

VK Multimedia Information Systems



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Dienstags, 16.00 Uhr c.t., E.2.69



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Addendum: BM25



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- BM-25 weighting based on Roberston et al.
 - df_j is the document frequency of term j
 - dl is the document length
 - $avdl$ is the average document length across the collection
 - k_1 and b are free parameters

$$w_j(\bar{d}, C) := \frac{(k_1 + 1)d_j}{k_1((1 - b) + b\frac{dl}{avdl}) + d_j} \log \frac{N - df_j + 0.5}{df_j + 0.5}$$

$$W(\bar{d}, q, C) = \sum_j w_j(\bar{d}, C) \cdot q_j$$

Information Retrieval Basics: Agenda



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- **Probabilistic Model**
- Other Retrieval Models
- Common Retrieval Methods
 - Query Modification
 - Co-Occurrence
 - Relevance Feedback
- Retrieval Evaluation
- The Lucene Search Engine
- Exercise 02



Probabilistic Model



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- Introduced 1976
 - Robertson & Sparck Jones
 - Binary independence retrieval (BIR) model
 - Based on a probabilistic framework
- Basic idea:
 - Given a user query there is a set of documents, that contains only the relevant ones
 - This set is called the **ideal answer set**

Probabilistic Model: Basic Idea



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- Querying = specification of the ideal answer set.
 - We do not know the specification
 - We just have some terms to reflect it
- Initial guess for the specification:
 - Allows to generate a preliminary probabilistic description of the ideal answer set.
- User interaction then enhances the probabilistic description.

Probabilistic Model



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- For Query q und Document d_j :
 - Probabilistic Model tries to determine the **probability of relevance**
- Assumptions
 - The probability of relevance depends on q and D only
 - The ideal answer set is labeled R
 - R maximizes the probability of relevance
 - Rank: $P(d_j \text{ relevant for } q)/P(d_j \text{ not relevant for } q)$
- Note:
 - No way to compute the probability is given
 - No sample space for the computation is given.

Probabilistic Model: Definition



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Definition Probabilistic Model:

- All weights are binary:
 - $w_{i,j} \in \{0,1\}, w_{i,q} \in \{0,1\}$
- q part of the set of index terms k_i
- Ideal Answer Set is R , not relevant documents: $\bar{R}$
- Probability that d_j is relevant for q :

$$P(R | \vec{d}_j)$$

- Probability that d_j is not relevant for q :

$$P(\bar{R} | \vec{d}_j)$$

Probabilistic Model: Definition



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- Similarity q and d_j :
$$\text{sim}(d_j, q) = \frac{P(R | \vec{d}_j)}{P(\bar{R} | \vec{d}_j)}$$
- Using Bayes' Rule:
$$\text{sim}(d_j, q) = \frac{P(R | \vec{d}_j)}{P(\bar{R} | \vec{d}_j)} = \frac{P(\vec{d}_j | R) \times P(R)}{P(\vec{d}_j | \bar{R}) \times P(\bar{R})}$$
- Probability for randomly selecting d_j out of R $P(\vec{d}_j | R)$
- Probability for a randomly selected document to be in R $P(R)$

Probabilistic Model: Definition



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- As $P(R) = P(\bar{R})$ $sim(d_j, q) \approx \frac{P(\vec{d}_j | R)}{P(\vec{d}_j | \bar{R})}$

- Assuming independent index terms:

$$sim(d_j, q) \approx \frac{(\prod_{g_i(\vec{d}_j)=1} P(k_i | R)) \times (\prod_{g_i(\vec{d}_j)=0} P(\bar{k}_i | R))}{(\prod_{g_i(\vec{d}_j)=1} P(k_i | \bar{R})) \times (\prod_{g_i(\vec{d}_j)=0} P(\bar{k}_i | \bar{R}))}$$

- $P(k_i | R)$ Probability that k_i is in a randomly selected document from R
- $P(\bar{k}_i | R)$ Probability that k_i is not in a randomly selected document from R
- the same for $P(k_i | \bar{R})$, $P(\bar{k}_i | \bar{R})$

Probabilistic Model: Definition



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Simplification based on

- $P(k_i | R) + P(\bar{k}_i | R) = 1$
- Using logarithms
- And ignoring factors constant for all documents:

$$\text{sim}(dj, q) \approx \sum_{i=1}^t w_{i,q} \times w_{i,j} \times \left(\log \frac{P(k_i | R)}{1 - P(k_i | R)} + \log \frac{1 - P(k_i | \bar{R})}{P(k_i | \bar{R})} \right)$$

- Problems
 - R is not known at query time
 - Therefore we cannot calculate $P(k_i | R)$ and $P(k_i | \bar{R})$

Probabilistic Model: Starting Probabilities (i)



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- Assumptions:

- $P(k_i|R)$ is constant for all k_i (e.g. 0.5)
- Distribution of index terms k_i in $\hat{R}$ is $\sim$ distribution of index terms k_i in D

$$P(k_i | R) = 0,5 \quad P(k_i | \bar{R}) = \frac{n_i}{N}$$

- n_i ... number of document containing k_i
- $N = |D|$

Probabilistic Model: Starting Probabilities (ii)



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- Based on these assumptions a ranked list is generated
- Iterative enhancement
 - Automatically, without user interaction
 - V is set of top ranked documents (up to r docs)
 - V_i is subset of V containing k_i
 - These variables also denote the set cardinality.

$$P(k_i | R) = \frac{V_i}{V} \quad P(k_i | \bar{R}) = \frac{n_i - V_i}{N - V}$$

Probabilistic Model: Starting Probabilities (iii)



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- Problems with small numbers, e.g.
 - V is 1, V_i is 0
 - e.g. with constant adjustment factor

$$P(k_i | R) = \frac{V_i + 0,5}{V + 1} \quad P(k_i | \bar{R}) = \frac{n_i - V_i + 0,5}{N - V + 1}$$

- or not constant:

$$P(k_i | R) = \frac{V_i + \frac{n_i}{N}}{V + 1} \quad P(k_i | \bar{R}) = \frac{n_i - V_i + \frac{n_i}{N}}{N - V + 1}$$

Probabilistic Model



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- Advantages:
 - Relevance is decreasing order of probability
 - Therefore partial match is supported
- Disadvantages
 - Initial guessing of R
 - Binary weights
 - Independence assumption of index terms

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Set Theoretic Models: Fuzzy Set Model



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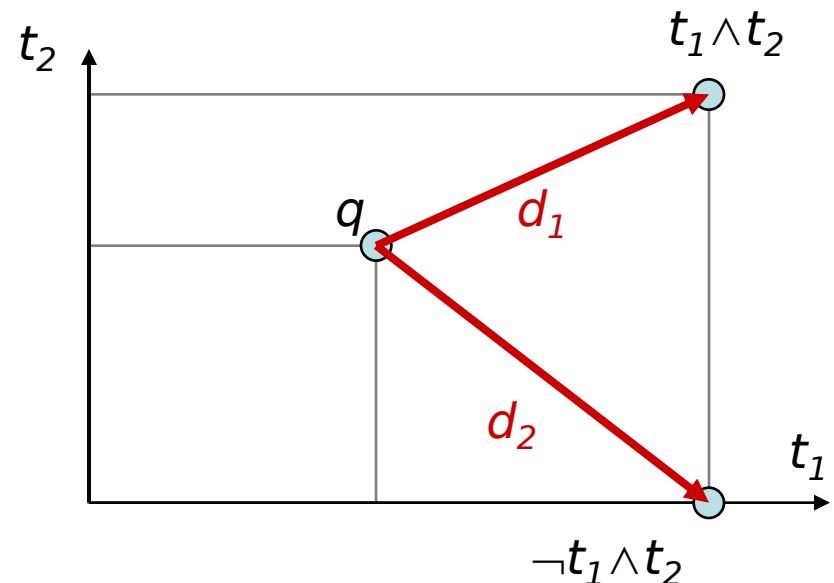
- Each query term defines a fuzzy set
- Each document has a **degree of membership**
 - e.g. d_1 is part of set of term t_1 at 70%
- Done e.g. with query expansion (co-occurrence or thesaurus)

Set Theoretic Models: Extended Boolean Model



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- Incorporates **non binary** weights
- Geometric interpretation:
 - Distance between document vector and
 - desired Boolean state (query)



Algebraic Models: Generalized Vector Space M.



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- Term independence not necessary
- Terms (as dimensions) are not orthogonal and may be linear dependent.
- Smaller linear independent units exist.
 - $m \dots$ minterm
 - Constructed from co-occurrence: 2^t minterms
- Dimensionality a problem
 - Number of active minterms (which actually occur in a document)
 - Depends on the number of documents

Algebraic Models: Latent Semantic Indexing M.



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- Introduced 1988, LSI / LSA
- Concept matching vs. term matching
- Mapping documents & terms to concept space:
 - Fewer dimensions
 - Like clustering

Algebraic Models: Latent Semantic Indexing M.



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- Let M_{ij} be the document term matrix
 - with t rows (terms) and N cols (docs)
- Decompose M_{ij} into $K * S * D^t$
 - K .. matrix of eigenvectors from term-to-term (co-occurrence) matrix
 - D^t .. matrix of eigenvectors from doc-to-doc matrix
 - S .. $r \times r$ diagonal matrix of singular values with $r = \min(t, N)$, the rank of M_{ij}

Algebraic Models: Latent Semantic Indexing M.



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- With $M_{ij} = K * S * D^t \dots$
- Only the s largest singular values from S :
 - Others are deleted
 - Respective columns in K and D^t remain
- $M_s = K_s * S_s * D_s^t \dots$
 - $s < r$ is new rank of M
 - s large enough to fit in all data
 - s small enough to cut out unnecessary details

Algebraic Models: Latent Semantic Indexing M.



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- Reduced doc-to-doc matrix:
 - $M_s^t * M_s$ is $N \times N$ Matrix quantifying the relationship between documents
- Retrieval is based on pseudo-document
 - Let column 0 in M_{ij} be the query
 - Calculate $M_s^t * M_s$
 - First row (or column) gives the relevance

Algebraic Models: Latent Semantic Indexing M.



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- Advantages
 - M even more sparse
 - Retrieval on a “conceptual” level
- Disadvantages
 - Doc-to-doc matrix might be quite big
 - Therefore: Processing time

Example LSA ...



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Example of text data: Titles of Some Technical Memos

- c1: *Human machine interface for ABC computer applications*
- c2: *A survey of user opinion of computer system response time*
- c3: *The EPS user interface management system*
- c4: *System and human system engineering testing of EPS*
- c5: *Relation of user perceived response time to error measurement*

- m1: *The generation of random, binary, ordered trees*
- m2: *The intersection graph of paths in trees*
- m3: *Graph minors IV: Widths of trees and well-quasi-ordering*
- m4: *Graph minors: A survey*

from Landauer, T. K., Foltz, P. W., & Laham, D. (1998). Introduction to Latent Semantic Analysis. *Discourse Processes*, 25, 259-284.

Example LSA ...



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$\{X\} =$

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

from Landauer, T. K., Foltz, P. W., & Laham, D. (1998). *Introduction to Latent Semantic Analysis*. *Discourse Processes*, 25, 259-284.

Example LSA ...



$\{W\} =$

0.22	-0.11	0.29	-0.41	-0.11	-0.34	0.52	-0.06	-0.41
0.20	-0.07	0.14	-0.55	0.28	0.50	-0.07	-0.01	-0.11
0.24	0.04	-0.16	-0.59	-0.11	-0.25	-0.30	0.06	0.49
0.40	0.06	-0.34	0.10	0.33	0.38	0.00	0.00	0.01
0.64	-0.17	0.36	0.33	-0.16	-0.21	-0.17	0.03	0.27
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.30	-0.14	0.33	0.19	0.11	0.27	0.03	-0.02	-0.17
0.21	0.27	-0.18	-0.03	-0.54	0.08	-0.47	-0.04	-0.58
0.01	0.49	0.23	0.03	0.59	-0.39	-0.29	0.25	-0.23
0.04	0.62	0.22	0.00	-0.07	0.11	0.16	-0.68	0.23
0.03	0.45	0.14	-0.01	-0.30	0.28	0.34	0.68	0.18

$\{S\} =$

3.34								
	2.54							
		2.35						
			1.64					
				1.50				
					1.31			
						0.85		
							0.56	
								0.36

$\{P\} =$

0.20	0.61	0.46	0.54	0.28	0.00	0.01	0.02	0.08
-0.06	0.17	-0.13	-0.23	0.11	0.19	0.44	0.62	0.53
0.11	-0.50	0.21	0.57	-0.51	0.10	0.19	0.25	0.08
-0.95	-0.03	0.04	0.27	0.15	0.02	0.02	0.01	-0.03
0.05	-0.21	0.38	-0.21	0.33	0.39	0.35	0.15	-0.60
-0.08	-0.26	0.72	-0.37	0.03	-0.30	-0.21	0.00	0.36
0.18	-0.43	-0.24	0.26	0.67	-0.34	-0.15	0.25	0.04
-0.01	0.05	0.01	-0.02	-0.06	0.45	-0.76	0.45	-0.07
-0.06	0.24	0.02	-0.08	-0.26	-0.62	0.02	0.52	-0.45

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	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	0.16	0.40	0.38	0.47	0.18	-0.05	-0.12	-0.16	-0.09
interface	0.14	0.37	0.33	0.40	0.16	-0.03	-0.07	-0.10	-0.04
computer	0.15	0.51	0.36	0.41	0.24	0.02	0.06	0.09	0.12
user	0.26	0.84	0.61	0.70	0.39	0.03	0.08	0.12	0.19
system	0.45	1.23	1.05	1.27	0.56	-0.07	-0.15	-0.21	-0.05
response	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
time	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
EPS	0.22	0.55	0.51	0.63	0.24	-0.07	-0.14	-0.20	-0.11
survey	0.10	0.53	0.23	0.21	0.27	0.14	0.31	0.44	0.42
trees	-0.06	0.23	-0.14	-0.27	0.14	0.24	0.55	0.77	0.66
graph	-0.06	0.34	-0.15	-0.30	0.20	0.31	0.69	0.98	0.85
minors	-0.04	0.25	-0.10	-0.21	0.15	0.22	0.50	0.71	0.62

[illegible]

Example LSA ...



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Correlations between titles in raw data:

	c1	c2	c3	c4	c5	m1	m2	m3
c2	-0.19							
c3	0.00	0.00						
c4	0.00	0.00	0.47					
c5	-0.33	0.58	0.00	-0.31				
m1	-0.17	-0.30	-0.21	-0.16	-0.17			
m2	-0.26	-0.45	-0.32	-0.24	-0.26	0.67		
m3	-0.33	-0.58	-0.41	-0.31	-0.33	0.52	0.77	
m4	-0.33	-0.19	-0.41	-0.31	-0.33	-0.17	0.26	0.56

0.02
-0.30 0.44

Correlations in two dimensional space:

c2	0.91							
c3	1.00	0.91						
c4	1.00	0.88	1.00					
c5	0.85	0.99	0.85	0.81				
m1	-0.85	-0.56	-0.85	-0.88	-0.45			
m2	-0.85	-0.56	-0.85	-0.88	-0.44	1.00		
m3	-0.85	-0.56	-0.85	-0.88	-0.44	1.00	1.00	
m4	-0.81	-0.50	-0.81	-0.84	-0.37	1.00	1.00	1.00

0.92
-0.72 1.00

Algebraic Models: Neural Network M. / Associative Retrieval



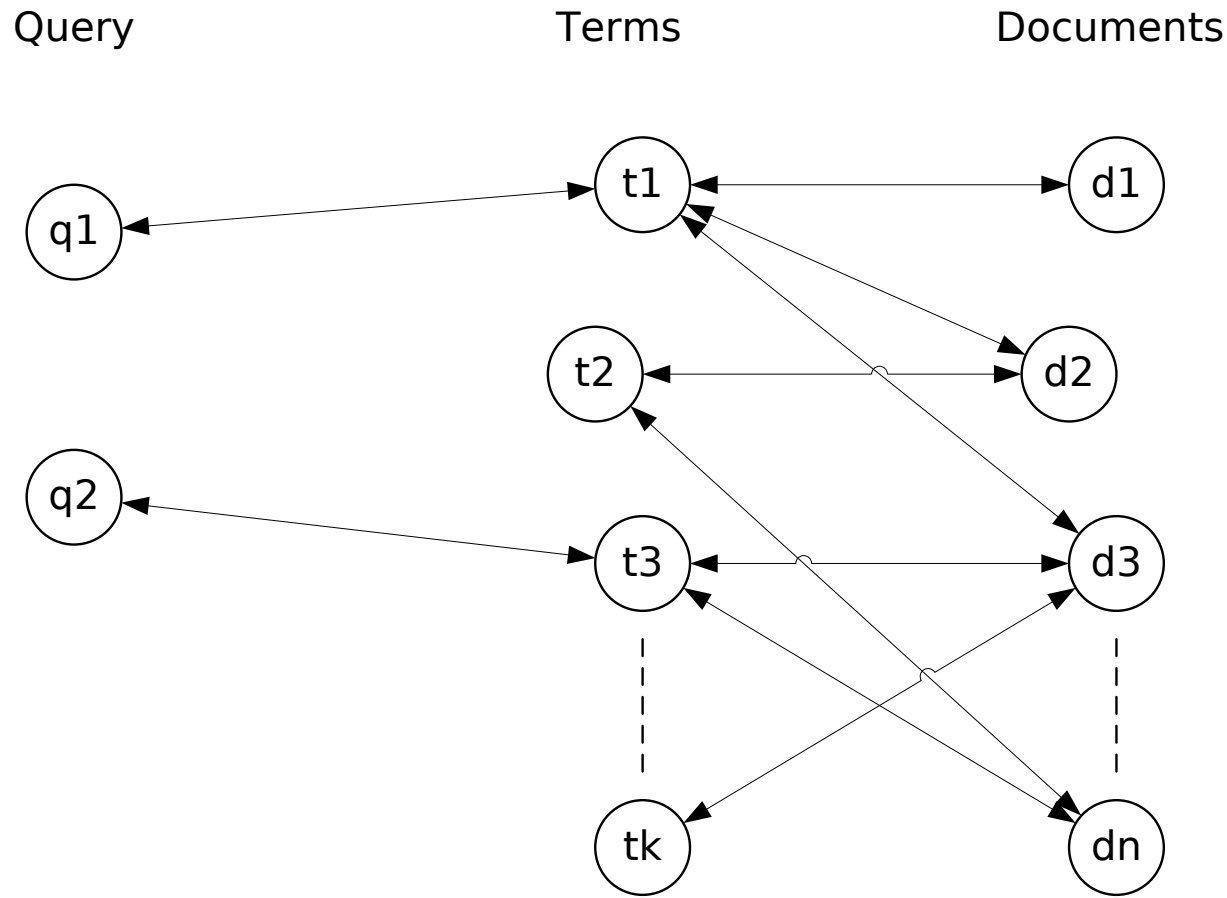
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- Neural Network:
 - Neurons emit signals to other neurons
 - Graph interconnected by synaptic connections
- Three levels:
 - Query terms, terms & documents

Algebraic Models: Neural Network M. / Associative Retrieval



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Algebraic Models: Neural Network M. / Associative Retrieval



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- Query term is “activated”
 - Usually with weight 1
 - Query term weight is used to “weaken” the signal
- Connected terms receive signal
 - Term weight “weakens” the signal
- Connected documents receive signal
 - Different activation sources are “combined”

Algebraic Models: Neural Network M. / Associative Retrieval



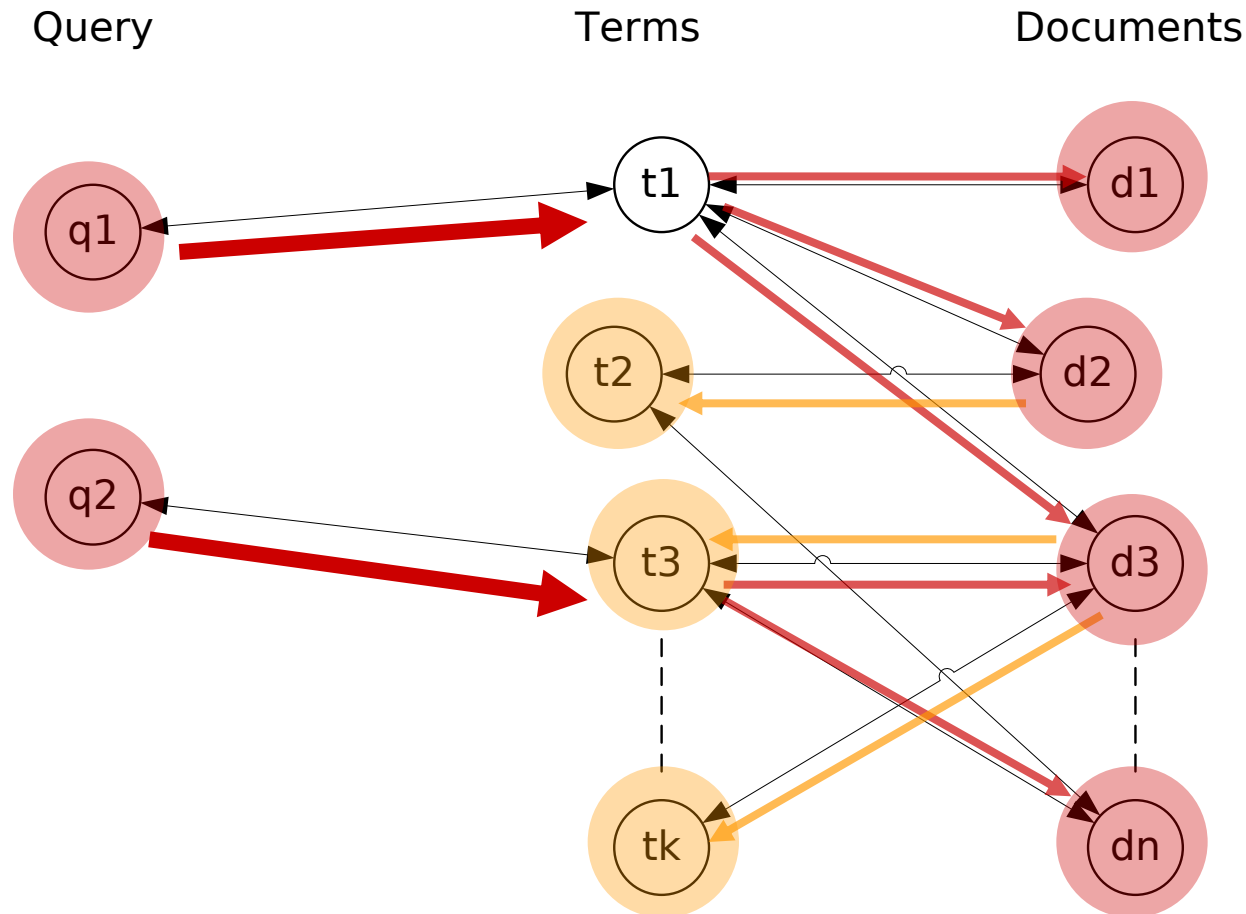
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- First round query terms $\rightarrow$ terms $\rightarrow$ docs
 - Equivalent to vector model
- Further rounds increase retrieval performance

Algebraic Models: Neural Network M. / Associative Retrieval



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Algebraic Models: Neural Network M. / Associative Retrieval



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- Advantages
 - Works on generic digraphs
 - Edges can be created on the fly
 - Nodes can be re-weighted on the fly
- Disadvantages
 - Graph might be too big for main memory
 - Tuning of weights is complicated
 - Selection of appropriate concepts: Back-propagation etc.

Alternative Model: Suffix Tree Retrieval M.



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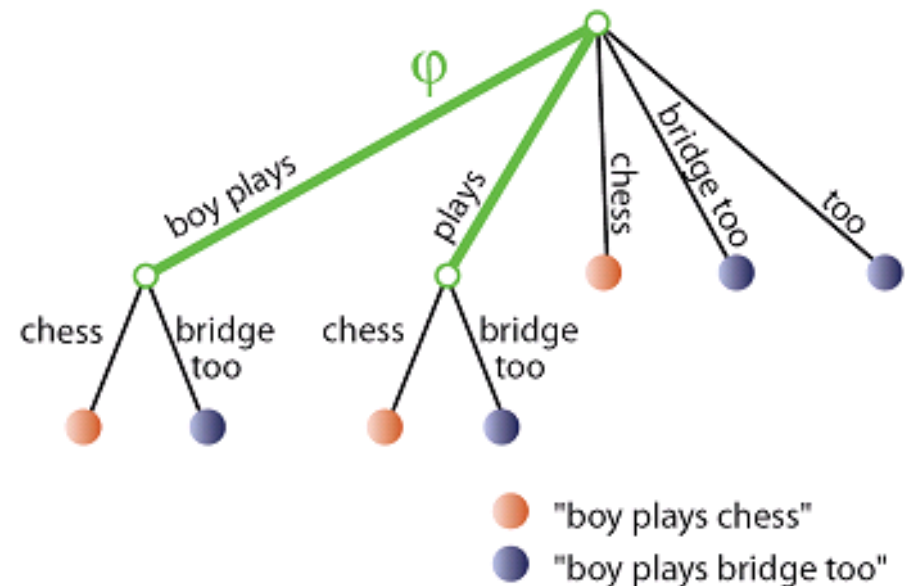
- Operates on document suffixes:
 - “The quick brown fox” has the suffixes:
 - *The quick brown fox, quick brown fox, brown fox, fox*
- Integrates word order
 - Therefore terms are not independent
- Builds a tree with the suffixes

Alternative Model: Suffix Tree Retrieval M.



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- Example
 - d1 = "boy plays chess"
 - d2 = "boy plays bridge too"



Alternative Model: Suffix Tree Retrieval M.



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- Similarity is assessed based on traversed edges in the tree
- Different metrics used as relevance function:
 - Jaccard coefficient
 - TF*IDF weighting

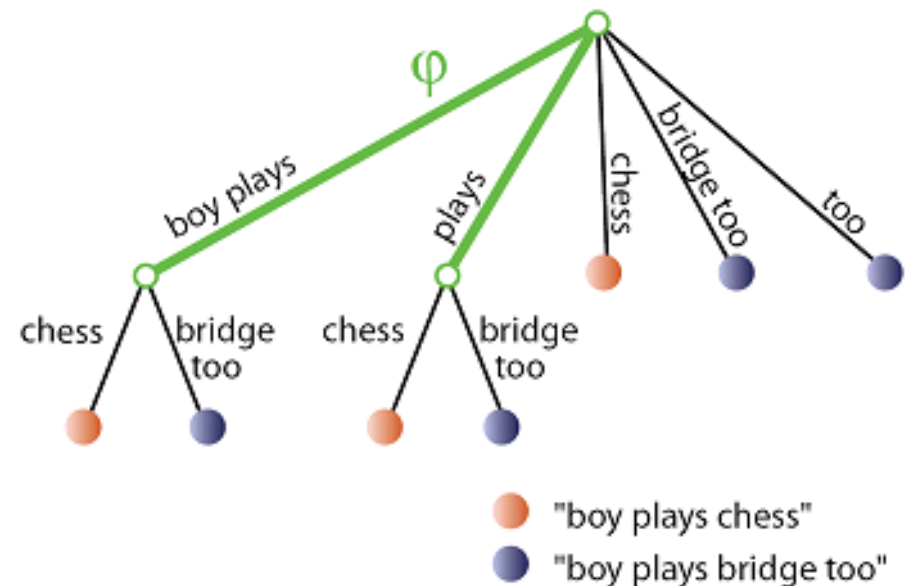
Alternative Model: Suffix Tree Retrieval M.



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- Jaccard coefficient
 - Two document d^+ and d^-
 - Edge sets E^+ , E^- : traversed upon insertion of d^+ , d^-

$$\varphi_{ST} = \frac{|E^+ \cap E^-|}{|E^+ \cup E^-|}$$



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Query Modification



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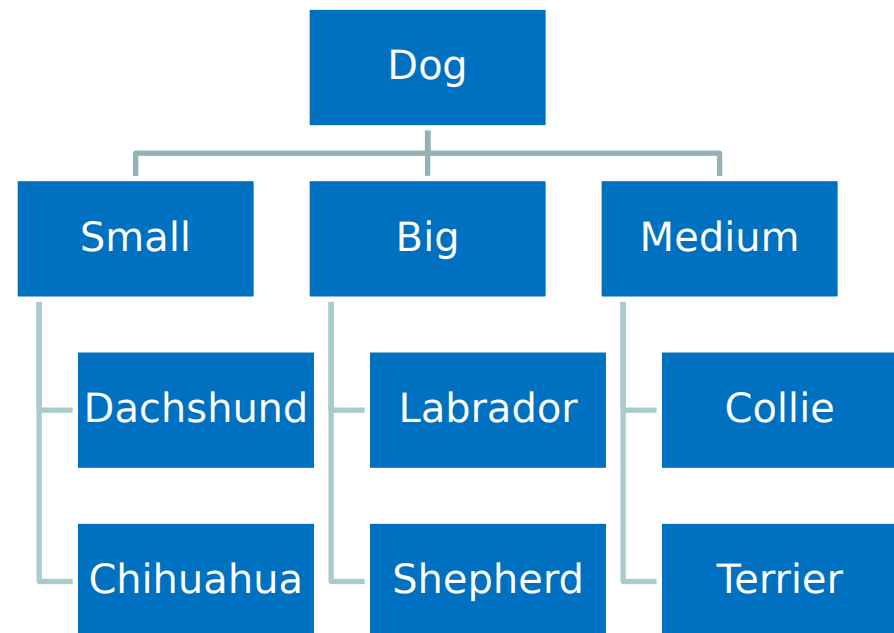
- Query expansion
 - General method to increase either
 - number of results
 - or accuracy
 - Query itself is modified:
 - Terms are added (co-occurrence, thesaurii)

Query Expansion



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- Integrate existing knowledge
 - Taxonomies
 - Ontologies
- Modify query
 - Related terms
 - Narrower terms
 - Broader terms



Term Reweighting



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- To improve accuracy of ranking
- Query term weights are changed
 - Note: no terms are added / removed
 - Result ranking changes

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Co-Occurrence



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- Try to quantify the relation between terms
 - Based on how often they occur together
 - Not based on the position
- Let M_{ij} be the document term matrix
 - with t rows (terms) and N cols (docs)
- M^*M^t ($t \times t$) is the “co-occurrence” matrix

Co-Occurrence: Example



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	d1	d2	d3	d4	d5
computer	7	7	0	8	3
pda	5	1	4	0	3
cellphone	0	1	5	0	0
wlan	6	1	0	0	4
network	1	2	0	6	0

7	5	0	6	1
7	1	1	1	2
0	4	5	0	0
8	0	0	0	6
3	3	0	4	0

Co-Occurrence: Example



<http://www.uni-klu.ac.at>

	computer	pda	cellphone	wlan	network
computer	171	51	7	61	69
pda	51	51	21	43	7
cellphone	7	21	26	1	2
wlan	61	43	1	53	8
network	69	7	2	8	41

Co-Occurrence: Weighting



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- Inverse term frequency: $itf_j = \log(t/t_j)$
 - t_j .. number of distinct index terms in doc d_j
 - t ... number of terms
- $f_{i,j}$... Raw frequency of term i in doc j

$$w_{i,j} = \frac{(0,5 + 0,5 \cdot \frac{f_{i,j}}{\max_j(f_{i,j})}) \cdot itf_j}{\sqrt{\sum_{l=1}^N (0,5 + 0,5 \cdot \frac{f_{i,l}}{\max_l(f_{i,l})})^2 \cdot itf_j^2}}$$

Co-Occurrence & Query Expansion



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	computer	pda	cellphone	wlan	network
computer	171	51	7	61	69
pda	51	51	21	43	7
cellphone	7	21	26	1	2
wlan	61	43	1	53	8
network	69	7	2	8	41

Query: *cellphone*



Query: *cellphone OR pda*

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Relevance Feedback



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- Popular Query Reformulation Strategy:
 - User gets list of docs presented
 - User marks relevant documents
 - In practice ~10-20 docs are presented
 - Query is refined, new search is issued
- Proposed Effect:
 - Query moves more toward relevant docs
 - Away from non relevant docs
 - User does not have to tune herself

Relevance Feedback



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- $D_r \subset D$... set of relevant docs identified by the user
- $D_n \subset D$... set of non relevant docs
- $C_r \subset D$... set of relevant docs
- α, β, γ ... tuning parameters

Relevance Feedback



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- Considering an optimal query
 - Unlikely and therefore hypothetical
- Which vector retrieves C_r best?

$$\vec{q}_{OPT} = \frac{1}{|C_r|} \cdot \sum_{\forall \vec{d}_j \in C_r} \vec{d}_j - \frac{1}{N - |C_r|} \cdot \sum_{\forall \vec{d}_j \notin C_r} \vec{d}_j$$

Relevance Feedback



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$$\text{Rocchio: } \vec{q}_m = \alpha \cdot \vec{q} + \frac{\beta}{|D_r|} \cdot \sum_{\forall \vec{d}_j \in D_r} \vec{d}_j - \frac{\gamma}{|D_n|} \cdot \sum_{\forall \vec{d}_j \in D_n} \vec{d}_j$$

$$\text{Ide: } \vec{q}_m = \alpha \cdot \vec{q} + \beta \cdot \sum_{\forall \vec{d}_j \in D_r} \vec{d}_j - \gamma \cdot \sum_{\forall \vec{d}_j \in D_n} \vec{d}_j$$

$$\text{Ide-Dec-Hi: } \vec{q}_m = \alpha \cdot \vec{q} + \beta \cdot \sum_{\forall \vec{d}_j \in D_r} \vec{d}_j - \gamma \max_{\text{non-relevant}}(\vec{d}_j)$$

Relevance Feedback



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- Rochio
 - Based on q_{OPT} , α was 1 in original idea
- Ide
 - $\alpha=\beta=\gamma=1$ in original idea
- Ide-Dec-Hi
 - $\max_{\text{non-relevant}} \dots$ highest ranked doc of D_n
- All three techniques yield similar results ...

Relevance Feedback



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- Evaluation issues:
 - Boosts retrieval performance
 - Relevant documents are ranked top
 - But: Already marked by the user
- Evaluation remains complicated issue

Information Retrieval Basics: Agenda



<http://www.uni-klu.ac.at>

- Probabilistic Model
- Other Retrieval Models
- Common Retrieval Methods
 - Query Modification
 - Co-Occurrence
 - Relevance Feedback
- **Retrieval Evaluation**
- The Lucene Search Engine
- Exercise 02

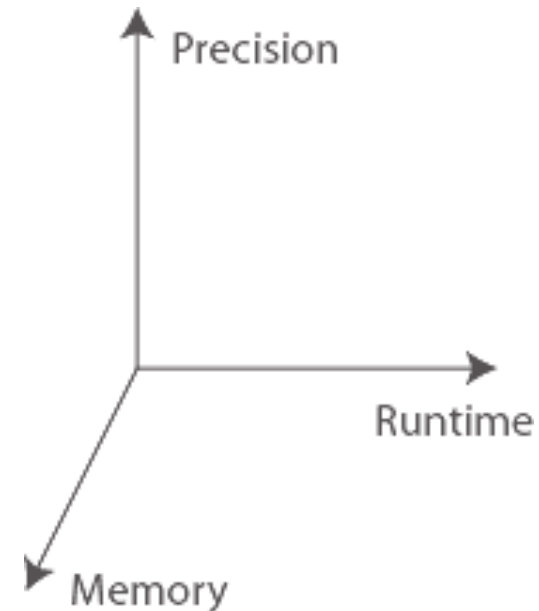


Retrieval Evaluation: Motivation



<http://www.uni-klu.ac.at>

- Compare **objectively** different
 - Search engines
 - Models & Weighting Schemes
 - Methods & Techniques
- Scope
 - Academic
 - Commercial & Industrial
- Different aspects
 - Runtime, Retrieval performance



Retrieval Evaluation



<http://www.uni-klu.ac.at>

- Comparability issues:
 - Test collections
 - Experts assessing retrieval performance
 - Metrics
 - What's good? / What's bad?
- Overall problem:
 - What is relevant?

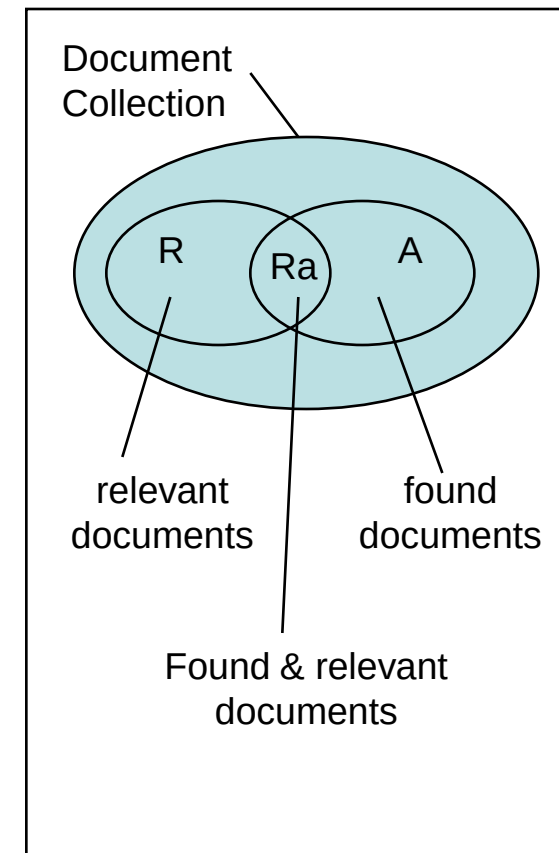
Metrics: Precision & Recall



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Within a document collection D
with a given query q

- $|R|$.. num. of relevant docs
- $|A|$.. num. of found docs
- $|R_a|$.. num. found & relevant



Metrics: Precision



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$$\text{Precision} = \frac{|Ra|}{|A|} = \frac{\text{found relevant docs}}{\text{found docs}}$$

- Gives % how many of the actual found documents have been relevant
- Between 0 and 1
 - Optimum: 1 ... all found docs are relevant

Metrics: Recall



<http://www.uni-klu.ac.at>

$$\text{Recall} = \frac{|Ra|}{|R|} = \frac{\text{found relevant docs}}{\text{relevant docs}}$$

- Gives % how many of the actual relevant documents have been found
- Between 0 and 1
 - Optimum: 1 ... all relevant docs are found

Metrics: Precision & Recall



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- With a query only 1 document has been found, but this one is relevant (100 would be relevant):
 - Precision & Recall
 - **Precision = 1**
 - **Recall = 0,01**

Metrics: Precision & Recall



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- With a query all documents of D have been found (5% of D would be relevant)
 - Precision & Recall?
 - **Precision = 0,05**
 - **Recall = 1**

Example



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- $D = \{D00, D01, \dots D99\}$
- Query 1:
 - Result Set 1: **$\{D2, D14, D25, D76, D84, D98\}$**
 - Relevant Docs $\{D1, D2, D14, D22, D23, D25, D84, D89, D90, D98\}$
- Query 2:
 - Result Set 1: **$\{D10, D14, D60, D63, D77, D95\}$**
 - Relevant Docs $\{D10, D14\}$

Recall vs. Precision Plot



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- Assumption:
 - Result list is sorted by descending relevance
 - User investigates result list linearly
 - Precision and Recall change
- Approach:
 - Map different states to graph

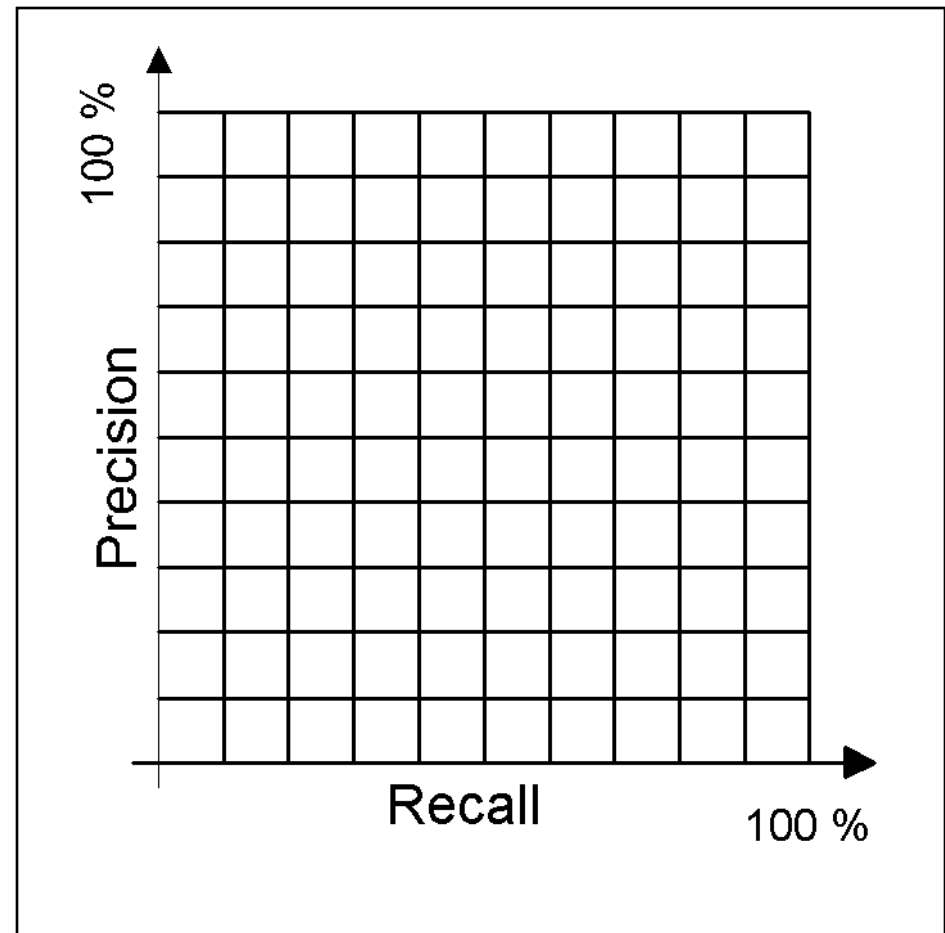
Recall vs. Precision Plot



<http://www.uni-klu.ac.at>

01. d123 *	06. D9 *	11. d38
02. d84	07. d511	12. d48
03. d56 *	08. d129	13. d250
04. d6	09. d187	14. d113
05. d8	10. d25 *	15. d3 *

$R_q = \{d3, d5, d9, d25, d39, d44, d56, d71, d89, d123\} \rightarrow 10$



Recall vs. Precision Plot

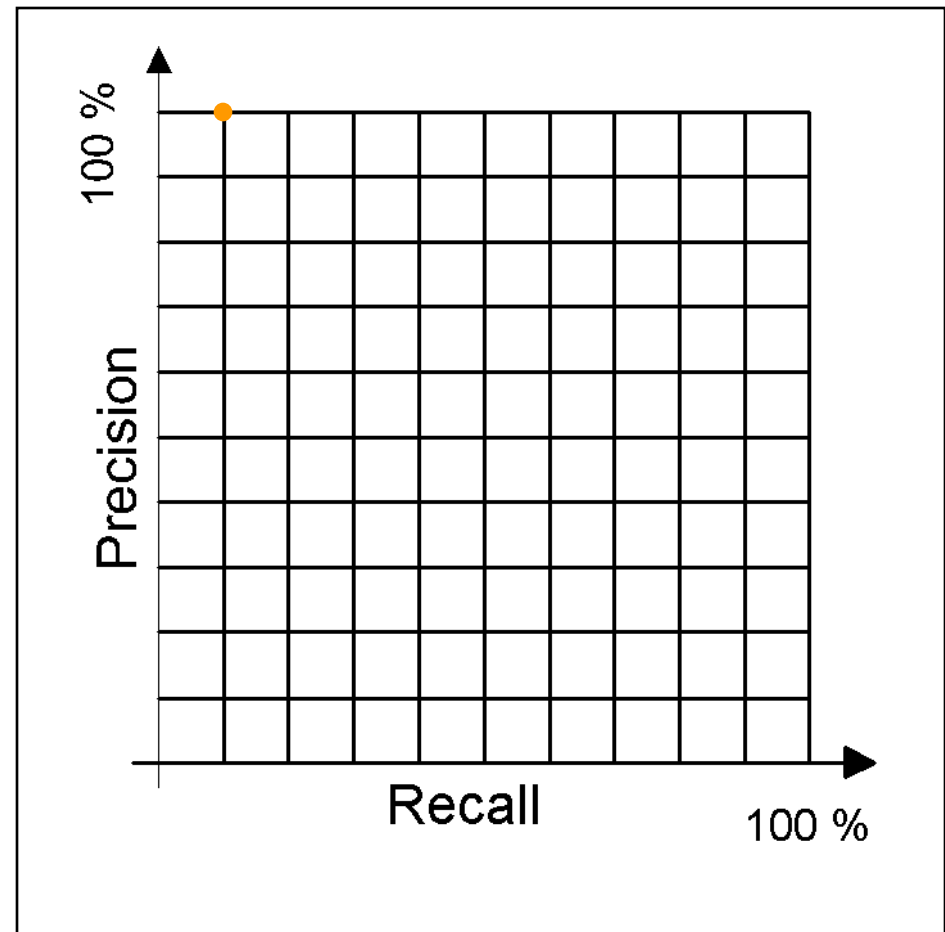


<http://www.uni-klu.ac.at>

- | | | |
|------------|-----------|----------|
| 01. d123 * | 06. D9 * | 11. d38 |
| 02. d84 | 07. d511 | 12. d48 |
| 03. d56 * | 08. d129 | 13. d250 |
| 04. d6 | 09. d187 | 14. d113 |
| 05. d8 | 10. d25 * | 15. d3 * |

$$\text{Recall} = \frac{|Ra|}{R} = \frac{1}{10}$$

$$\text{Precision} = \frac{|Ra|}{A} = \frac{1}{1}$$



Recall and Precision

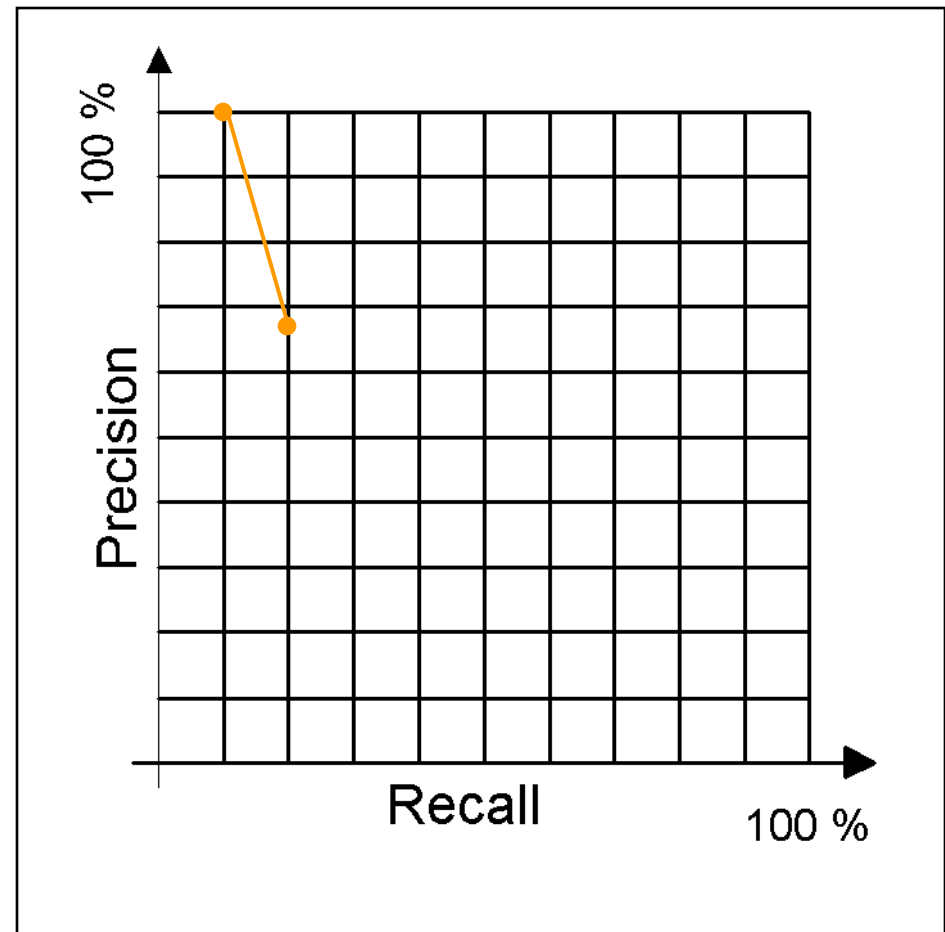


<http://www.uni-klu.ac.at>

01. d123 *	06. D9 *	11. d38
02. d84	07. d511	12. d48
03. d56 *	08. d129	13. d250
04. d6	09. d187	14. d113
05. d8	10. d25 *	15. d3 *

$$\text{Recall} = \frac{|Ra|}{R} = \frac{2}{10}$$

$$\text{Precision} = \frac{|Ra|}{A} = \frac{2}{3}$$

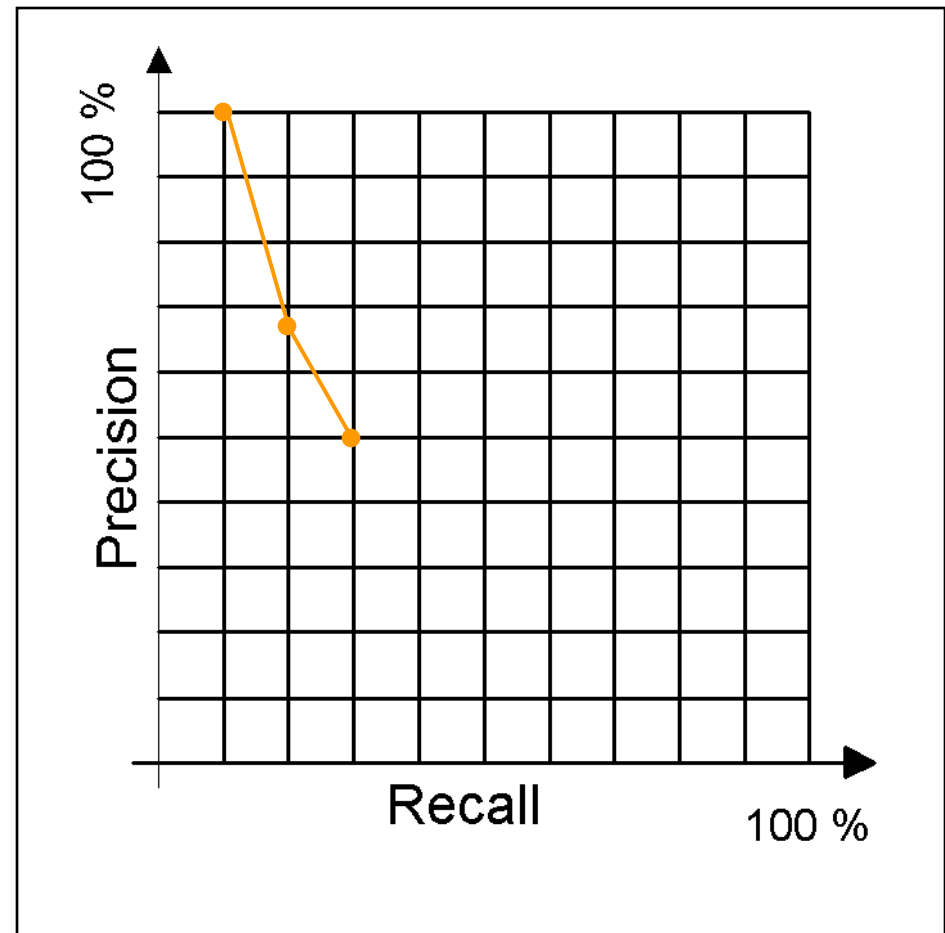


Recall and Precision



<http://www.uni-klu.ac.at>

01. d123 *	06. D9 *	11. d38
02. d84	07. d511	12. d48
03. d56 *	08. d129	13. d250
04. d6	09. d187	14. d113
05. d8	10. d25 *	15. d3 *

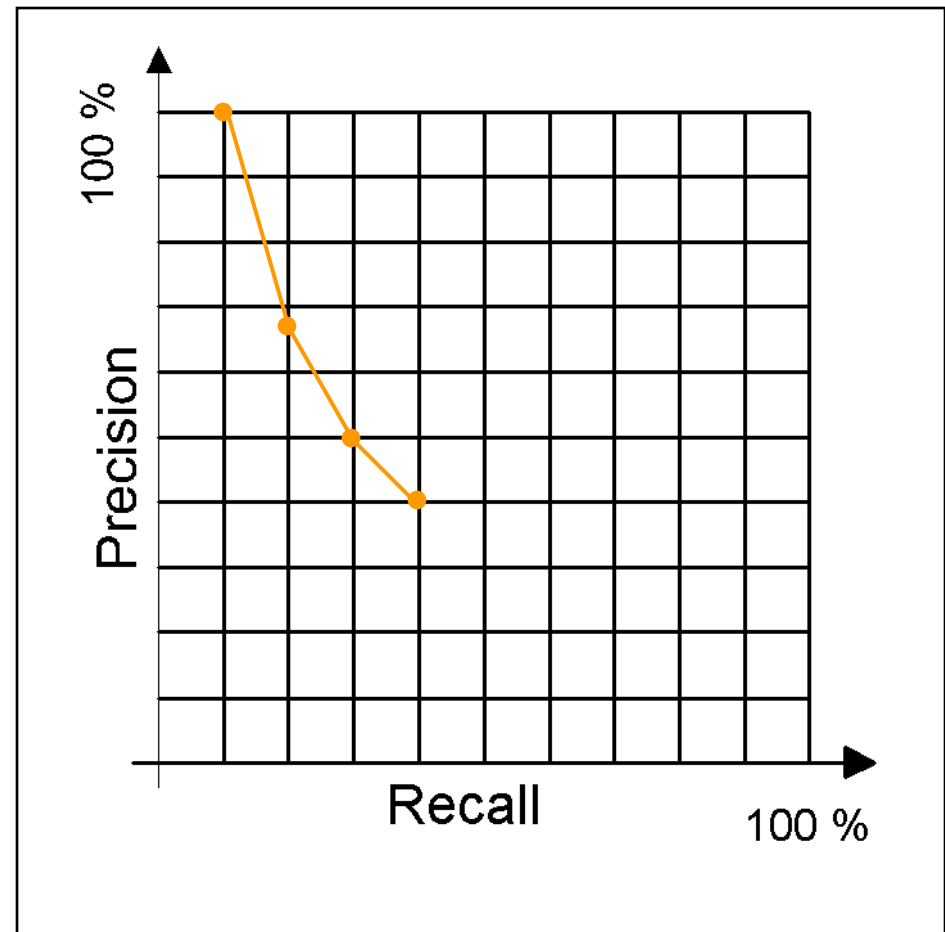


Recall and Precision



<http://www.uni-klu.ac.at>

01. d123 *	06. D9 *	11. d38
02. d84	07. d511	12. d48
03. d56 *	08. d129	13. d250
04. d6	09. d187	14. d113
05. d8	10. d25 *	15. d3 *

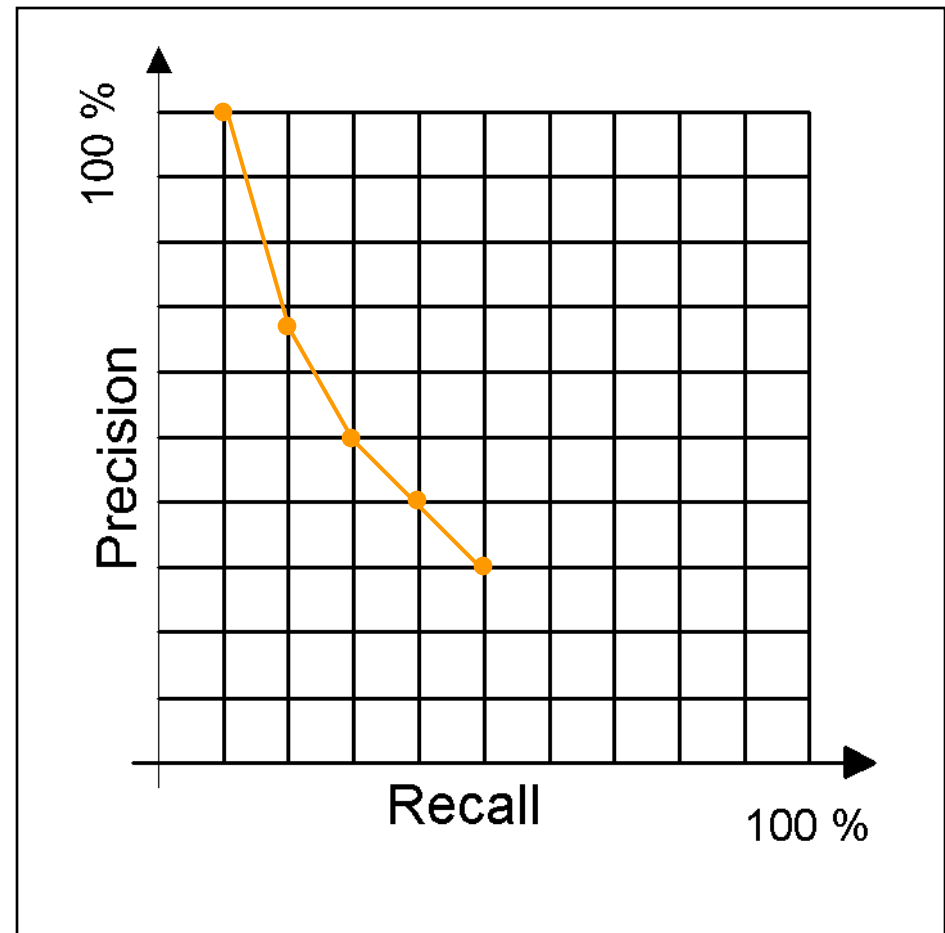


Recall and Precision



<http://www.uni-klu.ac.at>

01. d123 *	06. D9 *	11. d38
02. d84	07. d511	12. d48
03. d56 *	08. d129	13. d250
04. d6	09. d187	14. d113
05. d8	10. d25 *	15. d3 *



F-Measure



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$$E(j) = 1 - \frac{1 + b^2}{\frac{b^2}{\text{recall}(j)} + \frac{1}{\text{precision}(j)}}$$

$F(j) = 1 - E(j)$... van Rijsbergen

- Lower values -> lower performance
- If $b=1$, $F(j)$ is average
- If $b=0$, $F(j)$ is precision
- If $b=\text{inf}$, $F(j)$ is recall
- $b=2$ is a common choice

Mean Average Precision (MAP)



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- Find average precision for each query
- Compute mean AP over all queries
 - Macroaverage: All queries are considered equal
- For average recall-precision curves
 - Average at standard recall points

Mean Average Precision (MAP)



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Example: Query Q1:

1. D12 (relevant) -> Precision: 1
2. D61
3. D39 (relevant) -> Precision: 2/3
4. D75 (relevant) -> Precision: 3/4
5. D66
6. D14 (relevant) -> Precision: 4/6
7. D52
8. D33 (relevant) -> Precision: 5/8

- Average Precision: $(1 + 2/3 + \dots) / 5 = 0.742$

Mean Average Precision (MAP)



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- Compute MAP:
 - Q1: 0,742
 - Q2: 0,633
 - Q3: 0,874
 - Q4: 0,722
- $MAP = (0,742 + 0,633 + ..) / 4 = 0,743$

Test Collections & Initiatives



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- Aim:
 - Provide data, topic & results
- Prominent Initiatives
 - Text Retrieval Conference (TREC)
 - Initiative for the Evaluation of XML Retrieval (INEX)
 - Cross Language Evaluation Forume (CLEF)

The TREC Collection



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- Aim: Support IR Research on big data collections with
 - Test collection
 - Uniform measures and methods
 - Platform for comparison & challenges
- TREC collection size increases steadily
- Several different tracks:
 - Ad hoc, Web, Blog, Confusion, Genomics Track, Question Answering, Spam, Terabyte
- Examples:
 - Spam: ~ 91.000 messages (300 MB zipped)
 - Ad hoc has 5 sets:
 - e.g. Disk 5: 260.000 documents (1 GB zipped)

Summary: Evaluation



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- Lots of measures exist besides Precision & Recall
- Selection based on Use Case & Scenario
- Initiatives & Collections allow comparison
- Also user centered evaluation methods exist
- collections & initiatives are criticized:
 - Handling of outliers, significance of differences, ...

Information Retrieval Basics: Agenda



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- Probabilistic Model
- Other Retrieval Models
- Common Retrieval Methods
 - Co-Occurrence
 - Relevance Feedback
- Retrieval Evaluation
- **The Lucene Search Engine**
- Exercise 02



Lucene



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- A **Java** text search engine
 - .NET Implementation exists
 - Also used in PHP, etc.
- Initiated by Doug Cutting
 - Now paid by Yahoo!

- Implements an **inverted list**
 - Stores term -> document
 - Per field (e.g. title, content, ...)
 - And additional information (count, position, length, etc.)
 - File format & storage.
- Preprocesses input
 - Stemming, etc.
- Provides search & index update
 - Query, Ranking

Lucene: Basic Usage



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Let lucene-{version}.jar and lucene-demos-{version}.jar be in your classpath

- To index files type:
 - `java org.apache.lucene.demo.IndexFiles [dir]`
- To search in the index type:
 - `java org.apache.lucene.demo.SearchFiles`

Lucene: Queries



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- Lucene has an extensive query parser
 - Parses text to internal representation
- Lucene supports several types of queries
 - Field based: title:"multimedia information"
 - Boolean clauses: multimedia AND image
 - Wildcards: te?t OR te*t
 - Fuzzy search: roam~ (e.g. *foam* and *roams*)
 - Proximity search: "java apache"~10
 - Term boosting: java^4 apache

Lucene File Format



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- Definitions:
 - An index contains a sequence of documents.
 - A document is a sequence of fields.
 - A field is a named sequence of terms.
 - A term is a string.
- Lucene uses
 - different types of fields:
 - stored, indexed, tokenized
 - Sub-indexes (segments, upon insertion)

Lucene: Usage



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- IndexWriter
 - Writes documents to the index
 - Uses Analyzer
- IndexSearcher
 - Searching documents in an index
 - Same Analyzer as for indexing needed
 - A Hits object is returned
- Document
 - Groups fields to logical unit

Lucene: Features



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- It's really fast & stable
 - Even compared to commercial products
- Handles multiple indexes
 - MultiReader, distributed search
- Has strong development support
 - Yahoo! & Apache (top level project)
- Lots of Stemmers, Tokenizers, etc.
 - English, German, Korean, Chinese, ...

Lucene: Projects & Tools



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- Nutch
 - Open source internet search engine
- Lucene .NET
 - Source code port to .NET
- Solr
 - Search server supporting web services, REST, ..
- Luke
 - GUI index management tool

Luke Demo ...



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Luke - Lucene Index Toolbox, v 0.8 (2008-02-08)

File Tools Settings Help

Overview Documents Search Files Plugins

Index name: **C:\Temp\index** [Re-open] [Close]

Number of fields: **3**

Number of documents: **10**

Number of terms: **11342**

Has deletions?: **No**

Index version: **1205851672503**

Last modified: **Tue Mar 18 15:47:52 CET 2008**

Directory implementation: **org.apache.lucene.store.FSDirectory**

Select fields from the list below, and press button to view top terms in these fields. No selection means all fields.

Available Fields: **<contents>** **<modified>** **<path>** [Show top terms >>]

Number of top terms: **50**

Hint: use Shift-Click to select ranges, or Ctrl-Click to select multiple fields (or unselect all).

Top ranking terms. (Right-click for more options)

No	Rank	Field	Text
1	6	<contents>	lucene
2	6	<contents>	apache
3	5	<contents>	2
4	5	<contents>	http
5	5	<contents>	s
6	5	<contents>	1
7	5	<contents>	3
8	5	<contents>	c
9	5	<contents>	4
10	4	<contents>	8
11	4	<contents>	7

Index name: **C:\Temp\index**

Information Retrieval Basics: Agenda



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- Probabilistic Model
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- **Exercise 02**



Exercise 02 (a)



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- Retrieval Evaluation
 - Gegeben sind eine Collection von 35 Dokumenten
 - Eine Query und eine (ungeordnete) Liste von relevanten Dokumenten zur Query
 - Die gereihten Ergebnislisten zweier Suchmaschinen (A1 und A2)
- Ihre Aufgabe
 - Berechnen Sie die Precision & Recall
 - Zeichnen Sie einen Precision vs. Recall Plot
 - Vergleichen Sie die Retrievalperformance der beiden Suchmaschinen.

Exercise 02 (b)



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- Berechnen Sie die Assoziationsmatrizen
 - Term 2 Term & Document 2 Document
 - Finden Sie einen Term für eine Query Expansion der Query “Amsel”
 - Finden Sie das Document, das dem Document d1 am ähnlichsten ist.
 - Tipps:
 - Excel MMULT (siehe Hilfe)
 - Kopieren -> Inhalte einfügen (transponiert)

Nicht vergessen!



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- Ergebnisse schicken!

Frohe Ostern!



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