upGrad

#LifeKoKaroLift

GLOBAL PROGRAM

IN

MACHINE LEARNING

AND

ARTIFICIAL INTELLIGENCE

upGrad

SESSION : INTRODUCTION TO NEURAL NETWORKS

Instructor : SACHIN KUMAR
Master Trainer (UpGrad)

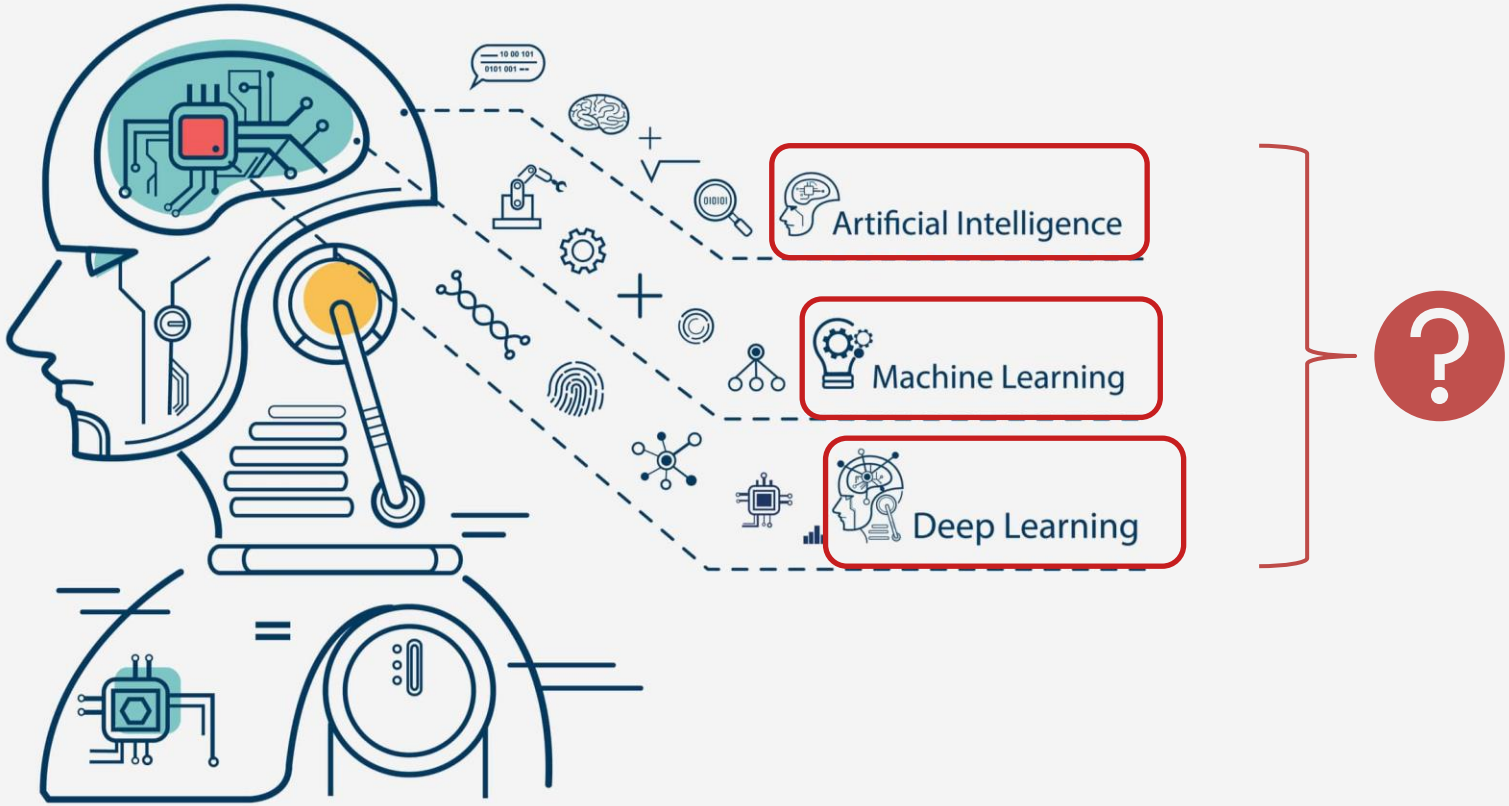
Agenda

upGrad

- Introduction
  - Machine Learning & AI
  - Problems faced by traditional ML algorithms
- Perceptron – The building block
  - What is a Perceptron?
  - Activation functions
- Structure of an ANN & Feedforward in Neural Networks
  - How does an ANN look like?
  - Notations used for layers, input, outputs etc
  - Different inputs & outputs to a Neural
  - Feedforward in an Artificial Neural Network
  - Types of Neural Networks
- Backpropagation in an ANN
  - Training an ANN
  - Cost Function for Regression/Classification
  - Gradient Descent
  - Feedforward and Backprop equations
- TensorFlow playground
  - Building an ANN
  - Training an ANN
  - Changes in Parameters
- Doubt resolution

Artificial Intelligence/Machine Learning /Deep Learning

upGrad



Artificial Intelligence/Machine Learning /Deep Learning

upGrad

ARTIFICIAL INTELLIEGENCE

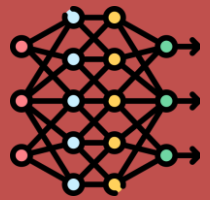
Techniques that help computer mimic "cognitive" functions associated with the human mind,

MACHINE LEARNING

Ability to learn pattern from data without being explicitly programmed

DEEP LEARNING

Extract pattern from data using Deep Neural Networks



Building Thinking Machines has been a challenge for inventors !

Easy for computers to do:

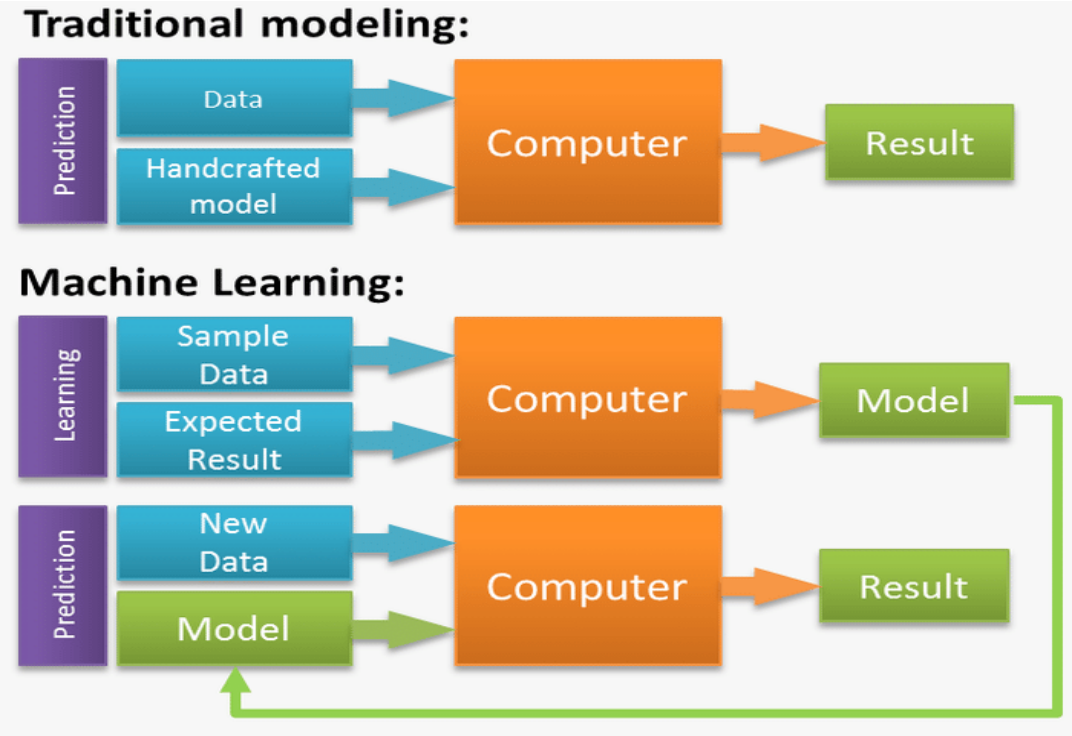
- Extensive mathematical computations
- Querying from a large corpus of text
- Combinatorial like Chess playing

Hard for computers to do:

- Recognize images and faces
- Understand spoken language
- Recognize feelings
- Learning from few mistakes

Machine Learning was a Paradigm Shift

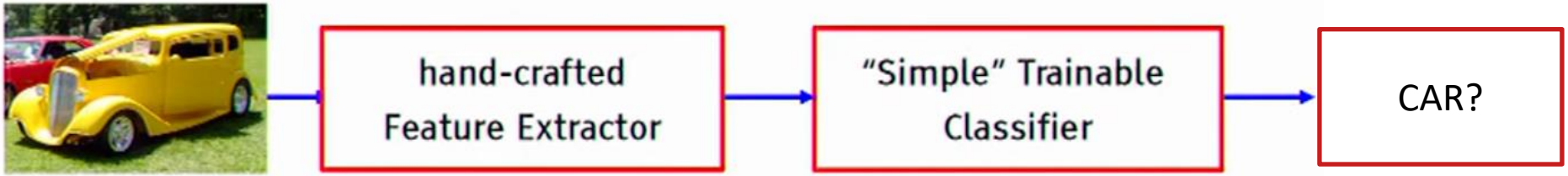
upGrad



But Not for All Class of Problems

upGrad

- Fixed/engineered features (or fixed kernel) + trainable classifier

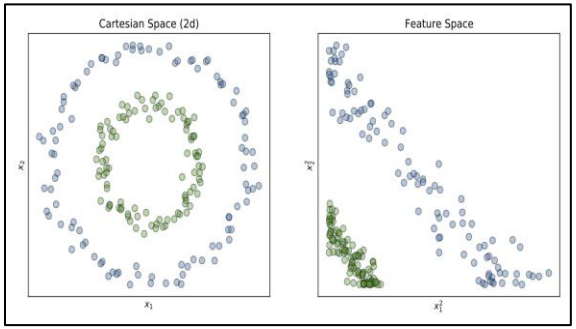


The challenge to Machine Learning proved to be solving the tasks that are easy for people to perform, but hard for people to describe formally.

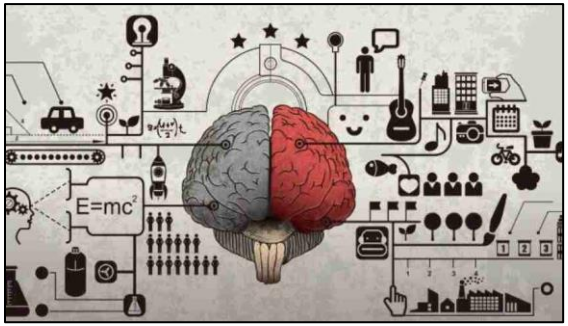
Challenges with Traditional Machine Learning

upGrad

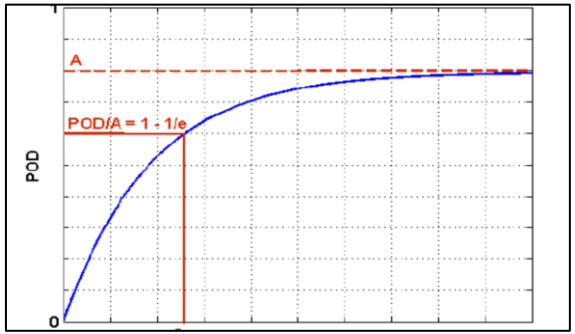
Require domain expertise to handcraft useful features



Results heavily depend on Feature Representation



Cannot solve extremely complex problems



Has an upper limit to Performance

Deep Learning as an Answer

upGrad

Learning hard-to-describe problem:

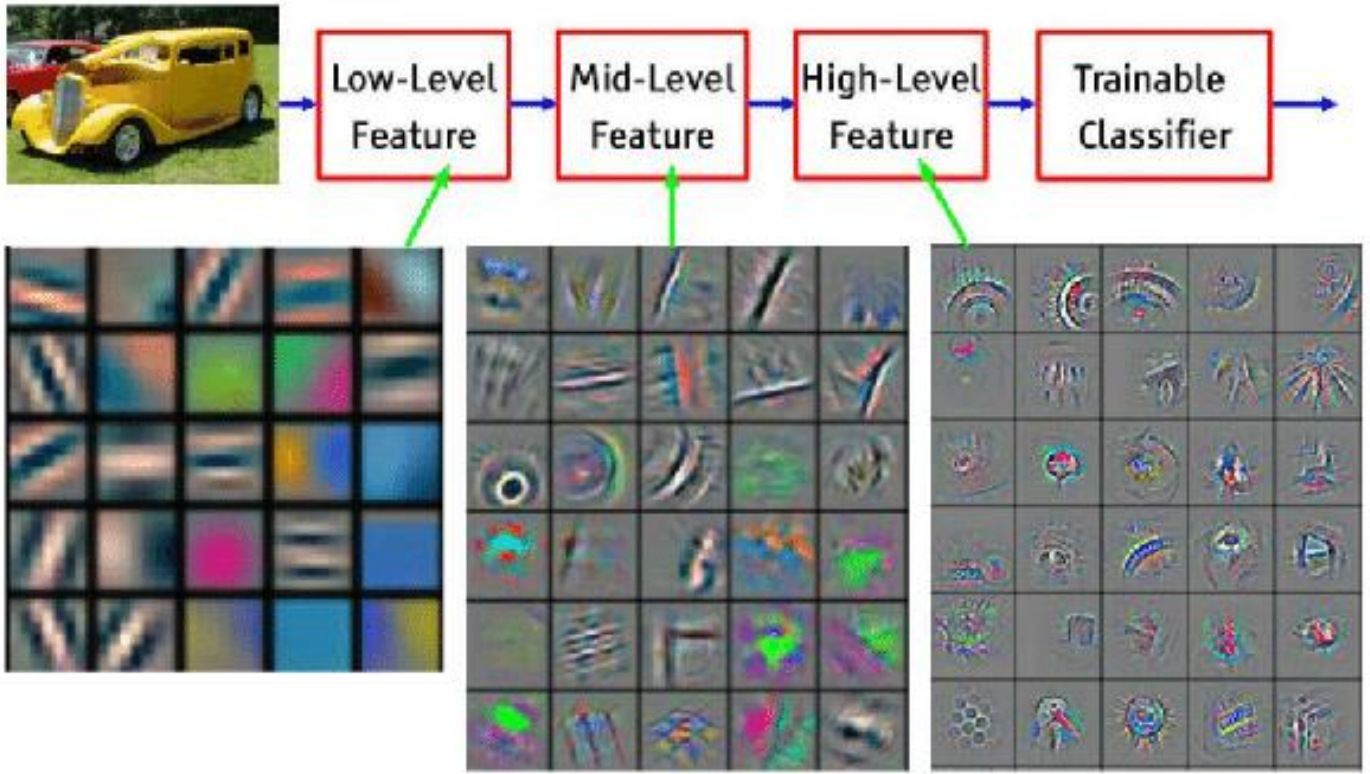
- Allow computers to learn from experience
- Understand the world in terms of a hierarchy of concepts
- Each concept defined through its relation to simpler concepts.

Advantages:

- No need for human operators to formally specify all the knowledge that the computer needs
- The hierarchy of concepts enables the computer to learn complicated concepts by building them out of simpler ones.

Deep Learning aka Hierarchical Feature Learning

upGrad



AI has come a long way ...

upGrad

1950's

– Samuel's checker player
– Selfridge's Pandemonium

1960's

– Neural networks: Perceptron
– Pattern recognition
– Learning in the limit theory
– Minsky and Papert prove limitations of Perceptron

1970's

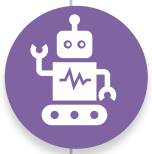
– Symbolic concept induction
– Winston's arch learner
– Expert systems and the knowledge acquisition bottleneck
– Quinlan's ID3
– Michalski's AQ and soybean diagnosis
– Mathematical discovery with AM

1980's

– Advanced decision tree and rule learning
– Explanation-based Learning (EBL)
– Learning and planning and problem solving
– Utility problem
– Analogy
– Cognitive Architectures
– Resurgence of neural networks (backpropagation)

1990's

– Data mining
– Adaptive software agents and web applications
– Text learning
– Reinforcement learning (RL)
– Ensembles: Bagging, Boosting, and Stacking
– Bayes Net learning



2000's

– Support vector machines & kernel methods
– Graphical models
– Statistical relational learning
– Transfer learning
– Sequence labeling
– Personalized assistants that learn
– Learning in robotics and vision

2010's

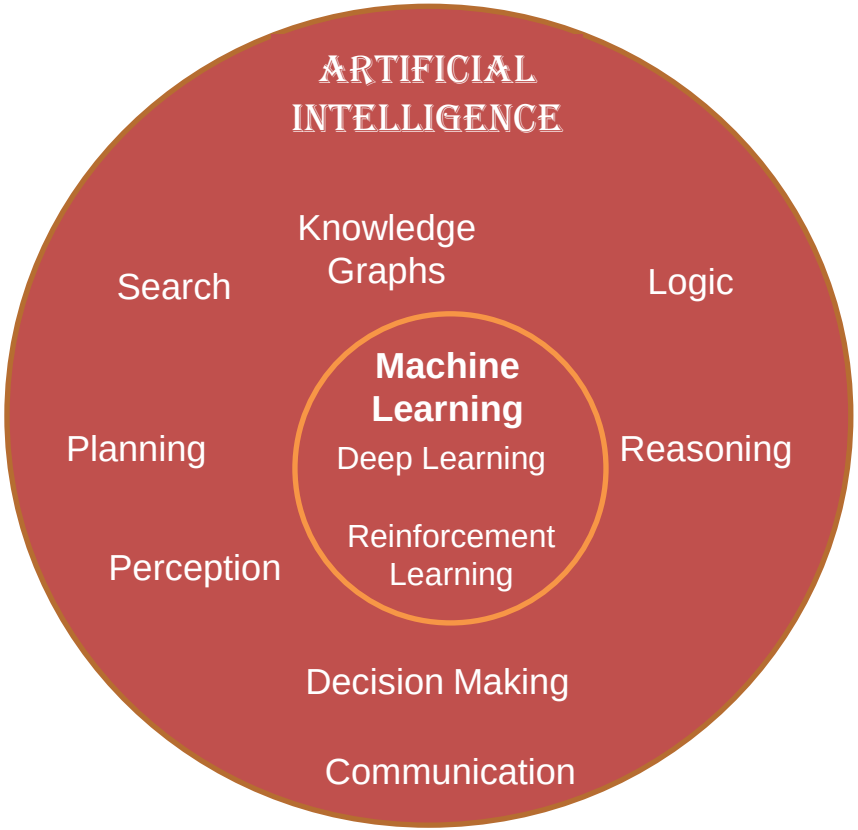
– Deep learning systems
– Learning for big data
– Bayesian methods
– Multi-task & lifelong learning
– Applications to vision, speech, social networks, learning to read

2020's

– Natural Language Understanding
– Generative Models (GANs)
– Transformers
– Large Language Models

Artificial Intelligence is a broad set of Technology

upGrad



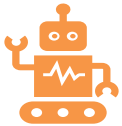
Ability of Machines to mimic "cognitive" functions that we associate with the human mind, such as "learning, seeing, interpreting and problem solving"

Examples of Artificial Intelligence Applications

upGrad

Computer Vision

Speech Recognition



Personal Assistant

Medical Diagnosis

Chatbots

Assisted driving Cars

Categorization of Artificial Intelligence

upGrad

Narrow/Weak AI

AI created for a single or narrow set of task.

Computer Algorithms that perform tasks it is trained for. Cannot think or comprehend.

Used in industries due to its high efficiency and speed, over humans.

General AI

AI that can be broad and perform multiple tasks.

A type of AI that will think and function like humans

Still a far off reality, as the tools required to build it are not available yet.

Super AI

AI capable of surpassing human intelligence by manifesting cognitive skills and developing thinking skills of its own.

Envisioned to come from compounding growth of AI algorithms and recursive self-improvement.

Applications of Narrow AI

upGrad

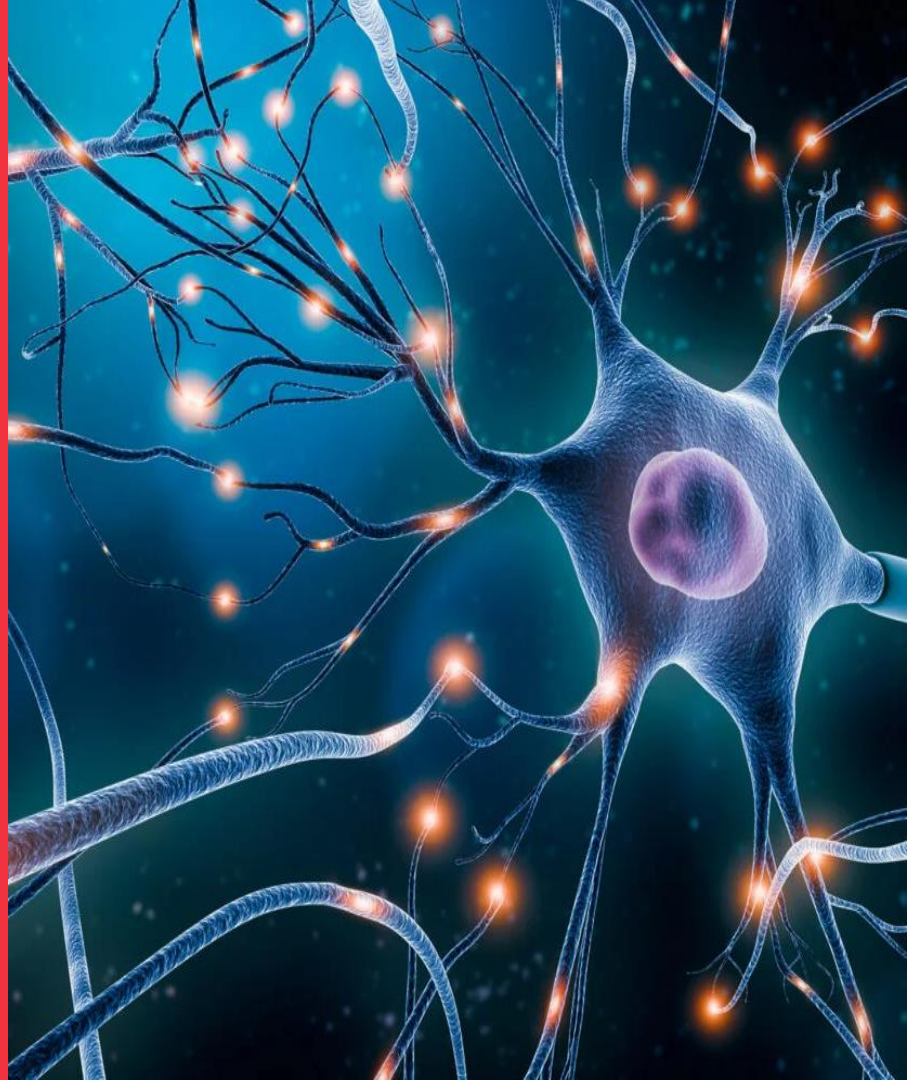
- Text Data
  - Text Categorization
  - POS/NER/Semantics
  - Text Summarization
  - Text Generation
  - Language Translation

- Image Data
  - Categorization
  - Character Recognition
  - Object Detection
  - Face Recognition
  - Image Generation

- Voice Data
  - Speech to Text
  - Speech Synthesis
  - Music Recognition

upGrad

Perceptron and Activation Functions

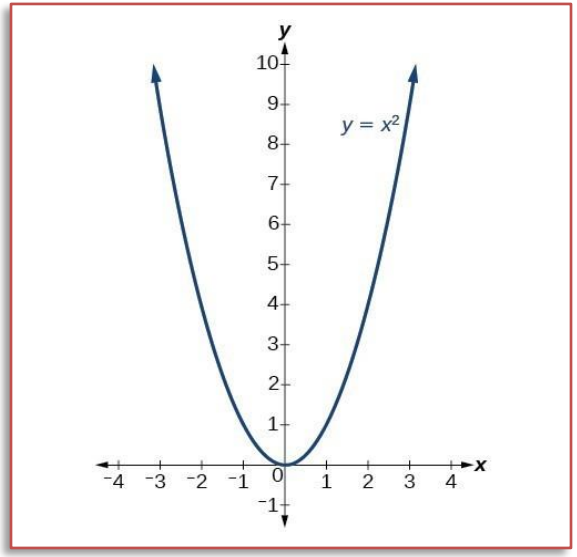


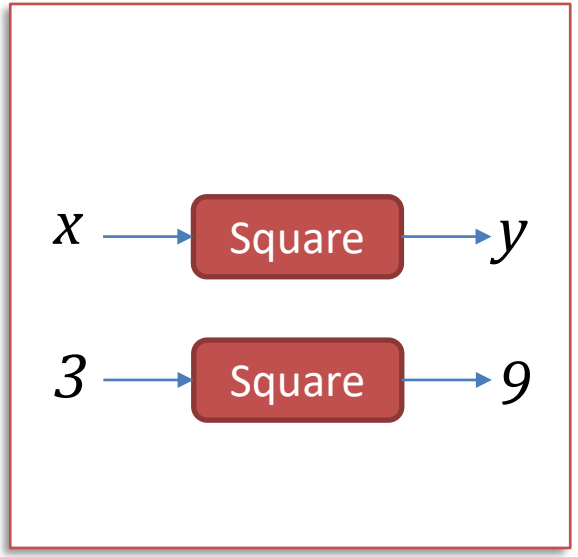
Representation of a Function

upGrad

$y = f(x)$

$f(x) = x^2$



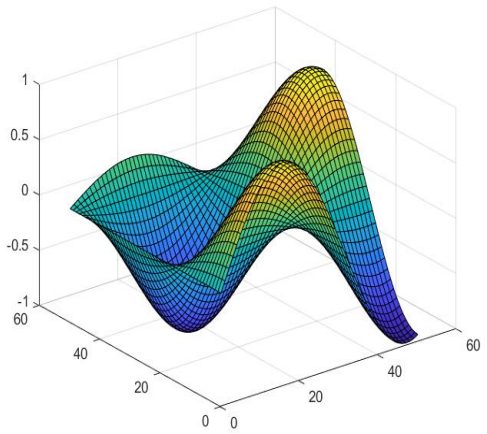


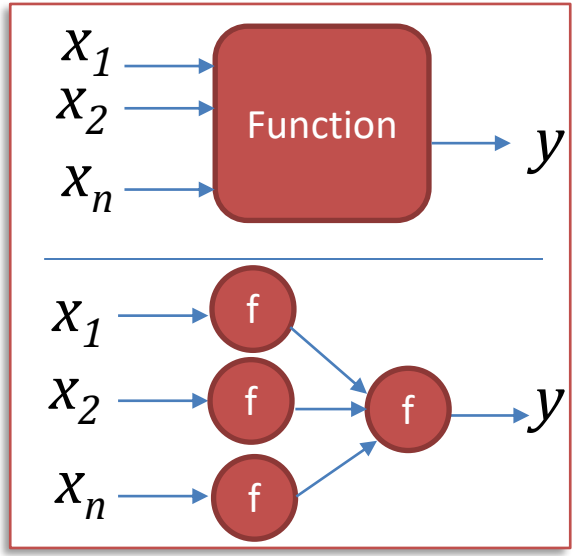
Representation of a Function – in Higher Dimension

upGrad

$$Y = f(W, X)$$

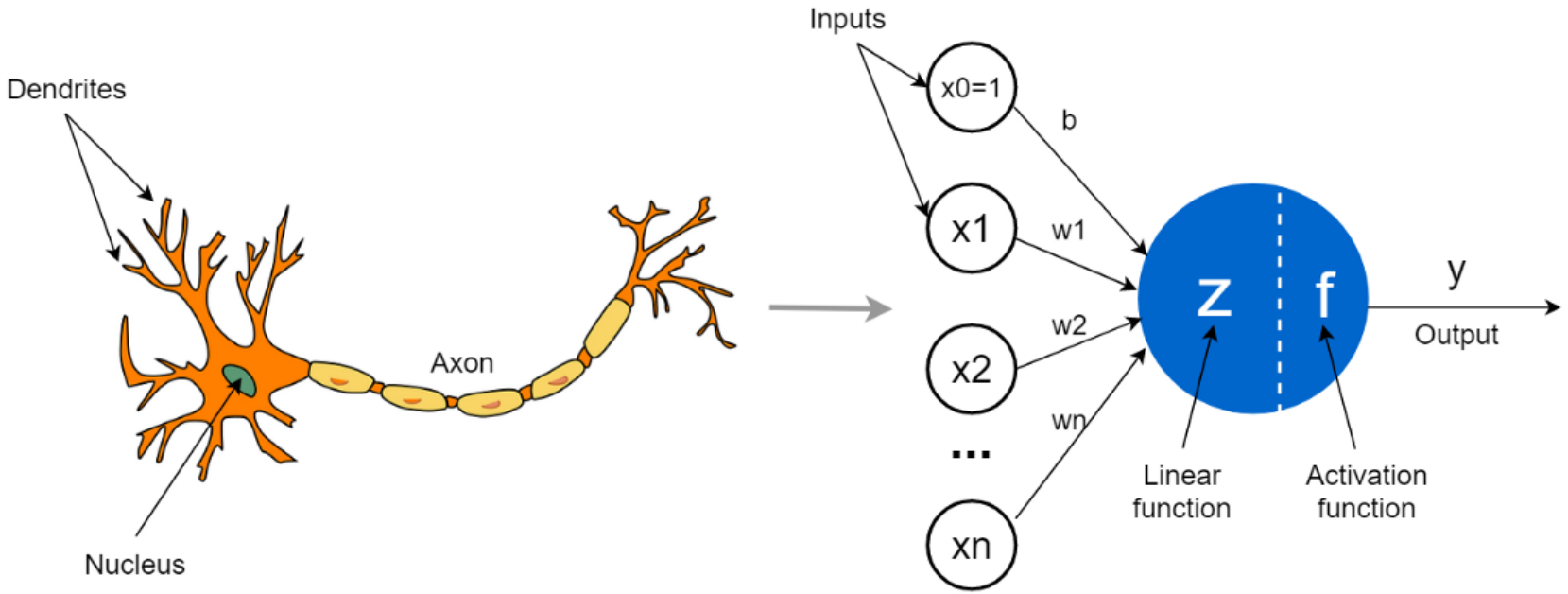
$$y_1 = w_1x_1 + w_2x_2 + \ldots + w_nx_n$$





Artificial Neural Network – Inspired by Nature

upGrad

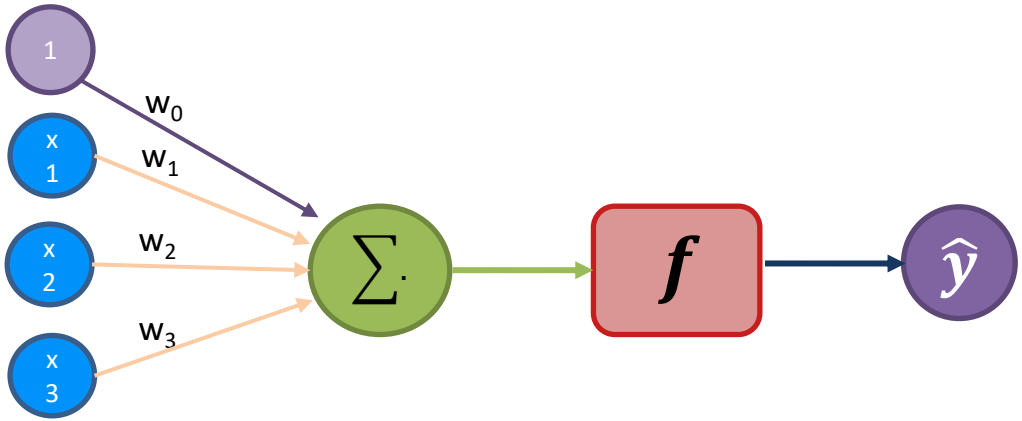


Biological Neuron

Artificial Neuron

A Closer Look At The Perceptron

upGrad



Inputs Weights *Summation* *Activation Function* *Predicted value*

Non-linear Function

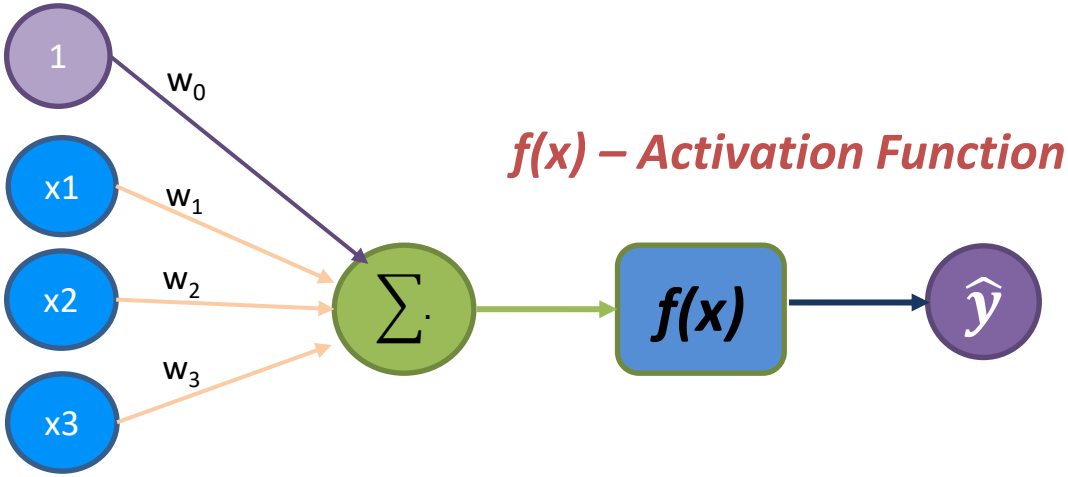
$$\hat{y} = f(\sum x_i . wi)$$

$$\hat{y} = f(w_0 + \sum x_i . wi)$$

$$\hat{y} = f(W^T . X) \qquad X = 1, x_1, x_{2,.}$$

FORWARD PROPOGATION

The Perceptron Can Take Many Forms



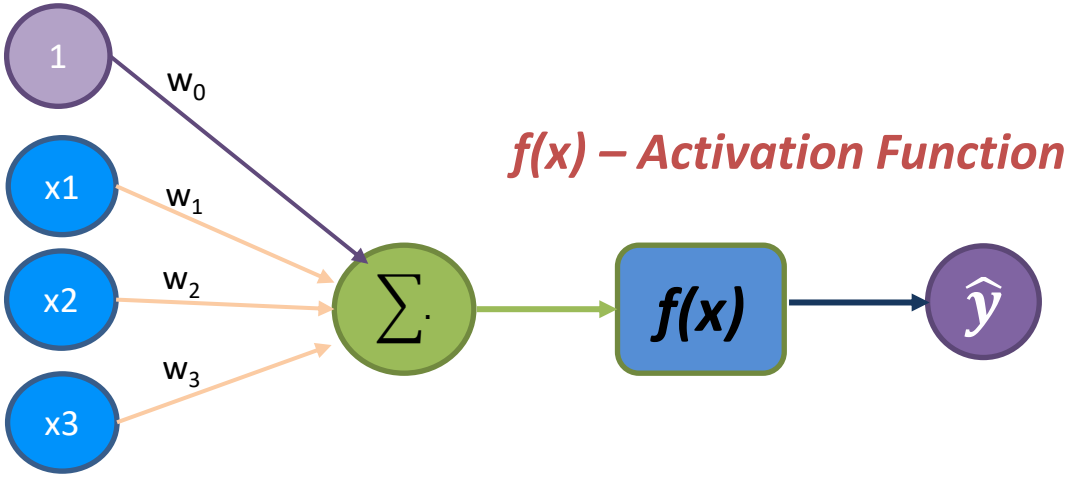
f(x) – Activation Function

$$\hat{y} = f(w_0 + \sum x_i . wi)$$

Let, f(x) = 1 [Linear]

$Y = w_0 + w_1x_1 + w_2x_2 + w_3x_3$ [Linear Regression]

The Perceptron Can Take Many Forms



f(x) – Activation Function

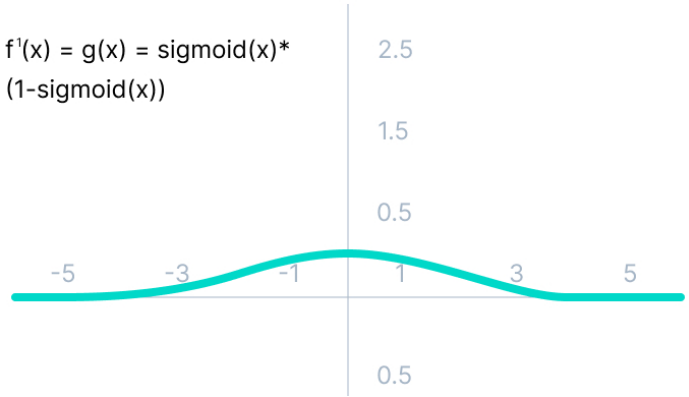
$$\hat{y} = \boldsymbol{f}\left(w_0 + \sum x_i . wi \right)$$

Let, f(x) = $1/(1+ e^{-x})$ [Sigmoid]

$$Y = \frac{e^{(w0 + w1x1 + w2x2 + w3x3)}}{1+e^{(w0 + w1x1 + w2x2 + w3x3)}}$$ [Logistic Regression]

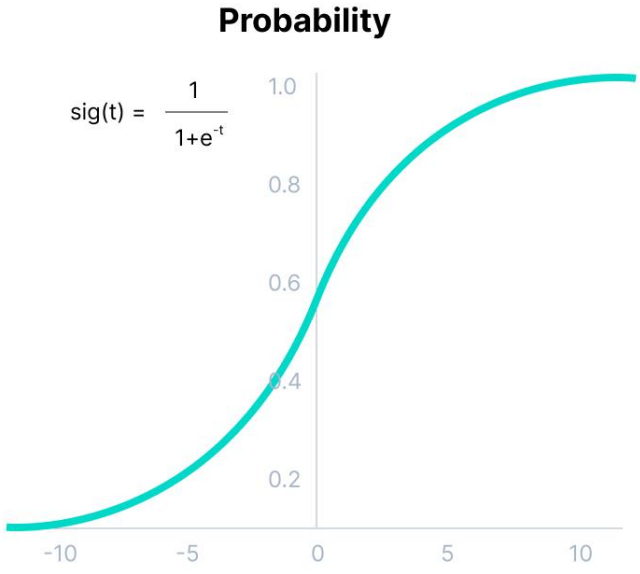
Sigmoid Function

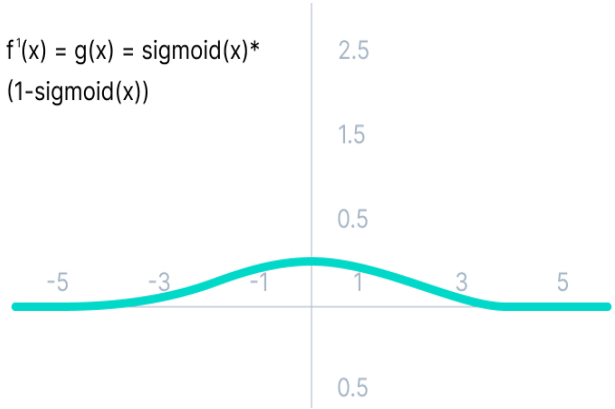
$$f(x) = \frac{1}{1 + e^{-x}}$$



Softmax Activation Function

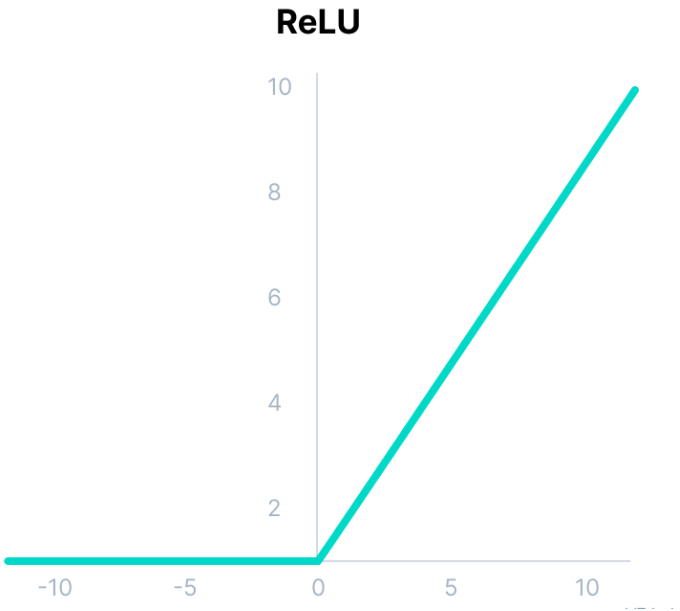
$$\text{softmax}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$





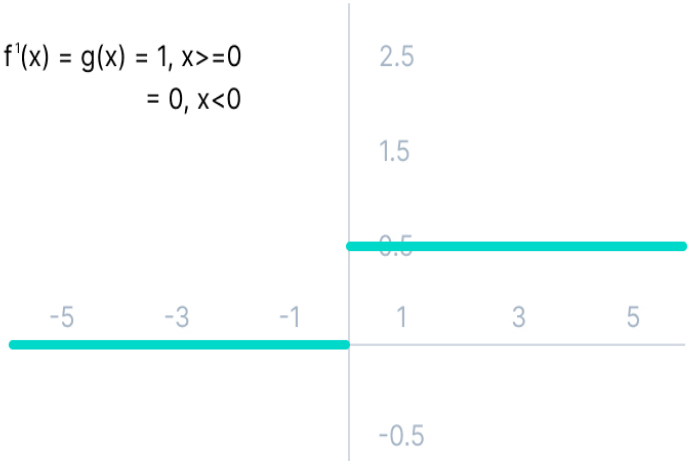
Rectified Linear Unit

$$f(x) = max\ (0, x)$$



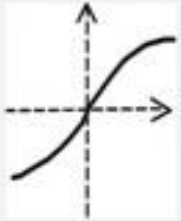
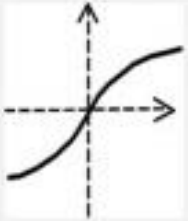
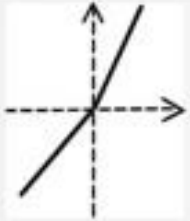
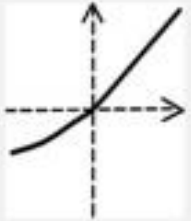
$f'(x) = g(x) = 1, x>=0$

$= 0, x<0$



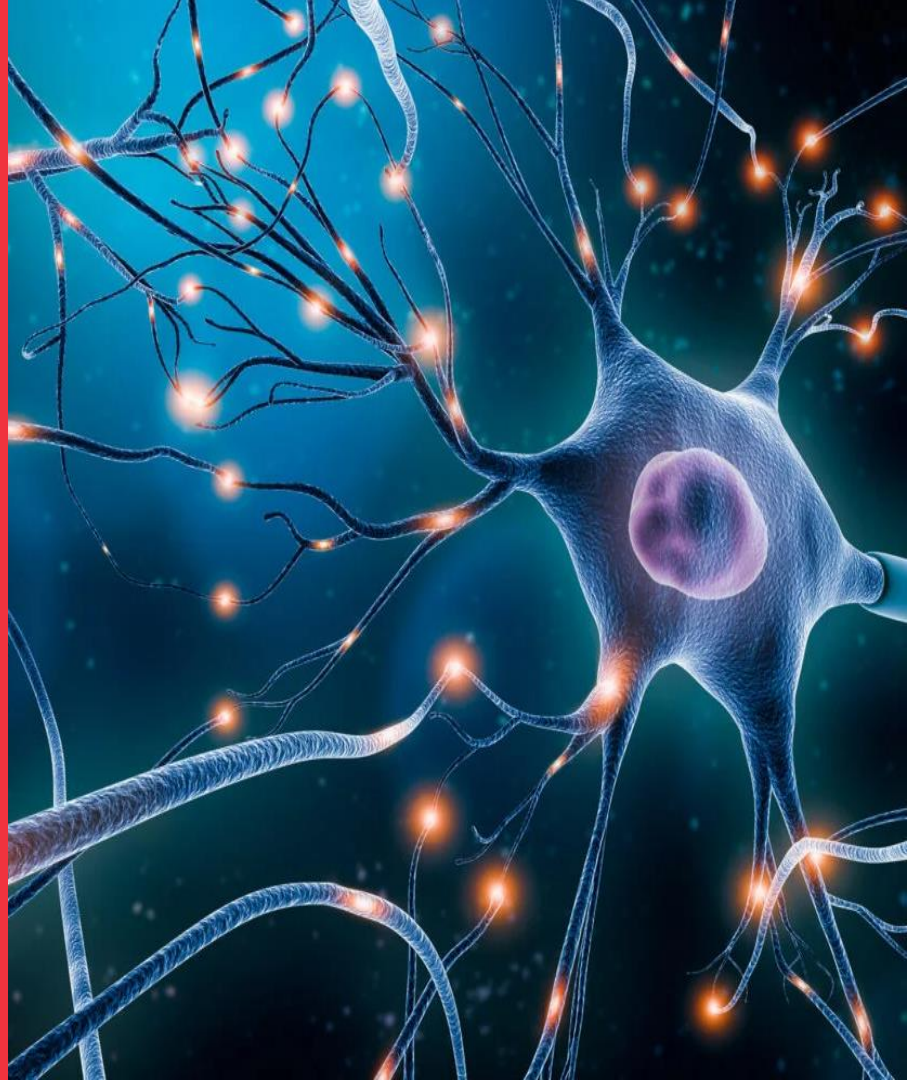
Other Activation Functions

upGrad

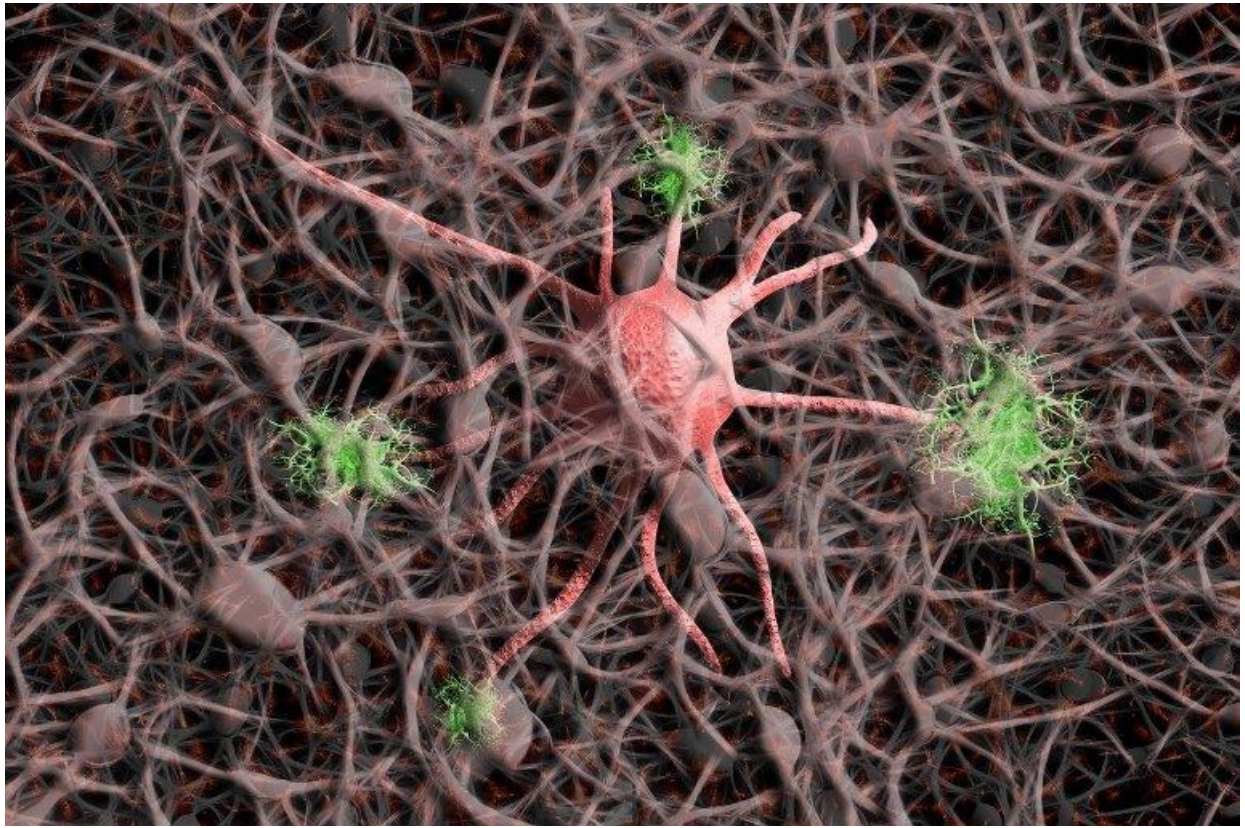
Binary Step	Logistic	TanH	ArcTan	ReLU	PreLU	ELU	SoftPlus
							
$f(x) = \begin{cases} 0 \text{ for } x<0 \\ 1 \text{ for } x\geq 0 \end{cases}$	$f(x) = \frac{1}{1+e^{-x}}$	$f(x) = tangh(x) = \frac{2}{1+e^{-2x}} - 1$	$f(x) = tan^{-1}(x)$	$f(x) = \begin{cases} 0 \text{ for } x<0 \\ x \text{ for } x\geq 0 \end{cases}$	$f(x) = \begin{cases} \propto x \text{ for } x<0 \\ x \text{ for } x\geq 0 \end{cases}$	$f(x) = \begin{cases} \propto (e^{-x}-1) \text{ for } x<0 \\ x \text{ for } x\geq 0 \end{cases}$	$f(x) = log_e(1+e^x)$
$f'(x) = \begin{cases} 0 \text{ for } x\neq 0 \\ ? \text{ for } x=0 \end{cases}$	$f'(x) = f(x)(1-f(x))$	$f'(x) = 1-f(x)^2$	$f'(x) = \frac{1}{x^2+1}$	$f'(x) = \begin{cases} 0 \text{ for } x<0 \\ 1 \text{ for } x\geq 0 \end{cases}$	$f'(x) = \begin{cases} \propto \text{ for } x<0 \\ 1 \text{ for } x\geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x)+\propto \text{ for } x<0 \\ 1 \text{ for } x\geq 0 \end{cases}$	$f'(x) = \frac{1}{1+e^{-x}}$

upGrad

Artificial Neural Networks



Biological Brain

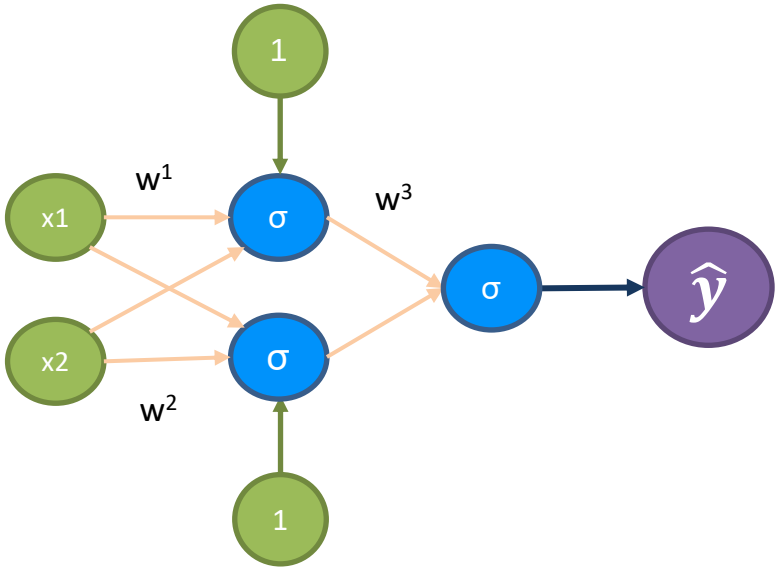


Human Brain:

- 60% Fat
- 100 Billion Neurons
- 1000 trillion Synapses – connections
- Connection store memory and process information.

A Simple Multi-Layered Perceptron

upGrad



x_1, x_2 — Input

$\alpha_1 = \sigma(w_i x_i + b_1)$

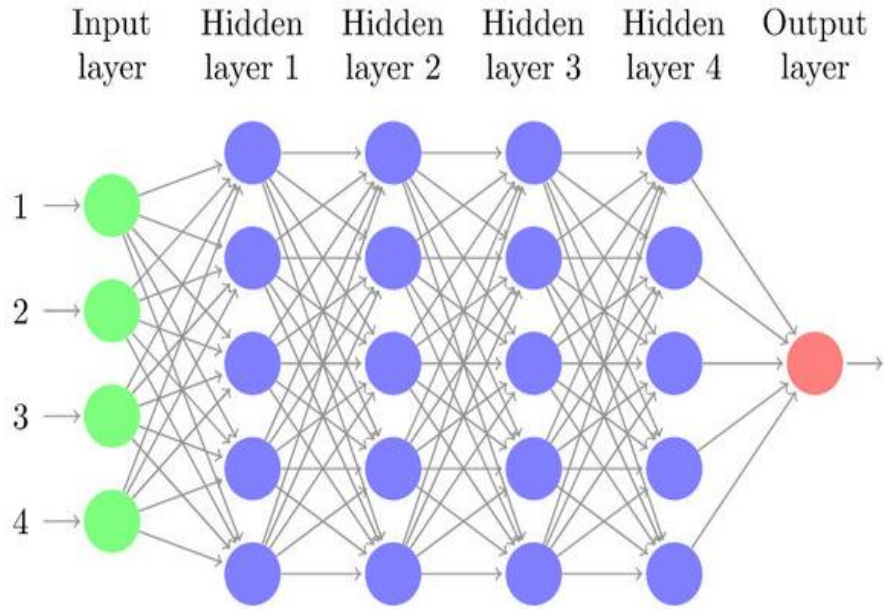
$\alpha_2 = \sigma(w_i x_i + b_2)$ — Intermediate

$\hat{y} = \sigma(w^3{}_1 \alpha_1 + w^3{}_2 \alpha_2)$ — Output

Multi-layered perceptron sum together the simple linear function, and each output a non linear function. The more layers we have in our hidden layer, the more complex non linear models we can find.

MLP – Universal Function Approximator

upGrad



- Multi Layer Perceptron – 3 or more layers of nonlinearly-activating nodes.
- MLPs are fully connected.
  - Node i → w * Node j

MLP – Universal Function Approximator

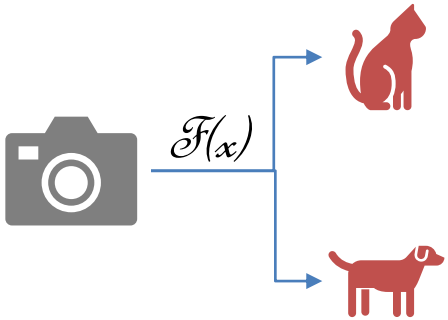
upGrad

- ***MLPs are universal function approximators !!***

- Cybenko's theorem : Given any known/unknown function, there exists a MLP that can approximate the function to an arbitrary degree of precision.
  - The network can be 1 layered with unbounded no of neurons
  - The network can be multi-layered with bounded no of neurons.

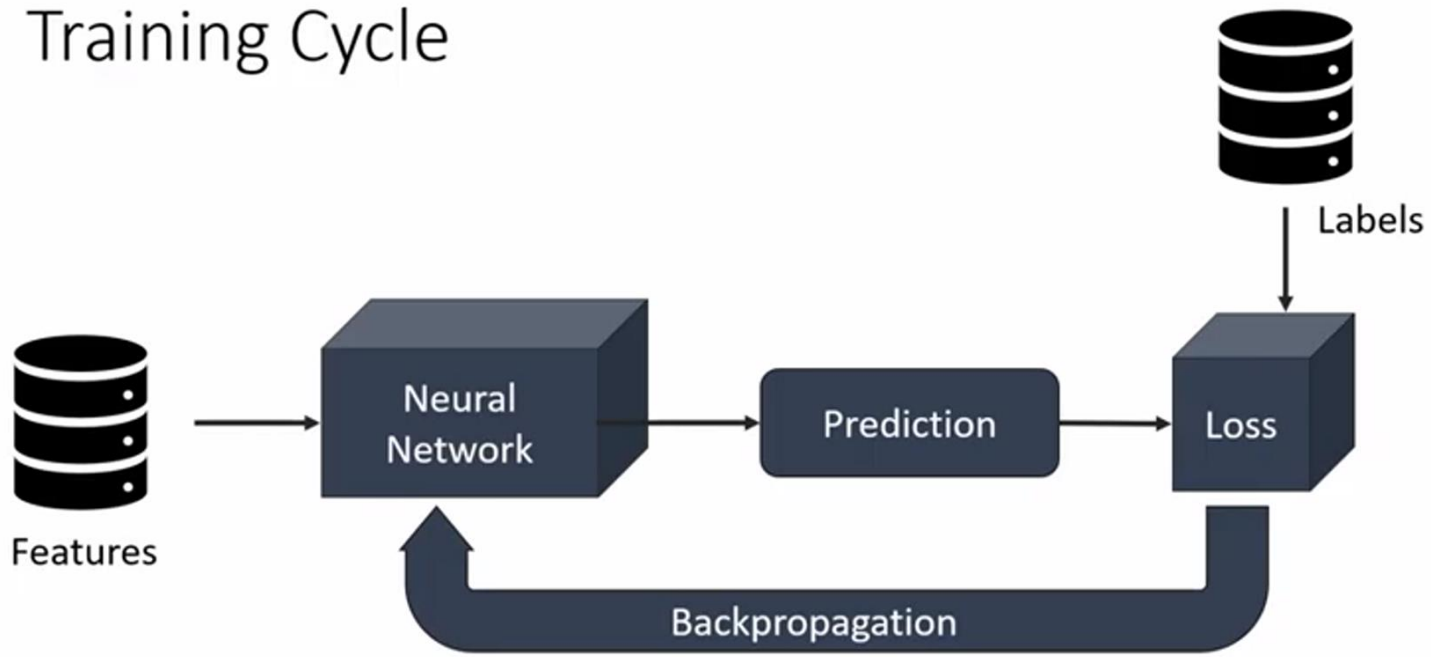
- Learning = δ(connection weights) after each piece of data is processed.

- MLP learn hierarchical feature representations. Do not require feature engineering.



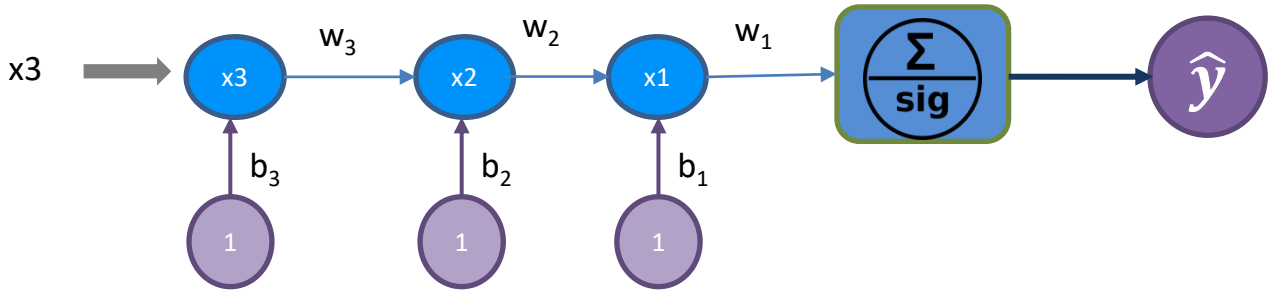
Training a Artificial Neural Network

upGrad



Training a Simple Network

upGrad



1 Define the Network

$$\hat{y} = f(w_1 x_1 + b_1)$$

$$x_1 = (w_2 x_2 + b_2)$$

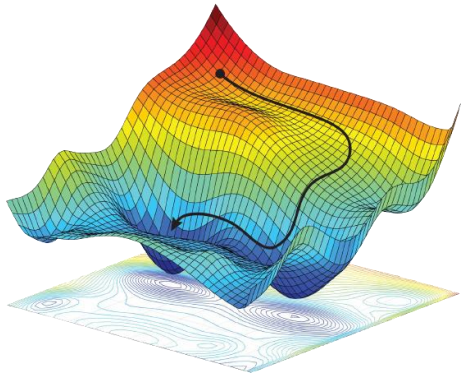
$$x_2 = (w_3 x_3 + b_3)$$

2 Define the Cost Function

$$L(w): \sum (y - \hat{y})^2$$

- *Quantifies model performance*
- *# Continuous and mostly differentiable*

3 Learn the weights/biases



Gradient Descent

- Gradient descent is an optimization algorithm used to find the values of parameters (coefficients) of a function (f) that minimizes a cost function (cost).

- Gradient descent is best used when the parameters cannot be calculated analytically .

- It finds the parameters using an iterative method:
    - The goal is to continue to try different values for the coefficients, evaluate their cost and select new coefficients that have a slightly better (lower) cost.
    - Repeating this process enough times will lead to the coefficients that result in the minimum cost.

Gradient Descent

Gradient descent :

1. Estimate the error using current weights (randomly initialized)
2. Find the derivative(gradient) of the cost function.
3. Move in the direction opposite of the gradient, until convergence.

Gradient Descent Update Rule:

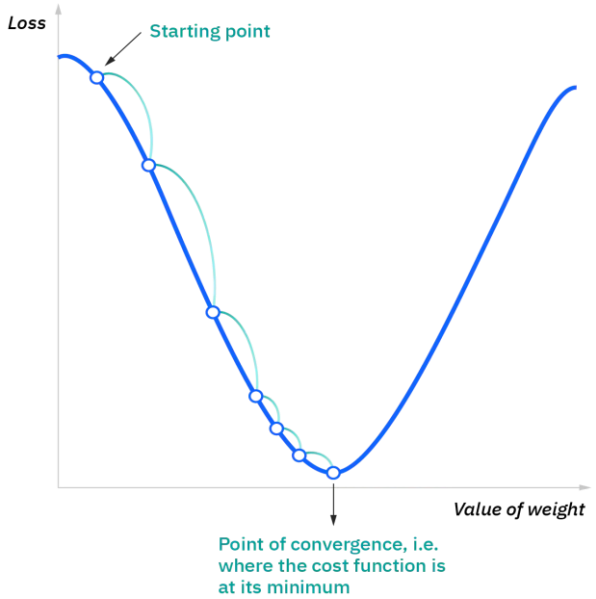
$$\text{repeat until convergence } \{$$

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

(for j=1 to j=k)

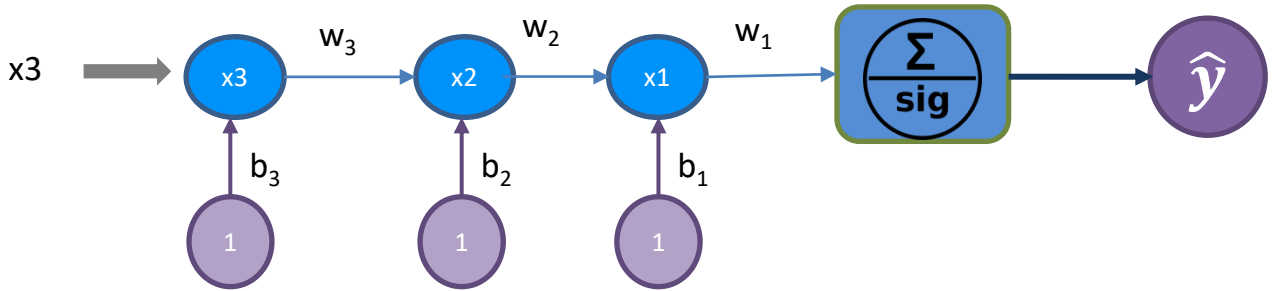
$$\}$$

α – learning rate
j - features



Training a Simple Network – Back Propagation

upGrad



Find the weights (w1, w2, w3) such that the cost is minimized

$$L(w): \sum (y - \hat{y})^2$$

1. *Start with random weights (w1, w2, w3)*
2. *Change w_j such that*

$$w_j =: w_j - \alpha * \frac{\partial L}{\partial wj}$$

BACKWARD PROPOGATION

1. $$\frac{\partial L}{\partial w1} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial w1}$$
2. $$\frac{\partial L}{\partial w2} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial x1} * \frac{\partial x1}{\partial w2}$$
3. $$\frac{\partial L}{\partial w3} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial x1} * \frac{\partial x1}{\partial x2} * \frac{\partial x2}{\partial w3}$$

Cost Functions - Regression

upGrad

Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE with L1 Regularization

$$\text{Cost} = \sum_{i=0}^{N}(y_i - \sum_{j=0}^{M} x_{ij}W_j)^2 + \lambda \sum_{j=0}^{M} |W_j|$$

MSE with L2 Regularization

$$\text{Cost} = \sum_{i=0}^{N}(y_i - \sum_{j=0}^{M} x_{ij}W_j)^2 + \lambda \sum_{j=0}^{M} W_j^2$$

Loss function

Regularization Term

Mean Square Log Error

$$MSLE = \frac{1}{n}\sum_{i=1}^{n}(\log(Y_i) - \log(\hat{Y}_i))^2$$

Huber Loss Function

$$L_\delta(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2 & \text{for} |y - f(x)| \le \delta, \\ \delta |y - f(x)| - \frac{1}{2}\delta^2 & \text{otherwise.} \end{cases}$$

Cost Functions - Classification

upGrad

Binary Cross Entropy – Binary Classification

$$J = -\sum_{i=1}^{N} y_i \log(h_\theta(x_i)) + (1 - y_i) \log(1 - h_\theta(x_i))$$

Cross Entropy – Multi Class Classification

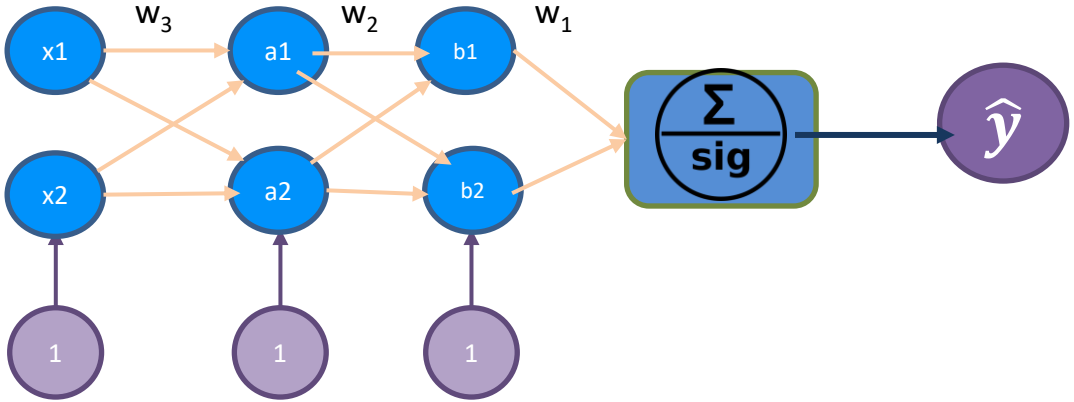
$$\text{cross-entropy} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{k} t_{i,j} \log(p_{i,j})$$

Kullback Leibler Divergence Loss (KL Loss)

$$D_{KL}(P||Q) = \begin{cases} -\sum_x P(x).log\frac{Q(x)}{P(x)} = \sum_x P(x).log\frac{P(x)}{Q(x)}, & for\ discrete\ distributions \\ -\int P(x).log\frac{Q(x)}{P(x)}.dx = \int P(x).log\frac{P(x)}{Q(x)}.dx, & for\ continuous\ distributions \end{cases}$$

Training more Complex Networks

upGrad



$$\frac{\partial L}{\partial w} = \left[\frac{\partial L}{\partial b}\right] * \left[\frac{\partial b}{\partial a}\right] * \left[\frac{\partial a}{\partial x}\right]$$

Derivative of a vector w.r.t another vector yields a Matrix – **Jacobian**

Linear Algebra & Matrix Calculus

Types of Gradient Descent

upGrad

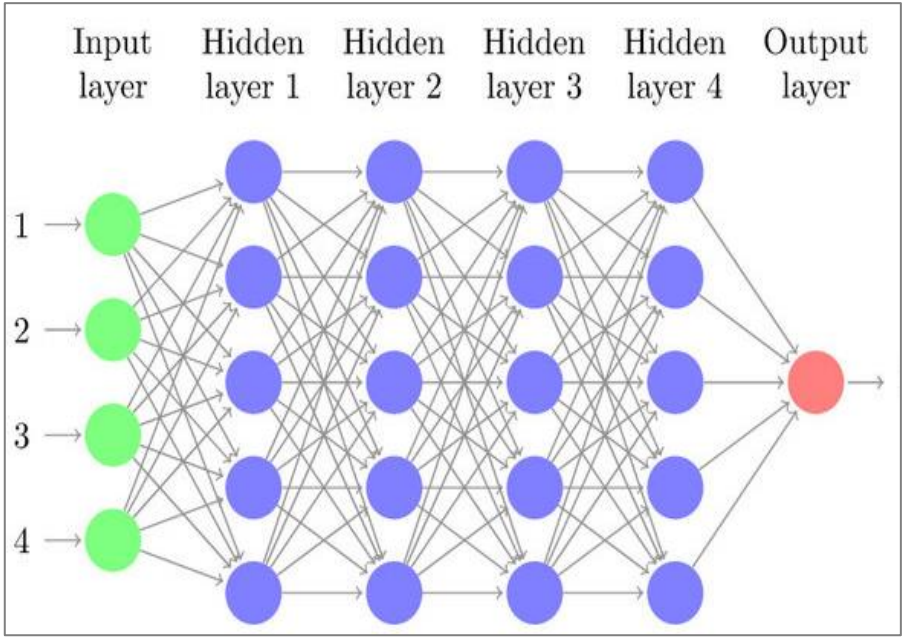
Batch Gradient Descent	Mini-Batch Gradient Descent	Stochastic Gradient Descent
Uses ALL training samples to calculate Error, for adjusting weights	Uses A random sample to calculate Error, for adjusting weights	Uses ONE training Sample to calculate Error, for adjusting weights. Also called “Online” training.
Good for small datasets. Very time consuming with large datasets, large feature set.	Compromise between the two and works well in both cases. Efficient use of matrix multiplication, especially using GPUs.	Good for very big dataset with large no of features and redundant data.

Parameters and Hyper-Parameters of Neural Network

upGrad

Parameters:

- Weights
- Biases

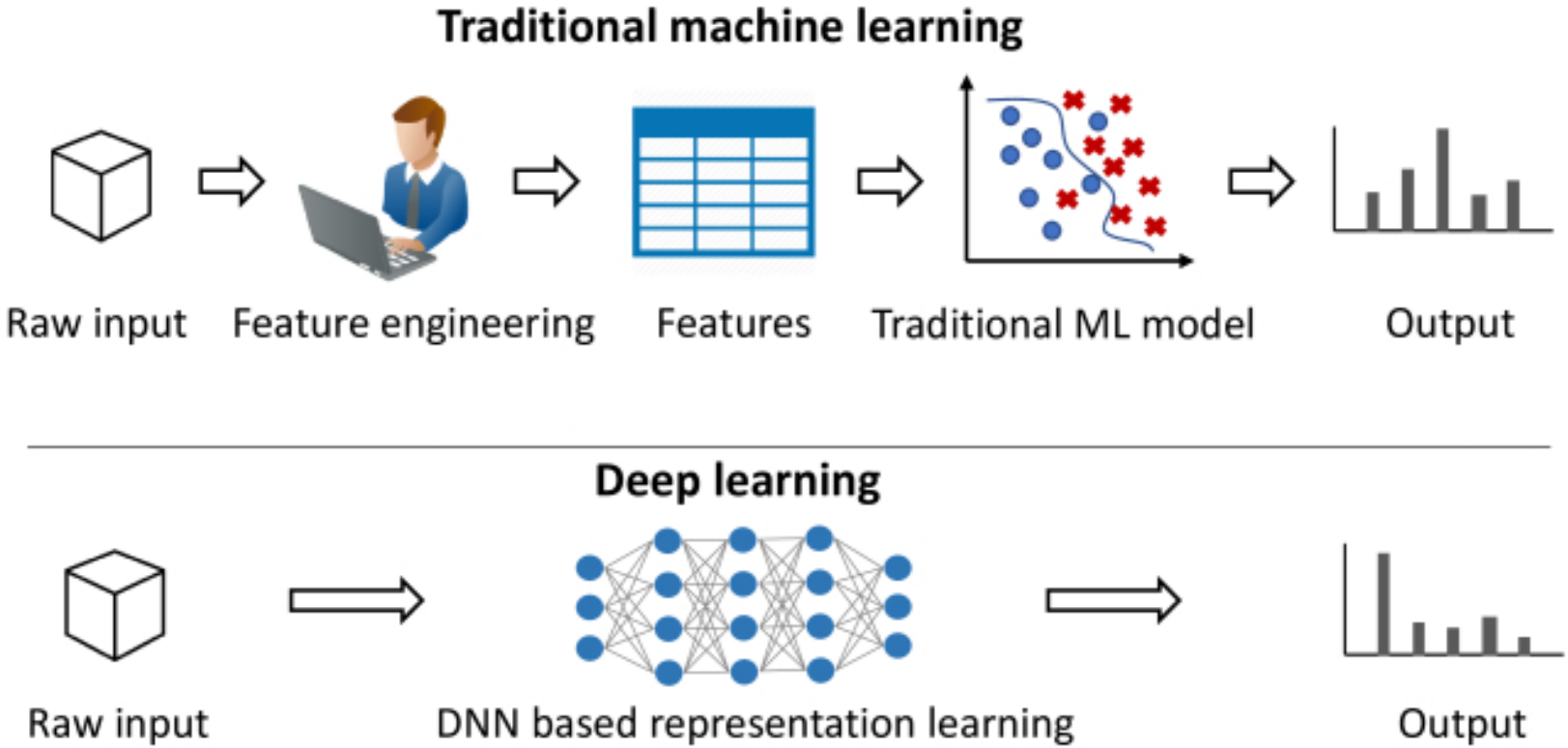


Hyper Parameters:

- Number of layers
- Number of neurons in the input, hidden and output layers
- Activation Function
- Regularization
- Learning rate
- Batch Size
- Number of epochs

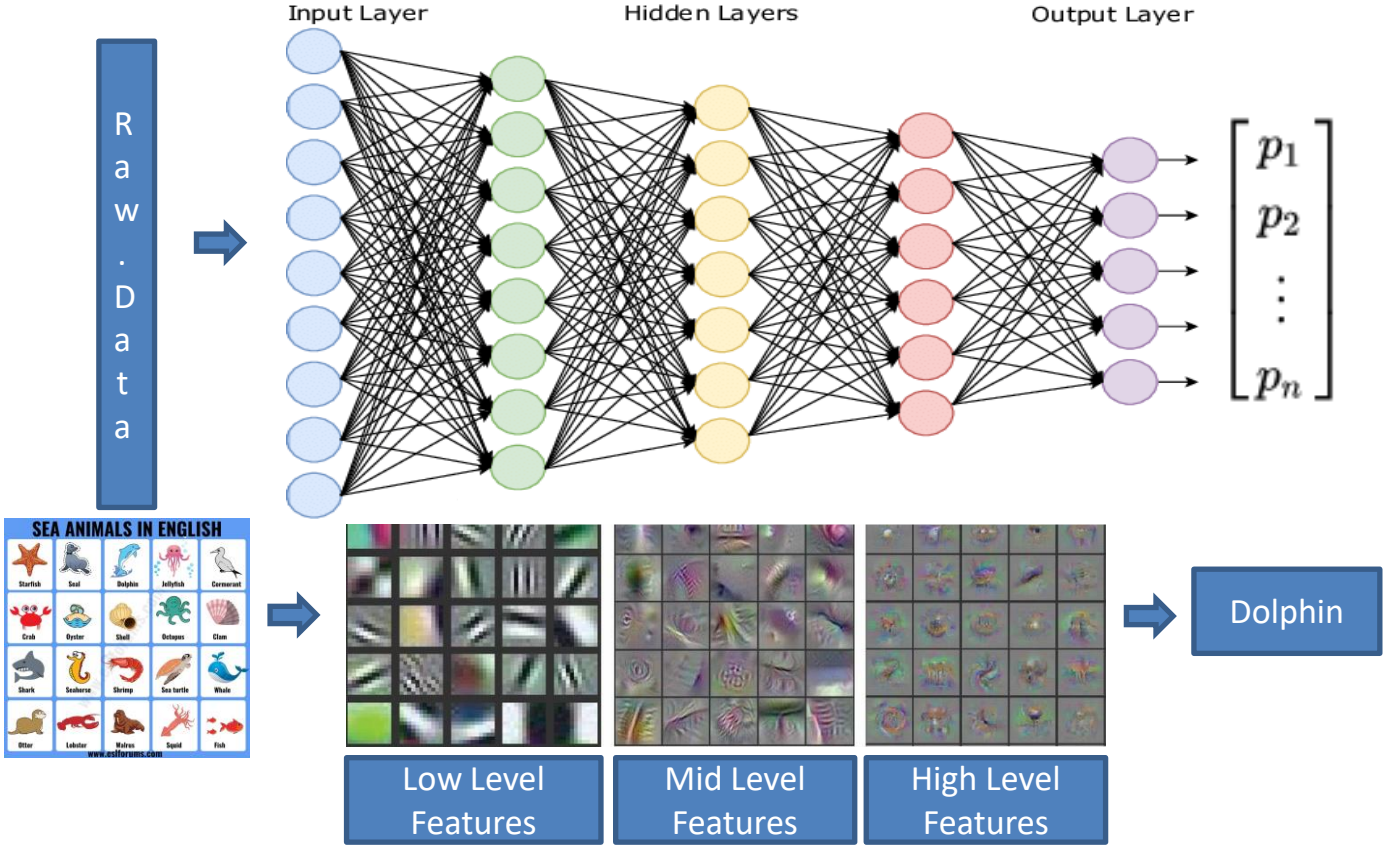
Deep Learning automated Feature Extraction

upGrad



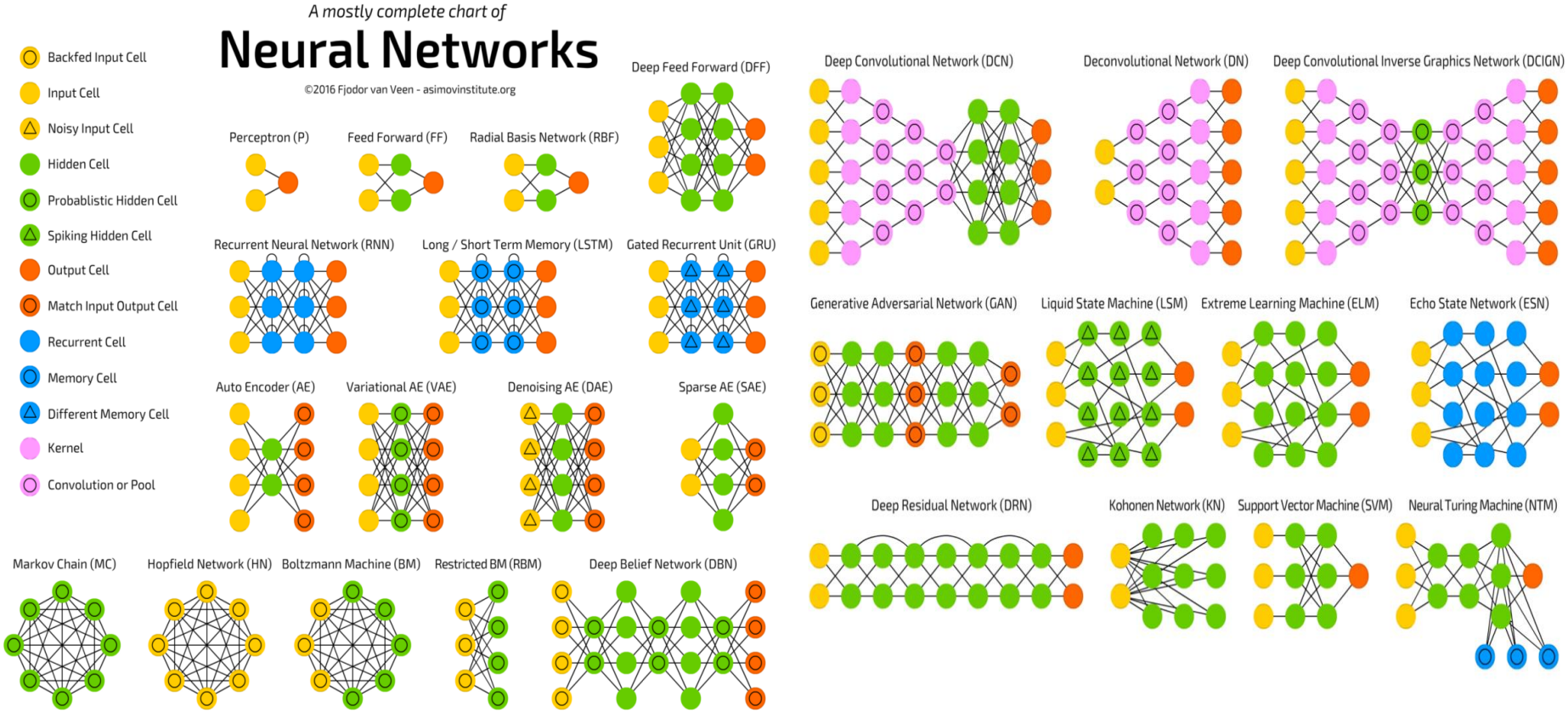
CNN- Illustration of Hierarchical Feature Extraction

upGrad



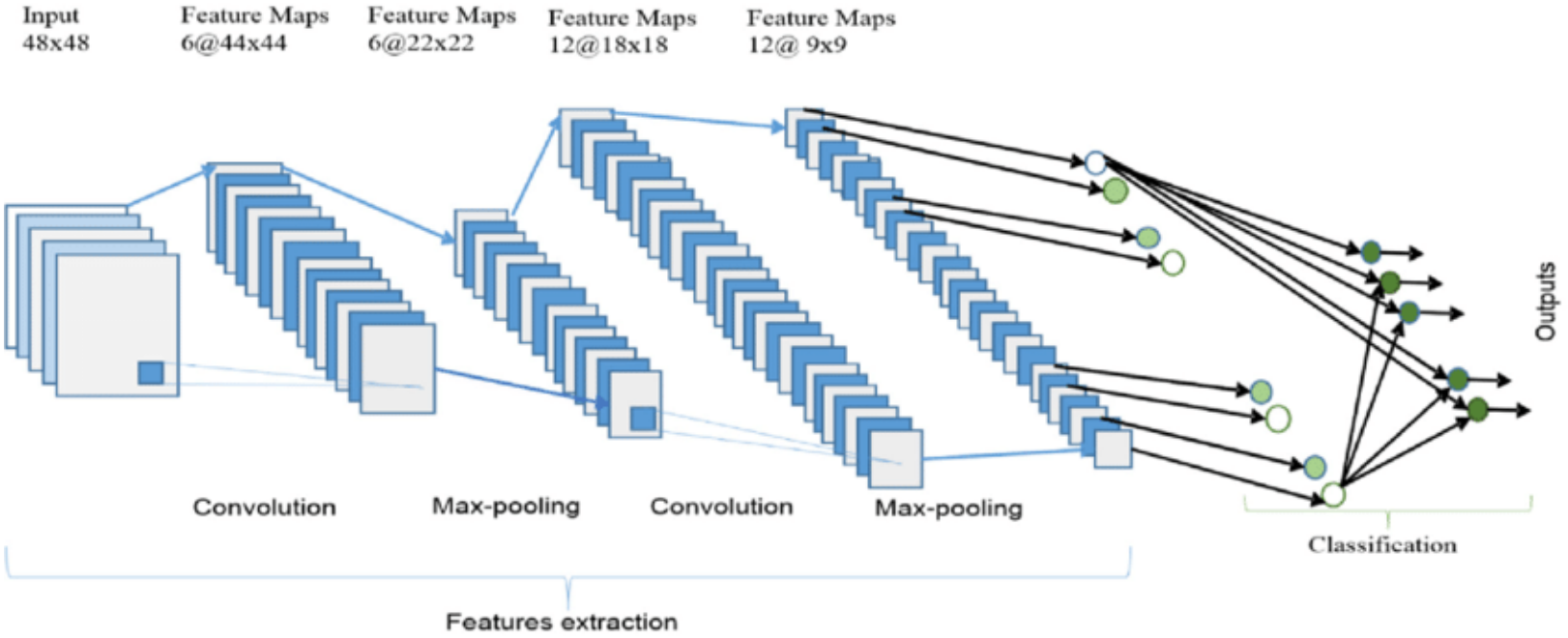
Neural Network Architectures

upGrad



Convolutional Neural Network – Network the See

upGrad

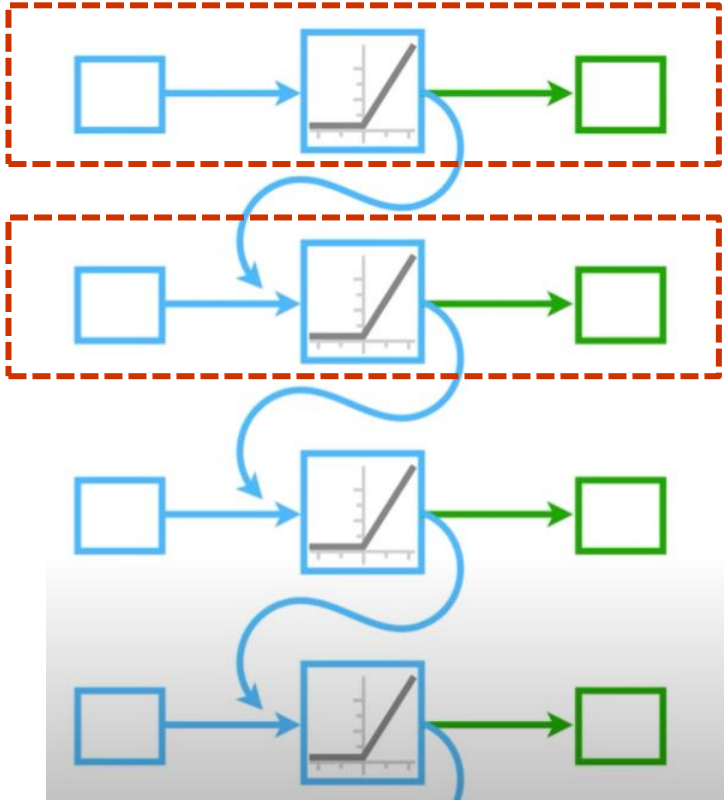


- Sequence of ***convolution*** (of filters) and ***pooling*** of pixel values exploit spatial locality- enforce a local connectivity pattern between neurons of adjacent layers. The learned "filters" produce the strongest response to a spatially local input pattern.
- Each filter is replicated across the entire visual field – leading to translation invariance

Recurrent Neural Network – Feedback Loop

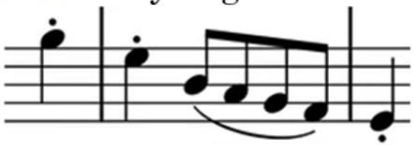
upGrad

- RNN is a class of ANN with connections between nodes (cycle) - Output from some nodes to affect subsequent input to the same nodes.
- Exhibit temporal dynamic behavior.
- Process variable length sequences of inputs and generate variable sequence output.
- RNN can take a series of inputs with no predetermined limit on size and generate variable sequence output:
  1. Vector-Sequence Models — Image caption:
  2. Sequence-Vector Model — Sentiment analysis of a movie
  3. Sequence-to-Sequence Model - Language translation



Recurrent Neural Network – Applications

upGrad

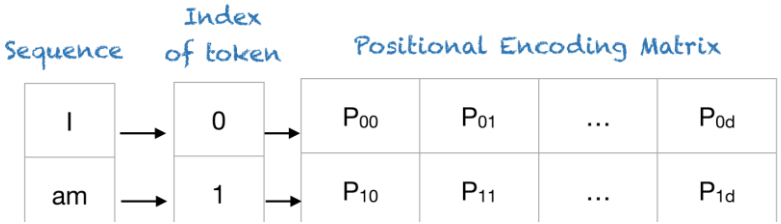
Speech recognition		→	"The quick brown fox jumped over the lazy dog."
Music generation	Ø	→	
Sentiment classification	"There is nothing to like in this movie."	→	★☆☆☆☆
DNA sequence analysis	AGCCCCTGTGAGGAACTAG	→	AGCCCCTGTGAGGAACTAG
Machine translation	Voulez-vous chanter avec moi?	→	Do you want to sing with me?
Video activity recognition		→	Running
Name entity recognition	Yesterday, Harry Potter met Hermione Granger.	→	Yesterday, Harry Potter met Hermione Granger.

Transformer – Attention Mechanism

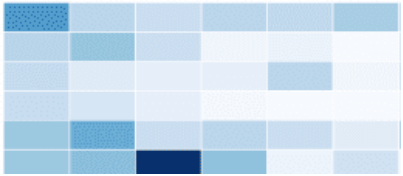
upGrad

The transformer neural network is a novel architecture that aims to solve sequence-to-sequence tasks while handling long-range dependencies.

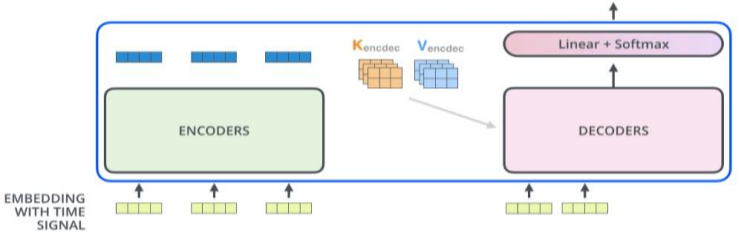
1. Positional encoding : Word embeddings are combined with their position in the sentence. This allows to input the entire sentence at once, and parallelize the process (using GPU)



2. Self – Attention : Derive the relationship between each word with all other words in the input (using Query, Key and Value mechanism)

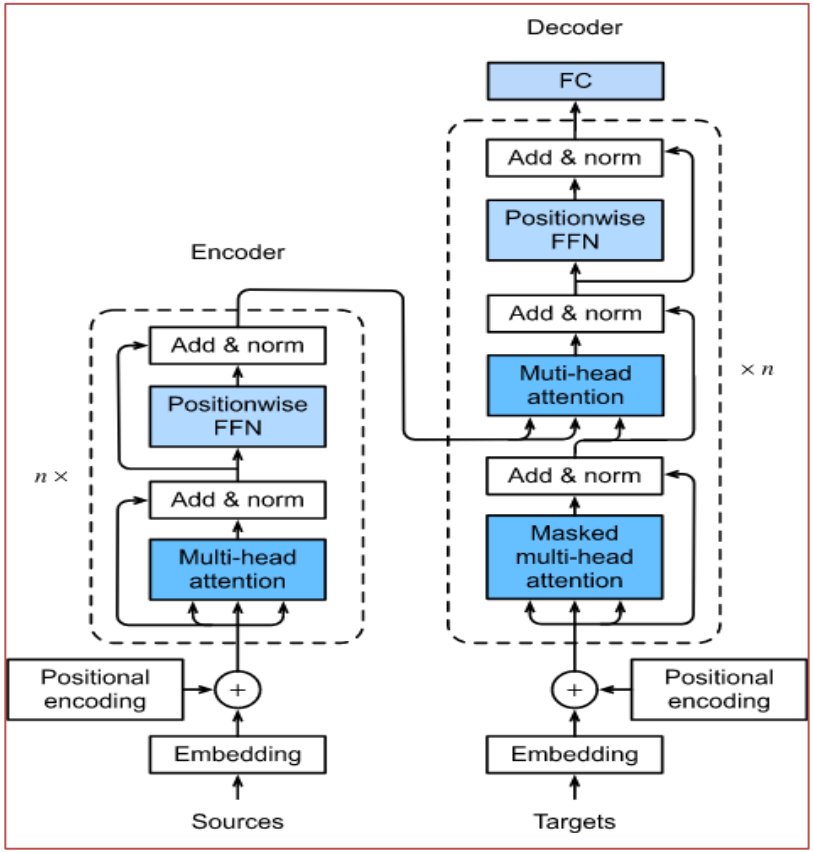


3. Decoding: The decoder generates the output sentence by defining the conditional probability distribution of a target sequence given a contextualized encoding sequence.



Transformer Archictecture

upGrad



Famous Transformer Examples

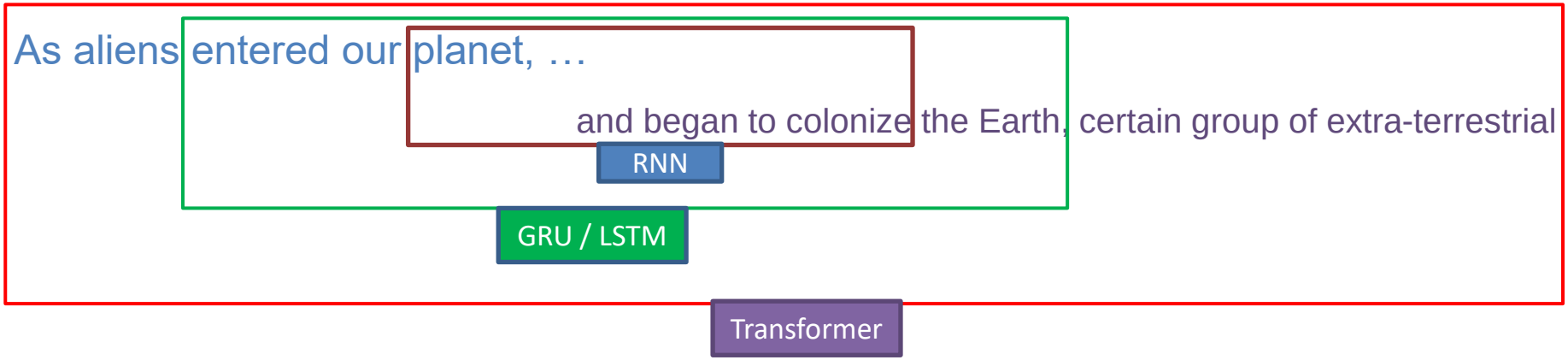
upGrad

- BERT :
  - Bidirectional Encoder Representations from Transformers is a transformer-based machine learning technique for natural language processing.
  - BERT was created and published in 2018 by Google.
  - BERT is a deeply bidirectional, unsupervised language representation, pre-trained using only a plain text corpus.

- GPT-3 :
  - **Generative Pre-trained Transformer 3** is a language model that uses deep learning to produce human-like text.
  - GPT-3, which was introduced in May 2020, by OpenAI.
  - The architecture is a standard transformer network (with a few tweaks) with 175 billion parameters.

Attention – RNN vs LSTM vs Transformer

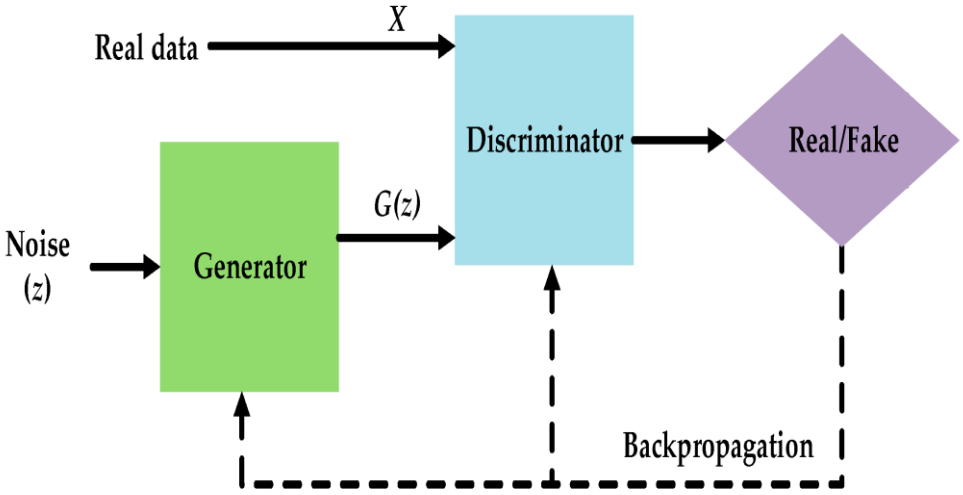
upGrad



Generative Adversarial Networks

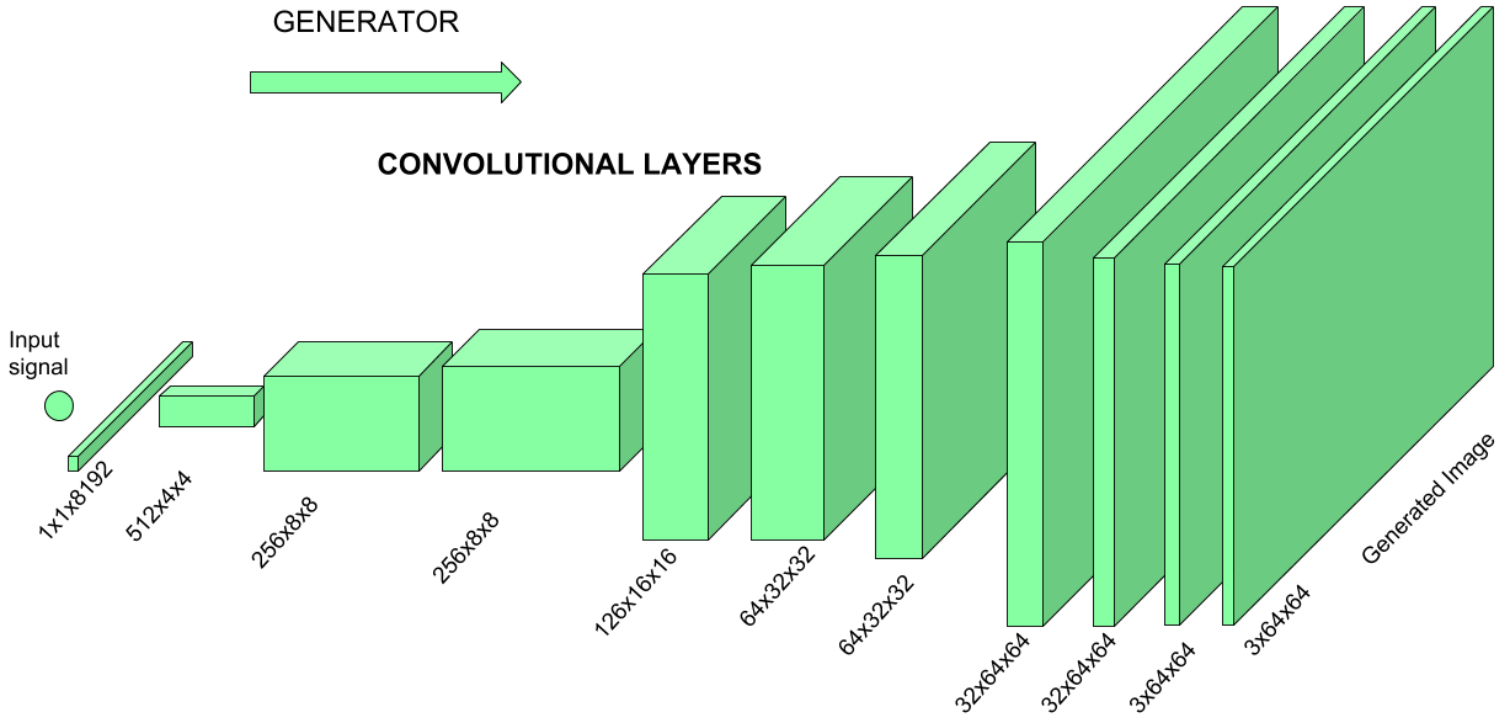
upGrad

- GAN is a class of ML frameworks where two neural networks contest with each other in the form of a zero-sum game.
- Given a training set, this technique learns to generate new data with the same statistics as the training set.
- For example, a GAN trained on photographs can generate new photographs that look at least superficially authentic to human observers, having many realistic characteristics.



Generator of GAN

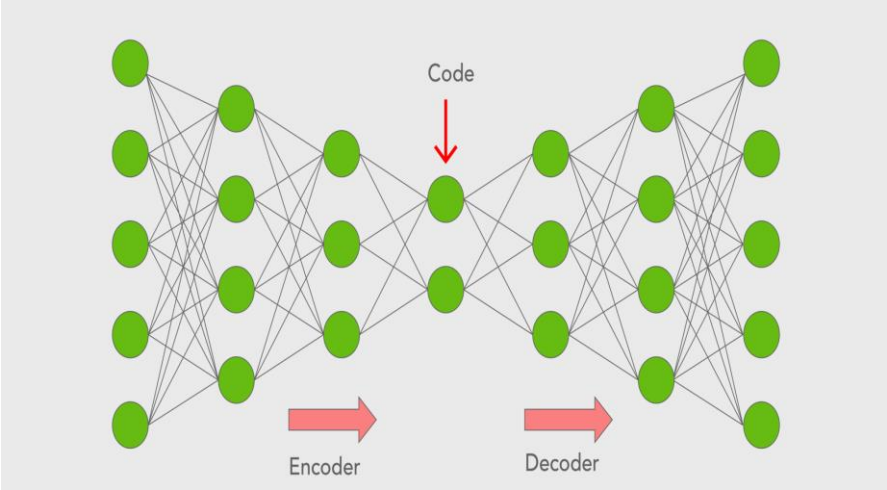
upGrad



Auto Encoders

upGrad

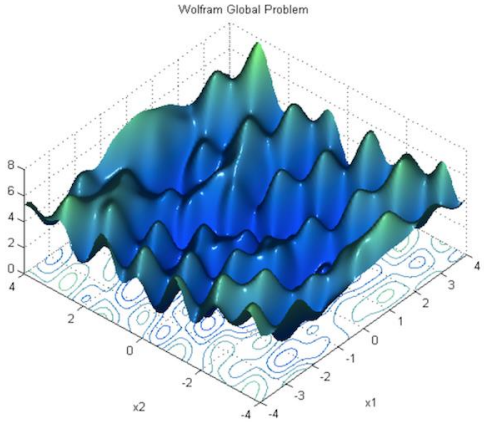
- Autoencoders operate by taking in data, compressing and encoding the data, and then reconstructing the data from the encoding representation.
- The model is trained until the loss is minimized and the data is reproduced as closely as possible.
- Through this process, an autoencoder can learn the important features of the data
- Used for dimensionality reduction, data denoising, feature extraction, image generation, sequence to sequence prediction, and recommendation systems.



Challenges of Deep Learning

upGrad

Large Dataset



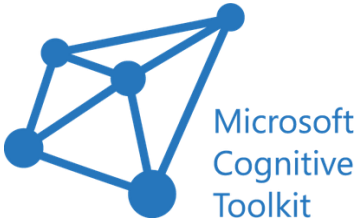
Global Minima

Resource & Time

Framework for Deep Learning

upGrad

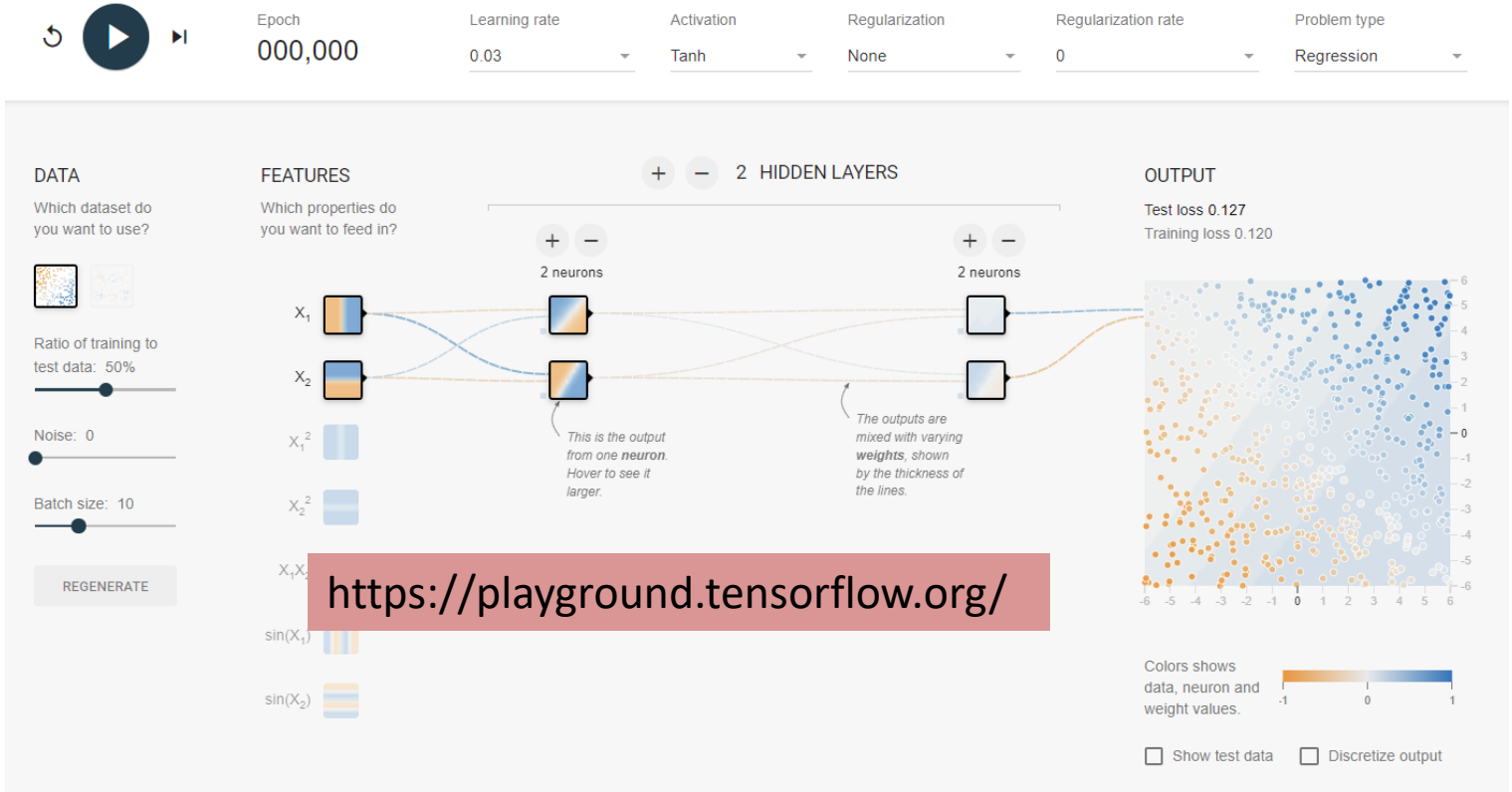
Caffe



theano

TensorFlow Playground

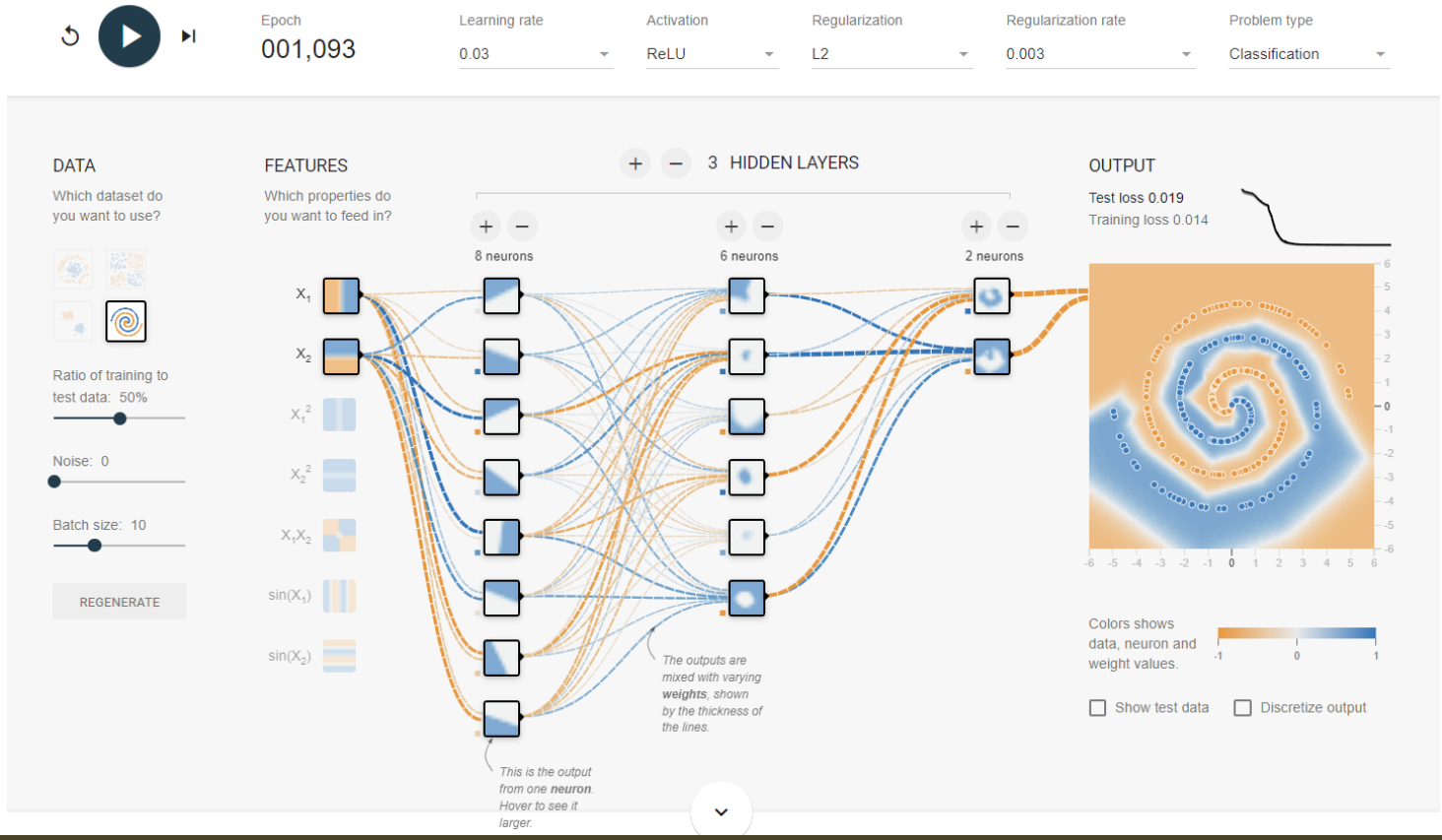
upGrad



https://playground.tensorflow.org/

Tensorflow Playground

upGrad



Discussion

upGrad

upGrad
#LifeKoKaroLift

Thank You!