Transfer Learning and Hybrid Machine Learning and Deep Learning

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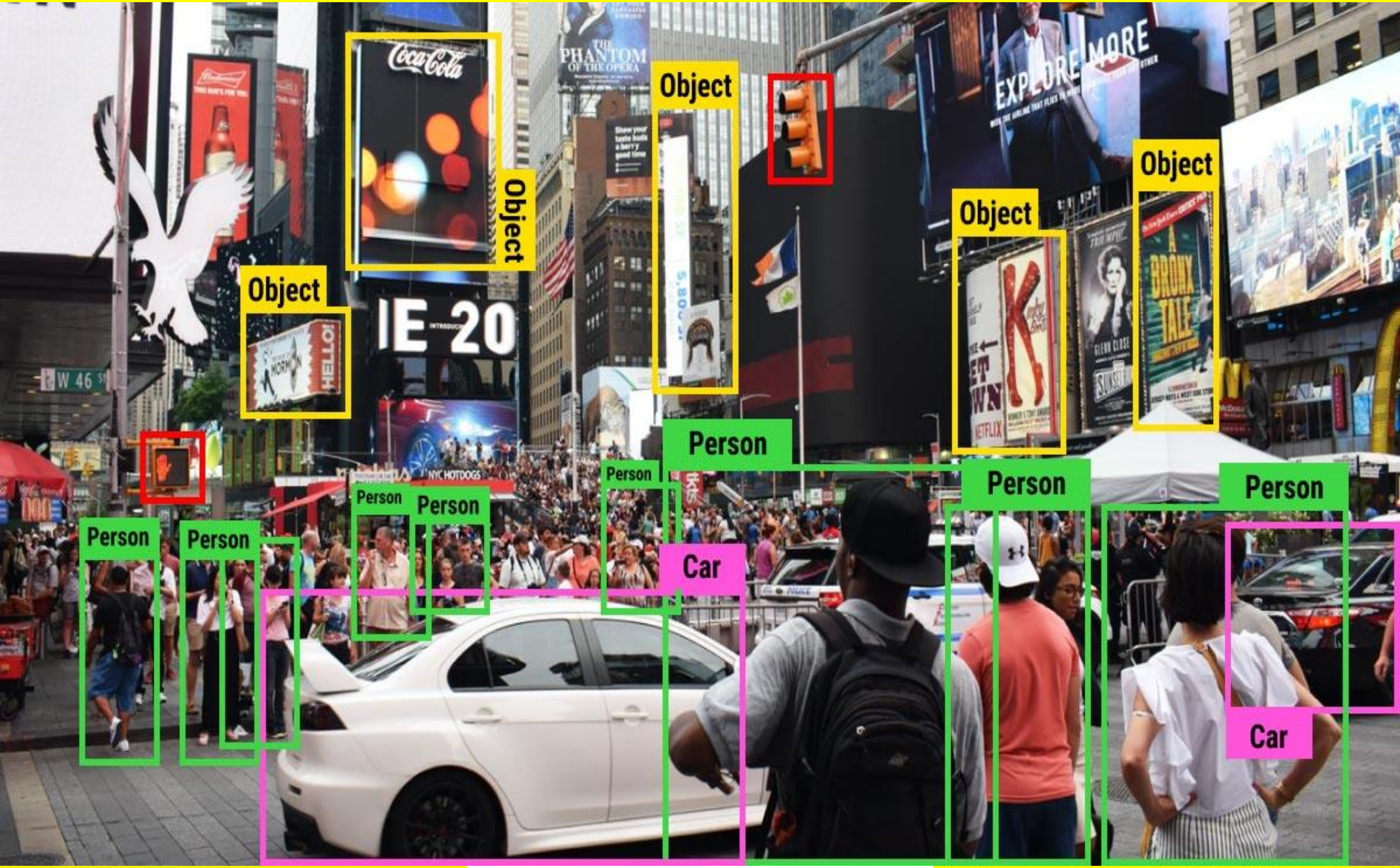
MOTIVATION

MOTIVATION


Object
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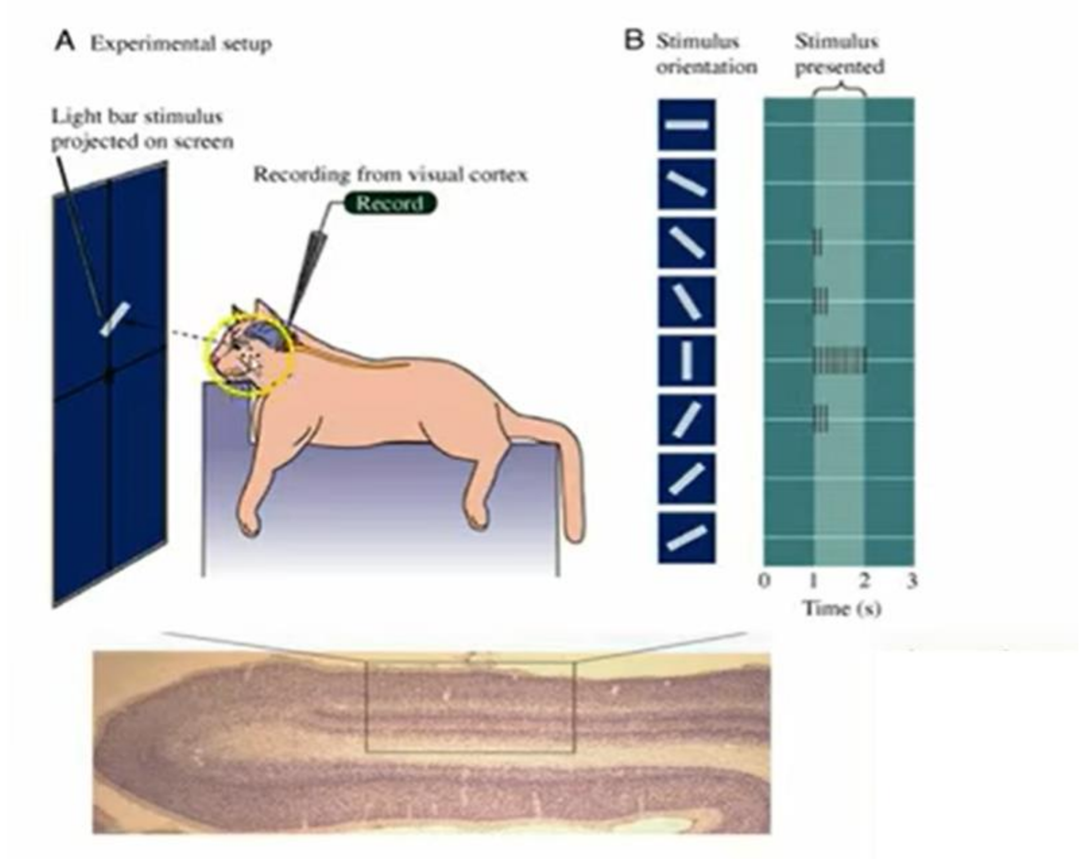
MOTIVATION


Object Tracking
Pose Estimation
Object Detection
Action Recognition
Autonomous Navigation
3D Reconstruction
Crowd Understanding
Urban Scene Understanding
Indoor Scene Understanding
Multi-agent Collaboration
Human Training
Aerial Surveying
Image
Image Label
Depth/Multi-View
User Input
Video
Physics
Segmentation/Bounding Box
Camera Localization

CONVOLUTIONAL NEURAL NETWORKS

- Popularly called **as CNN or Convnets.**
- https://en.wikipedia.org/wiki/David_H._Hubel#Research
- https://www.youtube.com/watch?v=v20-E_2bT2c
- **Hubel and Wiesel** received the Nobel Prize.



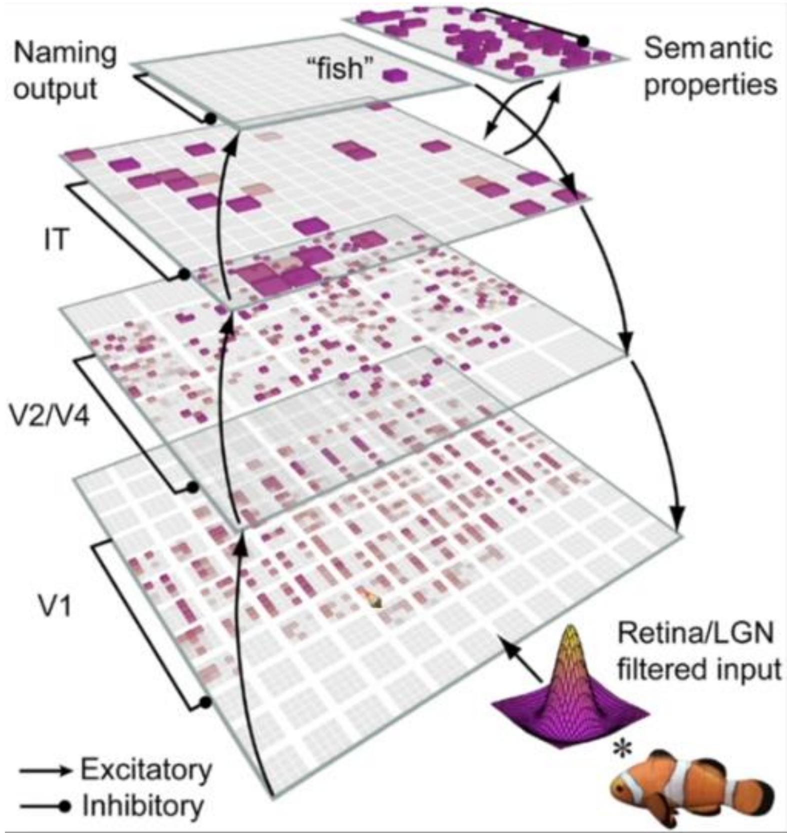
KEY FINDINGS

- Some neurons in the visual cortex fires when lines at specific angle is presented.
- There is a special region called ***primary visual cortex that detects edges***.
- There are some more complex neurons that detect motion, depth, color, shapes, complex edges like faces.

Functional specialization

Match each visual area to its corresponding function:

V1	Motion / **Edges**
V2	Stereo
V3	Color
V3a	Texture segregation
V3b	Segmentation, grouping
V4	Recognition
V7	Face recognition
MT	Attention
MST	Working memory/mental imagery
etc	Etc.



CONVOLUTION: EDGE DETECTION

We detect edges by applying Convolution operator on the i/p image.

Gray Scale Image
(6X6)

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

*

Sobel Horizontal Edge Detector/ Kernel

1	2	1
0	0	0
-1	-2	-1

Convolution

Kernel / Filter / Mask / Operator

CONVOLUTION: EDGE DETECTION

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

A

*

1	2	1
0	0	0
-1	-2	-1

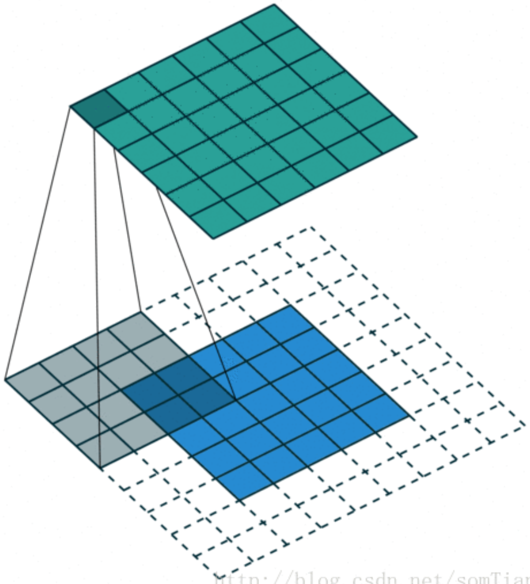
K

=

0	0	0	0
-1020	-1020	-1020	-1020
-1020	-1020	-1020	-1020
0	0	0	0

R

0*1 + 0*2 + 0*1 +
0*0 + 0*0 + 0*0 +
-1*0 + -2*0 + -1*0 +
= 0



CONVOLUTION: EDGE DETECTION

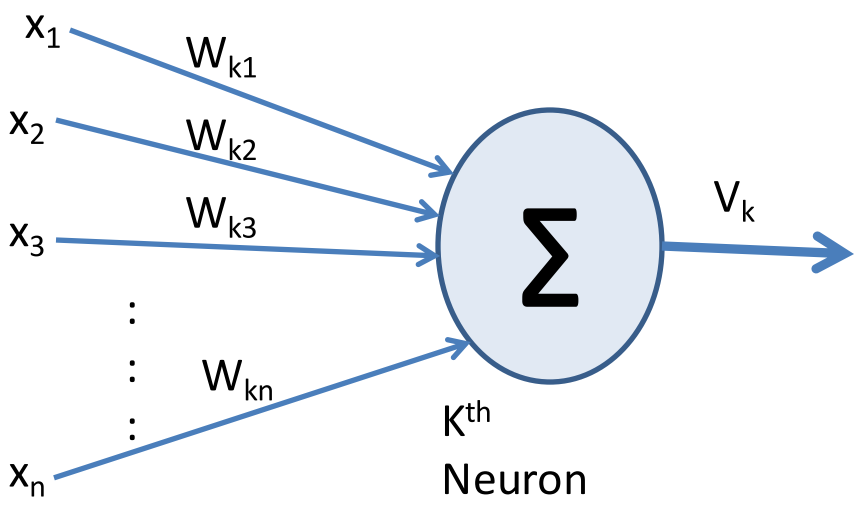
0	0	0	0
-1020	-1020	-1020	-1020
-1020	-1020	-1020	-1020
0	0	0	0

Normalization

255	255	255	255
0	0	0	0
0	0	0	0
255	255	255	255

CONVOLUTION: EDGE DETECTION

- Convolution is a generalization of a dot product.
- We can achieve it through the operation of a neuron in the neural network.



$$V_k = W_{k1} * x_1 + W_{k2} * x_2 + W_{k3} * x_3 + \ldots + W_{kn} * x_n$$

CONVOLUTION: EDGE DETECTION

- Sobel Kernel
  - Horizontal can detect Horizontal Edge
  - Vertical can detect Vertical Edge

- Kernels can be of any size Typically a square matrix.

Sobel Vertical Edge Detector/ Kernel

1	0	-1
2	0	-2
1	0	-1

CONVOLUTION: EDGE DETECTION

Formulation [edit]

The operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives – one for horizontal changes, and one for vertical. If we define **A** as the source image, and $\mathbf{G}_x$ and $\mathbf{G}_y$ are two images which at each point contain the horizontal and vertical derivative approximations respectively, the computations are as follows:[2]

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \quad \text{and} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

where $*$ here denotes the 2-dimensional signal processing convolution operation.

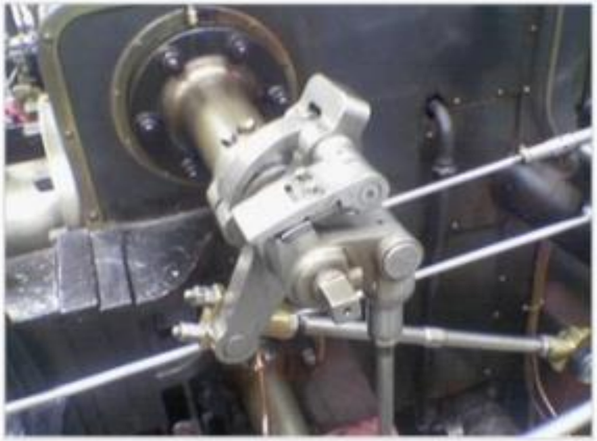
Since the Sobel kernels can be decomposed as the products of an averaging and a differentiation kernel, they compute the gradient with smoothing. For example, $\mathbf{G_x}$ can be written as

$$\begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} +1 & 0 & -1 \end{bmatrix}$$

The x-coordinate is defined here as increasing in the "right"-direction, and the y-coordinate is defined as increasing in the "down"-direction. At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using:

$$\mathbf{G} = \sqrt{{\mathbf{G}_x}^2 + {\mathbf{G}_y}^2}$$

Using this information, we can also calculate the gradient's direction:



A color picture of a steam engine

The Sobel operator applied to that image

MOTIVATION FOR PADDING

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

*

1	2	1
0	0	0
-1	-2	-1

=

0	0	0	0
-1020	-1020	-1020	-1020
-1020	-1020	-1020	-1020
0	0	0	0

- By Performing Convolution operation using 3 X 3 matrix on an input image of 6X6, We have got a 4X4 result.
- By Performing Convolution operation using **K** X **K** matrix (filter) on an input image of **N** X **N**, We have got a **N-K+1** X **N-K+1** result.
- This results in reduction in Dimension.
- How not to reduce the dimension of the original Image.

PADDING

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

*

1	2	1
0	0	0
-1	-2	-1

=

0	0	0	0
-1020	-1020	-1020	-1020
-1020	-1020	-1020	-1020
0	0	0	0

0	0	0	0	0	0
0	0	0	0	0	0
0	-1020	-1020	-1020	-1020	0
0	-1020	-1020	-1020	-1020	0
0	0	0	0	0	0
0	0	0	0	0	0

– This can be achieved by padding 1 row and 1 column of zeros around the resultant matrix. **This is called padding by 1.**

PADDING

- If you add Zero in padding it is called Zero Padding. (Extensively Used because of Simplicity)

- You can do same value padding.

- Padding ***m*** results in ***n+2m*** size

0	0	0	0	0	0
0	0	0	0	0	0
0	-1020	-1020	-1020	-1020	0
0	-1020	-1020	-1020	-1020	0
0	0	0	0	0	0
0	0	0	0	0	0

0	0	0	0	0	0
0	0	0	0	0	0
1020	-1020	-1020	-1020	-1020	1020
1020	-1020	-1020	-1020	-1020	1020
0	0	0	0	0	0
0	0	0	0	0	0

STRIDE

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

A

*

1	2	1
0	0	0
-1	-2	-1

K

=

0	0	0	0
-1020	-1020	-1020	-1020
-1020	-1020	-1020	-1020
0	0	0	0

R

Stride 1= Shift by 1 column/row

STRIDE

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

A

*

1	2	1
0	0	0
-1	-2	-1

K

=

0	0	0	0
-1020	-1020	-1020	-1020
-1020	-1020	-1020	-1020
0	0	0	0

R

Stride 2= Shift by 2 column/row

STRIDE

A

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
255	255	255	255	255	255
255	255	255	255	255	255
255	255	255	255	255	255

*

K

1	2	1
0	0	0
-1	-2	-1

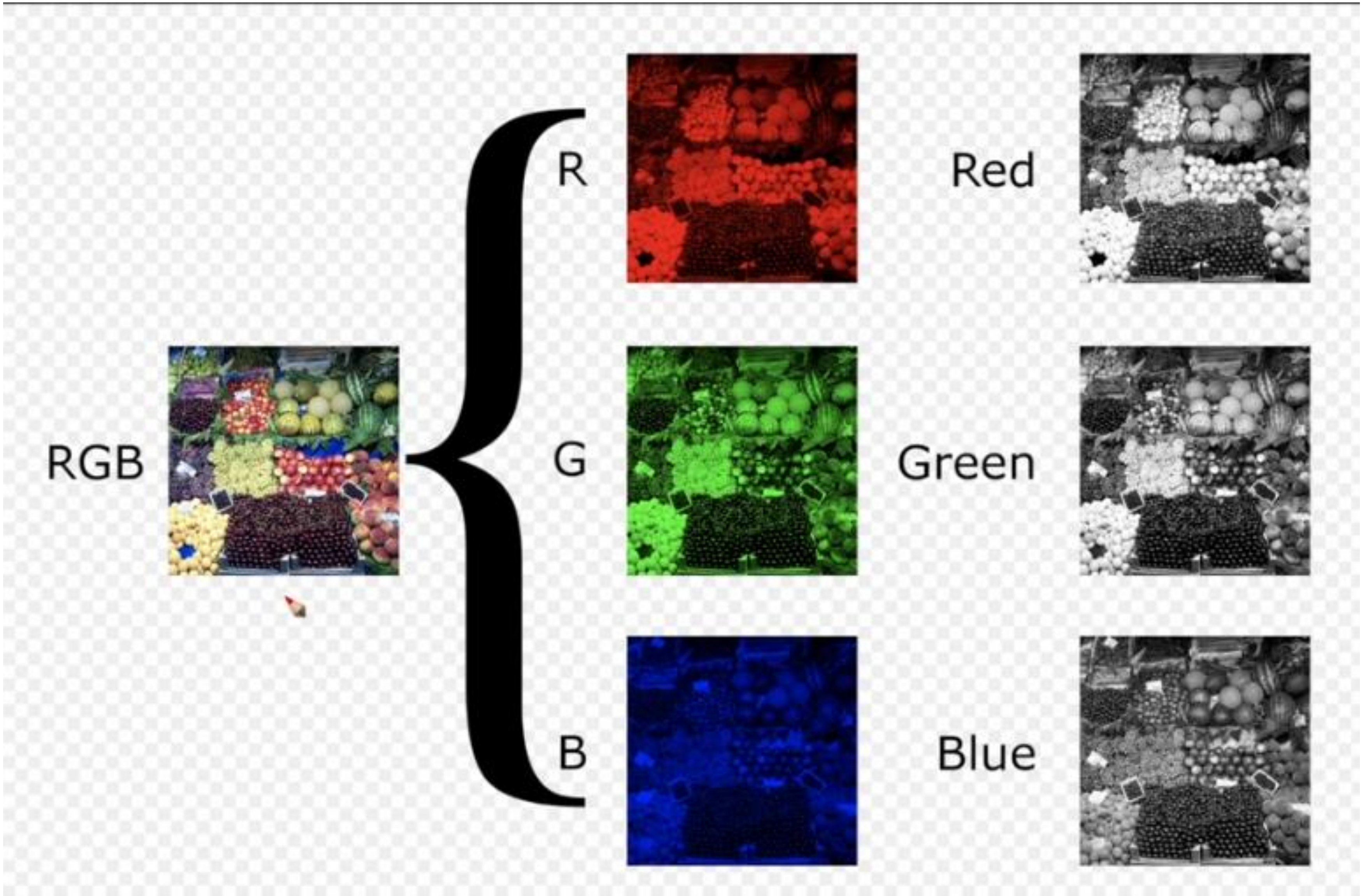
=

R

0	0	0	0
-1020	-1020	-1020	-1020
-1020	-1020	-1020	-1020
0	0	0	0

n X n → **Stride=s and Kernel= kX k** → $\left(\left\lfloor \frac{n-k}{s} \right\rfloor + 1\right) \text{ X } \left(\left\lfloor \frac{n-k}{s} \right\rfloor + 1\right)$

CONVOLUTION IN AN RGB IMAGE



CONVOLUTION IN AN RGB IMAGE

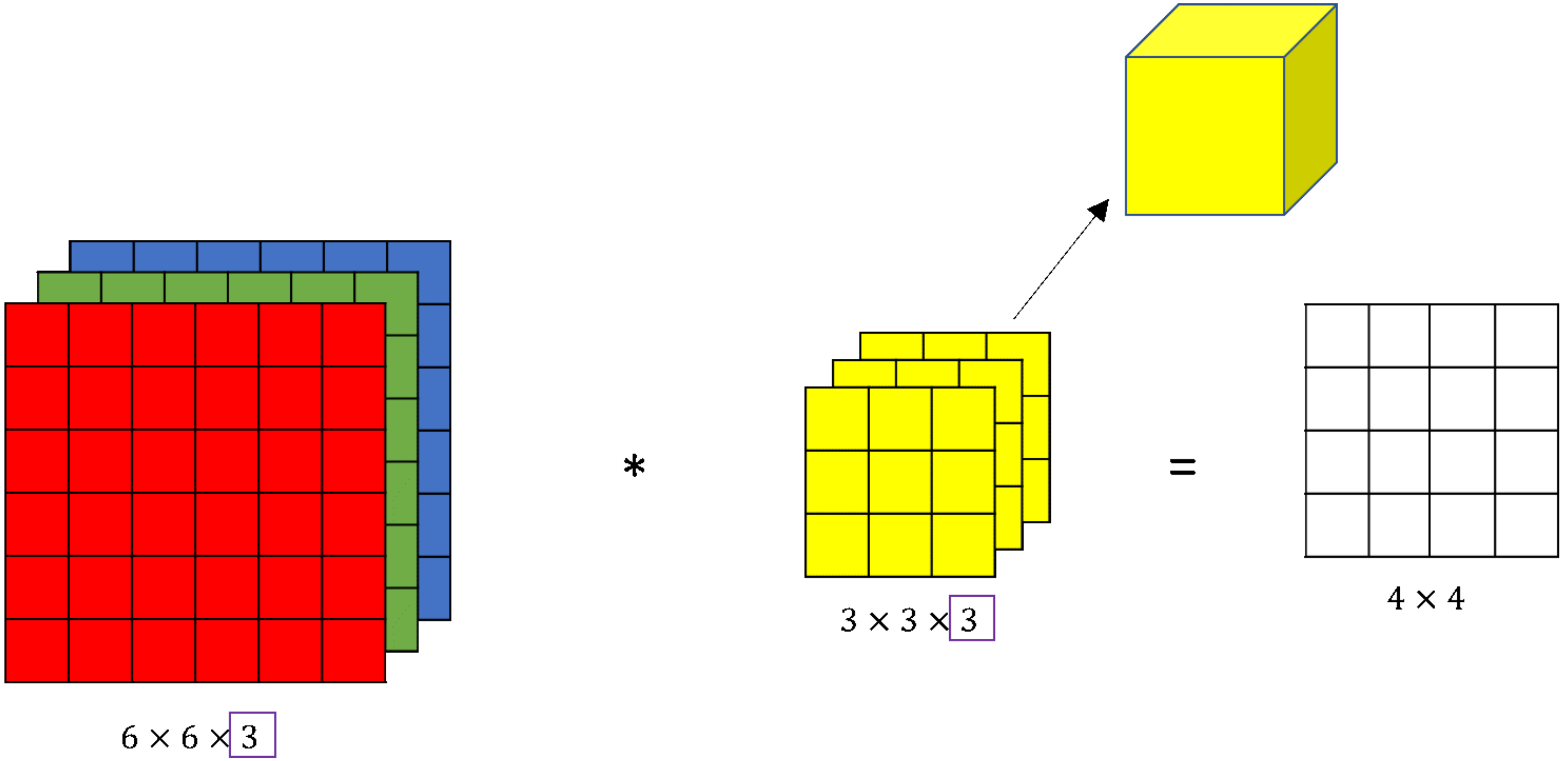
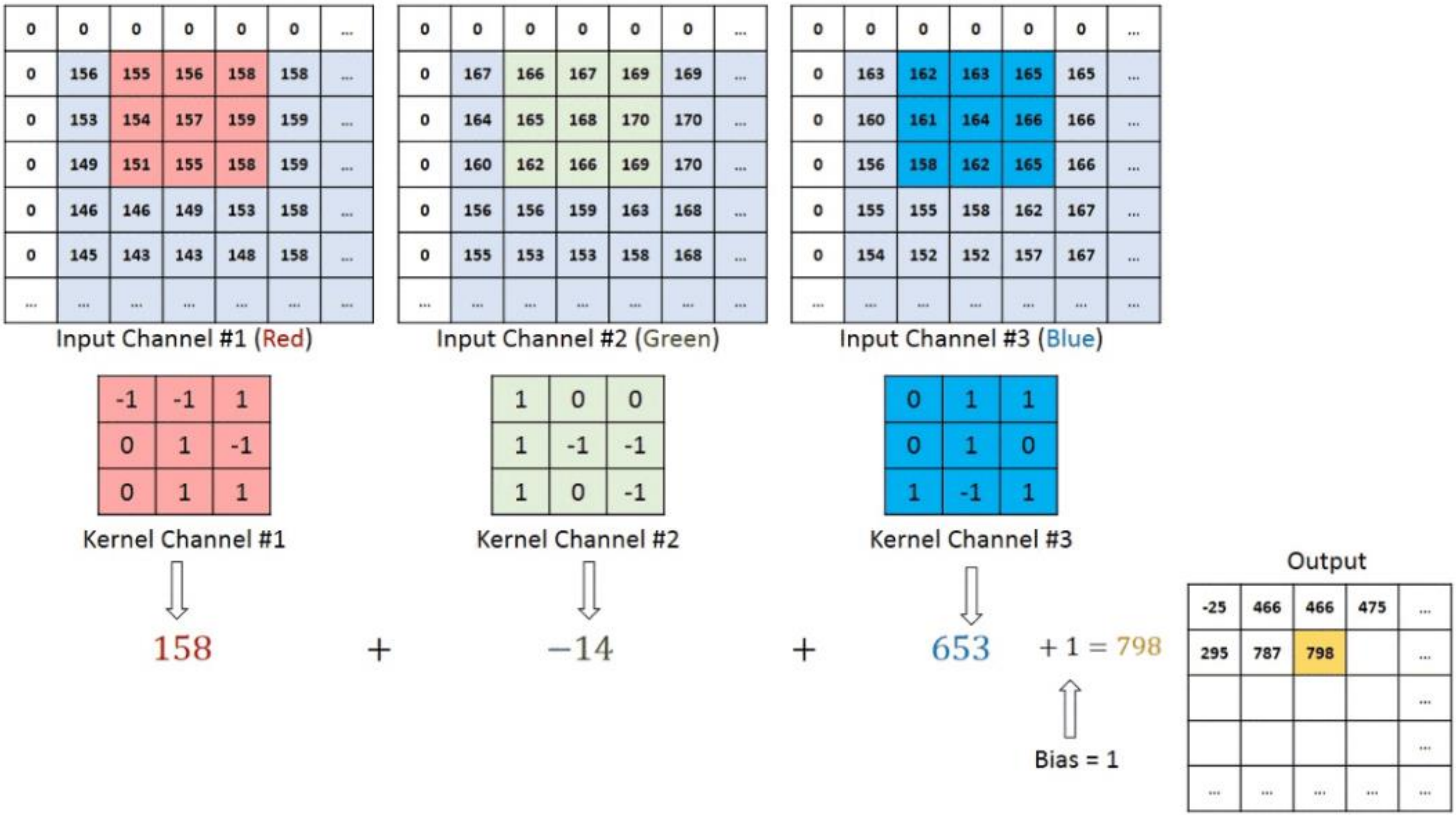


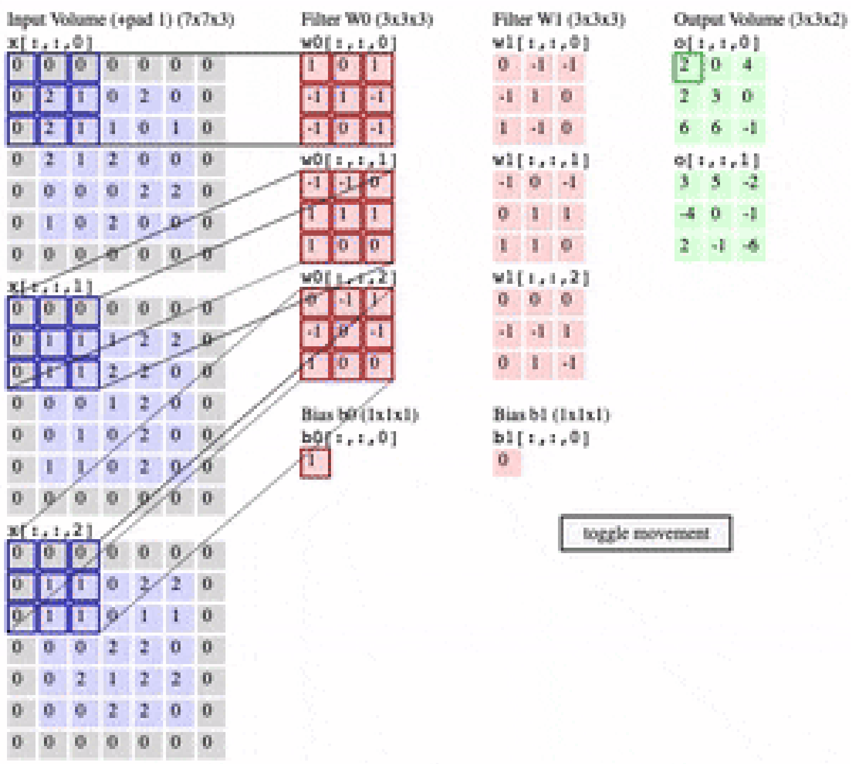
Image Kernel Result

CONVOLUTION IN AN RGB IMAGE

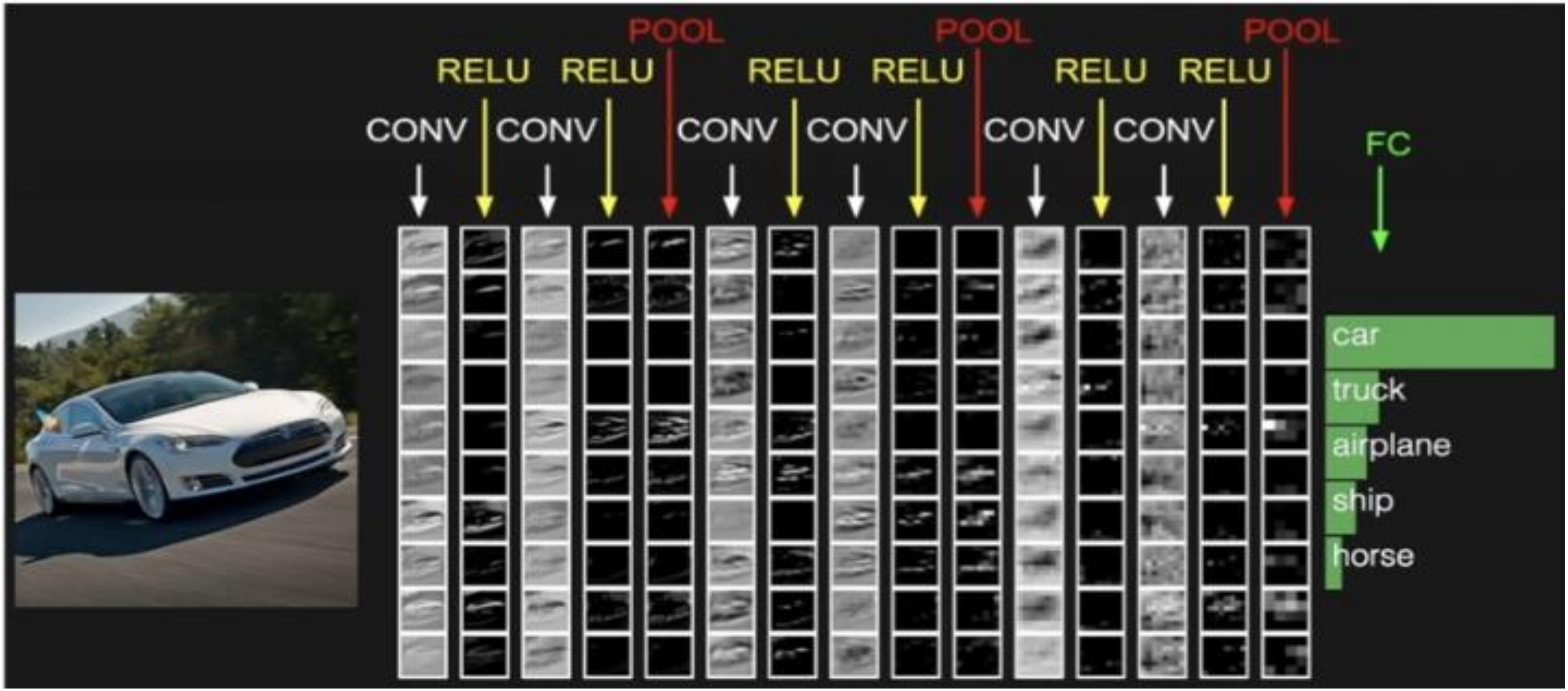


CONVOLUTION LAYER IN CNN

- Biologically Inspired
- Multiple Edge Detectors: Multiple Kernels
- In MLP, we learn the weights
- In CNN, We learn the kernel matrices

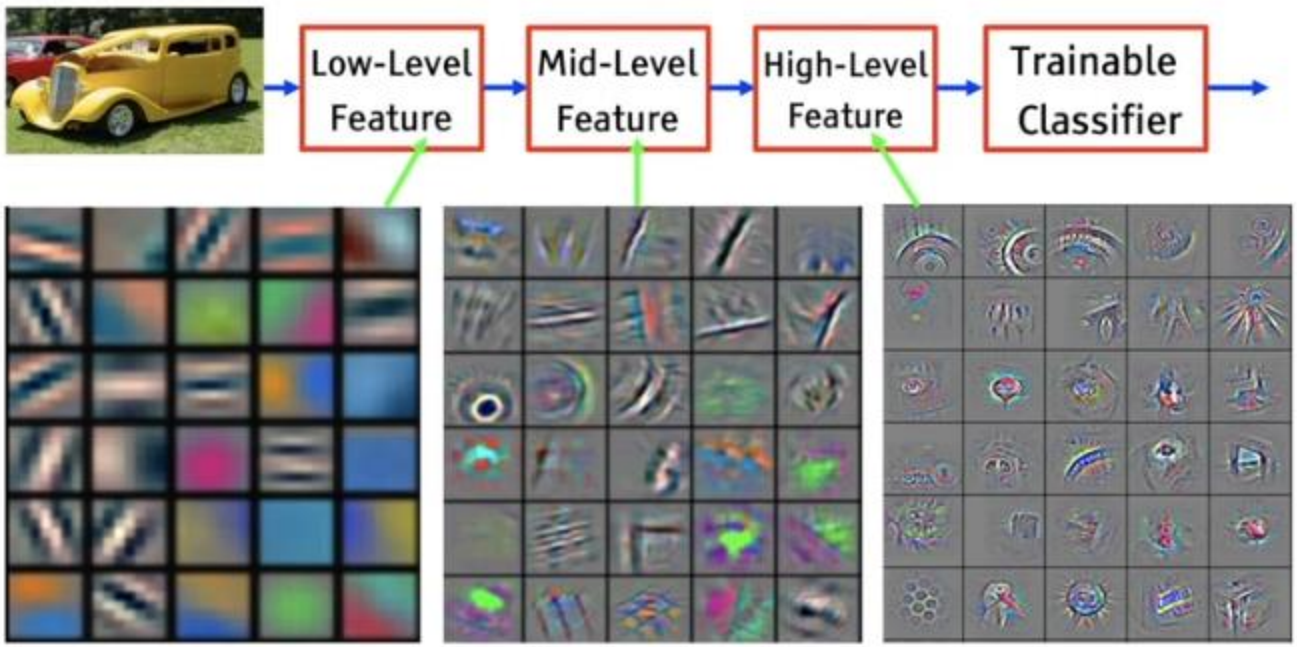


CONVOLUTION LAYER IN CNN



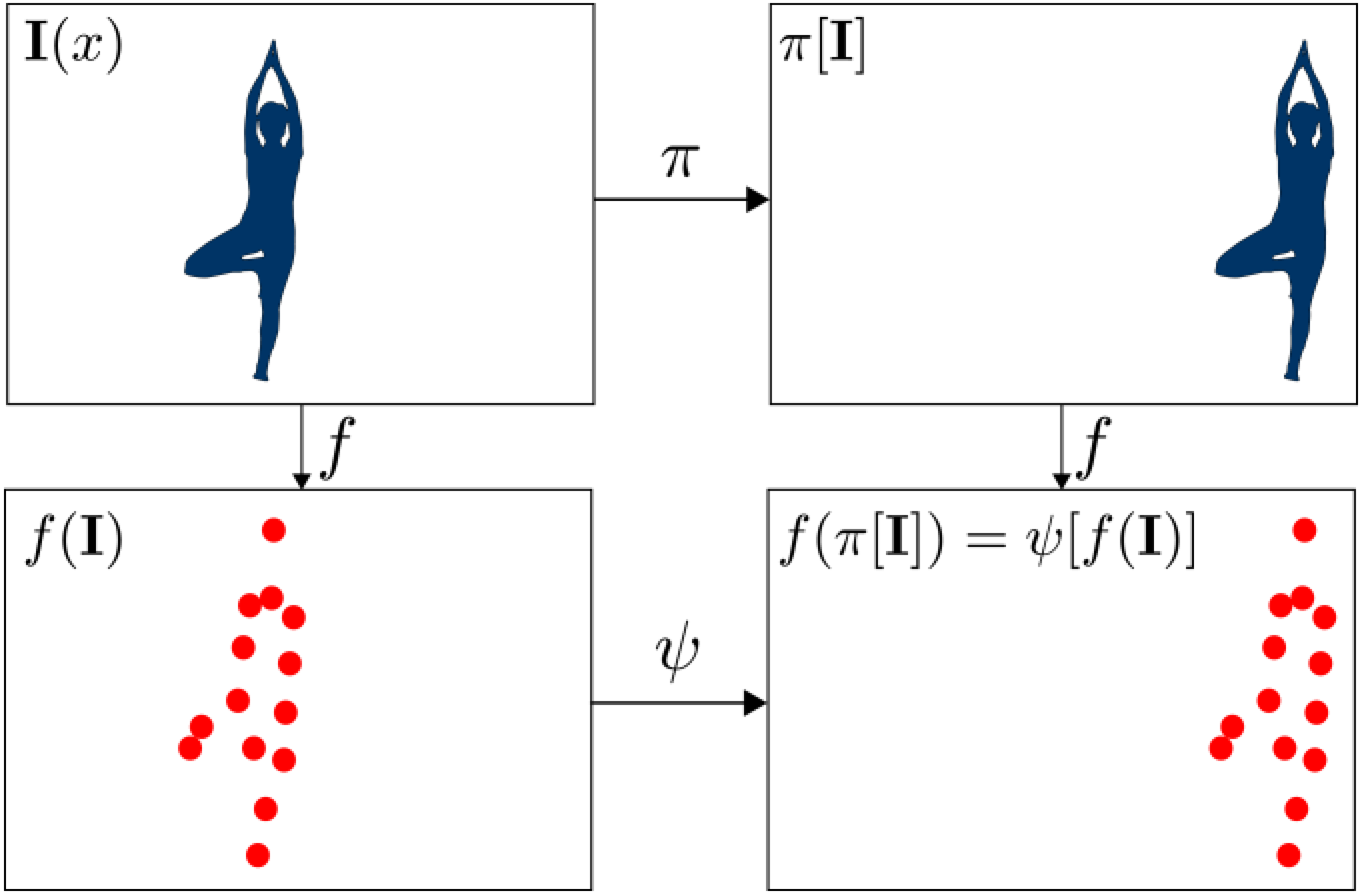
WHY MULTIPLE LAYERS?

- Hierarchy of representations with increasing level of abstraction
- Each stage is a kind of trainable feature transform
- Image recognition: Pixel → edge → texton → motif → part → object
- Text: Character → word → word group → clause → sentence → story
- Speech: Sample → spectral band → sound → … → phone → phoneme → word



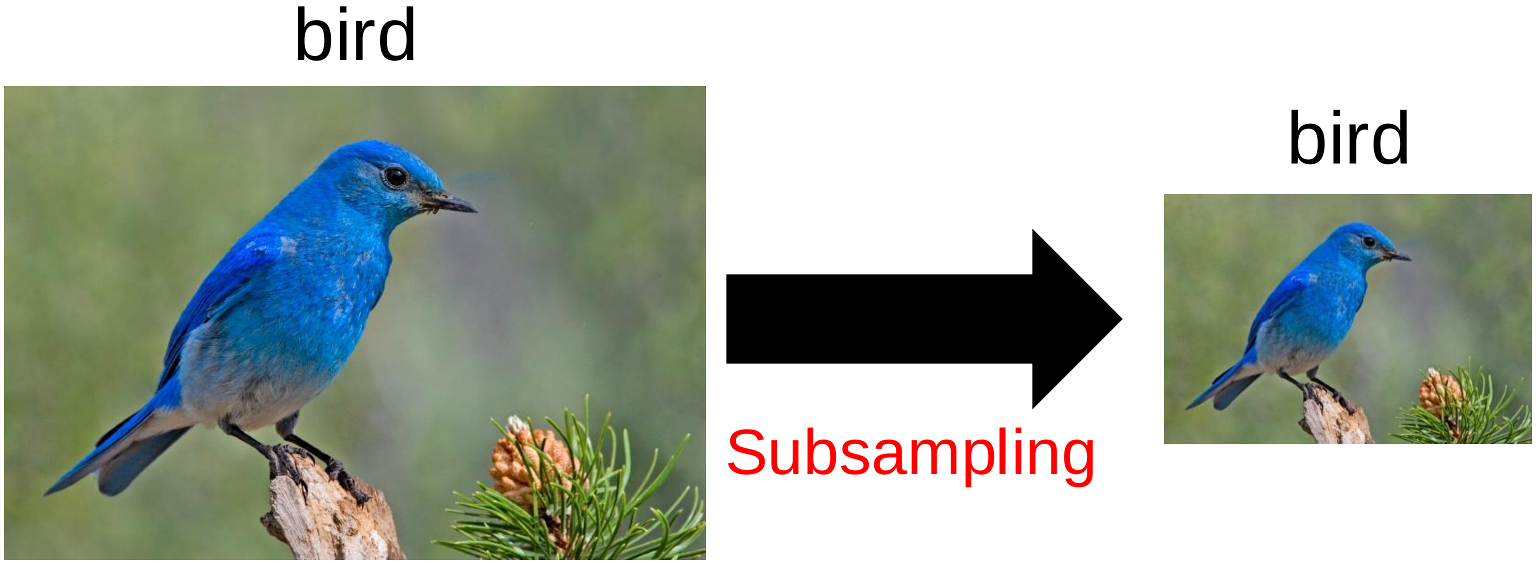
MOTIVATION FOR POOLING

- **Location Invariant:** Changing the location will not change the object.



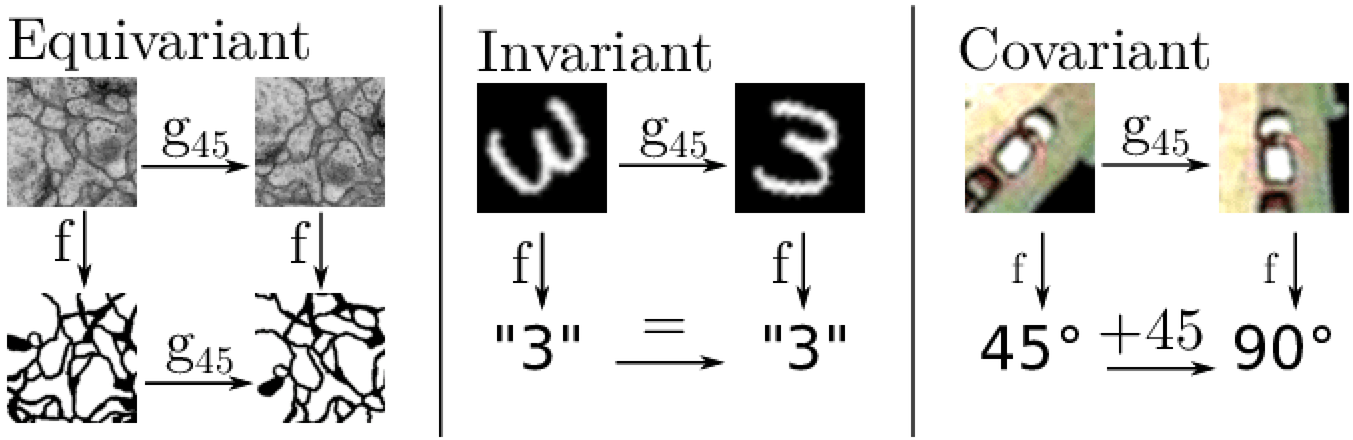
Motivation for Pooling

- **Scale Invariant:** Subsampling Image will not change the Image



Motivation for Pooling

- **Rotation Invariant:** Rotating an image will not change the Object.



MOTIVATION FOR POOLING

- **Pooling is a concept** that makes the CNN models **invariant to *Location, Scale and Rotation.***

POOLING

- **E.g. Max Pooling**
  - Let’s have a 4X4 image with kernel size 2X2 and Stride 2

- Popular method

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

How Derivative of Pooling works in CNN

Derivatives of Pooling

Pooling layer subsamples statistics to obtain summary statistics with any aggregate function (or filter) *g* whose input is vector, and output is scalar. Subsampling is an operation like convolution, however *g* is applied to disjoint (non-overlapping) regions.

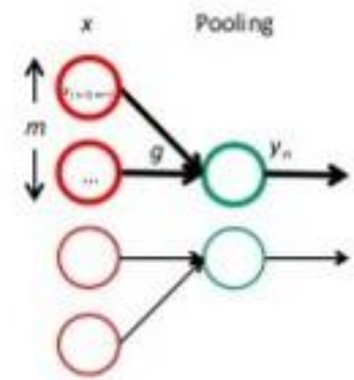
- Definition: *subsample* (or *downsample*)

  Let *m* be the size of pooling region, *x* be the input, and *y* be the output of the pooling layer. subsample(*f*, *g*)[*n*] denotes the *n*-th element of subsample(*f*, *g*).

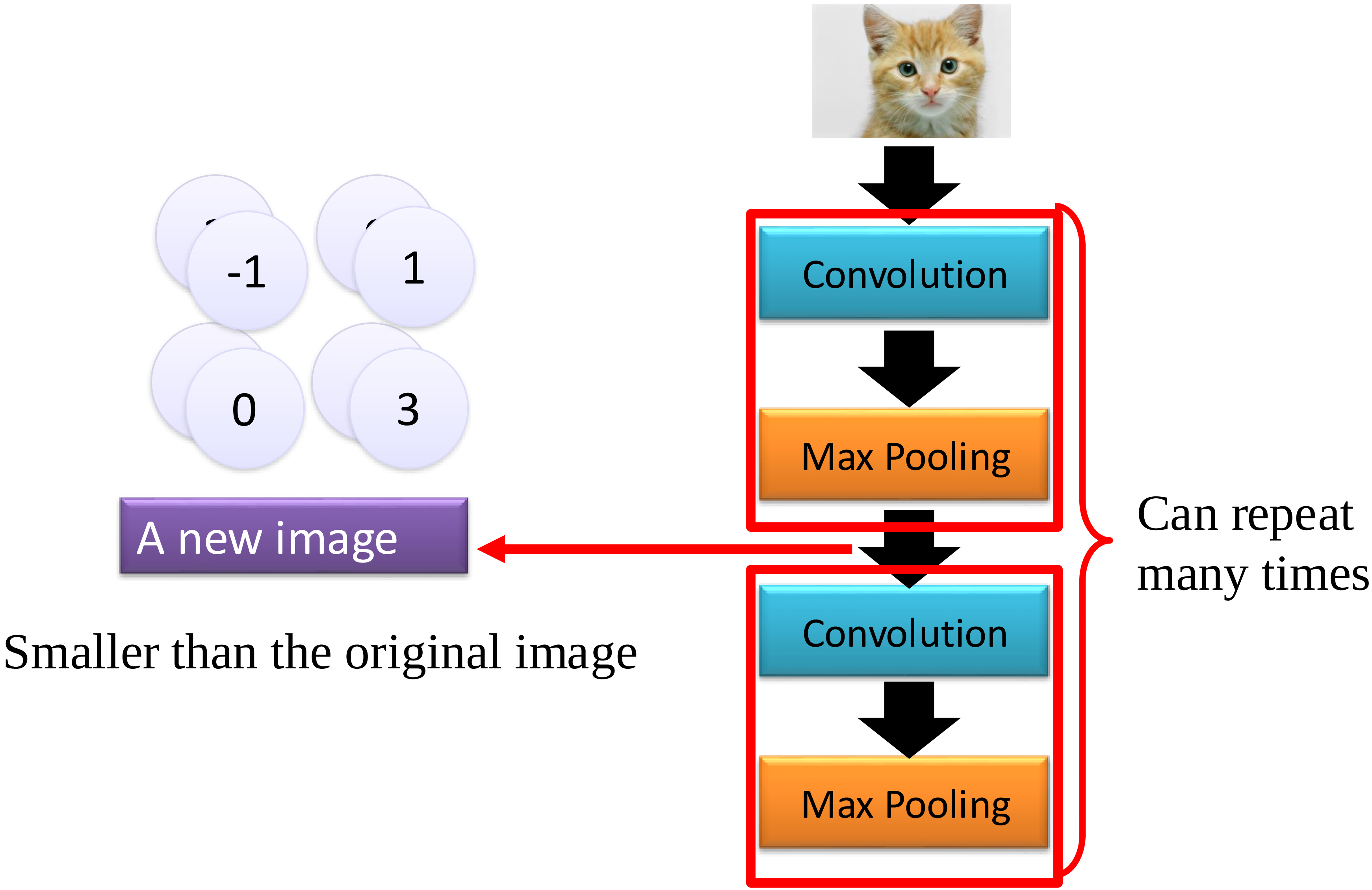
$$y_n = \text{subsample}(x, g)[n] = g\left(x_{(n-1)m+1:nm}\right)$$

$$y = \text{subsample}(x, g) = [y_n]$$

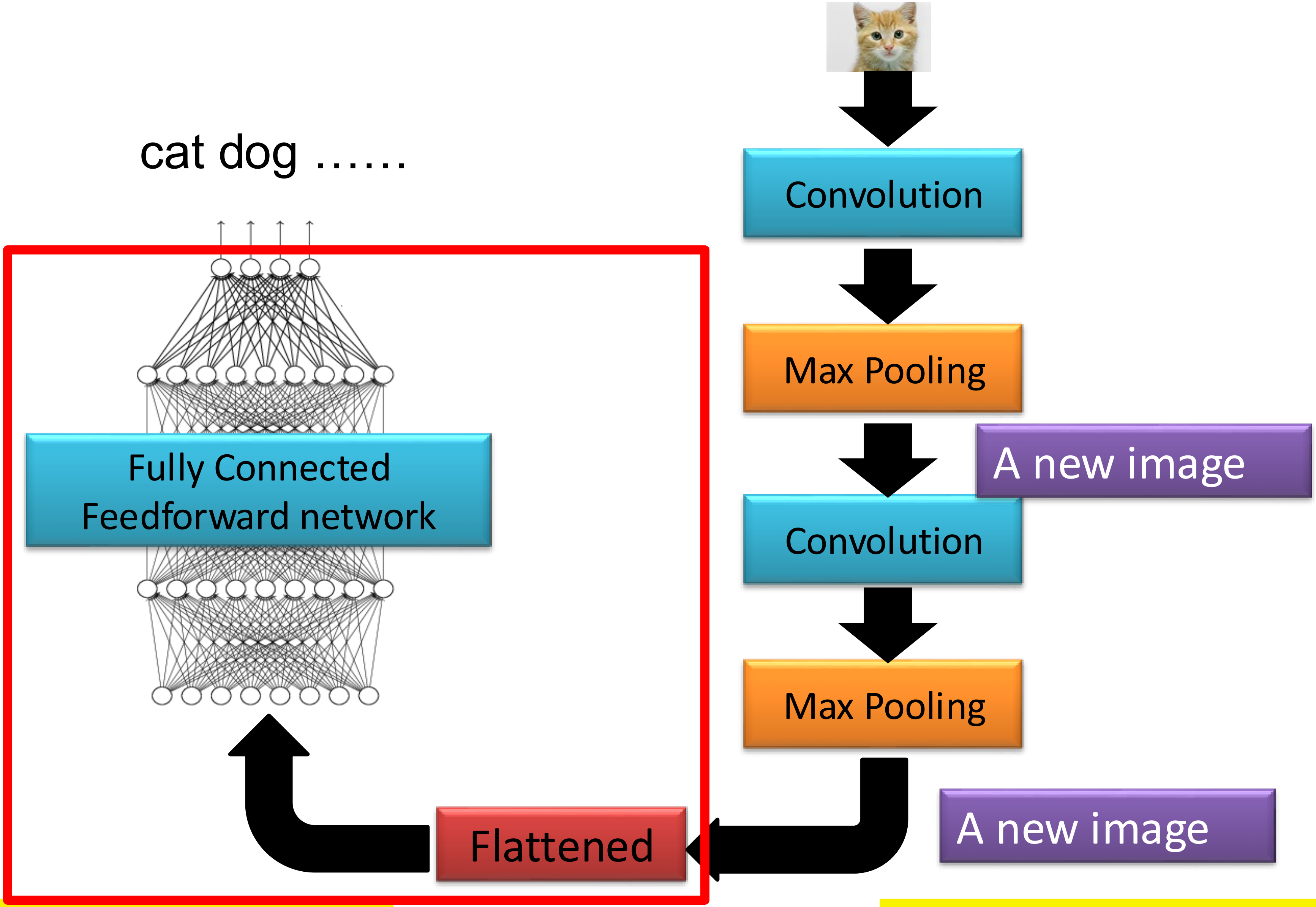
$$g(x) = \begin{cases} \dfrac{\sum_{k=1}^{m} x_k}{m}, \quad \dfrac{\partial g}{\partial x} = \dfrac{1}{m} & \text{mean pooling} \\ \max(x), \quad \dfrac{\partial g}{\partial x_i} = \begin{cases} 1 \text{ if } x_i = \max(x) \\ 0 \text{ otherwise} \end{cases} & \text{max pooling} \\ \|x\|_p = \left(\sum_{k=1}^{m} |x_k|^p\right)^{1/p}, \quad \dfrac{\partial g}{\partial x_i} = \left(\sum_{k=1}^{m} |x_k|^p\right)^{1/p-1} |x_i|^{p-1} & L^p \text{ pooling} \\ \text{or any other differentiable } \mathbf{R}^m \to \mathbf{R} \text{ functions} \end{cases}$$



CONVNETS


-1
1
0
3
A new image
Smaller than the original image
Convolution
Max Pooling
Convolution
Max Pooling
Can repeat many times

CONVNETS


cat dog ……
Convolution
Max Pooling
A new image
Convolution
Max Pooling
A new image
Fully Connected
Feedforward network
Flattened

POPULAR CNN MODELS

- LeNet
- AlexNet
- VGGNet
  - VGG16
  - VGG19
- ResNets
- GoogLeNet

LENET

- https://d2l.ai/chapter_convolutional-neural-networks/lenet.html

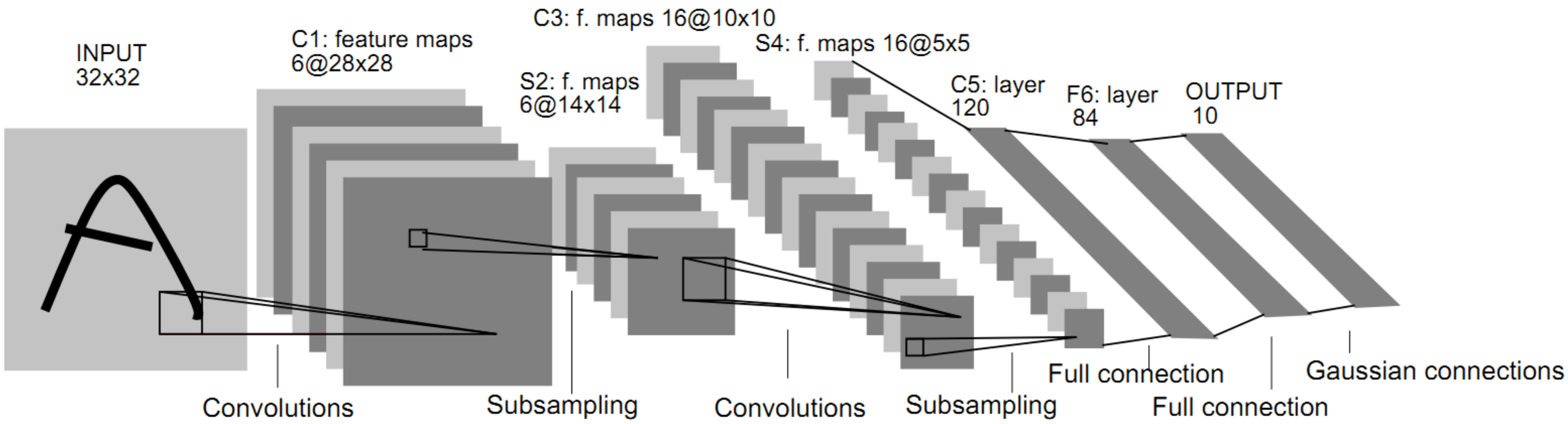


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278-2324.

LENET

https://d2l.ai/chapter_convolutional-neural-networks/lenet.html

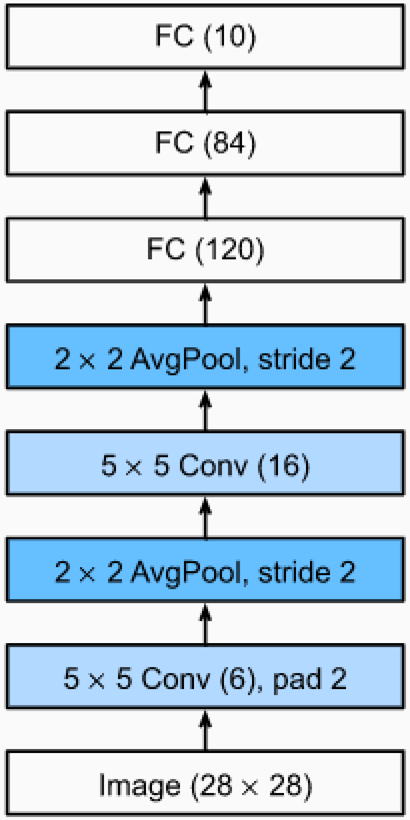
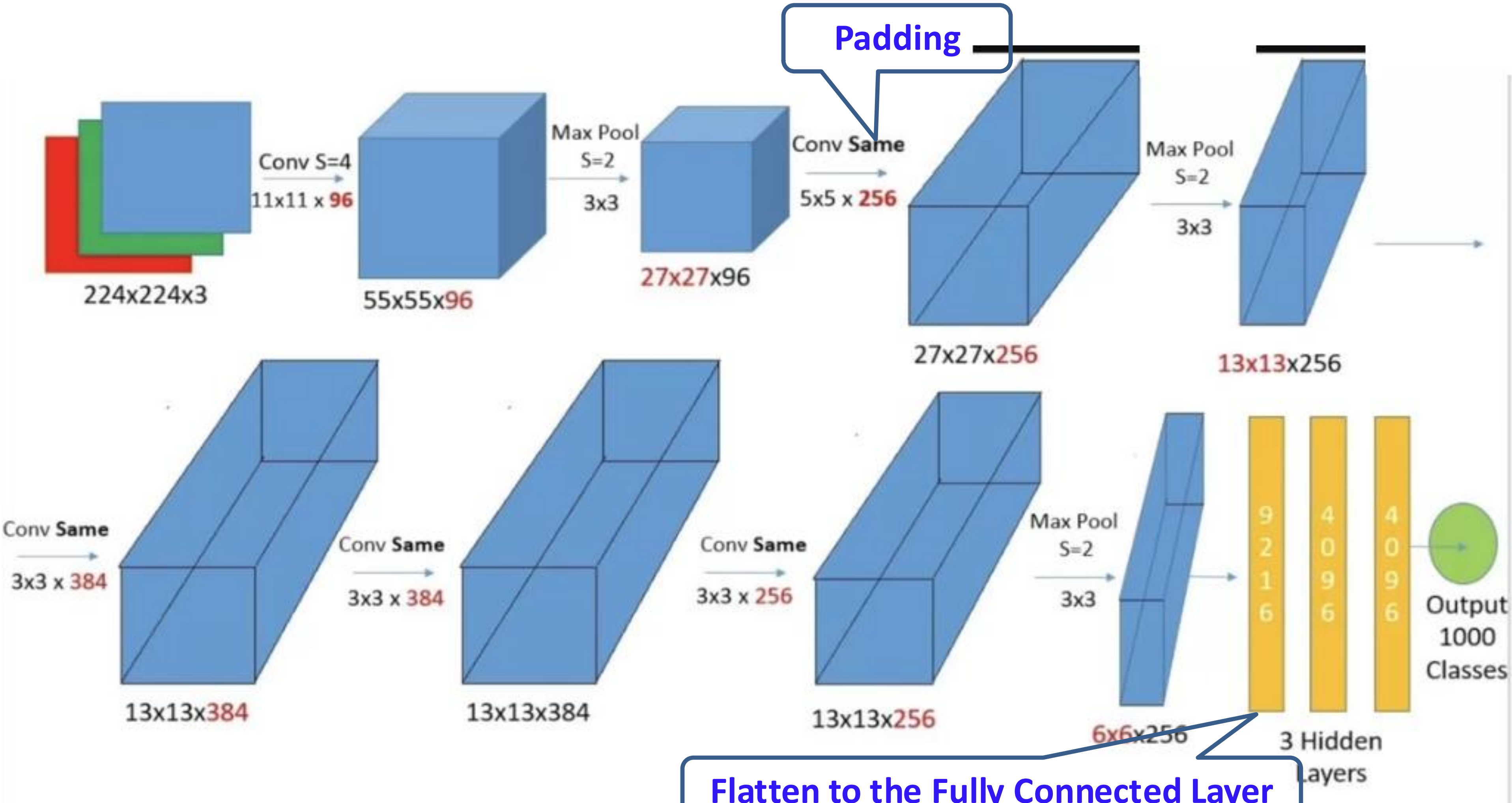


Fig. 6.6.2 Compressed notation for LeNet-5.

AlexNet



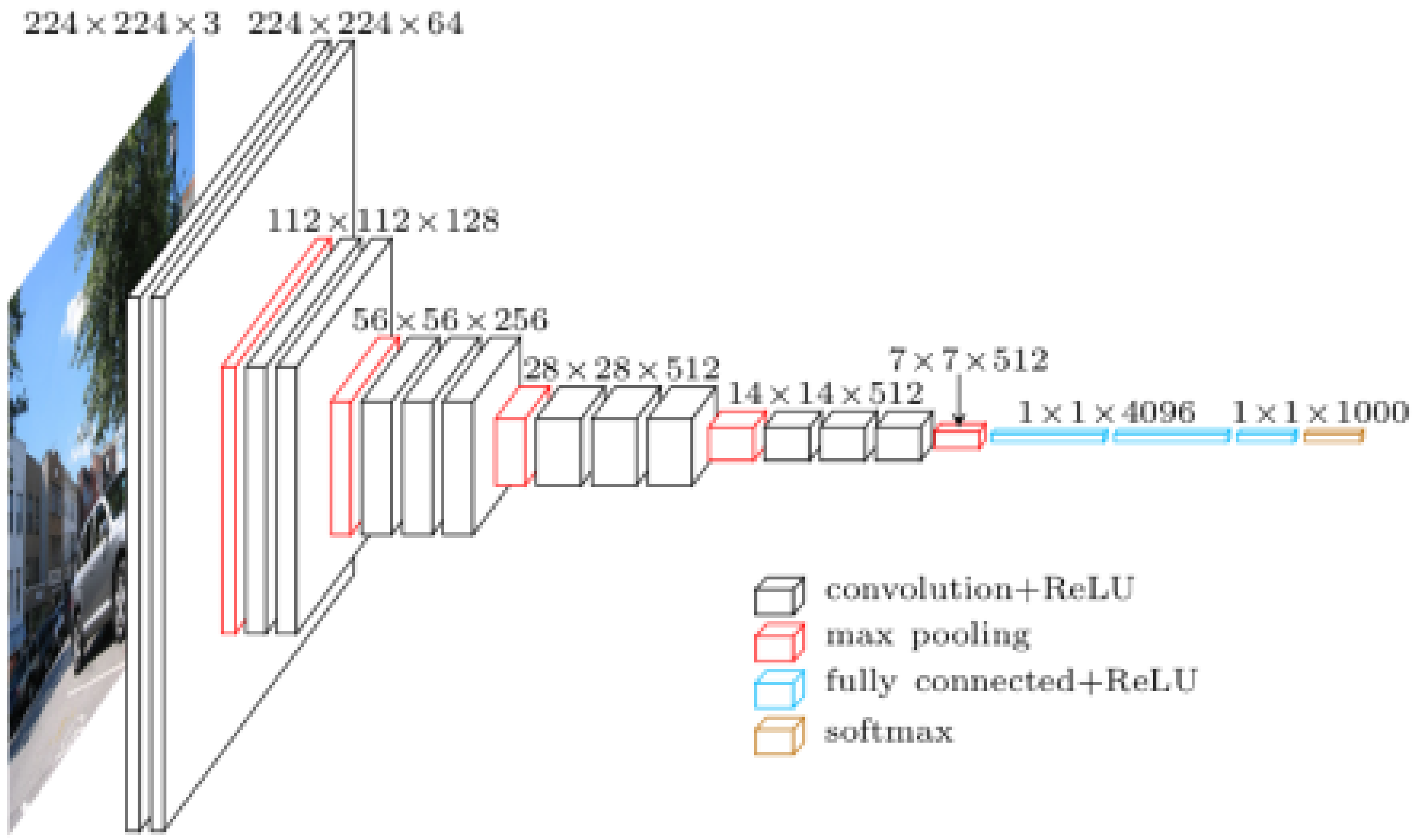
Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. NIPS'12 Proceedings of the 25th International Conference on Neural Information Processing Systems, Lake Tahoe, Nevada, 3-6 December. 1: 1097-1105.

VGGNET- VGG16

All Convolution (3X3 Kernel, Stride=1, Padding='Same')
All MaxPool (2X2, Stride=2)

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556.*

VGGNET- VGG16

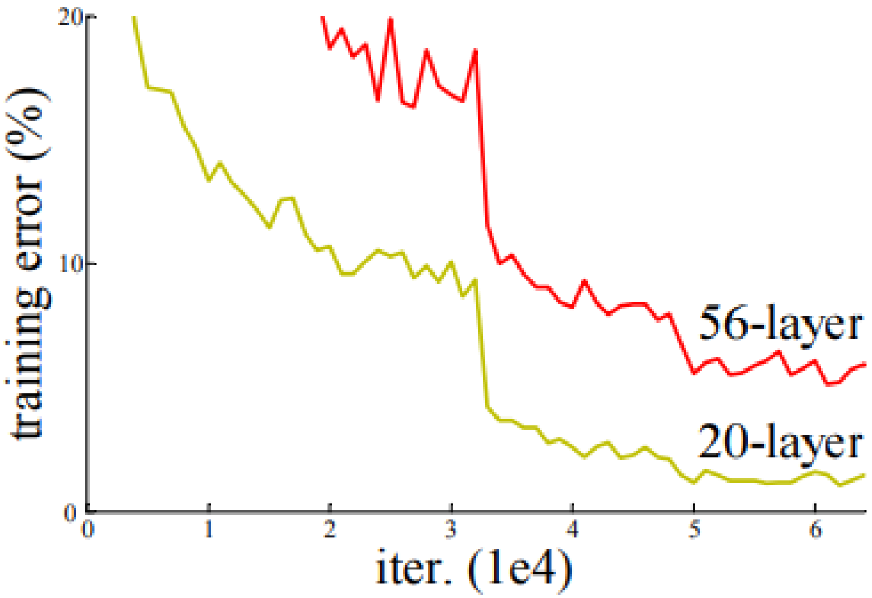


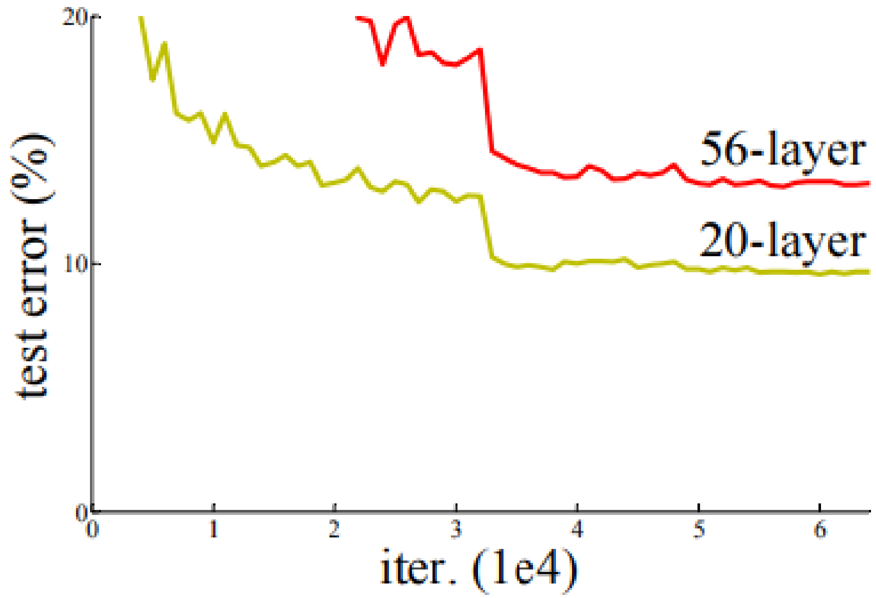
VGG-16

- Reference

https://github.com/keras-team/keras-applications/blob/master/keras_applications/vgg16.py

RESIDUAL NETWORKS: RESNETS





He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

RESIDUAL NETWORKS: RESNETS

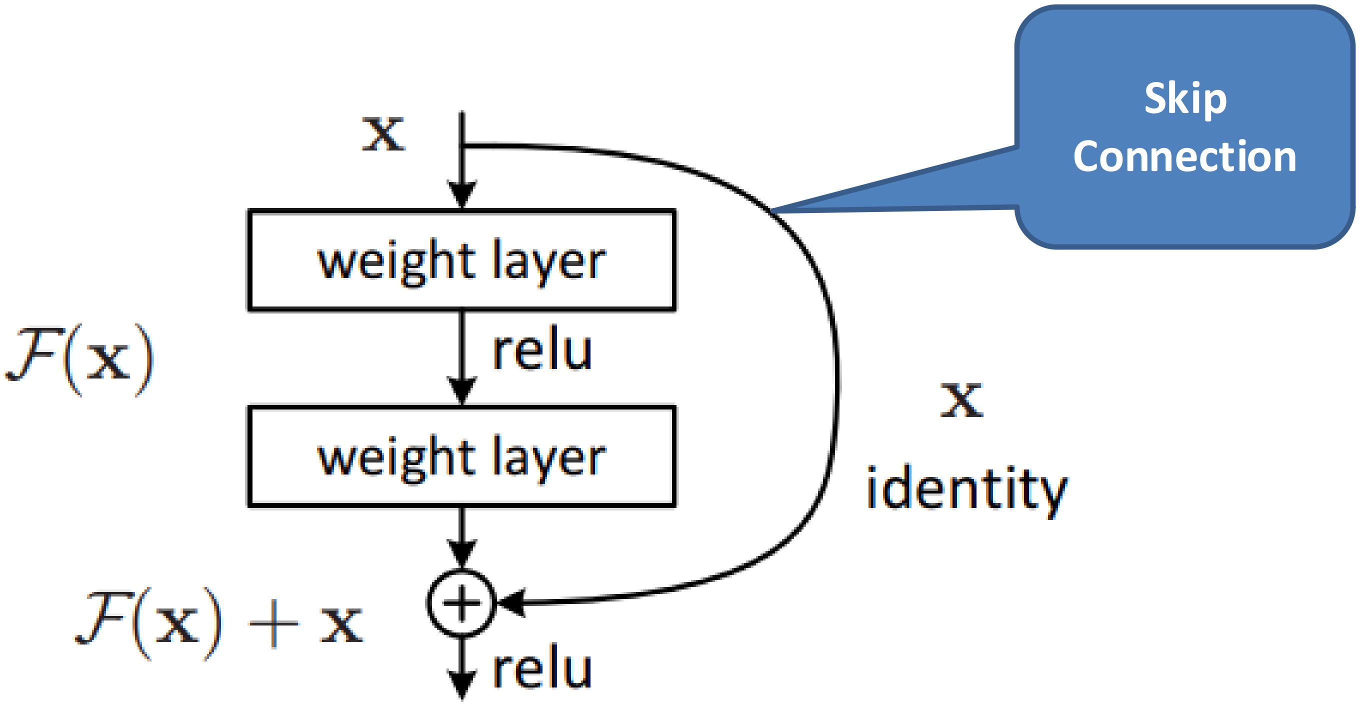
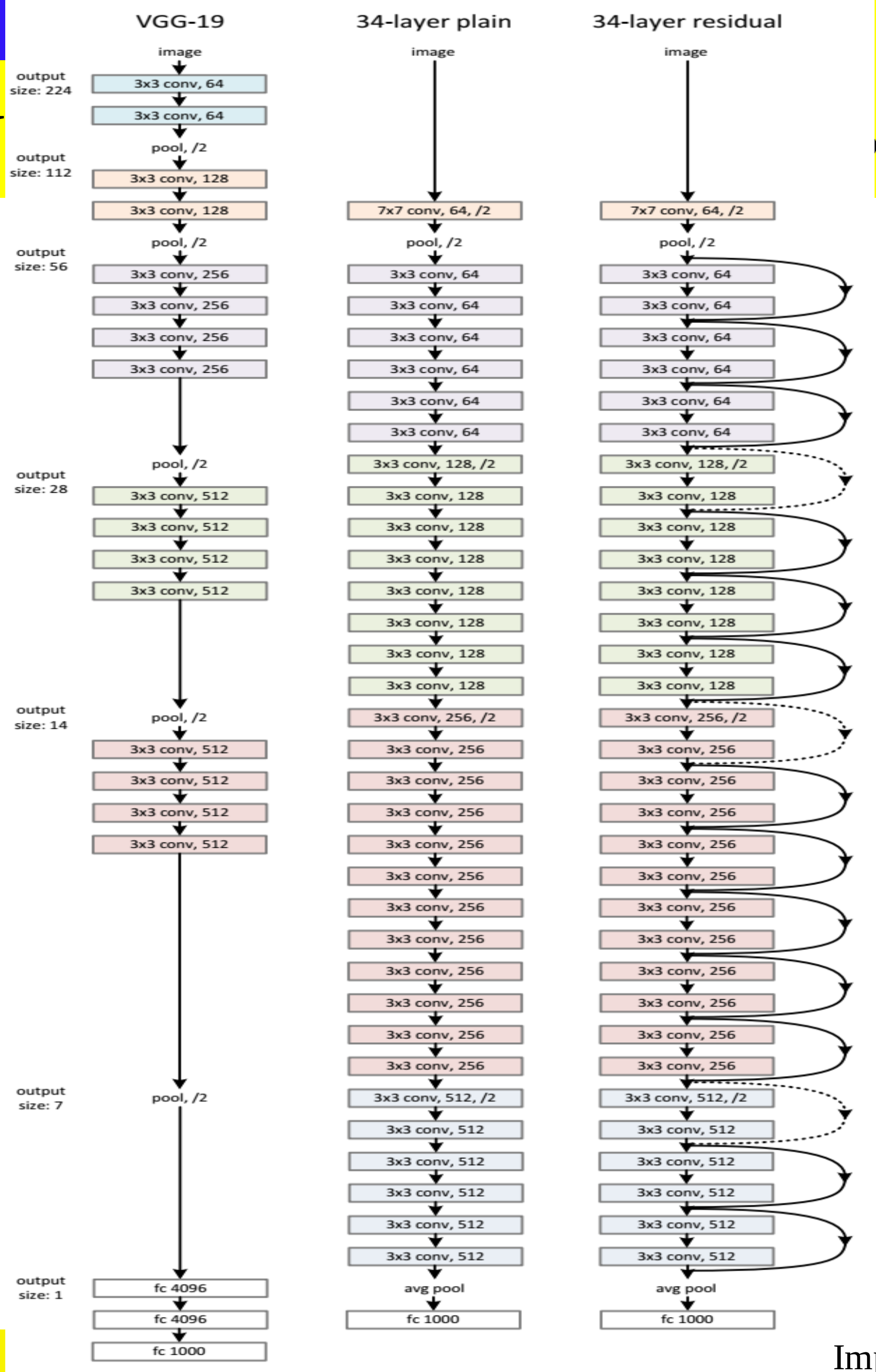


Figure 2. Residual learning: a building block.

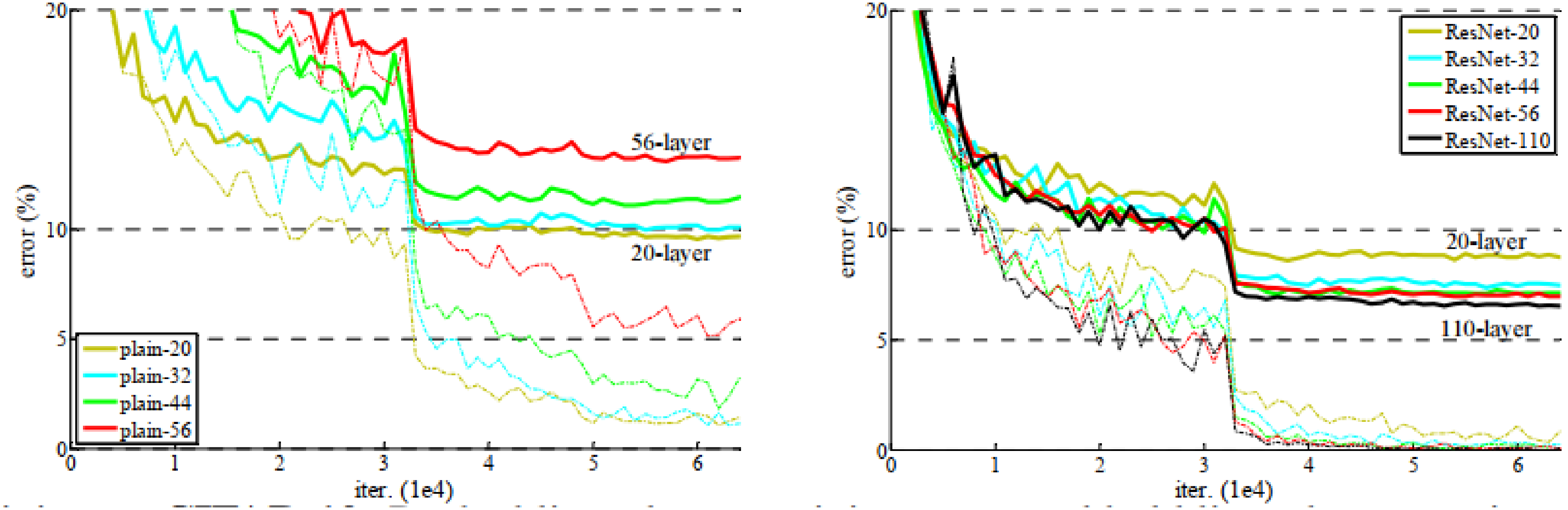
He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

RESIDU



Improvement in Performance due to Resudual

RESIDUAL NETWORKS: RESNETS

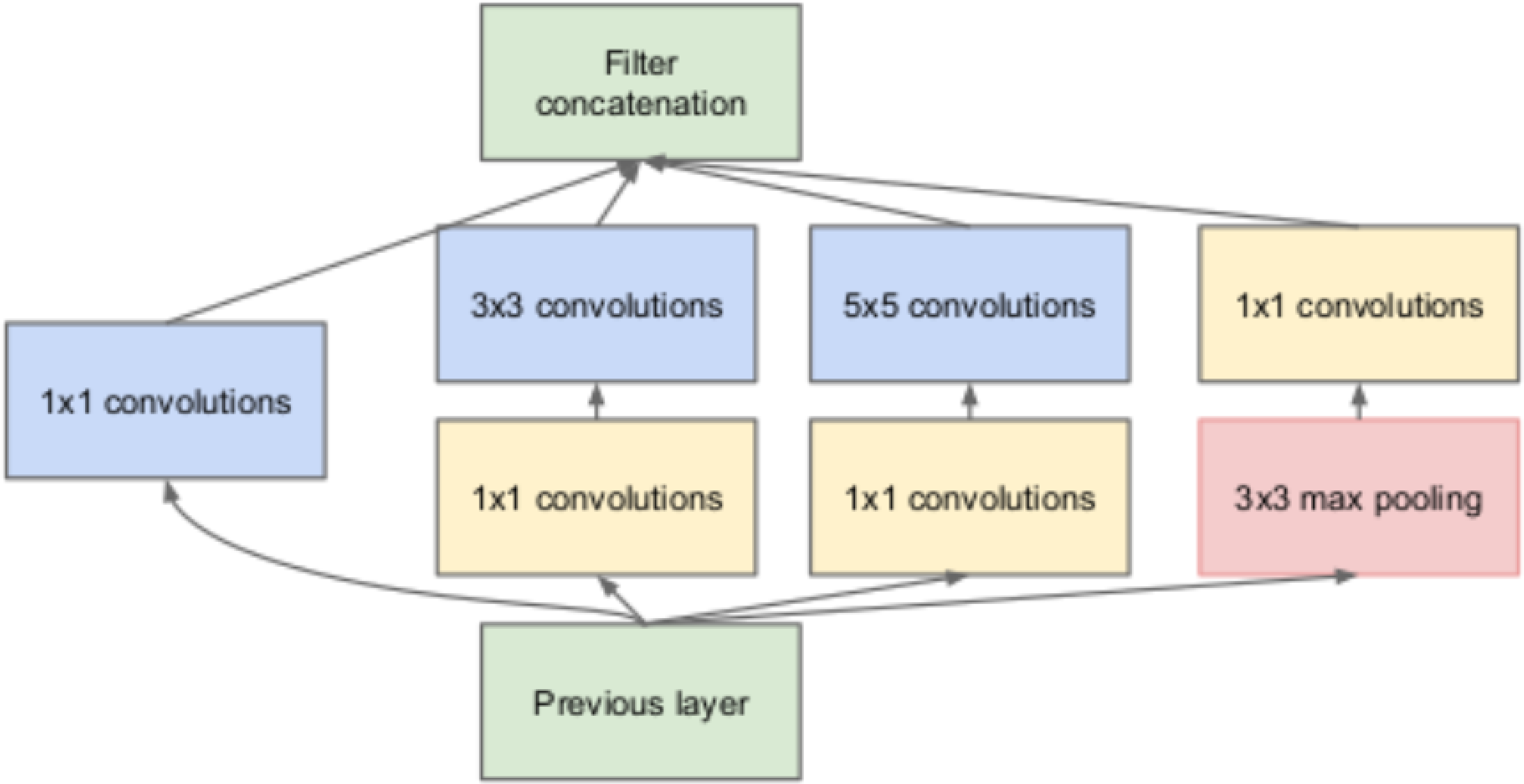


References…

RESNETS-50

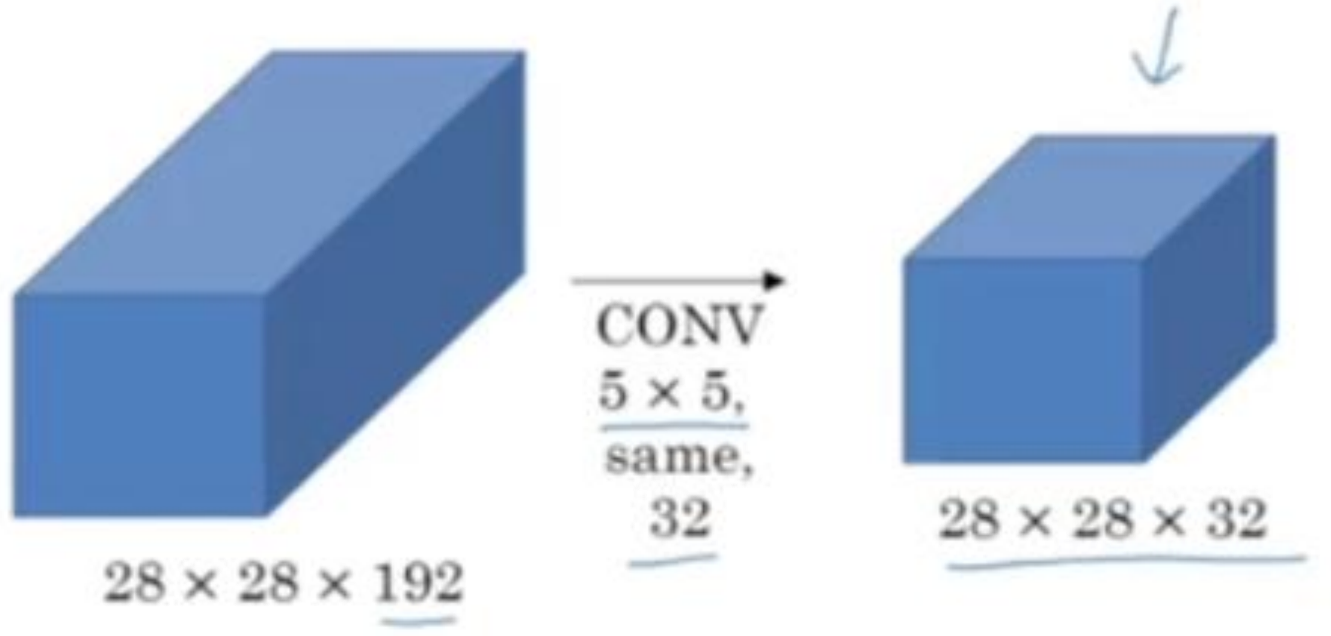
https://github.com/keras-team/keras-applications/blob/master/keras_applications/resnet50.py

INCEPTION MODULE MOTIVATION



Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826).

INCEPTION MODULE MOTIVATION



Input: 28x28x192

Filter: Conv 5x5x192, same, 32

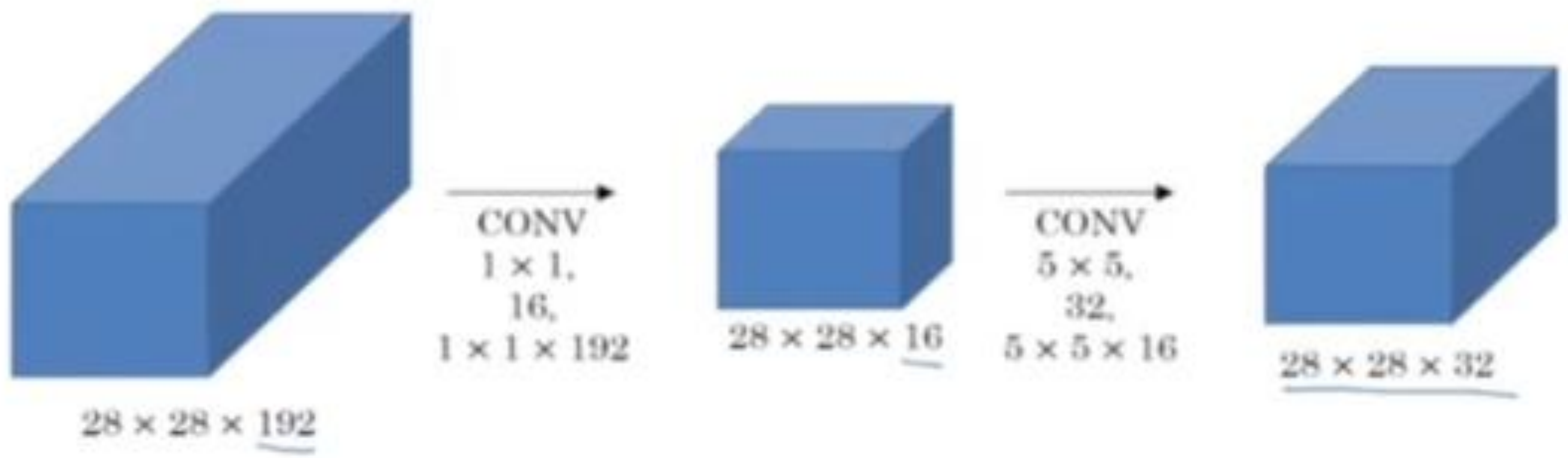
Output: 28x28x32

Total number of calculations = (28 * 28 * 32) * (5 * 5 * 192) = 120 Million !!

INCEPTION MODULE MOTIVATION

Using 1x1 Convolution to reduce computation cost

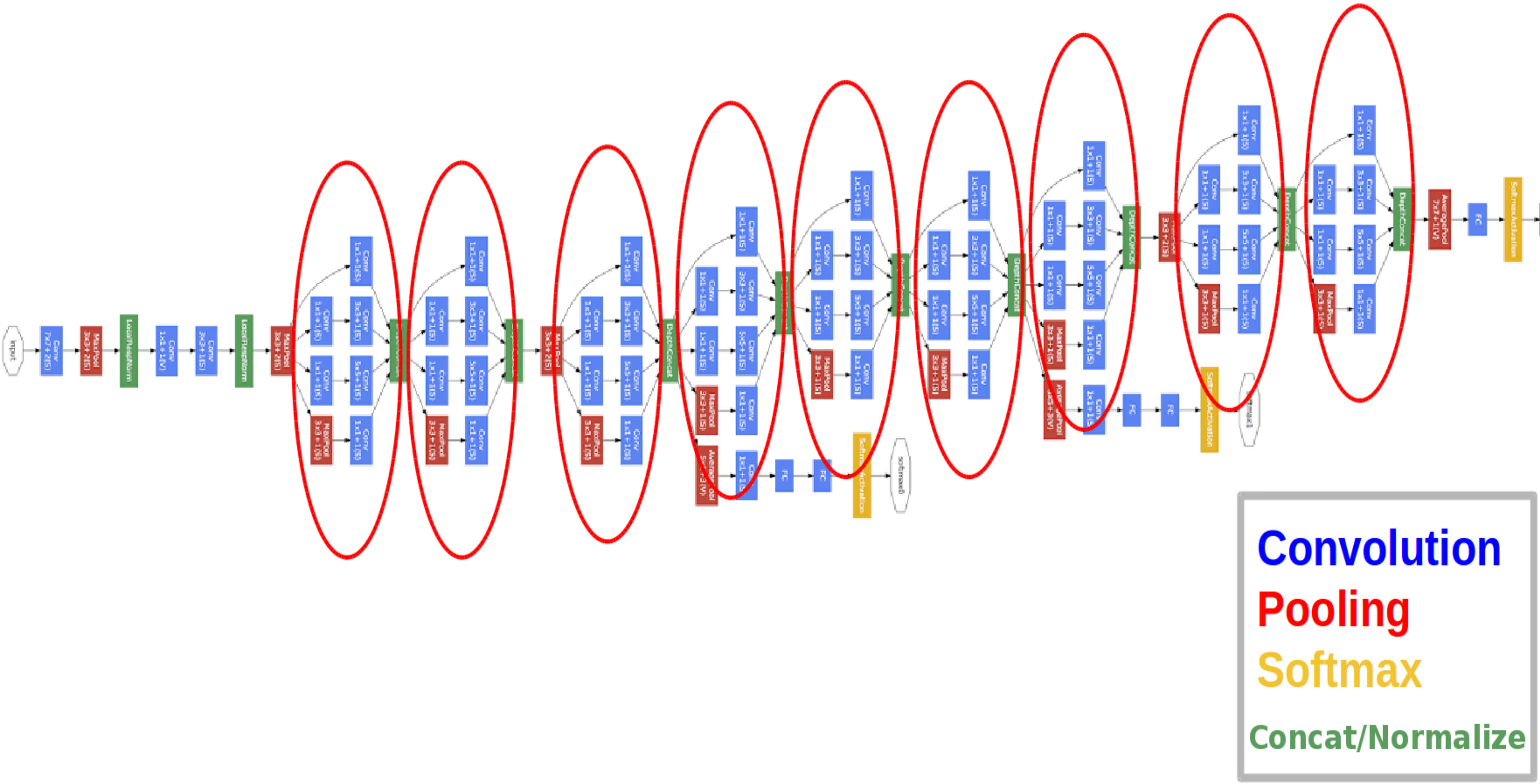
A 1x1 convolution is added before the 5x5 cvonvolution -= Also called a **bottleneck layer**



Total number of calculations = [(28 * 28 * 16) * (1 * 1 * 192)] + [(28 * 28 * 32) * (5 * 5 * 16)]

= 12.4 Million !! (earlier the cost was 120 Million)

GoogLeNet



LeNet-5, AlexNet, VGG-19, GoogLeNet for MNIST Dataset

http://euler.stat.yale.edu/~tba3/stat665/lectures/lec18/notebook18.html

TRANSFER LEARNING

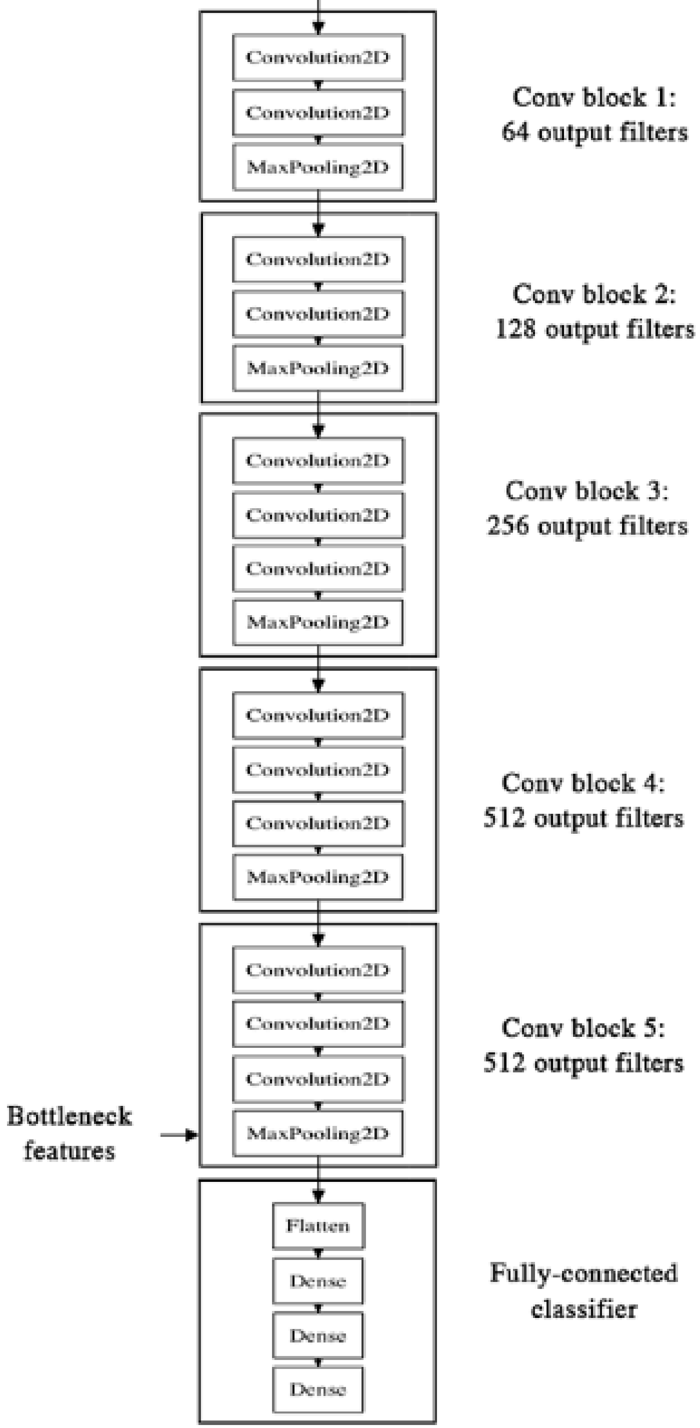
Transfer learning (TL) is **a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem**.

-Wikipedia

TRANSFER LEARNING

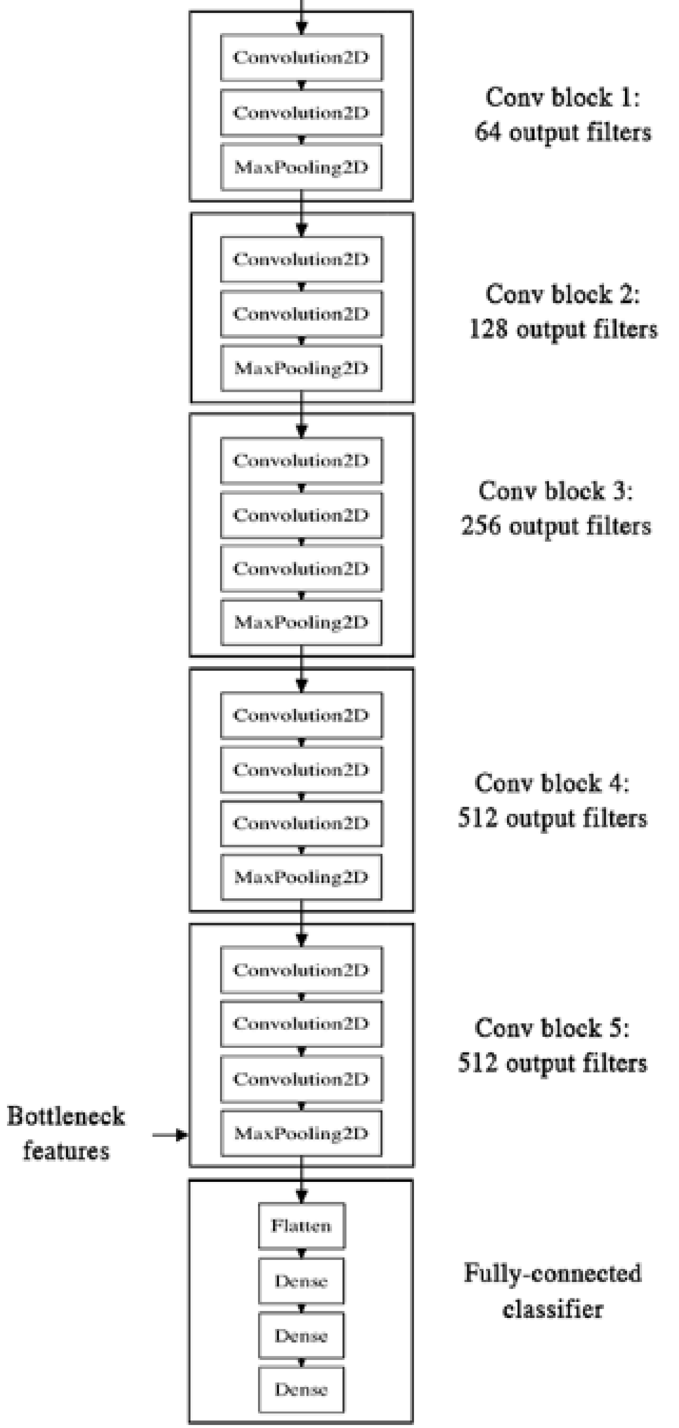
https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html

- VGGNet Trained using IMAGENET



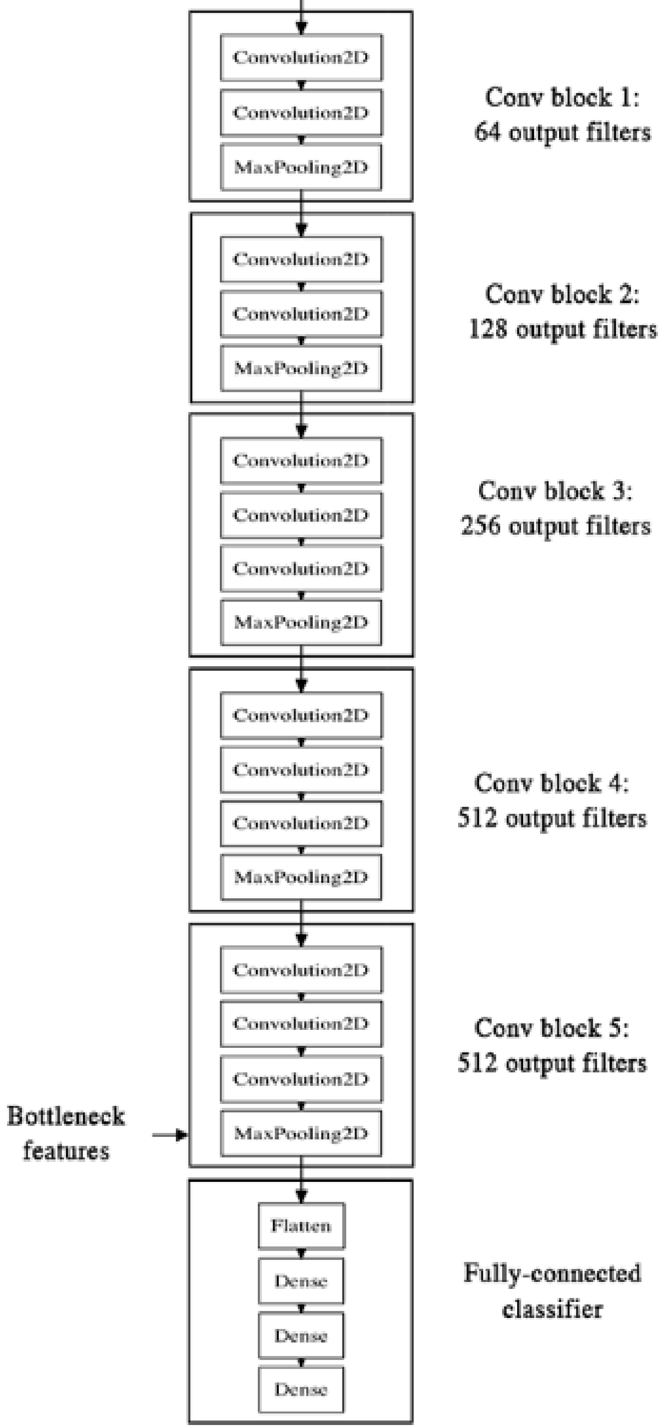
TRANSFER LEARNING(CASE-0)

- **Pre-Trained CNN Models**
  - **Use the Pre-trained CNN to predict the new dataset**



TRANSFER LEARNING(CASE-1)

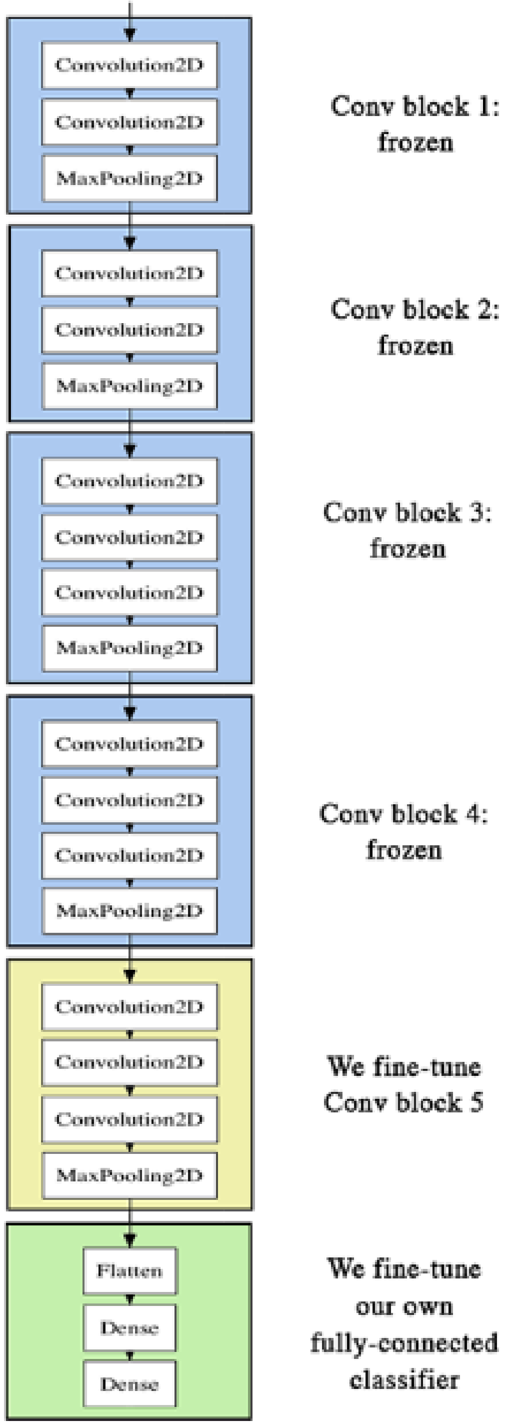
- **Pre-Trained CNN Models + ML Classifiers**
  - **Remove the last Dense Connected Layer**
  - **Take Bottleneck features and use it on a Shallow ML Classifiers**
  - **Here Pre-Trained CNN is used for Feature Engineering**



Transfer Learning (Case-2)

- **Fine Tuning the last two layers of CNN**
  - **Take the Original Dataset and Pretrained CNN Models**
  - **Freeze the early layers (Don't Change)**
  - **Fine tune the last two layers using the new dataset**

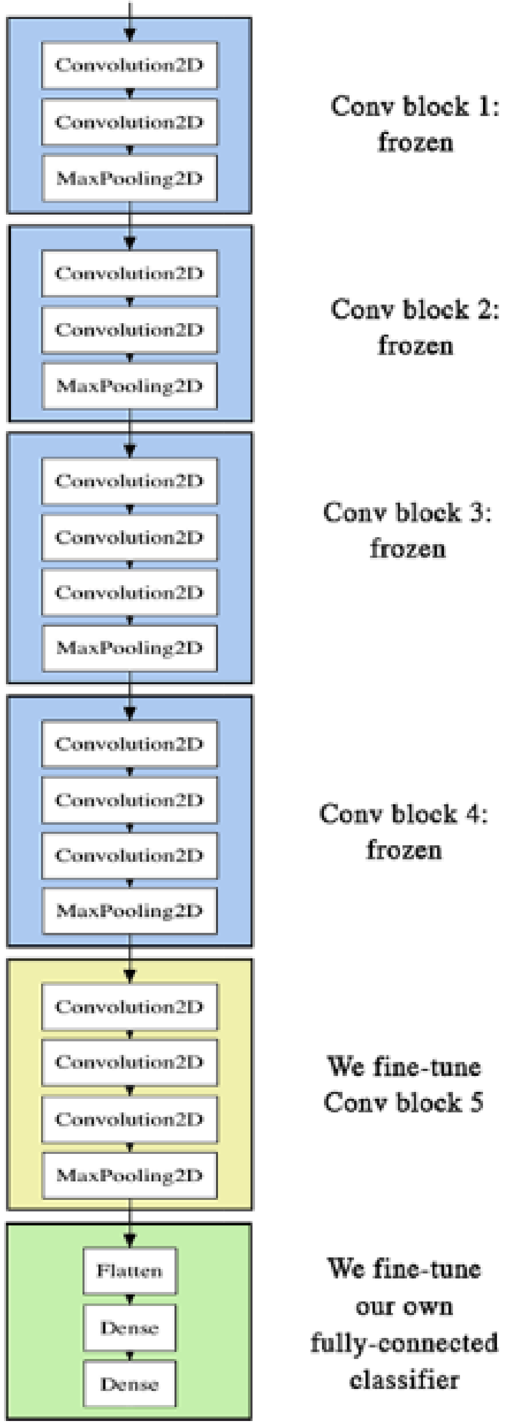
While fine tuning ensure small learning rate



TRANSFER LEARNING (CASE-3)

- **Fine Tuning the Complete model taking the pretrained model as initial model**
  - **Take the Original Dataset and Pretrained CNN Models**
  - **Fine tune the complete model using the new dataset**

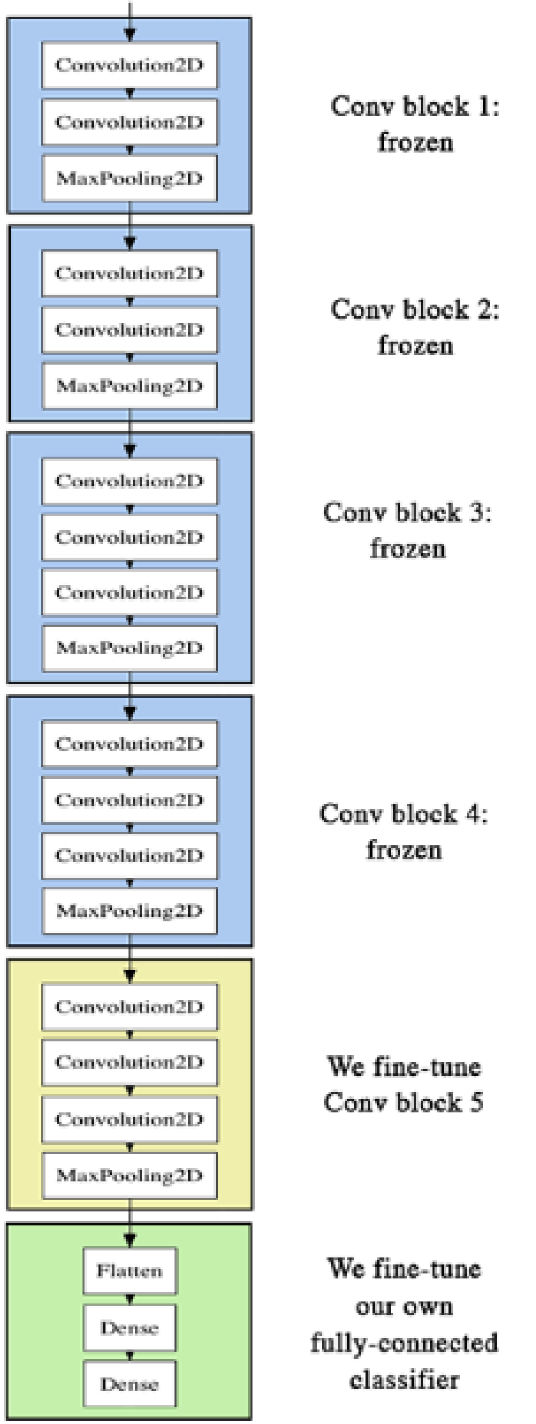
While fine tuning ensure small learning rate



TRANSFER LEARNING (CASE-4)

- **Dump everything & Retrain from Scratch**

Not widely used



How to Choose the Type of Transfer Learning

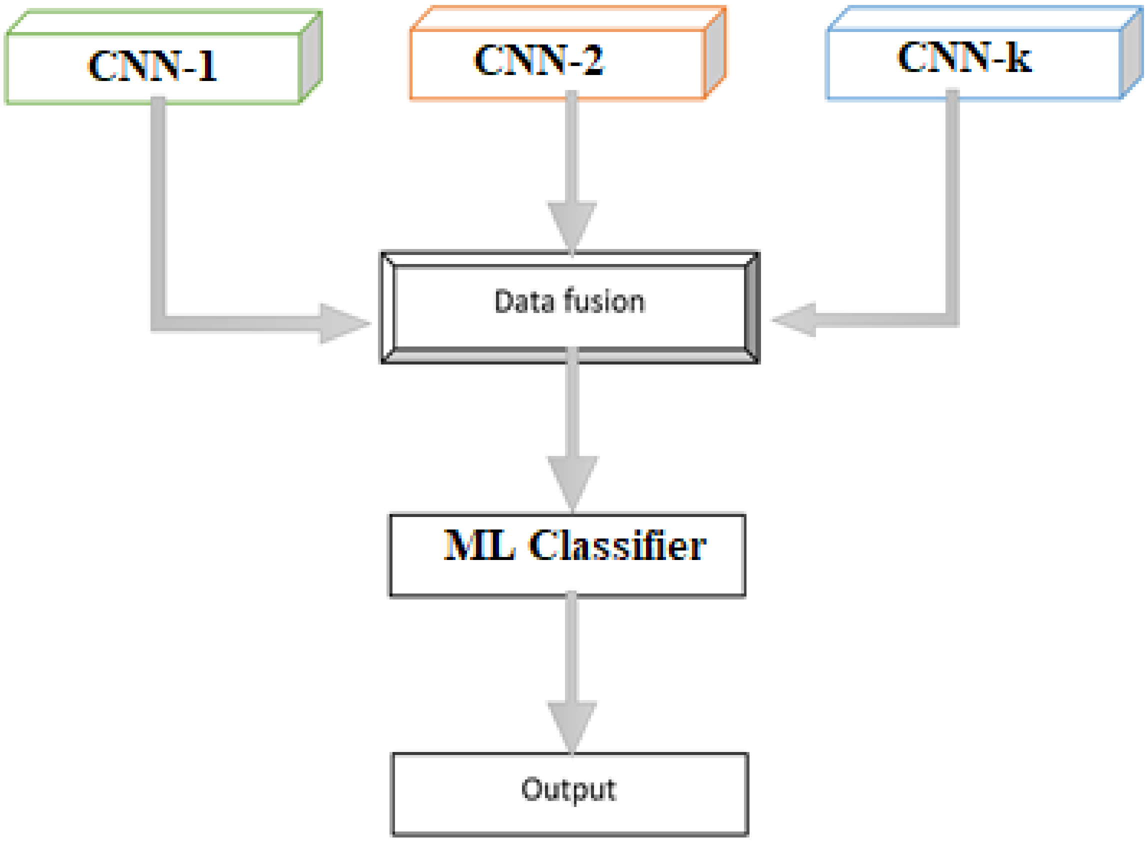
- **Based on:**
  - Size of the Dataset
  - Characteristic of the new dataset to the Imagenet Dataset

https://cs231n.github.io/transfer-learning/

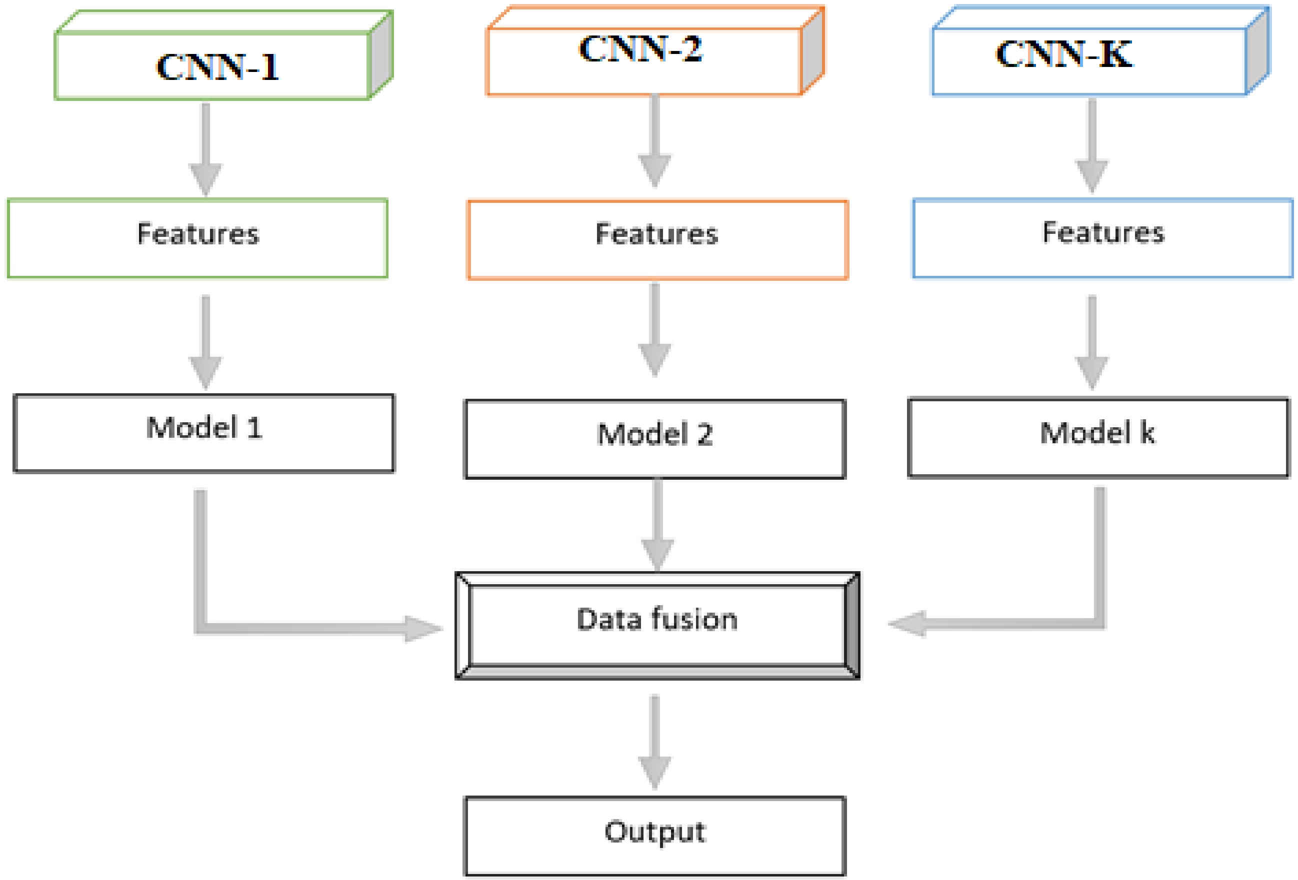
How to Choose the Type of Transfer Learning

- Case:1
  - If Size(Dataset)=Small and Similar to (IMAGENET)
    - Use Case-1 of Transfer Learning
- Case:2
  - If Size(Dataset)=Large and Similar to (IMAGENET)
    - Use Case-3 of Transfer Learning
- Case:3
  - If Size(Dataset)=Medium and Similar to (IMAGENET)
    - Use Case-2 of Transfer Learning
- Case:4
  - If Size(Dataset)=Small and DisSimilar to (IMAGENET)
    - Use Initial Layers and dump middle layers and use flatten and train a Shallow ML model.
- Case:5
  - If Size(Dataset)=Large and DisSimilar to (IMAGENET)
    - Initialize the Model using pretrained CNN and tune the whole model.

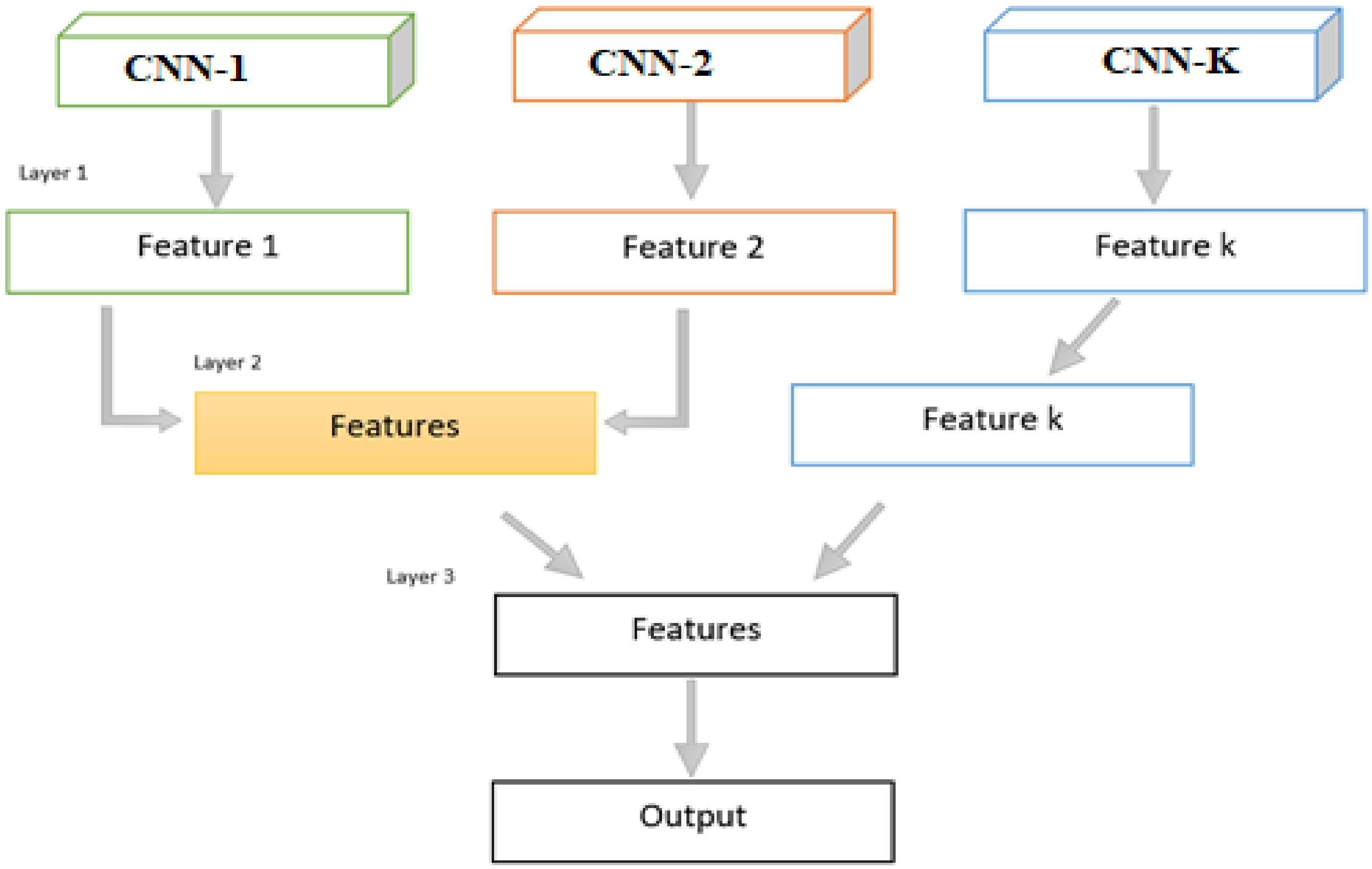
EARLY FUSION (OR FEATURE LEVEL FUSION)



LATE FUSION (OR DECISION LEVEL FUSION)



INTERMEDIATE FUSION



For Your Valuable Time.