Boston University CS 506 - Lance Galletti

## K-means - Lloyd's Algorithm

Q1: Will this algorithm always converge? Yes. The dataset has a finite number of points, and therefore there are a finite number of ways to assign points to k clusters (number of clusters = number of points).

**Proof** (by contradiction): Suppose it does not converge. Then, either:

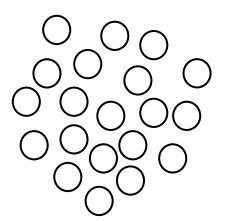
- 1. The minimum of the cost function is only reached in the limit (i.e. after an infinite number of iterations).
  - Impossible because we are iterating over a finite set of partitions
- The algorithm gets stuck in a cycle / loop
   Impossible since this would require having a clustering that has a lower cost than itself and we know:
  - If old ≠ new clustering then the cost has improved
  - If old = new clustering then the cost is unchanged

**Conclusion**: Lloyd's Algorithm always converges!

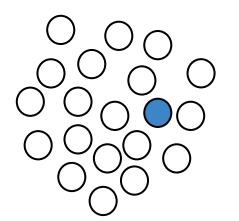
## K-means - Lloyd's Algorithm

Q2: Will this always converge to the optimal solution?

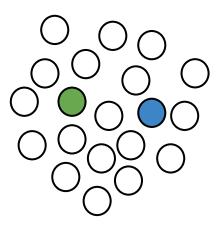
no



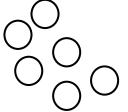


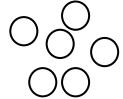


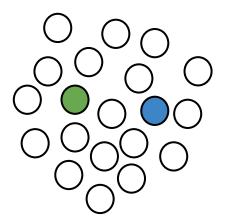


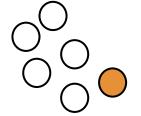


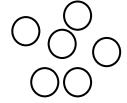
two centers are too close to each other

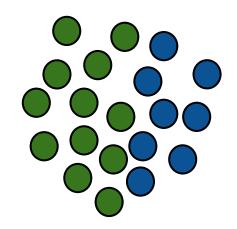


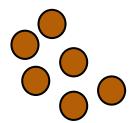


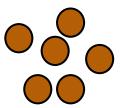




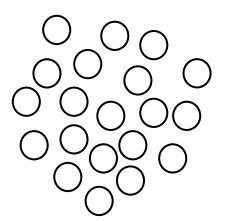




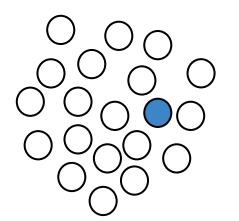




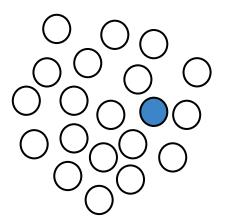
# What's the problem?

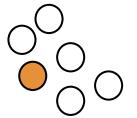


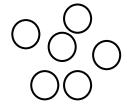


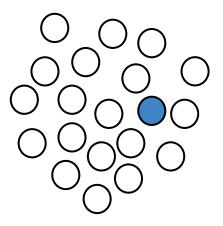




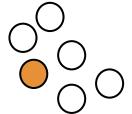


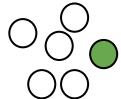


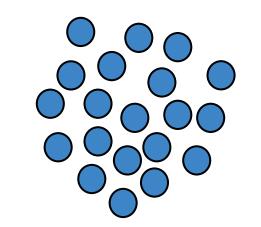


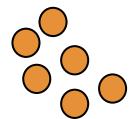


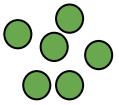
pick the next point furthest from the previous



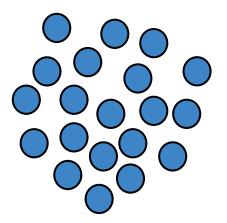


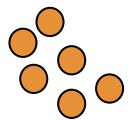


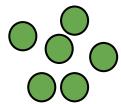




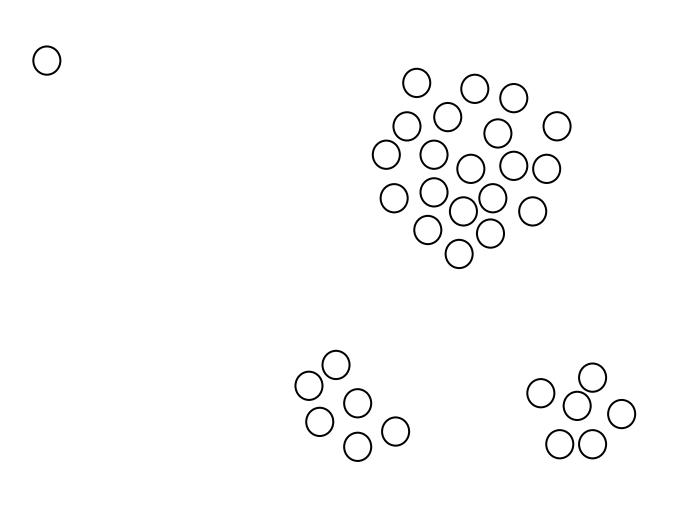
#### **Farthest First Traversal**



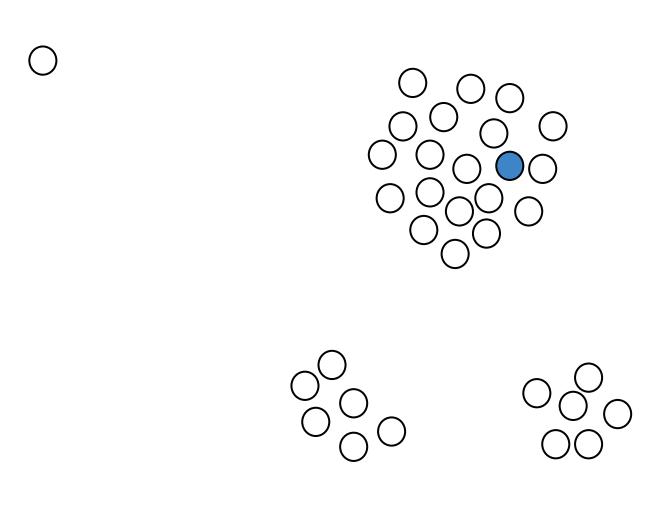




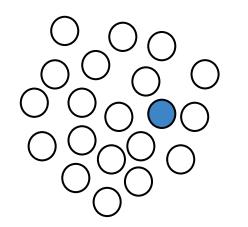
# But...

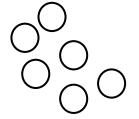


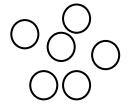


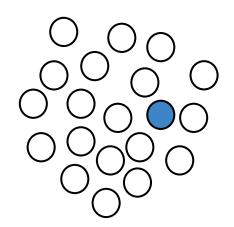


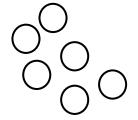


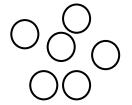


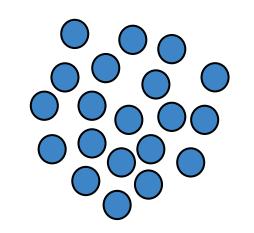


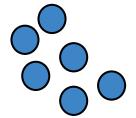


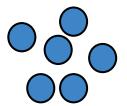




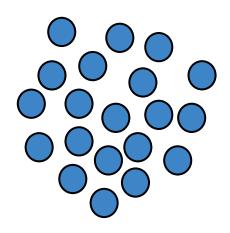


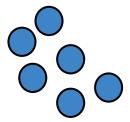


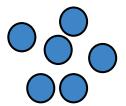




# Random would have been better

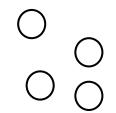


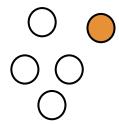


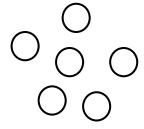


Initialize with a combination of the two methods:

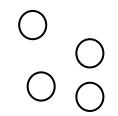
- Start with a random center
- 2. Let D(x) be the distance between x and the closest of the centers picked so far. Choose the next center with probability proportional to  $D(x)^2$

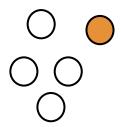


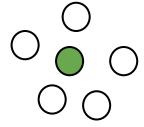






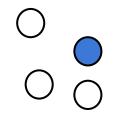


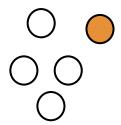


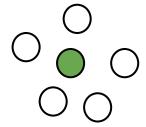




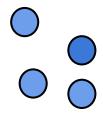


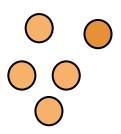




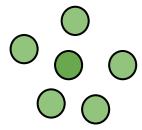


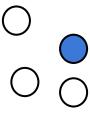


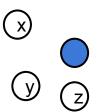




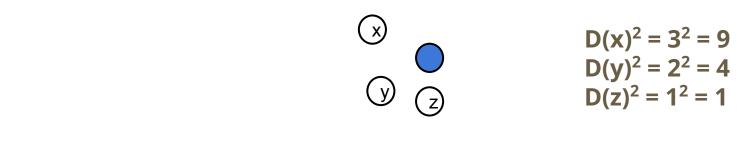
No reason to use k-means over k-means++

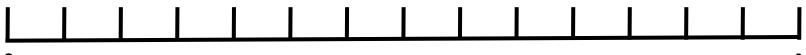


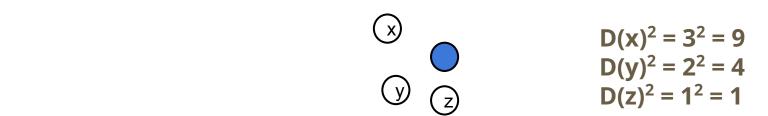




$$D(x)^2 = 3^2 = 9$$
  
 $D(y)^2 = 2^2 = 4$   
 $D(z)^2 = 1^2 = 1$ 









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$$D(z)^{2} = 1^{2} = 1$$

$$= D(x)^{2} + D(y)^{2} + D(z)^{2} = 14$$

$$D(x)^{2} = 3^{2} = 9$$

$$D(y)^{2} = 2^{2} = 4$$

$$D(z)^{2} = 1^{2} = 1$$



#### K-means++

Q3: the black box returns "12" as the random number generated. Which point do we choose for the next center (x, y, or z)?



0

#### K-means++

Q4: the black box returns "4" as the random number generated. Which point do we choose for the next center (x, y, or z)?

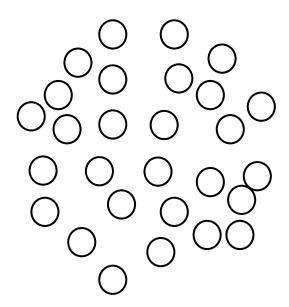


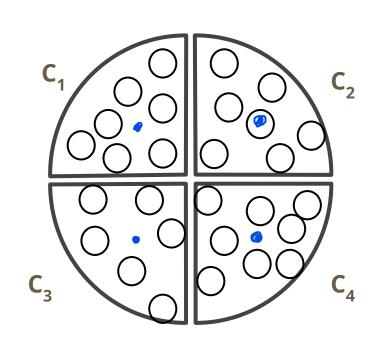
0

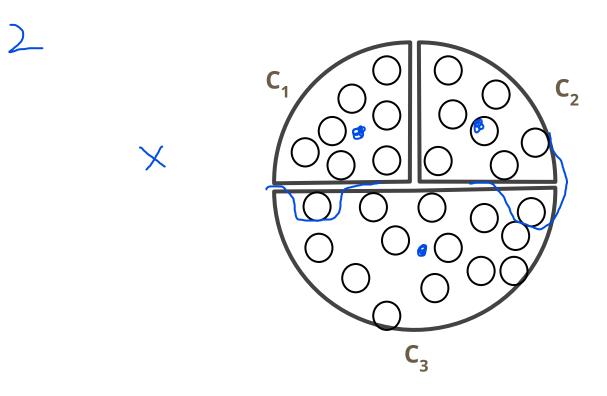
#### K-means++

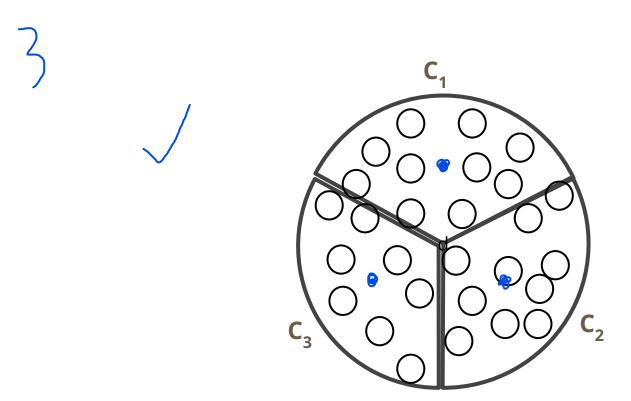
What happens if the black box can only generate numbers between 0 and 1?

# **Kmeans Quizz (take 2)**

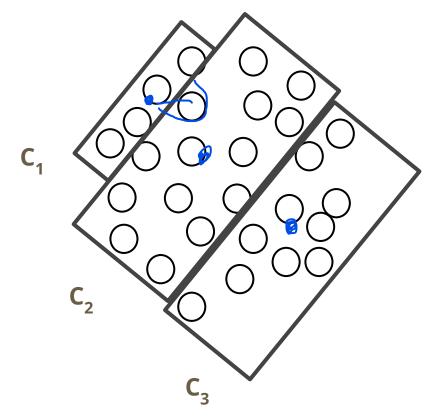


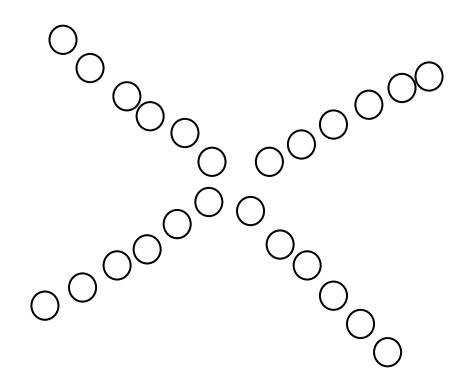




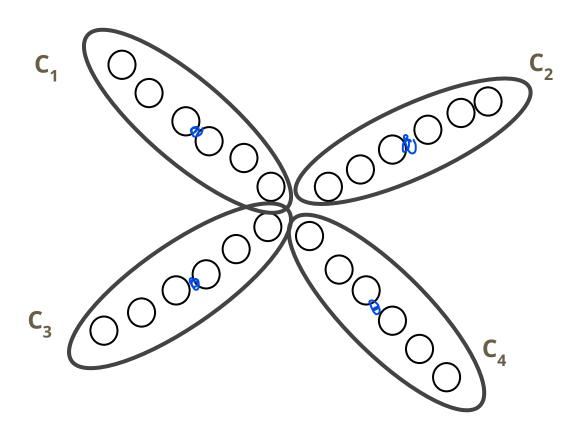


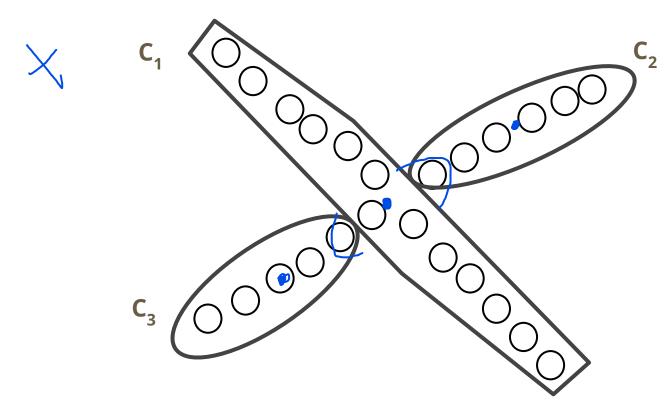


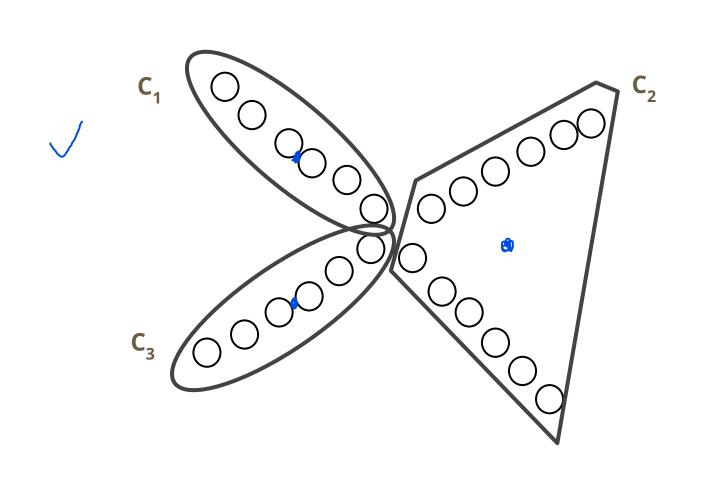


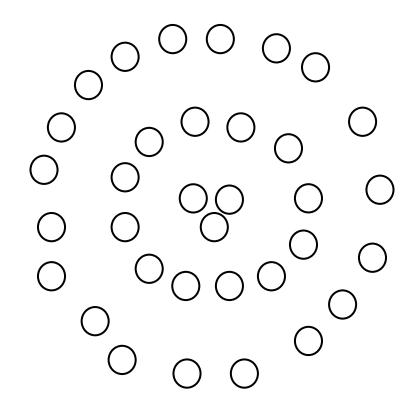






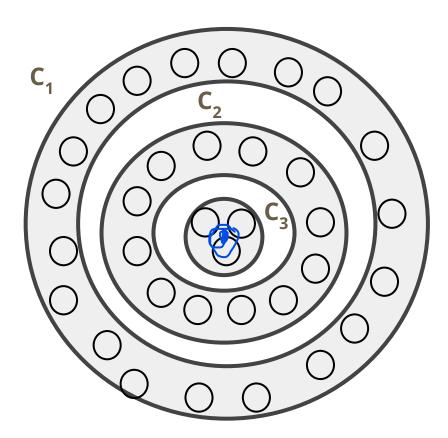


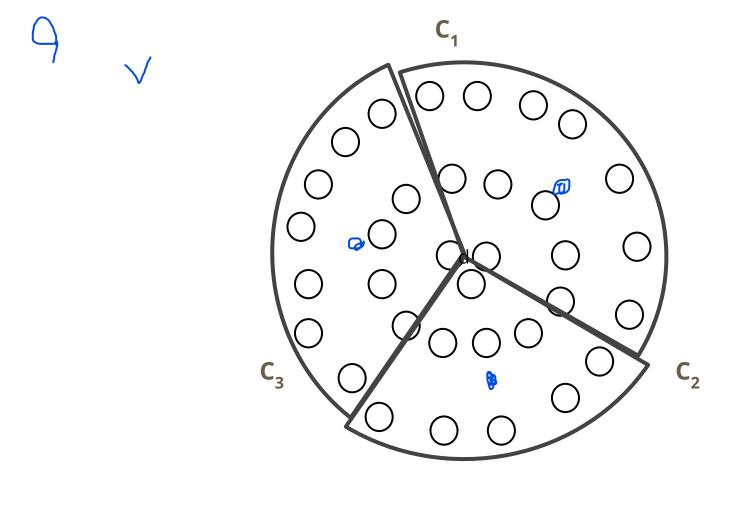


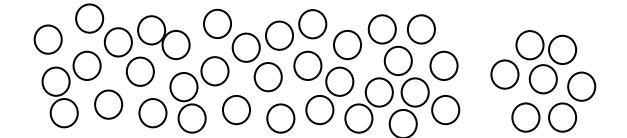




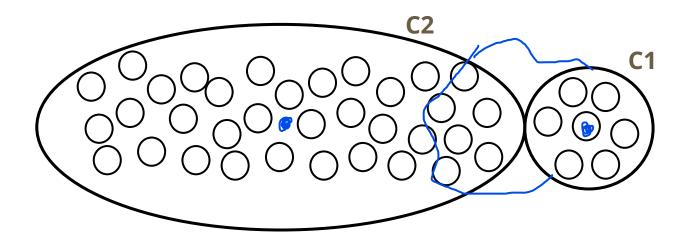






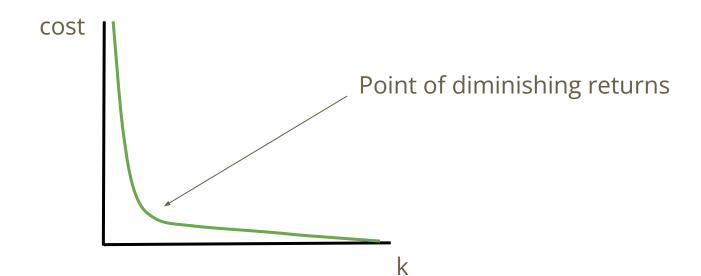


10 X



## How to choose the right k?

1. Iterate through different values of k (elbow method)



### How to choose the right k?

- 1. Iterate through different values of k (elbow method)
- 2. Use empirical / domain-specific knowledge Example: Is there a known approximate distribution of the data? (K-means is good for spherical gaussians)
- 3. Metric for evaluating a clustering output

#### **Evaluation**

Recall our goal: Find a clustering such that

- Similar data points are in the same cluster
- Dissimilar data points are in different clusters

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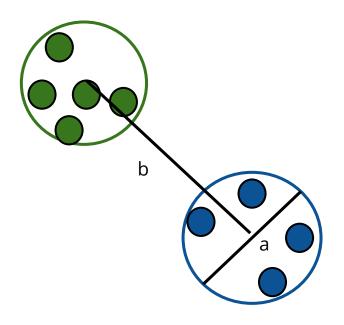
#### **Evaluation**

K-means cost function tells us the within-cluster distances between points will be small overall.

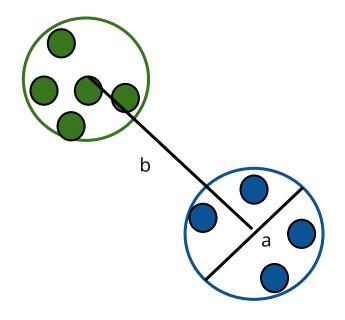
But what about the intra-cluster distance? Are the clusters we created far? How far? Relative to what?

#### **Discuss - 5min**

Define a metric that evaluates how spread out the clusters are from one another.



a: average within-cluster distance b: average intra-cluster distance inter

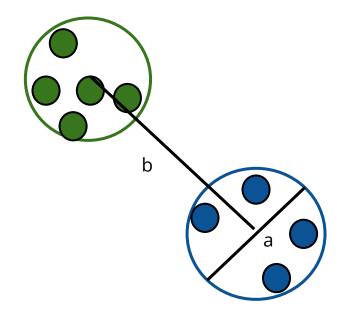


a: average within-cluster distance

b: average intra-cluster distance

What does it mean for (b - a) to be 0?

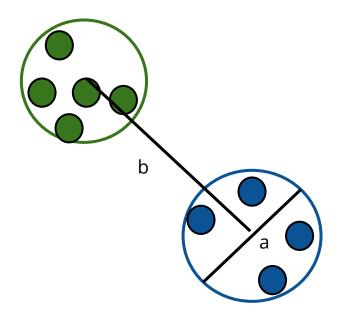
two clusters are next to each other.



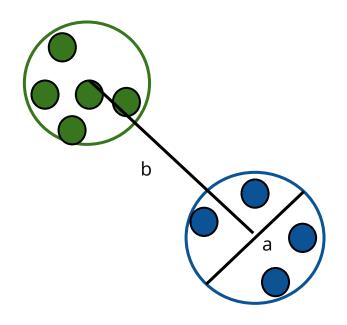
a: average within-cluster distance

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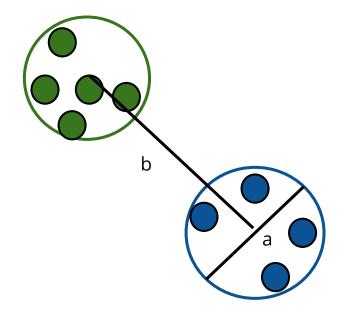
What does it mean for (b - a) to be large?



The value of (b-a) doesn't mean much by itself. Can we compare it to something so that the ratio becomes a value between 0 and 1?

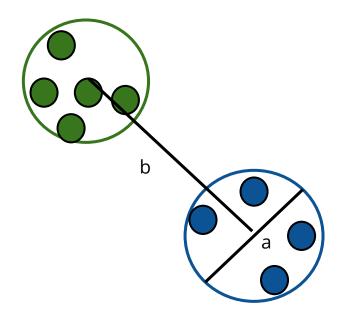


(b - a) / max(a, b)



What does it mean for (b - a) / max(a, b) to be close to 1?

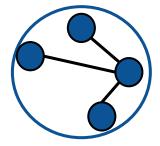
a is very small



What does it mean for (b - a) / max(a, b) to be close to 0?



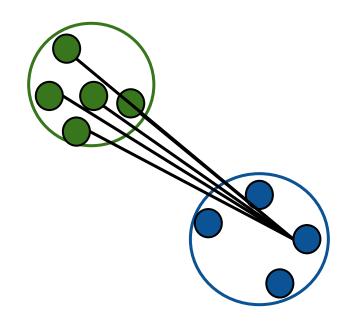
For each data point i: a<sub>i</sub>: mean distance from point i to every other point in its cluster



For each data point i:

a<sub>i</sub>: mean distance from point i to every other point in its cluster

b<sub>i</sub>: smallest mean distance from point i to every point in another cluster

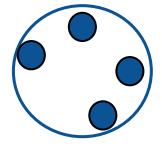




For each data point i:

a<sub>i</sub>: mean distance from point i to every other point in its cluster

b<sub>i</sub>: smallest mean distance from point i to every point in another cluster



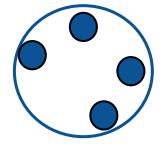
$$s_i = (b_i - a_i) / max(a_i, b_i)$$

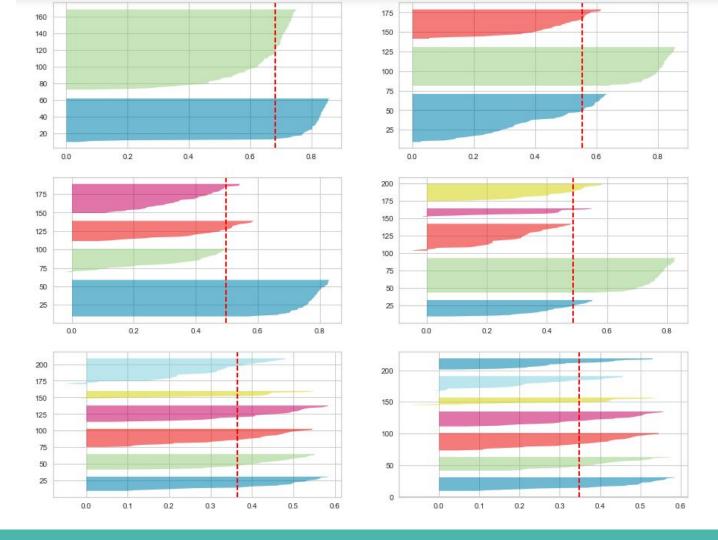


$$s_i = (b_i - a_i) / max(a_i, b_i)$$

Silhouette score plot

OR return the mean s<sub>i</sub> over the entire dataset as a measure of goodness of fit





#### **K-means Variations**

- 1. K-medians (uses the L₁ norm / manhattan distance)
- 2. K-medoids (any distance function + the centers must be in the dataset)
- 3. Weighted K-means (each point has a different weight when computing the mean)