

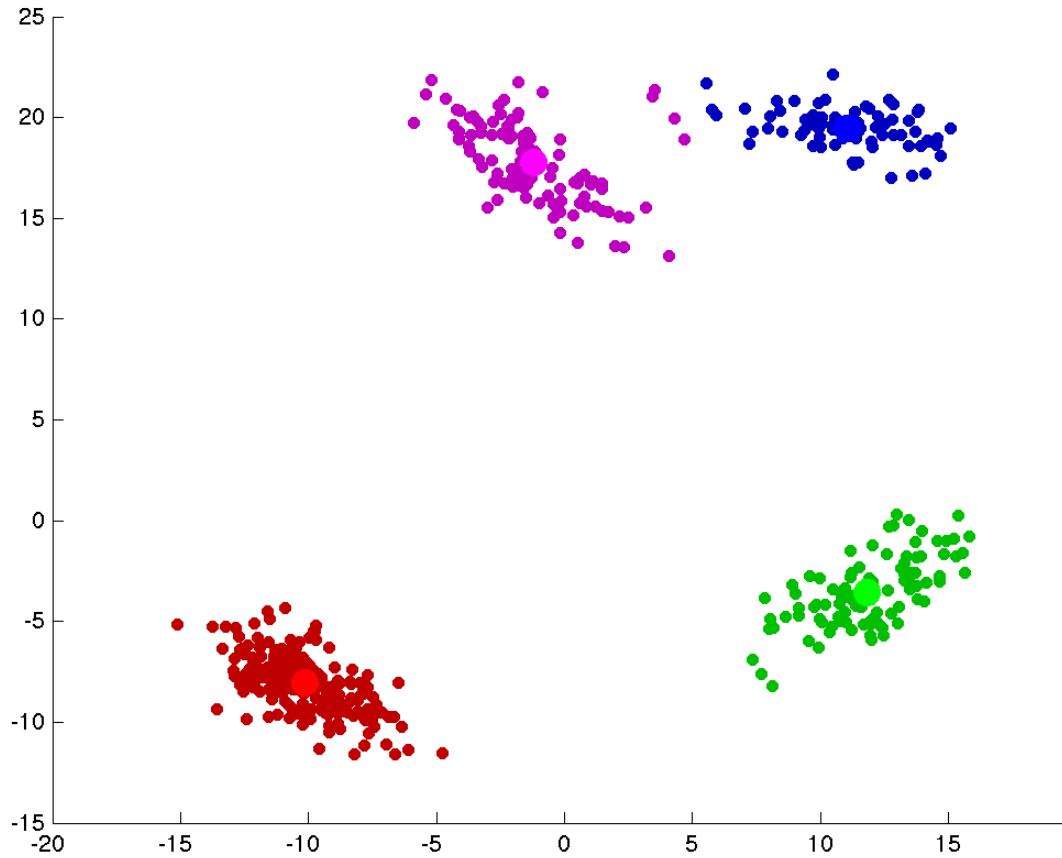
CPSC 340: Machine Learning and Data Mining

More Clustering

Fall 2019

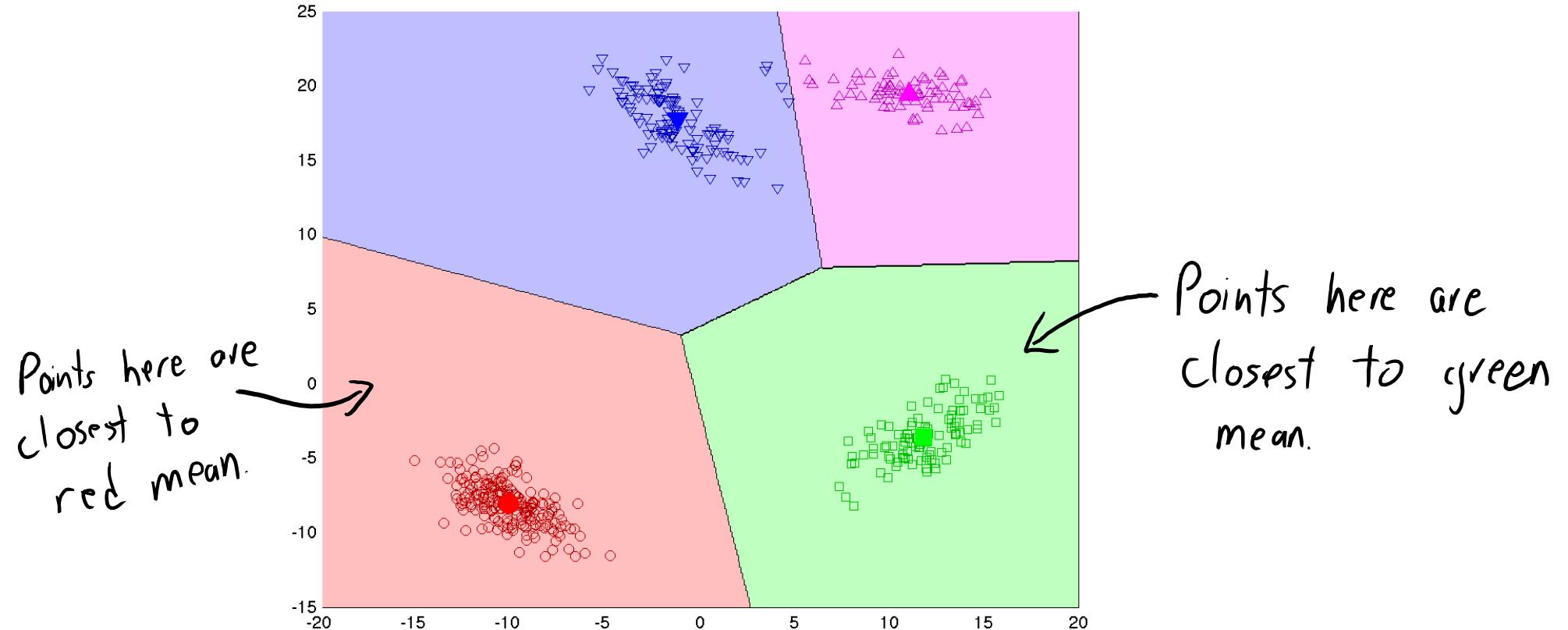
Last Time: K-Means Clustering

- We want to **cluster** data:
 - Assign examples to groups.
- **K-means clustering:**
 - Define groups by “means”
 - Assigns examples to nearest mean.
(And updates means during training.)
- Also used for **vector quantization**:
 - Use **means** as “prototypes” of groups.
 - “Pick clothing sizes or spaghetti sauces”.
- Issues with k-means:
 - Fast but sensitive to initialization.
 - Choosing ‘k’ is annoying.



Shape of K-Means Clusters

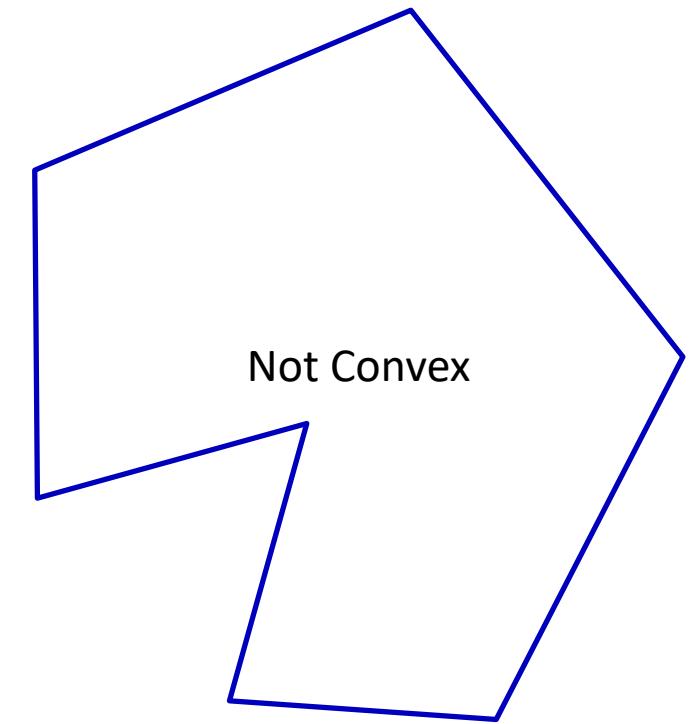
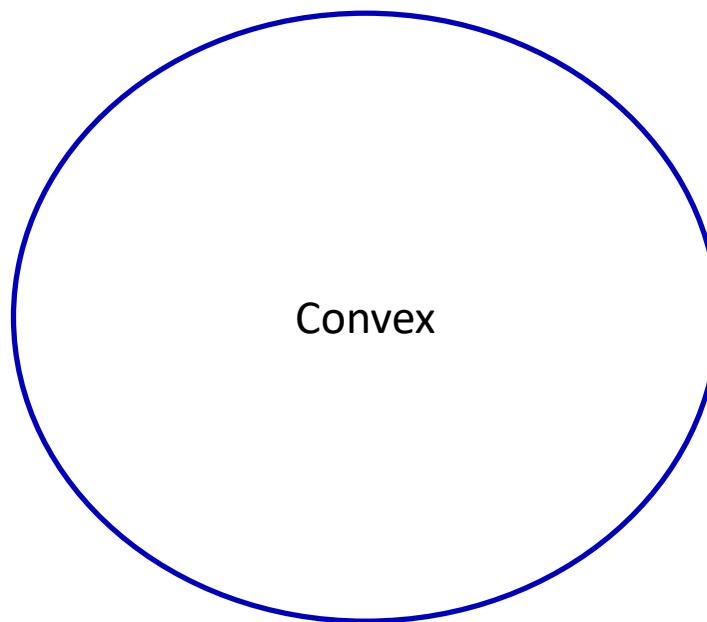
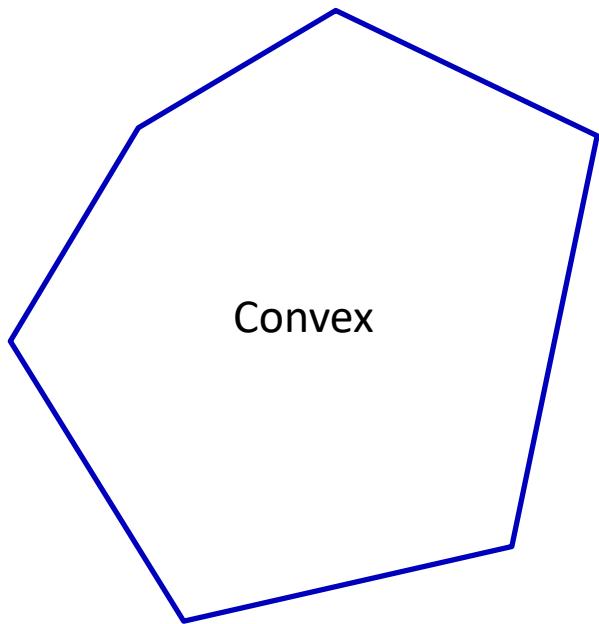
- K-means partitions the space based on the “closest mean”:



- Observe that the clusters are convex regions (proof in bonus).

Convex Sets

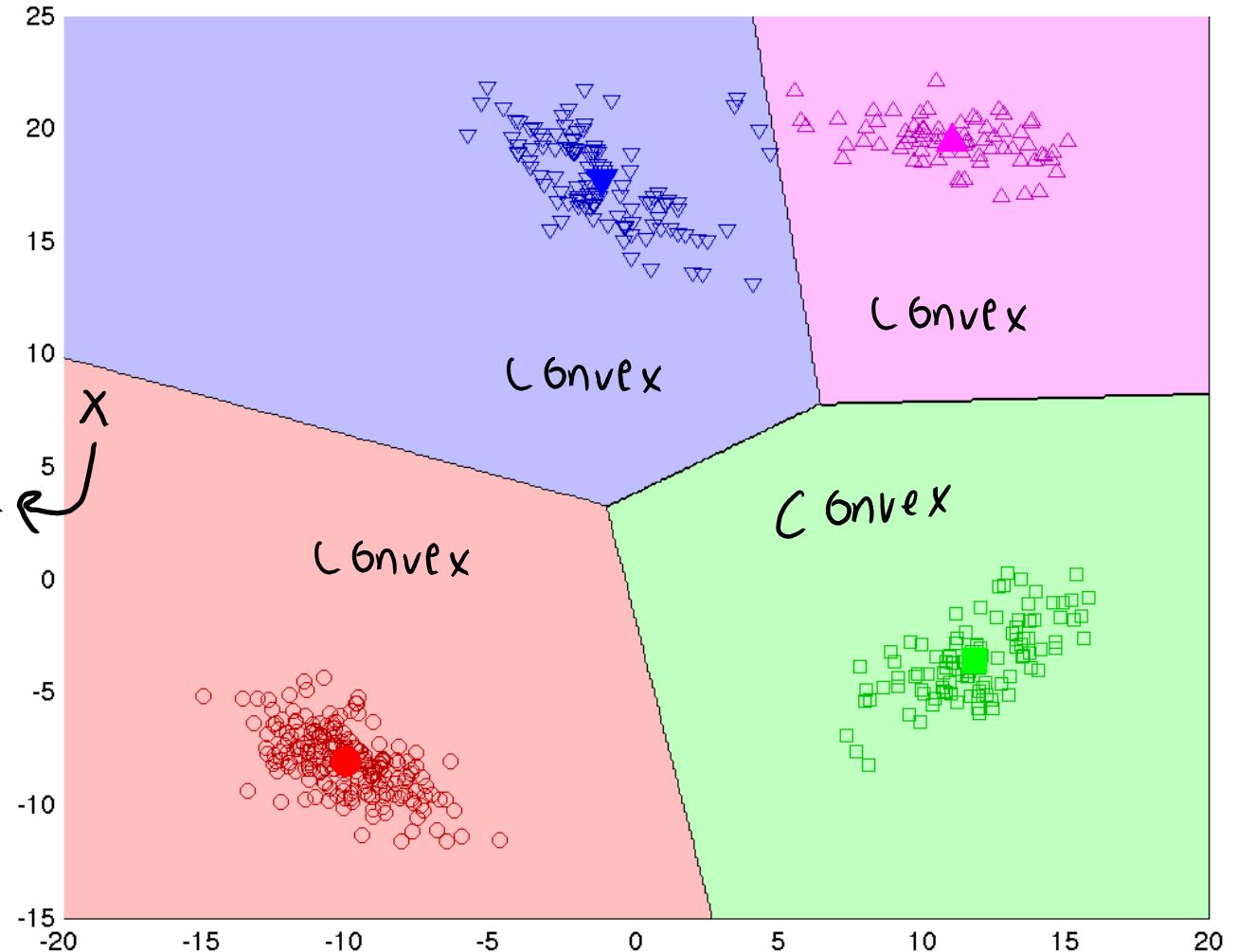
- A set is **convex** if **line between two points in the set stays in the set.**



Shape of K-Means Clusters

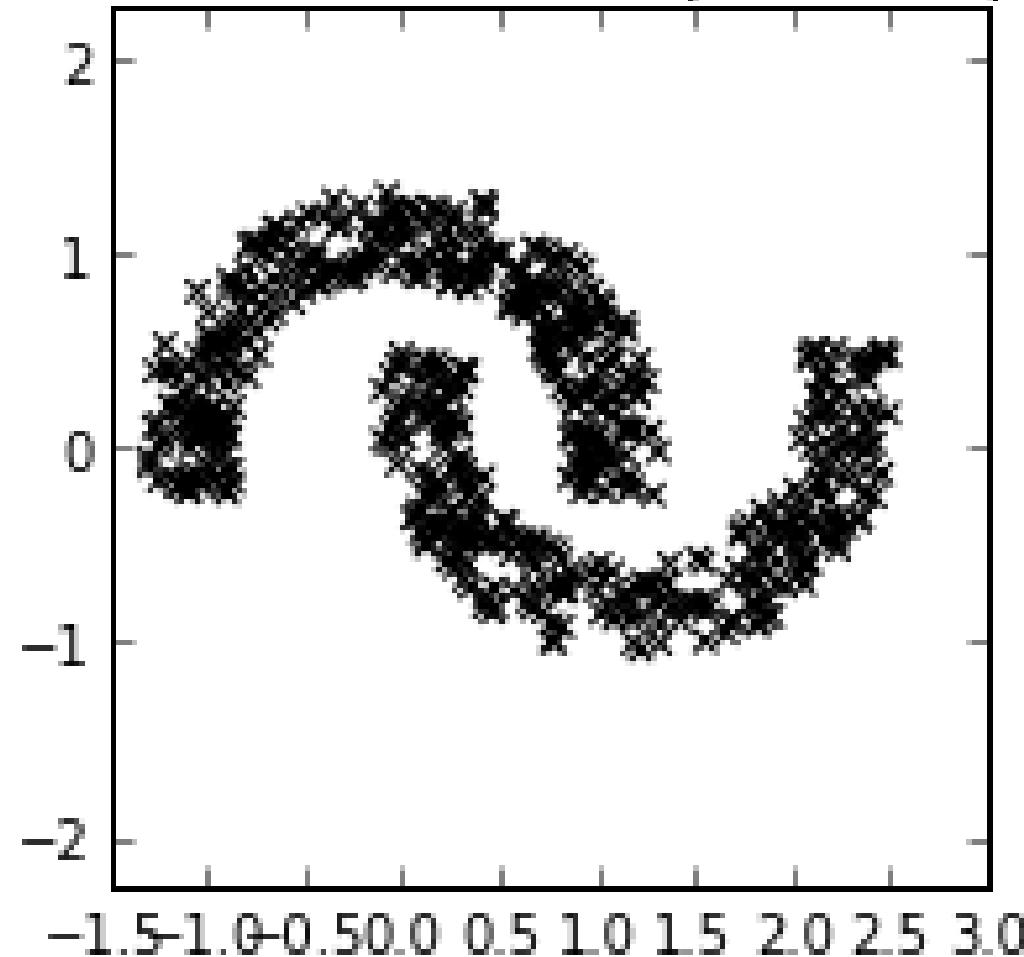
Issues with shape of k-means clusters:

1. Clusters in the data might not be convex.
2. Does this point really belong in red cluster?

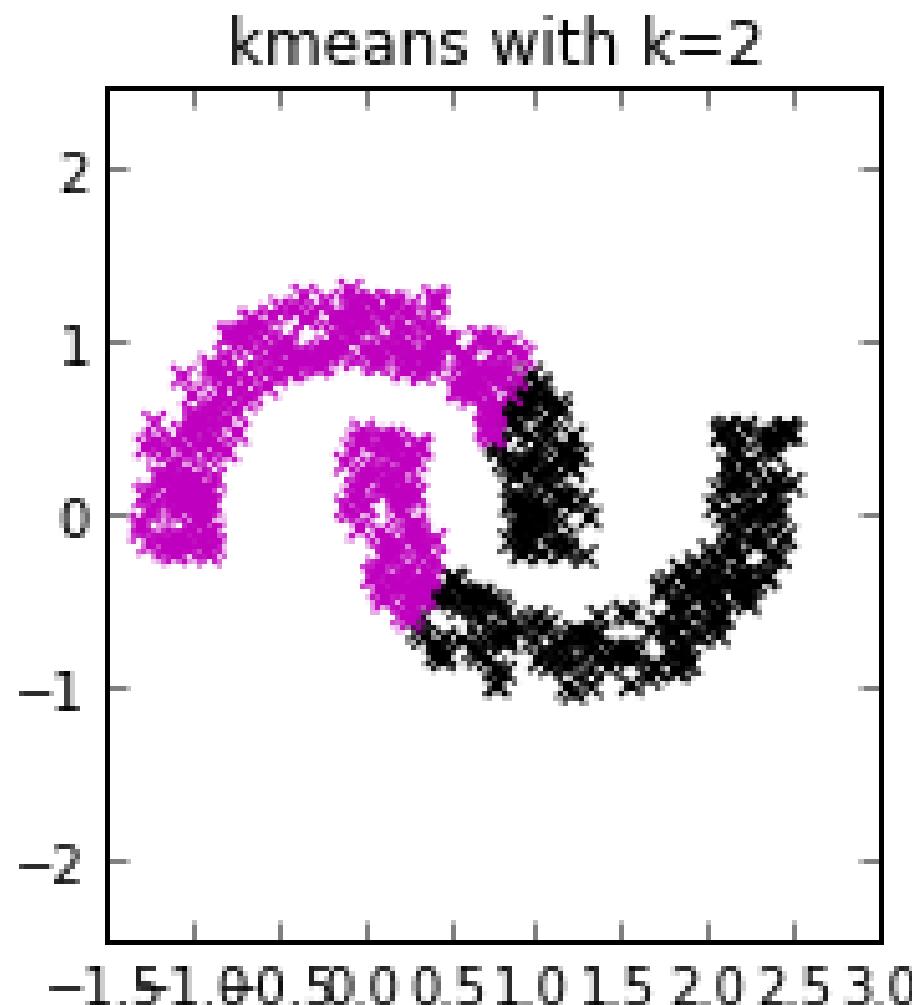


K-Means with Non-Convex Clusters

Non-convex banana-shaped data points

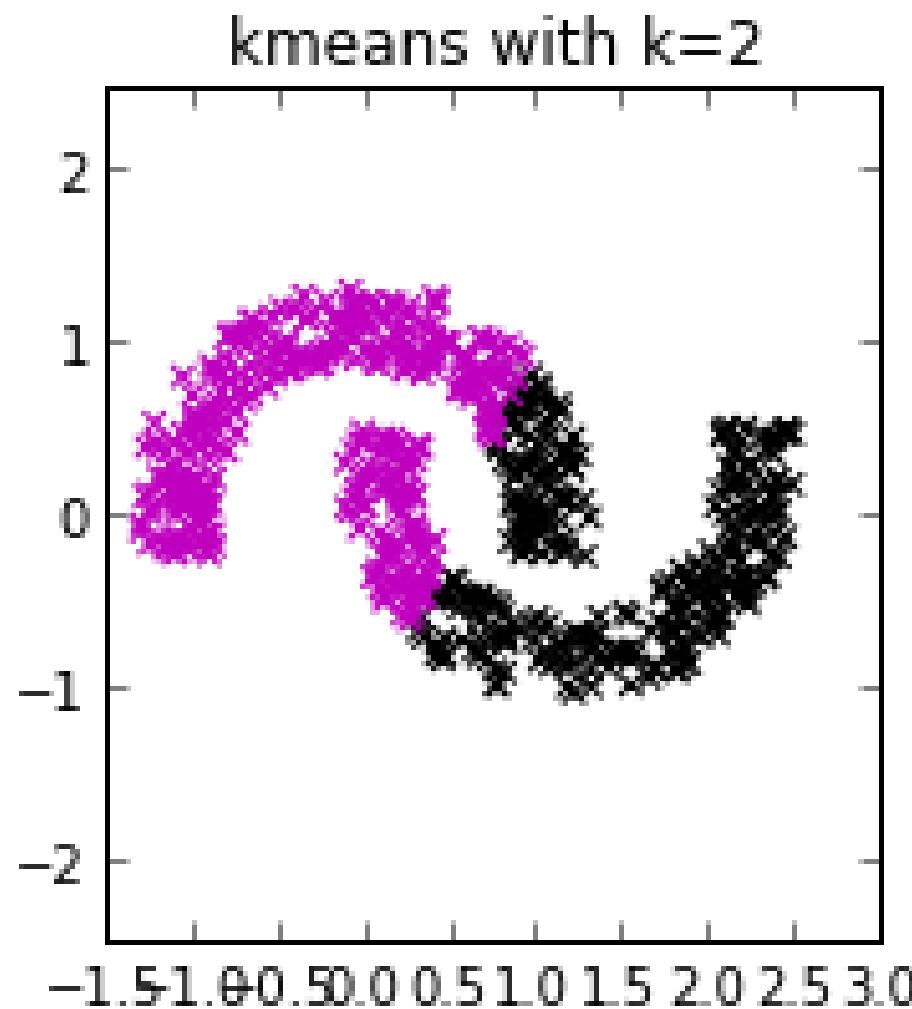


K-Means with Non-Convex Clusters



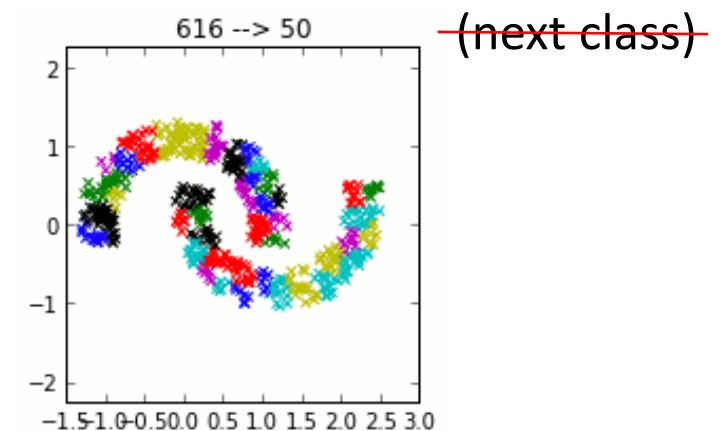
K-means **cannot separate** some
non-convex clusters

K-Means with Non-Convex Clusters



K-means **cannot separate**
non-convex clusters

Though over-clustering can help



G john snow - Google Sea X +

← → ⌂ ⌂ google.ca/search?safe=off&tbo=isch&q=john+snow&nfpr=1&sa=X&ved=0ahUKEwj9gsnWsLXWAhUJ8mMKHUAQBdQQvgUIkAloAQ&biw=1440&bih=750&d

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Google john snow

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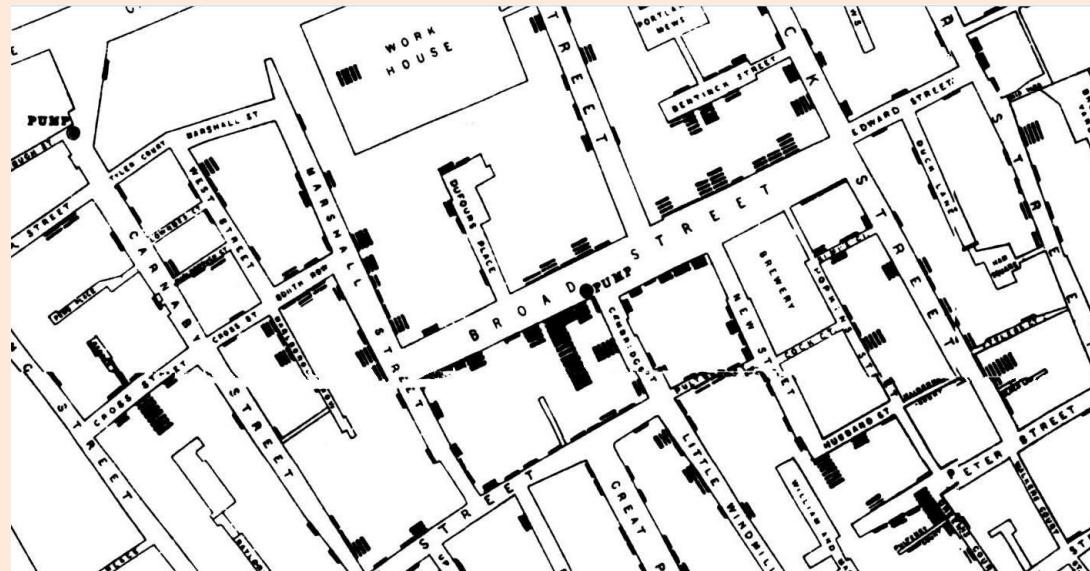
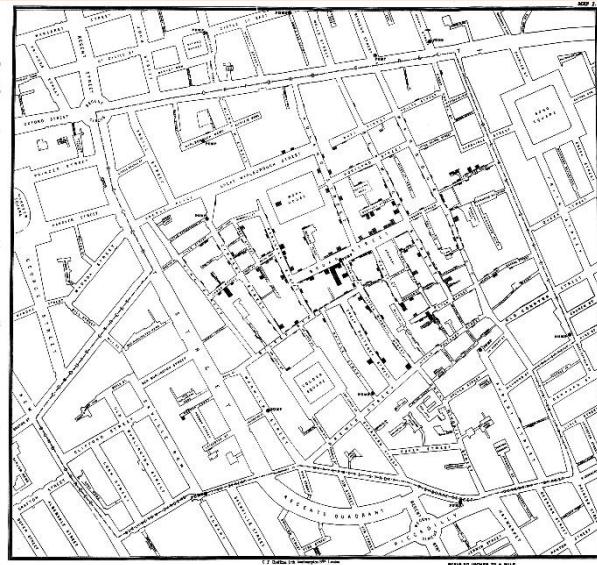
wallpaper funny season 6 winter is coming meme genderbent let it snow real life ghost wallpaper hd the watch meme his wolf game throne simpsons >

Did you mean: jon snow

The image shows a Google search results page for 'john snow'. The search bar at the top contains the query 'john snow'. Below the search bar, there are several filter buttons: 'All' (gray), 'Images' (blue, indicating the current selection), 'News', 'Videos', 'Maps', and 'More'. To the right of these are 'Settings' and 'Tools' buttons. Further right are 'View saved' and 'SafeSearch' dropdown menus. Below the search bar is a row of colored buttons with search terms: 'wallpaper' (green), 'funny' (teal), 'season 6' (dark blue), 'winter is coming meme' (purple), 'genderbent' (pink), 'let it snow' (red), 'real life' (orange), 'ghost' (yellow), 'wallpaper hd' (light green), 'the watch meme' (teal), 'his wolf' (blue), 'game throne' (dark blue), and 'simpsons' (purple). A 'Did you mean: jon snow' link is present. The main content area displays a grid of 30 image thumbnails. The first row contains 8 thumbnails, the second row contains 10, and the third row contains 12. The images include Kit Harington as Jon Snow in various costumes (including Night's Watch and Starks), historical figures named John Snow, and various fan art and memes related to the character.

John Snow and Cholera Epidemic

- John Snow's 1854 spatial histogram of deaths from cholera:



- Found cluster of cholera deaths around a particular water pump.
 - Went against airborne theory, but pump later found to be contaminated.
 - “Father” of epidemiology.

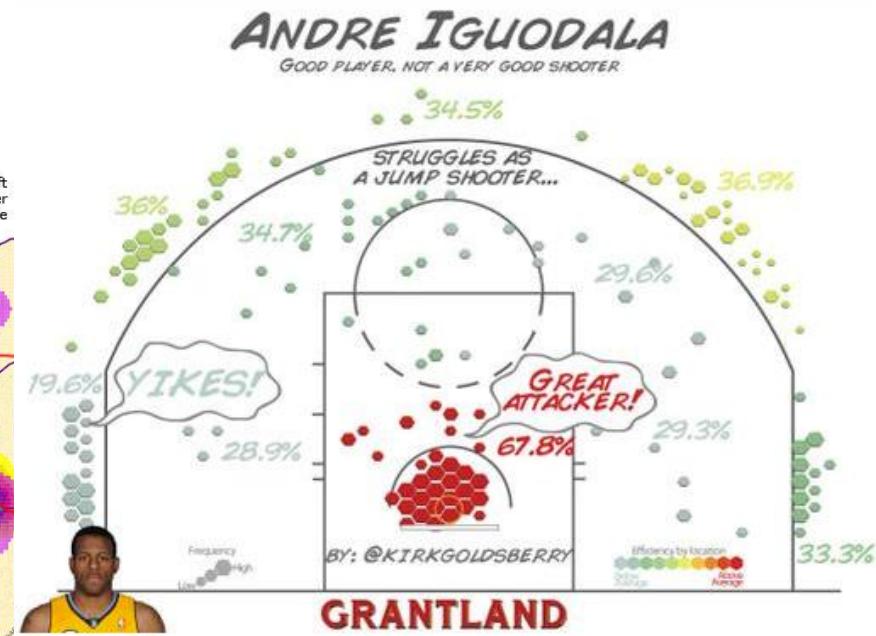
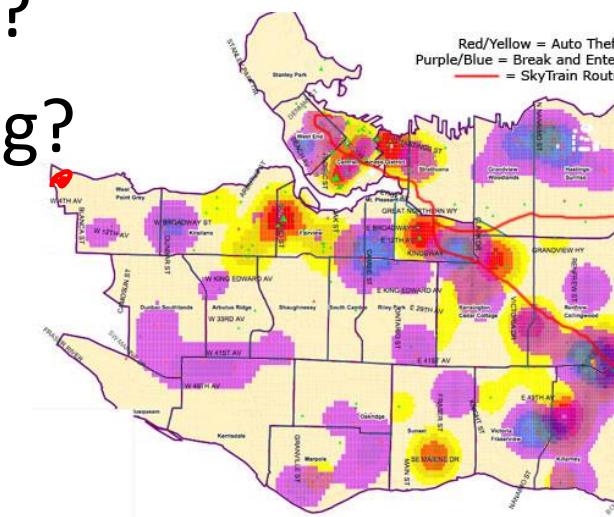
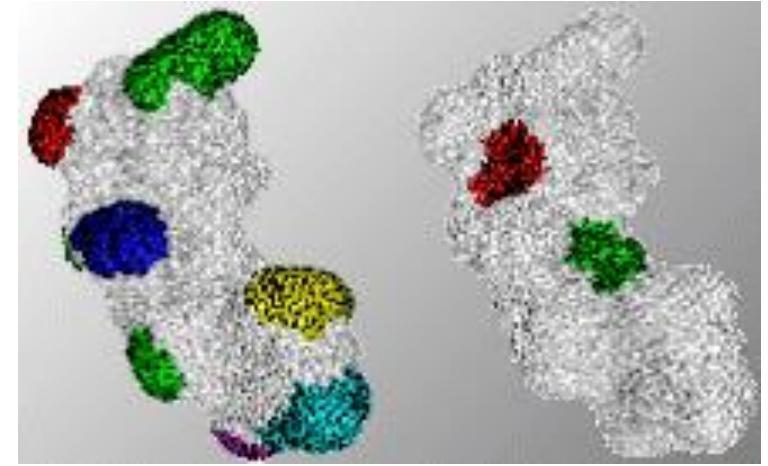
Motivation for Density-Based Clustering

- Density-based clustering:
 - Clusters are defined by “dense” regions.
 - Examples in non-dense regions don’t get clustered.
 - Not trying to “partition” the space.
- Clusters can be non-convex:
 - Elephant clusters affected by vegetation, mountains, rivers, water access, etc.
- It’s a non-parametric clustering method:
 - No fixed number of clusters ‘k’.
 - Clusters can become more complicated with more data.



Other Potential Applications

- Where are high crime regions of a city?
- Where should taxis patrol?
- Where does Iguodala make/miss shots?
- Which products are similar to this one?
- Which pictures are in the same place?
- Where can proteins ‘dock’?
- Where are people tweeting?



https://en.wikipedia.org/wiki/Cluster_analysis

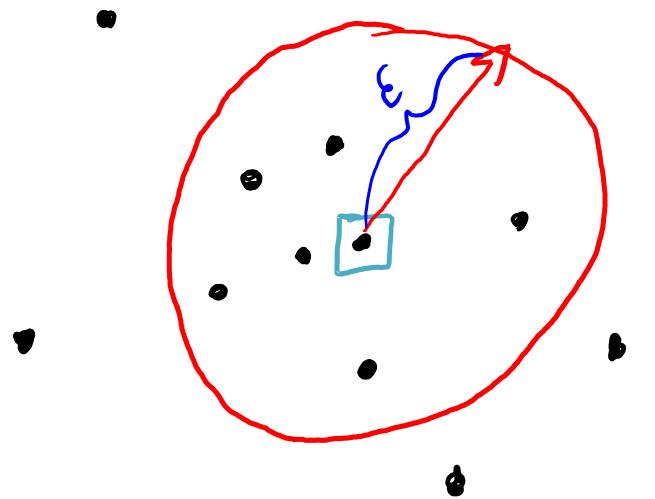
<https://www.flickr.com/photos/dbarefoot/420194128/>

<http://letsgowarriors.com/replacing-jarrett-jack/2013/10/04/>

<http://www.dbs.informatik.uni-muenchen.de/Forschung/KDD/Clustering/>

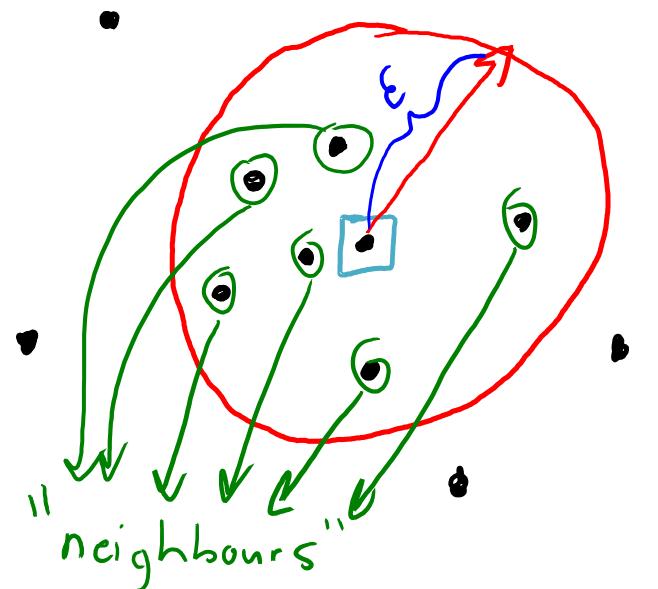
Density-Based Clustering

- Density-based clustering algorithm (DBSCAN) has two hyperparameters:
 - Epsilon (ε): distance we use to decide if another point is a “neighbour”.



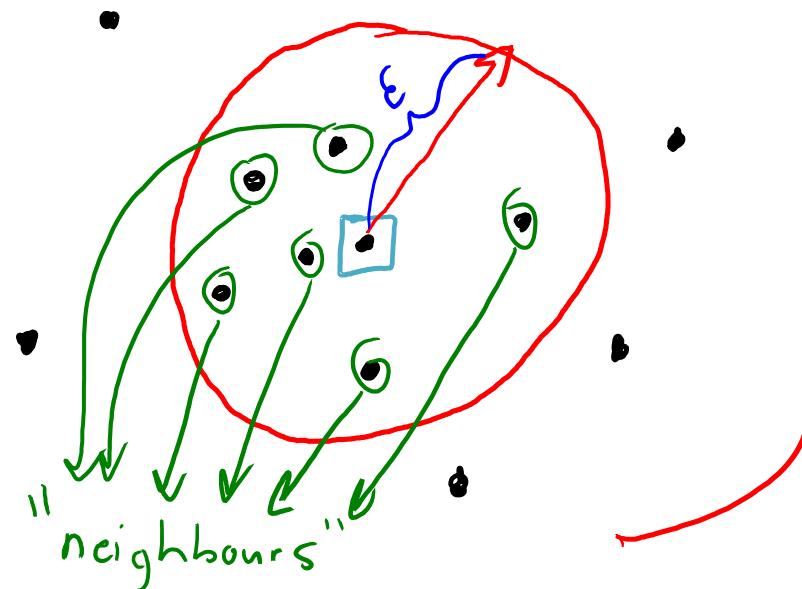
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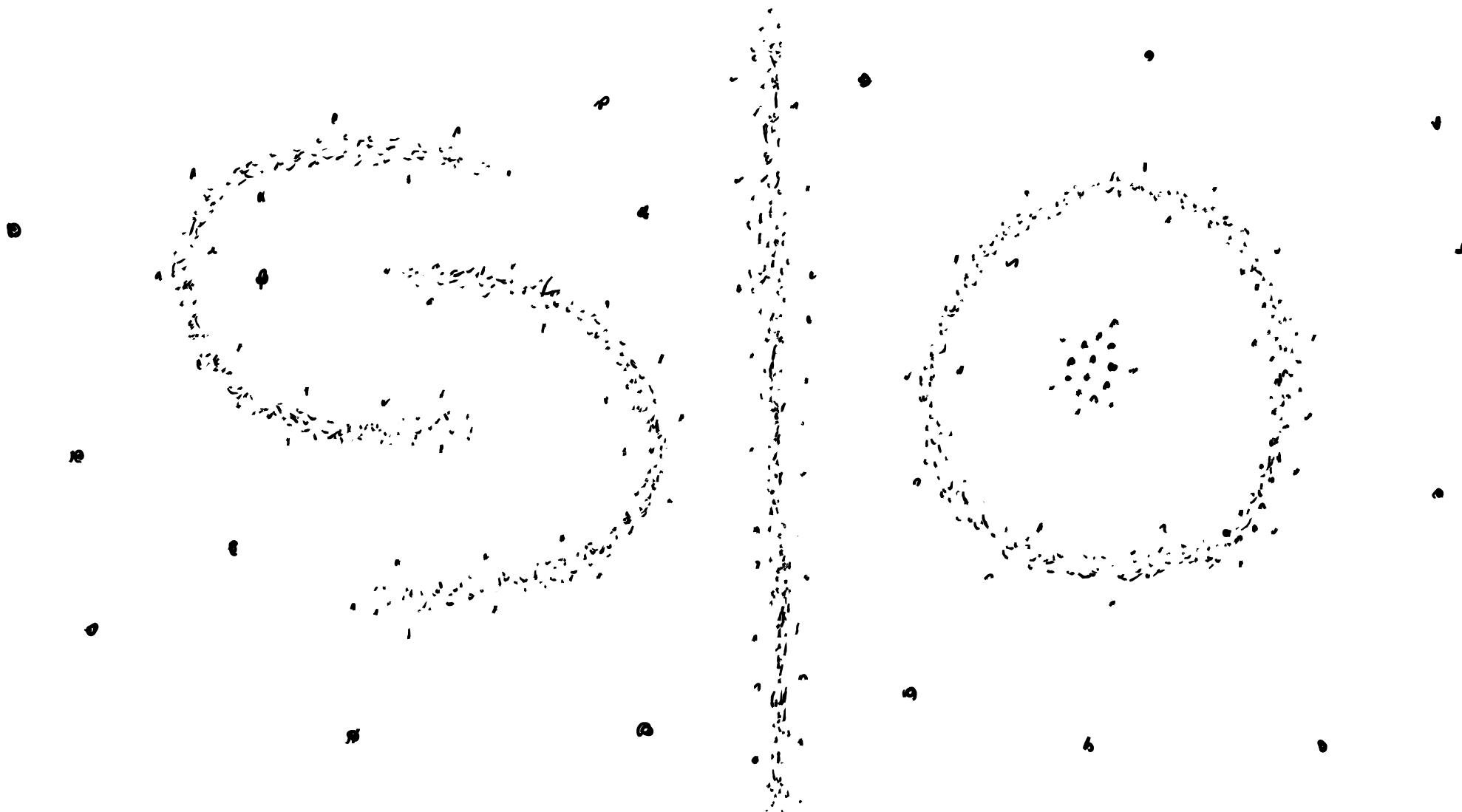
Density-Based Clustering

- Density-based clustering algorithm (DBSCAN) has two hyperparameters:
 - Epsilon (ϵ): distance we use to decide if another point is a “neighbour”.
 - MinNeighbours: number of neighbours needed to say a region is “dense”.
 - If you have at least minNeighbours “neighbours”, you are called a “core” point.
- Main idea: merge all neighbouring core points to form clusters.

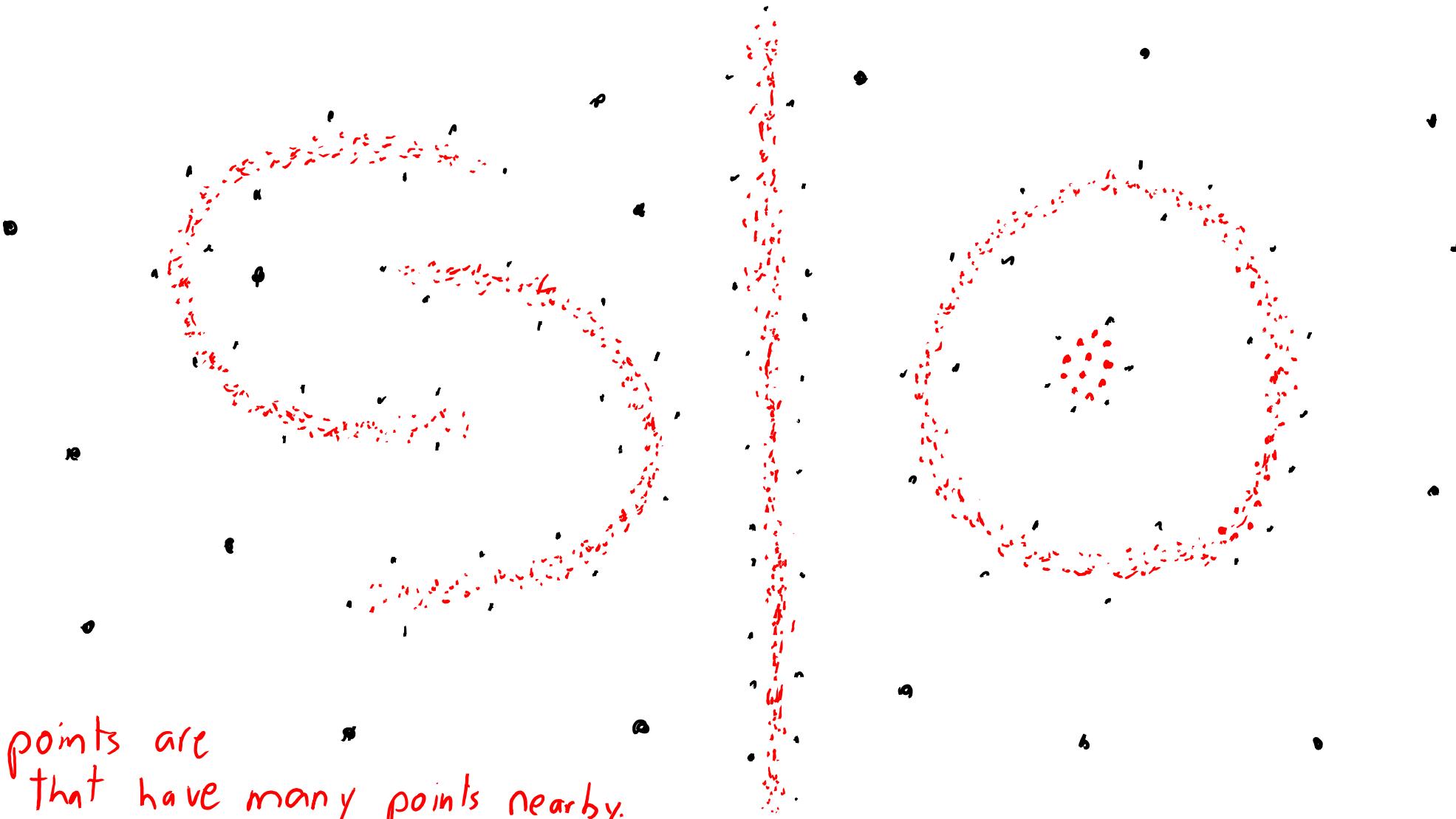


→ Eg, if minNeighbours = 3
then this is a "core" point since 6 points are "neighbours"

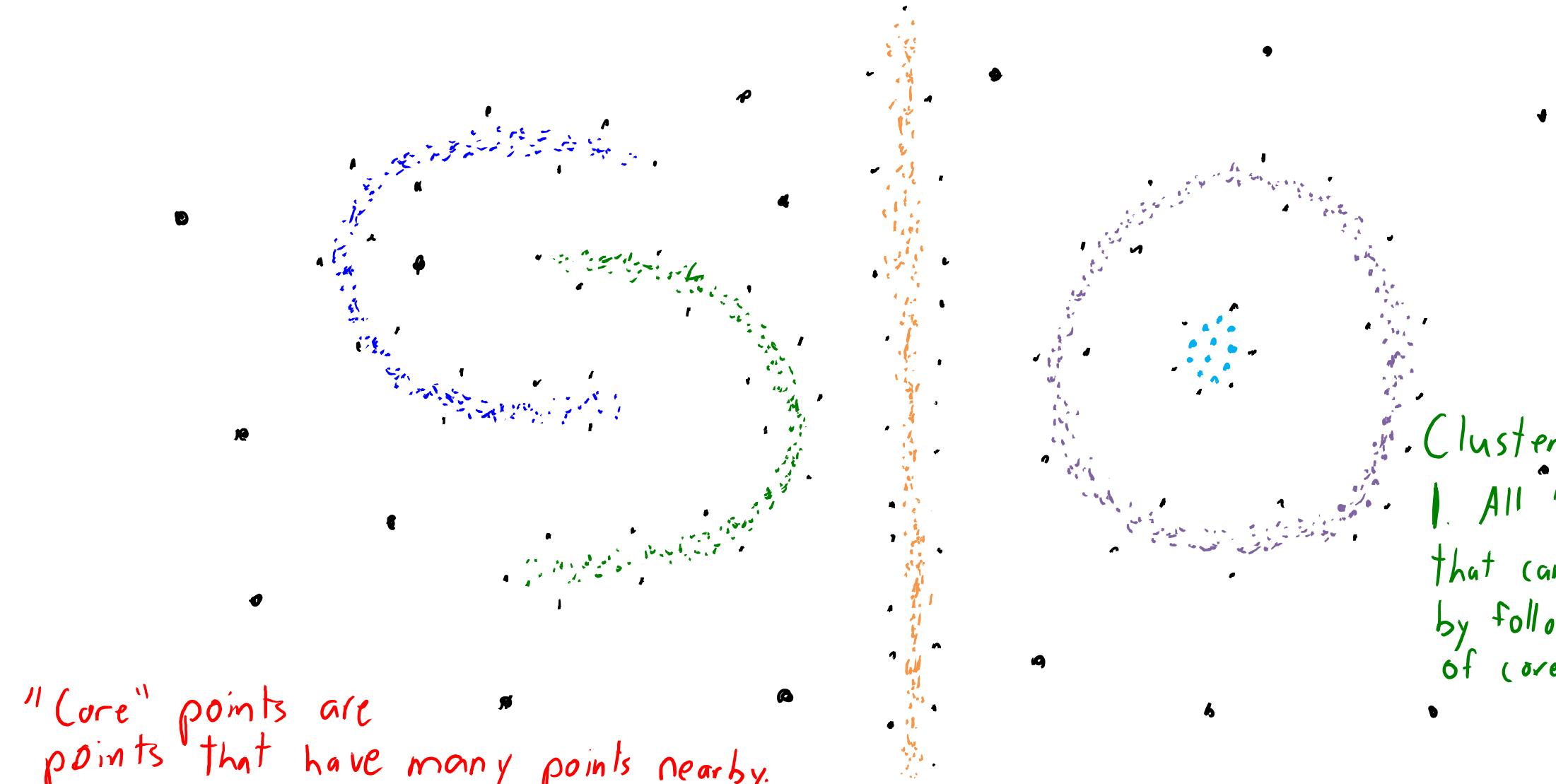
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Density-Based Clustering

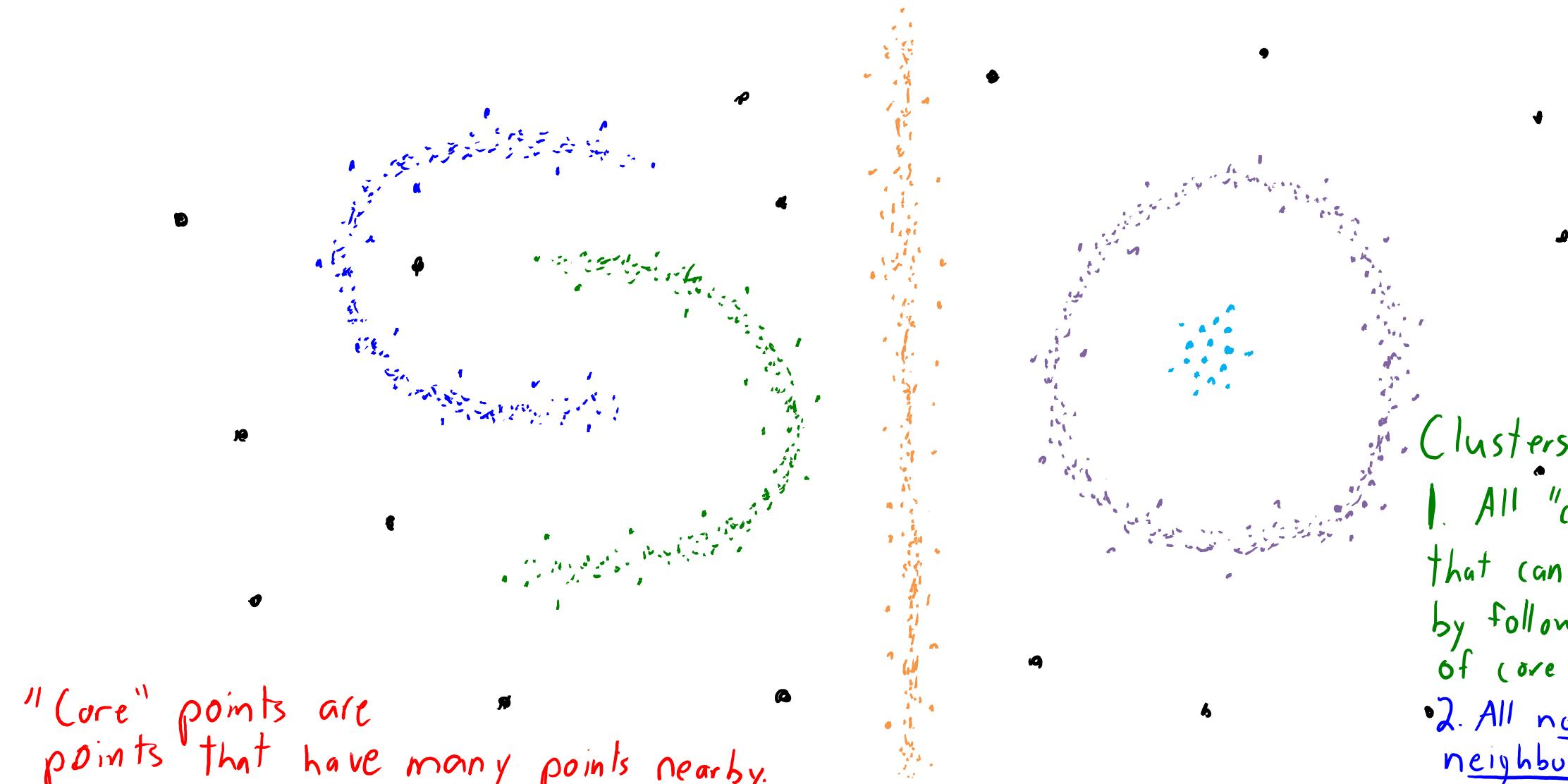


Density-Based Clustering



- Clusters contain:
1. All "core" points that can be reached by following a sequence of core points.

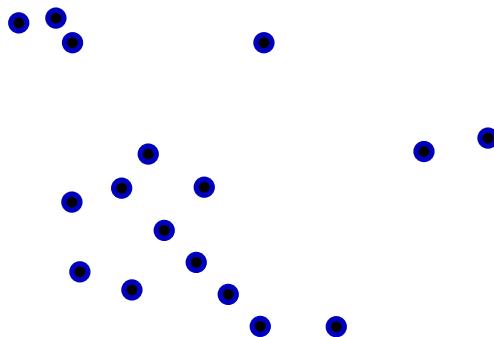
Density-Based Clustering



- Clusters contain:
 1. All "core" points that can be reached by following a sequence of core points.
 2. All non-core neighbours of core points (boundary points)

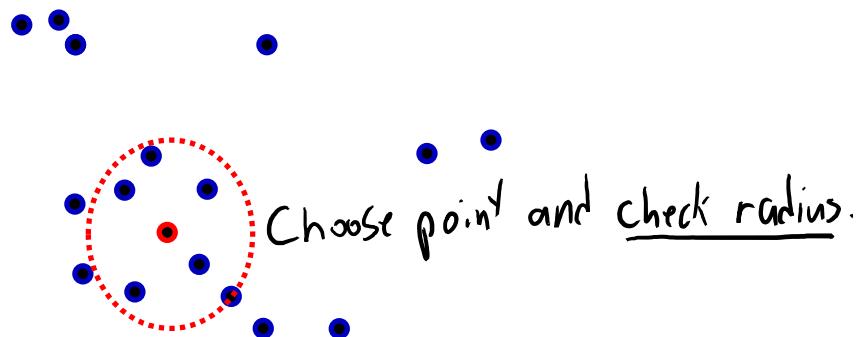
Density-Based Clustering (Example)

- Each “core” point defines a cluster:
 - Consisting of “core” point and all its “neighbours”.
- Merge clusters if “core” points are “neighbours” of each other.



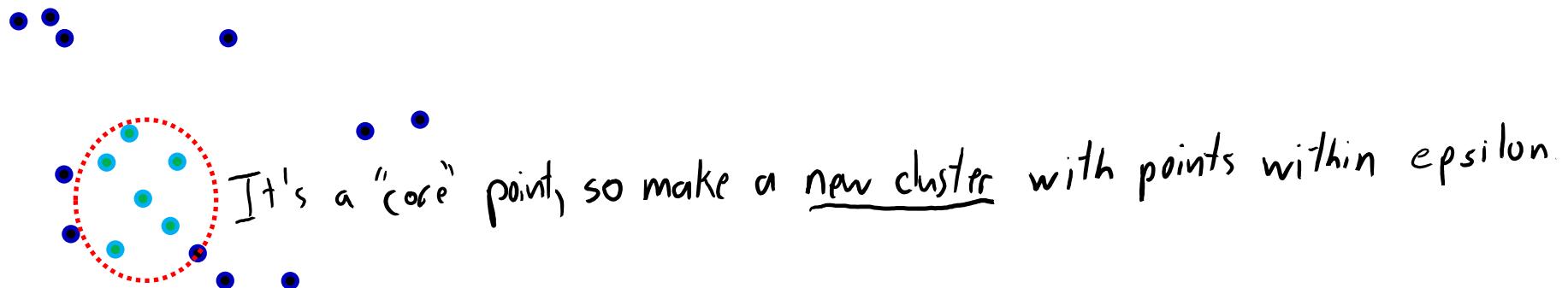
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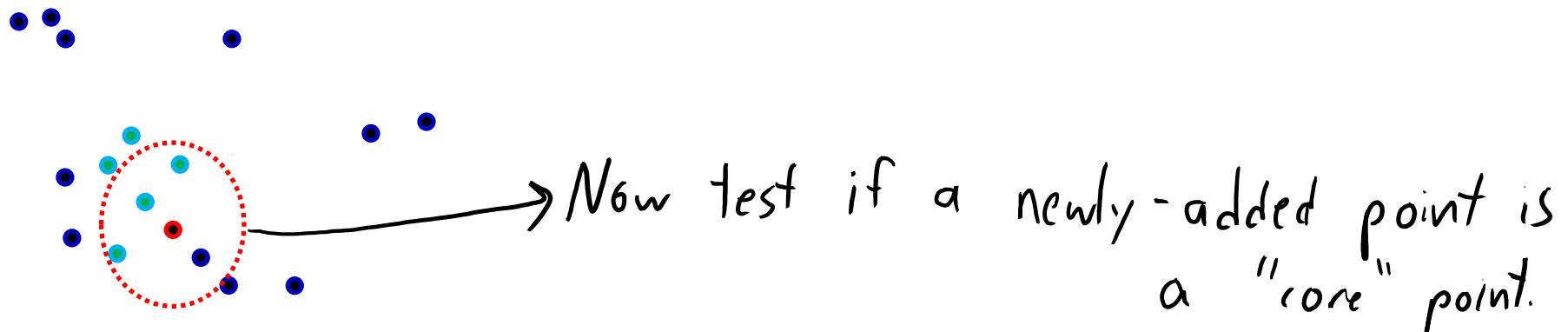
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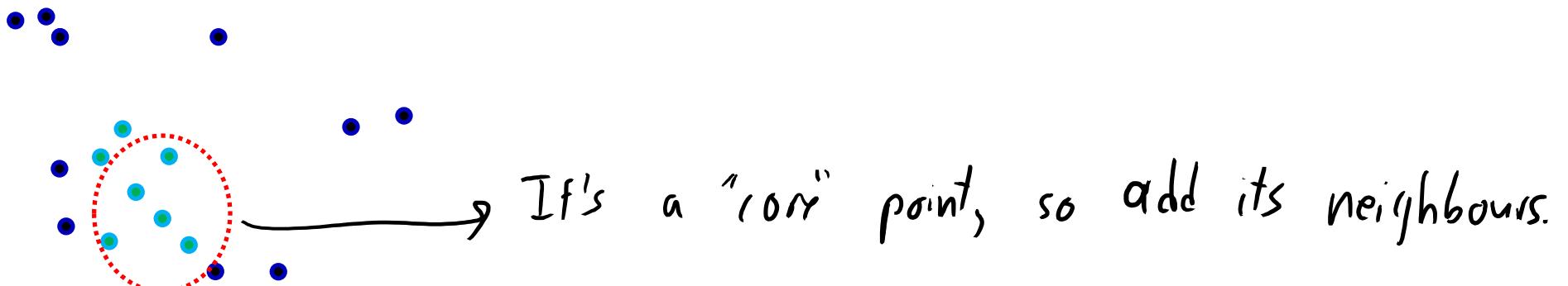
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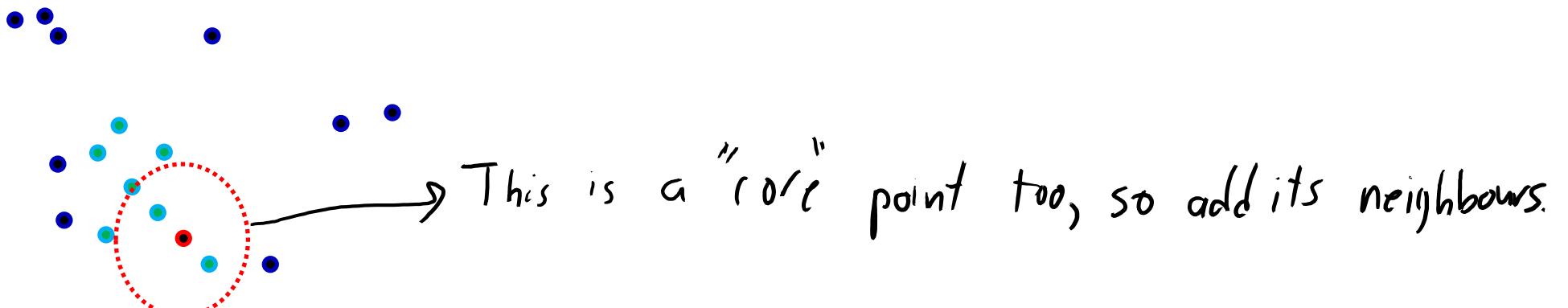
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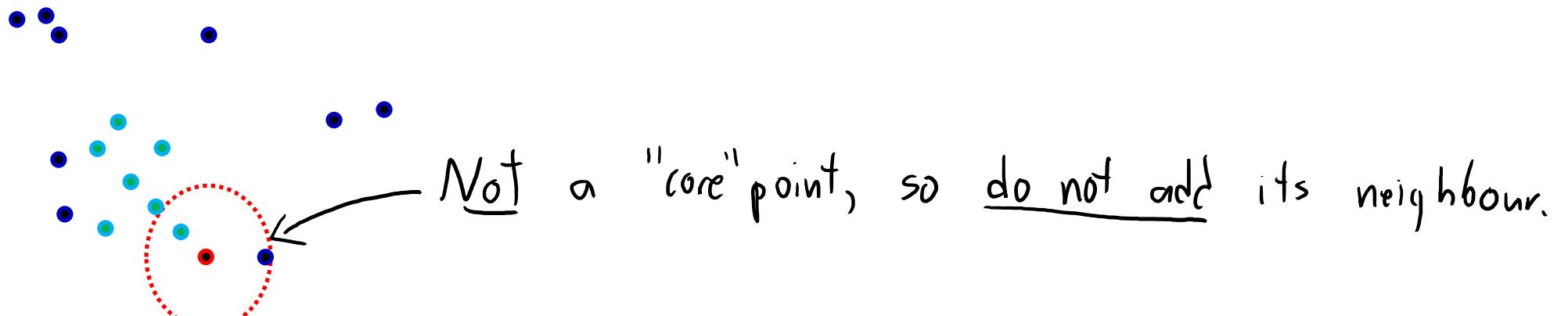
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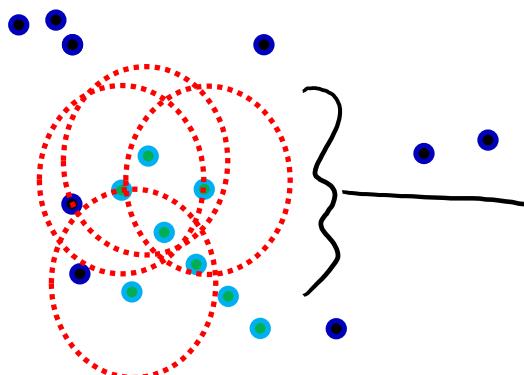
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Density-Based Clustering (Example)

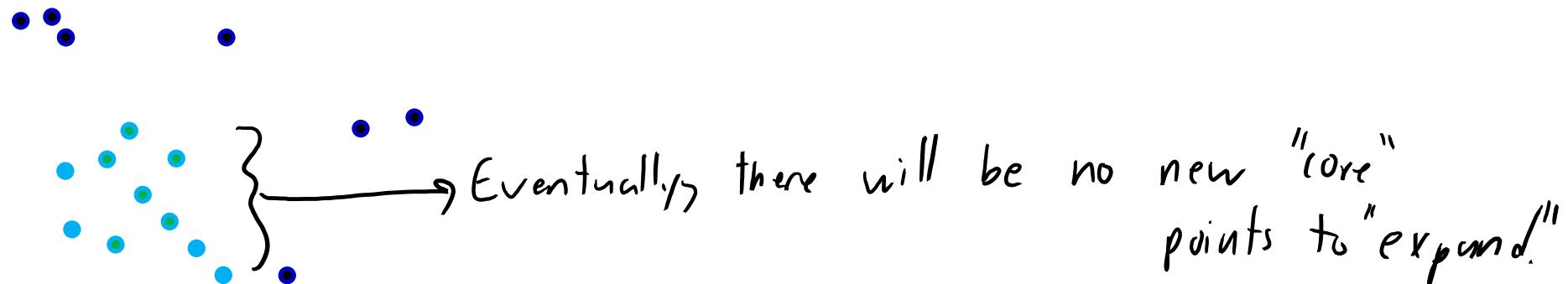
- Each “core” point defines a cluster:
 - Consisting of “core” point and all its “neighbours”.
- Merge clusters if “core” points are “neighbours” of each other.



Continue testing whether the other cluster point are "core" points.

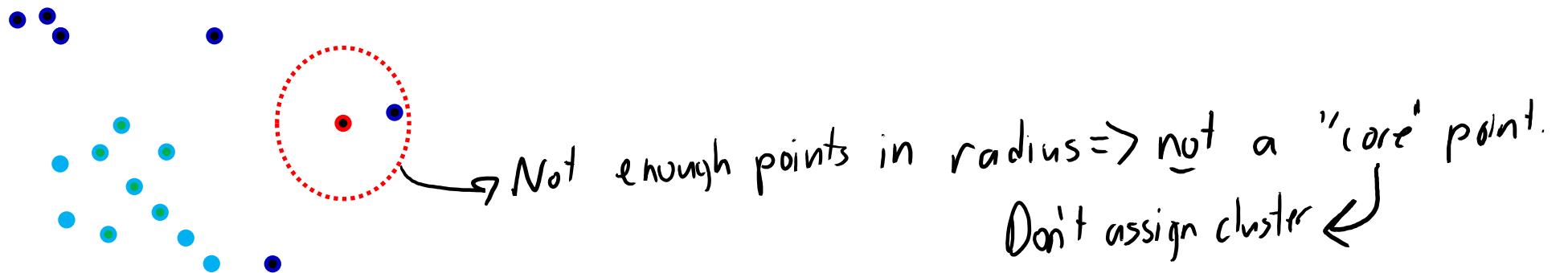
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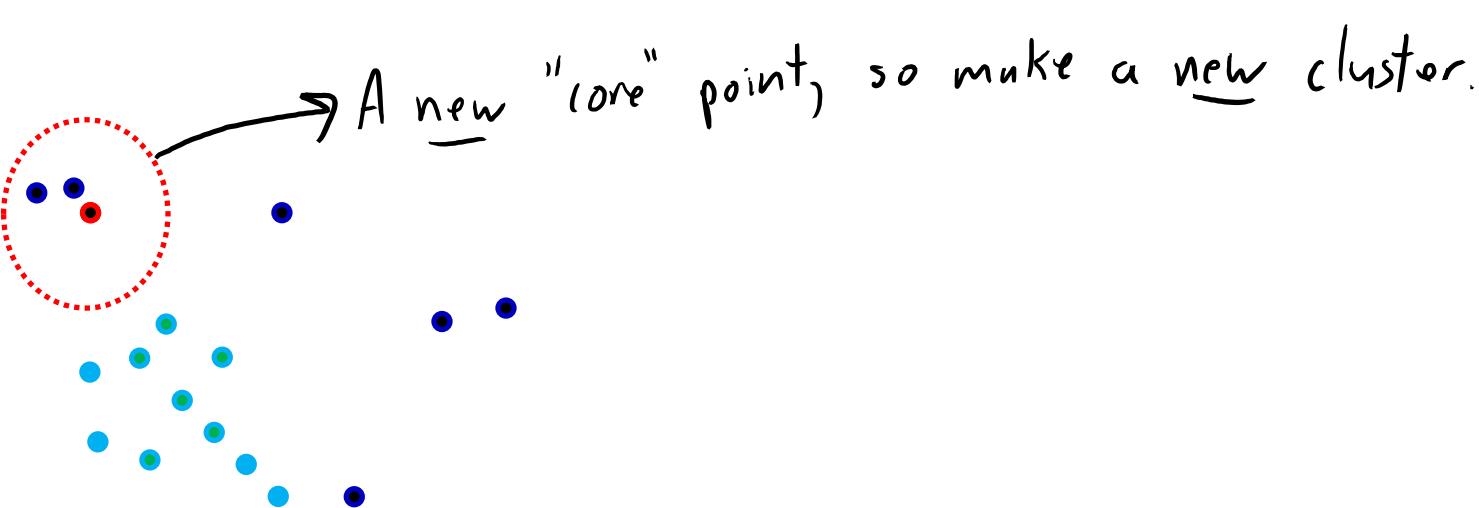
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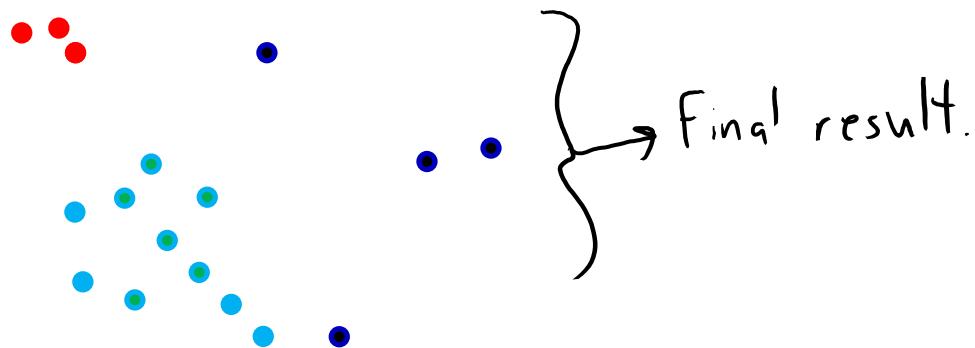
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Density-Based Clustering (Example)

- Each “core” point defines a cluster:
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Density-Based Clustering Pseudo-Code

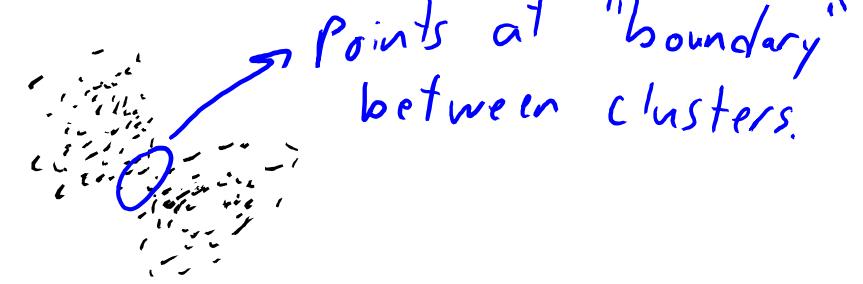
- For each example x_i :
 - If x_i is already assigned to a cluster, do nothing.
 - Test whether x_i is a ‘core’ point ($\geq \text{minNeighbours}$ examples within ‘ ϵ ’).
 - If x_i is not core point, do nothing (this could be an outlier).
 - If x_i is a core point, make a new cluster and “expand” the cluster.
- “Expand” cluster function:
 - Assign to this cluster all x_j within distance ‘ ϵ ’ of core point x_i to cluster.
 - For each new “core” point found, “expand” cluster (recursively).

Density-Based Clustering in Action



[Interactive demo](#)

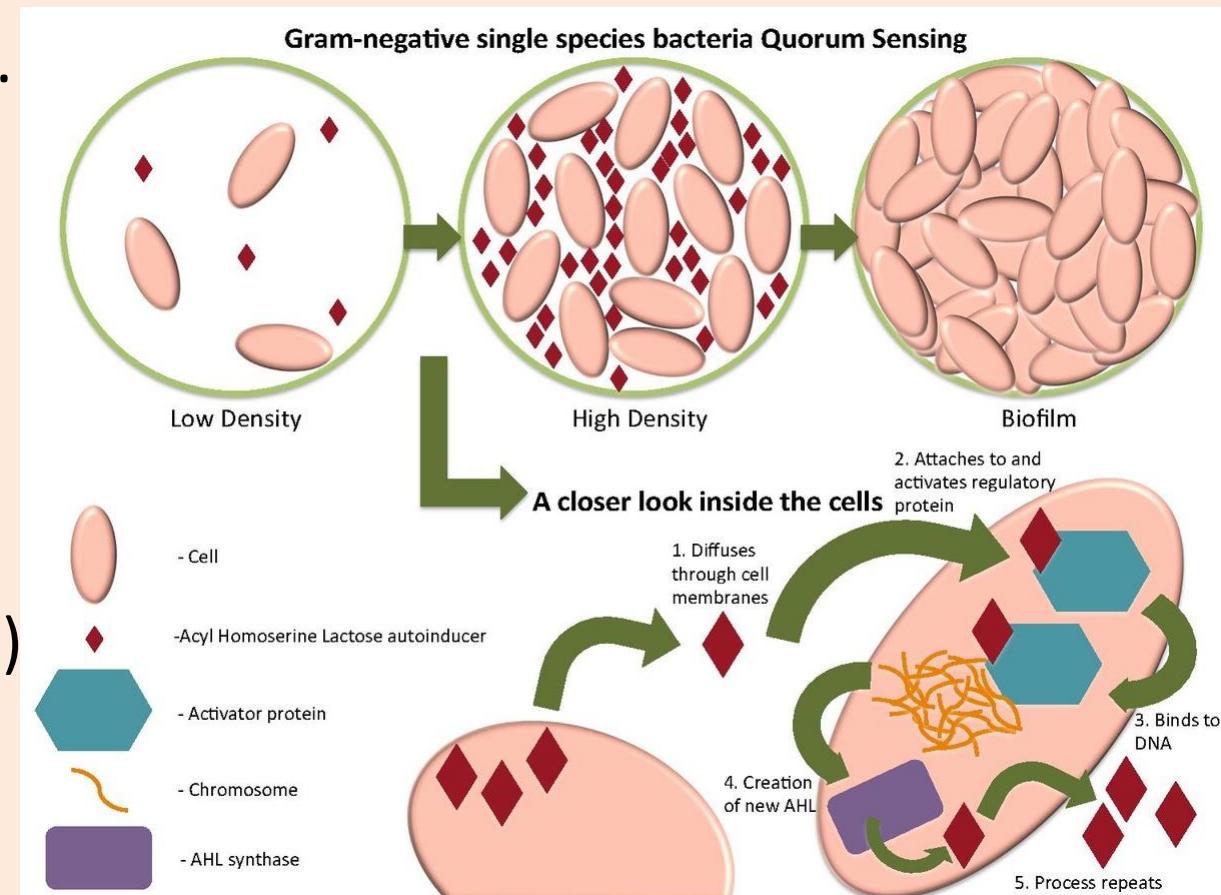
Density-Based Clustering Issues

- Some points are not assigned to a cluster.
 - Good or bad, depending on the application.
- Ambiguity of “non-core” (boundary) points:

Points at “boundary” between clusters.
- Sensitive to the choice of ε and minNeighbours.
 - Original paper proposed an “elbow” method (see bonus slide).
 - Otherwise, not sensitive to initialization (except for boundary points).
- If you get a new example, finding cluster is expensive.
 - Need to compute distances to training points.
- In high-dimensions, need a lot of points to ‘fill’ the space.

Density-Based Clustering in Nature

- Quorum sensing:
 - Bacteria continuously release a particular molecule.
 - They have sensors for this molecule.
- If sensors become very active:
 - It means cell density is high.
 - Causes cascade of changes in cells.
(Some cells “stick together” to form a physical cluster via “biofilm”.)



(pause)

Ensemble Clustering

question ★

stop following 23 views

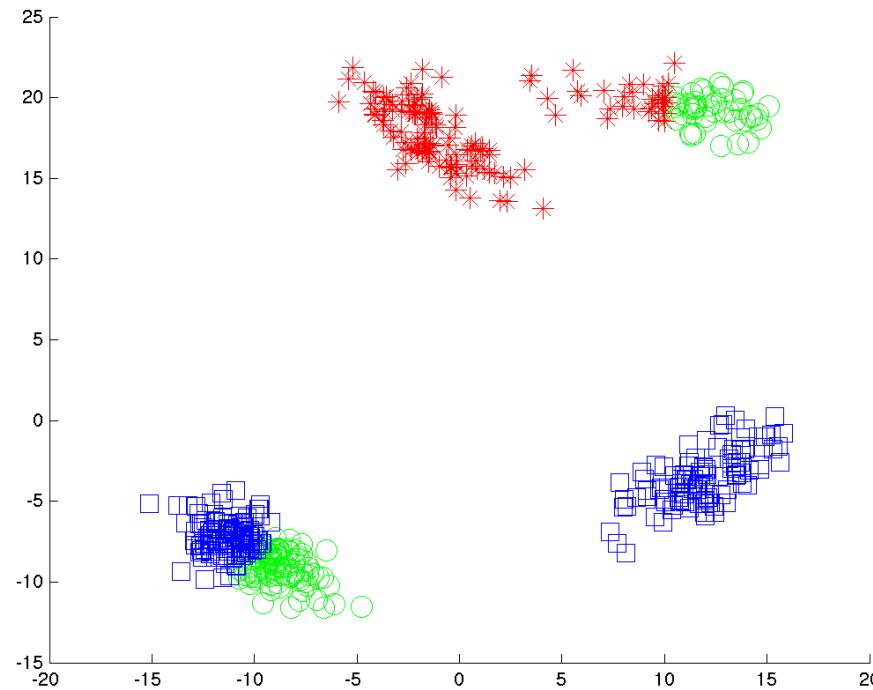
Multiple random runs of K means

I was wondering how running K Means (original version, not K means ++) several times with random initializations can help us make an accurate model. K Means outputs the class labels of all the samples. We definitely can't use mode of all the labels it got in different runs because class labels from different runs don't make any sense when compared. We somehow have to see what points are coming in the same cluster in a lot of runs..I am not sure, how do we do it?

- We can consider **ensemble methods** for clustering.
 - “Consensus clustering”
- It's a good/important idea:
 - **Bootstrapping** is widely-used.
 - “Do clusters change if the data was slightly different?”
- But we **need to be careful** about how we combine models.

Ensemble Clustering

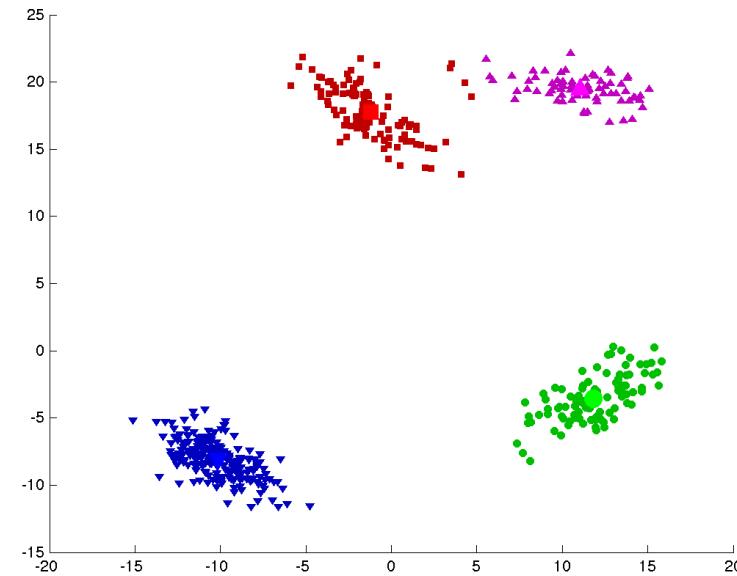
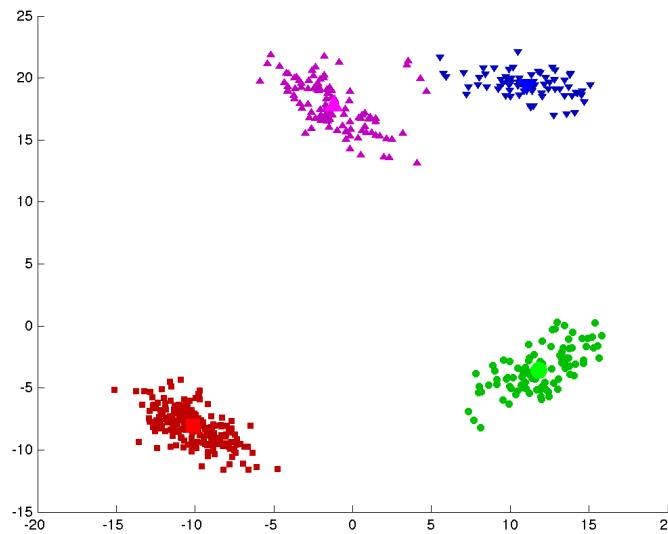
- E.g., run k-means 20 times and then cluster using the mode of each \hat{y}_i .
- Normally, averaging across models doing different things is good.



- But this is a bad ensemble method: worse than k-means on its own.

Label Switching Problem

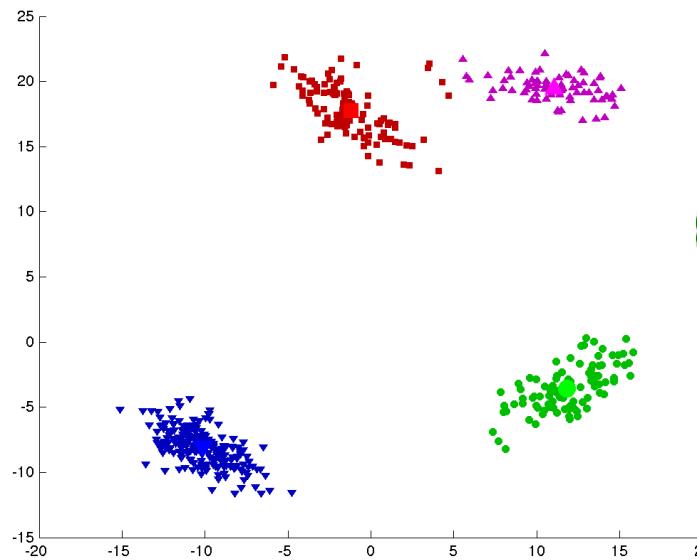
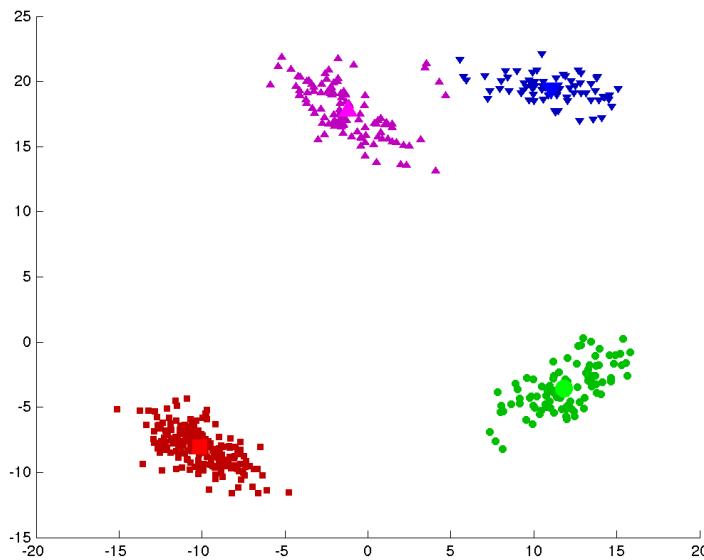
- This doesn't work because of “label switching” problem:
 - The cluster labels \hat{y}_i are meaningless.
 - We could get same clustering with permuted labels (“exchangeable”):



- All \hat{y}_i become equally likely as number of initializations increases.

Addressing Label Switching Problem

- Ensembles can't depend on label "meaning":
 - Don't ask "**is point x_i in red square cluster?**", which is meaningless.
 - Ask "**is point x_i in the same cluster as x_j ?**", which is meaningful.

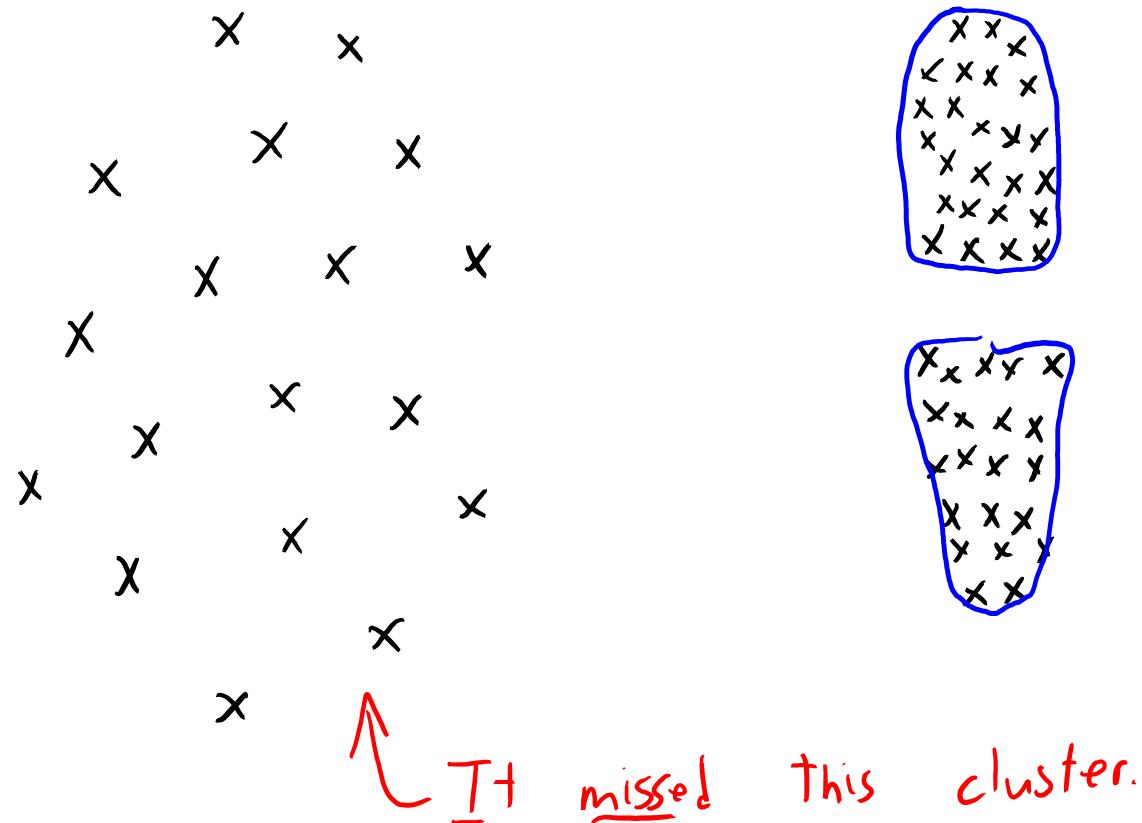


- Bonus slides give an example method ("UBClustering").

(pause)

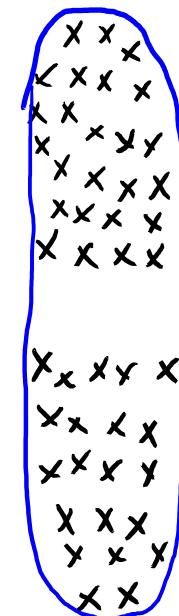
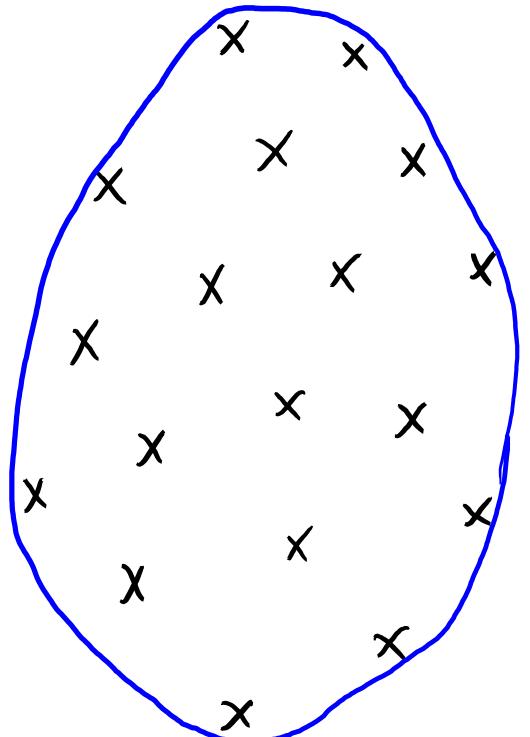
Differing Densities

- Consider density-based clustering on this data:



Differing Densities

- Increase epsilon and run it again:

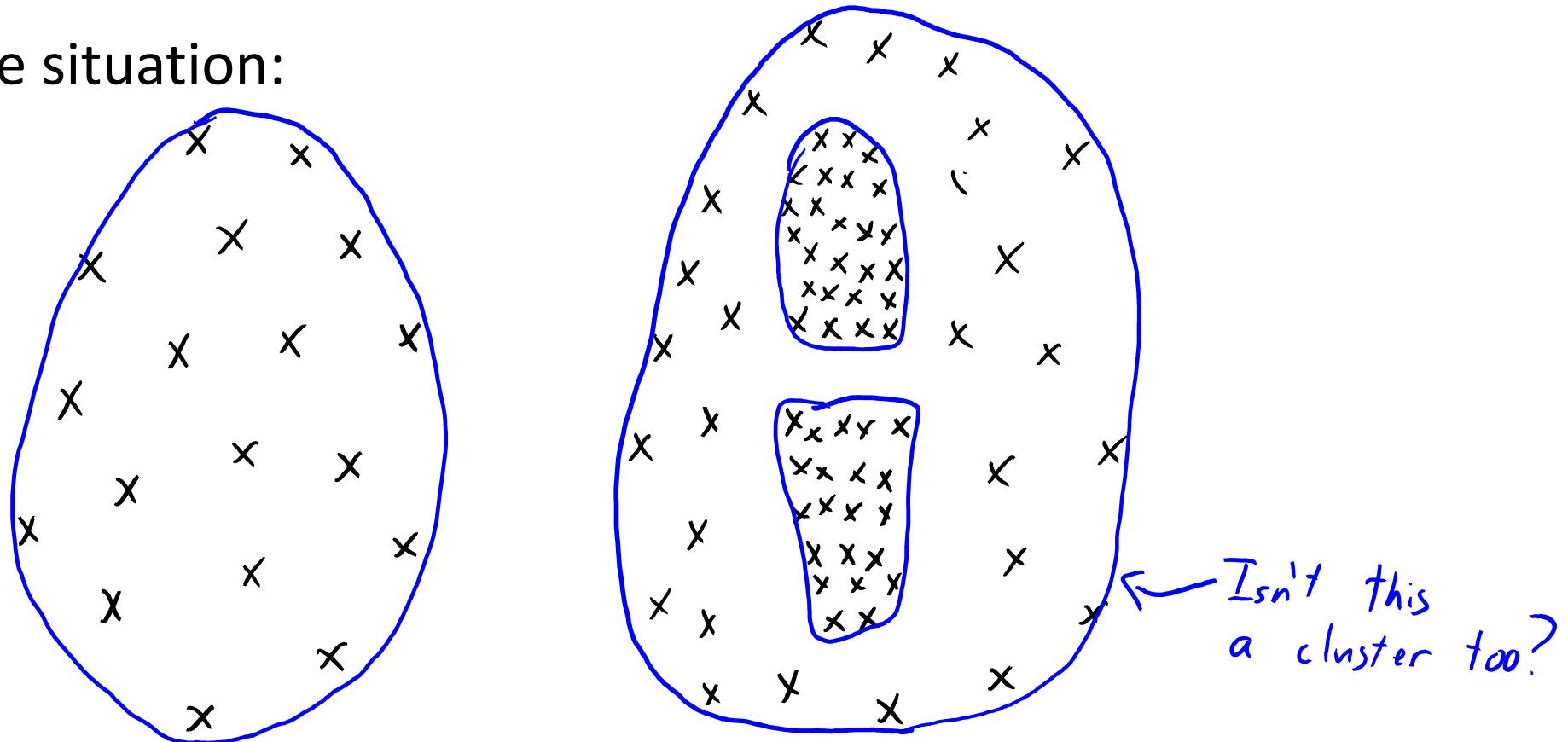


These 2 clusters
are now "close."

- There may be no density-level that gives you 3 clusters.

Differing Densities

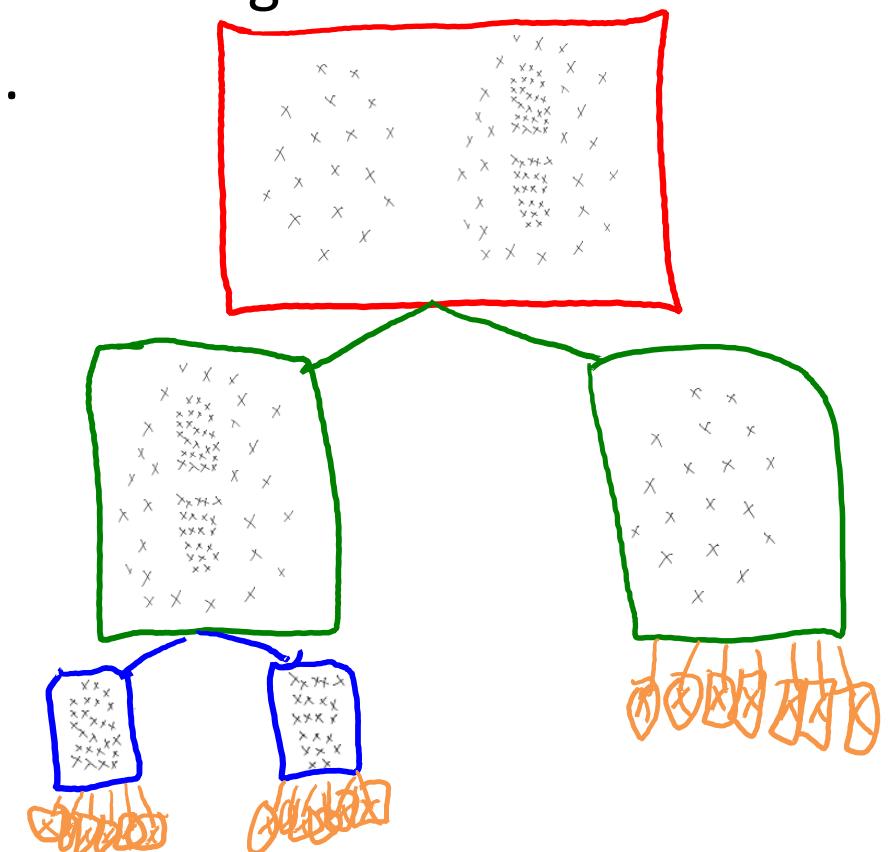
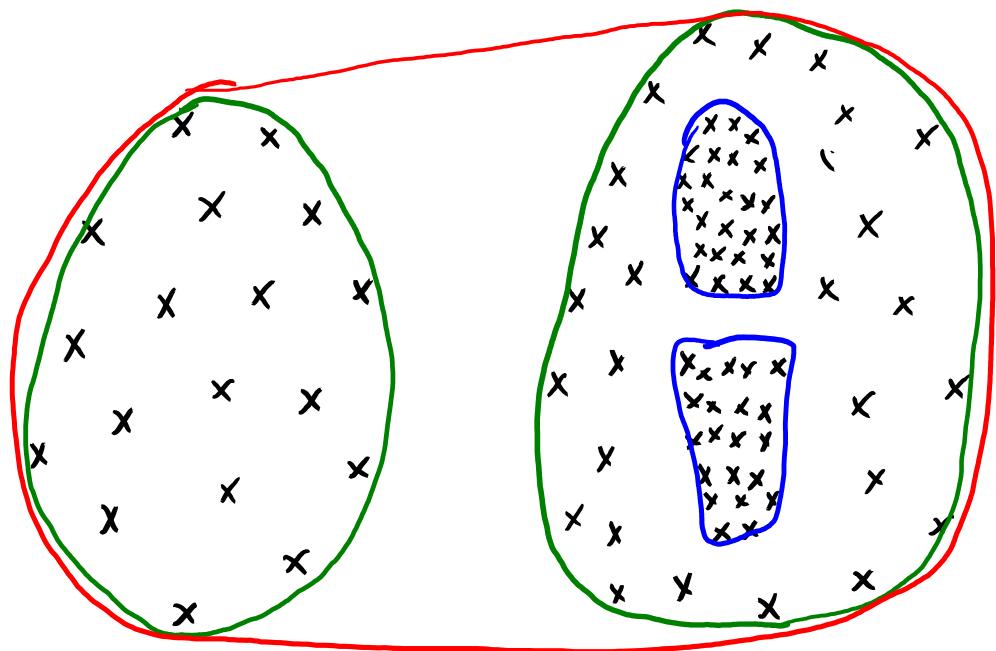
- Here is a worse situation:



- Now you need to choose between coarse/fine clusters.
- Instead of fixed clustering, we often want **hierarchical clustering**.

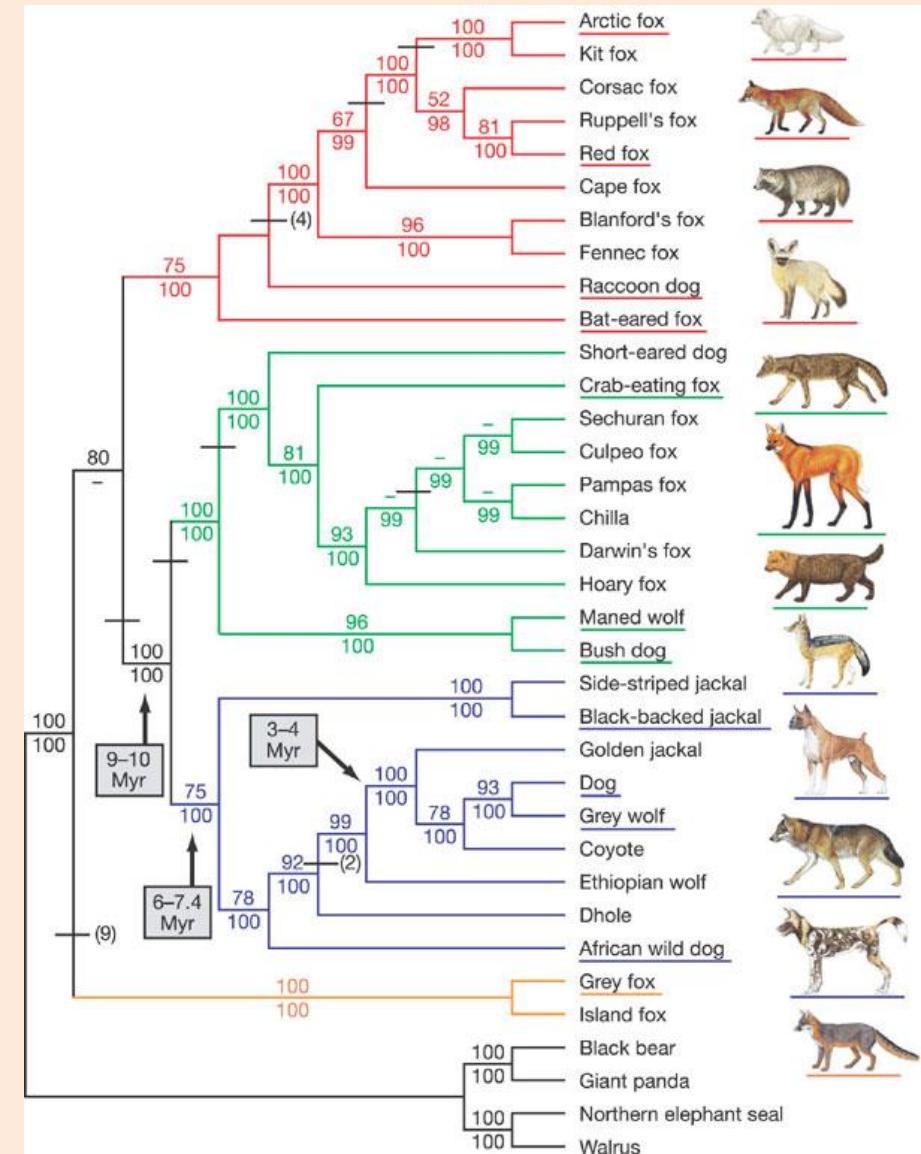
Hierarchical Clustering

- Hierarchical clustering produces a tree of clusterings.
 - Each node in the tree splits the data into 2 or more clusters.
 - Much more information than using a fixed clustering.
 - Often have individual data points as leaves.



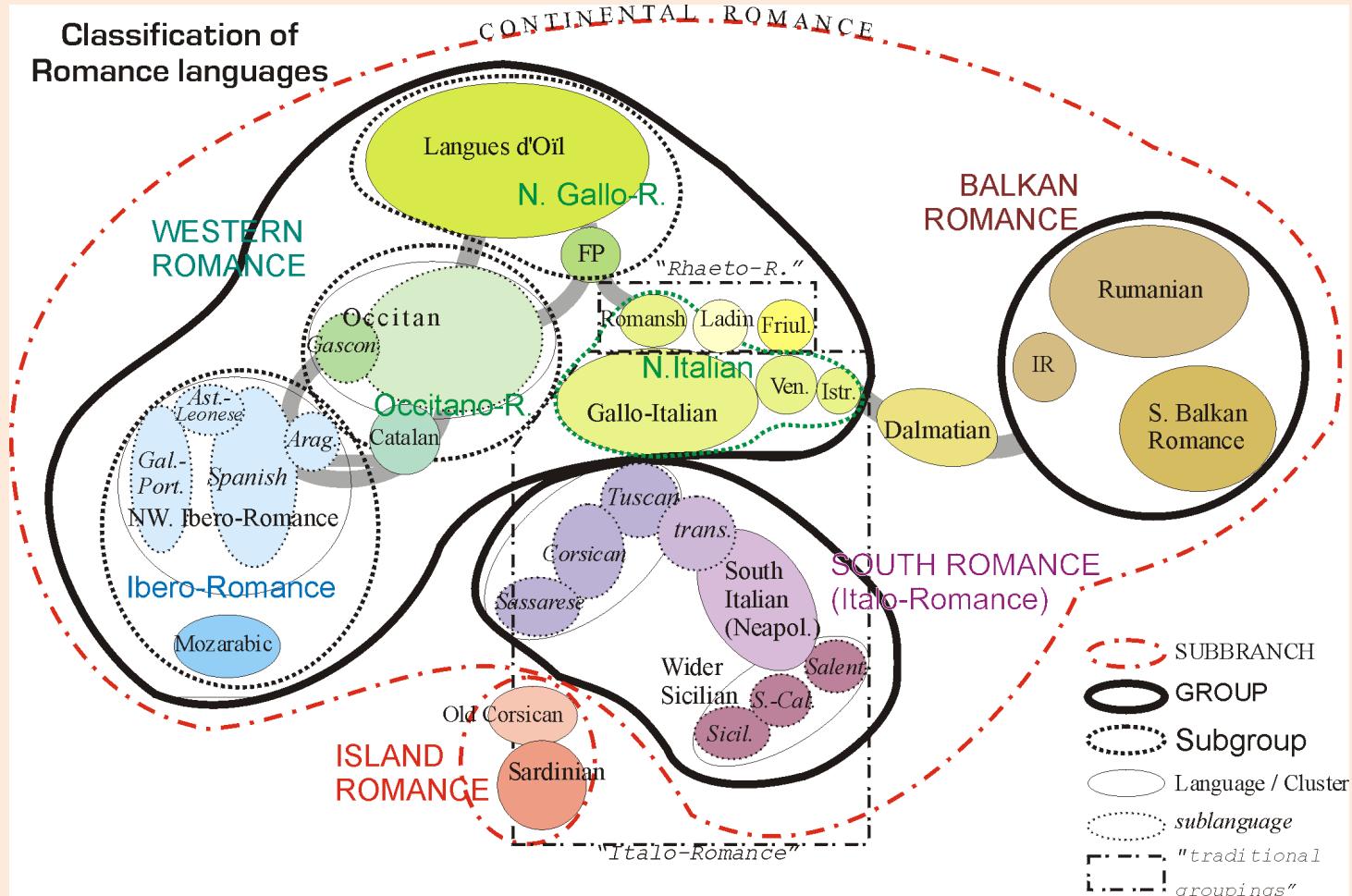
Application: Phylogenetics

- We sequence genomes of a set of organisms.
- Can we construct the “tree of life”?
- Comments on this application:
 - On the right are individuals.
 - As you go left, clusters merge.
 - Merges are ‘common ancestors’.
- More useful information in the plot:
 - Line lengths: chosen here to approximate time.
 - Numbers: #clusterings across bootstrap samples.
 - ‘Outgroups’ (walrus, panda) are a sanity check.



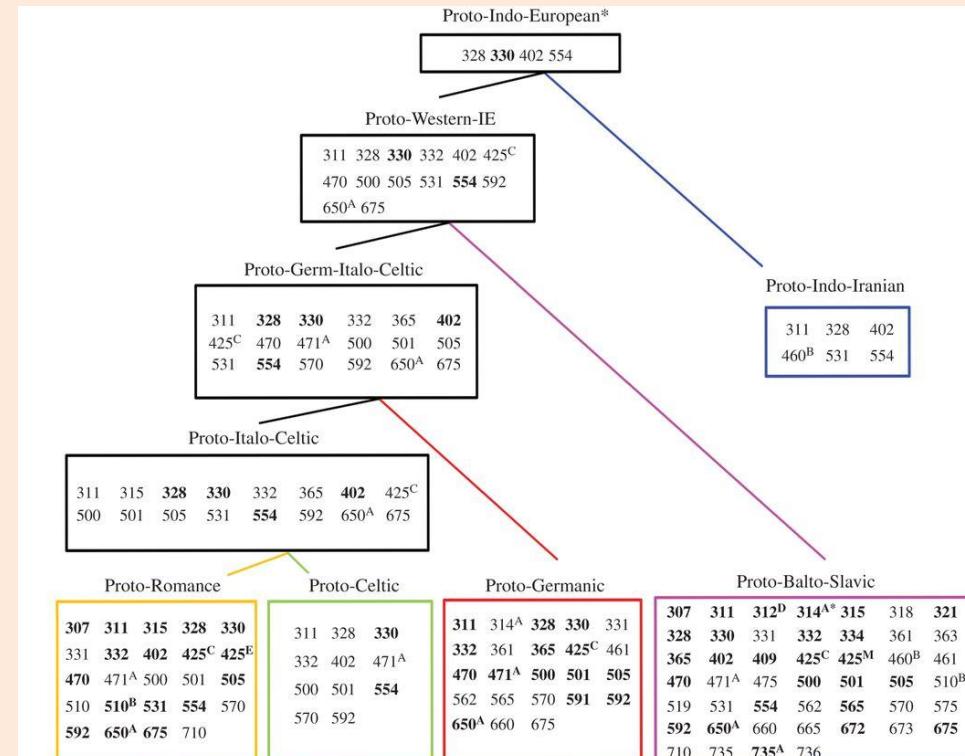
Application: Phylogenetics

- Comparative method in linguistics studies evolution of languages:



Application: Phylogenetics

- January 2016: evolution of fairy tales.
 - Evidence that “Devil and the Smith” goes back to bronze age.
 - “Beauty and the Beast” published in 1740, but might be 2500-6000 years old.

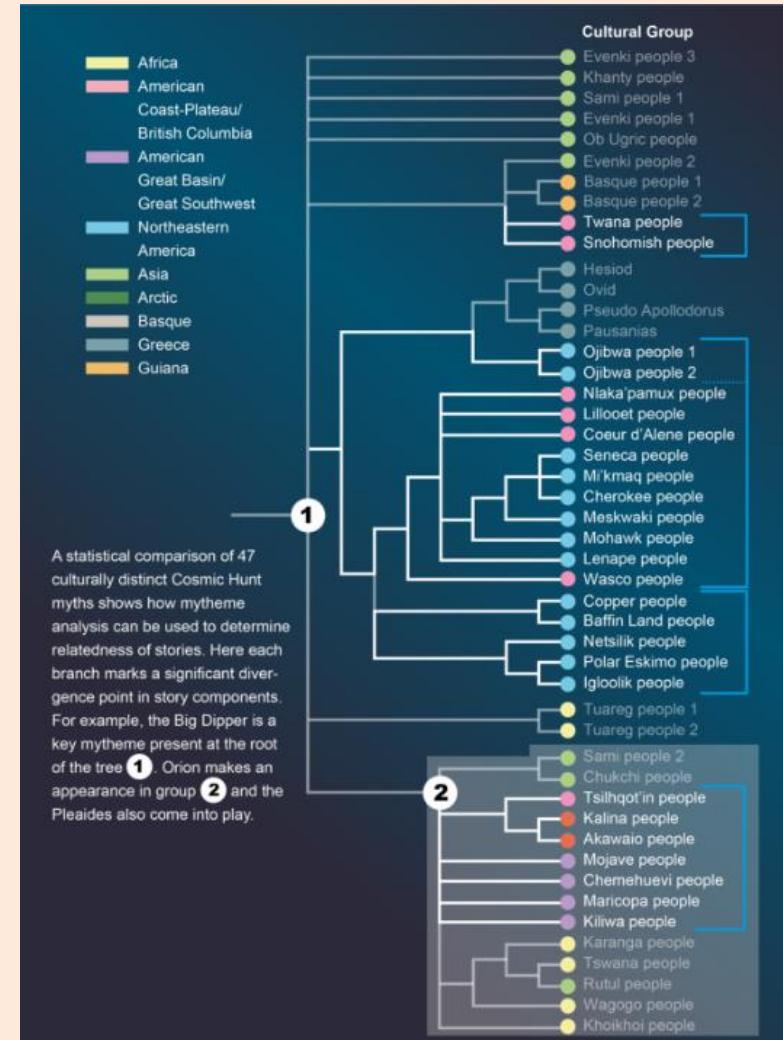


International tale types

307	The Princess in the Coffin	409	The Girl as Wolf	562	The Spirit in the Blue Light
311	Rescue by Sister	425C	Beauty and the Beast	565	The Magic Mill
312D	Rescue by the Brother	425E	The Enchanted Husband	570	The Rabbit-Herd
314A	The Shepherd and the Giants	425M	The Snake Bridegroom	575	The Prince's Wings
314A*	Animal Helper in the Flight	460B	The Journey	591	The Thieving Pot
315	The Faithless Sister	461	Three Hairs	592	The Dance Among Thorns
318	The Faithless Wife	470	Friends in Life and Death	650A	Strong John
321	Eyes Recovered from Witch	471A	The Monk and the Bird	660	The Three Doctors
328	The Boy Steals Ogre's Treasure	475	The Man as the Heater	665	The Man who Flew and Swam
330	The Smith and the Devil	500	Supernatural Helper	672	The Serpent's Crown
331	The Spirit in the Bottle	501	The Three Old Spinning Women	673	The White Serpent's Flesh
332	Godfather Death	505	The Grateful Dead	675	The Lazy Boy
334	Household of the Witch	510	Cinderella and Peau d'Âne	710	Our Lady's Child
361	Bear Skin	510B	Peau d'Âne	735	The Rich and the Poor Man
363	The Corpse-Eater	519	The Strong Woman as Bride	735A	Bad Luck Imprisoned
365	The Dead Bridegroom	531	The Clever Horse	736	Luck and Wealth
402	The Animal Bride	554	The Grateful Animals		

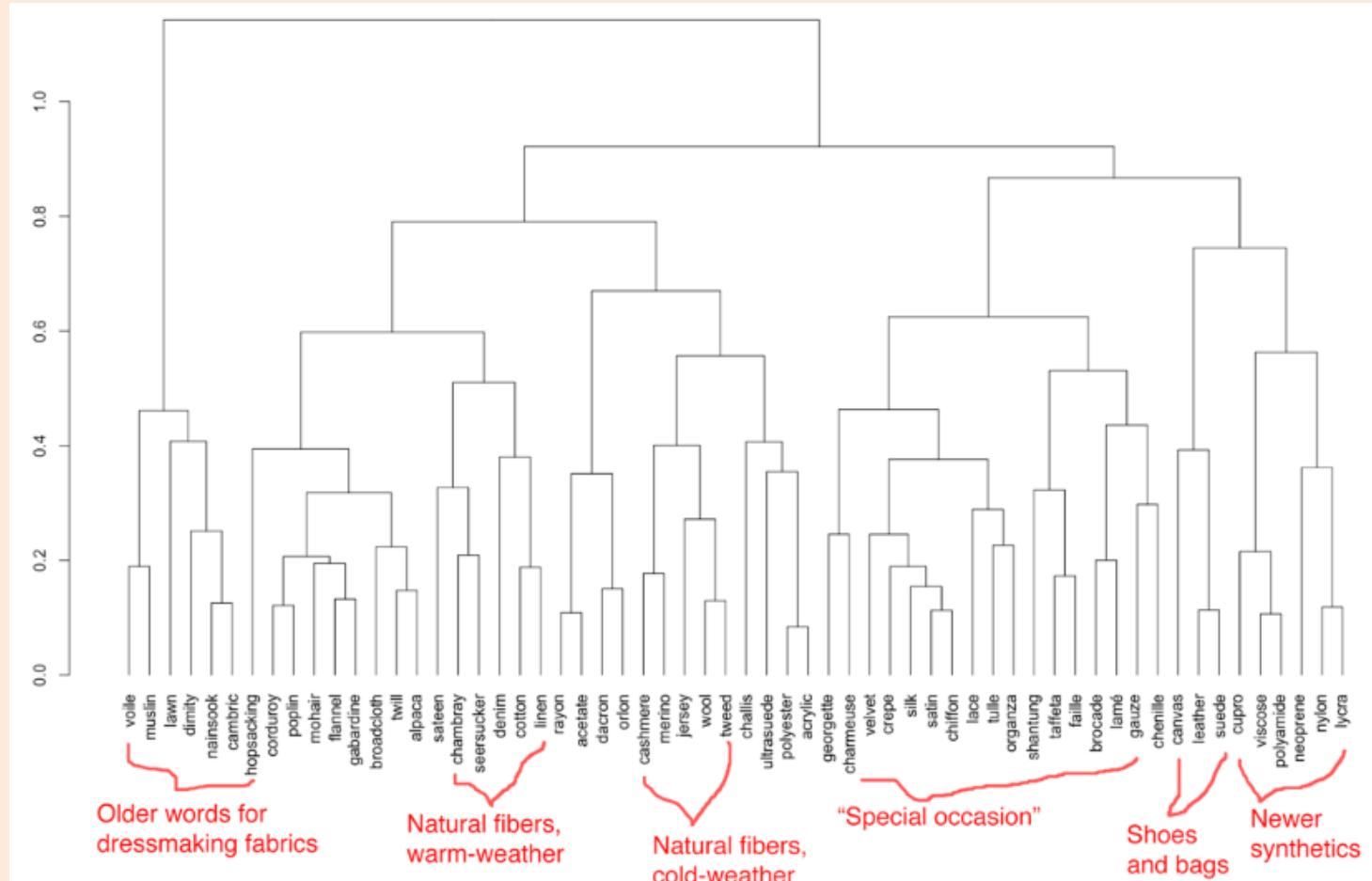
Application: Phylogenetics

- January 2016: evolution of fairy tales.
 - Evidence that “Devil and the Smith” goes back to bronze age.
 - “Beauty and the Beast” published in 1740, but might be 2500-6000 years old.
- September 2016: evolution of myths.
 - “Cosmic hunt” story:
 - Person hunts animal that becomes constellation.
 - Previously known to be at least 15,000 years old.
 - May go back to paleololithic period.



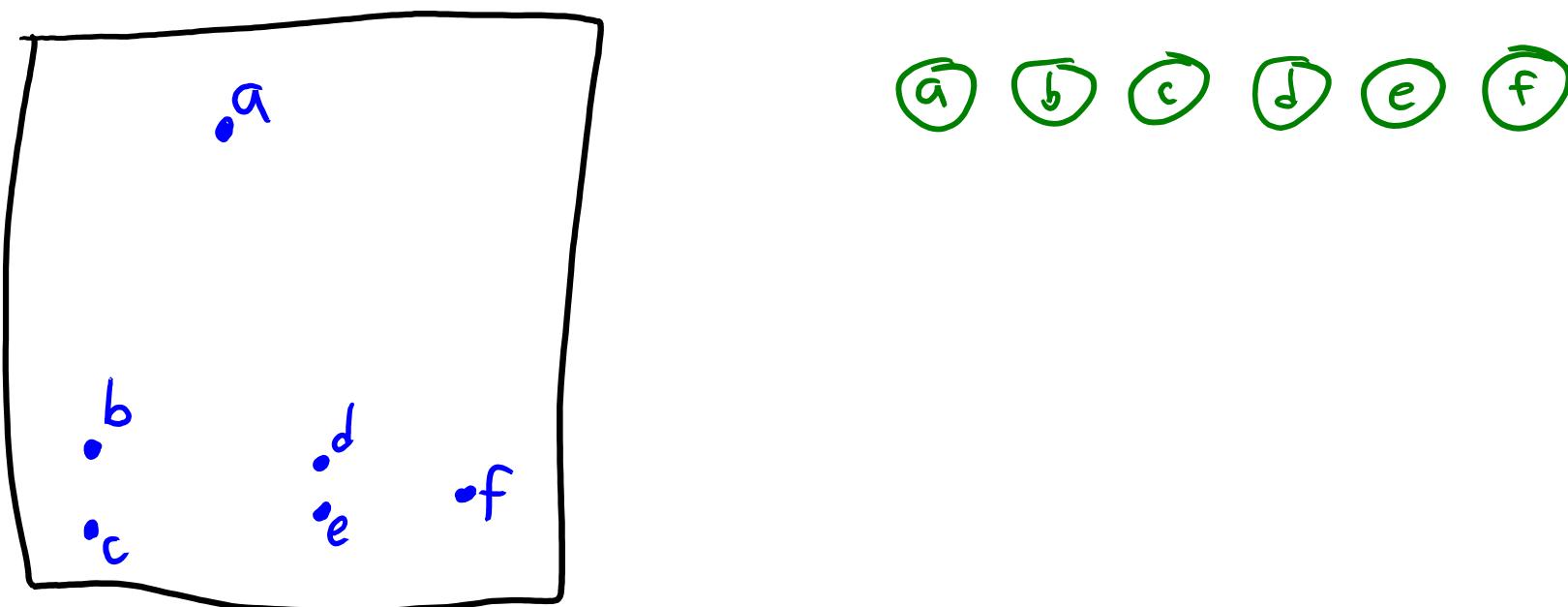
Application: Fashion?

- Hierarchical clustering of clothing material words in Vogue:



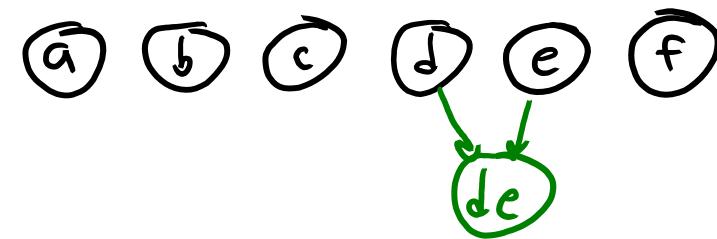
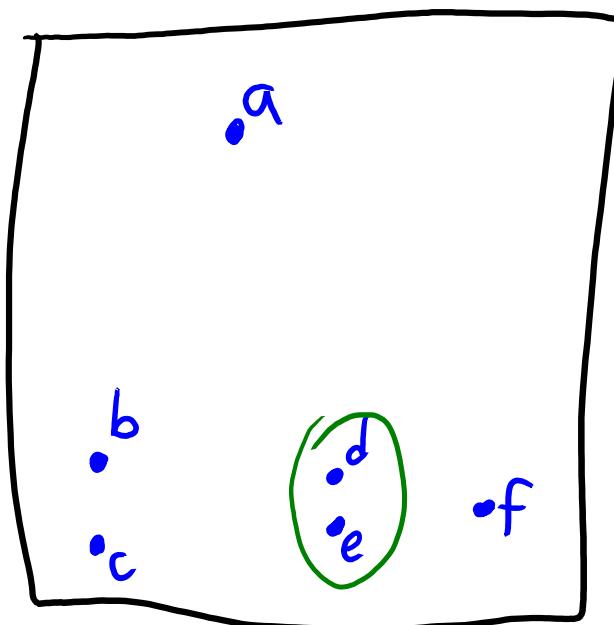
Agglomerative (Bottom-Up) Clustering

- Most common hierarchical method: **agglomerative clustering**.
 1. Starts with each point in its own cluster.



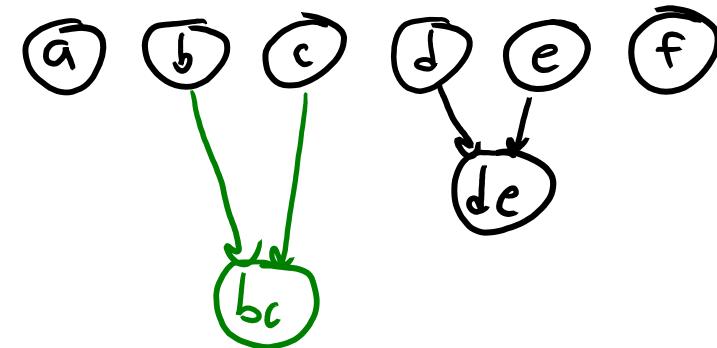
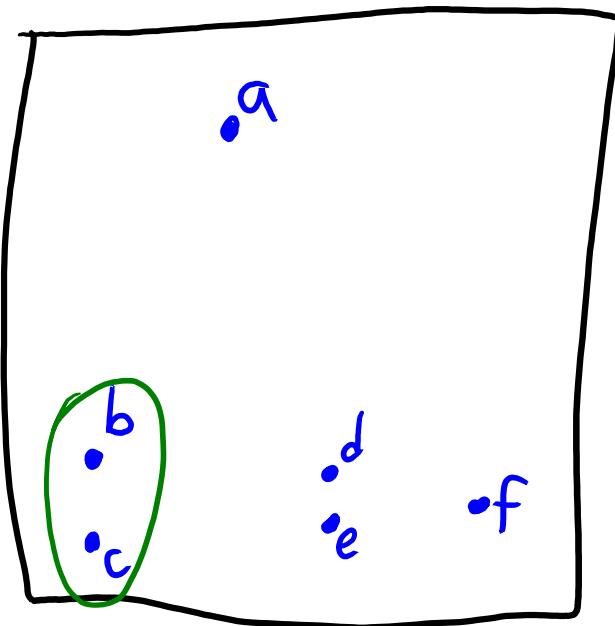
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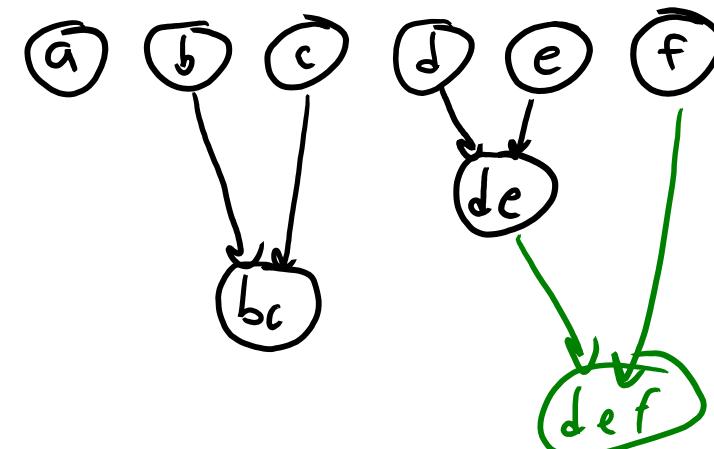
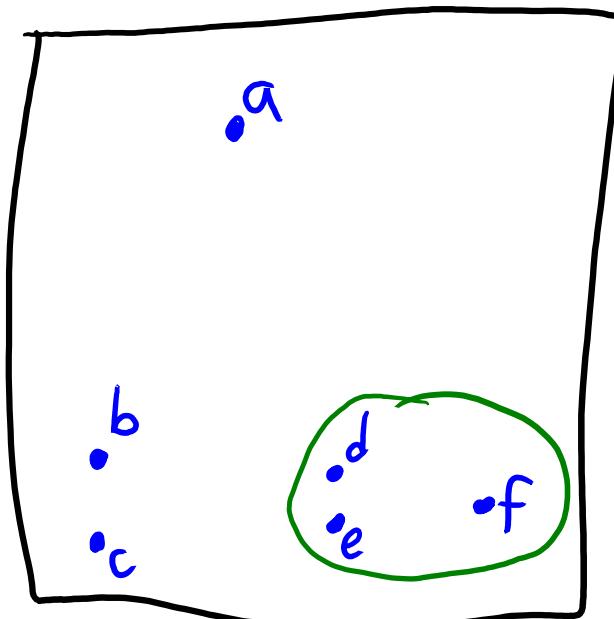
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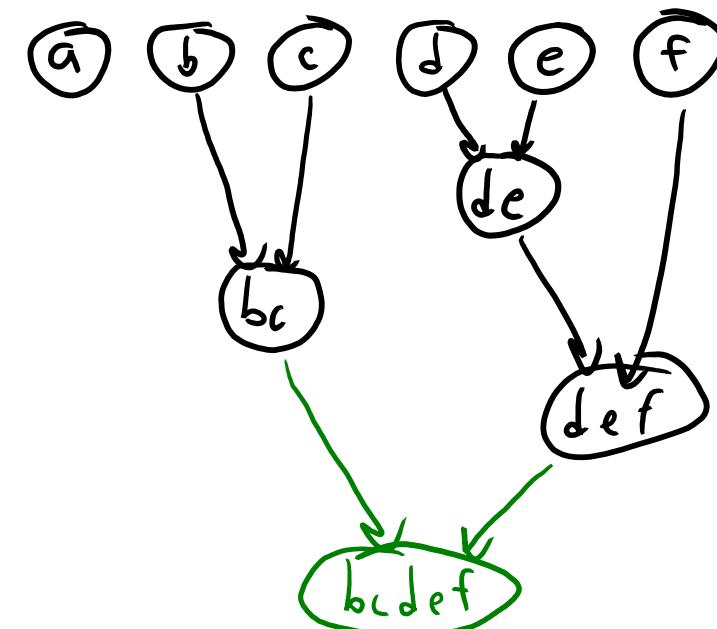
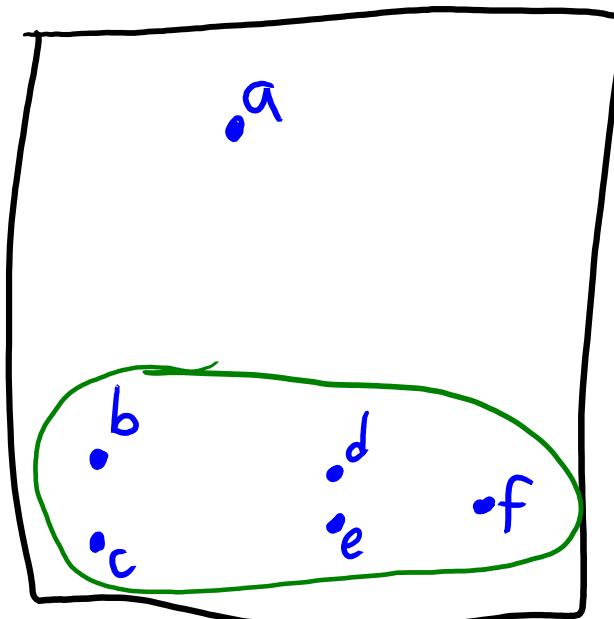
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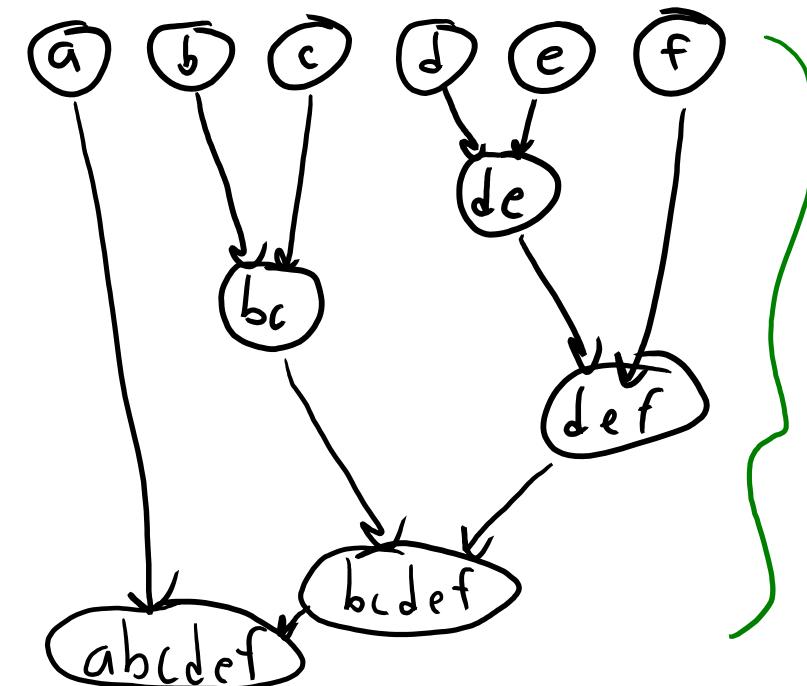
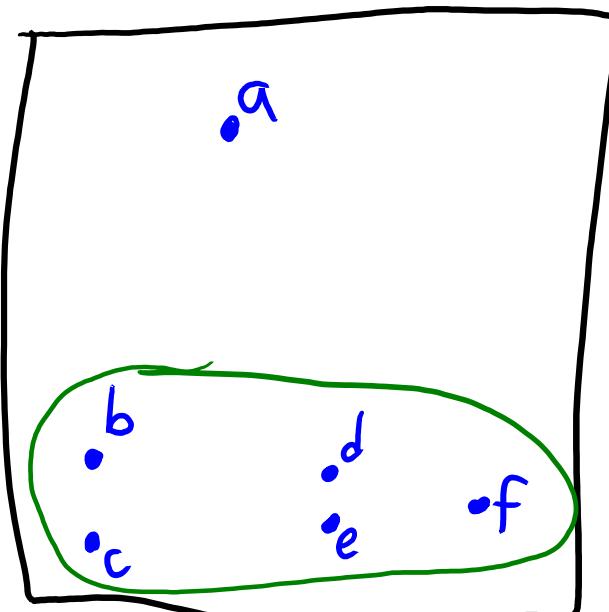
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Agglomerative (Bottom-Up) Clustering

- Most common hierarchical method: **agglomerative clustering**.
 1. Starts with each point in its own cluster.
 2. Each step merges the two “closest” clusters.
 3. Stop with one big cluster that has all points.



[Animation](#)

Agglomerative (Bottom-Up) Clustering

- Reinvented by different fields under different names (“UPGMA”).
- Needs a “distance” between two clusters.
- A standard choice: distance between means of the clusters.
 - Not necessarily the best, many choices exist (bonus slide).
- Cost is $O(n^3d)$ for basic implementation.
 - Each step costs $O(n^2d)$, and each step might only cluster 1 new point.

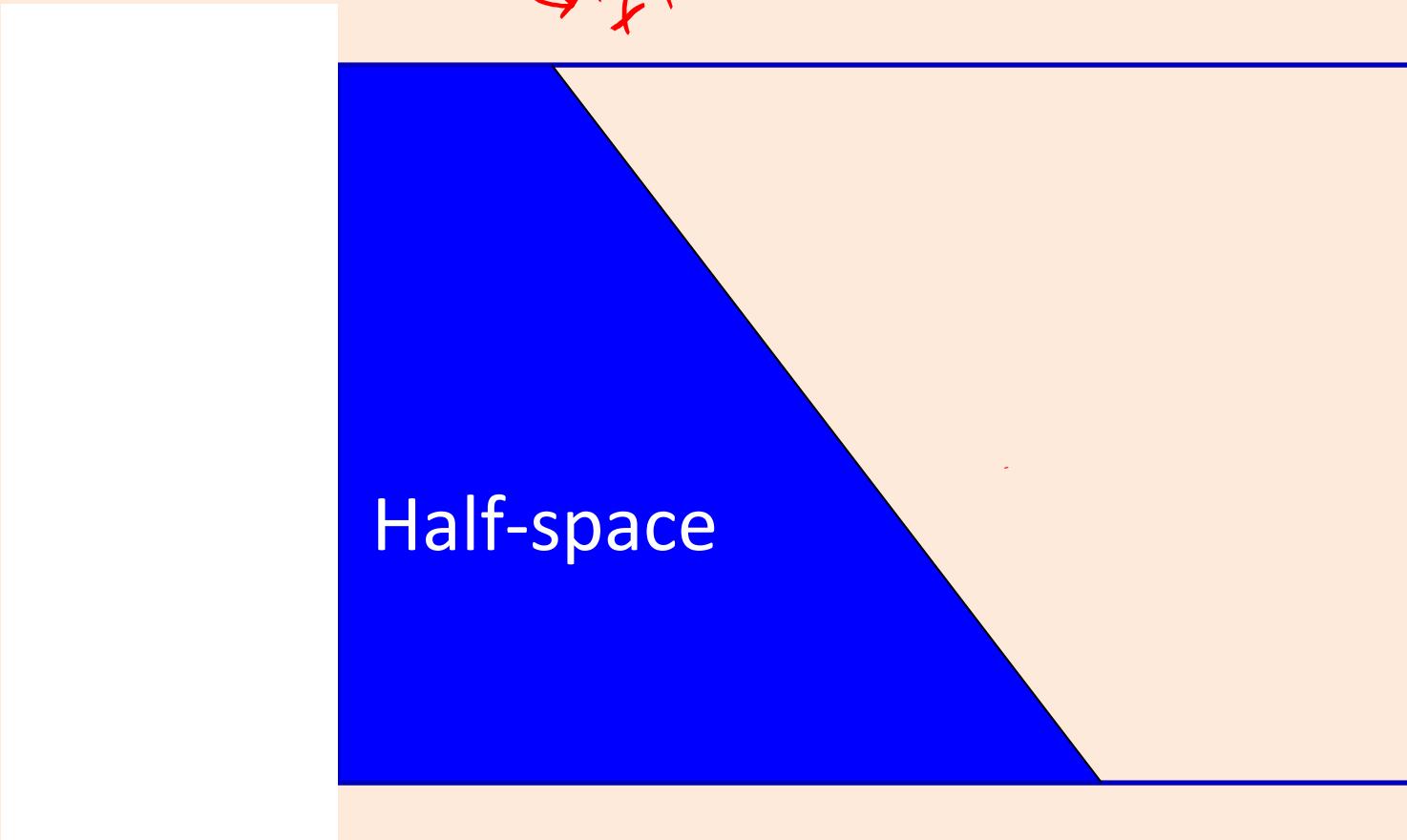
Summary

- Shape of K-means clusters:
 - Partitions space into convex sets.
- Density-based clustering:
 - “Expand” and “merge” dense regions of points to find clusters.
 - Not sensitive to initialization or outliers.
 - Useful for finding non-convex connected clusters.
- Ensemble clustering: combines multiple clusterings.
 - Can work well but need to account for label switching.
- Hierarchical clustering: more informative than fixed clustering.
- Agglomerative clustering: standard hierarchical clustering method.
 - Each point starts as a cluster, sequentially merge clusters.
- Next time:
 - Discovering (and then ignoring) a hole in the ozone layer.

Why are k-means clusters convex?

- K-means clusters are formed by the **intersection** of **half-spaces**.

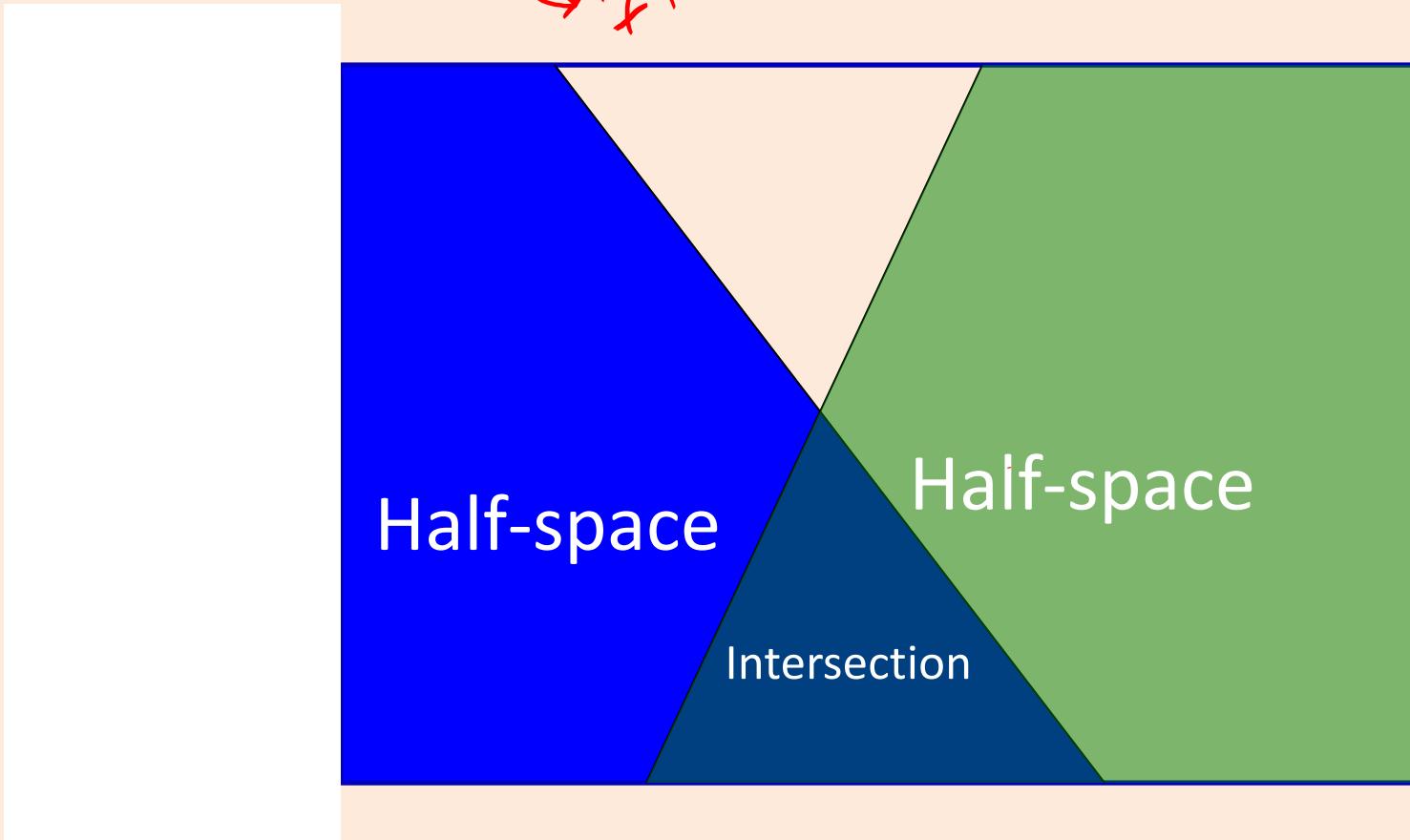
Half-space is Set of points satisfying a linear inequality, like $\sum_{j=1}^d a_j x_j \leq b$



Why are k-means clusters convex?

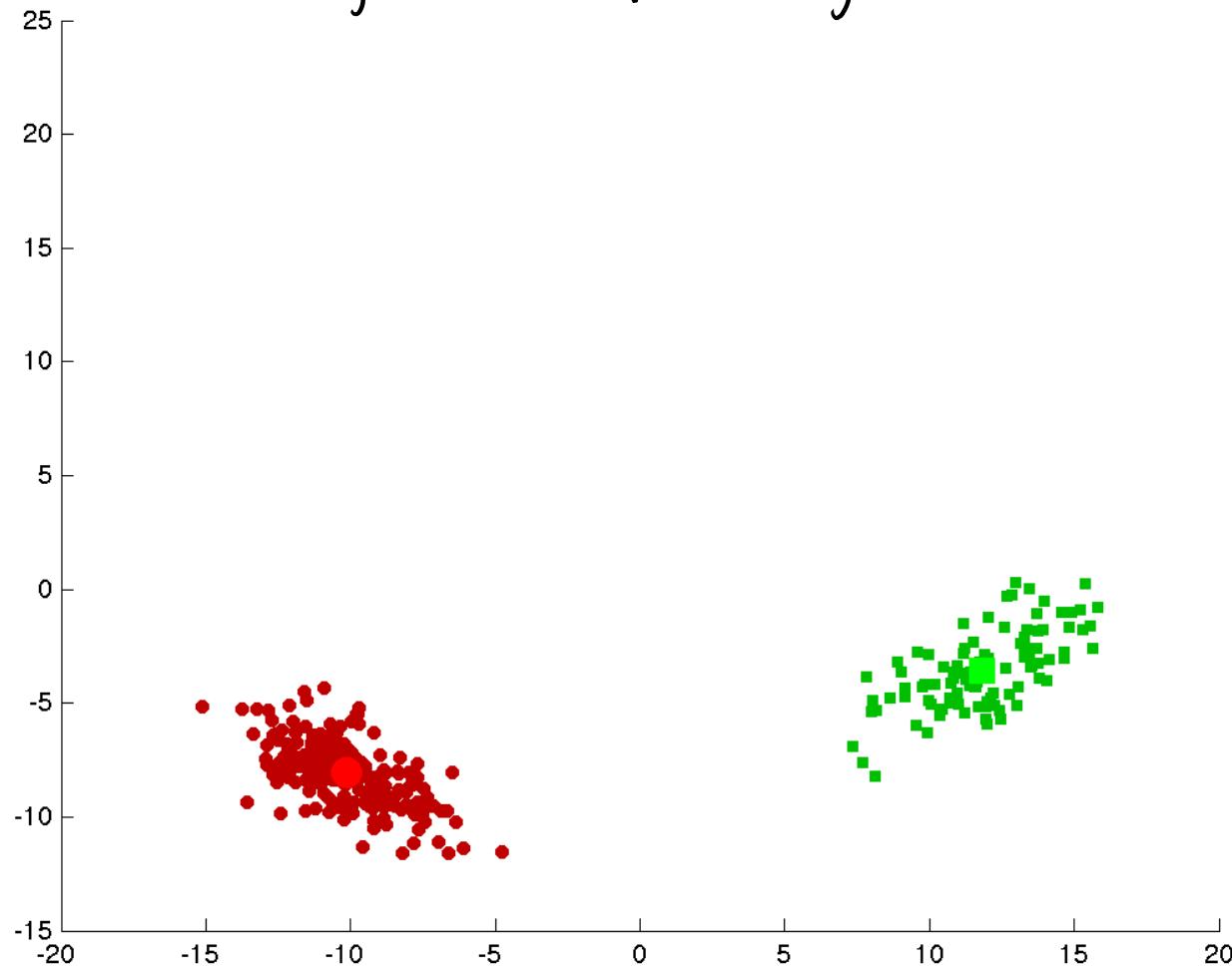
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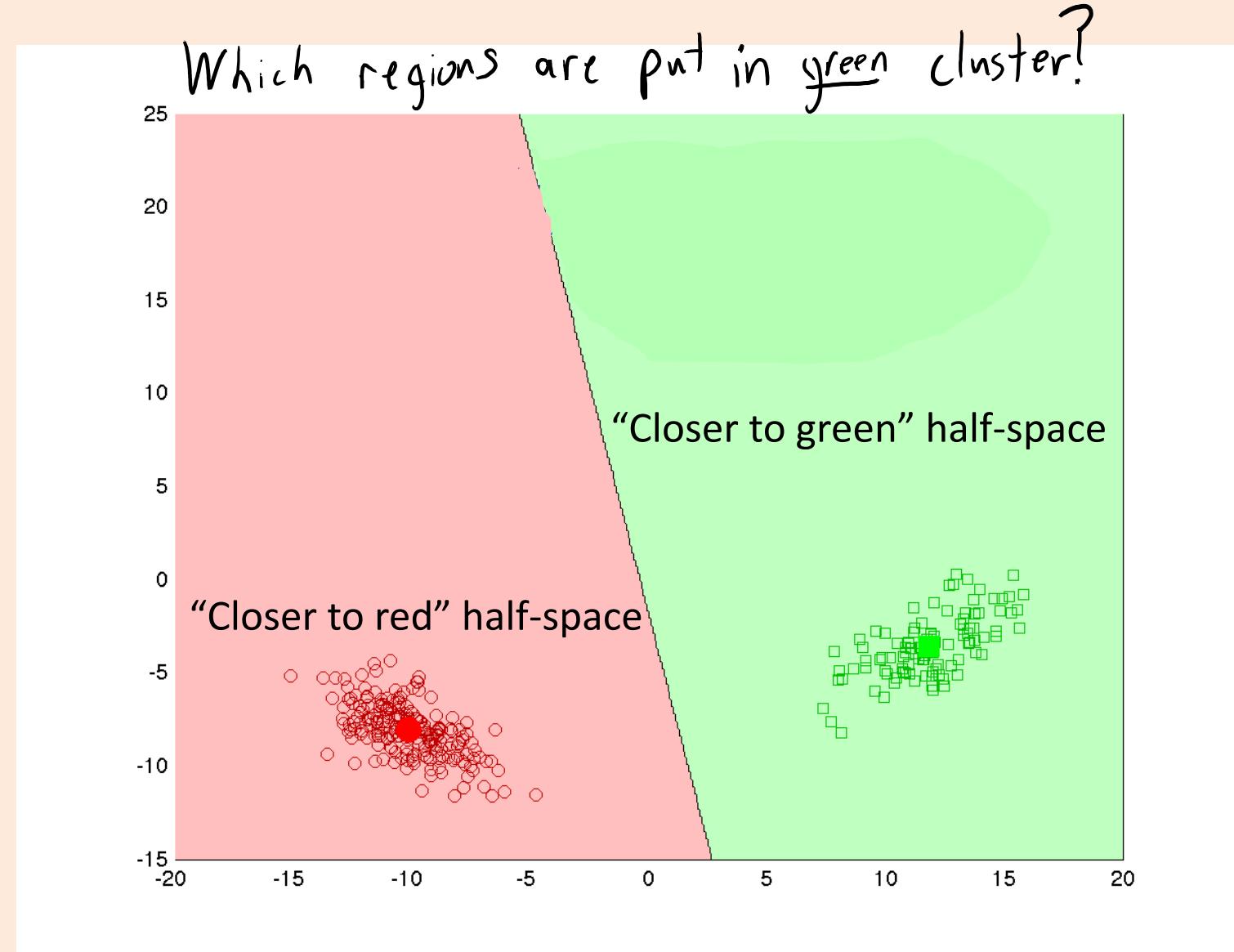


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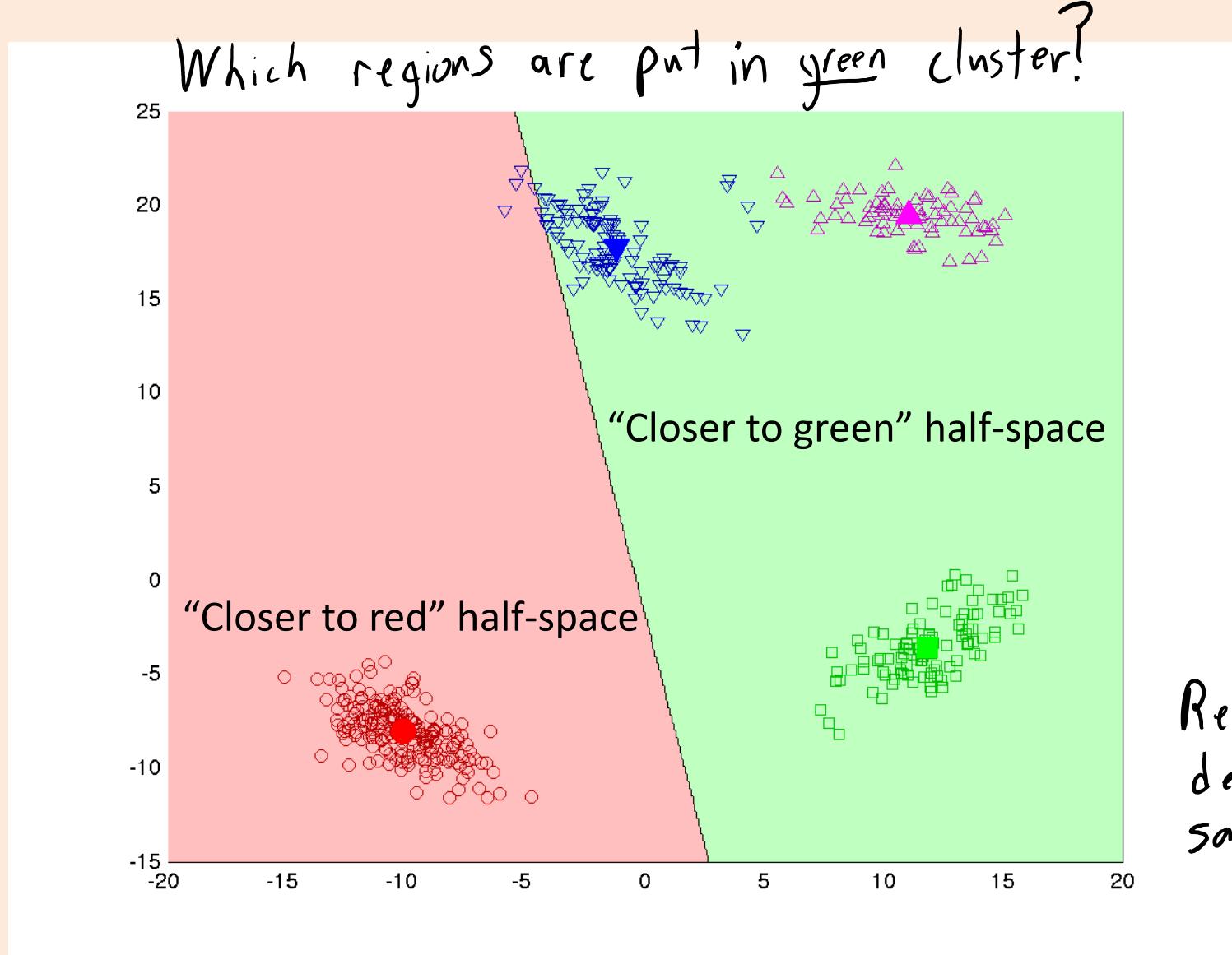
Which regions are put in green cluster?



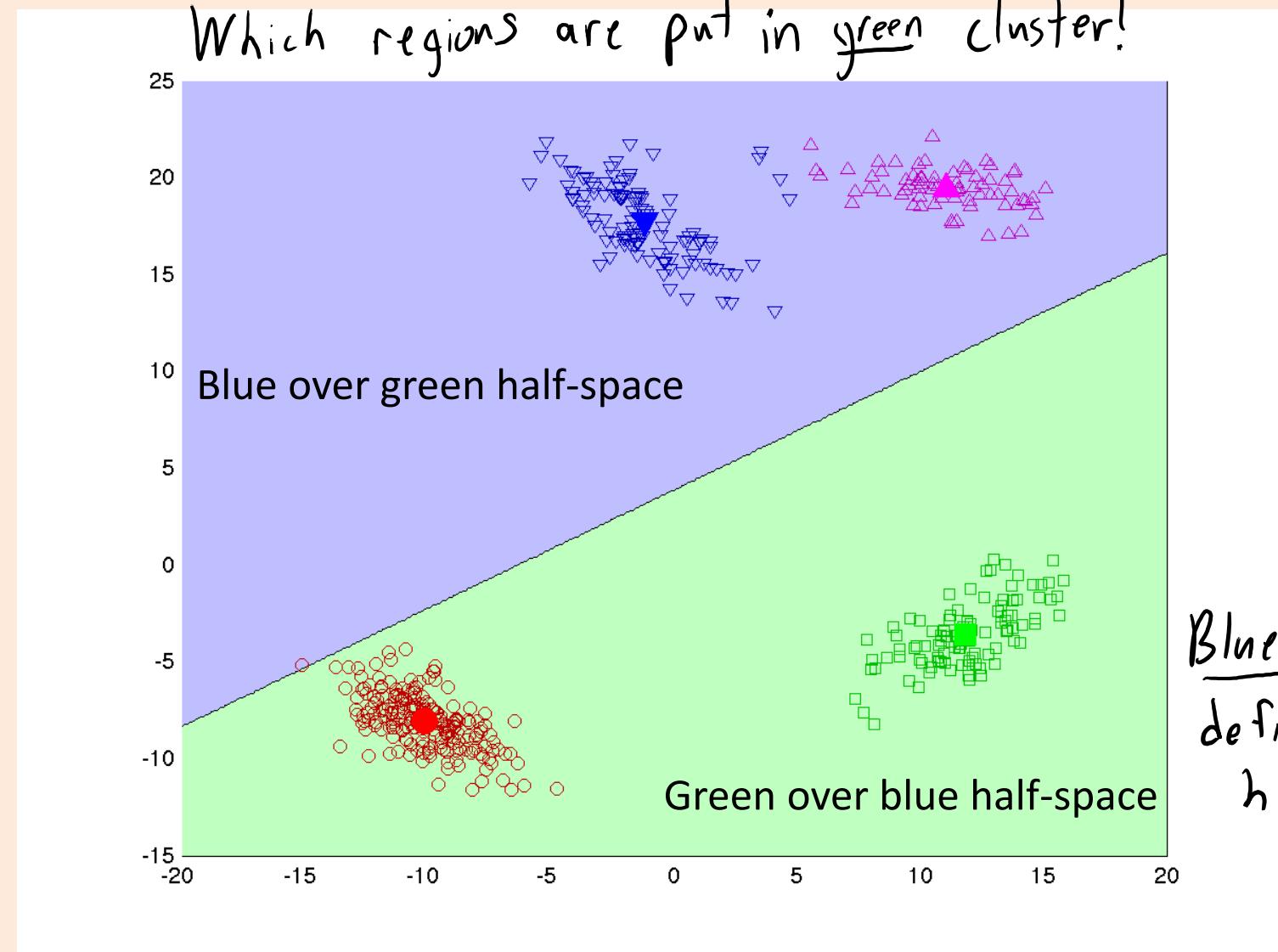
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Why are k-means clusters convex?

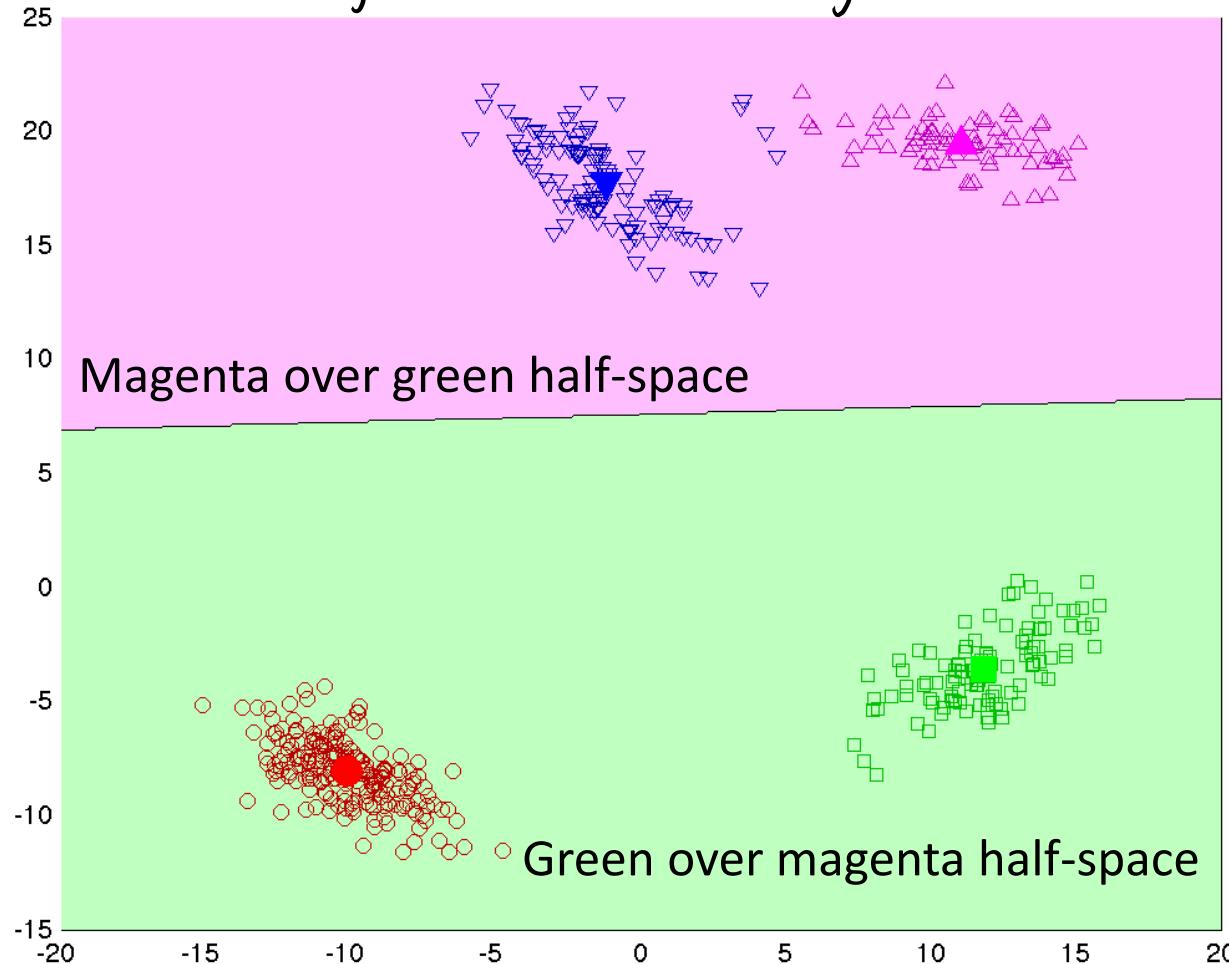


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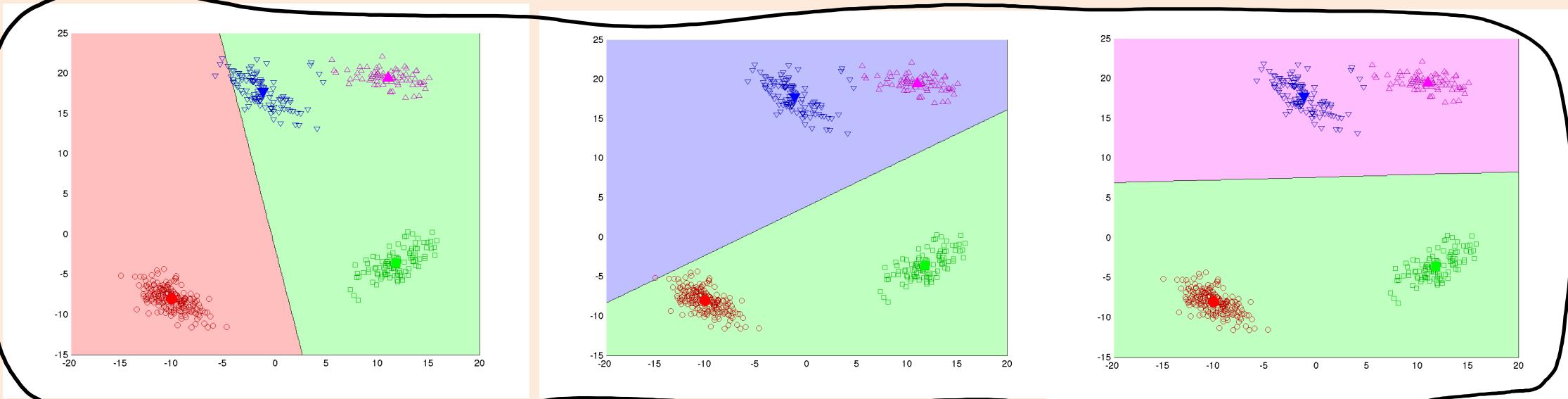


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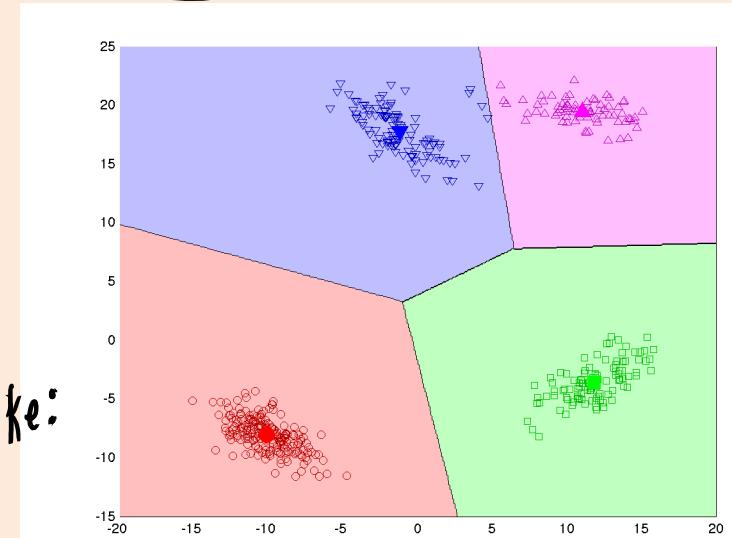


Why are k-means clusters convex?



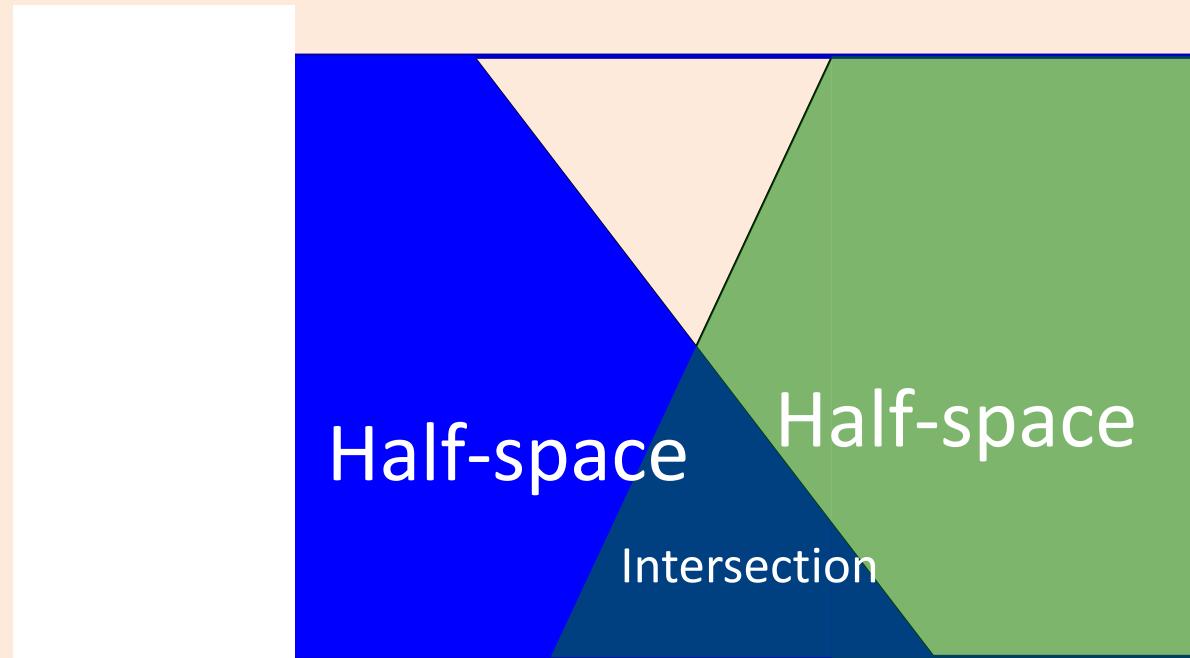
Green "cluster" is the intersection of
these three half-spaces.

Here is what the
four clusters look like:



Why are k-means clusters convex?

- Half-spaces are convex sets.
- Intersection of convex sets is a convex set.
- So intersection of half-spaces is convex.



Why are k-means clusters convex?

- Formal proof that “cluster 1” is convex (works for other clusters).

Let x_i and x_j be arbitrary points in cluster 1.

$$\rightarrow \text{By def'n of cluster 1, } \|x_i - w_i\| \leq \|x_i - w_c\| \text{ for all } c \quad \left. \begin{array}{l} \text{equality} \\ \|x_j - w_i\| \leq \|x_j - w_c\| \text{ for all } c \end{array} \right\} \text{for } c=1$$

\rightarrow Let x_m be an arbitrary point between x_i and x_j .

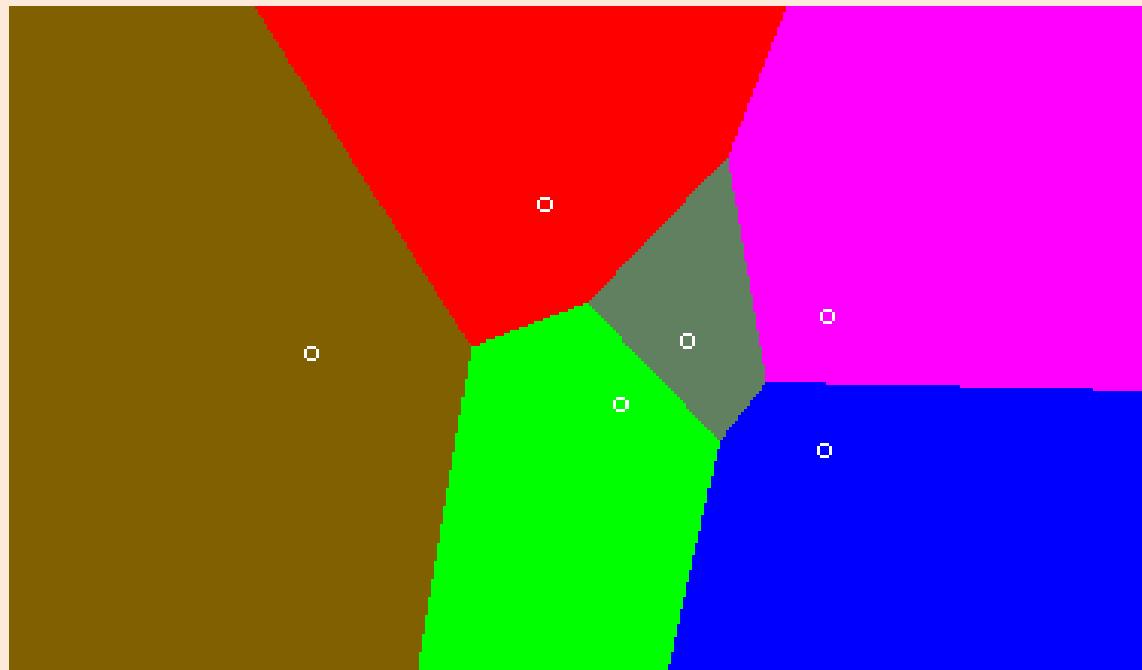
\rightarrow So we can write it as $x_m = \theta x_i + (1-\theta)x_j$ for some $\theta \in [0, 1]$

$$\begin{aligned} \text{Then } \|x_m - w_i\| &= \|\theta x_i + (1-\theta)x_j - (\theta w_i + (1-\theta)w_j)\| && (w_j = \theta w_i + (1-\theta)w_i) \\ &\leq \|\theta x_i - \theta w_i\| + \|(1-\theta)x_j - (1-\theta)w_j\| && (\text{triangle inequality}) \end{aligned}$$

$$\begin{aligned} x_i \text{ and } x_j \in \text{cluster 1} \quad &\left\{ \begin{array}{l} = \theta \|x_i - w_i\| + (1-\theta) \|x_j - w_j\| \quad (\text{homogeneity of norms}) \\ \leq \theta \|x_i - w_c\| + (1-\theta) \|x_j - w_c\| = \|x_j - w_c\| \text{ so } x_m \text{ is in cluster 1} \end{array} \right. \end{aligned}$$

Voronoi Diagrams

- The k-means partition can be visualized as a [Voronoi diagram](#):



- Can be a useful visualization of “nearest available” problems.
 - E.g., [nearest tube station in London](#).

Density-Based Clustering Runtime

question ★

stop following

72 views

Actions ▾

DBSCAN Training time & Testing time

This is a follow-up inquiry post with Mike about the DBScan, would like to know:

1. Training runtime of DBScan, under k iterations (training set X has n examples and d features)
2. Testing runtime for a single example in DBScan; Testing runtime for test set of size t in DBScan,



the instructors' answer, where instructors collectively construct a single answer

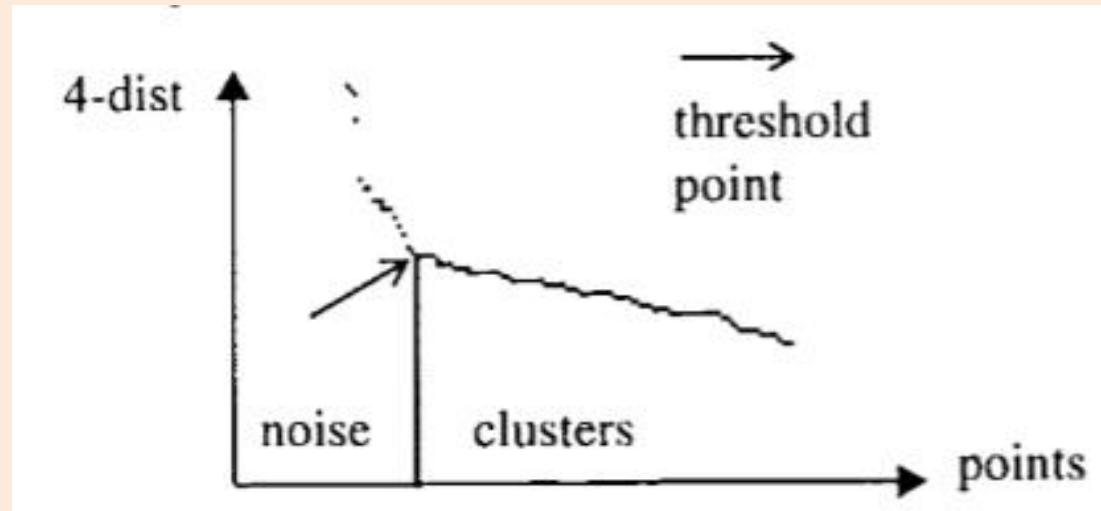
For training, you'll check that each point is a core point exactly once. This check costs $O(nd)$ since you measure the distance to each other point, leading to a total training cost of $O(n^2d)$.

(There are ways to speed this up, like grid-based pruning.)

We didn't define how to apply the DBSCAN model to test data. But a plausible way is to test if the new point is a neighbor of any existing core points. If you have m core points, you would be able to do this in $O(md)$.

“Elbow” Method for Density-Based Clustering

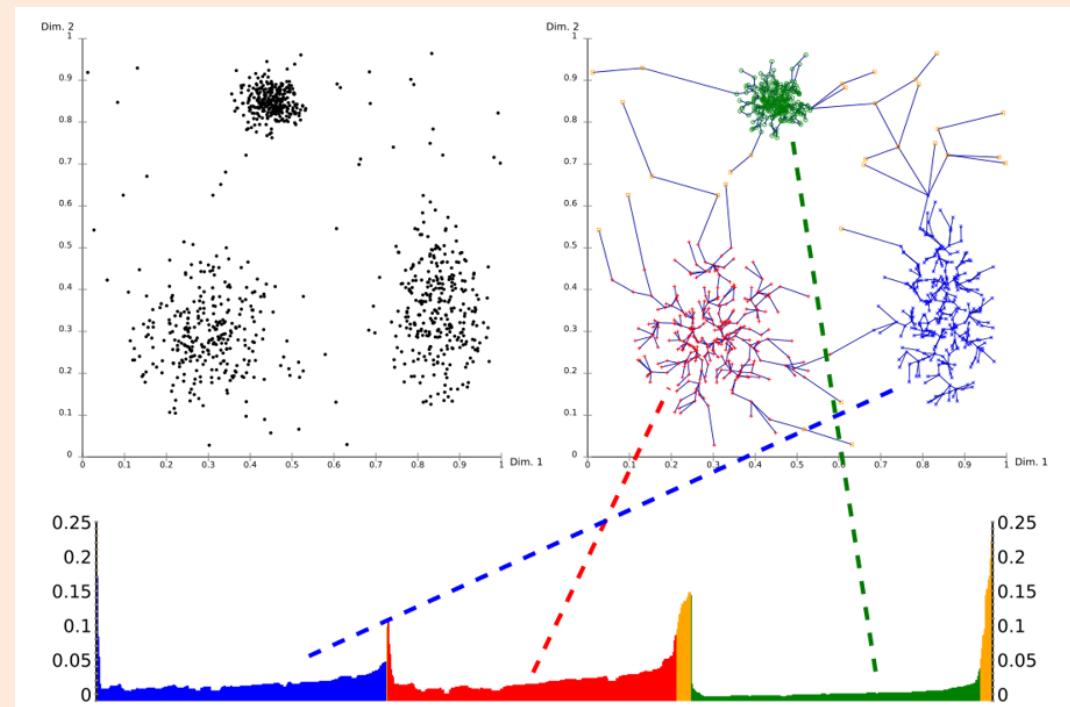
- From the original DBSCAN paper:
 - Choose some ‘k’ (they suggest 4) and set minNeighbours=k.
 - Compute distance of each points to its ‘k’ nearest neighbours.
 - Sort the points based on these distances and plot the distances:



- Look for an “elbow” to choose ϵ .

OPTICS

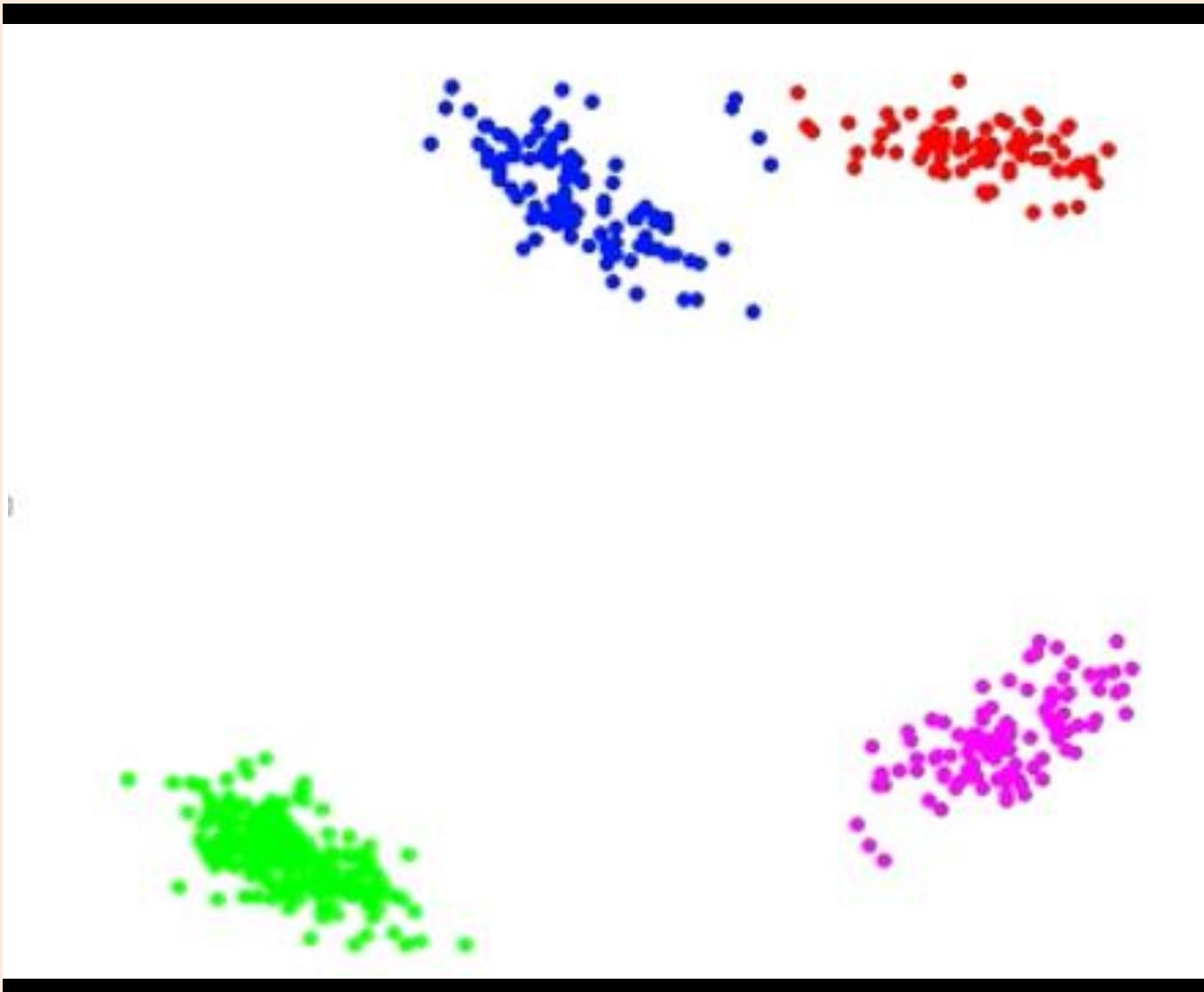
- Related to the DBSCAN “elbow” is “OPTICS”.
 - Sort the points so that neighbours are close to each other in the ordering.
 - Plot the distance from each point to the next point.
 - Clusters should correspond to sequencers with low distance.



UBClustering Algorithm

- Let's define a new ensemble clustering method: **UBClustering**.
 1. Run k-means with 'm' different random initializations.
 2. For each example i and j :
 - Count the number of times x_i and x_j are in the same cluster.
 - Define $p(i,j) = \text{count}(x_i \text{ in same cluster as } x_j)/m$.
 3. Put x_i and x_j in the same cluster if $p(i,j) > 0.5$.
- Like DBSCAN merge clusters in step 3 if i or j are already assigned.
 - You can implement this with a DBSCAN code (just changes “distance”).
 - Each x_i has an x_j in its cluster with $p(i,j) > 0.5$.
 - Some points are not assigned to any cluster.

UBClustering Algorithm



It looks like DBSCAN, but far-away points will be assigned to a cluster if they always appear in same cluster as other points.

Distances between Clusters

- Other choices of the distance between two clusters:
 - “Single-link”: minimum distance between points in clusters.
 - “Average-link”: average distance between points in clusters.
 - “Complete-link”: maximum distance between points in clusters.
 - Ward’s method: minimize within-cluster variance.
 - “Centroid-link”: distance between a representative point in the cluster.
 - Useful for distance measures on non-Euclidean spaces (like Jaccard similarity).
 - “Centroid” often defined as point in cluster minimizing average distance to other points.

Cost of Agglomerative Clustering

- One step of agglomerative clustering costs $O(n^2d)$:
 - We need to do the $O(d)$ distance calculation between up to $O(n^2)$ points.
 - This is assuming the standard distance functions.
- We do at most $O(n)$ steps:
 - Starting with ‘n’ clusters and merging 2 clusters on each step, after $O(n)$ steps we’ll only have 1 cluster left (though typically it will be much smaller).
- This gives a total cost of $O(n^3d)$.
- This can be reduced to $O(n^2d \log n)$ with a priority queue:
 - Store distances in a sorted order, only update the distances that change.
- For single- and complete-linkage, you can get it down to $O(n^2d)$.
 - “SLINK” and “CLINK” algorithms.

Bonus Slide: Divisive (Top-Down) Clustering

- Start with all examples in one cluster, then start dividing.
- E.g., run k-means on a cluster, then run again on resulting clusters.
 - A clustering analogue of decision tree learning.

