

CPSC 340: Machine Learning and Data Mining

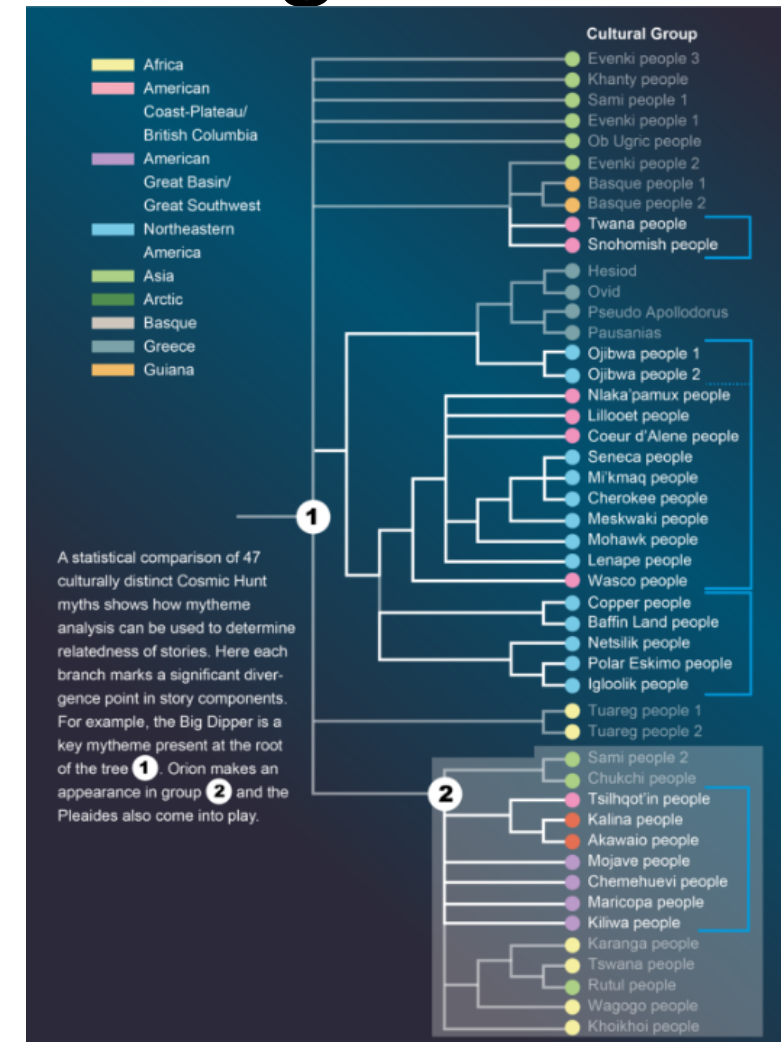
Outlier Detection

Admin

- hw1 solutions will be posted later today
- Next tutorial topic: hw2
 - go through some of the provided code
 - vector quantization
- Reminder: midterm on March 1st

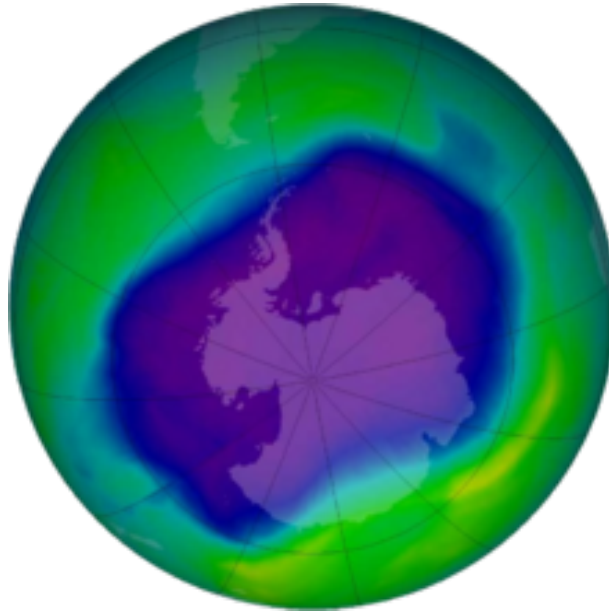
Last Time: Hierarchical Clustering

- We discussed **hierarchical clustering**:
 - Perform **clustering at multiple scales**.
 - Output is usually a **tree diagram** (“dendrogram”).
 - Reveals much more structure in data.
 - Usually non-parametric:
 - At finest scale, every point is its own clusters.
- Important application is **phylogenetics**.



Motivating Example: Finding Holes in Ozone Layer

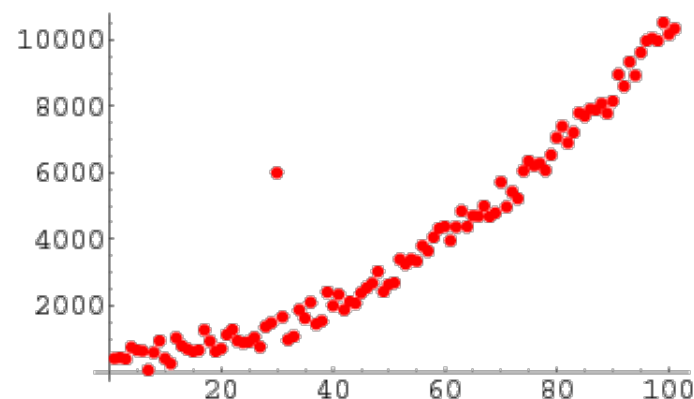
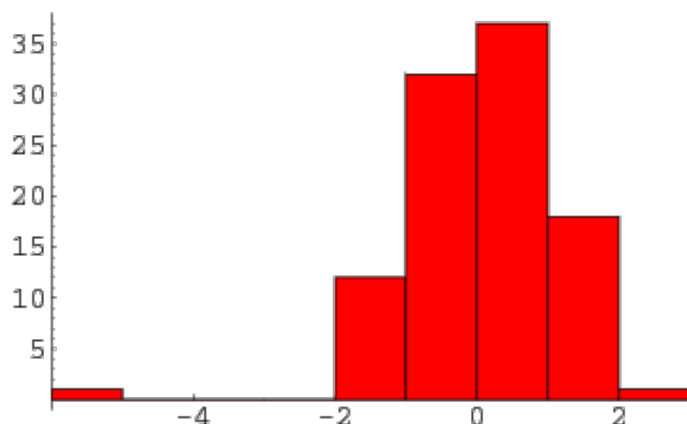
- The huge Antarctic ozone hole was “discovered” in 1985.



- It had been in satellite data since 1976:
 - But it was flagged and filtered out by quality-control algorithm.

Outlier Detection


- **Outlier detection:**
 - Find observations that are “unusually different” from the others.
 - Also known as “anomaly detection”.
 - May want to remove outliers, or be interested in the outliers themselves.



- **Some sources of outliers:**
 - Measurement errors.
 - Data entry errors.
 - Contamination of data from different sources.
 - Rare events.

Applications of Outlier Detection

- Data cleaning.
- Security and fault detection (network intrusion, DOS attacks).
- Fraud detection (credit cards, stocks, voting irregularities).

Transaction Date	▼ Posted Date	Transaction Details	Debit	Credit
Aug. 27, 2015	Aug. 28, 2015	 BEAN AROUND THE WORLD VANCOUVER, BC	\$10.95	

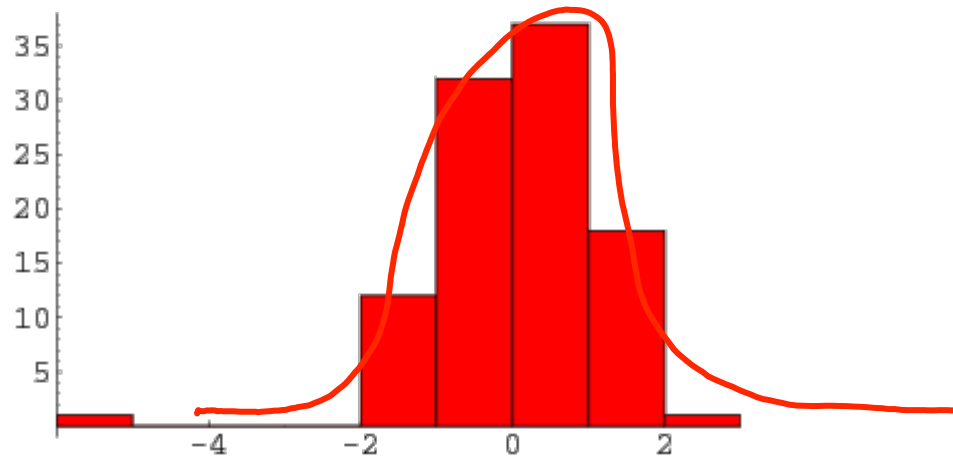
- Detecting natural disasters (earthquakes, particularly underwater).
- Astronomy (find new classes of stars/planets).
- Genetics (identifying individuals with new/ancient genes).

Classes of Methods for Outlier Detection

1. Model-based methods.
 2. Graphical approaches.
 3. Cluster-based methods.
 4. Distance-based methods.
 5. Supervised-learning methods.
- Warning: this is the topic with the most ambiguous “solutions”.
 - Next week we’ll get back to topics with more concrete solutions.

Model-Based Outlier Detection

- Model-based outlier detection:
 1. Fit a probabilistic model.
 2. Outliers are examples with low probability.

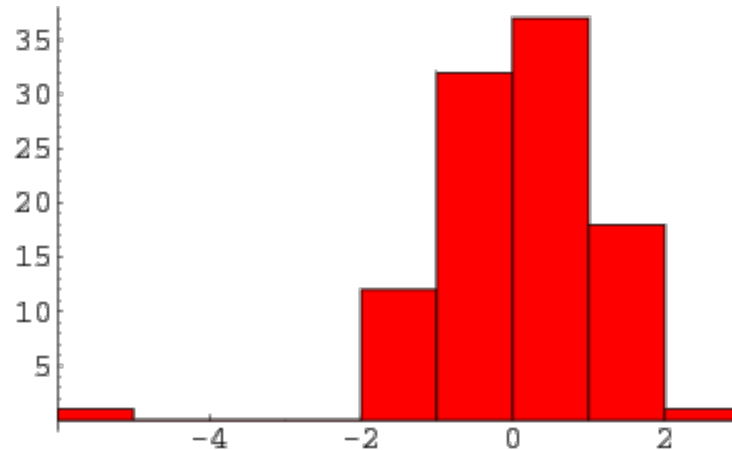


- Simplest approach is z-score:
 - If $z_i > 3$, then 97% of data is larger than x_i ?

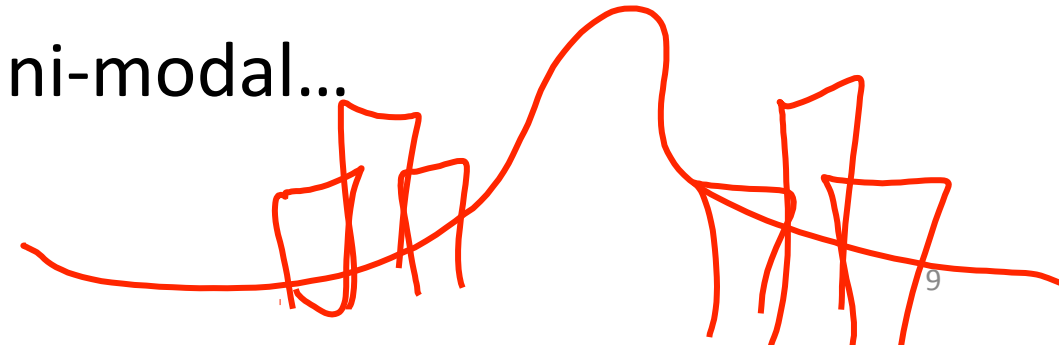
$$z_i = \frac{x_i - \mu}{\sigma}$$

Problems with Z-Score

- The z-score relies on mean and standard deviation:
 - These **measures are sensitive to outliers**.



- Possible fixes: **use quantiles, or sequentially remove worse outlier.**
- The z-score also assumes that data is uni-modal...



Global vs. Local Outliers

- Is the **red point** an outlier?



Global vs. Local Outliers

- Is the **red point** an outlier? What if add the **blue points**?



Global vs. Local Outliers

- Is the **red point** an outlier? What if add the **blue points**?



- Red point has the **lowest z-score**.
 - In the first case it was a “global” outlier.
 - In this second case it’s a “local” outlier:
 - It’s within the range of the data, but is far away from other points.
- In general, hard to give precise definition of ‘outliers’.

Global vs. Local Outliers

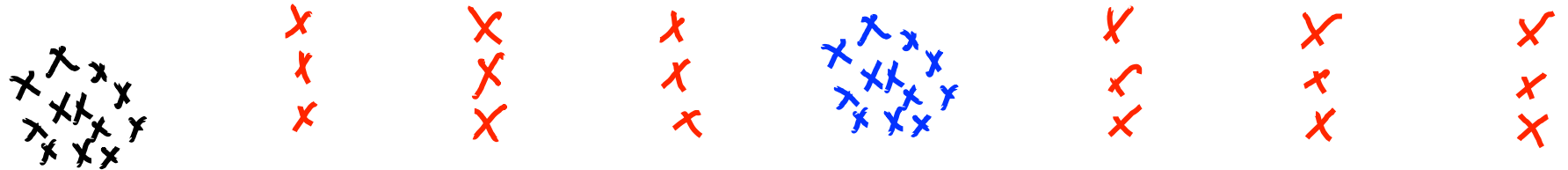
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 - Can we have **outlier groups**?

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- In general, hard to give precise definition of ‘outliers’.
 - Can we have **outlier groups**?
 - What about repeating patterns?

Graphical Outlier Detection

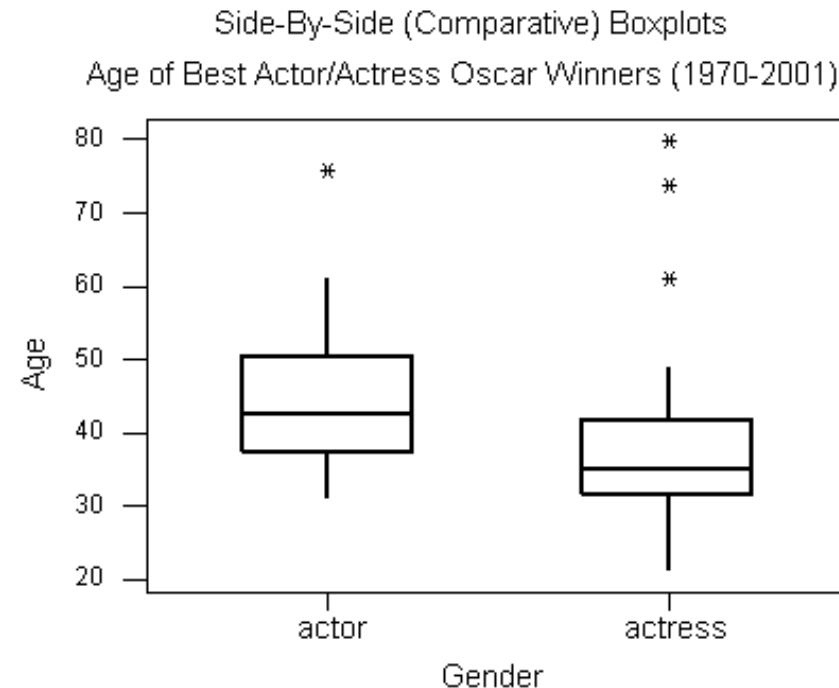
- Graphical approach to outlier detection:

1. Look at a plot of the data.
2. Human decides if data is an outlier.

- Examples:

1. Box plot:

- Visualization of quantiles/outliers.
- Only 1 variable at a time.



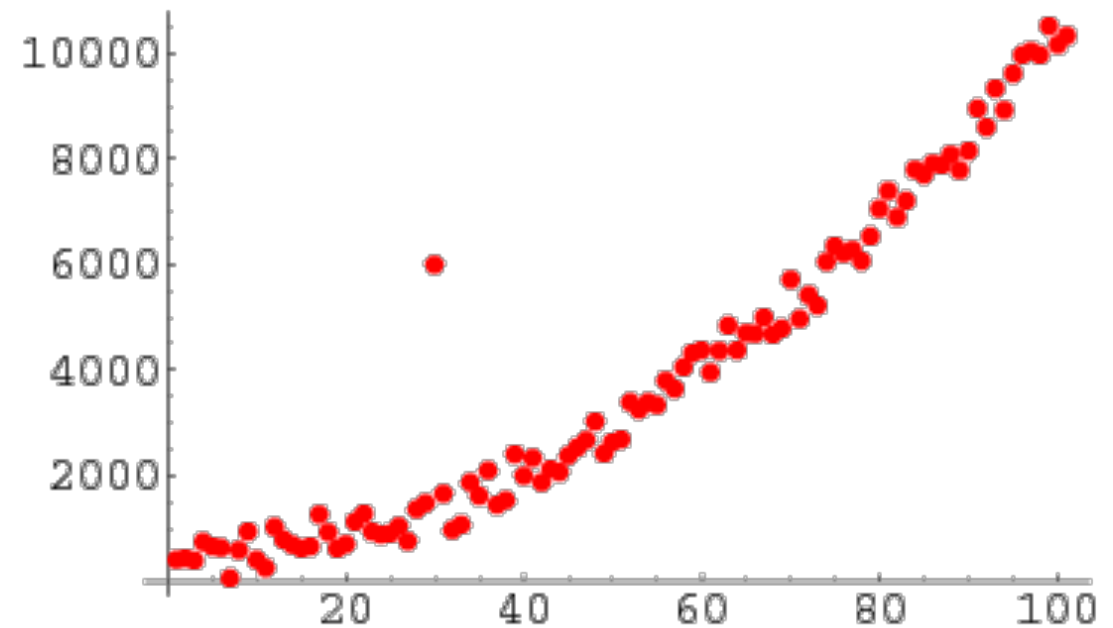
Graphical Outlier Detection

- Graphical approach to outlier detection:

1. Look at a plot of the data.
2. Human decides if data is an outlier.

- Examples:

1. Box plot.
2. Scatterplot:
 - Can detect complex patterns.
 - Only 2 variables at a time.



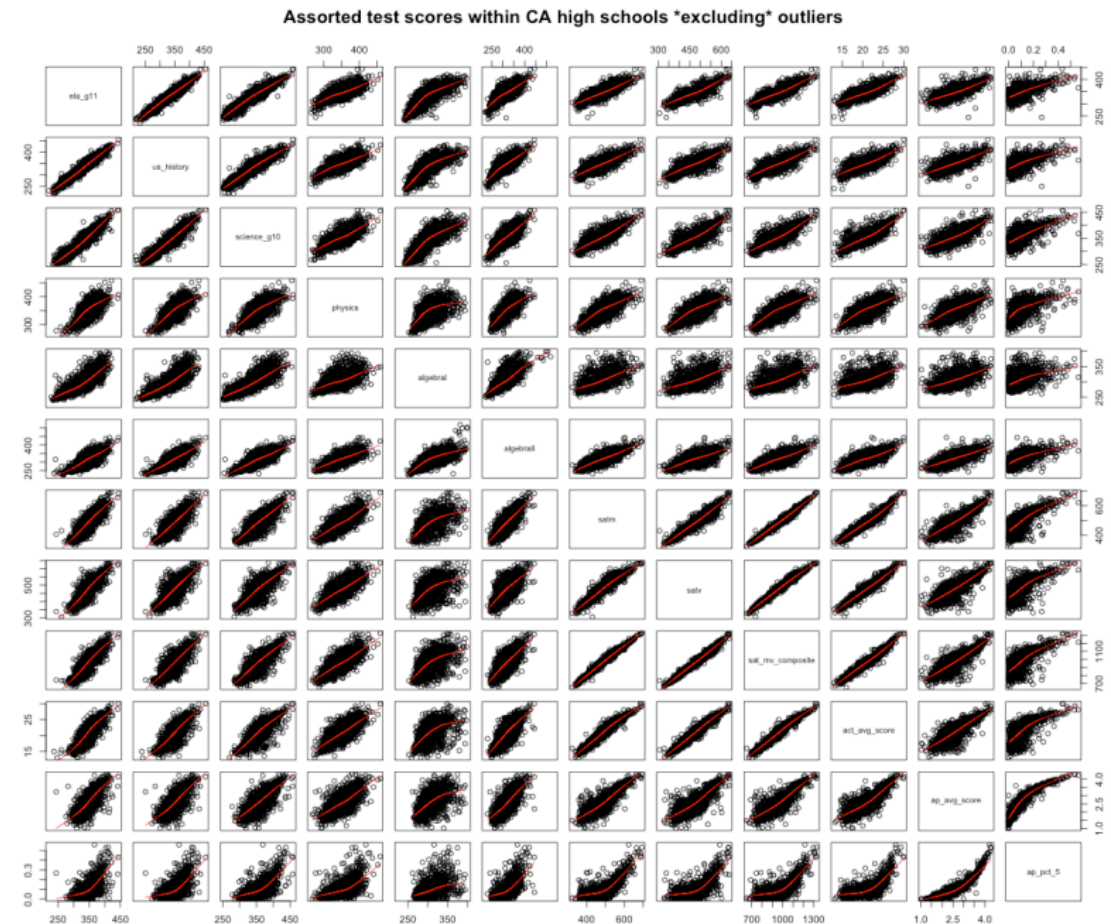
Graphical Outlier Detection

- Graphical approach to outlier detection:

1. Look at a plot of the data.
2. Human decides if data is an outlier.

- Examples:

1. Box plot.
2. Scatterplot.
3. Scatterplot array:
 - Look at all combinations of variables.
 - But laborious in high-dimensions.
 - Still only 2 variables at a time.



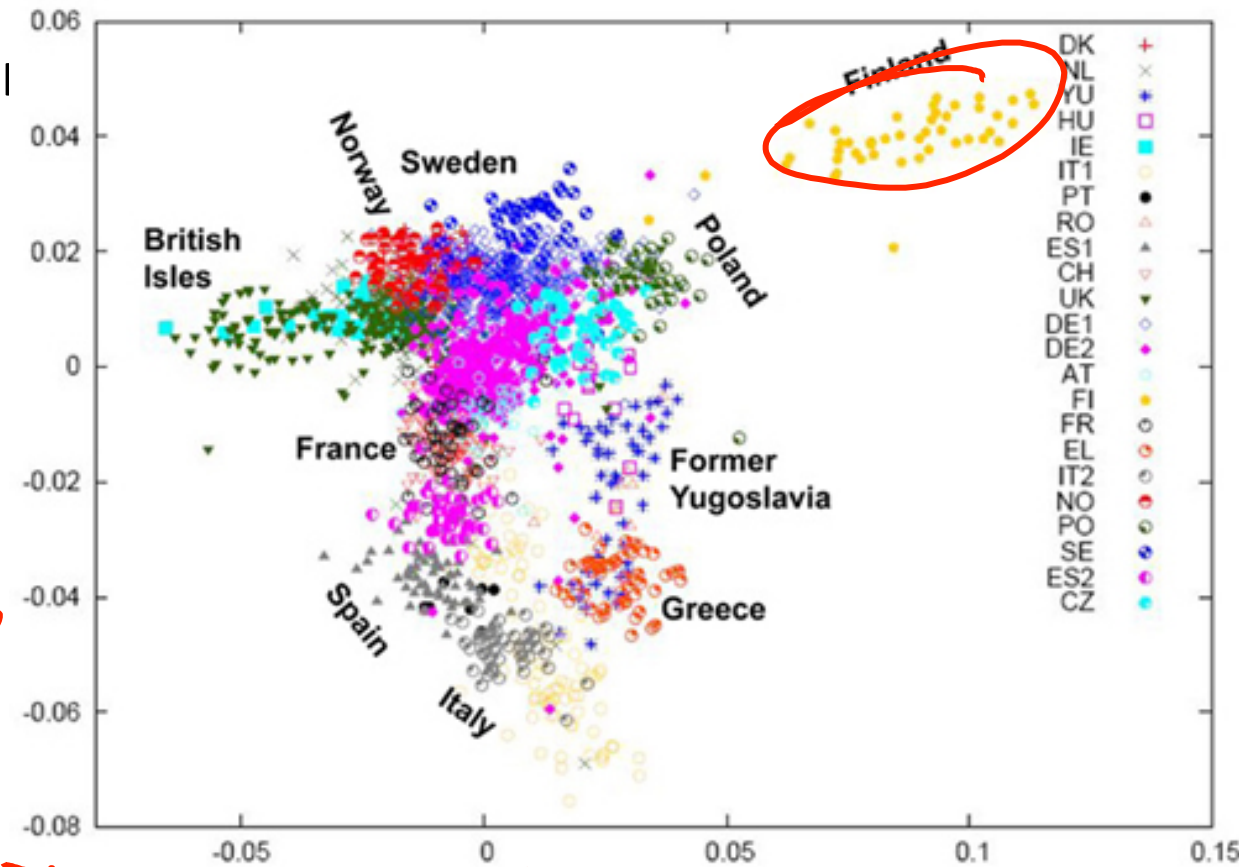
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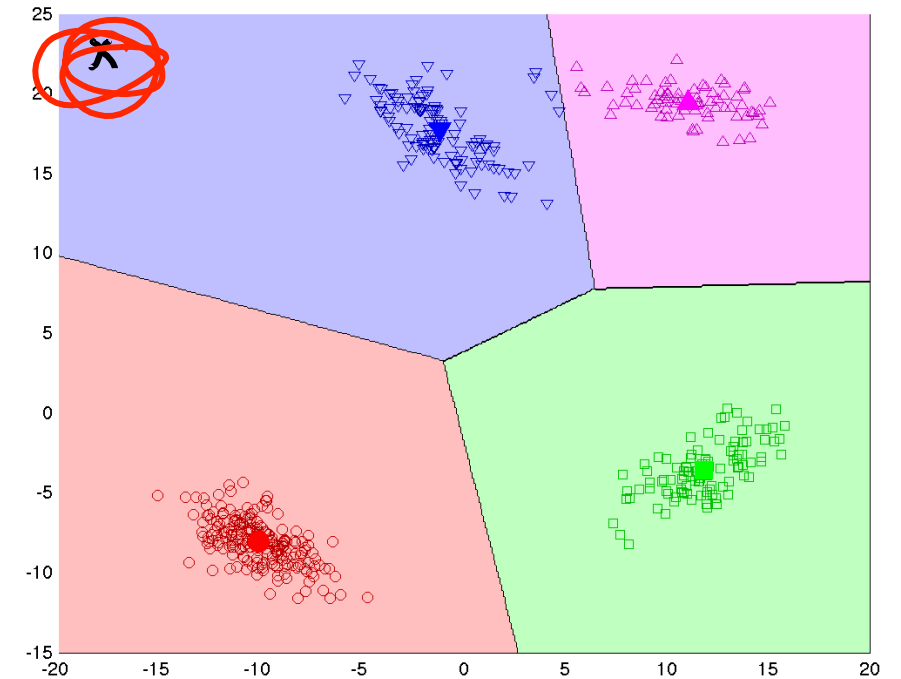
- Examples:

1. Box plot.
2. Scatterplot.
3. Scatterplot array.
4. Scatterplot of 2-dimensional PCA:
 - 'See' high-dimensional structure.
 - But PCA is sensitive to outliers.
 - There might be info in higher PCs.



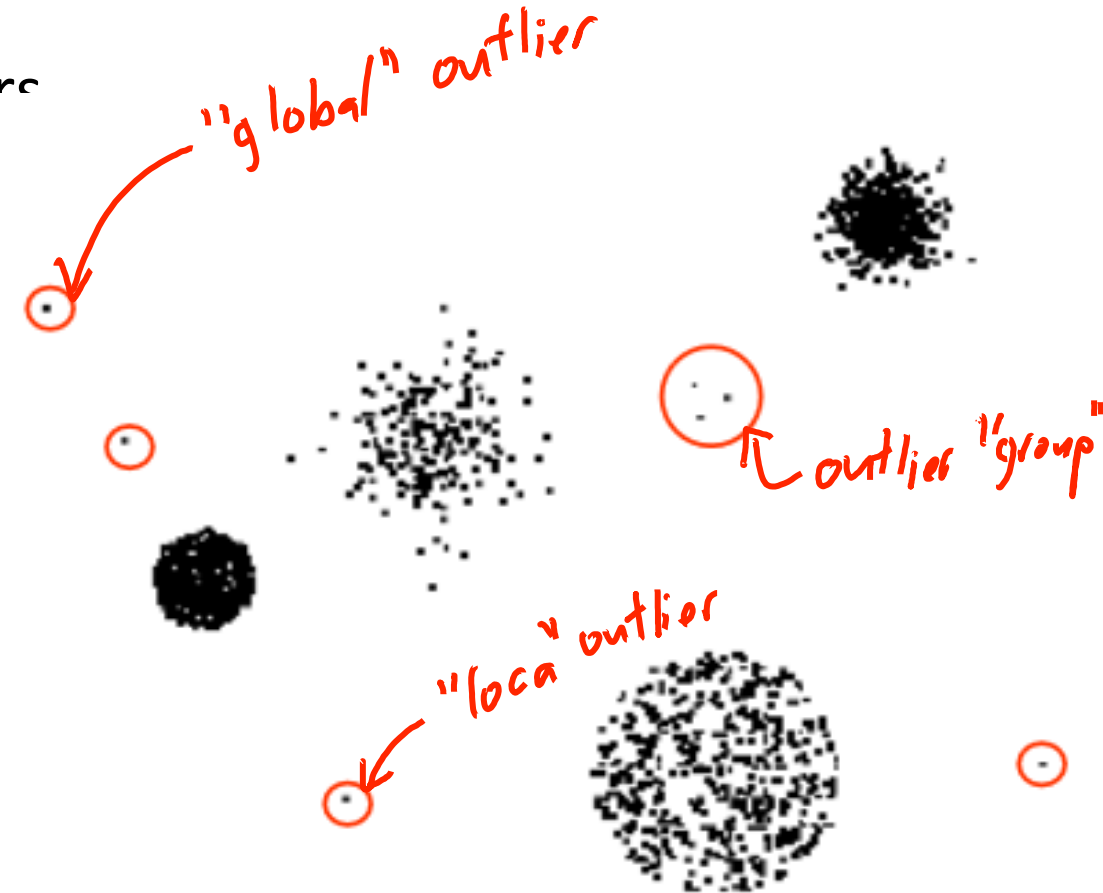
Cluster-Based Outlier Detection

- Detect outliers based on clustering:
 1. Cluster the data.
 2. Find points that don't belong to clusters.
- Examples:
 1. K-means:
 - Find points that are far away from any mean.
 - Find clusters with a small number of points.



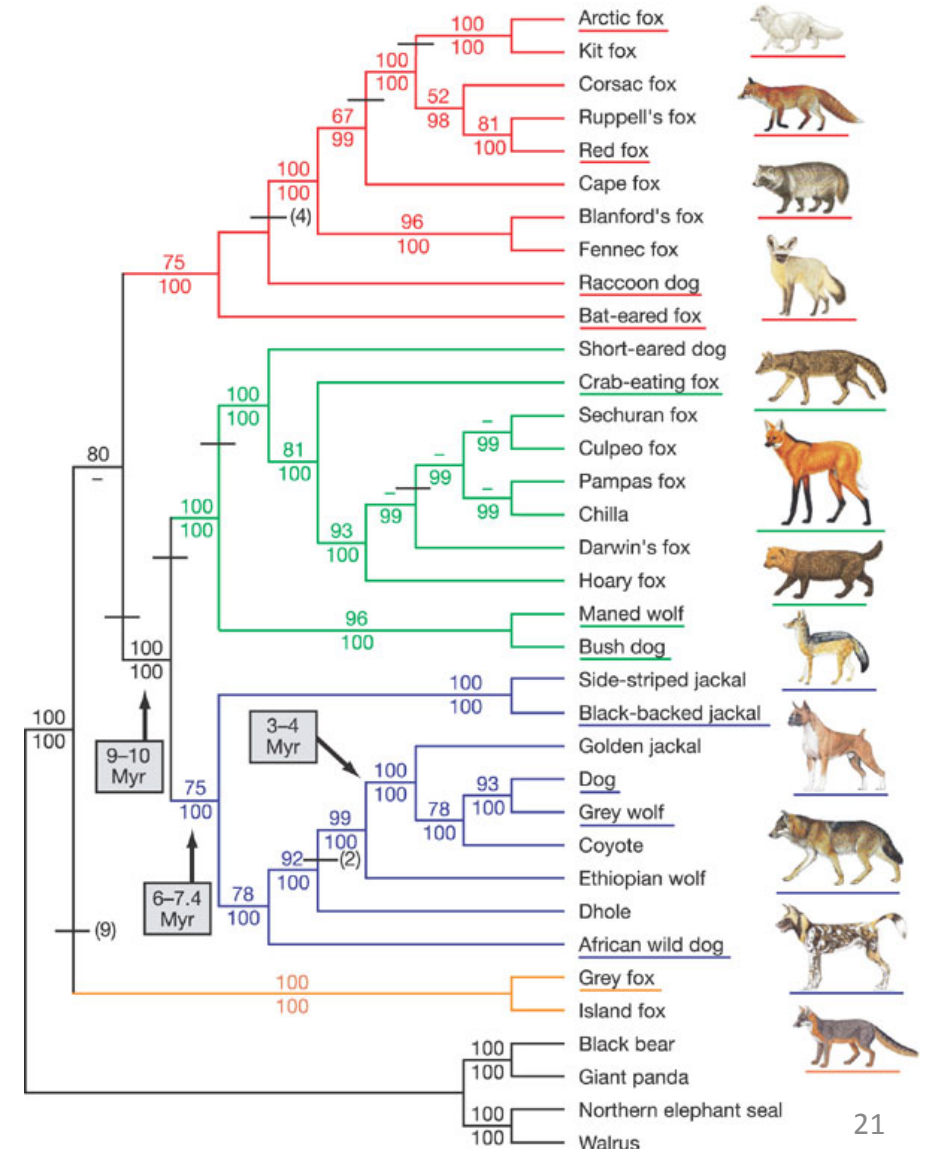
Cluster-Based Outlier Detection

- Detect outliers based on clustering:
 1. Cluster the data.
 2. Find points that don't belong to clusters.
- Examples:
 1. K-means.
 2. Density-based clustering:
 - Outliers are points not assigned to cluster.



Cluster-Based Outlier Detection

- Detect outliers based on clustering:
 1. Cluster the data.
 2. Find points that don't belong to clusters.
- Examples:
 1. K-means.
 2. Density-based clustering.
 3. Hierarchical clustering:
 - Outliers take longer to join other groups.
 - Also good for outlier groups.

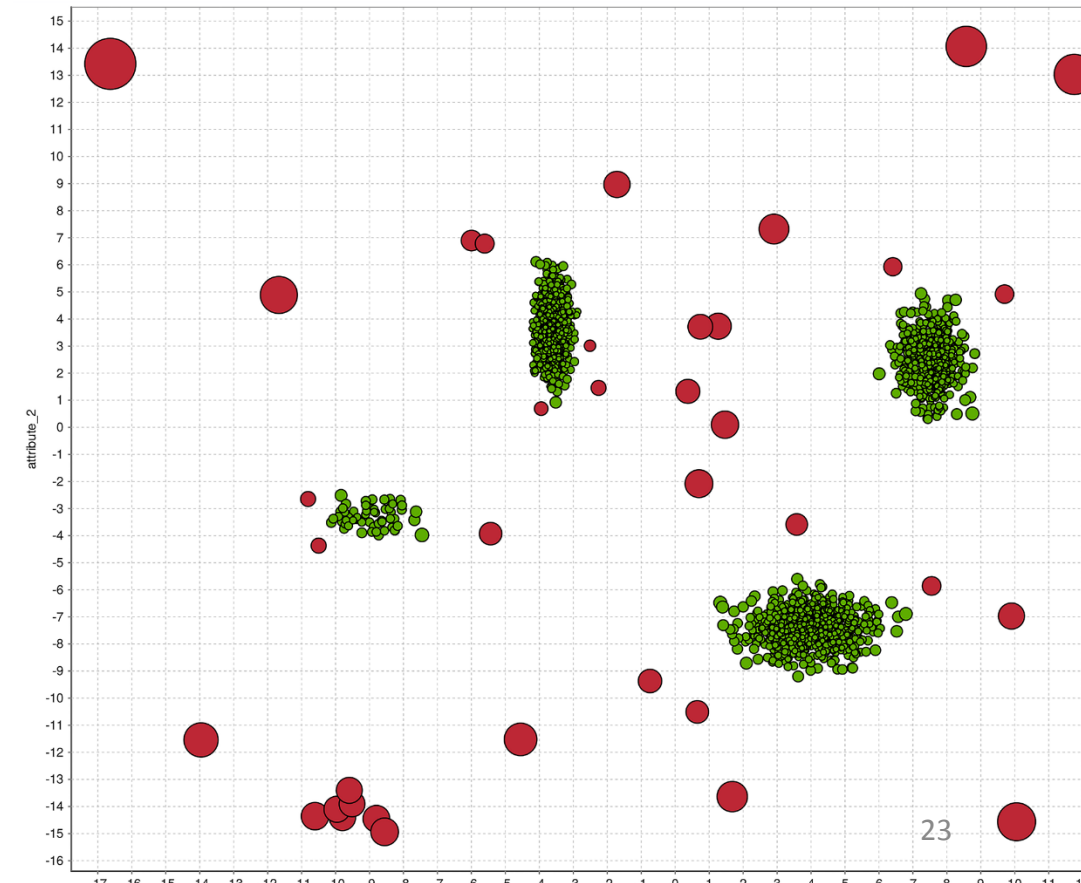


Distance-Based Outlier Detection

- Most of these approaches are **based on distances**.
- Can we skip the models/plot/clusters and directly use distances?
 - Directly **measure of how close objects are to their neighbours**.
- Examples:
 - How many points lie in a radius 'r'?
 - What is distance to k^{th} nearest neighbour?

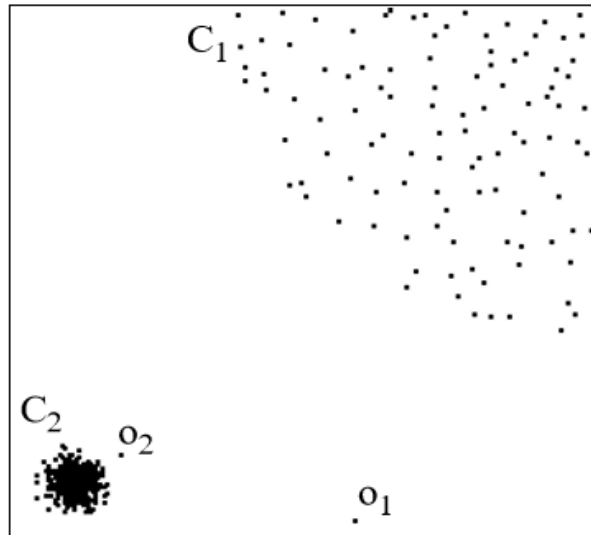
Global Distance-Based Outlier Detection: KNN

- KNN outlier detection:
 - For each point, compute the **average distance to its KNN**.
 - Sort these values.
 - Choose the biggest values as outliers.
- Goldstein and Uchida [2016]:
 - Compared 19 methods on 10 datasets.
 - KNN best for finding “global” outliers.
 - “Local” outliers better detected by LOF...



Local Distance-Based Outlier Detection

- As with density-based clustering, **problem with differing densities:**



- Outlier o_2 has similar density as elements of cluster C_1 .
- Solution: “local outlier factor” (LOF) and variations like **outlierness**:
 - Is point “**relatively**” **far away** from its neighbours?

Outlierness

- Let $N_k(x_i)$ be the **k-nearest neighbours** of x_i .
- Let $D_k(x_i)$ be the **average distance** to k-nearest neighbours:

$$D_k(x_i) = \frac{1}{k} \sum_{j \in N_k(x_i)} \|x_i - x_j\|$$

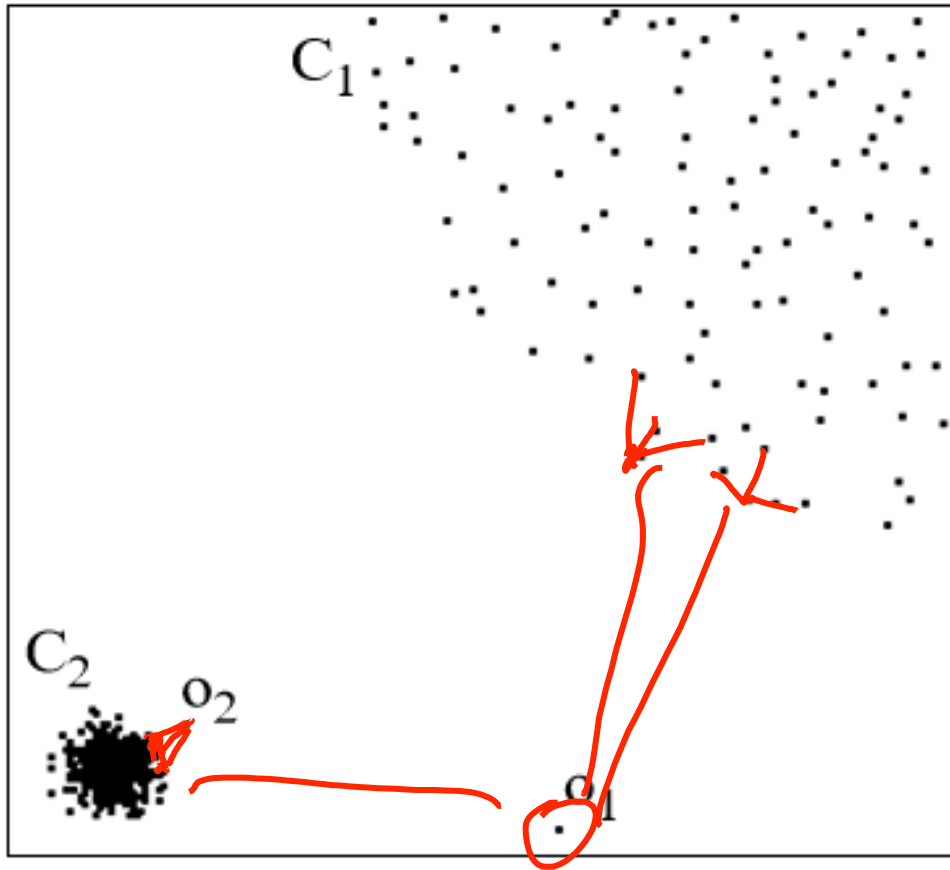
- **Outlierness** is ratio of $D_k(x_i)$ to average $D_k(x_j)$ for its neighbours 'j':

$$O_k(x_i) = \frac{D_k(x_i)}{\frac{1}{k} \sum_{j \in N_k(x_i)} D_k(x_j)}$$

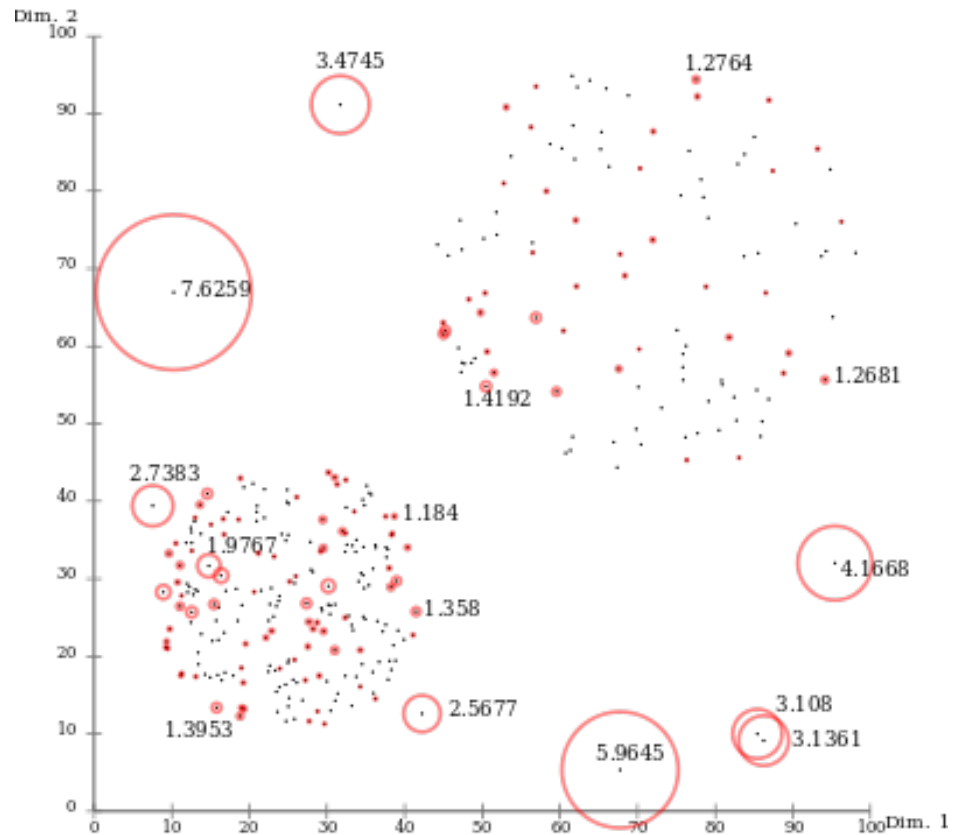
- If outlierness > 1 , x_i is **further away from neighbours** than expected.

Outlierness

- Outlierness finds o_1 and o_2 :

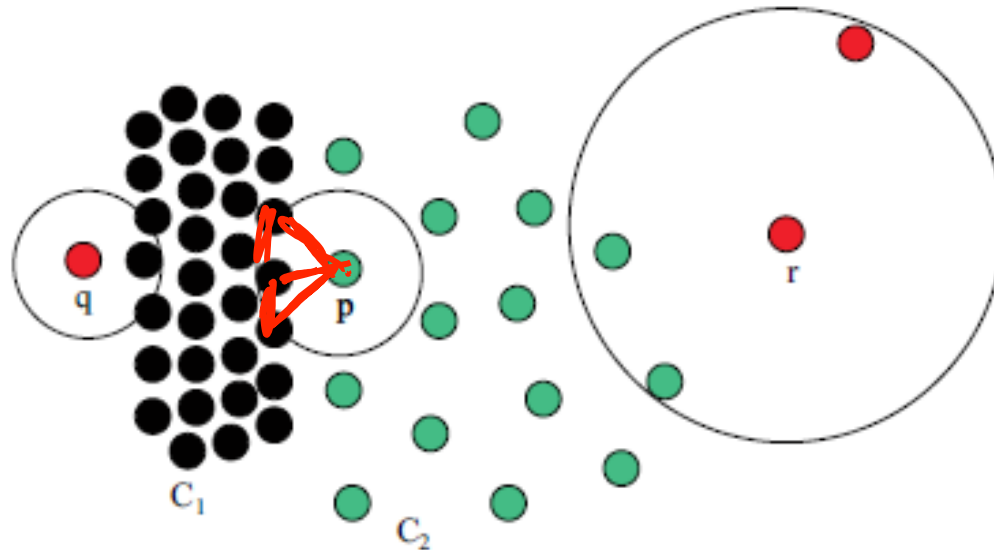


- More complicated data:



Outlierness with Close Clusters

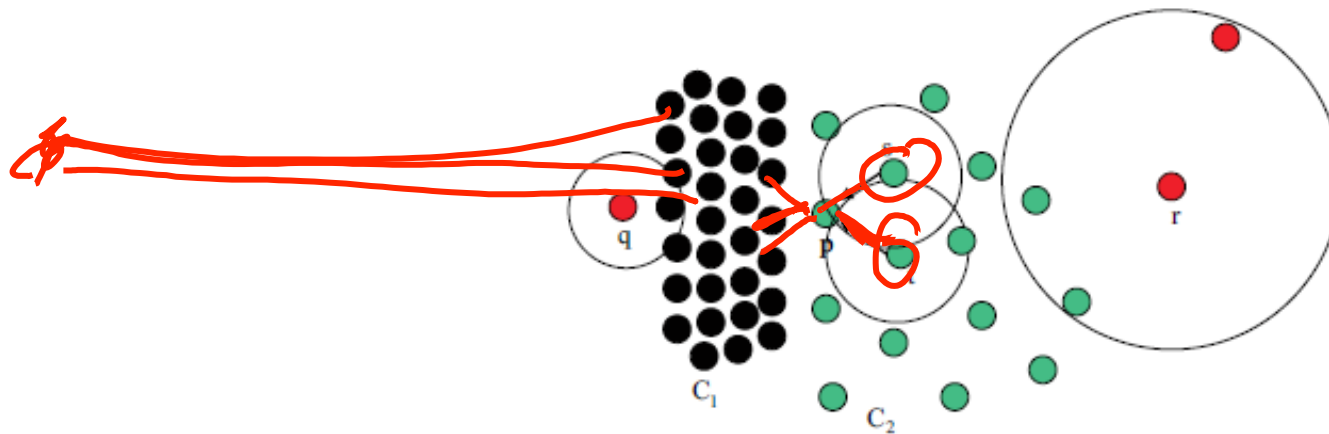
- If clusters are close, outlierness gives unintuitive results:



- In this example, 'p' has higher outlierness than 'q' and 'r':
 - The green points are not part of the KNN list of 'p' for small 'k'.

Outlierness with Close Clusters

- ‘Influenced outlierness’ (INFLO) ratio:
 - Include in denominator the ‘reverse’ k-nearest neighbours:
 - Points that have ‘p’ in KNN list.
 - Adds ‘s’ and ‘t’ from bigger cluster that includes ‘p’:



- But still has problems:
 - Dealing with hierarchical clusters.
 - Yields many false positives if you have “global” outliers.
 - Goldstein and Uchida [2016] recommend just using KNN.

Supervised Outlier Detection

- Final approach to outlier detection is to use supervised learning:
 - $y_i = 1$ if x_i is an outlier.
 - $y_i = 0$ if x_i is a regular point.
- Let's us use our great methods for supervised learning:
 - We can find very complicated outlier patterns.
- But it needs supervision:
 - We need to know what outliers look like.
 - We may not detect new “types” of outliers.

Summary

- **Outlier detection** is the task of finding unusually different objects.
 - A concept that is very difficult to define.
- **Model-based** methods check if objects are unlikely in fitted model.
- **Graphical** methods plot data and use human to find outliers.
- **Cluster-based** methods check whether objects belong to clusters.
- **Distance-based** methods measure relative distance to neighbours.
- **Supervised-learning** methods just turn it into supervised learning.

- Next time: “customers who bought this item also bought...”