

Text Based Information Retrieval Search Engine

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ABSTRACT

This document is regarding the project presentation on Text based search engine. In this we are analysing the challenge faced in retrieval of document, Methods used to make document retrieval more efficient and will try to create a hybrid model which will implement various approach and try to find best solution to retrieve the query more efficiently.

1 MOTIVATION AND PRECISE PROBLEM STATEMENT

According to the Pew Internet American Life Project, Web search continues its explosive growth there are over 107 million Web-search users in the United States alone, in June 2004, and they did over 3.9 billion queries. A study at the beginning of 2005 says indexable web size is at least 11.5 billion pages. Thus search algorithmic efficiency is as important as ever: although processor speeds are increasing and hardware is getting less expensive every day, the size of the corpus and the number of searches is growing at an even faster pace. Since 2016, IBM Marketing Cloud study 90 % of the data on the internet has been created. All People, businesses, and devices have become data factories that are pumping out incredible amounts of information to the web each day.

Over 3.5 Billion Google researches are attended worldwide every breath of each day. That is 2 trillion explorations per year worldwide. That is above 40,000 search questions per second. With an increase in data available on the internet, getting difficult to retrieve a result from such large data that is becoming a challenge. Here we will discuss Some features used to make retrieval of data more efficient from Big data.

A. TF-IDF Model Analysis and it's Variant for Document Retrieval[10]

.. The TF-IDF power is a mathematical measure used to estimate how important a word is to a group or corpus document.

It takes preprocessing Steps like tokenization, stemming/lemmatization, normalization, stops word removing, etc. are applied on each document.

for each document in the collection, It generates weighted term vectors and the user query. Then the retrieval is based on the similarity between the query vector and document vectors. The output documents are ranked according to this similarity.

B. Index Compression Techniques [12].

In inverted index compression, our goal is to compress a sequence of integers, either a sequence of d-gaps obtained by taking the difference between each docID and the previous docID, or a sequence of frequency values. In addition, we always deduct one from each d-gap and frequency, so that the integers to be compressed are non-negative but do include 0 values

C. Information Retrieval for Swedish using Stemming[3]

Stemming is a technique to transform different inflections and derivations of the same word into one common "stem." Stemming can mean both prefix and suffix removal.

Our information retrieval system uses traditional information retrieval techniques extended with stemming techniques and normalization of both the query and text and other technologies such as caching, data compression, early termination, and massively parallel processing.

2 CHALLENGES

discussed unique problems at high level that appeared to search engines[7]

- **Storage in Computing power:** As many indices need to be stored, collecting a lot of data from the web via crawling will require a lot of storage.
Resolved: We can resolve the storage by using big storage like cloud and computation power can be resolved by referring for computer which has high performance
- **Spam** Search Engine optimization and various techniques can be used for page rank manipulation, which might not give the best results.
Resolved: Spam can be resolved by using different ranking algorithm
- **Quality Evaluation:** Determining the status of various ranking algorithms is a specially challenging query. Popular search engines benefit from massive quantities of user-behavior data they can employ to help estimate ranking. Users normally will not attempt to give exact feedback but give implicit feedback, such as the outcomes they agreed.
Resolved: Joachims [8] suggested experimental technique which merge the result of two ranking algorithm in a single set of result. So comparisons between two algorithm is done in this way. Joachims uses number of clicks as quality metric and show under which condition which algorithm retrieve more relevant links than others.
- **Content Quality:** Quality of the content depends on the person; different people have a different perspective when searching for a query. E.g., "I saw a girl with Binoculars." has two different interpretations.
Resolved: we can Resolve the content quality by link analysis and text-based judgement

3 IDEA OF PROJECT

This model is a hybrid model by the combination of various techniques (Such as tokenization, stopwords removal, stemming, inverted indexing) to overcome the limitations and create an optimized search engine.

4 DATASET

The dataset can be found [here](#).

There has a XML file format of input data for this wiki search. It contains two major part in this data.

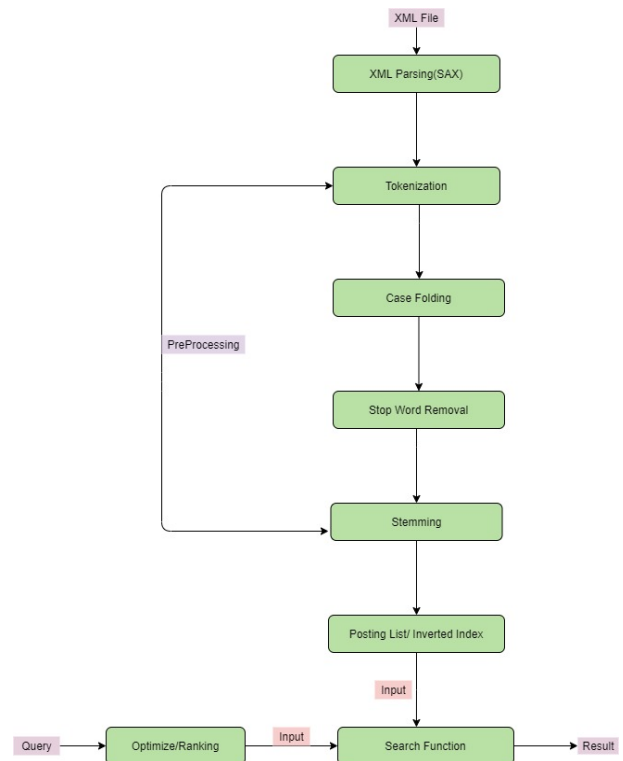
1. Title

2. Body

Title represents title of the document, which will be final result for any search and body part contains multiple things such as category, reference link, content of documents etc.

5 METHODOLOGY

Project Flow



- XML parsing was done at XML data using SAX parser because it is most suitable for large data-sets.
- Tokenization was applied at the parsed data.
- Case folding was applied at tokenized data.
- Stemming was applied at case folded data.
- Posting list/inverted index was created on the stemmed data.

6 RESULT

The Output file can be found [here](#).

3. Text Based Information Retrieval Search Engine

The screenshot shows a Windows desktop with several open applications. In the background, a Google search for "indexing-lynbx" is visible, showing results for a GitHub repository and a Medium article. In the foreground, a terminal window is open, displaying a command to run a Python script named "indexing-lynbx.py" with the argument "wikipedia". The terminal output shows the script processing a list of Wikipedia documents, extracting titles, categories, and positions, and saving them to a file named "indexing-lynbx_output.json".

```
➤ leading.py: Colabify x
➤ cobb:research.google.com/docs/TIZ_tu5y6tG3a?hl=en&open=1&docId=3046200&docId=3046200
Apps Gmail Calendar YouTube Maps Importer Compare texts doc Time Watchlist Docs Connectors, Sheets... What Do Google...
JupyterLab
File Edit View Insert Runtime Tools Help All changes saved
Code + Text
Connect + Editing
Preprocessing (Tokenization, Case folding, Stopword removal, Stemming)
1 for event, context in context:
    tag = re.sub(r'"/', "", context.tag)
    if event == "tag":
        if tag == "Title":
            title_text = context.text
            position = document.title.tell()
            document.title.position.append(position)
            document.title.write(title_text + "\n")
            title_tag = title_text.lower()
            words = re.split(pattern, title_text)
            for word in words:
                word = word.lower()
            if word in store_stemmed_words:
                word = store_stemmed_words[word]
            else:
                stem = stemmer.stem(word)
                store_stemmed_words[word] = stem
            word = stem
            if len(word) <= 2:
                continue
            if word and word not in stop_words:
                if word not in title_freq:
                    title_freq[word] = 1
```

[illegible]

```

def inverted_indexing():
    for word in category_freq:
        if word not in category_inverted_index:
            category_inverted_index[word] = {}
            category_inverted_index[word].append(word)
            category_freq.clear()

    for word in index_freq:
        if word not in index_inverted_index:
            index_inverted_index[word] = {}
            index_inverted_index[word].append(word)
            index_freq.clear()

    if document_outcome:
        store_stemmed_word = {}

    if document_outcome_page_document:
        filename = "category_inverted_index_search_title_" + str(count) + ".txt"
        write_data(filename, category_inverted_index, title_inverted_index)
        filename = "category_inverted_index_search_category_" + str(count) + ".txt"
        write_data(filename, category_inverted_index, category_inverted_index)
        filename = "category_inverted_index_search_index_" + str(count) + ".txt"
        write_data(filename, index_inverted_index, index_inverted_index)
        filename = "category_inverted_index_search_body_text_" + str(count) + ".txt"
        write_data(filename, body_inverted_index, body_inverted_index)
        count = count + 1

    filename = "category_inverted_index_search_position_page"
    write_data(filename, position_page_inverted_index, position_page_inverted_index)
    count = count + 1

```

```

def search(query):
    if word not in document_words:
        document_words[word] = {}
        document_words[word].append(word)
        final_posting_list = posting_list[word]

    idf = math.log(document_no / len(final_posting_list))
    documents_score = {}

    for post in final_posting_list:
        doc_no = int(post.split(',')[0])
        word_freq = int(post.split(',')[1])
        tf = 1 + math.log(word_freq)
        documents_score[doc_no] = round(idf * tf, 2)

    count = 0
    for document in documents_score.keys():
        score = score + str(document) + " " + str(documents_score[document]) + " "
        count = count + 1
        score = score[0:-1] + "\n"

    output_data = {}
    output_data[output_f_no] = write_data(score)

    output_data[output_f_no].close()

    for f_no in range(count):
        filename = "category_inverted_index_search_position_page"
        write_data(filename, "word" + str(f_no) + ".txt", documents_score)

```

Posting list

```

def generate_posting_list():
    for f in type_of_files:
        heap = []
        input_files = []
        output_file = f + "output.txt"
        output_ptr = open(output_file, "w")
        output_files.append(output_ptr)
        output_f_no = len(output_files) - 1

    for file_no in range(count):
        filename = f + str(file_no) + ".txt"
        fptr = open(filename, "r")
        if os.stat(filename).st_size == 0:
            continue
        input_files.append(fptr)

    if len(input_files) == 0:
        break

    for file_no in range(count):
        line = input_files[file_no].readline()[1:]
        word = line.split(" ")
        heap.append(line, file_no)
        except Exception as e:
            print(e)
            heapify(heap)
            file_no = 0
            while file_no < count:
                line = input_files[file_no].readline()[1:]
                word = line.split(" ")
                heap.append(line, file_no)
                file_no = file_no + 1

    while file_no < count:
        line, f_no = heap[0]
        word = line.split(" ")
        posting_list = line.split(" ")
        next_line = input_files[f_no].readline()[1:]
        if next_line:
            heappush(heap, (next_line, f_no))
        else:
            file_no = file_no + 1

    while file_no < count:
        next_line, next_f_no = heap[0]
        next_word = next_line.split(" ")
        next_posting_list = next_line.split(" ")
        except Exception as e:
            print(e)
            break

    if next_word == word:
        posting_list = posting_list + " " + next_posting_list
        next_line = input_files[next_f_no].readline()[1:]
        if next_line:
            heappush(heap, (next_line, next_f_no))
        else:
            file_no = file_no + 1

    while file_no < count:
        next_line, next_f_no = heap[0]
        next_word = next_line.split(" ")
        next_posting_list = next_line.split(" ")
        except Exception as e:
            print(e)
            break

    if word not in document_words:
        document_words[word] = {}
        document_words[word].append(word)
        final_posting_list = posting_list[word]

```

7 FUTURE WORKS

- Query Normalisation.
 - Tokenization of query.
 - Removal of stop words.
 - Case Folding of stop-words removed query.
 - Stemming of case folded.
 - Determine which of the logic operations should be used for getting appropriate results.
- Searching for documents when posting list /inverted index and optimized query will be passed as input in searching algorithm and it will give most related documents related to query using TF-IDF and word count.[4]

8 CITATIONS AND BIBLIOGRAPHIES

Sampling search-engine results[1],In this sampling is done on small part of data instead of full data.Analysis of tf-idf model and its variant for document retrieval authors worked with numerical as well as textual data and tried to find out which word, phrase or set of numbers can be considered more important relating to a particular query using different variation of vectorization techniques focusing more on TF-IDF.Improving precision in information retrieval for swedish using stemming ,Stemming make the words in its root form,defines how stemming improves both precision and recall for the swedish text.Inverted index compression and query processing with optimized document Ordering discussed how using previously optimised ordering , they developed a method in the compression technique that gives a higher throughput than most of the algorithms already present elsewhere Information retrieval on the world wide web[6] discussed navigation on web, how

documents on web is represented, and models for retrieving information. Intelligent Search Engine algorithms on indexing and searching of text documents using text representation[9] describes and compares various indexing and searching technique with their complexities and which algorithm can be used for increasing indexing and searching speed in various circumstances. The authors of the paper, Document clustering: TF-IDF approach[2] provide a new overview of clustering the document where the similar documents can be clustered together, which makes the process of retrieving data much faster and efficient. CiteSeerX: AI in a Digital Library Search Engine,[11] article mentions how various machine learning and artificial intelligence techniques can be used for fast information retrieval, by using metadata , tables , subsections as features in the training model. The authors in the paper,[5] describe a basic procedure to use nificantly boost the page ranking process. The paper uses distributed format to compute the page rank.

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