

# Medical Search Engine

**Information Retrieval Project – January 2025** 

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### Introduction

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The project focus is to develop a Search Engine for Medical Information Retrieval.

Given the dataset and the initial code found on the course page, the project structure follows these parts:

- Analysis of the Dataset
- Retrieval Pipelines and Experiments
- Improvements to the baseline using Query Expansion
- Final Considerations and Future Works





# Analysis of the Dataset



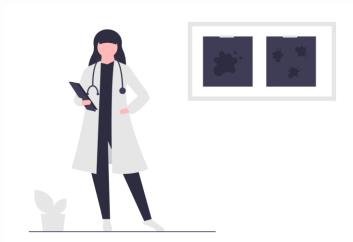


Before starting to analize the dataset we need to **preprocess** the data:

- Tokenization
- Normalization and Removal of Stopwords
- Stemming
- Lemmatization

Then the analysis focuses on:

- Documents Text (Abstract) and Title
- Query Text
- Relevance Judgements







#### For both **Documents** and **Queries** we have analyzed:

- Token Count and Structure
- Vocabulary Size
- Distribution of number of terms using Histograms
- Distribution of most frequent terms using Word Clouds
- Upper and Lower tail analysis (with Outliers)

#### For the **Relevance Judgments**:

- Scores Distribution
- Distribution of number of relevant documents per Query
- Min/Max number of documents retrieved



## Analysis of the Dataset - Tokens



#### For Document Text as Example: we can see the effect of the preprocessing

	text	title	doc_id	original_text_tokens	stemmed_text_tokens	lemmatized_text_tokens	original_term_count	stemmed_term_count	lemmatized_term_count
1954	INTRODUCTION: Although penile blood flow (PBF) has been recommended as an additional diagnostic test in identifying erectile dysfunction (ED) patients at risk for latent cardiovascular disease, no study has ever assessed the possible association of PBF and the relational component of sexual func	Male sexuality and cardiovascular risk. A cohort study in patients with erectile dysfunction.		[introduction, although, penile, blood, flow, pbf, recommended, additional, diagnostic, test, identifying, erectile, dysfunction, ed, patients, risk, latent, cardiovascular, disease, study, ever, assessed, possible, association, pbf, relational, component, sexual, function, incident, major, card	[introduct, although, penil, blood, flow, pbf, recommend, addit, diagnost, test, identifi, erectil, dysfunct, ed, patient, risk, latent, cardiovascular, diseas, studi, ever, assess, possibl, associ, pbf, relat, compon, sexual, function, incid, major, cardiovascular, event, mace, aim, aim, studi,	[introduction, although, penile, blood, flow, pbf, recommended, additional, diagnostic, test, identifying, erectile, dysfunction, ed, patient, risk, latent, cardiovascular, disease, study, ever, assessed, possible, association, pbf, relational, component, sexual, function, incident, major, cardi	123	114	122

#### Token Information and Vocabulary Sizes for Original, Stemmed and Lemmatized Tokens

Type (Abstract)	Vocabulary Size	vs Original	vs Stemmed	vs Lemmatization
Original	24283	0	7018	2266
Stemmed	17265	-7018	0	-4752
Lemmatized	22017	-2266	4752	0

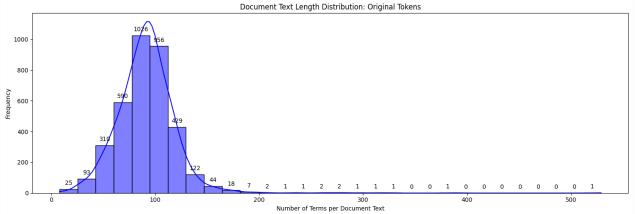
## Analysis of the Dataset - Distributions





#### For Document Text as Example:

- We can see the most frequent terms in the word cloud.
- The distributions (which are very similar between Documents and Queries) show a normal distribution.



## Analysis of the Dataset - QRels

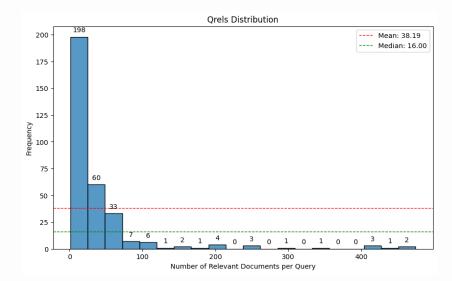




Query ID	Number of Relevant Documents	Doc ID (Example)
PLAIN-681	1	MED-5017
PLAIN-660	475	MED-2509, MED-1374

#### For QRels Example:

- We can see the two levels of relevance (scores).
- The distribution shows the number of relevant documents per query.
- The table is an example of Min/Max relevant documents per Query.





# Pipelines and Experiments





The process of Retrieval Pipelines and Experiments follows these steps:

- Indexing
- Building the Pipeline
- Evaluation
- In-Depth Analysis of Queries
  - Top 10 Queries in Precision@10
  - Inconsistencies in QRels and Relevant Pairs (Not shown here because of length)







The indexing has been done using two distinct Stemmers:

- PorterStemmer
- SnowballStemmer, which is an improved version of PorterStemmer with multiple language supported.

#### And specifically on:

- Only Document Text
- Only Document Titles
- Both Document Titles and Text

```
Number of documents: 3633
Number of terms: 18596
Number of postings: 336960
Number of fields: 2
Number of tokens: 567901
Field names: [title, text]
Positions: false
```

#### **PorterStemmer**

Number of documents: 3633 Number of terms: 18596 Number of postings: 336960 Number of fields: 2 Number of tokens: 567901 Field names: [title, text] Positions: false

SnowballStemmer

 The two Stemmers behave the same, probably because the dataset contains specifical terms for medical purposes.

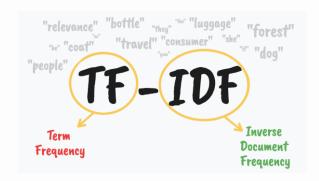




Two different Models have been used for the Retrieval Pipelines and Evaluation:

- BM25
- TF-IDF





The metrics considered for evaluation purposes are:

- Precision@10
- Recall@10
- Mean Average Precision
- Normalized Discounted Cumulative Gain

## Pipelines and Experiments - Results



Indexing Type	Model	P@10	R@10	МАР	NDCG
Only Documents Titles	BM25	0.169	0.109	0.099	0.203
Only Documents Titles	TF-IDF	0.168	0.109	0.098	0.203
Only Doguments Toyt	BM25	0.226	0.145	0.146	0.295
Only Documents Text	TF-IDF	0.227	0.146	0.146	0.295
Both Documents Titles and Text	BM25	0.232	0.150	0.149	0.298
both Documents Titles and Text	TF-IDF	0.231	0.148	0.148	0.298

The results shown consider only the SnowballStemmer as the performances are the same as PorterStemmer

The performances are not particularly high, but we can try to improve them using **Query Expansion**.

### Pipelines and Experiments - Top 10 Queries



For every indexer and stemmer we have shown the top 10 queries for **Precision@10**, for example considering **SnowballStemmer and Indexing on both Text and Titles**:

Top 1	0 Queries by	P@10	in BM25 results:
	qid	P@10	query
155	PLAIN-1837	1.0	pesticides
153	PLAIN-1805	1.0	Parkinsons disease
169	PLAIN-1983	1.0	rapamycin
215	PLAIN-2530	1.0	Infectobesity Adenovirus 36 and Childhood Obesity
145	PLAIN-1710	1.0	neurocysticercosis
148	PLAIN-1741	1.0	nuts
63	PLAIN-721	1.0	BMAA
14	PLAIN-153	1.0	How Should I Take Probiotics
57	PLAIN-660	1.0	beans
43	PLAIN-488	0.9	adenovirus 36

Top 1	.0 Queries by	P@10	in TF-IDF results:
	qid	P@10	query
169	PLAIN-1983	1.0	rapamycin
63	PLAIN-721	1.0	ВМАА
215	PLAIN-2530	1.0	Infectobesity Adenovirus 36 and Childhood Obesity
155	PLAIN-1837	1.0	pesticides
14	PLAIN-153	1.0	How Should I Take Probiotics
145	PLAIN-1710	1.0	neurocysticercosis
148	PLAIN-1741	1.0	nuts
153	PLAIN-1805	1.0	Parkinsons disease
57	PLAIN-660	1.0	beans
176	PLAIN-2061	0.9	seafood

TF-IDF Model

### Pipelines and Experiments – Worst 10 Queries



For every indexer and stemmer we have also shown the worst 10 queries for **Precision@10**, for example considering **SnowballStemmer and Indexing on both Text and Titles**:

Worst	10 Queries	by P@16	in BM25 res	ılts:
	qid	P@10		query
206	PLAIN-2440	0.0	More Than an A	pple a Day Combating Common Diseases
212	PLAIN-2500	0.0	The Sat	urated Fat Studies Buttering Up the Public
127	PLAIN-1485	0.0		lard
128	PLAIN-1496	0.0		leeks
130	PLAIN-1516	0.0		Lindane
132	PLAIN-1537	0.0		lowcarb diets
133	PLAIN-1547	0.0		lyme disease
115	PLAIN-1353	0.0		hernia
117	PLAIN-1374	0.0		hormonal dysfunction
298	PLAIN-3392	0.0		Healthiest Airplane Beverage

Wo	orst	10	Queri	ies	by	P@10	in	TF-IC	DF	resul	lts:		
			q	id	P@	10							query
1	130	PL/	AIN-15	16	(	0.0						Lii	ndane
1	161	PL	AIN-18	97	(	0.0				poly	propy	lene	olastic
1	160	PL/	AIN-18	87	(	0.0					poiso	nous	plants
1	159	PL/	AIN-18	77	(	0.0					plar	ntbase	ed diet
1	151	PL/	AIN-17	84	(	0.0						oxen	meat
1	146	PL/	AIN-17	21	(	0.0					NIH	AARP	study
1	144	PL/	AIN-17	00	(	0.0				١	Vative	Ame	ricans
1	143	PL/	AIN-16	90	(	0.0		Natio	na	l Acad	lemy	of Sci	ences
2	221	PL/	4IN-25	90	(	0.0	ا ەכ	/egeta	ria	ns Ge	t Eno	ugh F	rotein
2	217	PL/	4IN-25	50	(	).0 B	arrie	ers to l	He	art Dis	sease	Prev	ention

**BM25 Model** 

**TF-IDF Model** 



# Query Expansion



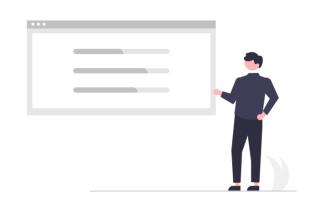


Provided by **PyTerrier**, we have used the following techniques:

- RM3 Relevance Model
- Bo1 Divergence
- Kullback Leibler Divergence

As an extra experiment we have also tried the **spaCy** Library. SpaCy uses **Word Embeddings** for Query Expansion.

The baseline used for comparation is the best one found in the previous part.



## **Query Expansion - Results**



Query Expansion Technique	Model	P@10	R@10	МАР	NDCG
Oviginal Overige	BM25	0.232	0.150	O.148	0.298
Original Queries	TF-IDF	0.231	0.148	O.148	0.298
DM2 Evappoin	BM25	0.253	0.169	0.173	0.375
RM3 Expansion	TF-IDF	0.251	0.168	0.173	0.376
Bo1 Divergence Expansion	BM25	0.251	0.165	0.174	0.373
boi bivergence expansion	TF-IDF	0.251	0.165	0.173	0.373
KL Divergence Expansion	BM25	0.250	0.164	0.174	0.373
RE Divergence Expansion	TF-IDF	0.250	0.165	0.173	0.374
	BM25	0.201	0.134	0.130	0.294
spaCy Query Expansion	TF-IDF	0.200	0.140	0.129	0.294

Besides **spaCy**, we can see some improvements in the overall performance, with the three techniques provided by PyTerrier producing similar results.





Query ld	Query
PLAIN-2	Do Cholesterol Statin Drugs Cause Breast Cancer co nothin somethin and that cause space sha havin nuff where
PLAIN-12	Exploiting Autophagy to Live Longer co and that cause vs havin there pm not
PLAIN-23	How to Reduce Exposure to Alkylphenols Through Your Diet dare and that cause havin these nt s
PLAIN-3432	Healthy Chocolate Milkshakes cinnamon diet raspberries sweeteners health dietary
PLAIN-44	Who Should be Careful About Curcumin should somethin that cause need you

We can see that **spaCy** doesn't put very coherent words, probably because of the highly technical language.

-> A possible solution: SciSpaCy



# Final Considerations

### Final Considerations and Future Works



In **conclusion**, the results obtained show little difference but constant improvements. The **average metrics** are not really high but there is room for improvements in possible future works:

- Neural Re-ranking using BERT or using Pseudo Relevance Feedback.
- Query expansion using other techniques such as LLMs or using SciSpaCy.
- Using different Models for the retrieval pipelines.





	Recall@50	Recall@1000
tfidf only text PorterStemmer	0.208	0.360
tfidf only title PorterStemmer	0.162	0.222
tfidf title text PorterStemmer	0.214	0.365
tfidf only text SnowballStemmer	0.208	0.360
tfidf only title SnowballStemmer	0.162	0.222
tfidf title text SnowballStemmer	0.214	0.365
bm25 only text PorterStemmer	0.210	0.359
bm25 only title PorterStemmer	0.162	0.222
bm25 title text PorterStemmer	0.215	0.363
bm25 only text SnowballStemmer	0.210	0.359
bm25 only title SnowballStemmer	0.162	0.222
bm25 title text SnowballStemmer	0.215	0.363

Higher @K -> Higher Recall





	P@5	P@10	P@25	P@50	P@100	Rprec
tfidf only text PorterStemmer	0.289	0.227	0.143	0.098	0.064	0.169
tfidf only title PorterStemmer	0.226	0.168	0.103	0.065	0.040	0.118
tfidf title text PorterStemmer	0.297	0.231	0.145	0.100	0.065	0.171
tfidf only text SnowballStemmer	0.289	0.227	0.143	0.098	0.064	0.169
tfidf only title SnowballStemmer	0.226	0.168	0.103	0.065	0.040	0.118
tfidf title text SnowballStemmer	0.297	0.231	0.145	0.100	0.065	0.171
bm25 only text PorterStemmer	0.290	0.226	0.144	0.098	0.064	0.168
bm25 only title PorterStemmer	0.225	0.169	0.104	0.065	0.040	0.118
bm25 title text PorterStemmer	0.298	0.233	0.146	0.100	0.065	0.171
bm25 only text SnowballStemmer	0.290	0.226	0.144	0.098	0.064	0.168
bm25 only title SnowballStemmer	0.225	0.169	0.104	0.065	0.040	0.118
bm25 title text SnowballStemmer	0.298	0.233	0.146	0.100	0.065	0.171

Higher @K -> Lower Precision

