# Convolutional Neural Networks (CNNs)

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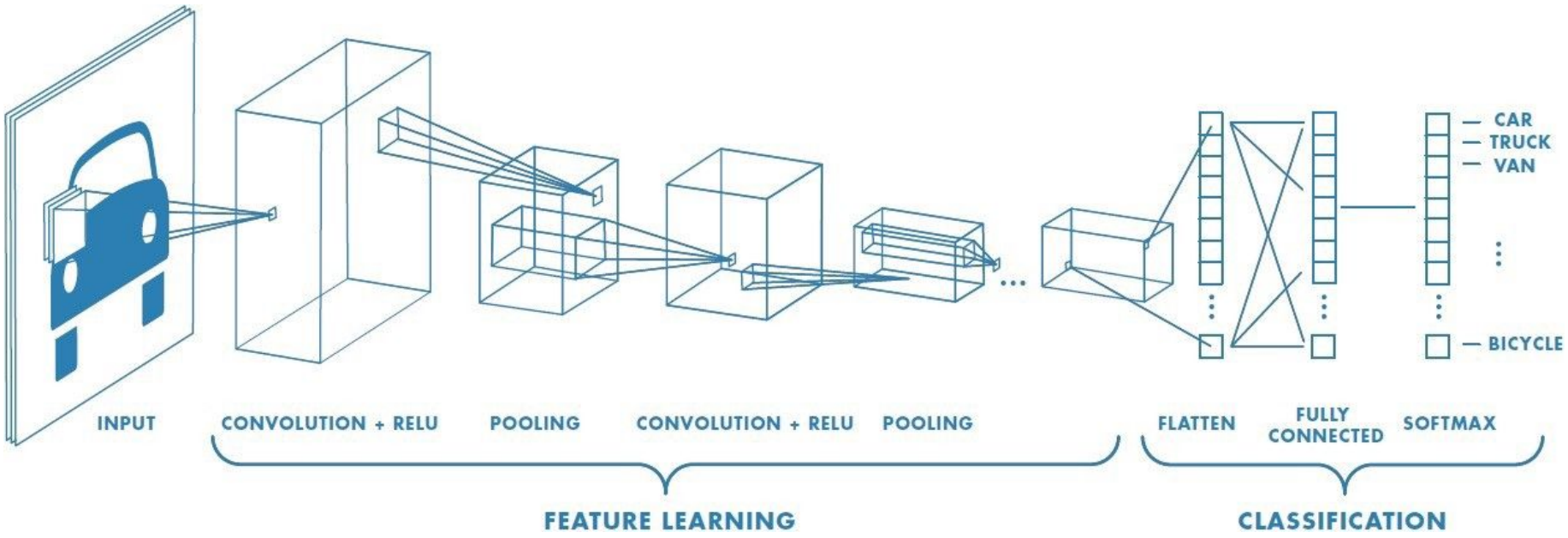
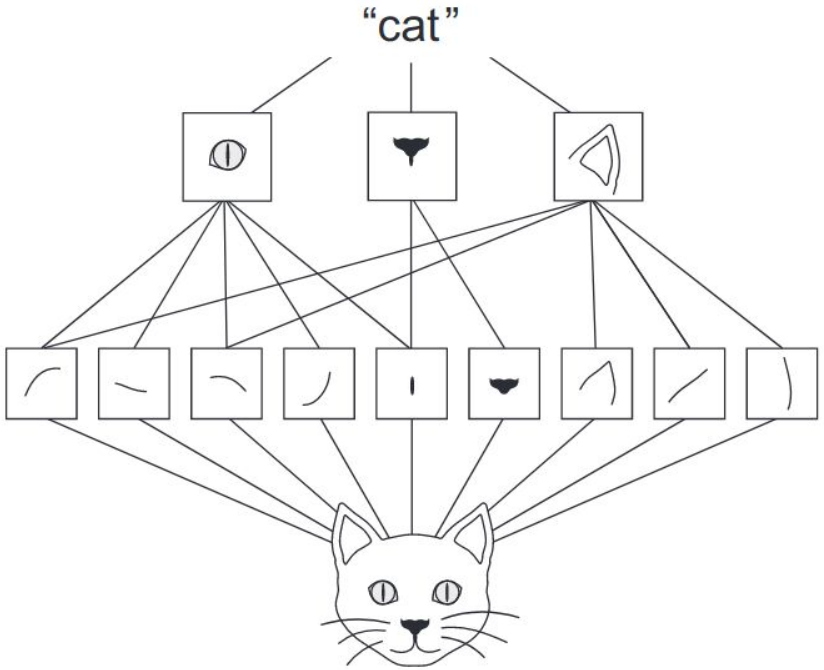
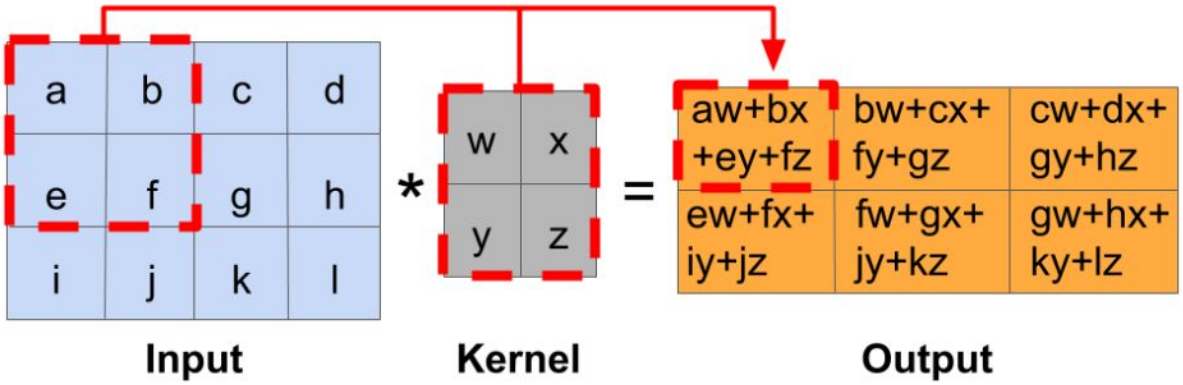


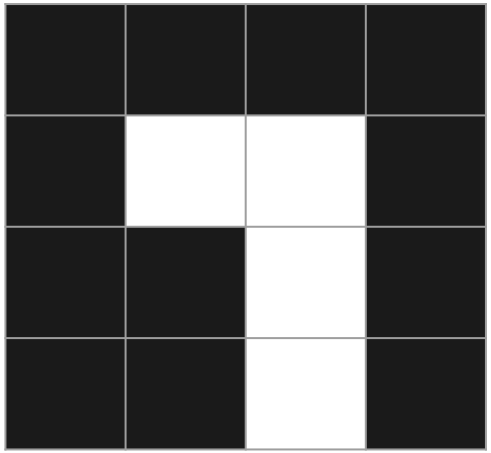

“cat”

# Convolution




Fuente: Bengio, Goodfellow y Courville (2016)

# Convolution



| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

# Convolution

Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

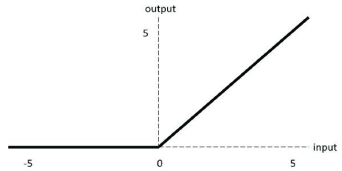
| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

# Convolution

Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

ReLU




Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

Output (3x3)

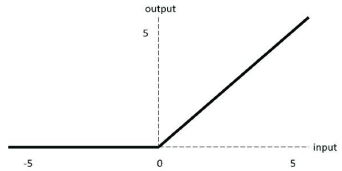
| | | |
|---|---|---|
| 1 | | |
| | | |
| | | |

# Convolution

Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

ReLU




Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

Output (3x3)

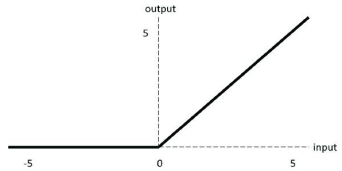
| | | |
|---|---|---|
| 1 | 1 | |
| | | |
| | | |

# Convolution

Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

ReLU




Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| | | |
| | | |

# Convolution

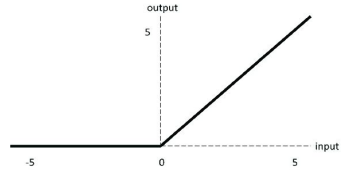
Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

ReLU




Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | | |
| | | |

# Convolution

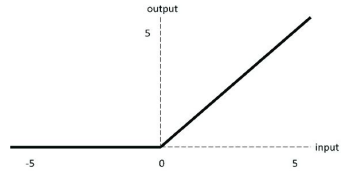
Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

ReLU




Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 3 | |
| | | |

# Convolution

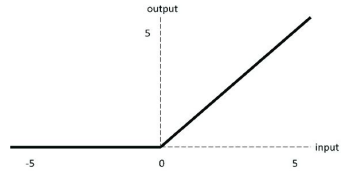
Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

ReLU




Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 3 | 1 |
| | | |

# Convolution

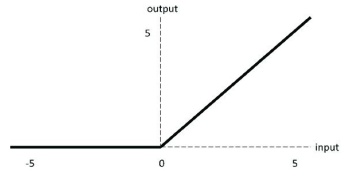
Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

ReLU




Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 3 | 1 |
| 0 | | |

# Convolution

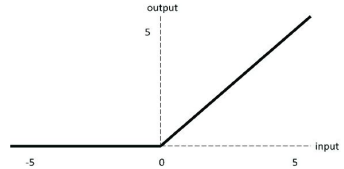
Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

ReLU




Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 3 | 1 |
| 0 | 2 | |

# Convolution

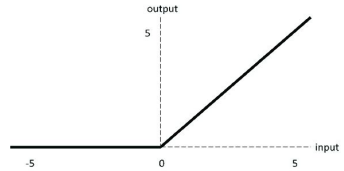
Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

ReLU




Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 3 | 1 |
| 0 | 2 | 1 |

# Convolution

Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

Output (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 3 | 1 |
| 0 | 2 | 1 |

# Max-Pooling (2x2)

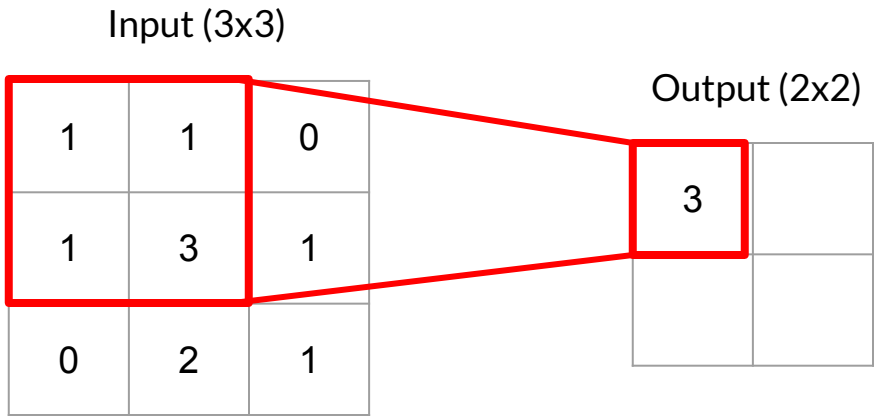
Input (3x3)

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 1 | 3 | 1 |
| 0 | 2 | 1 |

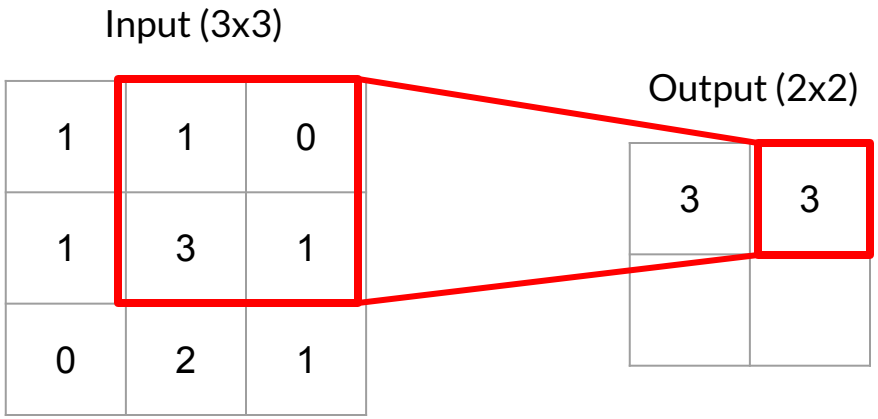
Output (2x2)

| | |
|---|---|
| | |
| | |

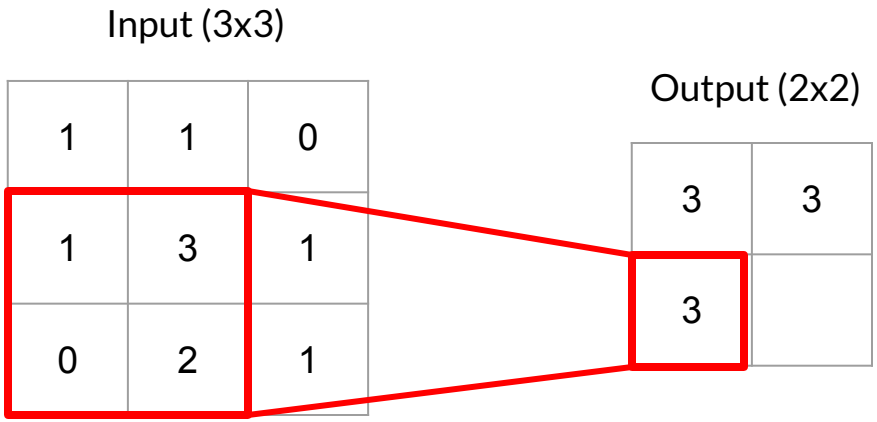
# Max-Pooling (2x2)



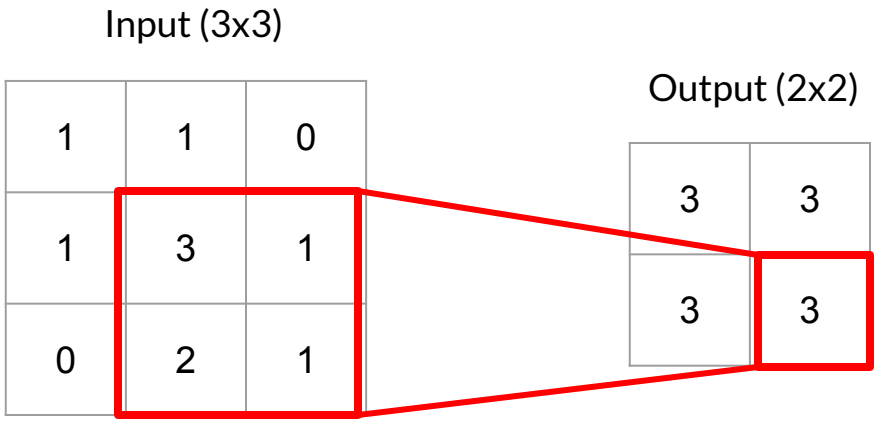
# Max-Pooling (2x2)



# Max-Pooling (2x2)



# Max-Pooling (2x2)



# Convolution

Kernel (2x2)

| | |
|---|---|
| 1 | 1 |
| 0 | 1 |

Input (4x4)

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 |

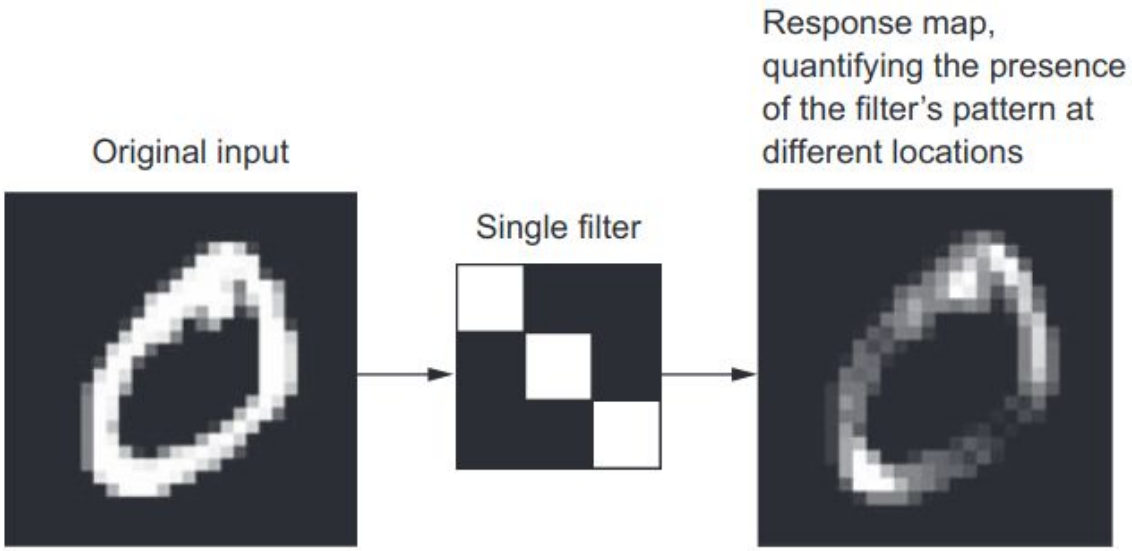
Conv.

Max-Pooling (2x2)

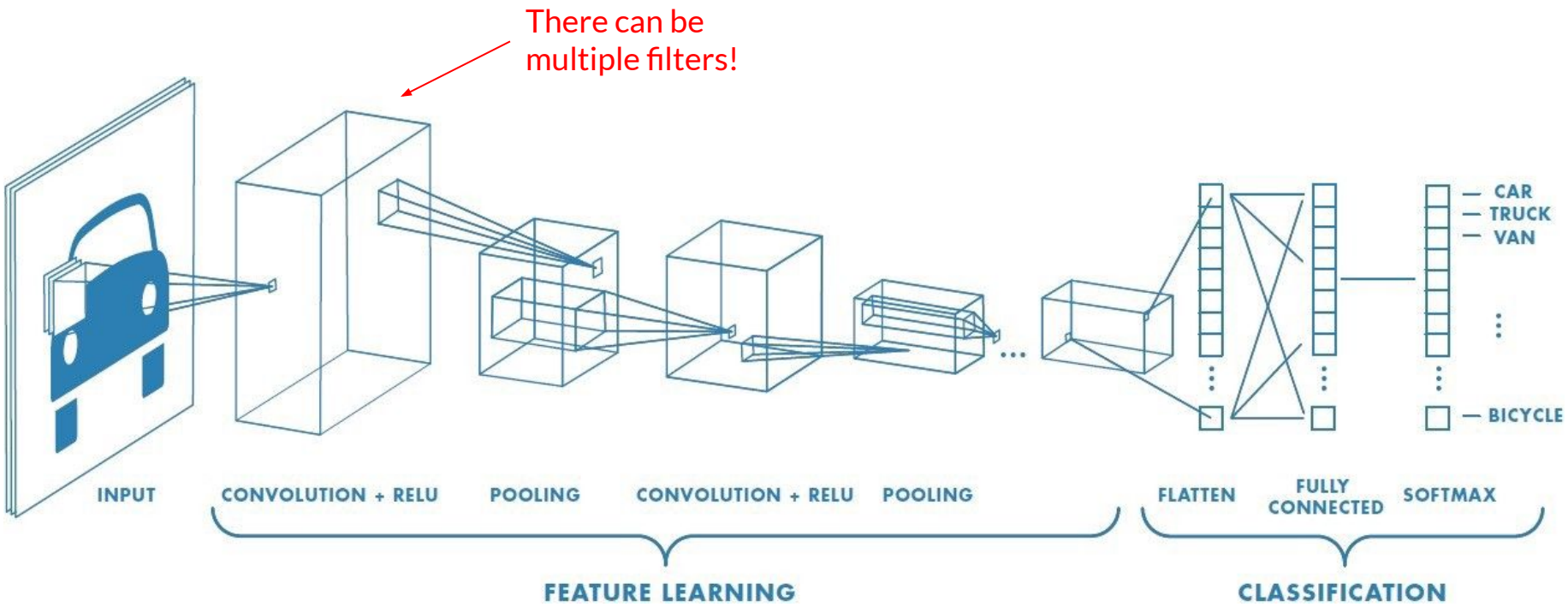
Output (2x2)

| | |
|---|---|
| 3 | 3 |
| 3 | 3 |

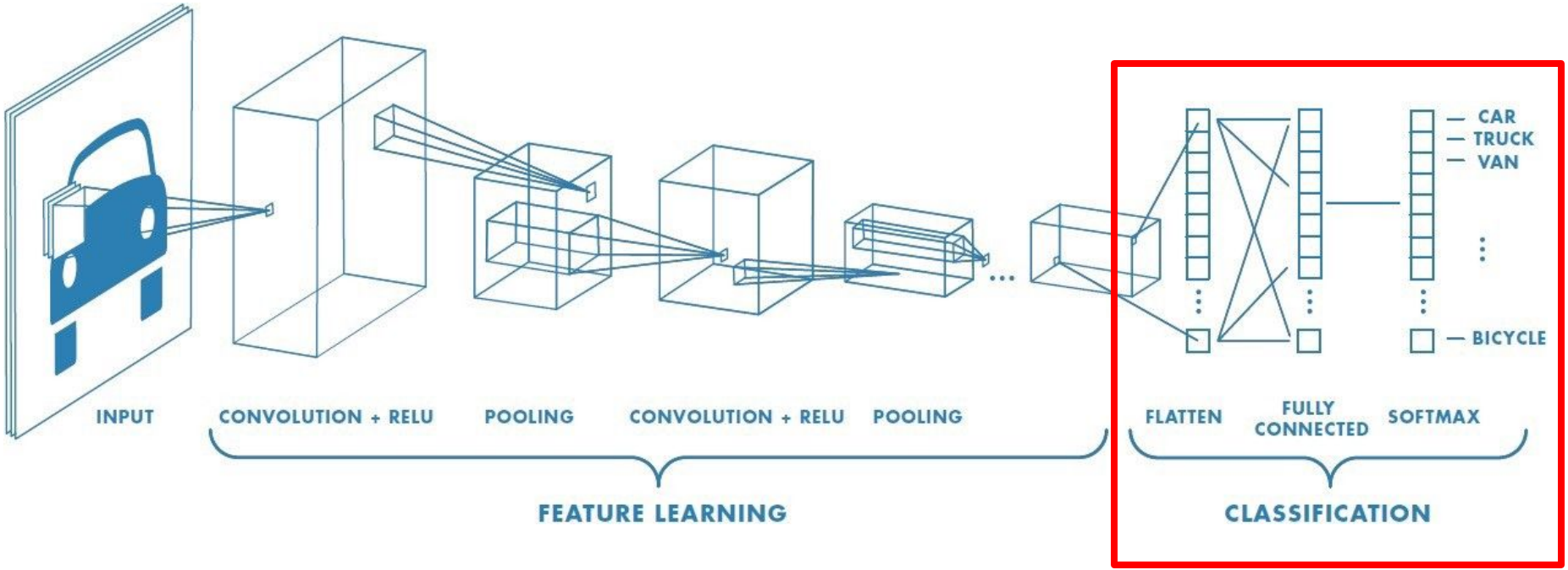
# Convolution



# Convolutional Neural Networks (CNNs)



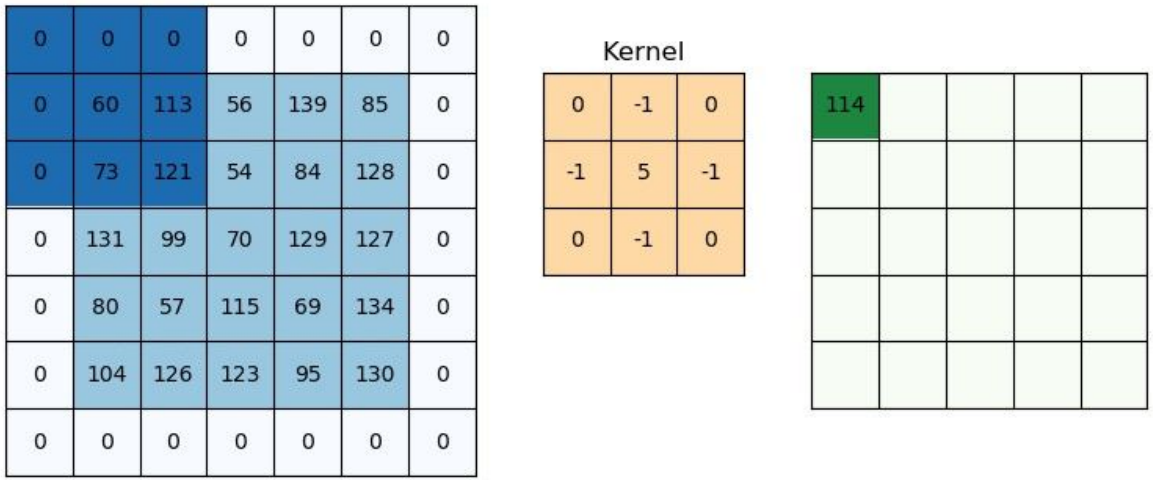
# Convolutional Neural Networks (CNNs)



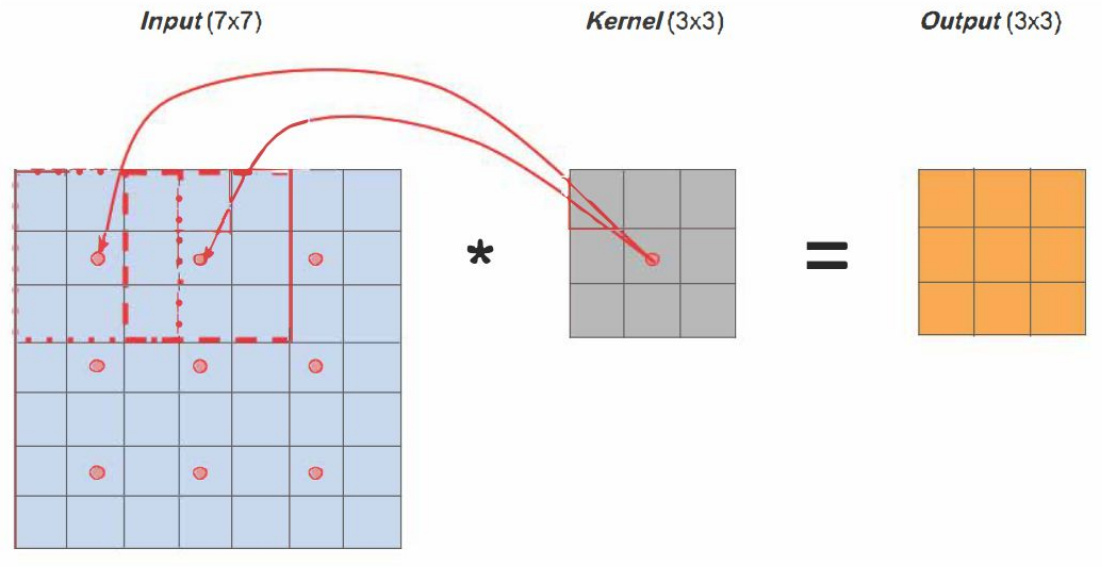
# Convolution

https://adamharley.com/nn_vis/cnn/2d.html

# Padding


0 0 0 0 0 0 0
0 60 113 56 139 85 0
0 73 121 54 84 128 0
0 131 99 70 129 127 0
0 80 57 115 69 134 0
0 104 126 123 95 130 0
0 0 0 0 0 0 0
Kernel
0 -1 0
-1 5 -1
0 -1 0
114

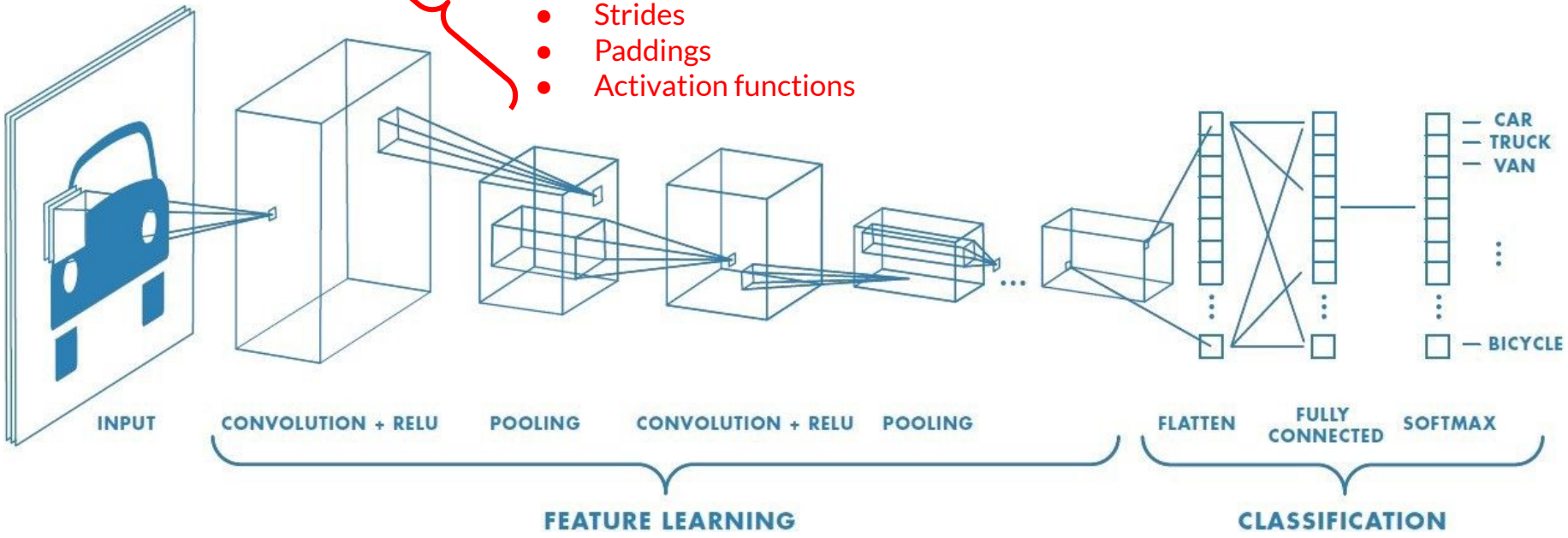
# Stride = 2



# Convolutional Neural Networks (CNNs)

**Convolution**

- Num. Kernels
- Kernel sizes
- Strides
- Paddings
- Activation functions

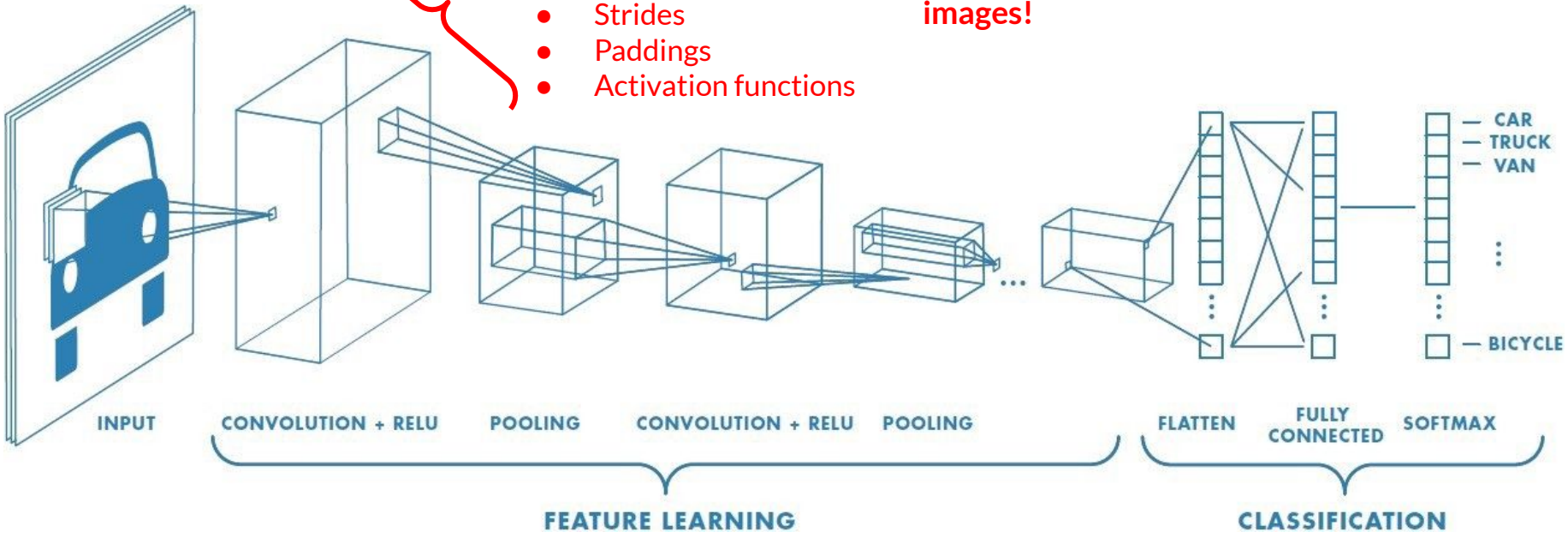


# Convolutional Neural Networks (CNNs)

**Convolution**

- Num. Kernels
- Kernel sizes
- Strides
- Paddings
- Activation functions

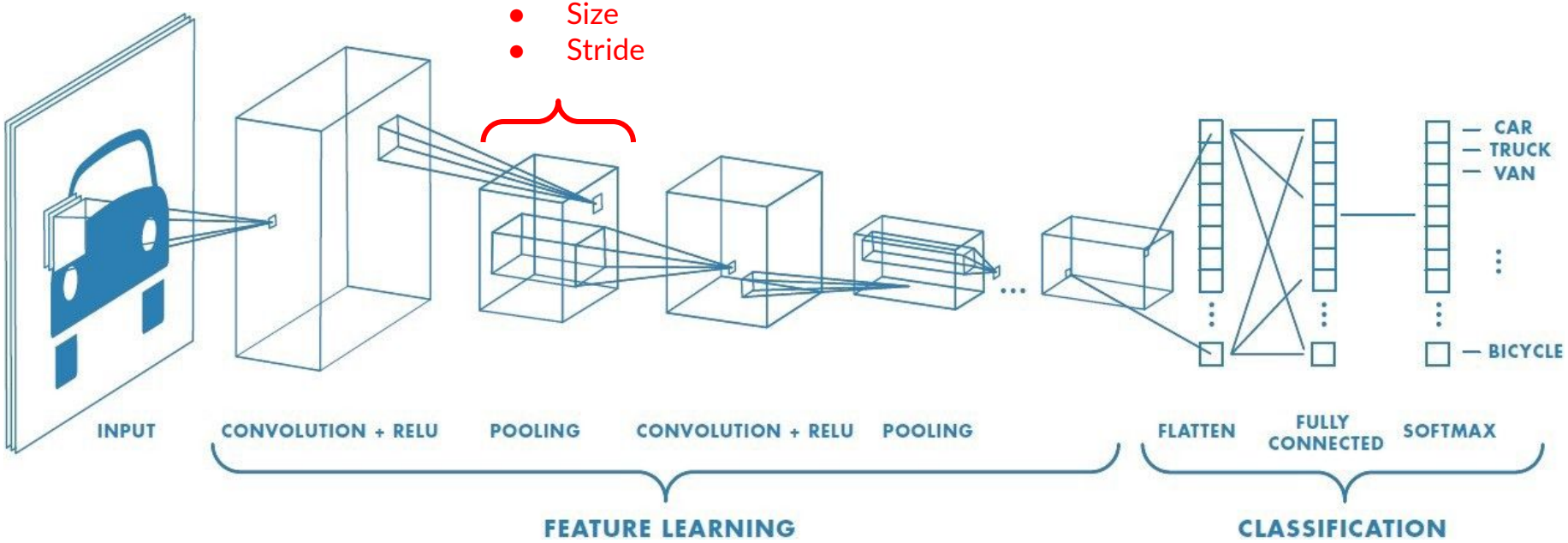
**NN learns best kernel values for predicting supervised images!**



# Convolutional Neural Networks (CNNs)

**Pooling**

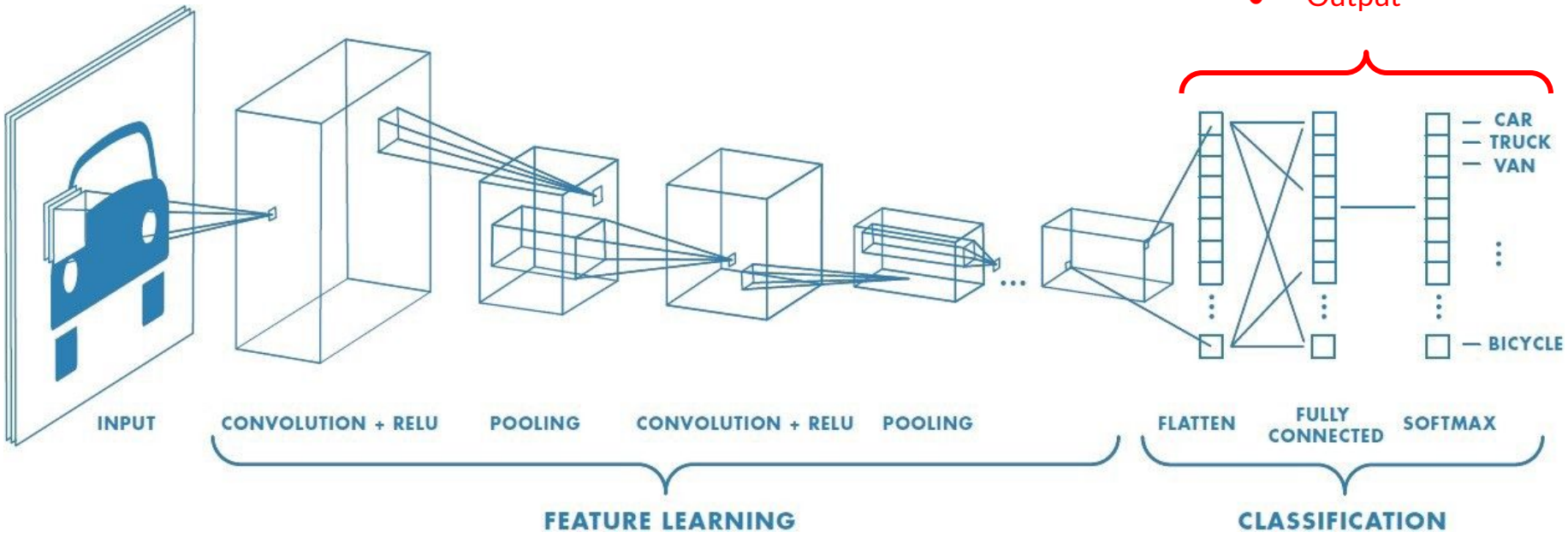
- Type
- Size
- Stride



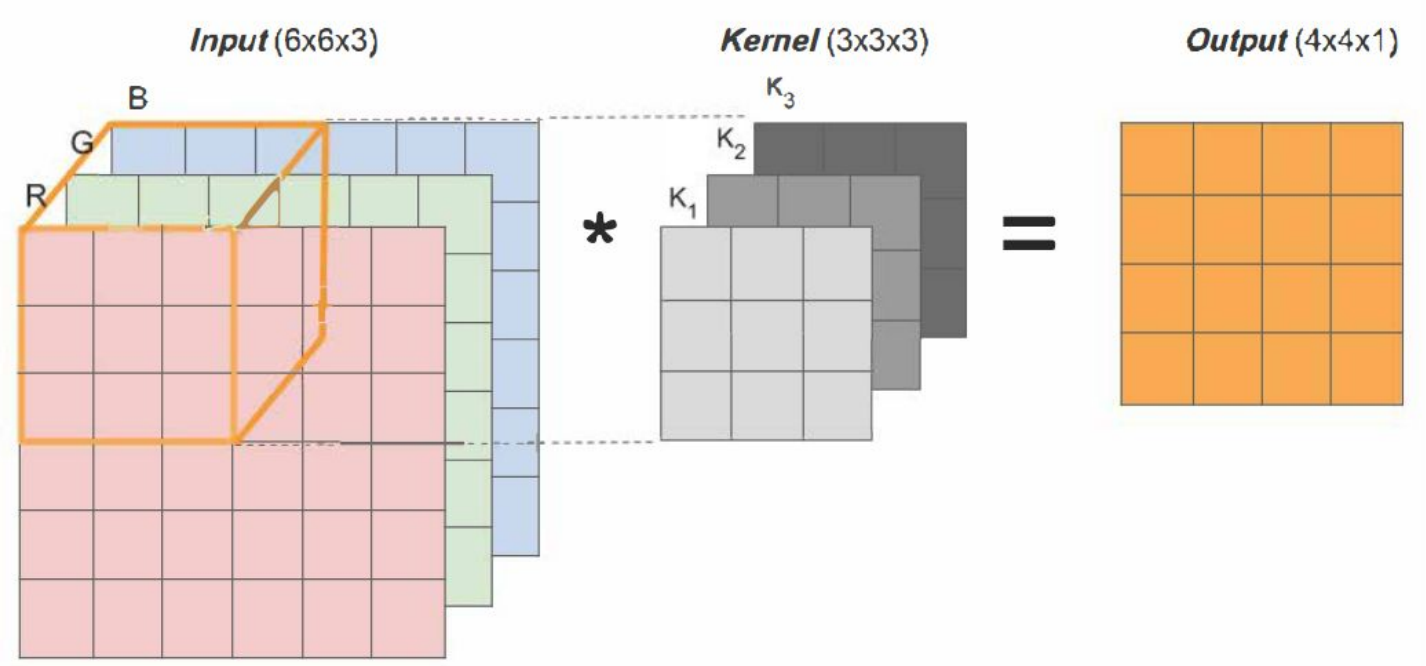
# Convolutional Neural Networks (CNNs)

**FC**

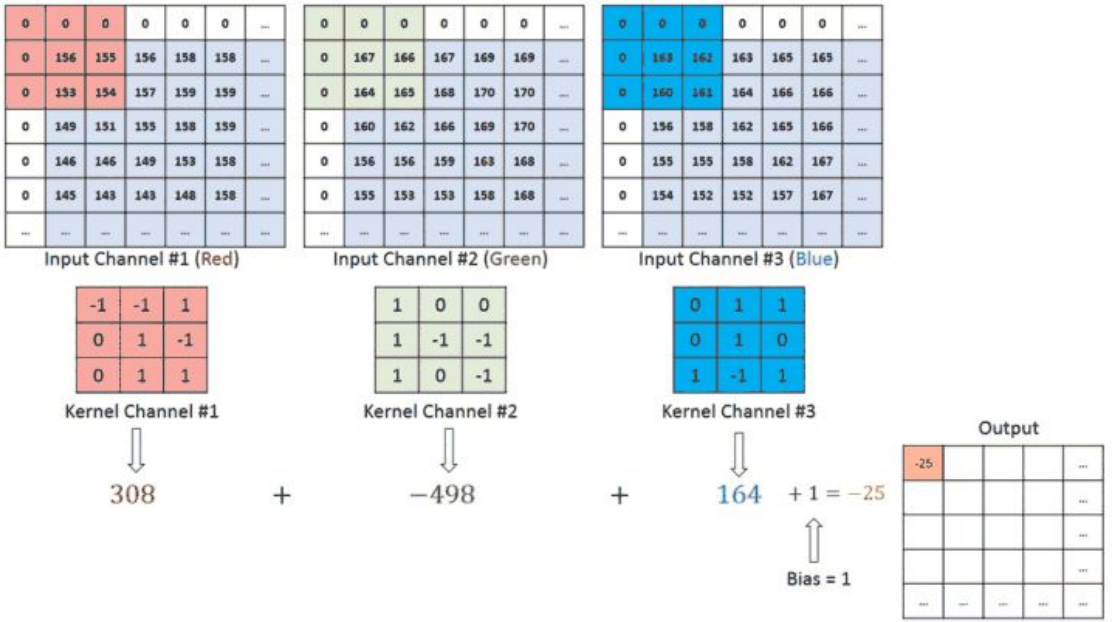
- Num. layers
- Num. neurons
- Activations
- Output



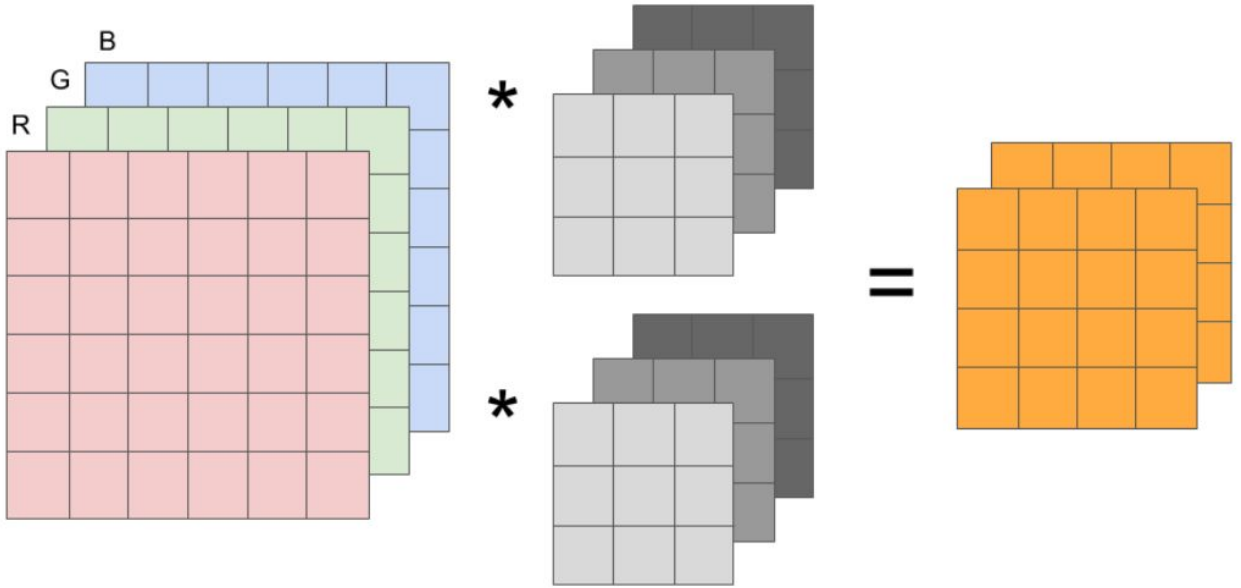
# RGB Convolution



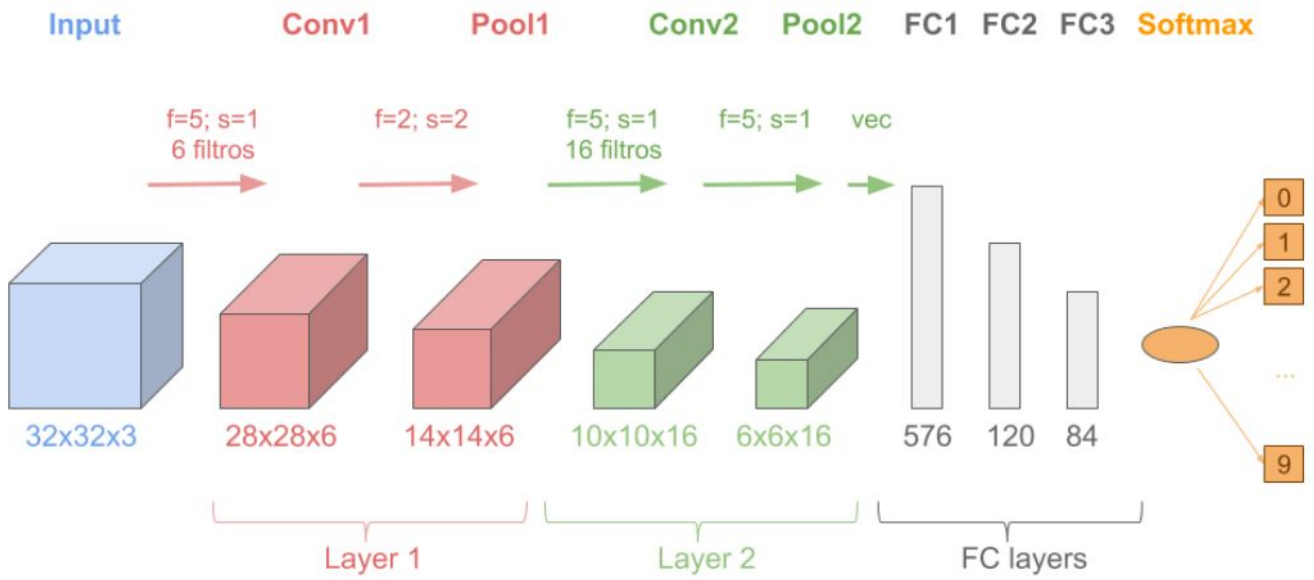
# RGB Convolution



# RGB Convolution



# Inspired in LeNet-5




Fuente: LeCun y col. (1989)

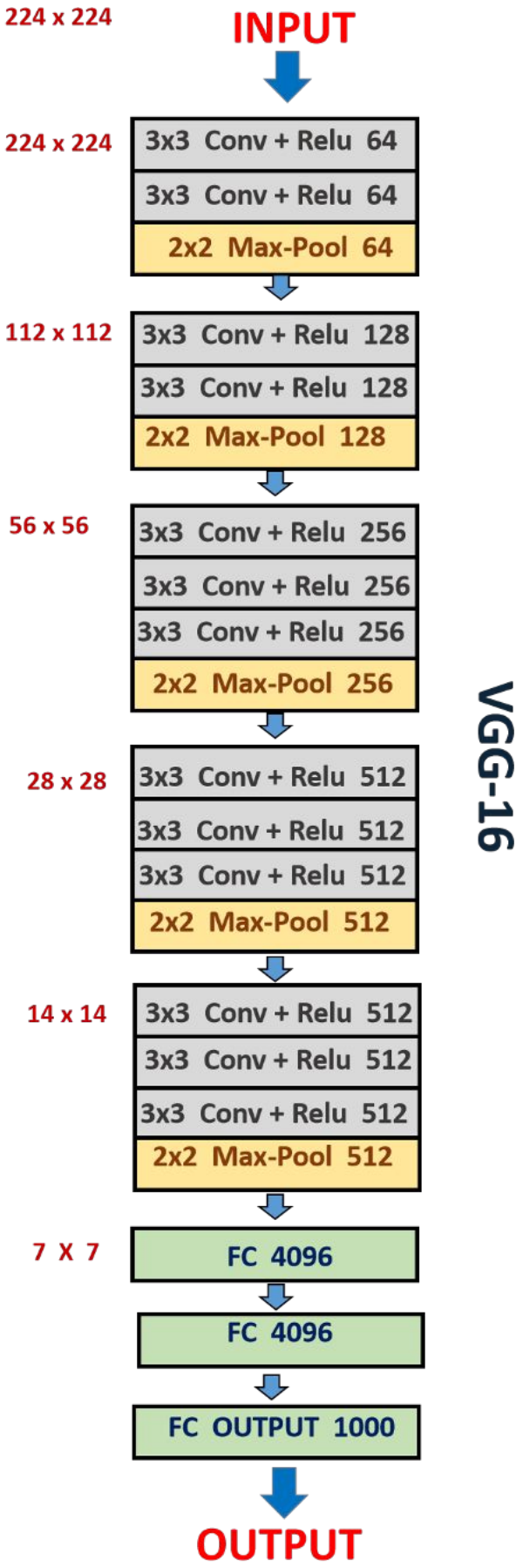
# Famous CNN architectures

| Model name | Number of parameters [Millions] | ImageNet Top 1 Accuracy | Year |
|---|---|---|---|
| AlexNet | 60 M | 63.3 % | 2012 |
| Inception V1 | 5 M | 69.8 % | 2014 |
| VGG 16 | 138 M | 74.4 % | 2014 |
| VGG 19 | 144 M | 74.5 % | 2014 |
| Inception V2 | 11.2 M | 74.8 % | 2015 |
| ResNet-50 | 26 M | 77.15 % | 2015 |
| ResNet-152 | 60 M | 78.57 % | 2015 |
| Inception V3 | 27 M | 78.8 % | 2015 |
| DenseNet-121 | 8 M | 74.98 % | 2016 |
| DenseNet-264 | 22M | 77.85 % | 2016 |
| BiT-L (ResNet) | 928 M | 87.54 % | 2019 |
| NoisyStudent EfficientNet-L2 | 480 M | 88.4 % | 2020 |
| Meta Pseudo Labels | 480 M | 90.2 % | 2021 |

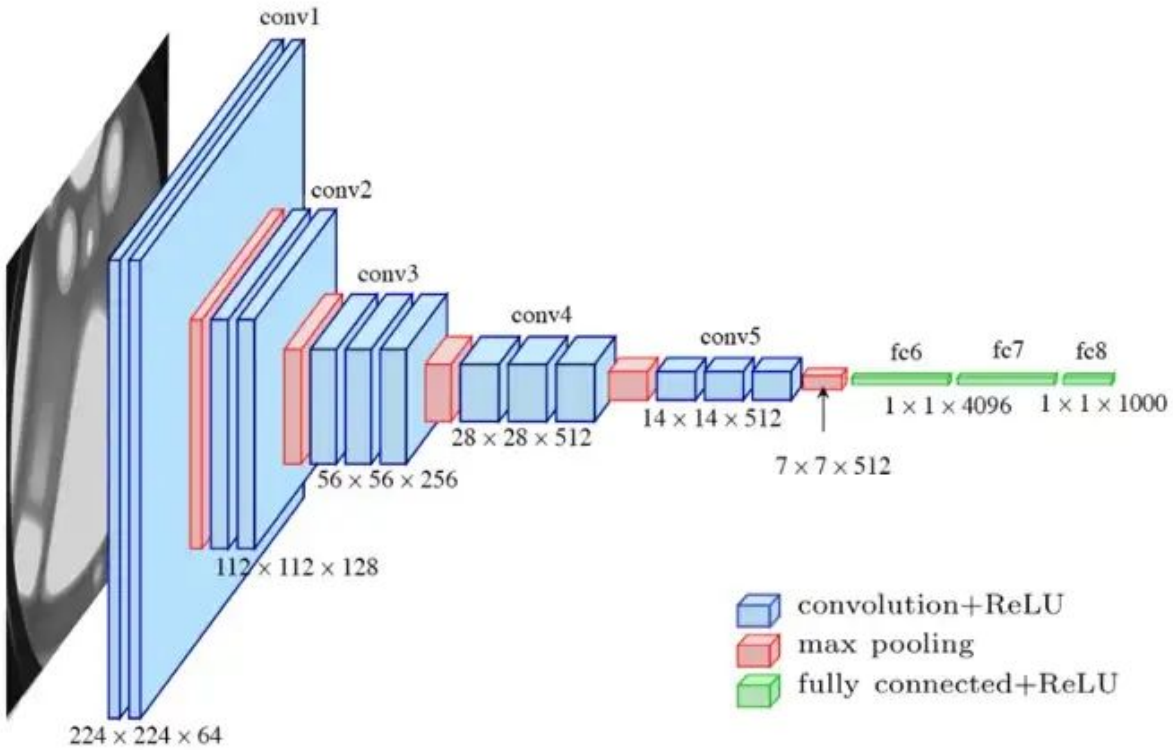
# Famous CNN architectures

https://theaisummer.com/cnn-architectures/

https://keras.io/api/applications/


224 x 224
INPUT
224 x 224
3x3 Conv + Relu 64
3x3 Conv + Relu 64
2x2 Max-Pool 64
112 x 112
3x3 Conv + Relu 128
3x3 Conv + Relu 128
2x2 Max-Pool 128
56 x 56
3x3 Conv + Relu 256
3x3 Conv + Relu 256
3x3 Conv + Relu 256
2x2 Max-Pool 256
28 x 28
3x3 Conv + Relu 512
3x3 Conv + Relu 512
3x3 Conv + Relu 512
2x2 Max-Pool 512
14 x 14
3x3 Conv + Relu 512
3x3 Conv + Relu 512
3x3 Conv + Relu 512
2x2 Max-Pool 512
7 X 7
FC 4096
FC 4096
FC OUTPUT 1000
OUTPUT
VGG-16

# VGG-16


conv1
conv2
conv3
conv4
conv5
fc6
fc7
fc8
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
convolution+ReLU
max pooling
fully connected+ReLU

# Building CNNs – Recommendations

- Number of kernels
  - Small number in the first layers and increase it as you go deeper.
    - Early layers capture simple patterns and then you combine these in deeper layers.
  - Starting with 32 or 64 filters is common.

# Building CNNs – Recommendations

- Kernel sizes
  - 3x3 and 5x5 are common options.
  - Smaller are usually preferred for capturing more specific details.
  - Sometimes, large kernels (e.g. 7x7) in the first layers for capturing general patterns.

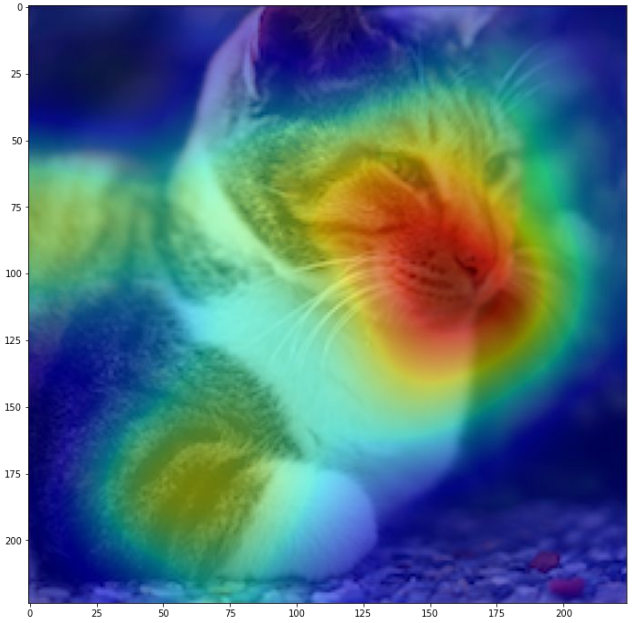
# Building CNNs – Recommendations

- Pooling layers
  - Generally used for reducing dimensions.
  - Using too many can imply losing valuable information.
  - 2x2 is very common, with greater poolings you risk losing valuable information.

# Building CNNs – Recommendations

- Stride
  - A stride of 1 is common in convolutional layers.
  - A stride of 2 is common in pooling layers for reducing the dimensions of the image.

# Interpretability




# Misleading classification

“panda”

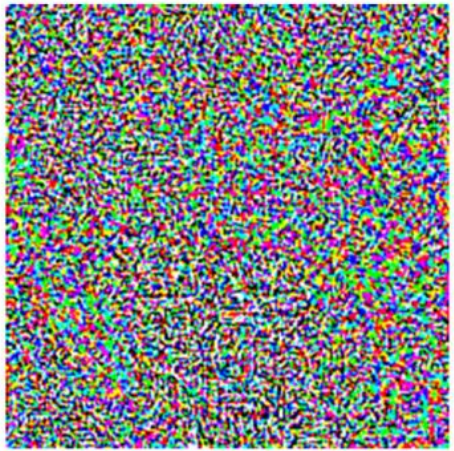
57.7% confidence

# Misleading classification

“panda”

57.7% confidence

$+ .007 \times$



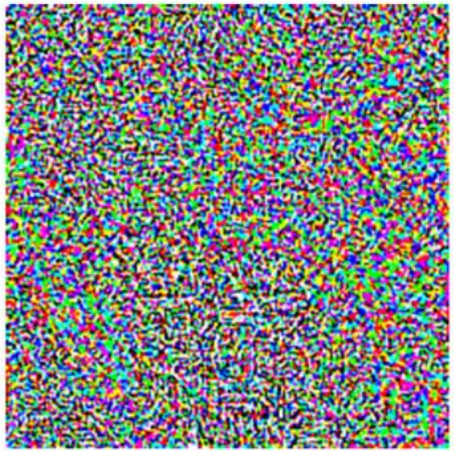
$=$

“gibbon”

99.3% confidence


# Misleading classification

$+ .007 \times$



$=$

“panda”

57.7% confidence

“gibbon”

99.3% confidence

# Resources

- https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-convolutional-neural-networks