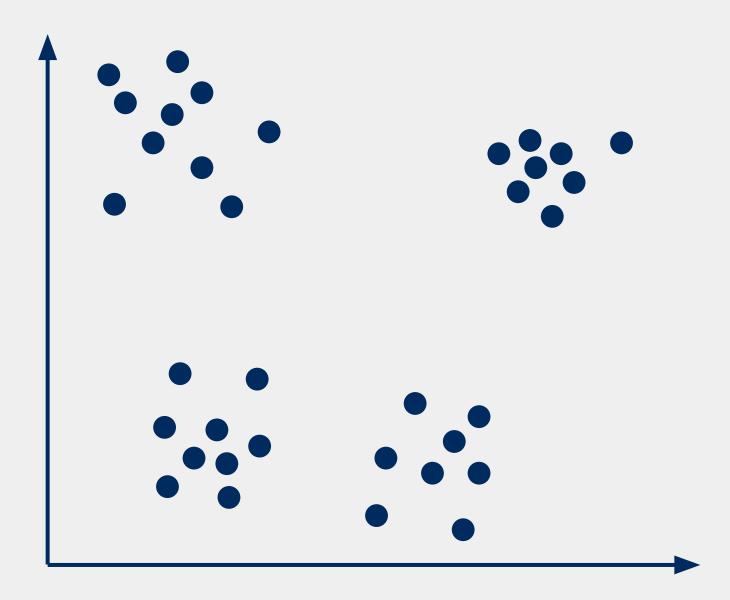
CS 1501

Clustering

The Clustering Problem

Given a collection of examples, group them into classes based on how similar they are to each other

Clustering example



Machine learning approaches

- Supervised learning
 - Use a dataset of labelled examples (training) to produce a model that can output an appropriate label for new inputs
- Unsupervised learning
 - Use an unlabelled dataset to produce a model to map inputs onto useful values or vectors
- Semi-supervised learning
 - Same goal as supervised learning, but input also contains a (usually much larger) set of unlabelled examples
- Reinforcement learning

Machine learning terms

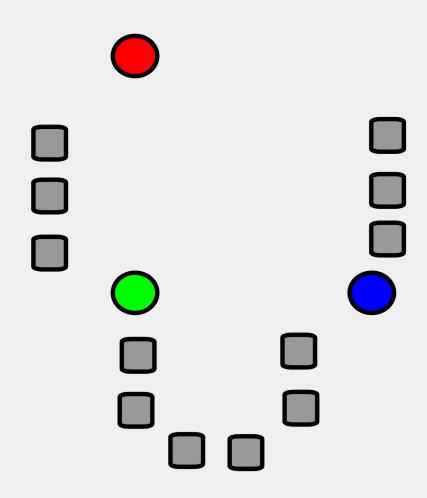
- Our data set is a collection of *examples*, each of which has attributes (or *features*) in common with other examples
 - Each example with d attributes is described in the input by a d-dimensional feature vector
- A hyperparameter is set before running the algorithm
 - In contrast to a parameter that helps to define the model learned by the learning algorithm
 - For our clustering examples, the number of clusters desired could be a hyperparameter

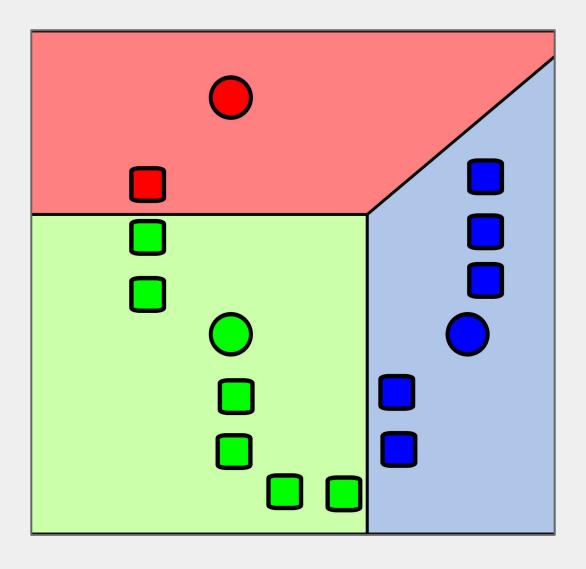
The k-means Clustering Problem

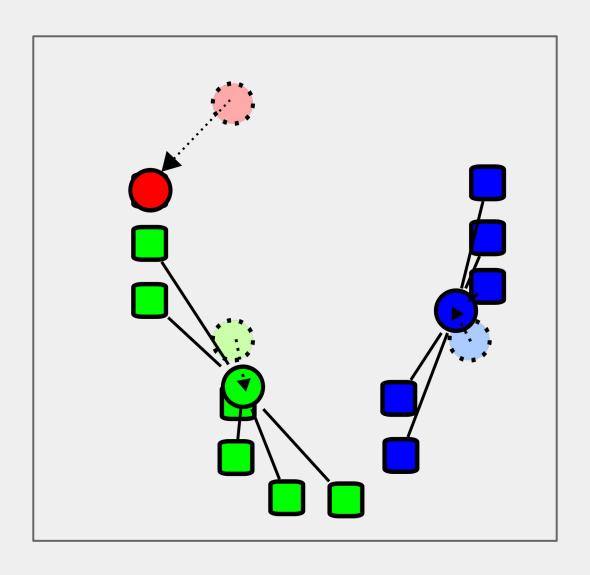
Given a collection of *d*-dimensional feature vectors, group them into clusters that minimize the sum of distances from each example to the centroid of its cluster

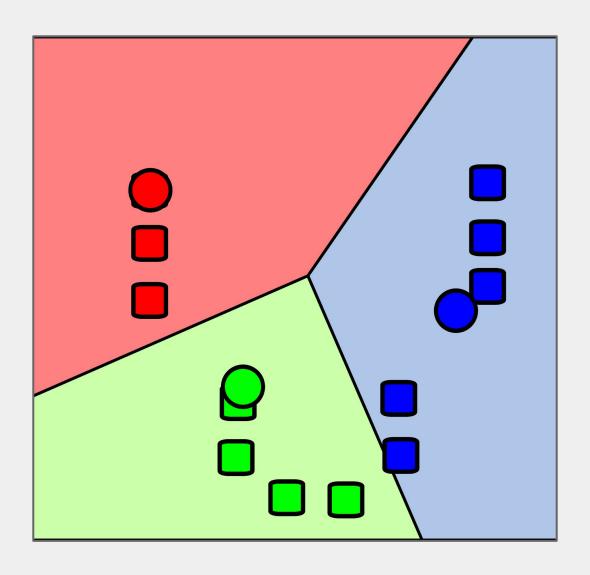
Naive k-means (Lloyd's)

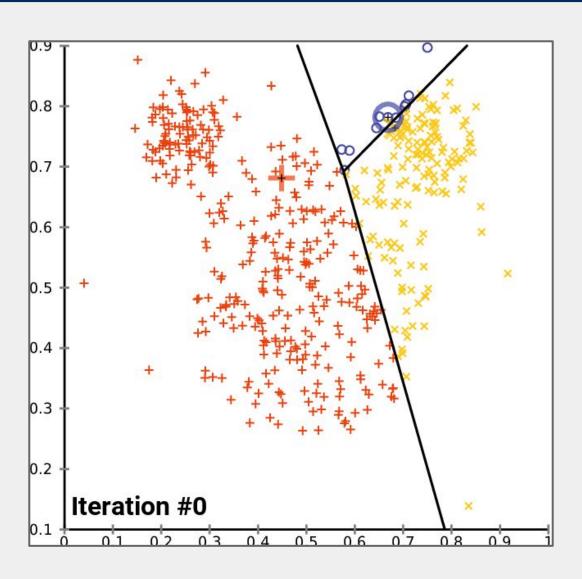
- Pick starting "means" (initial centroids)
 - E.g., randomly pick examples from the input set
 - E.g., randomly pick points in *d*-dimensional space
- Assign all examples to a cluster based on the centroid they are closest to by some distance metric (e.g., Euclidean)
- For each cluster, compute the new centroid as the mean of all feature vectors in that cluster
- Redo assignments/centroid calculation until convergence
 - I.e., no examples are assigned to new clusters after new centroids are computed

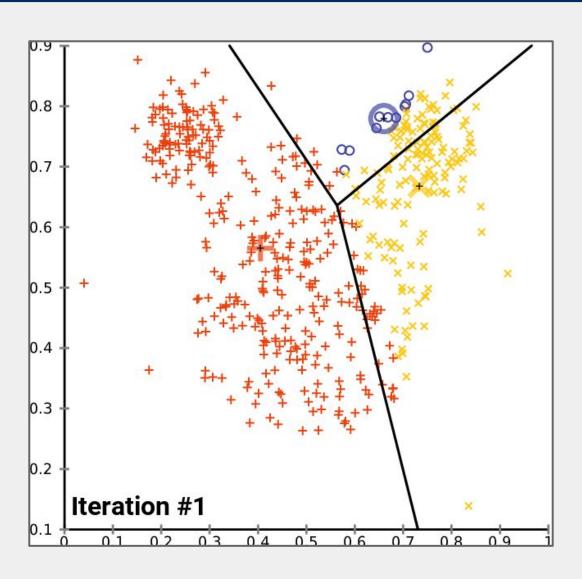


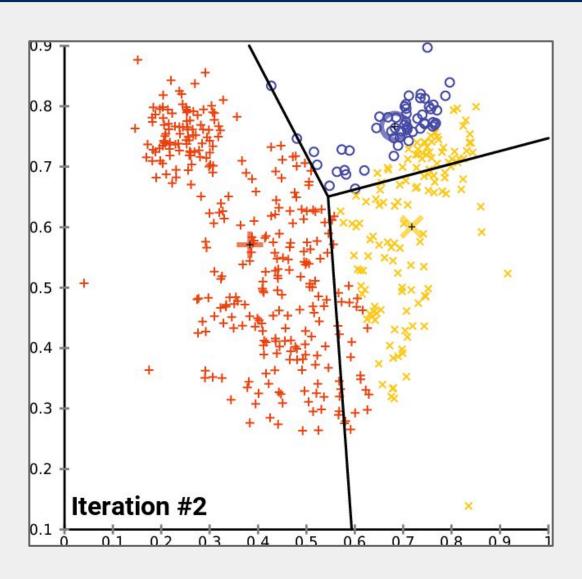


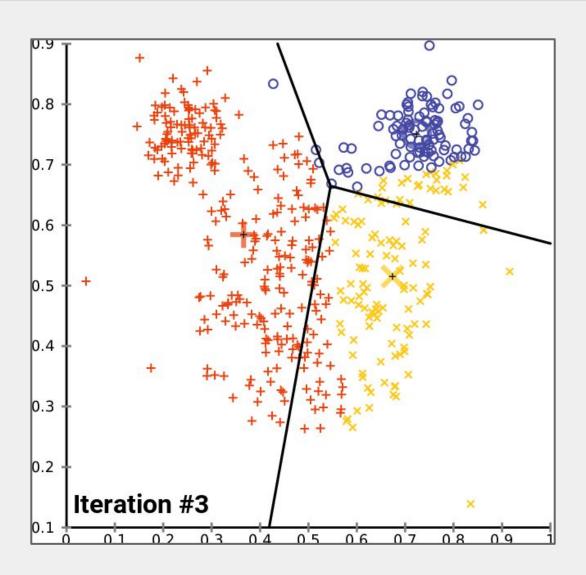


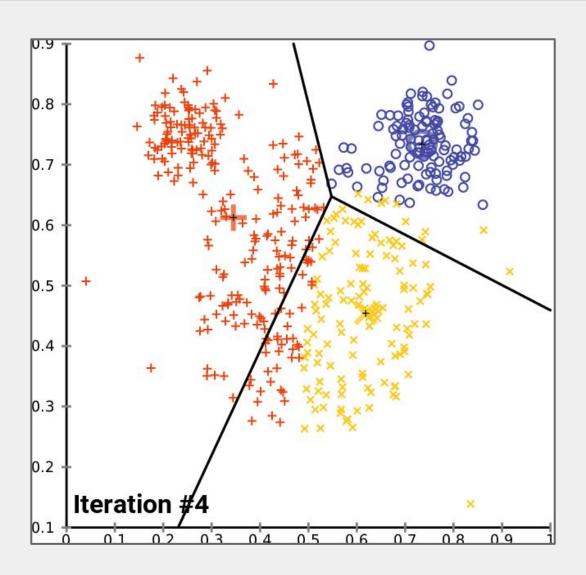


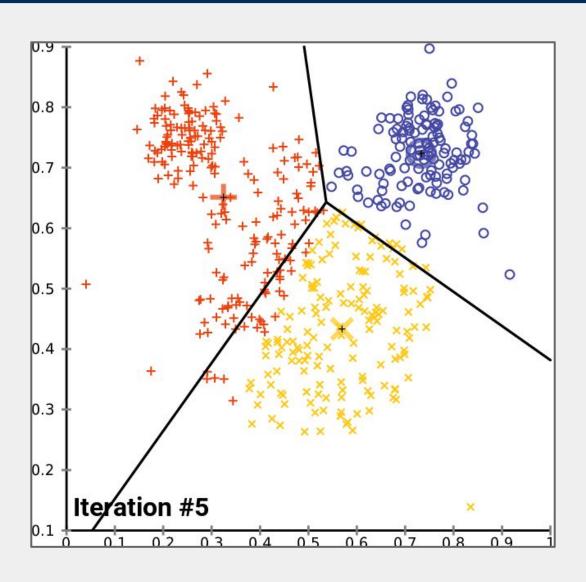


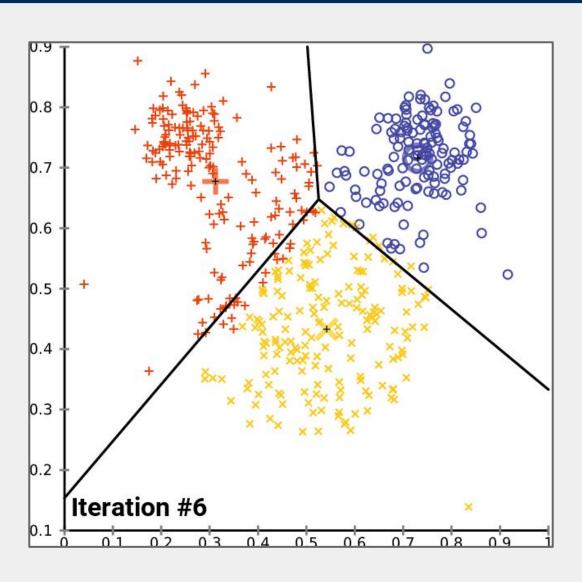


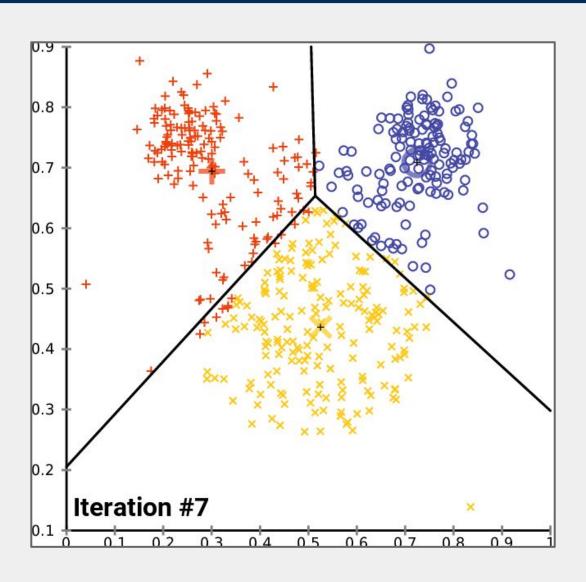


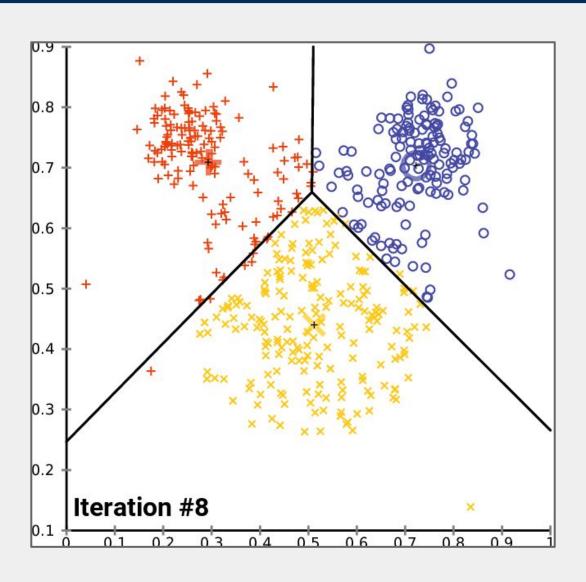


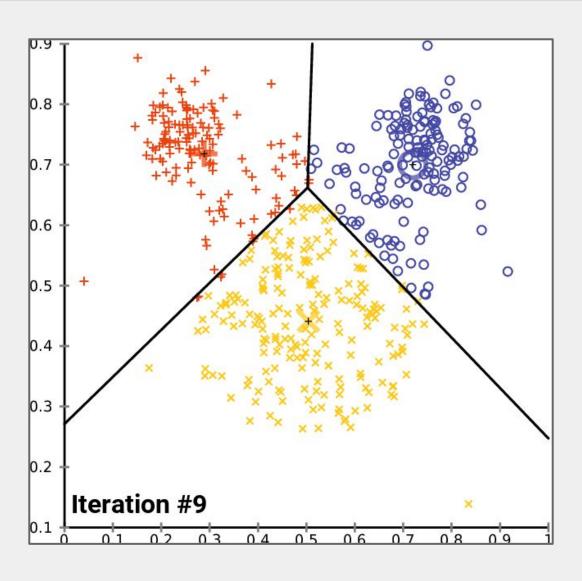


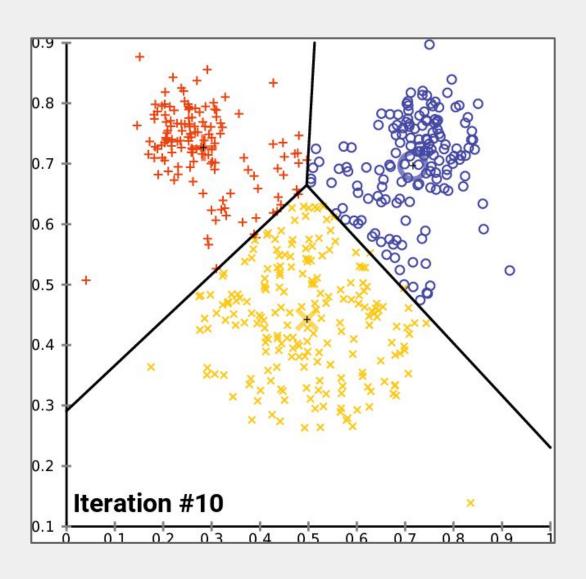


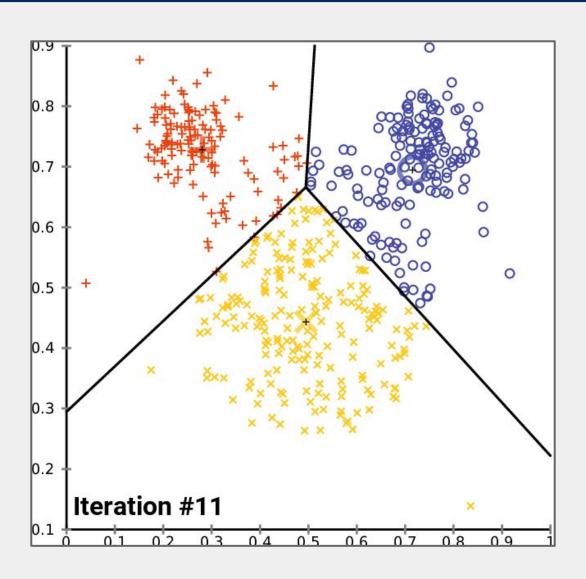


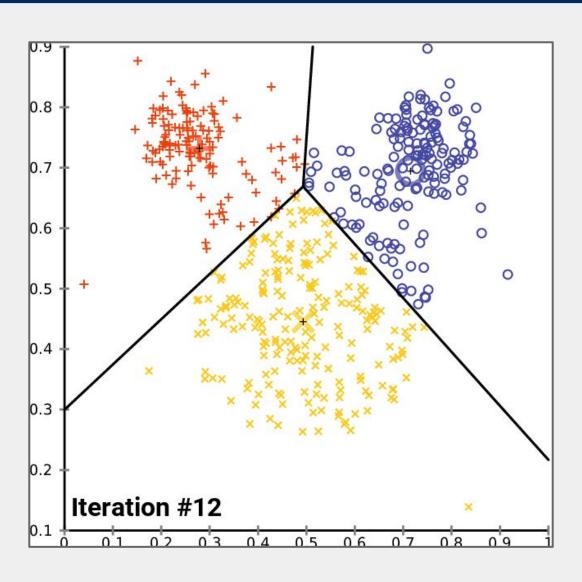


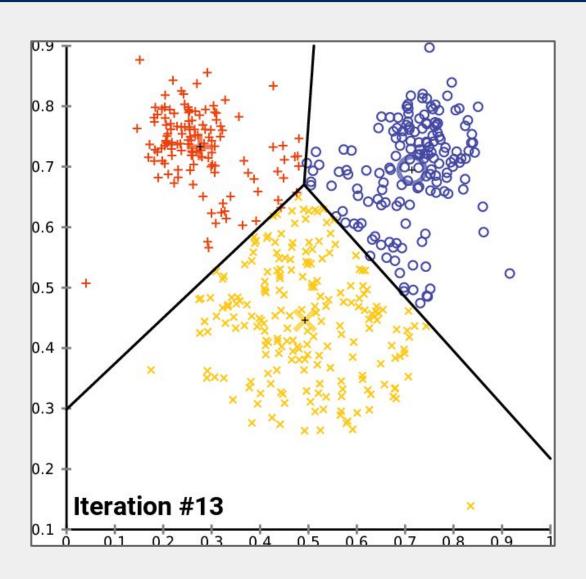


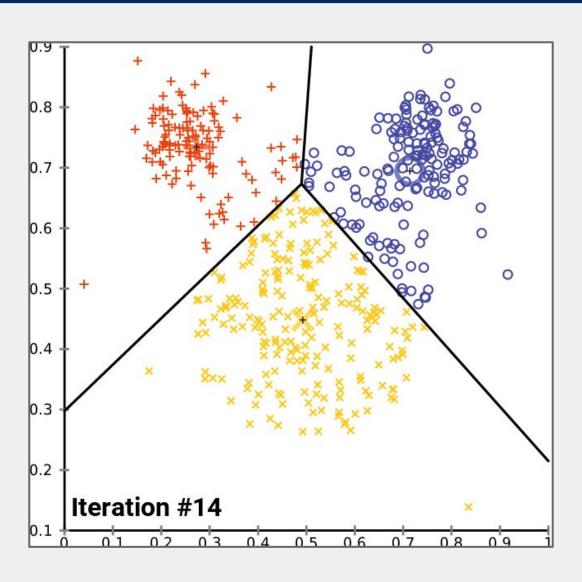












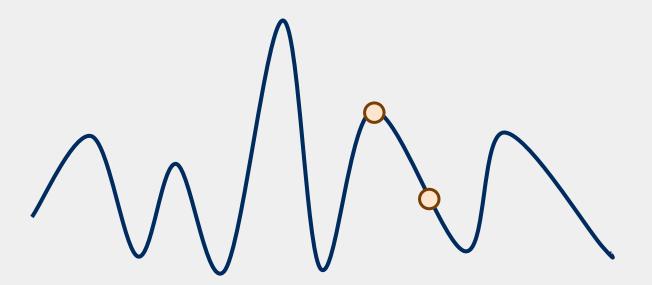
So...

- Runtime?
- To assign to clusters...
 - For each of the *n* examples
 - Compute the distance to each of the *k* centroids
 - Which will take O(d) time

- ...
- And we need to do that each iteration!
 - How many iterations will we need??

Wait...

- Does this even solve the problem?
 - Nope!
 - We could end up stuck in a local optimum
 - Optimal only within neighboring possible solutions
 - Not globally optimal across all possible solutions



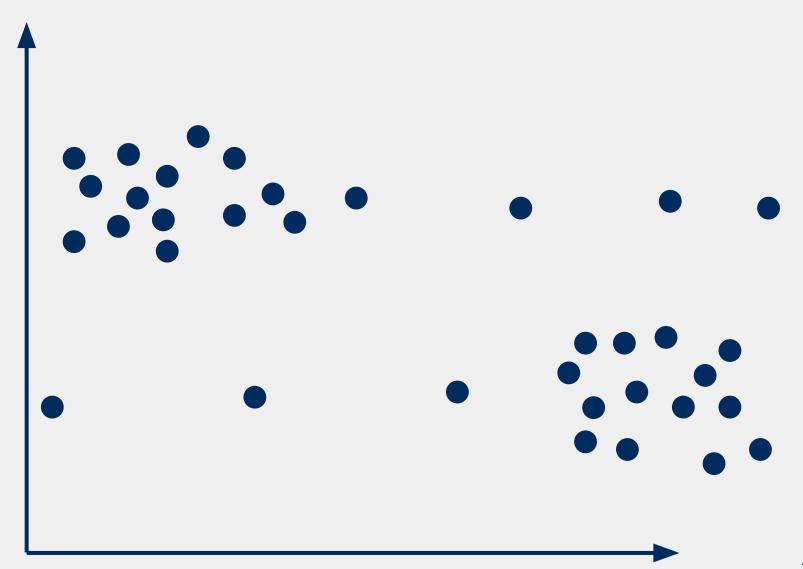
k-means clustering is NP-Hard

- What does NP-Hard mean?
 - Informally: At least as computationally expensive to solve as the most computationally expensive problems in NP
 - Even more informally: Probably takes way too long to run
- So what can we do, on average, get better clustering solutions more quickly?

k-means++

- Goal: spread out the initial clusters as much as possible
- For the *initial assignment*:
 - Pick the first initial centroid uniformly at random
 - The for the next *k*-1 centroids:
 - For each example not already picked:
 - Find the distance to its closest centroid
 - Select the next centroid at random but weighted by those computed distances
 - Further distance means more likely to be selected
- Then proceed with Lloyds as before

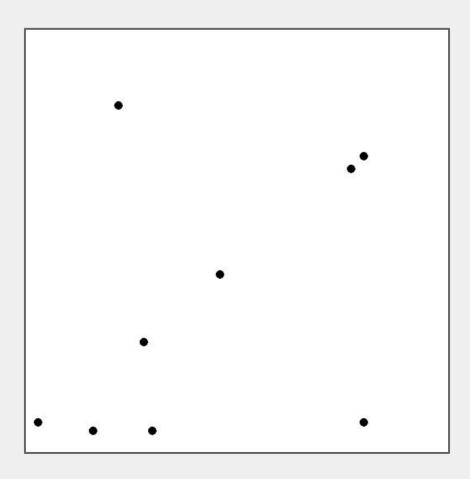
Is k-means always the clustering we want?



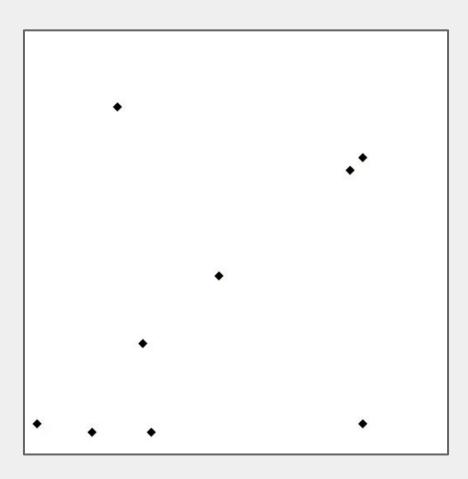
Voronoi diagrams

 Partition a plane to group all points closest to each of a given set of objects together

Euclidean distance Voronoi diagram



Manhattan distance Voronoi diagram



There's alot more to clustering

- Many more approaches to tackle k-means
- Can we do anything to try and figure out what k should be set to?
- And many other clustering algorithms out there!