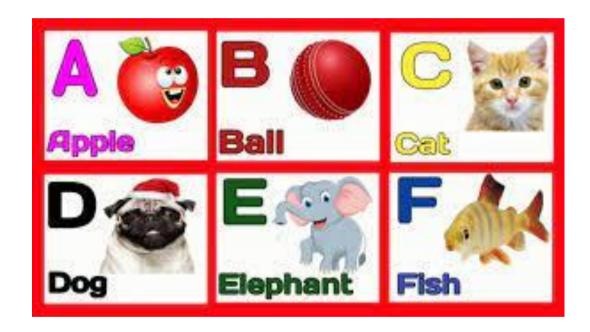
# Introduction to Deep Learning

#### Introduction

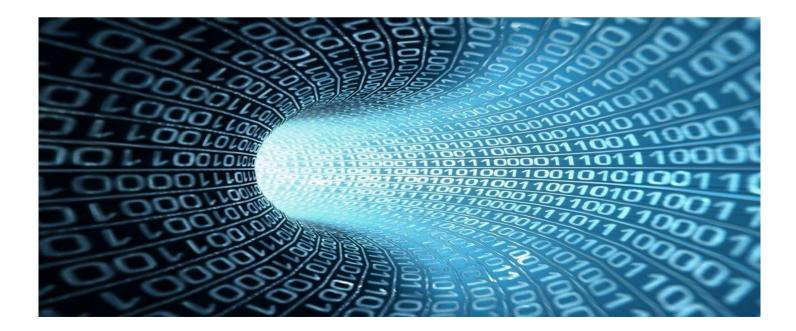
Learn English Alphabets with books having colorful pictures



Why images when objective is to learn the alphabet?

# What is Deep Learning?

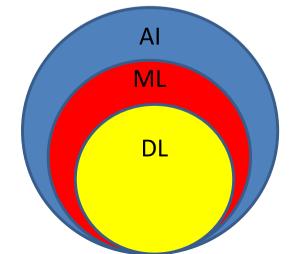
- Type of machine learning that imitates the way humans gain certain types of knowledge
- Extremely beneficial to data scientists for interpreting large amounts of data
  - Deep learning makes this process faster and easier



# What is Deep Learning

- Intelligence to process information which can be used for future decision
  - Al builds algorithms to achieve this and perform predictions
  - ML is subset of AI teaches algorithms to learn from experiences without being explicitly programmed
  - DL uses neural networks to extract useful patterns/features from raw data and using them to perform

a task



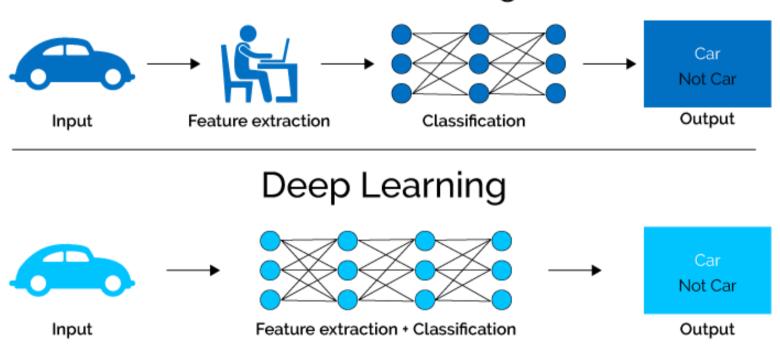
## Deep Learning

- Deep learning algorithms
  - Run data through several "layers" of neural network algorithm
  - Each layer passes a simplified representation of data to next layer
- Machine Learning algorithms:
  - Work well on datasets that have up to a few hundred features
  - An unstructured dataset has large number of features difficult for traditional machine learning algorithms to handle
  - Ex. an 800 \* 1000 pixel image in RGB color has 2.4 million features

# Why Deep Learning

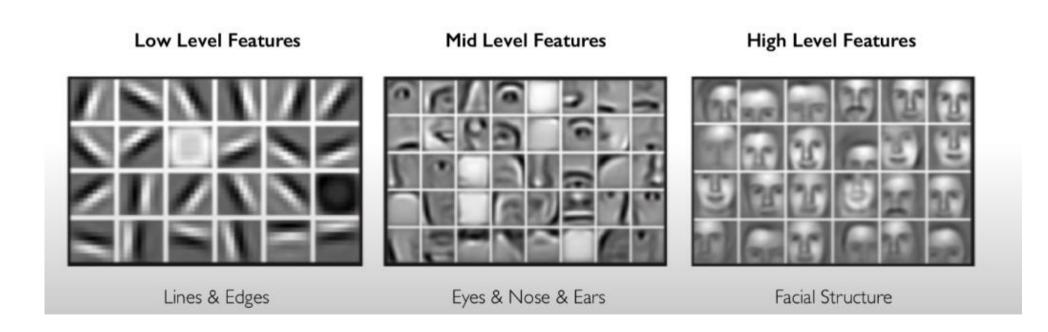
 Hand-engineered/handcrafted features are time consuming and not scalable in practice

Machine Learning

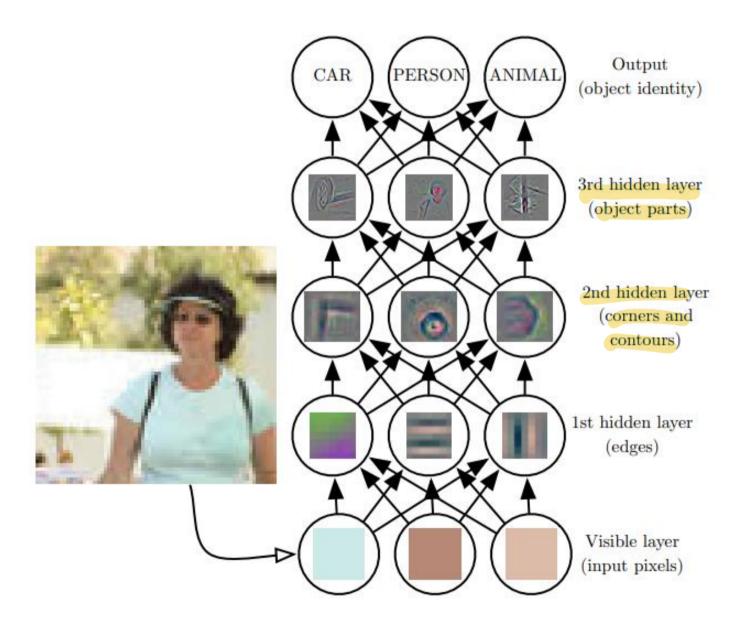


# Why Deep Learning

 Key - learn underlying features directly from data in an hierarchical manner

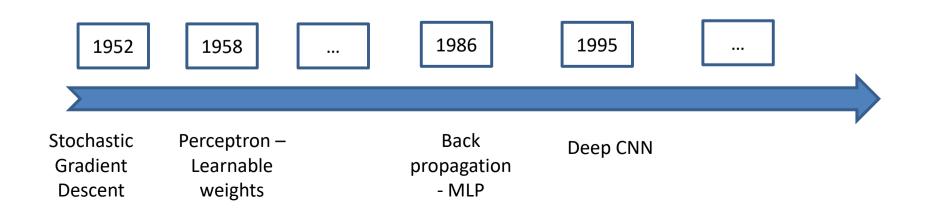


## Why Deep Learning

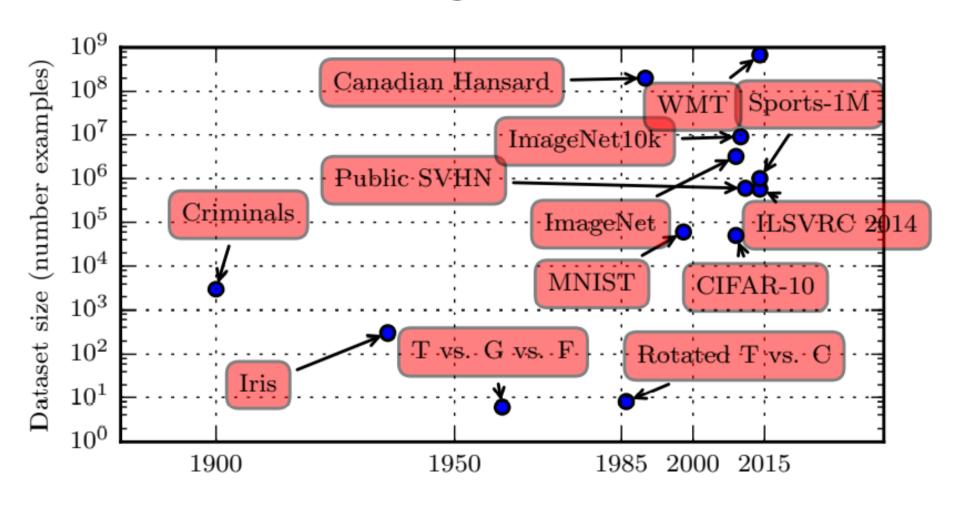


# Why Deep Learning Now?

- Data is more pervasive Big Data
  - Larger datasets, easier collection and storage
- Hardware Graphics Processing Units (GPUs)
- Parallelizable algorithms
- Software better techniques, new models, open source toolboxes



## **Growing Datasets**



Аc

IRIS: <a href="https://archive.ics.uci.edu/ml/datasets/iris">https://archive.ics.uci.edu/ml/datasets/iris</a>

MNIST: <a href="http://yann.lecun.com/exdb/mnist/">http://yann.lecun.com/exdb/mnist/</a>

ImageNet: https://www.image-net.org/download.php

#### **MNIST** Dataset

8	9	0	1	2	3	4	7	8	9	0	1	2	3	4	5	6	7	8	6
4	2	6	4	7	5	5	4	7	8	9	2	9	3	9	3	8	2	0	5
			4																
3	0	6	2	7	1	1	8	1	1	1	3	8	9	7	6	7	4	1	6
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3	7	8	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6	7	0
/	2	3	4	5	6	7	8	9	8	1	0	5	5	1	9	٥	4	7	9
3	8	4	7	7	8	5	0	6	5	5	3	3	3	9	8	7	4	0	6
7	0	0	6	2	7	7	3	2	8	8	7	8	4	6	0	a	0	3	6
8	7	7	5	9	9	3	2	4	9	٠4	6	5	3	2	Ś	5	9	4	/
6	5	O	1	ュ	3	4	5	6	7	ક	9	0	1	2	3	4	5	6	っ
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4	7	૪	9	2	9	3	9	ઉ	8	2	0	9	૪	0	5	6	٥	F	Ø
4	2	6	5	5	5	4	3	4	ı	5	3	0	૪	3	0	6	2	7	1
1	૪	1	7	7	3	8	5	4	2	O	9	7	6	7	4	1	6	8	4
7	క	7	a	6	7	7	9	જ	0	6	9	4	9	9	6	2	3	7	1
9	2	2	5	3	7	8	0	1	2	3	4	5	6	7	8	0	1	2	3
			7			_						_		_				_	_
9	9	8	5	3	7	0	7	7	5	7	9	9	4	7	0	3	4	1	4
4	7	5	8	1	4	8	4	1	8	6	6	4	6	3	5	7	2	5	9

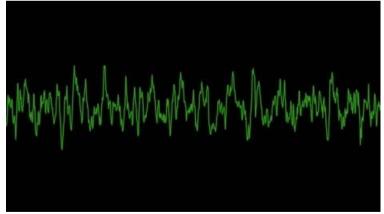
#### Structured vs. Unstructured Data

Size	No. of bedrooms	Price (in Lakhs)
150	2	80
200	3	120
380	4	250



Age	Ad Id	Click
25	10682	1
16	2051	0
58	31289	1

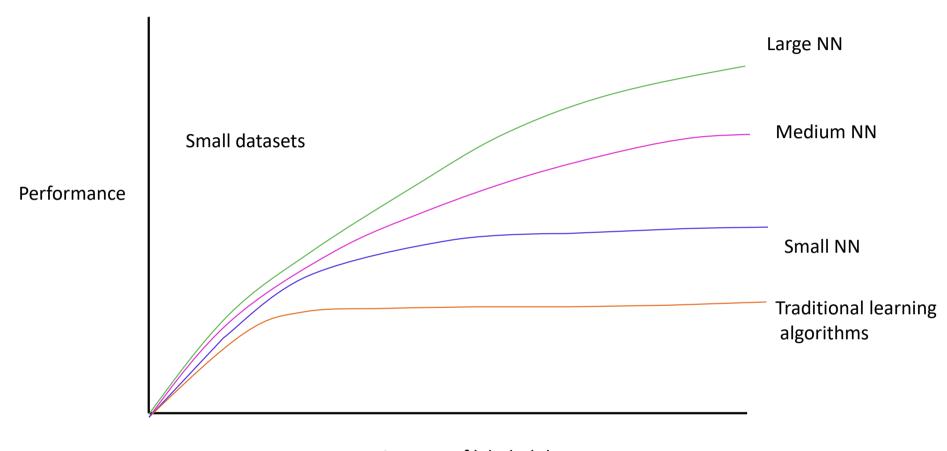




Text

Once upon a time, in a land far far away ....

# Effect of Data Scaling



Amount of labeled data

Two things to be considered for high level of performance:

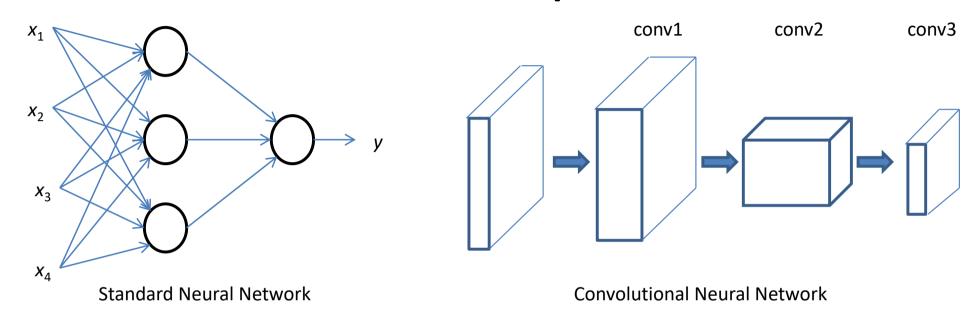
- 1. Able to train a big enough neural network
- 2. Large amount of labeled data

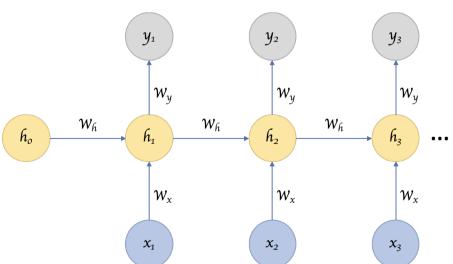
## Supervised Learning

 Given a data set and correct output relationship between input and output

Input	Output	Application	Type of NN		
Home features	Price	Real estate	Standard NN		
Image	Object (12000)	Photo tagging	CNN		
Audio	Text transcript	Speech recognition	RNN		
English	French	Machine translation	RNN		
Sensor information	Position of objects on road	Autonomous driving	Hybrid		
Ad, user information	Ad click?	Online advertising	Standard NN		
Sensor information	Sunny?	Weather forecasting	Standard NN		

## NN examples





**Recurrent Neural Network** 

https://gotensor.com/2019/02/28/recurrent-neural-networks-remembering-whats-important/

#### **APPLICATIONS**

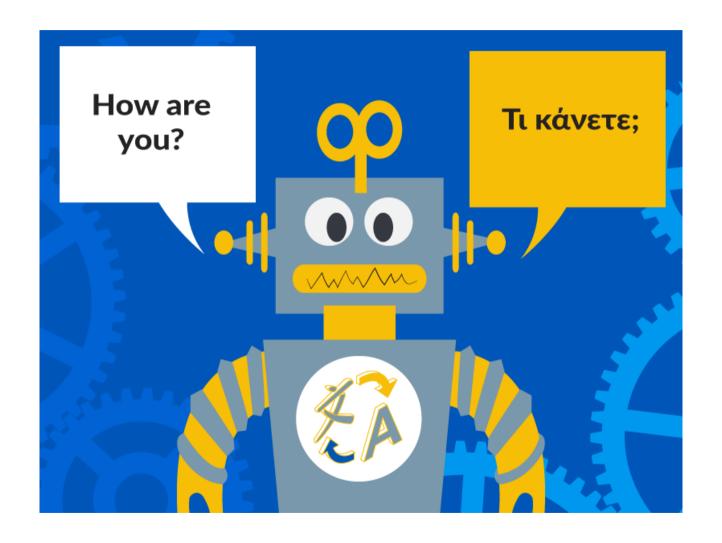
## Language Modeling

 $P(S) = P(Where) \times P(are \mid Where) \times P(we \mid Where are) \times P(going \mid Where are we)$ 

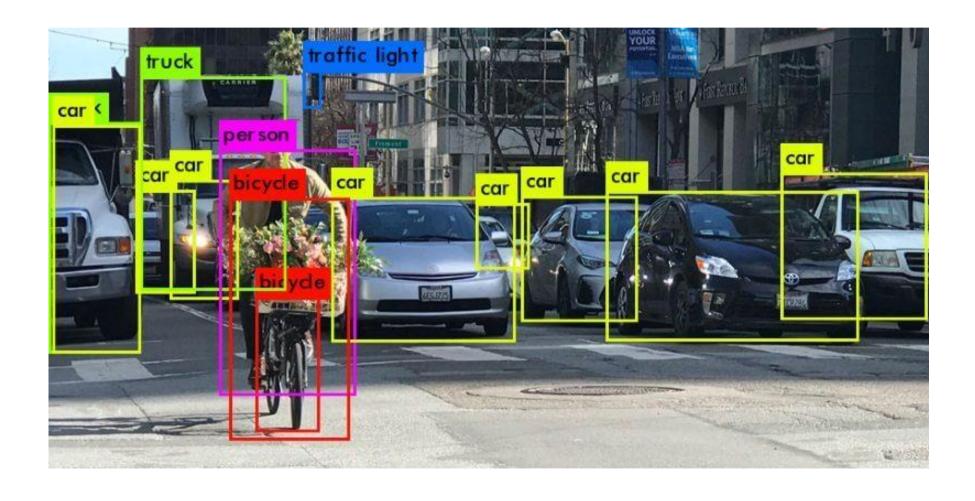
# Speech Recognition



#### **Machine Translation**



# Object Detection/Recognition



## **Image Captioning**

a train traveling down a track next to a forest.



a group of young boys playing soccer on a field.



Evergreen\*

## Generating Authentic Photos



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