Available online at www.elixirpublishers.com (Elixir International Journal)

Computer Science and Engineering

Elixir Comp. Sci. & Engg. 66 (2014) 20784-20787

Awakening to reality

Elixir ISSN: 2229-712X

A survey on effective webmining algorithms

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ARTICLE INFO

Article history:
Received: 21 May 2013;
Received in revised form:
19 December 2013;
Accepted: 18 January 2014;

Keywords
HITS, Page Rank,
Weighted Pagerank,
Topic Sensitive Pagerank algorithm.

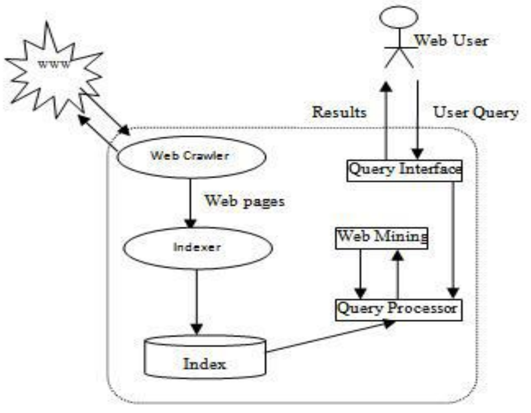
ABSTRACT

This paper presents three algorithms and one proposed algorithm to find relevant pages for a given Web page (URL). The first algorithm comes from the Pagerank analysis of the Web pages. It is intuitive and easy to implement. The second one takes advantage of HITS to identify relevant pages more precisely and effectively. The third one shows the advantages and limitations of Weighted Pagerank algorithm and the final proposed algorithm based on Topic Sensitive Pagerank algorithm. These algorithms could be used for various Web applications, such as enhancing Web search. The ideas and techniques in this work would be helpful to other Web-related researches.

Introduction

In general, the World Wide Web (www) is a system of interlinked hypertext documents [1]. WWW provides an architectural framework for accessing linked documents spread out over millions of machines all over the Internet [2]. Retrieving useful information from the vast sea of data on World Wide Web has been one of the most challenging tasks. Web search engines have surfaced as a useful technique that helps in searching for useful information on the World Wide Web using search strings provided by the user. The search results of a search engine are generally presented as a list often referred to as search engine results pages (SERPs). To locate any information from the web, the user accesses his favorite search engine, issues queries and clicks on the returned pages [3]. The search results returned by a search engines are a mixture of large amount of relevant and irrelevant information [4]. Any user cannot read all web pages returned in response to the user's query. Hence, search engines help users trace relevant pages worth considering by displaying the resultant pages in a ranked order using different page rank algorithms [4]. Web-page ranking is a search-engine optimization technique used by search engines for ranking hundred thousands of web pages in a relative order of importance. Conventional search engine technology can be broadly classified into two main categories of search engines: the crawler based engine and the human-powered directories based engine [5]. A human-powered directory, for instance the Open Directory depends on humans for its listings [6]. The web pages in such a setting are stored in different directories on the basis of their category. When a query is fired, it is categorized first and then the appropriate directory is searched to locate the web page. They are constructed when the owner of a website submits the site for a review along with a short description of the site [3]. A search is generally based on the matches only in the descriptions submitted.

Crawler-based search engines, for instance Google, create their listings automatically [6]. They "crawl" or "spider" the web, to search for pages matching user requests. Once they generate result sets, people can navigate through the results. Crawler-based search engines retrieve contents of web pages using indexers [6]. Indexers are used to store and index information regarding retrieved pages. The Ranker determines the importance of web pages returned and the Retrieval Engine performs lookups on index tables. The web page ranking algorithms play their role at the last component [7]. Exactly what information the user wants is unpredictable. So the web page ranking algorithms are designed to anticipate the user requirements from various static (e.g., number of hyperlinks, textual content) and dynamic (e.g., popularity) features [7]. They are important factors for making one search engine better than another [7]. Web search ranking algorithms play an important role in ranking web pages so that the user could get the good result which is more relevant to the user's query [8]. The following figure illustrates the working of a typical search engine, which shows the flow graph for a searched query by a web user.



Web Search Engine

In this paper, we introduce and discuss various algorithms and techniques that we developed for web community mining and analysis.

Page Rank Algorithm

Page Rank algorithm is the most commonly used algorithm for ranking the various pages. Working of the Page Rank algorithm depends upon link structure of the web pages. The Page Rank algorithm is based on the concepts that if a page contains important links towards it then the links of this page towards the other page are also to be considered as important pages. The Page

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Rank considers the back link in deciding the rank score. If the addition of the all the ranks of the back links is large then the page then it is provided a large rank [9][10][11][12]. A simplified version of PageRank is given by:

$$PR(u) = \sum_{v\in B_u} \frac{PR(v)}{L(v)},$$

Where the PageRank value for a web page u is dependent on the PageRank values for each web page v out of the set Bu (this set contains all pages linking to web page u), divided by the number L(v) of links from page v. An example of back link is shown in Figure 1.1 below. U is the back link of V & W and V & W are the back links of X.

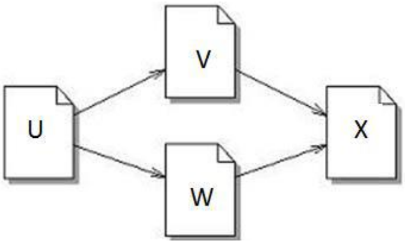

Figure 1.1: Illustration of back links

Hits Algorithm

HITS algorithm ranks the web page by processing in links and out links of the web pages. In this algorithm a web page is named as authority if the web page is pointed by many hyper links and a web page is named as HUB if the page point to various hyperlinks. An Illustration of HUB and authority are shown in Figure 2.1.

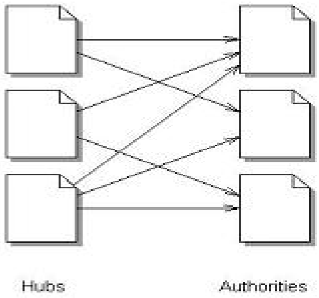

Figure 2.1: Illustration of Hub and Authorities

HITS is technically, a link based algorithm. In HITS [13] algorithm, ranking of the web page is decided by analyzing their textual contents against a given query. After collection of the web pages, the HITS algorithm concentrates on the structure of the web only, neglecting their textual contents. Original HITS algorithm has some problems which are given below.

(i) High rank value is given to some popular website that is not highly relevant to the given query.

(ii) Drift of the topic occurs when the hub has multiple topics as equivalent weights are given to all of the outlinks of a hub page. Figure 2.2 shows an Illustration of HITS process.

To minimize the problem of the original HITS algorithm, a clever algorithm is proposed by reference [10]. Clever algorithm is the modification of standard original HITS algorithm.

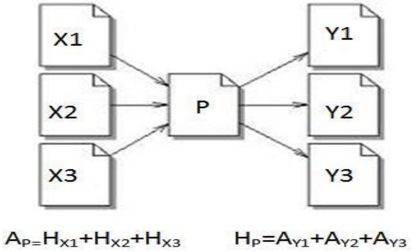

Figure 2.2: Illustration of HITS process

This algorithm provides a weight value to every link depending on the terms of queries and endpoints of the link. An anchor tag is combined to decide the weights to the link and a large hub is broken down into smaller parts so that every hub page is concentrated only on one topic. Another limitation of standard HITS algorithm is that it assumes equal weights to all the links pointing to a webpage and it fails to identify the facts that some links may be more important than the other. To resolve this problem, a probabilistic analogue of the HITS (PHITS) algorithm is proposed by reference [14]. A probabilistic explanation of relationship of term document is provided by PHITS. It is able to identify authoritative document as claimed by the author. PHITS gives better results as compared to original HITS algorithm. Other difference between PHITS and standard HITS is that PHITS can estimate the probabilities of authorities compared to standard HITS algorithm, which can provide only the scalar magnitude of authority [9].

Weighted Page Rank Algorithm

Weighted Page Rank [9] Algorithm is proposed by Wenpu Xing and Ali Ghorbani. Weighted page rank algorithm (WPR) is the modification of the original page rank algorithm. WPR decides the rank score based on the popularity of the pages by taking into consideration the importance of both the in-links and out-links of the pages. This algorithm provides high value of rank to the more popular pages and does not equally divide the rank of a page among it’s out-link pages. Every out-link page is given a rank value based on its popularity. Popularity of a page is decided by observing its number of in links and out links. Simulation of WPR is done using the Website of Saint Thomas University and simulation results show that WPR algorithm finds larger number of relevant pages compared to standard page rank algorithm. As suggested by the author, the performance of WPR is to be tested by using different websites and future work include to calculate the rank score by utilizing more than one level of reference page list and increasing the number of human user to classify the web pages.

Topic Sensitive Pagerank

In Topic Sensitive PageRank, several scores are computed: multiple importance scores for each page under several topics that form a composite PageRank score for those pages matching the query. During the offline crawling process, 16 topic-sensitive PageRank vectors are generated, using as a guideline the top-level category from Open Directory Project (ODP). At query time, the similarity of the query is compared to each of these vectors or topics; and subsequently, instead of using a single global ranking vector, the linear combination of the topic-sensitive vectors is weighed using the similarity of the query to the topics. This method yields a very accurate set of results relevant to the context of the particular query.

Proposed Methodology

Our technique Topic sensitive weighted page rank makes use of a subset of the ODP category structure that is associated with individual information needs. This subset is processed locally, aiming at enhancing generic results offered by search engines. Processing entails introducing importance weights to those parts of the ODP structure that correspond to user-specific preferences. The results of local processing are subsequently combined with global knowledge to derive an aggregate ranking of web results. In the following subsection we describe in more detail the theoretical model used and the algorithmic steps deployed.

A. *Background*

Our proposed techniques is the following. Consider an arbitrary search engine uses a graphs structure G(V,E) of categories, in order to categorize web pages. Graph G consists of nodes $v \in V$ that denote categories and every edge $vi, \in E$ denotes that vj is a subcategory of vi and is assigned a weight$d(vivj \in$ 0,1). It assumed that every web page is tagged with a specific category. Overall, the proposed approach introduces the idea of incrementally selecting subgraph $Gsub$ of G. This subgraph can be constructed according to set of some basic topic choosen from ODP. In the extreme case $Gsub \equiv G$. Every category v of G'will be assigned a relevance-importance weight $\beta\ v$ >0. These weights are used in order to categorize pages returned to the end user, when posing a query. In particular, the position (rank) of a page pin the result-set of an arbitrary user query will be given by a function of the form: $\emptyset(\beta\ \gamma\ p\ ,\sigma\ p$)). In the above function, (p) is the category that a page p belongs to, (p)) is the relevance-importance accordingto the ranking algorithm of the engine, and function ∅() indicates how the final ranking will be biased towards machine ranking or category importance defined (for example, $\emptyset\ \propto,\beta$ $=(\alpha+\beta)/2$). In general, we have introduced the function ∅() that combines search engine ranking and our proposed ranking techniques in order to provide better scalability of our solution's.

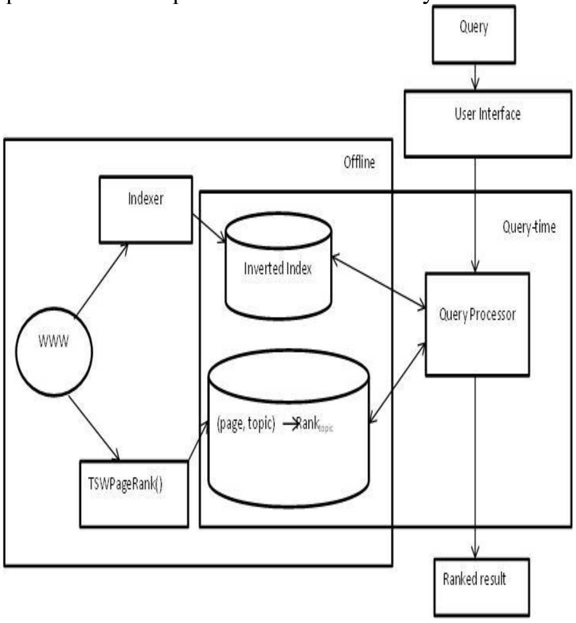

Figure 5.1 Proposed System Architecture

B. *Offline Methodology Roadmap*

In our approach, the first step is to generate a biased weighted pagerank vectors using a set of some basis topics. This step is the pre-processing step of the web crawler. This step is performed offline. We select these topics from freely available Open Directory Project as dmoz.

Let Tj be the set of URLs in the ODP category cj . Then we will computes the Weighted PageRank vector vj for topic cj where

$$vji = \begin{cases} \dfrac{1}{|\mathrm{Tj}|} & \mathrm{i} \in \mathrm{Tj} \\ 0, & \mathrm{i} \notin \mathrm{Tj} \end{cases}$$

The Weighted PageRank vector for topic cj is given WPR (α,) where α is bias factor.

We also computes the some class term vectors Dj consisteing of the term in document below each of the top-level categories.

C. *Compute Importance Score At Query Time*

The second step of our approach will be performed at the time of query. User will provide a query q, let q' be the context of q. In other words, if the query was issued by highlighting the term q in some Web page u, then q' consists of the terms in u. alternatively, we could use only those terms in u nearby the highlighted term, as often times a single Web page may discuss a variety of topics. For ordinary queries not done in context, let q' = q. Using a unigram language model, with parameters set to their maximum-likelihood estimates, we compute the class probabilities for each of the 16 top-level ODP classes, conditioned on q'. Let q' be the i th term in the query (or query context) q'. Then given the query q, we compute for each cj the following:

$$P\ cj/q' = P\ cj\ \frac{.P(q'/cj)\ \propto P\ }{P(q')} cj.\ \pi\ \ (qi'/cj)$$

$((qi')/cj)$ is easily computed from the class term-vector Dj . The quantity (cj) is not as straight forward. We chose to make it uniform, although we could personalize the query results for different users by varying this distribution. In other words, for some user k, we can use a prior distribution Pk(cj) that reflects the interests of user k. Using a text index, we retrieve URLs for all documents containing the original query terms q. Finally, we compute the query-sensitive importance score of each of these retrieved URLs as follows.

Let $rankjd$ be the rank of document d given by the rank vector WPR (α, j) (i.e., the rank vector for topic c). For the Web document d, we compute the query-sensitive importance score sqd as follows.

$$sqd = \sum P\ (cj/q')\ .rank_{jd}$$

The results are ranked according to this composite scoresqd. The above query-sensitive Weighted PageRank computation has the following probabilistic interpretation, in terms of the "random surfer" model [26]. Let wj be the coefficient used to weight the jth rank vector, with wjj=1 (e.g. wj=(cjq)). Then note that the equality

$$\sum_{j}[wj_j \overrightarrow{WPR\ (\alpha},v\ j)] = \overrightarrow{WPR\ (}\alpha, \sum_{j}[wjv\ \overrightarrow{j]})$$

holds, as shown in Appendix A. Thus we see that the following random walk on theWeb yields the topic-sensitive score sqd. With probability $1-\alpha$, a random surfer on page u follows an outlink of u (where the particular outlink is chosen uniformly at random). With probability (cj/q'), the surfer instead jumps to one of the pages in Tj (where the particular page in Tj is chosen uniformly at random). The long term visit probability that the surfer is at page v is exactly given by the composite score sqd defined above. Thus, topics exert influence over the final score in proportion to their affinity with the query (or query context).

Conclusion

In this paper, we have discussed three algorithms advantages and limitations and we have proposed a new concept based on Topic-Sensitive PageRank and Weighted PageRank for web page ranking.Out this approach is based on the PageRank algorithm, and provides a scalable approach for search rankings using Link analysis. For each Web page, compute an importance score per topic. At query time, these importance scores are combined based on the topics of the query and associated context to form a composite PageRank score for those pages matching the query. This score can be used in conjunction with other scoring schemes to produce a final rank for the result pages with respect to the query. This algorithm will improve the order of web pages in the result list so that user may get the relevant pages easily.

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