Scoring, term weighting, the vector space model [1]

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[1] Vorlage: Folien von M. Schütze

Overview

1 Term frequency

2 tf-idf weighting

3 The vector space

Outline

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Ranked retrieval

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- Most users are not capable of writing Boolean queries (or they are, but they think it's too much work).
- Most users don't want to wade through 1000s of results.
- This is particularly true of web search.

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- With a ranked list of documents it does not matter how large the retrieved set is.

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- This score measures how well document and query "match".

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- We will look at a number of alternatives for doing this.

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- Always assigns a number between 0 and 1.

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- ... instead of $|A \cap B|/|A \cup B|$ (Jaccard) for length normalization.

Recall: Binary incidence matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Anthony	1	1	0	0	0	1	
Brutus	1	1	0	1	0	0	
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
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From now on, we will use the frequencies of terms

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Anthony	157	73	0	0	0	1	
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Caesar	232	227	0	2	1	0	
Calpurnia	0	10	0	0	0	0	
Cleopatra	57	0	0	0	0	0	
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- For now: bag of words model

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- The document frequency is the number of documents in the collection that the term occurs in.

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- So we use the log transformation for both term frequency and document frequency.

Examples for idf

Compute idf_t using the formula: $\mathrm{idf}_t = \log_{10} \frac{1{,}000{,}000}{\mathrm{df}_t}$

term	df_t	idf_t
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animal	100	
sunday	1000	
fly	10,000	
under	100,000	
the	1,000,000	

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- Questions about idf?

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insurance	10440	3997
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- This example suggests that df is better for weighting that cf.

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- Note: the "-" in tf-idf is a hyphen, not a minus sign!
- Alternative names: tf.idf, tf x idf

Summary: tf-idf

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Term, collection and document frequency

Quantity	Symbol	Definition
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Outline

1 Term frequency

2 tf-idf weighting

3 The vector space

Binary → count → weight matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Anthony	5.25	3.18	0.0	0.0	0.0	0.35	
Brutus	1.21	6.10	0.0	1.0	0.0	0.0	
Caesar	8.59	2.54	0.0	1.51	0.25	0.0	
Calpurnia	0.0	1.54	0.0	0.0	0.0	0.0	
Cleopatra	2.85	0.0	0.0	0.0	0.0	0.0	
mercy	1.51	0.0	1.90	0.12	5.25	0.88	
worser	1.37	0.0	0.11	4.15	0.25	1.95	
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- This is a very sparse vector - most entries are zero.

Queries as vectors

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- proximity = similarity
- proximity $\approx$ negative distance
- Recall: We're doing this because we want to get away from the you're-either-in-or-out Boolean model.
- Instead: rank more relevant documents higher than less relevant documents

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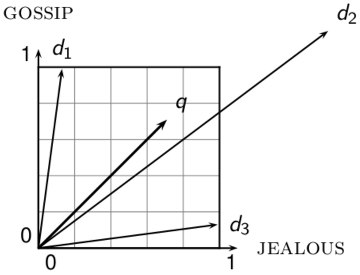
- Euclidean distance is a bad idea . . .
- . . . because Euclidean distance is large for vectors of different lengths.

Why distance is a bad idea



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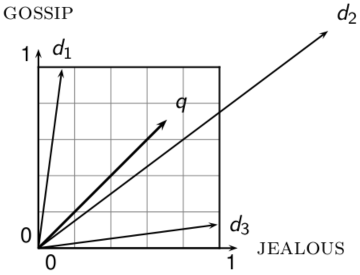

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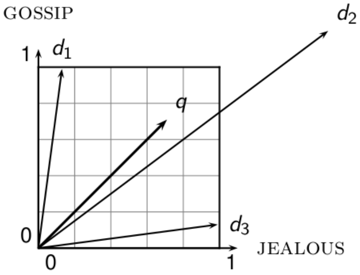

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Questions about basic vector space setup?

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Use angle instead of distance

- Rank documents according to angle with query
- Thought experiment: take a document d and append it to itself. Call this document d'.
- "Semantically" d and d' have the same content.
- The angle between the two documents is 0, corresponding to maximal similarity.
- The Euclidean distance between the two documents can be quite large.

From angles to cosines

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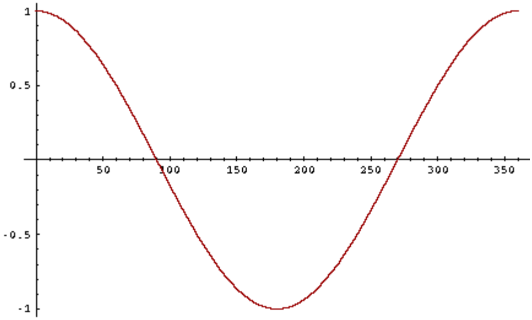
- Cosine is a monotonically decreasing function of the angle for the interval $[0^\circ, 180^\circ]$

Cosine



What about angles $> 180°$?

Length normalization

- How do we compute the cosine?

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- ...since after normalization: $||x||_2 = \sqrt{\sum_i x_i^2} = 1.0$
- As a result, longer documents and shorter documents have weights of the same order of magnitude.
- Effect on the two documents d and d' (d appended to itself) from earlier slide: they have identical vectors after length-normalization.

Cosine similarity between query and document

$$\cos(\vec{q},\vec{d}) = \text{sim}(\vec{q},\vec{d}) = \frac{\vec{q}\cdot\vec{d}}{|\vec{q}||\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2}\sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

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- $|\vec{q}|$ and $|\vec{d}|$ are the lengths of $\vec{q}$ and $\vec{d}$.
- This is the cosine similarity of $\vec{q}$ and $\vec{d}$ . . . . . . or, equivalently, the cosine of the angle between $\vec{q}$ and $\vec{d}$.

Cosine for normalized vectors

- For normalized vectors, the cosine is equivalent to the dot product or scalar product.

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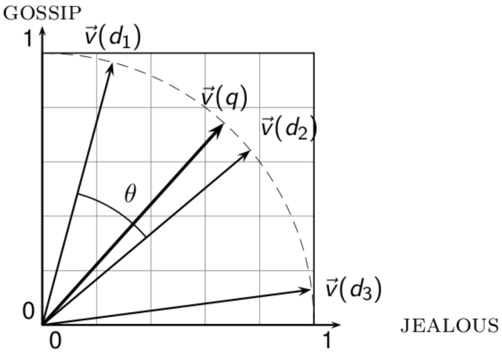
- $\cos(\vec{q}, \vec{d}) = \vec{q} \cdot \vec{d} = \sum_i q_i \cdot d_i$ (if $\vec{q}$ and $\vec{d}$ are length-normalized).

Cosine similarity illustrated



Cosine: Example

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term frequencies (counts)

term	SaS	PaP	WH
affection	115	58	20
jealous	10	7	11
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(To simplify this example, we don't do idf weighting.)

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- Why do we have $\cos(\text{SaS},\text{PaP}) > \cos(\text{SAS},\text{WH})$?

Computing the cosine score

Components of tf-idf weighting

Term frequency		Document frequency		Normalization	
n (natural)	$\text{tf}_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1 + \log(\text{tf}_{t,d})$	t (idf)	$\log \frac{N}{\text{df}_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2+w_2^2+\ldots+w_M^2}}$
a (augmented)	$0.5 + \frac{0.5\times\text{tf}_{t,d}}{\max_t(\text{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N-\text{df}_t}{\text{df}_t}\}$	u (pivoted unique)	$1/u$
b (boolean)	$\begin{cases} 1 & \text{if } \text{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$			b (byte size)	$1/\mathit{CharLength}^{\alpha}$, $\alpha < 1$
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Default: no weighting

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Query: "best car insurance". Document: "car insurance auto insurance".

word	query					document				product
	tf-raw	tf-wght	df	idf	weight	tf-raw	tf-wght	weight	n'lized	
auto										
best										
car										
insurance										

Key to columns: tf-raw: raw (unweighted) term frequency, tf-wght: logarithmically weighted term frequency, df: document frequency, idf: inverse document frequency, weight: the final weight of the term in the query or document, n'lized: document weights after cosine normalization, product: the product of final query weight and final document weight

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word	query					document				product
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car	1									
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Query: "best car insurance". Document: "car insurance auto insurance".

word	query					document				product
	tf-raw	tf-wght	df	idf	weight	tf-raw	tf-wght	weight	n'lized	
auto	0					1				
best	1					0				
car	1					1				
insurance	1					2				

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best	1	1				0	0			
car	1	1				1	1			
insurance	1	1				2	1.3			

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best	1	1	50000			0	0			
car	1	1	10000			1	1			
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car	1	1	10000	2.0	2.0	1	1	1	0.52	
insurance	1	1	1000	3.0	3.0	2	1.3	1.3	0.68	

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$\sqrt{1^2 + 0^2 + 1^2 + 1.3^2} \approx 1.92$
$1/1.92 \approx 0.52$
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car	1	1	10000	2.0	2.0	1	1	1	0.52	1.04
insurance	1	1	1000	3.0	3.0	2	1.3	1.3	0.68	2.04

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Final similarity score between query and document: $\sum_i w_{qi} \cdot w_{di} = 0 + 0 + 1.04 + 2.04 = 3.08$

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best	1	1	50000	1.3	1.3	0	0	0	0	0
car	1	1	10000	2.0	2.0	1	1	1	0.52	1.04
insurance	1	1	1000	3.0	3.0	2	1.3	1.3	0.68	2.04

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Questions?

Summary: Ranked retrieval in the vector space model

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Summary: Ranked retrieval in the vector space model

- Represent the query as a weighted tf-idf vector
- Represent each document as a weighted tf-idf vector
- Compute the cosine similarity between the query vector and each document vector
- Rank documents with respect to the query
- Return the top K (e.g., $K = 10$) to the user

Resources

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- Okapi BM25 (a state-of-the-art weighting method, 11.4.3 of IIR)