

<u>Unit 4 Unsupervised Learning (2</u>

2. Limitations of the K Means

Course > weeks)

> <u>Lecture 14. Clustering 2</u> > Algorithm

# 2. Limitations of the K Means Algorithm Limitations of the K Means Algorithm

Start of transcript. Skip to the end.

So today, we will continue the conversation

about unsupervised learning, unsupervised learning.





And we will continue talking about clustering.

And I will start my lecture by briefly summarizing

what we've seen last time, which covered the discussion

about K-means algorithm



#### Video

Download video file

# Transcripts

<u>Download SubRip (.srt) file</u> <u>Download Text (.txt) file</u>

# 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  $x^{(i)}$  to the closest  $z_i$ . i.e., assign each  $x^{(i)}$ .
  - 2. Given  $C_1, \ldots, C_K$  find the best representatives  $z_1, \ldots, z_K$  such that

$$\operatorname{argmin}_{z_1,...,z_K} \sum_{j=1}^k \sum_{i \in C_j} \left\| x^{(i)} - z_j 
ight\|^2$$

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

- $lacksquare C_1,\ldots,C_K$  found by the algorithm is always a partition of  $ig\{x_1,\ldots,x_nig\}$
- lacksquare It is always guaranteed that the K representatives  $z_1,\dots,z_K\in ig\{x_1,\dots,x_nig\}$
- lacksquare The algorithm may output different  $C_1,\ldots,C_K$  and  $z_1,\ldots,z_K$  depending on the initialization of line 1
- ✓ Line 2b of the algorithm(Given  $C_1, \ldots, C_K$  find the best representatives  $z_1, \ldots, z_K$  such that ...) 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 2b of the algorithm above,  $z_1,\ldots,z_K$  are given by

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

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 2b of the algorithm

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

is a simplification(or special case) of

$$\operatorname{Cost}\left(C_{1}, \ldots C_{K}
ight) = \min_{j=z_{1}, ..., z_{K}} \sum_{j=1}^{k} \sum_{i \in C_{j}} \left\|x^{(i)} - z_{j}
ight\|^{2}$$

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

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 1 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?



No

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

Yes



#### **Solution:**

When  $\sigma_1^2=\sigma_2^2$ , the boundary between the 2 optimal clusters is the midpoint between  $\mu_1$  and  $\mu_2$ . 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 between 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 erroneously assign more points to the cluster with a smaller variance.

Submit

You have used 2 of 2 attempts

**1** Answers are displayed within the problem

### Discussion

**Topic:** Unit 4 Unsupervised Learning (2 weeks) :Lecture 14. Clustering 2 / 2. Limitations of the K Means Algorithm

**Hide Discussion** 

Add a Post

**≮** All Posts

## Limitations of kmeans algorithm 2

+

discussion posted about 15 hours ago by sandipan dey

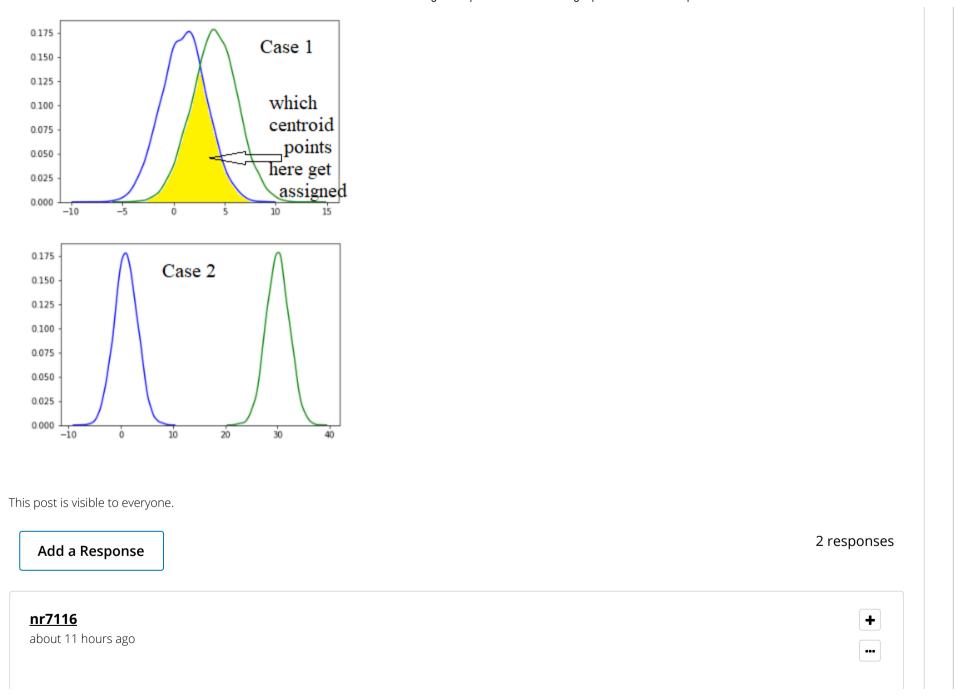
\*

Should not the answer for the first case ( $\sigma_1 = \sigma_2$ ) depend on the difference between  $\mu_1$ ,  $\mu_2$  and how they are related to  $\sigma_1$ ,  $\sigma_2$ ? For example, let's consider the following 2 cases:

---

1. 
$$\mu_2 \in [\mu_1 - \sigma_1, \mu_1 + \sigma_1]$$
  
2.  $\mu_2 \notin [\mu_1 - 3\sigma_1, \mu_1 + 3\sigma_1]$ 

Will the chance that the k-means will find the optimal partition be same in these two cases, assuming all other variabilities (e.g., initialization etc.) fixed?



I had the same doubt. But since it was not given, I made simplifying assumption that means are well separated with no overlapping point - that gives an answer that is accepted. I have realized that though this was s a lecture on a unsupervised learning, question are mostly straight out of lecture with little googling read:-) making it supervised learning for me Previous units had enough cases of unsupervised googling read to get answers!

Add a comment

#### **BrendanWood**

about 4 hours ago

It should not matter what the means of the underlying Gaussian distributions are in this case. Note that we are not concerned whether the representatives of the clusters are equal to the means, we are just concerned that the two clusters (that the K-means algorithm determines) happen to coincide with the optimal clustering as defined in the question.

(Actually, I guess it matters that  $\mu_1 \neq \mu_2$ , or else the problem doesn't really make any sense, since there's nothing to separate)

Add a comment

Showing all responses

Add a response:

8/2/2019	2. Limitations of the K Means Algorithm   Lecture 14. Clustering 2   6.86x Courseware   edX
	Preview
	Submit

© All Rights Reserved