

COMP6237 Data Mining

Lecture 2: Discovering Groups

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Lecture slides available here:

<http://comp6237.ecs.soton.ac.uk/jon.html>

(Thanks to Prof. Jonathon Hare and Dr. Jo Grundy for providing the lecture materials used to develop the slides.)

Recap – Recommendation System

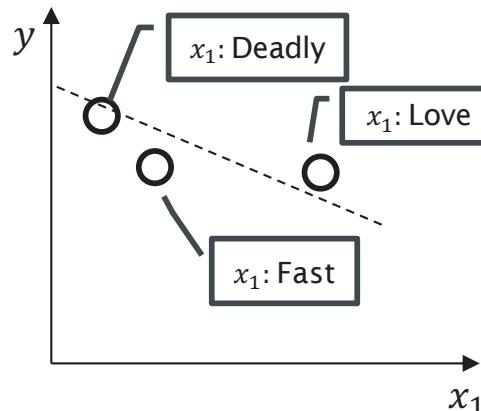
Content-based

Film	Dave	x_1 romance	x_2 action	y
Love Really	4	1	0.1	
Deadly Weapon	5	0.1	1	
Fast and Cross	4	0.2	0.9	
Star Battles	?	0.1	1	$y_t = ?$

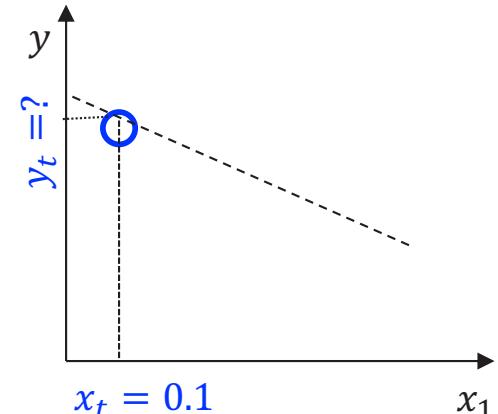
$$\min_{\theta} \frac{1}{m} \sum_{i=1}^m (\theta^T X_i - y)^2$$

$$x(\text{Love}) = (x_1, x_2) = (1, 0.1)$$

1. Fitting User Behavior



2. Prediction



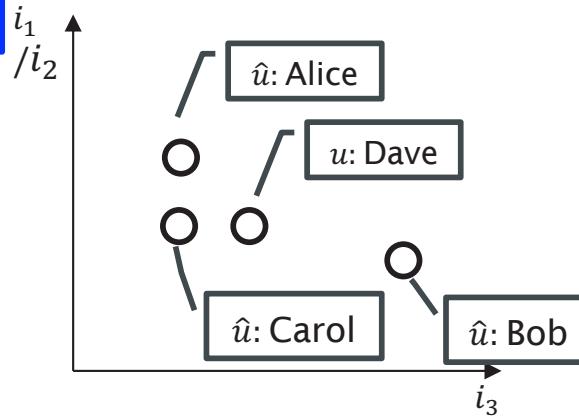
User-based Collaborative

Film	Alice	Bob	Carol	Dave
Love Really	4	1		4
Deadly Weapon		1	4	5
Fast and Cross	5		5	4
Star Battles	1	5	2	?

$$r_{u,i} = \frac{\sum_{\hat{u} \in U} sim(u, \hat{u}) r_{\hat{u},i}}{\sum_{\hat{u} \in U} |sim(u, \hat{u})|}$$

$$\hat{u}(\text{Alice}) = (i_1, i_3) = (4, 5)$$

1. Finding Similar Users



2. Prediction

$$\text{Sim}(\text{Dave}, \text{Alice}) = 0.8$$

$$\text{Sim}(\text{Dave}, \text{Carol}) = 0.6$$

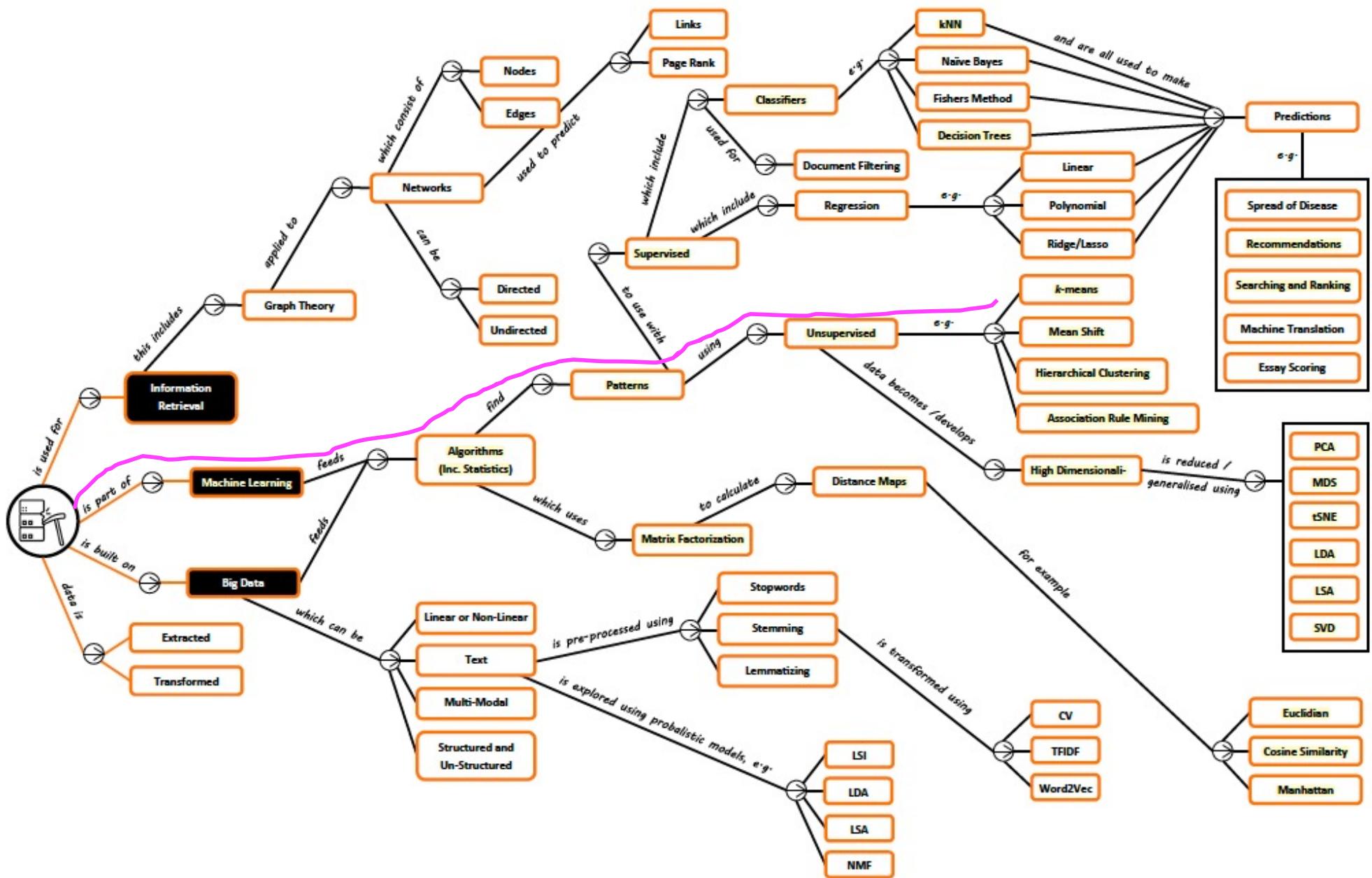
$$r_{u,t} = \frac{0.8 \times 1 + 0.6 \times 2}{0.8 + 0.6}$$

Cosine Similarity:

$$\cos(\theta) = \frac{\mathbf{p} \cdot \mathbf{q}}{|\mathbf{p}| |\mathbf{q}|}$$

$$= \frac{\sum_{i=1}^N p_i q_i}{\sqrt{\sum_{i=1}^N p_i^2} \sqrt{\sum_{i=1}^N q_i^2}}$$

Discovering Groups – Roadmap



Discovering Groups – Textbook

CHAPTER 3

Discovering Groups

- ▶ Programming Collective Intelligence: Building Smart Web 2.0 Applications *T. Segaran.*

Chapter 7

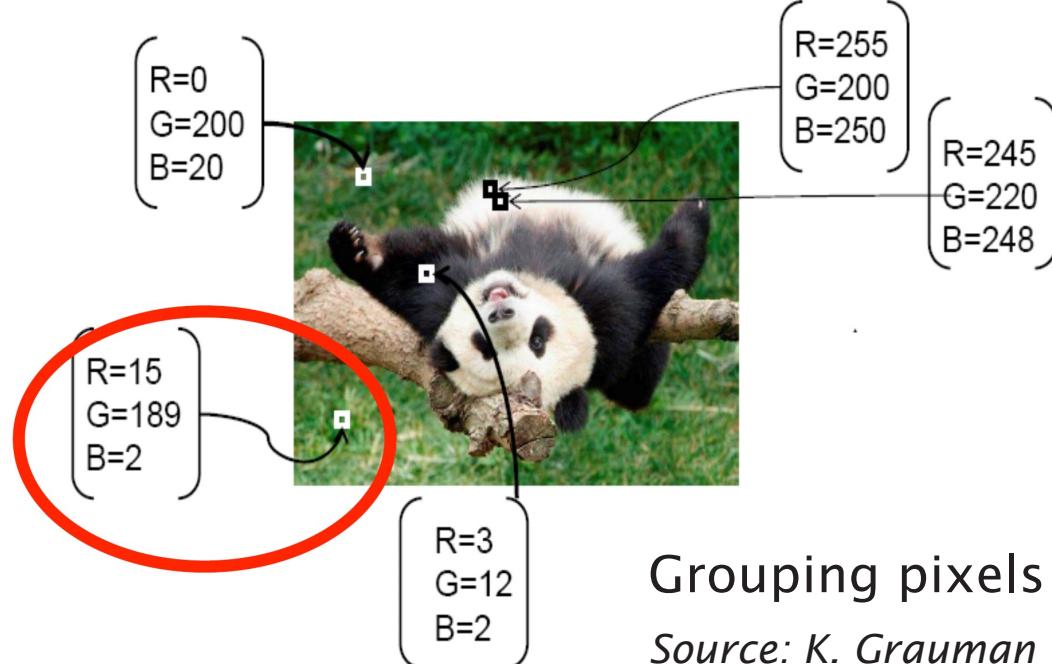
Clustering

Clustering is the process of examining a collection of “points,” and grouping the points into “clusters” according to some distance measure. The goal is that points in the same cluster have a small distance from one another, while points in different clusters are at a large distance from one another. A suggestion of

- ▶ Mining of Massive Datasets J. Leskovec *et al*

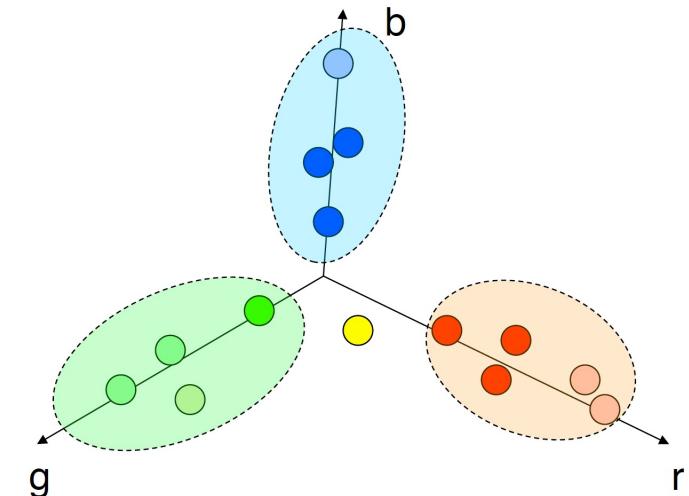
Discovering Groups – Overview (1/5)

- Grouping data, just using the feature vectors
 - Unsupervised: no group labels for training
 - Key idea: data with similar features grouped together
 - Can be
 - Soft (allow overlapping groups)
 - Hard (each item assigned to one group)



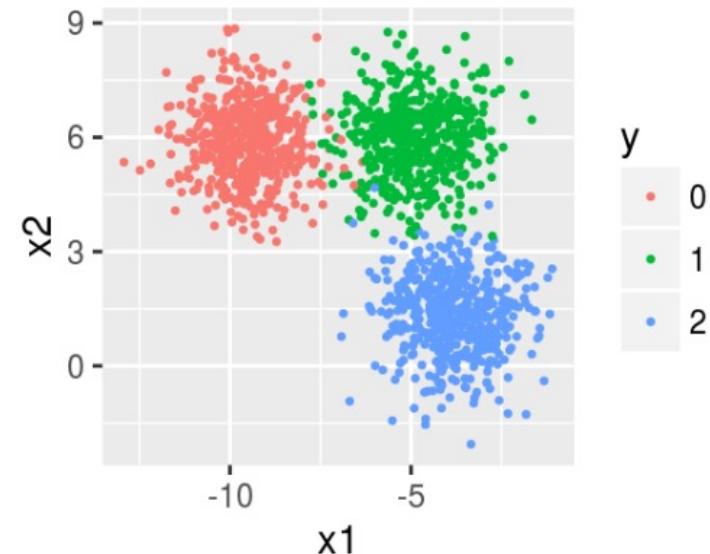
Grouping pixels based on **color** similarity
Source: K. Grauman

Feature space:
color value (3D)

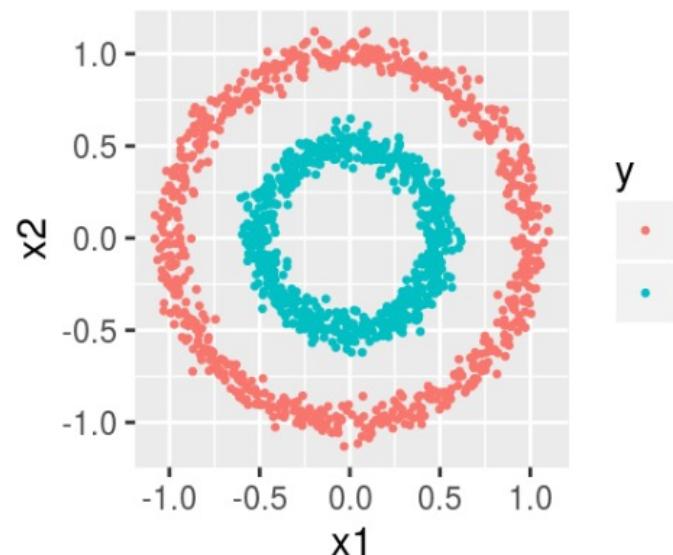


Discovering Groups – Overview (2/5)

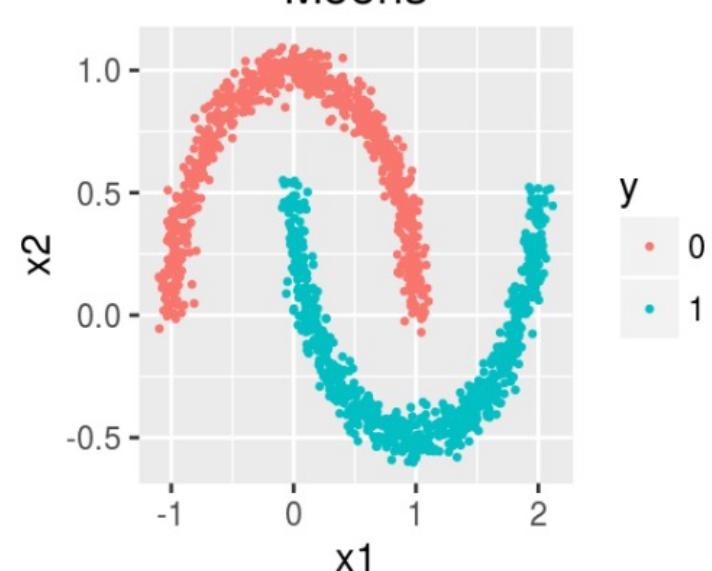
Blobs



Circles

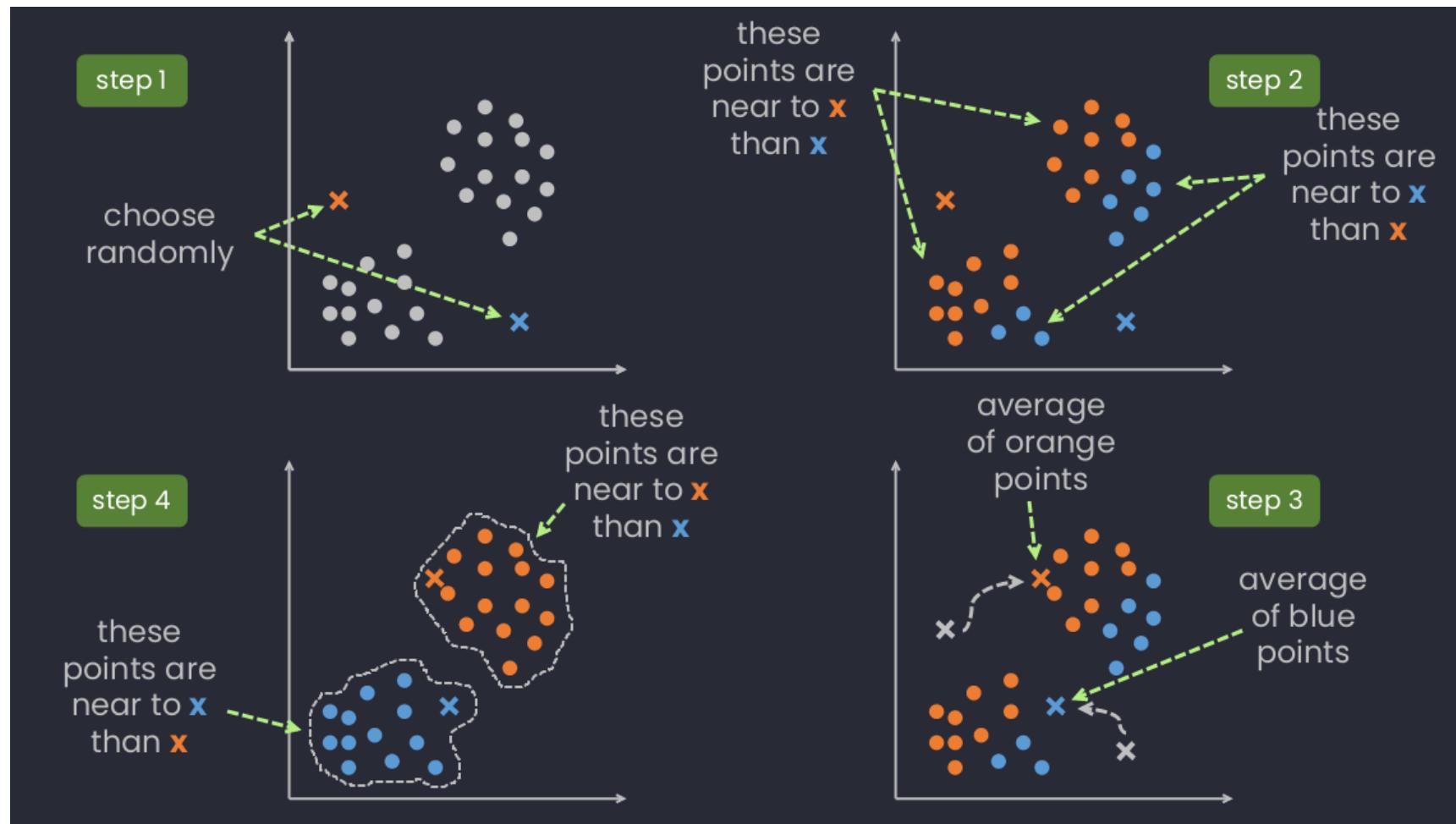


Moons



Discovering Groups – Overview (3/5)

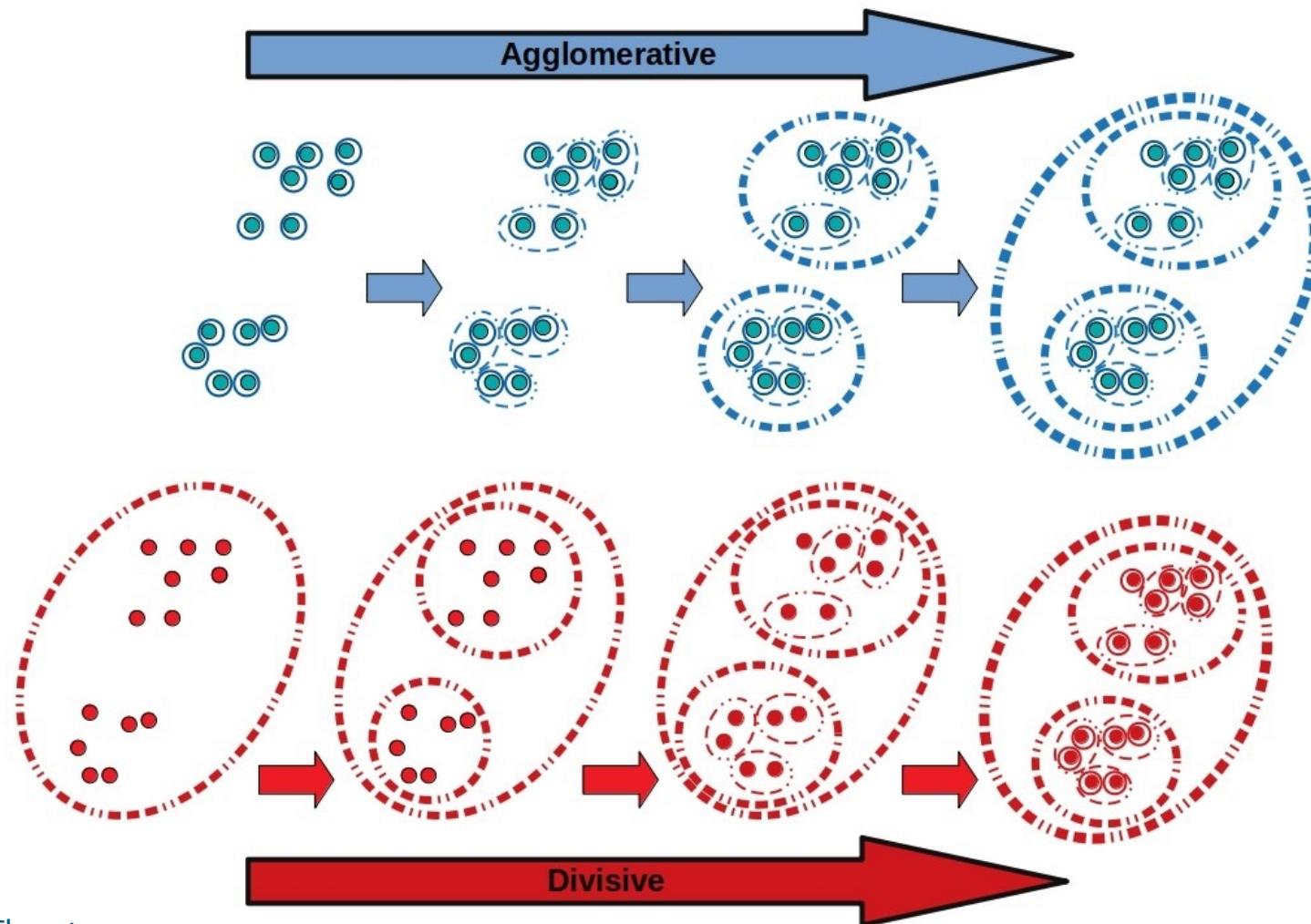
Clustering Algorithm (1/3) – K-means



Credict: Pratik Thorat

Discovering Groups – Overview (4/5)

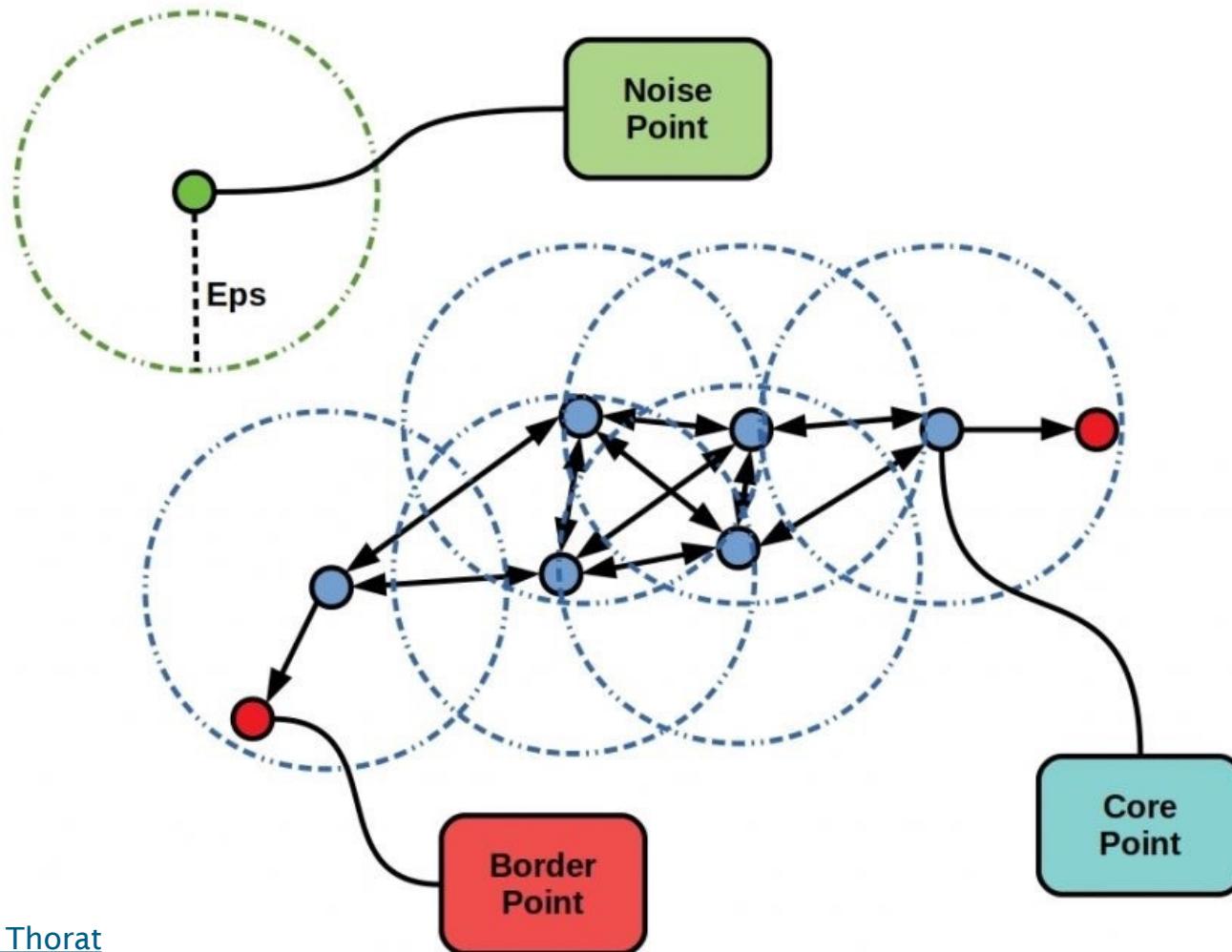
Clustering Algorithm (2/3) – Agglomerative (Divisive not learned in this lecture)



Credit: Pratik Thorat

Discovering Groups – Overview (5/5)

Clustering Algorithm (2/3) – DBSCAN



Credit: Pratik Thorat

Discovering Groups – Learning Outcomes

- **LO1:** Comprehend the key ideas and the essential mathematical formulations employed in clustering methods (exam).
 - ❖ E.g., how is sum of squared error (SSE) defined?
 - ❖ E.g., understand the pros and cons of the learned algorithms
- **LO2:** Compute the fundamental stages of learned clustering approaches (exam).
 - ❖ E.g., given a dataset and a distance metric, be prepared to follow the selected clustering algorithm to cluster the instances in the dataset
- **LO3:** Implement and evaluate the learned clustering algorithms using Python (course work)

Assessment hints: Multi-choice Questions (single answer: concepts, calculation etc)

- *Textbook Exercises: textbooks (Programming + Mining)*
- *Other Exercises: <https://www-users.cse.umn.edu/~kumar001/dmbook/sol.pdf>*
- *ChatGPT or other AI-based techs*

Discovering Groups – K-means

- Given: data set $\{\mathbf{x}_1, \dots, \mathbf{x}_N\}$, number of clusters K
- Goal: find cluster centers $\{\boldsymbol{\mu}_1, \dots, \boldsymbol{\mu}_K\}$ so that

$$J = \sum_{n=1}^N \sum_{k=1}^K r_{nk} \|\mathbf{x}_n - \boldsymbol{\mu}_k\|^2$$

is minimal, where $r_{nk} = 1$ if \mathbf{x}_n is assigned to $\boldsymbol{\mu}_k$

- Idea: compute r_{nk} and $\boldsymbol{\mu}_k$ iteratively Otherwise, $r_{n,k} = 0$

The used objective function is **Sum of Squared Error (SSE)**

Discovering Groups – K-means

Algorithm 1: K Means clustering

Data: X, K

initialise K centroids;

while *positions of centroids change* **do**

for *each data point* **do**

 | assign to nearest centroid

end

for *each centroid* **do**

 | move to average of assigned data points

end

end

return centroids, assignments;

A special case of Expectation Maximisation - why?

Discovering Groups – K-means

Algorithm 2: K Means clustering

Data: X, K

initialise K centroids;

while *positions of centroids change* **do**

for *each data point* **do**

 assign to nearest centroid ; *// Expectation of associations* E-step: Estimate the posterior probabilities...

end

for *each centroid* **do**

 move to average of assigned data points ; *// Maximisation of likelihood* M-step: Estimate new parameters

end

end

return centroids, assignments;

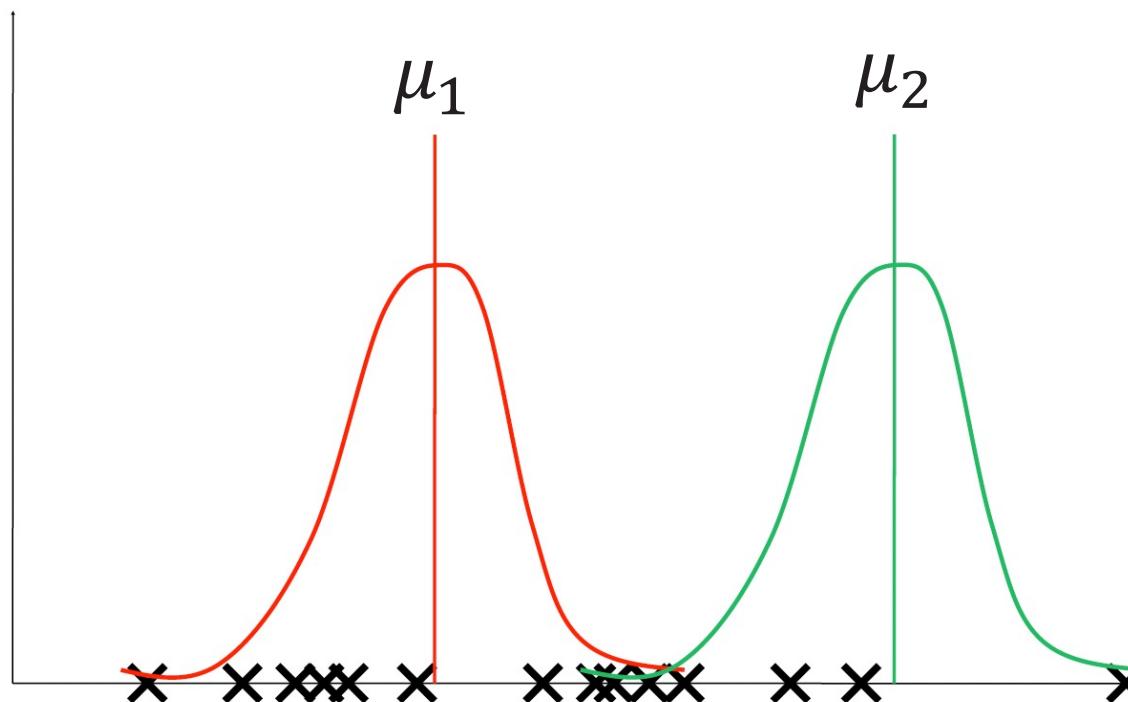
Assumes spherical clusters

Lecture: Maximum Likelihood Estimation

Discovering Groups – K-means

1D Example

Initialize cluster means: $\{\mu_1, \dots, \mu_K\}$

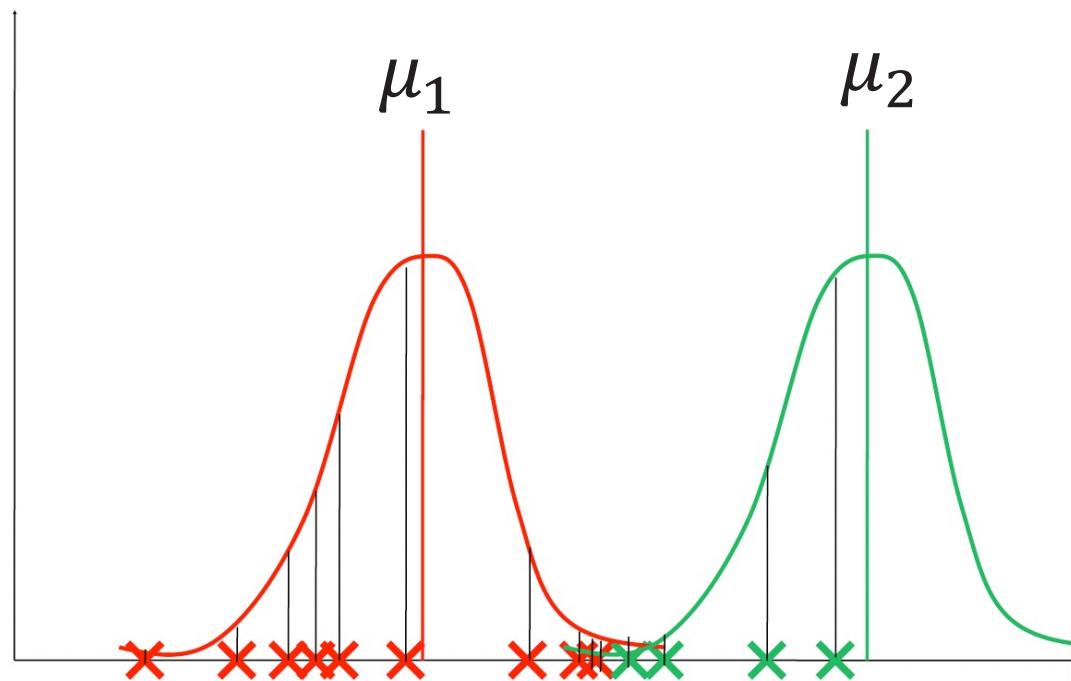


Discovering Groups – K-means

1D Example

Find optimal assignments:

$$r_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_j \| \mathbf{x}_n - \boldsymbol{\mu}_j \| \\ 0 & \text{otherwise} \end{cases}$$



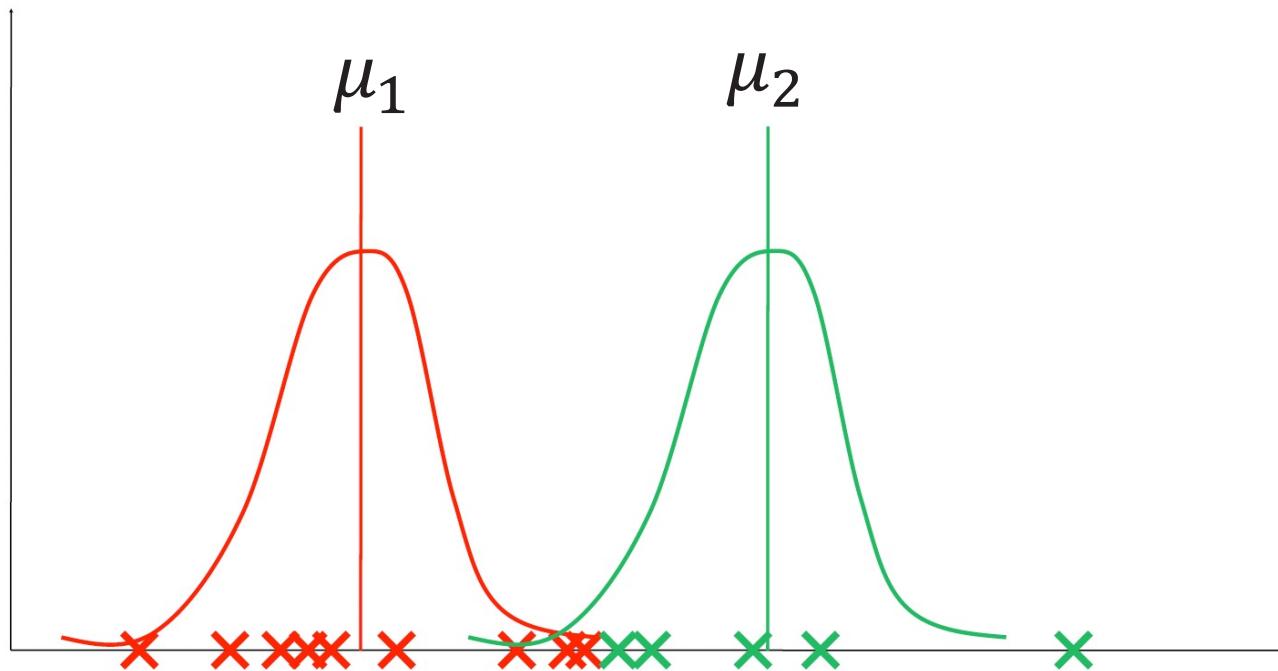
Discovering Groups – K-means

1D Example

Find new optimal means:

$$\frac{\partial J}{\partial \mu_k} = 2 \sum_{n=1}^N r_{nk} (\mathbf{x}_n - \boldsymbol{\mu}_k) \stackrel{!}{=} 0$$

$$\Rightarrow \boldsymbol{\mu}_k = \frac{\sum_{n=1}^N r_{nk} \mathbf{x}_n}{\sum_{n=1}^N r_{nk}}$$

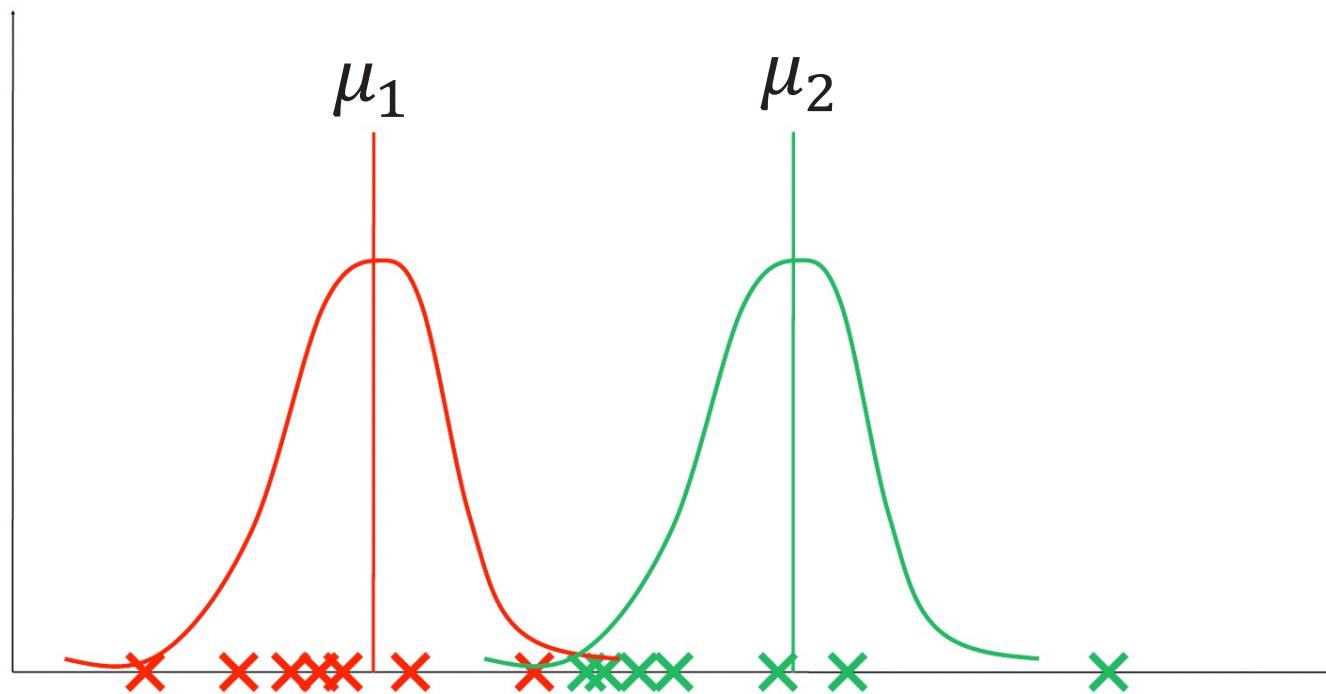


Discovering Groups – K-means

1D Example

Find new optimal assignments:

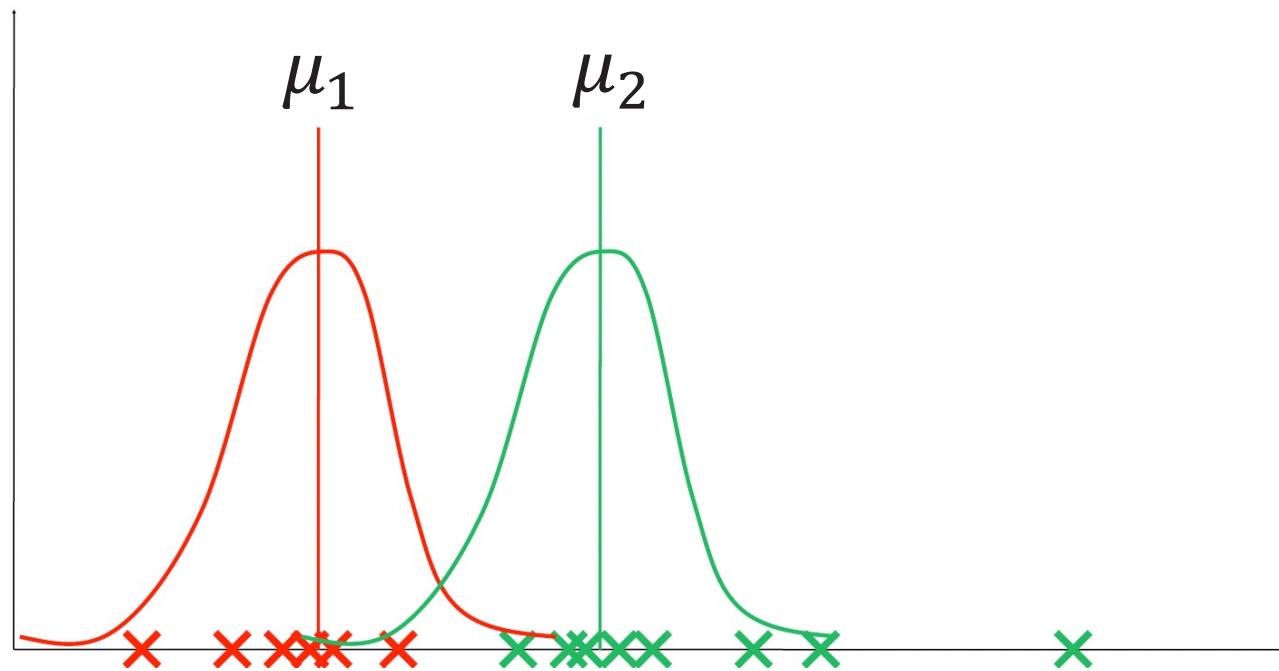
$$r_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_j \| \mathbf{x}_n - \boldsymbol{\mu}_j \| \\ 0 & \text{otherwise} \end{cases}$$



Discovering Groups – K-means

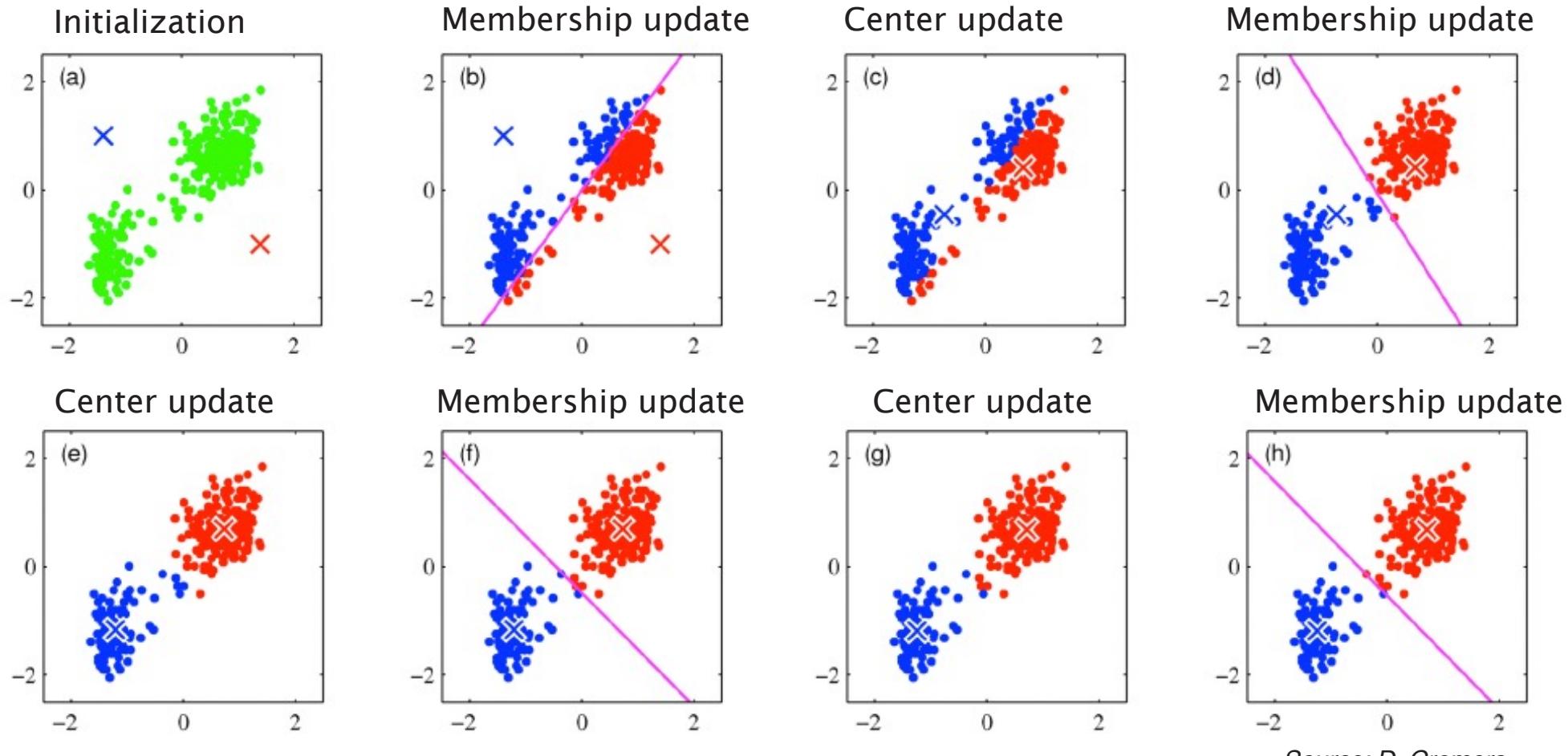
1D Example

Iterate these steps until means and assignments do not change any more



Discovering Groups – K-means

2D Example

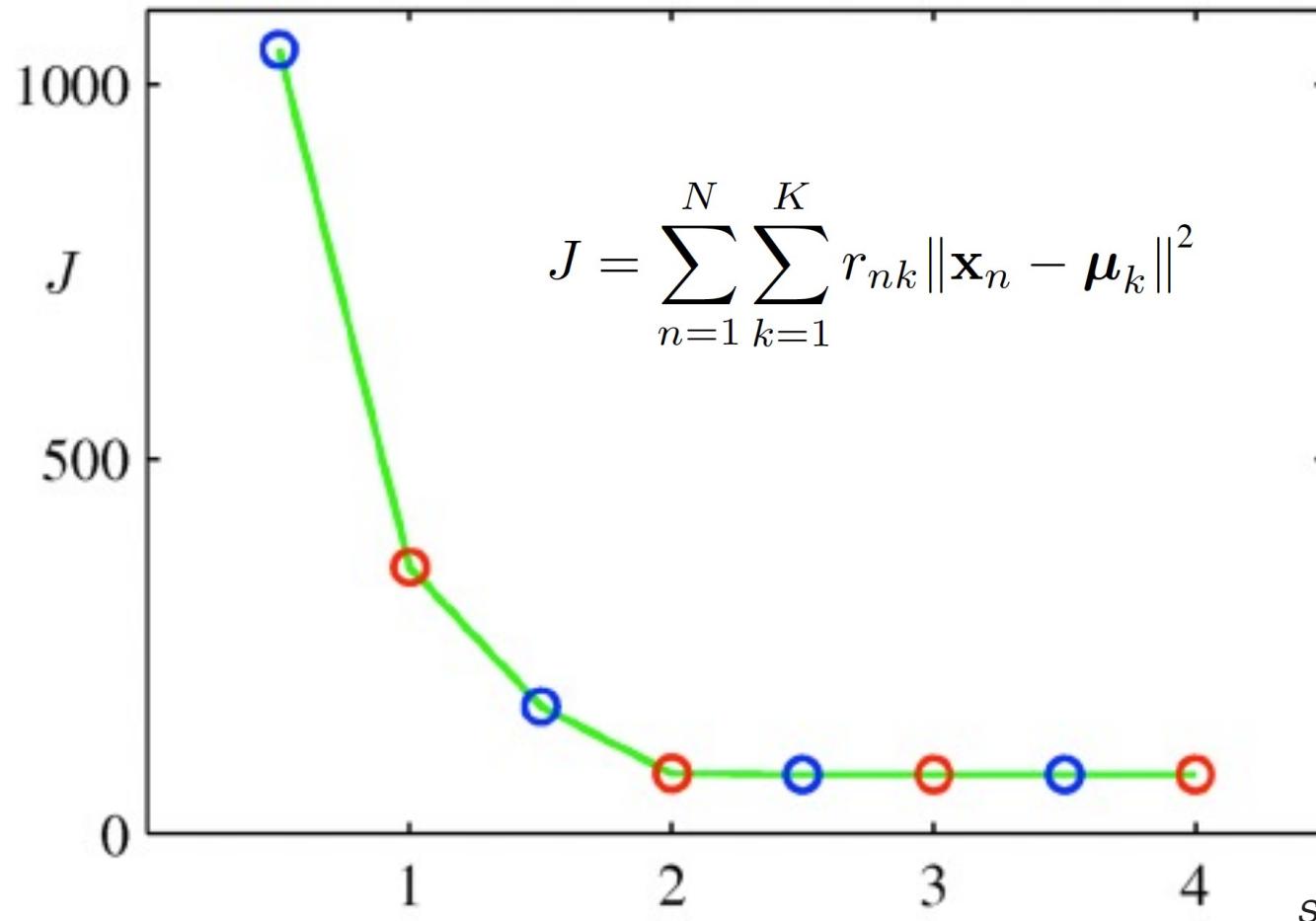


Source: D. Cremers

- Real data set
- Random initialization
- Magenta line is ‘decision boundary’

Discovering Groups – K-means

Sum of Squared Error (SSE) Curve



- After every step the cost function J is minimized
- Blue steps: update assignments
- Red steps: update means
- Convergence after 4 rounds

Discovering Groups – K-means

K-means can quickly and cheaply cluster data.

Problems?

- need to specify the cluster number k
- depends on good initial centroid guesses
- may converge on local minimum
- assumes spherical data (or ellipsoid-shaped clusters, or at best convex clusters)

Gaussian Mixture models (GMM) can work better, using a generalization of K-means (assuming each cluster is Gaussian), not discussed in this lecture.

Discovering Groups – DBSCAN

- **Idea:** uses the **local density** of points to determine the clusters, rather than using only the distance between points

$$N_\epsilon(\mathbf{x}) = B_d(\mathbf{x}, \epsilon) = \{\mathbf{y} \mid \delta(\mathbf{x}, \mathbf{y}) \leq \epsilon\}$$

where $\delta(\mathbf{x}, \mathbf{y})$ represents the distance between \mathbf{x} and \mathbf{y} , ϵ indicates **Max radius**, and \mathbf{x} is a **core point** if $|N_\epsilon(\mathbf{x})| \geq minpts$, where $minpts$ is a **Min number** that is user-defined local density or frequency threshold

- \mathbf{x} belongs to a density-based cluster when

$$|N_\epsilon(\mathbf{x})| \geq minpts \text{ or } \mathbf{x} \in N_\epsilon(\mathbf{z})$$

where \mathbf{z} is another data point, $minpts$ is a **Min number** that is user-defined local density or frequency threshold

Max radius is the limit on which to look for neighbours

Min number is the lower limit on what can be in a cluster

Discovering Groups – DBSCAN

Algorithm 3: DBSCAN

Data: X , eps , min_pts

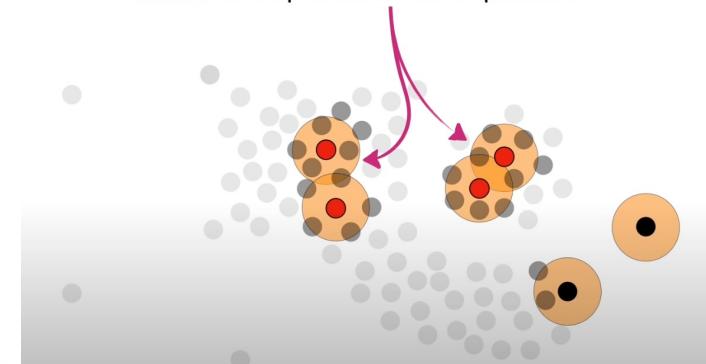
initialise labels list as zeros, count list, core list;

Find neighbours for each point, Find core points;
 $|N_\epsilon(\mathbf{x})| \geq \text{minpts}$
 $\text{class} = 1$;

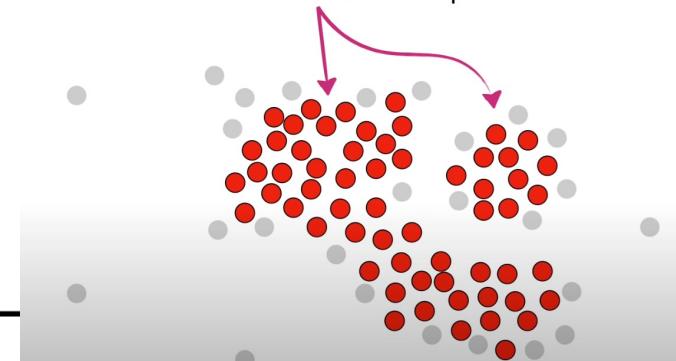
```

for each core point  $p$  do
    add neighbours( $p$ ) to queue;
    while queue not empty do
        neighbours = next(queue);
        for  $q$  in neighbours do
            set label( $q = \text{class}$ );
            if label( $q$ ) is 'core' then
                | add neighbours( $q$ ) to queue
            end
        end
    end
     $\text{class} = \text{class} + 1$ 
end
return labels;
```

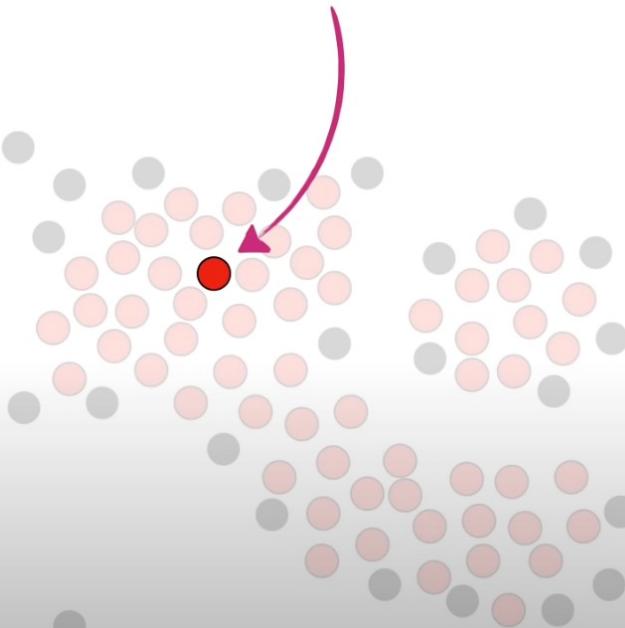
Anyway, these 4 points are some of the
Core Points, because their **orange circles**
overlap at least 4 other points...



Ultimately, we can call all of these **red points** **Core Points** because they are all close to 4 or more other points...

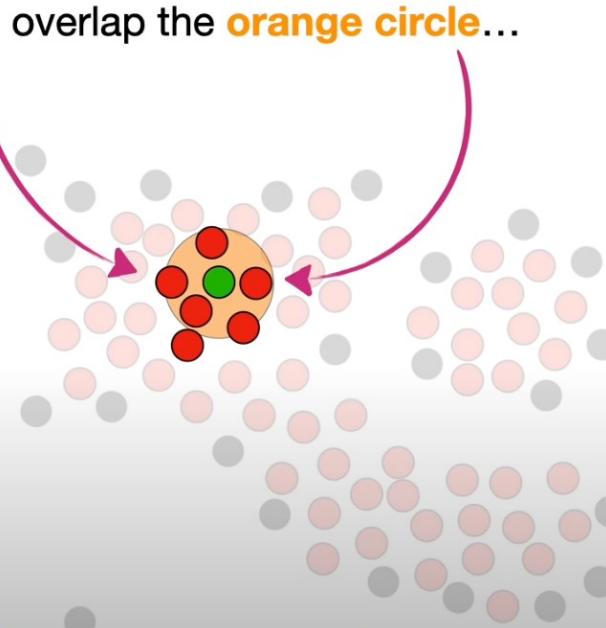


Now we randomly pick
a **Core Point**...

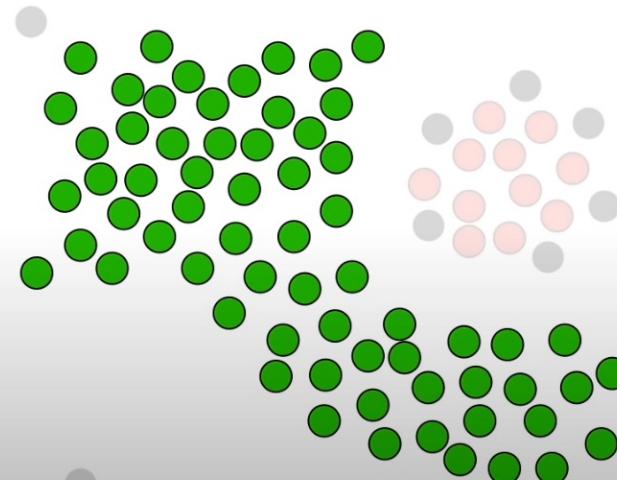
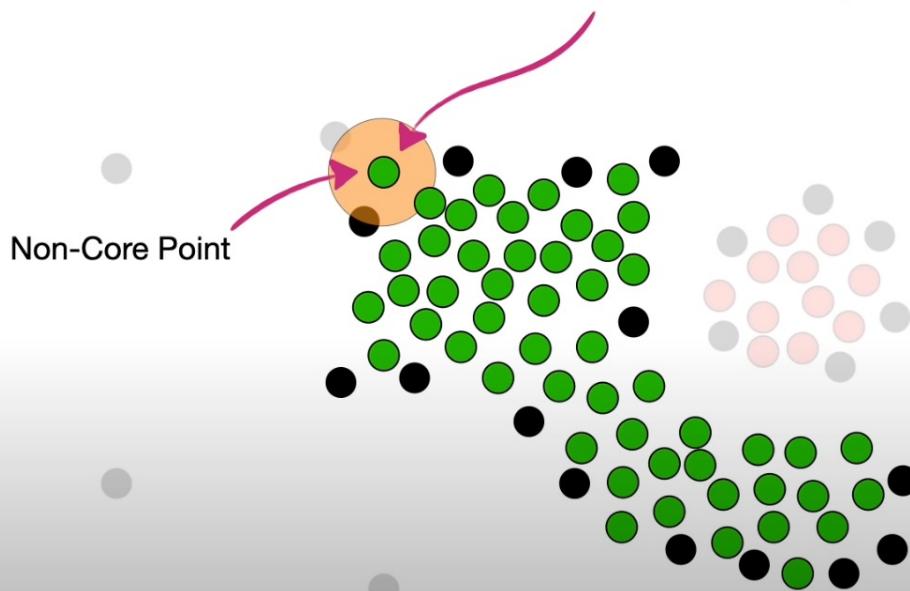


However, because this is not a **Core Point**, we do not use it to extend the **first cluster** any further.

Next, the **Core Points** that are close to the **first cluster**, meaning they overlap the **orange circle**...



And now we are done creating the **first cluster**.



Discovering Groups – DBSCAN

DBSCAN works well on any shape of data and is robust to outliers.

Problems?

- can struggle in high dimensions
- needs a distance parameter
- same parameter may not work for different cluster density
- need also minimum number specified

Discovering Groups – Hierarchical Clustering

Creates a **binary tree** that **recursively groups** pairs of similar items or clusters

Can be:

- Agglomerative (bottom up)
- Divisive (top down)

We will look at Agglomerative clustering. Needs a distance measure.

Discovering Groups – Hierarchical Clustering

Algorithm 4: Hierarchical Agglomerative Clustering

Data: N data points with feature vectors X_i , $i = 1 \dots N$

$numClusters = N$;

while $numClusters > 1$ **do**

cluster1, cluster2 = FindClosestClusters();

merge(cluster1, cluster2);

end

The distance between the clusters is evaluated using a linkage criterion.

If each merge is recorded, a binary tree structure linking the clusters can be formed.

This gives a **dendrogram**

Discovering Groups – Hierarchical Clustering

Linkage criterion: A measure of dissimilarity between clusters

Centroid Based:

- Dissimilarity is equal to distance between centroids
- Needs numeric feature vectors

Distance-Based:

- Dissimilarity is a function of distance between items in clusters
- Only needs precomputed measure of similarity between items

We could compute a distance matrix between points

Discovering Groups – Hierarchical Clustering

Centroid based linkage:

- WPGMC: Weighted Pair Group Method with Centroids.
When two clusters are combined into a new cluster, the average of the two centroids is the new centroid
- UPGMC: Unweighted Pair Group Method with Centroids.
When two clusters are combined into a new cluster, the new centroid is recalculated based on the positions of the items

Discovering Groups – Hierarchical Clustering

Distance based linkage:

- ▶ **Minimum**, or **single-linkage clustering** Distance between two closest members

$$\min d(a, b) : a \in A, b \in B$$

Produces long, thin clusters

- ▶ **Maximum**, or **complete-linkage clustering** Distance between two most distant members

$$\max d(a, b) : a \in A, b \in B$$

Finds compact clusters, approximately equal diameter

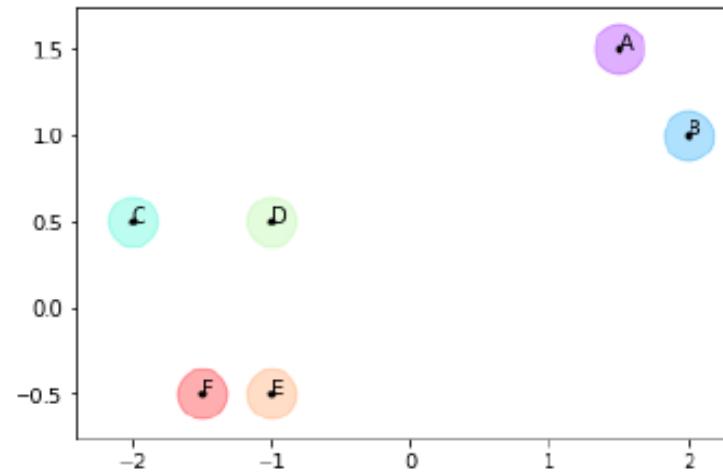
- ▶ **Mean** or **Average Linkage Clustering (UPGMA)**: Unweighted Pairwise Group Method with Arithmetic Mean):

$$\frac{1}{|A||B|} \sum_{a \in A} \sum_{b \in B} d(a, b)$$

Discovering Groups – Agglomerative Clustering

With sample data:

$$X = \begin{bmatrix} 1.5 & 1.5 \\ 2.0 & 1.0 \\ 2.0 & 0.5 \\ -1.0 & 0.5 \\ -1.5 & -0.5 \\ -1 & 0.5 \end{bmatrix}$$



Distance matrix: *demo distances, not ground truth*

	A	B	C	D	E	F
A	0	0.7	2.7	1.8	...	
B	0.7	0	...			
C	2.7		0	...		
D	1.8			0	...	
F	:				0	...

Discovering Groups - Agglomerative Clustering

Algorithm 4: Hierarchical Agglomerative Clustering

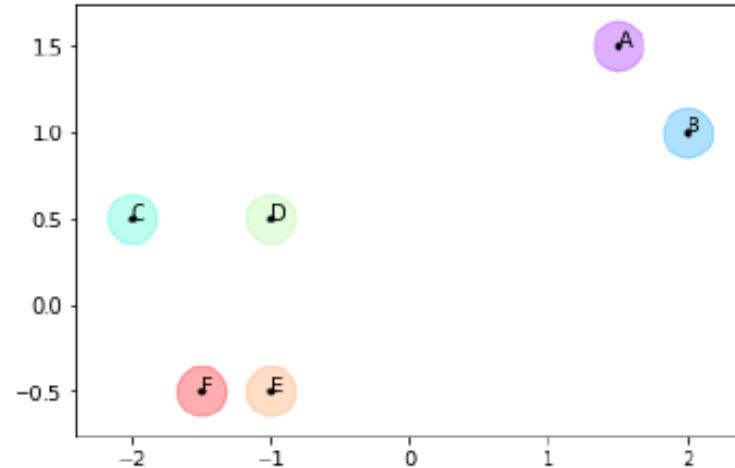
Data: N data points with feature vectors X_i $i = 1 \dots N$

$numClusters = N$;

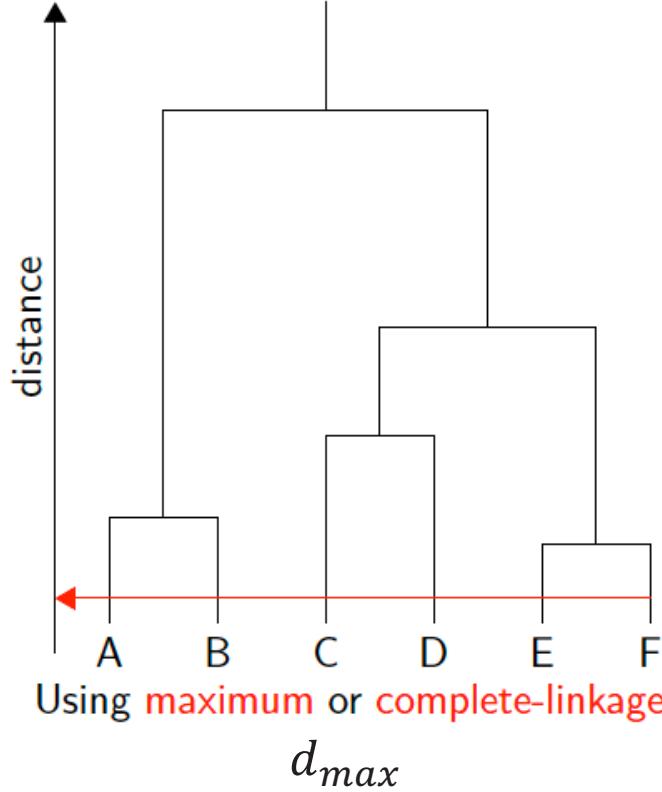
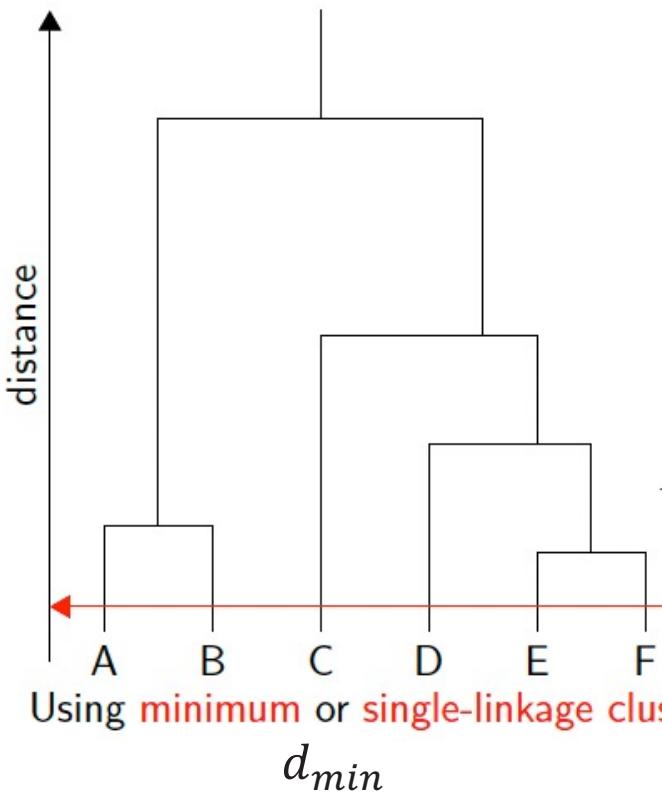
while $numClusters > 1$ **do**

cluster1, cluster2 = FindClosestClusters();
merge(cluster1, cluster2);

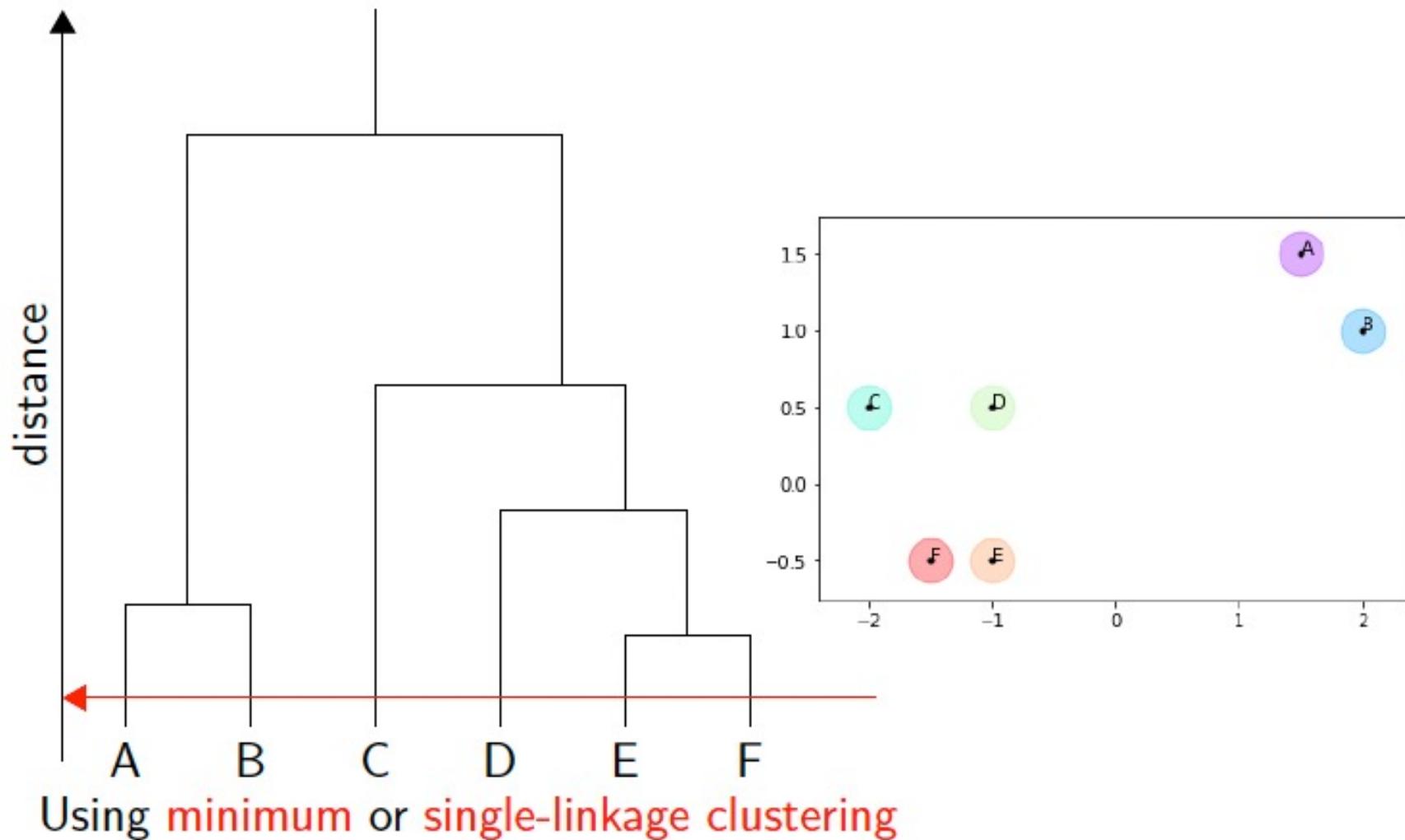
end



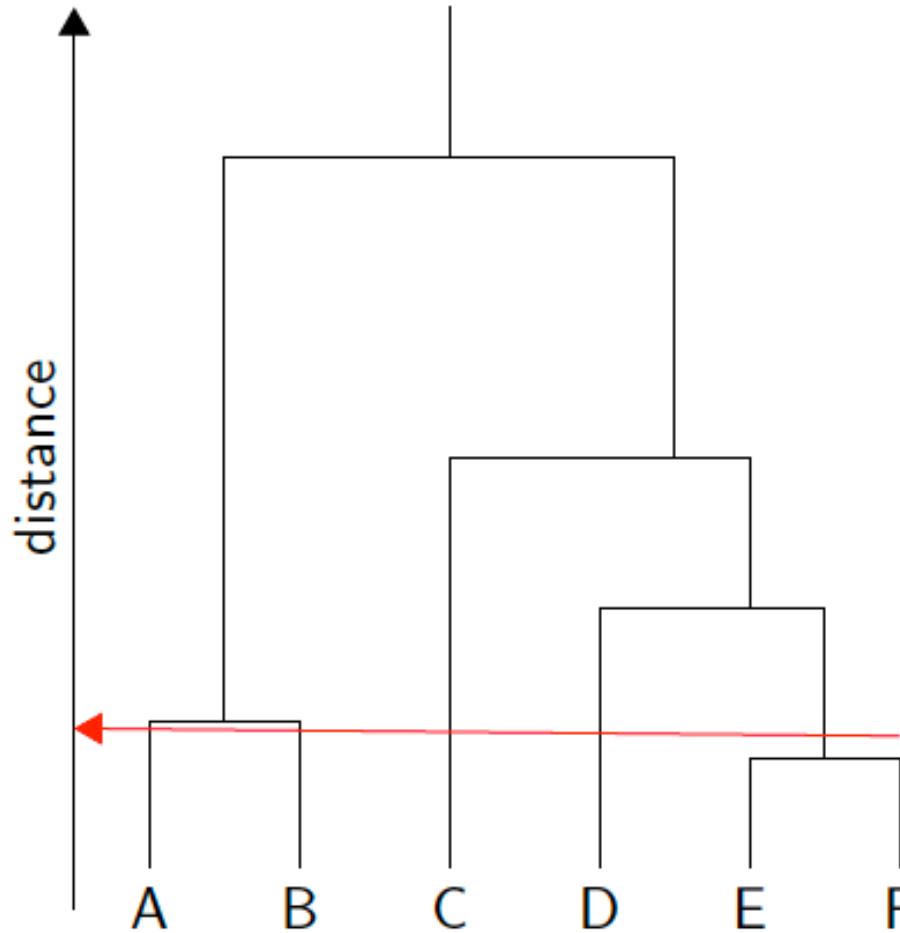
Dendograms



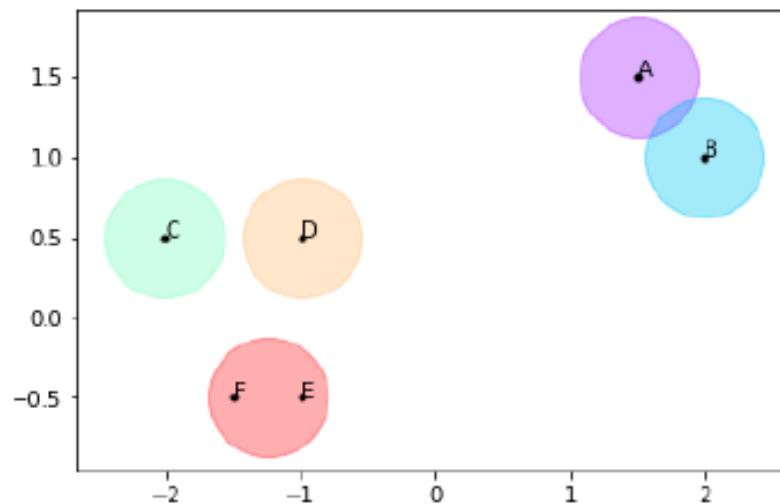
Discovering Groups – Agglomerative Clustering



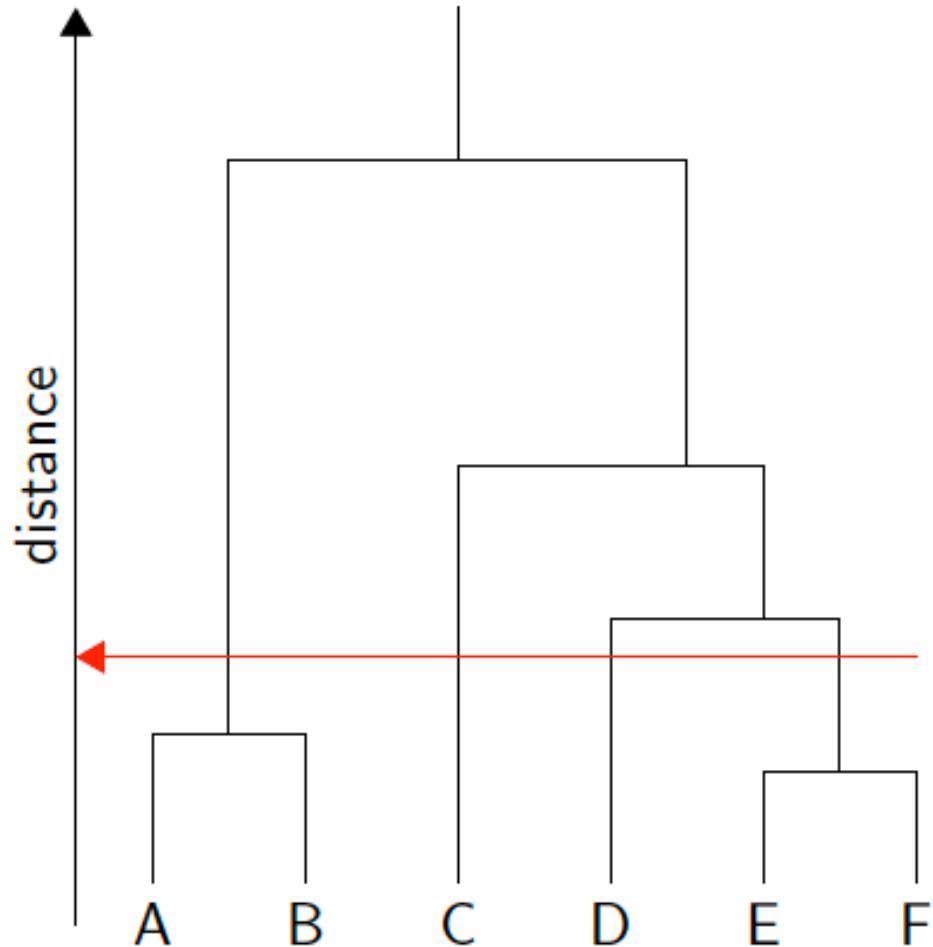
Discovering Groups – Agglomerative Clustering



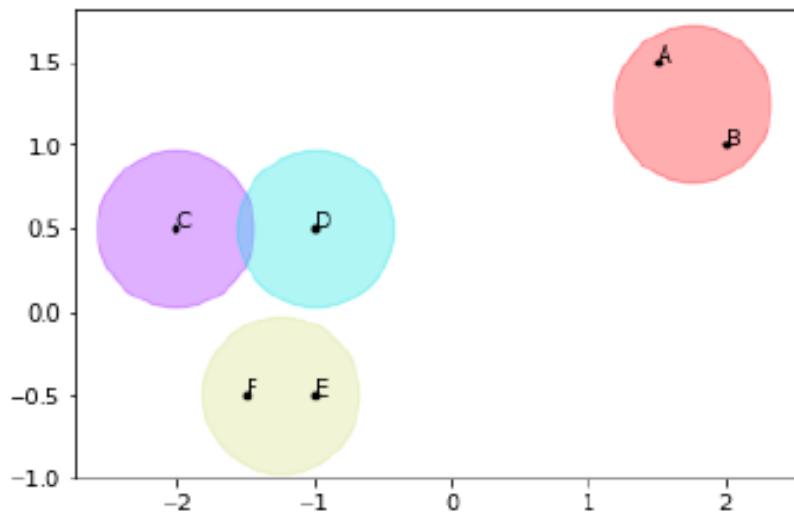
Using minimum or single-linkage clustering



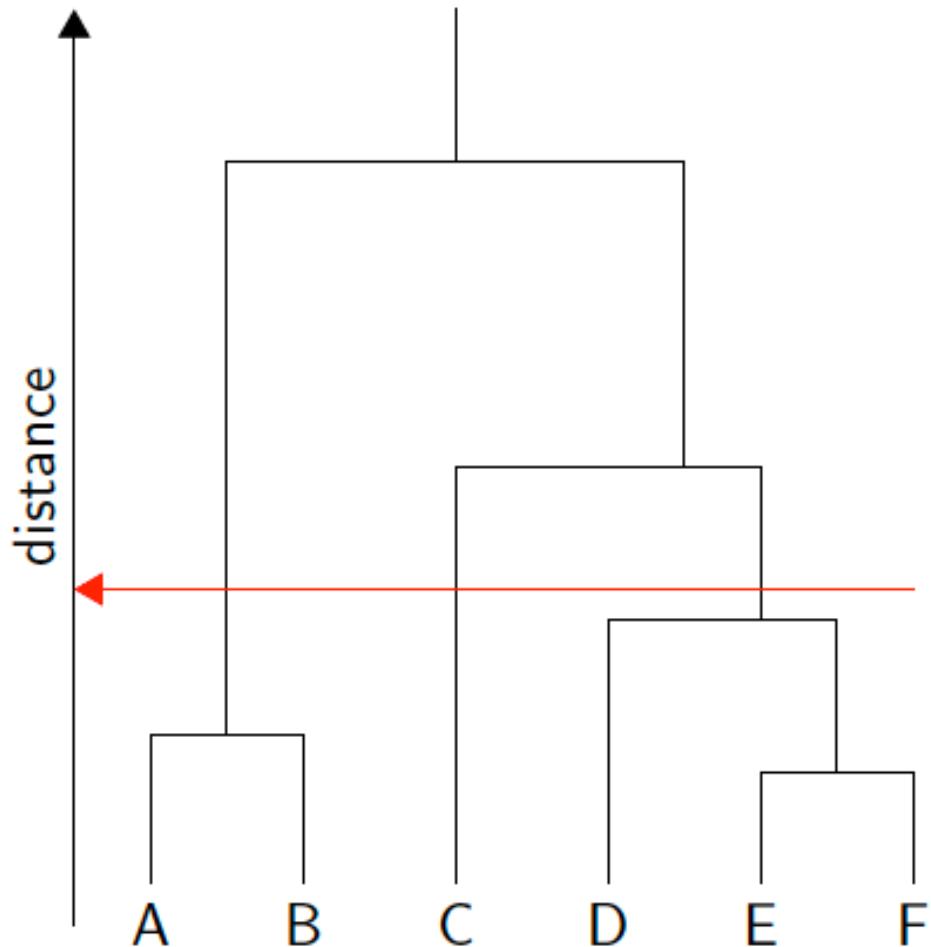
Discovering Groups – Agglomerative Clustering



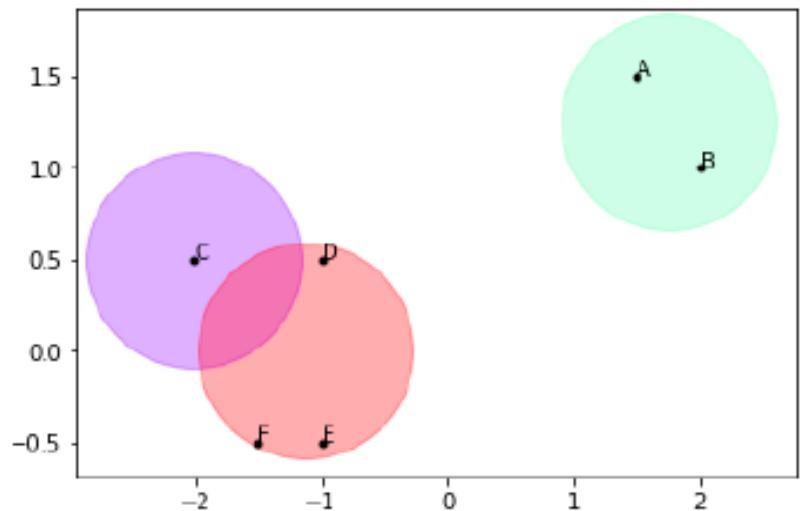
Using minimum or single-linkage clustering



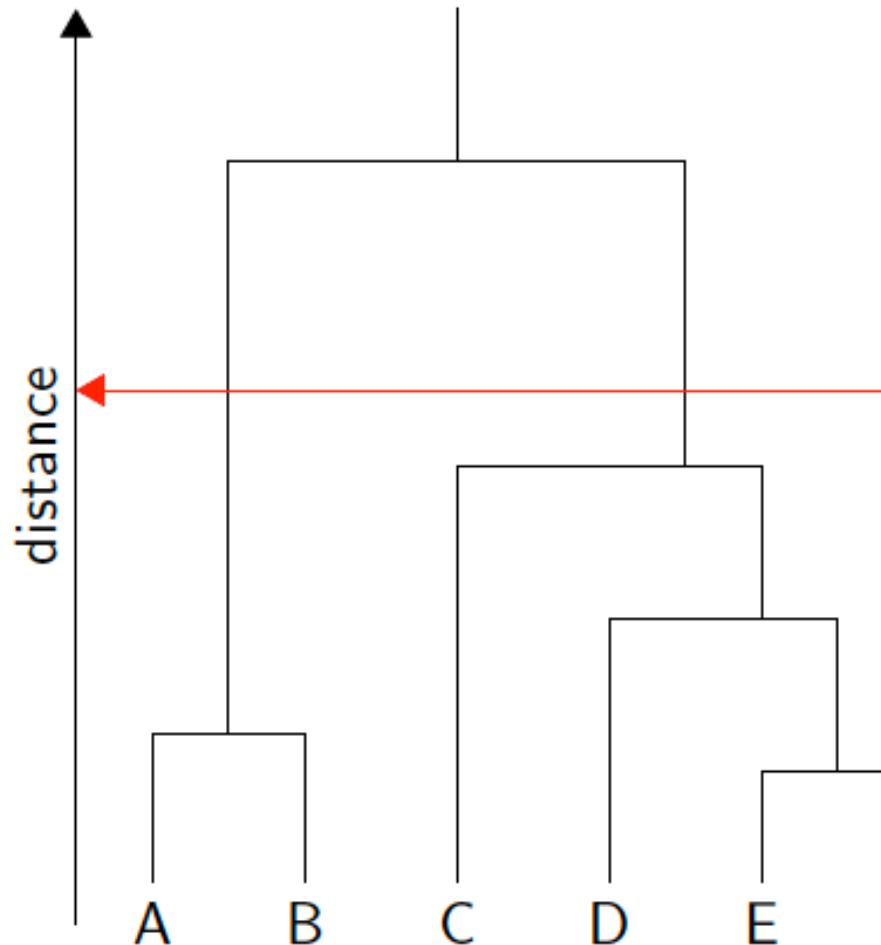
Discovering Groups – Agglomerative Clustering



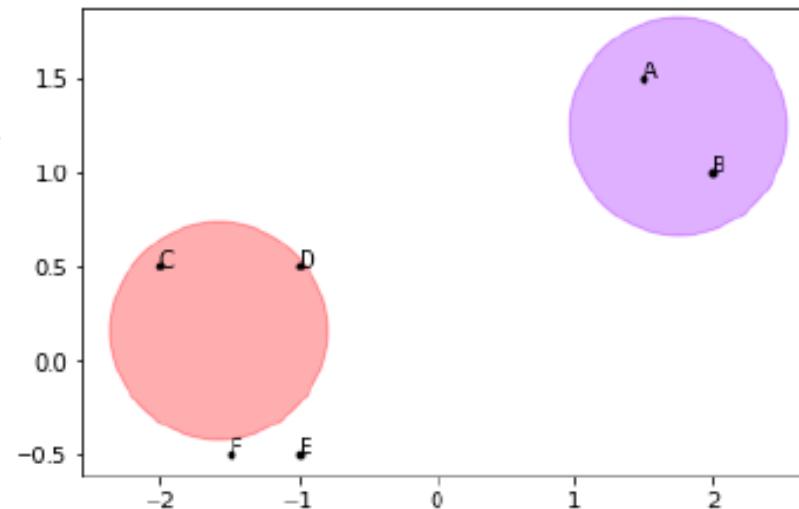
Using **minimum** or **single-linkage** clustering



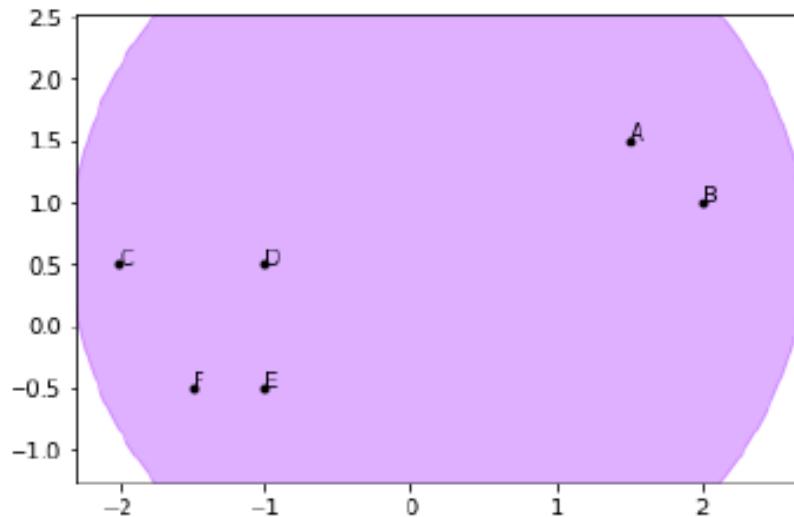
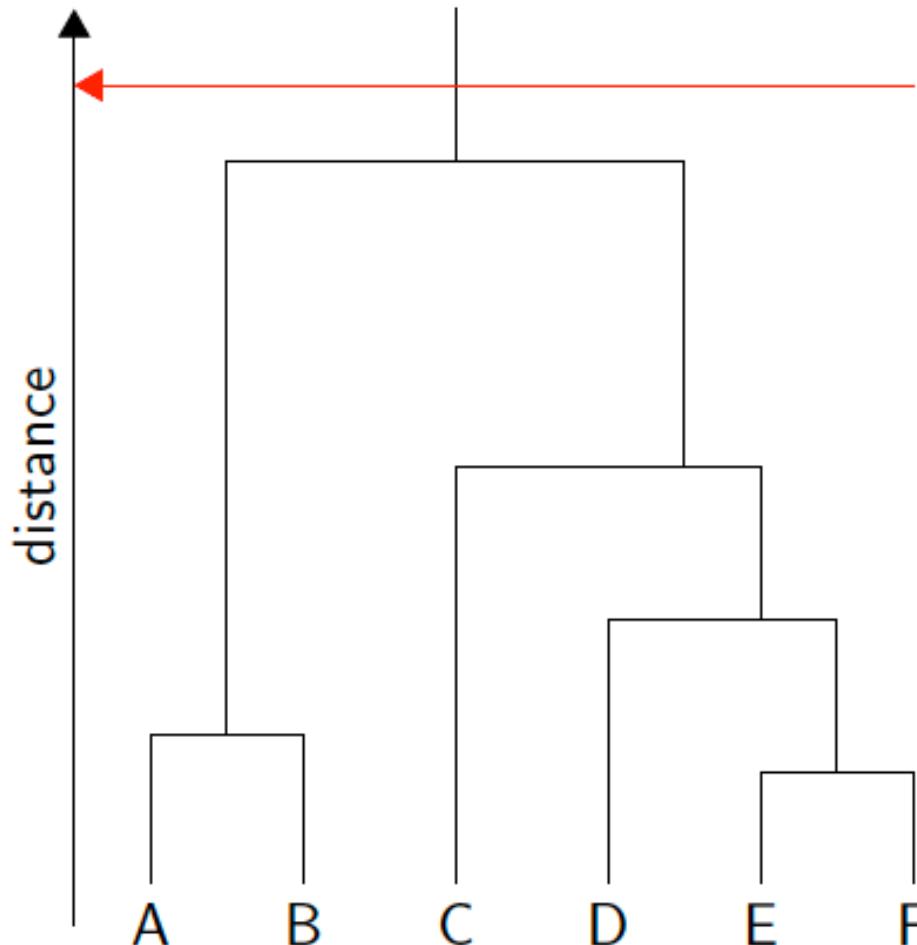
Discovering Groups – Agglomerative Clustering



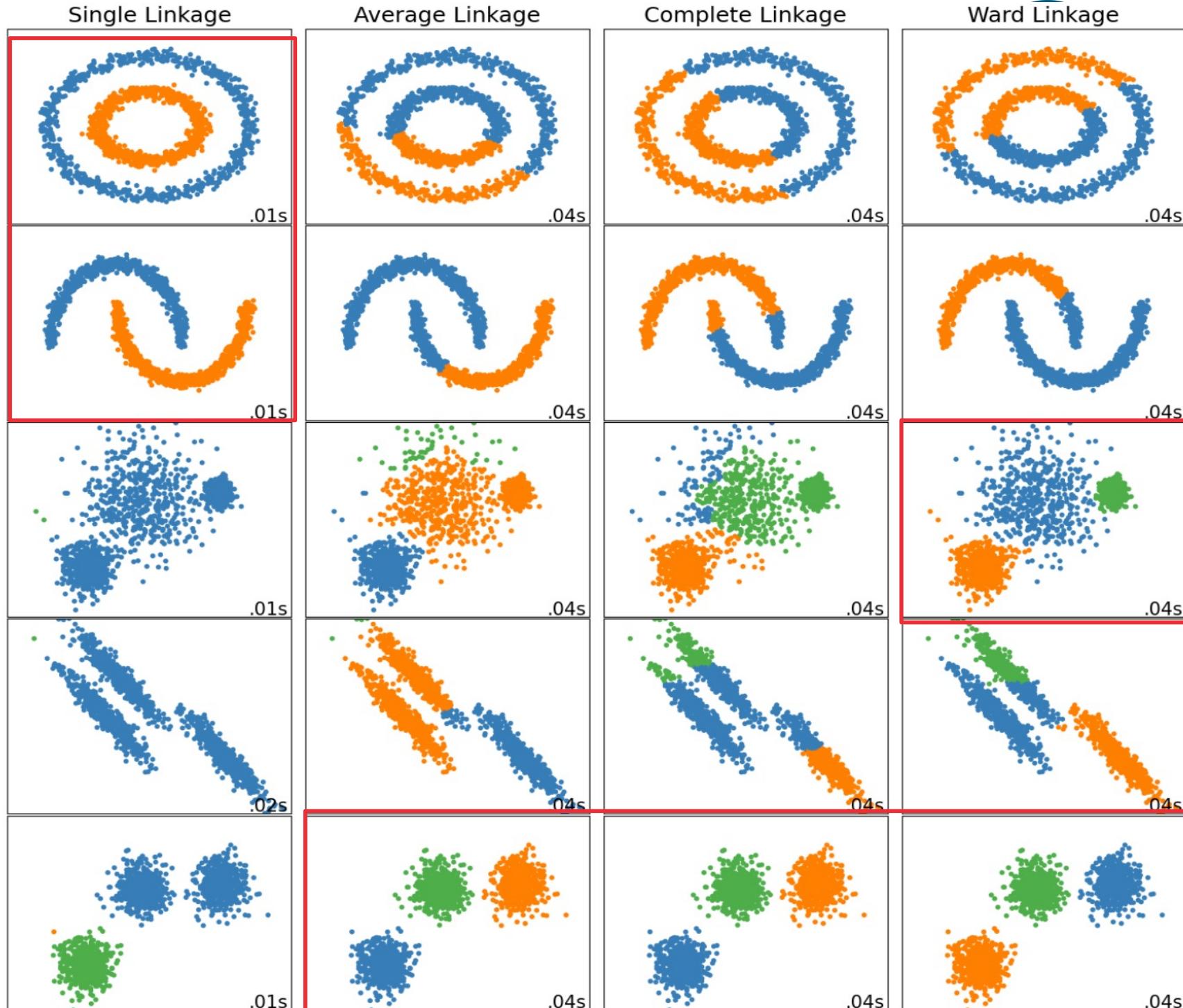
Using minimum or single-linkage clustering



Discovering Groups – Agglomerative Clustering



Using minimum or single-linkage clustering



Source: https://scikit-learn.org/stable/auto_examples/cluster/plot_linkage_comparison.html#sphx-glr-auto-examples-cluster-plot-linkage-comparison-py

Discovering Groups – Hierarchical Clustering

Pros:

- No need to pre-specify cluster numbers; cut the dendrogram at the desired level for the clusters.
- Dendograms easily summarize data into a hierarchy, facilitating cluster examination and interpretation.

Cons:

- Needs a threshold to determine the number of clusters
- Non-trivial to select the best linkage method

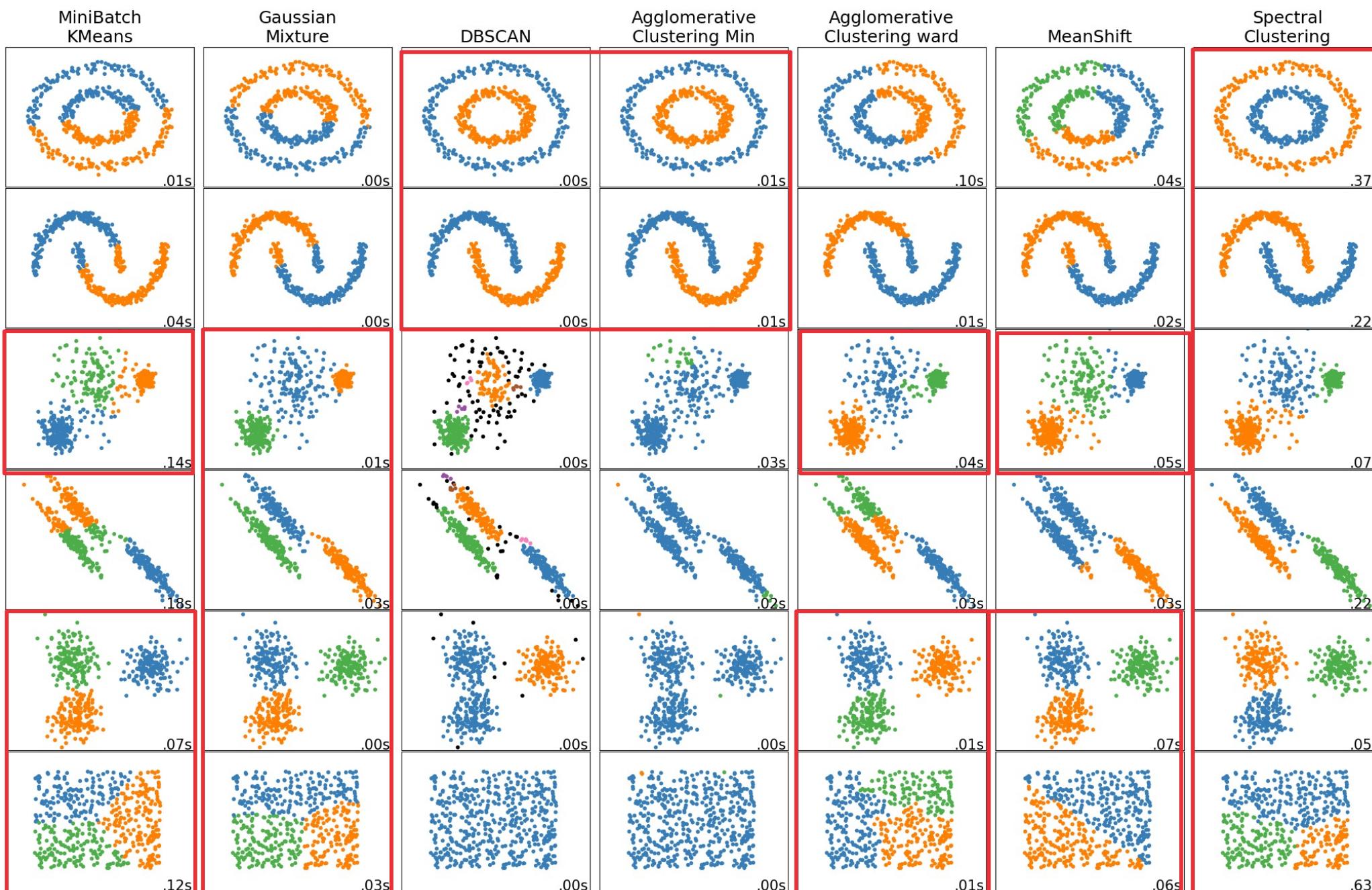
Discovering Groups – Summary

Clustering is a key way to understand your data.

There are many different approaches

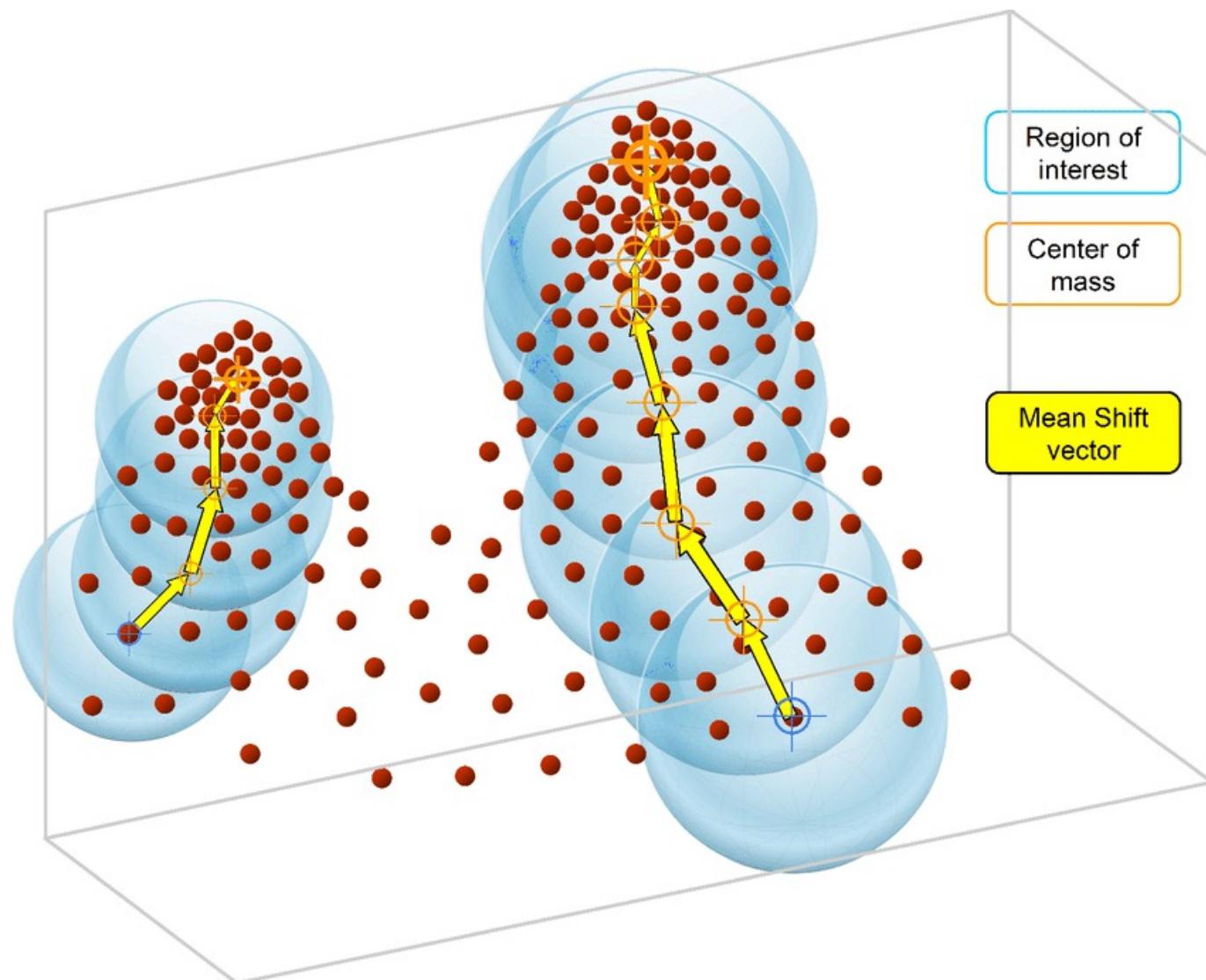
- ▶ K Means - Need to chose K
- ▶ DBSCAN - need to choose min points and radius
- ▶ Hierarchical Agglomerative Clustering - needs a threshold or number of clusters

They are a very good way to start exploring a dataset



Source: https://scikit-learn.org/stable/auto_examples/cluster/plot_cluster_comparison.html#sphx-glr-auto-examples-cluster-plot-cluster-comparison-py

Discovering Groups – Appendix (1/2)



<https://ailephant.com/how-to-program-mean-shift/>

Discovering Groups – Appendix (2/2)

Spectral Clustering - Intuition

Eigenvectors of the Laplacian matrix provide an embedding of the data based on similarity.

Disconnected subgraphs

