

Text Mining & Bioinformatics

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- Introduction and objectives
- Metrics
- Words
- Tasks
- Methodologies
- Text Categorization

Objectives

- Introduce how text mining can support bioinformatics tasks
- Explain how text mining operate with biological entities and the « biological » ecosystem
- Stimulate your interest into a satellite - yet very lifeful - bioscience field

- Text Mining is like Data Mining but works with textual contents
- ... So any statistical analysis can be performed with text mining provided the content is available in text ?
- Answer: **Jein !**

- Natural language processing, computational linguistics (+)
- Machine learning / data mining (++)
- **Information retrieval (+++)**

Common application fields

- Information retrieval
- Biocuration support tools → tools to maintain KB
- Biological modelling, e.g. biotic interactions

User level tasks

- Search – Foundations
- Triage (i.e., binary classification)
- Keyword assignment (i.e., multi-class classification)
- (Named-)Entity recognition
- Extract passages or more complex entities (e.g. protein protein interactions)

User level tasks

- Summarization
- Retrieval-augmented summarization
- ChatBots

- Precision
- Recall
- Other metrics...

- Like most data mining tasks, information retrieval and text mining tasks are assessed using two dimensions metrics

Precision

- Given 5 relevant documents in a collection for a given query, a search engine returns **10** documents, including **3**, which are pertinent
- $P = 3/10 = 0.30$ or 30%

Recall

- Given **5** relevant documents in a collection for a given query, a search engine returns 10 documents, including **3**, which are pertinent
- $\text{Recall} = 3/5 = 0.60$ or 60%

Precision

- Given 8 relevant documents in a collection for a given query, a search engine returns 10 documents, including 8, which are pertinent
- Please compute the precision ?

Recall

- Given 8 relevant documents in a collection for a given query, a search engine returns 10 documents, including 8, which are pertinent
- Please compute the recall ?

Recall vs. Precision

- Precision is usually regarded as more important because redundancy is (usually) high in large collections...
- Exceptions are numerous
 - Looking for allergies of patients
 - Looking for rare variants
 - Looking for known items
 - [...]

Exemple

■ Rare variants

<https://variomes.text-analytics.ch/>

■ SynVar (expansion engine)

<https://goldorak.hesge.ch/synvar>

Variant P53 (R213L)

MEDLINE (2 documents)

PubMed Central (37 documents)

Clinical Trials (1 document)

Supplementary data (60 documents)

Sort and highlight

+

 Sort

+

 Highlight

Filters

-

 Date

2013

2023

-

 Sections

37 documents

1

The spectrum of subclonal TP53 mutations in chronic lymphocytic leukemia: A next generation sequencing retrospective study

PMID:35961859. PMC10086786. Giuseppa De Luca, Giannamaria Cerruti, Sonia Lastraioli, Romana Conte, Adalberto Ibatici, et al. 2022. Hematological Oncology. research-article. **MEDLINE PubMedCentral EuropePMC SIBiLS**

gene

full_text

spliceite_5 (ex.5) c.376-2A>T Aberrant splicing 2.43 10,433 254 6 c.570_573delTCCT p.(Pro191fs) Frameshift deletion 6.3 11,723 740 6 c.638G>T p.(Arg213Leu) Missense 1.65 5260 87 7 c.742C>T p.(Arg248Trp

full_text

.(Ile232Phe) Missense 29.1 14,904 513 8 c.826G>A p.(Ala276Thr) Missense 47.4 4247 2013 8 c.842 A>G p.(Asp281Gly) Missense 2.2 8235 177 6 c.638G>T p.(Arg213Leu) Missense 31.4 1241 389 7 c.716A>C p.(Asn239Thr

score 1.00

Synthetic metrics

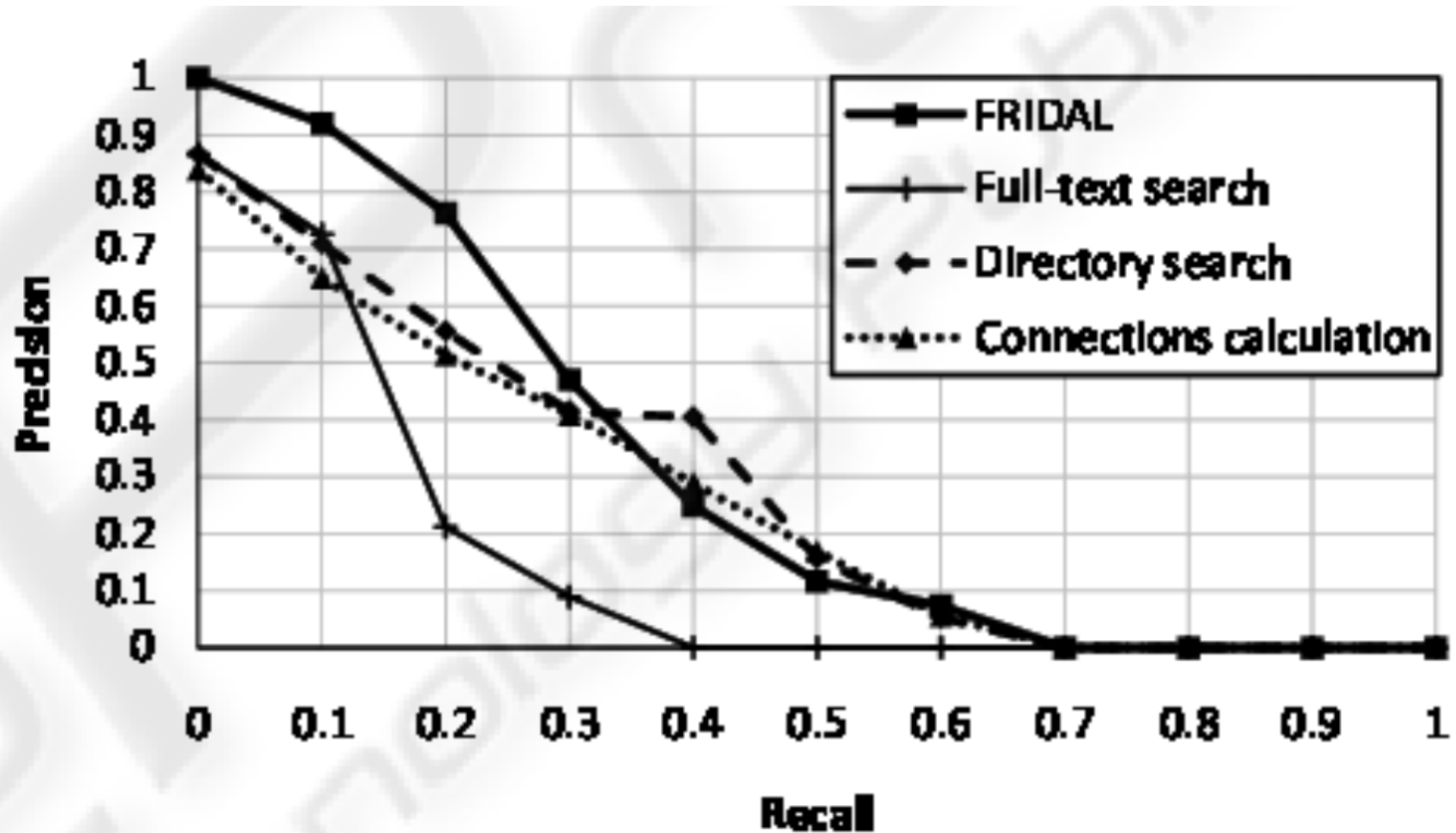
■ Rank

- R^{th-1} is more important than R^{th}
- So, we compute average precision at different rank values (10, 20, ... 30%, ...)
- Mean average precision

■ F1 and related metrics

- Harmonic or geometric mean
- Utility metrics
 - E.g., $0.9 \times \text{Recall} + 0.1 \times \text{Precision}$

Example



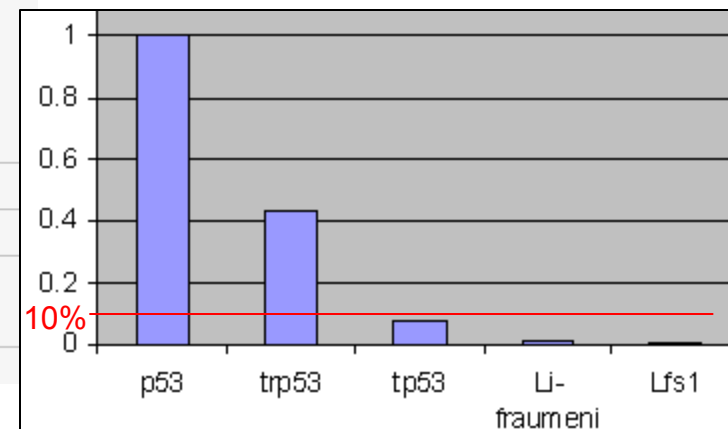
Feature normalization

- Words
- Subwords (character N-grams)
- Stems
- Word N-grams
- Syntactic entities (noun phrases, verb phrases, ...),
- Semantic entities (gene names, chem. compounds, diseases, ...)

Term normalization: database & ontology vs. reality !

<input type="checkbox"/> Antigen NY-CO-13	Protein	SwissProt:P04637
<input type="checkbox"/> Cellular tumor antigen p53	Protein [preferred]	SwissProt:P04637
<input type="checkbox"/> FLJ92943	Gene	EntrezGene:7157
<input type="checkbox"/> LFS1	Gene	EntrezGene:7157 HGNC:11998
<input type="checkbox"/> Li-Fraumeni syndrome	Gene	HGNC:11998
<input type="checkbox"/> p53	Gene	EntrezGene:7157 HGNC:11998
<input type="checkbox"/> P53	Gene	OMIM:191170 SwissProt:P04637
<input type="checkbox"/> p53 antigen	Gene	EntrezGene:7157
<input type="checkbox"/> p53 transformation suppressor	Gene	EntrezGene:7157
<input type="checkbox"/> p53 tumor suppressor	Gene	EntrezGene:7157
<input type="checkbox"/> phosphoprotein p53	Gene	EntrezGene:7157
<input type="checkbox"/> Phosphoprotein p53	Protein	SwissProt:P04637
<input type="checkbox"/> TP53	Gene [preferred]	HGNC:11998 SwissProt:P04637 Gene EntrezGene:7157 OMIM:191170
<input type="checkbox"/> transformation-related protein 53	Gene	EntrezGene:7157
<input type="checkbox"/> TRANSFORMATION-RELATED PROTEIN 53	Gene	OMIM:191170
<input type="checkbox"/> TRP53	Gene	EntrezGene:7157 OMIM:191170
<input type="checkbox"/> tumor protein p53	Gene [preferred]	HGNC:11998

Synonyms	#
p53	53362
trp53	23364
tp53	4156
li-fraumeni	775
lfs1	431



- i, ii, iii → 1, 2, 3 (e.g. *histone deacetylase iii*)
- Greek letters (e.g α -*tubulin*)
- Hyphenation «-»: {alphatubulin, alpha, tubulin)
- Chemistry
 - Inchi
 - SMILES
 - PubChem, chEBI, DrugBank...

Stemming vs. Lemmatization (needs syntactic analysis)

Original	Stemming	Lemmatization
New	New	New
York	York	York
is	is	be
the	the	the
most	most	most
densely	dens	densely
populated	popul	populated
city	citi	city
in	in	in
the	the	the
United	Unite	United
States	State	States

Impact of normalization and expansion ?

- Recall

- Precision

Normalization and expansion impact

■ Recall

Normalization/expansion improves recall

■ Precision

Normalization/expansion degrades precision

→ No free lunch and fine-tuning are needed !

Back end tasks – intelligent stuff that computers can do ☺

- Ranker

- Classifier

- ... and both are the same: a classifier is a ranker with a threshold !

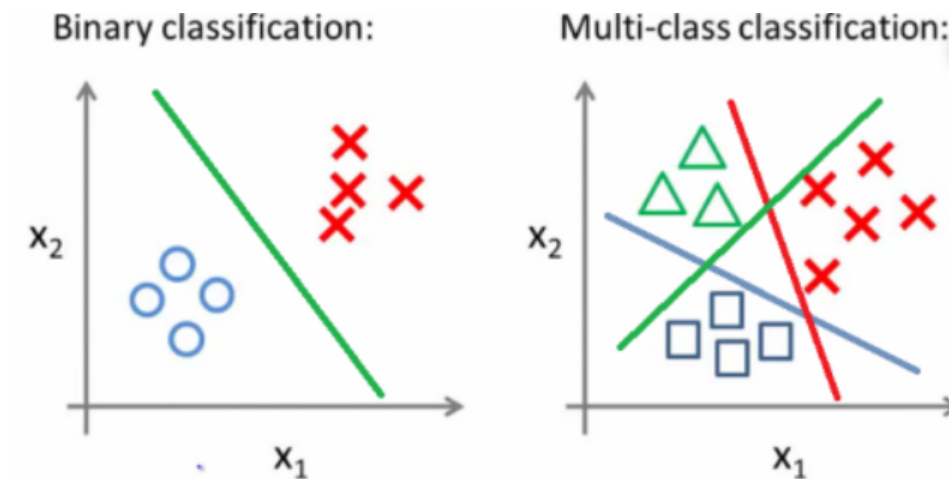
- Regression (ok for structured data)

Ranking and text mining features

- Given an objective function, rank a collection of text !
- Objective function = distance, precision, recall, ...

Classification: one-class, binary, ...

- With n binary classifiers, we can design n -class categorizers



■ PubMed

- Boolean & Ante-chronological
- « Best match »
 - Vector-space
 - Learning to rank

■ EuropePMC

- Vector-space (Lucene)

■ SIBiLS

- Vector-space (Lucene)
- Combination of weighting schema (Terrier)

Boolean vs. Vector-space systems

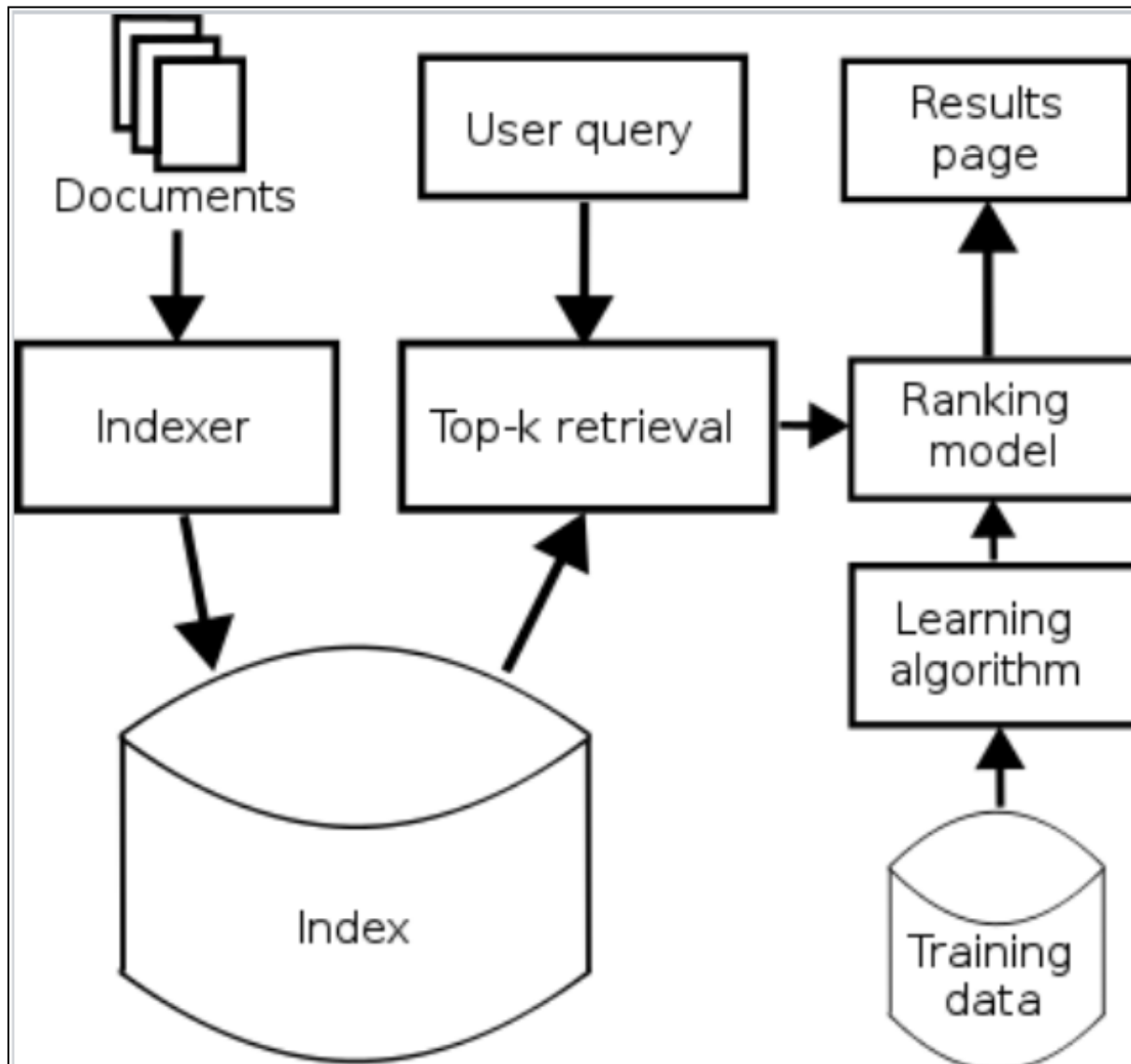
- Boolean: would return results satisfying the query using AND, OR, NOT operators

- Vector-space does the same but the ranking is based on the differential weighting of:
 - TF: Term frequency
The more frequent a term in a document the stronger the association with that document
 - IDF: Inverse document frequency
The more rare a term in a document collection the stronger the association with a document it appears in
 - Document normalization factor
Longer documents tend to have more words irrespective on the relevance of those words

Weighting schema

Term frequency		Document frequency		Normalization	
n (natural)	$tf_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1 + \log(tf_{t,d})$	t (idf)	$\log \frac{N}{df_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2 + w_2^2 + \dots + w_M^2}}$
a (augmented)	$0.5 + \frac{0.5 \times tf_{t,d}}{\max_t(tf_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N - df_t}{df_t}\}$	u (pivoted unique)	$1/u$ (Section 6.4.4)
b (boolean)	$\begin{cases} 1 & \text{if } tf_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$			b (byte size)	$1/CharLength^\alpha, \alpha < 1$
L (log ave)	$\frac{1 + \log(tf_{t,d})}{1 + \log(\text{ave}_{t \in d}(tf_{t,d}))}$				

Machine learning for retrieval ? Yes, learning to rank

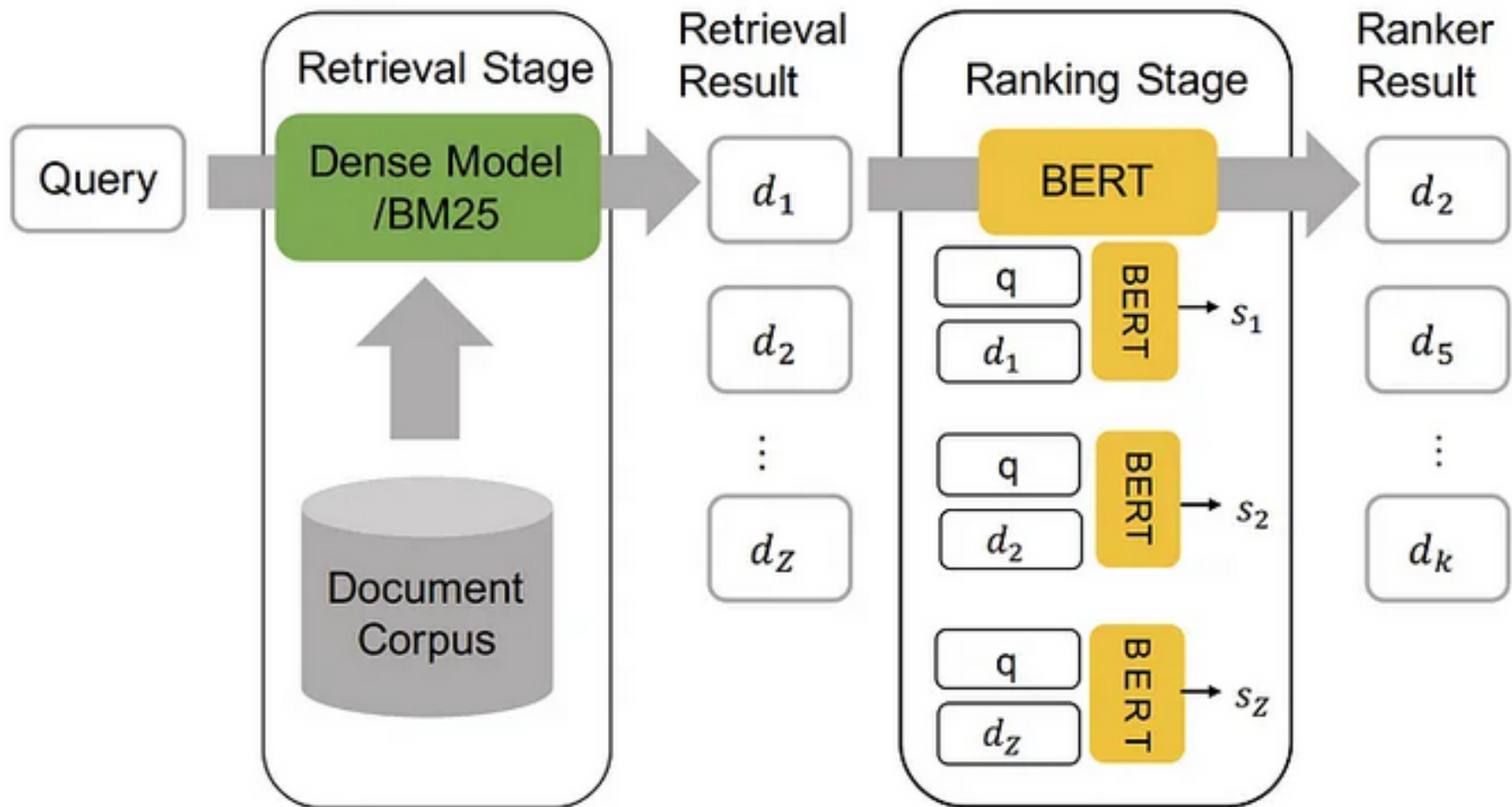


Zero-shot learning does not exist...

Language models did improved the ability to learn with little data

Typically in IR, you need 2-3 iterations or min. 20-30 queries to start learning something useful !

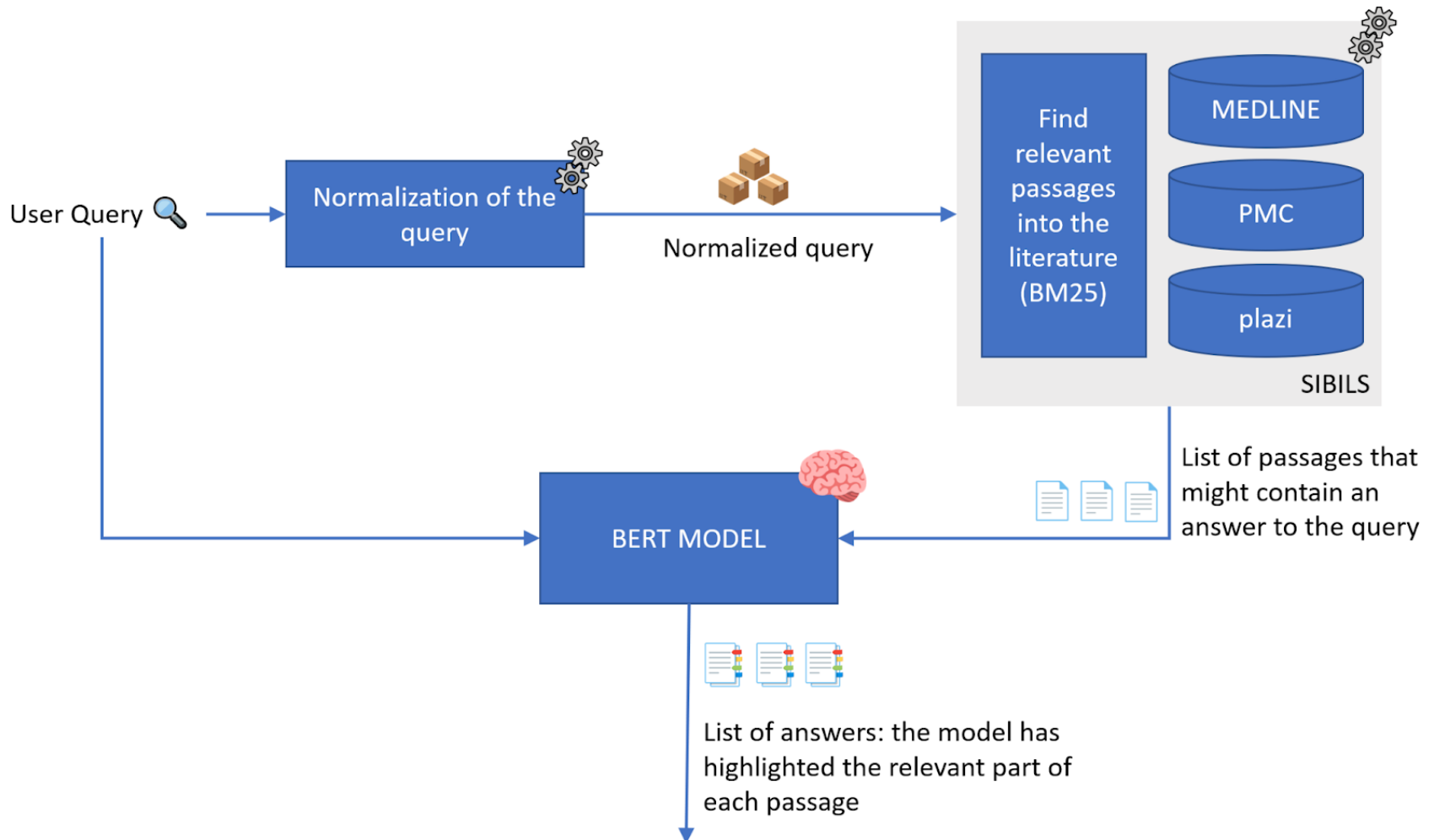
Search + pre-trained language models such as BERT



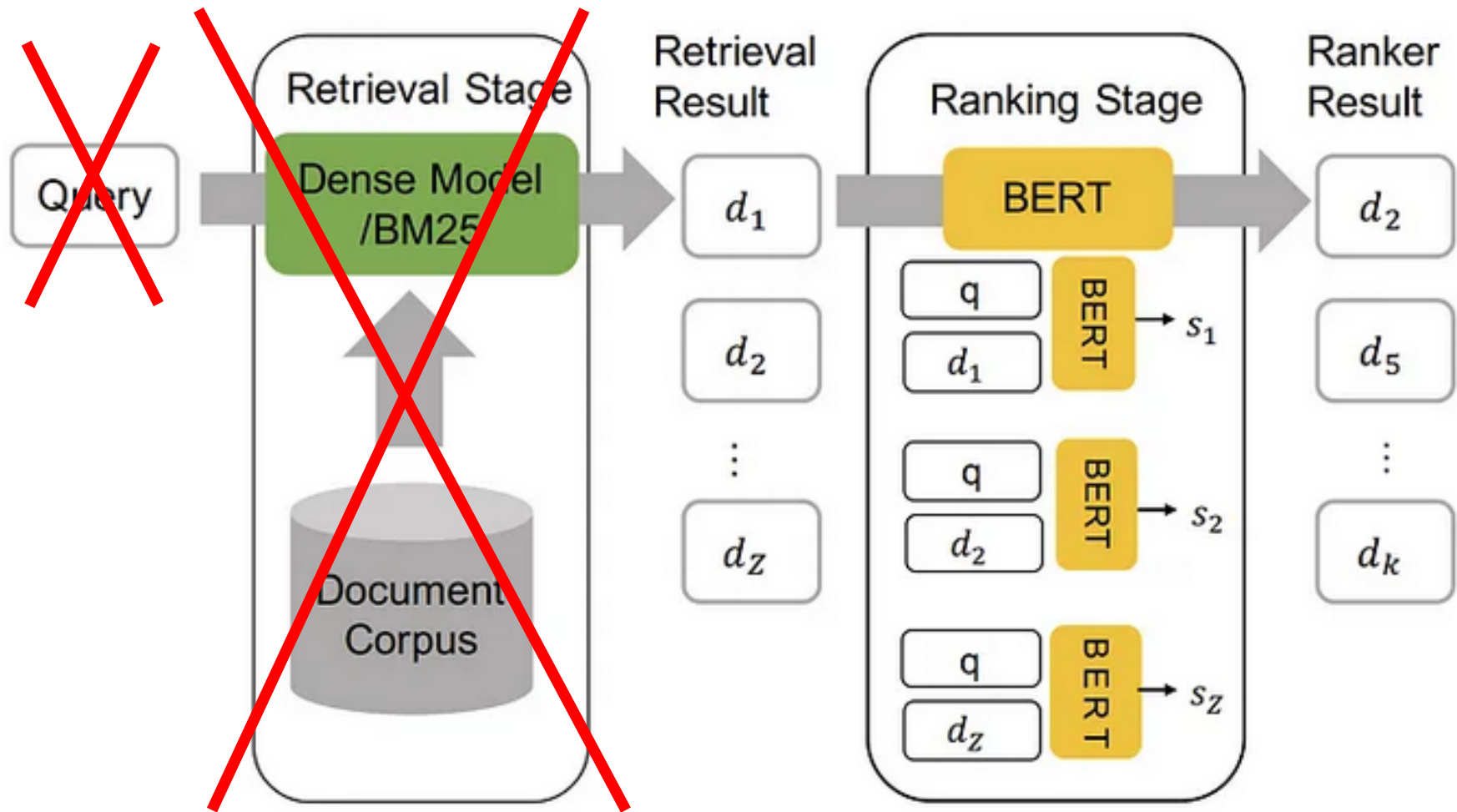
Sparse retrievers → Large matrix, mostly sparse
Dense retrievers → Embeddings

Question Answering

■ <https://sibils.text-analytics.ch/search/>



Zero search cases also can occur...



Sparse retrievers → Large matrix, mostly sparse
Dense retrievers → Embeddings

CellTriage: query independent model-based curation support

Results for 2023-10-23 to 2023-10-29

MEDLINE (2000 documents)

2000 documents with your filters (Total: 2000 documents)

Sort

By relevance

By date

Filters

☐ Cellosaurus

PAE-iPS-4 (795)

UiE-iPS-1 (676)

CRL-6440 (260)

[+] More

☐ Species

Homo sapiens (775)

1

Generation of induced pluripotent stem cell lines from pediatric patients with congenital myotonic dystrophy (CBRCULi012-A and CBRCULi013-A) and Age-Matched controls (CBRCULi010-A and CBRCULi011-A).

37871474. De Serres-Bérard Thiéry, Jauvin Dominic, Puymirat Jack, Chahine Mohamed. 2023-10-23. Stem cell research. Journal Article **MEDLINE**. **Doi**. **BiodiversityPMC**. **BiotXplorer**.

score
1.00



2

Development of Stable **CHO-K1** Cell Lines Overexpressing Full-Length Human CD20 Antigen.

37873643. Mohammadkhani Niloufar, Rahimpour Azam, Hoseinpoor Reyhaneh, Rajabibazi Masoumeh. 2023-10-24. Iranian biomedical journal. Journal Article **MEDLINE**. **Doi**. **BiodiversityPMC**. **BiotXplorer**.

score
1.00



3

Development and characterization of a new muscle cell culture system from *Clarias magur* (Hamilton, 1822).

37878191. Dhivyakumari Sekar, Chaudhari Aparna, Brahmane Manoj P, Das Dhanjit Kumar, Sathiyarayanan Arjunan, et al. 2023-10-25. Fish physiology and biochemistry. Journal Article **MEDLINE**. **Doi**. **BiodiversityPMC**. **BiotXplorer**.

score
1.00



4

Xeno-free generation of new Yazd human embryonic stem cell lines (Yazd4-7) as a prior stage toward good manufacturing practice of clinical-grade raw materials from discarded embryos: **A lab** resources report.

37885973. Hajizadeh-Tafti Fatemeh, Golzadeh Jalal, Akyash Fatemeh, Tahajjodi Somayyeh-Sadat, Farashahi-Yazd Ehsan, Heidarian-Meimandi Hassan, Aflatoonian Behrouz. 2023-10-27. International journal of reproductive biomedicine. Journal Article **MEDLINE**.

score
1.00

<https://sibils.text-analytics.ch/search/celltriage>

Thank you for your attention !