

CS540 Introduction to Artificial Intelligence

Lecture 11

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Based on lecture slides by Jerry Zhu, Yingyu Liang, and Charles Dyer

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Midterm

Admin

- The midterms are:
- A: Too Easy
- B: Easy
- C: (B, D)
- D: Hard
- E: Too Hard

no lecture
on Friday

The - Fri

Unsupervised Learning

Motivation

- Supervised learning: $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$.
 - Unsupervised learning: x_1, x_2, \dots, x_n .
 - There are a few common tasks without labels.
- ①** Clustering: separate instances into groups. *Group index 0, 1, 2 ... k.*
- ②** Novelty (outlier) detection: find instances that are different. *0, 1*
- ③** Dimensionality reduction: represent each instance with a lower dimensional feature vector while maintaining key characteristics.

$$\begin{pmatrix} 0.1 \\ 0.2 \end{pmatrix}$$

$$\begin{pmatrix} 0.1 \\ 0.3 \end{pmatrix}$$

$$\begin{pmatrix} 1.1 \\ 1.2 \end{pmatrix}$$

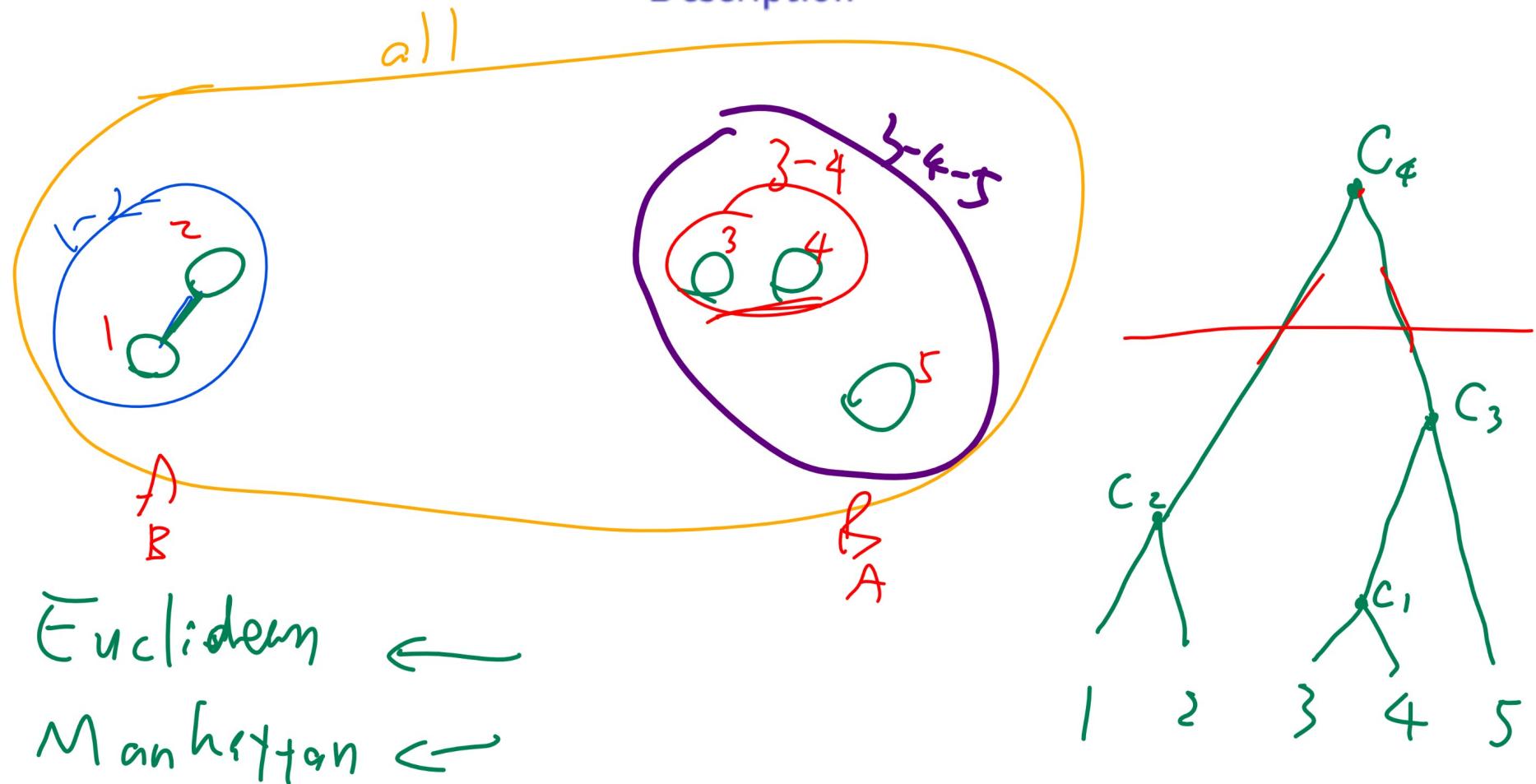
Hierarchical Clustering

Description

- Start with each instance as a cluster.
- Merge clusters that are closest to each other.
- Result in a binary tree with close clusters as children.

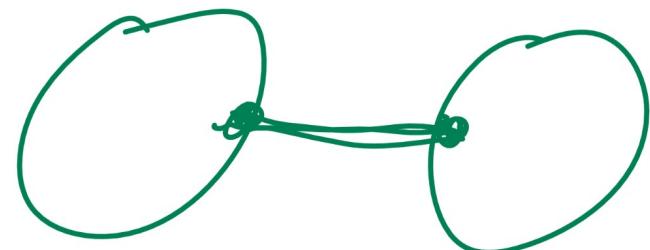
Hierarchical Clustering Diagram

Description



Single Linkage Distance

Definition



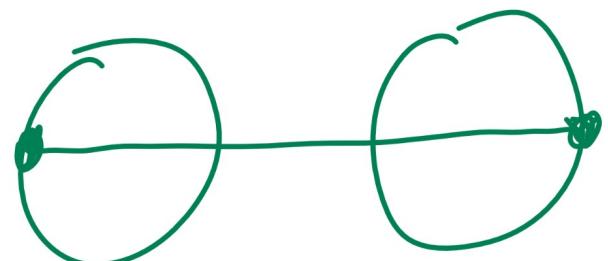
- Usually, the distance between two clusters is measured by the single-linkage distance.

$$d(C_k, C_{k'}) = \min \{ d(x_i, x_{i'}) : x_i \in C_k, x_{i'} \in C_{k'} \}$$

- It is the shortest distance from any instance in one cluster to any instance in the other cluster.

Complete Linkage Distance

Definition



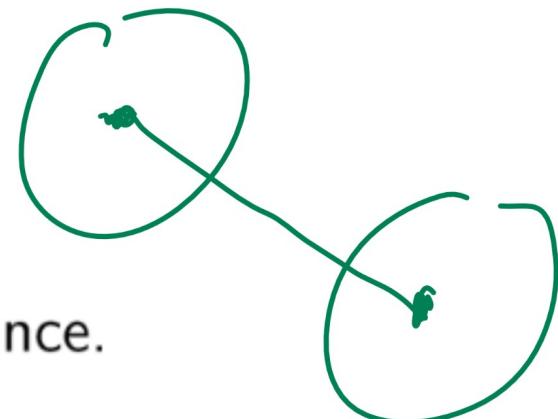
- Another measure is complete-linkage distance,

$$d(C_k, C_{k'}) = \max \{ d(x_i, x_{i'}) : x_i \in C_k, x_{i'} \in C_{k'} \}$$

- It is the longest distance from any instance in one cluster to any instance in the other cluster.

Average Linkage Distance Diagram

Definition



- Another measure is average-linkage distance.

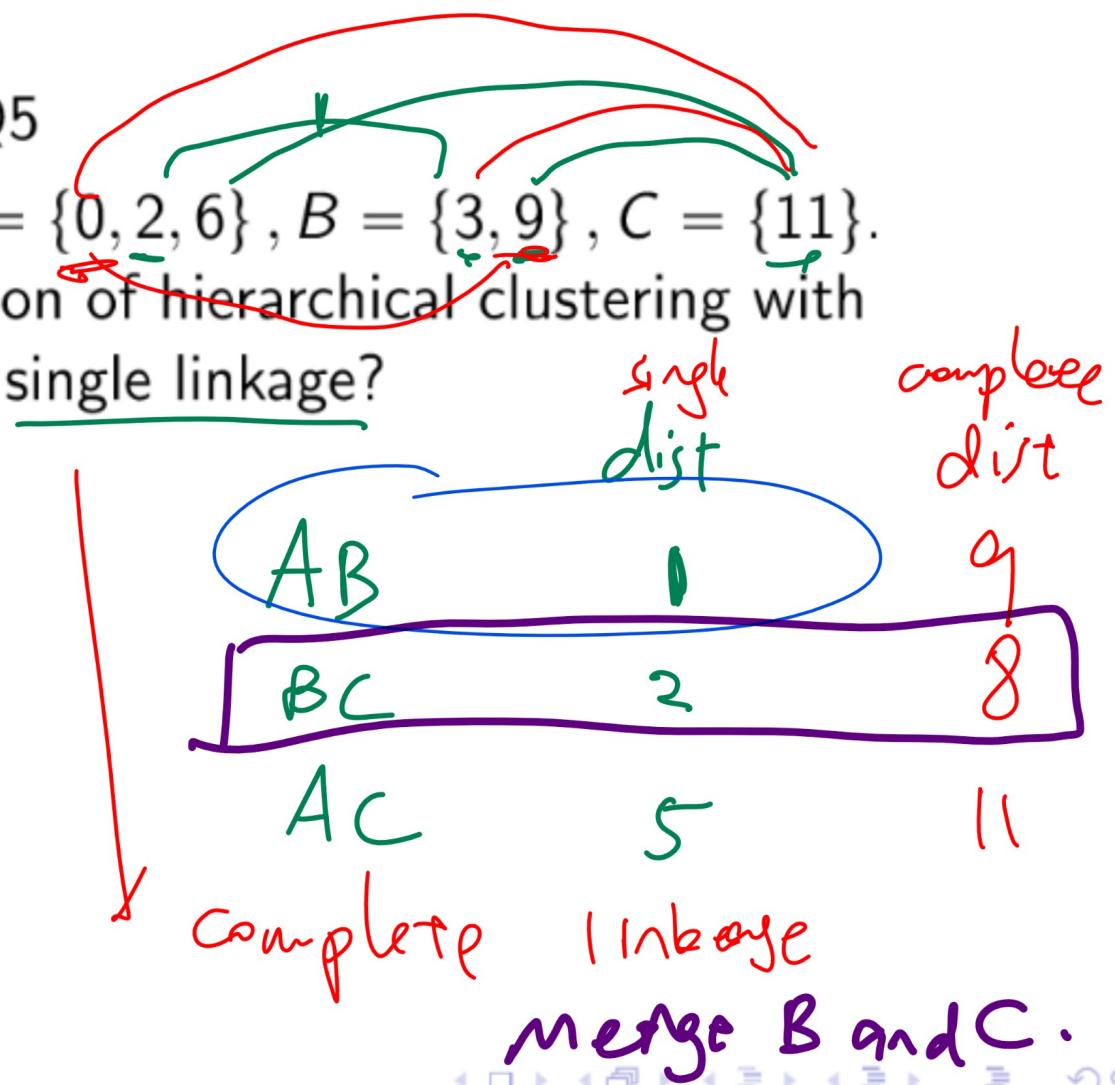
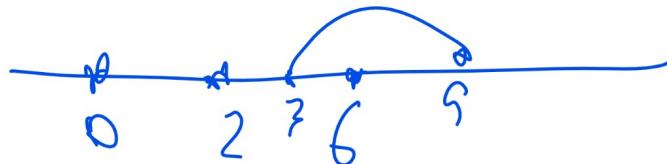
$$d(C_k, C_{k'}) = \frac{1}{|C_k||C_{k'}|} \sum_{x_i \in C_k, x_{i'} \in C_{k'}} d(x_i, x_{i'})$$

- It is the average distance from any instance in one cluster to any instance in the other cluster.

Hierarchical Clustering 1

Quiz

- Spring 2018 Midterm Q5
- Given three clusters $A = \{0, 2, 6\}$, $B = \{3, 9\}$, $C = \{11\}$.
What is the next iteration of hierarchical clustering with Euclidean distance and single linkage?
- A: Merge A and B .
- B: Merge A and C .
- C: Merge B and C .



Hierarchical Clustering 2

Quiz

Q 2

- Spring 2018 Midterm Q5
- Given three clusters $A = \{0, 1\}$, $B = \{4, 8\}$, $C = \{10, 11\}$. What is the next iteration of hierarchical clustering with Euclidean distance and complete linkage?
- A: Merge A and B .
- B: Merge A and C .
- C: Merge B and C .

Hierarchical Clustering 3

Quiz

Q3

- Spring 2018 Midterm Q5
- Given three clusters $A = \{0, 1\}$, $B = \{4, 8\}$, $C = \{10, 11\}$.
What is the next iteration of hierarchical clustering with Euclidean distance and single linkage?
- A: Merge A and B .
- B: Merge A and C .
- C: Merge B and C .

Hierarchical Clustering 4

Quiz

- Spring 2018 Midterm Q5
- Given three clusters $A = \{0, 2, 6\}$, $B = \{3, 9\}$, $C = \{11\}$. What is the next iteration of hierarchical clustering with Euclidean distance and complete linkage?
 - A: Merge A and B .
 - B: Merge A and C .
 - C: Merge B and C .

Hierarchical Clustering 3

Quiz	A	B	CD	E
A	0	1075	2013	996
B		0	2687	2037
CD			0	1059
E				0

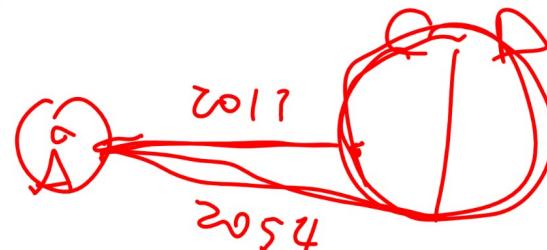
- Spring 2017 Midterm Q4
- Given the distance between the clusters so far. Which pair of clusters will be merged using single linkage.

P4

-	A	B	C	D	E
A	0	1075	2013	2054	996
B	1075	0	3272	2687	2037
C	2013	3272	0	808	1307
D	2054	2687	808	0	1059

pairwise
distmin
in
table

E 996 2037 1307 1059 0



complete 2054

Hierarchical Clustering 4

Quiz

- Given the distance between the clusters so far. Which pair of clusters will be merged using complete linkage.

-	A	B	C	D	E
A	0	1075	2013	2054	996
B	1075	0	3272	2687	2037
C	2013	3272	0	808	1307
D	2054	2687	808	0	1059

Hierarchical Clustering 5

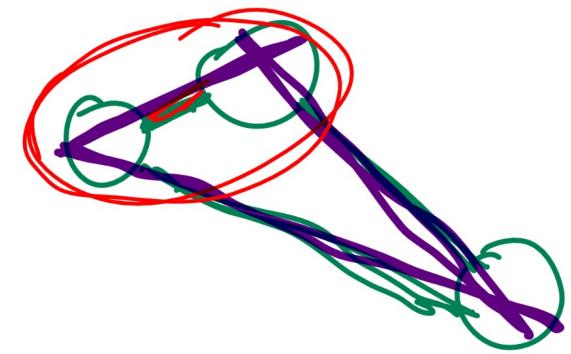
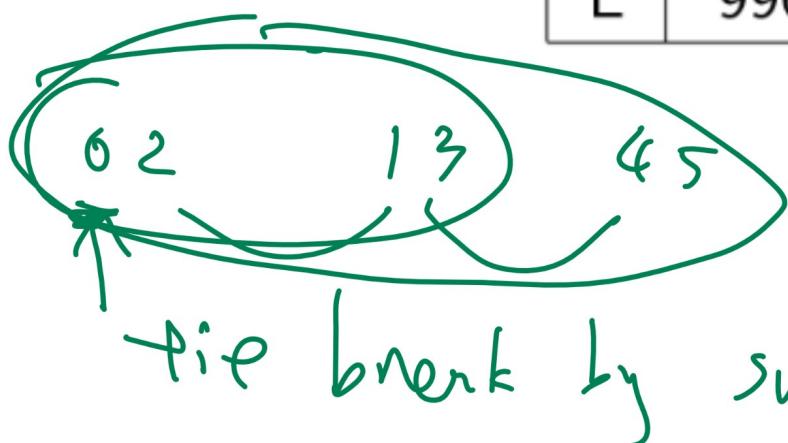
Quiz

Q 4

select one of them

- Given the distance between the clusters so far. Which pair of clusters will be merged using single linkage.

-	A	B	C D	E
A	0	1075	2013	996
B	1075	0	2687	2037
C D	2013	2687	0	1059
E	996	2037	1059	0



Hierarchical Clustering

Algorithm

- Input: instances: $\{x_i\}_{i=1}^n$, the number of clusters K , and a distance function d .
- Output: a list of clusters $C = C_1, C_2, \dots, C_K$.
- Initialize for $t = 0$.

$$C^{(0)} = C_1^{(0)}, \dots, C_n^{(0)}, \text{ where } C_k^{(0)} = \{x_k\}, k = 1, 2, \dots, n$$

- Loop for $t = 1, 2, \dots, n - k + 1$.

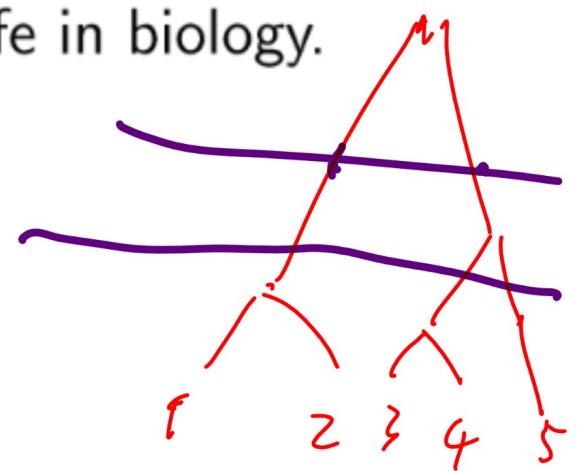
$$(k_1^*, k_2^*) = \arg \min_{k_1, k_2} d \left(C_{k_1}^{(t-1)}, C_{k_2}^{(t-1)} \right)$$

$$C^{(t)} = \left(C_{k_1^*}^{(t-1)} \cup C_{k_2^*}^{(t-1)} \right), C_1^{(t-1)}, \dots \text{ no } k_1^*, k_2^*, \dots, C_n^{(t-1)}$$

Number of Clusters

Discussion

- K can be chosen using prior knowledge about X .
- The algorithm can stop merging as soon as all the between-cluster distances are larger than some fixed R .
- The binary tree generated in the process is often called dendrogram, or taxonomy, or a hierarchy of data points.
- An example of a dendrogram is the tree of life in biology.



K Means Clustering

Description

- This is not K Nearest Neighbor.
- Start with random cluster centers.
- Assign each point to its closest center.
- Update all cluster centers as the center of its points.

K Means Clustering Diagram

Description

Distortion

Distortion

- Distortion for a point is the distance from the point to its cluster center.
- Total distortion is the sum of distortion for all points.

min

$$D_K = \sum_{i=1}^n d(x_i, c_{k^*(x_i)}(x_i))$$

$$k^*(x) = \arg \min_{k=1,2,\dots,K} d(x, c_k)$$

Objective Function

Definition

- When using Euclidean distance, sometimes total distortion is defined as sum of squared distances.

$$\min D_K = \sum_{i=1}^n d_2(x_i, c_{k^*(x_i)})^2$$

index

by GD

- This algorithm stop in finite steps.
- This algorithm is trying to minimize the total distortion but fails.

P4

start with multiple random initial centers

local min

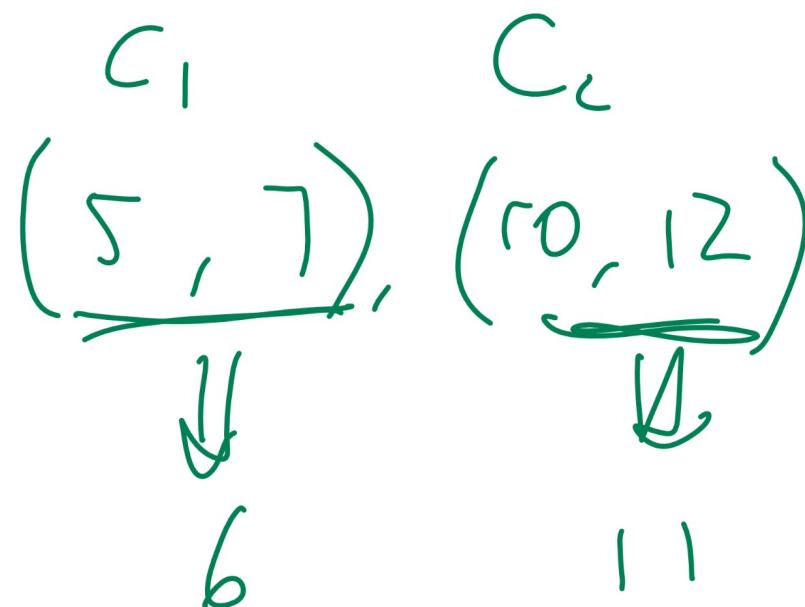
Objective Function Counterexample

Definition

K Means Clustering 1

Quiz

- 2 8
- Spring 2018 Midterm Q5
 - Given data $\{5, 7, 10, 12\}$ and initial cluster centers $c_1 = 3, c_2 = 13$, what is the initial clusters?
 - A: $\{5, 7\}$ and $\{10, 12\}$
 - B: $\{5\}$ and $\{7, 10, 12\}$
 - C: $\{5, 7, 10\}$ and $\{12\}$



K Means Clustering 2

Quiz

- Spring 2018 Midterm Q5
- Given data $\{5, 7, 10, 12\}$ and initial cluster centers

$c_1 = 3, c_2 = 13$, what are the clusters in the next iteration?

- A: $\{5, 7\}$ and $\{10, 12\}$
- B: $\{5\}$ and $\{7, 10, 12\}$
- C: $\{5, 7, 10\}$ and $\{12\}$

$$c_1 = 6, \quad c_2 = 11$$

K Means Clustering 3

Quiz

Q5

- Given data -2, 0, 10 and initial cluster centers $c_1 = -4$, $c_2 = 1$, what is the initial clusters?
 - A: $\{\emptyset\}$ and -2, 0, 10
 - B: -2 and $\{0, 10\}$
 - C: -2, 0 and {10}
 - D: -2, 0, 10 and $\{\emptyset\}$

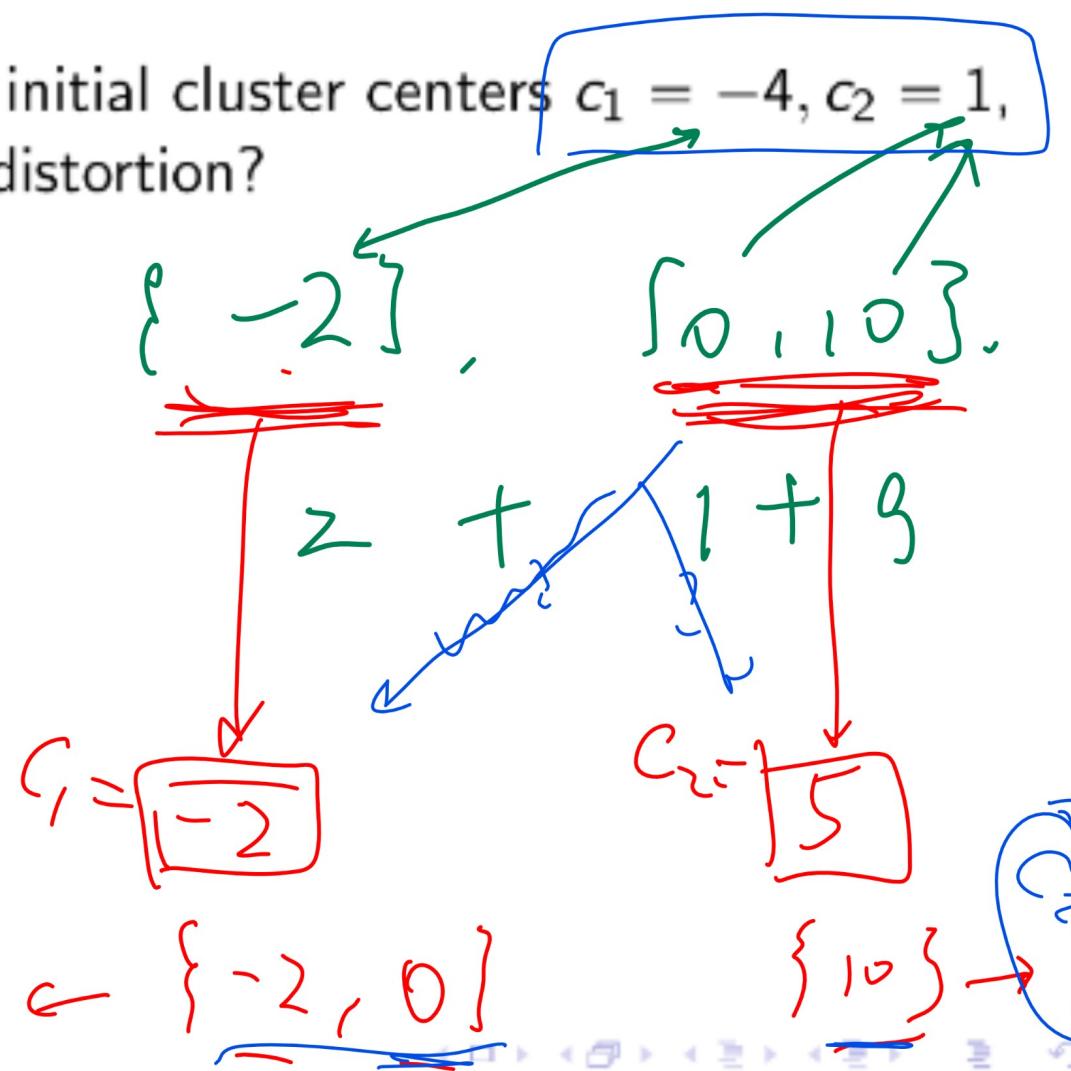
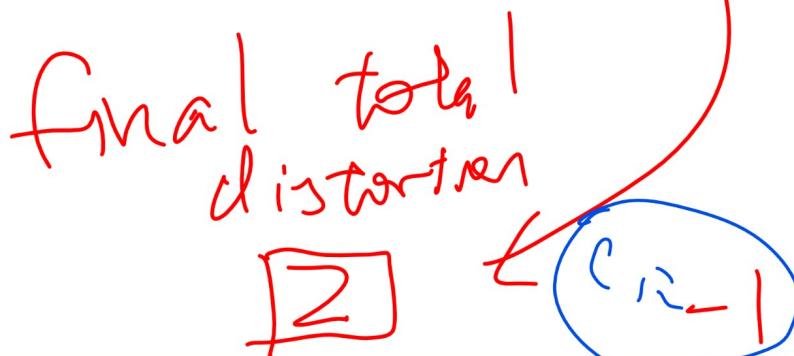
Total Distortion 1

Quiz

Q6

- Given data $-2, 0, 10$ and initial cluster centers $c_1 = -4, c_2 = 1$, what is the initial total distortion?

- A: 0
- B: 2
- C: 12
- D: 13
- E: 15



K Means Clustering 4

$$\left[\begin{array}{c} \phi(x_1)^T \phi(x_1) \\ \phi(x_1)^T \phi(x_2) \\ \phi(x_2)^T \phi(x_1) \\ \phi(x_2)^T \phi(x_2) \end{array} \right] \xrightarrow{\text{Quiz}} \left[\begin{array}{c} \phi(x_1)^T \phi(x_1) \\ \phi(x_1)^T \phi(x_2) \\ \phi(x_2)^T \phi(x_1) \\ \phi(x_2)^T \phi(x_2) \end{array} \right] \xrightarrow{\text{Kernel for } z \text{ instances}} N \times N$$

- Given data -2, 0, 10 and initial cluster centers $c_1 = -4, c_2 = 1$, what are the clusters in the next iteration?
- A: $\{\emptyset\}$ and -2, 0, 10
- B: -2 and $\{0, 10\}$
- C: -2, 0 and $\{10\}$
- D: -2, 0, 10 and $\{\emptyset\}$

estimate

$\Pr(X_1|Y)$

compute

$\Pr(Y|X_3)$

generative,

5 classes
 $Y = \{0, 1, 2, 3, 4\}$

$$\Pr(Y=4) = 1 - \Pr(Y=0) = \Pr(Y=4)$$

$$4 + 20 = 4$$

$$X_1 | Y=0, X_1 | Y=1 \sim$$

$2 \times 5 \times 2$

~~Naive Bayes~~

Total Distortion 2

 x_1, x_2

Quiz
 x_1, x_2

$x_1 = 0, 1, 2$
 $x = -2, 1, 2, 3, 4$
 $2 \times 5 \times 2$

- Given data -2, 0, 10 and initial cluster centers $c_1 = -4, c_2 = 1$, what is the final total distortion?
 - A: 0
 - B: 2
 - C: 12
 - D: 13
 - E: 15

K Means Clustering

Algorithm

- Input: instances: $\{x_i\}_{i=1}^n$, the number of clusters K , and a distance function d .
- Output: a list of clusters $C = C_1, C_2, \dots, C_K$.
- Initialize $t = 0$.

$c_k^{(0)} = K$ random points

- Loop until $c^{(t)} = c^{(t-1)}$.

$$C_k^{(t-1)} = \left\{ x : k = \arg \min_{k' \in 1, 2, \dots, K} d(x, c_k^{(t-1)}) \right\}$$

$$c_k^{(t)} = \frac{1}{|C_k^{(t-1)}|} \sum_{x \in C_k^{(t-1)}} x$$

Number of Clusters

Discussion

- There are a few ways to pick the number of clusters K .
 - ① K can be chosen using prior knowledge about X .
 - ② K can be the one that minimizes distortion? No, when $K = n$, distortion = 0.
 - ③ K can be the one that minimizes distortion + regularizer.

$$K^* = \arg \min_k (D_k + \lambda \cdot m \cdot k \cdot \log n)$$

↓ trade off ↑ choose
D

- λ is a fixed constant chosen arbitrarily.

Initial Clusters

Discussion



- There are a few ways to initialize the clusters.

① K uniform random points in $\{x_i\}_{i=1}^n$.

repeat many times

② 1 uniform random point in $\{x_i\}_{i=1}^n$ as $c_1^{(0)}$, then find the farthest point in $\{x_i\}_{i=1}^n$ from $c_1^{(0)}$ as $c_2^{(0)}$, and find the farthest point in $\{x_i\}_{i=1}^n$ from the closer of $c_1^{(0)}$ and $c_2^{(0)}$ as $c_3^{(0)}$, and repeat this K times.

why P4