k-Means Clustering

He He
Slides based on Lecture 13a from David Rosenberg's course materials
(https://github.com/davidrosenberg/mlcourse)

CDS, NYU

April 27, 2021

Logistics

Final exam

- Period: 5:00pm EST, May 13 – 5:00pm EST, May 14

- Format: on Gradescope, same as midterm

- Coverage: mainly about material after week 6 but can overlap with basic concepts before week 6

- Submission: can upload either image format (e.g. JPEG or PNG) or PDF
 - Make sure you leave enough time for submission!

Unsupervised learning

Goal Discover interesting *structure* in the data.

Formulation Density estimation: $p(x; \theta)$ (often with *latent* variables).

Examples
- Discover *clusters*: cluster data into groups.

- Discover *factors*: project high-dimensional data to a small number of "meaningful" dimensions, i.e. dimensionality reduction.

- Discover *graph structures*: learn joint distribution of correlated variables, i.e. graphical models.
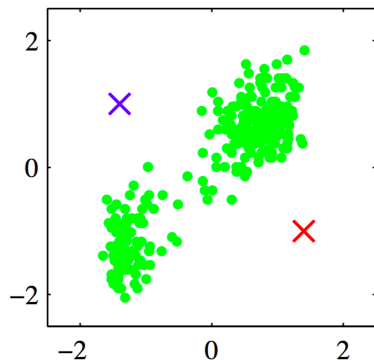
Example: Old Faithful Geyser

Old Faithful Geyser Eruptions
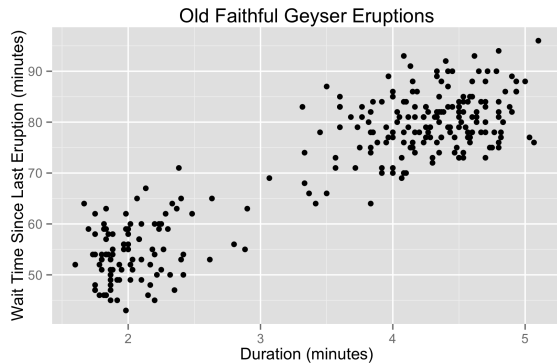
- Looks like two clusters.

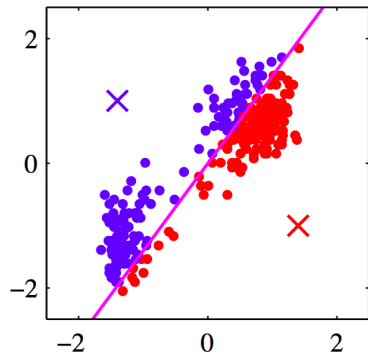- How to find these clusters algorithmically?

k-Means: By Example

- Standardize the data.

- Choose two cluster centers.

From Bishop's *Pattern recognition and machine learning*, Figure 9.1(a).
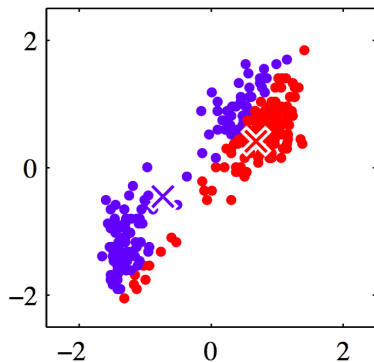
k-means: by example

- Assign each point to closest center.

From Bishop's *Pattern recognition and machine learning*, Figure 9.1(b).
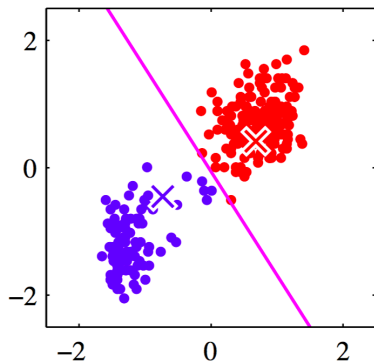
k-means: by example

- Compute new cluster centers.

From Bishop's *Pattern recognition and machine learning*, Figure 9.1(c).

k-means: by example

- Assign points to closest center.

k-means: by example

- Compute cluster centers.

From Bishop's *Pattern recognition and machine learning*, Figure 9.1(e).

k-means: by example

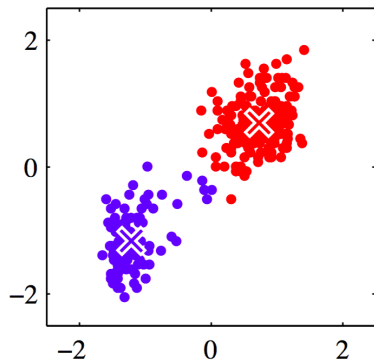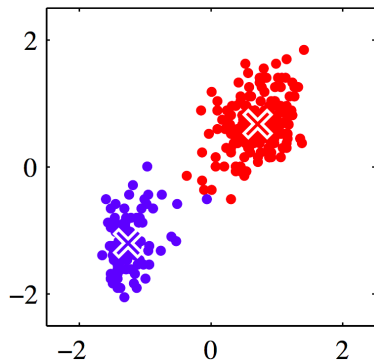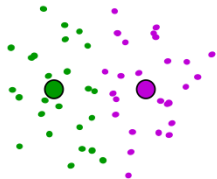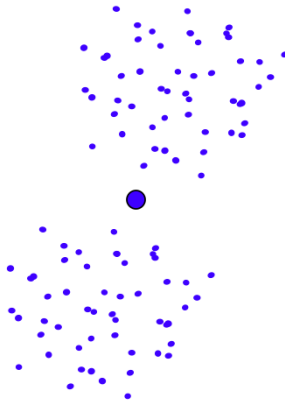- Iterate until convergence.

From Bishop's *Pattern recognition and machine learning*, Figure 9.1(i).

Suboptimal Local Minimum

- The clustering for $k = 3$ below is a local minimum, but suboptimal:

Would be better to have
one cluster here

… and two clusters here

From Sontag's DS-GA 1003, 2014, Lecture 8.

Formalize k-Means

- Dataset $\mathcal{D} = \{x_1, \ldots, x_n\} \subset \mathcal{X}$ where $\mathcal{X} = \mathbb{R}^d$.

- Goal: Partition data $\mathcal{D}$ into k disjoint sets $C_1, \ldots, C_k$.

- Let $c_i \in \{1, \ldots, k\}$ be the cluster assignment of x_i.

- The **centroid** of C_i is defined to be

$$\mu_i = \underset{\mu \in \mathcal{X}}{\arg\min} \sum_{x \in C_i} \|x - \mu\|^2. \qquad \text{mean of } C_i \qquad (1)$$

- The k-means objective is to minimize the distance between each example and its cluster centroid:

$$J(c, \mu) = \sum_{i=1}^{n} \|x_i - \mu_{c_i}\|^2. \qquad (2)$$

k-Means: Algorithm

1. Initialize: Randomly choose initial centroids $\mu_1, \ldots, \mu_k \in \mathsf{R}^d$.
2. Repeat until convergence (i.e. c_i doesn't change anymore):
   1. For all i, set

   $$c_i \leftarrow \arg\min_j \|x_i - \mu_j\|^2. \qquad \text{Minimize } J \text{ w.r.t. } c \text{ while fixing } \mu \qquad (3)$$

   2. For all j, set

   $$\mu_j \leftarrow \frac{1}{|C_j|} \sum_{x \in C_j} x. \qquad \text{Minimze } J \text{ w.r.t. } \mu \text{ while fixing } c. \qquad (4)$$

- Recall the objective: $J(c, \mu) = \sum_{i=1}^n \|x_i - \mu_{c_i}\|^2$.

Avoid bad local minima

k-means converges to a local minimum.

- J is non-convex, thus no guarantee to converging to the global minimum.

Avoid getting stuck with bad local minima:

- Re-run with random initial centroids.

- k-means++: choose initial centroids that spread over all data points.
  - Randomly choose the first centroid from the data points $\mathcal{D}$.
  - Sequentially choose subsequent centroids from points that are farther away from current centroids:
    - Compute distance between each x_i and the closest already chosen centroids.
    - Randomly choose next centroid with probability proportional to the computed distance squared.

Summary

We've seen

- Clustering—an unsupervised learning problem that aims to discover group assignments.

- k-means:
  - Algorithm: alternating between assigning points to clusters and computing cluster centroids.
  - Objective: minmizing some loss function by cooridinate descent.
  - Converge to a local minimum.

Next, probabilistic model of clustering.

- A generative model of x.

- Maximum likelihood estimation.