## Machine Learning: Classification versus Clustering

#### The Classification problem:

 We start with a database of objects whose classes are already known

The database is known as the training database since it allows us to train a model, which learns to distinguish among those objects

 We take a new sample, and we want to know its class

#### Example of classification:

 Suppose we have a database storing info of different people, together with their emotions:

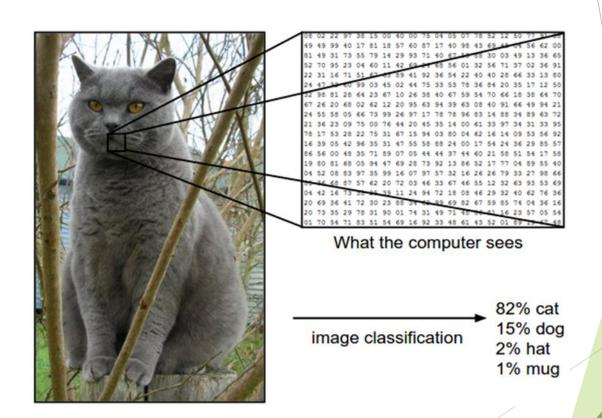


 We want to be able to use this database to assign an emotion to a test face: which is the emotion of this picture?

#### The k-Nearest Neighbours:

- The k-Nearest Neighbours (k-NN) classification algorithm considers the k-neighbours of the test sample and assigns it to the majority of the class
- Question 1: What is a digital image?
- Question 2: What makes two items count as similar, and how do we measure similarity?

#### What is a digital image?



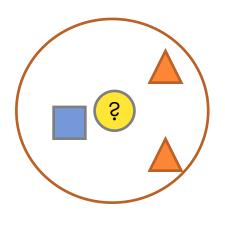
## What makes two items count as similar?

#### Euclidean distance:

- The k-NN algorithm interprets each object in the database as a point in the space; that is, each attribute is a feature, a coordinate in the plane
- The similarity of two points is measured as the distance between them

Euclidean\_dist 
$$((x,y),(a,b)) = \sqrt{(x-a)^2 + (y-b)^2}$$

#### k-NN Algorithm:



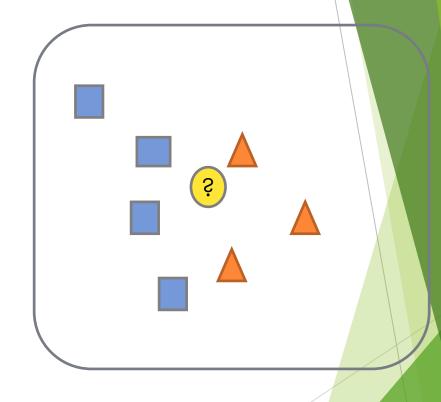
#### o It requires:

- 1. The set of stored labeled records (training set)
- A distance metric to compute the distance between records
- 3. The value of *k*, the number of nearest neighbors to consider
- To classify an unknown record (test sample);
  - Compute distance to all other training records
  - Identify k nearest neighbors
  - Use class labels of nearest training samples to assign the class (e.g., by taking majority vote) to the test sample

#### Challenges of k-NN:

- Choosing the value of k:
- If k is too small, sensitive to noise points
- If k is too large, neighborhood may include points from other classes
- Choose an odd value for k, to eliminate ties

Q: Give the class for K=1, 3, 5



#### Problems of k-NN:

- Computationally intensive, especially when the size of the training set grows
- High dimension
- Accuracy can be severely degraded by the presence of noisy or irrelevant features

#### Clustering:

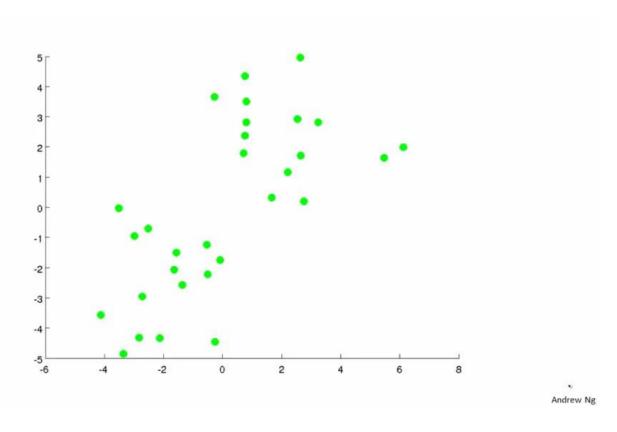
- The process of organizing objects into groups whose members are similar in some way
   A cluster is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters
- The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data

#### Example of clustering:

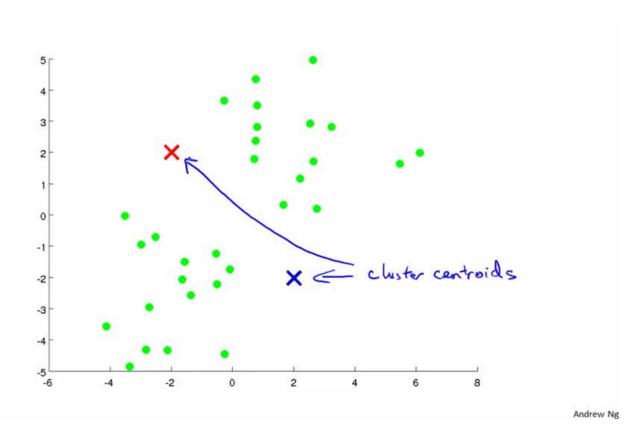
- Marketing: finding groups of customers with similar behavior given a large database of customer data containing their properties and past buying records
- Biology: clustering of plants and animals given their features
- Insurance: identifying groups of motor insurance policy holders with a high average claim cost; identifying frauds
- WWW: document clustering; clustering weblog data to discover groups of similar access patterns

#### K-means algorithm (1/6):

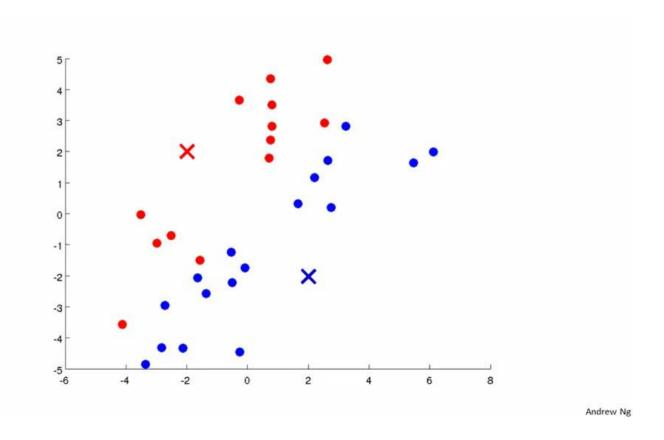
(Coursera, Machine Learning course - week 8)



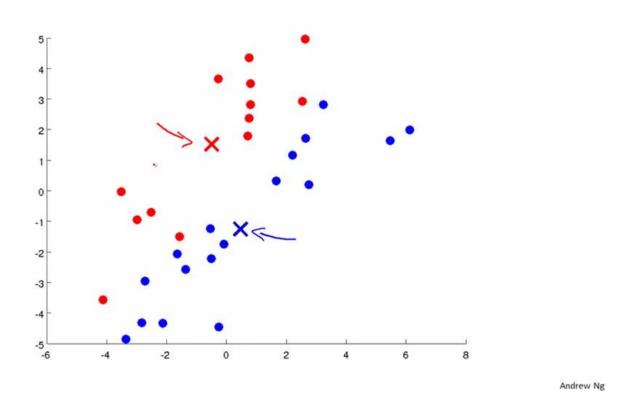
## K-means algorithm (2/6):



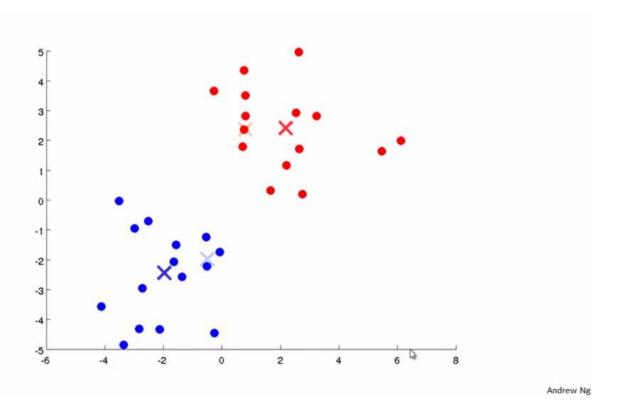
#### K-means algorithm (3/6):



#### K-means algorithm (4/6):



## K-means algorithm (5/6):



#### K-means algorithm (6/6):

#### K-means algorithm

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Randomly initialize K cluster centroids \mu_1, \mu_2, \dots, \mu_K \in \mathbb{R}^n Repeat \{ for i = 1 to m c^{(i)} := index (from 1 to K) of cluster centroid closest to x^{(i)} for k = 1 to K \mu_k := average (mean) of points assigned to cluster k
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# Requirements of clustering algorithms:

- scalability
- dealing with different types of attributes
- o discovering clusters with arbitrary shape
- o ability to deal with noise and outliers
- high dimensionality