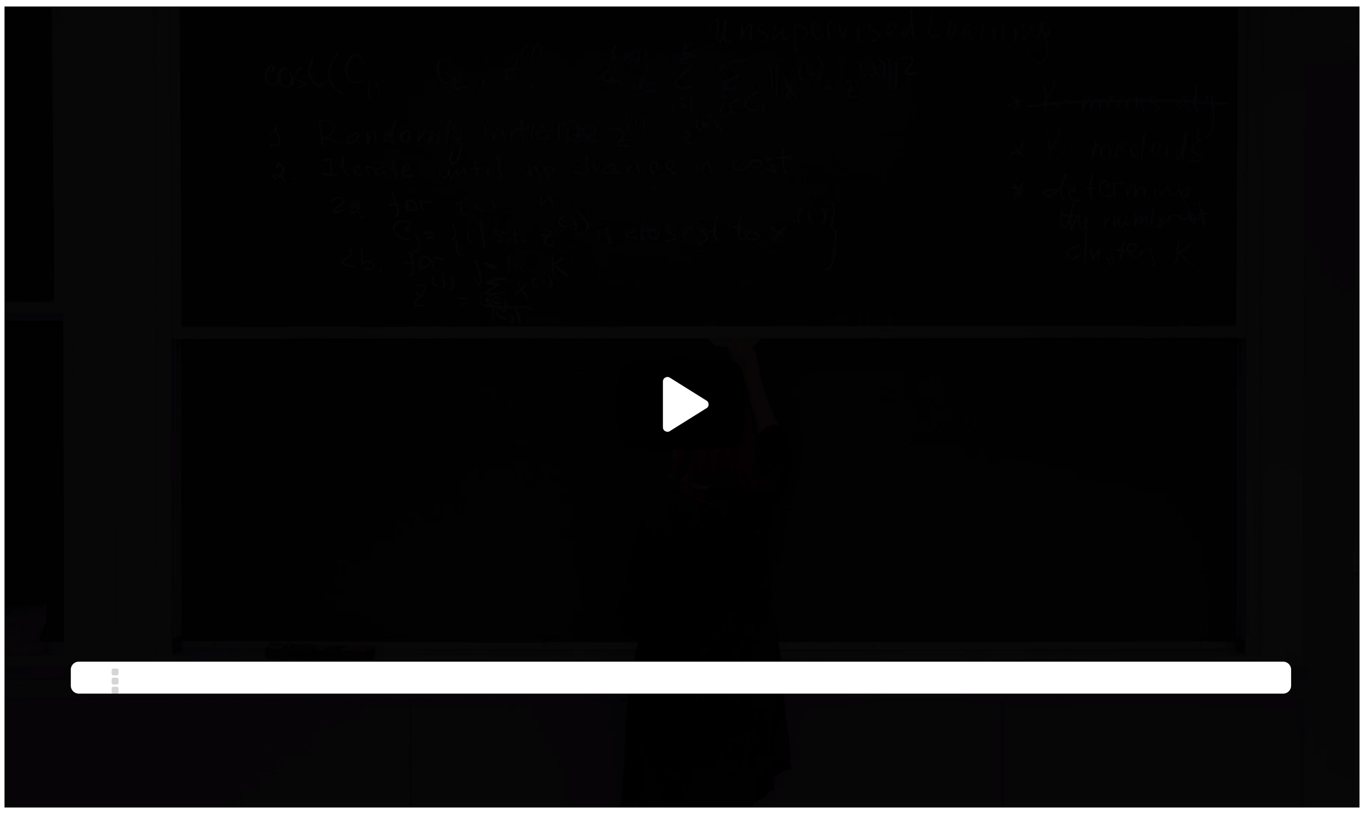
2. Limitations of the K Means Algorithm

Limitations of the K Means Algorithm



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works with your metrics.

So with these two limitation in mind, again,

making a representative part of the original points and ability

to work with any distance metrics,

we are moving towards the new algorithm

that we need to consider, K-medoid.

So we've done with summarizing K-means,

and we can start now talking about K-medoids,

which will resolve two of those constraints.

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Limitations of the K-Means Algorithm

1/1 point (graded)
Remember that the K-Means Algorithm is given as below:

1. Randomly select $z_1, \ldots, z_K$
2. Iterate
   1. Given $z_1, \ldots, z_K$, assign each data point $x^{(i)}$ to the closest z_j, so that

$$\text{Cost}\,(z_1, \ldots z_K) = \sum_{i=1}^{n} \min_{j=1,\ldots,k} \left\| x^{(i)} - z_j \right\|^2$$

   2. Given $C_1, \ldots, C_K$ find the best representatives $z_1, \ldots, z_K$, i.e. find $z_1, \ldots, z_K$ such that

$$z_j = \text{argmin}_z \sum_{i \in C_j} \|x^{(i)} - z\|^2 = \frac{\sum_{i \in C_j} x^{(i)}}{|C_j|}$$

where $|C_j|$ is the number of points in C_j.

Which of the following are **false** about K-Means Algorithm? Please choose all those apply.

- [ ] $C_1, \ldots, C_K$ found by the algorithm is always a partition of $\{x_1, \ldots, x_n\}$
- [x] It is always guaranteed that the K representatives $z_1, \ldots, z_K \in \{x_1, \ldots, x_n\}$ ✔
- [ ] The algorithm may output different $C_1, .., C_K$ and $z_1, \ldots, z_K$ depending on the initialization of line 1
- [x] Line 2.2 of the algorithm(Given $C_1, \ldots, C_K$ find the best representatives $z_1, \ldots, z_K$ ...) finds the cost-minimizing representatives $z_1, \ldots z_K$ for all cost functions ✔

✔

Solution:

It is not guaranteed that $z_1, \ldots, z_K \in \{x_1, \ldots, x_n\}$, because as in line 2.2 of the algorithm above, $z_1, \ldots, z_K$ are given by

$$z_j = \frac{\sum_{i \in C_j} x^{(i)}}{|C_j|}$$

There is no guarantee that the centroid of all $x^{(i)}$ in a cluster will itself belong to $\{x_1, \ldots, x_n\}$. Depending on the application context, such as when clustering Google News articles, it can be problematic that a representative of a clustering is not an actual datapoint.

Also, as we saw in the last lecture, line 2.2 of the algorithm

$$z_j = \frac{\sum_{i \in C_j x^{(i)}}}{|C_j|}$$

is a simplification(or special case) of

$$\text{Cost}\left(C_1, \ldots C_K\right) = \min_{j=z_1, \ldots, z_K} \sum_{j=1}^{k} \sum_{i \in C_j} \|x^{(i)} - z_j\|^2$$

when the cost function is the euclidean distance function($\|x^{(i)} - z_j\|^2$).

These two points are the **limitations** of the K-Means algorithm. We saw in the last lecture that clustering always outputs $C_1, \ldots, C_K$ that is a partition of $\{x_1, \ldots, x_n\}$, and that the result of clustering depends on the initialization of $z_1, \ldots, z_K$.

Submit   You have used 2 of 3 attempts

Answers are displayed within the problem

Limitations of the K-Means Algorithm 2

2/2 points (graded)

Suppose we have a 1D dataset drawn from 2 different Gaussian distribution $\mathcal{N}\left(\mu_1, \sigma_1^2\right), \mathcal{N}\left(\mu_2, \sigma_2^2\right)$. The dataset contains n data points from each of the two distributions for some large number n. If we define the optimal clustering is to assign each point to the most likely Gaussian distribution given the knowledge of the generating distribution, consider the case where $\sigma_1^2 = \sigma_2^2$, would you expect a 2-means algorithm to approximate the optimal clustering?

- (•) Yes ✔
- ( ) No

Now if $\sigma_1^2 >> \sigma_2^2$, would you expect a 2-means algorithm to approximate the optimal clustering?

- ○ Yes
- ◉ No ✔

Solution:

When $\sigma_1^2 = \sigma_2^2$, the boundary between the 2 optimal clusters is the midpoint between μ_1 and μ_2. The 2 centroids found by the 2-means algorithm will also be equidistant from this boundary and therefore the assignment to clusters will be a similar split around the midpoint.
When $\sigma_1^2 >> \sigma_2^2$, the boundary betwwen the 2 optimal clusters is closer to one centroid then the other. Since the 2-means algorithm will always have an equidistant split between the two centroids, this behavior cannot be reproduced and thus k-means clustering will erroneoously assign more points to the cluster with a smaller variance.

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Discussion

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