VK Multimedia Information Systems

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Dienstags, 16.oo Uhr c.t., E.1.42

Exercise

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

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

	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		

	d1	d2	d3	d4	d6	d6	idf			q1	q2
amsel	1	3	2	1	0	0	0,4055			0,00	1,00
drossel	1	0	0	1	0	0	1,0986			0,00	0,00
ei	0	0	3	1	0	1	0,6931			0,00	1,00
elster	0	0	0	2	0	0	1,7918			0,00	0,00
falke	1	0	0	0	1	0	1,0986			0,00	0,00
fink	1	0	0	0	0	0	1,7918			0,00	0,00
flug	1	1	1	0	1	0	0,4055			0,00	0,00
katze	0	0	0	0	1	0	1,7918			0,00	0,00
konstruktion	0	0	0	0	0	1	1,7918			1,00	0,00
kuckuck	0	0	1	0	0	0	1,7918			0,00	0,00
nest	0	1	2	0	2	1	0,4055			1,00	1,00
spatz	1	1	0	0	0	2	0,6931			1,00	0,00
vogel	1	1	1	1	1	0	0,1823			1,00	0,00
max	*1*	*3*	*3*	*2*	*2*	*2*					

	d1	d2	d3	d4	d6	d6	idf			q1	q2
amsel	1,00	1,00	0,67	0,50	0,00	0,00	0,4055			0,20	0,41
drossel	1,00	0,00	0,00	0,50	0,00	0,00	1,0986			0,55	0,55
ei	0,00	0,00	1,00	0,50	0,00	0,50	0,6931			0,35	0,69
elster	0,00	0,00	0,00	1,00	0,00	0,00	1,7918			0,90	0,90
falke	1,00	0,00	0,00	0,00	0,50	0,00	1,0986			0,55	0,55
fink	1,00	0,00	0,00	0,00	0,00	0,00	1,7918			0,90	0,90
flug	1,00	0,33	0,33	0,00	0,50	0,00	0,4055			0,20	0,20
katze	0,00	0,00	0,00	0,00	0,50	0,00	1,7918			0,90	0,90
konstruktion	0,00	0,00	0,00	0,00	0,00	0,50	1,7918			1,79	0,90
kuckuck	0,00	0,00	0,33	0,00	0,00	0,00	1,7918			0,90	0,90
nest	0,00	0,33	0,67	0,00	1,00	0,50	0,4055			0,41	0,41
spatz	1,00	0,33	0,00	0,00	0,00	1,00	0,6931			0,69	0,35
vogel	1,00	0,33	0,33	0,50	0,50	0,00	0,1823			0,18	0,09

r_q1	0,440	0,206	0,281	0,386	0,332	0,528	
r_q2	0,486	0,265	0,462	0,528	0,381	0,429	

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

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

- Probability that d_j is not relevant for q:

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

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

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

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

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)

- 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

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

  - or not constant:

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

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

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Other Retrieval Models: Set Theoretic Models

- 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

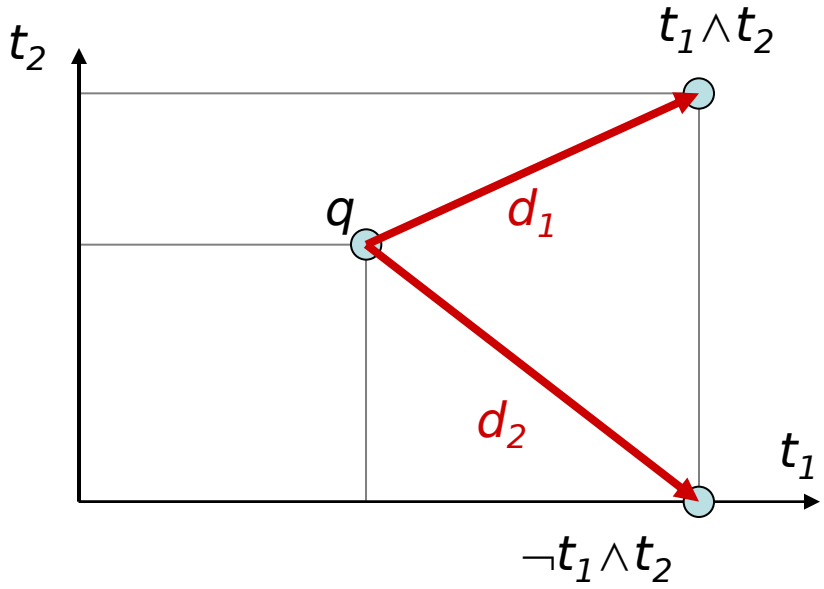
- Generalized Vector Space Model
  - Term independence not necessary
  - Terms are not orthogonal and my be linear dependent.
  - Smaller linear independent units exist.

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

- 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 x r diagonal matrix of singular values with $r=min(t,N)$, the rank of M_{ij}

Algebraic Models: Latent Semantic Indexing M.

- 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
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

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:

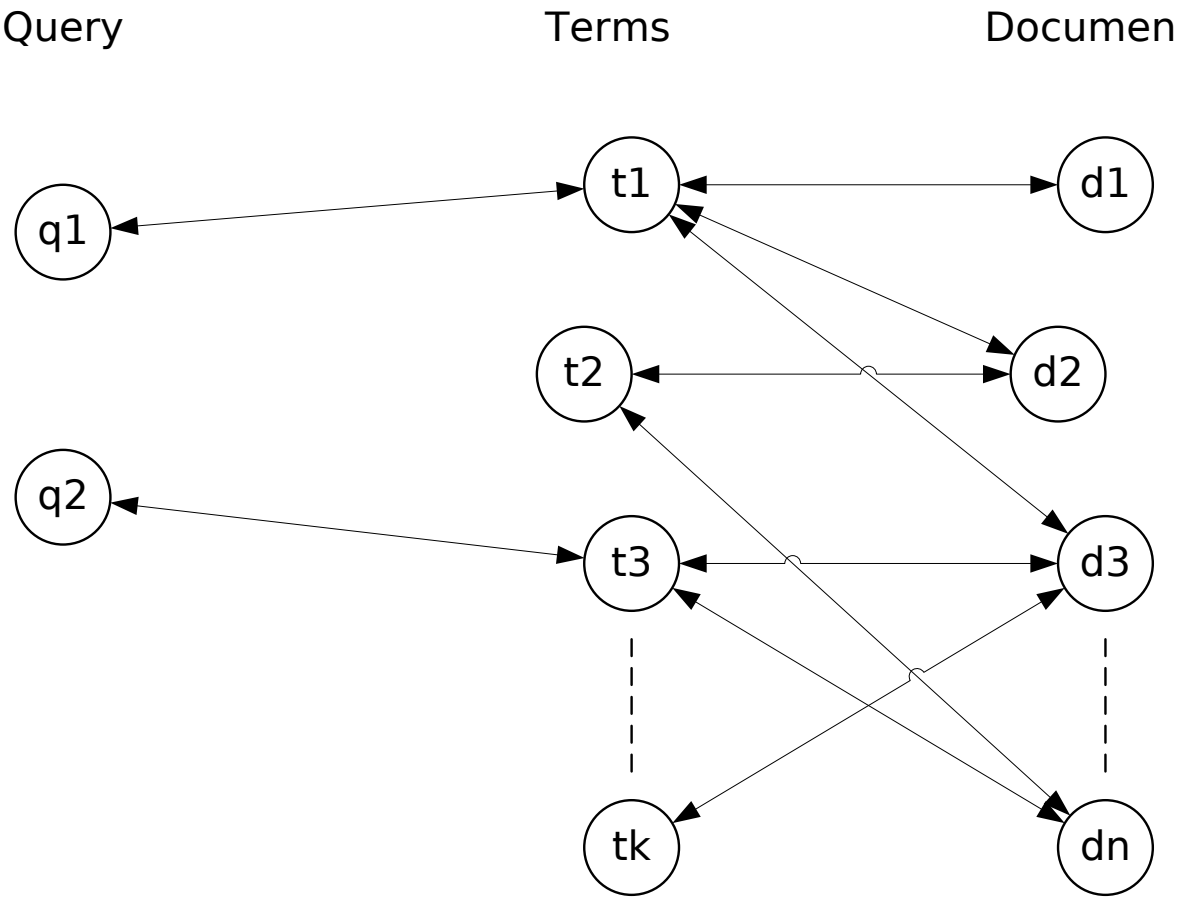
c2	0.91						
c3	1.00	0.91					
c4	1.00	0.88	1.00				
c5	0.85	0.99	0.85	0.81			
m1	-0.85	-0.56	-0.85	-0.88	-0.45		
m2	-0.85	-0.56	-0.85	-0.88	-0.44	1.00	
m3	-0.85	-0.56	-0.85	-0.88	-0.44	1.00	1.00
m4	-0.81	-0.50	-0.81	-0.84	-0.37	1.00	1.00	1.00

	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



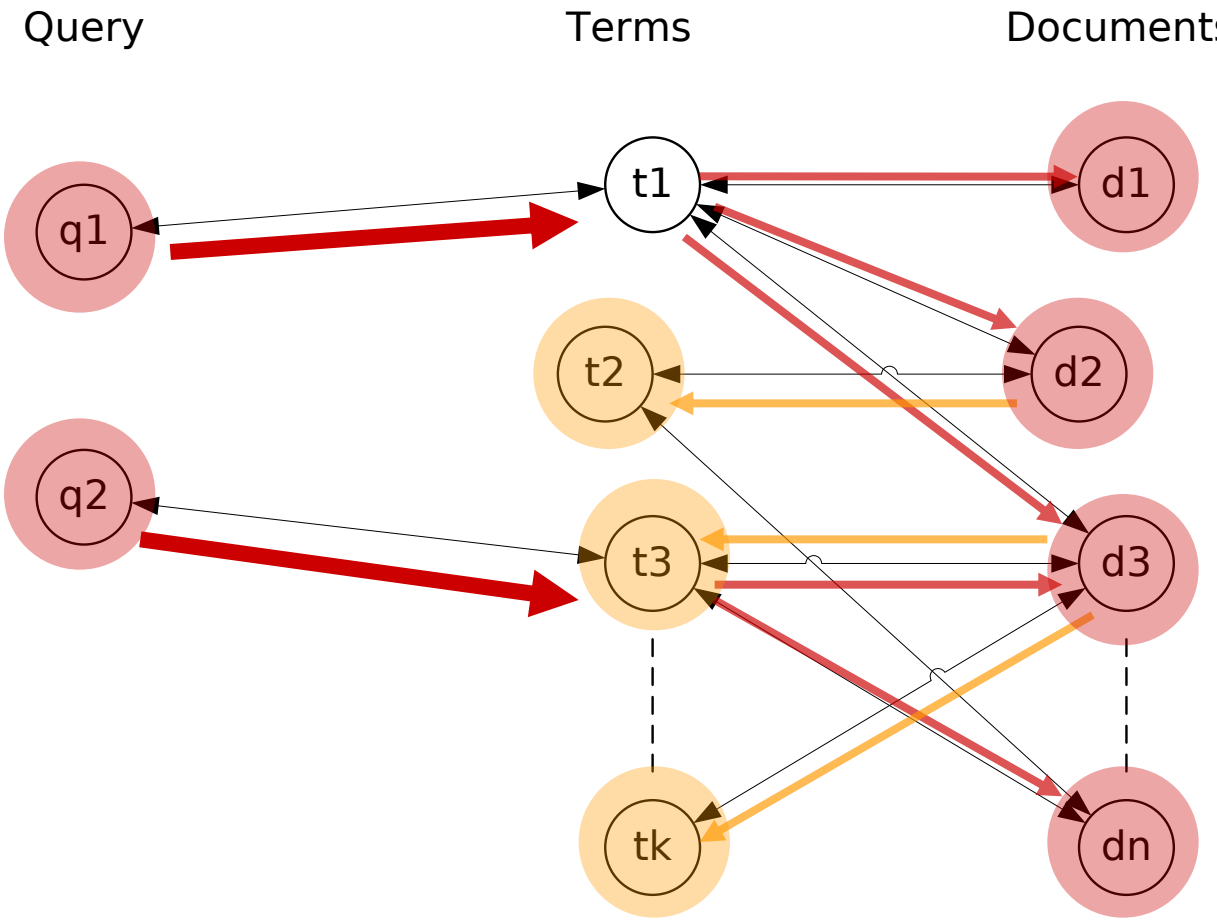
Algebraic Models: Neural Network M. / Associative Retrieval

- 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



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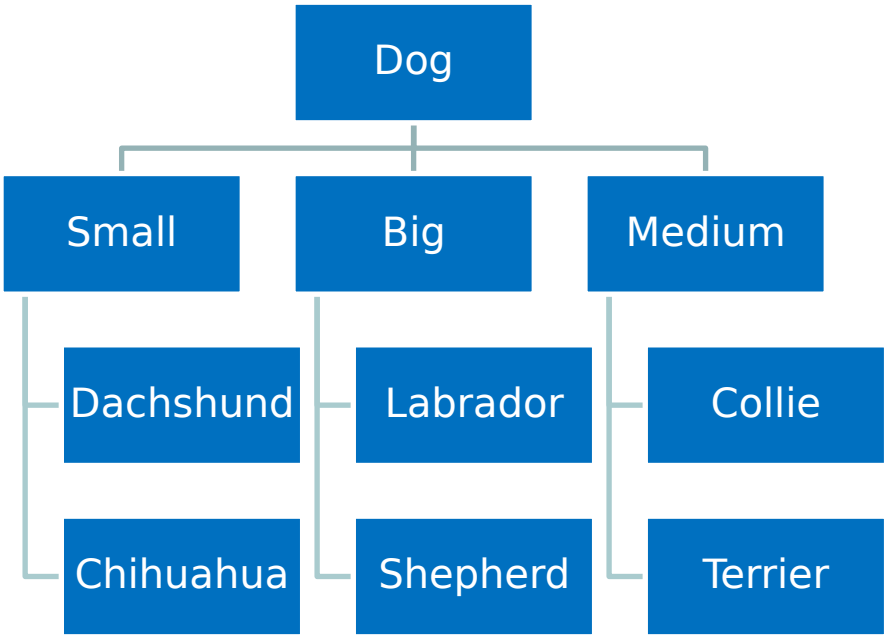
- Exercise 02

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

- 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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- Probabilistic Model
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- **Common Retrieval Methods**
  - 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 (tx€$\times t$) 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

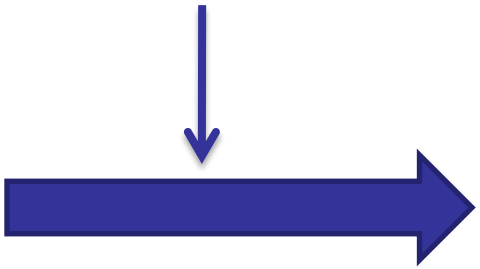
7	5	0	6	1
7	1	1	1	2
0	4	5	0	0
8	0	0	0	6
3	3	0	4	0

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

	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

- 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
  - Typically~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 / OO Calc
  - 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