TTDS CW3 Report
A Search Engine to Explore ArXiv Abstracts

S2039234, S1953279, S2017787, S2065617, S2016083, S2094002

***Abstract*—The arXiv explorer is a website to explore the abstract of papers on arXiv. It can do key word query in abstracts, as well as extra functions like result filtering, query expansion, input auto complete and recommendation based on view history. The system is a live system hosted on DigitalOcean that can crawl new articles and update the database and index daily. Till the article is written, the dataset has over 1.85 million articles and is increasing at the speed of 1000 articles per day. To implement the functions as well as improve the performance and reliability of the system, we adapted a fusion rank retrieval model. The sub models of the fusion model are TFIDF and BM25-TLS, which is one of the most outperforming model. The rank score index has about 200 million entries and need about 29GB disk space to store. We also adopted many performance optimizations like database indexing, Redis caching, incremental index update and etc, to make our system a near real time system. We wrote a web UI to display and a android application for android users. The website is available at https://arxiv.canuse.xyz, the application is available at https://arxiv.canuse.xyz/app.apk and the open-source project is hosted at https://github.com/canuse/arXiv_explorer under the MIT License.**

***Index Terms*—BM25, TFIDF, Information Retrieval**

I. Introduction

ArXiv is a free distribution and open access service for more than 1.8 million scholarly papers in the fields of physics, mathematics, computer science, quantitative biology, quantitative finance, statistics, electrical engineering and systems science, and economics [1]. Comparing with tradition publications and journals, submit preprint on arXiv is much faster and easier. Comparing with articles on blogs and online discussions, it is more formal, reliable and allow peer review. Thus it is getting popular among researchers and the authors are likely to publish preprint articles and exchange ideas on arXiv recently. As is shown in figure 1, the volume, variety and velocity of new paper being uploaded every month increases sharply. This largely increased the effectiveness of researching [2], but brought new issues as well. For example, it is becoming more and more difficult for researchers to obtain useful information like current research trend, potential scooping and new ideas form the huge tile of data on the website. To address this issue, a system which can search keyword in abstracts and make recommendations based on previous visit history is highly needed.

A. Related Work

Before designing our system, we would like to find and analyse some existing projects that target at similar issue. In this part, we will discuss these projects and analyse their strengthen and weakness.

ArXiv Search The arXiv itself hosts a simple search system that allow user search in their database. The search system is comprehensive, users can use keyword search in different fields including title, abstract and authors, then filter based on category or submission date. The database is updated frequently in a daily basis. However, the system cannot make recommendation or expand the user's input, which is difficult for new users.

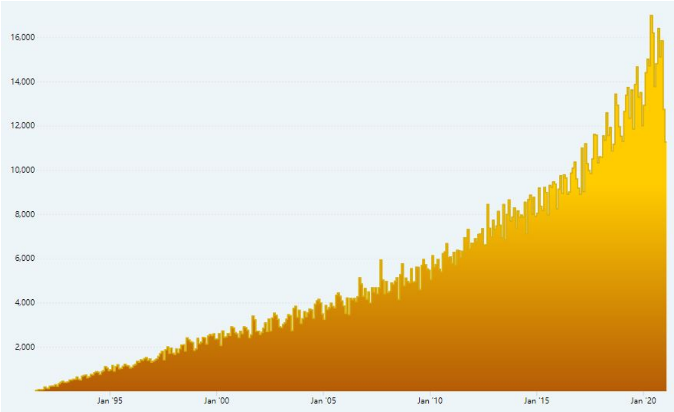

Fig. 1. The number of submission monthly on arXiv.org. Picture from arXiv usage statistics.

Google Scholar Google Scholar is one of the most popular and advanced scholar articles search engine. It contains mature query recommendation, expansion and correction, which is very easy to use. However, it is design for generous purpose, which does not fit arXiv well. The system do not support filter by categories and the database is not updated as frequent as arXiv search.

B. Project Functions

Based on the analyse of relative projects, we designed and implemented an abstract search engine system to fit the motion and demand, which contains five major functions.

Query Search: The system has a keyword search function that allows user search in abstracts and titles. The user can type keywords in the search box and select advance search options, then the system will return a list of articles that fit the query input, ordered by relevance.

Query Expansion: We implemented a query expansion to hint user. When the user search a word, the system will expand the query based on the top related articles and display expanded result to the user. The user can click the link to do a more precise search.

Recommendation: We implemented a recommendation model that can recommend articles to the user. The model will make recommendation based on user's recent activity, it will generate a list of new papers that have the same topic of the user's reading history.

Auto Complete: We implemented a input auto complete function. When the user type words in the query input box, this function will provide alternative words to the user in the drop-down menu.

Multi-platform: The service is hosted on a VPS and user can use the system through web browser or Android application on different platforms.

C. Project Highlights

In this section, we will briefly introduce the highlights of our project.

Model Fusion: The project applied a fusion rank retrieval model to improve the performance and reliance of the system, which is introduced in section VI.

BM25-TLS: The project applied a novel BM25-TLS rank retrieval model, which is an improved BM25 model that eliminated hyper-parameter k. As far as we known and illustrated in paper [3], this model outperforms any other main stream rank retrievals on many datasets. The theory and implementation of the model will be introduced in section VII.

TFIDF: The project applied a simple and effective information retrieval model, TF-IDF, and made some improvements. Compared to BM25, it's simpler and faster. The theory and implement of TFIDF model is introduced in section VIII.

Live Index Update: The system is a live system that will automatically crawl new data into the database and update the index. The spider to crawl data and preprocessing methods are introduced in section III and IV.

Incremental Update: The system adopted a incremental update of index and rank score. When new data is crawled and the index need to be rebuilt, the system will only rebuild the affected part instead of the whole system, which will save time and memory. This is introduced in section XII.E.

Hugh Dataset: The dataset we work on contains over 1.85 million articles and is increasing in the speed of about 1000 articles per day. The index and rank score index of the dataset has over 200 million entries and need over 29GB space to storage.

Near Real-time System: We have tried many performance optimizations including database b-tree indexing, Redis caching, CDN, load balance and etc to provide a near real-time search system. The system now can respond most requests in less than 1 second. The exception that need more time is to query words that is very common in documents like *computer*, to process a very long query sentence (more than 6 terms) or under high concurrency. The optimizations are detailed introduced in section XII.

Auto complete, Recommendation and Query Expansion: Our project provided a number of useful functions, including auto complete based on database, recommendation system based on view history and query expansion based on searching results.

Multi-platform: We provided both web UI for web browsers and an Android application for Android User.

D. Arrangement of the Report

The arrangement of the rest parts of the report is as follows. Section II is the design and overview of the system architecture. Section III is the design of spider to crawl data and section IV is the preprocessing steps adopted after the data is crawled. Section V introduces the term appearance index that stores the term's appearance in documents and its persistence. Section VI will be the fusion model and functions provided by the model and section VII and VIII will be theory and implementation of two rank retrieval models of the fusion model, TFIDF and BM25-TLS. Section IX will be the design and implement of server API and section X will be the design and implement of webUI and Android application. Section XI will be the deployment of the project and current running status while section XII will be the performance optimizations tried. Finally, the conclusion and future work will be illustrated in section XIII and followed by the introduction of authors and their amount of work.

II. System Architecture Overview

The overview of the system is shown in figure 2, it can be divided into two parts, server side and client side. The server side contains functional services and data storage while the client side contains GUI to display information. In this section, we will introduce the system architecture in a high level.

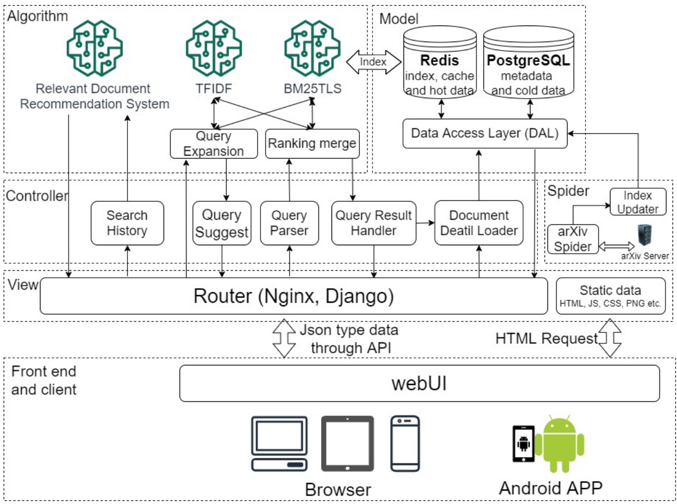

Fig. 2. System Architecture

A. Server Side Design

The server side was mainly written in Python and Django. It applied the mature MVC development model, which stands for Model, View and Controller. The Model is responsible for data storage and persistence, which contains databases, ORM model and Data Access Layer(DAL) which unified the interface of different databases. The controller is the core of the server side, it contains varies of complex logic to complete a variety of different services. For example, the controller in our project contains a spider service to crawl data every day, some indexing services to build and update index, a recommendation service and a query service. The View is responsible for API routing and requests preprocessing. The API accept requests from client and breaks down one request to many sub-requests. Then it call different functions provided by the controller to complete each sub-request. Finally, it summaries the result of those sub-requests and return the processed respond to client through API.

B. Database Selection and Data Access Layer(DAL)

We choose PostgreSQL and Redis as our database. To uniform the access API of these two databases, we implemented a Data Access Layer.

PostgreSQL. We have decided to use PostgreSQL as our database system. PostgreSQL is a powerful, open source object-relational database system. It comes with many features aimed to build applications, protect data integrity and build fault-tolerant environments, as well as help to manage data no matter how big or small the dataset is. PostgreSQL is also highly extensible, users can define their own data types, add third party extensions or build custom functions like bloom filter. The reason we choose PostgreSQL is that it supports data structure like json/jsonb that other popular relational databases like MySQL and Oracle don't support well.

Redis. Unlike PostgreSQL which is a relational database management system (RDBMS), Redis is an in-memory key-value NoSQL database with optional durability. It can offer memory efficiency, fast operating speed and high availability, which is more suitable for the applications or cache system that need in-time response. The reason we choose Redis is that some data, like term appearance index and rank index cache are frequently used and are in key-value like structure.

Data Access Layer (DAL). Since two different databases are used and their python interface API are different, developer may spent more effort when coding functions using both databases and switching from one database(i.e PostgreSQL only in development) to multi databases(i.e PostgreSQL + Redis cache in production). Thus, a service to warp up database interfaces and provide a uniform access interface is very useful in development and deployment, which also known as Data Access Layer (DAL). In DAL design, functions to access two databases are stored in different files, but the function name and behavior in two files are the same, the only difference is that they applied different database as the back-end. Thus, to switch from PostgreSQL to Redis will only need to import a different file and vise versa. The code of service don't need to change, which minimized the development and deployment effort.

1) Tool to connect PostgreSQL: Our project is built on Django, which has a build in ORM model to define the structure of stored data and commit to database. We just write the model structure and the code to perform query logic, and Django will take charge of all the dirty work of communicating with the database. Django provide a rich, dynamic database-access API, for example, we can use `Model.objects.get()` or `Model.objects.filter()` to select or filter particular data by value of attributes. We also can easily change, update or delete data.

2) Tool to connect Redis: The interface we used to connect and operate Redis database is the python redis client installed pip. The tool have interface to all redis build-in functions like *has key* and datatypes like *hash*.

C. Client Side Design

The client side contains a webUI and an Android application(APK). The webUI is written in HTML and JQuery, as well as some open-source CSS libraries (Purecss), icons and other JavaScript libraries. The webUI applied the Responsive Web Design (RVD) which will dynamically change the order of elements to fit different size of screen and different platforms. The android application is written in kotlin, to support android user. User can use all function through a browser, but the application may have a better experience in the article recommendation.

D. Data Transfer Between Server and Client

The client and server communicate through Restful API and Json serialized data. This allows third party developer to develop their own UI base on our server API. The database, server and static resource of client(HTML, CSS, JS and Pictures) is hosted on the digital ocean VPS, while the source code is stored in GitHub repo.

III. Data Obtain, Raw Format, Preprocessing, Storage and Access

A. Data Obtain and Raw Data Structure

Most of the data is obtained from the arXiv Dataset in Kaggle. The dataset is freely available via Google Cloud Storage buckets. The metadata file is provided in the json format, we then migrate it into database. A spider is implemented to crawl data from arXiv on daily basis, due to the Kaggle bulk data is not updated so frequently. Since arXiv supports the OAI protocol for metadata harvesting (OAI-PMH) which provide access to metadata for all articles, updated daily with new articles, we can easily obtained metadata of all articles identified by their unique arXiv id through this interface. The base URL of OAI-PMH is http://export.arxiv.org/oai2?verb=Identify. The metadata accessed is in XML format, and we parse the XML metadata by using python ElementTree XML and Document Object Model API, then we update the database with the parsed metadata. The arXiv id is generated in order with the form: YYMM.number. The number is zero-padded to 5-digits and increase from 00001 each month. A log is used to record the arXiv id of the latest updated article in the dataset, so that at the next crawl time the spider don't need to redownload existing data. After comparing the latest article id in dataset and in the arXiv website, the list of articles needed update is acquired. The metadata of these article will then be processed and the index will be updated.

B. Data Crawling Error and Solution

The data crawled from arxiv OAI-PMH portal may have error due to the maintaining of server or the poor network connection. When a transmission error occurred, we will retry the request and redownload the data after 3600 seconds.

The XML data may be not in correct form, too. Sometimes there are some missing fields due to the arXiv portal maintain. When this happens, we will also try to redownload the data after 3600 seconds.

C. Arxiv Metadata Storage

The `arxiv_document` collections contains articles with relevant features such as article titles, authors, categories, abstracts and more. The original dataset is collected from Kaggle as a json file, we first use SQLAlchemy – a database toolkit for Python to import the data into PostgreSQL. All search functions of the project are based on information in this table. This table is indexed by a unique Arxiv ID of each article. Below shows an example of the metadata of an article in the table. The title and abstract of the article is the most important information used for the search engine. The data crawled by the spider will also be stored in the same format.

```
{example:
    "id": "0704.0001"
    "submitter": "Pavel Nadolsky"
    "authors":  "C. Bal\'azs,
            E. L. Berger, P. Nadolsky"
    "title":  "Calculation of prompt
            diphoton production cross
            sections at Tevatron and
            LHC energies"
    "comments": "37 pages, 15 figures"
    "doi": "10.1103/PhysRevD.76.013009"
    "categories": "hep-ph"
    "abstract": A fully differential
            calculation in perturbative
            quantum ..."
}
```

IV. Preprocessing

A. Normalization, Tokenization, Stemming and Stopwords Removal

We noticed that some words in the dataset is not written in English, such as é è ê in French. This will create problems in indexing and querying. To solve this, we first normalize the abstracts and titles of all articles using python unicodedata module with 'NFKD' form. This is implemented while crawling metadata from arXiv website, so all documents stored in database have already been normalized. When implement a search engine, the presence of equivalent code points must be taken into account. By transforming the unicode string to a normal form, users searching for a particular code point sequence would be able to find other visually indistinguishable glyph that have a different, but canonically equivalent, code point representation. This is quite useful for multi-language searching.

Then a common preprocessing module is applied for a given input document, which can be either the title or the abstract of an article from database. After converting all upper cases to lower cases in the document, the regular expression module re in python is used for tokenization to find all terms consist of one or more alphanumeric characters. In this way, the document would be split at any non-alphanumeric character. This is a simple but effective method for tokenization. Then stop words are removed for a given list of words after tokenization. Then Porter stemmer is used to remove morphological affixes from words, leaving only the word stem. Evidence [3] shows that converting all characters to lowercase and applying stemming can significantly improve the searching results. Removing the stopwords helps to reduce the amount of vocabulary, so the index created later will be smaller and less complex.

B. Reverse Preprocessing

While stemming each word, the original word and stemmed word pair will be saved or updated to *StemPair* table in our database. In query expansion, due to the stemmed word is hard to understand for users, stemmed terms need to be recovered to original words using this table and sent to client side. Reverse preprocessing is also used in query auto-completion.

V. Indexing and Index Persistence

In this section, we will discuss the structure and persistence of Term Appearance Index. The Term Appearance Index records the number of appearance of each word in every document, which is the basis of retrieval model and is used in the calculation of rank score (the relative score of term and document, will be explained in next section). The term appearance can be stored both in-memory and in database. The in-memory index is used for rank score calculating while the in database index is used for index persistence. When new paper is crawled and the index need to update, it will load the old index from database into memory, then update it. The reason of adapting in-memory index when updating is that the index building procedure contains many select, update and delete options that will cause a lot of time in disk-io. After the index is fully built, the in-memory index will be written to the database for storage.

A. In-memory Index Structure

The in-memory term appearance index is stored in a Python class, *BaseIndex*, whose only property is a dictionary. The key of the dictionary is stemmed terms and the value of the key is a appearance dictionary of that stemmed word. The appearance dictionary of each term is also a dictionary whose key is arxiv_id and value is the term appearance in the corresponding paper. A special term, WORDCOUNT, is also in the index, who stored the length of each paper.

The *BaseIndex* class has some build-in functions to process change of query of the index. *add_term(term,paper)* will add 1 to the term appearance in paper. *get_document_freq(term)* will return the document frequqncy of the term, which is *len(index[term].keys())*. *get_term_freq(term, arxiv_id)* will return the term frequency in one paper, which is *index[term][arxiv_id]*. *get_document_length(arxiv_id)* will return the length of one document, which is *index["WORDCOUNT"][arxiv_id]*.

B. Index Persistence

The term appearance index in the database can be stored either in PostgreSQL or Redis. The option to store in PostgreSQL acts as a legacy option for VPS will small memory, while the option to store in Redis is the default option for system with larger memory to achieve higher performance. Please notice that though the Redis is an in-database indexing, the data is still in memory and the performance is similar to in-memory indexing. The storage structure in PostgreSQL is a table, whose unique primary key is the term and the field term_freq stores the jsonized index of the appearance dictionary of that term. The storage structure in Redis is using the hash datatype. The hash datatype works like dictionary. The key of one hash type instance is the stemmed term connected with the arxiv_id while the value is the term appearance in that paper. The functions in the BaseIndex class described above is also implemented in the index persistence module.

The PostgreSQL version is implemented in *IndexPersistence.py*, and the Redis version is implemented in *IndexPersistenceRedis.py*. The function name and behavior in two files are the same, the only difference is that they applied different database as the back-end. Thus, to switch from legacy code to Redis will only need to import a different file and vise versa, which minimized the deployment effort.

VI. Rank Retrieval Model Overview

In this section, we will introduce the rank retrieval model we designed. We designed a fusion model that includes two different retrieval model, TFIDF and BM25-TLS. The TFIDF is a traditional approach that aims to provide a stable service, while the BM25-TLS is a new, outperforming approach. Two retrieval models works as the other's backup, to eliminate the risk that both two index are unavailable. In this section, we will first introduce the rank score and its persistence, then we will introduce the query functions implementation using the rank score, finally we will introduce the fusion model. The calculation of rank score with TFIDF or BM25-TLS, will be introduced in the following section.

A. Rank Score

Rank score is the score to quantify the relativity between one term and one document under one rank retrieval model. Higher rank score represents that the term is more related to the document and vice versa. Though different model uses different formula to calculate the rank score, they mostly based on the frequency of term in one document and the frequency of term in all documents. The rank scores of the same term and document may be different under different rank retrieval models, but the order relation of terms and documents are similar. The rank score of one term and one document under one rank retrieval model is $r(q,d,m)$, q represents query term, d represents document and m represents retrieval model. For example, $r(''computer'',1,TFIDF)$ represents the rank score of computer in document 1 under model TFIDF.

B. Rank Score Storage

The rank score $r(q,d,m)$ is invariant when the whole document set is nit changed, that is, the rank score can be stored to reduce duplicated calculation. The rank score storage can be either in PostgreSQL or in Redis, depend on the size of memory available.

In postgreSQL, we use the `arxiv_rank` table, which contains four columns: word, article ID (Arxiv ID), algorithm and ranking value to store the ranking value. Below shows an example of the ranking table.

```
{example:
    "word": "finit"
    "paper": "0906.1352"
    "algorithm": "BM25TLS"
    "rank\_value": 4.18660680409255
}
```

In Redis, we use hash key-value pair to store the rank score. The key is a conjunction of term, document and model like *computer-1-TFIDF* while the value is the rank score.

C. Rank Retrieval Function in One Model

In every Rank Retrieval Model, we implemented some functions to query results from rank score, which includes Key Words Query, Get Documents Topic, Get Relative Document and Query Expansion. In this part, we will only discuss the result generated by one model. The fusion of different models is discussed in the next subsection.

1) Key Words Query: The key words query function takes a list of processed word as input, and returns a ordered list that contains relative document id and its relative score. The steps of key word query is as shown in pseudo code 1. Firstly, the algorithm will get the all document id that contain any of the query terms by searching in the term appearance index(use build-in filter search in postgresql or has hash key in redis). Then the algorithm will calculate the rank score of every term and document in the model, the calculate here may be calculate from index or use previous cached result. Then the algorithm update(add) the relative value of the document by that score. Finally the algorithm sorted the relative value list in descending order and return.

Algorithm 1 Key Words Query

Require: $terms$: preprocessed query term list;

```
relative_list=
for term in terms do
    documents=document_contain_term(term)
    for doc in documents do
        relative_list[doc] += r(term,doc,model)
    end for
end for
return  return relative_list.sort()
```

2) Get Documents Topic: The get documents topic function takes a list of document id as input and return a list of terms that represents the documents topic. The steps of key word query is as shown in pseudo code 2. Firstly, the algorithm will get all terms in the document list. Then the algorithm will calculate the rank score of every term and document in the model, and update(add) the word list. Finally the algorithm sorted the word list in descending order and return.

Algorithm 2 Get Documents Topic

Require: $documents$: Documents list;

```
word_list=
for doc in documents do
    for term in doc.content do
        relative_list[doc] += r(term,doc,model)
    end for
end for
return  return word_list.sort()
```

3) Get Relevant Documents: The get relevant documents function takes a list of document as input and return another list of documents, which is the most relevant documents to the input list. Note that there may be duplicated documents in the input and return list. The steps of key word query is as shown in pseudo code 3. Firstly, the algorithm will get the topic of the input document list by calling Get Documents Topic function. Then the algorithm will use the topic as search words and call Key Words Query. The return value of Key Words Query will be the return value of this function. The number of topic is set to 10, to balance performance and relevance.

Algorithm 3 Get Documents Topic

Require: $documents$: Documents list;

```
topic=get_documents_topic(documents)[:10]
return  key_words_query(topic)
```

4) Query Expansion: The query expansion function take a list of term as input and return a extended list of word that is the query expansion of the input list. There will be no duplicated terms in the input list and return list. The steps of key word query is as shown in pseudo code 4. Firstly, the algorithm will do key word search by using the input list. Then the algorithm will use the top 10 documents as the query expansion documents and get their topic. The return value of Key Words Query will be processed to remove duplicated word and be the return value of this function. The number of relative documents is set to 10, to balance performance and relevance.

Algorithm 4 Get Documents Topic

Require: $terms$: term_list;

```
related_documents=key_words_query(term_list)[:10]
extended_list=get_documents_topic(related_documents)
for term in extended_list do
    if term in term_list then
        extend_list.remove(term)
    end if
end for
return  extend_list
```

D. Model Fusion

Model fusion is a useful strategy to improve the performance of a system in many aspects including deep learning and modeling. In our project, we applied a fusion rank retrieval model that has two sub-models, BM25-TLS and TFIDF. In this part, we will first introduce the reason why we adapt a fusion model and its advantages. Then, we will introduce the strategy to implement the fusion model. The implementation of each sub-model, however, will not be discussed in this part, they will be detailed discussed in the following two sections.

1) Advantage of Model Fusion: There are mainly two reasons to adapt a model fusion of TFIDF and BM25-TLS. The first reason is that a model fusion can increase the precision and call rate of a system, which will provide better query result. Another reason is that two model can act as backups. When one model is down, or is updating its index, the other model can act as the update so that the service will not be unavailable.

2) Implementation of Model Query Functions: The model query functions of the fusion model are the same as those of each sub-model, that is Key Words Query, Get Documents Topic, Get Relevant Documents and Query Expansion. When a function of fusion model is called, take Key Words Query as an example, the system will call two sub systems separately, and obtain two returns, $result_BM25$ from BM25-TLS model and $result - TFIDF$ from TFIDF model. Both $result_BM25$ and $result - TFIDF$ are an ordered list of items, each item contains a document id and its relative value to the query string, as described above. The fusion model will merge two ordered list into one list and return the merged list. The list merging method is based on Borda Count, which will be introduced below.

3) Ordered List Merge with Borda Count: Since two sub-model are different, the relative value may have different range, so it is not proper to merge two lists directly by adding the relative value. Borda Count is designed to solve this problem, it is based on votes. Firstly, we will normalize the relative value into the same range. The normalization method we applied is 0-1 normalization, that is the each value v in list $V = v_1, v_2 ... v_n$ will be normalized to $v' = \frac{v - min(V)}{max(V) - min(V)} + min(V)$ Then we will do vote procedure, each document in two sub-model list will vote for the document with a weight of its normalized relative value. Finally, we will sort the new merged list.

VII. BM25-TLS Model and its Implementation

The second model we applied is BM25-TLS. In this section, we will discuss the design and implementation of the BM25-TLS model.

A. Relation Between BM25-TLS and BM25

The BM25-TLS is a improved BM25 rank retrieval model based on the BM25-T [4] and BM25-LS [5] proposed by Lv and Zhai. The original BM25 formula is shown in equation 1, the Q stand for query string, d stand for document list, N stand for total document amount, d_j stand for term frequency in one document and df_j stands for document term frequency. The original BM25 model has two hyper-parameters, k that controls the term frequency priority and b that controls the penalty on different length text. Researchers pointed out that setting the same k and b is unfair to different terms [6]–[8] and different system have different best k,b setting [3], which will cause a lot of time to finding the best k and b when migrating to a new system. The BM-25T model focus on finding a way to automatically adjust k for every term [4], while BM25-LS model focus on adjusting b for paper with different length [5]. Research shows that both BM25-T and BM25-LS outperforms the original BM25 model as well as other TFIDF based or Language Model(LM) based model in two datasets *Training INEX 2009* and *Training INEX 2010* [3]. In this section, we will introduce the theory of the model first, and then we will introduce the implement of the model query functions.

$$score(Q, d) = \sum_{j \in Q} \frac{(k_1 + 1) * d_j}{k_1 * (1 - b + b * \frac{dl}{avgdl}) + d_j} * log(\frac{N}{df_j}) \tag{1}$$

B. BM25-TLS Model Theory Introduction

The model we applied is the BM25-TLS rank model, which combines the BM25-T and BM-25LS. The basic formula of the ranking model is shown in equation 2. In equation 2, k_1' stands for the estimate k value of the term, which was calculated by the argmin equation. Different term will have its own k_1', it is determined by the term appearance frequency. δ stands for the least rank gain from document. The k_1' comes from model BM25-T and δ come from BM25-LS.

$$score(Q,d) = \sum_{t \in Q} ((\frac{(k_1'+1)*c_{td}}{k_1'+c_{td}}) + \delta) * log(\frac{N}{df_j})$$

$$\begin{aligned} & where: \\ & k_1' = arg_{k1}min(g_{k1} - \frac{\sum_{D \in C_w} log(c_{td})+1}{df_t})^2 \\ & c_{td} = \frac{tf_{td}}{1-b+b*(\frac{dl}{avgdl})} \\ & g_{k1} = \frac{k_1}{k_1-1} * log(k_1) \end{aligned} \tag{2}$$

1) BM25-T: adapting k_1 for different terms: In BM25 retrieval function, higher term frequency in one document will result in a higher ranking score of this term in the document. A straight forward non-parametric estimate of score is $score(term, document) \propto p(X \leq t)$, where t stand for term frequency in the document and X is the sample of term frequency in all documents. This sub-linear relation between term frequency and ranking score was controlled by k_1 [4]. It is obvious that different terms have different term frequency distribution, so the parameter k_1 which describes this relation should be different in every term. However, in practice, the k_1 a preset hyper parameter and is the same in all terms. This lowers the effort to specify a k_1 value to all terms manually, but reduced the performance of the model.

The BM25-T model tried to solve this problem by generating adapting k_1 for every terms. By studying and static analyzing many datasets, Lv and Zhai notice that the distribution of term frequency in one document can be described in a Log-logistic distribution. They proposed a Log-logistic model in equation 3, where rank score of one term in one document is proportional to the possibility of the document with less term appearance, which equals to a log-logistic distribution $F(t|k_1, \beta)$.

$$p(X \leq t) = F(t|k_1, \beta) = \frac{t^\beta}{k_1^\beta + t^\beta} \tag{3}$$

To normalize the highest rank in all terms, we set β to 1, so the relation between score, document and term is $p(X \leq t) = \frac{t}{k_1+t}$. Then a log-moment estimation method is applied to fit this model with the term frequency distribution of one term. The value of k_1 can be calculated by solving the minimization equation:

$$\begin{aligned} & k_1' = arg_{k1}min(g_{k1} - \frac{\sum_{D \in C_w} log(c_{td})+1}{df_t})^2 \\ & c_{td} = \frac{tf_{td}}{1-b+b*(\frac{dl}{avgdl})} \\ & g_{k1} = \frac{k_1}{k_1-1} * log(k_1) \end{aligned} \tag{4}$$

In this approach, the parameter k_1 is no longer a hyper parameter but a inner parameter calculated by the sample. Different term will have its own k_1, with will fit the real-world situation better than the original BM25 model.

2) BM25-LS: Least Score for long documents: Long document contains more terms, so that a term is more likely to appear more times in long documents. To eliminate this error brought by document length, the BM25 model penalize long documents by reducing the rank of term in long documents, which was controlled by b. However, this approach does not always positive effect, the rank of terms that only appear once or very few times in long documents are also lowered. [7] Lv and Zhang proposed a BM25-LS (aka BM25+) model to process long documents [5]. In this approach, each term appearance is assigned a lower-bound contribution. In other words, however long the document is, an appearance of term will contribute at least a certain value. Their experiment shows that set the least contribution to 1 will fit most data collections and the value of b is not important [5].

C. BM25-TLS Rank Score Implementation

The implementation of BM25-TLS is very simple, it just implemented every step in the theory. When we calculate the rank score of one term in one documentation, there are two steps. Firstly, we will calculate the estimated k_1' value for the term using formla 3. The argmin function is implemented by iterating k from 0 to 5, for the function to minimize is monotonically increasing when k increases. Then it can calculate the rank score of the term in the documentation by foumla 2.

VIII. TFIDF Model and its Implementation

Another information retrieval model applied in this project is TFIDF. In this section, we will introduce the theory of TFIDF and how it is implemented in our project.

A. TFIDF Model Theory Introduction

The TFIDF algorithm is shown in equation 5, where t represents term, d represents document, Q represents query, tf_{td} represents the frequency of term t appearing in document d, df_t represents the number of documents that contain term t. TF is the frequency of term in a document. Larger TF indicates that term t appears frequently in document d. IDF, Inverse Document Frequency is represented as $\log_{10}(\frac{N}{df_t})$ in equation 5. If term t appears in a lot of documents, which means a document cannot distinguish from other documents by term t. When df_t gets larger, the value of IDF will be smaller. By multipling terms containing TF and IDF, we can get the weight of term t for document d. The introducing of IDF to the formula adjusts the weight by increasing the weight of important words and decreasing the weight of words that appears in too many documents. The principle of TFIDF is very simple and easy to be implemented. It's widely used for information retrieving.

$$score(Q,d) = \sum_{t \in Q \cap d} (1 + \log_{10} tf_{td}) \times \log_{10}(\frac{N}{df_t}) \tag{5}$$

B. TFIDF Rank Score Implementation

The implementation of TFIDF is to caculate the weight of term t in document d and store the weight in the index. To get the score of query containing multiple terms, we need to add the weight of terms for a document up to get the score of the document for the query. Then, rank documents by the score and we can get the query result.

IX. Implementation of Server API

A. Key Word Query

The conventional advanced key word query is provided by our search engine. Users can not only search the articles by key words, but also search by setting up custom conditions, such as the article's posting time, category, etc.

The flowchart of key words query is shown in figure 3 The key words and query conditions are extracted from a HTTP request sent from the user's browser. Then, a serial of pre-processing is conducted. For example, the key words are stemmed, time and category conditions are converted. The possible articles are returned by calling our searching algorithm API and filtered by the custom conditions. If those are conditions not provided, not articles will be filtered. Finally, the articles will be dumped as a JSON string and be wrapped up as a HTTP response to send to user's browser.

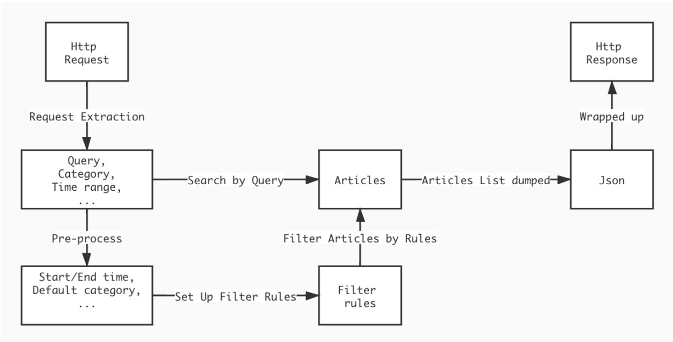

Fig. 3. Process of key word query

B. Query Expansion

Apart from the searching by explicit key words, the search engine also provide the associative-word searching function. The key words typed by users will be expanded by our algorithm, so that the searching results will better suits.

C. Relative Document Recommendation

Return a list of articles based on the recent browsing records or by random.

The browsing records are stored in session. If there are valid browsing records, extract the common topics from last 10 records. If not, generate topics by random. Get relative articles from database by the topics, and project the ID, title, authors and categories. As shown in Figure 4

D. Query Auto-complete

Complete the incomplete query by providing recommended complete query dynamically and automatically.

Query string as input, split on blank space into array of words and store words without last word. Stem the last word and subsequently search the stem_pair table and return words matching the stemmed word. Finally, splice the matching words and the stored original query, return a list of recommended queries. As shown in Figure 5.

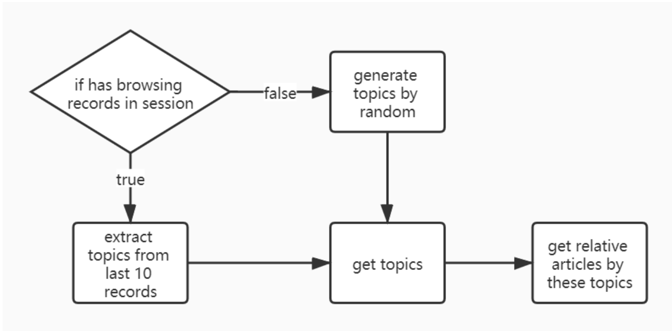

Fig. 4. Process of relative document recommendation

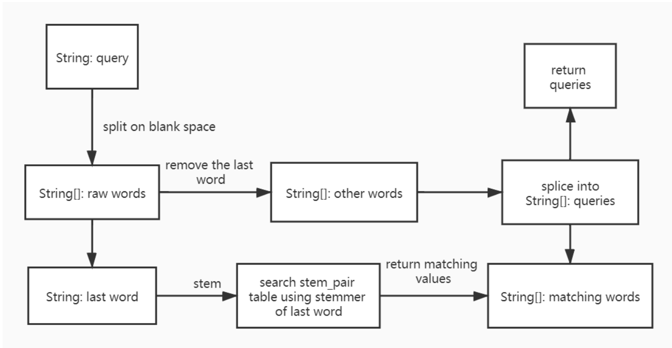

Fig. 5. Process of auto-complete

X. WebUI and Application

A. Web UI design

We utilize a small CSS module named ”Pure.CSS” to decorate our website. We add school logo and name of our search engine in the page. You can also see some recommendation articles at the bottom of the navigation page. All text are set as centered. There are some humanized improvements based on the fundamental functions. By double clicking ”Advance” button, you can fold the potential options. We add the top button at the right bottom corner for readers to get back to the top of page conveniently. Also, the ”next page” and ”previous page” buttons are designed to return to the top automatically, which is similar to most of the website we use. Other minor modifications include the sequence of content for each piece of results, position of present page display, arrangement format for potential options in ”Advance”, fixing bug which shows garbled when clicking the recommend key words.

B. Android Application

We notice that the session we applied to store user visit history is not stable. The session may be cleared when the browser restarts, and may behavior differently in different browser, which will cause the recommendation system not work properly. We therefore designed a Android Application based on Android webview, which can provide a uniformed session. The apk can be download at https://arxiv.canuse.xyz/app.apk.

XI. Server Deployment and Current Status

In this section, we will discuss the deployment of the project and the tools we used to maintain the project.

A. Sever Deployment Tools

1) Nginx: Nginx is a popular web server that can be used for load balance, proxy, request redirect, gateway and many other web functions. In our project, we will use Nginx as the gateway. The Nginx server will identify requests to different destination and redirect them to the correct ip and port. For example, a static resource request URL (like HTML, js, css file or pictures) will be redirect to the path of static resource folder (like /var/www/static/) and the dynamic request to API (like query) will be redirect to the Django server. With the help of Nginx, the static files and the API can share the same domain. The Nginx can also make the service more secure, it can configure access rate limit, access authority, xss attack protect and many other operations.

2) uWSGI: The uWSGI is a high performance web hosting service for python. The default Django server is only for development propose and does not support high concurrency, so we choose uWSGI as the service host.

B. Server Environment

The service will be deployed on a Digital Ocean VPS server, which has 1 virtual CPU core, 1 GB RAM and 50GB Disk The system running is Debian 10, the postgreSQL version is 13, the Nginx version is 1.14.2, the Python version is 3.7.3 and the Django version is 3.1.4.

C. Service Deployment

The service is deployed on the VPS server. We first start the nginx server, then start the service using uWSGI. The request to static resource will be processed directly by Nginx, and the request to dynamic resource will be routed to uWSGI and processed by django.

The update of document will be triggered on UTC+0 21:30 every day by Django-apscheduler. Django-apscheduler is a Django extension to execute scheduled tasks. The Django-apscheduler task will call a function daily, and the function will run the crawl program to crawl new data from arXiv, then update the index.

D. Current Server Status

The demo and the Minimum Viable Product is available and online on Feb15. Till this part of the report is written (Mar16), there are a total of 491 unique visitors visited our website, average 25 users per day since March, as shown in figure 6. The traffic of our website is increasing every day. Top search engines including Google(34 crawls), Yandex(20 crawls) and Bing(8 crawls) had indexed our website. We felt great sense of fulfillment that our website do attracted some user and helped them.

XII. Performance Optimization

In this section, we will discuss the strategy we applied to increase the performance of our project.

A. Pre-calculate all Rank Scores

In practise, we found out that it will take about 2 minute to finish a single word query, which is very unacceptable. We then do a performance investigation and find out that most time is consumed in the procedure of calculating rank score from the index, even we cache previous calculation results. Thus we decide to use space to exchange for time. We pre-calculated all rank scores, that is every unique (term, document, model) pair and store them into the database. The calculation will cost about 6 hours and the size of rank score table is over 29GB, with over 200 million entries. The calculation of query score change from calculating from the index into searching in the database. With this optimization, the query time decreased to about 10 seconds.

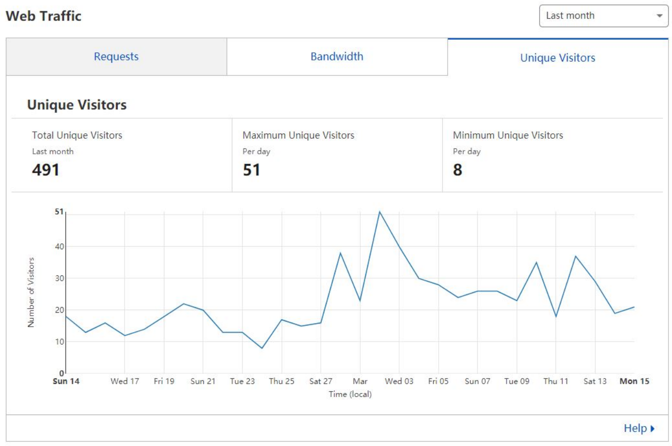

Fig. 6. Unique Visitor of the Website

B. Database Index

Though the query time is much acceptable, it is still too long for a real-time search. Most time are consumed in disk-io of database queries, because the size of table is 29GB, far more bigger than physical memory size(2GB). Database index is a index on database column or columns, that can accelerate the compare process in database queries. Common indexes in PostgreSQL includes B-Tree, Hash, GIN, Inverse Index and Bloom Filter. The size of index is much smaller than the size of whole table, which is possible to store into the memory. We find out that Hash and B-Tree index suit out project best, however, Hash index need far more time to build (over 100 hour on 1 million entries) than B-tree (about 30 minute on 1 billion entries). So we finally choose B-Tree to be our index on rank score table. We found out that the query are usually on column (term, model) and (document, model), so we build to separate index on both columns. The total size of index is about 3.5GB. After this optimization, the query time of most requests decreases to about 2 second, which is acceptable for a near real-time system.

C. Cache on API and Functions

Though the query time is optimized to about 1 second per query, the system may still face performance problem in high concurrency. We found out that some functions are called more than once with the same parameter under different requests, like function to query the appearance of term ”computer” will be executed in both request to query ”computer optimization” and ”computer science”. Caching the result of the appearance of term means that only the first query ”computer optimization” will be calculated and the second query will only need to calculate ”science” and get the result of ”computer” from cache. The more often a term is appeared, the more likely it can gain performance boost from caching. In practise, we applied the django build-in cache system. It takes Redis as back-end, and can store a certain amount of history result. The expire policy of cache is set to

LRU, which stands for Least Resent Usage, when the cache is full, the first unused item will be deleted from cache.

D. CDN

Though cache can accelerate the dynamic resource requests, it is not so useful in accelerating the static resource requests. The reason is that the most time consuming procedure in static resource requests is the network. A criteria to measure the performance of requests is TTFB(Time To First Byte), which stands for the time from sending a request to the time the browser receive response from server. With out CDN, all static resource requests will go to the server. With CDN, the CDN will cache some static resources, the requests will only go to the nearest CDN edge node. For example, if a user in Paris want to access our website, his request for static resources will go to the server in London with out CDN, but with CDN, his request will only go to the node in Paris, which is faster. In practise, we choose Cloudflare as the CDN provider. By using the Cloudflare CDN, the TTFB to open our website reduce from 1s to 500ms.

E. Incremental Update

When updating index, we found out that it will cost over 6 hours and 20+ GB memory to fully update the index, which is unacceptable on a VPS with limited CPU and RAM. Thus incremental update become the only possible way. Only the index and rank score of term appeared in new documents will be updated. We also made some modification to the BM25-TLS and TFIDF model to allow them support incremental update. Firstly, we change the document number in IDF part into a fixed number, 20000. This will change the rank score of terms, but the ratio of different terms are the same (equal to $log(N)/log(2000000)$, so the relevance value is modified proportionally and the result will be the same. Secondly, we change the average document length of BM25-TLS to 81, which is the average of first 1.8M documents. The reason is that the average length of all documents can be seen as identical after 1.8M samples, due to the *Law of large numbers* and the *Central limit theorem*. After the modifications, the index can be update incrementally, which now only cost 1 hour and 1 GB memory.

F. Load Balance and Distributed System

Please notice that this is only tested in development and not deployed on final server

Though every effort we known had been tried to optimize the system, the system still can not sustain concurrency of 20 users querying at the same time. The idea of distributed system and load balance came into our mine. In short, we will have more servers to hold the requests, each server are identical to other servers. One server, will be the master server and will act like the gateway. The gateway on that server will scatter the requests to other servers randomly. This is done by the Nginx on the master server, whose configuration code is like:

```
upstream djangoserver {
    server x.x.x.x:pppp;
    server y.y.y.y:pppp;
    ...
}
...other configurations...
location /api/ {
    proxy_pass http://djangoserver;
}
```

There are two reasons that we didn't apply this optimization in final server. The first reason is that the service currently do not have that high concurrency, adding more server will only be a waste of money. We can add them back when it is needed. The second reason is that the session may not working for different requests are redirected to different server randomly, which lowers the user experience.

XIII. Conclusion and Future work

A. Conclusion

In this group project, we design a search engine to search in abstract and title of articles on arXiv, as well as some extra functions include auto complete, query expansion, recommendation based on history and web UI and Android application. The dataset contains over 1.8M articles and is increasing everyday. We also implemented a real time spider that will continuously crawl new articles and update them into the database and index daily. We applied a fusion model based on TFIDF and BM25-TLS, which is one of the most outperforming rank retrieval models. The final size of rank score index is over 29GB and contains over 200M entries. We also carried out a series of performance optimizations including database indexing, pre-calculated rank score, caching, incremental update and etc. Finally the query system is optimized to a near real time system that can respond about 1 second. Till the report is written, the system have about 25 visits per day.

B. Future Work

Though the system satisfied us, it still have many potential improvements that can be done in the future.

Firstly, the algorithms are not examined properly. We choose the algorithms by reviewing papers and their result, but not reproduce their experiments. For example, the BM25-TLS algorithm may only outperforms in the *Training INEX 2009* dataset tested by the paper [3], but performs bad in our arXiv dataset. Further experiments in this aspect is necessary, but due to the time limit, we didn't conduct these experiments.

Secondly, there are only very few functions available now. The SEO for search engine like Google and many other function like feedback system and login system, which will greatly increase the user's experience, are not designed and implemented. In the future, we can rebuild the website to make it better.

Thirdly, we can try to cover not only title and abstract, but the main content, or other paper submission systems and publishers like IEEE and Springer. This will make our system more useful and comprehensive and bring us more potential users. However, it might be difficult for the size of index will be much bigger so more optimizations are needed and there may be legal problems.

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Individual Contributions

Jiao Yunpeng (S2017787)

I have contributed to designing the back-end architecture with Junchen, where the front-end request gets extracted and the database and the ranking algorithm APIs are called to retrieve the candidate articles. I implemented over half of the back-end API functions and tested them with unit tests.

Below, I list the highlights of the APIs I implemented. The conventional query with keywords and conditions API is the most important function in the back-end. According to the request for different result pages, only the outcomes that ranking at that range are returned which improves the efficiency of our website. The recommendation article API also improves the user's experience. With the session function, the clicked articles are stored and used to find related articles which can help users find the results.

Zhang Wenzhi (S2016083)

Responsible for the implementation of server API, focusing on the Relative Document Recommendation and Query Auto-complete, and finished relative report part. Relative Document Recommendation try to use information gathered from user, which is recent browsing records, to provide recommended articles. Query Auto-complete provides user with options of complete query and help with more specific search. Both enhance the user experience.

Liu Junchen (S2039234)

With some experience in similar project before, I was responsible for the system architecture design. I've also finished some coding work including the implementation of arxiv spider, preprocessing, indexing, functional API of fusion model, BM25-TLS rank retrieval model, Android application, performance optimization and server deployment, as well as the report writing of those parts.

Ruan Yuanyuan (S2094002)

I take charge of the database part, responsible for data storage and persistence. I used PostgreSQL and Redis as our database, implement a data access layer for these two databases. I built ORM models in Django, designed tables to maintain the original dataset, store rank score for different algorithms and stem-word pairs. I also finish the report writing which related to database and data storage, help with data obtain, arxiv spider and preprocessing part.

Shu Peng (s2065617)

I am responsible for the web page UI part. I design the overall layout of the website including the school logo, showing the name of searching engine, text alignment. I adjust the showing results so that article title and authors are clearer. I also add some additional functions such as back to top button, folding the advance options by double clicking the Advance button, automatically back to top for both next and previous page button. Besides, I help to fix some bugs which can be found when using the search engine.

Liu Mengyuan (S1953279)

I'm responsible for the implementation of TFIDF rank retrieval model, cooperating with Liu Junchen. I complete the code with the functional API provided by Junchen. After finishing the coding of TFIDF algorithm part, I integrate it with BM25-TFL rank retrieval model to get a better result.