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Information Retrieval, and the Vector Space Model

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Search Engines

Goal: Find documents relevant to a query

Examples:

1. Boolean query:

Monte Carlo AND (importance OR stratification) AND NOT Chevrolet

- 2. Natural language query: Is it raining in Topanga?
- List of words:
 Efron bootstrap resample

Vector Space Model

Word counts

Most engines use word counts in documents

Most use other things too

- links
- titles
- position of word in document
- sponsorship
- present and past user feedback

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Term Document Matrix

 $f_{ij} \equiv$ number of times term T_i is in document D_j

Documents

- 1. web page
- 2. article
- 3. section
- 4. paragraph
- 5. sentence

<u>Terms</u>

- 1. word e.g. "airplane"
- 2. n-gram e.g. "airp", "irpl", "rpla", "plan", "lane"
- 3. collocation e.g. "white house" or "New York"

Term-document matrices are huge and sparse

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Further processing

Stop words Ignore very common words "the" "and" "what"

Stemming Strip words to root

reformation reformative reformed reforming \rightarrow reform

tf-idf

Term frequency, inverse document frequency

$$f_{ij} \rightarrow w_{ij} = (1 + \log(f_{ij})) \times \left(1 + \log\left(\frac{N}{f_{i+}}\right)\right)$$

where

N = Number of documents

 f_{i+} = Number of documents with at least one t_i

There are many variations

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4.39

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2.67

Example

Vector Space Model

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Vector Space Model

Example ctd						
f_{i+}	f_{ij}	Term				
24	29	TOMORROW				
28	31	SPENT				
7	12	FACTS				
38	63	EXPLOSIVES				
24	29	LEADING				
36	45	NATIONS				
9	18	0				
58	91	1				
44	85	2				
23	31	OPPORTUNITY				
74	136	GENERAL				
8	10	TEARS				
11	13	VIDEOTAPE				
17	32	DEVICES				
37	43	FACE				
13	14	ALONE				
33	35	ALONG				
27	37	HAVEN				
86	137	FACT				

Vector space

Each document is a vector $D_j = (w_{1j}, \ldots, w_{Tj})'$ of transformed counts

Document similarity could be

$$D'_j D_k$$
 or $rac{D'_j D_k}{\|D_j\| \|D_k\|}$

A query Q is a (very short) document

Precision-recall

Given Q rank N documents in order of relevance

Suppose there are ${\boldsymbol R}$ truly relevant documents

Precision =

% of first n ranked documents that are relevant $\ensuremath{\mathsf{Recall}} =$

% of R relevant documents among first n ranked documents

0

0

0

0

0

8

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Transposing it

A document has a weighted list of words

A word has a weighted list of documents

Query with a list of documents:

- 1. Todays documents...word NASDAQ is hot
- 2. All documents in bovine set
- 3. All documents in dental set

Also

"Words are known by the company they keep"

Do "boat" queries find "ship" docs?

Maybe we should "cluster" the terms

Let $W = (w_{ij})$

Clustering: approximate by

$$\widehat{W}_{ij} = \sum_{k=1}^{K} \theta_{ik} \mu_{kj}$$

 μ_k is k'th cluster mean

 θ_{ik} is 1 if term *i* in cluster *k*, zero else

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Latent semantic indexing

SVD:

$$W_{ij} = \sum_{k=1}^{\min(N,T)} \lambda_k u_{ik} v'_{jk}$$
$$\widehat{W}_{ij} = \sum_{k=1}^{K} \lambda_k u_{ik} v'_{jk}$$

May find a nautical singular vector u_k with "boat" and "ship" and "starboard" etc.

Run queries on \widehat{W} with $K\ll N$

- SVD looks a bit like clusters
- First few singular values have "less noise"
- $\widehat{W}'Q$ much faster than W'Q
- Less storage too

Vector Space Model

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