Comparative Visualization: Interactive Designs and Algorithms Depending on Data and Tasks

Tatiana von Landesberger[1], Kathrin Ballweg[1], Hans-Jörg Schulz[2], Natalie Kerracher[3], Margit Pohl[4]
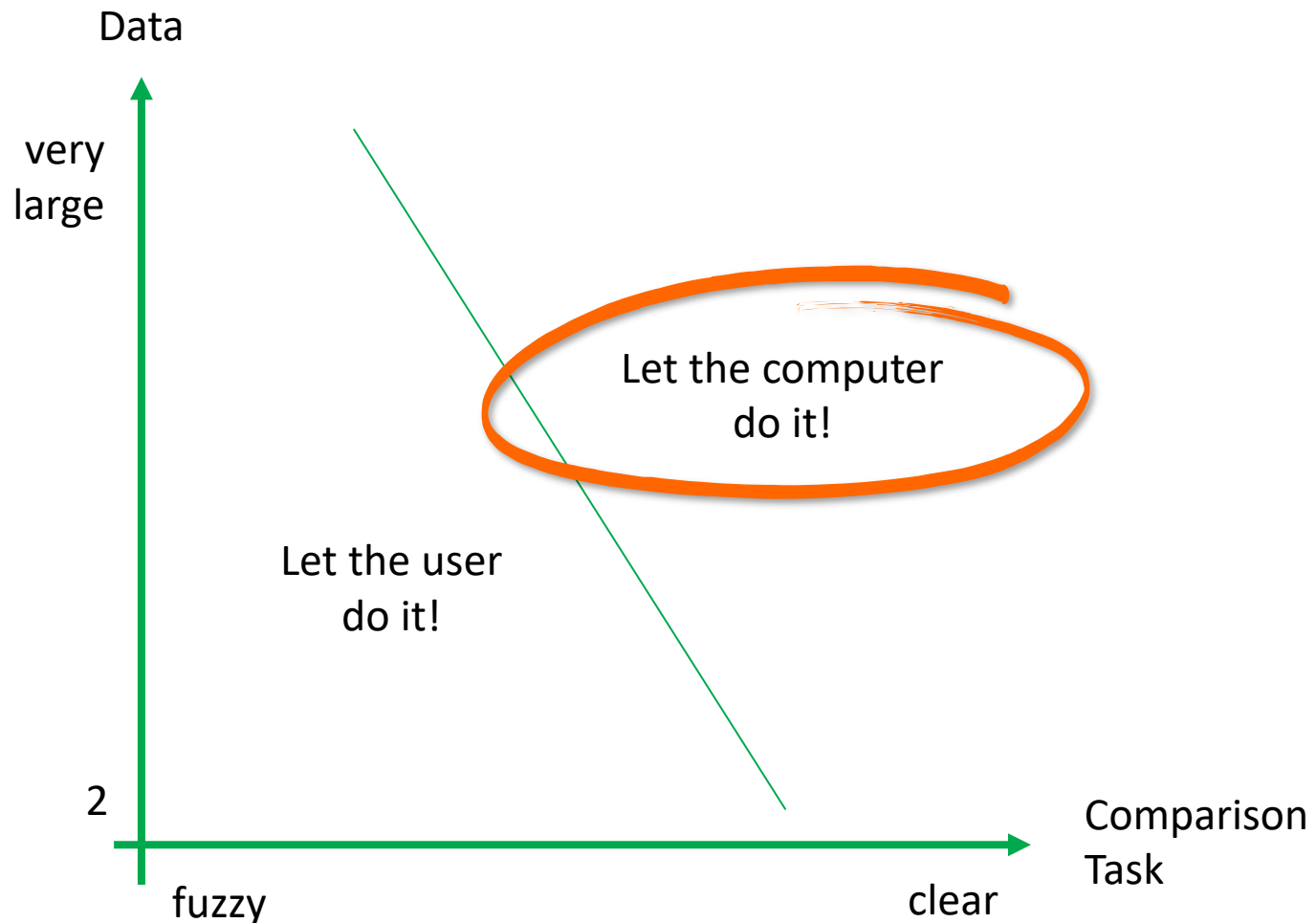
VIS Tutorial 2018

1. TU Darmstadt, Darmstadt, Germany
2. Aarhus University, Denmark
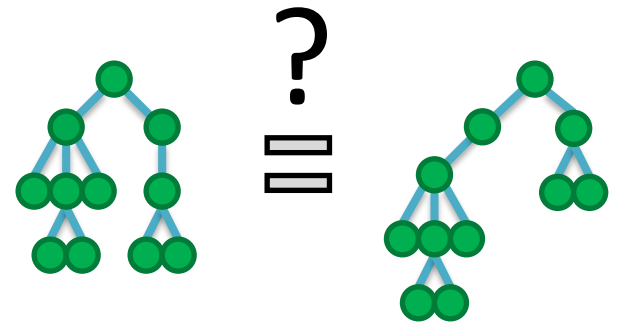3. Edinburgh Napier University, UK
4. TU Wien, Austria

PART II:
ALGORITHMIC COMPARISON

Who performs the comparison?

Data

very
large

Let the computer
do it!

Let the user
do it!

2

fuzzy

clear

Comparison
Task

1-to-1 Comparison

MATCHING

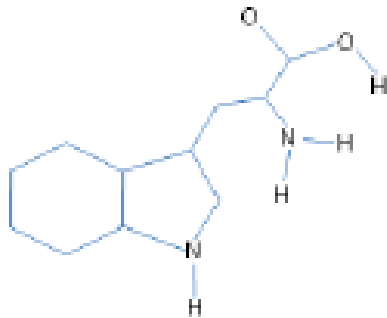# Definition

Matching:

Determination if a data object is related to another in quality, structure, or amount.

Levels of Relational Strictness:
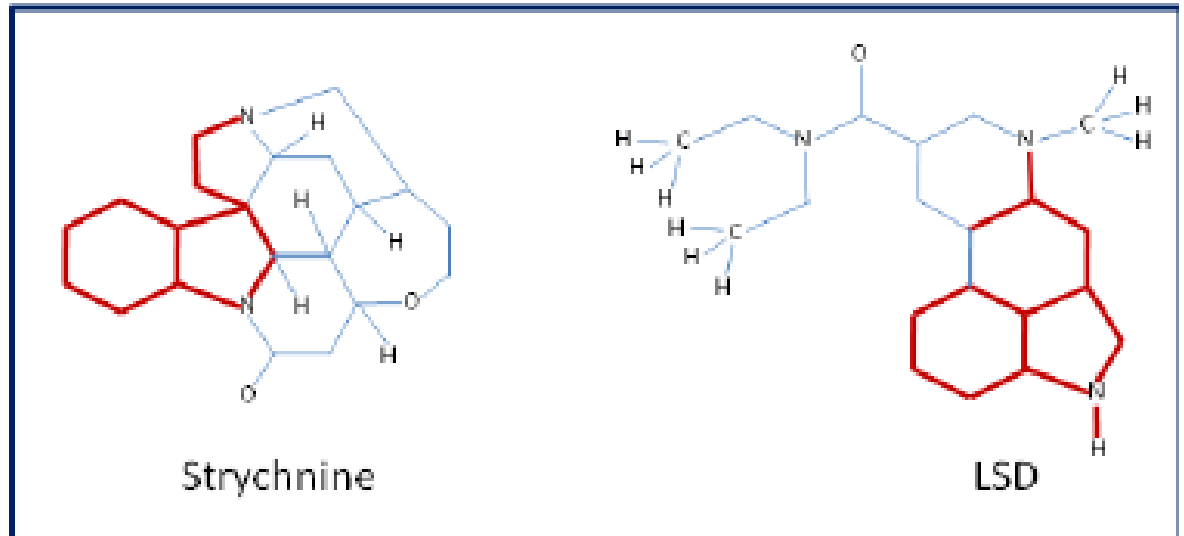
- Identity

- Equivalency

- Similarity

Exact vs. Inexact Matching

query

results

L-tryptophan

Strychnine

LSD

image taken from [Mongiovi et al. 2010]

Principal Pragmatic Approach

Given a Matching Algorithm, e.g.

- String Matching (RegEx, BLAST,…)

- Time Series Matching (DTW, LCSS, DISSIM,…)

- Graph Matching (TALE, SIGMA,…)

Transform data to string/pseudo-time series/ graph and process with given algorithm.

BLAST: [Altschul et al. 1990]   DTW: [Berndt & Clifford 1994]   LCSS: [Vlachos et al. 2002]
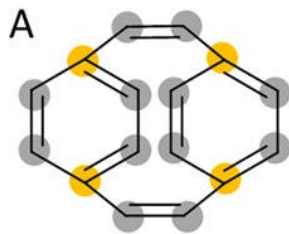
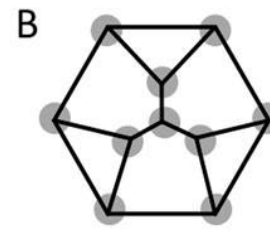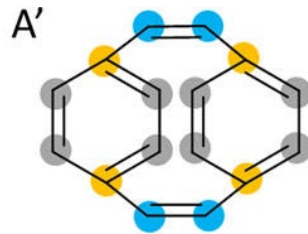DISSIM: [Frentzos et al. 2007]   TALE: [Tian & Patel 2008]   SIGMA: [Mongiovi et al. 2010]
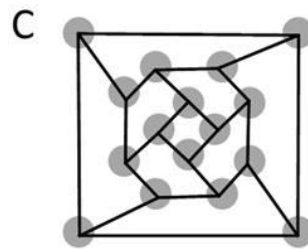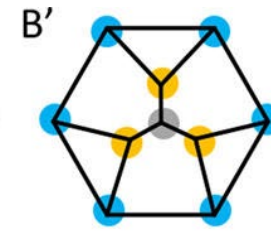
Graph -> String Conversion

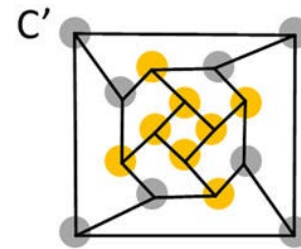## Canonical Labeling, Canonization

C1=CC2=CC=C1\C=C/C1=CC=C(C=C1)\C=C/2
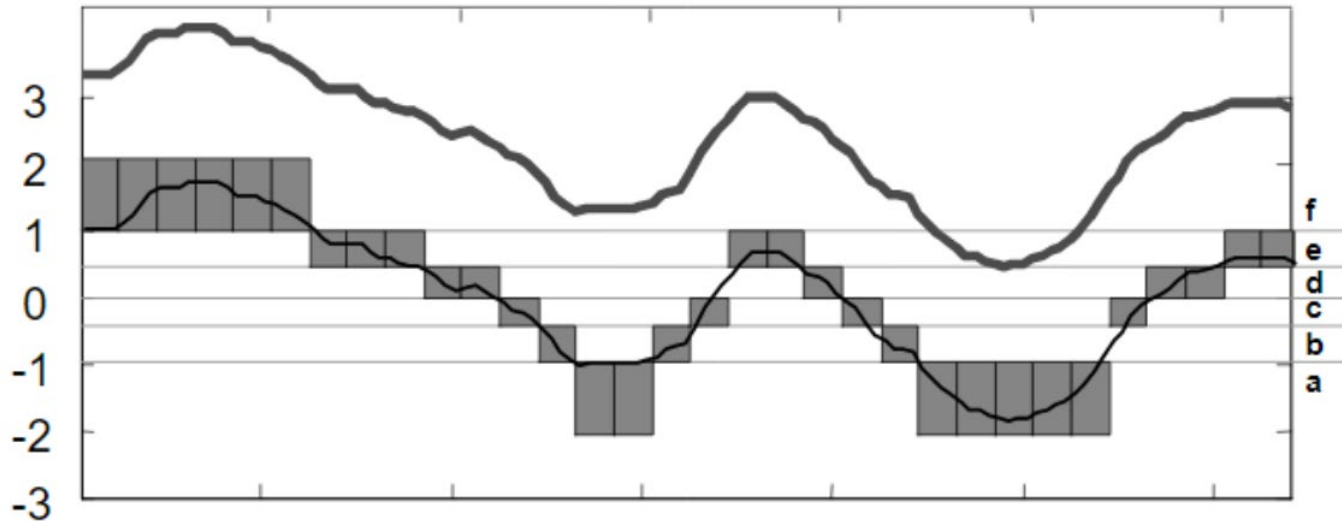
C12C3C4C5C6C1C6C(C23)C45

C12C3C4C1C1C5C6C7C8C6C1C4C8C3C7C25

Time Series -> String Conversion

Symbolic Aggregate Approximation (SAX)

fffffeeeddcbaabceedcbaaaaacddee

Image -> Pseudo-Time Series

Column- / Row-wise Aggregates
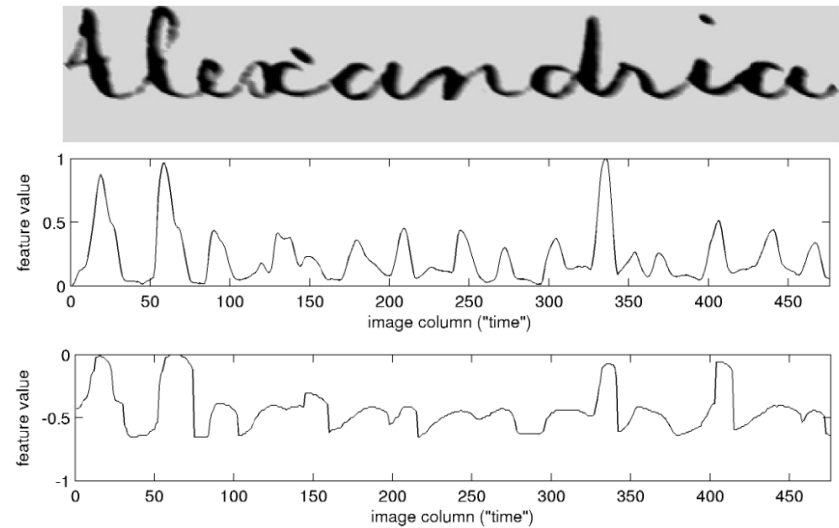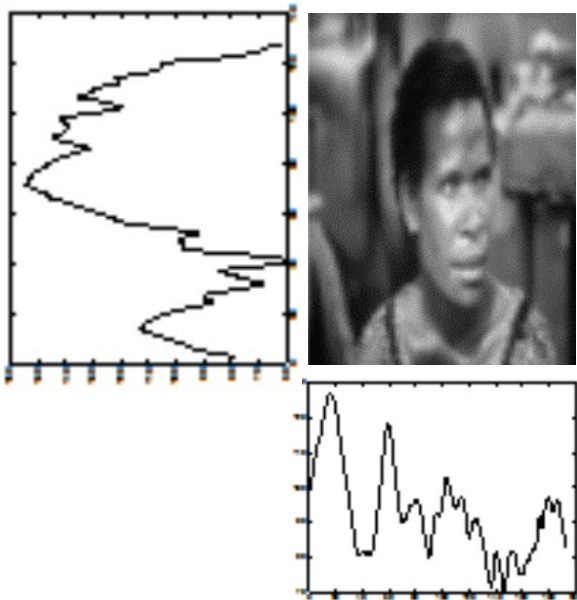
Shape -> Pseudo-Time Series

Boundary Extraction w.r.t. Centroid

Texas
Duran
Arrowhead
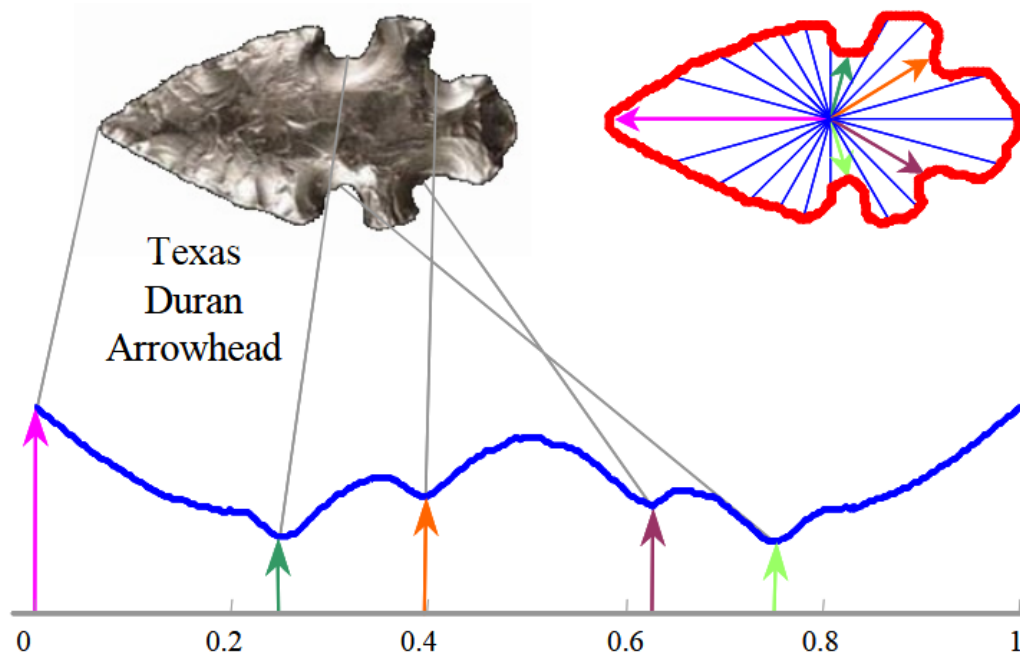
Image -> Graph Conversion
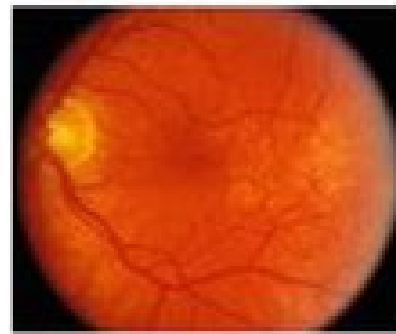
[Deng et al. 2010]
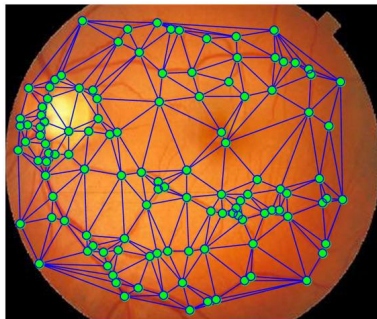
Delauney
Triangulation
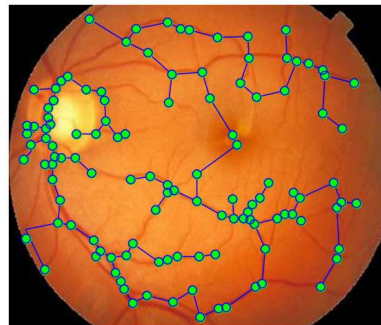
Minimum
Spanning Tree
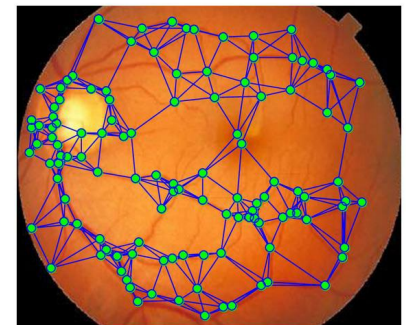
k-nearest
Neighbors

On Distance Metrics
Example: Euclidian Distance
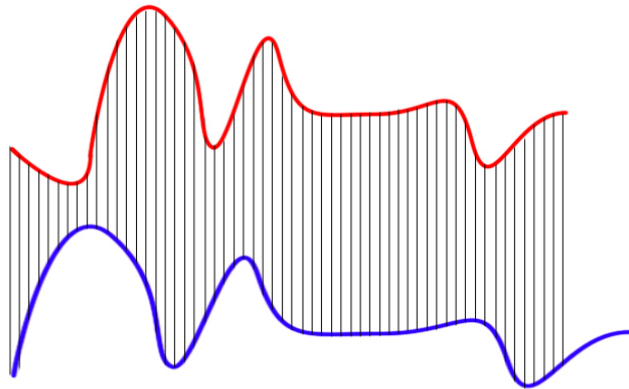
Euclidean Matching
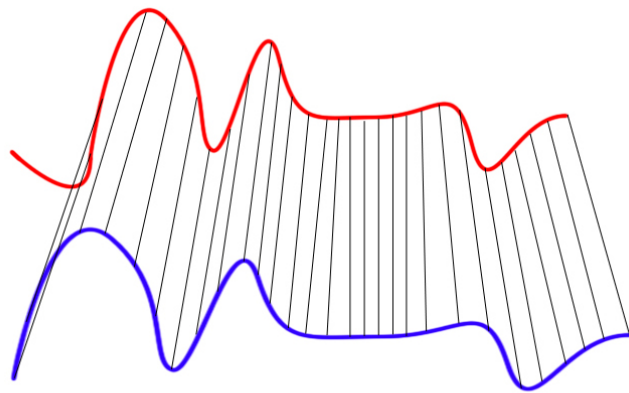
Dynamic Time Warping Matching

image taken from Wikipedia

Further Reading:
Ding et al. 2008 – "Querying and mining of time series data: experimental comparison of representations and distance measures"

Aghabozorgi et al. 2015 – "Time-series clustering – A decade review"

Bagnall et al. 2017 – "The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances"

On Distance Metrics

Example: Edit Distance
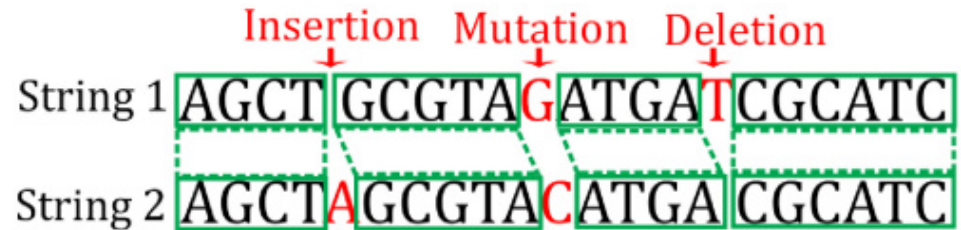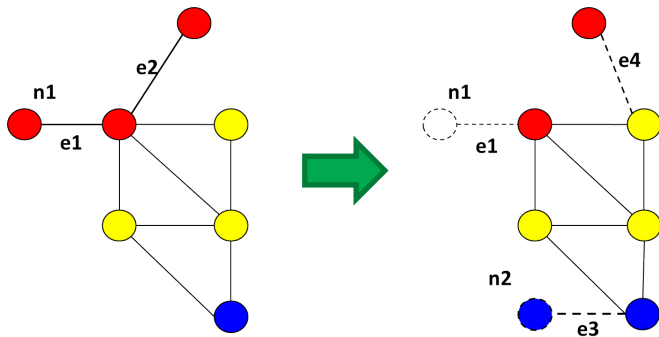
image source: http://gedevo.mpi-inf.mpg.de

image taken from [Maleki et al. 2017]

Further Reading:
Emmert-Streib et al. 2016 – "Fifty years of graph matching, network alignment and network comparison"

Further Reading:
Yu et al. 2016 – "String similarity search and join: a survey"

osa = Optimal String Alignment distance
lv = Levenshtein distance
dl = Full Damerau-Levenshtein distance
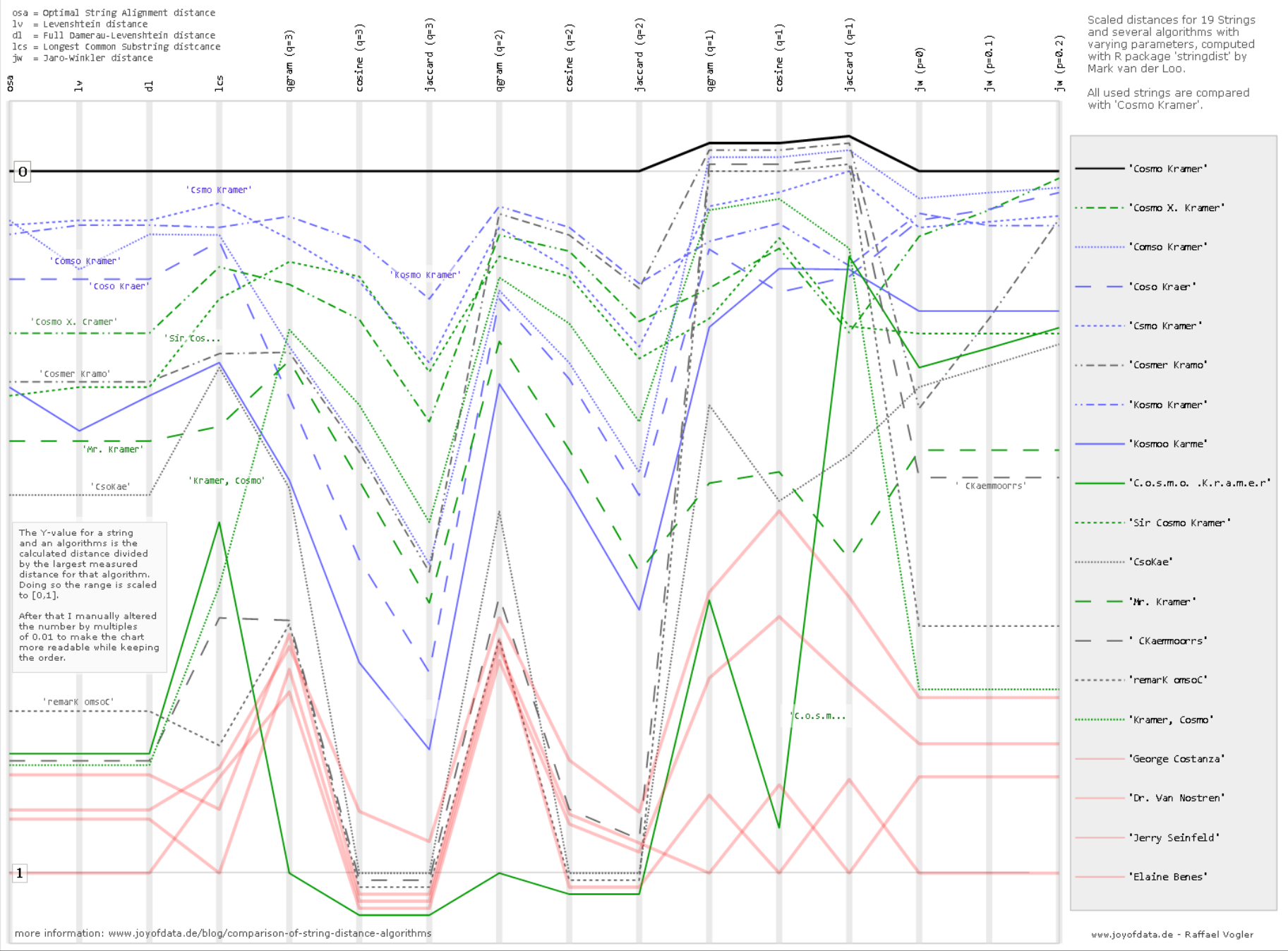lcs = Longest Common Substring distcance
jw = Jaro-Winkler distance

Scaled distances for 19 Strings and several algorithms with varying parameters, computed with R package 'stringdist' by Mark van der Loo.

All used strings are compared with 'Cosmo Kramer'.

The Y-value for a string and an algorithms is the calculated distance divided by the largest measured distance for that algorithm. Doing so the range is scaled to [0,1].

After that I manually altered the number by multiples of 0.01 to make the chart more readable while keeping the order.

Legend:
- 'Cosmo Kramer'
- 'Cosmo X. Kramer'
- 'Comso Kramer'
- 'Coso Kraer'
- 'Csmo Kramer'
- 'Cosmer Kramo'
- 'Kosmo Kramer'
- 'Kosmoo Karme'
- 'C.o.s.m.o. .K.r.a.m.e.r'
- 'Sir Cosmo Kramer'
- 'CsoKae'
- 'Mr. Kramer'
- ' CKaenmoorrs'
- 'remarK omsoC'
- 'Kramer, Cosmo'
- 'George Costanza'
- 'Dr. Van Nostren'
- 'Jerry Seinfeld'
- 'Elaine Benes'

more information: www.joyofdata.de/blog/comparison-of-string-distance-algorithms

www.joyofdata.de - Raffael Vogler

https://www.joyofdata.de/blog/comparison-of-string-distance-algorithms/

A Survey of Measures and Methods for Matching Geospatial Vector Datasets

EMERSON M. A. XAVIER, Brazilian Army Geographic Service
FRANCISCO J. ARIZA-LÓPEZ and MANUEL A. UREÑA-CÁMARA, Universidad de Jaén

The field of Geographical Information Systems (GIS) has experienced a rapid and ongoing growth of available sources for geospatial data. This growth has demanded more data integration in order to explore the benefits of these data further. However, many data providers implies many points of view for the same phenomena: geospatial features. We need sophisticated procedures aiming to find the correspondences between two vector datasets, a process named *geospatial data matching*. Similarity measures are key-tools for matching methods, so it is interesting to review these concepts together. This article provides a survey of 30 years of research into the measures and methods facing geospatial data matching. Our survey presents related work and develops a common taxonomy that permits us to compare measures and methods. This study points out relevant issues that may help to discover the potential of these approaches in many applications, like data integration, conflation, quality evaluation, and data management.

SURVEY PAPER

Approximate data instance matching: a survey

Carina Friedrich Dorneles · **Rodrigo Gonçalves** ·
Ronaldo dos Santos Mello

Abstract   Approximate data matching is a central problem in several data management processes, such as data integration, data cleaning, approximate queries, similarity search and so on. An approximate matching process aims at defining whether two data represent the same real-world object. For atomic values (strings, dates, etc), similarity functions have been defined for several value domains (person names, addresses, and so on). For matching aggregated values, such as relational tuples and XML trees, approaches alternate from the definition of simple functions that combine values of similarity of record attributes to sophisticated techniques based on machine learning, for example. For complex data comparison, including structured and semistructured documents, existing approaches use both structure and data for the comparison, by either considering or not considering data semantics. This survey presents terminology and concepts that base approximated data matching, as well as discusses related work on the use of similarity functions in such a subject.
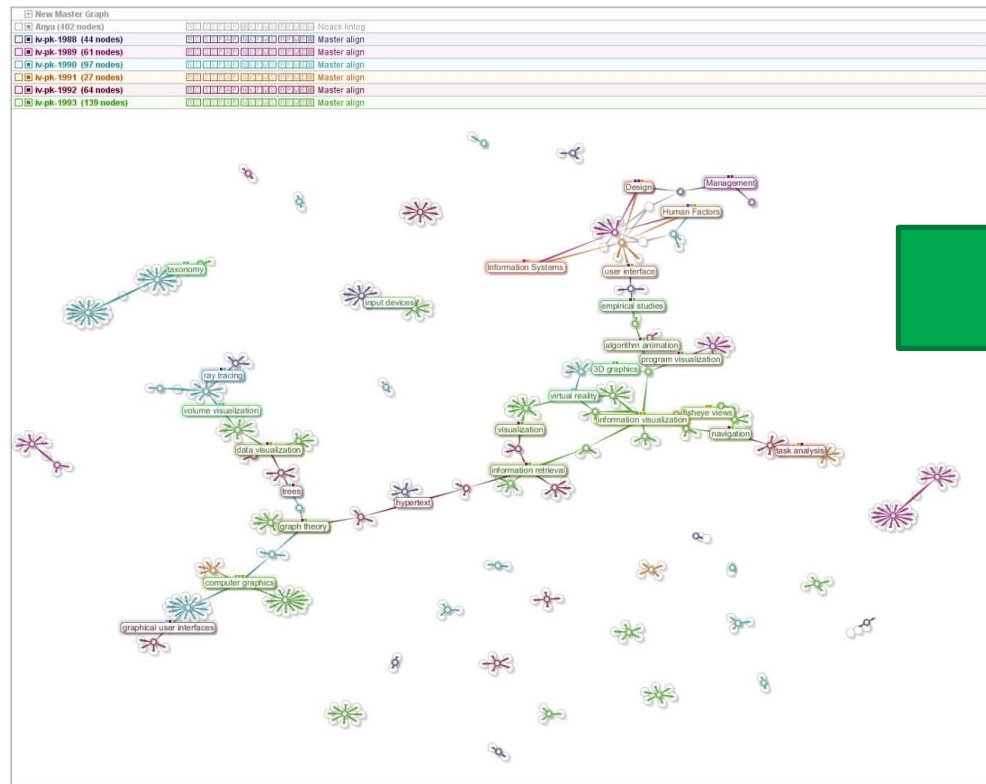
Example: Interactive Entity Resolution with D-Dupe
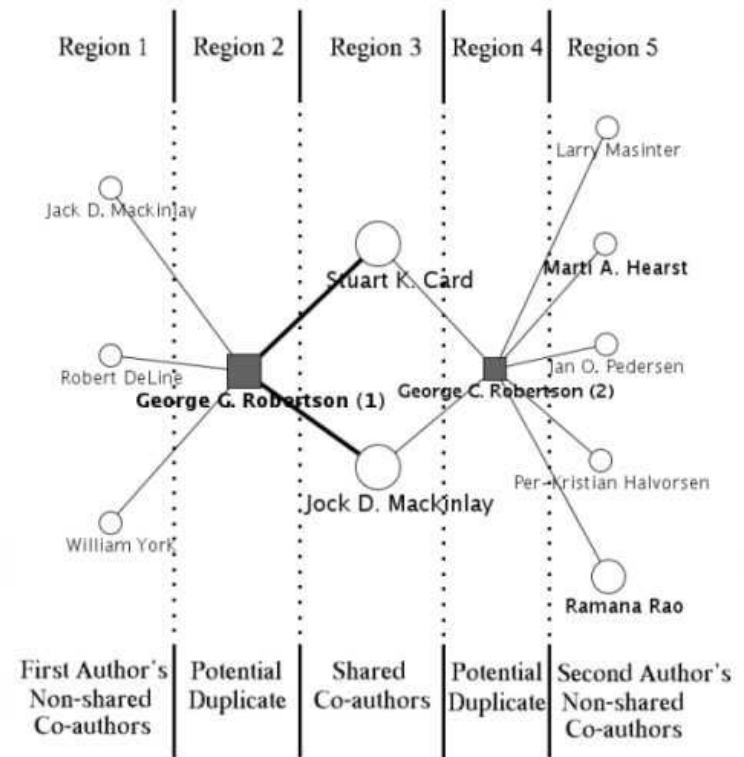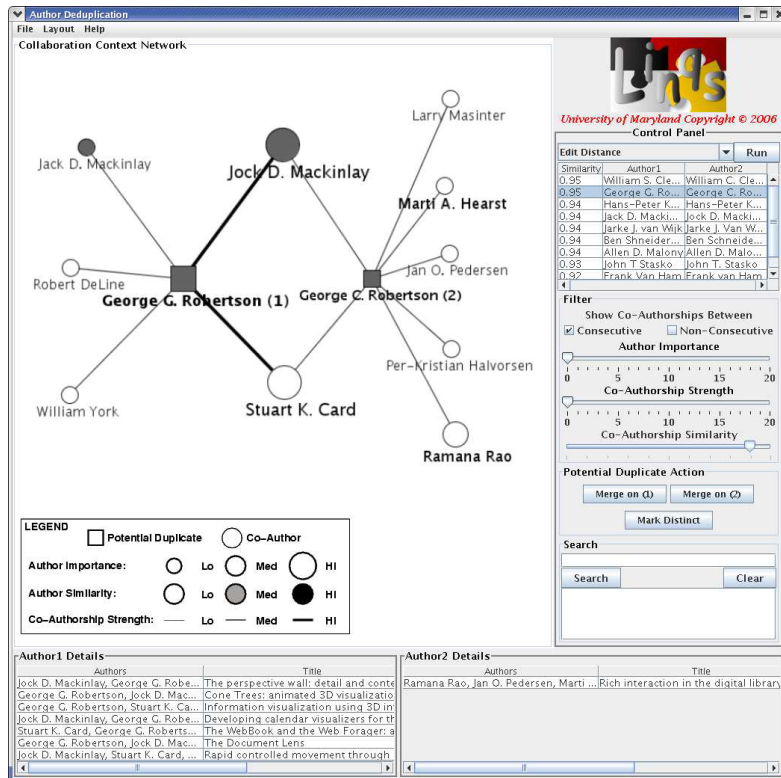
[Bilgic et al. 2006]

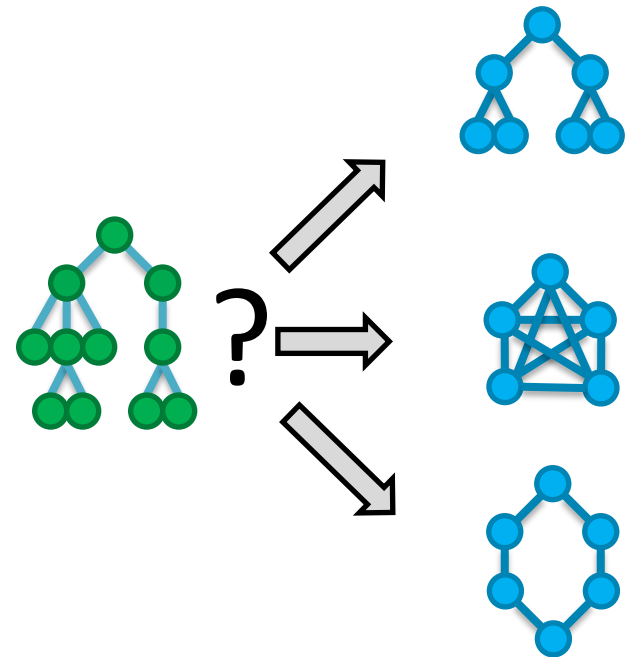# Example: Multi-Layer Comparison for Multiple Graphs
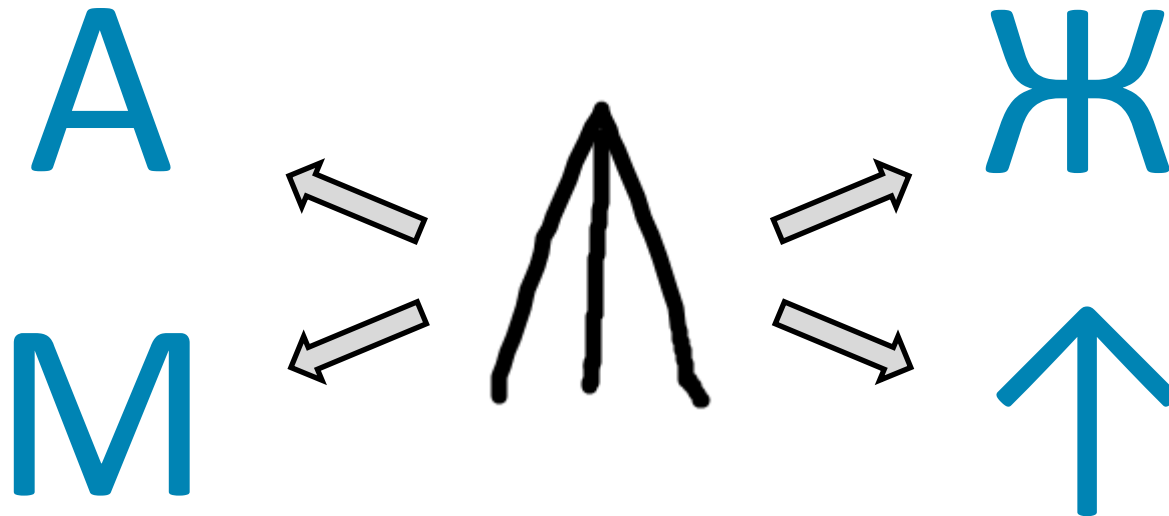

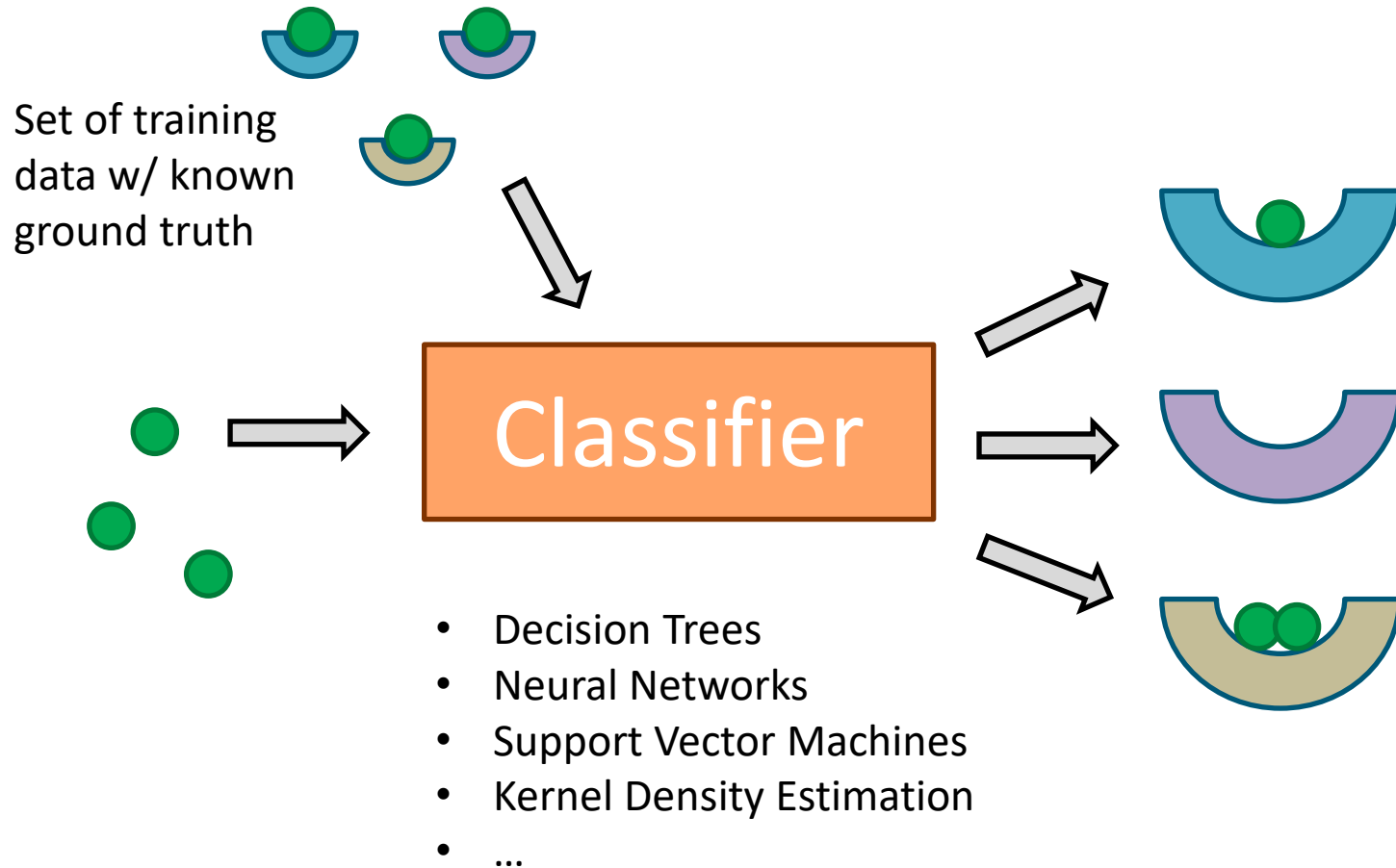[Hascoët & Dragicevic 2012]

1-to-many Comparison

CLASSIFICATION

Definition

Classification:

Assignment of a data object to a particular group according to its features, structure, or origin.
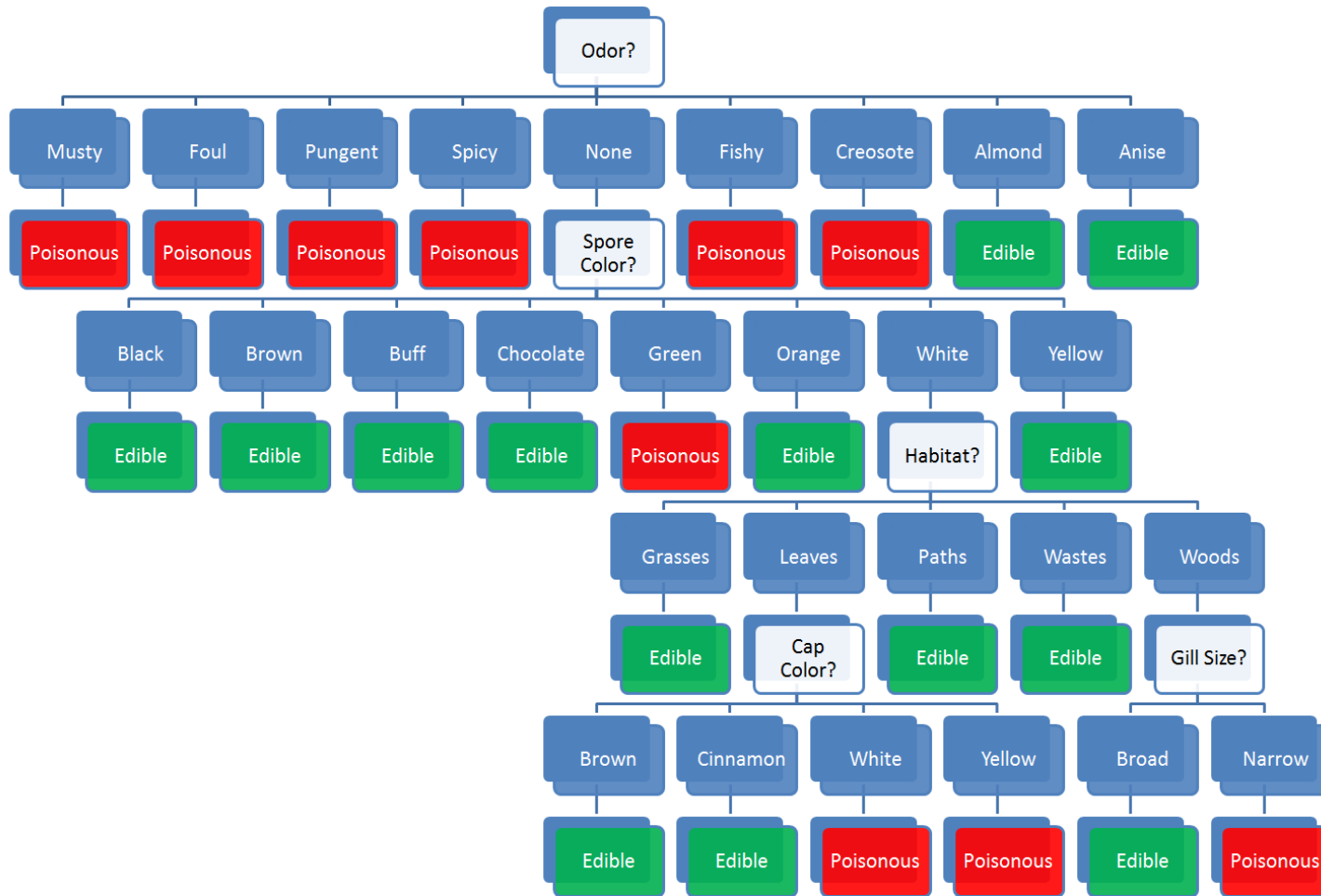
Classification as Supervised Learning

Set of training
data w/ known
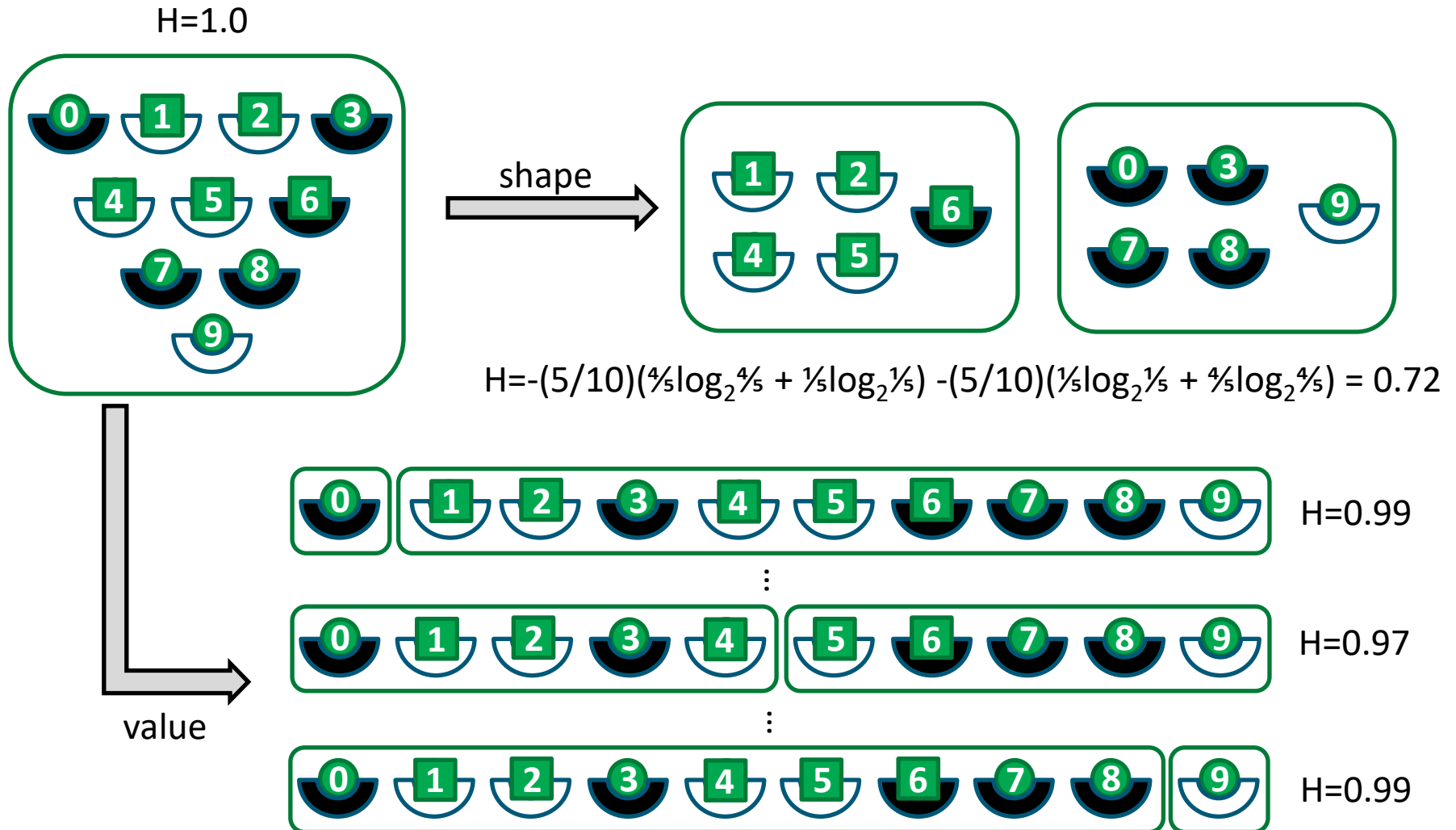ground truth

Classifier

- Decision Trees
- Neural Networks
- Support Vector Machines
- Kernel Density Estimation
- …

Decision Trees

image taken from https://gieseanw.wordpress.com/2012/03/03/decision-tree-learning/

How to Build a Decision Tree?

Split(Dataset):

For all data attributes A in data:

   Compute entropy gain when splitting by A

Decision Tree Example

H=1.0

shape

$H=-(5/10)(\tfrac{4}{5}\log_2\tfrac{4}{5} + \tfrac{1}{5}\log_2\tfrac{1}{5}) -(5/10)(\tfrac{1}{5}\log_2\tfrac{1}{5} + \tfrac{4}{5}\log_2\tfrac{4}{5}) = 0.72$

value

H=0.99

⋮

H=0.97

⋮

H=0.99

How to Build a Decision Tree?

Split(Dataset):

For all data attributes A in data:

     Compute entropy gain when splitting by A

Subdivide Dataset by A w/ highest gain

For all generated data subsets:

     If entropy(Data subset)>0

         Split(Data subset)

Decision Tree Example
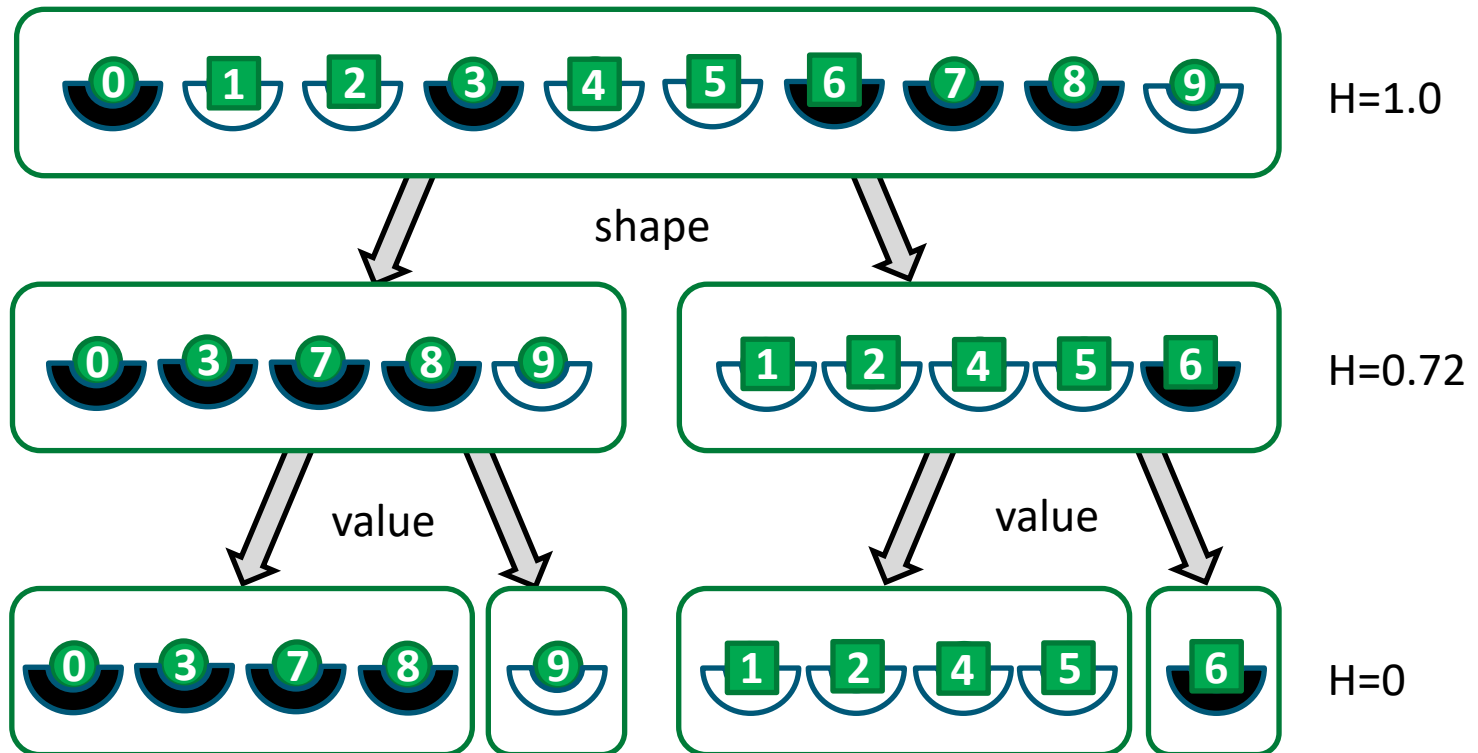
How to Build a Decision Tree?

Algorithms: ID3, C4.5, C5.0 [Quinlan 1993]

Downsides:

- No optimality guarantee (greedy approach)
  --> backtracking to escape local minima

- Possible overfitting (large trees)
  --> pruning of subtrees, or random forests

- Hard splits on continuous data
  --> soft splits that evaluate both branches

Example: Interactive Decision Tree Construction with BaobabView
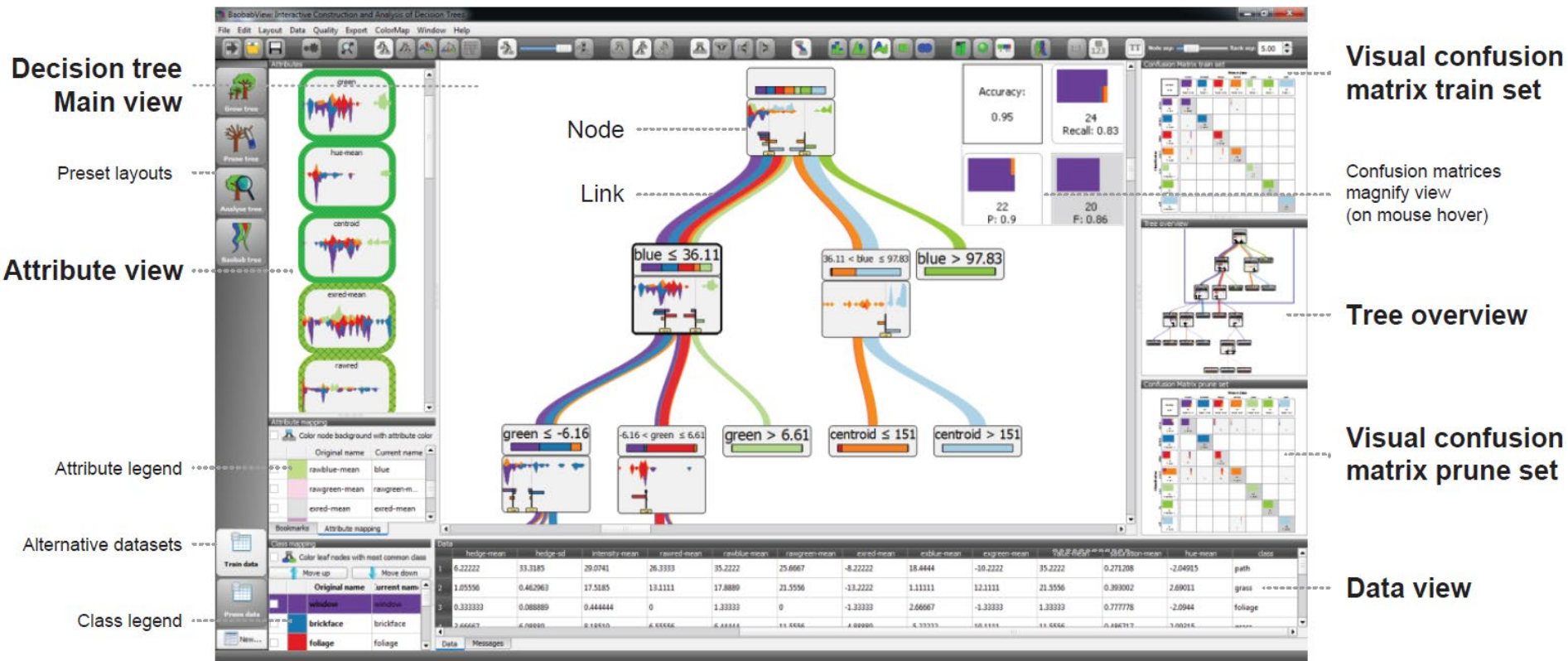
[v.d.Elzen & v.Wijk 2011]

Example: Interactive Decision Tree Construction with BaobabView
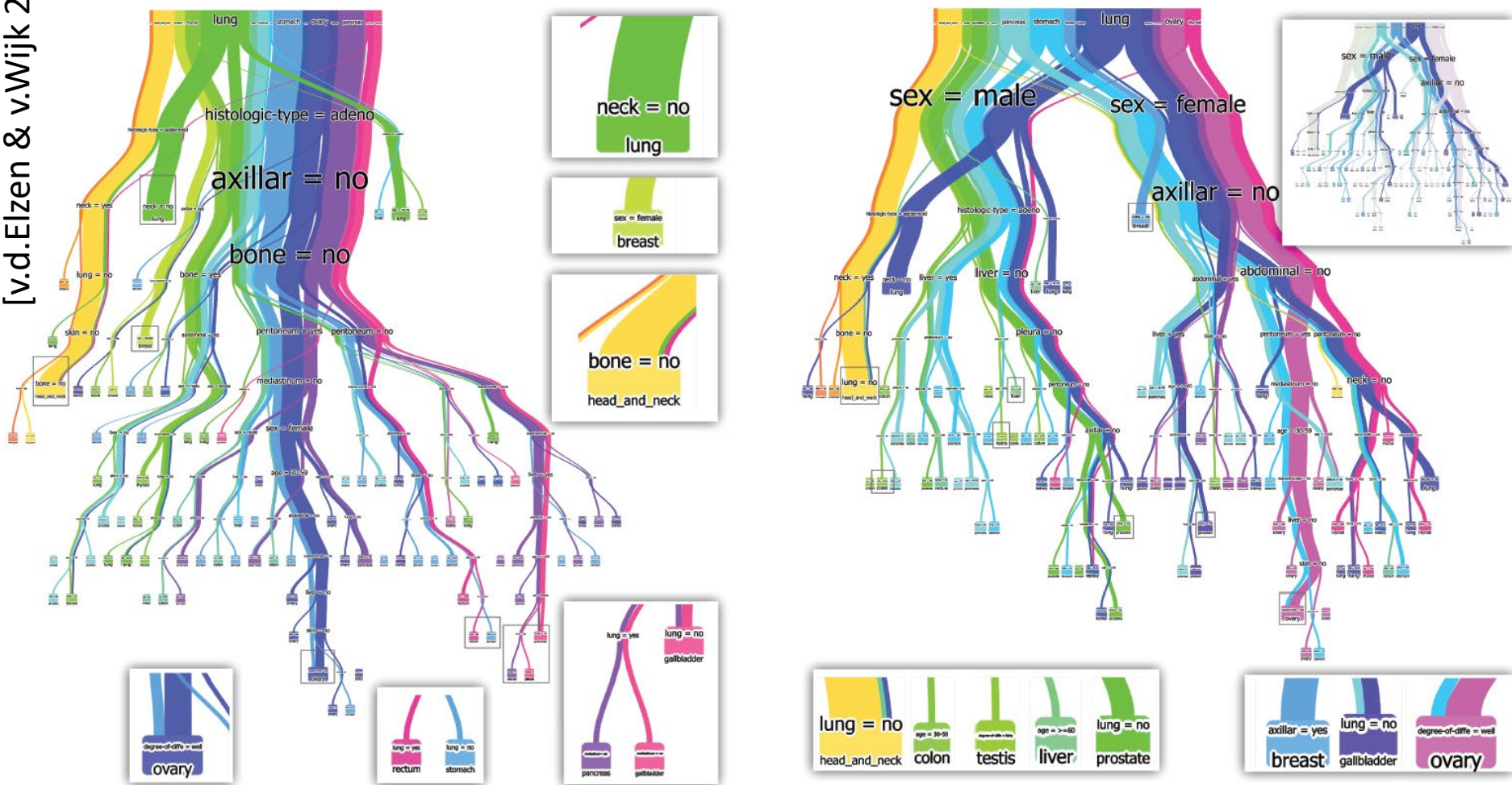
[v.d.Elzen & v.Wijk 2011]

Example: Analysis of Probabilistic Classifiers with Confusion Wheels
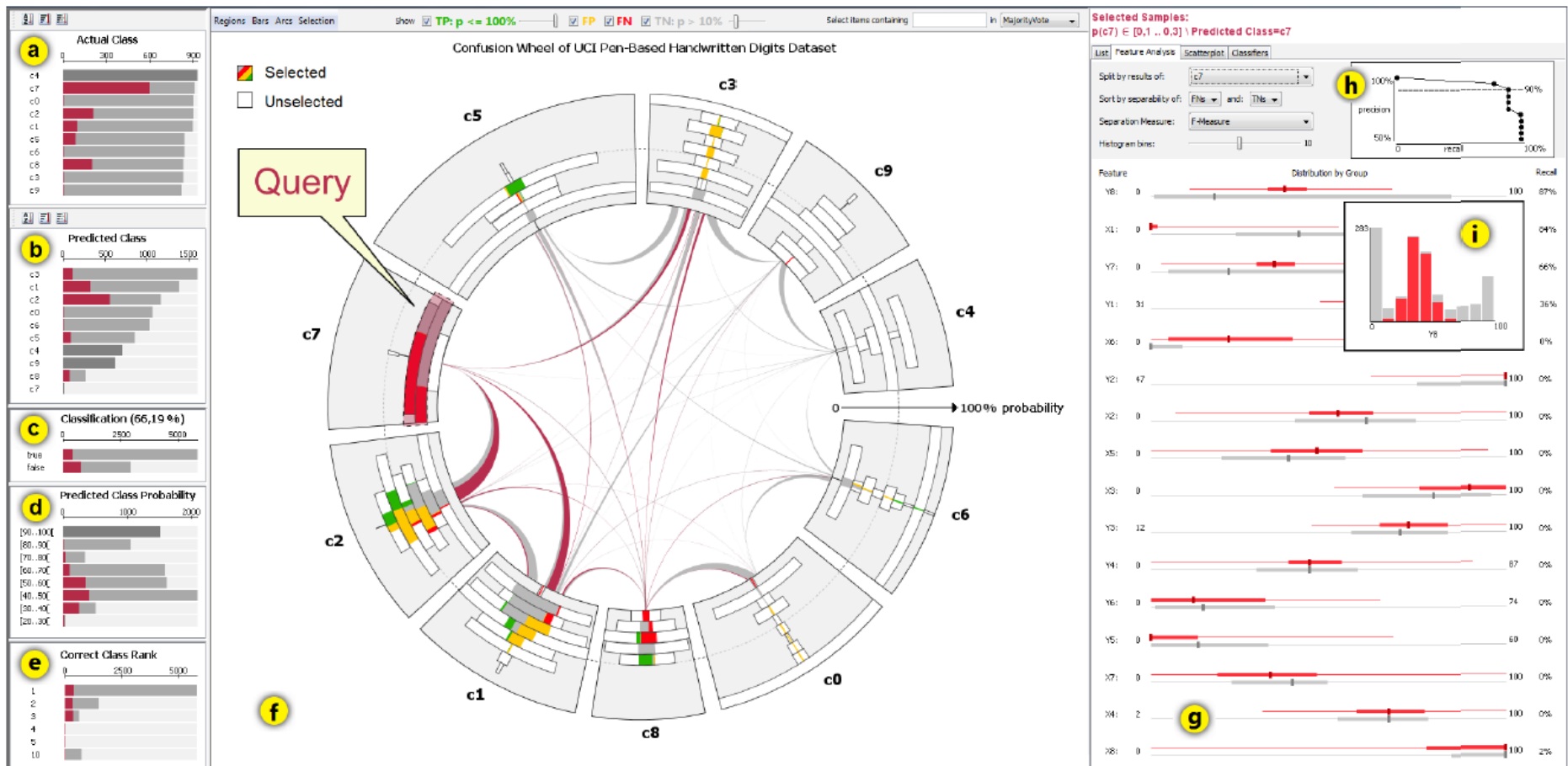
[Alsallakh et al. 2014]

Example: Analysis of Probabilistic Classifiers with Confusion Wheels
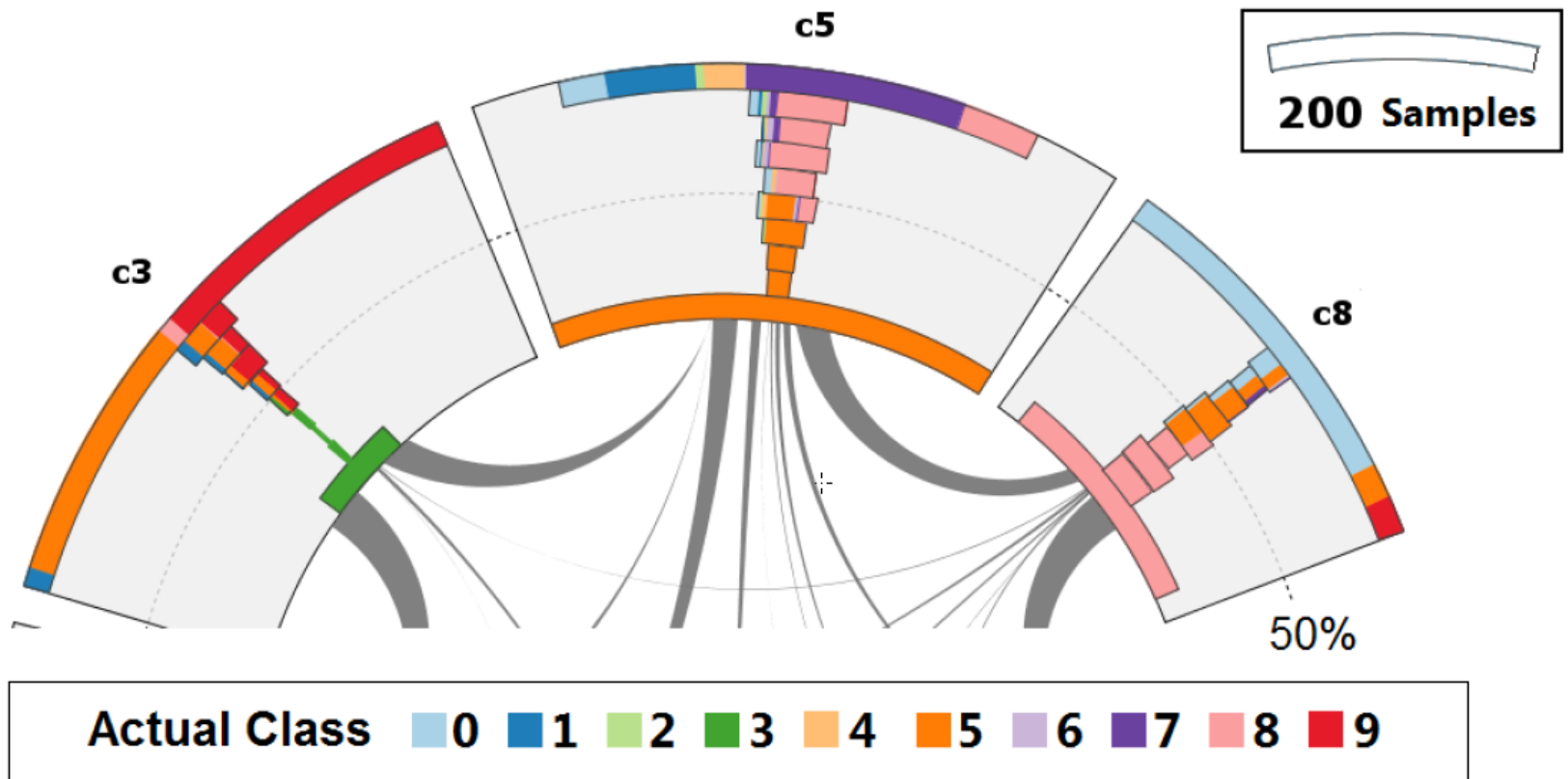
[Alsallakh et al. 2014]

many-to-many Comparison

CLUSTERING
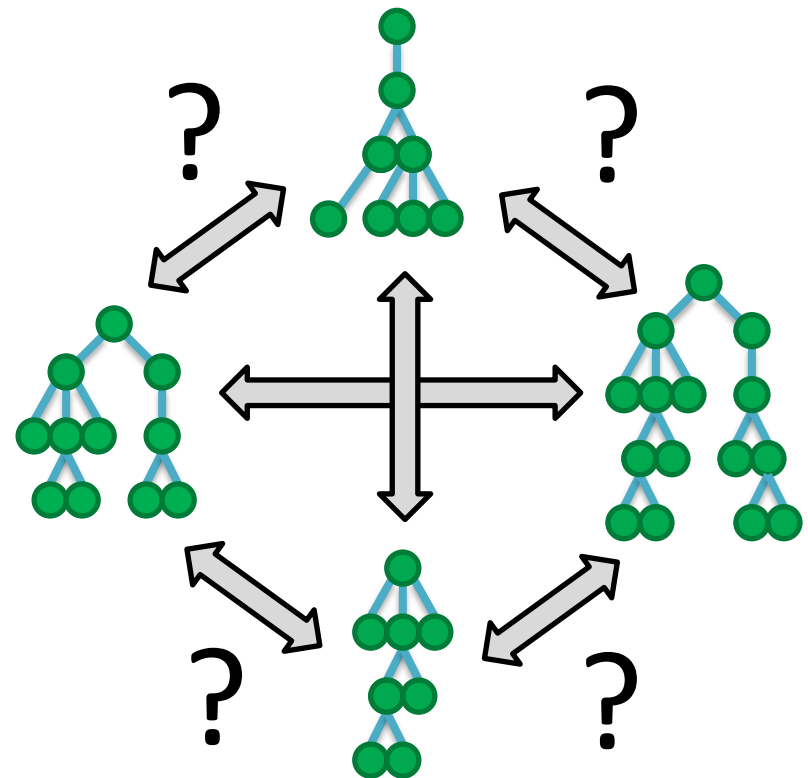
Definition

Clustering: Gathering a number of related data objects into groups, so that data objects within one group are more related to each other than to data objects from other groups.

- **given:** (dis-)similarity measure/matrix
  - n-dimensional, numerical data: Euclidean Distance
  - network data: Graph-theoretic Distance
  - strings of text: Edit Distance

- **sought:** grouping of the data w.r.t. that measure

Clustering as Unsupervised Learning

Similarity metric / matrix

Clusterer

- k-means
- DBSCAN
- Hierarchical Clustering
- Spectral Clustering
- …
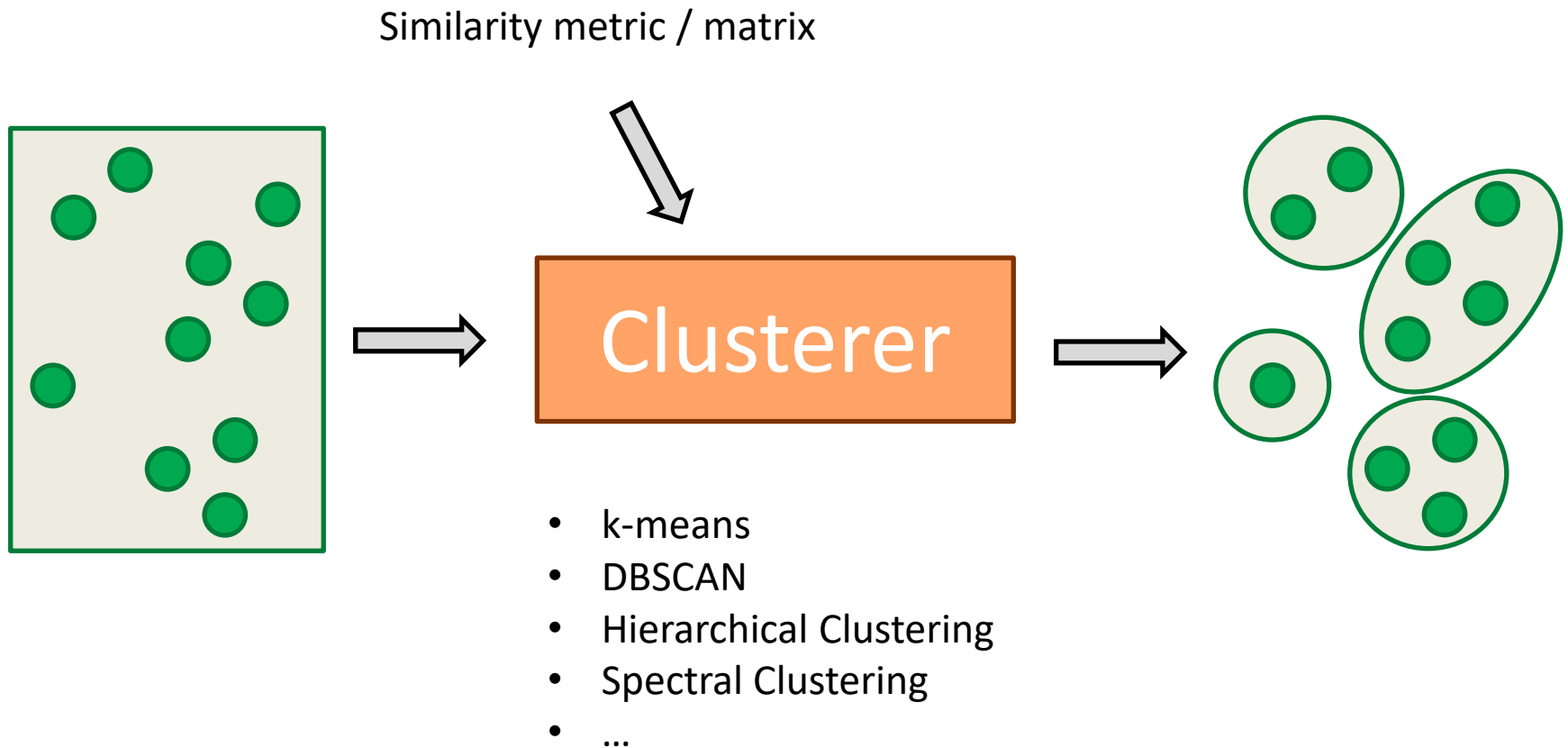
What makes a "good" clustering?

- **Compact:** elements in cluster are similar

- **Separated:** clusters are different

- **Balanced:** cluster membership is equally probable

- **Parsimonious:** much fewer clusters than data objects

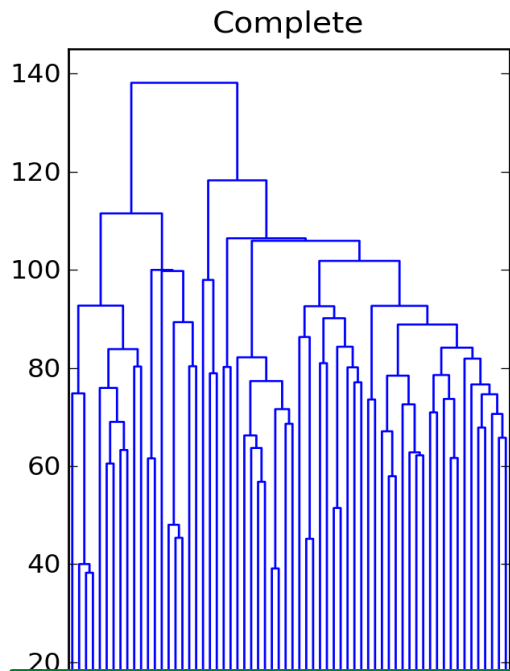Source: Cosma Shalizi (2009)

k-Means Clustering
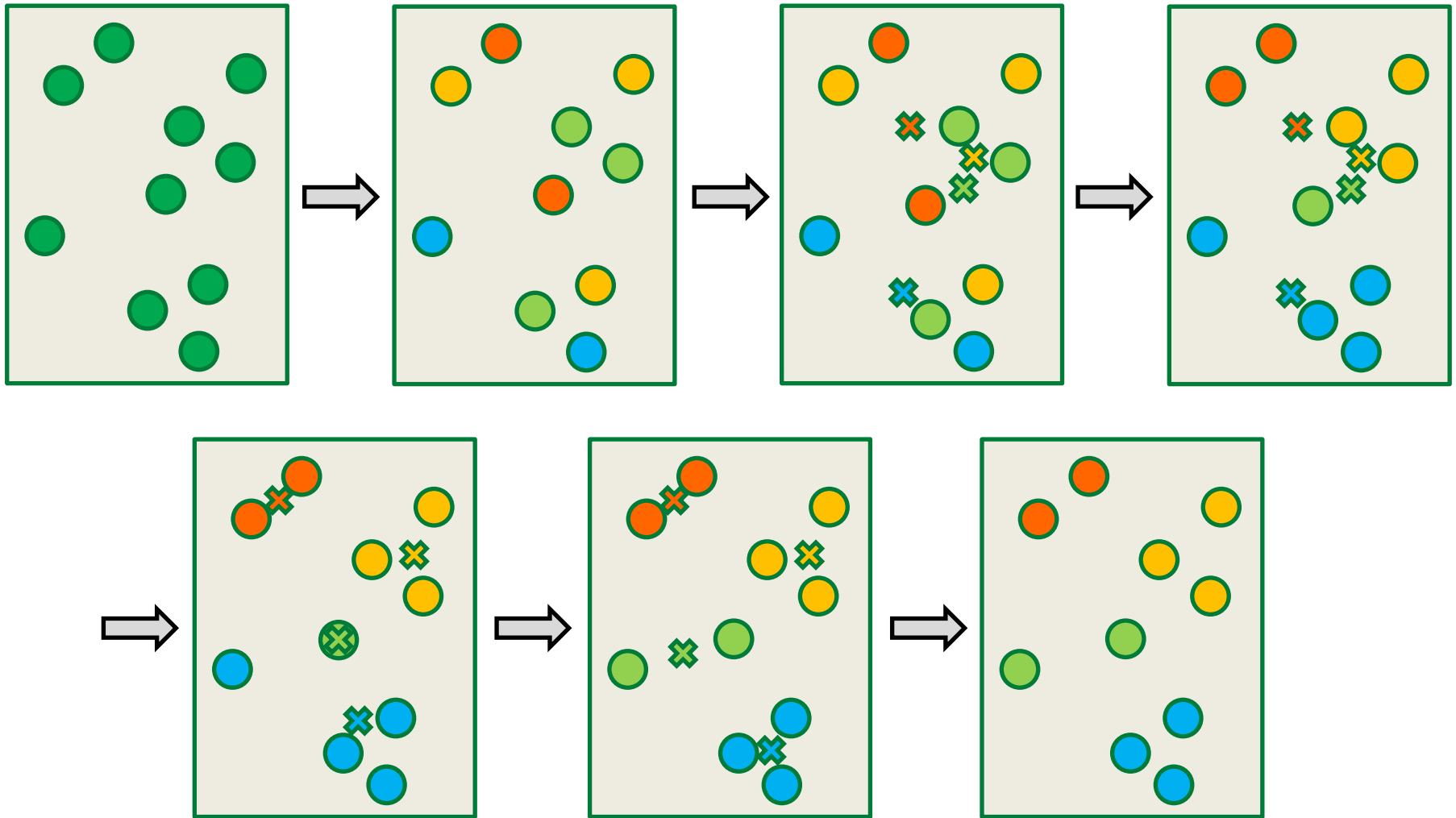
DBSCAN
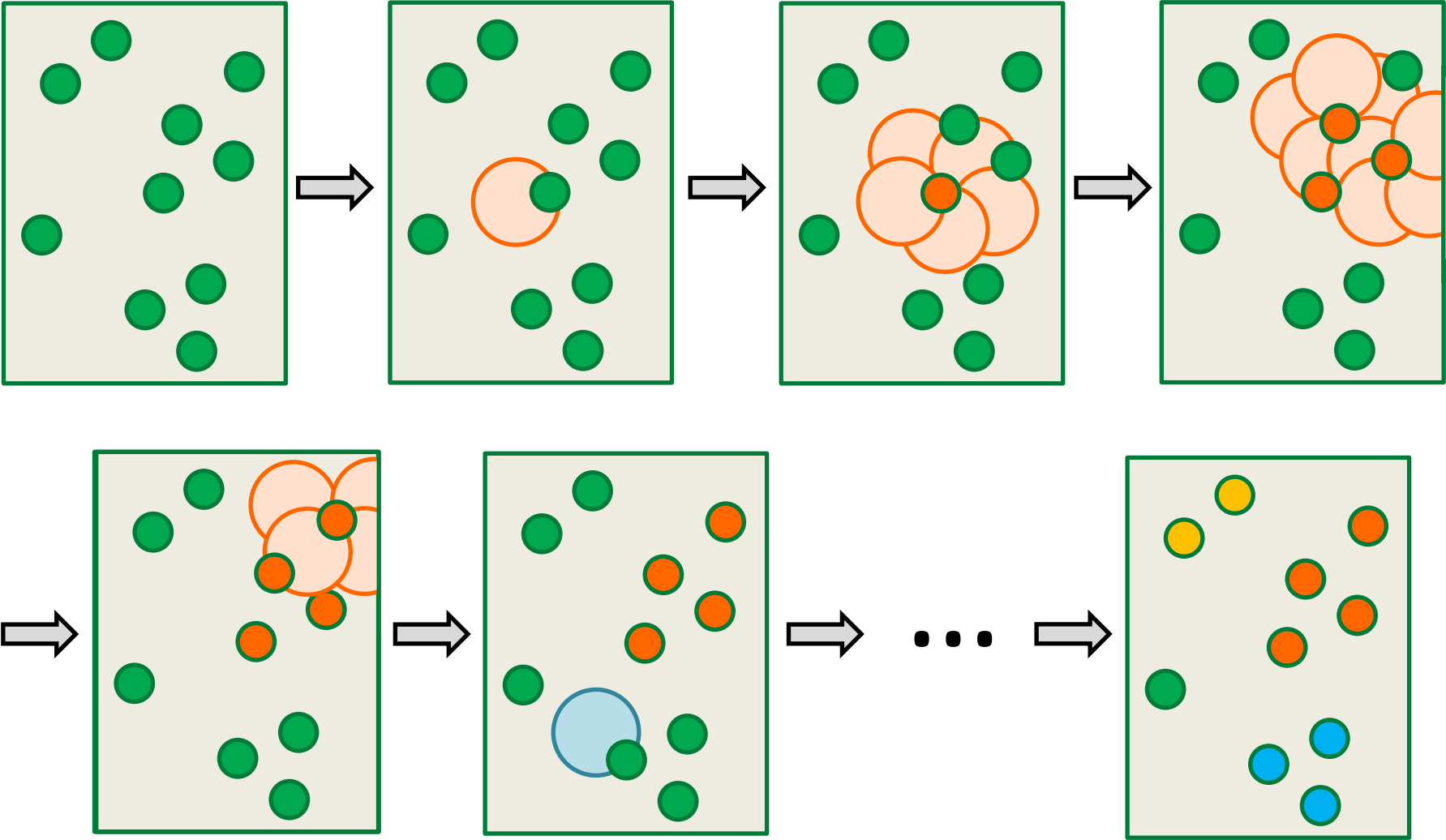
Hierarchical Clustering
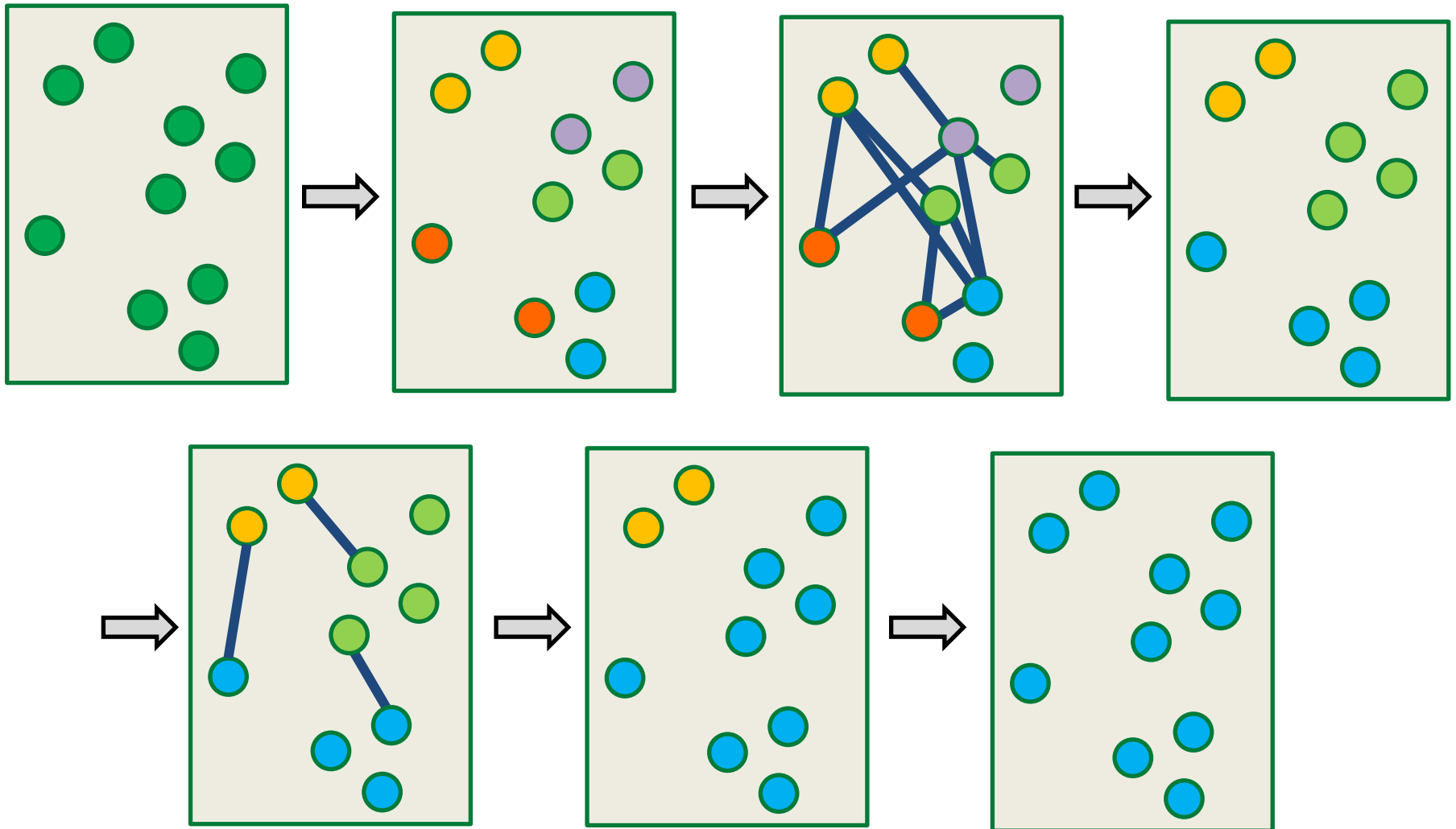
Types of Hierarchical Clustering

- Directionality of the clustering:

    - **Top-down:** divisive

    - **Bottom-up:** agglomerative

- Linkage metrics:

    - **Single Linkage:** nearest neighbor

    - **Complete Linkage:** farthest neighbor

    - **Average Linkage:** all neighbors

Effect of different Linkage metrics

tends to construct small, evenly sized clusters
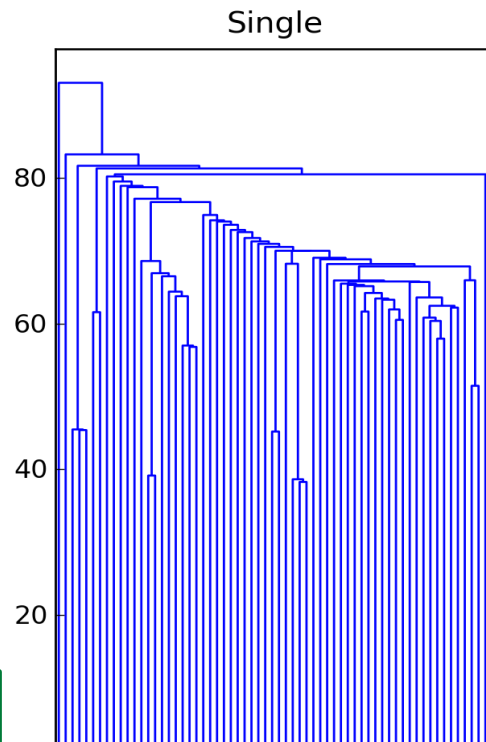
tends to construct chains of clusters
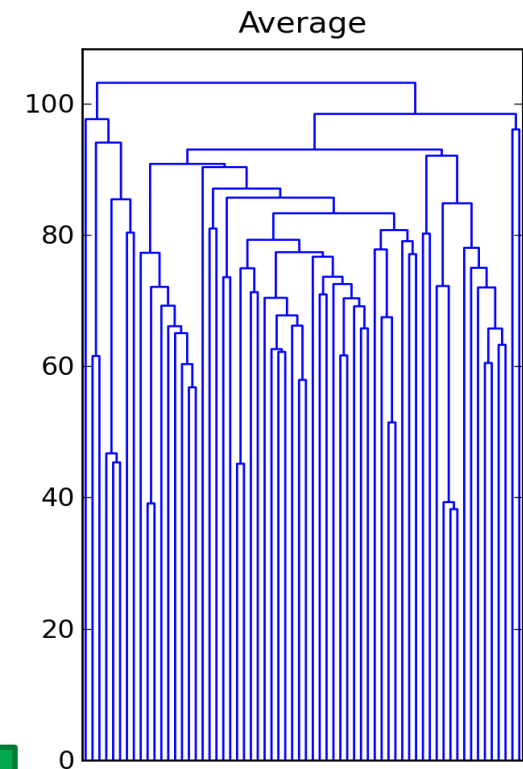
Images taken from Jonathan Taylor (2010)

Comparison

k-Means: O(n) runtime, but requires parameter k
        --> elbow method

DBSCAN: O(n*log n) runtime, no k required,
        robust to outliers, but problematic for
        uneven density distributions
        --> hierarchical variant: OPTICS or HDBSCAN

Hierarchical Clustering: $O(n^2)$ runtime, yields
        multiple cluster granularities in a single run

When there is no obviously "right" way to cluster…

- Consensus Clustering

  - NP complete

- Heuristics:

  - **Quantitative/metric-based: CSPA**
    Cluster-based Similarity Partitioning Algorithm

  - **Structural/graph-based: HGPA**
    Hyper-Graph Partitioning Algorithm

Example: Compare Clusterings with Caleydo Matchmaker

[Lex et al. 2010]
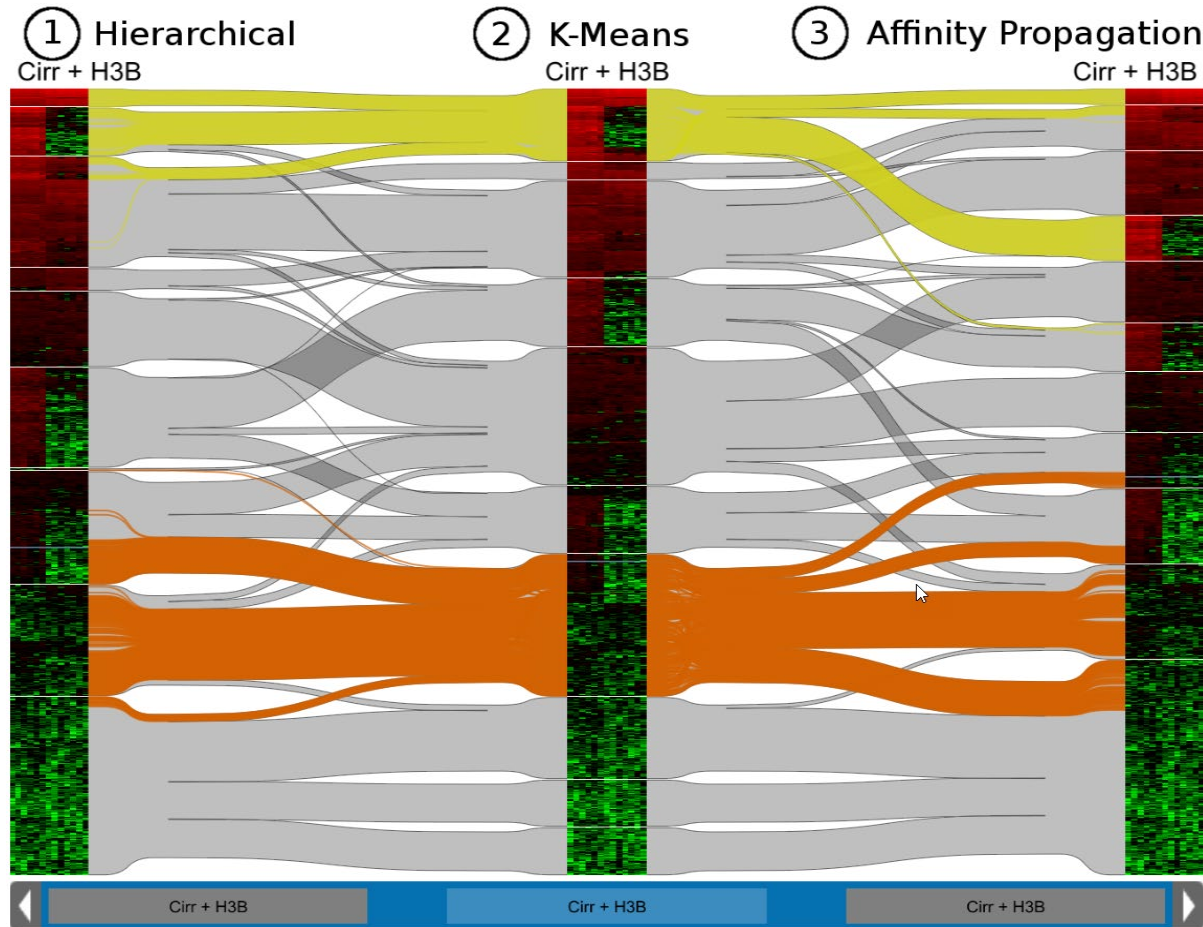
Example: Comparison between Cluster Parameters with Clustrophile

[Cavallo & Demiralp 2018]