Information retrieval in health

Indexation, Models, Evaluation

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 - Knowledge engineering
 - Terminologies and ontologies, semantic web
 - Information retrieval & automatic indexing

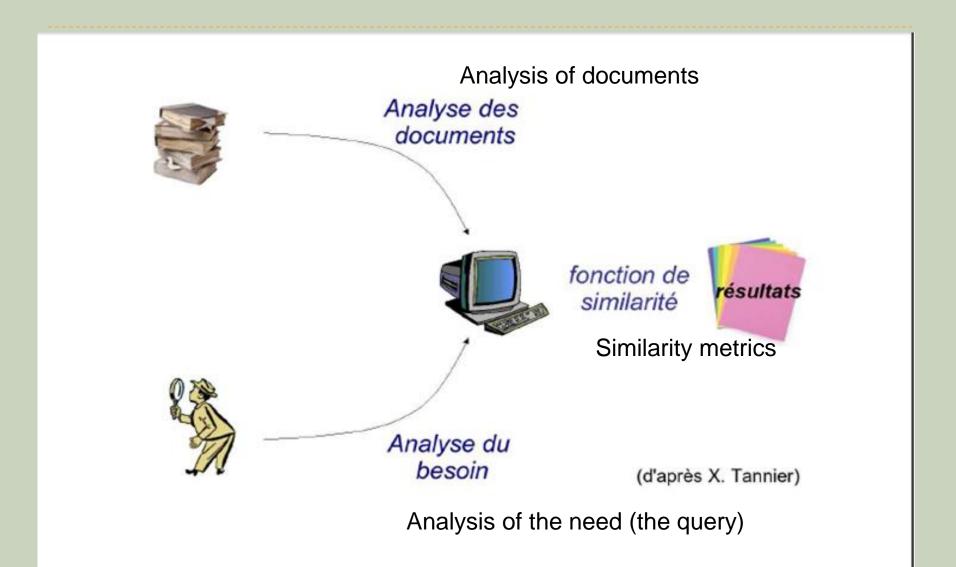
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Information retrieval (IR)

Introduction and main principles of the indexation

IR: General schema



IR: Main difficulties

- Access, coverage, & response time +++
 - Large documentary databases (health big data)
- Relevance
 - (automatic) metrics to measure relevance (evaluation)
 - Informational need of one give person? Context +++?
- Exploitation
 - Relevant documents may not be available in local language
 - huge problem in France;
 - less in Israel, where everyone speaks N languages, with N -> ∞
 - Queried information is difficult to obtain inside the document
 - Q&A vs. documentary information system

Information retrieval: evolutions

Previously

- Documentary bases were structured and of small size
- Access by metadata which describe documents
- Use of documentary languages by specialists (librarians & information scientists)

Nowadays

- Most documents in electronic format and multimedia
- A lot of formats to represent information (sometimes proprietary)
- Documents dynamically created
- Document databases with private access (invivisble Web)
- More and more unstructured data
- Appearence of semi-structured documents (discharge summaries)

Performance of IR

> Ranking of retrieved documents by decreasing scores

- date of the document (newest first –PubMed, CISMeF-)
- quality/reputation of the source
- quality of the indexing vs. the query
- commercial link (Google)
- Evaluation by the end-user depending on:
 - Relevance of documents
 Variable from one end-user to an other, his/her knowldege, the context
 - response time of the system
 - Ergonomy of the system
 - Perceived ergonomy (SUS questionnaire)

> Automatic evaluation:

- Boolean comparison of returned documents vs. « ideal » answers (most of the time, manual gold standard)
- Precision & recall
- Evaluation campaigns of IR systems

Criteria to measure information retrieval & indexing

	Relevant	Non relevant	
Transmitted documents	А	В	A+B
Non transmitted documents	С	D	C+D
	A+C	B+D	

Recall= A/A+C= *true positive rate*= *sensitivity* ; silence = 1 - recall = C/A+C = False negative

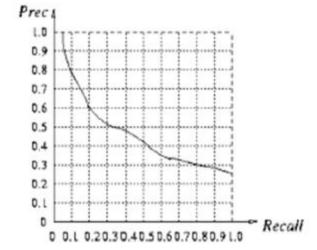
Precision = A/A+B = *positive predictive value (PPV)*; noise = 1 – precision = B/A+B = False positive

Criteria to measure information retrieval & indexing

- F-measure = weighted average of the precision and recall
- General F-measure
 - F_β = (1+ $β^2$) PxR / ($β^2$ x P) + R
- ▶ **F**₁
 - In most of cases, $\beta = 1$, then $F_1 = 2 PxR / P + R$
- According to the context, the developed system will optimize
 - either P or either R
- Other measures
 - MAP (Mean Average Precision) : area under the curve R/P
 - P@5, P@10 : precision after 5, 10 found documents => in favor of high/very high précision
 - Error rate = (FP + FN) / relevant

Automatic evaluation

- Recall increases with the number of transmitted documents,
- whereas the *precision* diminishes
- P/R curve to caracterize IR Systems



- Specific cases:
 - On very large documentary information systems, the relevance of the first documents (the first page syndrome) is more important than the recall => minimization of the noise
 - Secondary objective: miminization of the response time

Indexing

Searching the entire corpus of documents to answer a query is impossible:

- Too many documents
- Response time much too high
- Therefore, a preliminary phase is mandatory: automatic ndexing
- The goal of the automatic indexation is to « *transform documents into substitutes able to represent their content* » [Salton et McGill, 1983]
- Manual indexing in bibliographic databases (MEDLINE, CISMeF)
 - Among difficulties, language used in documents is a main barrier
 - Indexing is language dependant +++

Lexical-based Approach

Remove genitives	Presence of urinary reducing substances - finding	
Replace punctuation with spaces	Presence of urinary reducing substances finding	Normalia
Remove Stop words	Presence urinary reducing substances finding	zation
Lowercase	presence urinary reducing substances finding	1 proces
Uninflect each word	presence urinary reduce substance find	ess
Word order sort	find presence reduce substance urinary	



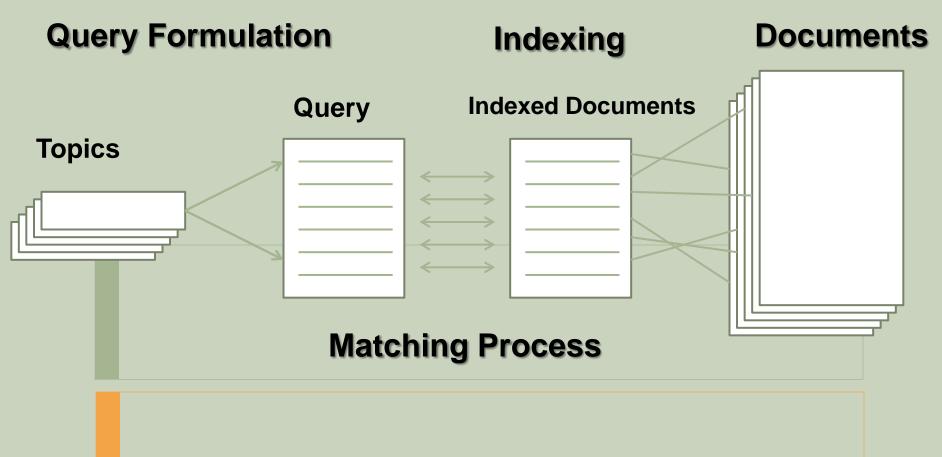
Types of Index

Index may take several forms

- Simple words: e.g.: university; sings \rightarrow sing
- **Terms:** e.g. reducing Ph, asthma, Aspirin-Induced
- Entry (descriptor) of a thesaurus : e.g. MeSH
- Concept of a formal ontology: e.g. FMA in anatomy
- Index are more or less easy to exctract
- Index are more or less discriminant
 - **Good**: antigen, amyloïd, fiever (in the context of health)
 - Bad: enfants, raised, developping
 - Very Bad (stop word): a, for, after...

An inverse file associates the index to the documents

Indexing & Information Retrieval



Characteristics of the language & IR

- Contrarily to artificial languages, the language is:
 - Implicit: everything is not included in document (e.g. discharge summaries); depending on the context +++
 - Redondant: the language offers many different ways to formulate (more or less) the same content
 - Ambiguous: a same expression may be interpreted in several ways (e.g. acronyms)
- IR is even more complex:
 - Words may have different meanings in documents
 - Atomic meaning could be either words or expression (combinantion of words) => choice of the « bag of words » algorithm in the SIBM team

The language is implicit

- Implicit informations are *lacking* to correctly interpret the meaning of a document
- This implicit informations may be correctly « extrapolated » by a human (mainly taking into account context and knowledge)
- For automatic indexing, the context and knowledge could be (partially) resolved using semantic web technologies (e.g. semantic expansion)

Redondancy of the language

- Synonymy is a strict equivalence of meaning between two expressions (or words):
 - total : automobile & car (EXACT MATCH SKOS RELATION)
 - > partial:
 - hypernym (generic term): vehicule & bike (BTNT –SKOS RELATION)
 - hyponym (specific term): BMX & bike (NTBT –SKOS RELATION)
 - meronymy (part of): finger & hand
 - holonymy (total of) : upper limb & arm
 - acronyms: as soon as possible & ASAP => generate a lot of ambiguity
 - circumlocutions: lave-vaisselle et machine à laver la vaisselle
 - Partial synonymy is used in UMLS => generate a lot of noise
 - Partial synonymy is used in SIBM => need to be evaluated

Ambiguity of the language

- Homonyms (homographs & polysemy) are words with same characters but a diffrent meaning
 - Acronyms are most of the time homonyms +++
 - In French, IVG (a diagnosis or a procedure)
- Homographs are words that belong to different categories but with at least one same inflected form:
- Potential important role of UMLS semantic types to reduce this ambiguity
 - UMLS metathesarus of US National Library of Medicine
 - Over 2 millions medical concepts; each of them with a least of semantic type (e.g. diagnosis, procedure)

Ambiguity of the language

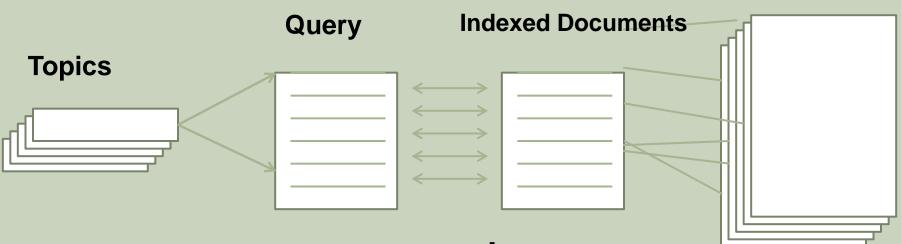
- Polysemy are words with several meanings and where all the inflected forms are the same
- More a word is used, more the probability of polysemy is high
- Necessary to define the meaning of a word in the right context
 - One main difficulty in NLP (word sense disambiguation) & Semantic Web
 - Secondary prevention (GP)
 secondary prevention (public health)
 - Secondary prevention (GP) \approx tertiary prevention (public health)
 - Not an Exact Match relation; Use the See Also (or Close) relation

Properties of the indexing

- Index are used to represent the content of documents:
 - They represent only a part of the content of the documents
 - They may take several forms (e.g. simple words, terms, expressions, entries of a thesaurus, etc.)
 - They are more ore less difficult to extract
 - Their storage need more or less memory (see later on NoSQL vs. SQL vs. SPARQL)

Process of indexing

Query Formulation Indexing Documents



Strong contraintes fortes de l'indexation

- Storing large amount of information in a minimal space
- Extracting all necessary information
- Allowing efficient access to the index during IR
- Allowing dynamic indexing

Chain of indexing

 Segmentation of documents into smaller units (sentences)

Drawback: loss of meaning between sentences

Linguistic normalization

Production of indexing files

Segmentation of documents

Characteristics of documents :

- formats of file (text, HTML, PDF, etc.)
- Coding (ASCII, ISO-LATIN-X, Unicode)
- language(s)
- non linguistics signes (mathematic formulas, presentation, images, ...etc.)
- A collection de documents may contain several languages
 - One index per language or a unique index
 - NLP tools to identify a specific langage
- Level of indexing:
 - Overall documents /subpart of a document / subset of documents (e.g. web site)

Textual normalization

- Possibility to normalize elements before indexing
 - suppression of *points* into acronyms (U.S.A. in USA)
 - suppression of accents (météo : meteo)
 - suppression of some majuscules (Et : et)
- normalization of several data and information
 - Jates: 14 juillet 1789 : 14/07/1789 (Fr) : 1789/07/14 (US)
 - Data about money: \$400 : 400 dollars
 - organizations: IMF: International Monetary Fund
 - Choice of several normalizations may be based on end-users usages
- Possibility not to normalize index:
 - Size of index more important
 - Need of mechanisms to expand the query (semantic expansion)

Linguistic normalization

Several techniques to correct

- reaccentuation (meteo météo)
- orthographic corrections (inofrmation information)
- grammaticale corrections (the roses looks! the roses look)
- Bring several elements to a single form
- **Stemming** (words of the same stem)

used in linguistic morphology and information retrieval to describe the process for reducing inflected words to their word stem, base or root form—generally a written word form.

□ malade, malades, maladie, maladies, maladive devient malad

Lemmatisation: (words of the same lemme)

in linguistics, the process of grouping together the different inflected forms of a word so they can be analysed as a single item

stomach, gastric, => canonic form: for a verb, infinitif or for noun, masculin singular: stomach

Linguistic normalization

phonetic normalization (same pronounciation)

- □ Chebyshev : tchebycheff
- □ Alzeimer : alzheimer
- Very useful in medicine with complex terms (including names of diseases after his/her discoverer
- Use of other relations (semantic web)
 - Synonyms
 - Hyponyms (explosion in information sciences; subsumption in computer science)
 - Semantic expansion (between terminologies)
 - kill, assassinate, beat to death, defeat, destroy, do away with, do in, eliminate, eradicate, execute, exterminate, extinguish, finish off, knock off, liquidate, mop up, murder, pip, rack up, shoot dead, slaughter (Source <u>www.sensegate.com</u>) => kill

Phonetic normalization

- Words with same pronunciation
- Language dependent +++
- Create a set of words (or expressions) with the same pronounciation
- Soundex algorithm (English):
 - Every word is compressed to a reduced form of 4 characters
 - Creation of an index of reduced forms of phonetic equivalents
 - Extract of the algorithm:
 - Keep the first letter of a word
 - Replace the letters a, e, i, o, u, h, w, y by 0
 - Other correspondences: B, F, P, V by 1; C, G, J, K, Q, S, X, Z by 2
 - Suppression of repeated numbers & 0
 - Obtention of a normalized code
 - \Box Herman \rightarrow H655

Normalisation: stemming

- Bring back differents words to their respective stemming
 - Rules are dependent of the language +++
 - E.g. Porter algorithm for English
 - □ automates, automatic, automation => automat
 - □ For French, *malade, malades, maladie, maladies, maladive* => *malad*
- Some conventions about reduction phases (for French)
 - Rule examples: sses => ss; ies => i ; ational => ate ; tional : tion
- Linguistic normalisation:
 - Significant reducing of index size
 - A lot of pontential errors => P < 1 and R < 1</p>
 - Impossibility to distingish among several forms of the same stemming via the index

Spelling correction

- Spelling corrections may be due to input errors or wrong OCRs
- Two main approaches
 - Correction in the index
 - Correction in the IR queries (our approach)
- Two main approaches to correct spelling:
 - Correction of words in isolation (ex: inofrmation)
 - Calculation of a distance
 - Possibility to weight operations taking into account frequent errors: input (a→ q), OCR (D→ O)
 - Correction of words in context (flight form Eathrow)
 - Use of large corpora or most frequent queries (log) => our approach

Similiarity distances: Levenshtein & Stoilos

- Levenshtein distance:
 - Minimal number of elementary operations to go from chain c₁ to chain c₂

$$LevNorm(c_1, c_2) = \frac{Lev(c_1, c_2)}{Max(length(c_1), length(c_2))}$$

Stoilos distance:

 Similarity between two entities depends on their common chains and their differences

$$Sim(s_1, s_2) = Comm(s_1, s_2) - Diff(s_1, s_2) + winkler(s_1, s_2)$$

Normalisation: variants

- Grouping the term variants (difficult task +++) :
 - Genetic disease
 - Basic terme
 - Disease is genetic
 - syntaxic variant
 - Hereditary disease
 - Semantic variant
 - Genetically determined forms of the disease
 - variante morpho-syntaxique
 - Disease is familial
 - variante syntaxico-sémantique
 - Transmissible neurodegenerative diseases
 - variante syntaxico-sémantique

Importance of index

- All indexes in documents do not have the same importance
 Use of stop words lists, quite complex in health
 - Stop word most of the time will not be a stop word in a specific context

bag-of-words model

- Number of occurrences of a term in each document
- **Frequency of a term in a document**
- Do no take care into account the ordre of the word (in the bag)
- Indexing the longest bag of words
- How to handle the importance of a term in a document inside a corpus
 - ponderation by *tf.idf*

tf.idf ponderation

Calcul of the weight of a term in a document :

 $W_{i,d} = tf_{i,d} * idf_i$

- \Box *tf_{i,d}:* frequency of term *i* in the document *d*
- *idf_i* : importance of a term *i* into the collection of documents (inverse document frequency)
- simple metrics: inverse of number of documents in the collection containing the term

$$w_{i,d} = tf_{i,d} * \frac{1}{df_i}$$

- Most used metrics: log of the ratio between the number of documents in the collection and the number of documents containing the term
 - The weight of a term increases:

$$w_{i,d} = tf_{i,d} * \log(\frac{N}{df_i})$$

- □ With frequency of the term in the document
- With scarcity of the term in documents in the collection

Information retrieval

Main models and Evaluation

Information retrieval

Models of retrieval Three main approaches Evaluation Main metrics Pooling Evaluation campaigns

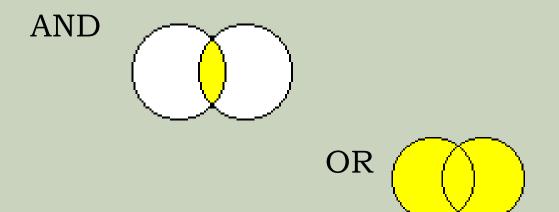
Three main approaches

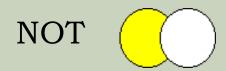
- I. Models based on set theory
 - Boolean model
- > 2. Algebric models
 - vectorial model
- 3. Probabilistic model
- Bayes theorem

Boolean model

- First and simplest model
- Based on theory of sets and Boole algebra
- The terms of the query are either present or absent
 - Binary weight of terms, 0 ou 1
- Therefore, a document is either relevant or not
 - Binary relevance, never partial (exact model)
- The query is built with logic operators
 - AND, OR, NOT
 - (cycling OR swimming) AND NOT doping
- The document is relevant if and only if its content respect the Boolean query

Boolean querying





Searching by proximity

X NEAR(N) Y

- Searching X AND Y separated by less than N words (excluding stop words)
- Use of position index
- Interesting because searching documents containing X AND Y without limit will generate too many noise
- Need to build the outset of every word in the documents

Potential extensions

X NEAR(N) Y

Weighting of keywords

- "olympic games AND Beijing AND (swimming:3 OR cycling:4 OR track & fields:2)"
- Allows a result ranking by best choices performed by the enduser
- => Extended Boolean model

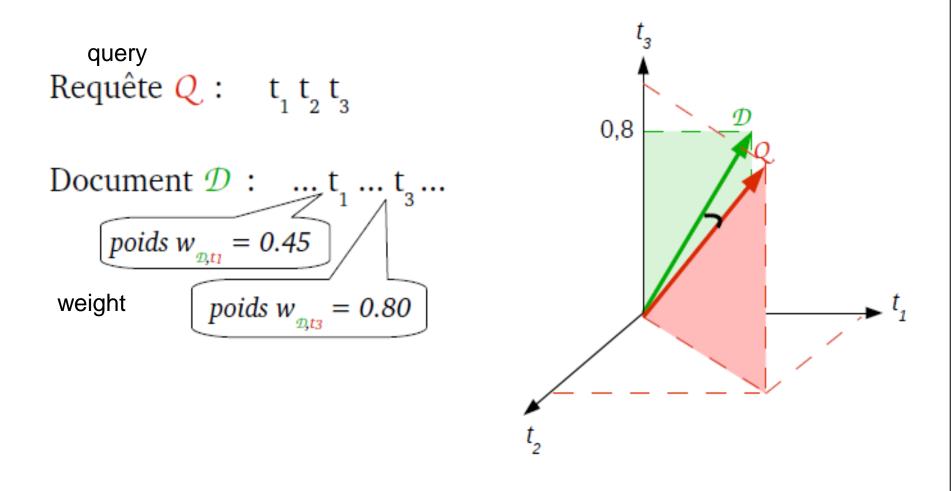
Boolean model: pro & cons

- Pro:
 - The model is transparent & simple to understand for the user
 - No hidden parameters
 - Reason to select a document is quite clear: this document is relevant for a logic query
 - Adaptated to specialists (information scientists & librarians) & controlled vocabularies
- Cons:
- Quite difficult to build a complex Boolean query: binary criterion not so efficient
- Possible to weight terms (extended Boolean model)
- Impossible to perform a ranking of the results

Vector model

- Algebraic model :
 - Terms & documents are represented as vectors
 - Similarity measures between a query and a document
 - Ranking list according to this similarity
- Similarity measures: more two documents contain the same terms, more the probability that they represent the same information is high
- Terms & documents are represented as vectors
 - Each dimension corresponds to a separate term
 - > The lenghth of the vector is proportional to the weight of the terms
 - Relevance of a document corresponds to similarity between query vector and document vector

Vector model



Vector model: similarity mesures

• Dice

$$RSV(\vec{Q},\vec{D}) = \frac{2\sum w_{iQ} \times w_{iD}}{\sum w_{iQ} + \sum w_{iD}} \frac{2|A \cap B|}{|A| + |B|}$$

Jaccard

$$RSV(\vec{Q},\vec{D}) = \frac{\sum w_{iQ} \times w_{iD}}{\sum w_{iQ} + \sum w_{iD} - \sum w_{iQ} \times w_{iD}} \qquad \frac{|A \cap B|}{|A \cup B|}$$

Overlap

$$RSV(\vec{Q},\vec{D}) = \frac{\sum w_{iQ} \times w_{iD}}{min(\sum w_{iD}, \sum w_{iQ})} \qquad \frac{|A \cap B|}{min(|A|, |B|)}$$

Vector model: similarity mesures

Produit scalaire
 Scalar product

$$RSV(\vec{Q}, \vec{D}Q) = \vec{Q}. \vec{D} = \sum_{i=1}^{n} w_{iQ} \times w_{iD}$$

• Cosinus de l'angle Cosine of the angle

$$RSV(\vec{Q},\vec{D}) = \frac{\vec{Q}.\vec{D}}{|\vec{Q}| \times |\vec{D}|} = \frac{\sum w_{iQ} \times w_{iD}}{\sqrt{\sum w_{iQ}^2} \times \sqrt{\sum w_{iD}^2}}$$

Distance euclidienne

Euclidian distance

Vector model: pro & cons

Pro:

- Query language is more simple (liste de mots clés)
- Better results thanks to the weights
- Selection of documents with partial relevance is possible
- Ranking possible based on the matching documents/query
- Cons:
- In this model, all the terms independent (main problem +++)
- « black box » syndrome => the end user does not understand why a document is selected according to the query
- Overall, vector model is the most used model in IR (not true in health)

Evaluation campaigns

- TREC (Text REtrieval Conference) :
- Every year since 1992
- Sponsored by DARPA
- Several research axes:
 - Multimedia: image, vidéo, Web
 - Specific query types: Q&A, interactive, cross-lingual
- Specific domains: genomics, law
- Specific ways of expression: blogs, spams...
- CLEF (CrossLanguage Evaluation Forum), for European languages
- NTCIR, for Asian languages

Evolutions in the indexing

- Several modalities of web indexation that may be intricated
 - Documentary Indexation: thesaurus, description of ressources
 - Automated Indexation: based on NLP (Natural Language Processing)
 - **Social Indexation**: tags of web 2.0
 - Semantic Indexation: metadata (XML, RDF) and ontologies (OWL)

Automatic indexation: semantic search engines

- Appearence of new search engines:
 - Hakia:
 - Born in 2006
 - Natural langage
 - Mixte of semantic analysis, ontology, fuzzy logic, and artificial intellingence

Powerset:

- Born in May 2008; bought by Microsoft in July 2008
- Semantic search on Wikipedia
- Analysis of sentence containging the words of the query
- Proposal of new key-words

Evolutions in indexation: Social indexation: tags & folksonomies

The principle of folksonomy:

- Form of « collaborative decentralized spontaneous classification », based on terms chosen s' appuyant sur les termes choisis par les utilisateurs
- **Objectif :** facilitate the indexing of contents and IR
- Tags may be applied to web signets, photos, vidéos, or blogs (tag clouds)
- Creation of a community of « specialists » among Internet endusers

CISMeF semantic search engine

Born in 2000

- Then, based on one single terminology (MeSH), identical with PubMed ATM & bilinguism (Fr En)
- Based on « bag of words » algorithm & Boolean querying
 - match on MeSH thesaurus & title of documents (first step)
 - If no answer, query on CISMeF metadata (Dublin Core)
 - If no answer, query of full text (Oracle tool, Google CSE)
- 2006: multiterminology
- > 2012: multilinguism
- > 2015: NoSQL

Lexical-based Approach (NLP)

Remove genitives	Presence of urinary reducing substances - finding	No
Replace punctuation with spaces	Presence of urinary reducing substances finding	ormali
Remove Stop words	Presence urinary reducing substances finding	zation
Lowercase	presence urinary reducing substances finding	proces
Uninflect each word	presence urinary reduce substance find) ess
Word order sort	find presence reduce substance urinary	



2014: shift from Oracle SQL to NoSQL

- NoSQL vs. SPARQL vs. SQL (two junior engineers)
- Best response time with NoSQL
- Choice of Infinispan datagrid
 - stand-alone into one hospital +++ confidentiality of health data
- For optimal perfomance, nearly all the data are placed in RAM => 128 Go RAM
- Serialisation of the data on file systems
- Use of Lucent indexes for textual query (previously SQL)
- SOA (service oriented) architecture
- Powerful server(s)
 - Xeon 2690 v3 biprocessor; each proc with 12 cores (17501 CPU mark); 128 Go RAM
 - Efficient on parrallel and sequential processing

Automatic indexing in SIBM

- ECMT v3 MultiTerminology Concept Extractor
 - Based on crosslingual multiterminology portal <u>www.hetop.eu</u>
 - \simeq 500,000 concepts in French (>327,000 different CUIs)
 - Language dependent
 - Integrated in a software suite (Alicante)
- To be compared to several tools existing for health English
 - Based on UMLS (more than 2 million concepts)



Extracteur de Concepts Multi-Terminologique (ECMT v3)

Examens paracliniques : * Biologie : globule plaquettes 245 000 mm3, TP 88 , ionogramn 3,8 mmol I, ASAT 23, ALAT 25, phosphatase Radiographie pulmonaire : récidive d'un pne régulier et sinusal sans trouble de la repolar supra aortiques et trans- crânien (23 04): tl interne gauche dès son origine, sténose de irrégulière du bulbe ancienne calcifiée, évalu artères vertébrales droite et gauche. Pas d' au niveau du polygone de Willis et notamme

artère carotide commune (MSH D 017536)

- catégorie(s): médecine et chirurgie vasculaire; cardiologie; partie du corps, organe ou composant d'un organe; système d'organisme;
- ascendant(s): arborescence MeSH (MSH_D_ARBO); artères carotides (MSH_D_002339); système cardiovasculaire (MSH_D_002319); artères (MSH_D_001158); Anatomie (MSH_D_A); vaisseaux sanguins (MSH_D_001808);
- descendant(s) : artère carotide interne (MSH_D_002343); artère carotide externe (MSH_D_002342);
- relié(s): artère carotide primitive, sai (SNO_NO_T-45100);

postérieures. * Angioscanner des TSA (12 04) : présence d'une infiltration athéromateuse au niveau de la crosse aortigue. Infiltration athéromateuse calcifiée au niveau de l'artère carotide commune. Au niveau du bulbe, infiltration athéromateuse plus importante avec présence d'une plaque calcifiée quasi circonférentielle. Thrombose complète de la carotide interne sur tout son trajet depuis le bulbe jusqu'à sa portion terminale. A droite, infiltration athéromateuse prédominant également au niveau du bulbe avec présence de plaque calcifiée sans sténose significative retrouvée. Calcifications au niveau de l'artère carotide interne dans sa portion intra caverneuse. Sténose moyennement serrée de l' origine de la vertébrale droite. Plusieurs boucles vasculaires sur le trajet de la vertébrale droite. Artère vertébrale gauche est le siège de boucle vasculaire. Pas de sténose significative retrouvée. Au niveau du polygone de Willis, celui-ci est bien opacifié avec présence d'une artère communicante antérieure et des deux artères communicantes postérieures. * Scanner thoracique sans et avec injection : plusieurs adénopathies centimétriques connues stables, épanchement péricardique gauche, dont l'épaisseur maximale mesure 16,4 mm. Bonne opacification des gros vaisseaux médiastinaux. On retrouve la lésion bourgeonnante au sein de la lumière de la bronche souche gauche mesurée ce jour à 22 x 33 mm, responsable d'une atélectasie complète du poumon gauche. Présence d'un emphysème sous cutané thoracique antérieur gauche et axillaire gauche en rapport avec le drainage thoracique. * Echographie de stress : non réalisable en raison du pneumothorax. Evolution dans le service : Sur le plan respiratoire : le patient bénéficie de la pose d'un drain thoracique à gauche pour évacuation de l' épanchement aérique. La radiographie pulmonaire après mise en place montre un décollement persistant ainsi qu'une atélectasie du lobe inférieur gauche, avec ascension de la coupole diaphragmatique. Le drain est donc mis en aspiration sans amélioration de la radiographie thoracique. Une fibroscopie bronchique est réalisée et montre une obstruction par un caillot frais au niveau du tronc souche gauche expliquant la non réexpension du poumon. Compte tenu de la taille du caillot, nous programmons une bronchoscopie au tube rigide sous anesthésie générale le 16 04 2009 qui permet la thermocoagulation de la lésion qui apparaît comme un caillot, puis extraction de celui-ci. Après extraction, il existe un saignement régulier issu de B6 qui inonde l'arbre bronchique gauche. On procède à un nettoyage au fibroscope souple de tout le lobe supérieur qui apparaît sain, sans anomalie. La lobaire inférieure est totalement obstruée par un caillot. La lobaire inférieure est cathétérisable mais l'orifice d' entrée est totalement déformé, refoulé par une tumeur issue de B6 saignant facilement au contact. On termine le geste en thermocoagulant B6. Des biopsies de carène, éperon lobaire supérieur et inférieur gauche sont réalisées et sont négatives.

D000410 C0001899 MSH. ancien C0580836 SNO G-A463 anesthésie MED C0002903 T140 anesthésie générale SNO P1-C0010 C0002915 anesthésie générale MSH D000768 C0002915 anesthésie pour bronchoscopie SNO P1-C2A04 C0198953 anomalie M-01130 C1457869 pas SNO antérieur SNO G-A105 C1704448 aorte, sai SNO T-42000 C0003483 appareil respiratoire, sai T-20000 C0521346 SNO arbre SNO L-D0012 C0040811 artère carotide commune C0162859 MSH D017536 artère carotide interne D002343 C0007276 MSH artère cérébrale postérieure C0149576 MSH D020769 artère communicante antérieure C0149562 SNO T-45530 artère communicante postérieure T-45320 C0149559 SNO artère vertébrale C0042559 MSH D014711 artère vertébrale droite SNO T-45710 C0226230 artère vertébrale gauche SNO T-45720 C0226231 artères MSH D001158 C0003842 aspartate aminotransferases MSH D001219 C0004002 aspiration SNO F-29200 C0700198 aspiration (technique) MSH D013396 C0038638 atélectasie D2-60300 C0004144 SNO atélectasie complète D2-60306 C0264497 SNO atélectasie pulmonaire D001261 C0004144 MSH athérome SNO M-52100 C0264956 B05BC02 - urée ATC B05BC02 C0041942 biopsie SNO P1-03100 C0005558 biopsie MSH. D001706 C0005558 bon SNO G-A223 C0205170 bronche souche gauche SNO T-26500 C0225630 bronche, sai SNO T-26000 C0205039 bronches MSH D001980 C0006255

Ter. Code

SNO G-C410

SNO G-C470

F-06305

D000124

T-D8100

SNO

MSH

SNO

CUI

C0332310

C1331475

C0231301

C0004454

C0001072 non

Cond. Ctxt.

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Effacer

er 33 phrases annotées en 270 ms. 194 codes distincts identifiés.

Metrics of ECMT (April 2015 CLEF eHealth in French)

	TP	FP	FN	Р	R	F 1
Anatomy	142	149	54	0.4880	0.7245	0.5832
Chemistry	153	38	108	0.8010	0.5862	0.6670
Devices	13	12	6	0.5200	0.6842	0.5909
Disorders	375	96	209	0.7962	0.6421	0.7109
Geography	14	4	7	0.7778	0.6667	0.7179
Live Beings	125	38	31	0.7669	0.8013	0.7837
Objects	3	16	28	0.1579	0.0968	0.1200
Phenotype	14	35	17	0.2857	0.4516	0.3500
Physiology	60	33	74	0.6452	0.4478	0.5286
Procedure	195	105	109	0.6500	0.6414	0.6457
Overall	1094	526	643	0.6753	0.6298	0.6518

Results obtained in 2015 and 2016 from the training

set (832 documents) provided by CLEF e-Health

		Exact mate	h	Inexact match			
	Precision	Recall	F-measure	Precision	Recall	F-measure	
2015 results	0,2660	0,1285	0,1732	0,6848	0,5113	0,5855	
2016 results	0,4643	0,6154	0,5293	0,6886	0,7835	0,7330	
Variation	+74%	+379%	+206%	+0,55%	+53%	+25%	

• 2015 : participation in the CLEF e-Health challenge

https://sites.google.com/site/clefehealth2015/

- Addresses clinical named entity recognition in languages other than English
- 2016 : Deduplication of identical terms from multiples terminologies
 Reevaluation in the 2016 CLEF e-Health challenge

Detailed 2016 results obtained from the training set (832 documents)

provided by CLEF e-Health 2015, indexed with ECMT

2016	Entity Recognition : exact match						Entity Recognition : inexact match					
	TP	FP	FN	Precision	Recall	F1	TP	FP	FN	Precision	Recall	F1
ANAT	151	340	64	0,3075	0,7023	0,4278	216	275	46	0,4399	0,8244	0,5737
CHEM	172	172	106	0,5000	0,6187	0,5531	257	87	63	0,7471	0,8031	0,7741
DEVI	17	22	9	0,4359	0,6538	0,5231	23	16	5	0,5897	0,8214	0,6866
DISO	465	485	267	0,4895	0,6352	0,5529	789	161	134	0,8305	0,8548	0,8425
GEOG	26	7	12	0,7879	0,6842	0,7324	28	5	11	0,8485	0,7179	0,7778
LIVB	170	124	94	0,5782	0,6439	0,6093	223	71	67	0,7585	0,7690	0,7637
OBJC	8	19	36	0,2963	0,1818	0,2254	8	19	36	0,2963	0,1818	0,2254
PHEN	13	47	41	0,2167	0,2407	0,2281	15	45	40	0,2500	0,2727	0,2609
PHYS	81	79	74	0,5063	0,5226	0,5143	102	58	67	0,6375	0,6036	0,6201
PROC	276	296	159	0,4825	0,6345	0,5482	384	188	96	0,6713	0,8000	0,7300
Overall	1 379	1 591	862	0,4643	0,6154	0,5293	2 045	925	565	0,6886	0,7835	0,7330

Disparities between UMLS semantic groups :

ANAT (anatomy), DISO (disorders) : ICD10, MeSH, FMA...

 OBJC (objects, food), PHEN (natural, environmental phenomenon or process) : few terminological resources

2015	Entity Recognition : exact match						Entity Recognition : inexact match					
	TP	FP	FN	Precision	Recall	F1	TP	FP	FN	Precision	Recall	F1
ANAT	90	401	498	0,1833	0,1531	0,1668	225	266	155	0,4582	0,5921	0,5166
CHEM	98	246	1 064	0,2849	0,0843	0,1301	250	94	211	0,7267	0,5423	0,6211
DEVI	7	32	56	0,1795	0,1111	0,1373	22	17	29	0,5641	0,4314	0,4889
DISO	276	674	1 782	0,2905	0,1341	0,1835	784	166	537	0,8253	0,5935	0,6904
GEOG	23	10	31	0,6970	0,4259	0,5287	28	5	25	0,8485	0,5283	0,6512
LIVB	94	200	381	0,3197	0,1979	0,2445	196	98	153	0,6667	0,5616	0,6096
OBJC	4	23	117	0,1481	0,0331	0,0541	12	15	105	0,4444	0,1026	0,1667
PHEN	11	49	130	0,1833	0,0780	0,1095	19	41	117	0,3167	0,1397	0,1939
PHYS	41	119	441	0,2563	0,0851	0,1277	93	67	305	0,5813	0,2337	0,3333
PROC	146	426	860	0,2552	0,1451	0,1850	405	167	307	0,7080	0,5688	0,6308
Overall	790	2 180	5 360	0,2660	0,1285	0,1732	2 034	936	1 944	0,6848	0,5113	0,5855
	Entity Recognition : exact match											
2016	Entity R	ecognitic	on : exact	t match			Entity R	ecognitic	on : inexa	act match	1	
2016	Entity Ro	ecognitic FP	on : exact		Recall	F1	Entity R	ecognitic FP	on : inexa		Recall	F1
2016 ANAT	-	-			Recall 0,7023	F1 0,4278	-	—				F1 0,5737
	TP	FP	FN	Precision			TP	FP	FN	Precision	Recall	
ANAT	TP 151	FP 340	FN 64	Precision 0,3075	0,7023	0,4278	TP 216	FP 275	FN 46	Precision 0,4399	Recall 0,8244	0,5737
ANAT CHEM	TP 151 172	FP 340 172	FN 64 106	Precision 0,3075 0,5000	0,7023 0,6187	0,4278 0,5531	TP 216 257	FP 275 87	FN 46 63	Precision 0,4399 0,7471	Recall 0,8244 0,8031	0,5737 0,7741
ANAT CHEM DEVI	TP 151 172 17	FP 340 172 22	FN 64 106 9	Precision 0,3075 0,5000 0,4359	0,7023 0,6187 0,6538	0,4278 0,5531 0,5231	TP 216 257 23	FP 275 87 16	FN 46 63 5	Precision 0,4399 0,7471 0,5897	Recall 0,8244 0,8031 0,8214	0,5737 0,7741 0,6866
ANAT CHEM DEVI DISO	TP 151 172 17 465	FP 340 172 22 485	FN 64 106 9 267	Precision 0,3075 0,5000 0,4359 0,4895	0,7023 0,6187 0,6538 0,6352	0,4278 0,5531 0,5231 0,5529	TP 216 257 23 789	FP 275 87 16 161	FN 46 63 5 134	Precision 0,4399 0,7471 0,5897 0,8305	Recall 0,8244 0,8031 0,8214 0,8548	0,5737 0,7741 0,6866 0,8425
ANAT CHEM DEVI DISO GEOG	TP 151 172 17 465 26	FP 340 172 22 485 7	FN 64 106 9 267 12	Precision 0,3075 0,5000 0,4359 0,4895 0,7879 0,5782	0,7023 0,6187 0,6538 0,6352 0,6842 0,6439	0,4278 0,5531 0,5231 0,5529 0,7324 0,6093	TP 216 257 23 789 28	FP 275 87 16 161 5	FN 46 63 5 134 11	Precision 0,4399 0,7471 0,5897 0,8305 0,8485 0,7585	Recall 0,8244 0,8031 0,8214 0,8548 0,7179	0,5737 0,7741 0,6866 0,8425 0,7778 0,7637
ANAT CHEM DEVI DISO GEOG LIVB	TP 151 172 17 465 26 170	FP 340 172 22 485 7 124 19	FN 64 106 9 267 12 94	Precision 0,3075 0,5000 0,4359 0,4895 0,7879 0,5782	0,7023 0,6187 0,6538 0,6352 0,6842 0,6439	0,4278 0,5531 0,5231 0,5529 0,7324 0,6093	TP 216 257 23 789 28 223	FP 275 87 16 161 5 71	FN 46 63 5 134 11 67	Precision 0,4399 0,7471 0,5897 0,8305 0,8485 0,7585	Recall 0,8244 0,8031 0,8214 0,8548 0,7179	0,5737 0,7741 0,6866 0,8425 0,7778 0,7637
ANAT CHEM DEVI DISO GEOG LIVB OBJC	TP 151 172 17 465 26 170 8	FP 340 172 22 485 7 124 19	FN 64 106 9 267 12 94 36	Precision 0,3075 0,5000 0,4359 0,4895 0,7879 0,5782 0,2963	0,7023 0,6187 0,6538 0,6352 0,6842 0,6439 0,1818	0,4278 0,5531 0,5231 0,5529 0,7324 0,6093 0,2254	TP 216 257 23 789 28 223 8 8	FP 275 87 16 161 5 71 71	FN 46 63 5 134 11 67 36	Precision 0,4399 0,7471 0,5897 0,8305 0,8485 0,7585 0,2963	Recall 0,8244 0,8031 0,8214 0,8548 0,7179 0,7690 0,1818	0,5737 0,7741 0,6866 0,8425 0,7778 0,7637 0,2254
ANAT CHEM DEVI DISO GEOG LIVB OBJC PHEN	TP 151 172 17 465 26 170 8 13	FP 340 172 22 485 7 124 19 47 79	FN 64 106 9 267 12 94 36 41	Precision 0,3075 0,5000 0,4359 0,4895 0,7879 0,5782 0,2963 0,2167	0,7023 0,6187 0,6538 0,6352 0,6842 0,6439 0,1818 0,2407	0,4278 0,5531 0,5231 0,5529 0,7324 0,6093 0,2254 0,2281	TP 216 257 23 789 28 223 8 223 8 15	FP 275 87 16 161 5 71 5 71 19 45	FN 46 63 5 134 11 67 36 40	Precision 0,4399 0,7471 0,5897 0,8305 0,8485 0,7585 0,2963 0,2500	Recall 0,8244 0,8031 0,8548 0,7179 0,7690 0,1818 0,2727 0,6036	0,5737 0,7741 0,6866 0,8425 0,7778 0,7637 0,2254 0,2609

Results on CepiDC corpus

Run	ECMT	Exact match + Speller correction	Partial match (Leweinstein distance)
Precision	0.69	0.64	0.72
Recall	0.23	0.62	0.69
Time per line	40ms	70ms	120ms

Similiarity distances: Stoilos

communality function:

$$Comm(s_1, s_2) = \frac{2 * \sum_{i} length(MaxComSubString_i)}{length(s_1) + length(s_2)}$$

Example : S₁ = « Trigonocepahlie » et S₂ = « Trigonocephalie »

Comm(Trigonocepahlie, Trigonocephalie) = 0.866.

length(MaxComSubString1)=length(Trigonocep)=10
length(MaxComSubString2)=length(lie)=3

Similiarity distances: Stoilos

- Difference function:
- Based on length of chains, which where not matched at the previous step

$$Diff(s_{1}, s_{2}) = \frac{uLen_{s_{1}} * uLen_{s_{2}}}{p + (1 - p) * (uLen_{s_{1}} + uLen_{s_{2}} - uLen_{s_{1}} * uLen_{s_{2}})}$$

 $S_1 =$ « Trigonocepahlie » et $S_2 =$ « Trigonocephalie » p=0.6; uLen $S_1 = 2/15$ et uLen $S_2 = 2/15$; Then: Diff $(S_1, S_2) = 0.0254$.

• Winkler parameter:

Winkler
$$(s_1, s_2) = L * P * (1 - Comm(s_1, s_2))$$