Master Degree in Artificial Intelligence for Science and Technology

Introduction to Cluster Analysis



Fabio Stella

Department of Informatics, Systems and Communication
University of Milan-Bicocca
fabio.stella@unimib.it

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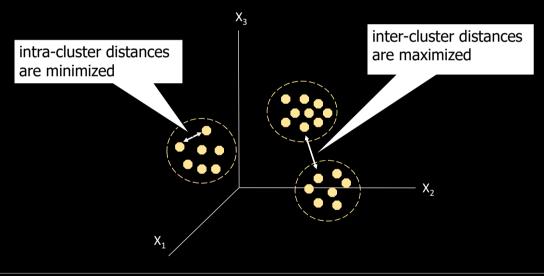
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OUTLOOK

- CLUSTER ANALYSIS
- UNDERSTANDING AND SUMMARIZING
- TYPES OF CLUSTERING
- TYPES OF CLUSTERS
- COMPONENTS OF CLUSTER ANALYSIS

WHAT IS CLUSTER ANALYSIS?

Given a set of objects, place them in groups such that the objects in a group are similar (or related) to one another and different from (or unrelated to) the objects in other groups.

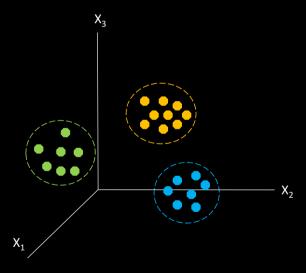


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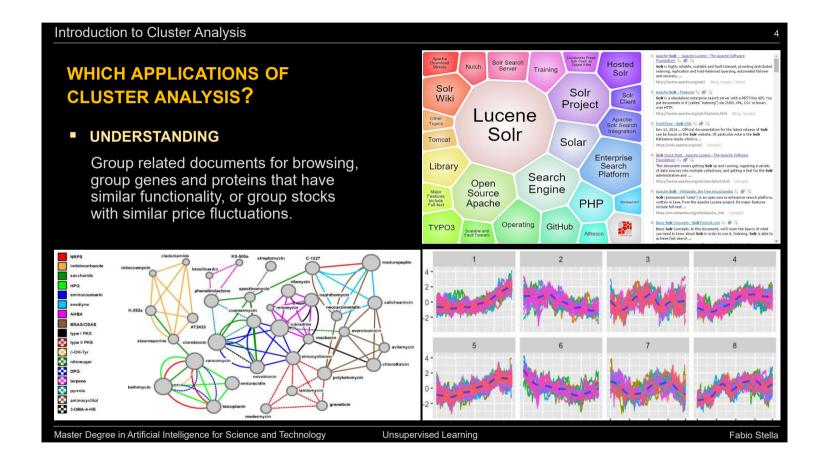
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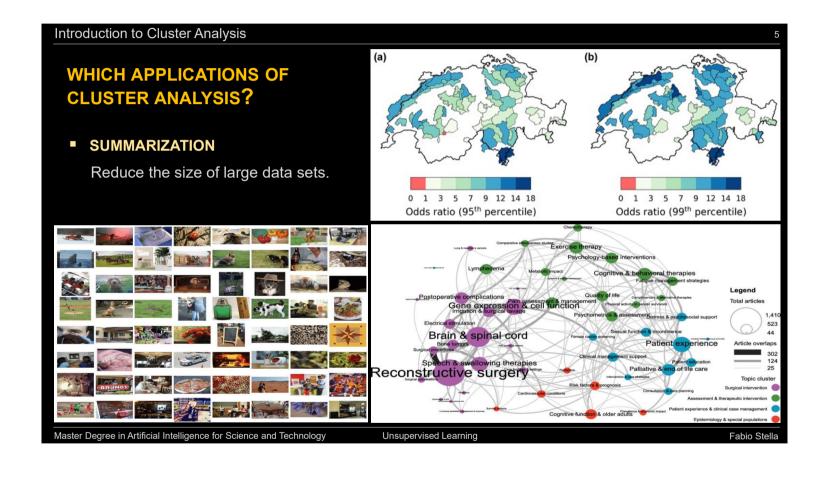
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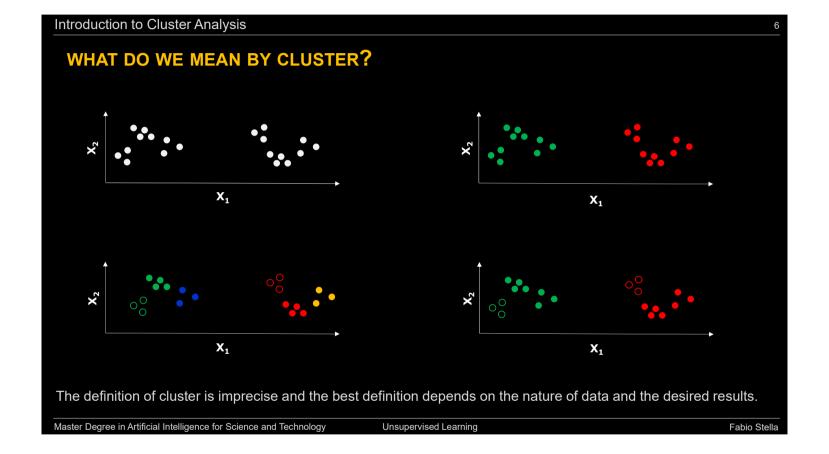


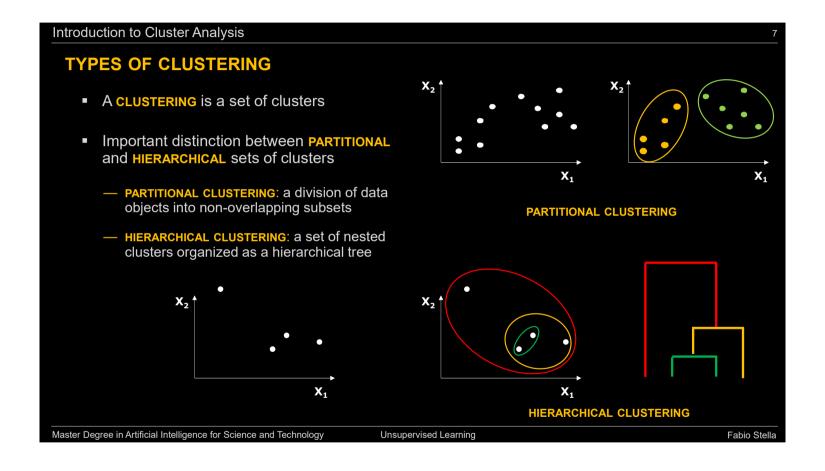
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OTHER DISTINCTIONS BETWEEN SETS OF CLUSTERS

- EXCLUSIVE versus NON-EXCLUSIVE
 - In non-exclusive clusterings, points may belong to multiple clusters
 - Can belong to multiple classes or could be 'BORDER' points
- FUZZY CLUSTERING (ONE TYPE OF NON-EXCLUSIVE)
 - In fuzzy clustering, a point belongs to every cluster with some weight between 0 and 1
 - Weights must sum to 1
 - Probabilistic clustering has similar characteristics
- PARTIAL versus COMPLETE
 - In some cases, we only want to cluster some of the data
 - Data can contain **OUTLIERS** or **ANOMALOUS OBSERVATIONS**

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TYPES OF CLUSTERS

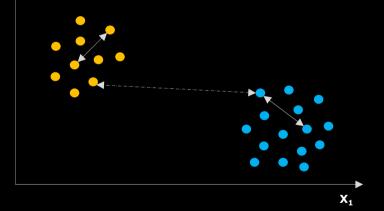
- Well-separated clusters
- Prototype-based clusters
- Contiguity-based clusters
- Density-based clusters
- Described by an Objective Function

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Each object in the cluster is closer (more similar) to every other object in the same cluster than to any object not in the cluster.

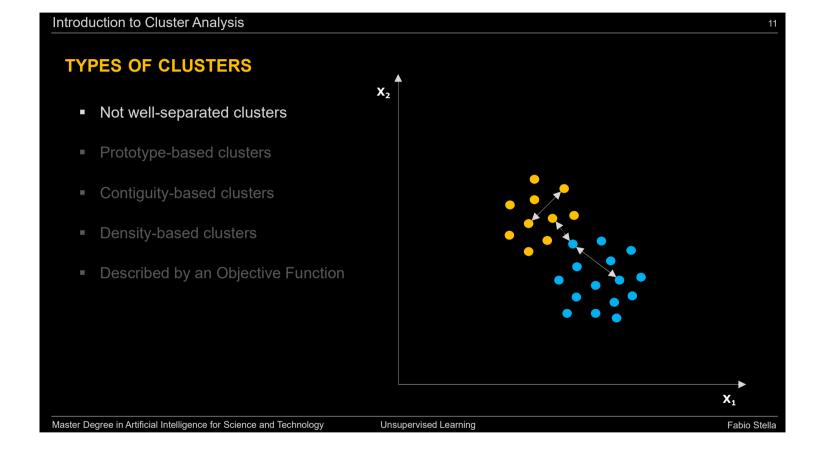
A threshold can be used to specify that all objects in a cluster must be sufficiently close to one another. Idealistic definition of cluster, satisfied only when the data contains natural clusters that are quite far from each other.

Does not need to be globular, can have any shape.



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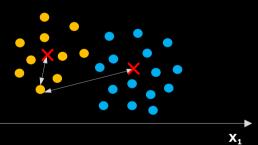
Each object is closer (more similar) to the **PROTOTYPE** that defines the cluster than to the prototype of any other cluster.

For continuous attributes, the prototype of a cluster is often the **CENTROID**, i.e. the average of all the objects in the cluster.

When the centroid is not representative (categorical attributes) then the MEDOID (most representative object of the cluster) is used.

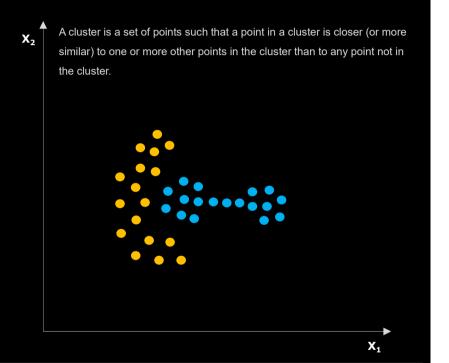
Tends to be globular.

X PROTOTYPE



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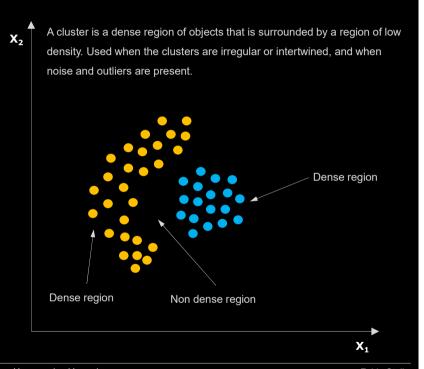
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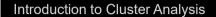
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- Finds clusters that minimize or maximize an objective function.
- Enumerate all possible ways of dividing the points into clusters and evaluate the `goodness' of each potential set of clusters by using the given objective function. (NP Hard).
- Can have global or local objectives.
 - Hierarchical clustering algorithms typically have local objectives
 - Partitional algorithms typically have global objectives
- A variation of the global objective function approach is to fit the data to a parameterized model.
 - Parameters for the model are determined from the data.
 - Mixture models assume that the data is a 'mixture' of a number of statistical distributions.

CHARACTERISTICS OF THE INPUT DATA ARE IMPORTANT

- Type of PROXIMITY or DENSITY MEASURE
 - Central to clustering
 - Depends on data and application
- Data characteristics that affect proximity and/or density are
 - DIMENSIONALITY
 - Sparseness
 - ATTRIBUTE TYPE
 - SPECIAL RELATIONSHIPS IN THE DATA
 - For example, autocorrelation
 - DISTRIBUTION OF THE DATA
- Noise and Outliers
 - Often interfere with the operation of the clustering algorithm
- Clusters of DIFFERING SIZES, DENSITIES, and SHAPES



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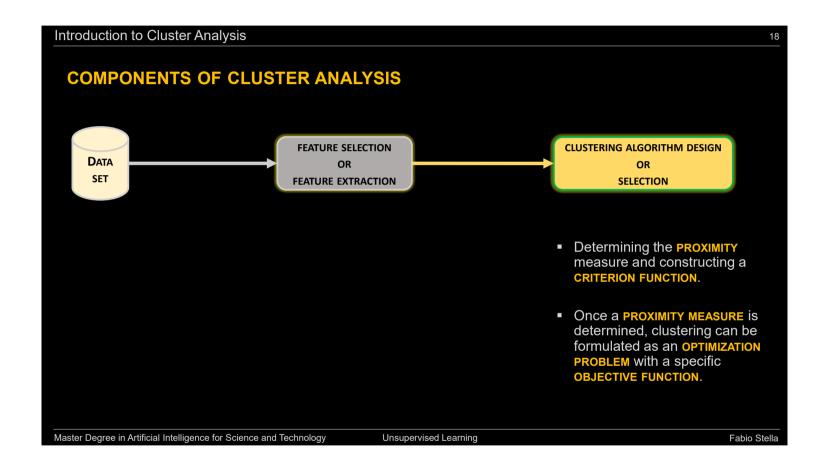
COMPONENTS OF CLUSTER ANALYSIS

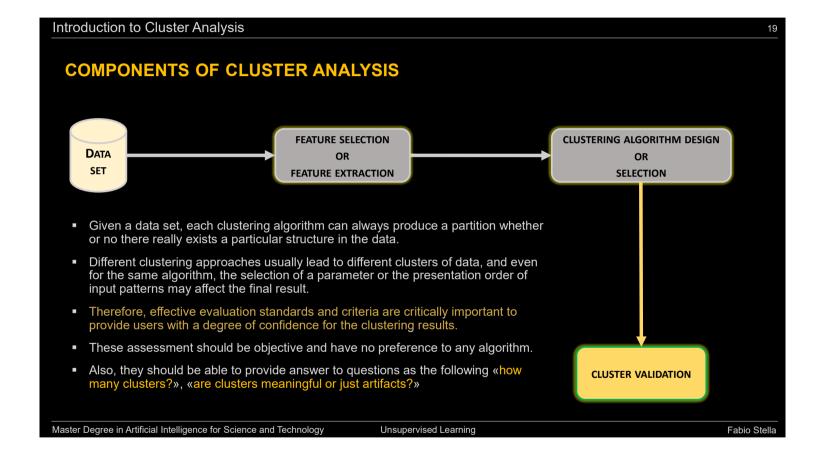


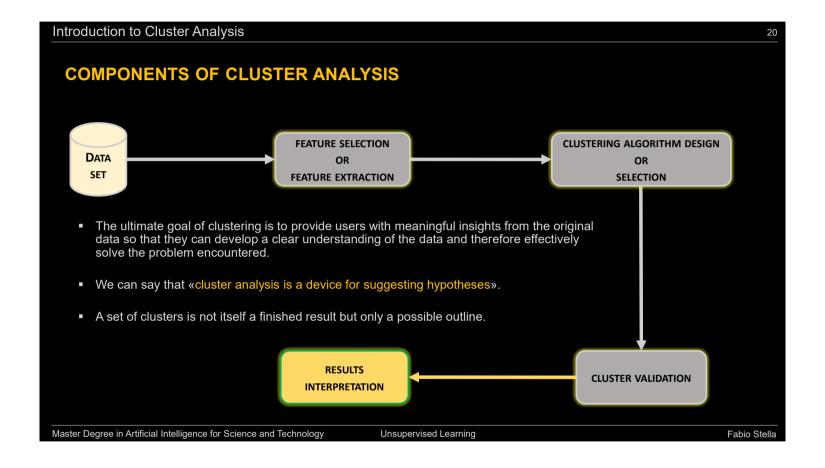
- **FEATURE SELECTION** assures the retention of the meaning of the original attributes.
- **FEATURE EXTRACTION** is capable of producing features that could be of better use in uncovering the data structure. However, it may generate features that are difficult to interpret.
- Ideal features should be of use in distinguishing patterns belonging to different clusters, immune to noise, and easy to obtain and interpret.

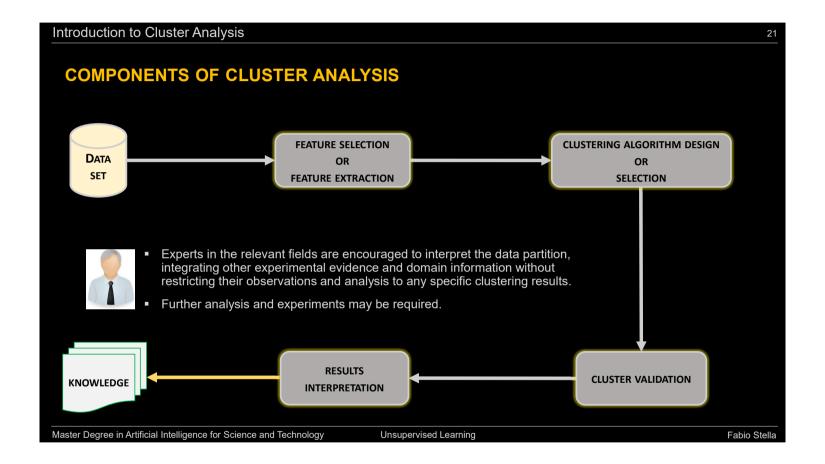
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RECAP

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