Solutions for higher Complexities

- if data mining algorithms has a super linear complexity parallel processing and hardware can help, but do not solve the problem
- runtimes can only be reduced by limiting the number of input objects
- solution:
  - reduce the input data to set of objects having a smaller cardinality
  - perform data mining on the reduced input set

⇒ Results may vary from using the complete data set

⇒ parallel processing can be used for this preprocessing step

Sampling

Idea: Select a limited subset from the input data.

- Random sampling: draw k times from the data set and remove the drawn the elements
- Bootstrapping: draw k times from the input data set but do not exclude the drawn elements from the set
- Stratified sample: Draw a sample which maintains a the distribution w.r.t. to set of attributes (e.g., class labels)

⇒ compute how many instances for attribute value (combination of attribute values) should be contained in the sample

⇒ Partition the input data w.r.t. to the values/ value combinations

⇒ draw the computed amount from each partition

Spatial Sampling

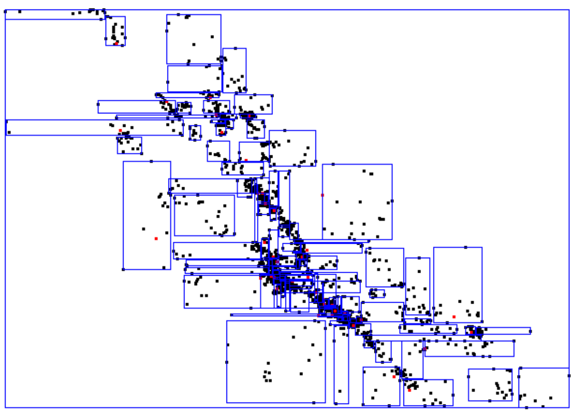
Index-based Sampling [Ester, Kriegel & Xu 1995]

- random sampling is problematic in spatial data
- use spatial index structures to estimate spatial distributions
  - index structures try to group similar objects (similar effect to clustering)
  - index structures are usually built up in an efficient way
  - allow fast access for similarity queries

Spatial Sampling

Method

- build up an R*-tree
- sample a set of objects from all leaf nodes



Structure of an R*-tree

Micro-Clustering

BIRCH [Zhang, Ramakrishnan & Linvy 1996]

Method

- Build a compact description of micro clusters (cluster features)
- organize custer features in a tree structure (CF-tree)
- leafs of the tree have a maximal expansion
- data mining algorithms use the leaf nodes as data objects

- Birch is a hierarchical clustering approach
- the topology of the tree is dependent on the insertion order
- building up a Birch tree can be done in linear time

DATABASE SYSTEMS GROUP

Micro-Clustering

LMU

Basic concepts

- *Cluster Features* of a set *C* $\{X_1,.., X_n\}$: *CF* = (N, LS, SS)
- $N = |C|$ cardinality of C
- $LS = \sum_{i=1}^{N} \vec{X}_i$ linear sum of the vectors X_i
- $SS = \sum_{i=1}^{N} \vec{X}_i^2 = \sum_{i=1}^{N} \langle X_i, X_i \rangle$ *sum of squared vector lengths*

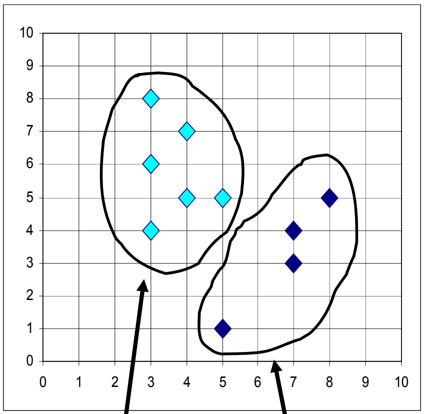
CF can be used to compute:

- the centroid of C (representing object)
- standard deviation of the distance from X_1 *to the centroid*

Micro-Clustering

Example:

(3,4)
(4,5)
(5,5)
(3,6)
(4,7)
(3,8)



(5,1)
(7,3)
(7,4)
(8,5)

$CF_1 = (6, (22,35),299)$

$CF_2 = (4, (27,13),238)$

Micro-Clustering

Additivity theorem

for two disjunctive clusters C_1 und C_2 the following equation holds:

$$CF(C_1 \cup C_2) = CF(C_1) + CF(C_2) = (N_1 + N_2, LS_1 + LS_2, QS_1 + QS_2)$$

i.e., clusters can be computed incrementally and easilymerged into one cluster.

Distance between CFs = distance between centroids

Definition

A CF-tree is a height balanced tree where all nodes are described by cluser features.

CF-tree

Properties of CF Trees

- Each inner node contains at most B entries [CF_i, $child_i$] where CF_i is the CF vector of the i^{th} subcluster $child_i$
- A lead node contains at most L entries *of the form* [CF_i].
- each leaf has two pointers previous and next to a allow sequential access
- for each lead node the diameter of all contained entries is less than the threshold *T.*

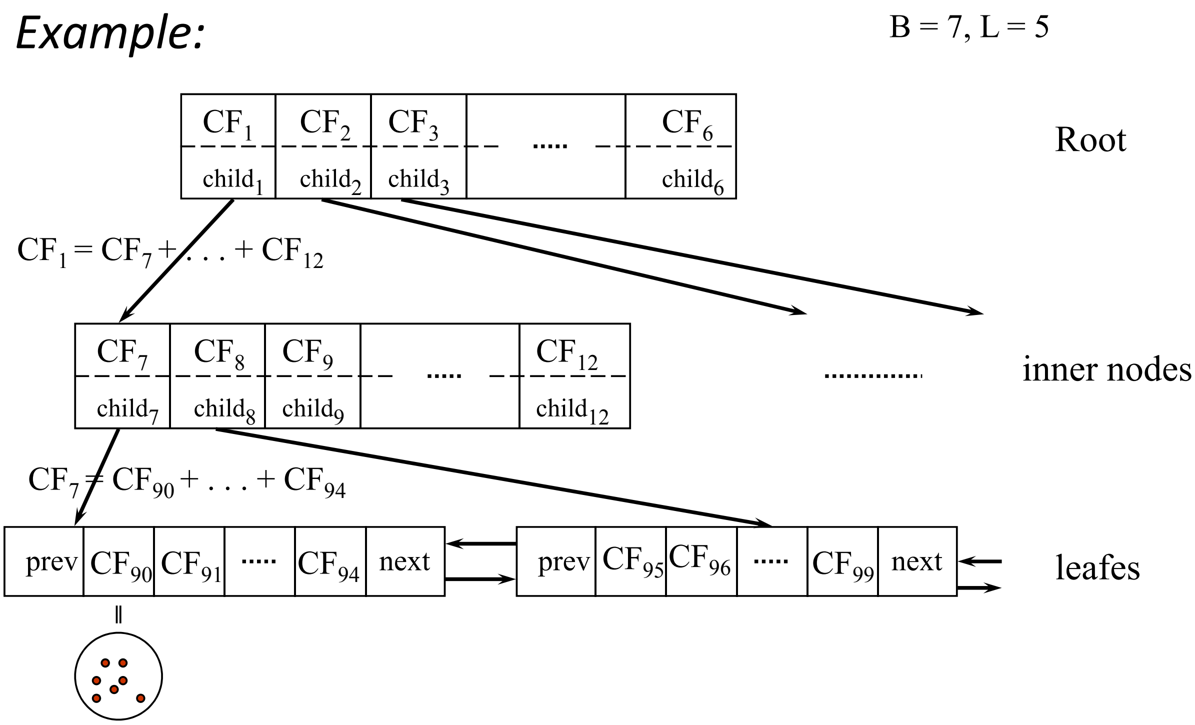
CF-tree

Construction of a CF-tree (analogue to constructing a B^+-tree)

- transform the data set p into a CF vector $CF_p=(1, p, p^2)$
- insert CF_p into the subtree having the minimal distance
- when reaching the leaf level, CF_p *is inserted into the closest leaf*
- *if after insertion the diameter is still < T then* CF_p *is absorbed into the leaf*
- else CF_p is removed from the leaf and spawns a new leaf .
- if the parent node has more than B entries, split the node:
  - select the pair of CFs having the largest distance seed CFs
  - assign the remaining CFs to the closer one of the seed CFs

Micro-Clustering

Example:



Micro-Clustering

Using Birch for Data Clustering

Phase 1

- construct a CF-tree by successively adding new vectors

Phase 2 (loop until number of leafes is small enough)

- if the CF-tree B_1 still contains to many leafes, adjust the treshold to $T_2 > T_1$
- Construct CF-tree B_2 w.r.t. T_2 by successively inserting the leaf CF‘s of B_1

Phase 3

- Apply clustering algorithms
- Clustering algorithm can use special distance measures on CFs

Micro-Clustering

Discussion

advantages:

- compression rate is adjustable
- efficient method to build a representative sample
  - construction on secondary storages: O(n log n)
  - construction in main memory CF-Baums: O(n)

disadvantages:

- *only suitable for numerical vector spaces*
- *results depend on insertion order*

DATABASE SYSTEMS GROUP

Micro-Clustering

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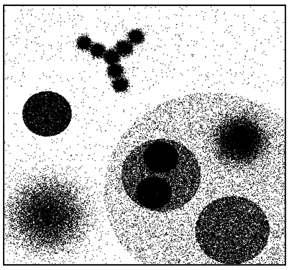
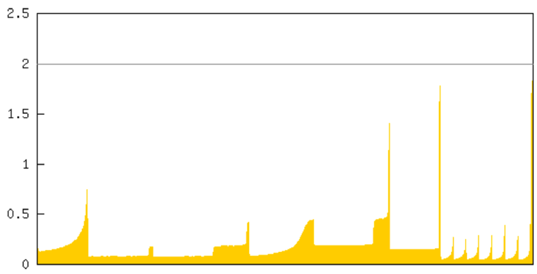
Data Bubbles [Breunig, Kriegel, Kröger, Sander 2001]

Original DB and OPTICS-plot

1 mio. data points



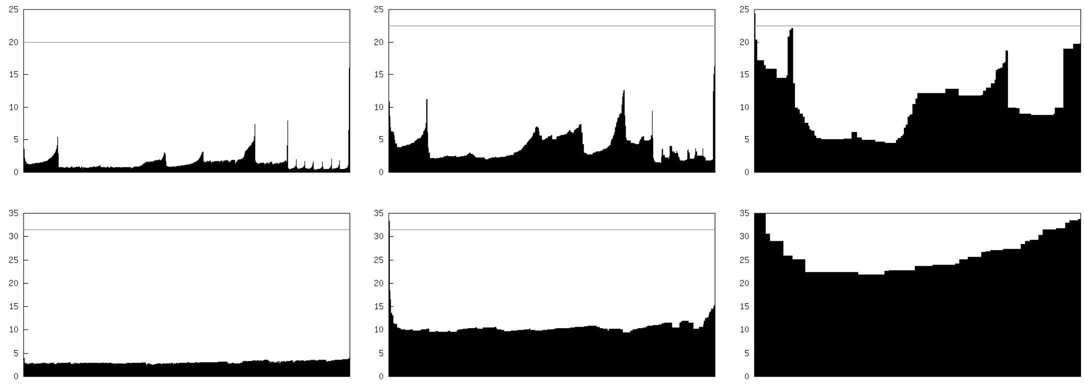


OPTICS-plots for compressed data

k=10,000 k=1,000 k=200

Sampling

BIRCH



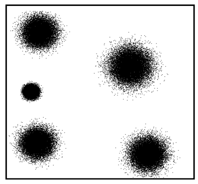
Micro-Clustering

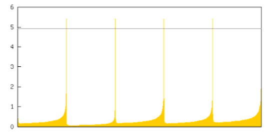
There are three problems making the result unstable:

1. Lost Objects
   many objects are not in the plot (plot is too small)
2. Size Distortions
   Cluster are too small or too large relative to other clusters
3. Structural Distortions
   hierarchical cluster structures are lost

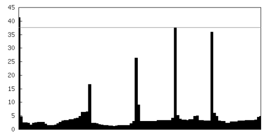
Solutions:

- Post processing Lost Objects and Size Distortions
  use nn-classifier and replace all representative objects by the set of represented objects
- Data Bubbles can solve structural distortions

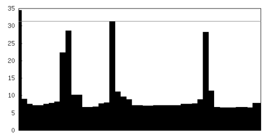




OPTICS original



Sampling 100 Obj.

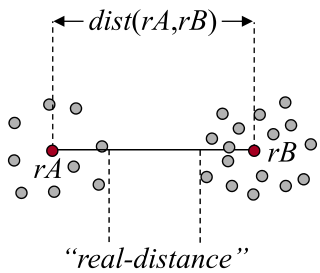


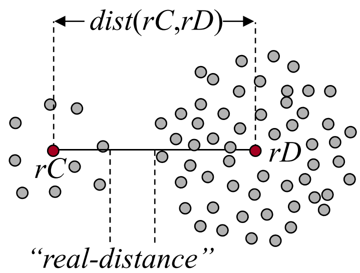
CF 100 Obj.

Micro-Clustering

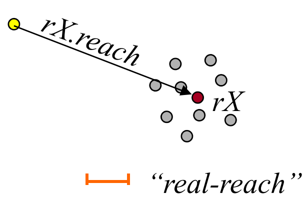
reasons for structural distortions:

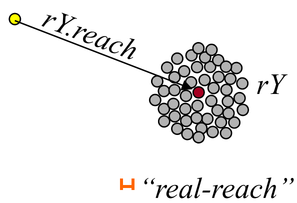
- Distance between the original objects is only badly described by the distance between the centroids.





- the reachability distance of a representative objects does really approximate the reachability distance of the represented objects





Micro-Clustering

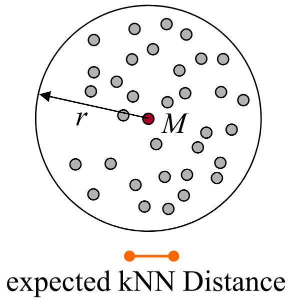
Data Bubble: adds more information to representations

Definition: **Data Bubble**

– Data Bubble $B=(n, M, r)$ of the set $X=\{X_i\}$ containing *n objects*

$$M = \left(\sum_{i=1}^{n} X_i\right) / n$$ centroid of X

$$r = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(X_i - X_j)^2}{n\cdot(n-1)}}$$ is the *radius* of X.



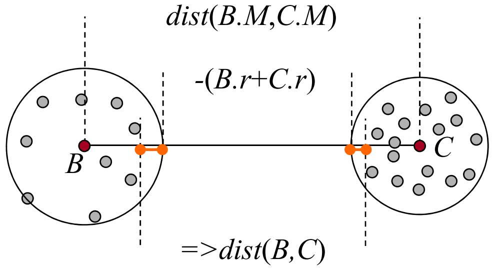
– Expected *k*NN Distance of the objects X_i in a data bubble (assuming a uniform distribution)

$$nnDist(k,B) = r \cdot \left(\frac{k}{n}\right)^{d}$$

– Data Bubbles can either be generated from samples or CFs

Micro-Clustering

- Definition: Distance between Data Bubbles

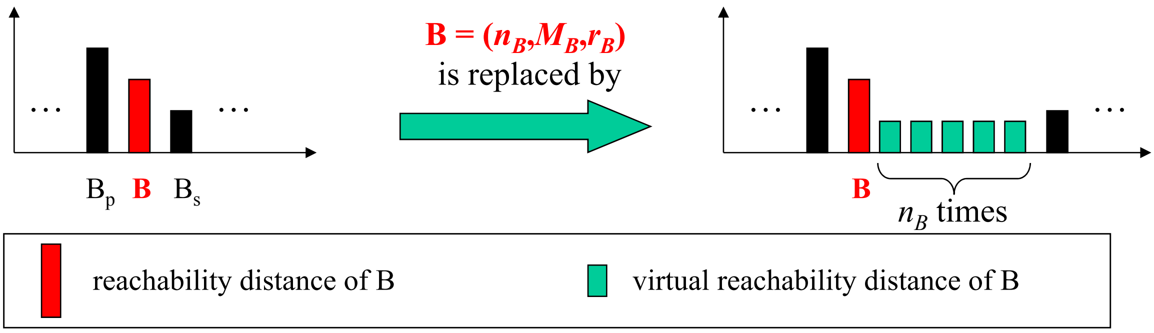


- Definition: Core- and reachability distance for data bubbles are defined in the same way as for points
- Definition: virtual reachability distance of a data bublle
  – expected *kNN*-distance within the the data bubble
  – better approximation of the reachability distance of the represented objects

Micro-Clustering

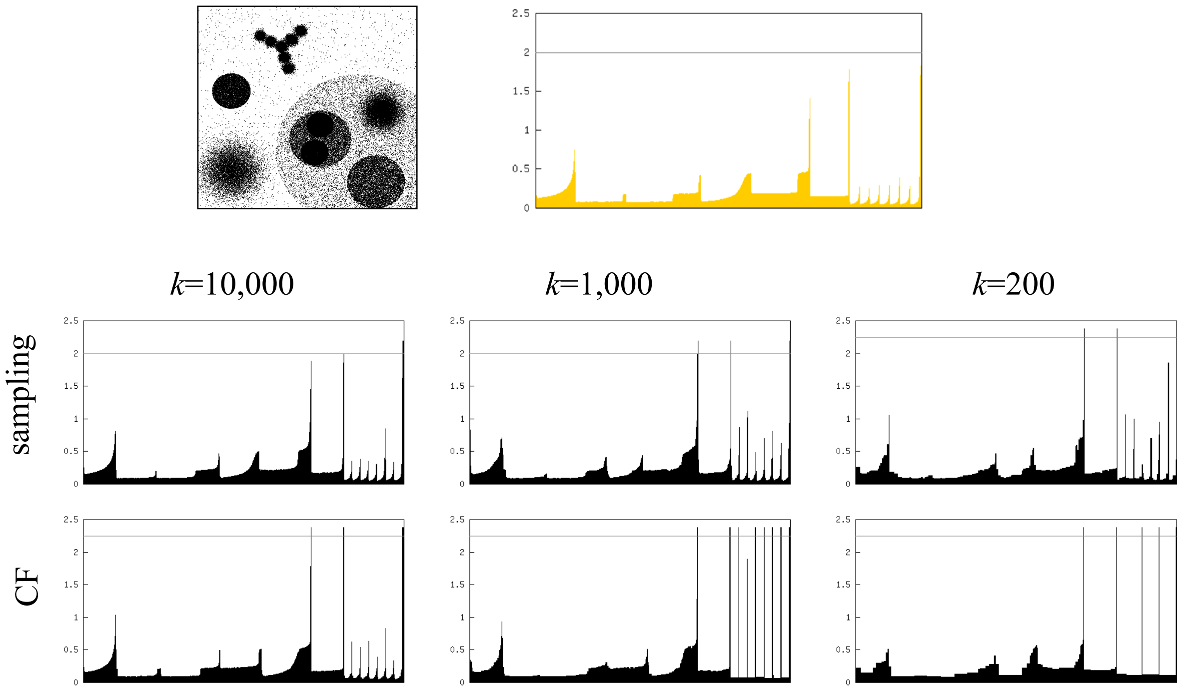
- Clustering using Data Bubbles:
  - Generate *m* Data Bubbles from *m* sample objects or CF-features
  - Cluster the set of data bubbles using OPTICS
  - Generate reachability plot:

    for each data bubble *B*:
    - Plot the reachability distance *B.reach* (generated by the running OPTICS on the data bubbles)
    - For points being represented by B, plot the virtual reachability distance of *B*



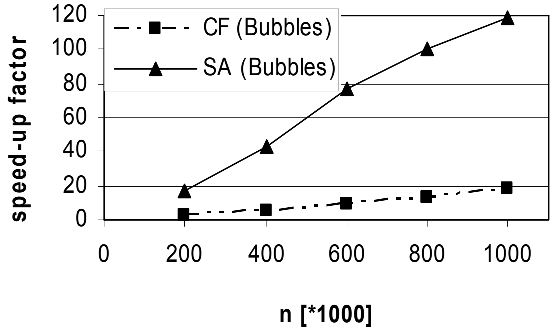
Micro-Clustering

Results of using data bubbles based on sampling and CF

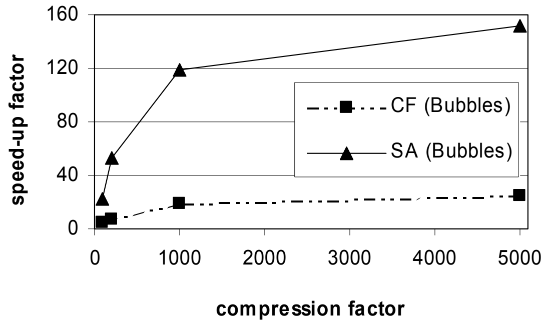


Micro-Clustering

Speed-Up



Speed-Up



w.r.t to number of data objects

wr.t. compression ratio for 1 million data objects

Discussion Micro-Clustering and Sampling

- often the same results can be achieved on much smaller samples
- it is important that the data distributed is sufficiently represented by the data set
- Sampling and Micro-Clustering try to approximate the spatial data distribution by a smaller subset of the data
- there are similar approaches for classification

  instance selection:
  - Select samples from each class which allow to approximate the class margins
  - samples being very “typical” for a class might be useful to learn a discrimination function of a good classifier.
  - similar to the concept of support vectors in SVMs

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