2011

Downloading Deep Web Data from Real Web Services

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by

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A Thesis
Submitted to the Faculty of Graduate Studies
through Computer Science
in Partial Fulfillment of the Requirements for
the Degree of Master of Science at the
University of Windsor

Windsor, Ontario, Canada

2011

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ABSTRACT

Data of deep web in general is stored in a database or a file system that is only accessible via web query forms or through web service interfaces. One challenge of deep web crawling is how to select meaningful queries to acquire data. There is substantial research on the selection of queries, such as the approach based on the set covering problem where greedy algorithm or its variation is used. These methods are not extensively studied in the context of real web services, which may impose new challenges for deep web crawling. This thesis studies several query selection methods on Microsoft's Bing web service, especially the impact of the ranking of the returns in real data sources. Our results show that for unranked data sources, weighted method performed a little better then un-weighted set covering algorithm. For ranked data sources, document frequent estimation is necessary to harvest data more efficiently.

Keywords: deep web, set covering problem, greedy, weighted, document frequency

DEDICATION

This thesis is dedicated to my families who have supported me all the way since the beginning of my studies with patience, understanding, and love.

Also, this thesis is dedicated to all those who helped me during my studies. If each thing in my memory has weight, many things happened in the University of Windsor must be selected.

ACKNOWLEDGEMENTS

I am heartily thankful to my supervisor, Dr. Jianguo Lu, who gave me critical suggestions, honest criticisms and painstaking comments helping me to finish the research and writing of this thesis. Without his guidance and support, this thesis would not have been possible.

I also would like to thank my internal reader, Dr. Jessica Chen, my external reader, Dr. Kevin Li, and my thesis committee chair, Dr. Alioune Ngom for spending their time in reviewing this thesis and attending my thesis proposal and defence.

As well as, a special thanks to Frank Luo and Guanghui Luo with whom I built the framework of WS-Crawler together in a course project.

Finally, I would like to show my gratitude to Yan Wang and Shaohua Wang for their valuable advices and supports.

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CHAPTER I

INTRODUCTION

The Deep Web [4] data refer to the content that is dynamically generated from databases or file systems. The information served on the Deep Web is accessible through query interfaces such as html forms or web services. Many organizations, such as “Arxiv.org”, “Bing.com” or “Amazon.com”, provide web service interfaces to access their deep web data. Since data are hidden behind query interfaces, the deep web are also called as the Hidden Web [7] [10] or invisible web [10]. The figure below is a part of the home page of “Arxiv.org”. This website provides a large number of academic documents. In most cases, users look for the document that they want by using the html query form at the top.

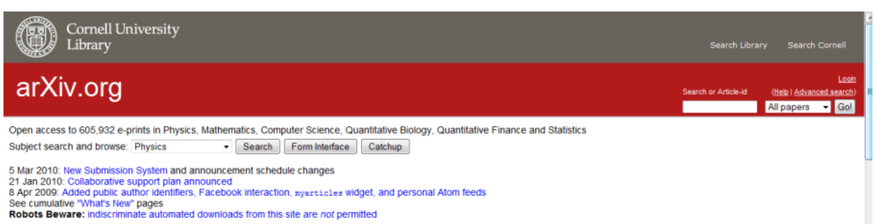


Figure 1: A part of Arxiv.org home page

The deep web often contains a large amount of documents which are often of high quality and value to users. Since there are no static links to those deep web documents, deep web content is beyond the reach of traditional search engines [5]. In order to access such content, users have to type in one or several keywords in the html forms and submit the query. According to the research [4], the content of deep web is about 500 times greater than that visible to conventional search engines. Hence how to utilize the deep web content becomes a major challenge within the information retrieval community.

The thesis focuses on the task of downloading the deep web data from real web services. We have developed a web-service crawler named “WS Crawler”, implemented and experimented with four query selection algorithms for deep web crawling. Our objective is to evaluate their efficiency for retrieving data from different real data sources via web service.

In order to share their data to users, some deep web sites provide web service for client application to access their online databases. Web service is a technology that enables application-to-application interaction over the network – regardless of platform, language, or data formats. By exposing web APIs (Application Programming Interfaces) on the network, functionalities of web service can be activated using HTTP requests. Through these APIs, client application can access remote content. Advantages of using web services include: no need to fill html query form and no need to extract relevant data from html result page.

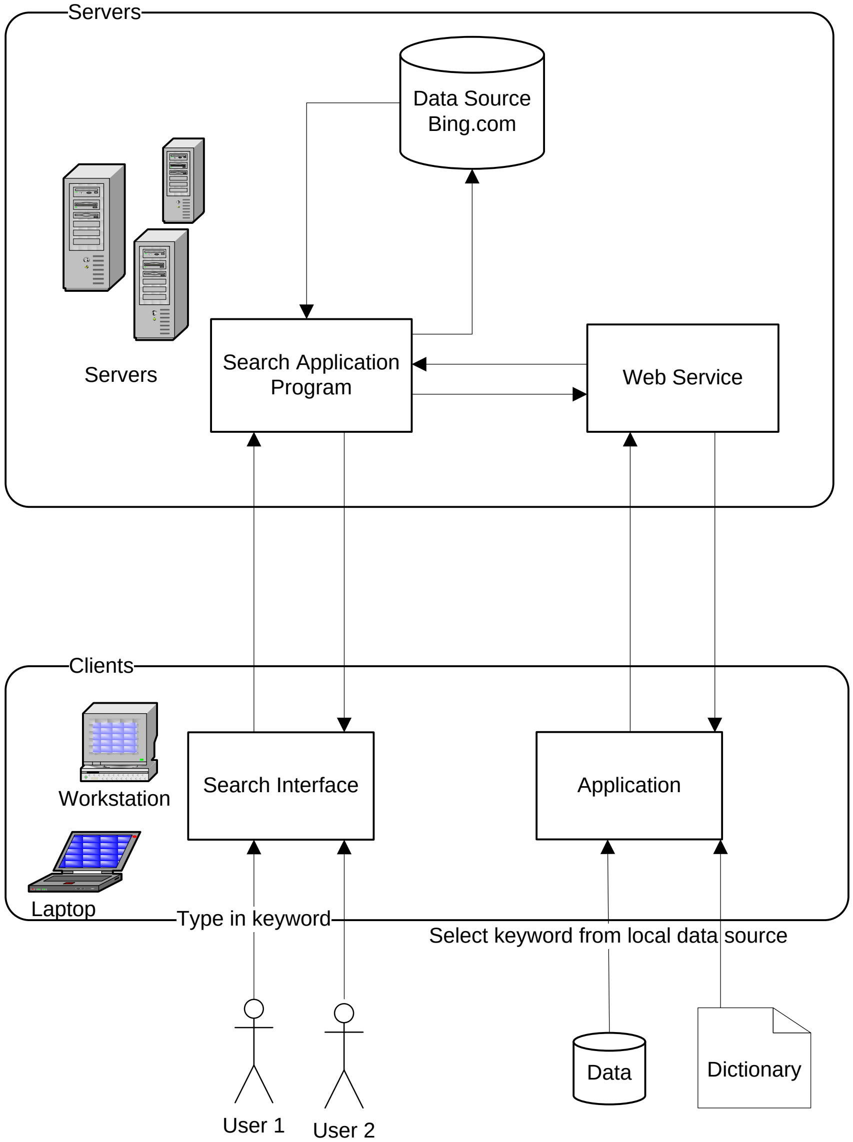


Figure 2: Accessing Bing content by two ways: search interface or web service

Deep web content in general is stored in a database. By the type of the database, they can be categorized either as an unstructured (textual) database or as a structured database [24]. An unstructured database is a site that mainly contains plain-text documents (e.g., legal documents). In contrast, a structured database is a site that often contains relational data, such as an online book store that may have multiple fields such as title, author, and ISBN etc. For a textual database, the search interface usually provides a simple keyword textbox. Conversely, the interface to a structured database may allow the users to submit multiple attributes (e.g., searching cars by company name, brand, or the year of production). The interface may contain a combination of text box, radio button, dropdown menu etc.

Textual database mainly contains plain-text documents, such as papers, law documents, and news articles etc. Html query form of a textual database usually only provides a single textbox to fill in keywords, as shown in Figure 1. It is an html search form from arXiv.org. The arXiv database is textual. It contains about 500,000 papers. Structured database mainly contains relational data, such as on line store database. Html query form of structure database often provides multiple textboxes to fill in keywords.

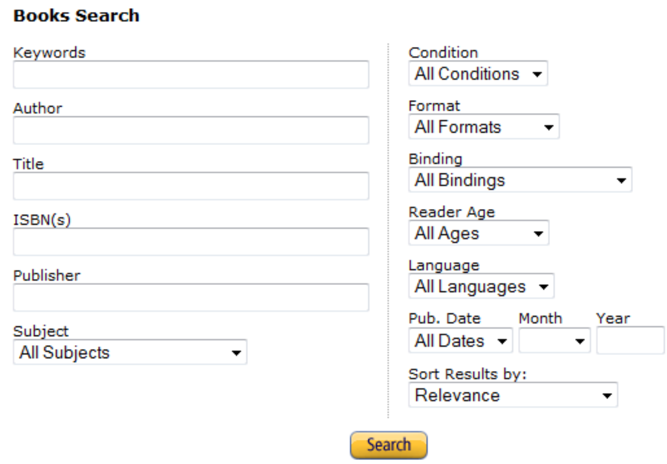


Figure 3: Html Search Form of Amazon Book Store

Here is an example from Amazon on line book store. You can search a book by author, title, or ISBN etc. Our research is related to textual database.

With millions of databases connected to the internet, we cannot ignore data hidden behind search interface. To utilize deep web content, virtual integration and surfacing are the two main applications.

The virtual integration approach [9] [25] is to provide a uniform interface to access a specific kind of data from different deep web sources. To build such an application, we need to identify the domain (e.g., book, airline ticket, or real-estate) of each deep web and analyze the html search interface. Thus, an automatic integration system often contains an automatic identification system and a semantic system. The identification system is to analyze the query interface or contents of a deep web site and to identify the domain that it belongs to. For example, we have known a large amount of deep web sites. Now, we are only interested in the online book store sites. So a first step, we need to found out those sites that are related to our desired information about book.

After that, we already have a set of deep web sites in a domain of interest. Then, we need to build a unified query interface to search those sites at the same time. To create a unified query interface, a semantic system is necessary to build and manage semantic mappings on the search interfaces of those deep web sites. In short, it is to map queries to difference search interfaces. Then integration system will extract, combine, and rank the results retrieved form difference data sources. Finally, present regenerative results to the users. Generally, a virtual integration provides more experience to user besides search. For instance, we search a book in a virtual integration search engine. The results are retrieved from the difference online book stores, such as “amazon.com”, “ebay.com”, and “indigo.ca”. In addition to return those results, the search engine also provides the best price of the book. For that reason, virtual integration is more suitable for the structure databases.

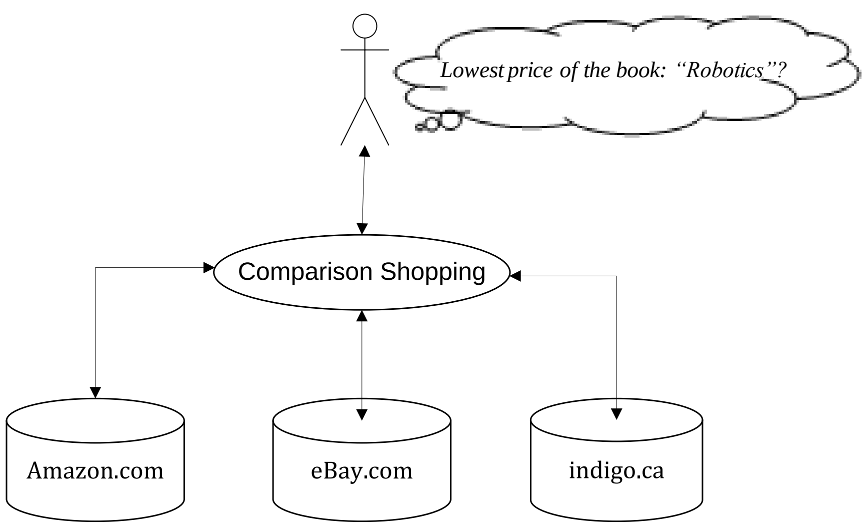


Figure 4: Virtual Integration – Comparison Shopping

The surfacing approach is also called deep web crawling which downloads hidden content through sending a set of queries. Commercial search engines, say Google, have begun to surface the deep web. The surfaced results are already added into the Google search engine index today. In general, the challenges of deep web crawling include: how to process html query form [18]; how to extract relevant data from result pages [15] [2]; and how to choose a set of queries [20] [16] [18] [21] [3] [22]. An excellent crawler should surface the deep web sites automatically. Hence, the crawler needs an approach to process html query form and extract relevant data from result pages automatically. We use web service in our experiments, so we do not need to process the html query form, and the results is XML file format. For that reason, we can focus on query selection problem.

The real environment usually sets up a return limitation for the maximal number of results. Most of the earlier methods are designed to download a deep web site without return limitation. Therefore, they cannot work well when return limitation exists. We present a DF-Weighted Greedy algorithm to cope with this challenge.

Experiments are carried on three data sources which are "cs.berkeley.edu", "uwaterloo.ca", and "ctv.ca". The size of the first data source is small, which contains about 30,000 web pages. This means return limitation problem is not serious in this data source, because the number of most matches will not surpass the limit. The other two data sources are larger than the first one. The number of web pages of "uwaterloo.ca" and "ctv.ca" are approximate 150,000, and 140,000. The experimental results show our DF-Weighted greedy works well when downloading the data from the last two data sources.

In addition to the introduction section, there are five sections in this thesis. Section 2 introduces relative work. It includes the difference types of query selection approaches for deep web crawling. Section 3 introduces set covering problem and how to convert a query selection problem to a set covering problem. In section 4, we present three sampling based algorithms: Greedy, Weighted Greedy and DF-Weighted Greedy. Section 5 describes our experiments and gives the results. Finally, the conclusion and future work are given in section 6.

CHAPTER II

RELATED WORK

The key problem of deep web crawling is how to choose a set of queries to submit to the query form. There are many ways to select keywords.

A primitive solution can be randomly selecting some words from a dictionary. However this solution is not efficient, due to that a large number of rare queries may not match any page, or there could be many overlapping returns. Instead of selecting keywords from dictionary, several algorithms have been developed to select keywords.

Currently, most approaches that had been developed are to analyze and choose the queries from the documents downloaded from the previous queries submitted to the deep web database. They can be categorized as: Graph approach [1] [24], Incremental approach [20] [18], and Sampling based approach [16] [3] [22]. Graph approach is used to download structured database, so it is not discussed in my thesis.

2.1 Incremental approach

Incremental approach selects queries from the documents that have been downloaded. The number of documents increases as more queries are sent, thus this kind of approach are called incremental approach.

Ntoulas et al. [20] propose an adaptive method. Their approach selects the query returning most new documents per unit iteratively. Since there is no prior knowledge of all the document frequencies of the queries, this method requires the estimation of the document frequencies based on the documents already downloaded. From this estimation and the occurrences of the queries in the downloaded documents, the number of matched new documents can be estimated. They propose two ways to estimate. The first method which is called independence estimator assumes that the occurrence probability of a term in the subset of documents is equal to that in the entire document set. Based on the frequency of a term in the subset of documents $N(q_i \mid \text{subset collection})$, the method can estimate how many times a particular term occurs in the entire document set $N(q_i)$. Then we can estimate the number of new documents by: $N_{new}(q_i) = N(q_i) - N(q_i \mid \text{subset collection})$.

The method of Zipf estimator [13] is to estimate the frequency of terms inside document collection by following a power law distribution. That is, the frequency of a term within the document collection is given by the formula:

$$N(q_i) = \alpha (r + \beta)^{-\Upsilon}, \qquad (1)$$

where r is the rank of the term and α, β, and Υ are constants that depend on the document collection. Based on the subset of documents that we have downloaded, we can estimate α, β, and Υ by the approach which is mentioned in [20]. Given the ranking r of a term inside the subset of document collection, N(qi) can be calculated by formula (1). They compare three keyword selection policies: random (Keywords are randomly selected from dictionary.), generic-frequency (Keywords are selected from 5.5-million-web-page corpus based on their decreasing frequency.), and their adaptive algorithm. The experimental result shows that adaptive algorithm (Keywords are selected from the subset of documents) performs remarkably well in all cases. The approaches proposed in

[20], select queries from an incremental document collection. Therefore, we call this kind of approach as incremental approach. Incremental approach selects queries from an incremental document collection. That means you need to analyze each document once it is downloaded and calculate the document frequency again for each term. This step will be very time-consuming, if we count the document frequency for every query at each round. In order to calculate document frequency efficiently, Ntoulas' solution computes the document frequency by updating the query statistics table after we submit a new query and download more documents. However maintaining this table still is difficult.

Term	DF
Software	20
Science	30
Computer	80

Total pages downloaded: 100

(a) After issuing q_1 up to q_{i-1}

Term	DF
Java	10
Science	5
Computer	20

New pages downloaded: 20

(b) By issuing q_i

Term	DF
Software	30
Science	35
Computer	100
Java	10

Total pages downloaded: 120

(c) After issuing q_1 up to q_i

Figure 5: Statistic Table: Document Frequency of Terms

The sampling-based approach [16] [3] firstly creates a sample database and builds a set of queries from the sample database, rather than iteratively selecting keywords from an incremental subset of document collection until crawling ends.

Madhavan et al. [18] develop a deep-web crawling system. Because the system is an industry product, it needs to consider how to select seed queries. Their system detects the feature of the query interfaces. Since they need to process difference languages, their approach does not select queries from a dictionary. Instead, they select the seed queries from the html query form. After that, the iterative probing and keyword selection approach is similar to that proposed in [20].

Their query selection policy is based on TF-IDF that is the popular measure in the information retrieval. TF-IDF measures the importance of the word by the formula below.

$$tfidf(w,p) = tf(w,p) \times idf(w) \qquad (2)$$

This formula consists of two parts: $tf(w,p)$ and $idf(w)$. tf(w, p) is the term frequency of the term w in page p, and measures the importance of the word w in page p.

$$tf(w,p) = n_{w,p}/N_p \text{ ,}$$

where $n_{w,p}$ represents the number of times a word w occurs in web page p; N_p is the total number of terms in page p.

idf (w) (inverse document frequency) measures the importance of the word among all web pages, and is calculated by log $(\frac{D}{d_w})$ where D is the total number of web pages and d_w is the number of web pages where the term w appears.

Madhavan et al's method adds the top 25 words on every web page sorted by their TF-IDF values into the query pool. From the query pool, they remove the following two kinds of terms.

- Eliminate the high frequency terms, such as the terms that have appeared in many web pages (e.g. over 80%), since these terms could be from menus or advertisements.
- Delete the terms which occur only on one page, since many of these terms are meaningless words that are not from the contents of web pages, such as nonsensical or idiosyncratic words that could not be indexed by the search engine.

The remaining words are issued to deep web as queries and a new set of web pages are downloaded. Then this is repeated again in the new iteration. Additionally, their approach emphasizes breadth oriented crawling that is quite different to prior researches. They observed the statistic data on Google.com and found the results returned to users were more dependent on the number of deep web sites. They analyzed 10 millions of deep web sites. They discovered the top 10,000 deep web sites accounted for 50% of Deep-Web results, while even the top 100,000 deep web sites only accounted for 85%. This observation causes their focus on crawling as many deep web sites as possible, rather than surfacing on specific deep web sites.

2.2 Sampling based approach

In [21] [3], Barbosa et al. propose an approach to siphon the deep web by selecting keyword with highest frequency from the sample document collection. This algorithm selects the highest frequency keyword from the potential keyword list and is expected to lead a high coverage. It is composed of two phases: phase 1 selects a set of words from the html search form and randomly issues them until a non-empty result page is returned. By extracting high-frequency words from the results page, their algorithm creates an initial keyword list. Then it iteratively updates the frequency of words in the list and adds new high-frequency words into the list by randomly issuing the word in the list until the number of submission reaches the threshold. In phase 2, the approach selects the most frequency keyword from the keyword list to construct a new query in each round until the number of submission is up to maximum times.

In [16], Lu et al. further improve the sampling based method. Keywords are selected from a fixed sample database by a set covering algorithm. Those queries which can cover most documents in the sample database are expected to cover most of data in the entire database. The framework of this approach is showing in the figure below. For sampling based approach, queries are selected from the sample set of documents from the total database. This approach consists of three phases:

1) Create a sample DB: Issue the initial keywords to the total DB, obtain the matched documents, and then construct a sample database;

2) Construct the query pool: Analyze all the documents in the sample DB, apply set-covering algorithm to select the keywords and generate a query pool;

3) Send the queries to Total DB to retrieve documents.

The advantage of this method is that only a small part of documents need to be downloaded, because crawler sometimes may only need to know the URL, not the entire documents. Our focus is sampling based approach. Hence, more detail about sampling based approach will be described in Chapter IV.

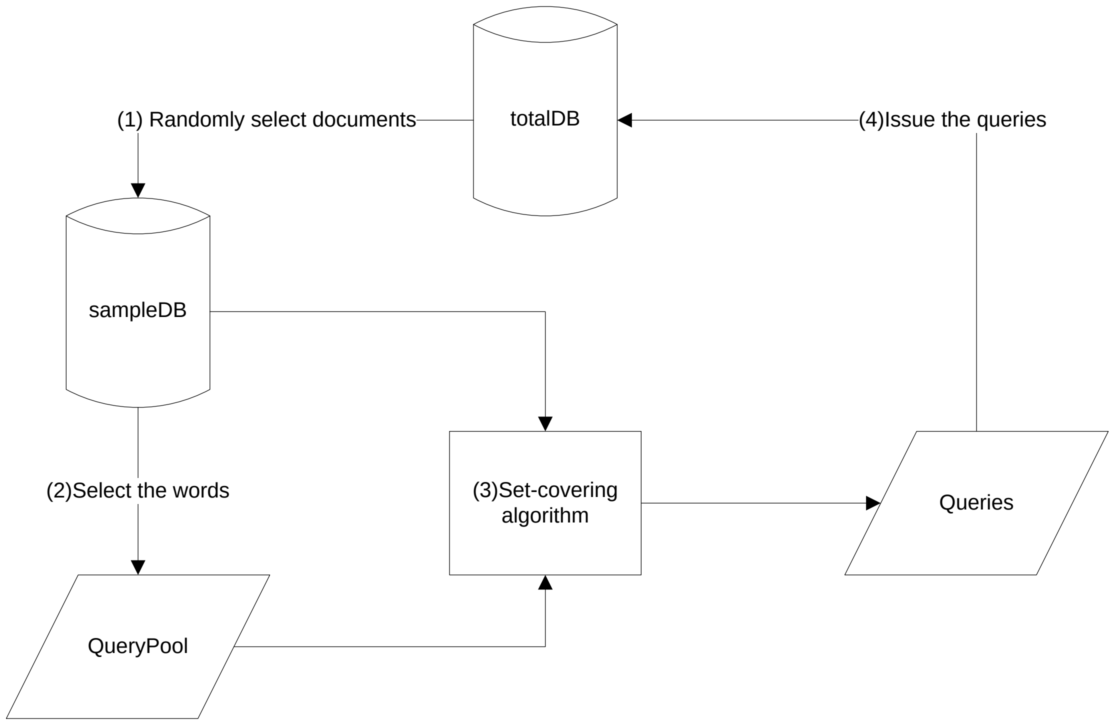


Figure 6: The framework of Lu's sample-based approach

CHAPTER III

SET COVERING PROBLEM

One of key problems of deep web crawling is to select a set of meaningful keywords. Selecting queries from a document collection is a popular method. Ntoulas et al [20] are the first to use set-covering problem to represent the query selection problem.

Set-covering problem is a typical NP problem [6]. It can be described as the following: given a finite set U and a family X of subsets of U, the solution is to find a cover C whose union is U and it is a subfamily of X. The set-covering problem can be divided into two problems. One is the set covering decision problem, i.e., given a pair (U,X) and an integer *k*; the question is to decide whether there is a cover of size *k* or less. The set-covering decision problem is NP-Complete. The other is the set covering optimization problem, i.e., given a pair (U,X) the goal is to find minimum-size subsets O whose elements cover all of U. The set covering optimization problem is NP-hard [11].

More formally, given U and X as follows:

$$U = \bigcup_{S \in X} S$$

The set covering optimization problem is to find a family of sets O such that

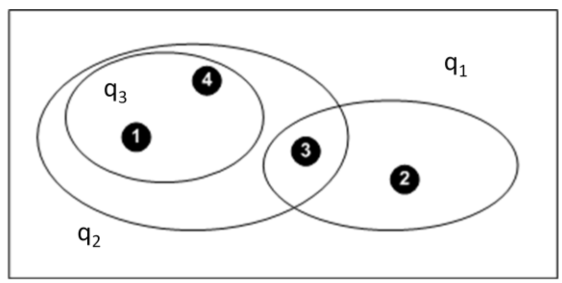
$$U = \bigcup_{S \in O} S \ \ where\ O \subseteq X$$

, and the cost of O is minimum.

The input of the set covering problem is often represented by a query-document matrix as illustrated in Figure 7. In Figure 7 (a), the matrix represents the relationship between three queries (q1, q2, q3) and four documents (d1, d2, d3, d4). If the cell (i,j) is 1, query in the ith row (q_i) is contained in the document in the jth column (d_j). This matrix representation can be illustrated by Figure 7 (b). The rectangle in Figure 7 (b) represents the whole document set. Each document is represented as a black point inside the rectangle. Every oval in the figure (b) represents a set of documents covered by a query.

	d_1	d_2	d_3	d_4
q_1	0	1	1	0
q_2	1	0	1	1
q_3	1	0	0	1

(a) documents



(b) Set covering problem

Figure 7: Formalization of the query selection problem

The minimum set cover problem can be formulated as the Integer Linear Program [11]. According to the integer linear program formulation in [11], we formalize the set covering problem for query selection as the following: Let A is an m*n matrix of 0 and 1 representing a document collection like Figure 7(a). The set covering problem is to find a solution m-vector S whose S_i = 0 or 1 (i = 1,…,m) that is representing whether the query i is either chosen or not. C_i is an m-vector of positive integer that is representing the cost of each query, and $C_i = \sum_{j=1}^{n} A_{ij}$, where i = 1,…,m. E is an n-vector of ones that is representing every document in the matrix A is covered. More formally, it can be formulated as below:

$$minimize(C^T S) \tag{3}$$

$$Subject\ to\ :\ A^T \times S \geq E\ , \tag{4}$$

where S_i = {0,1| i = 1,…,m}; E_i = {1|i=1,…,n}; C_i = {$\sum_{j=1}^{n} A_{ij}$ | i = 1,…,m}.

For instance, there are two solutions: {q1, q2} and {q1, q3} for the problem in the Figure 7. From the Figure 7 (a), we can know:

$$\text{A} = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$

There are three subset q_1, q_2, and q_3 in the matrix A. By the definition of C:

$$\text{C} = \{2, 3, 2\}$$

First step, we verify both solutions are satisfied with the condition.

$$\text{Subject to:} \quad \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \end{bmatrix}^T \times S \geq E, where\ E = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

For the solution {q_1, q_2}: $$S = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

$$\text{Thus, } LHS = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

$$\text{LHS}=\begin{bmatrix} 1 \\ 1 \\ 2 \\ 1 \end{bmatrix} > \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = E$$

For the solution {q_1, q_3}: $S = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$

$$\text{Thus, } LHS = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \times \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

$$\text{LHS}=\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = E$$

Therefore, both solutions subject to the condition:

$$A^T \times S \geq E$$

In the next step, we calculate the cost for both solutions.

For the solution {q_1, q_2}:

$$\text{Total cost} = C^T S$$

$$= \begin{bmatrix} 2 \\ 3 \\ 2 \end{bmatrix}^T \times \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

$$= 5$$

For the solution {q_1, q_3}:

$$\text{Total cost} = C^T S$$

$$= \begin{bmatrix} 2 \\ 3 \\ 2 \end{bmatrix}^T \times \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

$$= 4$$

By the objective function Formula (3), we know the solution 2 is better than the solution 1.

CHAPTER IV

SET COVERING ALGORITHMS

Set covering problem has been proved to be NP-Complete [6]. Optimal solution is hard to obtain within polynomial time. Various optimization algorithms are developed, such as Greedy, Weighted Greedy, Genetic, and Clustering etc. Traditional Greedy and Weighted Greedy algorithms will be implemented in experiment section.

4.1. Greedy Algorithm

One popular algorithm for set covering problem is the greedy algorithm which chooses queries according to one rule: at each round, always selects the query that covers the largest number of new documents per unit cost. A greedy algorithm makes the locally "best" choice at each stage, but it is not the best choice globally. Assuming we have constructed a query pool with a set of queries, greedy algorithm is to find the most effective query from the query pool.

Greedy Algorithm:

Input: m * n Matrix A;

Output: A solution m-vector S;

$df_i = \sum_{j=1}^{n} A_{ij}$;

B = A;

E is an n-vector, and initializes every element to 1;

S and c is an m-vector, and initialize every element to 0;

while $A^T \times S < E$ {

for(i=1; i<= m; i++){

$new_i = \sum_{j=1}^{n} B_{ij}$;

$c_i = df_i / new_i$;

}

Find a k which minimizes c_k ;

S_k =1;

Remove the kth row and jth column from B, if $cell_{ij}$ =1;

}

for (j = 1; j <=m; j++){

if(S_j = 1 and A_j is redundant) S_j = 0;

}

return S;

For example, the matrix below represents a sample database which contains nine documents (d1, d2, d3, …, d9). Suppose our query pool includes six queries (q1, q2, q3, q4, q5, and q6).

	d1	d2	d3	d4	d5	d6	d7	d8	d9
q1	0	0	0	0	0	0	1	0	1
q2	0	0	0	0	1	0	1	0	1
q3	1	0	0	0	0	1	0	0	0
q4	0	0	0	0	0	1	1	1	0
q5	1	1	0	1	1	0	0	0	1
q6	1	1	1	1	0	0	0	0	0

Table 1: Greedy algorithm example (1)

By the rule mentioned above, we can convert the matrix to a set-covering problem as the figure below. We choose sets (queries) by greedy algorithm to cover all documents. The whole procedure is listed as following:

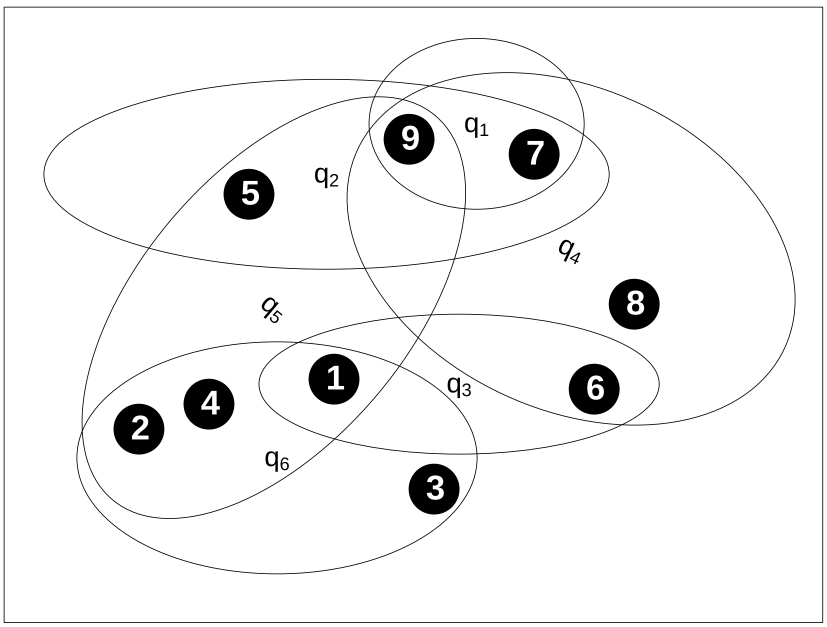


Figure 8 : Set-covering Formalization (Example)

Round 1: Add q_5 into query pool, the value of new/df for each query is equal to 1. As a result, we randomly select the query with largest df.

	d1	d2	d3	d4	d5	d6	d7	d8	d9	df	new	new/df
q1	0	0	0	0	0	0	1	0	1	2	2	1
q2	0	0	0	0	1	0	1	0	1	3	3	1
q3	1	0	0	0	0	1	0	0	0	2	2	1
q4	0	0	0	0	0	1	1	1	1	4	4	1
q5	1	1	0	1	1	0	0	0	1	5	5	1
q6	1	1	1	1	0	0	0	0	0	4	4	1

Table 2: Greedy algorithm example (2)

Round 2: Add q_4 into query pool, since new/df(q_4) = ¾ is maximum value in the last column.

	d1	d2	d3	d4	d5	d6	d7	d8	d9	df	new	new/df
q1	0	0	0	0	0	0	1	0	1	2	1	1/2
q2	0	0	0	0	1	0	1	0	1	3	1	1/3
q3	1	0	0	0	0	1	0	0	0	2	1	1/2
q4	0	0	0	0	0	1	1	1	1	4	3	3/4
q5	1	1	0	1	1	0	0	0	1	5	--	--
q6	1	1	1	1	0	0	0	0	0	4	1	1/4

Table 3: Greedy algorithm example (3)

Round 3: Add q_6 into query pool, since new/df(q_6) = ¼ is maximum value in the last column.

	d1	d2	d3	d4	d5	d6	d7	d8	d9	df	new	new/df
q1	0	0	0	0	0	0	1	0	1	2	0	0
q2	0	0	0	0	1	0	1	0	1	3	0	0
q3	1	0	0	0	0	1	0	0	0	2	0	0
q4	0	0	0	0	0	1	1	1	1	4	--	--
q5	1	1	0	1	1	0	0	0	1	5	--	--
q6	1	1	1	1	0	0	0	0	0	4	1	1/4

Table 4: Greedy algorithm example (4)

Therefore, the Solution of this example is $\{q_5, q_4, q_6\}$.

The whole procedure of choosing sets by the greedy algorithm can be transferred to set covering view as picture below.

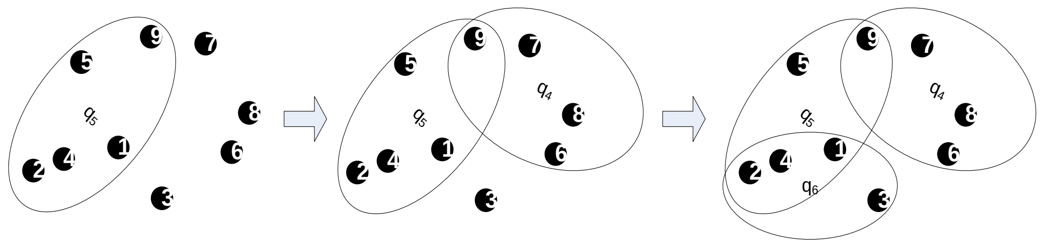


Figure 9: the whole procedure of Greedy Algorithm

Check whether the solution {q_5, q_4, q_6} covers all the documents by:

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T \times S \geq E, \ where\ E = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \ S = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\text{Thus, } LHS = \begin{bmatrix} 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 & 0 \end{bmatrix} \times \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 2 \\ 2 \\ 1 \\ 2 \\ 1 \\ 1 \\ 1 \\ 1 \\ 2 \end{bmatrix} > \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = E$$

Therefore, all the documents are covered by the solution {q_5, q_4, q_6}.

Next, calculate the cost of the solution $\{q_5, q_4, q_6\}$:

$$\text{Total cost} = C^T S$$

$$= \begin{bmatrix} 2 \\ 3 \\ 2 \\ 4 \\ 5 \\ 4 \end{bmatrix}^T \times \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

$$= 13$$

4.2. Weighted Algorithm

Traditional set covering algorithms do not work well when applied to deep web crawling due to various special features of the application domain. Typically, most set covering algorithms ignore the distribution of document frequencies. In [34], the authors developed a new set covering algorithm that targets the deep web crawling. Instead of straightforward greedy set covering algorithm, it introduces weights into the greedy strategy. They use Document Frequency df (the number of documents that contain a specific earlier query.), Document Weight dw (the inverse of the number of terms in QP that occurs in the document), and Query Weight qw(the sum of the document weights of all documents containing term q). The weighted greedy algorithm is based on choosing the query with the smallest df/qw.

To improve simple greedy algorithm and decrease the overlap, the weighted greedy algorithm introduces weights into the greedy strategy and propose a weighted greedy algorithm instead of a straightforward greedy set covering algorithm. The definitions are introduced as follows:

Definition 3 (Document Weight): Let D={d_1,…,d_m} be the SampleDB and QP={q_1,…,q_n} be the QueryPool. We consider each document as a set of terms and use the notation $q_j \epsilon$ di to indicate that a term q_j occurs in the document d_i. The weight of a document with respect to QP and d_i (1⩽i⩽m), denoted by dw(d_i, QP) (or d_w for shot), is the inverse of the number of terms in QP that occurs in the document d_i, i.e.

$$\mathbf{dw} = \frac{\mathbf{1}}{|\mathbf{di} \cap \mathbf{QP}|}$$

Definition 4 (Query Weight): The weight of a query q_j (1≤j≤n) in QP with respect to D, denoted by qw(q_j, QP) (or qw for short), is the sum of the document weights of all documents containing term q_j, i.e.,

$$\mathbf{qw} = \sum_{\mathbf{qj \epsilon di, di \epsilon D}} \mathbf{dw}$$

Weighted Greedy Algorithm:

Input: m * n Matrix A;

Output: A solution m-vector S;

$df_i = \sum_{j=1}^{n} A_{ij}$;

```
B = A;

E is an n-vector, and initializes every element to 1;

S and c is an m-vector, and initialize every element to 0;

While A^T × S < E {

    for( i=1; i<= m; i++){

    qw_i = B_i^T × dw ;

    c_i = df_i / qw_i;

    }

    Find a k which minimizes c_k ;

      S_k =1;

    Remove the kth row and jth column from B, if cell_ij =1;

}

for (j = 1; j <=m; j++){

    if(S_j = 1 and A_j is redundant) S_j = 0;

}

return S;
```

The weighted greedy algorithm always selects the next query with the largest "qw/df". Based on this rule, the weighted greedy algorithm selects keywords from SampleDB as queries which have lower overlapping rate. This algorithm retrieves a much better result than the simple greedy method in the SampleDB, so it should be expected to retrieve a better result in the TotalDB.

By Weighted Greedy Algorithm, we can get the Solution #2(q_6, q_4, q_2) for example 2.

Round 1:

	d1	d2	d3	d4	d5	d6	d7	d8	d9	df	qw	qw/df
q1	0	0	0	0	0	0	0.333	0	0.25	2	0.583	0.292
q2	0	0	0	0	0.5	0	0.333	0	0.25	3	1.083	0.361
q3	1	0	0	0	0	0.5	0	0	0	2	1.5	0.75
q4	0	0	0	0	0	0.5	0.333	1	0.25	4	2.083	0.521
q5	0.5	0.5	0	0.5	0.5	0	0	0	0.25	5	2.25	0.45
q6	0.5	0.5	1	0.5	0	0	0	0	0	4	2.5	0.625

Table 5: Wighted Greedy algorithm example (1)

Round 2:

	d1	d2	d3	d4	d5	d6	d7	d8	d9	df	qw	qw/df
q1	0	0	0	0	0	0	0.333	0	0.25	2	0.583	0.292
q2	0	0	0	0	0.5	0	0.333	0	0.25	3	1.083	0.361
q3	1	0	0	0	0	0.5	0	0	0	2	0.5	0.25
q4	0	0	0	0	0	0.5	0.333	1	0.25	4	2.083	0.521
q5	0.5	0.5	0	0.5	0.5	0	0	0	0.25	5	0.75	0.15
q6	0.5	0.5	1	0.5	0	0	0	0	0	4	-	-

Table 6: Wighted Greedy algorithm example (2)

Round 3:

	d1	d2	d3	d4	d5	d6	d7	d8	d9	df	qw	qw/df
q1	0	0	0	0	0	0	0.333	0	0.25	2	0	0
q2	0	0	0	0	0.5	0	0.333	0	0.25	3	0.5	0.1667
q3	1	0	0	0	0	0.5	0	0	0	2	0	0
q4	0	0	0	0	0	0.5	0.333	1	0.25	4	-	-
q5	0.5	0.5	0	0.5	0.5	0	0	0	0.25	5	0.5	0.1
q6	0.5	0.5	1	0.5	0	0	0	0	0	4	-	-

Table 7: Wighted Greedy algorithm example (3)

We transfer the whole procedure of choosing sets by the weighted greedy algorithm in set covering view as picture below.

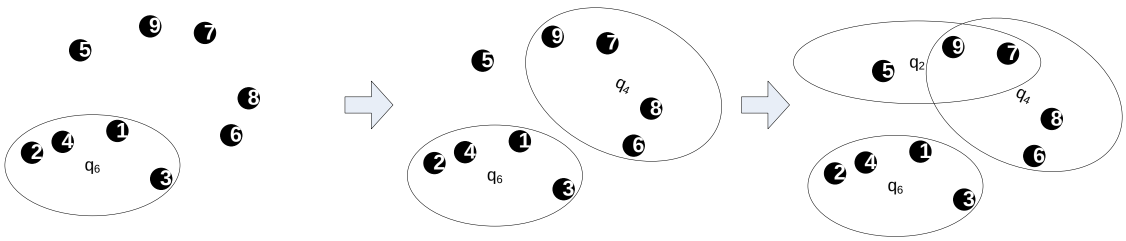


Figure 10 : the whole procedure in set covering view (by Weighted Greedy Algorithm)

Check whether the solution {q_6, q_4, q_2} covers all the documents by:

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T \times S \geq E, \quad where\ E = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \quad S = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}$$

$$\text{Thus, } LHS = \begin{bmatrix} 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 & 0 \end{bmatrix} \times \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 2 \\ 1 \\ 2 \end{bmatrix} > \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = E$$

Therefore, all the documents are covered by the solution {q_6, q_4, q_2}.

Next, calculate the cost of the solution {q_6, q_4, q_2}:

$$\text{Total cost} = C^T S$$

$$= \begin{bmatrix} 2 \\ 3 \\ 2 \\ 4 \\ 5 \\ 4 \end{bmatrix}^T \times \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}$$

$$= 11$$

By comparing with the cost in the example of section 4.1, we can see the solution given by weighted greedy algorithm is better than the solution generated by conventional greedy algorithm.

4.3. Ranking Problem

Return limitation and ranking policy results in the ranking problem. Many hidden web sites set up a limit k for the number of results. When a query matches a large number of documents, the deep web sites only return at most k documents. This is called return limitation. Ranking policy is the rule of sorting results.

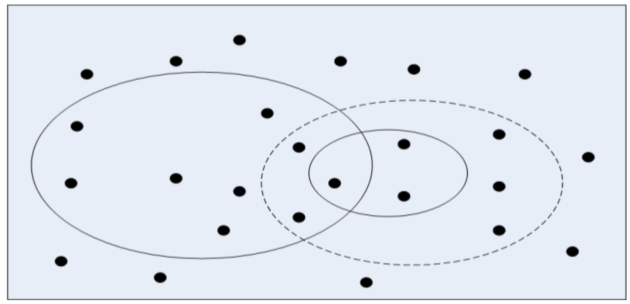


Figure 11: A deep web site usually set up a return limitation

Ranking policy generally could be either static or dynamic. A static ranking, say the web service of “twitter.com”, sorts the results by the order of date and time. A dynamic ranking could sort the results by the relevance to the query. Those documents that are highly related to the search query will be listed on the top. The more relevant to the search query, the position of a document is closer to the top. However for the commercial search engines, the ranking policy is much more complex. Generally, the commercial search engines rank the results mainly by the order of relevance and importance. The relevance of web pages will be evaluated by many factors: such as the number of occurrence times, the position of appearance, and whether the title contains the term etc. The importance of web pages will be measured by other criteria, e.g., the number of links to the web page from the other websites and the reputation of those websites. Once the search engine has sorted a list of documents with their scores, it will choose the top k documents as the results for a query.

The return limitation gives us a great challenge to download data from the deep web sites. For example, the greedy algorithm and the weighted greedy algorithm likely select the terms with high document frequency as queries. These queries are supposed to match a large number of documents. However because of the return limitation, only at maximal k number of documents can be downloaded.

When a deep web site sets up a return limitation, the rule of ranking is also a critical problem for deep web crawling. By Lu et al. [17]'s previous research, if a search engine commits static ranking rule, there is the following result:

$$M \leq \frac{k}{df_q} \times N, \qquad (5)$$

where M is the number of documents that can be downloaded; k is the return limitation; df_q is the lower bound of document frequencies of all queries sent; N is data source size.

This formula shows that if we select high frequency terms as queries, fewer documents can be downloaded. For example, suppose we keep submitting queries whose document frequency is greater than 200 to a deep web search engine whose k equals to 100. By Equation 5, if the search engine lists the result with static ranking policy, the total number of documents which can be downloaded should be:

$$M \leq N \times \frac{100}{200};$$

$$= \frac{1}{2} N;$$

No matter how many queries are sent. Despite dynamic ranking policy could alleviate such a ranking problem, those popular terms are still not a good choice. Therefore our idea is to select the queries whose document frequencies are less than k. Our proposed method improves the weighted algorithm by always selecting the queries whose document frequency is less than k. However we do not know the document frequency of a term until we submit the term as query. Hence, we have to estimate the document frequency of a term. One straight-forward method is to estimate the document frequency of a term in the total database by using sample database. Assuming that the probability of a term in the sample database and the total database is the same, the document frequency of a term can be estimated by:

$$\widehat{df}_{TotalDB} = df_{SampleDB} \times |TotalDB|/|SampleDB| \qquad (6)$$

The method that we apply document frequency estimation method on the weighted greedy algorithm to choose queries from the sample database is called DF-Weighted algorithm.

DF-Weighted firstly estimates the document frequency of total database for all the terms in the sample database. The terms whose document frequency is less than k are selected to generate a matrix with all the documents covered by them. After that, the matrix is processed as the input of weighted greedy algorithm. Then weighted greedy algorithm outputs a set of queries.

CHAPTER V

EXPERIMENTS

5.1. Experimental Environment

The task of our experiments is to evaluate various downloading policies described in Charter 3 on real deep web sites. We select Bing web service as our test bed and use slices of the data indexed in Bing as various deep web data sources. Those slices can be web sites, such as cs.berkeley.edu, which can be accessed using Bing search syntax "site: cs.berkeley.edu". Such search interface and the results from Bing are quite similar to the search box provided by the web site itself. Thus we can simulate the access to almost all the web sites as searchable deep web data sources.

For example, if we plan to test on "cs.berkeley.ca", we can repeatedly submit queries to Bing search engine like "site: cs.berkeley.edu [query]", as shown in Figure 12.

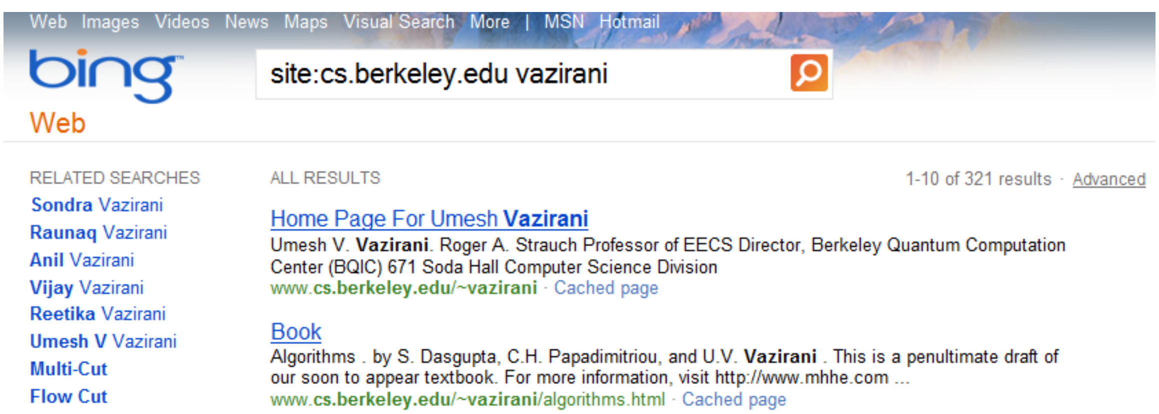
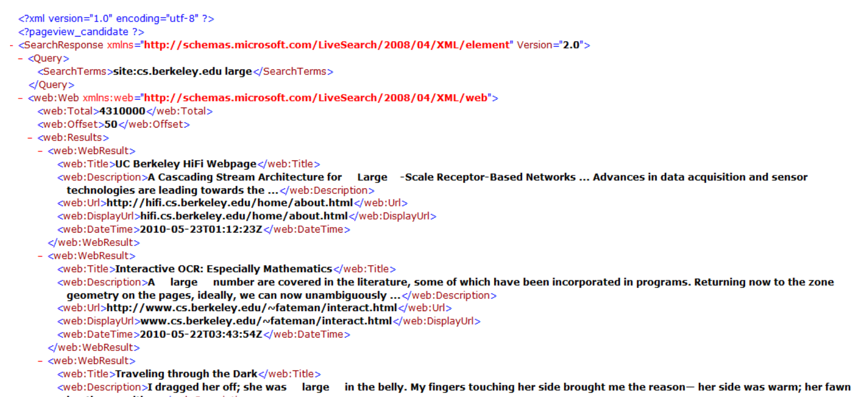


Figure 12: The results for "site:cs.berkeley.edu vazirani"

In this thesis, instead of using html form search interface, we submit the queries to Bing web service. Therefore we do not need to fill the html query form and extract the data from html result pages.

Bing API provides HTTP Get to implement the process of submitting requests. A request to the HTTP endpoint consists of an HTTP GET request to the appropriate URI. There are two URIs, one for XML results and one for JSON results. The XML format is used in our experiment. So we submit our requests to the URI: " http://api.search.live.net/xml.aspx" . If we want to query the site "cs.berkeley.edu" for the pages matching the term "large", the complete request sent to Bing web service is:

http://api.search.live.net/xml.aspx?Appid=<AppID>&query=site:cs.berkeley.edu%20large&sources=web.



```
<?xml version="1.0" encoding="utf-8" ?>
<?pageview_candidate ?>
- <SearchResponse xmlns="http://schemas.microsoft.com/LiveSearch/2008/04/XML/element" Version="2.0">
  - <Query>
      <SearchTerms>site:cs.berkeley.edu large</SearchTerms>
    </Query>
  - <web:Web xmlns:web="http://schemas.microsoft.com/LiveSearch/2008/04/XML/web">
      <web:Total>4310000</web:Total>
      <web:Offset>50</web:Offset>
    - <web:Results>
      - <web:WebResult>
          <web:Title>UC Berkeley HiFi Webpage</web:Title>
          <web:Description>A Cascading Stream Architecture for Large -Scale Receptor-Based Networks ... Advances in data acquisition and sensor
            technologies are leading towards the ...</web:Description>
          <web:Url>http://hifi.cs.berkeley.edu/home/about.html</web:Url>
          <web:DisplayUrl>hifi.cs.berkeley.edu/home/about.html</web:DisplayUrl>
          <web:DateTime>2010-05-23T01:12:23Z</web:DateTime>
        </web:WebResult>
      - <web:WebResult>
          <web:Title>Interactive OCR: Especially Mathematics</web:Title>
          <web:Description>A large number are covered in the literature, some of which have been incorporated in programs. Returning now to the zone
            geometry on the pages, ideally, we can now unambiguously ...</web:Description>
          <web:Url>http://www.cs.berkeley.edu/~fateman/interact.html</web:Url>
          <web:DisplayUrl>www.cs.berkeley.edu/~fateman/interact.html</web:DisplayUrl>
          <web:DateTime>2010-05-22T03:43:54Z</web:DateTime>
        </web:WebResult>
      - <web:WebResult>
          <web:Title>Traveling through the Dark</web:Title>
          <web:Description>I dragged her off; she was large in the belly. My fingers touching her side brought me the reason— her side was warm; her fawn
```


Figure 13: Response page from Bing web service

The picture above is a portion of response page. Several returned elements are explained below:

1) The Total element, "<web:Total>", contains the estimated number of results for a particular request. Since Bing web service usually provides a very

inaccurate number, we use our own estimation of the size by exhaustively sending a very large number of queries.

2) The Offset element, "<web:offset>", indicates the current position of the result set you are processing. You can change Offset using the optional Offset parameter. Each response page at most contains 50 results. This means, if a query matches 100 results, you need to submit this query twice to Bing web services. For example, if you wanted to ask for 50 results at a time, you would pass "web.count=50" as part of the query string. If you wanted to get the next 50 results after getting the first results, you would pass "web.offset=51". The full URI would be as the following:

   http://api.search.live.net/xml.aspx?

   Appid=<AppID>&query=site:cs.berkeley.edu%20large&sources=web

   &web.count=50&web.offset=51

Bing web service imposes some challenges for deep web crawling, such as return limitation, ranking of the returns, paginated results, and inter-page overlapping.

1) Return limit, only top one thousand of results can be returned per query.
2) Inter-page overlap: Bing web service sometimes even could return same documents when you issue a query. In our experimental result, we had pruned this kind of duplicate.
3) Ranking criteria: Comparing local simulation data source, we do not know the rule of Bing search engine for ranking results. This problem also gives us a new challenge to download deep web data.

In order to facilitate the experiment on Bing web service, we build a web service crawler. The figure below is the GUI and the dataflow diagram of our crawler. To make the crawler more flexible, the system is independent of algorithms. A query selection algorithm output the queries to a text file. And our WS-Crawler read the queries from the text file and creates a query pool.

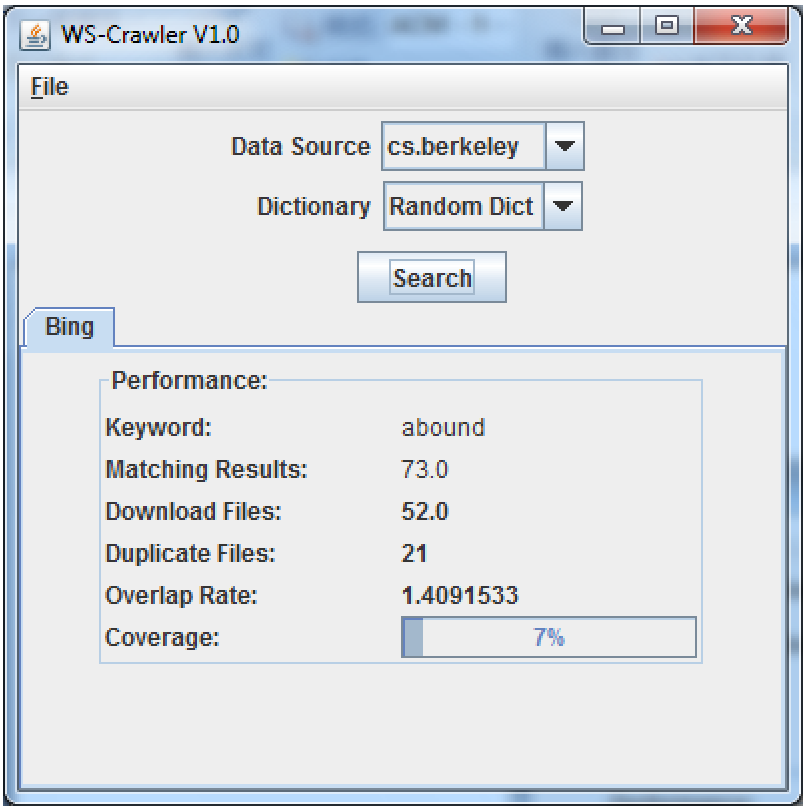


Figure 14: The user interface of our crawler

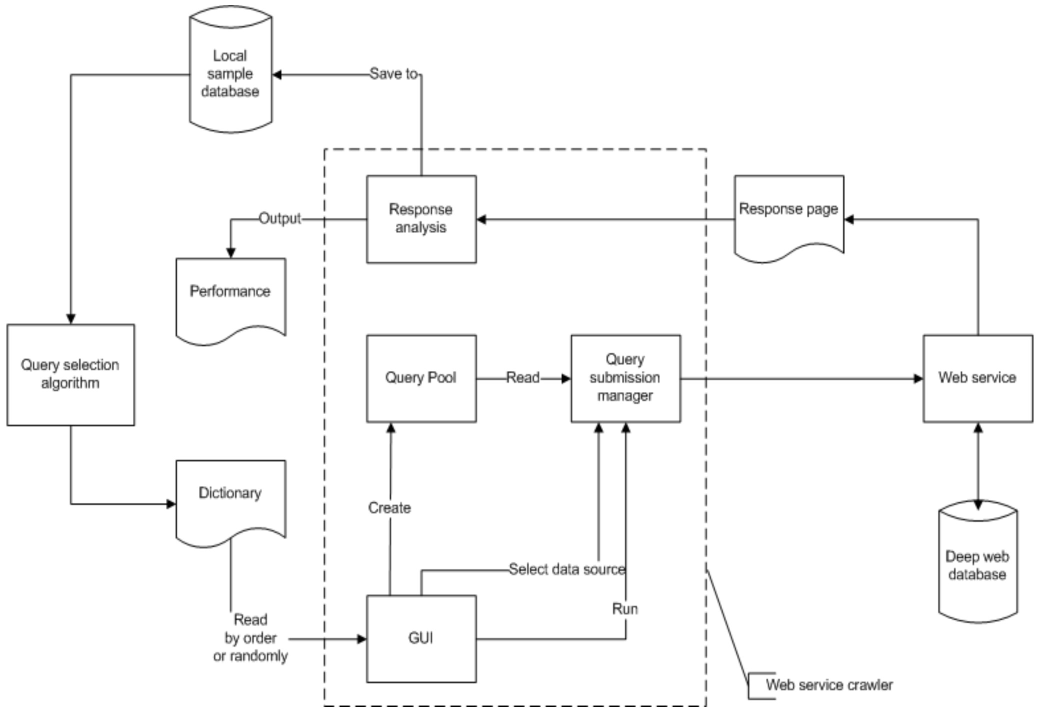


Figure 15: Dataflow diagram of our crawler

5.2. Evaluation Criteria

When we select queries from documents by different algorithms, the solutions should be also different. In order to evaluate which solution performance is better, we select Hit Rate [22] and Overlapping Rate [22] as our evaluation criteria.

Hit rate is to measure how many percentages of documents are harvested by the crawler. So Hit Rate is equal to the number of unique documents downloaded divide by the total number of documents in the web database.

$$HR(Q, DB) = \frac{|\bigcup_{j=1}^{i} S(q_j, DB)|}{|DB|} \quad (7)$$

Overlapping rate is used to measure the communication cost. In the formula (8), Overlapping Rate is equal to the number of documents downloaded, including duplicate documents divide by the number of unique documents downloaded.

$$OR(Q, DB) = \frac{\sum_{j=0}^{i} |\, S(q_j, DB)|}{|\bigcup_{j=0}^{i} S\big(q_j, DB\big)\,|} \qquad (8)$$

For example, we have a document set which contains 4 documents (d_1, d_2, d_3, and d_4). There are 3 queries (q_1, q_2, and q_3) in our query pool. The relation between the documents and queries is shown in the Figure 7. We have two solutions that can cover all of documents. One is $\{q_1, q_2\}$, and the other is $\{q_1, q_3\}$.

Solution 1:

$$\mathrm{OR}(\{\mathrm{q}_1, \mathrm{q}_2\}, \mathrm{DB}) = \frac{2+3}{4} = 1.25$$

$$\mathrm{HR}(\{\mathrm{q}_1, \mathrm{q}_2\}, \mathrm{DB}) = \frac{4}{4} = 100\%$$

Solution 2:

$$\mathrm{OR}(\{\mathrm{q}_1, \mathrm{q}_3\}, \mathrm{DB}) = \frac{2+2}{4} = 1$$

$$\mathrm{HR}(\{\mathrm{q}_1, \mathrm{q}_3\}, \mathrm{DB}) = \frac{4}{4} = 100\%$$

The hit rate for both solutions is same. However the overlapping rate of solution 2 is lower, this means the solution 2 reaches 100 percent coverage with less documents downloaded. Therefore, the solution 2 is better than the solution 1.

5.3. Experiments

5.3.1 Sample Databases Creation

The experiments are carried on three data sources: "cs.berkeley.edu", "uwaterloo.ca", and "ctv.ca". For each data source, we create three samples whose sizes are approximately 5%, 10%, and 20% of the original data source. We create three different sample databases for each data source. The sizes of those sample databases are approximately 5%, 10%, and 20%. the sample databases are built as follows:

1) Randomly select queries from the Webster dictionary that contains about 59000 terms;
2) Issue some of those queries to Bing web service and download more than 20% documents;
3) All those documents can be divided into many portions by queries. We randomly compose those sets of documents into about 5%, 10%, or 20% document collection;
4) Use Lucene (a tool to index the documents) to create sample databases.

Data Source	cs.berkeley.edu	uwaterloo.ca	ctv.ca
Approximate (N)	30,000	150,000	140,000
Sample Size	1548	8019	6911
	3319	13924	14504
	6066	29690	28568

Table 8: Description of Data Sources and Sample Databases

5.3.2 Ranking Strength Observation on the Data Sources

Ranking problem has a great effect on the performance of downloading data from the deep web sites. Thus to measure the ranking strength of the data sources is necessary. Ranking strength is measured by calculating the percentage of queries which are within the return limitation. All the selected terms whose document frequency is bigger than 1 from the three sample databases (20%N). All those terms are submitted to the Bing web service and k has default value 1000. Then we can get the number of terms whose document frequencies are less than 100 and 200.

Data Source	Approximate (N)	Terms Num (tn)	df_{100}	df_{100} /tn	df_{200}	df_{200} / tn	Ranking Strength
cs.berkeley.edu	30,000	48,522	36,546	75%	39,627	81%	weak
uwaterloo.ca	150,000	271,530	173,438	64%	184,403	68%	middle
ctv.ca	140,000	116,073	63,638	55%	69,385	59%	strong

Table 9: Percentage of Terms within k

From Table 9, we can make the following observation:

Because the size of data source “cs.berkeley.edu” is small, the matches of the most of queries do not exceed the return limit. Therefore ranking strength in this data source is weak.

Despite the size of “ctv.ca” and “uwaterloo.ca” is very close, words of “ctv.ca” are very generic. The percentage of popular terms of “ctv.ca” is higher than “uwaterloo.ca”. Hence ranking strength of “ctv.ca” is stronger than “uwaterloo.ca”.

5.3.3 Comparison on Query Selection Policies

We evaluate four query selection policies on 27 combinations of experiment environments. For each data source, we set up three different return limitations (100, 200 and 1000) and three different sample databases (approximately 5%, 10%, and 20%). We evaluated the four query selection policies as the following:

- Random: Randomly selects queries from the Webster dictionary;
- Sampling based policies: Greedy, Weighted Greedy, and DF-Weighted greedy policies.

As mentioned before, those sampling based algorithms select queries from the matrixes. However if we generate the matrix by exporting all the terms from a sample database, this matrix will be so large that the memory of our computer cannot afford it. By the research of [16], we keep randomly selecting terms from the sample database until the total document frequencies of terms is 20 times of the size of sample database. We used those terms to create the matrix as mentioned in the section 3. Finally three sampling based algorithms are run on the matrix.

Because we evaluate the crawling performance by comparing the value of OR and HR. In our experiments, we design a chart to record the value of OR, HR and the raw data as Table 10.

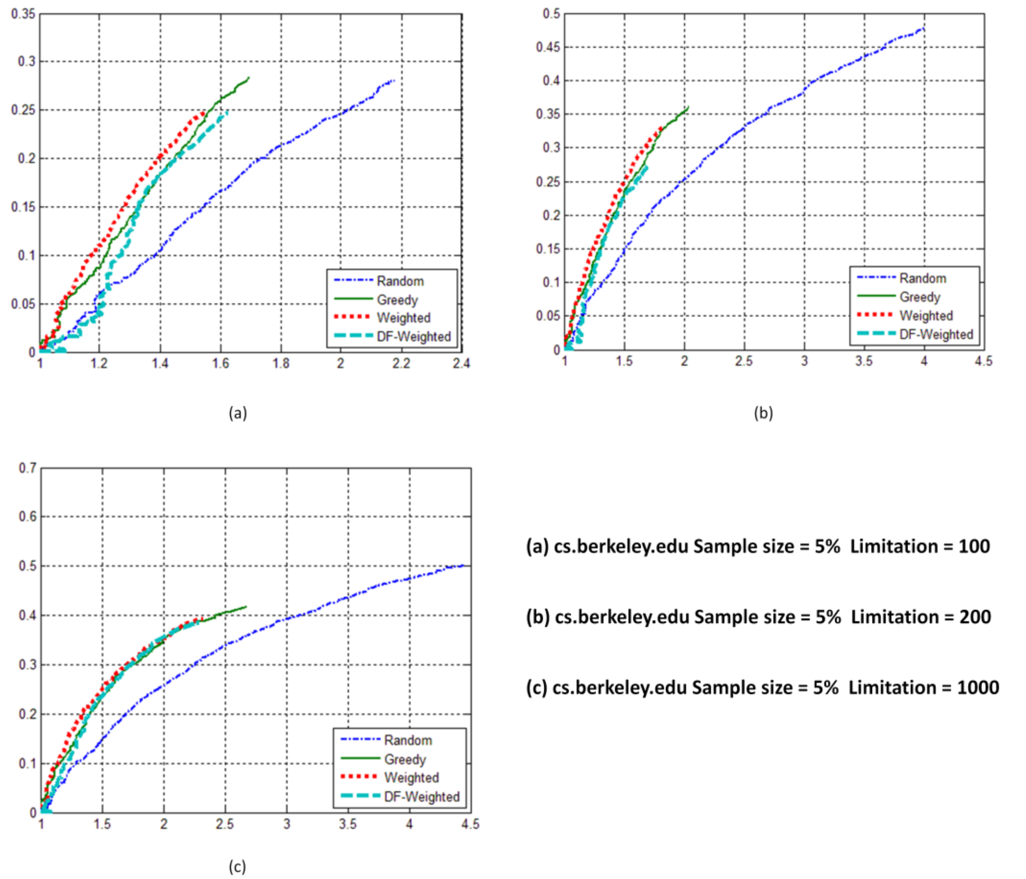
Query	est mi	mi	ui	di	Mi	Ni	or	OR	HR
q_1									
q_2									
….									
q_i									

Table 10: Experiment record chart

Below is the explanation for the columns in the table 9:

1) est mi: matches estimated by Bing search engine;
2) mi: actual matches;
3) ui : the number of new documents retrieved by a query;
4) di: the number of duplicate documents retrieved by a query;
5) Mi: the number of total matches (includes duplicate docs) retrieved by $\{q_1 \ldots q_i\}$;
6) Ni: the number of total unique documents retrieved by $\{q_1 \ldots q_i\}$;
7) or: the overlapping rate of a query;
8) OR: the overlapping rate up to $q_{i;}$
9) HR: the hit rate up to $q_{i.}$

After running 108 (4×27) experiments on 27 combinations, we create 27 performance diagrams. The values of OR are plotted on x-axis, and the values of HR are plotted on y-axis. All performance diagrams are listed in the appendix I. We select some representative diagrams to list below.



(a) cs.berkeley.edu Sample size = 5% Limitation = 100

(b) cs.berkeley.edu Sample size = 5% Limitation = 200

(c) cs.berkeley.edu Sample size = 5% Limitation = 1000

Figure 16: Performance Diagrams of cs.berkeley.edu

The first three diagrams come from the data source “cs.berkeley.edu”. As said before, the ranking strength of this data source with respect to the queries is weak. Most of queries issued do not exceed return limitation k. In other words, the Weighted Greedy is similar to the DF-Weighted. Thus our proposed method does not show any advantage in this data source.

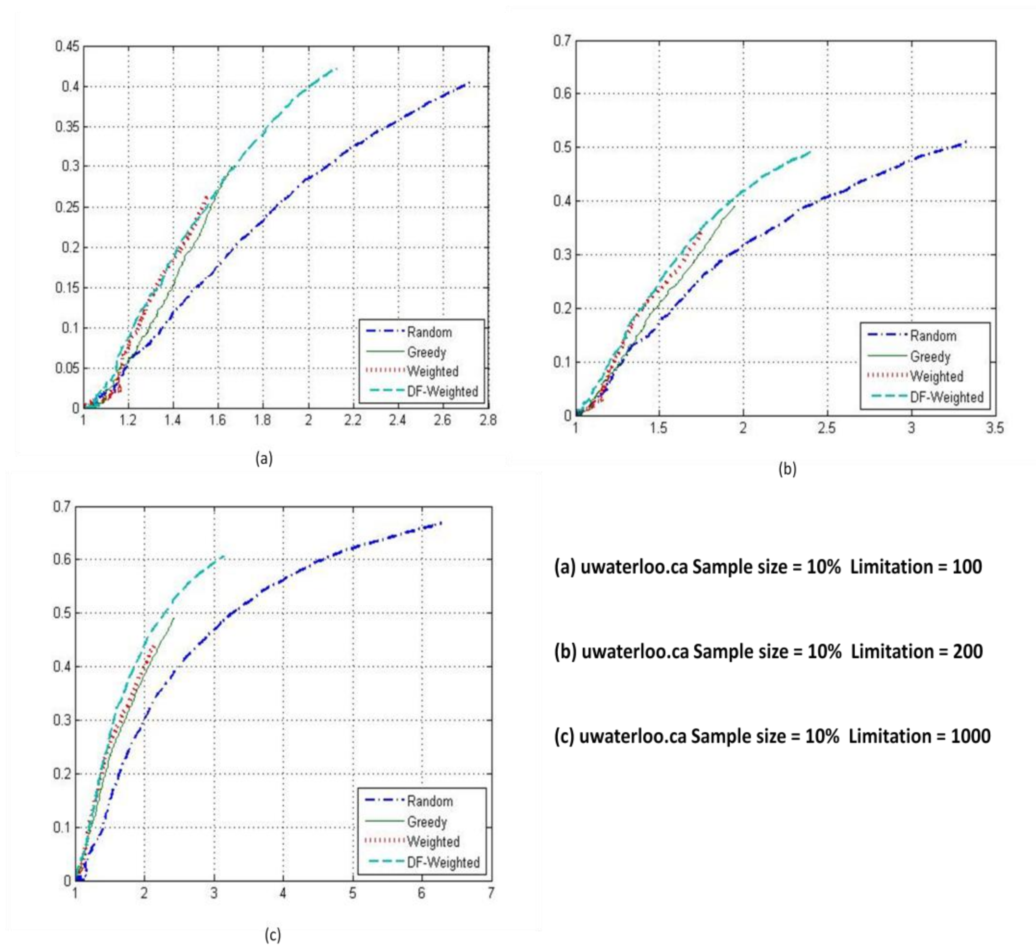


Figure 17: Performance Diagrams of uwaterloo.ca

However things change in the performance diagrams of "uwaterloo.ca". As ranking strength becomes stronger, DF-Weighted performs better in the data sources: "uwaterloo.ca". This can be observed from Figure 17. DF-Weighted performs best in terms of OR.

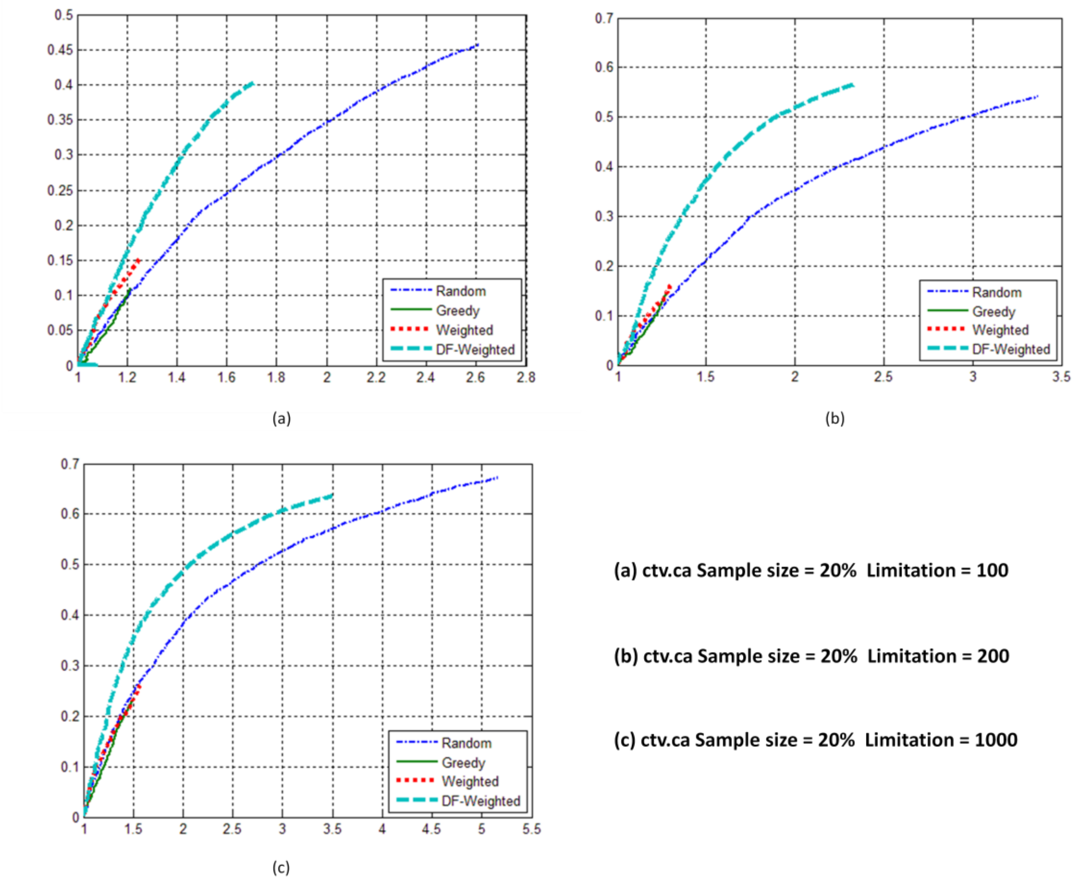


Figure 18: Performance Diagrams of ctv.ca

Greedy algorithm and weighted algorithm are originally designed to solve un-ranking data sources. But the ranking strength of "ctv.ca" is just strongest in three data sources. From the Figure 18, diagrams show ranking problem gives a great trouble to both algorithms. Let's take an example to explain. "Home" is a word with highest document frequency and appears in the most of web pages of "ctv.ca". According to the rule of the greedy algorithm, the word "home" must be selected by the greedy algorithm. However, it cannot retrieve as much as expected documents, due to return limitation. Therefore, it is difficult to achieve a high HR for the greedy and weighted algorithm. But our DF-Weighted algorithm just could solve this problem perfectly. Performance diagrams also show DF-Weighted performs best in terms of OR in the data sources "uwaterloo.ca" and "ctv.ca". To make it clearer, we construct a table (Table 11). We list their HR at a fix OR value for two data sources: "uwaterloo.ca" and "ctv.ca". We can observe DF-Weighted greedy algorithm performs best except the situation in the first row.

				Random Dictionary	Greedy	Weighted	DF-Weighted
data	Sample size(%)	k	OR	HR(%)	HR(%)	HR(%)	HR(%)
uwaterloo.ca	5	100	1.4	12	19	20	19
		200	1.4	16	22	23	25
		1000	1.4	15	25	25	30
	10	100	1.4	12	15	19	19
		200	1.4	16	20	23	23
		1000	1.4	15	23	25	25
	20	100	1.4	12	18	21	22
		200	1.4	16	20	22	22.5
		1000	1.4	15	19	22	23
ctv.ca	5	100	1.4	17.5	-	-	26.5
		200	1.4	18	-	-	27
		1000	1.4	21.5	-	-	26
	10	100	1.4	17.5	-	-	29
		200	1.4	18	-	-	30
		1000	1.4	21.5	-	-	31
	20	100	1.4	17.5	-	-	29
		200	1.4	18	-	-	32
		1000	1.4	21.5	-	-	32

Table 11: Comparison of DF-Weighted and others

Additionally, from all the performance diagrams, we also found: between greedy algorithm and weighted greedy algorithm, the latter one outperforms the former a little bit in the most of cases. To make it clearer, we construct a new table (Table 12). We list their HR at a fix OR value for two data sources: “cs.berkeley.edu” and “uwaterloo.ca”. We can observe weighted greedy algorithm always performs better than greedy algorithm.

				Greedy	Weighted
data	Sample size (%)	k	OR	HR(%)	HR(%)
cs.berkeley.edu	5	100	1.5	21	24
		200	1.5	23	25
		1000	1.5	22	23
	10	100	1.5	19	22
		200	1.5	20	22
		1000	1.5	21	23
	20	100	1.5	23	23
		200	1.5	24	26
		1000	1.5	24	26
uwaterloo.ca	5	100	1.4	19	20
		200	1.4	22	23
		1000	1.4	25	25
	10	100	1.4	15	19
		200	1.4	20	23
		1000	1.4	23	25
	20	100	1.4	18	21
		200	1.4	20	22
		1000	1.4	19	22

Table 12: Comparison of Greedy and Weighted

5.3.4 Effect of Ranking Problem on HDF

Barbosa’s algorithm always selects highest document frequency queries at each round. In order to clear the effect of ranking problem on the high document frequency queries, we perform a set of experiments. In the experiment of section 5.3.2, we already get the actual document frequency for the terms by submitting all terms in the sample database to the Bing web service. Then we extract all the terms whose document frequency is at least 200 to generate a new set of queries and store them in a text file. The text file is called HDF dictionary.

Sample database (20%N)	Terms (df > 1)	Terms (df ≥200)
cs.berkeley.edu	48,522	5,339
uwaterloo.ca	271,530	25,042
ctv.ca	232,146	20,269

Table 13: The number of terms for three data sources

At the beginning, we set up k to 100 for all the experiments. In the first experiment, we randomly submit the sample terms. We call this approach Sample Random. In the second experiment, we select those queries in the HDF dictionary as queries. Due to this approach always selects high frequency queries, it is denoted by HDF. In order to generate enough super high document frequency terms, we create a set of disjunctive queries by randomly combining the terms of HDF dictionary with OR rule, say "initially OR heidelberg OR social OR theatres OR overall OR include". In the third experiment, we issue the disjunctive queries containing five terms. That approach is called HDF5. In the same way, the approach issuing a set of disjunctive queries with 10 or 15 terms is denoted by HDF10 or HDF15. We donate those four approaches selecting high document frequency queries to HDF policy. The performance diagrams of five approaches on three data sources are given in Figure 19.

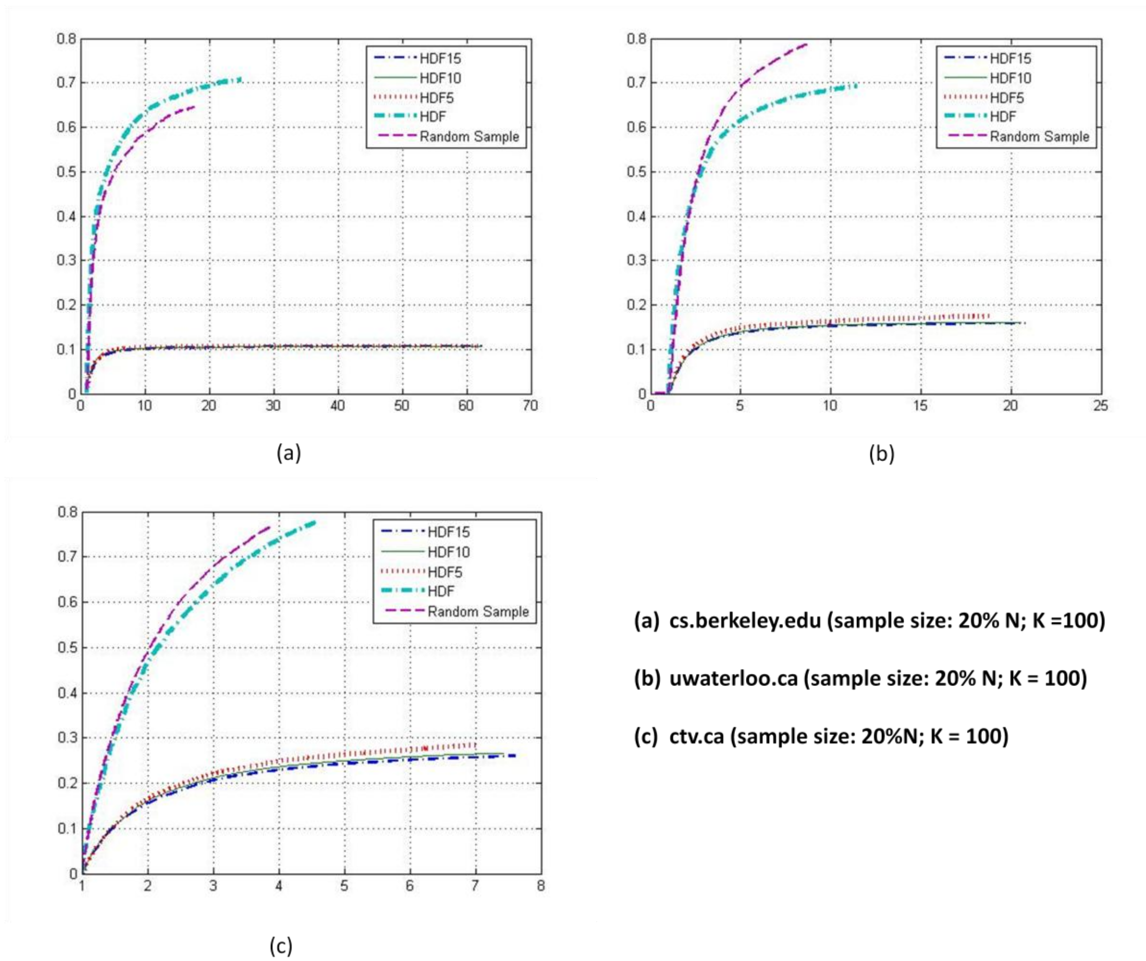


Figure 19: Comparison on Random Sample Terms and High DF Terms

In Figure 19, we can make the following observation: For HDF policy, the document frequency of queries are higher, the performance performs worse. In the Figure 19 (a), when ranking strength of the “cs.berkeley.edu” is weak, the performance of HDF approach beats Random Sample approach. However as ranking strength becomes stronger in the “uwaterloo.ca” and “ctv.ca”, the performance of HDF approach is even worse than the Random Sample approach. Those experiments prove HDF policy cannot achieve good performance for the ranking data sources.

CHAPTER VI

CONCLUSION AND FUTURE WORK

6.1 Conclusion

This thesis studies query selection problem so that our crawler efficiently accesses the content of deep web. To achieve this goal, we select the candidate queries from a sample database using set covering algorithms.

A conventional method for the set covering problem is the greedy algorithm. And the weighted greedy is a variation of the greedy by introducing query weight. Additionally, in order to focus on query selection problem, we access the deep web via web services. Most of these services set up a return limitation for the results. To increase the crawling performance, we developed DF-Weighted algorithm by introducing document frequency estimation based on the sample database.

We carry out our experiments on Bing web service and choose “cs.berkeley.edu”, “uwaterloo.ca”, and “ctv.ca” as the data sources. We choose HR and OR as the evaluation criteria. We evaluate four query selection policies: random queries from dictionary, greedy algorithm, weighted greedy algorithm, and df-weighted algorithm. Experimental evaluation shows:

- Weighted greedy algorithm outperforms the greedy algorithm in most experiments.
- The DF-Weighted algorithm achieves excellent performance in the strong ranking data sources.

- It is difficult for HDF policy to achieve good performance in the ranking data sources.

6.2 Future Work

The limit of the number of returns is a big challenge for crawling deep web. The limitation is stricter, it is more necessary to adopt a good query selection approach for a deep web crawler. The df-weighted algorithm achieves a surprising result in the experiments, but document frequency estimation method is indeed very naive. Beside independent maximum likelihood estimation method (our approach), some other approaches [14] [23] [19] [13] have been proposed. If we incorporate these estimation methods into the queries selection technique, we believe this should be helpful to achieve better performance.

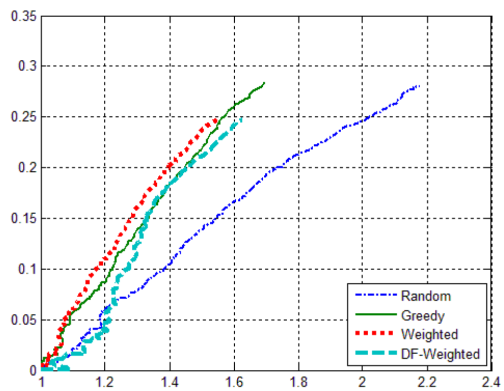
We also discover, when the size of data source is pretty large (e.g. >1 million) and the return limitation (e.g. 10) is very small, it is very hard to achieve a high HR. To solve this problem, the multiple keywords combination is a possible method. The main problem is how to combine a query with several keywords without exceed the return limitation and with low cost.

In this thesis, we only focus on the textual database. But how to select queries to download relational database is also interesting topic. For the relational database, html query form usually also provide multiple attributes interface. We can apply the same idea that we used to select promise query for each attribute by estimating the document frequency based sample database. Predicting the document frequency of the values of multiple attributes also should be a big challenge.

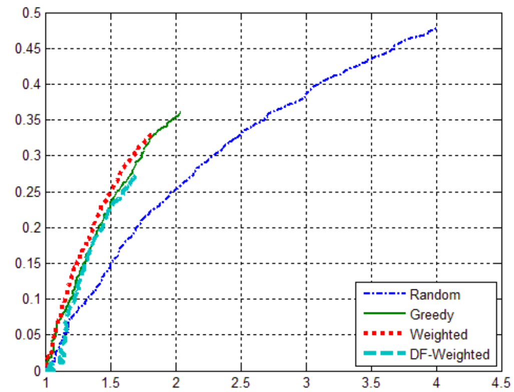
APPENDIX I

All Experimental Results of 27 Combinations:

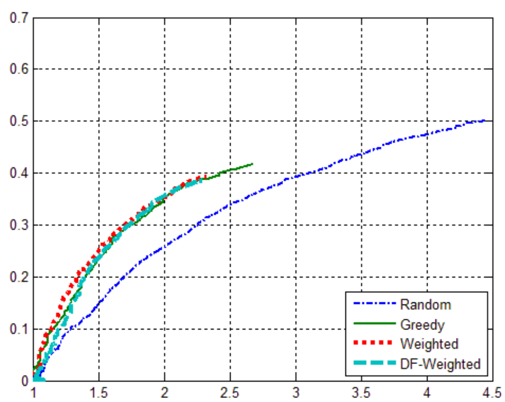
(a) cs.berkeley.edu Sample size = 5% Limitation = 100



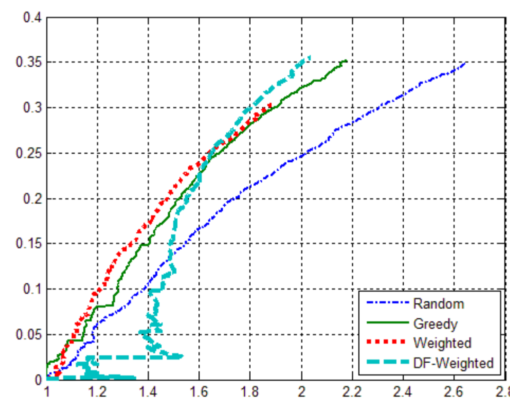
(b) cs.berkeley.edu Sample size = 5% Limitation = 200



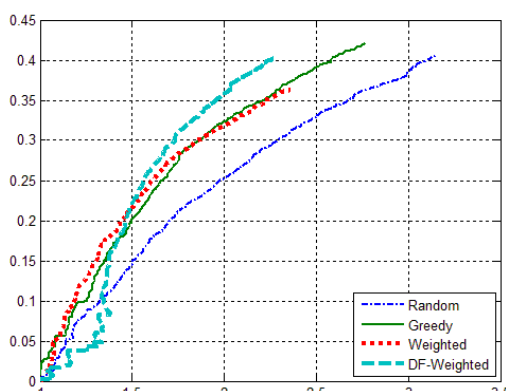
(c) cs.berkeley.edu Sample size = 5% Limitation = 1000



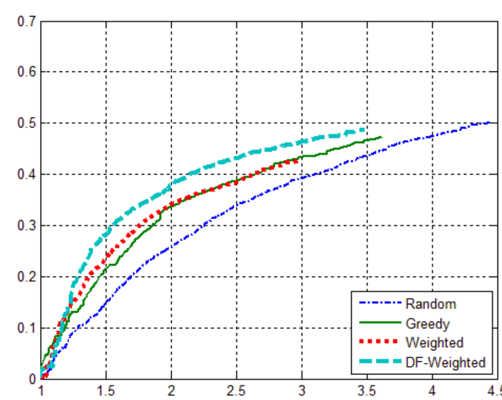
cs.berkeley.edu Sample size = 10% Limitation = 100



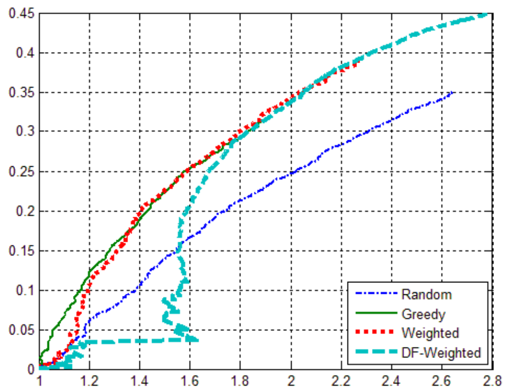
cs.berkeley.edu Sample size = 10% Limitation = 200



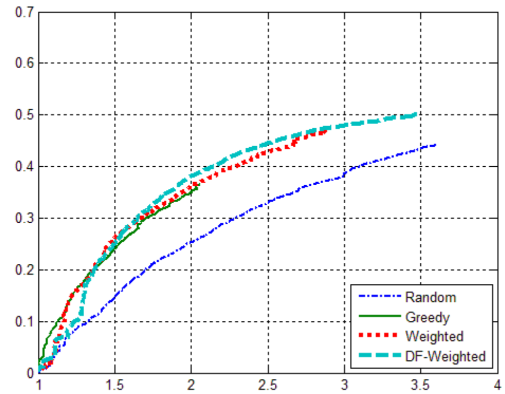
cs.berkeley.edu Sample size = 10% Limitation = 1000



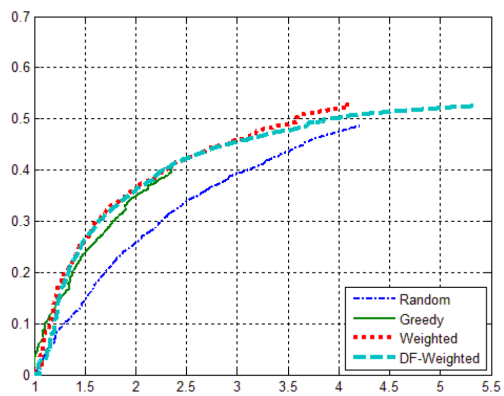
cs.berkeley.edu Sample size = 20% Limitation = 100



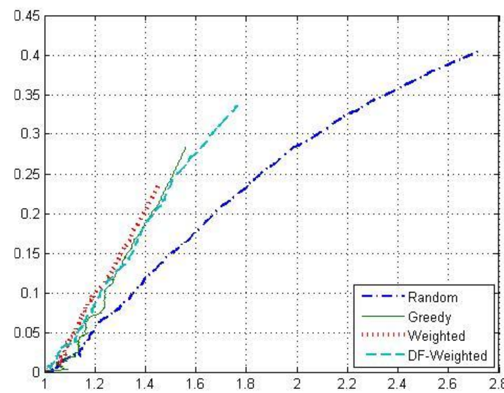
cs.berkeley.edu Sample size = 20% Limitation = 200



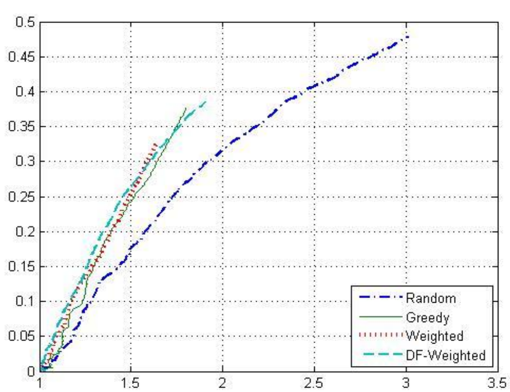
cs.berkeley.edu Sample size = 20% Limitation = 1000



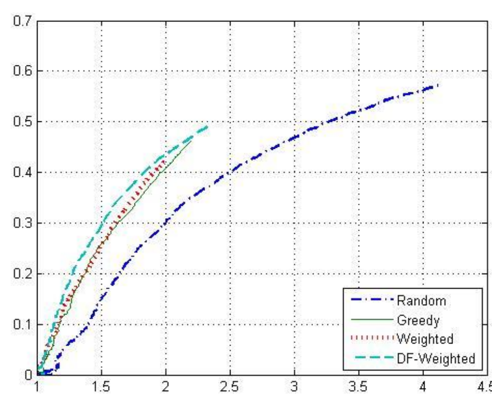
uwaterloo.ca Sample size = 5% Limitation = 100



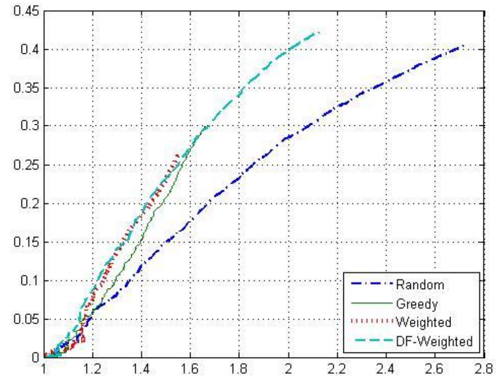
uwaterloo.ca Sample size = 5% Limitation = 200



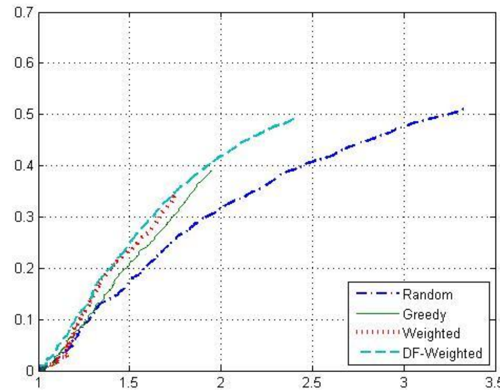
uwaterloo.ca Sample size = 5% Limitation = 1000



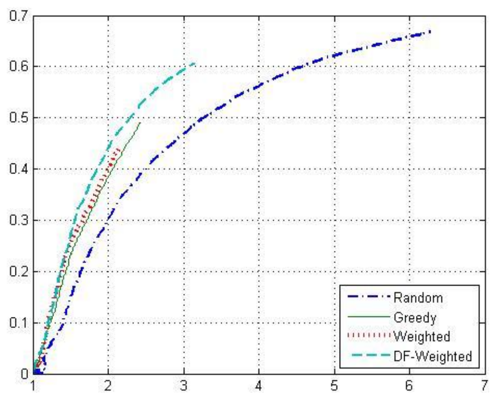
uwaterloo.ca Sample size = 10% Limitation = 100



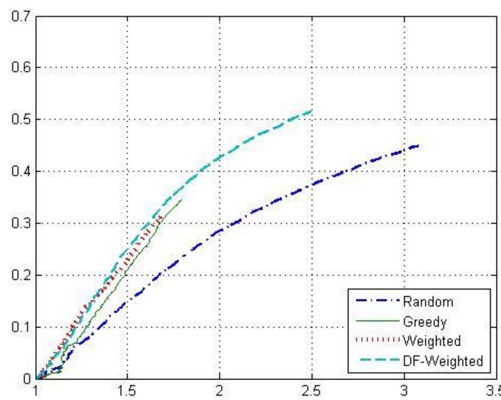
uwaterloo.ca Sample size = 10% Limitation = 200



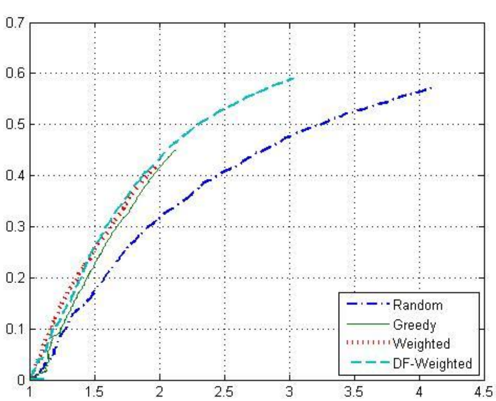
uwaterloo.ca Sample size = 10% Limitation = 1000



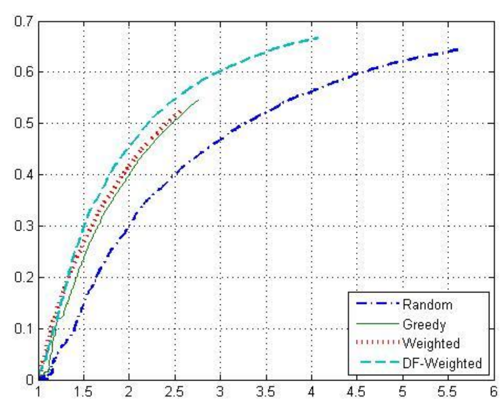
uwaterloo.ca Sample size = 20% Limitation = 100

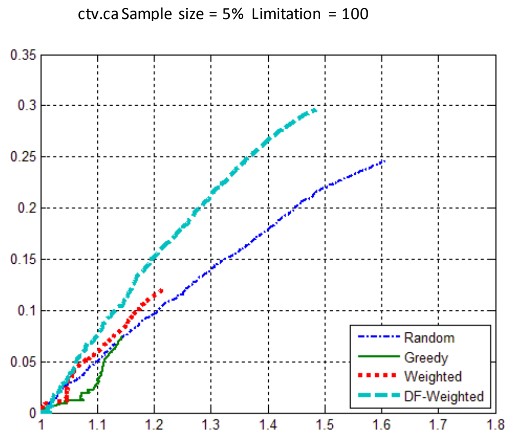


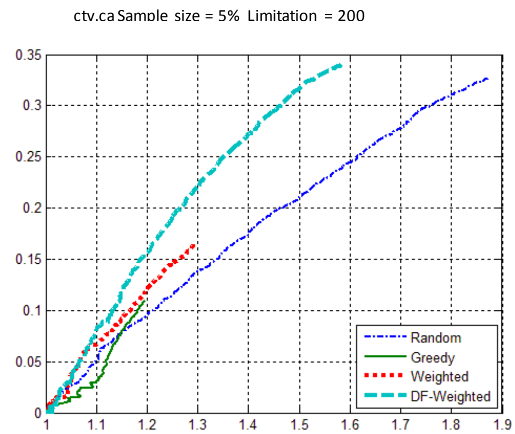
uwaterloo.ca Sample size = 20% Limitation = 200

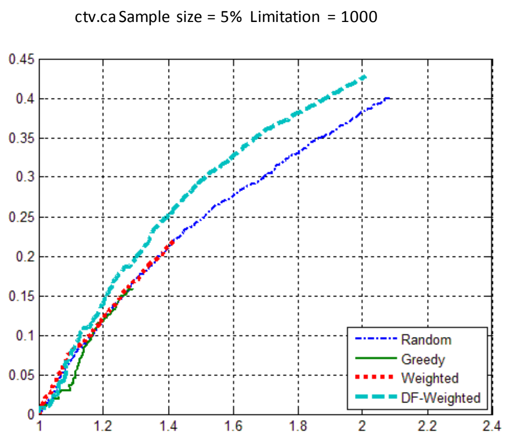


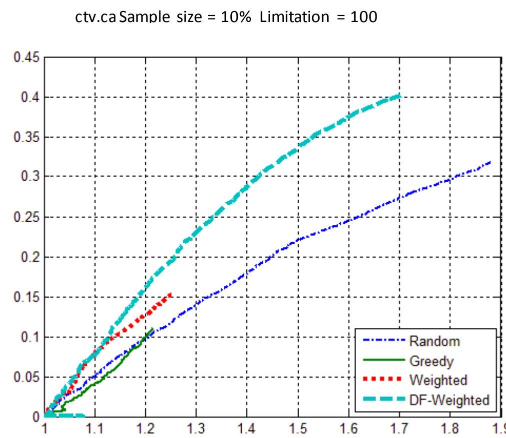
uwaterloo.ca Sample size = 20% Limitation = 1000

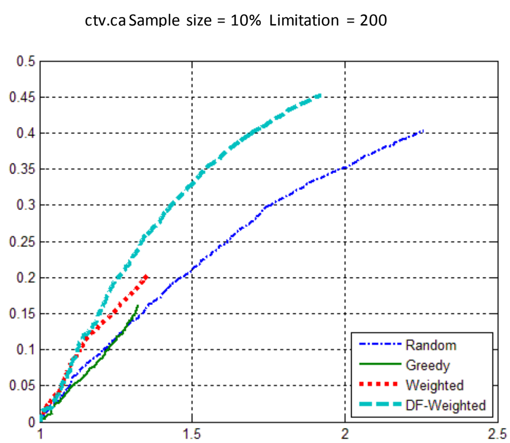


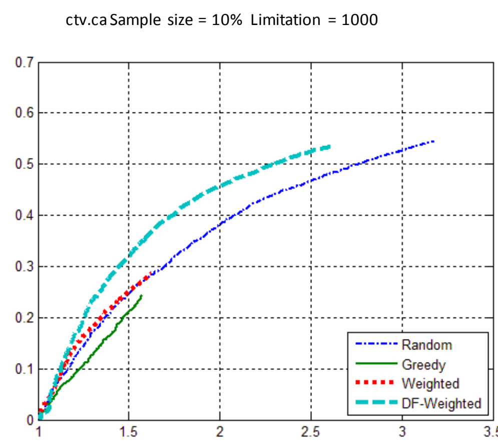

ctv.ca Sample size = 5% Limitation = 100
Random
Greedy
Weighted
DF-Weighted

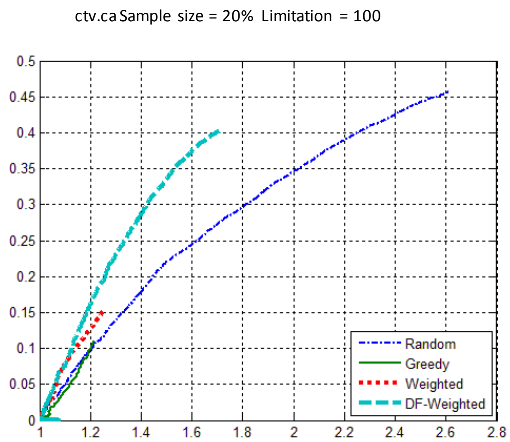

ctv.ca Sample size = 5% Limitation = 200
Random
Greedy
Weighted
DF-Weighted

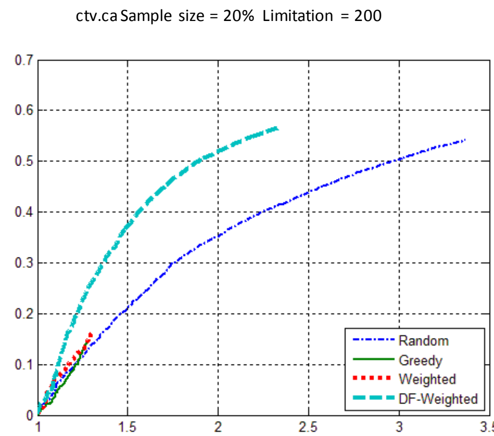

ctv.ca Sample size = 5% Limitation = 1000
Random
Greedy
Weighted
DF-Weighted

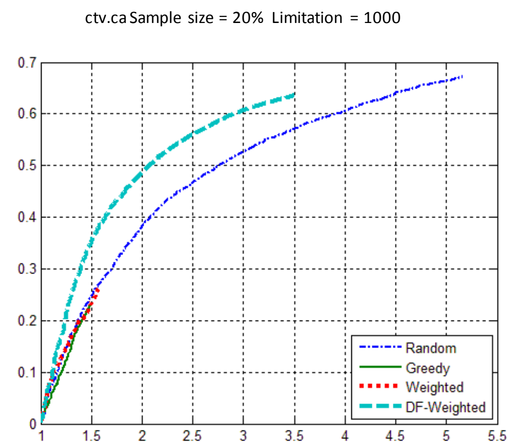

ctv.ca Sample size = 10% Limitation = 100
Random
Greedy
Weighted
DF-Weighted


ctv.ca Sample size = 10% Limitation = 200
Random
Greedy
Weighted
DF-Weighted


ctv.ca Sample size = 10% Limitation = 1000
Random
Greedy
Weighted
DF-Weighted


ctv.ca Sample size = 20% Limitation = 100
Random
Greedy
Weighted
DF-Weighted


ctv.ca Sample size = 20% Limitation = 200
Random
Greedy
Weighted
DF-Weighted


ctv.ca Sample size = 20% Limitation = 1000
Random
Greedy
Weighted
DF-Weighted

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