Neural Networks

Date: 4^{th} march

Reminder: Programming Assignment Due Friday

Give Quiz NN

Allows model to have more flexibility

Why note work with a thresholded perceptron? $\rightarrow$ Not differentiable

Gradient: Implement Multiperceptron Python.

Programming Assignment 2: Real World Problem and use Neural Network.

$$ w_1.x_1 + w_2.x_2 + w_3.x_3... = w^Tx \rightarrow y$$

stack units, all similar to each other. $ \rightarrow $ layer

Each can get many inputs, but one output (For now)

stack layers to create an architecture. One output layer. If Regression - one output If Classification - number of classes output

1. Number of units in a layer $\rightarrow$ width of the layer

Just having linear units is not enough, we want to have non-linearity.

So change our unit. Instead of linear unit, we use a non-linear unit.

$$ w_1.x_1 + w_2.x_2 + w_3.x_3... = w^Tx \rightarrow y \sum x_i.w_i \rightarrow activation function (f) $$

Activation Function

1. Sigmoid Function

$$ f(z) = \frac{1}{1 + \exp(-z)}$$

2. tanh unit:

$$ f(z) = \frac{\exp(z) - \exp(-z)}{\exp(z) + \exp(-z)} $$

3. RELU Unit: Rectified Linear Unit

$$ f(z) = max(0,z) $$

Different layers can have different activation functions.

Multi-Layered Perceptron (MLP) - K-way classification

$x \in R^4$

Input Layer | Hidden Layer | Output Layer

Lets say you have trained neural network

Every layer, every unit gets a bias. (Bias Signal)

Bias Term: *Reason different from regression. It could happen our inputs might not be enough to produce an output.*

Other end n outputs

One of those outputs will be highest.

Note: These outputs will not sum up to one. Caliberate the output to probabilities by normalization and softmax

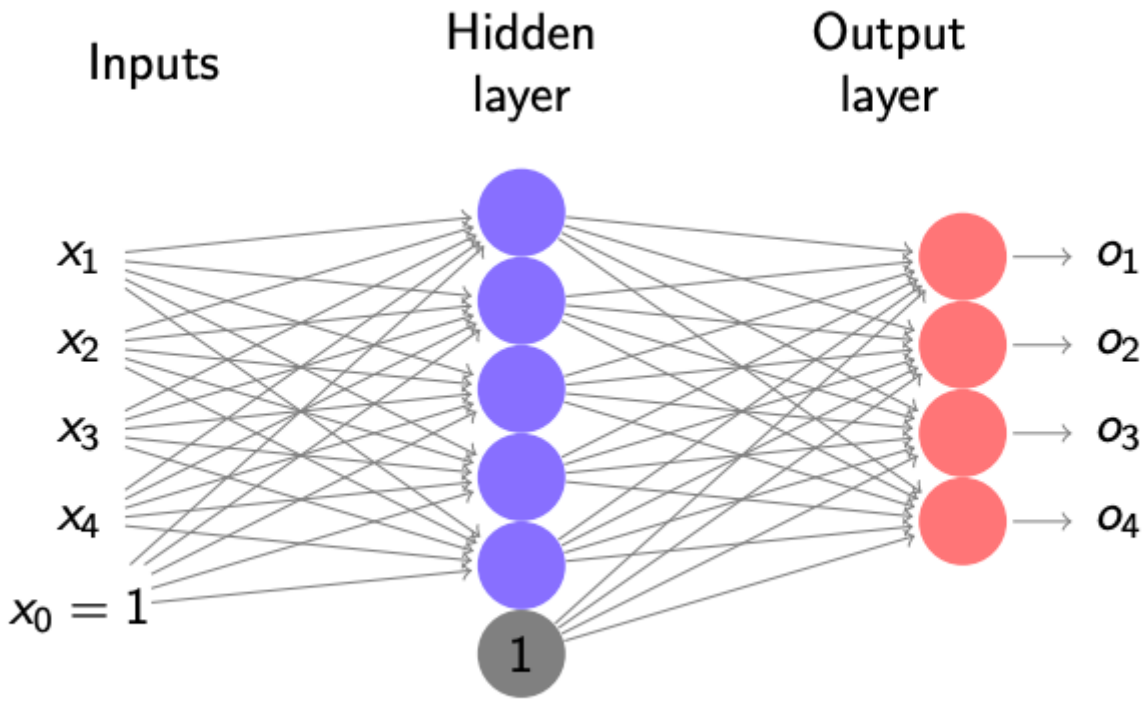
Let $x \in R^2$

$z_1 = \sigma(w_1^{(1)T}.x)$

$o_1 = w_1^{(1)T}.\left(\begin{array}{c} z_1\ z_2\ 1 \end{array}\right) $

Activation Output of a unit

Note: Neural networks are called as universal approximator.



Dimensionality **Turn off some layers**

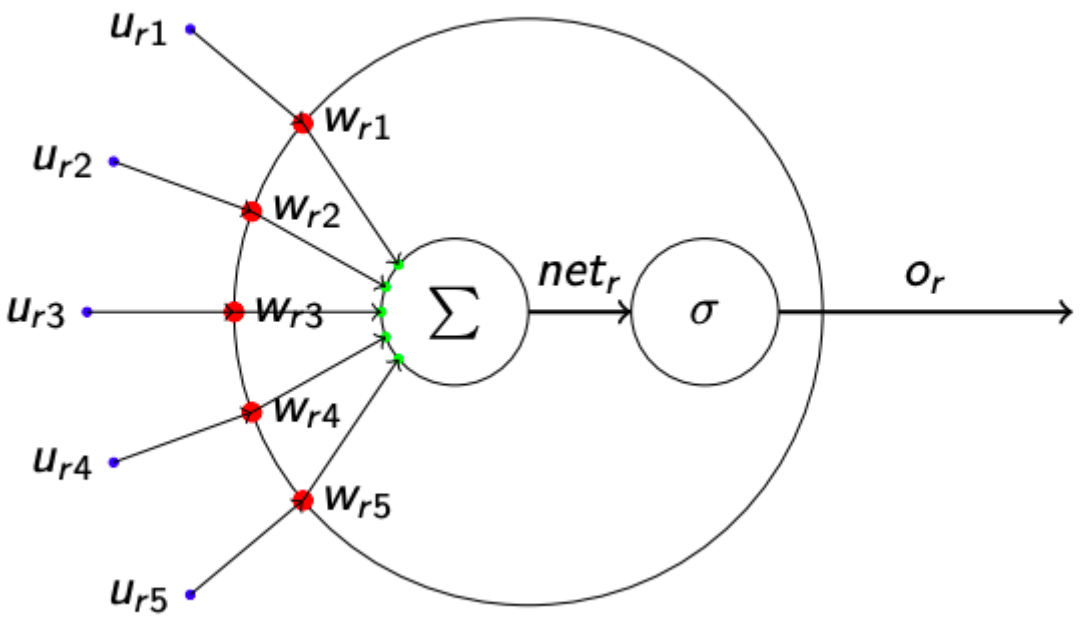
Effect of having too many layers.

How do we train a network?

Take some X $(x_1, x_2 ...)$ **Gradient Descent**

Error is computed after output layer. Relate that error downstream weights.

1. First calculate error at output
2. Use that to calculate GD back. **(Back Propagation)**



compute $W_T.x \rightarrow Y$

Some $x \rightarrow \left(\begin{array}{c} 1\ x_1\ x_2\ x_3\ \end{array}\right)$

Intialize the weight vector:

$$ L(w) = \frac{1}{2}. (y - w^T.x)^2$$

$$ \frac{d}{d w_0}L(w) = -2(y-w^Tx)$$

$$ \frac{d}{d w_1}L(w) = -2(y-w^Tx).x_1$$

New weight:

$$ w_0 = w_0 - \mu \frac{d}{dw_0} L(w)$$ $$ w_0 = w_0 - \mu (-(y-w^T.x))$$ $$ w_1 = w_1 - \mu (-(y-w^T.x).x_1)$$

In MLP, at each unit, find error using back propagation and multiply it with output...