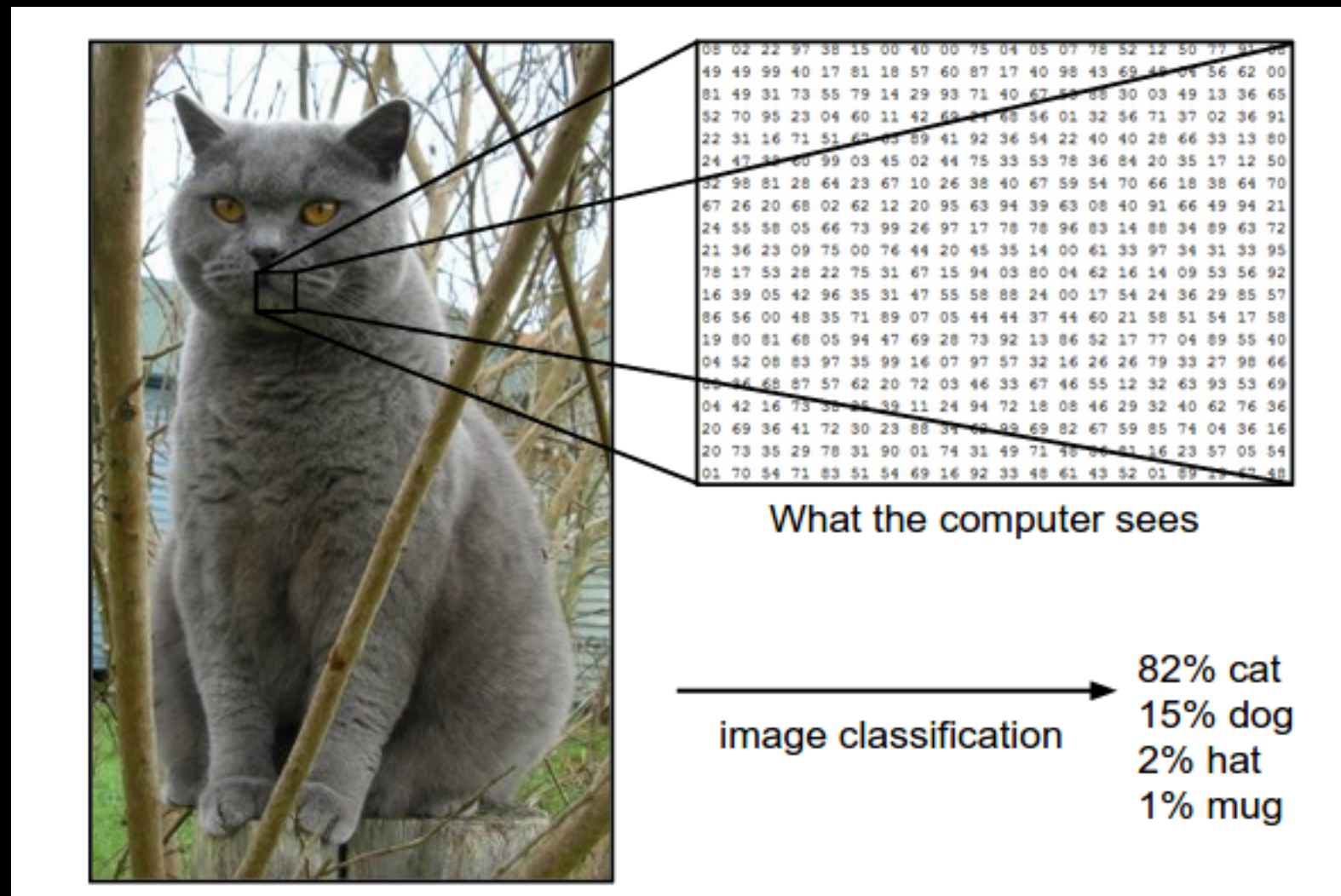


# Image Classification

# Agenda

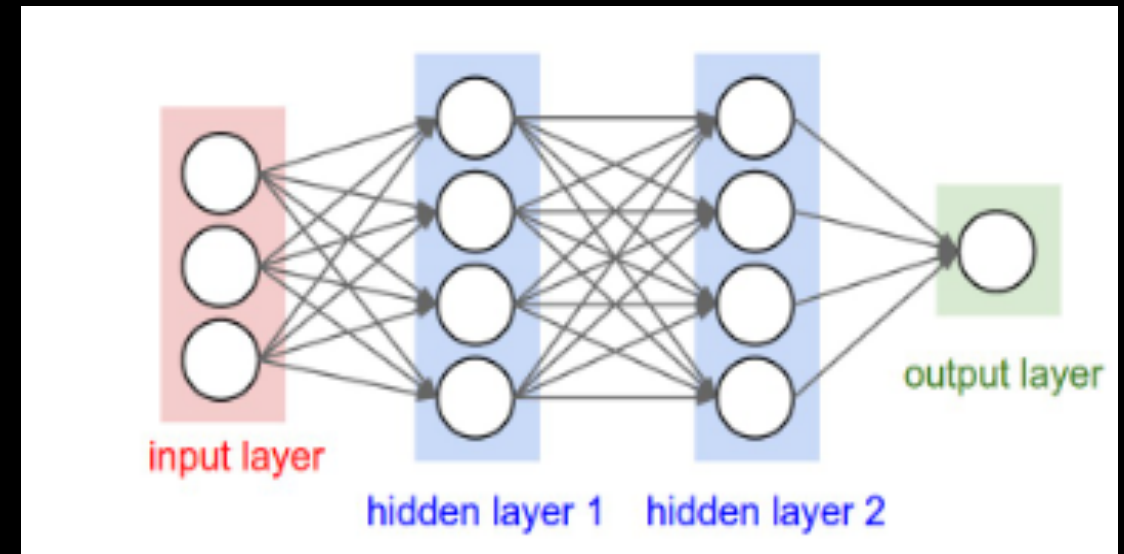
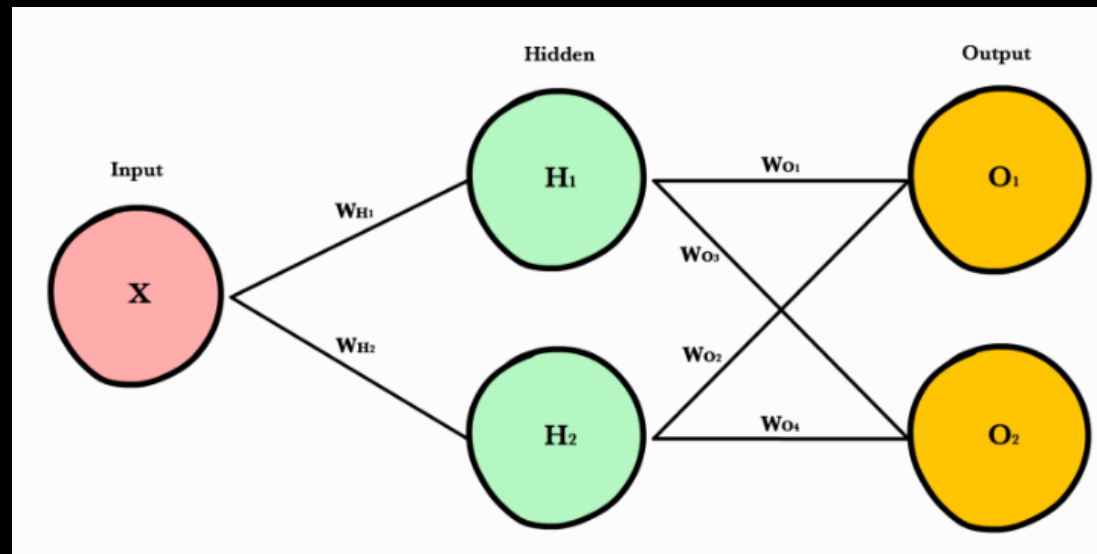
- What is Image Classification?
- What are Convolutional Neural Networks?
- Outline
  - PyTorch
  - Automatic Differentiation
  - Dog breed dataset
  - Binary classification
  - Multi class classification

# Image Classification

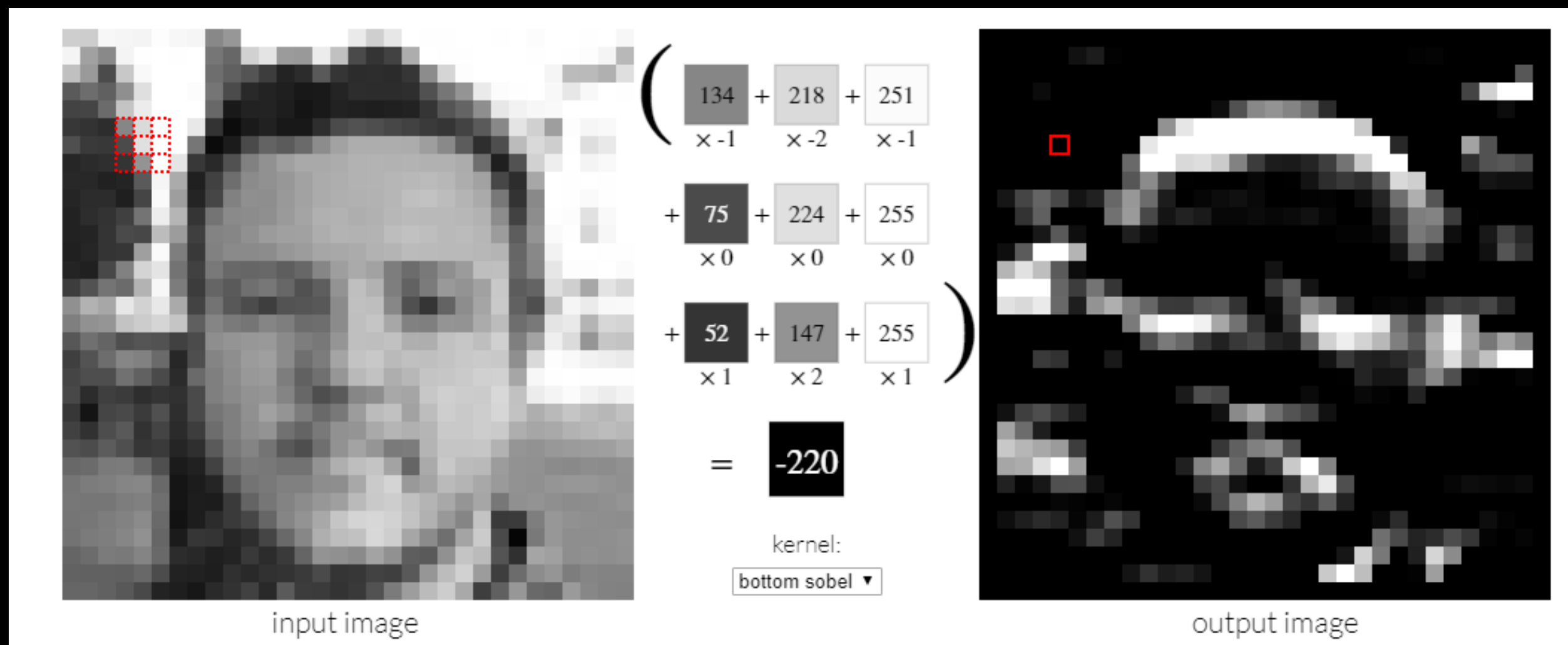


- Simplest problem: Assign a label to an image
- Several variants of image classification problems – let us focus on the simplest!

# Neural networks

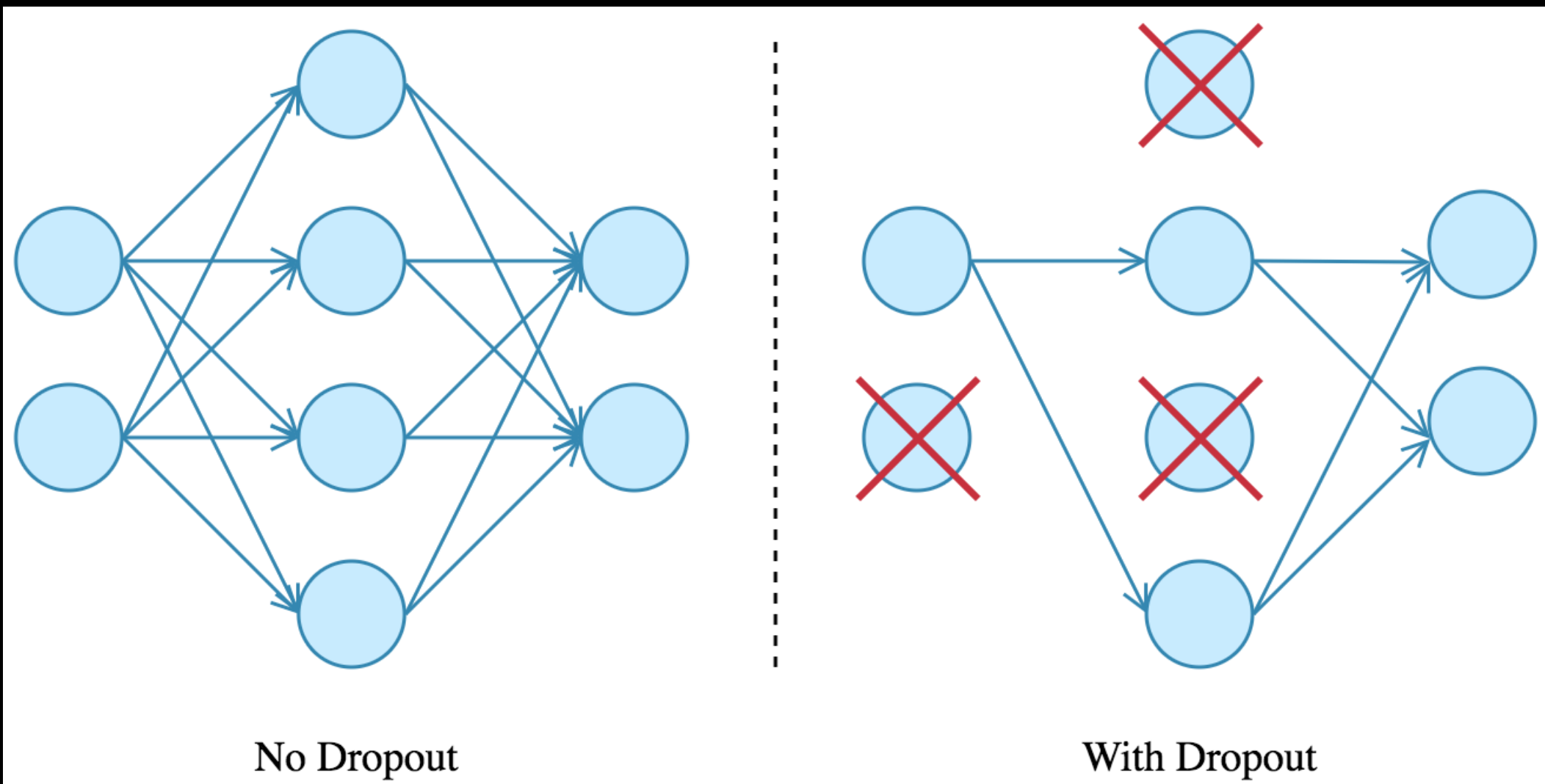


- Dense neural network - every node is connected to every other node
- For deep networks, very expensive!

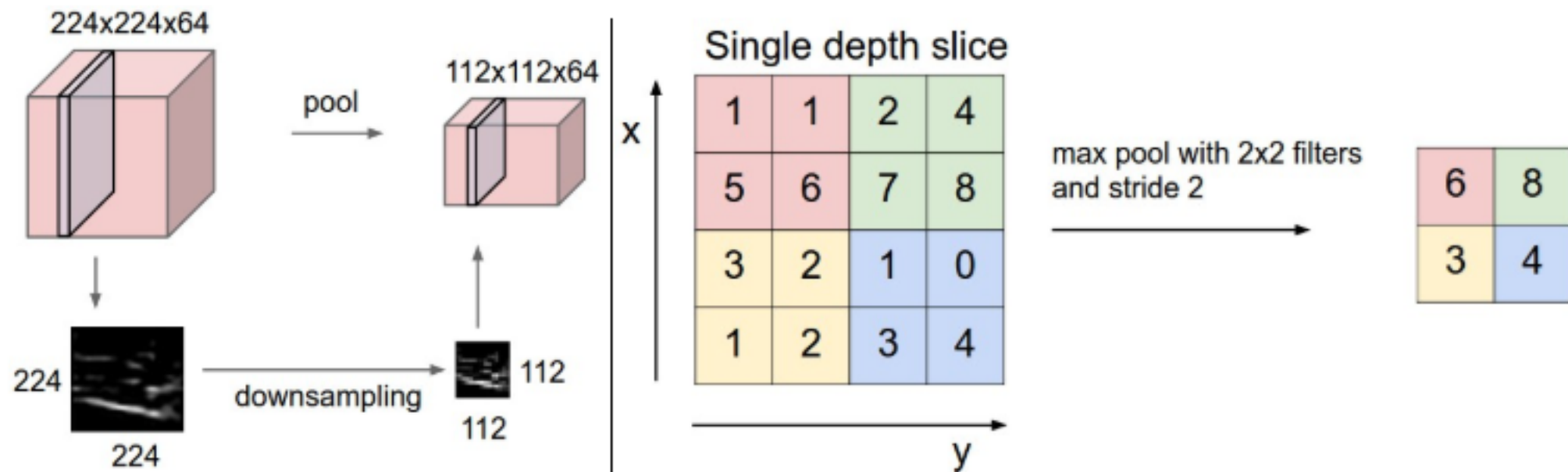


# Convolutional Layer

- Link: <http://setosa.io/ev/image-kernels/>
- Link: <http://cs231n.github.io/convolutional-networks/>



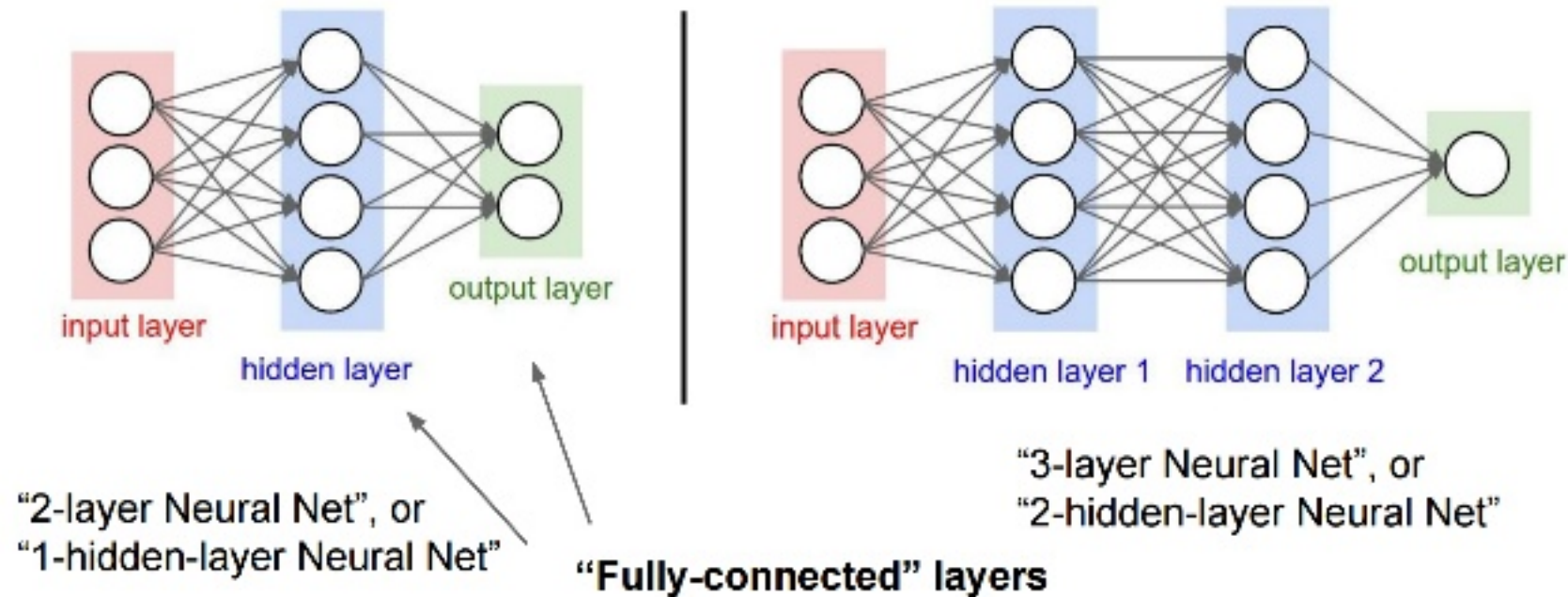
# Dropout Layer



Pooling layer downsamples the volume spatially, independently in each depth slice of the input volume. **Left:** In this example, the input volume of size  $[224 \times 224 \times 64]$  is pooled with filter size 2, stride 2 into output volume of size  $[112 \times 112 \times 64]$ . Notice that the volume depth is preserved. **Right:** The most common downsampling operation is max, giving rise to **max pooling**, here shown with a stride of 2. That is, each max is taken over 4 numbers (little  $2 \times 2$  square).

# Pooling Layer

## Fully connected neural network



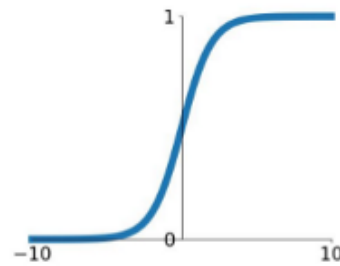
# Fully Connected Layer



# Activation Functions

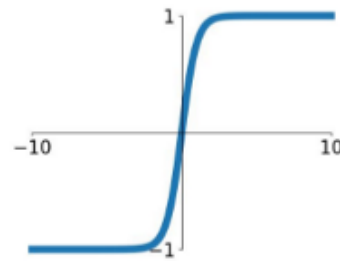
**Sigmoid**

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



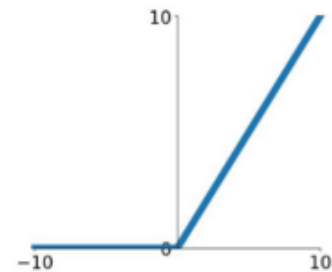
**tanh**

$$\tanh(x)$$



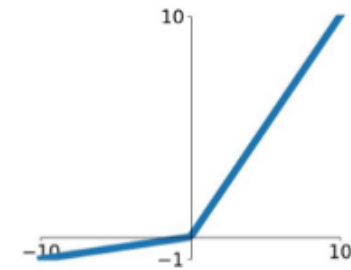
**ReLU**

$$\max(0, x)$$



**Leaky ReLU**

$$\max(0.1x, x)$$

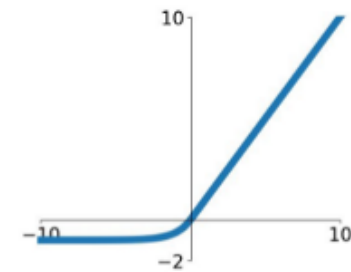


**Maxout**

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

**ELU**

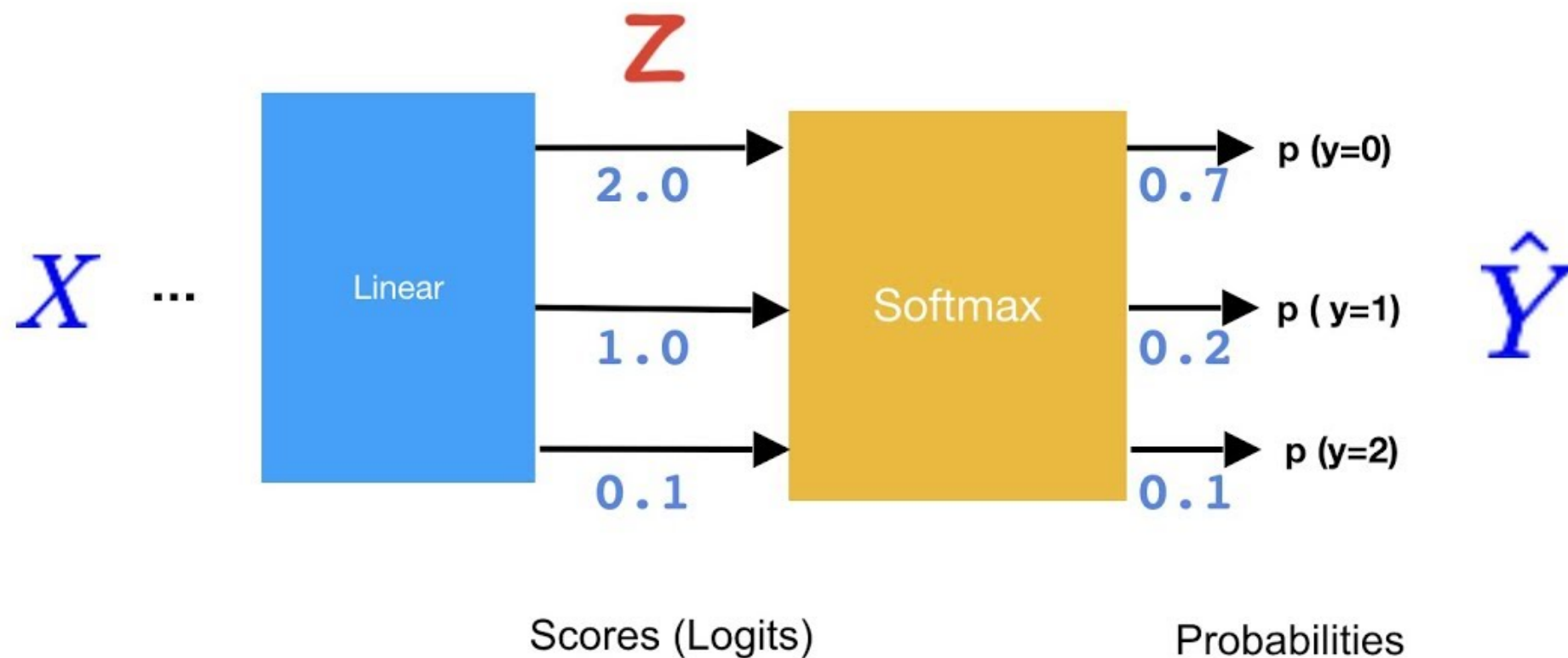
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



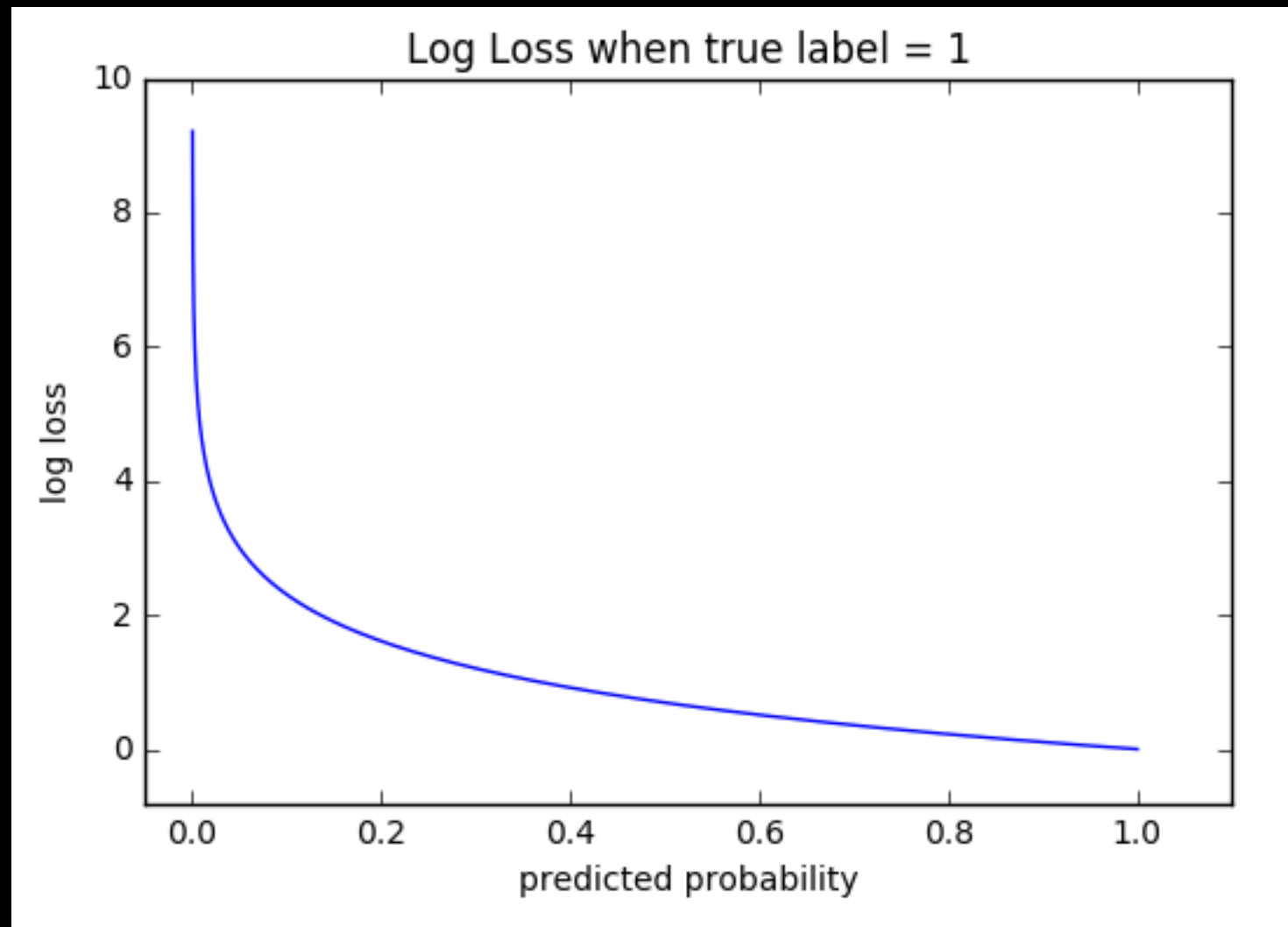
# Activation Function

# Meet Softmax

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} \quad \text{for } j = 1, \dots, K.$$



# Softmax



# Cross Entropy or Log Loss

Link: <https://datawookie.netlify.com/blog/2015/12/making-sense-of-logarithmic-loss/>