Introduction to Convolutional Neural Networks

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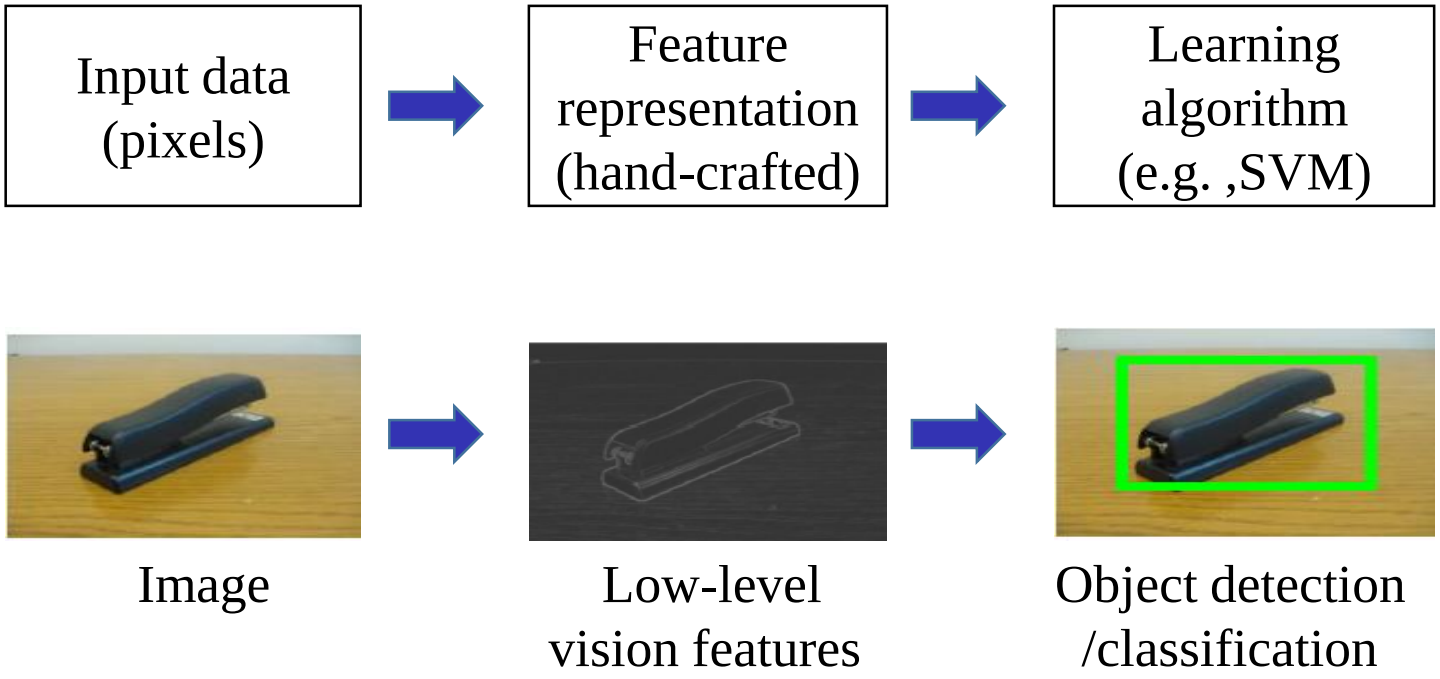
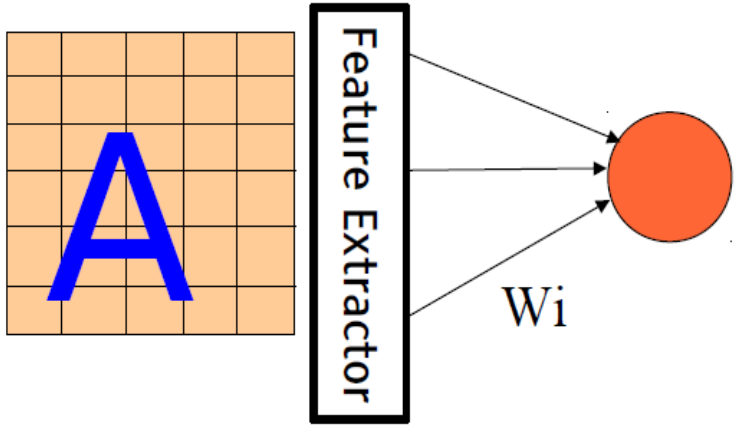
Traditional Recognition Methods



Traditional Recognition Methods

$$y = \text{sign}\left(\sum_{i=1}^{N} \mathbf{W}_i F_i(\mathbf{X}) + \text{b}\right)$$

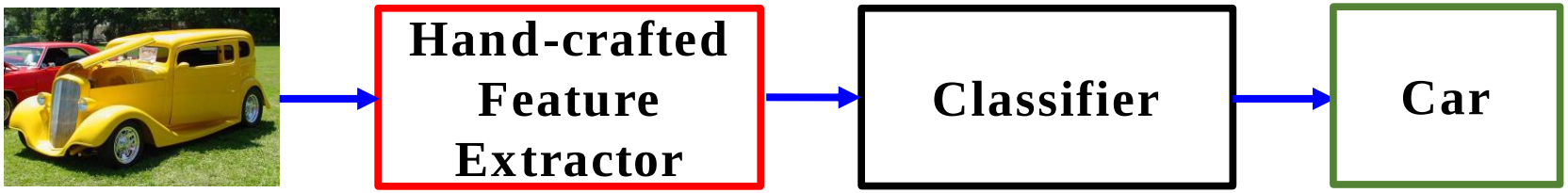


Linear Classifier

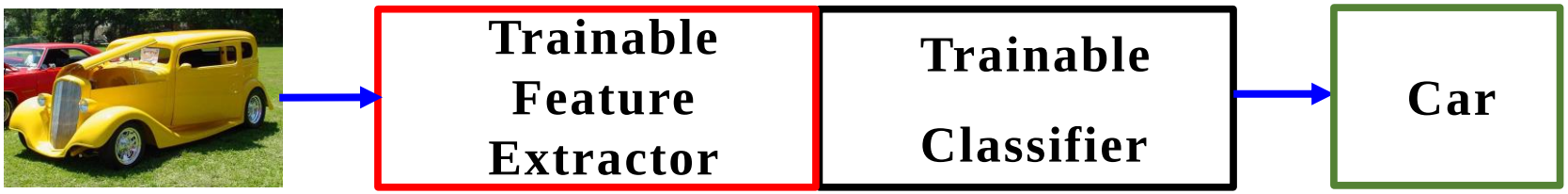
- **Linear classifier** is on top of a simple **feature extractor**
- Highly depend on the **quality of extracted feature**
- Designing a feature extractor requires **considerable efforts**

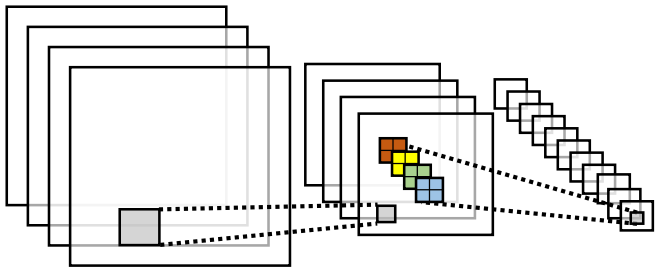
Traditional Methods vs Deep Learning

- Traditional recognition with **hand-crafted feature**, e.g. SIFT and LBP feature

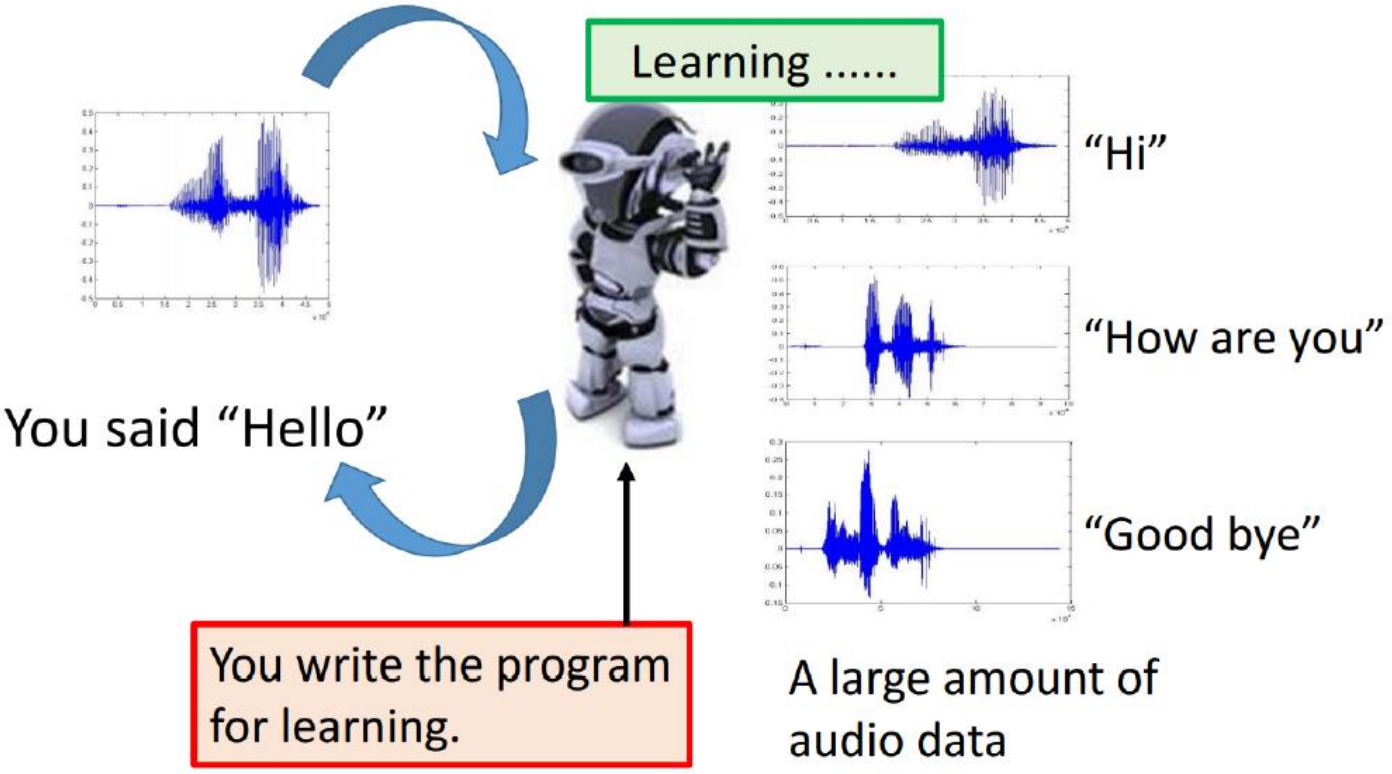


- Deep learning / Feature learning





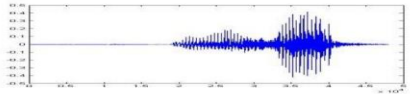
What is Deep Learning?



Deep Learning

Looking for a Function f:

- Speech Recognition

$f($  $)=$ "How are you"

- Image Recognition

$f($  $)=$ "Cat"

- Playing Go

$f($  $)=$ "5-5" (next move)

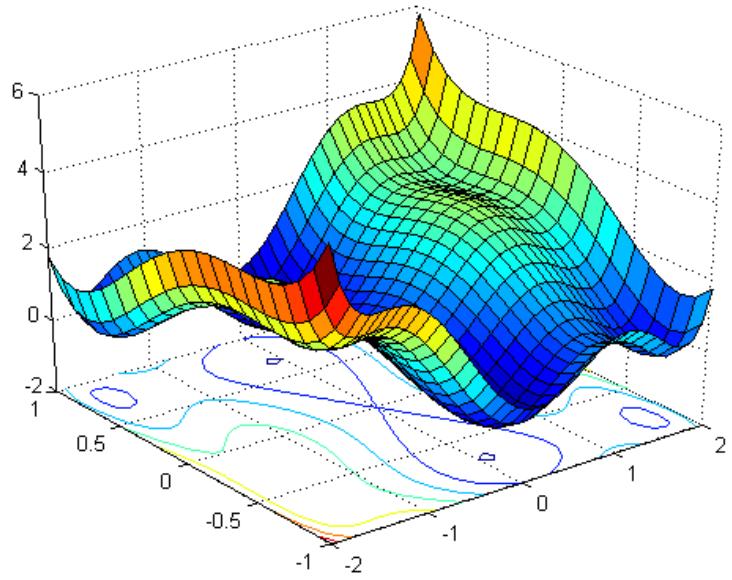
- Dialogue System

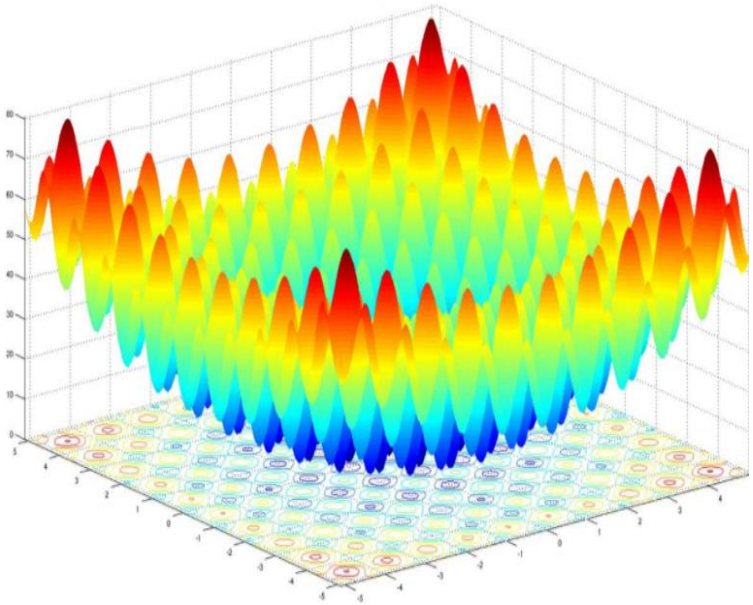
$f($ "Hi" $)=$ "Hello"

(what the user said) (system response)

Deep Learning

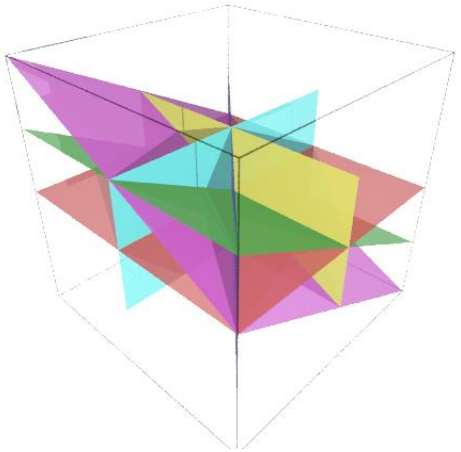
- Looking for a **Function** f:

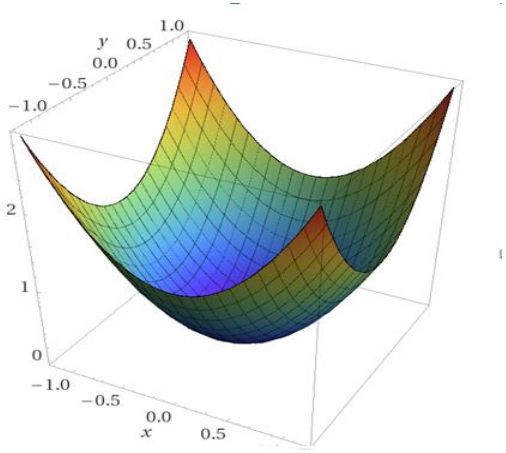


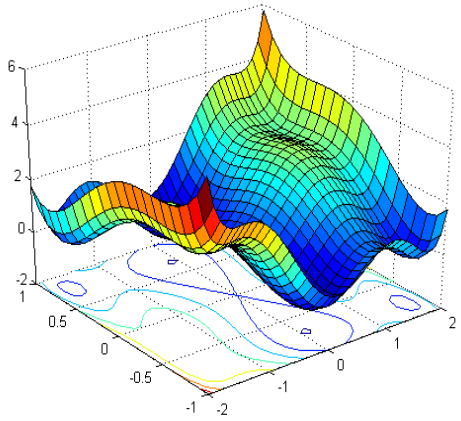


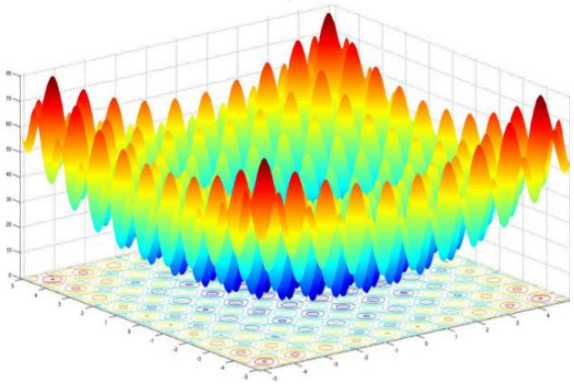
Deep Learning

- What kind of functions can we choose?









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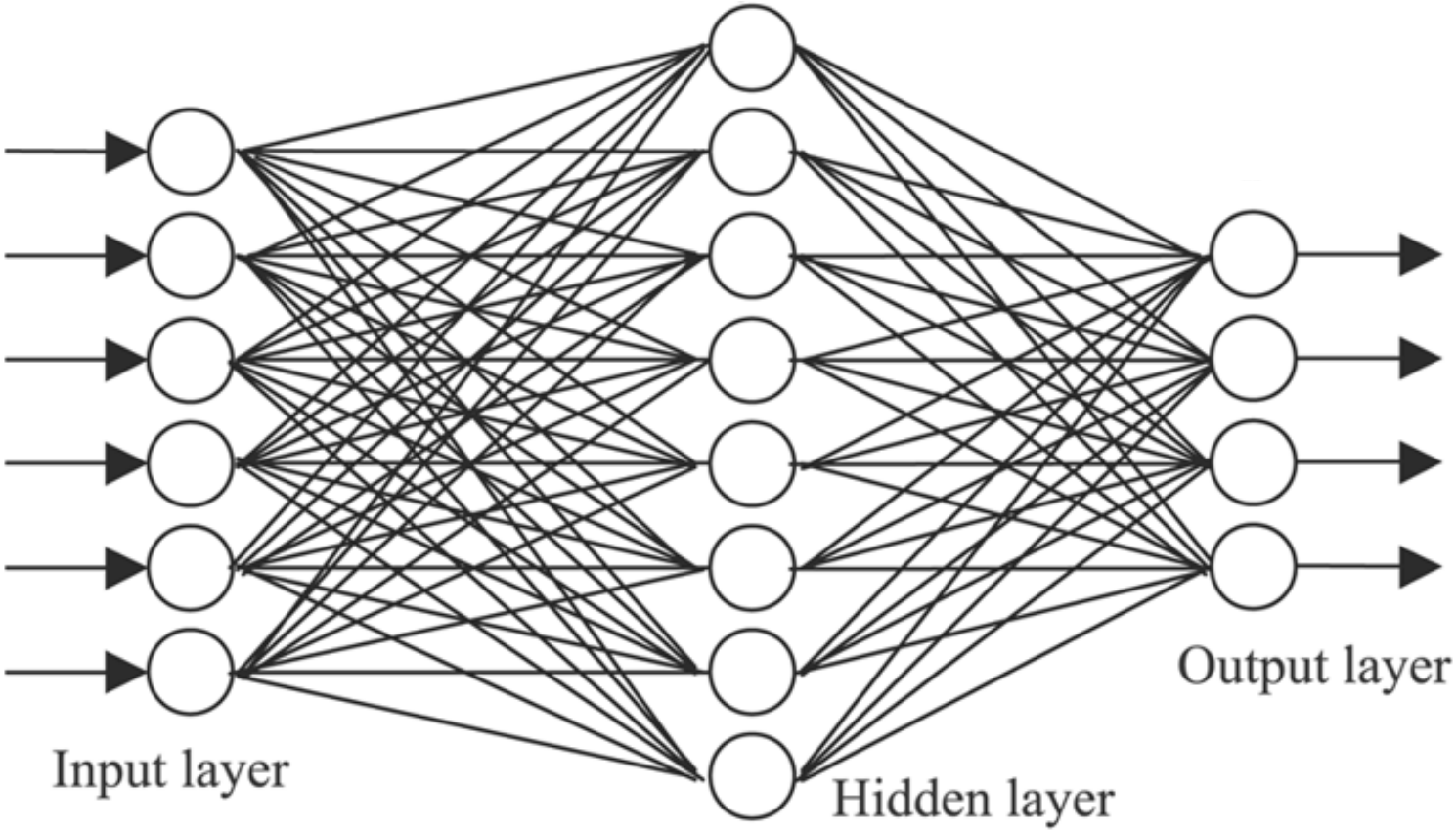
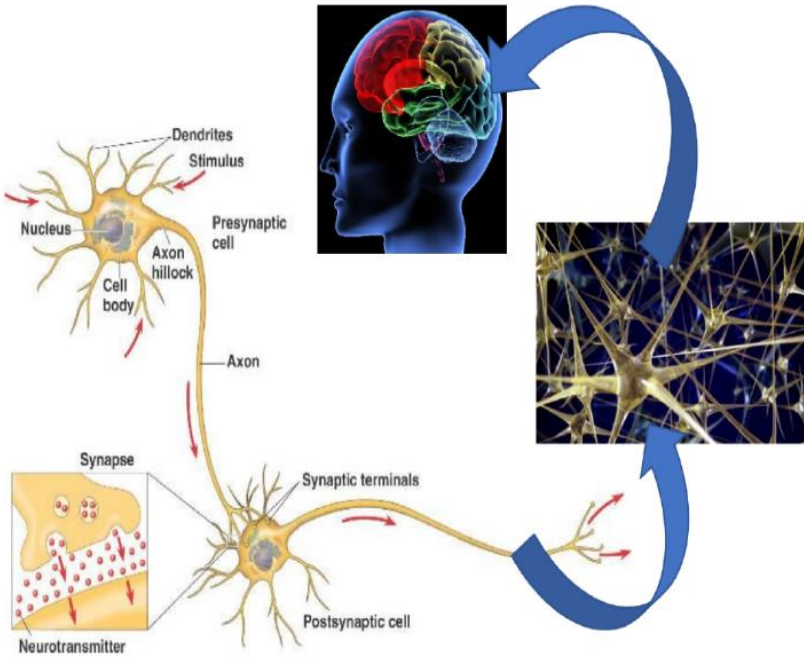
Neural Networks

- To approximate the function, we can build **neural networks**:

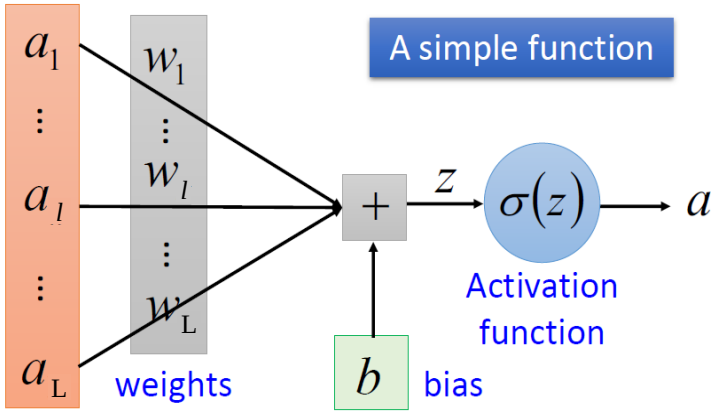


Neurons in Human Brains

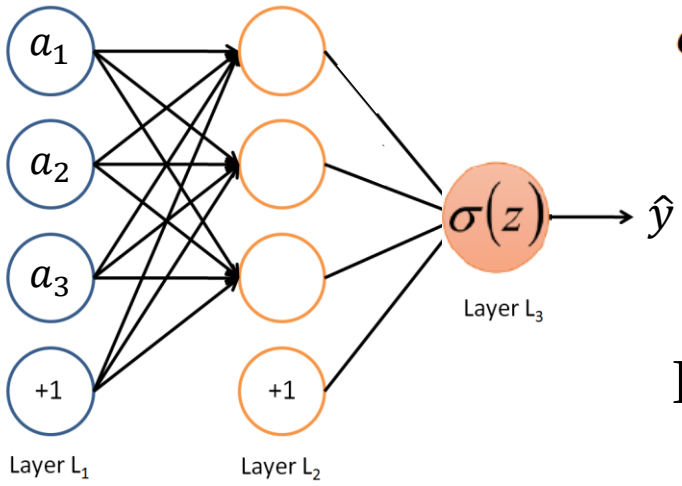


Neuron

$$z = a_1 w_1 + \cdots + a_l w_l + \cdots + a_L w_L + b$$

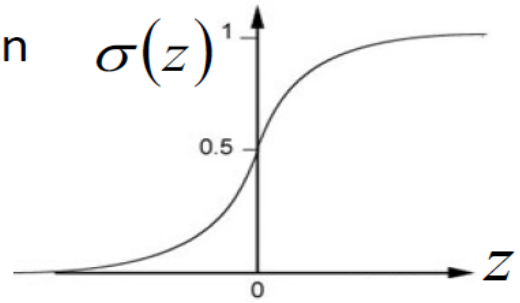


Neural Networks



Sigmoid Function

$$\sigma(z) = \frac{1}{1+e^{-z}}$$



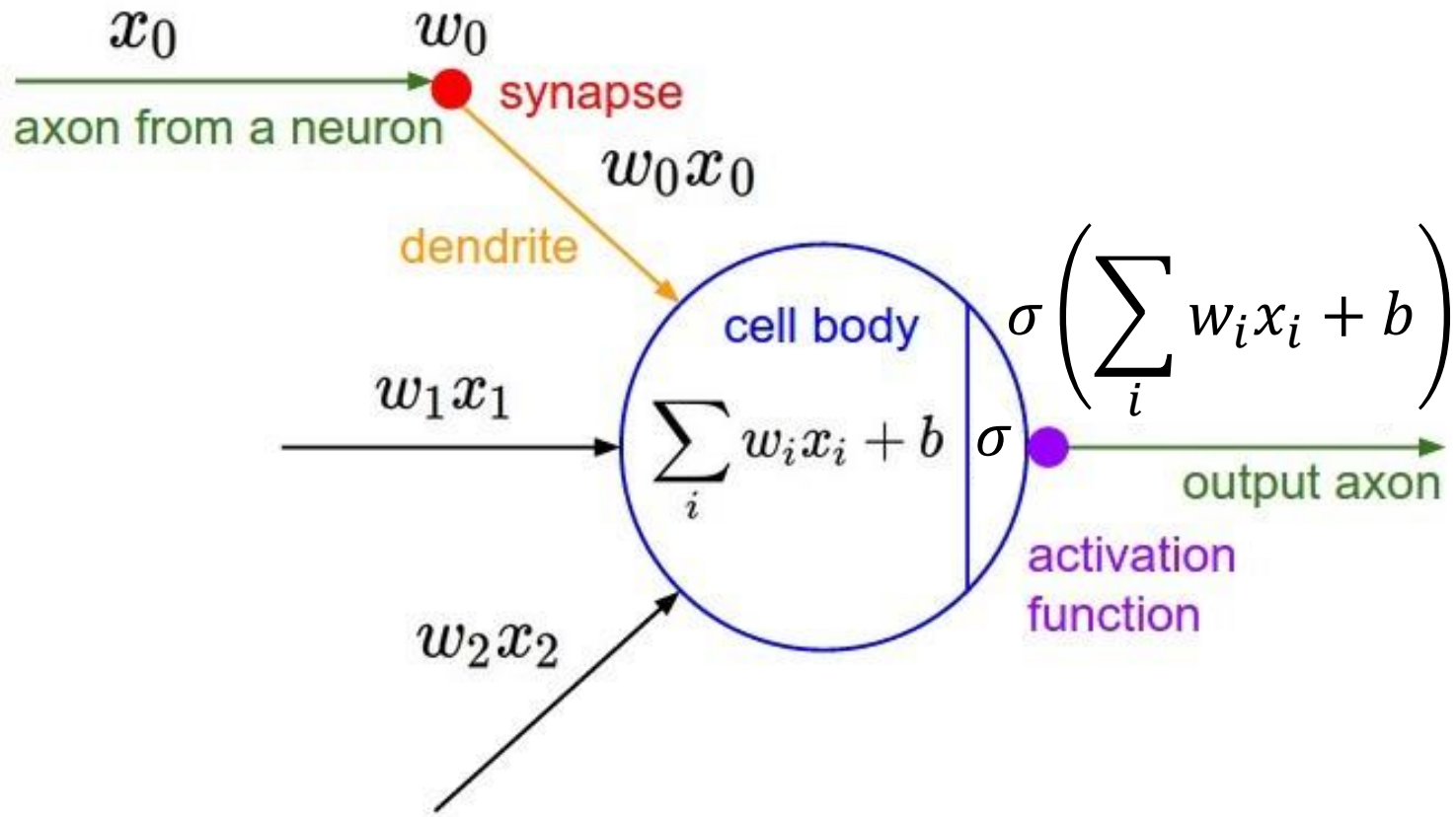
$$\text{Loss function } \mathcal{L} = \sum_{i=1}^{n} \|\hat{y}_i - y_i\|^2$$

Representation Theory (Kurt Hornik, 1991)

A feed-forward neural network with **a single hidden layer** containing a **finite number of neurons** can approximate continuous function on compact subsets of $\mathbf{R}^n$ under mild assumptions on the **activation function**

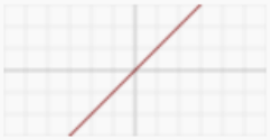
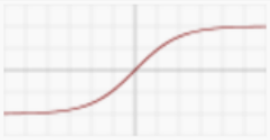
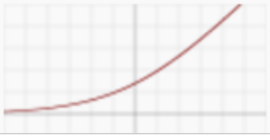
Activation Function

- **Description**: keep value within an acceptable and useful range



Activation Layer

- Activation functions: **nonlinear** and **continuously differentiable**

Activation Function	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Sigmoid		$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1-f(x))$
Tanh		$f(x) = \frac{2}{1+e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ReLU		$f(x) = \max(x, 0)$	$f'(x) = 1\{x \geq 0\}$
SoftPlus		$f(x) = ln(1+e^{x})$	$f'(x) = \frac{1}{1+e^{-x}}$

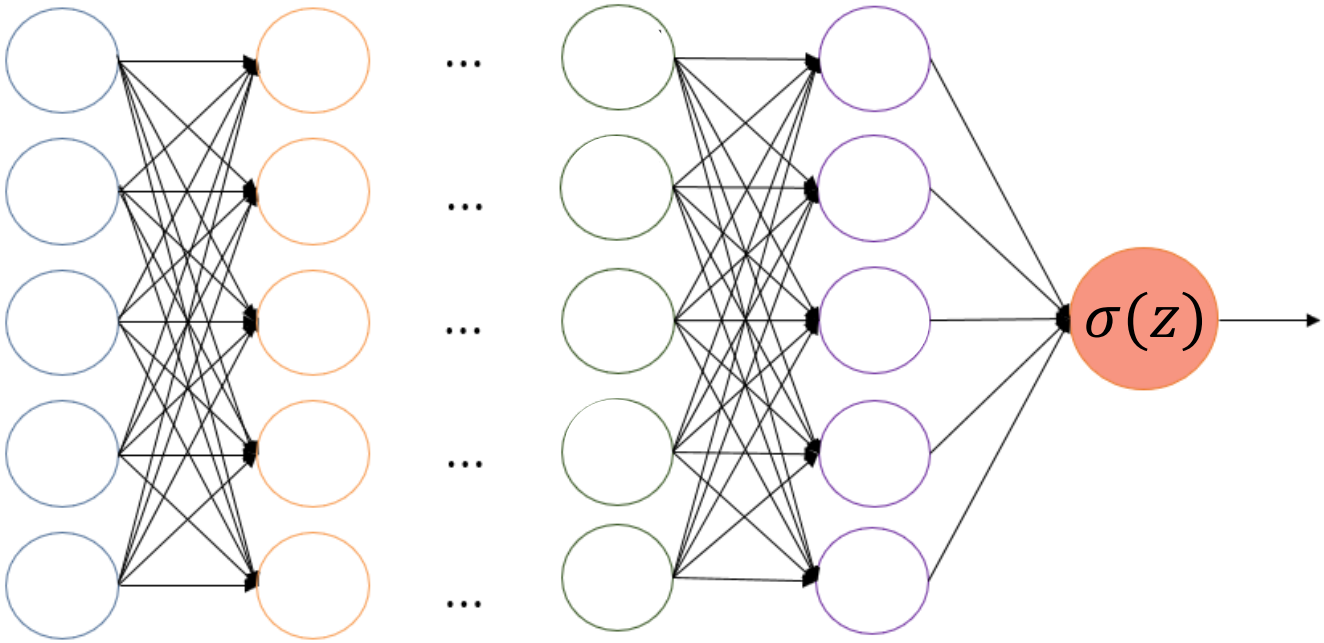
From Shallow to Deep Neural Networks

Function Approximation Theory (Shiyu Liang, 2017)

Shallow networks require **exponentially more neurons** than a deep network to achieve the same level of accuracy for function approximation

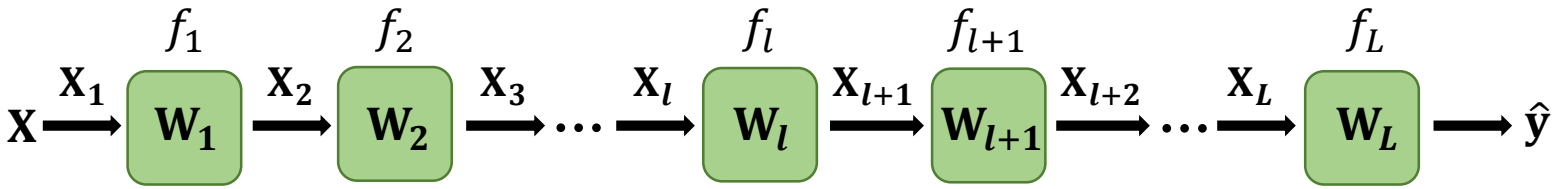
Shallow neural network → Need a lot of parameters → **Hard for training**

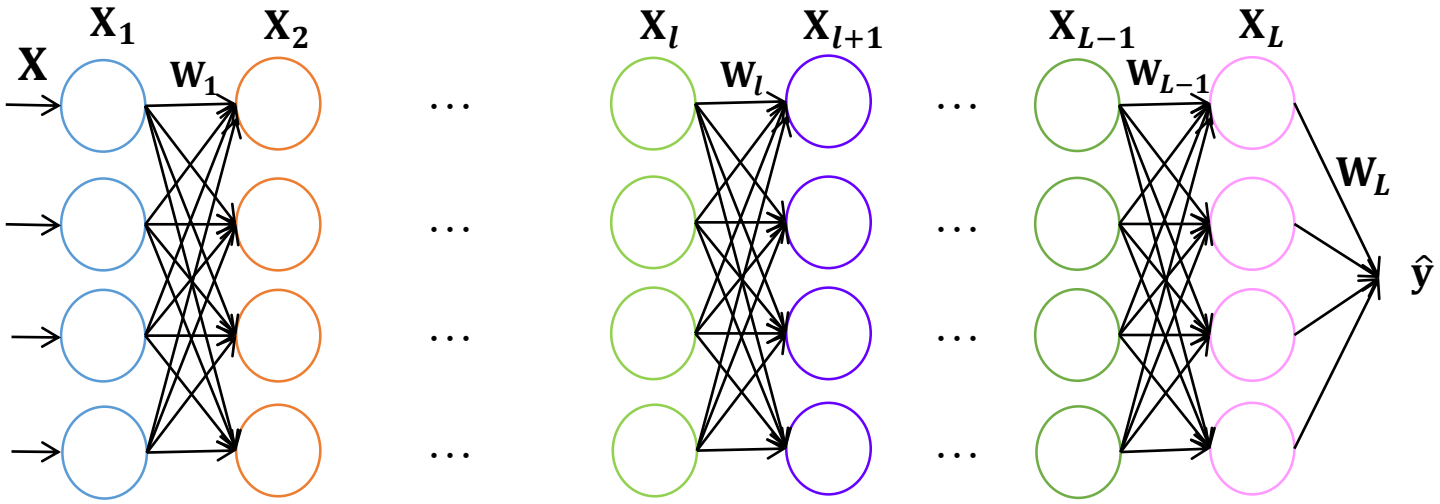
To approximate $F(\mathbf{X})$, we can build a **deep** neural network with less parameters:



From Shallow to Deep Neural Networks

To approximate $F(\mathbf{X})$, we can build a **deep** neural network with **LESS parameters**:





$\mathbf{X}$: input data

$\hat{\mathbf{y}}$: prediction of the model

$\mathbf{X}_l$: output of Layer l

f_l : function of Layer l

$\mathbf{W}_l$: parameters of Layer l

The output of layer l, i.e. $\mathbf{X_{l+1}}$ is the input of f_{l+1}

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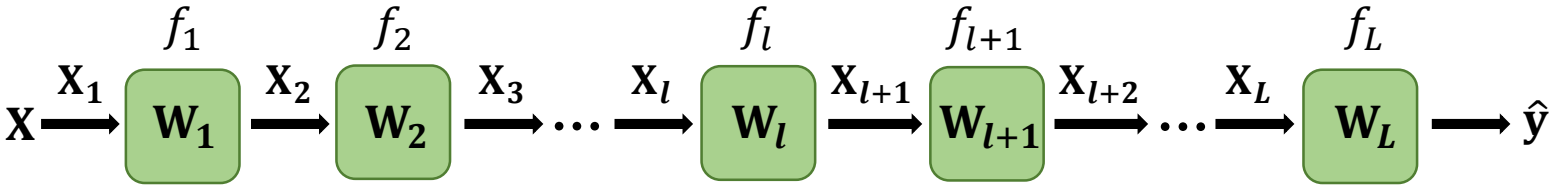
Forward propagation of neural networks



$$f = f_L \circ f_{L-1} \circ \cdots \circ f_2 \circ f_1$$

Prediction for Networks f : Forward Propagation

- Given input data $\mathbf{X}$, the forward propagation of a neural network f is to **predict** the output $\hat{\mathbf{y}}$ of $\mathbf{X}$
- Rewrite the network as a Composite Function

$$\hat{\mathbf{y}} = f(\mathbf{X}) = f_L \circ f_{L-1} \circ \cdots \circ f_2 \circ f_1(\mathbf{X})$$

- Detailed prediction process:

$$\begin{aligned}
\mathbf{X}_1 &= \mathbf{X} \\
\mathbf{X}_2 &= f_1(\mathbf{X}_1, \mathbf{W}_1) \\
&\vdots \\
\mathbf{X}_{l+1} &= f_l(\mathbf{X}_l, \mathbf{W}_l) \\
&\vdots \\
\mathbf{X}_L &= f_{L-1}(\mathbf{X}_{L-1}, \mathbf{W}_{L-1}) \\
\hat{y} &= f_L(\mathbf{X}_L, \mathbf{W}_L)
\end{aligned}$$

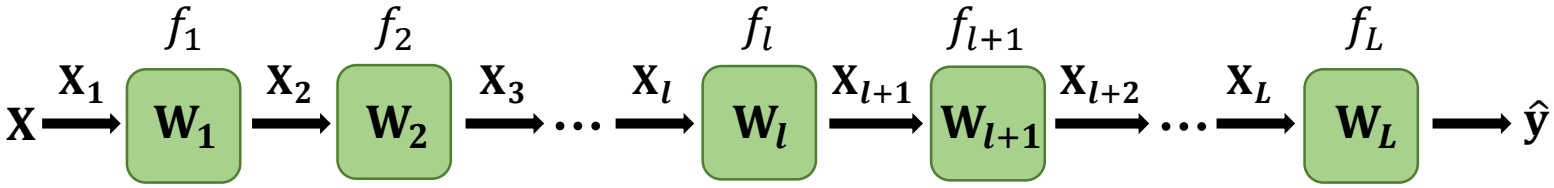
$$\hat{\mathbf{y}} = f(\mathbf{X})$$

$$f_l = \sigma(h_l(\mathbf{X}_l, \mathbf{W}_l))$$

Example:

$$h_l = \mathbf{W}_l * \mathbf{X}_l$$

$$\sigma = \mathrm{ReLU}(\cdot)$$



Forward Propagation: Prediction of Networks

- Detailed prediction process:

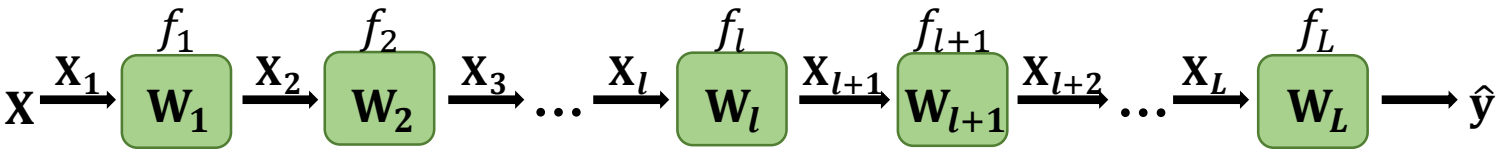
$$\mathbf{X}_1 = \mathbf{X}$$
$$\mathbf{X}_2 = f_1(\mathbf{X}_1, \mathbf{W}_1)$$
$$\vdots$$
$$\mathbf{X}_{l+1} = f_l(\mathbf{X}_l, \mathbf{W}_l)$$
$$\vdots$$
$$\mathbf{X}_L = f_{L-1}(\mathbf{X}_{L-1}, \mathbf{W}_{L-1})$$
$$\hat{\boldsymbol{y}} = f_L(\mathbf{X}_L, \mathbf{W}_L)$$

Compact Form

- Forward propagation for any layer l :

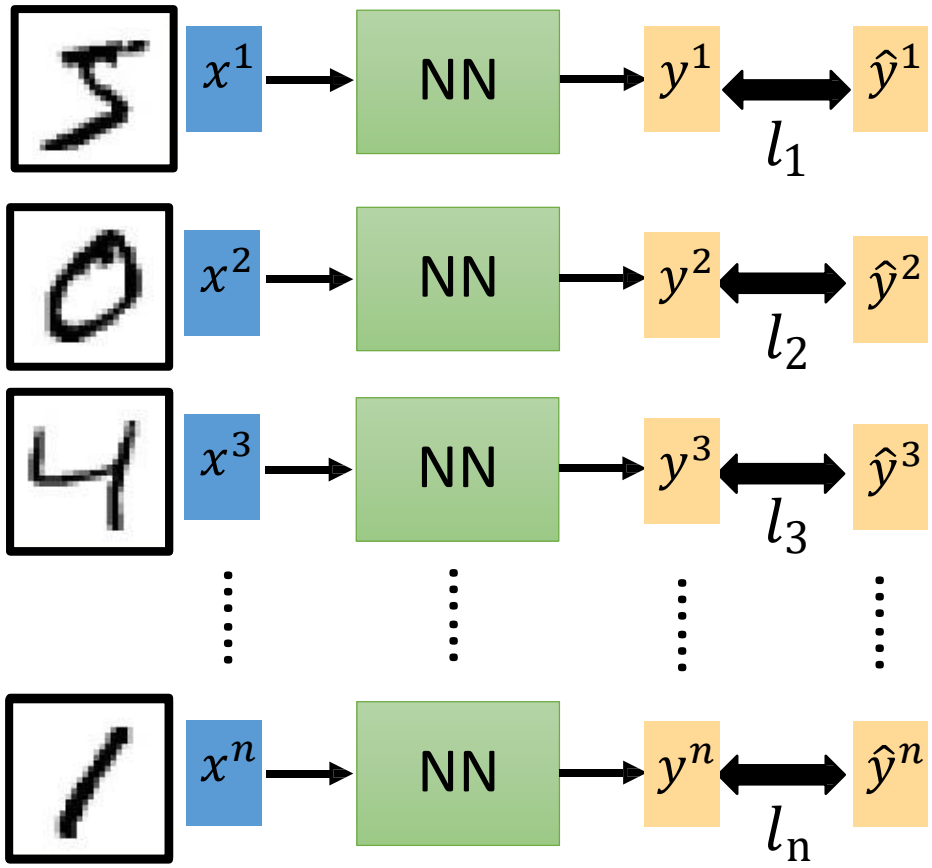
$$\begin{cases} \mathbf{Z}_l = h_l(\mathbf{X}_l, \mathbf{W}_l) \\ \mathbf{X}_{l+1} = \sigma(\mathbf{Z}_l) \end{cases}$$

h_l: some linear function
σ: some activation function



Example of Forward Prediction

For all training data:



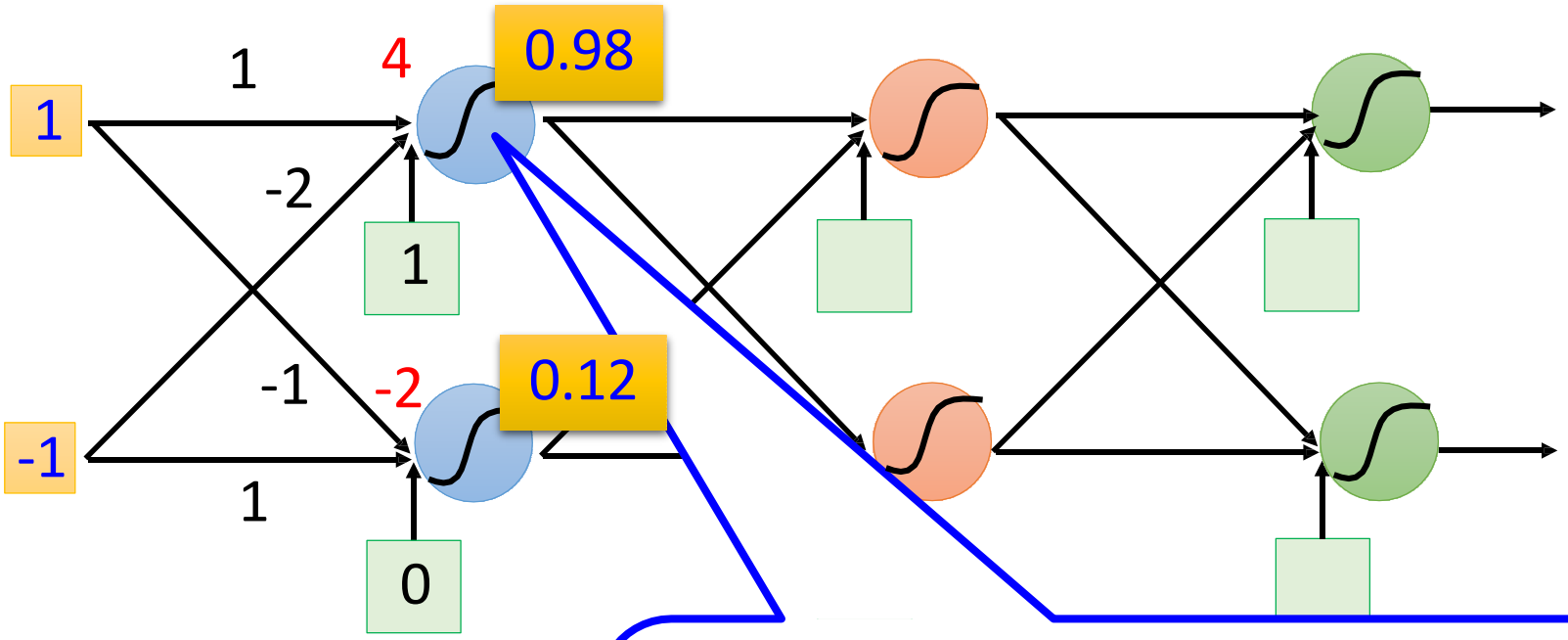
Total loss: $\mathcal{L} = \sum_{r=1}^{n} l_r$

As small as possible

Find ***a function in function set*** that minimizes total loss $\mathcal{L}$

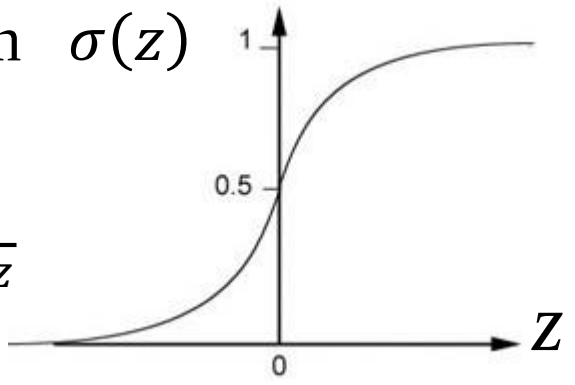
Find ***the network parameters*** $\mathbf{W}^*$ that minimize total loss $\mathcal{L}$

Example for Forward Propagation

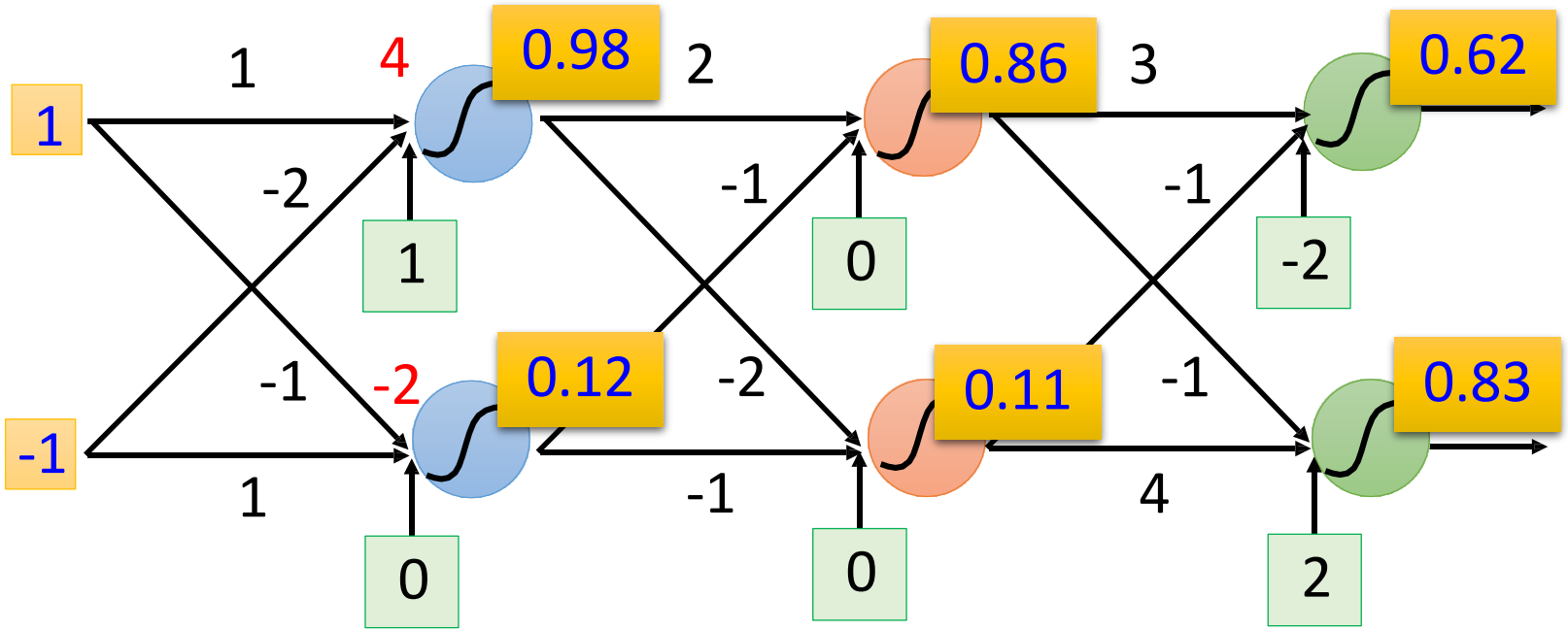


Sigmoid function $\sigma(z)$

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

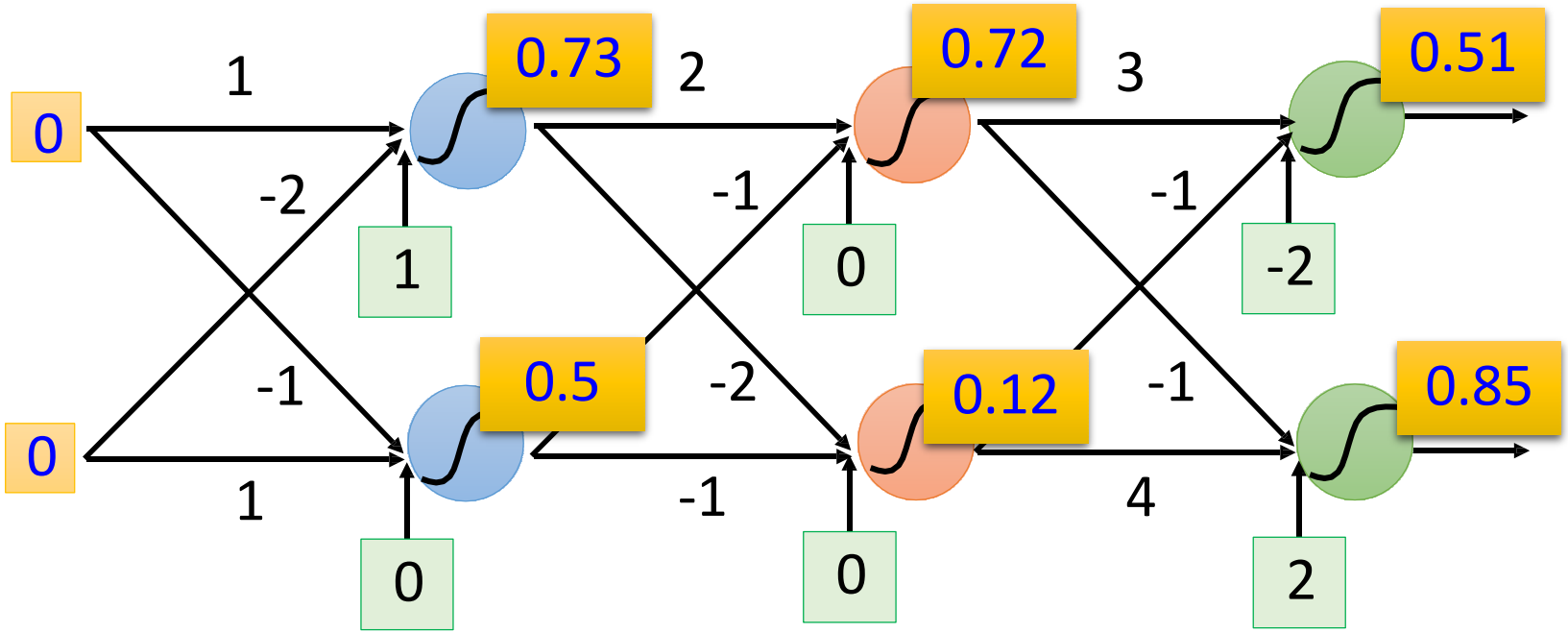


Example for Forward Propagation



$$f\left(\begin{bmatrix}1\\-1\end{bmatrix}\right) = \begin{bmatrix}0.62\\0.83\end{bmatrix}$$

Example for Forward Propagation



$$f\left(\begin{bmatrix}0\\0\end{bmatrix}\right) = \begin{bmatrix}0.51\\0.85\end{bmatrix}$$

Contents

Backpropagation of neural networks

How to Learn Model Parameters $\{\mathbf{W}_l\}$?

- We minimize the following regularized loss function:

Regularized Loss function:

$$\min_{\mathbf{W}} \frac{1}{N}\sum_{i=1}^{N}\mathcal{L}(\mathbf{y}_i, \hat{\mathbf{y}}_i) + \frac{1}{2}\lambda\|\mathbf{W}\|_F^2$$

$\mathbf{W}$ – parameters $\quad \mathcal{L}$ – loss function

$\mathbf{y}_i$ – ground-truth label $\quad \hat{\mathbf{y}}_i$ – predicted label

Connection to previous models?

- Linear Regression?
- Support Vector Machine?
- Logistic Regression?
- Softmax Regression?
- AdaBoost?
- GBDT?

- Gradient Descent: update the parameters $\mathbf{W}_l$ by

$$\mathbf{W}_l' = \mathbf{W}_l - \eta \cdot \frac{\partial \mathcal{L}}{\partial \mathbf{W}_l} \qquad (1)$$

where η is the learning rate

How to compute the gradient $\frac{\partial \mathcal{L}}{\partial \mathbf{W}_l}$?

How to Compute Gradient $\frac{\partial \mathcal{L}}{\partial \mathbf{W}_l}$?

- Recall the loss function can be rewritten as the Composite Function:

$$\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = \mathcal{L} \circ f_L \circ f_{L-1} \circ \cdots \circ f_l(\mathbf{W}_l) \circ \cdots \circ f_2 \circ f_1$$

Computing the gradient $\frac{\partial \mathcal{L}}{\partial \mathbf{W}_l}$ is extremely difficult!

- Let us resort to **Chain Rule** to compute the gradient

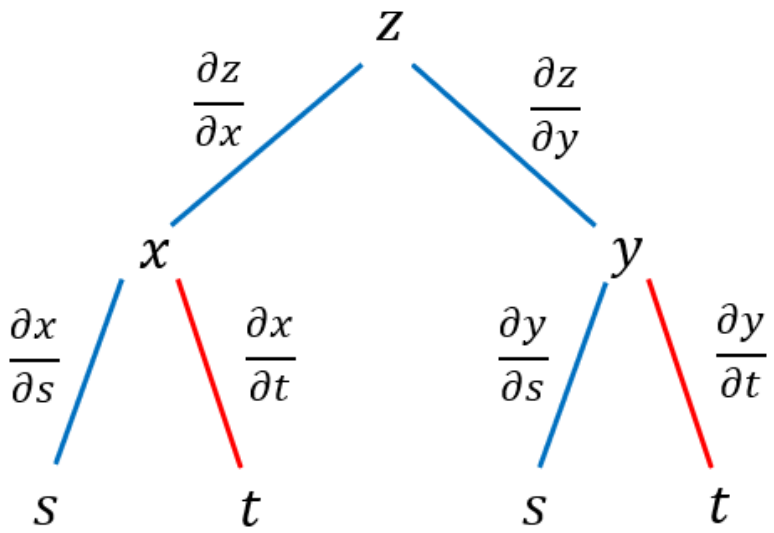
$$z = x \circ s \implies \boxed{\frac{\partial z}{\partial s} = \frac{\partial z}{\partial x}\frac{\partial x}{\partial s}} \quad ?$$

Chain Rule Revisited

- Suppose we have the following differentiable functions:

$$\begin{cases} z = f(x, y) \\ x = g(s, t) \\ y = h(s, t) \end{cases}$$

How to compute $\frac{\partial z}{\partial s}$ and $\frac{\partial z}{\partial t}$?



- We have **Chain Rule** as below:

$$\frac{\partial z}{\partial s} = \frac{\partial z}{\partial x}\frac{\partial x}{\partial s} + \frac{\partial z}{\partial y}\frac{\partial y}{\partial s}$$

$$\frac{\partial z}{\partial t} = \frac{\partial z}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial z}{\partial y}\frac{\partial y}{\partial t}$$

Gradient Computation of Neural Network f

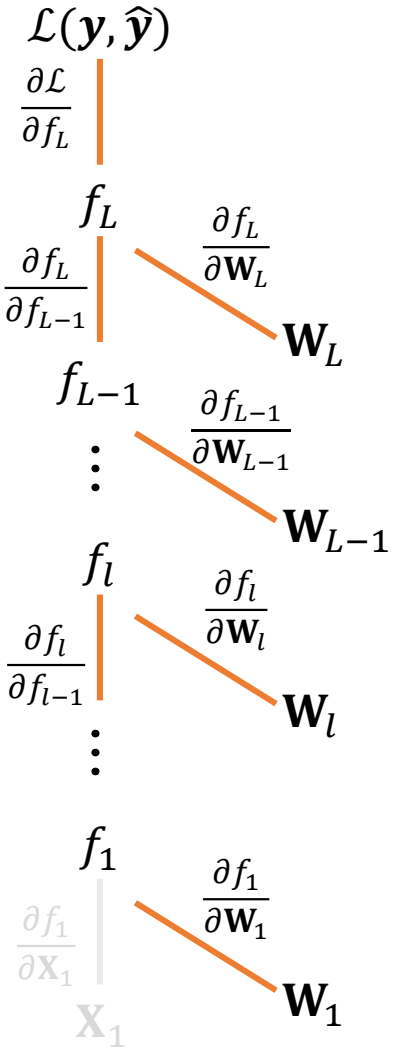
$$\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = \mathcal{L} \circ f_L \circ f_{L-1} \circ \cdots \circ f_l \circ \cdots \circ f_2 \circ f_1(\mathbf{W}_1)$$

How to compute the gradient $\frac{\partial \mathcal{L}}{\partial \mathbf{W}_1}$?

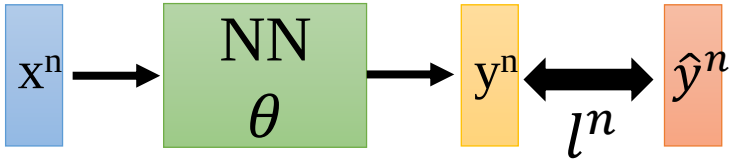
- According to **Chain Rule**, we have

$$\frac{\partial \mathcal{L}(\mathbf{y}, \hat{\mathbf{y}})}{\partial \mathbf{W}_1} = \boxed{\frac{\partial \mathcal{L}}{\partial f_L} \cdot \frac{\partial f_L}{\partial f_{L-1}} \cdot \cdots \cdot \frac{\partial f_3}{\partial f_2} \cdot \frac{\partial f_2}{\partial f_1}} \cdot \frac{\partial f_1}{\partial \mathbf{W}_1}$$

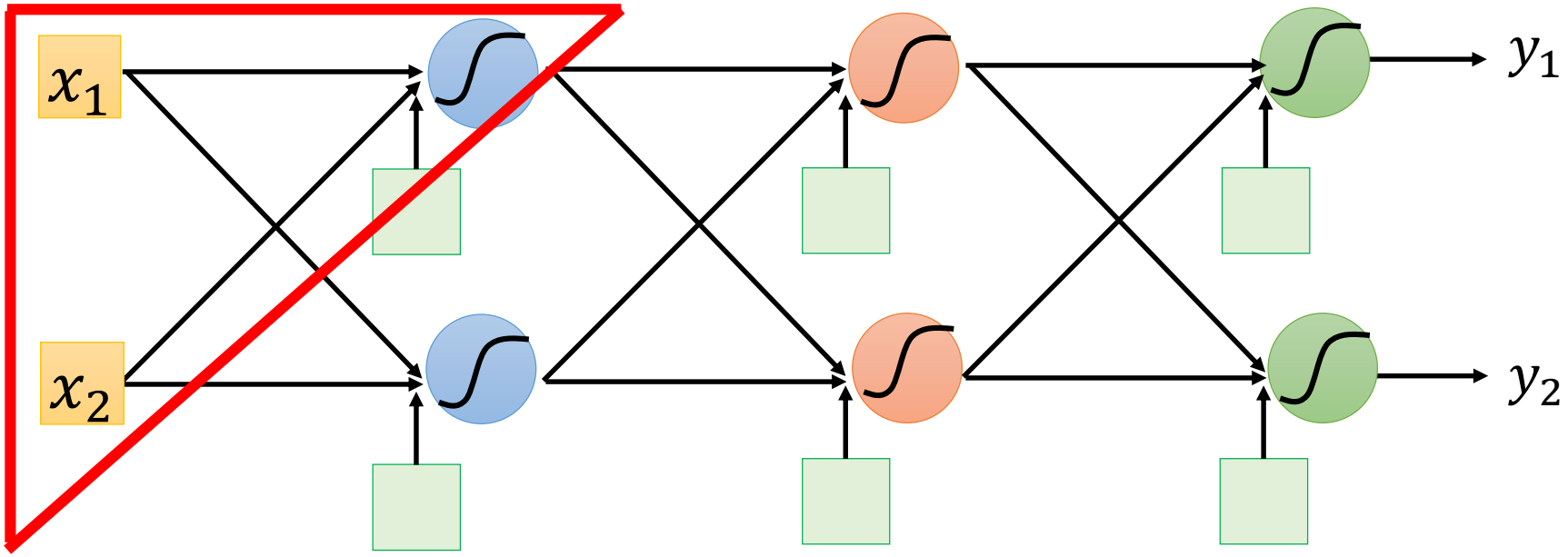
Gradient Chain



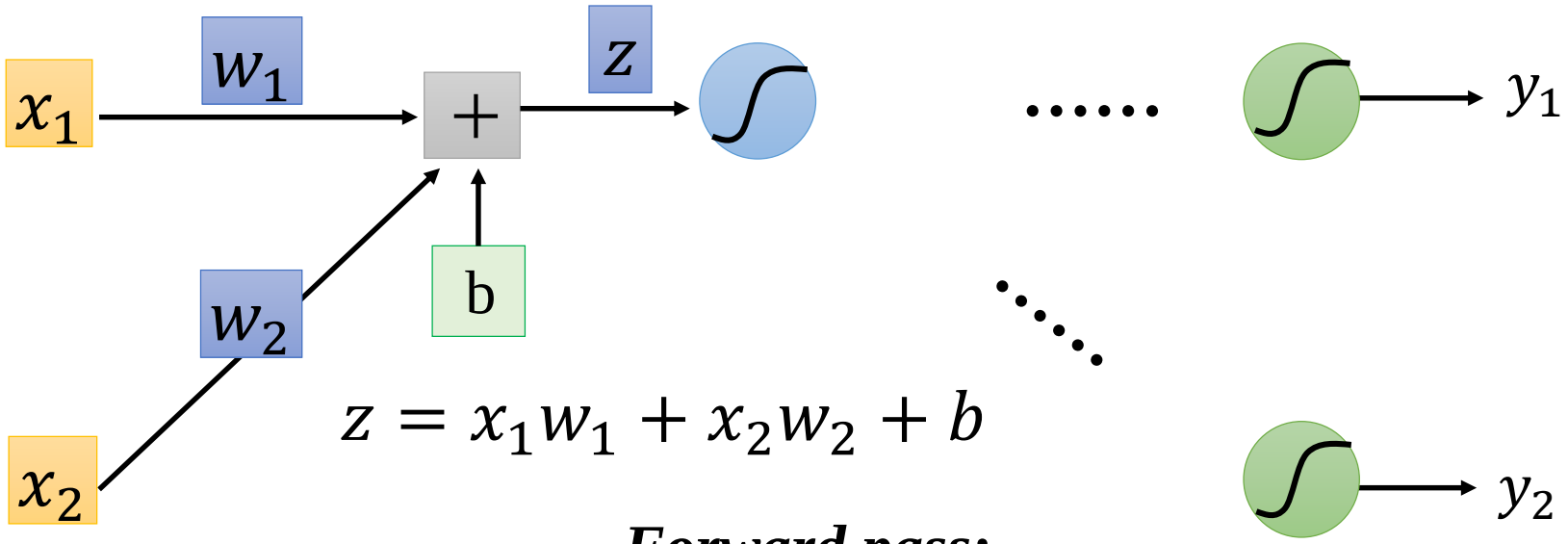
Example for Backpropagation



$$L(\theta) = \sum_{n=1}^{N} l^n(\theta) \quad \Rightarrow \quad \frac{\partial L(\theta)}{\partial w} = \sum_{n=1}^{N} \frac{\partial l^n(\theta)}{\partial w}$$



Example for Backpropagation



$$z = x_1 w_1 + x_2 w_2 + b$$

Forward pass:

Compute $\partial z / \partial w$ for all parameters

$$\frac{\partial l}{\partial w} = \frac{\partial z}{\partial w} \frac{\partial l}{\partial z}$$

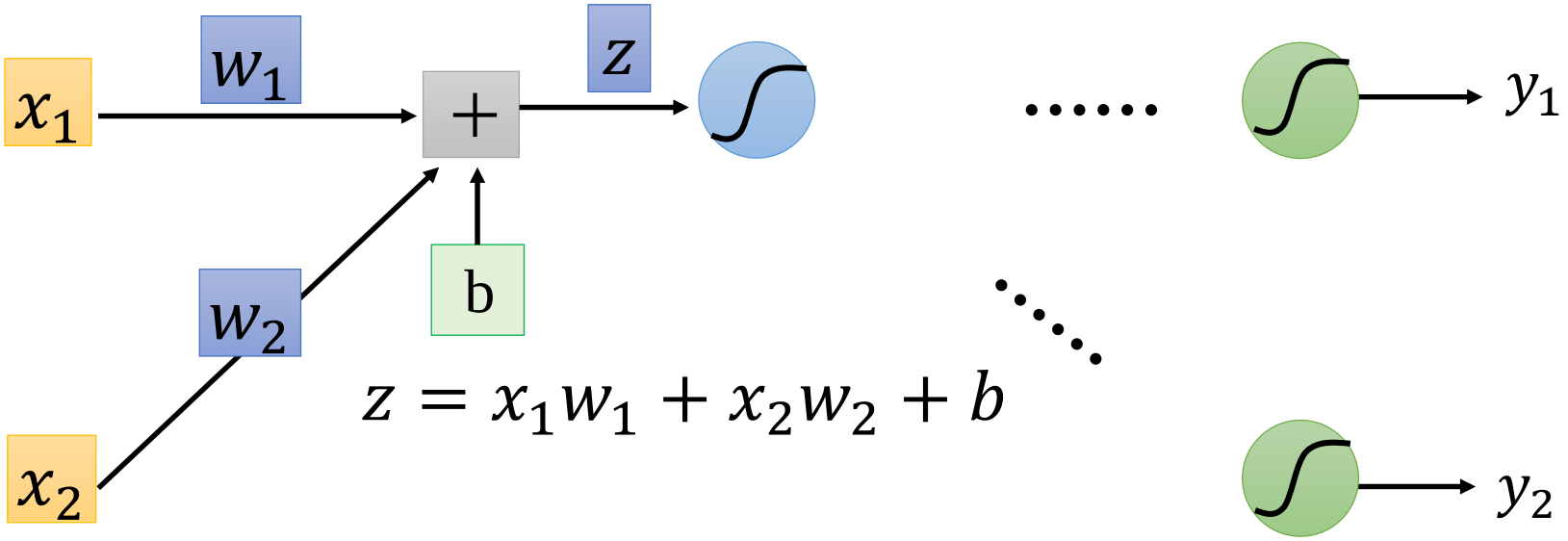
(Chain rule)

Backward pass:

Compute $\partial l / \partial z$ for all activation function inputs z

Example for Backpropagation - Forward pass

Compute $\partial z/\partial w$ for all parameters



$$z = x_1 w_1 + x_2 w_2 + b$$

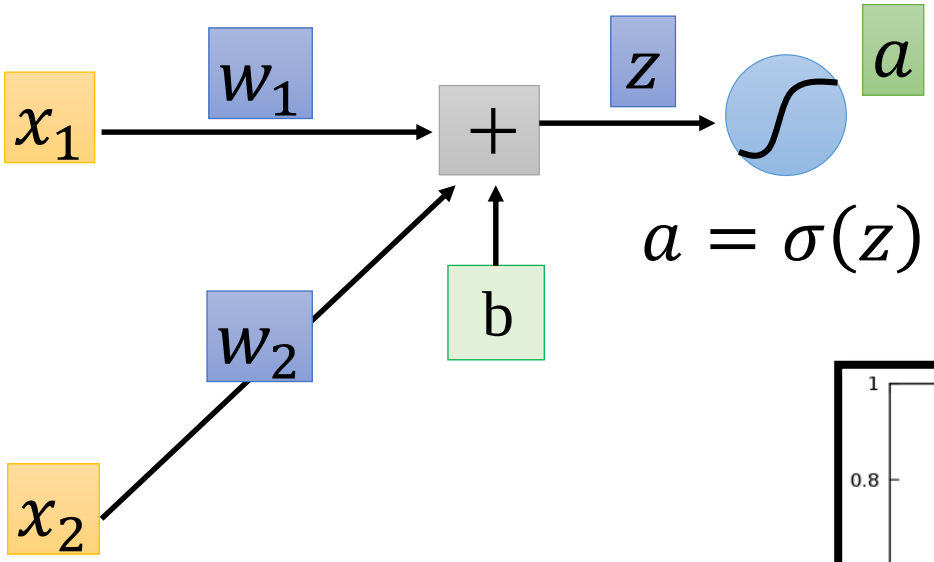
$$\partial z/\partial w_1 = x_1$$

$$\partial z/\partial w_2 = x_2$$

The value of the input connected by the weight

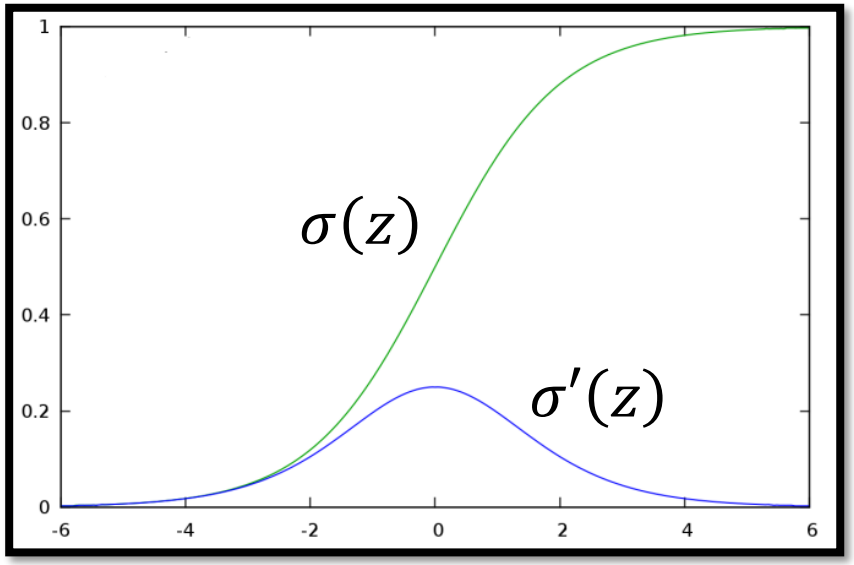
Example for Backpropagation - Back pass

Compute $\partial l/\partial z$ for all activation function inputs z



$$\frac{\partial l}{\partial z} = \frac{\partial a}{\partial z}\frac{\partial l}{\partial a}$$

$\Rightarrow \sigma'(z)$

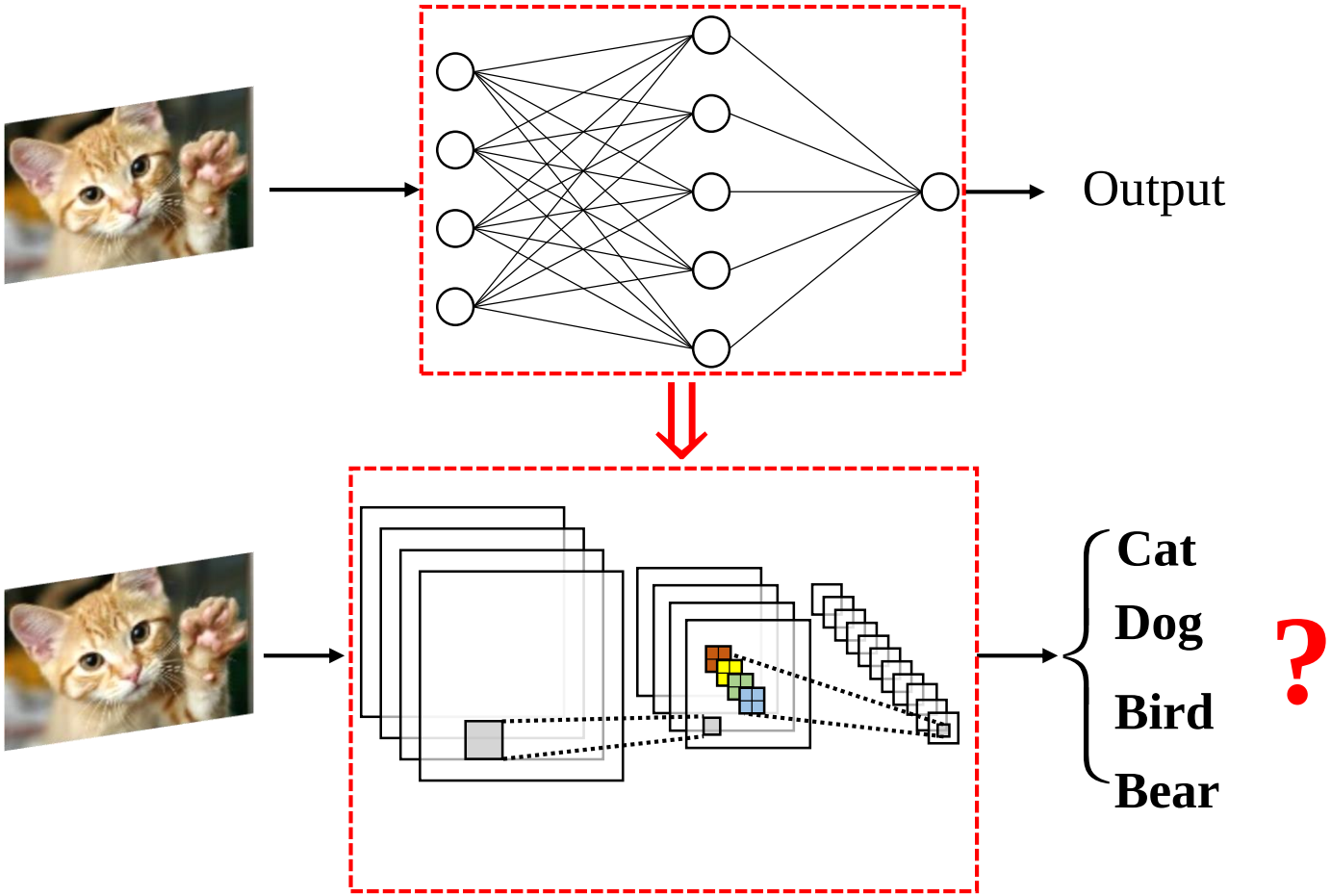


Comparison of Training Algorithms

Method	Advantages	Disadvantages
Gradient Descent (GD)	1. Accurate search direction 2. Suitable for parallelization	1. Slow convergence speed 2. Need huge memory for big data
Stochastic Gradient Descent (SGD)	1. Cheap for each step 2. Suitable for big data	1. Need more steps 2. Not stable 3. Hard for parallelization
Mini-Batch Gradient Descent (MBGD)	1. Converge faster than GD 2. More accurate update than SGD 3. Suitable for parallelization 4. Suitable for large data	1. Require adding learning-decay to decrease the learning rate 2. Less stable than GD

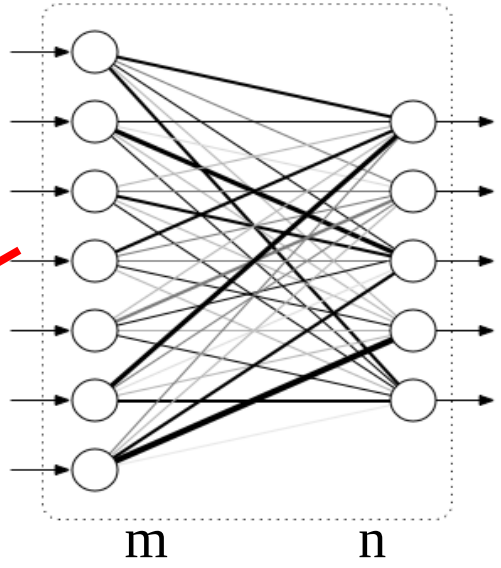
Contents

From Neural Networks to Convolutional Neural Networks

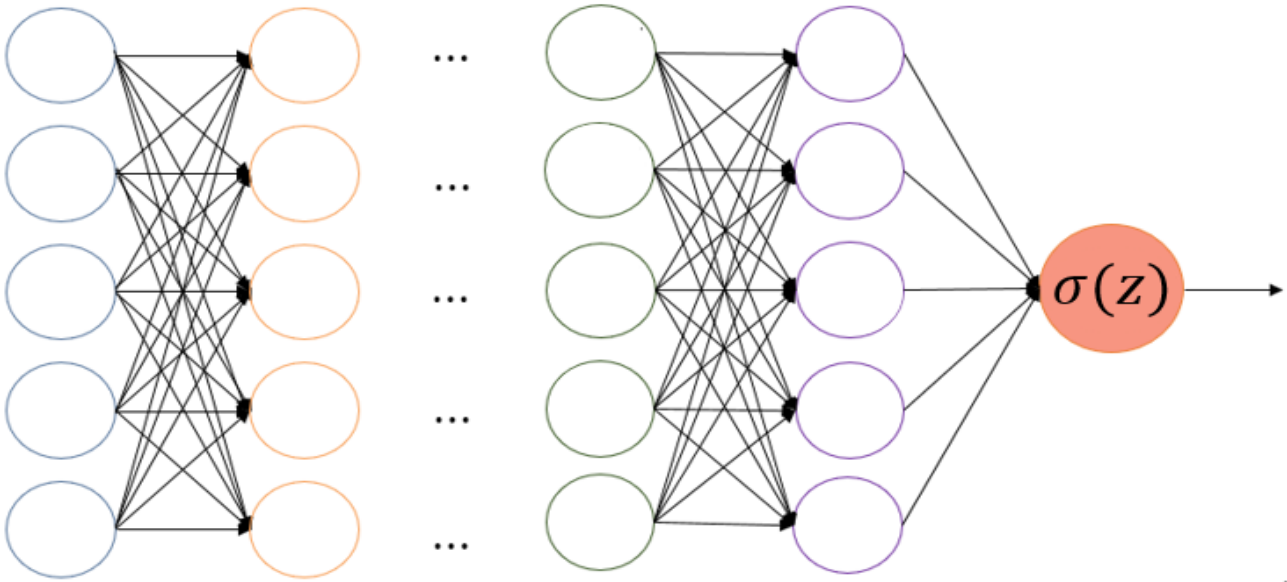


Why Convolutional Layer

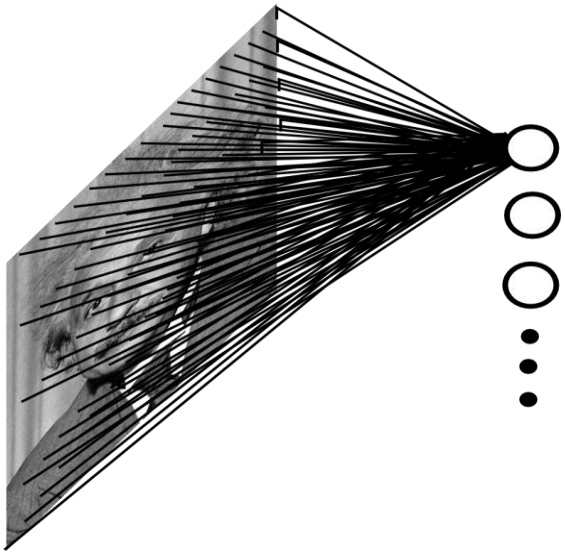
- Fully Connected Neural Networks
- $m \times n$ connections
- $m \times n$ can be very large



Too many connections



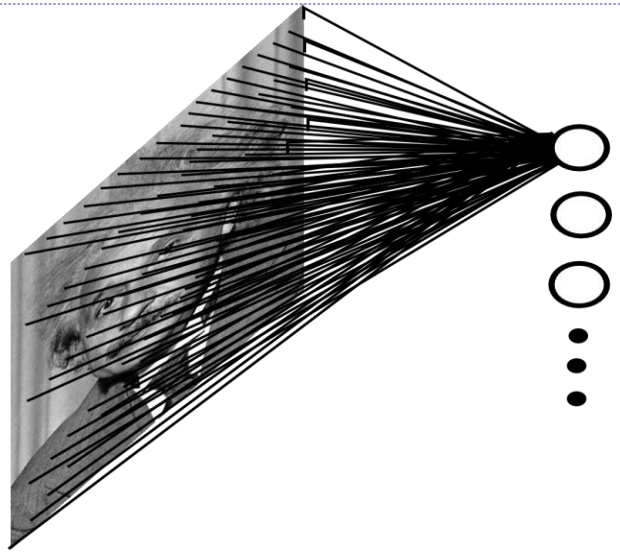
Too Many Connections and Parameters



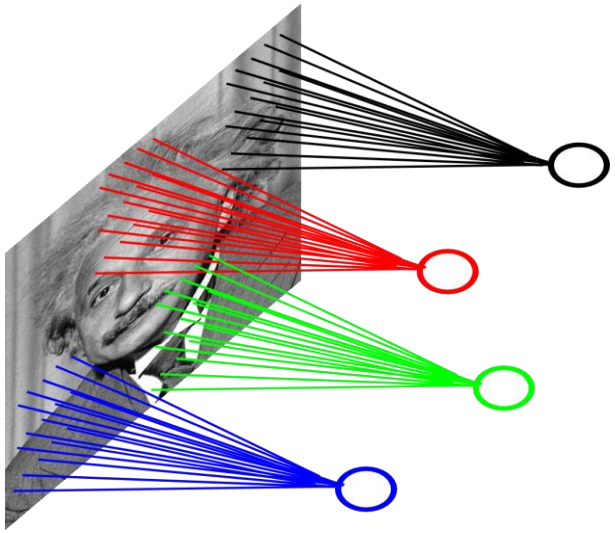
Input Size	#hidden units	#Connections
3x3	n	9n
32x32	n	1024n
224x224	n	50176n
1000x1000	n	10^6n

Too many parameters

From Full Connections to Local Connections



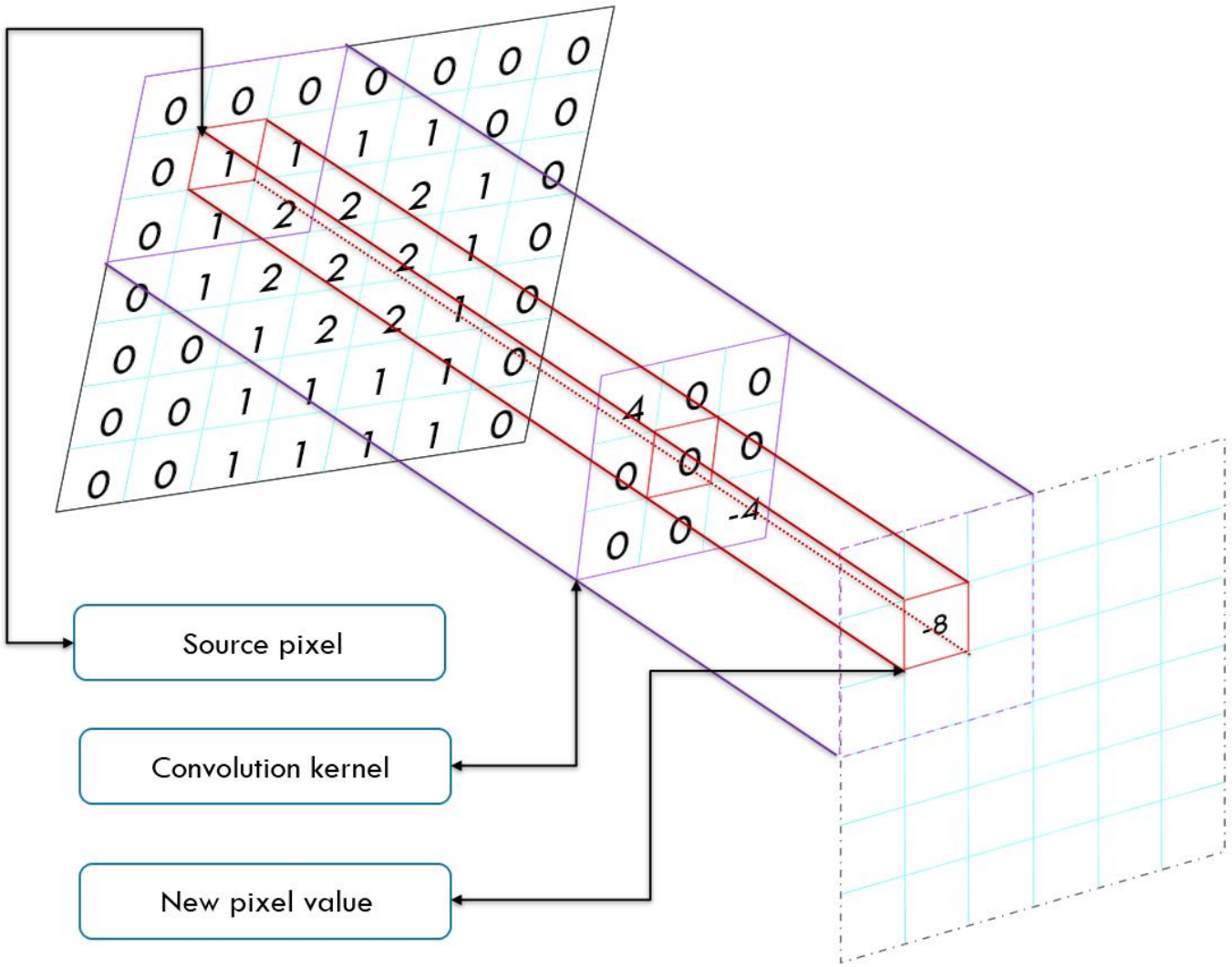
Full connections



Local connections

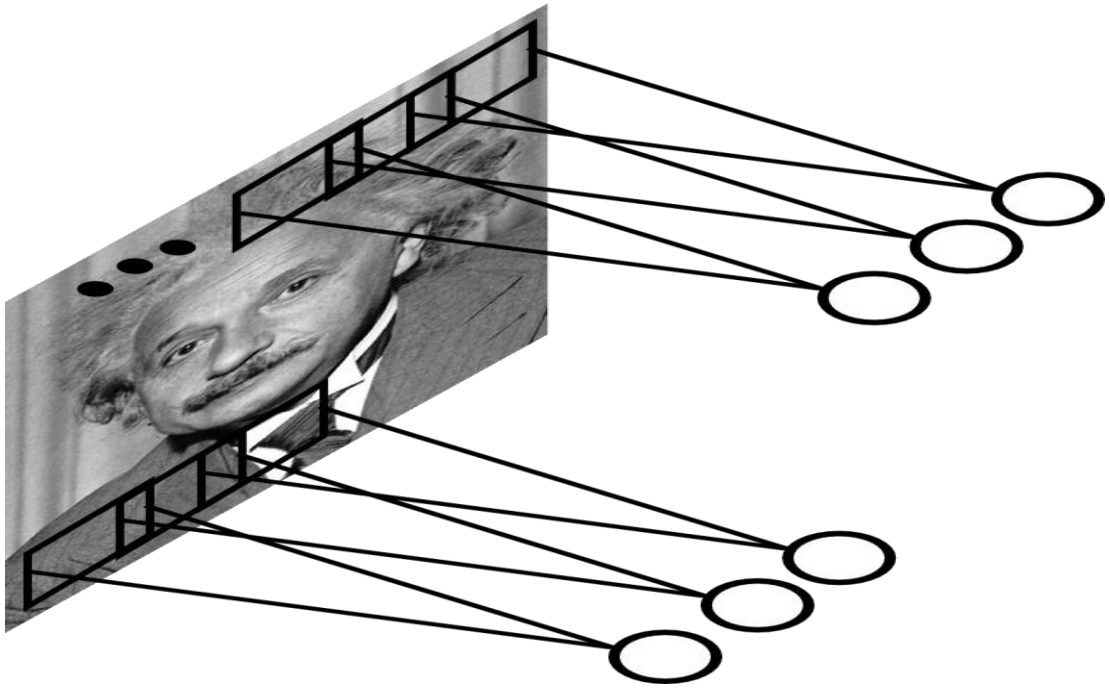
Reduce the number of parameters

Convolution as Local Connections



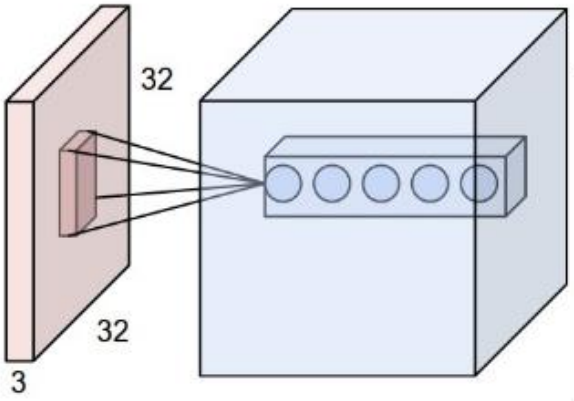
Further Reduce Parameters: Weights Sharing

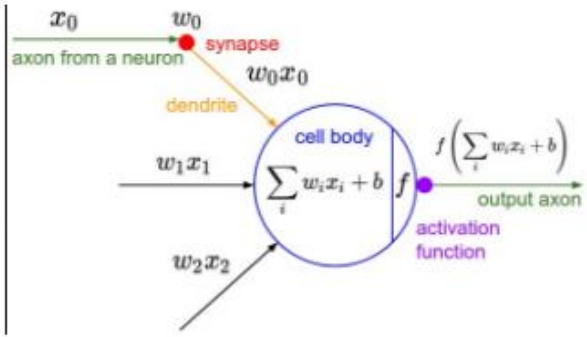
- Apply **the same filter** across the whole image
- Apply many kernels
- Each kernel is associated with one feature map

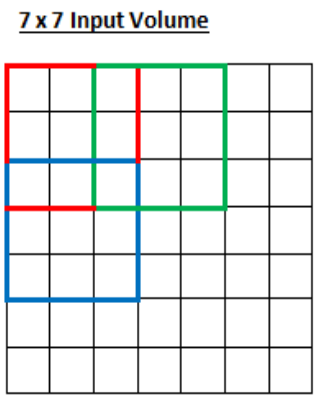


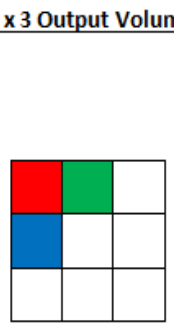
Convolutional Layer

Filter

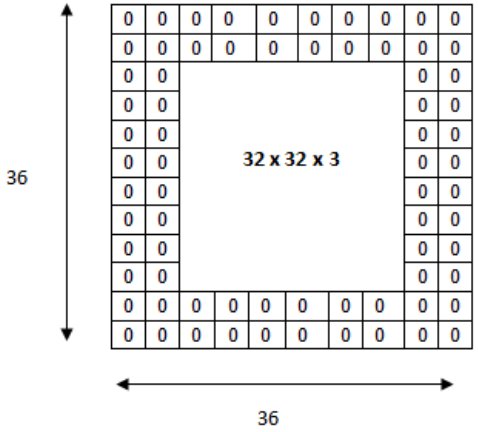






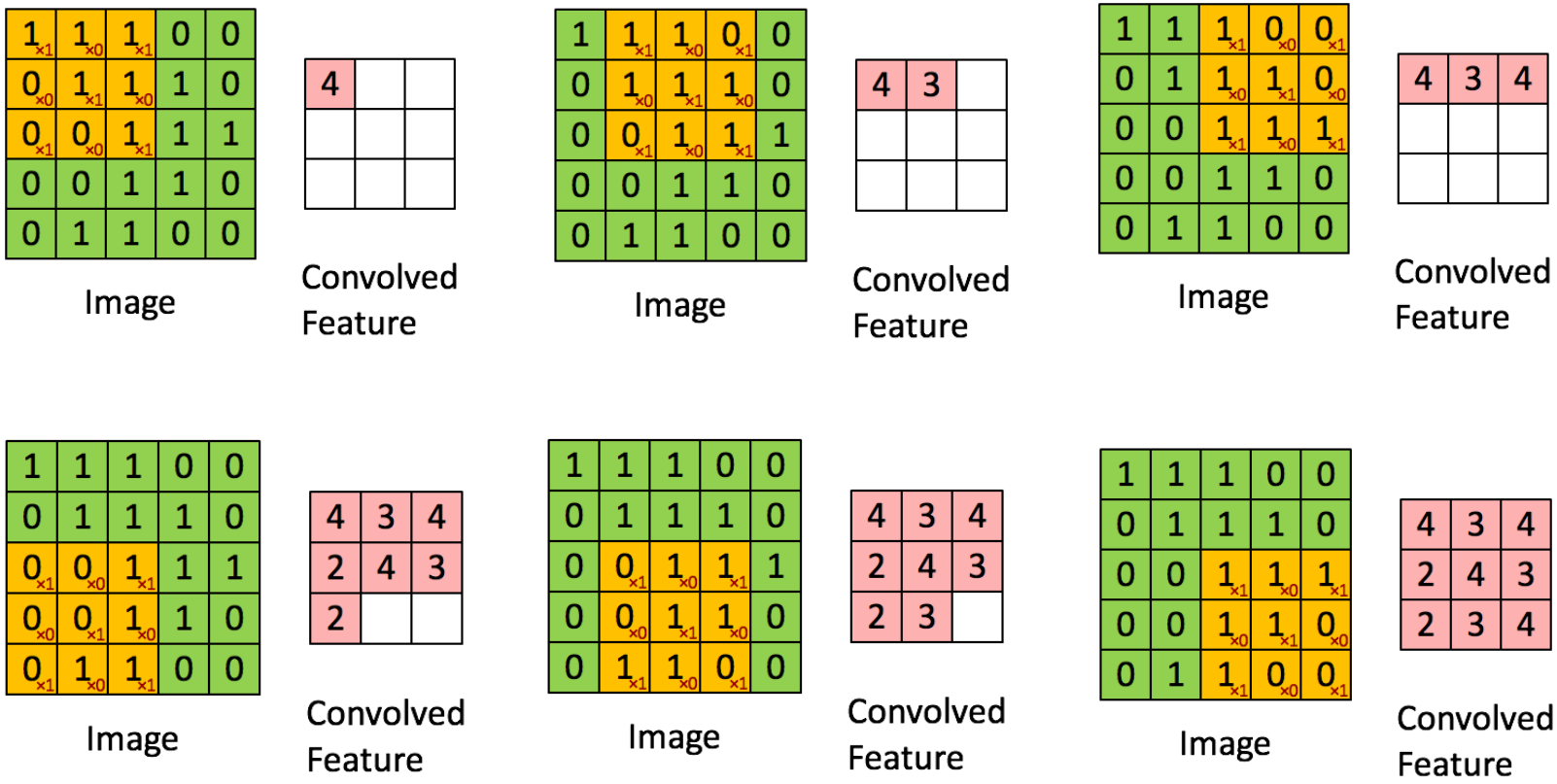


Stride

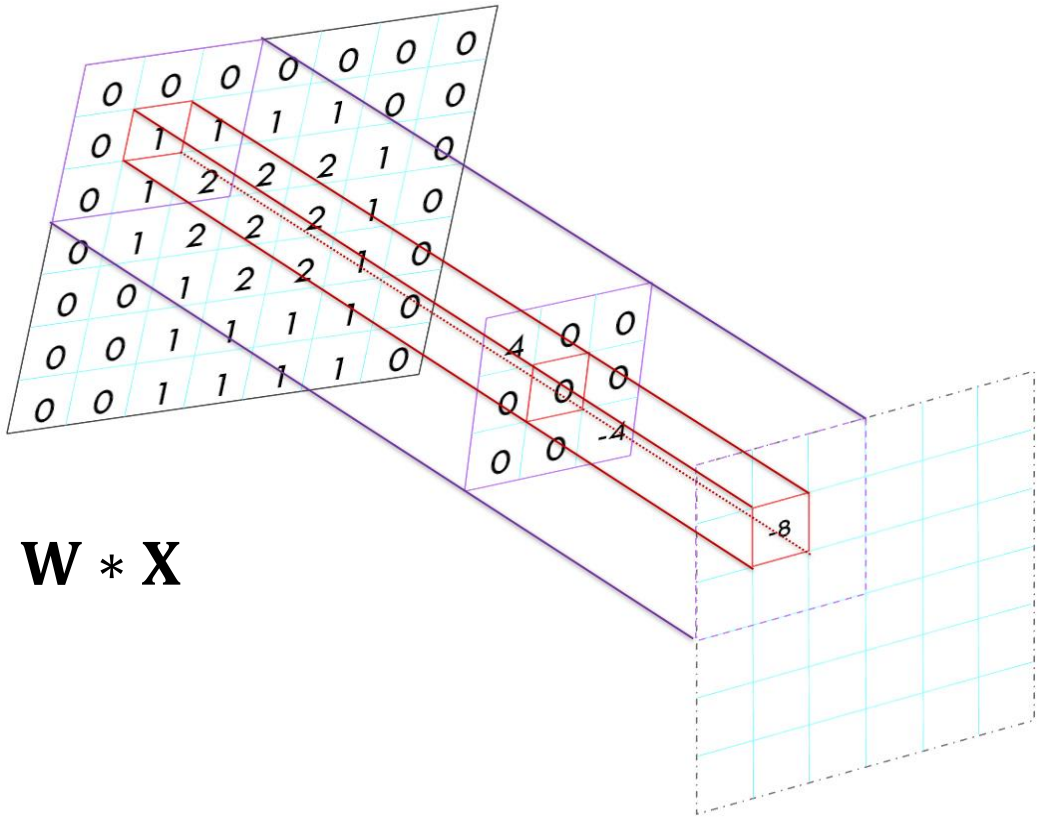


Padding

Example: Convolution with Scanning



Properties of Convolution



- **Linear Operation** : $\mathbf{Y} = \mathbf{W} * \mathbf{X}$
- Shift-invariant
- Size: odd by odd (3×3, 5×5, 7×7)

Why Local Connections and Parameter Sharing

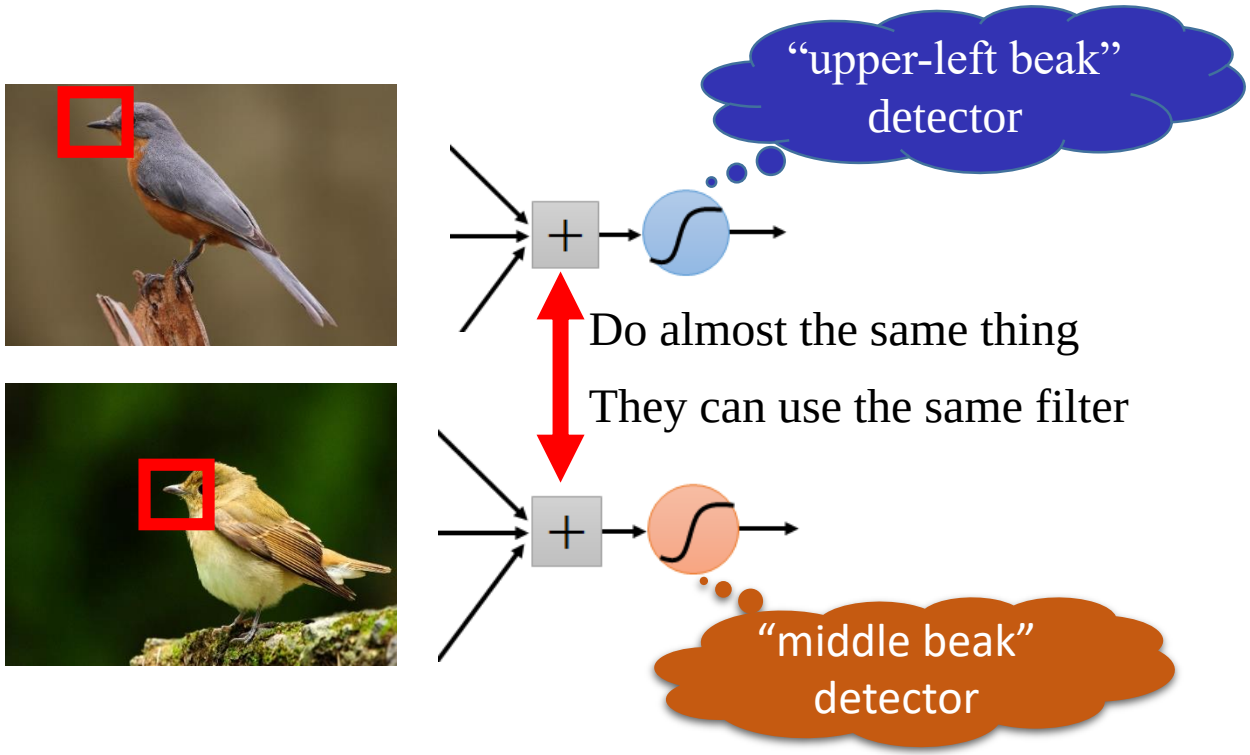
- Some patterns are much smaller than the whole image

A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters

Why Local Connections

- The same patterns appear in different regions.



Typical Convolution Examples

Original

$$\ast \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} =$$

Typical Convolution Examples

Sharpen

$$*\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix} =$$

Typical Convolution Examples

Sharpen with more details

-1	-1	-1	-1	-1
-1	2	2	2	-1
-1	2	8	2	-1
-1	2	2	2	-1
-1	-1	-1	-1	-1

=

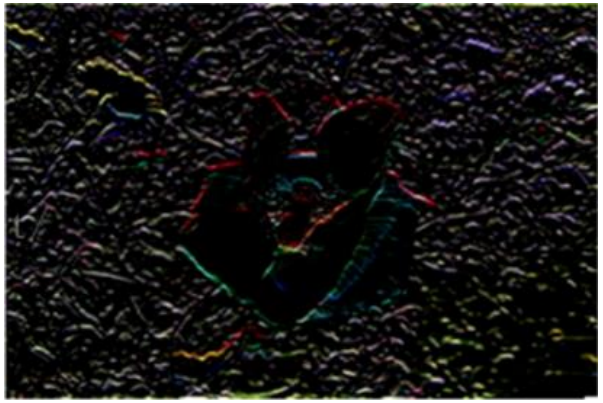
Typical Convolution Examples

Horizontal edge detection

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

$*$

$=$



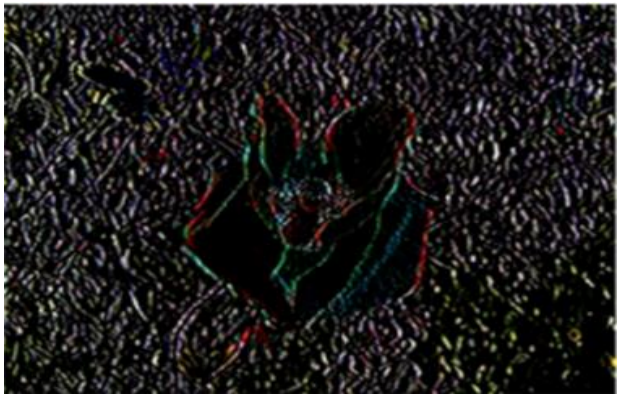
Typical Convolution Examples

Vertical edge detection

$*$

0	0	-1	0	0
0	0	-1	0	0
0	0	4	0	0
0	0	-1	0	0
0	0	-1	0	0

$=$

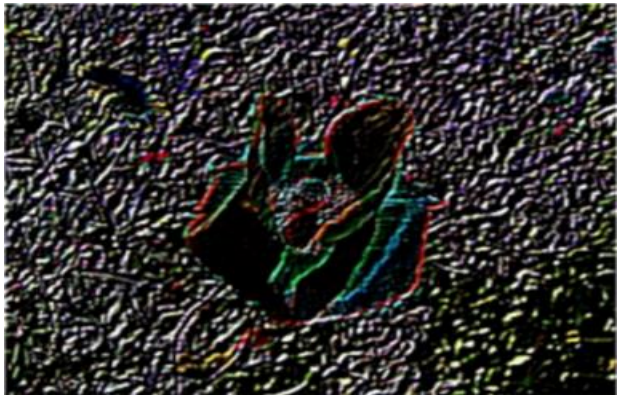


Typical Convolution Examples

45 degree edge detection

-1	0	0	0	0
0	-2	0	0	0
0	0	6	0	0
0	0	0	-2	0
0	0	0	0	-1

=



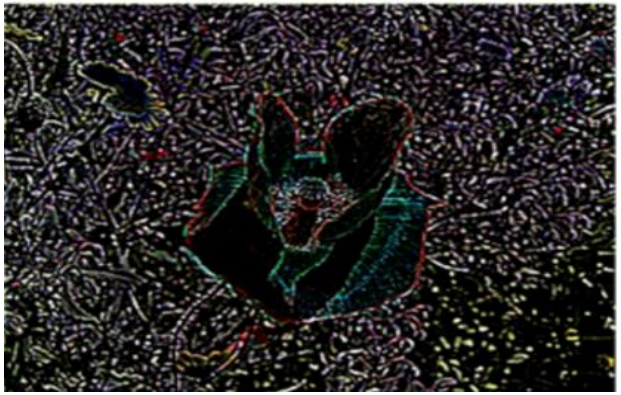
Typical Convolution Examples

All direction edge detection

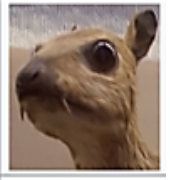
$*$

-1	-1	-1
-1	8	-1
-1	-1	-1

$=$

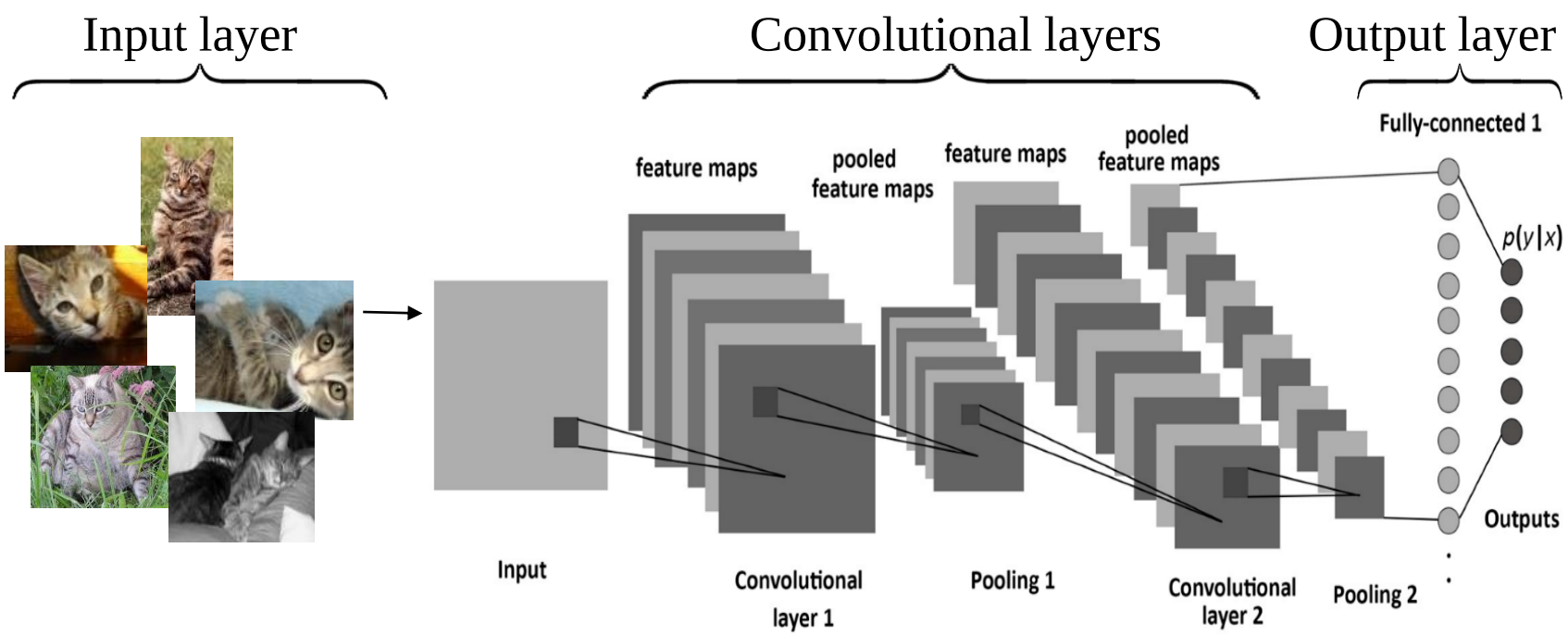


Some Typical Kernels

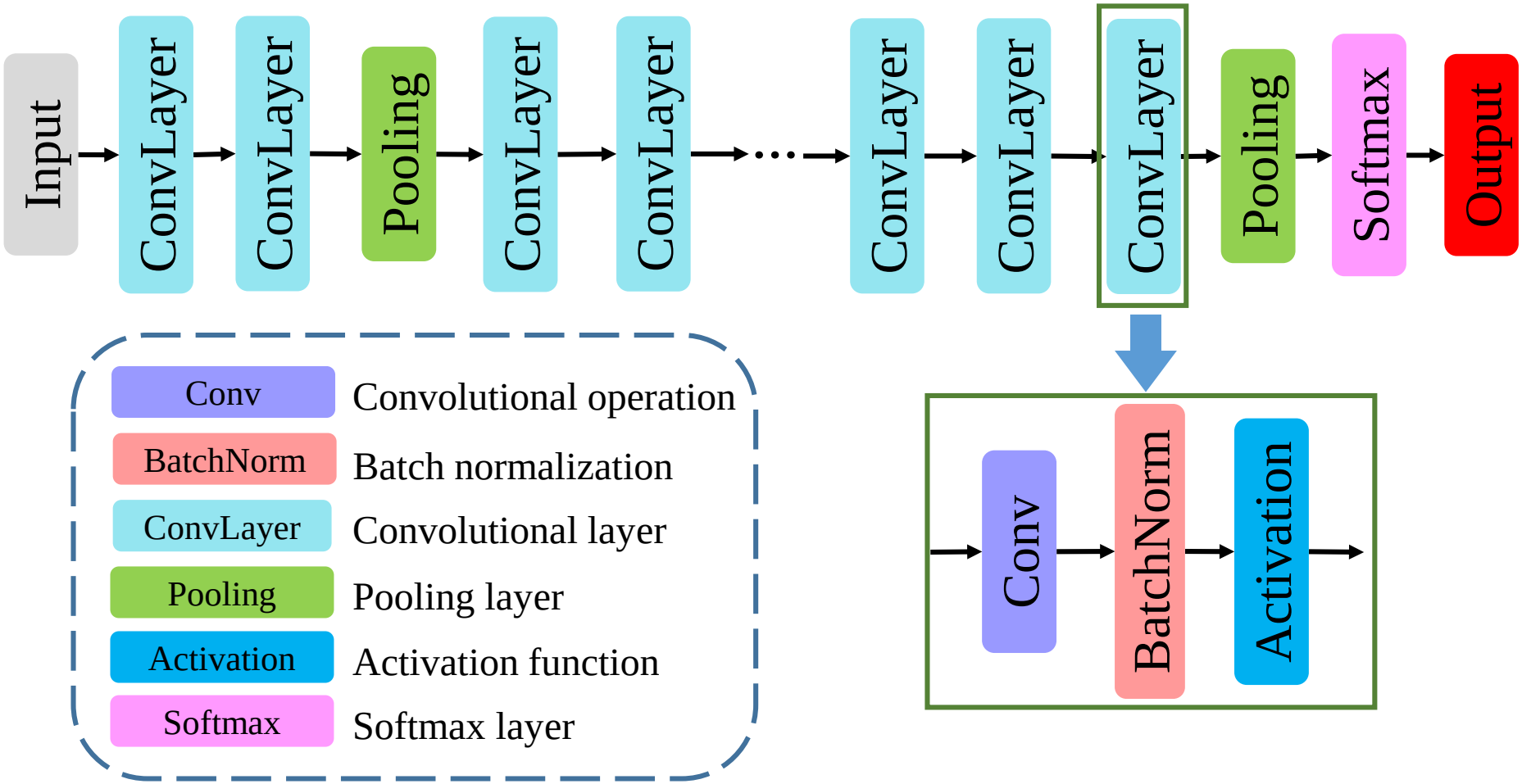
Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	

Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	

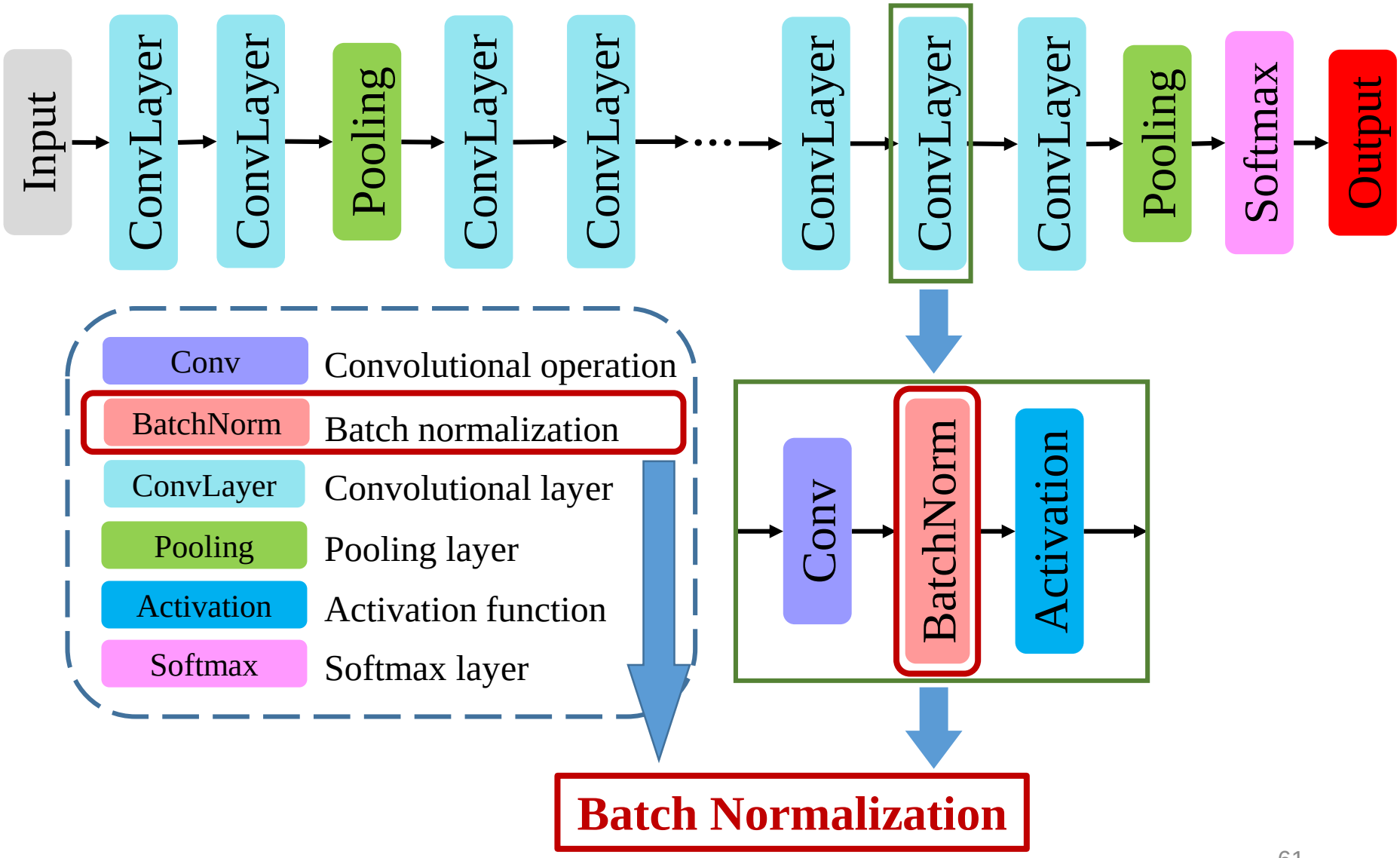
Convolutional Neural Networks



Basic Concepts of Convolutional Neural Networks



Batch Normalization



Batch Normalization Layer

- **Internal Covariate Shift**:
  features are normalized to have zero-mean and unit variance

- **Feature Normalization:**
  distribution changes during training

- **Batch Normalization:**

  Input: Values of $\mathbf{x}$: $\mathbf{x} = \{x_1, \ldots, x_m\}$;

  Parameters to be learned: γ, β

  Output: $\{y_i = BN_{\gamma,\beta}(\mathbf{x})\}$

Normalization in Each Channel

- **Compute data mean per channel**

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i$$

- **Compute data variance per channel**

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_B)^2$$

- **Normalization: Linear Transformation**

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}}$$

- **Rescale the normalized value to restore the representation power**

$$y_i = \gamma \hat{x}_i + \beta$$

Backpropagation for Batch Normalization Layer

$$\frac{\partial l}{\partial \hat{x}_i} = \frac{\partial l}{\partial y_i} \cdot \gamma$$

$$\frac{\partial l}{\partial {\sigma_B}^2} = \sum_{i=1}^{m} \frac{\partial l}{\partial \hat{x}_i} \cdot (x_i - \mu_B) \cdot \frac{-1}{2} ({\sigma_B}^2 + \varepsilon)^{-3/2}$$

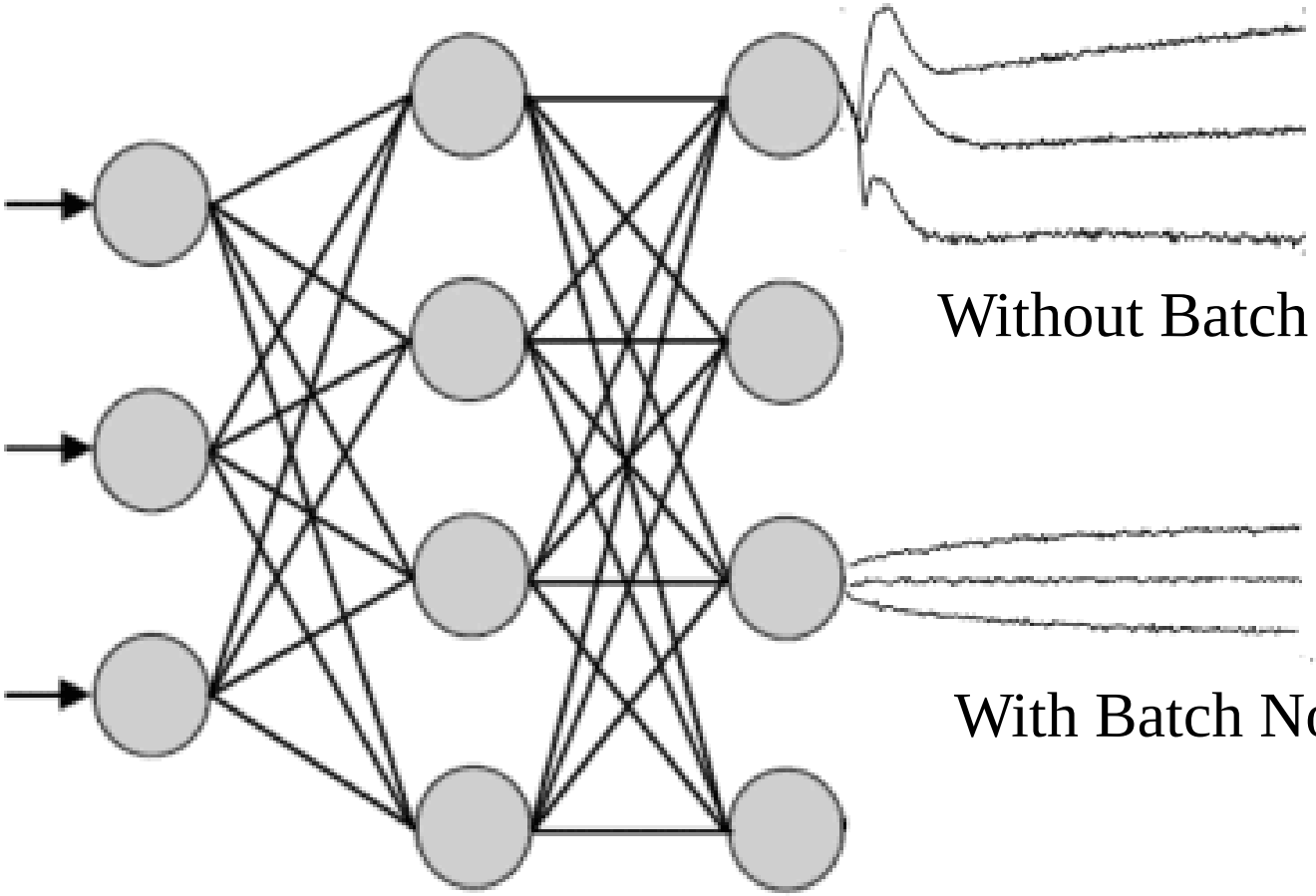
$$\frac{\partial l}{\partial \mu_B} = \left(\sum_{i=1}^{m} \frac{\partial l}{\partial \hat{x}_i} \cdot \frac{-1}{\sqrt{{\sigma_B}^2 + \varepsilon}}\right) + \frac{\partial l}{\partial {\sigma_B}^2} \cdot \frac{\sum_{i=1}^{m} -2(x_i - \mu_B)}{m}$$

$$\frac{\partial l}{\partial x_i} = \frac{\partial l}{\partial \hat{x}_i} \cdot \frac{-1}{\sqrt{{\sigma_B}^2 + \varepsilon}} + \frac{\partial l}{\partial {\sigma_B}^2} \cdot \frac{2(x_i - \mu_B)}{m} + \frac{\partial l}{\partial \mu_B} \cdot \frac{1}{m}$$

$$\frac{\partial l}{\partial \gamma} = \sum_{i=1}^{m} \frac{\partial l}{\partial y_i} \cdot \partial \hat{x}_i$$

$$\frac{\partial l}{\partial \beta} = \sum_{i=1}^{m} \frac{\partial l}{\partial y_i}$$

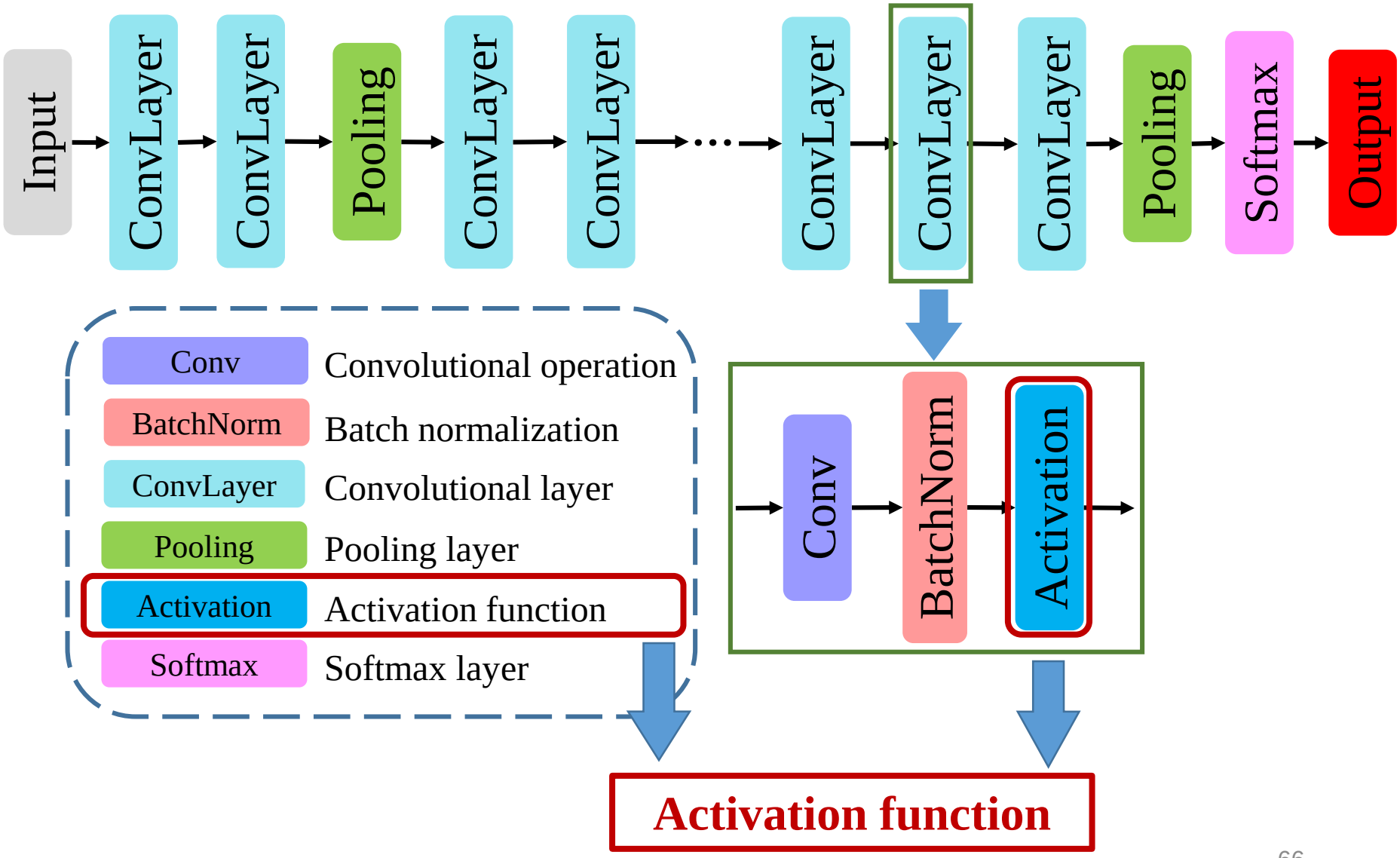
Effect of Batch Normalization



Without Batch Normalization

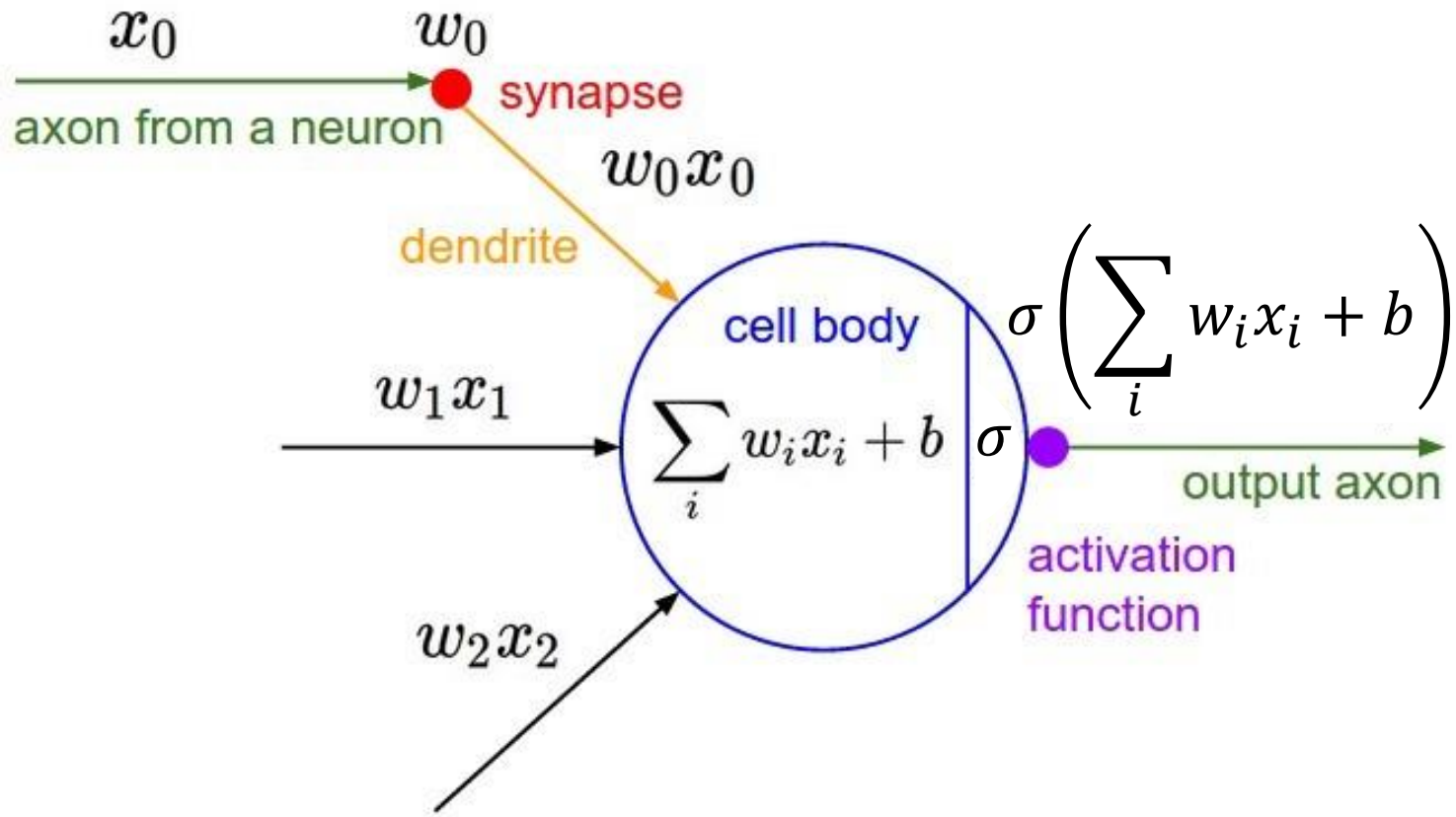
With Batch Normalization

Activation Layer



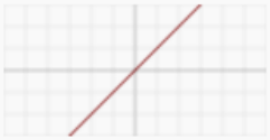
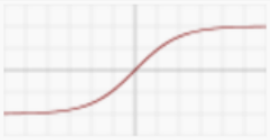
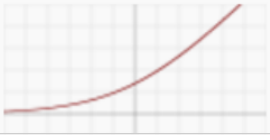
Activation Function

- **Description**: keep value within an acceptable and useful range



Activation Function

- Activation functions: **nonlinear** and **continuously differentiable**

Activation Function	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Sigmoid		$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1-f(x))$
Tanh		$f(x) = \frac{2}{1+e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ReLU		$f(x) = \max(x, 0)$	$f'(x) = 1\{x \geq 0\}$
SoftPlus		$f(x) = ln(1+e^{x})$	$f'(x) = \frac{1}{1+e^{-x}}$

Rectified Linear Unit (ReLU)

- **ReLU:**

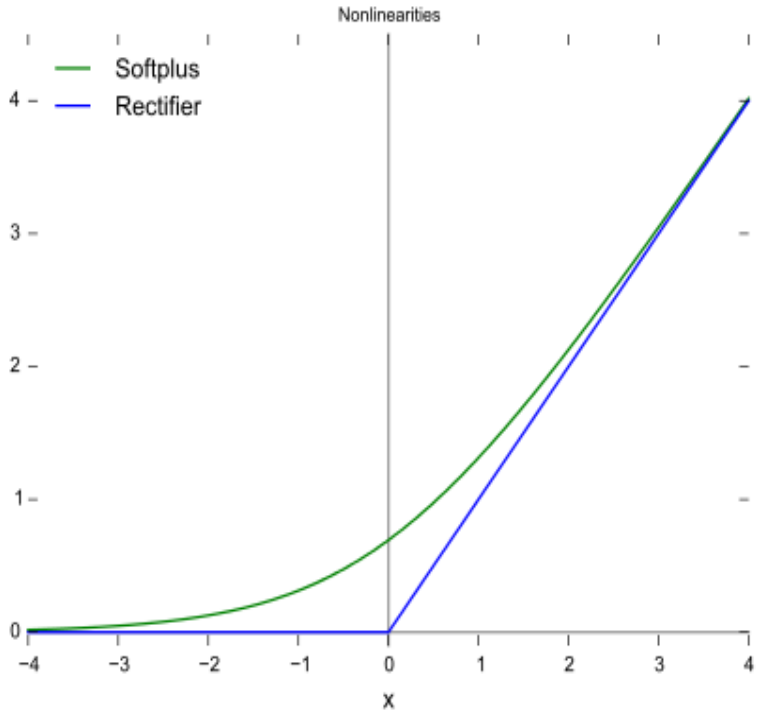
Forward $y = \max(x, 0)$

Backward $\frac{\partial y}{\partial x} = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$

- **Softplus:**

Forward $y = \ln[1 + e^x]$

Backward $\frac{\partial y}{\partial x} = \frac{1}{1 + e^{-x}}$



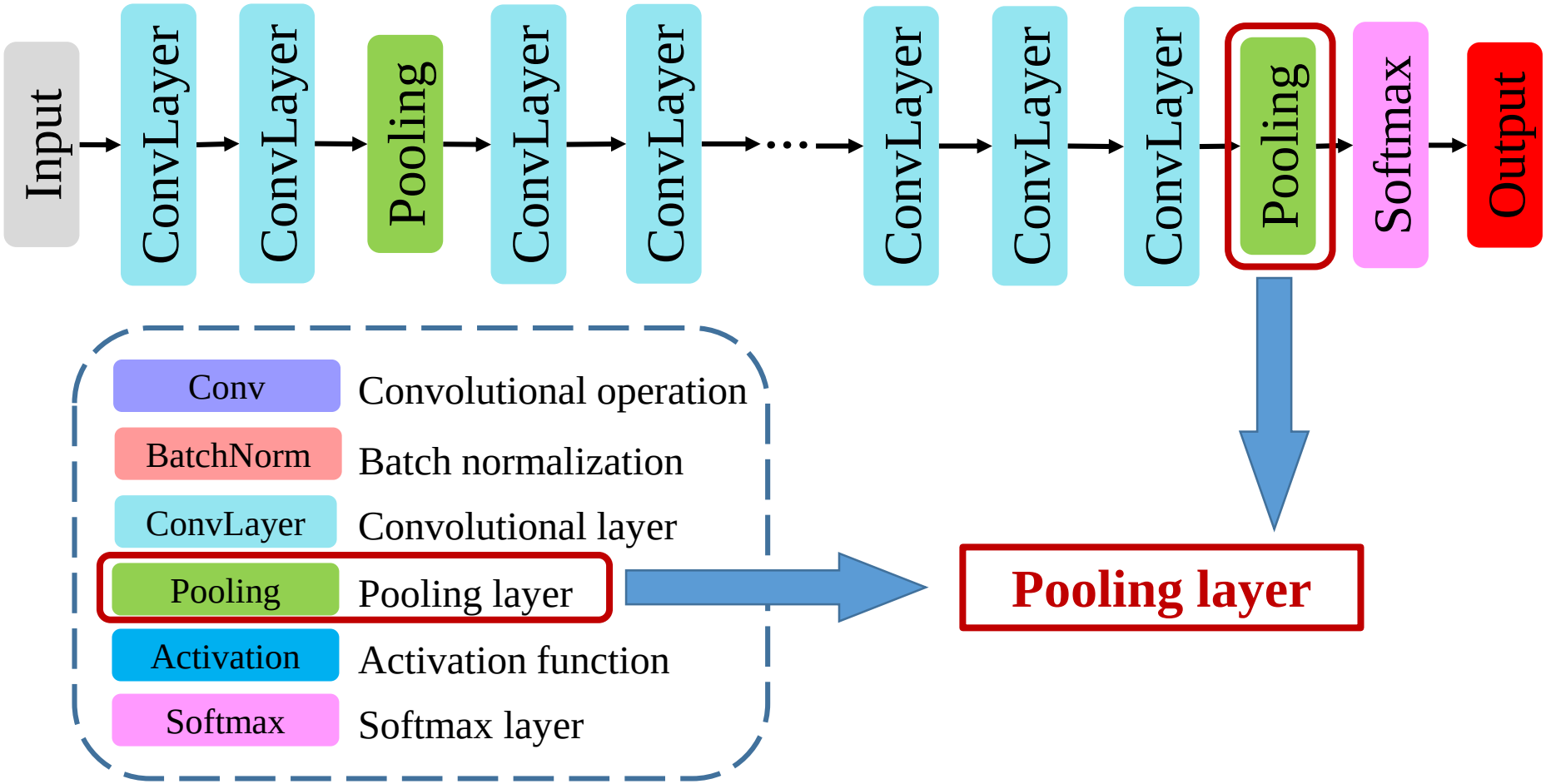
Leaky ReLU

- Guarantee a **small** and **non-zero** gradient when the unit is not active.

Forward $y = \begin{cases} x & \text{if } x > 0 \\ ax & \text{otherwise} \end{cases} \Leftrightarrow y = \max(x, ax)$ where a<1

Backward $y = \begin{cases} 1 & \text{if } x > 0 \\ a & \text{otherwise} \end{cases}$

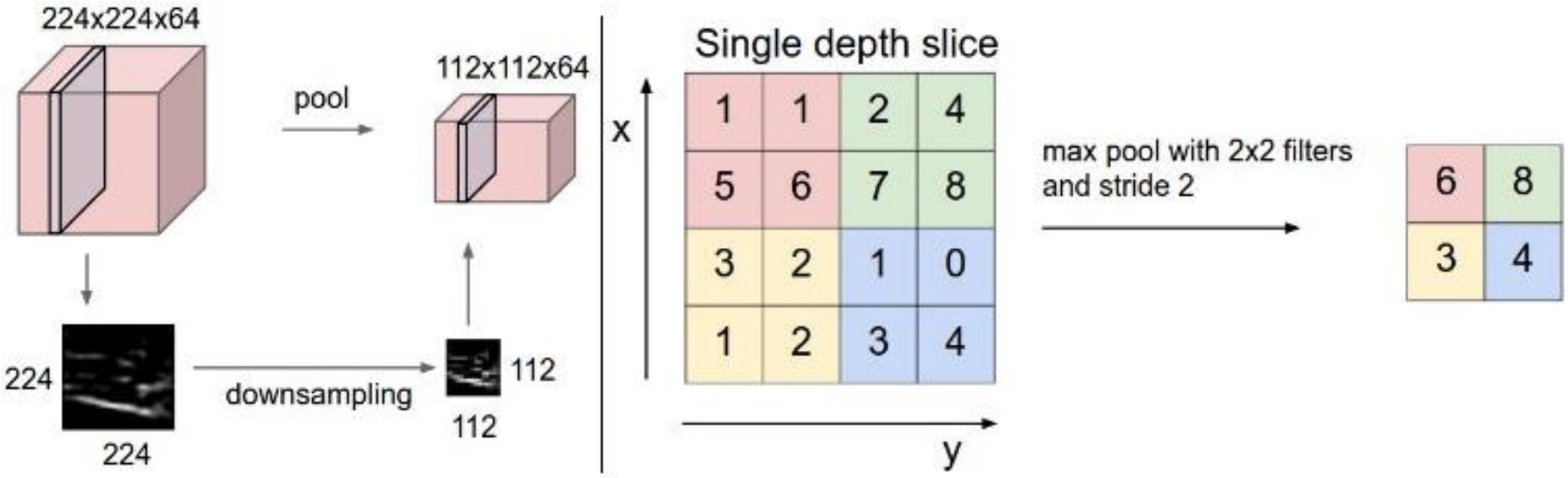
Pooling Layer



Pooling Layer

Max pooling:

- Max value of a cluster of neurons
- Nonlinear down-sampling



Pooling Layer

Reduce **spatial size** of the representation and the **number of parameters**

Forward

- Input data size: $W_1 \times H_1 \times C_1$
- Output data size: $W_2 \times H_2 \times C_2$

$$W_2 = [(W_1 - F)/S + 1]$$

$$H_2 = [(H_1 - F)/S + 1]$$

$$C_2 = C_1$$

where S is Spatial extent, F is Stride, and C is the number of channel

Forward propagation and **backpropagation** of Convolutional Neural Networks

Prediction for CNN f : Forward Propagation

- Given input data **X** and a convolutional neural network f, forward propagation is to compute the **prediction $\hat{\mathbf{y}}$** of **X,** namely

$$\hat{\mathbf{y}} = f(\mathbf{X})$$

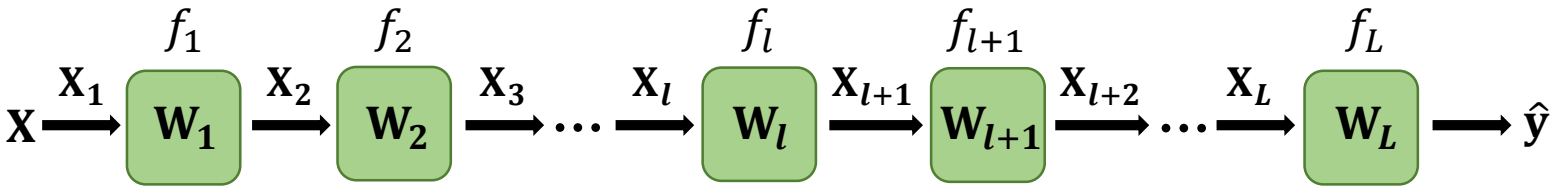
- Detailed prediction process:

$$\begin{aligned}
\mathbf{X}_1 &= \mathbf{X} \\
\mathbf{X}_2 &= f_1(\mathbf{X}_1, \mathbf{W}_1) \\
&\vdots \\
\mathbf{X}_{l+1} &= f_l(\mathbf{X}_l, \mathbf{W}_l) \\
&\vdots \\
\mathbf{X}_L &= f_{L-1}(\mathbf{X}_{L-1}, \mathbf{W}_{L-1}) \\
\hat{y} &= f_L(\mathbf{X}_L, \mathbf{W}_L)
\end{aligned}$$

$f_l = \sigma(h_l(\mathbf{X}_l, \mathbf{W}_l))$

σ is some activation function

$h_l = \mathbf{W}_l * \mathbf{X}_l$ is the Convolutional Operation—a linear operation



How to Learn Parameters $\{\mathbf{W}_l\}$ in CNNs?

- We minimize the following regularized loss function:

Regularized Loss Function:

$$\min_{\mathbf{W}} \frac{1}{N}\sum_{i=1}^{N}\mathcal{L}(\mathbf{y}_i, \hat{\mathbf{y}}_i) + \frac{1}{2}\lambda\|\mathbf{W}\|_F^2$$

$\mathbf{W}$ – parameters N – number of samples $\mathcal{L}$ – loss function

$\mathbf{y}_i$ – i^{th} ground-truth label $\hat{\mathbf{y}}_i$ – i^{th} predicted label

- To minimize the loss, we update the parameters $\mathbf{W}_l$ by using **(Stochastic) Gradient Descent**:

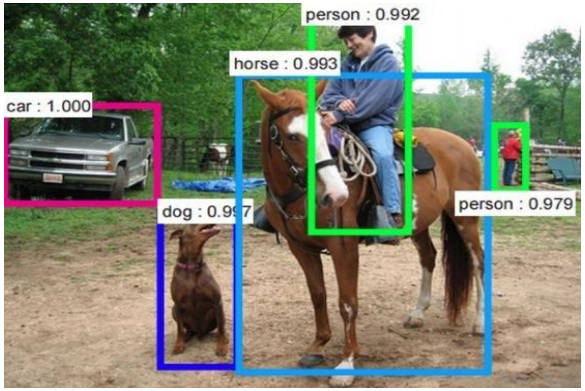
$$\mathbf{W}_l' = \mathbf{W}_l - \eta \cdot \frac{\partial \mathcal{L}}{\partial \mathbf{W}_l} \quad (2)$$

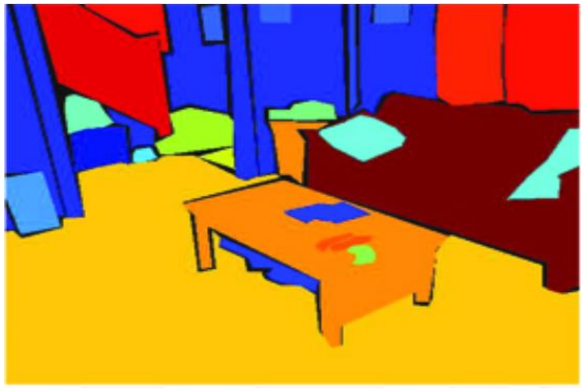
where η is the learning rate and gradient $\frac{\partial \mathcal{L}}{\partial \mathbf{W}_l}$ is computed by **backpropagation**

Contents

Deep learning Applications

- Image Classification; Object Detection; Image Segmentation





- Pedestrian Detection; Lane Detection; Traffic Sign Recognition

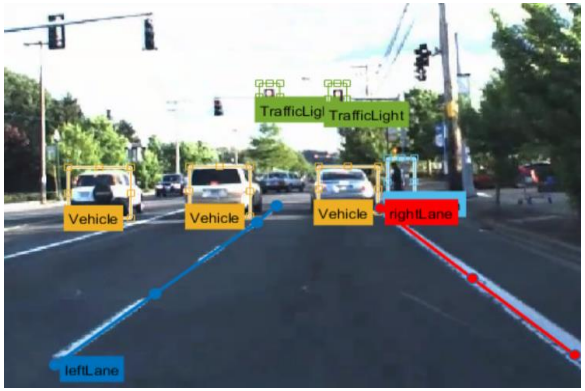
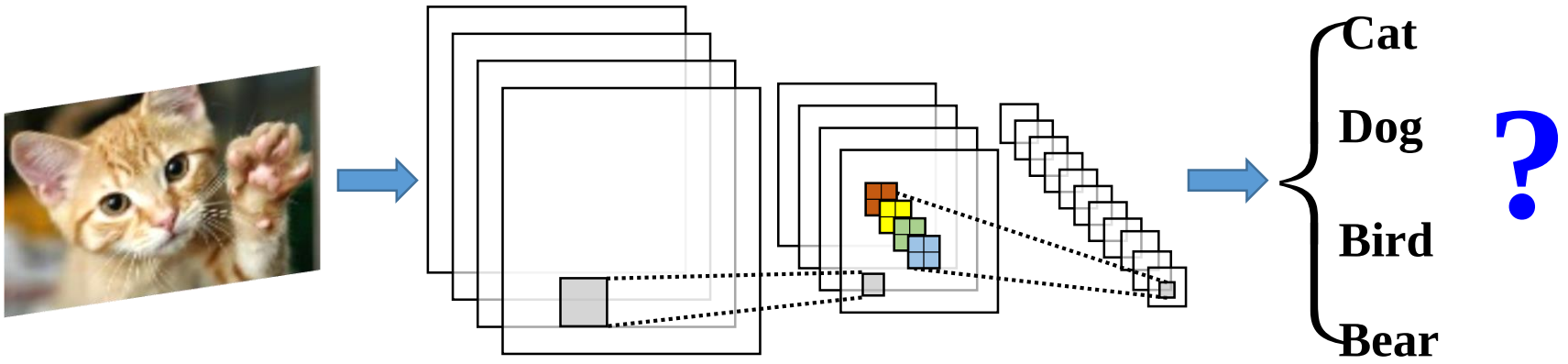
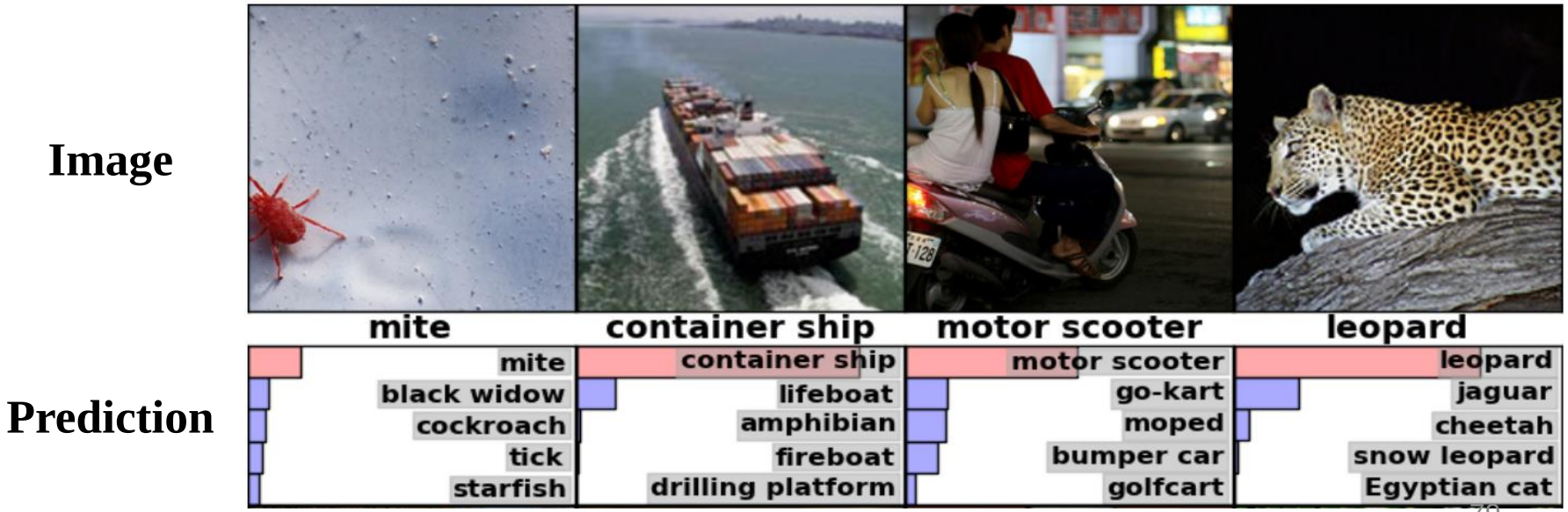


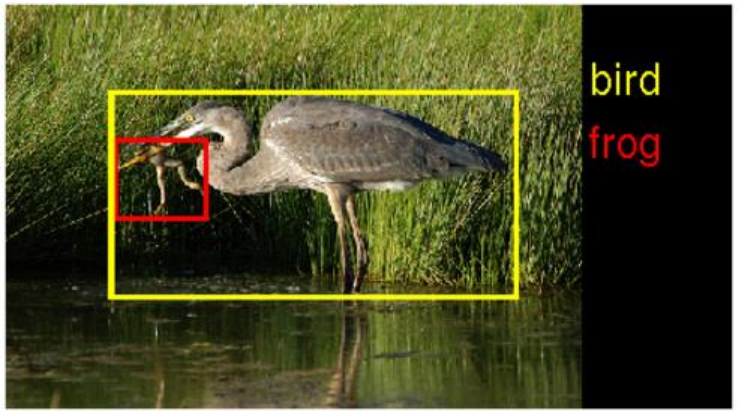
Image Recognition

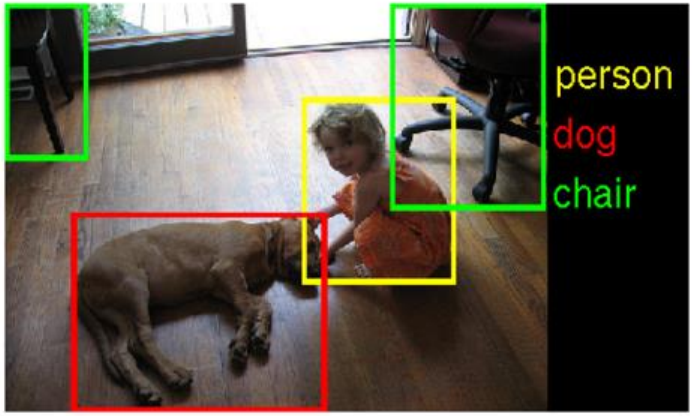


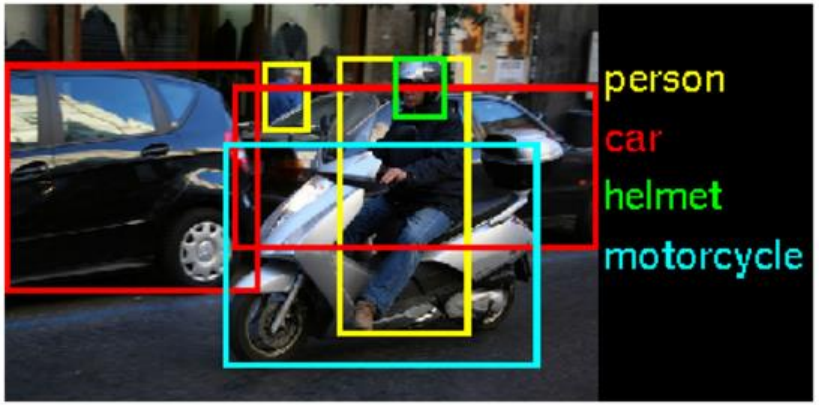
Convolutional Neural Network



Object Detection

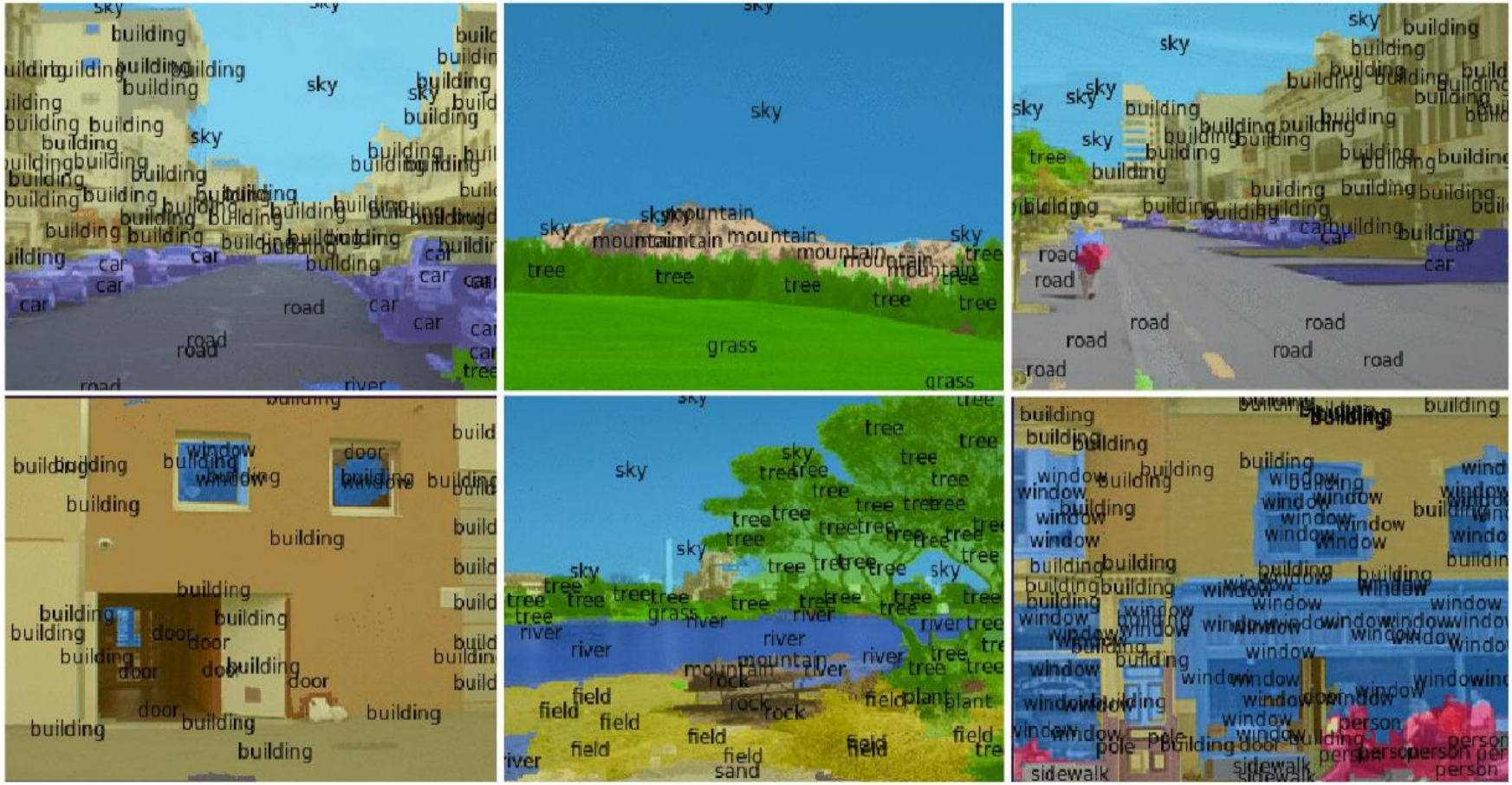






Semantic Labeling

- Labeling every pixel with the object category it belongs to



Scene Parsing

- Each output sees a large input context

Other Recognition Applications

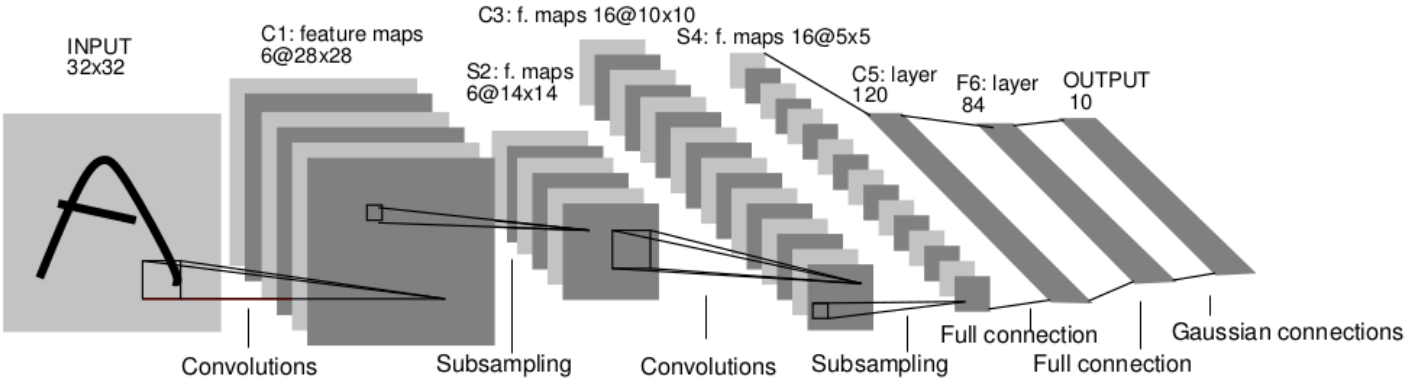
- Traffic Sign Recognition (GTSRB)
  - German Traffic Sign Reco Bench
  - 99.2% accuracy

- House Number Recognition (Google)
  - Street View House Numbers
  - 94.3 % accuracy

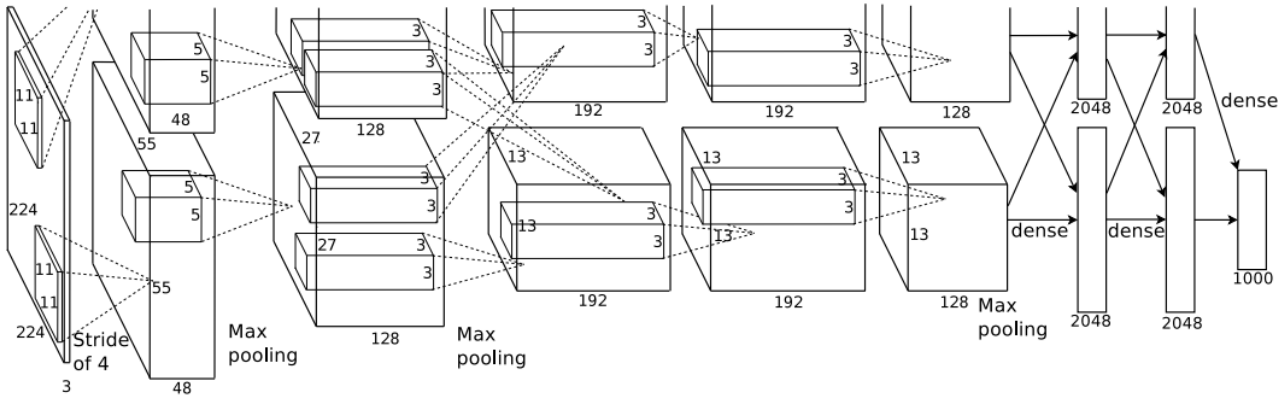
Classical CNNs

Classical CNNs

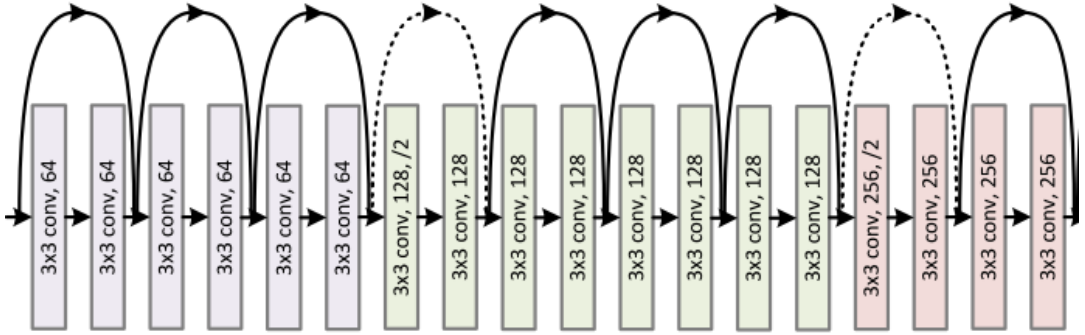
LeNet



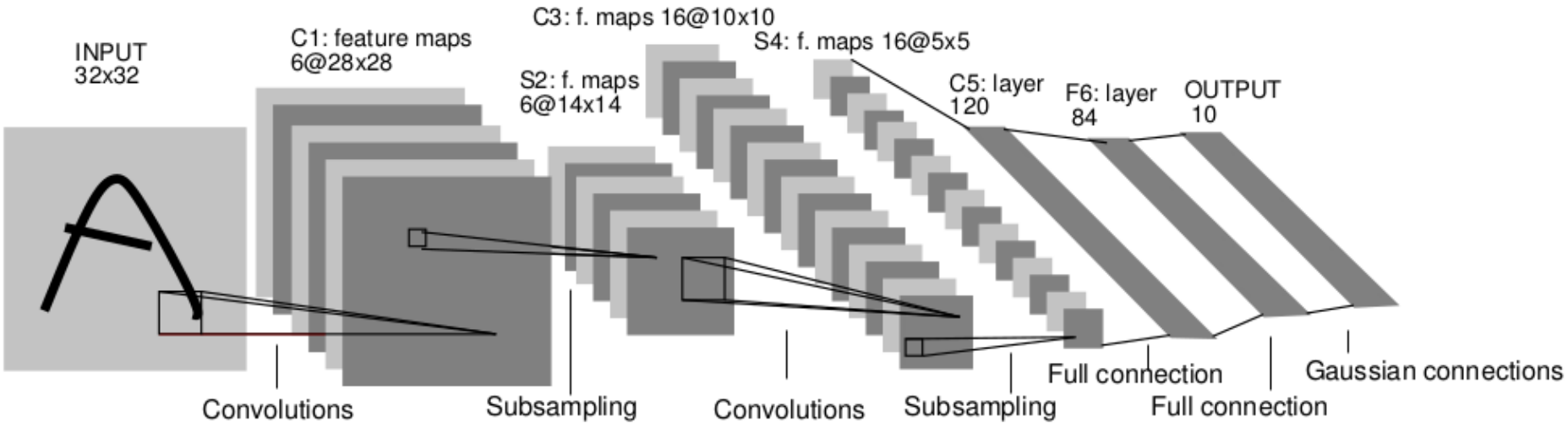
AlexNet



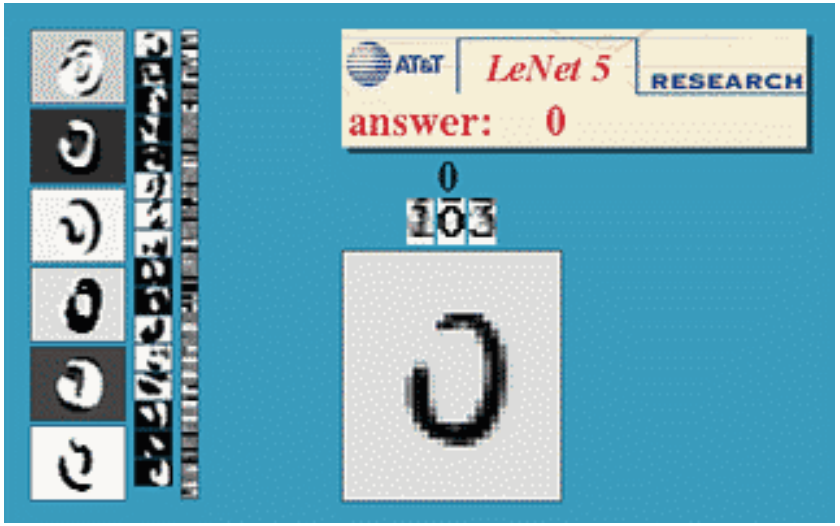
ResNet



LeNet

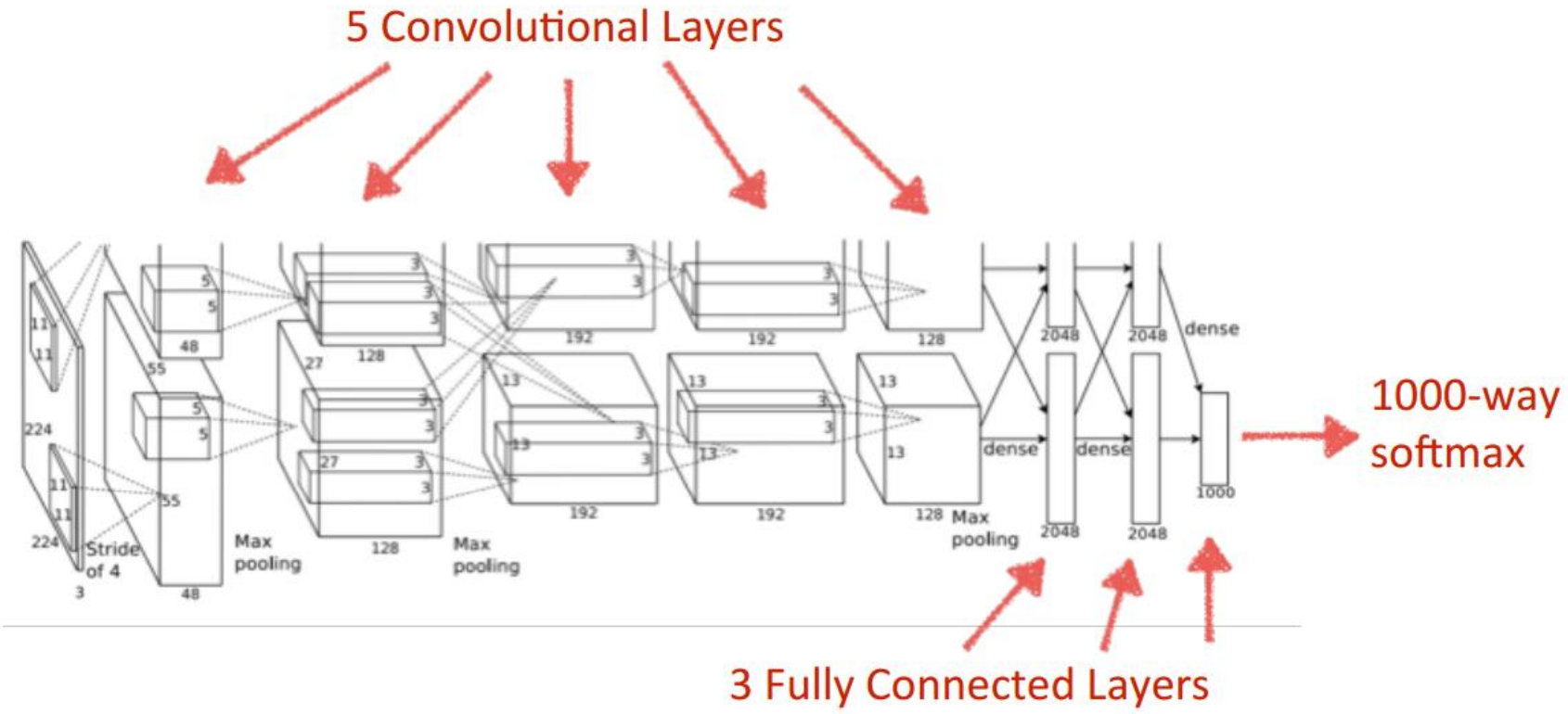


- **Handwriting number recognition**

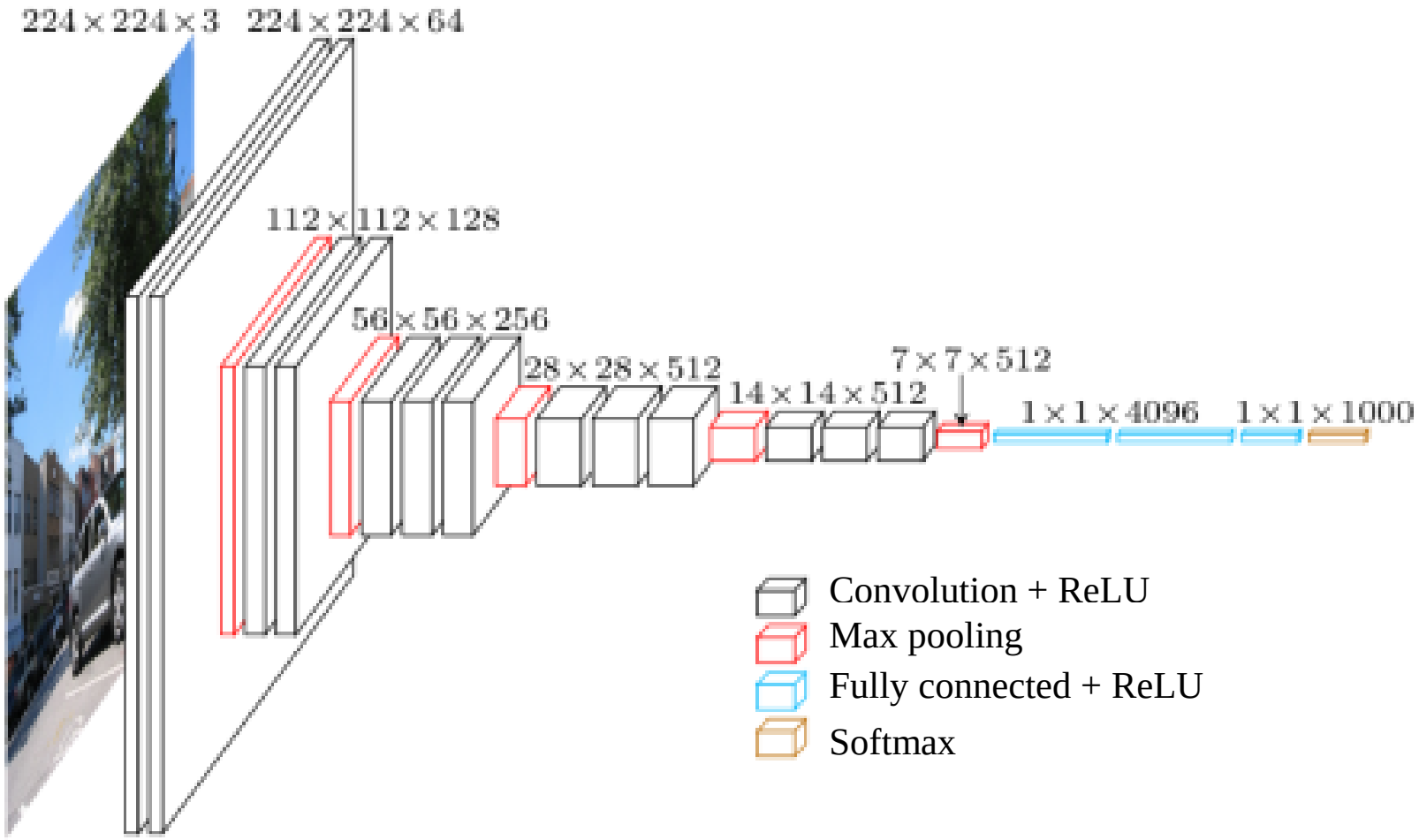


AlexNet

- Trained the network on ImageNet.
- Used ReLU for the nonlinearity functions
- Implemented dropout layers to combat overfitting issue



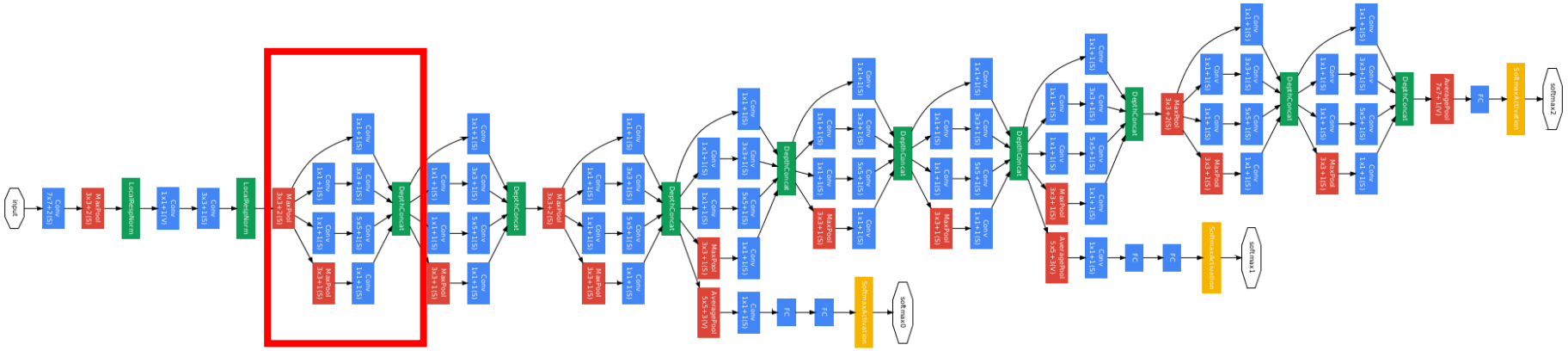
VGG


224 × 224 × 3
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
Convolution + ReLU
Max pooling
Fully connected + ReLU
Softmax

Six Different Architectures of VGG Net

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB imag)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

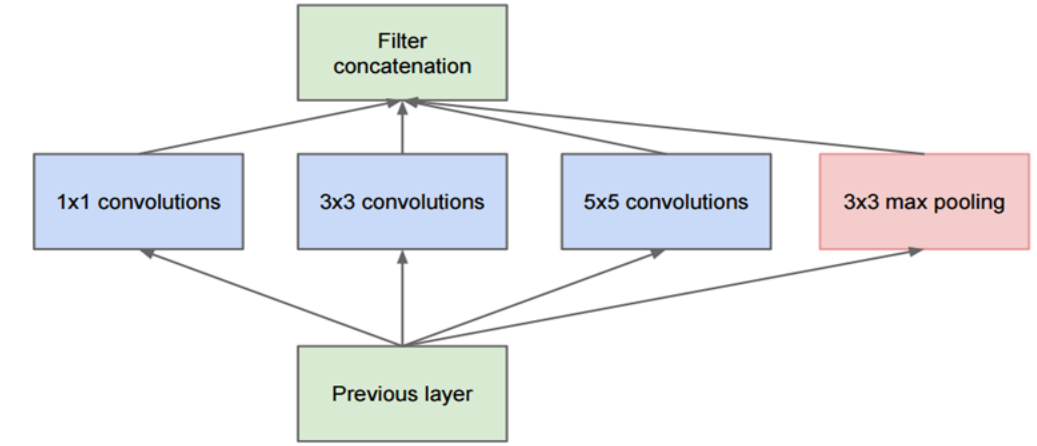
GoogLeNet



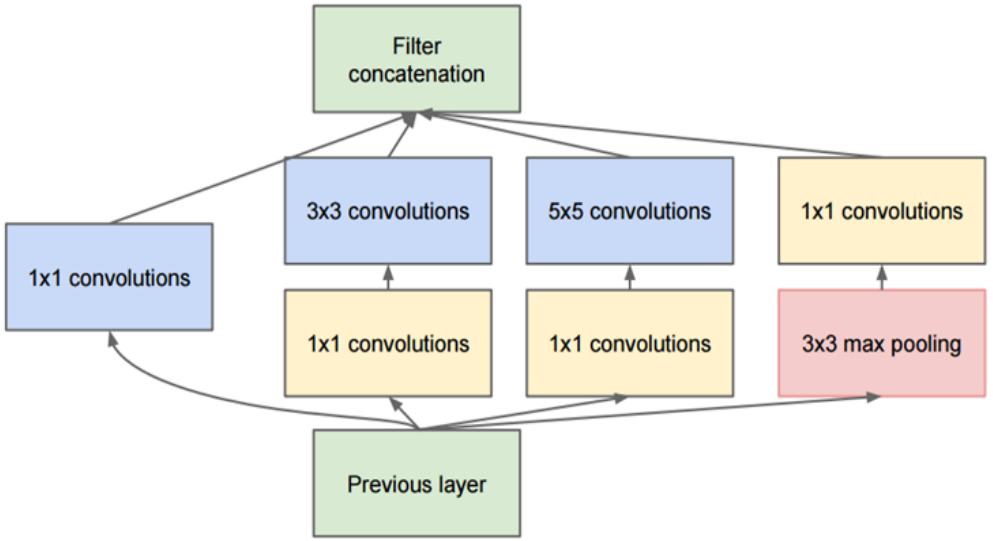
- Used 9 Inception modules, over **100** layers (very deep)
- Uses 12x **fewer parameters** than AlexNet
- Trained on **multiple GPUs** within a week

Inception Module

- Basic Inception Module

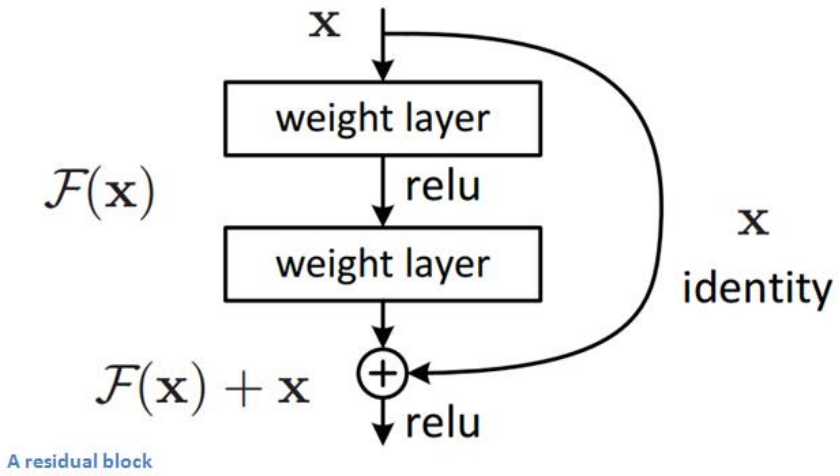


- Full Inception Module



Full Inception module

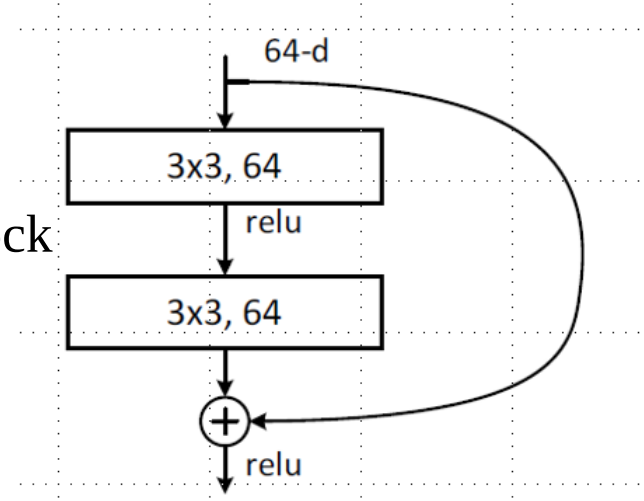
Residual Network



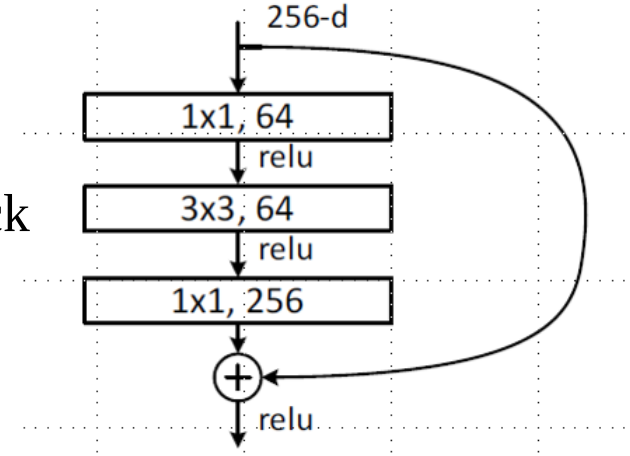
$$y = \mathcal{F}(x) + x$$

Residual Term

Basic Block

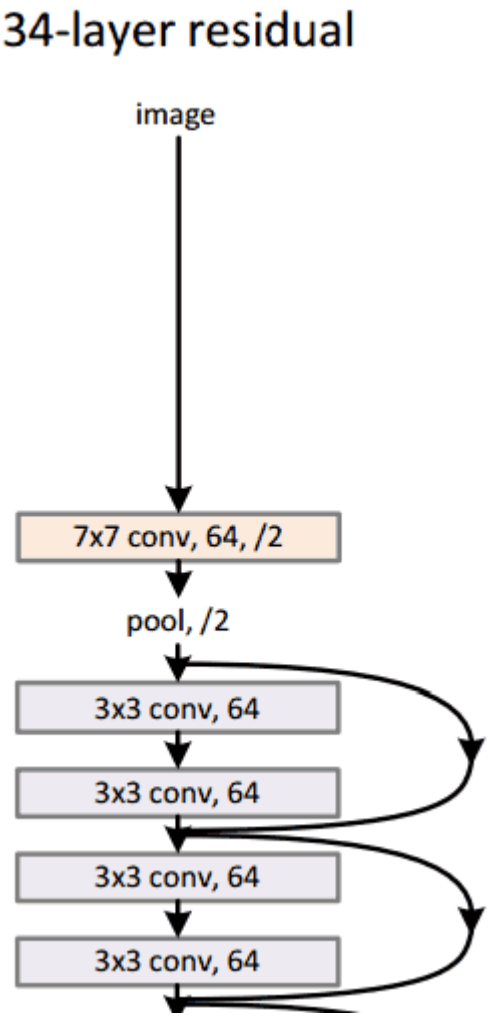


Bottleneck



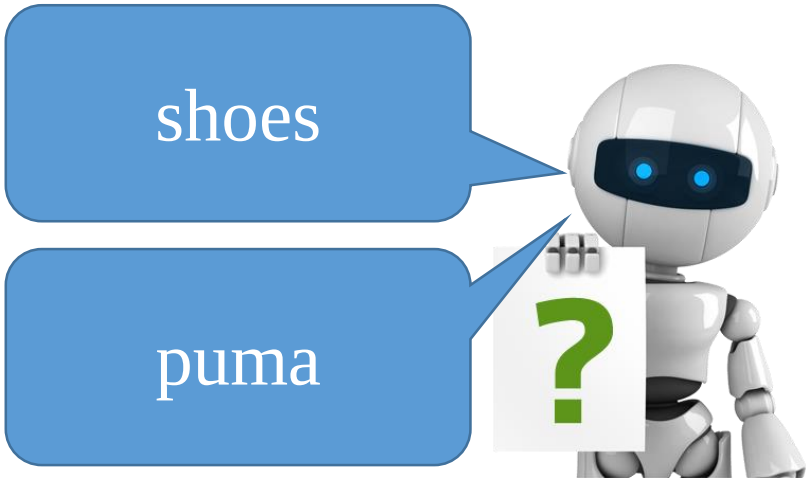
Residual Network

- **Residual** learning
- **Ultra-deep** 152 and 200 layers
- Trained a **1202-layer** network
- Trained on an **8 GPUs** machine



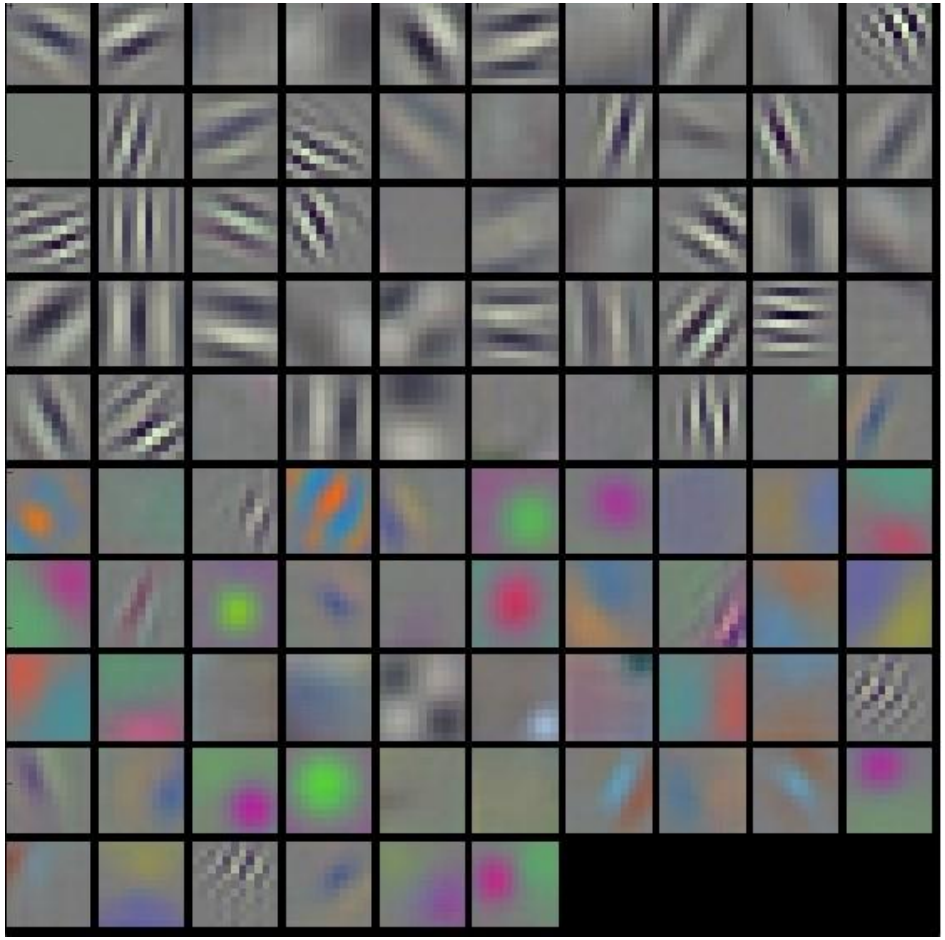
What does machine learn in CNNs?

What does Machine Learn?



First Convolutional Layer

- Typical-looking filters on the trained first layer

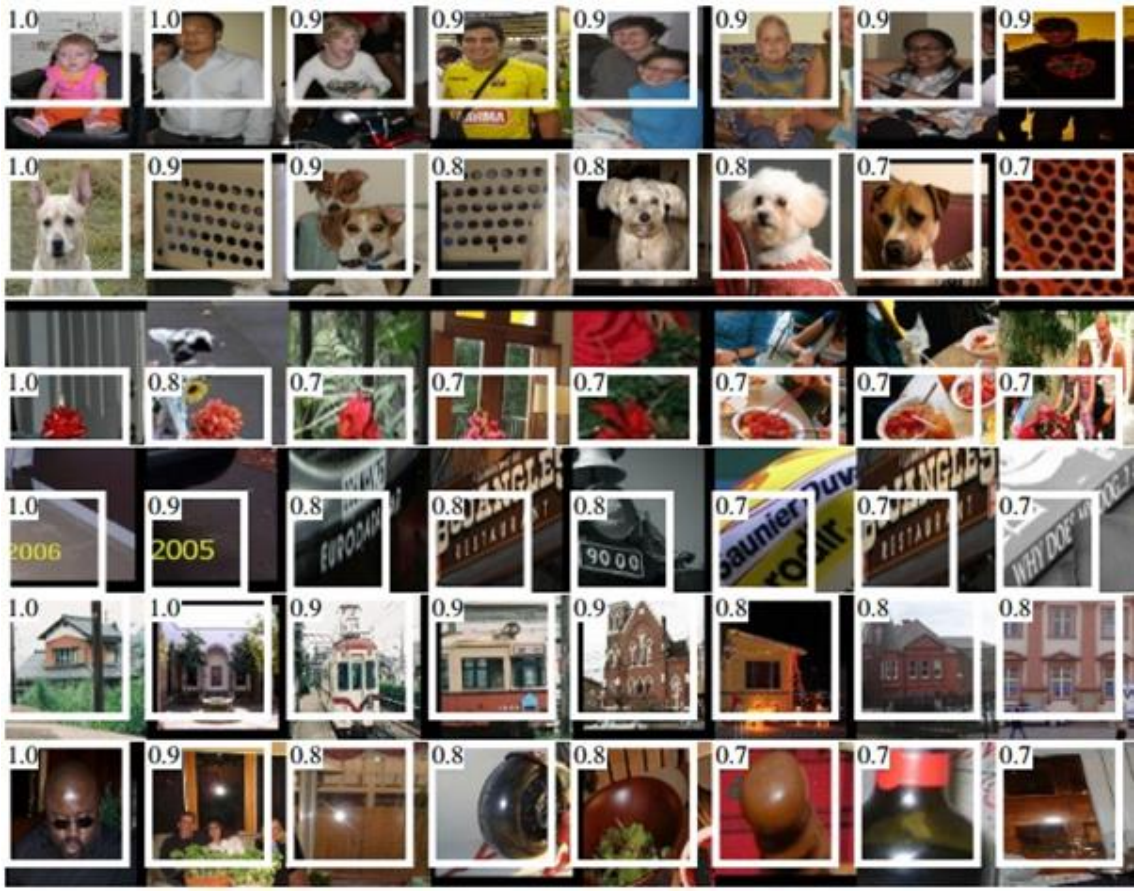


11 x 11
(AlexNet)

http://cs231n.github.io/understanding-cnn/

How about Higher Layers?

- Which images make a specific neuron activate?

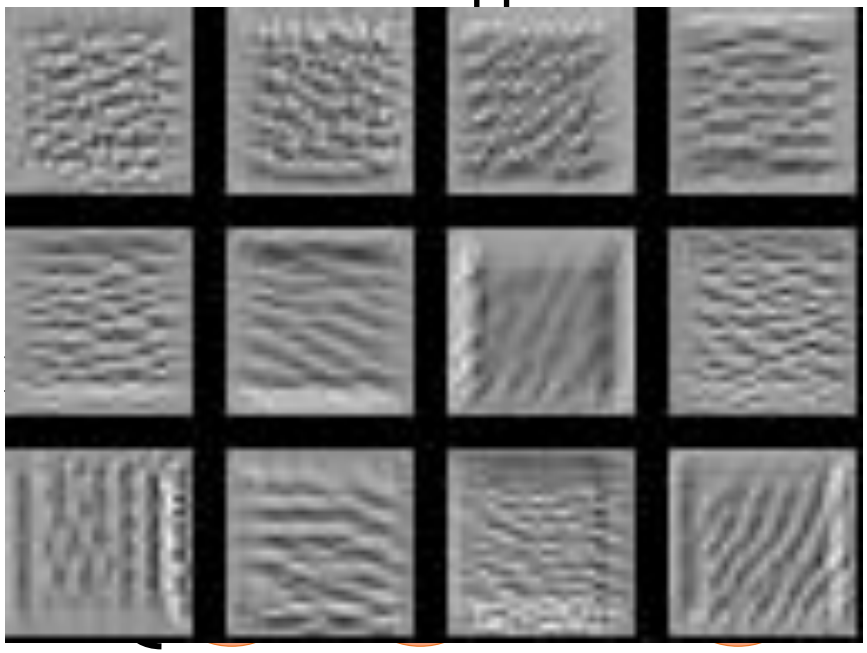


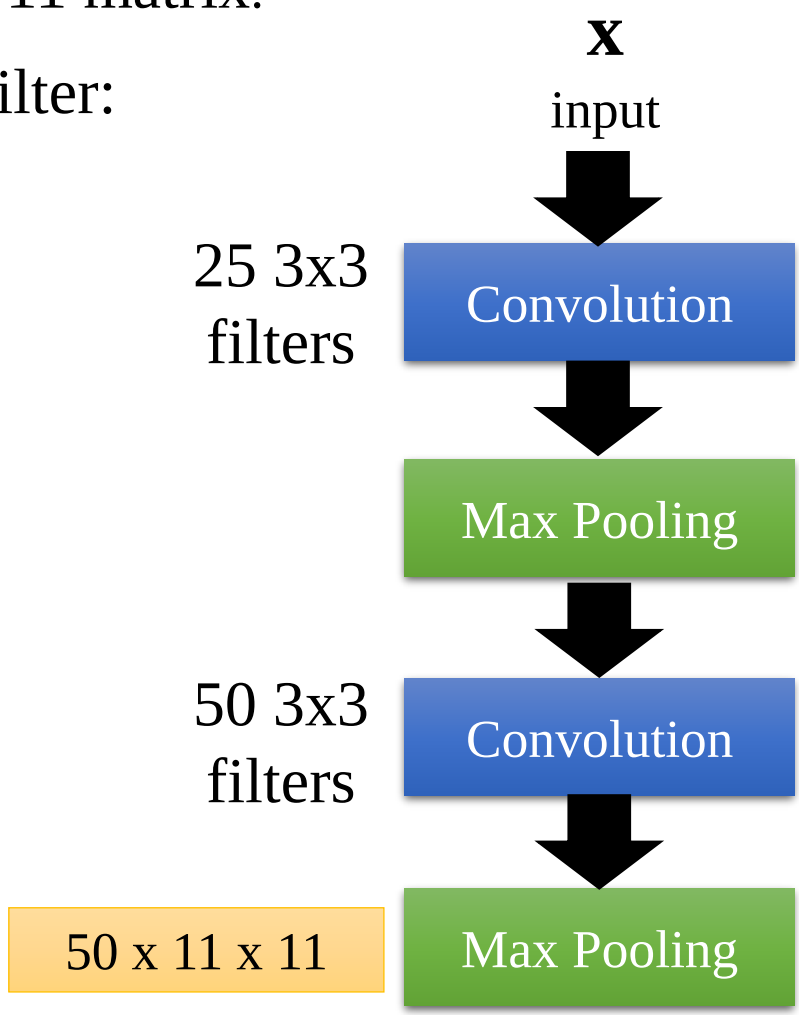
Ross Girshick, Jeff Donahue, Trevor Darrell, Jitendra Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR, 2014

What does Machine Learn?

- The output of the k-th filter is a 11 x 11 matrix.
- Degree of the activation of the k-th filter:

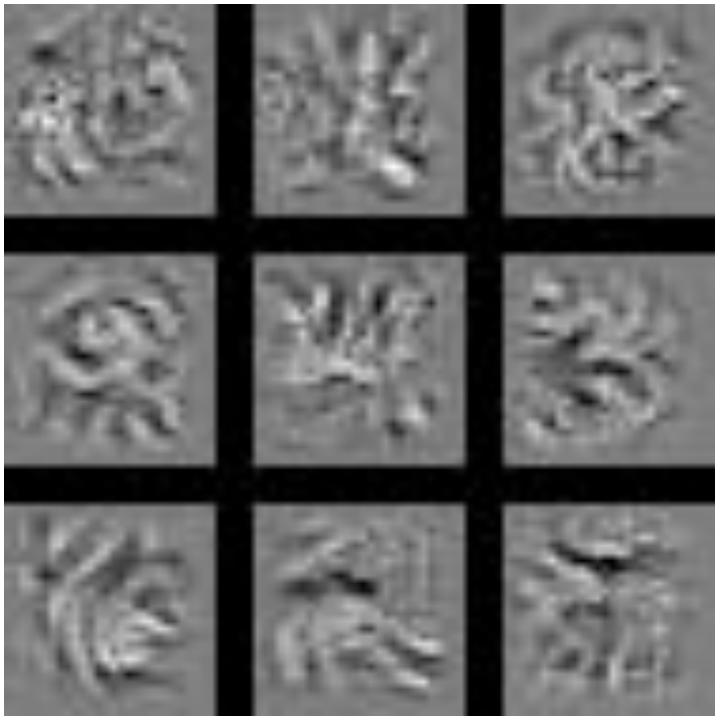
$$a^k = \sum_{i=1}^{11} \sum_{j=1}^{11} a_{ij}^k$$



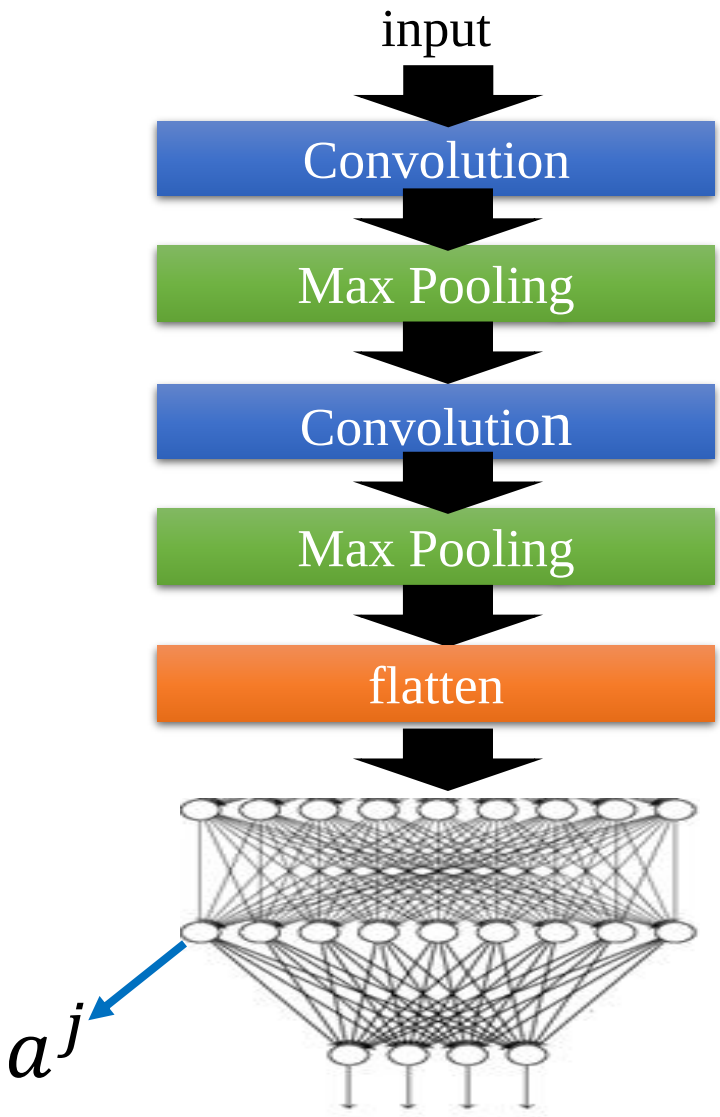


What does Machine Learn?

- Find an image maximizing the output of neuron: $\mathbf{x}^* = \arg\max_{\mathbf{x}} a^j$

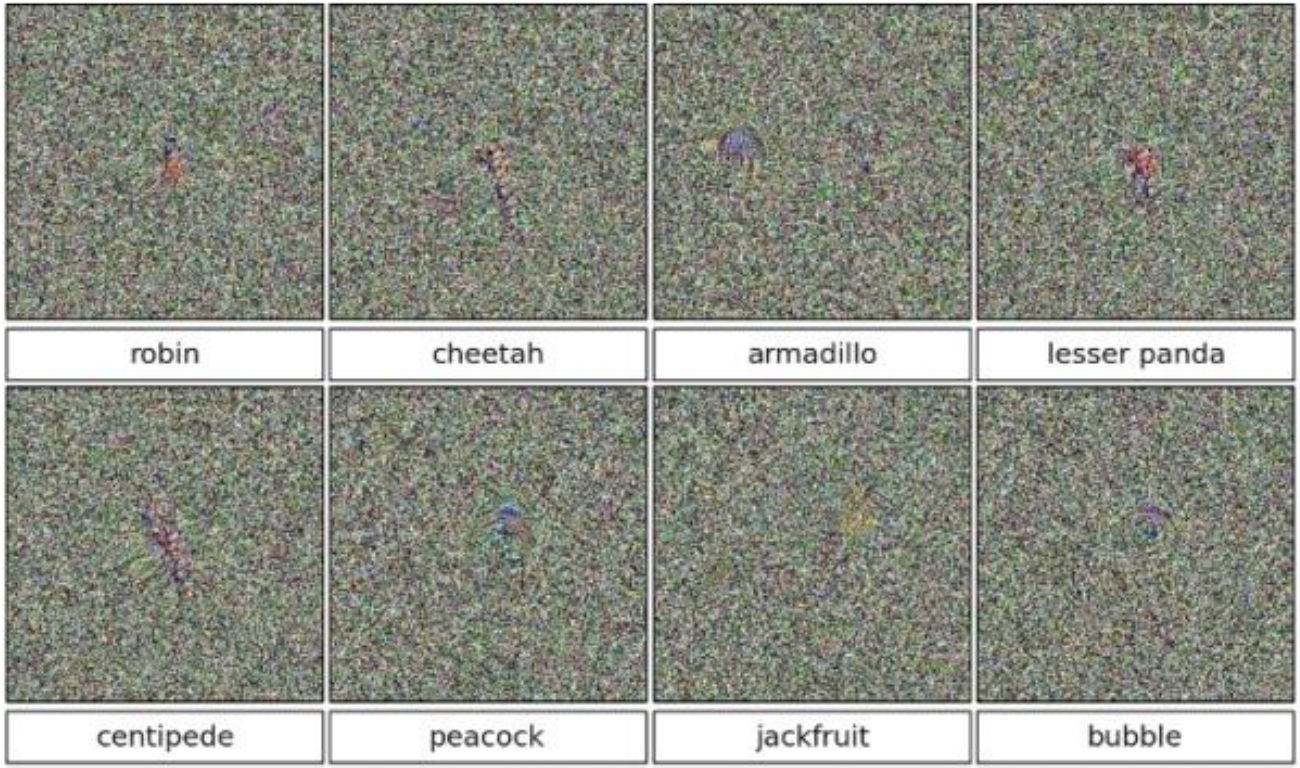


- Each figure corresponds to a neuron



Will Deep Neural Networks be Fooled?

- Evolved images that are unrecognizable to humans but DNNs can recognize



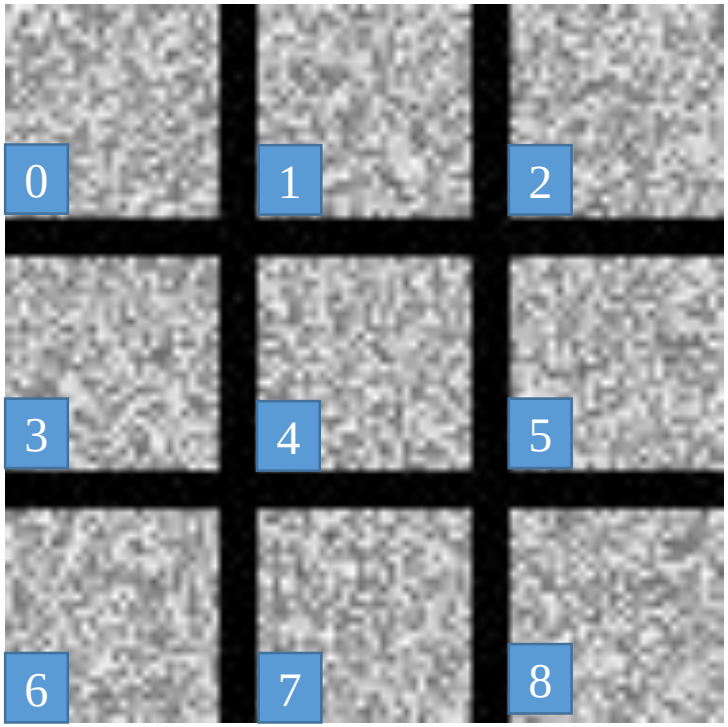
(Deep Neural Networks are Easily Fooled
https://www.youtube.com/watch?v=M2IebCN9Ht4)

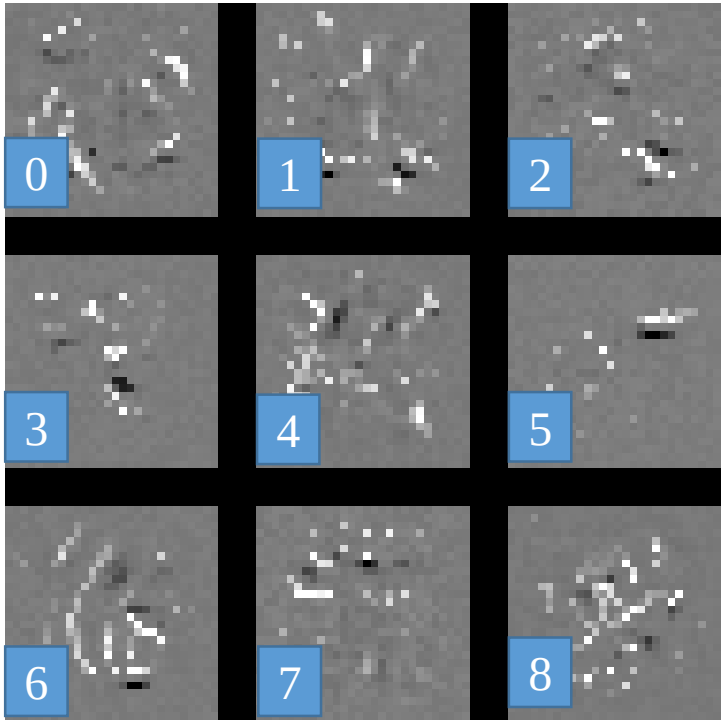
What does Machine Learn?

$$\mathbf{x}^* = \arg\max_{\mathbf{x}} y^i$$

Over all pixel values

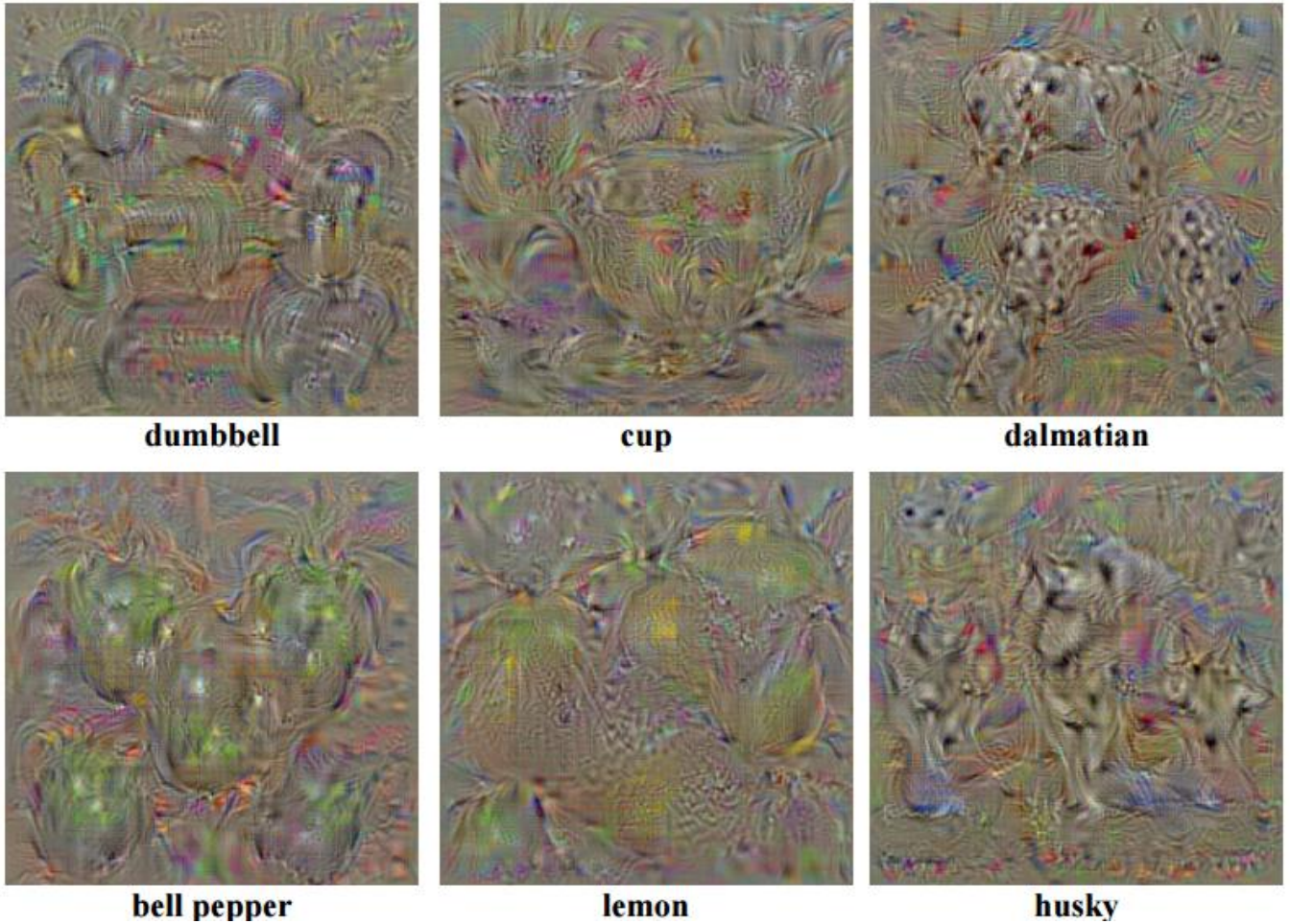
$$\mathbf{X}^* = \arg\max_{X} \left(y^i - \sum_{i,j} |\mathbf{X}_{ij}| \right)$$





What does Machine Learn?

- Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR, 2014

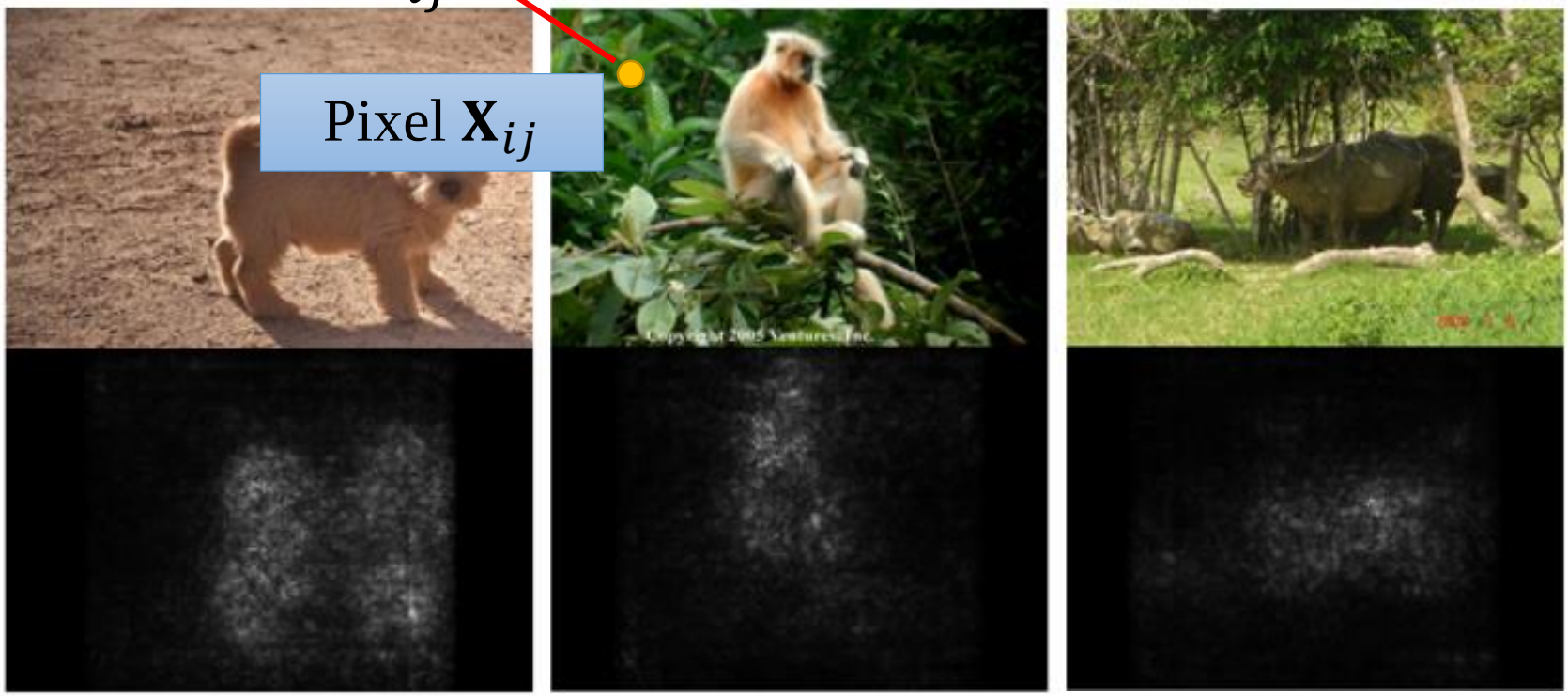


What does Machine Learn?

- Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR, 2014

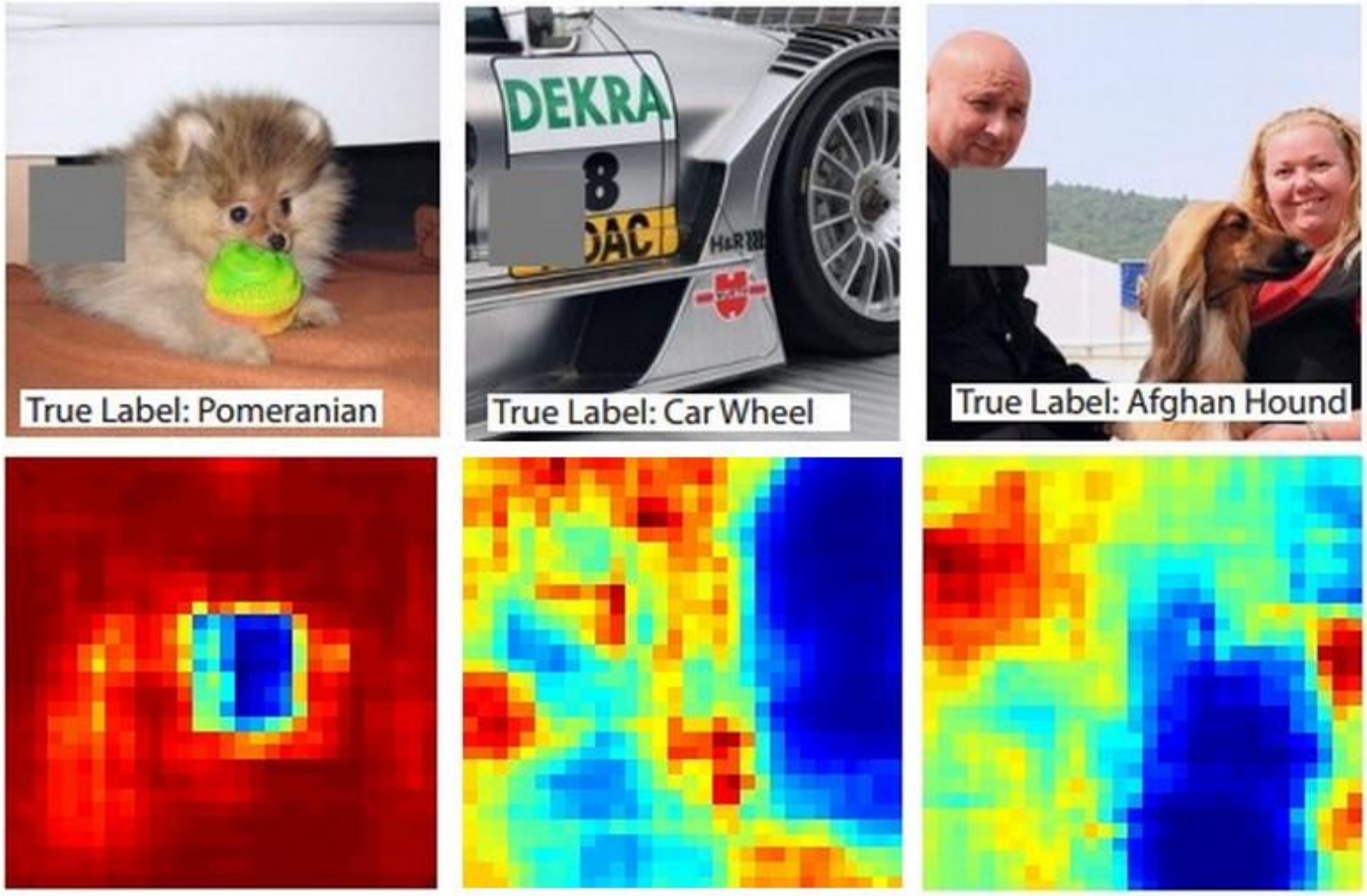
$$\left|\frac{\partial y_k}{\partial X_{ij}}\right|$$

y_k: the predicted class of the model



What does Machine Learn?

- Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818-833)



Thank you