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.

IR main steps


WIKIPEDIA
The Free Encyclopedia

Main page
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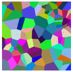
Information retrieval

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

Latent semantics: low rank approximation

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Theorem

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.

PageRank

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What PageRank is good for?
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How does it work?

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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

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

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

until $\delta \leq \epsilon$;

Algorithm 2: simplified PageRank

Machine learning in IR

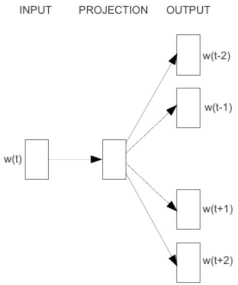
Embeddings: a general technique with many derivatives

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 + small context
`fastText`	Tokens
`BERT`	Tokens + their context
`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.

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

Machine learning and IR performance evaluations

Evaluation of IR systems

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For measuring relevance: **Collection of documents** ranked by relevance associated to a query.

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Need a gold standard  and indicators  .

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For measuring correctness: **Collection of documents** associated to a query.

For measuring relevance: **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*.

What can be an indicator?

Indicators for binary gold standards[1]

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

Question

What is a False Positive? True Negative?

[1] 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
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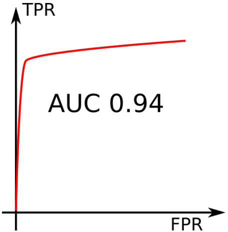

$$TPR_\tau = \frac{TP_\tau}{P}, FPR_\tau = \frac{FP_\tau}{N}$$

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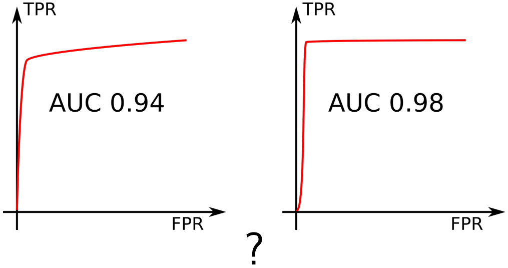
Beware of summary indicators!

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



Indicators for rank gold standards[2]

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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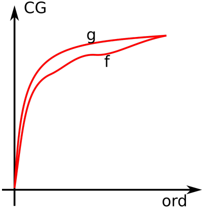
How can we say that f_1 is better than f_2?

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*[3] function:

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

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:

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

[3] One can choose different discount functions, but $\frac{1}{\log i}$ 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?

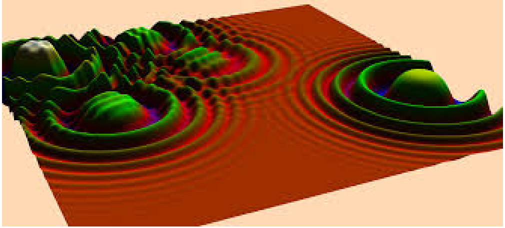
Can use the expected $\mathsf{NDCG}(q, f_i)$ summary statistic:

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

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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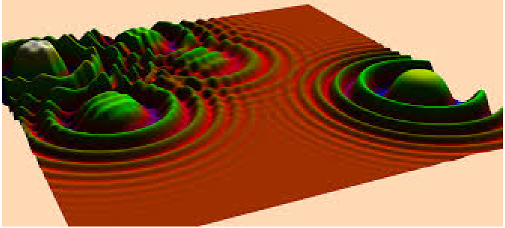

What parameters are we talking about?

Some parameters to tune

At the semantics level:

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

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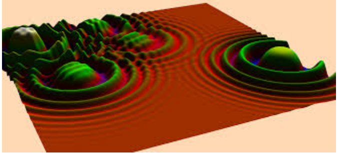
But also...

...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:

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

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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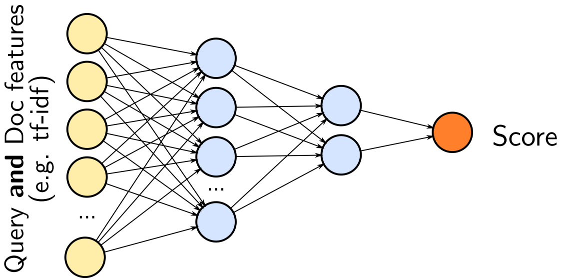
Why learning only few parameters? Why not learning directly:



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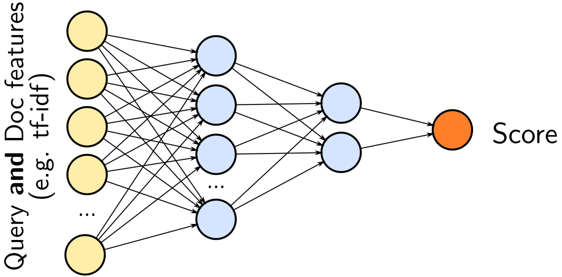

Issue

Curse of dimensionality, training set limitation, overtraining.

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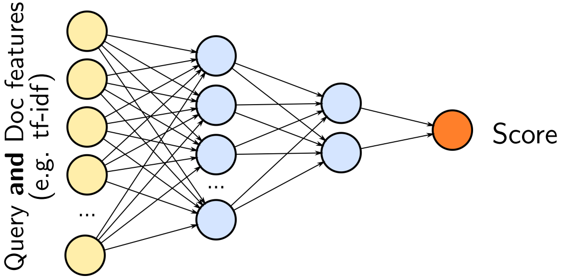

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Way out

Decrease the number of features or/and **expand the training set**.

Increasing the training set

If you own a popular search engine, imagine a simple way of increasing your training set.

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Click-through strategy: $g : (q, d) \mapsto$ nb of clicks on d

Reducing the dimensionality

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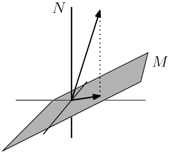

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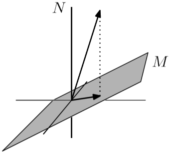
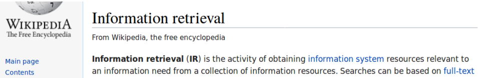


Embeddings.

Wrap-up I



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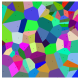

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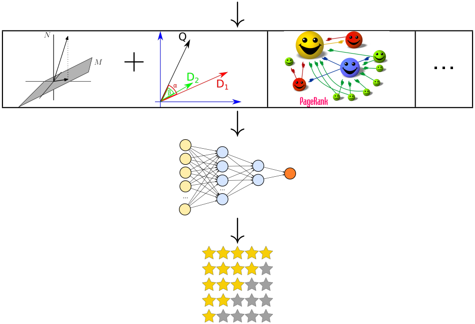
Wrap-up II

? last US elections



Hope you enjoyed.

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

Extras