Universität Konstanz

Label Hierarchy Inference in Property Graph Databases

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Running Example

Simple example, with no overlapping labels and a perfect hierarchy:

Node.name	Node.labels
Fernando’s	restaurant, italian
Arche	restaurant, vietnamese
Bangkok	restaurant, thai
CampusCafe	cafe, wifi
Endlicht	cafe, latenight
Pano	cafe, breakfast
Lago	shopping, mall
Seerhein Center	shopping, cheap
Seepark	Shopping, expensive

1.1 Motivation

- Implicit hierarchical structure in many data sets
- implicit in property graph
- no explicit representation in Neo4J or the property graph model

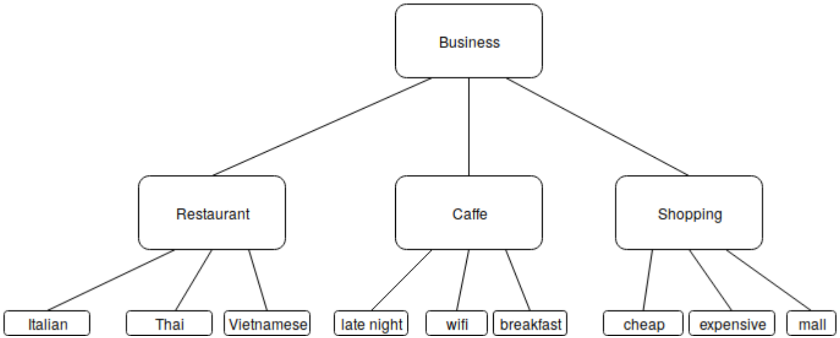
In practice it may help:

- Missing labels & other data impurities can be fixed
- Neo4J cardinality estimation can be improved
- and many others

However that’s not what is dealt with here

1.2 Problem Definition

Given: Set of labels $\{l_i, l_j, l_k, ...\}$
Wanted: Taxonomy/Hierarchy of labels



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2 Solutions: Hierarchical Clustering

2.1 Approaches

3 different approaches were considered:

1. Agglomerative clustering
2. Two-step clustering
3. Conceptual clustering

Common for 1 & 2

- Each data instance is set of labels
- distance measure is set similarity e.g. jaccard or l1 on vectorized representation
- Dendrograms got flattened

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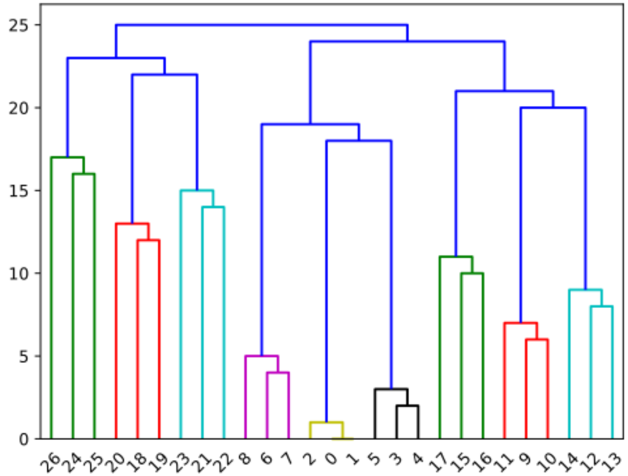
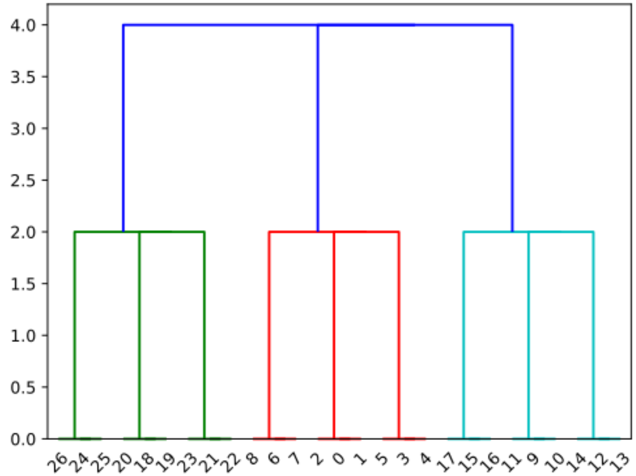
Single Linkage Clustering

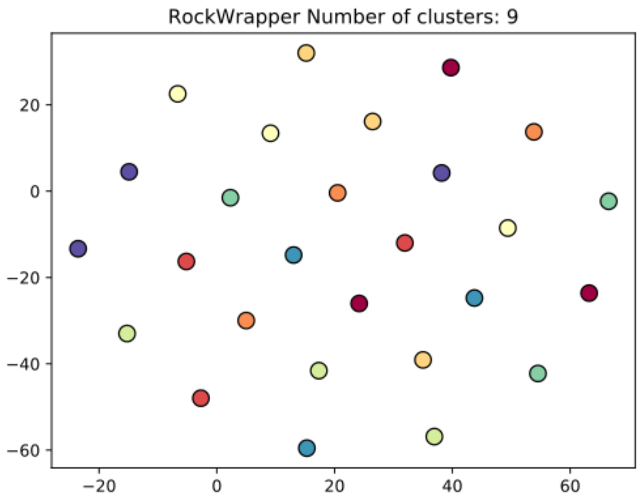
Merge the two clusters with the smallest distance per cluster/set of labels
Implementation of SciPy [1]
In the following: Enhanced plots and result trees: non-standard single linkage!

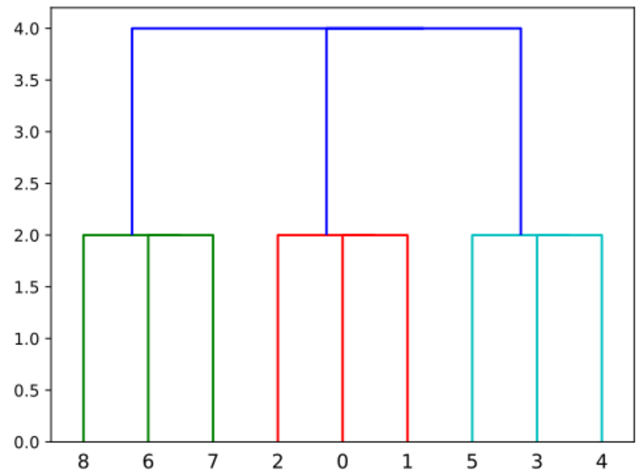




Two-step clustering

Idea: reduce number of observations by other clustering and then do hierarchical clustering.
Implementations as before, plus Scikit-Learn [2] and PyClustering [3].





Conceptual clustering

Idea: Build a hierarchy of label sets/concepts with descriptions and integrate instances iteratively, splitting when too distinct
Comparable to decision trees, form of divisive clustering. Implementation of MacLellan et al. [4]

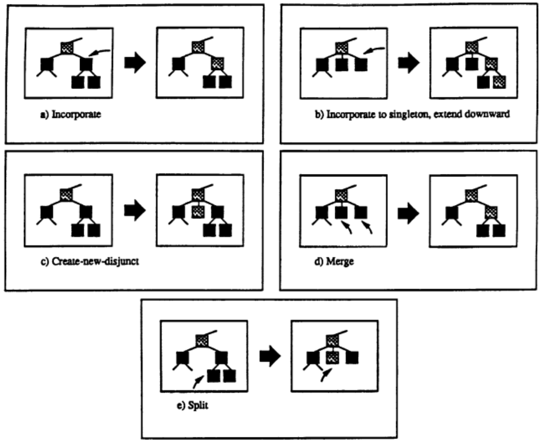


Figure 4. COBWEB's learning operators.

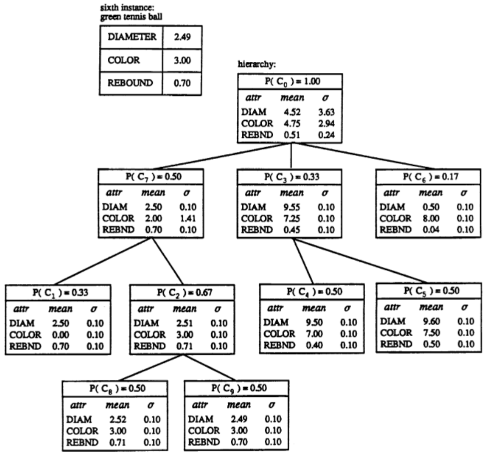


Figure 12. COBWEB hierarchy after the sixth instance of a ball.

3.1 Setup

noise $\equiv$ take a node and remove $\vee$ rename a label

```
"id":24,"labels":"l2, l22",
"id":25,"labels":"l22",
"id":26,"labels":"l1"
```

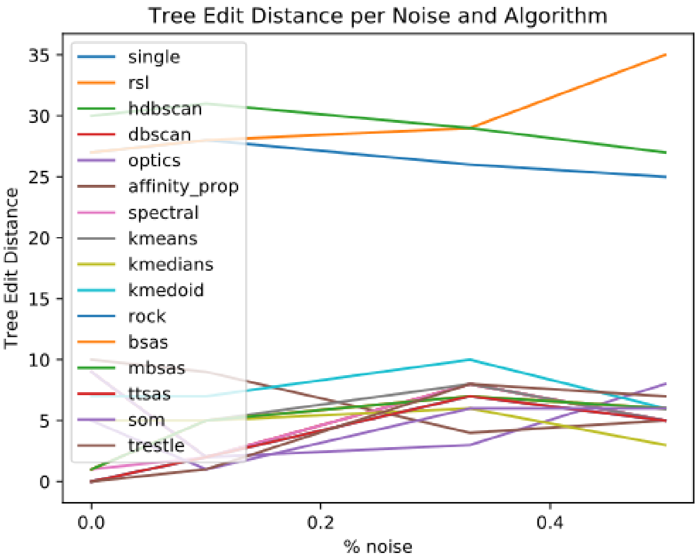
Run the algorithm on each of the variations:

1. no noise
2. 10% noise
3. 33% noise
4. 50% noise

Convert the output into a bracket tree

Metric for how much resulting hierarchy deviates from perfect: Tree Edit Distance [5] [6]

3.2 Results



Tree Edit Distance per Noise and Algorithm
Tree Edit Distance
% noise
0.0
0.2
0.4
0
5
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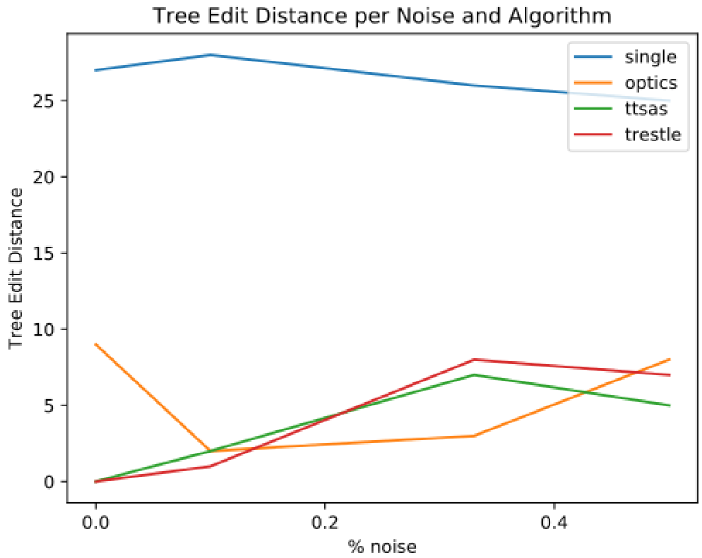
15
20
25
30
35
single
rsl
hdbscan
dbscan
optics
affinity_prop
spectral
kmeans
kmedians
kmedoid
rock
bsas
mbsas
ttsas
som
trestle



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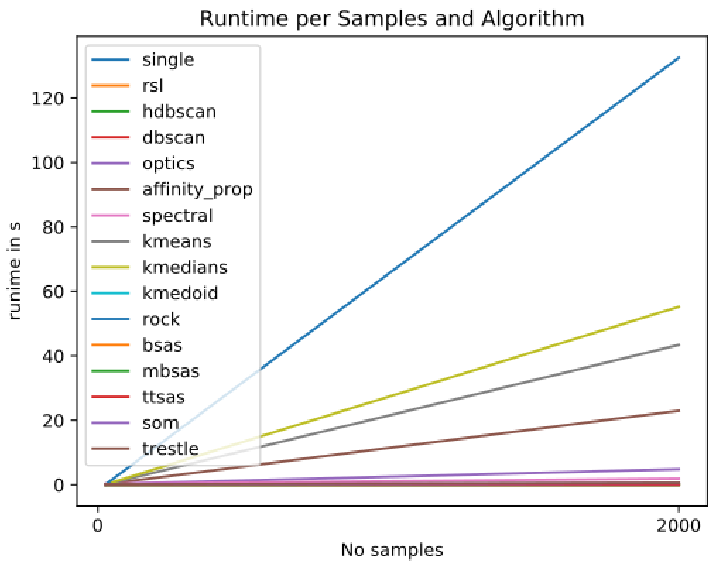
Runtime per Samples and Algorithm
single
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dbscan
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affinity_prop
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kmedoid
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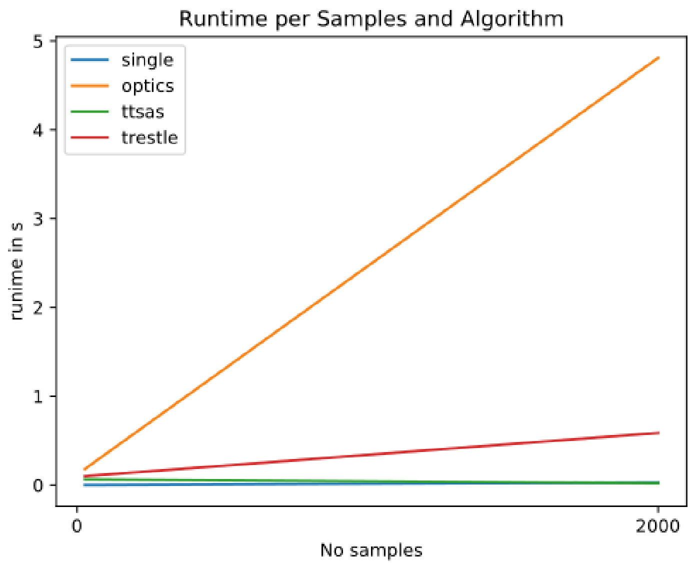
80
100
120
0
2000
No samples


Runtime per Samples and Algorithm
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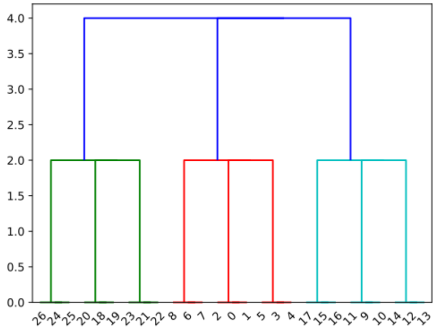
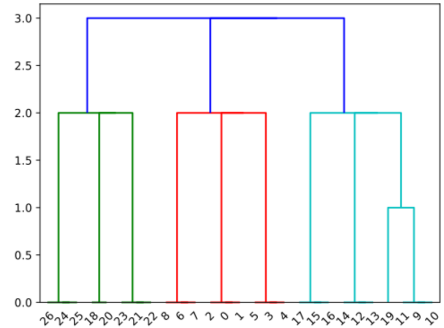
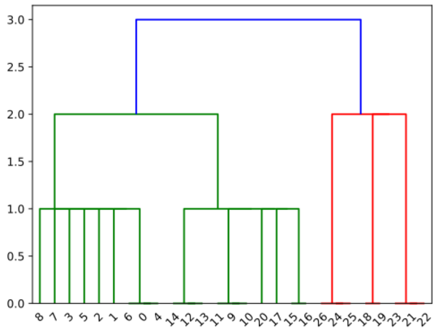
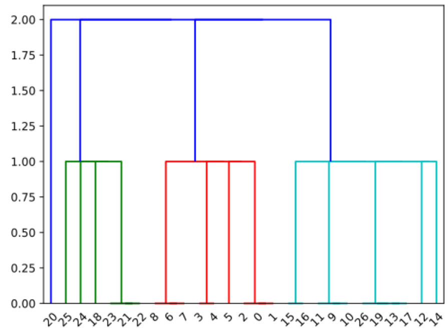
2000
No samples

Agglomerative Clustering: Single Linkage

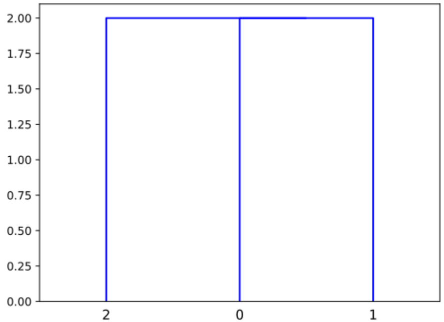


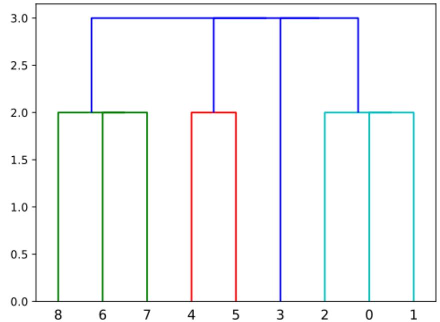


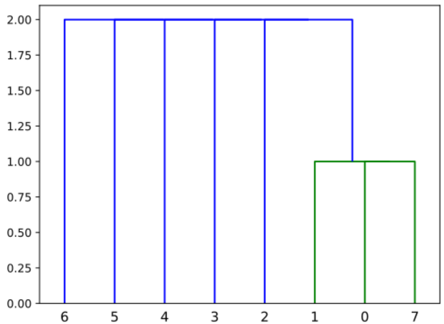


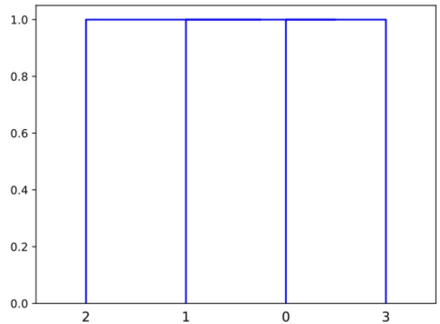


Two-Step Clustering: OPTICS

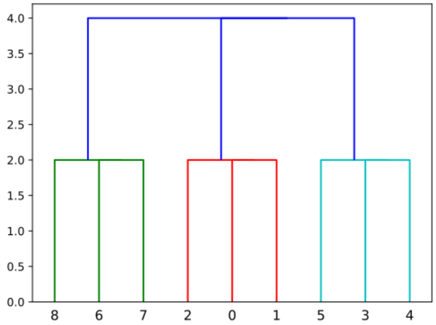


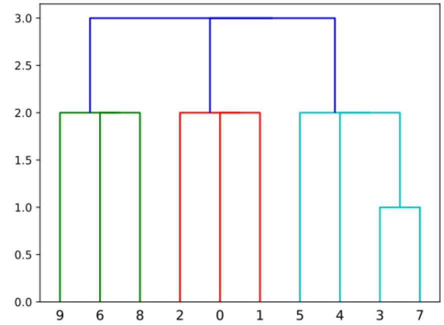


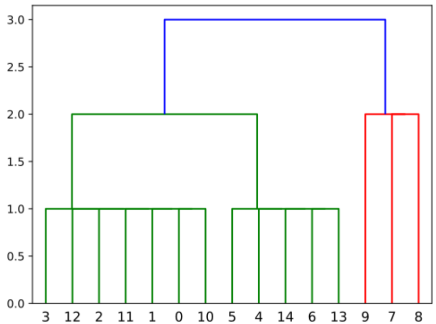


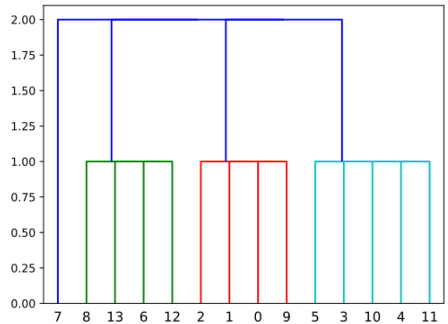


Two-Step Clustering: TTSAS

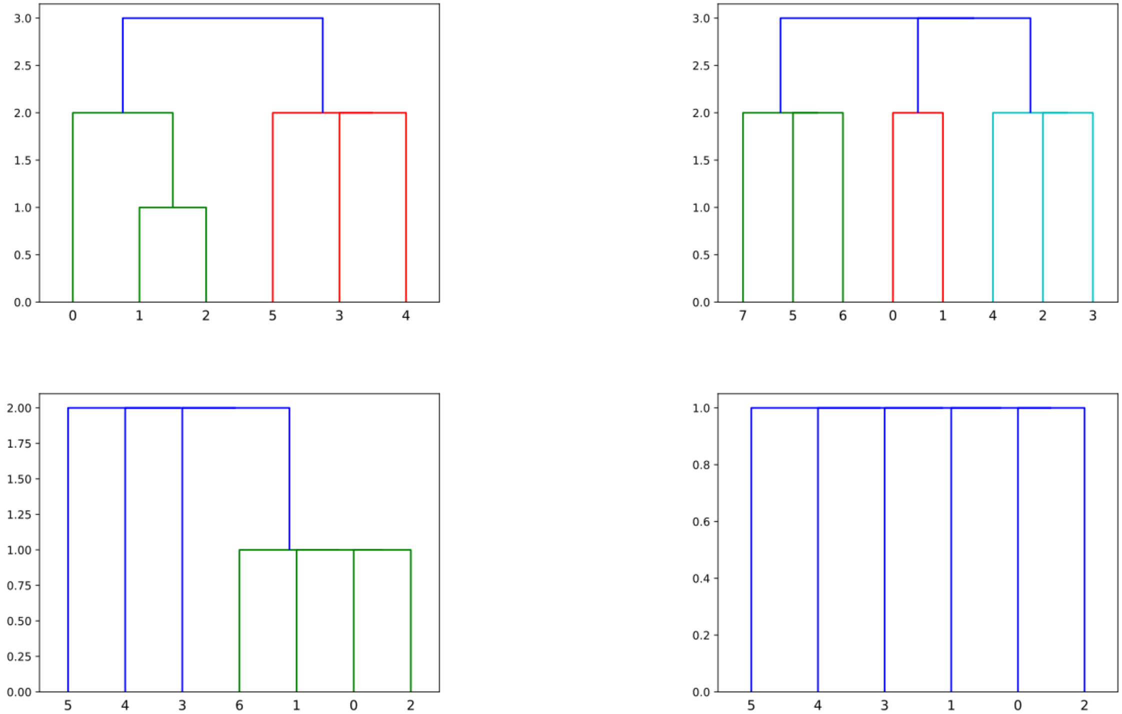




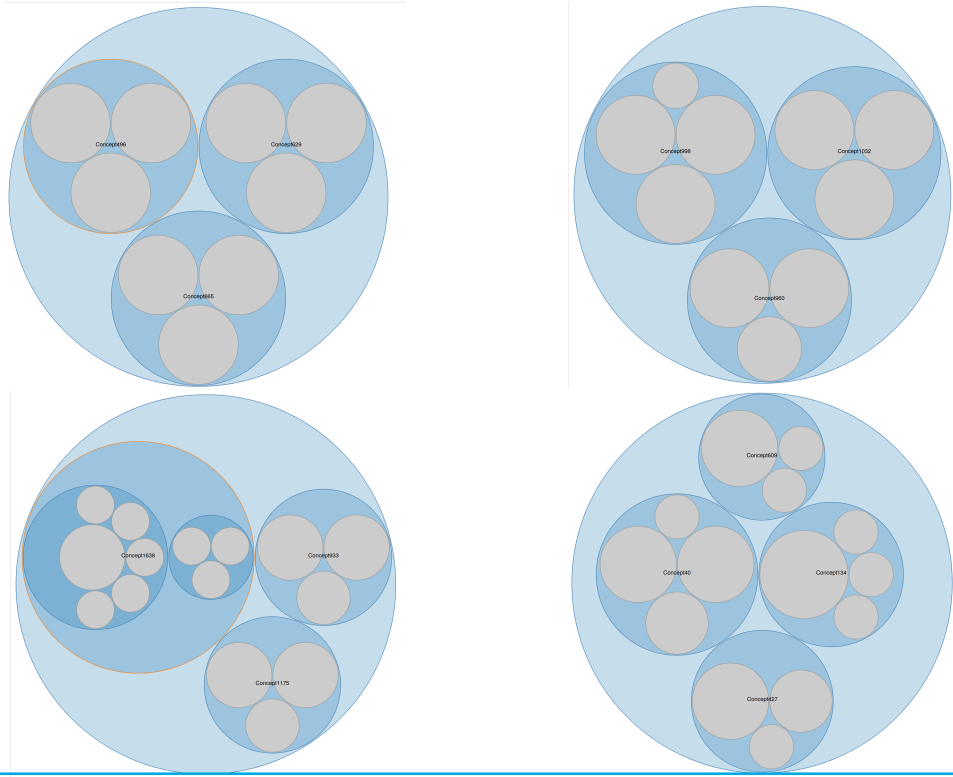




Two-Step Clustering: SOM



Conceptual Clustering: Trestle



Approaches I & II

P1: One merge per level $\Rightarrow$ not a proper tree with levels

P2: Merges are always between two clusters $\Rightarrow$ Flattening

P3: Breaks down immediately when introducing noise

P4: First step clustering algorithms are highly dependent on hyper-parameter tuning:
$\Rightarrow$ Randomized parameter search

Conceptual Clustering

- Outlier detection
- Preprocessing e.g. list flattening
- weighting of attributes (reliable vs. noisy)

What to achieve with thesis

Improve/extend the conceptual clustering framework:

- leverage graph edges/relationships to make algorithm more robust:
  - neighbourhood
  - ego net
  - recursive feature extraction
- deal with outliers
- cut the hierarchy tree in robust only sub-trees

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