



Computer
Science

CSC380: Principles of Data Science

Clustering

Xinchen Yu

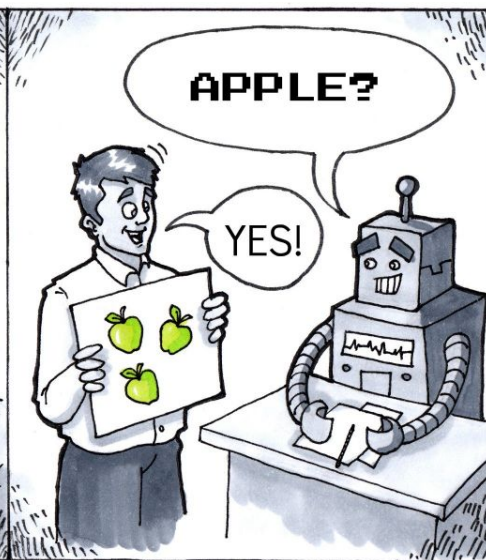
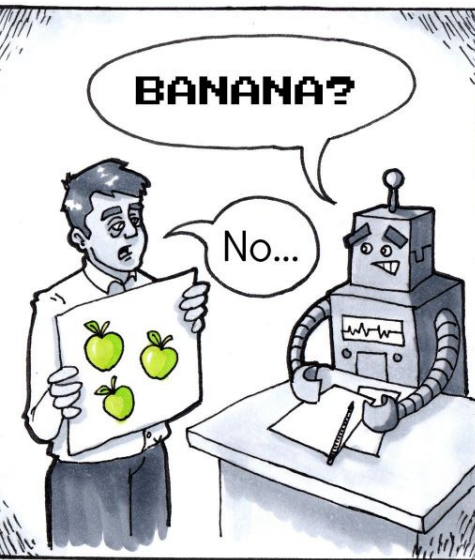
- Fill out SCS (<https://scsonline.oia.arizona.edu/>) – if 80% responses, will add 5 points to the homework with lowest grade.
- No lecture next Tuesday, Apr 30
 - You can prepare final exam or work on practice problems in groups and I will do Q&A in person
 - Meinel Optical Sci, Rm 410 (same room)

Announcements

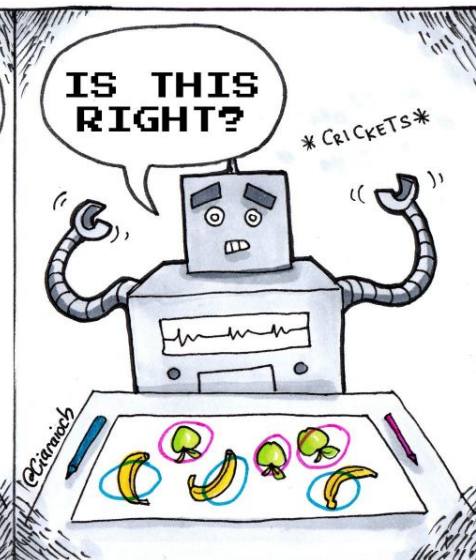
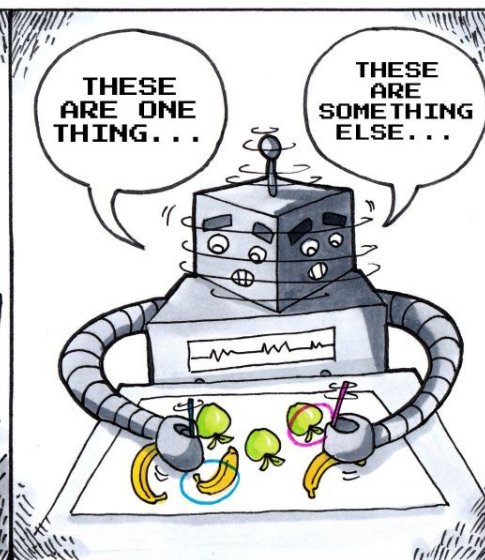
- Final exam
 - Time: Wednesday May 8, 3:30 - 5:30pm
 - Location: Meinel Optical Sci, Rm 410 (same room)
 - What you can bring:
 - one letter size cheat sheet, you can use double sides
 - calculator (not necessary)

Announcements

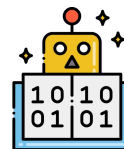
- ~20 questions and 50% questions will be before midterm.
- Practice questions has been out, keys will be out next week
- No coding questions
- How to prepare
 - **Slides**
 - Practice problems (helpful but do not only rely on it!)
 - HW questions before midterm



Supervised Learning



Unsupervised Learning



Task 1 : Group These Set of Document into 3 Groups based on meaning

Doc1 : Health , Medicine, Doctor

Doc 2 : Machine Learning, Computer

Doc 3 : Environment, Planet

Doc 4 : Pollution, Climate Crisis

Doc 5 : Covid, Health , Doctor



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Task 1 : Group These Set of Document into 3 Groups based on meaning

Doc1 : Health , Medicine, Doctor

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Doc 3 : Environment,
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Crisis

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Learning, Computer



-
- make
sad
cry
feel
bad
people
laugh
makes
sick
tired
mad
angry
upset
difficult
wanna
felt
making
- “feelings”
- younger
brother
baby
sister
boy
older
bro
big
small
sis
bro
cousin
sisters
brothers
mom
dad
joke
stopped
head
girl
asked
fat
kid
called
dead
office
found
mum
ugly
throw
dad
joke
stopped
head
girl
asked
fat
kid
called
- “family”
- red
sitting
completely
sleep
deserve
kicked
bus
move
tonight
bed
late
low
father
half
car
front
crazy
side
pushed
night
kicked
bus
move
tonight
bed
late
low
father
half
car
front
crazy
side
pushed
night
- “school”
- lost
commit
died
sad
bring
dream
death
point
family
wanted
life
killed
god
due
stand
everyday
win
heard
taylor
- “suicide”
- talking
teacher
school
today
grade
class
remember
stand
found
trouble
ist
girl
started
true
girls
alot
remember
standing
found
trouble
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girl
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- “physical bullying”
- dead
office
found
mum
ugly
called
fat
kid
called
- “verbal bullying”

In the Conference of North American Chapter of the Association for Computational Linguistics: Human Language Technologies (**NAACL HLT**), 2012. [pdf]

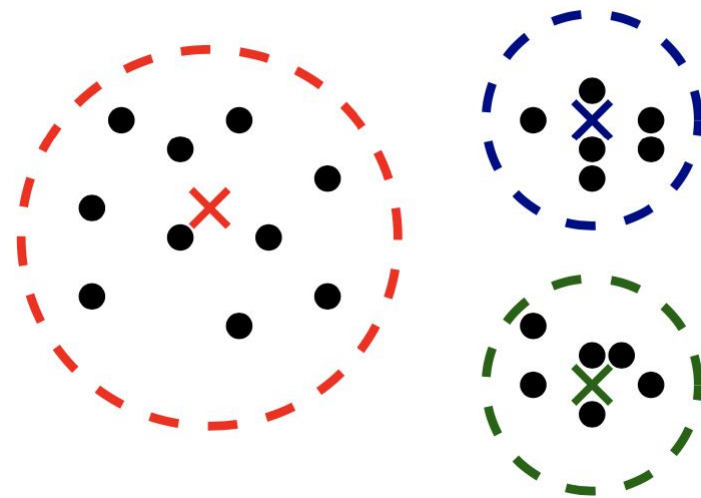
- Learning with unlabeled data
- What can we expect to learn?
 - **Clustering**: obtain partition of the data that are well-separated.
 - a preliminary classification without predefined class labels.
 - **Components**: extract common components
 - e.g., topic modeling given a set of articles: each article talks about a few topics => extract the topics that appear frequently.
- How can we use?
 - As a summary of the data
 - **Exploratory data analysis**: what are the **patterns** even without labels?
 - As a 'preprocessing techniques'
 - e.g., extract useful **features** using soft clustering assignments

- Input: k : the number of clusters (hyperparameter)

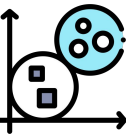
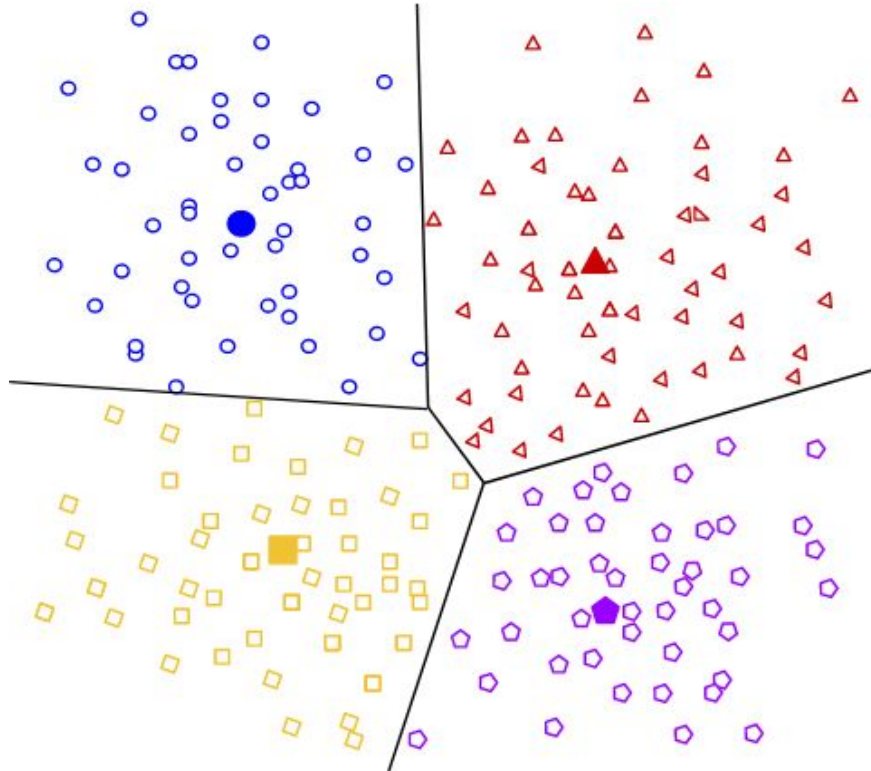
$$S = \{x_1, \dots, x_n\}$$

- Output

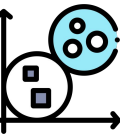
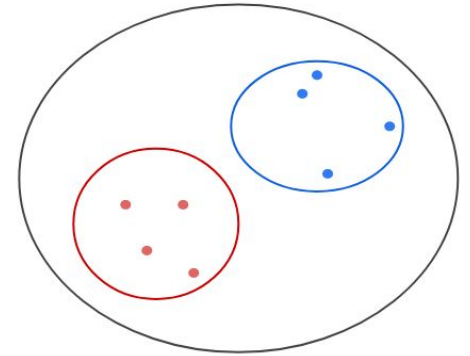
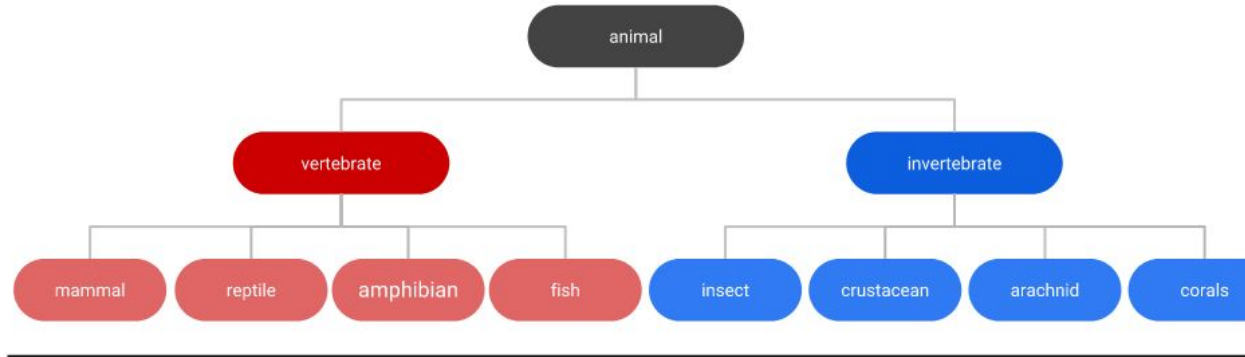
- partition $\{G_i\}_{i=1}^k$ s.t. $S = \cup_i G_i$ (disjoint union).
- often, we also obtain 'centroids'



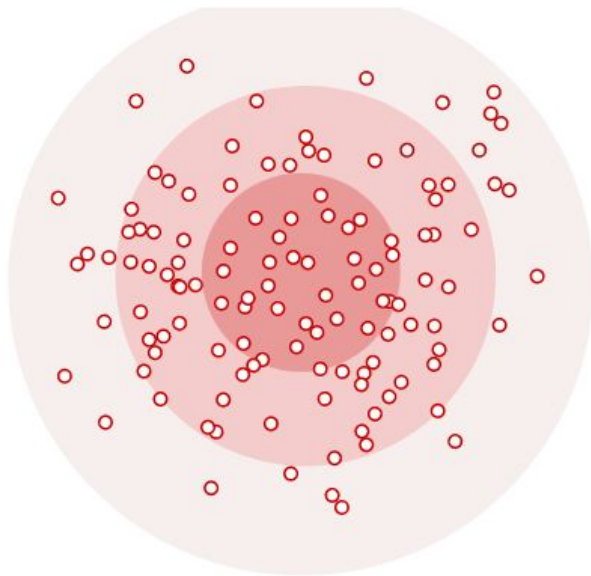
Centroid-based Clustering



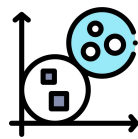
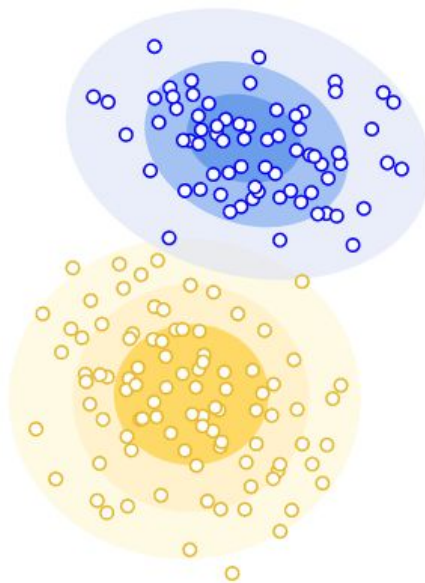
Hierarchical Clustering



Distribution-based Clustering



(probabilistic treatment)

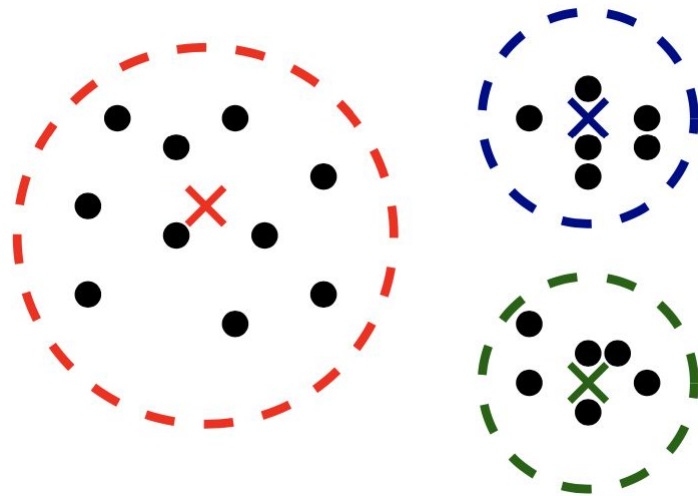


- Input: k : the number of clusters (hyperparameter)

$$S = \{x_1, \dots, x_n\}$$

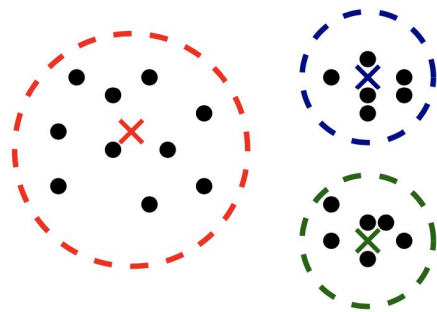
- Output

- partition $\{G_i\}_{i=1}^k$ s.t. $S = \cup_i G_i$ (disjoint union).
- often, we also obtain 'centroids'



- Q: if we are given the groups, what would be a reasonable definition of centroids?
 - The point that has the minimum average distance to the datapoints?
 - The datapoint that has the minimum average distance to the datapoints?
 - The point that has the minimum average squared distance to the datapoints?
- => Turns out, the last one corresponds to the average point!

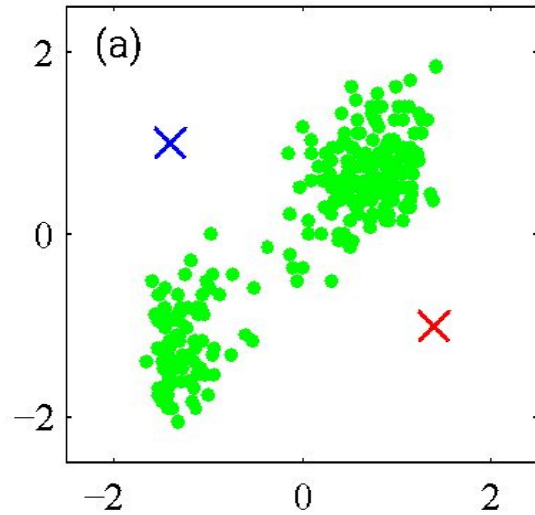
Lloyd's algorithm: solve it approximately (heuristic)



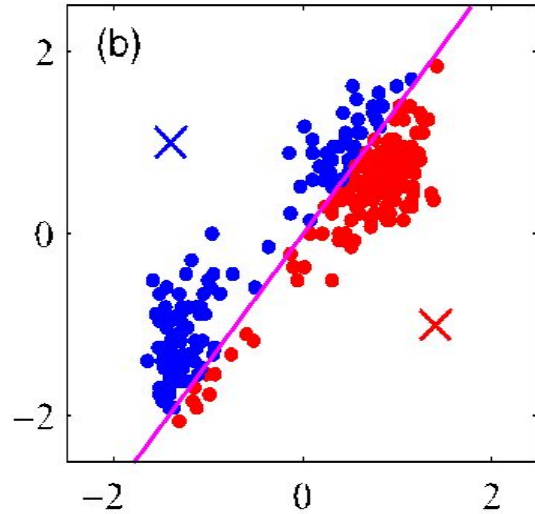
Observation: The chicken-and-egg problem.

- If you knew the **cluster assignments**... just find the **centroids** as the average
- If you knew the **centroids**... make **cluster assignments** by the closest centroid.

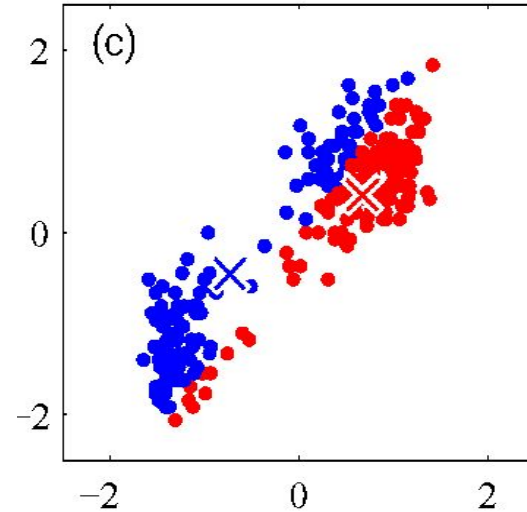
Why not: start from some centroids and then alternate between the two?



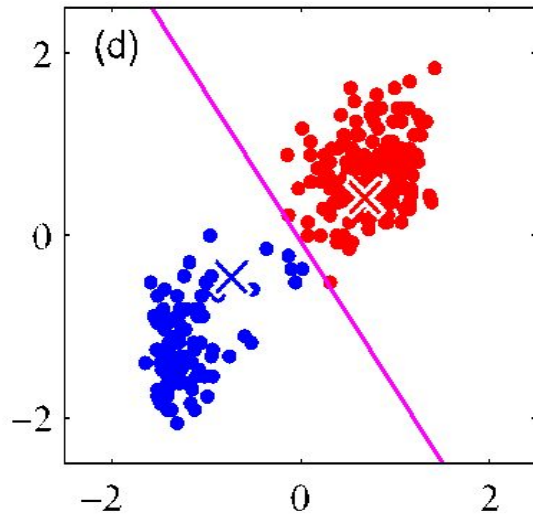
Arbitrary/random initialization of c_1 and c_2



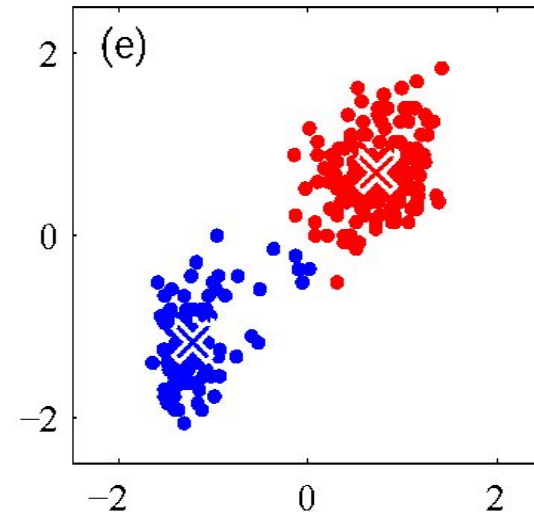
(A) update the cluster assignments.



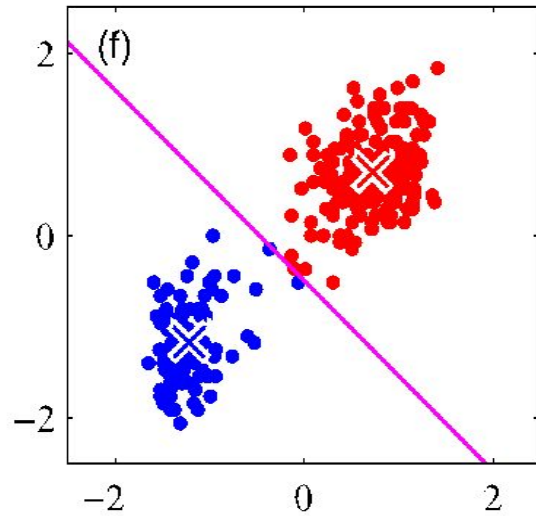
(B) Update the centroids $\{c_j\}$



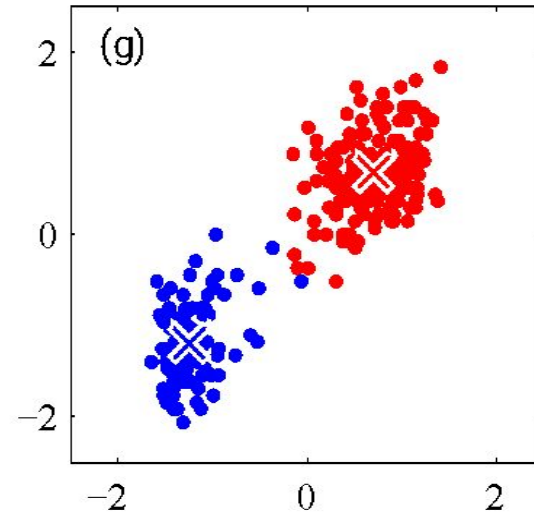
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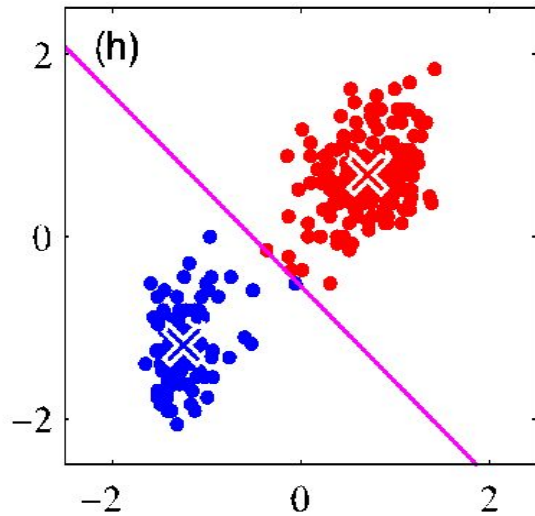
(B) Update the centroids $\{c_j\}$



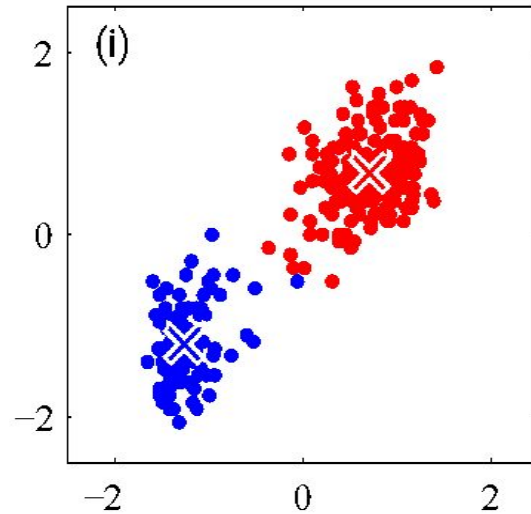
(A) update the cluster assignments.



(B) Update the centroids $\{c_j\}$

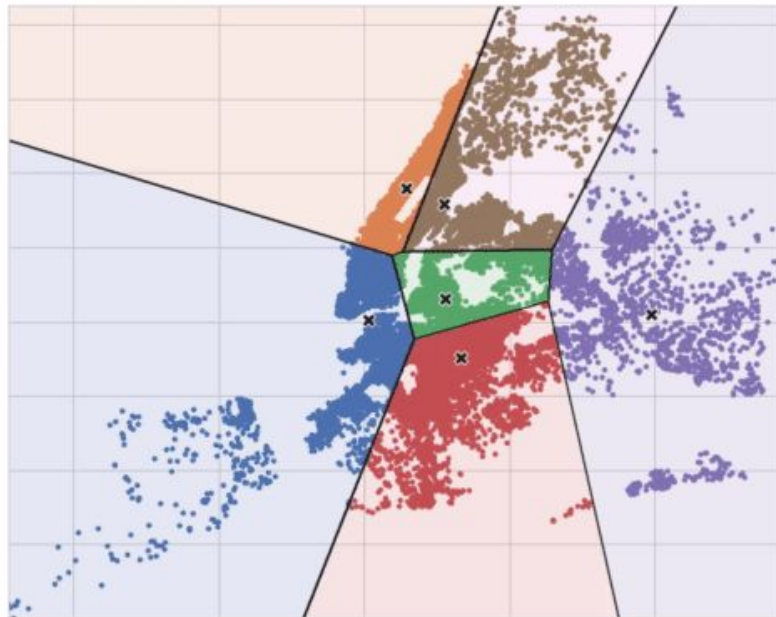


(A) update the cluster assignments.



(B) Update the centroids $\{c_j\}$

Iterating until Convergence

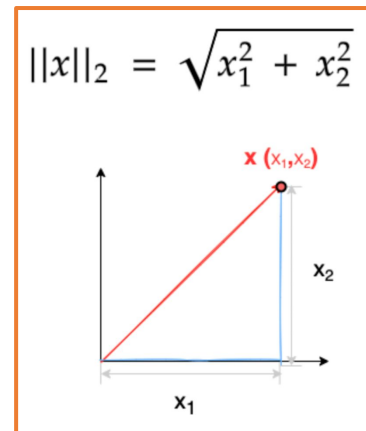


Input: k : num. of clusters, $S = \{x_1, \dots, x_n\}$

[Initialize] Pick c_1, \dots, c_k as randomly selected points from S (see next slides for alternatives)

For $t=1, 2, \dots, \text{max_iter}$

- **[Assignments]** $\forall x \in S, \quad a_t(x) = \arg \min_{j \in [k]} \|x - c_j\|_2^2$
- If $t \neq 1$ AND $a_t(x) = a_{t-1}(x), \forall x \in S$
 - break



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- If $t \neq 1$ AND $a_t(x) = a_{t-1}(x), \forall x \in S$
 - break
- ***[Centroids]*** $\forall j \in [k], \quad c_j \leftarrow \text{average}(\{x \in S: a_t(x) = j\})$

Output: c_1, \dots, c_k and $\{a_t(x_i)\}_{i \in [n]}$

But,

It may converge to a local rather than global minimum.

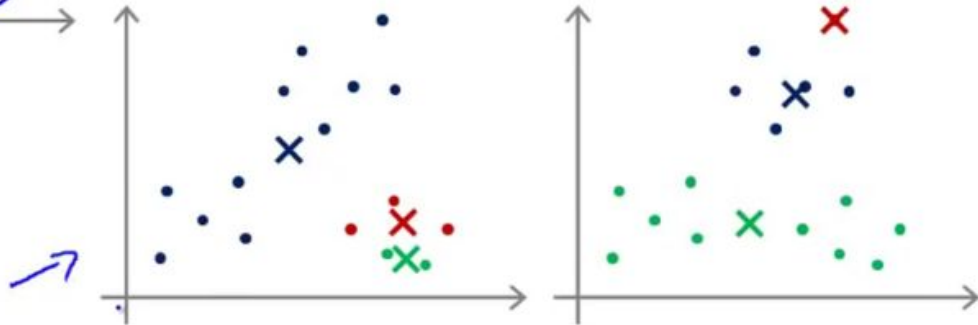
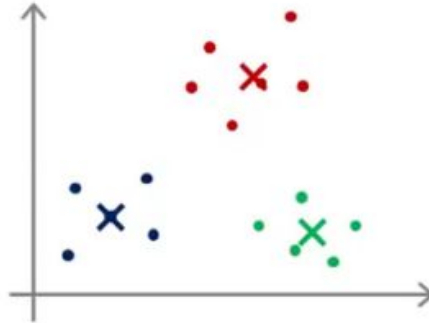
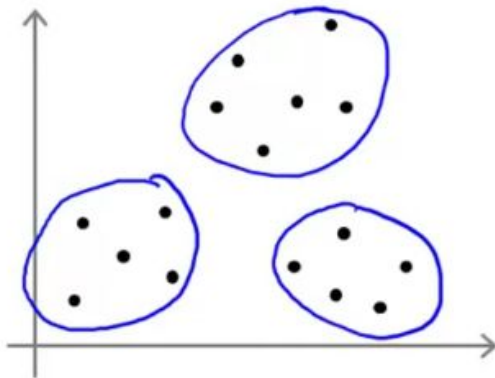
The diagram shows the objective function J for K-means clustering, with several annotations explaining its components:

- number of clusters**: Points to the variable k in the outer summation.
- number of cases**: Points to the variable n in the inner summation.
- case i** : Points to the index i in the inner summation.
- centroid for cluster j** : Points to the variable c_j .
- Distance function**: A bracket under the term $\|x_i^{(j)} - c_j\|^2$ indicates that this term represents the squared distance between a case and its assigned centroid.
- objective function**: Points to the variable J .

$$J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2$$



Local optima



Andrew Ng



- You usually get suboptimal solutions
- You usually get different solutions every time you run.
- **Standard practice**: Run it 50 times and take the one that achieves the smallest objective function
 - Recall:
$$\min_{c_1, \dots, c_k} \sum_{i=1}^n \min_{j \in [k]} \|x_i - c_j\|_2^2$$
 Each run of algorithm outputs c_1, \dots, c_k .
Compute this to evaluate the quality!
- And/or, change the initialization (next slide)
 - Idea: ensure that we pick a widespread c_1, \dots, c_k

- ***k*-means++**

- Pick $c_1 \in \{x_1, \dots, x_n\}$ uniformly at random
- For $j = 2, \dots, k$
 - Define a distribution $\forall i \in [n], \mathbb{P}(c_j = x_i) \propto \min_{j'=1, \dots, j-1} \|x_i - c_{j'}\|_2^2$
 - Draw c_j from the distribution above.

More likely to choose x_i
that is farthest from
already-chosen centroids.

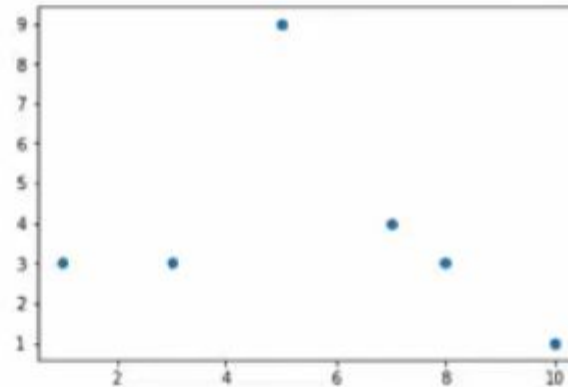
=> has a mathematical guarantee that it will be better than an arbitrary starting point!

Suppose we have the small dataset

☞ $[(7,4),(8,3),(5,9),(3,3),(1,3),(10,1)]$ to which we wish to assign 3 clusters.

We begin by randomly selecting $(7,4)$ to be a cluster center.

x	$\min(d(x, z_i)^2)$
$(7,4)$	
$(8,3)$	
$(5,9)$	
$(3,3)$	
$(1,3)$	
$(10,1)$	

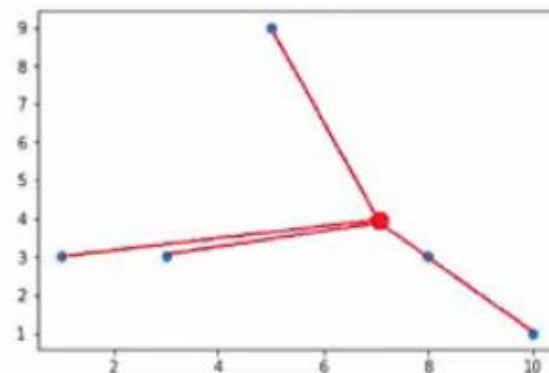


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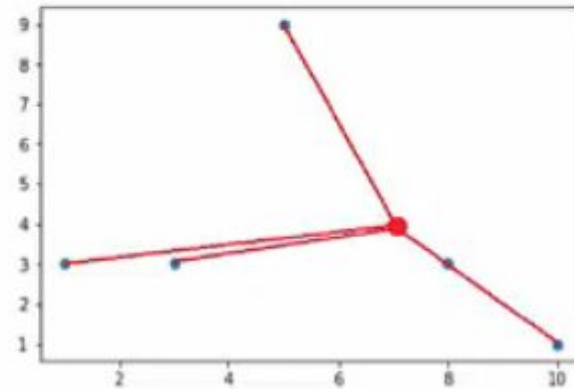
x	$\min(d(x, z_i)^2)$
$(7,4)$	-
$(8,3)$	2
$(5,9)$	29
$(3,3)$	17
$(1,3)$	37
$(10,1)$	18



Suppose we have the small dataset
 $[(7,4), (8,3), (5,9), (3,3), (1,3), (10,1)]$ to which we wish to assign 3 clusters.

We begin by randomly selecting $(7,4)$ to be a cluster center.

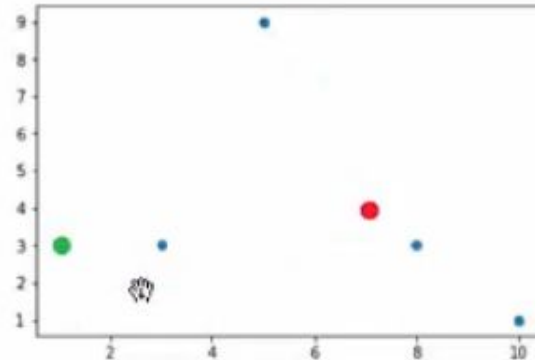
x	prob
$(7,4)$	-
$(8,3)$	$2/103$
$(5,9)$	$29/103$
$(3,3)$	$17/103$
$(1,3)$	$37/103$
$(10,1)$	$18/103$



Suppose we have the small dataset
[(7,4),(8,3),(5,9),(3,3),(1,3),(10,1)] to which we wish to assign 3
clusters.

We add (1,3) to the list of cluster centers.

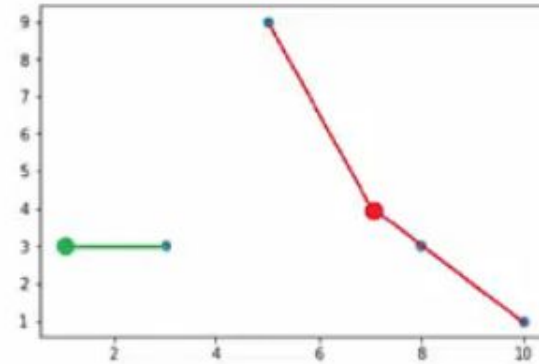
x	$\min(d(x, z_i)^2)$
(7,4)	-
(8,3)	
(5,9)	
(3,3)	
(1,3)	-
(10,1)	



Suppose we have the small dataset
[(7,4),(8,3),(5,9),(3,3),(1,3),(10,1)] to which we wish to assign 3
clusters.

We add (1,3) to the list of cluster centers.

x	$\min(d(x, z_i)^2)$
(7,4)	-
(8,3)	2
(5,9)	29
(3,3)	4
(1,3)	-
(10,1)	18

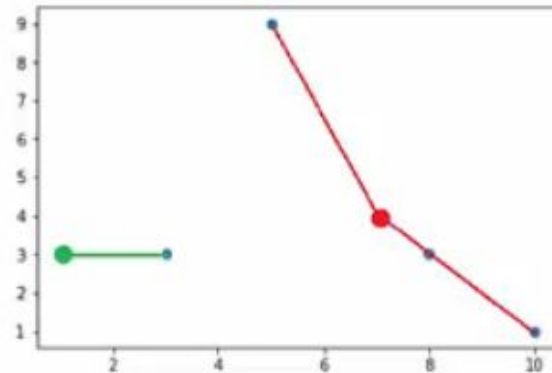


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$[(7,4),(8,3),(5,9),(3,3),(1,3),(10,1)]$ to which we wish to assign 3 clusters.

We add $(1,3)$ to the list of cluster centers.

x	prob
$(7,4)$	-
$(8,3)$	$2/53$
$(5,9)$	$29/53$
$(3,3)$	$4/53$
$(1,3)$	-
$(10,1)$	$18/53$

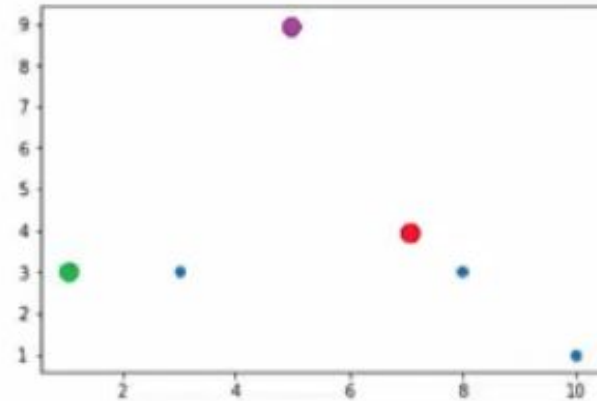


Suppose we have the small dataset

$[(7,4),(8,3),(5,9),(3,3),(1,3),(10,1)]$ to which we wish to assign 3 clusters.

We add $(5,9)$ to the list of cluster centers.

x	prob
$(7,4)$	-
$(8,3)$	
$(5,9)$	-
$(3,3)$	
$(1,3)$	-
$(10,1)$	



- No principled way.
- Elbow method: calculate Within-Cluster-Sum of Squared Errors (WSS) and choose k where WSS starts to diminish.

Objective function

