

# CPSC 340: Machine Learning and Data Mining

Outlier Detection

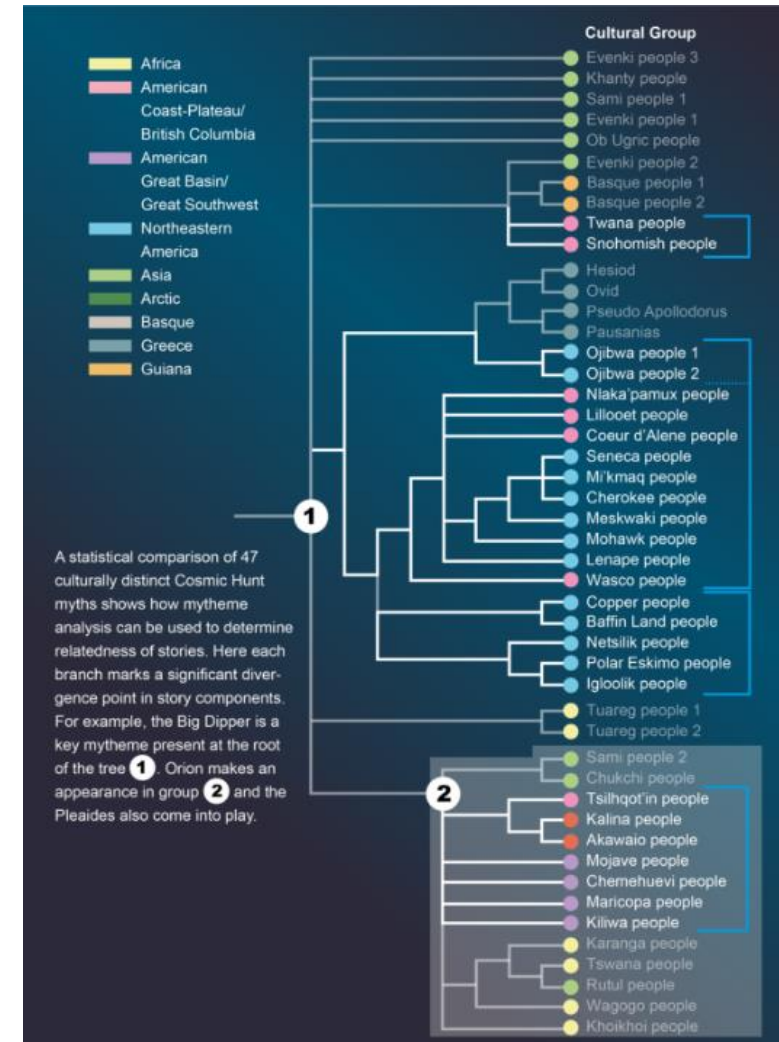
Fall 2016

# Admin

- Assignment 1 solutions will be posted after class.
- **Assignment 2** is out:
  - Due next Friday, but start early!
- **Calculus and linear algebra terms to review** for next week:
  - Vector addition and multiplication:  $\alpha x + \beta y$ .
  - Inner-product:  $x^T y$ .
  - Matrix multiplication:  $Xw$ .
  - Solving linear systems:  $Ax = b$ .
  - Matrix inverse:  $X^{-1}$ .
  - Norms:  $\|x\|$ .
  - Gradient:  $\nabla f(x)$ .
  - Stationary points:  $\nabla f(x) = 0$ .
  - Convex functions:  $f''(x) \geq 0$ .

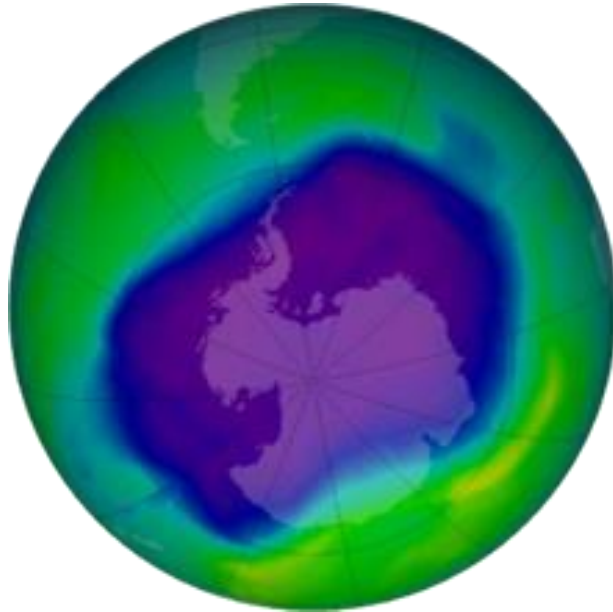
# Last Time: Hierarchical Clustering

- 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**.
  - Scientific American yesterday:
    - “Scientists Trace Society’s Myths to Primordial Origins”
    - “Cosmic Hunt”: Man hunts animal that becomes constellation.



# Motivating Example: Finding Holes in Ozone Layer

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

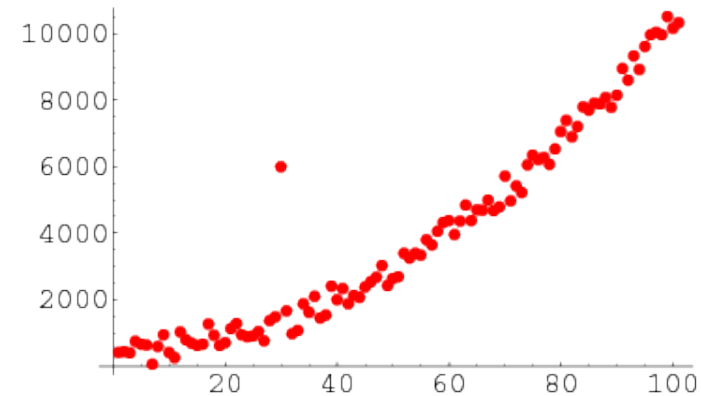
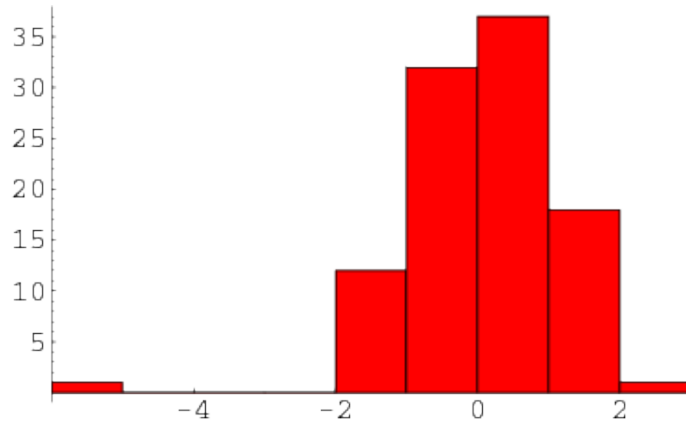


- It had been in satellite data since 1976:
  - But it was flagged and filtered out by quality-control algorithm.

# 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	

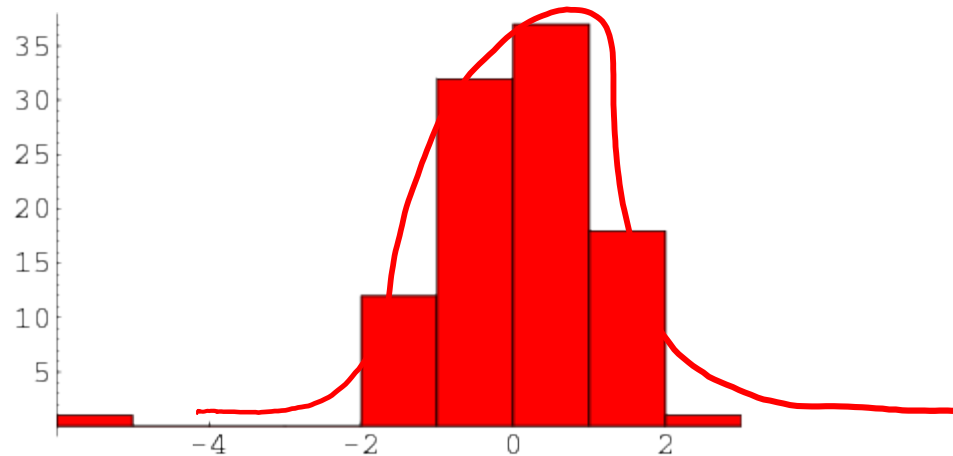
- Detecting natural disasters (earthquakes, particularly underwater).
- Astronomy (find new classes of stars/planets).
- Genetics (identifying individuals with new/ancient genes).

# 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**.



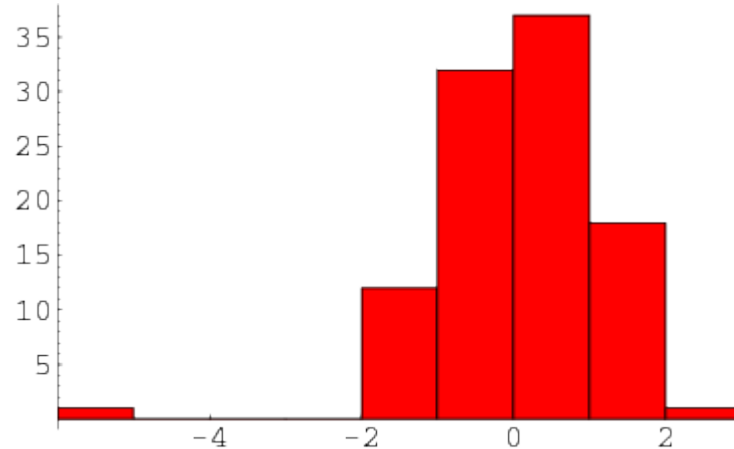
- Simplest approach is **z-score**:
  - If  $z_i > 3$ , 97% of data is larger than  $x_i$ ?

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

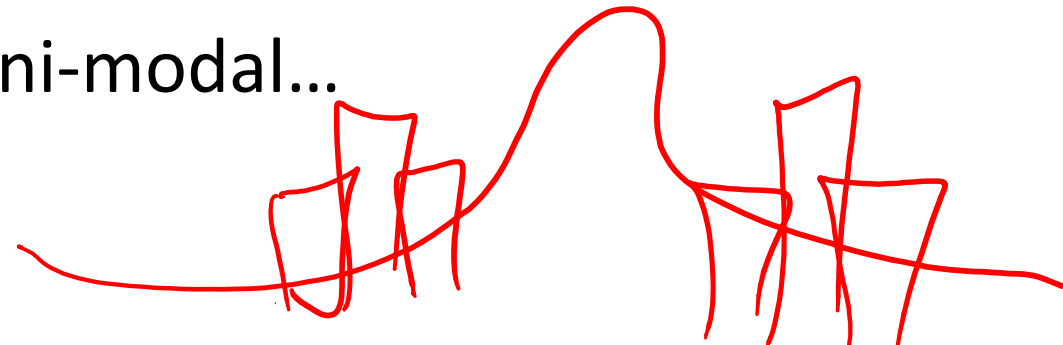


# Problems with Z-Score

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



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



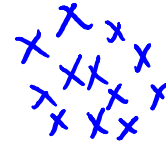
# Global vs. Local Outliers

- 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

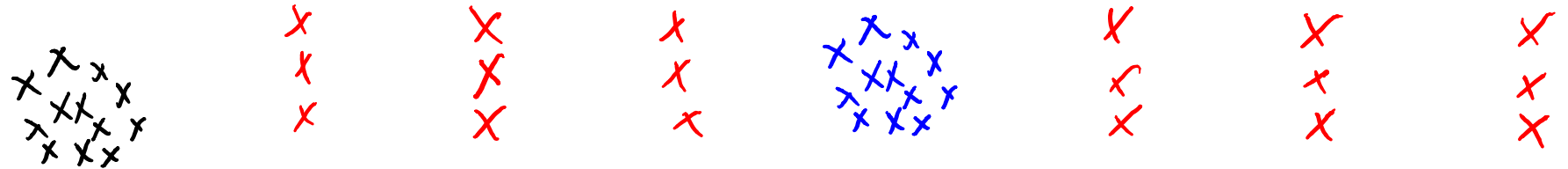
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  - Can we have **outlier groups**?

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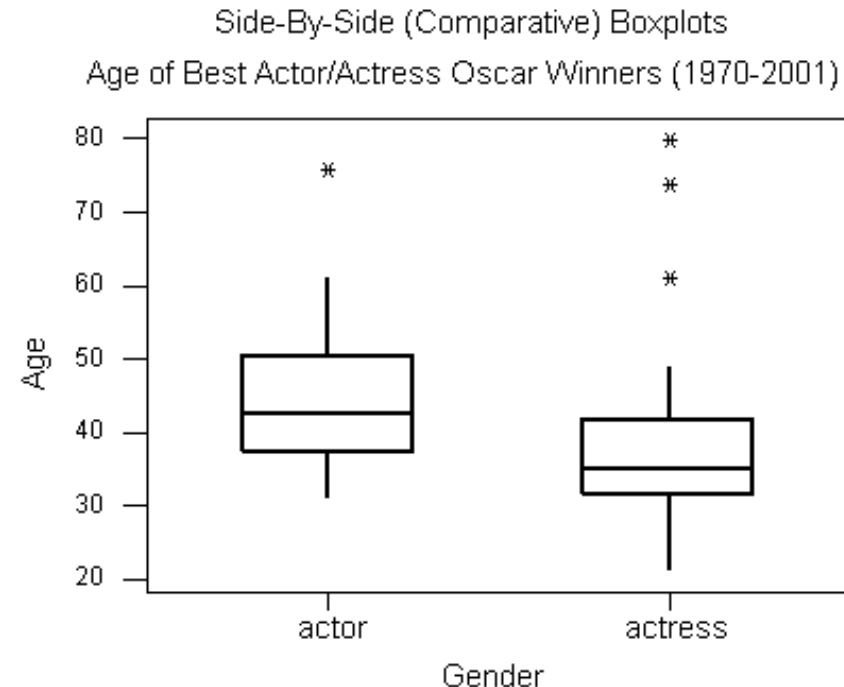
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- In general, hard to give precise definition of ‘outliers’.
  - Can we have **outlier groups**?
  - What about repeating patterns?

# 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:

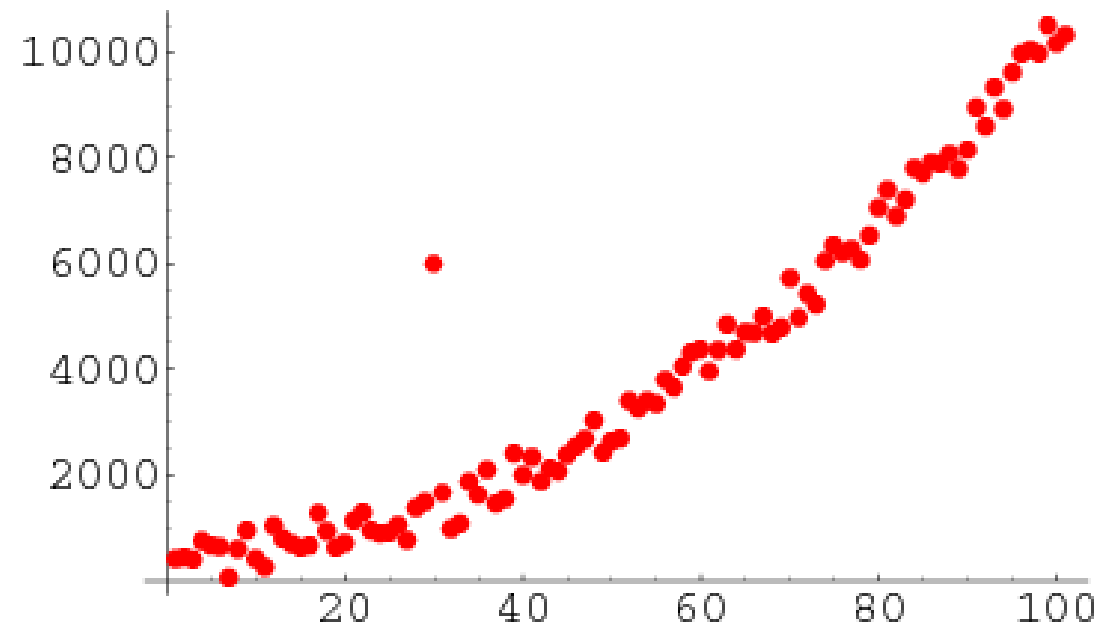
1. Box plot:

- 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.





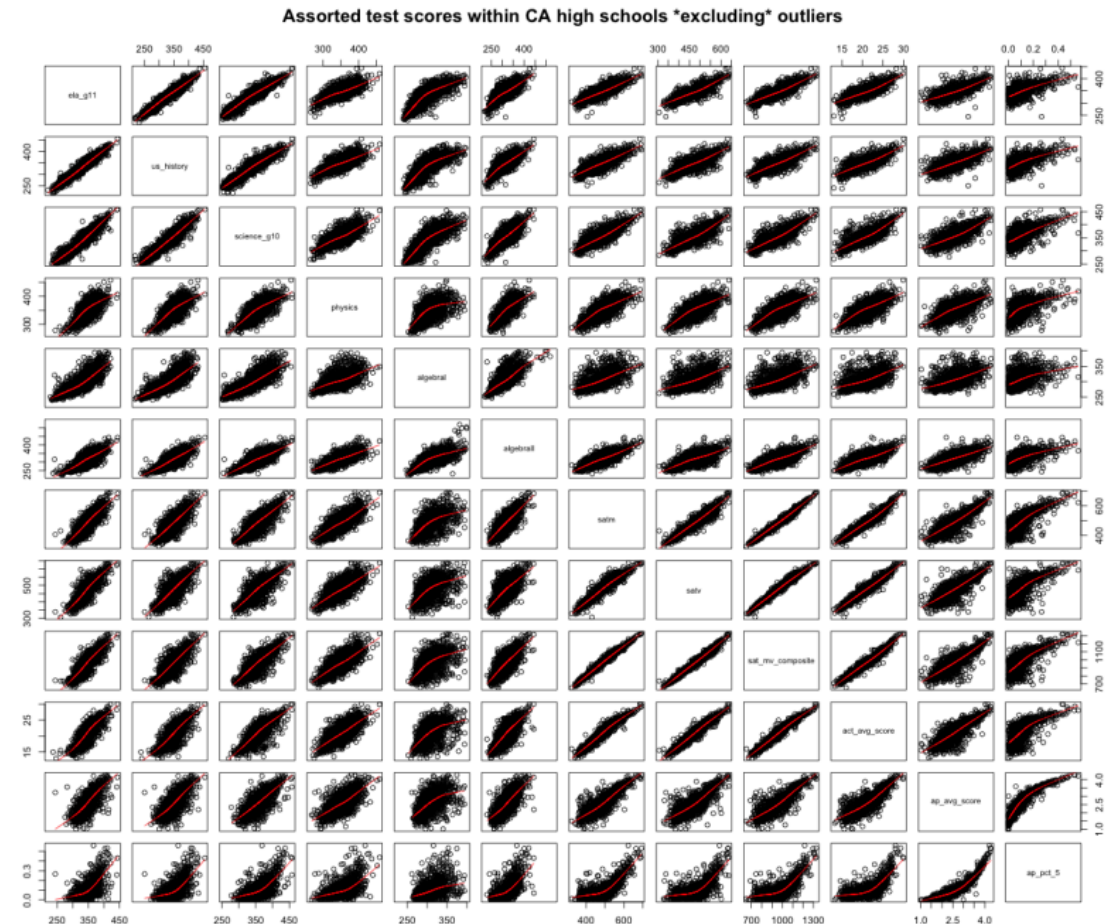
# Graphical Outlier Detection

- **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.



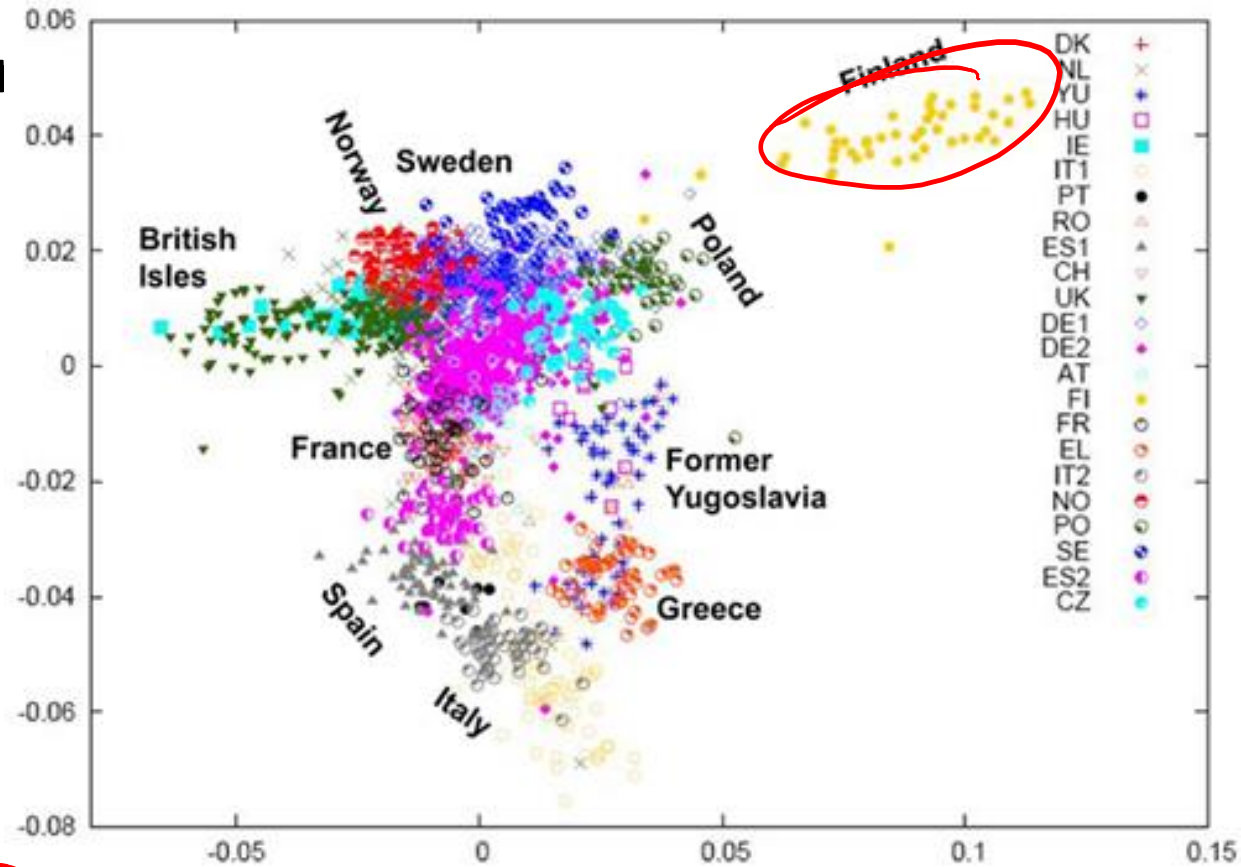
# Graphical Outlier Detection

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- **Examples:**

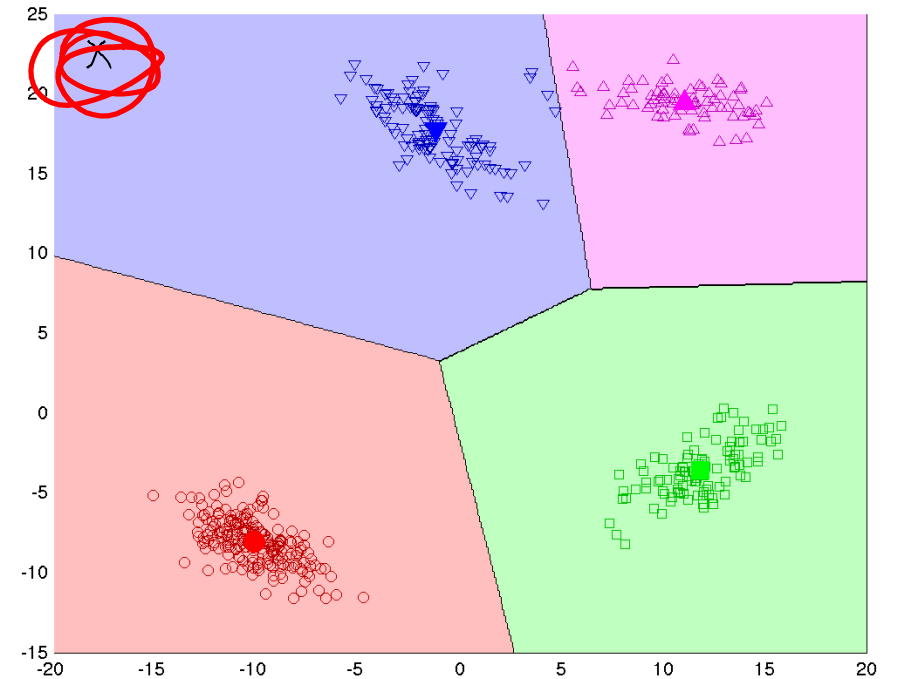
1. Box plot.
2. Scatterplot.
3. Scatterplot array.
4. **Scatterplot of 2-dimensional PCA:**
  - 'See' high-dimensional structure.
  - But **PCA is sensitive to outliers.**
  - There **might be info in higher PCs.**



→ We'll cover PCA later in this course.

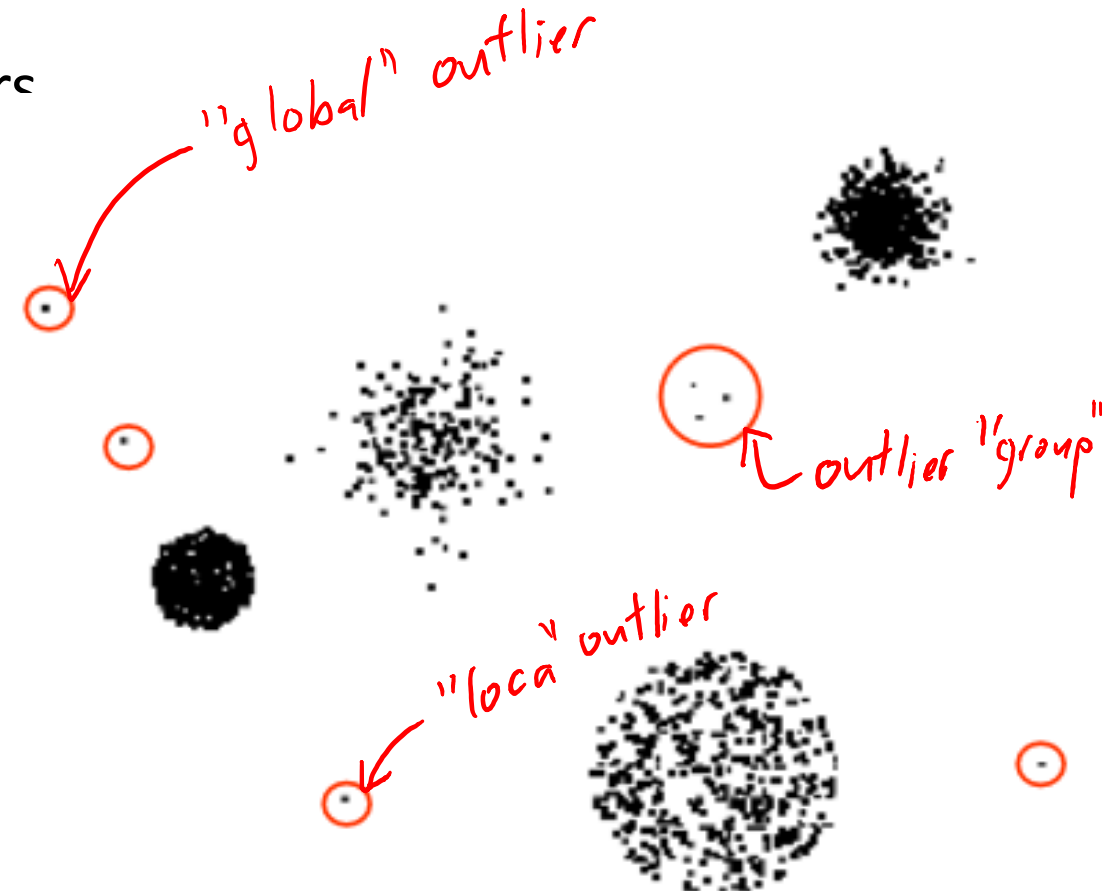
# Cluster-Based Outlier Detection

- 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.



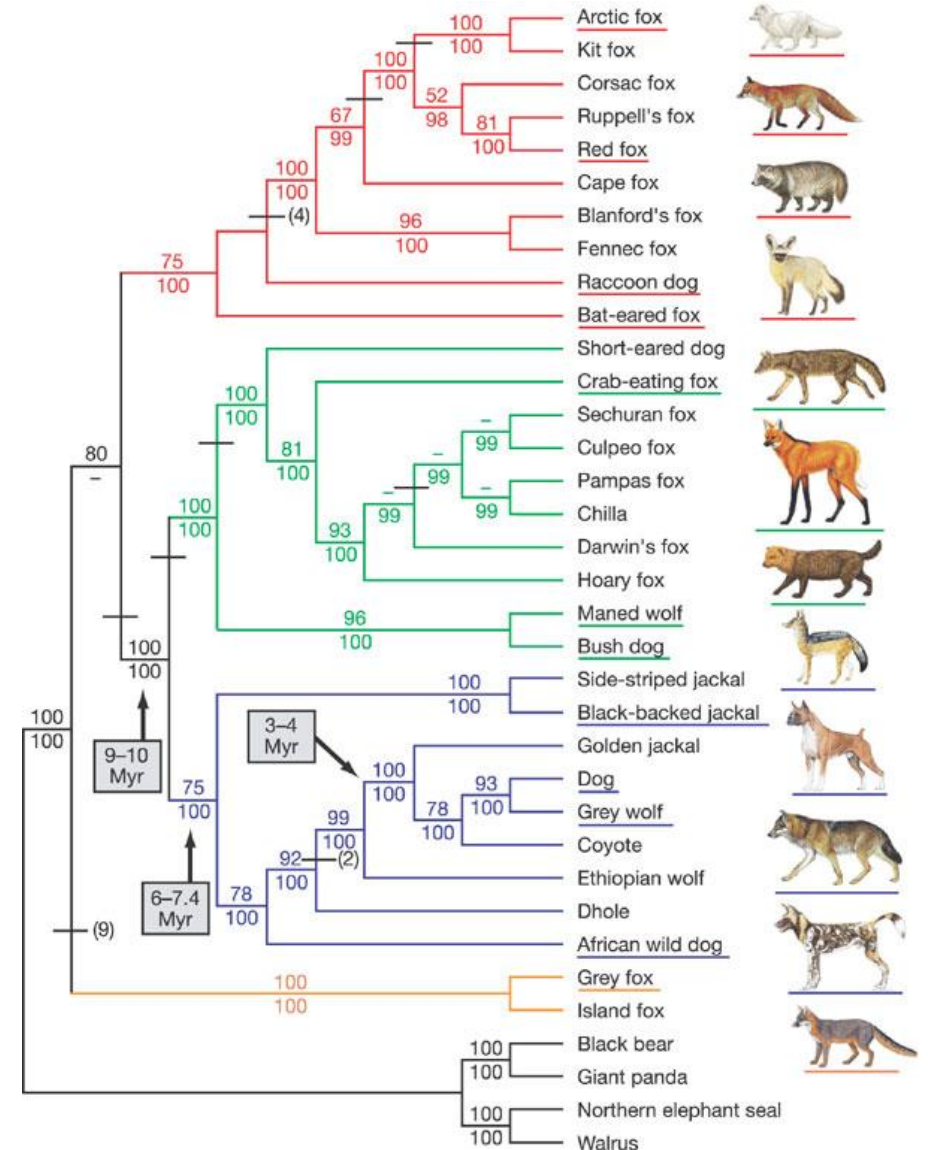
# Cluster-Based Outlier Detection

- Detect outliers based on clustering:
  1. Cluster the data.
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- 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.

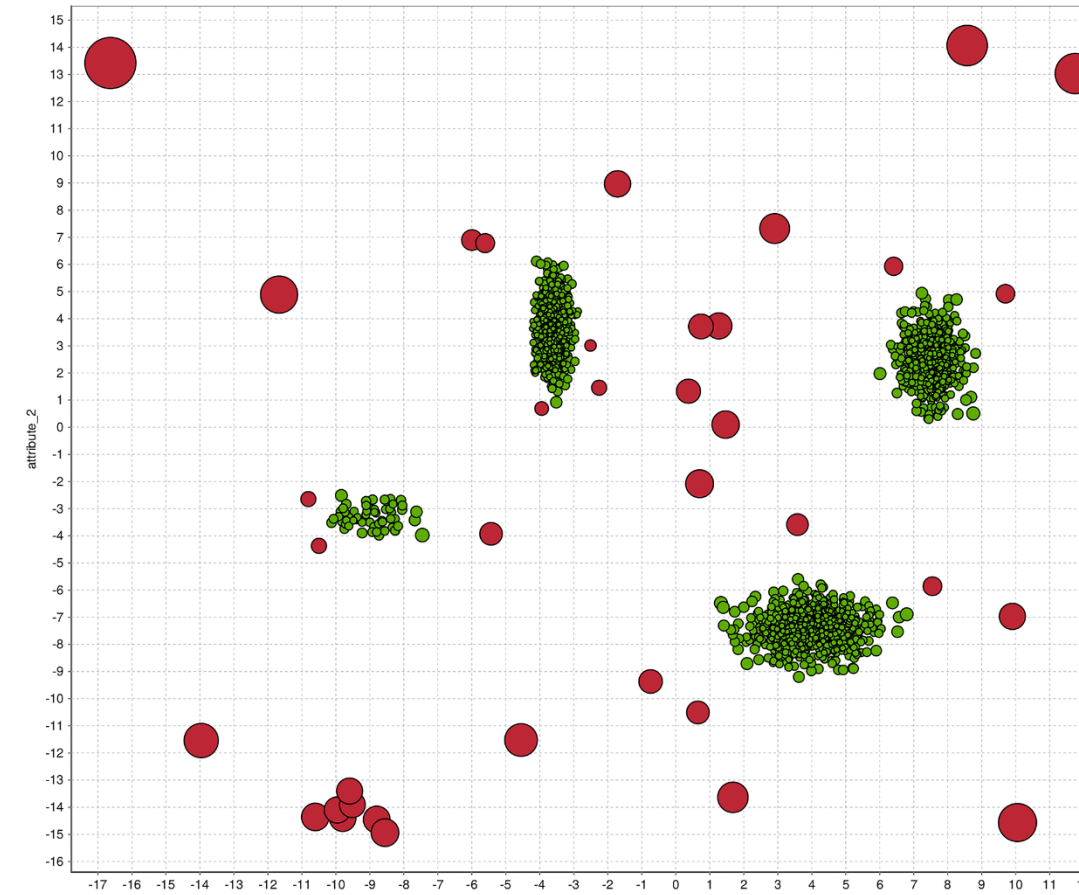


# Distance-Based Outlier Detection

- 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  $k^{\text{th}}$  nearest neighbour?

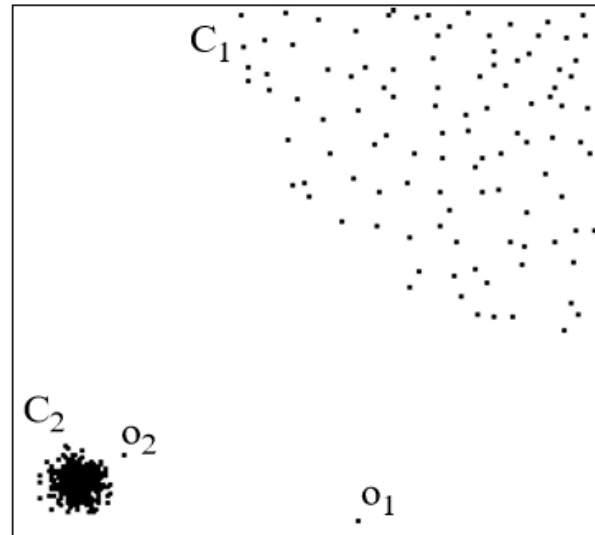
# Global Distance-Based Outlier Detection: KNN

- **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:

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

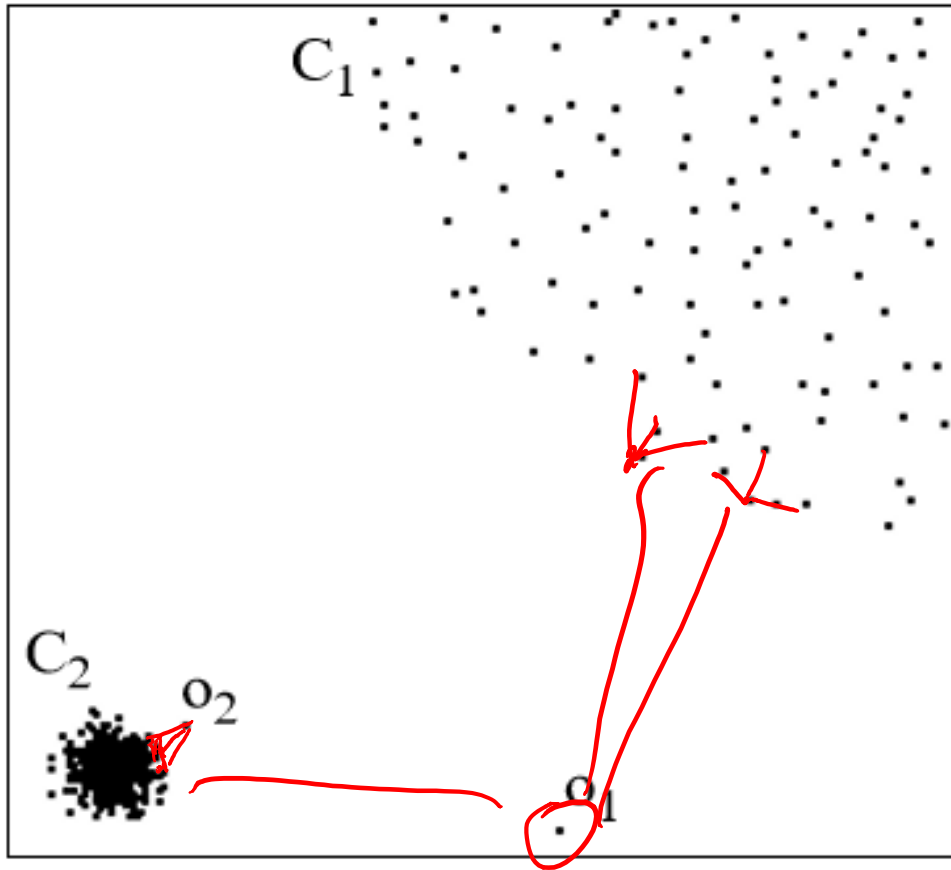
- **Outlierness** is ratio of  $D_k(x_i)$  to average  $D_k(x_j)$  for its neighbours 'j':

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

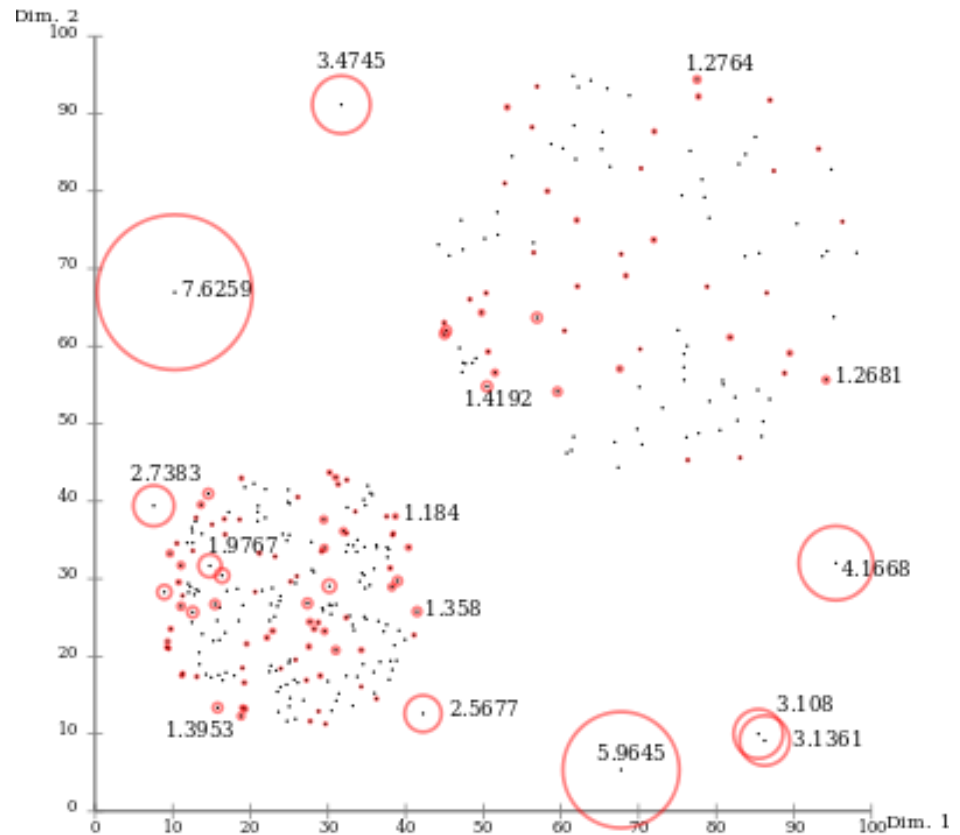
- If outlierness  $> 1$ ,  $x_i$  is **further away from neighbours** than expected.

# Outlierness Ratio

- Outlierness finds  $o_1$  and  $o_2$ :

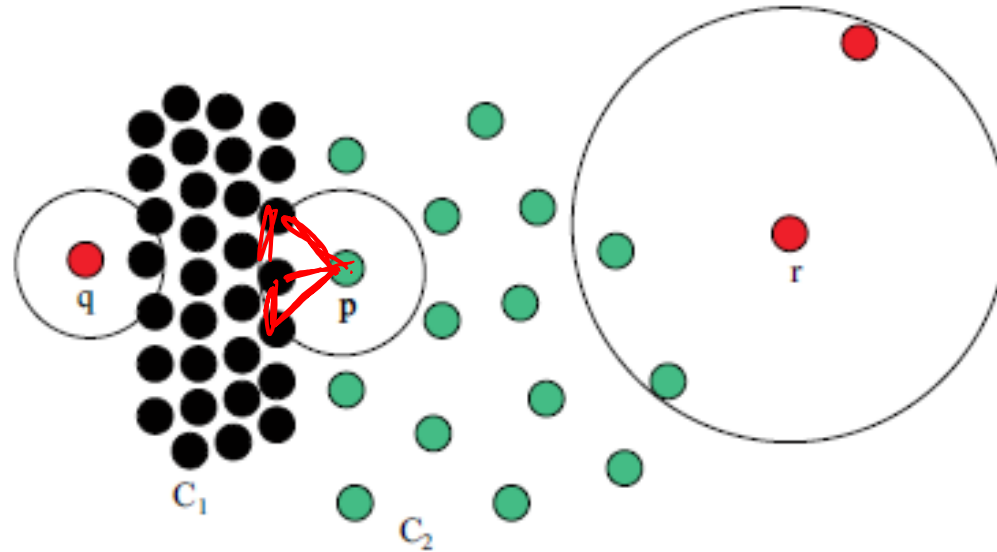


- More complicated data:



# Outlierness with Close Clusters

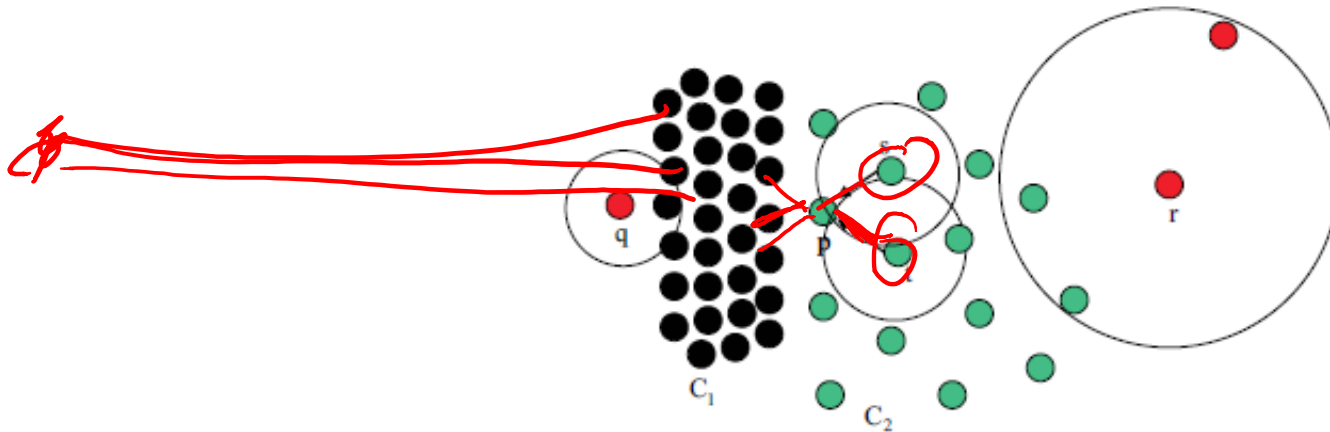
- If clusters are close, outlierness gives unintuitive results:



- 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 task of finding unusually different object.
  - 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”.