ECE 20875
Python for Data Science

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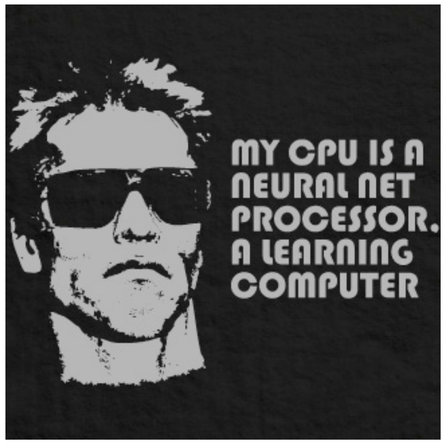
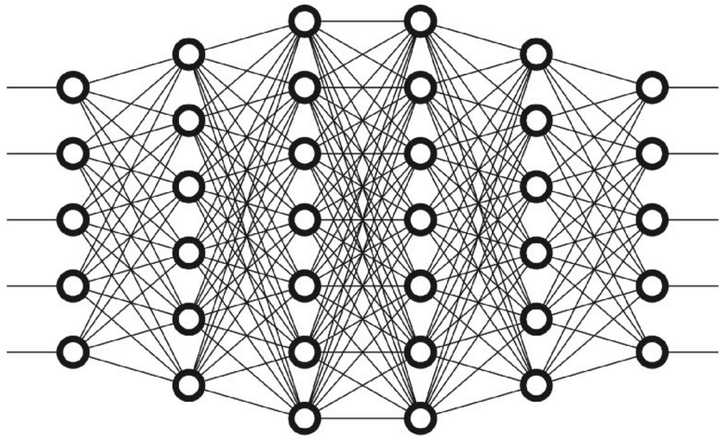
introduction to neural networks

neural networks

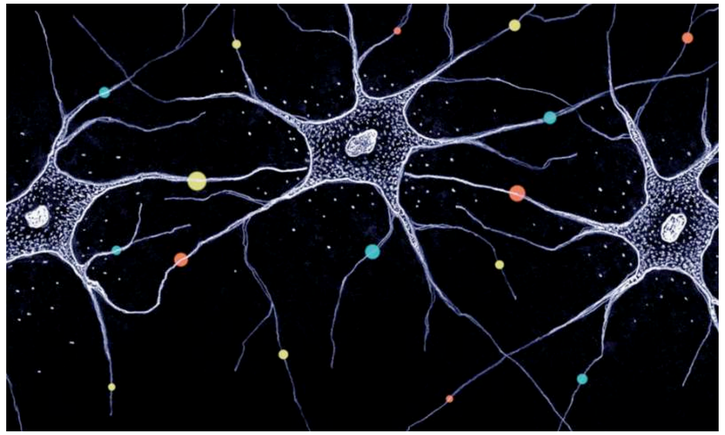


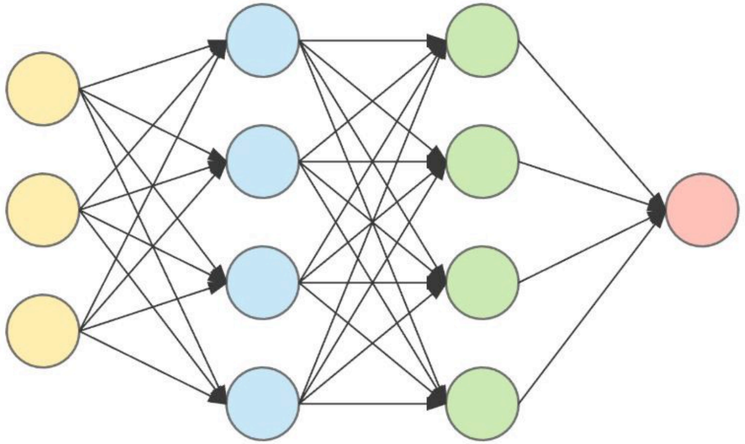
- Show up everywhere (including in pop culture)
  - Machine translation
  - Image recognition
  - Video generation
  - …
- Form the basis of the **deep learning** field
- Too many use cases for us to cover in this class
  - We will focus on neural networks used as **classifiers**



neurons

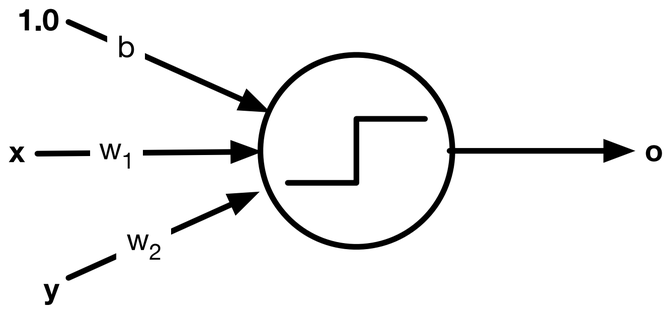
- The fundamental building blocks of neural networks are called **neurons**
  - Each has an **activation function**, modeled loosely after neurons in the brain, which “activate” when given enough stimulus
  - The human brain is estimated to have more than 10 billion neurons, to give you an idea
- Can view a neuron graphically as a “node” with inputs, and weights
  - The input to the activation function is the dot product of the input and weights





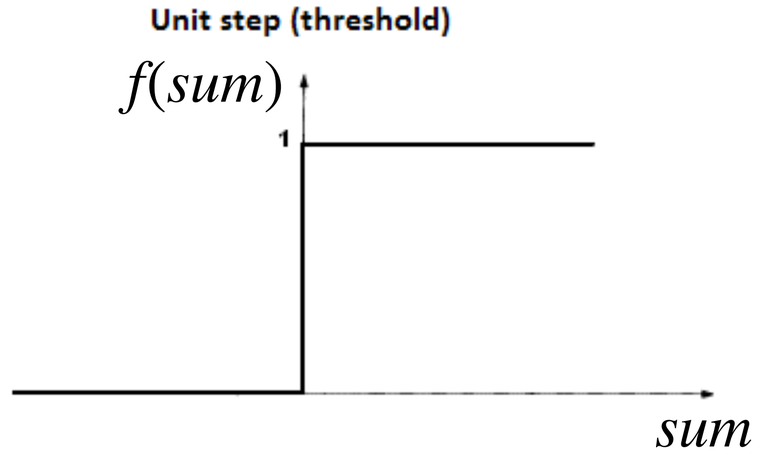
perceptrons

- A **perceptron** is the simplest form of a neuron
  - Activation function is the (Heaviside) **unit step function**: either “on” or “off”
- It uses the following **linear decision boundary**:



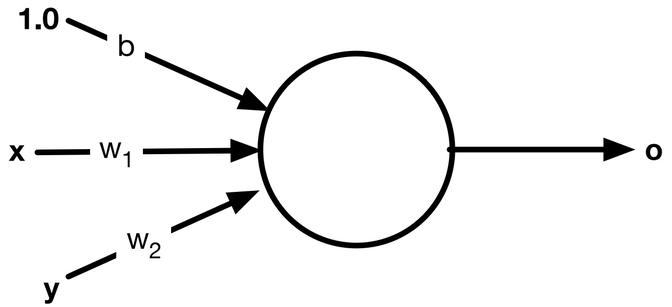
$$sum = \begin{bmatrix} b & w_1 & w_2 \end{bmatrix} \begin{bmatrix} 1.0 \\ x \\ y \end{bmatrix}$$

$$o = f(sum) = \begin{cases} 0, & sum \leq 0 \\ 1, & sum > 0 \end{cases}$$

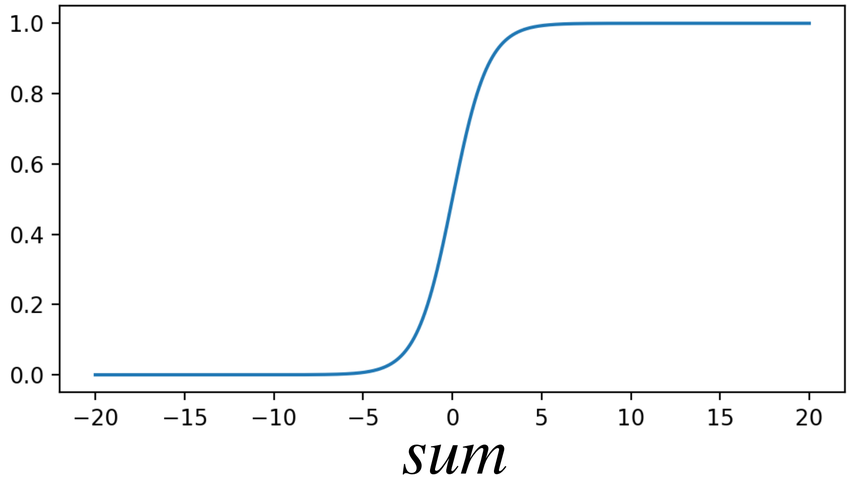


logistic regression: single layer NN

- Learning becomes a problem, because the unit step function cannot be differentiated
  - We need to somehow “smoothen” the transition at $sum = 0$
- One common activation function that does this is the **sigmoidal activation**, shown to the right
  - We can readily calculate the derivative
- This is just logistic regression: A neural network with a single layer and sigmoidal activation



$$o = f(sum) = \frac{1}{1 + e^{-sum}}$$

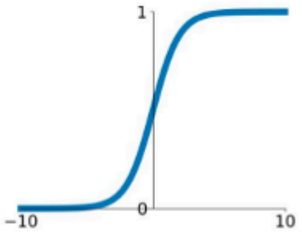


choices of activation functions

- The sigmoid function is computationally expensive, though
- There are many other activation functions we can use too. For example:
  - `tanh`: Hyperbolic tangent, has steeper derivatives than sigmoid
  - `ReLU`: Much easier to compute, but the outputs can be very large
  - `Leaky ReLU`: Allows the output of `ReLU` below 0 to be slightly negative

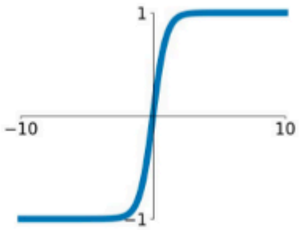
Sigmoid

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



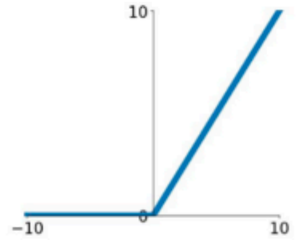
tanh

$\tanh(x)$



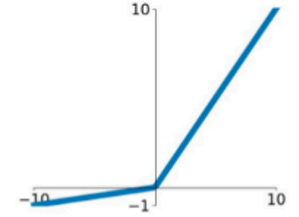
ReLU

$\max(0, x)$



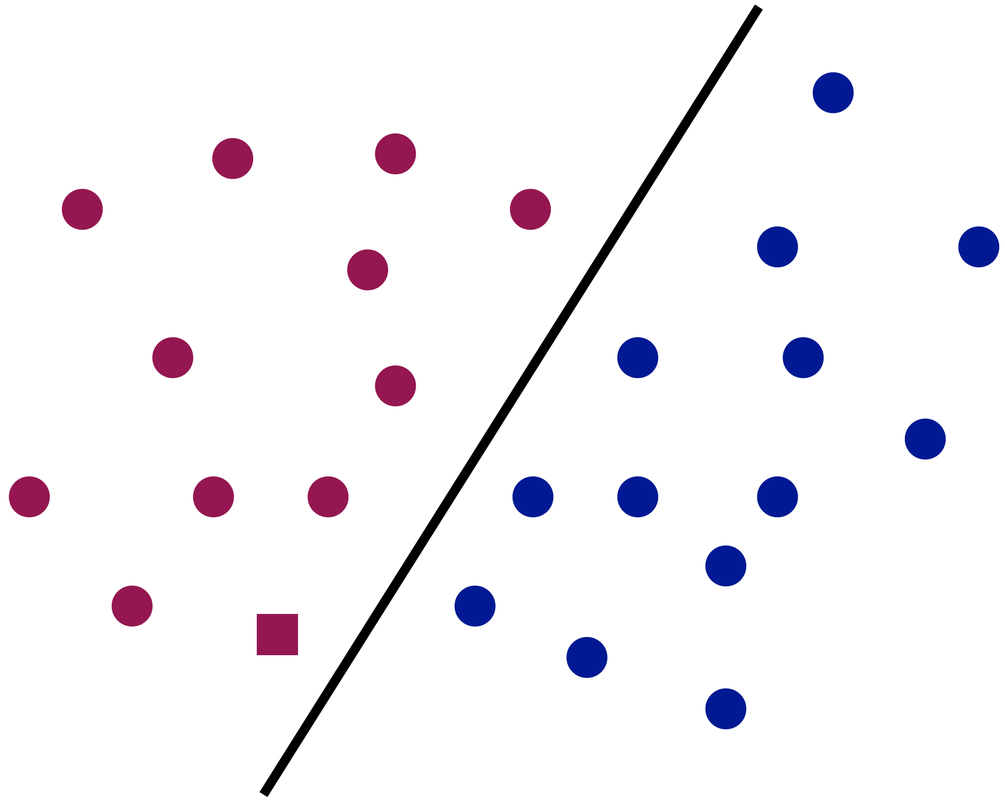
Leaky ReLU

$\max(0.1x, x)$



decision boundaries

- Basic classification problem for neural networks:
  - I have a set of labeled **training data**
  - Learn a **decision boundary** that separates the two classes of data
- Given a **new point**
  - Classify it using the decision boundary you learned
  - Similar to other classifiers we looked at!



creating decisions with neurons

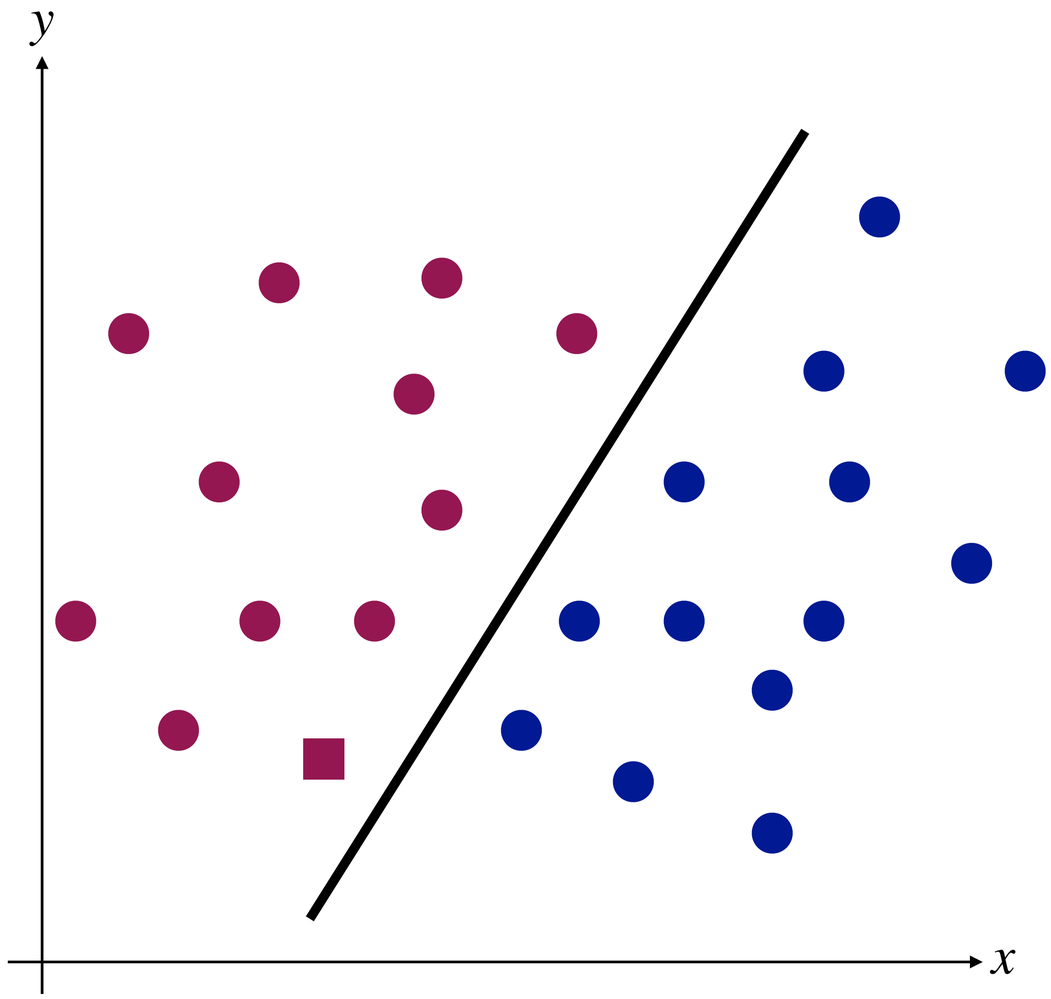
- The basic idea of neural networks is to add layers of complexity on how decision boundaries are defined

- A perceptron will induce a decision boundary that is a straight line, i.e.,

$$f(x, y) = \begin{cases} 0, & b + w_1 x + w_2 y \leq 0 \\ 1, & b + w_1 x + w_2 y > 0 \end{cases}$$

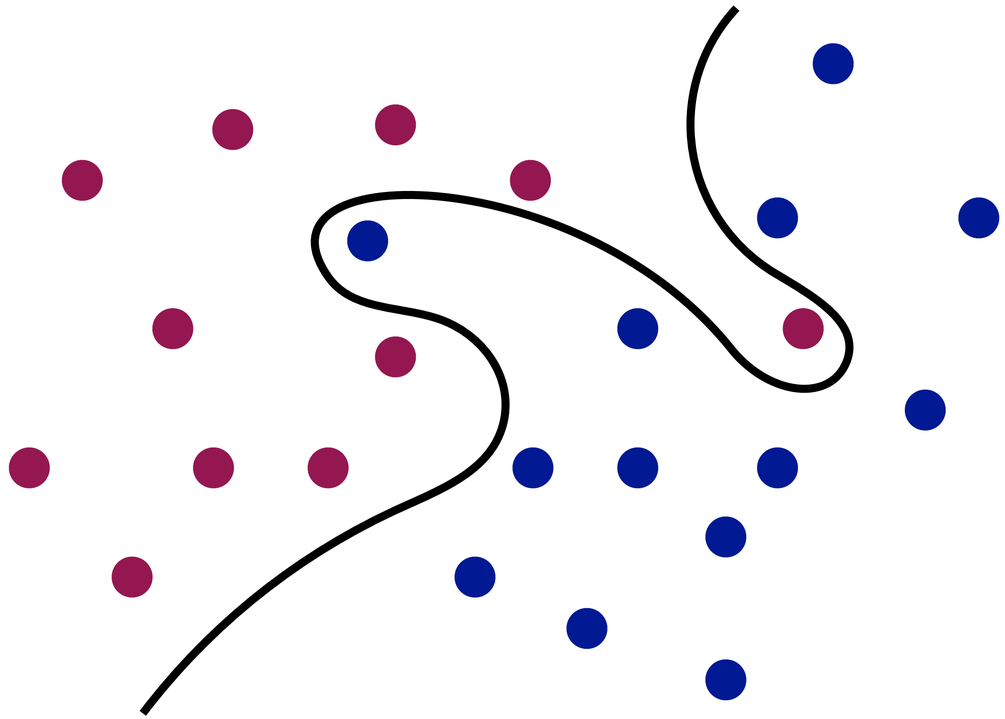
  - How do we learn the parameters w_1, w_2, and b of this model?

  - Instead of gradient descent, there is a "special" algorithm for perceptrons



non-linear decision boundaries

- The special **perceptron training algorithm** is guaranteed to converge if a **linear decision boundary** exists
- But if no linear boundary exists, the algorithm will not converge, not even to an imperfect solution
- Perceptrons cannot learn non-linear decision boundaries!
- To learn them, we need two things:
  - Multiple layers of neurons
  - Smoother activation functions



multi-layer NN structure and intuition

(a) The building block of neural networks (a single **neuron**) is like a little logistic regression model:

1. Weighted summation of n inputs: $z = \sum_{i=1}^{n} w_i x_i$
2. Activation function: $y = f(z) = f\left(\sum_{i=1}^{n} w_i x_i \right)$

(b) We can put many of these neurons together to form a **feed-forward neural network**
(or sometimes simply **deep NN** or **multilayer NN**)

1. Each neuron computes weighted summation and activation function
2. Stacking the neurons vertically forms a NN **layer**
3. Feeding the output of one layer as the input to the next layer creates a **deep NN (DNN)**

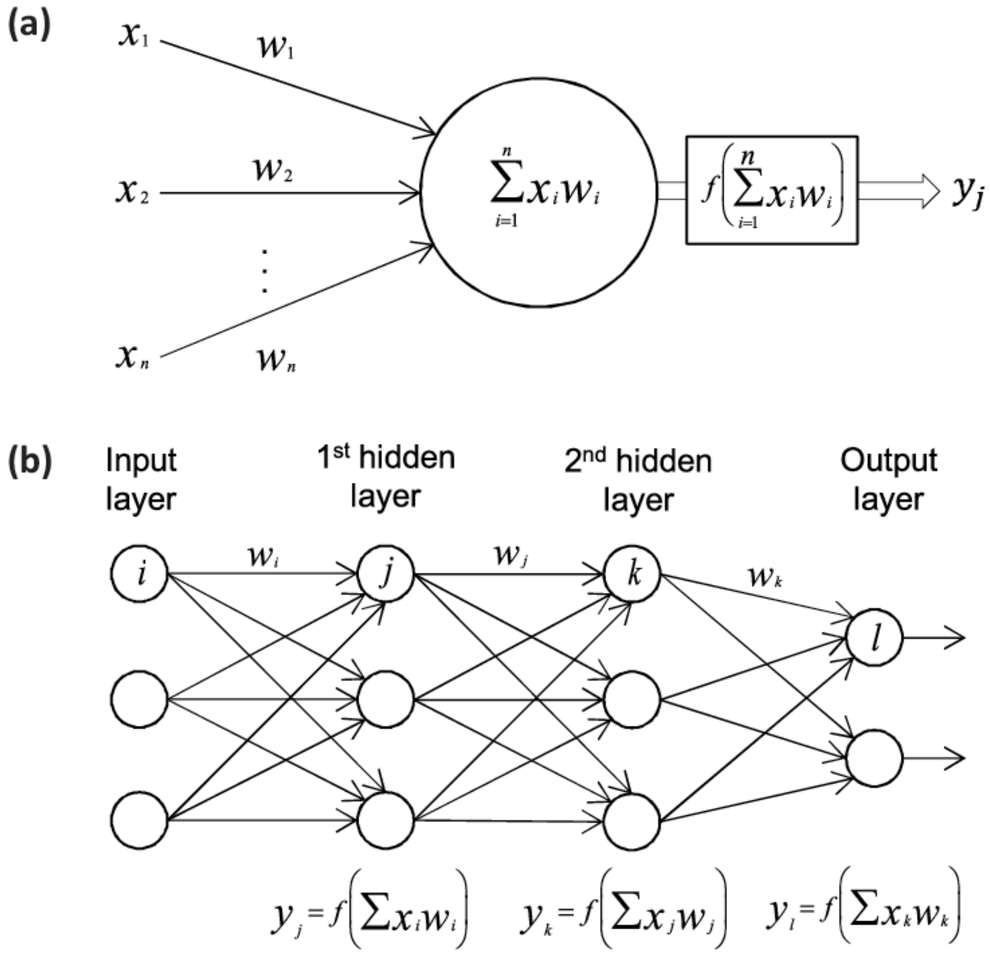


Figure from: Vieira, Sandra & Pinaya, Walter & Mechelli, Andrea. (2017). Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: Methods and applications. Neuroscience & Biobehavioral Reviews. 74. 10.1016/j.neubiorev.2017.01.002.

multi-layer NN mathematical form

1. Notice that the weighted summation for neuron j can be seen as a dot product:

$$z_j = \sum_{i=1}^{n} w_i x_i = \mathbf{w}_j^T \mathbf{x}$$

2. When stacking neurons vertically the layer outputs can be seen as a matrix multiplication:

$$\begin{aligned} z_1 &= \mathbf{w}_1^T \mathbf{x} \\ z_2 &= \mathbf{w}_2^T \mathbf{x} \\ &\vdots \\ z_n &= \mathbf{w}_n^T \mathbf{x} \end{aligned} \quad , \quad \text{which can be written as } \mathbf{z} = \begin{bmatrix} \mathbf{w}_1^T \\ \mathbf{w}_2^T \\ \vdots \\ \mathbf{w}_n^T \end{bmatrix} \mathbf{x} = W\mathbf{x}$$

3. Now the activation function is applied *independently* to each output:

$$\begin{aligned} y_1 &= f(z_1) \\ y_2 &= f(z_2) \\ &\vdots \\ y_n &= f(z_n) \end{aligned} \quad , \quad \text{which can be written as } \mathbf{y} = \begin{bmatrix} f(z_1) \\ f(z_2) \\ \vdots \\ f(z_n) \end{bmatrix} = f(\mathbf{z})$$

4. Thus we can write a DNN mathematically as function composition:

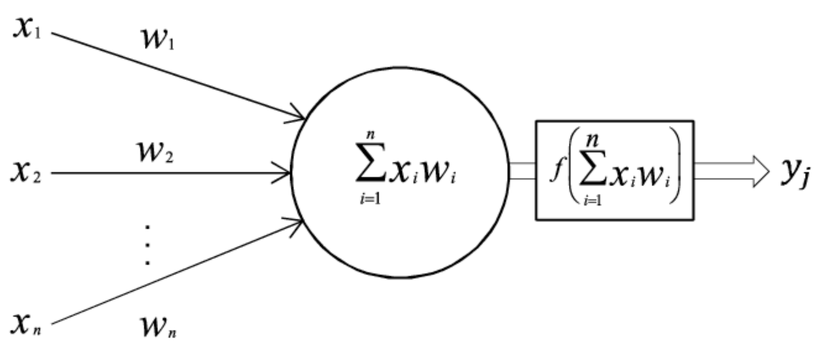
$$DNN(\mathbf{x}) = \mathbf{f}(W^{(3)}\,\mathbf{f}(W^{(2)}\,\underbrace{\mathbf{f}(W^{(1)}\mathbf{x})}_{\text{Layer 1}})) \quad \text{(Layer 2 / Output layer)}$$

, or equivalently

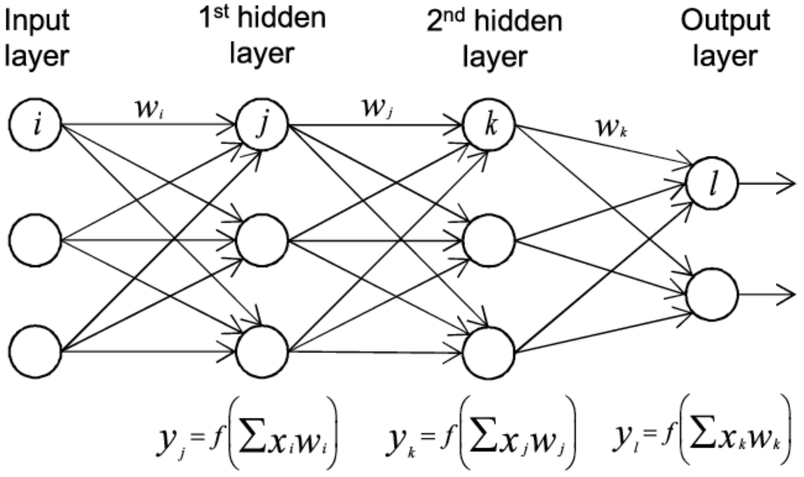
$$\begin{aligned} \mathbf{z^{(1)}} &= W^{(1)}\mathbf{x} \\ \mathbf{y^{(1)}} &= \mathbf{f}(\mathbf{z^{(1)}}) \\ \mathbf{z^{(2)}} &= W^{(2)}\mathbf{y^{(1)}} \\ \mathbf{y^{(2)}} &= \mathbf{f}(\mathbf{z^{(2)}}) \\ \mathbf{z^{(3)}} &= W^{(3)}\mathbf{y^{(2)}} \\ \mathbf{y^{(3)}} &= \mathbf{f}(\mathbf{z^{(3)}}) \end{aligned}$$

Alternating between **linear** transformation and **non-linear** activation functions

(a)



(b)



example of non-linear decision boundary

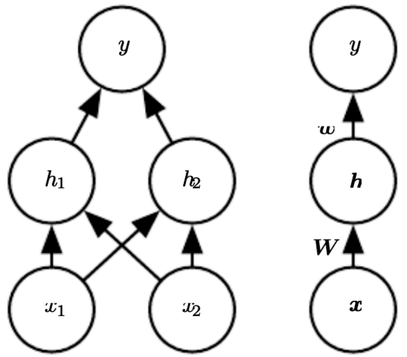
- Consider XOR classification function (clearly not a linear decision boundary)
- We will use simple 2 layer NN:

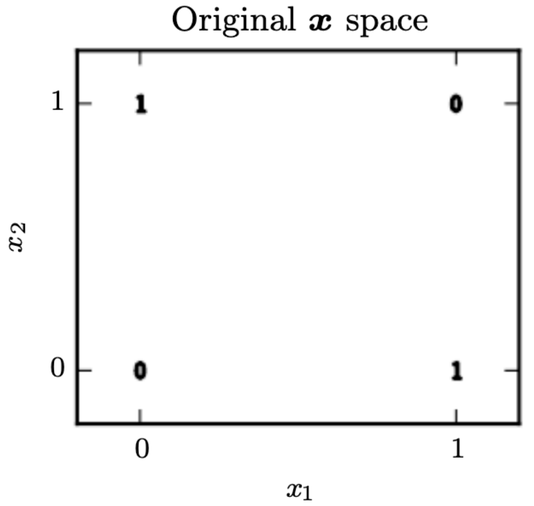
$$\mathbf{h} = \text{ReLU}(W\mathbf{x} + \mathbf{c}) = \max\{0, W\mathbf{x} + \mathbf{c}\}$$

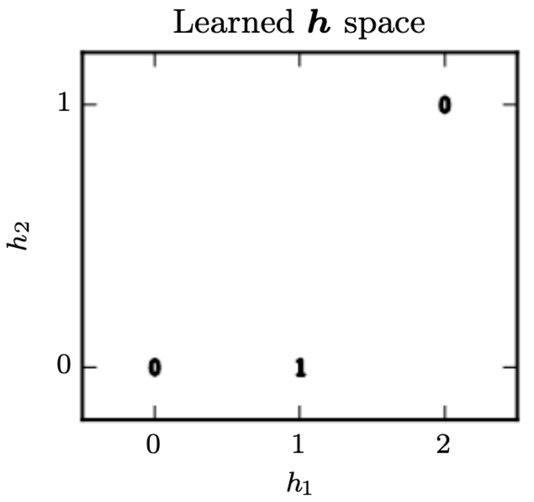
$$y = \mathbf{w}^T\mathbf{h}$$

- Solution:

$$W = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, \quad \mathbf{c} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}, \quad \mathbf{w} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$$







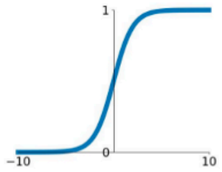
https://www.deeplearningbook.org/contents/mlp.html

architecture and parameters of NN

- **Depth**: # of layers
- **Width**: # of neurons per layer
- **Activations**: sigmoid, ReLU, tanh, etc.

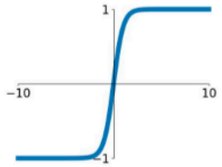
Sigmoid

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



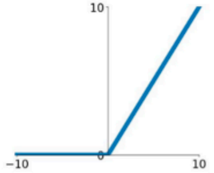
tanh

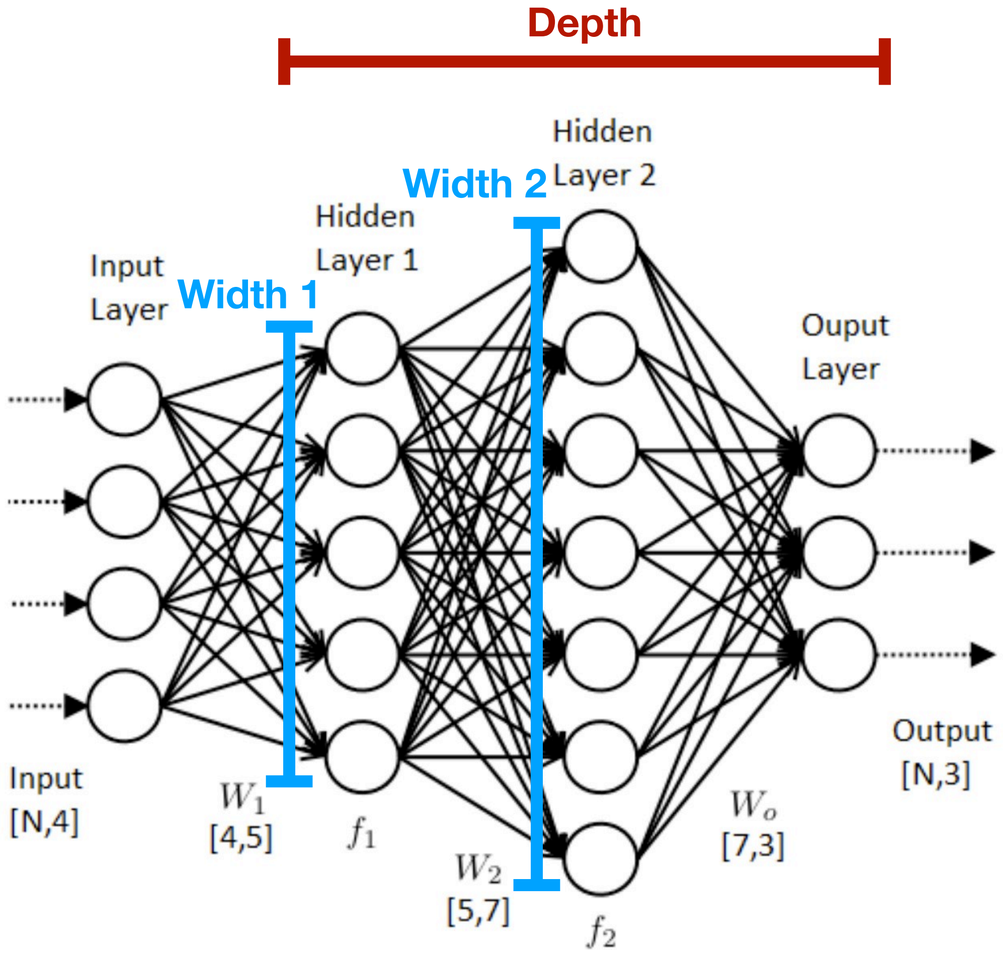
$\tanh(x)$



ReLU

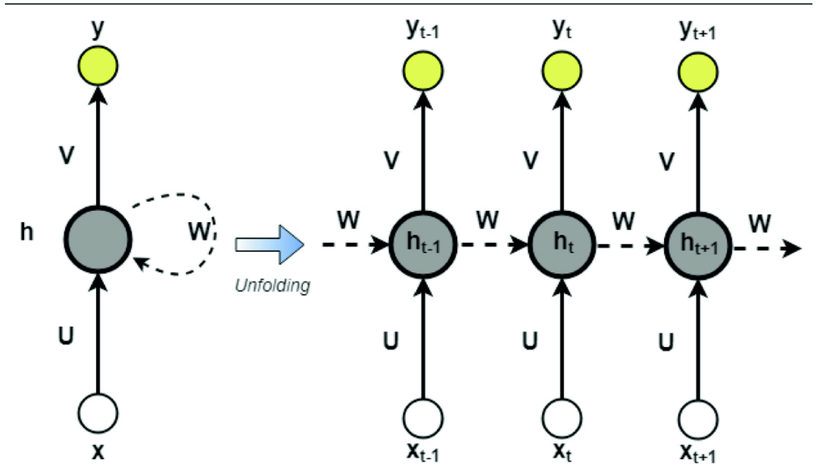
$\max(0, x)$

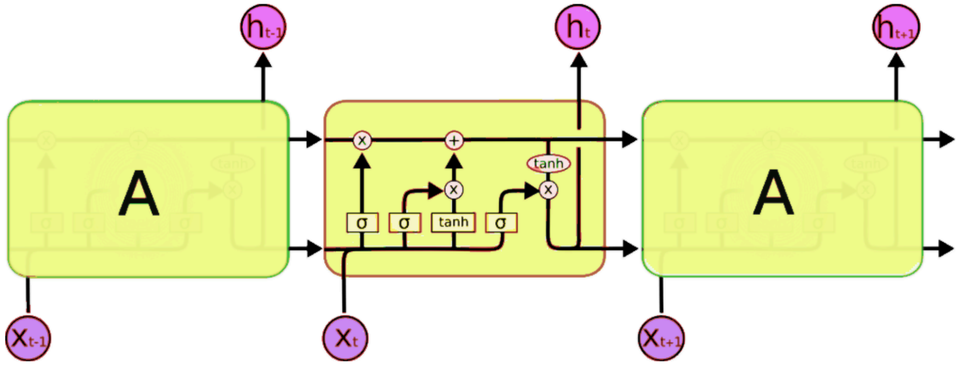




neural network architectures

- A plethora of neural network architectures have been proposed, for different applications
  - Multi-layer Perceptron (**MLP**): Cascading perceptrons
  - Recurrent Neural Networks (**RNN**): Sequential data modeling
  - Convolutional Neural Networks (**CNN**): Image recognition
  - Long Short Term Memory (**LSTM**): Memory cells with “forgetting” factors
  - Transformer (most recent), Gated Recurrent Units (**GRU**), Hopfield Networks, Boltzmann Machines, Generative Adversarial Networks (**GAN**), …





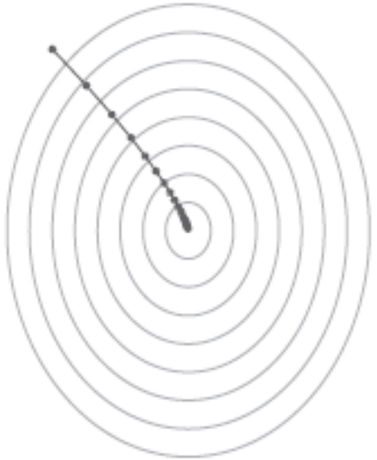
learning neural networks

- **(Batch) Gradient descent (GD)** can be computationally expensive for large datasets (e.g, 1M images)
  - *Every update* requires computing and summing 10^6 gradients
    $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \alpha \sum_{i=1}^{n=10^6} \nabla F(x_i, y_i, \mathbf{w}^{(t)})$
  - If we add a normalizing constant of $1/n$, we can view this update as taking the expected gradient over all data samples:
    $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \alpha \frac{1}{n} \sum_{i=1}^{n} \nabla F(x_i, y_i, \mathbf{w}^{(t)}) = \mathbf{w}^{(t)} - \alpha \mathbb{E}[\nabla F(x_i, y_i, \mathbf{w}^{(t)})]$
- **Stochastic gradient descent (SGD)** massively reduces the computational complexity by only using 1 sample at each time step t, (x_t, y_t):

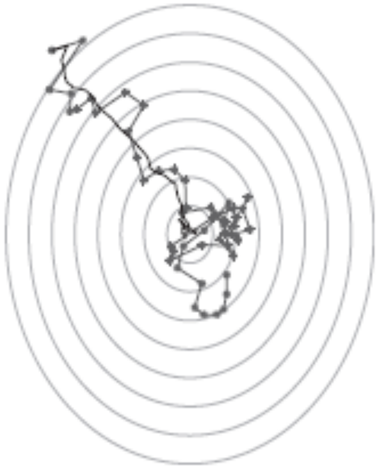
  $\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \alpha \mathbb{E}[\nabla F(x_i, y_i, \mathbf{w}^{(t)})] = \mathbf{w}^{(t)} - \alpha \nabla F(x_t, y_t, \mathbf{w}^{(t)})$

  - Note that the *variance of the steps* is much higher but the *cost is much lower*
  - Sometimes called **amortized learning** because it amortizes (spreads out) the computational cost across many iterations
  - **Mini-batch gradient descent** is actually used in practice where often 64, 128 or 256 samples are used in each batch (bridging between SGD and GD)

Gradient descent



Stochastic Gradient Descent



SGD for a sigmoidal neuron

- Letting y_i be the label of datapoint i, $\mathbf{w} = (w_1, w_2, \dots)$ be the vector of weights, and $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots)$ be the datapoint vector, define the error $E(\mathbf{x}_i)$ of the output of a specific input:

$$E(\mathbf{x}_i) = \frac{1}{2}\left(y_i - f(sum)\right)^2 = \frac{1}{2}\left(y_i - f(\mathbf{w}^T\mathbf{x}_i)\right)^2$$

- For SGD, we only need the partial derivative for one specific input

$$\frac{\partial E(\mathbf{x}_i)}{\partial w_j} = \frac{\partial E(\mathbf{x}_i)}{\partial f(sum)} \cdot \frac{\partial f(sum)}{\partial sum} \cdot \frac{\partial sum}{\partial w_j} = -\underbrace{(y_i - f(sum)) \cdot f(sum)(1 - f(sum))}_{\text{Denote as } \delta_0 \text{ since same for every } w_j} \cdot x_{ij}$$

  - Remember that $\frac{\partial f(x)}{\partial x} = f(x)(1 - f(x))$ when f is a sigmoid

SGD for a sigmoidal neuron

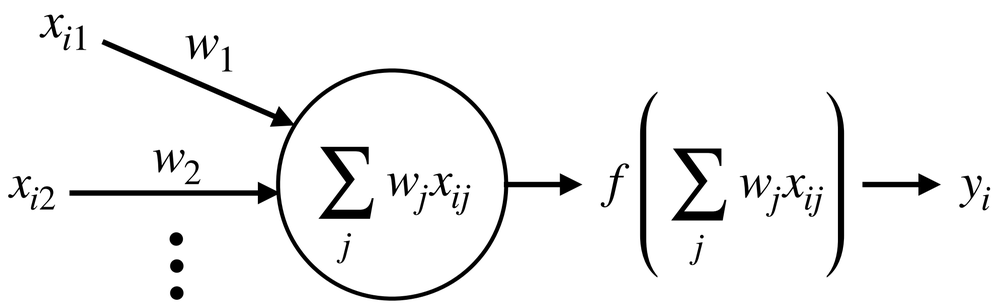
- From previous slide:

$$\frac{\partial E(\mathbf{x}_i)}{\partial w_j} = \frac{\partial E(\mathbf{x}_i)}{\partial f(sum)} \cdot \frac{\partial f(sum)}{\partial sum} \cdot \frac{\partial sum}{\partial w_j} = -\underbrace{(y_i - f(sum)) \cdot f(sum)(1 - f(sum))}_{\text{Denote as } \delta_0 \text{ since same for every } w_j} \cdot x_{ij}$$

- Thus, our SGD update rule becomes:

$$w_j^{(t+1)} = w_j^{(t)} + \alpha \cdot \delta_0 \cdot x_{ij}$$

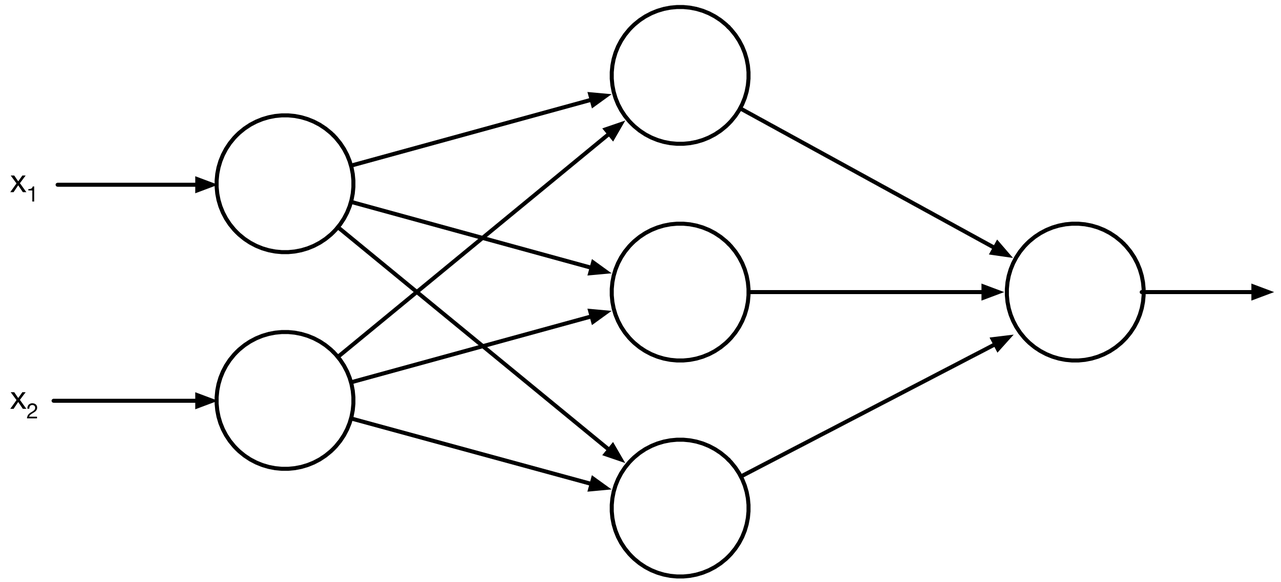
$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} + \alpha \cdot \delta_0 \cdot \mathbf{x}_i$$



  - Importantly, δ_0 is reused for every w_j, so we only have to compute it once for each t

learning complex separators

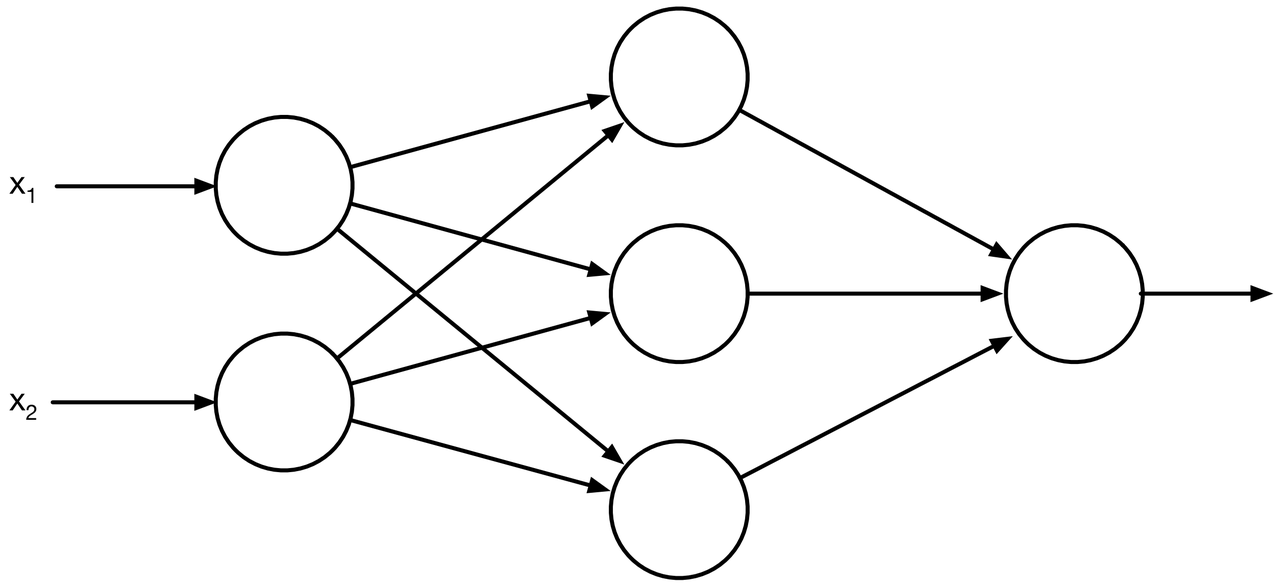
- So far we have only used one neuron (logistic regression)
- Let's build up to more complex models by cascading neurons
- "Running" the classifier is the same as before
  - Pass weighted sum of inputs through activation function, that output becomes the input to the next neuron
  - This is the **inference** stage
- The **training** stage of learning the weights is a little trickier, but not by much!



learning complex separators

- Learning the weights of the edges to the output neuron is easy — same as learning for a single neuron

- But what about the weights on the inputs to the hidden layer?



updating the deltas

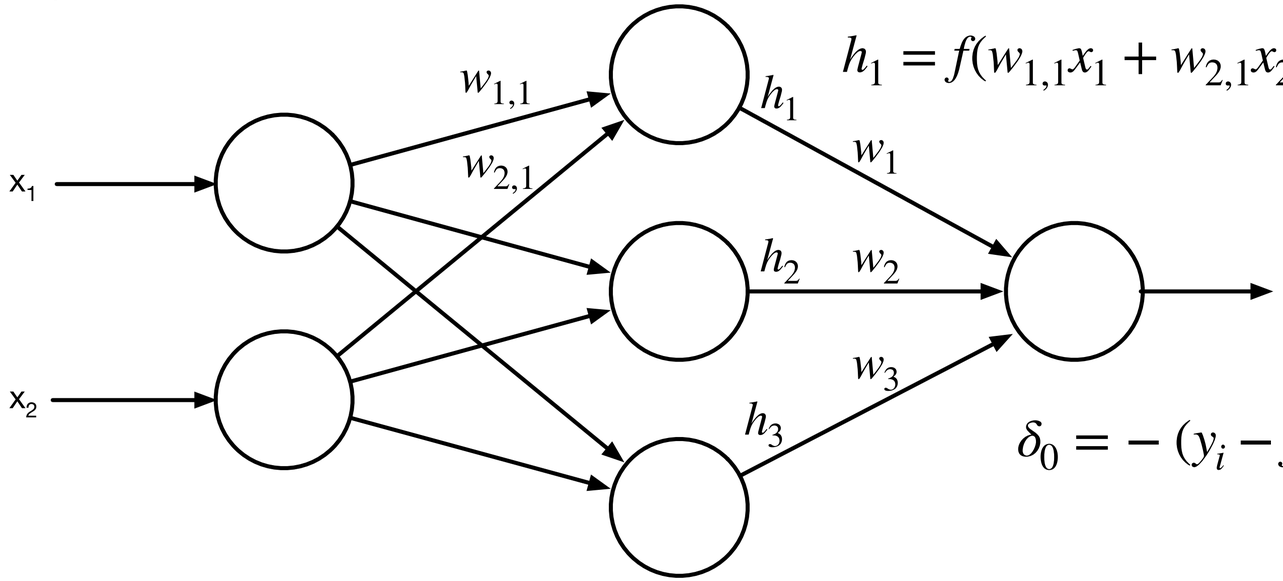
- Consider the network below. The output of this hidden layer is a vector $\mathbf{h}$. We can write the error of the network as:

$$E(\mathbf{w}) = \frac{1}{2}(y_i - f(w_1 h_1 + w_2 h_2 + w_3 h_3))^2 = \frac{1}{2}(y_i - f(w_1 f(w_{1,1} x_1 + w_{2,1} x_2) + w_2 h_2 + w_3 h_3))^2$$

- The change in output error with respect to $w_{1,1}$ is:

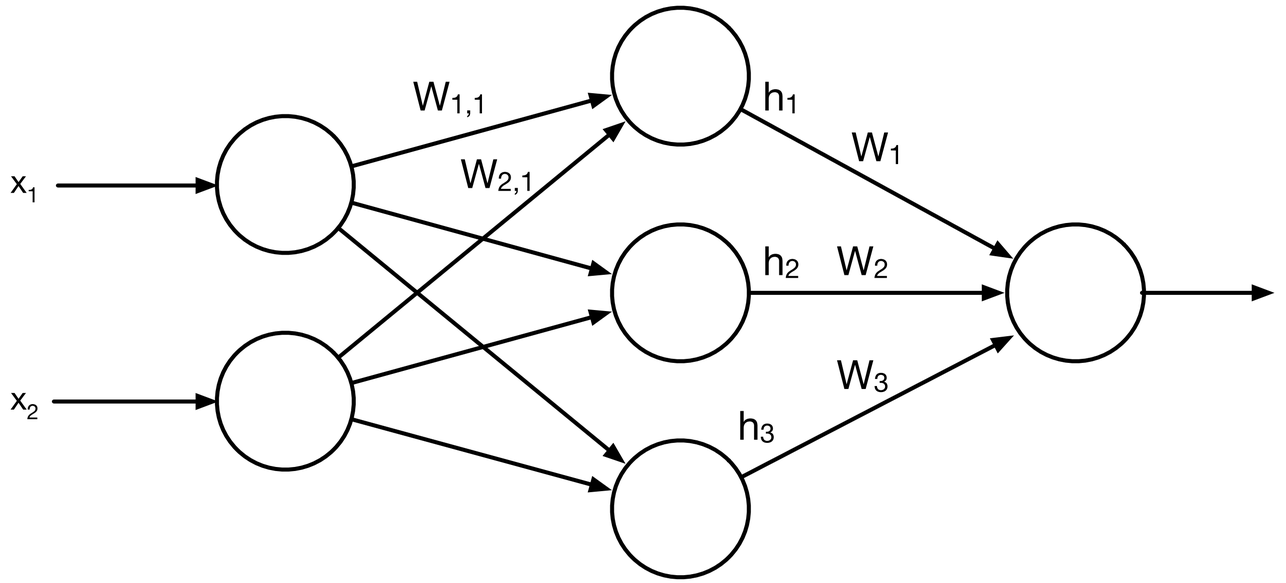
$$\frac{\partial E}{\partial w_{1,1}} = \frac{\partial E}{\partial h_1} \cdot \frac{\partial h_1}{\partial sum_{h_1}} \cdot \frac{\partial\, sum_{h_1}}{\partial w_{1,1}} = -\delta_0 w_1 \cdot f'(sum_{h_1}) \cdot x_1 = -\delta_{h_1} \cdot x_1$$

this term has the same form as what we derived for a single neuron previously



essence of backpropagation

- Computing the gradient for each neuron gives us the delta ($\delta_0, \delta_{h_1}, \ldots$) for the “upstream” neurons, so we can keep pushing error back
- This gives us the essence of **backpropagation** for training neural networks
  - **Forward pass**: Compute outputs of each neuron
  - **Backward pass**: Push errors (deltas, $\delta_0, \delta_{h_1}, \ldots$) weighted by edges to compute how the weights change.
  - Update: Apply stochastic gradient descent to each weight. Repeat.

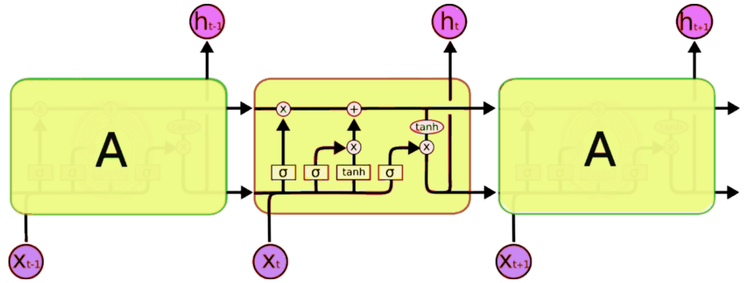


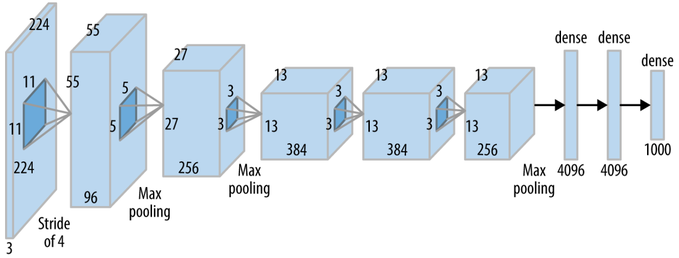
automatic differentiation

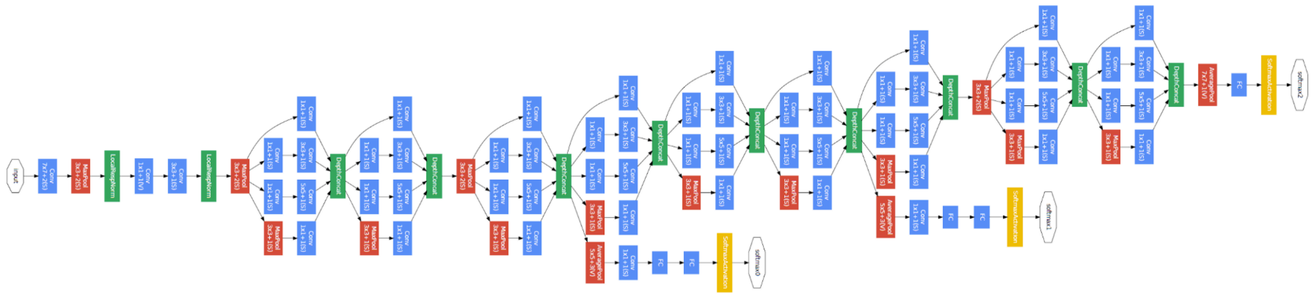
- In the past, the gradients for every model were computed by hand
- Recently, everyone has started to use **automatic differentiation**
  - Actually, the idea has been around for a long time (and our own Prof. Jeffrey Siskind worked on this many years ago)
  - Only recently popularized in the software packages **TensorFlow** (Google) and **PyTorch** (Facebook)
- Importantly, this enables *model definition* and *learning algorithm* to be **decoupled**
  - Define your model however you want, just like writing a program, then use automatic differentiation to automatically learn the model

TensorFlow

PyTorch







implementing neural networks

- sklearn now has a built in MLP module:

```
from sklearn.neural_network import MLPClassifier

mlp = MLPClassifier(hidden_layer_sizes=(13,13,13),max_iter=500)
```

- For more complex neural networks, we typically leverage other machine learning libraries/platforms:
  - pytorch (https://pytorch.org/)
  - tensorflow (https://www.tensorflow.org/)
  - Both have Python interfaces

TensorFlow

PyTorch

deep learning training

- With deep learning, we have non-linear (and non-convex) error functions
- Therefore SGD is not guaranteed to converge to the global optimum solution
- A lot of research is devoted to …
  - Speeding up backpropagation, with methods like the Adam optimizer, or by distributing training across many nodes
  - Finding conditions for global solutions in neural networks