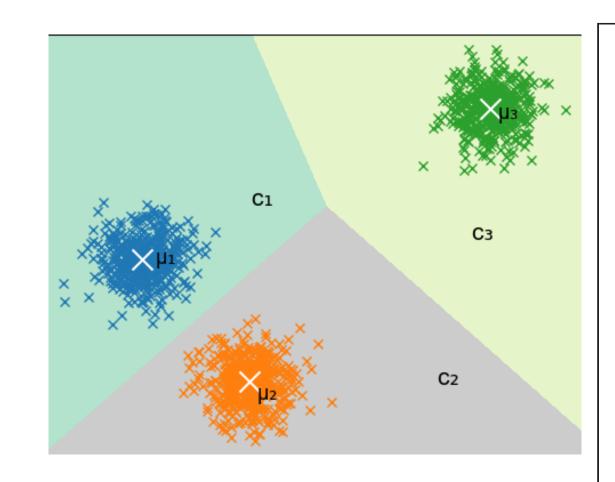
# Euclidean k-Means Clustering with $\alpha$ -Center Proximity

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# **PROBLEM**

k means:  $\min_{\mu_1,...,\mu_k} \sum_{i=1}^k \sum_{x \in C_i} ||x - \mu_i||^2$ .



 $\alpha$ -Center Proximal Clustering:  $\forall i \neq j, x \in C_i$ ,

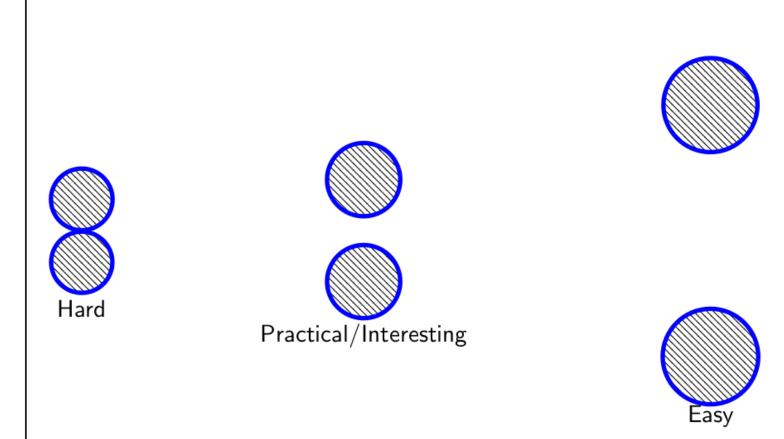
$$||x - \mu_j|| > \alpha ||x - \mu_i||$$

**Aim:** Given  $\alpha > 1$ , k, n points in  $\mathbb{R}^d$ , find the minimum cost  $\alpha$ -center proximal k-means clustering.

**Motivation:** Larger the value of  $\alpha$ , the more separated are the clusters. A way to get the "ground-truth" clustering.

## **MOTIVATION**

- Small *k*-means cost alone does not imply stable or meaningful clusters in practice.
- Real-world data have  $\alpha$  close to 1.
- Realistic model: most of the points satisfy  $\alpha$ -center proximal clustering, except a small fraction.



Intuition of  $\alpha$ -center proximal instances

# **OUR RESULTS**

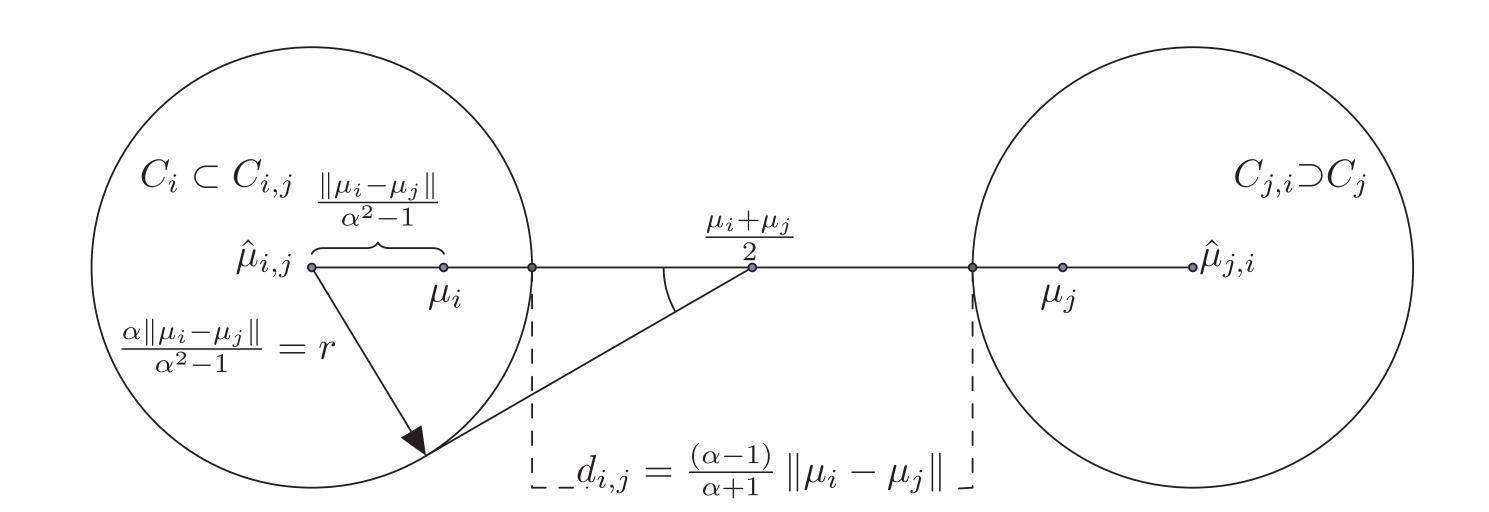
**Best known:** For  $\alpha \geq 2$ , [AMM'17] can find the  $\alpha$ -center proximal clustering in polynomial time.

## **Our Results:**

- 1. **Algorithmic:** If the  $\alpha$ -center proximal clustering of the minimum k-means cost has  $\omega$ -balanced clusters, then our algorithm outputs the minimum cost  $\alpha$ -center proximal clustering with a constant probability in time  $O(nd2^{\text{poly}(k/\omega(\alpha-1))})$ , where  $\omega$  is a balance parameter. This holds for *any* value of  $\alpha > 1$ . We can also handle some class of outliers.
- 2. **Hardness:** There exists a value of  $\alpha$  and  $\varepsilon_0 > 0$  such that it is NP-hard to approximate minimum k-means cost  $\omega$ -balanced  $\alpha$ -center proximal clustering within a factor of  $(1 + \varepsilon_0)$ . The value of k depends on n in the construction.

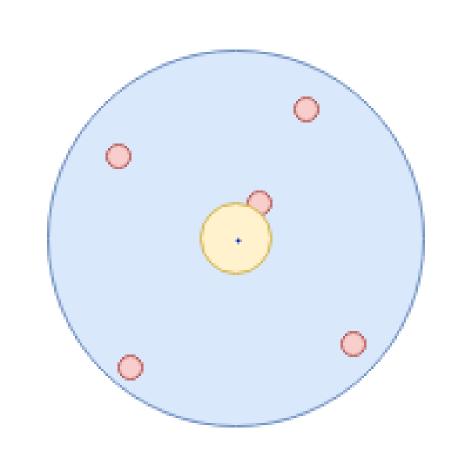
### GEOMETRY

This holds for all pairs of  $\alpha$ -center proximal clusters. The geometric property was also noted by [TV'10].



# MAIN IDEA

**Approximate Caratheodory Theorem:** Sample points uniformly at random from a cluster of bounded radius. Mean of the sample is close to the cluster mean.



**Idea:** We can approximate mean of a cluster up to an additive error of  $\frac{d_{i,j}}{2}$ , and still recover the exact clustering!

# **OUTLIERS**

**Model:** Let Z denote the set of outliers, and |Z| is known to us. We assume that the set of outliers satisfy the following property. For all  $i, j \in [k]$ ,  $x \in C_i$ , and  $z \in Z$ 

$$||z - \mu_j|| > \alpha ||x - \mu_i||.$$

**Idea:** Since outliers are "far-away", and |Z| is known, we can sample sufficient number of points based on  $\omega$  and |Z|, and get close to the means of each cluster. We use means to get the clusters and then remove the farthest |Z| points.

### **ALGORITHM AND ANALYSIS**

## Algorithm:

- 1: Sample poly  $\left(\frac{1}{\omega}, k, \frac{\alpha}{(\alpha 1)^2}\right)$  points uniformly at random.  $\triangleright$  this ensures sufficient points from all clusters
- 2: Go over all the k partitions of these points (k+1) in case of outliers).  $\triangleright$  at least one of the partitions corresponds to desired clustering
- 3: Assign all points to nearest center, and output clustering which is α-center proximal with lowest k-means cost.
  ▷ one of the clusterings will be the desired clustering due to the approximate Caratheodory theorem

**Runtime:** Step 3 takes time O(nd) for each clustering. Step 2 produces  $2^{\text{poly}\left(\frac{1}{\omega},k,\frac{\alpha}{(\alpha-1)^2}\right)}$  number of clusterings. Therefore, the total running time is  $O(nd2^{\text{poly}(k/\omega(\alpha-1))})$ .

## HARDNESS

- 1. [ACKS'15] showed hardness of approximation of Euclidean k-means clustering using reduction from the vertex cover problem on triangle-free graphs.
- 2. We show that the instance given by [ACKS'15] is  $\alpha$ -center proximal.

#### REFERENCES

[ACKS'15] Pranjal Awasthi and Moses Charikar and Ravishankar Krishnaswamy and Ali Kemal Sinop. The Hardness of Approximation of Euclidean *k*-Means. *SoCG*, 2015.

[AMM'17] Haris Angelidakis and Konstantin Makarychev and Yury Makarychev. Algorithms for Stable and Perturbation-Resilient Problems. *STOC*, 2017.

[TV'10] Matus Telgarsky and Andrea Vattani. Hartigan's Method: *k*-means Clustering without Voronoi. *AISTATS*, 2010.