# From Perceptron to Deep Learning

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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.

# Disclaimer

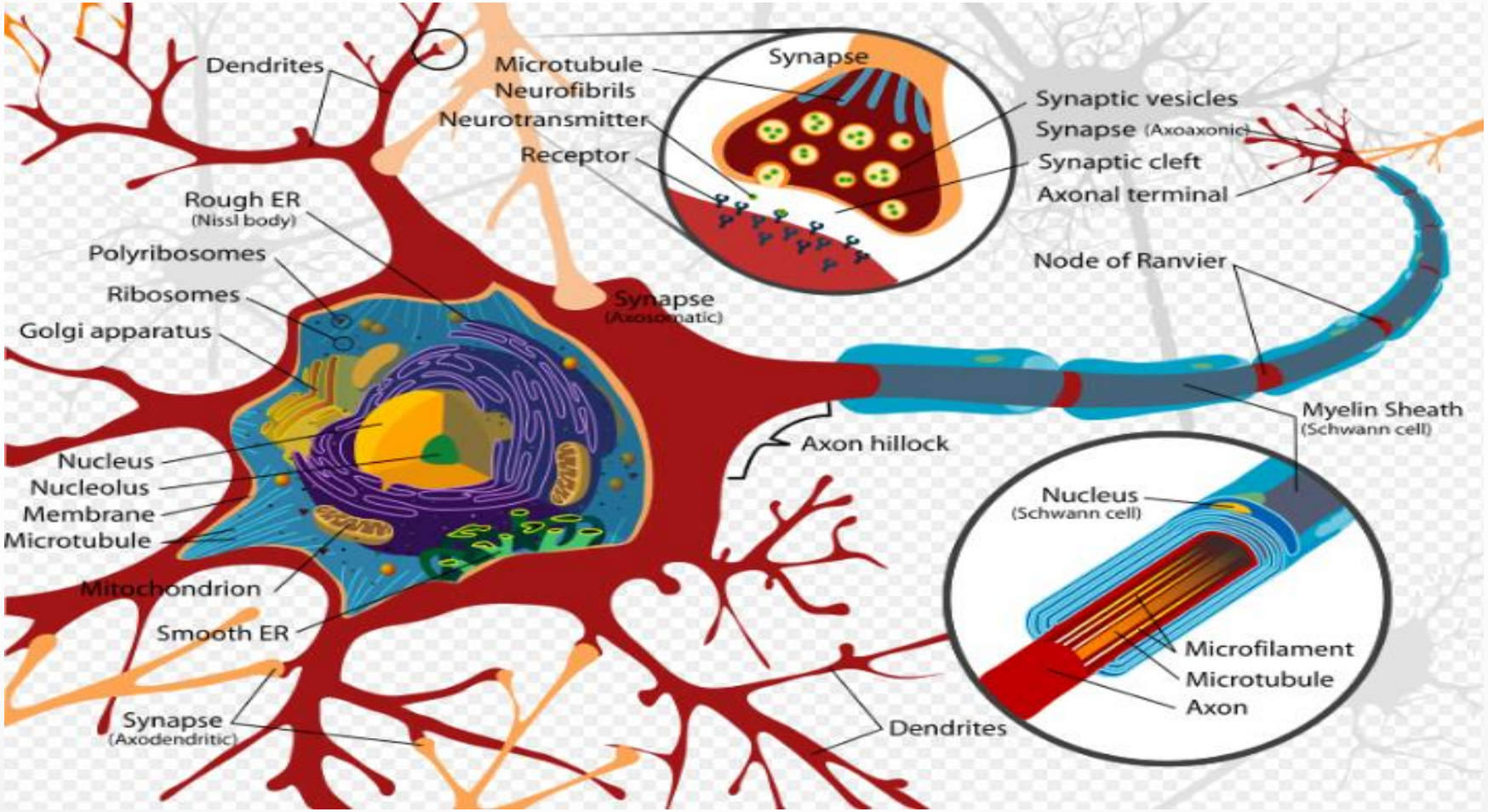
This lecture is compiled from my lectures as well as materials gathering from lectures found in public domains.

# Outline

- Theoretical Foundation
  - Perceptron
  - Multi-Layer Perceptron
  - Deep Learning: CNN Based Computer Vision

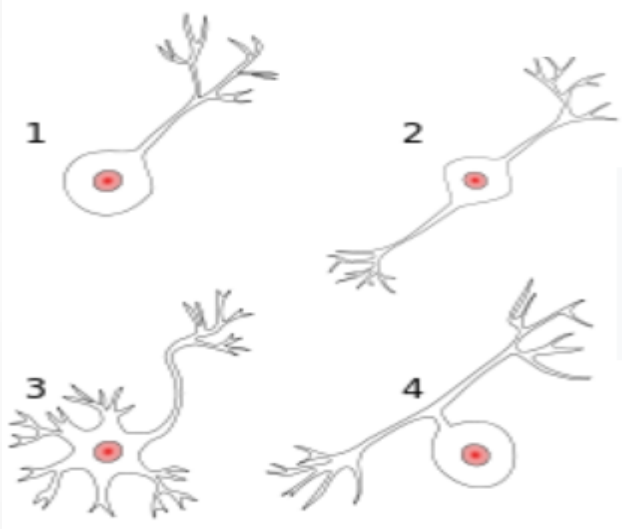
# Perceptron

# Neurons



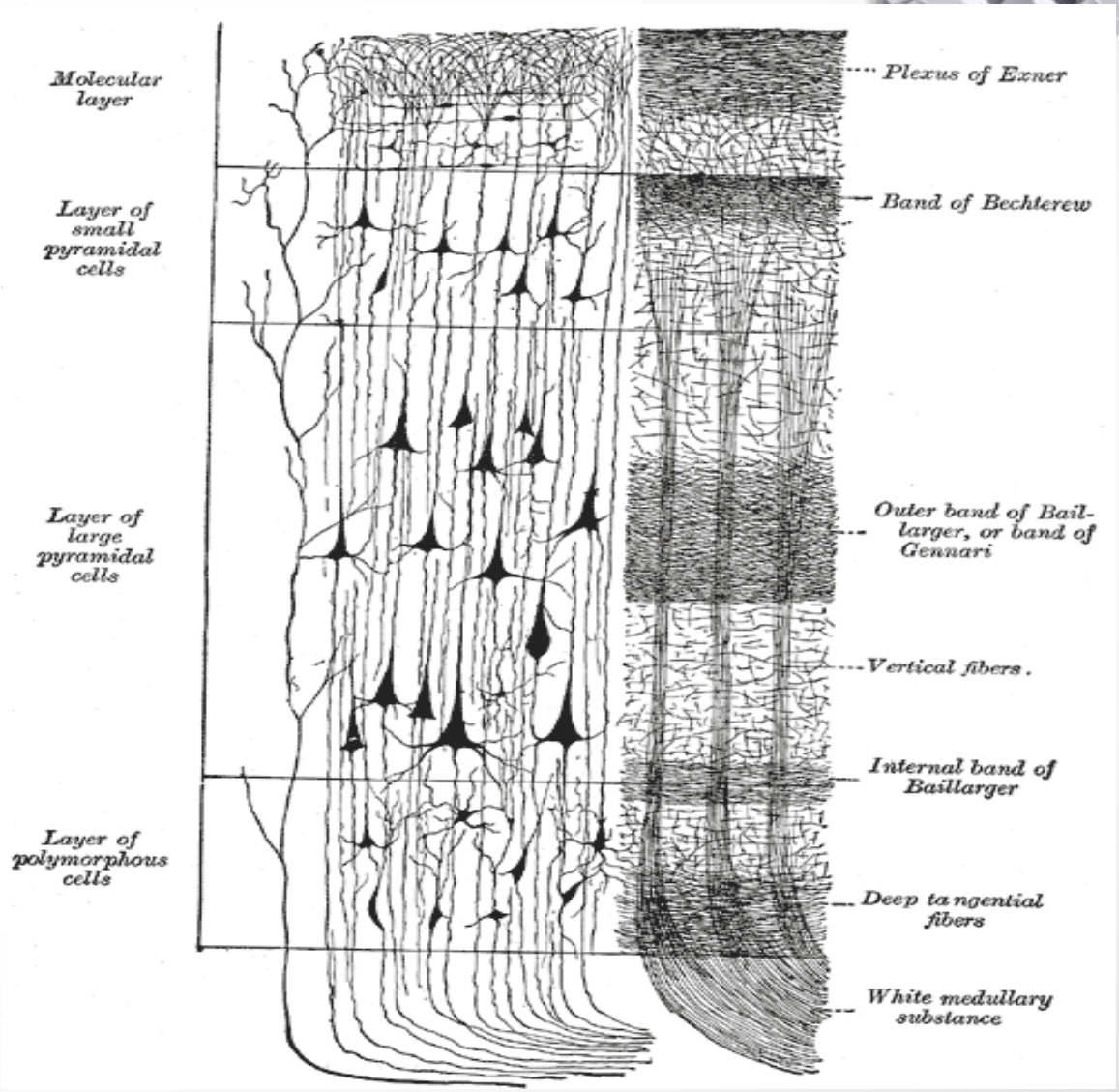

wikipedia

# Neurons



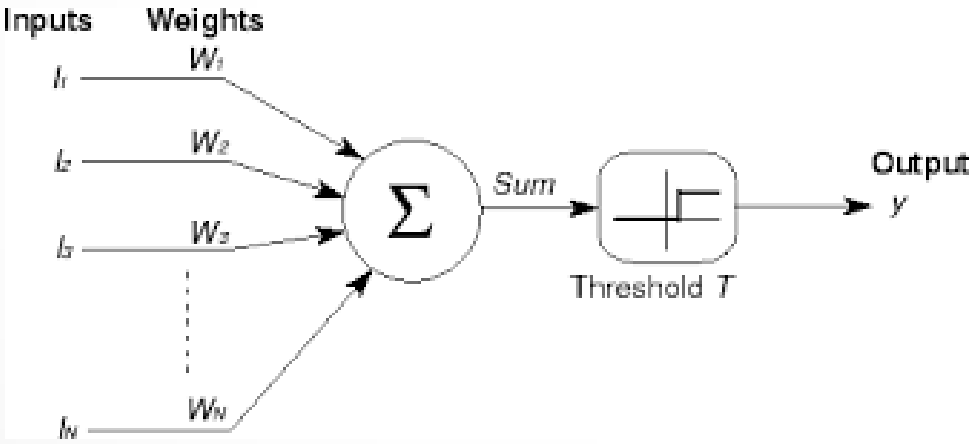

Different kinds of neurons:
1 Unipolar neuron
2 Bipolar neuron
3 Multipolar neuron
4 Pseudounipolar neuron

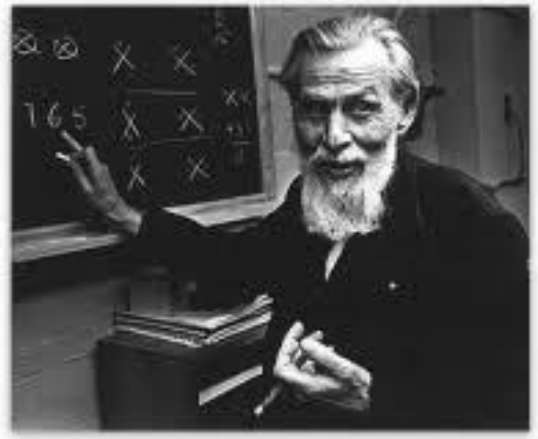
wikipedia



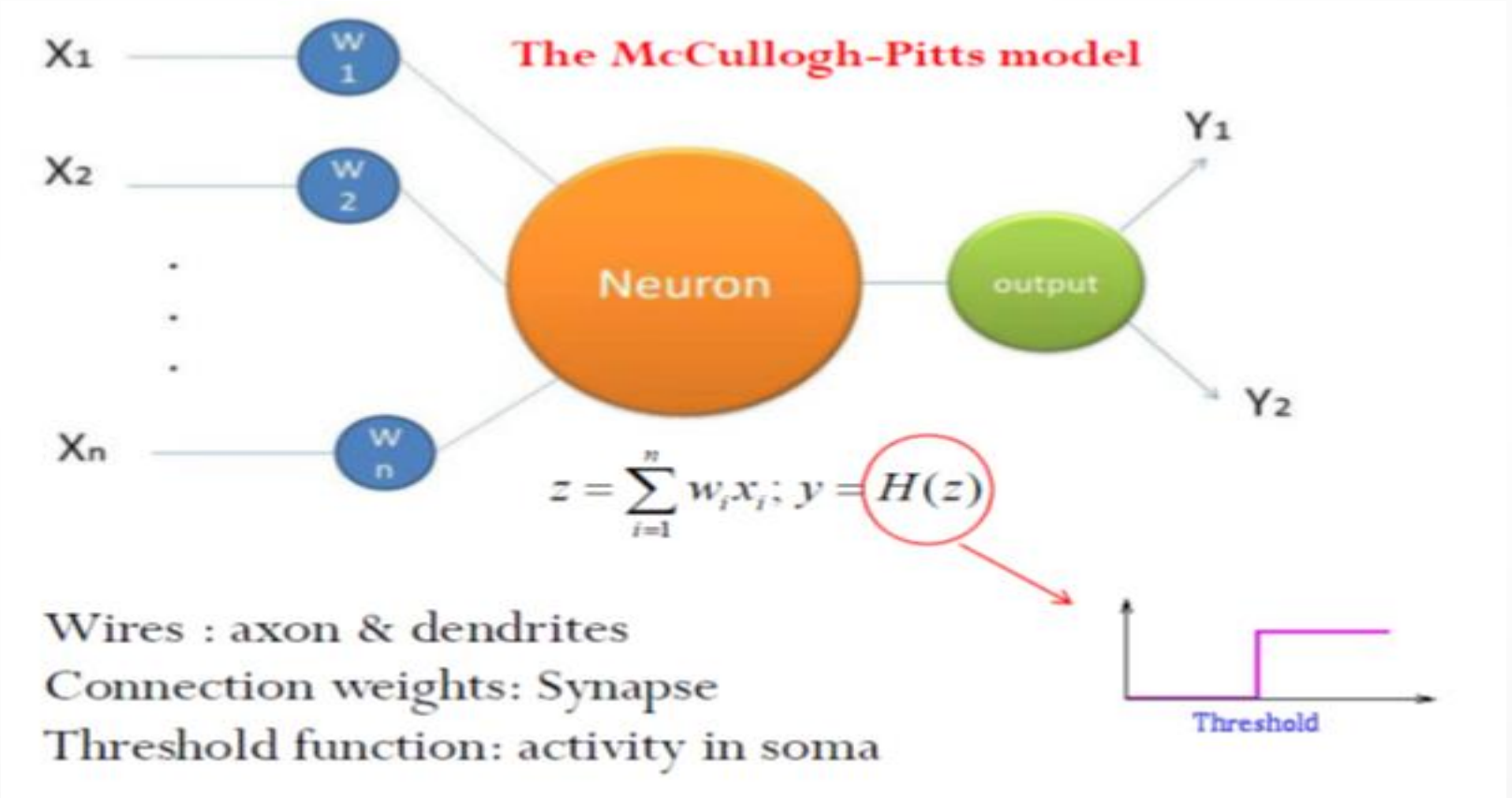
# Threshold Logic Unit

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



# Perceptrons



# Implementing Perceptrons

- How to solve for W

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

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

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

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

# Perceptrons

- The perceptron is an algorithm for learning a classifier function.

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

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

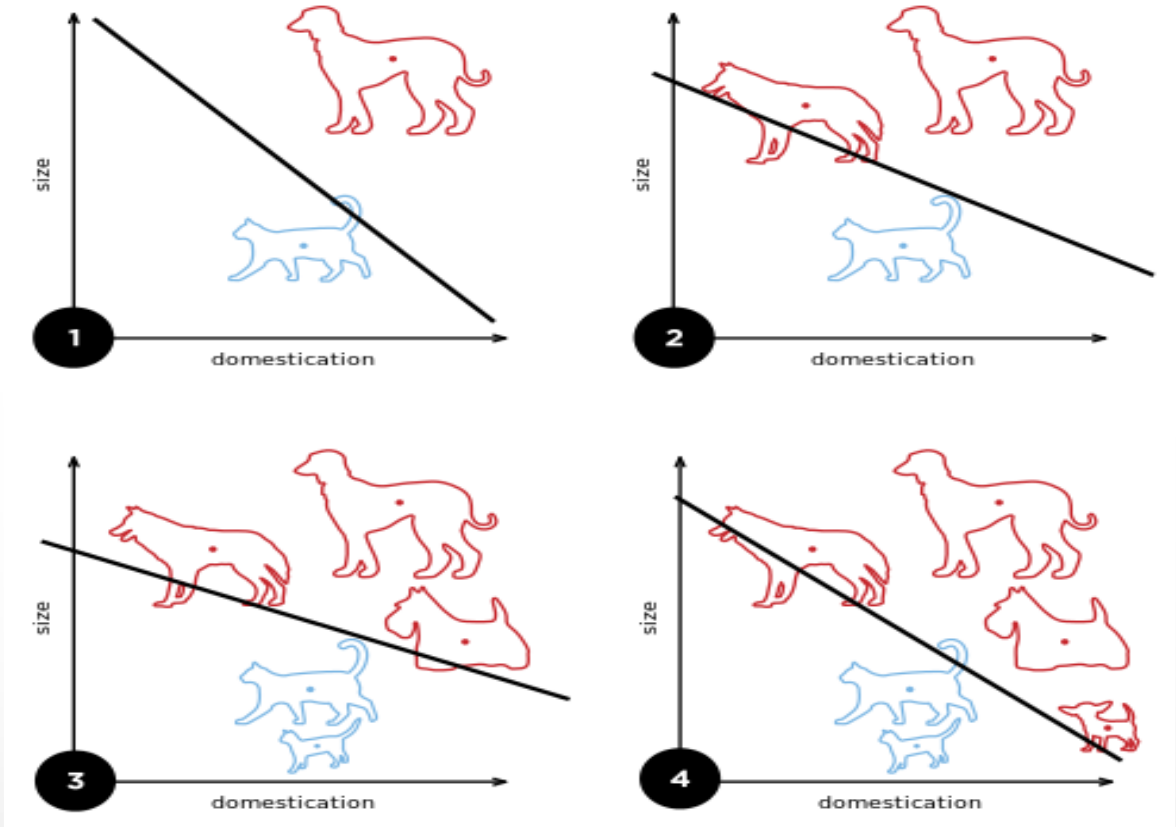
- The perceptron is an artificial neuron using the Heaviside step function as the activation function.

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

# Perceptron Learning Rule

- Rosenblatt: Perceptron

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

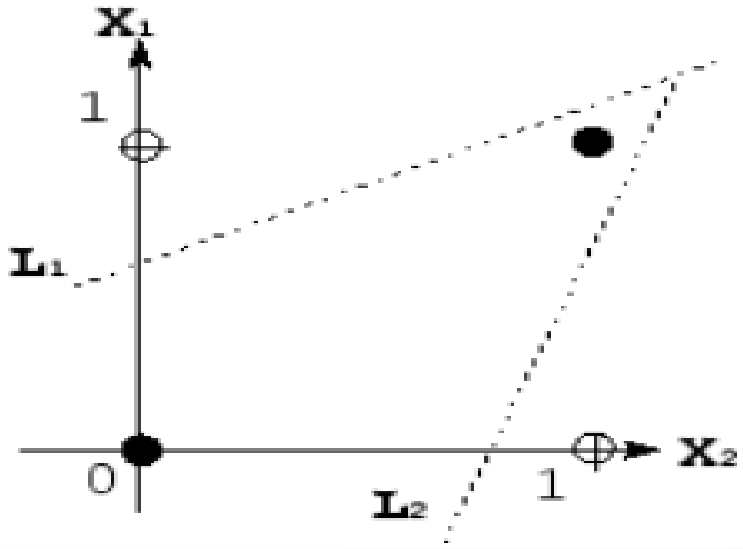


# Limitation of Perceptrons

- 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 |

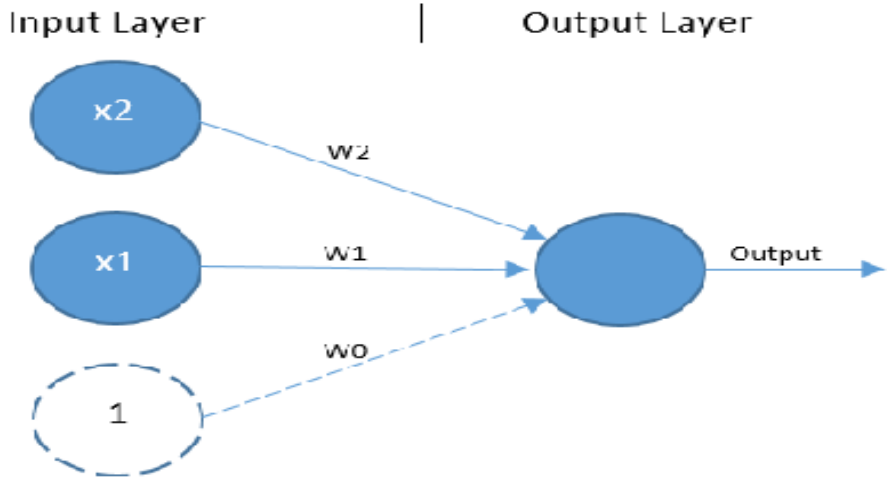
$Y = X_1 \oplus X_2$



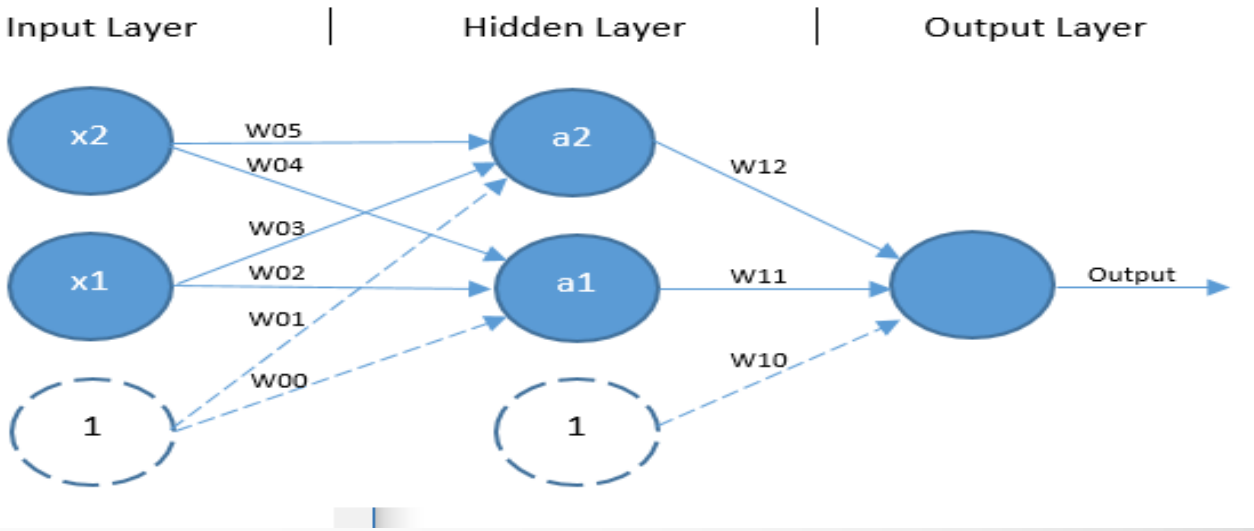
# Limitation of Perceptrons

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

perceptron

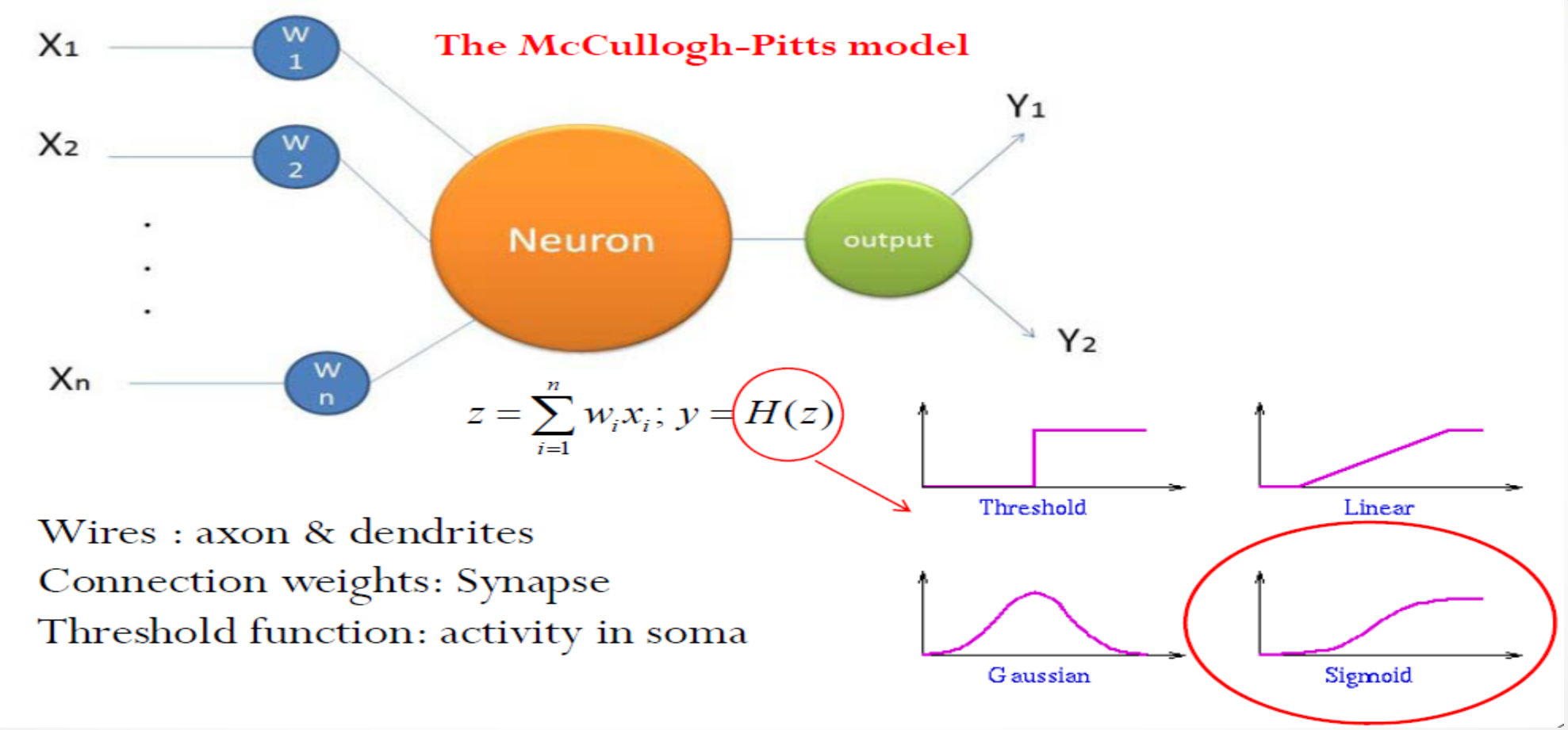



MLP

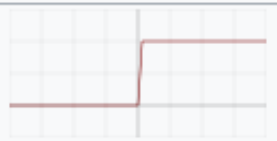
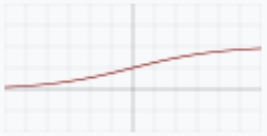
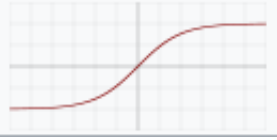
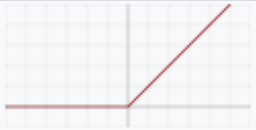


# Multi-Layer Perceptron

# Activation Functions



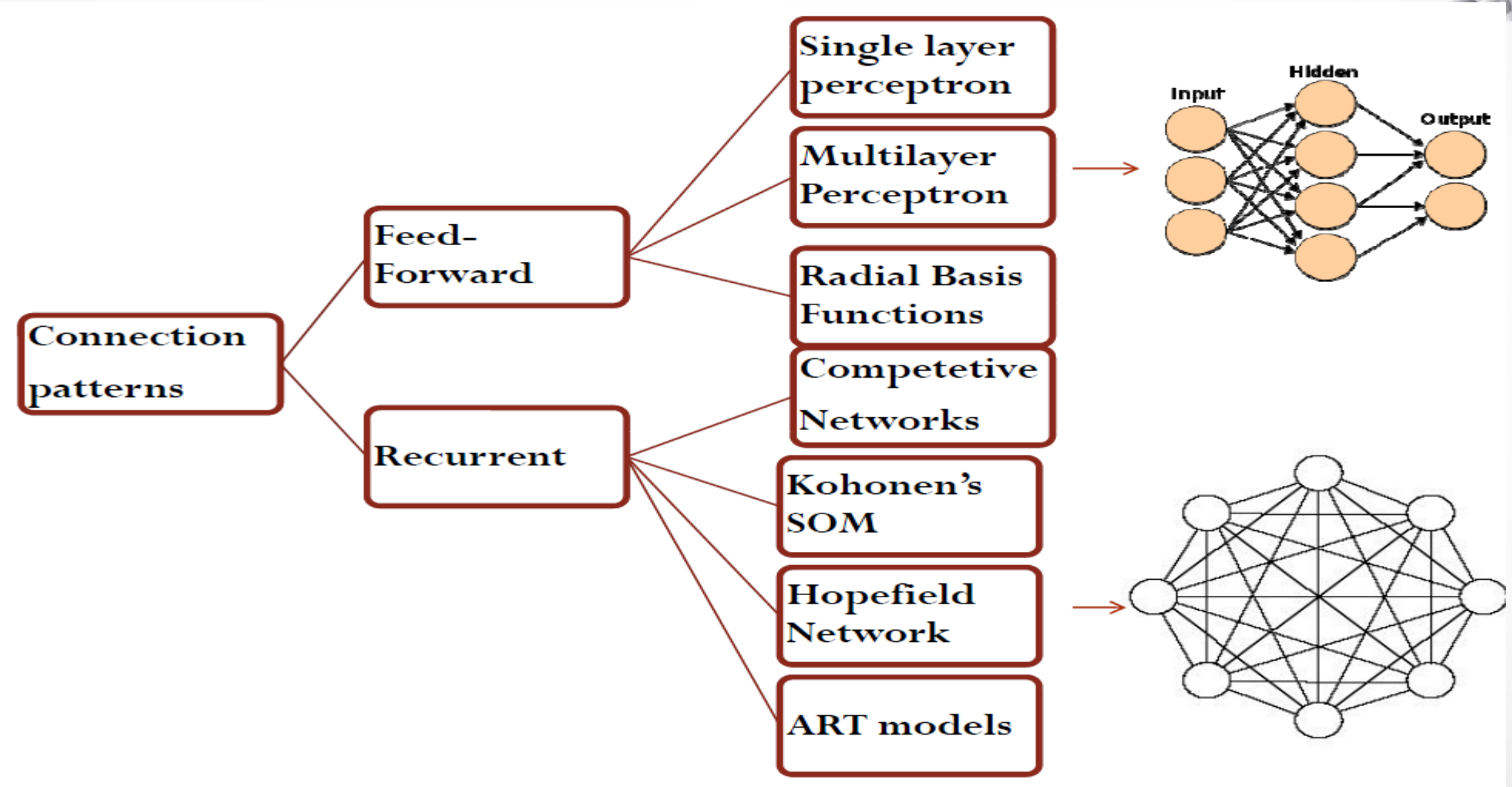
# Activation Functions

| | | | |
|---|---|---|---|
| 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] |  | $f(\alpha, x) = \begin{cases} \alpha(e^{x}-1) & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$ | $f'(\alpha, x) = \begin{cases} f(\alpha, x)+\alpha & \text{for } x \leq 0 \\ 1 & \text{for } x > 0 \end{cases}$ |

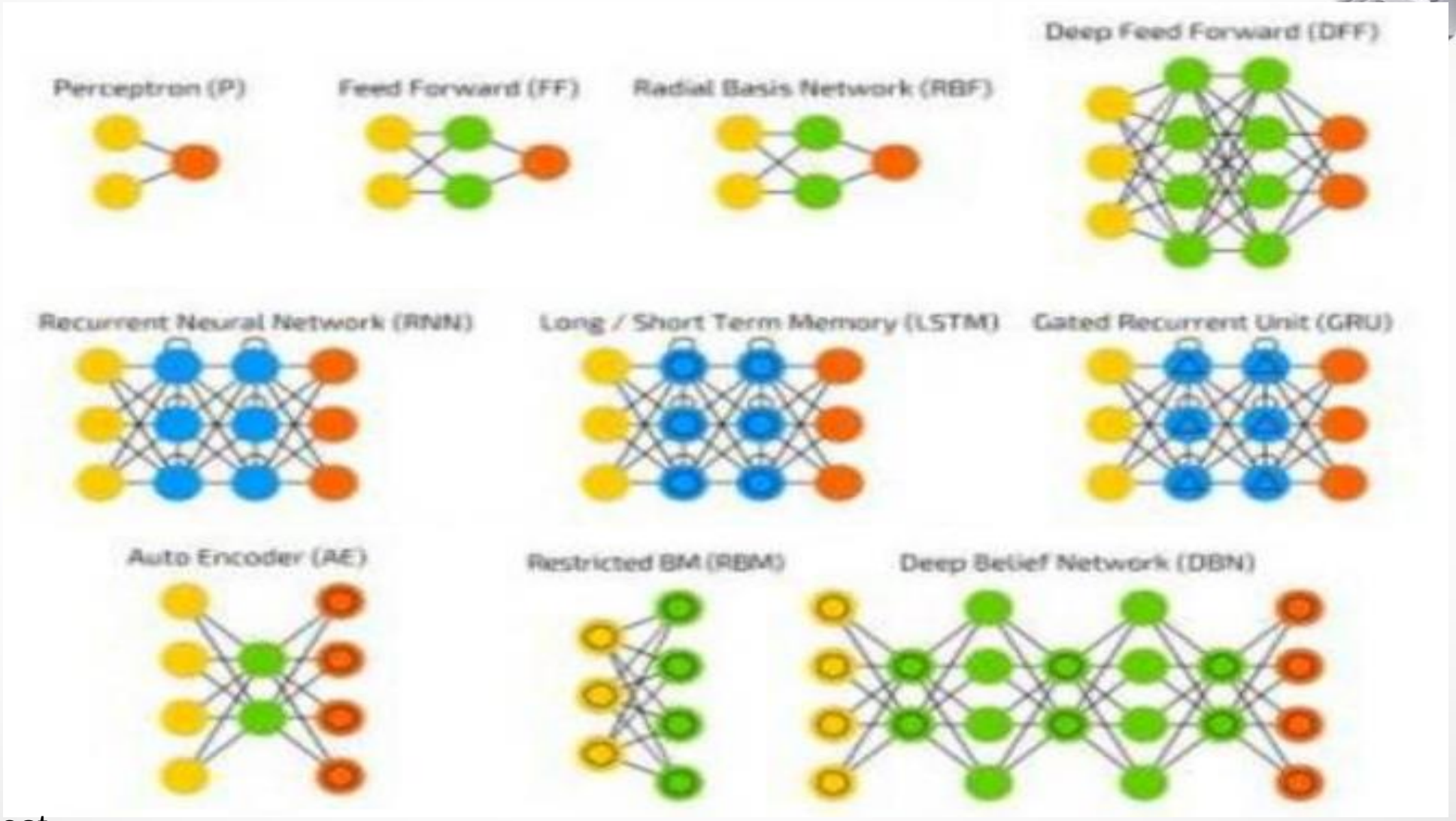
# Artificial Neural Networks

- 1940: Mcculloch and Pitts
  - A logical calculus of the ideas immanent in nervous activity
- 1957: 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)

# Artificial Neural Networks

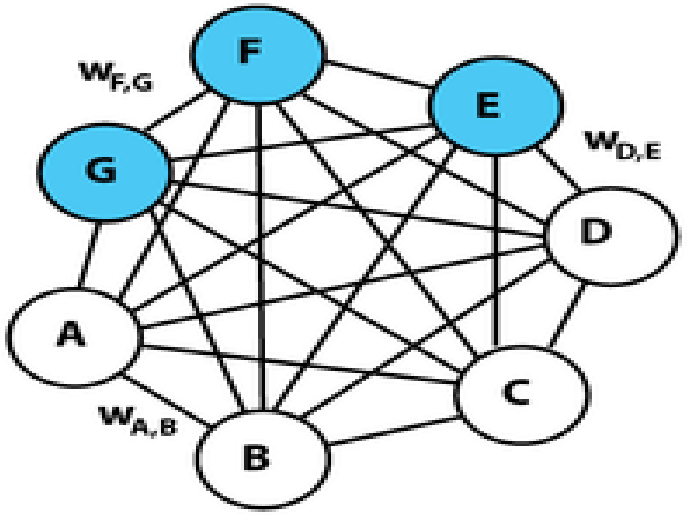


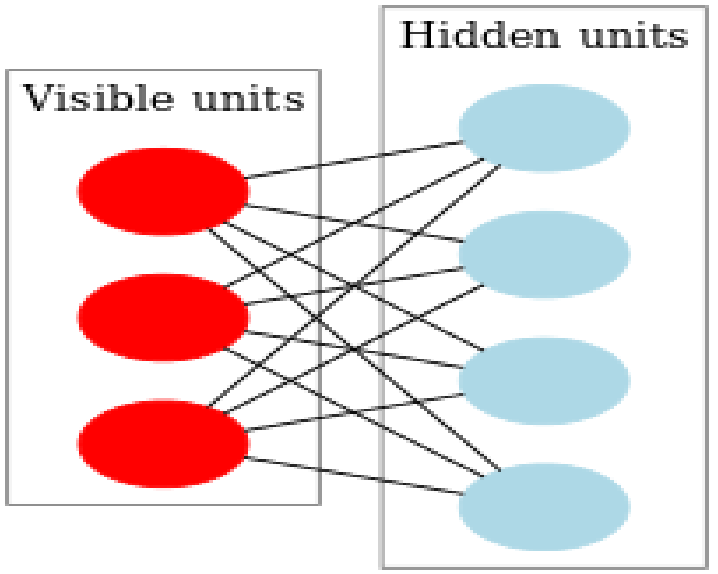
# Artificial Neural Networks



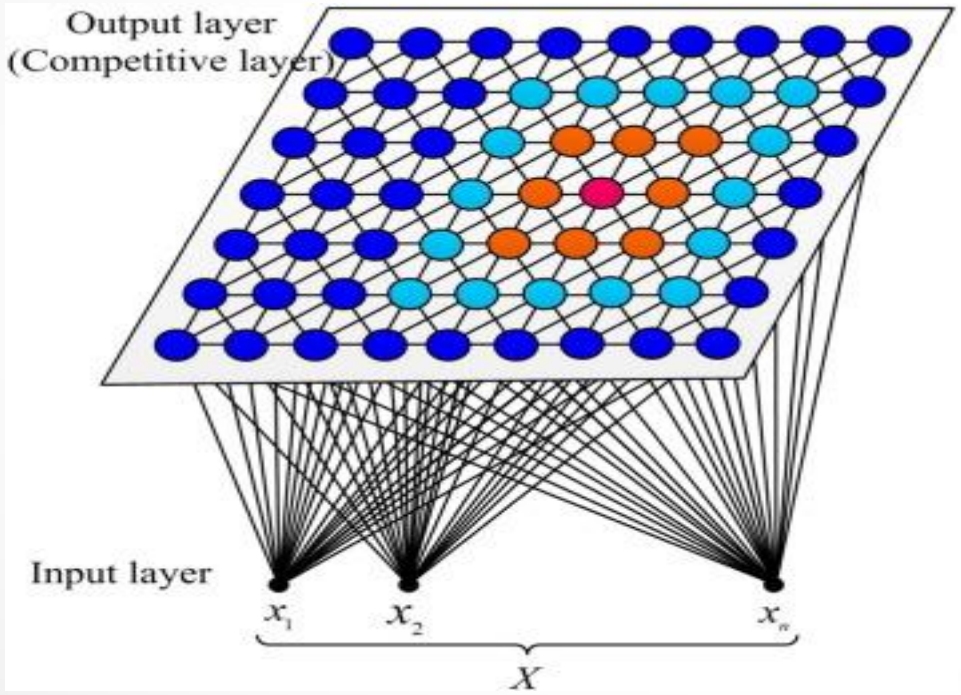

Credit: pinterest

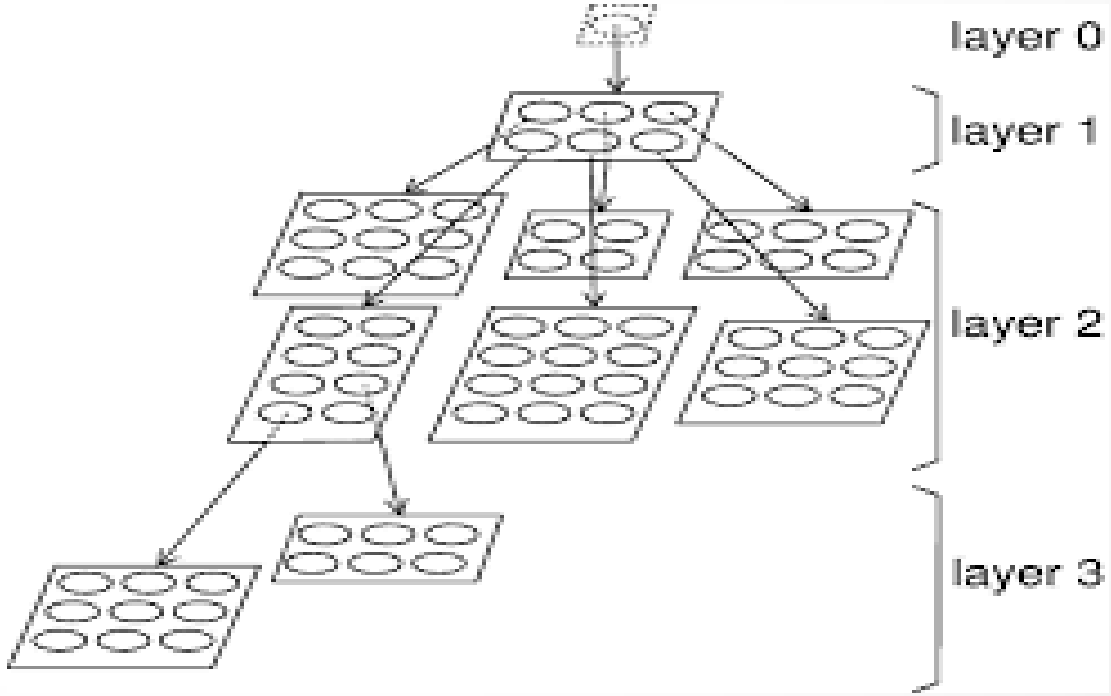
# Artificial Neural Networks



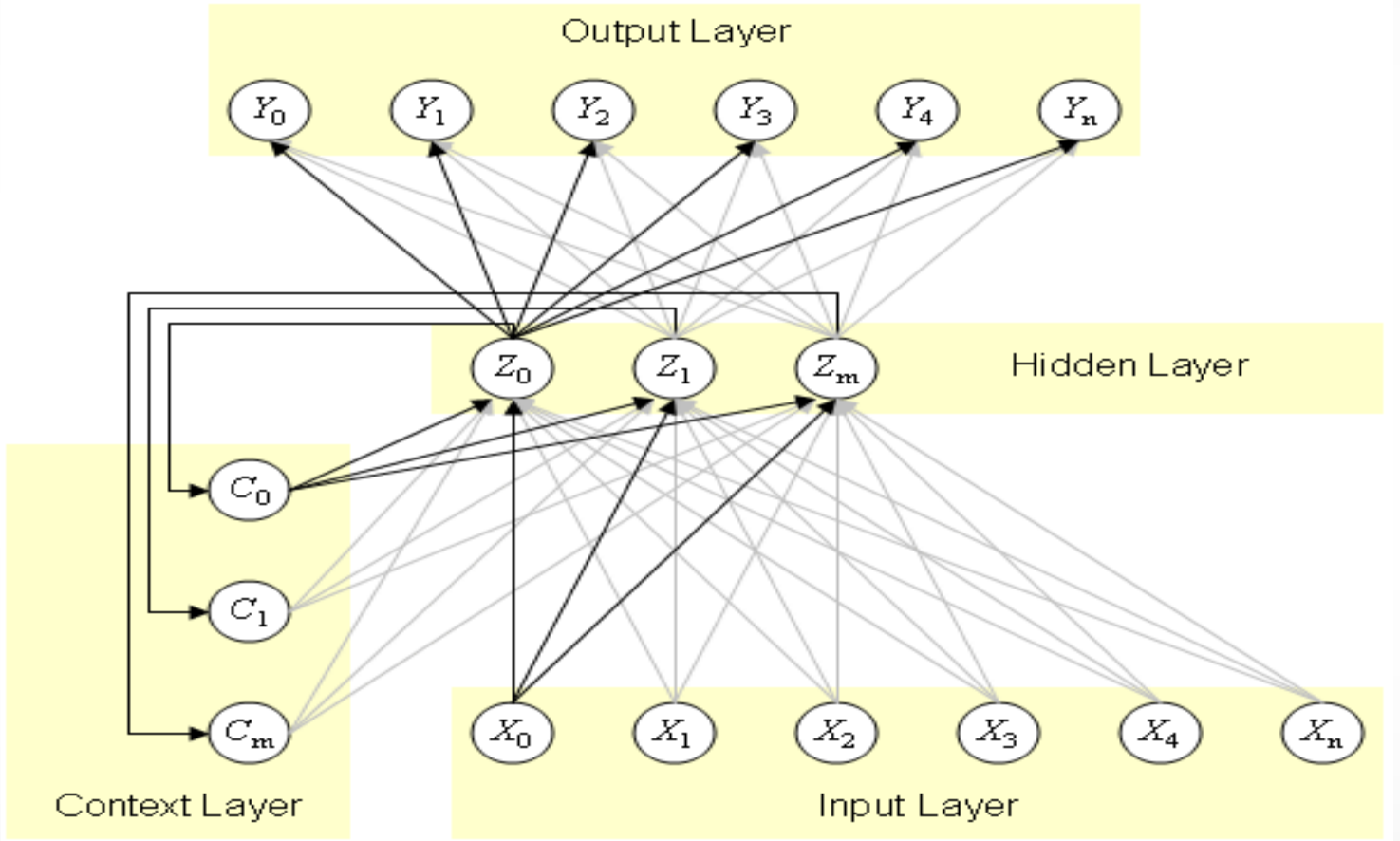
# Artificial Neural Networks



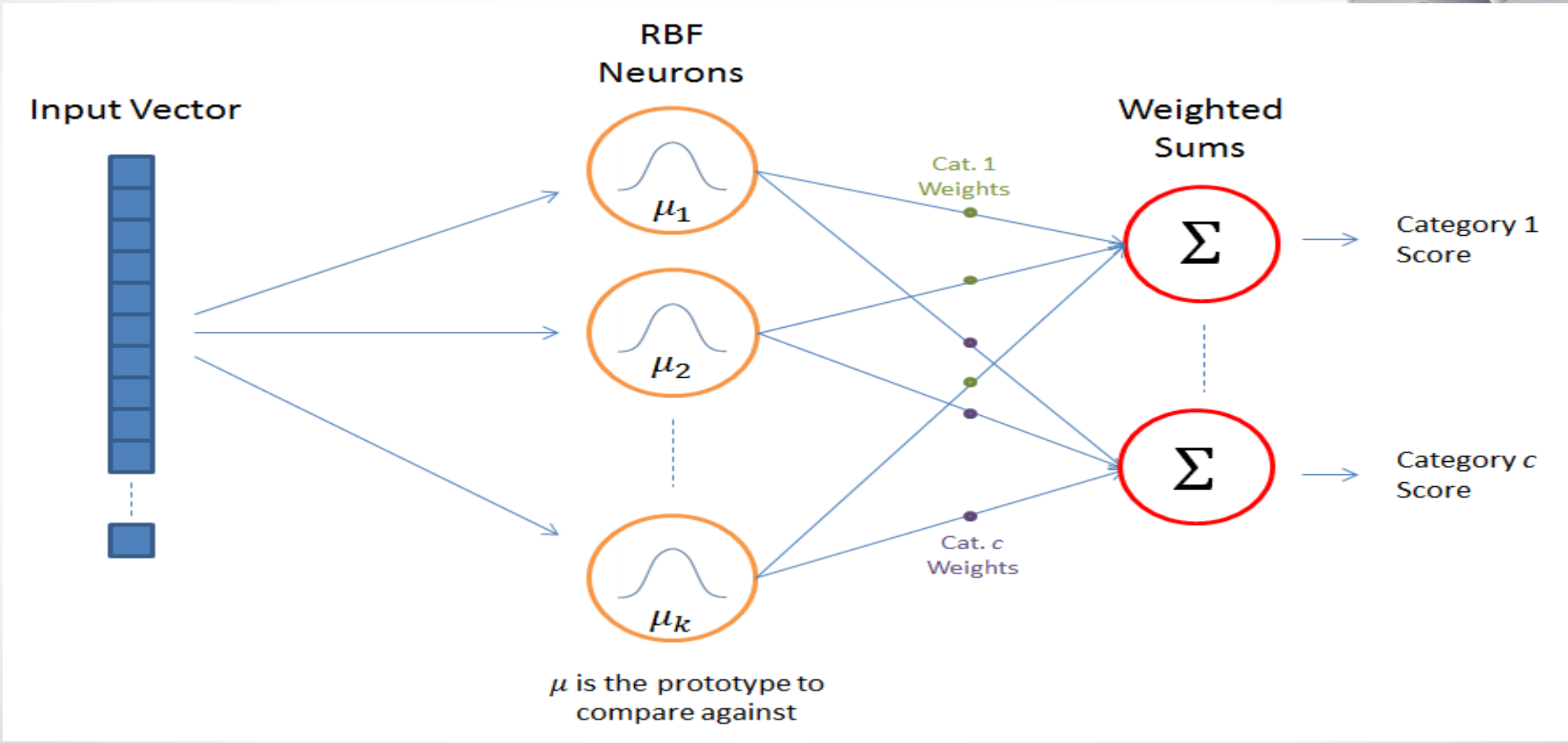

Credit: google

# Artificial Neural Networks




Credit: google

# Artificial Neural Networks




Credit: google

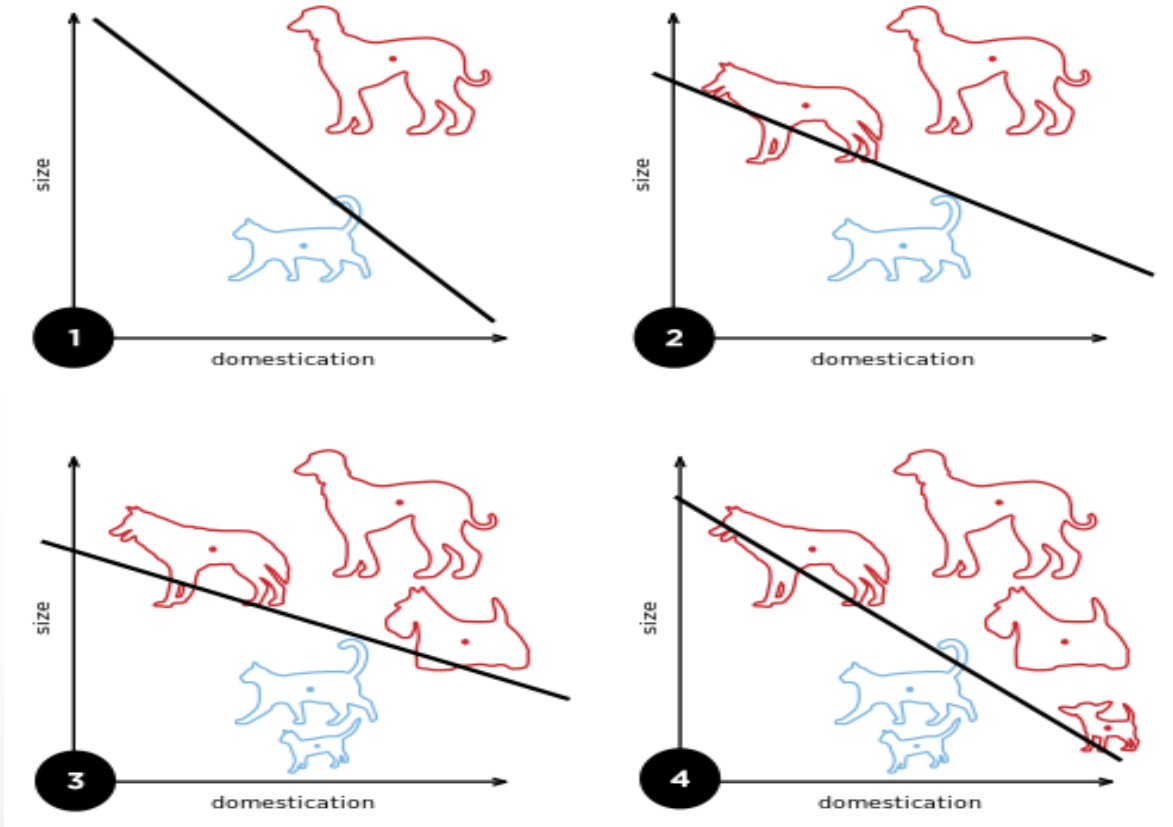
# Learning

- 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

# Learning: Perceptron

- Rosenblatt: Perceptron

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



# Backpropagation (Rumelhart 1986)

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

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

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

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

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

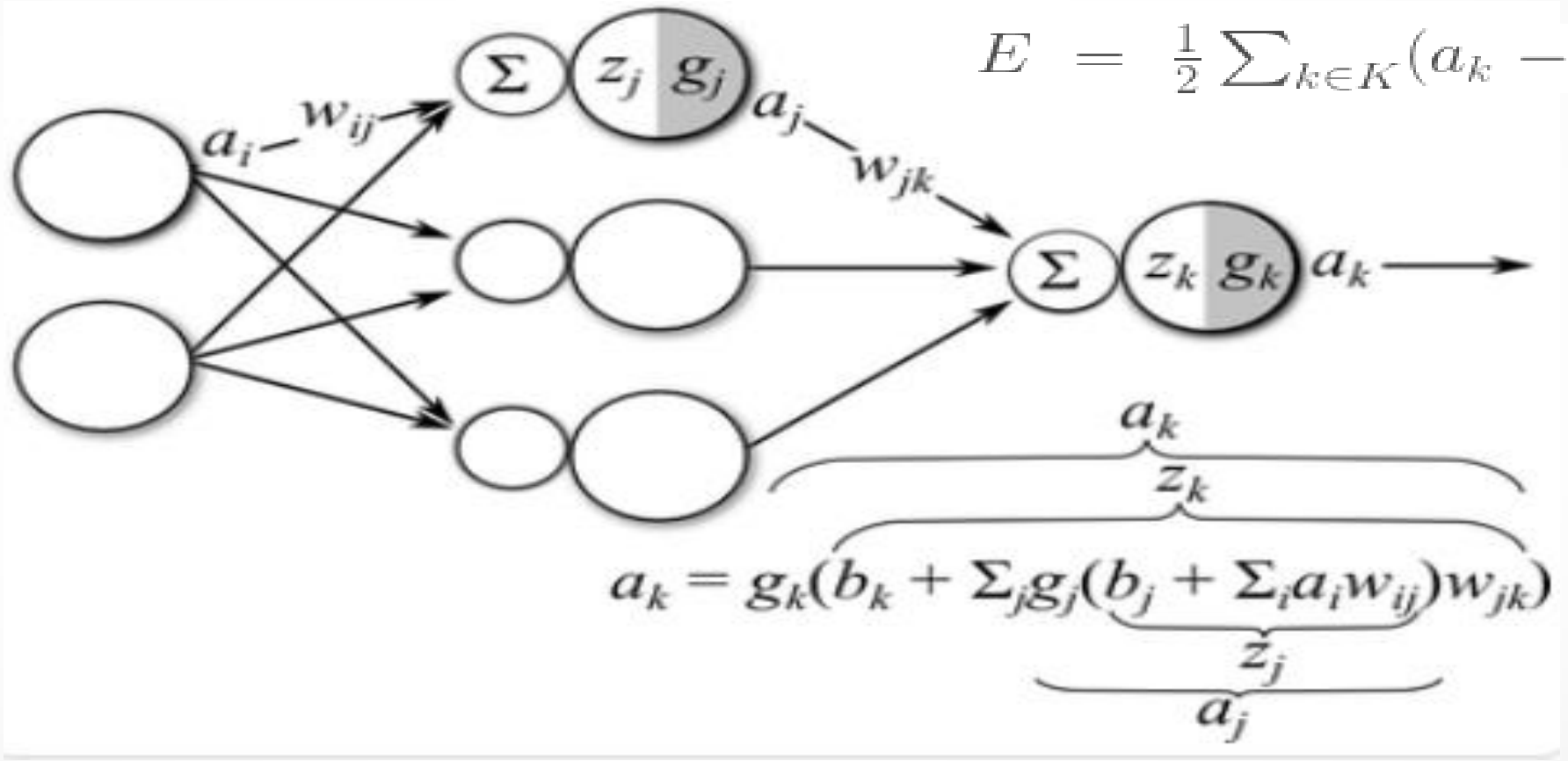
$$\frac{\partial \mathrm{net}_j}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}}\left(\sum_{i=1}^{n} w_{ij} o_i\right) = \frac{\partial}{\partial w_{ij}} w_{ij} o_i = o_i$$

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

Acknowledgement

The following backpropagation is adapted from https://theclevermachine.wordpress.com/2014/09/06/derivation-error-backpropagation-gradient-descent-for-neural-networks/

# Backpropagation




https://theclevermachine.wordpress.com/2014/09/06/derivation-error-backpropagation-gradient-descent-for-neural-networks/

# Backpropagation

$$E = \frac{1}{2}\sum_{k\in K}(a_k - t_k)^2$$

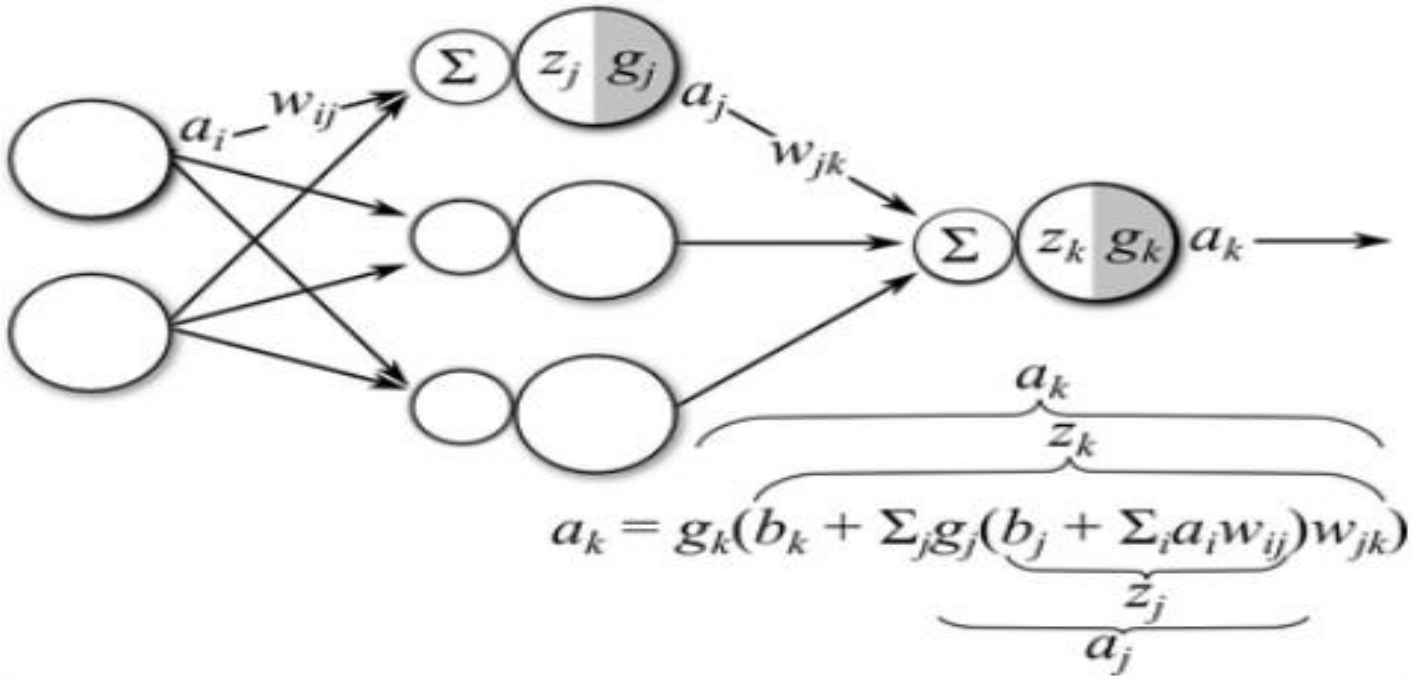
$$\begin{aligned}\frac{\partial E}{\partial w_{jk}} &= \frac{1}{2}\sum_{k\in K}(a_k - t_k)^2 \\ &= (a_k - t_k)\frac{\partial}{\partial w_{jk}}(a_k - t_k)\end{aligned}$$

$$\begin{aligned}\frac{\partial E}{\partial w_{jk}} &= (a_k - t_k)\frac{\partial}{\partial w_{jk}}a_k \\ &= (a_k - t_k)\frac{\partial}{\partial w_{jk}}g_k(z_k) \\ &= (a_k - t_k)g_k'(z_k)\frac{\partial}{\partial w_{jk}}z_k,\end{aligned}$$

$$z_k = b_j + \sum_j g_j(z_j)w_{jk}$$

$$\frac{\partial z_k}{\partial w_{jk}} = g_j(z_j) = a_j$$

$$\frac{\partial E}{\partial w_{jk}} = (a_k - t_k)g_k'(z_k)a_j$$




$$\delta_k = (a_k - t_k)g_k'(z_k)$$

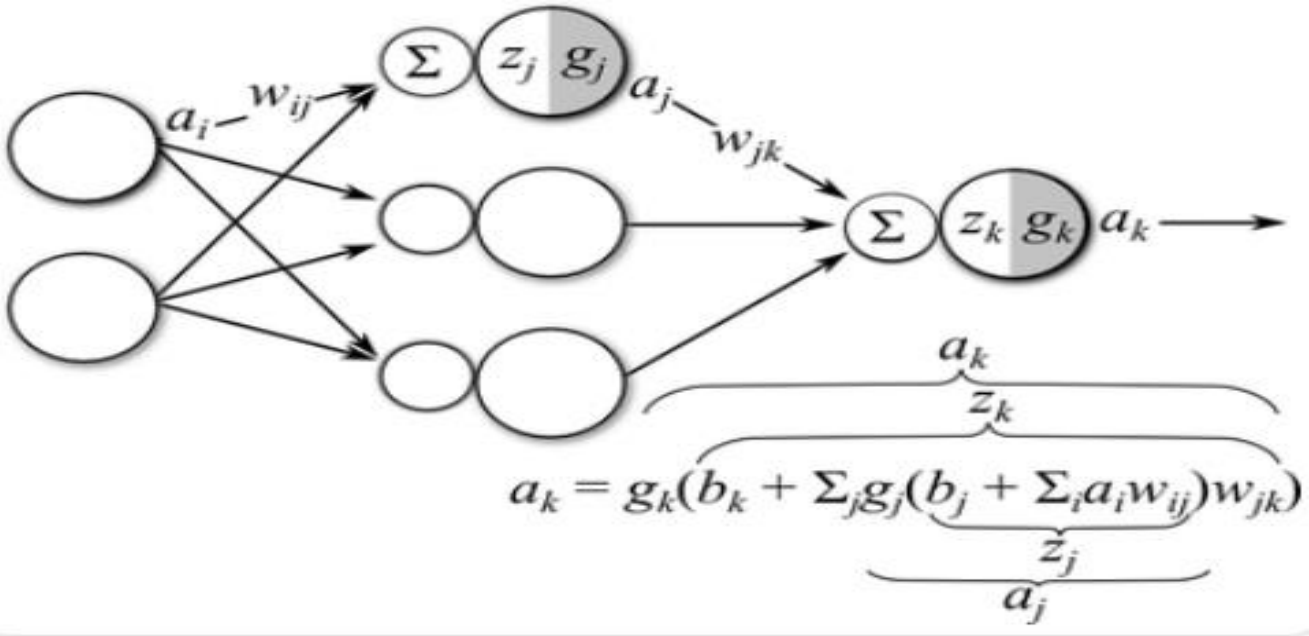
$$\frac{\partial E}{\partial w_{jk}} = \delta_k a_j$$

$$\begin{aligned}\frac{\partial E}{\partial b_k} &= (a_k - t_k)g_k'(z_k)(1) \\ &= \delta_k\end{aligned}$$

# Backpropagation

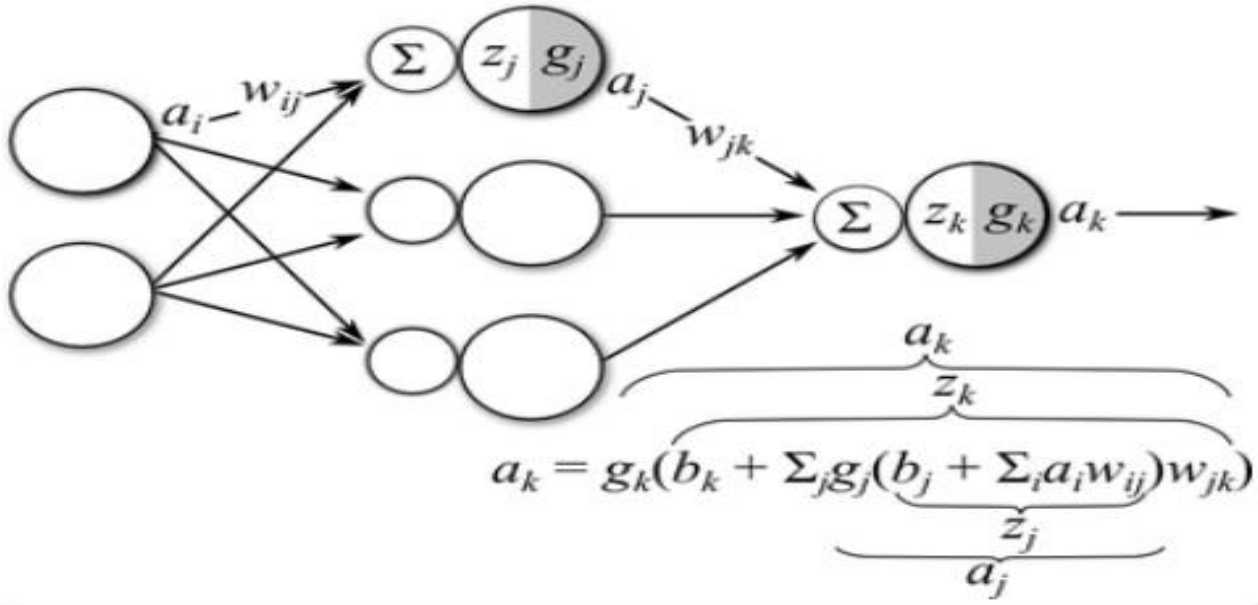
$$E = \frac{1}{2}\sum_{k\in K}(a_k - t_k)^2$$

$$\begin{aligned}
\frac{\partial E}{\partial w_{ij}} &= \frac{1}{2}\sum_{k\in K}(a_k - t_k)^2 \\
&= \sum_{k\in K}(a_k - t_k)\frac{\partial}{\partial w_{ij}}a_k \\
\frac{\partial E}{\partial w_{ij}} &= \sum_{k\in K}(a_k - t_k)\frac{\partial}{\partial w_{ij}}g_k(z_k) \\
&= \sum_{k\in K}(a_k - t_k)g'_k(z_k)\frac{\partial}{\partial w_{ij}}z_k \\
z_k &= b_k + \sum_j a_j w_{jk} \\
&= b_k + \sum_j g_j(z_j)w_{jk} \\
&= b_k + \sum_j g_j(b_i + \sum_i z_i w_{ij})w_{jk}
\end{aligned}$$



# Backpropagation

$$
\begin{aligned}
\frac{\partial z_k}{\partial w_{ij}} &= \frac{\partial z_k}{\partial a_j}\frac{\partial a_j}{\partial w_{ij}} \\
&= \frac{\partial}{\partial a_j} a_j w_{jk} \frac{\partial a_j}{\partial w_{ij}} \\
&= w_{jk}\frac{\partial a_j}{\partial w_{ij}} \\
&= w_{jk}\frac{\partial g_j(z_j)}{\partial w_{ij}} \\
&= w_{jk} g_j'(z_j)\frac{\partial z_j}{\partial w_{ij}} \\
&= w_{jk} g_j'(z_j)\frac{\partial}{\partial w_{ij}}(b_i + \textstyle\sum_i a_i w_{ij}) \\
&= w_{jk} g_j'(z_j) a_i
\end{aligned}
$$




$$
\begin{aligned}
\frac{\partial E}{\partial w_{ij}} &= \textstyle\sum_{k\in K}(a_k - t_k) g_k'(z_k) w_{jk} g_j'(z_j) a_i \\
&= g_j'(z_j) a_i \textstyle\sum_{k\in K}(a_k - t_k) g_k'(z_k) w_{jk} \\
&= a_i g_j'(z_j) \textstyle\sum_{k\in K} \delta_k w_{jk}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial E}{\partial w_{ij}} &= a_i g_j'(z_j) \textstyle\sum_{k\in K} \delta_k w_{jk} \\
&= \delta_j a_i \\
\text{where} & \\
\delta_j &= g_j'(z_j) \textstyle\sum_{k\in K} \delta_k w_{jk}
\end{aligned}
$$

# Backpropagation

$$\begin{aligned}\frac{\partial E}{\partial w_{ij}} &= a_i g'_j(z_j) \sum_{k \in K} \delta_k w_{jk} \\ &= \delta_j a_i\end{aligned}$$

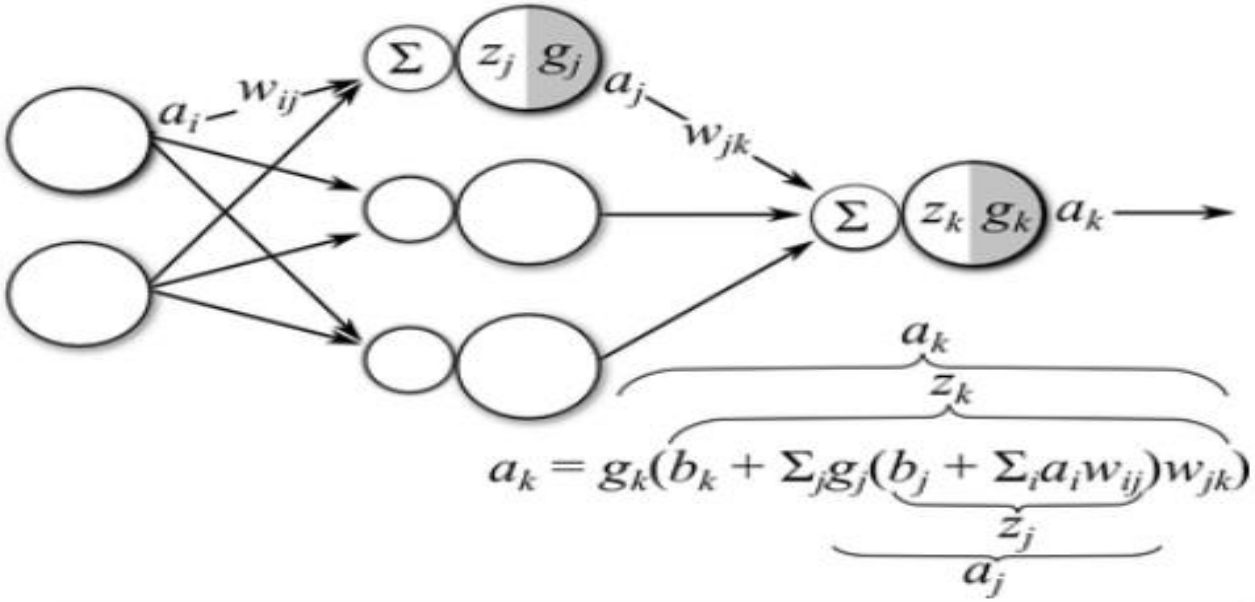
where

$$\delta_j = g'_j(z_j) \sum_{k \in K} \delta_k w_{jk}$$

$$\begin{aligned}\frac{\partial z_k}{\partial b_i} &= w_{jk} g'_j(z_j) \frac{\partial z_j}{\partial b_i} \\ &= w_{jk} g'_j(z_j) \frac{\partial}{\partial b_i}(b_i + \sum_i a_i w_{ij}) \\ &= w_{jk} g'_j(z_j)(1),\end{aligned}$$

giving

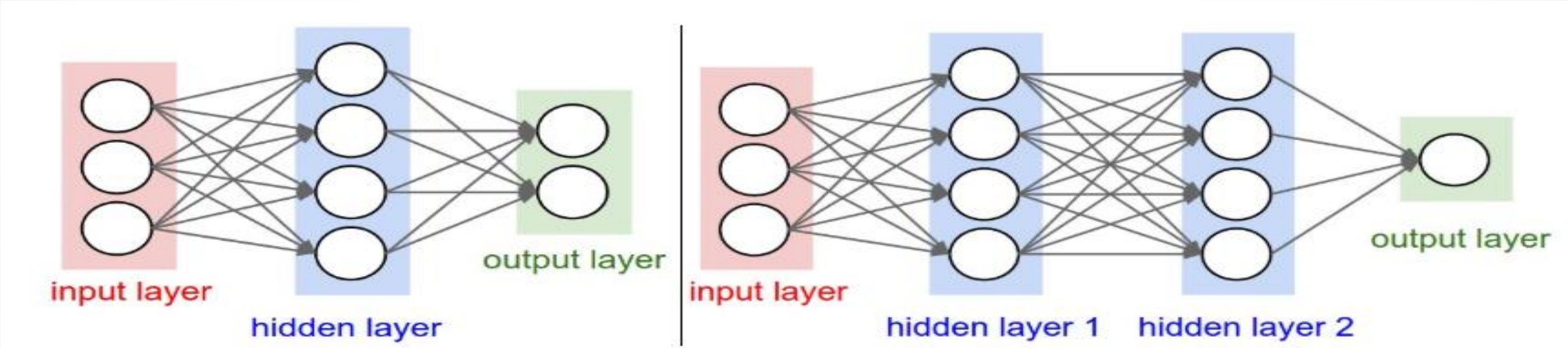
$$\begin{aligned}\frac{\partial E}{\partial b_i} &= g'_j(z_j) \sum_{k \in K} \delta_k w_{jk} \\ &= \delta_j\end{aligned}$$



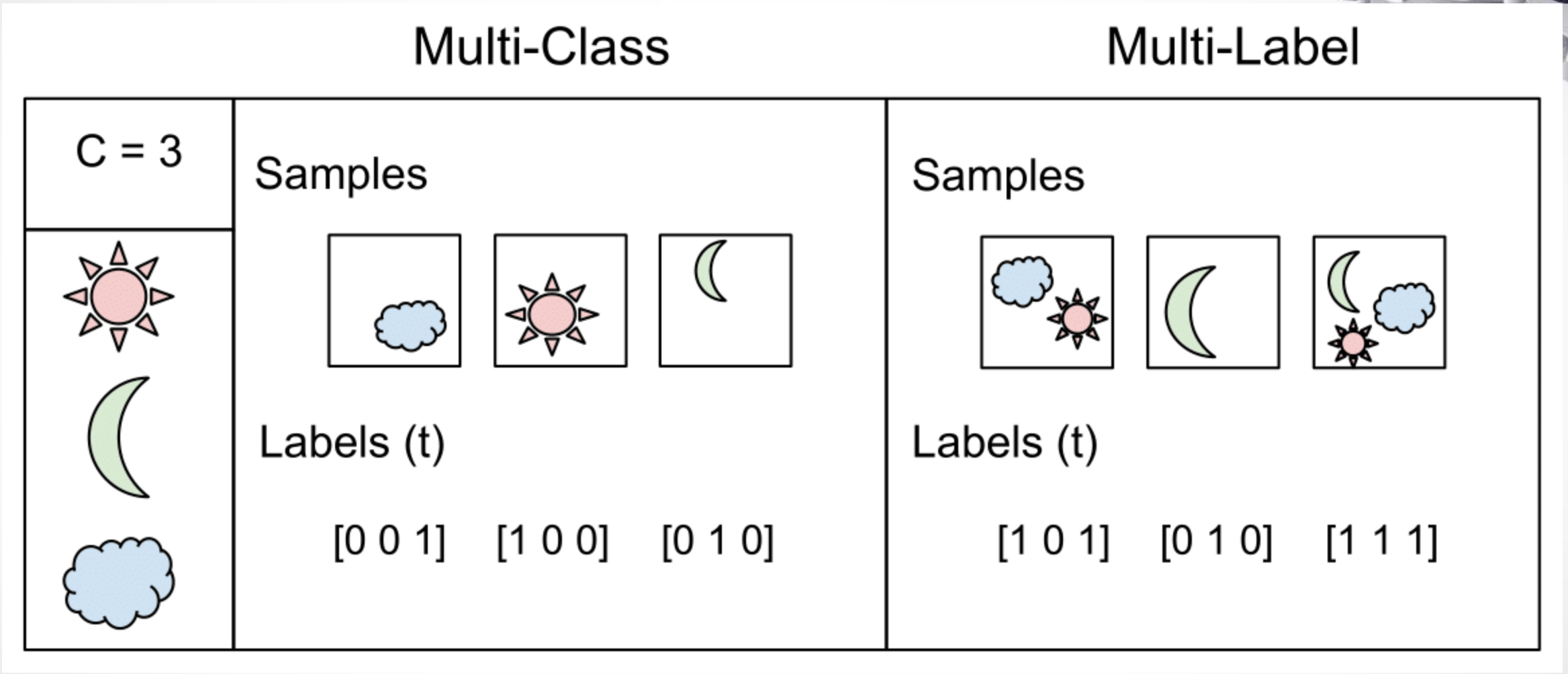

$$E = \frac{1}{2} \sum_{k \in K} (a_k - t_k)^2$$

$$\theta \leftarrow \theta - \eta \frac{\partial E}{\partial \theta}$$

# Summary: Feedforward Neural Networks



# Summary: Multi-class / Multi-Label

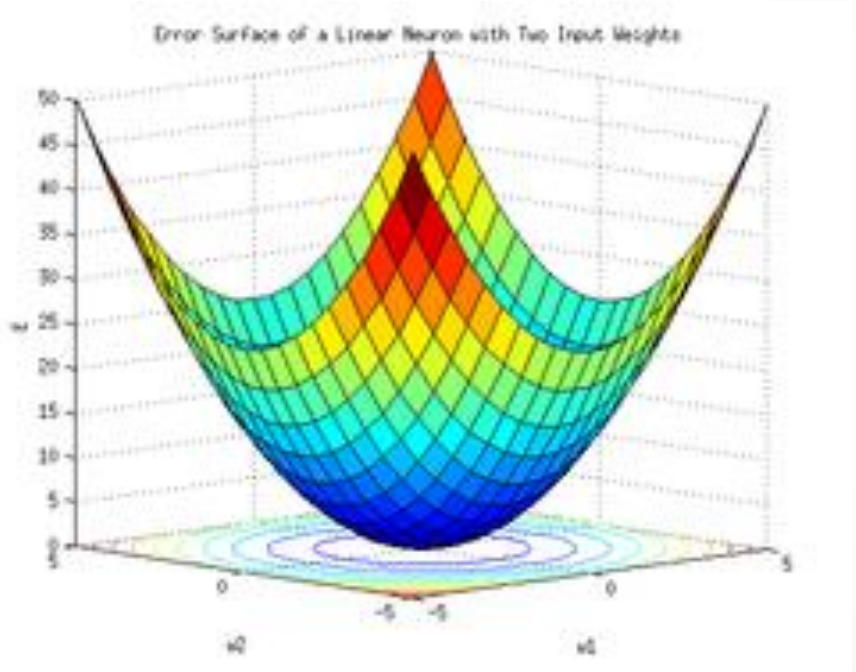



https://gombru.github.io/2018/05/23/cross_entropy_loss/

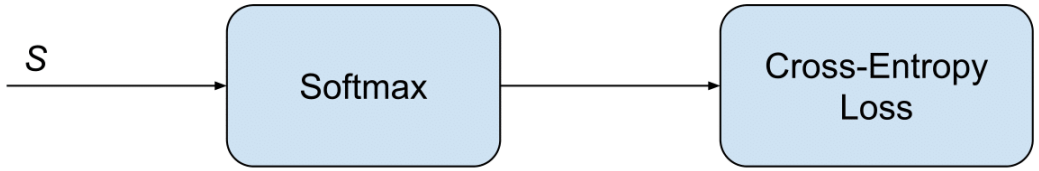
# Square Error Loss

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

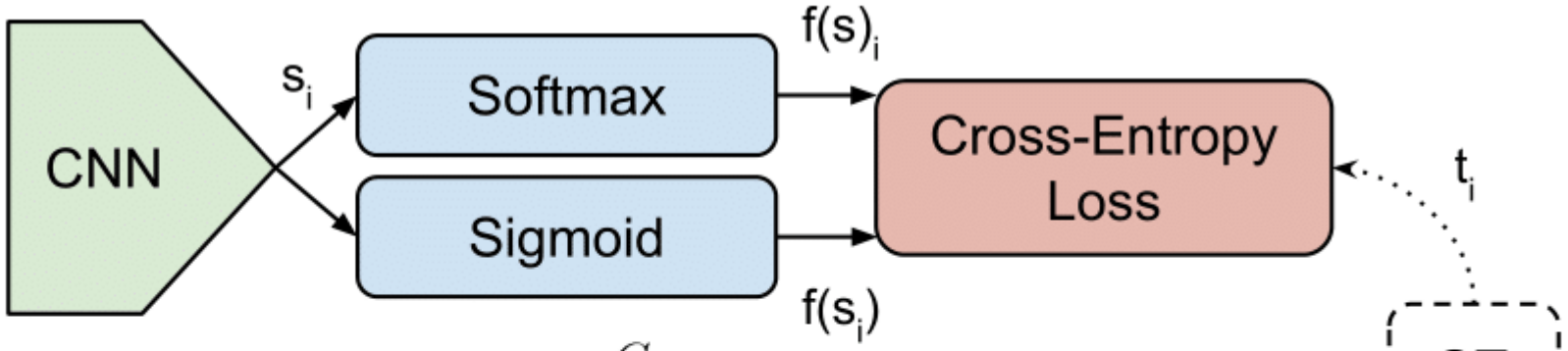
```
def MSE(y,yHat):
    return np.sum((y-yHat )**2) / y.size
```



# Cross Entropy Loss




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




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

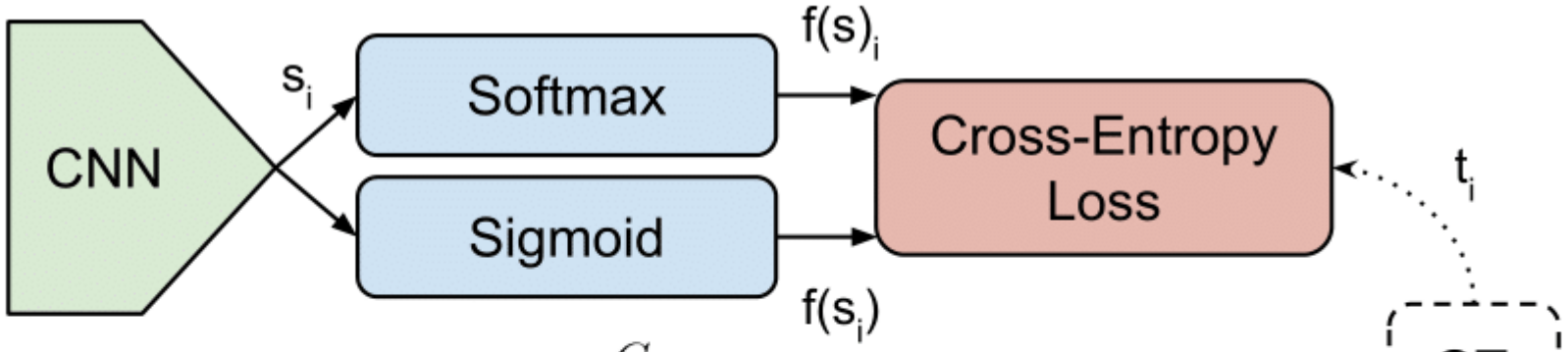
$$CE = -\sum_{i=1}^{C'=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1 - t_1) log(1 - f(s_1))$$

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

# Cross Entropy Loss


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

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

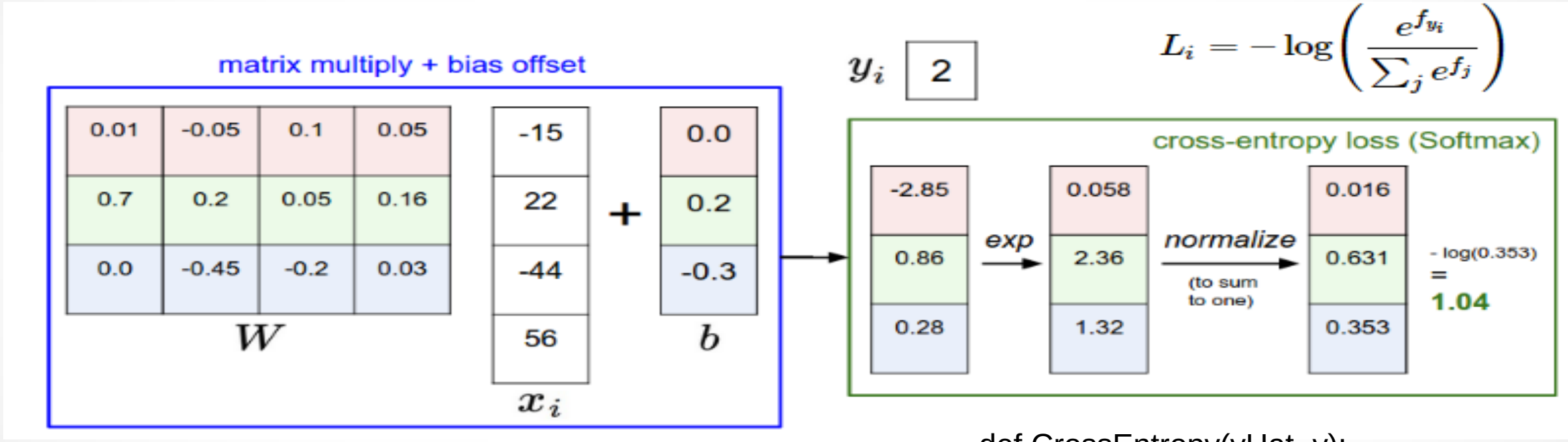



$$CE = -\sum_{i}^{C} t_i log(f(s)_i)$$

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

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

# Cross Entropy Loss




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

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

# 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

# Stochastic Gradient Descent

- 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.

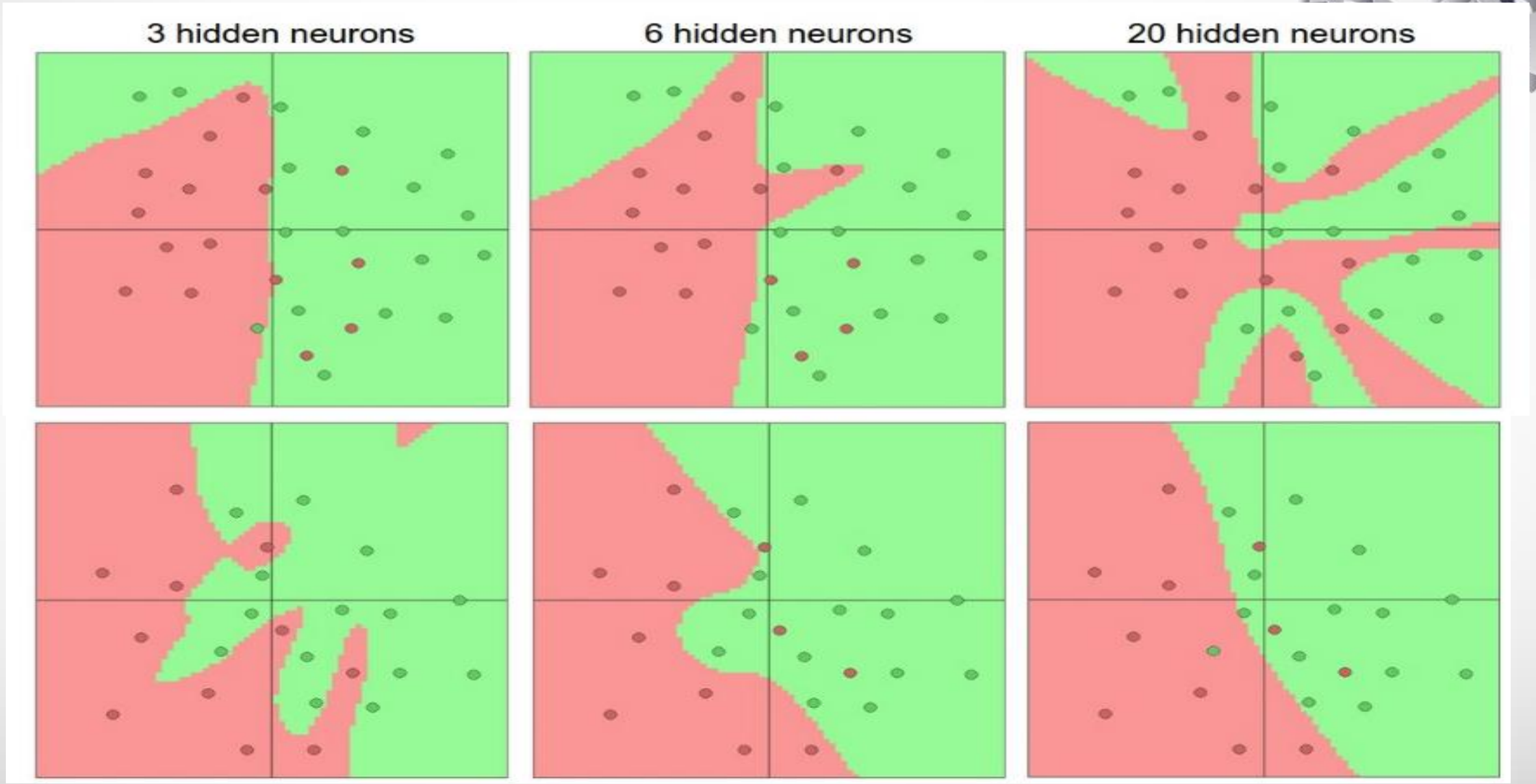
$$Q(w) = \frac{1}{n}\sum_{i=1}^{n} Q_i(w), \qquad Q_i(w) \text{ is the loss function}$$

a standard (or "batch") gradient descent method

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

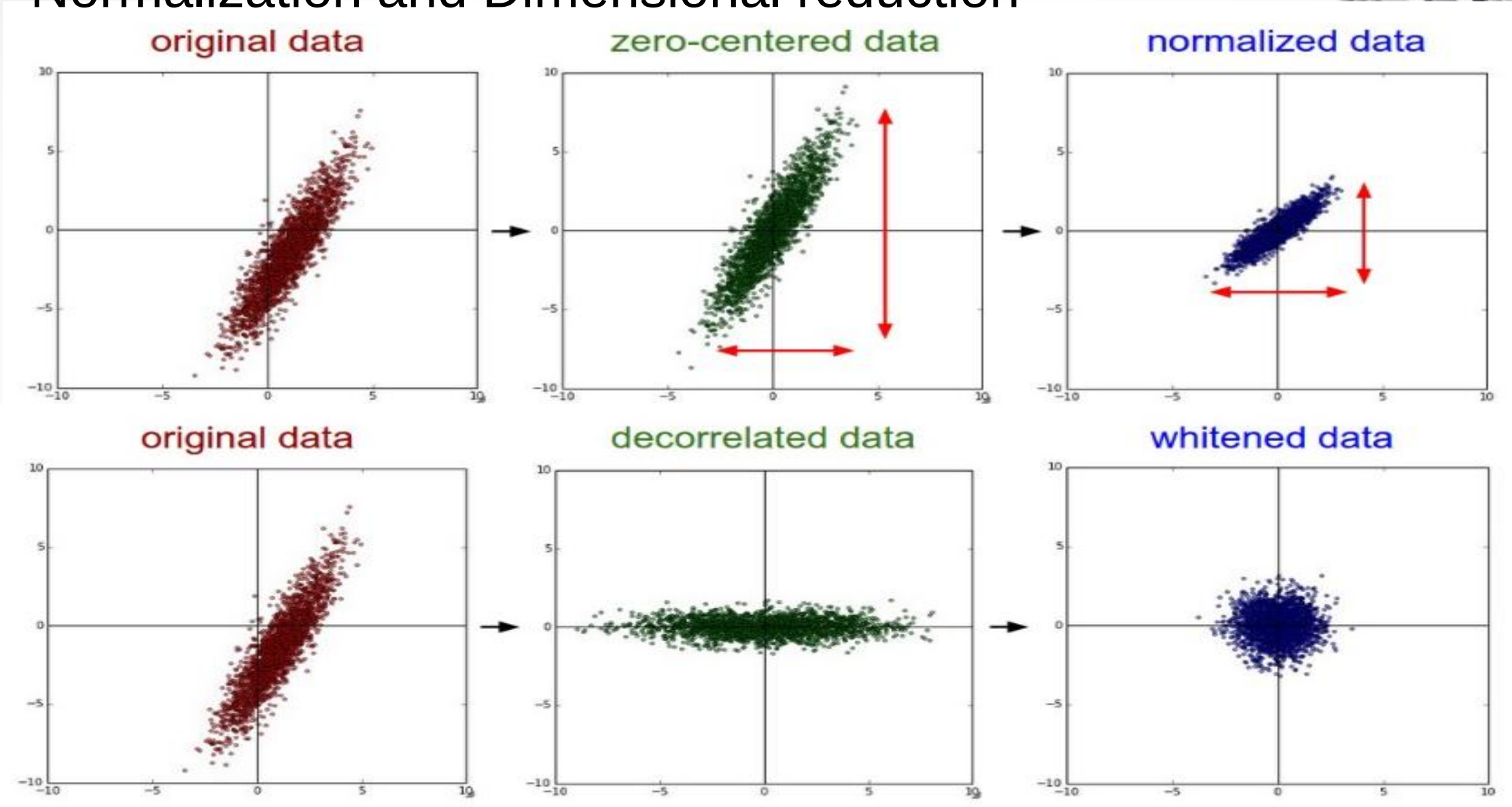
Wikipedia

# Effects of Network Structure

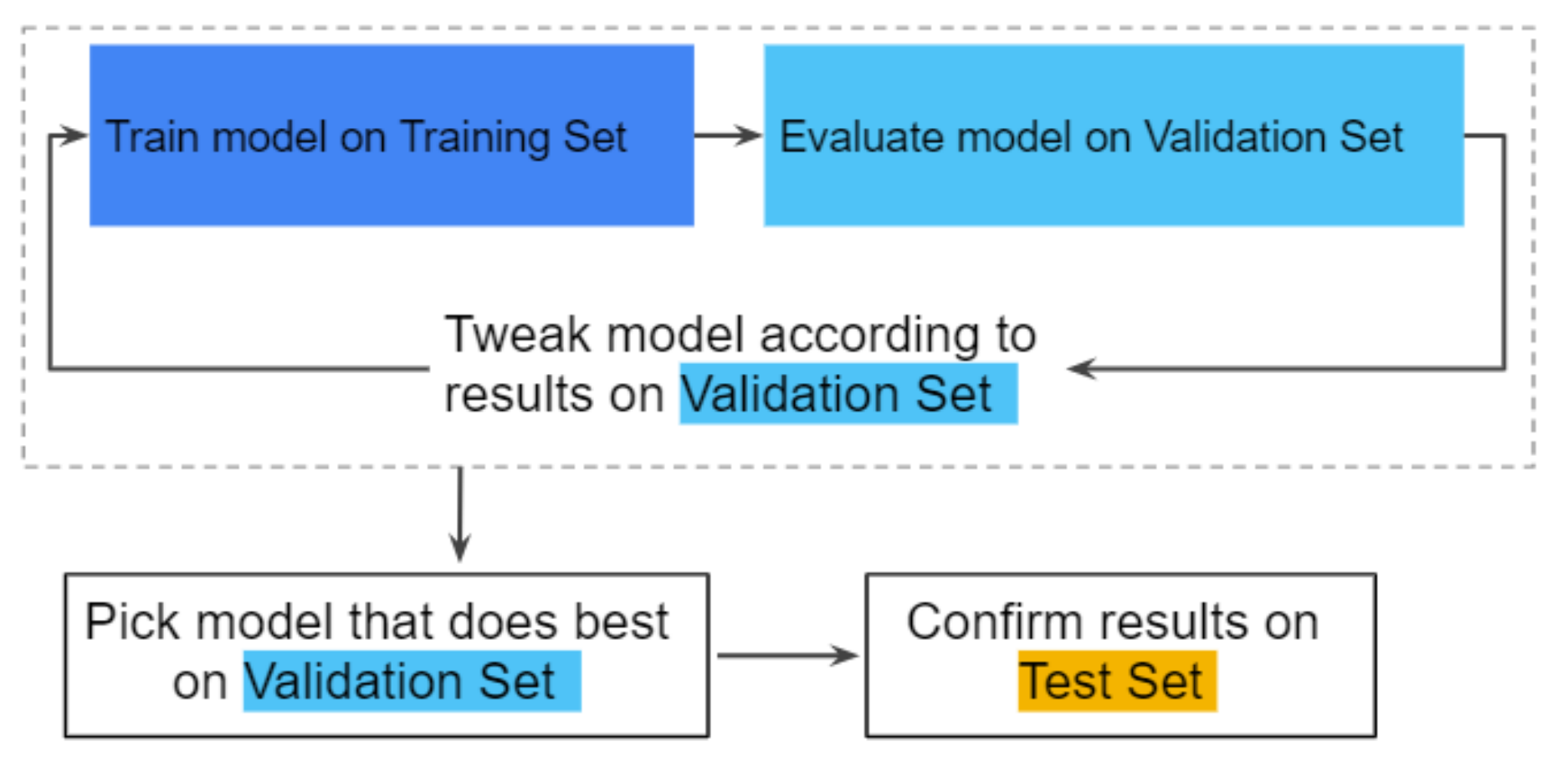


# Data Preprocessing

- Normalization and Dimensional reduction

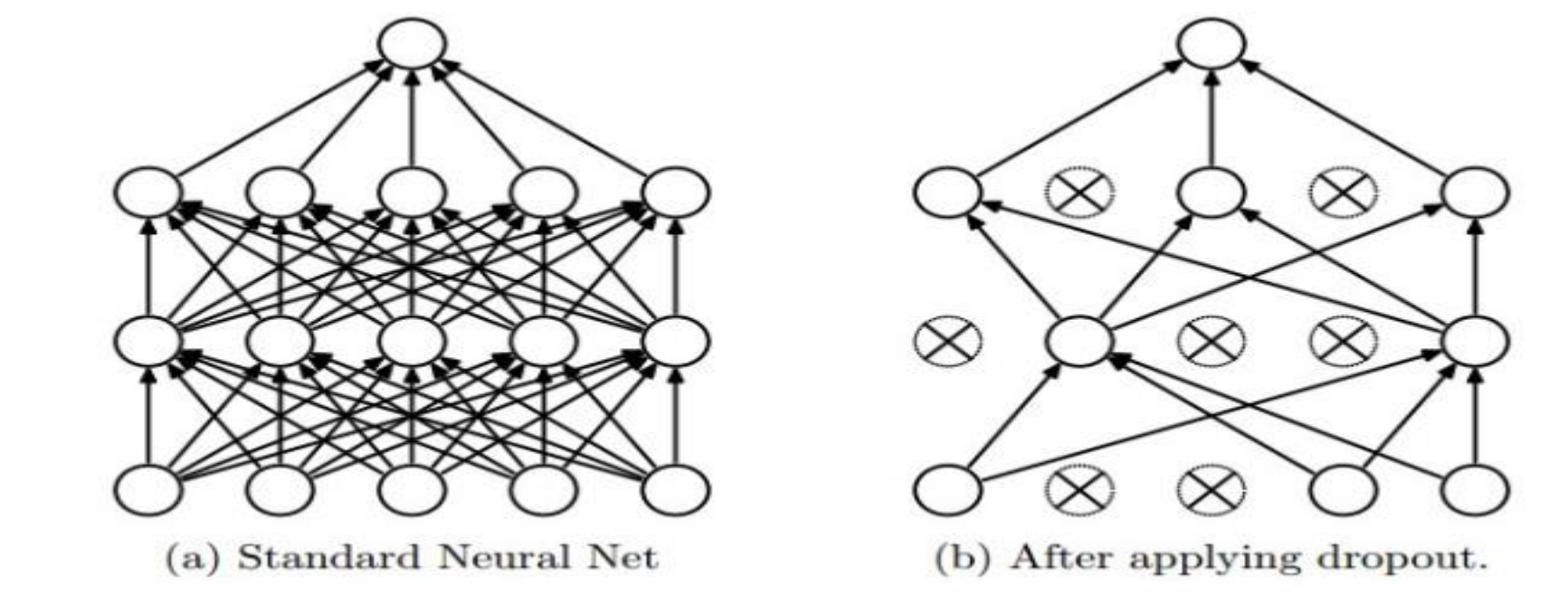


# Training, Validation & Test Set



# Dropout

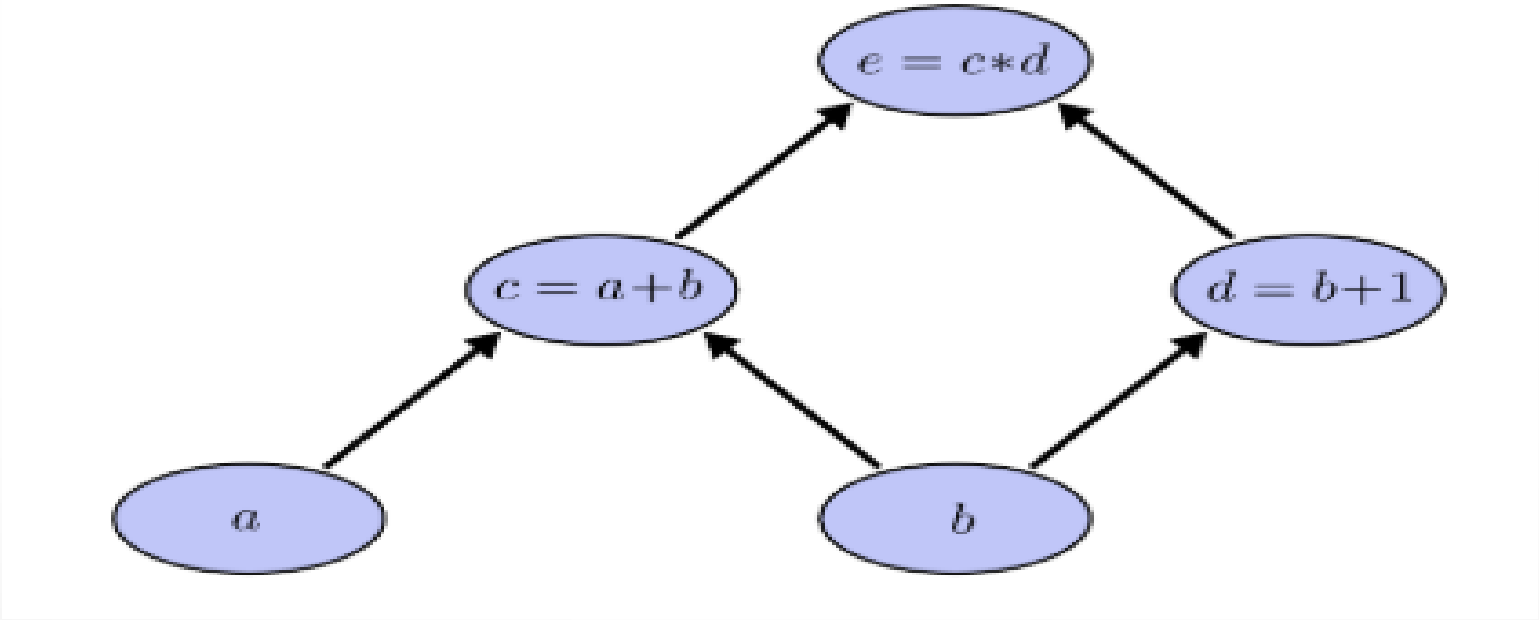
- Deal with overfitting with dropout



# Computational Graph & TensorFlow

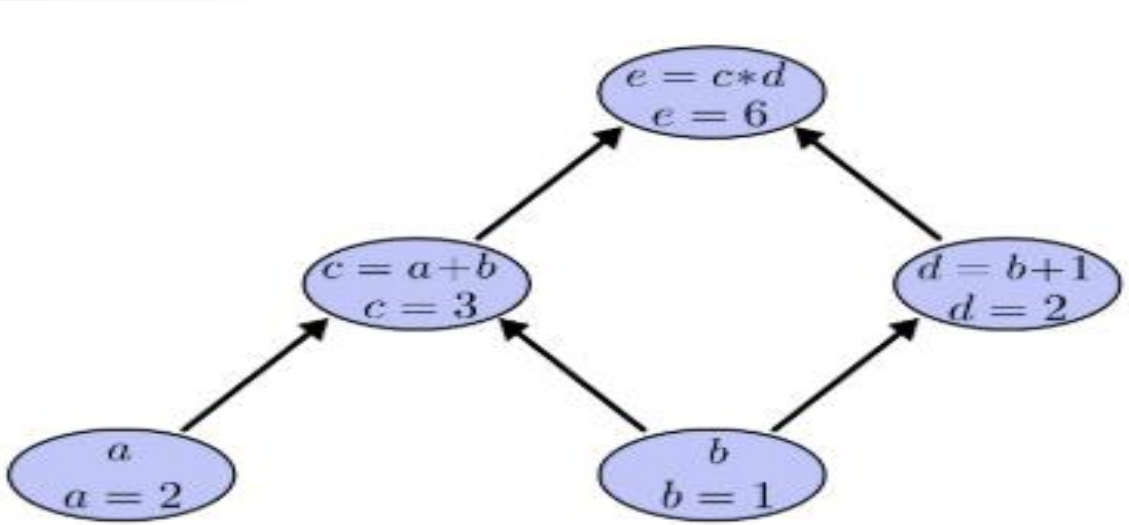
# Learning: Computational Graph

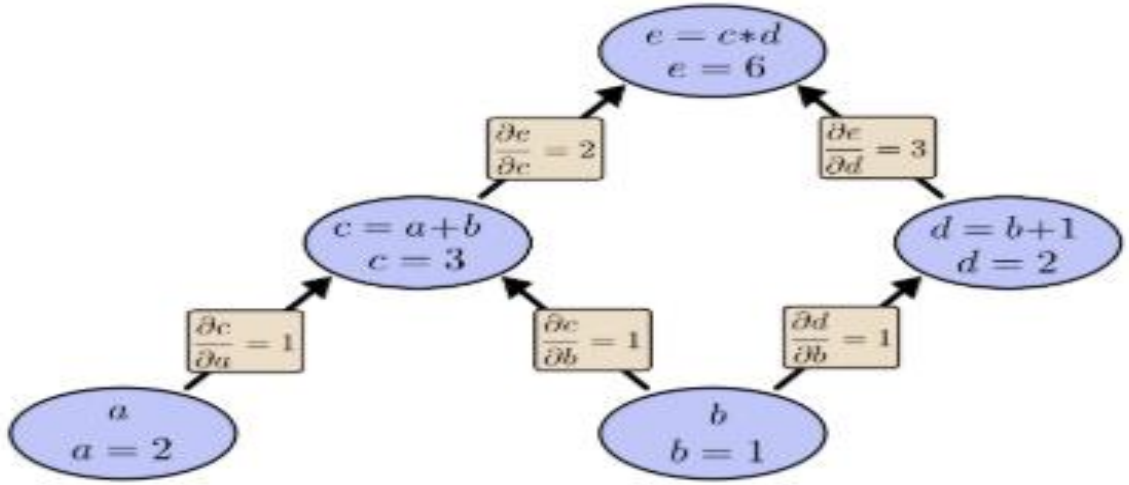
- Backpropagation can be computed via flow in the computational graph




http://colah.github.io/posts/2015-08-Backprop/

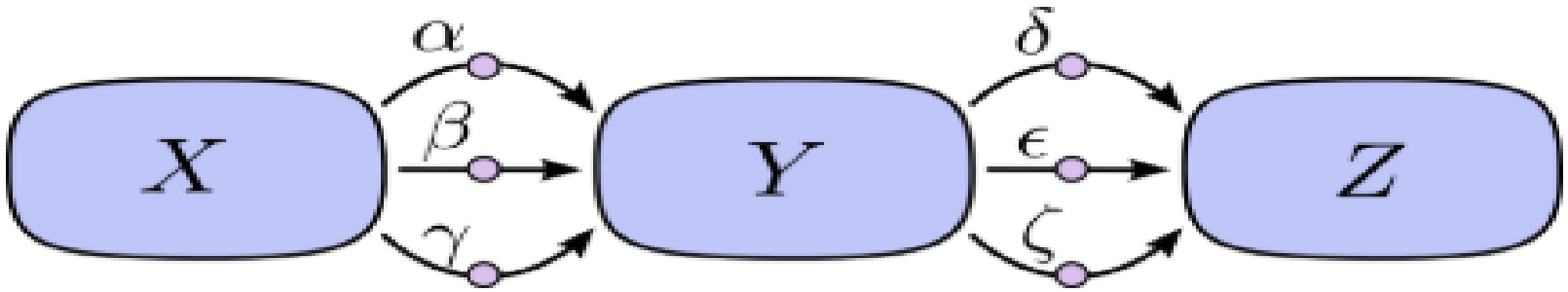
# Computational Graph




http://colah.github.io/posts/2015-08-Backprop/

# Computational Graph

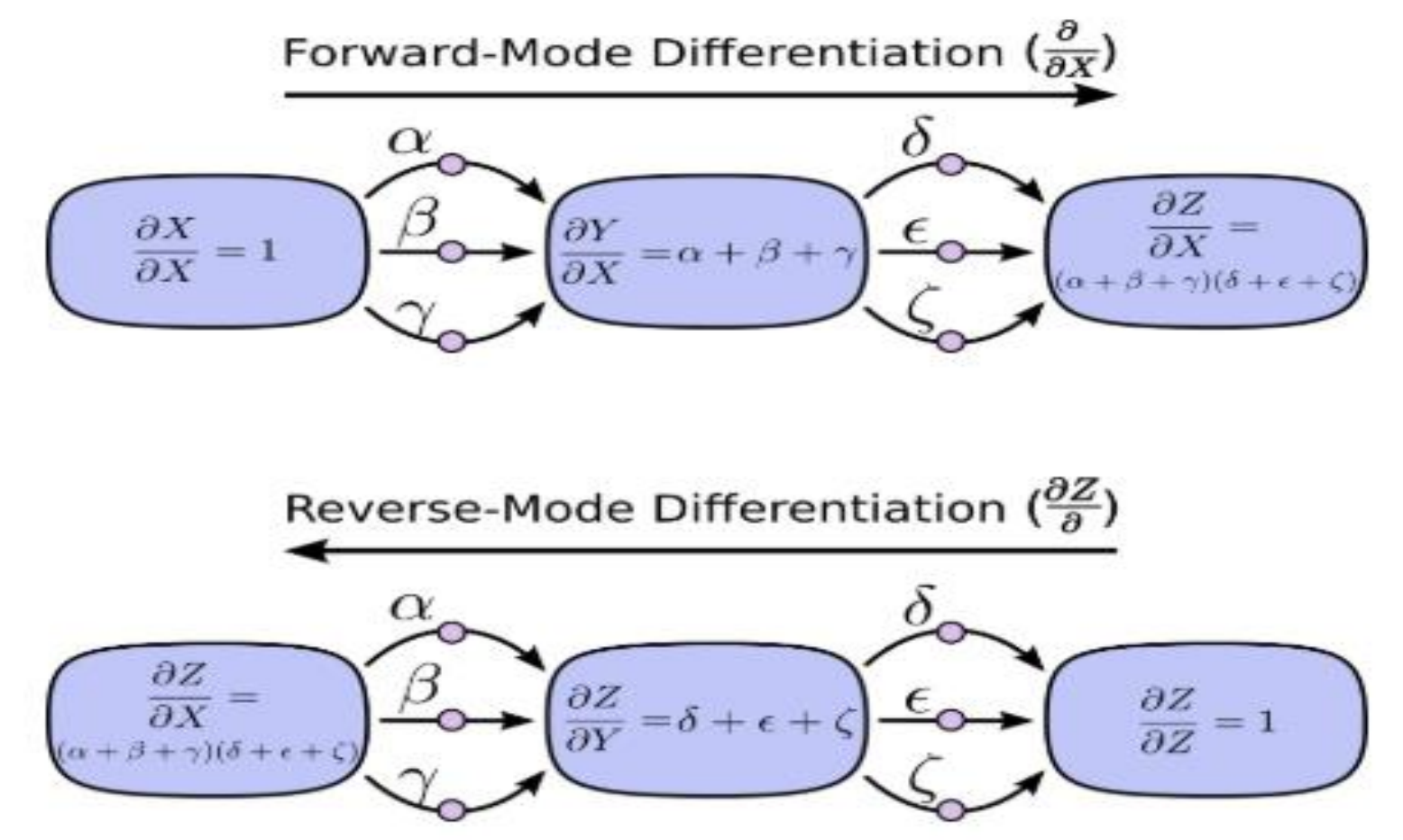



In the above diagram, there are three paths from $X$ to $Y$, and a further three paths from $Y$ to $Z$. If we want to get the derivative $\frac{\partial Z}{\partial X}$ by summing over all paths, we need to sum over $3 * 3 = 9$ paths:

$$\frac{\partial Z}{\partial X} = \alpha\delta + \alpha\epsilon + \alpha\zeta + \beta\delta + \beta\epsilon + \beta\zeta + \gamma\delta + \gamma\epsilon + \gamma\zeta$$

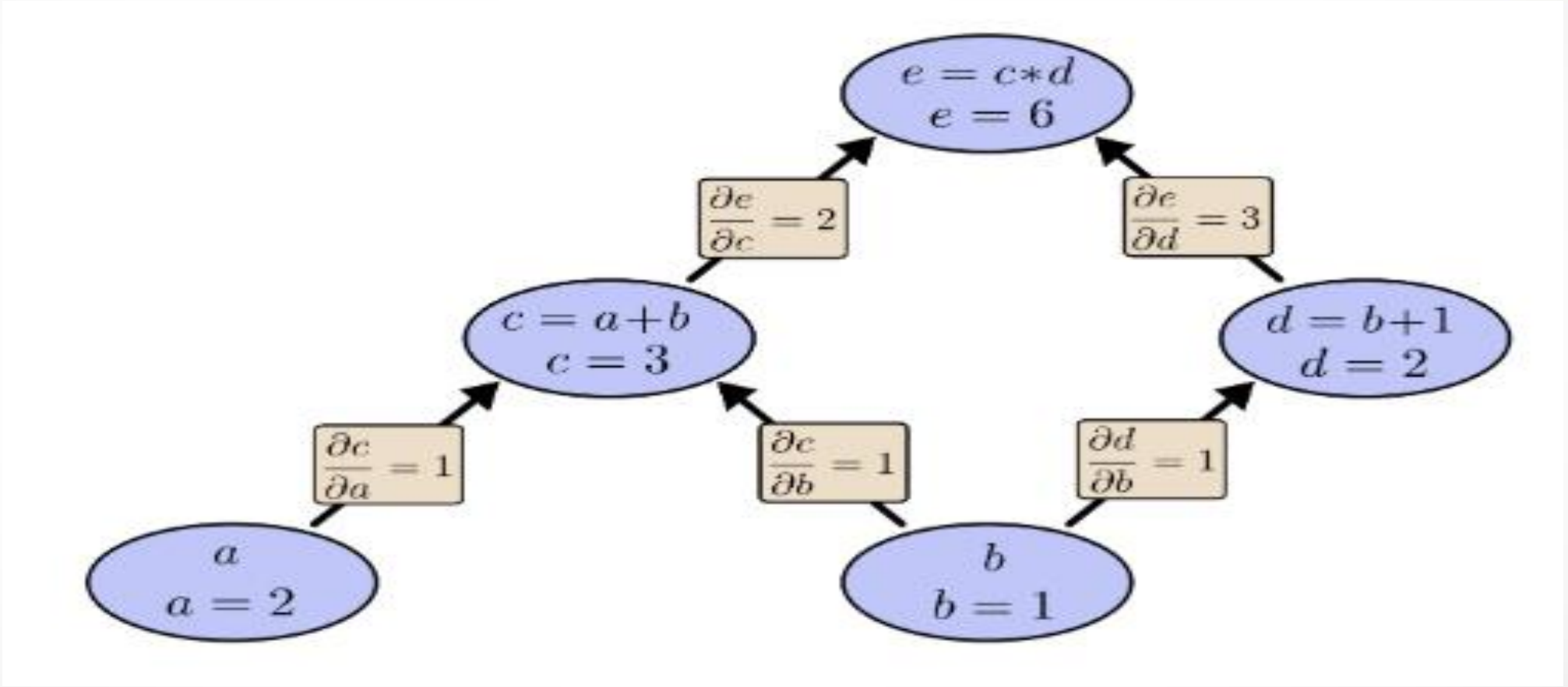
http://colah.github.io/posts/2015-08-Backprop/

# Computational Graph



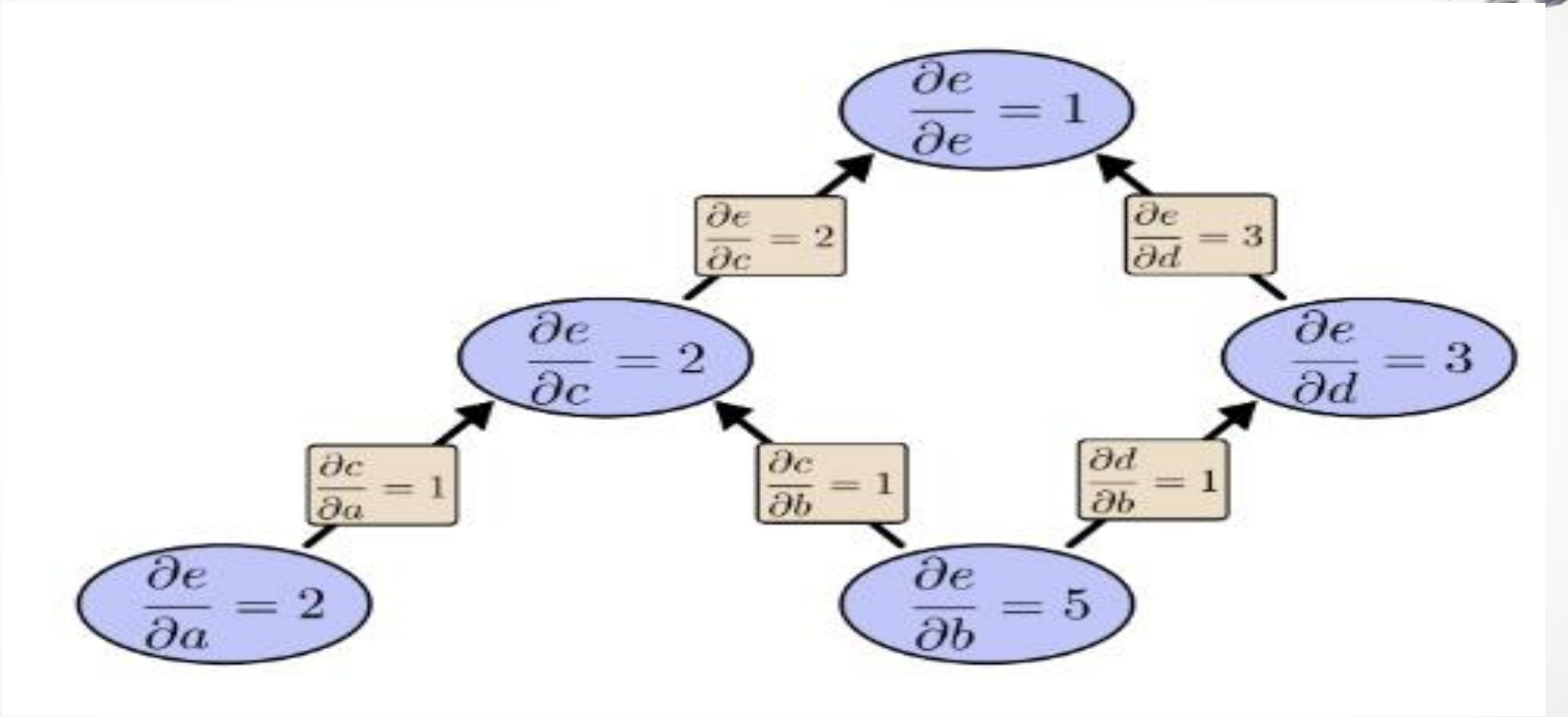

http://colah.github.io/posts/2015-08-Backprop/

# Computational Graph



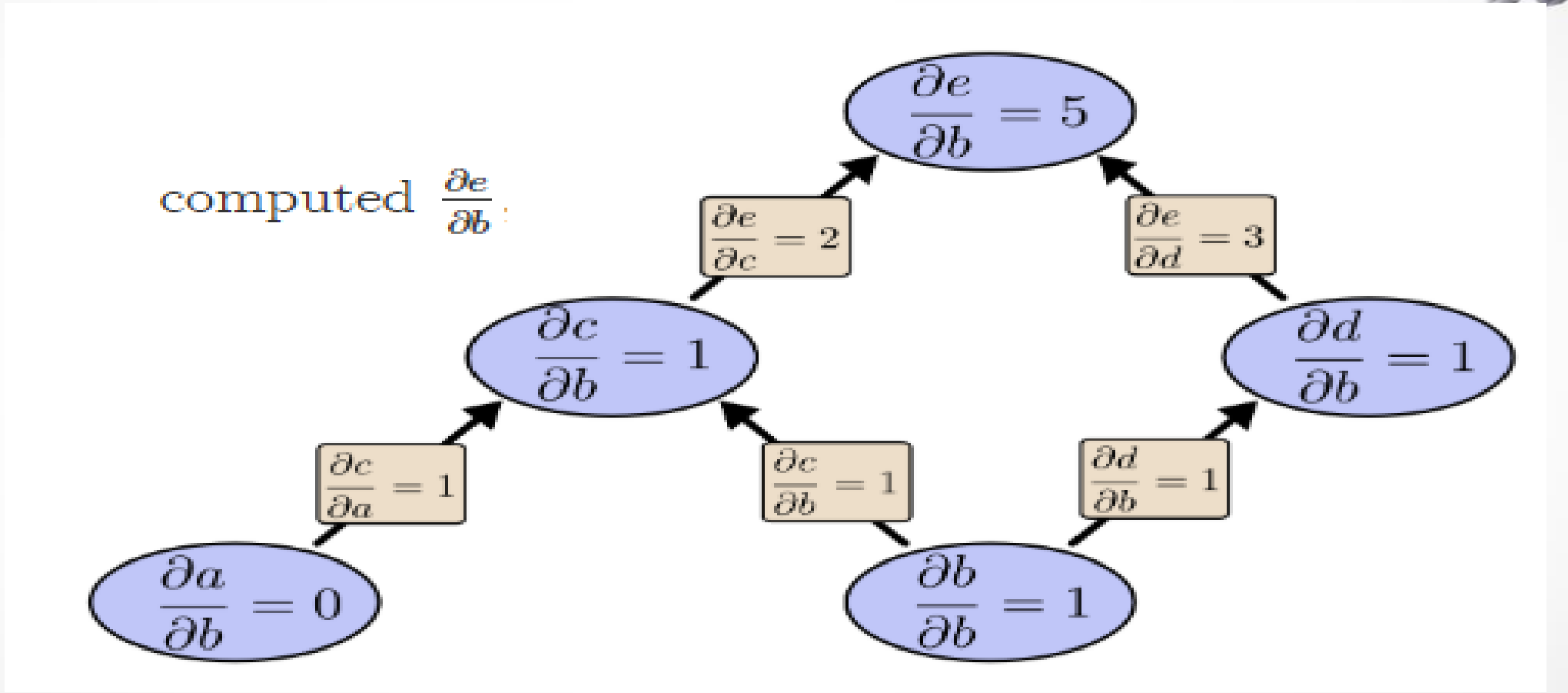

http://colah.github.io/posts/2015-08-Backprop/

# Computational Graph




http://colah.github.io/posts/2015-08-Backprop/

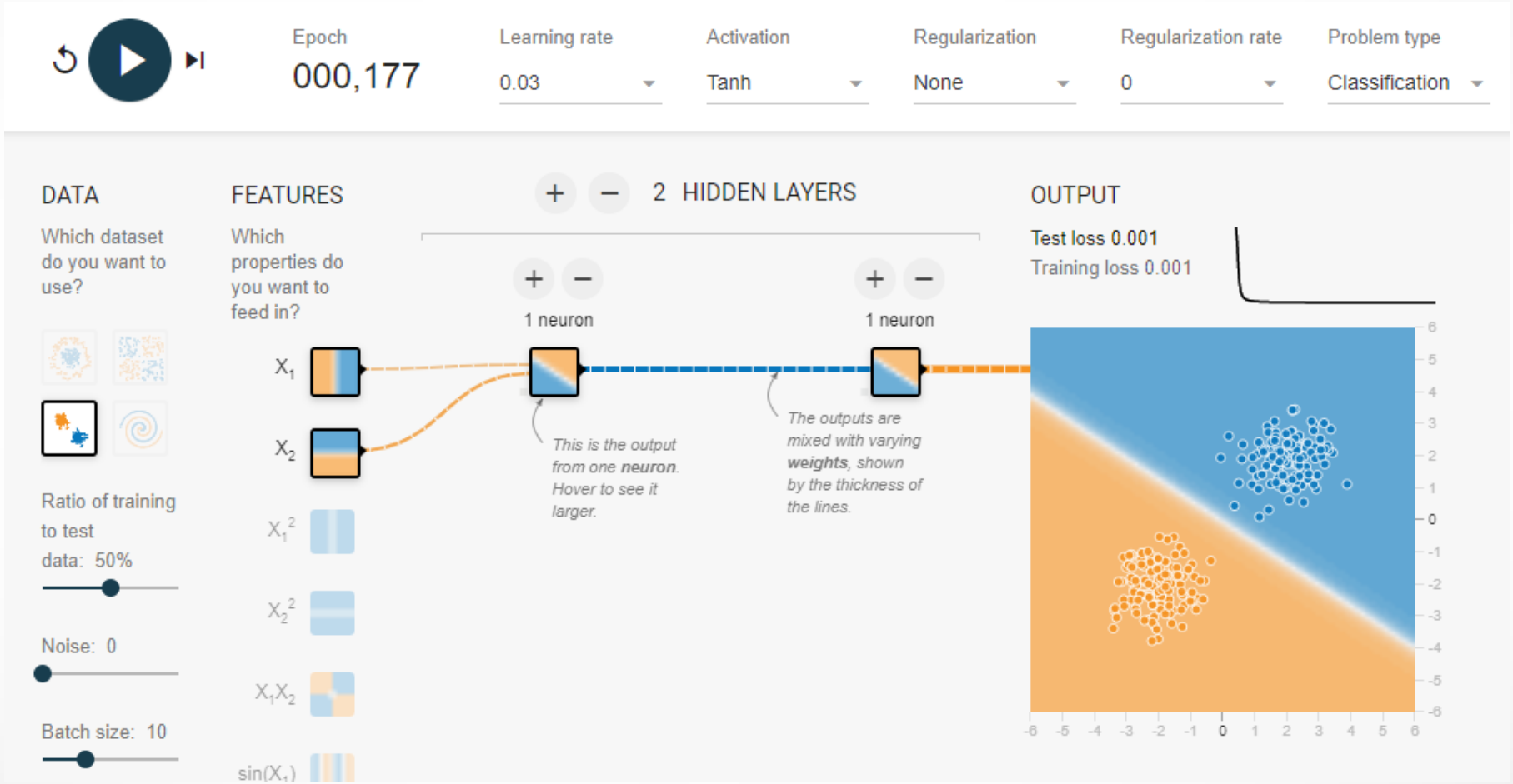
# Computational Graph




http://colah.github.io/posts/2015-08-Backprop/

# TensorFlow ANN Playground

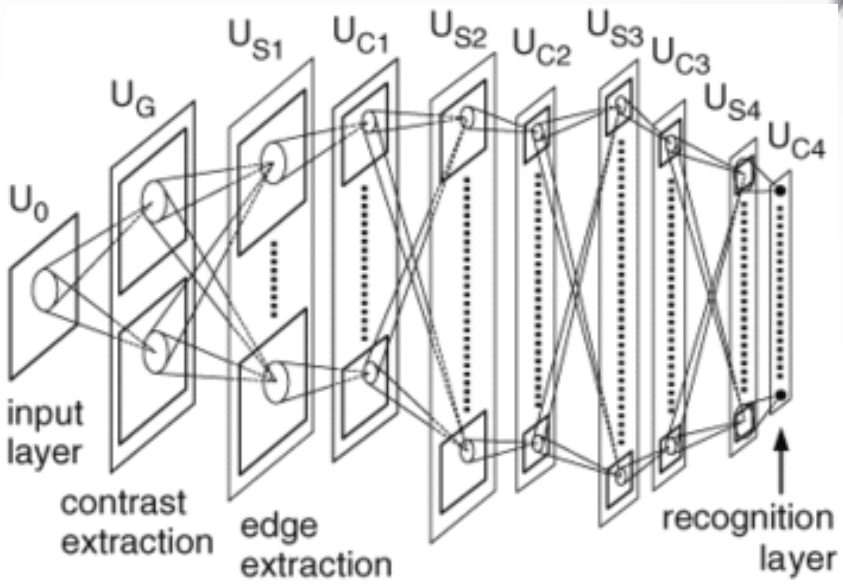
- https://playground.tensorflow.org

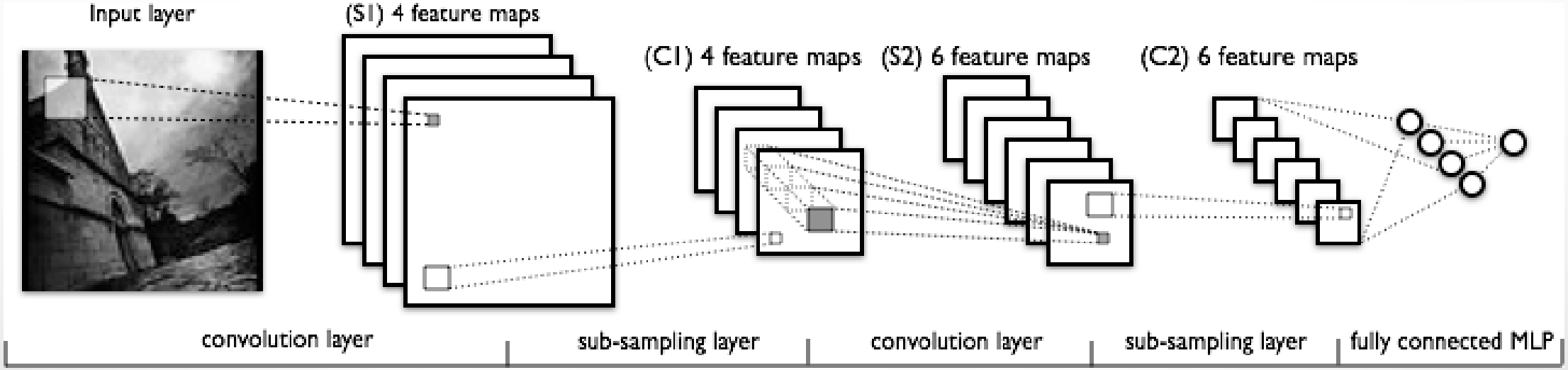


# Deep Learning

## CNN based computer vision

# A Brief History of Deep Learning



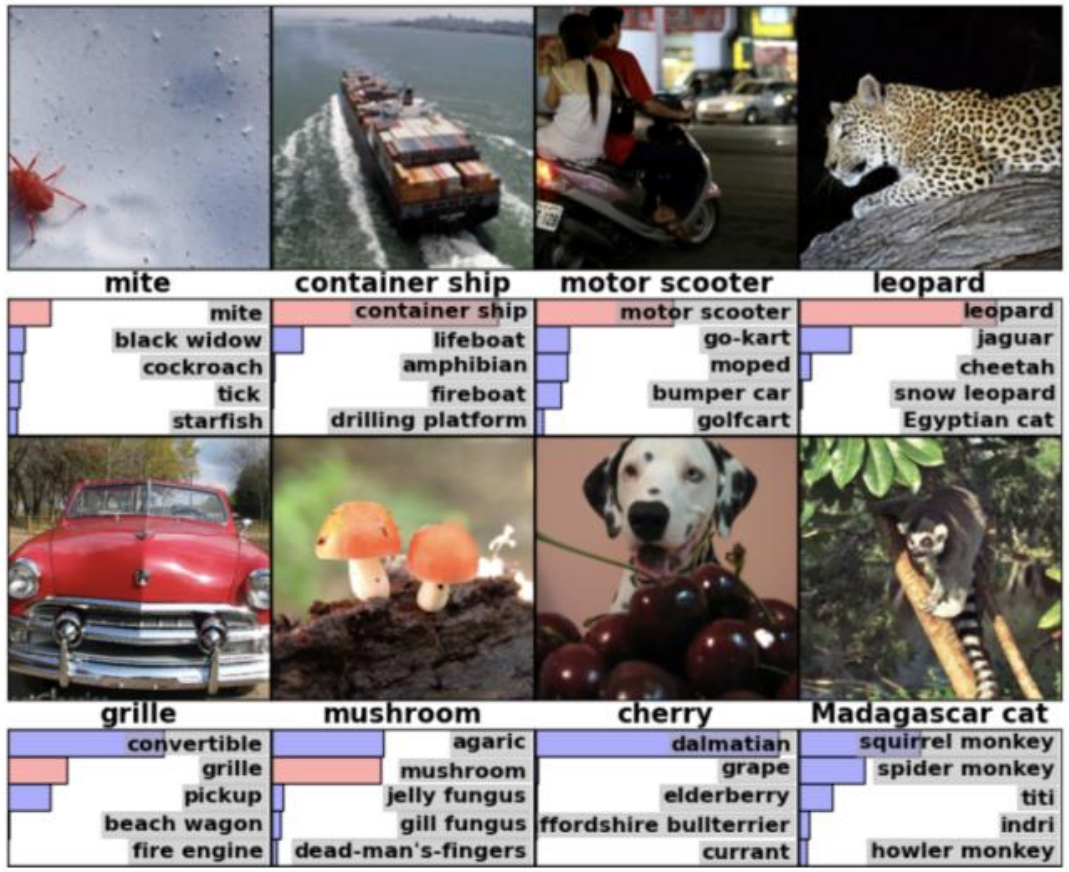



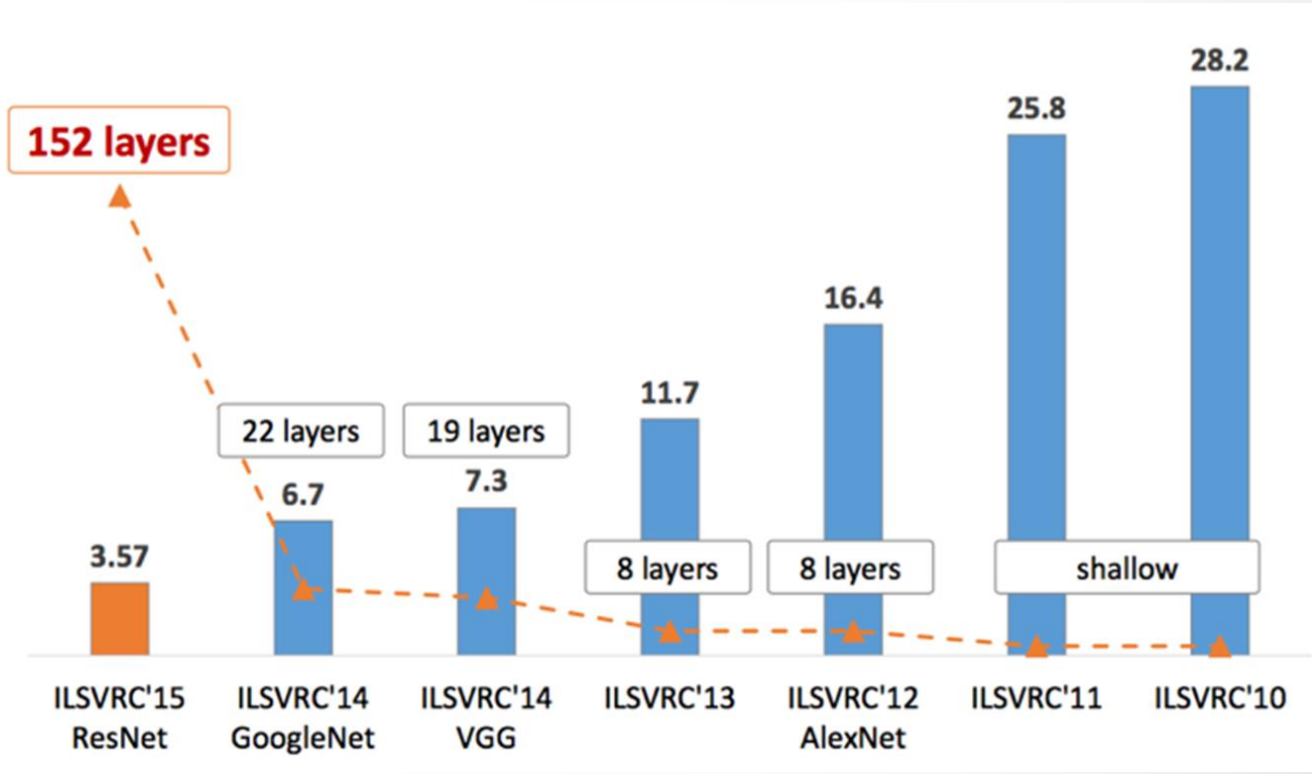
# A Brief History of Deep Learning

- 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.



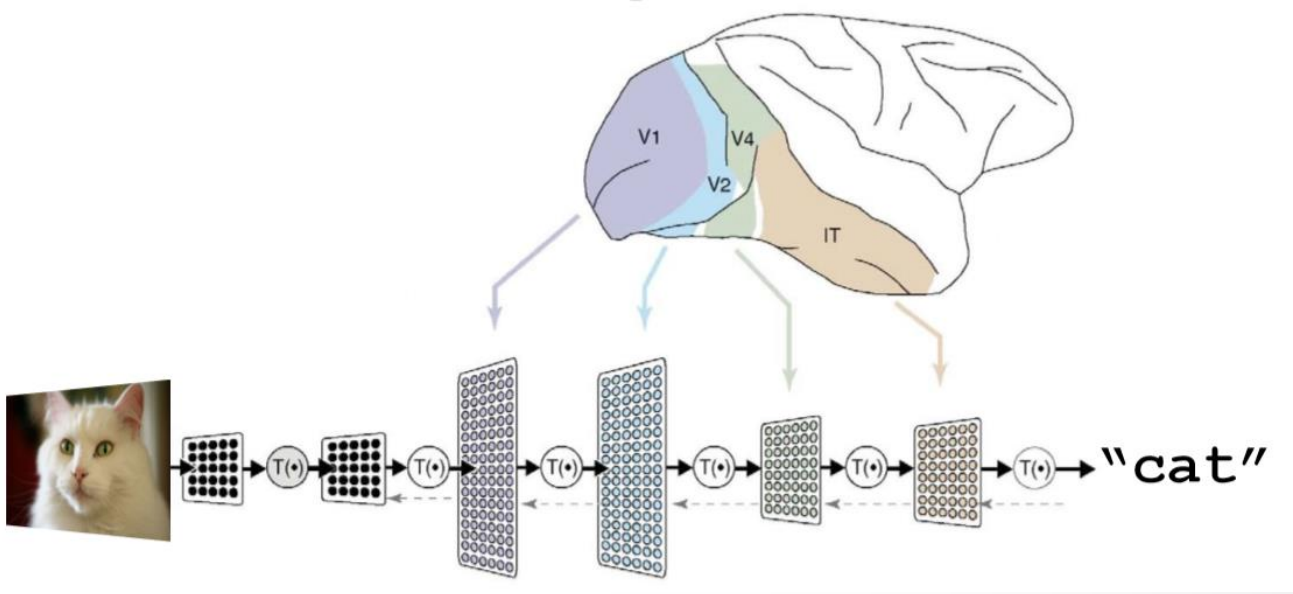

# ImageNet (Fei-Fei Li, 2009)



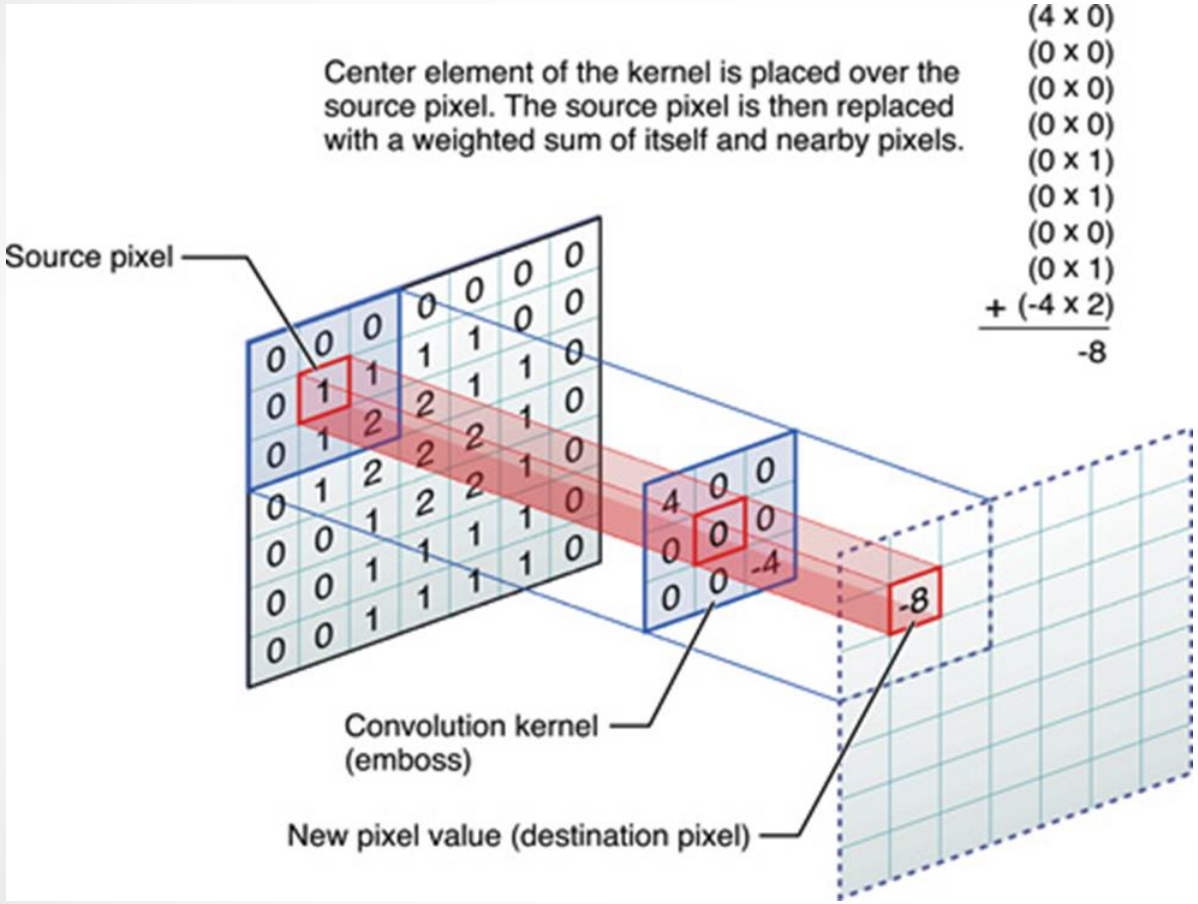



# Why does CNN Perform Better?

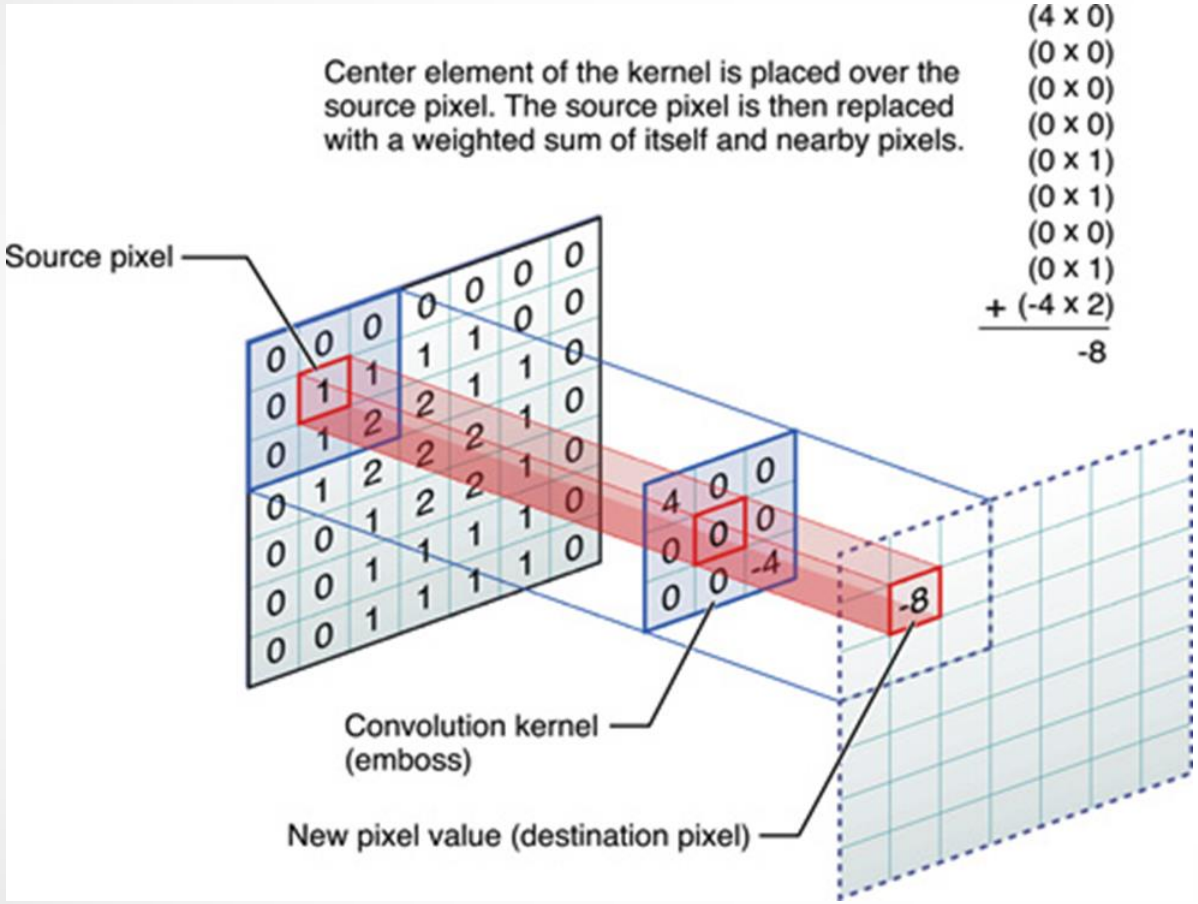
- CNN shares many commonalities with real brains.
  - Each neuron is connected to a small subset of neurons.
  - Each neuron perform simple function e.g., Sigmoid, ReLU.
  - Each subset of neurons learn specialised features (representation learning).

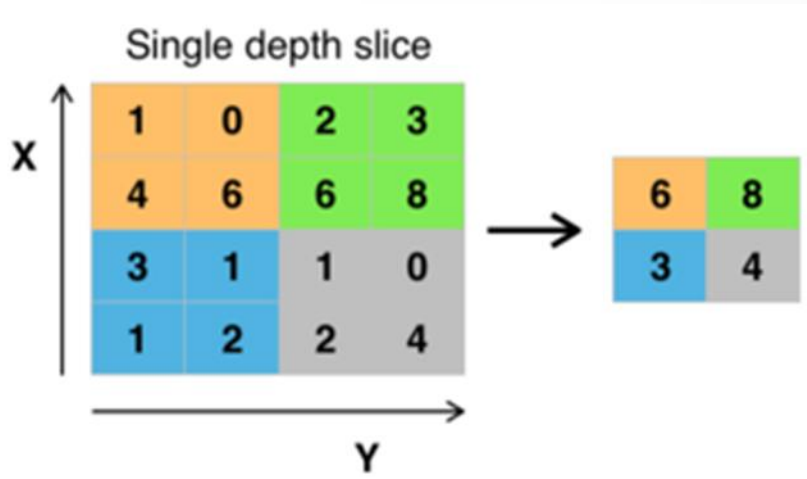


# Convolutional Neural Network

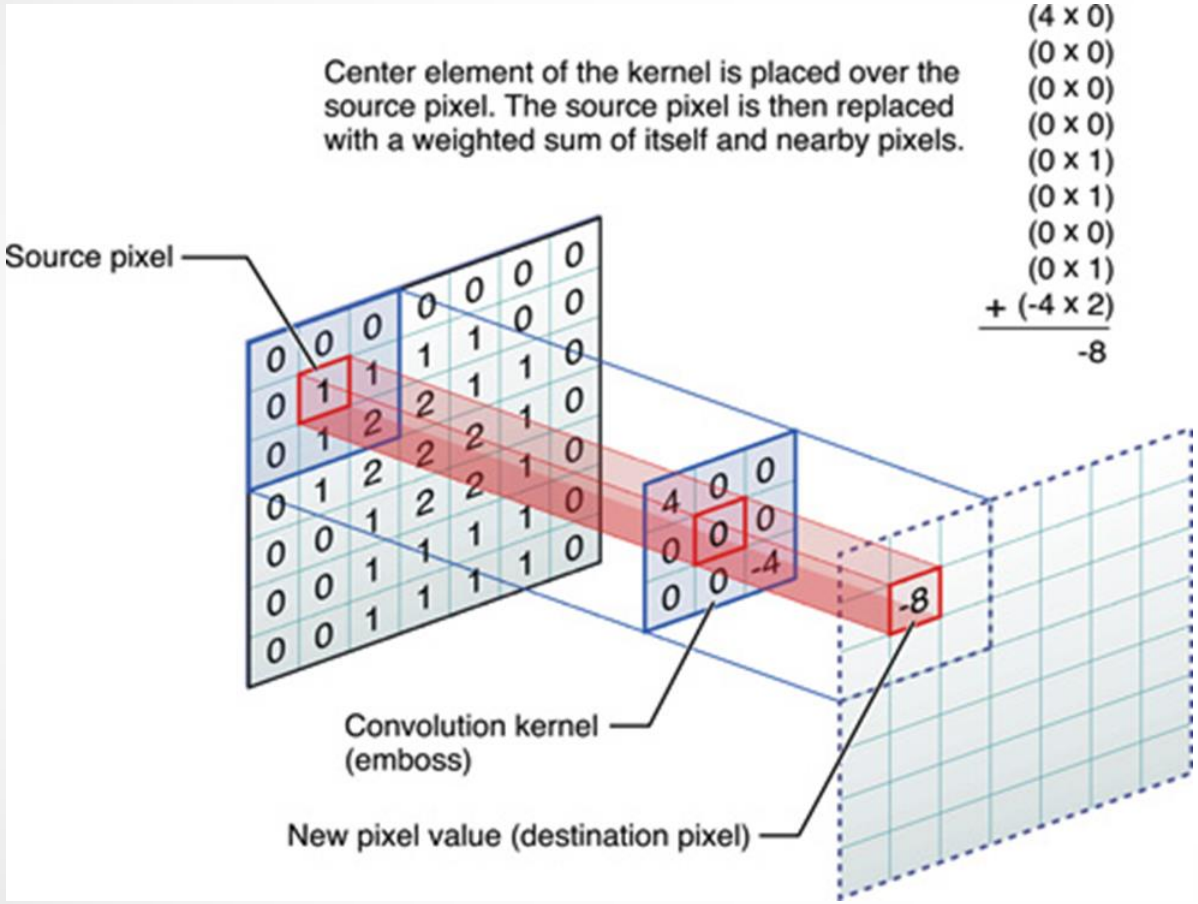


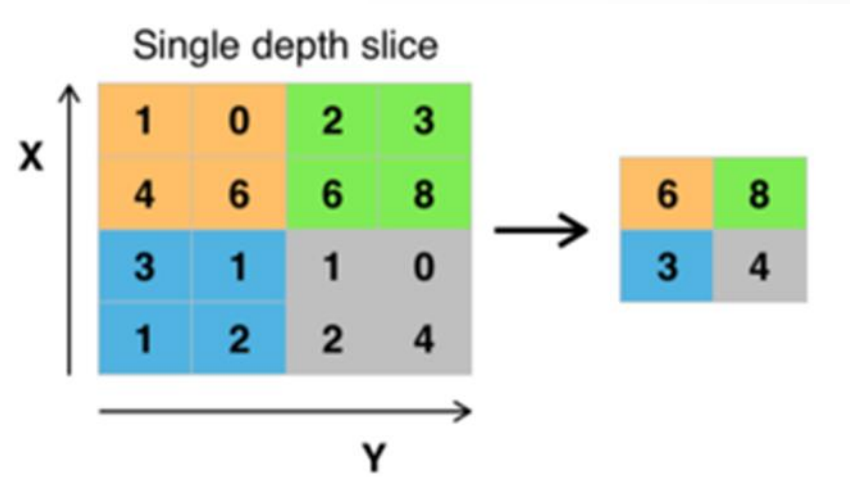
# Convolutional Neural Network

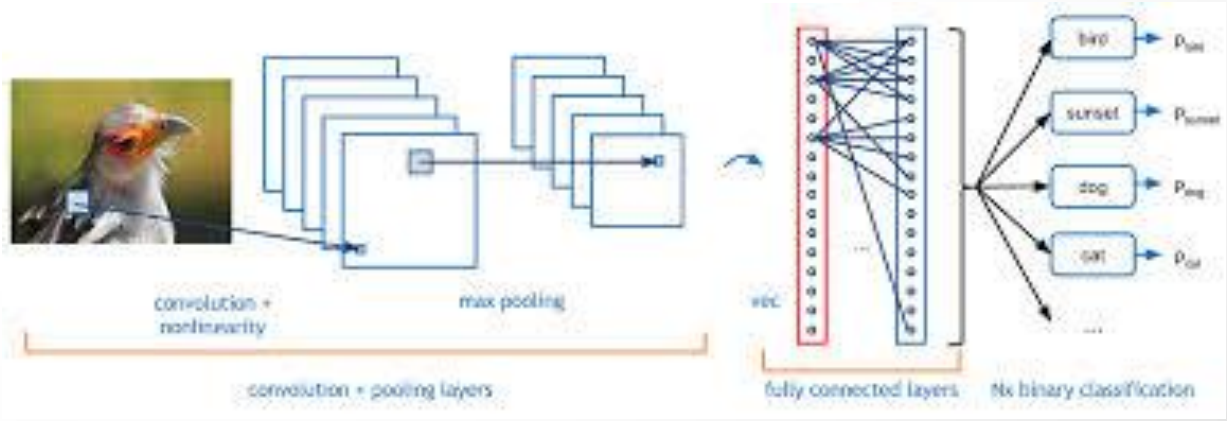


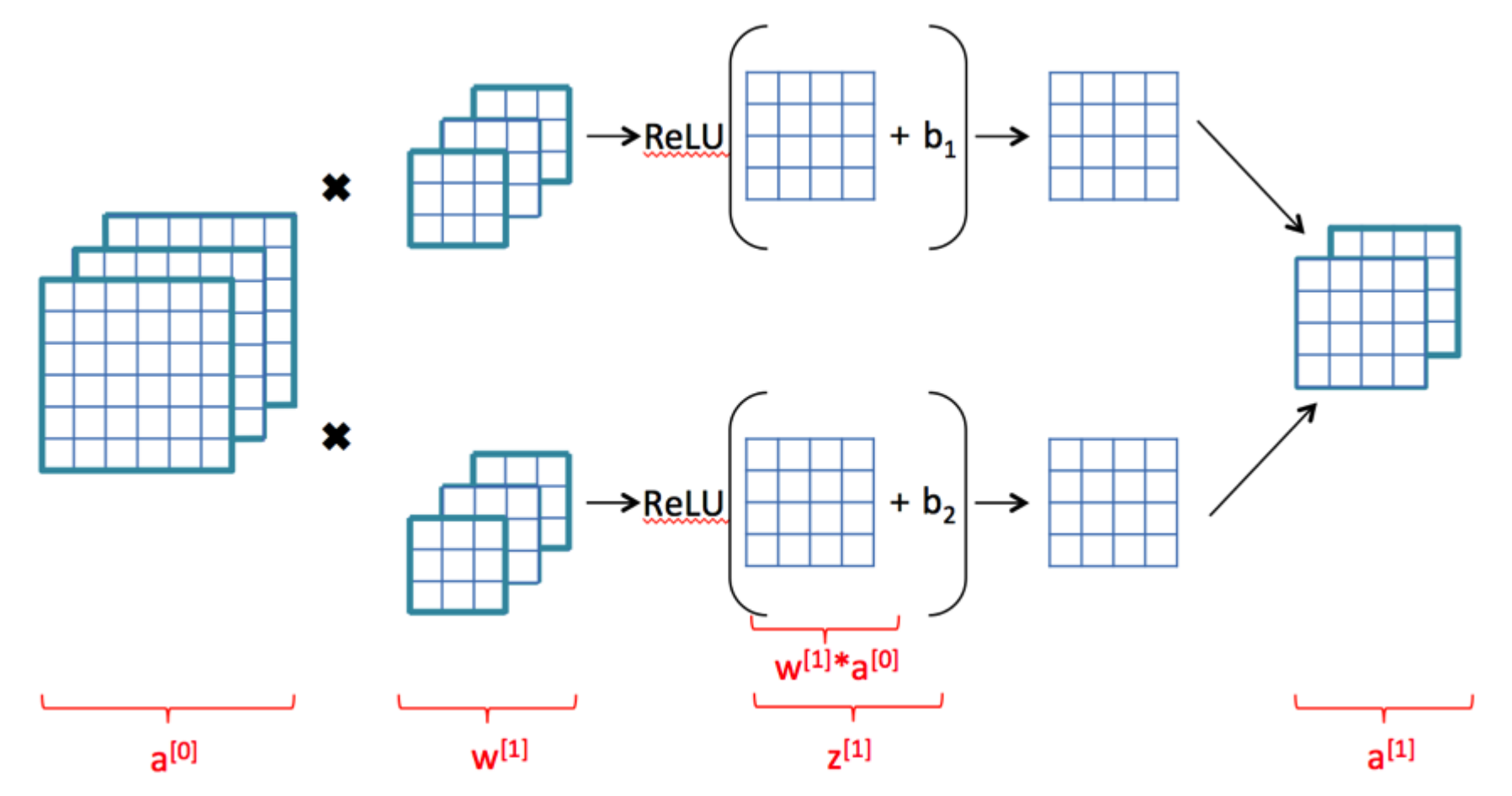
# Convolutional Neural Network



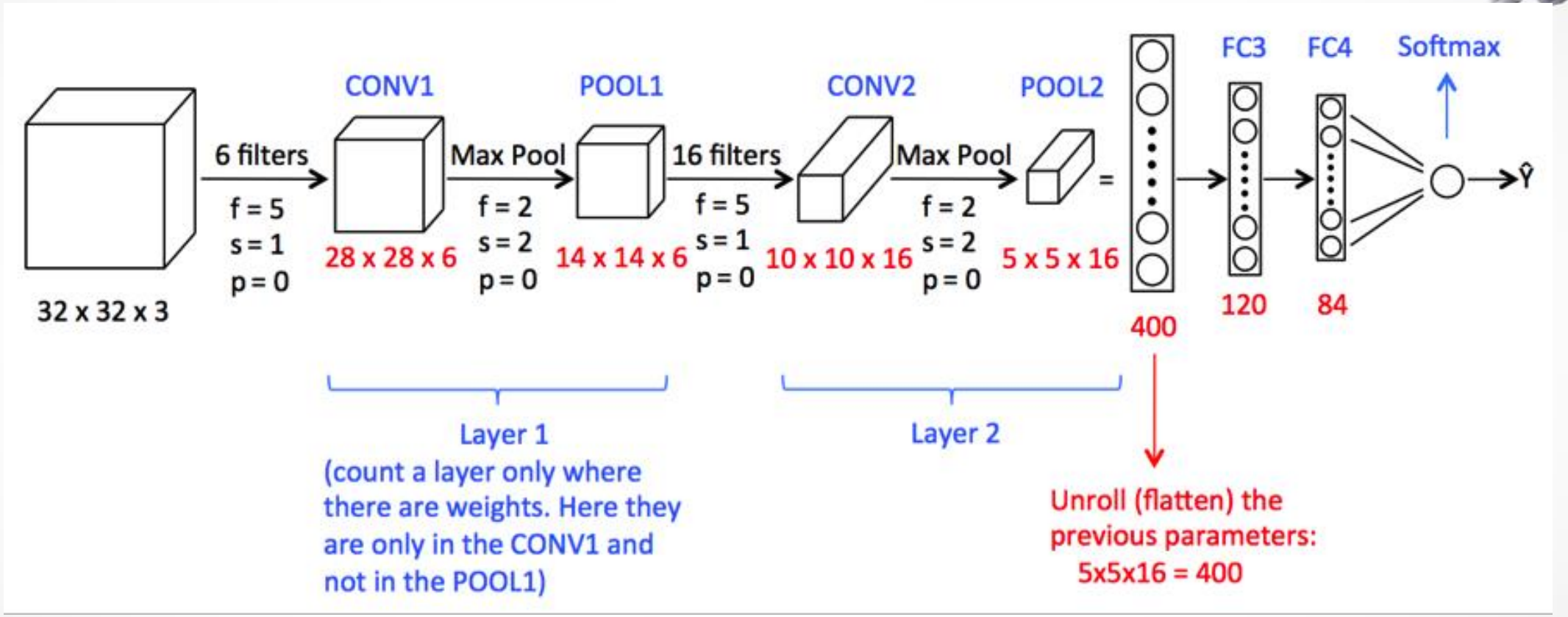



# Convolutional Neural Network



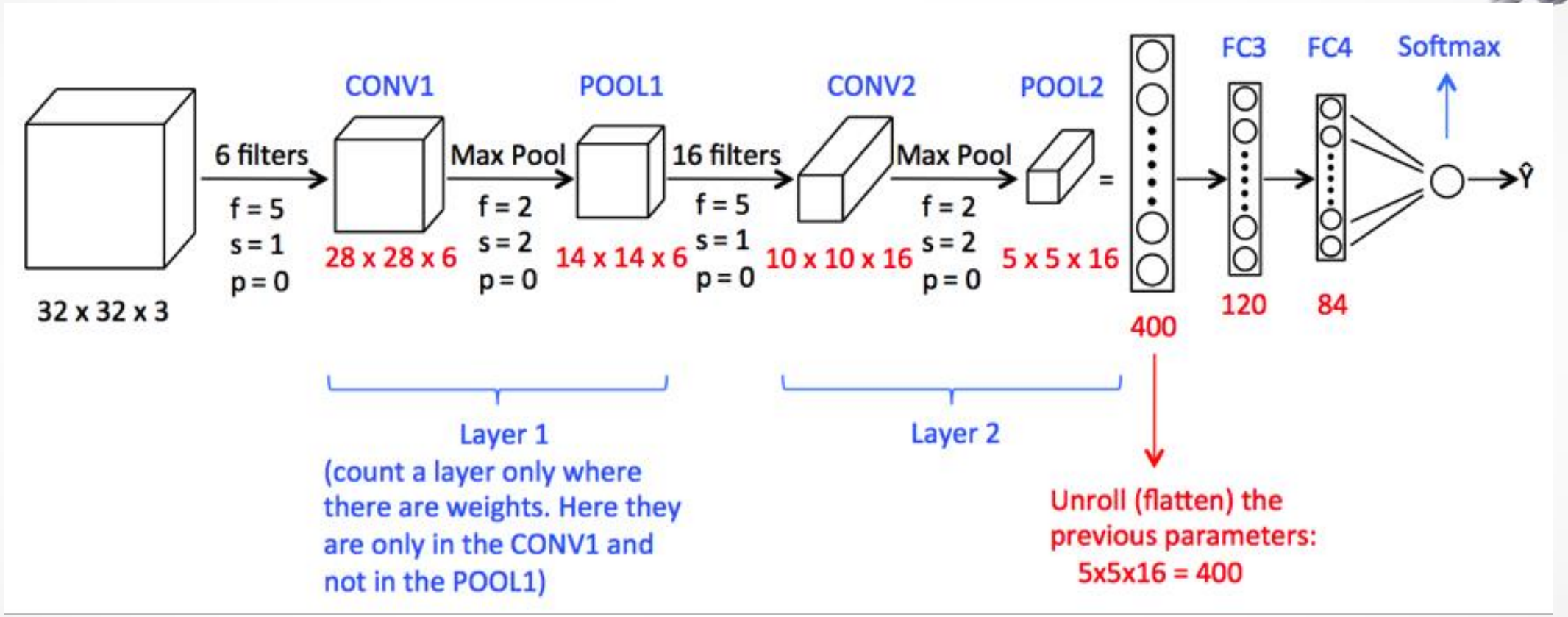

https://medium.com/machine-learning-bites/deeplearning-series-convolutional-neural-networks-a9c2f2ee1524

# Convolutional Neural Network




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

# Convolutional Neural Network

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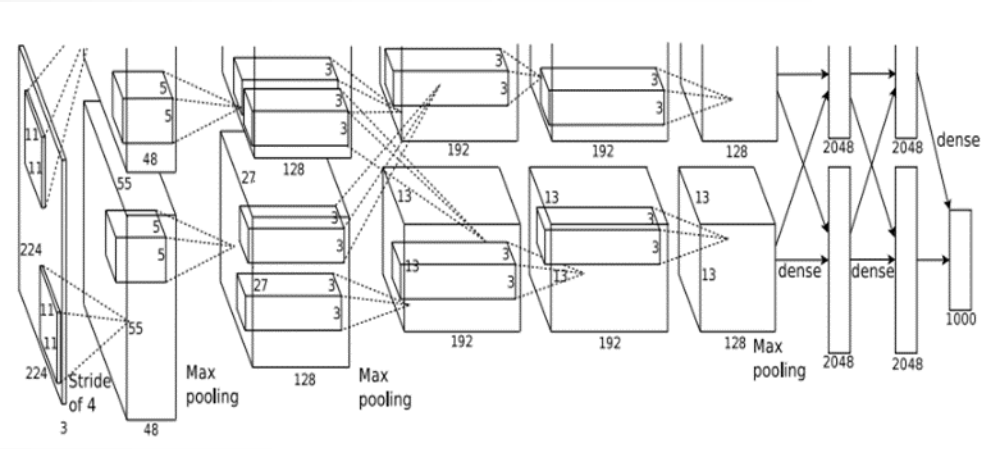
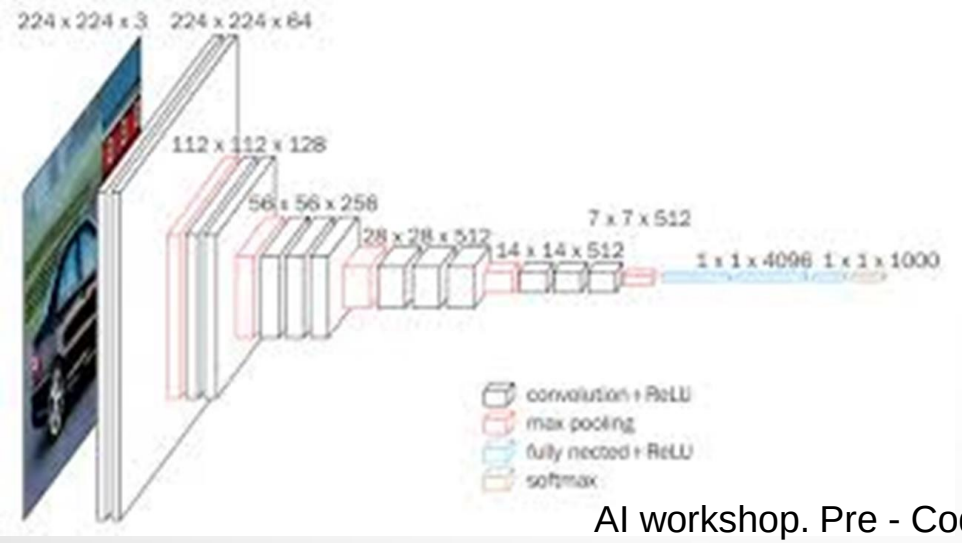
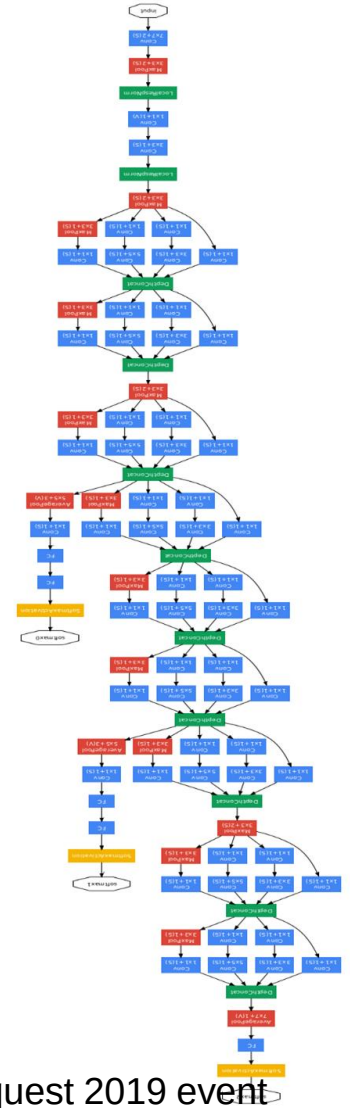
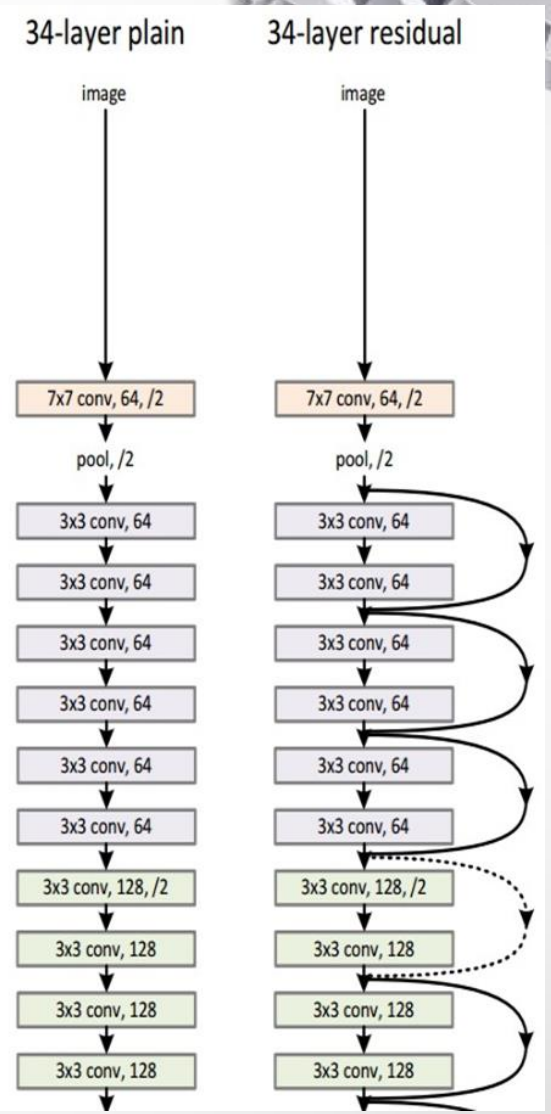
# Convolutional Neural Networks

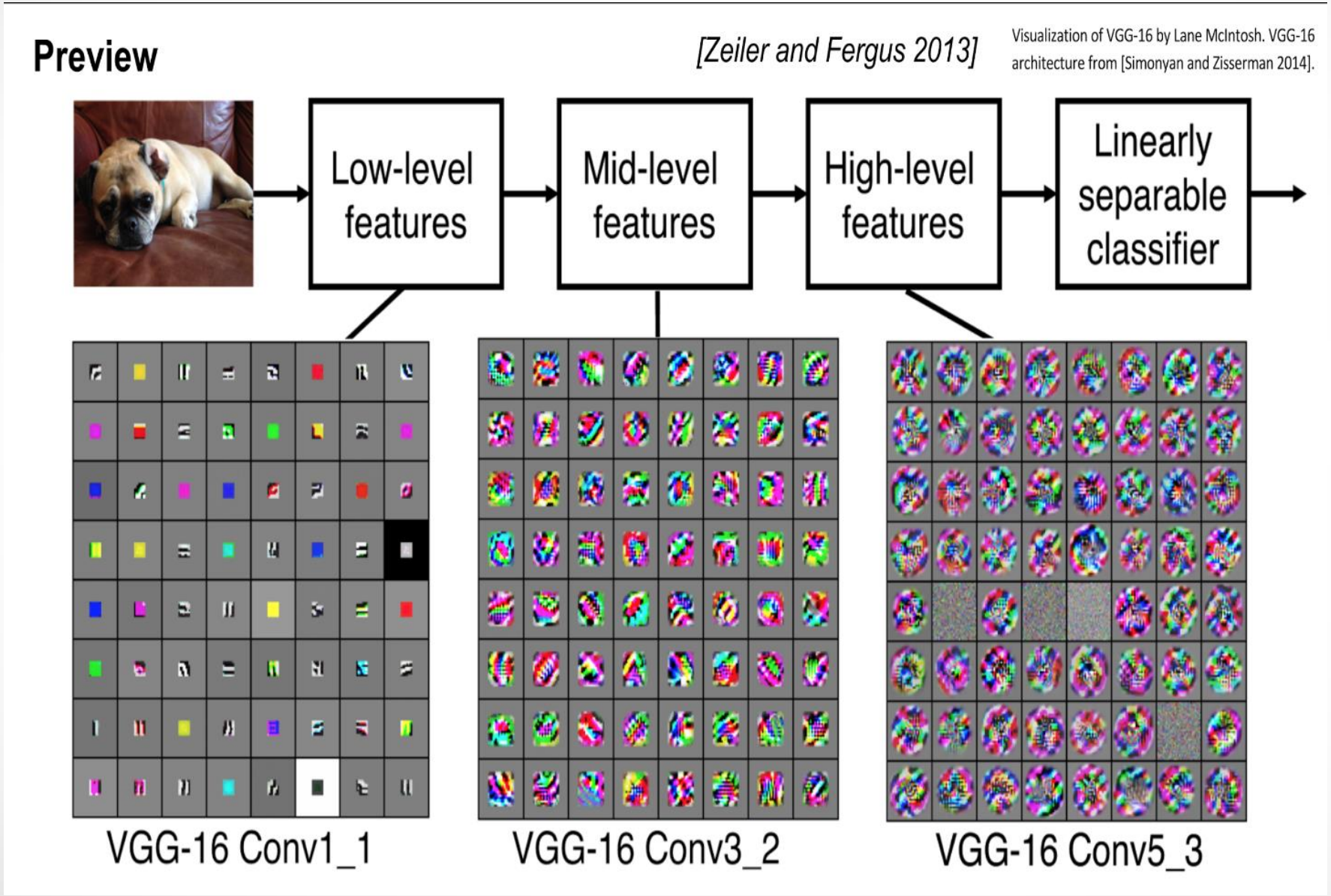


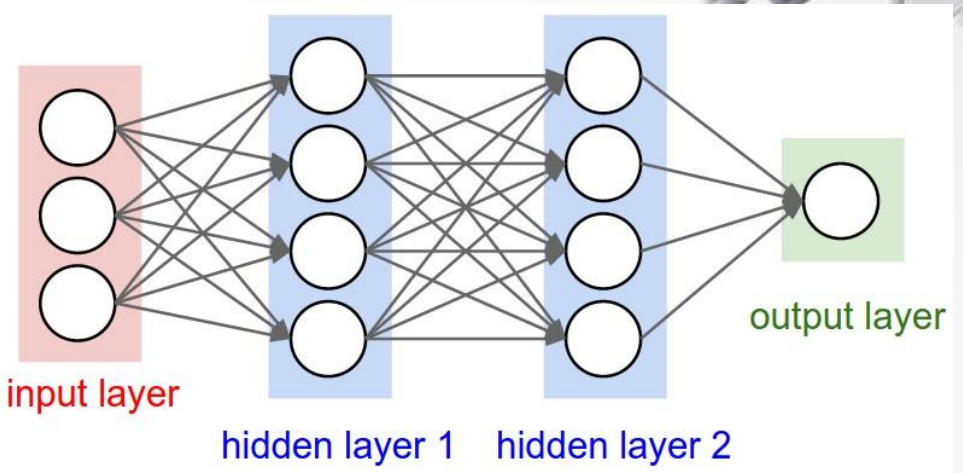


# End-to-End Approach (self learned features)

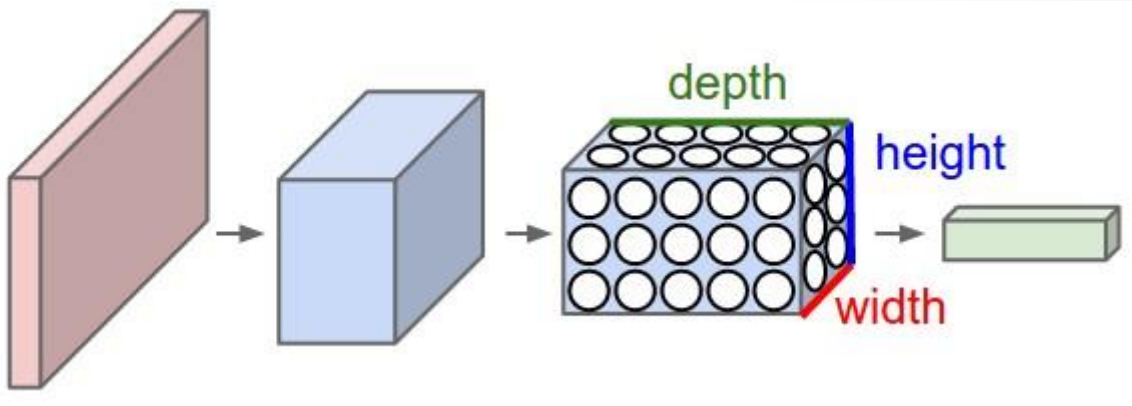


# Recap: MLP & CNN

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

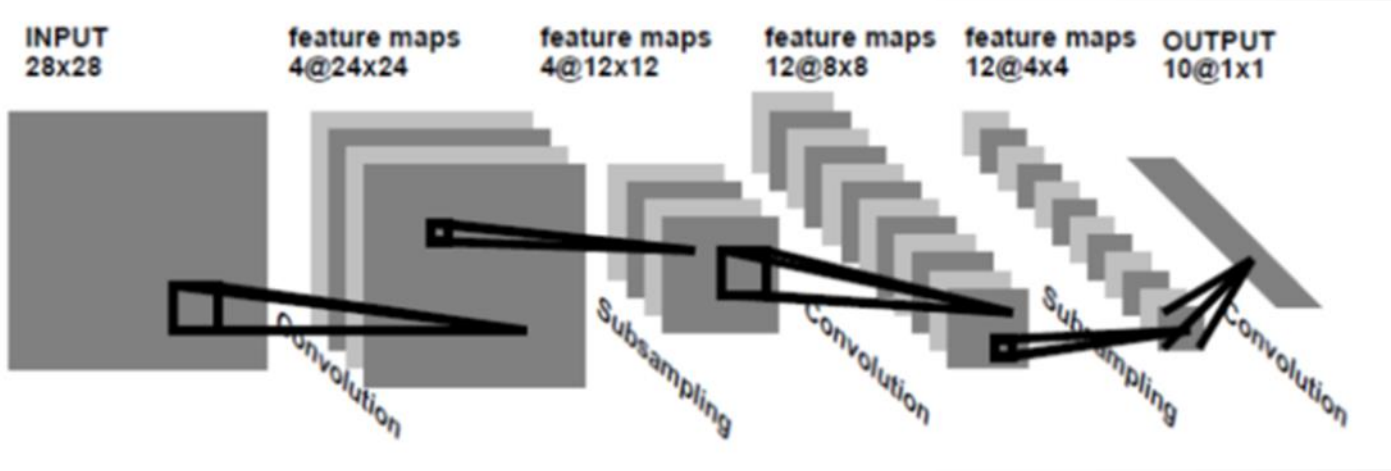



- Convolutional layer
- Pooling layer
- Normalization layer
- Dropout
- Fully connected layer



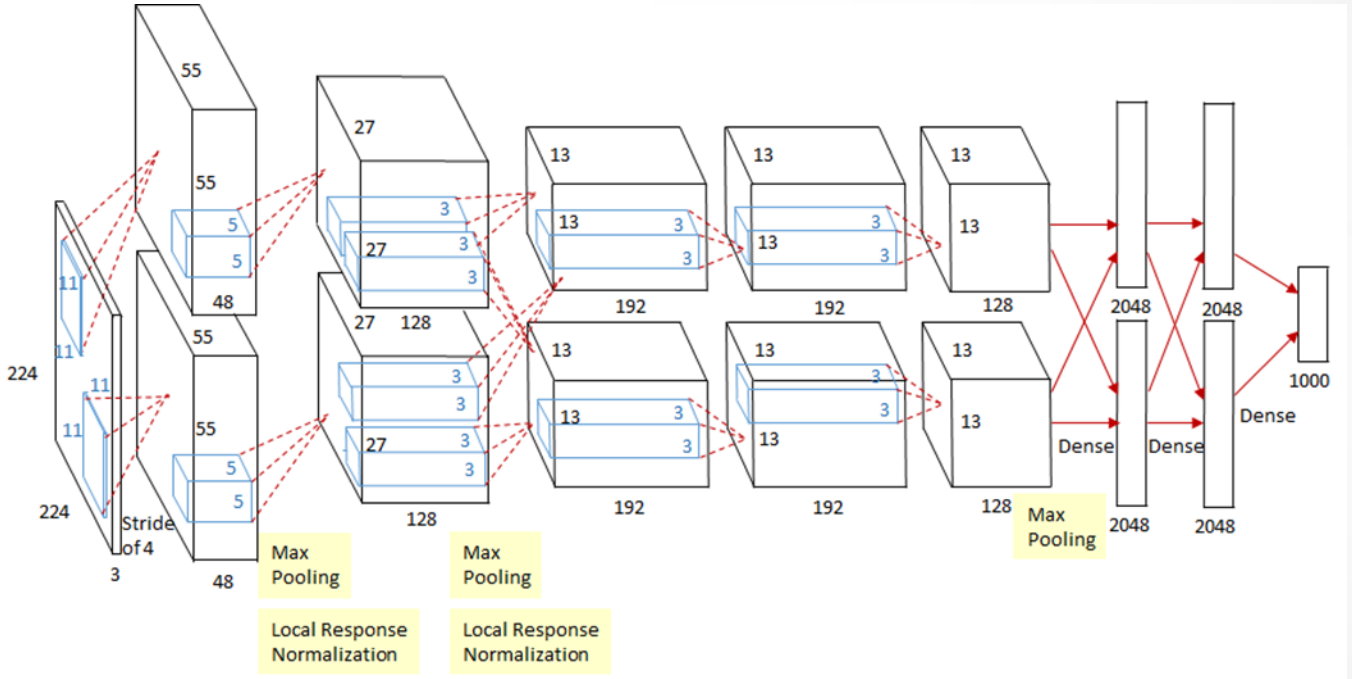
# Deep Learning for Image Classification Tasks

**LeNet**
AlexNet
ZFNet
VGGNet
SPPNet
GoogLeNet / Inception-v1
BN-Inception / Inception-v2
Inception-v3
Inception-v4
Xception
MobileNetV1
ResNet
DenseNet



# Deep Learning for Image Classification Tasks

- LeNet
- **AlexNet**
- ZFNet
- VGGNet
- SPPNet
- GoogLeNet / Inception-v1
- BN-Inception / Inception-v2
- Inception-v3
- Inception-v4
- Xception
- MobileNetV1
- ResNet
- DenseNet



# Deep Learning for Image Classification Tasks

- LeNet
- AlexNet
- **ZFNet**
- VGGNet
- SPPNet
- GoogLeNet / Inception-v1
- BN-Inception / Inception-v2
- Inception-v3
- Inception-v4
- Xception
- MobileNetV1
- ResNet
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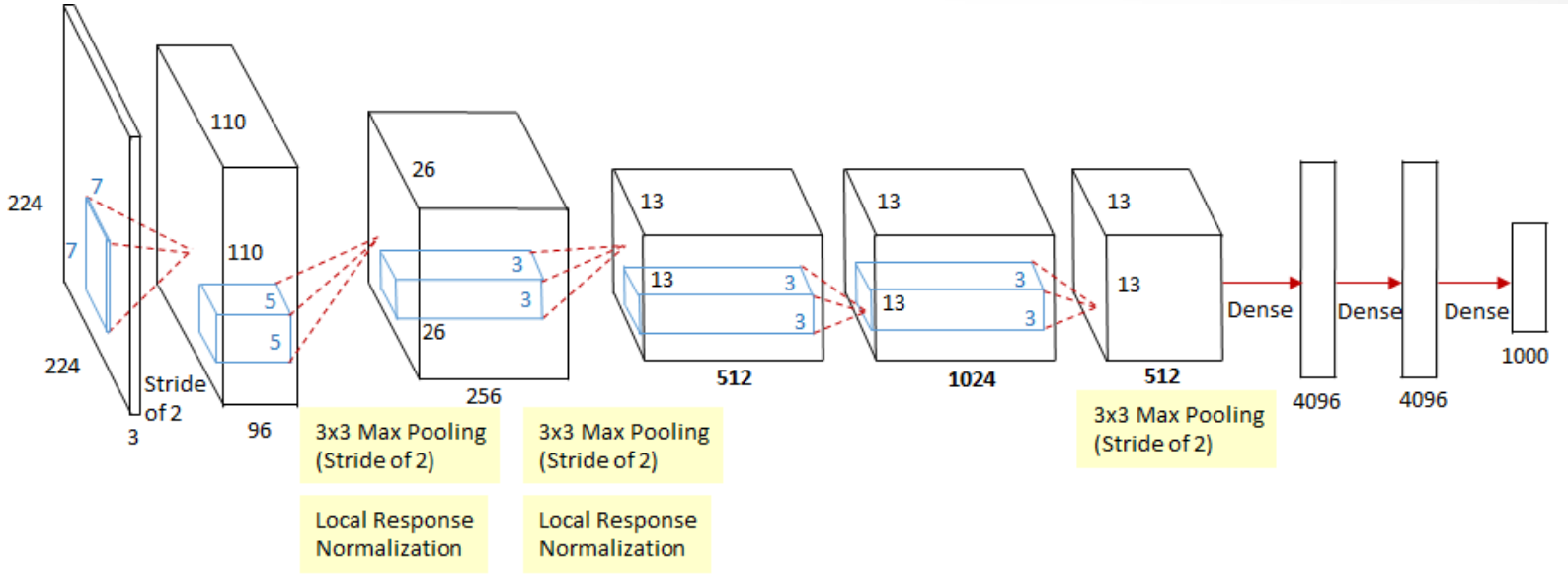

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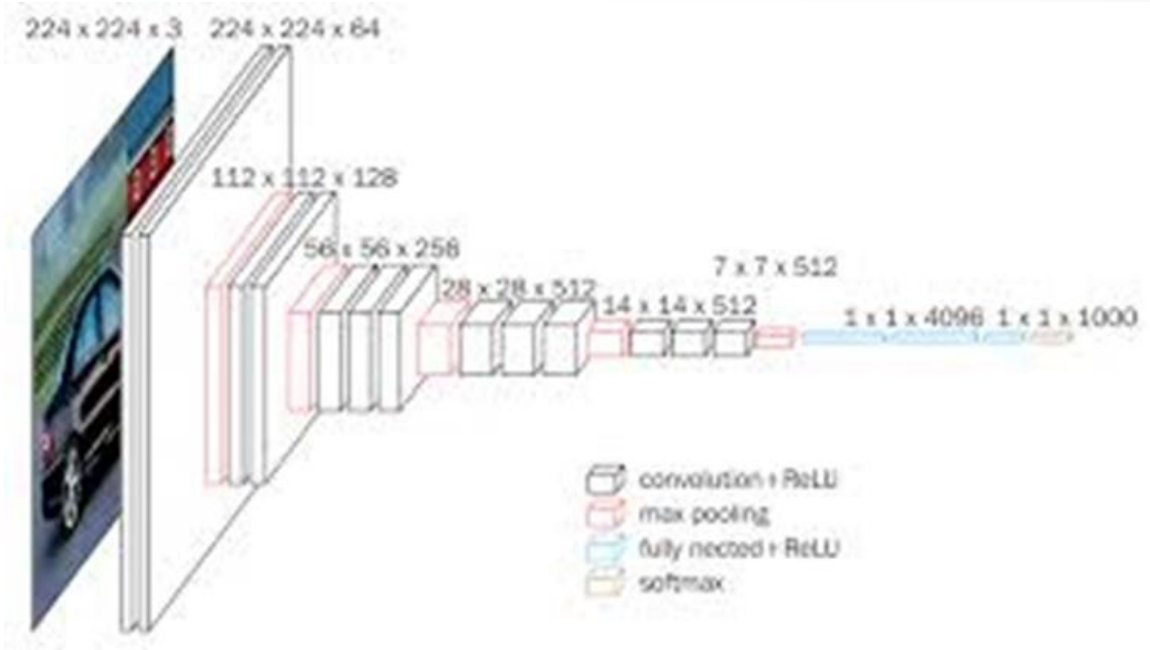

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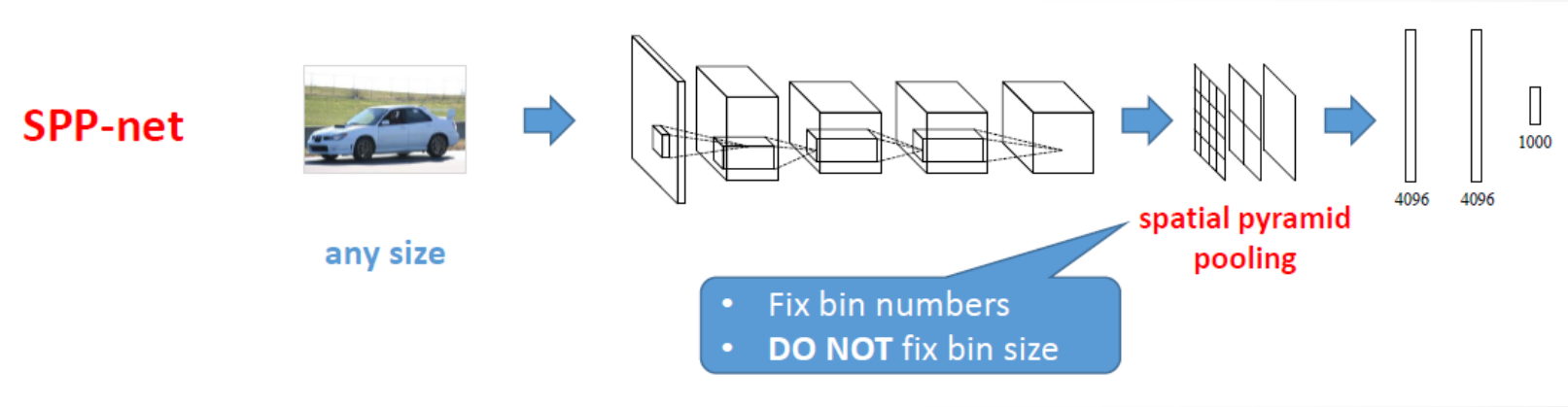

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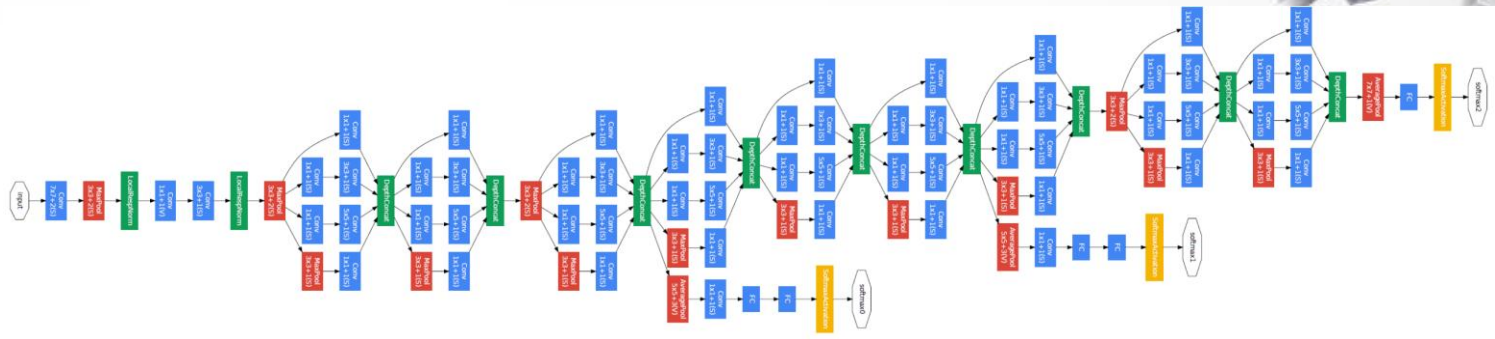

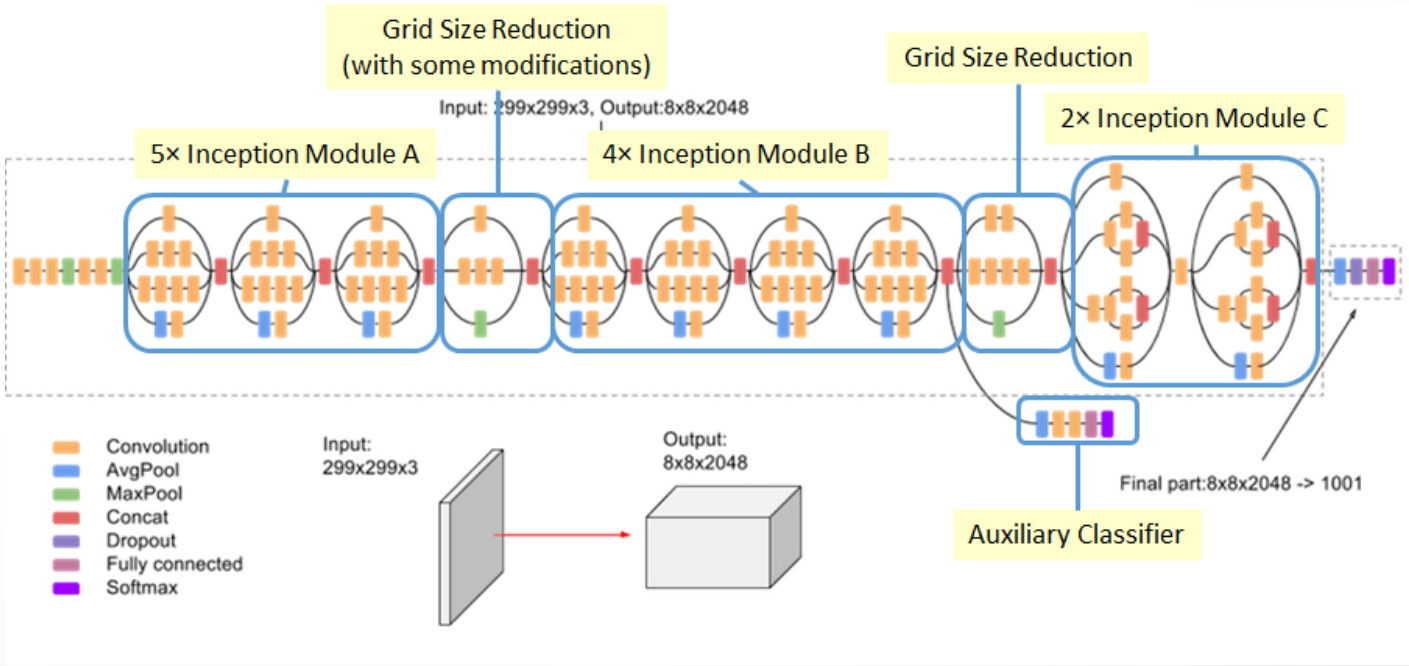

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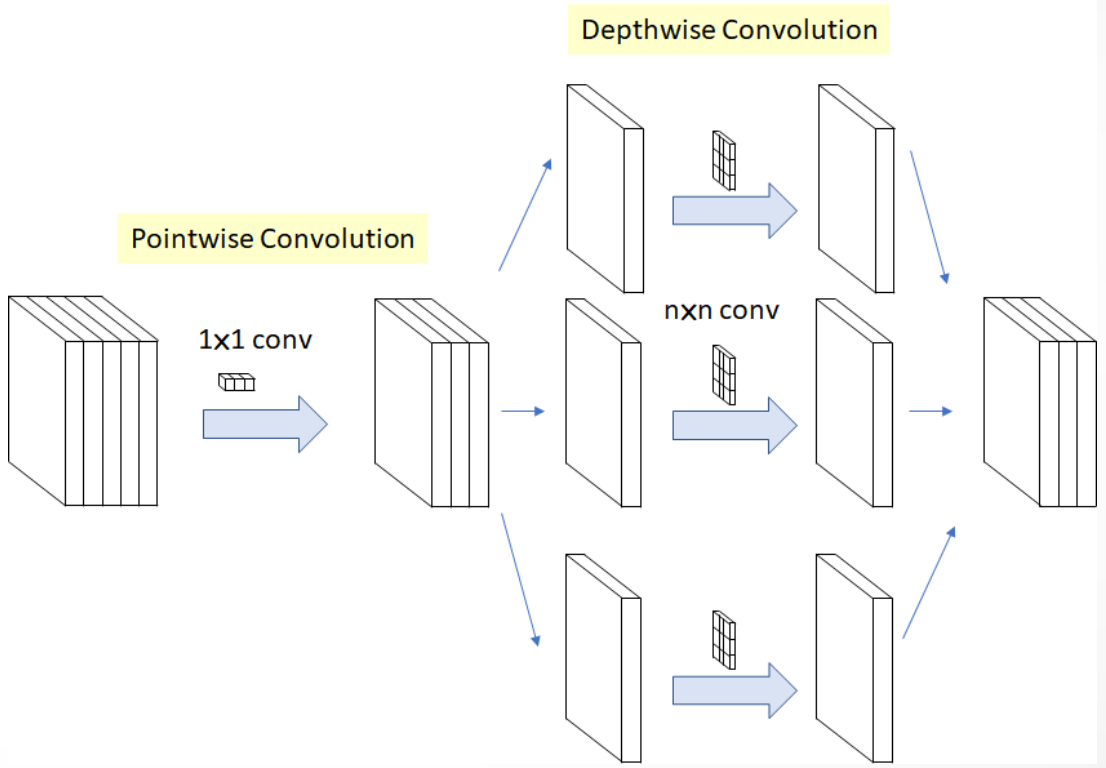

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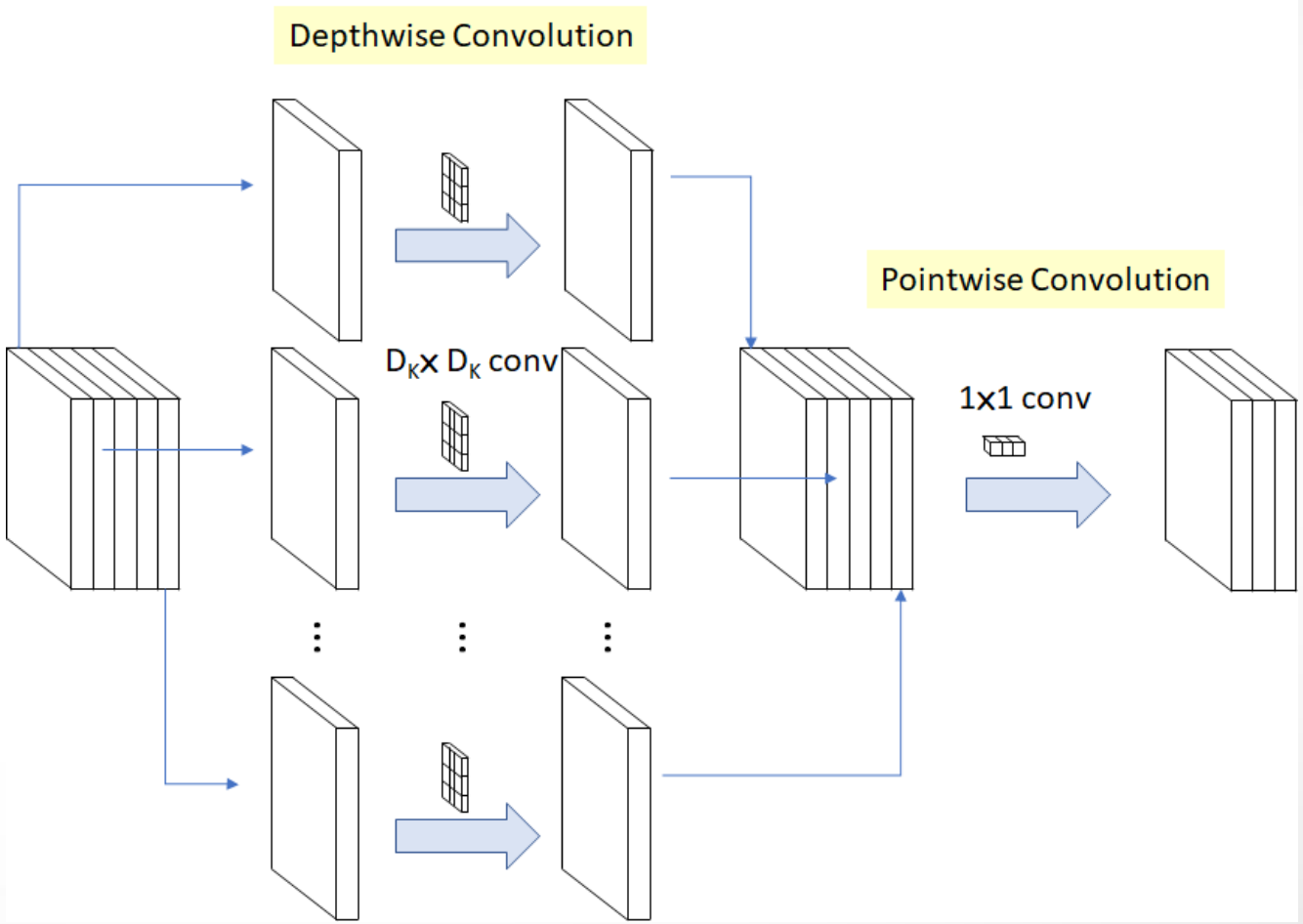

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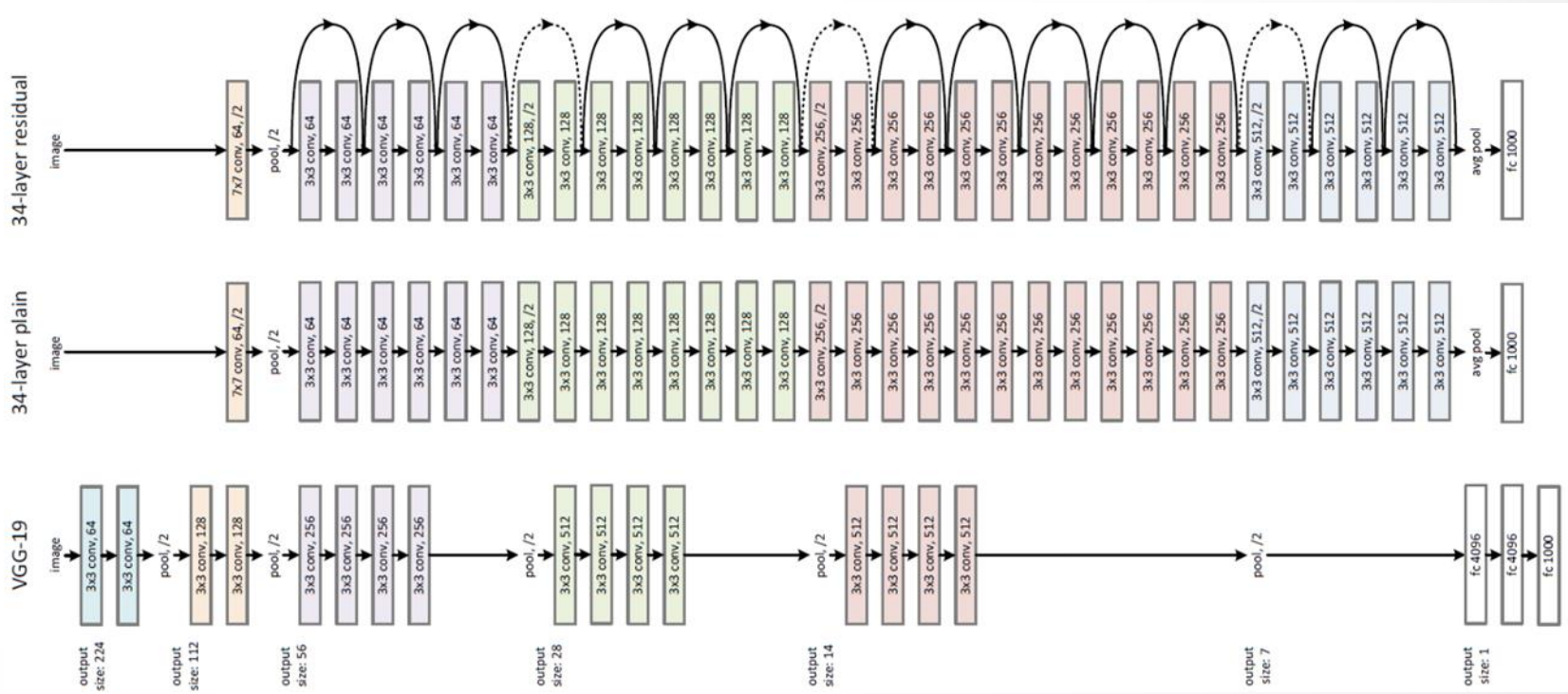

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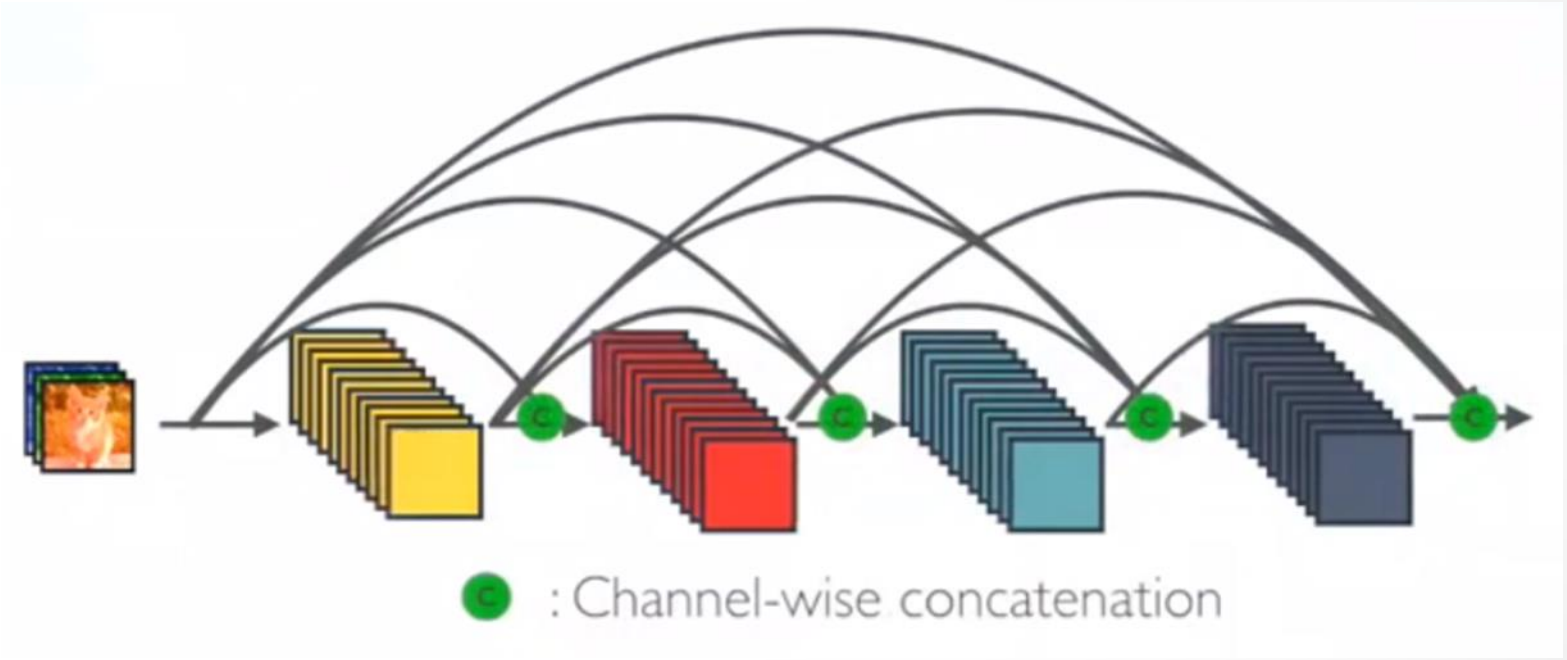
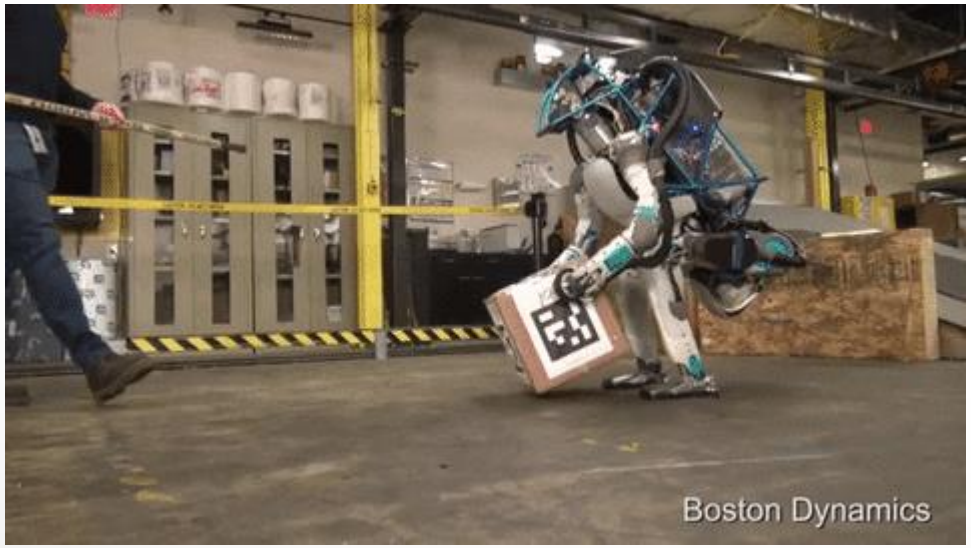


# Some Characteristics of CNN

- 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

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  - The availability of data
  - The progress of hardware, software
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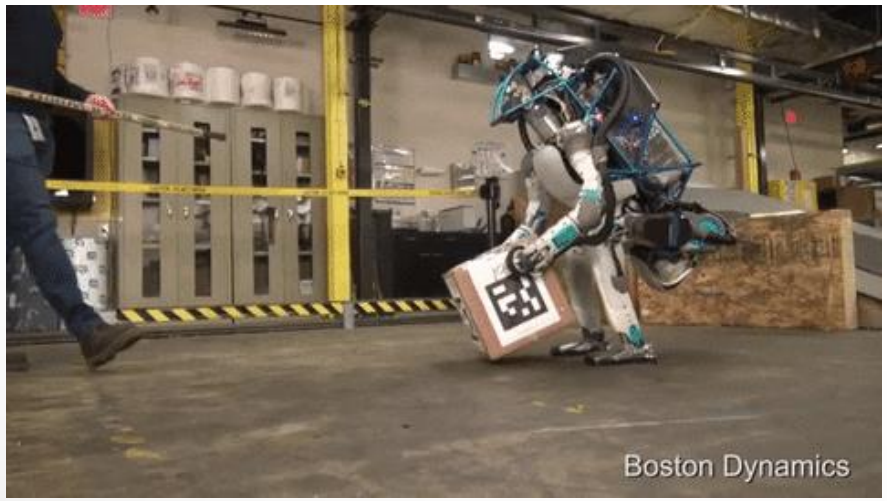


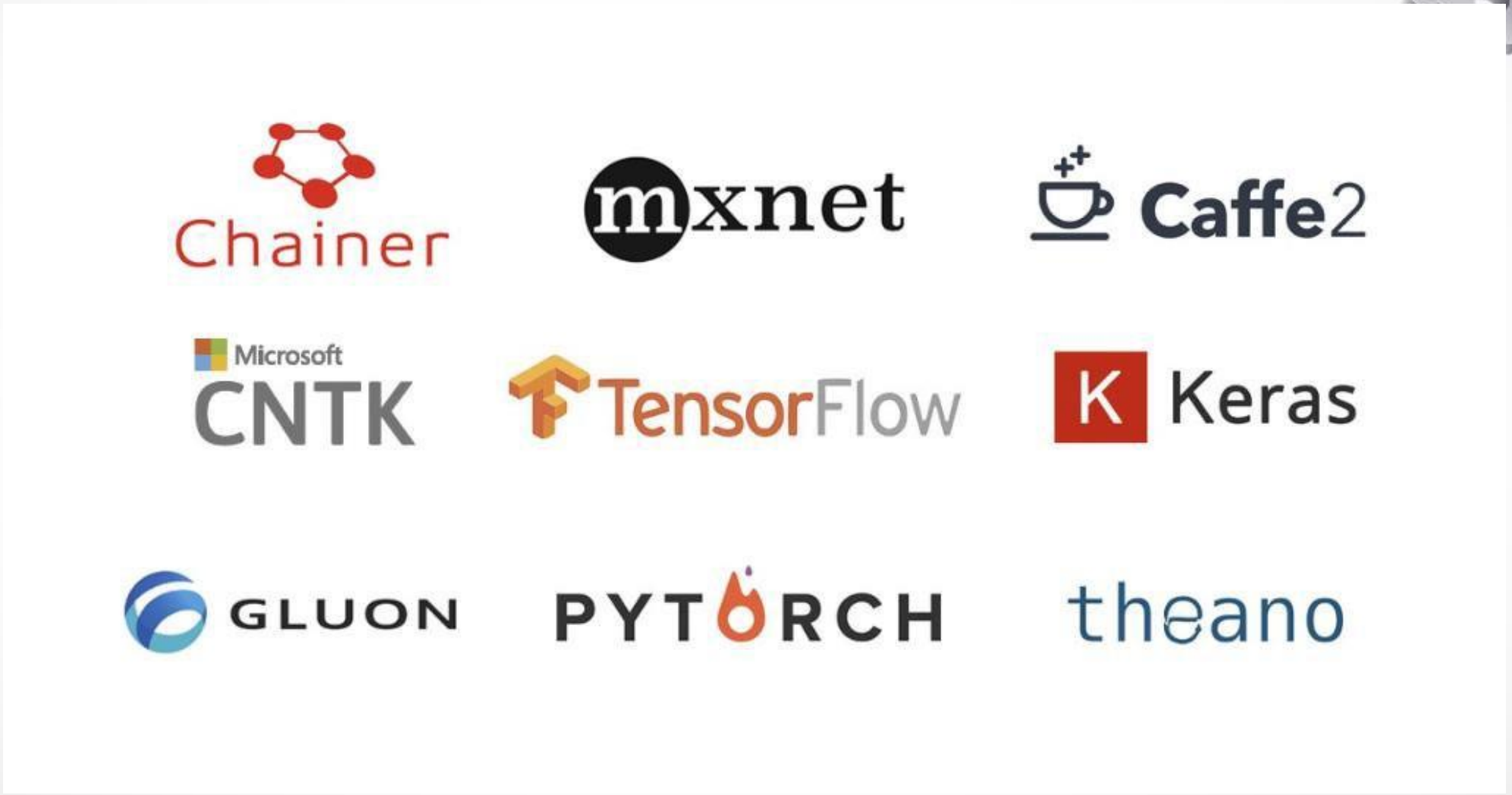

## Deep Learning

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

## Challenges

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

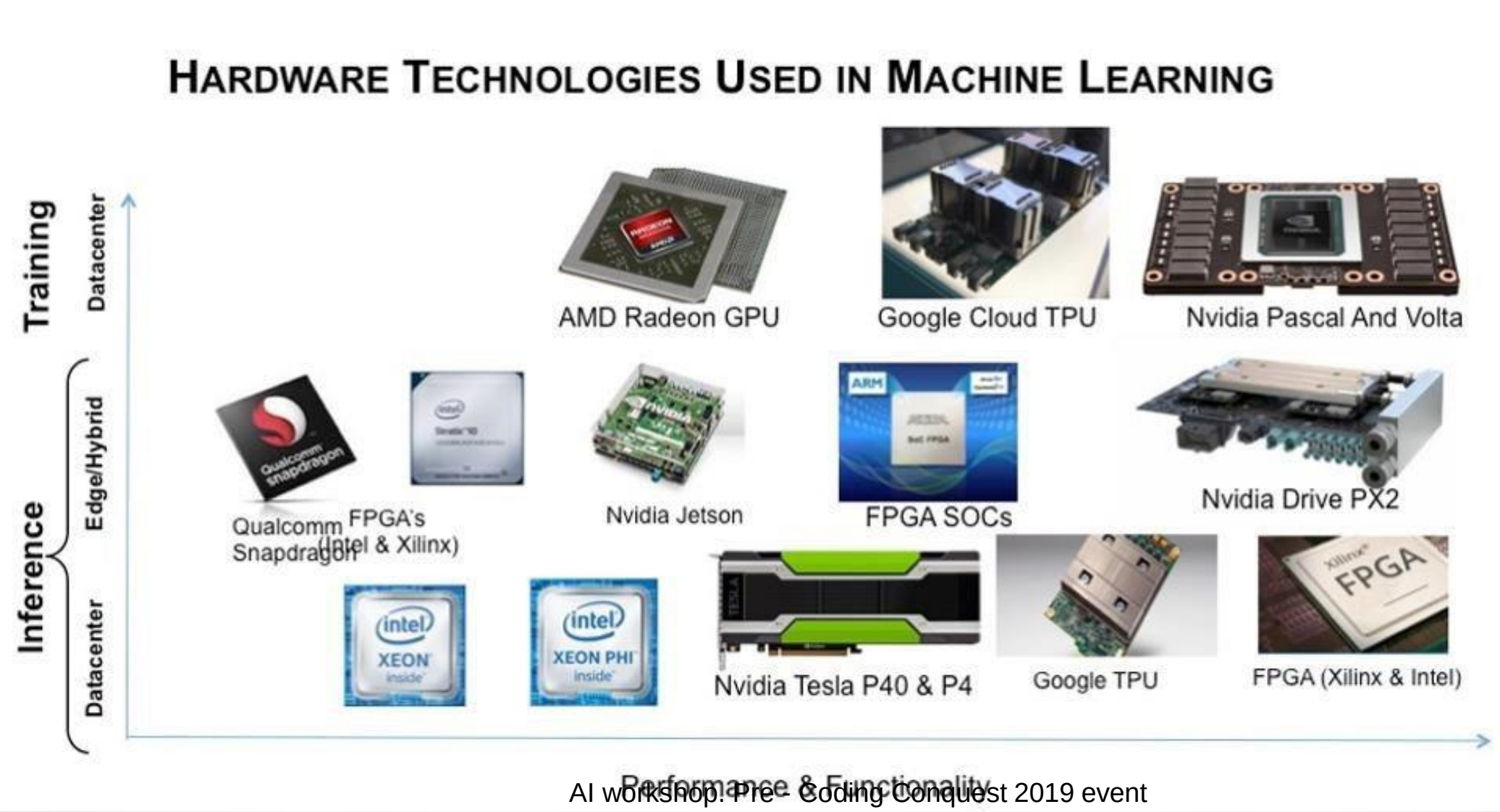
# Deep Learning Frameworks



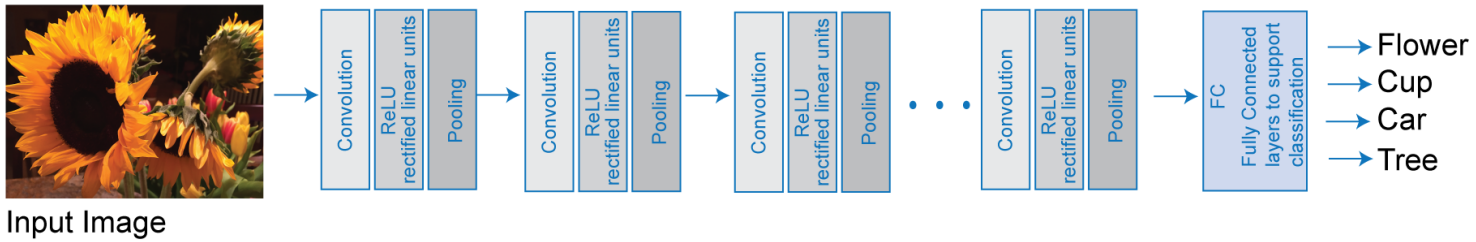
# Hardware Landscape

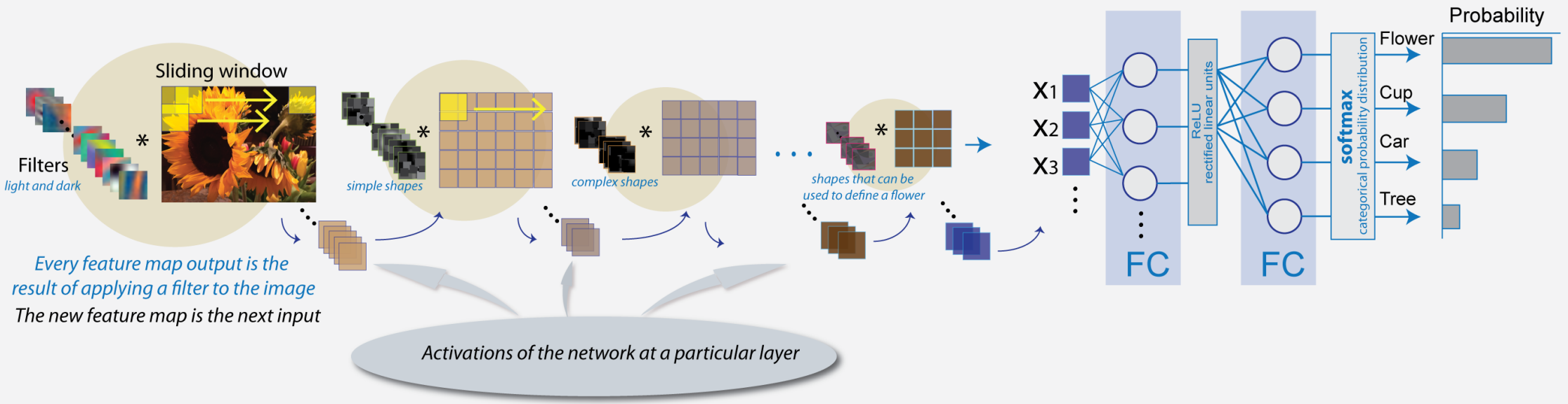
- There are four major types of technology that can be used to accelerate the training and use of deep neural networks:
- CPUs,
- GPUs,
- Field-programmable gate arrays (FPGAs), and
- Application-specific integrated circuits (ASICs).

# 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