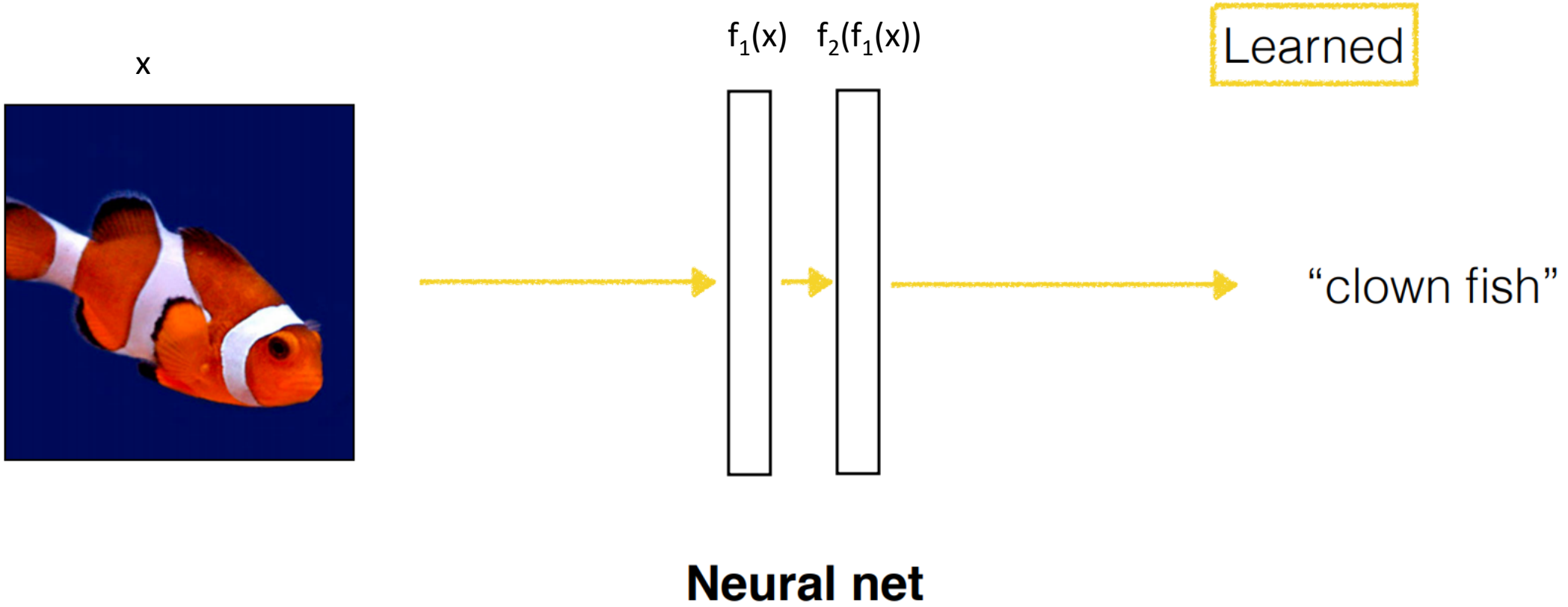
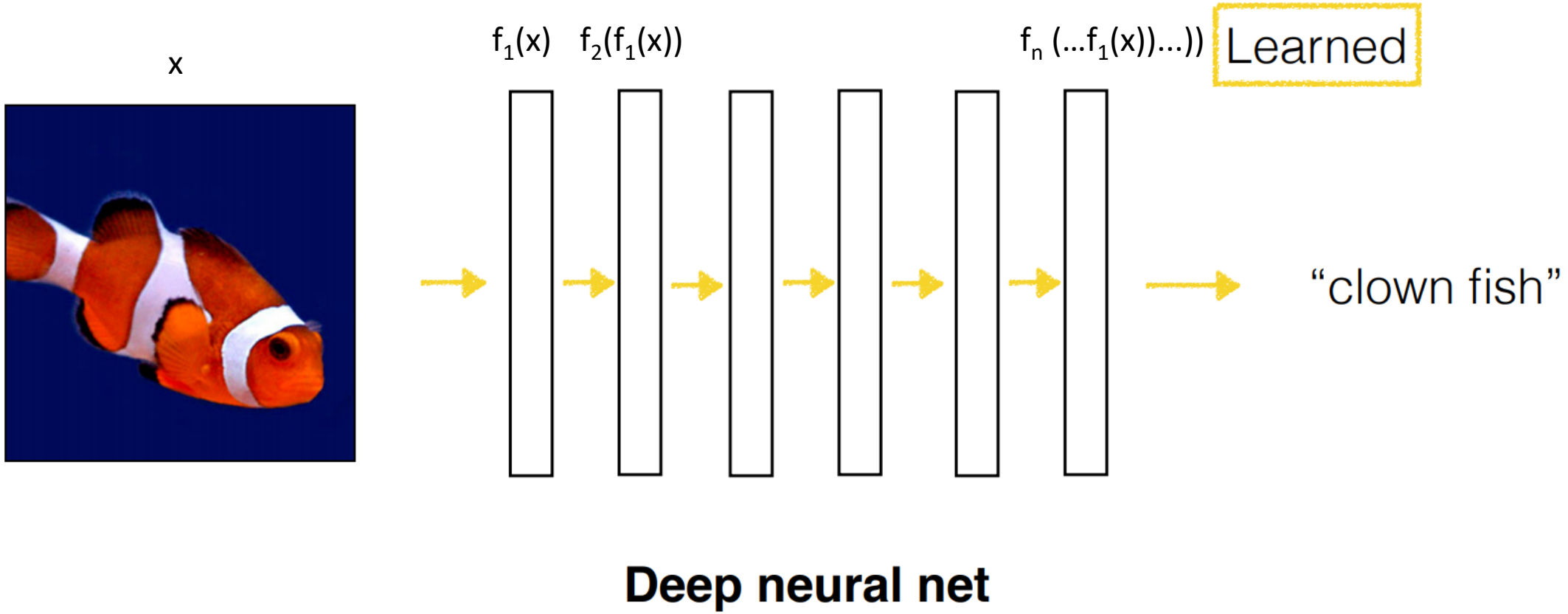
Neural Networks

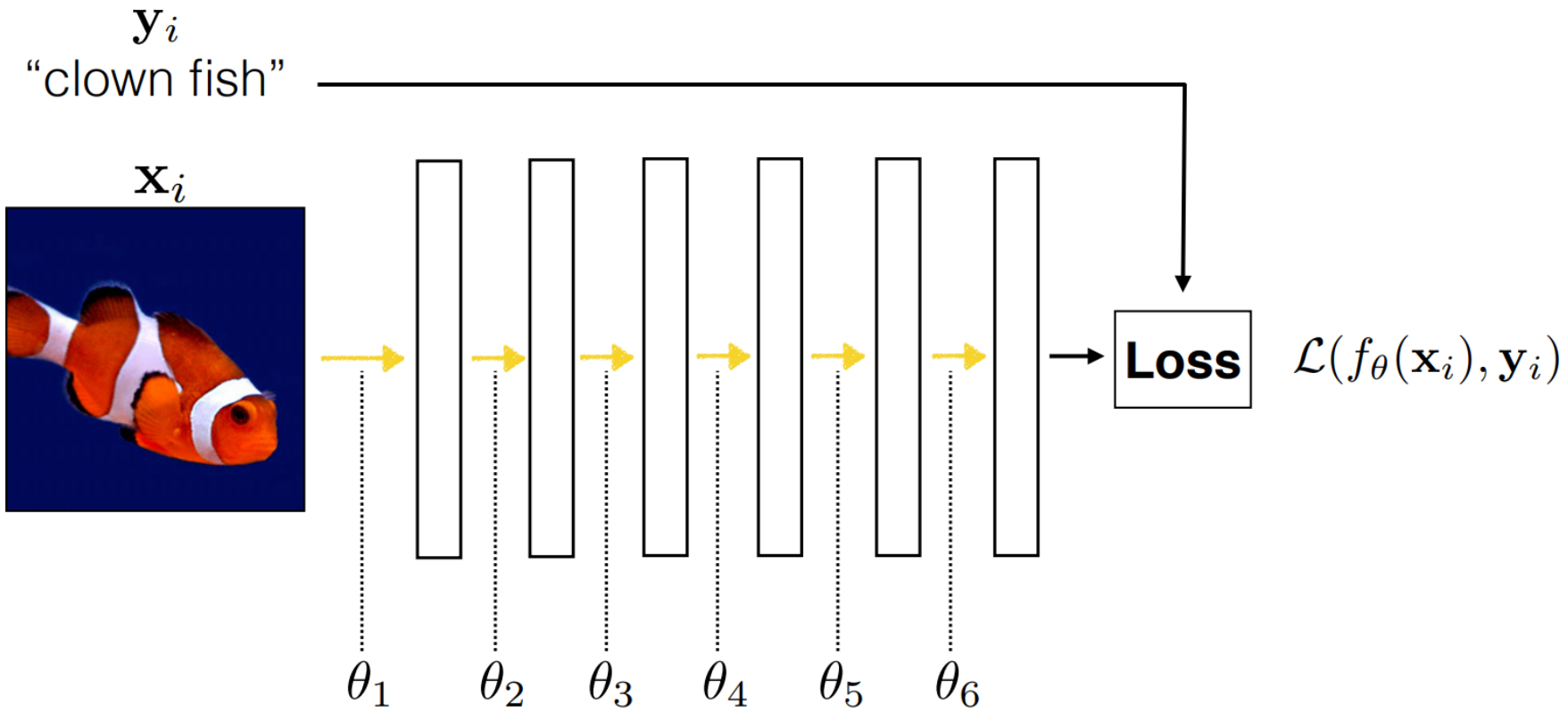
Object Recognition



Object Recognition



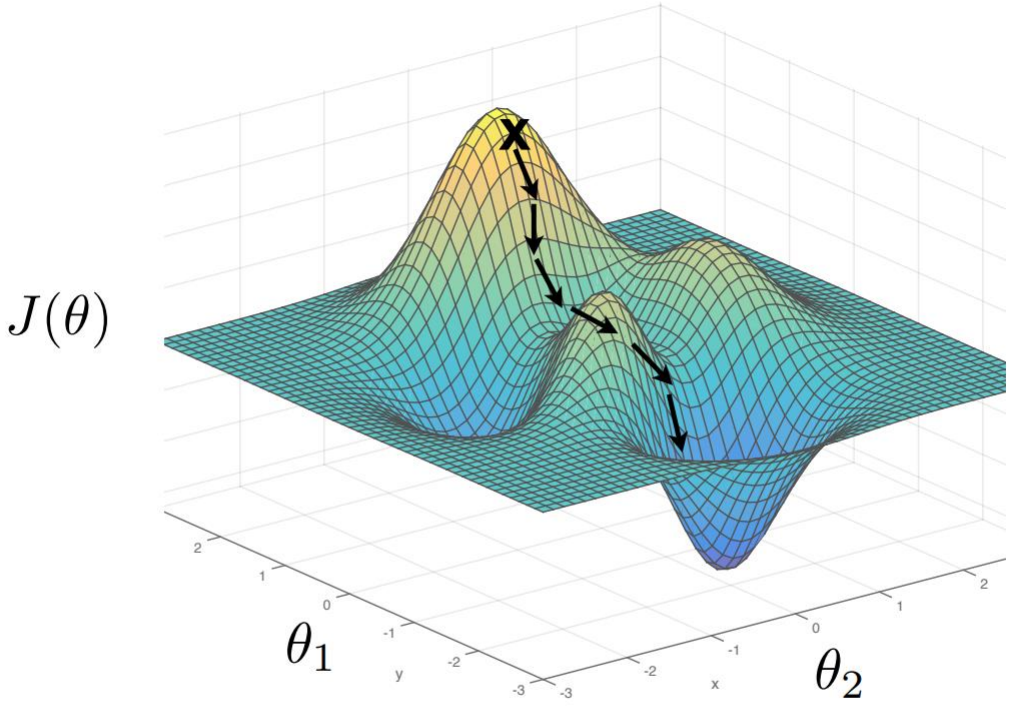
Object Recognition



$$\theta^* = \arg\min_\theta \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)$$

Gradient Descent

- Gradient descent is an optimization algorithm used to minimize some function by iteratively moving in the direction of steepest descent as defined by the negative of the gradient



$$\theta^* = \arg\min_{\theta} J(\theta)$$

Gradient Descent

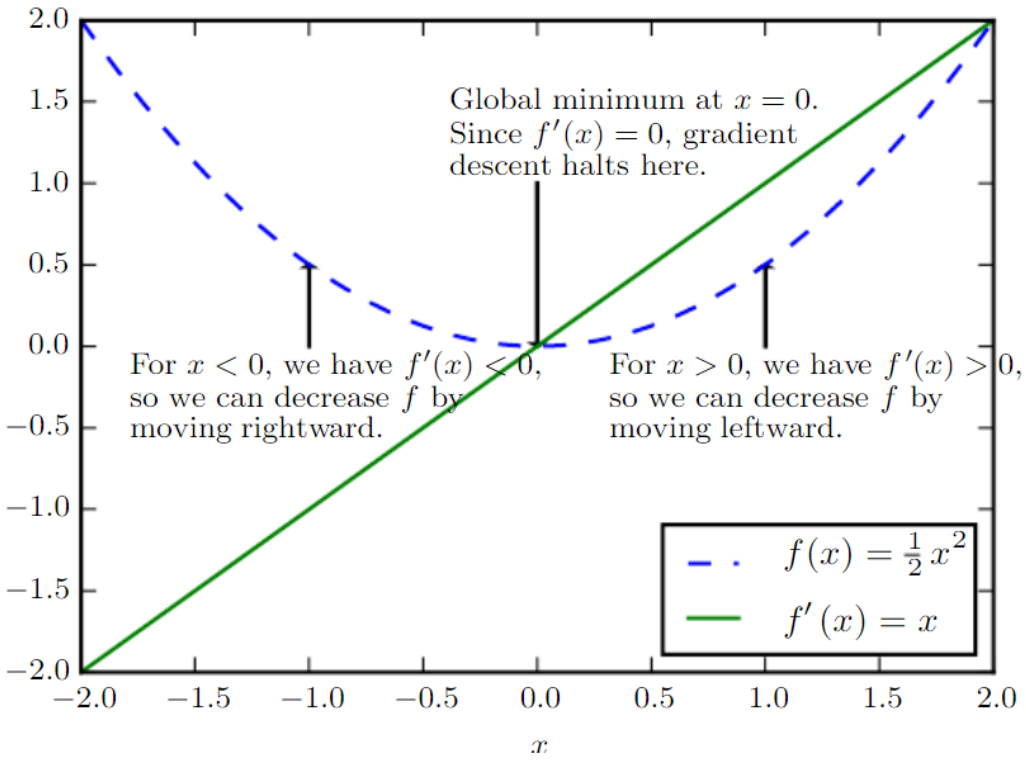


Figure 4.1: Gradient descent. An illustration of how the gradient descent algorithm uses the derivatives of a function to follow the function downhill to a minimum.

Gradient Descent

$$\theta^* = \arg\min_{\theta} \underbrace{\sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)}_{J(\theta)}$$

One iteration of gradient descent:

$$\theta^{t+1} = \theta^t - \eta_t \left. \frac{\partial J(\theta)}{\partial \theta} \right|_{\theta=\theta^t}$$

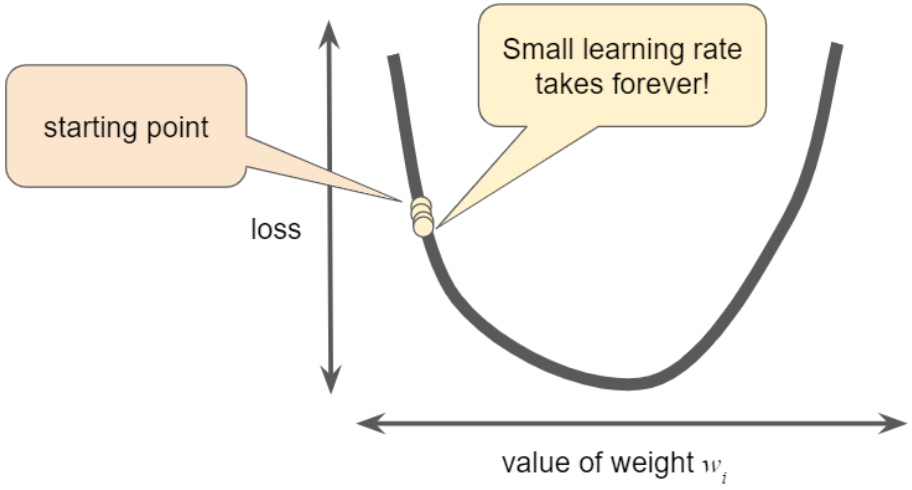
learning rate

Learning Rate

$$\theta^{t+1} = \theta^t - \eta_t \frac{\partial J(\theta)}{\partial \theta}\bigg|_{\theta=\theta^t}$$

learning rate

- The learning rate parameter controls how much the optimization algorithm learns at each iteration
- A very low learning algorithm will take a long time to converge

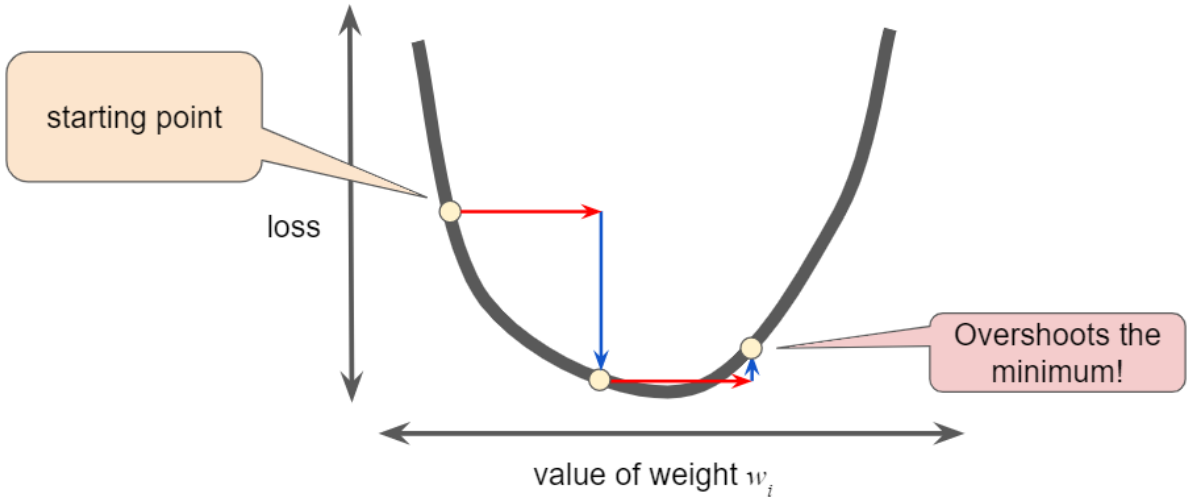


Learning Rate

$$\theta^{t+1} = \theta^t - \eta_t \frac{\partial J(\theta)}{\partial \theta}\bigg|_{\theta=\theta^t}$$

learning rate

- The learning rate parameter controls how much the optimization algorithm learns at each iteration
- A high learning rate will cause the algorithm to miss the optimal solution



Learning Rate

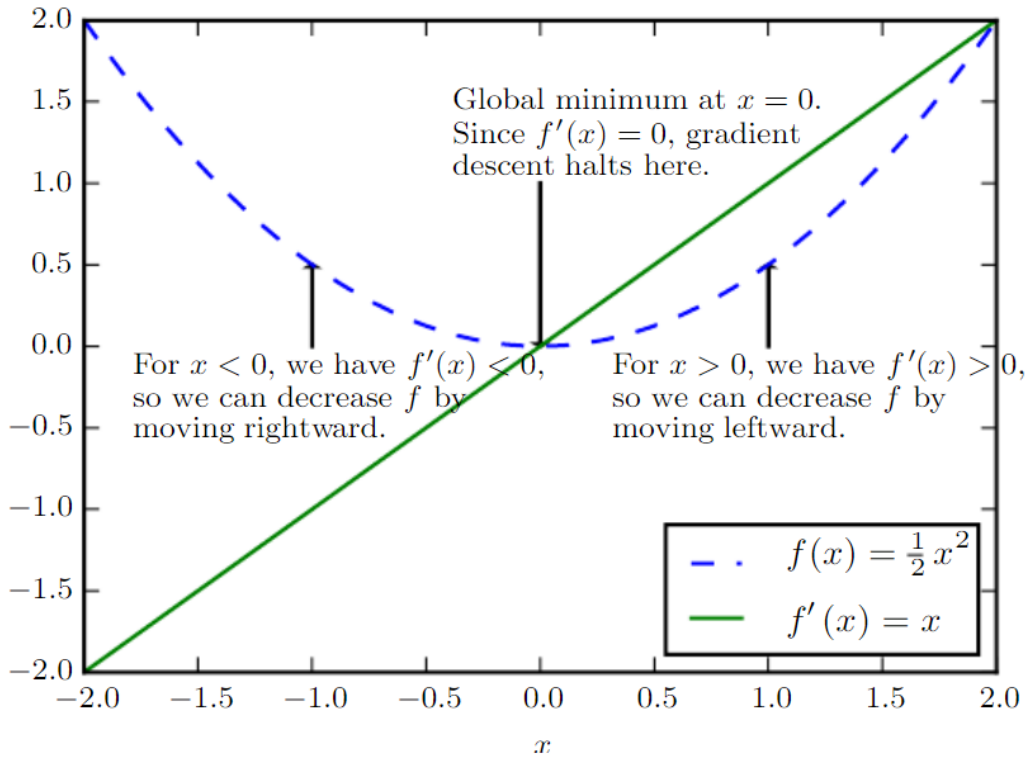


Figure 4.1: Gradient descent. An illustration of how the gradient descent algorithm uses the derivatives of a function to follow the function downhill to a minimum.

Learning rate

- Several gradient descent variants exist.
- These methods differ in the way the way they **update** the learning rate.
- A good comparison between these methods is provided in

  https://ruder.io/optimizing-gradient-descent/

  (run the animation)

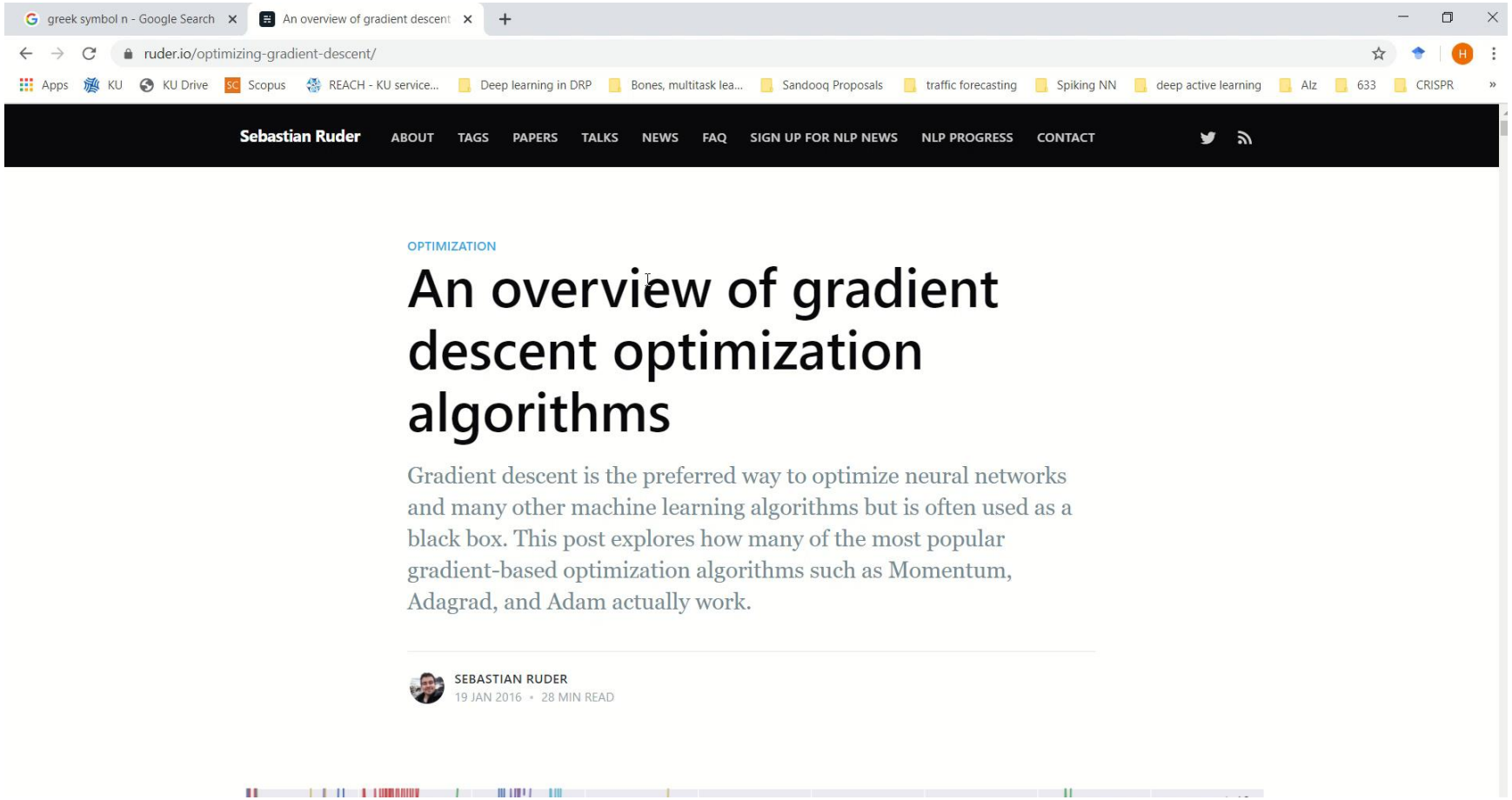
$$\theta^* = \arg\min_{\theta} \underbrace{\sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i)}_{J(\theta)}$$

One iteration of gradient descent:

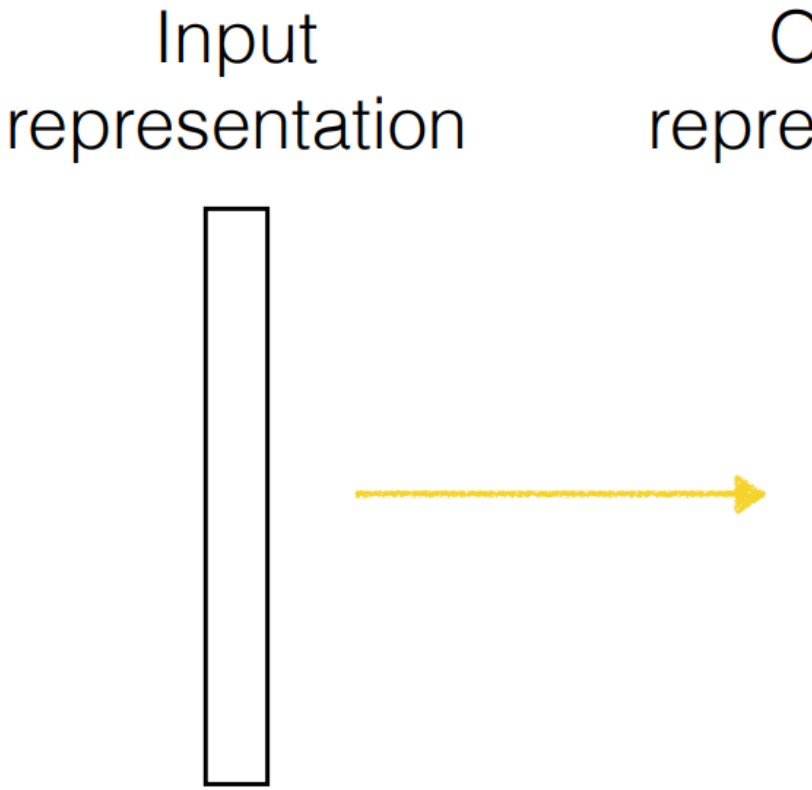
$$\theta^{t+1} = \theta^t - \eta_t \left. \frac{\partial J(\theta)}{\partial \theta} \right|_{\theta=\theta^t}$$

learning rate

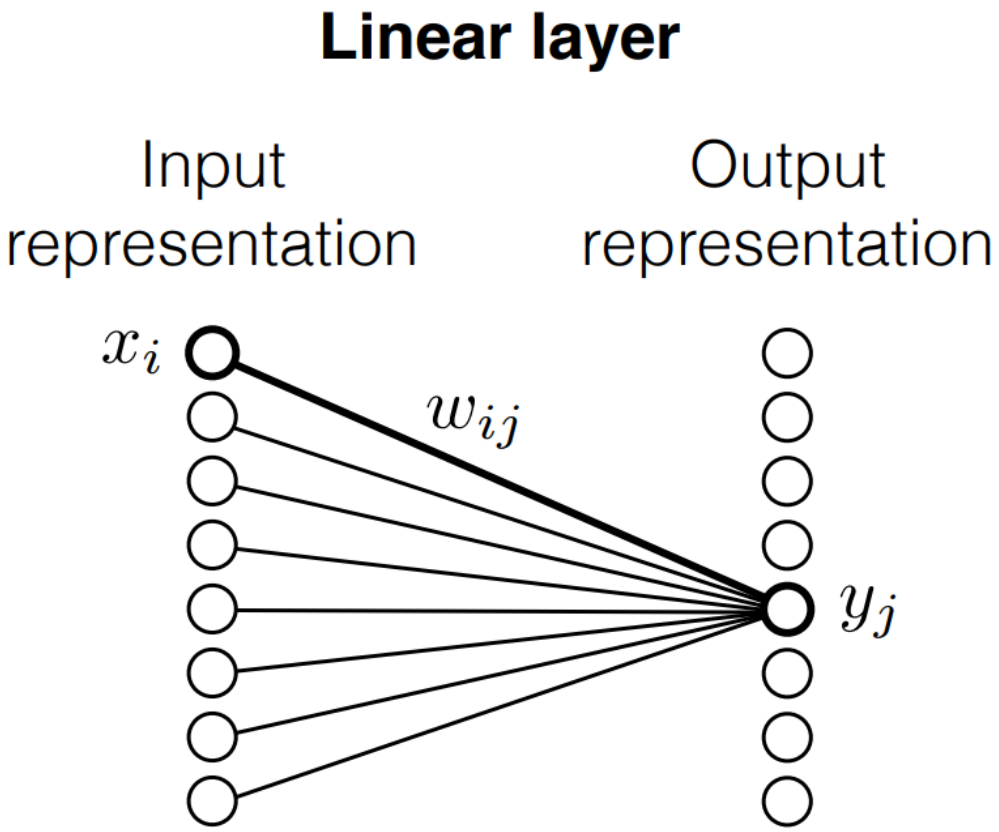
Learning rate



Computation in a neural net

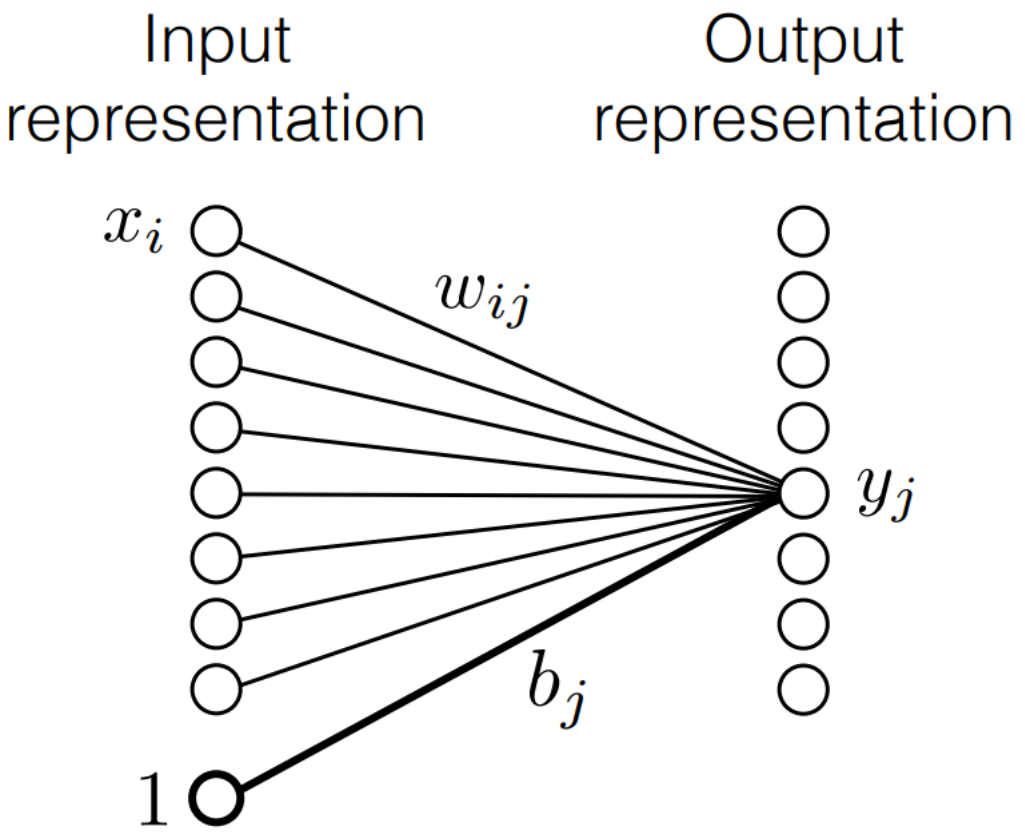


Computation in a neural net



$$y_j = \sum_i w_{ij} x_i$$

Computation in a neural net

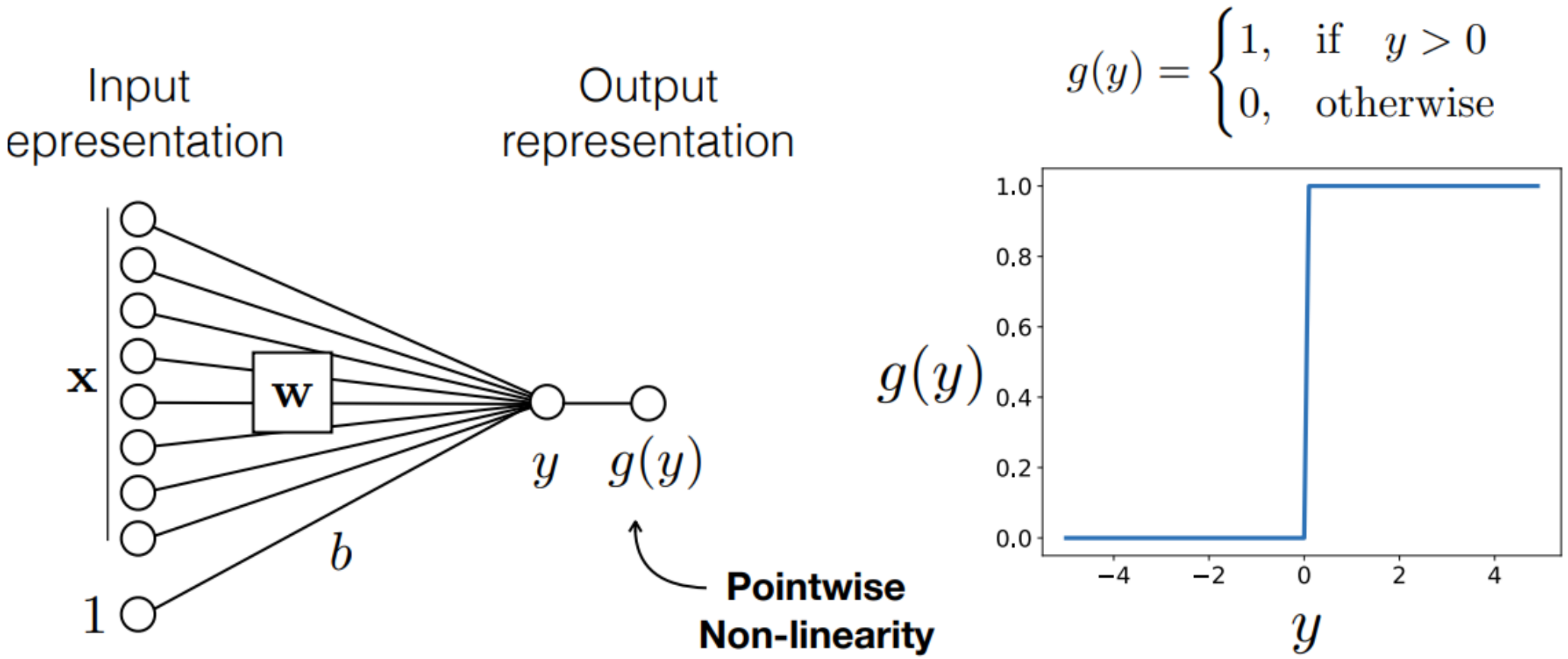


$$y_j = \sum_i w_{ij} x_i + b_j$$

weights

bias

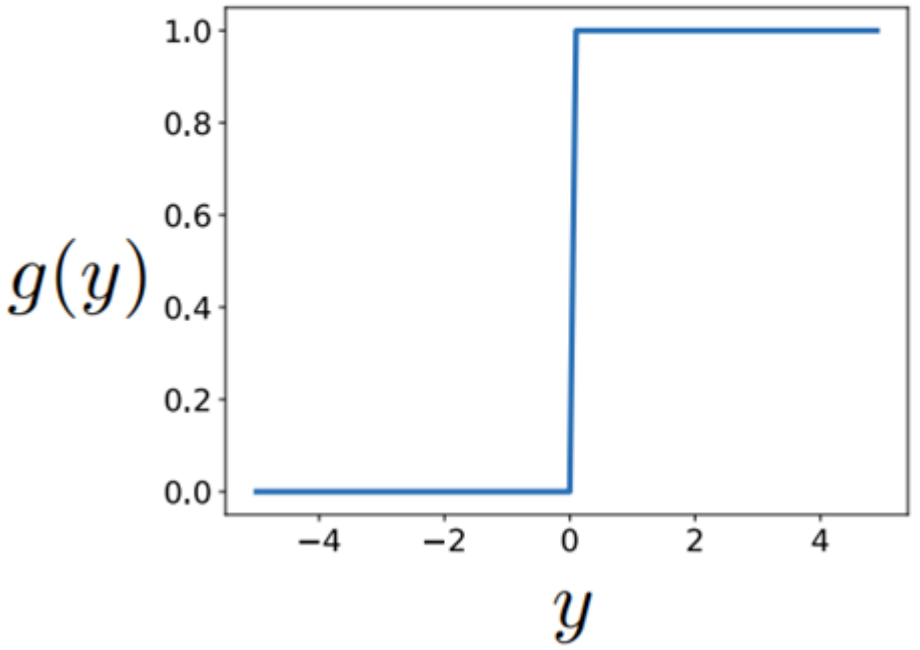
Using a Neural Network for Classification



Using Neural Networks for Classification

- $g(y)$ is non-differentiable function, smooth transition functions are easier to optimize and provide better results

$$g(y) = \begin{cases} 1, & \text{if} \quad y > 0 \\ 0, & \text{otherwise} \end{cases}$$

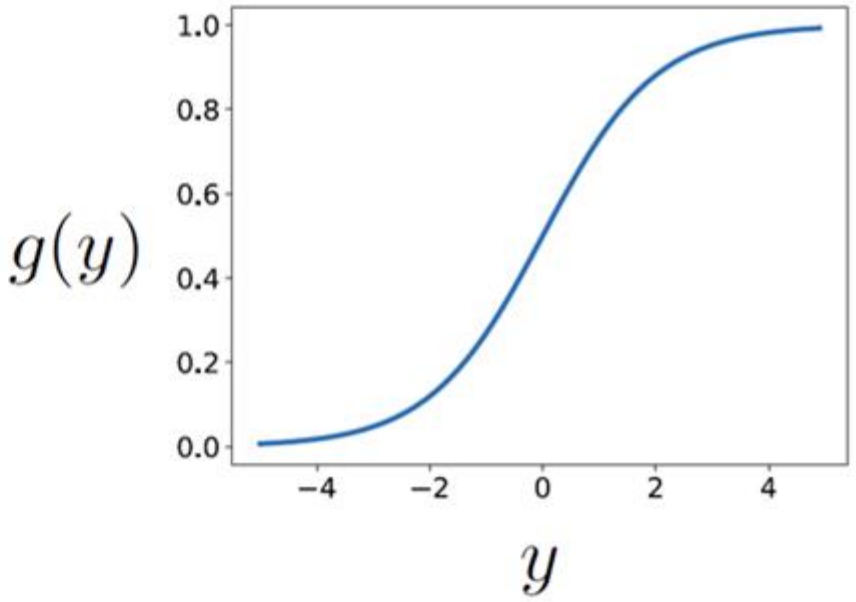


Using Neural Networks for Classification

- Interpretation as firing rate of neuron
- Bounded between [0,1]
- Saturation for large +/- inputs
- Gradients go to zero
- Outputs centered at 0.5

Sigmoid

$$g(y) = \frac{1}{1 + e^{-y}}$$



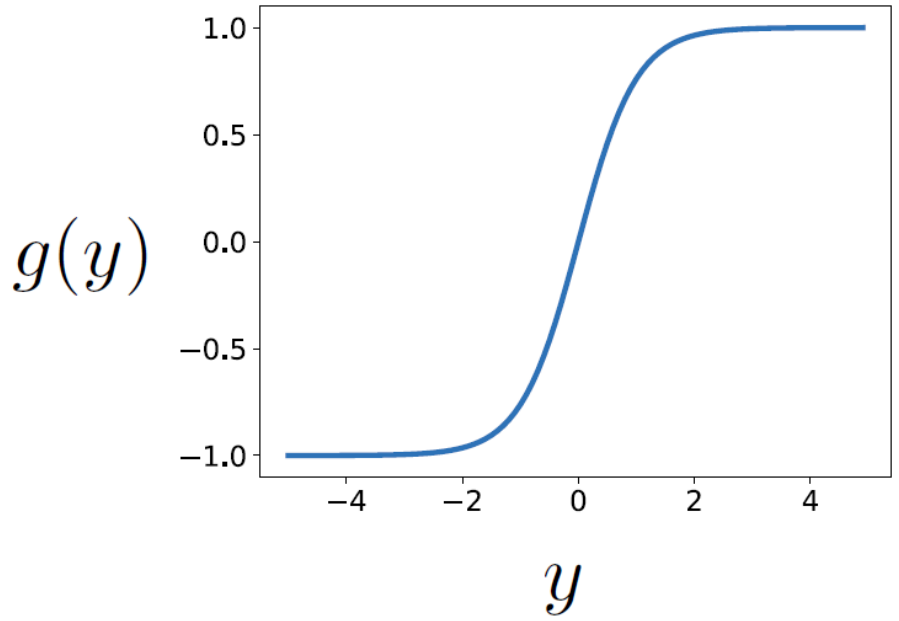
Using Neural Networks for Classification

- Bounded between [-1,+1]
- Saturation for large +/- inputs
- Gradients go to zero
- Outputs centered at 0
- Preferable to sigmoid

tanh(x) = 2 sigmoid(2x) –1

Tanh

$$g(y) = \frac{e^{y} - e^{-y}}{e^{y} + e^{-y}}$$

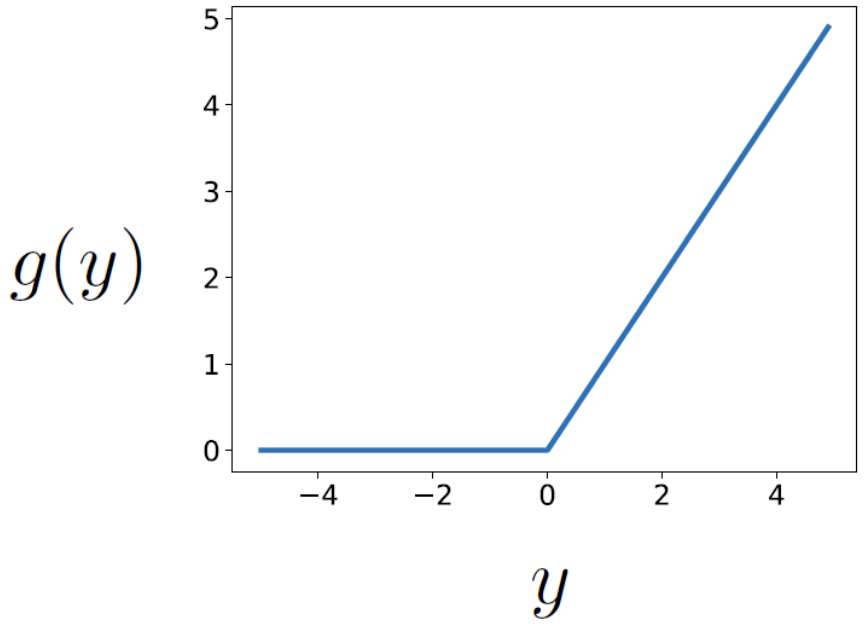


Using Neural Networks for Classification

- Unbounded output (on positive side)
- Efficient to implement: $\frac{\partial g}{\partial y} = \begin{cases} 0, & \text{if} \quad y < 0 \\ 1, & \text{if} \quad y \geq 0 \end{cases}$
- Also seems to help convergence (see 6x speedup vs tanh in [Krizhevsky et al.])
- Drawback: if strongly in negative region, unit is dead forever (no gradient).
- Default choice: widely used in current models.

Rectified linear unit (ReLU)

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

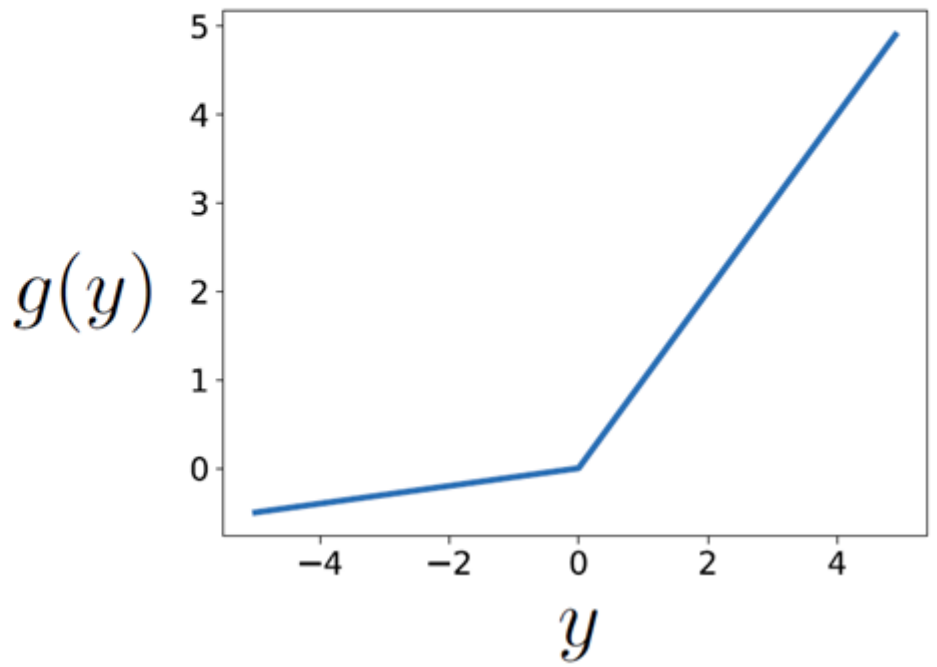


Using Neural Networks for Classification

- where α is small (e.g. 0.02)
- Efficient to implement: $\frac{\partial g}{\partial y} = \begin{cases} a, & \text{if} \quad y < 0 \\ 1, & \text{if} \quad y \geq 0 \end{cases}$
- Also known as probabilistic ReLU (PReLU)
- Has non-zero gradients everywhere (unlike ReLU)
- α can also be learned (see Kaiming He et al. 2015).

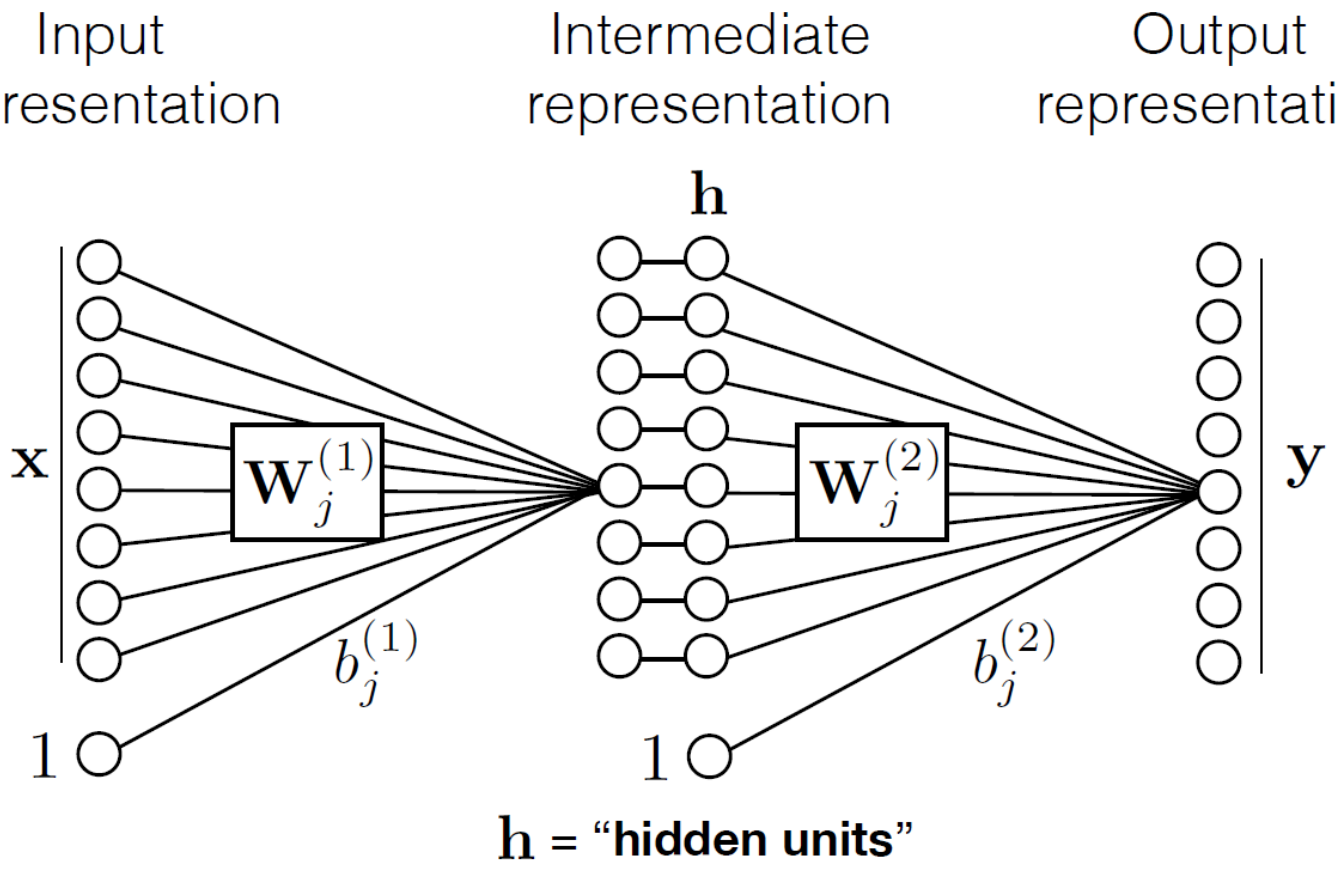
Leaky ReLU

$$g(y) = \begin{cases} \max(0, y), & \text{if} \quad y \geq 0 \\ a \min(0, y), & \text{if} \quad y < 0 \end{cases}$$



Stacking Layers

By stacking layers, neural networks can provide solutions that goes beyond linear problems.



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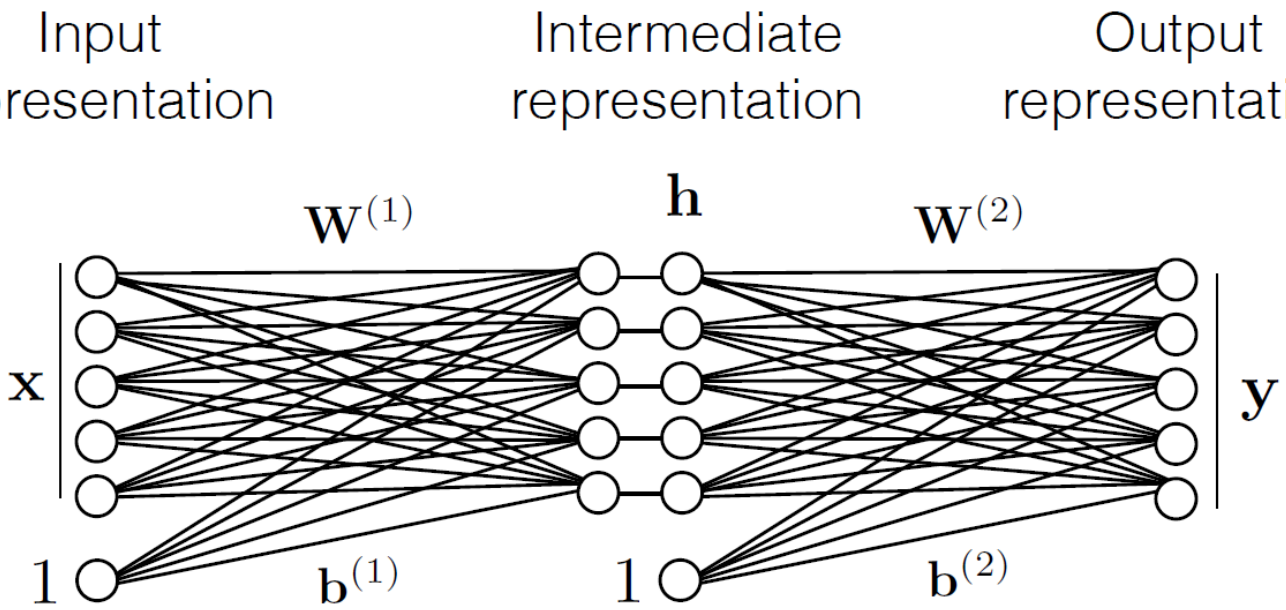
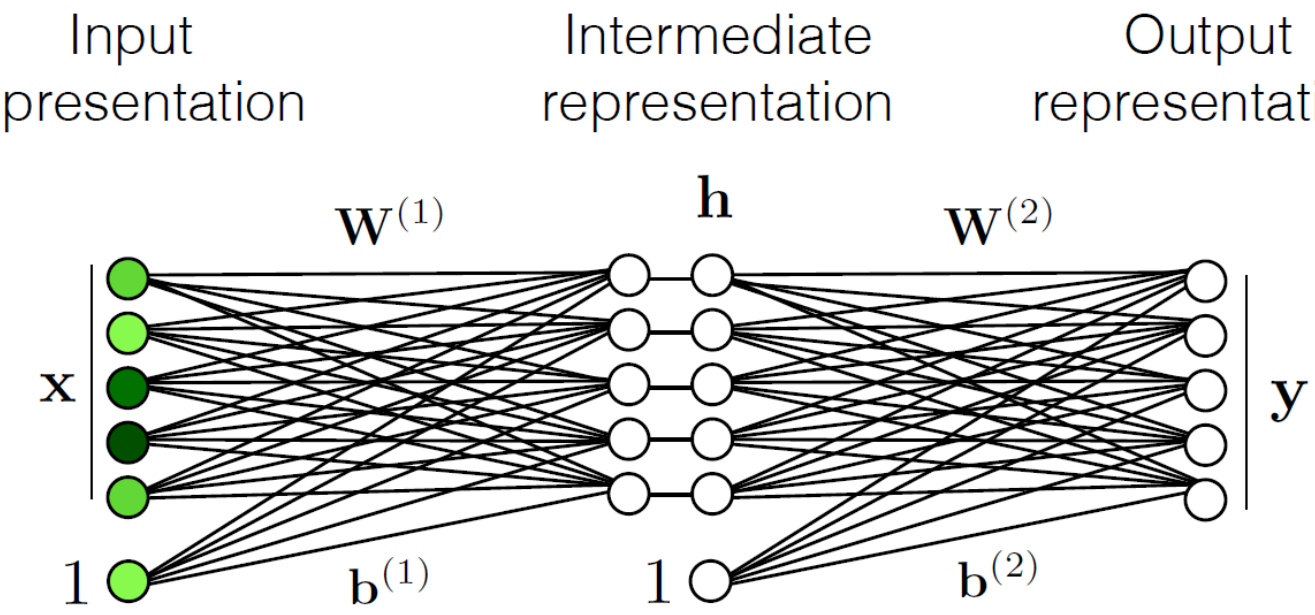


$$\mathbf{h} = g(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}) \qquad \mathbf{y} = \mathbf{W}^{(2)}\mathbf{h} + \mathbf{b}^{(2)}$$

$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Stacking Layers



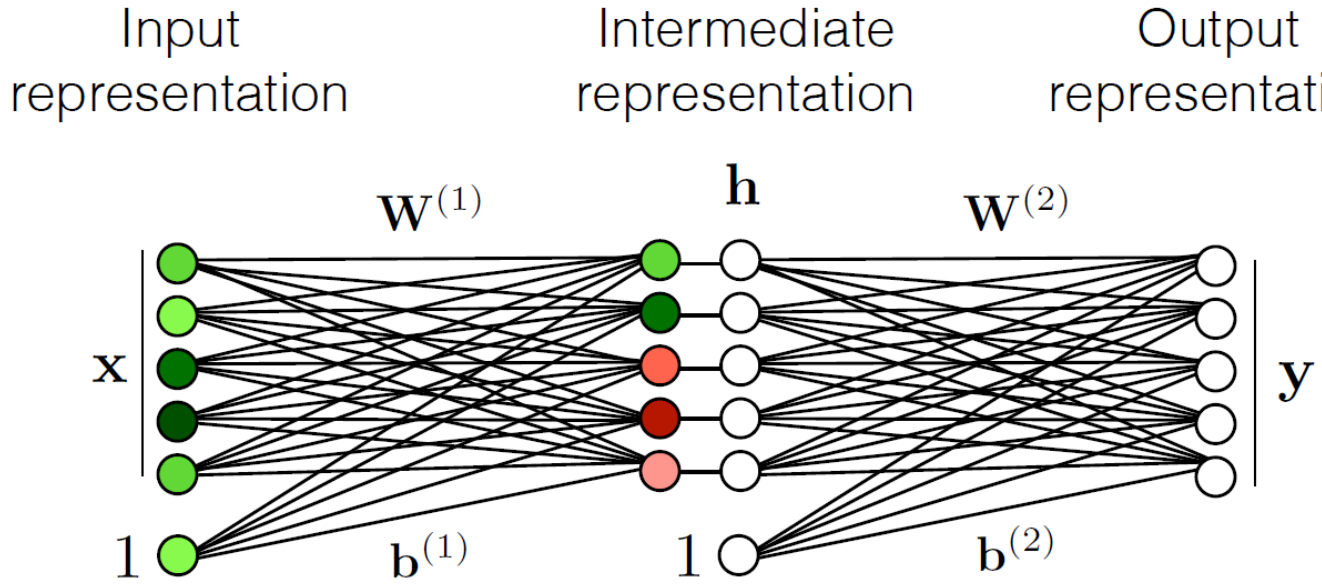
positive

negative

$$\mathbf{h} = g(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}) \qquad \mathbf{y} = \mathbf{W}^{(2)}\mathbf{h} + \mathbf{b}^{(2)}$$

$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Stacking Layers



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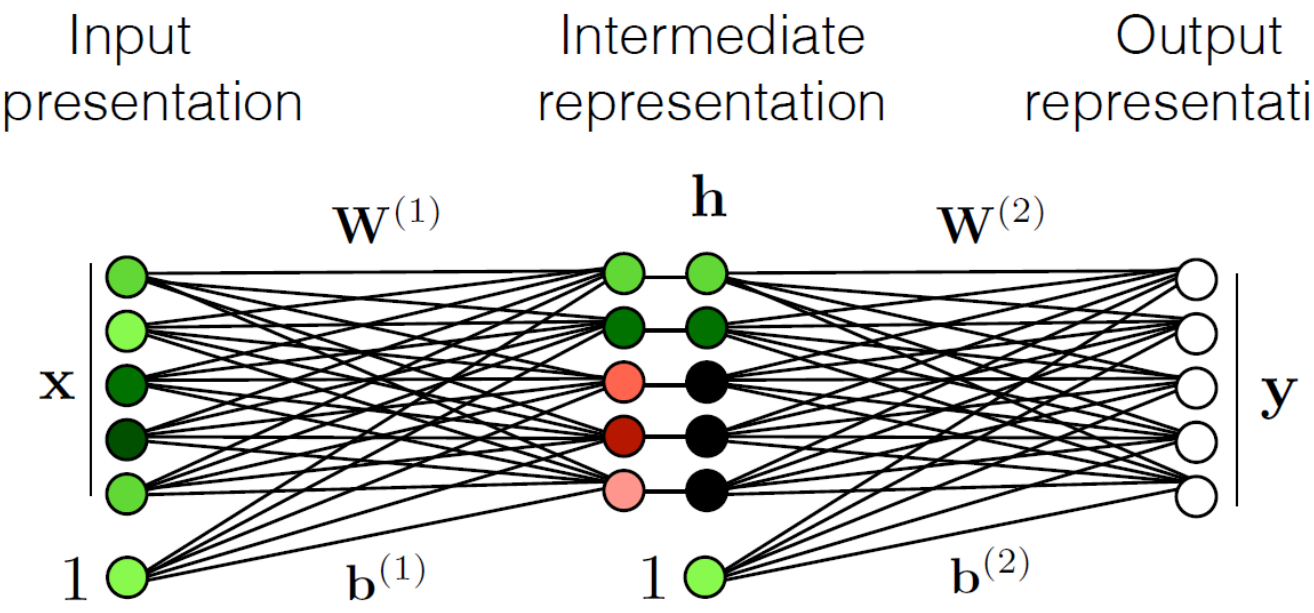
Stacking Layers



positive

negative

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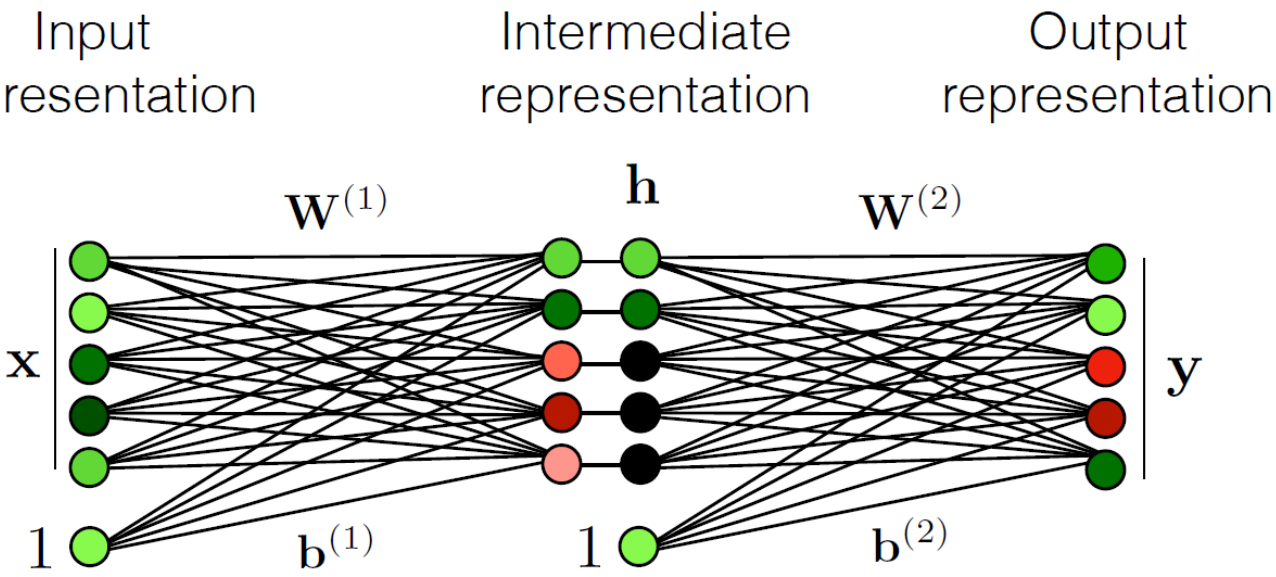
Stacking Layers



positive

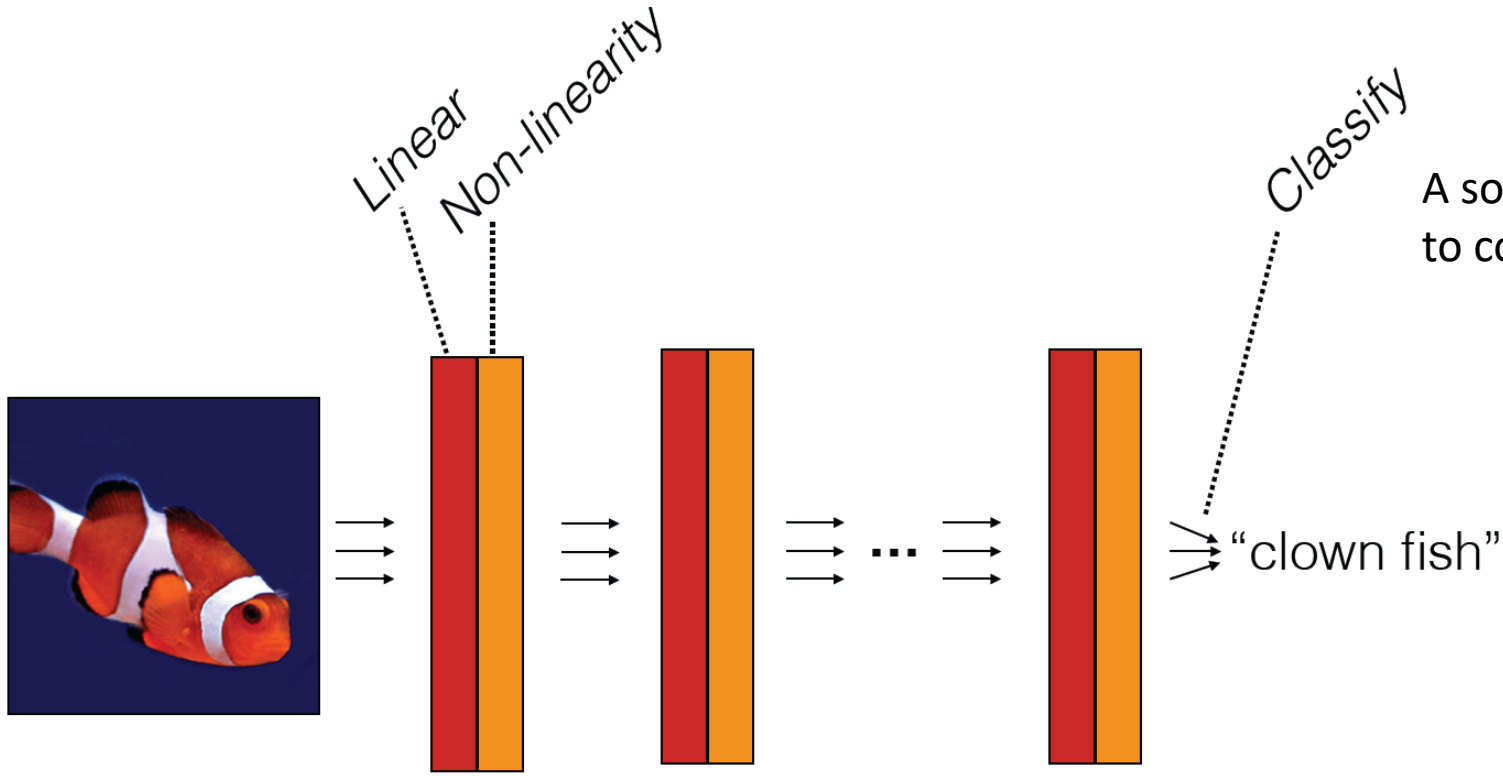
negative

$$\mathbf{h} = g(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}) \qquad \mathbf{y} = \mathbf{W}^{(2)}\mathbf{h} + \mathbf{b}^{(2)}$$

$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

These layers are called **Fully Connected (FC)** layers

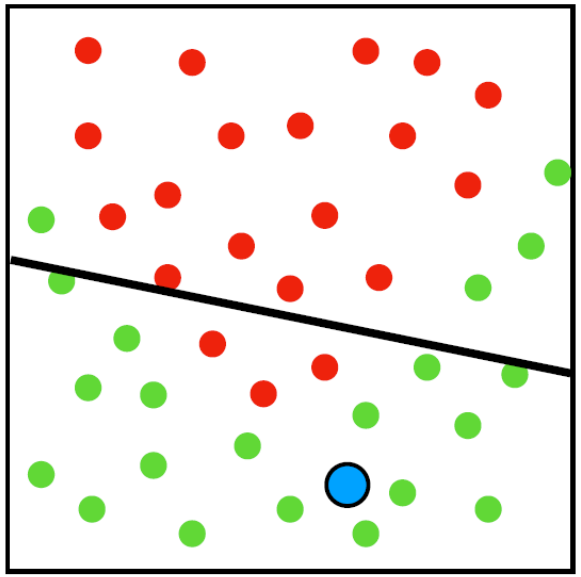
Deep Networks



$$f(\mathbf{x}) = f_L(\ldots f_2(f_1(\mathbf{x})))$$

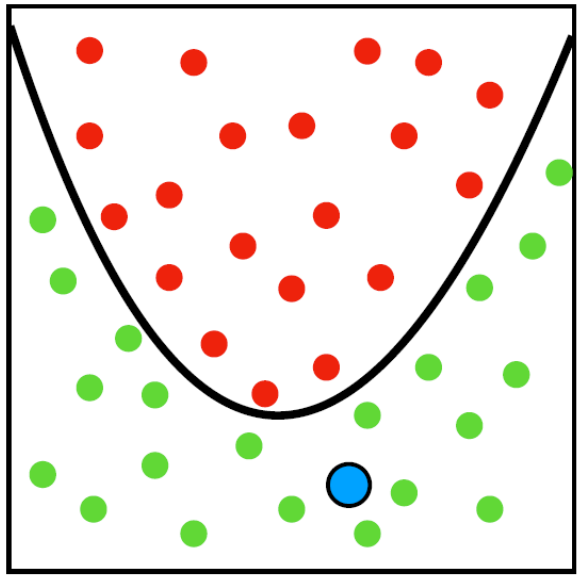
Model Order: Correct number of layers

What class is ● ?



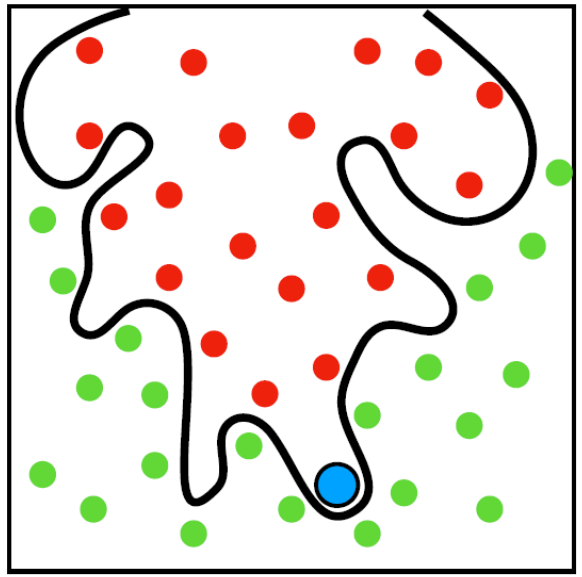
Answer: ●

Underfitting



Answer: ●

Appropriate model



Answer: ●

Overfitting

Classifier layer

Image Classification Using Neural Networks

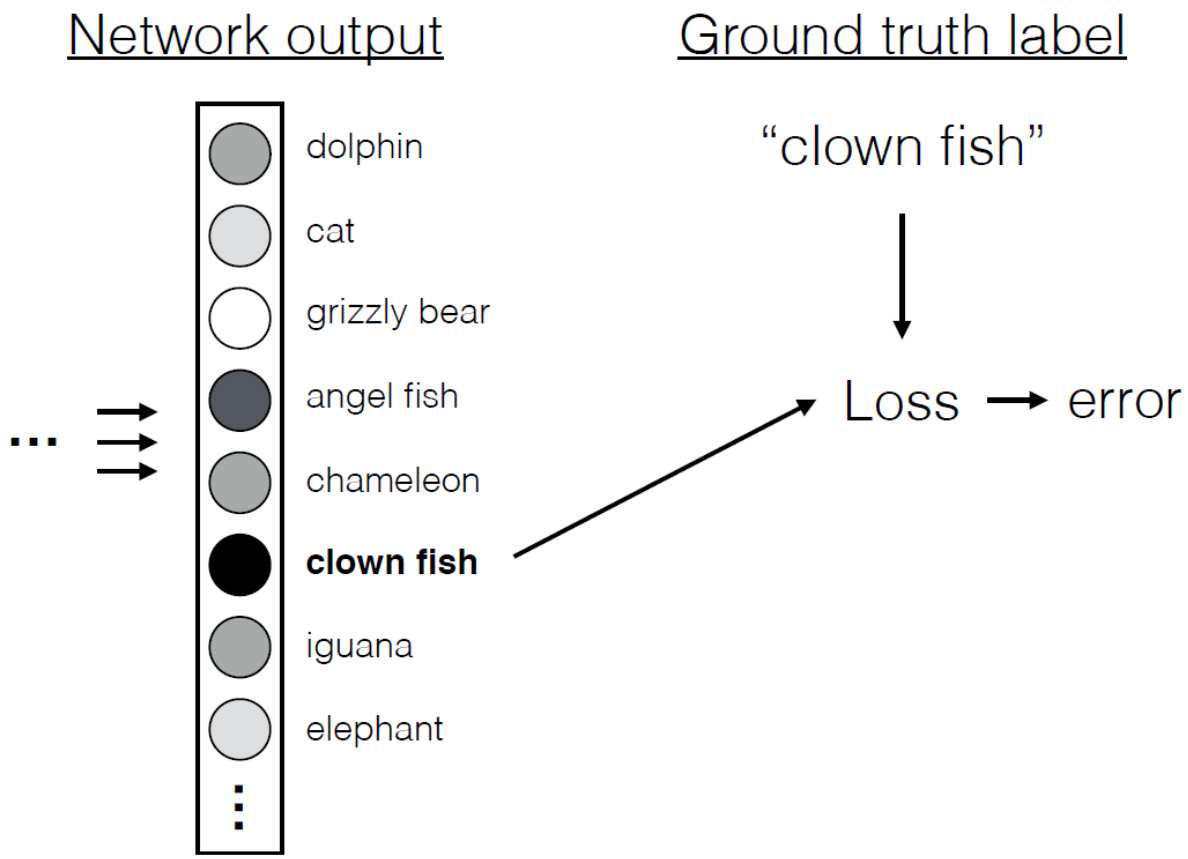


Image Classification Using Neural Networks

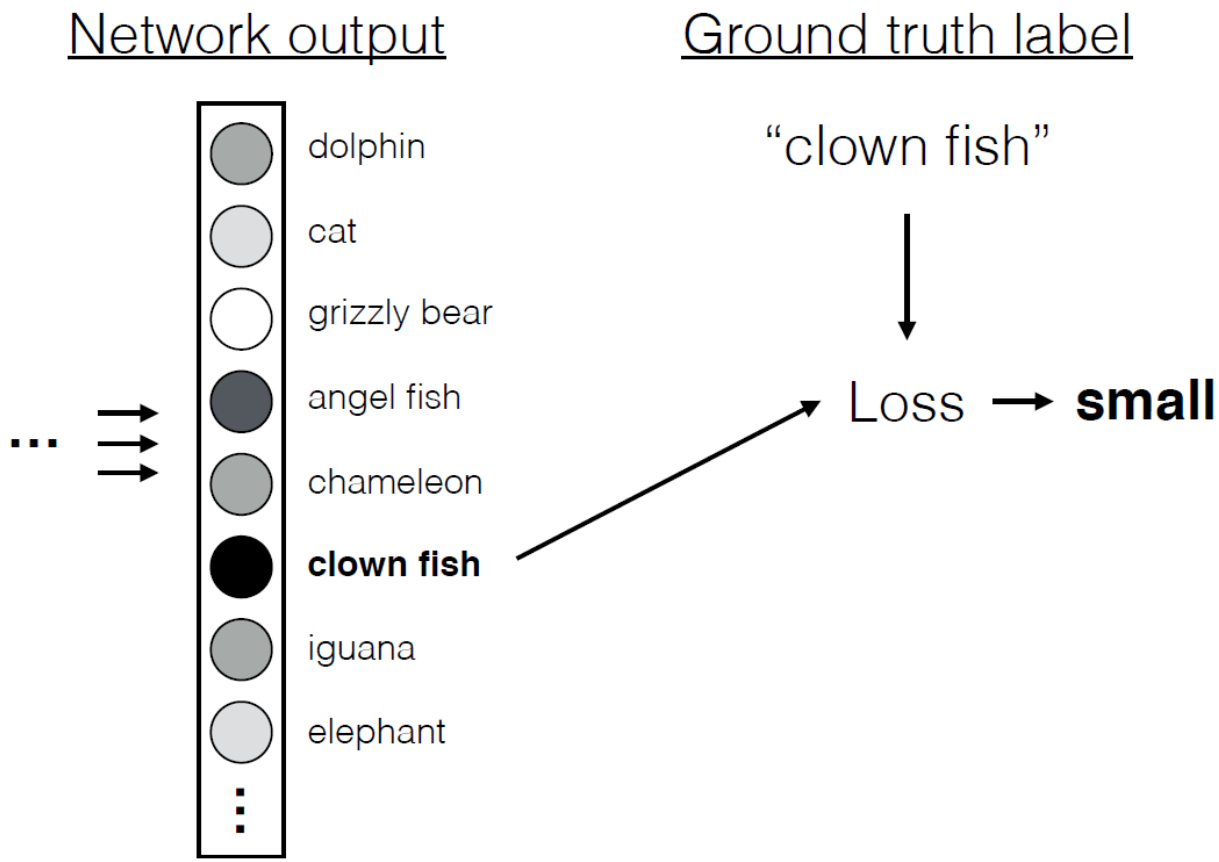
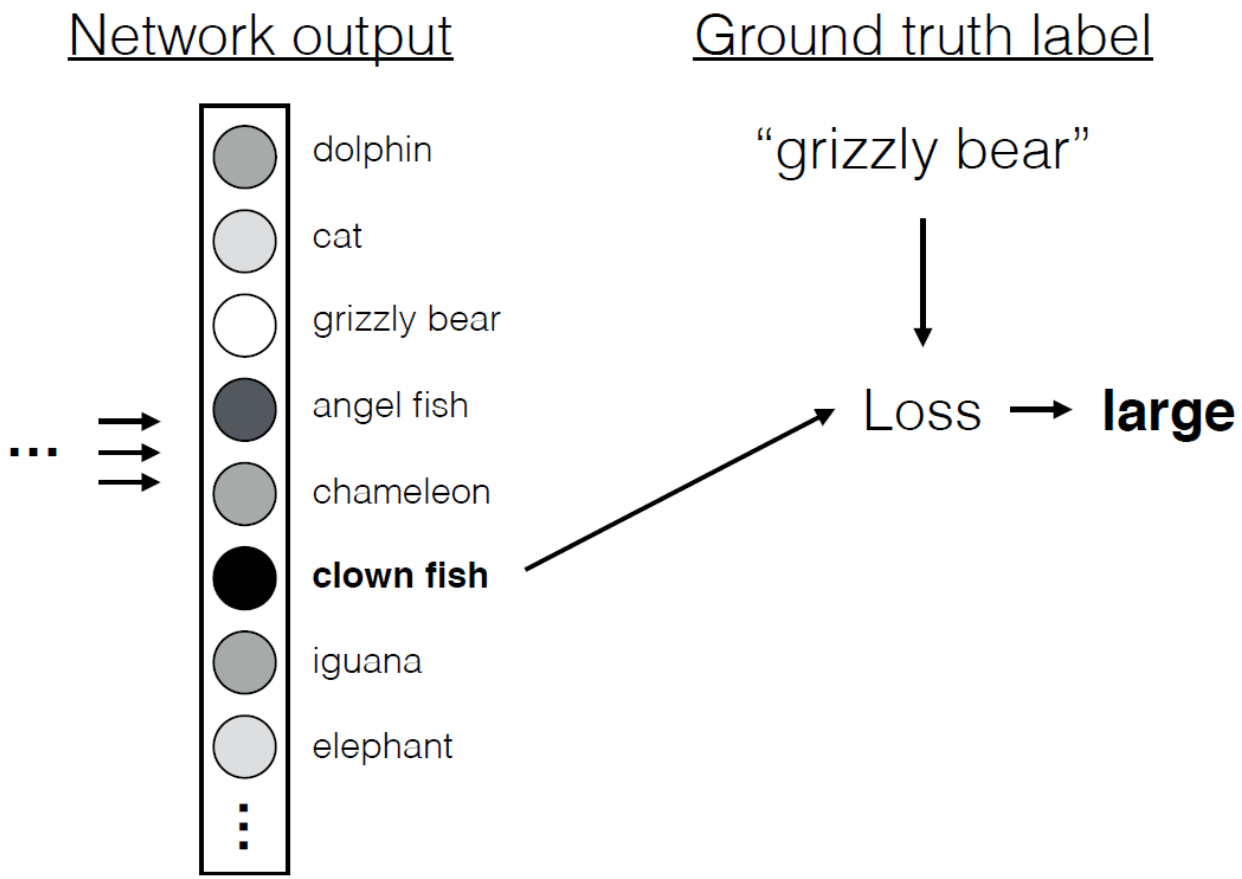


Image Classification Using Neural Networks



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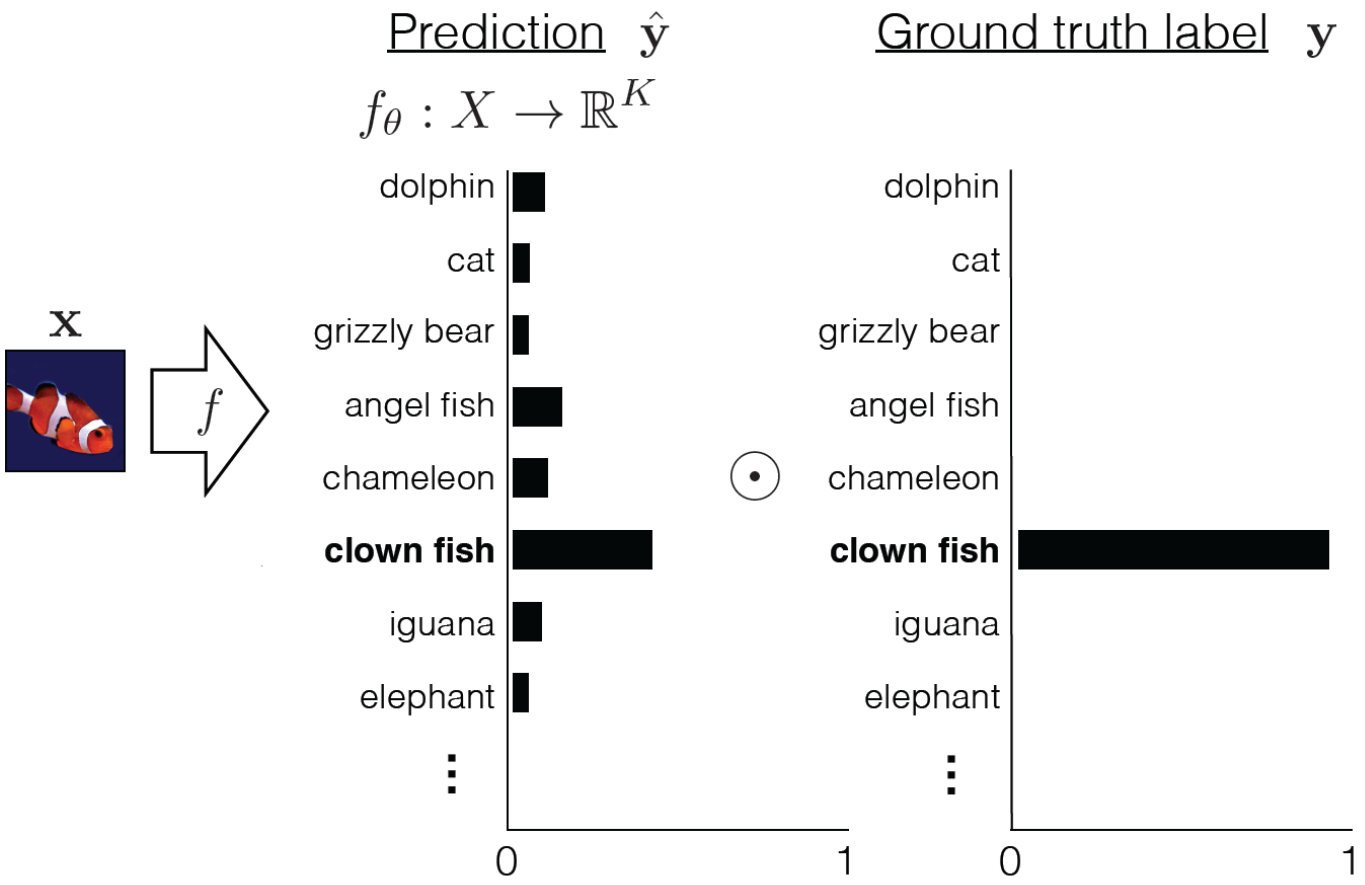

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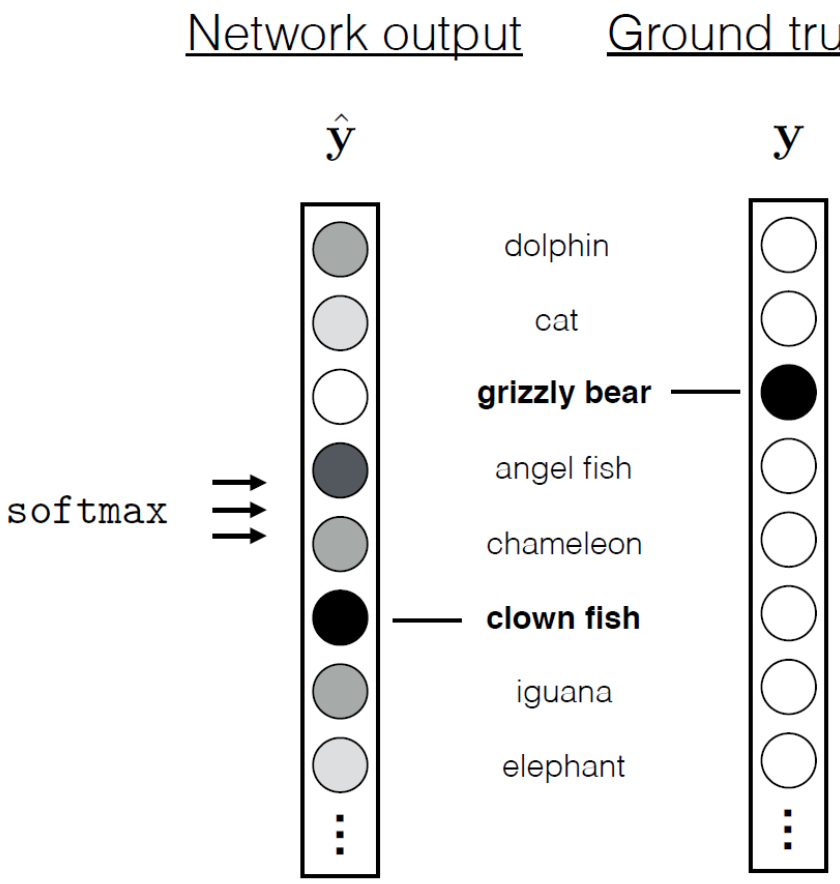
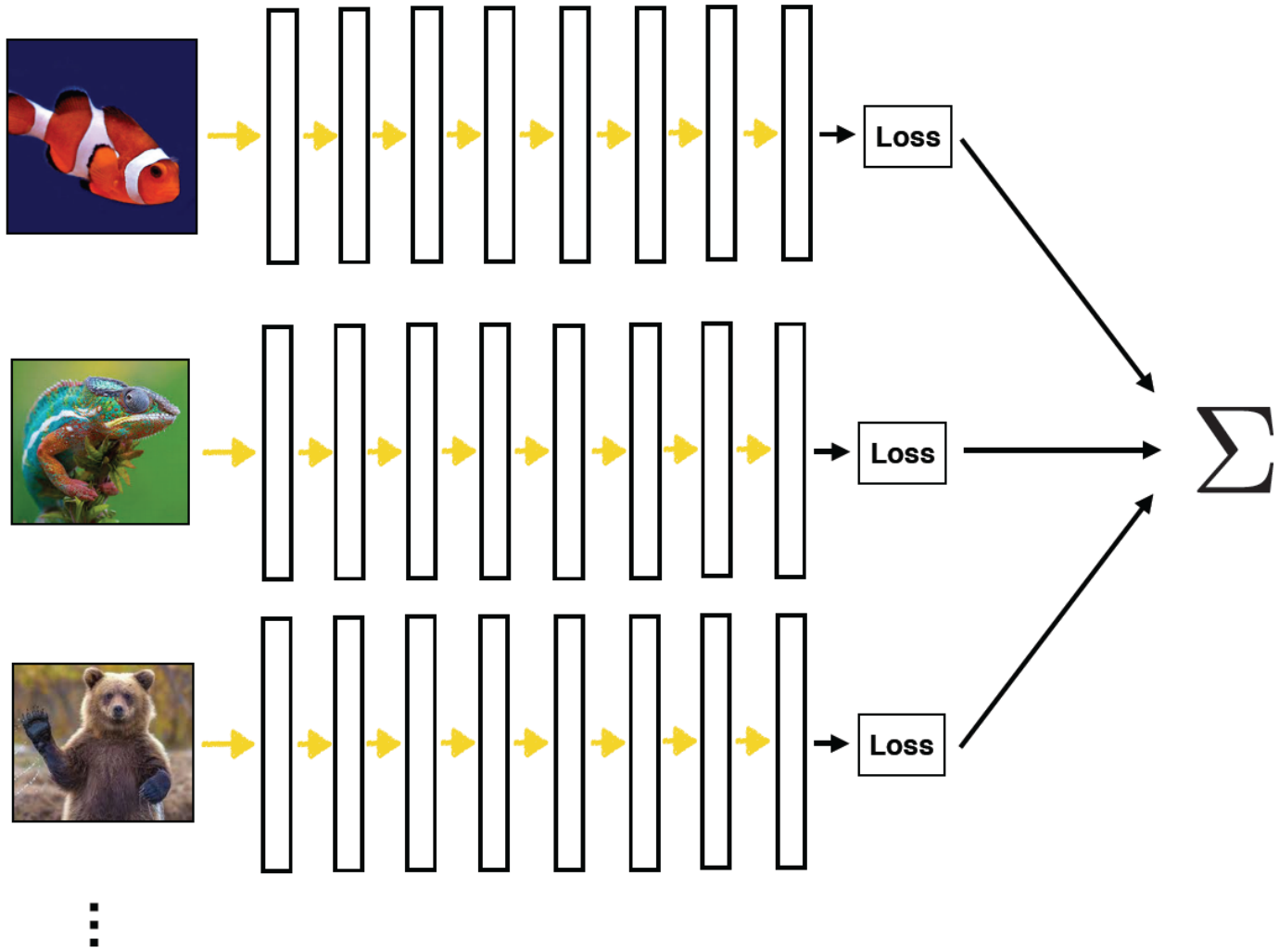


Probability of the observed data under the model

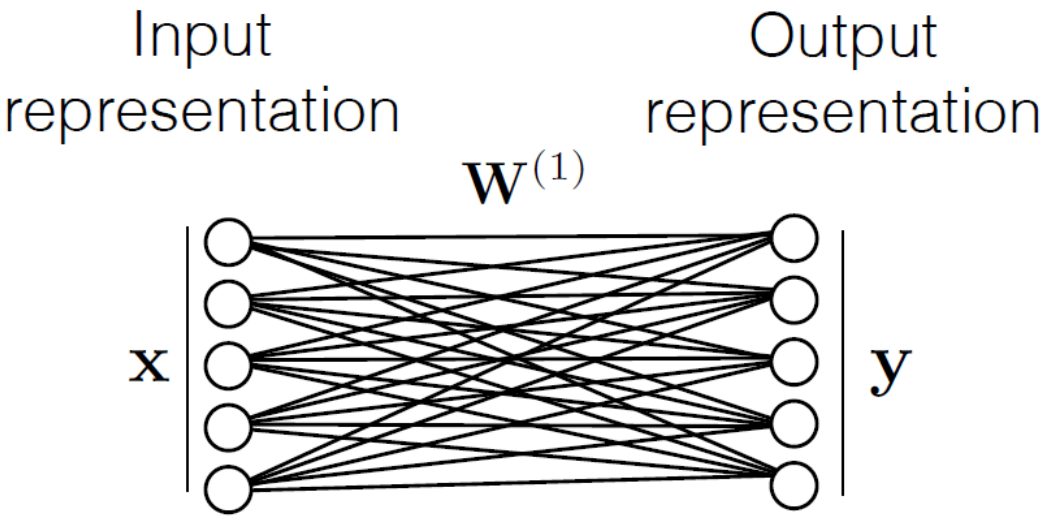
$$H(\mathbf{y}, \hat{\mathbf{y}}) = -\sum_{k=1}^{K} y_k \log \hat{y}_k$$

In this example, a very high loss is incurred due to misclassification

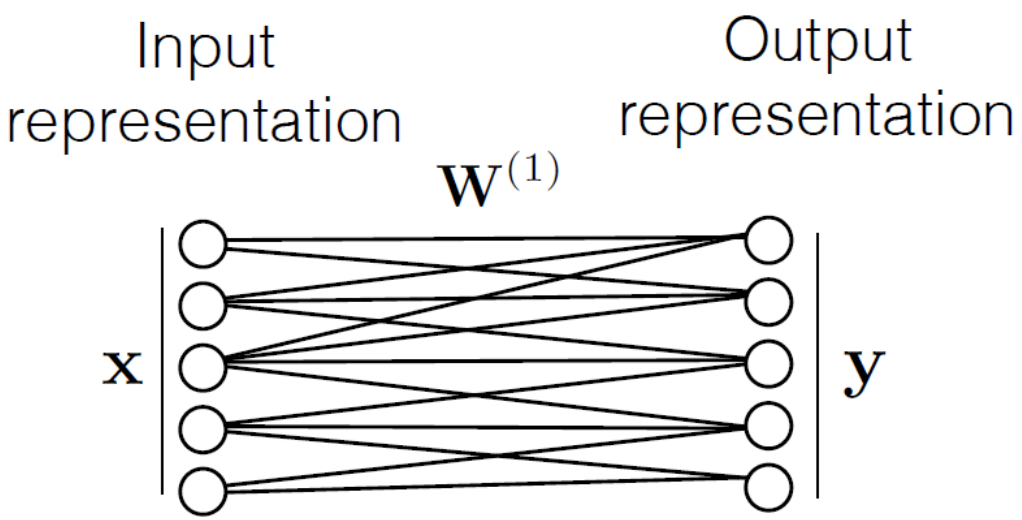
Parallel Processing



Connectivity patterns



Fully connected layer



Locally connected layer (Sparse W)

Convolutional Layer

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

x filter

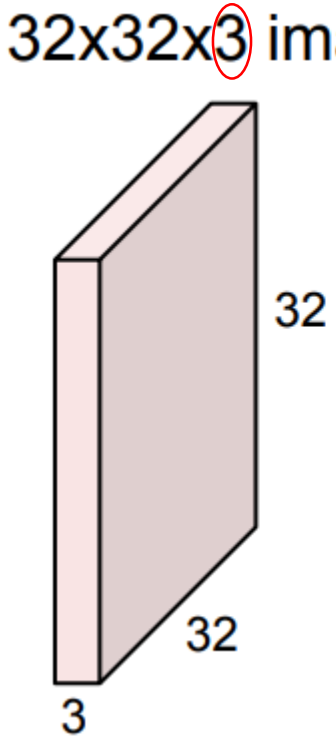
+1	+2	+1
0	0	0
-1	-2	-1

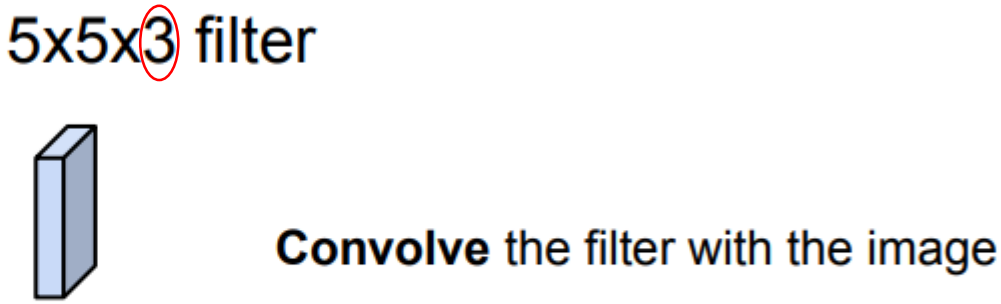
y filter

Sobel X and Y filters

Traditionally, filter weights were designed. Convolutional layers learn filter weights from training data

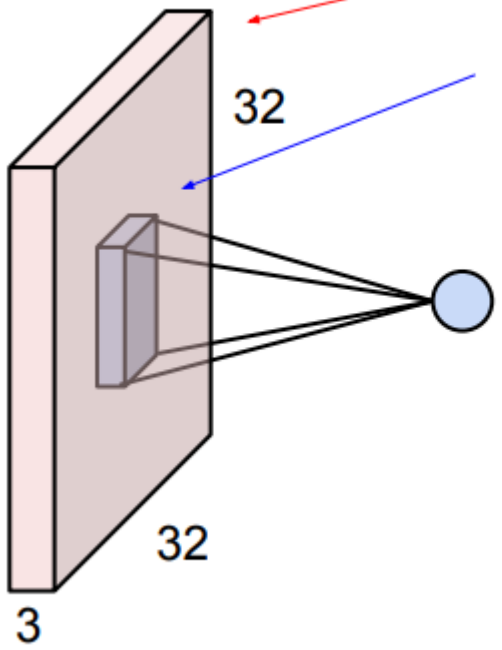
Convolutional Layer





What if the image was grayscale?

Convolutional Layer



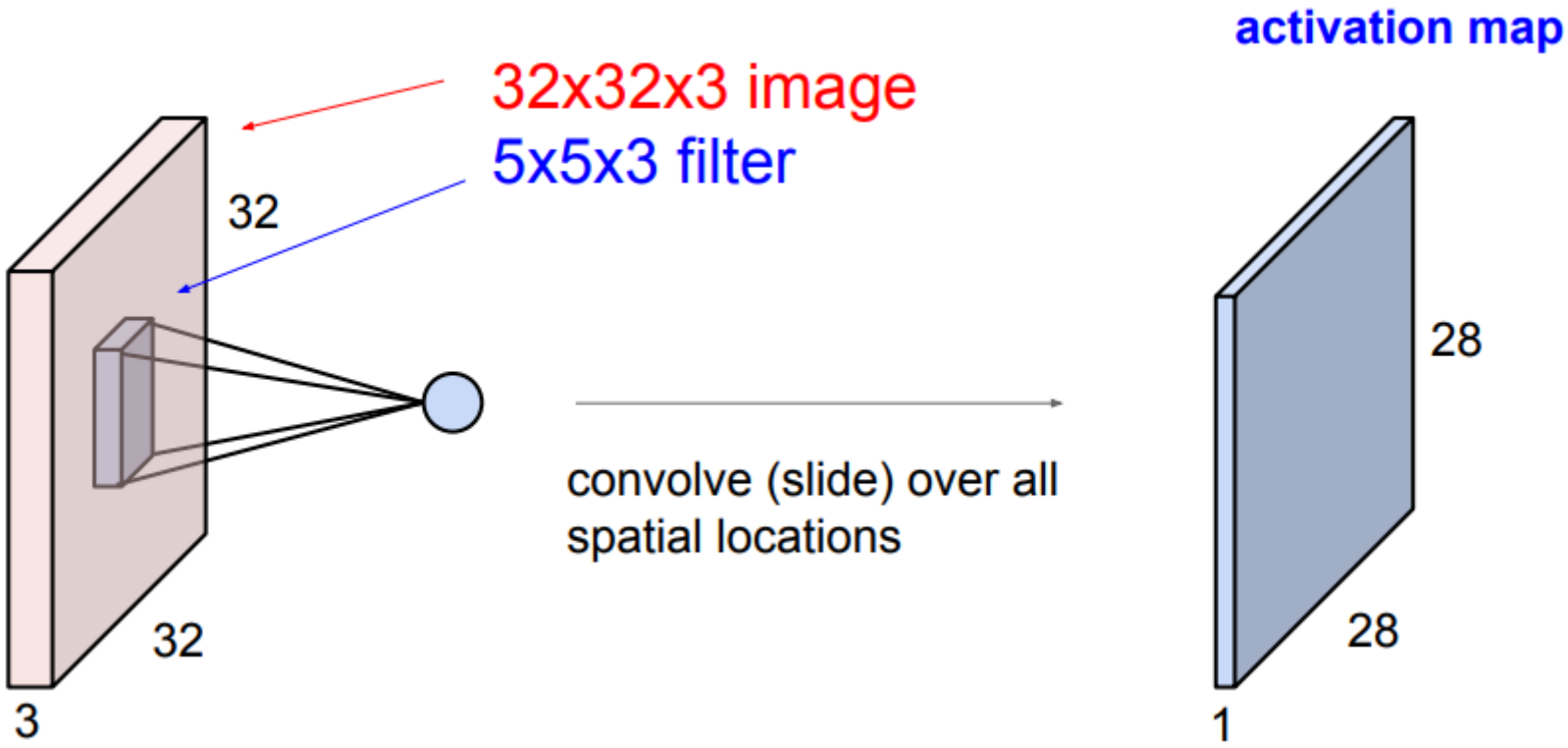
32x32x3 image

5x5x3 filter w

1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

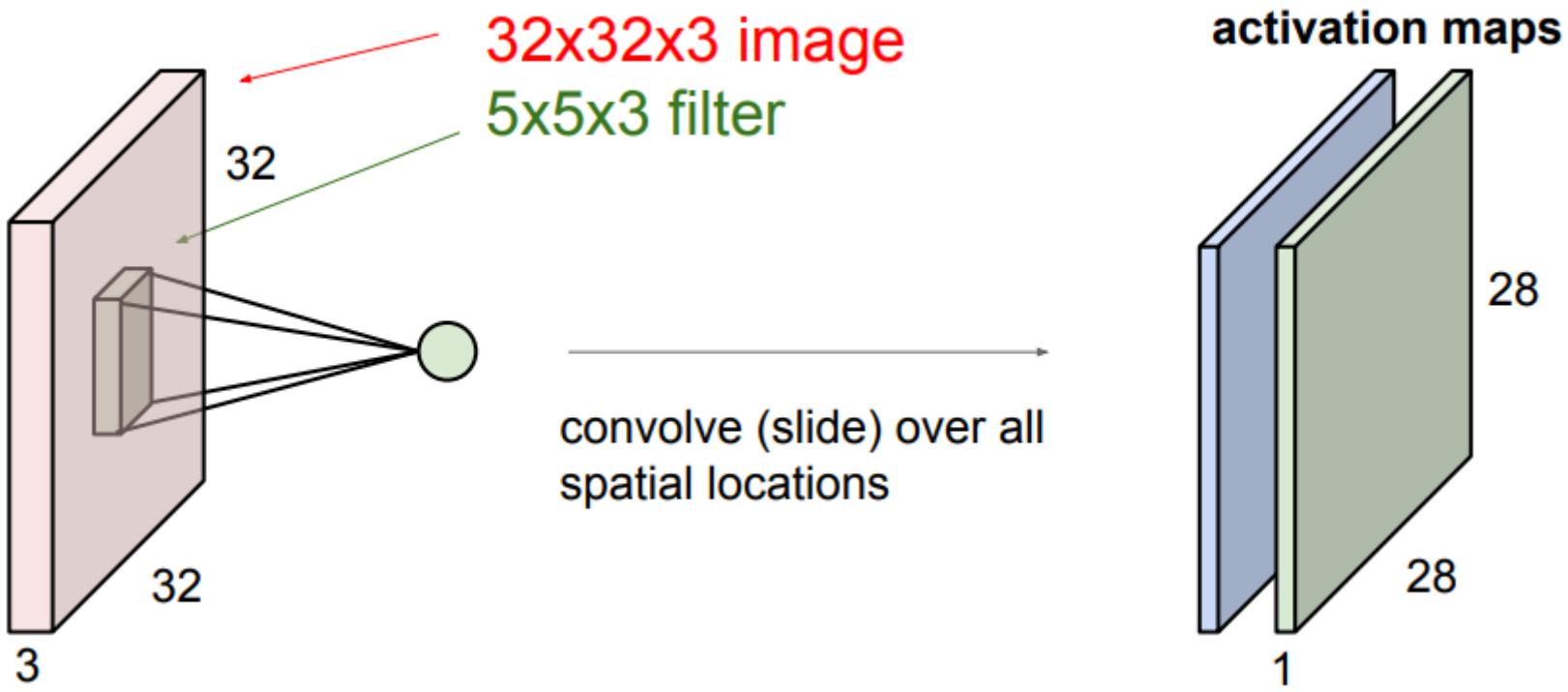
$$w^T x + b$$

Convolutional Layer



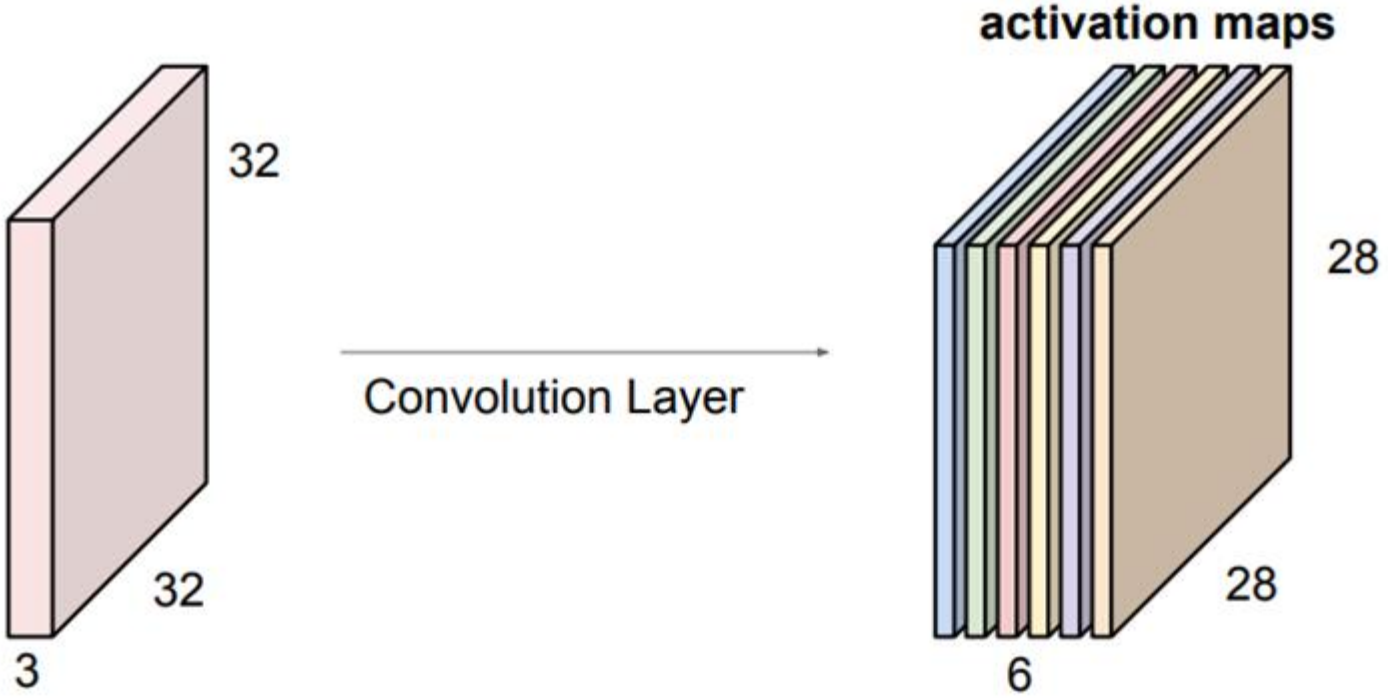
Zero-padding (optional) was not used
so output is smaller in size

Convolutional Layer



Convolutional Layer

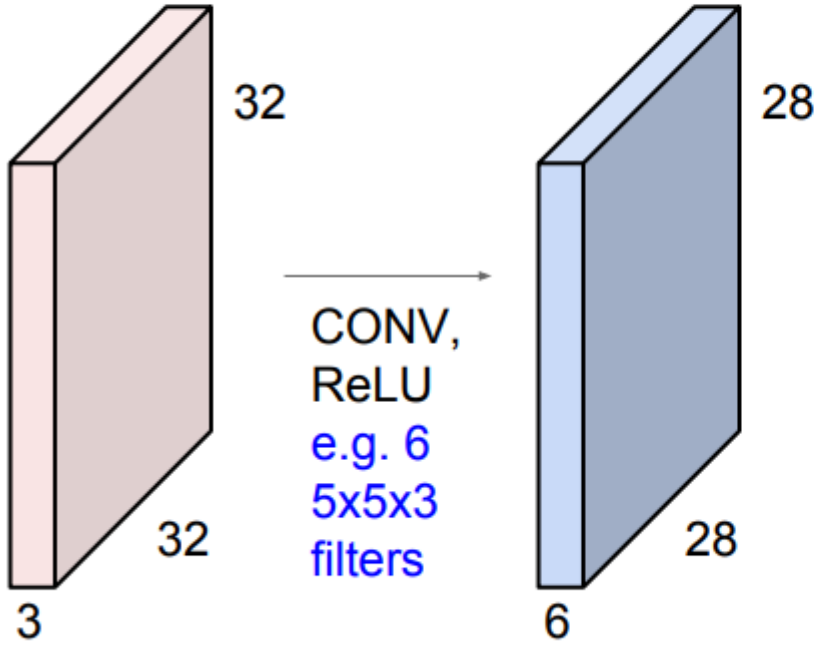
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6

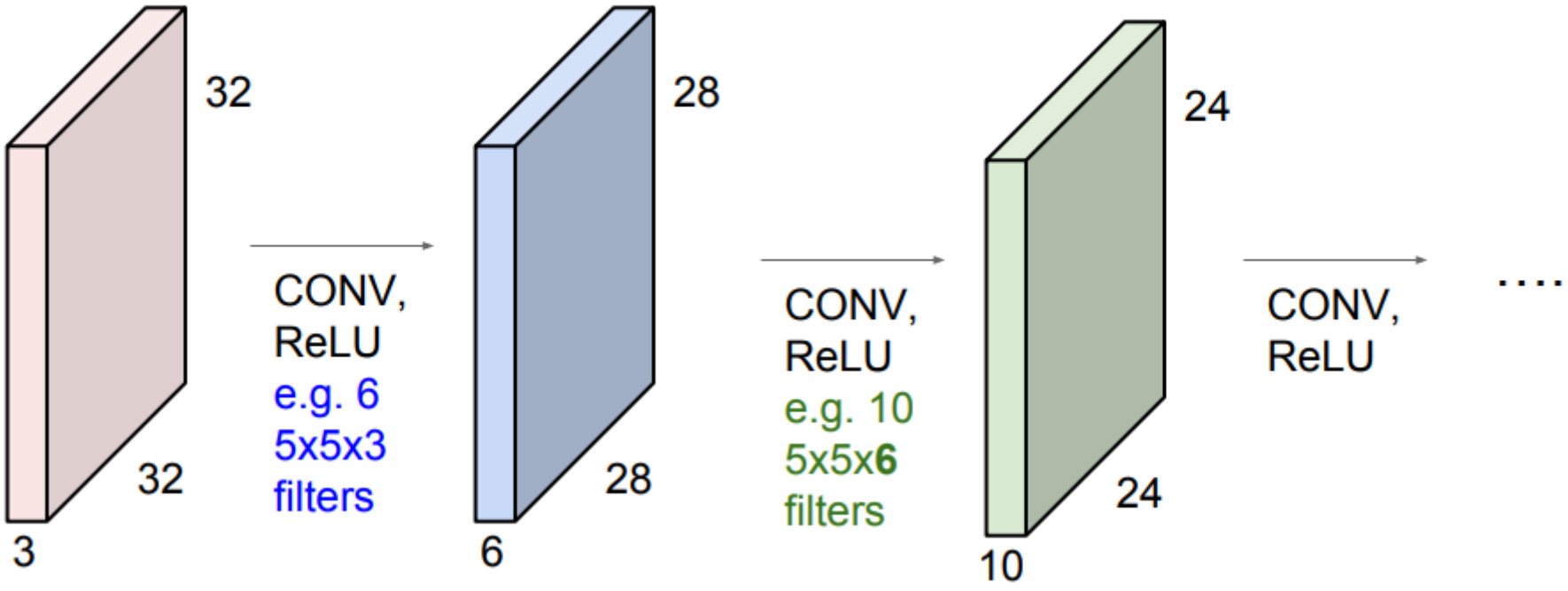
Convolutional Layer

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



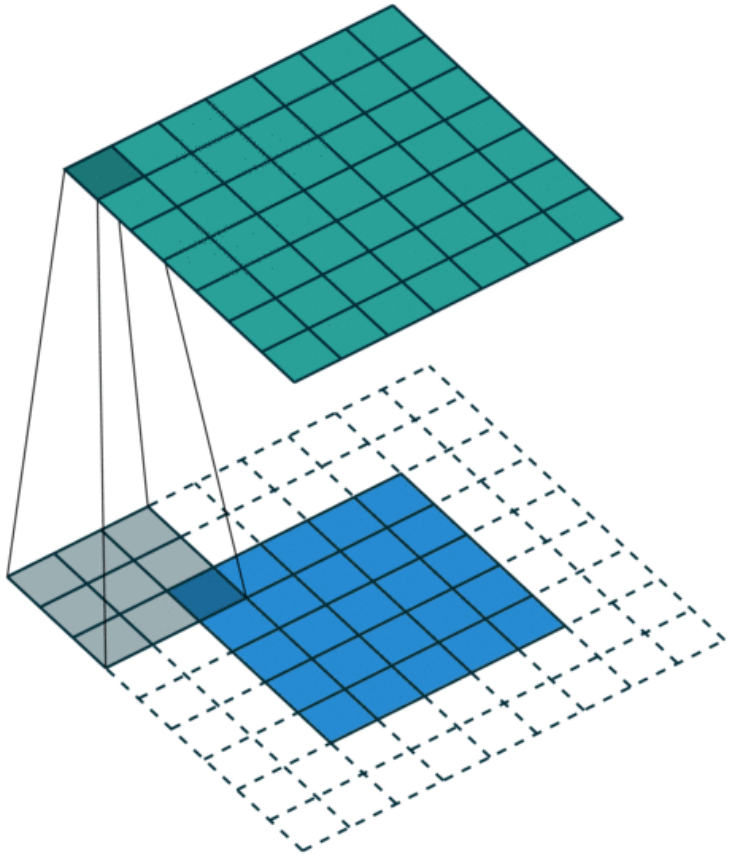
Convolutional Layer

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Other Types of Convolutions
Strided Convolutions

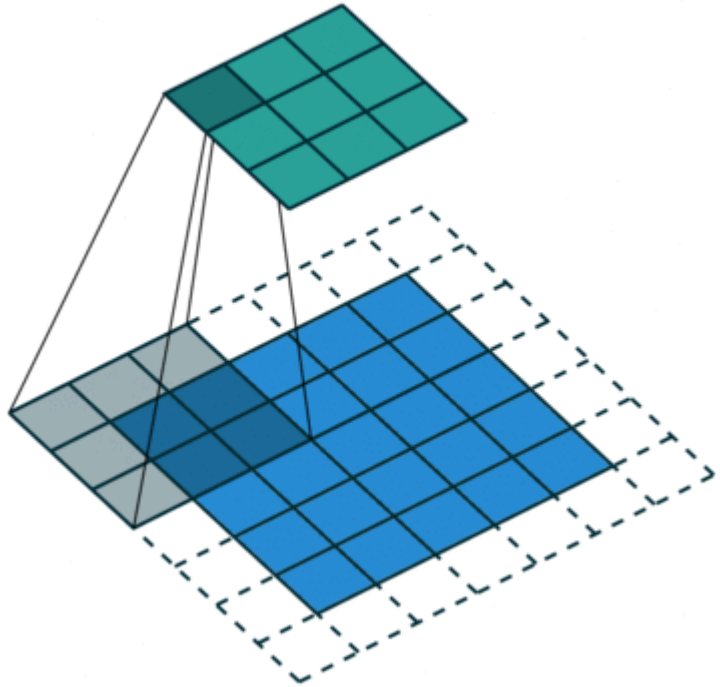
A 3x3 convolution with a stride =1 (default)



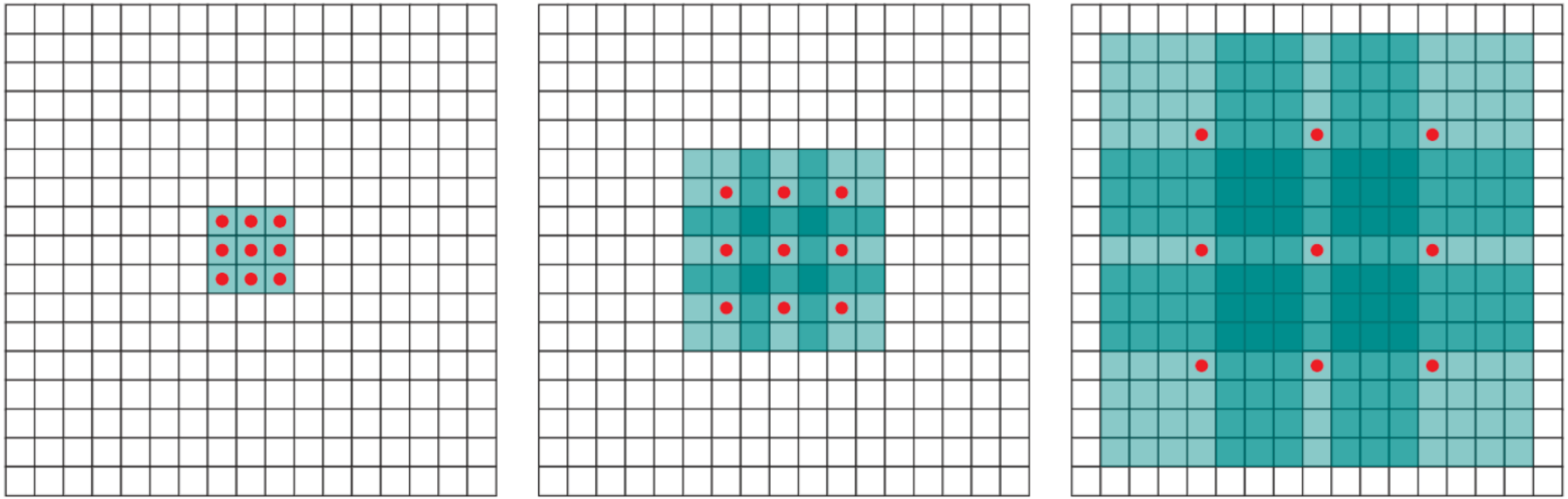
Other Types of Convolutions
Strided Convolutions

A 3x3 convolution with a stride =2

A way to summarize information, forces the network to focus on the big picture



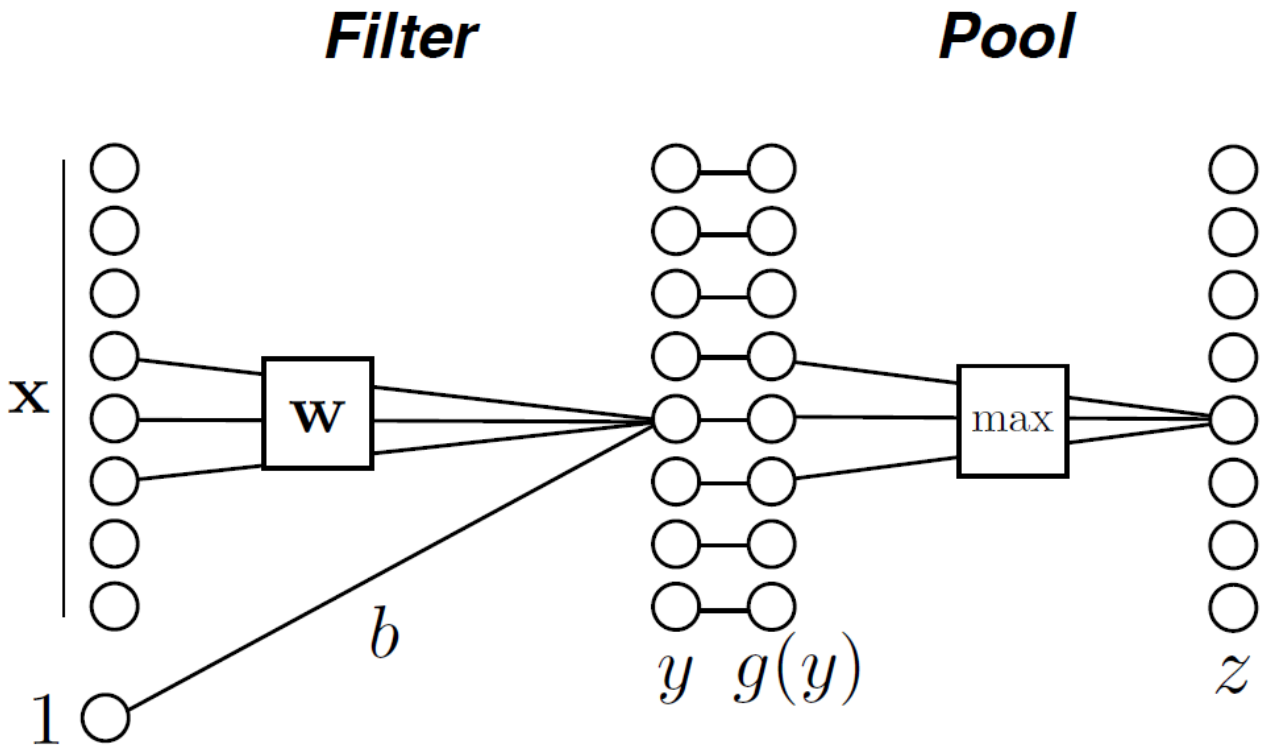
Other Types of Convolutions
Dilated Convolutions



(a) Default convolution (b) Convolution with dilation factor 2 (c) Convolution with dilation factor 4

This is equivalent to adding 0 in the filters for all places where the input value should be ignored (locations with on red dots)

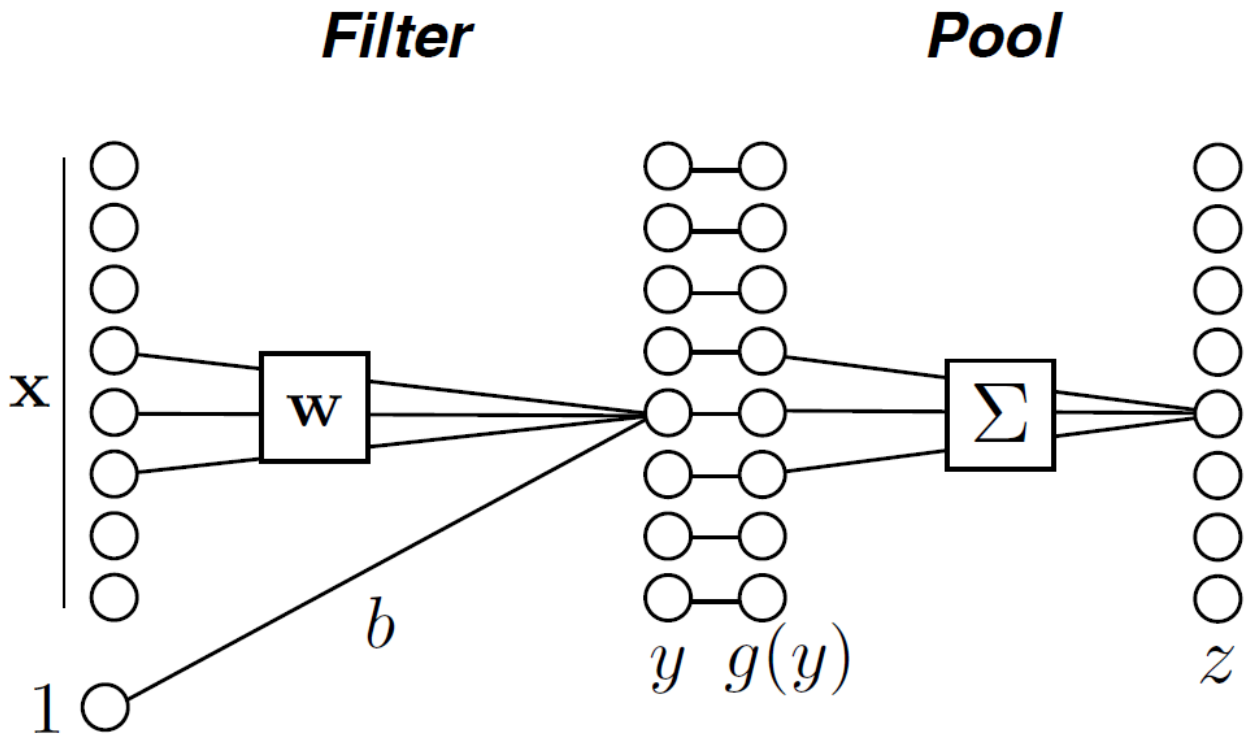
Max Pooling



Max pooling

$$z_k = \max_{j \in \mathcal{N}(j)} g(y_j)$$

Average Pooling



Max pooling

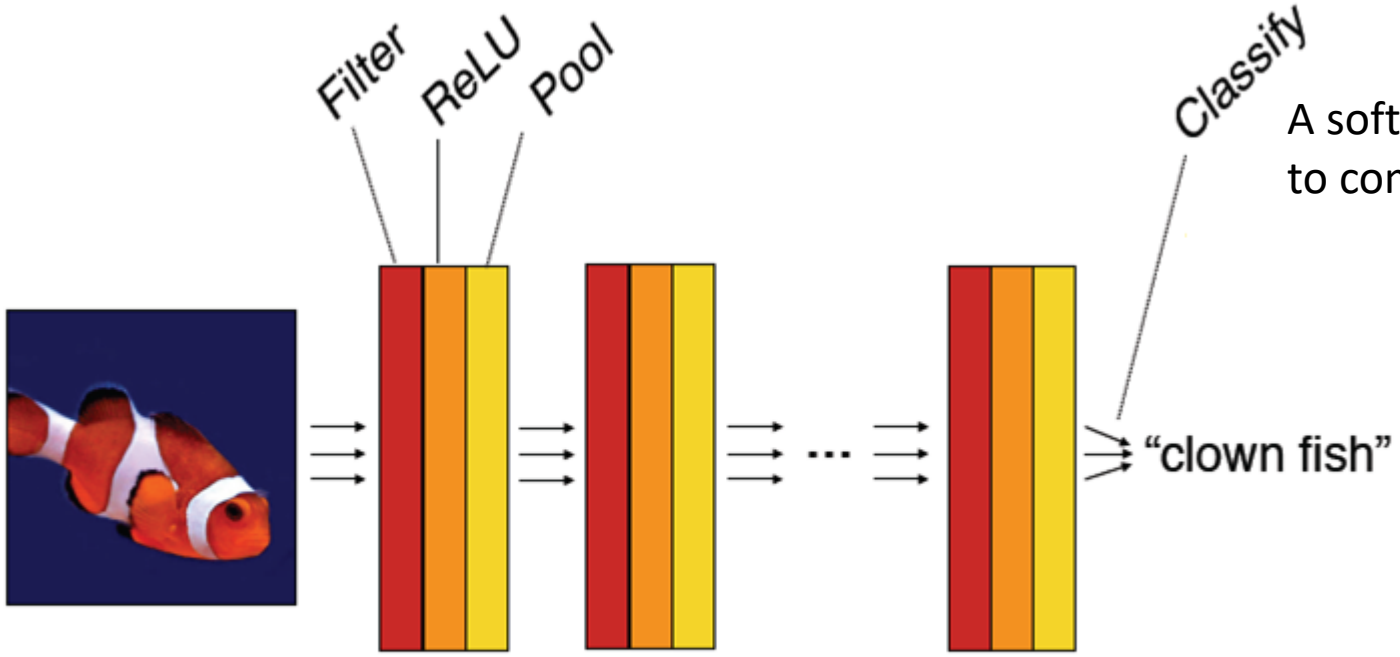
$$z_k = \max_{j \in \mathcal{N}(j)} g(y_j)$$

Mean pooling

$$z_k = \frac{1}{|\mathcal{N}|} \sum_{j \in \mathcal{N}(j)} g(y_j)$$

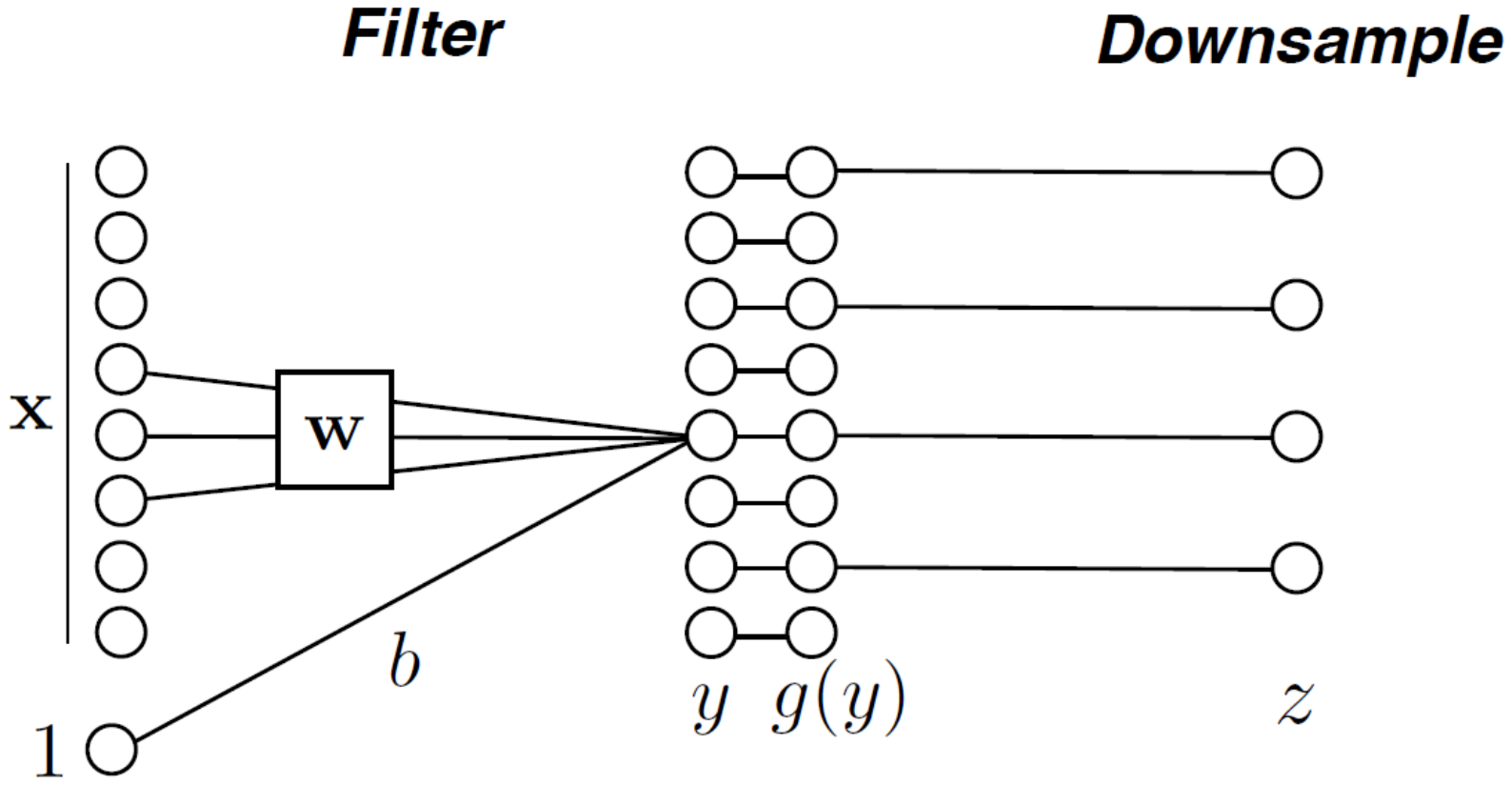
Pooling achieves stability to deformations

Implementation in NN



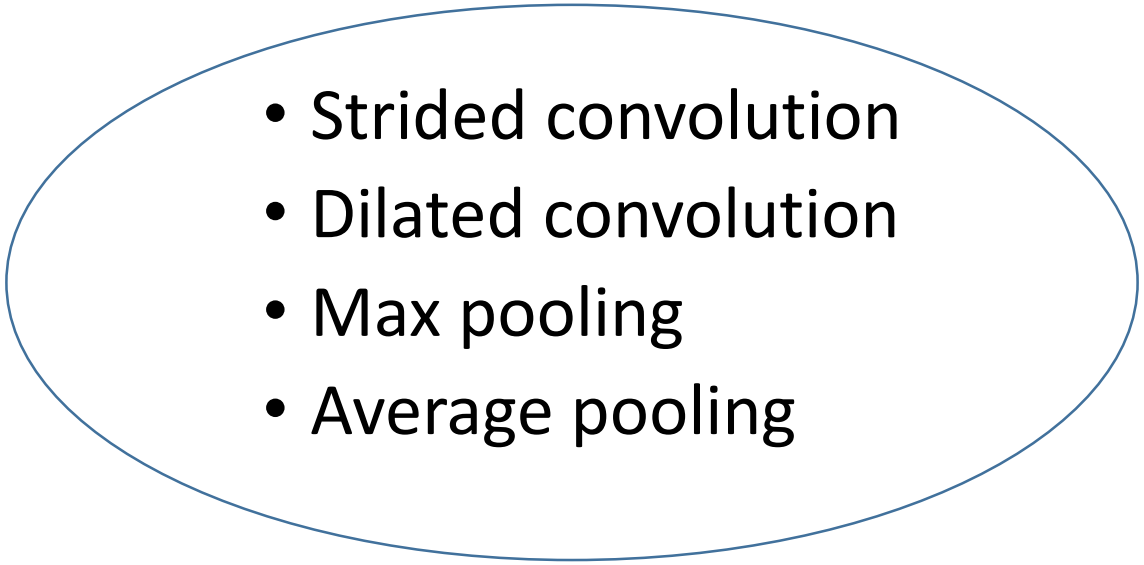
$$f(\mathbf{x}) = f_L(\ldots f_2(f_1(\mathbf{x})))$$

Downsampling



Using a stride parameter larger than 1 has the effect of downsampling

Summarizing Data



Summarizes data in a neural network

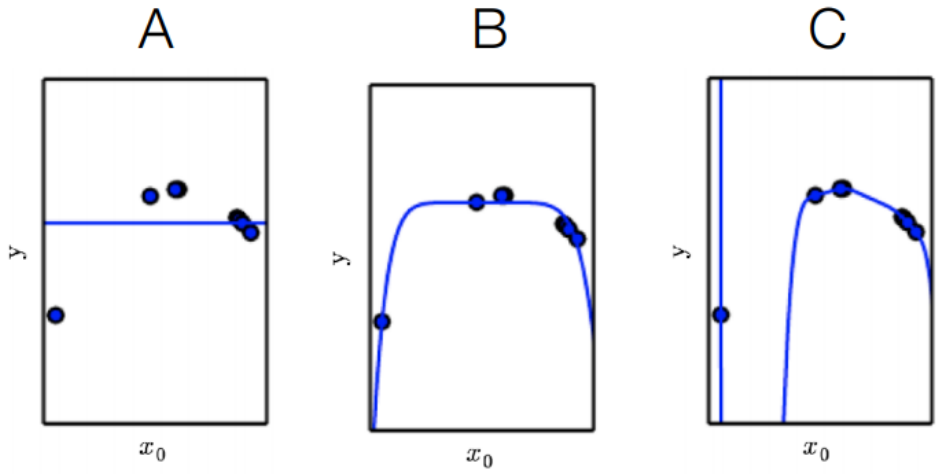
Regularizing Deep Nets

- Deep nets use millions of parameters organized in a hierarchical manner.
- On many datasets, it is easy to overfit — we may have more free parameters than data points to constrain them.
- One solution is to increase the size of training data, this is often expensive and time consuming
- Another solution is the use of regularizes
- How can we regularize to prevent the network from overfitting?
    1. Fewer neurons, fewer layers
    2. Weight decay
    3. Dropout
    4. Normalization layers

Recall: regularized least squares

$$f_\theta(x) = \sum_{k=0}^{K} \theta_k x^k$$

$$\theta^* = \arg\min_\theta \sum_{I=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i) + \lambda \|\theta\|_2^2$$



Low λ — C

Medium λ — B

High λ — A

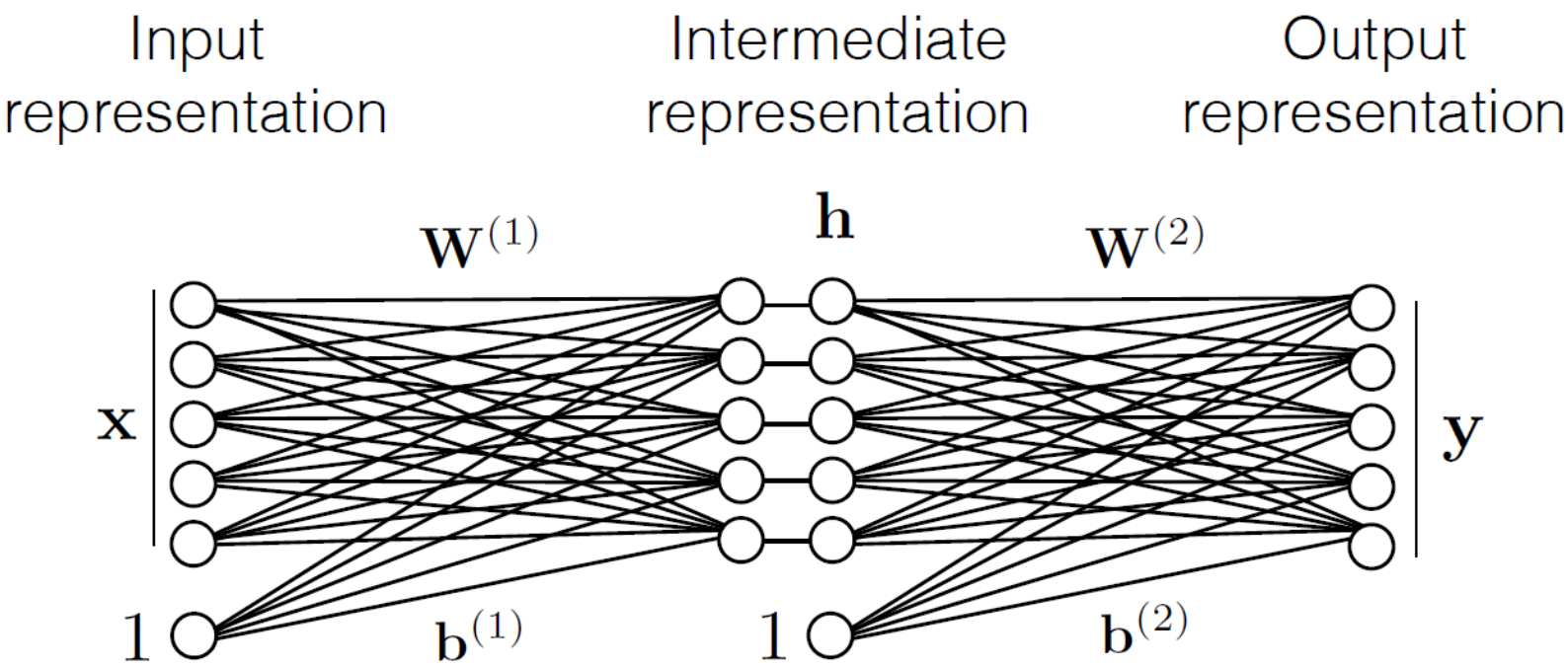
[Adapted from "Deep Learning", Goodfellow et al.]

Regularizing weights in NN

$$\theta^* = \arg\min_{\theta} \sum_{i=1}^{N} \mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i) + R(\theta)$$

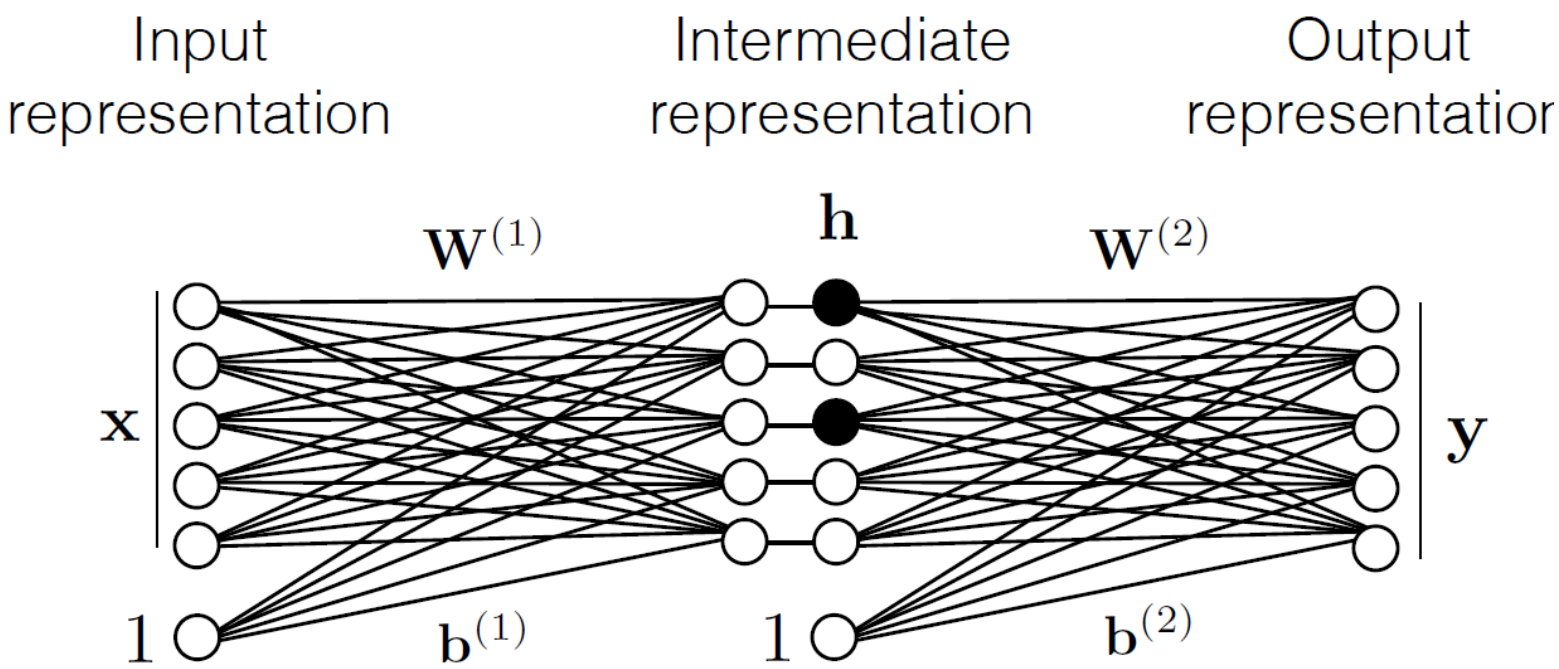
$$R(\mathbf{W}) = \lambda \|\mathbf{W}\|_2^2$$ ⟵ **weight decay**

Dropout



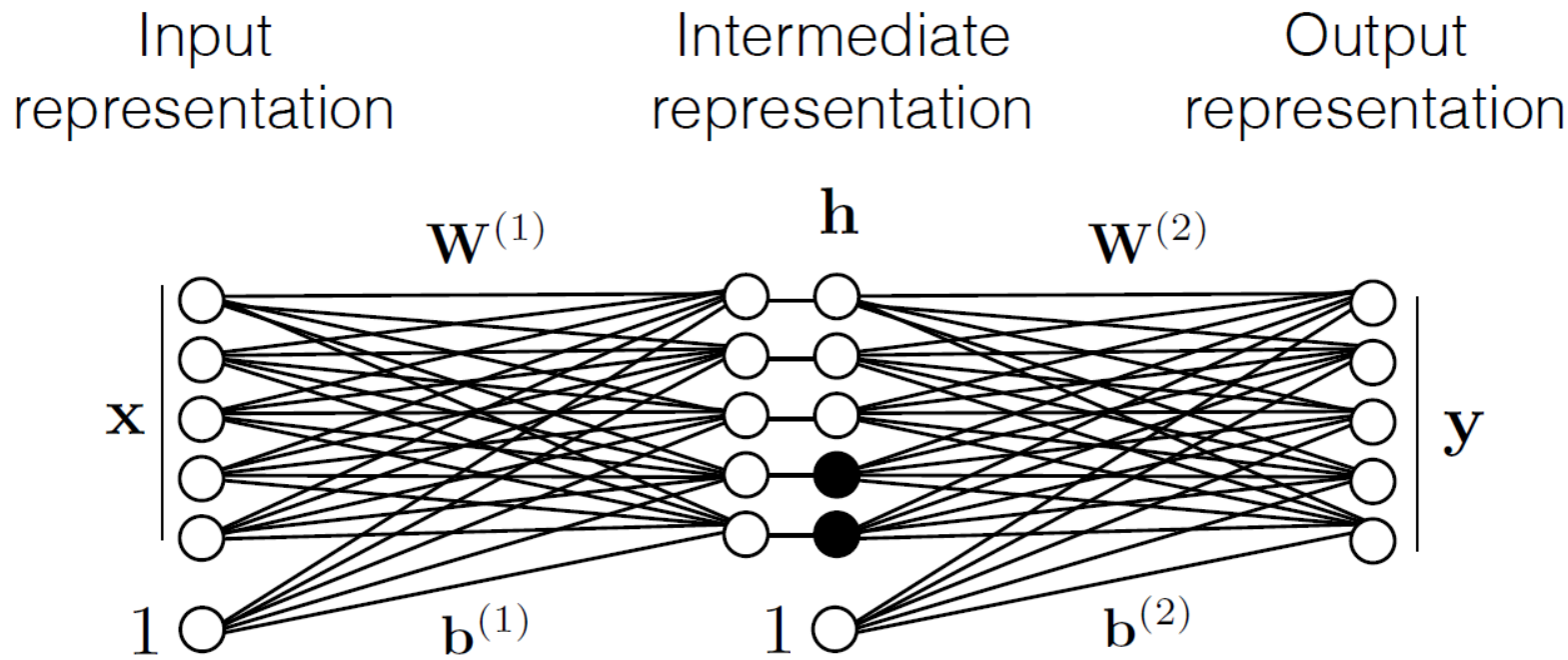
$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Dropout



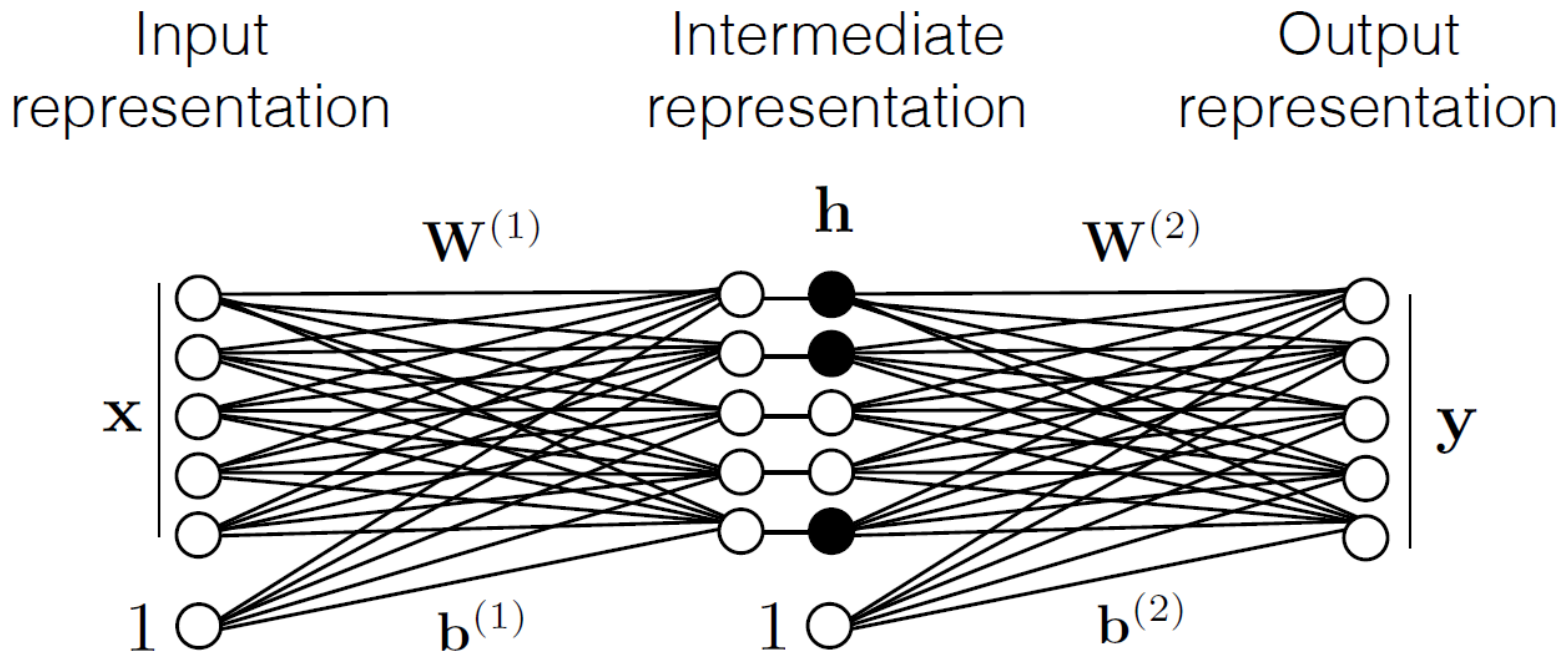
$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Dropout



$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

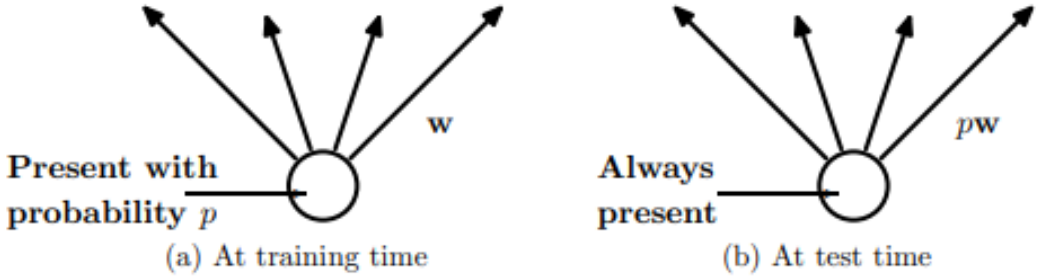
Dropout



$$\theta = \{\mathbf{W}^{(1)}, \ldots, \mathbf{W}^{(L)}, \mathbf{b}^{(1)}, \ldots, \mathbf{b}^{(L)}\}$$

Dropout

- The idea is to randomly drop hidden units (along with their connections) from the neural network during training



(a) At training time (b) At test time

- This allows units not to rely too much on other units.
- Neurons learn to perform well in a wide variety of different contexts provided by the other hidden units

Normalization

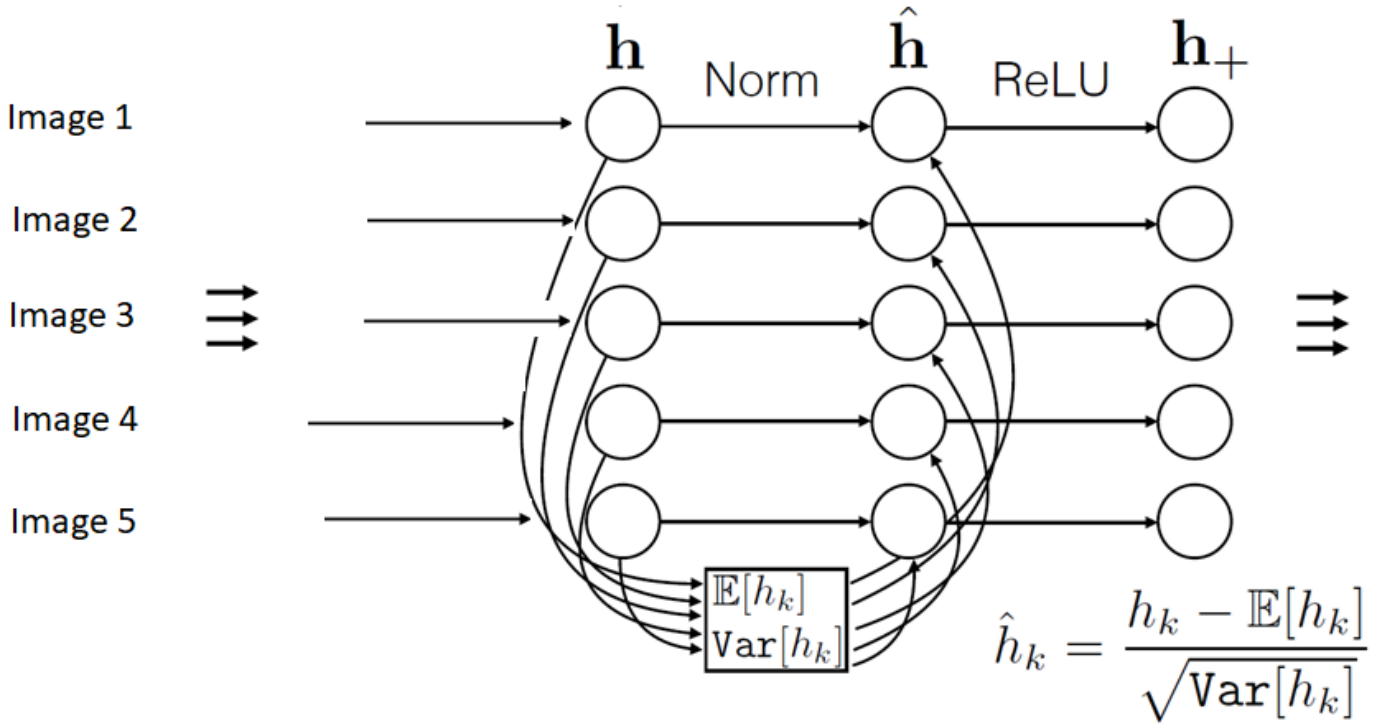
- Normalization is a regularization technique that can help improve the performance of NNs.
- Subtract the mean and divide by standard deviation

$$z = \frac{x - \mu}{\sigma}$$

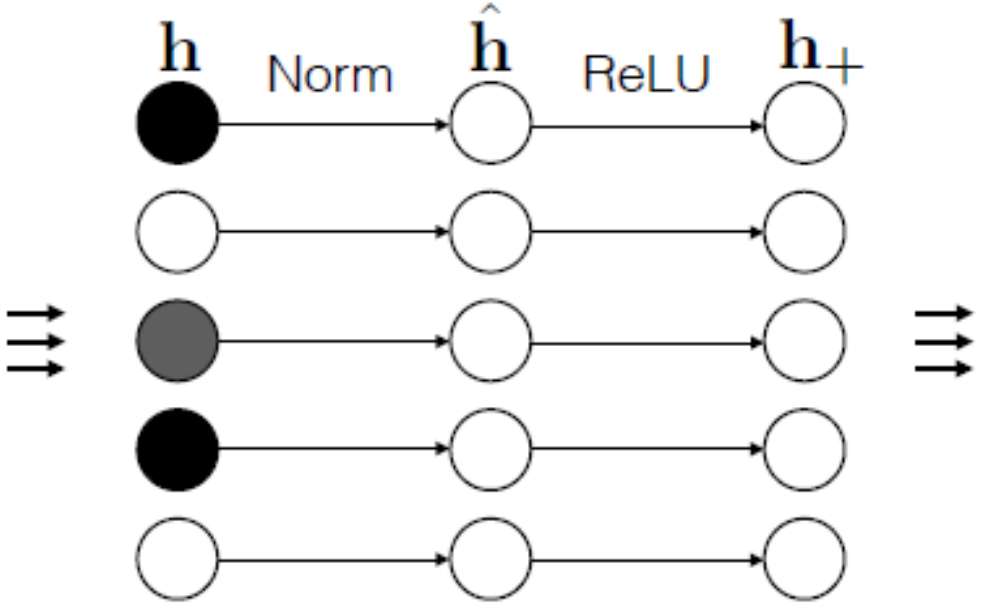
- The new mean is 0 and standard deviation of 1.
- Necessary for comparing numbers from different scales (e.g. TOEFL vs IELTS).
- Input data is often normalized before feeding them to a neural network. In addition normalization layers normalizes the weights and biases in the network.

Normalization layers

Assume that training is performed in batches, where each “minibatch” is composed of 5 data samples.

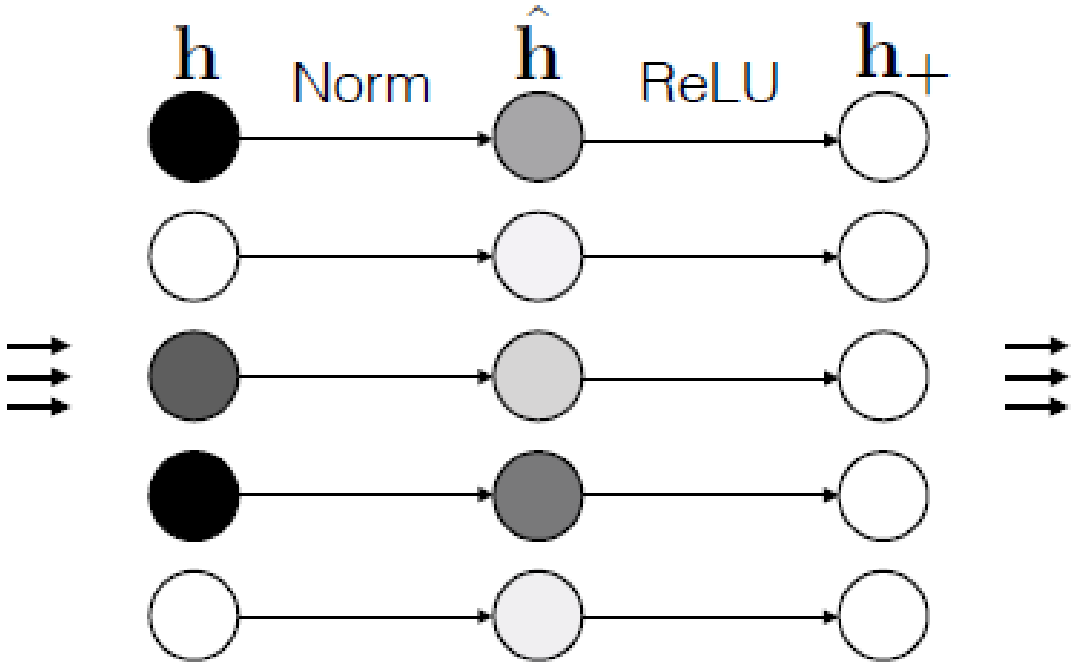


Normalization layers (Batch Normalization)



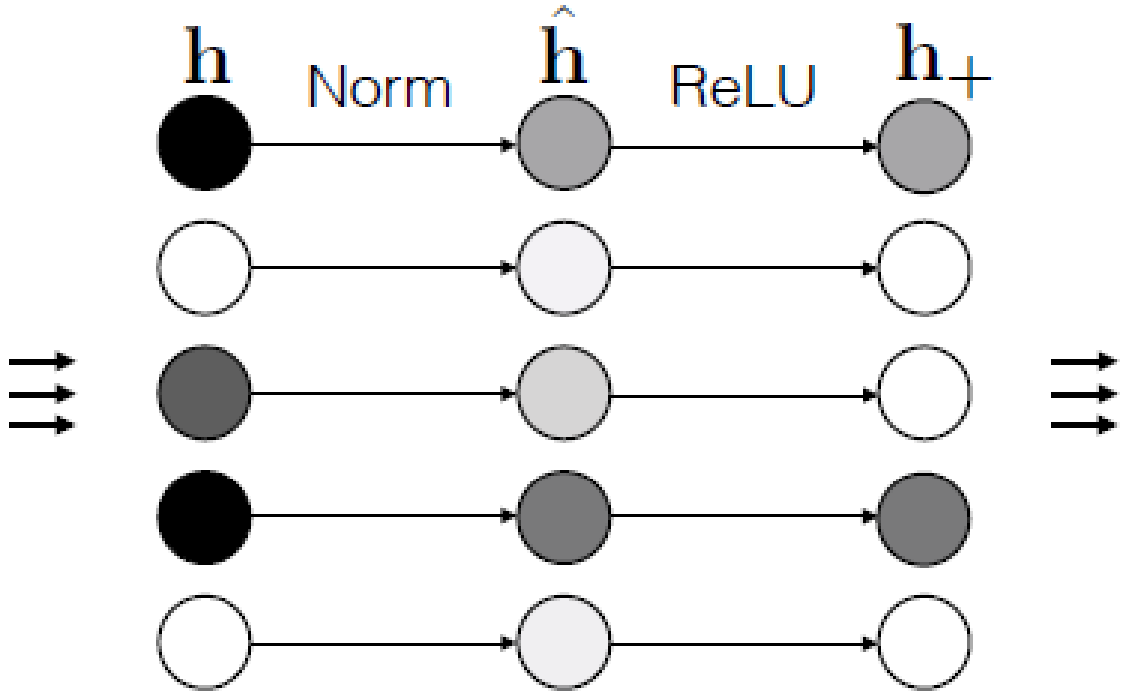
$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Normalization layers



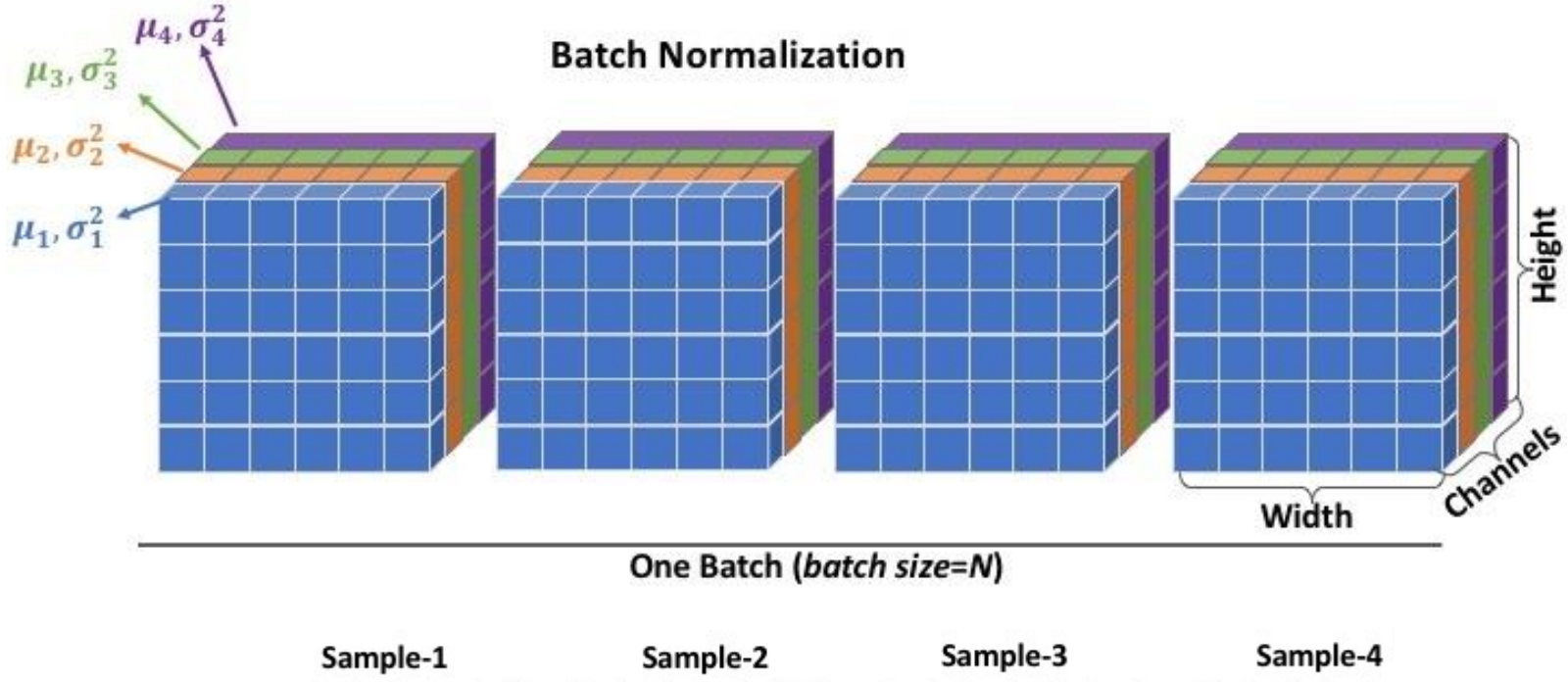
$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Normalization layers



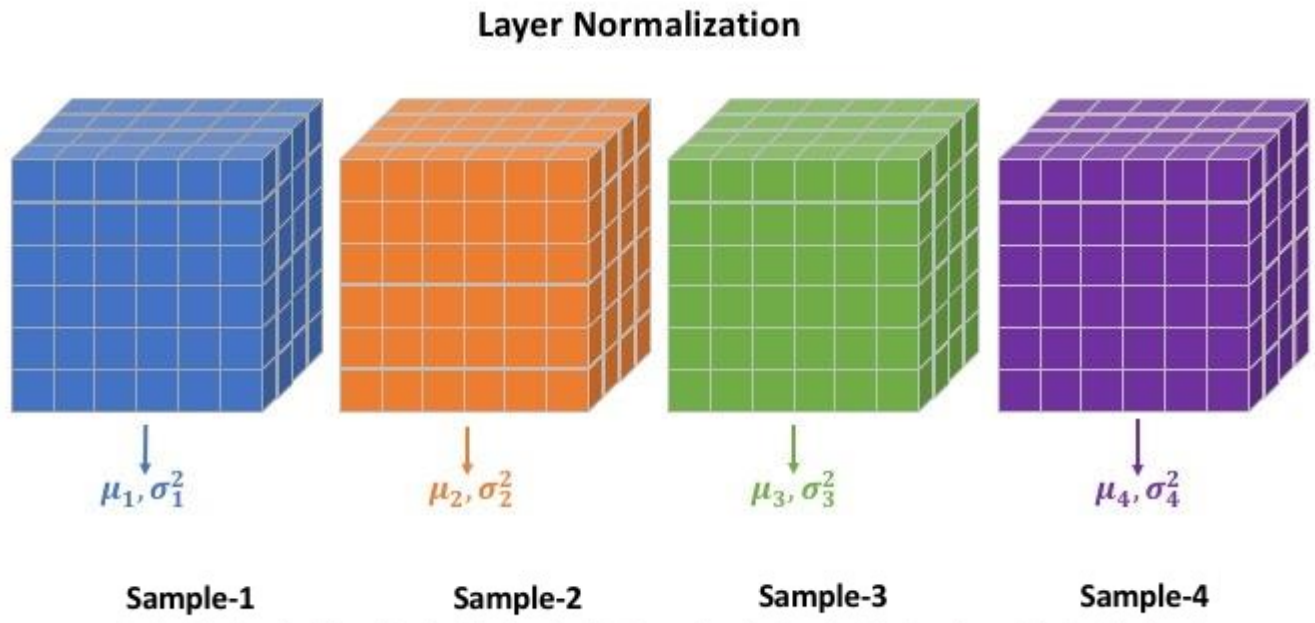
$$\hat{h}_k = \frac{h_k - \mathbb{E}[h_k]}{\sqrt{\mathtt{Var}[h_k]}}$$

Main types of normalization:
1. Batch Normalization



Normalization is applied for each uniformly colored region in the figure

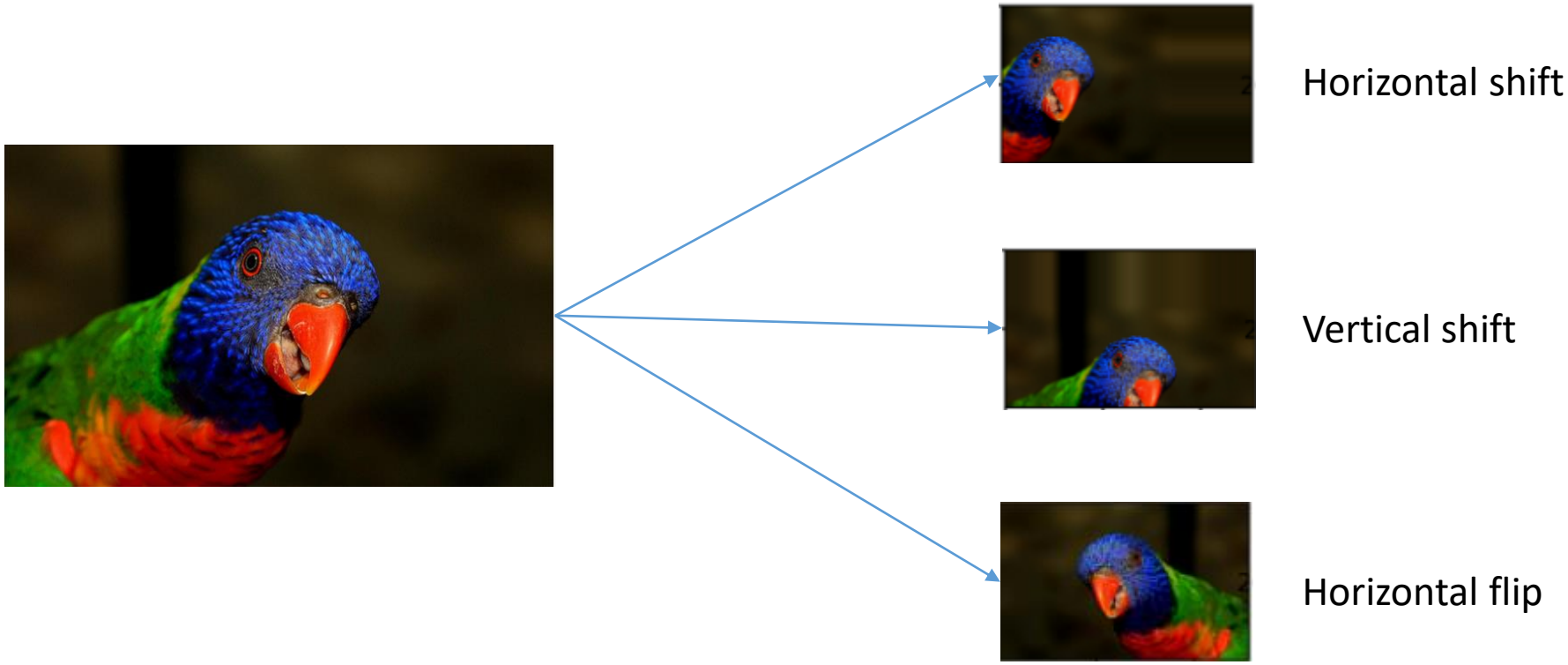
2. Layer Normalization



Normalization is applied for each uniformly colored region in the figure

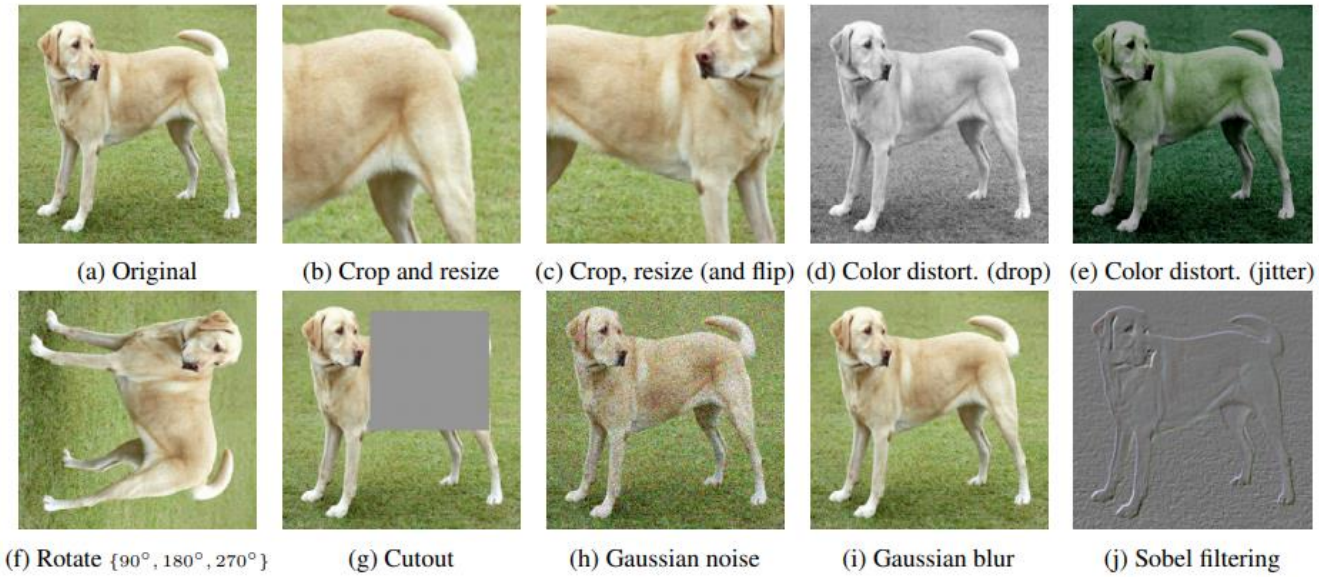
Data Augmentation

- Data augmentation provides a simple and effective way to add more images to your dataset



Data Augmentation

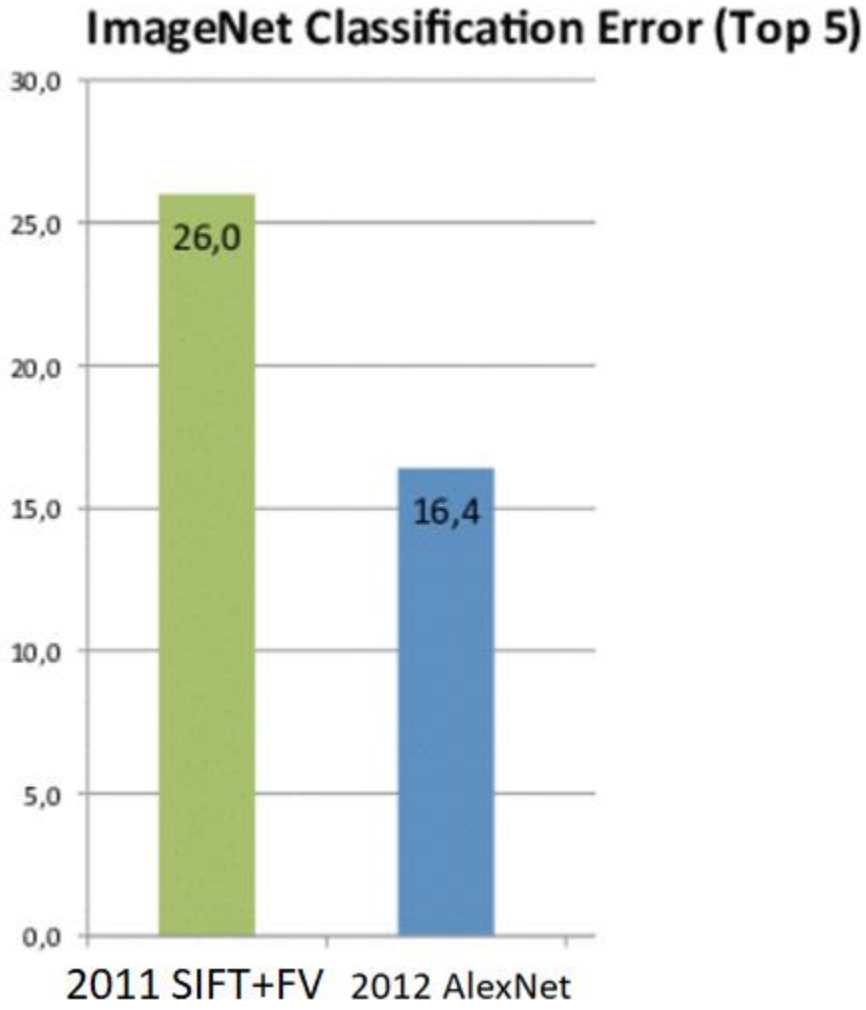
- Other possible operations
  - Rotations
  - Color distortions
  - Gaussian smoothing
  - Gaussian noise
  - Sobel filtering
  - Random crop + resize.
  - ….

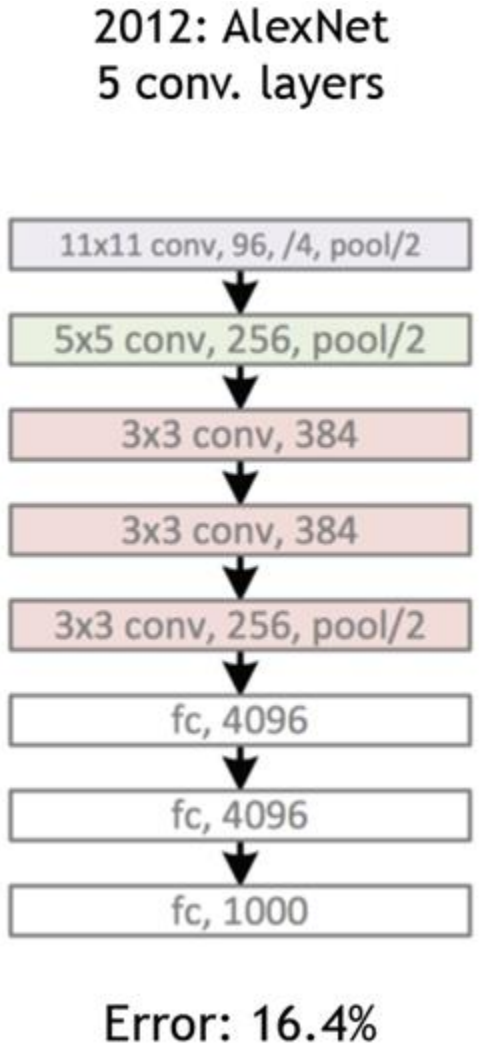


Examples of known CNN networks

- Alexnet
- VGG-Net
- ResNet: Residual Neural Networks
- DenseNet: Dense Neural Networks

Alexnet

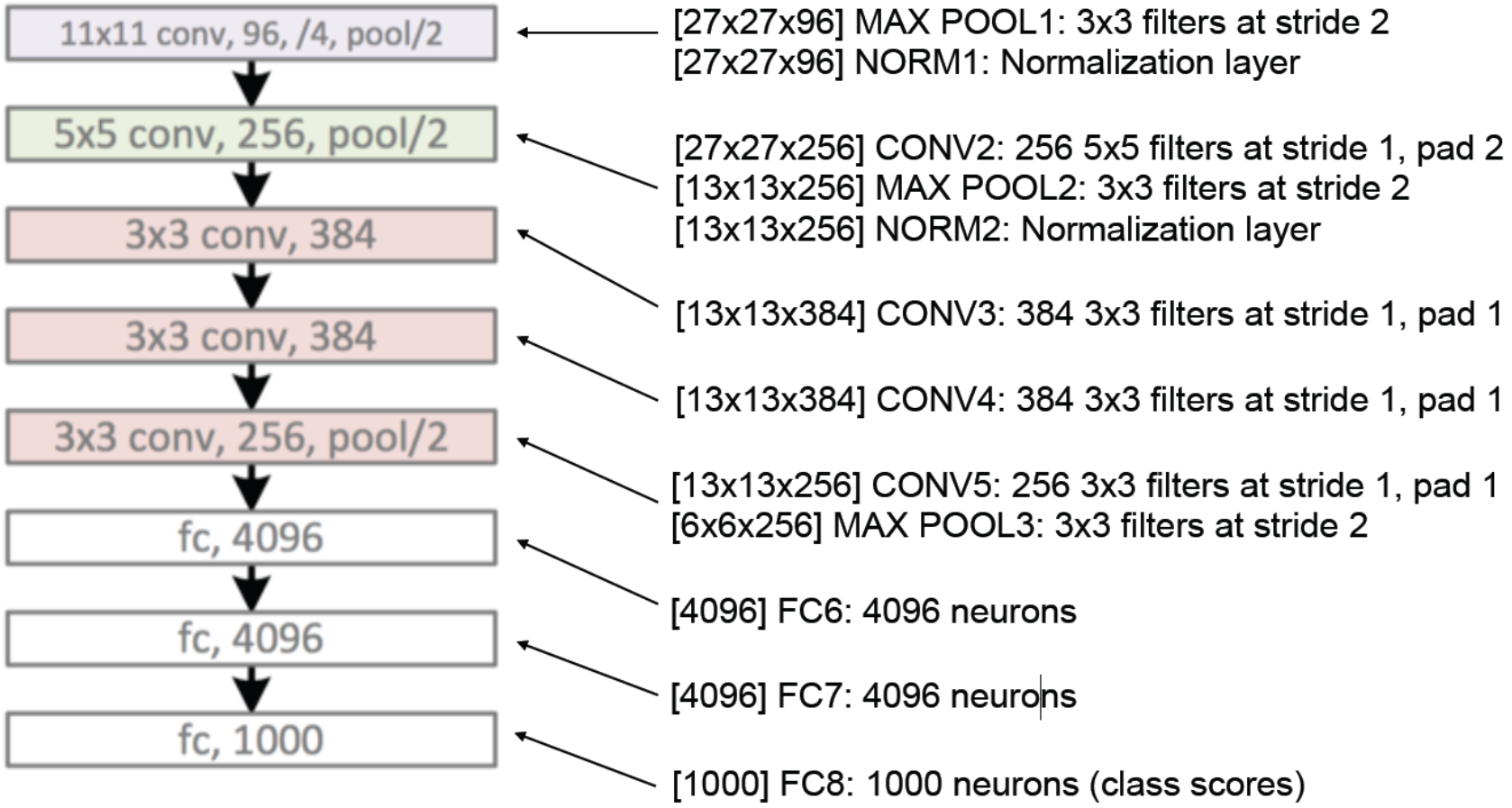




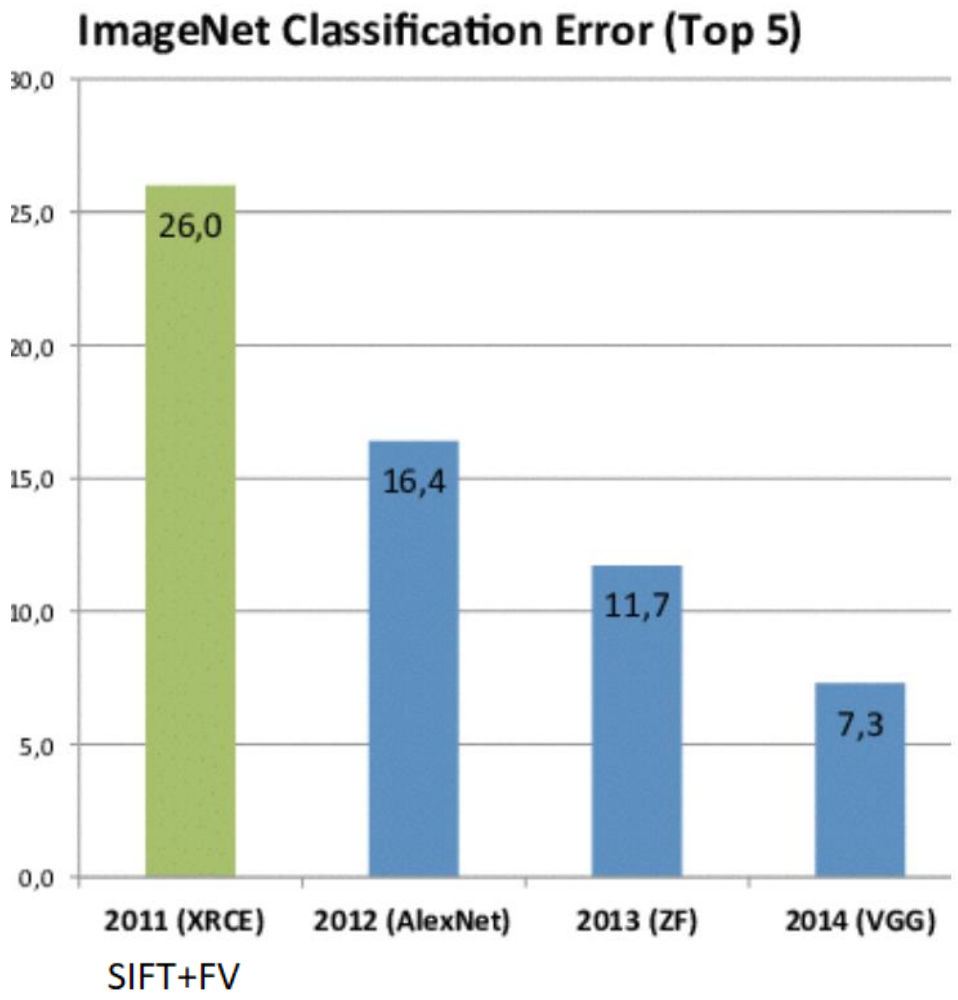
Identifying the 1000 classes in the dataset

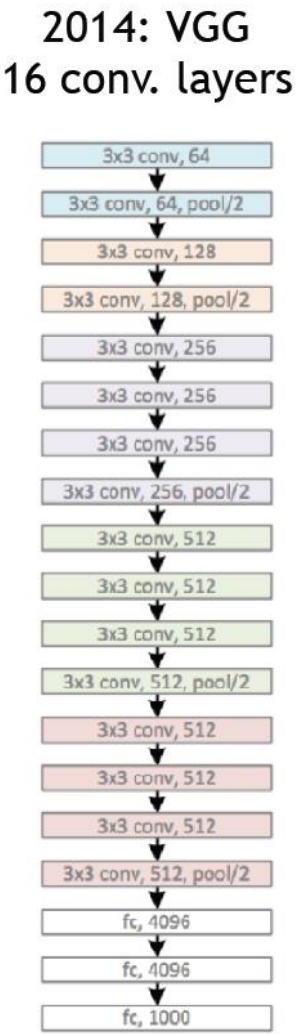
ImageNet 2012 challenge object classes: http://image-net.org/challenges/LSVRC/2012/browse-synsets

Alexnet


[227x227x3] INPUT
11x11 conv, 96, /4, pool/2
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
5x5 conv, 256, pool/2
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
3x3 conv, 384
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
3x3 conv, 384
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
3x3 conv, 256, pool/2
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
fc, 4096
[4096] FC6: 4096 neurons
fc, 4096
[4096] FC7: 4096 neurons
fc, 1000
[1000] FC8: 1000 neurons (class scores)

VGG-Net


ImageNet Classification Error (Top 5)
30,0
25,0
20,0
15,0
10,0
5,0
0,0
26,0
16,4
11,7
7,3
2011 (XRCE)
2012 (AlexNet)
2013 (ZF)
2014 (VGG)
SIFT+FV

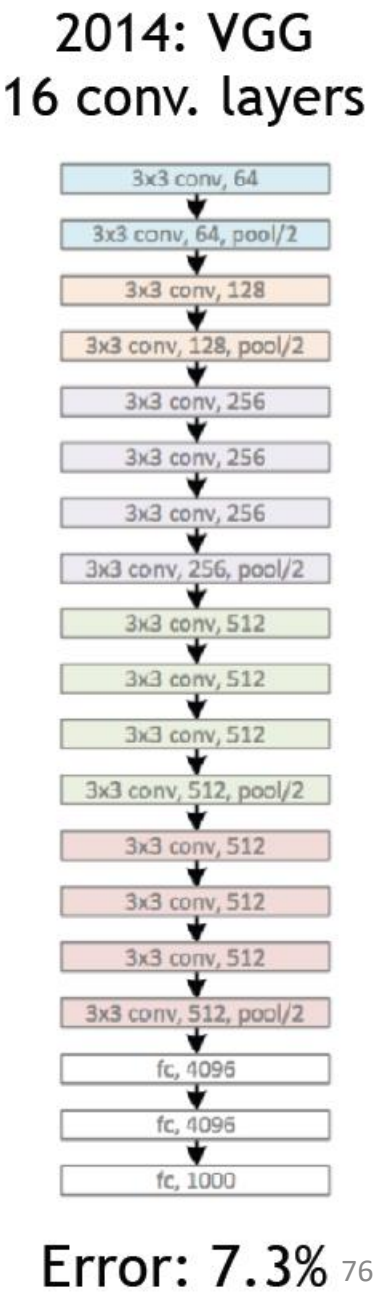

2014: VGG
16 conv. layers
3x3 conv, 64
3x3 conv, 64, pool/2
3x3 conv, 128
3x3 conv, 128, pool/2
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256, pool/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512, pool/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512, pool/2
fc, 4096
fc, 4096
fc, 1000
Error: 7.3%

VGG-Net

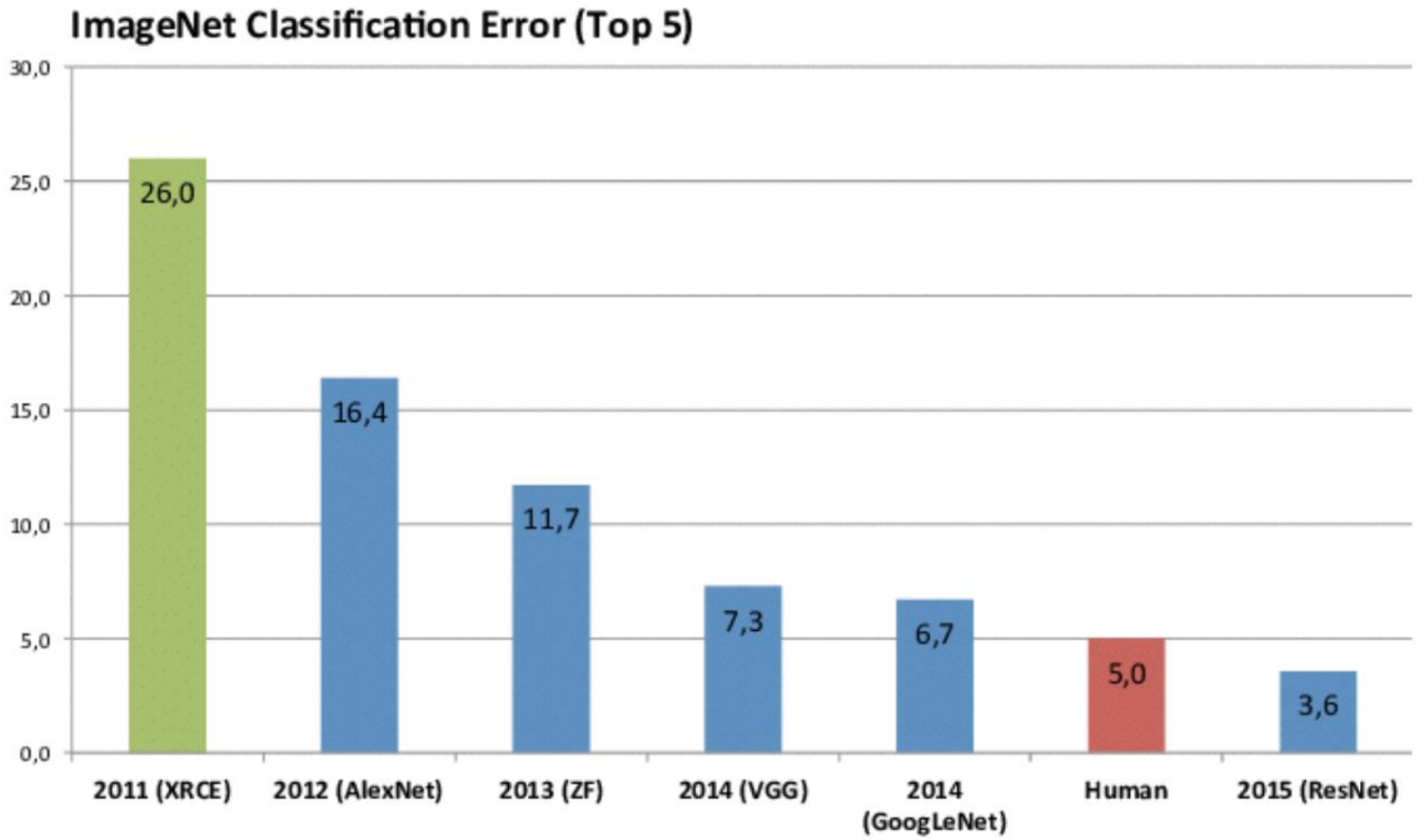
- Important Features: Fixed size convolutions 3 x 3
- Increased depth,

AlexNet: 5 Conv. layers + 3 FC

VGG-Net: 16 Conv. layers + 3 FC



ResNet



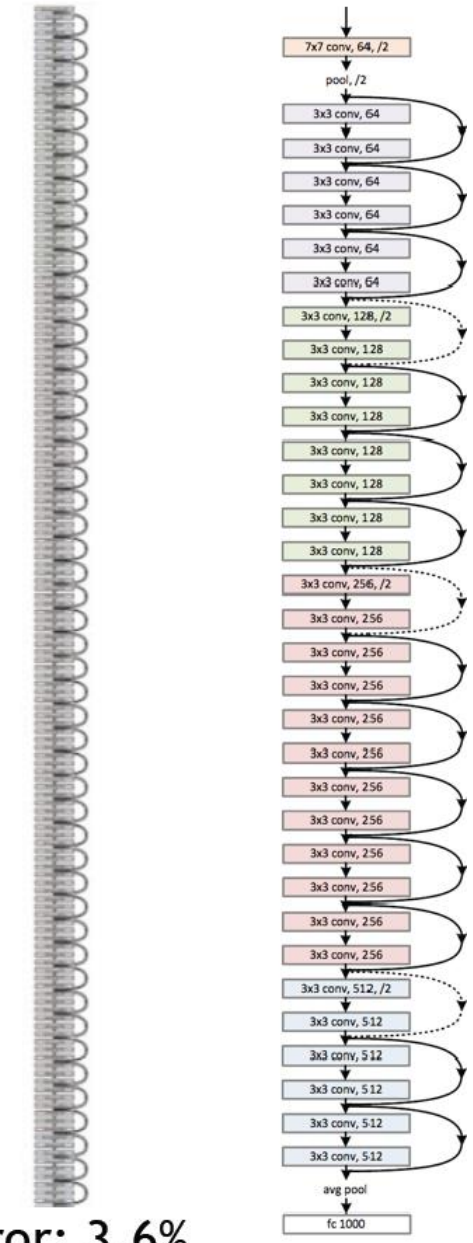
2016: ResNet
>100 conv. layers

Error: 3.6%

Is the network better than humans?

ResNet

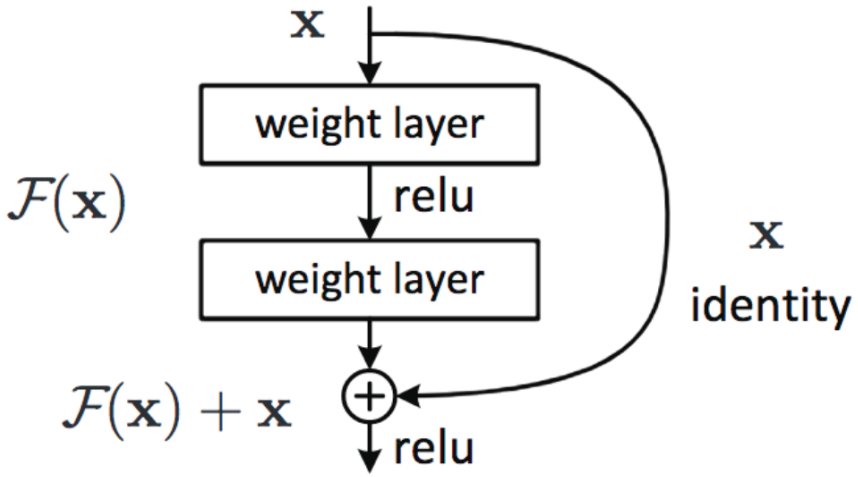
2016: ResNet
>100 conv. layers



Error: 3.6%

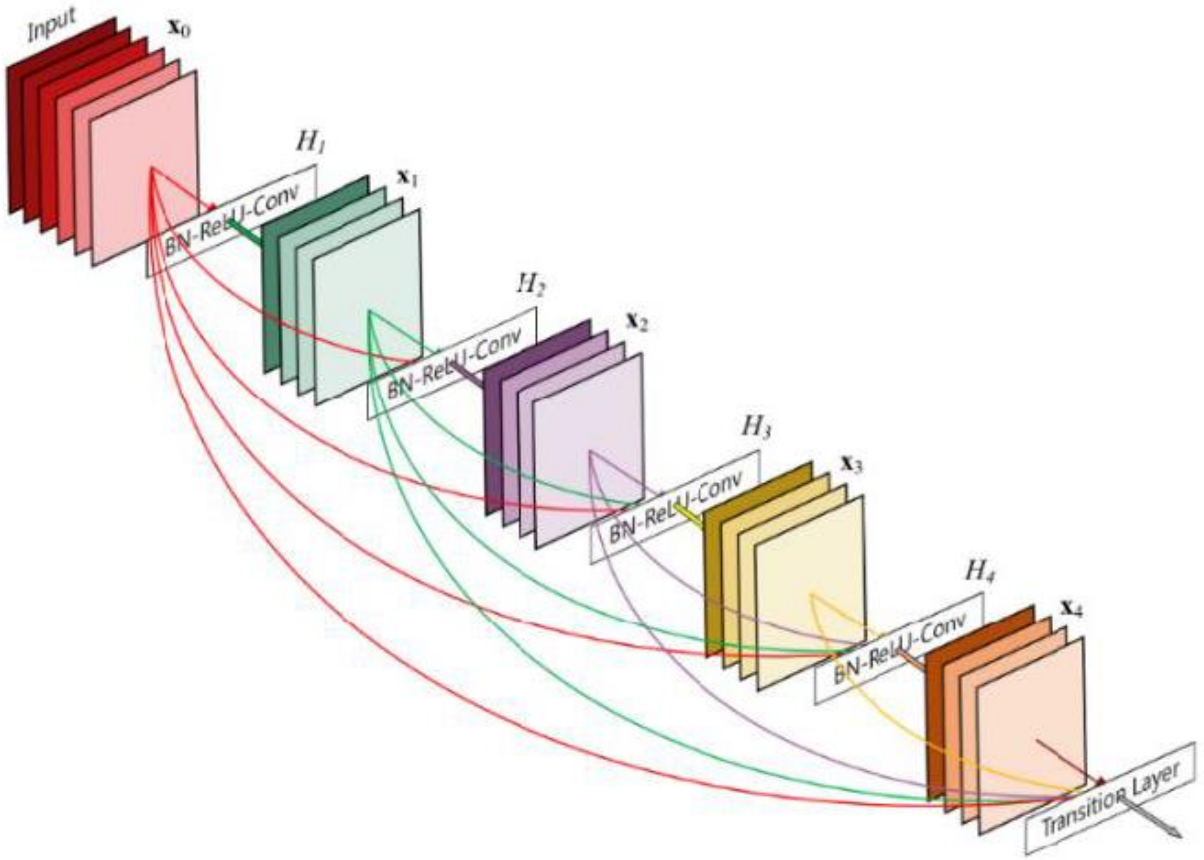
Main developments

- Increased depth possible through residual blocks



Dense Nets

- Taking the idea of ResNet to the extreme



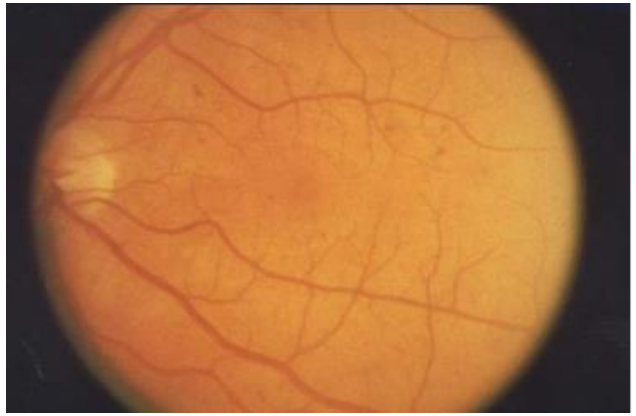
Transfer Learning

- The concept of taking an existing, trained model and training it further, either as is or as part of a new model. Also, known as fine tuning.
- Example 1: Assume your goal is to build a neural network that can classify the different types of cars.
- Instead of training the network from scratch, you start with a pertained model on ImageNet and fine-tune the model to fit your new dataset (i.e. initialize the network with ImageNet weights).
- Its common to freeze early layers during training with a new dataset.

Transfer Learning

- Example 2
- The goal is to build a binary detector for injured retinas.

  Start with a network trained with ImageNet or a similar dataset. Freeze the weights in initial layers. Change the output layer to binary and train the network



- This approach can use existing knowledge in the network before adapting to new problems.