Information retrieval

Evaluation of retrieval systems and learn to rank

Clovis Galiez

Laboratoire Jean Kuntzmann, Statistiques pour les sciences du Vivant et de l'Homme

January 4, 2022

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


WIKIPEDIA
The Free Encyclopedia

Main page
Contents

Information retrieval

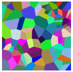
From Wikipedia, the free encyclopedia

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

The tf-idf matrix

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 ?

The tf-idf matrix

Definition

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

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

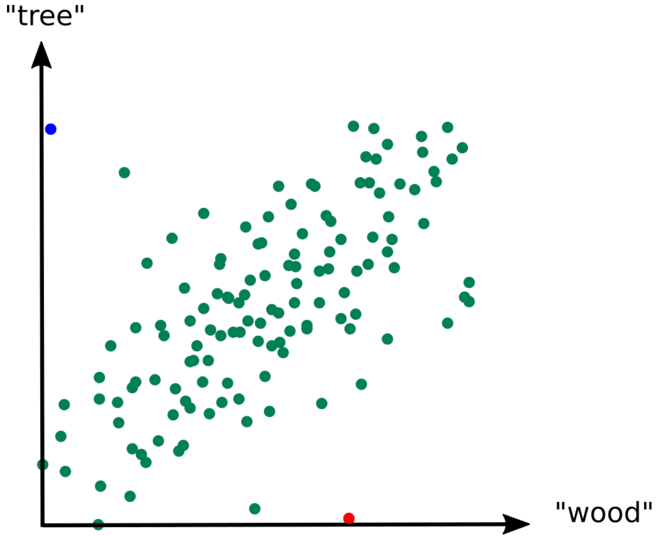
is called the **tf-idf** (term frequency-inverse document frequency) representation.

Question

What are the advantages of the vector model ?

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

Exploiting token correlation in documents



Latent semantics: low rank approximation

Latent semantics: low rank approximation

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.

Latent semantics: low rank approximation

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.

Question

What are the eigenvectors of $M^\top M$? What do they represent?

Latent semantics: low rank approximation

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.

Question

What are the eigenvectors of $M^\top M$? What do they represent?

Question

What NLP issue does the IR latent semantics takle?

PageRank

Question

What PageRank is good for?
What data is used as input?
How does it work?

PageRank

Question

What PageRank is good for?
What data is used as input?
How does it work?

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

From (linear) latent semantics to embeddings

In latent semantics, we define base vectors of the vector space of token frequencies that represent

From (linear) latent semantics to embeddings

In latent semantics, we define base vectors of the vector space of token frequencies that represent **concepts**.

From (linear) latent semantics to embeddings

In latent semantics, we define base vectors of the vector space of token frequencies that represent **concepts**.
We represent documents by projecting their

From (linear) latent semantics to embeddings

In latent semantics, we define base vectors of the vector space of token frequencies that represent **concepts**.
We represent documents by projecting their frequency vector in the low dimensional space formed by the important

From (linear) latent semantics to embeddings

In latent semantics, we define base vectors of the vector space of token frequencies that represent **concepts**.
We represent documents by projecting their frequency vector in the low dimensional space formed by the important **eigen vectors**.

From (linear) latent semantics to embeddings

In latent semantics, we define base vectors of the vector space of token frequencies that represent **concepts**.
We represent documents by projecting their frequency vector in the low dimensional space formed by the important **eigen vectors**.

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

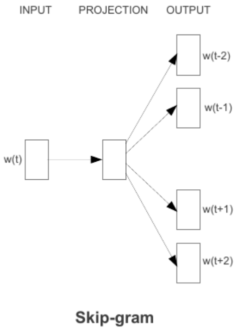
Embeddings: a general technique with many derivatives

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.



[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

How to evaluate the performances of an IR system?

Evaluation of IR systems

Google vs Qwant

How to evaluate the performances of an IR system?

Need a gold standard and indicators.

Evaluation of IR systems

vs

How to evaluate the performances of an IR system?

Need a gold standard and indicators.

What gold standard?

It depends...

Evaluation of IR systems

Google vs Qwant

How to evaluate the performances of an IR system?

Need a gold standard and indicators.

What gold standard?

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

Evaluation of IR systems

vs

How to evaluate the performances of an IR system?

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.

Evaluation of IR systems

Google vs Qwant

How to evaluate the performances of an IR system?

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: $\text{dom}(g) = \{0, 1\}$.

Question

What is a False Positive? True Negative?

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

Indicators for binary gold standards[2]

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

Question

What is a False Positive? True Negative?
What is a good graphic to have an idea of the performance of a ranking system?

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

Indicators for binary gold standards[2]

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

Question

What is a False Positive? True Negative?
What is a good graphic to have an idea of the performance of a ranking system?

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

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

Indicators for binary gold standards[2]

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

Question

What is a False Positive? True Negative?
What is a good graphic to have an idea of the performance of a ranking system?

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

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

Indicators for binary gold standards[2]

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

Question

What is a False Positive? True Negative?
What is a good graphic to have an idea of the performance of a ranking system?

Query: q = results election U.S.

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

$\tau = 0.75$

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

Indicators for binary gold standards[2]

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

Question

What is a False Positive? True Negative?
What is a good graphic to have an idea of the performance of a ranking system?

Query: $q =$ results election U.S.

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

$\tau = 0.2$

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

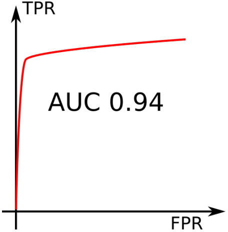
Indicators for binary gold standards[2]

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

Question

What is a False Positive? True Negative?
What is a good graphic to have an idea of the performance of a ranking system?

Query: $q =$ results election U.S.

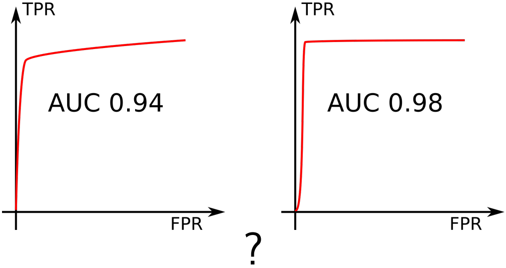


$$TPR_\tau = \frac{TP_\tau}{P}, FPR_\tau = \frac{FP_\tau}{N}$$

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

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?

[3] To be used for evaluation of relevance ranking for instance.

Indicators for rank gold standards[3]

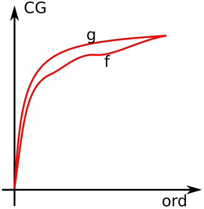
Ranking functions $f_1, f_2 : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$ (the higher, the more relevant the doc to the query).

How can we say that f_1 is better than f_2?

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 $f(q, \_)$.



[3]To be used for evaluation of relevance ranking for instance.

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?

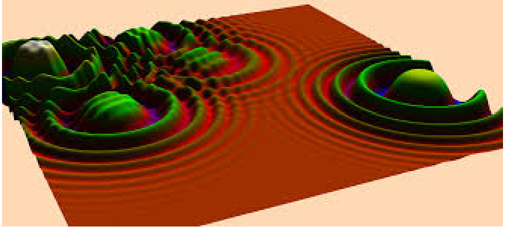
Can use the expected NDCG(q, f_i) summary statistic:

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

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

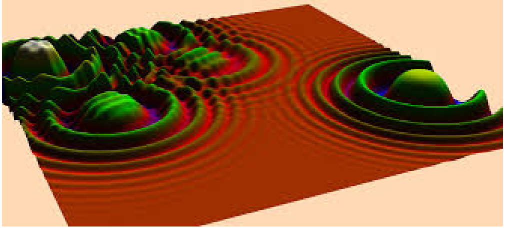
Learning the parameters

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



Learning the parameters

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



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)

Some parameters to tune

At the semantics level:

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

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy
- Important text scoring

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy
- Important text scoring
- The scoring system (cosine similarity, Euclidean distance, etc.)

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy
- Important text scoring
- The scoring system (cosine similarity, Euclidean distance, etc.)
- Latent semantics (e.g. size of the space)

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy
- Important text scoring
- The scoring system (cosine similarity, Euclidean distance, etc.)
- Latent semantics (e.g. size of the space)

At the ranking level:

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy
- Important text scoring
- The scoring system (cosine similarity, Euclidean distance, etc.)
- Latent semantics (e.g. size of the space)

At the ranking level:

- Source vector choice

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy
- Important text scoring
- The scoring system (cosine similarity, Euclidean distance, etc.)
- Latent semantics (e.g. size of the space)

At the ranking level:

- Source vector choice
- Prior distribution on links in a web page (e.g. important links)

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)
- Stemming
  - not enough: mother - maternal
  - too much: police - policy
- Important text scoring
- The scoring system (cosine similarity, Euclidean distance, etc.)
- Latent semantics (e.g. size of the space)

At the ranking level:

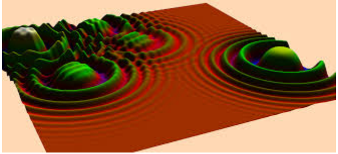
- Source vector choice
- Prior distribution on links in a web page (e.g. important links)

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

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



This is an optimization problem:

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

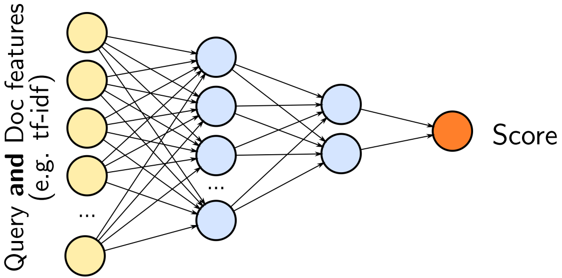
One can therefore use optimization strategies to maximize performance indicators by tuning p parameters.

Why not going further?

Why learning only few parameters?

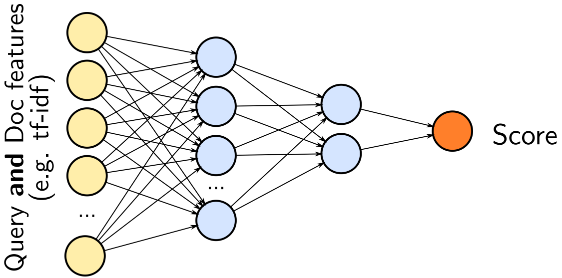
Why not going further?

Why learning only few parameters? Why not learning directly:



Why not going further?

Why learning only few parameters? Why not learning directly:



Issue

Curse of dimensionality, training set limitation, overtraining.

Ways out?

Avoiding overfitting

Two possible solutions to reduce overfitting:

Avoiding overfitting

Two possible solutions to reduce overfitting:

- Increase the training set:

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

Avoiding overfitting

Two possible solutions to reduce overfitting:

- Increase the training set:

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

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

Avoiding overfitting

Two possible solutions to reduce overfitting:

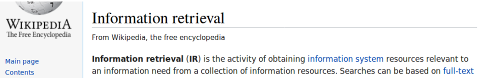
- Increase the training set:

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

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

- Reducing the dimensionality (embeddings, latent semantics)

Wrap-up I


WIKIPEDIA
The Free Encyclopedia

Main page
Contents

Information retrieval

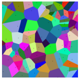
From Wikipedia, the free encyclopedia

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

↓

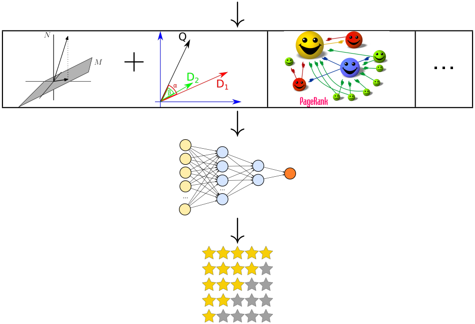
↓

↓



↓

? last US elections



Hope you enjoyed.

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

Extras