UNSW
THE UNIVERSITY OF NEW SOUTH WALES

Convolutional Neural Networks

Never Stand Still | Faculty of Engineering | COMP9444 Week 4a

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Learning Outcomes

By the end of this module, you will:

- learn “Why we need CNNs for Images/Videos?”
- learn building blocks of a typical CNN architecture
- describe convolutional network, including convolution operator, stride, padding, max pooling
- Identify the limitations of 2-layer neural networks
- explain the problem of vanishing or exploding gradients, and how it can be solved using techniques such as weight initialization, batch normalization, skip connections, dense blocks
- design a customized CNN model using building blocks
- learn how we can apply CNNs to solve various computer vision problems

Agenda

- What is Computer Vision?
- What are various applications of Computer Vision?
- What are Convolution Neural Networks (CNNs)?
- What are typical building blocks of a CNN?
- How can we arrange these building blocks to design a customized CNN architecture?
- Walkthrough of LeNet

Admin

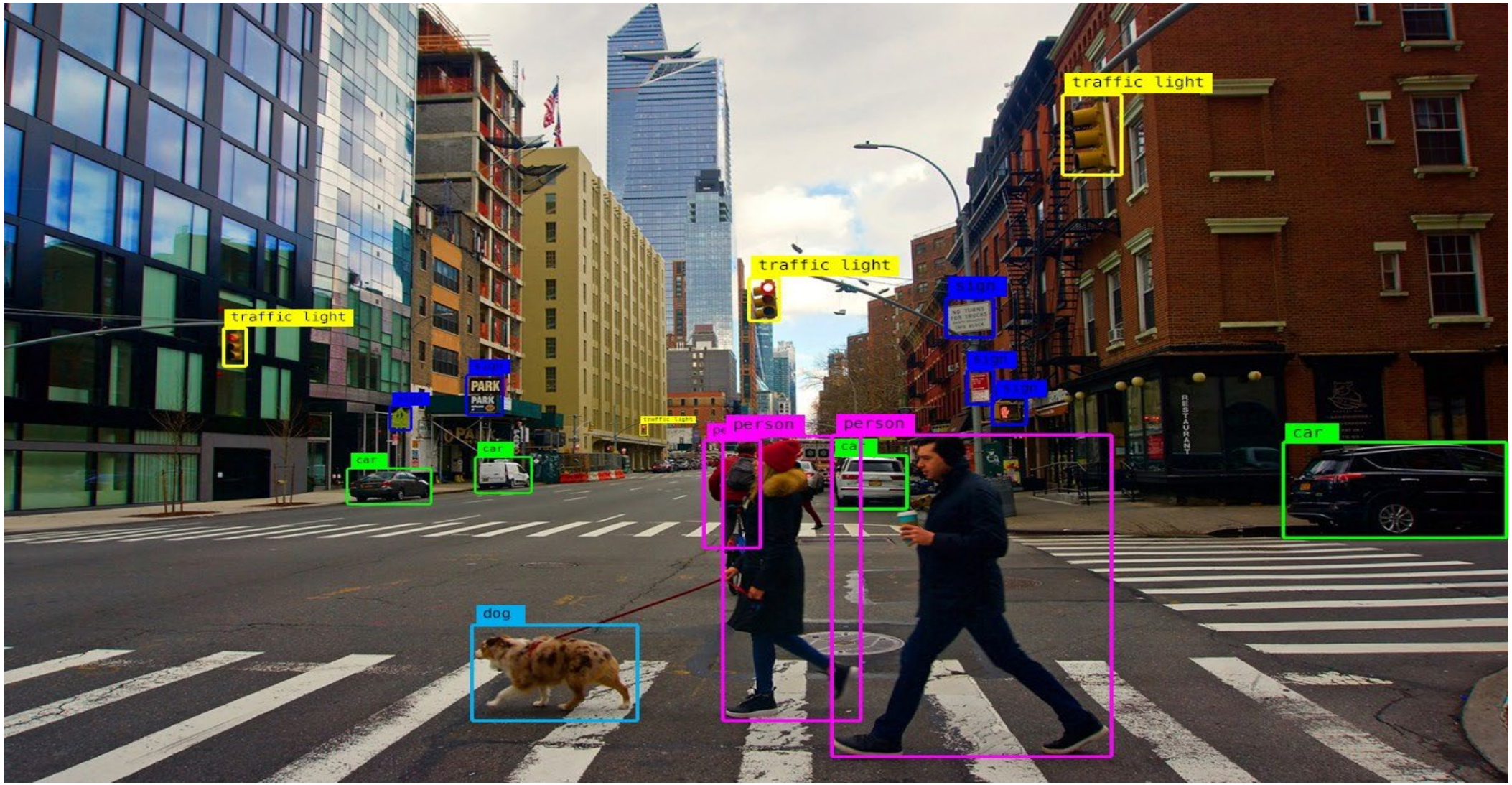
- Assignment 1 submission soon: 18 October, 2023 23:59 pm

- Project Work:
  - Form a team of 5 members
  - Start exploring project ideas

- Project submission:
  - Codebase (in the form of Jupyter Notebook) – Week 10 [19 November 2023, 23:59 pm]
  - 4 pages summary report – Week 10 [19 November 2023, 23:59 pm]
  - Group Presentation – Week 10 [in respective mentoring sessions]

Computer Vision

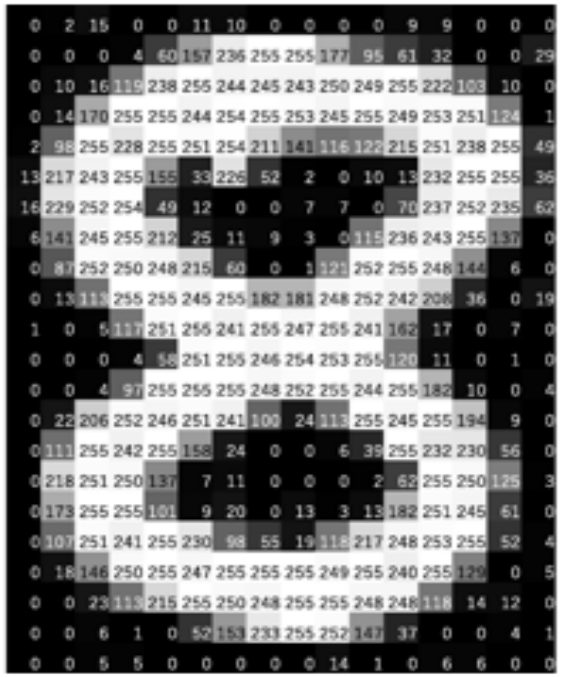
- Enabling machines to process, represent, understand, and generate visual data



Source: Computer Vision in Practice. https://levelup.gitconnected.com/deployment-computer-vision-in-practice-99b7bbb6aa7c

How computers see images?

- A matrix of numbers



What Computer Sees

```
  0   2  15   0   0  11  10   0   0   0   0   9   9   0   0   0
  0   0   0   4  60 157 236 255 255 177  95  61  32   0   0  29
  0  10  16 119 238 255 244 245 243 250 249 255 222 103  10   0
  0  14 170 255 255 244 254 255 253 245 255 249 253 251 124   1
  2  98 255 228 255 251 254 211 141 116 122 215 251 238 255  49
 13 217 243 255 155  33 226  52   2   0  10  13 232 255 255  36
 16 229 252 254  49  12   0   0   7   7   0  70 237 252 235  62
  6 141 245 255 212  25  11   9   3   0 115 236 243 255 137   0
  0  87 252 250 248 215  60   0   1 121 252 255 248 144   6   0
  0  13 113 255 255 245 255 182 181 248 252 242 208  36   0  19
  1   0   5 117 251 255 241 255 247 255 241 162  17   0   7   0
  0   0   0   4  58 251 255 246 254 253 255 120  11   0   1   0
  0   0   4  97 255 255 255 248 252 255 244 255 182  10   0   4
  0  22 206 252 246 251 241 100  24 113 255 245 255 194   9   0
  0 111 255 242 255 158  24   0   0   6  39 255 232 230  56   0
  0 218 251 250 137   7  11   0   0   0   2  62 255 250 125   3
  0 173 255 255 101   9  20   0  13   3  13 182 251 245  61   0
  0 107 251 241 255 230  98  55  19 118 217 248 253 255  52   4
  0  18 146 250 255 247 255 255 255 249 255 240 255 129   0   5
  0   0  23 113 215 255 250 248 255 255 248 248 118  14  12   0
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  0   0   5   5   0   0   0   0   0  14   1   0   6   6   0   0
```
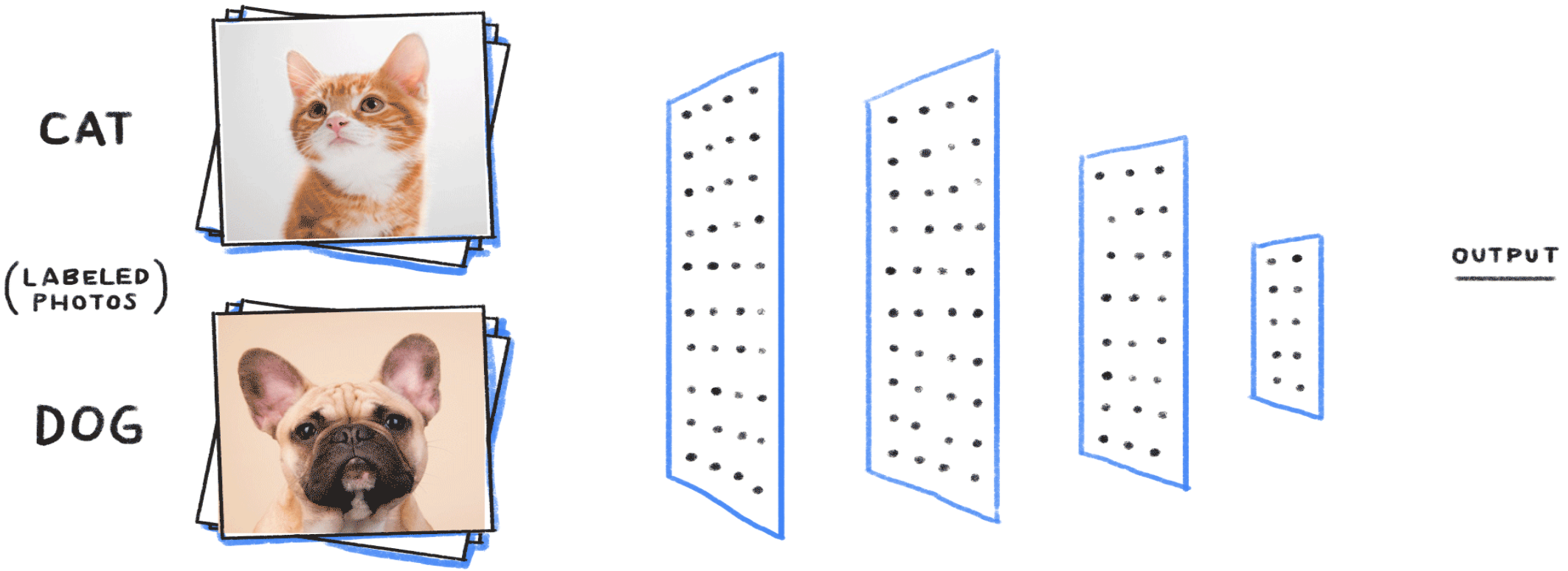


Source: https://medium.com/analytics-vidhya/cnn-series-part-1-how-do-computers-see-images-32462a0b33ca

CV Applications

- Image Classification



Source: Medium: Introduction to CNN & Image Classification Using CNN in PyTorch. https://medium.com/swlh/introduction-to-cnn-image-classification-using-cnn-in-pytorch-11eefae6d83c

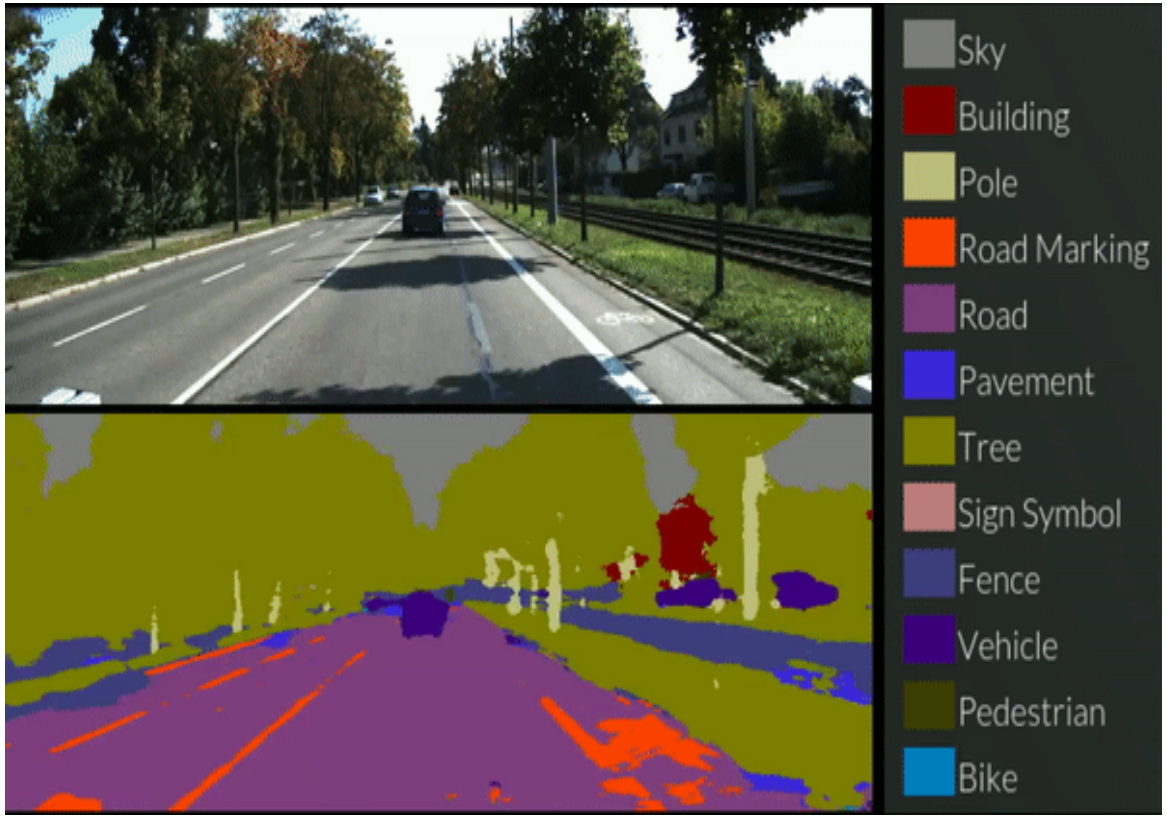
CV Applications

- Object Detection

Image Credit: Google Cloud Vision API. https://cloud.google.com/vision/docs/object-localizer

CV Applications

- Segmentation



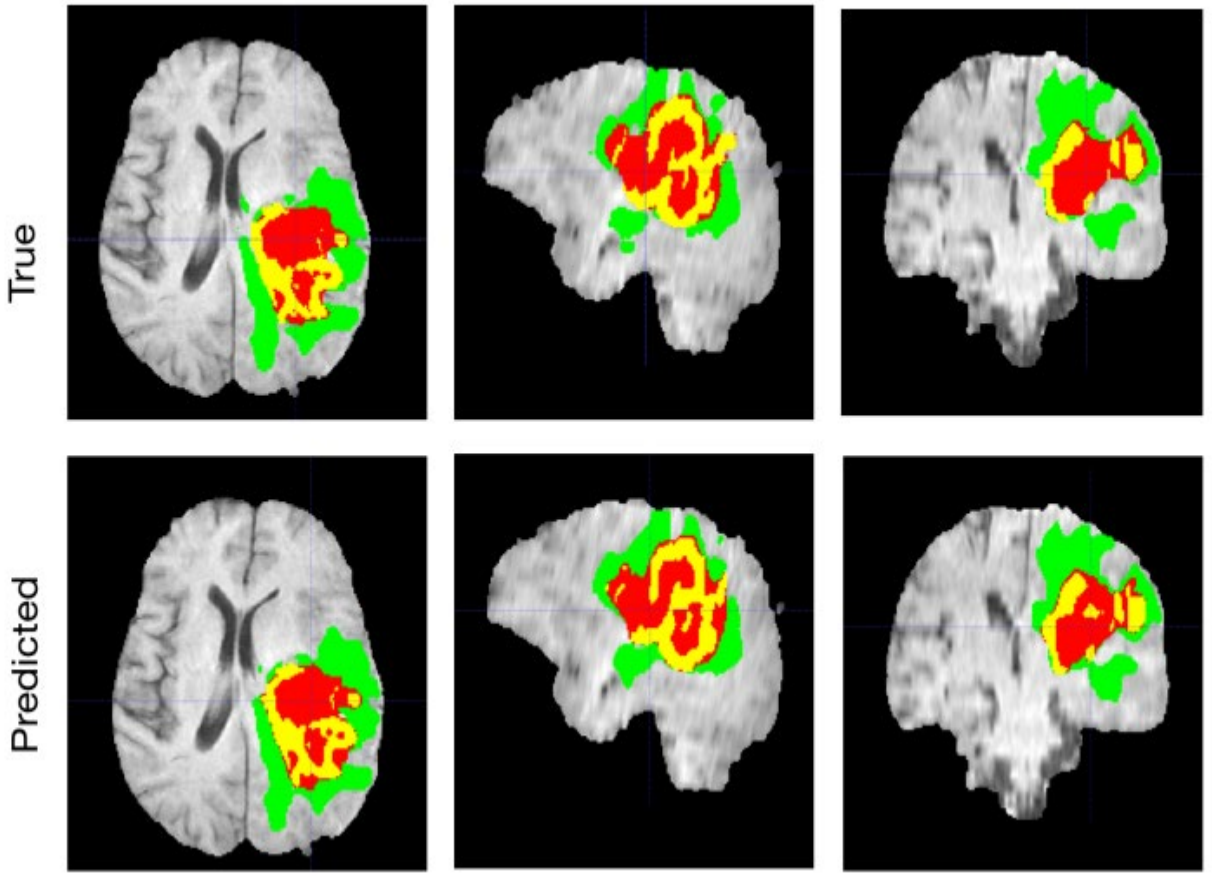
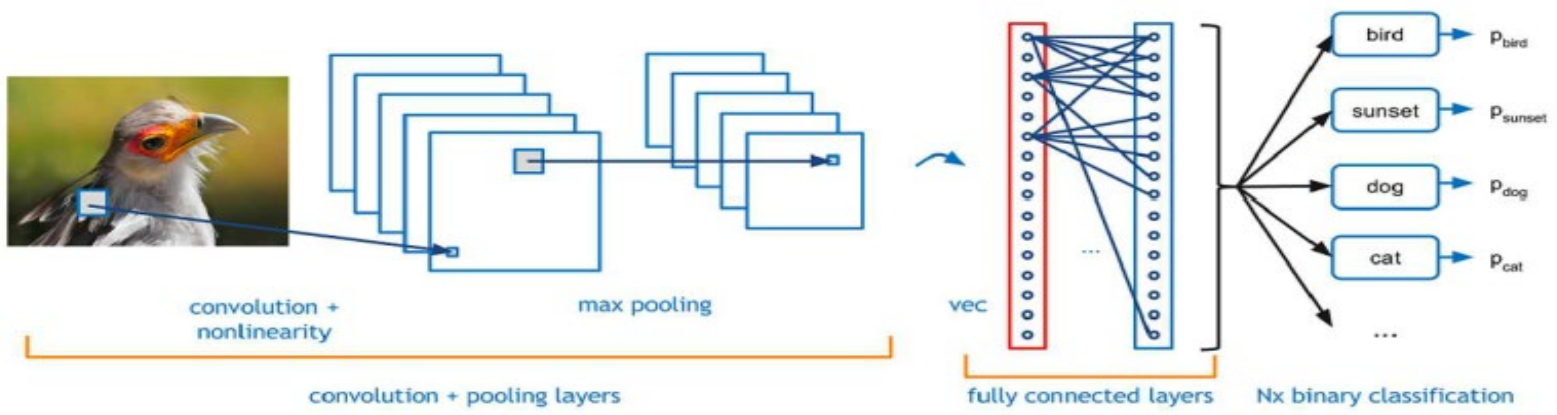


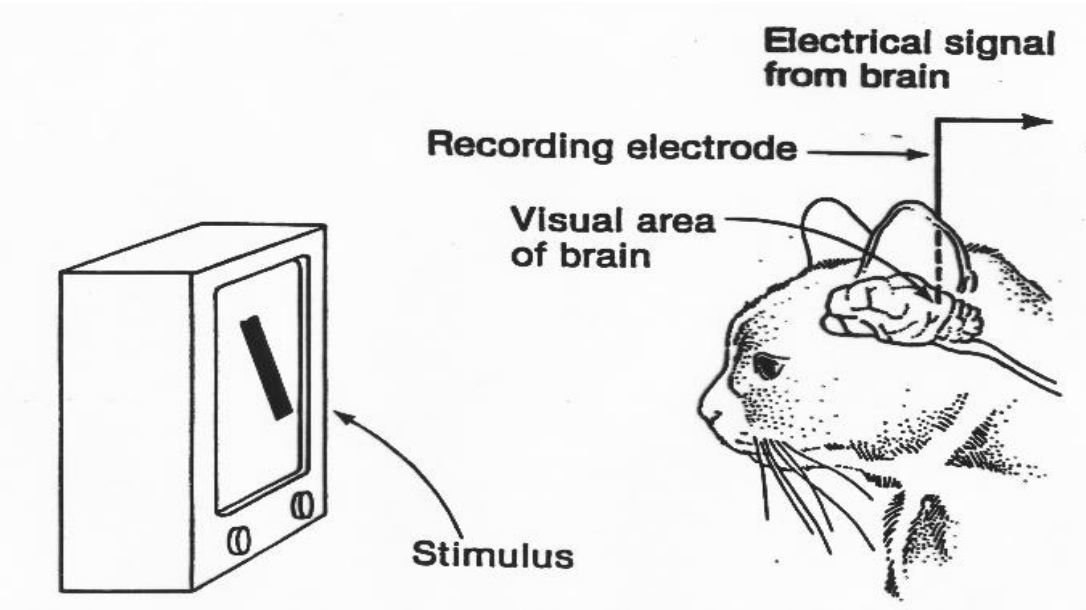
Image Credit: Analytics Vidhya: Introduction to Semantic Image Segmentation. https://medium.com/analytics-vidhya/introduction-to-semantic-image-segmentation-856cda5e5de8
Nvidia AI: Automatically segmenting brain tumours with AI. https://developer.nvidia.com/blog/automatically-segmenting-brain-tumors-with-ai/

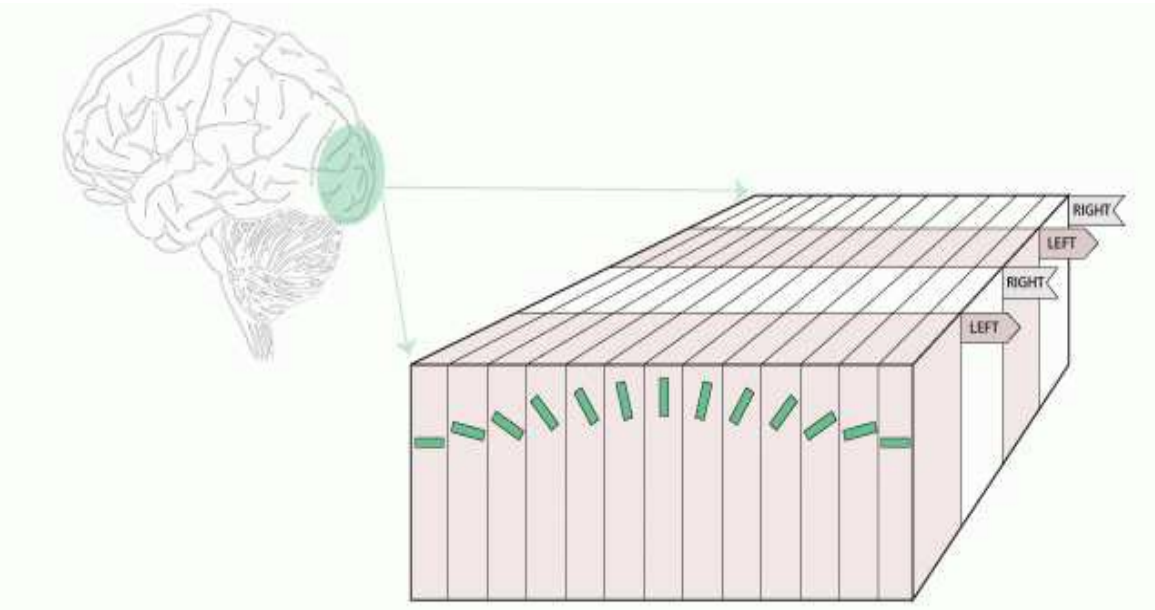
Convolutional Networks



- Suppose we want to classify an image as a bird, sunset, dog, cat, etc.
- If we can identify features such as feather, eye, or beak which provide useful information in one part of the image, then those features are likely to also be relevant in another part of the image.
- We can exploit this regularity by using a convolution layer which applies the same weights to different parts of the image.

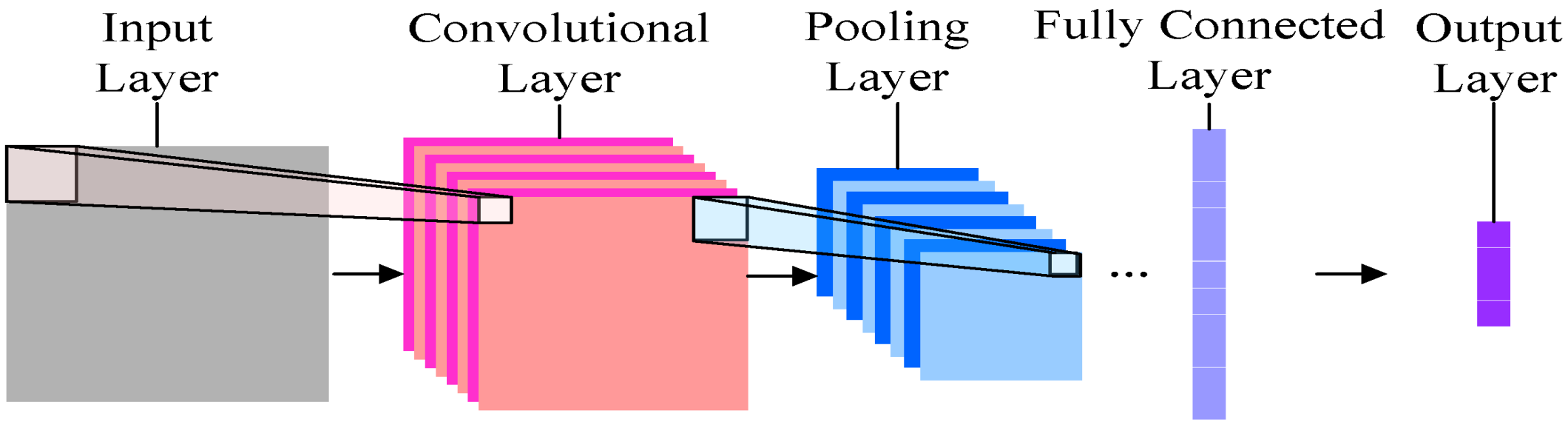
Hubel and Weisel – Visual Cortex





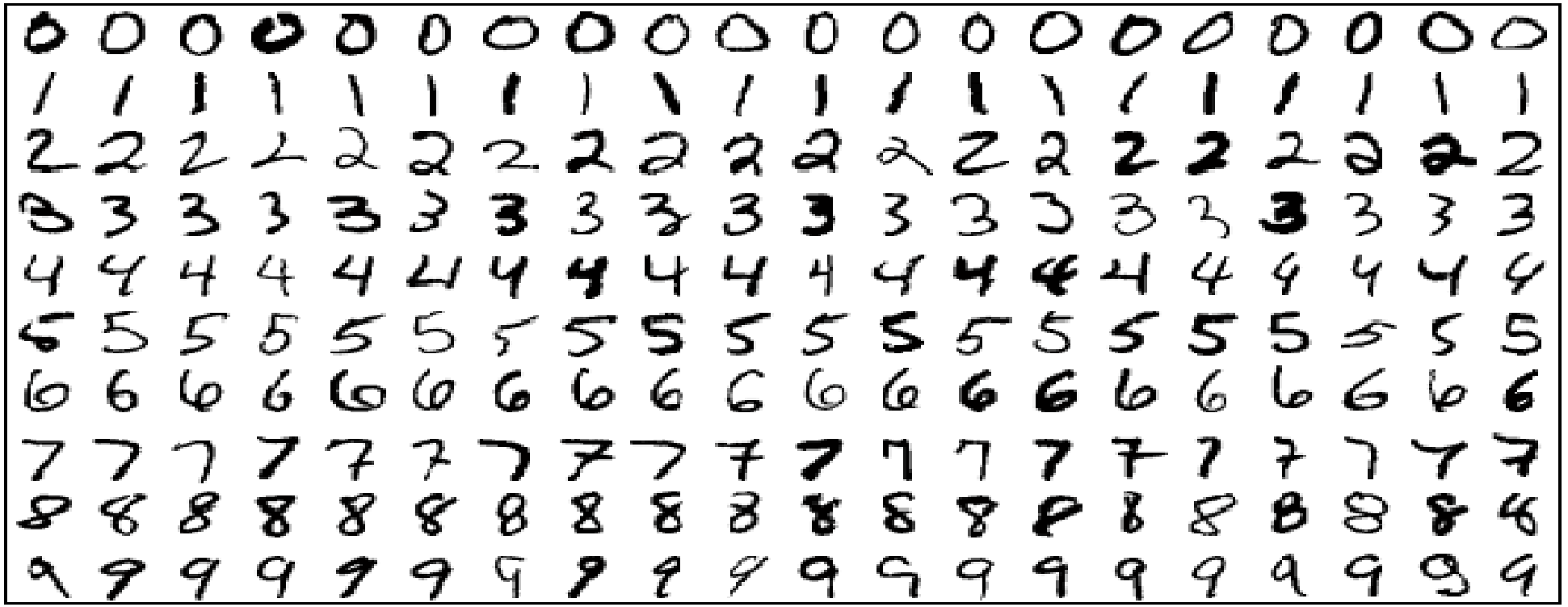
- cells in the visual cortex respond to lines at different angles
- Cells in V2 respond to more sophisticate visual features
- Convolutional Neural Networks are inspired by this neuroanatomy
- CNN's can now be simulated with massive parallelism, using GPU's

Convolutional Network Components



- **Convolutional layers**: extract shift-invariant features from the previous layer
- **Subsampling or pooling layers**: combine the activations of multiple units from the previous layer into one unit
- **Fully connected layers**: collect spatially diffuse information
- **Output layer**: choose between classes

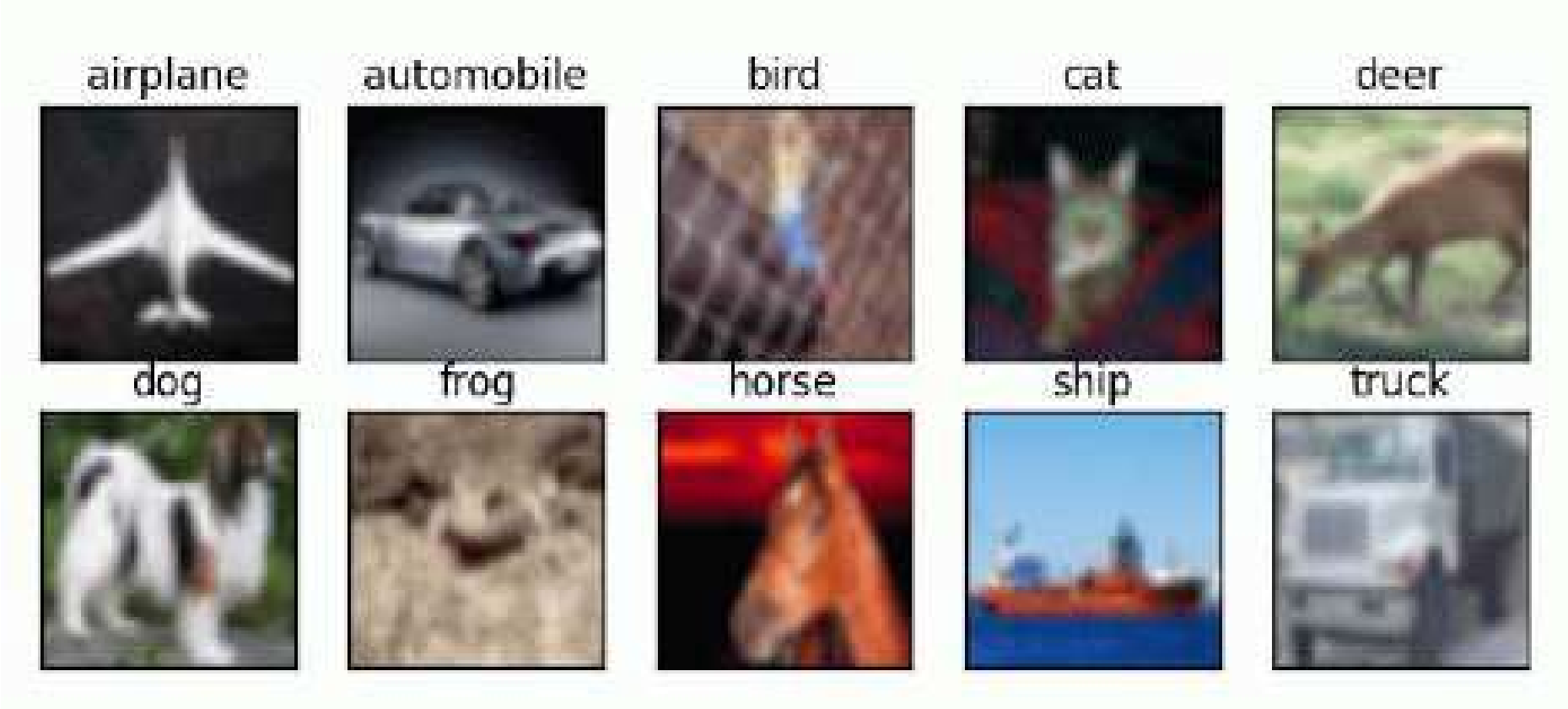
MNIST Handwritten Digit Dataset



- black and white images, resolution 28 x 28
- 60,000 images
- 10 classes (0, 1, 2, 3, 4, 5, 6, 7, 8, 9)

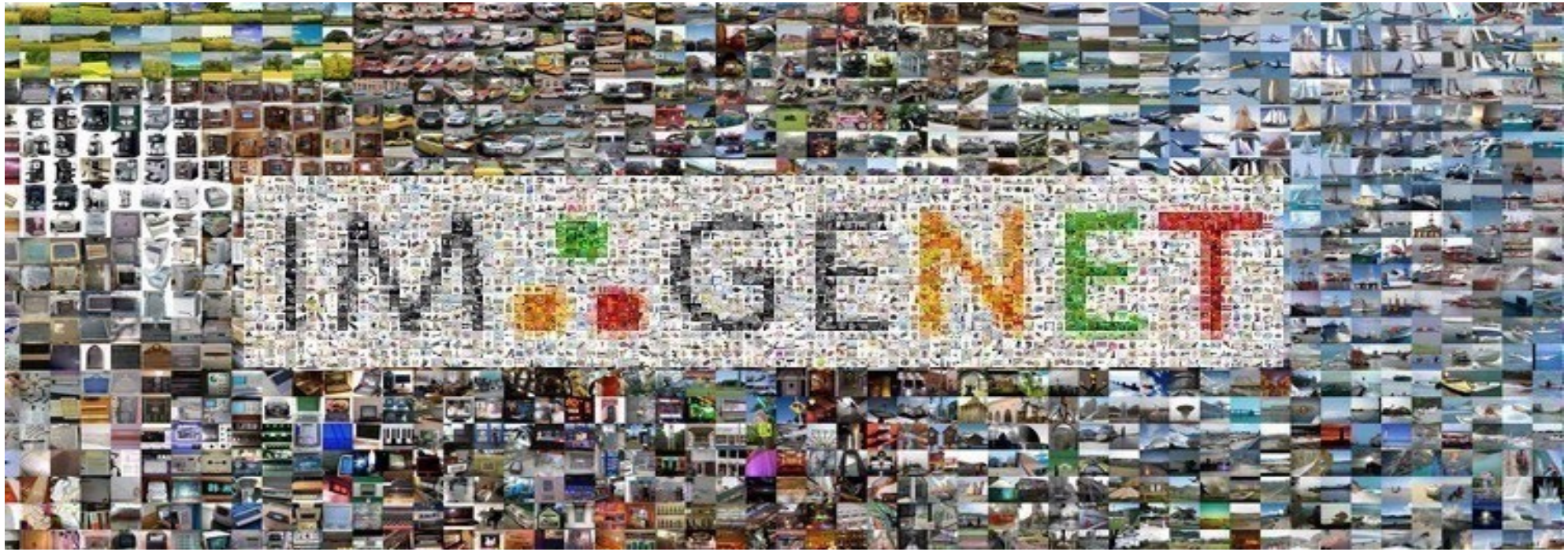
Image Credit:

CIFAR Image Dataset



- color images, resolution 32 x 32
- 50,000 images
- 10 classes

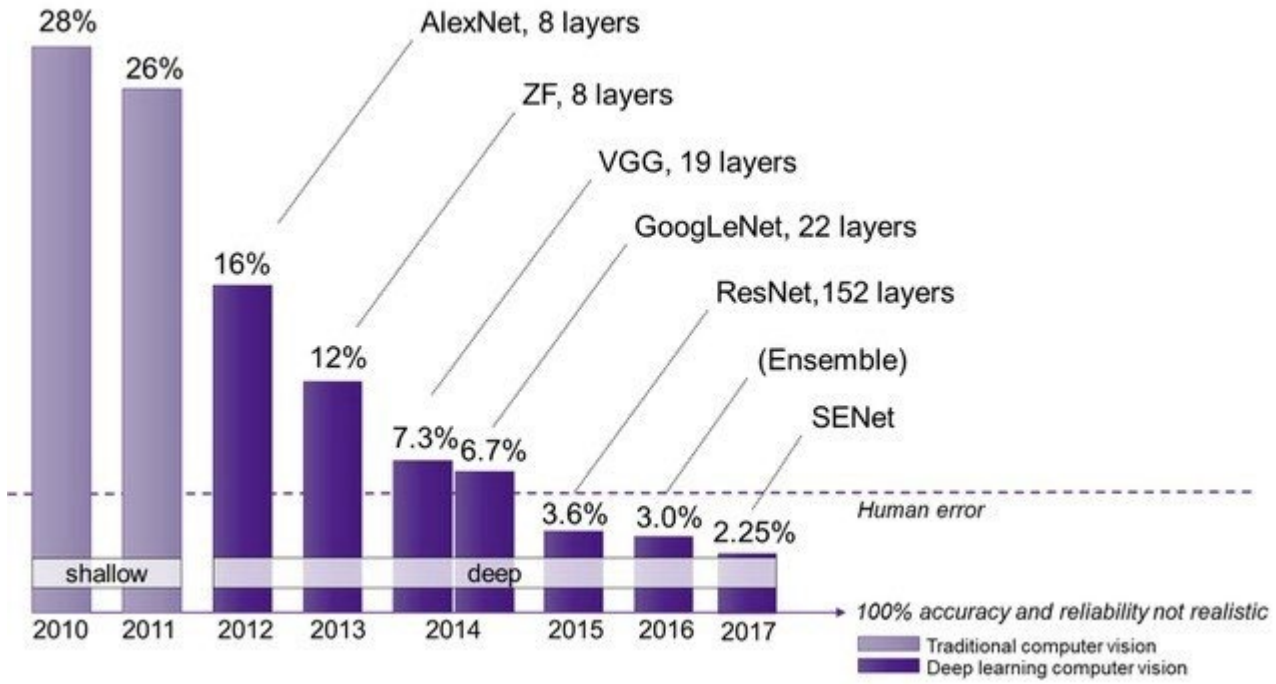
ImageNet LSVRC Dataset



- color images, resolution 227 x 227
- 1.2 million images
- 1000 classes

Convolutional Neural Networks (CNNs)

- A class of deep neural networks suitable for processing 2D/3D data. For e.g., Images and Videos
- CNNs can capture high-level representation of images/videos which can be used for end-tasks such as classification, object detection, segmentation, etc.
- A range of CNNs improving over the years



Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

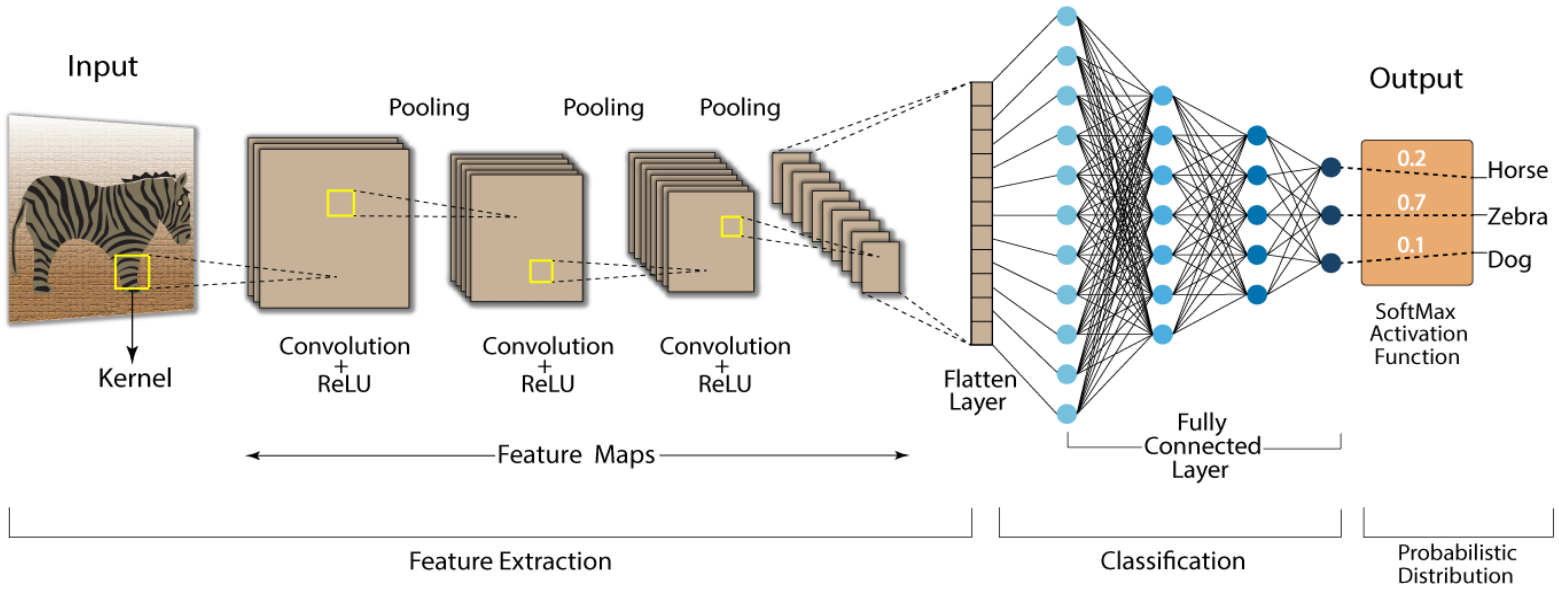
Why CNNs?

- **Regular Neural Networks (ANNs) don't scale well with increasing dimensions**
  - Image of dimensions 8 x 8: Considering color image having 3 channels, the input dimensions of the neural network would be 3 x 8 x 8 = 192 units (**Manageable**)
  - Image of dimensions 500 x 500: The input dimensions of the neural network would be 3 x 500 x 500 = 750,000 units (**Complexity and the number of parameters increasing exponentially -> unmanageable and inefficient**)
- CNNs leverage important ideas:
  - **sparse interaction** : Making kernel smaller than the input e.g., an image, we can detect meaningful information that is much smaller than thousands or millions of pixels. This means storing fewer parameters requiring less memory.
  - **parameter sharing** : In CNNs we have weight sharing. For getting output, weights applied to one input are the same as the weight applied elsewhere.
  - **equivariant representation** : Due to weight sharing, CNN have a property of equivariance to translation, which means if we change the input in a way, the output will also get changed in the same way.

Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

CNN Architecture

- A typical CNN architecture consists of the following layers:
  - Convolution layer
  - ReLU layer (non-linearity)
  - Pooling layer
  - Flattening
  - Fully-connected layer
  - Output layer



- There can be multiple steps of convolution followed by pooling, before reaching the fully connected layers.

Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

Convolution Operator

Continuous convolution

$$s(t) = (x * w)(t) = \int x(a)w(t-a)da$$

Discrete convolution

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$$

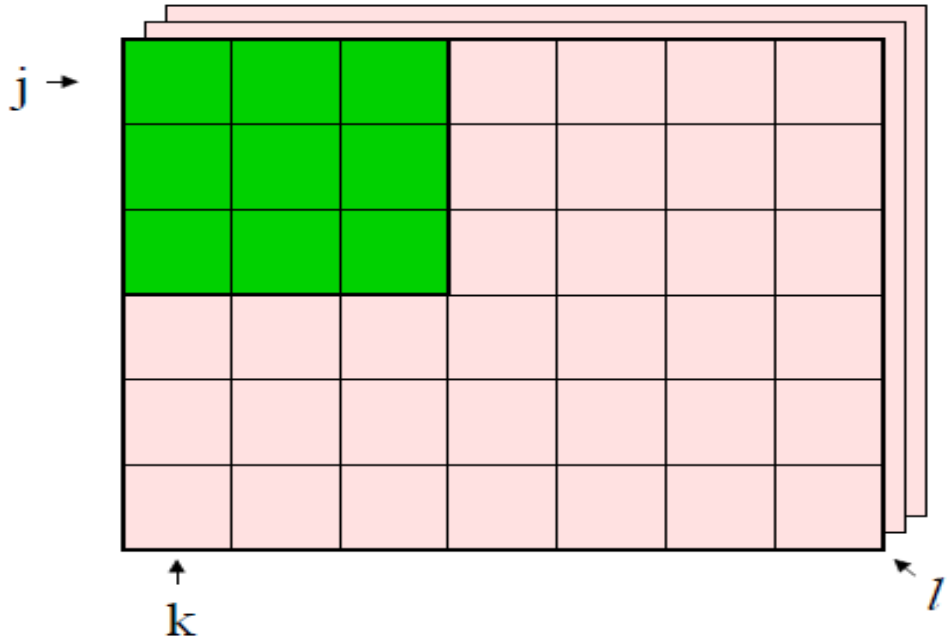
Two-dimensional convolution

$$S(j,k) = (K * I)(j,k) = \sum_m \sum_n K(m,n)I(j+m,k+n)$$

Note: Theoreticians sometimes write *I(j-m, k-n)* so that the operator is commutative.

But, computationally, it is easier to write it with a plus sign.

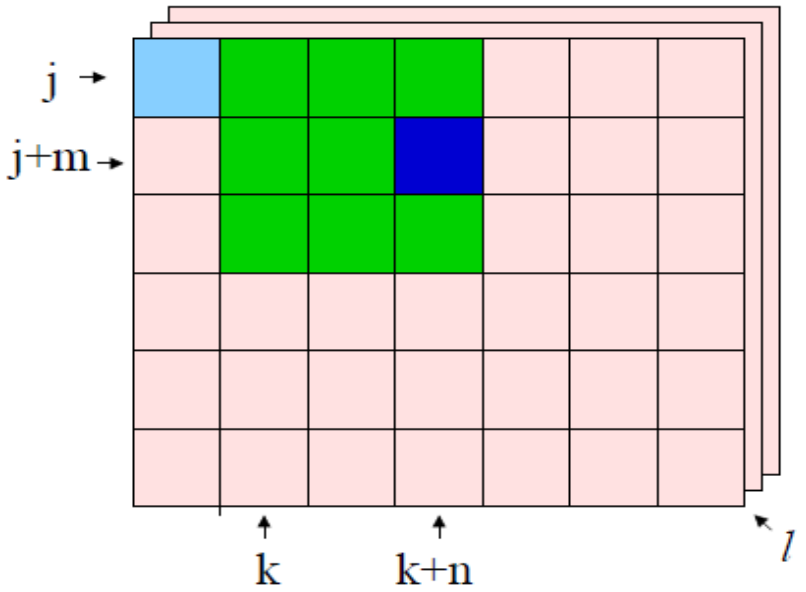
Convolutional Neural Networks



Assume the original image is *J x K*, with *L* channels.

We apply an *M x N "filter"* to these inputs to compute one hidden unit in the convolution layer. In this example, *J = 6, K = 7, L = 3, M = 3, N = 3*

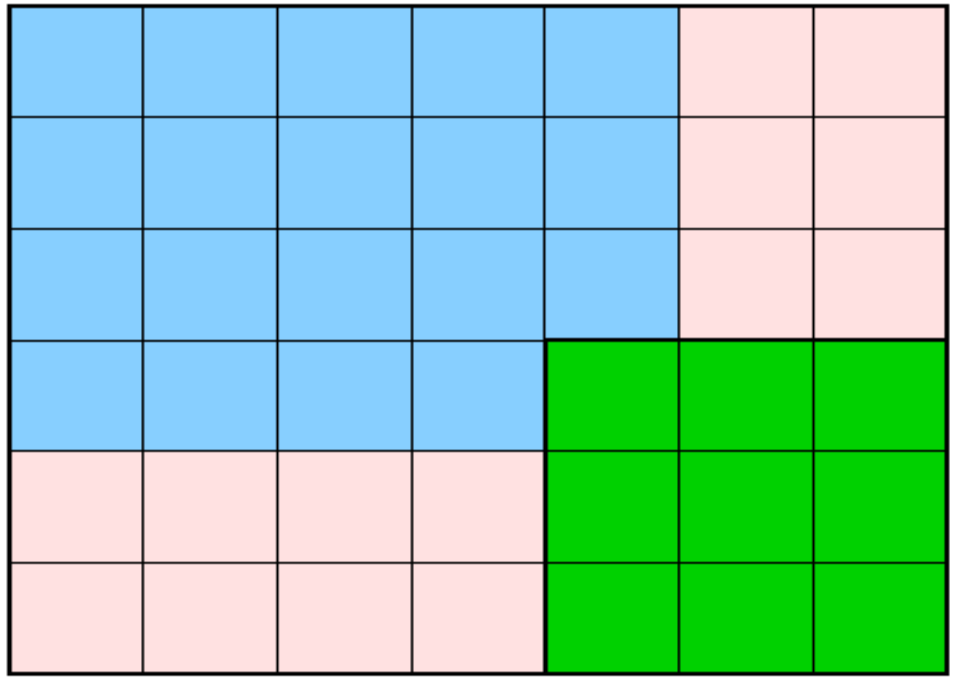
Convolutional Neural Networks



$$Z^i_{j,k} = g\left(b^i + \sum_l \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} K^i_{l,m,n} V^l_{j+m,k+n}\right)$$

The same weights are applied to the next ***M x N*** block of inputs, to compute the next hidden unit in the convolution layer ("weight sharing").

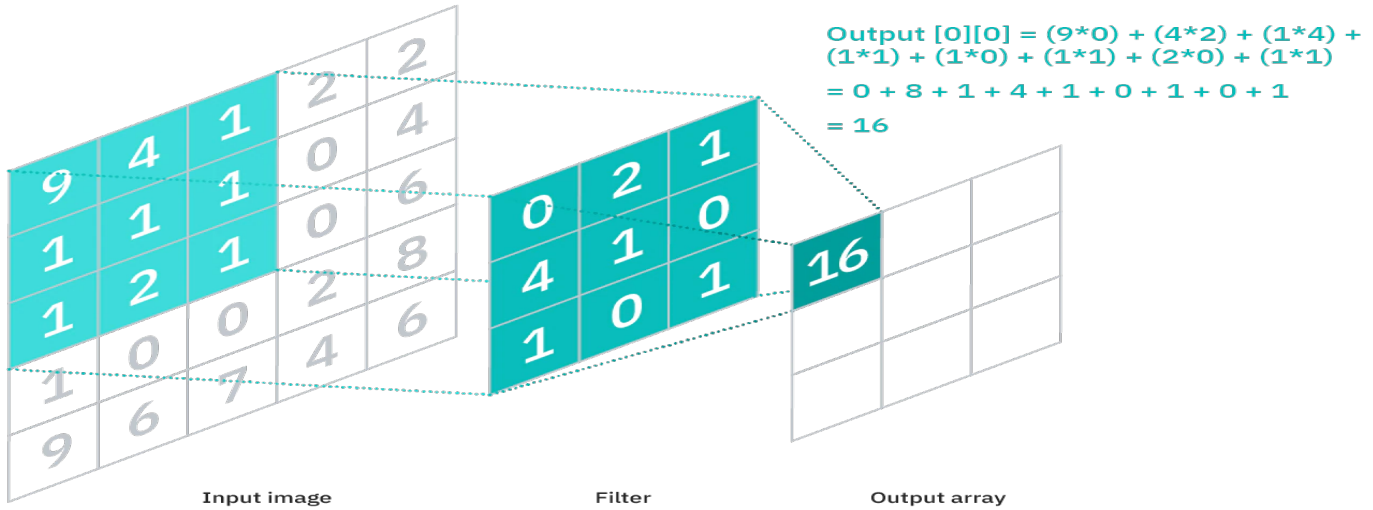
Convolutional Neural Networks



If the original image size is $J \times K$ and the filter size is $M \times N$, the convolution layer will be $(J + 1 - M) \times (K + 1 - N)$

Convolution Layer

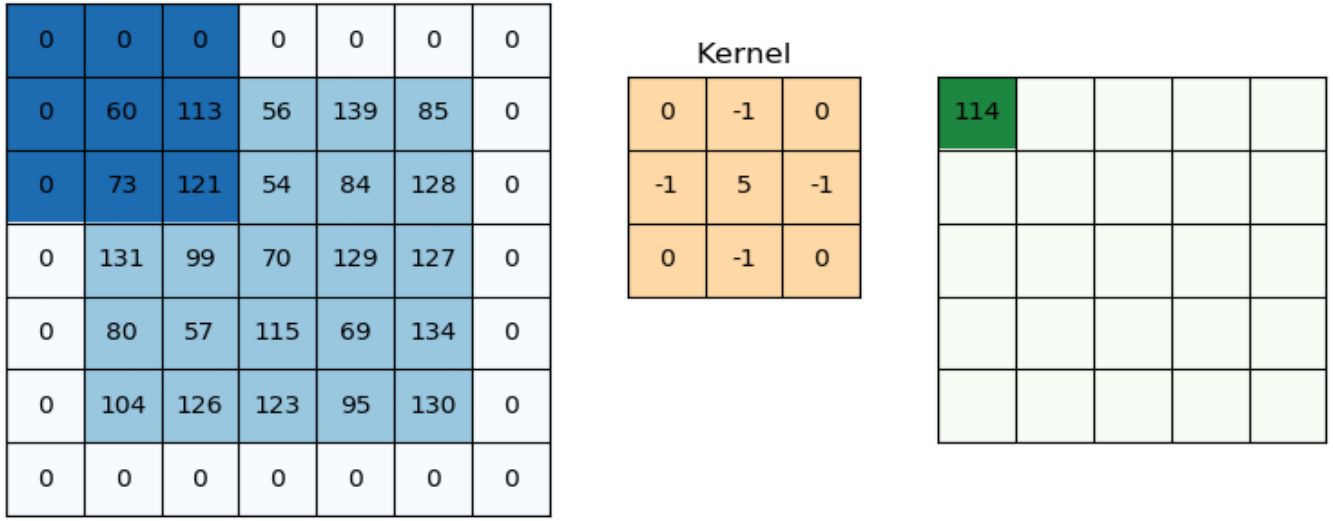
- The convolution layer detect features or visual features in images such as edges, lines, etc.
- The kernel (also, known as filter or feature detector) move across the receptive field of the image and extracts important features
- The filter carries out a convolution operation which is an element-wise product and sum between two matrices
- Given output value in the feature map does not have to connect to each pixel in the input image, it only needs to connect to the receptive filed, where the filter is being applied. This characteristic is described as “local connectivity”



Source: https://www.ibm.com/cloud/learn/convolutional-neural-networks

Convolution in action

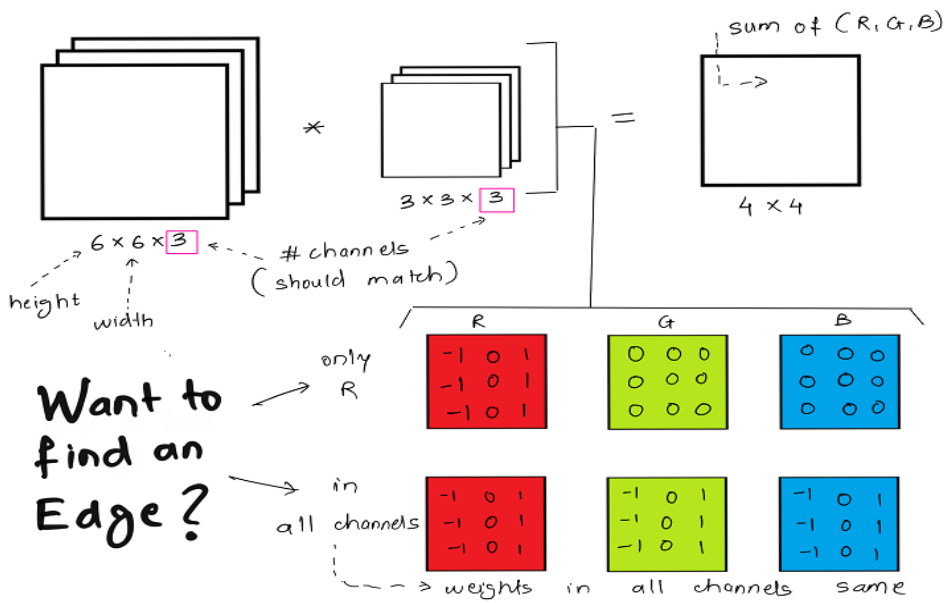
- We need multiple number of filters (feature detectors) to detect different curves/edges or features in the image
- The result of convolving filter over the entire image is an output matrix called feature maps or convolved features that stores the convolutions of the filter over various parts of the image
- N filters produces N feature maps

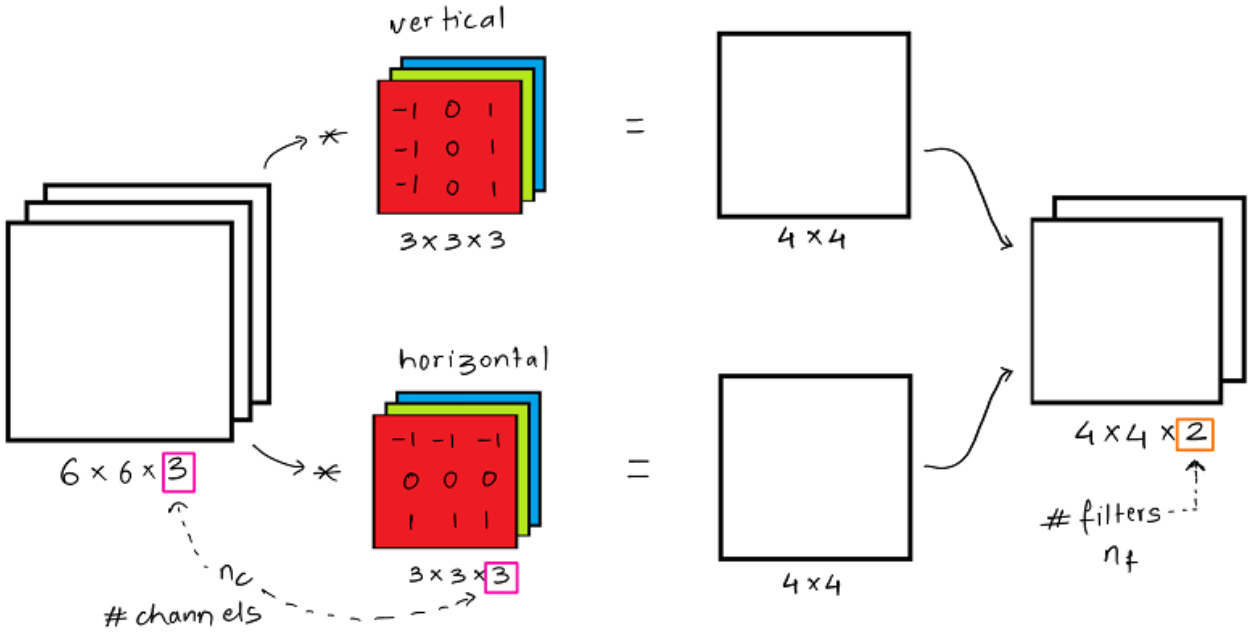


Source: https://www.kdnuggets.com/2020/06/introduction-convolutional-neural-networks.html

Convolution over color images (3 channels)

- If the image dimension is N x N x #channels, so the filter would also be of dimension f x f x #channels
- For extracting different features from an image, we need multiple filters

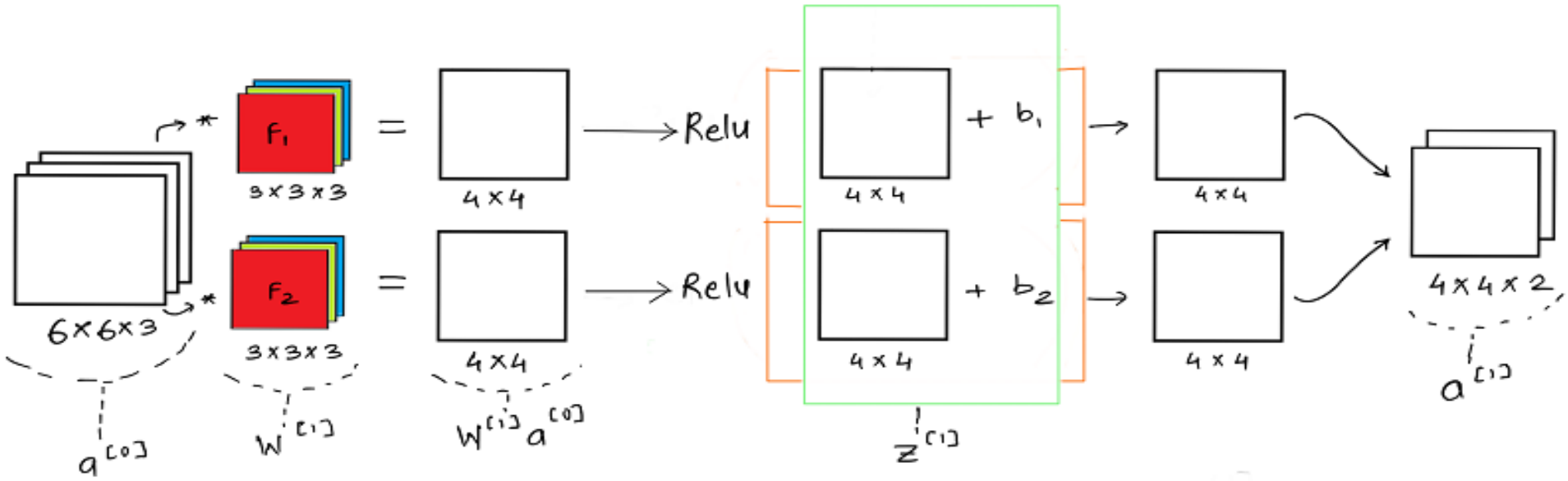




Source: https://towardsdatascience.com/convolutional-neural-network-ii-a11303f807dc

Convolution Layer

- One layer of Convolution over color image, having 2 filters



In any given neural network $z^{[1]} = W^{[1]} a^{[0]} + b^{[1]}$

$a^{[1]} = g(z^{[1]})$

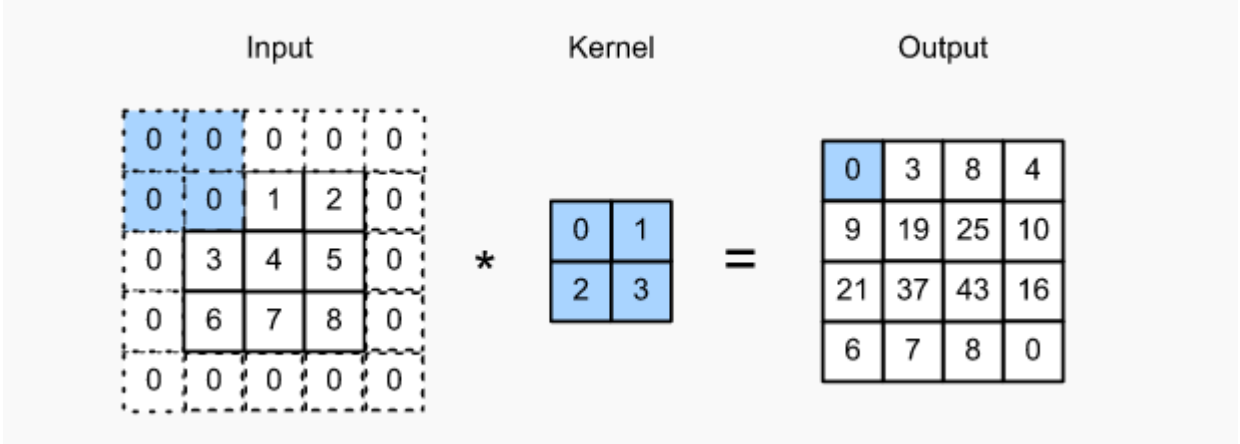
Relu function

Source: https://towardsdatascience.com/convolutional-neural-network-ii-a11303f807dc

Convolution Layer

- Three hyperparameters affect the volume size of the output:
  - **Number of filters**: N distinct filters would yield N different feature maps
  - **Stride**: The distance or the number of pixels, that the kernel moves over the input matrix.
  - **Padding**: Refers to the number of pixels added to an image when it is being processed by the kernel of a CNN. Zero padding, which set elements to zero which fall outside of the input matrix, is usually used when the filters do not fit the input image.
- If we have an image of size W x W x D, a kernel of spatial size F, and stride S, then the size of output volume can be determined by the formula. The output volume is of size Wout x Wout x D

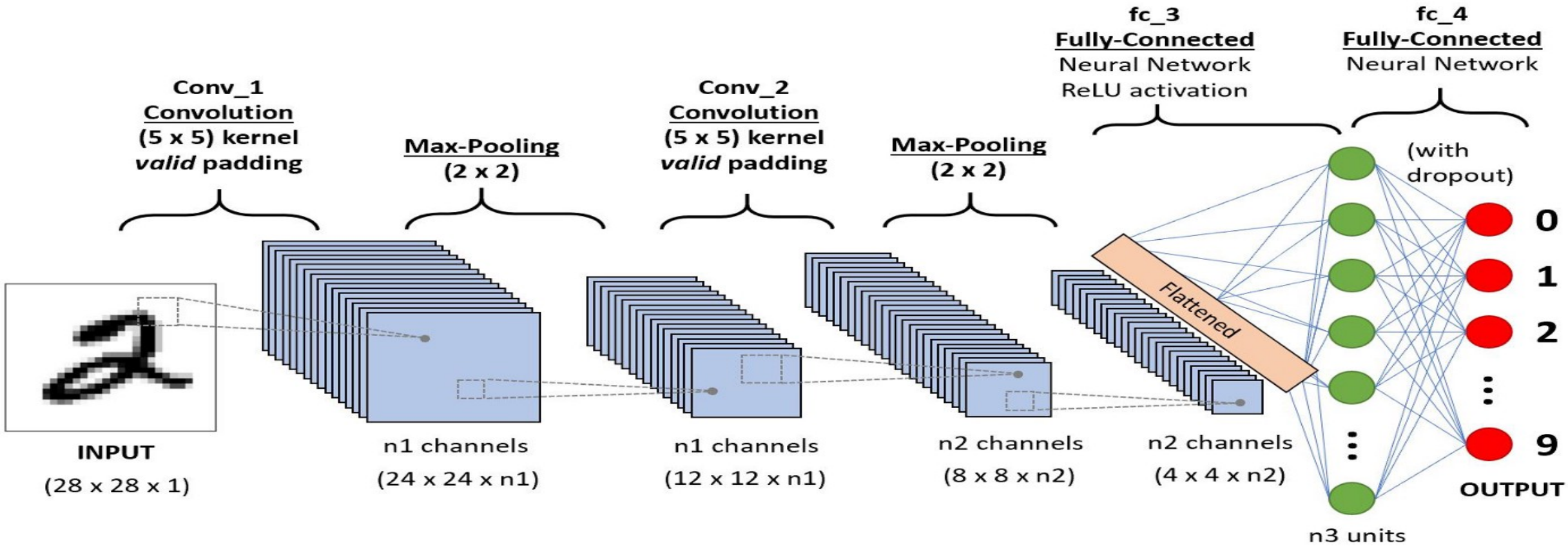
$$W_{out} = \frac{W - F}{S} + 1$$



Source: https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939

Convolution Layer

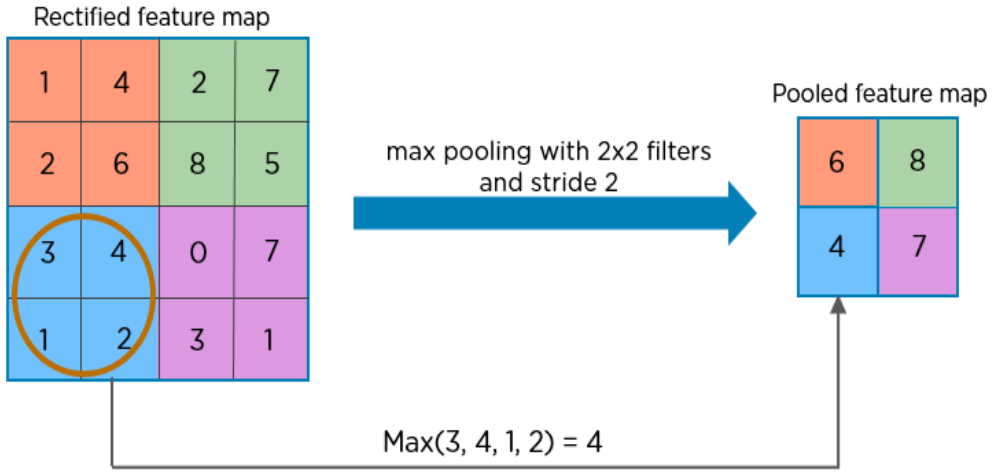
- Let's get numbers right

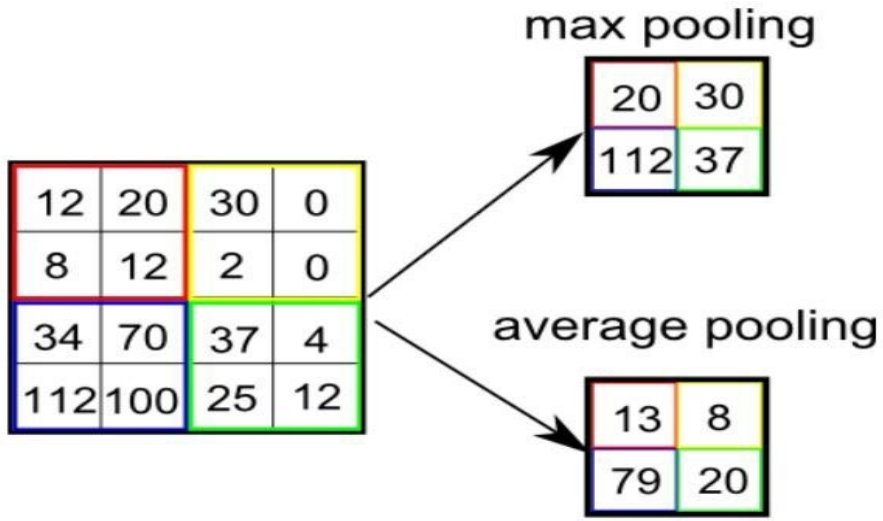


Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

Subsampling or Pooling Layer

- Pooling is a down-sampling operation that reduces the dimensionality of the feature map.
- Each ReLU feature map pass through the pooling layer to generate a pooled feature map.
- Two of the important pooling operations are:
  - Max pooling: As the filter moves across the input, it selects the pixel with the maximum value to send to the output array
  - Average pooling: As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.



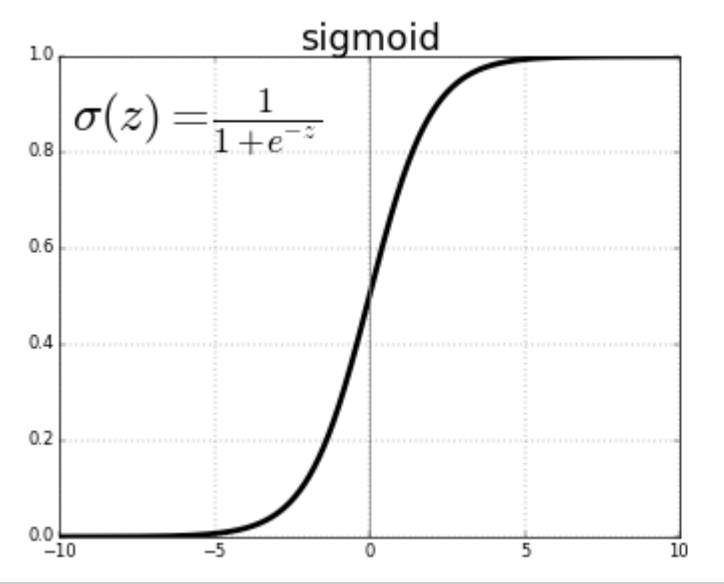


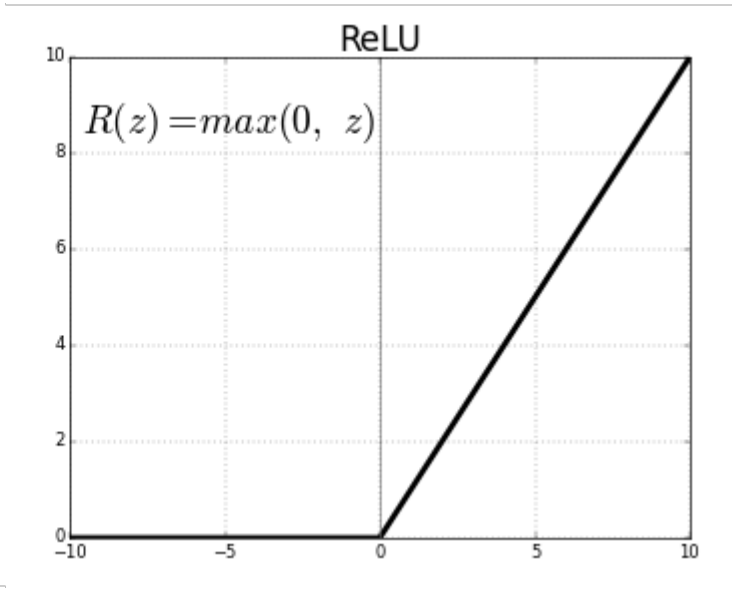
- Although there is information loss due to pooling, it helps to reduce complexity, improve efficiency, and limit risk of overfitting.

Source: https://www.simplilearn.com/tutorials/deep-learning-tutorial/convolutional-neural-network

Non-linearity layers (ReLU)

- Since convolution is a linear operation, non-linearity layers are often placed directly after the convolutional layer to introduce non-linearity to the activation map.
- Main non-linear operators are:
  - Sigmoid
  - Tanh
  - ReLU
- ReLU is more reliable and accelerates the model convergence

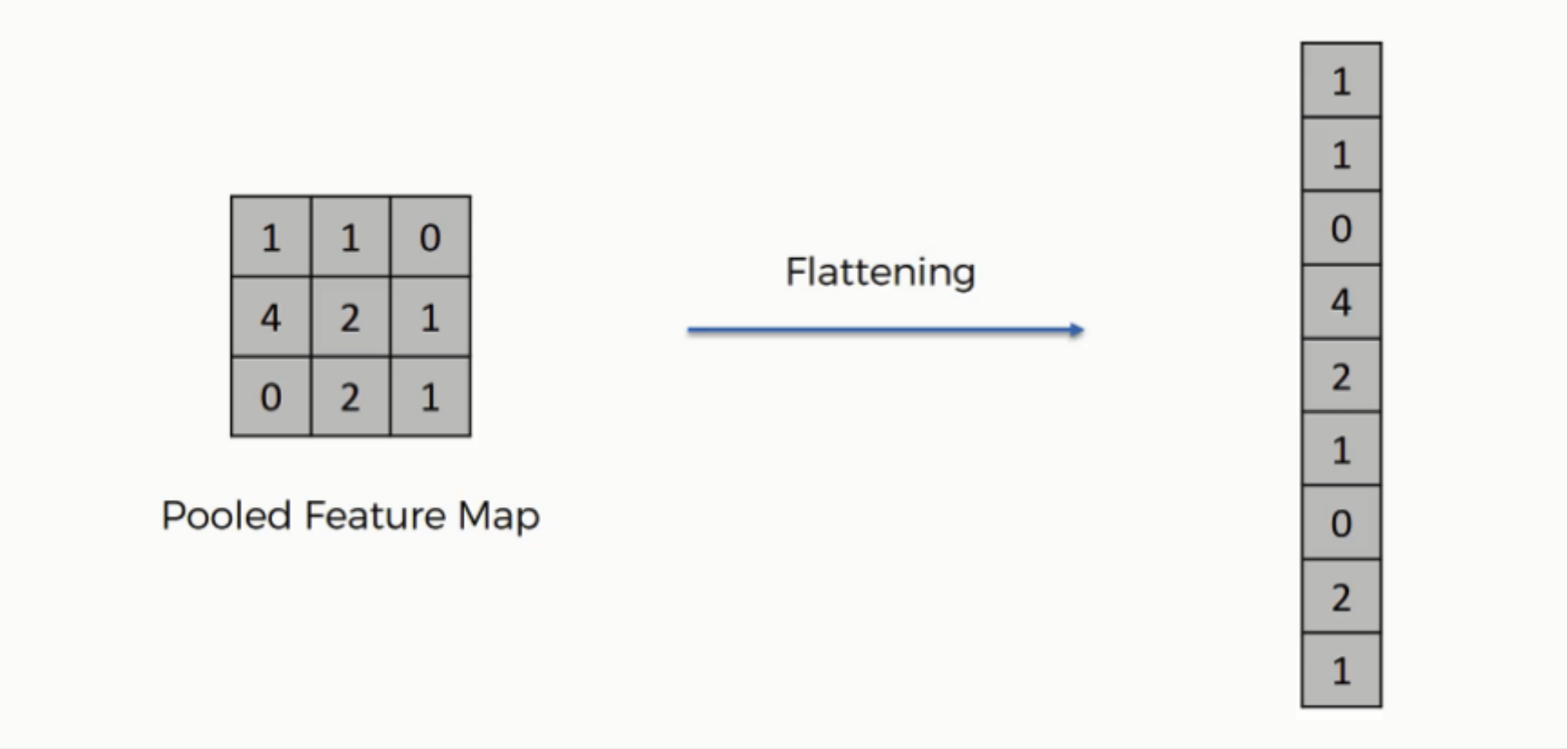




Source: https://towardsdatascience.com/activation-functions-neural-networks-1cbd9f8d91d6

Flattening

- After multiple convolution layers and pooling operations, the 3D representation of the image is converted into a feature vector that is passed into a multi-layer perception (MLP)



Source: https://www.kdnuggets.com/2020/06/introduction-convolutional-neural-networks.html

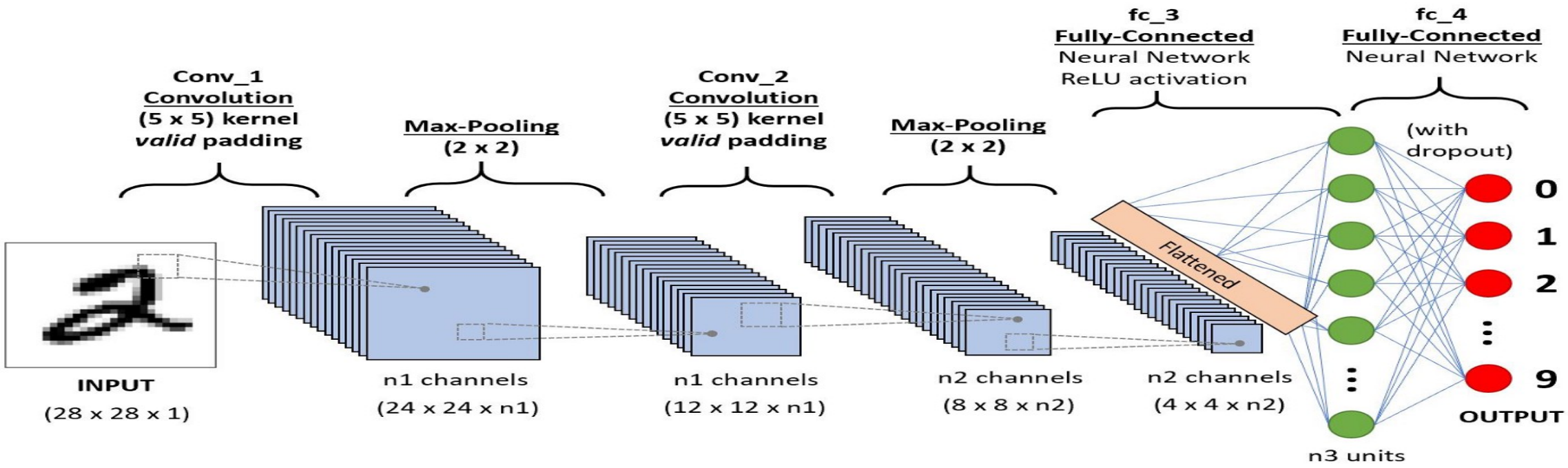
Fully-Connected Layer(s)

- The FC layer comprises the weights and biases together with the neurons and is used to connect the neurons between two separate layers.
- In FC layer, each node in the output layer connects directly to a node in the previous layer.
- The flattened feature map is passed through the FC layer(s)

Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

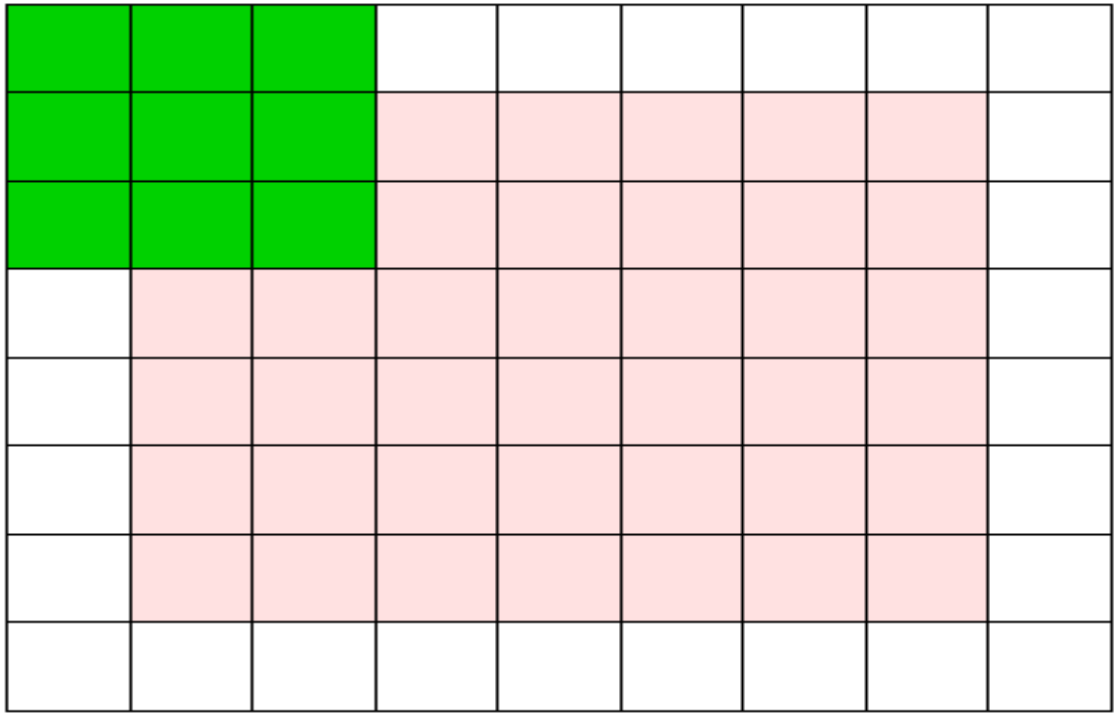
Output Layer

- The output layer produces the probability of each class given the input image
- This is the last layer containing the same number of neurons as the number of classes in the dataset
- The output of this layer passes through the Softmax activation function to normalize the output to have probability sum to one



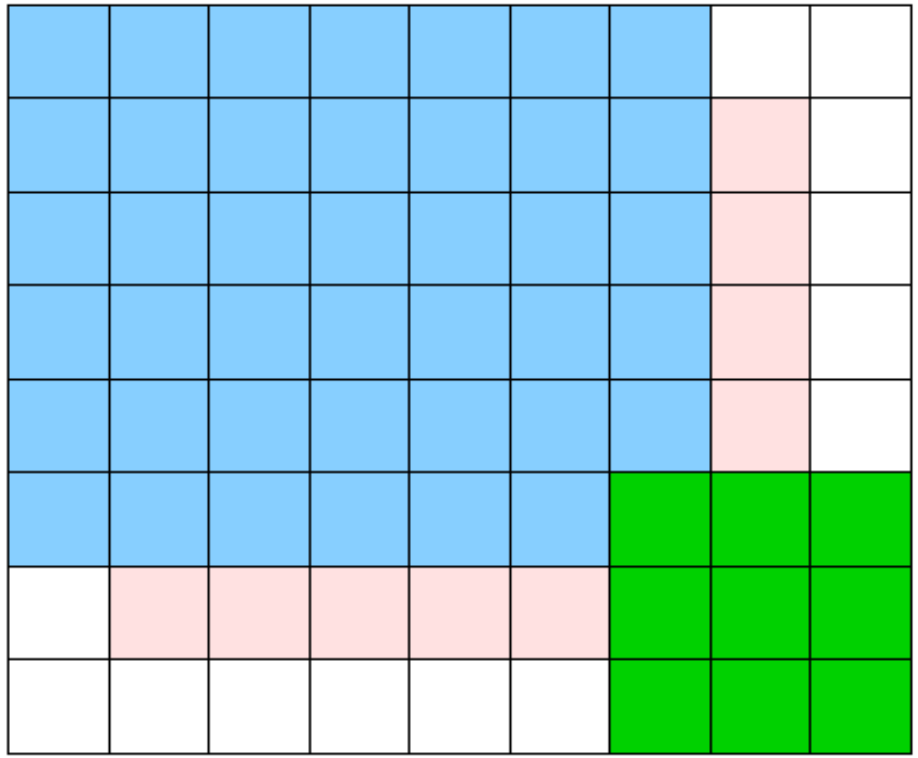
Source: Convolutional Neural Networks. https://medium.com/@rajat.k.91/convolutional-neural-networks-why-what-and-how-f8f6dbebb2f9

Convolution with Zero Padding



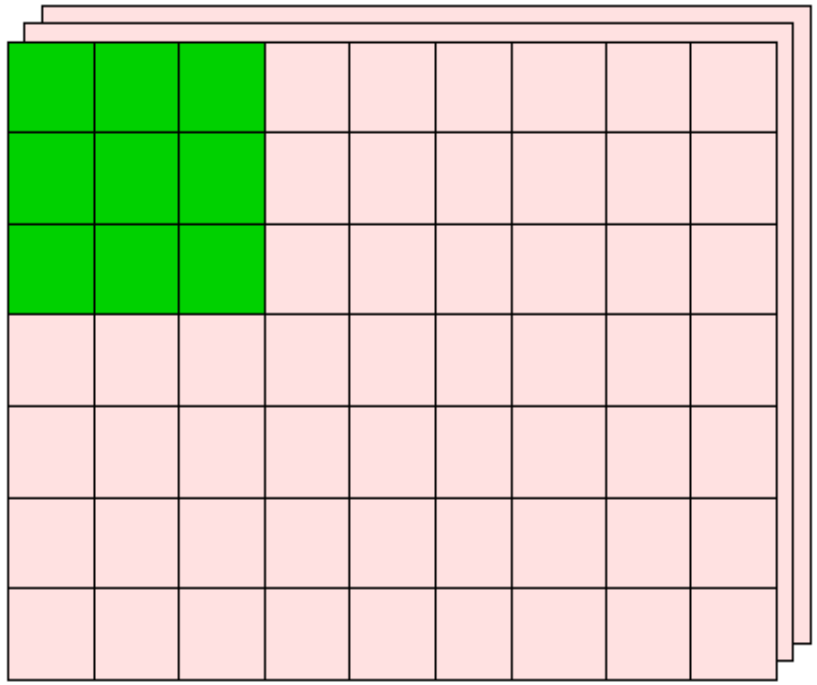
- Sometimes, we treat the off-edge inputs as zero (or some other value).
- This is known as **“Zero-Padding”**

Convolution with Zero Padding



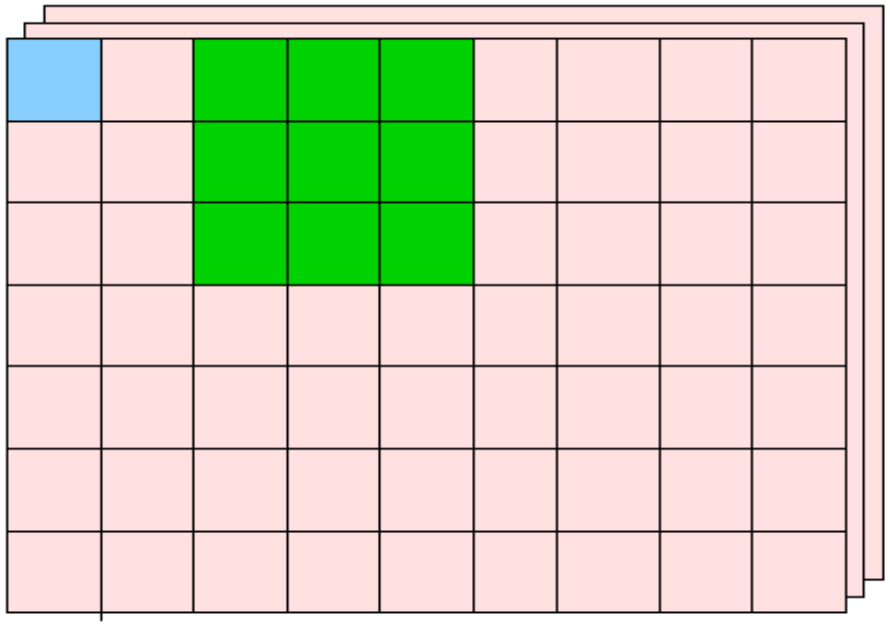
- With **"Zero-Padding",** the convolution layer is the same size as the original image (or the previous layer).

Stride



- Assume the original image is $J \times K$, with L channels.
- We again apply an $M \times N$ filter, but this time with a "stride" of $s > 1$
- In this example, $J = 7, K = 9, L = 3, M = 3, N = 3, s = 2$

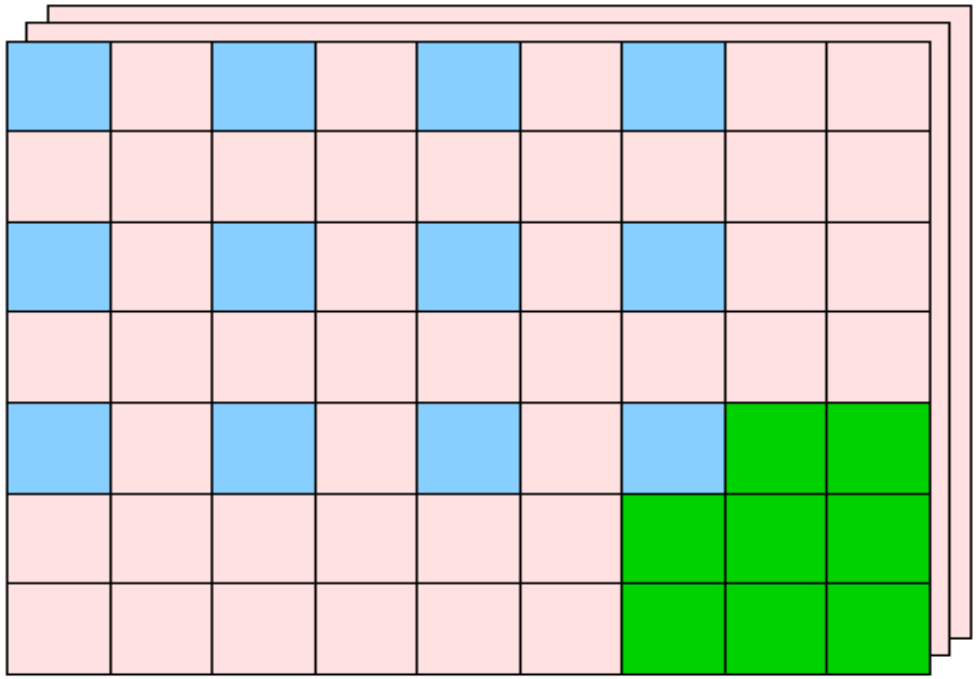
Stride



$$Z^i_{j,k} = g\left(b^i + \sum_l \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} K^i_{l,m,n} V^l_{j+m,k+n}\right)$$

- The same formula is used, but *j* and *k* are now incremented by *s* each time.
- The number of free parameters is *1 + L x M x N*

Stride Dimensions

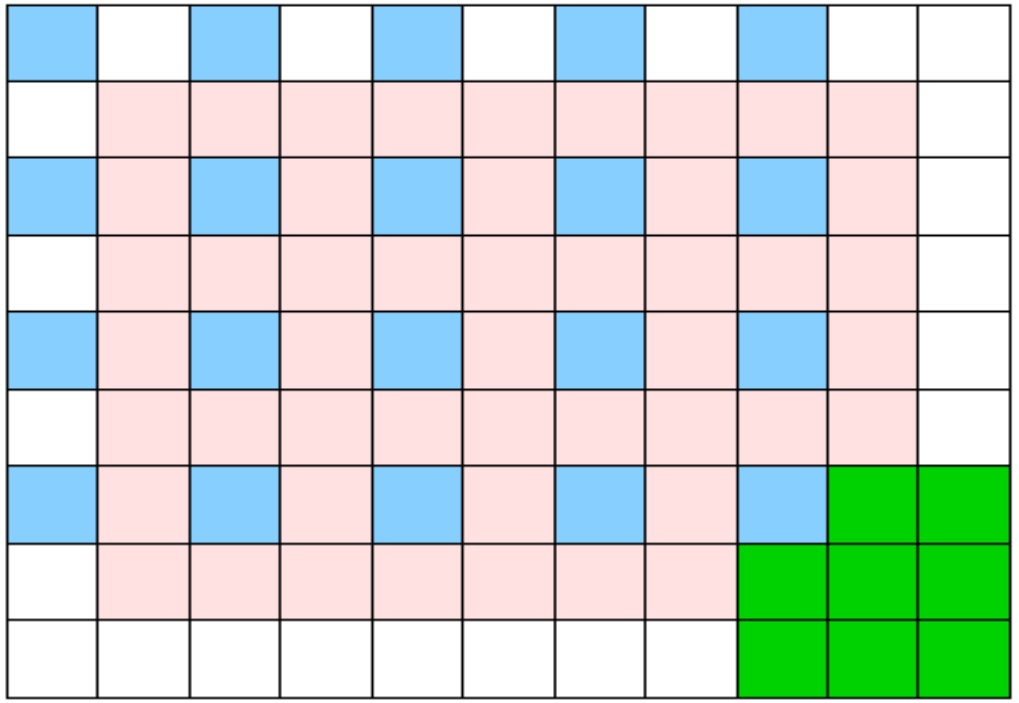


j takes on the values 0, s, 2s, …, (*J* – *M*)

k takes on the values 0, s, 2s, …, (*K* – *N*)

The next layer is *(1 + (J – M) / s)* x *(1 + (K – N) / s)*

Stride with Zero Padding



- When combined with zero-padding of width P,

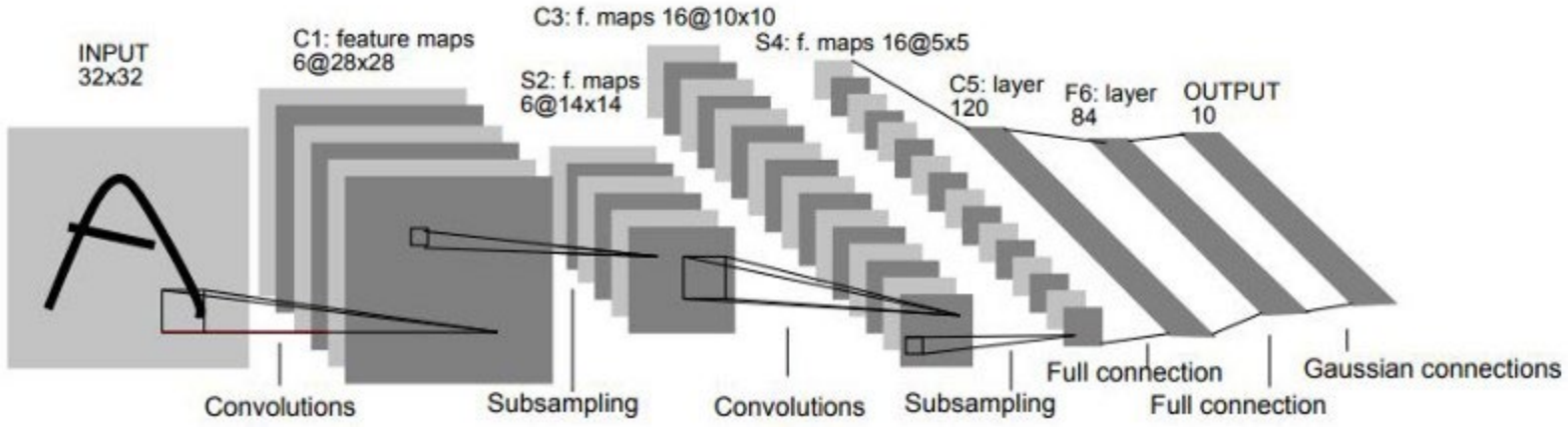
  j takes on the values 0, s, 2s, …, $(J + 2P - M)$

  k takes on the values 0, s, 2s, …, $(K + 2P - N)$

  The next layer is $(1 + (J + 2P - M)/s) \times (1 + (K + 2P - N)/s)$

A walk-through of LeNet

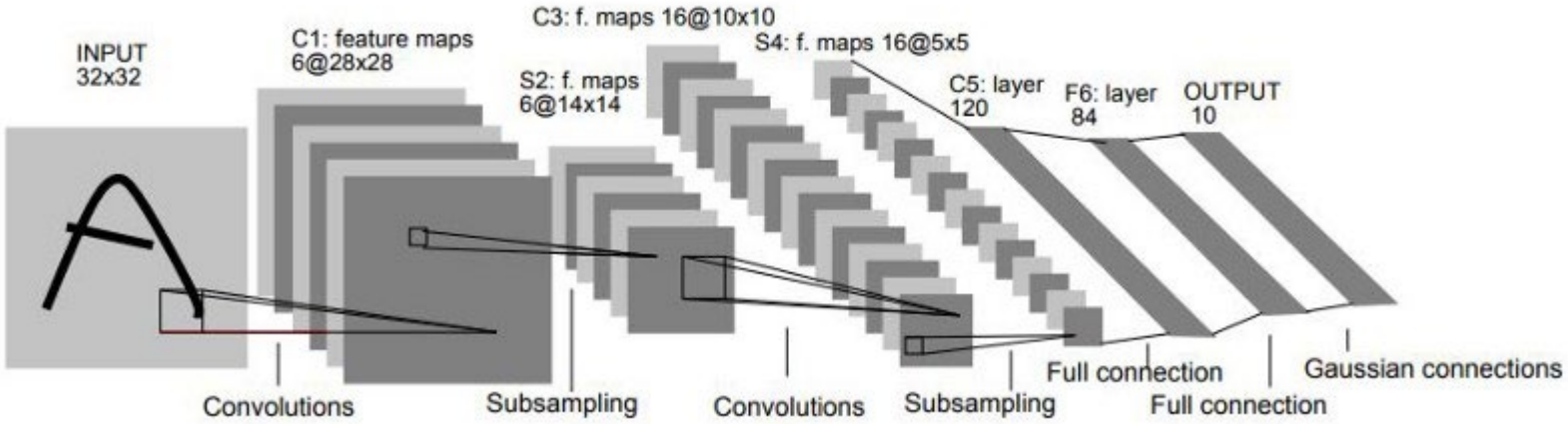
- LeNet contains 2 convolutional layers, 2 pooling layers, 2 fully-connected layers, and an output layer



Source: Lecun et al. (1998). Gradient-Based Learning Applied to Document Recognition

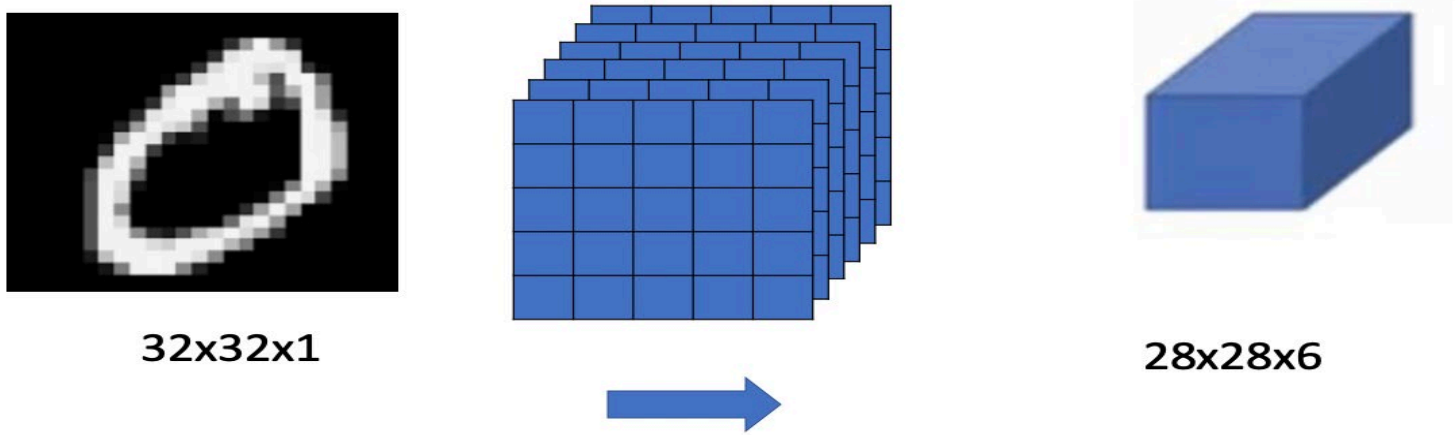
A walk-through of LeNet

- Convolution layer



Convolutional Layer

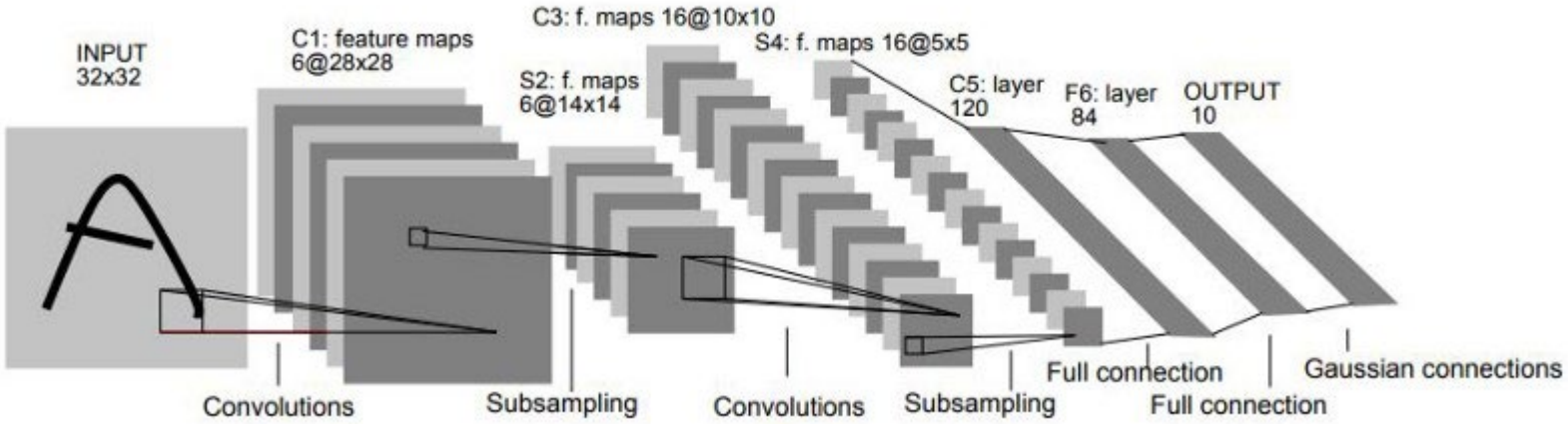
Filters: 6
Filter Size: 5x5
Stride: 1
Padding: 0



Source: https://programmathically.com/an-introduction-to-convolutional-neural-network-architecture/

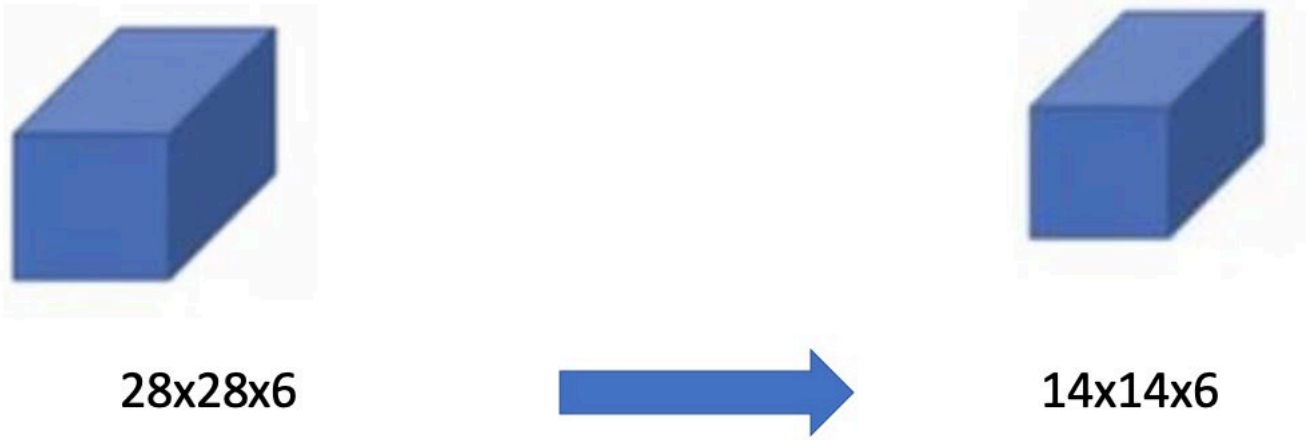
A walk-through of LeNet

- Pooling layer



Pooling Layer

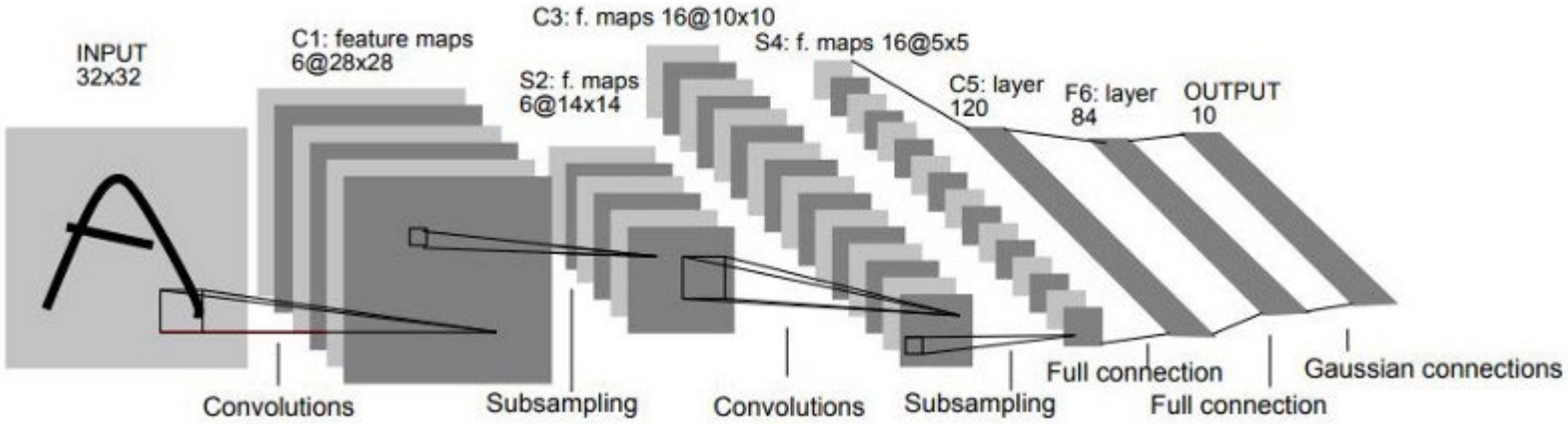
Filters: 6
Filter Size: 2x2
Stride: 2
Padding: 0



Source: https://programmathically.com/an-introduction-to-convolutional-neural-network-architecture/

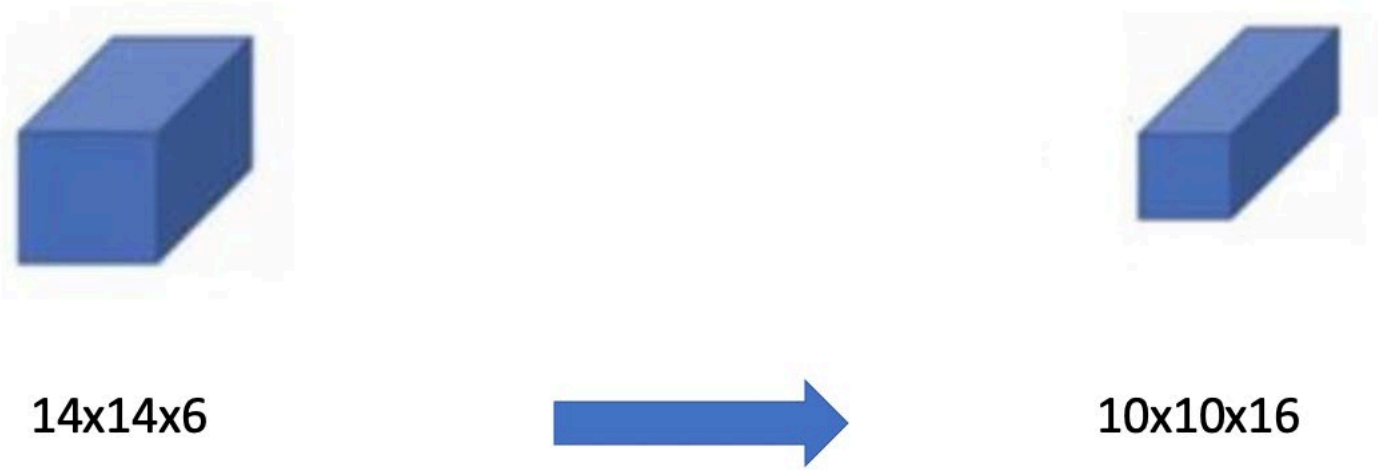
A walk-through of LeNet

- Convolution layer



Convolutional Layer

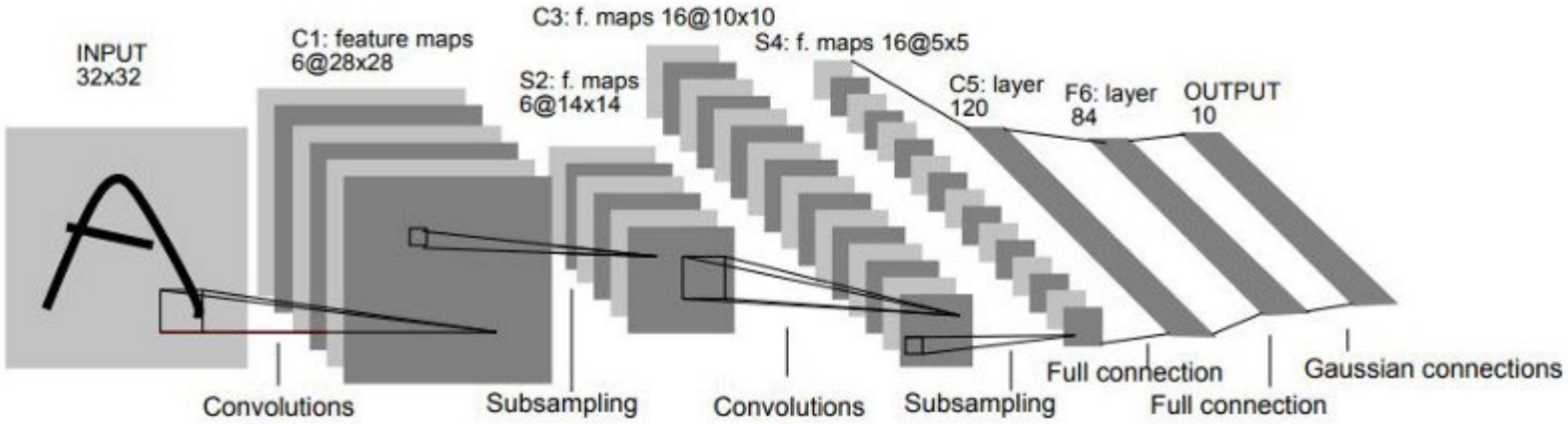
Filters: 16
Filter Size: 5x5
Stride: 1
Padding: 0



Source: https://programmathically.com/an-introduction-to-convolutional-neural-network-architecture/

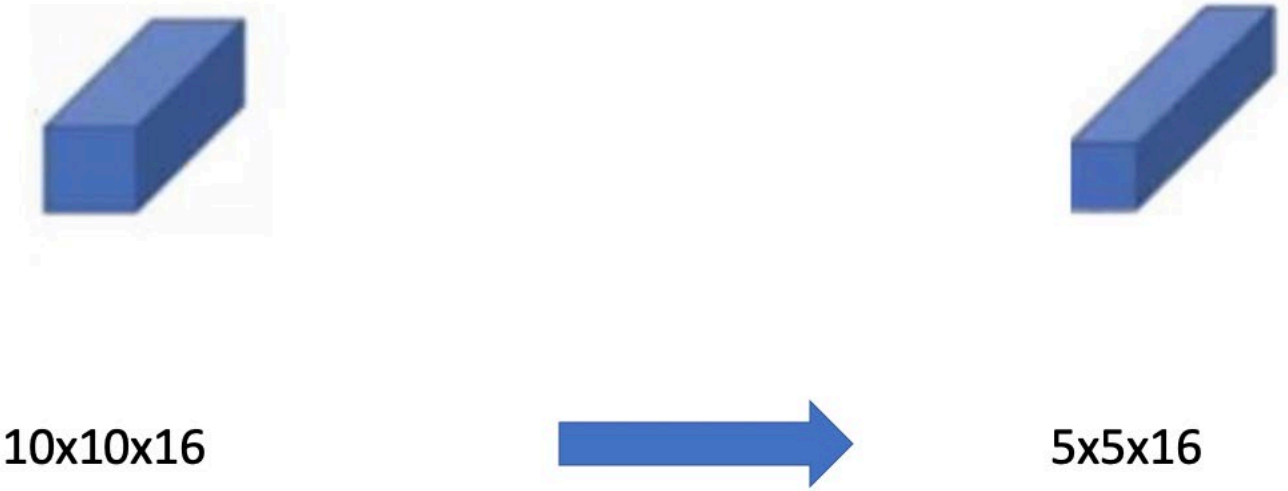
A walk-through of LeNet

- Pooling layer



Pooling Layer

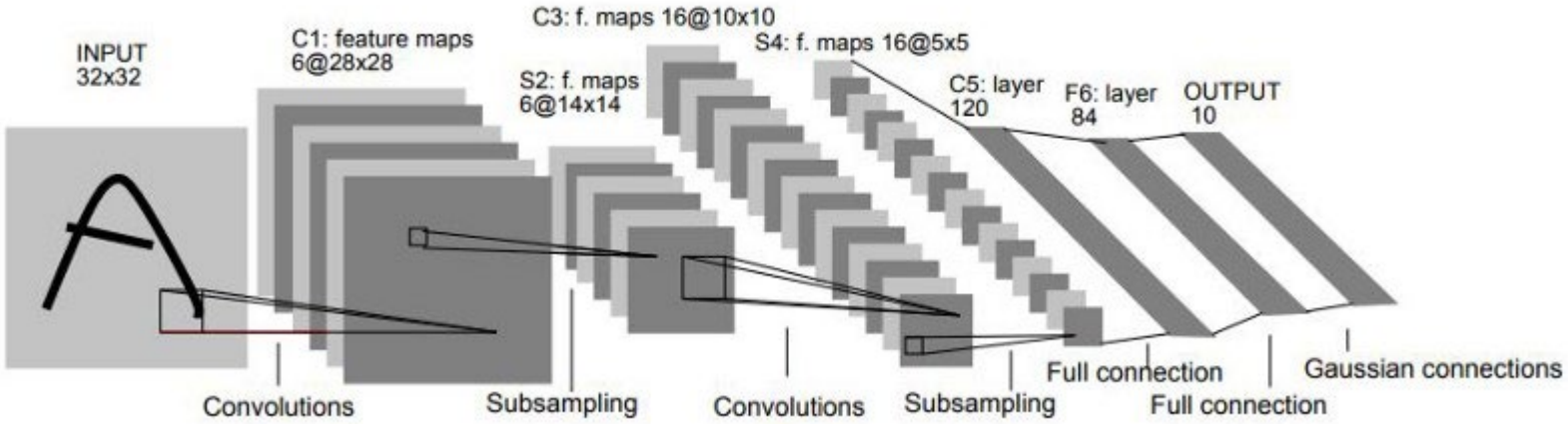
Filters: 16
Filter Size: 2x2
Stride: 2
Padding: 0

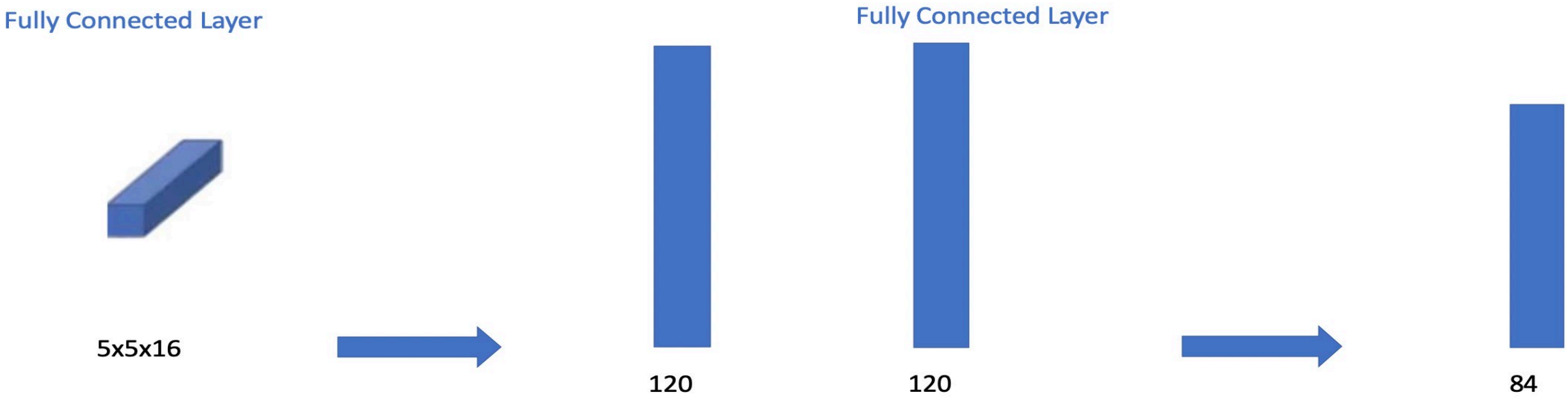


Source: https://programmathically.com/an-introduction-to-convolutional-neural-network-architecture/

A walk-through of LeNet

- Flattening + FC layers
  - 5 x 5 x 16 = 400 neurons

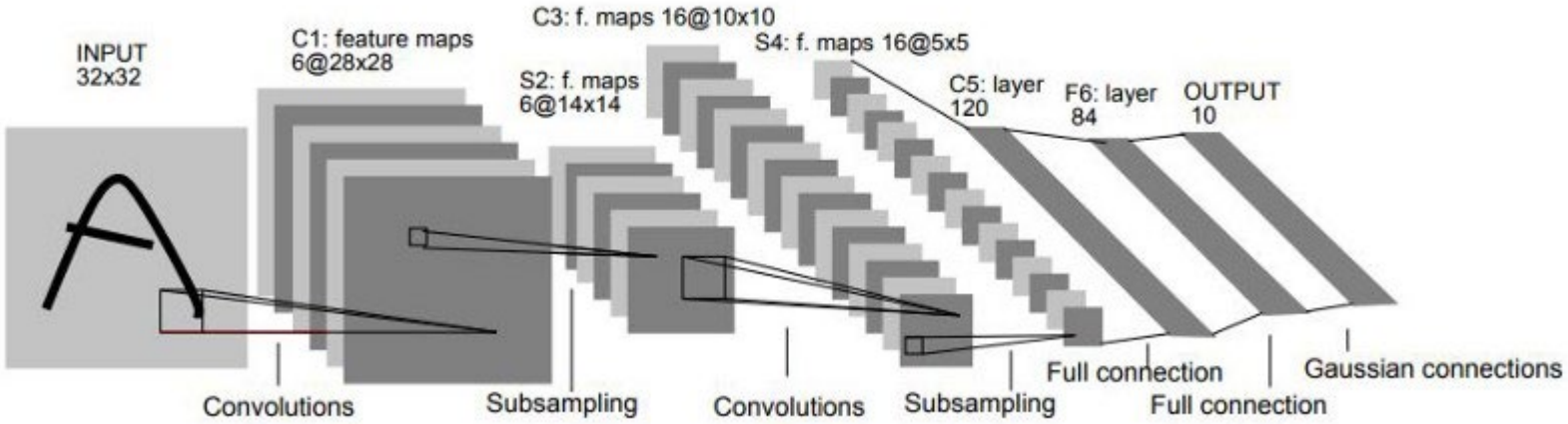


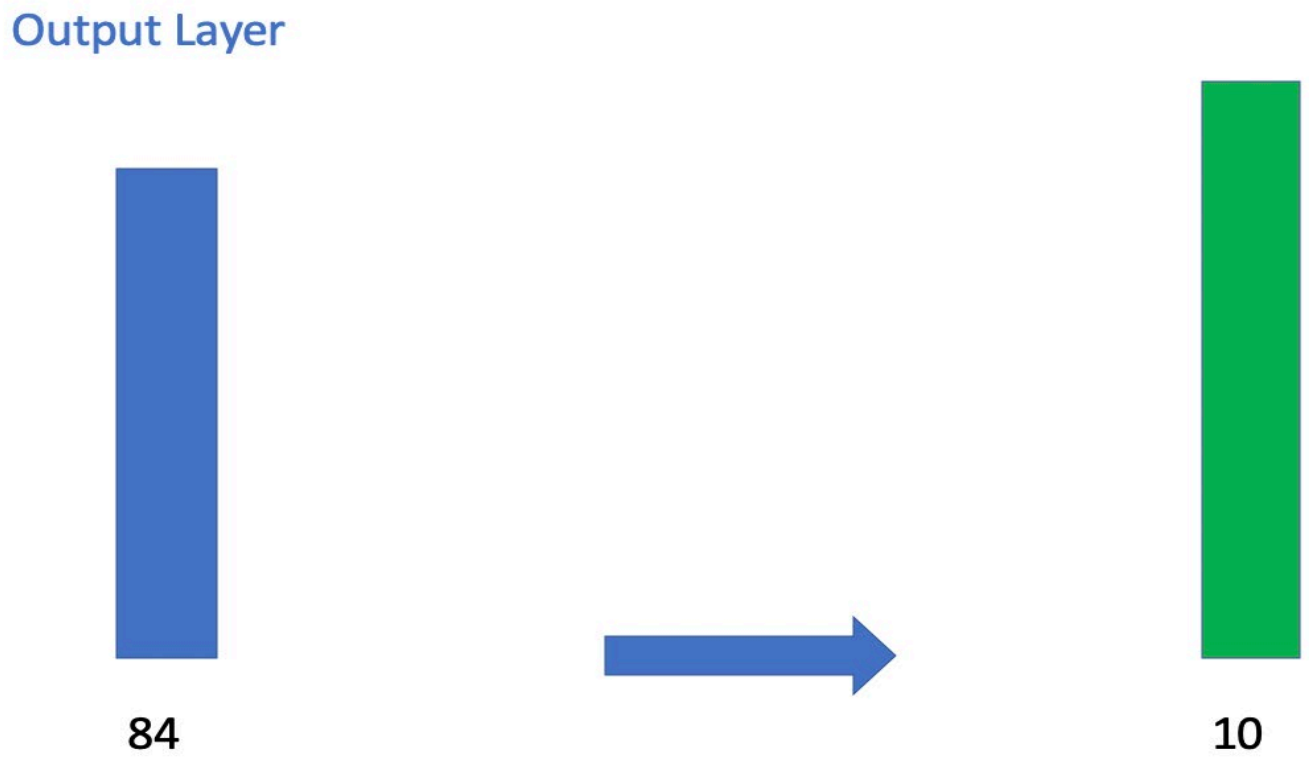


Source: https://programmathically.com/an-introduction-to-convolutional-neural-network-architecture/

A walk-through of LeNet

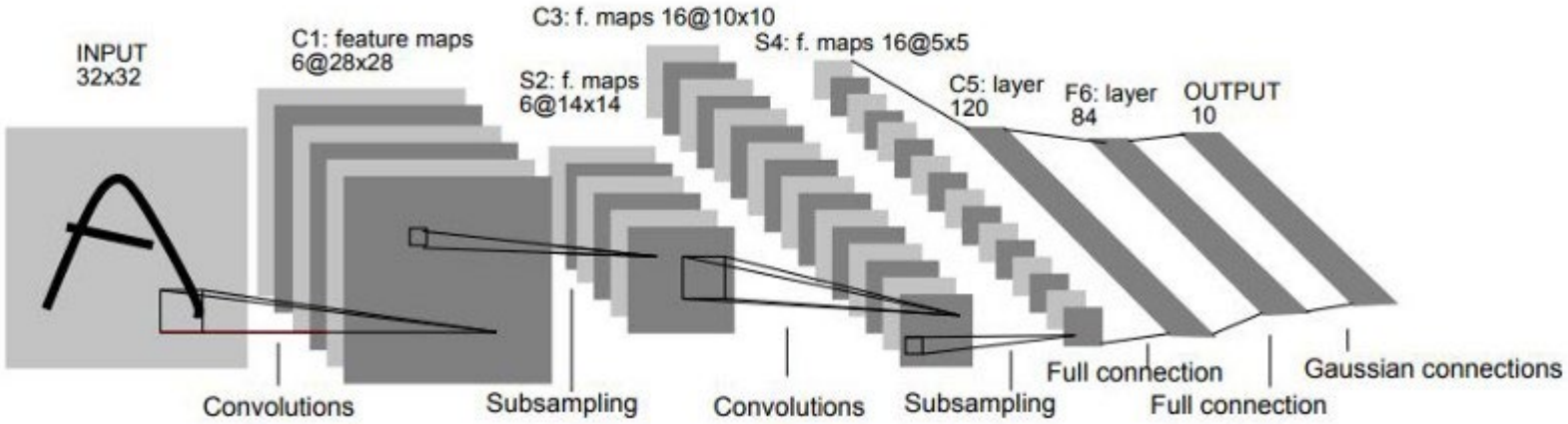
- Output layer
  - MNIST dataset (10 digits)





Source: https://programmathically.com/an-introduction-to-convolutional-neural-network-architecture/

Example: LeNet



For example, in the first convolutional layer of LeNet (greyscale images), $J = K = 32$, $M = N = 5$.

The width of the next layer is

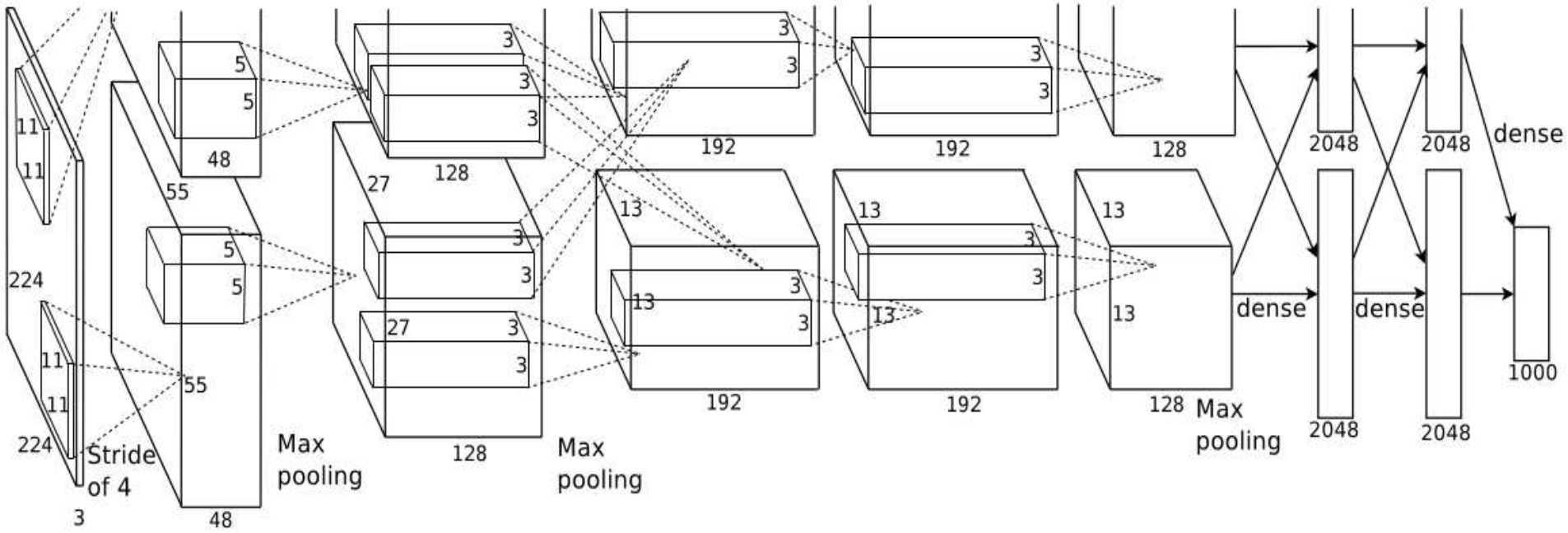
$$J + 1 - M = 32 + 1 - 5 = 28$$

Question: If there are 6 filters in this layer, compute the number of:

weights per filter?	$1 + 5 \times 5 \times 1$	$=$	26
neurons?	$28 \times 28 \times 6$	$=$	4704
connections?	$28 \times 28 \times 6 \times 26$	$=$	122304
independent parameters?	6×26	$=$	156

Source: https://programmathically.com/an-introduction-to-convolutional-neural-network-architecture/

AlexNet (2012)



- 5 convolutional layers + 3 fully-connected layers
- max-pooling with overlapping stride
- softmax with 1000 classes
- 2 parallel GPUs which interact only at certain layers

Example: AlexNet Conv Layer 1

- In the first convolutional layer of AlexNet,

  J = K = 224, P = 2, M = N = 11, s = 4

The width of the next layer is

$$1 + (J + 2P - M) / s = 1 + (224 + 2 \times 2 - 11)/ 4 = 55$$

Question: If there are 96 filters in this layer, compute the number of:

weights per neuron?

neurons?

connections?

independent parameters?

Overlapping Pooling

- In the previous layer is J x K, and max pooling is applied with width F and stride s, the size of the next layer will be

$$(1 + (J - F) / s) \times (1 + (K - F)/ s)$$

Question: If max pooling with width 3 and stride 2 is applied to the features of size 55 x 55 in the first convolutional layer of AlexNet, what is the size of the next layer?

Answer:

Question: How many independent parameters does this add to the model?

Answer:

Overlapping Pooling

- In the previous layer is J x K, and max pooling is applied with width F and stride s, the size of the next layer will be

$$(1 + (J - F) / s) \times (1 + (K - F)/ s)$$

Question: If max pooling with width 3 and stride 2 is applied to the features of size 55 x 55 in the first convolutional layer of AlexNet, what is the size of the next layer?

Answer: $1 + (55 - 3)/ 2 = 27$

Question: How many independent parameters does this add to the model?

Answer: None! (no weights to be learned, just computing max)

How to train CNNs

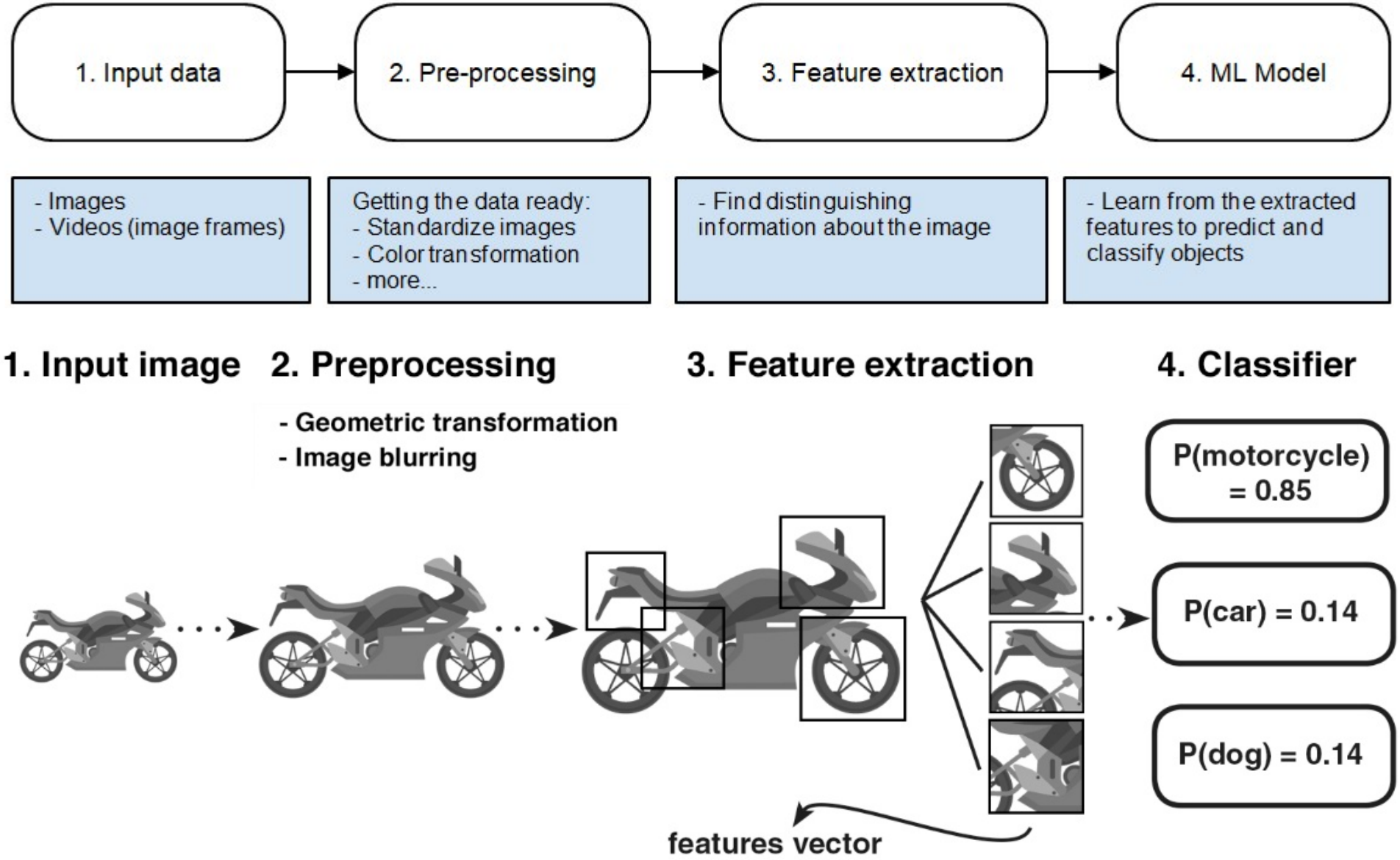
- A loss function is used to compute the model's prediction accuracy from the outputs
- Commonly used: Categorical cross-entropy loss function

$$L_{\text{CE}} = -\sum_{i=1}^{n} t_i \log(p_i), \quad \text{for n classes,}$$

where t_i is the truth label and p_i is the Softmax probability for the i^{th} class.

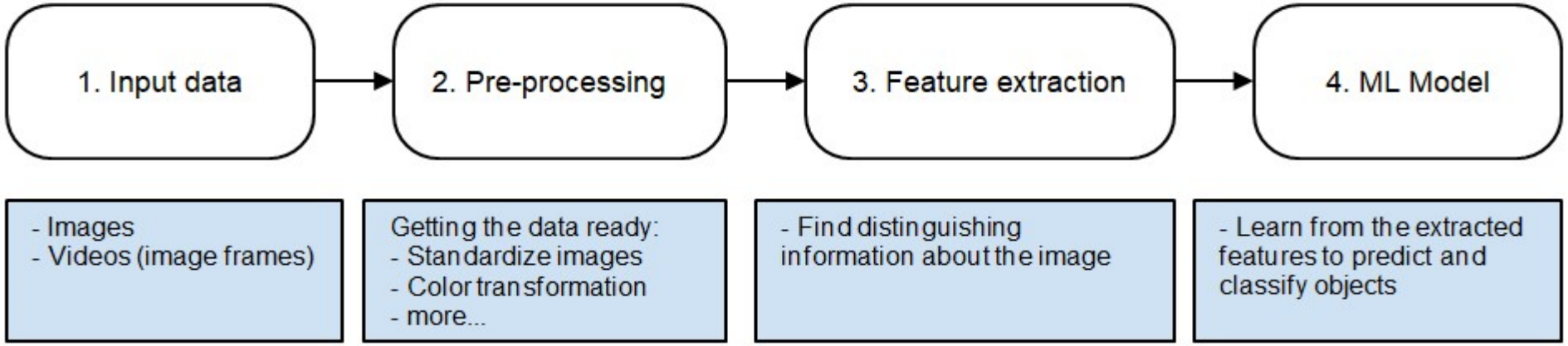
- The training objective is to minimize this loss
- The loss guides the backpropagation process to train the CNN model
- Gradient descent methods, such as Stochastic Gradient Descent (SGD) and the Adam optimizer, are commonly used algorithms for optimization

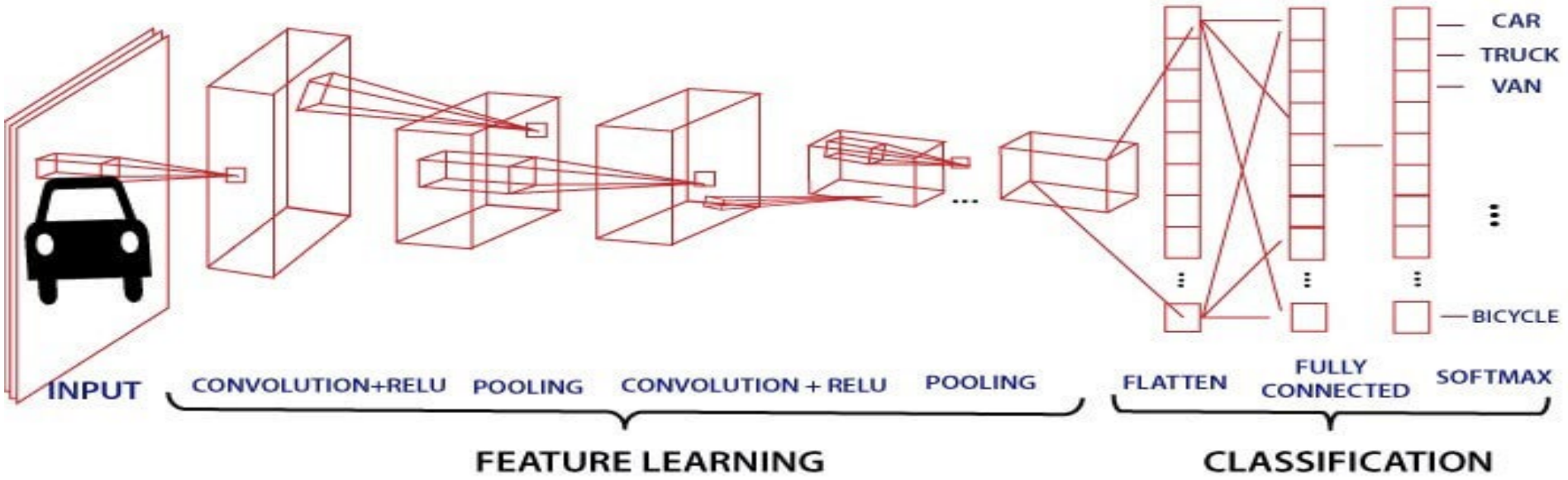
Traditional CV pipeline vs CNNs



Source: Mohamed Elgendy, Deep Learning for Vision Systems, Manning Publishers

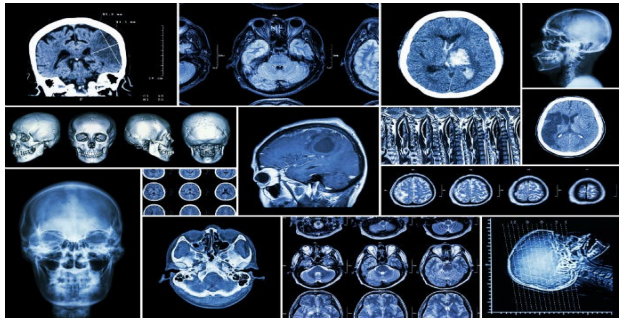
Traditional CV pipeline vs CNNs





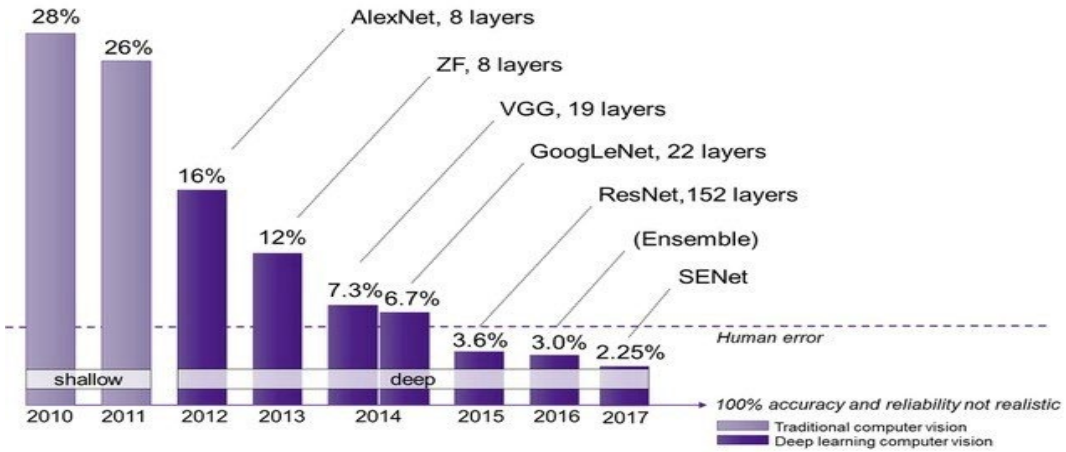
Why DL becoming so popular?

- Increasing availability of large-scale annotated datasets



- Improvement in computing power
  - Rise of Graphics Processing Units (GPUs)

- Advancements in algorithms
  - Better and bigger models
  - new insights and improved techniques to train models



- Open-source codebase + DL Frameworks

Deep Learning = convergence of data, models, and computing power

Important readings

- Understanding and calculating model parameters (weights)?

https://towardsdatascience.com/understanding-and-calculating-the-number-of-parameters-in-convolution-neural-networks-cnns-fc88790d530d

https://medium.com/@iamvarman/how-to-calculate-the-number-of-parameters-in-the-cnn-5bd55364d7ca

https://androidkt.com/calculating-number-parameters-pytorch-model/

Questions?

If you have any questions after today's lecture, post it on the Ed forum