

# Clustering.

## Unsupervised Learning

Maria-Florina Balcan

04/06/2015

### Reading:

- Chapter 14.3: Hastie, Tibshirani, Friedman.

### Additional resources:

- Center Based Clustering: A Foundational Perspective.  
Awasthi, Balcan. Handbook of Clustering Analysis. 2015.

# Clustering, Informal Goals

**Goal:** Automatically partition **unlabeled** data into groups of similar datapoints.

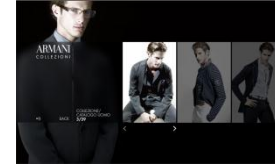
**Question:** When and why would we want to do this?

**Useful for:**

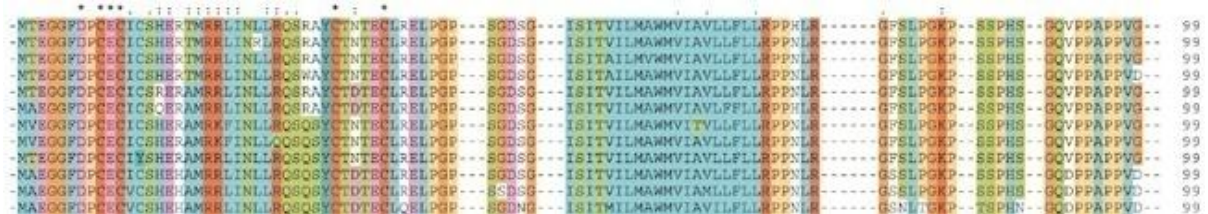
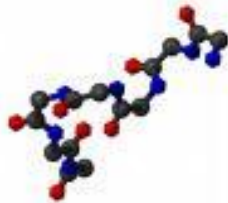
- Automatically organizing data.
- Understanding hidden structure in data.
- Preprocessing for further analysis.
  - Representing high-dimensional data in a low-dimensional space (e.g., for visualization purposes).

# Applications (Clustering comes up everywhere...)

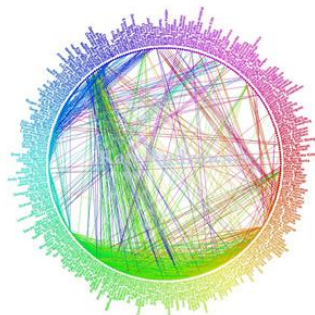
- Cluster news articles or web pages or search results by topic.



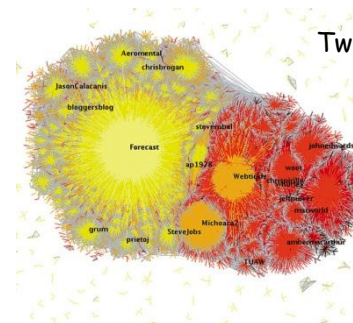
- Cluster protein sequences by function or genes according to expression profile.



- Cluster users of social networks by interest (community detection).



Facebook network



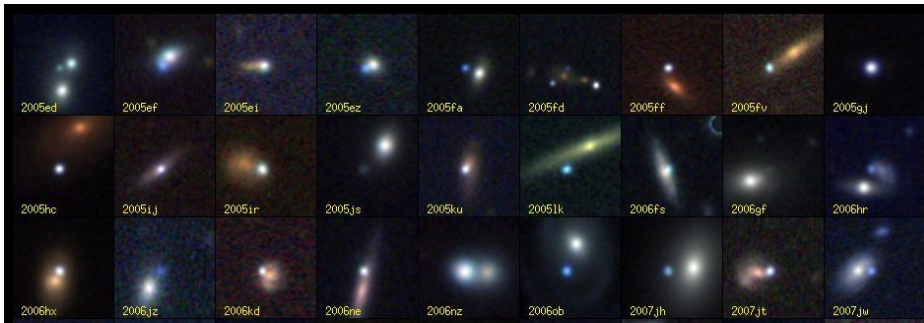
Twitter Network

# Applications (clustering comes up everywhere...)

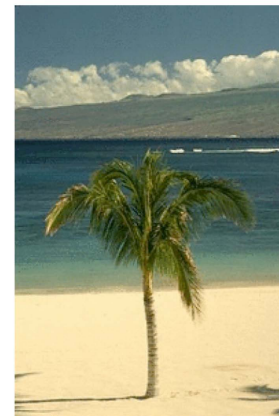
- Cluster customers according to purchase history.



- Cluster galaxies or nearby stars (e.g. Sloan Digital Sky Survey)



- Image segmentation (clustering pixels)



# Clustering

## Today:

- Objective based clustering
- Hierarchical clustering
- Mention overlapping clusters

[March 4<sup>th</sup>: EM-style algorithm for clustering for mixture of Gaussians (specific probabilistic model).]

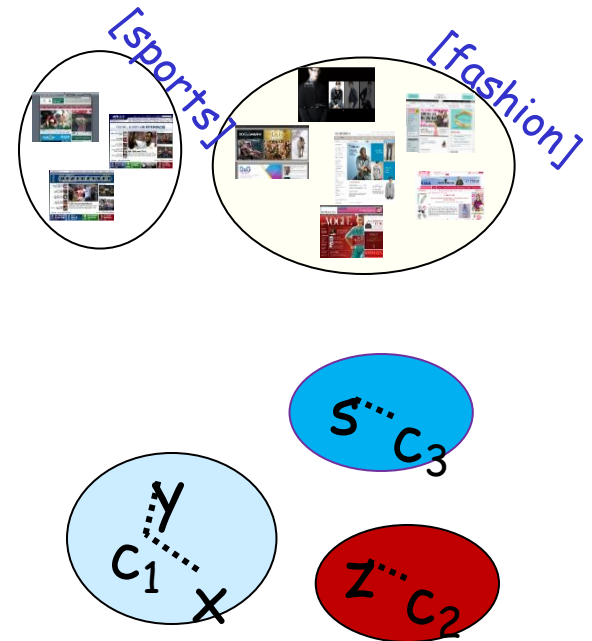
# Objective Based Clustering

**Input:** A set  $S$  of  $n$  points, also a **distance/dissimilarity** measure specifying the distance  $d(x,y)$  between pairs  $(x,y)$ .

E.g., # keywords in common, edit distance, wavelets coef., etc.

**Goal:** output a **partition of the data**.

- **k-means:** find center pts  $c_1, c_2, \dots, c_k$  to  
minimize  $\sum_{i=1}^n \min_{j \in \{1, \dots, k\}} d^2(x^i, c_j)$
- **k-median:** find center pts  $c_1, c_2, \dots, c_k$  to  
minimize  $\sum_{i=1}^n \min_{j \in \{1, \dots, k\}} d(x^i, c_j)$
- **K-center:** find partition to minimize the maxim radius



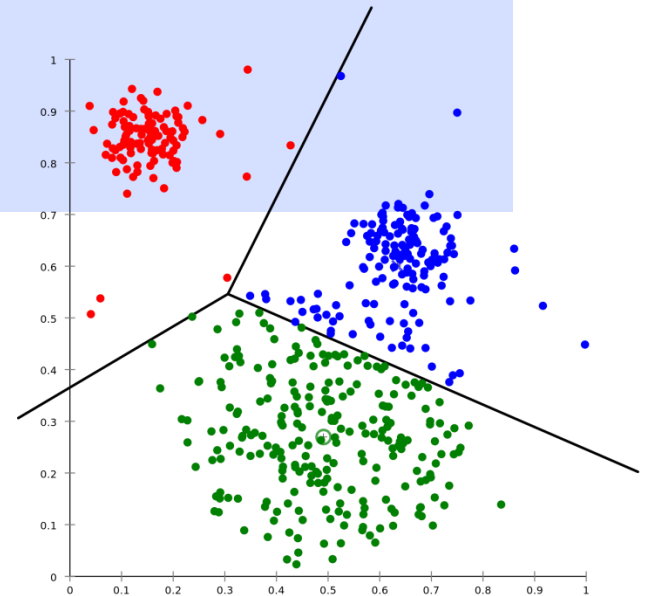
# Euclidean k-means Clustering

**Input:** A set of  $n$  datapoints  $\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^n$  in  $\mathbb{R}^d$   
target #clusters  $k$

**Output:**  $k$  representatives  $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k \in \mathbb{R}^d$

**Objective:** choose  $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k \in \mathbb{R}^d$  to minimize

$$\sum_{i=1}^n \min_{j \in \{1, \dots, k\}} \left\| \mathbf{x}^i - \mathbf{c}_j \right\|^2$$



# Euclidean k-means Clustering

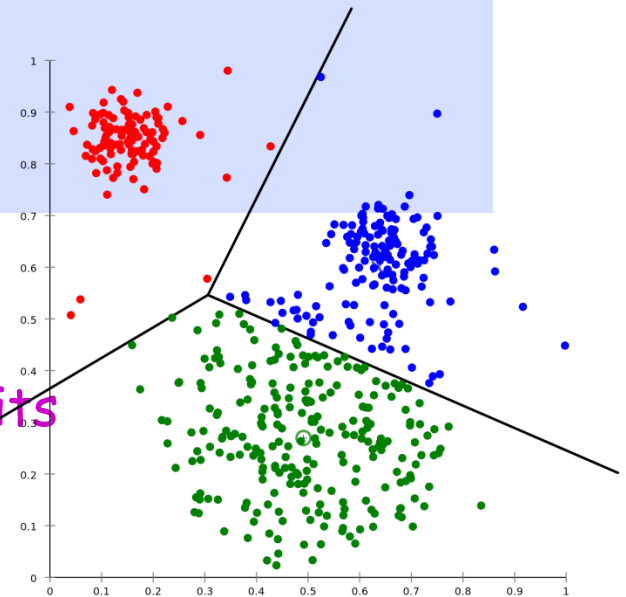
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$$\sum_{i=1}^n \min_{j \in \{1, \dots, k\}} \|\mathbf{x}^i - \mathbf{c}_j\|^2$$

Natural assignment: each point assigned to its  
closest center, leads to a Voronoi partition.





# Euclidean k-means Clustering

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**Computational complexity:**

NP hard: even for  $k = 2$  [Dagupta'08] or  
 $d = 2$  [Mahajan-Nimbhorkar-Varadarajan09]

**There are a couple of easy cases...**



# An Easy Case for k-means: $k=1$

**Input:** A set of  $n$  datapoints  $\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^n$  in  $\mathbb{R}^d$

**Output:**  $\mathbf{c} \in \mathbb{R}^d$  to minimize  $\sum_{i=1}^n \left\| \mathbf{x}^i - \mathbf{c} \right\|^2$

**Solution:** The optimal choice is  $\boldsymbol{\mu} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}^i$

Idea: bias/variance like decomposition

$$\frac{1}{n} \sum_{i=1}^n \left\| \mathbf{x}^i - \mathbf{c} \right\|^2 = \left\| \boldsymbol{\mu} - \mathbf{c} \right\|^2 + \frac{1}{n} \sum_{i=1}^n \left\| \mathbf{x}^i - \boldsymbol{\mu} \right\|^2$$

Avg k-means cost wrt  $\mathbf{c}$

Avg k-means cost wrt  $\boldsymbol{\mu}$

**Quiz**

So, the optimal choice for  $\mathbf{c}$  is  $\boldsymbol{\mu}$ .

# Common Heuristic in Practice: The Lloyd's method

[Least squares quantization in PCM, Lloyd, IEEE Transactions on Information Theory, 1982]

**Input:** A set of  $n$  datapoints  $\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^n$  in  $\mathbb{R}^d$

**Initialize** centers  $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k \in \mathbb{R}^d$  and  
clusters  $C_1, C_2, \dots, C_k$  in any way.

**Repeat** until there is no further change in the cost.

- For each  $j$ :  $C_j \leftarrow \{x \in S \text{ whose closest center is } \mathbf{c}_j\}$
- For each  $j$ :  $\mathbf{c}_j \leftarrow \text{mean of } C_j$

# Common Heuristic in Practice: The Lloyd's method

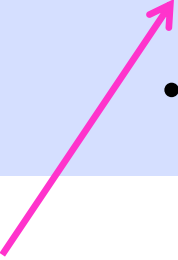
[Least squares quantization in PCM, Lloyd, IEEE Transactions on Information Theory, 1982]

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Holding  $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k$  fixed,  
pick optimal  $C_1, C_2, \dots, C_k$



Holding  $C_1, C_2, \dots, C_k$  fixed,  
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# Common Heuristic: The Lloyd's method

**Input:** A set of  $n$  datapoints  $\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^n$  in  $\mathbb{R}^d$

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**Note:** it always converges.

- the cost always drops and
- there is only a finite #s of Voronoi partitions  
(so a finite # of values the cost could take)

# Common Heuristic: The Lloyd's method

# Initialization for the Lloyd's method

**Input:** A set of  $n$  datapoints  $\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^n$  in  $\mathbb{R}^d$

**Initialize** centers  $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_k \in \mathbb{R}^d$  and  
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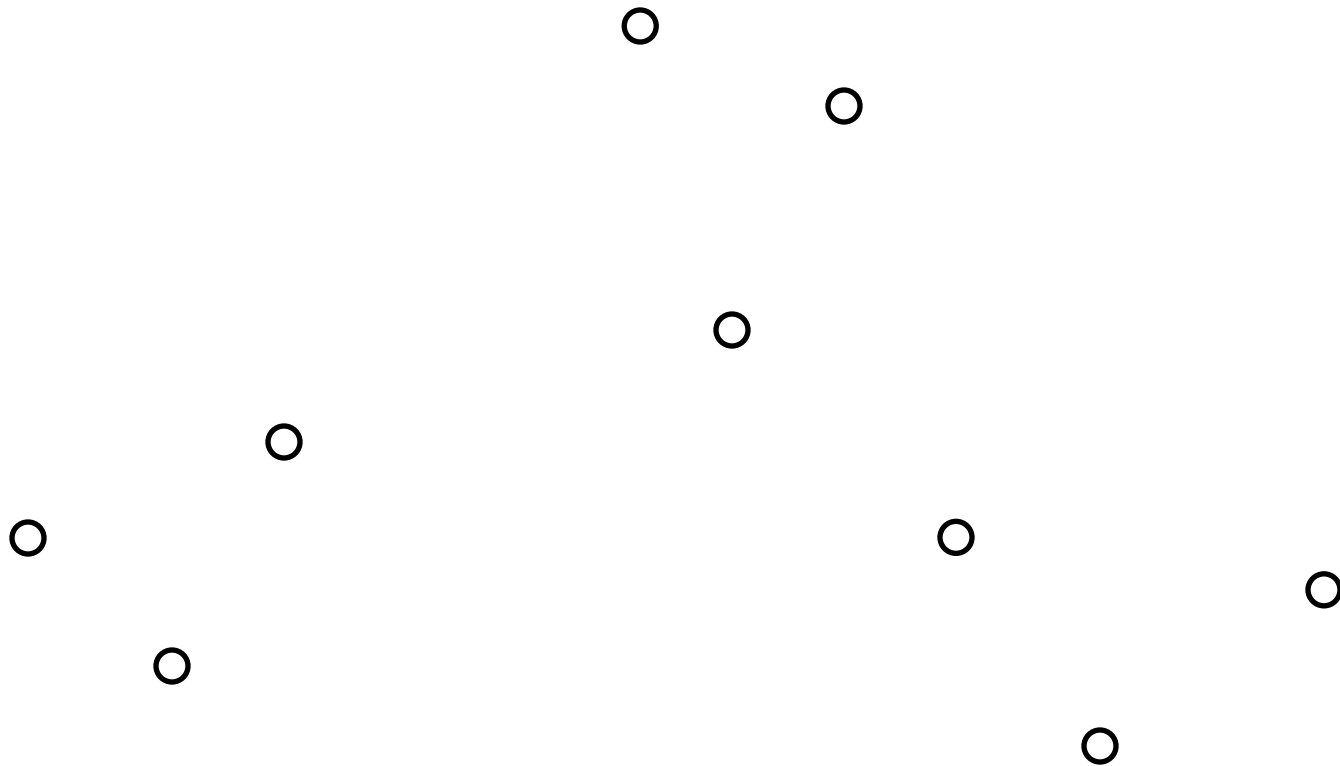
- **Initialization is crucial** (how fast it converges, quality of solution output)
- Discuss techniques commonly used in practice
  - Random centers from the datapoints (repeat a few times)
  - Furthest traversal
  - K-means ++ (works well and has provable guarantees)



Lloyd's method: Random Initialization

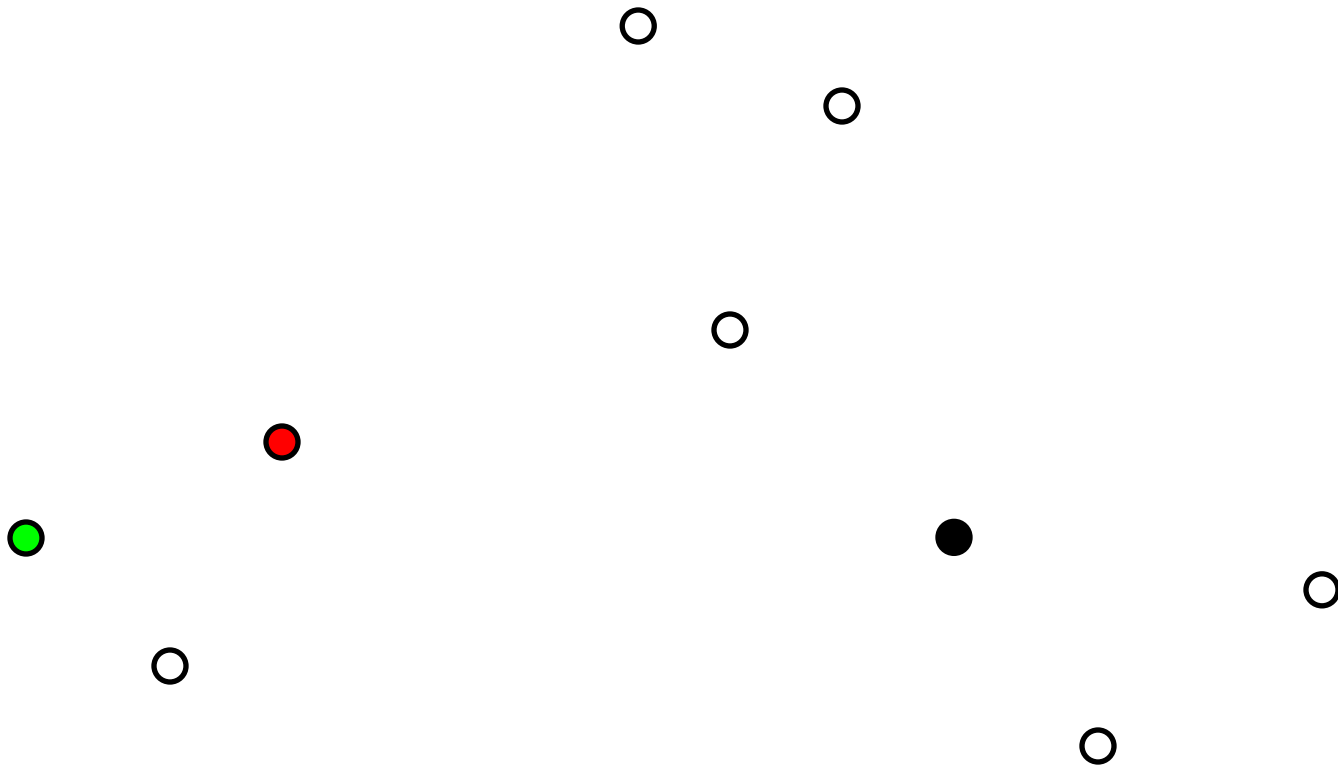
# Lloyd's method: Random Initialization

Example: Given a set of datapoints



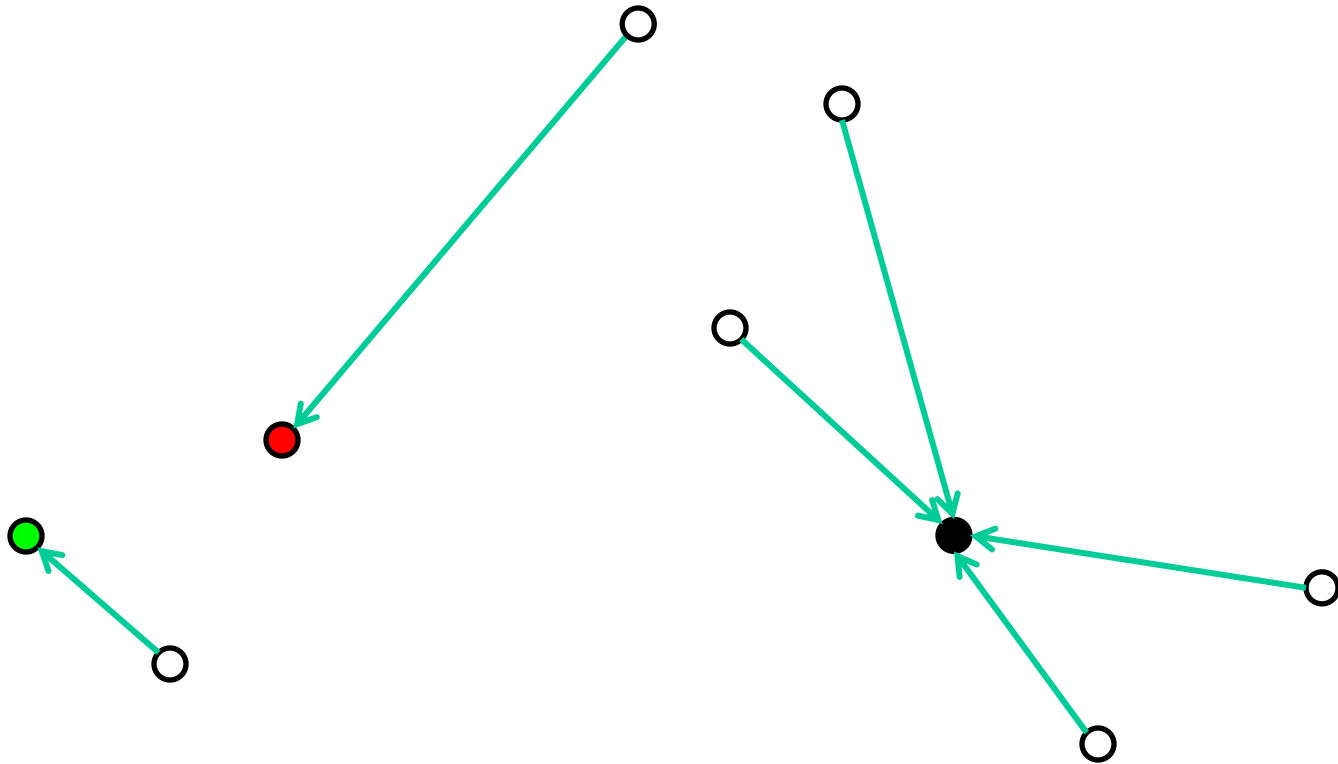
# Lloyd's method: Random Initialization

Select initial centers at random



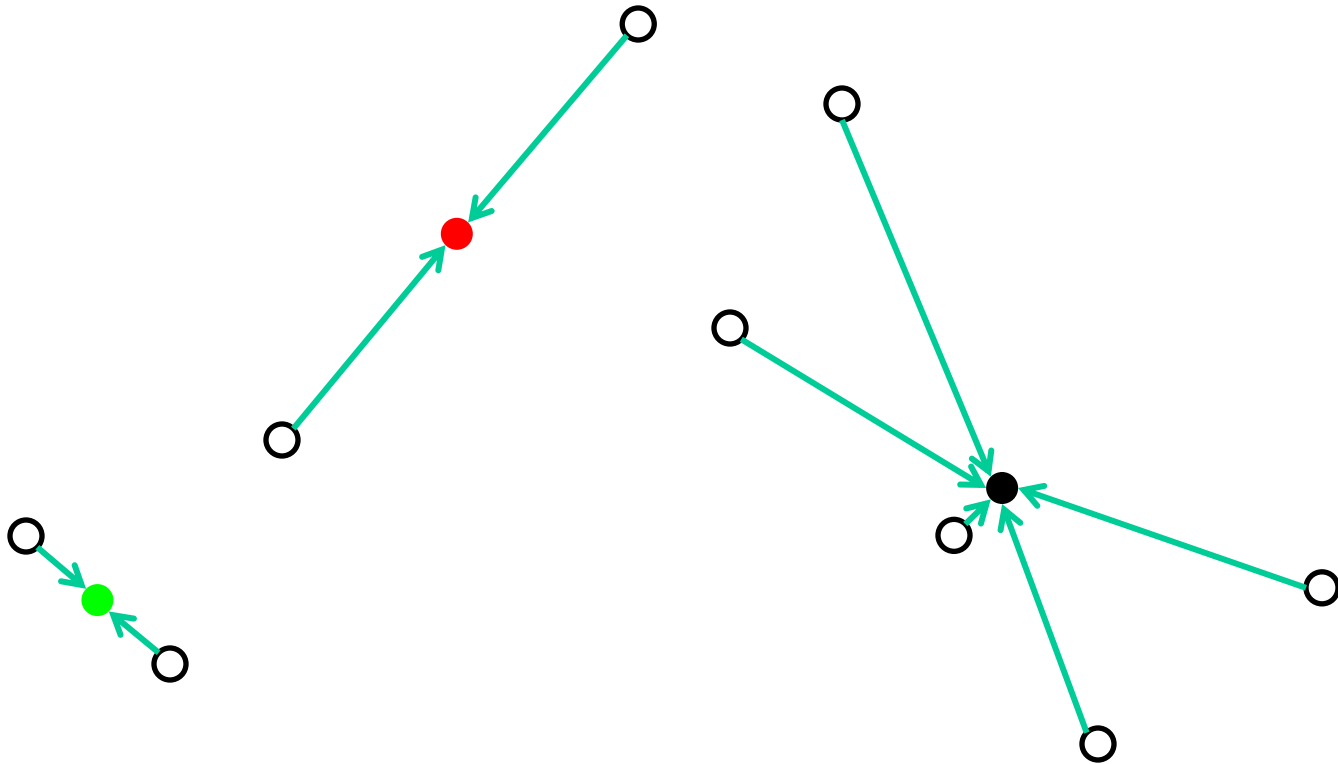
# Lloyd's method: Random Initialization

Assign each point to its nearest center



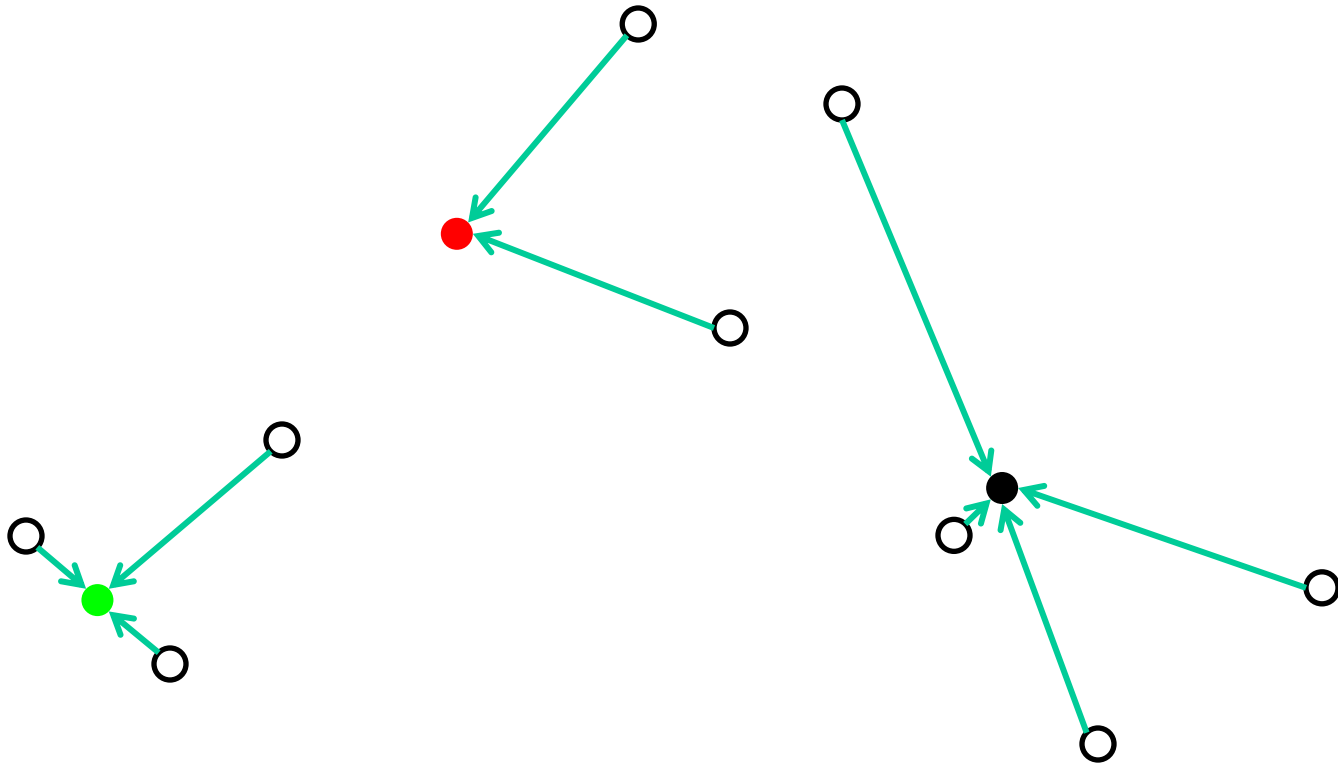
# Lloyd's method: Random Initialization

Recompute optimal centers given a fixed clustering



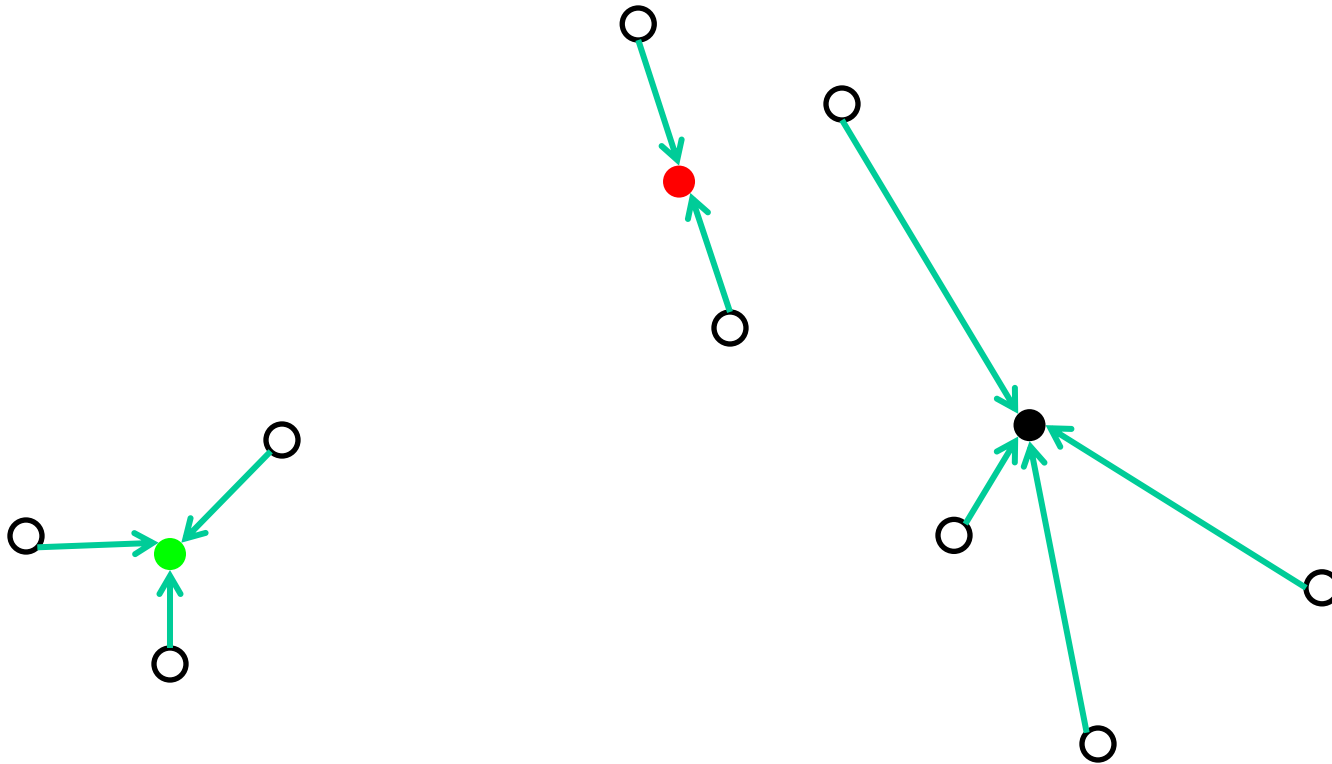
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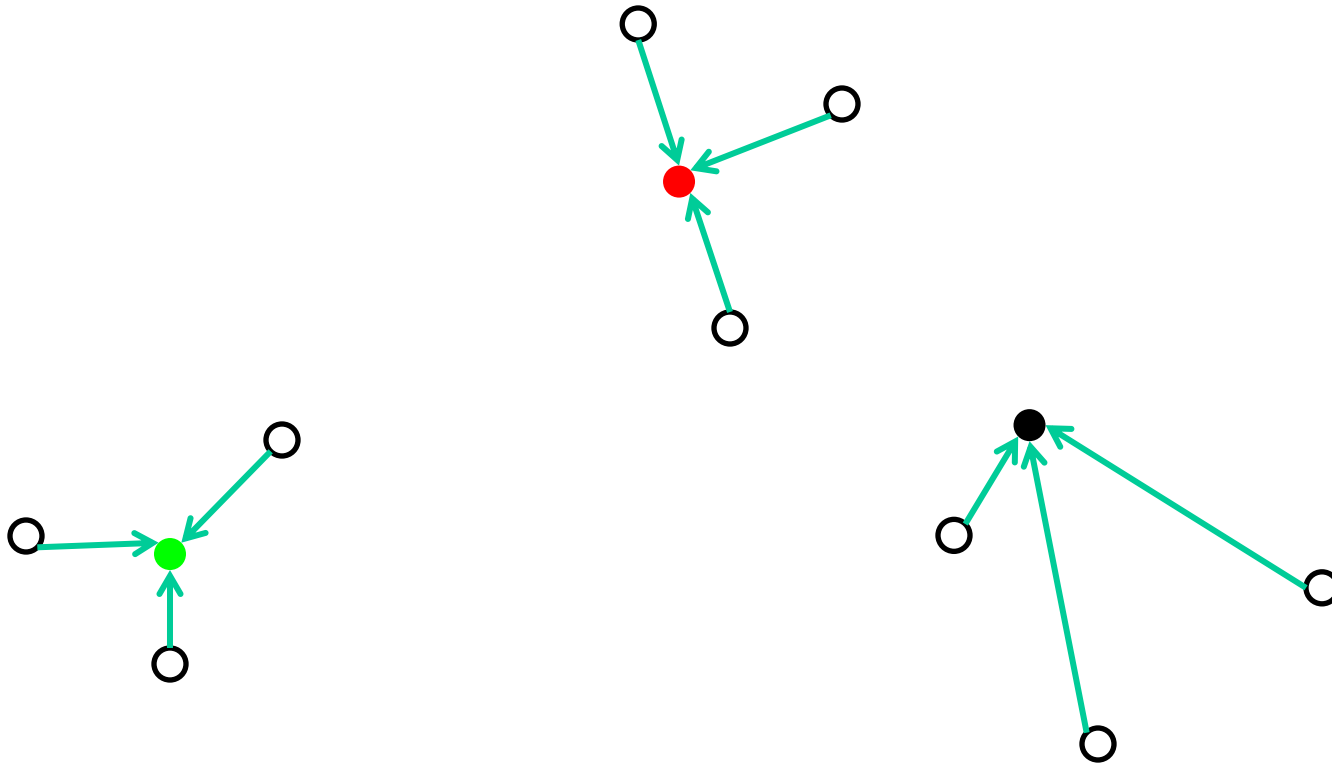
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# Lloyd's method: Random Initialization

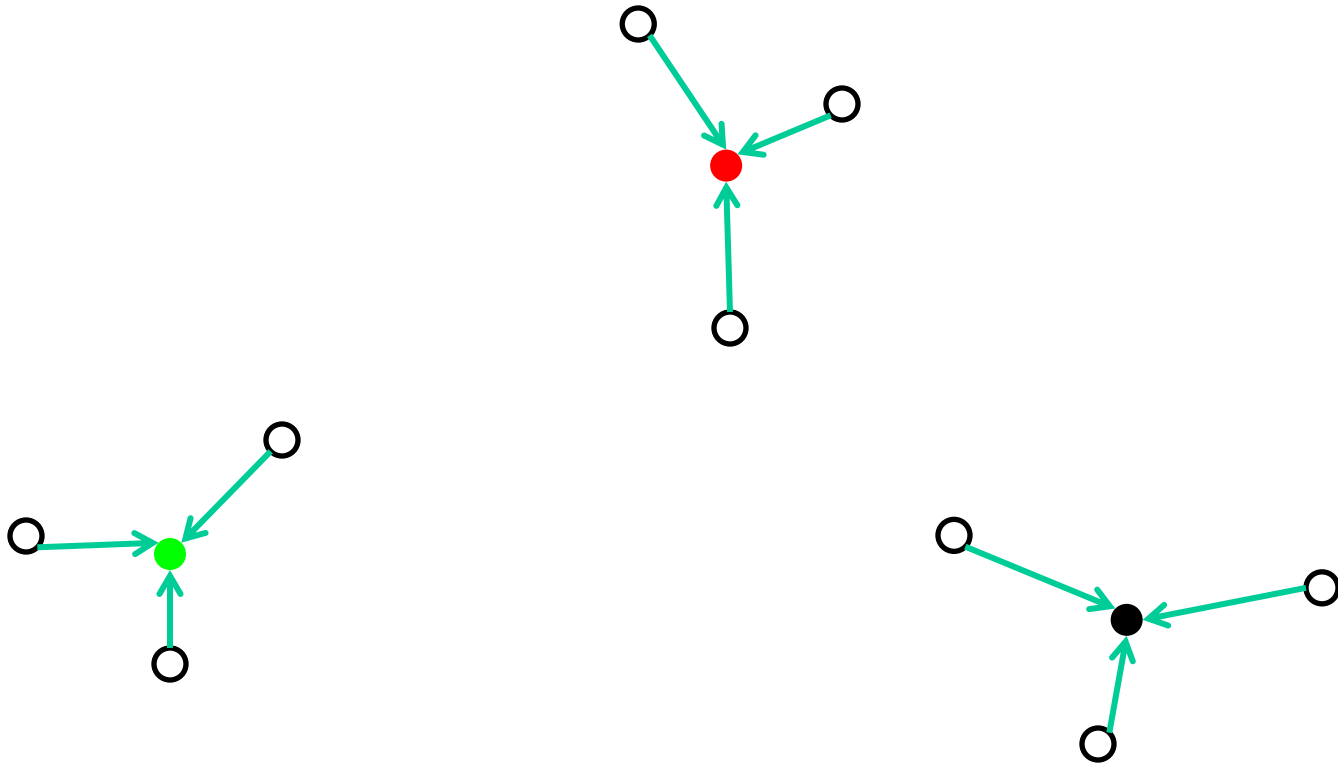
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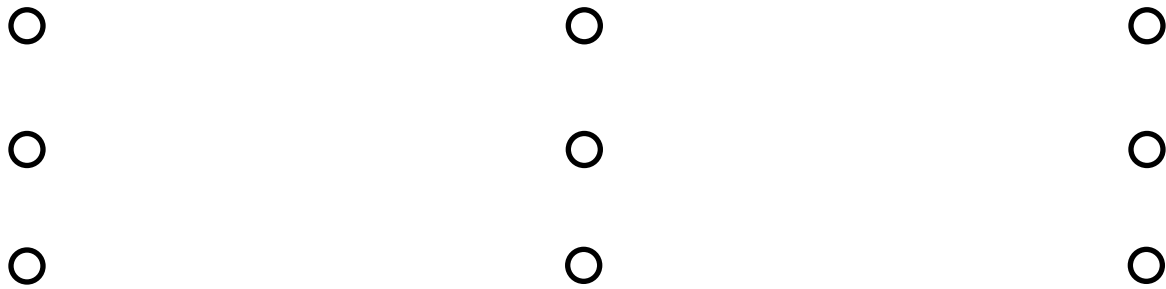
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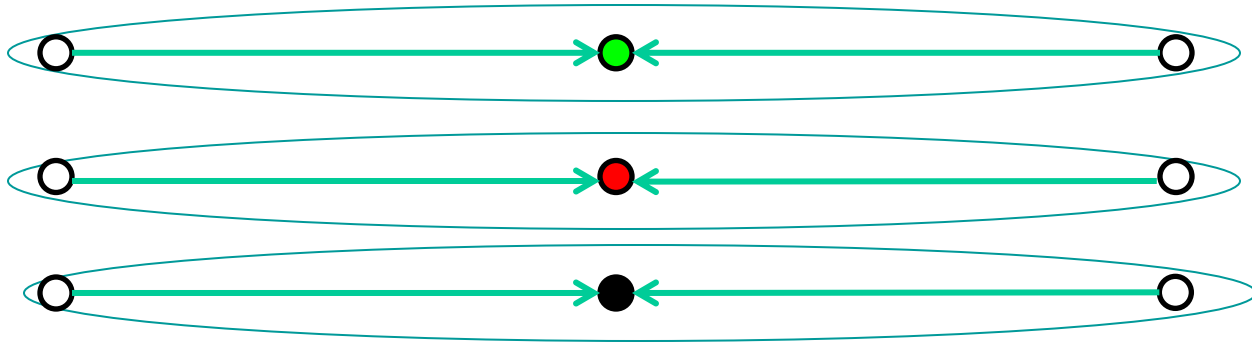
Get a good quality solution in this example.

# Lloyd's method: Performance



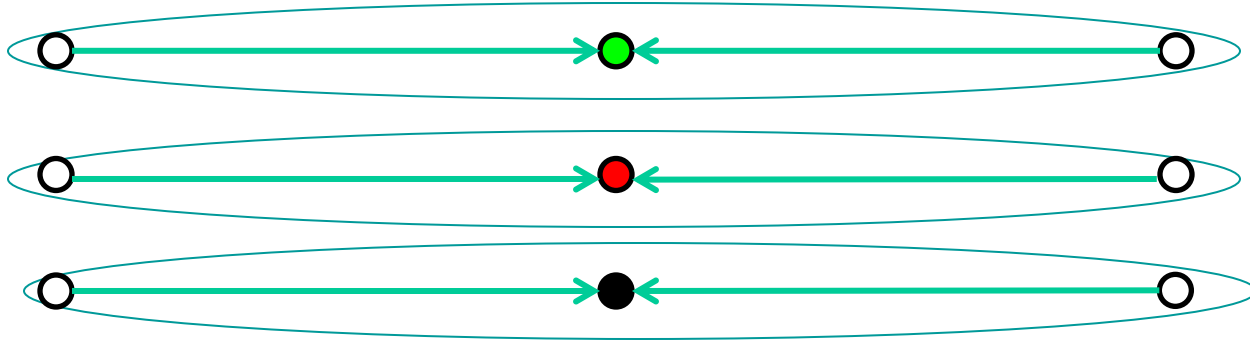
It always converges, but it may converge at a local optimum that is different from the global optimum, and in fact could be arbitrarily worse in terms of its score.

# Lloyd's method: Performance

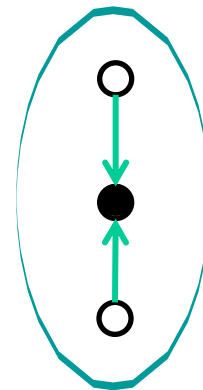
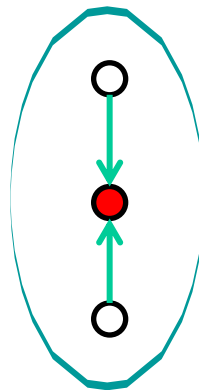
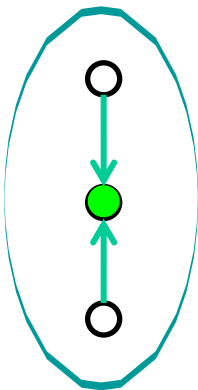


Local optimum: every point is assigned to its nearest center and every center is the mean value of its points.

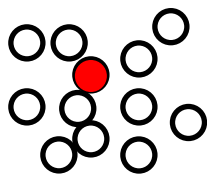
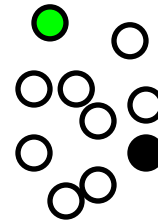
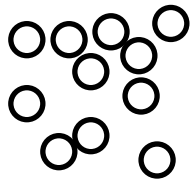
# Lloyd's method: Performance



.It is arbitrarily worse than optimum solution.... 🤔

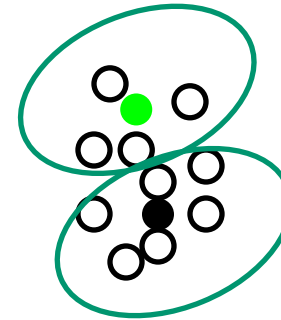
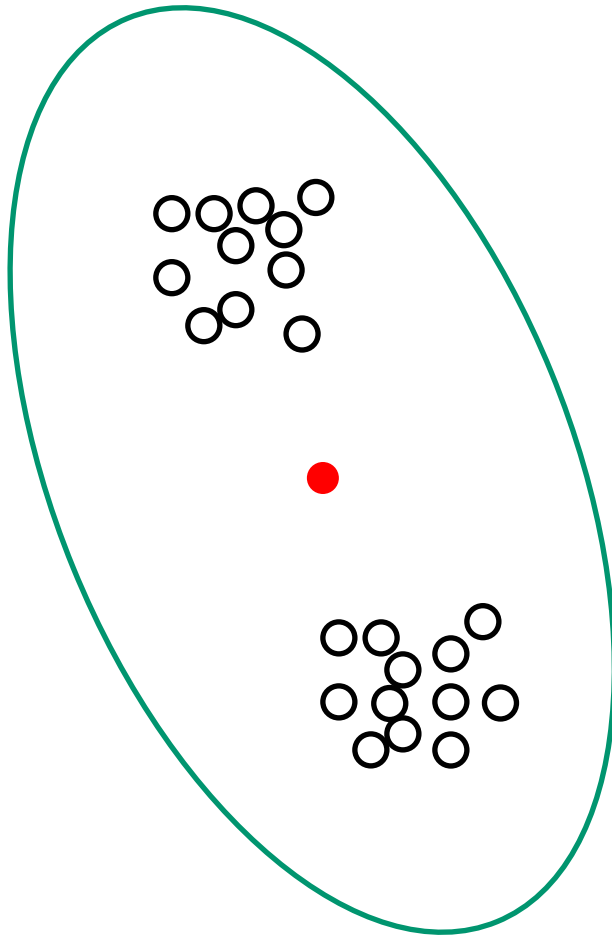


# Lloyd's method: Performance



This bad performance, can happen even with well separated Gaussian clusters.

# Lloyd's method: Performance



This bad performance, can happen even with well separated Gaussian clusters.

Some Gaussian are combined.....



# Lloyd's method: Performance

- If we do random initialization, as  $k$  increases, it becomes more likely we won't have perfectly picked one center per Gaussian in our initialization (so Lloyd's method will output a bad solution).
  - For  $k$  equal-sized Gaussians,  $\Pr[\text{each initial center is in a different Gaussian}] \approx \frac{k!}{k^k} \approx \frac{1}{e^k}$
  - Becomes unlikely as  $k$  gets large.

# Another Initialization Idea: Furthest Point Heuristic

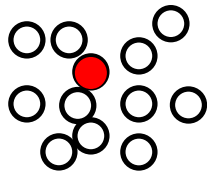
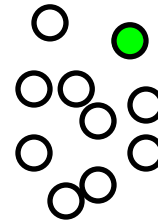
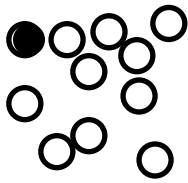
Choose  $\mathbf{c}_1$  arbitrarily (or at random).

- For  $j = 2, \dots, k$ 
  - Pick  $\mathbf{c}_j$  among datapoints  $\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^d$  that is farthest from previously chosen  $\mathbf{c}_1, \mathbf{c}_2, \dots, \mathbf{c}_{j-1}$

Fixes the Gaussian problem. But it can be thrown off by outliers....

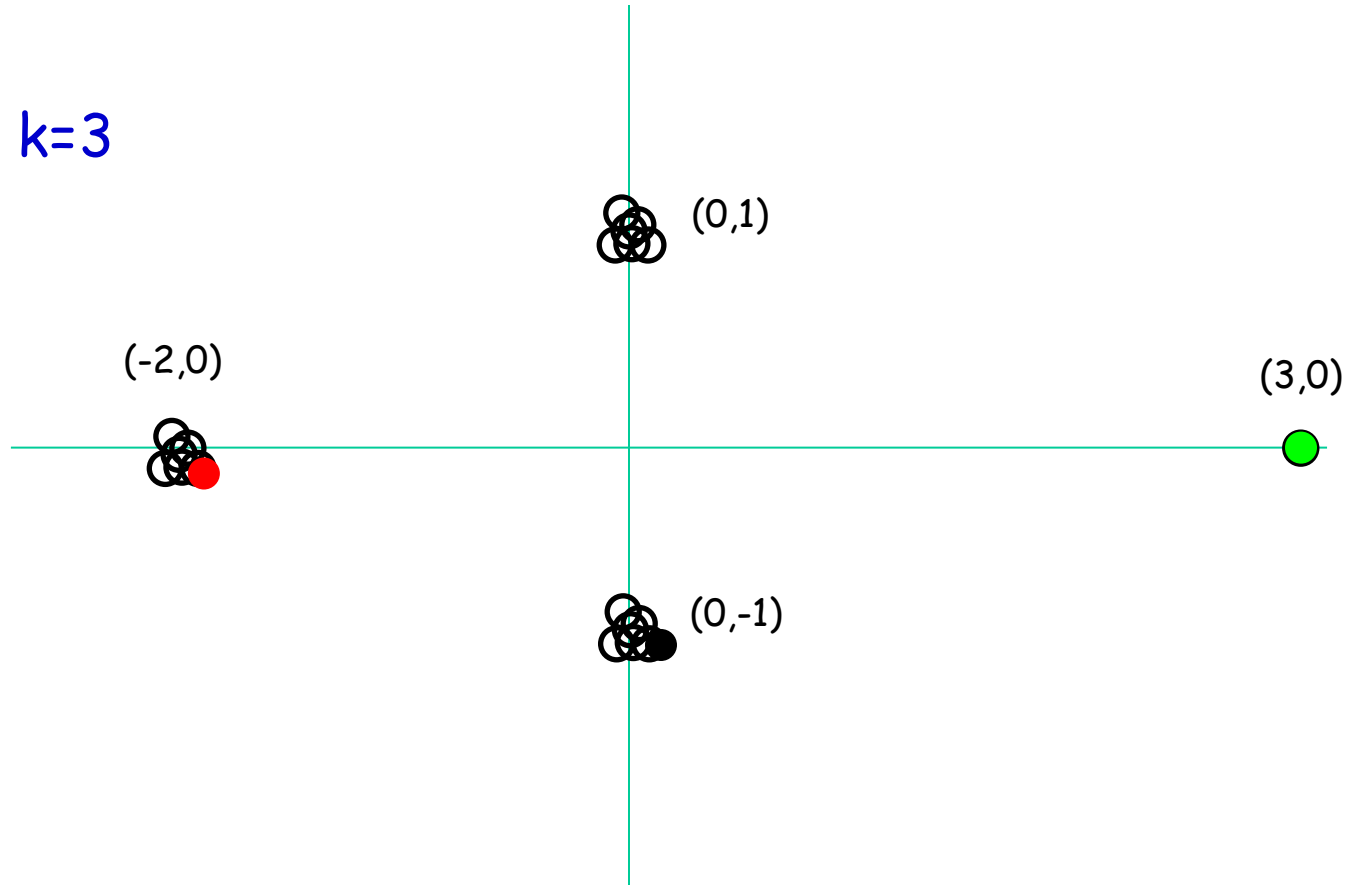


Furthest point heuristic does well on  
previous example



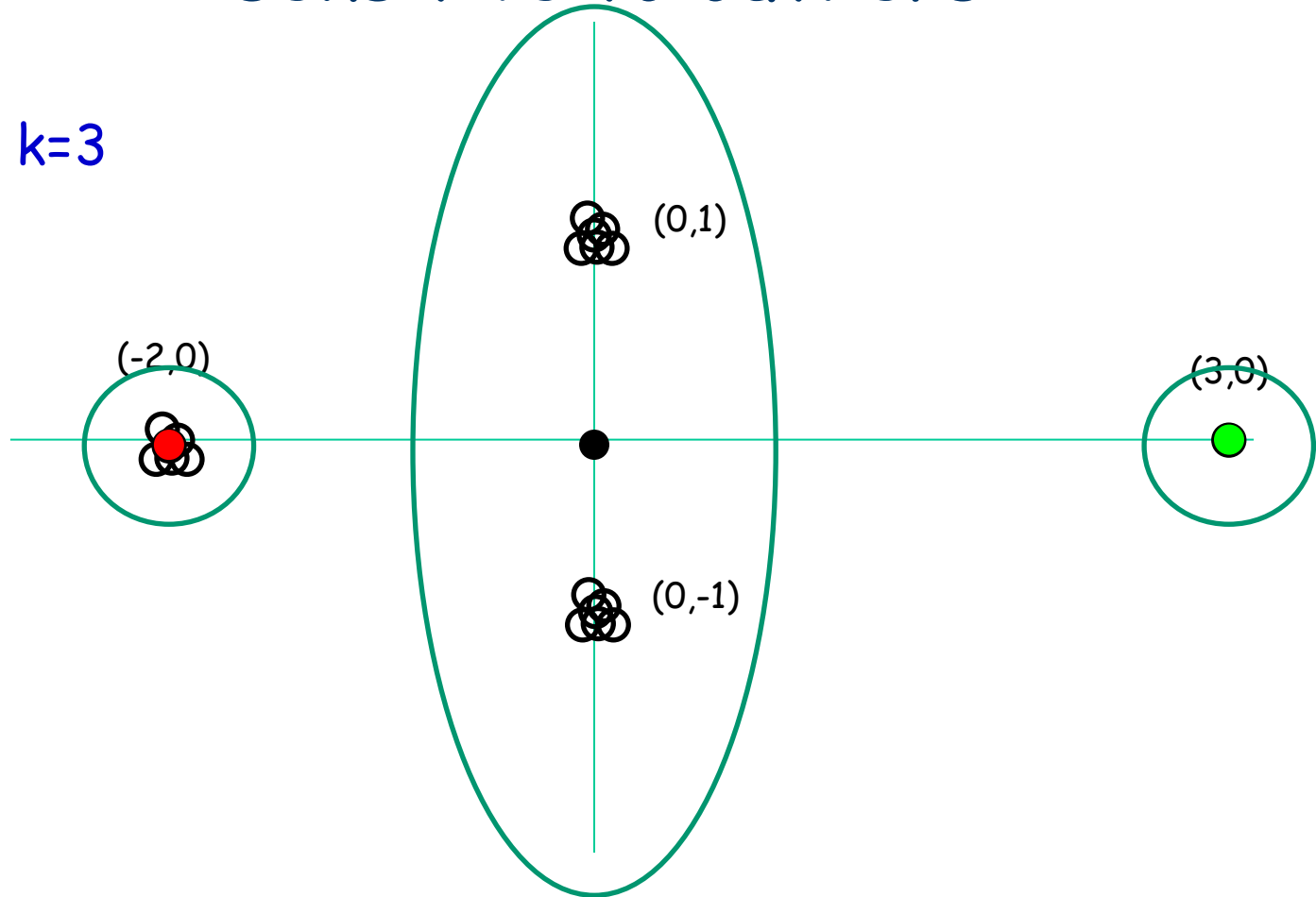
# Furthest point initialization heuristic sensitive to outliers

Assume  $k=3$



# Furthest point initialization heuristic sensitive to outliers

Assume  $k=3$



# K-means++ Initialization: $D^2$ sampling [AV07]

- Interpolate between random and furthest point initialization
- Let  $D(x)$  be the distance between a point  $x$  and its nearest center. Chose the next center proportional to  $D^2(x)$ .

- Choose  $c_1$  at random.
- For  $j = 2, \dots, k$ 
  - Pick  $c_j$  among  $x^1, x^2, \dots, x^n$  according to the distribution

$$\Pr(c_j = x^i) \propto \min_{j' < j} \|x^i - c_{j'}\|^2 D^2(x^i)$$

**Theorem:** K-means++ always attains an  $O(\log k)$  approximation to optimal k-means solution in expectation.

Running Lloyd's can only further improve the cost.

# K-means++ Idea: $D^2$ sampling

- Interpolate between random and furthest point initialization
- Let  $D(x)$  be the distance between a point  $x$  and its nearest center. Chose the next center proportional to  $D^\alpha(x)$ .
- $\alpha = 0$ , random sampling
- $\alpha = \infty$ , furthest point (Side note: it actually works well for k-center)
- $\alpha = 2$ , k-means++

Side note:  $\alpha = 1$ , works well for k-median

# K-means ++ Fix



# K-means++/ Lloyd's Running Time

- K-means ++ initialization:  $O(nd)$  and one pass over data to select next center. So  $O(nkd)$  time in total.
- Lloyd's method

Repeat until there is no change in the cost.

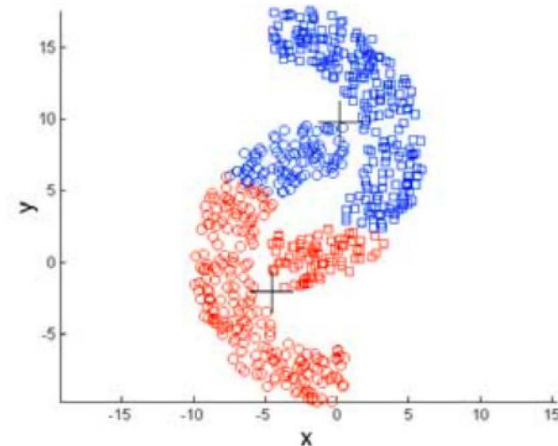
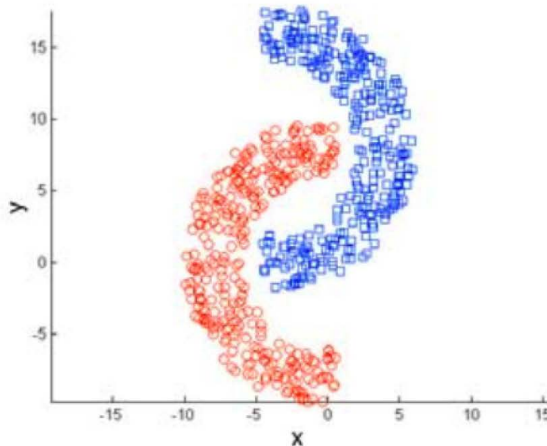
- For each  $j$ :  $C_j \leftarrow \{x \in S \text{ whose closest center is } c_j\}$
- For each  $j$ :  $c_j \leftarrow \text{mean of } C_j$

Each round takes time  $O(nkd)$ .

- Exponential # of rounds in the worst case [AV07].
- Expected polynomial time in the smoothed analysis model!

# K-means++/ Lloyd's Summary

- K-means++ always attains an  $O(\log k)$  approximation to optimal k-means solution in expectation.
- Running Lloyd's can only further improve the cost.
- Exponential # of rounds in the worst case [\[AV07\]](#).
- Expected polynomial time in the smoothed analysis model!
- Does well in practice.

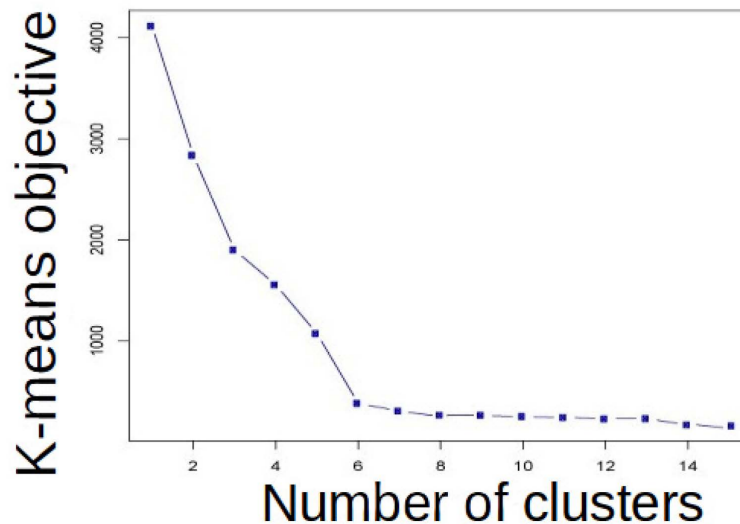




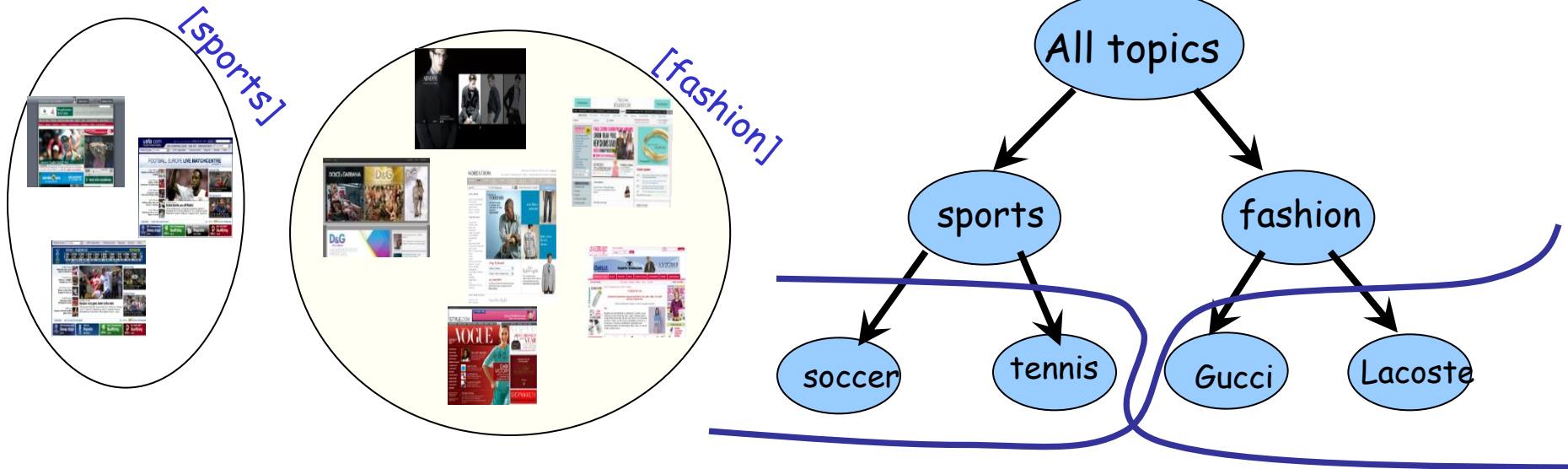
# Kernel K-means

# What value of k???

- Heuristic: Find large gap between  $k-1$ -means cost and  $k$ -means cost.
- According to information criteria (AIC, BIC, etc.)
- Try hierarchical clustering.



# Hierarchical Clustering

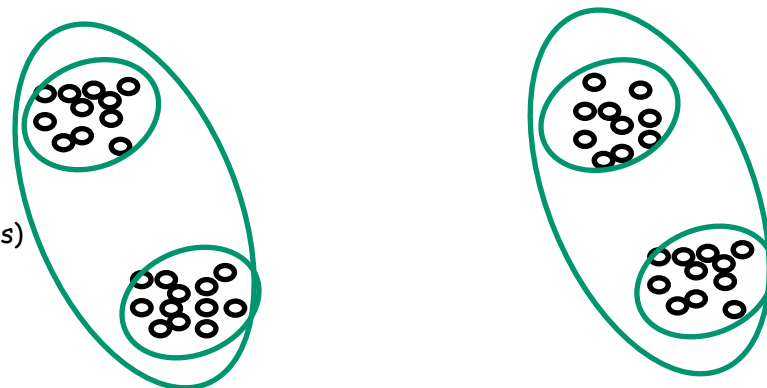


- A hierarchy might be more natural.
- Different users might care about different levels of granularity or even prunings.

# Hierarchical Clustering

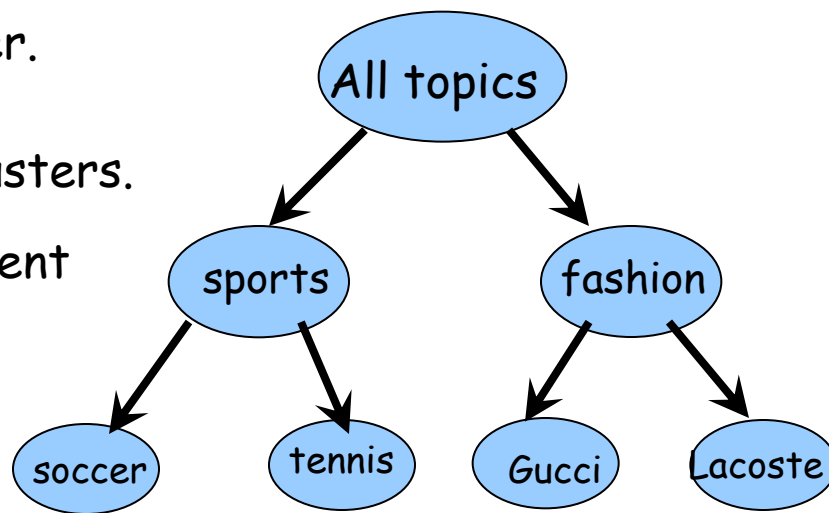
## Top-down (divisive)

- Partition data into 2-groups (e.g., 2-means)
- Recursively cluster each group.



## Bottom-Up (agglomerative)

- Start with every point in its own cluster.
- Repeatedly merge the "closest" two clusters.
- Different defs of "closest" give different algorithms.

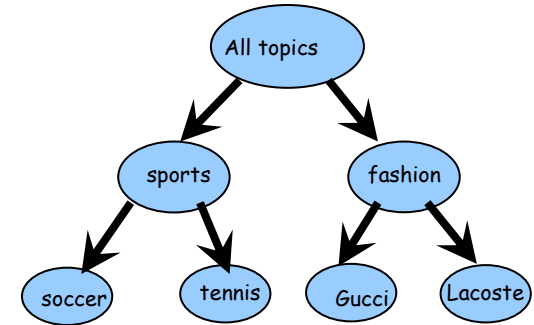


# Bottom-Up (agglomerative)

Have a **distance** measure on pairs of objects.

$d(x,y)$  - distance between  $x$  and  $y$

E.g., # keywords in common, edit distance, etc

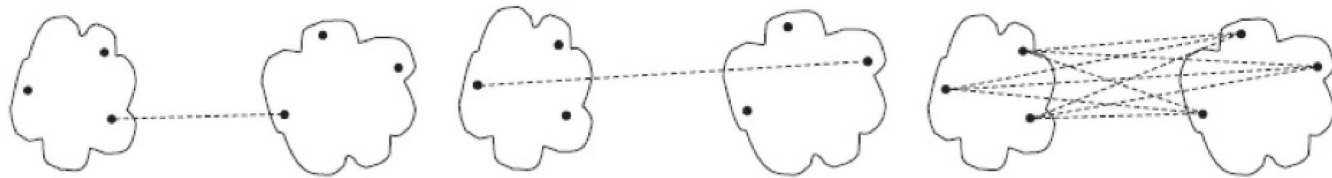


- Single linkage:  $\text{dist}(A, B) = \min_{x \in A, x' \in B'} \text{dist}(x, x')$

- Complete linkage:  $\text{dist}(A, B) = \max_{x \in A, x' \in B'} \text{dist}(x, x')$

- Average linkage:  $\text{dist}(A, B) = \text{avg}_{x \in A, x' \in B'} \text{dist}(x, x')$

- Ward's method



(a) MIN (single link.)

(b) MAX (complete link.)

(c) Group average.

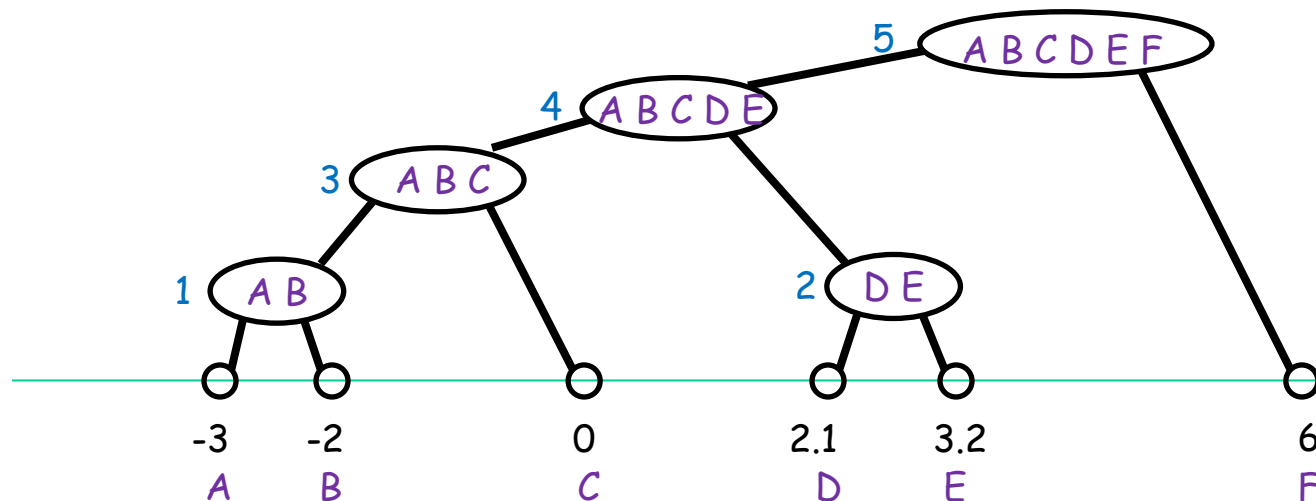
# Single Linkage

Bottom-up (agglomerative)

- Start with every point in its own cluster.
- Repeatedly merge the "closest" two clusters.

Single linkage:  $\text{dist}(A, B) = \min_{x \in A, x' \in B} \text{dist}(x, x')$

Dendrogram



# Single Linkage

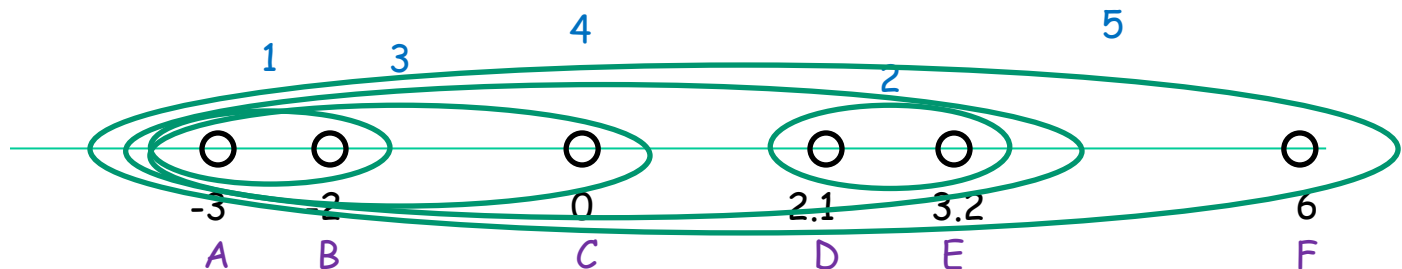
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One way to think of it: at any moment, we see connected components of the graph where connect any two pts of distance  $< r$ .

Watch as  $r$  grows (only  $n-1$  relevant values because we only merge at value of  $r$  corresponding to values of  $r$  in different clusters).



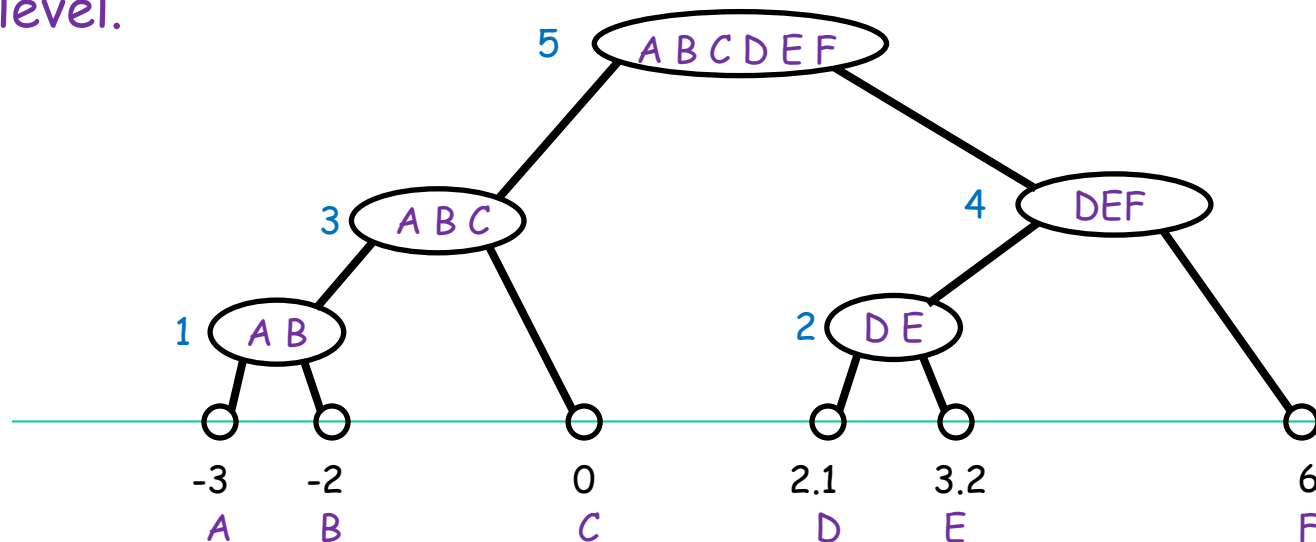
# Complete Linkage

Bottom-up (agglomerative)

- Start with every point in its own cluster.
- Repeatedly merge the "closest" two clusters.

Complete linkage:  $\text{dist}(A, B) = \max_{x \in A, x' \in B} \text{dist}(x, x')$

One way to think of it: keep max diameter as small as possible at any level.





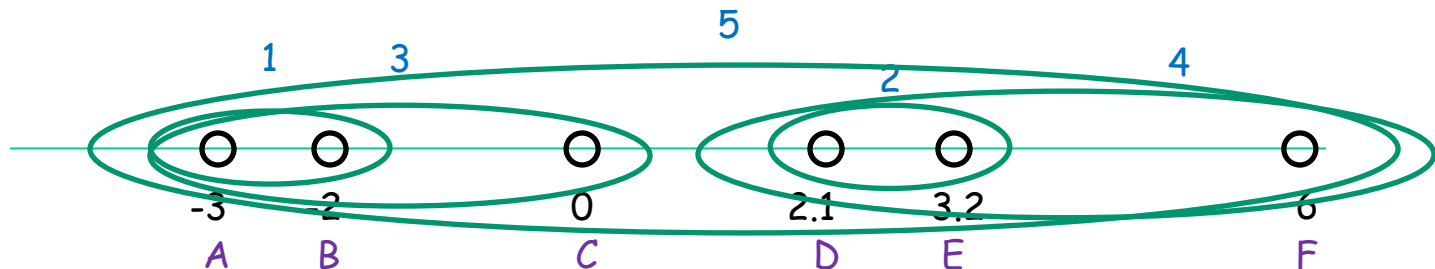
# Complete Linkage

## Bottom-up (agglomerative)

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One way to think of it: keep max diameter as small as possible.



# Ward's Method

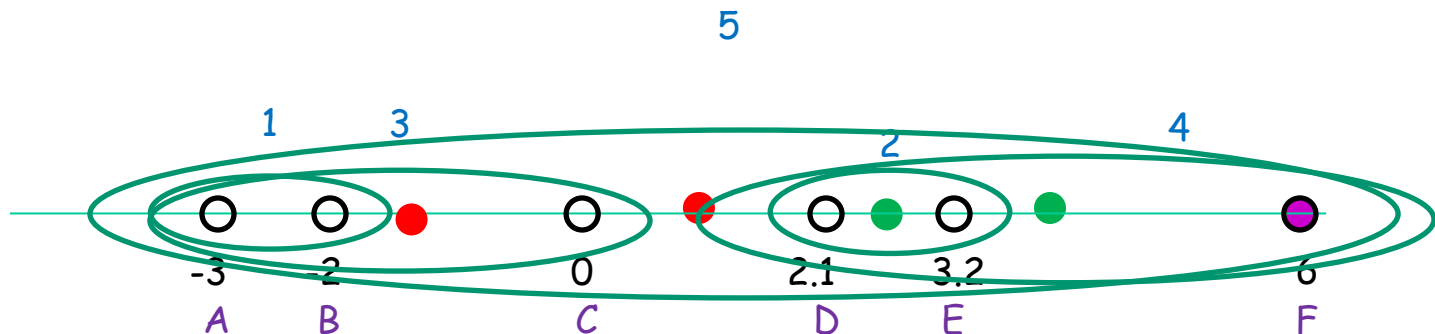
## Bottom-up (agglomerative)

- Start with every point in its own cluster.
- Repeatedly merge the "closest" two clusters.

Ward's method:  $\text{dist}(C, C') = \frac{|C| \cdot |C'|}{|C| + |C'|} \|\text{mean}(C) - \text{mean}(C')\|^2$

Merge the two clusters such that the **increase in k-means cost** is as small as possible.

Works well in practice.



# Running time

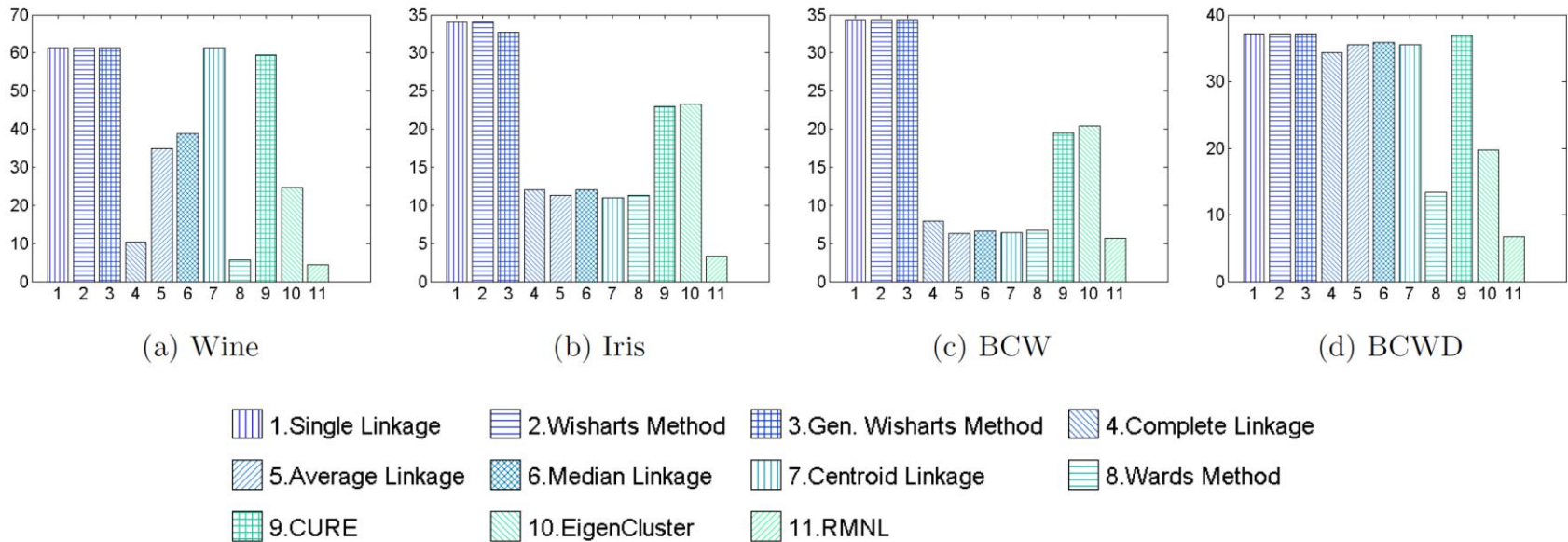
- Each algorithm starts with  $N$  clusters, and performs  $N-1$  merges.
- For each algorithm, computing  $\text{dist}(C, C')$  can be done in time  $O(|C| \cdot |C'|)$ . (e.g., examining  $\text{dist}(x, x')$  for all  $x \in C, x' \in C'$ )
- Time to compute all pairwise distances and take smallest is  $O(N^2)$ .
- Overall time is  $O(N^3)$ .

In fact, can run all these algorithms in time  $O(N^2 \log N)$ .

See: Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, Introduction to Information Retrieval, Cambridge University Press. 2008. <http://www-nlp.stanford.edu/IR-book/>

# Hierarchical Clustering Experiments

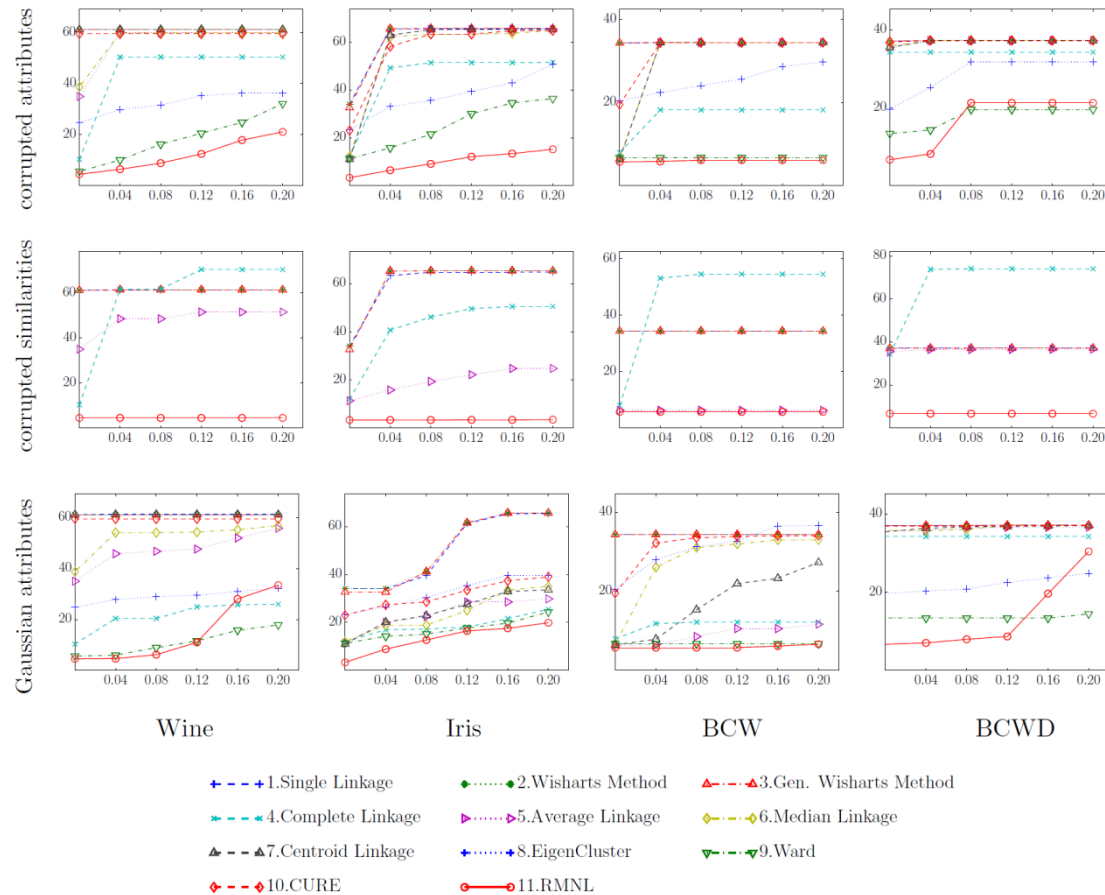
[BLG, JMLR'15]



Ward's method does the best among classic techniques.

# Hierarchical Clustering Experiments

[BLG, JMLR'15]



Ward's method does the best among classic techniques.

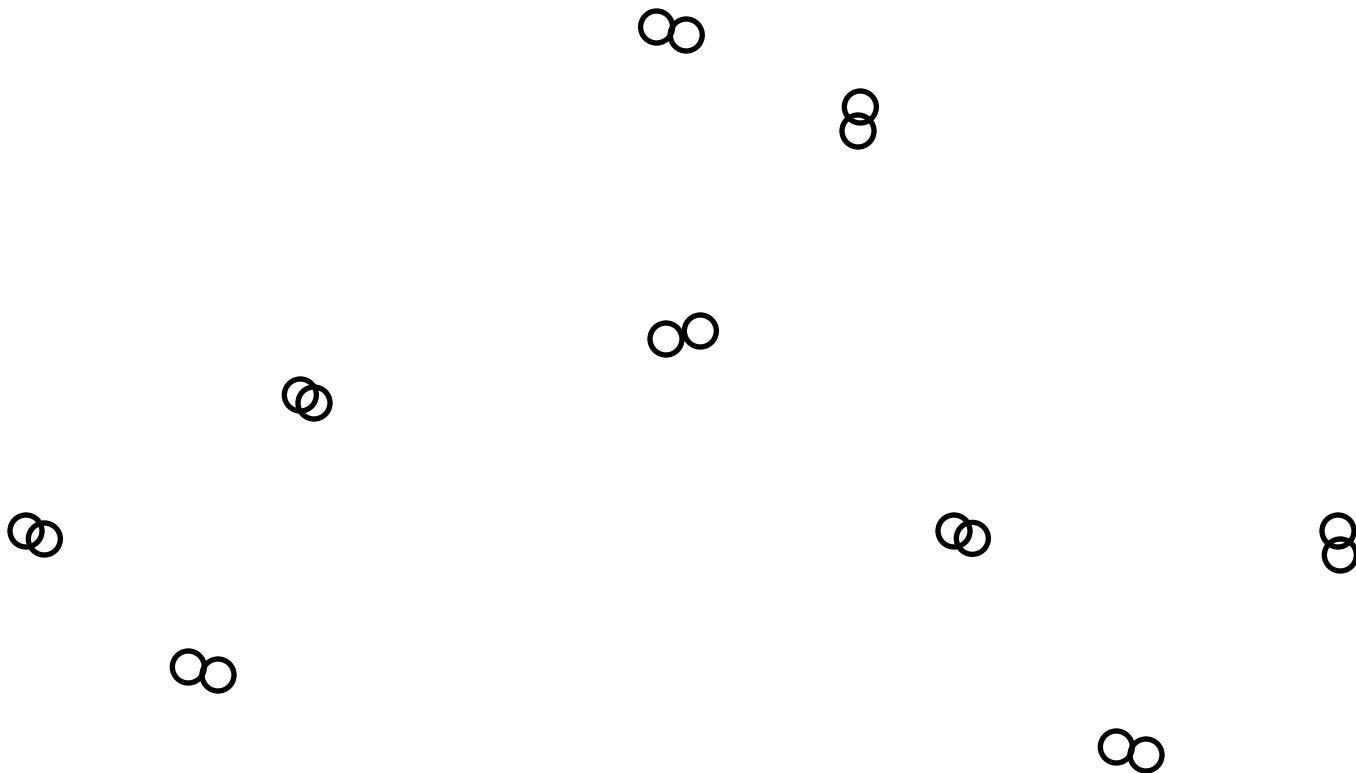
# What You Should Know

- Partitional Clustering. k-means and k-means ++
  - Lloyd's method
  - Initialization techniques (random, furthest traversal, k-means++)
- Hierarchical Clustering.
  - Single linkage, Complete Linkage, Ward's method

*Additional Slides*

# Smoothed analysis model

- Imagine a worst-case input.
- But then add small *Gaussian* perturbation to each data point.

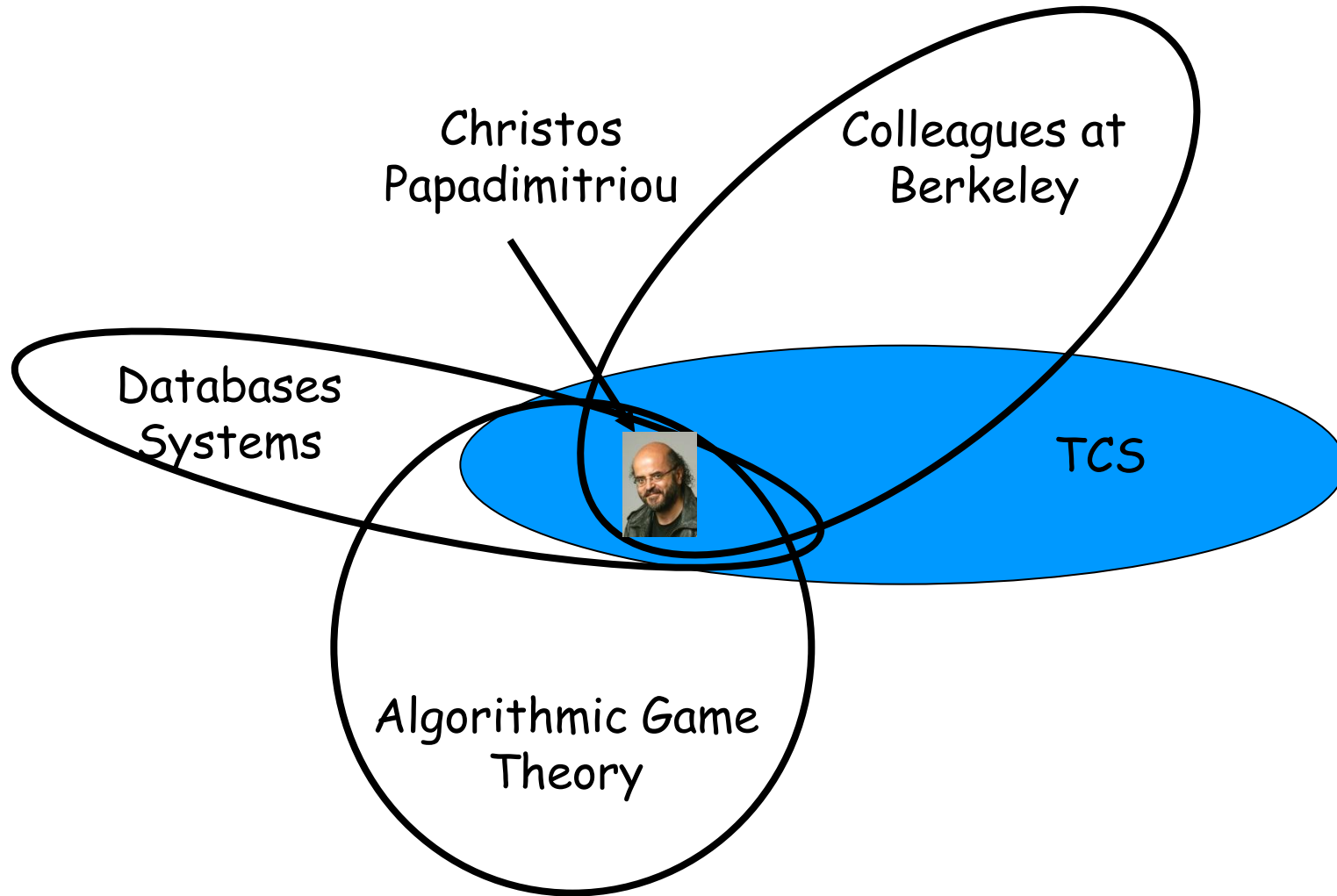




# Smoothed analysis model

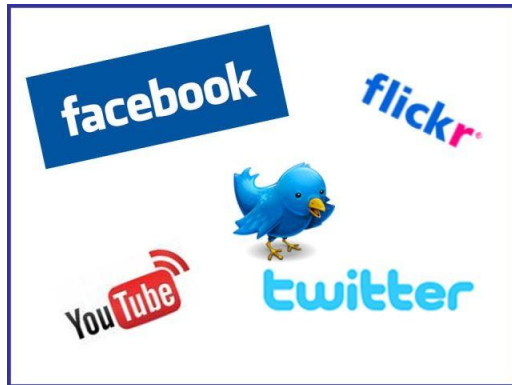
- Imagine a worst-case input.
- But then add small Gaussian perturbation to each data point.
- Theorem [Arthur-Manthey-Roglin 2009]:
  - $E[\text{number of rounds until Lloyd's converges}]$  if add Gaussian perturbation with variance  $\sigma^2$  is polynomial in  $n, 1/\sigma$ .
  - The actual bound is :  $O\left(\frac{n^{34}k^{34}d^8}{\sigma^6}\right)$
- Might still find local opt that is far from global opt.

# Overlapping Clusters: Communities



# Overlapping Clusters: Communities

- Social networks
- Professional networks



- Product Purchasing Networks, Citation Networks, Biological Networks, etc

# Overlapping Clusters: Communities

