Lecture 14 - Clustering

DSC 40A, Winter 2024

Announcements

- HW4 posted last Friday, due this upcoming Friday
  - Top predictors on last HW4 problem earns extra credit on midterm 1

- Midterm 1 solution posted today, grade will be available by Wednesday
  - Note: your final exam grade is determined by **Max{Midterm 1, Final Part I} + Max{Midterm 2, Final Part II}**

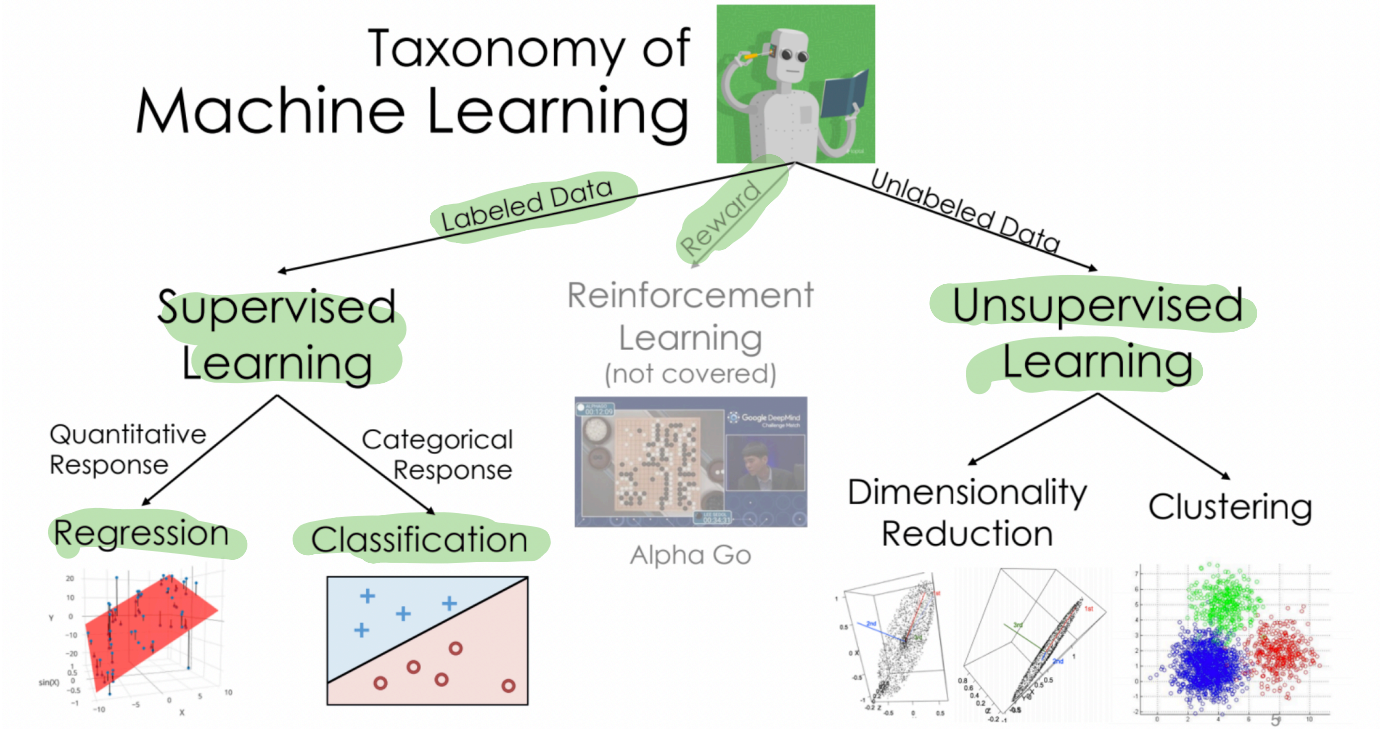
  - If you are not satisfied with your midterm grade, you can replace it by doing well in the Final

Agenda

- HW4 Competition: Neutrino and High Purity Germanium Detector
- The clustering problem.
- k-Means Clustering algorithm.
- Why does k-Means work?
- Practical considerations.

Neutrino and HPGe Detector

The clustering problem



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[1]taken from Joseph Gonzalez at UC Berkeley

Question: how might we “cluster” these points into groups?

$n = 11 \quad d = 2 \quad k = 3$

Problem statement: clustering

Goal: Given a list of n data points, stored as vectors in $\mathbb{R}^d$, $\vec{x}_1, \vec{x}_2, ..., \vec{x}_n$, and a positive integer k, **place the data points into k groups of nearby points**.

- These groups are called "clusters".
- Think about groups as **colors**.
  - i.e., the goal of clustering is to assign each point a color, such that points of the same color are close to one another.
- Note, unlike with regression, there is no "right answer" that we are trying to predict — there is no y!
  - Clustering is an **unsupervised** method.

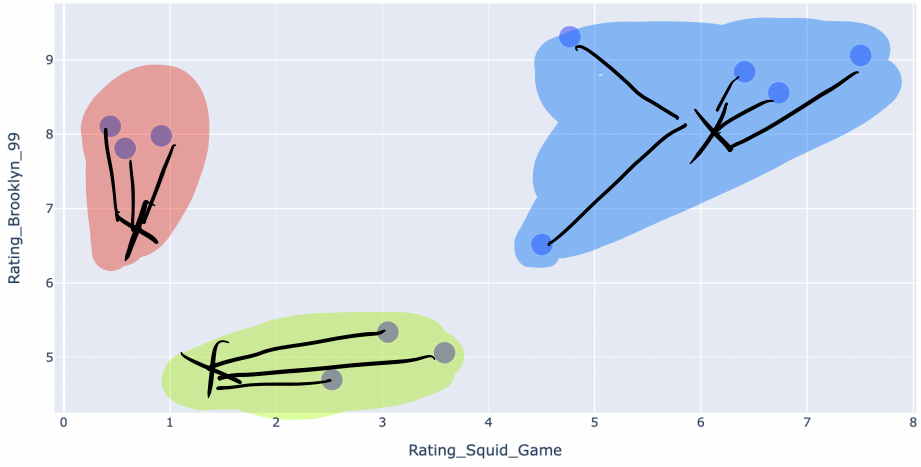
How do we define a group?

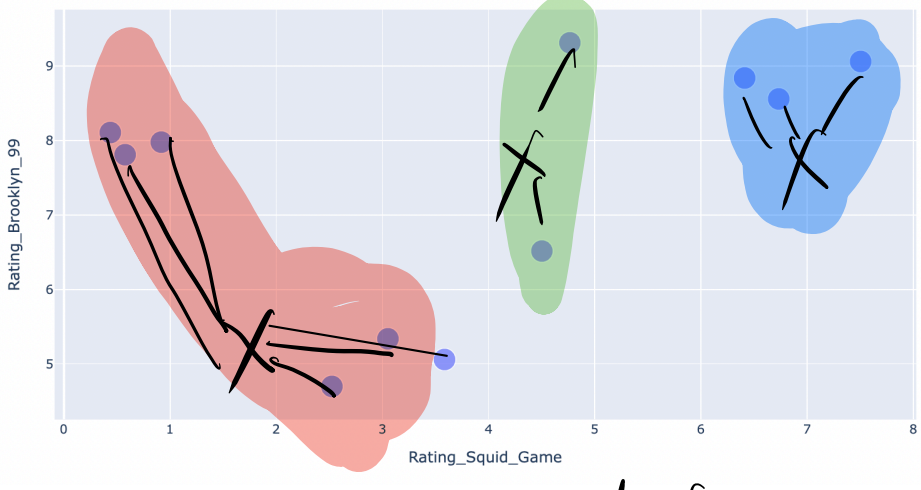
- One solution: pick k cluster centers, i.e. **centroids**:

$$\vec{\mu}_1, \vec{\mu}_2, ..., \vec{\mu}_k \text{ in } \mathbb{R}^d$$

- These k centroids define the k groups.
- Each data point "belongs" to the group corresponding to the nearest centroid.
- This reduces our problem from being "find the best group for each data point" to being "find the best locations for the centroids".

Shorter line: centroid is closer to each of its points





Cost = sum of (line length)^2

placement of centroid determines clustering

How do we pick the centroids?

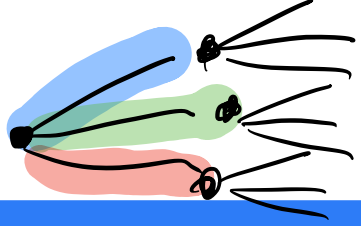
- Let's come up with an **cost function**, C, which describes how good a set of centroids is.
  - Cost functions are a generalization of empirical risk functions.

- One possible cost function:

$$C(\mu_1, \mu_2, ..., \mu_k) = \text{total squared distance of each data point } \vec{x}_i \text{ to its closest centroid } \mu_j$$

- This C has a special name, **inertia**.

- Lower values of C lead to "better" clusterings.
  - **Goal:** Find the centroids $\mu_1, \mu_2, ..., \mu_k$ that minimize C.



Discussion Question

Suppose we have n data points, $\vec{x}_1, \vec{x}_2, ..., \vec{x}_n$, each of which are in $\mathbb{R}^d$.
Suppose we want to cluster our dataset into k clusters.
How many ways can we assign points to clusters?

a) $d \cdot k$
b) d^k
c) n^k
d) k^n
e) $n \cdot k \cdot d$

k·k·k····k (n)

n data points
how many ways
to assign one of the k
colors to each point?

k colors option for 1st point * k color options for 2nd point

How do we minimize inertia?

- **Problem**: there are exponentially many possible clusterings. It would take too long to try them all.
- **Another Problem**: we can't use calculus or algebra to minimize C, since to calculate C we need to know which points are in which clusters.
- We need another solution.

k-Means Clustering

k-Means Clustering, i.e. Lloyd's Algorithm

Here's an algorithm that attempts to minimize inertia:

1. Pick a value of k and randomly initialize k centroids.
2. Keep the centroids fixed, and update the groups.
   - Assign each point to the nearest centroid.

   (color each point to its nearest centroid)
3. Keep the groups fixed, and update the centroids.
   - Move each centroid to the center of its group.

   (point w/ average coordinate)
4. Repeat steps 2 and 3 until the centroids stop changing.

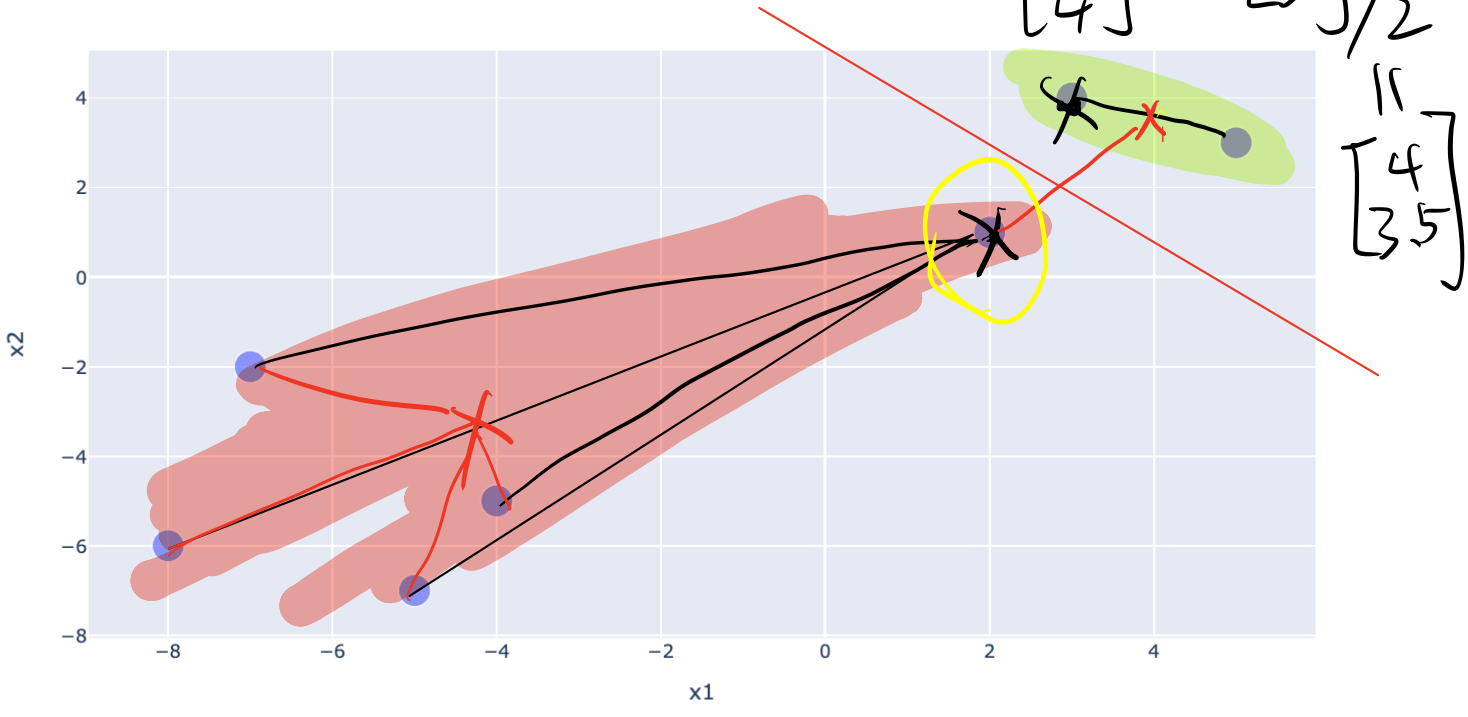
Example

See the following site for an interactive visualization of k-Means Clustering: https://tinyurl.com/40akmeans

An example by hand

Suppose we choose the initial centroids $\mu_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ and $\mu_2 = \begin{bmatrix} 3 \\ 4 \end{bmatrix}$.

Where will the centroids move to after one iteration of k-Means Clustering?



Demo

Let's see k-Means Clustering in action. Follow along here.

Why does k-Means work?

What is the goal of k-Means Clustering?

- Recall, our goal is to find the centroids $\mu_1, \mu_2, ..., \mu_k$ that minimize inertia:

$$C(\mu_1, \mu_2, ..., \mu_k) = \text{total squared distance of each data point } \vec{x}_i \text{ to its closest centroid } \mu_j$$

- Let's argue that each step of the k-Means Clustering algorithm reduces inertia.
  - After enough iterations, inertia will be small enough.

Why does k-Means work? (Step 1)

Step 1: Pick a value of k and randomly initialize k centroids.

- After initializing our k centroids, we have an initial value of inertia. We are going to argue that this only decreases.

Why does k-Means work? (Step 2)

Step 2: Keep the centroids fixed, and update the groups by assigning each point to the nearest centroid.

- Assuming the centroids are fixed, for each $\vec{x}_i$ we have a choice — which group should it be a part of?
- Whichever group we choose, inertia will be calculated using the squared distance between $\vec{x}_i$ and that group's centroid.
- Thus, to minimize inertia, we assign each $\vec{x}_i$ to the group corresponding to the closest centroid.

Note that this analysis holds every time we're at Step 2, not just the first time.

Why does k-Means work? (Step 3)

Step 3: Keep the groups fixed, and update the centroids by moving each centroid to the center of its group (by averaging coordinates).

- Before we justify why this is optimal, let's revisit inertia.

Aside: separating inertia

- Inertia:

$$C(\mu_1, \mu_2, ..., \mu_k) = \text{total squared distance of each data point } \vec{x}_i \text{ to its closest centroid } \mu_j$$

- Note that an equivalent way to write inertia is

$$C(\mu_1, \mu_2, ..., \mu_k) = C(\mu_1) + C(\mu_2) + ... + C(\mu_k) \text{ where}$$
$$C(\mu_j) = \text{total squared distance of each data point } \vec{x}_i \text{ in group } j \text{ to centroid } \mu_j$$

- What's the point?

Why does k-Means work? (Step 3)

$C(\mu_1, \mu_2, \ldots, \mu_k) = C(\mu_1) + C(\mu_2) + \ldots + C(\mu_k)$ where

$C(\mu_j)$ = total squared distance of each data point $\vec{x}_i$ in group j to centroid μ_j

Step 3: Keep the groups fixed, and update the centroids by moving each centroid to the center of its group (by averaging coordinates).

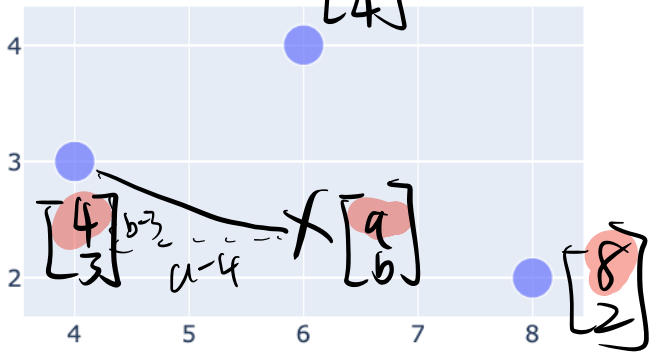
- Let's argue why this minimizes $C(\mu_j)$, for each group j.

Why does k-Means work? (Step 3)

$C(\mu_j)$ = total squared distance of each data point $\vec{x}_i$ in group j to centroid μ_j

Suppose group j contains the points (4, 3), (6, 4), and (8, 2).

Where should we put $\mu_j = \begin{bmatrix} a \\ b \end{bmatrix}$ to minimize $C(\mu_j)$?



$C(a,b) = (a-4)^2 + (b-3)^2 + (a-6)^2 + (b-4)^2 + (a-8)^2 + (b-2)^2$

$\text{distance} = \sqrt{(a-4)^2 + (b-3)^2}$

$\text{distance}^2 = (a-4)^2 + (b-3)^2$

Why does k-Means work? (Step 3)

$$C(a,b) = (a-4)^2 + (b-3)^2 + (a-6)^2 + (b-4)^2 + (a-8)^2 + (b-2)^2$$

$$\frac{\partial C}{\partial a} = 2(a-4) + 2\cdot(a-6) + 2(a-8) = 0$$

$$a - 4 + a - 6 + a - 8 = 0$$

$$3a = 4 + 6 + 8$$

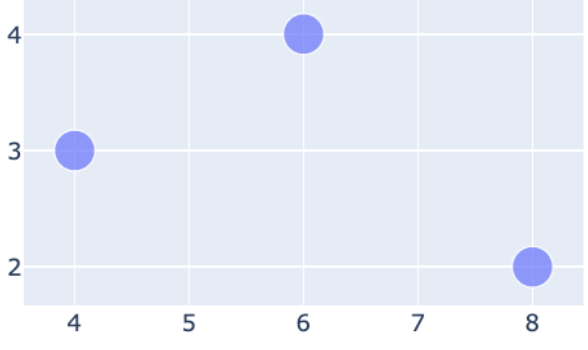
$$a = \frac{4+6+8}{3} = \text{mean}_x$$

Why does k-Means work? (Step 3)

$C(\mu_j)$ = total squared distance of each data point $\vec{x}_i$ in group j to centroid μ_j

Suppose group j contains the points $(4, 3)$, $(6, 4)$, and $(8, 2)$.

Where should we put $\mu_j = \begin{bmatrix} a \\ b \end{bmatrix}$ to minimize $C(\mu_j)$?



Cost and empirical risk

- On the previous slide, we saw a function of the form

$$C(\mu_j) = C(a, b) = (4 - a)^2 + (3 - b)^2 + (6 - a)^2 + (4 - b)^2 + (8 - a)^2 + (2 - b)^2$$

- $C(a, b)$ can be thought of as the sum of two separate functions, $f(a)$ and $g(b)$.
  - $f(a) = (4 - a)^2 + (6 - a)^2 + (8 - a)^2$ computes the total squared distance of each x_1 coordinate to a.
  - From earlier in the course, we know that $a^* = \frac{4+6+8}{3} = 6$ minimizes $f(a)$.

Practical considerations

Initialization

- Depending on our initial centroids, k-Means may "converge" to a clustering that doesn't actually have the lowest possible inertia.
  - In other words, like gradient descent, k-Means can get caught in a **local minimum**.

- Some solutions:
  - Run k-Means several times, each with different randomly chosen initial centroids. Keep track of the inertia of the final result in each attempt. Choose the attempt with the lowest inertia.

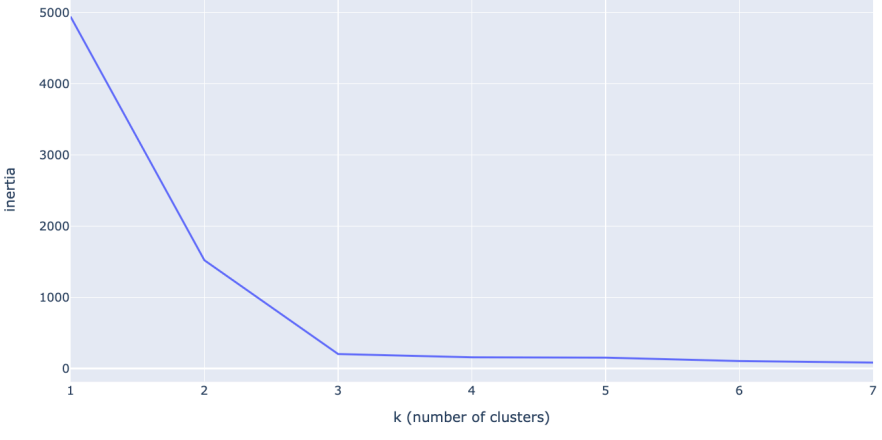
  - **k-Means++**: choose one initial centroid at random, and place other centroids far from all other centroids.

Choosing k

- Note that as k increases, inertia decreases.
  - Intuitively, as we add more centroids, the distance between each point and its closest centroid will drop.
- But the goal of clustering is to put data points into groups, and having a large number of groups may not be meaningful.
- This suggests a tradeoff between k and inertia.

The “elbow” method

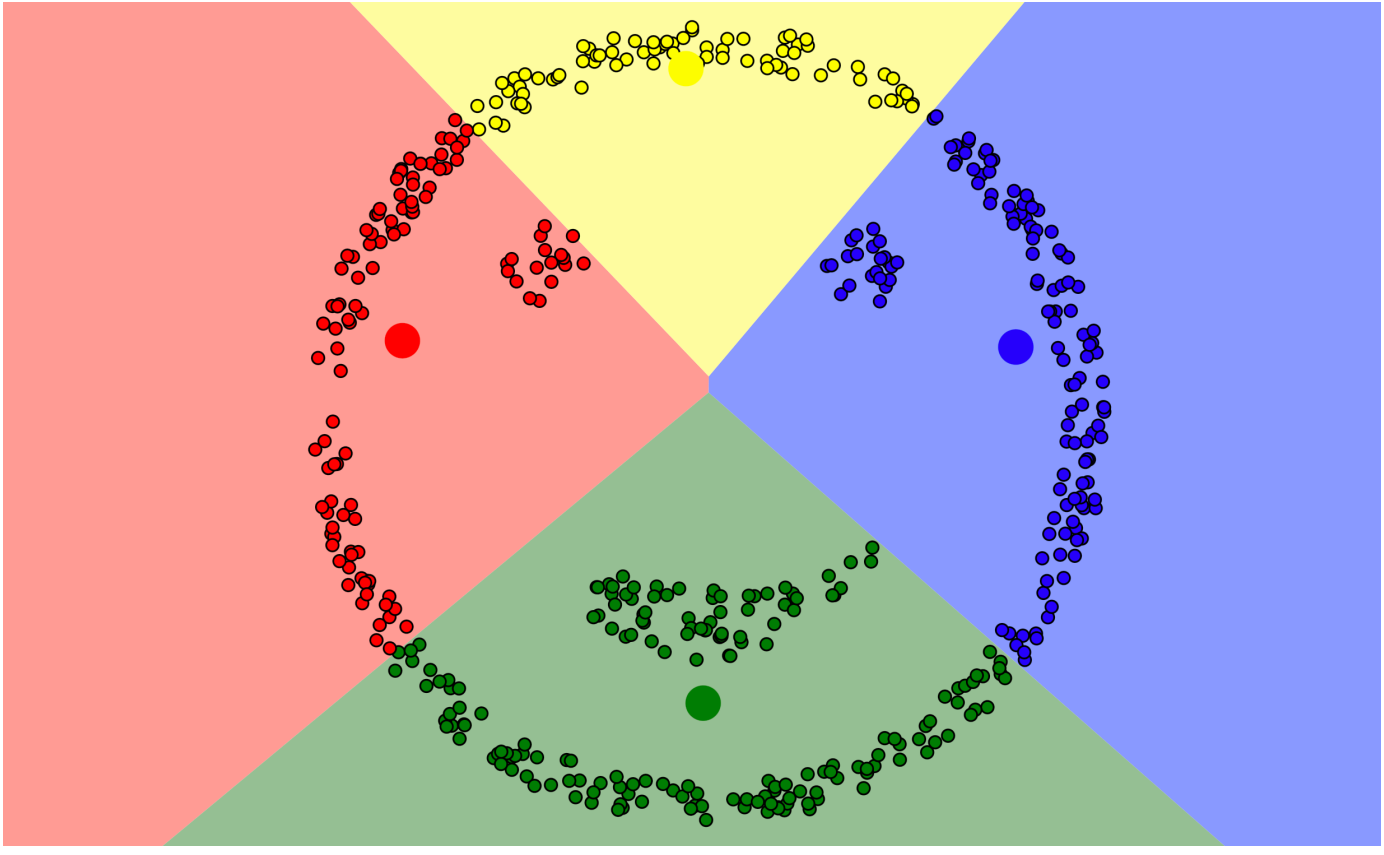
- Strategy: run k-Means Clustering for many choices of k (e.g. $k = 1, 2, 3, ..., 8$).
- Compute the value of inertia for each resulting set of centroids.
- Plot a graph of inertia vs k.
- Choose the value of k that appears at an “elbow”.



See the notebook for a demo.

Low inertia isn't everything!

- Even if k-Means works as intended and finds the choice of centroids that minimize inertia, the resulting clustering may not look "right" to us humans.
  - Recall, inertia measures the total squared distance to centroids.
  - This metric doesn't always match our intuition.
- Let's look at some examples at https://tinyurl.com/40akmeans.
  - Go to "I'll Choose" and "Smiley Face". Good luck!



Other clustering techniques

- k-Means Clustering is just one way to cluster data.
- There are many others, each of which work differently and produce different kinds of results.
- Another common technique: **agglomerative clustering**.
  - High level: start out with each point being in its own cluster. Repeatedly combine clusters until only k are left.
- Check out this chart.

Summary

- k-Means Clustering attempts to minimize inertia.
  - We showed that it minimizes inertia at each step, but it's possible that it converges to a local minimum.
  - Different initial centroids can lead to different clusterings.
- To choose k, the number of clusters, we can use the elbow method.
- Next time: switching gears to probability and combinatorics.