Pitt HexAI Mini Summer Camp 2023

Lecture #2: Introduction to Deep Learning

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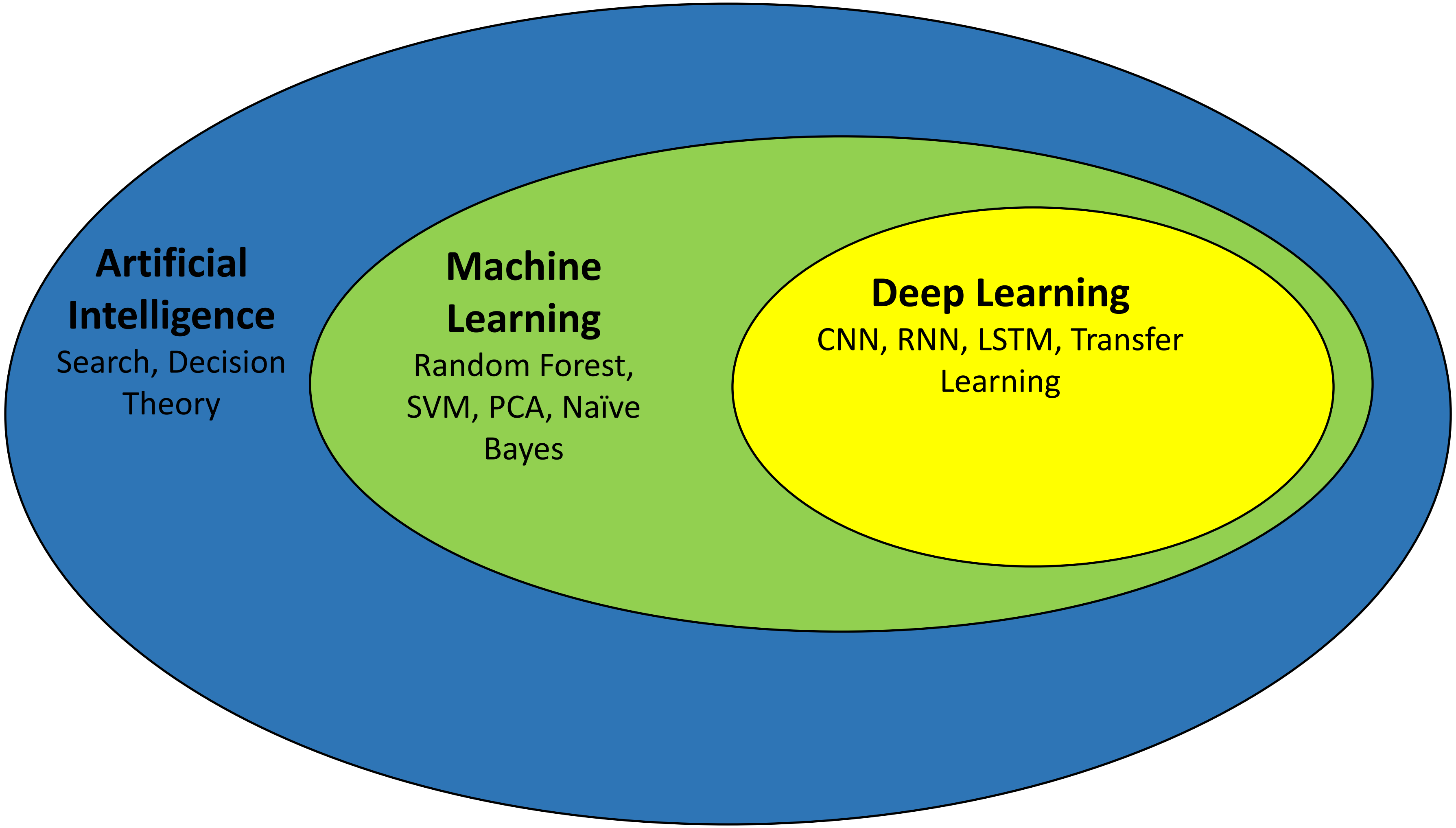
Learning Objectives:

- Understand what is deep learning and why we are using it?
- Demonstrate the Artificial Neural Networks and their applications
- Understand and explain “Universality” in deep learning
- Demonstrate shallow and deep neural networks
- Understand deep learning history and next big jumps

Deep Learning; What and Why?



Deep Learning; What and Why?

Machine Learning Tasks

Descriptive Machine Learning Algorithms (<u>What happened?</u>)

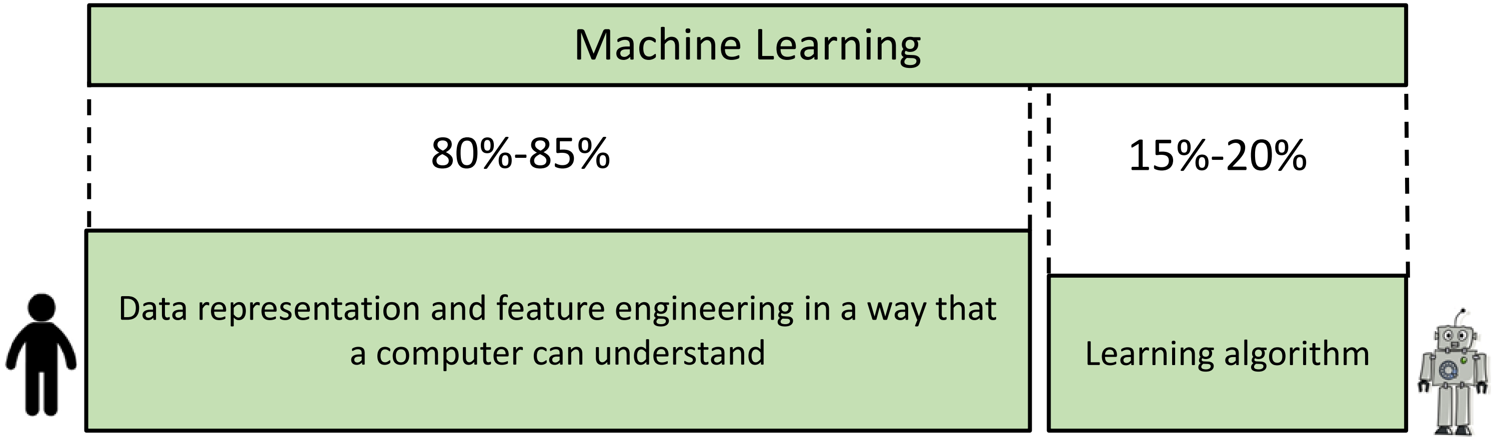
- **Clustering:** Grouping of samples (instances) given un-labeled data.
- **Summarization:** Finding a compact description for a data set.
- **Association Rules:** Discovering interesting relations between variables in a large DB.

Predictive Machine Learning Algorithms (<u>What will be happened?</u>)

- **Regression:** Attempting to predict a continuous attribute.
- **Classification:** Predicting the sample (instance) class from pre-labeled samples.

Deep Learning; What and Why?

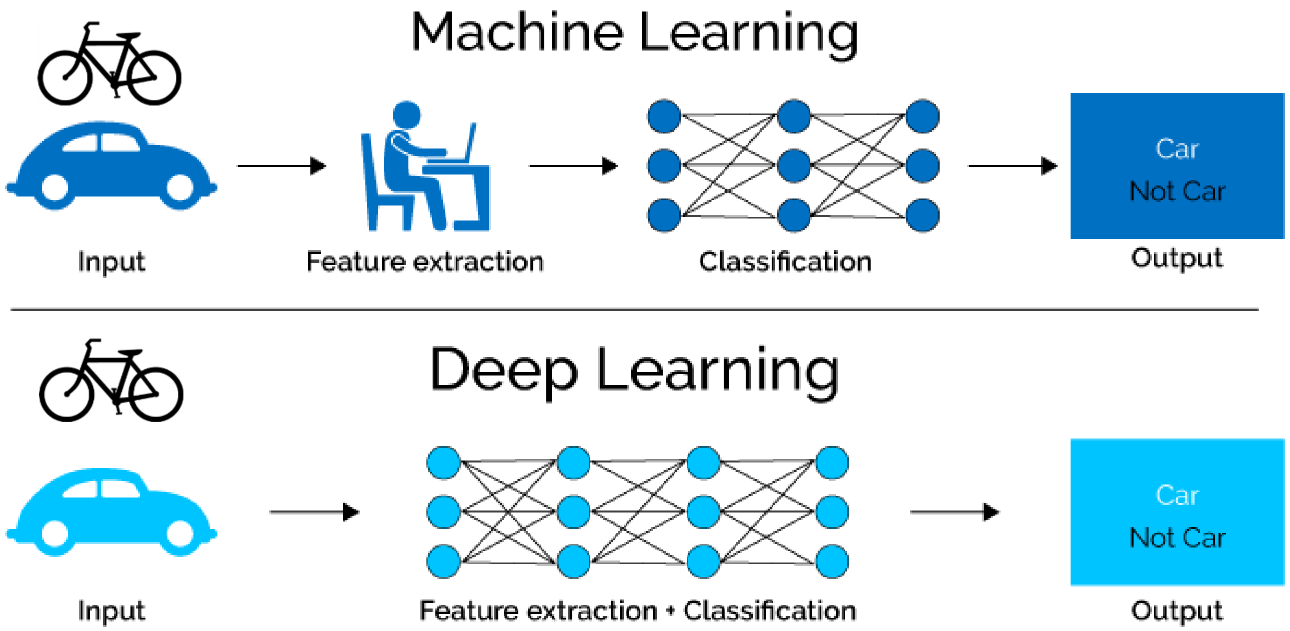
- Most **machine learning** methods work well because of **human-designed representation** and **input features**.
- **Machine learning** becomes **just optimizing weights** to best make a final prediction.



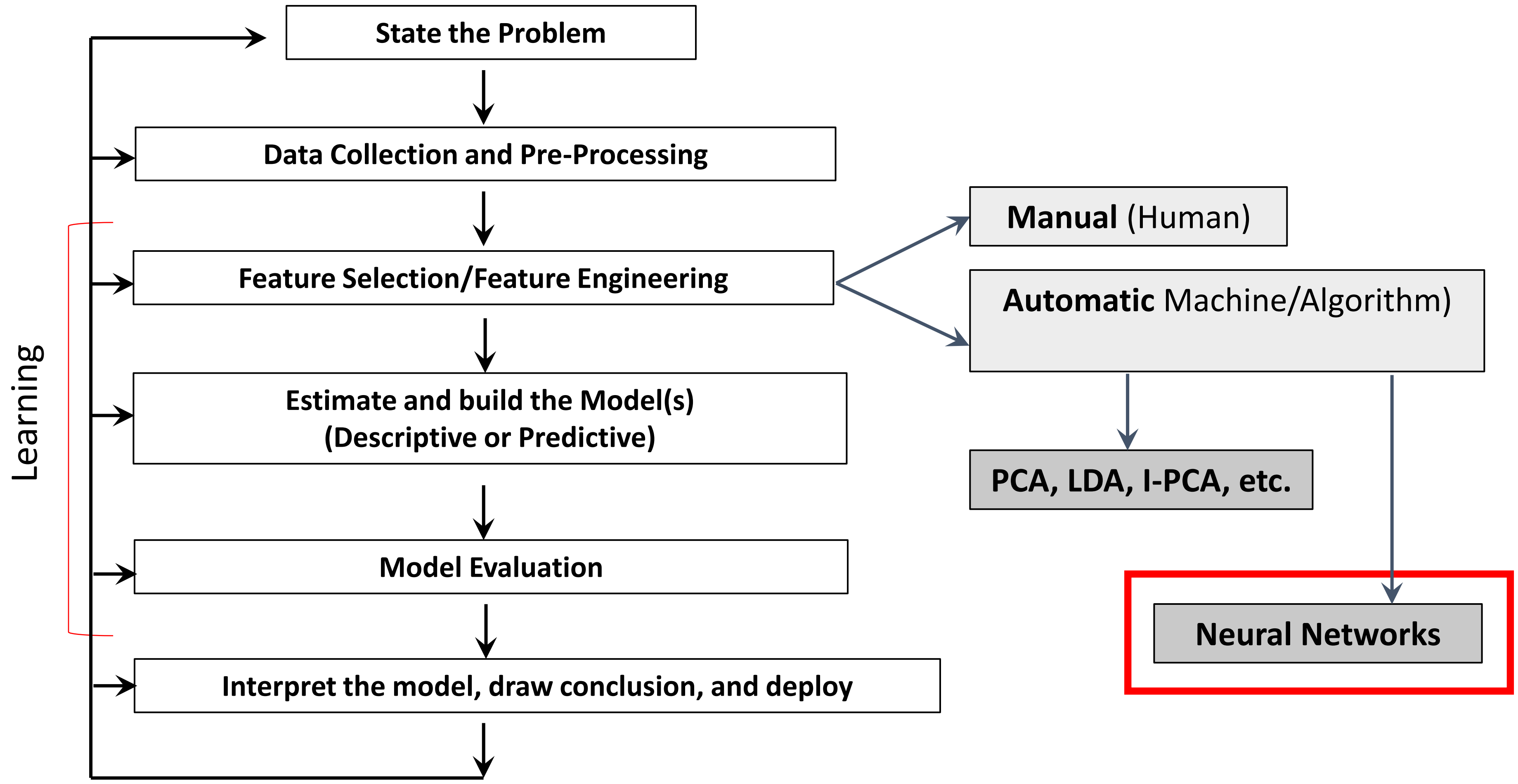
- <u>Problem</u>: **Manually designed features** are often **over-specified**, **incomplete**, and take a **long time** to **design** and **validate**.

Deep Learning; What and Why?

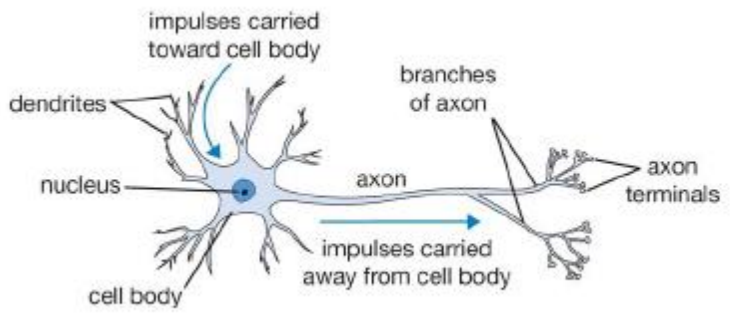
- **Deep Learning algorithms** attempt to **automatically learn good features** or **representation**.
- **Deep Learning** provides a very **flexible** and **universal** learnable framework for representing a variety of data types, such as visual data, linguistics, audio streams, and time series.

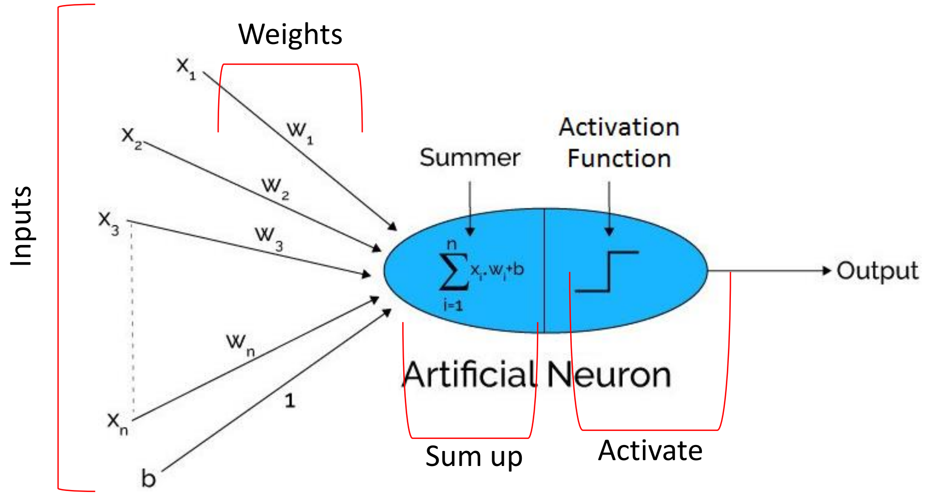


Deep Learning; What and Why?



Artificial Neural Networks (ANNs)

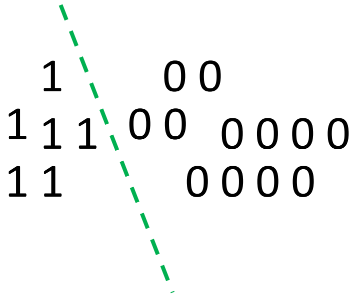




Neuron: Computational building block for the "Brain"
Human Brain: ~100 to 1000 trillion synapses

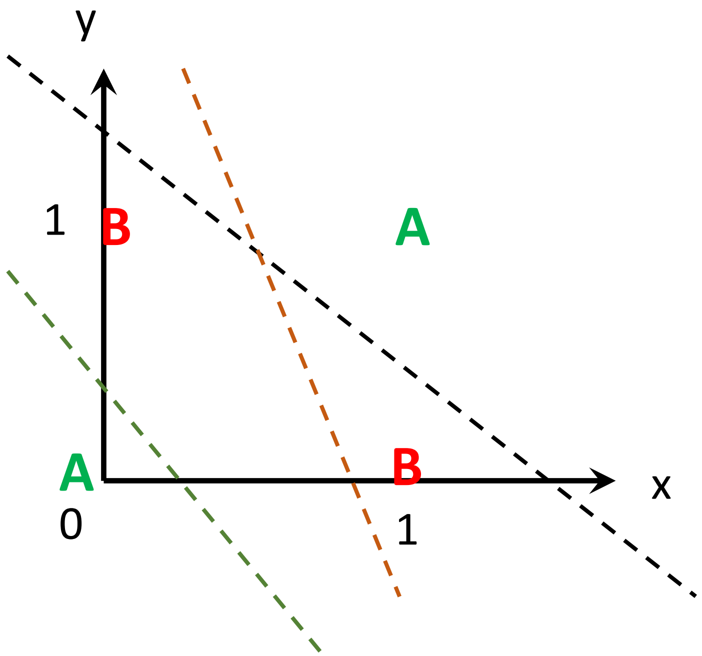
Artificial Neuron: Computational building block for the "Neural Networks"
Neural Network: ~1 to 10 billion synapses

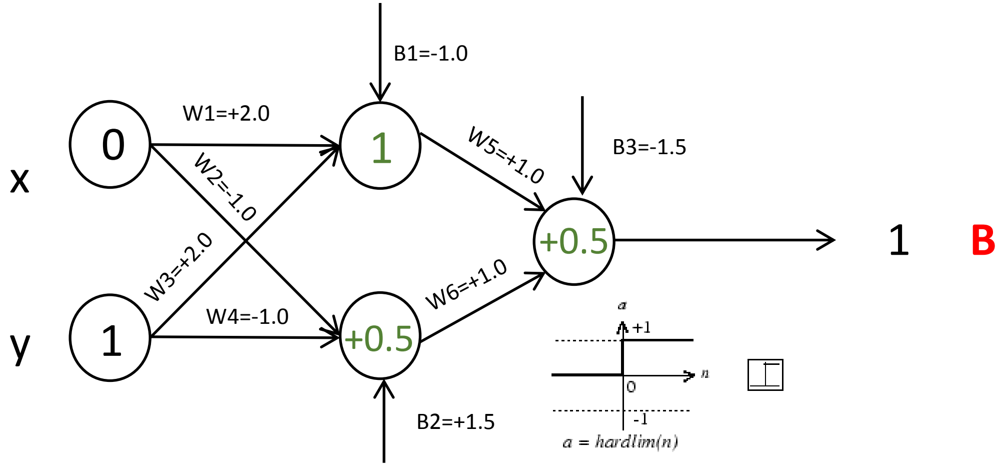
Human brains have ~10,000 computational power than the best computer brain



- **Universality:** for any arbitrary function f(x), there exists a neural network that closely approximates it for any input x.
- **Universality is an incredible property to neural networks, and it holds for just 1 hidden layer.**

x	y	x XOR y	Class
0	0	0	A
0	1	1	B
1	0	1	B
1	1	0	A

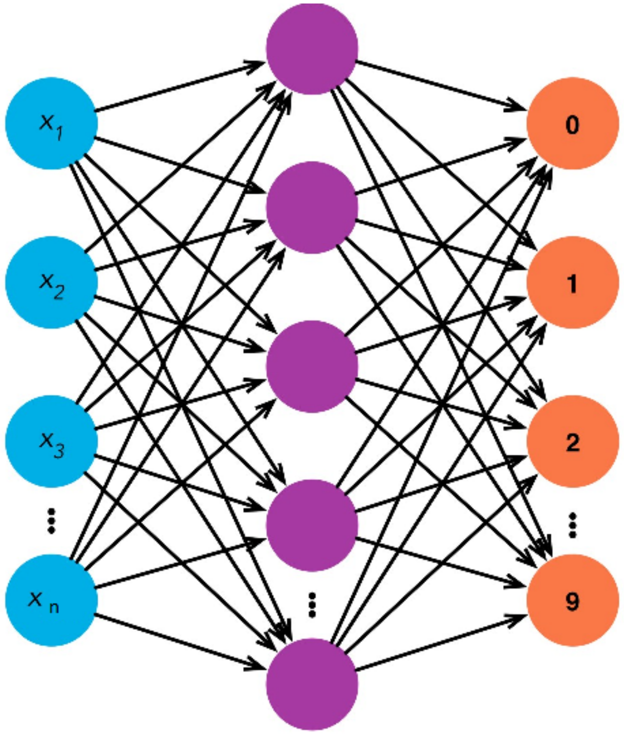




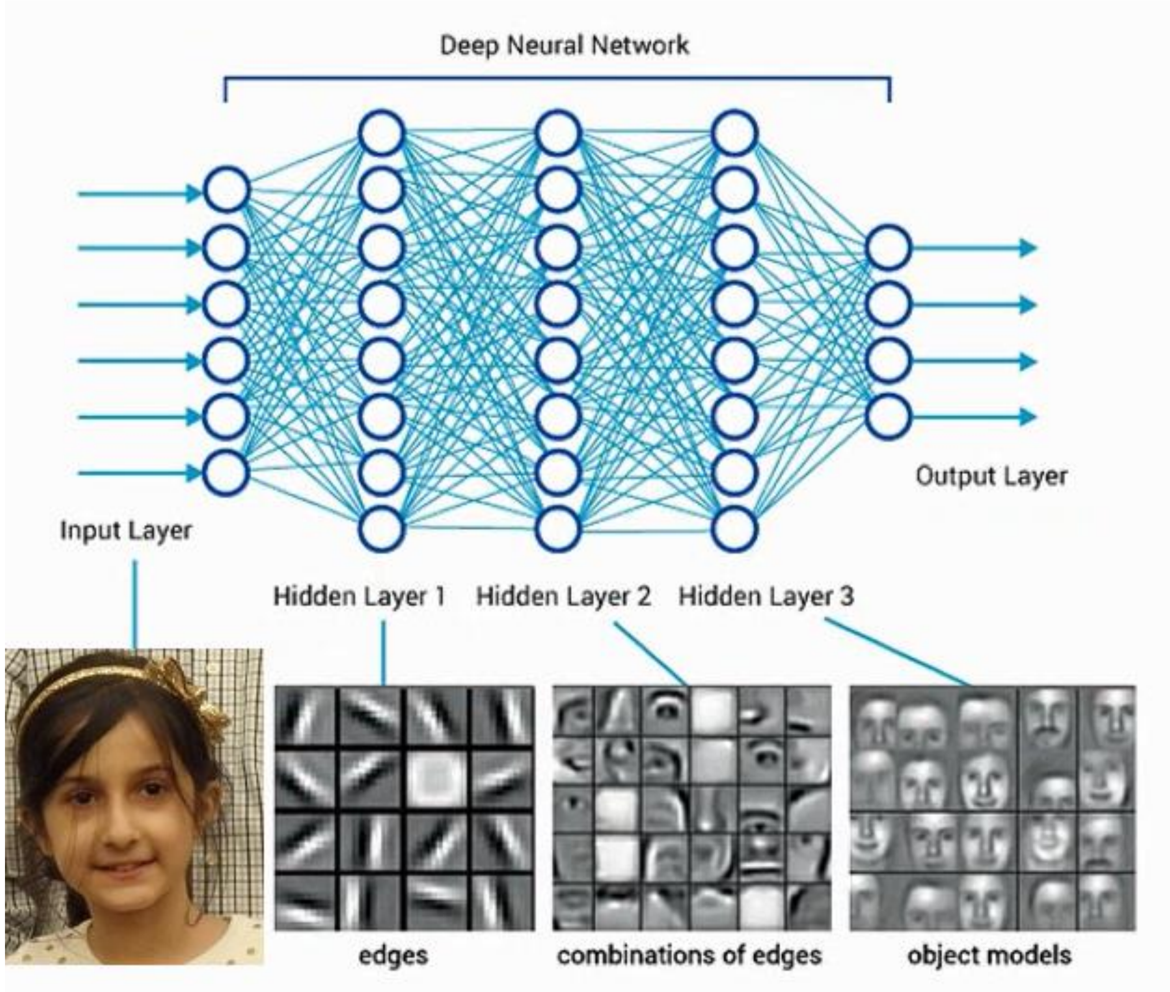
Hard-Limit Transfer Function

Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = max(0, z)$	Multi-layer Neural Networks	

Image from: http://rasbt.github.io



Shallow Neural Network



Deep Neural Network

Deep ANNs

The first **CNN**, LeNet, to read and understand hand-wri
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The first **RNN**

Deep Learning stagnation and inactivity.

Reasons:

- Lack of large-scale training data
- Lack of high performance

Hinton, G.E., Osindero, S. and

CNN won several competitions in Image Classification, Object Recognition.

IMAGENET

Thank you!

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