VK Multimedia Information Systems

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Exercise

- Given a document collection ...
- Find the results to a query ...
  - Employing the Boolean model
  - Employing the vector model (with TF*IDF)

- Some hints:
  - Excel:
    - Sheet on homepage
    - Use functions “Summenprodukt” & “Quadratesumme”

Exercise

- Document collection (6 documents)
  - spatz, amsel, vogel, drossel, fink, falke, flug
  - spatz, vogel, flug, nest, amsel, amsel, amsel
  - kuckuck, nest, nest, ei, ei, ei, flug, amsel, amsel, vogel
  - amsel, elster, elster, drossel, vogel, ei
  - falke, katze, nest, nest, flug, vogel
  - spatz, spatz, konstruktion, nest, ei
- Queries:
  - spatz, vogel, nest, konstruktion
  - amsel, ei, nest

Exercise

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	d1	d2	d3	d4	d6	d6	idf
amsel	1	3	2	1			
drossel	1			1			
ei			3	1		1	
elster				2			
falke	1				1		
fink	1						
flug	1	1	1		1		
katze					1		
konstruktion						1	
kuckuck			1				
nest		1	2		2	1	
spatz	1	1				2	
vogel	1	1	1	1	1		

Information Retrieval Basics: Agenda

- **Probabilistic Model**
- Other Retrieval Models
- Common Retrieval Methods
  - Query Modification
  - Co-Occurrence
  - Relevance Feedback
- Exercise 02

Probabilistic Model

- 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

- 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

- 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 relevant for q)/P(d_j not relevant for q)
- Note:
  - No way to compute the probability is given
  - No sample space for the computation is given.

Probabilistic Model: Definition

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: $\overline{R}$
- Probability that d_j is relevant for q:

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

- Probability that d_j is not relevant for q:

$$P(\overline{R} \mid \vec{d}_j)$$

Probabilistic Model: Definition

- Similarity q and d_j:

$$sim(d_j, q) = \frac{P(R \mid \vec{d}_j)}{P(\overline{R} \mid \vec{d}_j)}$$

- Using Bayes' Rule:

$$sim(d_j, q) = \frac{P(R \mid \vec{d}_j)}{P(\overline{R} \mid \vec{d}_j)} = \frac{P(\vec{d}_j \mid R) \times P(R)}{P(\vec{d}_j \mid \overline{R}) \times P(\overline{R})}$$

- Probability for randomly selecting d_j out of R

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

- Probability for a randomly selected document to be in R

$$P(R)$$

Probabilistic Model: Definition

- As $P(R) = P(\overline{R})$ $\quad sim(d_j, q) \approx \frac{P(\vec{d}_j \mid R)}{P(\vec{d}_j \mid \overline{R})}$
- Assuming independent index terms:

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

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

Probabilistic Model: Definition

Simplification based on

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

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

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

Probabilistic Model: Starting Probabilities (i)

- 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 ~ distribution of index terms k_i in D

$$P(k_i \mid R) = 0{,}5 \qquad P(k_i \mid \overline{R}) = \frac{n_i}{N}$$

  - 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.

$$P(k_i \mid R) = \frac{V_i}{V} \qquad P(k_i \mid \overline{R}) = \frac{n_i - V_i}{N - V}$$

Probabilistic Model: Starting Probabilities (iii)

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

$$P(k_i \mid R) = \frac{V_i + 0{,}5}{V + 1} \qquad P(k_i \mid \overline{R}) = \frac{n_i - V_i + 0{,}5}{N - V + 1}$$

  - or not constant:

$$P(k_i \mid R) = \frac{V_i + \frac{n_i}{N}}{V + 1} \qquad P(k_i \mid \overline{R}) = \frac{n_i - V_i + \frac{n_i}{N}}{N - V + 1}$$

Probabilistic Model

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

Other Retrieval Models: Set Theoretic Models

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- Fuzzy Set Model
  - Each query term defines a fuzzy set
  - Each document has a **degree of membership**
  - Done e.g. with query expansion (co-occurrence or thesaurus)
- Extended Boolean Model
  - Incorporates non binary weights
  - Geometric interpretation: Distance between document vector and desired Boolean state (query)

Other Retrieval Models: Algebraic

- Generalized Vector Space Model
  - Term independence not necessary
  - Terms are not orthogonal and my be linear dependent.
  - Smaller linear independent units exist.

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Set Theoretic Models: Fuzzy Set Model

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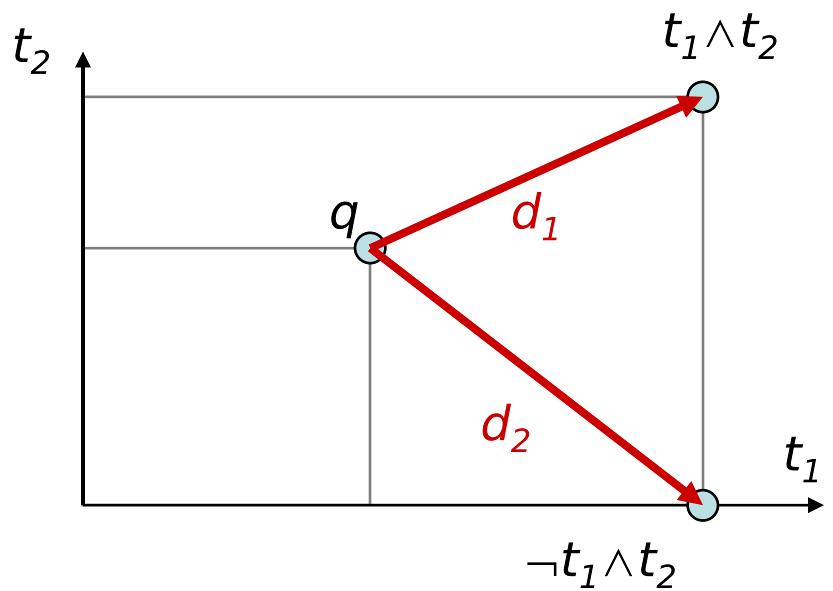
- Incorporates **non binary** weights
- Geometric interpretation:
  - Distance between document vector and
  - desired Boolean state (query)



Algebraic Models: Generalized Vector Space M.

- Term independence not necessary
- Terms (as dimensions) are not orthogonal and may be linear dependent.
- Smaller linear independent units exist.
  - m ... 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.

- 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.

- 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-occurence) 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 $M_{ij} = K*S*D^t$ ...
- Only the *s* largest singular values from *S*:
  - Others are deleted
  - Respective columns in *K* and D^t remain
- $M_s = K_s*S_s*D^t_s$ ...
  - $s < r$ 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.

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

Algebraic Models: Latent Semantic Indexing M.

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

Example LSA ...

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 ...

$$\{X\} =$$

	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

Example LSA …

	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

	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
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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

Example LSA ...

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:

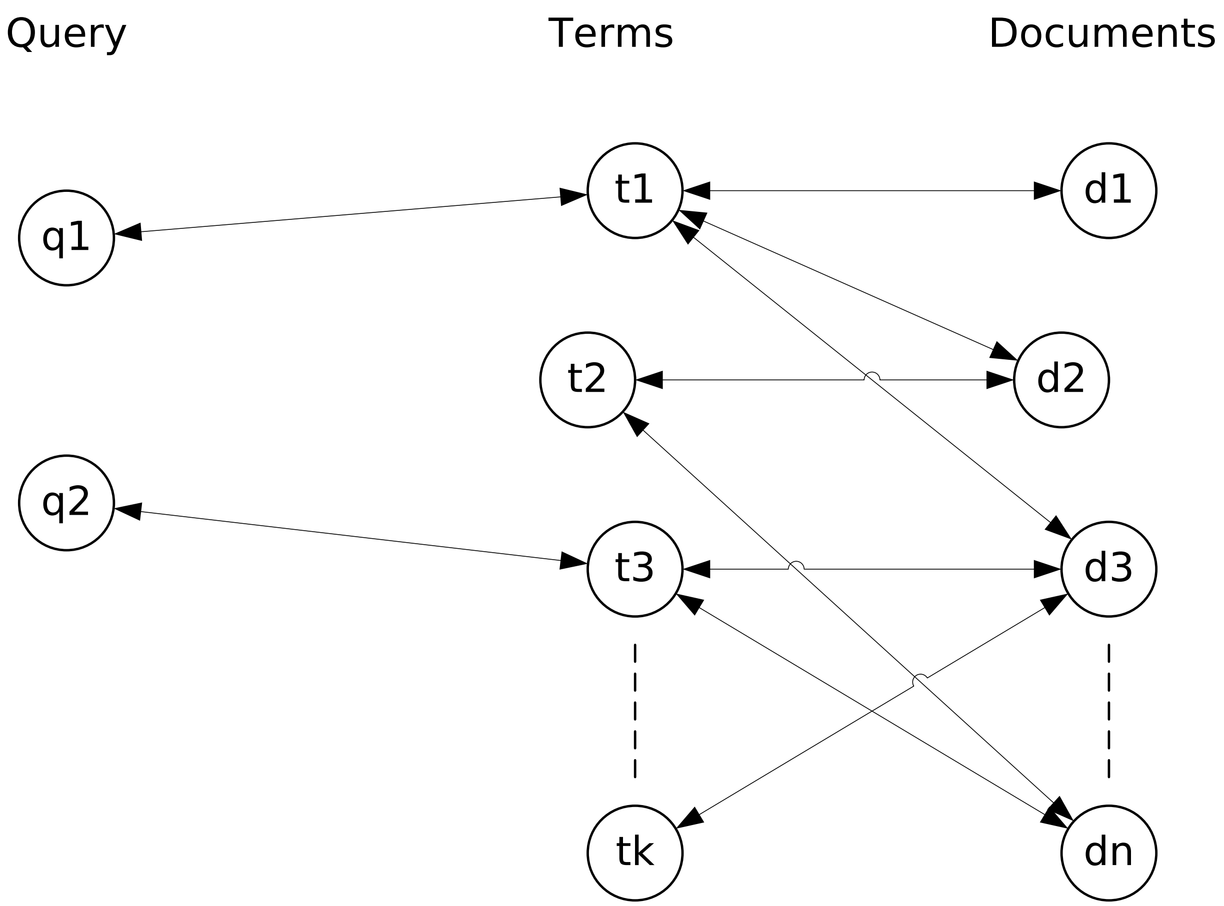
c2	0.91							
c3	1.00	0.91						
c4	1.00	0.88	1.00					
c5	0.85	0.99	0.85	0.81				
m1	-0.85	-0.56	-0.85	-0.88	-0.45			
m2	-0.85	-0.56	-0.85	-0.88	-0.44	1.00		
m3	-0.85	-0.56	-0.85	-0.88	-0.44	1.00	1.00	
m4	-0.81	-0.50	-0.81	-0.84	-0.37	1.00	1.00	1.00

0.92	
-0.72	1.00

Algebraic Models: Neural Network M. / Associative Retrieval

- 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



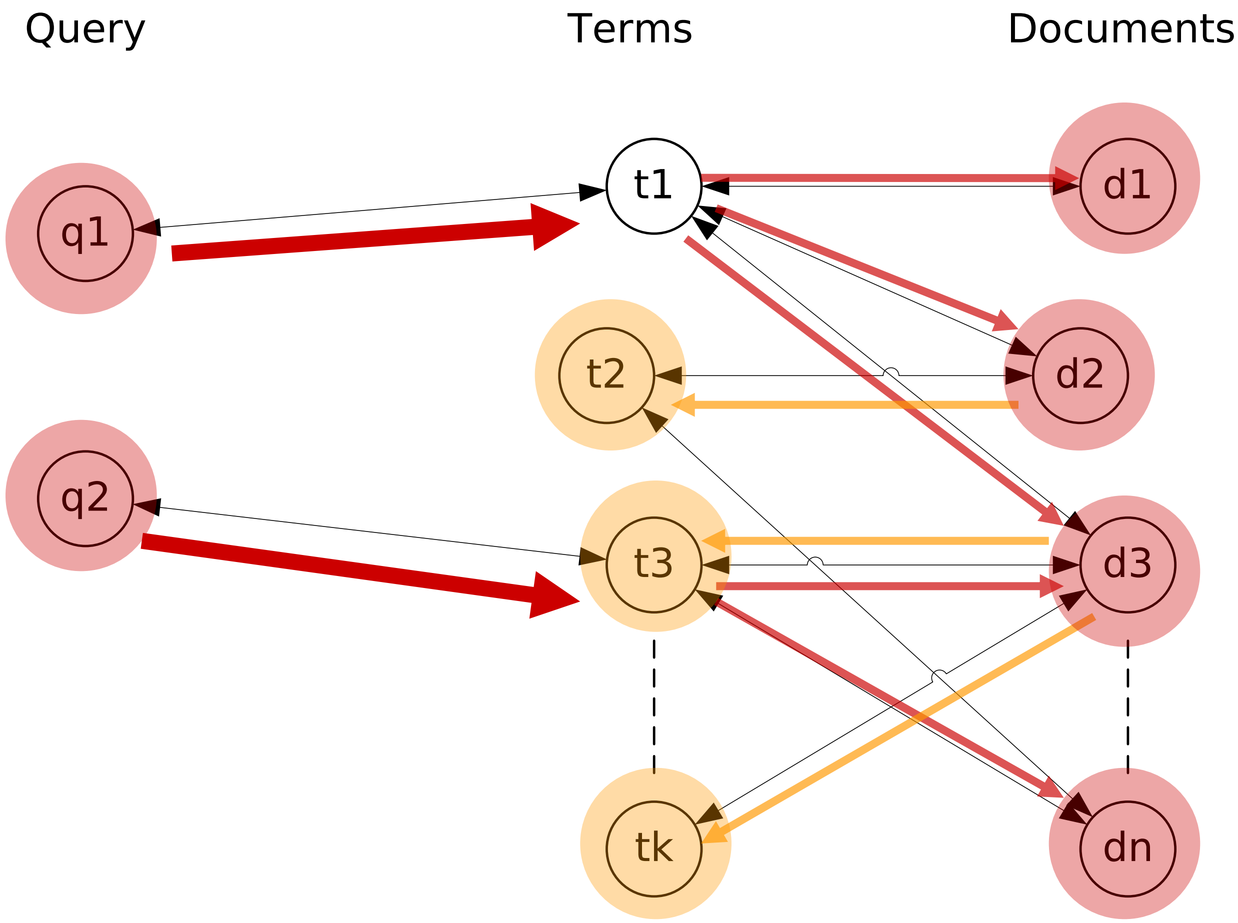
Algebraic Models: Neural Network M. / Associative Retrieval

- 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

- First round query terms -> terms -> docs
  - Equivalent to vector model
- Further rounds increase retrieval performance

Algebraic Models: Neural Network M. / Associative Retrieval



Algebraic Models: Neural Network M. / Associative Retrieval

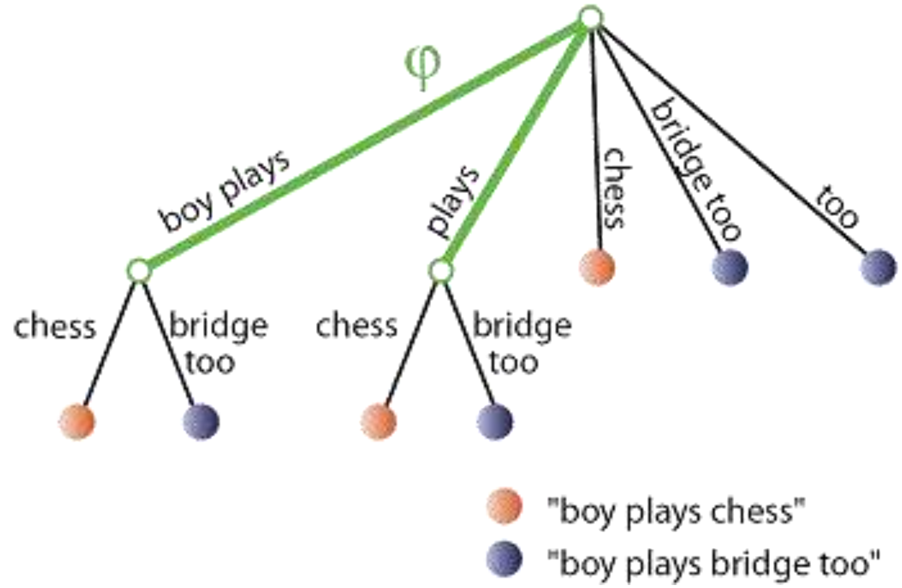
- Advantages
  - Works on generic digraphs
  - Edges can be created on the fly
  - Nodes can be re-weighted on the fly
- Disadvantages
  - Graph might be too big for main memory
  - Tuning of weights is complicated
  - Selection of appropriate concepts: Back-propagation etc.

Alternative Model: Suffix Tree Retrieval M.

- 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.

- Example
  - d1 = “boy plays chess”
  - d2 = “boy plays bridge too”



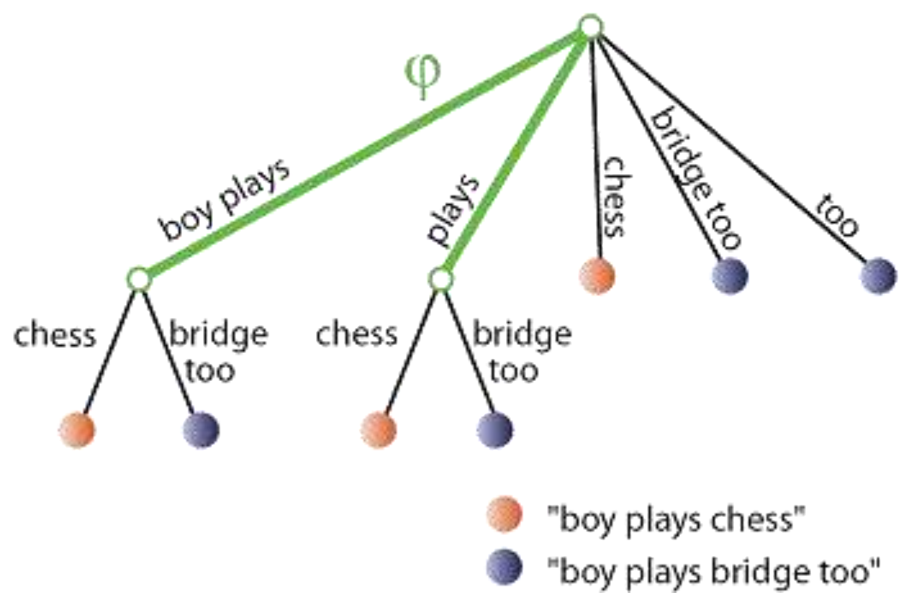
Alternative Model: Suffix Tree Retrieval M.

- 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.

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

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



Information Retrieval Basics: Agenda

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- Probabilistic Model
- Other Retrieval Models
- **Common Retrieval Methods**
  - **Query Modification**
  - Co-Occurrence
  - Relevance Feedback
- Exercise 02

Query Modification

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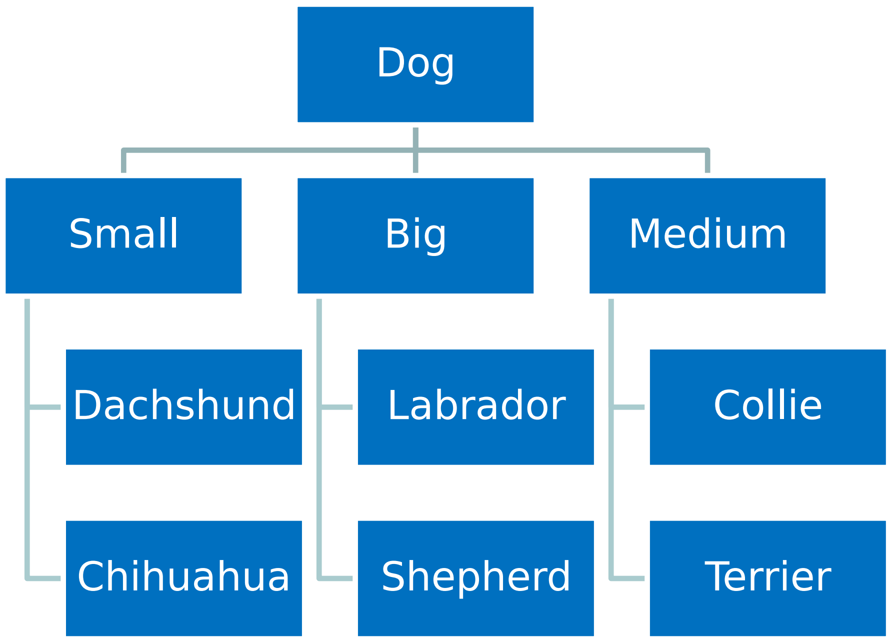
- Integrate existing knowledge
  - Taxonomies
  - Ontologies
- Modify query
  - Related terms
  - Narrower terms
  - Broader terms



Term Reweighting

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

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  - Query Modification
  - **Co-Occurrence**
  - Relevance Feedback
- Retrieval Evaluation
- The Lucene Search Engine
- Exercise 02

Co-Occurrence

- 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

	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

	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 & 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*

Information Retrieval Basics: Agenda

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

- Probabilistic Model
- Other Retrieval Models
- **Common Retrieval Methods**
  - Query Modification
  - Co-Occurrence
  - **Relevance Feedback**
- Exercise 02

Relevance Feedback

- 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

- $D_r \subset D$... 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
- $\alpha,\ \beta,\ \gamma$ ... tuning parameters

Relevance Feedback

- 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

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

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

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

Relevance Feedback

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

- All three techniques yield similar results ...

Relevance Feedback

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

Information Retrieval Basics: Agenda

- Probabilistic Model
- Other Retrieval Models
- Common Retrieval Methods
  - Co-Occurrence
  - Relevance Feedback
- **Exercise 02**

Exercise 02

- Co-Occurrence
  - Document-term matrix from exercise 01
  - Compute term-term co-occurrence
  - Find the most 3 relevant terms for "*kuckuck*" and "*ei*"
- Hints
  - Use MMULT in Excel / Scalc
  - Consult help for matrix formulas
  - Find .xls file on the course page

Exercise 2+

- Install R: http://www.r-project.org/
- Apply LSA to Exercise 2 before computing the term-term co-occurrence
  - x <- cbind(1, 3, 2, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 3, 1, 0, 1,0, 0, 0, 2, 0, 0,1, 0, 0, 0, 1, 0,1, 0, 0, 0, 0, 0,1, 1, 1, 0, 1, 0,0, 0, 0, 0, 1, 0,0, 0, 0, 0, 0, 1,0, 0, 1, 0, 0, 0,0, 1, 2, 0, 2, 1,1, 1, 0, 0, 0, 2,1, 1, 1, 1, 1, 0)
  - x <- matrix(x, ncol=6)
  - ?svd // helps with svd, %*% is matrix multiplication, use diag() for d