Neural Networks in Deep Learning

1. Machine Learning vs. Deep Learning

Two key reasons why researchers and experts tend to prefer Deep Learning over Machine Learning:

- Decision Boundary
- Feature Engineering

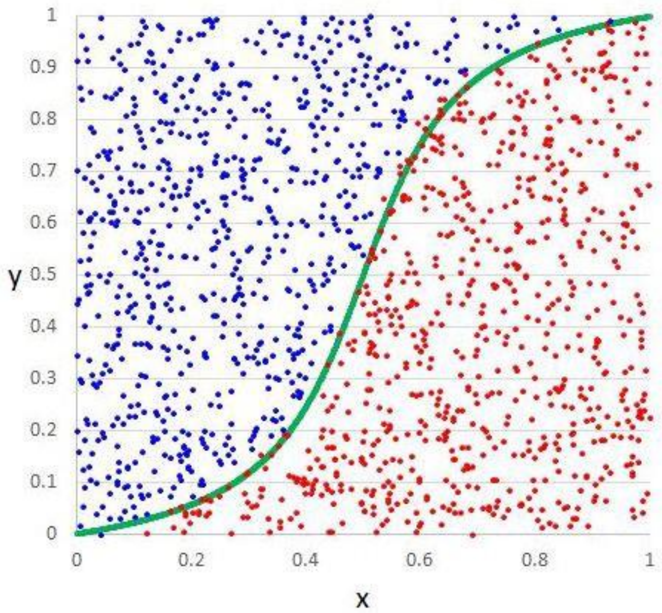
Decision Boundary

Every Machine Learning algorithm learns the mapping from an input to output. In other words, the parametric algorithm learns a function with a few sets of weights

Input -> f(w1,w2…..wn) -> Output

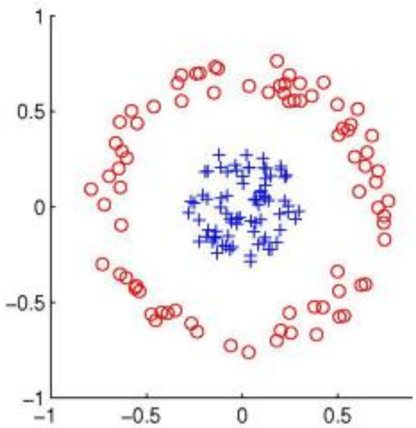
In the case of classification problems, the algorithm learns the function that separates 2 classes — this is known as a **Decision boundary**. A decision boundary helps us in determining whether a given data point belongs to a positive class or a negative class.

For example, in the case of logistic regression, the learning function is a Sigmoid function that tries to separate the 2 classes:



Decision boundary of logistic regression

As you can see here, the logistic regression algorithm learns the linear decision boundary. It cannot learn decision boundaries for nonlinear data like this one:



Nonlinear data

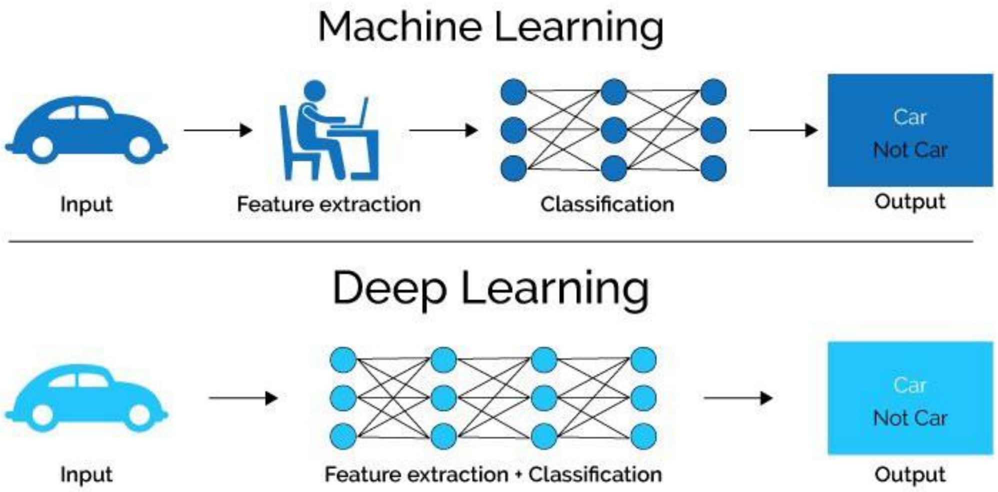
Similarly, every Machine Learning algorithm is not capable of learning all the functions. This limits the problems these algorithms can solve that involve a complex relationship.

Feature Engineering

Feature engineering is a key step in the model building process. It is a two-step process:

In feature extraction, we extract all the required features for our problem statement and in feature selection, we select the important features that improve the performance of our machine learning or deep learning model.

Consider an image classification problem. Extracting features manually from an image needs strong knowledge of the subject as well as the domain. It is an extremely time-consuming process. Thanks to Deep Learning, we can automate the process of Feature Engineering!



Comparison between Machine Learning & Deep Learning

Now that we understand the importance of deep learning and why it transcends traditional machine learning algorithms, let's get into the crux of this article. We will discuss the different types of neural networks that you will work with to solve deep learning problems.

2. Different types of Neural Networks in Deep Learning

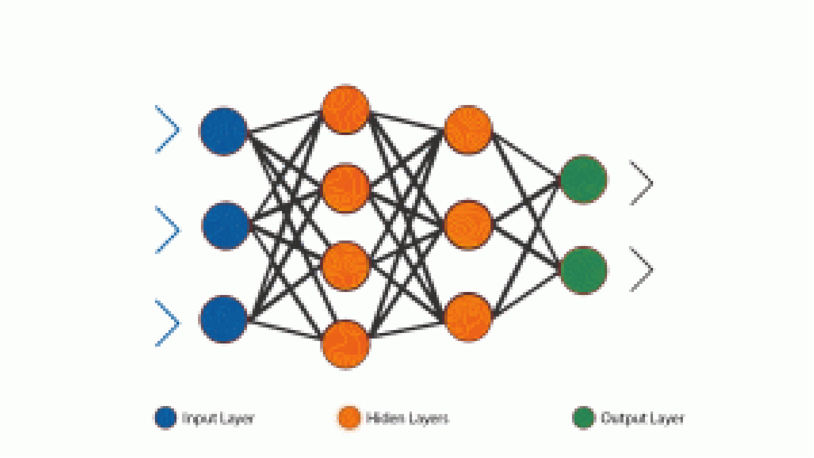
This article focuses on three important types of neural networks that form the basis for most pre-trained models in deep learning:

- Artificial Neural Networks (ANN)
- Convolution Neural Networks (CNN)
- Recurrent Neural Networks (RNN)

Let's discuss each neural network in detail.

2.1. Artificial Neural Network (ANN)

A single perceptron (or neuron) can be imagined as a Logistic Regression. Artificial Neural Network, or ANN, is a group of multiple perceptrons/ neurons at each layer. ANN is also known as a **Feed-Forward Neural network** because inputs are processed only in the forward direction:



ANN

As you can see here, ANN consists of 3 layers — Input, Hidden and Output. The input layer accepts the inputs, the hidden layer processes the inputs, and the output layer produces the result. Essentially, each layer tries to learn certain weights.

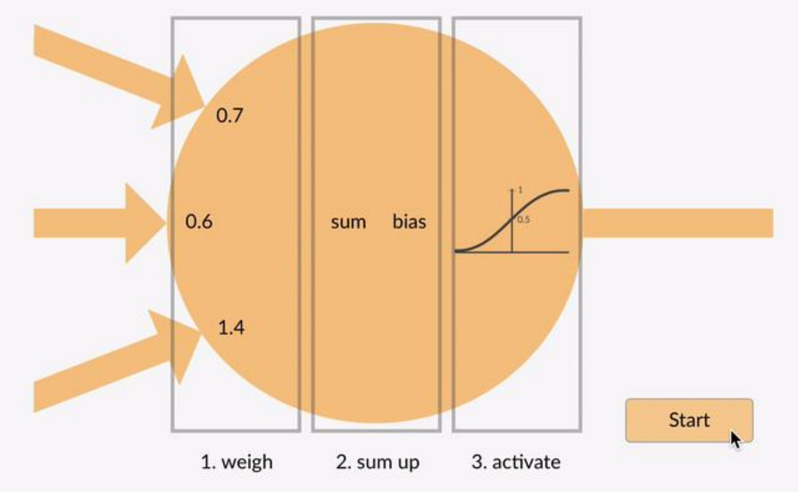
ANNs can be used to solve problems related to:

- Tabular data
- Image data
- Text data

Advantages of Artificial Neural Network (ANN)

Artificial Neural Network is capable of learning any nonlinear function. Hence, these networks are popularly known as **Universal Function Approximators**. ANNs have the capacity to learn weights that map any input to the output.

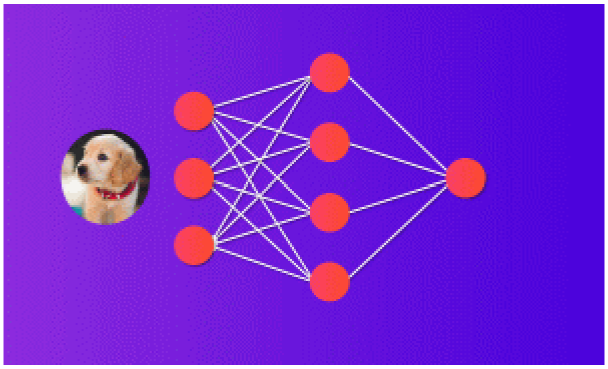
One of the main reasons behind universal approximation is the **activation function**. Activation functions introduce nonlinear properties to the network. This helps the network learn any complex relationship between input and output.



Challenges with Artificial Neural Network (ANN)

1. While solving an image classification problem using ANN, the first step is to convert a 2-dimensional image into a 1-dimensional vector prior to training the model. This has two drawbacks:

- The number of trainable parameters increases drastically with an increase in the size of the image

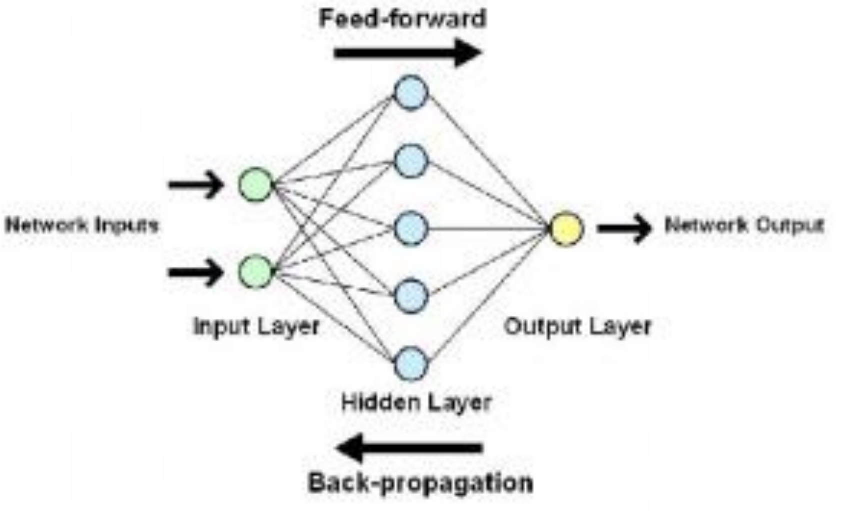


ANN: Image classification

In the above scenario, if the size of the image is 224*224, then the number of trainable parameters at the first hidden layer with just 4 neurons is 602,112. That’s huge!

2. ANN loses the spatial features of an image. Spatial features refer to the arrangement of the pixels in an image. I will touch upon this in detail in the following sections

3. One common problem in all these neural networks is the **Vanishing and Exploding Gradient**. This problem is associated with the **back propagation** algorithm. The weights of a neural network are updated through this back propagation algorithm by finding the gradients:



Backward Propagation

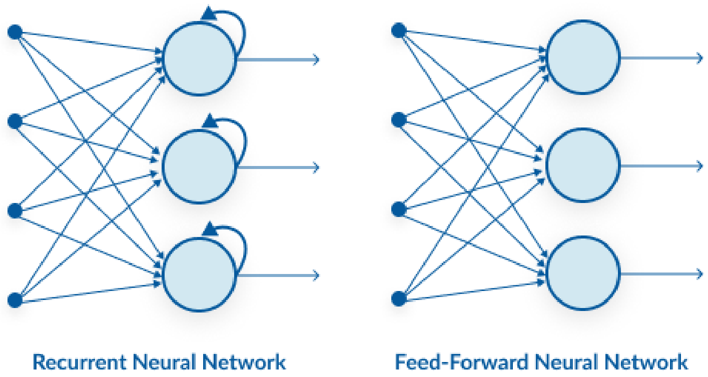
So, in the case of a very deep neural network (network with a large number of hidden layers), the gradient vanishes or explodes as it propagates backward which leads to vanishing and exploding gradient.

Now, let us see how to overcome the limitations of ANN using two different architectures — Recurrent Neural Networks (RNN) and Convolution Neural Networks (CNN).

2.2. Recurrent Neural Network (RNN)

Let us first try to understand the difference between an RNN and an ANN from the architecture perspective:

A looping constraint on the hidden layer of ANN turns to RNN.



As you can see here, RNN has a recurrent connection on the hidden state. This looping constraint ensures that sequential information is captured in the input data.

You should go through the below tutorial to learn more about how RNNs work under the hood (and how to build one in Python):

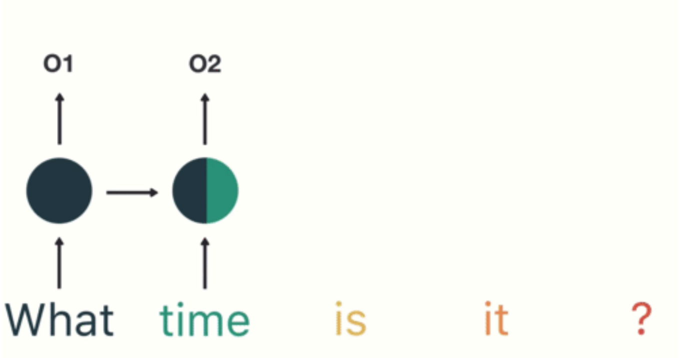
- *Fundamentals of Deep Learning – Introduction to Recurrent Neural Networks*

We can use recurrent neural networks to solve the problems related to:

- Time Series data
- Text data
- Audio data

Advantages of Recurrent Neural Network (RNN)

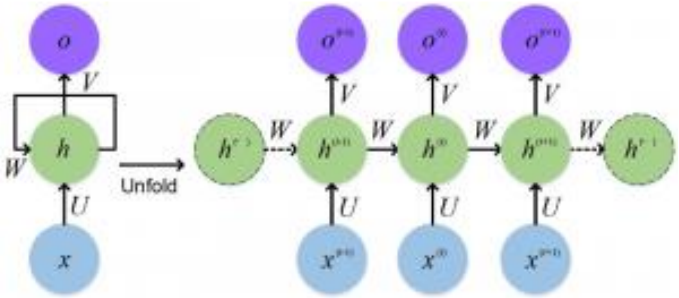
- RNN captures the sequential information present in the input data i.e. dependency between the words in the text while making predictions:



Many2Many Seq2Seq model

As you can see here, the output (o1, o2, o3, o4) at each time step depends not only on the current word but also on the previous words.

- RNNs share the parameters across different time steps. This is popularly known as **Parameter Sharing**. This results in fewer parameters to train and decreases the computational cost

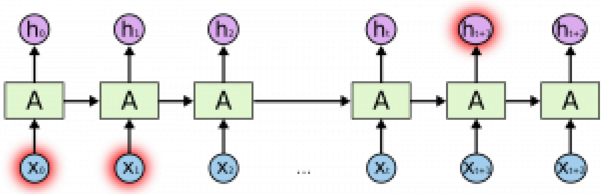


Unrolled RNN

As shown in the above figure, 3 weight matrices — U, W, V, are the weight matrices that are shared across all the time steps.

Challenges with Recurrent Neural Networks (RNN)

- Deep RNNs (RNNs with a large number of time steps) also suffer from the vanishing and exploding gradient problem which is a common problem in all the different types of neural networks.



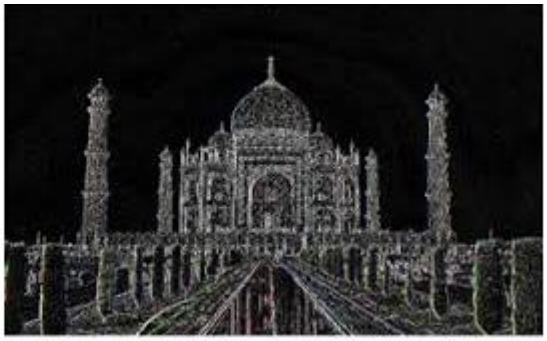
Vanishing Gradient (RNN)

As you can see here, the gradient computed at the last time step vanishes as it reaches the initial time step.

2.3. Convolution Neural Network (CNN)

Convolutional neural networks (CNN) are all the rage in the deep learning community right now. These CNN models are being used across different applications and domains, and they’re especially prevalent in image and video processing projects.

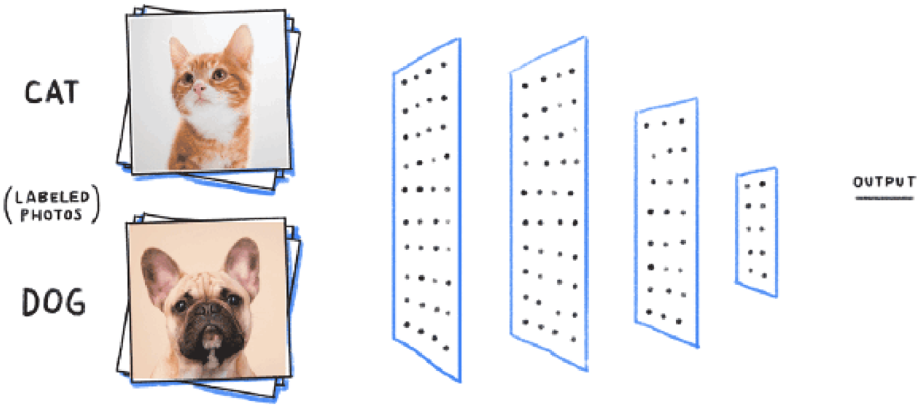
The building blocks of CNNs are filters a.k.a. kernels. Kernels are used to extract the relevant features from the input using the convolution operation. Let’s try to grasp the importance of filters using images as input data. Convolving an image with filters results in a feature map:



Though convolutional neural networks were introduced to solve problems related to image data, they perform impressively on sequential inputs as well.

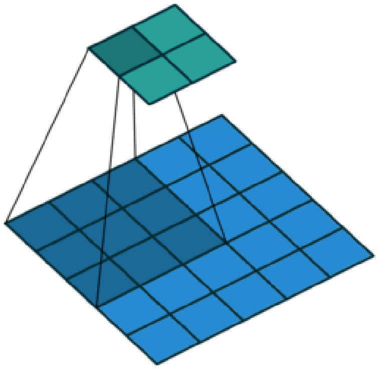
Advantages of Convolution Neural Network (CNN)

CNN learns the filters automatically without mentioning it explicitly. These filters help in extracting the right and relevant features from the input data



CNN- Image Classification

- CNN captures the **spatial features** from an image. Spatial features refer to the arrangement of pixels and the relationship between them in an image. They help us in identifying the object accurately, the location of an object, as well as its relation with other objects in an image
- CNN also follows the concept of **parameter sharing**. A single filter is applied across different parts of an input to produce a feature map:

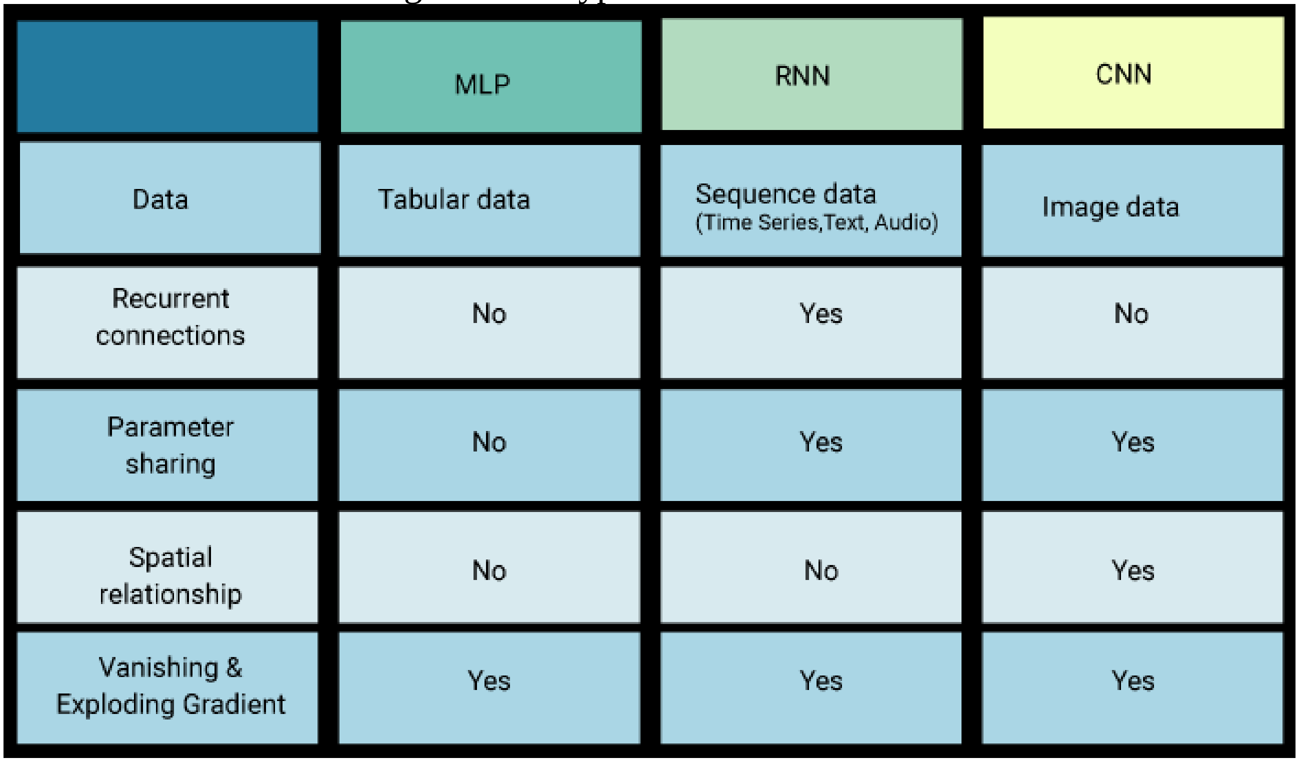


Convolving image with a filter

Notice that the 2*2 feature map is produced by sliding the same 3*3 filter across different parts of an image.

3. Comparing the Different Types of Neural Networks (MLP(ANN) vs. RNN vs. CNN)

Some of the differences among different types of neural networks:



	MLP	RNN	CNN
Data	Tabular data	Sequence data (Time Series,Text, Audio)	Image data
Recurrent connections	No	Yes	No
Parameter sharing	No	Yes	Yes
Spatial relationship	No	No	Yes
Vanishing & Exploding Gradient	Yes	Yes	Yes