

Clustering

PHYS591000 2022.03.08

Outline

- Unsupervised learning and K-means clustering
- Dimensionality reduction: Principal component analysis (PCA)
- Remarks on other clustering algorithms

Warming up

- Access control of the building has been granted.
- As usual, take 3 mins to introduce yourself to your teammate for this week!
 - “Were you OK during the blackout last Thursday?”
 - “Let’s work together to make this week nice and easy!”

Unsupervised learning

- The training data are not **labeled** (no information of the **ground truth** given to the model).
- Physics example: Divide the stars/astronomical objects into different groups according to their similarities given the observation data (Lab for today) – **Clustering**

K-means Clustering

- K-means is one of the ‘classic’ methods for clustering:

Step 0. Choose K = number of clusters you wish to assign

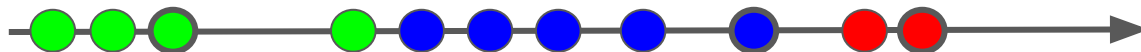
Step 1. *Randomly* select K data points as centers of initial clusters (“centroids”)



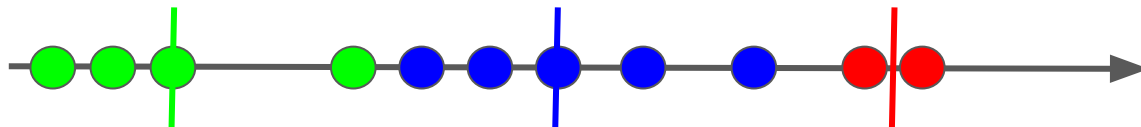
K-means Clustering

- K-means is one of the 'classic' methods for clustering:

Step 2. Assign each point to its closest centroid



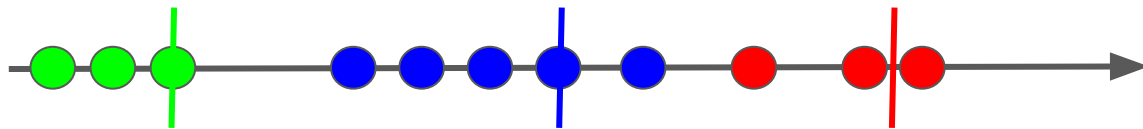
Step 3. Re-compute the new means (centers) of the clusters



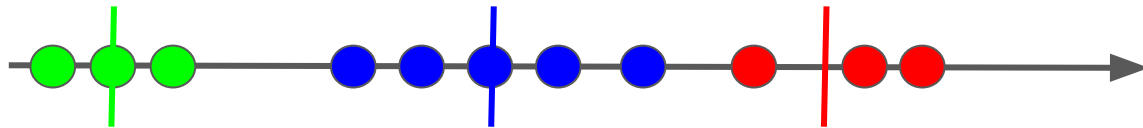
K-means Clustering

- K-means is one of the 'classic' methods for clustering:

Step 4. Assign each point using the new centers

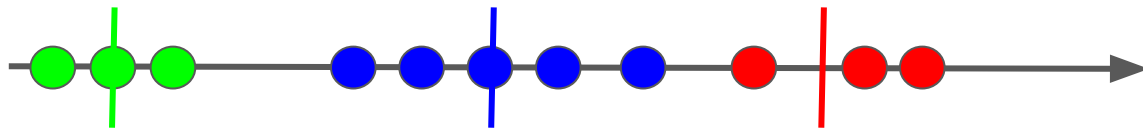


Step 5. Re-compute the new means (centers) of the clusters

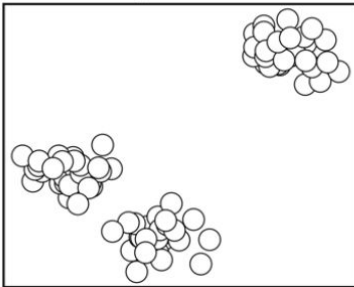


K-means Clustering

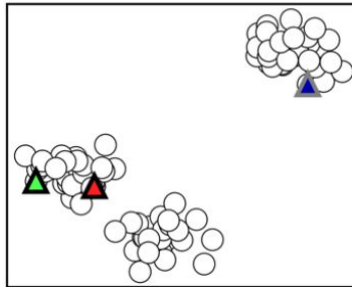
- Repeat 'finding new means' → 'reassign points according to new means' a few times until the centers converge (the positions no longer change).



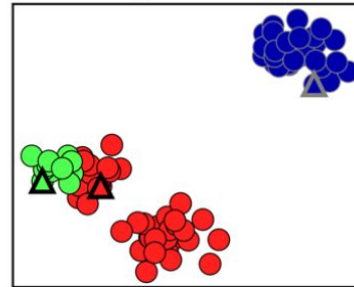
Input data



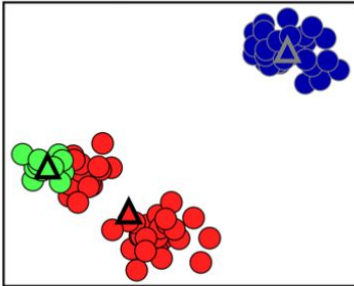
Initialization



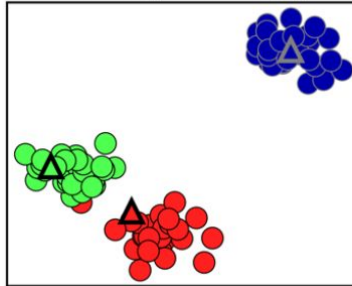
Assign Points (1)



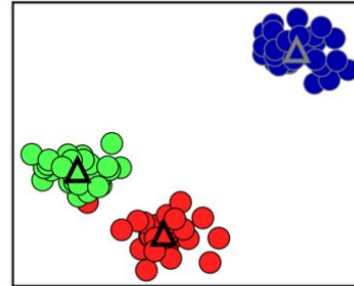
Recompute Centers (1)



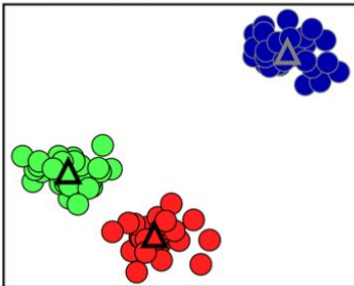
Reassign Points (2)



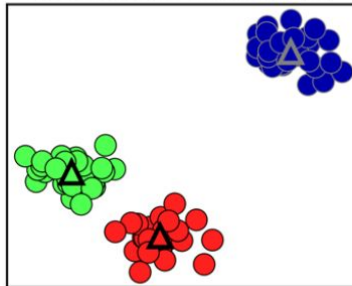
Recompute Centers (2)



Reassign Points (3)



Recompute Centers (3)

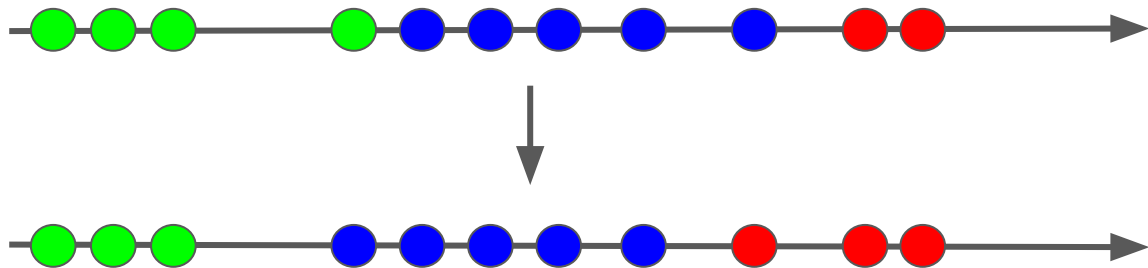


K-means Clustering

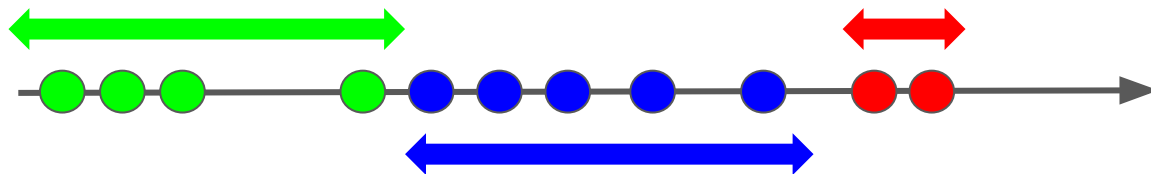
- Q: How to find the 'right' K (number of clusters)?
 - Domain knowledge
 - Evaluate the performance of different choices of K
- One metric is the sum of (squared) distances of each point to its closest centroid.

K-means Clustering

- Sum of distances (intuitively, 'sizes of clusters') can be a way to evaluate the performance of clustering. Compare the initial and final clustering of the previous case:

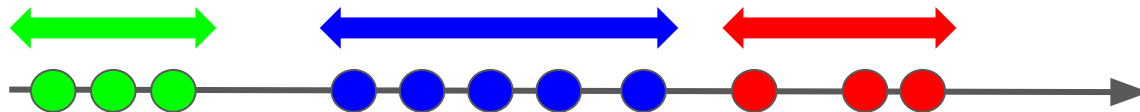


K-means Clustering



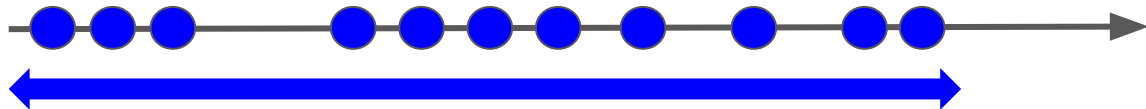
Sum of 'sizes' of clusters =

Sum of 'sizes' of clusters = Considered as 'better' for the same K

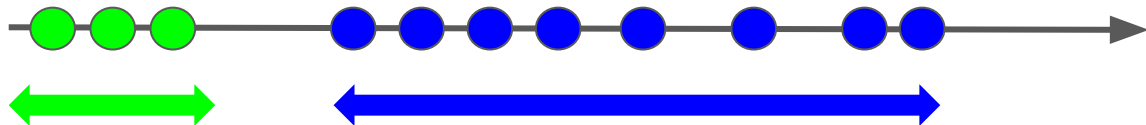


K-means Clustering

- Compare the sum for different K: $K=1$ is the largest

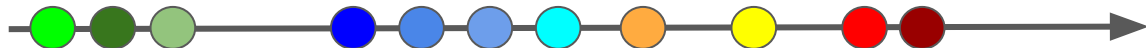


$K=2$ will make it smaller:



K-means Clustering

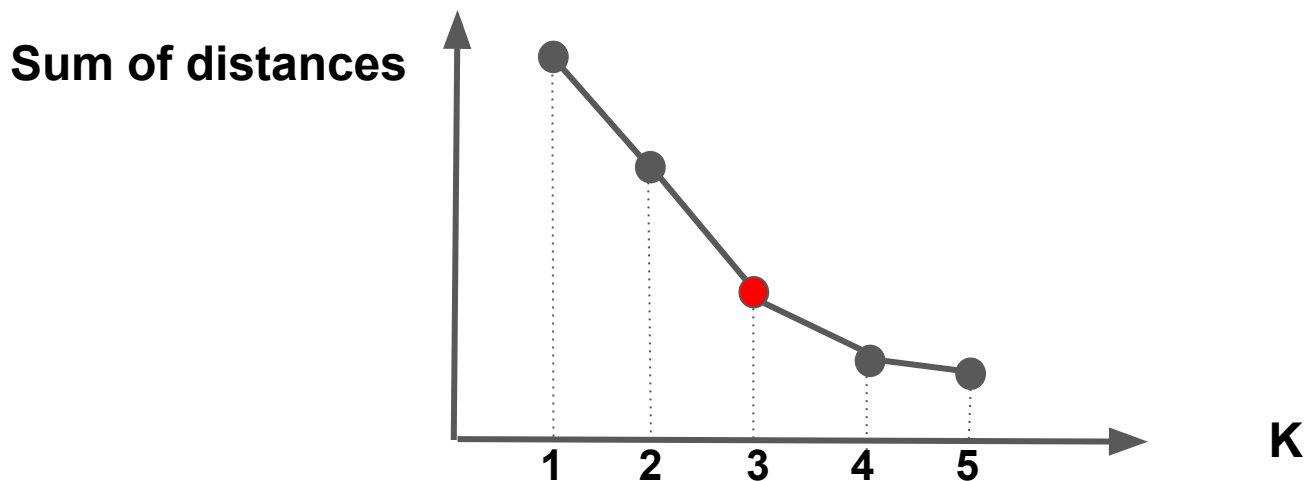
- And the sum will be 0 when $K = \text{number of points}$



Apparently that won't be useful for any purpose...

K-means Clustering: Elbow Plot

- If we plot the sum v.s. K there is usually an 'elbow' point beyond which the reduction is less significant.

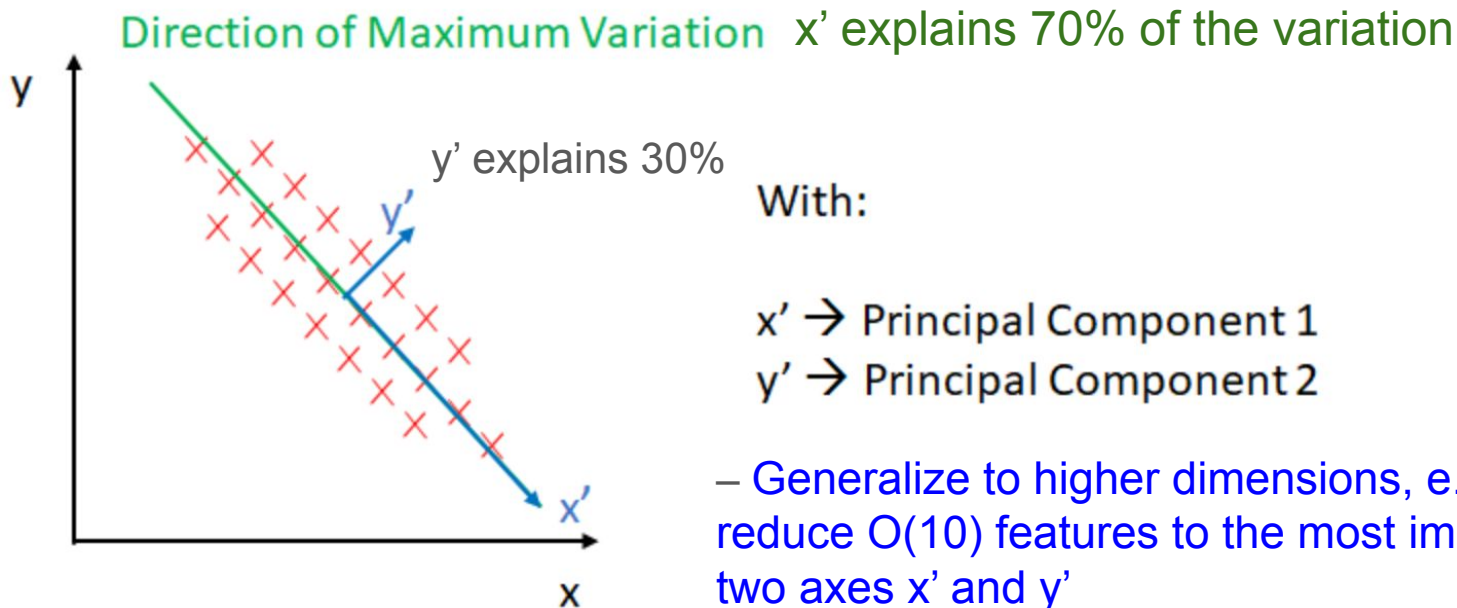


Data Representation

- We often collect a lot of information in our data, e.g. for each star we record 10 quantities we can observe.
- It will be difficult to visualize and/or do clustering in this 10-dimensional feature space!
- We can simplify the data by using a lower dimensional representation → **Dimensionality reduction**

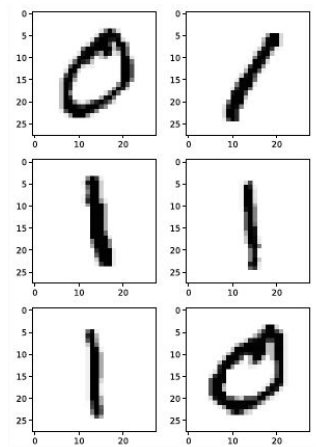
Dimensionality Reduction

- One way is to do a Principal Component Analysis (PCA)



In-class exercise for this week

- Let's turn to the in-class exercise this week: We'll use 0's and 1's from the MNIST dataset again!
 - `x_train`: 28*28 images; each pixel is associated with a number from 0-255 (~ the amount of 'ink')
- We'll use PCA to plot the data, and do K-means clustering to see if it can separate the data into the two 'correct' clusters.

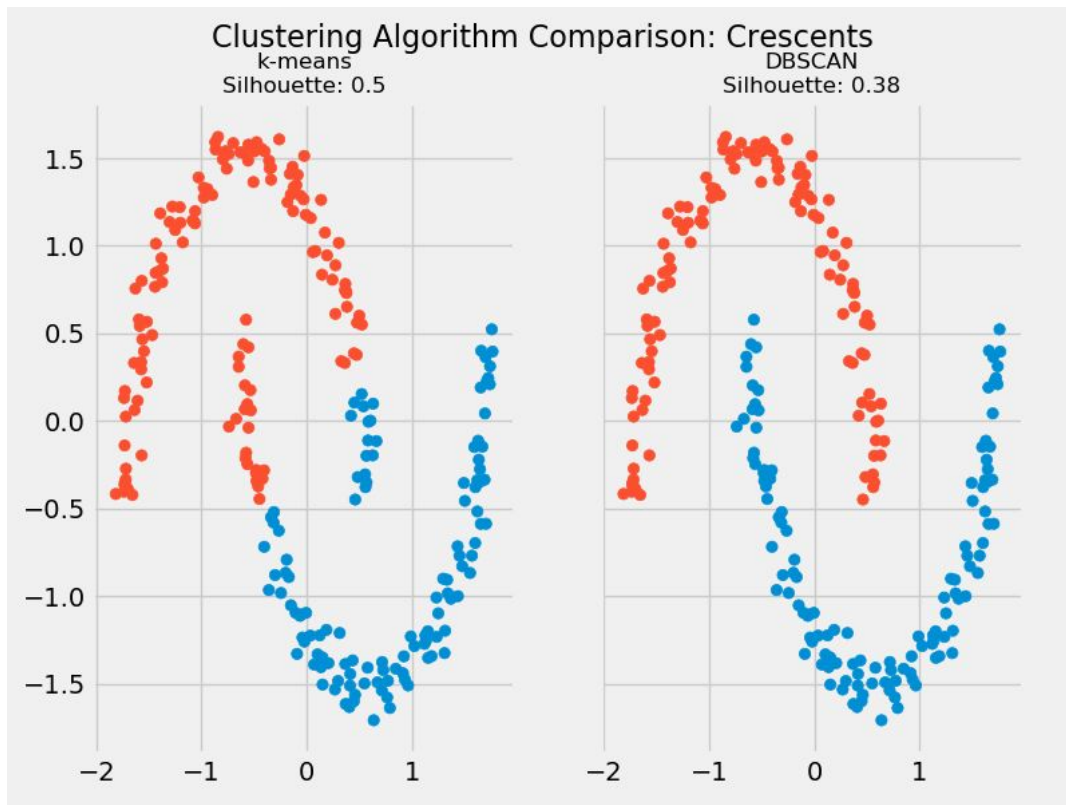


Remarks on other clustering algorithms

- K-Means do not work well for non-spherical clusters.
- Instead one can use density-based algorithms e.g. DBSCAN

Remarks on other clustering algorithms

K-Means



DBSCAN

Lab for this week

- For the Lab this week, we'll use astrophysics data from "Spitzer From Molecular Cores to Planet-Forming Disks (C2D)" project.
- It contains spectrum energy data of three kinds of astronomical objects. We'll do
 - K-means clustering (unsupervised learning)
 - KNN classification (supervised learning)