Summary Visual Analytics

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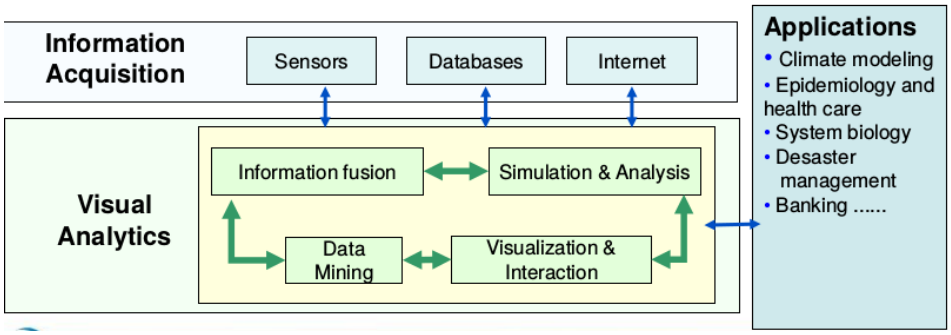
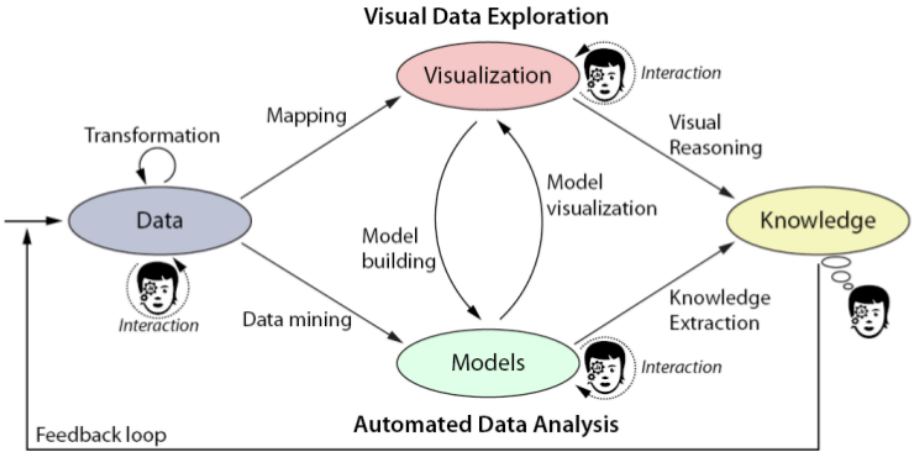
Contents

1 Introduction

- Visual Analytics is the science of analytical reasoning facilitated by interactive visual interfaces.
- An integrated combination of data analytics and interactive visual exploration.
- aims at supporting analysts
- Information is no more the bottleneck. Instead, analytical capabilities are essential.
- insights about, trends, patterns and relations as well as new hypothesis



- The scaleability challenge: information, variables, display, human
- Components
  - Analytical reasoning How to maximise human capacity to perceive, understand, and reason about complex and dynamic data and situations?
  - Visual representations and interaction techniques How to augment cognitive reasoning with perceptual reasoning through visual representations and interaction?
  - Data representations and transformations How to transform data into a representation that is appropriate to the analytical task and effectively conveys the important content?
  - Production, presentation, and dissemination How to convey analytical results in meaningful ways to various audiences? (Also to justify the efforts of visual analytics)



- Filtering operates on data values and includes
  - Data cleansing
  - Analytical computations, e.g. statistics

- reproducible results
- Major applications
  - Business and finance
  - Emergency management
  - Security
  - Sport analytics
  - Astronomy
  - Network analytics
  - Climate and weather research

2 Clustering

Clustering is part of an exploratory data analysis where users have little a priori information and serves to define groups automatically (unsupervised learning).

What is clustering good for?

- Learn the structure of data, e.g. define subgroups for customer segmentation (business analytics)
- A preprocess for selective visualization (show only certain clusters) or for focus-context visualization (show cluster representatives as overview and all instances as detailed view)
- A preprocess for classification, e.g. as input for a decision tree search

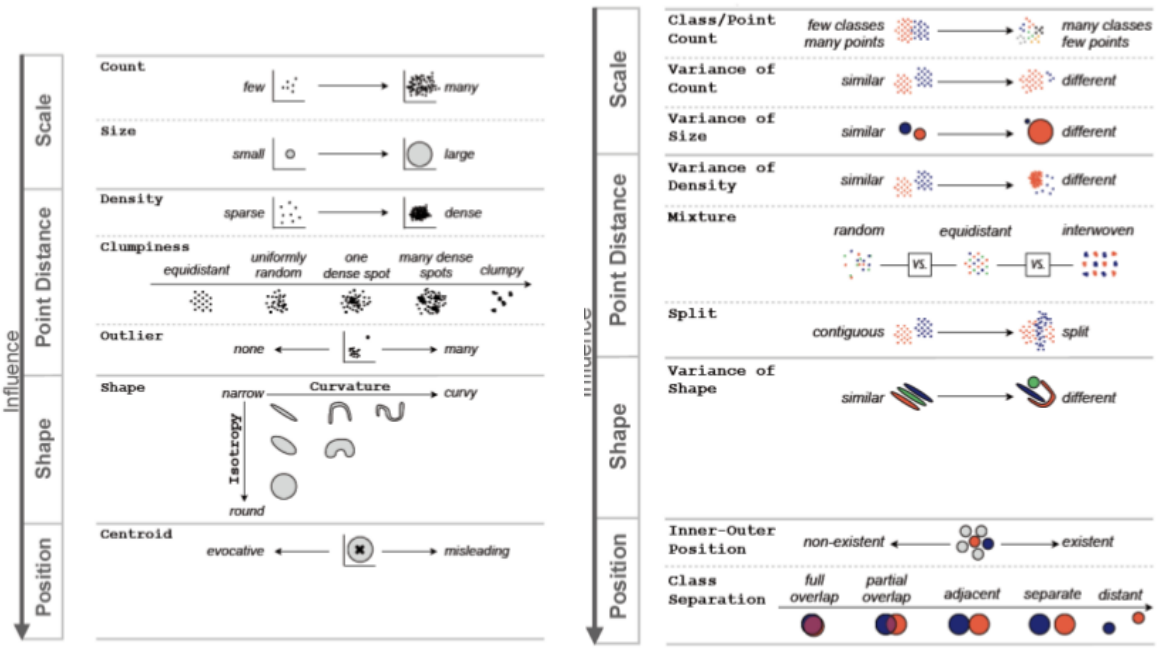
According to the model, clustering is performed

- In a hierarchic or non-hierarchic manner
- In a fuzzy or binary manner (hard)
- In a deterministic or non-deterministic manner
- Using various distance measures

Outliers (not belonging to any cluster) are possible with some approaches.
It is easier to interactively merge clusters (right image) than to separate an erroneously connected cluster.

2.1 Clustering Methods

- K-Means
- Optics
- Density-Based
- Agglomerative Hierarchical
- Clustering Ensembles



→ Fuzzy/Hard clustering

Clustering may be based on

- A distance model
- A density model
- A hierarchy model where clusters are assumed to exist at different levels

k-means:

- Partioning of a dataset in k groups
- follows a centroid model (a cluster is defined by its center)
- random initialization
- convex clusters
- not robust
- k must be known
- not deterministic

Fuzzy c-means

- With fuzzy clustering objects on the boundaries between cluster centers are not forced to fully belong to one of them, but are assigned membership degrees between 0 and 1 indicating partial memberships

Density base clustering

- do not require an a priori number of expected clusters and generate clusters of arbitrary shapes.

- Optics and DB-SCAN
- Basic concept: density-connectivity → two objects are density connected , if there is a chain of dense objects that connect the objects

Hierarchical clustering

- generates a hierarchy of clustering results
- Elements are connected and assigned to a cluster, if their distance is below a threshold
- If the threshold is increased, low level clusters get connected to higher level clusters
- Thus, a hierarchy arises bottom up (agglomerative)
- Essential parameters of hierarchical clustering are:
  - Distance function, e.g. Euclidean, Manhattan, Mahalanobis distance
  - Linkage criterion
  - The method is not suitable for large element numbers

The results of clustering may be improved by with a priori knowledge: Must-link constraints, Cannot-link constraints.
Clustering in general is an unsupervised method; clustering with constraints is supervised

Temporal Clustering

- reflect changes over time
- requires to reflect how clusters emerge, merge, split or disappear

Multiple Clustering
Clustering results depend on

- the algorithm used,
- on the parameters and in case of stochastic algorithms
- on the initialization.

Strategies: Compute a first clustering C_1 and compute a second clustering C_2 that fulfils two properties:
– The clustering quality is high.
– The difference between C_2 and C_1 is high.

2.2 Summary

- Clustering supports explorative data analysis
- A variety of clustering methods exists fitting to different cluster models.
- Multiple clusterings may provide alternative (and valid) perspectives on the data.
  – Visual analysis to understand the result and the influence of parameters
- Clustering is evaluated by means of quality measures (silhouette coefficient, ...) and expert feedback based on appropriate visualizations
  – Cluster quality has many aspects – too many to be sufficiently represented by one scalar quality value

3 Subspace Clustering

3.1 Strategies for subspace search and clustering

Subspace search refers to methods aiming at finding low-dimensional representations of a HD dataset useful for grouping (clusterable subspaces).
Subspace search requires heuristics to prune the search: For n dimensions: 2 n -1 possible axis-aligned subspaces.

Two tasks to be solved:

- Search relevant subspaces and provide a measure of 'interestingness' for ranking – Since this may take long, it is reasonably a non-interactive preprocess
- Cluster data in these subspaces

Related tasks in visual subspace analysis (Tatu, 2009):

- Display the subspaces (involved dimensions)
- Display similarity between subspaces (w.r.t. involved dimensions and topology)
- Display the clustering results in these subspaces
- Show relations between subspace clusters

3.2 Methods for subspace search and clustering

Subspace search algorithms aim at finding features that correlate locally.

Different methods:

- Subspace search algorithms only return subspaces (where any global clustering may be applied)
- Subspace clustering techniques combine subspace search and clustering

Assumptions and Heuristics

- Since the number of possible arbitrarily oriented sub- spaces is infinite, assumptions and heuristics are used.
- Most algorithms search only for axis-aligned subspaces
- Some algorithms (again) expect a certain number of clusters and optimize subspace search accordingly
- Some algorithms are biased towards low dimensional clusters

Preprocessing

- Treatment of incomplete datasets
- If categorical variables are not treated separately, they are transformed to numbers

- Normalization

Subspace search without clustering 'Ranking Interesting Subspaces' (RIS) Subspace Search: Surfing - returns relevant subspaces ranked by 'interestingness' (Compute the differences of the k nn-distance to the mean)
→ prefer subspace with high variance and avoid high redundancy

Paradigms:

- Cell-based (CLIQUE)
- Density-based (SUBCLUE)
- Clustering-based - steered by global parameters, e.g. number of clusters (Proculus)

3.3 Visualization of Clustering Results

A multitude of information needs to be conveyed:

- the overlapping dimensions of subspaces,
- the overlapping subspaces,
- the membership of objects to subspaces.

Major techniques:

- Parallel coordinates
- Scatterplot visualizations
- Heatmaps
- Linked views (overview and detailed visualizations)
- Matrix-based visualization

General workflow:
HD Data ⇒ Interesting Subspaces ⇒ Redundancy Reduced View ⇒ Cluster Colored View

3.4 Evaluation

Interisting are small clusters with high entropy.

4 Clustering Validation

4.1 Validation of Clustering Results

How does she know whether the results are good? Cluster purity measures are used

- Silhoutte coefficient

  - Relation of distance to own cluster and to other clusters
  - is in between -1 and 1
- Centroid measure
- Grid-based measures

4.2 Introduction

4.3 Visualization of Clustering Results

5 BiClusters

6 Scatter plots

7 Dimension Reduction

8 Association Rule Mining

9 Decision Trees

10 Regression Based Analysis

11 Temporal Event Sequences

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