From Perceptron to Deep Learning

DLAI3 Workshop, 1 July 2020

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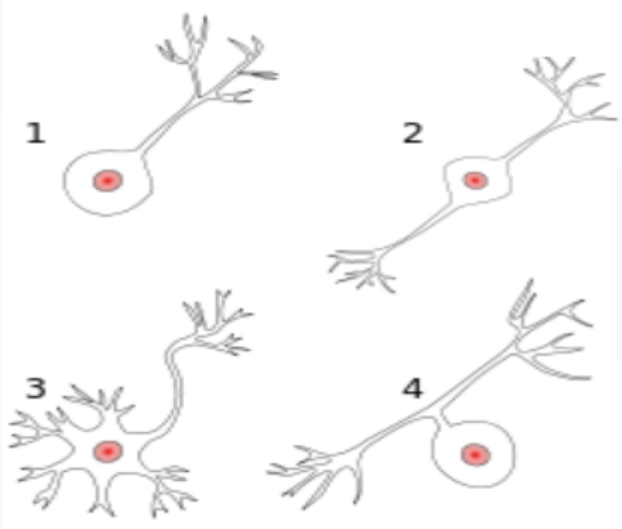
meme
A meme (/ˈ mi: m/ meem), a neologism coined by Richard Dawkins, is "an idea, behavior, or style that spreads from person to person within a culture". A meme acts as a unit for carrying cultural ideas, symbols, or practices that can be transmitted from one mind to another through writing, speech, gestures, rituals, or other imitable phenomena with a mimicked theme.

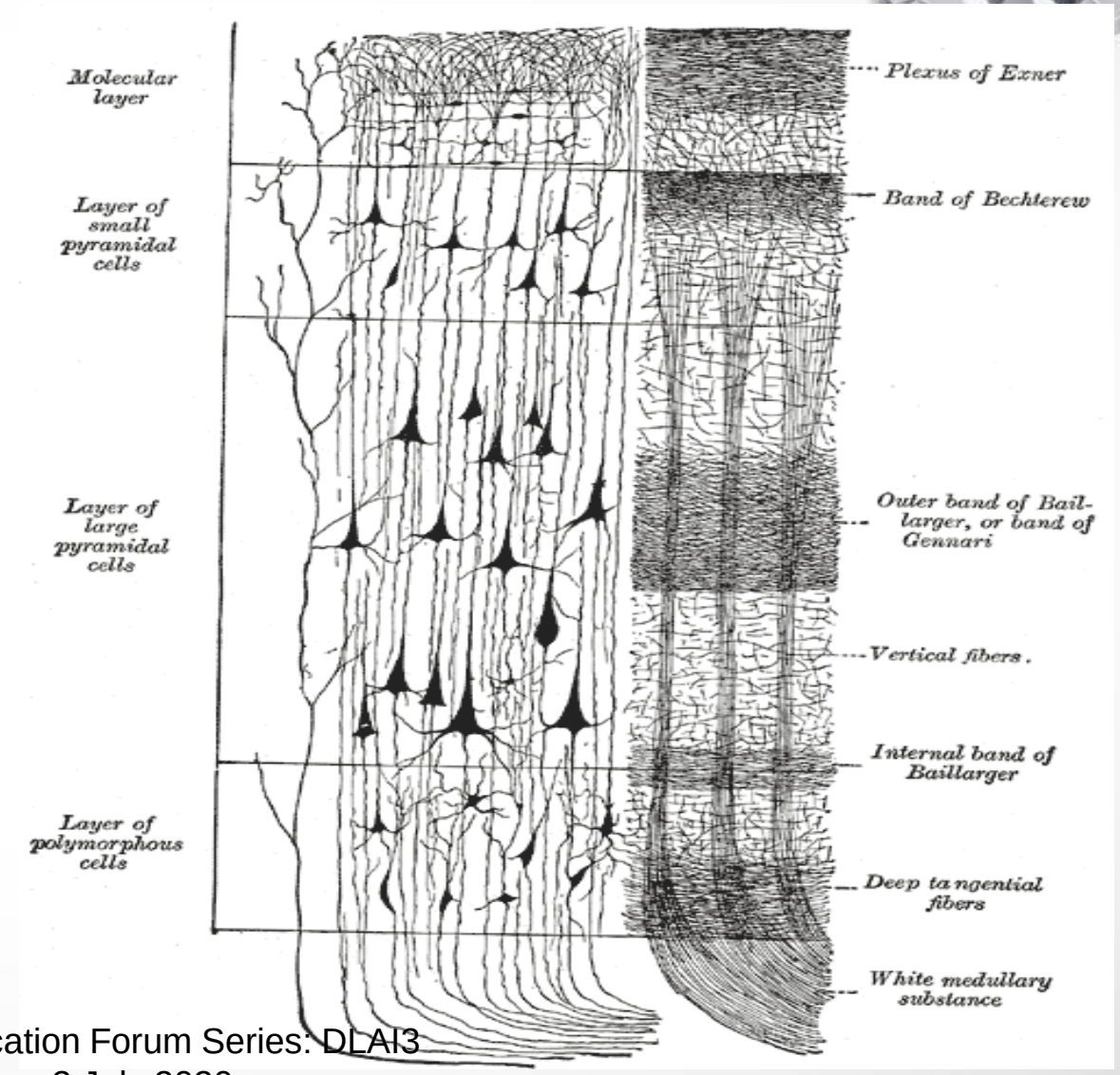
Outline

- Session 1: Overview of ANN & CNN
  - Actual Neurons and Perceptron
  - Multi-Layer Perceptron
  - Deep Learning: CNN Based Computer Vision
- Session 2: Representation of Input Image
- Session 3: Tensorflow

Neurons

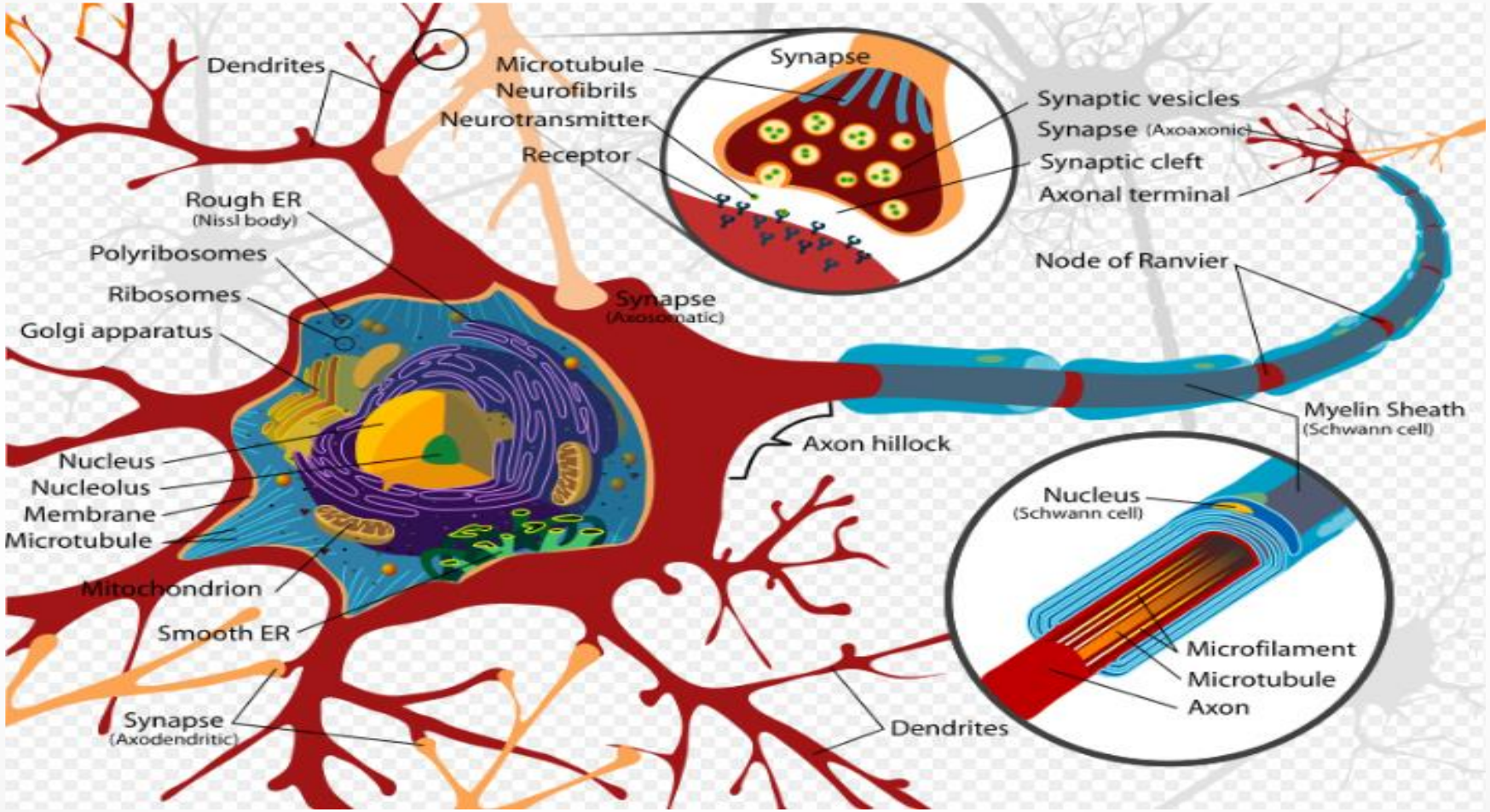


Different kinds of neurons:
1 Unipolar neuron
2 Bipolar neuron
3 Multipolar neuron
4 Pseudounipolar neuron



wikipedia

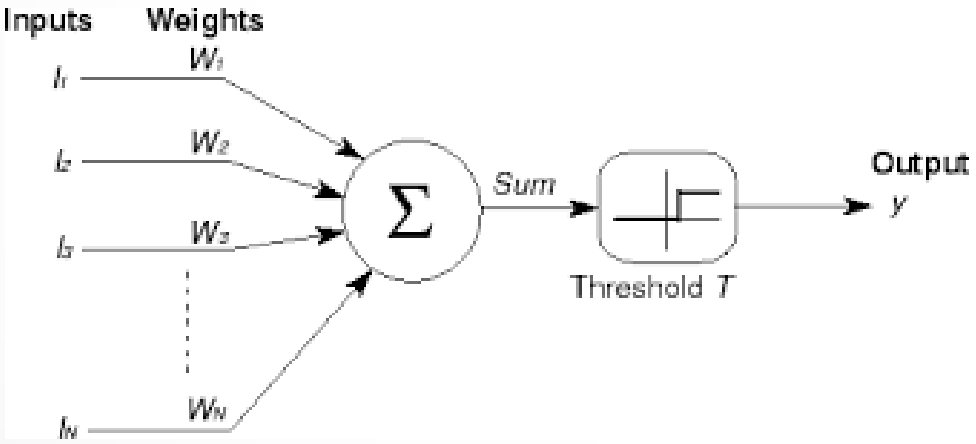
Neurons

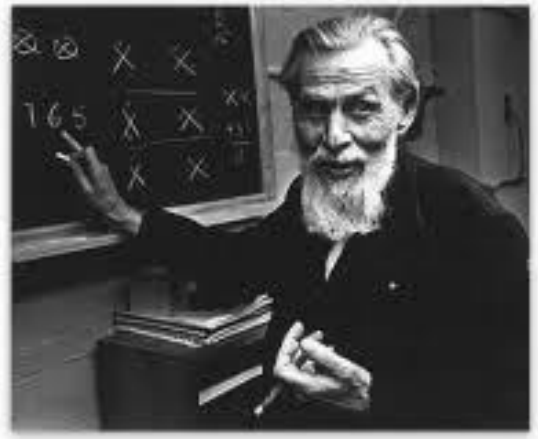


Wikipedia (approx. 21*10^9 [-70, 40] mv)

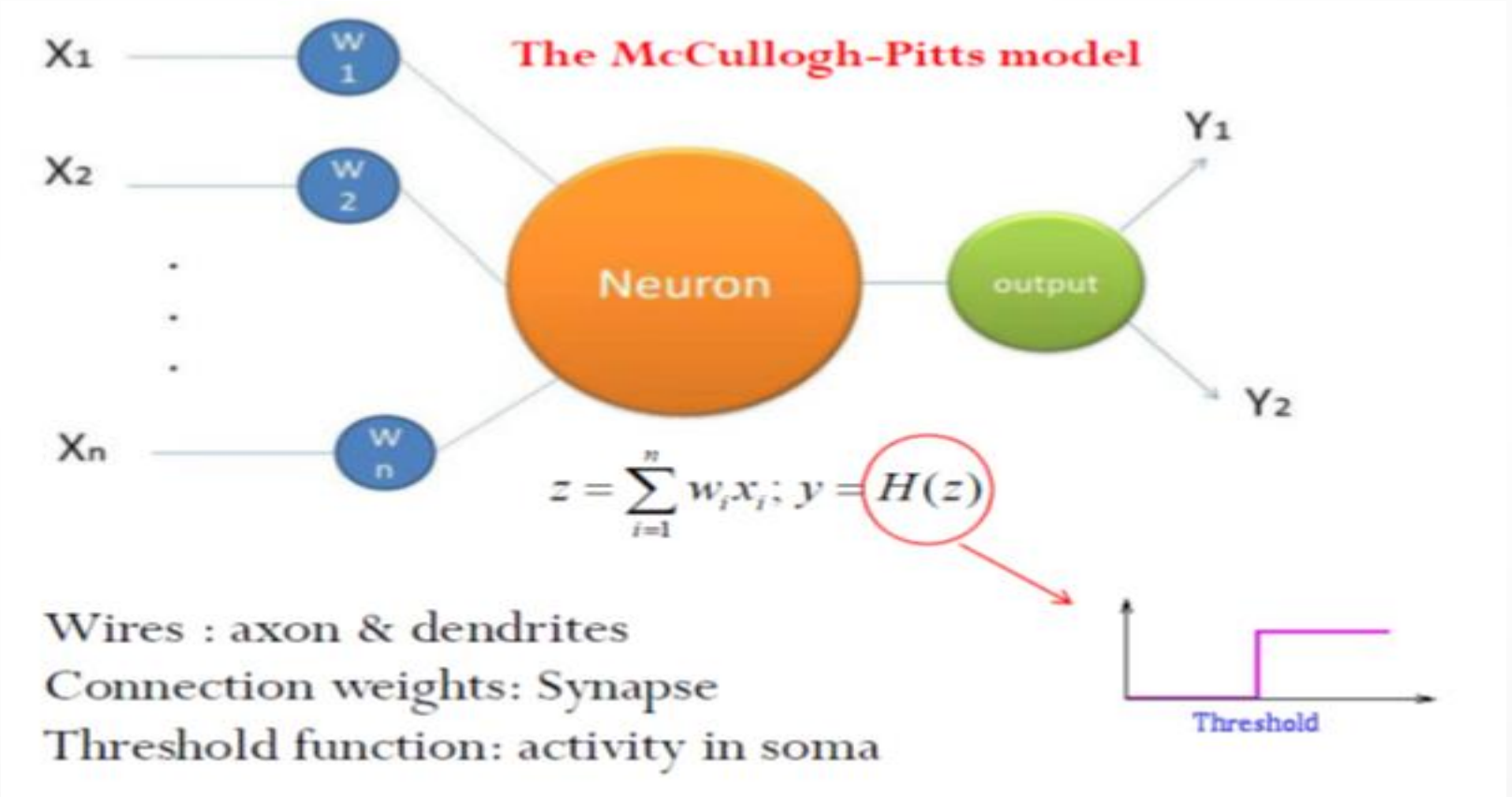
Threshold Logic Unit

- The early artificial neuron was the Threshold Logic Unit (TLU), or Linear Threshold Unit, first proposed by Warren McCulloch and Walter Pitts in 1943.





Threshold Logic Unit



How to determine the values of W?

- How to solve for W

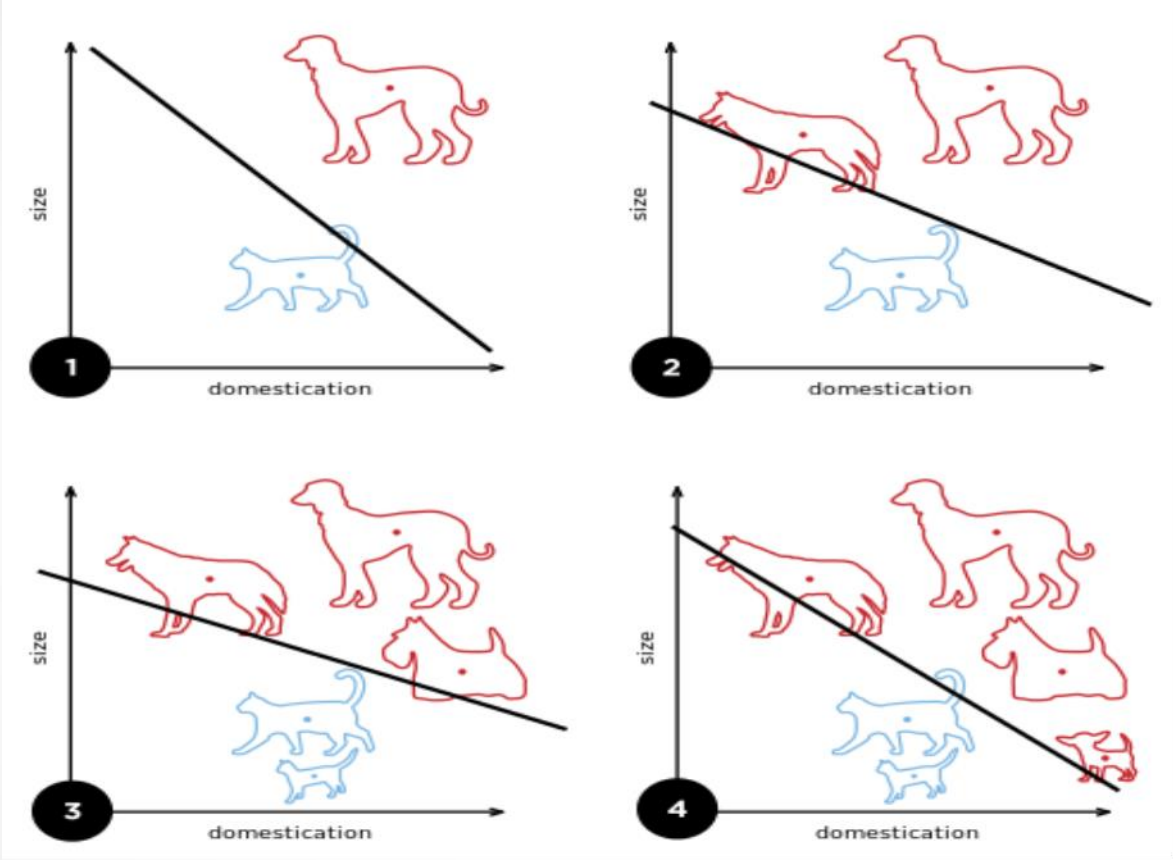
$$f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbf{w} \cdot \mathbf{x} \text{ is } \sum_{i=1}^{m} w_i x_i$$

https://en.wikipedia.org/wiki/Perceptron

  - Randomly
  - Analytically
  - Optimization algorithm e.g., gradient descent

Rosenblatt's Perceptron Learning Rule



$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i}$$

- The perceptron is an artificial neuron using the Heaviside step function as the activation function.
- The perceptron learning rule is an algorithm for learning a classifier function. It was invented in 1958 by Frank Rosenblatt.

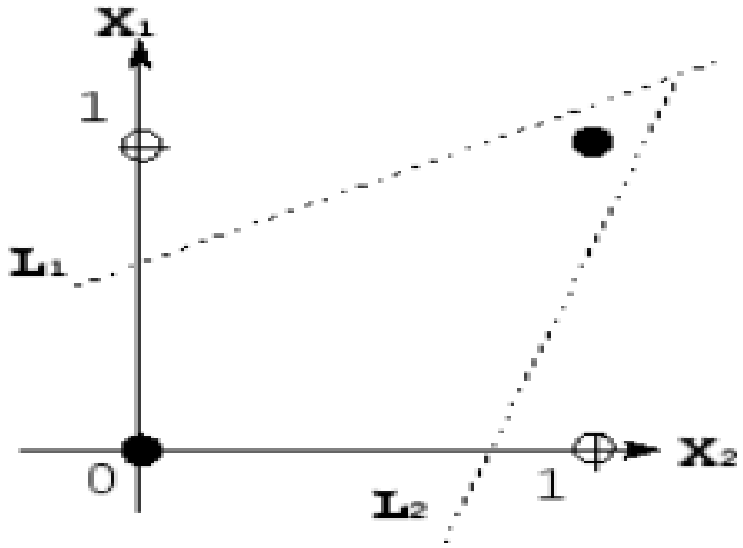
https://en.wikipedia.org/wiki/Perceptron

Limitation of a Perceptron

- The perceptron can distinguish a linearly separable function. Hence a single perceptron cannot deal with an xor function.

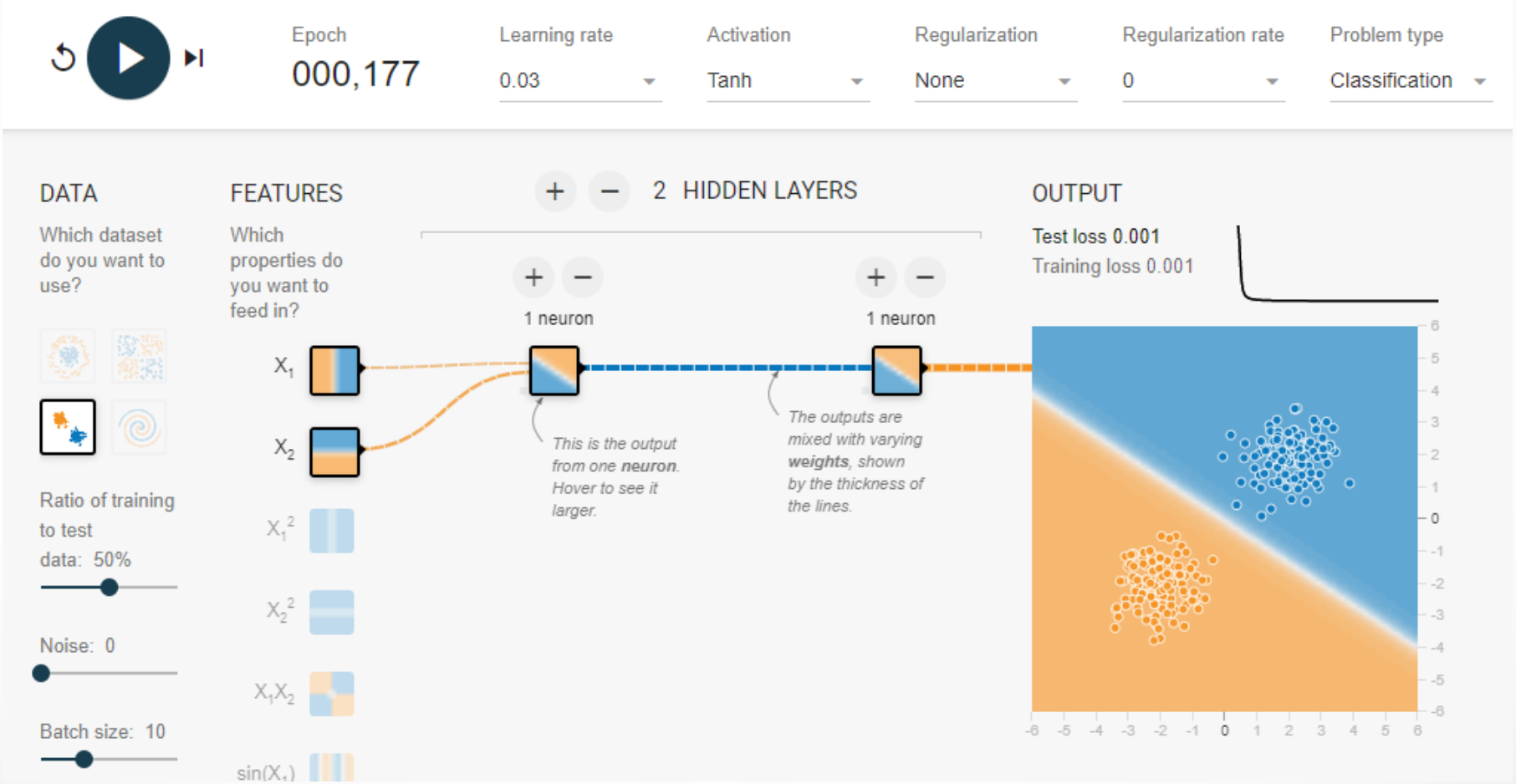
X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0

$Y = X_1 \oplus X_2$



TensorFlow ANN Playground

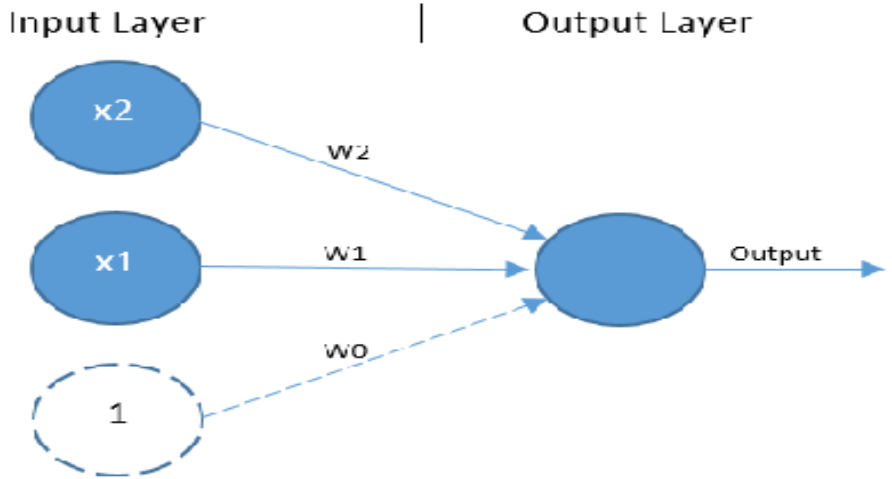
- https://playground.tensorflow.org



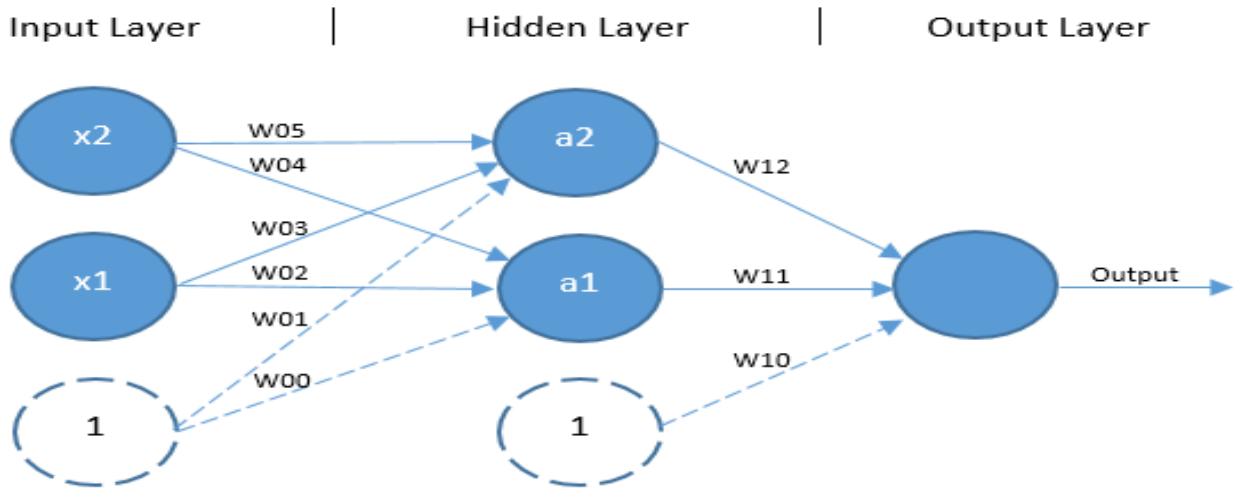
Limitation of Perceptrons

- Adding two perceptrons in a hidden layer, then it can handle an xor function.

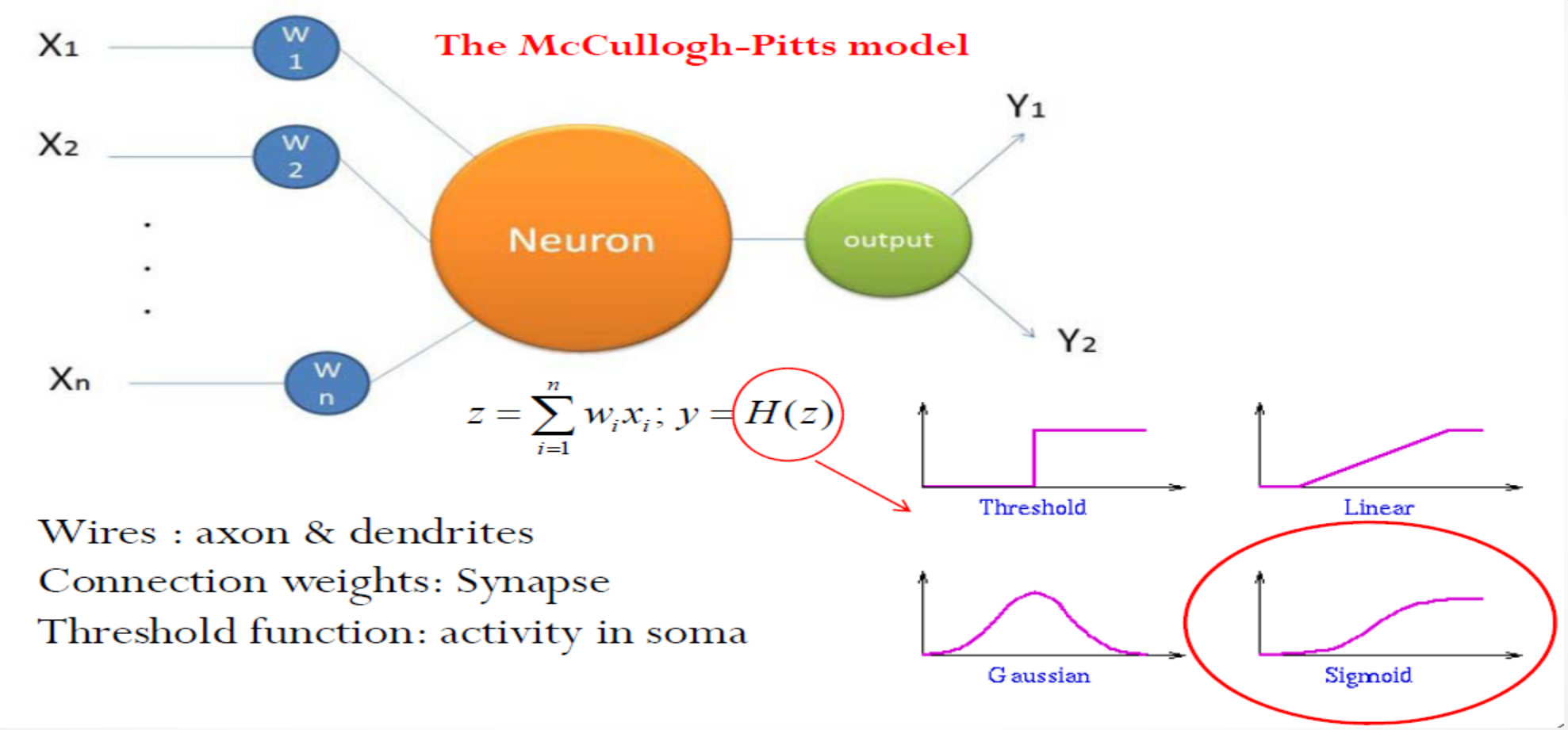
perceptron



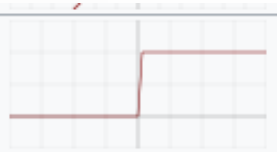
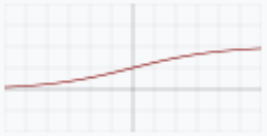
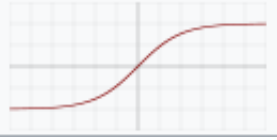
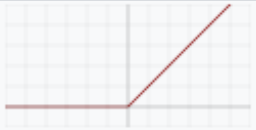
MLP



Activation Functions



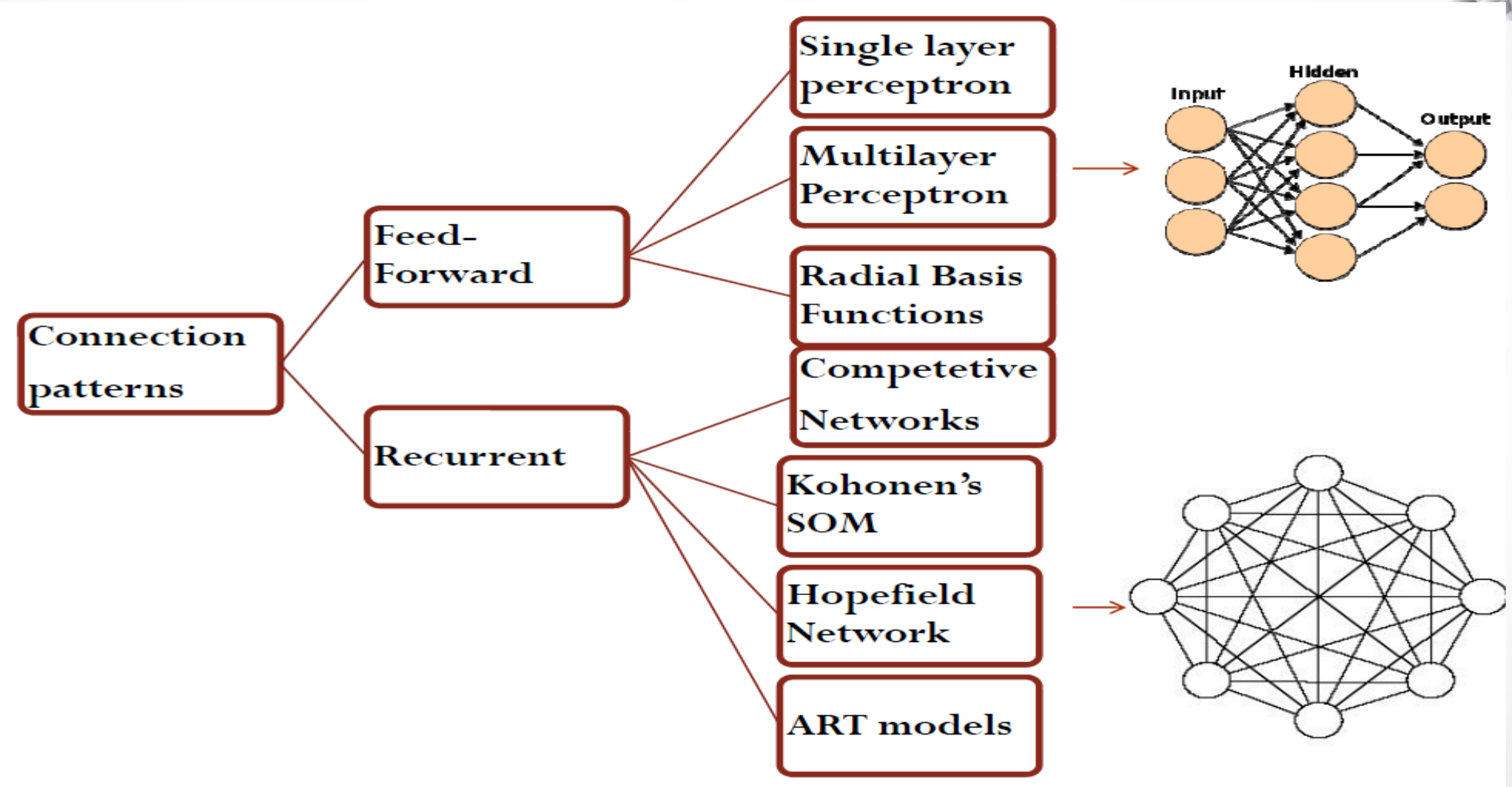
Activation Functions

Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a.k.a. Sigmoid or Soft step)		$f(x) = \sigma(x) = \frac{1}{1+e^{-x}}$ [1]	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{(e^{x} - e^{-x})}{(e^{x} + e^{-x})}$	$f'(x) = 1 - f(x)^2$
Rectified linear unit (ReLU)[15]		$f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ 1 & \text{for } x > 0 \end{cases}$
Exponential linear unit (ELU)[20]		$f(\alpha, x) = \begin{cases} \alpha(e^{x} - 1) & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$	$f'(\alpha, x) = \begin{cases} f(\alpha, x) + \alpha & \text{for } x \leq 0 \\ 1 & \text{for } x > 0 \end{cases}$

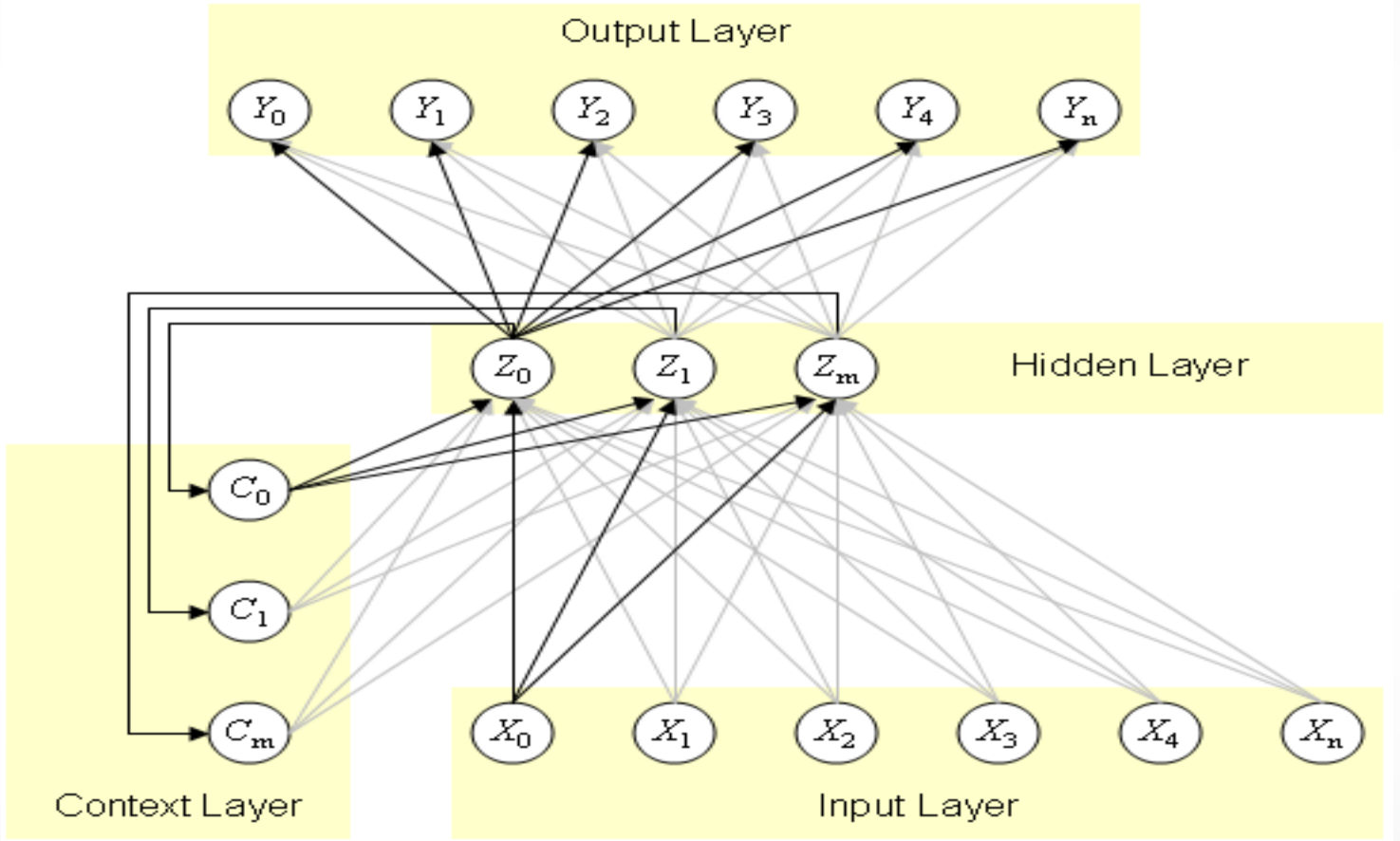
Artificial Neural Networks

- 1940: Mcculloch and Pitts
  - A logical calculus of the ideas immanent in nervous activity
- 1958: Frank Rosenblatt
  - The perceptron learning algorithm, convergence theorem
- 1960: Minsky and Papert
  - Perceptrons cannot deal with XOR
- 1980: Werbos and Rumelhart
  - Back-propagation learning algorithm
- 1980: Hopfield
  - Hopfield's energy approach (recurrent neural network)
- 1980 - now: Fukushima, LeCun, Hinton, Schmidhuber, etc

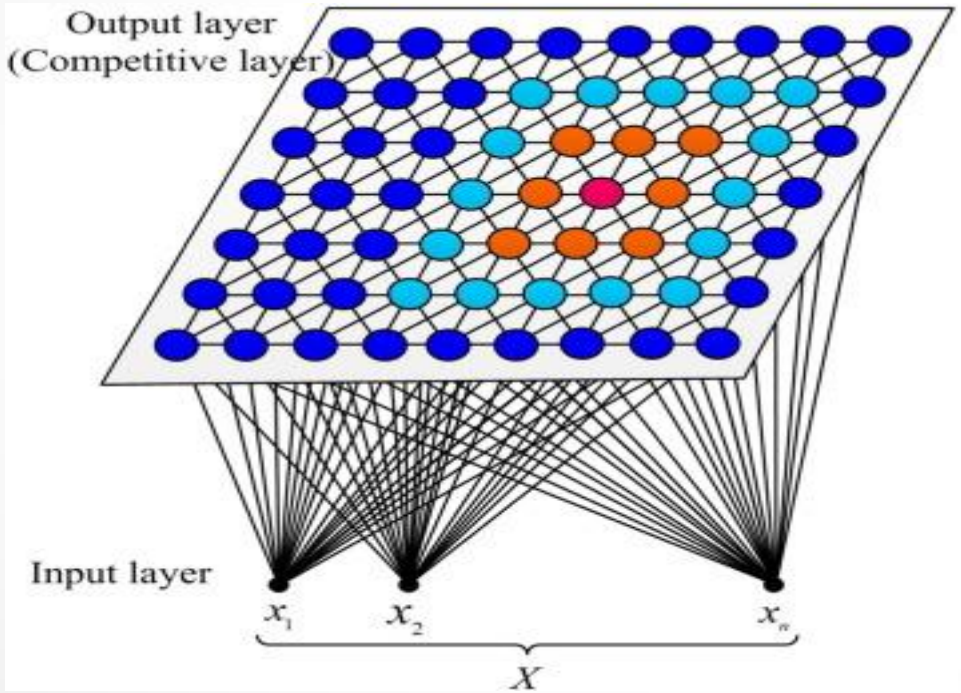
Artificial Neural Networks

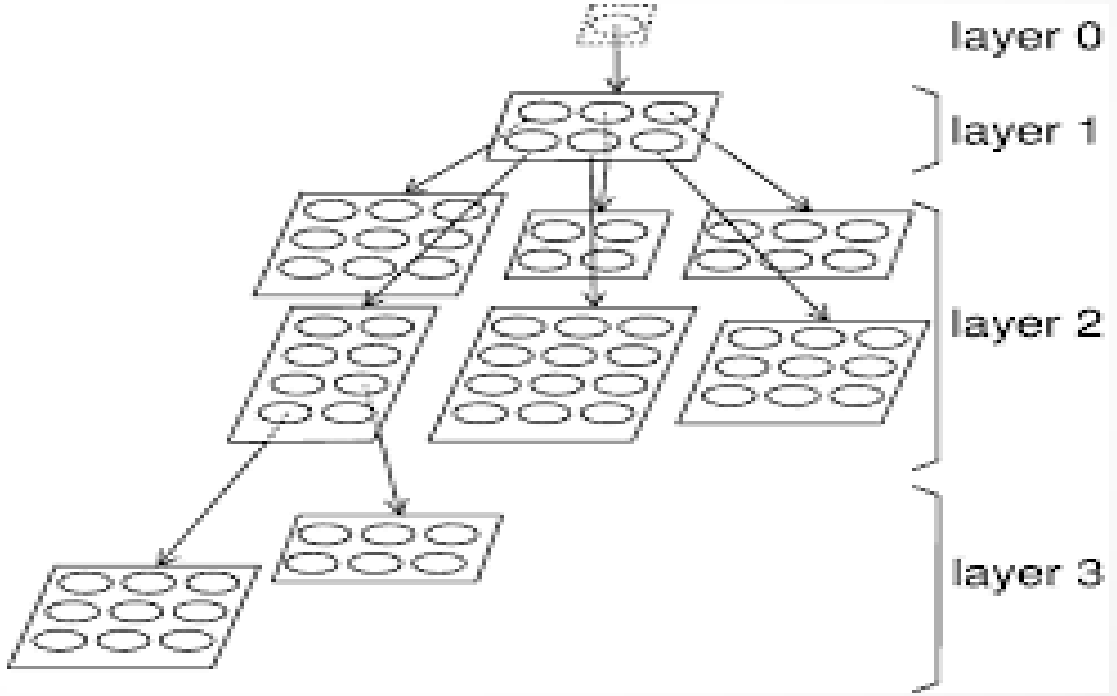


Artificial Neural Networks



Artificial Neural Networks





Learning

- Learning Paradigms
  - Supervised
  - Unsupervised
  - Hybrid
- Learning Approaches
  - Hebbian rules: cells that fire together wire together
  - Competitive learning: increasing specialization of cells
  - Hopfield networks: associative memory
  - Error correction: backpropagation

Backpropagation (Rumelhart 1986)

$$E = \tfrac{1}{2}(t - y)^2 \qquad \frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial o_j}\frac{\partial o_j}{\partial \mathrm{net}_j}\frac{\partial \mathrm{net}_j}{\partial w_{ij}}$$

$$o_j = \varphi(\mathrm{net}_j) = \varphi\left(\sum_{i=1}^{n} w_{ij} o_i\right)$$

$$\varphi(z) = \frac{1}{1 + e^{-z}} \qquad \frac{d\varphi}{dz}(z) = \varphi(z)(1 - \varphi(z))$$

$$\frac{\partial E}{\partial o_j} = \frac{\partial E}{\partial y} = \frac{\partial}{\partial y}\frac{1}{2}(t - y)^2 = y - t$$

$$\frac{\partial o_j}{\partial \mathrm{net}_j} = \frac{\partial}{\partial \mathrm{net}_j}\varphi(\mathrm{net}_j) = \varphi(\mathrm{net}_j)(1 - \varphi(\mathrm{net}_j))$$

$$\frac{\partial \mathrm{net}_j}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}}\left(\sum_{i=1}^{n} w_{ij} o_i\right) = \frac{\partial}{\partial w_{ij}} w_{ij} o_i = o_i$$

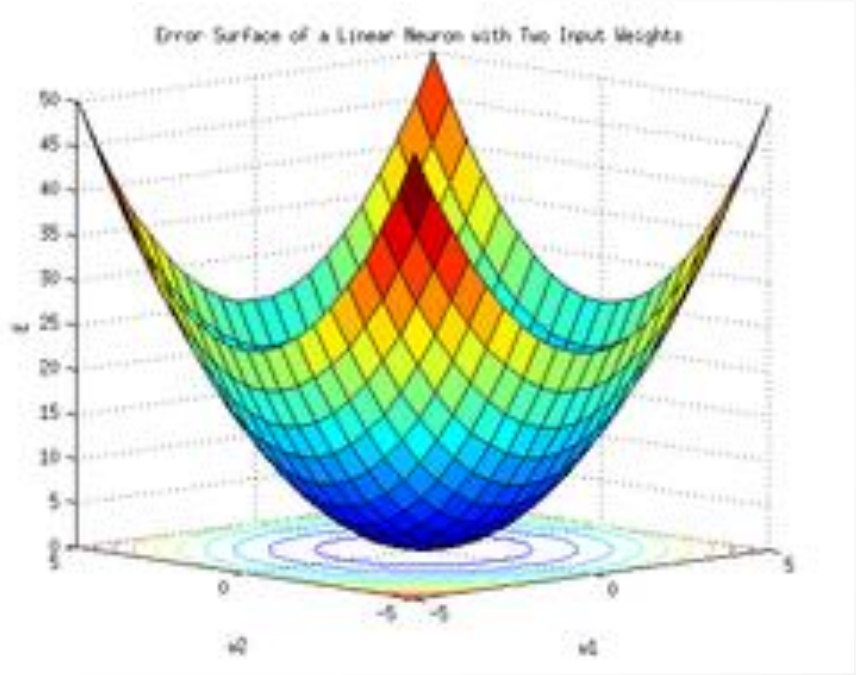
$$\frac{\partial E}{\partial w_{ij}} = (o_j - t)\, o_j (1 - o_j)\, o_i$$

Square Error Loss

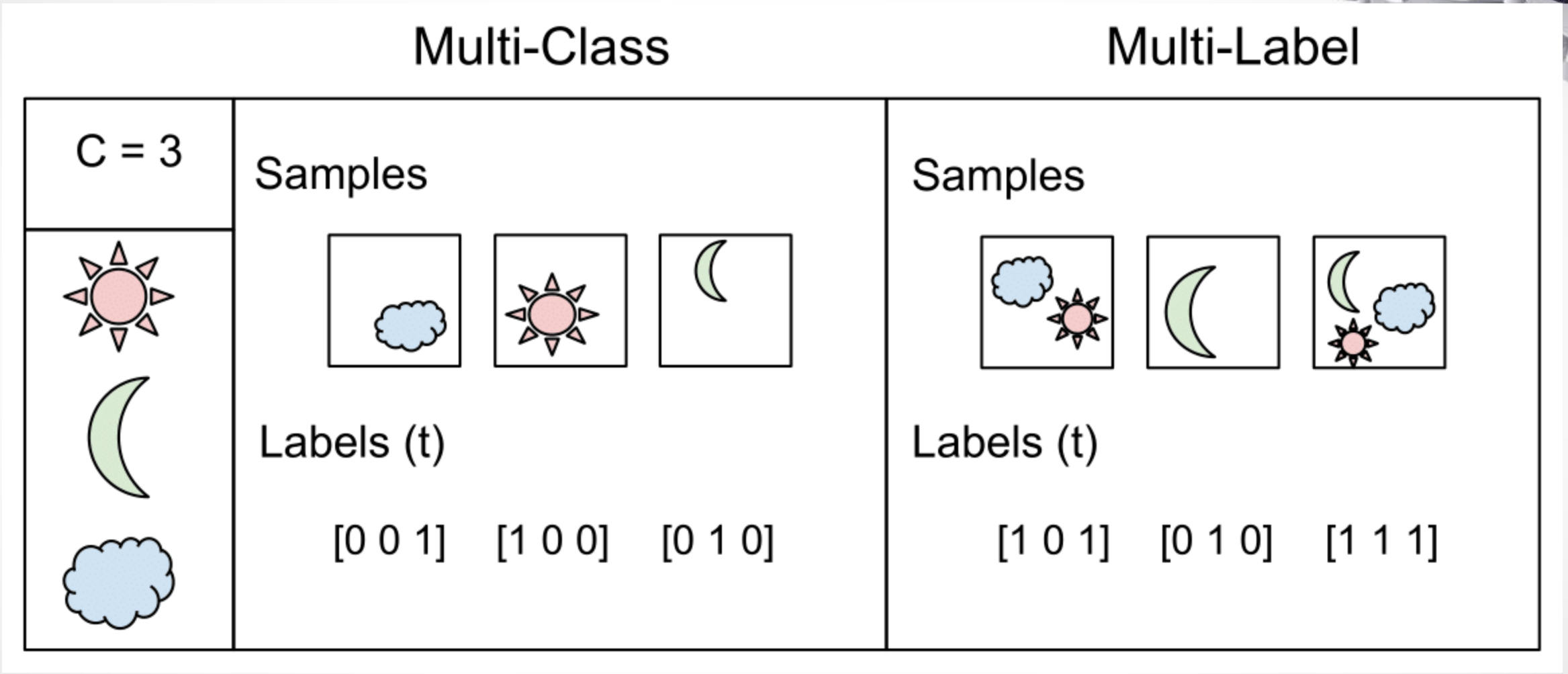
$$E = (t - y)^2$$

```
def MSE(t,y):
    return np.sum((t-y)**2) / y.size
```

- One-Hot encoding
- Use a binary vector of length *n* to represent labels of *n* possible classes
- Ex. [0 0 1], [1 0 0], [0 1 0]

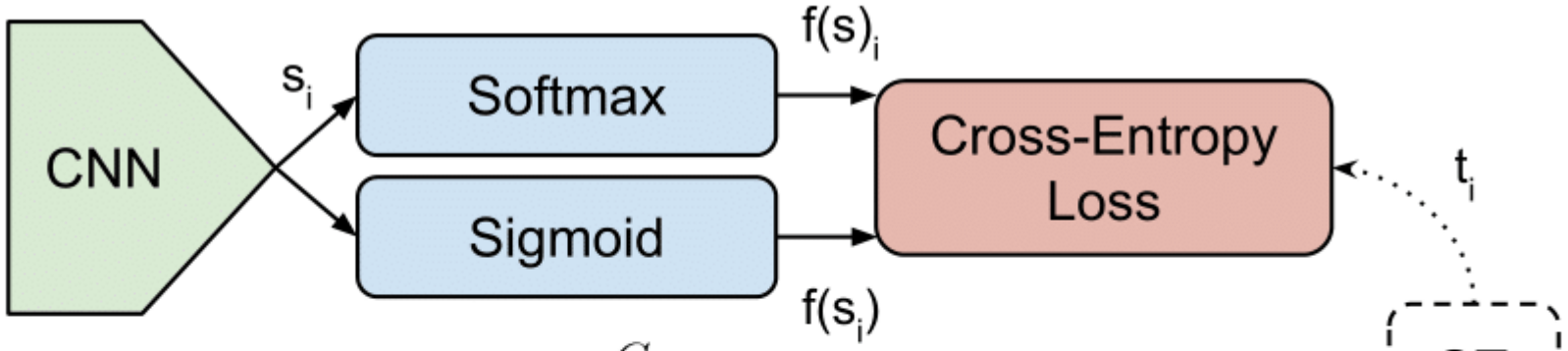


Multi-class / Multi-Label



https://gombru.github.io/2018/05/23/cross_entropy_loss/

Cross Entropy Loss

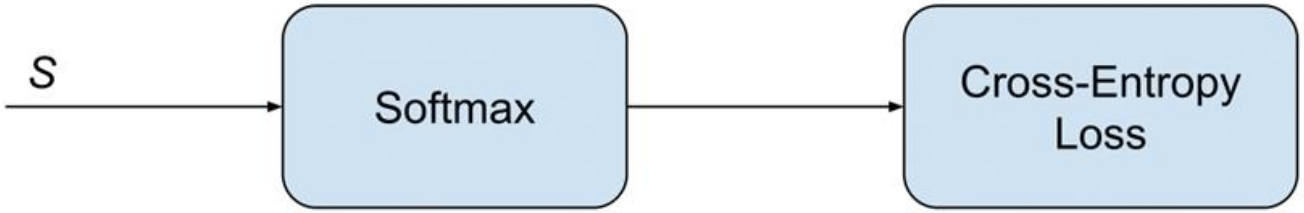


$$CE = -\sum_{i}^{C} t_i log(f(s)_i)$$

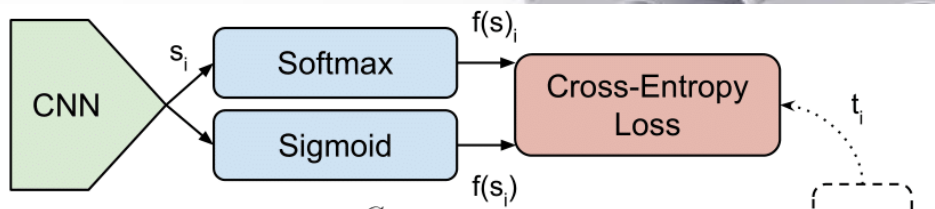
$$CE = -\sum_{i=1}^{C'=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1 - t_1) log(1 - f(s_1))$$

https://gombru.github.io/2018/05/23/cross_entropy_loss/

Categorical Cross Entropy Loss

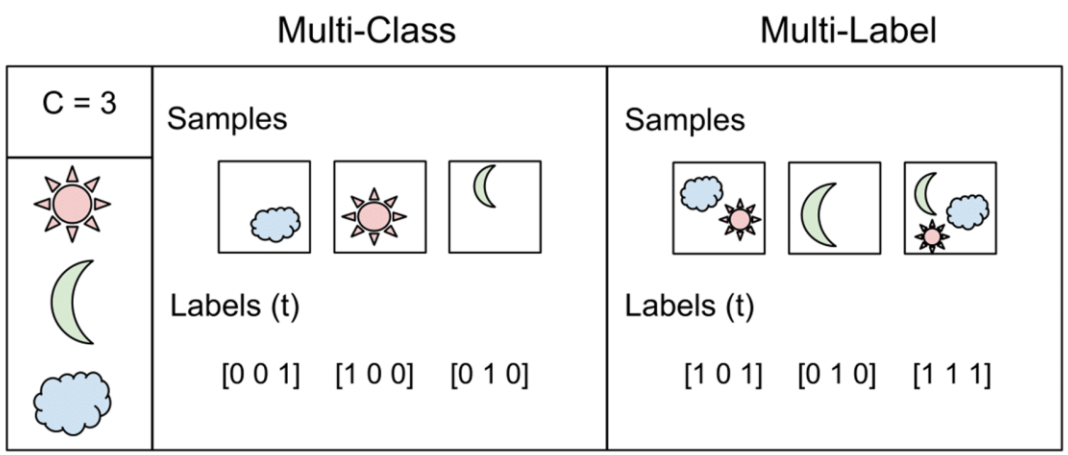


$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \qquad CE = -\sum_i^C t_i log(f(s)_i)$$



$$CE = -\sum_i^C t_i log(f(s)_i)$$

$$CE = -\sum_{i=1}^{C'=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1-t_1) log(1-f(s_1))$$



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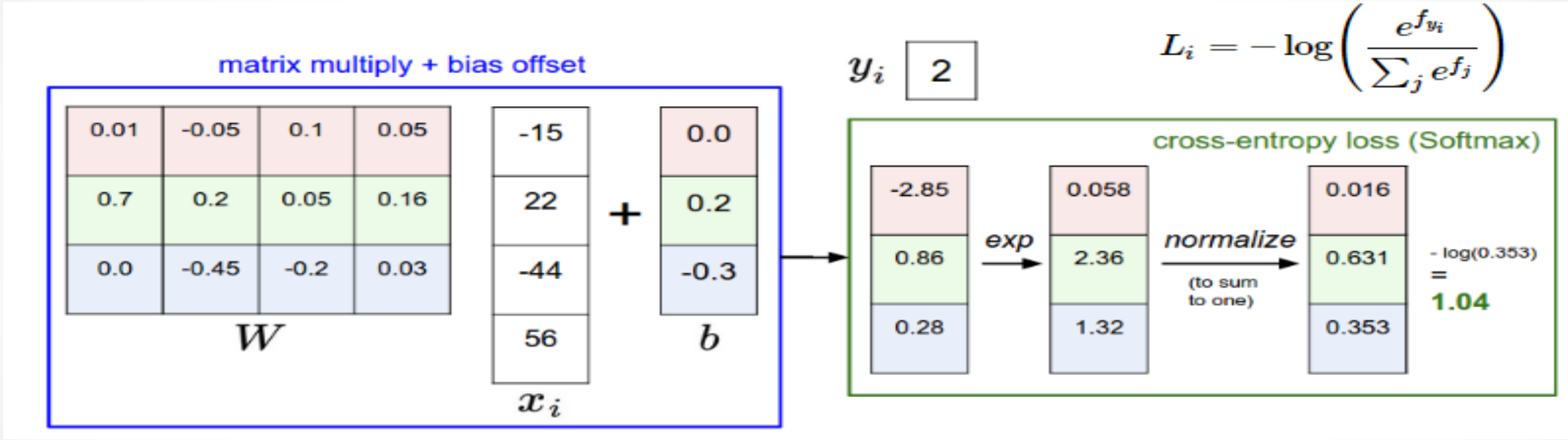
Categorical Cross Entropy Loss

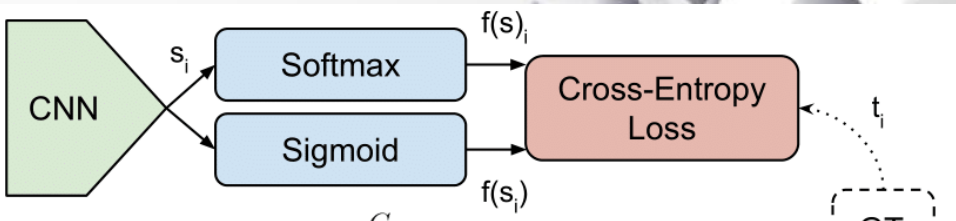


softmax = tf.exp(logits) / tf.reduce_sum(tf.exp(logits), axis)

Binary Cross Entropy Loss

$$CE = -t_1 log(f(s_1)) - (1 - t_1) log(1 - f(s_1))$$

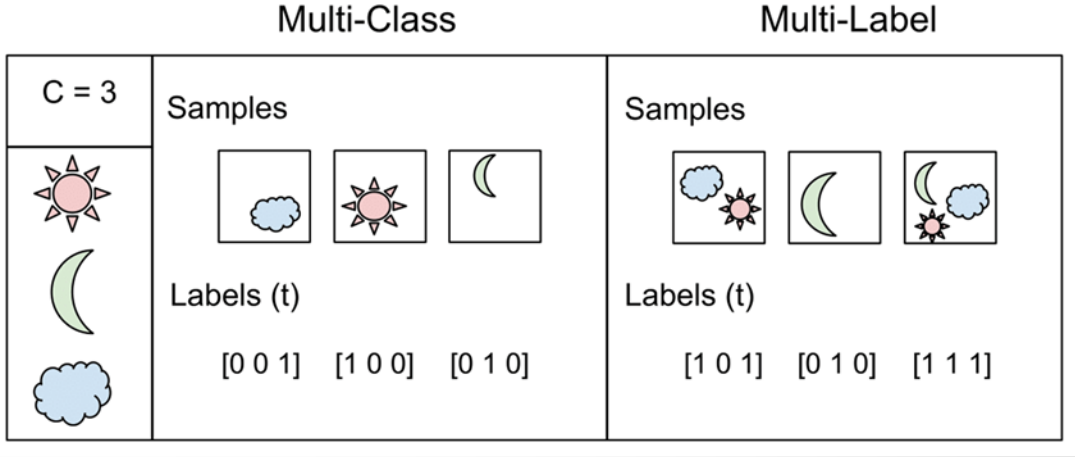
$$f(s_i) = \frac{1}{1 + e^{-s_i}}$$



$$CE = -\sum_{i}^{C} t_i log(f(s)_i)$$

$$CE = -\sum_{i=1}^{C'=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1 - t_1) log(1 - f(s_1))$$

```
def BinaryCrossEntropy(yHat, y):
    if y == 1:
      return -log(yHat)
    else:
      return -log(1 - yHat)
```



https://gombru.github.io/2018/05/23/cross_entropy_loss/

Gradient and Stochastic Gradient Descent

- Stochastic gradient descent can be regarded as a stochastic approximation of gradient descent optimization, since it replaces the actual gradient (calculated from the entire data set) by an estimate thereof (calculated from a randomly selected subset of the data).
- Stochastic gradient descent is a popular algorithm for training a wide range of models in machine learning.
- When combined with the backpropagation algorithm, it is the de facto standard algorithm for training artificial neural networks.

Wikipedia

Gradient and Stochastic Gradient Descent

$$Q(w) = \frac{1}{n}\sum_{i=1}^{n} Q_i(w), \qquad Q_i(w) \text{ is the loss function}$$

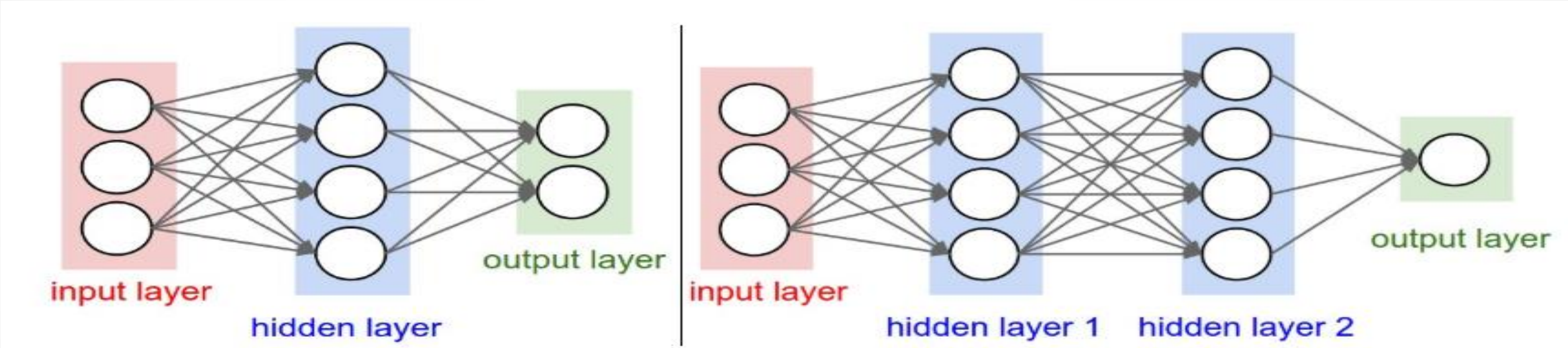
a standard (or "batch") gradient descent method

$$w := w - \eta \nabla Q(w) = w - \eta \sum_{i=1}^{n} \nabla Q_i(w)/n,$$

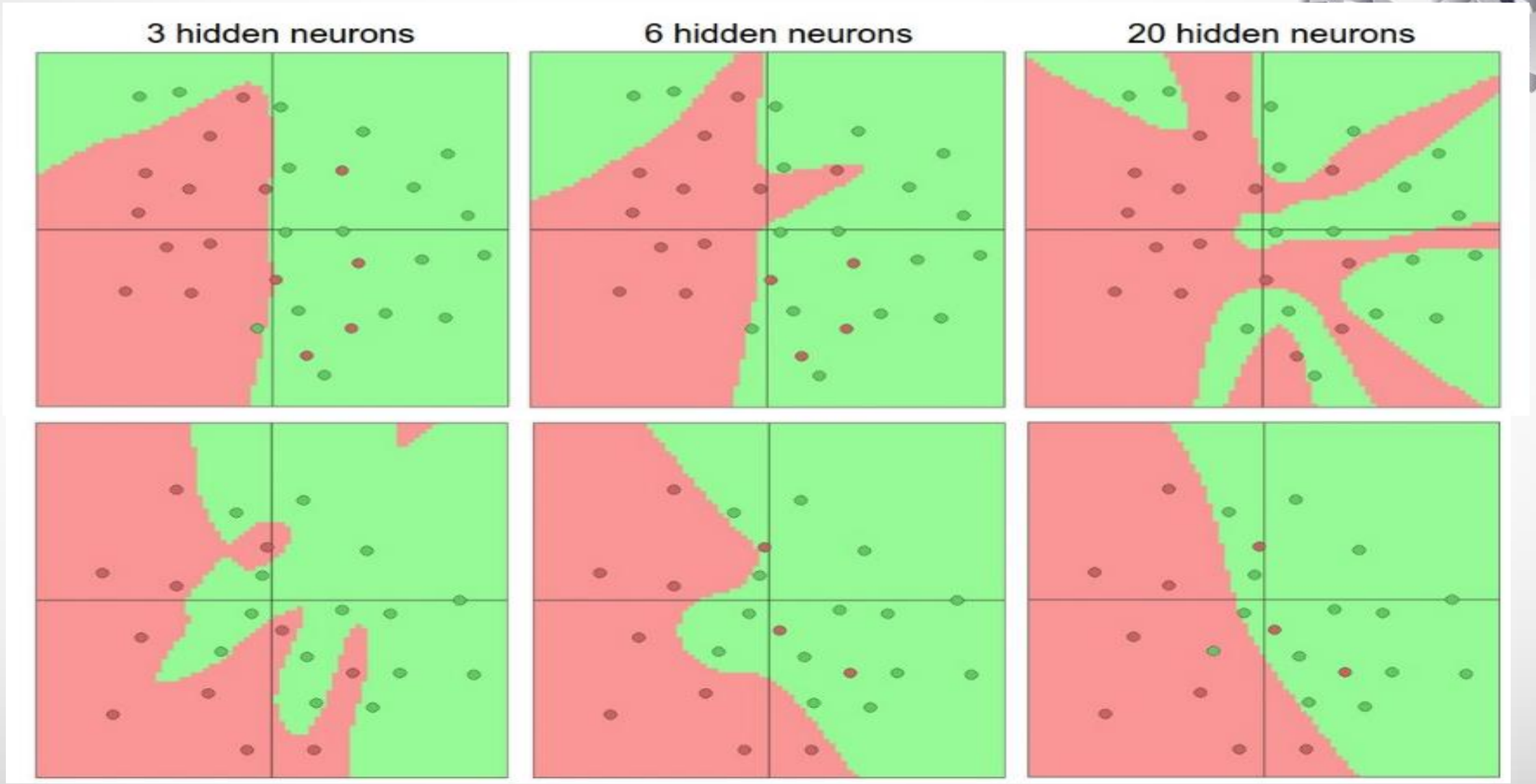
- A compromise between computing the true gradient and the gradient at a single example is to compute the gradient against more than one training example (called a "mini-batch") at each step. This can perform significantly better than "true" stochastic gradient descent described.

Wikipedia

Summary: Feedforward Neural Networks

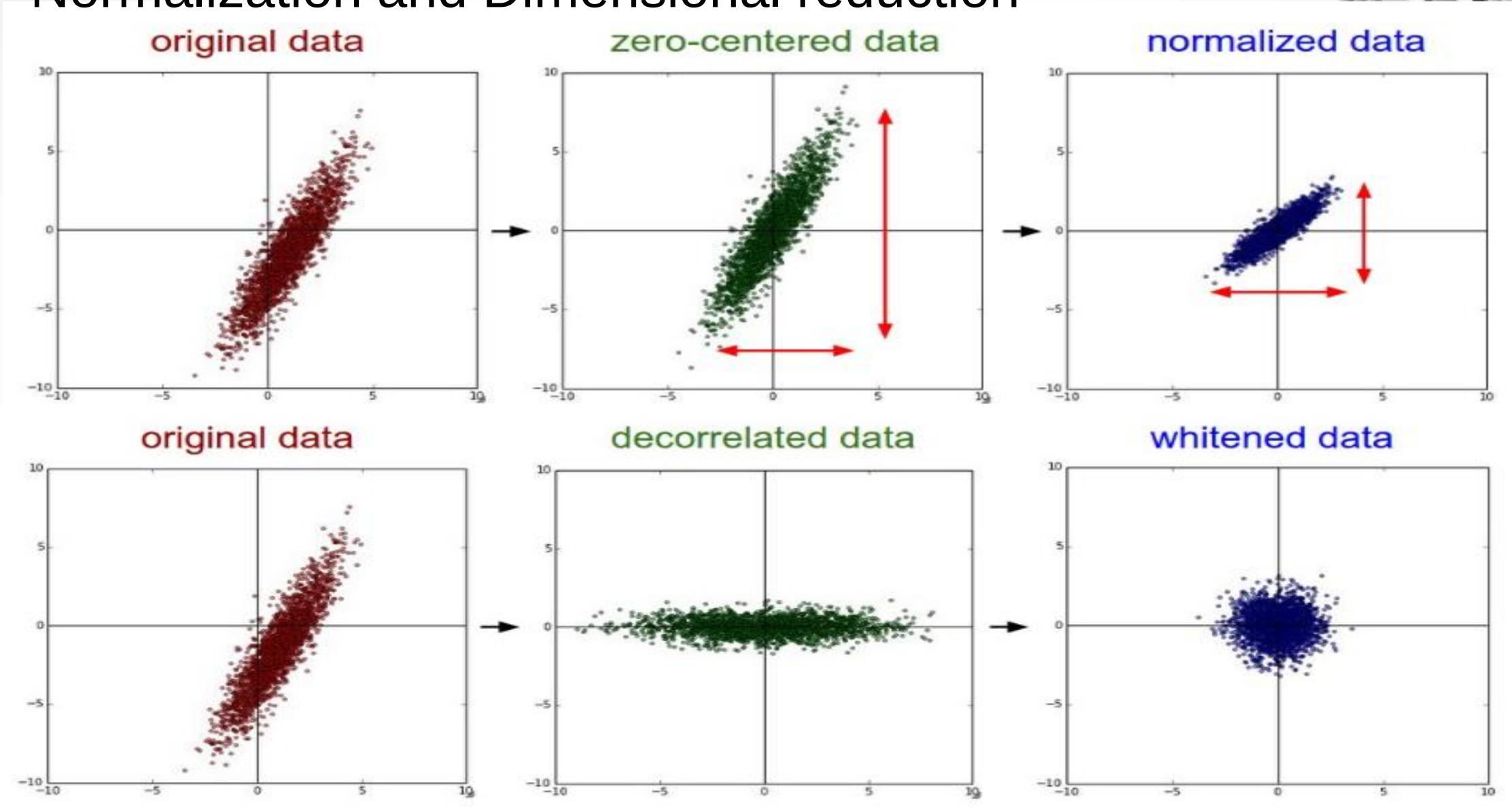


Effects of Network Structure

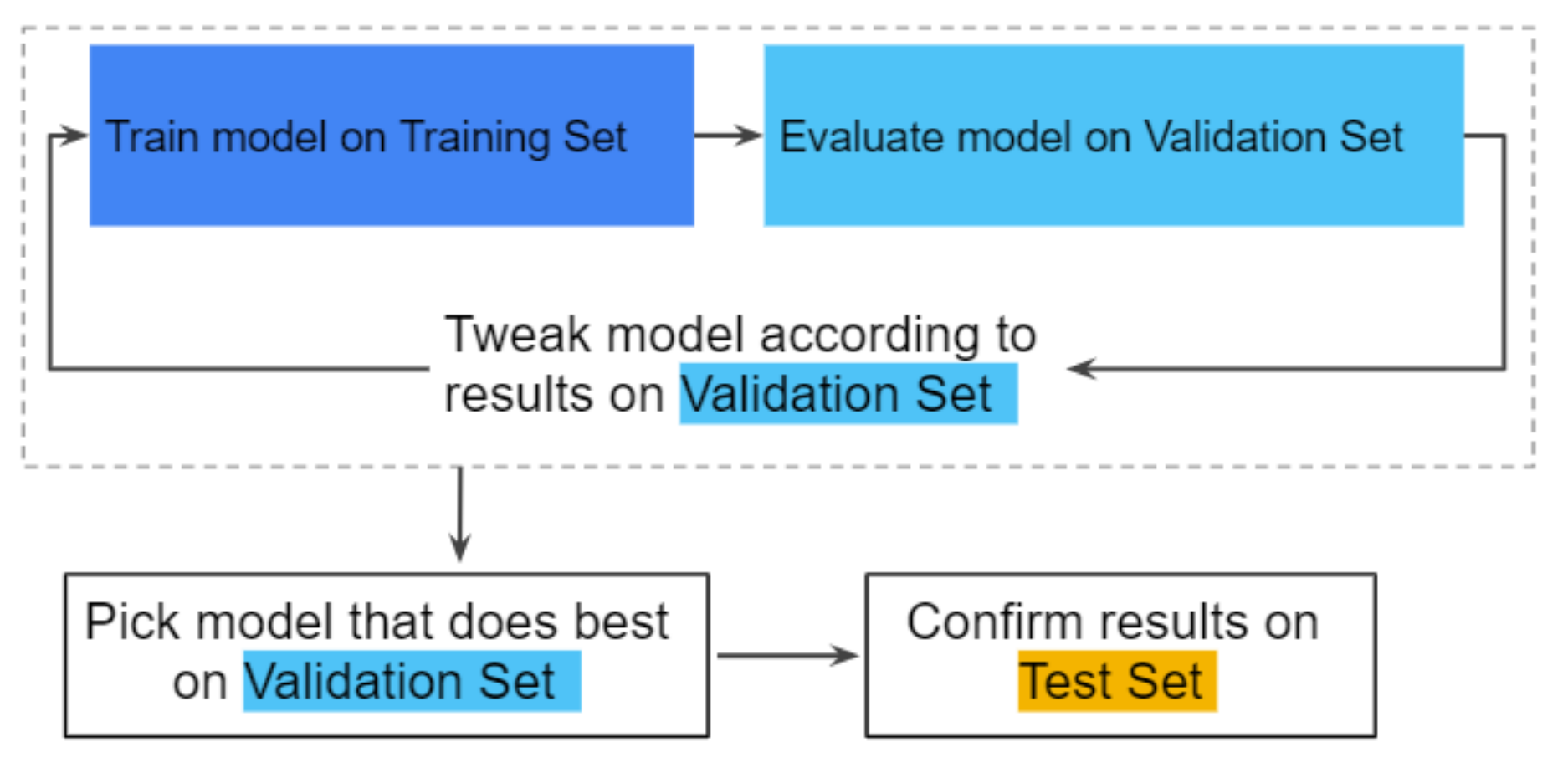


Data Preprocessing

- Normalization and Dimensional reduction



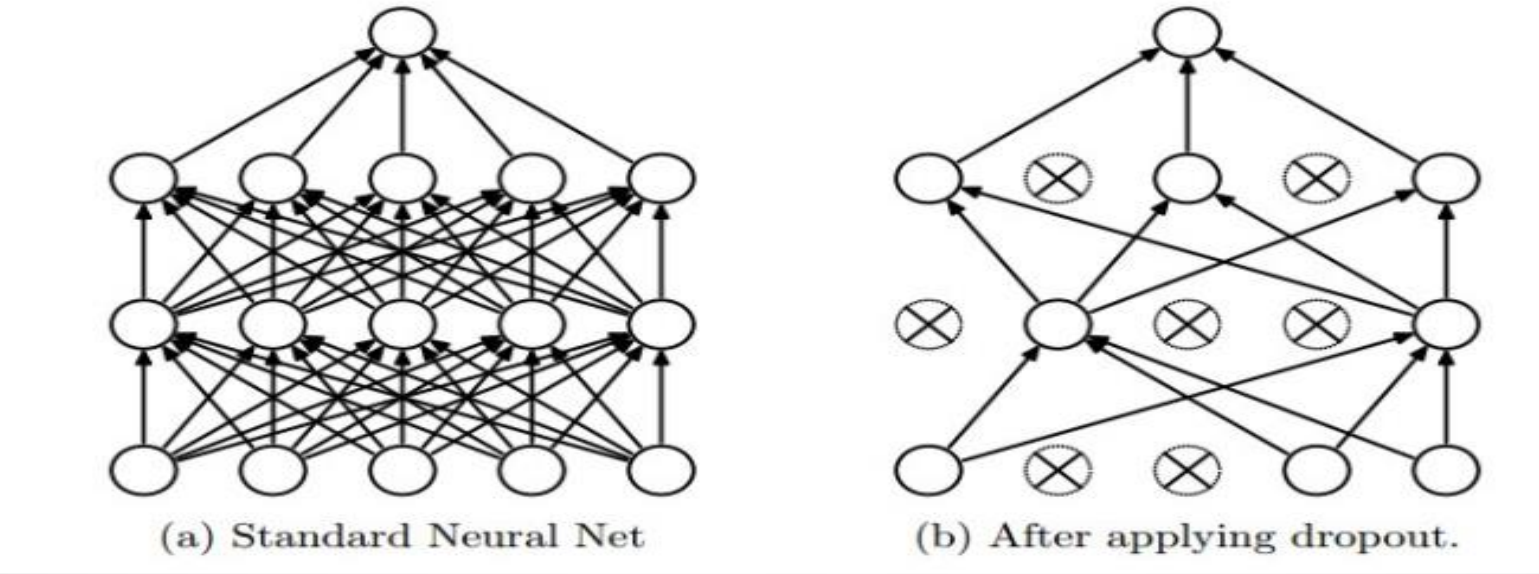
Training, Validation & Test Set



Overfitting

Deal with overfitting by

- Adding regularization terms
- Implementing dropout



(a) Standard Neural Net

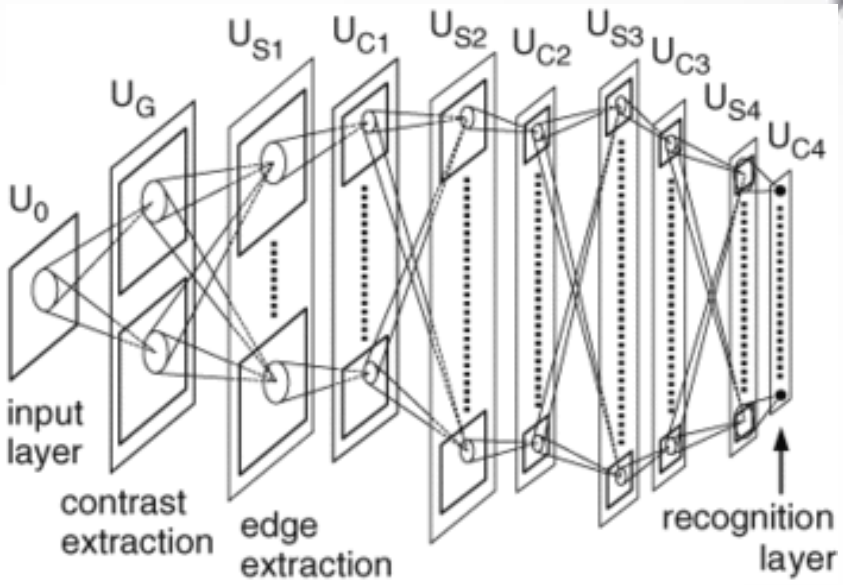
(b) After applying dropout.

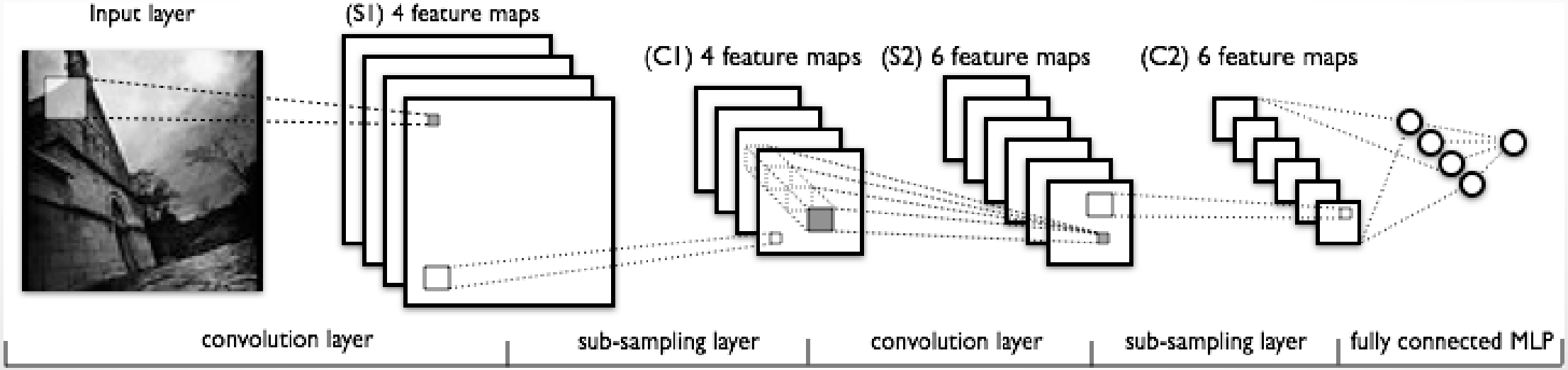
Deep Learning

CNN based computer vision

APNNS/IEEE Education Forum Series: DLAI3
29 June – 3 July 2020

A Brief History of Deep Learning



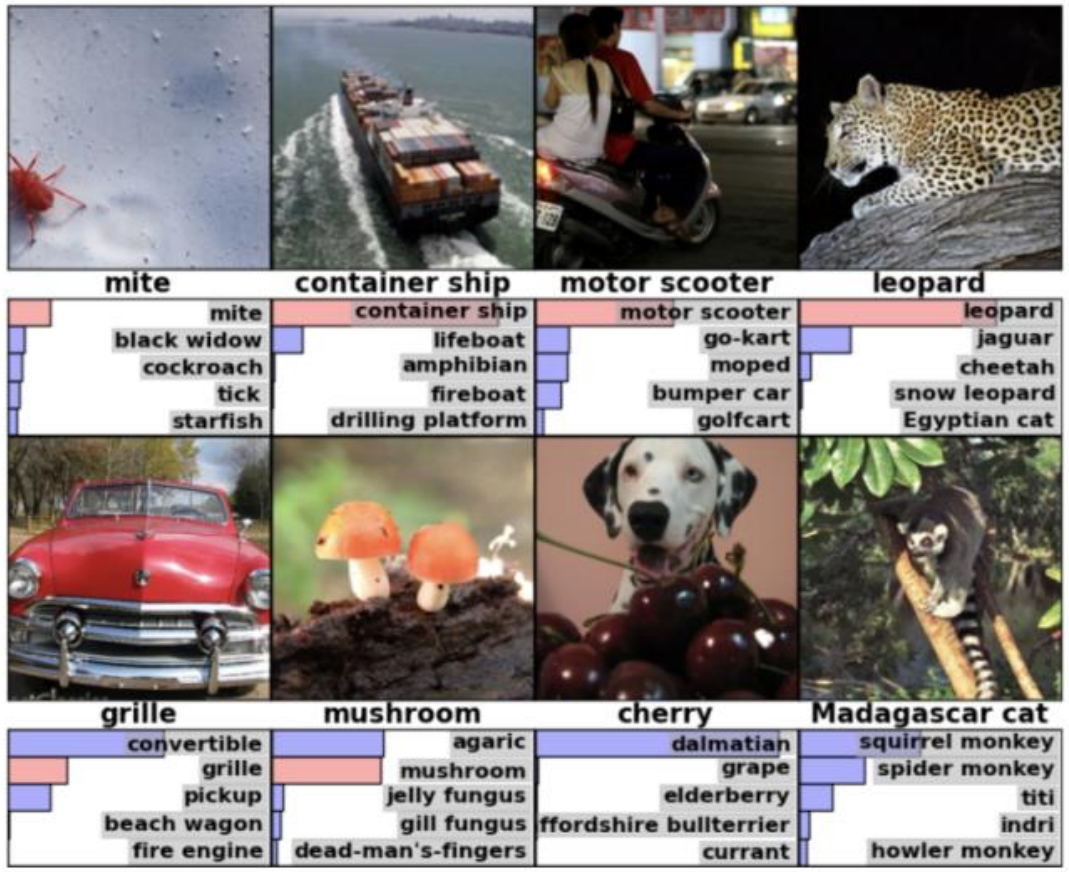


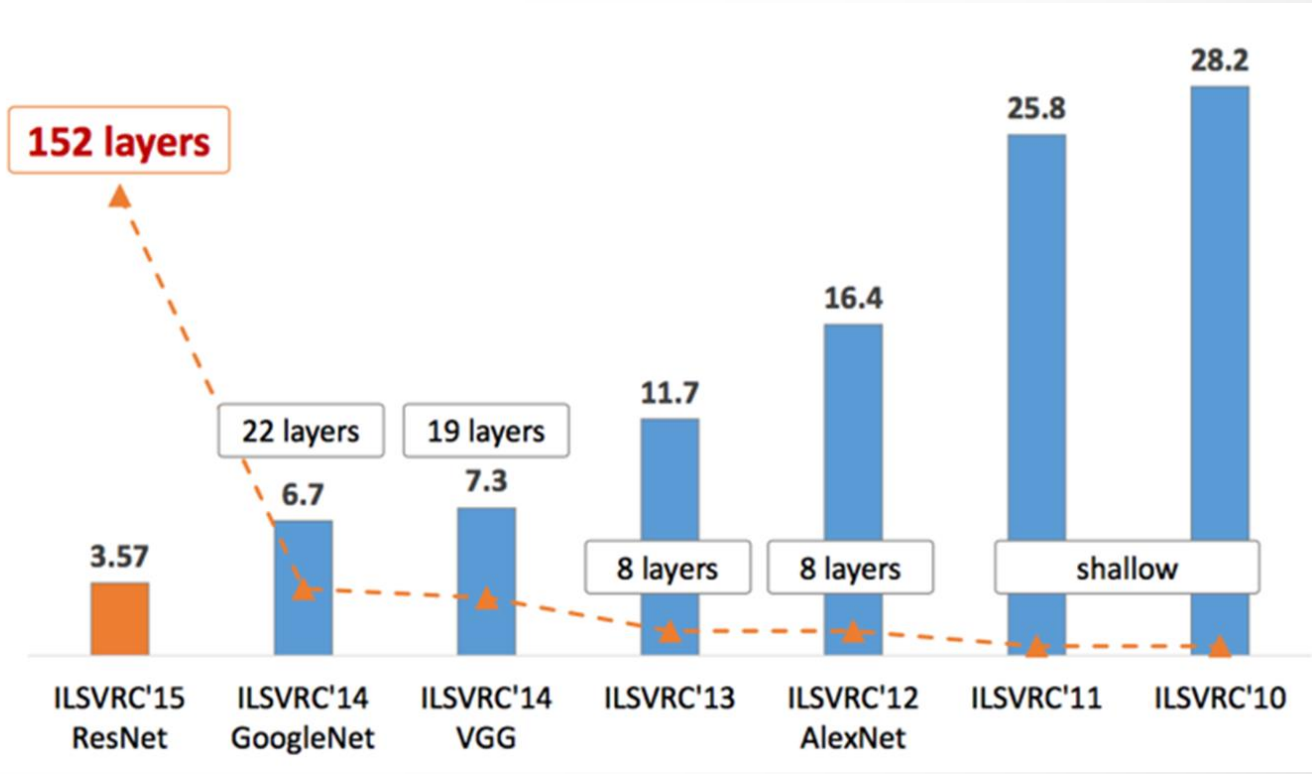
A Brief History of Deep Learning

- Hubel and Wiesel (1959) found two types of important cells in the visual primary cortex: *simple cell* and *complex cell.*
- The Neocognitron (Fukushima, 1979) was inspired by the model proposed by Hubel & Wiesel.
- Convolutional neural network (Yann LeCun, 1989) was also inspired by this line of concepts.



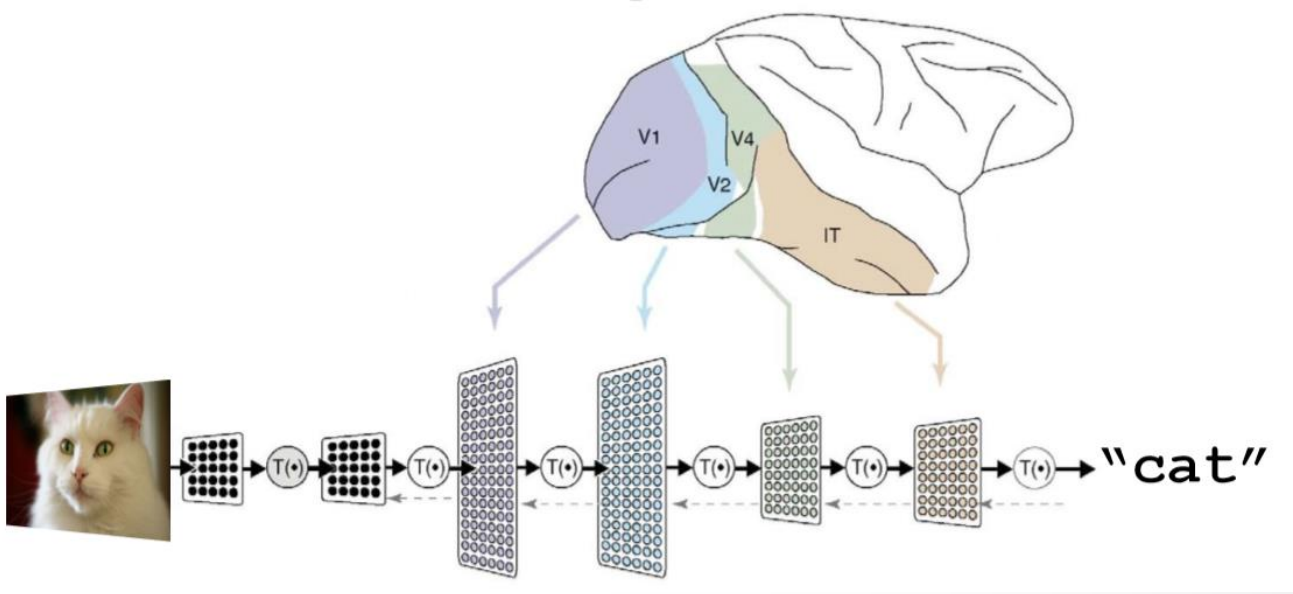

ImageNet (Fei-Fei Li, 2009)



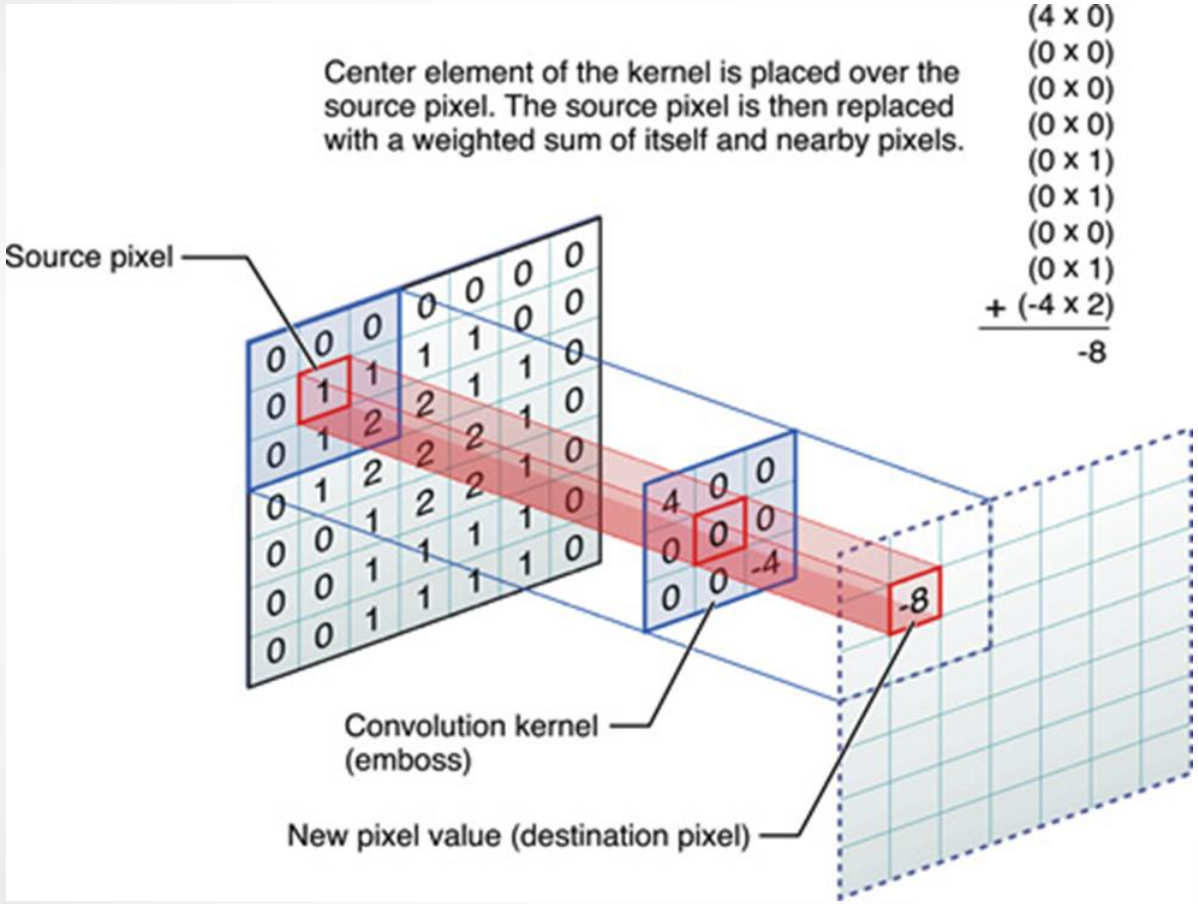


Why does CNN Perform Better?

- CNN shares many interesting commonalities with real brains.
  - Each neuron is connected to a small subset of neurons.
  - Each neuron perform simple function e.g., Sigmoid, ReLU.
  - Each subset of neurons learn specialised features (representation learning).



Convolutional Neural Network



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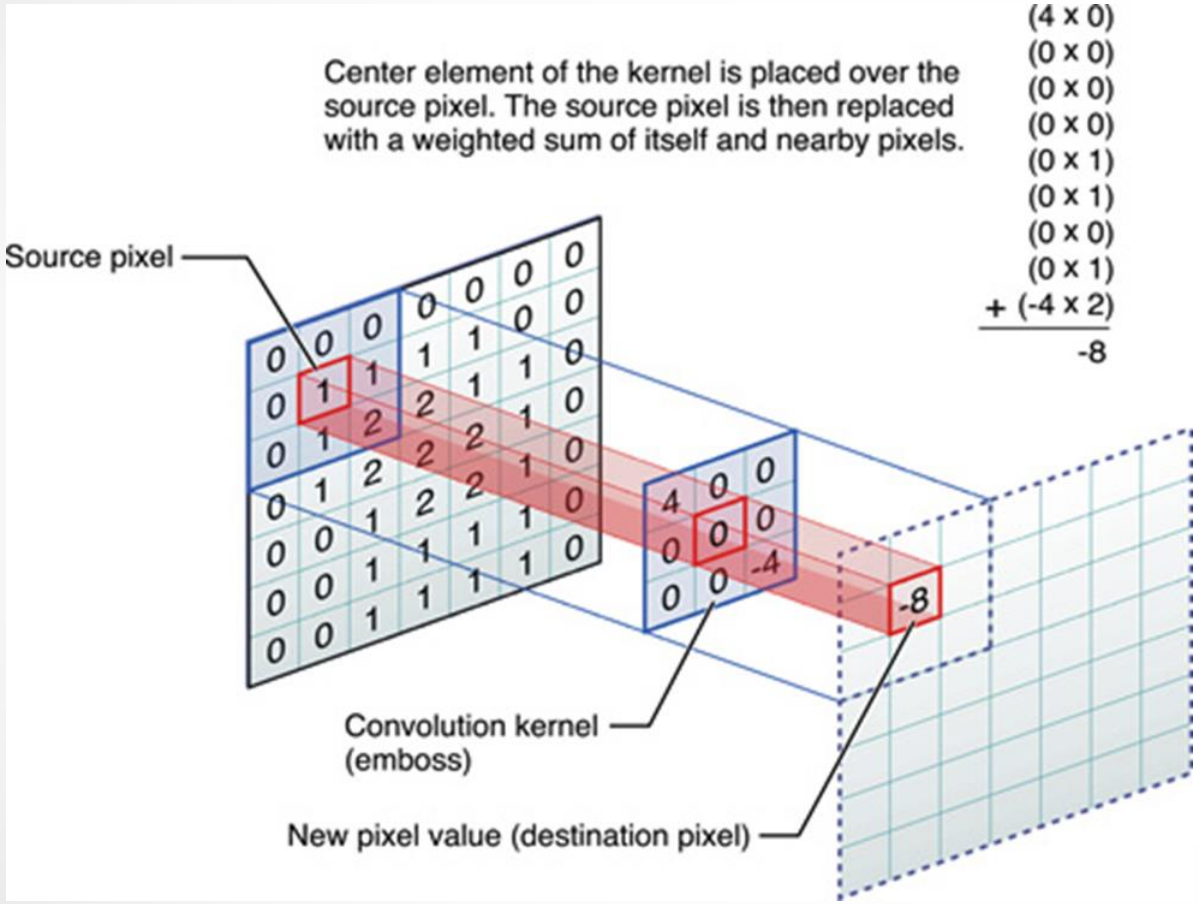
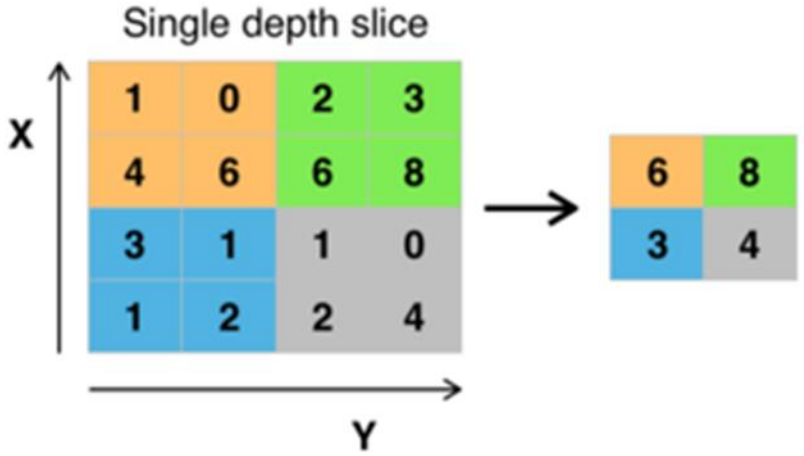
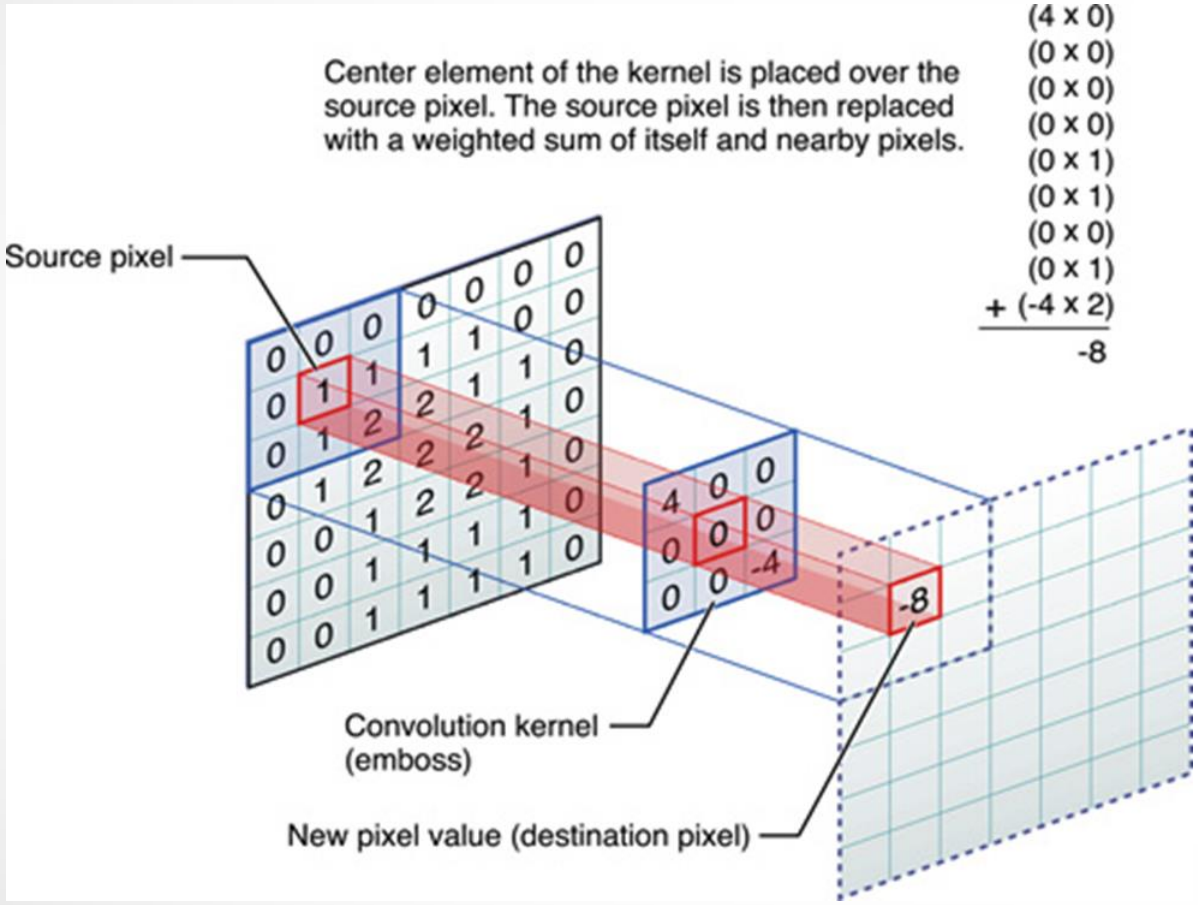
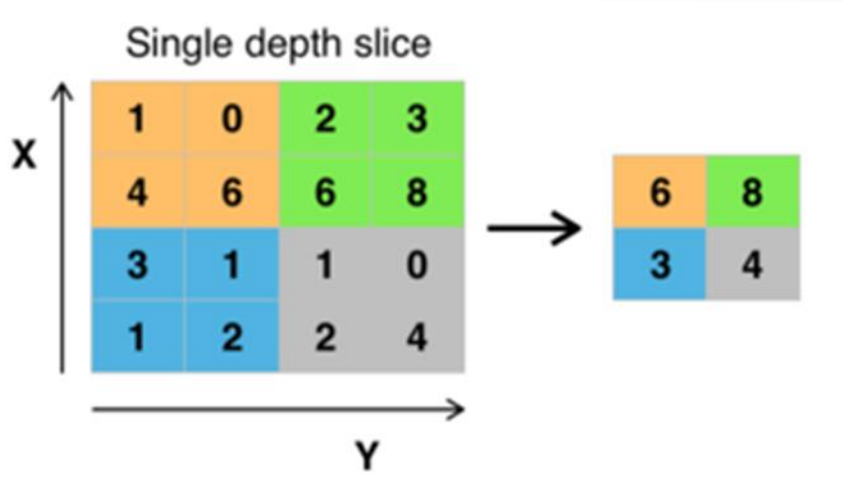
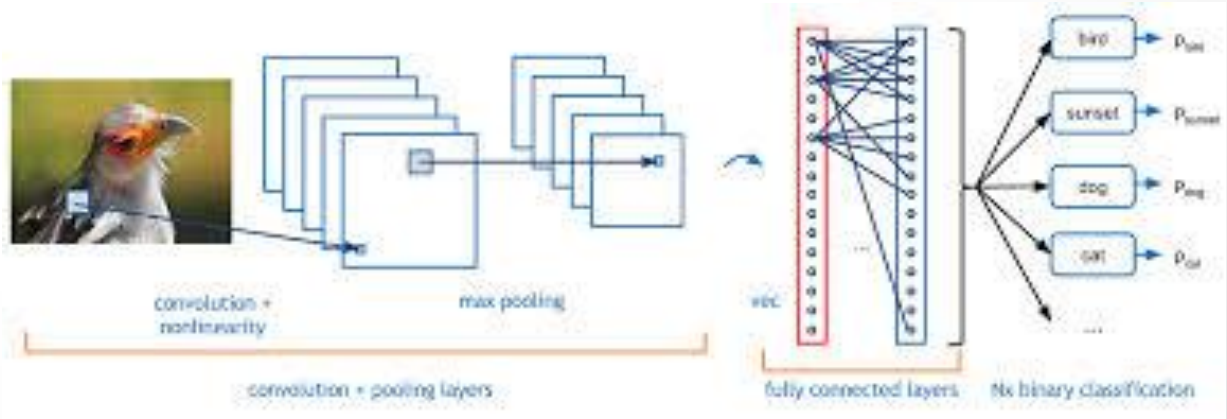




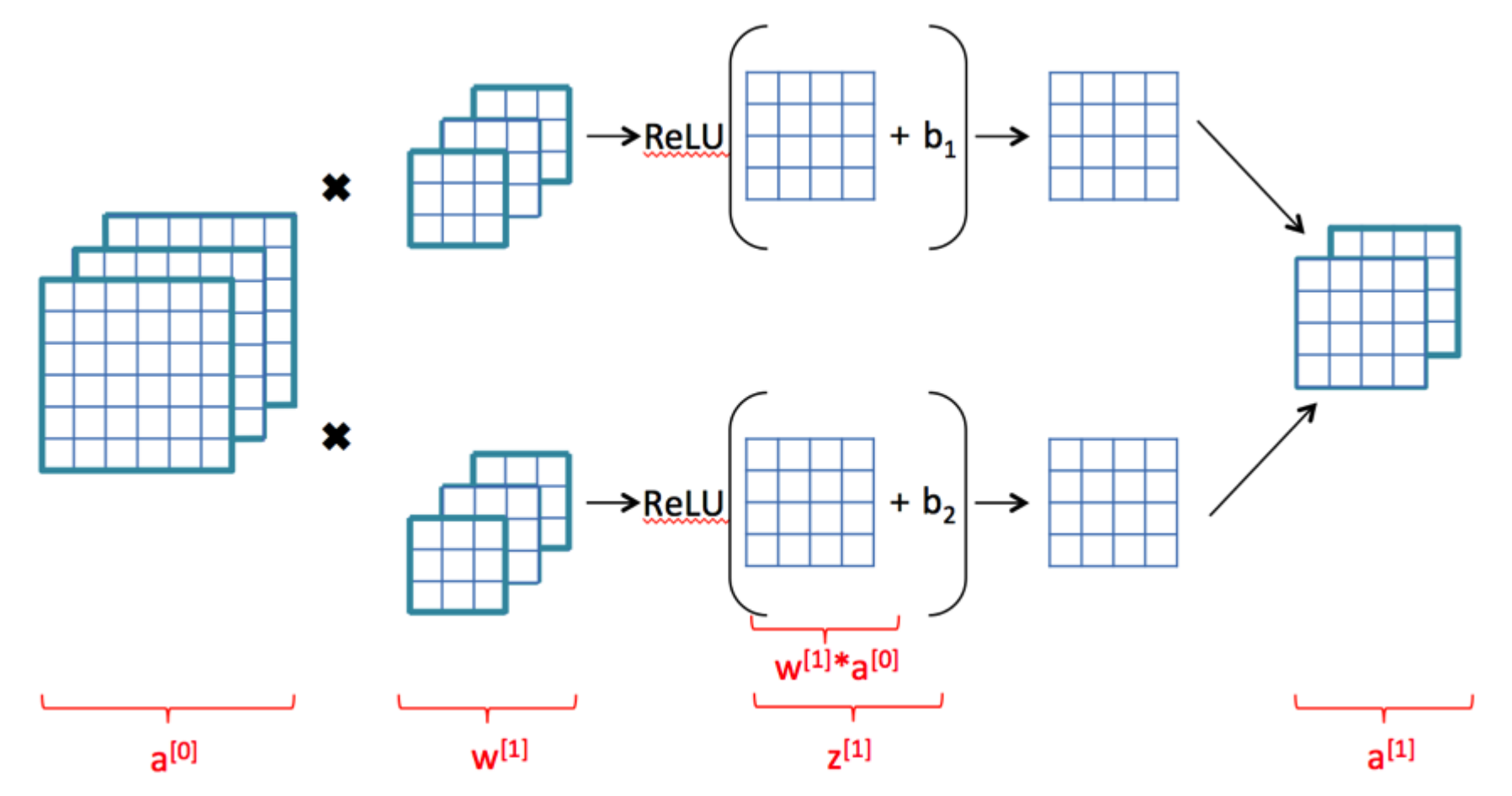
Convolutional Neural Network





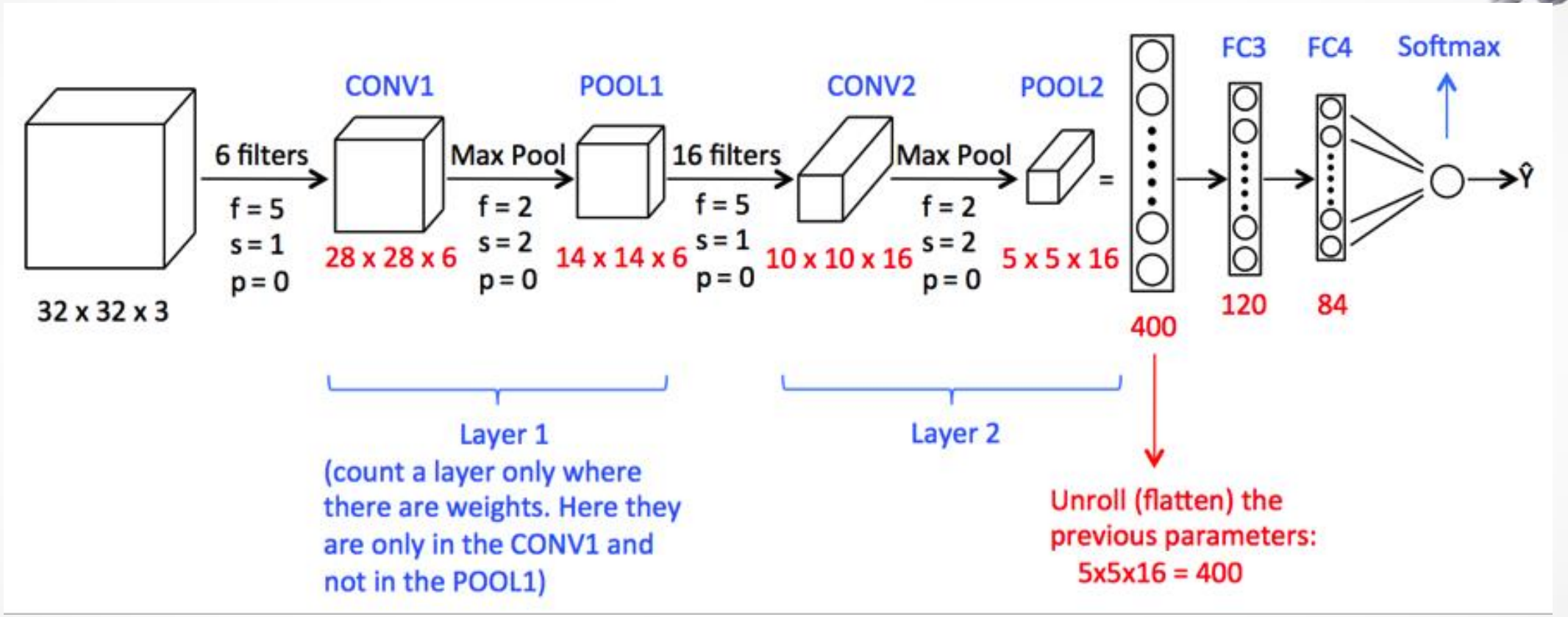


Convolutional Neural Network



https://medium.com/machine-learning-bites/deeplearning-series-convolutional-neural-networks-a9c2f2ee1524

Convolutional Neural Network



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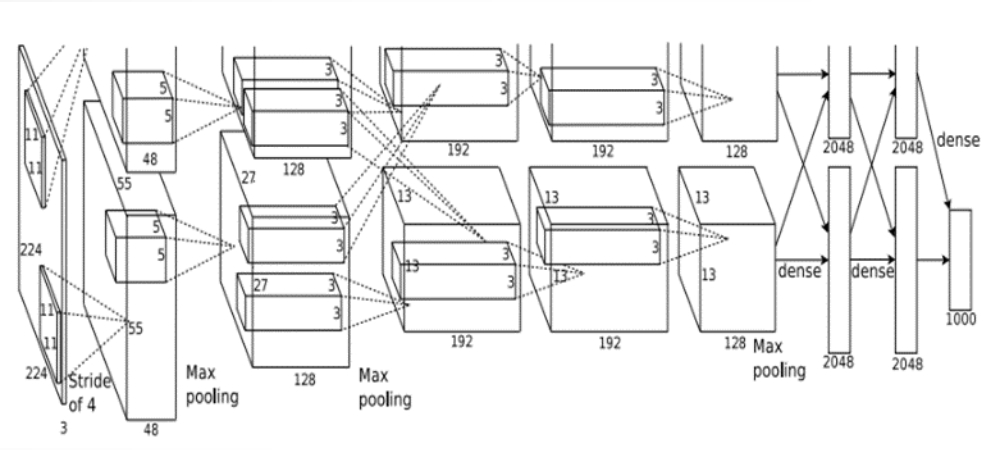
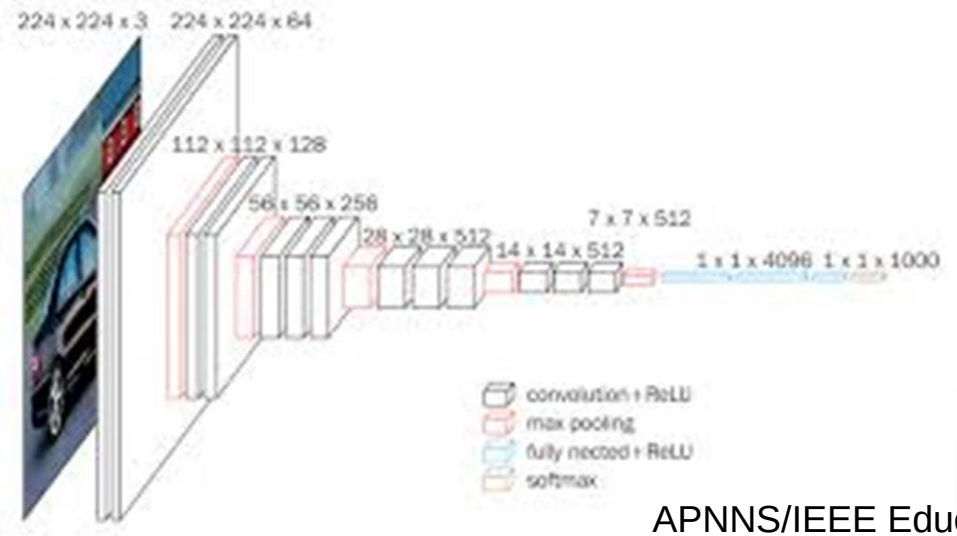
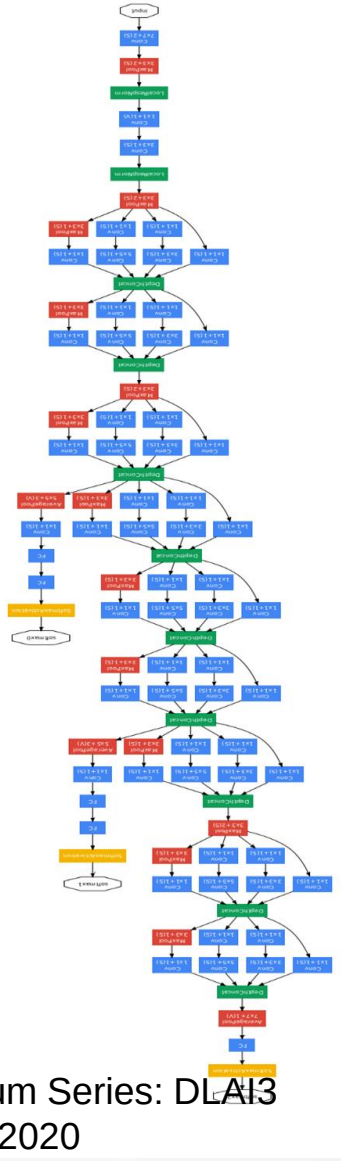
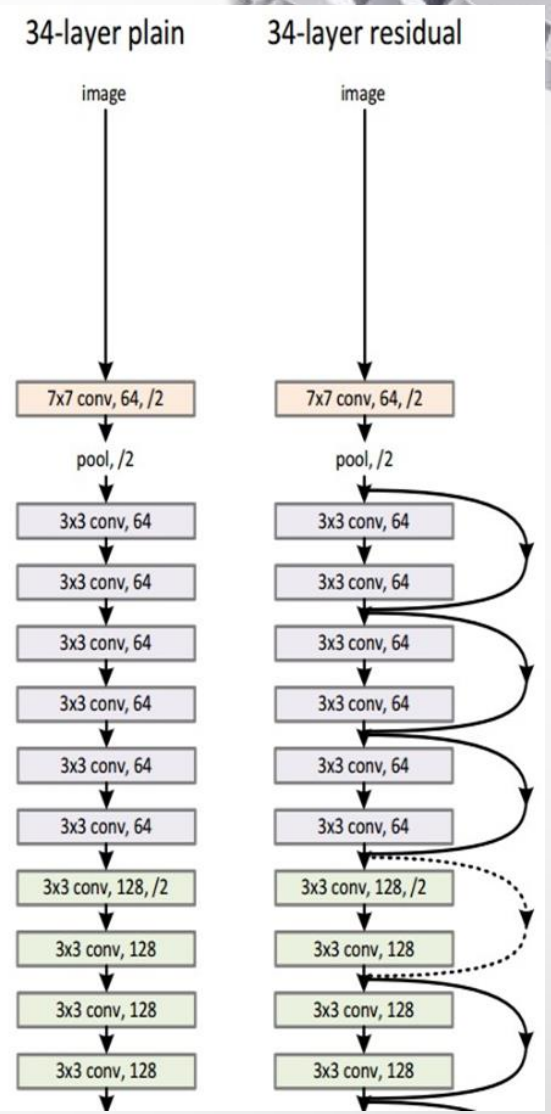
Convolutional Neural Networks

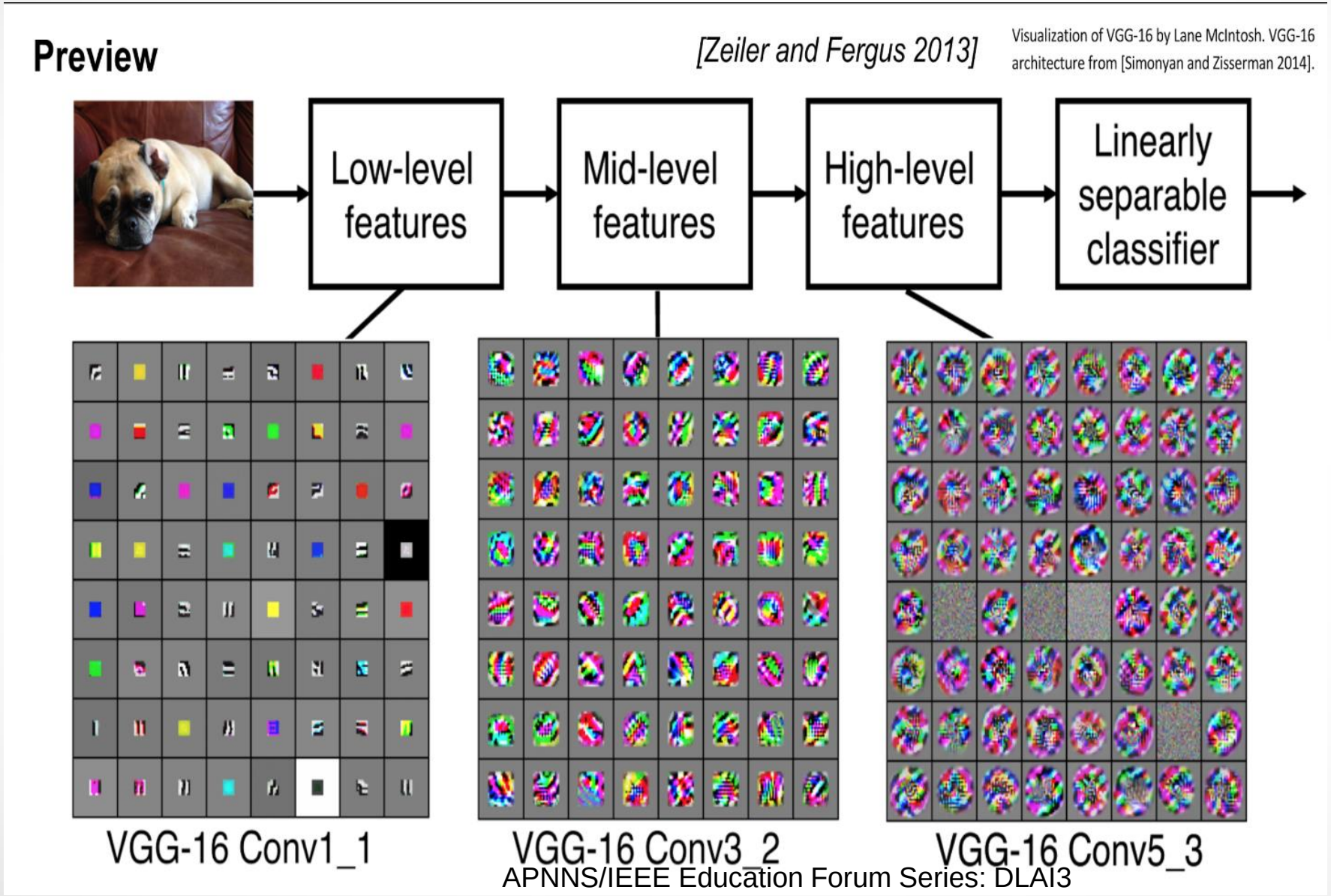






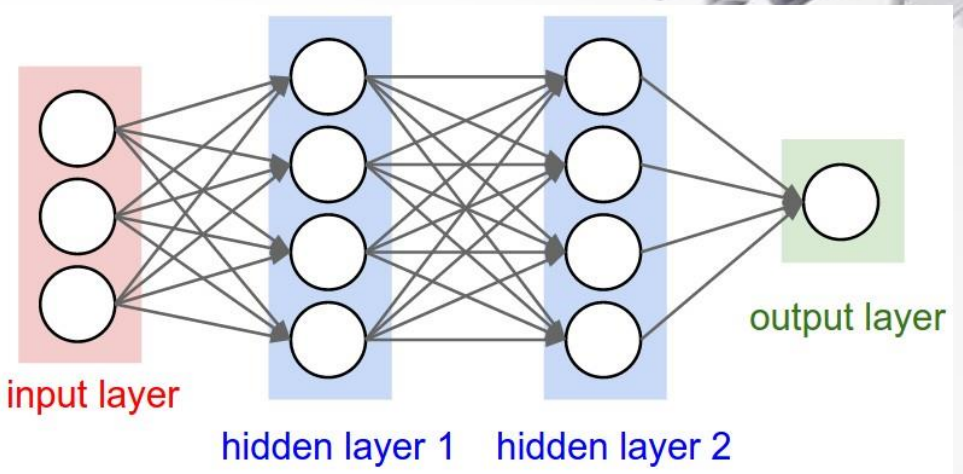


End-to-End Approach (self learned features)

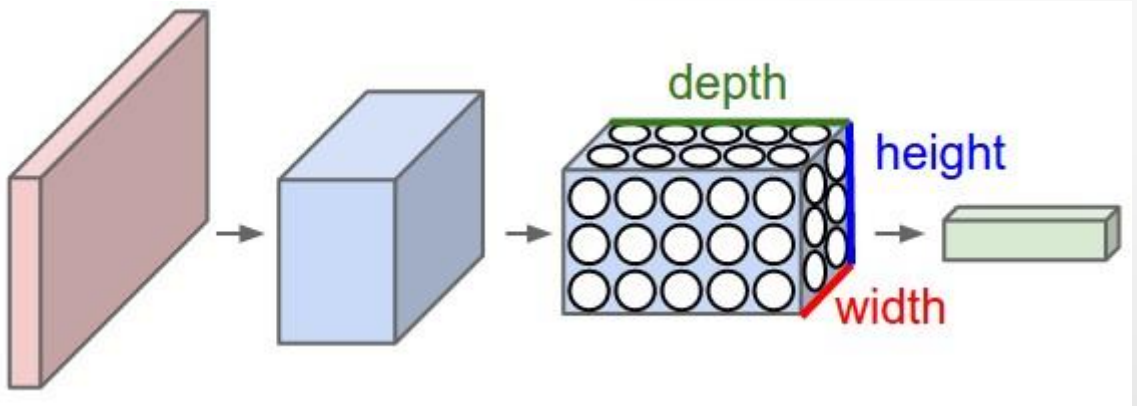


Recap: MLP & CNN

- Should MLP be wide rather than deep?
- Vanishing Gradient Problem

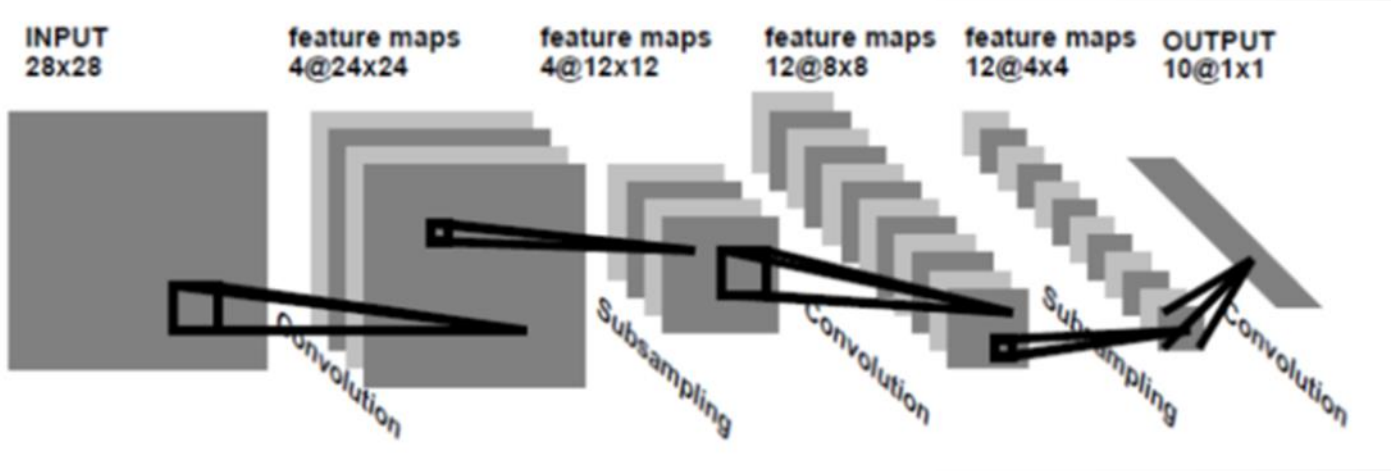


- Convolutional layer
- Pooling layer
- Normalization layer
- Dropout
- Fully connected layer



Deep Learning for Image Classification Tasks

LeNet
AlexNet
ZFNet
VGGNet
SPPNet
GoogLeNet / Inception-v1
BN-Inception / Inception-v2
Inception-v3, Inception-v4
Xception
MobileNet
ResNet
DenseNet
NASNet



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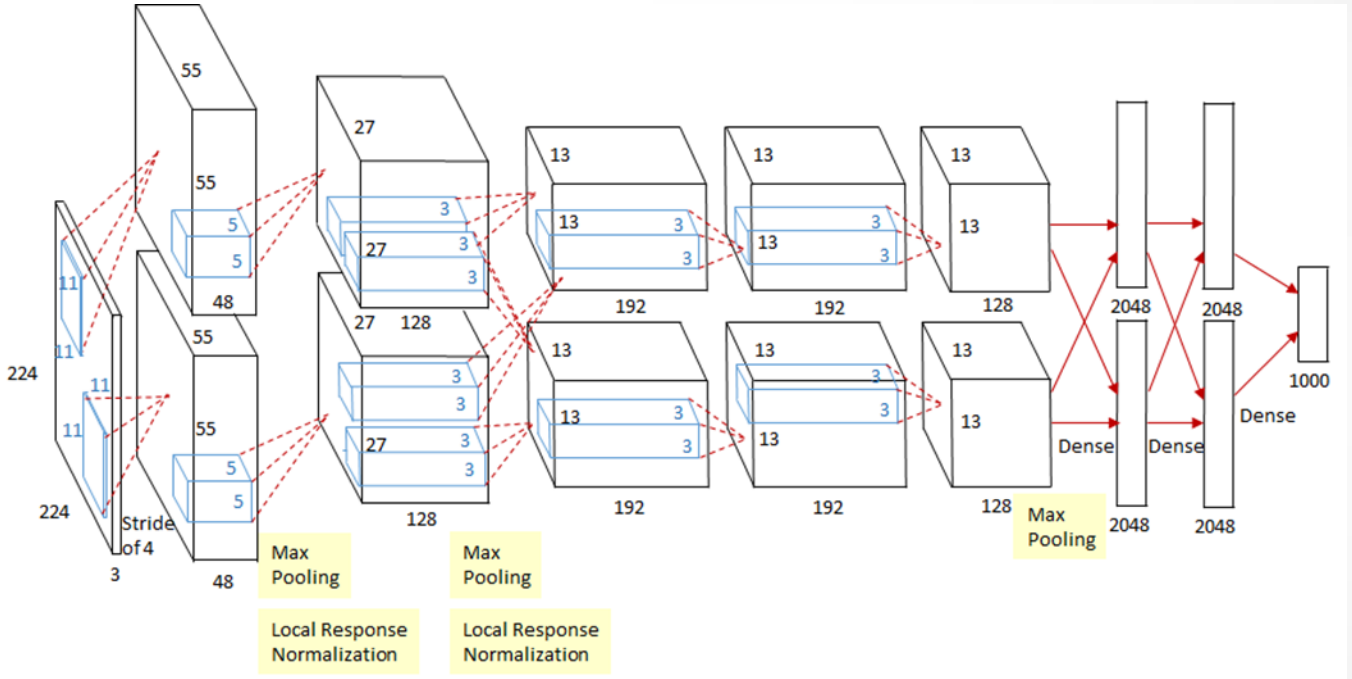

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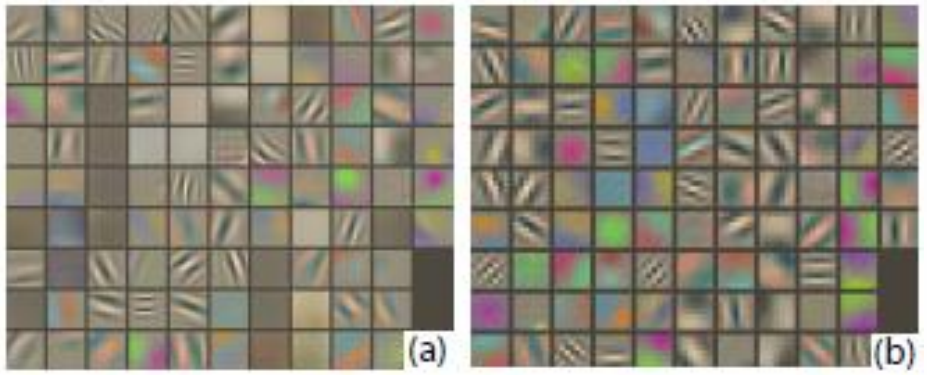

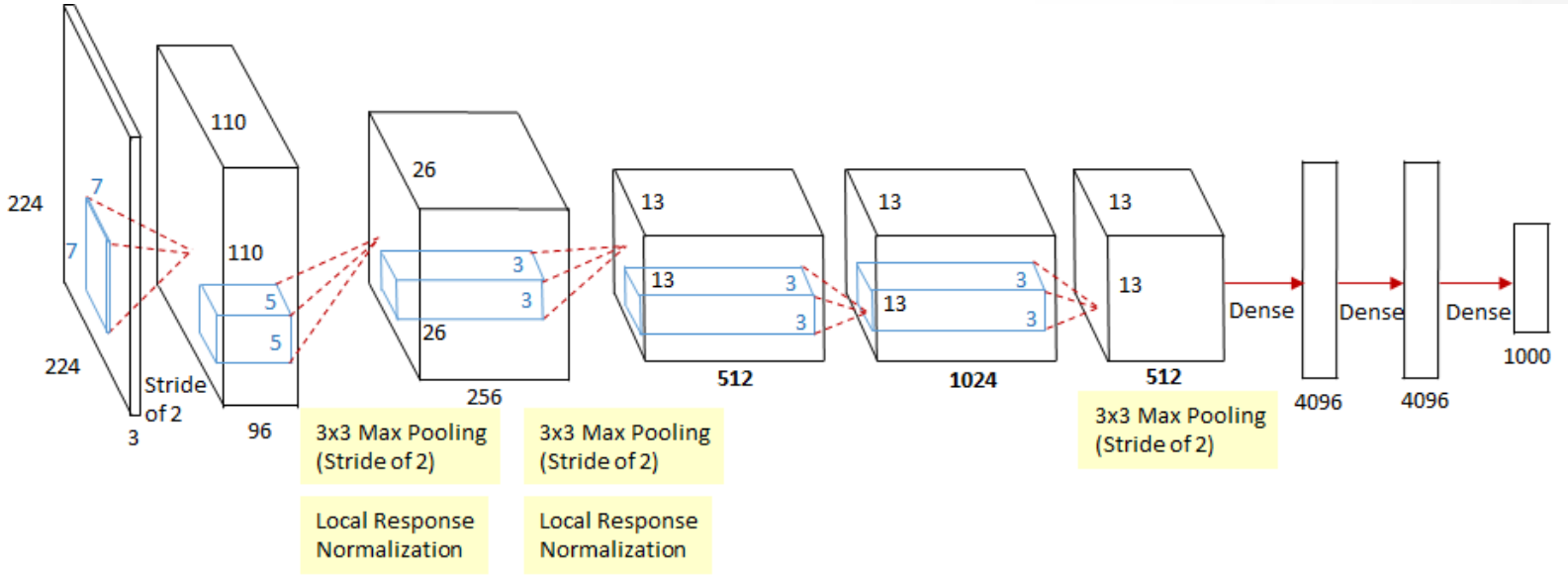

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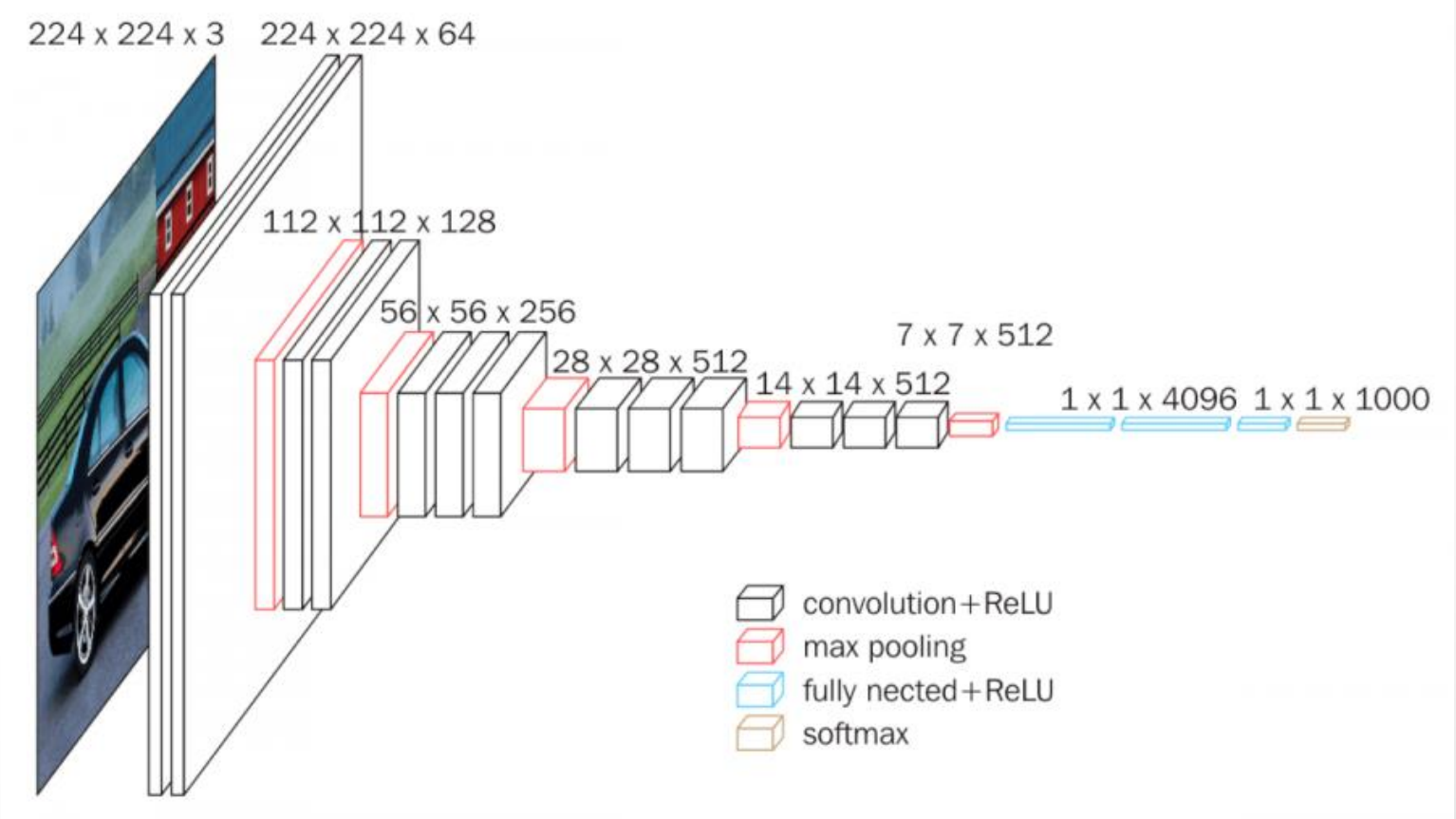

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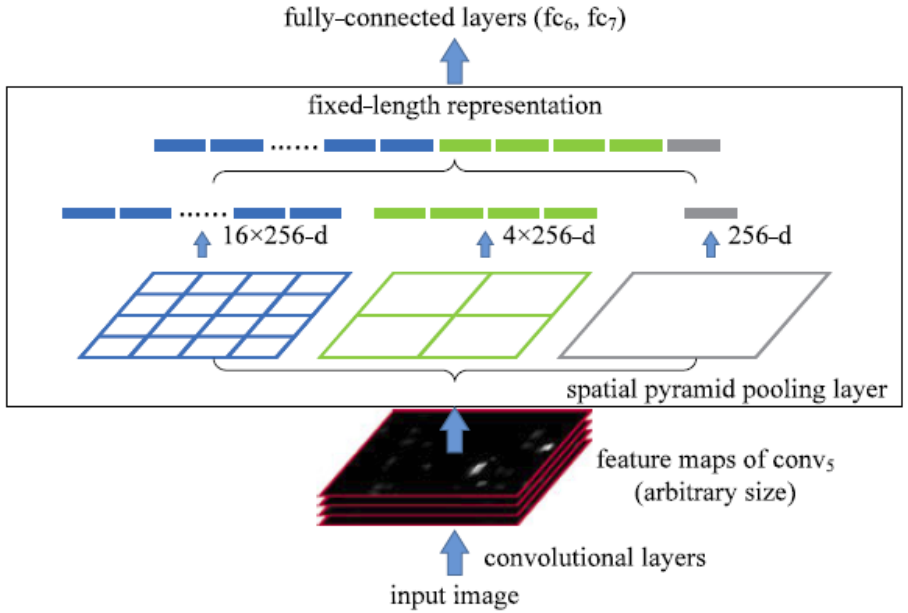

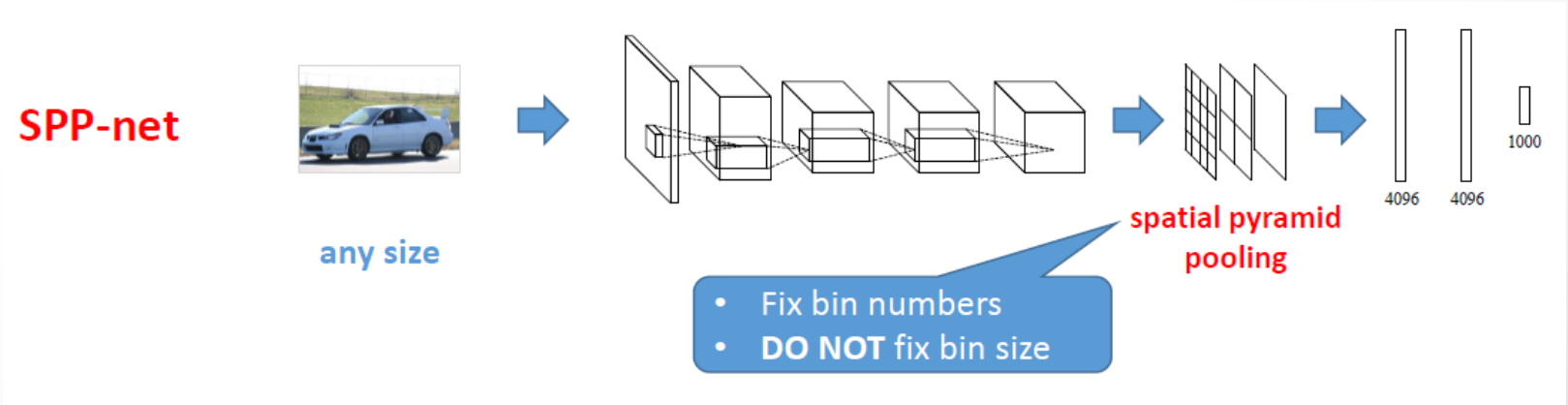

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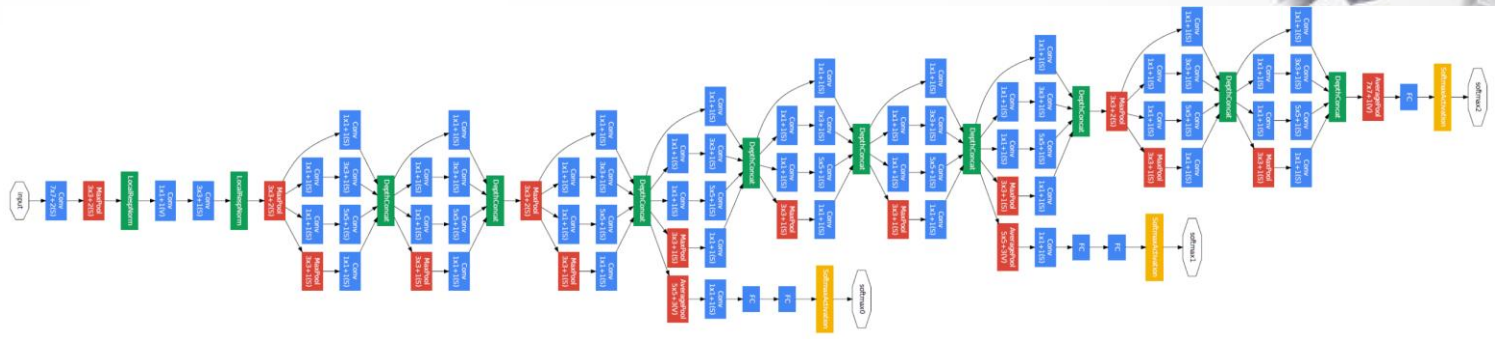

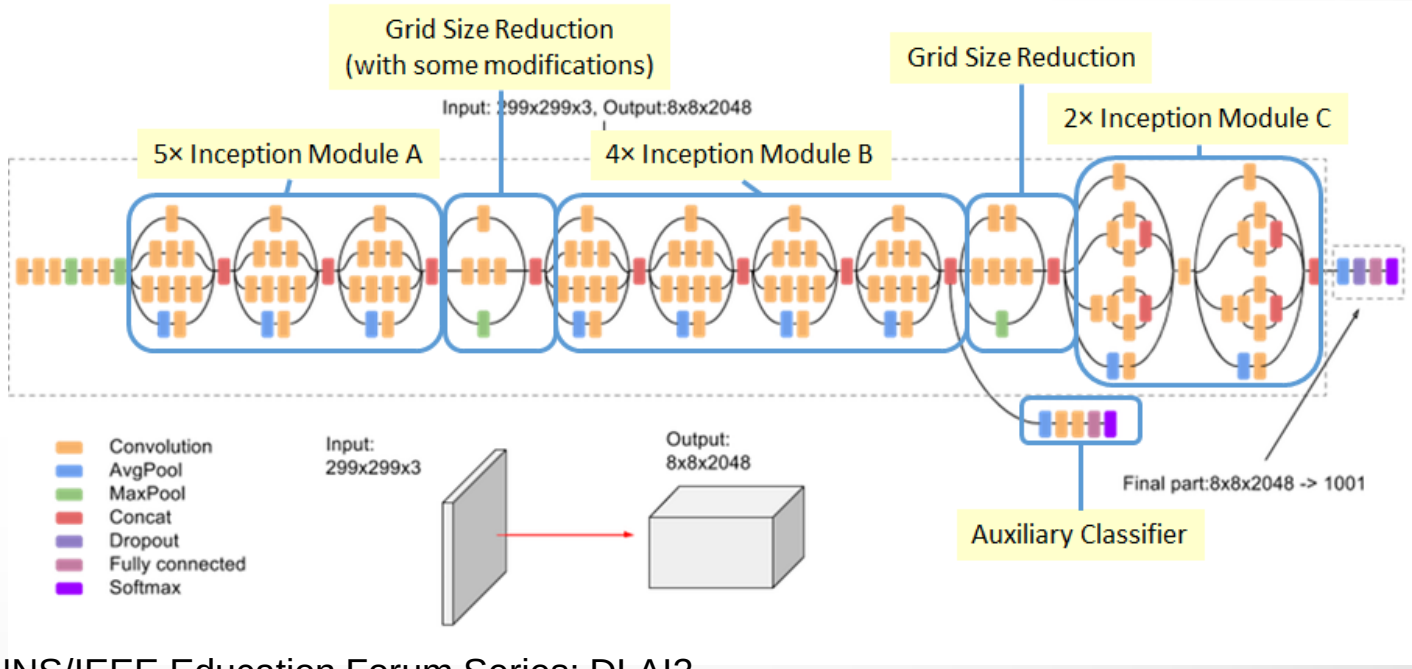

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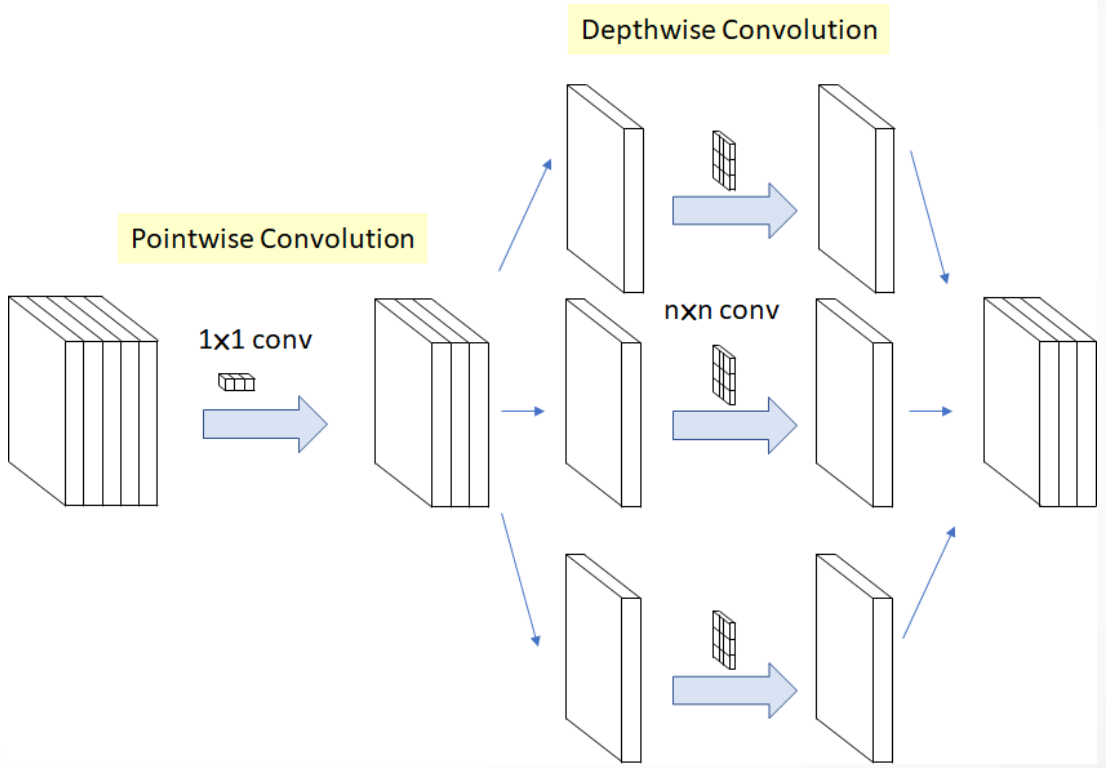

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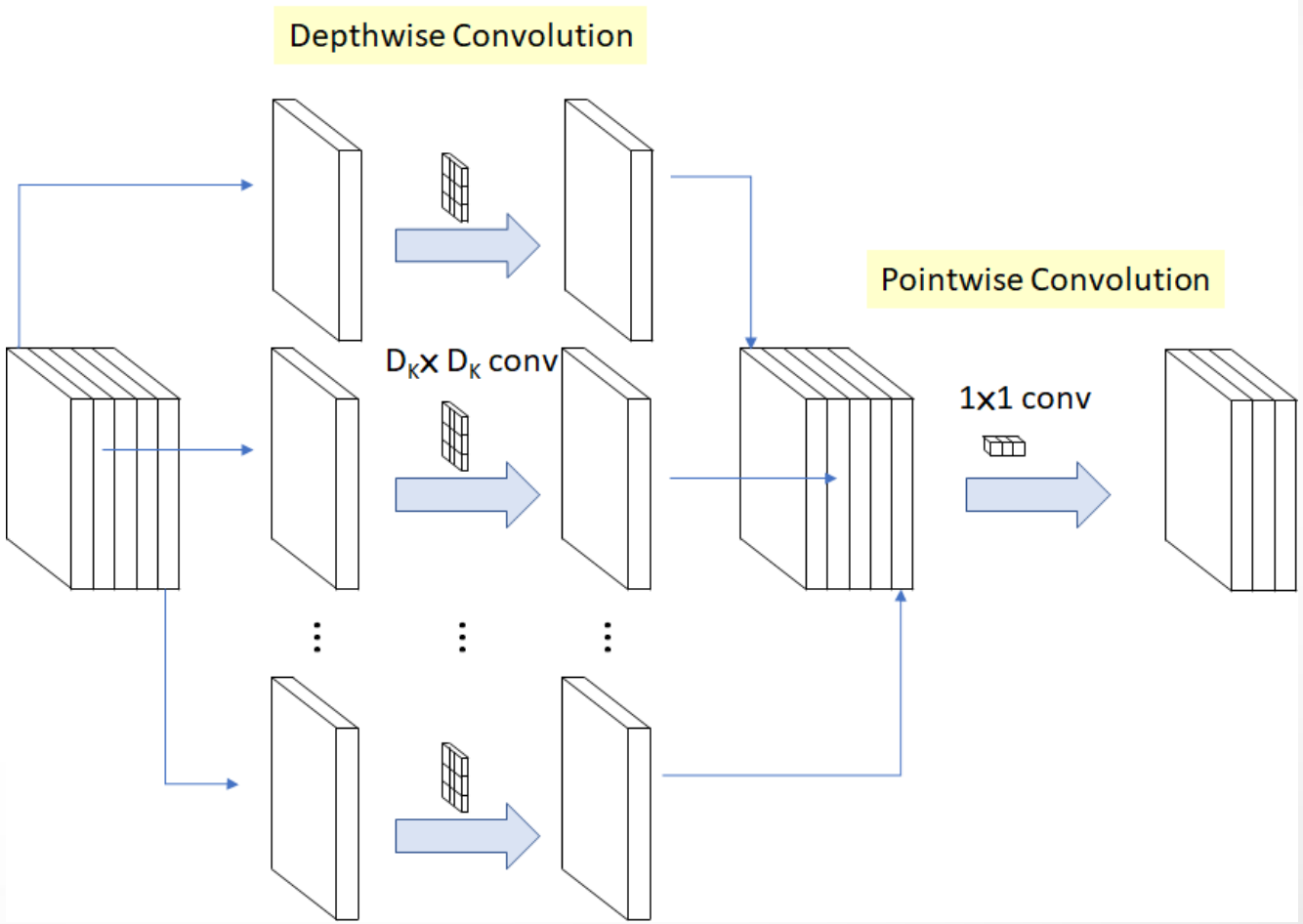

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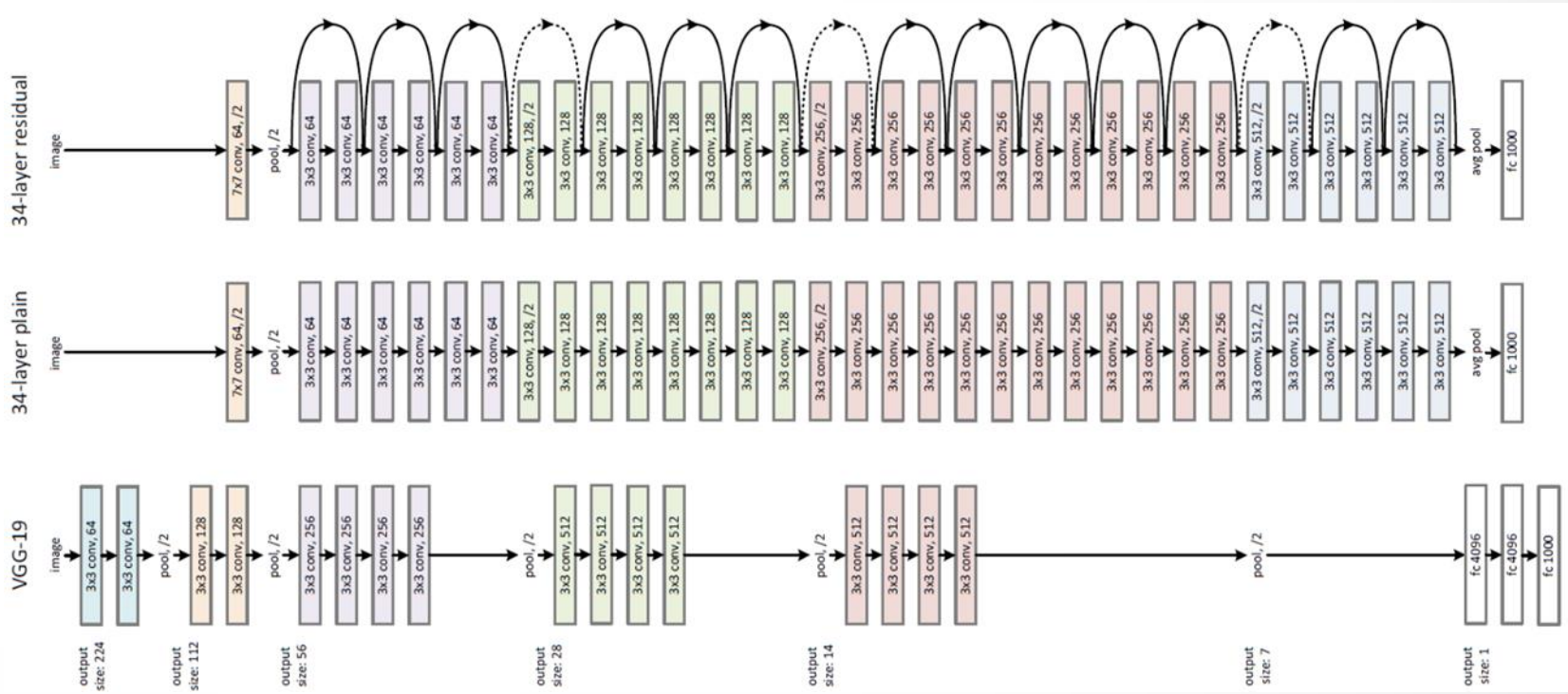

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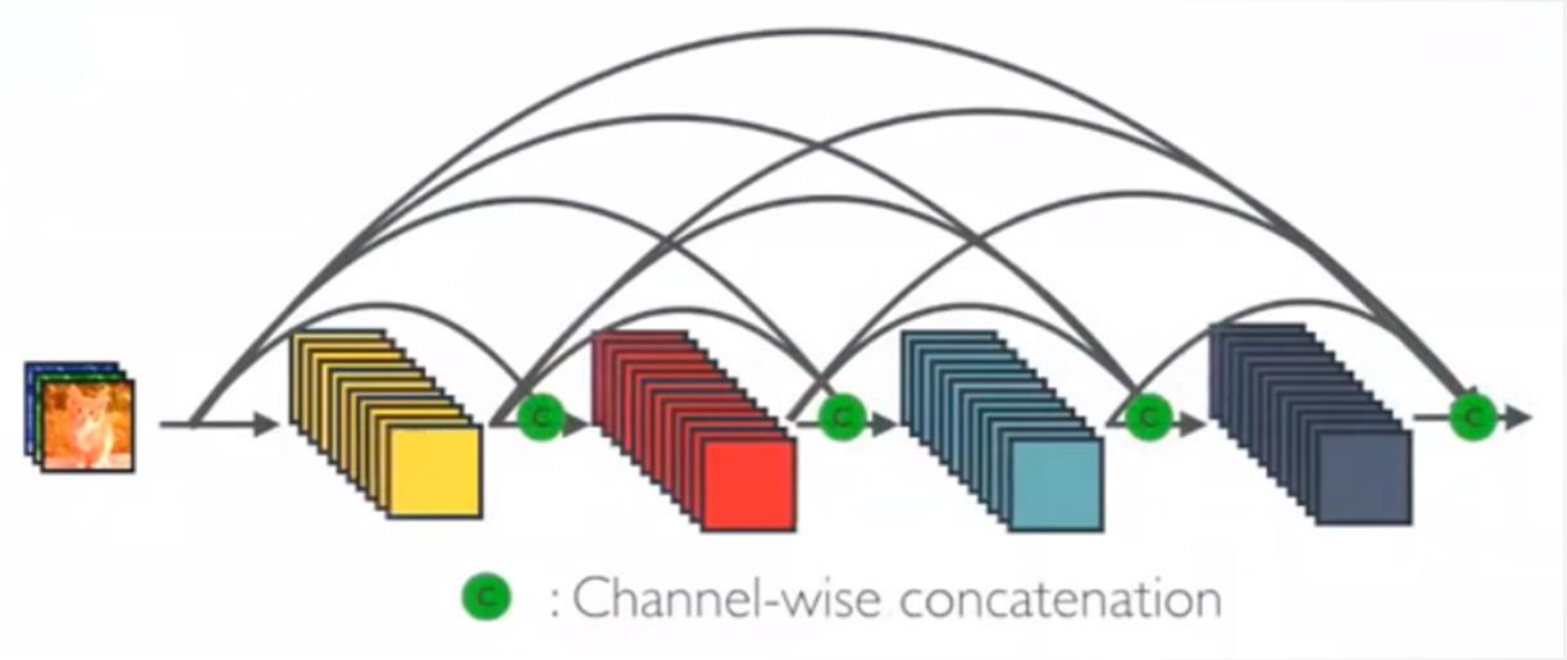

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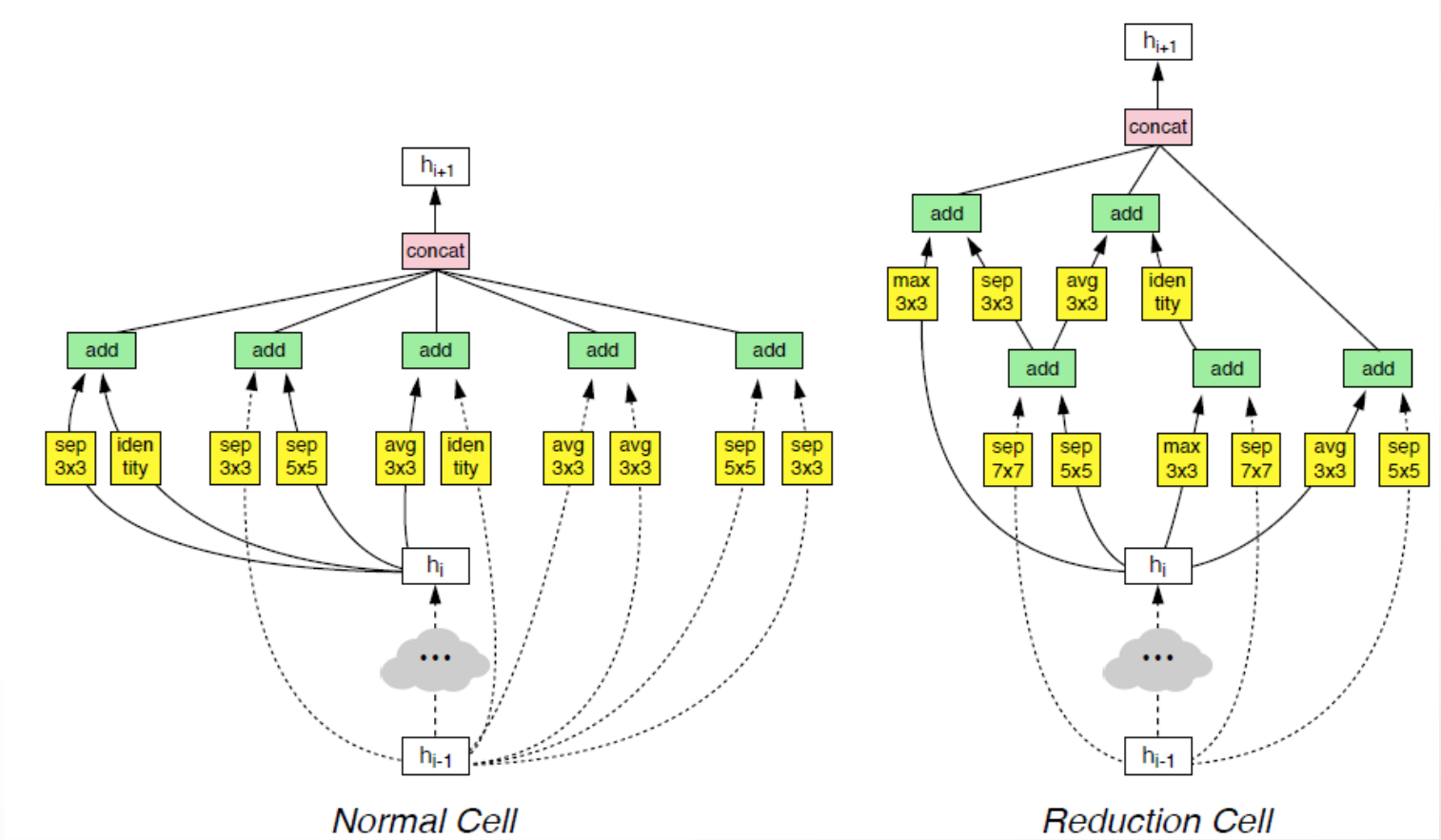
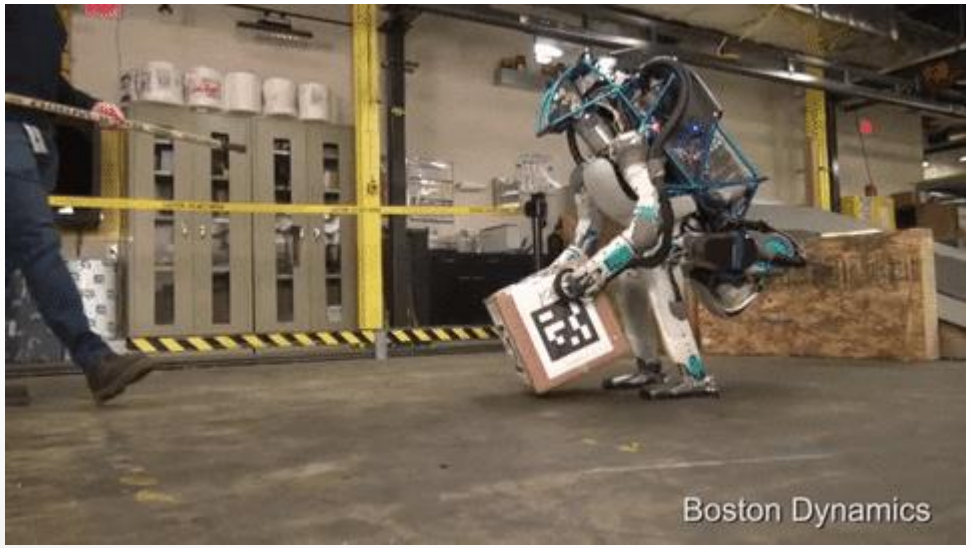


Some Characteristics of CNN

- A deep network seems to have a better performance than a wide network, given the same amount of nodes.
- Skip connections between layers close to the input and those close to the output could improve training efficiency and performance of the CNN.
- The CNN architecture gets deeper and denser:
  - LeNet5 has 5 layers
  - VGG16 and VGG19 have 16 and 19 layers respectively
  - Residual Networks (ResNets) have more than 100 layers

The Resurgence of Deep Learning

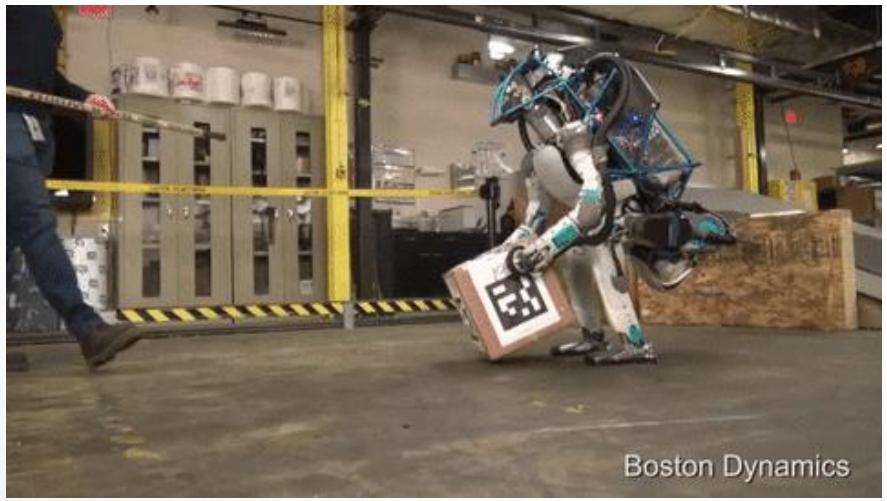
- Ecosystem
  - The availability of data
  - The progress of hardware, software
  - The progress of ICT infrastructure



Matching of
Problems & Solutions

The Resurgence of Deep Learning

- Ecosystem
  - The availability of data
  - The progress of hardware, software
  - The progress of ICT infrastructure



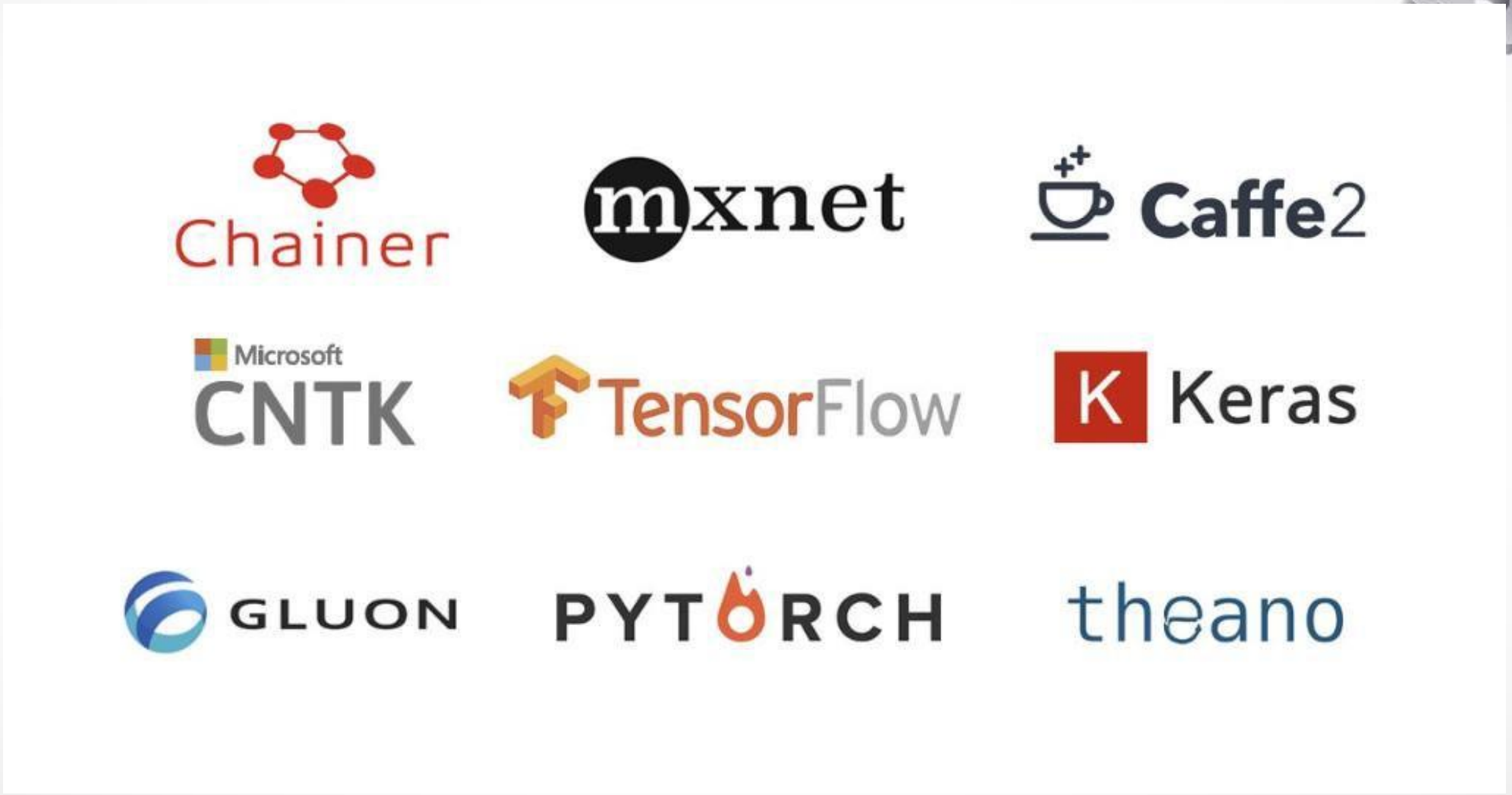
Deep Learning

- Good performance
- End-to-end approach (representation learning)

Challenges

- Speed and accuracy in open-ended real life problems
- The whole ecosystem is still developing

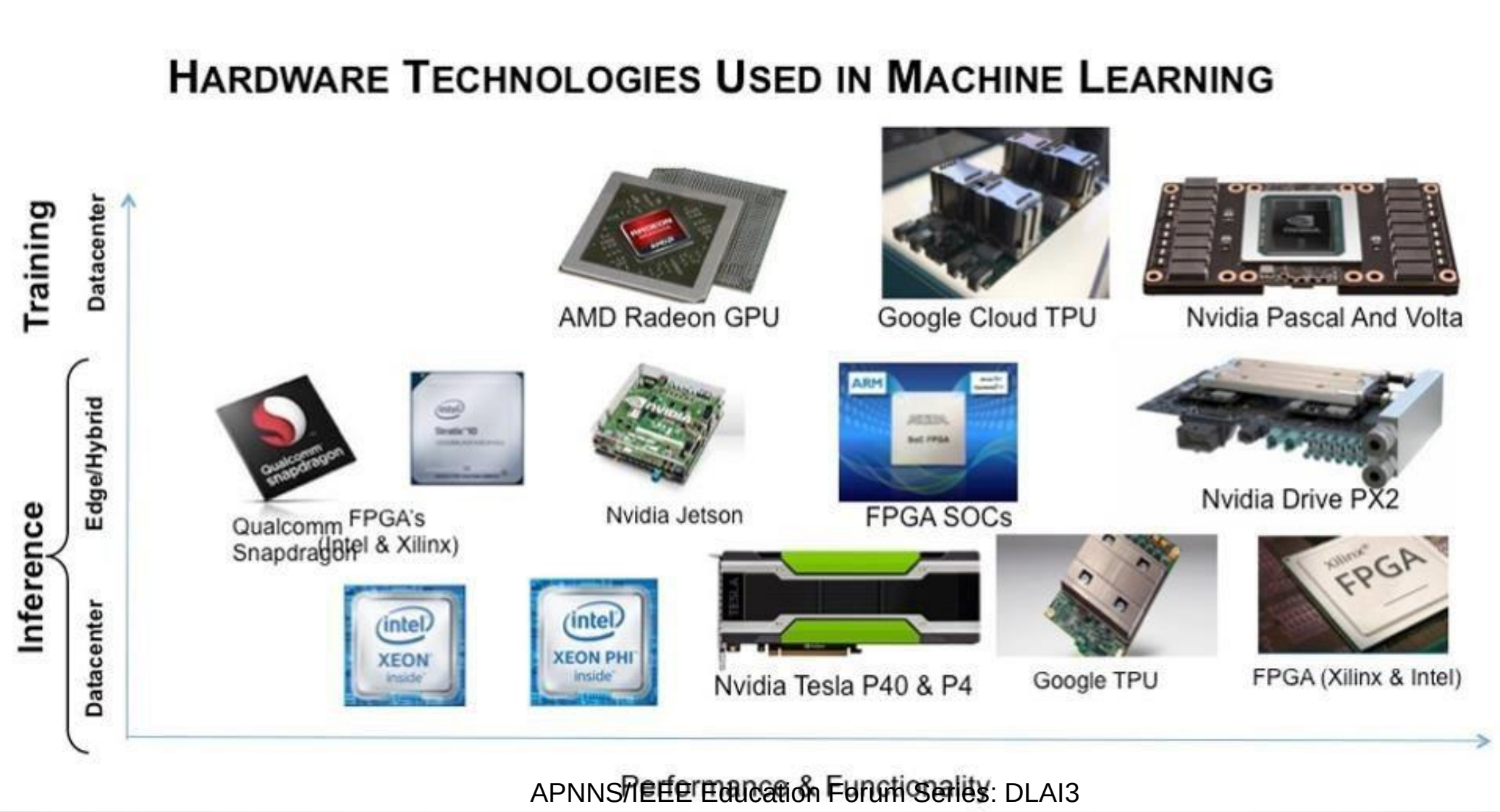
Deep Learning Frameworks



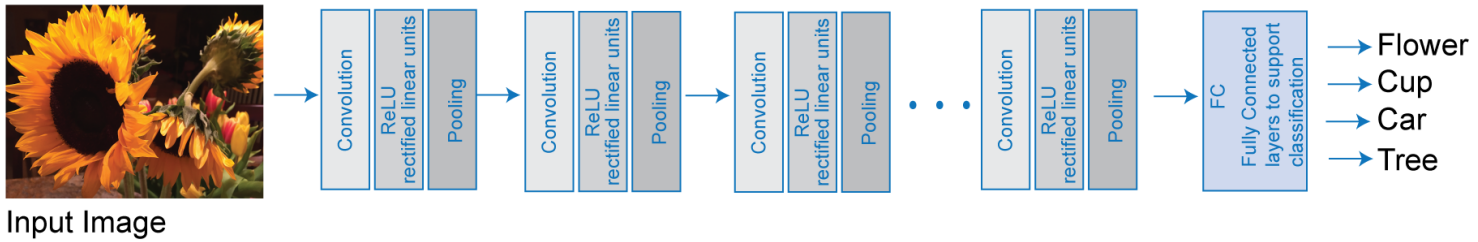
Hardware Landscape

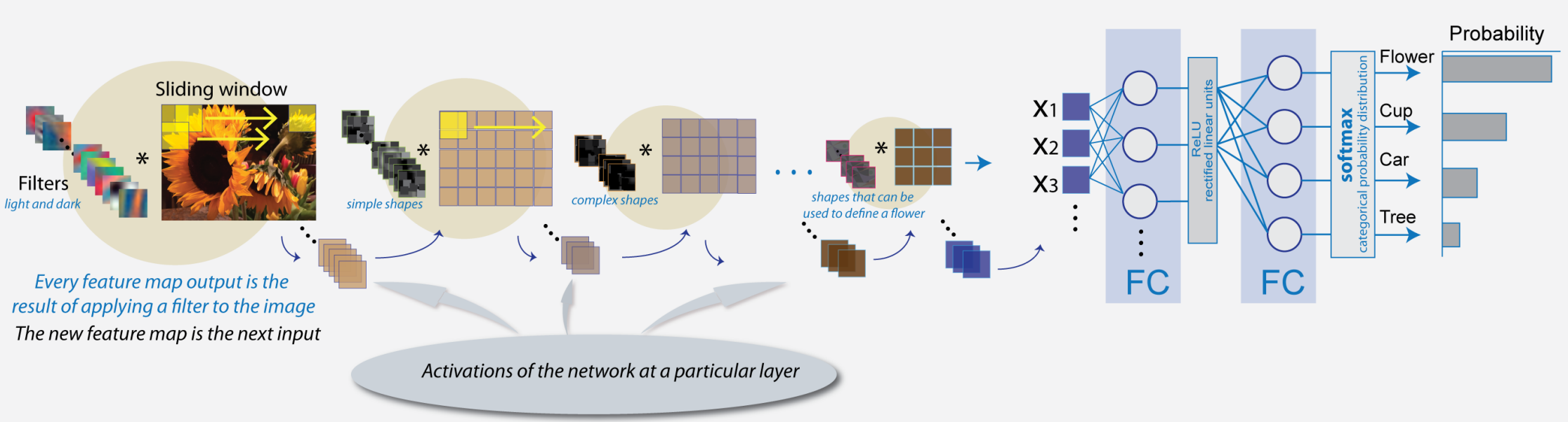
- There are four major types of technology that can be used to accelerate the training and use of deep neural networks:
- CPUs
- GPUs
- TPUs
- Field-programmable gate arrays (FPGAs), and
- Application-specific integrated circuits (ASICs).

Hardware Landscape



Q & A


Input Image
Convolution
ReLU rectified linear units
Pooling
Convolution
ReLU rectified linear units
Pooling
Convolution
ReLU rectified linear units
Pooling
Convolution
ReLU rectified linear units
Pooling
FC Fully Connected layers to support classification
Flower
Cup
Car
Tree


Sliding window
Filters
light and dark
simple shapes
complex shapes
shapes that can be used to define a flower
Every feature map output is the result of applying a filter to the image
The new feature map is the next input
Activations of the network at a particular layer
X1
X2
X3
FC
ReLU rectified linear units
FC
softmax
categorical probability distribution
Probability
Flower
Cup
Car
Tree