ScalableRecursiveTop-DownHierarchicalClustering Approach withimplicit Model SelectionforTextual Data Sets

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Outline

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  - Facetted Retrieval
  - Scatter/Gather
  - Visual Analysis of unstructured document sets
- Clustering Approach
  - Overview
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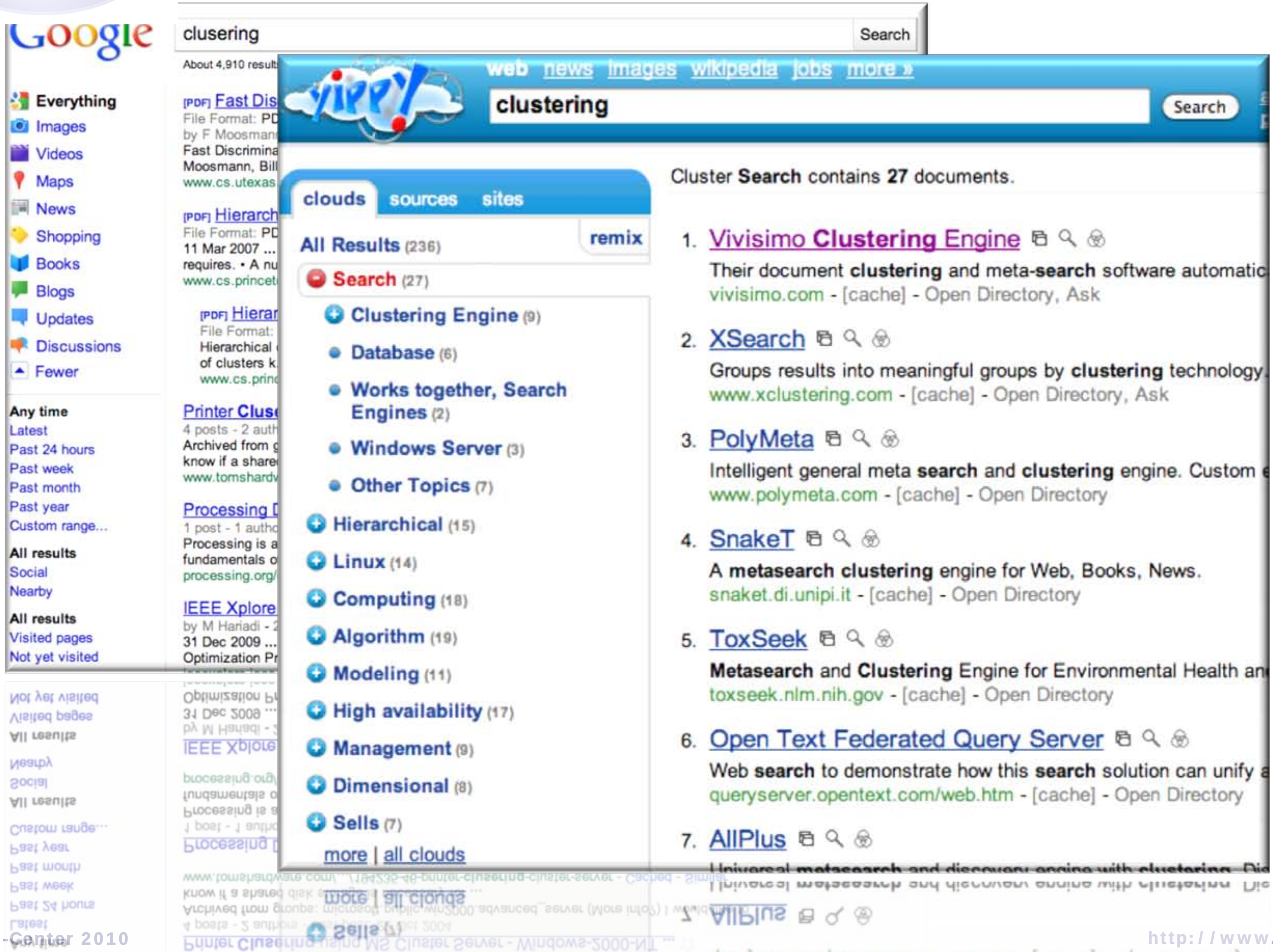
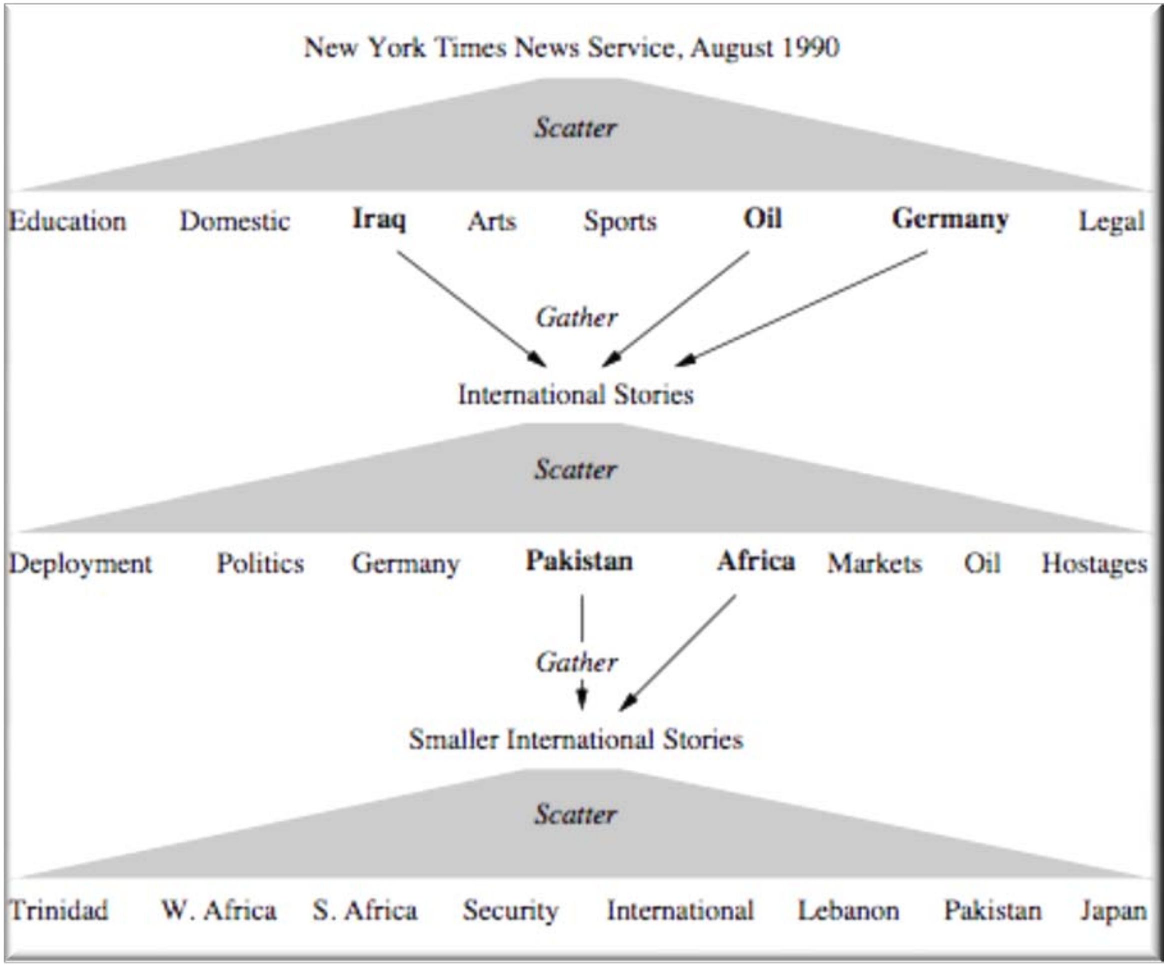
  - Modifications
- Experiments
  - Visual Analysis
  - Inex

Motivation
Facetted Retrieval

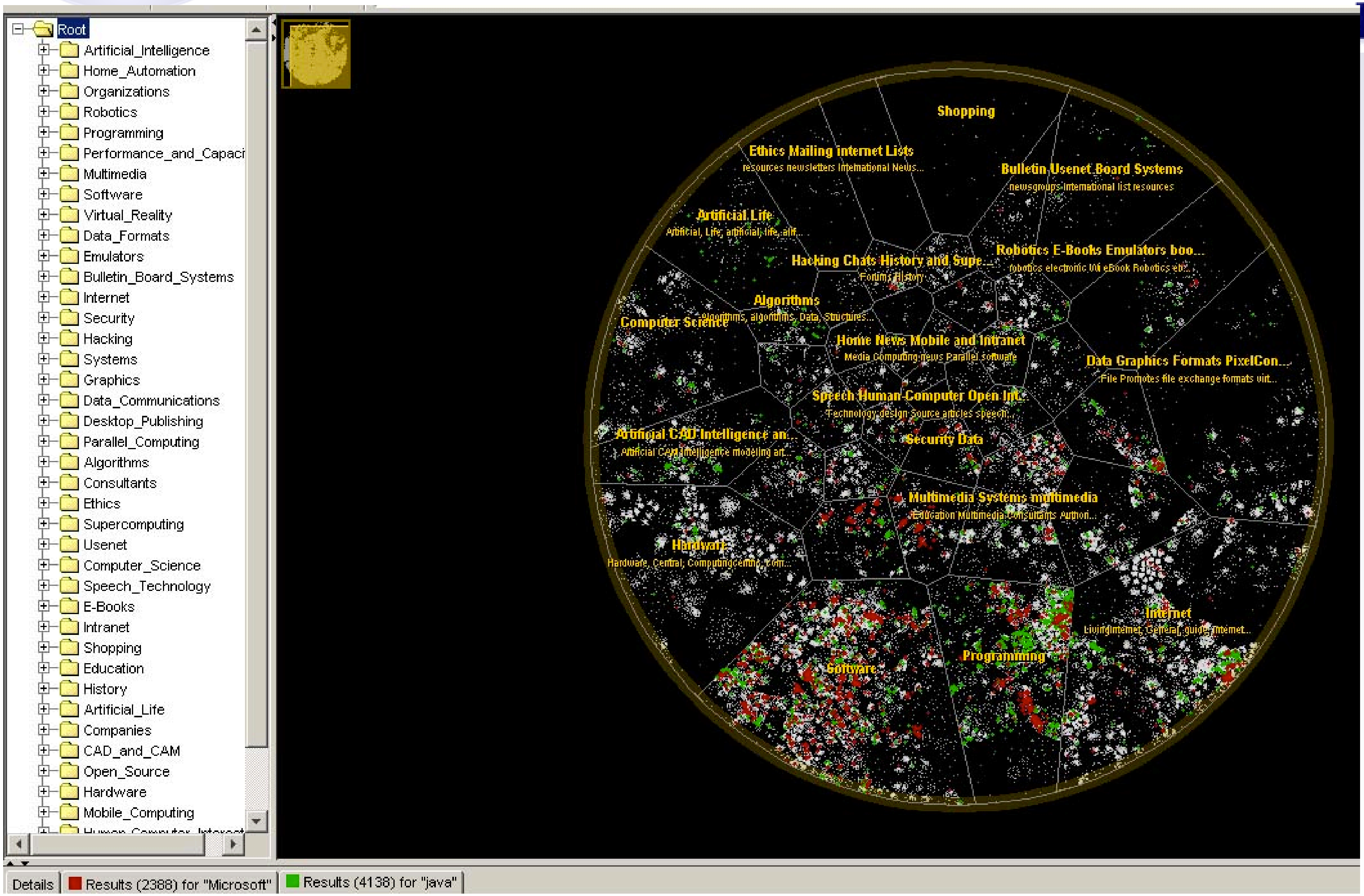


Motivation

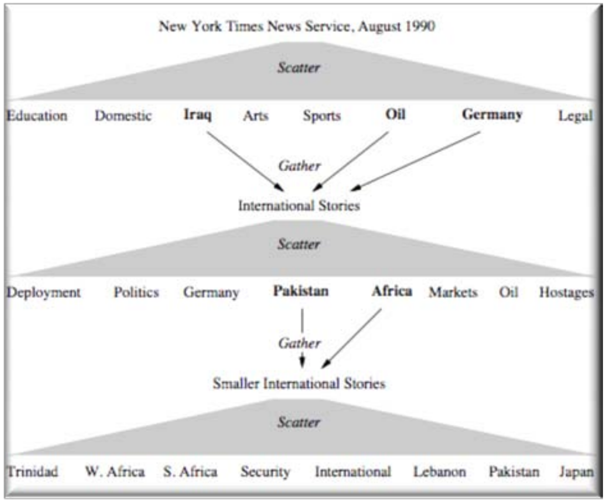
Scatter/Gather [Cutting et. al. 1992]



Motivation
InfoSky: Visual Exploration [Andrews et. al. 2002]



Motivation
InfoSky + Scatter/Gather



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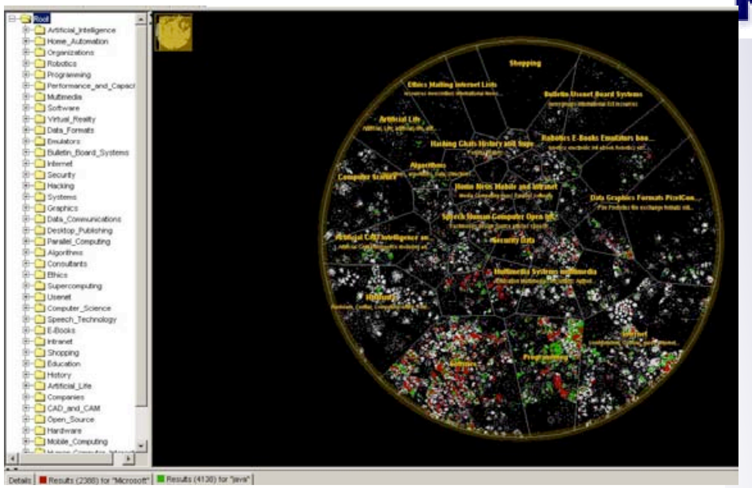


- Automatic creation of the cluster hierarchy while retaining InfoSky‘s analysis capabilities

Questions

- What is an efficient hierarchical clustering algorithm therefore?
- How to combine statistical data set properties with visual requirments?

Contributions

- Hierarchical, top-down, polythetic, documentclusteringapproach
- Dynamicclusterstructure on eachlevel of thehierarchysupportingsplitting and merging of clusters.
- Constraints on themaximum and minimumnumber of elements per hierarchylevel
- Resultingreducedcomputationalcosts of the layout algorithm
- Scalable to datasetsconsisting of millions of documentswith a reasonabletrade-offbetweenruntimeand accuracy

Top-Down, scalableclusteringalgorithmforcreating a topicalhierarchy

Clustering Overview

Divide and conquer: decompose into tasks starting at the root node

For every task

- Step 1: Preprocess documents to be clustered
  - Bag-of-Words, BM 25, cosine inner product
- Step 2: Cluster documents using a flat clustering algorithm
- Step 3: Split and merge clusters till constraints are met
- Step 4: Recursion: Evaluate the stopping criterion for dividing into further sub-tasks
- Step 5: Cluster Labeling
- Step 6: Project clusters into a 2 dimensional space

Clustering
Step 2: Clustering Algorithm (1/4)

Given a set of documents X, find a set of K groups of similar documents (clusters)

- Utilize existing clustering methods
  - HAC, DBScan or Chameleon > $O(n^2)$
  - BIRCH fast and storage efficient, but order dependent
- Growing k-means -
  - Online Competitive Learning with Winner-takes it all approach
  - trade-off between runtime and accuracy [Zhao and Karypis 02]
  - Allows for efficient model selection (determine k)

Clustering
Step 2: Clustering Algorithm (2 / 4)

Algorithm 1 Growing Spherical K-Means

input:
$\mathcal{X} = \{x_1, \ldots, x_N\}$ with $x_i \in \Re^d$, K, l, η, ν
output:
$\mathcal{C} = \{c_1, \ldots, c_K\}$, $\mathcal{Y} = \{y_1, \ldots, y_N\}$ $\forall\ y_n \in \{1, \ldots, K\}$
steps:

initialize centroids c_1 and c_2 by a seeding mechanism
for $m = 2$ to K **do**

Init and loopformaximumk-clusters

for $n = 1$ to N **do**
$y_p = y_n$
$y_n = \arg\max_{1 \le k \le m} x_n^T c_k$
$c_{y_n} = c_{y_n} + \eta x_n$
$c_{y_p} = c_{y_p} - \nu x_n$

Update clusterhypothesis

if $||c_{y_n}|| - 1.0 > l$ **then**
$c_{y_n} = \frac{c_{y_n}}{||c_{y_n}||}$

Runtimeimprovement of centroid update

for $n = 1$ to N **do**
$y_n = \arg\max_{1 \le k \le m} x_n^T c_k$
$s_k = s_k + \max_{1 \le k \le m} x_n^T c_k$

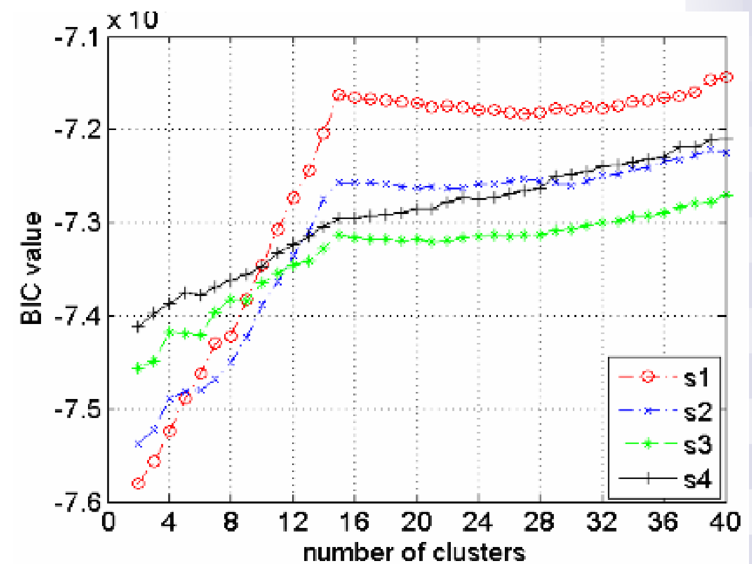
Assigndocuments andaveragesimilarity

if $m < K$ **then**
$c_i = \arg\min_{1 \le k \le m} S(c_k)$
$x_j = \arg\min_{x \in \mathcal{X}_i} x^T c_i$ with $\mathcal{X}_i = \{x_n | y_n = i\}$
$c_t = \frac{c_i - x_j}{2}$, $\mathcal{C} = \mathcal{C} \cup \{c_t\}$

Createm-thcentroid

Clustering
Step 2: Clustering Algorithm (3 / 4)

- Model Selection methods
  - Obtain fitness criterion for different number of clusters (Bayesian Information Criterion (BIC), Stability based approaches)
  - Monotonical increasing/decreasing
  - Overtraining on the data
  - Determine the „best cluster number“ using knee-point detection [Zhao et. al. 2008]



- Efficient calculation for the growing k-means by simply calculating the fitness criterion for each new centroid

Clustering
Step 2: Clustering Algorithm (4/4)

Heuristics

- Efficient update rules [Zhong 2005]

  Move a fraction of the distance between sample and centroid

  $$c_{y_n} = \frac{c_{y_n} + \eta(x_n - c_{y_n})}{||c_{y_n} + \eta(x_n - c_{y_n})||}$$

  Simply update the angle and ignore non unit length

  Track norm changes and rescale after norm exceeds numerical boundaries

  $$\begin{aligned} & c_{y_n} = c_{y_n} + \eta x_n \\ & c_{y_p} = c_{y_p} - \nu x_n \\ & \textbf{if } ||c_{y_n}|| - 1.0 > l \textbf{ then} \\ & \quad c_{y_n} = \frac{c_{y_n}}{||c_{y_n}||} \end{aligned}$$

- Decreasing learning rate with the size of the cluster for balancing

$$\eta = 1/|\sqrt{\mathcal{X}_{k(x)}}|$$

Clustering
Step 3: Split and Merge

Split and Merge Clusters to fulfill the following constraints

- # Cluster at one level
  - Merge the most similar cluster if #cluster > maximum number of clusters
  - Split the least coherent or biggest cluster if #cluster < minimum number of clusters
- # documents in a cluster
  - Below the Maximum number of documents for a cluster ➔ clusterokforbrowsing
  - More than 1.5 times the upper limit to ensure meaningfull clustering at next hierarchical level

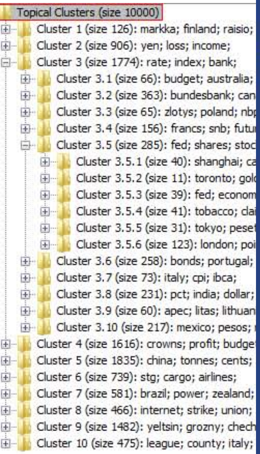
If all clusters fullfill this constraint, cluster recursively (Step 4)

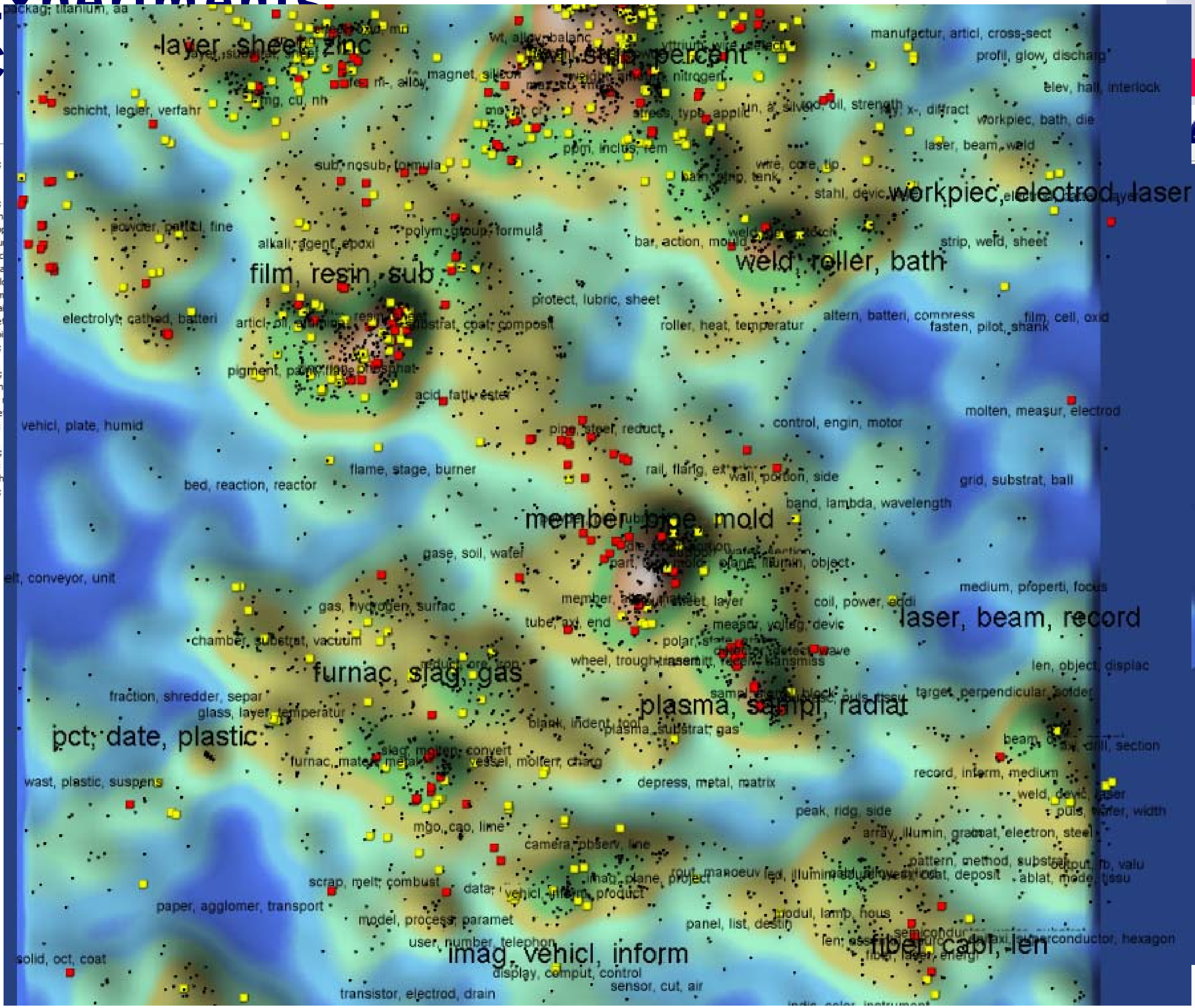
Clustering
Step 5&6: Labeling & Projection

- Labeling via Jensen Shannon Divergence
  - JSD best suited
  - Exploit hierarchical structures (not focus of this work)

- Projection [Andrews et. Al. 2004]
  - Force directed placement $O(n^3)$
  - Recursive application on cluster hierarchy using document and cluster centroids as points to layout
  - Due to the constraints we achieve a runtime of roughly $O(n*\log(n))$
  - Voronoiinscription of rectangular Layout

Experiments
C





Experiments
Clustering based Visualisation

- Preliminary user evaluation
  - Combination of visualisation and standard components helpful for explorative tasks [Andrews et. Al. 2002]
  - Improved interaction and navigation paradigms to support explorative search tasks
  - Patent analysis tasks improved in real world use case
  - Suitable for high recall search tasks
- Detailed evaluation still missing.

Experiments
INEX Clustering

- Initiativ for Evaluation of XML Retrieval
- XML Mining Track – Cluster the English Wikipedia
  - Small data set 54k documents
  - Large data set 2.6 Million Documents
  - Preprocessed document vectors (uni and bi-grams)
- Ground truth provided by YAGO ontology, but no hierarchical structure
- Document assigned to each cluster on the path to facilitat multi cluster assignment as it is the case in Wikipedia

Experiments
INEX Clustering

- 10,467 Clusters for the small data set
  - 4 Minutes to compute on a 16GB Quad Core including I/O

MacroPurity	BIC	Stability
73k Categories	0.4959	0.4945
12k Categories	0.5473	0.5303

- 133,704 Clusters on the large data set
  - Runtime 2 hours
  - 348 k Categories: Macro Purity of 0.4457
  - 12k Categories: Macro Purity of 0.5359
- Clusters appear to be reasonable, but good evaluation strategy remains an open issue
  - High level clusters are more important
  - Accurate ground truth reflecting good browsing strategies

Summary & Conclusio

- Motivation: Support explorative search tasks via Retrieval by browsing
- Needed: Scalable Clustering algorithm
  - Hierarchie Layout as constraint
  - Model selection
- Top-down, recursive algorithm with different model selection strategy
- Experiments
  - Used in visual analysis application
  - INEX Clustering evaluation
- Evaluation for explorative analysis task remains an open problem

Thansk for your attention

Questions?

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