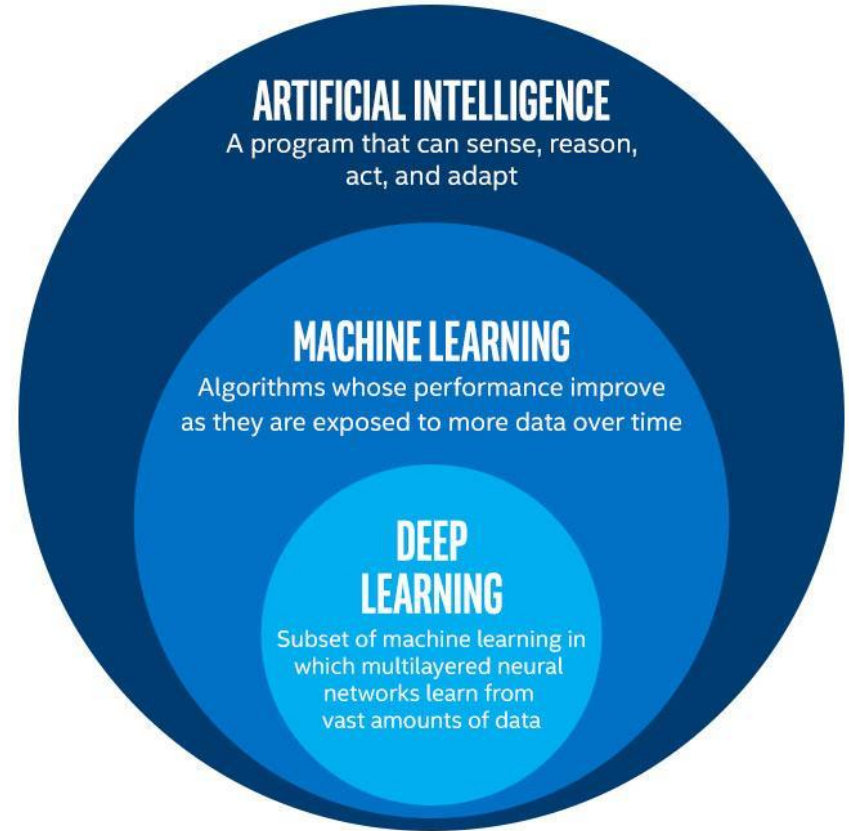


Introduction to ML

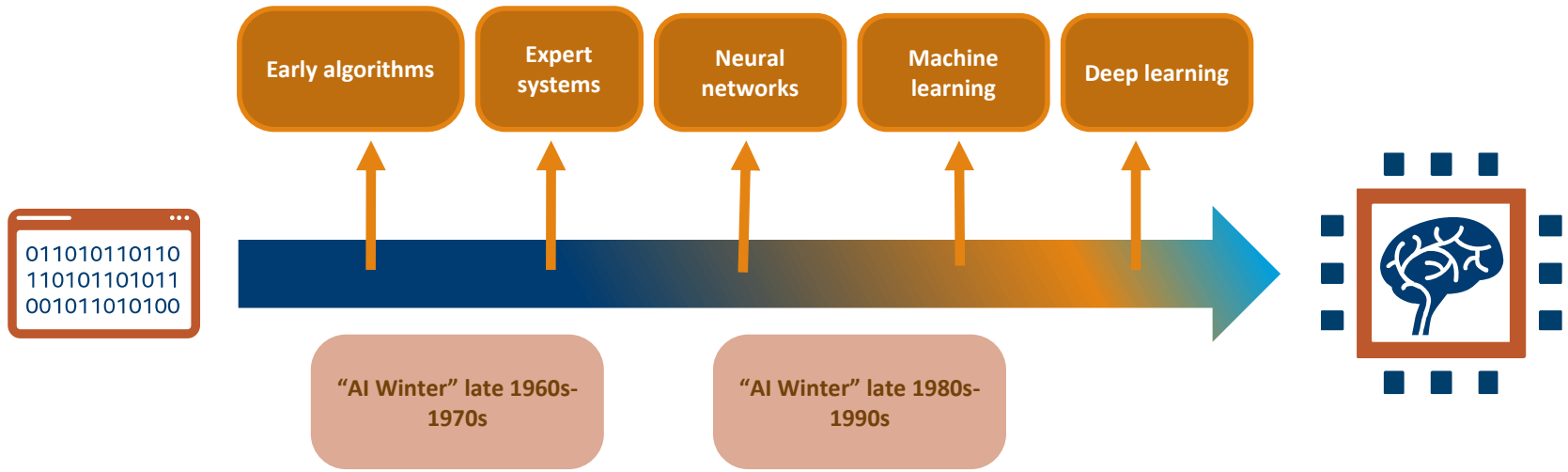
Definitions

- **Artificial Intelligence**
 - Human Intelligence Exhibited by Machines
- **Machine Learning**
 - An Approach to Achieve Artificial Intelligence
- **Deep Learning**
 - A Technique for Implementing Machine Learning



History of AI

AI has experienced several hype cycles, where it has oscillated between periods of excitement and disappointment.



Modern AI

Deep Learning Breakthroughs (2012 – Present)

- In 2012, deep learning beats previous benchmark on the ImageNet competition.
- In 2013, deep learning is used to understand “conceptual meaning” of words.
- In 2014, similar breakthroughs appeared in language translation.
- These have led to advancements in Web Search, Document Search, Document Summarization, and Machine Translation.

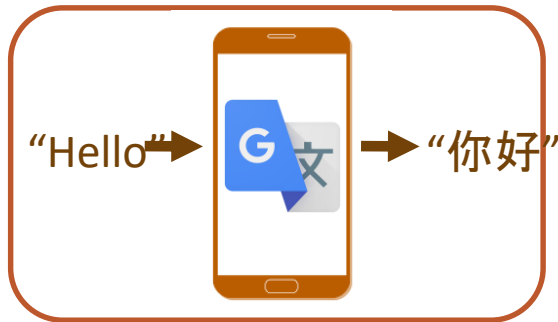
Image classification



“Dog”

“Cat”

As of 2015, computers can be trained to perform better on this task than humans.



Google Translate

Deep Learning Breakthroughs (2012 – Present)

- In 2014, computer vision algorithm can describe photos.
- In 2015, Deep learning platform TensorFlow is developed.
- In 2016, DeepMind's AlphaGo, developed by Aja Huang, beats Go master Lee Se-dol.



Autonomous Mars rover

Modern AI (2012 – Present): Deep Learning Impact

Computer vision



Self-driving cars:
object detection



Healthcare:
improved diagnosis

Natural language



Communication:
language translation

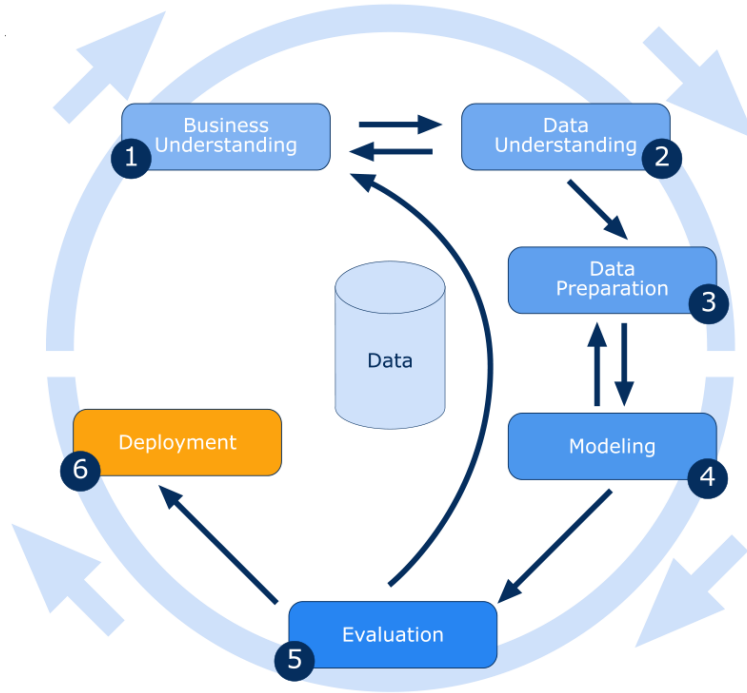
AI Applications

AI Usage Growth

								
CONSUMER	HEALTH	FINANCE	RETAIL	GOVERNMENT	ENERGY	TRANSPORT	INDUSTRIAL	OTHER
Smart Assistants Chatbots Search Personalization Augmented Reality Robots	Enhanced Diagnostics Drug Discovery Patient Care Research Sensory Aids	Algorithmic Trading Fraud Detection Research Personal Finance Risk Mitigation	Support Experience Marketing Merchandising Loyalty Supply Chain Security	Defense Data Insights Safety & Security Resident Engagement Smarter Cities	Oil & Gas Exploration Smart Grid Operational Improvement Conservation	Autonomous Cars Automated Trucking Aerospace Shipping Search & Rescue	Factory Automation Predictive Maintenance Precision Agriculture Field Automation	Advertising Education Gaming Professional & IT Services Telco/Media Space Exploration Sports

Data Science Workflow

CRISP-DM (Data Science work flow)



The cross industry standard process for data mining, **CRISP-DM**, is a data mining process model that data mining experts use to tackle problems

Very iterative process

Approach for Data Science Projects

Business Problem Definition

- Define business objectives and frame the problem
- Layout project plans
- Validate with stake-holders



Through the Initial discussion with stake holders

Understand SYSTEMS, Data and processes

- Understand systems involved and business process
- Gain domain knowledge
- Collect, describe and explore the available data
- Verify data quality



Evaluate and choose Solution approach

- What are solution paths to address the need.
- Select simplest and proven solution path - consult with experts that have solved similar problems in the domain

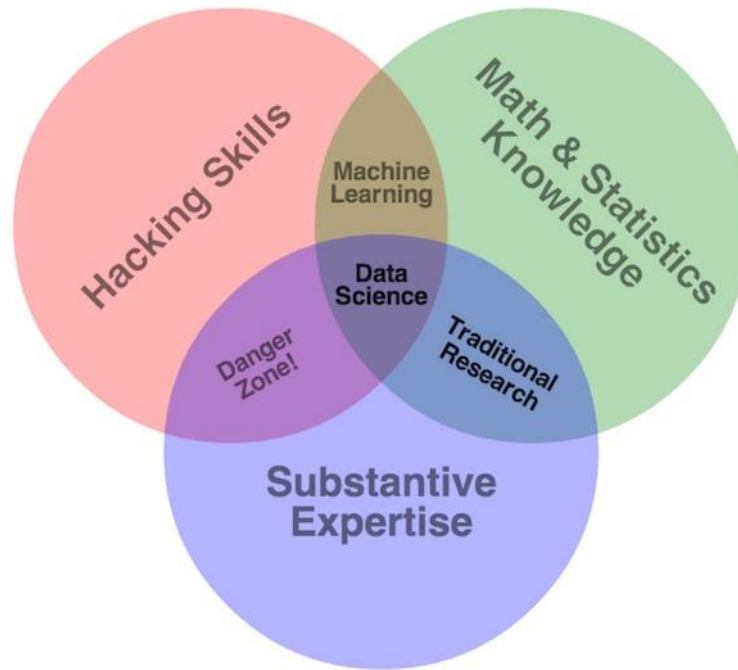


Implement, Test, Validate

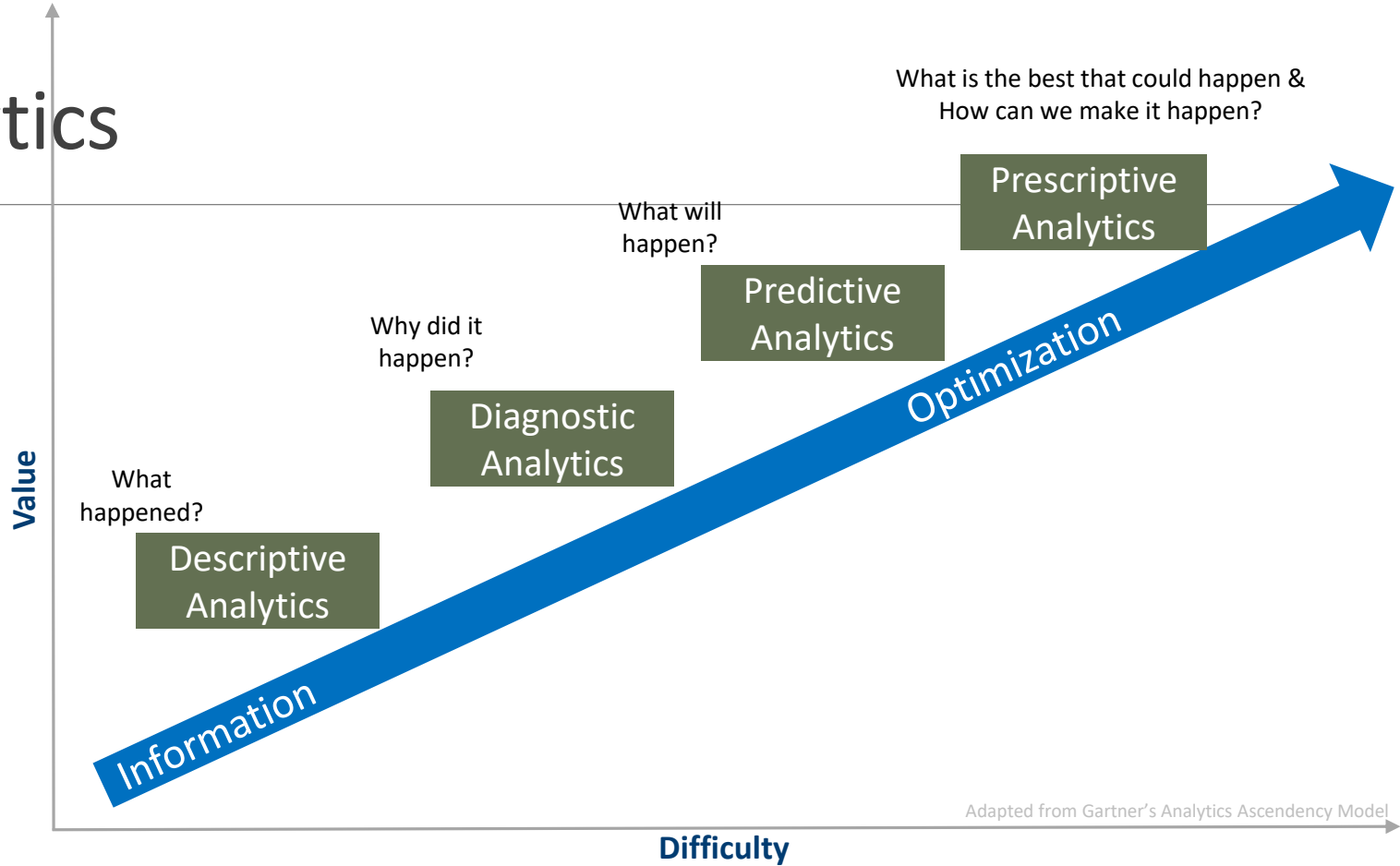
- Develop/implement chosen algorithm, validate
- Pilot & ensure the solution properly addresses business problem
- Produce deployment plan that meets sustainability needs



Data Science Skill Sets



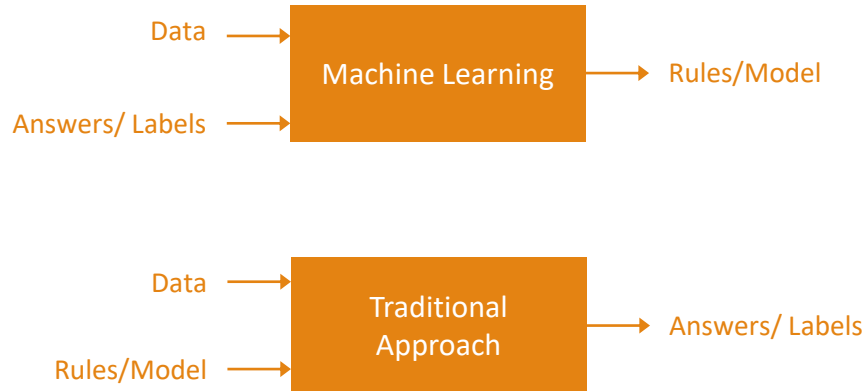
Analytics



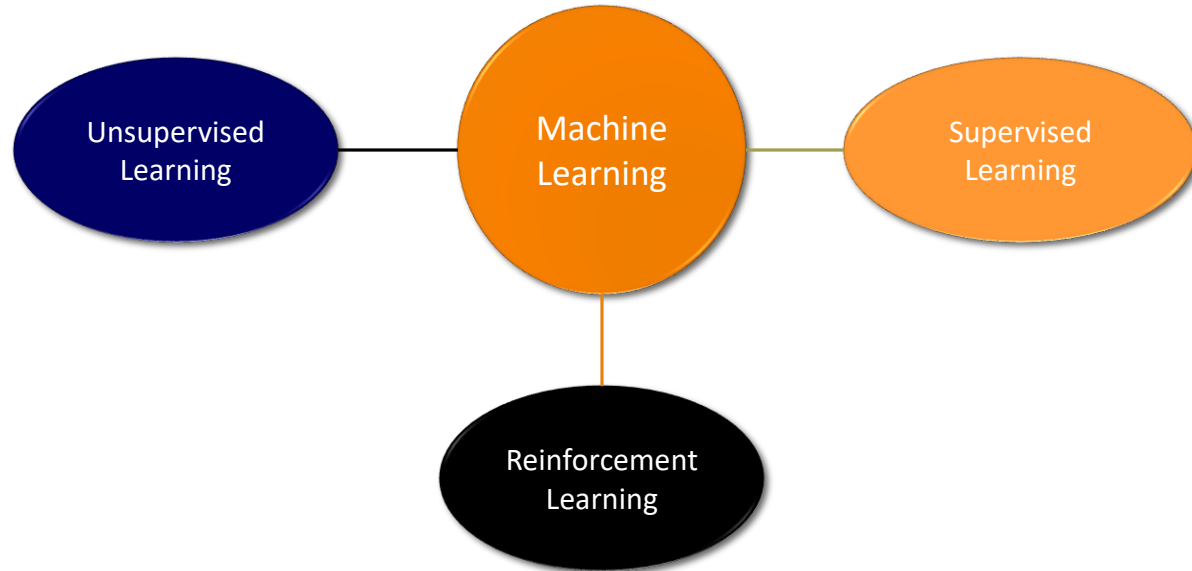
Machine Learning

Machine Learning

Machine Learning relates with the study, design, and development of models and algorithms that give computers the capability to learn from data, instead of requiring explicit programming of hard-coded rules/logic.



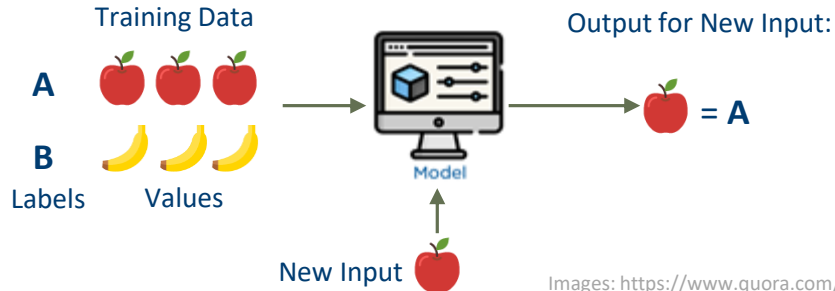
Machine Learning algorithms



Supervised vs. unsupervised learning

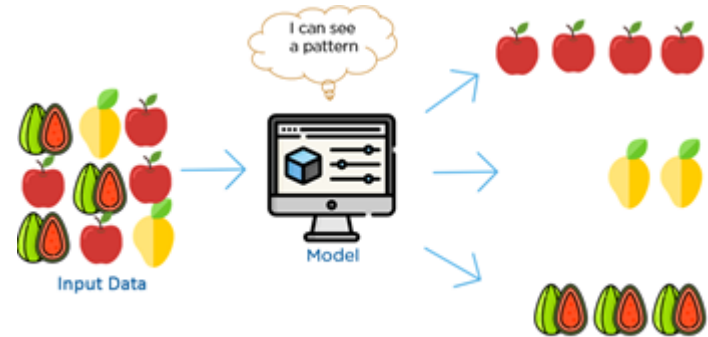
Supervised

- Begin with data we **already know the desired output**
- Use **Training data** to derive relationships between the input features and desired output
- Predict future outcomes from derived relationships from training data



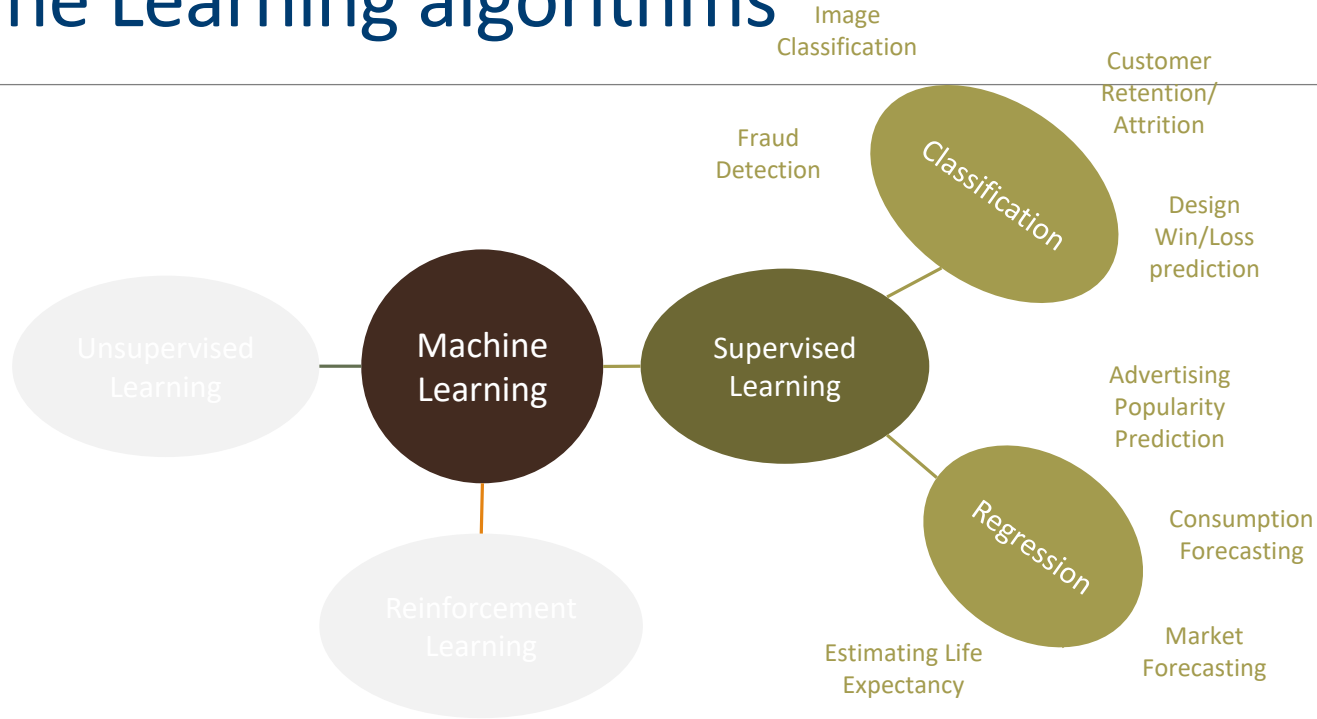
Unsupervised

- Begin with little or no idea what our results should look like
- Derive **structure** from data where we don't necessarily know the effect of the variables.



Images: <https://www.quora.com/What-is-the-difference-between-supervised-and-unsupervised-learning-algorithms>

Machine Learning algorithms



Supervised Learning – Classification



Iris setosa



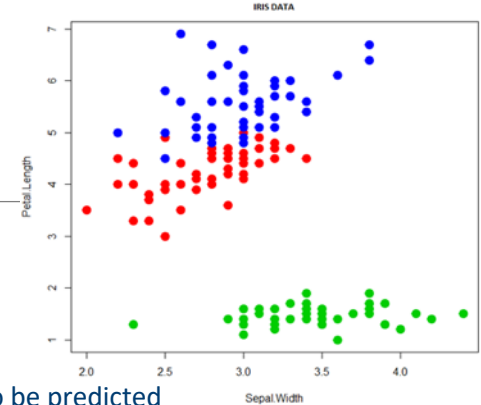
Iris versicolor



Iris virginica

Input / observation / attribute: categorical or numeric

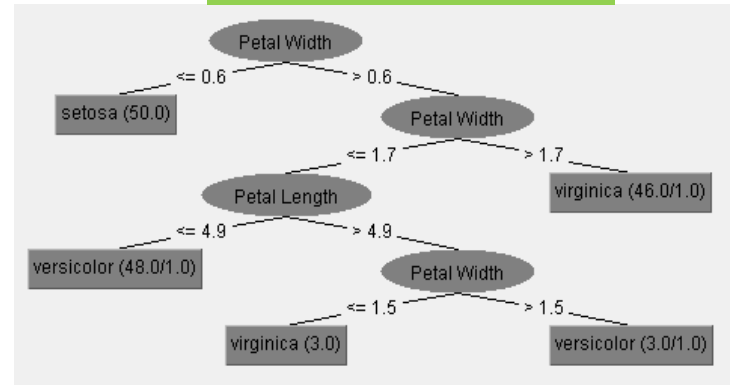
Output / response / label: categorical



Target: Columns to be predicted

sepal length	sepal width	petal length	petal width	Flowername
5.1	3.5	1.4	0.2	Iris-setosa
4.9	3	1.4	0.2	Iris-setosa
4.7	3.2	1.3	0.2	Iris-setosa
7	3.2	4.7	1.4	Iris-versicolor
6.4	3.2	4.5	1.5	Iris-versicolor
6.9	3.1	4.9	1.5	Iris-versicolor
6	3	4.8	1.8	Iris-virginica
6.9	3.1	5.4	2.1	Iris-virginica
6.7	3.1	5.6	2.4	Iris-virginica

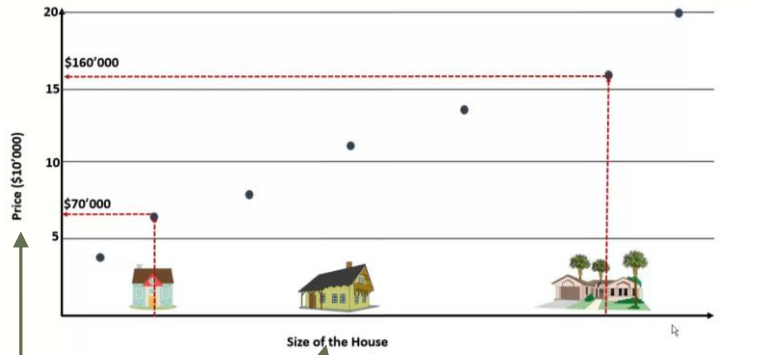
Decision Tree - Algorithm



Features : Attributes of the Data

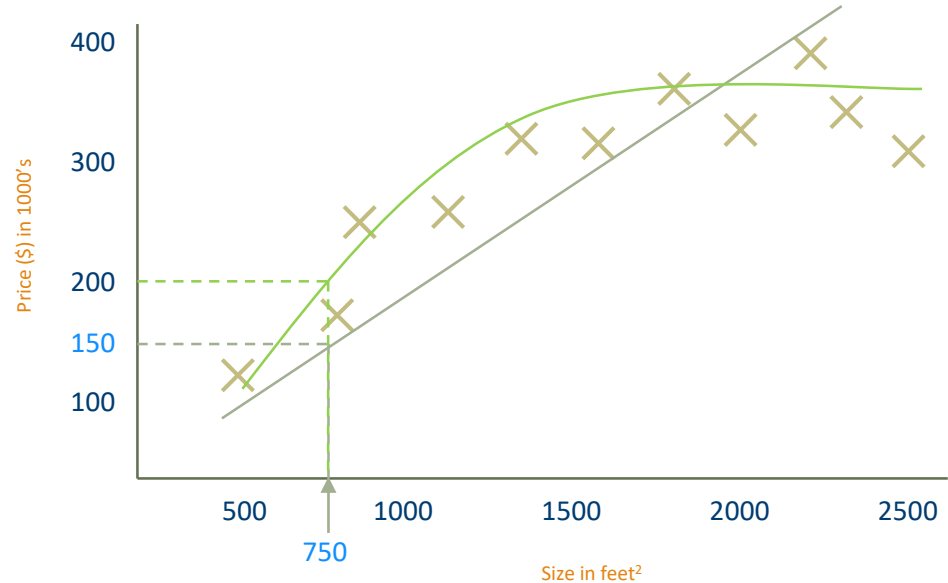
Supervised Learning – linear Regression Example

House price prediction



Label/Dependent variable: Price of the house in Dollars

Features : Size of the House in Square Feet's(Independent Variable)



Evaluation Metric

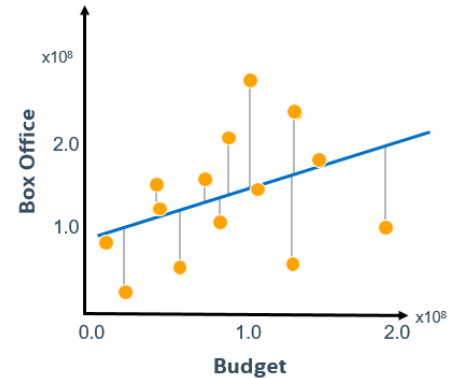
There are many metrics available* to measure performance, such as:

- **Accuracy:** how well predictions match true values.
- **Mean Squared Error:** average square distance between prediction and true value.

$$\min_{\beta_0, \beta_1} \frac{1}{m} \sum_{i=1}^m \left((\beta_0 + \beta_1 x_{obs}^{(i)}) - y_{obs}^{(i)} \right)^2$$



Accuracy target



**The wrong metric can be misleading or not capture the real problem.*

Which Model?

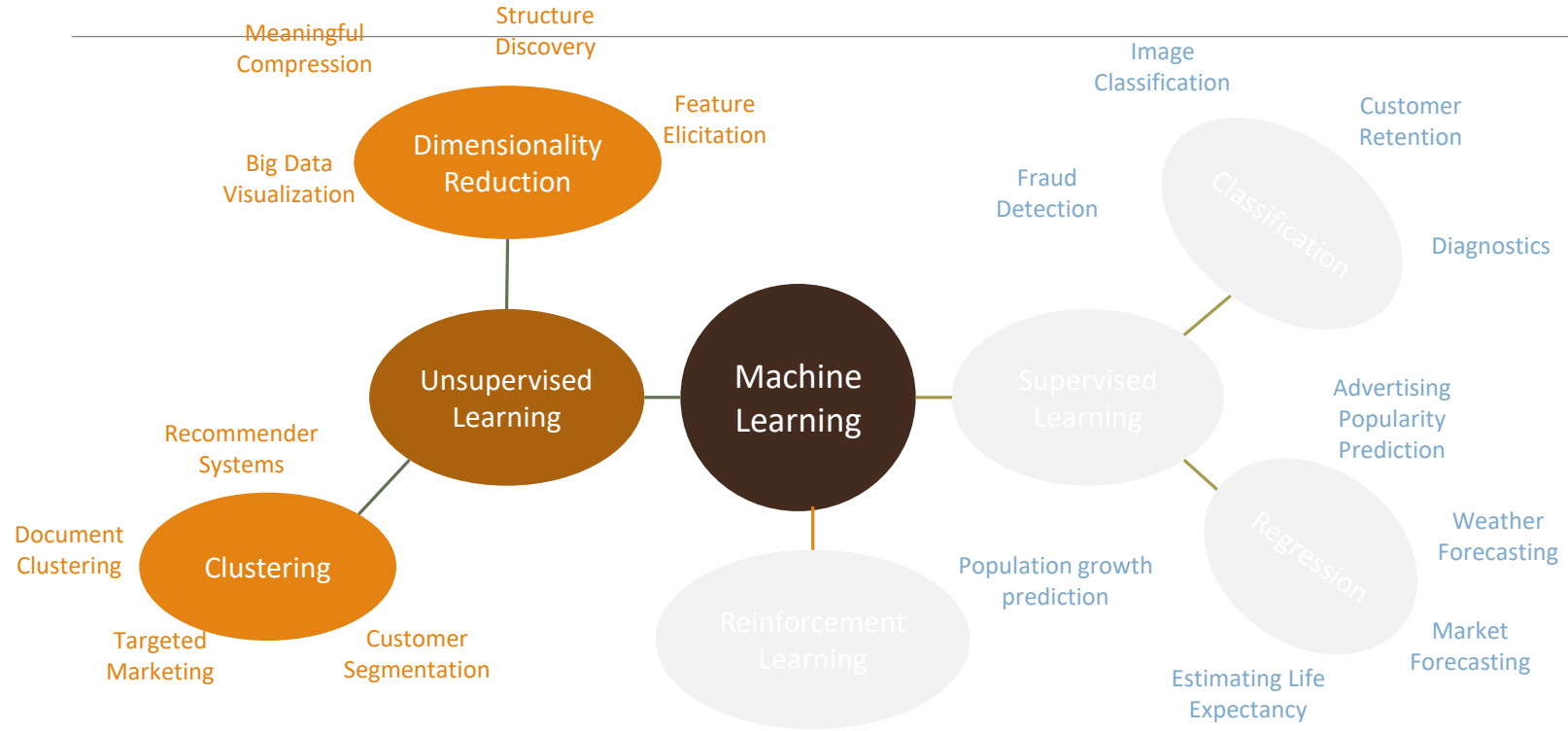
Some considerations when choosing are:

- Time needed for training
- Speed in making predictions
- Amount of data needed
- Type of data
- Problem complexity
- Ability to solve a complex problem
- Tendency to overcomplicate a simple one

Supervised Learning Algorithms

Algorithm	Classification/Regression	Comments
K-Nearest Neighbors	Classification & Regression	Instance based, suffers from curse of dimensionality
Linear Regression	Regression	Need follow certain assumptions
Naïve Bayes	Classification	Probability based. Inputs need to independent from each other.
Logistic Regression	Classification	Need follow certain assumptions
Support Vector Machines	Classification & Regression	Where class boundaries are well separated.
Decision Trees	Classification & Regression	Tree based. Not effective with low covariance.
Neural Networks	Classification & Regression	Non-linear functional approximation. Also used for unsupervised learning (DBNs)
Ensemble (Random Forests, Boosting, Bagging, Bucket of models, Stacking, etc)	Classification & Regression	Improved prediction performance from multiple hypothesis.

Machine Learning algorithms



Un Supervised – Customer Segmentation

TYPES OF CUSTOMER SEGMENTS



All Customers data from previous Transactions

Few example features
Extracted

1. Since how long been with us
2. #of times visits per month
3. Customer Gender and age
4. #of Referrals generated
-

Apply Unsupervised
Algorithm



CONVENIENCE SEEKERS

- VALUE CONVENIENCE IN DELIVERY, ORDERING
- HIGH INCOME
- LONG RELATIONSHIP, LARGE REFERRALS



NPV PER CUSTOMER



BRAND BUYERS

- BRAND BUYERS, NOT PRICE SENSITIVE
- HIGHEST INCOME, MORE OFTEN MALE
- EXPENSIVE TO ACQUIRE, BUT BUY MOST INITIALLY AND REFER MORE



CASUAL BUYERS

- NOT CONCERNED WITH PERISHABLES OR DELIVERY TIME WINDOWS
- SMALL SPENDING GROWTH



RELATIONSHIP SEEKERS

- INFLUENCED BY RETAILER BRAND, SUGGESTIONS, AND PROMOTIONS
- LOW INCOME
- SMALL SPENDING GROWTH/REFERRAL



BARGAIN HUNTERS

- PRICE IS PRIMARY AND PERISHABLES ARE NOT IMPORTANT
- LOW INCOME
- SMALL PURCHASES



SOURCE: BAIN/MAINSPRING ONLINE RETAILING SURVEY

Un Supervised – Market Basket Analysis



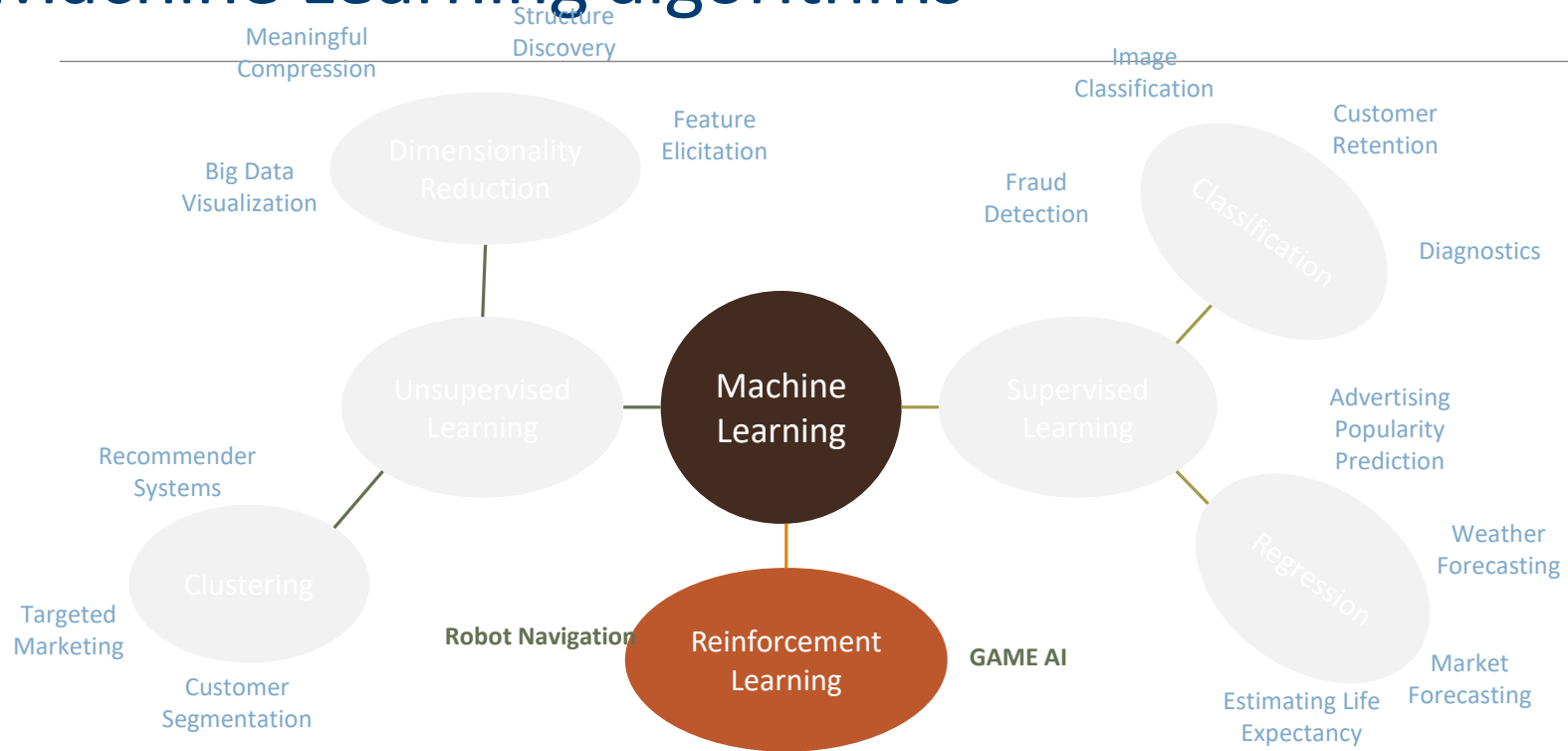
- ? Where should detergents be placed in the Store to maximize their sales?
- ? Are window cleaning products purchased when detergents and orange juice are bought together?
- ? Is soda typically purchased with bananas? Does the brand of soda make a difference?
- ? How are the demographics of the neighborhood affecting what customers are buying?

Image source: deepclimate.org



Market Basket Analysis

Machine Learning algorithms



Elements of Reinforcement Learning

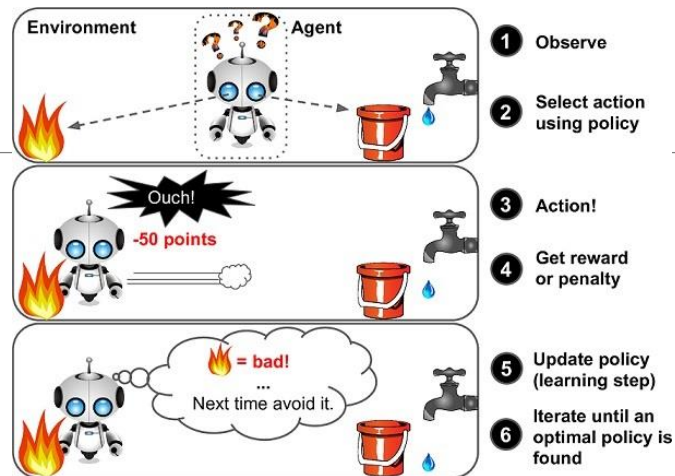
Agent: A robot / system/ a game player - capable of taking action

Environment: The universe the agent interacts with. Could be rules of a game for game playing, or other objects on road for a self driving car.

Policy: Defines the learning agent's way of behaving at a given time & environmental conditions.

Reward signal: Defines the goal in a reinforcement learning problem. On each time step, the environment sends to the reinforcement learning agent a single number, a *reward*. The agent's sole objective is to maximize the total reward it receives over the long run.

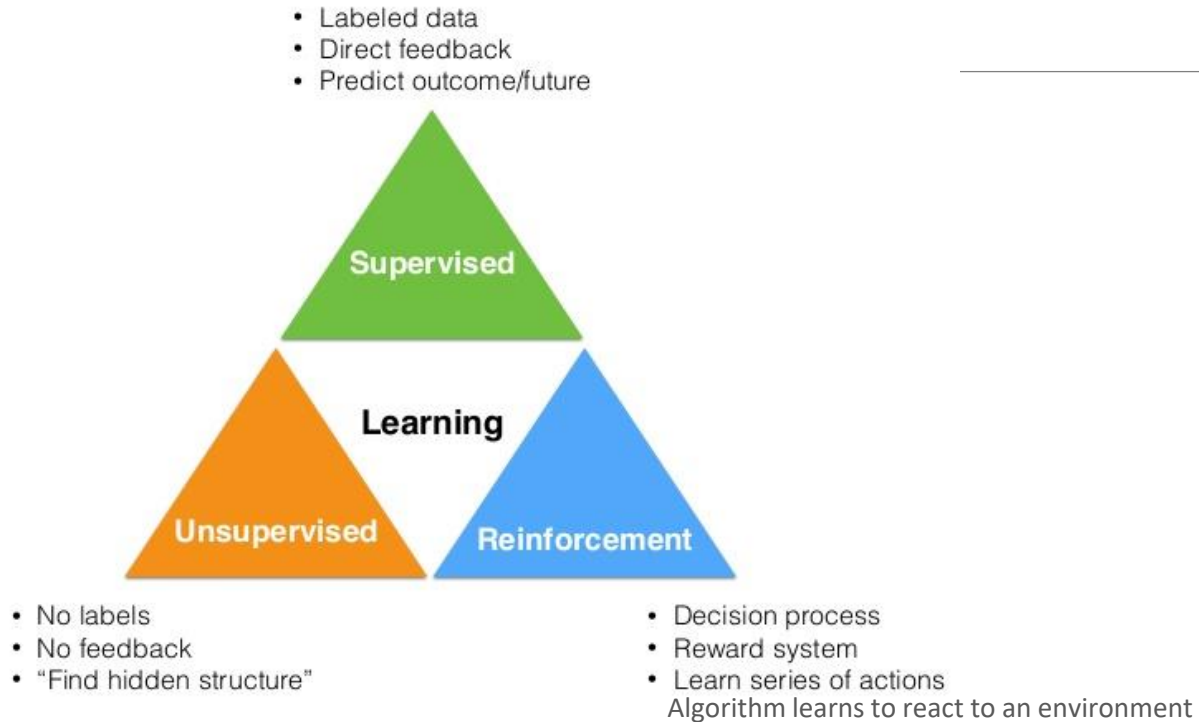
Value function: Specifies what is good in the long run. The value of a state is the total amount of reward an agent can expect to accumulate over the future, starting from that state. Whereas rewards determine the immediate, intrinsic desirability of environmental states



Reinforcement learning algorithms try to find the best ways to earn the greatest reward. Rewards can be winning a game, earning more money or beating other opponents. They present state-of-art results on very human task

In a nutshell, it is used to determine how to navigate uncertain environments in the most effective way.

Quick I



Source: <https://www.saagie.com/blog/machine-learning-pour-les-grand-meres>

Machine Learning in our Daily Lives

SPAM FILTERING

WEB SEARCH

POSTAL MAIL ROUTING

FRAUD DETECTION

MOVIE RECOMMENDATIONS

VEHICLE DRIVER ASSISTANCE

WEB ADVERTISEMENTS

SOCIAL NETWORKS

SPEECH RECOGNITION

Training and Testing Data

Using the dataset for training

Training Set: Data used during the training process.

Test Set: Data used to measure performance, simulating unseen data*.

sepal length	sepal width	petal length	petal width	species
6.7	3.0	5.2	2.3	virginica
6.4	2.8	5.6	2.1	virginica
4.6	3.4	1.4	0.3	setosa
6.9	3.1	4.9	1.5	versicolor
4.4	2.9	1.4	0.2	setosa
4.8	3.0	1.4	0.1	setosa
5.9	3.0	5.1	1.8	virginica
5.4	3.9	1.3	0.4	setosa
4.9	3.0	1.4	0.2	setosa
5.4	3.4	1.7	0.2	setosa

Training Set

Testing Set

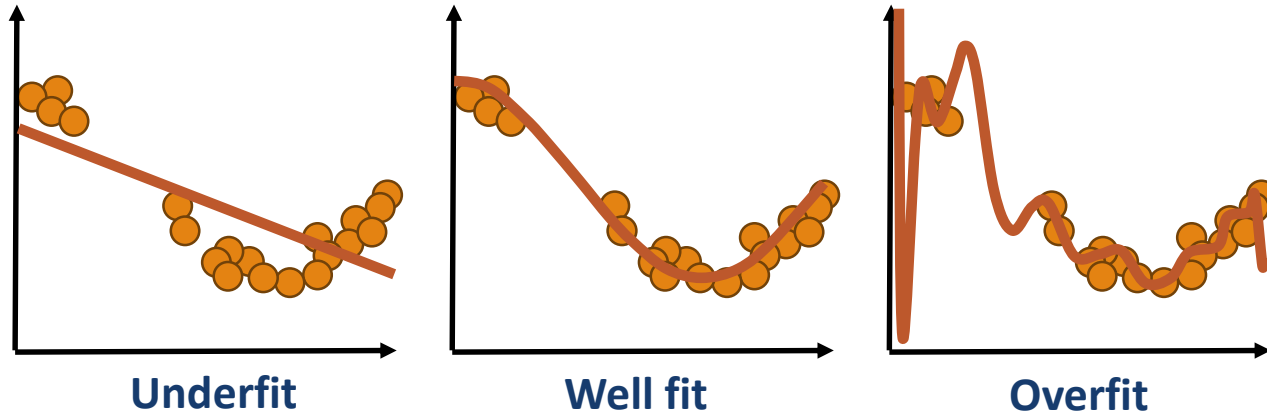
**Not used during the training process.*

Curve Fitting Problem(Over & Under fit)

Problem: Unseen data isn't available during training.

- How can performance be estimated?

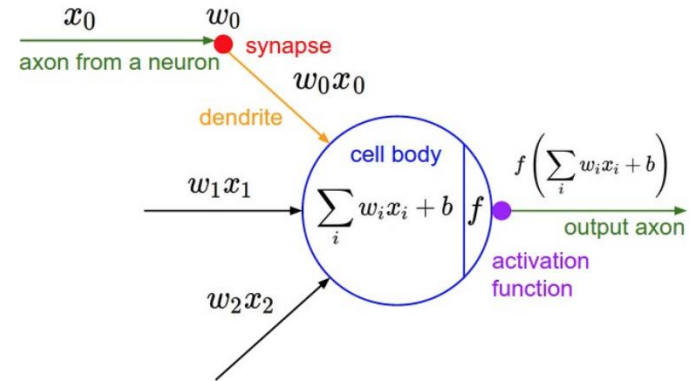
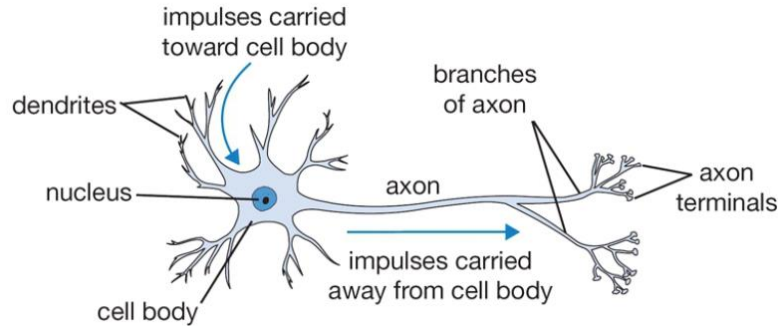
When measuring performance on the training data, there is a tendency to overfit.



Deep Learning

Neural Networks

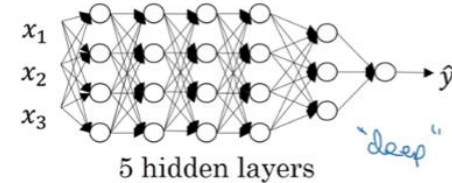
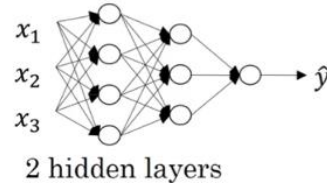
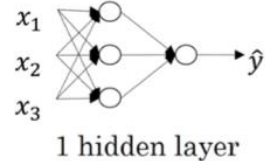
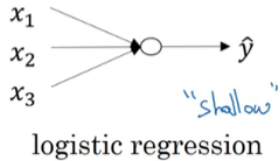
Neural Networks: Algorithms that try to mimic Human brain, was widely used in 80's and early 90's and popularity diminished in late 90's. Recent resurgence due to availability of Compute and Data.



DEEP LEARNING

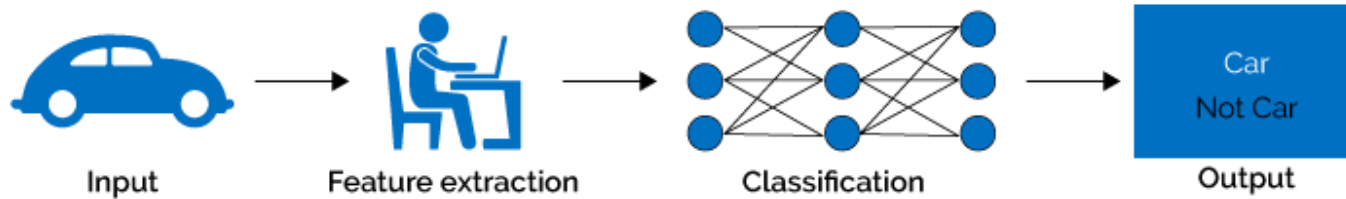
Deep Learning, refers to training Neural Networks, sometimes very large Neural Networks.

What is Deep Neural Network?

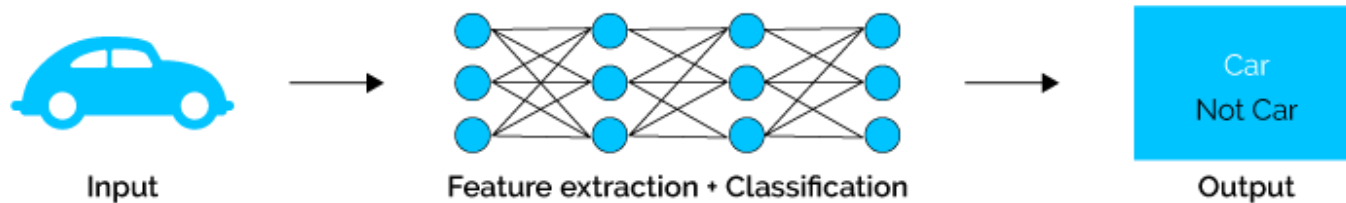


Why is Deep learning required

Machine Learning



Deep Learning



Green Channel

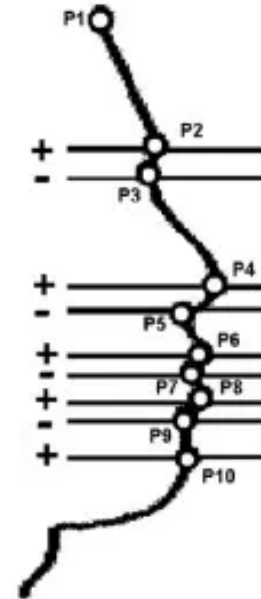
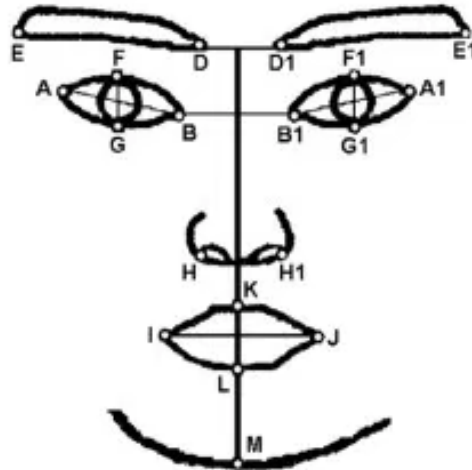
Blue Channel

[illegible]

- 39

MANUAL FEATURE Extraction FOR IMAGES IS COMPLEX

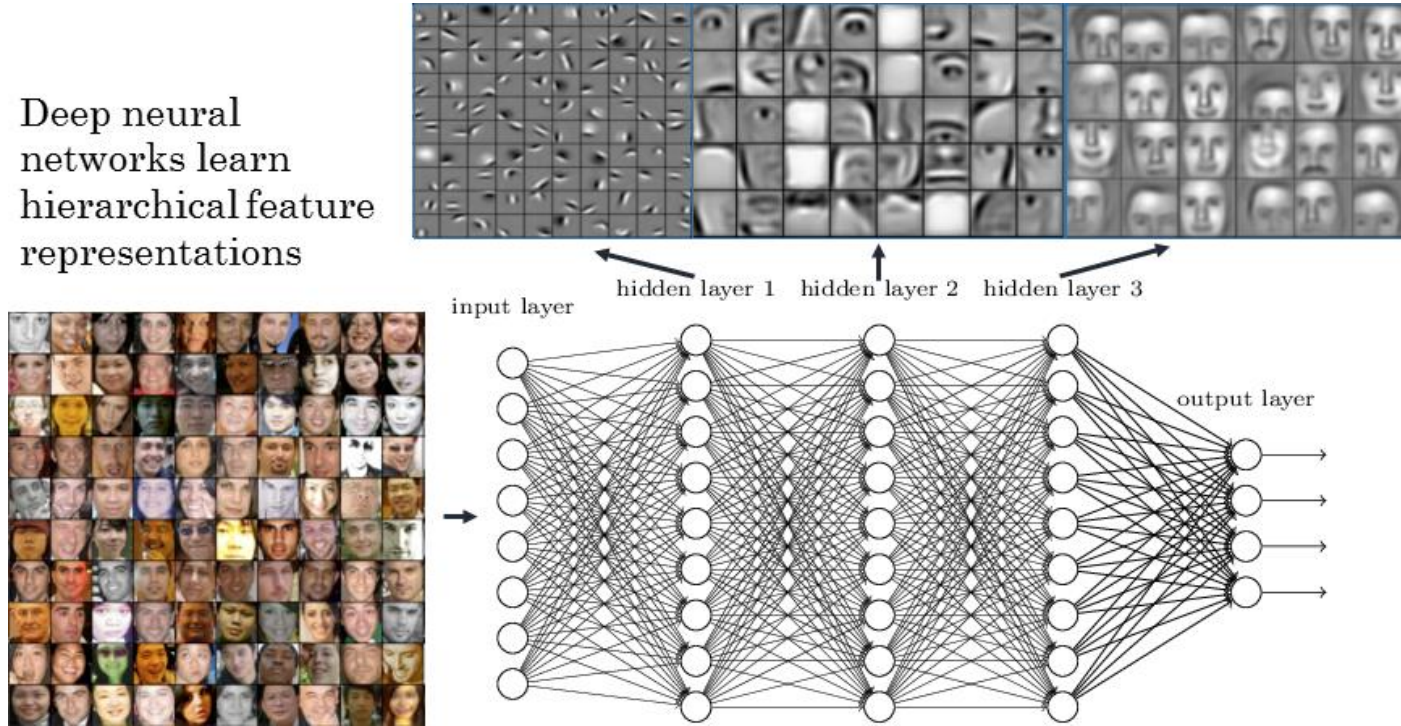
E, E1: outer corner of the eyebrow
D, D1: inner corner of the eyebrow
A, A1: outer corner of the eye
B, B1: inner corner of the eye
F, F1: top of the eye
G, G1: bottom of the eye
H, H1: outer corner of the nostril
K: top of the upper lip
L: bottom of the lower lip
I, J: mouth corner
M: tip of the chin



P1: top of the forehead
P2: eyebrow arcade
P3: root of the nose
P4: tip of the nose
P5: upper jaw
P6: upper lip
P7: lips attachment
(if tongue is visible:
P7' : tongue-lip attachment
P7'' : tip of the tongue
P7''' : tongue-lip attachment)
P8: lower lip
P9: lower jaw
P10: tip of the chin

DEEP LEARNING ENABLES AUTOMATED FEATURE EXTRACTION with ease

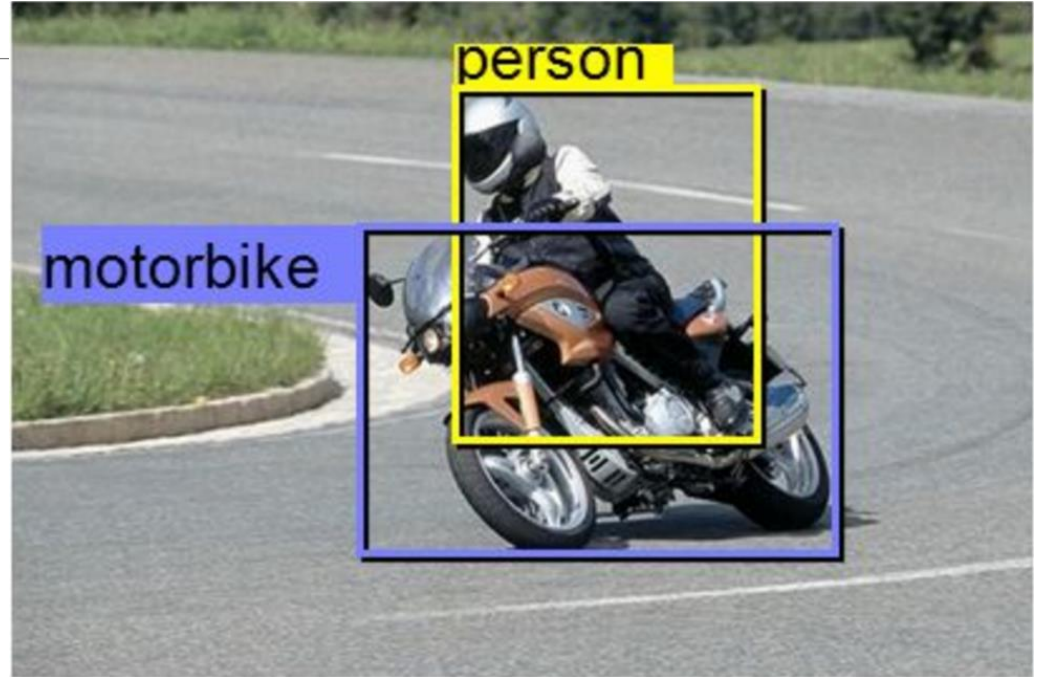
Deep neural networks learn hierarchical feature representations



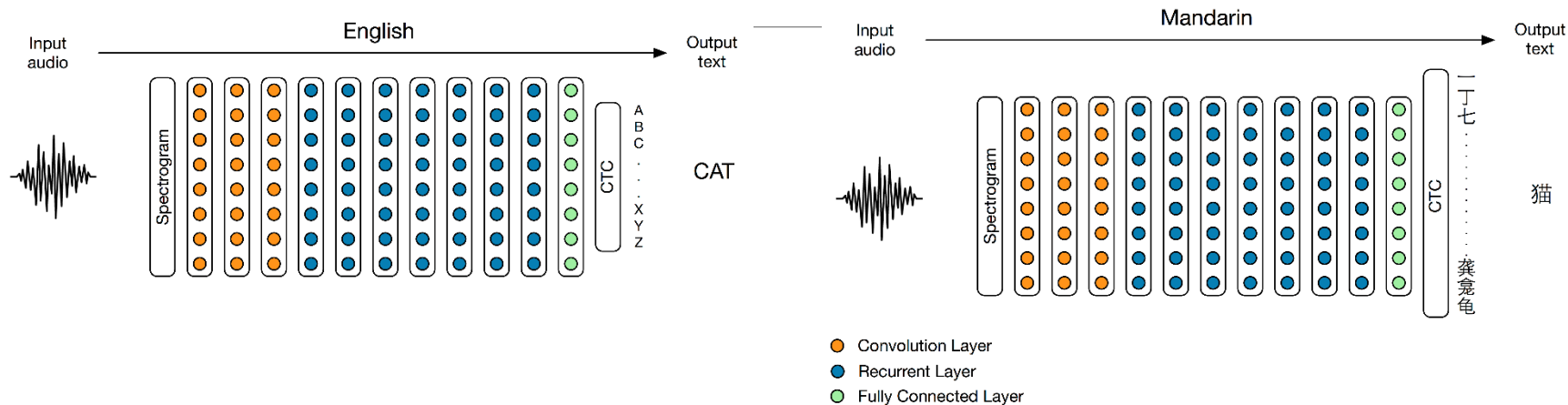
Classification and Detection

Detect and label the image

- Person
- Motor Bike



Speech Recognition and Language Translation



The same architecture is used for English and Mandarin Chinese speech recognition

<http://svail.github.io/mandarin/>

Scale drives deep learning progress

