NEURAL NETWORK (PCC-CSE-401G)

UNIT 1

Overview of biological neurons: Structure of biological neuron, neurobiological analogy, Biological neuron equivalencies to artificial neuron model, Evolution of neural network.

Activation Functions: Threshold functions, Signum function, Sigmoid function, Tan-hyperbolic function, Stochastic function, Ramp function, , Linear function, Identity function.

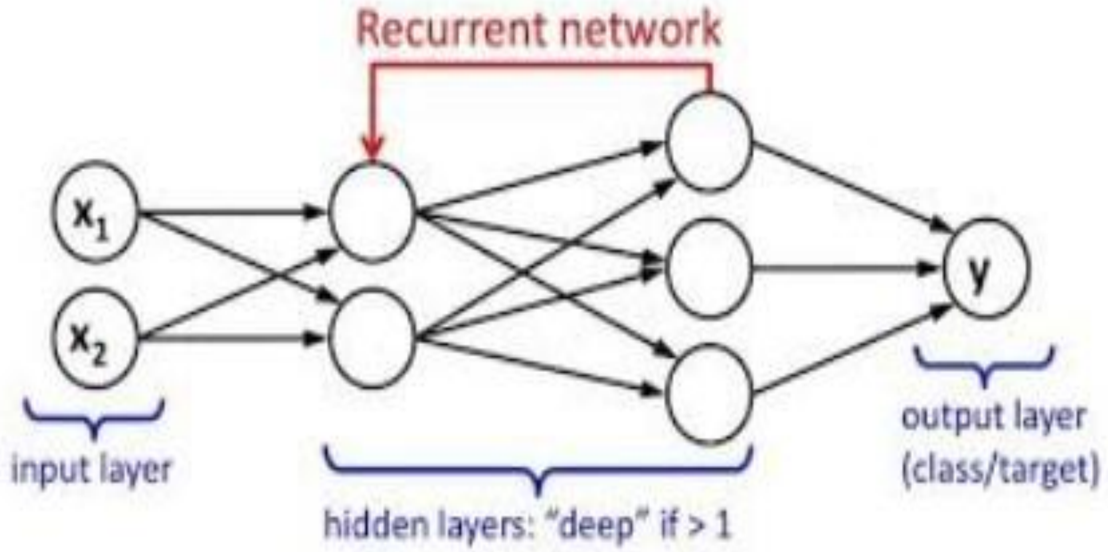
ANN Architecture: Feed forward network, Feed backward network, single and multilayer network, fully recurrent network,

Course Objectives:

1. To understand the different issues involved in the design and implementation of a Neural Networks.
2. To study the basic of neural network and its activation functions.
3. To understand and use of perceptron and its application in real world
4. To develop an understanding of essential NN concepts such as: learning, feed forward and feed backward
5. To design and build a simple NN model to solve a problem

What is a Recurrent Neural Network?

A Recurrent Neural Network is a type of neural network that contains loops, allowing information to be stored within the network. In short, Recurrent Neural Networks use their reasoning from previous experiences to inform the upcoming events. Recurrent models are valuable in their ability to sequence vectors, which opens up the API to performing more complicated tasks.



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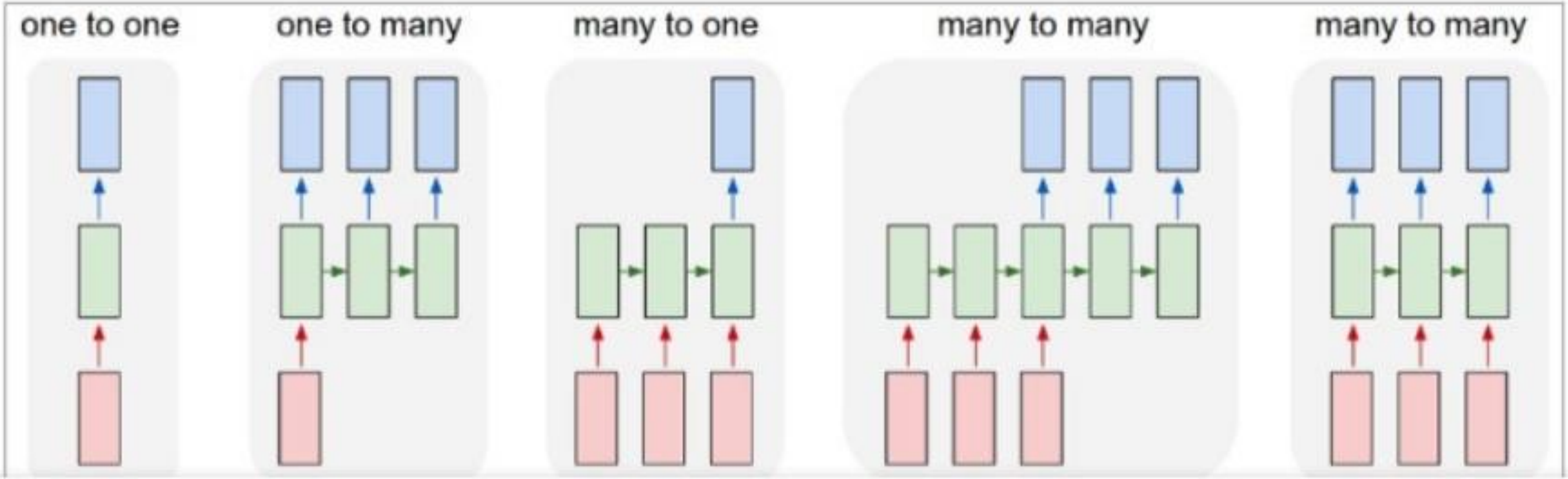
How do Recurrent Neural Networks work?

Recurrent Neural Networks can be thought of as a series of networks linked together. They often have a chain-like architecture, making them applicable for tasks such as speech recognition, language translation, etc. An RNN can be designed to operate across sequences of vectors in the input, output, or both. For example, a sequenced input may take a sentence as an input and output a positive or negative sentiment value. Alternatively, a sequenced output may take an image as an input, and produce a sentence as an output.



Let's imagine training a RNN to the word "happy," given the letters "h, a, p, y." The RNN will be trained on four separate examples, each corresponding to the likelihood that letters will fall into a intended sequence. For example, the network will be trained to understand the probability that the letter "a" should follow in the context of "h." Similarly, the letter "p" should appear after sequences of "ha." Again, a probability will be calculated for the letter "p" following the sequence "hap." The process will continue until probabilities are calculated to determine the likelihood of letters falling into the intended sequence. So, as the network receives each input, it will determine the probabilit of the subsequent letter based on the probability of the previous letter or sequence. Over time, the network can be updated to more accurately produce results.

Recurrent Neural Network Applications

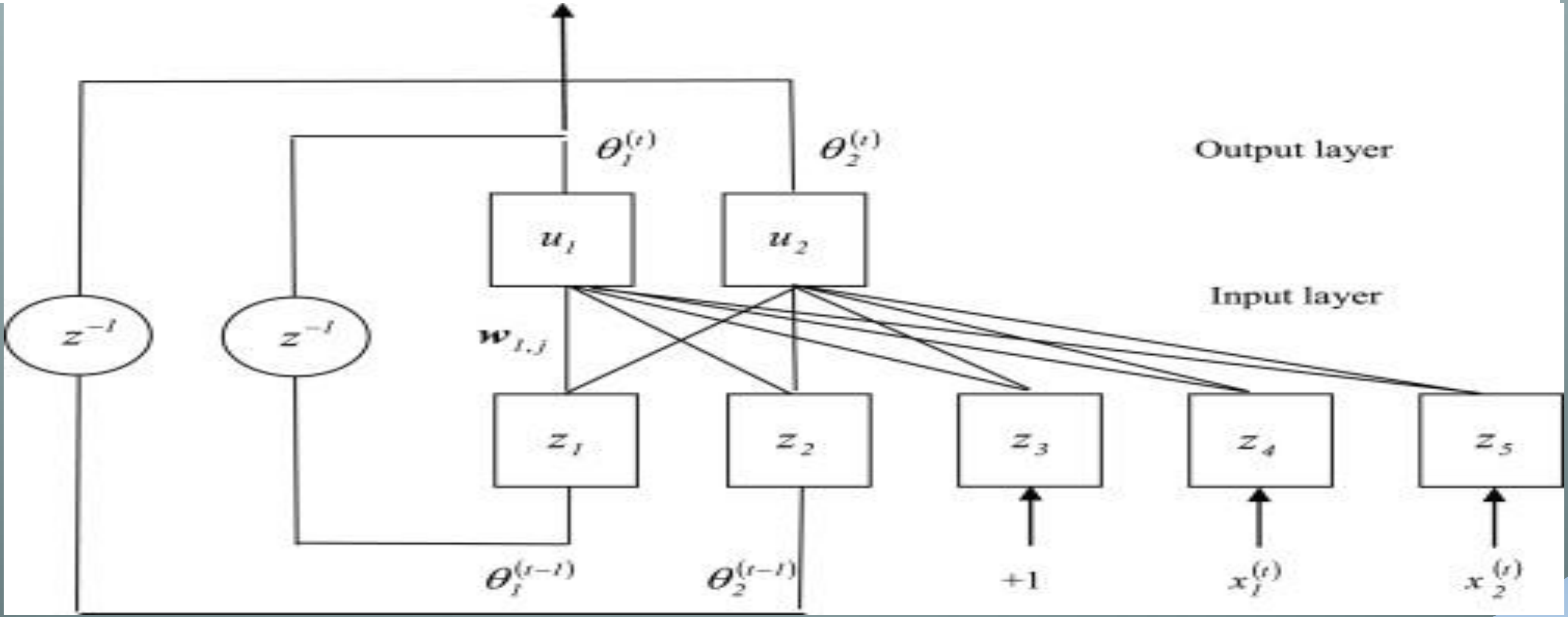
A common example of Recurrent Neural Networks is machine translation. For example, a neural network may take an input sentence in Spanish and translate it into a sentence in English. The network determines the likelihood of each word in the output sentence based upon the word itsel and the previous output sequence.

Recurrent Neural Networks- Introduction

Recurrent neural networks are not a too old neural network, they were developed in the 1980s.

- RNNs takes input as time series and provide an output as time series,
- They have at least one connection cycle.

One of the biggest uniqueness RNNs have is **"UAP- Universal Approximation Property"** thus they can approximate virtually any dynamical system. This unique property forces us to say recurrent neural networks have something magical about them.



Real life examples – Recurrent Neural Networks

When we deal with RNNs they show excellent and dynamic ability to deal with various input and output types. Before we go deeper let's have below real-life examples.

- **Varying Inputs & Fixed Outputs** – Speech, text recognition & sentiment classification – In today's time this can be the biggest relief for a bomb like social media to kick out negative comments. People who like to give only negative comments for anything and everything rather than helping as they have one motive PHD (Pull him/her down) someone's efforts. Classifying tweets/FB comments into positive and negative sentiment becomes easy here. Inputs with varying lengths, while the output is of a fixed length.
- **Fixed Inputs & Varying Outputs** – Image recognition (Captioning) – This is to describe the content in an image. Images as a single input but caption can be series or sequence of words as output. Kid riding bike, children playing park, young girls playing football or two girls dancing etc.
- **Varying Inputs & Varying Outputs** – Machine Translation – Language translation: Translating one language to another can be a tedious task for humans is done word by word from the dictionary but thanks for this amazing tool from google online translation to full text. This tool is so powerful which takes care of sentiments in each language, length and meanings with context. This is the case of varying inputs as well as varying outputs.

As seen above cases RNNs are used for mapping inputs to outputs of varying types, lengths. The underlying foundation for RNNs are always generalised in their application

THANKS