions:
    - Highest confidence score (HCC) in class
    - IOU vs the cell with HCC is below 0.5

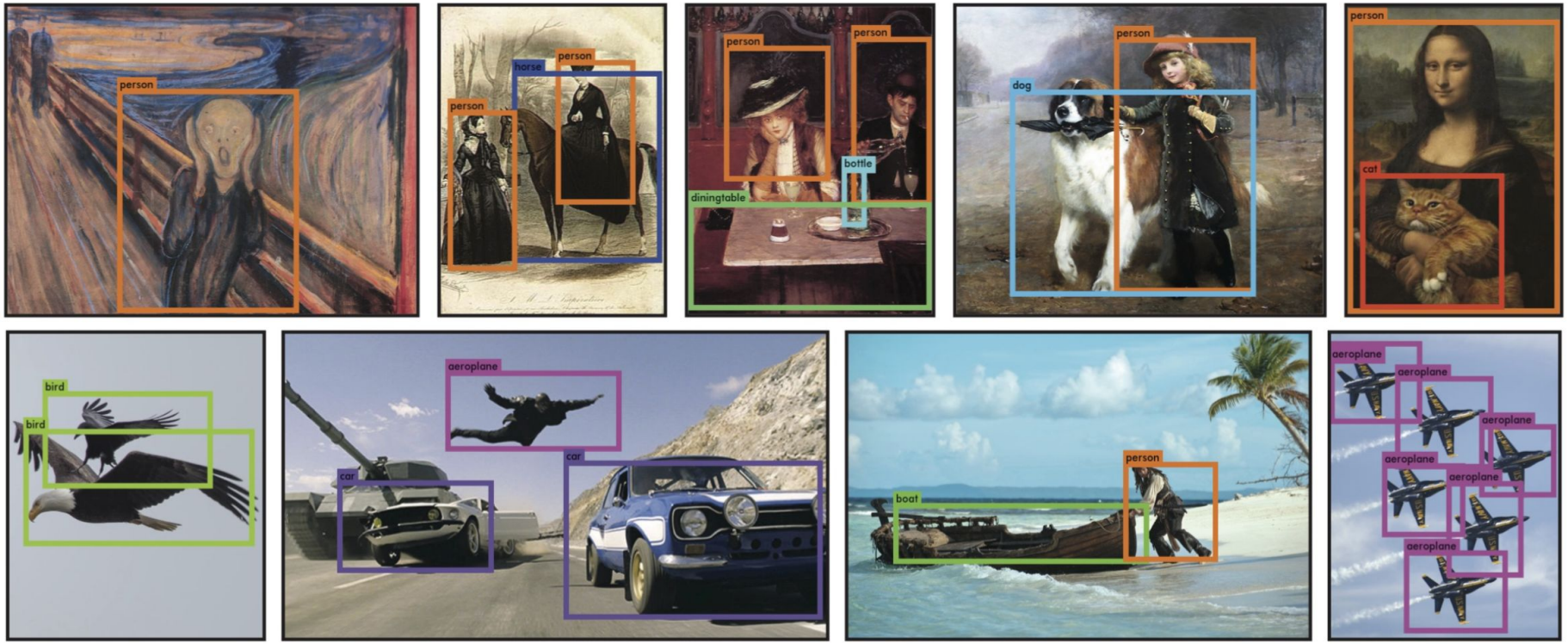
# YOLO: Non-max Suppression

| Cell | Class | Confidence Score | IOU vs HCC | Decision |
|---|---|---|---|---|
| 1 | A | 0.4 | 0.2 | Remove |
| 2 | A | 0.6 | 0.8 | Remove |
| 3 | A | 0.7 | 1 | Keep |
| 4 | B | 0.6 | 0.2 | Keep |
| 5 | B | 0.8 | 1 | Keep |

# YOLO: Architecture




Source: You Only Look Once: Unified, Real-Time Object Detection
Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi (2015)




Source: You Only Look Once: Unified, Real-Time Object Detection
Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi (2015)

# Demo

YOLO V3

https://www.youtube.com/watch?v=MPU2HistivI

Source: You Only Look Once: Unified, Real-Time Object Detection
Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi (2015)

# Demo

MobileNetObjectDetection.ipynb

# Instance Segmentation Task



**Problem**
Detect object class and pixels that belong to individual instances of that class.

Source: COCO (CC BY 4.0) / Flickr

# Stuff Segmentation Task


**Problem**
Detect non-object classes and pixels that belong to image regions of that class.

# Panoptic Task

Source: COCO (CC BY 4.0) / Flickr

# Keypoint Task

Source: COCO (CC BY 4.0) / Flickr

# DensePose Dataset

Examples of Annotations

Riza, A., G., et al. (2018)

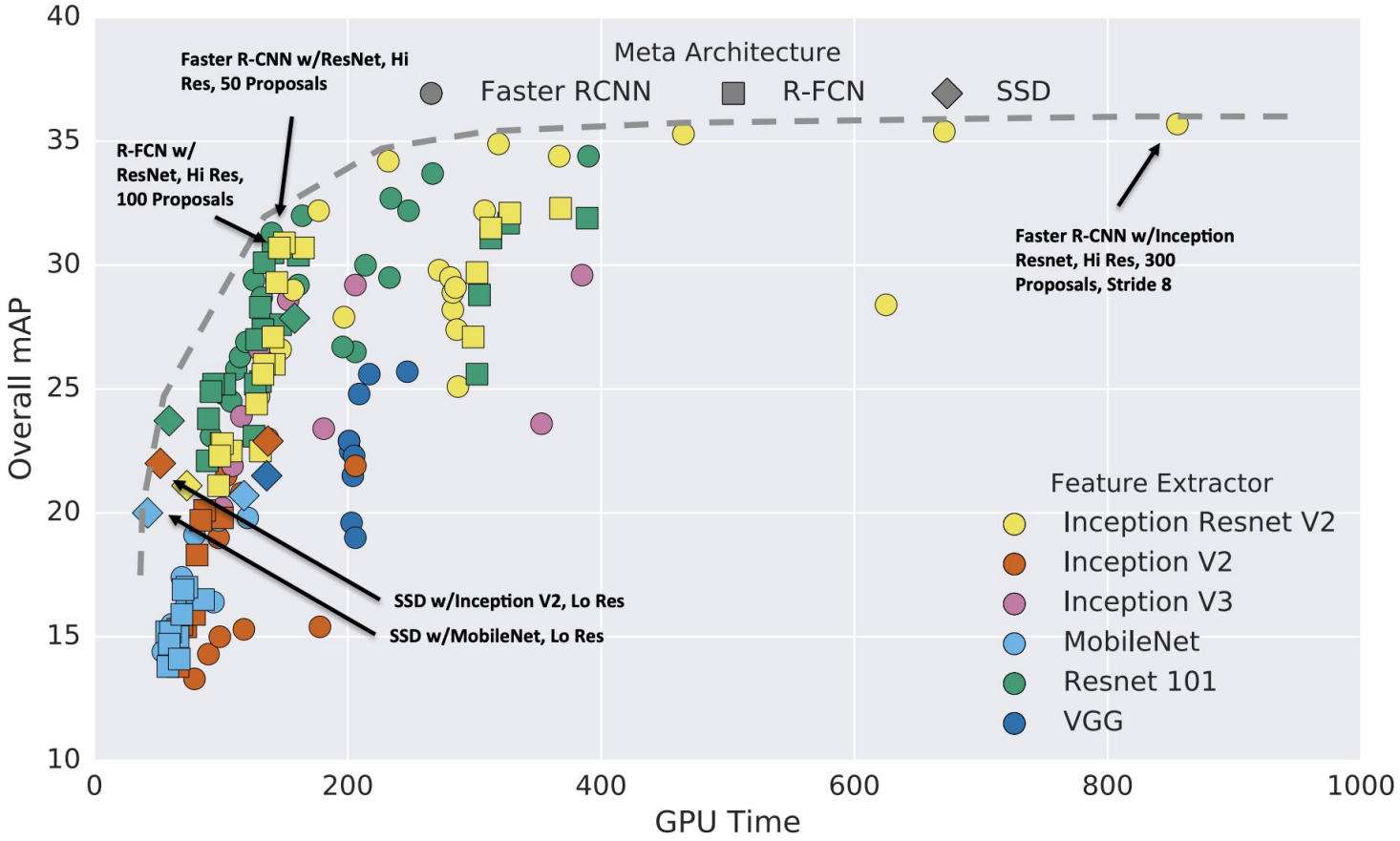
# Detectron2

Integrated Collection of Models:

- Bounding boxes
- Segmentation (Instance + Stuff)
- Keypoint
- Dense pose

Facebook AI Research
PyTorch


Facebook (2019), https://github.com/facebookresearch/detectron2




Source: Huang, J., et al (2017)

# Other Datasets

- http://host.robots.ox.ac.uk/pascal/VOC/voc2012/index.html
- https://visualgenome.org
- http://ufldl.stanford.edu/housenumbers/
- https://storage.googleapis.com/openimages/web/index.html
- http://places2.csail.mit.edu
- https://www.yf.io/p/lsun
- https://www.lvisdataset.org/

# Face Verification

**Problem**

Verify whether a previously unseen photo contains the face of a particular person.

**One Shot Learning**

**1)** None of the test persons appear in the training dataset.

**2)** Only one known photo per person in the testing dataset.

**Known Photo of Person A**

**Is this a photo of Person A?**

Source: https://thispersondoesnotexist.com/

# Face Recognition



**Known Persons**

**Problem**

Identify a person on a previously unseen photo from a list of persons with known photos.

**One Shot Learning**

**1)** None of the test persons appear in the training dataset.

**2)** Only one known photo per person in the testing dataset.

**Which known person is this photo of, if any?**

Source: https://thispersondoesnotexist.com/

# AWS Rekognition

**Product**

~ $0.001 / image

Available as a convenient API

**Features**

Object/scene detection

Face recognition and analysis

Both photo and video input

Image to text

# Demo

## AWS Rekognition

# References


1. A Survey on Deep Transfer Learning (Tan, C., et al., 2018)
2. **Deep Learning (Goodfellow, I., Bengio, Y, and Courville, A., 2016)**
3. Deep Residual Learning for Image Recognition (He, K., et al., 2015)
4. DensePose: Dense Human Pose Estimation In The Wild (Riza, A., G., et al., 2018)
5. Do Better ImageNet Models Transfer Better? (Kornblith, S, et al, 2018)
6. Going deeper with convolutions (Szegedy, C., et al., 2014)
7. ImageNet Classification with Deep Convolutional Neural Networks (Krizhevsky, A., et al., 2012)
8. Speed/accuracy trade-offs for modern convolutional object detectors (Huang, J., et al., 2017)
9. Very Deep Convolutional Networks for Large-Scale Image Recognition (Simonyan, K., and Zisserman, A., 2015)
10. You Only Look Once: Unified, Real-Time Object Detection (Redmon, J., et al., 2016)

# Thanks

+ Q&A Time

(Image by a Stable Diffusion model)