Chapter 10: Deep Learning

Deep Learning

- Single Layer Neural Networks
- Multilayer Neural Networks
- Convolutional Neural Networks

Single Layer Neural Network

A neural network takes an input vector of p variables $X = (X_1, X_2, ..., X_p)$ and builds a nonlinear function $f(X)$ to predict the response Y.

Single Layer Neural Network

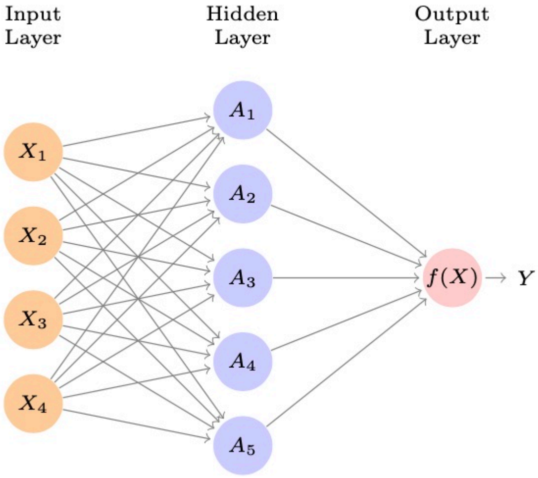


Figure 1: ISL 10.1

Activation Functions, $g(z)$

Values of $A_k = h_k(X)$ close to one are firing, while those close to zero are silent. These non-linear activations allow the model to capture complex nonlinearities and interaction effects.

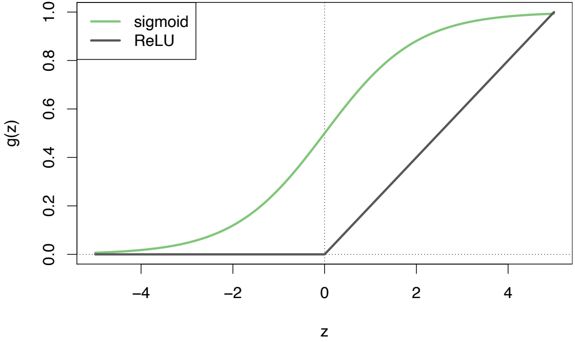


Figure 2: ISL 10.2

Activation Functions, $g(z)$

Rotation (linear transformations) + Squashing (non-linear transformations)!

$$A_k = h_k(X) = g(w_{k0} + \sum_{j=1}^{p} w_{kj} X_j)$$

Check out the video here by Alfredo Canziani for the NYU Deep Learning course. The whole course (http://bit.ly/DLSP21-home) is awesome!

Multilayer Neural Networks

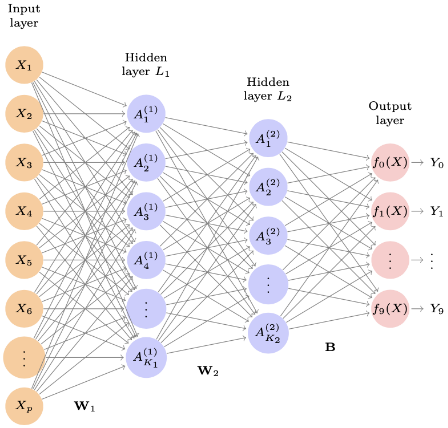


Figure 3: ISL 10.4

Input layer with $p = 784$ units and two hidden layers ($K_1 = 256$ units, $K_2 = 128$ units). **Why 10 output units?**

Convolutional Neural Networks

Neural networks became popular for image recognition in the 1980s but fell out of favor after that when SVMs, random forests, and boosting gained steam. They resurfaced after 2010 when large training databases started to become available.

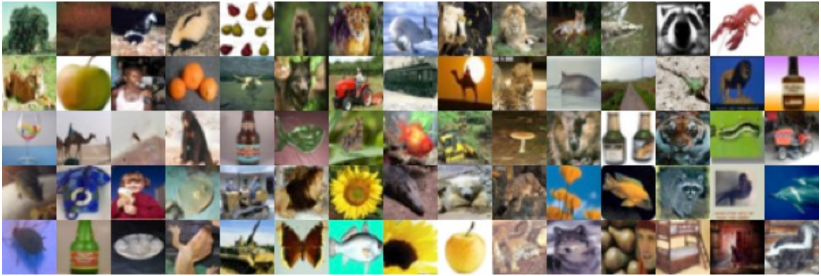
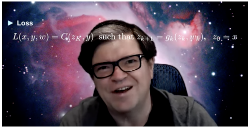


Figure 5: ISL 10.5

CIFAR100: 60,000 32x32 pixel images in three channels

Convolutional Neural Networks

“The world is compositional.” – Yann LeCun



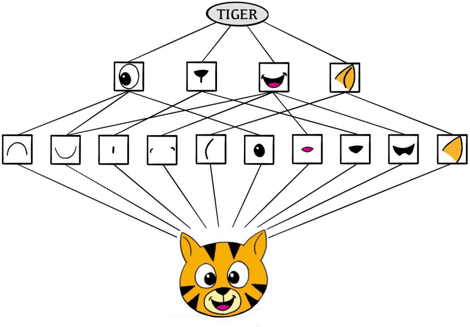


Figure 6: ISL 10.6

Convolutional Neural Networks learn hierarchical representations by extracting low-, mid-, and high-level features.

Convolutional Neural Networks

CNNs use two specialized types of hidden layers to build up this hierarchy: 1) convolution layers and 2) pooling layers.

Convolution Layers

Made up of a large number of convolution filters, each of which is a template that determines whether a particular local feature is present in an image.

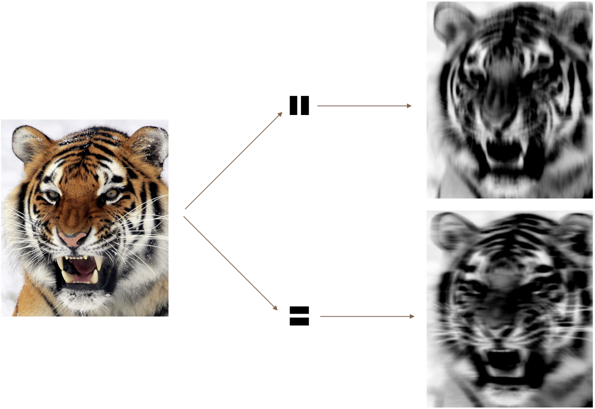
$$\text{Input Image} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \\ j & k & l \end{bmatrix} \quad \text{Convolution Filter} = \begin{bmatrix} \alpha & \beta \\ \gamma & \delta \end{bmatrix}.$$

$$\text{Convolved Image} = \begin{bmatrix} a\alpha + b\beta + d\gamma + e\delta & b\alpha + c\beta + e\gamma + f\delta \\ d\alpha + e\beta + g\gamma + h\delta & e\alpha + f\beta + h\gamma + i\delta \\ g\alpha + h\beta + j\gamma + k\delta & h\alpha + i\beta + k\gamma + l\delta \end{bmatrix}$$

Figure 7: ISL 10.6

Convolution Layers

The convolved image highlights regions of the original image that resemble the convolution filter.



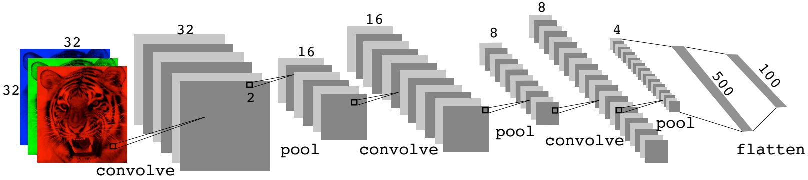
Pooling Layers

Used to condense a large image into a smaller summary image.

$$\text{Max pool} \begin{bmatrix} 1 & 2 & 5 & 3 \\ 3 & 0 & 1 & 2 \\ 2 & 1 & 3 & 4 \\ 1 & 1 & 2 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 3 & 5 \\ 2 & 4 \end{bmatrix}$$

Max pooling produces some *location invariance.*

Putting it all together



Convolution layers are interspersed with 2x2 max pool layers, before the 3-D feature maps are flattened (pixel maps treated as separate units) and fed into a fully-connected layer before reaching the output layer (a soft-max activation for 100 classes).