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REVIEW

Architecture of a Commercialized Search Engine Using Mobile Agents

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ABSTRACT

Shopping Search Engine (SSE) implies a unique challenge for validating distinct items available online in market place. For sellers, having a user finding relevant search results on top is very difficult. Buyers tend to click on and buy from the listings which appear first. Search engine optimization devotes that goal to influence such challenges. In current shopping search platforms, lots of irrelevant items retrieved from their indices; e.g. retrieving accessories of exact items rather than retrieving the items itself, regardless the price of item were considered or not. Also, users tend to move from shoppers to another searching for appropriate items where the time is crucial for consumers. In our proposal, we exploit the drawbacks of current shopping search engines, and the main goal of this research is to combine and merge multiple search results retrieved from some highly professional shopping sellers in the commercial market. Experimental results showed that our approach is more efficient and robust for retrieving a complete list of desired and relevant items with respect to all query space.

CCS CONCEPTS

Information systems - Commercial-specific retrieval

1. Introduction

Traditional information retrievals provide services to help users locate content on the World Wide Web (WWW). Most information retrievals assist most users to find generally accessible data, but others focus on particular data that are available privately. Users turn to search algorithms to find useful and high-relevant information. Shopper's information retrievals are different from general-purpose Web information retrievals if the user tends to search for commercial items. Unlike a traditional web archive, a marketplace such as eBay sees rapid change to that document collection, with approximately 20% of the collection changing every day. Also unlike a web archive, changes in the document collection must be propagated to the users immediately [10]. This superiority comes from the advantage of the structure of online product catalogues with clearly identified characteristics, such as price, description, and features. Similar to traditional information retrieval algorithms, shopping search algorithm is kept secret for dealing with idea of the algorithm. Recently, shopping searchers provide some valuable results that are simply beyond the algorithms of general searchers. However, it is fair to validate and assess quality of information since there are no quality standards or testing algorithms [13]. Retrieval algorithms vary in different models and there are few models to evaluate its quality. One of the drawbacks of current shopping engines is that they do not support users in finding the specific items

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respecting the desired properties in one-click. Alternatively, they allow buyers to use one keyword to describe the category that contains all items in the same properties. Therefore, the buyer tends to jump from category to category and from page to page in order to find the appropriate items or products. If buyers cannot find the relevant product in short period, they will go to another shopper to enhance their search. However, shopping searchers, as general web searchers, look for optimization in the commercialized websites using search models. Information in some economics literature assumed that search cost in some products has extremely reduced to zero since consumers are able to utilize professional search tools which are free of charge and easily to find and compare products on the Internet [14, 15]. Existing literature on buying search behaviour finds that using search tools to look for items versus its price dominates other search models [16]. Often, sellers focus on maximizing the traffic that comes via search engines to their searcher models. On the other hand, e-commerce is another business channel that developed and improved very fast; and consequently, the strategy has been improved numerous strong commercial organizations. Individual customer level has been rarely examined this is due to the use of the real-time persistent successful commerce [18]. However, due these difficulties, the obstacles are not merely affected the commercial searchers; but also the well-known classical or traditional searchers. The current general search engines, e.g. Google, MSN,.., etc. retrieve results from stores based on the indexed keywords or metadata meanwhile there is no substantial parameters, features, or arguments to rank them. In the commercial searchers, for example, each search agent ranks its results locally based on the available items stored in its index and there is no way to retrieve and compare the results available in other stores.

2. Our Overall Approach

As a solution to the mentioned constraints or obstacles, we aim in this approach to address it by merging results from different stores and index them in a real-time index using a herein proposed ranking algorithm. The index algorithm uses comparable strategy for filtering and ranking items. Our approach is programmed to give a model to commercialized sellers which aim to improve their products with high-level customer service. Making the matched items on the top of the list is the main goal of most product search models. We aimed to design a model that compromises and addresses the drawbacks of approaches and retrieves the desired items from industrial sellers by manipulating them as a stream of features. Manipulating the precise query string is the main challenge for industrial search engine. For instance, when a user queries a system by "*Camera Sony blue 400$*" or "*laptop hp core duo Red $900*", the commercial searchers allow short query string; e.g. "2 keywords" or even though they do not deal with the price. More concretely, recent shopping search results include several irrelevant items, such as the accessories that are not related to the specific item.

Our model uses some of major shopping services: "Walmart", "Amazon", "UsedOttawa", "eBay", "buy", "FUTURESHOP", "BESTBUY", "Zellers", "Shopping", "Overstock", and "Karmaloop" to manipulate with different kind of items. The proposed system uses a ranking schema showed by sorting and filtering for reordering the relevant items depending on the extracted parameters (adding taxes and shipping, and then ranking the final costs). Generally, shopping search engine, as general search engines, composites from four essential parts: crawling, indexing, searching, and presenting the results [24]. Figure 1 below shows the architecture of our system.

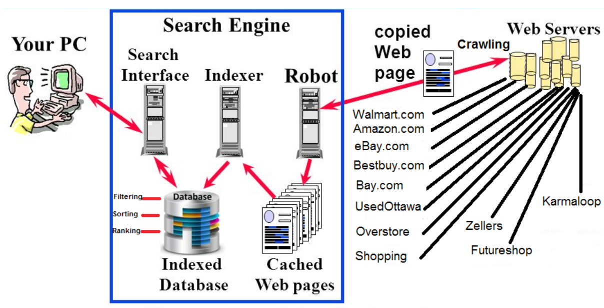

Figure 1. The Anatomy of Our Search Approach

2.1 Crawling the Collection

Generally, crawler or scraper is an algorithm that able to download web content by following hyper-links within these web pages to download the remote contents. The crawled contents can be in the same or in another domain. The scrapping continues and expires until reaching a particular depth e.g. no external links or the number of levels inside the link structure. Current search engines fail to index the content of shopping websites correctly due to the content mobility that change frequently every second. The Web is changing more and more and the content is dynamic by nature and include a lot of client-side and client-server interactivity [19]. We use our scratch algorithm for scrapping the specified shoppers as mentioned, in which we used "REST HTTP" to crawl our shopping sellers. The retrieved data was aggregated in an xml file for parsing.

2.2 Parsing the Data

Our system is designed to convenient to the user through

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using some features; such as selecting a specific seller, select all sellers, and there is no restriction in query length. As we mentioned, the proposal approach implies the eight largest Canadian shopping sellers. The users are able to select the all sellers in one step, or cancel any of them. The query field is corporate to receive the description of items from the user by defining them as a set of keywords. The query might involve full description to reduce the effect of ambiguity or the interference with other items that shared similar descriptions for different senses of the keywords. The description might start with the name of item, and then more precise description, e.g. the price, color, internal components, and so forth (e.g. “Laptop Dell Core Duo blue $700”). One of the basic reasons why the first term is referred to the name of item is that it uses for crawling and for connecting all shopping sellers. Means, the purpose of search each seller is to collect all pages and documents related to that item. The following are REST HTTP requests and regular expressions are used to scrap the corresponding sellers and to parsing the retrieval items:

Thereafter, attributes are extracted from each document by splitting the document into their items. Unfortunately, each seller has its own strategy that differs from others for storing the attributes in the documents; that means the documents in all sellers are unstructured. To overcome this difficulty, our algorithm used the prominent tags for extracting and parsing items. Filtering, sometimes called sifting, is used to filter out each document separately by discarding all items that did not match the user’s query keywords. Unfortunately, most search engine sellers merge all items related to specific keywords in the same category, e.g. “hp keyboard”, which means they merge “hp computers” with “hp accessories”. This also means, search engines were not able to distinguish between ‘hp’ as a singular word or as part of another word; all the parts in the same category were combined in one step. Hence, we used filtering algorithm to discard all irrelevant accessories and items from the final list. Price attribute is used to filtering out all items that imply price more than that queried by a user, e.g., “Toyota white Camry $10000” means discard all items that are not satisfy that properties. Some filters were applied depending on the items and the query string, such as: color, type, size, sex, model, and so forth. The system recommended users to querying the system using a price rather than without a price. Often, our algorithm uses a function that successfully applies to all items in order to filter the accessories related to the specified price. If the user does not specify the price, the result probably returns some related accessories (2%) if they existed in that category. Thereafter, all resulted items are stored in vector space in an XML file to merge them with the other results from other sellers. Sorting is used to reorder all items by users preferences e.g. “price”; in which, the list of items is ordered from the highest price to the desired price up to the cheapest item. The final result is presented to the user includes the full matching items that satisfy to the user’s query.

2.3 Filtering the Results

Reducing the relevant results in the searching list is the second challenge in all product sellers. Developing reliable filtering services for concerning some issues is a serious and challenging problem [21]. Often, agents in commercial shoppers use criteria that are relevant to users by viewing only the product that exploited the goal of that algorithm. For instance, in price metric, users may pick products exclusively under $100 by excluding all products over that price. Due to the historically poor of search results, users often browse many sellers to find a desired product (In some cases, users turn some search functions only if they cannot locate what they seeking). Often, filtering is very important for users who have little knowledge about the product. Filtering is more useful when there are many different arguments involved to a product. Shoppers often use a tool to persuade and influence a purchaser using a global filtering tool for their range of watches. Commercial product listings augment common filtering features, e.g. 'price', to enforce many users by their familiar tools. Moreover, they use other more concise filters, e.g. ‘Color’; ‘Class’, ‘Sex’, or ‘Age’. Some shopping searchers use filtering to classify items into classes or categories, e.g. “Electronics”, “Books”, “Arts”, etc. However, we compromised our search approach to use filtering attribute.

2.4 Sorting the Results

Sorting the results according to some properties is also important for all product search engines.

Sorting algorithm takes Web page content and creates keywords searching that enable online users to find pages they're looking for [20, 21]. Changing the relevancy of any item listing where the users can impose which strategy they want the items to be involved. For example, in “price”, users prefer to list the items based on price from low to high. Moving items with a certain feature on the top of page will help users who are not sure what they looking for. Reducing number of items in the product listing and moving some items from place to place is the main strategy for most information retrieval algorithms. The “eBay” and “Amazon” shoppers, for instance, pro-

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vide many criterions to sort search items, such as “sort by price” to sort in ranged amount (e.g., from $ to $) or by size (e.g., from inch to inch). Consumers, in somehow, find it is helpful when using sorting parameters, e.g. 'Bestselling', 'Publication date' or 'Average Customer Review'. Some shopping search engines do not scale well to support users for sorting the resulted items; hence, they mix the items without paying attention to the users’ needs. This leads to some effort needed to find specific items.

3. Query Processing

A more complex mining task is that of determining user intent rather than simply disambiguating the query string [10]. Most information retrieval algorithms use queries made up of a few keywords or short phrases. Other non-textual searchers allow users to impose queries in more exotic forms, e.g. hummed tunes or pictures. In whichever form, user tends to provide search algorithm with some feature to reduce the amount of possible items. Approximation of the user’s intentions in typical queries is another problem needs to be addressed. Due to some words in a query have many synonyms, query may forward to different possibilities, even within one category. Furthermore, the users may not have good attention of what they are looking for. With these realistic challenges, we assume a scalable product technique with high efficient resources which uses support vector machine to compute the similarity between the results of seller vector and the user’s vector. First, the items were classified into the correct level to significantly normalize on the search volume. Secondly, a vector similarity computation with weighting technique proposed by [12], and finally, the process ends with a ranking based on some criterions (brand, color, price, etc.) to ensure the ranked similar items located not just based on a particular class or category; but also, across similar aspects. The term in vector space W is defined as follows:

If item k does not exist in document $d_i \rightarrow w_{ik}=zero$, if item k exists in document $d_i \rightarrow w_{ik} > zero$ (w_{ik} denotes the weight of a term k in document d_i). The coefficient similarity between d_i and d_j is defined as follows:

$$Ssimilarity\left(d_i, q_j\right) = \frac{\sum_{k=1}^{n} w_{ik} w_{jk}}{|d_i||q_j|} \wedge |P_{qj}| \quad (1)$$

Where d_i and q_j are the weighted values and $|d_i|$ is the length of the document’s vector d_i, P is the mean value of price (greater than “0” and less than or equal to “p”).

4. Experimental Evaluation

In terms of evaluation, we aim to meet the user’s requirements and results must fit the commercial conditions for comparing different prices available for similar items in different stores. Often, public sellers are put their relevancy in a global domain and impose independent users to perform the judgments. Human relevance judgment is popular for evaluating the sellers in market [23]. In this section, we will do our judgment with crowdsourcing and we will discuss our experimental results obtained from sellers. When we have retrieved tens of results for each query, and we have completed judging hundreds of queries, we are able to compute the metrics and make comparisons between seller’s algorithms. Information retrieval algorithms usually use F-measure, precision, recall, and NDCG (Normalized Discounted Cumulative Gain) for computing the accuracy of results [24]. They are mouthful, but they are realistic-sense measures. More contrast, assuming that four-point scores, we assign “zero” for irrelevant items, “one” for partially relevant, “two” for relevant, and “three” for high relevant. Considering that a query is judged by a particular value, and the first four results that the searcher returns are evaluated as relevant, irrelevant, high relevant, and relevant. The cumulative gain is summed as “7” score. That means, the results are evaluated gradually based on the proposed ranked relevancy. More concretely, researchers showed that the goal of search engines is to return high relevant results at the top of the first page. The Discounted Gain issues this assessment consideration, which means, if the 3rd result is “high relevant”, the rank is first. But, when the 1st result is “relevant”, the rank is “third”. However, the final rank after four points is (3.5= 2 / 1 + 0 / 2 + 3 / 3 + 2 / 4). The DCG at a particular rank position p is defined as:

$$DCG_p = \sum_{i=1}^{p} \frac{rel_i}{\log_2(i+1)} \quad (2)$$

The average performance of ranking algorithm can be obtained by the *Normalized DCG* (*nDCG*) values for all queries; that is, a perfect ranking can be produced 1.0 and other values can be rounded on the interval between 0.0 and 1.0 cross-query comparable.

Table 1 shows the ranking of 20 queries run in all shoppers concurrently. The results showed the Cumulative Gain values to represent the accuracy of relevant items. The result of each seller is very important for comprising and for influencing the users to create their preference. All sellers discarded the attribute “price” in the query if it is implied. All results are higher and lower than the queried price; whereas results in our approach respect all query attributes, e.g. price, color, type... etc. The left value denotes the number of irrelevant items retrieved incorrectly; whilst the value on the right-side represents the total number

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of retrieved items (relevant plus irrelevant). Some fields were empty because there were not results returned by a seller for those queries, or sellers were not able to process a stream of keywords in the query field.

Table 1. The Accuracy of Twenty Queries Run in 11 Shoppers

Query	Amazon	Wal-Mart	eBay	Buy	Used Ottawa	Best Buy
Laptop dell $900	16/159	33/44	7/15	48/50	0/4	0/15
Camera Sony blue LCD $300	2/12	0/3	3/10	4/5	--	13/13
Chair blue $200	21/46	8/48	27/51	28/50	--	1/1
Toyota Camry 10000$			87/300	17/17	11/50	
Shoes women $160	10/47	14/48	24/78	6/46	--	4/4
Printer HP laser $250	½	14/15	7/7	32/50	--	0/4
Book Ecom-merce new $80	17/36	48/48	11/33	1/1	--	11/11
Transport medical chair	35/120	27/27	0/59	2/2	--	16/16
Shirt short girl	46/48	14/37	4/50	2/10	--	5/5
Laptop HP core duo 900$	3/3	17/52	17/52	39/41		0/2
Table wood half-moon $200	29/51	0/1	11/29	12/14	2/2	10/10
Hat newsboy black wool	2/2	--	8/8	12/23	--	27/27
Tricycle red $50	10/11	0/4	9/80	1/9	4/17	20/20
Toyota tire $500	15/16	48/48	17/21	1/1	19/25	3/3
Coat gray 150$	29/31	33/33	14/50	28/28	--	12/12
Drill hammer 50$~75$	7/16	46/48	15/41	43/50	--	26/26
Washer dryer $700	8/16	10/11	1/17	6/17	3/6	14/14
GPS $200	13/72	22/48	12/50	28/50	14/25	8/11
Coat women wool gray 100$	8/15	--	9/50	--	--	13/13
Stroller safari double jog-ging 200$	1/5	0/5	2/50	0/6	--	14/14
Average Error Rate	273/708 38.5%	334/520 64.2%	285/1051 27.1%	310/470 65.9%	53/129 41%	197/206 95.6%

Query	Overstore	Shopping	Kar-maloop	Zellers	Future Shop	SAMA
Laptop dell $900	16/159	14/47	48/48	--	0/2	0/43
Camera Sony blue LCD $300	2/12	2/3	48/48	--	3/3	0/6
Chair blue $200	21/46	37/96	48/48	--	0/1	4/76
Toyota Camry 10000$	2/2	40/40	48/48	--	1/1	0/32
Shoes women $160	10/47	11/48	24/78	--	15/15	0/97
Printer HP laser $250	1/2	48/48	7/7	--	0/2	1/107
Book Ecom-merce new $80	17/36	48/48	11/33	--	15/15	0/2
Transport medical chair	35/120	27/27	4/4	--	15/15	0/27
Shirt short girl	46/48	14/37		7/19	15/15	1/54
Laptop HP core duo 900$	3/3	17/52	40/40	--	0/1	1/23
Table wood half-moon $200	29/51	2/40	40/40	--	15/15	1/17
Hat newsboy black wool	2/2	0/40	0/1	--	15/15	0/64
Tricycle red $50	10/11	21/40	40/40	--	15/15	7/22
Toyota tire $500	10/10	28/40	2/2	--	15/15	0/11
Coat gray 150$	29/31	17/40	2/18	--	15/15	7/34
Drill hammer	3/5	7/40	6/6	--	15/15	0/59
Washer dryer $700	40/41	7/40	--	--	15/15	3/33
GPS $200	13/72	11/48	--	--	2/15	10/140
Coat women wool gray 100$	8/15	1/40	5/6	--	15/15	0/13
Stroller safari double jogging 200$	1/5	0/5	40/40	--	15/15	0/22
Average Error Rate Accuracy	298/718 41.5%	352/779 45.1%	413/507 81.4%	7/19 36.8%	201/220 91.3%	35/882 3.9 %

As stated in the table, the attribute "price" were not processed correctly and discarded by all sellers. According to our evaluation based on the average error rate mentioned by Cumulative Gain metric, "ebay.com" seller was ranked first due to it has a lower error rate "27.1%". Moreover, globally, it was categorized as a major seller [1]. Likewise, "futureshop.ca" has a highest error rate, showing that the seller was not able to influence their users on their query search and probably the reason why the seller shut down later. Finally, the error rate for our system was "3.9%", that means the precision value for our search model is "96.1%". Although, merging results process is more complicated than individual results process, our model improved the results and currently functioned along with the engineering reasons for working in this way. Figures 2 and 3 showed our experimental results in a different period of time using two metrics.

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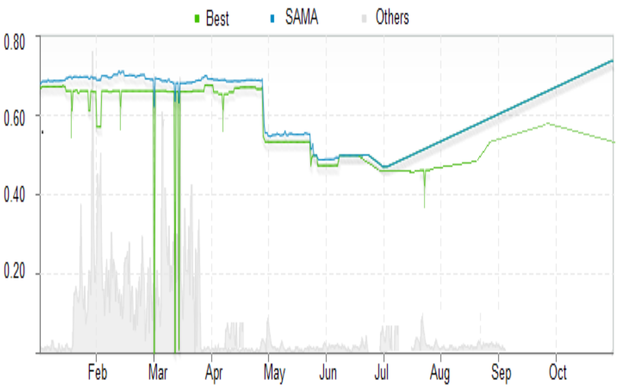

Figure 2. Discounted Cumulative Gain in a Different Period of Time

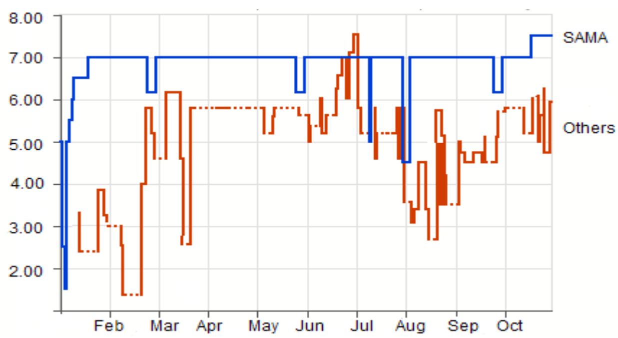

Figure 3. Average Precision in Different Periods of Time

5. Experimental Running

Several shopping search engines are available publically [4]. Our shopping approach was designed to generalize the information of items, including a screen shot of item, title, price in the desired range, and full description of items (snippets). If the user clicks on the desired item, he/she will transform to the actual item available in that seller. Many features involved in our approach; that is, a user is able to navigate in the frontend using forward and backward. The following figures 4, 5, and 6 represent our visual search system for running three query strings and the corresponding results:

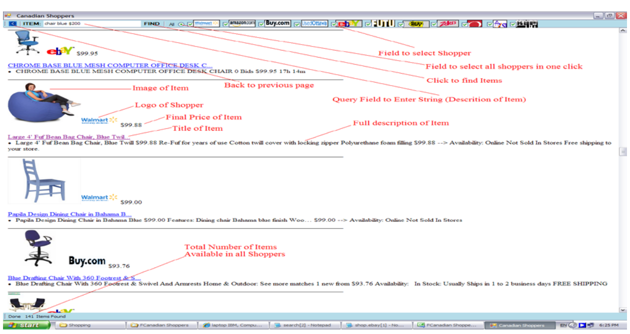

Figure 4. Our Searching Results for a Query "Chair Blue $200"

Figure 5. Our Searching Results for a Query "Laptop Dell Core $800"

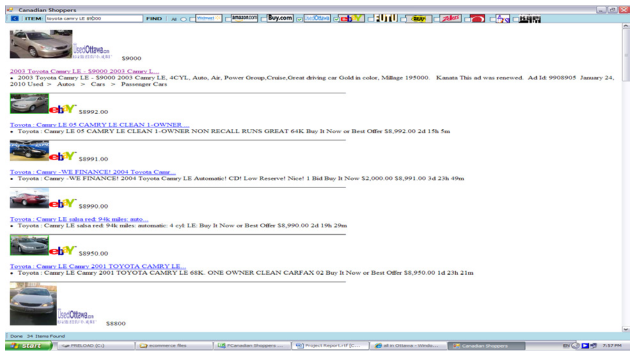

Figure 6: Our Searching Results for a Query "TOYOTA Camry LE $8000"

Figure 7 shows the output of running a query "*Laptop Dell Core $800*" at "ebay.com" to represent a top seller. The resulting list includes different items with all non-relevant accessories, e.g. items: memories, chargers, bags… etc. and prices lower and higher than the queried price.

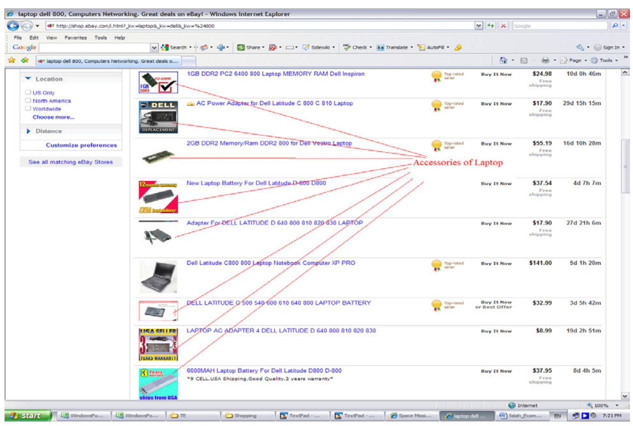

Figure 7. The Visual Search for a Query "*Laptop Dell Core $800*" Runs at Ebay.com Website

6. Related Works

Online commercialized product recommendations have been explored by several traditional models. For instance, the "Yoda" approach combined parametric filtering with

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content-based query for satisfying product recommendations [12]. Genetic algorithms have been used for fast online recommendation models by combining data from user navigation patterns. For instance, Online Purchase Environment system (HOPE) is a helpful model used data mining to generate suggestions for predicating both the user's query and the content of items [9]. Tagged fields with products were used to organize them into a hierarchical structure, and then, a nearest neighbour algorithm was used to find related products using customers purchased history. Lots of anthologies were used to build smarter seller models. The most successful models of anthologies were able to map a query into a more realistic form using domain-specific terminology. This will transform unstructured query into a more productive structured one that returns more relevant results [8]. In content-based information retrieval models, anthologies have been used to increase the relevancy and the performance of the retrieved results. An anthologist relatively novel application helped the interaction between the product space and the query space [7]. Other researchers were proposed that using linguistic anthologies in productive models has been found to be more effective in Web-based retrieval [6]. Initially, the components were firstly encoded into a wordy-sense lexical semantic graph. Another study [5] showed that significant influence factors on store satisfaction have little in common with others that impel shoppers to remain loyal to one store. Image based Search Engine is another platform proposed to deal with images from the large database for online shopping specially for fashion shopping. Researches [17] showed that their model helps user in finding the object/material available on online shopping sites. They showed things/objects/materials that were highly related to a non-textual-query by reducing the space accuracy.

7. Conclusion

In this contribution, we outline the architecture of our shopping searcher model which is a part of SAMA search engine[1, 2]. Our approach built from scratch to overcome the problem of traditional seller search engines. Based on the information collected from a small sample of other study, the best elements of ecommerce do not guarantee that consumers will visit a particular seller or remain loyal. The well-established sellers; e.g. “Amazon” and “eBay” are already invested significant resources to understand what consumers need and desire. It might be useful to emulate these established sellers since they have been and continue to be highly successful as they obtain high marks for customer satisfaction.

According to the Net Smart survey, the most reason why users tend to use Internet shoppers on Web is the convenience, saving money, and saving time. Regarding these reasons, online shopping must employ more efficient tools for helping users to get what they needs. In our study, we can also conclude that all selected sellers process their items but with the common drawbacks summarized as: First, the same items are available in different sellers; consequently make users to navigate from seller to another looking for suitable attributes of items e.g. “price”, “color”, “type”, etc. Second: Sellers are conflict to isolate the accessories from the actual items. Third: Filtering and sorting are weak for most sellers. However, our approach is not merely merge items retrieved from several stores; but rather, it merges, filters, and reranks items using some features mentioned previously in this proposed article.

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