Hardware Architectures for Deep Neural Networks

MICRO Tutorial

October 16, 2016

Website: http://eyeriss.mit.edu/tutorial.html

Massachusetts Institute of Technology

NVIDIA®

Speakers

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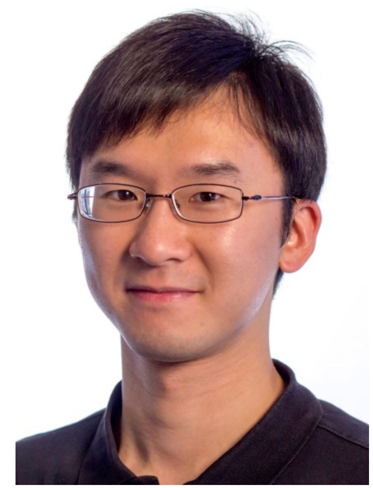

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PhD Candidate

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Outline

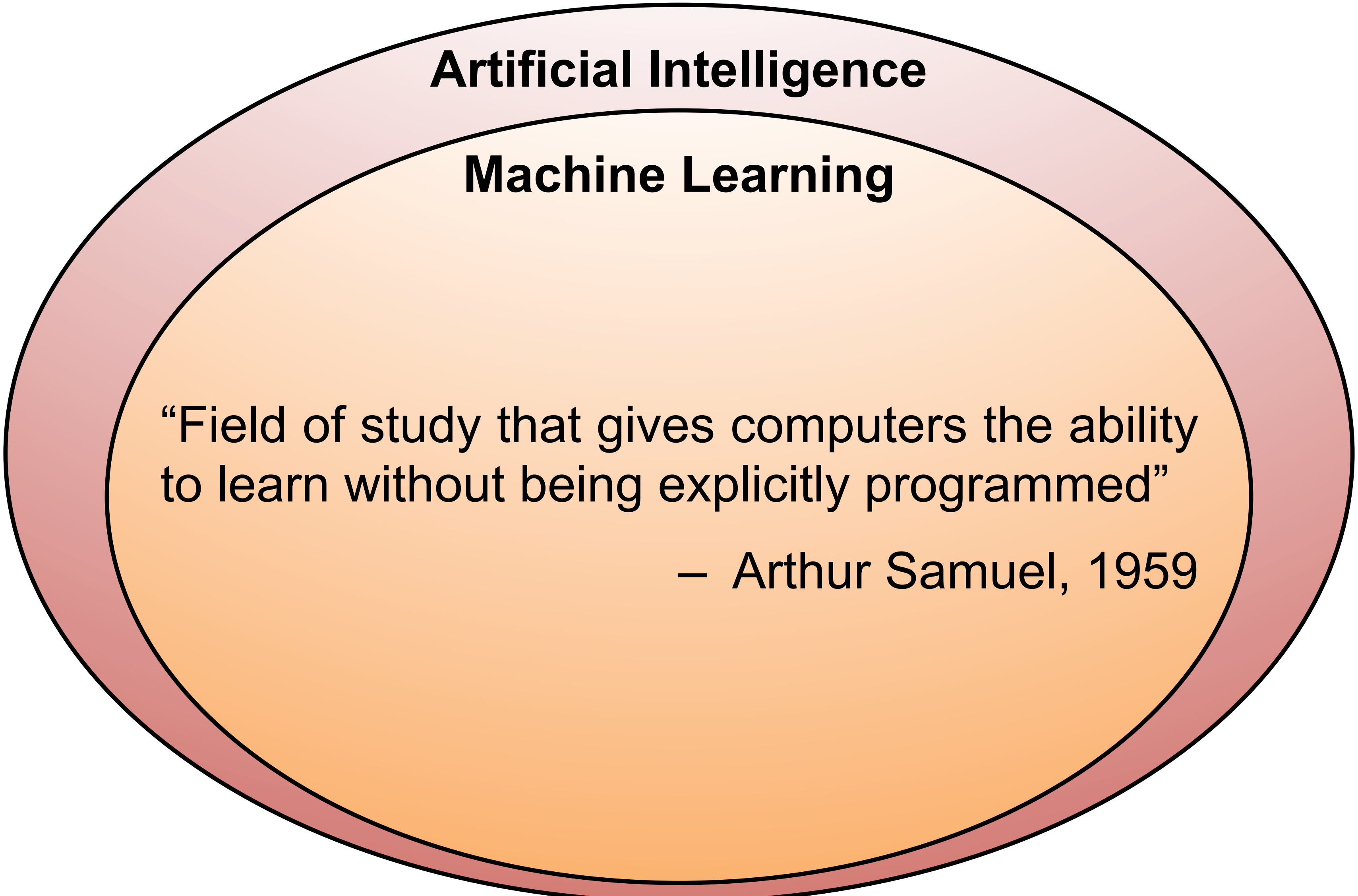
- Overview of Deep Neural Networks
- DNN Development Resources
- Survey of DNN Computation
- DNN Accelerators
- Network Optimizations
- Benchmarking Metrics for Evaluation
- DNN Training

Participant Takeaways

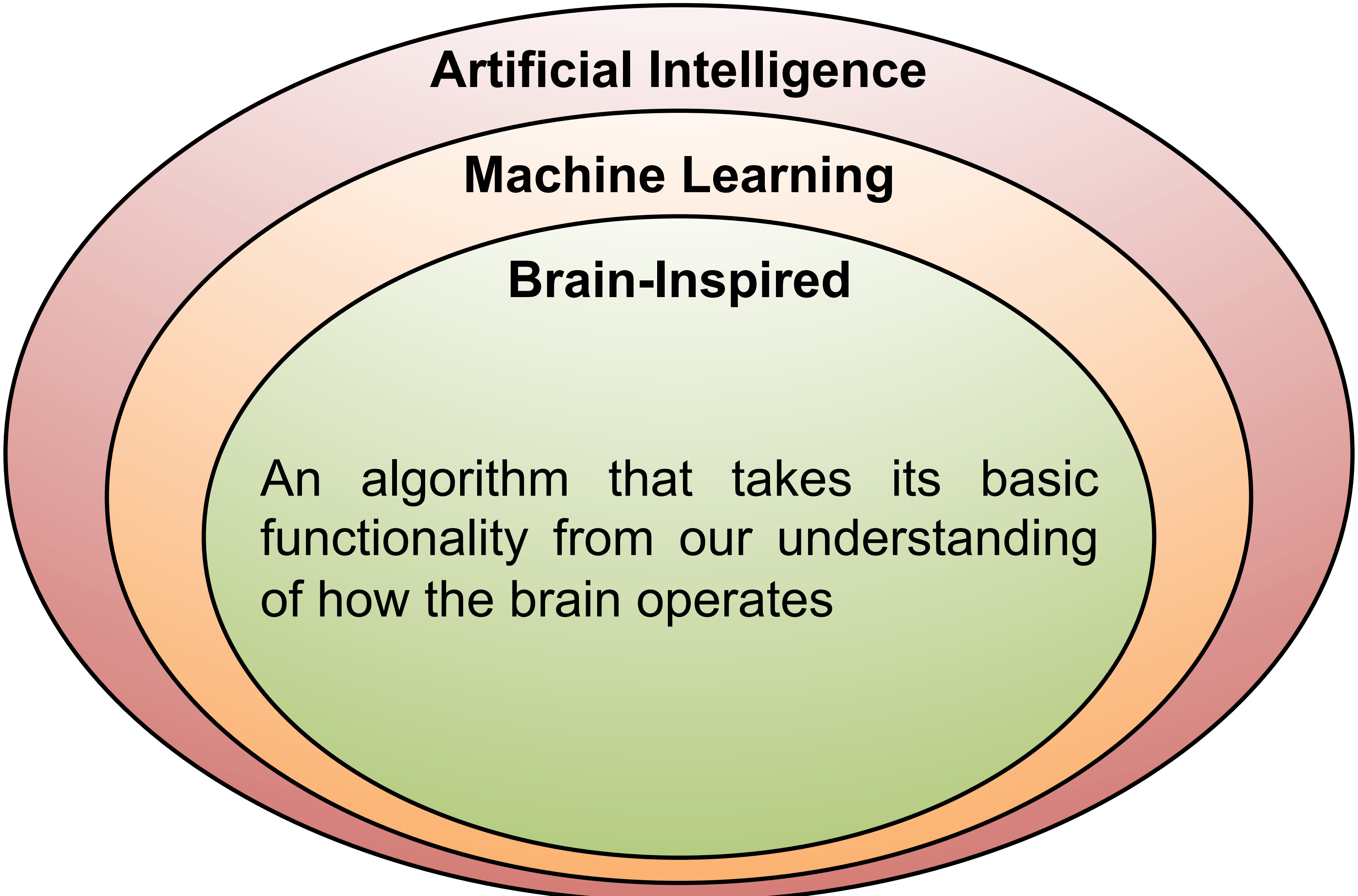
- Understand the key design considerations for DNNs
- Be able to evaluate different implementations of DNN with benchmarks and comparison metrics
- Understand the tradeoffs between various architectures and platforms
- Assess the utility of various optimization approaches
- Understand recent implementation trends and opportunities

Background of Deep Neural Networks

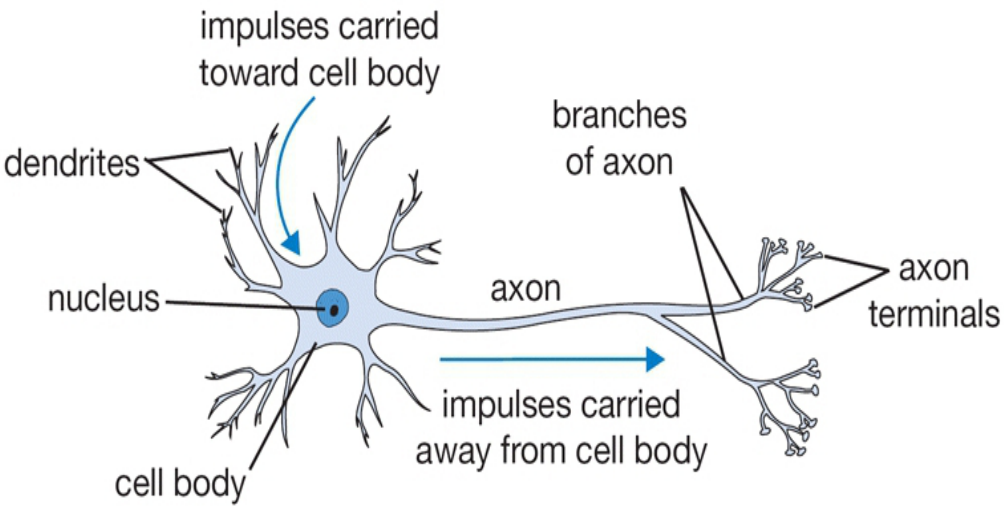
AI and Machine Learning

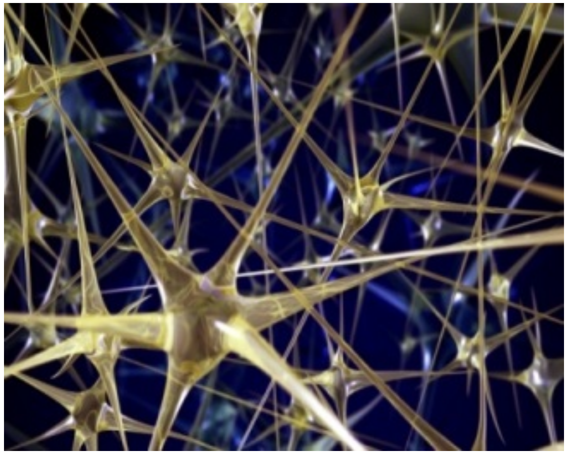


Brain-Inspired Machine Learning



How Does the Brain Work?

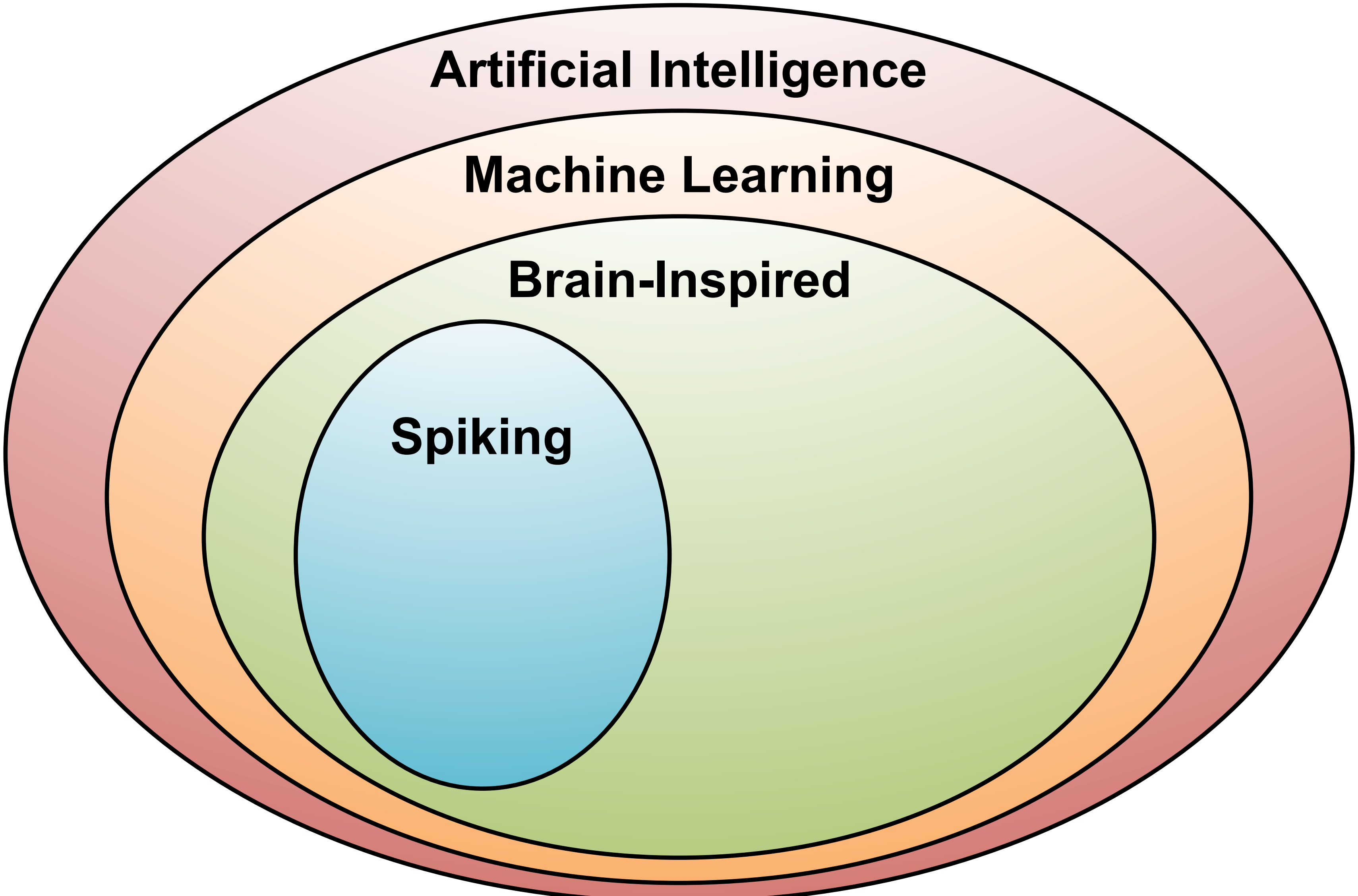




- The basic computational unit of the brain is a **neuron**
  → 86B neurons in the brain
- Neurons are connected with nearly **10^{14} – 10^{15} synapses**
- Neurons receive input signal from **dendrites** and produce output signal along **axon**, which interact with the dendrites of other neurons via **synaptic weights**
- Synaptic weights – learnable & control influence strength

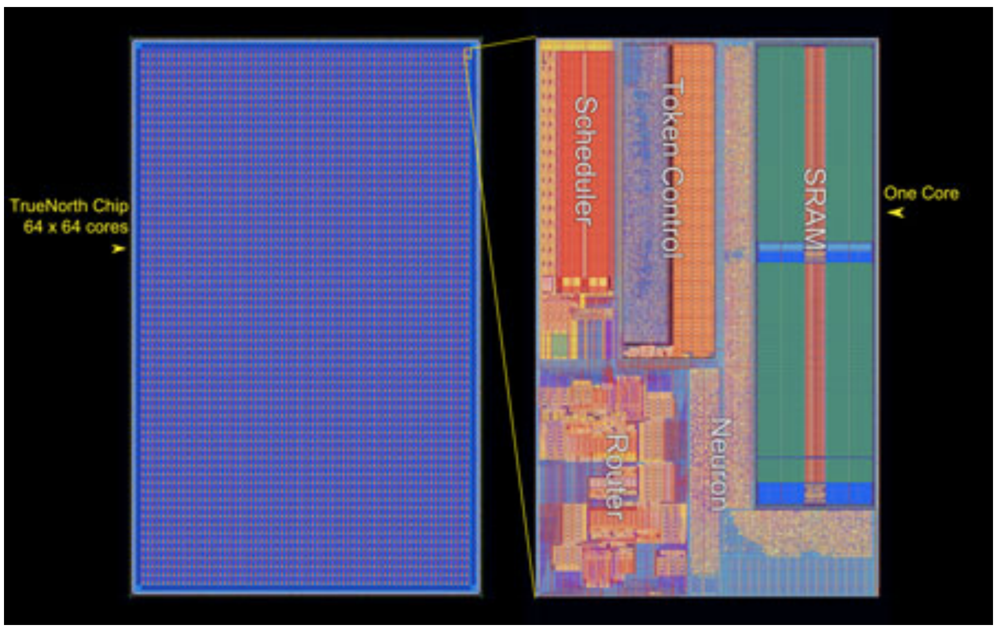
Image Source: Stanford

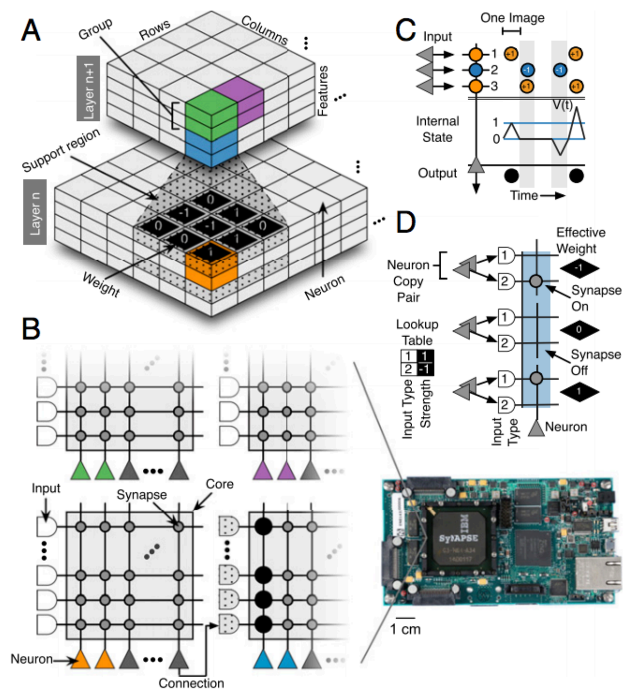
Spiking-based Machine Learning



Spiking Architecture

- Brain-inspired
- Integrate and fire
- Example: IBM TrueNorth

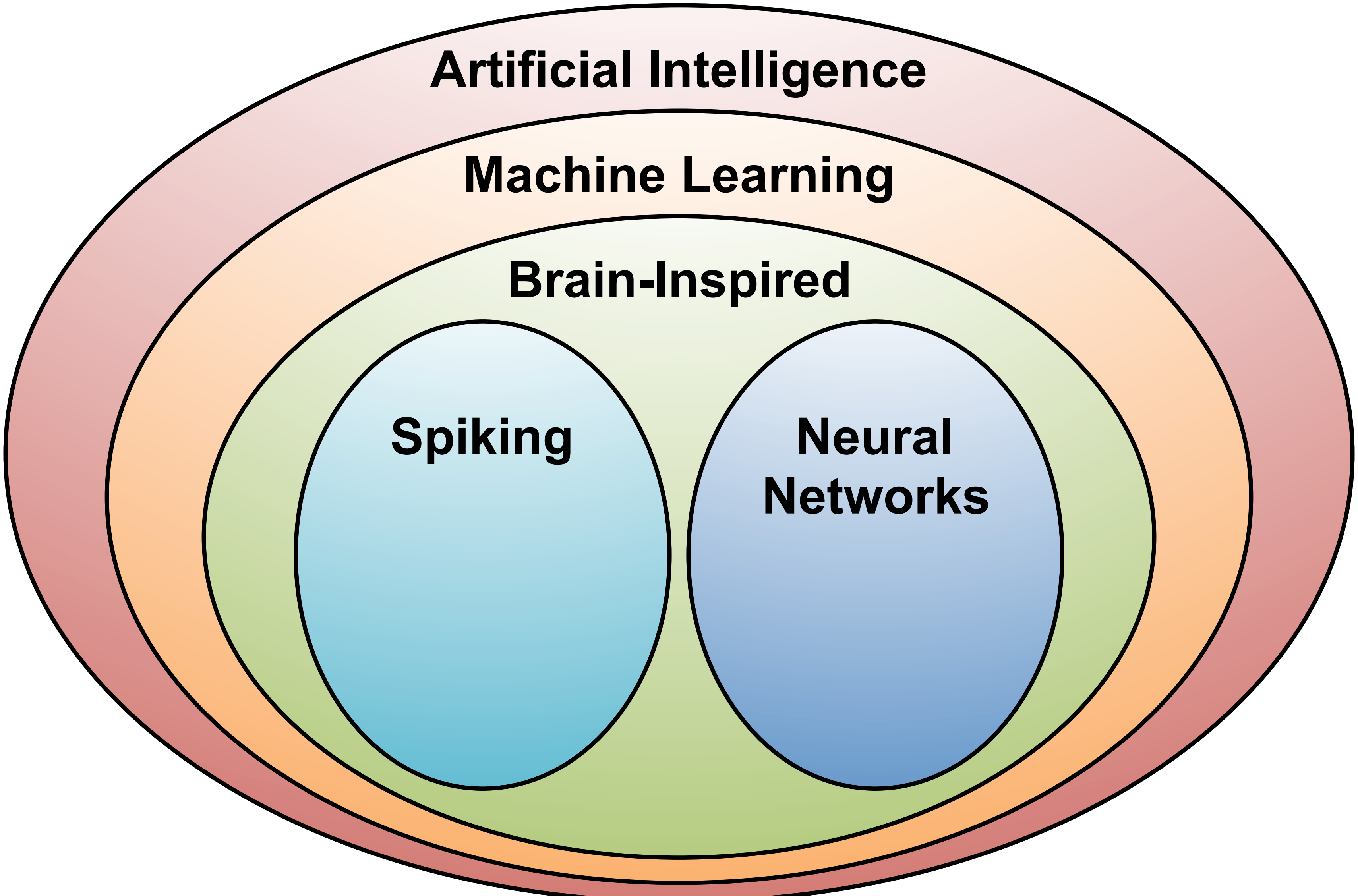




[Merolla et al., Science 2014; Esser et al., PNAS 2016]

http://www.research.ibm.com/articles/brain-chip.shtml

Machine Learning with Neural Networks



Neural Networks: Weighted Sum

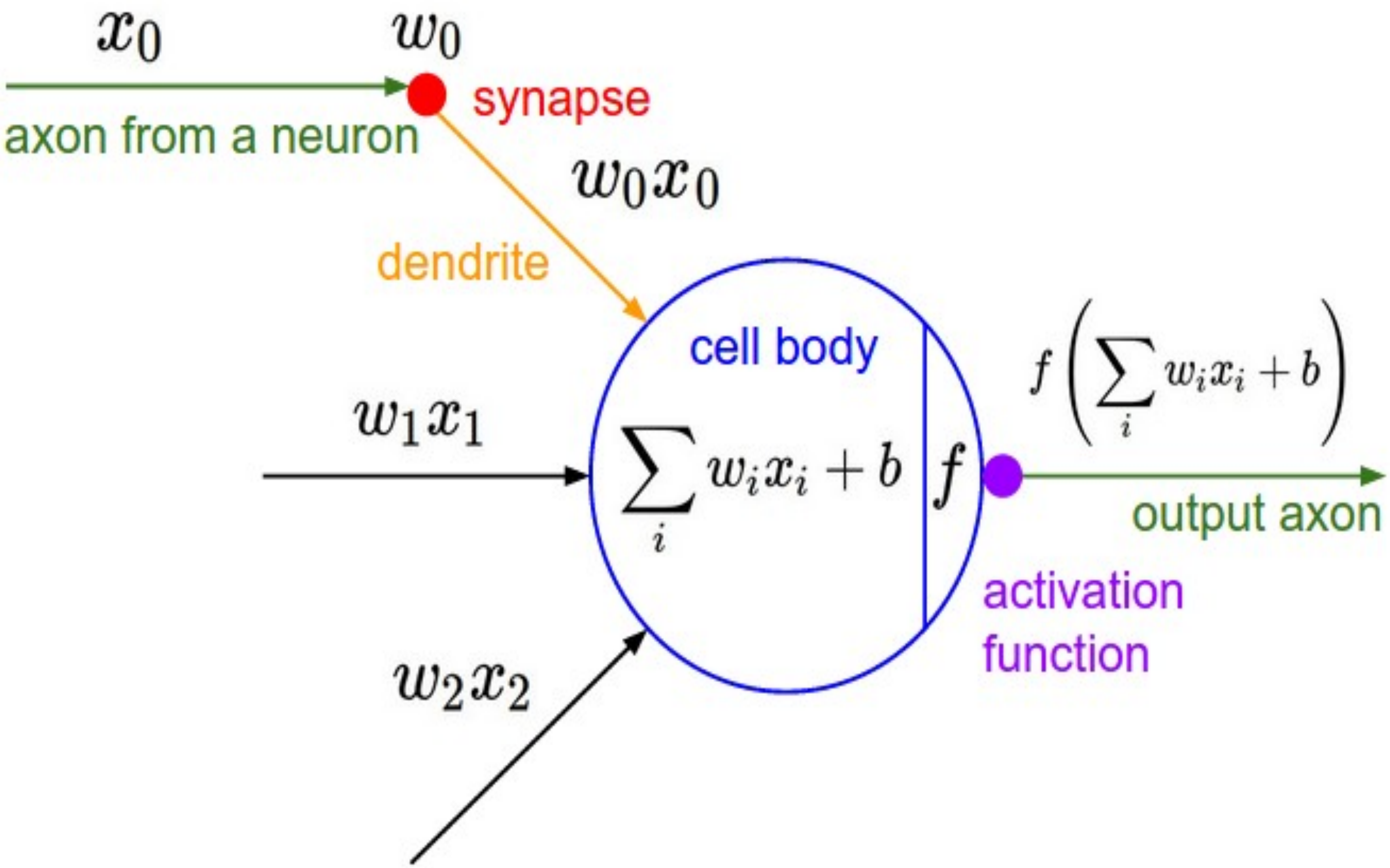


Image Source: Stanford

Many Weighted Sums

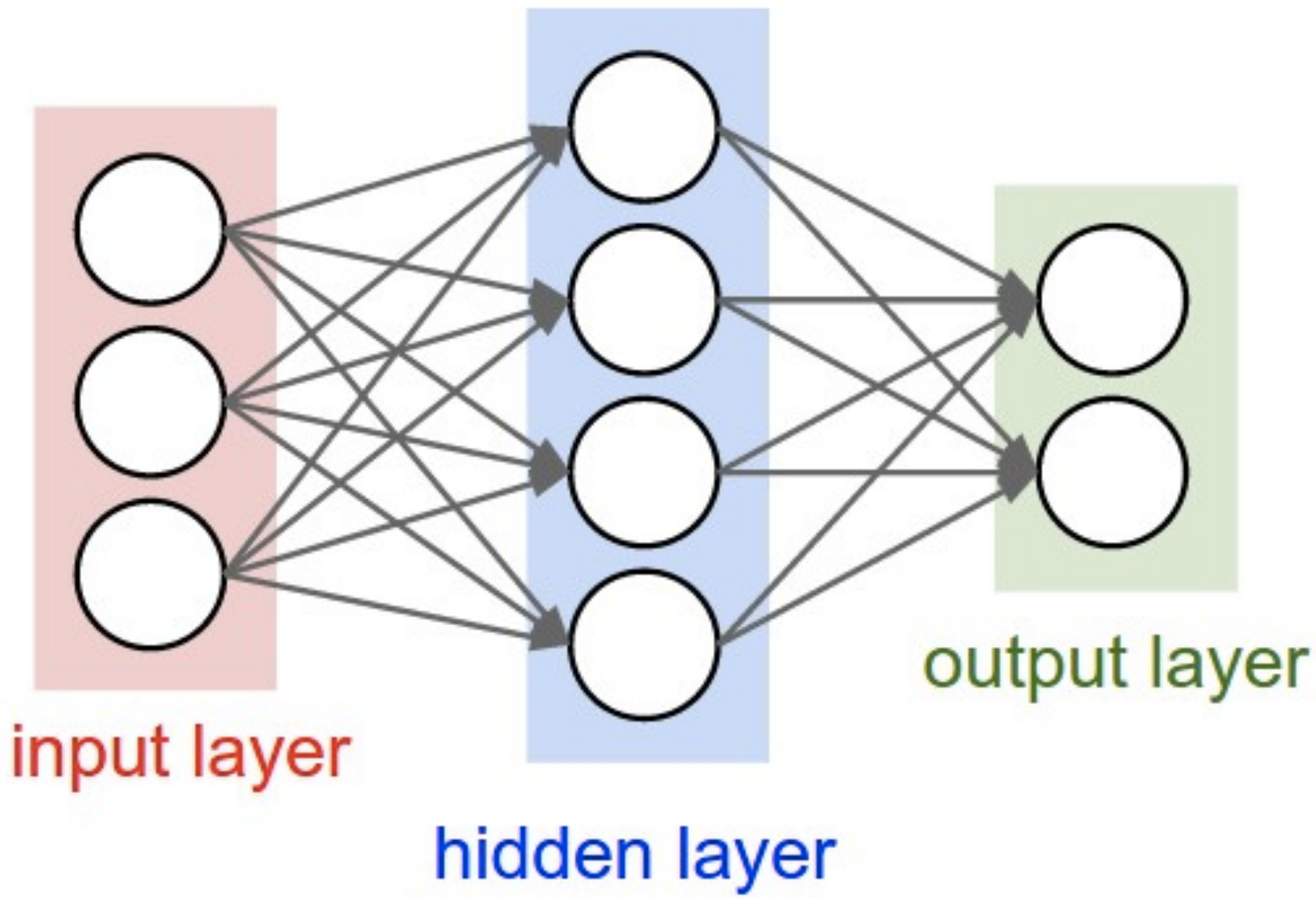
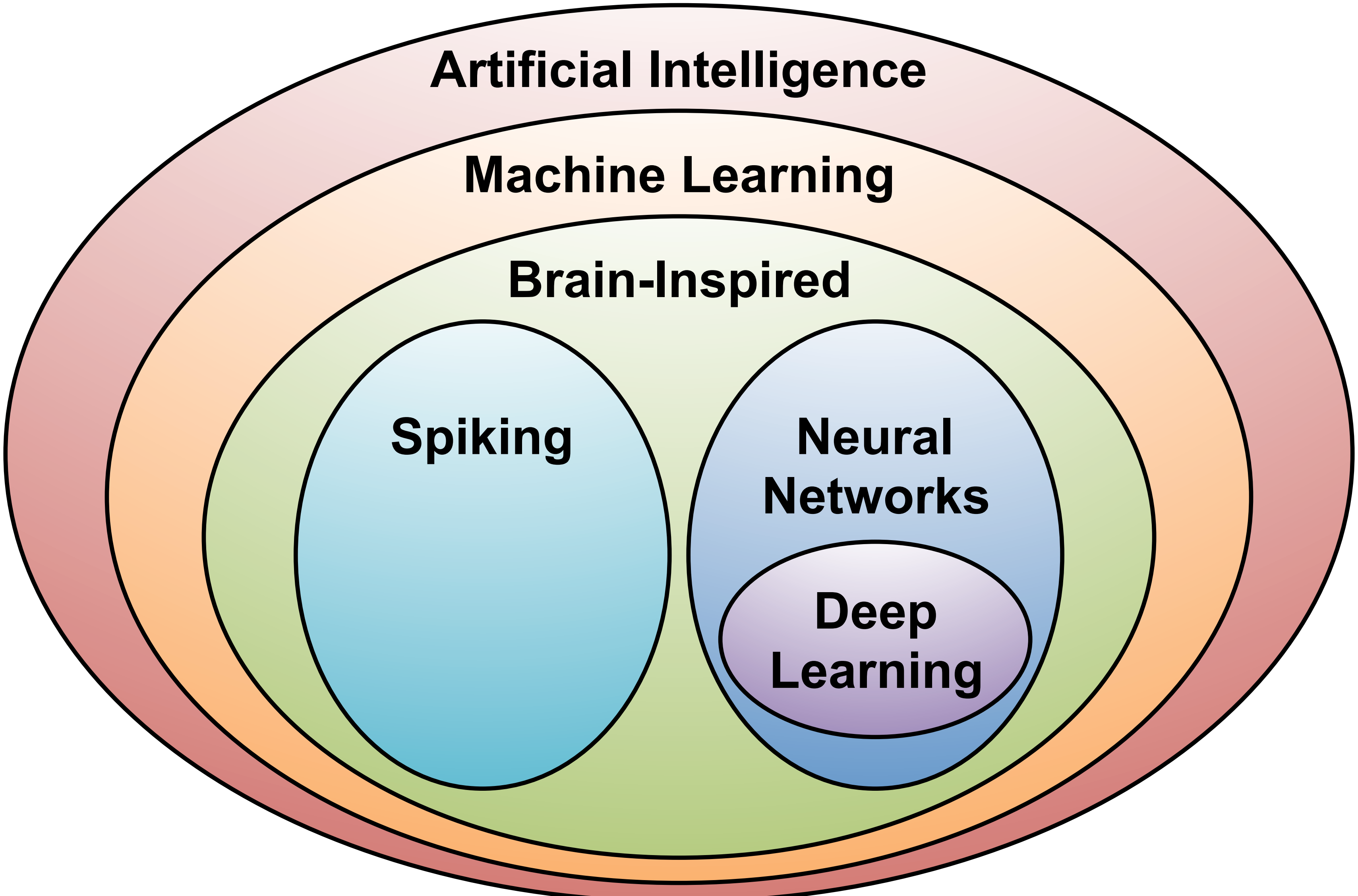


Image Source: Stanford

Deep Learning



What is Deep Learning?

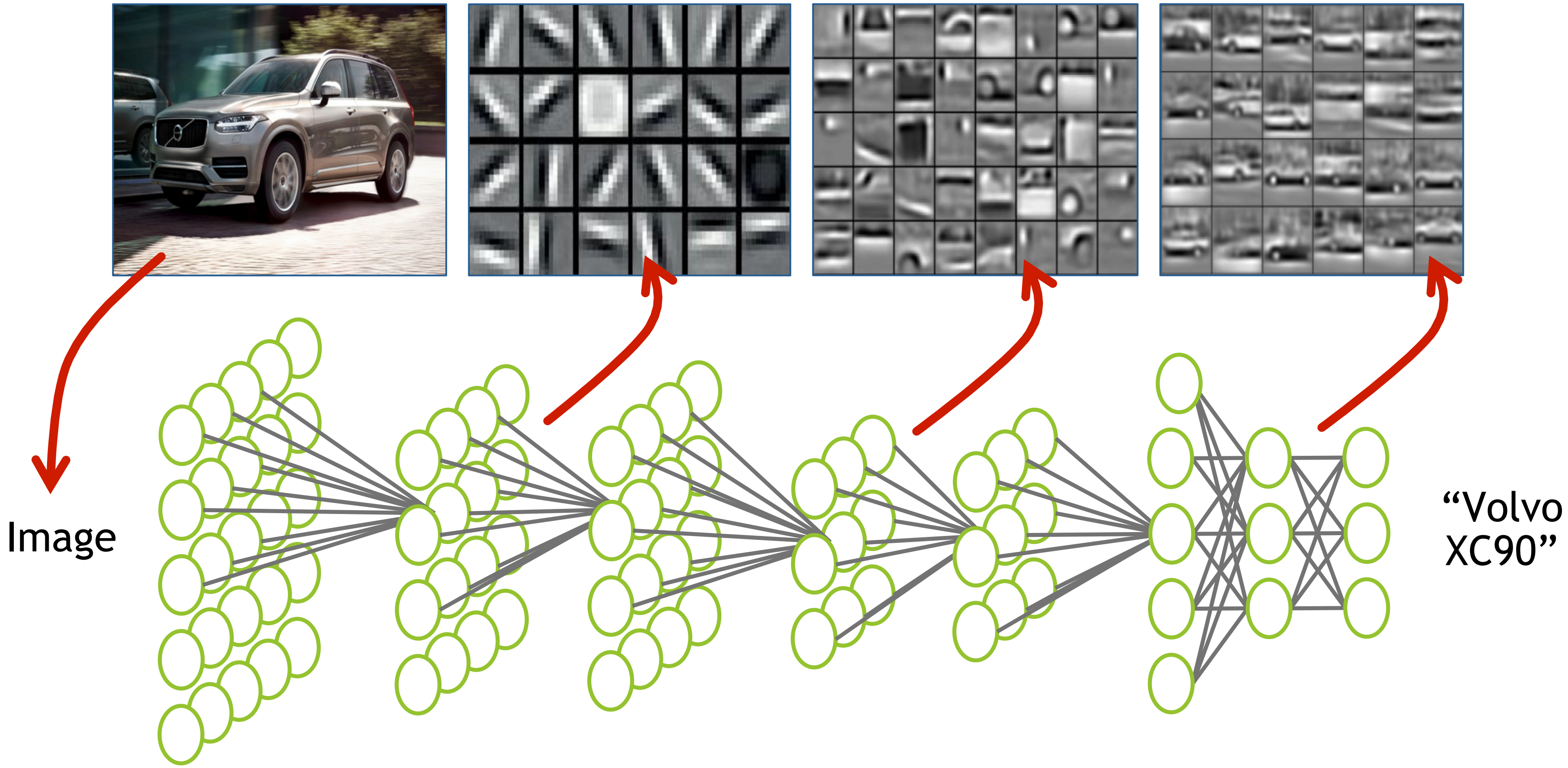


Image Source: [Lee et al., Comm. ACM 2011]

Why is Deep Learning Hot Now?

Big Data Availability

GPU Acceleration

New ML Techniques

facebook — **350M** images uploaded per day

Walmart — **2.5 Petabytes** of customer data hourly

YouTube — **300 hours** of video uploaded every minute

ImageNet Challenge

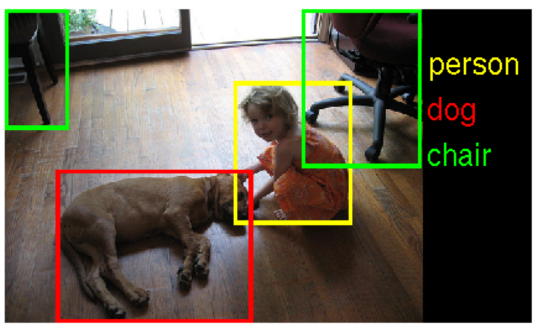
IMAGENET

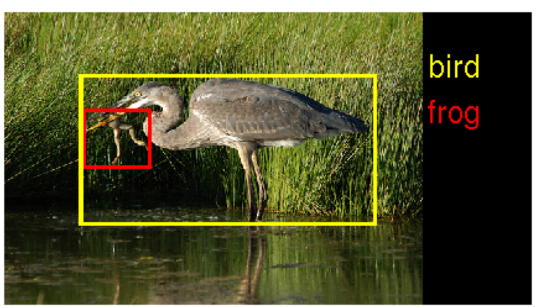
<u>Image Classification Task</u>:

1.2M training images • 1000 object categories

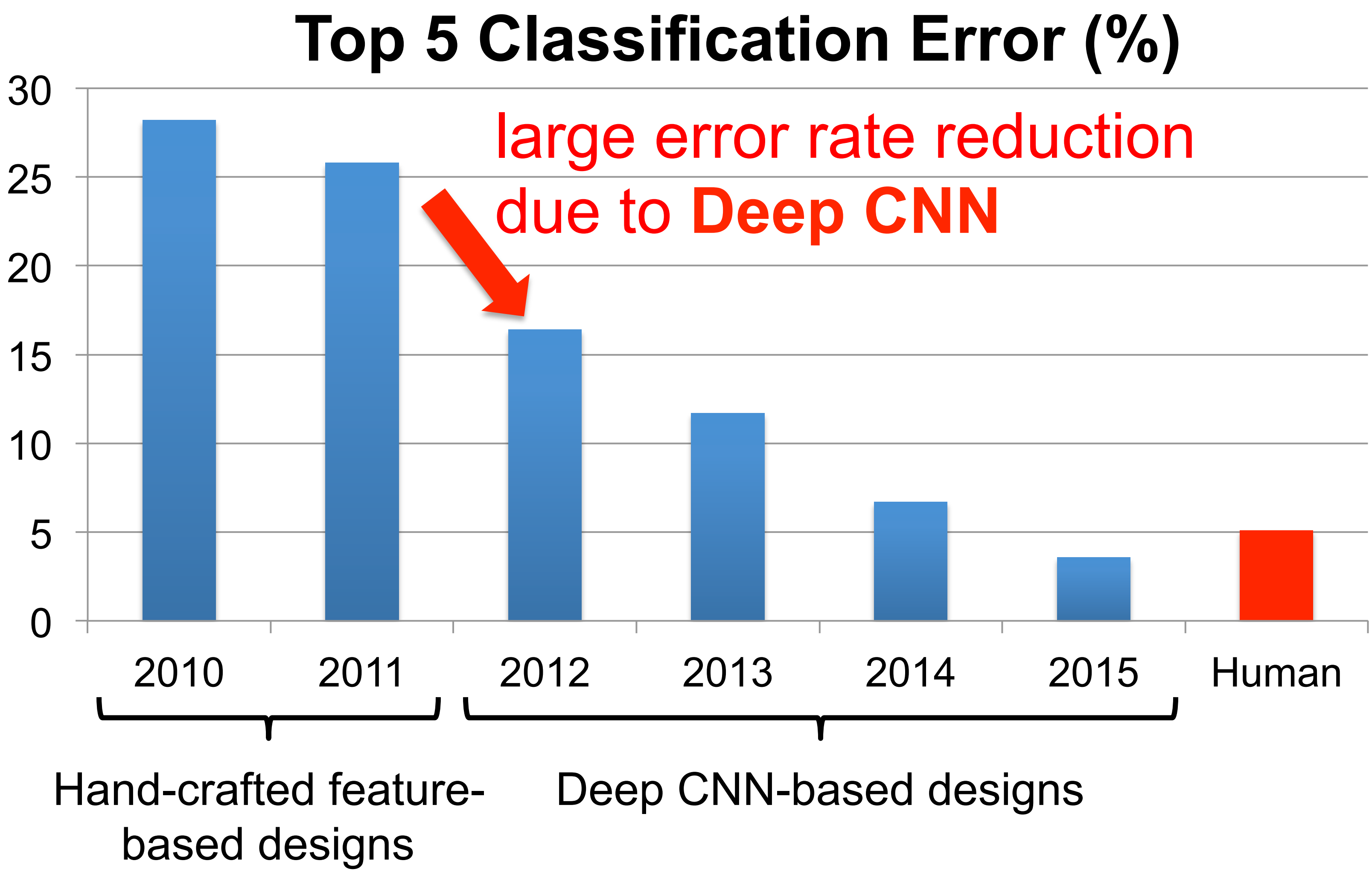
<u>Object Detection Task</u>:

456k training images • *200 object categories*



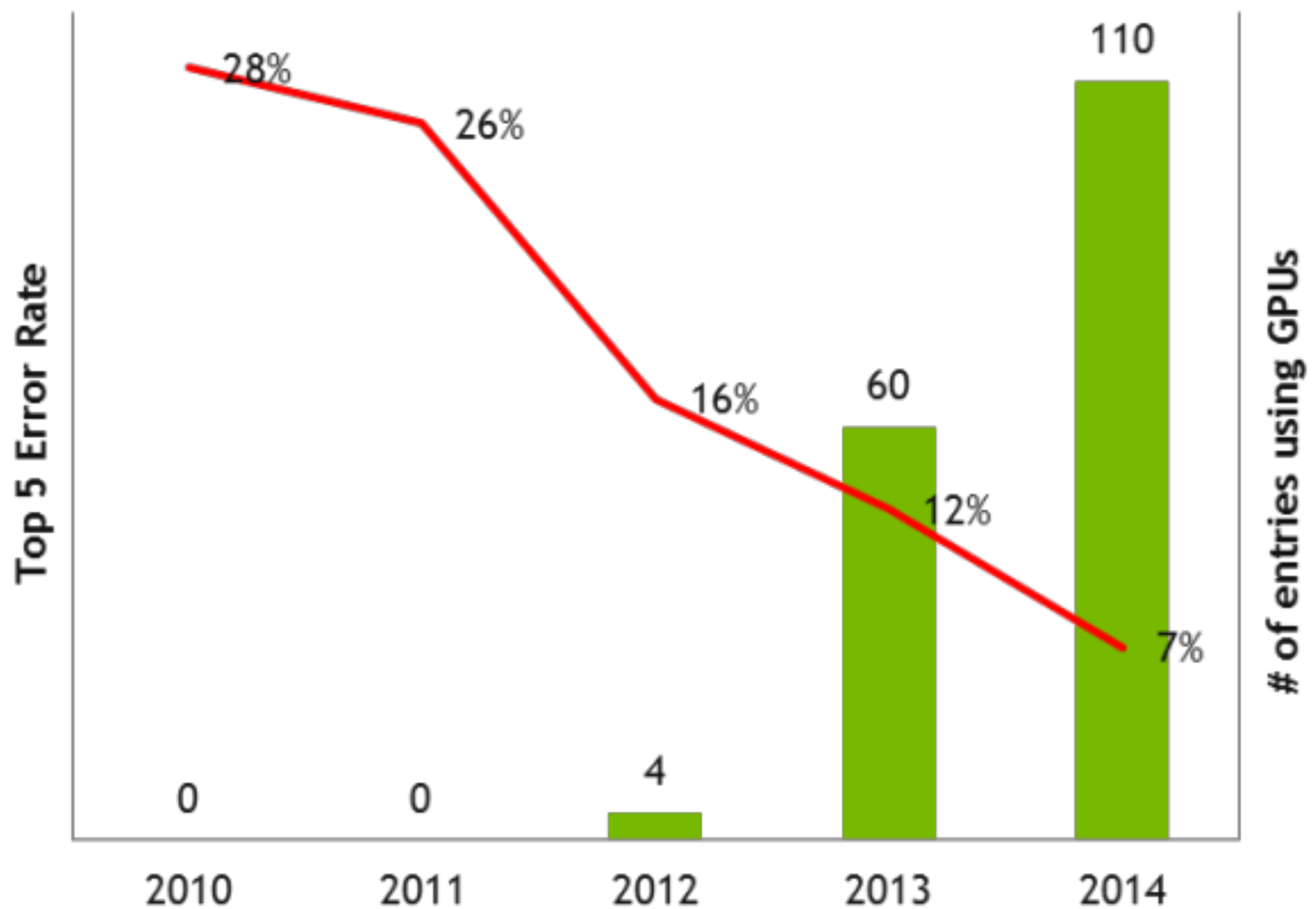


ImageNet: Image Classification Task



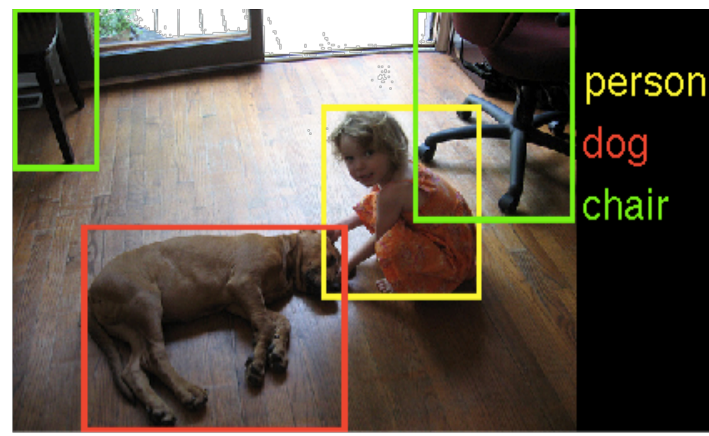
[Russakovsky et al., IJCV 2015]

GPU Usage for ImageNet Challenge



Deep Learning on Images

- Image Classification
- Object Localization
- Object Detection
- Image Segmentation
- Action Recognition
- Image Generation

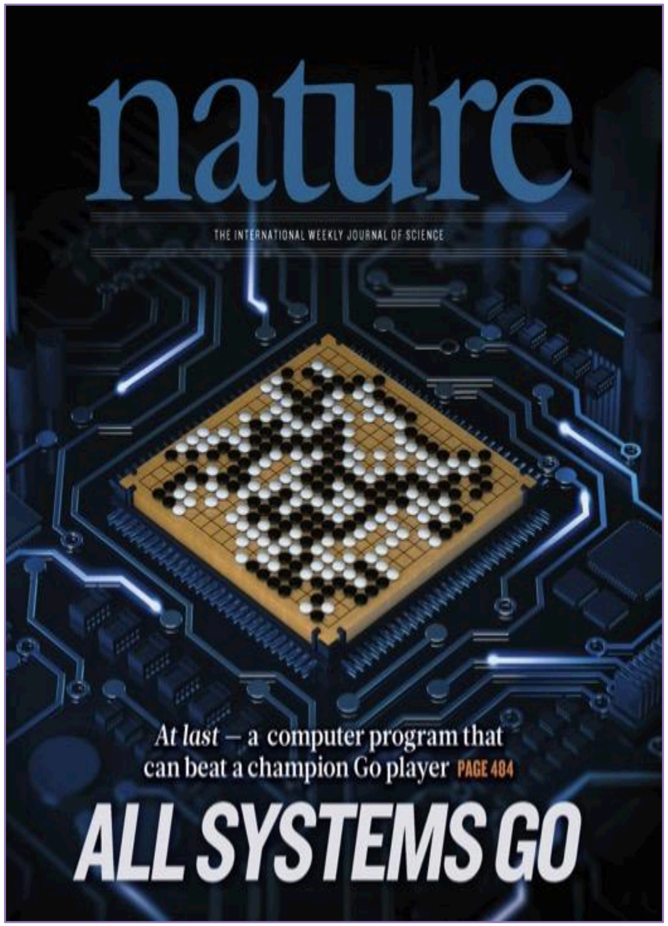


Deep Learning for Speech

- **Speech Recognition**
- **Natural Language Processing**
- **Speech Translation**
- **Audio Generation**

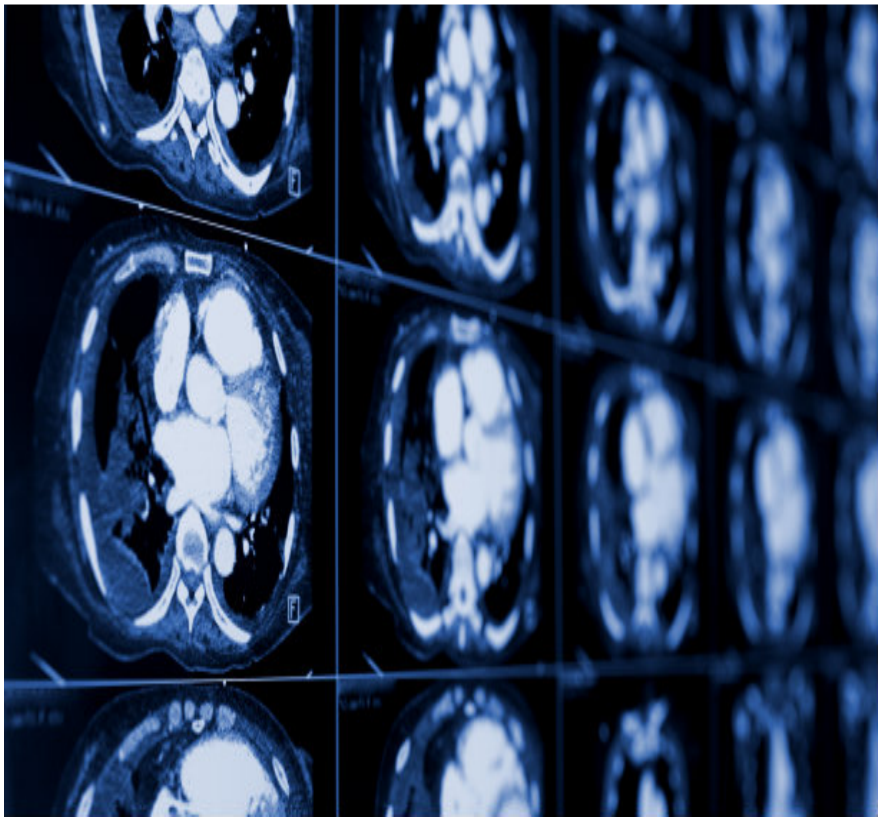
Deep Learning on Games

Google DeepMind AlphaGo



Medical Applications of Deep Learning

- **Brain Cancer Detection**



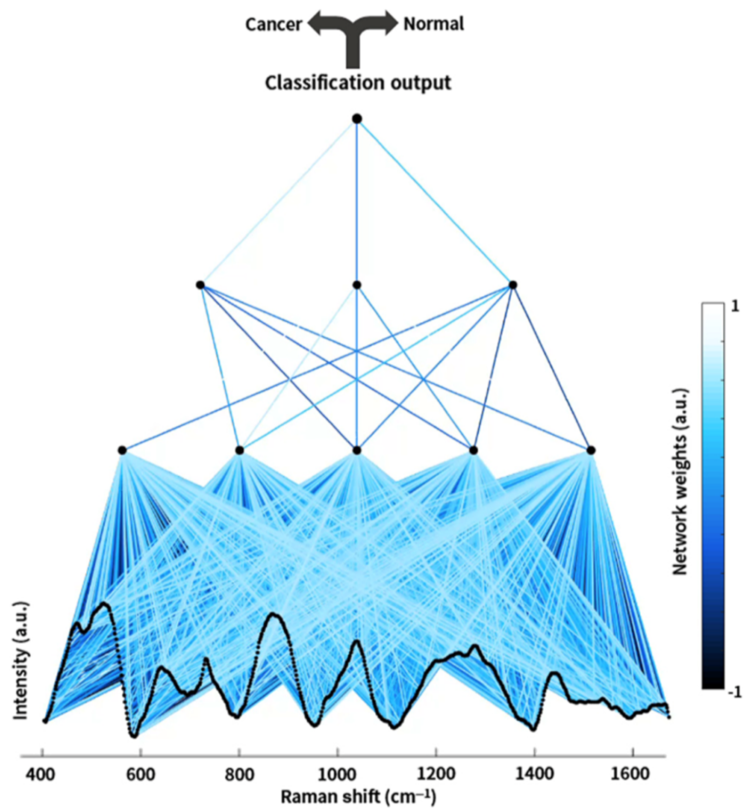
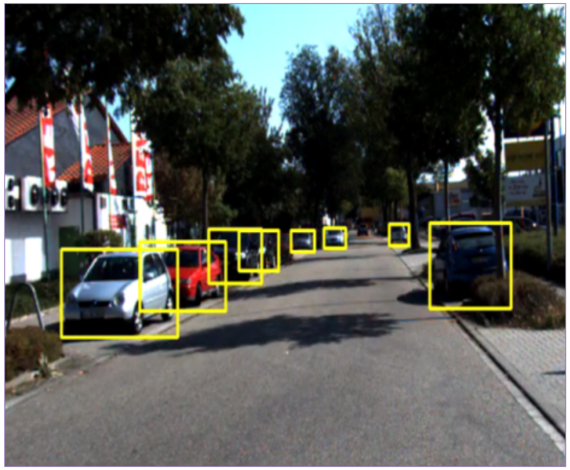
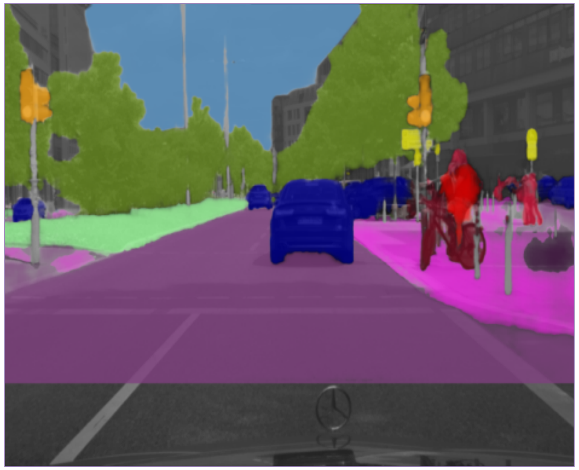
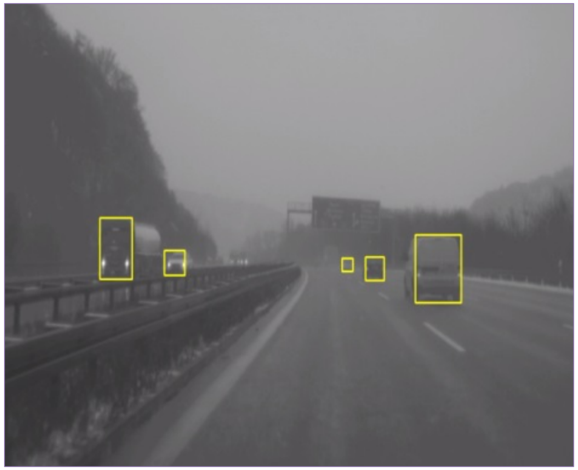


Image Source: [Jermyn et al., JBO 2016]

Deep Learning for Self-driving Cars



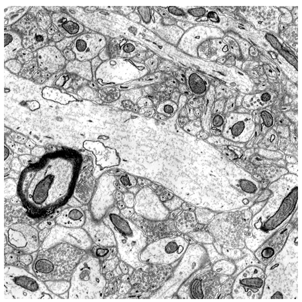




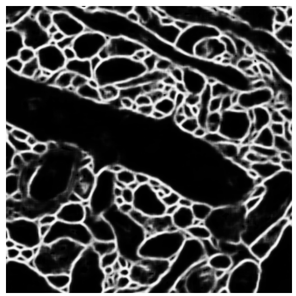
Connectomics – Finding Synapses

Machine Learning requires orders of Magnitude more computation than other parts

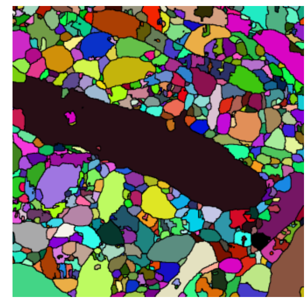
(1) EM



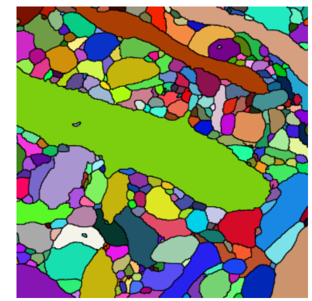
(2) ML Membrane Detection



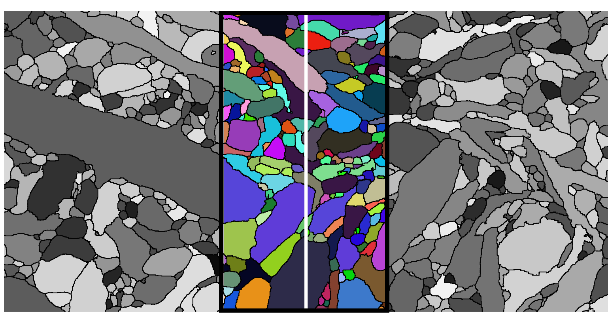
(3) Watershed



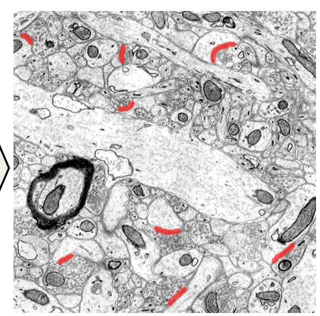
(4) Agglomeration



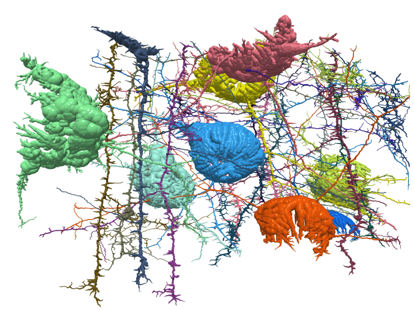
(5) Merging



(6) Synapses



(7) Skeletons



(8) Graph

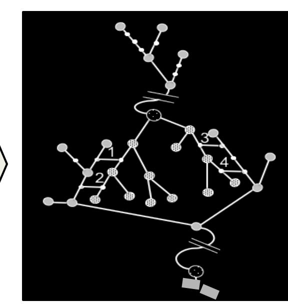


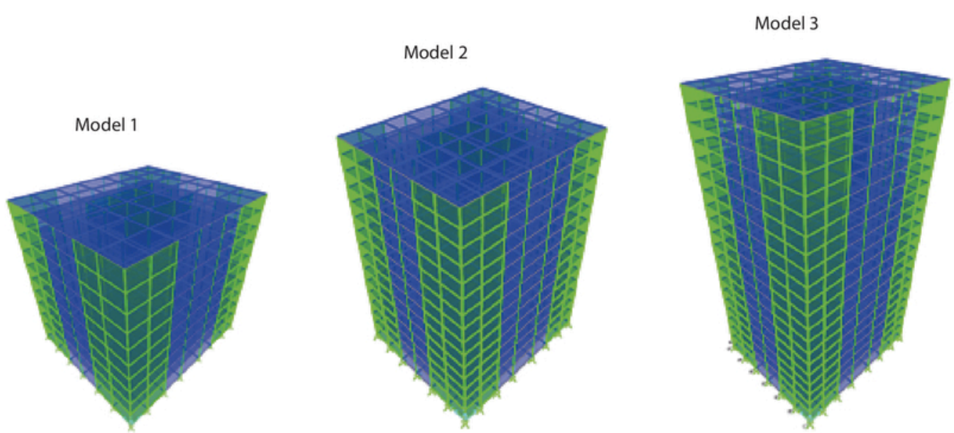
Image Source: MIT

Mature Applications

- **Image**
  - Classification: image to object class
  - Recognition: same as classification (except for faces)
  - Detection: assigning bounding boxes to objects
  - Segmentation: assigning object class to every pixel
- **Speech & Language**
  - Speech Recognition: audio to text
  - Translation
  - Natural Language Processing: text to meaning
  - Audio Generation: text to audio
- **Games**

Emerging Applications

- **Medical** (Cancer Detection, Pre-Natal)
- **Finance** (Trading, Energy Forecasting, Risk)
- **Infrastructure** (Structure Safety and Traffic)
- Weather Forecasting and Event Detection

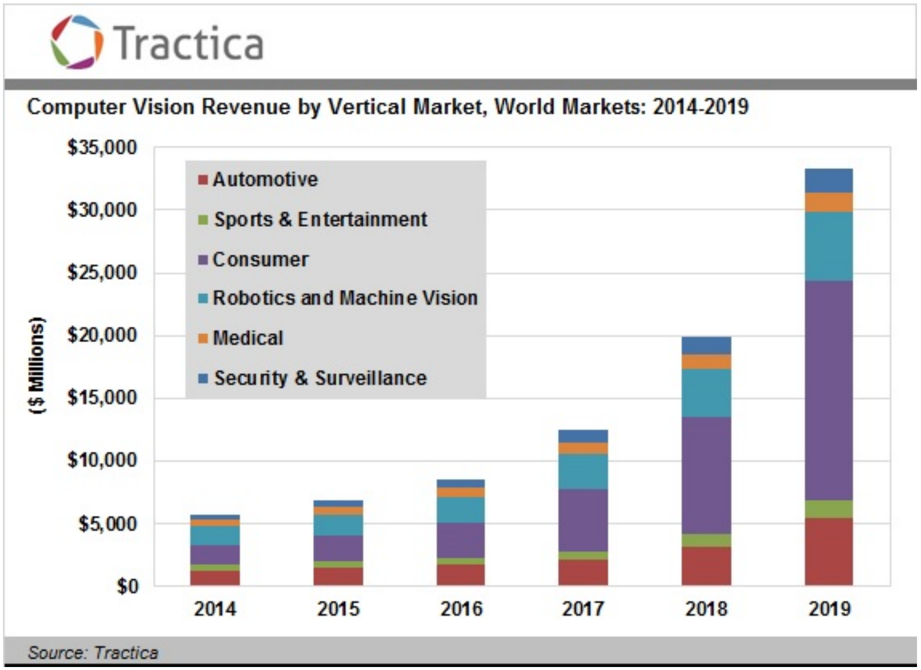


This tutorial will focus on image classification

http://www.nextplatform.com/2016/09/14/next-wave-deep-learning-applications/

Opportunities

$500B Market over 10 Years!



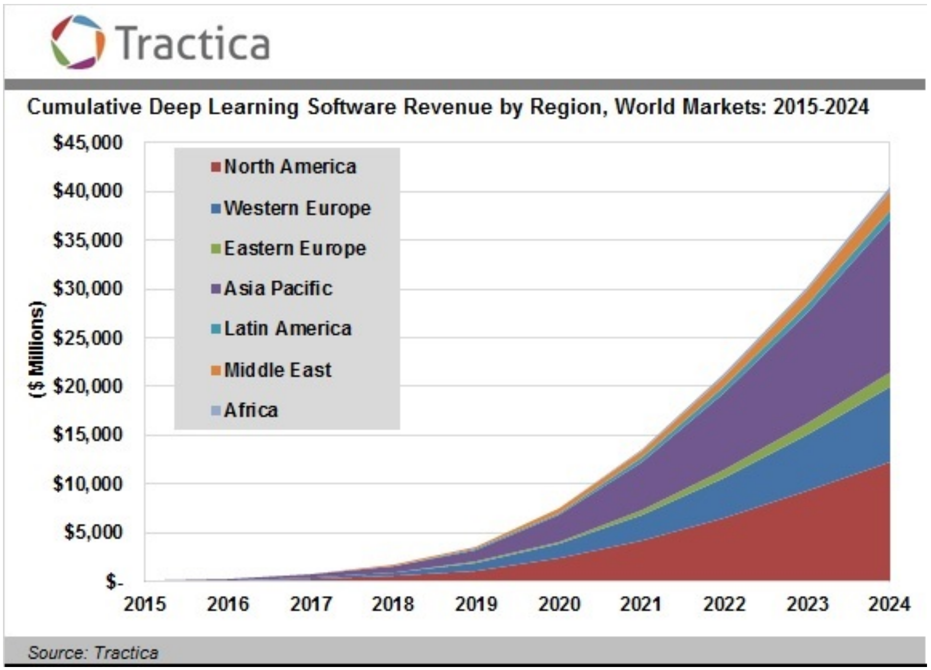


Image Source: Tractica

Opportunities

From EE Times – September 27, 2016

"Today the job of training machine learning models is limited by compute, if we had faster processors we'd run bigger models…in practice we train on a reasonable subset of data that can finish in a matter of months. We could use improvements of several orders of magnitude – 100x or greater."

– Greg Diamos, Senior Researcher, SVAIL, Baidu

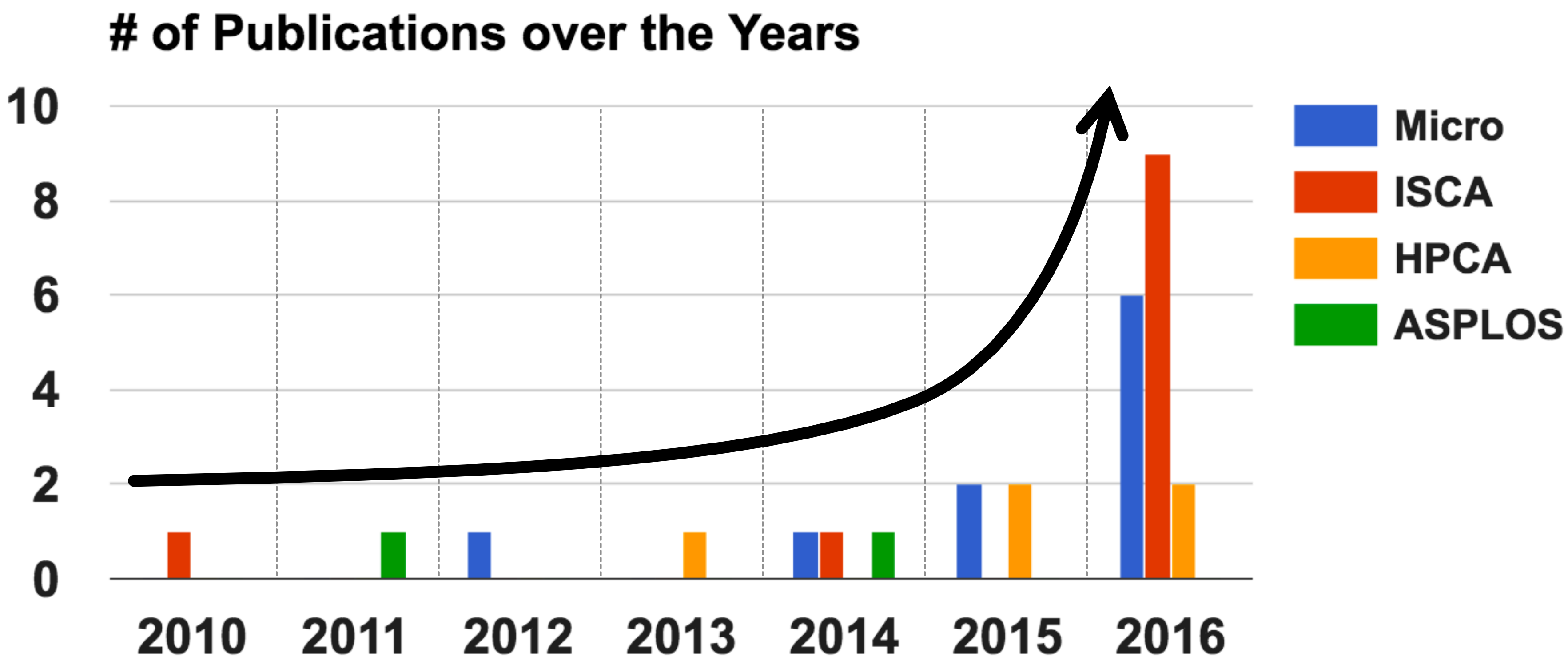
Overview of Deep Neural Networks

DNN Timeline

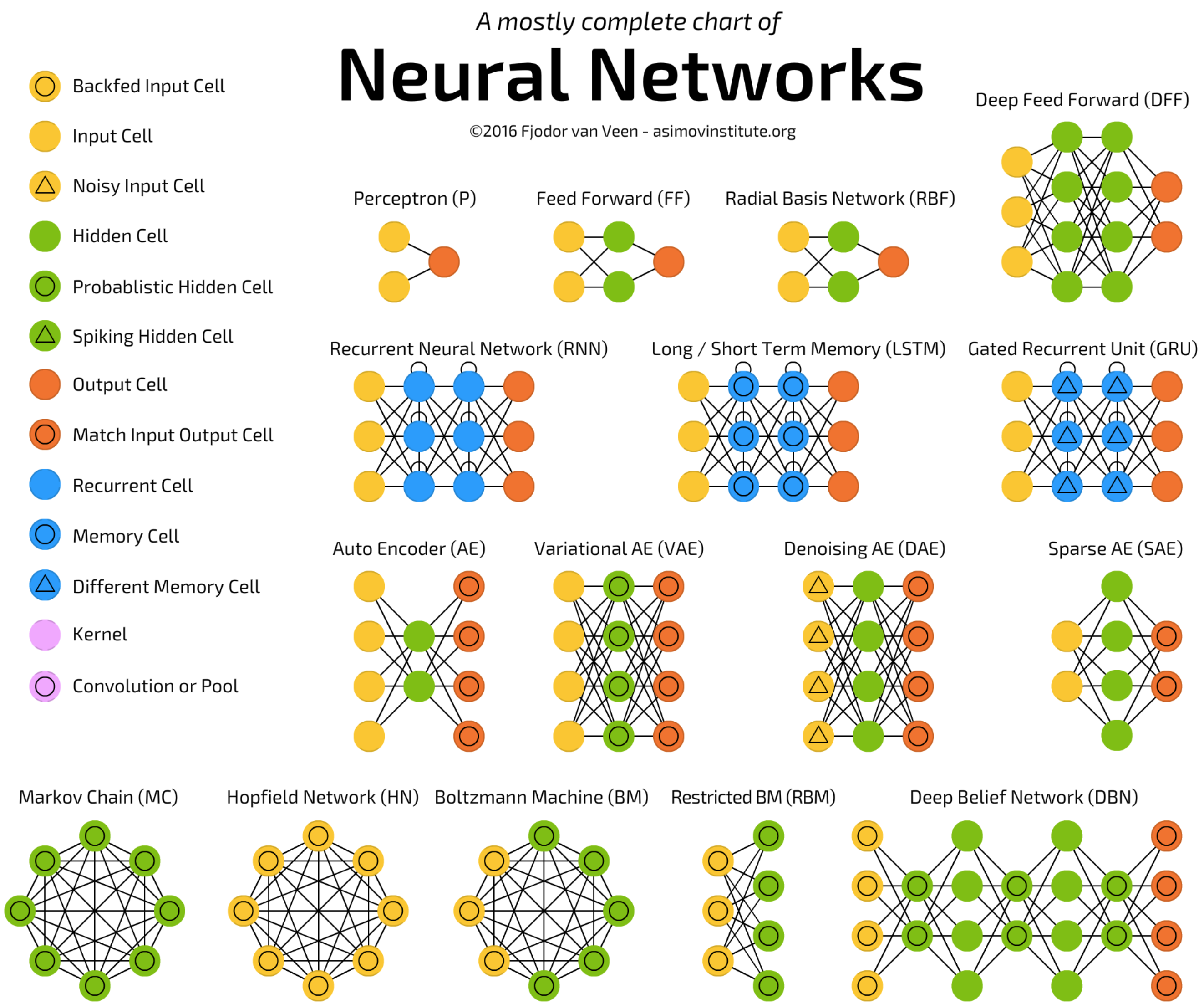
- **1940s: Neural networks were proposed**
- **1960s: Deep neural networks were proposed**
- **1990s: Early hardware for shallow neural nets**
  - Example: Intel ETANN (1992)
- **1998: LeNet for MNIST**
- **2011: Speech recognition using DNN (Microsoft)**
- **2012: Deep learning starts supplanting traditional ML**
  - AlexNet for image classification
- **Early 2010s: Rise of DNN accelerator research**
  - Examples: Neuflow, DianNao, etc.

Publications at Architecture Conferences

- **MICRO, ISCA, HPCA, ASPLOS**



So Many Neural Networks!



http://www.asimovinstitute.org/neural-network-zoo/

DNN Terminology 101

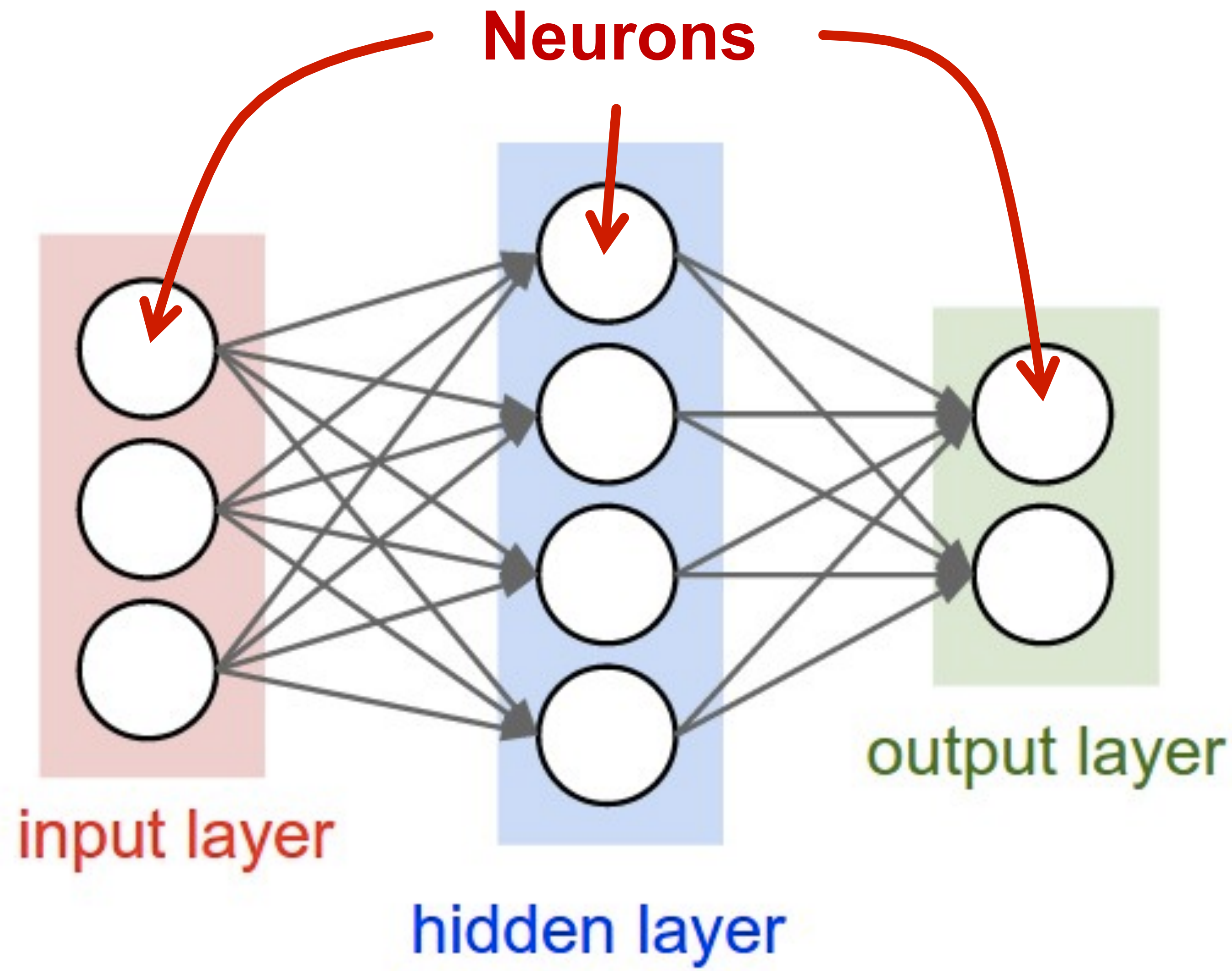


Image Source: Stanford

DNN Terminology 101

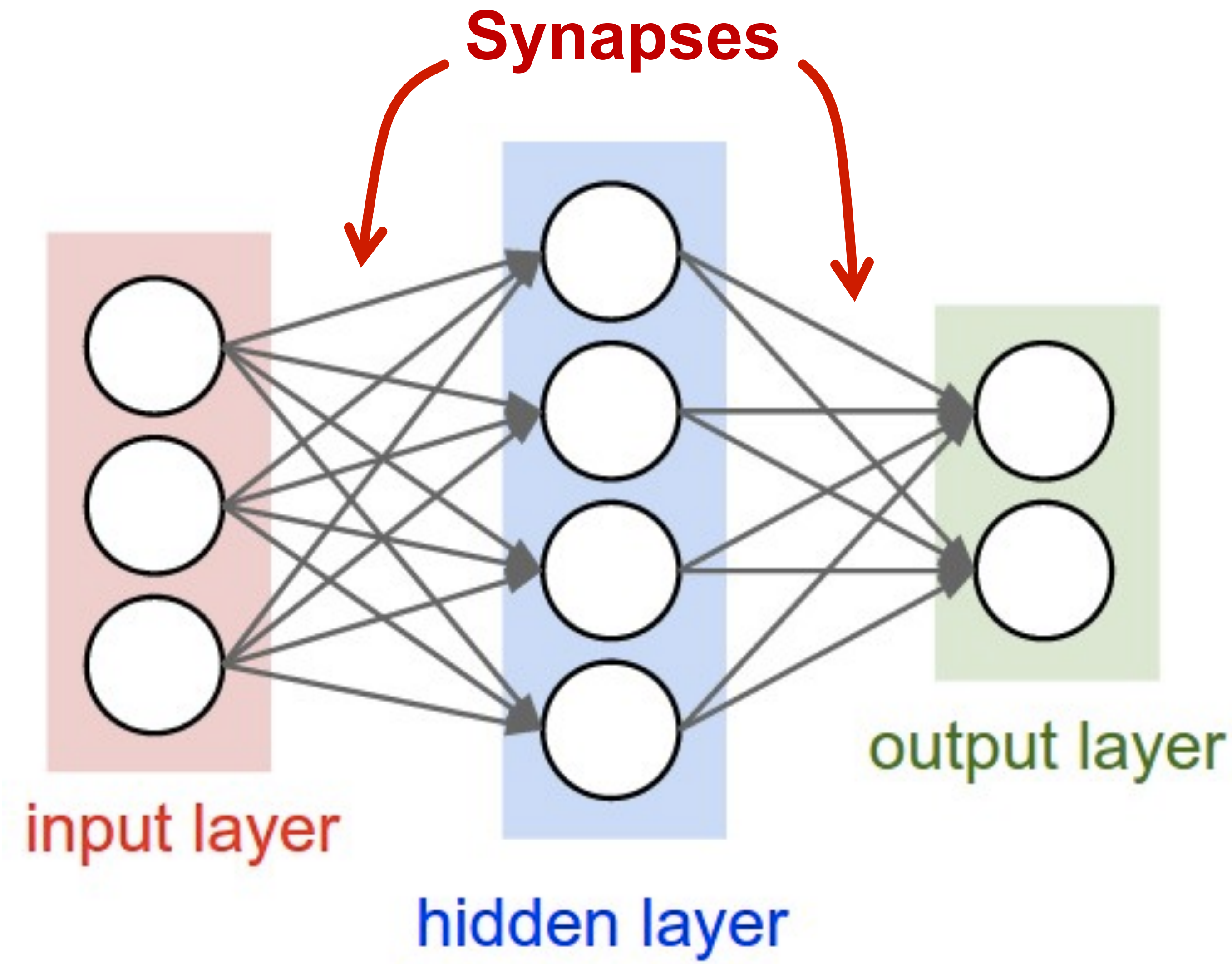


Image Source: Stanford

DNN Terminology 101

Each synapse has a **weight** for neuron **activation**

$Y_j = activation(\sum_{i=1}^{3} W_{ij} * X$

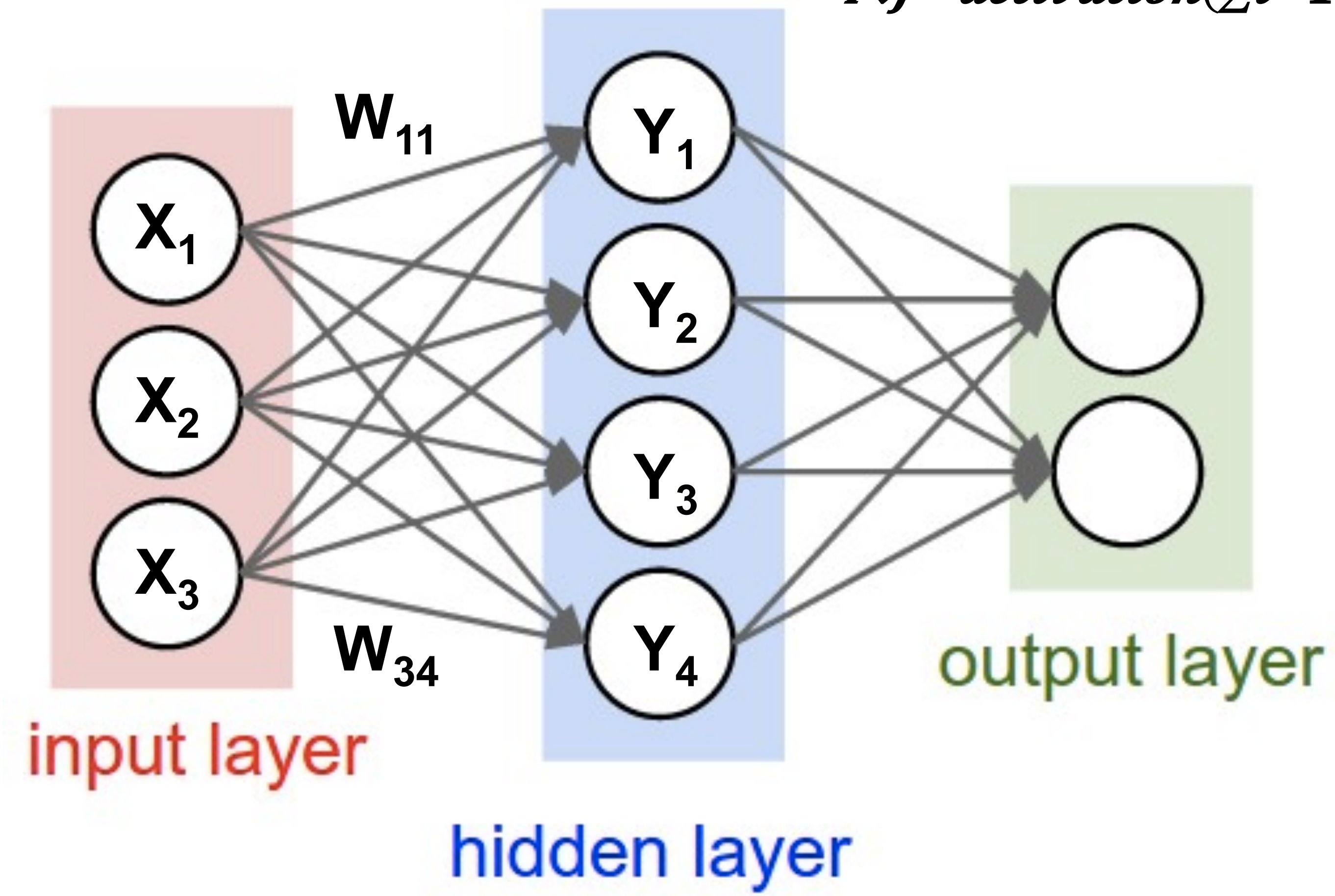


Image Source: Stanford

DNN Terminology 101

Weight Sharing: multiple synapses use the **same weight value**

$Y_j = activation(\sum_{i=1}^{3} W_{ij} * X$

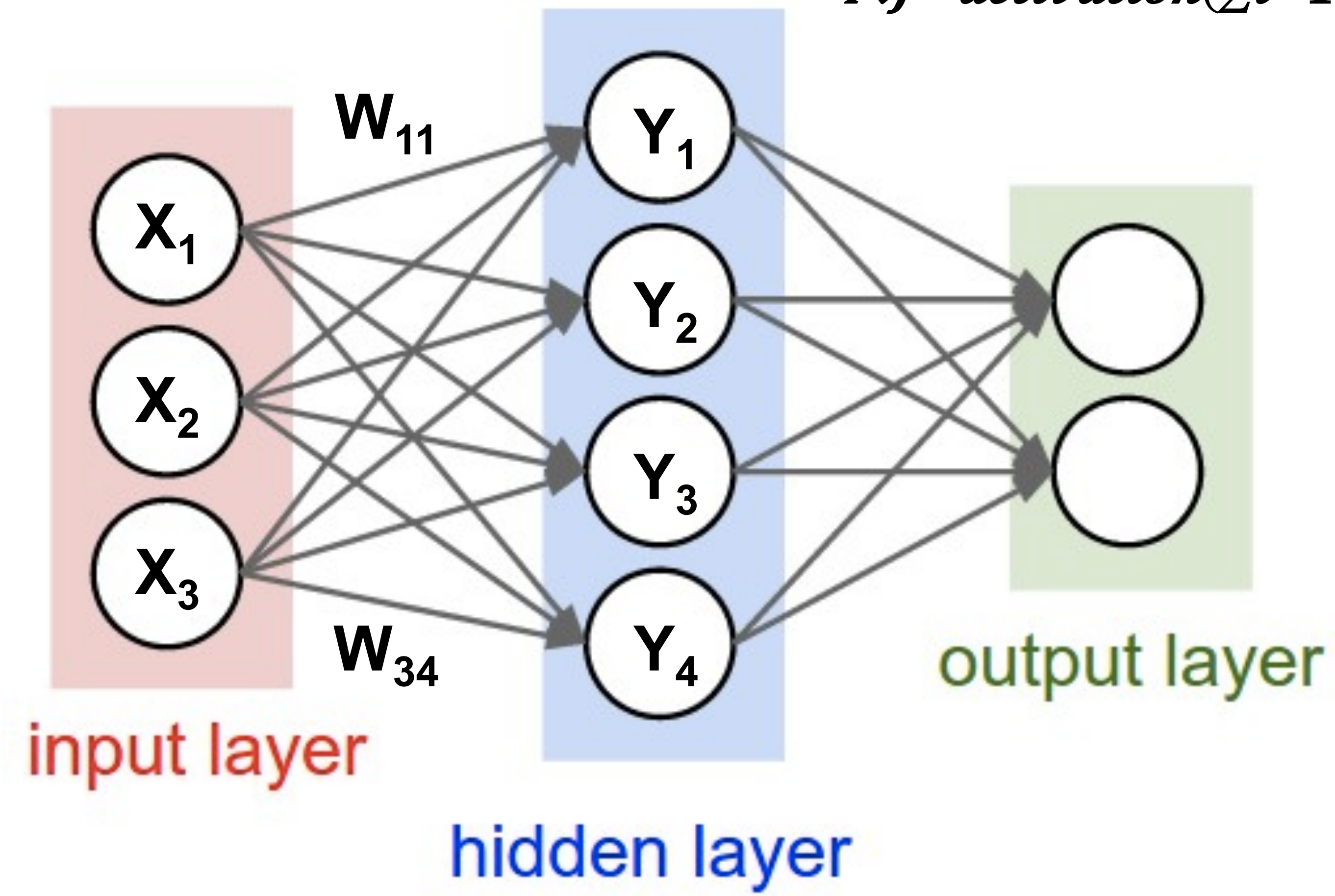


Image Source: Stanford

DNN Terminology 101

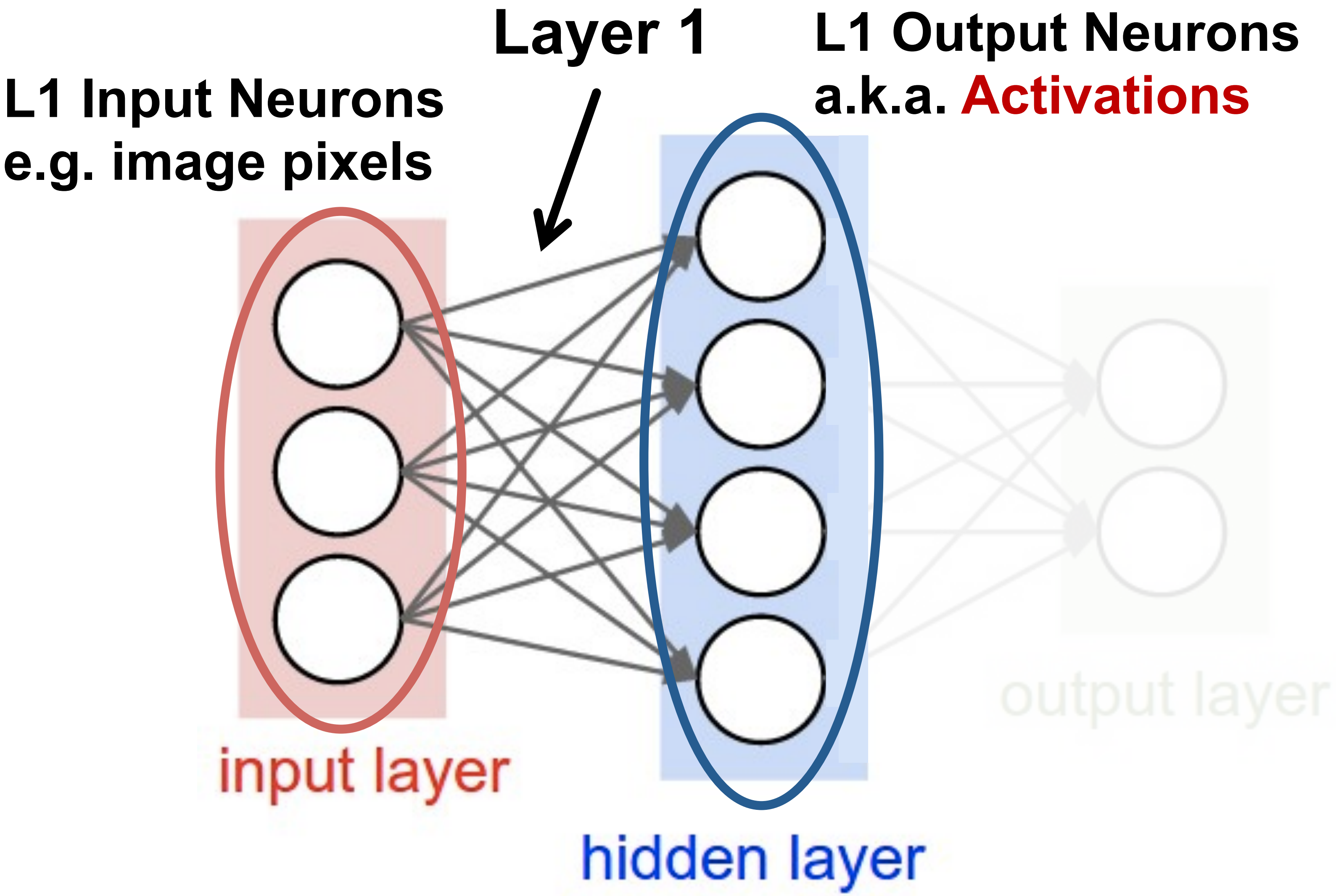


Image Source: Stanford

DNN Terminology 101

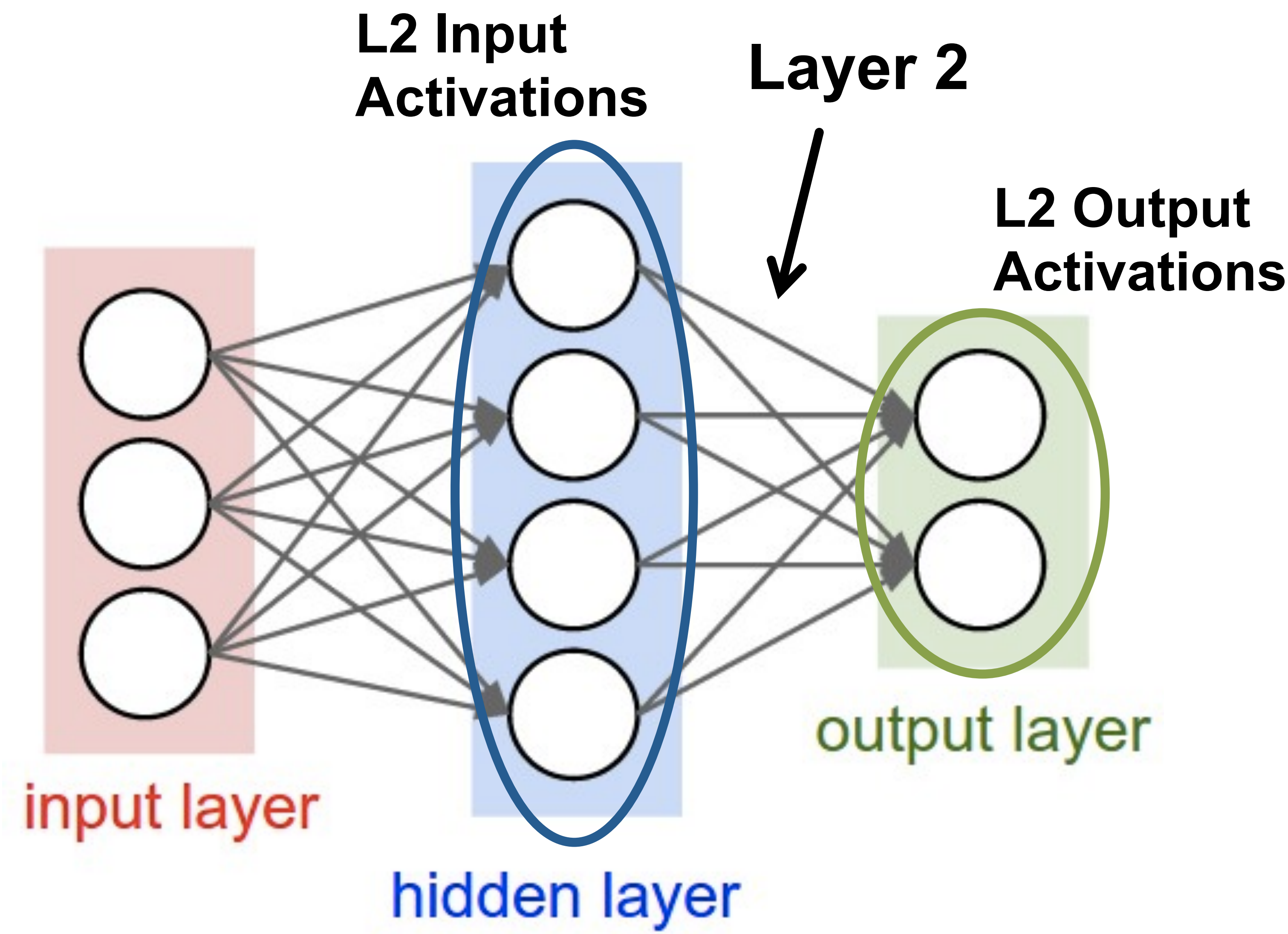


Image Source: Stanford

DNN Terminology 101

Fully-Connected: all i/p neurons connected to all o/p neurons

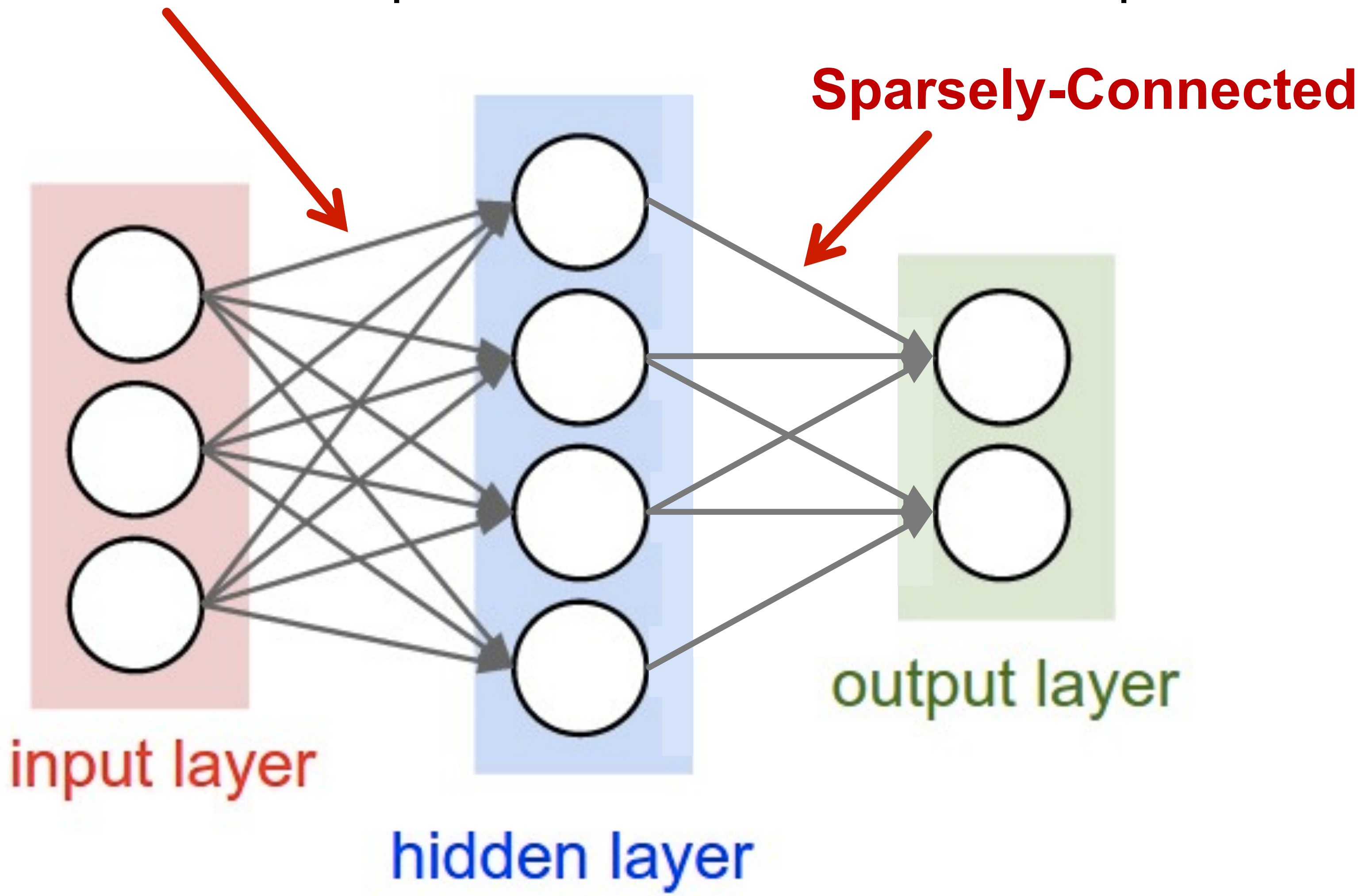


Image Source: Stanford

DNN Terminology 101

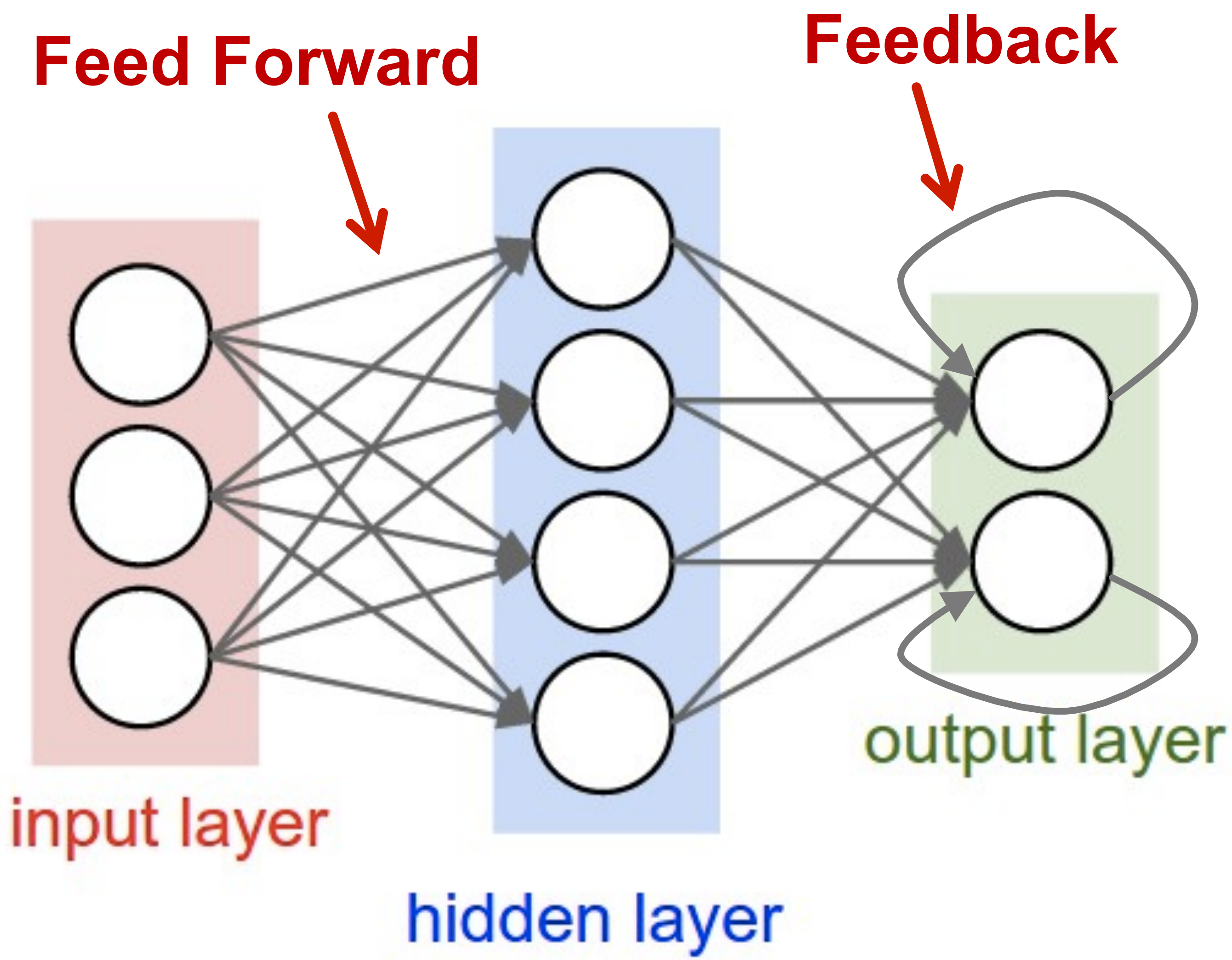


Image Source: Stanford

Popular Types of DNNs

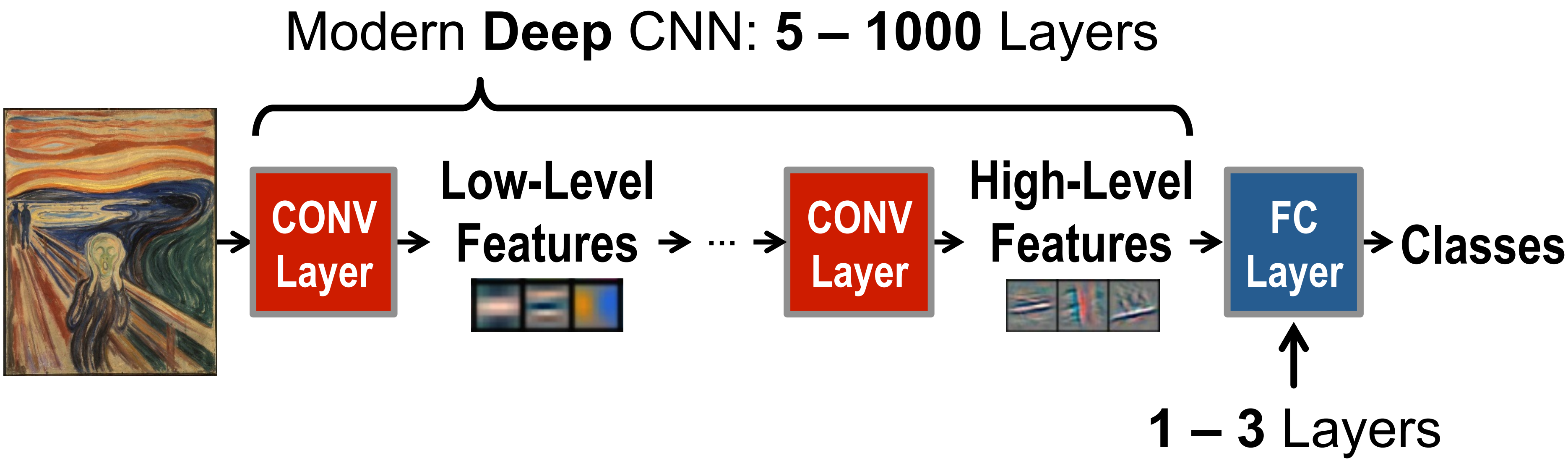
- **Fully-Connected NN**
  - feed forward, a.k.a. multilayer perceptron (MLP)
- **Convolutional NN (CNN)**
  - feed forward, sparsely-connected w/ weight sharing
- **Recurrent NN (RNN)**
  - feedback
- **Long Short-Term Memory (LSTM)**
  - feedback + Storage

Inference vs. Training

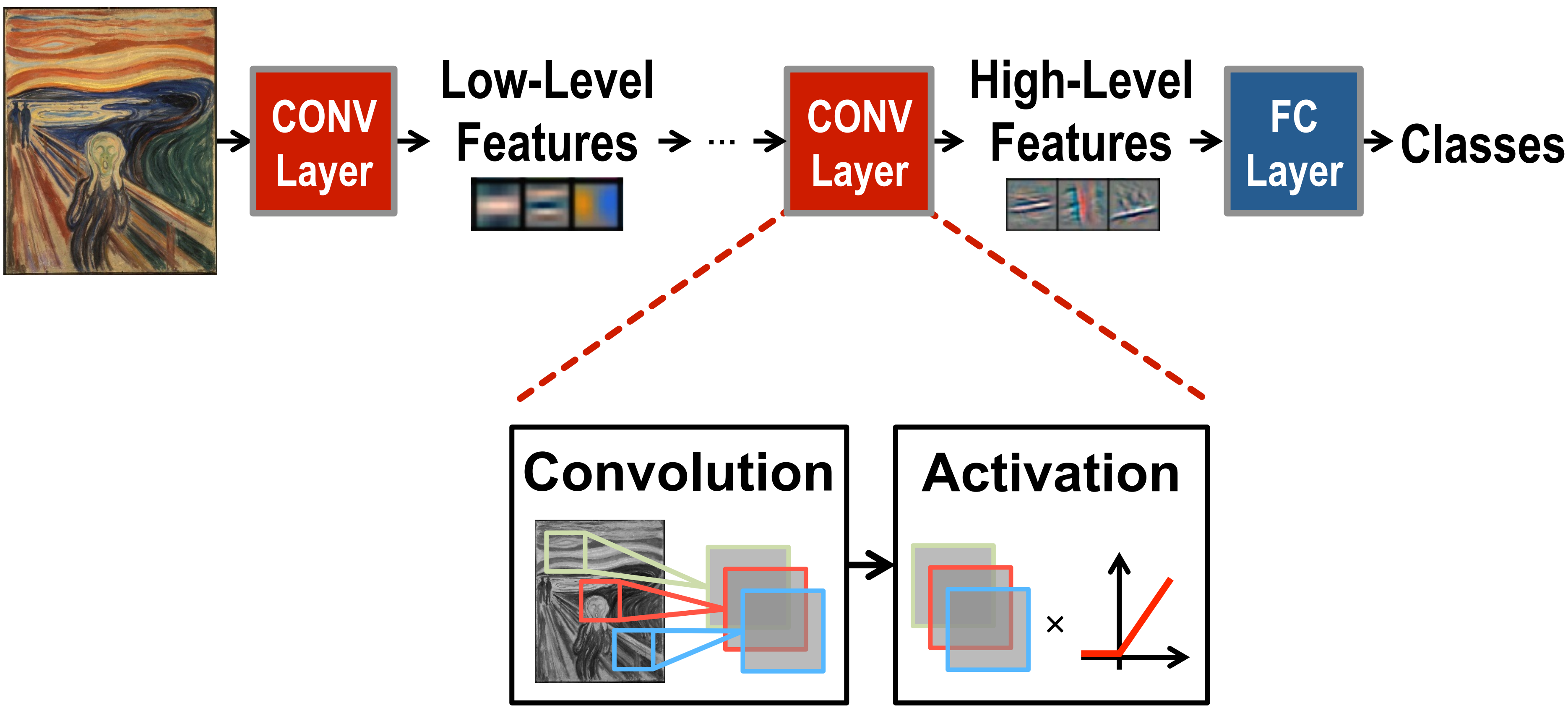
- **Training: Determine weights**
  - **Supervised:**
    - **Training set has inputs and outputs, i.e., labeled**
  - **Reinforcement:**
    - **Output assessed via rewards and punishments**
  - **Unsupervised:**
    - **Training set is unlabeled**
  - **Semi-supervised:**
    - **Training set is partially labeled**

- **Inference: Apply weights to determine output**

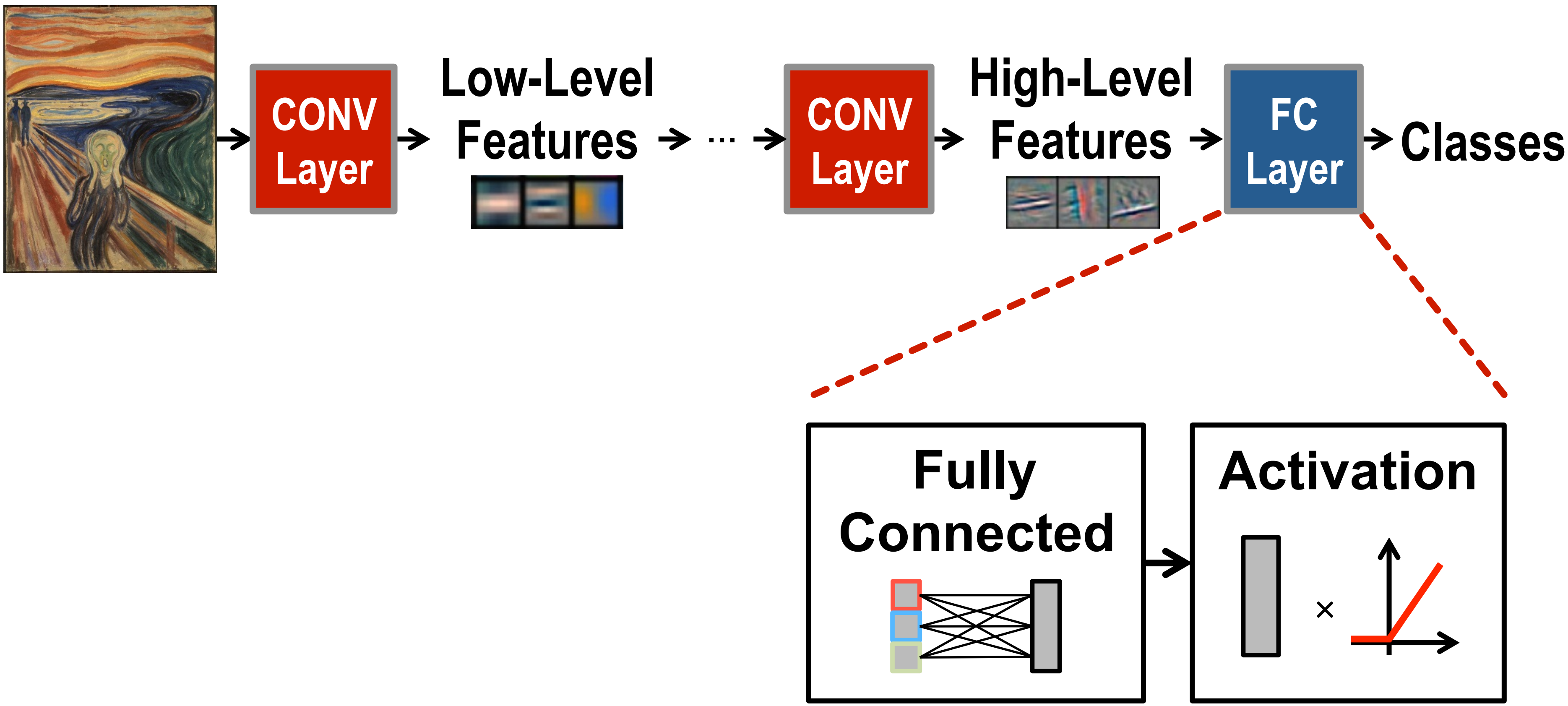
Deep Convolutional Neural Networks



Deep Convolutional Neural Networks

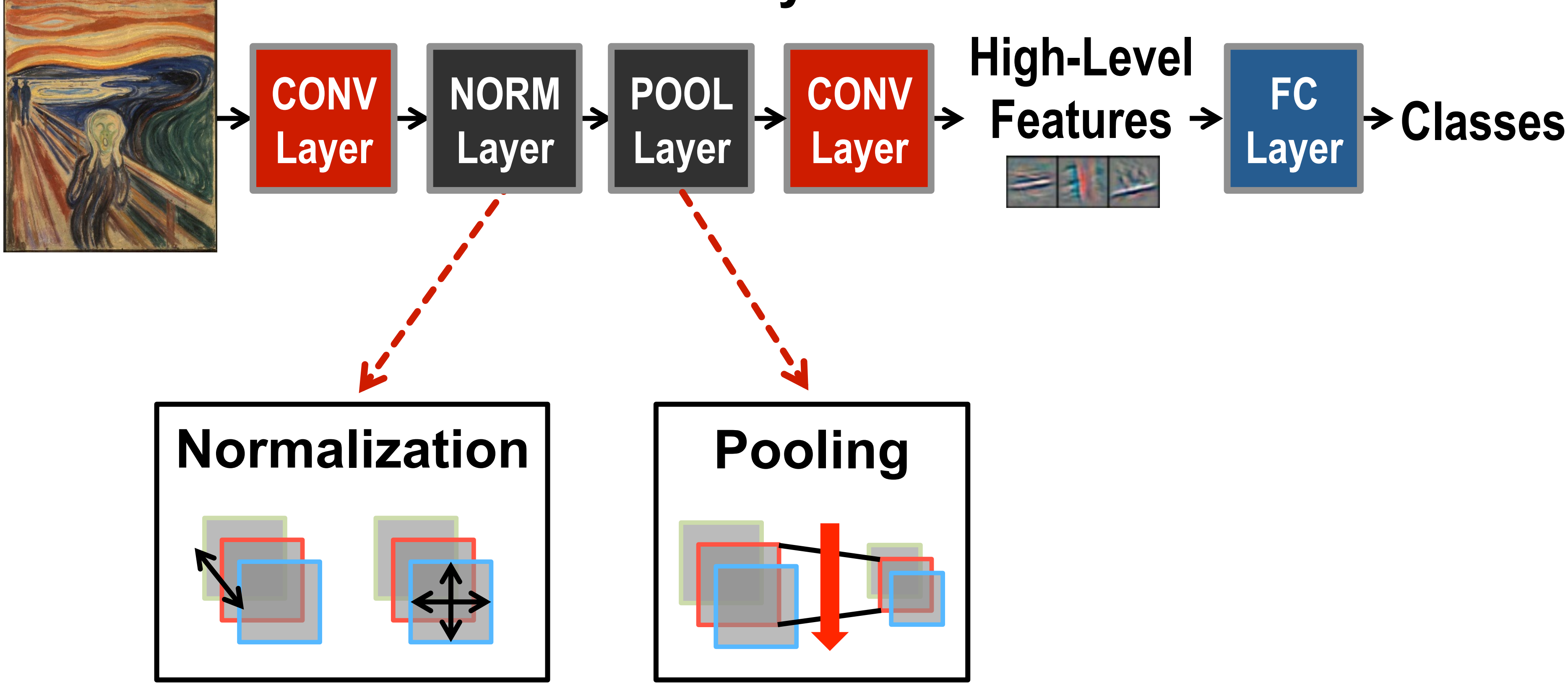


Deep Convolutional Neural Networks

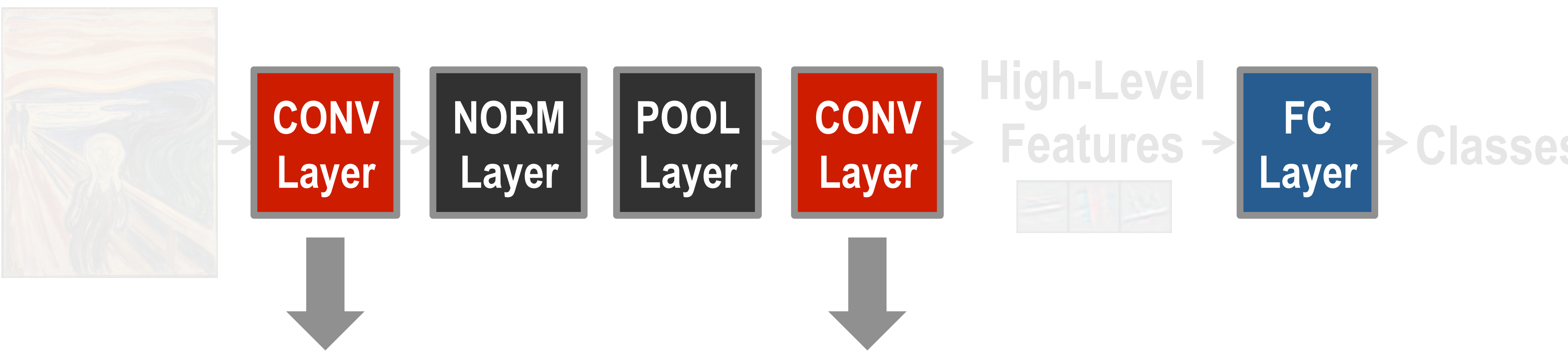


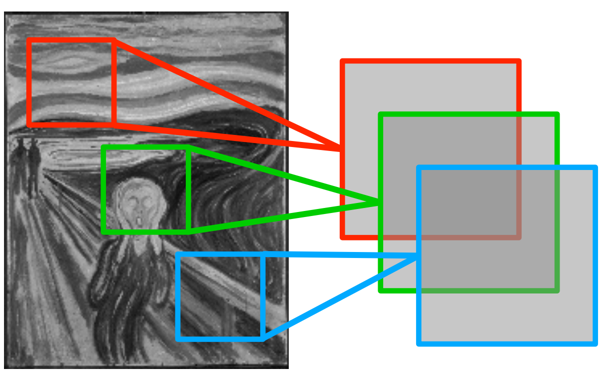
Deep Convolutional Neural Networks

Optional layers in between CONV and/or FC layers



Deep Convolutional Neural Networks



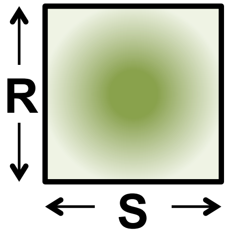


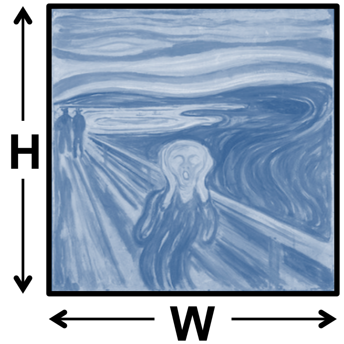
Convolutions account for more than 90% of overall computation, dominating **runtime** and **energy consumption**

Convolution (CONV) Layer

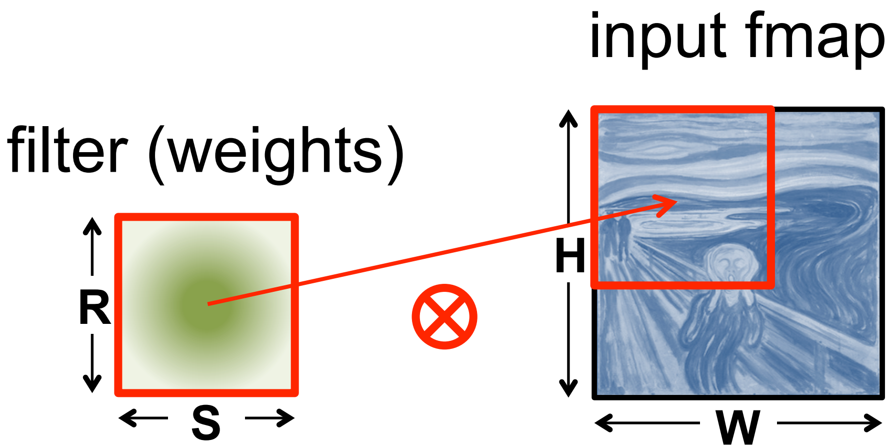
a plane of input activations
a.k.a. **input feature map (fmap)**

filter (weights)



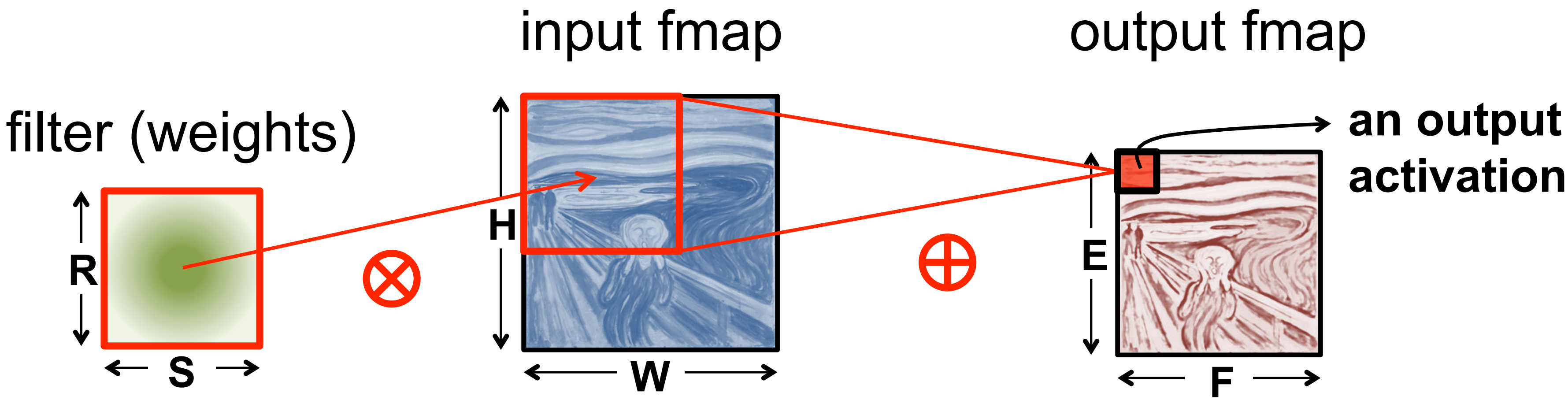


Convolution (CONV) Layer



Element-wise Multiplication

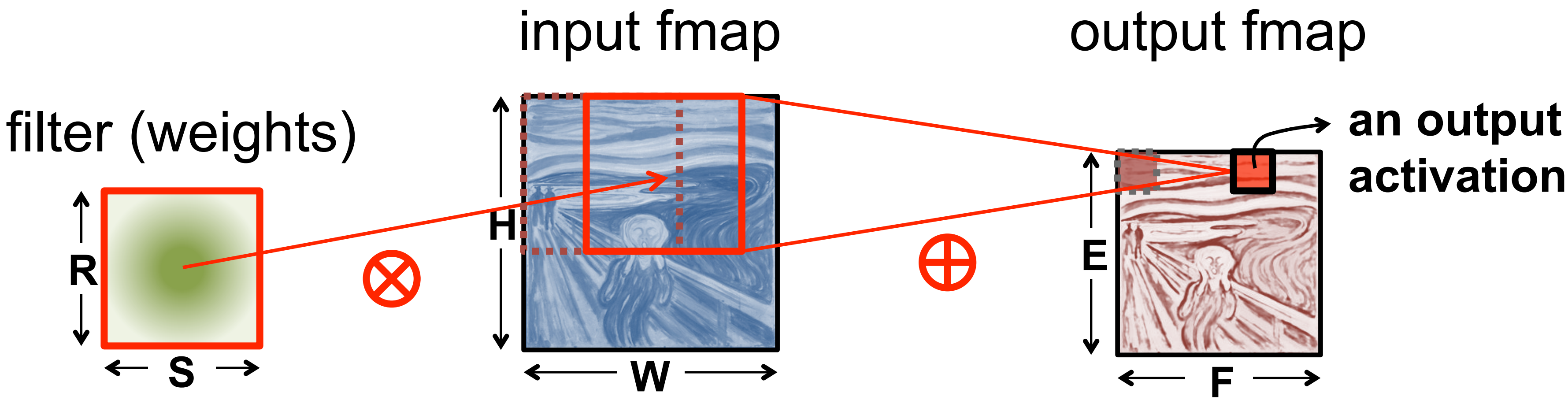
Convolution (CONV) Layer



Element-wise Multiplication

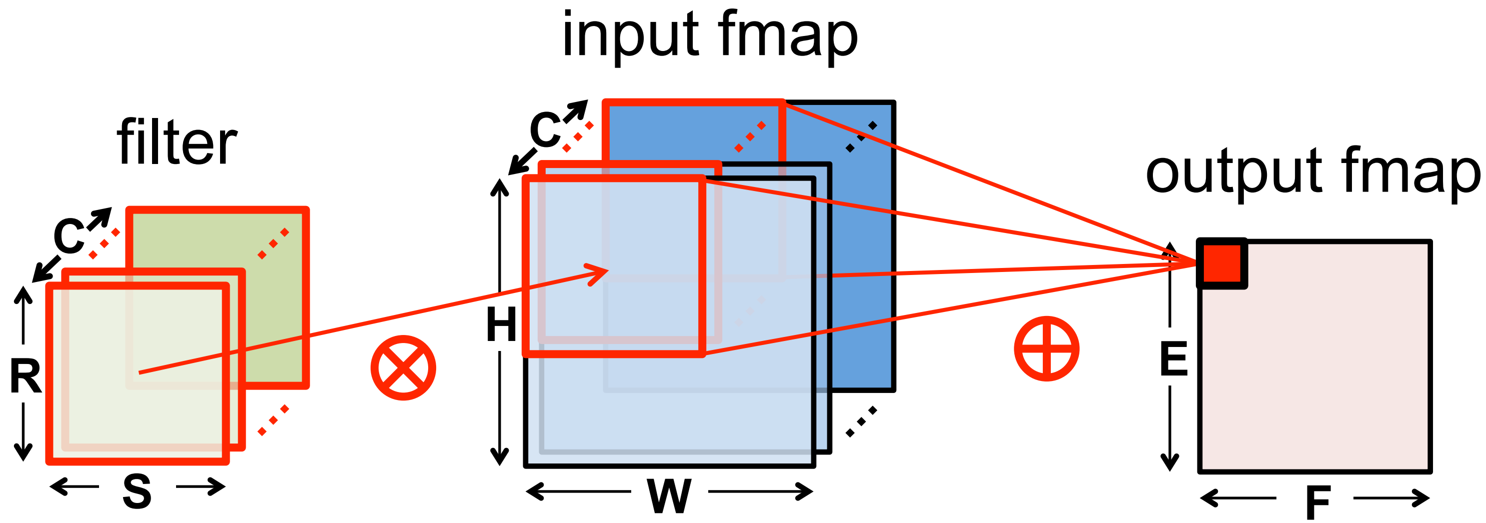
Partial Sum (psum) **Accumulation**

Convolution (CONV) Layer



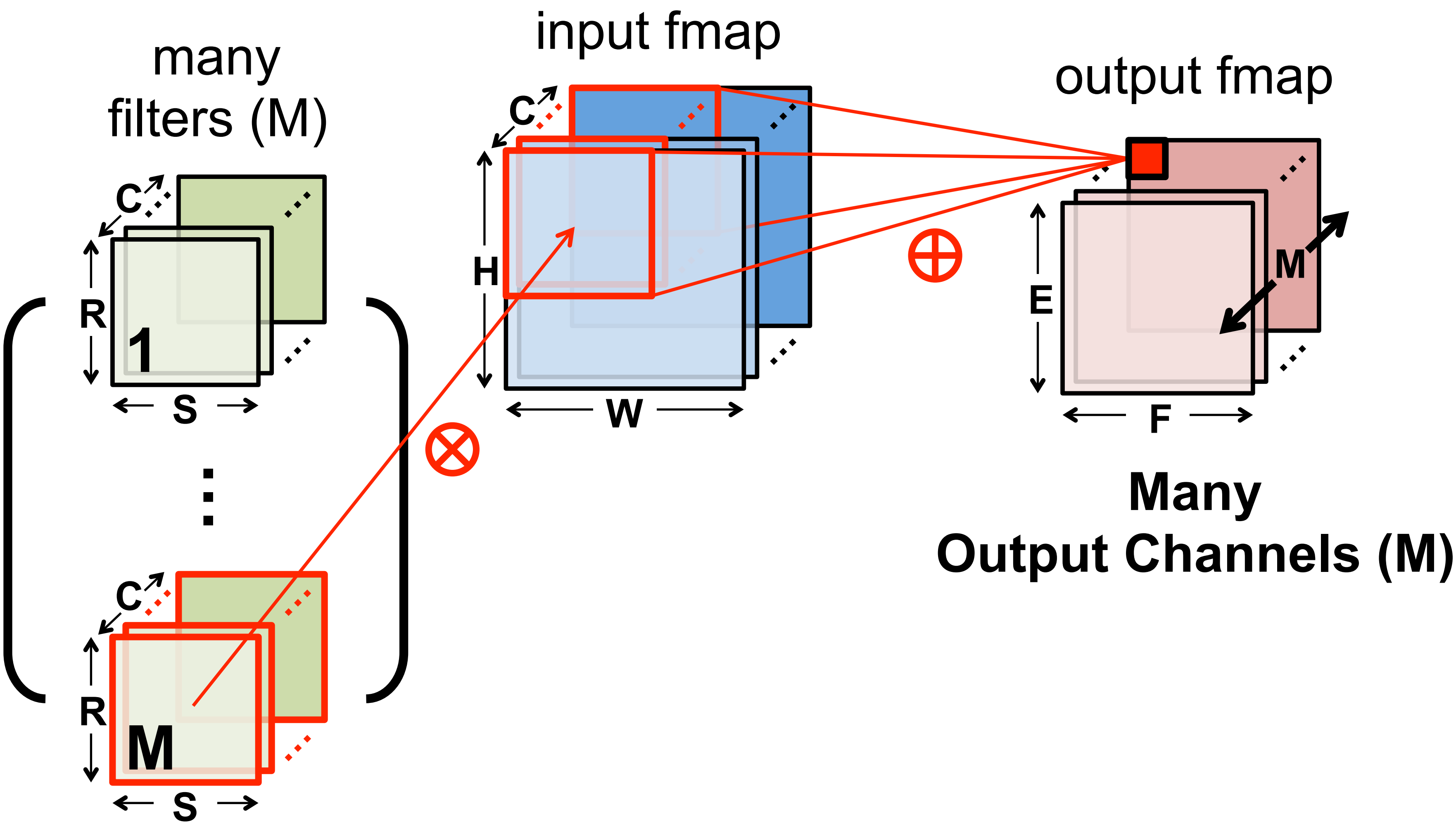
Sliding Window Processing

Convolution (CONV) Layer

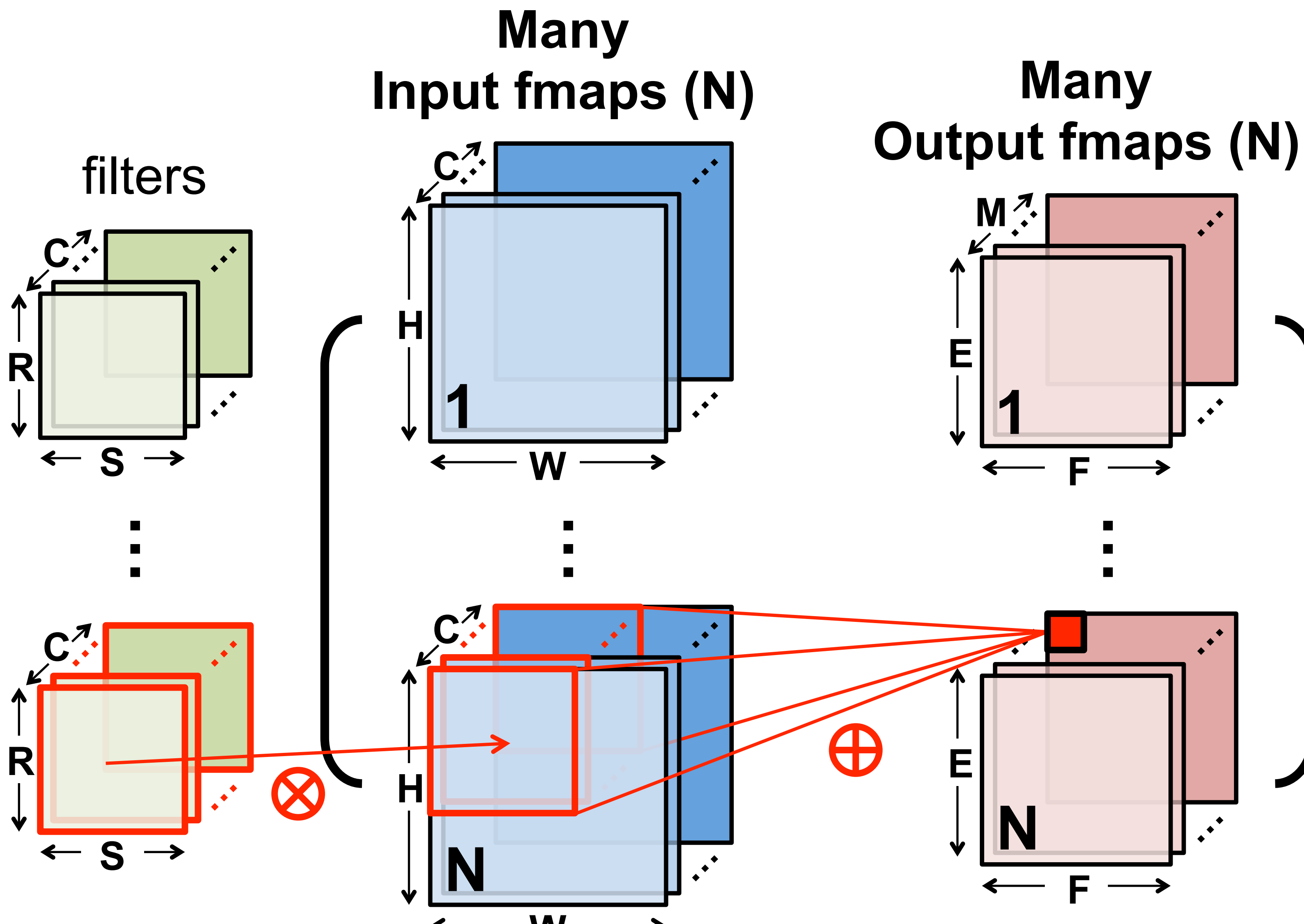


Many Input Channels (C)

Convolution (CONV) Layer



Convolution (CONV) Layer



CONV Layer Implementation

Output fmaps **Biases** **Input fmaps** **Filter weights**

$$\mathbf{O}[n][m][x][y] = \text{Activation}(\mathbf{B}[m] + \sum_{i=0}^{R-1}\sum_{j=0}^{S-1}\sum_{k=0}^{C-1} \mathbf{I}[n][k][Ux+i][Uy+j] \times \mathbf{W}[m][k][i][j]),$$

$$0 \le n < N, 0 \le m < M, 0 \le y < E, 0 \le x < F,$$

$$E = (H - R + U)/U, F = (W - S + U)/U.$$

Shape Parameter	Description
N	fmap batch size
M	# of filters / # of output fmap channels
C	# of input fmap/filter channels
H/W	input fmap height/width
R/S	filter height/width
E/F	output fmap height/width
U	convolution stride

CONV Layer Implementation

Naïve 7-layer for-loop implementation:

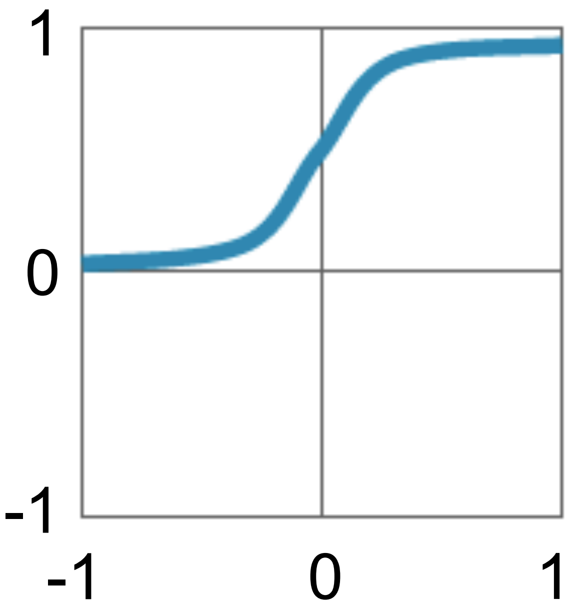
for each output fmap value

convolve a window and apply activation

```
for (n=0; n<N; n++) {
    for (m=0; m<M; m++) {
        for (x=0; x<F; x++) {
            for (y=0; y<E; y++) {

                O[n][m][x][y] = B[m];
                for (i=0; i<R; i++) {
                    for (j=0; j<S; j++) {
                        for (k=0; k<C; k++) {
                            O[n][m][x][y] += I[n][k][Ux+i][Uy+j] × W[m][k][i][j];
                        }
                    }
                }

                O[n][m][x][y] = Activation(O[n][m][x][y]);
            }
        }
    }
}
```

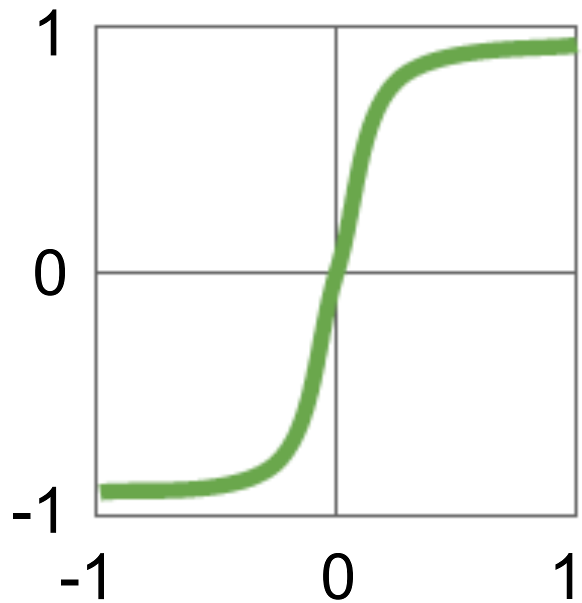
Traditional Activation Functions

Sigmoid



$$y=1/(1+e^{-x})$$

Hyperbolic Tangent

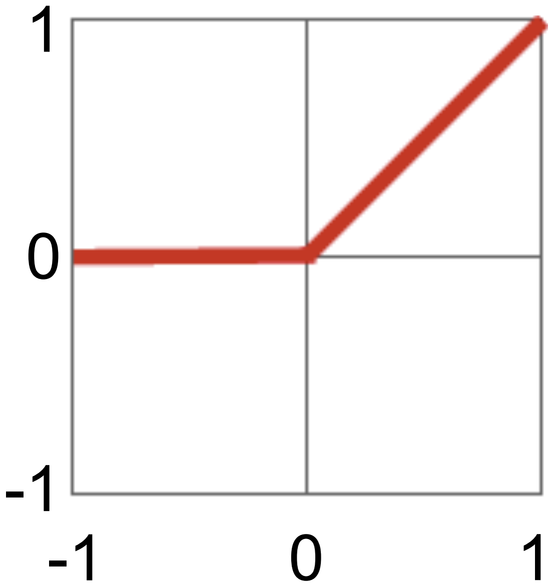


$$y=(e^{x}-e^{-x})/(e^{x}+e^{-x})$$

Image Source: Caffe Tutorial

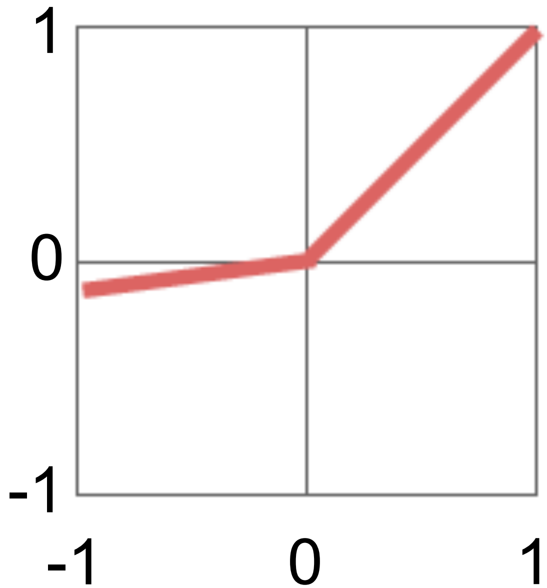
Modern Activation Functions

Rectified Linear Unit (ReLU)



$$y = \max(0, x)$$

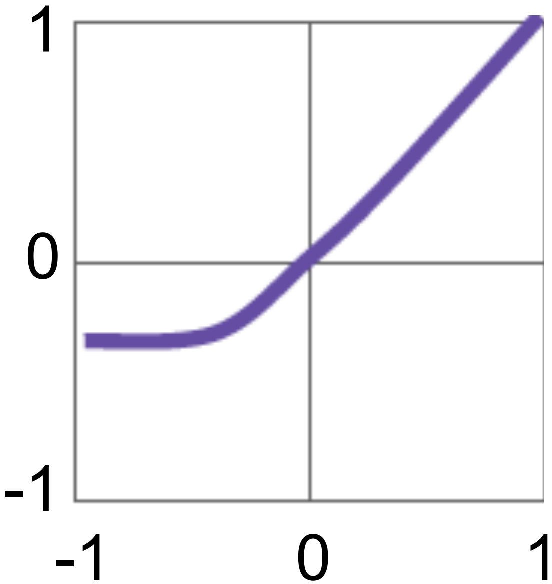
Leaky ReLU



$$y = \max(\alpha x, x)$$

α = small const. (e.g. 0.1)

Exponential LU

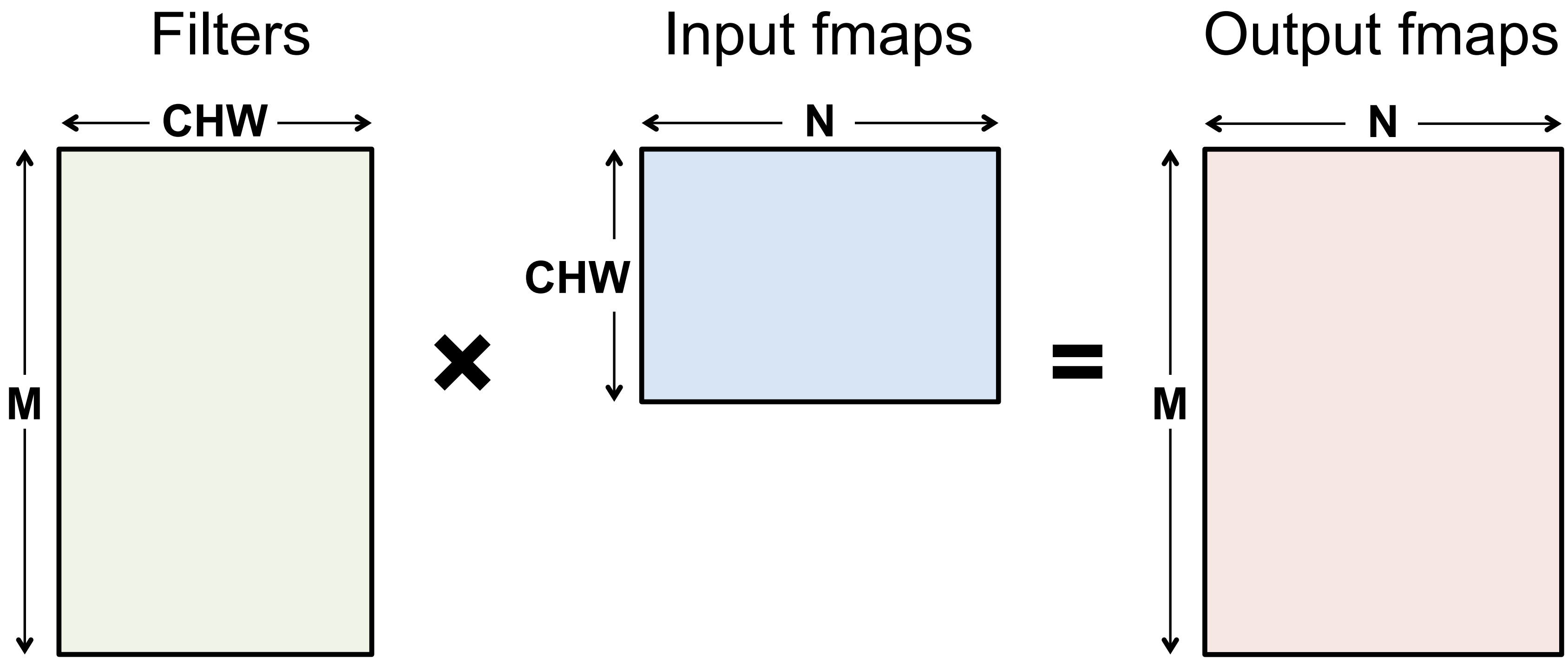


$$y = \begin{cases} x, & x \geq 0 \\ \alpha(e^x - 1), & x < 0 \end{cases}$$

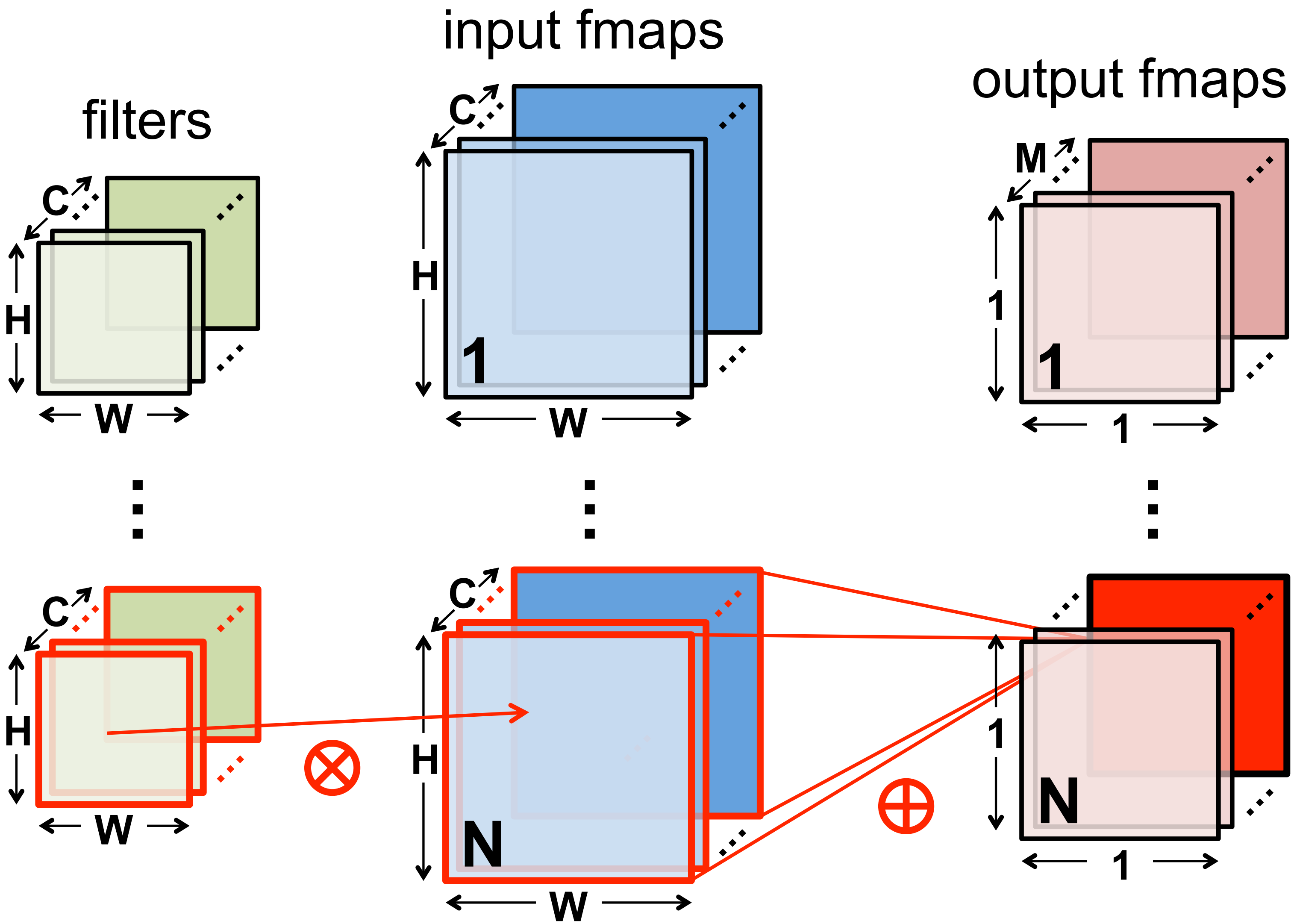
Image Source: Caffe Tutorial

Fully-Connected (FC) Layer

- Height and width of output fmaps are 1 (E = F = 1)
- Filters as large as input fmaps (R = H, S = W)
- Implementation: **Matrix Multiplication**



FC Layer – from CONV Layer POV



Pooling (POOL) Layer

- Reduce resolution of each channel independently
- Increase translation-invariance and noise-resilience
- Overlapping or non-overlapping → depending on stride

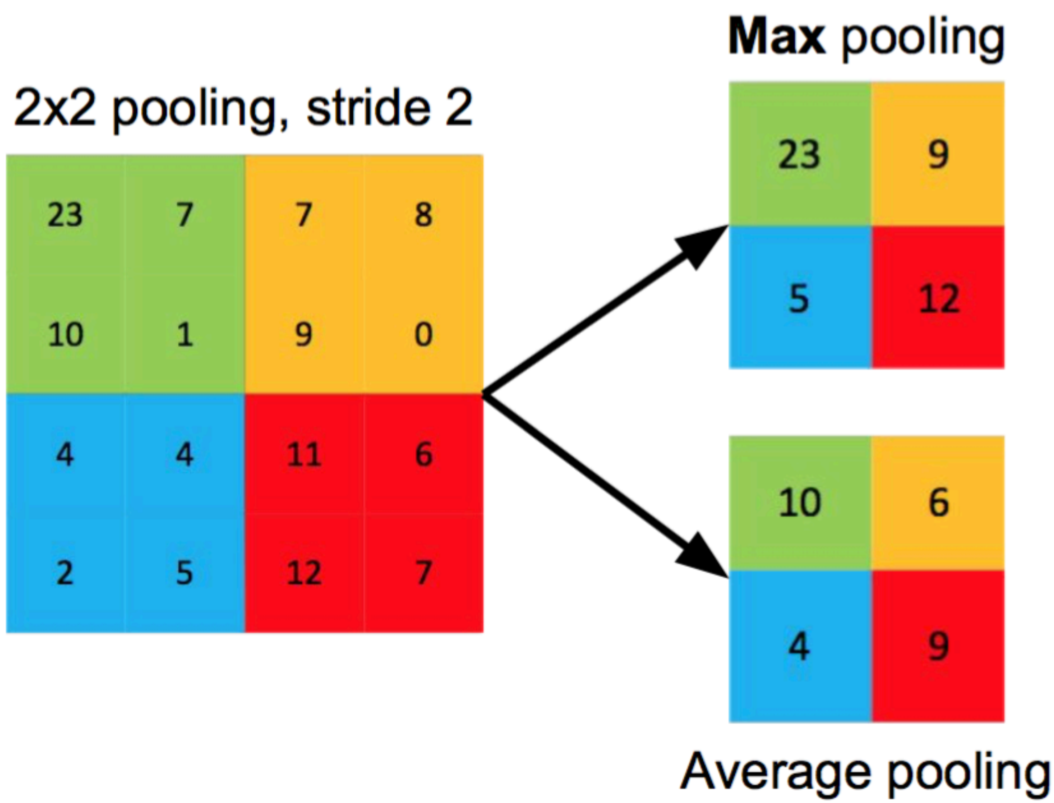


Image Source: Caffe Tutorial

POOL Layer Implementation

Naïve 6-layer for-loop max-pooling implementation:

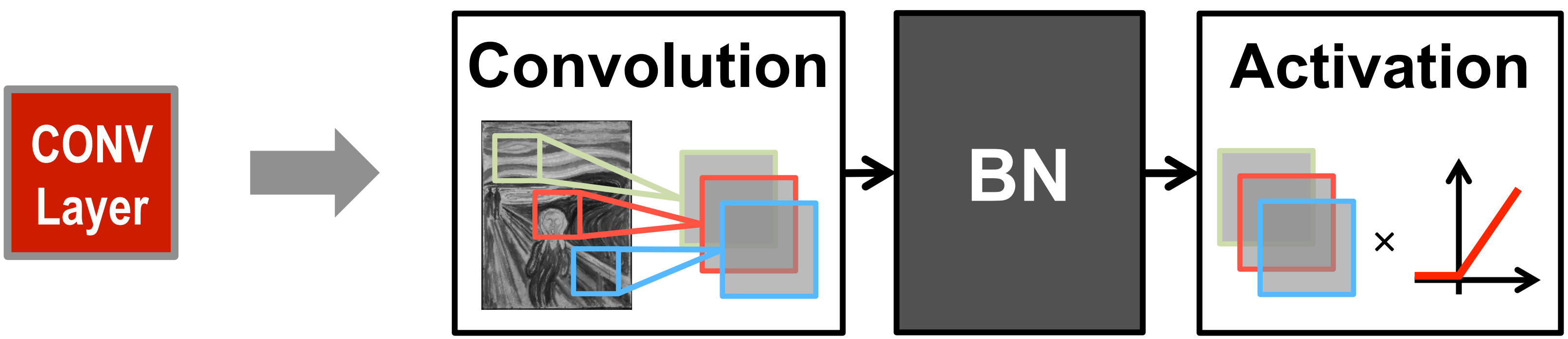
```
for (n=0; n<N; n++) {
    for (m=0; m<M; m++) {
        for (x=0; x<F; x++) {
            for (y=0; y<E; y++) {

                max = -Inf;
                for (i=0; i<R; i++) {
                    for (j=0; j<S; j++) {
                        if (I[n][m][Ux+i][Uy+j] > max) {
                            max = I[n][m][Ux+i][Uy+j];
                        }
                    }
                }

                O[n][m][x][y] = max;
            }
        }
    }
}
```

for each pooled value

find the max
with in a window

Normalization (NORM) Layer

- **Batch Normalization (BN)**
  - Normalize activations towards mean=0 and std. dev.=1 based on the statistics of the training dataset
  - put **in between** **CONV/FC** and **Activation function**



Believed to be key to getting high accuracy and faster training on very deep neural networks.

[Ioffe et al., ICML 2015]

BN Layer Implementation

- The normalized value is further scaled and shifted, the parameters of which are learned from training

data mean

learned scale factor

$$y = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}\gamma + \beta$$

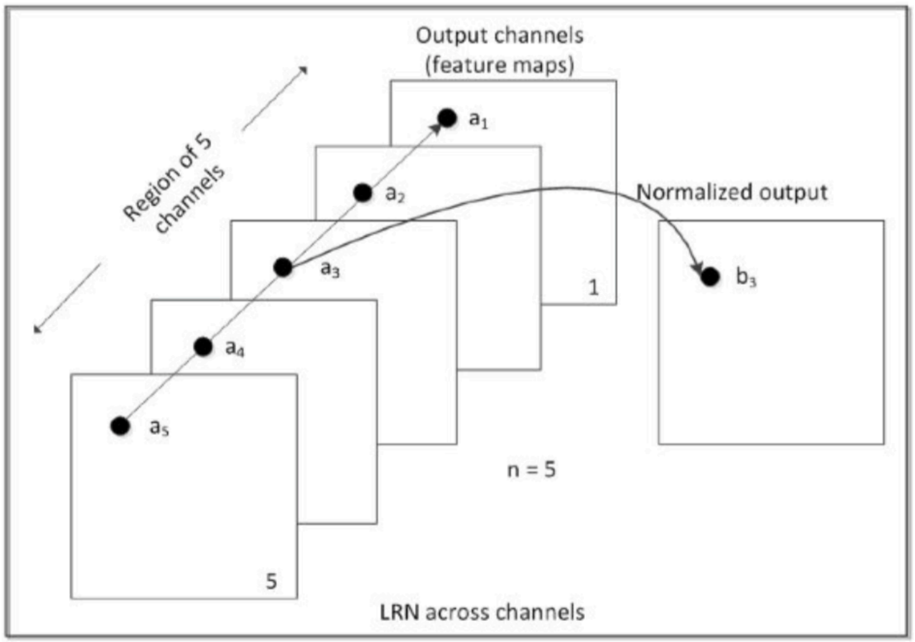
learned shift factor

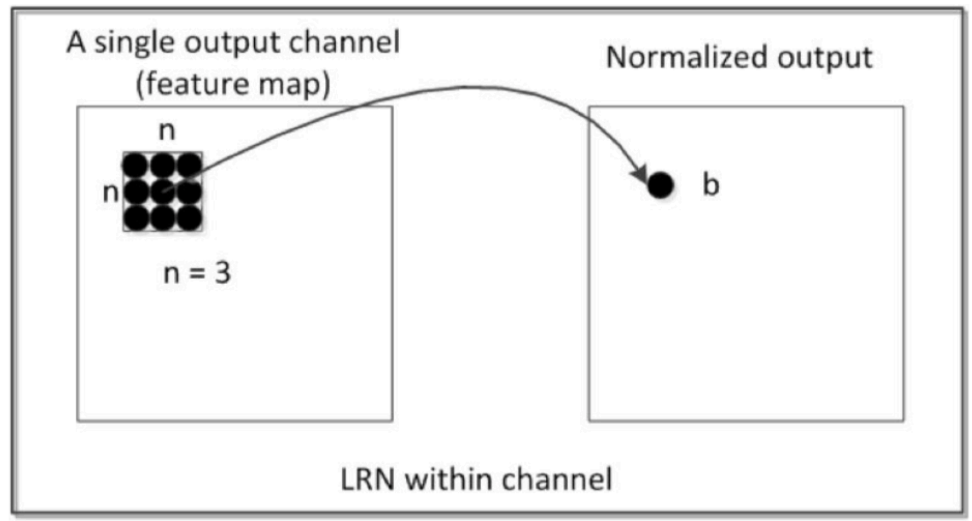
data std. dev.

small const. to avoid numerical problems

Normalization (NORM) Layer

- **Local Response Normalization (LRN)**
  - Tries to mimic the inhibition scheme in the brain





Now deprecated!

Image Source: Caffe Tutorial

Relevant Components for Tutorial

- **Typical operations that we will discuss:**
  - Convolution (CONV)
  - Fully-Connected (FC)
  - Max Pooling
  - ReLU