

# k-means clustering

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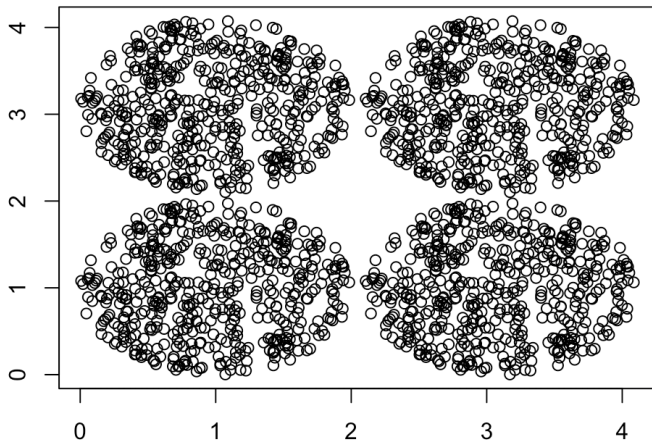
## motivation

data

```
0.7119179309333147 0.3223075093212125  
1.447028556223169 0.7809232076949447  
0.6243455331642681 1.677392470810183  
1.071158955927787 0.002688096076401636  
0.454724446488565 1.678180845796176  
1.520084768311829 0.5678501726972117  
0.3214112422507026 0.4457418099287268  
1.163581252141476 1.065477205954424  
0.7181000070975349 0.4043718368877932  
0.4243285665811839 1.684822147051808  
1.140083875725471 0.6767783209395194  
0.4465752419730048 1.149589001764944  
0.6968156094510446 1.32863597468871  
0.8737748082875728 0.8765138081444933  
1.856525620360119 1.211611496772893  
0.07921790967877074 1.318159593507866  
0.7212225181589228 0.5025936947245645  
1.769682310634134 1.540535837309194  
0.5165107360938345 1.42853857671274  
1.573784652871273 0.9138256257508311  
...
```

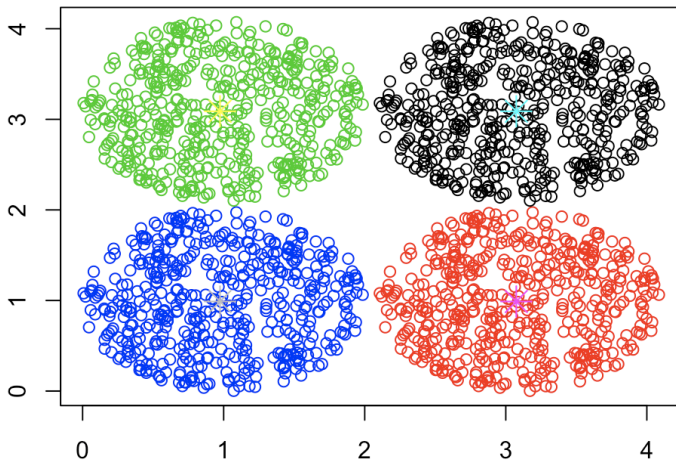
# motivation

plot



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plot



# What is clustering

- ▶ **unsupervised learning**

classification: no predefined classes and no training examples

**clustering**: Grouping a set of data objects into clusters such that the data objects are similar to one another within the same cluster, dissimilar to the objects in other clusters

## why clustering

- ▶ **goals** Find representatives for homogeneous groups  
Find “natural” clusters and describe their properties  
Find suitable and useful grouping “useful” Data Classes and  
find unusual data object :Outlier Detection

## what is k-means do

- ▶ partition based algorithm
- ▶ history: K-means(MacQueen,1967)
- ▶ **cluster**:The organization of unlabeled data into similarity groups called clusters.
- ▶ **centroid**:Each cluster has a cluster center

# kmeans algorithm

- ▶ key idea: minimize the squared error
- ▶ input: The number of  $k$  and a database containing  $n$  objects.
- ▶ output: A set of  $k$ -clusters that minimize the squared-error criterion.
- ▶ idea initialize  $k$  centroids  
iterate two steps to convergence
  - a) Assign step
  - b) recompute centroid steps



# algorithm

Select  $K$  points as the initial centroids

**Repeat:**

**Assignment steps:** Form  $K$  clusters by assigning all points to the closest centroids.

**Recompute centroid steps:** move each centroid to the center of the data-points assigned it.

**Until:** the centroid doesn't change

## when k-means convergence

- 1.no re-assignments of data points to different clusters
- 2.no change of centroids
- 3.minimum decrease in SSE

## insight algorithm

data points set  $D: \{x_1, x_2, \dots, x_n\}$   $x_i \in R^d$

k clusters, k centers,  $\mu_1, \dots, \mu_k \in R^d$

$$object = \sum_{j=1}^k \sum_{x_i \rightarrow \mu_j} \|x_i - \mu_j\|^2$$

how to express *the*  $\sum_{x_i \rightarrow \mu_j}$  *mathmatically*?

hint: STAT450 therom 10.2.3

## insight algorithm

adding indicator function(variable)

$$a_{ij} = \begin{cases} 1 & \text{if } x_i \rightarrow j \\ 0 & \text{else} \end{cases}$$

simplify to

$$object = \sum_{j=1}^k \sum_{i=1}^n a_{ij} \|x_i - \mu_j\|^2$$

## insight algorithm

minimize

$$object = \sum_{j=1}^k \sum_{i=1}^n a_{ij} \|x_i - \mu_j\|^2$$

idea:

1. fix  $\mu$ ,

then

2. fix  $a$

## insight algorithm

step 1: *fix*  $\mu$

minimize

$$object = \sum_{j=1}^k \sum_{i=1}^n a_{ij} \|x_i - \mu_j\|^2$$

with respect to  $a$ , say  $\mu_l$  is the nearest center to the point  $a$

$$a_{ij} = \begin{cases} 1 & j = \operatorname{argmin} \|x_i - \mu_j\| \\ 0 & \text{else} \end{cases}$$

## insight algorithm

step 2: fix  $a$

minimize

$$object = \sum_{j=1}^k \sum_{i=1}^n a_{ij} \|x_i - \mu_j\|^2$$

with respect to  $\mu$

for  $\mu_m \neq \mu_j, m \neq j$

$$object = \sum_{i=1}^n a_{ij} \nabla_{\mu_j} (x_i - \mu_j)^T (x_i - \mu_j) + \sum_{i=1}^n a_{ij} \nabla_{\mu_j} (x_i - \mu_m)^T (x_i - \mu_m)$$

second term=0  $object = \sum_{i=1}^n a_{ij} \nabla_{\mu_j} (x_i - \mu_j)^T (x_i - \mu_j)$

## insight algorithm

$$object = \sum_{i=1}^n a_{ij} \nabla_{\mu_j} (x_i - \mu_j)^T (x_i - \mu_j)$$

$$\nabla (x_i^T x_i - 2\mu_j^T x_i + \mu_j^T \mu_j) = -2x_i + 2\mu_j$$



## insight algorithm

$$object = \sum_{i=1}^n a_{ij} \nabla_{\mu_j} (x_i - \mu_j)^T (x_i - \mu_j)$$

$$\nabla (x_i^T x_i - 2\mu_j^T x_i + \mu_j^T \mu_j) = -2x_i + 2\mu_j$$

$$object = (x_i^T x_i - 2\mu_j^T x_i + \mu_j^T \mu_j) = -2x_i + 2\mu_j$$

$$-2 \sum_{i=1}^n a_{ij} x_i + 2\mu_j \sum_{i=1}^n a_{ij} = 0$$

$$\mu_j = \frac{\sum_{i=1}^n a_{ij} x_i}{\sum_{i=1}^n a_{ij}}$$

## insight algorithm

$$\frac{\partial}{\partial \mu_j} \nabla_{\mu_j} \text{object} = 2 \left( \sum_{i=1}^n a_{ij} \right) e_k$$

$$\nabla_{\mu_j} \text{object} = 2 \left( \sum_{i=1}^n a_{ij} \right) \mathbb{I} > 0$$

$$a_{ij} = \begin{cases} 1 & \text{if } x_i \rightarrow j \\ 0 & \text{else} \end{cases}$$

## insight algorithm

$$\nabla_{\mu_k} \text{object} = 2 \left( \sum_{i=1}^n a_{ij} \right) \mathbb{I} > 0$$

$$a_{ij} = \begin{cases} 1 & \text{if } x_i \rightarrow j \\ 0 & \text{else} \end{cases}$$

$$n_j = \sum_{i=1}^n a_{ij} = \text{number of points : } x_i \text{ assigned to } j$$

$$\mu_j = \frac{\sum_{i=1}^n a_{ij} x_i}{\sum_{i=1}^n a_{ij}}$$

## insight algorithm

$$n_j = \sum_{i=1}^n a_{ij} = \text{number of points : } x_i \text{ assigned to } j$$

$$\mu_j = \frac{\sum_{i=1}^n a_{ij} x_i}{\sum_{i=1}^n a_{ij}}$$

$$\mu_j = \frac{1}{n_j} \sum_{i: X_i \rightarrow \mu_j} x_i$$

## small example

suppose we have number set  $D=2,3,4,10,11,12,20,25,30$ , we want to cluster it into two groups, any guess for the two groups?

## small example

suppose we have data set  $D=2,3,4,10,11,12,20,25,30$ , we want to cluster it into two groups

Select 2 points as the initial centroids:

$$\mu_1 = 4, \mu_2 = 12$$

Assignment steps:  $\{2, 3, 4\}, \{10, 11, 12, 20, 25, 30\}$   
recompute centroid steps

$$\mu_1 = 3, \mu_2 = 18$$

Assignment steps:  $\{2, 3, 4, 10\}, \{11, 12, 20, 25, 30\}$   
recompute centroid steps

$$\mu_1 = 4.75, \mu_2 = 19.5$$

## small example

Assignment steps:  $\{2, 3, 4, 10, 11, 12\}, \{20, 25, 30\}$   
recompute centroid steps

$$\mu_1 = 7, \mu_2 = 25$$

Assignment steps:  $\{2, 3, 4, 10, 11, 12\}, \{20, 25, 30\}$   
Converges stop!

# determine value of k

## 1. Elbow Method

choose different k ,see the sum of squared error, we want a small k, get the minimize **sum of the squared errors**

plot a line chart of the SSE for each value of k. The line chart looks like an arm, then the "elbow" on the arm is the value of k that is the best.

question: what k values get the minimum the sum squared errors?



## determine k, average silhouette approach

**2. Silhouette coefficient** Cohesion  $a(x)$ : average distance for the point  $x$  to the points in the same cluster.

Separation  $b(x)$ : average distance for point  $x$  to the points in other clusters  $j$ . Find the minimum among the clusters.

$$b_x = \min(b_{i1}, b_{i2}, \dots, b_{ik})$$

silhouette  $s(x)$ :

$$s(x) = \frac{b(x) - a(x)}{\max(a(x), b(x))}$$
$$s(x) = \begin{cases} 1 - \frac{a(x)}{b(x)} & a(x) < b(x) \\ 0 & a(x) = b(x) \\ \frac{b(x)}{a(x)} & a(x) > b(x) \end{cases}$$

$$s(x) \in [-1, +1]:$$

-1=bad, 0=indifferent, 1=good

Silhouette coefficient (SC):  $SC = \frac{1}{N} \sum s(x)$

## big example

### **R example in higher dimension**

instead of using the build in kmeans. write own kmeans graph,goal is to plot the original data graph and the graph clustered by color

## advantage

**1.easy to understand and to implement**

**2.efficient: and fast** :k cluster n data points the running time to assign step data points to closest cluster  $O(KN)$

The running time for change the cluster center to the average assigned points  $O(N)$

## disadvantage

- 1.number of clusters,  $K$  , must be determined before hand.
- 2.it is sensitive to initial condition. Different initial condition may produce different result of cluster. may be trapped in the local optimum

questions

**any questions?**

## reference

Thank you for watching!

Hartigan, John A., and Manchek A. Wong. "Algorithm AS 136: A k-means clustering algorithm." Journal of the Royal Statistical Society. Series C (Applied Statistics) 28.1 (1979): 100-108.

Alsabti, Khaled, Sanjay Ranka, and Vineet Singh. "An efficient k-means clustering algorithm." (1997).

NG, Andrew. Lecture 13.2 — Clustering — KMeans Algorithm — [ Machine Learning — Andrew Ng ]. 2008, [towardsdatascience.com/andrew-ngs-machine-learning-course-in-python-kmeans-clustering-pca-b7ba6fafa74](https://towardsdatascience.com/andrew-ngs-machine-learning-course-in-python-kmeans-clustering-pca-b7ba6fafa74).

K mean clustering algorithm with solve e.

[www.youtube.com/watch?v=YWgcKSa2agt](https://www.youtube.com/watch?v=YWgcKSa2agt) = 621s.