Information retrieval

Flexible querying methods

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Today's outline

- Short summary of last lecture
- Embeddings
- Ranking

What to remember from last time?

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What are the main points you remember from last lectures?

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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
- Boolean querying are not flexible
- Easy to integrate information of tokens in the model **at no cost**
- tf-idf does not solve the synonymy issue

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	...
...	...	...	...	...	...	...

Vector representation of a document

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

$$D_t = \frac{\#\text{ t in D}}{\#\text{ tokens in D}} \times [-\log_2(\frac{\#\text{doc including token } t}{\#\text{docs}})]$$

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$||\vec{D}||_1$ 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

Querying a set of vector

Represent the query the same way:

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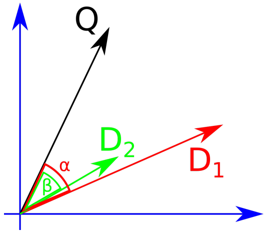
Dot product:

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

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.

The cosine 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?

With the vector space model, information of the tokens are now automatically taken into account.
Does it solve the synonymous problem?

Example

Query: `result elections United States`
Doc title: "White House election: live results!"

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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.

Embedding from data: introductory example

After the next *house*, you turn right.

Embedding from data: introductory example

After the next *house*, you turn right.
After the next *building*, you turn right.

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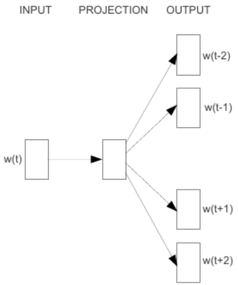
Hypothesis

The context of a word is giving its meaning. So similar context $\approx$ similar meaning.

Word2vec: predict the context of a token

The core idea of word2vec is to learn a vector representation allows to predict the context of the token. Thereby, tokens appearing in similar context will be encoded closely in the vector space.



Skip-gram

[Mikolov, Tomas; et al. (2013)]

word2vec's semantic relations

The word2vec embeddings have interesting semantic features[1].

Table 8: *Examples of the word pair relationships, using the best word vectors from Table 4 (Skip-gram model trained on 783M words with 300 dimensionality).*

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

[1]Note that `GloVe` is better at this

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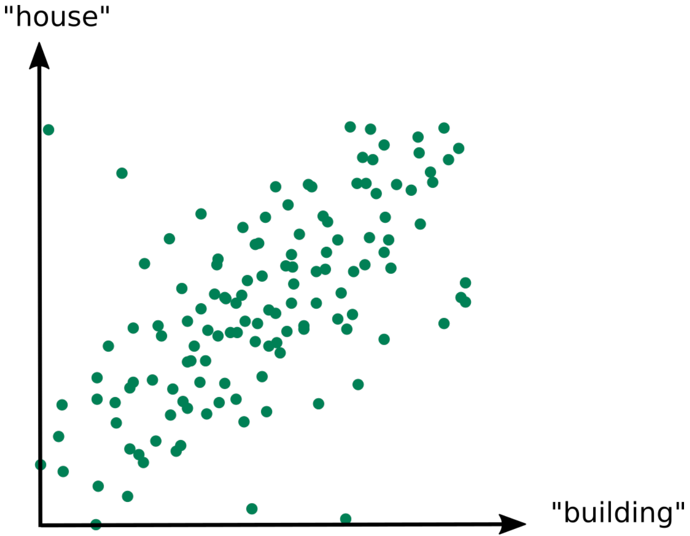
Locally sensitive hashing (LSH)

- Hash the query vector with k (discrete) hash functions: $\mathcal{O}(1)$
- Look for documents sharing same hash codes:: $\mathcal{O}(1)$
- Can compute exact scalar product against all retrieved documents.

Latent semantics: understand dimensionality reduction

Linear version of embeddings



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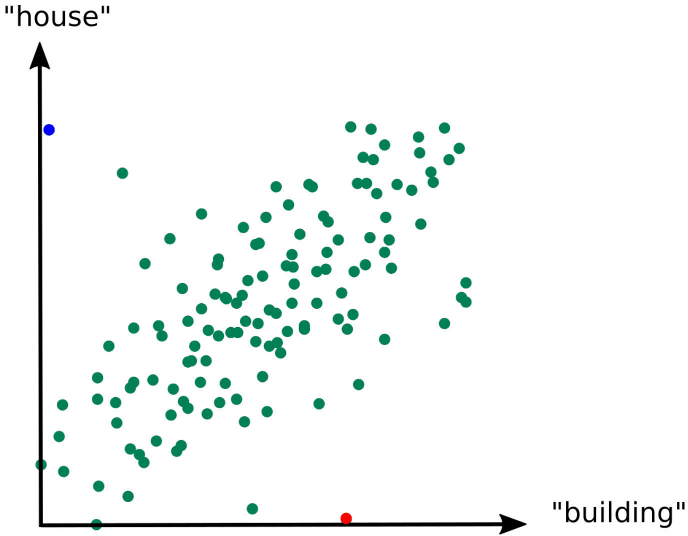

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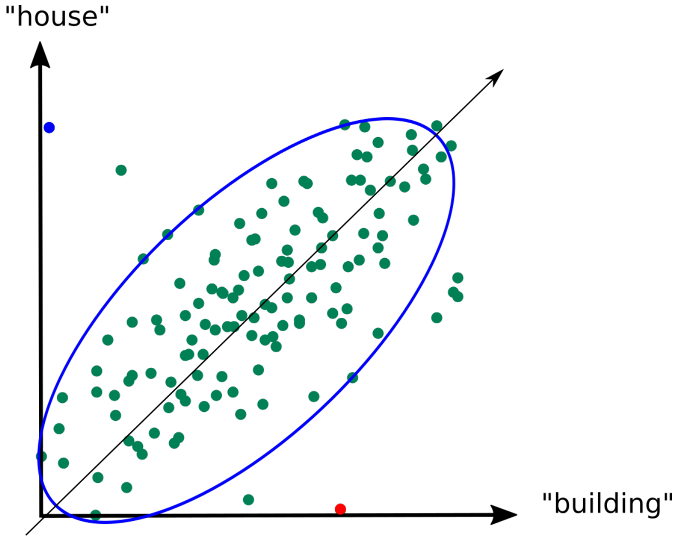

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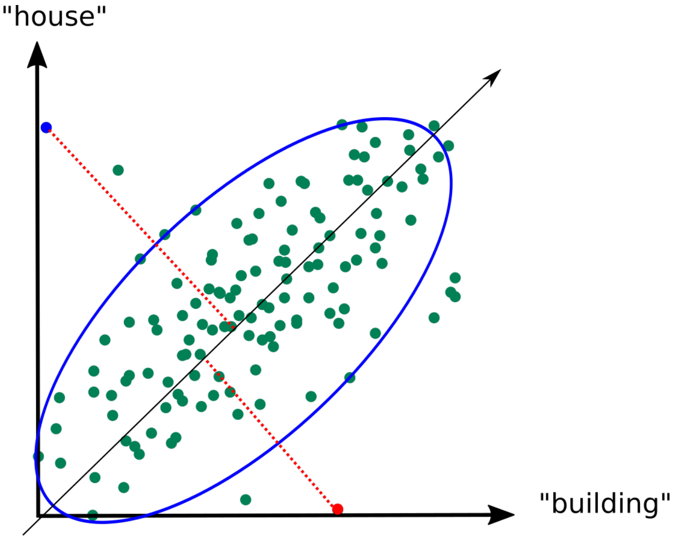

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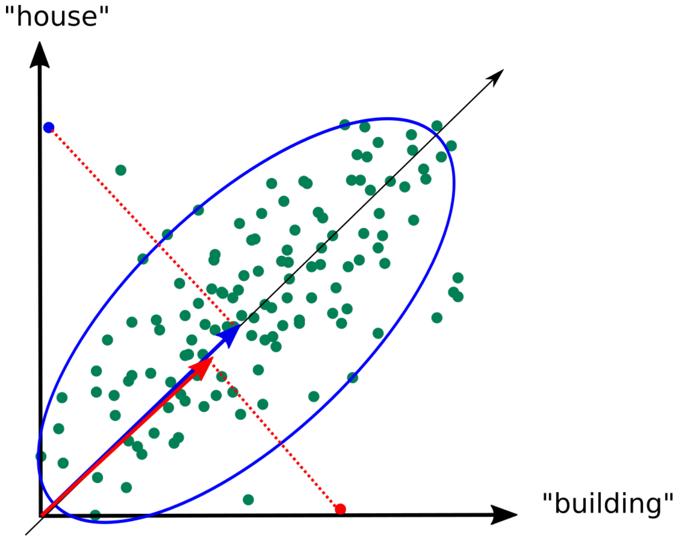

Special structure of the data: correlations

In practice a tf matrix looks like:

Interlude

Video

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PCA

PCA "discover" automatically those blocks

Data compresssion approach: Low rank approximation

Theorem (Eckart–Young–Mirsky)

The best[a] r-rank approximation $\hat{M}$ of M is given by the projection on the subspace formed by the eigenvectors of $M^\top M$ corresponding to the r biggest eigen values.

[a] In the sense minimizing $||M - \hat{M}||_F = \sum_{i,j}(m_{i,j} - \hat{m}_{i,j})^2$

The projection to the low rank space (columns of $V^\top$ in SVD decomposition $M = U\Sigma V^\top$) collapse similar (i.e. *correlated*) tokens to the same component. This space is called the **Latent semantic space**.

Code example for word2vec

```
>>> import gensim.downloader
>>> word2vec_vectors = gensim.downloader.load('word2vec-google-news-300')
[==================] 100.0% 1662.8/1662.8MB downloaded
>>> word2vec_vectors.get_vector("house")
array([ 1.57226562e-01, -7.08007812e-02,  5.39550781e-02, -1.89208984e-02,
    9.17968750e-02,  2.55126953e-02,  7.37304688e-02, -5.68847656e-02,
    ...
>>> word2vec_vectors.similarity("house","building")
0.4378754
>>> word2vec_vectors.similarity("house","dog")
0.25689757
>>> word2vec_vectors.similarity("house","happy")
0.11390656
```

Examples of biases in word2vec

```
>>> word2vec_vectors.similarity("man","father")
0.4201101
>>> word2vec_vectors.similarity("woman","mother")
0.60763067
>>> word2vec_vectors.similarity("man","smart")
0.09229658
>>> word2vec_vectors.similarity("woman","smart")
0.050040156
>>> word2vec_vectors.similarity("man","robber")
0.5585119
>>> word2vec_vectors.similarity("woman","robber")
0.45501366
>>> word2vec_vectors.similarity("mexican","thief")
0.12186743
>>> word2vec_vectors.similarity("american","thief")
0.036840104
```

Some open-source libraries

Some libs and features:

- Information Retrieval: Gensim (implements word2vec, fasttext and querying)
  - - : no transformer model
- NLP: Stanza (tokenization, named entity recognition)
- Embeddings: spaCy (in particular BERT)
- NLP+embeddings: Flair
  - - : few languages supported

Dealing with the *truth*

How to deal with the truth?

It is almost impossible to deal with truth judgment only from the document data.

However, we can assume that we trust information coming from *authorities* (well-known newspaper, official website, etc.).

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Idea

Rank the results of the querying system according to their authority.

How do we know who is the authority ?

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However, we can assume that we trust information coming from *authorities* (well-known newspaper, official website, etc.).

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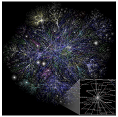
Rank the results of the querying system according to their authority.

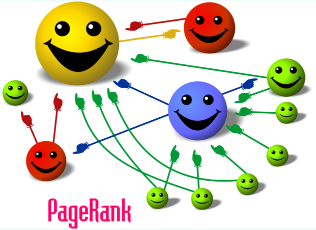
How do we know who is the authority ?

→ We extract it from the web structure  !

Authority and web structure

Who is the authority?

If you only represent the web by a graph where each node is a web page and each directed edge is an HTML link.



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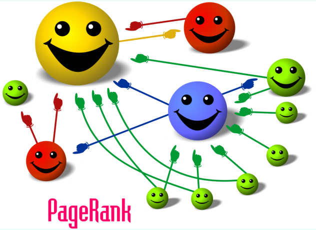

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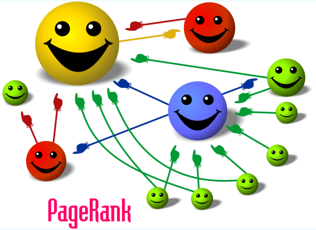

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Imagine an algorithm able to detect/rank authorities.

PageRank formalization (simple version)

Random surfer model

Imagine a user having the following behavior clicking on random links on the Internet.

The more links leading to a page, the more chance (and the more times) the user visits the page.

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The more links leading to a page, the more chance (and the more times) the user visits the page.
After a loooong time, we measure the average number of times the user visited a given page P, we denote R_P.

Definition of the rank according to PageRank

We define the authority/ranking of a page by the R_P value.

PageRank algorithm (simple version)

Data: $A :=$ graph of the WWW $\quad A_{ij} \quad = \quad \begin{cases} \frac{1}{N_j} & \text{if link from } j \text{ to } i \\ 0 & \text{else} \end{cases}$

Result: Ranking of web pages

$R^{(0)} := S$;

repeat

$\quad R^{(i+1)} \leftarrow AR^{(i)}$

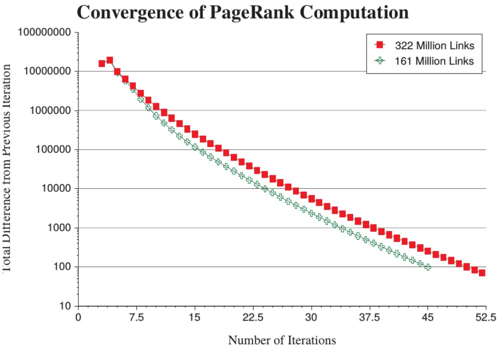
$\quad \delta \leftarrow ||R^{(i)} - R^{(i+1)}||_1$

until $\delta \leq \epsilon$;

Algorithm 1: simplified PageRank

Milestone of Google (algo designed by L. Page, Google co-founder), and drove the initial success of Google.

PageRank convergence



[L. Page, 98]

PageRank without sink effect

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The random eager surfer

Imagine the user having now the following behavior[a]

- click on a random link on the current web page with probability $p(t)$
- or jump to a random web page on the Internet with probability $1 - p(t)$

[a] In the original paper by Page, the balance between the two events is given by its trap feeling: the more trapped it gets, the more likely the user will jump somewhere else.

Full PageRank

To avoid a *sink* effect, we introduce random jumps to a set of pages encoded in E.

Data: Graph of the WWW

Result: Ranking of web pages

$R^{(0)} := S$;

repeat

$R^{(i+1)} \leftarrow AR^{(i)}$

$d \leftarrow ||R^{(i+1)}||_1 - ||R^{(i+1)}||_1$

$R^{(i+1)} \leftarrow R^{(i+1)} + d.E$

$\delta \leftarrow ||R^{(i)} - R^{(i+1)}||_1$

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Algorithm 2: PageRank

Full PageRank

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6 Personalized PageRank

An important component of the PageRank calculation is E – a vector over the Web pages which is used as a source of rank to make up for the rank sinks such as cycles with no outedges (see Section 2.4). However, aside from solving the problem of rank sinks, E turns out to be a powerful parameter to adjust the page ranks. Intuitively the E vector corresponds to the distribution of web pages that a random surfer periodically jumps to. As we see below, it can be used to give broad general views of the Web or views which are focussed and personalized to a particular individual.

We have performed most experiments with an E vector that is uniform over all web pages with

...

Such personalized page ranks may have a number of applications, including personal search engines. These search engines could save users a great deal of trouble by efficiently guessing a large part of their interests given simple input such as their bookmarks or home page. We show an example of this in Appendix A with the "Mitchell" query. In this example, we demonstrate that while there are many people on the web named Mitchell, the number one result is the home page of a colleague of John McCarthy named John Mitchell.

[L. Page, 98]

Summary

- Tf-Idf vector representation of a document
- Flexible vector queries (cosine similarity)
- Latent semantics (lower rank projection of the tf matrix)
- PageRank

Next lectures: can we make it?

- TP (Implemenation and experiments around IR systems)
  - Tokenizer
  - Tf-Idf matrix construction
  - Page Rank implementation
  - Mini-search engine
- (more) machine learning in IR

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If Q a binary vector over tokens, what does $M^\top MQ$ represent?

The cumulated frequencies of tokens in the (virtual) corpus matching Q.

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What does it mean that $M^\top MQ = \lambda.Q$?

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What does it mean that $M^\top MQ = \lambda.Q$? What if λ is small? big?

Algebra theorem

Eigenvectors of $M^\top M$, $\vec{C}_i$ are orthogonal and form a basis of the token space.
We can define a new scalar product:

$$\vec{D'} = \sum \alpha_i \vec{C}_i$$
$$\vec{Q'} = \sum \beta_i \vec{C}_i$$

We can compare search documents matching query Q using $\vec{D'}.\vec{Q'} = \sum \alpha_i.\beta_i$ or cosim$(\vec{D'}, \vec{Q'})$:)