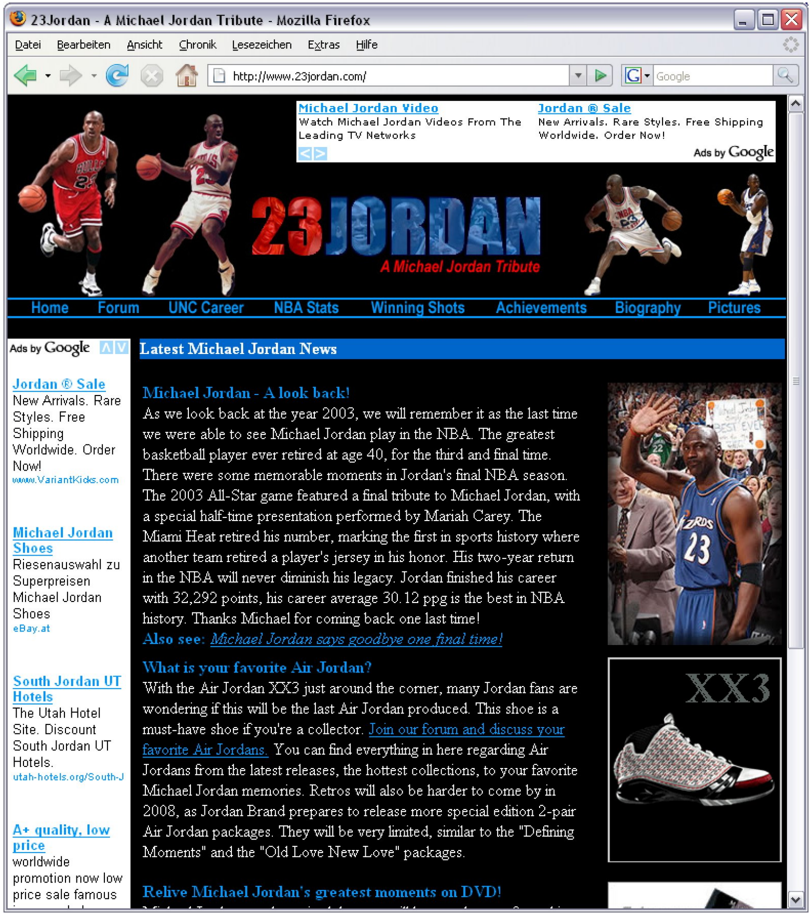
Chapter DM:II (continued)

II. Cluster Analysis

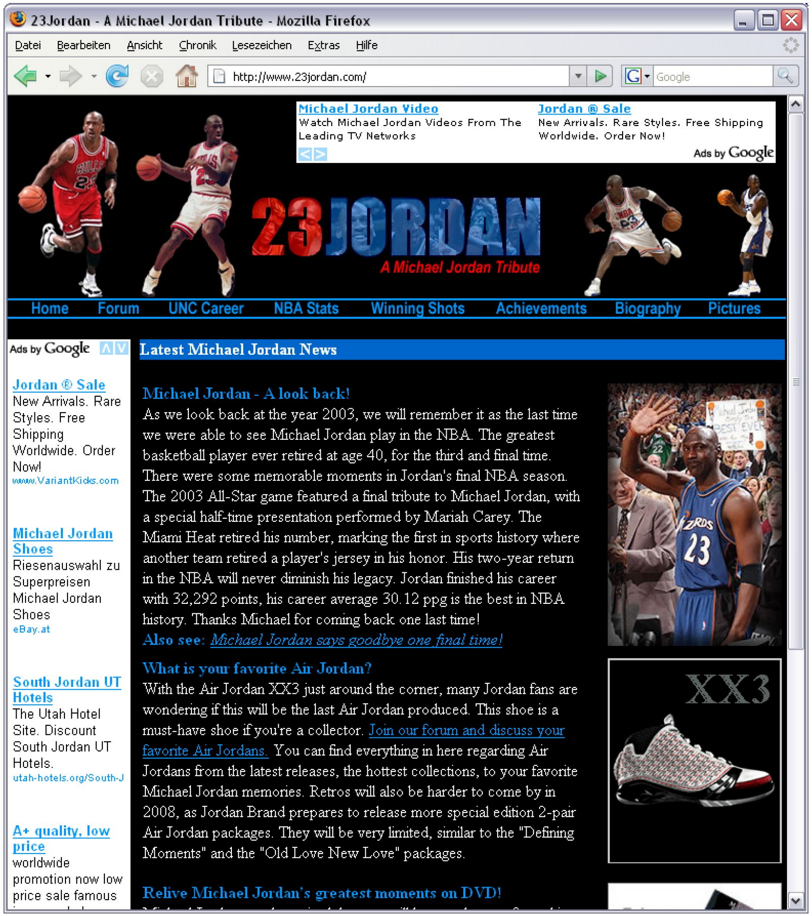
Constrained Cluster Analysis

Person Resolution Task



Constrained Cluster Analysis

Person Resolution Task



Constrained Cluster Analysis

Person Resolution Task

Constrained Cluster Analysis

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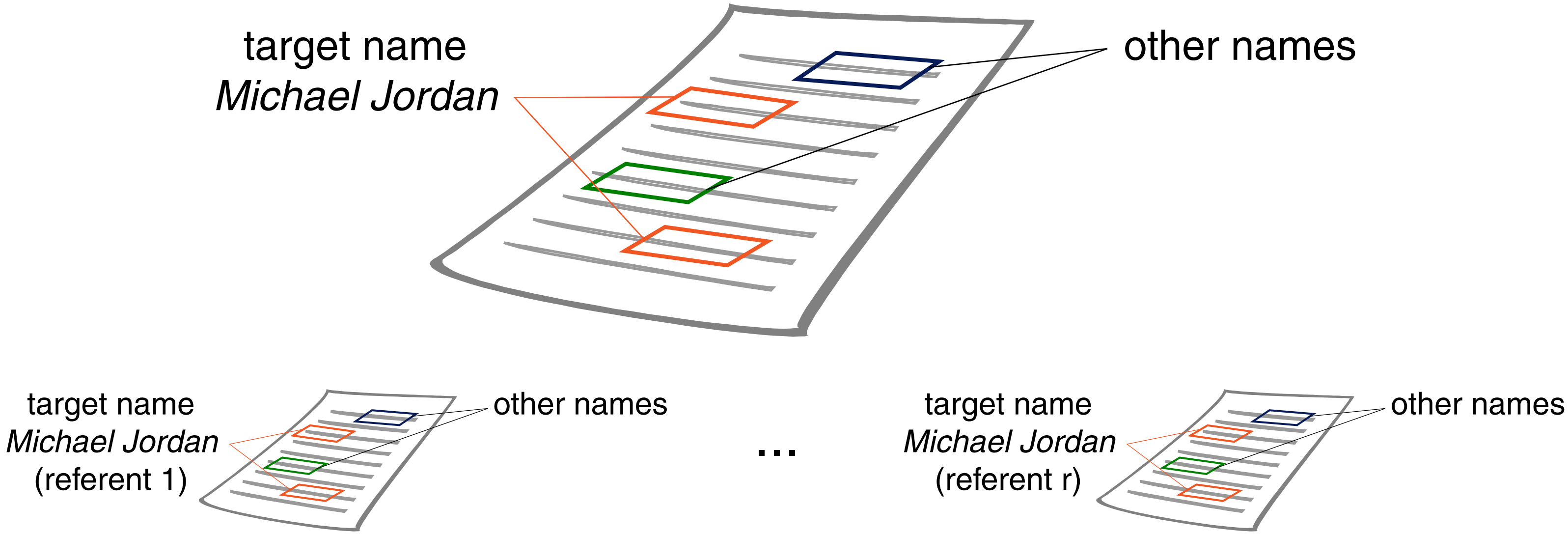
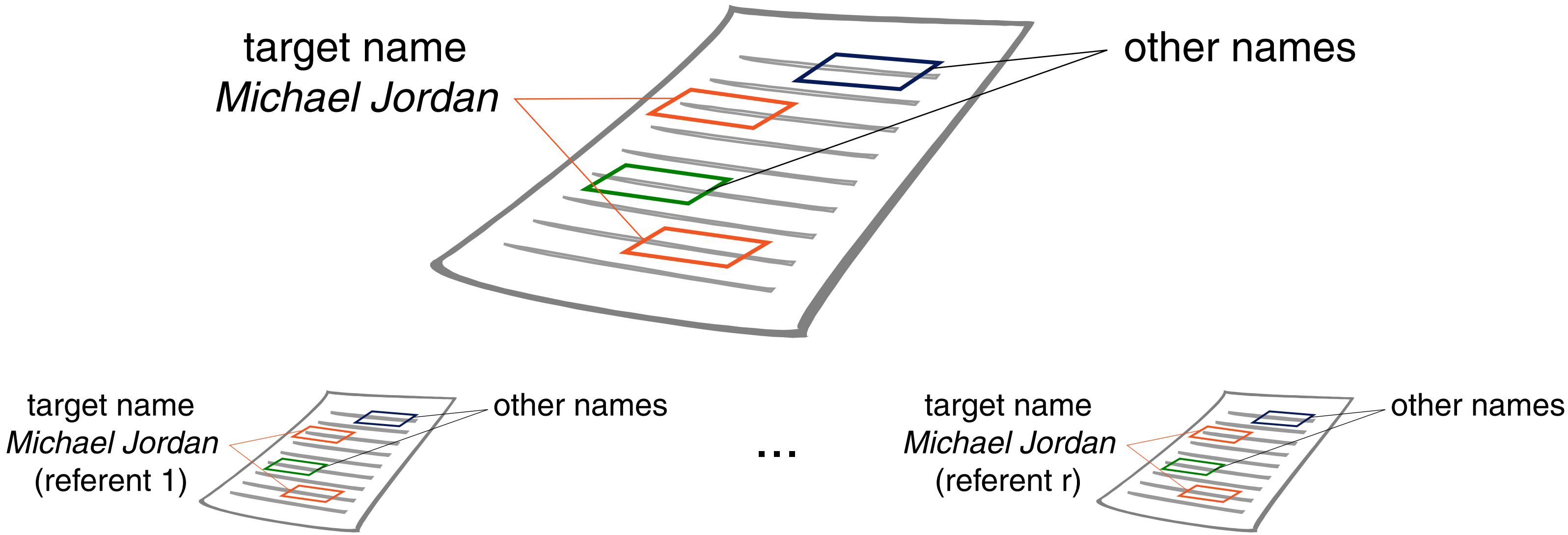


The basket ball player.

The statistician.

Constrained Cluster Analysis

Person Resolution Task



The basket ball player. *The statistician.*

- **Multi-document resolution task:**

Names, Target names:	$N = \{n_1, \ldots, n_l\}$,	$T \subset N$
Referents:	$R = \{r_1, \ldots, r_m\}$,	$\tau : R \to T$, $\lvert R \rvert \gg \lvert T \rvert$
Documents:	$D = \{d_1, \ldots, d_n\}$,	$\nu : D \to \mathcal{P}(N)$, $\lvert \nu(d_i) \cap T \rvert = 1$
A solution:	$\gamma : D \to R$,	s.t. $\tau(\gamma(d_i)) \in \nu(d_i)$

Constrained Cluster Analysis

Person Resolution Task

The basket ball player.

...

The statistician.

- **Facts about the Spock data mining challenge:**

  Target names: $|T| = 44$

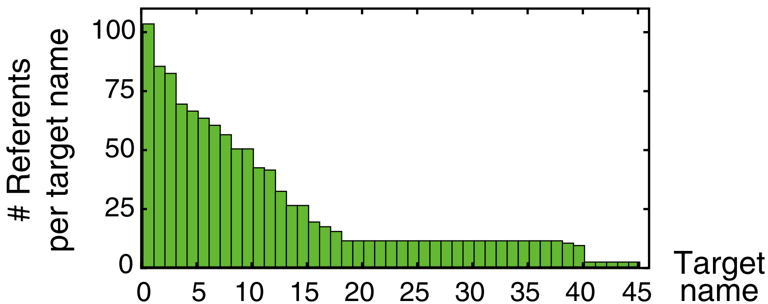
  Referents: $|R| = 1\,101$

  Documents: $|D_{train}| = 27\,000$ (labeled $\approx$ 2.3GB)

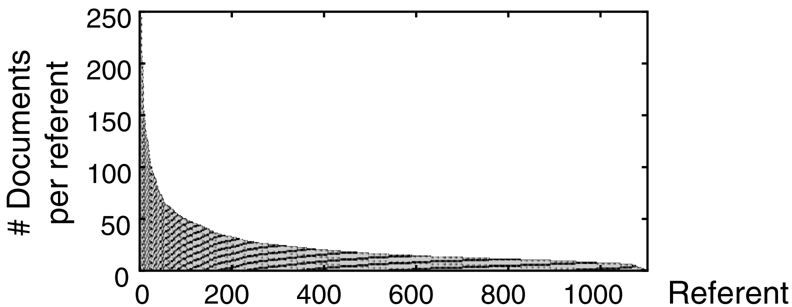
  $|D_{test}| = 75\,000$ (unlabeled $\approx$ 7.8GB)

Constrained Cluster Analysis

Person Resolution Task



- up to 105 referents for a single target name
- about 25 referents on average per target name



- about 23 documents on average per referent

- **Facts about the Spock data mining challenge:**

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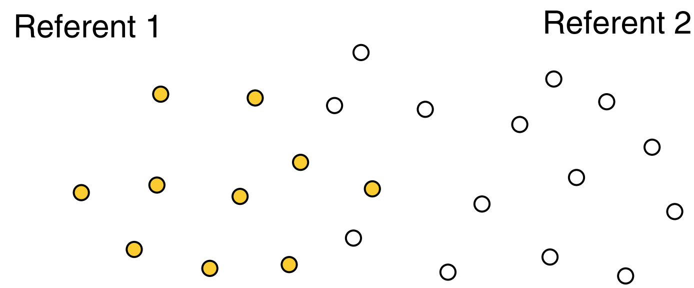
Constrained Cluster Analysis

Applied to Multi-Document Resolution



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   - global and context-based vector space models
   - explicit semantic analysis
   - ontology alignment

2. Learn class memberships (supervised) ➜ logistic regression

3. Find equivalence classes (unsupervised) ➜ cluster analysis:

   (a) adaptive graph thinning

   (b) multiple, density-based cluster analysis

   (c) clustering selection by expected density maximization

Constrained Cluster Analysis

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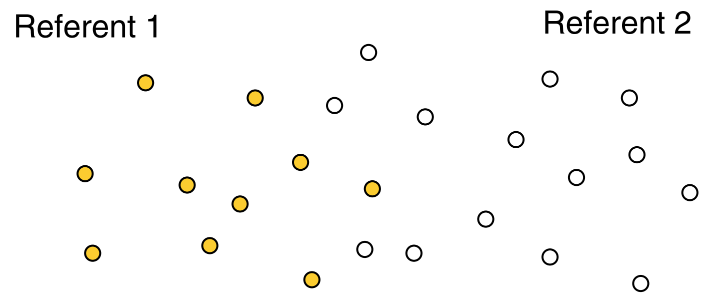

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Constrained Cluster Analysis

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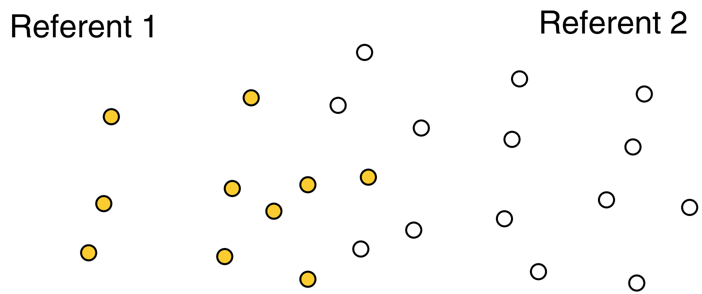

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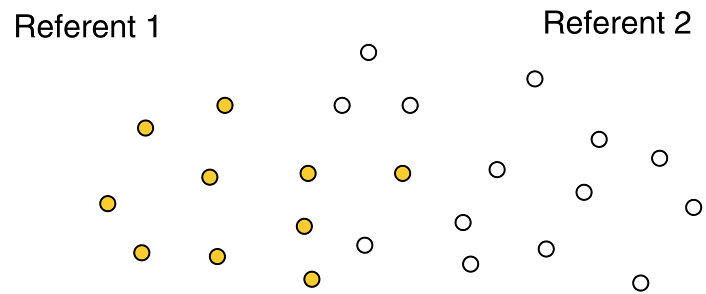

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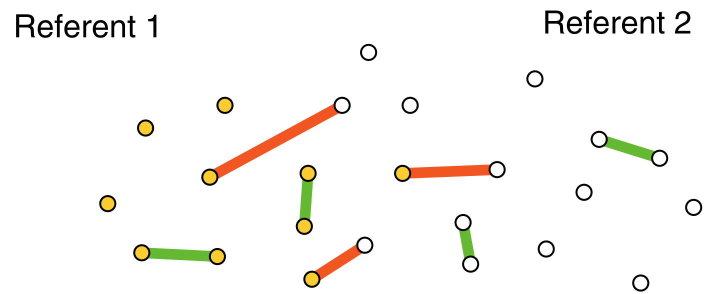

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Constrained Cluster Analysis

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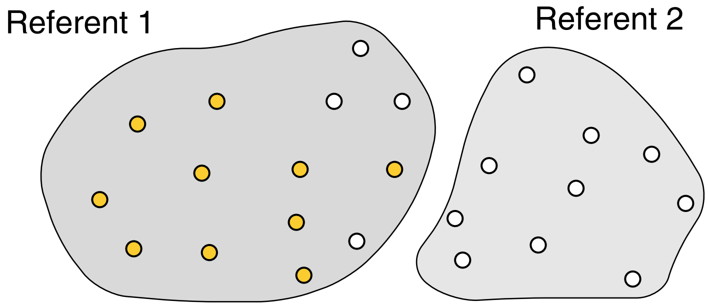

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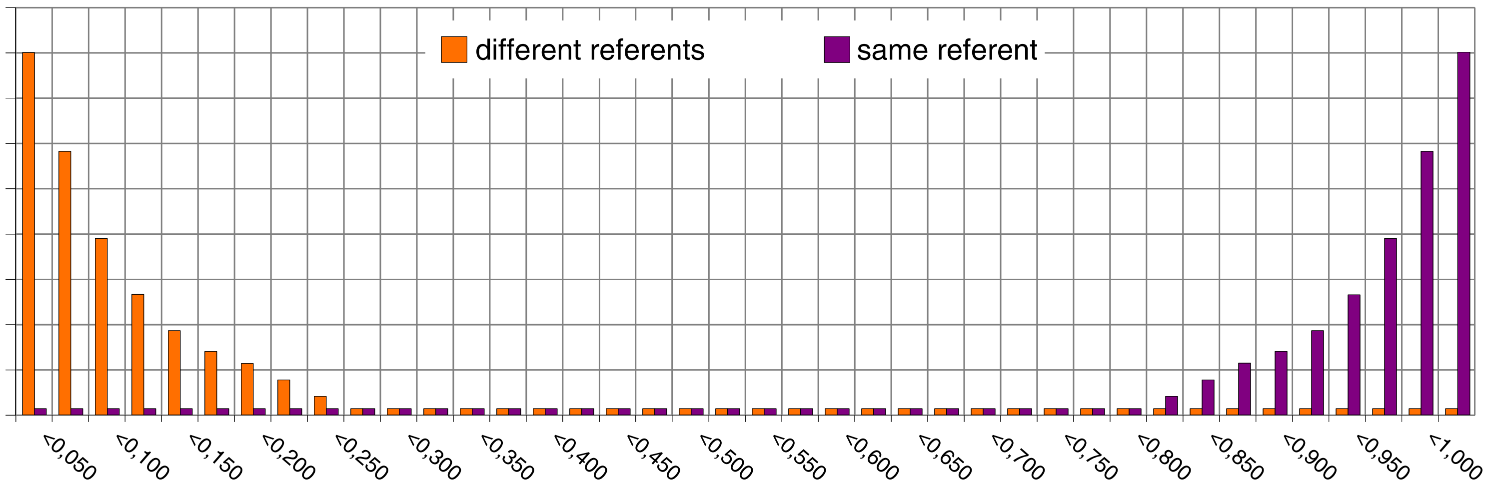
Constrained Cluster Analysis

Idealized Class Membership Distribution over Similarities



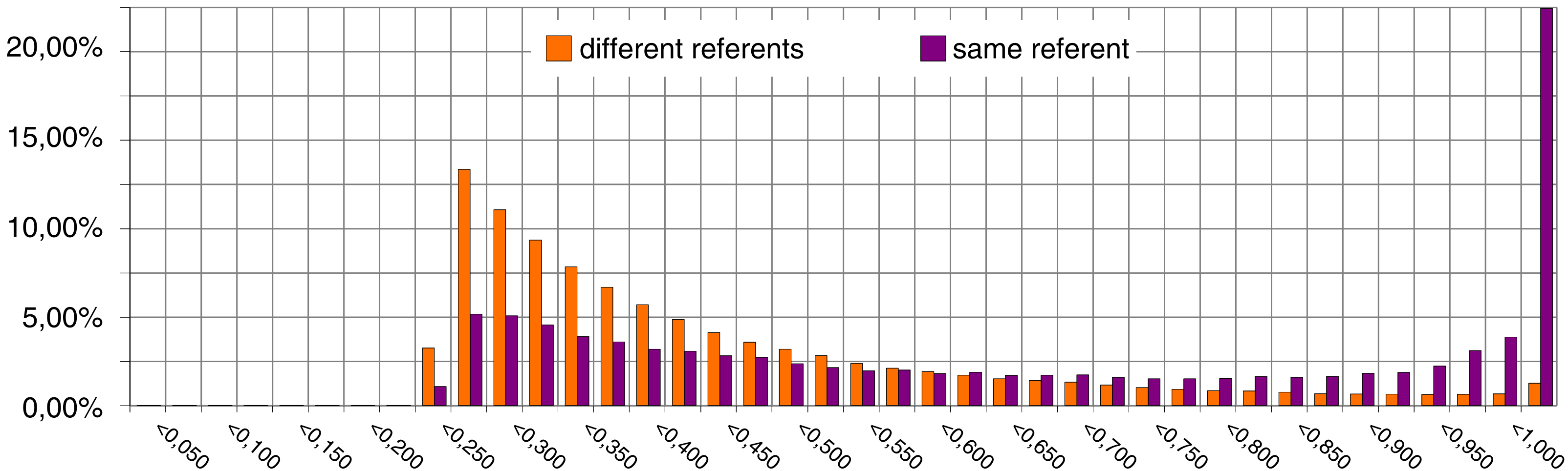
Similarity distributions for document pairs from different referents and same referent.

Logistic regression task:

- sample size: 400 000
- classes imbalance: non-target class : target class ≈ 25:1
- items are drawn uniformly distributed wrt. non-targets and targets
- items are uniformly distributed over the groups of target names

Constrained Cluster Analysis

Membership Distribution under *tf·idf* Vector Space Model

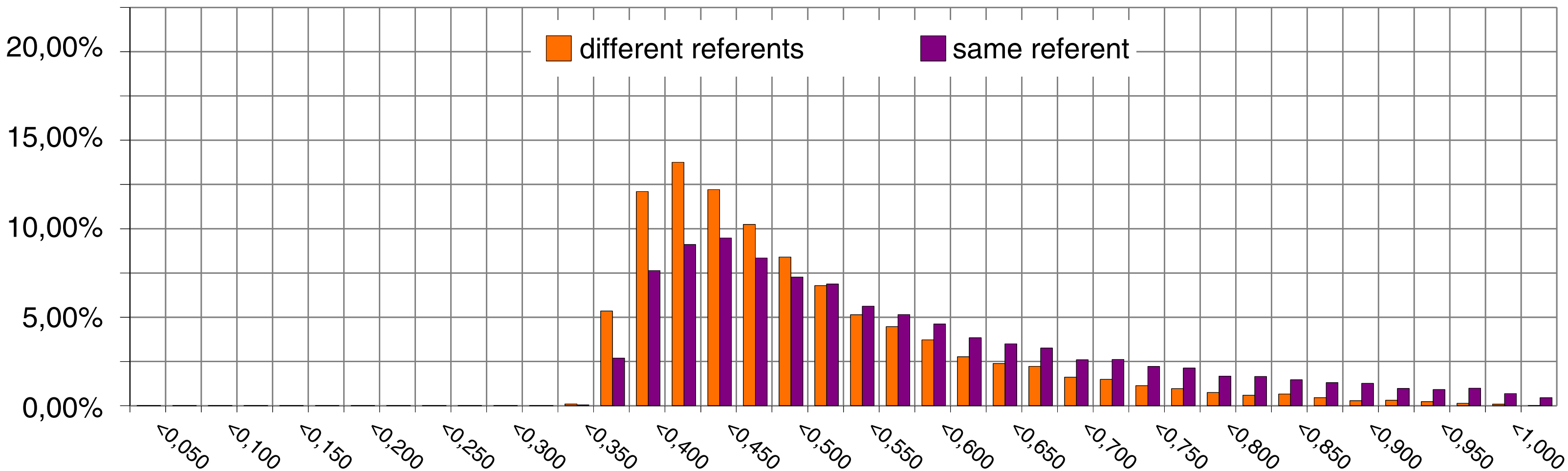


Model details:

- corpus size: 25 000 documents
- dictionary size: 1,2 Mio terms
- stopwords number: 850
- stopword volume: 36%

Constrained Cluster Analysis

Membership Distribution under Context-Based Vector Space Model



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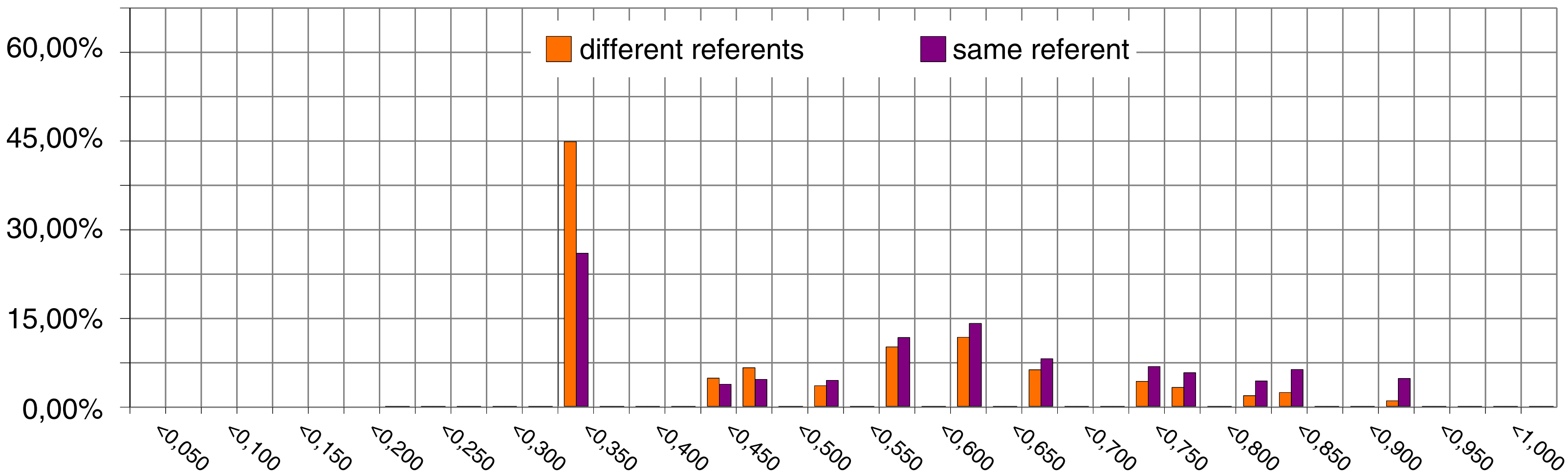
Constrained Cluster Analysis

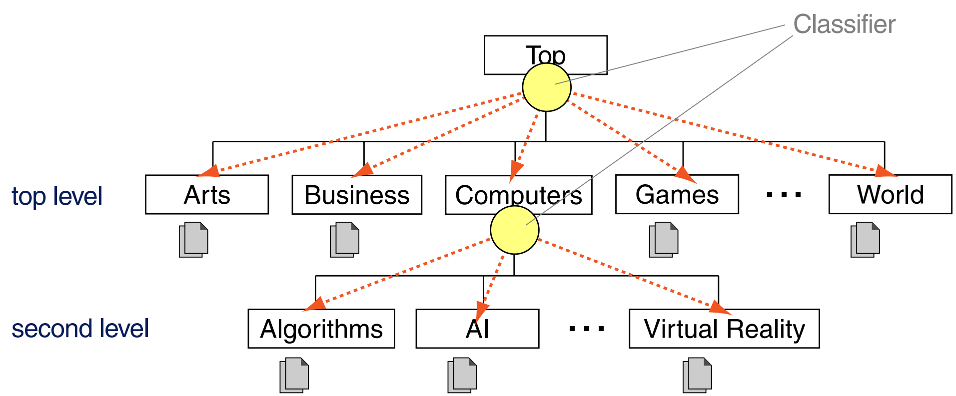
Membership Distribution under Ontology Alignment Model



Model details:

- DMOZ open directory project
- > 5 million documents

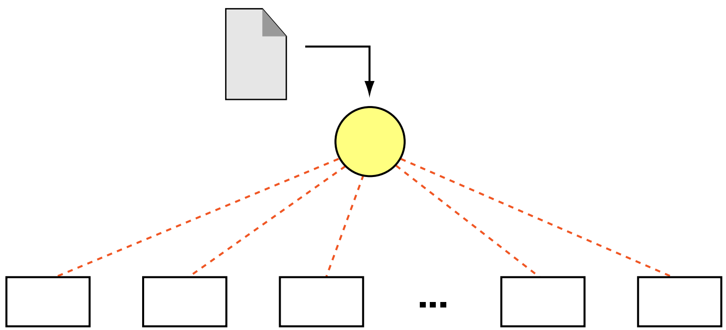
- 12 top-level categories
- 31 second level categories
- ML: hierarchical Bayes
- training set: 100 000 pages



Constrained Cluster Analysis

In-Depth: Multi-Class Hierarchical Classification

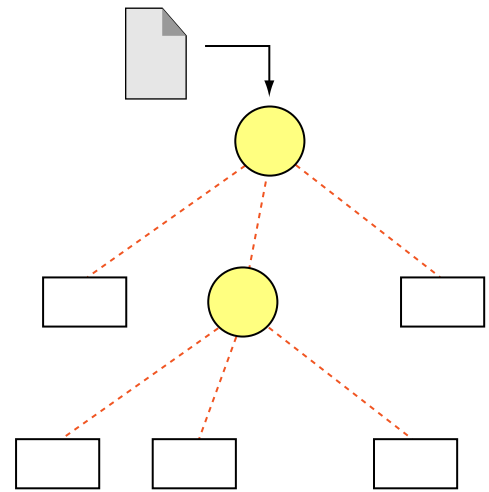
Flat (big-bang) classification



\+ simple realization

– loss of discriminative power with increasing number of categories

Hierarchical (top-down) classification



\+ specialized classifiers (divide and conquer)

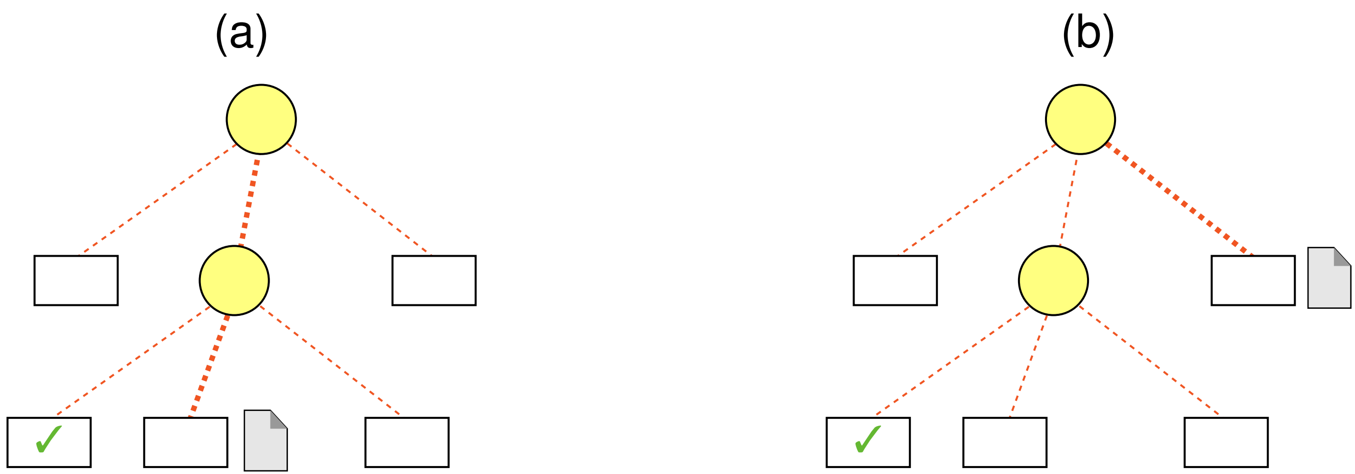
– misclassification at higher levels can never become repaired

Constrained Cluster Analysis

In-Depth: Multi-Class Hierarchical Classification

State of the art of effectiveness analyses:

1. independence assumption between categories
2. neglection of both hierarchical structure and degree of misclassification



Improvements:

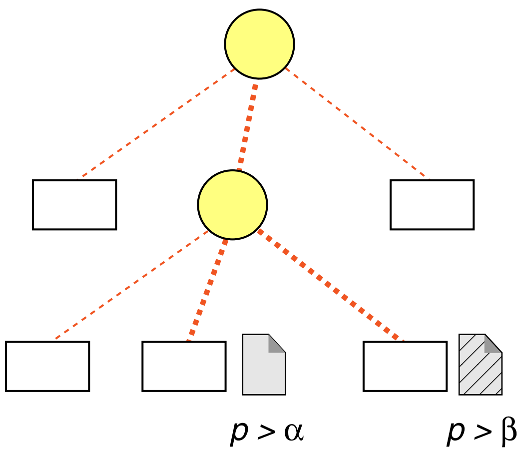
- Consider similarity $\varphi(C_i, C_j)$ between correct and wrong category.
- Consider graph distance $d(C_i, C_j)$ between correct and wrong category.

Constrained Cluster Analysis

In-Depth: Multi-Class Hierarchical Classification

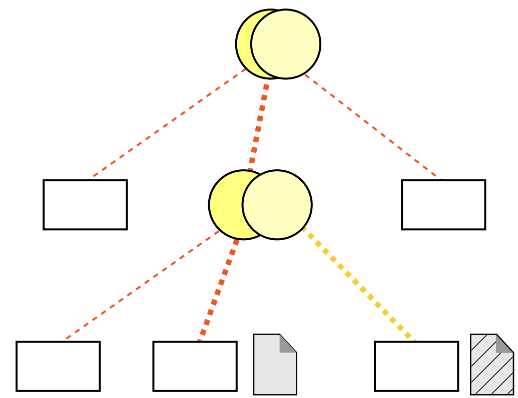
Improvements continued:

Multi-label (multi path) classification



- traverse more than one path and return all labels
- employ probabilistic classifiers with a threshold: split a path or not

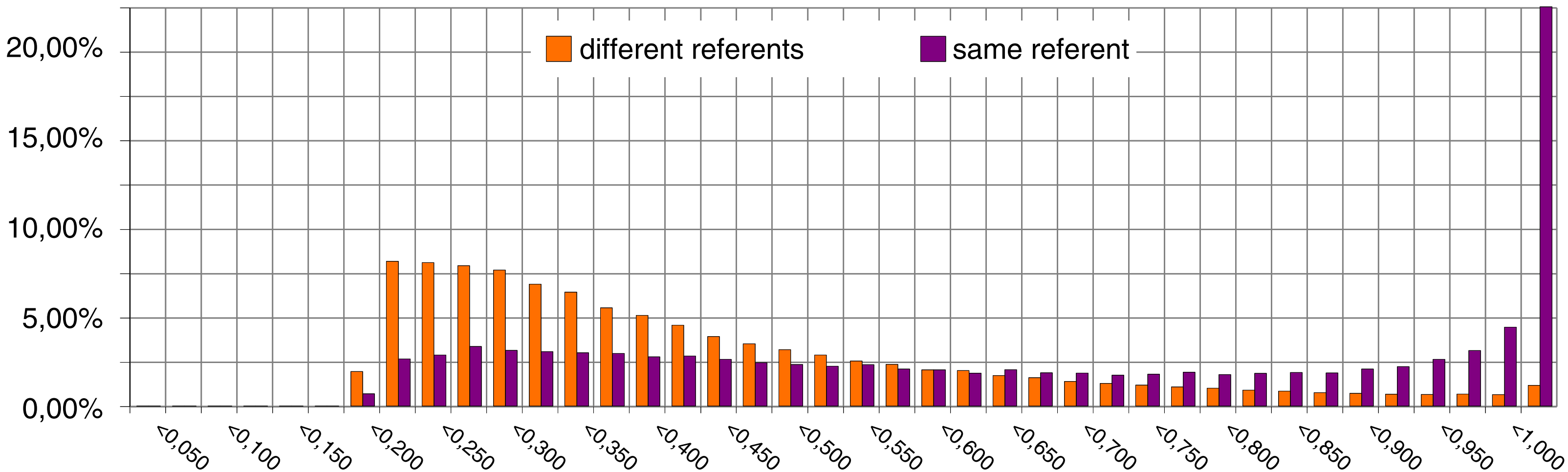
Multi-classifier (ensemble) classification



- classification result is a majority decision
- employ different classifier (different types or differently parameterized)

Constrained Cluster Analysis

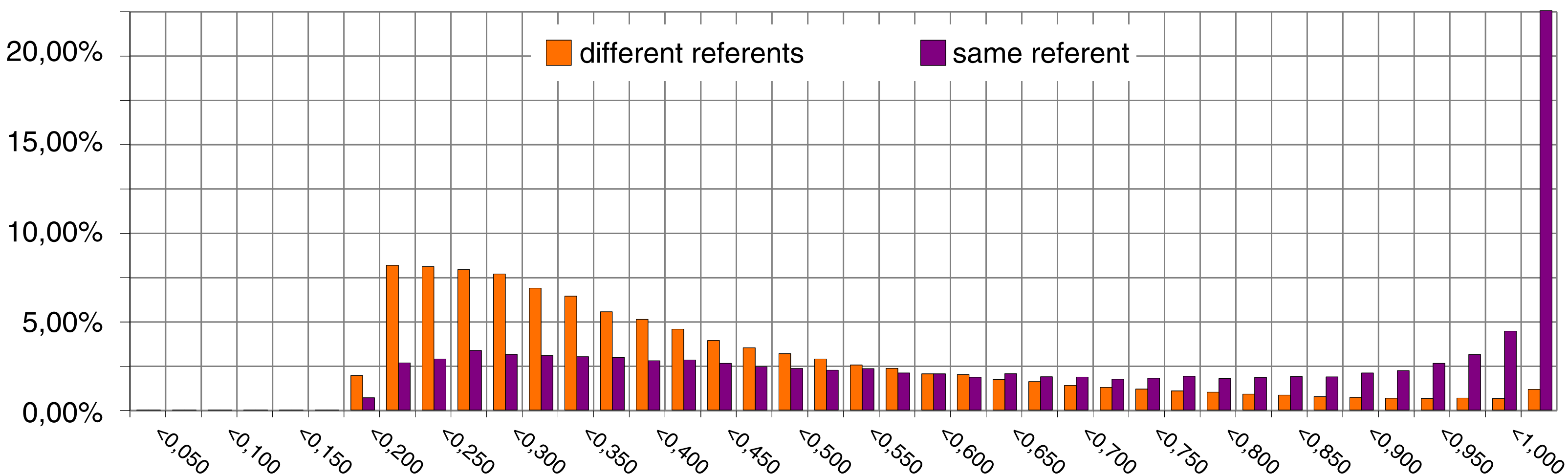
Membership Distribution under Optimized Retrieval Model Combination



Retrieval Model	$F_{1/3}$ -Measure
tf·*idf* vector space	0.39
context-based vector space	0.32
ESA Wikipedia persons	0.30
phrase structure grammar	0.17
ontology alignment	0.15
optimized combination	**0.42**

Constrained Cluster Analysis

Membership Distribution under Optimized Retrieval Model Combination



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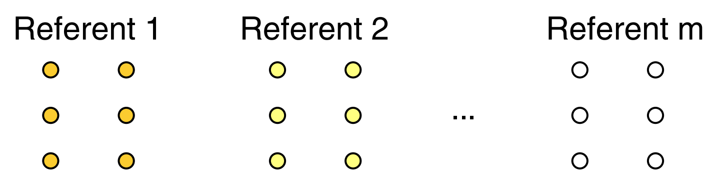

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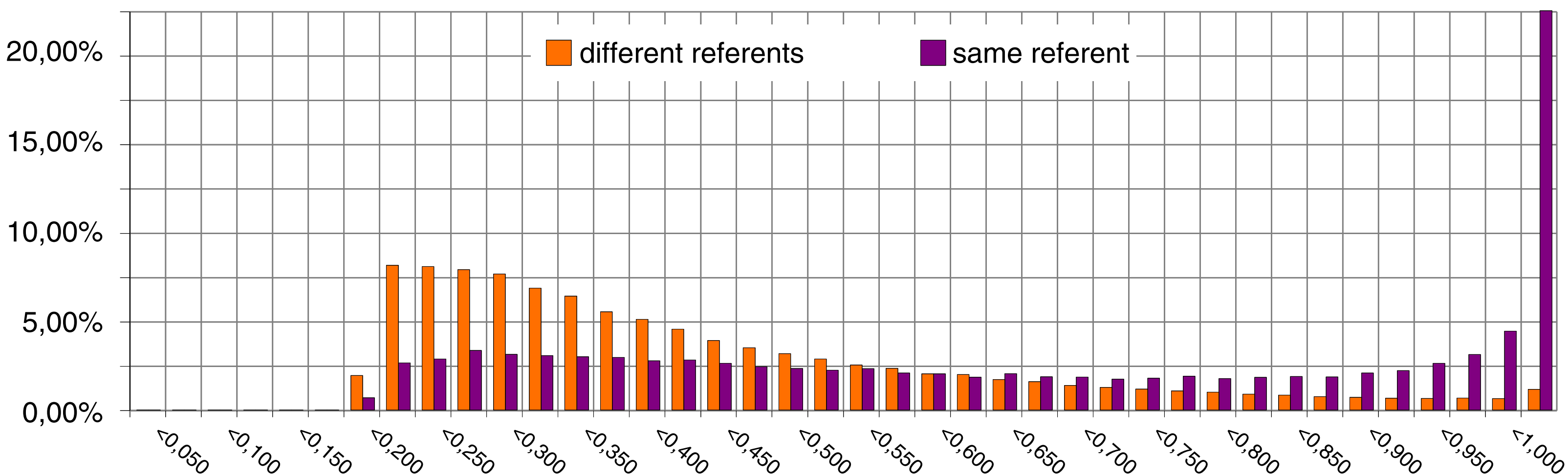

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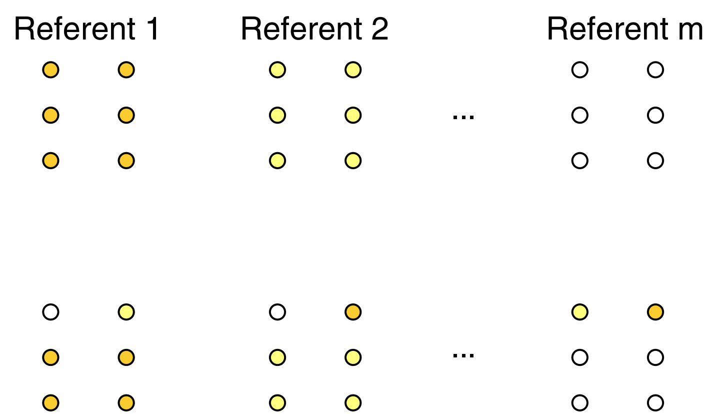

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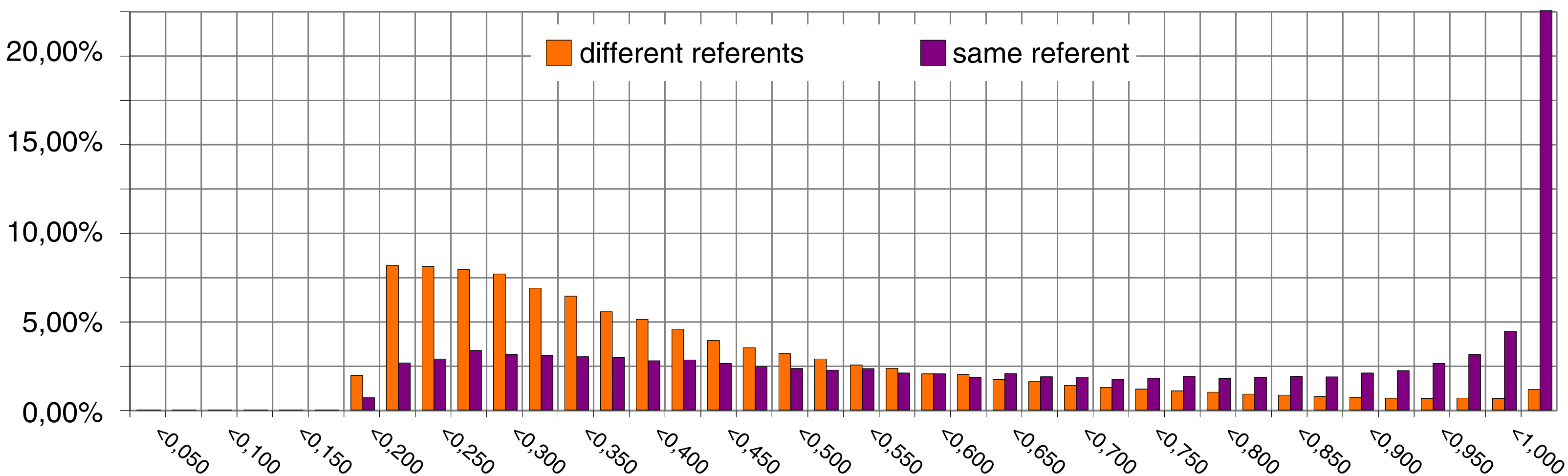

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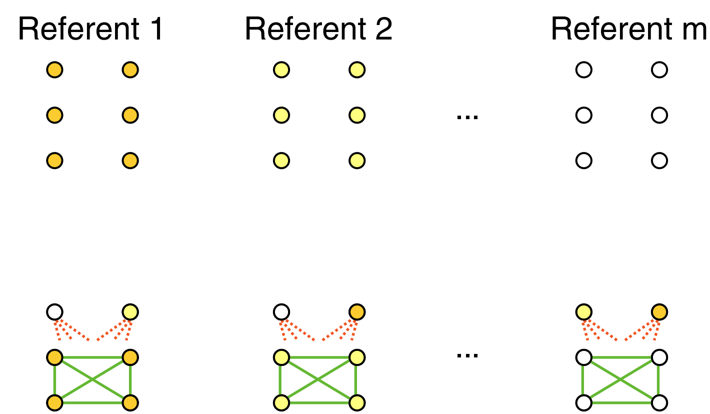

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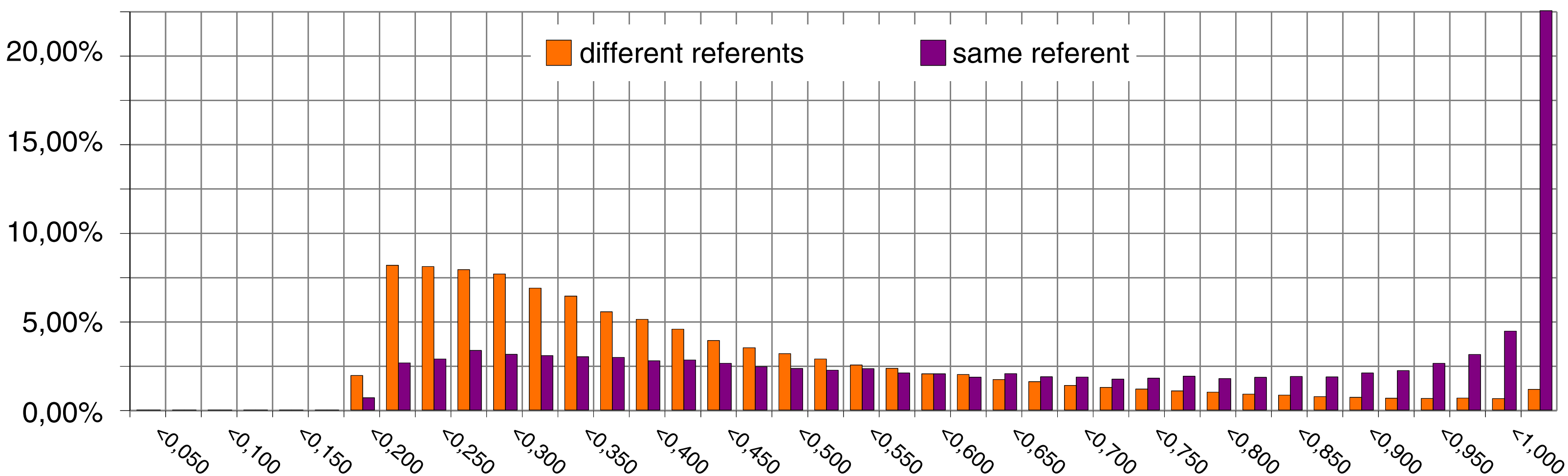
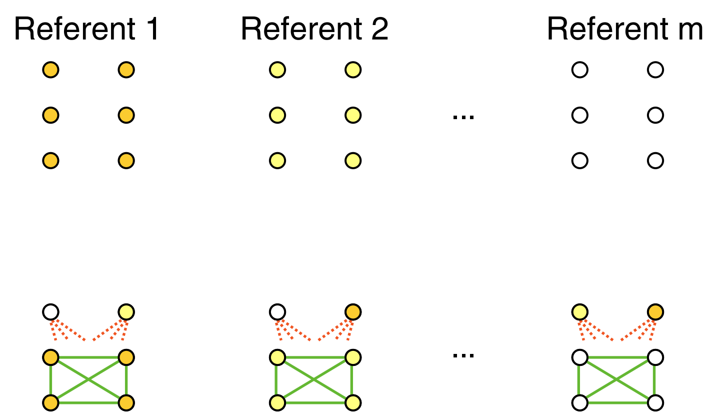


In the example:

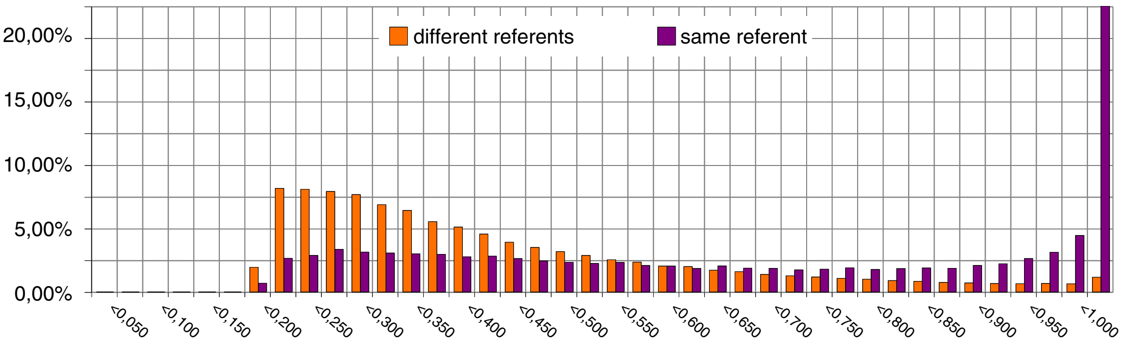
- precision = 0.4
- recall = 0.43
- $F_{1/3}$ = 0.41

(if false negatives are uniformly distributed)

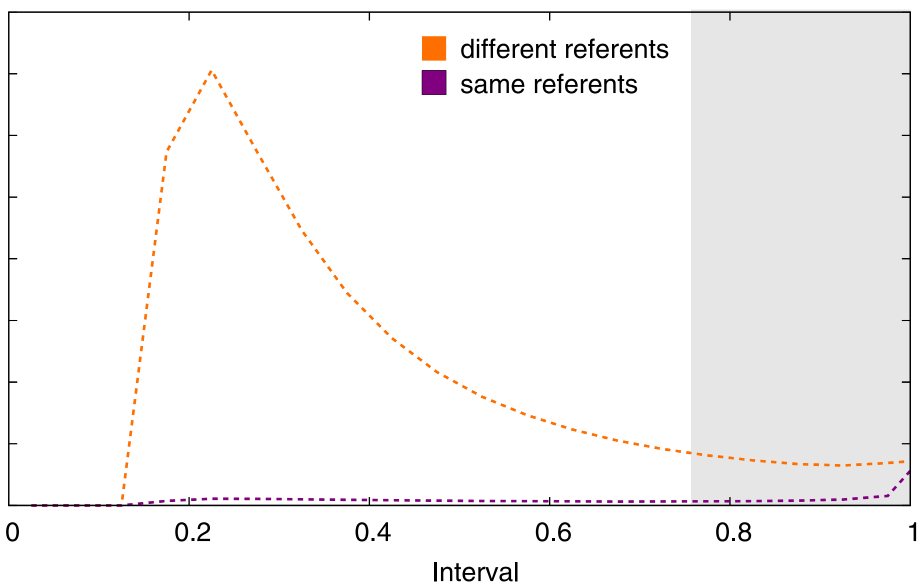


Constrained Cluster Analysis

In-Depth: Analysis of Classifier Effectiveness



Consideration of imbalance:



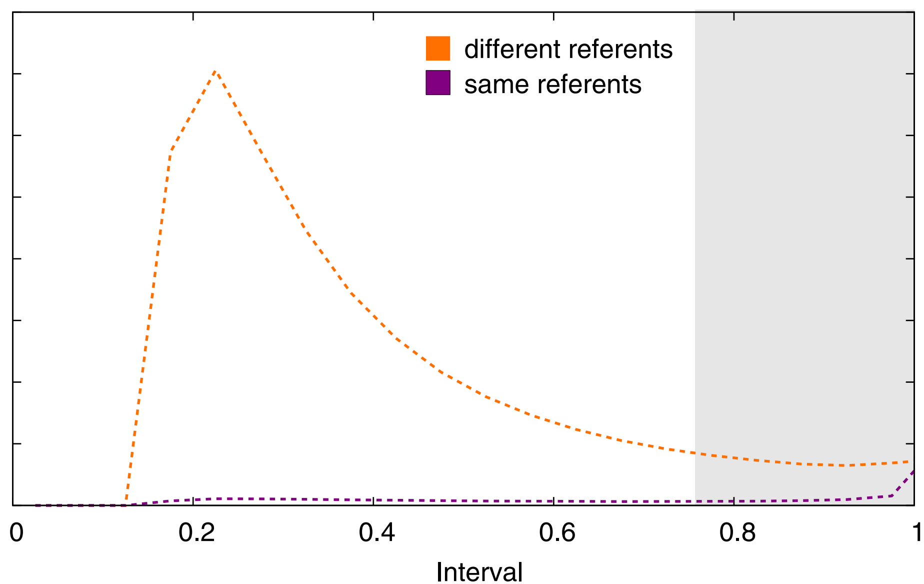
Constrained Cluster Analysis

In-Depth: Analysis of Classifier Effectiveness

- ❑ class imbalance factor (*CIF*) of 25
- ⇒ precision in interval [0.725; 1] for edges between same referents: $\approx$ 0.17

How can $F_{1/3}$ = 0.42 be achieved via cluster analysis?

Consideration of imbalance:



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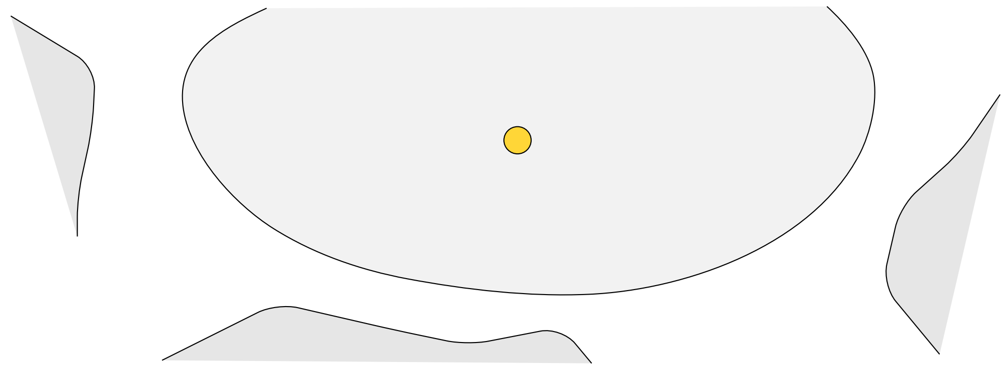


Assumption: uniform distribution of referents over documents (here: 25 clusters with $|C| = 23$)

- $\Rightarrow$ $|TP|$ true 1-similarities per cluster (here: 130 @ threshold 0.725)
- $\Rightarrow$ $\frac{|TP|}{|C|}$ degree of true positives per node (here: 11)
- $\Rightarrow$ $|TP|(\frac{1}{\textit{precision}} - 1)$ false 1-similarities per cluster (here: 760)

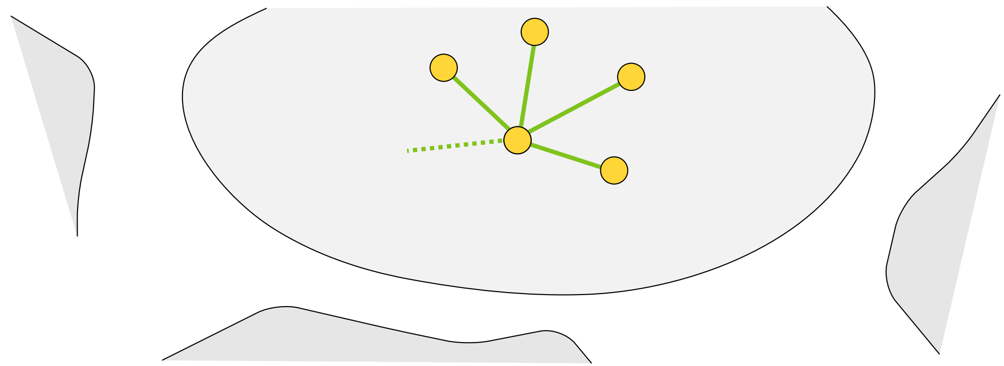
Density-based cluster analysis: effective false positives, FP^*, connect to same cluster

- $\Rightarrow$ analyze $P(|FP^*| > k \mid D, R_{iid})$ (here: $E(|FP^*|) = 2.7$)
- $\Rightarrow$ edge tie factor (*ETF*) specifies the excess of true positives until tie (here: $3 \ldots 5$)

$$ETF = \frac{|TP|}{|C| \cdot E(|FP^*|)}, \qquad \text{effective precision} = \textit{precision} \cdot \frac{CIF}{ETF}$$

Constrained Cluster Analysis

In-Depth: Analysis of Classifier Effectiveness



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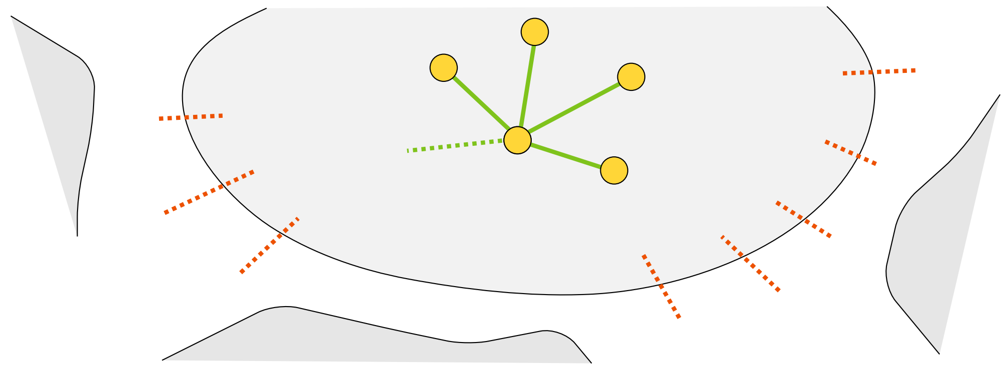

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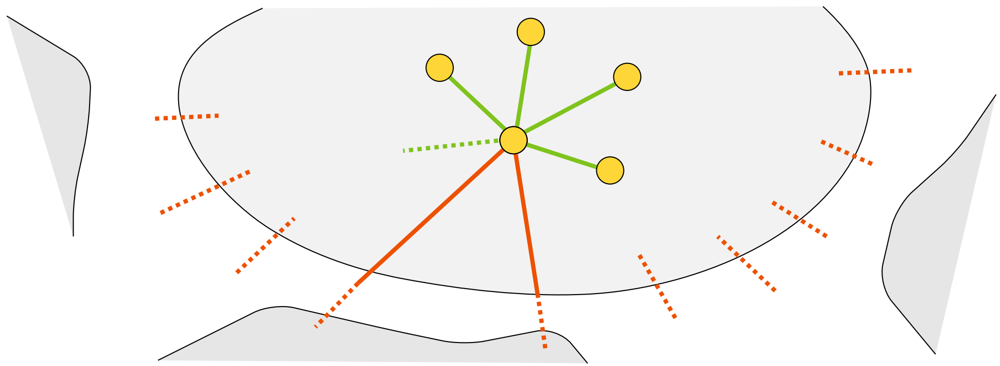

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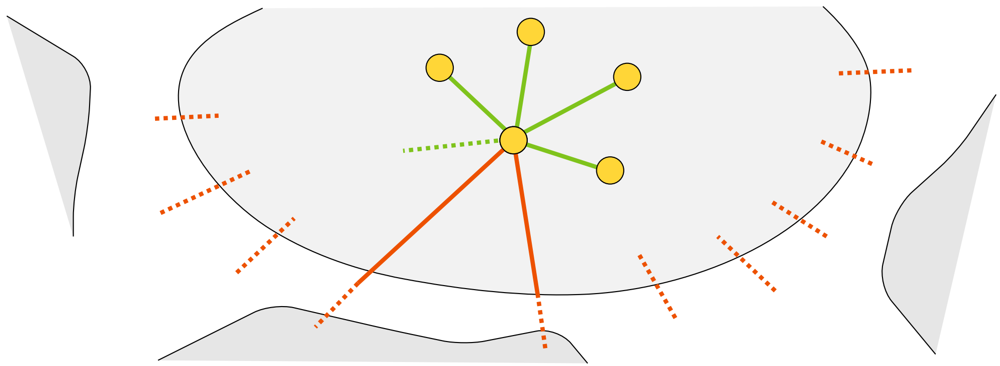

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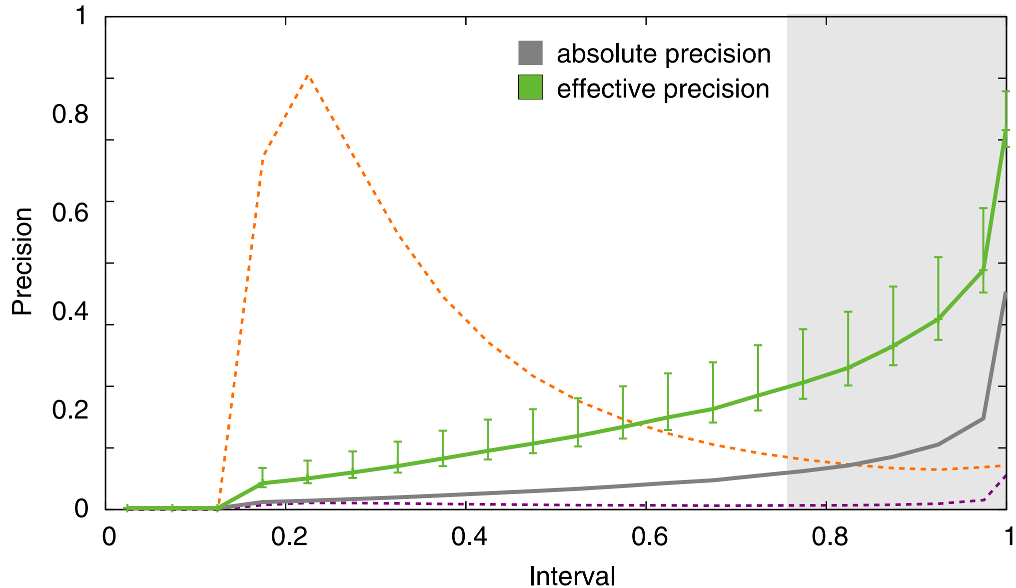

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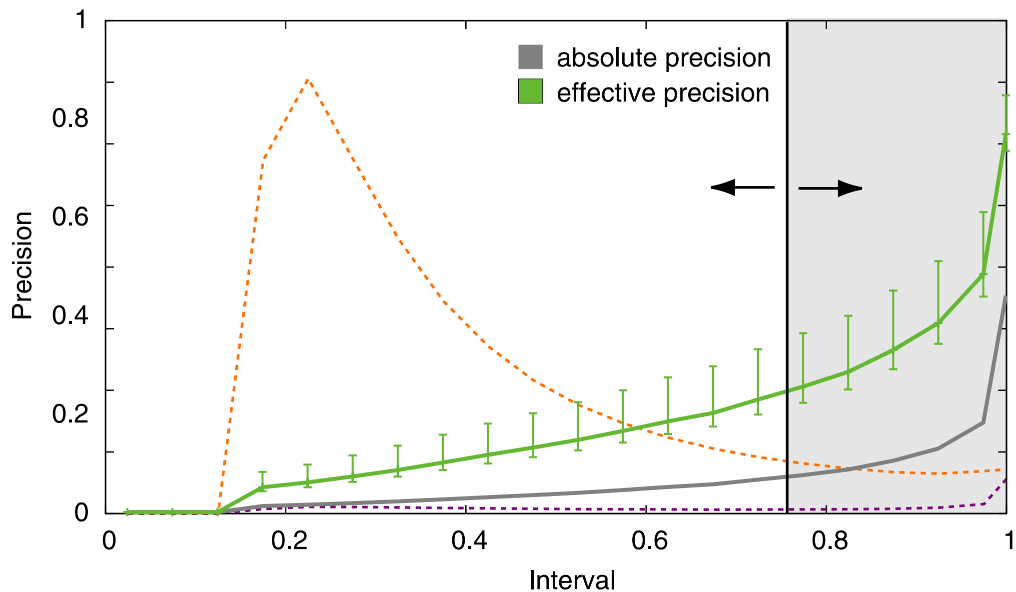
Constrained Cluster Analysis

In-Depth: Analysis of Classifier Effectiveness



Determine optimum similarity threshold for class-membership function:

$$\theta^* = \underset{\theta \in [0;1]}{\text{argmax}} \left\{ \frac{1+\alpha}{\frac{ETF}{precision_\theta \cdot CIF} + \frac{\alpha}{recall_\theta}} \right\}$$

θ^* considers co-variate shift, introduces model formation bias and sample selection bias.

Constrained Cluster Analysis

Model Selection: Our Risk Minimization Strategy

Retrieval Model	$F_{1/3}$ -Measure
tf·idf vector space	0.39
context-based vector space	0.32
ESA Wikipedia persons	0.30
phrase structure grammar	0.17
ontology alignment	0.15
optimized combination	**0.42**
Ensemble cluster analysis	**0.40**

Ensemble cluster analysis: higher bias, better generalization.

(1) Do we speculate on a better fit for D_{test}?

(2) Do we expect a significant covariate shift, more noise, etc. in D_{test}?

Constrained Cluster Analysis
Recap

1. Multi-document resolution can be tackled with constrained cluster analysis.
2. Constraints are derived from labeled examples.
3. Class membership function ties constraints to multiple retrieval models.
4. Advanced density-based clustering technology is key.

Constrained Cluster Analysis

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