Textual information retrieval Models

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2018/2019 [1]

1. freely inspired by Benjamin Piwowarski and Hinrich Schütze's courses

IR systems

- Document indexing
- Query analysis
- Search model
- Evaluation

Plan

Why index ?

- Objective : find documents relevant for the user query
- From the query **words**
- Impossible to go through the entire collection
  - too many documents → prohibitive response time
  - operations between terms (not, near...) complex

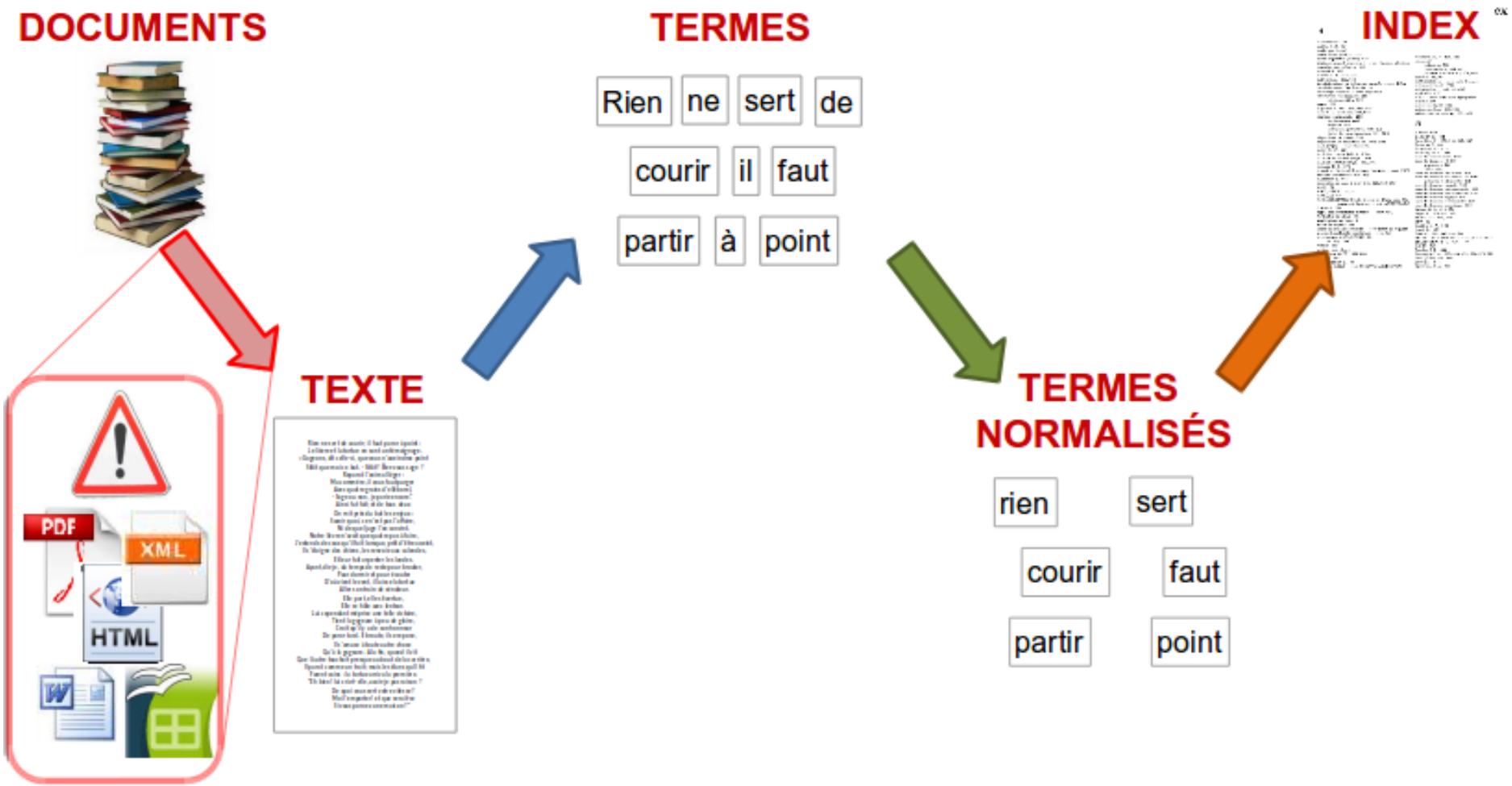
⇒ pre-processing = indexing

  - goal : "transform documents into substitutes capable to represent the documents content" (Salton et McGill, 1983)

Free vs controlled indexing

- free indexing : terms from documents
- controlled indexing : predefined terms
  - controlled vocabulary : avoids polysemy, synonymy, granularity problems

Documents


DOCUMENTS
TERMES
INDEX
Rien ne sert de
courir il faut
partir à point
TEXTE
PDF
XML
HTML
TERMES
NORMALISÉS
rien sert
courir faut
partir point

Formats

Formats

- HTML (diff : menus, tables, ads, appearance)
- raw text (structure ?)
- pdf (encoding, appearance)
- word (proprietay format, structure)
- excel (tables)
- openoffice (xml)

Taking the format into account

- detecting a document type is quite simple
- heuristics specific to each format to extract the text
- search engines raraly use the document structure

Language and encoding

Languages

- language identification = difficult problem
- multilingual information retrieval possible

Encoding

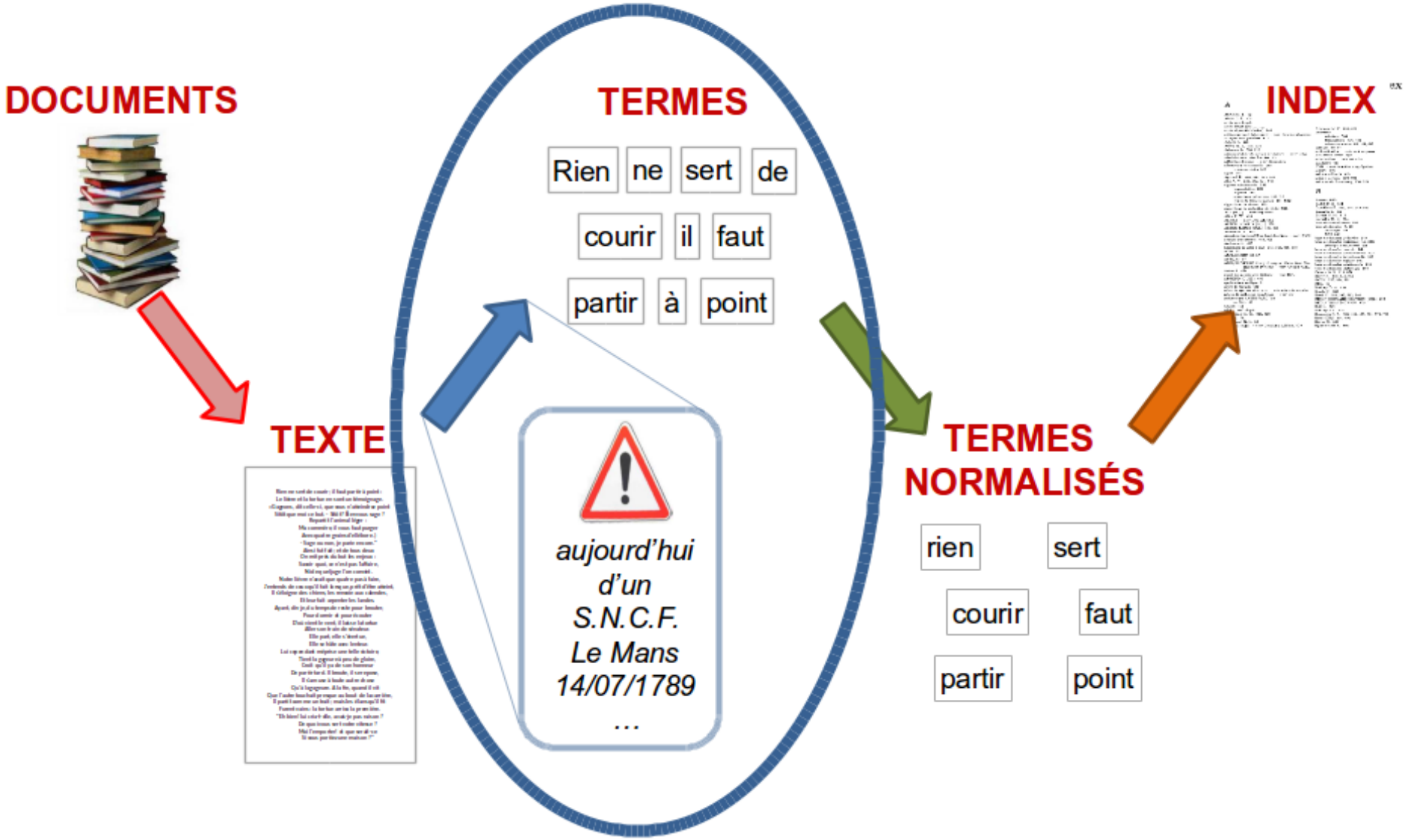
- errors in dealing with encoding → incorrect results

Document content

unit =

- file ?
- e-mail ?
  - with heading ?
  - with attachments ?
- set of files
  - website
  - document with multiple files
- ...

From text to terms



Tokenization

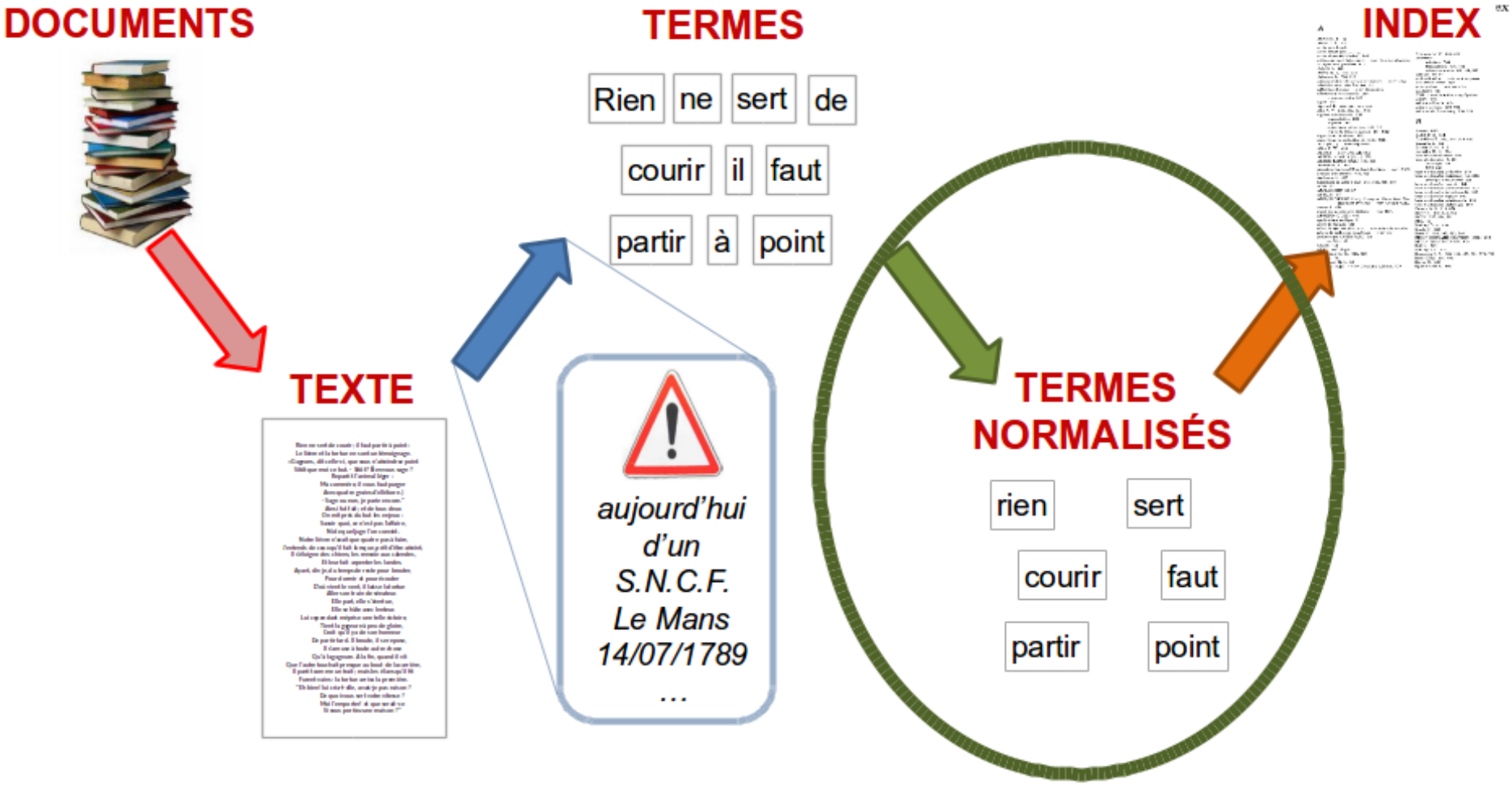
Tokenization = identification of elementary units

- **word** : substring as it appears in the text
- **term** (or type) : normalized word (case, morphology, spelling...)
  - set of terms = dictionary
- **token** : instance of a word or a term in a document

Difficulties of tokenization

- graphical variants of words with possible separators
  - États-Unis ou États Unis
- composed words in agglutinative languages
  - Lebensversicherungsgesellschaftsangestellter (employee from a lige insurance company)
- multiple alphabets in Japanese for example
- bidirectionnality of the reading sense in Arabic (numerals and letters)
- numbers : 555 3424, 24.09.2018
- ...

Normalization



Variant normalization (1/2)

- in documents and query
- variants that should be grouped
  - word variants including punctuation
    - U.S.A. and USA
    - morpho-syntaxe and morphosyntaxe
  - diacritic variants
    - in German, Tuebingen, Tübingen and Tubingen
    - in English, resume = résumé
  - proper names variants
    - Gorbatchov and Gorbatchev
- but
  - accents can be relevant
    - sur and sûr
    - pêche and péché
  - the case can be relevant
    - in German, mit and MIT
      (interaction between normalization and language detection)
    - in English, fed and Fed

Variant normalization (2/2)

- possibly asymetric
  - window → window, windows
  - windows → Windows, windows
  - Windows : non expansion
- + typos or spelling, OCR errors
- important criterion : how will the users write their query most often ?

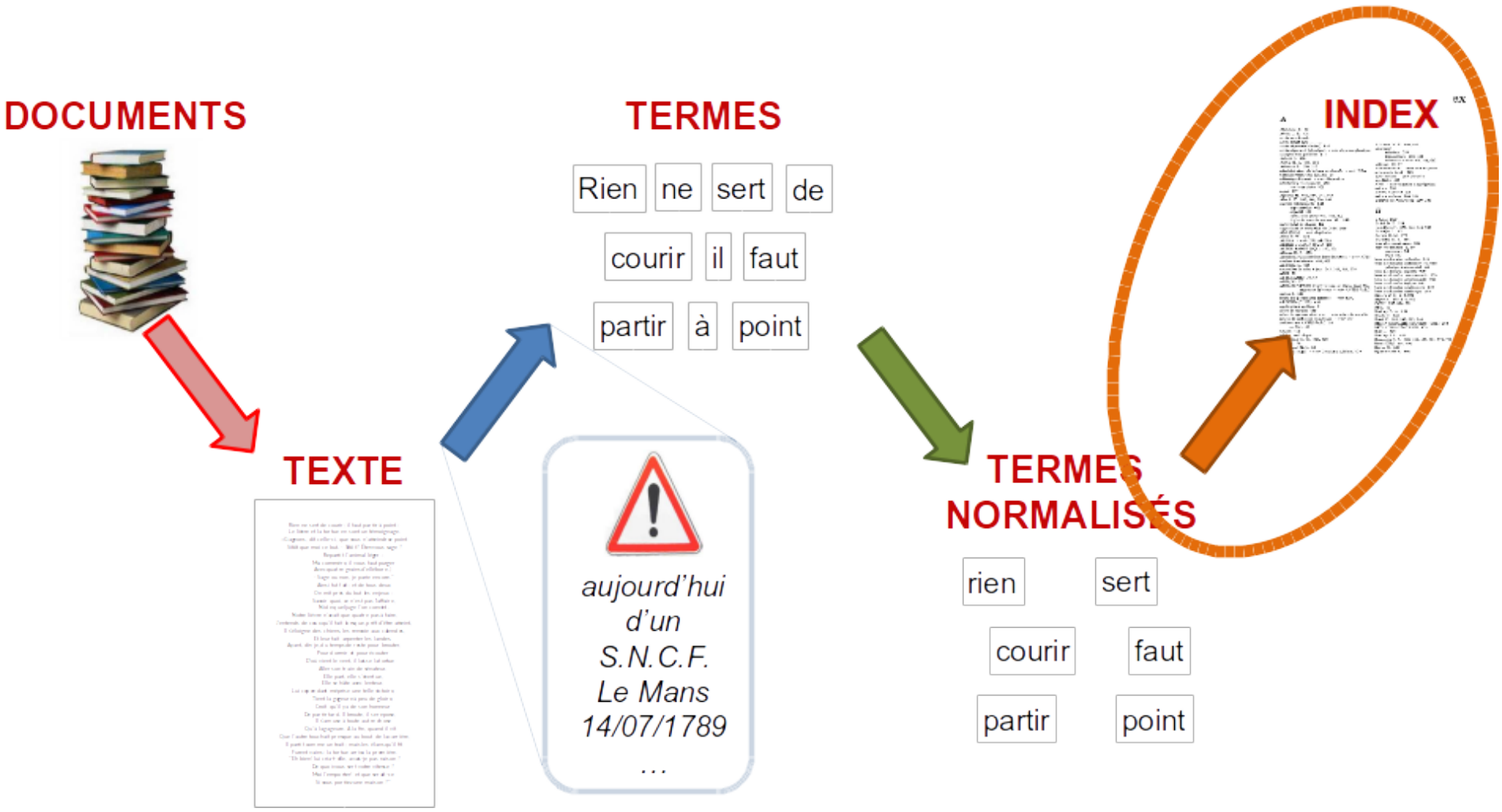
Morphological normalization

- use of analyses
  - lemmatization : chanteurs → chanteur, chantions → chanter
  - stemming : automate, automatique, automatisation → automat
    - in particular Porter algorithm, classical algorithm for English
    - stemming useful for certain queries, strongly worsens the results for others
  - POS tagging
- technics considered as mainly solved : low percentage of errors but difficult to reduce

Stop words

- word that do not add sense to the text
  - determiners : le, la
  - pronouns : je, nous
  - prepositions : sur, contre
- they are the most frequent in a language
  - the 30 most frequent words represent 30% of the word occurrences
  - delete them enables to gain much space in the index
- but
  - useful for multi-term queries : "pomme de terre", "les Chevaliers du Zodiaque"
  - sometimes bring sense in particular cases : "Let it be", "The Who", "être ou ne pas être"
  - compression actually enables to keep stopwords with little space

Index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Le Mans
14/07/1789
...
TERMES
NORMALISÉS
rien sert
courir faut
partir point

Incidence matrix

	Antoine & Cléopâtre	Jules César	La Tempête	Hamlet	Othello	Macbeth
Antoine	1	1	0	0	0	0
Brutus	1	1	0	1	0	0
César	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cléopâtre	1	0	0	0	0	0
pitié	1	0	1	1	1	1
pire	1	0	1	1	1	0

Incidence matrix

Brutus ET Cléopâtre ET PAS Calpurnia

	Antoine & Cléopâtre	Jules César	La Tempête	Hamlet	Othello	Macbeth
Antoine	1	1	0	0	0	0
Brutus	1	1	0	1	0	0
César	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cléopâtre	1	0	0	0	0	0
pitié	1	0	1	1	1	1
pire	1	0	1	1	1	0

Vecteurs d'incidence

¬Calpurnia	1	0	1	1	1	1

ET "bit à bit"

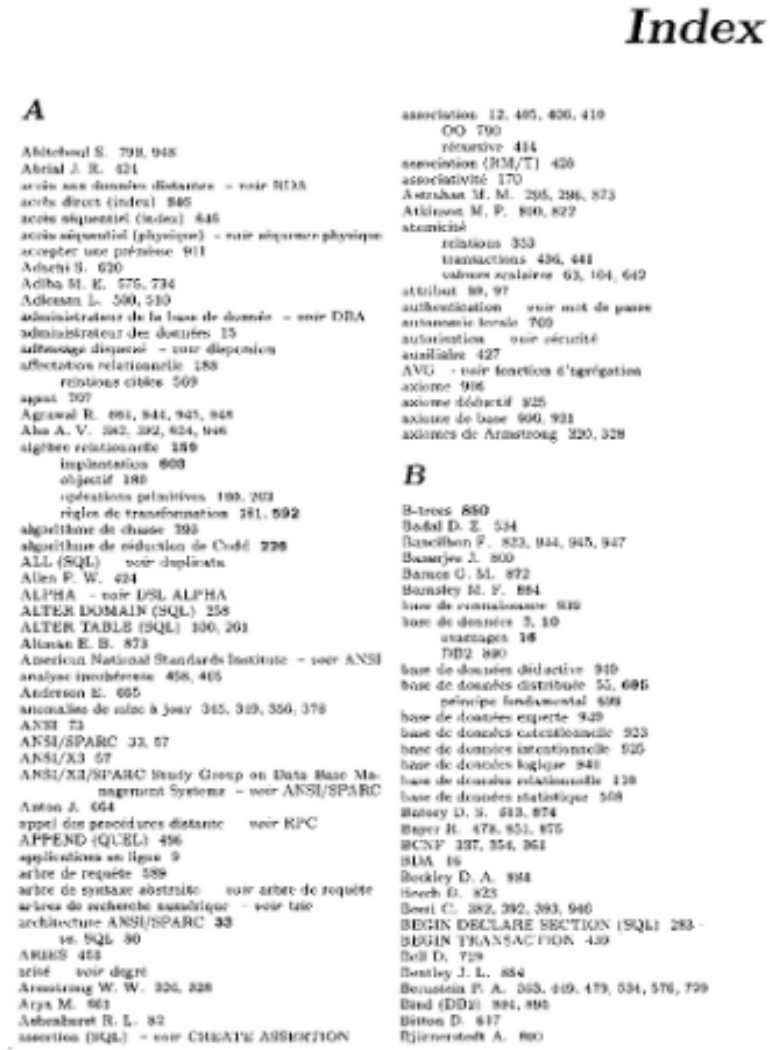
1	0	0	0	0	0

Incidence matrix

- impossible to use in practice
  - collection of a million documents
  - about 1000 words per document
  - total vocabulary of 500,000 distinct words

  → how many objects in the matrix ? how many 0s ? and 1s ?

Inverted index



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Inverted index

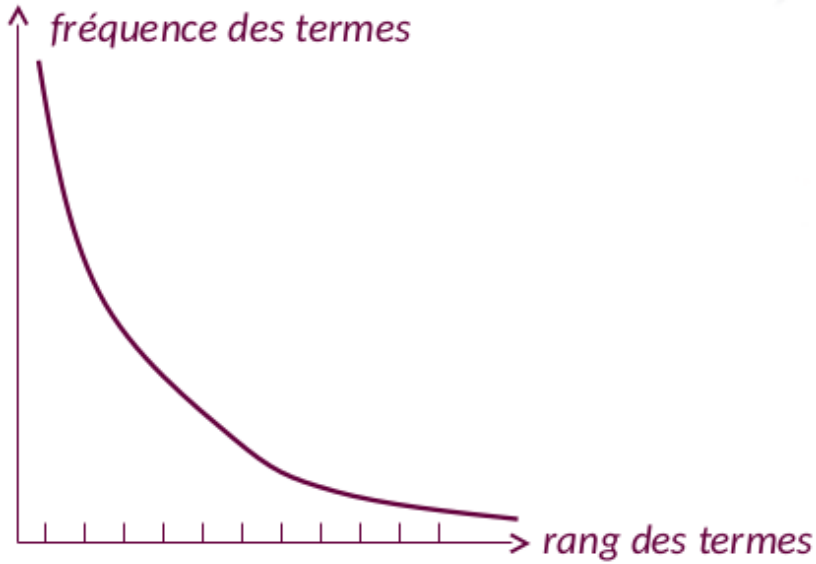
- classical notion of index
- associates indexes to documents that contain them (unique identifier)
  - a $\rightarrow$ d1, d2, d3, d4, d5...
  - à $\rightarrow$ d1, d2, d3, d4, d5...
  - abaissa $\rightarrow$ d3, d4...
  - abaissable $\rightarrow$ d5
  - abandon $\rightarrow$ d1, d5
  - abandonna $\rightarrow$ d2
  - ...

Vocabulary size

- The vocabulary increases with the colection
- Heaps law : M $= kT^b$ with
  - M vocabulary size
  - T number of tokens in the collection
  - b and k constants (typically b=0,5 and k = 30 to 100)
  - empirical law
- much worse for the Web !

Term frequency

- few frequent words and many rare words
- Zipf law : the n^th most frequent word has a frequency (= number of occurrences) proportional to $1/n$



tfidf

- in a query like in a document, all terms do not have the same importance
- intuition 1 : the more occurrences of a word a document contains, the more it is about this term $\rightarrow$ $\text{tf}_{t,d}$ = number of occurrences of term t in document d
- intuition 2 : very frequent words in all documents are less important (less discriminating) $\rightarrow$ df_t = number of documents that contain term t
- weight of a term $tf.idf_t, d = tf_{t,d} x log_{10} \frac{N}{df_t}$ (N = number of documents)

Weighted matrix

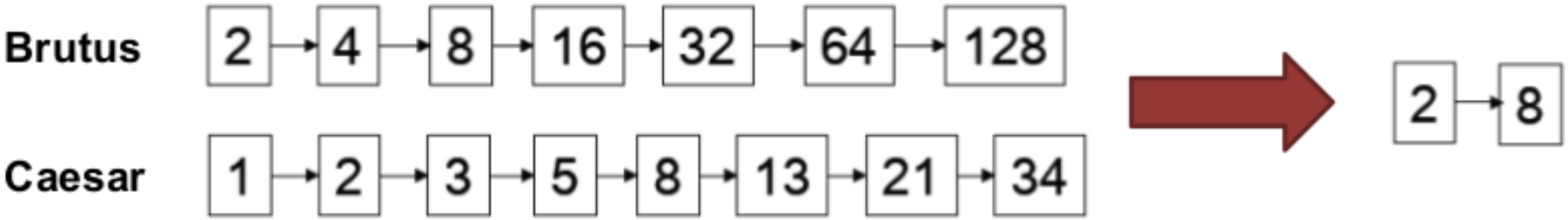
	Antoine & Cléopâtre	Jules César	La Tempête	Hamlet	Othello	Macbeth
Antoine	13,1	11,4	0	0	0	0
Brutus	3,0	8,3	0	1	0	0
César	2,3	2,3	0	0,5	0,3	0,3
Calpurnia	0	11,2	0	0	0	0
Cléopâtre	17,7	0	0	0	0	0
pitié	0,5	0	0,7	0,9	0,9	0,3
pire	1,2	0	0,6	0,6	0,6	0

each document is a vector in $\mathbb{R}^{|V|}$

Finding the documents

Brutus AND Caesar

- On **recherche** « **Brutus** » dans le dictionnaire
  → On récupère la liste de documents
- On **recherche** « **Caesar** » dans le dictionnaire
  → On récupère la liste de documents
- On **fusionne** les deux listes



Queries with phrases

- If a user formulates a query such as "Paris Saclay", a document containing "Le maire de Paris s'est arrêté dans un restaurant de Saclay aujourd'hui" is not likely to be relevant
- concept of phrase easy to understand for users
- a large part of web queries
- simple index insufficient
- two solutions :
  - n-grams index
  - positional index

N-gram

- n-gram = subsequence of n elements extracted from a given sequence
- here, word n-grams
  - unigrams : all words
  - bigrams : sequences of 2 words
- différent from a linguistic phrase

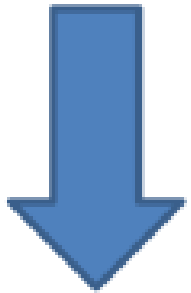
Bigrams index

- index, in addition to simple words, the text bigrams
- 1 bigram = 1 term from dictionary
- actually rarely used
  - query n-grams difficult to determine (Stanford University Palo Alto, Université Paris-Saclay Orsay)
  - index vocabulary very large

Positional index

- Idea : in the lists of documents in the index, add the position of each term occurrence in the document

terme	fréquence	→	D1	D3	D4



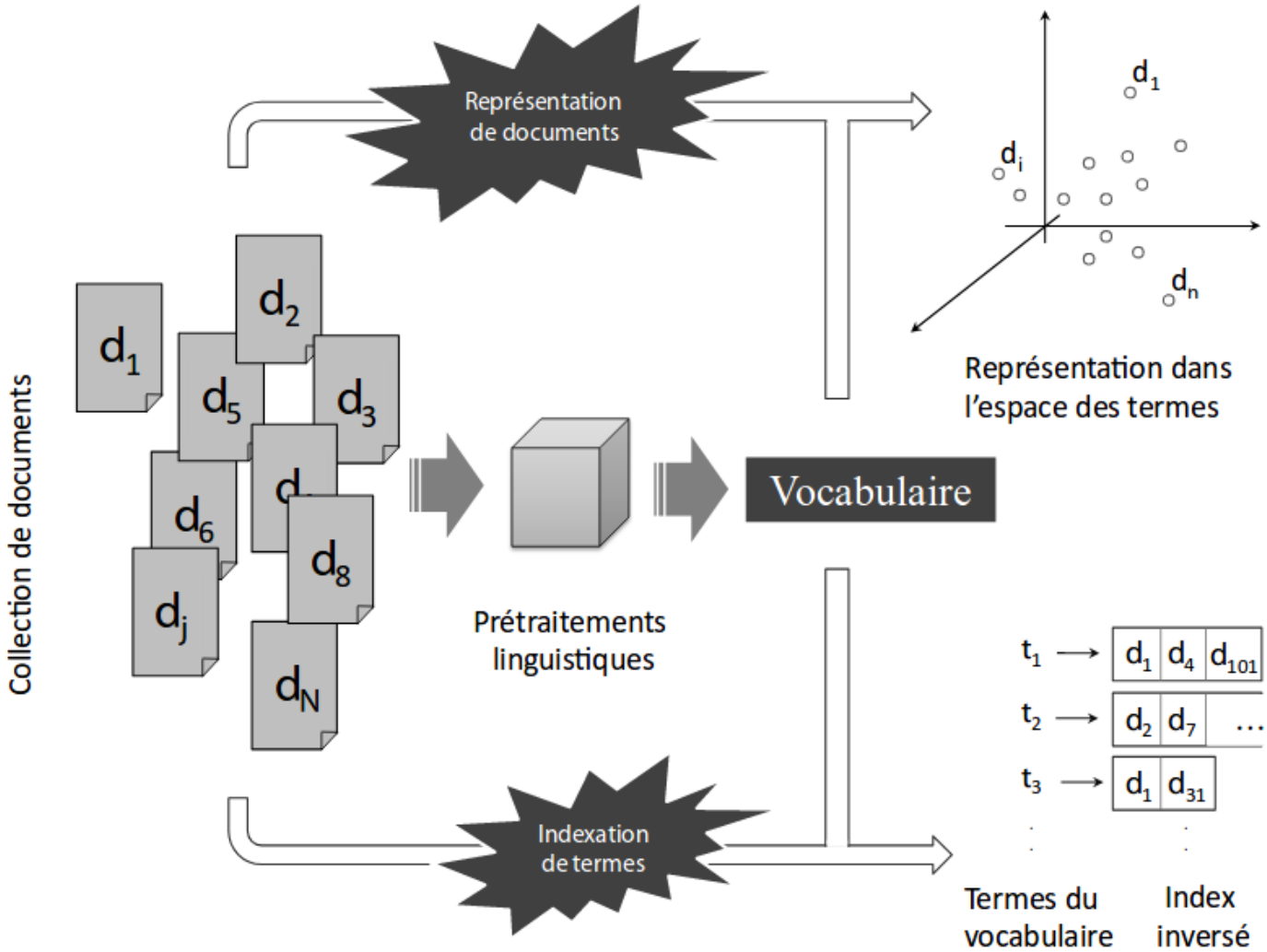
terme	fréquence	→	D1 : pos1, pos2, pos3
			D3 : pos1, pos2
			D4 : pos1, pos2, pos3

Traversing a positional index

- "Université Paris Saclay"
  - extraction of all dictionary entries
  - recursive use of the fusion algorithm, for documents then for positions
  - use of an incremental comparison instead of a strict equality

université	1252	→	D2 : 546
			D6 : 34, **87**, 145, 243
			D7 : 44, 87, 34
			...
paris	45	→	D2 : 547
			D6 : **88**, 543
			...
saclay	15345	→	D2 : 54, 90
			D6 : **89**
			D4 : 43

Plan



Recherche d'information, Applications, modèles et algorithmes de Massih-Reza Amini et Éric Gaussier

Search models : the three currents

- models based on set theory
  - boolean model
- algebric models
  - vectorial model
- probabilistic models
  - notion of relevance

from the beginning of IR (60s, 70s)

Boolean model

- first and simplest model
- based on set theory and Boolean algebra
- query tems either present or absent : binary weighting of terms, 0 or 1
- document soit pertinent soit non pertinent : pertinence binaire (modèle exact)
- query expressed with logical operators : AND, OR, NOT
  - (cyclisme OR natation) AND NOT dopage
  - document relevant iff its content respects the logical formula

Boolean model : example

Requête Q : `(cyclisme OR natation) AND NOT dopage`

Le document contient					Pertinence du document
cyclisme	natation	**cyclisme OR natation**	dopage	**NOT dopage**	
0	0	**0**	0	**1**	**0**
0	0	**0**	1	**0**	**0**
0	1	**1**	0	**1**	**1**
0	1	**1**	1	**0**	**0**
1	0	**1**	0	**1**	**1**
1	0	**1**	1	**0**	**0**
1	1	**1**	0	**1**	**1**
1	1	**1**	1	**0**	**0**

Boolean model : pros and cons

Pros

- precise : document contains terms or non
- understandable
- still used in many tools, such as electronic mail
- adapted for specialists when constraint vocabulary preferred (law)

Cons

- difficult to express long queries with boolean form
- binary criterion not very efficient
  - often too many of too few results
  - term weighting improves results (cf. exended boolean model)
- impossible ro rank the results
  - all returned documents are at the same level
  - users prefer a ranking when the list is long

Ranked lists of results

Why rank results ?

- most users
  - do not know how to write boolean queries
  - do not want to parse too many results (possibly millions of them)
- prefer ranked lists
  - from most useful to the user (relevant) to less useful
  - the number of results is no more a problem
  - the user parses as many as they want
- but requires an effective ranking algorithm
- statistical model
  - quantitative aspect of terms and documents
  - similarity measure between query and document

Ranked models

Ranking

- the number of results is not a problem any more : first 10
- if the ranking algorithm works correctly

Principle

- attribure a score to each query-document pair
  - according to the document relevance to the query
  - generally presence of query terms in the document
- rank documents by descending score

Vector space model

Vector space model

- Similarity measure : close representations ⇒ high probability that same information
- Documents and queries represented by vectors in a euclidian space with n dimensions (n : number of terms)
  - terms = axes
  - docs = vectors (sparse)
- Document relevance = degree of similarity between vectors of query and document
- Documents ranked from most similar to the query to less similar

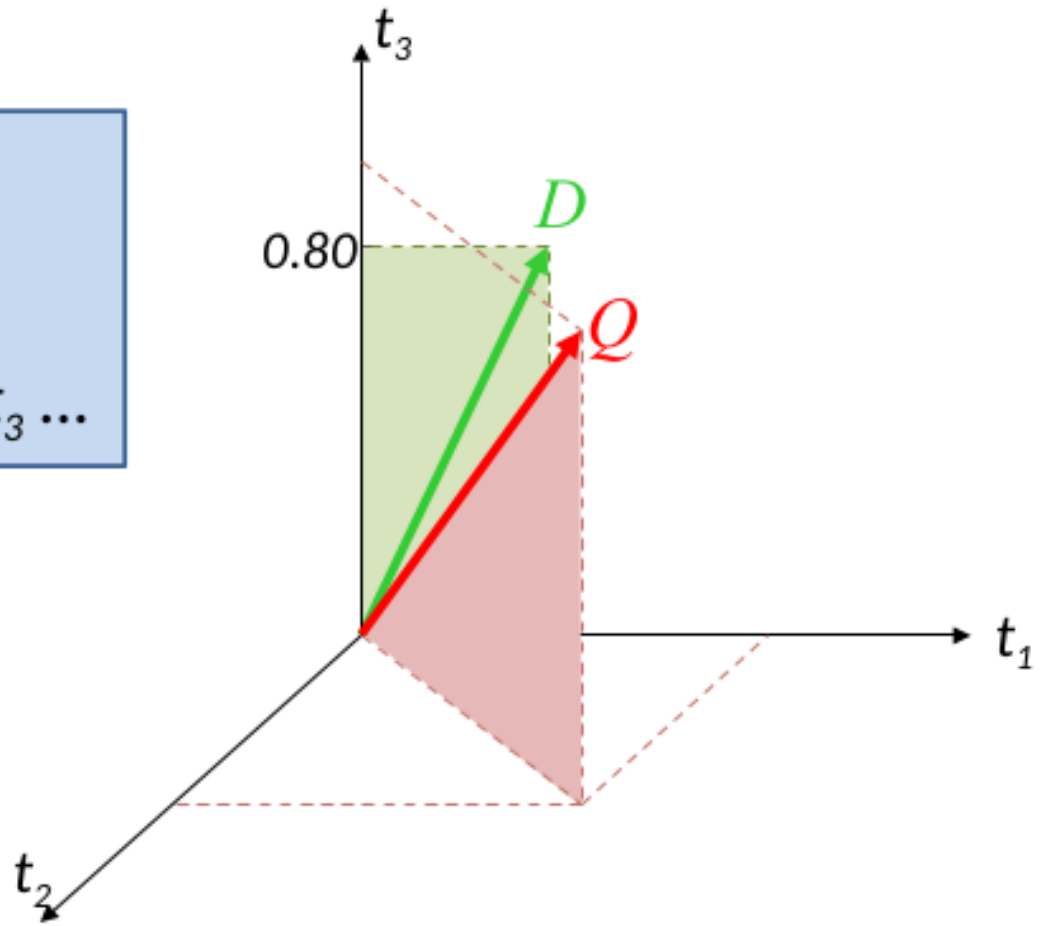
Vector space model

Requête Q : $t_1\ t_2\ t_3$

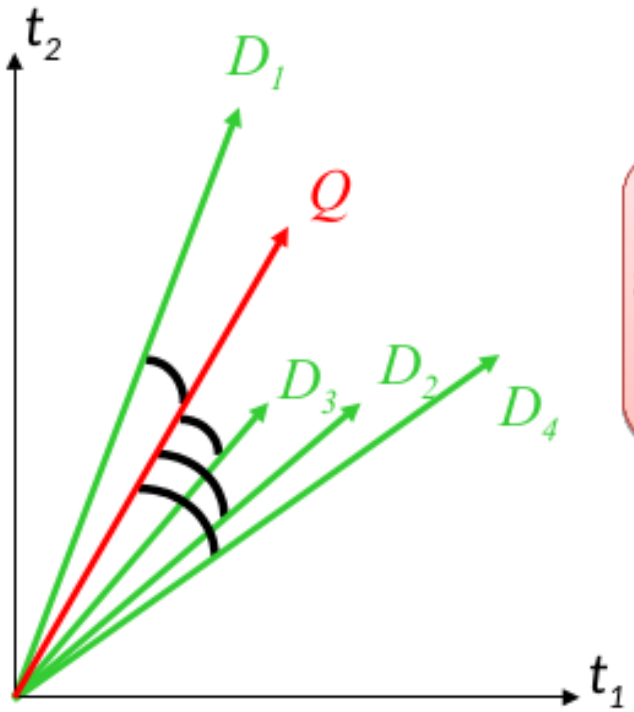
Document D : ... t_1 ... t_3 ...

Poids $w_{D,t1} = 0.45$

Poids $w_{D,t3} = 0.80$



Similarity measure



Cosinus

$$\text{sim}(\vec{Q},\vec{D}) = \frac{\vec{Q}\cdot\vec{D}}{|\vec{Q}|\times|\vec{D}|} = \frac{\sum_{i=1}^{n} w_{i,Q}\times w_{i,D}}{\sqrt{\sum {w^2}_{i,Q}}\times\sqrt{\sum {w^2}_{i,D}}}$$

(Le produit scalaire avec normalisation de la longueur des vecteurs)

Vector space models : pros and cons

Pros

- simple query language : keywords list
- performance better than boolean thanks to term weighting
- partial relevance of documents possible
- ranking of documents possible

Cons

- terms considered as independent
- query language less expressive
- understanding harder

Probabilistic model

Problem modelling

- estimation of the relevance probability of a document for a query
- binary notion of relevance :
  - $R_{d,q} = 1$ if d relevant for q
  - $R_{d,q} = 0$otherwise
- documents ranked by descending relevance probability
- relevance of each document supposed to be independent
- dyssymetry between query and document ($\neq$ vector space)

Probabilistic model : conclusion

- leading model :
  - Okapi BM25
    - non binary probabilistic model (term frequency) with document length normalization
    - robust and used a lot
- other probabilistic models
  - bayesian networks
  - language model
    - document = generative model that generates the query
- conclusion
  - problem of initial probabilities
  - independent terms
  - results close to vector space model

Learning to rank

Basic principle

- features that influence the relevance
  - query : length, idf means...
  - document : PageRank, spam probability, document date...
  - query + document : cosine similarity between query and document, minimal window in which query terms appear, zones...
- binary classification : relevant 1, not relevant 0
  - but how to learn regression score
- (document) pair learning
  - but errors do not have the same importance
  - sensitive to the number of relevant documents per query
  - first returned documents more important
- apprentissage de listes : optimiser MAP directement par exemple
  - difficult ML problem

Other models

- generalized vector space model
  - represents dependencies between terms
  - theoretically interesting, but effectiveness not proved
- Latent Semantic Indexing
  - proposes to study "concepts" instead of terms (idead of a text)
  - links documents between them and to query
  - enables to return documents containing no query word
  - less dimensions
  - better recall, lower precision

Plan

What is a good search engine ?

Criteria

- main criterion : user satisfaction ?
- fast
  - fast query analysis
  - fast index search
  - fast result ranking
- complete and up-to-date
  - all (or many) documents from the collection are used
  - new documents quickly added

  $\Rightarrow$ fast index building

  $\Rightarrow$ (on the Web) permanent, effective and fast discovery of the new documents
- most important : relevant

How to measure relevance ?

- Web search engine
  - the user clicks on some links and not others
  - the user comes back to the search engine
  - the user manages to perform a certain task
- e-commerce website
  - the user buys
  - the user buys quickly
  - a large proportion of visitors buy
- firm website
  - the user gains productivity
  - secured access
  - ...

What is a good evaluation ?

- evaluating a system aims at knowing :
  - if it performs the expected task
  - if it is better than the competition
  - how to improve it
- that means that the evaluation should be
  - reproducible
    - to evaluate several systems the same way
    - to assess the progress made
  - understandable
    - to identify the possible progress zones
  - fast
    - to evaluate each modification independently
  - objective

How to make relevance objective ?

- user need transformed into a query $\rightarrow$ 1st information loss
  - information need : je voudrais savoir si boire du vin rouge réduit le risque de problèmes de coeur
  - query : vin rouge problèmes coeur
  - doc : le coeur de son discours concernait le problème de l'industrie du vin qui peine à reconnaître le rôle de la consommation de vin rouge dans les accidents de voiture

  $\rightarrow$ doc relevant for the query but not for the need
- yet, relevance of the results compared to the information need
- relevance not binary : very relevant, not at all, a little, why not...
- in order to make relevance objective, simplified definition :
  - documents treated independently from each other
  - relevance transformed into a binary notion
- and use of test collections

Standard methodology

- document collection
  - representative of real documents
- set of information needs/queries
  - also representative
- relevance score for each document and each query
  - human judgements

standard benchmarks : TREC

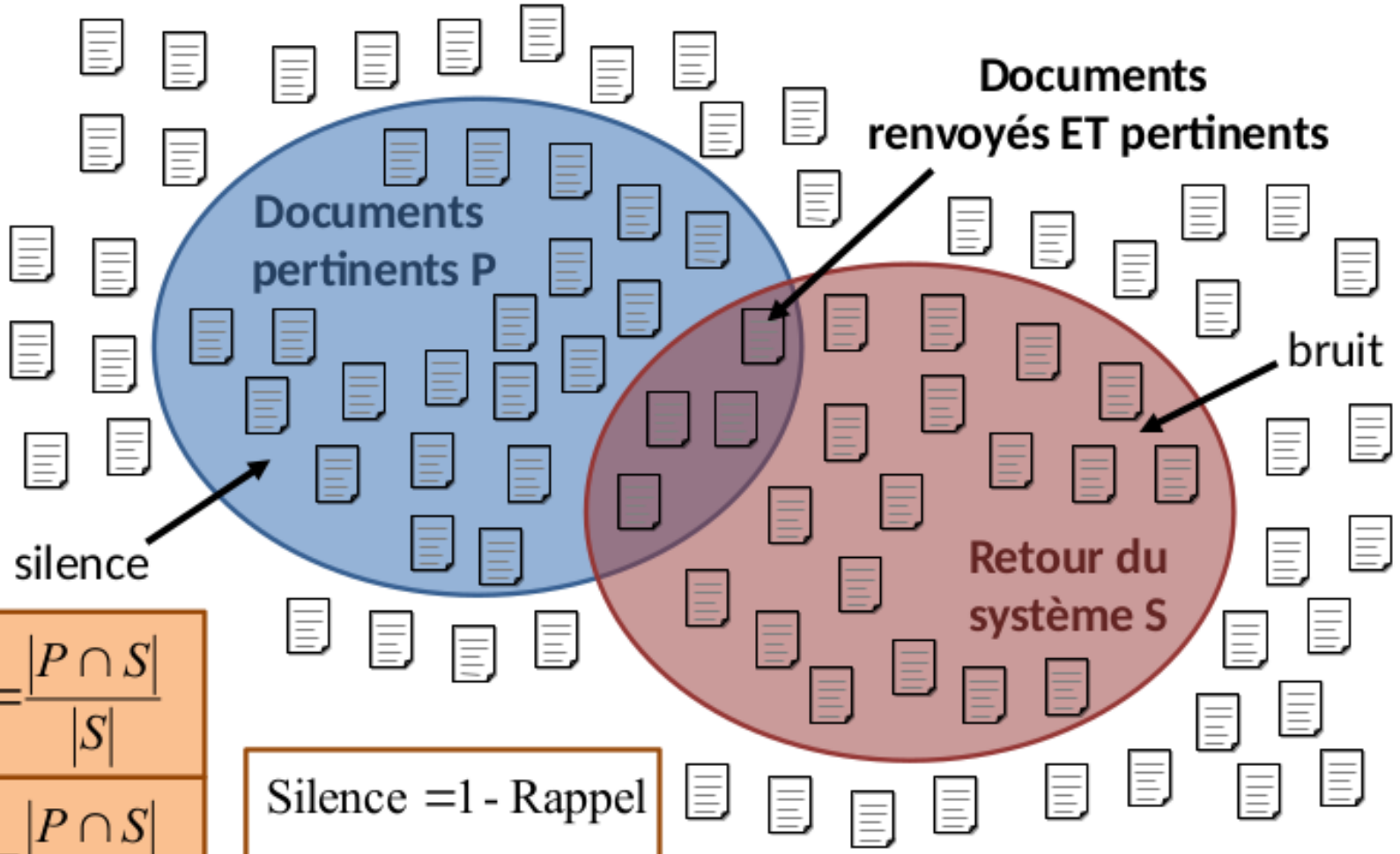
- Ad Hoc in particular (1992 to 1999)
- scores for the first k documents returned by systems

Test collections

Test collections make the experiments reproducible

- A protocol is defined
- A significative number of examples is manually judged
  - gold standard
  - A part can also serve as a development and/or training set
- An inter-annotator agreement is computed
  - To validate the objectivity
- System results are compared to expected results
- Imperfect bur precise metrics are defined

Evaluation : precision and recall



$$\text{Précision} = \frac{|P \cap S|}{|S|}$$

$$\text{Rappel} = \frac{|P \cap S|}{|P|}$$

Silence =1 - Rappel

Bruit =1 - Précision

Complementarity of precision and recall

Why not just precision ?

- precision = capacity of a system to return MOSTLY relevant documents
- Returning a single relevant document $\Rightarrow$ 100% precision
- not compatible with user satisfaction !

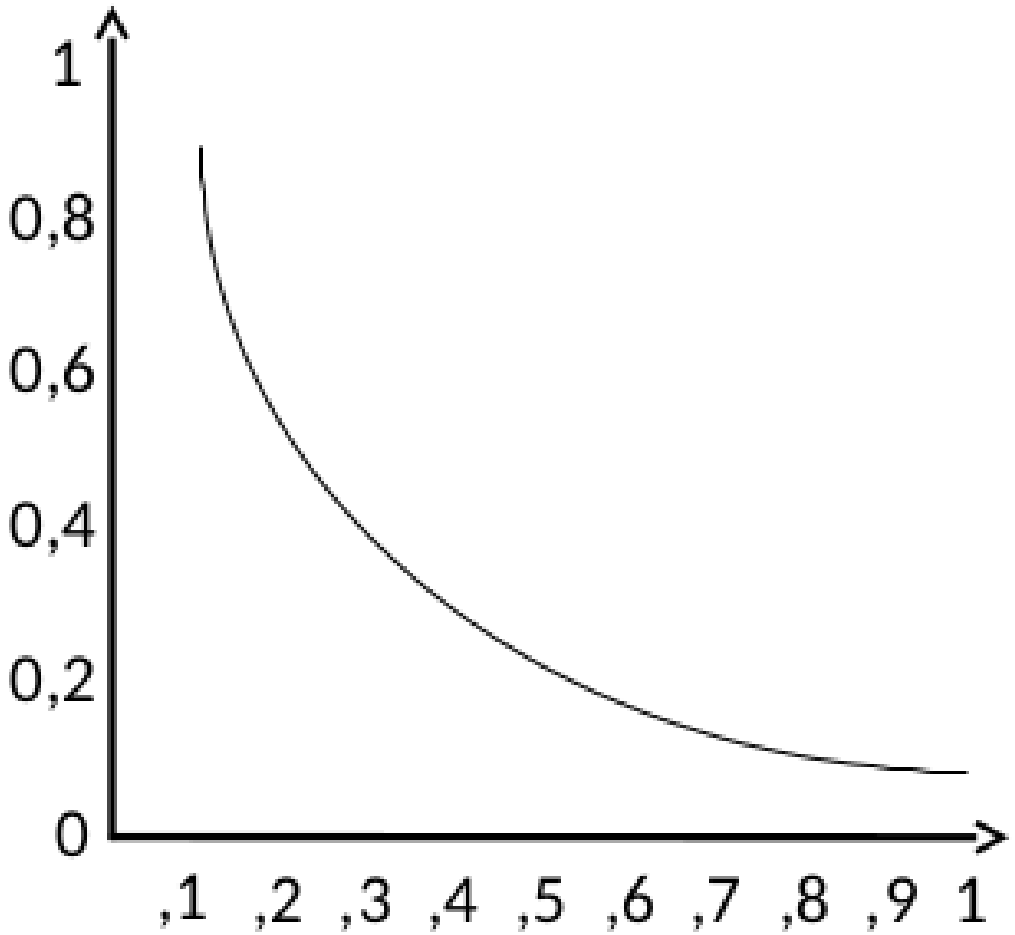
Why not just recall ?

- recall = capacity of a system to return ALL relevant documents
- Returning all the collection $\Rightarrow$ 100% recall
- not compatible with user satisfaction !

Recall/precision curve

- recall improves with number of answers
- precision decreases

recall/precision curve used to characterize IR systems



F-measure

to obtain a unique value, F-measure = harmonic mean

$F = \frac{1}{\alpha \frac{1}{p} + (1-\alpha)\frac{1}{R}} = \frac{(\beta^2+1)xPxR}{\beta^2 P + R}$ with $\alpha = \frac{1}{\beta^2+1}$

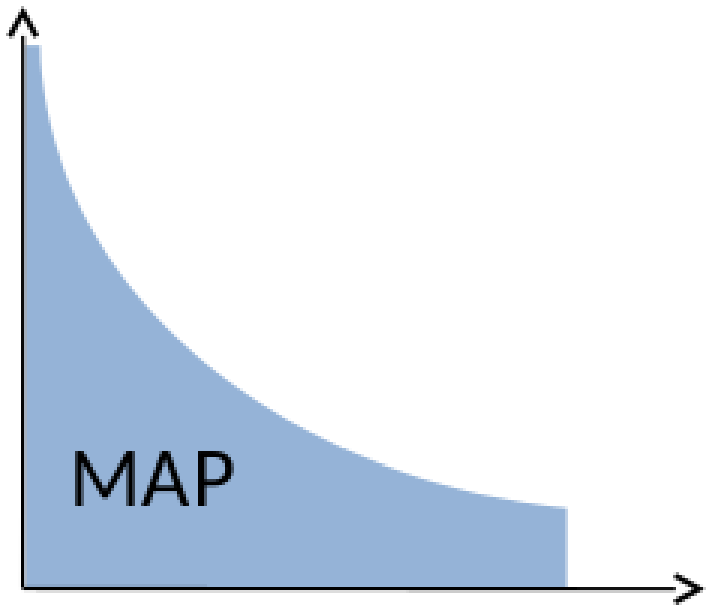
$\beta < 1$ favors precision, $\beta > 1$ recall

to give as much importance to precision and recall, $\beta = 1$

$F = \frac{2PR}{P+R}$

Other metrics

- MAP (Mean Average Precision) : area under the R/P curve
- to take into account result ranking :
  - P@5, P@10 : precision for first documents retrieved ; favors high precision
  - P@100
  - R/P curve for k variable
- error rate = (false positives + false negatives) / relevant
- and others...



Présentation des résultats

- the user must be able to identify the possibly relevant documents with their description $\rightarrow$ title, url, metadata
- often abstract too
  - static (independent of query)
  - dynamic : "snippets" from document that contains the query terms

References

- Recherche d'information, Applications, modèles et algorithmes de Massih-Reza Amini et Éric Gaussier (2e édition en 2017)
- Introduction to Information Retrieval, Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze (2008)