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SEARCH ENGINES AND WEB MINING

ITC 6008

Instructor: Dr. Lazaros Polymenakos

TEAM PROJECT:

Search Engine dedicated to Tech Products

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1. Abstract

This project revolves around the creation of a search engine that is dedicated to the retrieval of information about tech products. This information would be retrieved specifically on three sites (tomdsguide, digitaltrends, techadvisor). Several links were scrapped, specifically on the reviews and news sections offered by these sites. This procedure yielded around 102k articles which would be the repository for the search engine. After that, the whole corpus was pre-processed to be in the appropriate form for analysis. 3 different variations of the tf-idf were then computed for the articles along with the Bert embeddings for each sentence inside the corpus. The matrices produced were stored in a SciPy sparce matrix form in separate files. This would allow for a faster retrieval of them instead of doing this process each time a search is carried out. The umap algorithm was also performed on the Bert embeddings in order to reduce their high dimensionality nature. Moreover, the pre-trained models of tf-idf, Bert and umap were stored in a pickle format to be at hand for the encoding of the query. As for the query itself, a spell checker was constructed that would correct any misspells on it and also a corpus was constructed manually that would expand the query posed with similar ones. Then the query was embedded with tf-idf, and similarities were computed with the weights of the already embedded articles (once with stopwords and once without them). The 10 top articles were returned to the user based on the similarity of the tf-idf. Afterwards the query was embedded once again with Bert and similarities were computed this time with the sentences of the top 5 articles that the previous tf-idf method had fetched (hierarchical ranking). Several queries were used for testing and based on the relevance of the articles retrieved with the query posed, some metrics were computed that proved that hierarchical ranking was yielding

the best results. The last step of the information retrieval system was to build a classifier that would filter out any non-relevant articles and then some metrics were once again computed to evaluate the system. All these procedures would though be bypassed if the user performed a query that was already applied to the search engine. Finally, a user interface was set up for the user by utilizing the flask module. The flowchart below encapsulates the whole approach (Figure1).

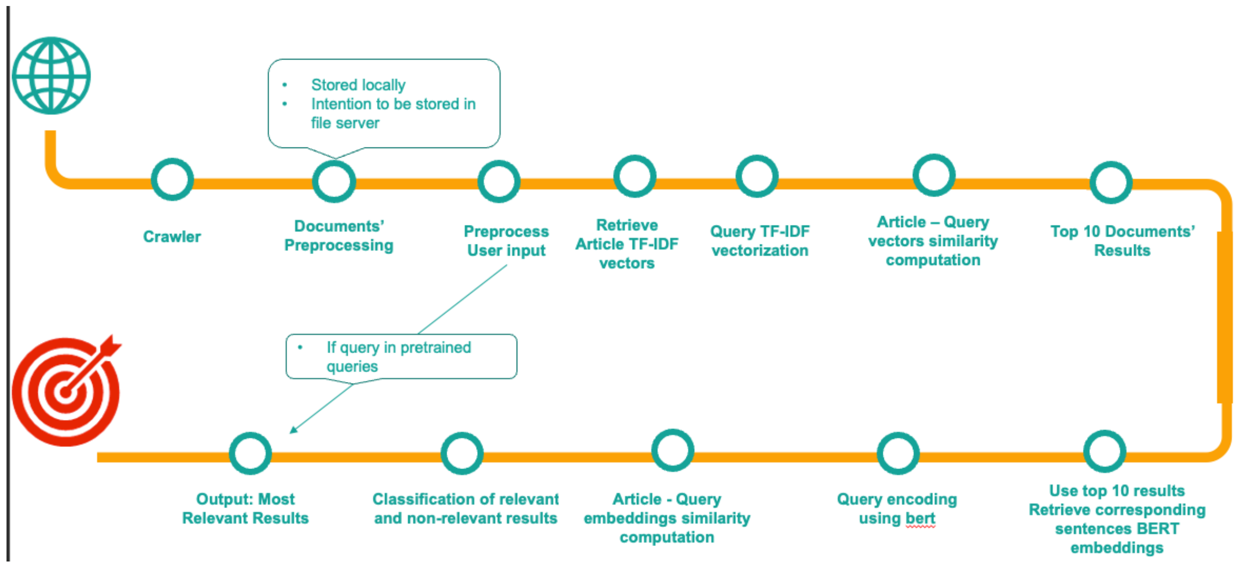

• Stored locally
• Intention to be stored in file server
Crawler
Documents' Preprocessing
Preprocess User input
Retrieve Article TF-IDF vectors
Query TF-IDF vectorization
Article – Query vectors similarity computation
Top 10 Documents' Results
• If query in pretrained queries
Output: Most Relevant Results
Classification of relevant and non-relevant results
Article - Query embeddings similarity computation
Query encoding using bert
Use top 10 results Retrieve corresponding sentences BERT embeddings

Figure 1 A flowchart representing the steps for the search engine

Keywords: search engine, tech, crawling, tf-idf, Bert

2. Introduction

Back in 1990, the World Wide Web (WWW) was invented. This innovative creation led us to the so called “Information Age”, which managed to connect the world. But its creator, Tim Berners-Lee, quickly understood that the WWW could be utilized as a free resource for everyone around the globe to communicate and share knowledge. This revolutionary invention changed every possible aspect of people’s lives but the flaw of such a breakthrough was evident even before its creation. How would users easily retrieve the information they seek without wading through several irrelevant sites? The idea that led to the solution for this problem predates the debut of the World Wide Web and is no other than the so-called search engines. A search engine is a software accessed on the Internet that searches a database of information according to the user’s query (computerhope, 2021). The first tool that was used for searching information online was called Archie and was created by Alan Emtage, but it bears no resemblance to the idea of a search engine that people have in the present days. It took several years and many different approaches to the search engine archetype until the widely known Google rose to prominence with its innovative algorithm PageRank. At this moment in time the information residing online is so vast that it basically covers the majority of human knowledge. Now imagine that you have “someone” that can help you retrieve that knowledge precisely, within an instant. This makes it evident that search engines are the backbone of today’s information retrieval and play a crucial role in our everyday lives.

For our project, we created a search engine that can retrieve information about tech gadgets. Although limited at the time to a specific part of the internet, this can be the base of a search engine that may fetch information from all around the web. In our report, we will explain the way the specific sites were crawled, how their content was pre-processed and finally the approach of filtering the results to satisfy the user's query.

3. Crawler creation

The first step in creating a search engine was to acquire the content that would be returned to the user after he poses his query. In order to do that a crawler was required that would browse 3 tech related sites (tomdsguide, digitaltrends, techadvisor) and specifically their news and reviews sections. So, by utilizing the Web spidering framework called Scrapy a spiderbot was initialized to browse the aforementioned sites. Certain URLs were set as the initial ones for the crawler, that would then perform concurrent requests to the domains to obtain each URL's content and all the links contained in it. All the links found were then filtered to restrict them to the 3 websites and then stored in a list. By storing them into a list, the crawler would be able to track which URLs had already been visited and scrapped and browse the ones that were not. From each address's content the crawler would parse only the parts with the URL, title and paragraph tags. All the information contained in them would then be stored in an xml file. Due to the huge selection of tech articles in sites like the ones crawled and the limited broadband speed it was easily understood that the process should be performed in small batches and in different computers simultaneously. This procedure granted us 102k unique articles of tech related products that would be the base of our search engine's corpus.

4. Pre-processing the corpus

The first step before setting up our information retrieval system was to pre-process our data to be in the appropriate form. First, all files that were stored in small batches were collected and concatenated in order to produce one data frame containing all the articles. The structure of the data frame produced was set to be, first the URL of the corresponding article, then its title and finally the actual content of it.

After creating the data frame, we had to make some minor adjustments to the text, like removing extra full stops or adding a whitespace after some of them since these caused issues with the tokenization. Moreover, we had to replace any existing contractions. A contraction is a word made by shortening and combining two words (edu.gcfglobal, n.d.). So, by replacing those, a more uniform corpus was produced, avoiding same words counting as different ones. Next, sentence tokenization was performed on the articles, which is the process of dividing a large quantity of text into smaller parts called tokens (Johnson, 2021).

The resulting data frame consisted of 2 million rows, with each row containing a sentence along with the corresponding URL that it was found in. From this set of sentences, all rows containing duplicate sentences were dropped along with the ones that had only punctuation marks in them. Moreover, sentences deriving from the headers and footers of a page were also dropped as they did not hold any useful information for our information retrieval system.

From the remaining sentences, Bert embeddings were produced. The reason behind that, is that Bert model helps computers understand the meaning of ambiguous language in text by using surrounding text to establish context (Lutkevich).

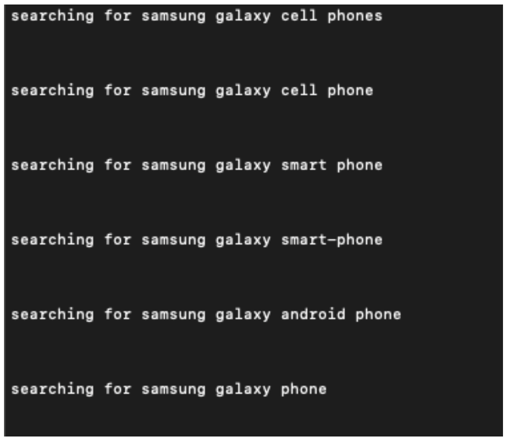
Then, the tf-idf vectorizer was applied on each one of the articles of the corpus. The tf-idf is a statistical measure that evaluates how relevant a word is to a document in a collection of documents (Stecanella, 2019). This procedure was performed in 3 different variations. Once for just the tf-idf of the articles. Another one for the tf-idf after the stopwords were removed. The last one was the tf-idf with the stopwords removed from the articles and by performing lemmatization to it.

The resulting embeddings of both Bert and tf-idf were stored in separate files in a SciPy sparse matrix form. By doing so, it would be easier and notably faster to perform a query and use these pre-made files than creating the embeddings each time. The data frame with all the articles containing the URLs, the titles and the content was saved in a csv format. Along with it, the data frame containing the final 1.1 million sentences and their corresponding URLs was also stored in a csv file. By inspecting the Bert embeddings, it was evident that keeping them as they were along with their high dimensionality nature would cause time inefficiencies. So, it was decided to apply the umap dimension reduction technique to them in order to reduce the dimension of their matrix. This was performed twice, with the first time reducing the dimensions from 768 to 350 and the second one from 768 to only 10. Besides the corpus, the query must be encoded with the same already trained model. Considering that, the models of Bert, tf-idf and umap were stored in a pickle format to be ready for use when a query is posed. Finally, in order to have a more tech-oriented corpus than the ones that the previously applied models use, a list with all the unique words contained in the articles was stored in a pickle format.

5. Query processing

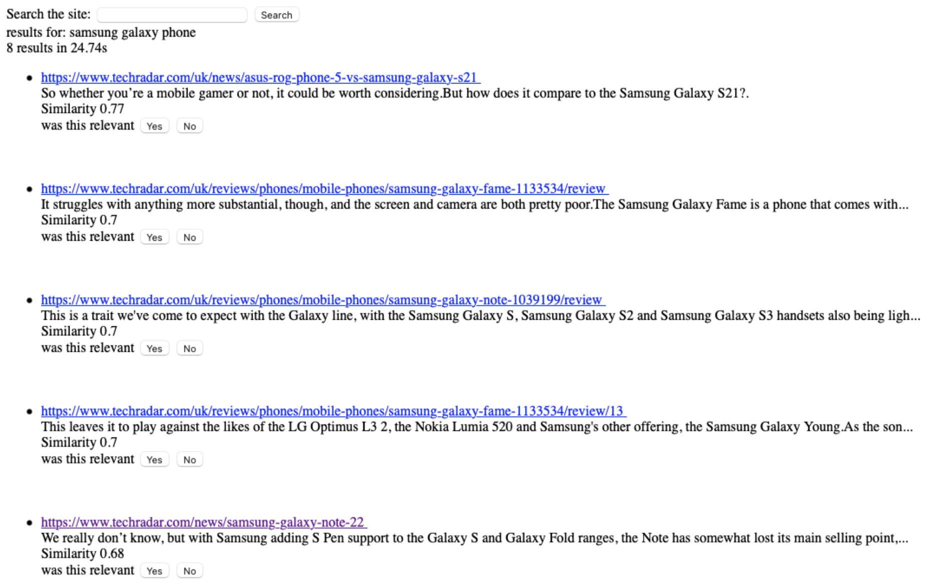
The next step after processing our main corpus was to adjust the way each query would be handled. The first step was to build an efficient spell checker by utilizing the minimum edit distance method. The minimum edit distance between two strings is the minimum number of editing operations (insertion, deletion, substitution) needed to transform one word into the other (Jurafsky, 2017).

An issue that had to be addressed was that by posing a query, the similarities with the articles on the corpus would be computed based only on the exact words that were used inside the query. In order to avoid missing any articles that use different wording than the query but with the same meaning, a query expansion was set up. It would create similar queries to be searched along with the original one by substituting words with the same meaning (Figures 2 & 3). This was done manually by creating a corpus that contained words along with their synonyms.



```
searching for samsung galaxy cell phones


searching for samsung galaxy cell phone


searching for samsung galaxy smart phone


searching for samsung galaxy smart-phone


searching for samsung galaxy android phone


searching for samsung galaxy phone
```

Figure 2 Expanded query



Search the site:

results for: samsung galaxy phone
8 results in 24.74s

- https://www.techradar.com/uk/news/asus-rog-phone-5-vs-samsung-galaxy-s21
  So whether you’re a mobile gamer or not, it could be worth considering.But how does it compare to the Samsung Galaxy S21?.
  Similarity 0.77
  was this relevant Yes No
- https://www.techradar.com/uk/reviews/phones/mobile-phones/samsung-galaxy-fame-1133534/review
  It struggles with anything more substantial, though, and the screen and camera are both pretty poor.The Samsung Galaxy Fame is a phone that comes with...
  Similarity 0.7
  was this relevant Yes No
- https://www.techradar.com/uk/reviews/phones/mobile-phones/samsung-galaxy-note-1039199/review
  This is a trait we've come to expect with the Galaxy line, with the Samsung Galaxy S, Samsung Galaxy S2 and Samsung Galaxy S3 handsets also being ligh...
  Similarity 0.7
  was this relevant Yes No
- https://www.techradar.com/uk/reviews/phones/mobile-phones/samsung-galaxy-fame-1133534/review/13
  This leaves it to play against the likes of the LG Optimus L3 2, the Nokia Lumia 520 and Samsung's other offering, the Samsung Galaxy Young.As the son...
  Similarity 0.7
  was this relevant Yes No
- https://www.techradar.com/news/samsung-galaxy-note-22
  We really don’t know, but with Samsung adding S Pen support to the Galaxy S and Galaxy Fold ranges, the Note has somewhat lost its main selling point,...
  Similarity 0.68
  was this relevant Yes No

Figure 3 Results after query expansion

6. Information Retrieval system

For our information retrieval system, we had several different approaches. For the first part that was about the tf-idf 3 variations were tested. The first one was to use the tf-idf along with the default settings set by scikit learn, the next one by removing any existing stopwords and then compute the tf-idf and the last one to remove the stopwords, lemmatize the corpus and then calculate the tf-idf. Then each performed query is embedded with the tf-idf vectorizer in order to compute the cosine similarity between the query and the computed tf-idfs of the articles. The cosine similarity is a measurement that quantifies the similarity between two or more vectors (Alake, 2020). So, after computing all the similarities the articles were sorted based on that metric. Considering that only a certain number of articles would be relevant to the performed query there was no reason of keeping all of them, so it was decided to return only the top 10 of them. This would also serve the purpose of creating the Bert embeddings much faster since there would be less sentences left. The next step was to embed the query once again, but this time by utilizing Bert. The similarities were then computed between those embeddings and the ones that were stored previously for the sentences using 3 different variations. The first with the matrix of the Bert embeddings having all 768 dimensions, the second one with the dimensions of the matrix reduced with umap to 350 and the last one with the dimensions reduced to only 10. This step was performed only for the top 10 articles that the previous tf-idf method had fetched. Next, after the reranking was performed only the top 5 articles were kept since the corpus was limited and only a few of the articles would be representative of the query posed. The approach above is called hierarchical reranking and is the process of reranking a list of items based on a metric that was already ranked given another metric. By applying both tf-idf and Bert methods we tried to avoid any unwanted results to be returned by our information retrieval system that a single method would not filter.

7. Evaluation of the Information Retrieval System

In order to evaluate our information retrieval system some metrics had to be calculated. To do that a set of 30 specific queries was created and performed for all of the different methods, and the results were marked either as relevant or irrelevant to the posed queries. By deciding each of the returned article's relevance, the precision, recall and f1 score were computed as the factors of efficiency of our method. After all the different combinations that were tested, the approach that proved to return the best results was to first use the tf-idf with lemmatization and the removal of stopwords and then apply Bert without reducing the dimensions with umap. So, the hierarchical method (with the classifier) was chosen to do the "dirty" work of filtering and ranking the articles. In the figure below, the f1 score off the several methos is presented (Figure 4).

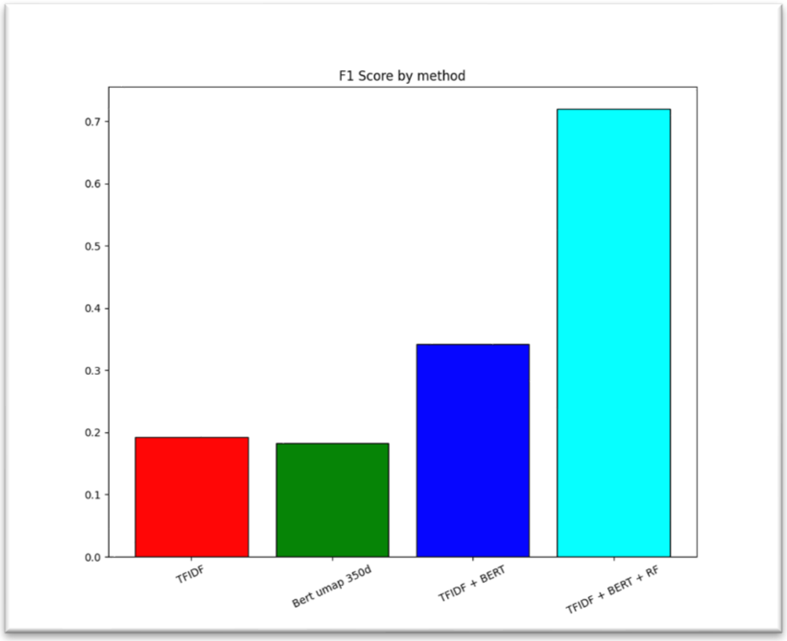
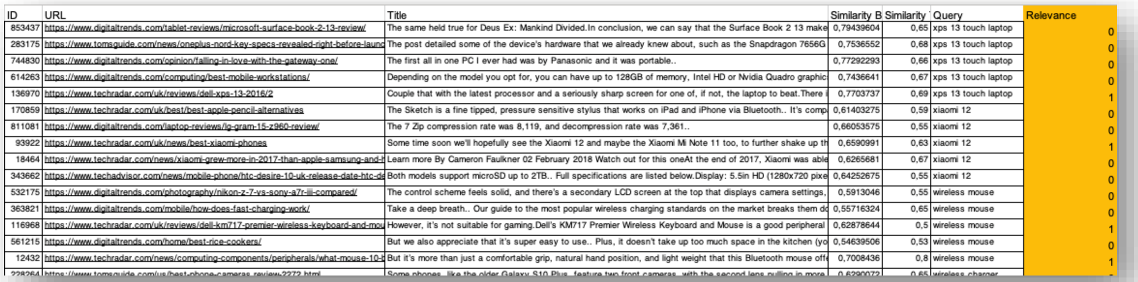


Figure 4 The f1 scores of the different methos used

8. Constructing a classifier

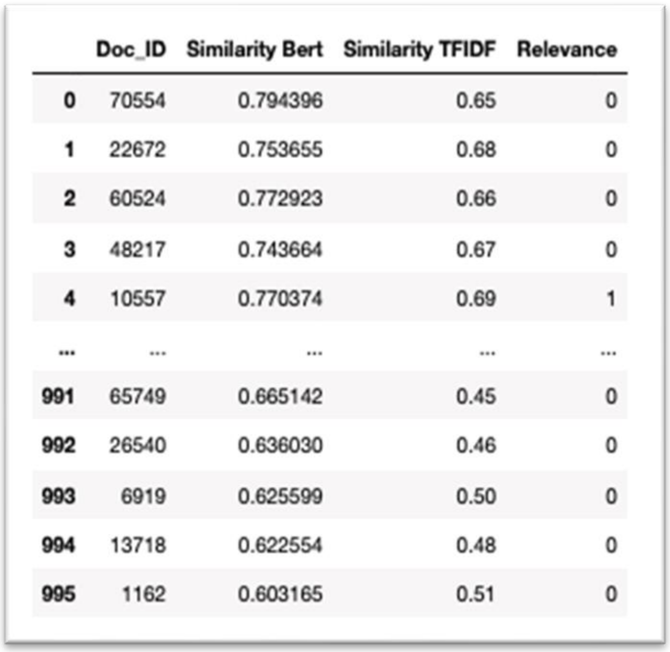
Even if the hierarchical ranking method seemed to return pretty satisfying results, it was possible that by classifying those results based on relevance could enhance our information retrieval system even more. Considering that, a dataset was used that consisted of the queries, the similarities based on tf-idf and Bert, the unique document id and a column that pointed whether a returned article was relevant or not (Figure 5).



ID	URL	Title	Similarity B	Similarity	Query	Relevance
853437	https://www.digitaltrends.com/tablet-reviews/microsoft-surface-book-2-13-review/	The same held true for Deus Ex: Mankind Divided.In conclusion, we can say that the Surface Book 2 13 make	0,79439604	0,65	xps 13 touch laptop	0
283175	https://www.tomsguide.com/news/oneplus-nord-key-specs-revealed-right-before-launc	The post detailed some of the device's hardware that we already knew about, such as the Snapdragon 7656G	0,7536552	0,68	xps 13 touch laptop	0
744830	https://www.digitaltrends.com/opinion/falling-in-love-with-the-gateway-one/	The first all in one PC I ever had was by Panasonic and it was portable..	0,77292293	0,66	xps 13 touch laptop	0
614263	https://www.digitaltrends.com/computing/best-mobile-workstations/	Depending on the model you opt for, you can have up to 128GB of memory, Intel HD or Nvidia Quadro graphic	0,7436641	0,67	xps 13 touch laptop	0
136970	https://www.techradar.com/uk/reviews/dell-xps-13-2016/2	Couple that with the latest processor and a seriously sharp screen for one of, if not, the laptop to beat.There i	0,7703737	0,69	xps 13 touch laptop	1
170859	https://www.techradar.com/uk/best/best-apple-pencil-alternatives	The Sketch is a fine tipped, pressure sensitive stylus that works on iPad and iPhone via Bluetooth.. It's comp	0,61403275	0,59	xiaomi 12	0
811081	https://www.digitaltrends.com/laptop-reviews/lg-gram-15-z960-review/	The 7 Zip compression rate was 8,119, and decompression rate was 7,361..	0,66053575	0,55	xiaomi 12	0
93922	https://www.techradar.com/uk/news/best-xiaomi-phones	Some time soon we'll hopefully see the Xiaomi 12 and maybe the Xiaomi Mi Note 11 too, to further shake up th	0,6590991	0,63	xiaomi 12	1
18464	https://www.techradar.com/news/xiaomi-grew-more-in-2017-than-apple-samsung-and-h	Learn more By Cameron Faulkner 02 February 2018 Watch out for this oneAt the end of 2017, Xiaomi was able	0,6265681	0,67	xiaomi 12	0
343662	https://www.techadvisor.com/news/mobile-phone/htc-desire-10-uk-release-date-htc-de	Both models support microSD up to 2TB.. Full specifications are listed below.Display: 5.5in HD (1280x720 pixe	0,64252675	0,55	xiaomi 12	0
532175	https://www.digitaltrends.com/photography/nikon-z-7-vs-sony-a7r-iii-compared/	The control scheme feels solid, and there's a secondary LCD screen at the top that displays camera settings,	0,5913046	0,55	wireless mouse	0
363821	https://www.digitaltrends.com/mobile/how-does-fast-charging-work/	Take a deep breath.. Our guide to the most popular wireless charging standards on the market breaks them do	0,55716324	0,65	wireless mouse	0
116968	https://www.techradar.com/uk/reviews/dell-km717-premier-wireless-keyboard-and-mou	However, it's not suitable for gaming.Dell's KM717 Premier Wireless Keyboard and Mouse is a good peripheral	0,62878644	0,5	wireless mouse	1
561215	https://www.digitaltrends.com/home/best-rice-cookers/	But we also appreciate that it's super easy to use.. Plus, it doesn't take up too much space in the kitchen (yo	0,54639506	0,53	wireless mouse	0
12432	https://www.techradar.com/news/computing-components/peripherals/what-mouse-10-b	But it's more than just a comfortable grip, natural hand position, and light weight that this Bluetooth mouse offe	0,7008436	0,8	wireless mouse	1
228264	https://www.tomsguide.com/us/best-phone-cameras,review-2272.html	Some phones, like the older Galaxy S10 Plus, feature two front cameras, with the second lens pulling in more	0,6290072	0,65	wireless charger	[illegible]

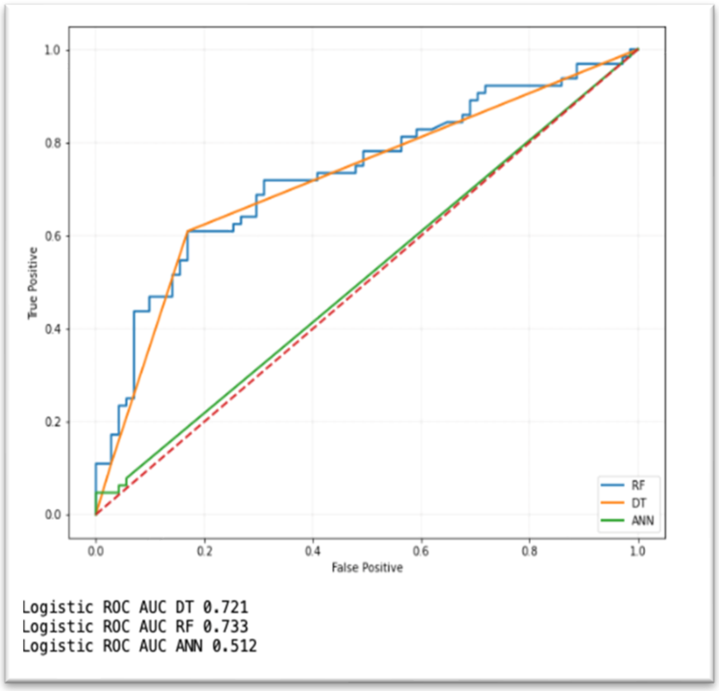
Figure 5 The dataset used to evaluate the returned articles

The classifier used as target column the one containing the relevance and the similarities and the documents' ids as attributes and its purpose was to discard any non-relevant articles that were not filtered out by the hierarchical ranking that was performed prior to this. This target column was constructed by performing manually 200 relevant to the corpus queries and specifying whether the 1000 articles returned, were relevant or not. Our first attempt on constructing the classifier used the dataset without the unique document id with the only attributes being the similarities of tf-idf and Bert. This approach returned an f1 score of 0.62 with the ANN classifier and far worse scores with the rest that were tested. After implementing the unique document id as an attribute that was related with the similarities corresponding to it (Figure 6), the classifier started to present its value. Even though the ANN this time scored a petty f1 score of 0.34, the decision tree and random forest classifier showed a significant improvement and returned an f1 score of 0.72. In order to visualize the results, the ROC curves were plotted for each classifier (Figure 7).



	Doc_ID	Similarity Bert	Similarity TFIDF	Relevance
0	70554	0.794396	0.65	0
1	22672	0.753655	0.68	0
2	60524	0.772923	0.66	0
3	48217	0.743664	0.67	0
4	10557	0.770374	0.69	1
...	...	...	...	...
991	65749	0.665142	0.45	0
992	26540	0.636030	0.46	0
993	6919	0.625599	0.50	0
994	13718	0.622554	0.48	0
995	1162	0.603165	0.51	0

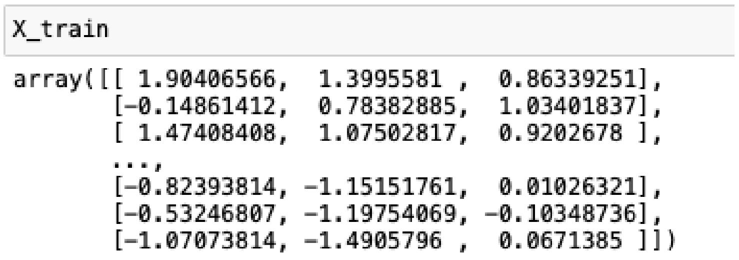
Figure 6 The dataset used for training with the Doc_id included



```
Logistic ROC AUC DT 0.721
Logistic ROC AUC RF 0.733
Logistic ROC AUC ANN 0.512
```

Figure 7 ROC curves without scaled data

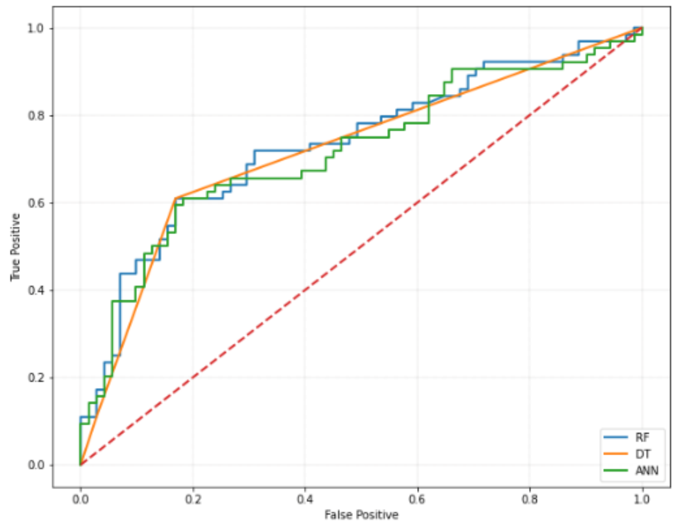
Another approach that had to be tested, was to scale our data (Figure 8). Metrics were computed once again for each classifier, along with the corresponding ROC curves (Figure 9 & 10).



```
X_train
```

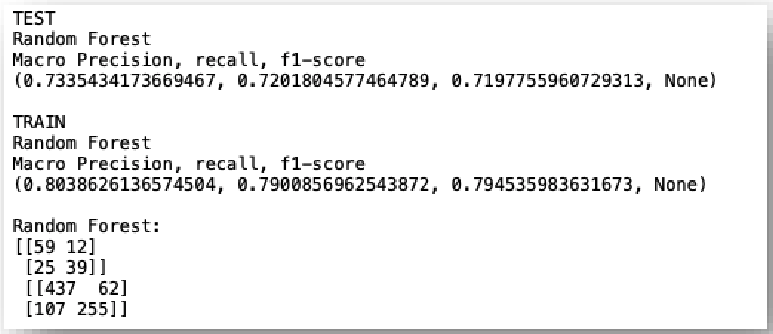
```
array([[ 1.90406566,  1.3995581 ,  0.86339251],
       [-0.14861412,  0.78382885,  1.03401837],
       [ 1.47408408,  1.07502817,  0.9202678 ],
       ...,
       [-0.82393814, -1.15151761,  0.01026321],
       [-0.53246807, -1.19754069, -0.10348736],
       [-1.07073814, -1.4905796 ,  0.0671385 ]])
```

Figure 8 Train set with scaled data



```
Logistic ROC AUC DT 0.721
Logistic ROC AUC RF 0.733
Logistic ROC AUC ANN 0.717
```

Figure 9 ROC curves of the classifiers with scaled data



```
TEST
Random Forest
Macro Precision, recall, f1-score
(0.7335434173669467, 0.7201804577464789, 0.7197755960729313, None)

TRAIN
Random Forest
Macro Precision, recall, f1-score
(0.8038626136574504, 0.7900856962543872, 0.794535983631673, None)

Random Forest:
[[59 12]
 [25 39]]
 [[437  62]
 [107 255]]
```

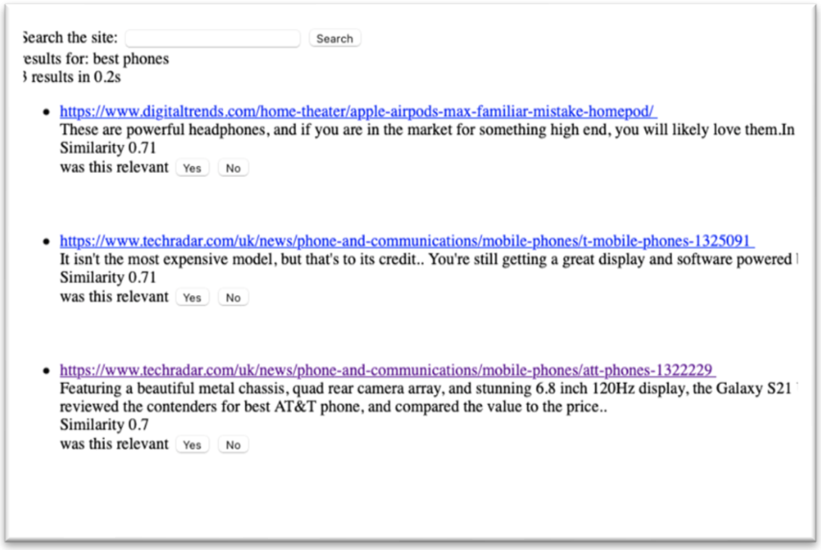
Figure 10 Precision, Recall, F1 score of Random Forest Classifier with scaled data

Despite the slight improvement of the ANN classifier when the data got scaled, the rest of the classifiers appeared to be unaffected by the scaling. So, the random forest classifier without scaling the data was picked as the best approach, to perform the filtering of the results.

If more articles could be evaluated for the training of the classifier, better results would be expected, but with the resources available the model is unsurprisingly underfitted.

9. Setting up the User Interface

But a search engine cannot exist as long as the user is not able to interact with it and perform queries. In order to resolve that, a user interface was constructed by utilizing flask (Figure 11). Flask is a web framework, included as a module in python that enables developers create web applications (pythonbasics, 2010).



Search the site:
esults for: best phones
3 results in 0.2s

- https://www.digitaltrends.com/home-theater/apple-airpods-max-familiar-mistake-homepod/
  These are powerful headphones, and if you are in the market for something high end, you will likely love them.In
  Similarity 0.71
  was this relevant Yes No

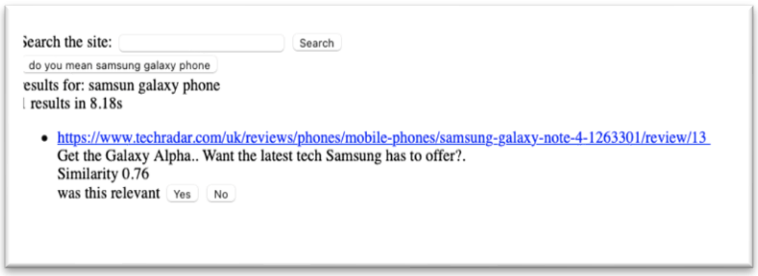
- https://www.techradar.com/uk/news/phone-and-communications/mobile-phones/t-mobile-phones-1325091
  It isn't the most expensive model, but that's to its credit.. You're still getting a great display and software powered
  Similarity 0.71
  was this relevant Yes No

- https://www.techradar.com/uk/news/phone-and-communications/mobile-phones/att-phones-1322229
  Featuring a beautiful metal chassis, quad rear camera array, and stunning 6.8 inch 120Hz display, the Galaxy S21
  reviewed the contenders for best AT&T phone, and compared the value to the price..
  Similarity 0.7
  was this relevant Yes No

Figure 11 The search engine from the user's point of view

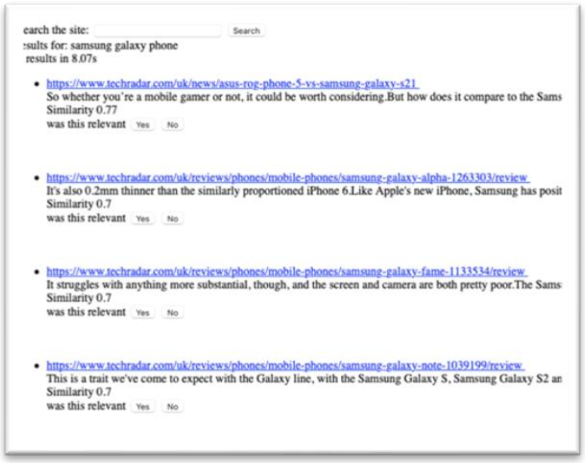
While the flask server is launching, all tf-idf, Bert and umap models get initialized. The reason behind that is to confine the calculations that need to be performed in the article retrieval process. The ones that are calculated in real time are the similarities between the query and the articles with both the tf-idf and Bert, the encoding of the actual query and finally the prediction of the classifier that was constructed. All these procedures are not time consuming and that is the motive behind storing all the models once, when our information retrieval system was set up. The benefits of such an approach proved to be extremely beneficial timewise. For example, with the tf-idf being computed each time the ranking was performed, a single search would take up to 14 seconds to return the results, while with the tf-idf stored the time taken was reduced to less than a second.

It is easily understood that when a user performs a query there is a high chance of a misspelled word being submitted. In order to resolve this issue most search engines that exist will correct the query and search for the edited one. Since the articles that our search engine is based on, are tech oriented, which means that many words may not have a meaning and be just names of gadgets, we decided that the correction of a typo must not be performed automatically. The search engine just suggests to the user a similar query to the one he posed and leaves the choice to his own discretion (Figures 12 & 13).


ɜearch the site: Search
do you mean samsung galaxy phone
esults for: samsun galaxy phone
l results in 8.18s

- https://www.techradar.com/uk/reviews/phones/mobile-phones/samsung-galaxy-note-4-1263301/review/13
  Get the Galaxy Alpha.. Want the latest tech Samsung has to offer?.
  Similarity 0.76
  was this relevant Yes No

Figure 12 Suggestion after misspelled search


earch the site:

:sults for: samsung galaxy phone
results in 8.07s

- https://www.techradar.com/uk/news/asus-rog-phone-5-vs-samsung-galaxy-s21
  So whether you're a mobile gamer or not, it could be worth considering.But how does it compare to the Sams
  Similarity 0.77
  was this relevant Yes No

- https://www.techradar.com/uk/reviews/phones/mobile-phones/samsung-galaxy-alpha-1263303/review
  It's also 0.2mm thinner than the similarly proportioned iPhone 6.Like Apple's new iPhone, Samsung has posit
  Similarity 0.7
  was this relevant Yes No

- https://www.techradar.com/uk/reviews/phones/mobile-phones/samsung-galaxy-fame-1133534/review
  It struggles with anything more substantial, though, and the screen and camera are both pretty poor.The Sams
  Similarity 0.7
  was this relevant Yes No

- https://www.techradar.com/uk/reviews/phones/mobile-phones/samsung-galaxy-note-1039199/review
  This is a trait we've come to expect with the Galaxy line, with the Samsung Galaxy S, Samsung Galaxy S2 an
  Similarity 0.7
  was this relevant Yes No

Figure 4 Search results after spell correction

After the query is performed by the user the results of the top n articles are returned to him. These results contain the corresponding URL of each article, the most similar sentence to the query in each page as a demonstration of the content that it encapsulates and the value of the similarity that was calculated for the hierarchical reranking by using tf-idf and then Bert. Finally, a bypass was inserted into the user interface that skips the whole procedure of the information retrieval system if the query performed by the user has already been searched for.

10. Possible Upgrades to the Search Engine

The whole procedure that our team followed led to an effective base for a tech-oriented search engine. Even though satisfying results were returning from the queries posed there will always be room for improvement. First, considering that a search is most of the times specified to a certain gadget, topic modelling could be performed on the articles. Topic modeling is a technique to extract the hidden topics for a collection of documents (Prabhakaran, 2018). By doing so, all the procedure would be performed to a subset of the corpus that has the same topic with the query, which would reduce the time of the whole process to less than a quarter.

Another approach that would lead to better results, would be to take into account the date and the location that an article was posted and re-rank the results based on them. For example, by not considering the date of the article, a query like “best phone” could bring results like a page about Nokia 3310 which may have been considered one of the best phones but that happened several years ago. Most of the times, the user performing the search looks for the most updated info about a topic. This issue occurred because our first approach was to store certain parts of each page, and the date and location were not contained in them, but that could be easily fixed if there were enough resources to re-download the whole corpus.

An alternative method that could be utilized, would be to store the articles in an online database instead of using data frames, as most popular search engines do. This would certainly be more time and space efficient and further improve our information retrieval.

Moreover, we could retrain the Bert model based on our corpus. Even if Bert is pretrained in two huge corpora like BookCorpus and the English Wikipedia, by training it once again on more domain-oriented documents, would probably lead to better results.

The last issue that our team faced and could be resolved is the difficulty in downloading articles from sites that use JavaScript in their coding and are not static. This could be tackled by either utilizing the Selenium module in Python or the Splash library of Scrapy and would allow us to access a wider variety of sites for our corpus.

11. Conclusion

By constructing our information retrieval system, we managed to create the base of a search engine where a user can look for tech-oriented articles. The way that the crawler, the preprocessing of the corpus and query, the information retrieval system, the user interface and generally the whole design was created proved to be efficient as no complications have emerged upon returning results to the user. The resulting outcome incorporates all the different traits required for an effective search engine even though tackling such a task proved to be really challenging. It is evident that by adjusting our method as mentioned in the previous section, our information retrieval system could be further improved to return more accurate results faster. But even for Google, it took over 20 years to reach the level of sophistication that we see today and get amazed of its performance. Concluding, the whole project allowed us to further understand the way that search engines operate which after all play a key role in people’s everyday lives in acquiring information and exploring the world. As Steve Jobs once quoted, “If you haven’t found it yet, keep looking” …in our search engine!

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