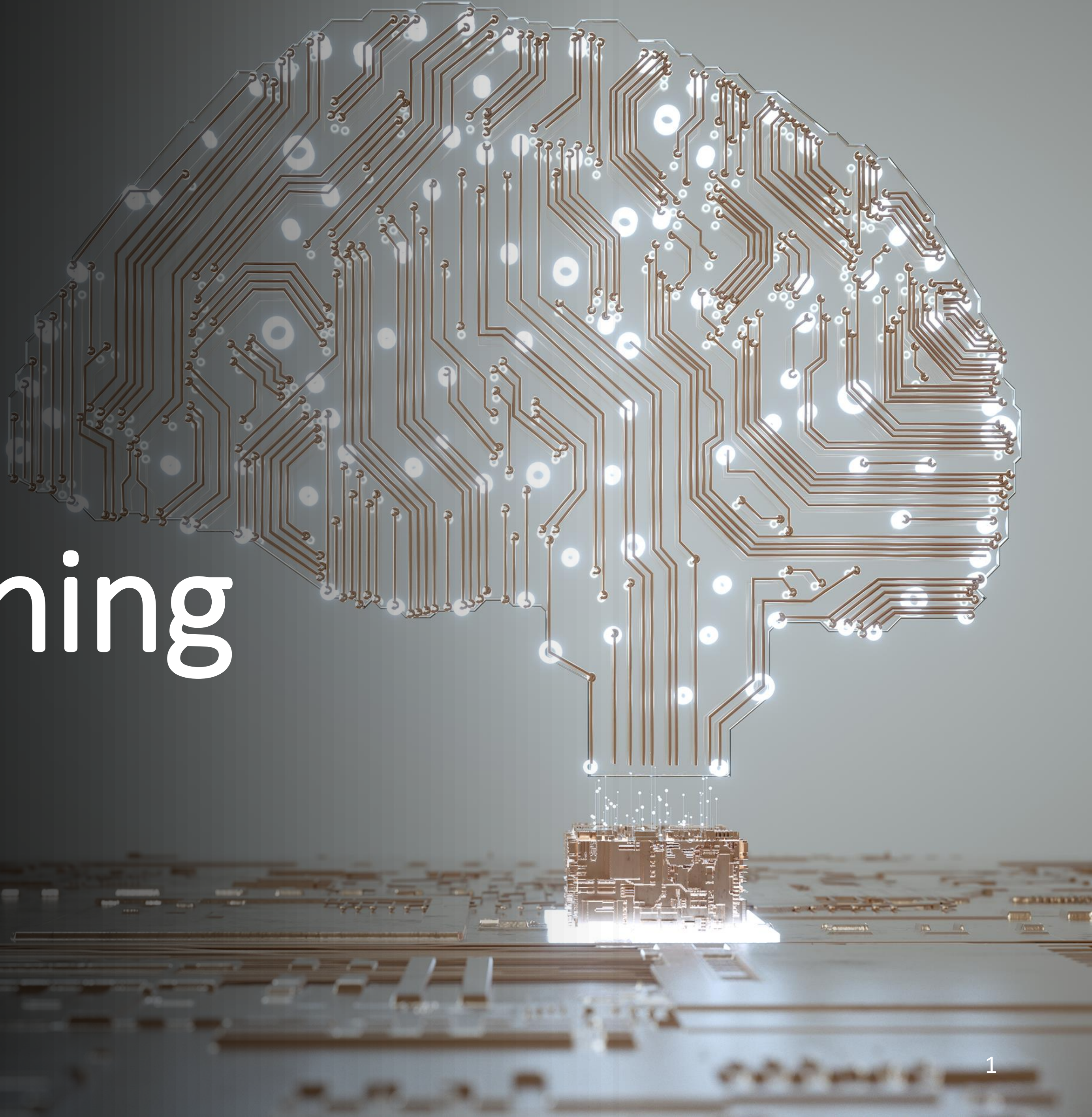
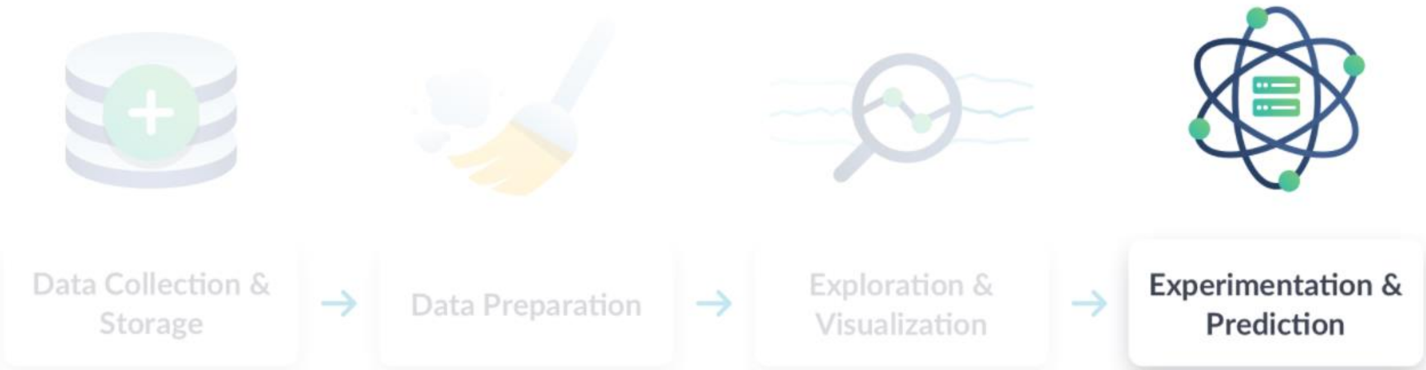
Machine Learning

GGE 6505/GGE5405 Introduction to
Big Data & Data Science



Data science workflow



Outline

Introduction to Artificial Intelligent

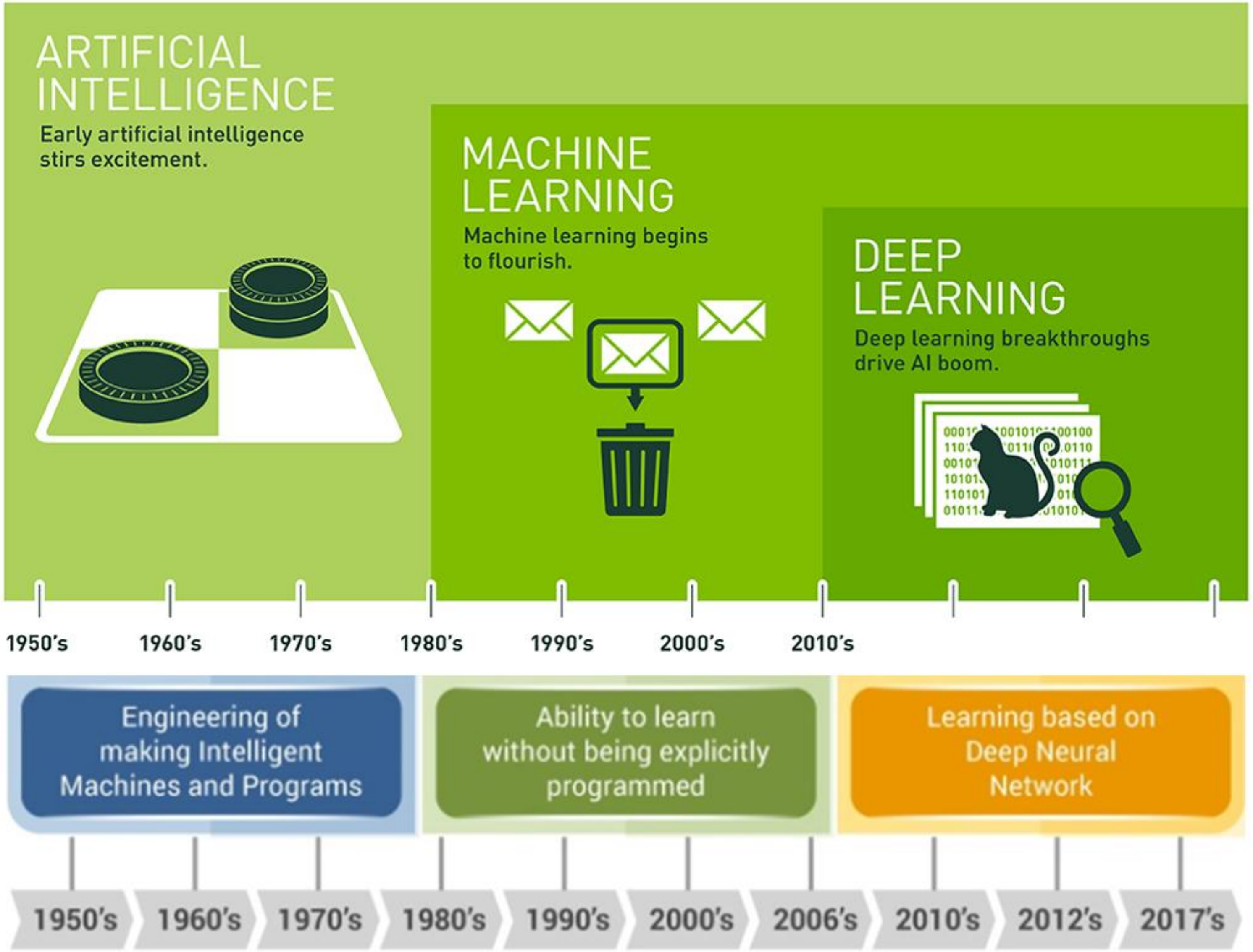
Machine Learning

Supervised and Unsupervised Learning

Deep learning

Artificial Intelligence

History of AI



Symbolic AI/Expert systems

For a fairly long time, many experts believed that human-level artificial intelligence could be achieved by having programmers handcraft a sufficiently large set of explicit rules for manipulating knowledge. This approach is known as symbolic AI and was the dominant paradigm in AI from the 1950s to the late 1980s.

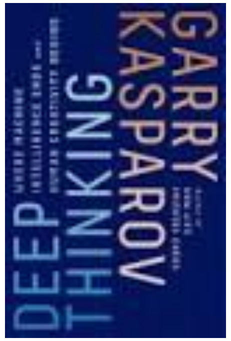
Expert systems are designed to solve complex problems by reasoning through bodies of knowledge, represented mainly as if–then rules rather than through conventional procedural code.

An expert system is a program that answers questions or solves problems about a specific domain of knowledge, using logical rules that are derived from the knowledge of experts.

Chess Game

- In 1997, Deep Blue (IBM) “beat” Garry Kasparov
- IBM’s stock increased by $18 billion at that year

“ I wondered, what if instead of
human versus machine
we played as partners?” (Kasparov 2017)



Deep Thinking: Where Machine Intelligence Ends and Human Creativity Begins (2017)
by Garry Kasparov

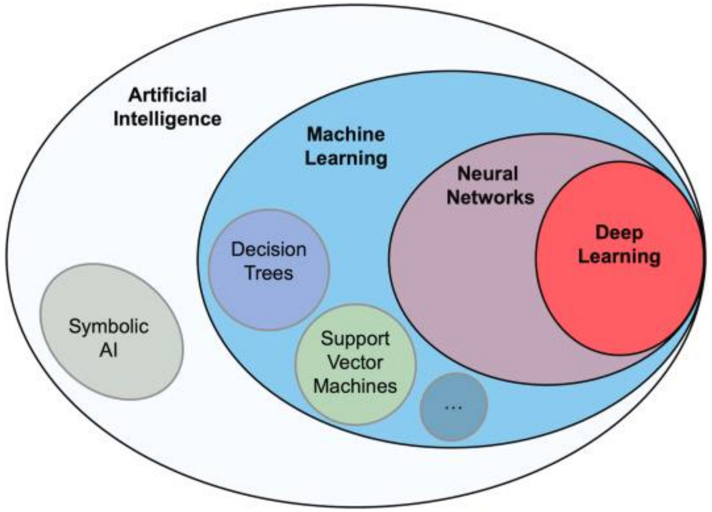
Approaches to AI

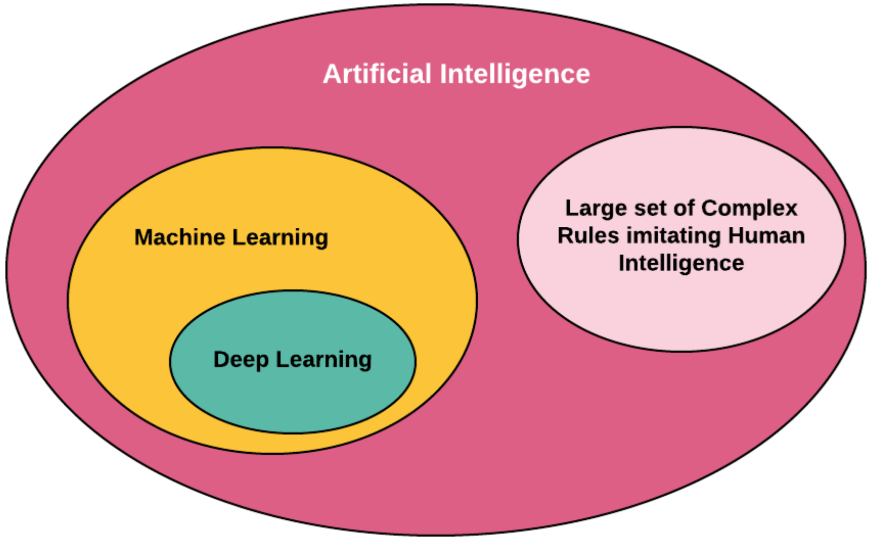
AI can be just a simple if else statements.

- Symbolic AI
- Neat vs Scruffy. World moved to neat.
- Narrow vs General
- Soft vs hard computing

Symbolic vs machine learning

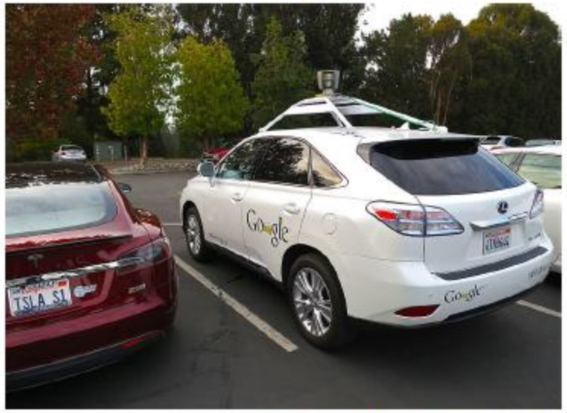
Symbolic AI is the field in which artificially intelligent systems were designed with if-else type logic. Programmers would attempt to define every possible scenario for the system to deal with. Until the late seventies this was the dominant form of AI system development.





Examples of Machine Learning

Self-driving cars



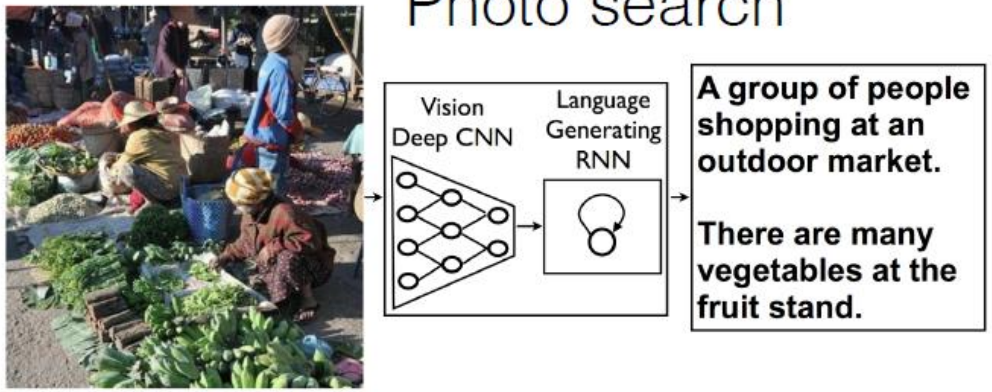
By Steve Jurvetson [CC BY 2.0]

Recommendation systems

http://commons.wikimedia.org/wiki/File:Netflix_logo.svg [public domain]

and many, many more ...

Photo search



http://googleresearch.blogspot.com/2014/11/a-picture-is-worth-thousand-coherent.html

AI vs machine learning

What is artificial intelligence (AI)?

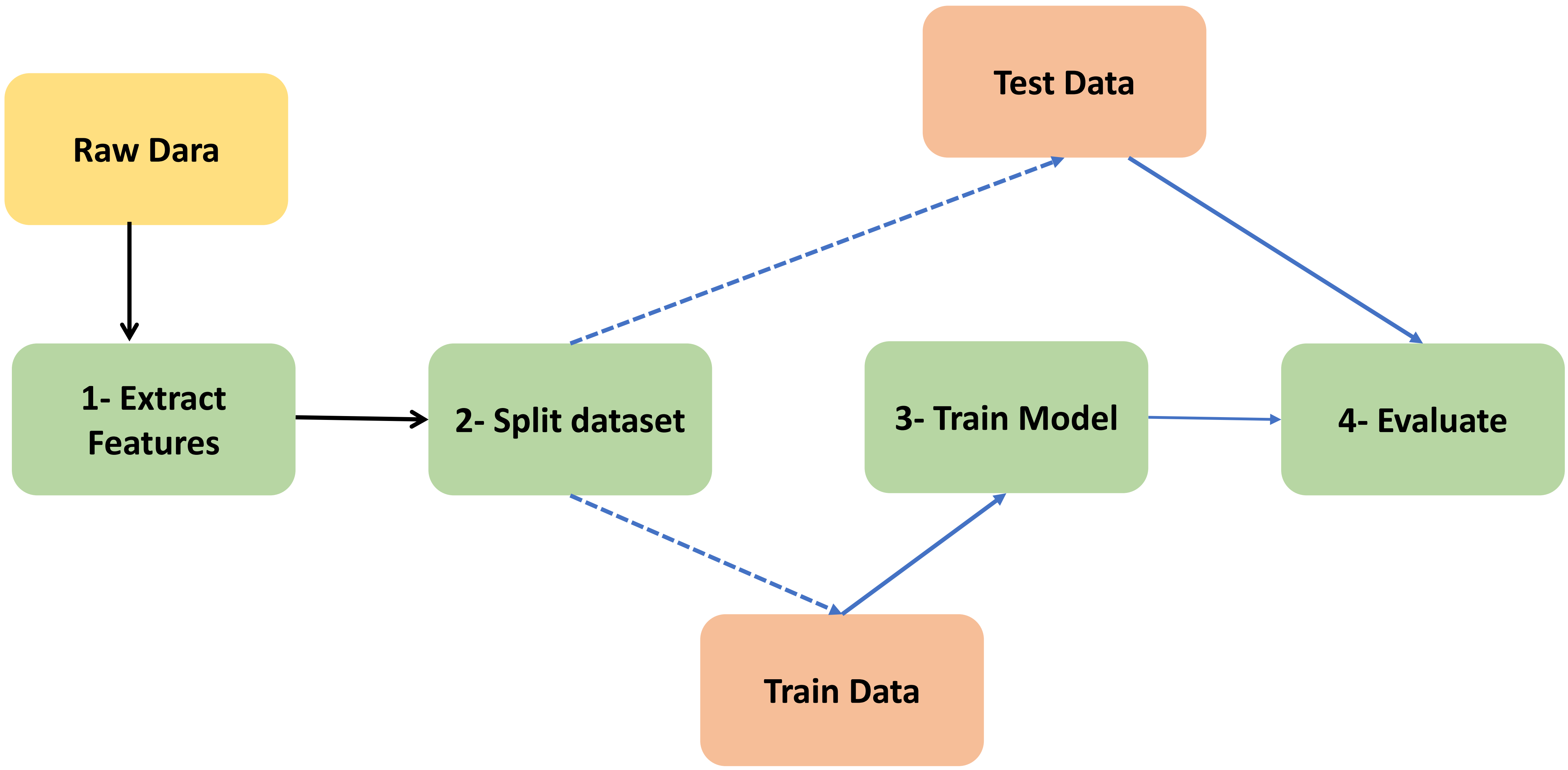
Artificial intelligence is the capability of a computer system to mimic human cognitive functions such as learning and problem-solving. Through AI, a computer system uses math and logic to simulate the reasoning that people use to learn from new information and make decisions.

What is machine learning?

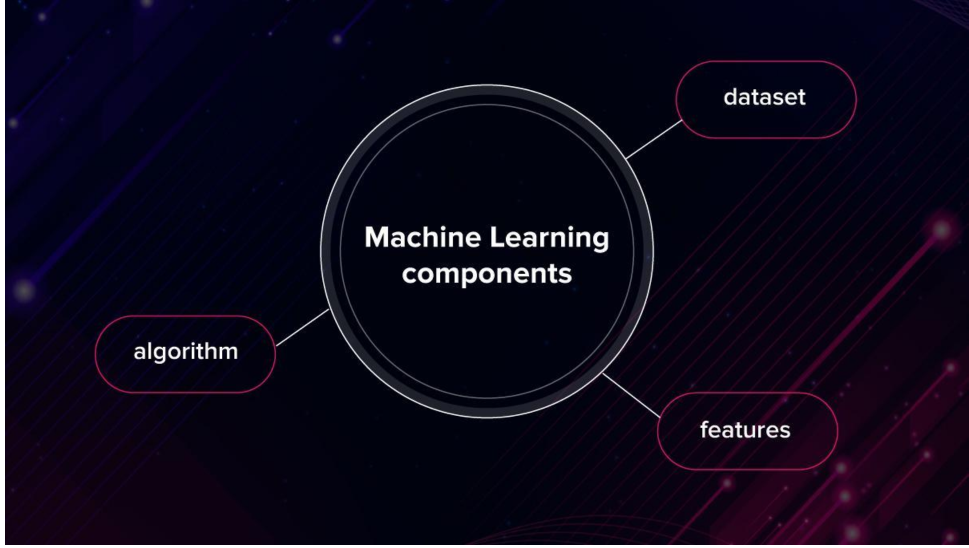
Machine learning is an application of AI. It's the process of using mathematical models of data to help a computer learn without direct instruction. This enables a computer system to continue learning and improving on its own, based on experience.

One aspect that separates machine learning from the knowledge graphs and expert systems is its ability to modify itself when exposed to more data; i.e. machine learning is dynamic and does not require human intervention to make certain changes. That makes it less brittle, and less reliant on human experts.

Machine Learning Workflow

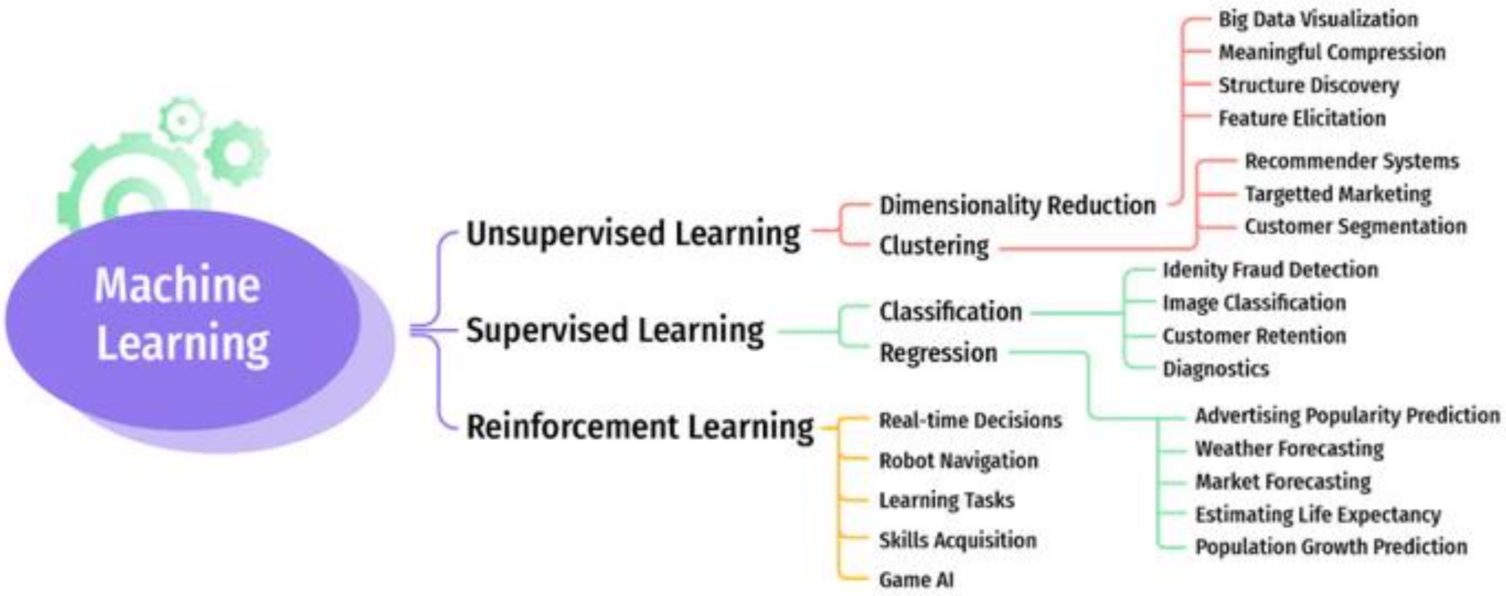


Machine Learning



Types:

- **Supervised learning**
- **Semi-supervised Learning (SSL)**
- **Unsupervised learning**
- **Reinforcement learning**



Supervised vs unsupervised learning

- **Supervised learning**
  - Training data is "labeled"
- **Unsupervised learning**
  - Training data only has features
  - Useful for:
    - Anomaly detection
    - Clustering, e.g., *dividing data into groups*

Target Variable

Blood sugar	Heart disease
118	True
98	False
110	True
126	True
99	False
105	False

Labels

Machine learning concepts | Theory (datacamp.com)

Supervised Learning

Unsupervised Learning

Reinforcement Learning

Supervised Learning

Supervised learning is a learning system that trains using labeled data (data in which the target variables are already known). The model learns how patterns in the feature matrix map to the target variables. When the trained machine is fed with a new dataset, it can use what it has learned to predict the target variables. This can also be called predictive modeling. Supervised learning is broadly split into two categories.

- Regression
    - Simple Linear Regression
    - Multiple Linear Regression
    - Polynomial Linear Regression
- Classification
    - KNN
    - Logistic Regression
    - Decision Tree
    - Naive Bayes
    - SVM…

Predictor variables

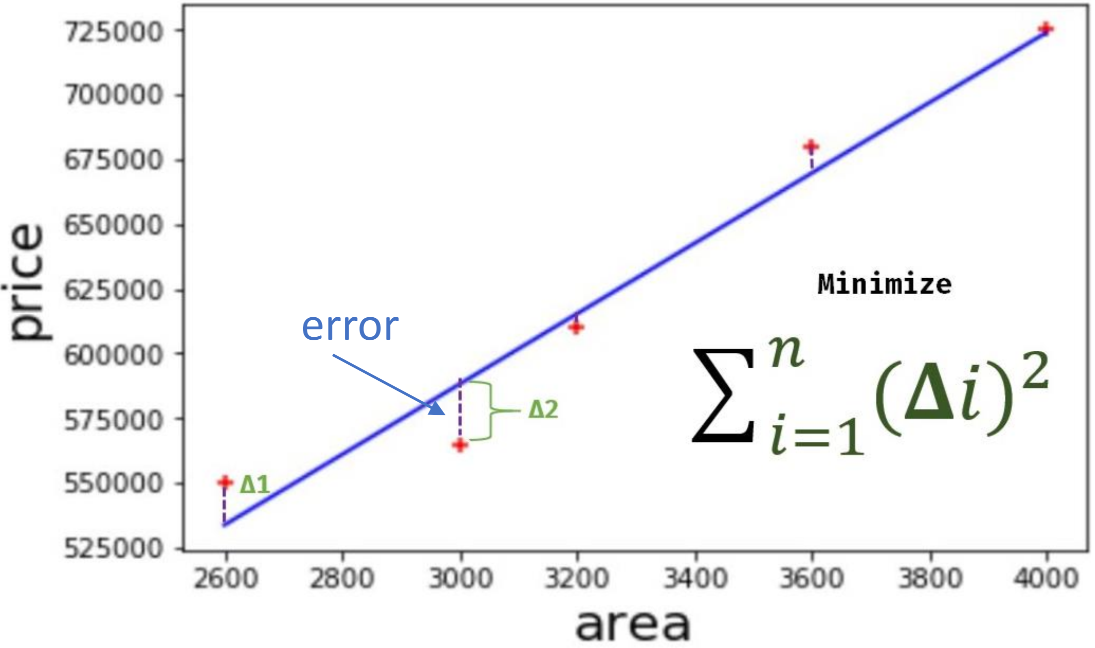
	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

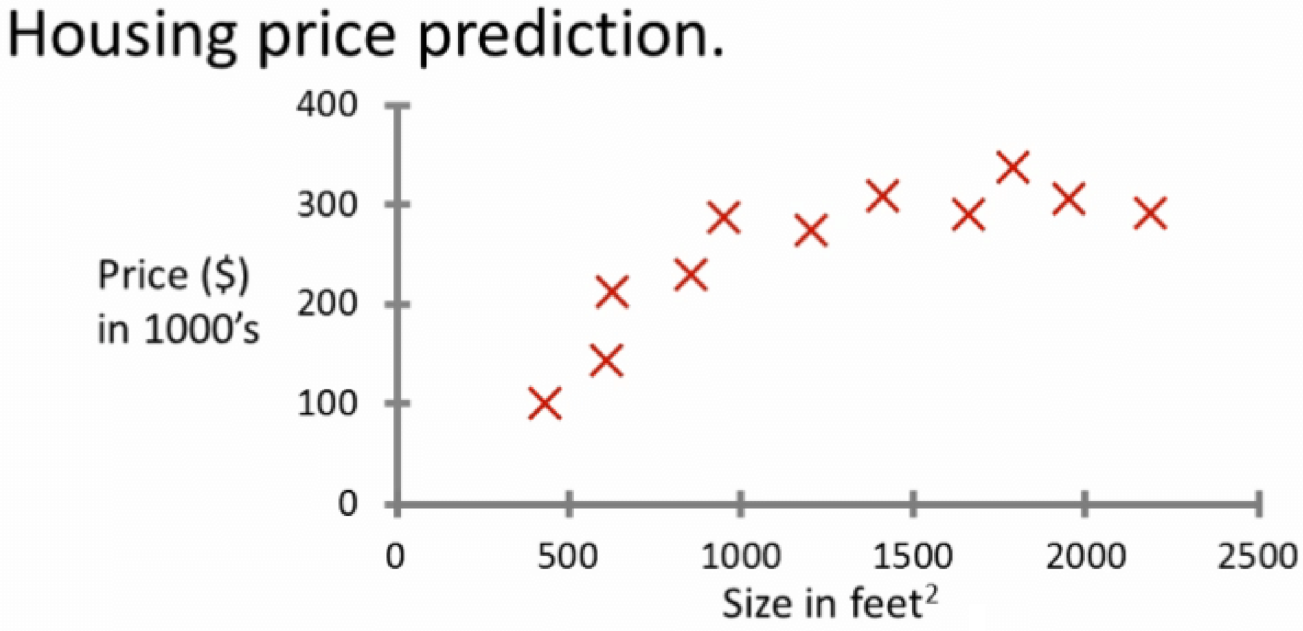
Target variable

species
setosa
setosa
setosa
setosa
setosa

1- Linear Regression

- Linear regression measures the link between one or more predictor variables and one outcome variable. For example, linear regression could help to enumerate the relative impacts of age, gender, and diet (the predictor variables) on height (the outcome variable).





1- Linear Regression

- Linear regression is a statistical model used to predict the relationship between independent and dependent variables

Slope

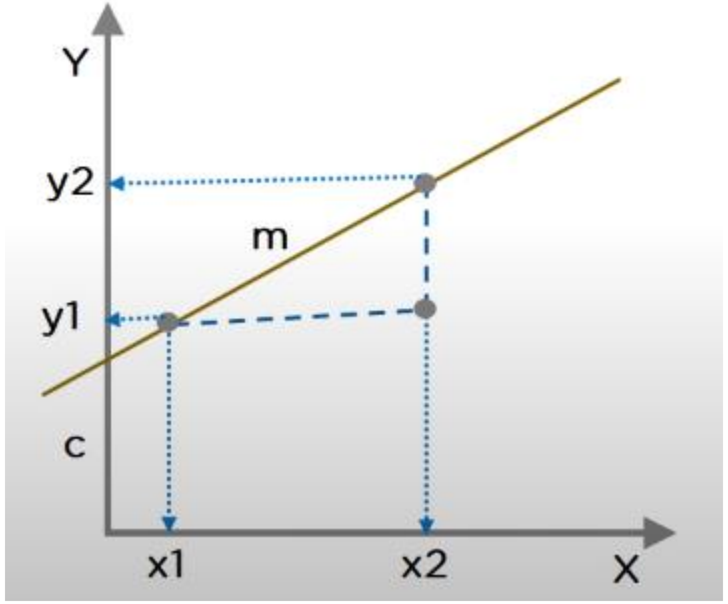
Coefficient of the line

$$y = m * x + c$$

Dependent variable

Independent variable

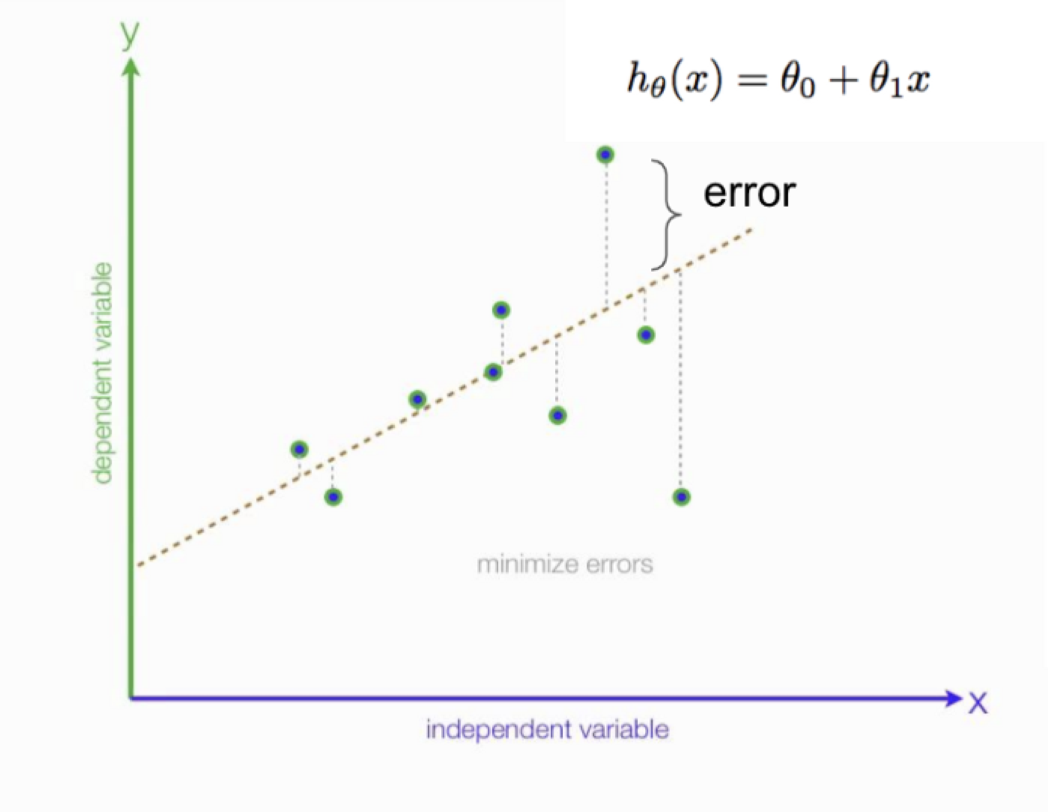
$$m = \frac{y2 - y1}{x2 - x1}$$



Important definitions!

Concept of Cost/Loss functions

Cost Function/Loss Function helps us to understand the difference between the predicted value & the actual value.



Hypothesis:

$$h_\theta(x) = \theta_0 + \theta_1 x$$

Parameters:

$$\theta_0, \theta_1$$

Cost Function:

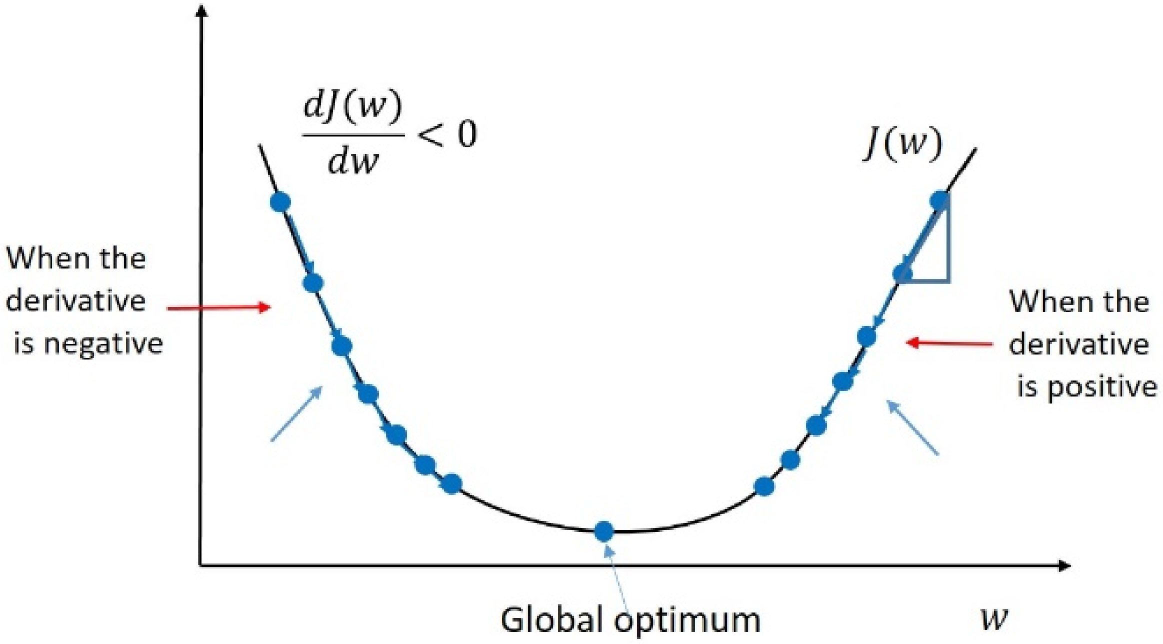
$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

Goal:

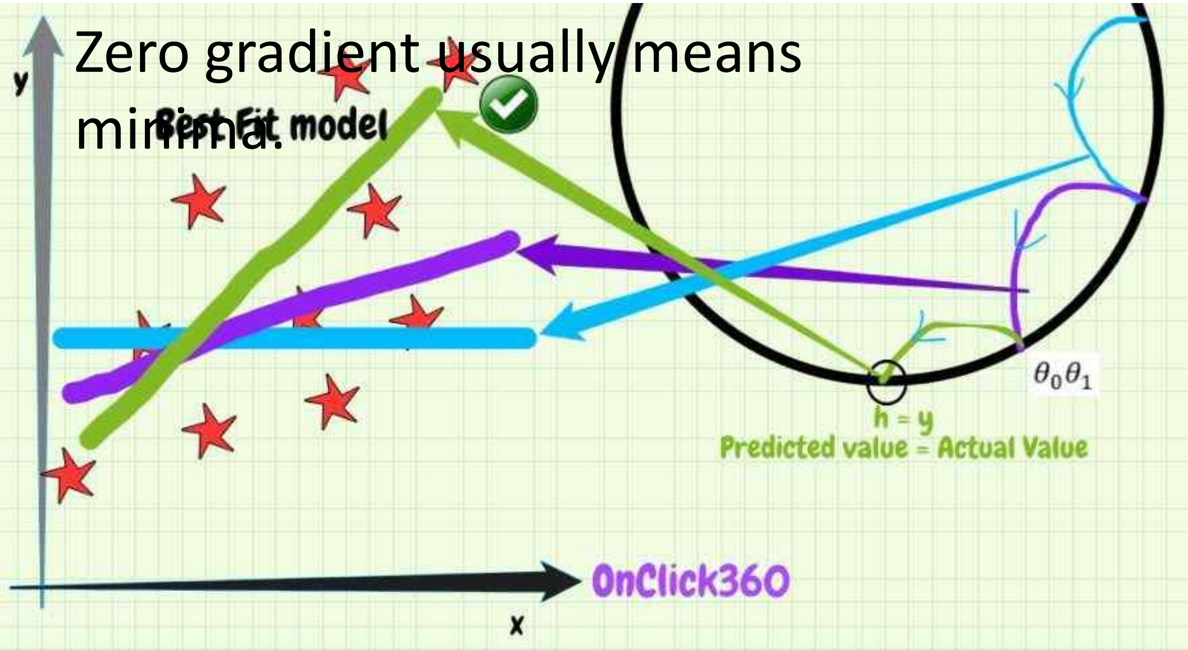
$$\underset{\theta_0, \theta_1}{minimize} J(\theta_0, \theta_1)$$

Gradient descent:
Finding the unknown coefficients b0, b1, b2, ..

The goal of machine learning algorithms is to minimize cost function. The slope of function tells us about the direction of the gradient.



Zero gradient usually means minima.

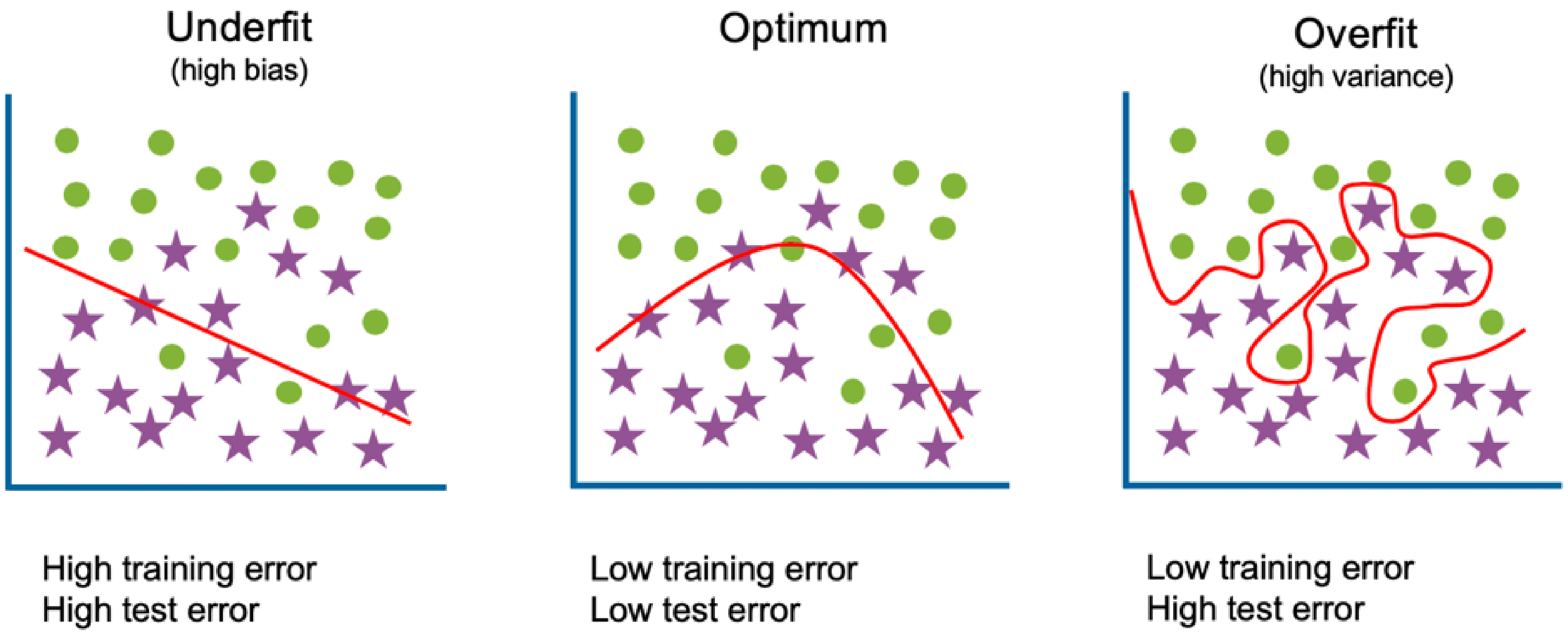


Error = J(w) = Cost function = F(y-y)’

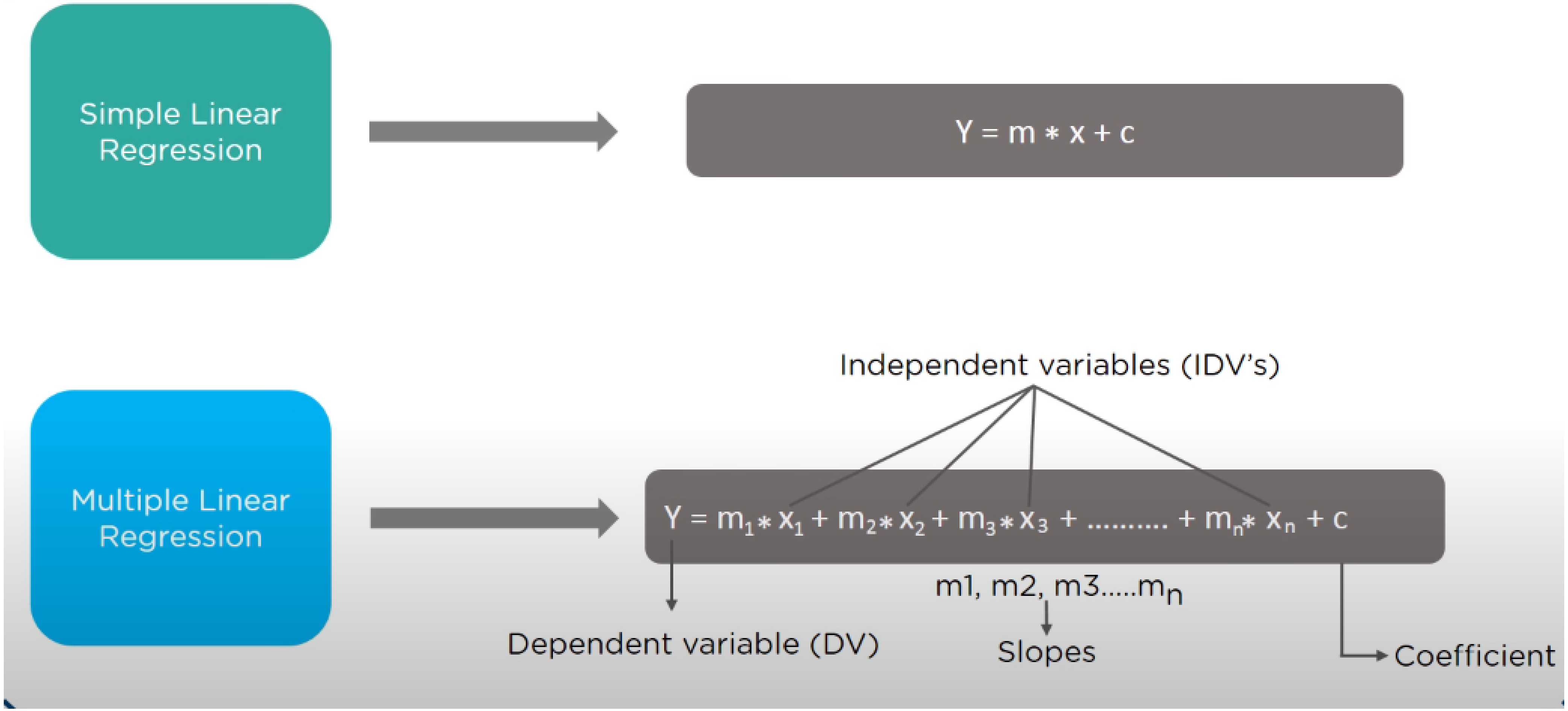
Where, Y – Actual Input and Y’ – Predicted output

Underfitting vs. Overfitting

- Underfitting: where a data model is unable to capture the relationship between the input and output variables accurately.
- Overfitting: when it contains too much complexity, resulting in high error rates on test data.



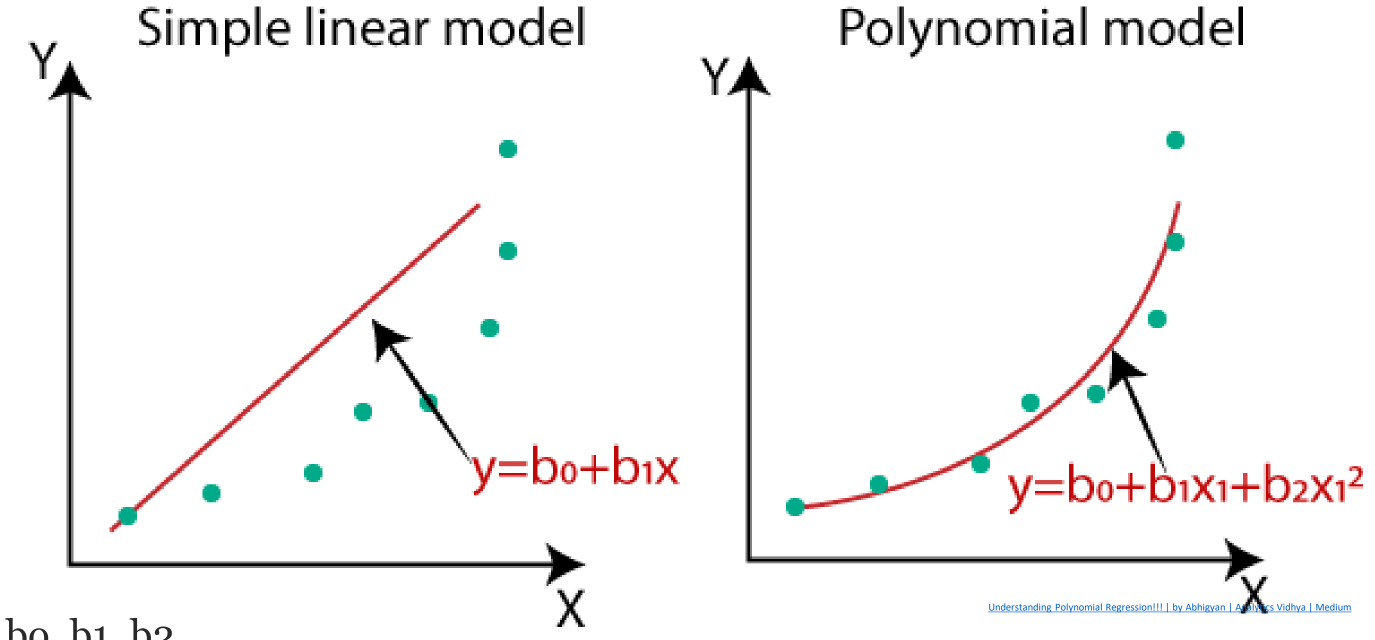
2- Multiple Linear Regression



3- Polynomial Regression

- **Polynomial Regression** is a form of regression analysis in which the relationship between the independent variables and dependent variables are modeled in the nth degree polynomial.

- Polynomial Regression is a special case of Linear Regression where we fit the **polynomial equation** on the data with a curvilinear relationship between the dependent and independent variables.



Understanding Polynomial Regression!!! | by Abhigyan | Analytics Vidhya | Medium

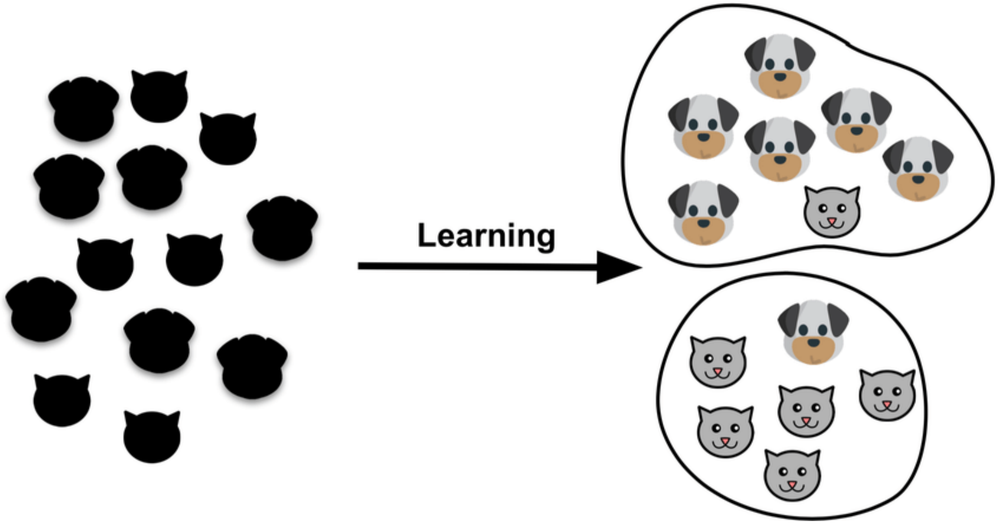
The goal is to find the unknowns b0, b1, b2,...

Precautions and Assumptions.
Linear Regression

- Linear Assumption. Linear regression assumes that the relationship between your input and output is linear.
- Remove Noise. Linear regression assumes that your input and output variables are not noisy.
- Remove Collinearity. Linear regression will over-fit your data when you have highly correlated input variables.
- Gaussian Distributions. Linear regression will make more reliable predictions if your input and output variables have a Gaussian distribution.
- Rescale Inputs: Linear regression will often make more reliable predictions if you rescale input variables using standardization or normalization.

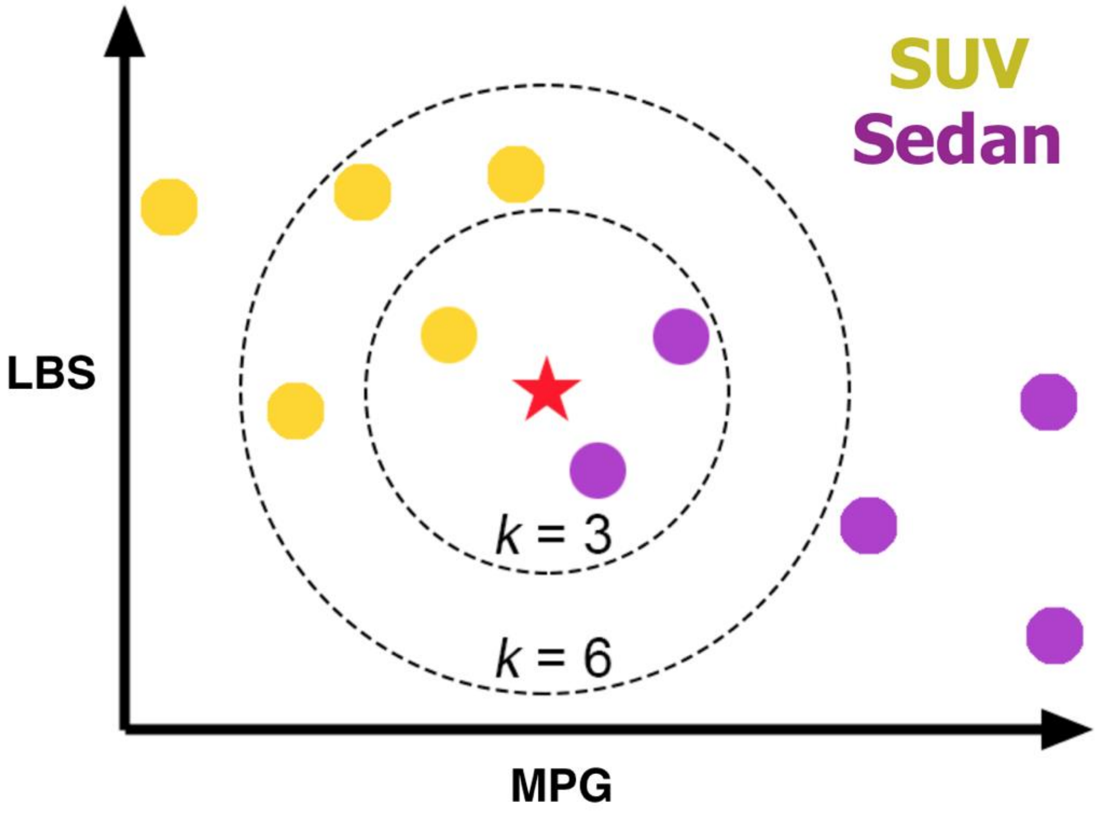
Classification

- Classification mainly deals with categorical target variables. A classification algorithm helps to predict which group or class a data point belongs to.
- When the prediction is between two classes, it is known as binary classification. An example is predicting whether or not a customer will buy a product (in this case, the classes are yes and no).
- If the prediction involves more than two target classes, it is known as multi-classification; for example, predicting all the items that a customer will buy.



- **Classification** = assigning a **category**
  - Will this customer **stop** its subscription?
    - *Yes, No*
  - Is this mole **cancerous**?
    - *Yes, No*
  - What **kind** of wine is that?
    - *Red, White, Rosé*
  - What **flower** is that?
    - *Rose, Tulip, Carnation, Lily*

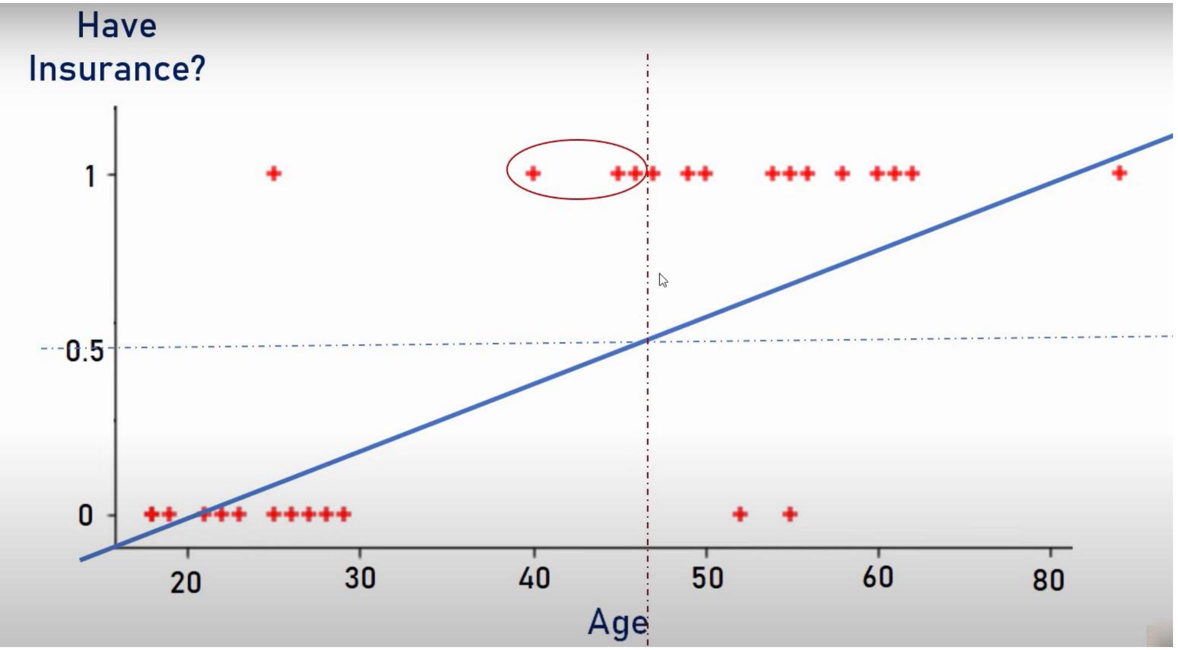
1- k-Nearest Neighbours(KNN)

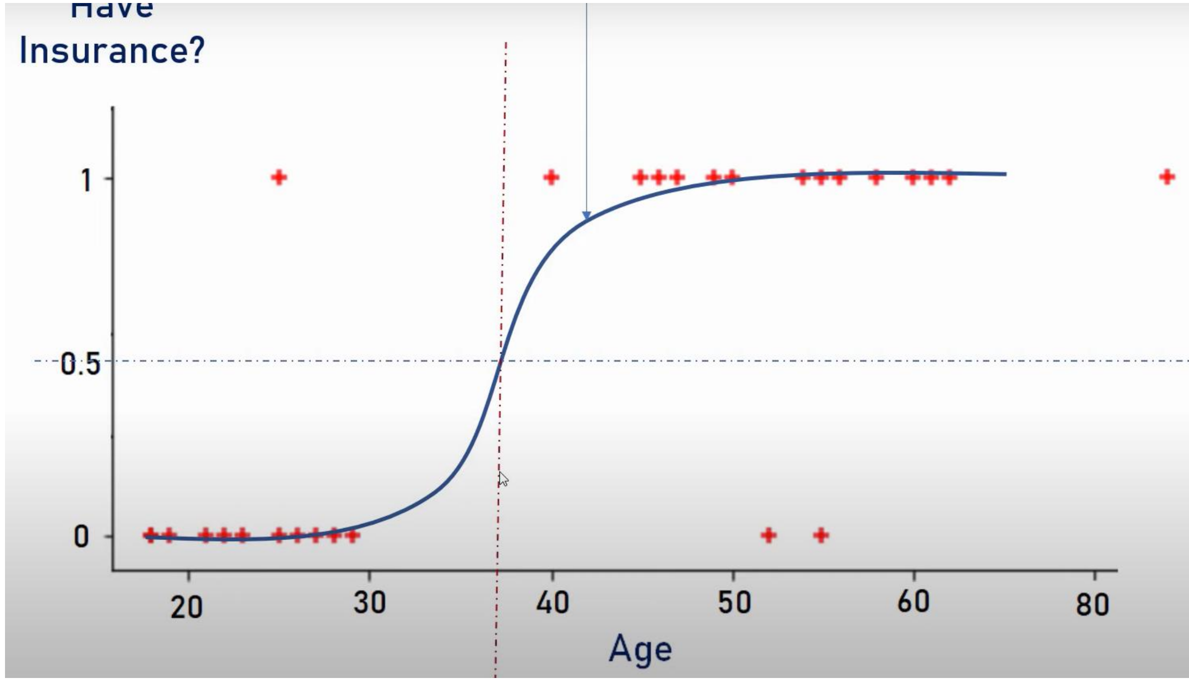


2- Logistic Regression

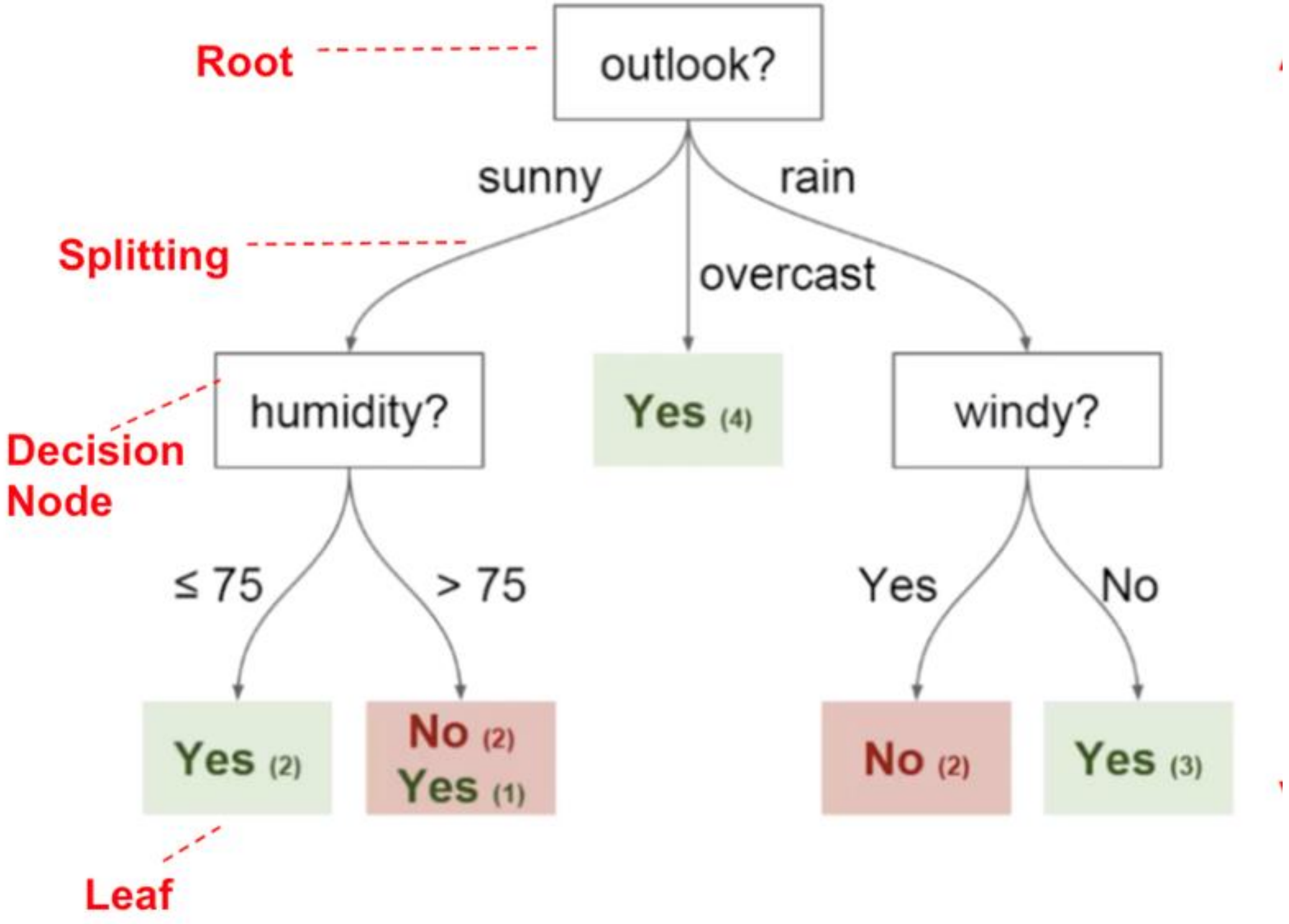
$$y = m * x + b$$

$$y = \frac{1}{1 + e^{-(m*x+b)}}$$





3- Decision trees



Should you go and play tennis? We all use decision trees for such decisions in real life.

How to choose splits in data

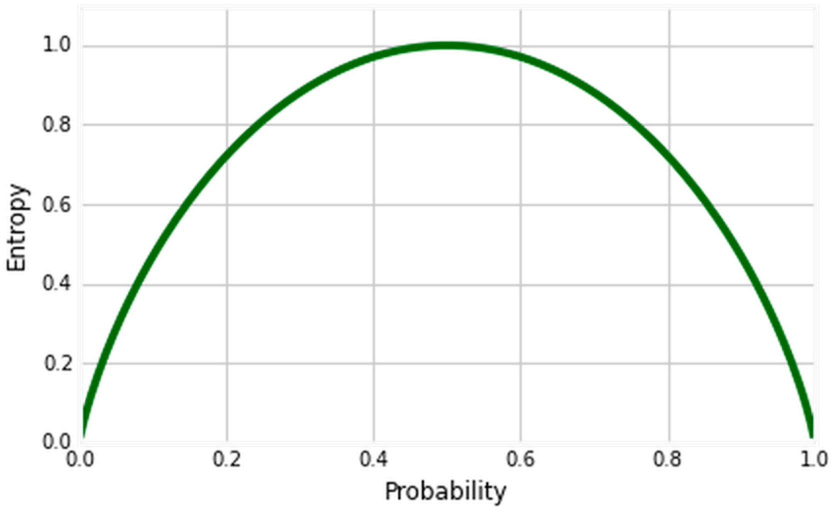
A successful decision tree is one that does a good job of “splitting” data into homogeneous groups.

Q. Based on which attribute (feature) to split? What is the best split?

A. Use the attribute with the highest Information Gain or Gini Gain

Entropy. Entropy is a measure of purity or a measure of uncertainty or randomness. Entropy controls how a Decision Tree decides to split the data. It actually affects how a Decision Tree draws its boundaries. Equation of entropy:

$$H = -\sum p(x) \log p(x)$$

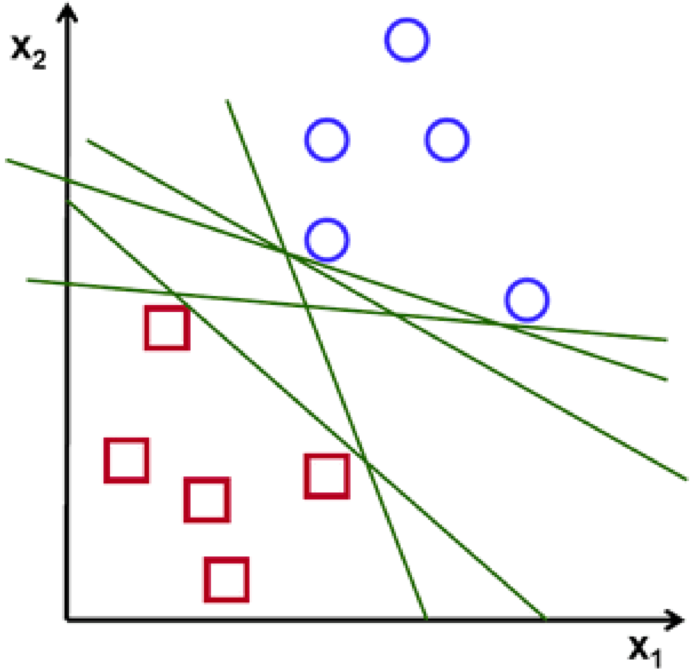


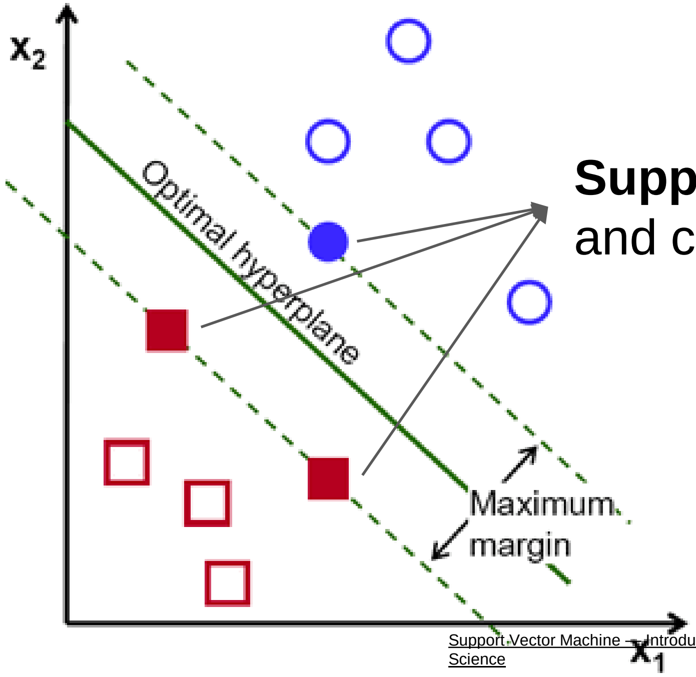
Information gain. Expected reduction in entropy due to partitioning

$$IG(Y, X) = E(Y) - E(Y|X)$$

4- Support Vector Machine(SVM)

The objective of the support vector machine algorithm is to find a hyperplane in N-dimensional space(N — the number of features) that distinctly classifies the data points.





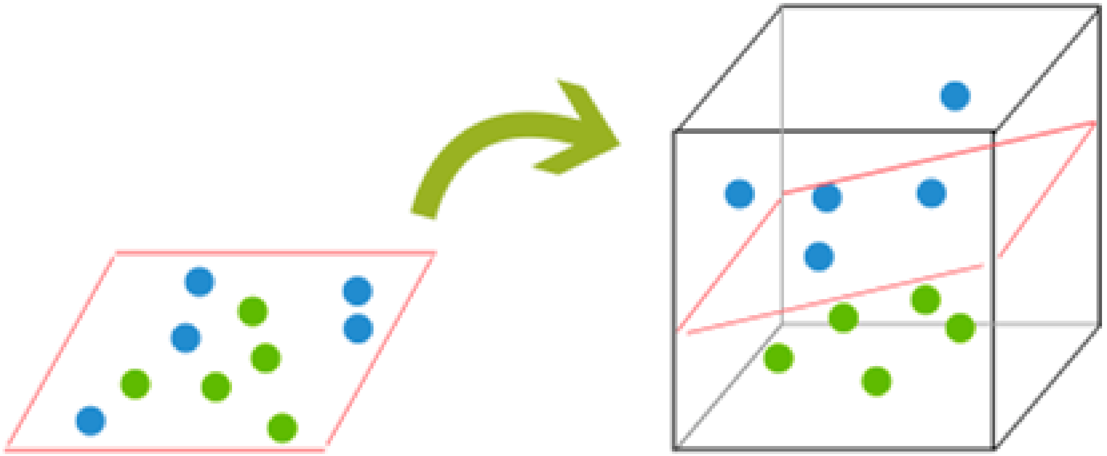
Support vectors: Solid squares and circle are the support vectors.

Support Vector Machine — Introduction to Machine Learning Algorithms | by Rohith Gandhi | Towards Data Science

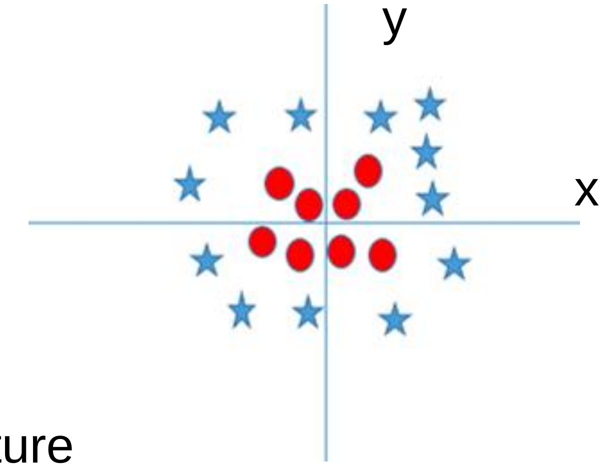
Support vectors are the data points nearest to the hyperplane, the points of a data set that, if removed, would alter the position of the dividing hyperplane.

The goal of SVM is to find a hyperplane that maximizes the maximum margins from the support vectors.

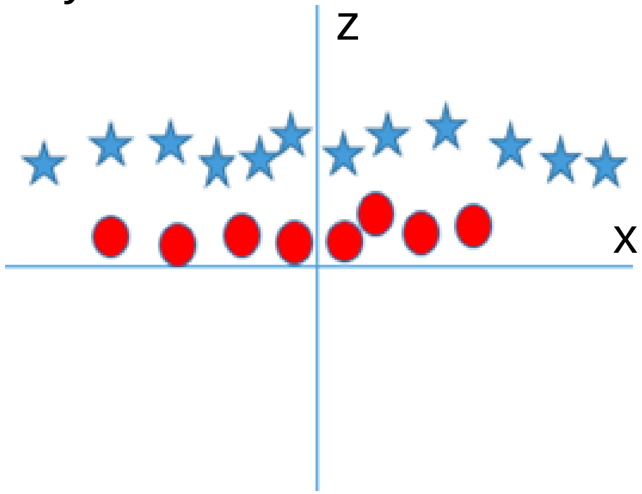
Linearly non-separable data



2-D to 3-D mapping.



Add a new feature (mapping) z=x^2+y^2.



For complex datasets data needs to be mapped into a higher dimension. Transforming linearly inseparable data to linearly separable ones. This is known as <u>SVM kernelling.</u>

SVM kernelling is a function that takes low dimensional input space and transforms it to a higher dimensional space i.e. it converts not separable problem to separable problem.

For any Machine Learning Technique:

Steps in python

- Problem?
- Import data
- Clean
- Data Selection
- Split the data
- Create/ pick model
- Train the model
- Make prediction
- Test model

Supervised Learning

Unsupervised Learning

Reinforcement Learning

- **Cluster Analysis: Basic Concepts**
- Partitioning Methods
- Hierarchical Methods
- Density-Based Methods
- Grid-Based Methods
- Evaluation of Clustering

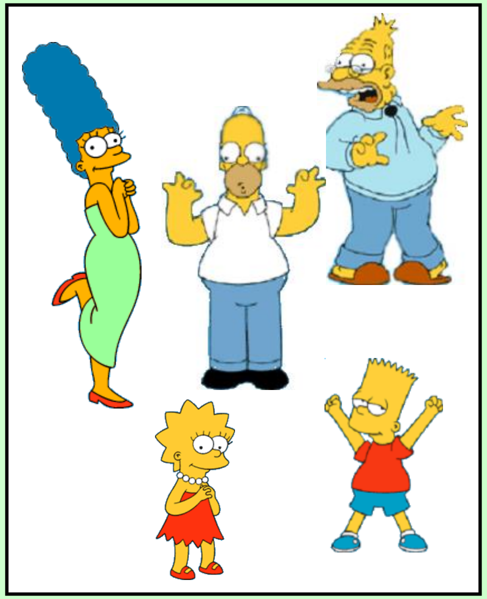
What is Cluster Analysis?

- Cluster: A collection of data objects
  - similar (or related) to one another within the same group
  - dissimilar (or unrelated) to the objects in other groups
- Cluster analysis (or *clustering*, *data segmentation, …*)
  - Finding similarities between data according to the characteristics found in the data and grouping similar data objects into clusters
- Unsupervised learning: no predefined classes (i.e., *learning by observations* vs. learning by examples: supervised)
- Typical applications
  - As a stand-alone tool to get insight into data distribution
  - As a preprocessing step for other algorithms

What is a natural grouping of these objects?

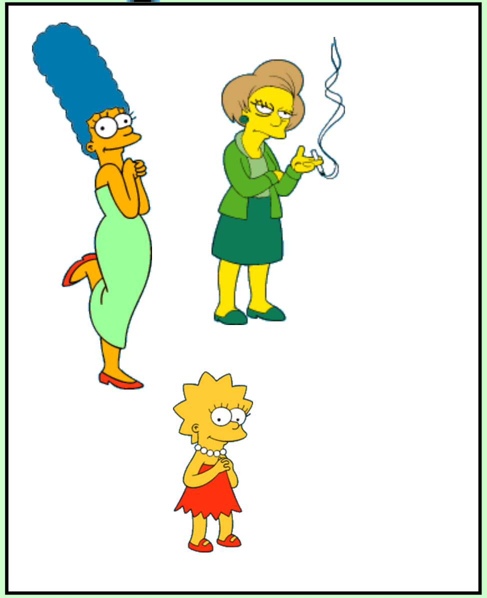
Slide from Eamonn Keogh

Clustering is subjective



Simpson's Family

School Employees



Females

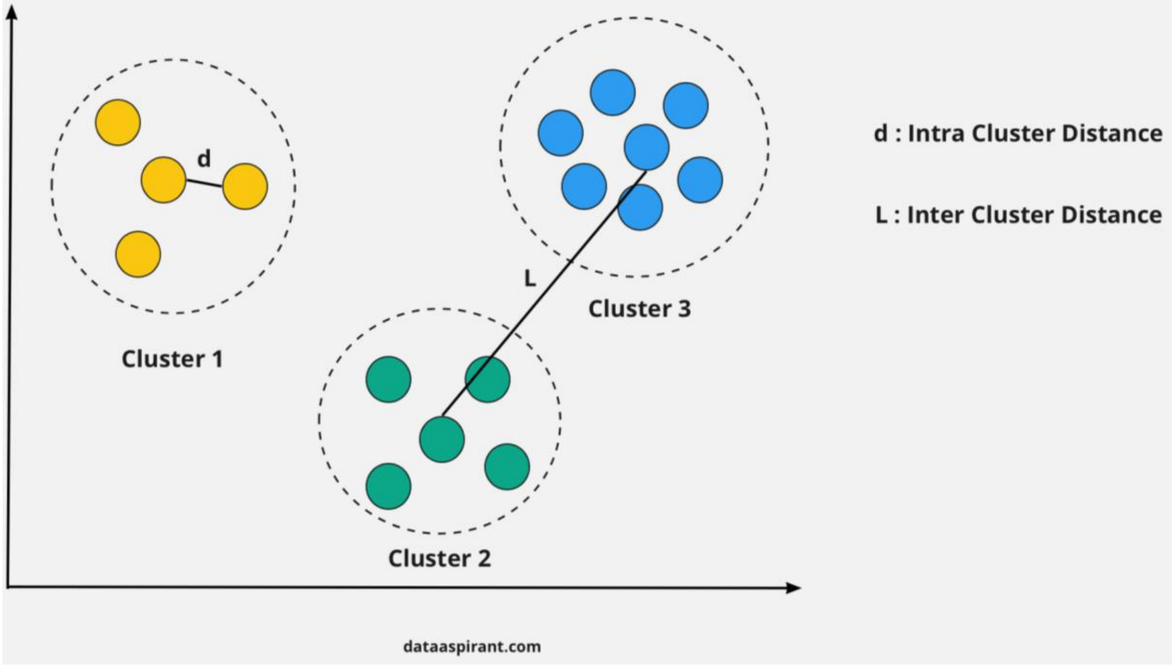
Males

Clustering for Data Understanding and Applications

- Retail: identify groups of households that are similar to each other
- Streaming services: identify viewers who have similar behavior.
- Land use: Identification of areas of similar land use in an earth observation database
- Marketing: Help marketers discover distinct groups in their customer bases, and then use this knowledge to develop targeted marketing programs
- City-planning: Identifying groups of houses according to their house type, value, and geographical location
- Earth-quake studies: Observed earth quake epicenters should be clustered along continent faults
- Climate: understanding earth climate, find patterns of atmospheric and ocean

Quality: What Is Good Clustering?

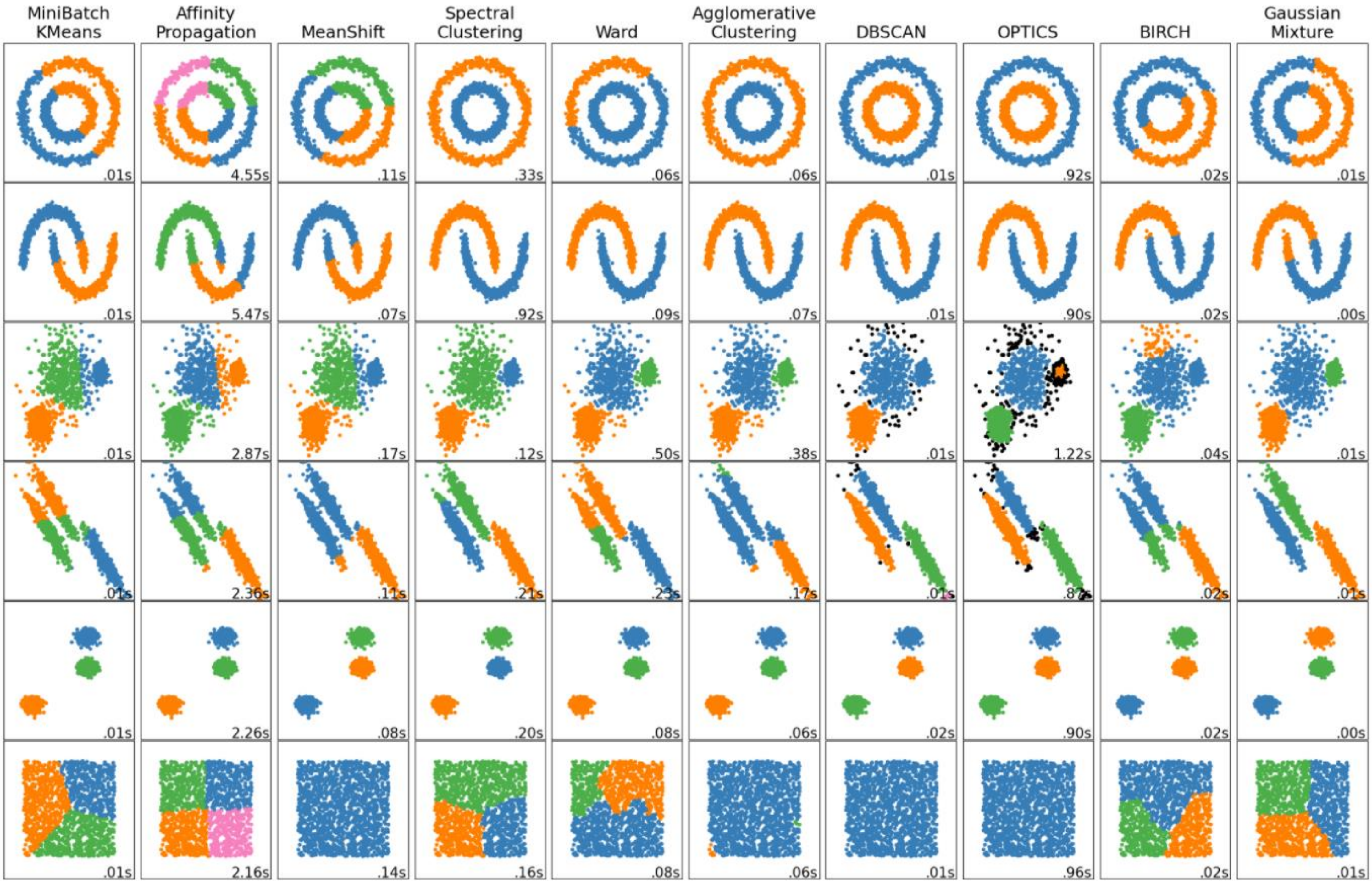
- A good clustering method will produce high quality clusters
  - high intra-class similarity: cohesive within clusters
  - low inter-class similarity: distinctive between clusters
- The quality of a clustering method depends on
  - the similarity measure used by the method
  - Its ability to discover some or all of the hidden patterns



Most common clustering methods

Method name	Parameters	Scalability	Usecase	Geometry (metric used)
K-Means	number of clusters	Very large `n_samples`, medium `n_clusters` with MiniBatch code	General-purpose, even cluster size, flat geometry, not too many clusters, inductive	Distances between points
Affinity propagation	damping, sample preference	Not scalable with n_samples	Many clusters, uneven cluster size, non-flat geometry, inductive	Graph distance (e.g. nearest-neighbor graph)
Mean-shift	bandwidth	Not scalable with `n_samples`	Many clusters, uneven cluster size, non-flat geometry, inductive	Distances between points
Spectral clustering	number of clusters	Medium `n_samples`, small `n_clusters`	Few clusters, even cluster size, non-flat geometry, transductive	Graph distance (e.g. nearest-neighbor graph)
Ward hierarchical clustering	number of clusters or distance threshold	Large `n_samples` and `n_clusters`	Many clusters, possibly connectivity constraints, transductive	Distances between points
Agglomerative clustering	number of clusters or distance threshold, linkage type, distance	Large `n_samples` and `n_clusters`	Many clusters, possibly connectivity constraints, non Euclidean distances, transductive	Any pairwise distance
DBSCAN	neighborhood size	Very large `n_samples`, medium `n_clusters`	Non-flat geometry, uneven cluster sizes, outlier removal, transductive	Distances between nearest points
OPTICS	minimum cluster membership	Very large `n_samples`, large `n_clusters`	Non-flat geometry, uneven cluster sizes, variable cluster density, outlier removal, transductive	Distances between points
Gaussian mixtures	many	Not scalable	Flat geometry, good for density estimation, inductive	Mahalanobis distances to centers
BIRCH	branching factor, threshold, optional global clusterer.	Large `n_clusters` and `n_samples`	Large dataset, outlier removal, data reduction, inductive	Euclidean distance between points

http://scikit-learn.org/stable/modules/clustering.html


MiniBatch KMeans
Affinity Propagation
MeanShift
Spectral Clustering
Ward
Agglomerative Clustering
DBSCAN
OPTICS
BIRCH
Gaussian Mixture
.01s
4.55s
.11s
.33s
.06s
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- Cluster Analysis: Basic Concepts
- **Partitioning Methods**
- Hierarchical Methods
- Density-Based Methods
- Grid-Based Methods
- Evaluation of Clustering

Partitioning Algorithms: Basic Concept

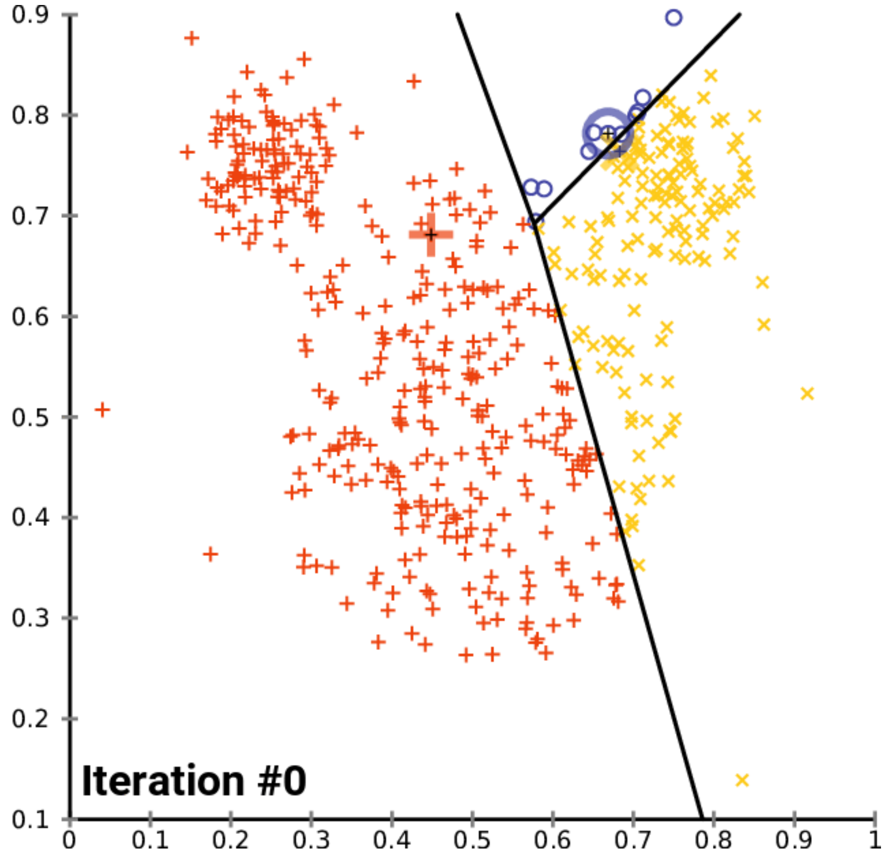
- Partitioning method: Partitioning a database ***D*** of ***n*** objects into a set of ***k*** clusters, such that the sum of squared distances is minimized (where c_i is the centroid or medoid of cluster C_i)

$$E = \Sigma_{i=1}^{k} \Sigma_{p \in C_i} (p - c_i)^2$$

- Given *k*, find a partition of *k clusters* that optimizes the chosen partitioning criterion
  - Heuristic methods: *k-means* and *k-medoids* algorithms
  - *k-means* (MacQueen'67, Lloyd'57/'82): Each cluster is represented by the center of the cluster
  - *k-medoids* or PAM (Partition around medoids) (Kaufman & Rousseeuw'87): Each cluster is represented by one of the objects in the cluster

The *K-Means* Clustering Method

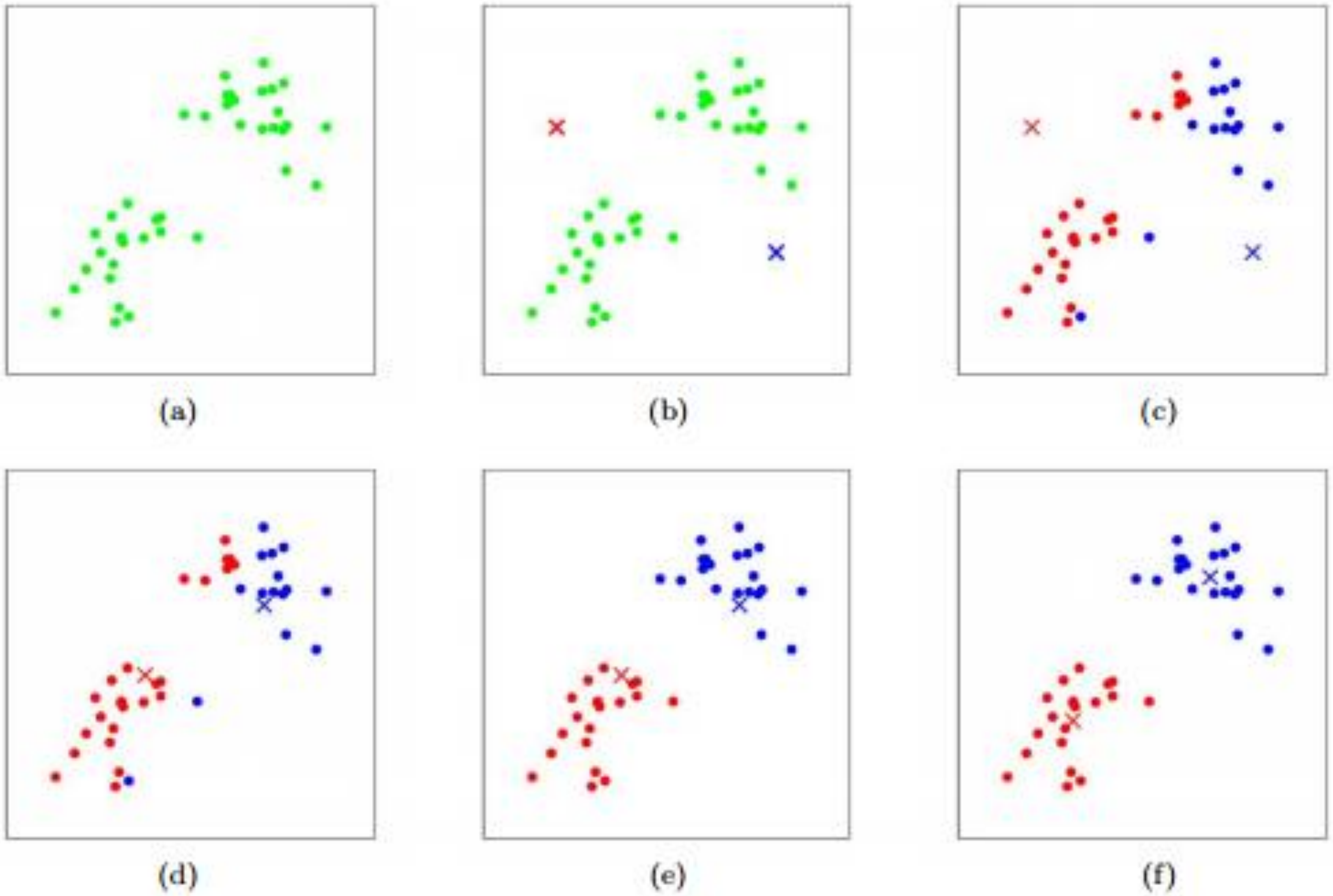
- Given *k*, the *k-means* algorithm is implemented in four steps:
  - Partition objects into *k* nonempty subsets
  - Compute seed points as the centroids of the clusters of the current partitioning (the centroid is the center, i.e., *mean point*, of the cluster)
  - Assign each object to the cluster with the nearest seed point
  - Go back to Step 2, stop when the assignment does not change



The *K-Means* Clustering Method

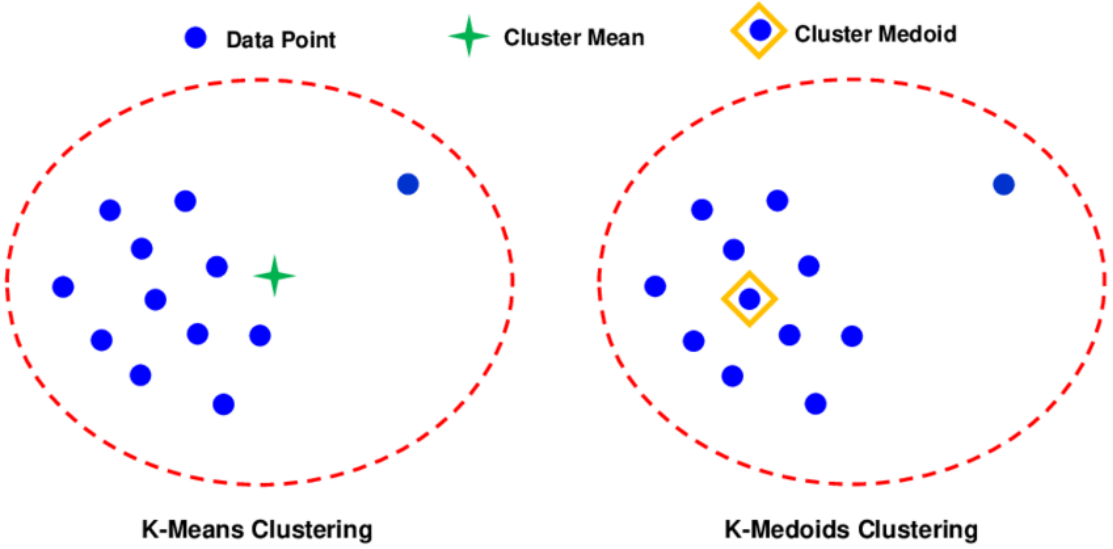
- An iterative clustering algorithm
  - Initialize: Pick *K* random points as cluster centers
  - Alternate:
    1. Assign data points to closest cluster center
    2. Change the cluster center to the average of its assigned points
  - Stop when no points' assignments change

```python
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=4)
kmeans.fit(X)
y_kmeans = kmeans.predict(X)
```

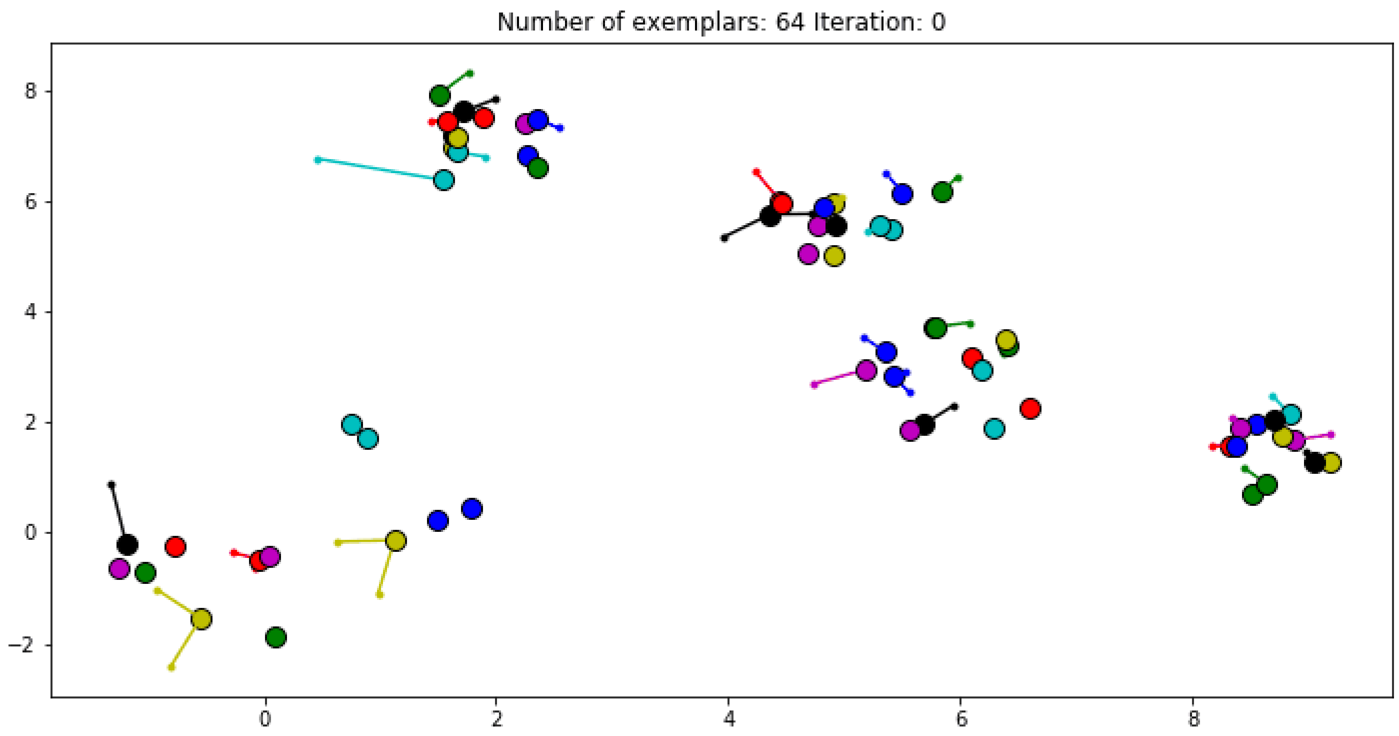


What Is the Problem of the K-Means Method?

- The k-means algorithm is sensitive to outliers !
  - Since an object with an extremely large value may substantially distort the distribution of the data
- K-Medoids: Instead of taking the **mean** value of the object in a cluster as a reference point, **medoids** can be used, which is the **most centrally located** object in a cluster



Affinity Propagation



❖Partitioning message passing algorithm
❖Determine the optimal number of clusters for the user
❖ Algorithm stops when convergence is achieved.

AP matrices

❖ Similarity Matrix: Similarity between any data points

❖ Responsibility Matrix: How well-suited point k is to be an exemplar for point i

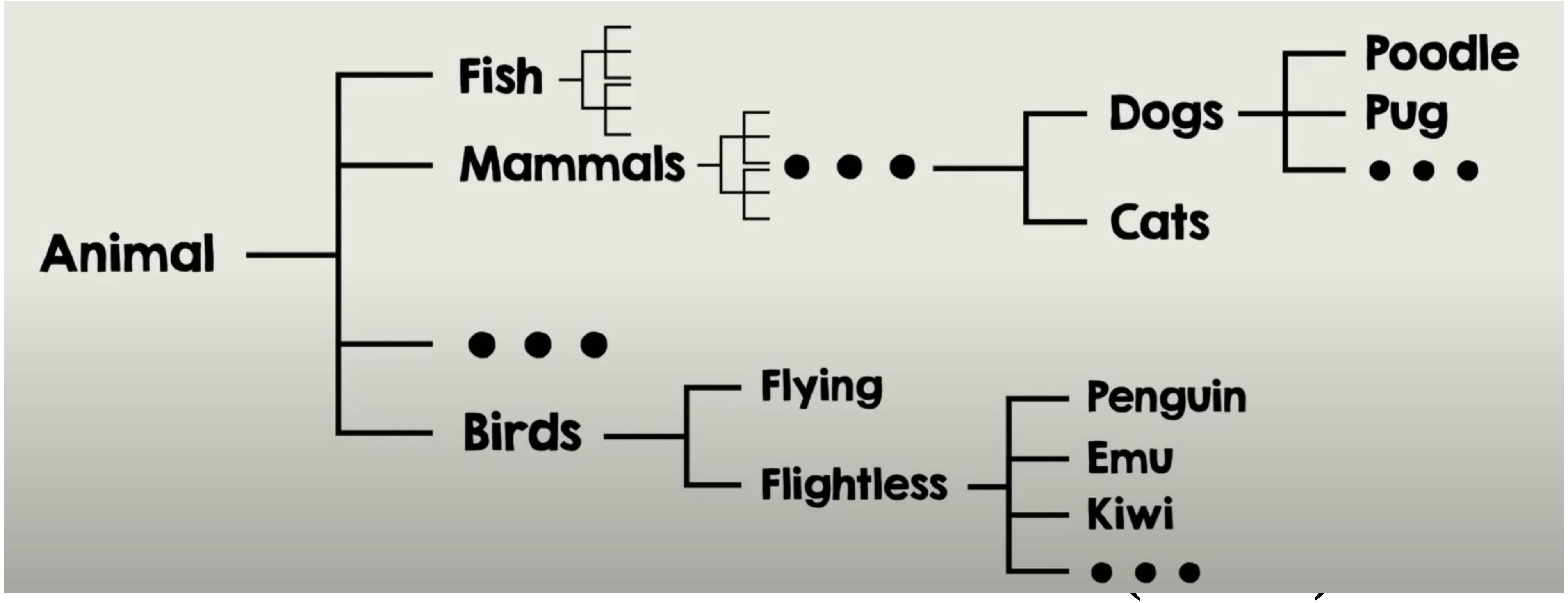
❖ Availability Matrix: Contains values that correspond to how available one object is to be an exemplar for another object

❖ Criterion Matrix: Sum of the availability matrix and responsibility matrix, the highest criterion value is designated as the exemplar

- Cluster Analysis: Basic Concepts
- Partitioning Methods
- **Hierarchical Methods**
- Density-Based Methods
- Grid-Based Methods
- Evaluation of Clustering

Hierarchical Clustering

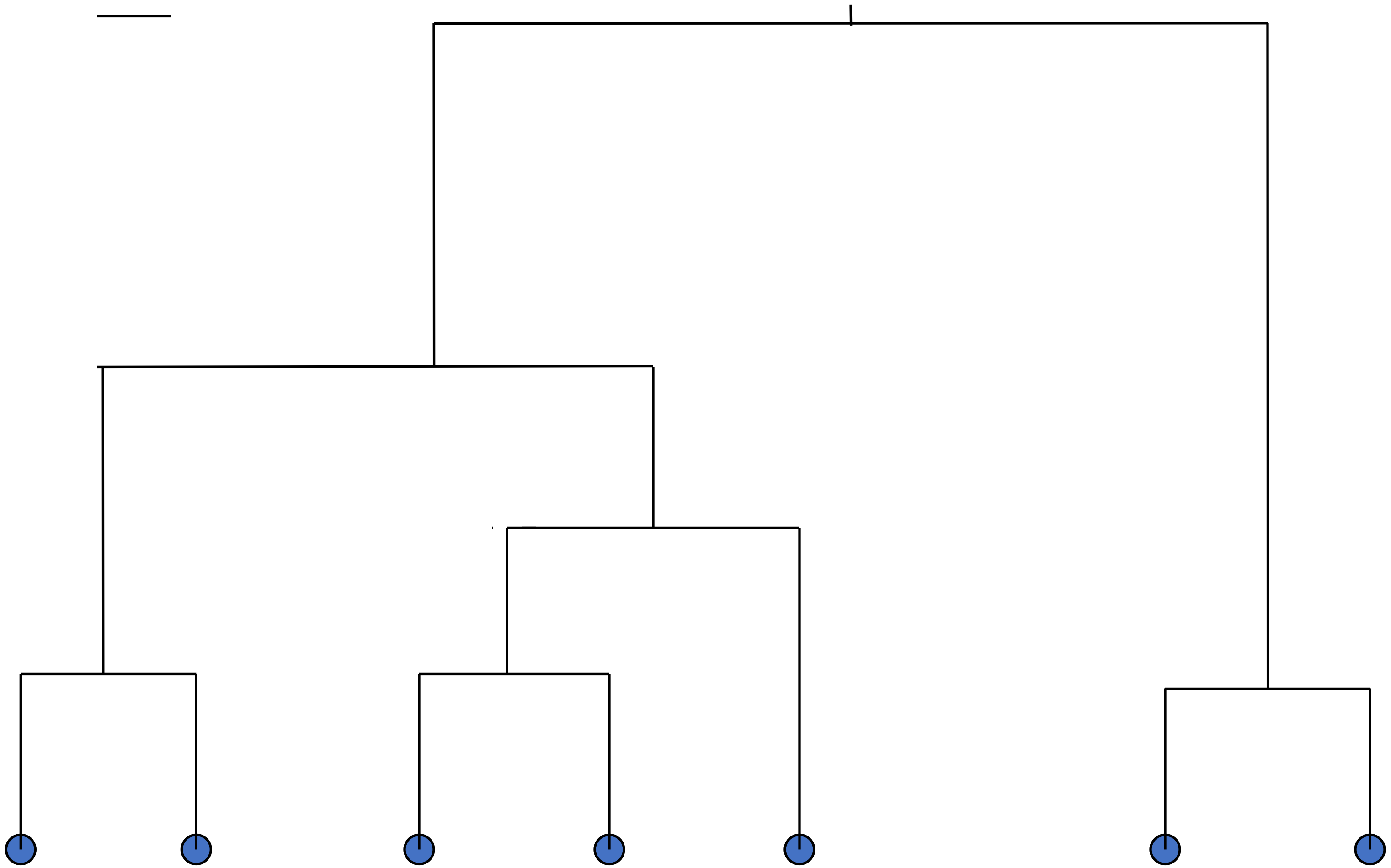
- Use distance matrix as clustering criteria. This method does not require the number of clusters ***k*** as an input, but needs a termination condition



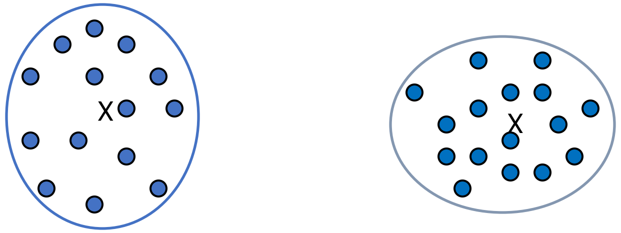
Dendrogram: Shows How Clusters are Merged

Decompose data objects into a several levels of nested partitioning (tree of clusters), called a dendrogram

A clustering of the data objects is obtained by cutting the dendrogram at the desired level, then each connected component forms a cluster



Distance between Clusters



- Single link: smallest distance between an element in one cluster and an element in the other, i.e., $dist(K_i, K_j) = min(t_{ip}, t_{jq})$
- Complete link: largest distance between an element in one cluster and an element in the other, i.e., $dist(K_i, K_j) = max(t_{ip}, t_{jq})$
- Average: avg distance between an element in one cluster and an element in the other, i.e., $dist(K_i, K_j) = avg(t_{ip}, t_{jq})$
- Centroid: distance between the centroids of two clusters, i.e., $dist(K_i, K_j) = dist(C_i, C_j)$
- Medoid: distance between the medoids of two clusters, i.e., $dist(K_i, K_j) = dist(M_i, M_j)$
  - Medoid: a chosen, centrally located object in the cluster

Centroid, Radius and Diameter of a Cluster (for numerical data sets)

- Centroid: the "middle" of a cluster

$$C_m = \frac{\sum_{i=1}^{N}(t_{ip})}{N}$$

- Radius: square root of average distance from any point of the cluster to its centroid

$$R_m = \sqrt{\frac{\sum_{i=1}^{N}(t_{ip} - c_m)^2}{N}}$$

- Diameter: square root of average mean squared distance between all pairs of points in the cluster

$$D_m = \sqrt{\frac{\sum_{i=1}^{N}\sum_{i=1}^{N}(t_{ip} - t_{iq})^2}{N(N-1)}}$$

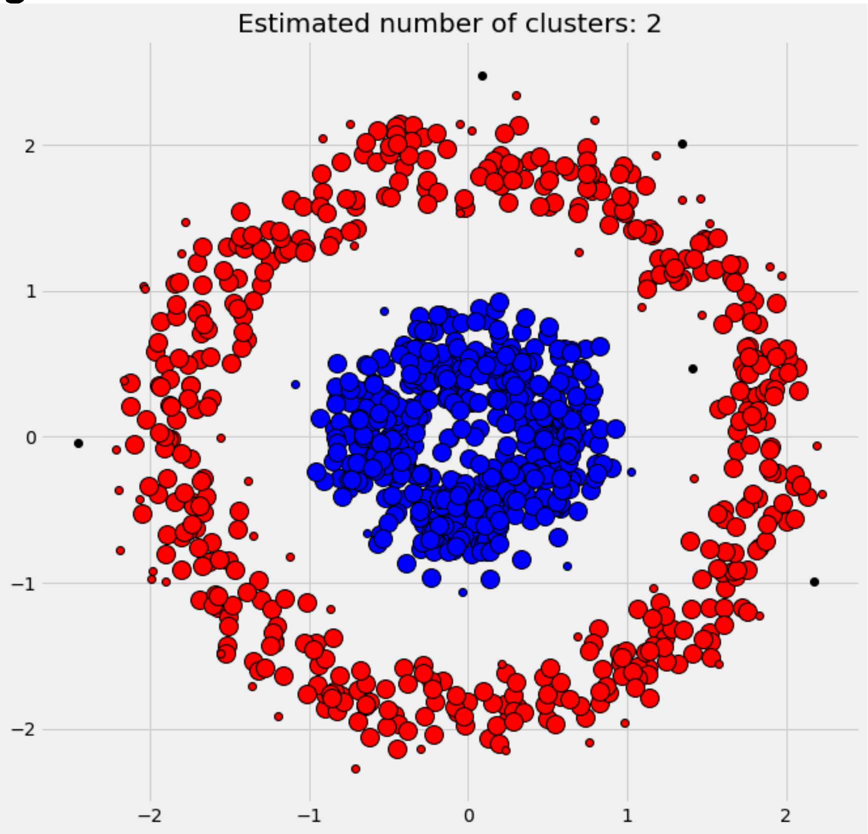
Extensions to Hierarchical Clustering

- Major weakness of agglomerative clustering methods
  - Can never undo what was done previously
  - Do not scale well: time complexity of at least $O(n^2)$, where n is the number of total objects

- Cluster Analysis: Basic Concepts
- Partitioning Methods
- Hierarchical Methods
- **Density-Based Methods**
- Grid-Based Methods
- Evaluation of Clustering
- Summary

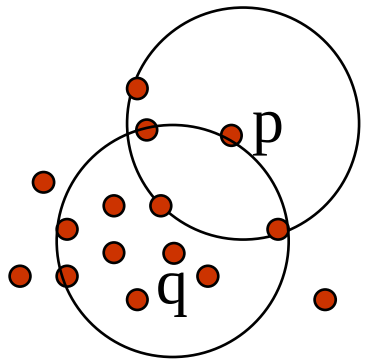
Density-Based Clustering Methods

- Clustering based on density (local cluster criterion), such as density-connected points
- Major features:
  - Discover clusters of arbitrary shape
  - Handle noise
  - One scan
  - Need density parameters as termination condition
- Several interesting studies:
  - <u>DBSCAN:</u> Ester, et al. (KDD'96)
  - <u>OPTICS</u>: Ankerst, et al (SIGMOD'99).
  - <u>DENCLUE</u>: Hinneburg & D. Keim (KDD'98)
  - <u>CLIQUE</u>: Agrawal, et al. (SIGMOD'98) (more grid-based)



Density-Based Clustering

- Two parameters*:*
  - *Eps*: Maximum radius of the neighbourhood
  - *MinPts*: Minimum number of points in an Eps-neighbourhood of that point

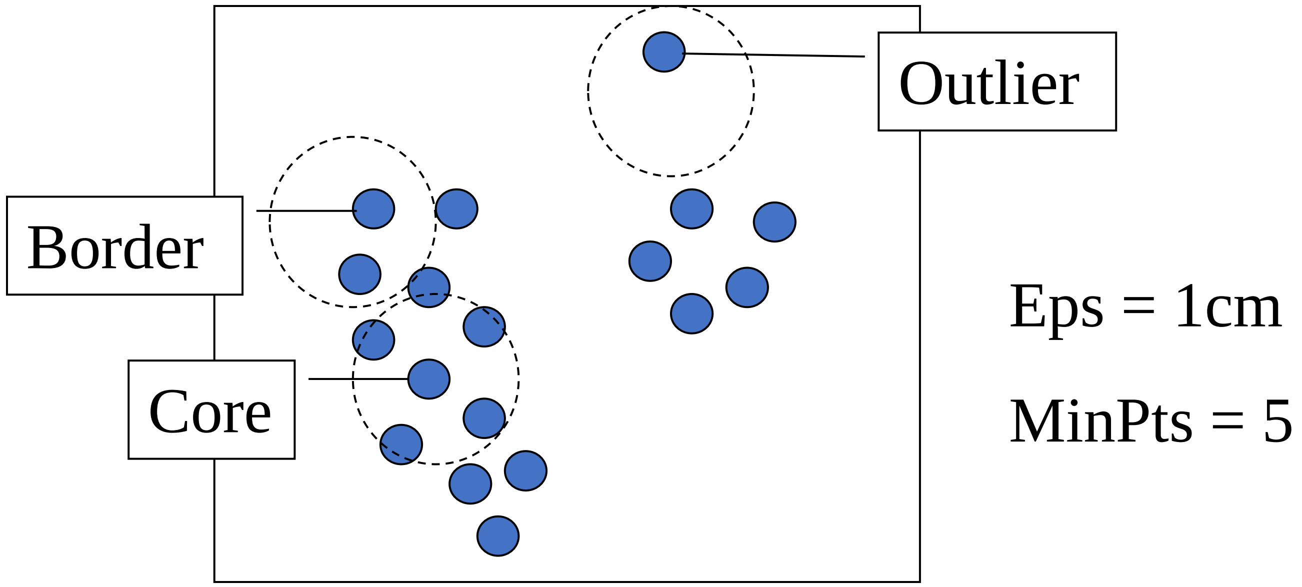


MinPts = 5

Eps = 1 cm

DBSCAN: Density-Based Spatial Clustering of Applications with Noise

- Relies on a *density-based* notion of cluster: A *cluster* is defined as a maximal set of density-connected points
- Discovers clusters of arbitrary shape in spatial databases with noise



DBSCAN: The Algorithm

- Arbitrary select a point *p*
- Retrieve all points density-reachable from *p* w.r.t. *Eps* and *MinPts*
- If *p* is a core point, a cluster is formed
- If *p* is a border point, no points are density-reachable from *p* and DBSCAN visits the next point of the database
- Continue the process until all of the points have been processed

- Cluster Analysis: Basic Concepts
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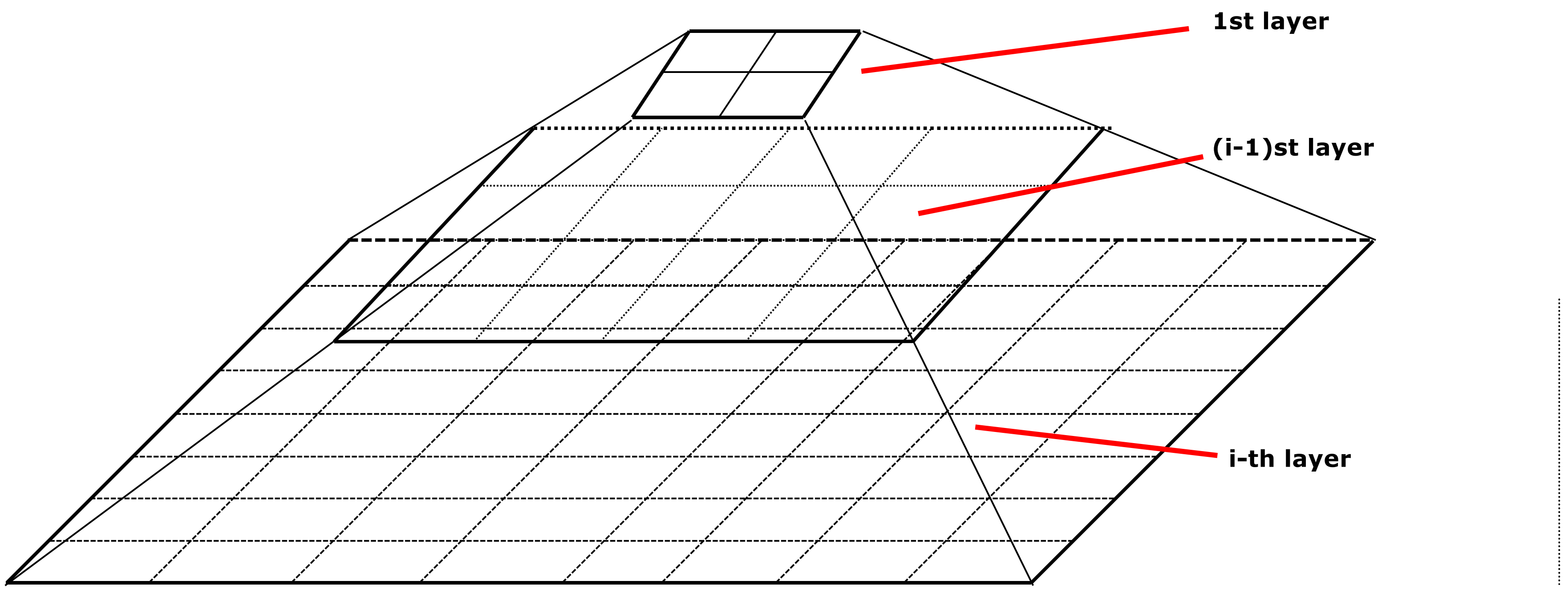
Grid-Based Clustering Method

- Using multi-resolution grid data structure
- Several interesting methods
  - STING (a STatistical INformation Grid approach) by Wang, Yang and Muntz (1997)
  - WaveCluster by Sheikholeslami, Chatterjee, and Zhang (VLDB’98)
    - A multi-resolution clustering approach using wavelet method
  - CLIQUE: Agrawal, et al. (SIGMOD’98)
    - Both grid-based and subspace clustering

STING: A Statistical Information Grid Approach

- The spatial area is divided into rectangular cells
- There are several levels of cells corresponding to different levels of resolution



- Cluster Analysis: Basic Concepts
- Partitioning Methods
- Hierarchical Methods
- Density-Based Methods
- Grid-Based Methods
- **Evaluation of Clustering**

1- Determine the Number of Clusters

- Empirical method
  - # of clusters $\approx\sqrt{n/2}$ for a dataset of n points
- Elbow method
  - Use the turning point in the curve of sum of within cluster variance w.r.t the # of clusters
- Cross validation method
  - Divide a given data set into *m* parts
  - Use *m* – 1 parts to obtain a clustering model
  - Use the remaining part to test the quality of the clustering
    - E.g., For each point in the test set, find the closest centroid, and use the sum of squared distance between all points in the test set and the closest centroids to measure how well the model fits the test set
  - For any k > 0, repeat it *m* times, compare the overall quality measure w.r.t. different *k's*, and find # of clusters that fits the data the best

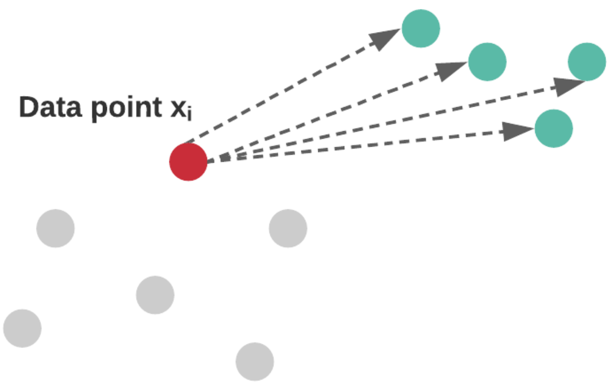
2- Measuring Clustering Quality

- Two methods: extrinsic vs. intrinsic
- Extrinsic: supervised, i.e., the ground truth is available
  - Compare a clustering against the ground truth using certain clustering quality measure
  - Ex. BCubed precision and recall metrics
- Intrinsic: unsupervised, i.e., the ground truth is unavailable
  - Evaluate the goodness of a clustering by considering how well the clusters are separated, and how compact the clusters are
  - Ex. Silhouette coefficient

Intrinsic Clustering Validation Phase
Silhouette Index

❖How similar a data point is to its own cluster compared to other clusters.

$$s_i = \frac{b_i - a_i}{\max(a_i, b_i)}$$



- Value bounded between [-1,1]
- High scores when clusters are well separated
- High computational complexity
- Higher value for convex clusters

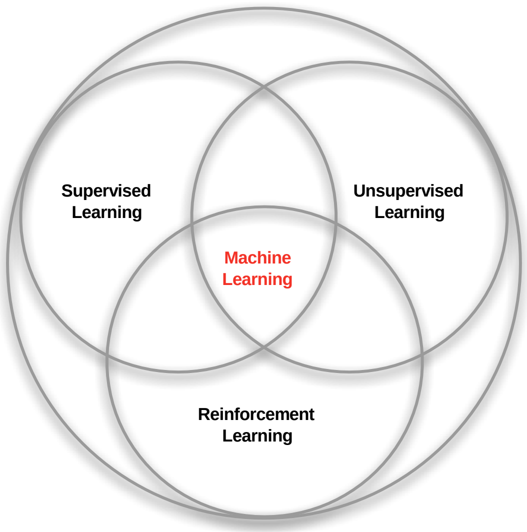
Supervised Learning

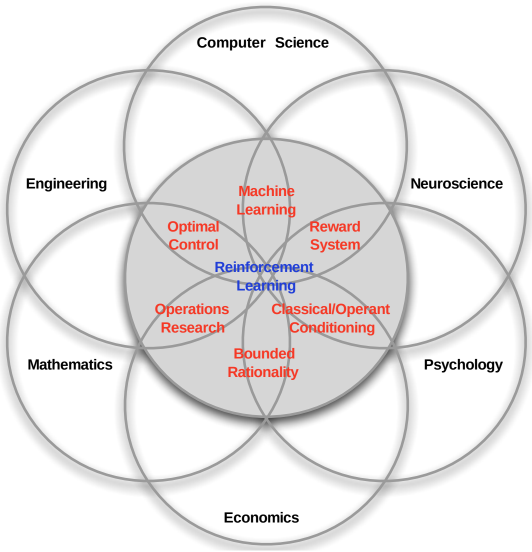
Unsupervised Learning

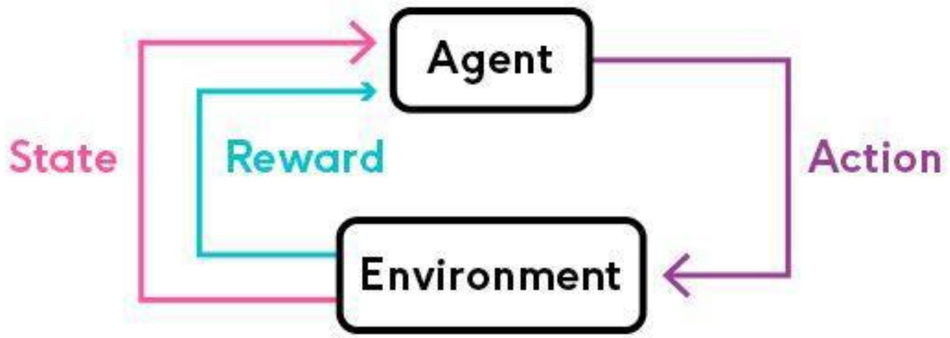
Reinforcement Learning

Reinforcement Learning

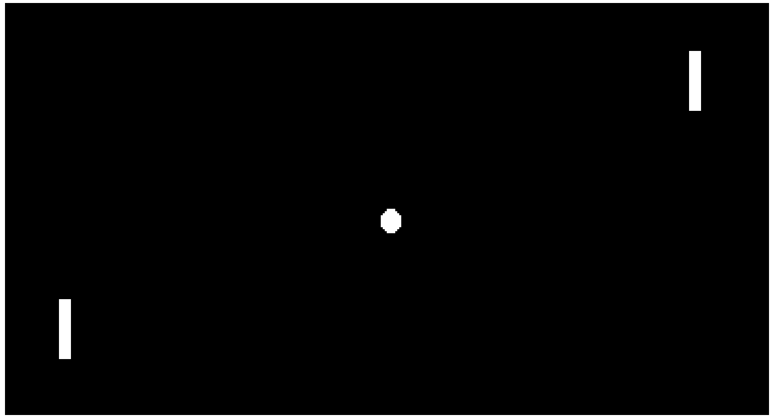
- Reinforcement learning (RL) is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward. Reinforcement learning is one of three basic machine learning paradigms, alongside supervised learning and unsupervised learning.
- **Goal**: Learn how to take actions in order to maximize reward







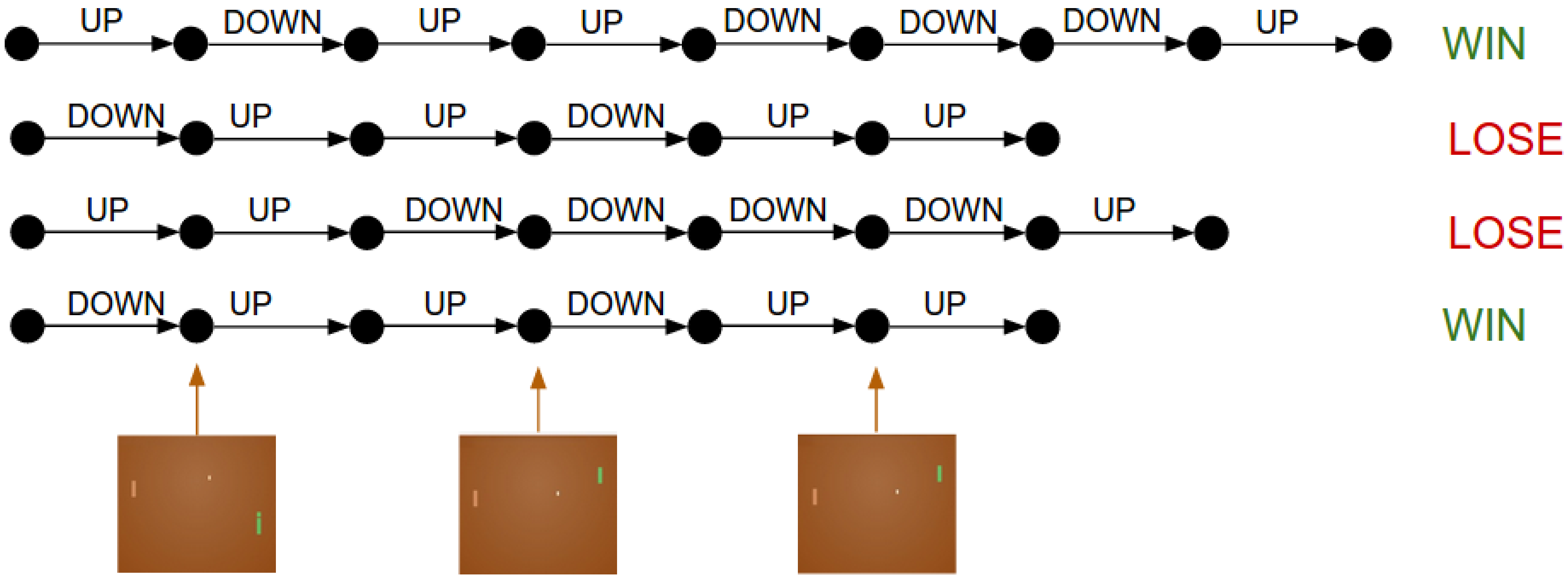
Atari Games: Pong



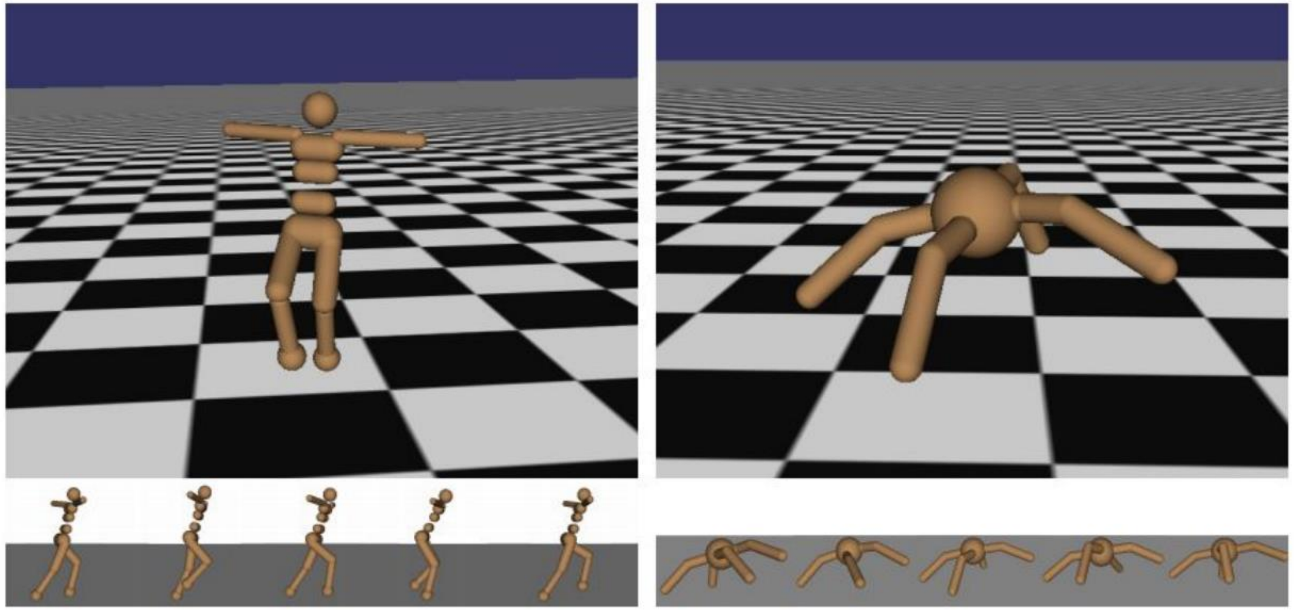
Objective: Complete the game with the highest score

State: Raw pixel inputs of the game state
Action: Game controls e.g. Up, Down
Reward: Score increase/decrease at each time step

[Deep Reinforcement Learning: Pong from Pixels (karpathy.github.io)](karpathy.github.io)


UP DOWN UP UP DOWN DOWN DOWN UP
WIN
DOWN UP UP DOWN UP UP
LOSE
UP UP DOWN DOWN DOWN DOWN UP
LOSE
DOWN UP UP DOWN UP UP
WIN

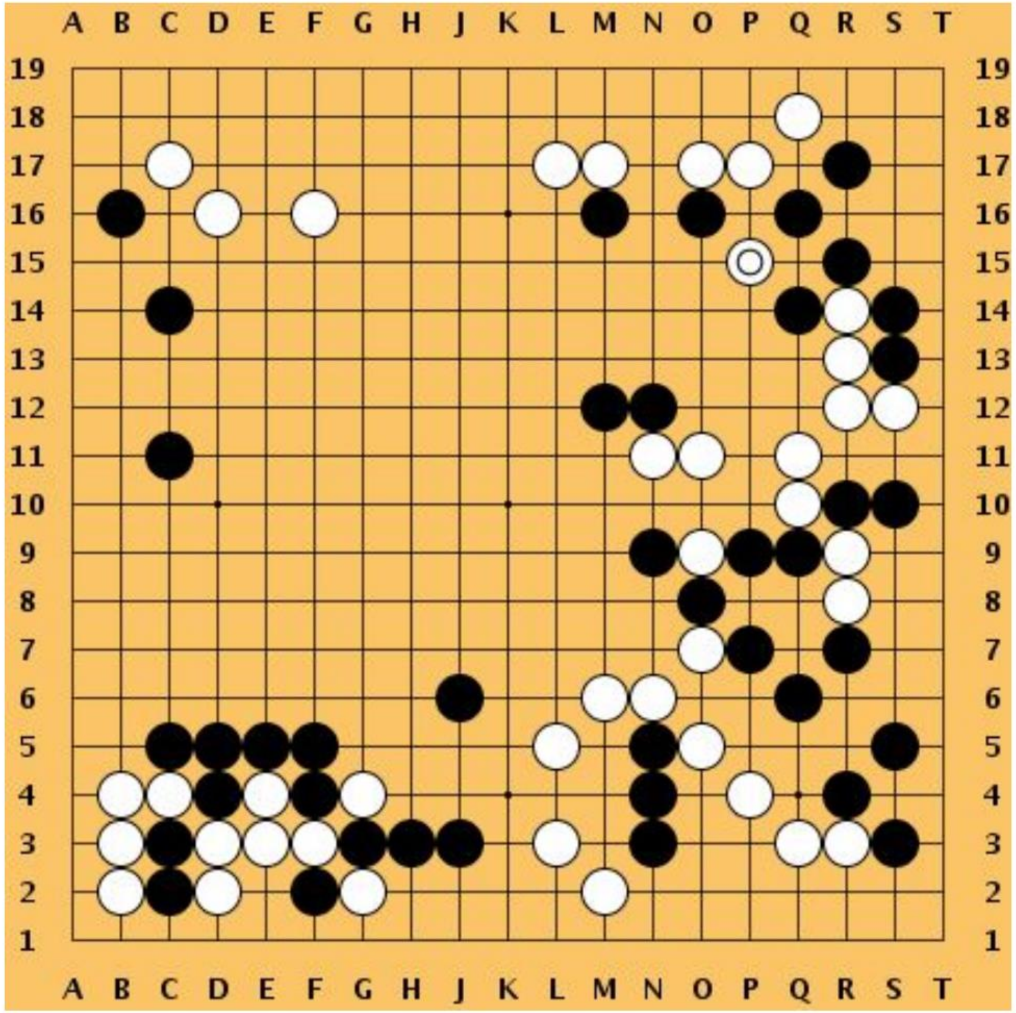
Robot Locomotion



Objective: Make the robot move forward

State: Angle and position of the joints
Action: Torques applied on joints
Reward: 1 at each time step upright + forward movement

Go

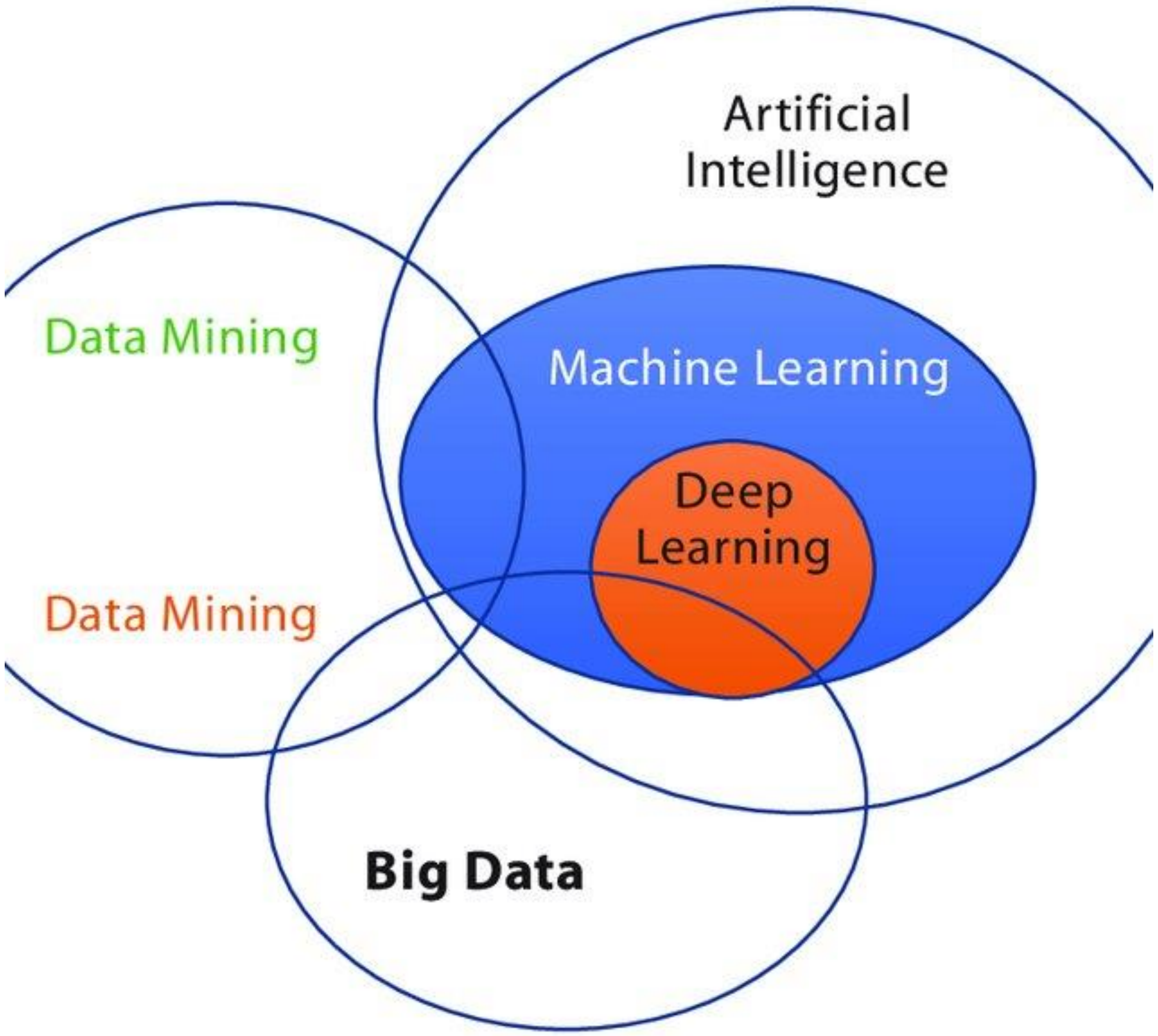


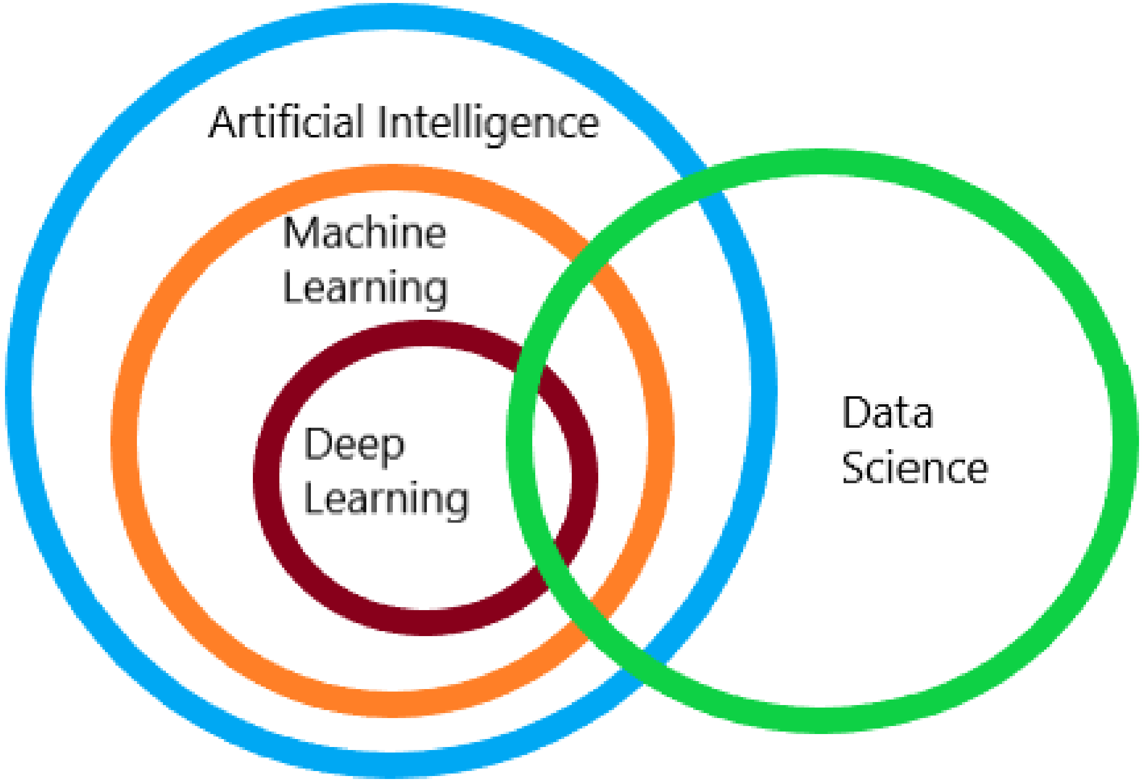
Objective: Win the game!

State: Position of all pieces
Action: Where to put the next piece down
Reward: 1 if win at the end of the game, 0 otherwise

Characteristics of Reinforcement Learning

- What makes reinforcement learning different from other machine learning paradigms?
  - There is no supervisor, only a *reward* signal
  - Feedback is delayed, not instantaneous
  - Time really matters (sequential, non i.i.d data)
  - Agent's actions affect the subsequent data it receives


Artificial Intelligence
Data Mining
Machine Learning
Deep Learning
Data Mining
Big Data


Artificial Intelligence
Machine Learning
Deep Learning
Data Science