



When applying a learning algorithm, some things are properties of the problem you are trying to solve, and some things are up to you to choose as the ML programmer.

Which of the following are properties of the problem?

- The data generating distribution
- The train/dev/test split
- The learning model
- The loss function





CMPS 460 – Spring 2022

MACHINE

LEARNING

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Image hosted by. WittySparks.com | Image source: Pixabay.com

3.b

K-Means Clustering





3.4-3.5

Roadmap ...



- A new algorithm
 - K-Means Clustering

- Fundamental Machine Learning Concepts
 - Unsupervised vs. supervised learning

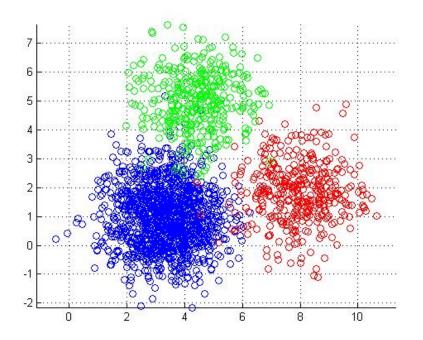


What is Clustering?

Clustering

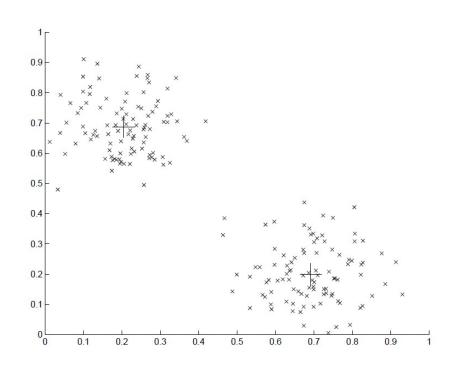


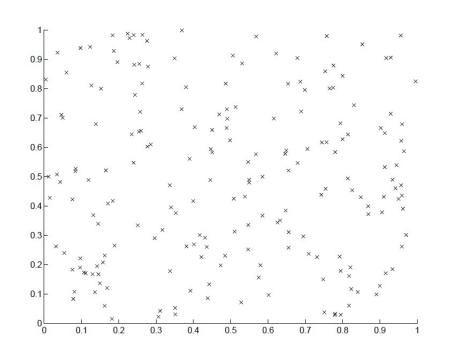
- Goal: automatically partition examples into groups of similar examples.
 - find the similarities between objects according to the object attributes and group the similar objects into clusters.





Different Underlying Structures





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Why Clustering?



Often used for exploratory analysis of the data

- Automatically organizing data
- Understanding hidden structure in data
- Preprocessing for further analysis

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What can we cluster in practice?

- news articles or web pages by topic
- protein sequences by function, or genes according to expression profile
- users of social networks by interest
- customers according to purchase history

• ...

Clustering Setup



Input

- a set S of n points $\{x_1, x_2, ..., x_n\}$ in feature space
- a distance measure specifying distance $d(x_i,x_j)$ between pairs (x_i,x_i)

Output

- A partition $\{S_1, S_2, ..., S_k\}$ of S

Supervised?

Unsupervised Learning



Clustering is an example of unsupervised learning.

We are not given examples of classes Y.

• There are **no predictions** made.

• Instead we have to discover clusters/structure in data.

Clustering



- How do I group these documents by topic?
- How do I group my customers by purchase patterns?

- Sort items into groups by similarity:
 - Items in a cluster are more similar to each other than they are to items in other clusters.
 - Need to detail the properties that characterize "similarity"
 - Or of distance, the "inverse" of similarity

Our Example: K-means Clustering

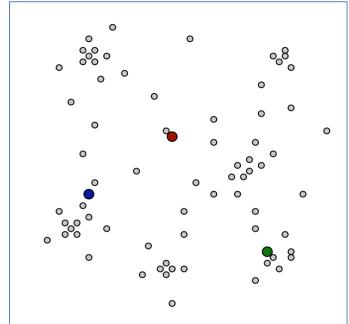


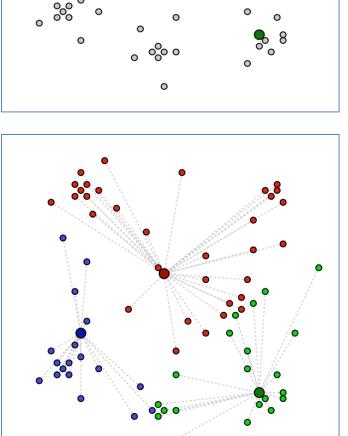
K-means Clustering

The Algorithm

- 1. Choose *K*; then select K random "centroids"
 - In our example, K=3

2. Assign each point to the cluster with the *closest* centroid



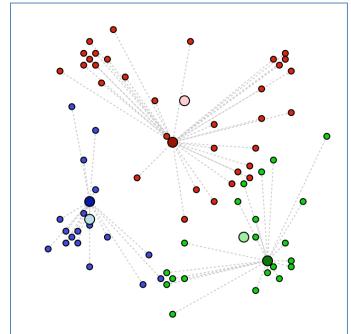


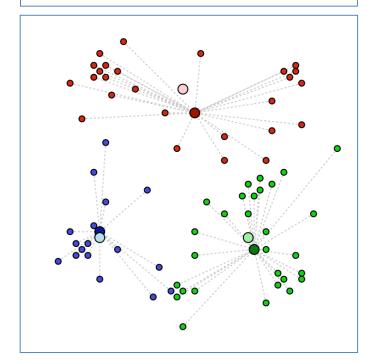


The Algorithm

3. Recalculate the resulting centroids

Repeat steps 2 & 3 until point assignments no longer change







K-means Clustering



Algorithm 4 K-MEANS(\mathbf{D} , K)

```
_{\tau} for k=\tau to K do
      \mu_k \leftarrow some random location
                                                       // randomly initialize mean for kth cluster
3: end for
4: repeat
      for n = \tau to N do
          z_n \leftarrow \operatorname{argmin}_k ||\mu_k - x_n||
                                                            // assign example n to closest center
      end for
      for k = 1 to K do
         \mathbf{X}_k \leftarrow \{ \mathbf{x}_n : \mathbf{z}_n = k \}
                                                                    // points assigned to cluster k
                                                                   // re-estimate mean of cluster k
          \mu_k \leftarrow \text{MEAN}(\mathbf{X}_k)
      end for
12: until \mus stop changing
13: return z
                                                                      // return cluster assignments
```

Visualization ...



https://www.naftaliharris.com/blog/visualizing-k-meansclustering/

K-means Properties



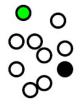
- Different initializations yield different results!
 - Doesn't necessarily converge to best partition

- K is a hyper-parameter
 - Needs to be set in advance (or learned on dev set)

Impact of Initialization



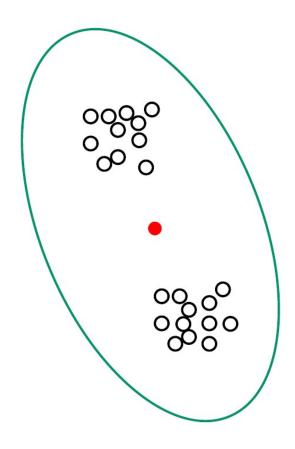


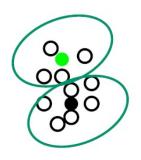




Impact of Initialization







Picking K



Heuristic: find the "elbow" of the within-sum-of-squares (wss) plot as a function of K.

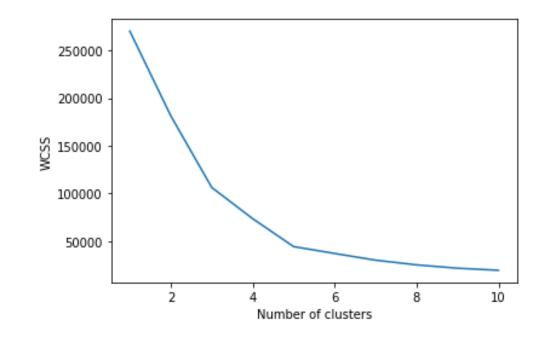
$$wss = \sum_{i=1}^{k} \sum_{j=1}^{n_i} |x_{ij} - c_i|^2$$

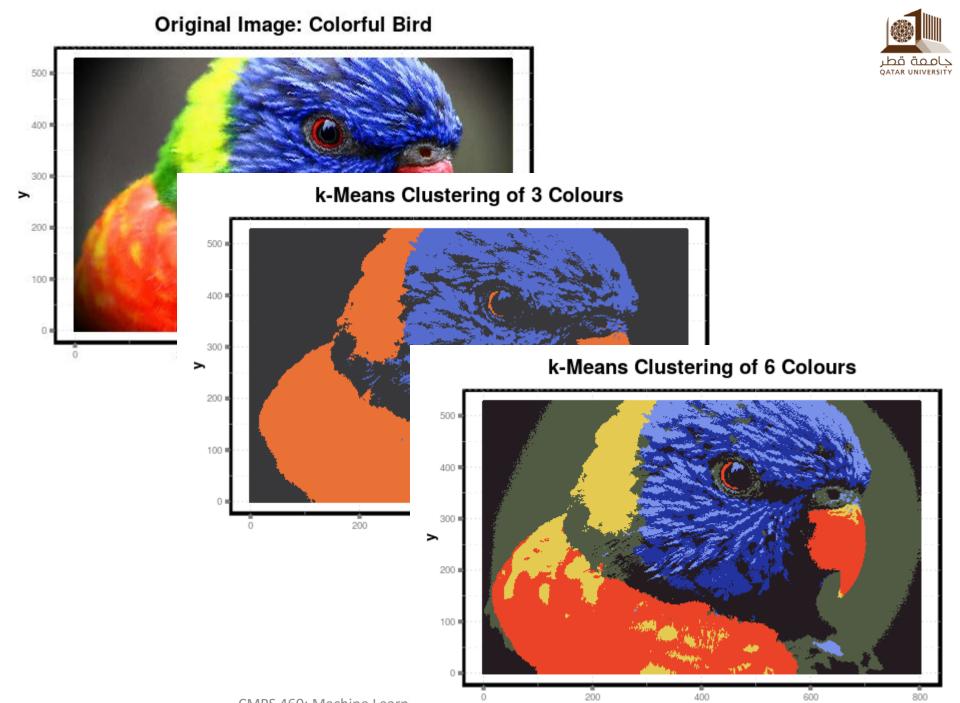
k: # of clusters

 n_i : # points in i^{th} cluster

 c_i : centroid of i^{th} cluster

 x_{ii} : j^{th} point of i^{th} cluster





х

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Use Cases



- Animals: height, weight and average lifespan
- Customers: household income, yearly purchase amount in dollars, family size
- Patients: record with measures of BMI, HBA1C, HDL
- Objects in image or video