Artificial Neural Networks

Gain an understanding of the structure and background of ANN

Gain an understanding of components and mechanism that enable Learning in a ANN

Gain an understanding of Different Deep Learning Models

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Lecture Content

What is an Artificial Neural Network

Structure and Components of a ANN

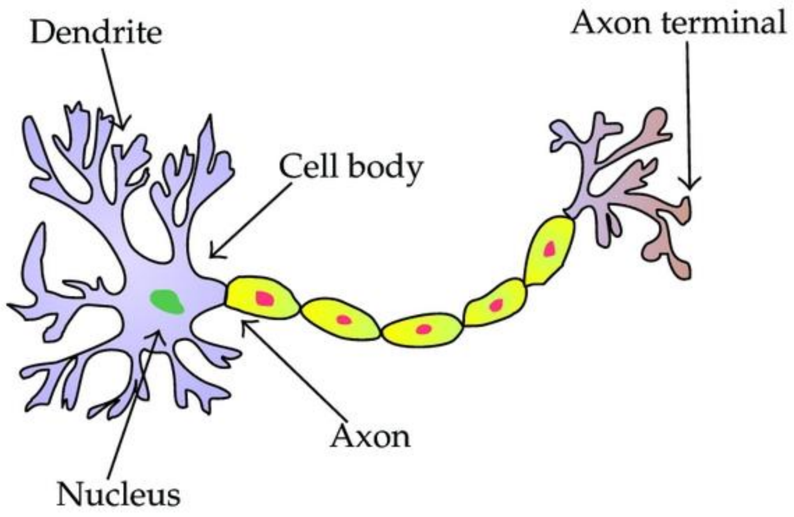
Forward Pass for Predicting Values

Why we need Activation Functions

Backward Pass

Biological Inspiration

- They were inspired by the Biological Neural Networks that makes up our Brains.
- Functionality is very similar
- But the inner mechanism has many differences



Mathematical Intuition

- Let us take a real-world example:
  - You go on shopping for a new Laptop. What are the factors you base your decision on?
    - The Price (x_P)
    - Is it better than the Current Phone. (x_b)
    - Is the merchant reliable. (x_r)
  - How do we make the Decision?
  - Which conditions should we emphasize?

It’s Decision-Making Time

$$x_P \cdot w_1 + x_b \cdot w_2 + x_r \cdot w_3 = y$$

- If y > 5 ➔ buy
- If y<= ➔ Do not buy

Contribution of the Weights on the Decision

$$x_P \cdot w_1 + x_b \cdot w_2 + x_r \cdot w_3 = y$$

- If y > 5 ➔ buy
- If y<= ➔ Do not buy

- W1?
- W2?
- W3?

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We Don’t want to buy from an unreliable Merchant

$$x_P \cdot w_1 + x_b \cdot w_2 + x_r \cdot w_3 = y$$

- If y >= t ➔ buy(1)
- If y< t ➔ Do not buy (0)

- W1?
- W2?
- W3 ➔

Generalizing the Decision Statement

$$y = \begin{cases} 0, x_P \cdot w_1 + x_b \cdot w_2 + x_r \cdot w_3 < t \\ 1, x_P \cdot w_1 + x_b \cdot w_2 + x_r \cdot w_3 \geq t \end{cases}$$

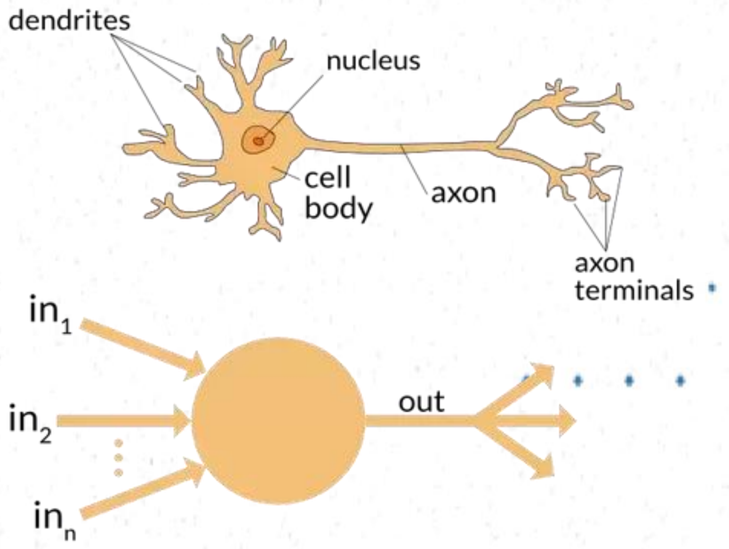
- Its easier to compute with vectors

$$y = \begin{cases} 0, x \cdot w < t \\ 1, x \cdot w \geq t \end{cases}$$

$$y = \begin{cases} 0, x \cdot w + b < 0 \\ 1, x \cdot w + b \geq 0 \end{cases}$$

A Perceptron

- Multiple inputs
- Corresponding weights
- Bias
- Single output



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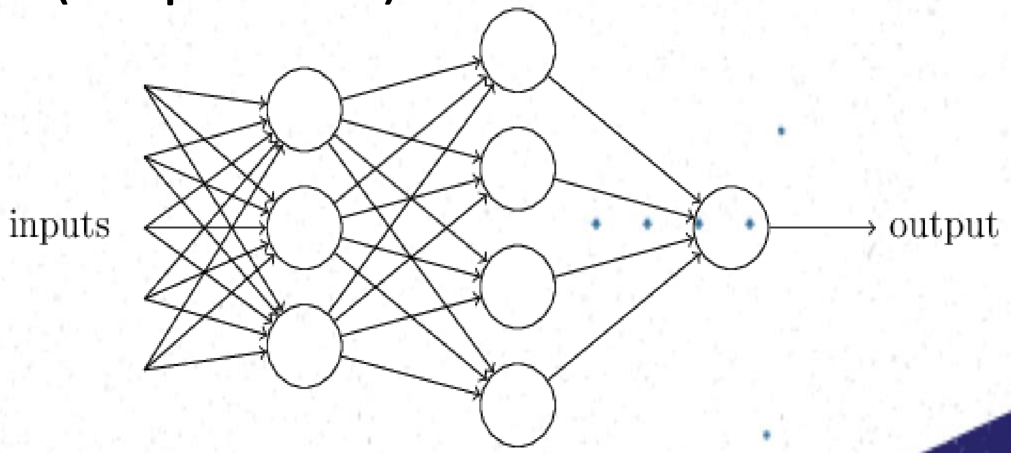
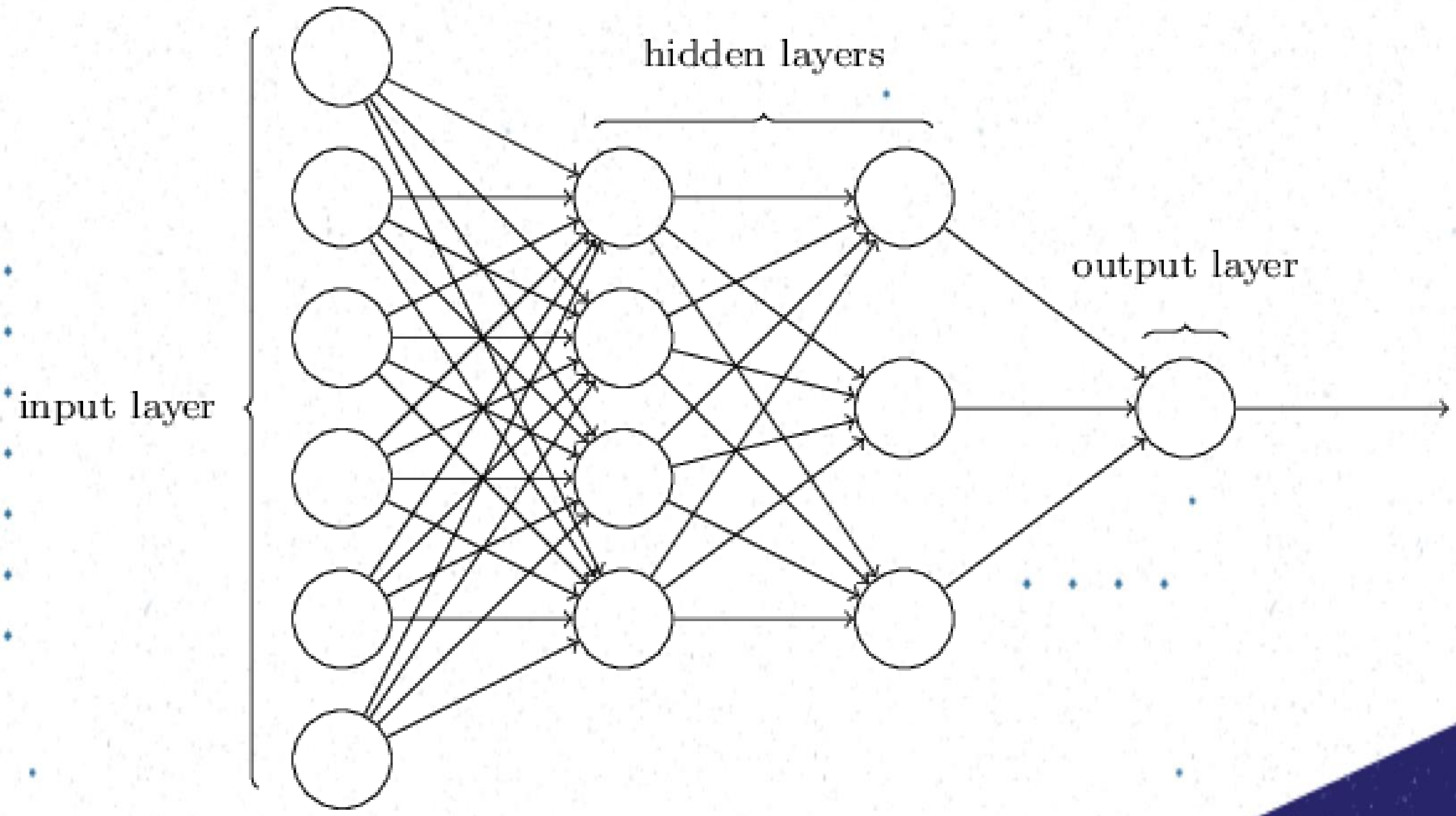
What is a Neural Network

- A Collection of Perceptron
- A Layer can be made by stacking a set of Perceptron to get the outputs from the previous layer or Inputs
- A network is a set of layers that are arranged in a organized manner (Sequential)



Structure of an ANN



ANN output vs Biological NN output

- Firing a Neuron
- 0 or 1

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More on Bias

- Bias = -Threshold value
- Use to shift the output value.

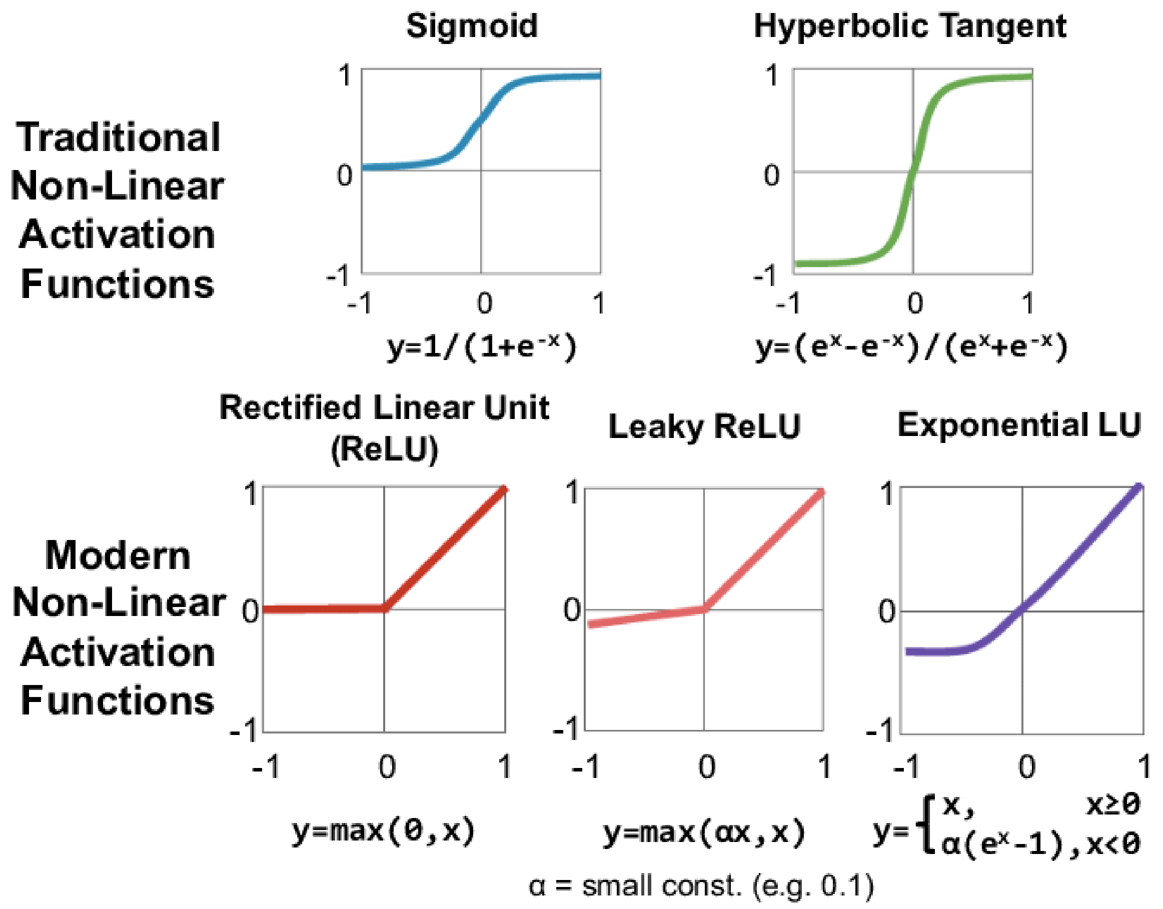
Activation Function

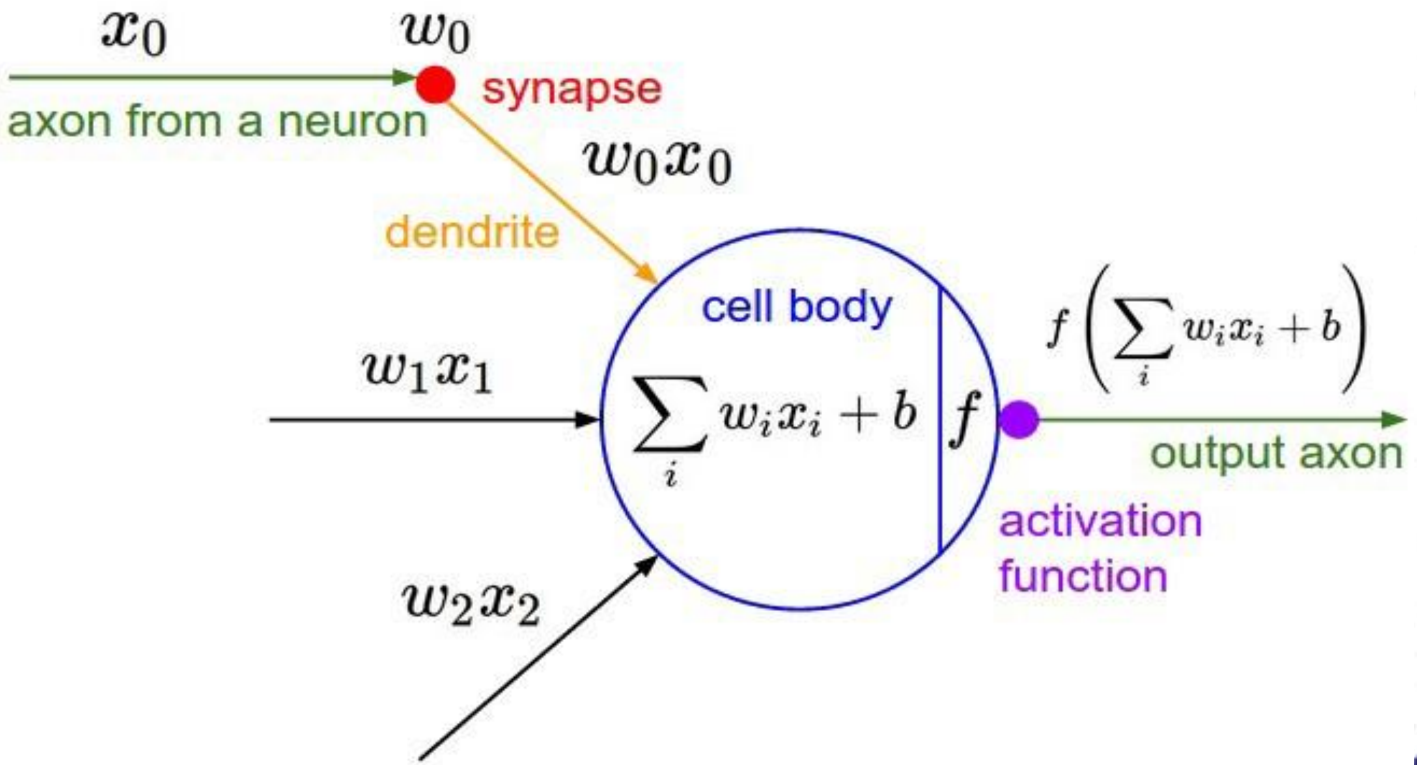
- Output of a Perceptron is binary
- This may not work all the time
- Linear output can be useful but will make it difficult to learn complex data
- We need a Non-Linear Continuous value ➔Activation Function.
- Normalize the values

How to Choose an Activation Function

- Any Function can be used as an Activation function if,
  - The function is continuous and differentiable everywhere (or almost everywhere).
  - The derivative of the function does not saturate (i.e., become very small, tending towards zero) over its expected input range. Very small derivatives tend to stall out the learning process.
  - The derivative does not explode (i.e., become very large, tending towards infinity), since this would lead to issues of numerical instability.)

Common Activation Functions




x_0
w_0
synapse
axon from a neuron
w_0x_0
dendrite
cell body
$\sum_i w_i x_i + b$
f
$f\left(\sum_i w_i x_i + b\right)$
w_1x_1
output axon
activation function
w_2x_2

Feed Forward Networks

- Most used type of ANN
- Signal Flow is uni-directional
- No signal loops.
  - MLP
  - CNN

In a Neural Network there are two functionalities. One is when we are learning, and the other one is when we are predicting the values.

When we use neural network for prediction, we use a 'Simple Forward Pass'. In this we have a 'bias', and 'all the different inputs' with the 'accompanying weights' and then able to easily compute the 'output' of the neuron or perceptron if know the activation function as well.

So, once we do a forward pass through all the difference perceptron, we would get an output. So that output computes the 'loss' of the forward pass. So, basically you are in a 'supervised learning approach', we have the label 'y' which is the 'actual value trying for the prediction', and 'y`' which is the value we get through the NN's prediction. When we get the difference between (y - y`), we able to obtain the loss value. There are several types of loss values.

$L = y - y'$

Which is direct loss like this. All though these loss functions are mostly similar to each other, there might be sudden differences, and they can be use based on what our data or labels look like or even we're going for a 'classification type' of a question or a 'regression type' of a question. So whole learning will be based on this loss function, so, whatever the value we compute through loss function as the loss will be used to update the 'weights' through the process called 'backpropagation'. So, what the NN trying to do through the learning process is to find the weight (w) and the bias (b) values for all the perceptrons such that it minimizes the loss function.

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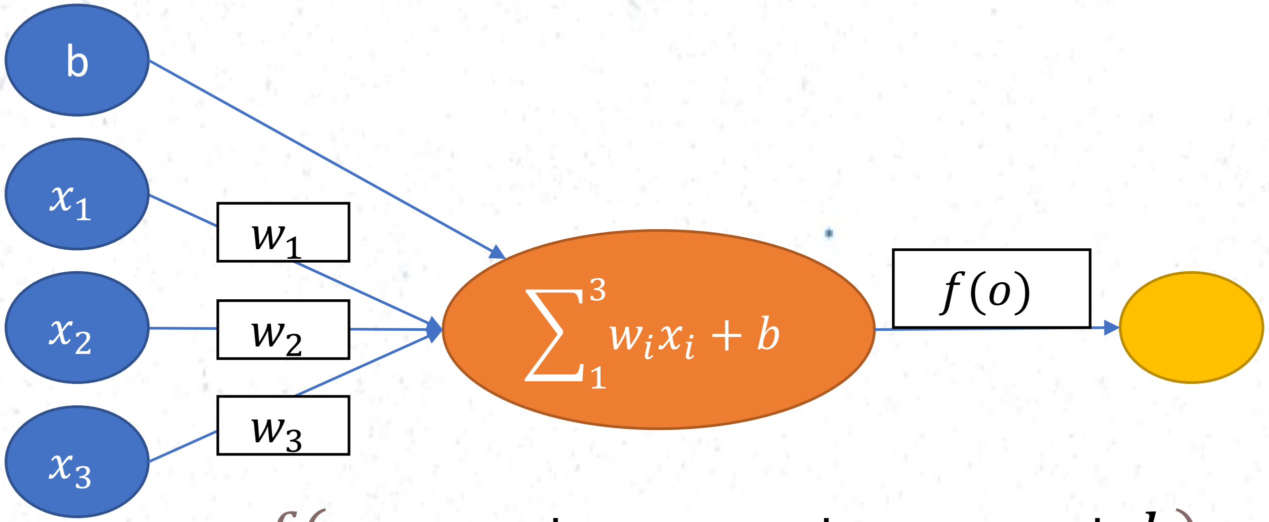
Forward Pass



$$y = f(x_1 \cdot w_1 + x_2 \cdot w_2 + x_3 \cdot w_3 + b)$$

$$y = f(x \cdot w + b)$$

$$w = [w_1 \;\; w_2 \;\; w_3 \;\; b\,]$$

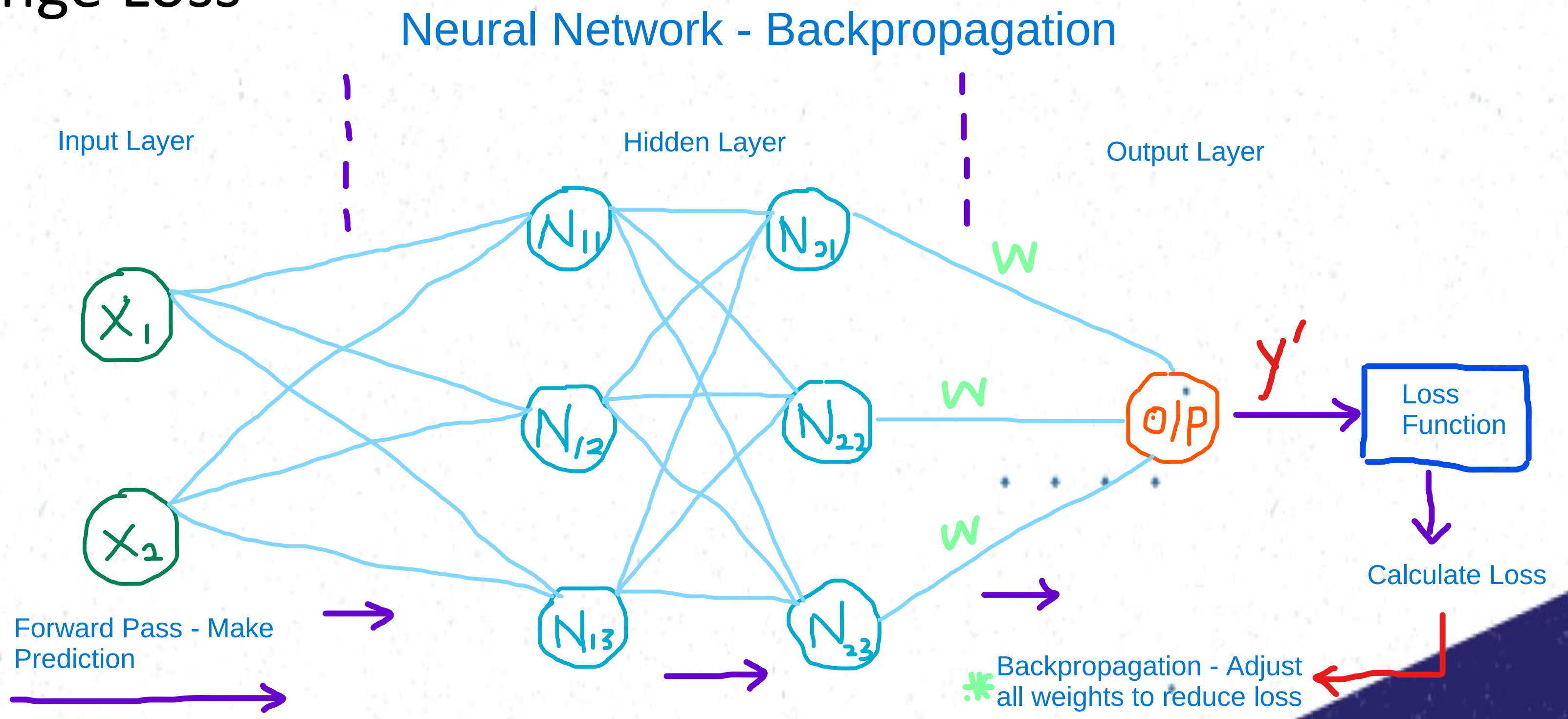
$$x = \begin{matrix} x_1 \\ x_2 \\ x_3 \\ 1 \end{matrix}$$

Loss Function (Cost)

- A measure of how well the network at Predicting the values.
- Notion of Learning is based on the Loss Function
- Goal of the Network is to find the w and b values such that the cost/loss is minimized.
- Number of Different Loss Functions are available

Different Loss Functions

- Mean Squared Error
- Hinge Loss



Computing Derivatives

$$
\begin{aligned}
\nabla w &= \frac{\partial}{\partial w}[\frac{1}{2} * (f(x) - y)^2] \\
&= \frac{1}{2} * [2 * (f(x) - y) * \frac{\partial}{\partial w}(f(x) - y)] \\
&= (f(x) - y) * \frac{\partial}{\partial w}(f(x)) \\
&= (f(x) - y) * \frac{\partial}{\partial w}\left(\frac{1}{1 + e^{-(wx+b)}}\right) \\
&= (f(x) - y) * f(x) * (1 - f(x)) * x
\end{aligned}
$$

$$
\begin{aligned}
&\frac{\partial}{\partial w}\left(\frac{1}{1 + e^{-(wx+b)}}\right) \\
&= \frac{-1}{(1 + e^{-(wx+b)})^2} \frac{\partial}{\partial w}(e^{-(wx+b)})) \\
&= \frac{-1}{(1 + e^{-(wx+b)})^2} * (e^{-(wx+b)}) \frac{\partial}{\partial w}(-(wx + b))) \\
&= \frac{-1}{(1 + e^{-(wx+b)})} * \frac{e^{-(wx+b)}}{(1 + e^{-(wx+b)})} * (-x) \\
&= \frac{1}{(1 + e^{-(wx+b)})} * \frac{e^{-(wx+b)}}{(1 + e^{-(wx+b)})} * (x) \\
&= f(x) * (1 - f(x)) * x
\end{aligned}
$$

Building Complete Neural Networks

- Stacking multiple Nerons to for a layer
- Organizing multiple Layers to form the network

Training a neural net

1. Randomly initialize weights
2. Implement forward propagation to get the output at each neuron
3. Compute the error at the output layer E_{total}
4. Implement backpropagation to compute partial derivatives $\frac{\partial E_{total}}{\partial w^{l}_{jk}}$
5. Use Gradient descent or any other optimization technique to update the weights to minimize E_{total}
6. Repeat this process over multiple iterations (epochs) until the error converges

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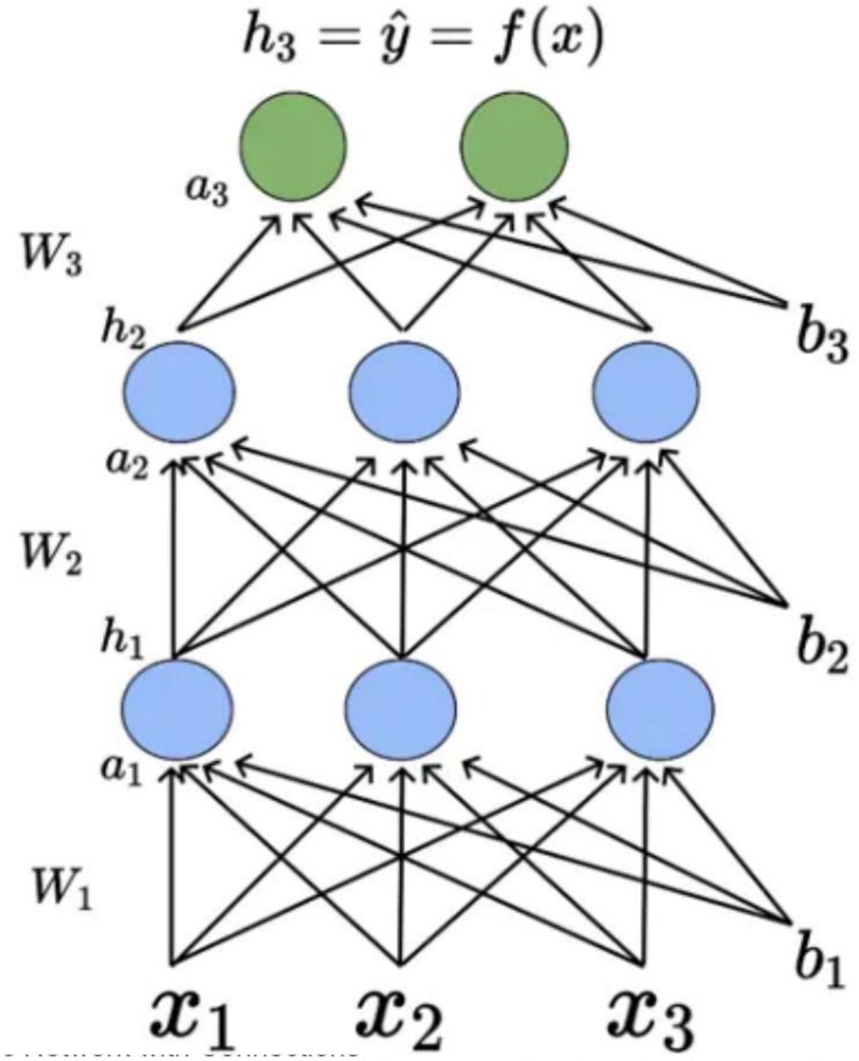
$h_3 = \hat{y} = f(x)$
a_3
W_3
h_2
b_3
a_2
W_2
h_1
b_2
a_1
W_1
b_1
x_1
x_2
x_3

Additional Reading

- book13.dvi (stanford.edu)

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When there are more hidden layers it will become a DNN. Each neuron in the hidden layer/s, will have an activation function once they do the sum of products, it will add the bias and then pass the value through the activation function which will give out the exact output signal. That will propagate to the next layer.

Multi-Layer Perceptron

Feedforward NN - this means information is just flowing in one-single direction, there is no information flow or feedback loops that humming from a layer in front of or a layer behind.

feedfoward

- MLP is a type of neural network that consists of multiple layers of neurons, including an input layer, one or more hidden layers, and an output layer.
- Each neuron in the hidden layers uses an activation function to transform the input signal into an output signal, which is then passed on to the next layer.
- MLP is a feedforward network, which means that information flows in only one direction, from the input layer to the output layer.

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Applications of MLP

- MLP can be used for a variety of tasks, including classification, regression, and prediction.
- MLP has been used for image classification, speech recognition, and natural language processing.
- MLP is particularly useful for tasks where there are complex relationships between the input and output variables.

Predicting linear and non-linear values: for an example if use 'California House Price Prediction' dataset we can use MLP for this.
Classification: classifying different customers into different levels or stages

Convolutional Neural Networks

- CNN is a type of neural network that is particularly well-suited for image and video processing tasks.

Because they are built in a way to handle large metrics like data effectively.

- CNN uses convolutional layers to extract features from images and reduce the dimensionality of the input data.
- The output from the convolutional layers is then passed through one or more fully connected layers to produce the final output.

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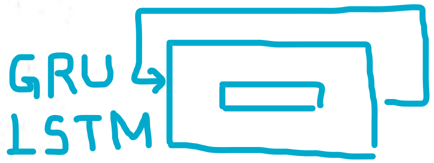
Applications of CNN

- CNN has been used for a variety of image and video processing tasks, including image classification, object detection, and segmentation.
- CNN has also been used in natural language processing tasks, such as text classification and sentiment analysis.
- CNN is particularly useful for tasks where the input data has a grid-like structure, such as images or videos.

The reason is RNN, for an example if we take different types of RNNs (GRU, LSTM, etc.,), if we take like GRU this has the mechanism where, they take the inputs and they have a small cell or place where they keep track of previous inputs, they do all the computations and send the computed values along with the next input into the model. There is a feedback loop here, so, that not exactly directly a feedforward type of a NN.

Recurrent Neural Networks



- RNN is a type of neural network that is particularly well-suited for sequence data, such as time-series data or natural language processing.(NLP)
- RNN uses feedback connections to allow information to be passed from one step in the sequence to the next.
- RNN can be trained using backpropagation through time, which is a variant of the standard backpropagation algorithm.

So likewise, RNNs similar to other feedforward NNs trained through backpropagation, but this time it called as 'backpropagation through time', because we have to count for the previous feedback loop as well.

Applications of RNN

- RNN has been used for a variety of sequence data tasks, including speech recognition, machine translation, and sentiment analysis.
- RNN can also be used for time-series forecasting
- RNN is particularly useful for tasks where the output at each step depends on the previous steps in the sequence.

Generative Adversarial Neural Networks

- GAN is a type of neural network that is used for generative tasks, such as image or text generation.
- GAN consists of two neural networks: a generator network and a discriminator network.
- The generator network generates new data samples, while the discriminator network evaluates the generated samples and tries to distinguish them from real data samples.

Applications of GAN

- GAN has been used for a variety of generative tasks, including image generation, text generation, and music generation.
- GAN can also be used for data augmentation, where it is used to generate new data samples to augment an existing dataset.
- GAN is particularly useful for tasks where the output needs to be highly realistic and similar to the input data.

Transformer's attention mechanism has basically main three parts. Value (V), Query (Q), and a Key (K). These are 3 vectors that we are trying to optimize. So, there are some sort of input sequence and all the inputs we broken down into different tokens and each token is embedding into set of numbers. So, each embedded value will be fed into query and key separately and the query and key separately try to identify the similarities or association between each one of the tokens within the set of inputs.

Transformers

Transformers are capable of retaining the memory of long time ago like an example they have several time longer memory times retaining capacity than RNNs. That is why transformers began to replace RNNs in applications like text generation.

- Transformers are a type of neural network architecture that were introduced in 2017 for natural language processing tasks.
- Transformers are based on a self-attention mechanism that allows the model to focus on different parts of the input sequence when processing each token.
- Unlike RNNs, Transformers can process the entire input sequence in parallel, making them much faster and more efficient for long sequences.

Applications of Tranformers

- Transformers have been used for a variety of natural language processing tasks, such as language translation, question answering, and text summarization.
- Transformers are particularly useful for tasks where the input and output sequences can have variable lengths, and where long-range dependencies are important.
- Transformers have also been applied to non-language tasks, such as image processing and music generation.

Generative Pre-Trained Transformers

- GPT models are a family of transformer-based neural networks that are designed for generative tasks, such as text generation.
- GPT models are pre-trained on large amounts of text data, and then fine-tuned on specific downstream tasks.
- GPT models use a left-to-right autoregressive language modeling objective, where the model predicts the next word in a sequence based on the previous words.