Information retrieval

Evaluation of retrieval systems and learn to rank

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Objectives of the course

- Acquire a culture in information retrieval
- Master the basics concepts allowing to understand:
  - what is at stake in novel IR methods
  - what are the technical limits

This will allow you to have the basics tools to analyze current limitations or lacks, and imagine novel solutions.

What's coming ahead (outline)

- Summary of last lectures
- Machine learning in IR:
  - Embeddings
  - Evaluation of IR systems
  - Learning to search
- Hands-on: complete your project!

IR main steps


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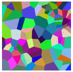
Information retrieval

From Wikipedia, the free encyclopedia

Information retrieval (**IR**) is the activity of obtaining information system resources relevant to an information need from a collection of information resources. Searches can be based on full-text



The tf-idf matrix

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Definition

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

$$D_t = \frac{\text{\# t in D}}{\text{\# tokens in D}} \times I(t)$$

is called the **tf-idf** (term frequency-inverse document frequency) representation.

Question

What are the advantages of the vector model ?

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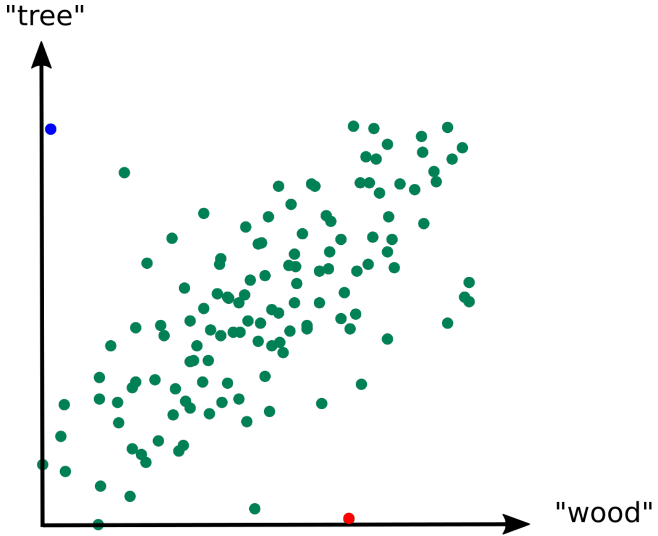
What are the advantages of the vector model ?

- Have a direct weightening by information carried by tokens
- Framework for latent semantics

Exploiting token correlation in documents



Latent semantics: low rank approximation

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Let M be the tf matrix: M_{ij} is the frequency of token j in document i. $M^\top M$ is symmetric and its eigenvectors are orthogonal and form a basis of the token space.

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What NLP issue does the IR latent semantics takle?

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

Result: Ranking of web pages

$R_0 := S$;

repeat

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

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

until $\delta \leq \epsilon$;

Algorithm 2: simplified PageRank

Machine learning in IR

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Recent techniques (well, mostly since 2013)

Machine learning techniques can be used to **learn better vector representation**[a] **of tokens**, and more generally of any data (document, sentence, word, image, etc.).

[a] aka embeddings

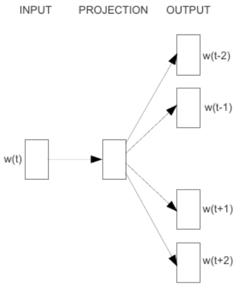
Embeddings: a general technique with many derivatives

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

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 latent semantics

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

Machine learning and IR performance evaluations

Evaluation of IR systems

Google vs Qwant

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Need a gold standard and indicators.

What gold standard?

It depends... For measuring correctness (binary outcome): **Collection of documents** associated to a query.
For measuring relevance (ordered outcome): **Collection of documents** ranked by relevance associated to a query.

Can be seen as a partial function $g : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}$ associating to a couple query-document its quantification of *correctness*, *relevance* or *truth*.

Indicators for binary gold standards[2]

Special case: $\mathrm{dom}(g) = \{0, 1\}$.

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What is a False Positive? True Negative?

[2] To be used for assessing correctness for instance.

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Query: q = results election U.S.

Document (d)	rank	g(q,d)
`Biology-Wikipedia`	0.82	0
`laposte.fr`	0.01	0
`election.gov.us/results`	0.9	1
`mediapart.fr/America`	0.7	1

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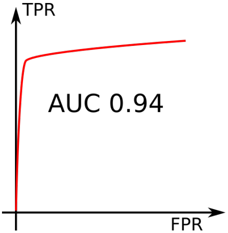

$$TPR_\tau = \frac{TP_\tau}{P}, FPR_\tau = \frac{FP_\tau}{N}$$

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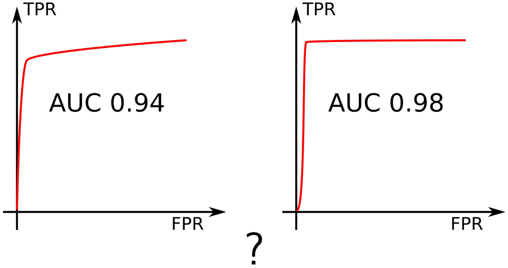
Beware of summary indicators!

Use the right summary indicator (e.g. AUC-ROC/AUC-ROC5).



Indicators for rank gold standards[3]

Ranking functions $f_1, f_2 : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$ (the higher, the more relevant the doc to the query).

How can we say that f_1 is better than f_2?

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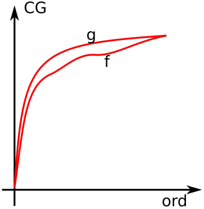
Ranking functions $f_1, f_2 : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$ (the higher, the more relevant the doc to the query).

How can we say that f_1 is better than f_2?

Given a gold standard $g : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$, we define the cumulative gain:

$$\mathsf{CG}_n(q, f) = \sum_{k:\mathsf{ord}_n(q,f)} g(q, k)$$

where $\mathsf{ord}_n(q, f)$ are the n first elements of $\mathcal{D}$ when sorting by $f(q, \_)$.



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Indicators for ranking, stressing first results

In the same spirit of the difference AUC/AUC5, one can stress more the first results, by weighting the relevance by a *discount*[4] function:

$$\mathsf{DCG}(q,f) = \sum_{k:\mathsf{ord}_{N_q}(q,f)} \frac{g(q,k)}{\log(k+1)}$$

where N_Q is $\mathsf{card}\{d|(q,d) \in \mathsf{dom}(g)\}$ and i is the index in the summation.

The normalized DCG is defined as:

$$\mathsf{NDCG}(q,f) = \frac{\mathsf{DCG}_{N_Q}(q,f)}{\mathsf{DCG}_{N_Q}(q,g)}$$

[4]One can choose different discount functions, but $\frac{1}{\log k}$ has nice theoretical foundations [Wang et al. JMLR 13] and is good in practice.

Comparing ranking strategies

Ranking functions $f_1, f_2 : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$. How can we say that f_1 is better than f_2?

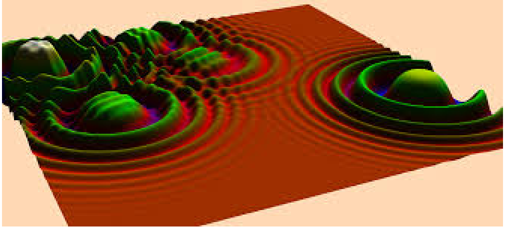
Can use the expected NDCG(q, f_i) summary statistic:

$$\rho_i = \frac{1}{Q} \sum_q \mathrm{NDCG}(q, f_i)$$

As usual, averaging can hide bad performance when the gold standard is dominated by high performance on many similar queries.

Learning the parameters

Having a gold standard not only allows evaluation, but also optimization of the parameters.



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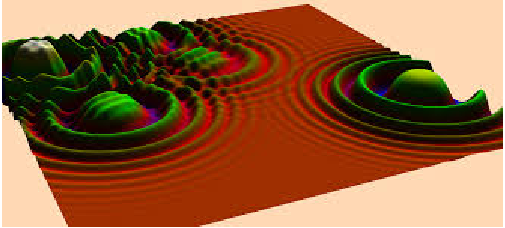

What parameters are we talking about?

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)

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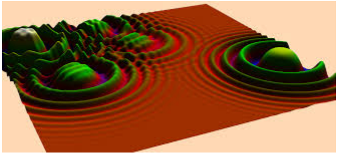
But also...

...the **trade-off** between the semantic scores (e.g. tf-idf vector model, text importance score) and the authority ranking score.

Optimize the objective function by tuning the parameters

$$\mathsf{obj} : \mathbb{R}^p \to \mathbb{R}$$



This is an optimization problem:

$$\arg\max_{\mathbb{R}^p} \mathsf{obj}$$

One can therefore use optimization strategies to maximize performance indicators by tuning p parameters.

Why not going further?

Why learning only few parameters?

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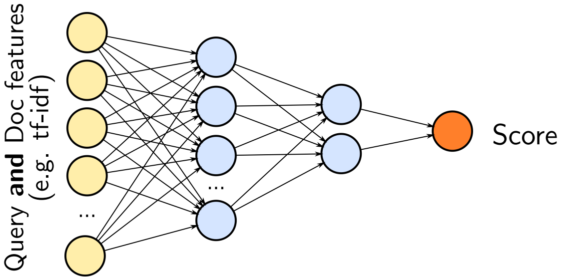
Why learning only few parameters? Why not learning directly:



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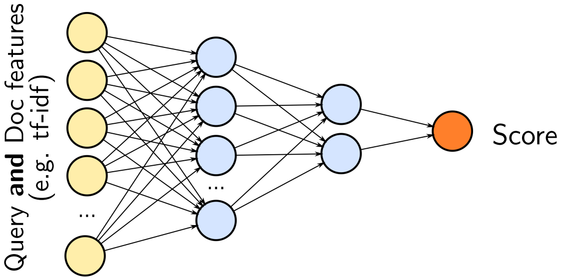

Issue

Curse of dimensionality, training set limitation, overtraining.

Ways out?

Avoiding overfitting

Two possible solutions to reduce overfitting:

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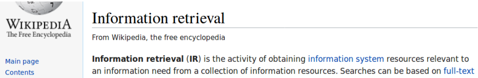
- Reducing the dimensionality (embeddings, latent semantics)

Wrap-up I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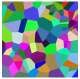
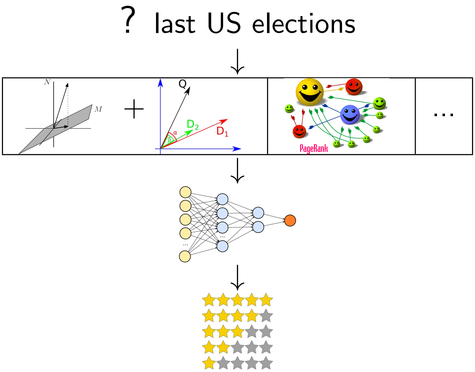
Information retrieval

From Wikipedia, the free encyclopedia

Information retrieval (**IR**) is the activity of obtaining information system resources relevant to an information need from a collection of information resources. Searches can be based on full-text




? last US elections
N
M
Q
D2
D1
PageRank
...

Hope you enjoyed.

Find the material on `http://clovisg.github.io`

Extras