Information retrieval

Flexible querying methods

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Today's outline

- Short summary of last lecture
- tf-idf
- Querying in the vector-space model
- (Latent semantics)

What to remember from last time?

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- Web IR is split in distinct steps:
  - Gathering and indexing data from the web (**crawling**)
  - Retrieving documents relevant to a query
  - Ranking the valid answers according to relevance
- The involved data is **big**

  Need efficient representation and algorithms

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The boolean querying does not rank

When querying using a boolean querying system, the output is binary.
$\rightarrow$Unable to distinguish the relevant matches from non-relevant ones.

The vector space model and the latent semantics

Representing documents as vectors in $\mathbb{R}^T$

From binary presence/absence...

	tok 1	tok 2	tok 3	tok 4	tok 5	...
	election	president	crazy	united	United States	...
doc 1	1	1	0	0	1	...
doc 2	0	1	1	0	1	...
doc 3	1	1	1	0	1	...
...	...	...	...	...	...	...

Representing documents as vectors in $\mathbb{R}^T$

...to real vector space.

	tok 1	tok 2	tok 3	tok 4	tok 5	...
	election	president	crazy	united	United States	...
doc 1	0.01	0.02	0	0	0.006	...
doc 2	0	0.013	0.001	0	0.001	...
doc 3	0.0031	0.008	0.0043	0	0.0021	...
...	...	...	...	...	...	...

What numbers can be useful here ?

Not every term is informative

How do you quantify information according to Shannon theory?

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Example: which book are you talking about?

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"the" is frequent	~ 1	Low
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Exercise

I throw a die. What is the more informative:

- the outcome is even
- the outcome is ≥ 5

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If we moreover ask for f to be continuous, there is only one possible class of functions: $-log_b$

The information of an event e is defined as $I(e) = -log_2(P(e))$

Information in the context of documents

Definition

We can now compute the information of a token as:

$$I(t) = -\log\left(\frac{\#\text{doc including token } t}{\#\text{docs}}\right)$$

Vector representation of a document

A document can be represented by a vector of the fraction information associated to each of its token:

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What does $||\vec{D}||_1$ represent?

$||\vec{D}||_1$ carries the total information carried by a document:

- low if the document contains only common tokens
- average if the document contains few exceptional tokens
- high if the document contains only exceptional items

The tf-idf matrix

Definition

The matrix M which rows – corresponding to each document – are:

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Question

What is the unit of elements of the tf-idf matrix?

Querying a set of vector

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Indeed, it makes sense: For each document, compute:

$$\vec{D} \cdot \vec{Q} = \sum_t D_t.Q_t$$

The higher the dot product, the more informative tokens $\vec{Q}$ and $\vec{D}$ share... and the more relevant should be the D with respect to the query Q.

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For querying purposes, one can select documents such that $\vec{D} \cdot \vec{Q} > \tau$, but it can directly be used for ranking documents.

Correcting for cheaters

Problem

Imagine a way of cheating with this approach.

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Content farms

$$\begin{array}{rcl}\vec{D}\cdot\vec{Q} & = & \sum_t D_t.Q_t \\ & = & \sum_t \frac{\#\text{ t in D}}{\#\text{ tokens in D}} \times I(t).\frac{\#\text{ t in Q}}{\#\text{ tokens in Q}} \times I(t) \\ & \propto & \frac{1}{\#\text{ tokens in D}} \sum_t \#\text{t in D} \times \#\text{t in Q} \times I(t)^2\end{array}$$

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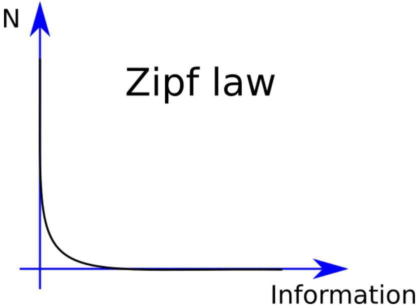
$$\begin{aligned}
\vec{D} \cdot \vec{Q} &= \sum_t D_t . Q_t \\
&= \sum_t \frac{\#\text{ t in D}}{\#\text{ tokens in D}} \times I(t) . \frac{\#\text{ t in Q}}{\#\text{ tokens in Q}} \times I(t) \\
&\propto \frac{1}{\#\text{ tokens in D}} \sum_t \#\text{t in D} \times \#\text{t in Q} \times I(t)^2
\end{aligned}$$

Documents containing many informative words will be selected and ranked first.

Content farms: pull informative words together



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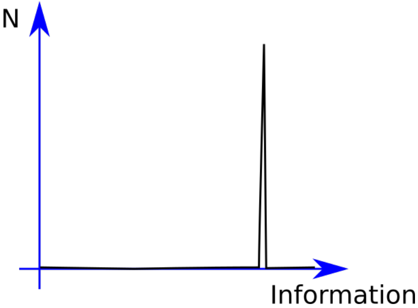

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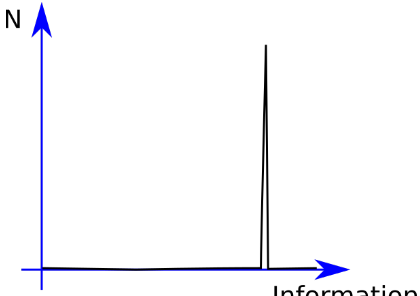

...Can "answer" many more queries

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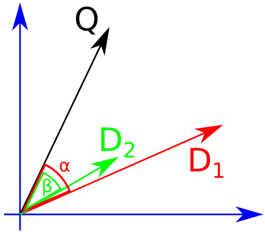

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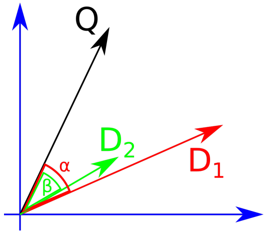

Correct by normalizing the similarity:

Consine similarity

$$\text{cosim}(\vec{D}, \vec{Q}) = \frac{\vec{D} \cdot \vec{Q}}{||\vec{D}||_2 . ||\vec{Q}||_2}$$

A flexible querying system?

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Does it solve the synonymous problem?

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As already pointed out, we could use a semantic approach (ontologies), but need a fixed and manually curated work.

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As already pointed out, we could use a semantic approach (ontologies), but need a fixed and manually curated work.
Can we work directly from the data?

Embeddings

From TF-IDF to Embeddings

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Embeddings

Embeddings aim at reducing space of tokens to less dimension in an useful way: a token will live in a small dimensional space ($D_E = 300$) such that semantically similar token lie close to each other in space.

Embeddings: the many derivatives

Many models have been developed for representing various type of data. Here is a small list of freely available models:

Model	Data represented
`word2vec`	Tokens
`GloVe`	Tokens
`fastText`	Tokens
`doc2vec`	Documents
`dna2vec`	Genomic sequences

... to be continued next lecture