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Estimating Google's search engine ranking function from a search engine optimization perspective

Google's
search engine
ranking
function

239

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Abstract

Purpose – The purpose of this paper is to estimate Google search engine's ranking function from a search engine optimization (SEO) perspective.

Design/methodology/approach – The paper proposed an estimation function that defines the query match score of a search result as the weighted sum of scores from a limited set of factors. The search results for a query are re-ranked according to the query match scores. The effectiveness was measured by comparing the new ranks with the original ranks of search results.

Findings – The proposed method achieved the best SEO effectiveness when using the top 20 search results for a query. The empirical results reveal that PageRank (PR) is the dominant factor in Google ranking function. The title follows as the second most important, and the snippet and the URL have roughly equal importance with variations among queries.

Research limitations/implications – This study considered a limited set of ranking factors. The empirical results reveal that SEO effectiveness can be assessed by a simple estimation of ranking function even when the ranks of the new and original result sets are quite dissimilar.

Practical implications – The findings indicate that web marketers should pay particular attention to a webpage's PR, and then place the keyword in URL, the page title, and snippet.

Originality/value – There have been ongoing concerns about how to formulate a simple strategy that can help a website get ranked higher in search engines. This study provides web marketers much needed empirical evidence about a simple way to foresee the ranking success of an SEO effort.

Keywords Web marketing, Latent semantic analysis, Search engine optimization, Search results ranking

Paper type Research paper

1. Introduction

Search engines such as Google and Yahoo have become the primary tools used to locate information on the internet. Several studies on user behavior indicated that most users click on websites listed on the first page of results and the proportion of users that view websites listed beyond the third page of results decreases rapidly (Lorigo *et al.*, 2006; Spink *et al.*, 2006; Enge *et al.*, 2012; Hopkins, 2012; Chuklin *et al.*, 2013). As a result, achieving a high ranking in search engine results is crucial to attracting traffic to a website and represents the main thrust of search engine marketing efforts. However, achieving high ranking is exceedingly difficult because search engines do not publicly release their ranking algorithms nor disclose information regarding the factors used in ranking. Theoretical discussions of ranking algorithms (Langville and Meyer, 2006; Manning *et al.*, 2009; Derhami *et al.*, 2013) can help reveal the actual workings of search engines; however, they do not provide practical guidelines for webmasters or marketers to conduct search engine optimization (SEO).



SEO refers to the efforts intended to improve the ranking of a website in the search results for given target keywords (Gandour and Regolini, 2011; Moreno and Martinez, 2013; Berman and Katona, 2013). SEO technique includes two major processes: off-page optimization and on-page optimization. Off-page optimization entails building backlinks on other well-reputed websites and thus boosting domain-level and page-level authority. On-page optimization SEO requires the optimization of web pages using target keywords in the title, snippets, and in the URL. The insertion of additional terms, semantically related to the target keyword, is considered an advanced SEO technique and is gaining popularity (Gennaro, 2015; Searchmetrics, 2015). Finding semantically related terms from small data sets is easy; however, this task can be troublesome for large data sets. This study sought to identify a set of terms semantically related to a given search query using latent semantic analysis (LSA) of the search results retrieved from search engines (Google, in particular). A search query is a word or a set of words a user types into the search box. We call each word in a search query as a query term. Then the relevance scores of the terms semantically related to the search query provide the foundation for computing the query match score for a search result (or simply referred to as a document). For each document, the weighted sum of the query match scores related to the title, snippet, URL, and off-page factors constitutes the query match score for the document. All of the documents retrieved for a given query are re-ranked according to the new match score. The newly generated ranks are then compared with their original counterparts to evaluate the effectiveness of the proposed method. This study differs with previous studies that re-rank search results with pseudo feedback relevance or external resources. Previous studies intend to improve the retrieval effectiveness so the users can find web pages most relevant to their query needs (Carpineto and Romano, 2012; Torkestani, 2012). This study instead focusses on how to measure SEO ranking success probability by a re-ranking approximation.

This study formulated the ranking function estimation problem as a curve-fitting process and constructed a simple mathematical function that best fits a series of documents for several queries. The factors of interest include details obtained directly from document's metadata, such as the title, snippets, and URL as well as publicly available Off-page factors such as PageRank (PR), the page quality score by Google. We present the proposed ranking function as the weighted sum of these factors with near-optimal weights generated using a genetic algorithm.

This paper is organized as follows. Section 2 reviews related work. Section 3 presents the proposed method. Section 4 discusses the experimental results. Finally, Section 5 concludes this study and proposes future directions.

2. Related work

2.1 Search ranking factors and SEO

Search engines rank search results according to a broad range of factors. Google is said to employ more than 200 factors in its ranking algorithm; most of which Google held as closely guarded secrets. According to the SEO starter guide (Google Inc., 2010), the factors related to search ranking include the title, meta description, anchor text, and various other on-page content-based factors. However, this guide barely mentions off-page (query-independent) factors, such as PR and the number of external links. Cutts (2011) conceptualizes the 200 plus factors into two categories: trust – an assessment of a site's authority and reputation, and relevance – an assessment of how well a page or site relates to a specific user query.

No SEO firms or industry professionals know the ranking details of any search engine. Even very successful SEO tools companies like Sistrix[1] have difficulty figuring

out the extent of change or what factors were weighted differently after a major Google algorithm update. Previous efforts to decipher the process of ranking details involve experimentation and observation. For example, Evans (2007), after examining 50 specially optimized web pages, discovered that the seven most popular techniques used by SEO practitioners are not necessarily effective. Of particular interest was that websites with a high PR have no guarantee of obtaining high ranking. Zhu and Wu (2011) derived top five factors for SEO including URL length, keyword in URL domain, keyword density in H1, keyword density in title, and URL layers based on a simple analysis of web pages content. Moreno and Martinez (2013) claimed that conducting SEO for websites to gain high visibility in search engine results also makes their content more accessible. Sagot *et al.* (2014) suggest that SEO process should use an integrated meta-model to cope with the variability and fluctuation of web pages ranking. The models employed include a conceptual model that transfers user needs into SEO objectives, an experimental model that implements the SEO practice to fulfill SEO objectives and a computation model that monitors the ranking of target websites.

Recently, several search metrics and SEO tool companies regularly published their ranking factors study reports. For example, SEOMoz[2] publishes a ranking factors report bi-annually based on survey of search professionals and data analysis results of the top 50 search results for over 10,000 queries across multiple categories. Similarly, Searchmetrics[3] has published an annual ranking factors study since 2012. Both firms unanimously claimed that the factors used in these reports are not what are being used in Google's ranking algorithm, but simply show the features of web pages that tend to rank higher. These studies generally use rank correlation coefficient to indicate the relationship between the rankings of search results and the feature values (e.g. total number of external links) of the search results on a per-feature basis. The factors that have relatively high correlation coefficient are considered to have strong influence on search engine ranking. Notably, the so-called factors are examined one by one, but not in groups of any combination form, for their individual correlation with search results rankings.

According to the ranking factor survey performed by SEOMoz (2011, 2013), the top three most important factors categories are domain-level authority link metrics, page-level link metrics, and page-level content-based metrics. Domain-level authority link metrics includes the number of root domains linking to the domain, the number of unique IPs linking to the domain, MozRank (MR) of the domain, and many more. Page-level link metrics entail link metrics to the individual ranking page such as number of links and MR. Page-level content-based metrics describe the use of the keyword in HTML code of web page such as the title tag, the body, the meta description, and the H1 tags. SEOMoz conclusively suggests that links are still the most important part of the algorithm and keyword usage on the page is still fundamental. Mavridis and Symeonidis (2015) presented a spearman correlation coefficient analysis of all the critical ranking factors based on data from three well-known web metrics sites. The authors argue that MR, Moz Page Authority, and Moz Domain Authority are highly correlated with search engine rankings. Additionally, the number of total links indicates positive correlation with search engine rankings. The ranking factor report by Searchmetrics (2015) reveals that the number of backlinks is still an important ranking factor. Meanwhile, the relevance of keywords in the description is falling, but the percentage of topic relevant terms on high-ranking websites has increased yet further.

The estimation of search ranking takes into accounts both content-based and query-independent features. PR, Google's static page score, is the commonly used query-independent ranking factor (Agichtein *et al.*, 2006; Bifet *et al.*, 2005; Fortunato *et al.*, 2008;

Richardson *et al.*, 2006; Hariri, 2011). Unfortunately, PR is updated once every few months, and the PR results that are made publically available differ from what Google uses in their ranking algorithm (Bifet *et al.*, 2005). Previously, SEO practitioners relied on the Yahoo Site Explorer for free access to valuable information, including external links and domains linked to websites; however, this service was shut down in November 2011. An alternative measure, MR, has attracted considerable attention. MR[4] is a link popularity score indicating the static importance of any webpage on the internet. Similar to PR, pages earn MR via the number and authority of other pages that link to them. To the best of our knowledge, it is the only publicly available query-independent score comparable to Google's PR. This study considers either PR or MR as a comprehensive ranking factor to represent the inclusion of domain-level and page-level authority link metrics.

2.2 Effectiveness of re-ranking

The effectiveness of search results re-ranking can be assessed from different perspectives. For example, SEO practitioners are interested in getting their target web pages ranked higher in search results. Information retrieval (IR) researchers are interested in the ways that would further improve the ranking of results returned by search engines.

From an SEO perspective, the effectiveness of re-ranking search results by a simple approximation require measuring how well the proposed method could still rank target web pages within top search engine results pages. The focus is on how many top-ranked web pages remain listed there after the re-ranking approximation.

From an IR perspective, the purpose of re-ranking search results is to measure how well a proposed ranking method can further improve the ranking of results returned by search engines. Query expansion via relevance feedback is one of the major approaches often taken by IR studies to enhance retrieval effectiveness (Manning *et al.*, 2009; Carpineto and Romano, 2012; Torkestani, 2012). Relevance feedback requires the user to give feedback on the relevance of documents in an initial set of outcomes. Then based on the user feedback the system expands or reformulates query terms needed for a revised set of outcomes. Pseudo-relevance feedback instead uses the top-ranked documents in the initial retrieval as relevant feedback and requires no user input at all. Additionally, external resources, e.g. Wikipedia, have been widely employed to augment the initial search in pseudo-relevance feedback. Several studies have reported significant improvement in retrieval performance on this subject (Masri *et al.*, 2013, Al-Shboul and Myaeng, 2014).

2.3 LSA

LSA, also known as latent semantic indexing, is a document analysis method used to uncover relationships among documents and the terms they contain as well as the semantic relationships among terms (Baeza-Yates and Ribeiro-Neto, 2011; Minhas and Kumar, 2013). For the purpose of ranking, the semantic relationship between a term and a given query is evaluated as a relevance score. So each document can be scored on the base of the relevance scores of the terms it contains.

The input of LSA is a term-by-document matrix A . The rows in A represent terms, and the columns represent documents. Matrix A contains non-zero and zero elements. A non-zero element typically indicates the *tf-idf* value of a given term in the corresponding document, while a zero element denotes that a particular term does not appear in the corresponding document (Baeza-Yates and Ribeiro-Neto, 2011).

The critical step in LSA is the factorization of matrix A using singular value decomposition (SVD) (Baeza-Yates and Ribeiro-Neto, 2011; Mirzal, 2013). The SVD of

an $m \times n$ matrix A is given by USV^T where U is an $m \times r$ orthogonal matrix, S is an $r \times r$ diagonal matrix with nonnegative real numbers on the diagonal, and V^T is an $r \times n$ orthogonal matrix. Intuitively, U and V can be considered as the term-to-concept and document-to-concept matrix, respectively. The diagonal entries of S are the singular values of A . Then a dimensionality reduction process is conducted to find the most significant k singular values while dropping out the rest singular values. The most significant k singular values intuitively indicate the most important hidden concepts or dimensions in the term-document matrix. Maintaining the largest k singular values is equivalent to preserving the first k columns of U and the first k rows of S and V^T . Finally, multiplying the reduced versions of U , S , and V^T generates the reduced version of A , such that $A_k = U_k S_k V_k^T$ as shown in Figure 1. A_k reveals the hidden semantic structure in the terms and relevant documents.

Creating a histogram of the relative variance of each singular value from the S matrix is the technique used to select the most significant k dimensions. The relative variance of a singular value s_j is defined as the square of s_j divided by the sum of the square of all singular values (Wall *et al.*, 2003). The value of k is the cutoff point where the cumulative relative variance of some leading dimensions exceeds a predefined dimension reduction threshold. Given an example of S matrix with singular values $\{0.29, 0.204, 0.132, 0.113, 0.089, \dots\}$, its histogram of cumulative relative variance is shown in Figure 2. We can choose $k = 3$, that is to select the first three dimensions, if the dimension reduction threshold is set at 0.8.

3. Proposed method

The proposed method includes three major steps: data crawling and preprocessing, LSA, and document scoring and re-ranking as shown in Figure 3.

$$\begin{bmatrix} A_k \end{bmatrix}^{(m \times n)} = \begin{bmatrix} U_k \end{bmatrix}^{(m \times r)} \begin{bmatrix} S_k \end{bmatrix}^{(r \times r)} \begin{bmatrix} V_k \end{bmatrix}^{(r \times n)}$$

Figure 1. Singular vector decomposition

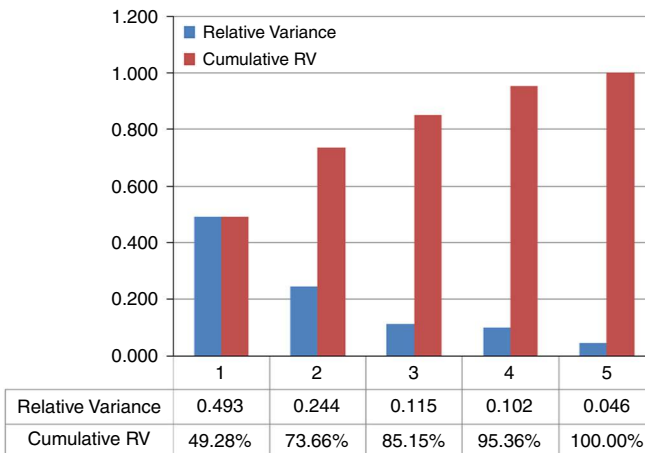


Figure 2. Example of cumulative relative variance

3.1 Data crawling and preprocessing

This step involves the retrieval of search results for a given query as well as data preprocessing. Search engines typically present search results as a ranked list of documents (or web pages). Once retrieving search results from a search engine, we conduct data preprocessing to parse out the title, snippet, and URL of each document as well as multi-word phrases from the parsed titles and snippets. The multi-word phrases are determined using a pairwise mutual information-based n-gram package developed by Kazembe (2011).

The reason we adopt multi-word phrases as semantically related terms is that Google is believed to employ phrase-based indexing and searching in their search engine, as revealed in a major Google patent (Patterson, 2009). For simplicity, both single words and multi-word phrases are referred to as “terms” in this study.

3.2 LSA

The first step in the LSA is the construction of a term-document matrix. The rows of the matrix comprise the terms obtained from data preprocessing, and the columns represent the documents. Each entry in the matrix is a term’s *tf-idf* score, indicating the significance of a term to the corresponding document in which the term appears. We used the open source Java Matrix Package, JAMA[5] to conduct the singular vector decomposition, that is, to transpose the original term-document matrix A into a dimension reduced version, such that $A_k = U_k S_k V_k^T$ as shown in Figure 1.

During the SVD process, the dimension reduction technique presented in Section 2.3 is applied to select the k most important dimensions. We examined the impact of the dimension reduction threshold on re-ranking effectiveness and presented the results in Section 4.

3.3 Document scoring and re-ranking

This step calculates a query-document match score for each document and then arranges the documents in descending order of this score. Thus, three things require to be accomplished. First, the relevance score of each term with respect to the given query must be determined by the reduced term-to-document matrix. Second, the query-document match score for each document is determined by combining the relevance scores of the terms it contains and the scores of other ranking factors, such as URL. Finally, the documents are re-ranked according to the resulting query-document match scores.

3.3.1 Determining the relevance scores of term to queries. This study quantified a term’s relevance score to a given query by computing the cosine similarity of their vector representations obtained from the corresponding rows in the reduced U matrix, i.e., the term-to-document matrix after LSA process. For example, “chemical,” “ecosystem,” and

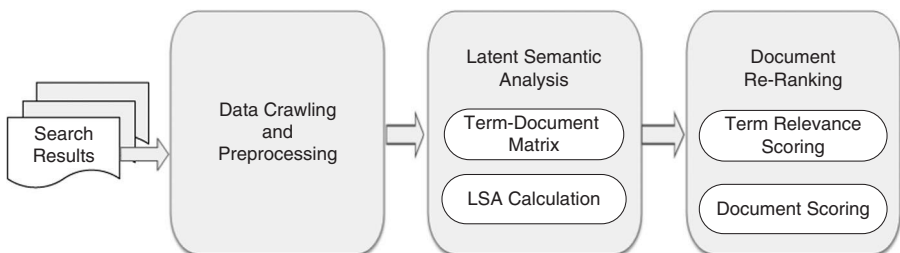


Figure 3.
System flow chart

“restoration” are some of the terms relevant to the query *oil spill*. Their relevance score to *oil spill* are 0.5409, 0.3531, and 8,951, respectively from our experimental results.

3.3.2 Document scoring. A query-document match score comprises components from on-page factors and off-page factors, as suggested in literature (Bifet *et al.*, 2005; Burges *et al.*, 2005; Fortunato *et al.*, 2008; Richardson *et al.*, 2006; Su *et al.*, 2010; Hariri, 2011; SEOmoz, 2011, 2013). The on-page factors considered in this study include a web page’s title, meta description, and URL. On the other hand, we chose PR and/or MR as the only off-page factor. The importance of title, meta description, URL, and PR to ranking are well known as indicated by high correlations in several ranking factors studies (Searchmetrics, 2015; SEOmoz, 2011, 2013.). This study does not intend to identify their importance to search ranking. Instead, we seek to determine their individual weights attributed to the query-document match score if they are used as ranking factors. The reason we only use title, meta description, and URL as on-page factors is that they are simply accessible from Google search results pages and are visible to search users. The minor difference is that meta description is called snippet in search engine terminology. Similarly, both PR and MR are accessible via publicly available application programming interfaces. Notably, both PR and MR are defined to include both link popularity and authority components. Using either PR or MR as a comprehensive off-page factor can avoid the efforts needed to fetch the backlinks and other signals related to links and authority for every search results under study. This shortcut simplifies the tedious data access work, especially for SEO practitioners without huge computation and bandwidth support.

This study defines the query-document match score of document d with respect to query q as the weighted sum of title score S_T , snippet score S_S , URL score S_U , and PR/MR score S_R . Moreover, the weights of factors, namely, W_T , W_S , W_U , and W_R , are determined using a genetic algorithm:

$$\text{Score}(d, q) = W_T \cdot S_T(d, q) + W_S \cdot S_S(d, q) + W_U \cdot S_U(d, q) + W_R \cdot S_R(d) \quad (1)$$

The query match scores for the title, snippet, and URL are calculated as follows. Notably, the calculation of title-query and snippet-query match scores consider both query and non-query terms identified with SVD, but the calculation of URL-query scores only takes query terms into account:

- (1) Title-query match score.

Consider query q with k query terms t_1, t_2, \dots, t_k . The title-query match score, as denoted $S_T(d, q)$ in Equation (1), is defined as follows:

$$\begin{aligned} \text{Title - query match score} &= \text{Query terms in title score} \\ &+ \text{Non-query terms in title score} \end{aligned} \quad (2)$$

where, the first component counts the query terms in title score, and the second one is the sum of the relevance scores of non-query terms that appear in the title. We then define the query terms in title score by the following:

$$\text{Query terms in title score} = \text{Query proximity} \times \text{Query prominence in title} \quad (3)$$

where, *Query proximity* computes how close together the query terms are in the title and *Query prominence* measures how close of the query terms are to the

beginning of the title. The design rationale is: the closer of the query terms the higher query proximity, and the close of the query terms to the beginning of the higher query prominence.

Query proximity considers only the query terms that appear in order as a sub-phrase of the query. Consider the query “*liquid packaging machine*” as a concrete example: the set of its sub-phrases would be {*liquid packaging machine, liquid packaging, liquid machine, packaging machine, liquid, packaging, machine*}. For each member of the sub-phrase set, the sum of the reciprocal rank of the terms it contains is calculated as its original sub-phrase score. Then a normalized weight is obtained by dividing its original score with that of the longest sub-phrase, i.e., the query itself. For example, the normalized sub-phrase weights for *liquid packaging machine, liquid packaging, and packaging machine* are $(1/1+1/2+1/3)/(1/1+1/2+1/3) = 1$, $(1/1+1/2)/(1/1+1/2+1/3) = 0.82$, and $(1/2+1/3)/(1/1+1/2+1/3) = 0.45$, respectively. Once more than one sub-phrases of the query appear in a given title, (e.g. **Liquid plastic packaging machine from packaging machine expert**), we select the one with the highest normalized weight (i.e. *liquid packaging machine*) as the matching sub-phrase to the given query. Notably in this example, the matching sub-phrase is loosely coupled, that is, each member follows its order in the query, but may not exactly occur next to each other. The query proximity comes into measuring the closeness of the query terms in the title as follows:

$$\text{Query proximity} = \frac{\text{Word count of the matching sub-phrase}}{\text{Word count of the smallest window in title containing all terms of the matching sub-phrase}} \quad (4)$$

We then define *query prominence* as the average of the prominence values of all query terms that appear in the document title. The term prominence in a title is given by the following:

$$\text{Term prominence} = \frac{(\text{Title length} - \text{average offset to its position in query})}{\text{Title length}} \quad (5)$$

By this definition, a multiply occurred query term increases the average offset to its original position in the query and has a lower term prominence. This design can prevent keyword spamming from obtaining a good prominence.

Consider the query *oil spill* and examples in Table I. For the title “**Oil spill** – Wikipedia, the free encyclopedia,” both the query proximity and the query prominence have a value of 1 so its query match score is 1. The reason is that both oil and spill appear at the beginning of the title and are in exactly the same order as in the query. For the title “**Oil Spill Response – Oil Spill**” the query term *oil* appears twice at the first and fourth positions of the title, its average-term offset is $((4-1) + (1-1))/2 = 1.5$. Thus, the term prominence of *oil* is $(5 - 1.5)/5 = 0.7$. Similarly, the term prominence of *spill* is 0.7.

Table I.
Title-query match
score examples
for search query
“Oil Spill”

Title	Query proximity	Query prominence	Match score
Oil spill – Wikipedia, the free encyclopedia	1	1	1
Oil Spill response – Oil Spill	1	0.7	0.7
Oil and chemical Spills : NOAA Watch	0.5	0.84	0.42

Then the query prominence for *oil spill* is 0.7. For the last title “Oil and Chemical Spills: NOAA Watch,” the smallest window size including all query terms is 4 and the word count of the matching sub-phrase (i.e. **Oil Spills**) is 2. Thus, its *query proximity* is 0.5. Then the term prominences for *Oil* and *Spill* are $(6-0)/6 = 1$ and $(6-2)/6 = 0.67$, respectively. Then the *query prominence* is $(1 + 0.67)/2 = 0.84$. We believe the ranking of the title-query match score is very consistent with what users perceive.

For the last example, one could actually decompose the phrase into “Oil spills” and “chemical spills.” From a query matching perspective, the title “Oil and Chemical Spills: NOAA Watch” has a lower query proximity, but a higher query prominence for query “*Oil Spill*” than that for query “*Chemical Spill*” as shown in Table II. Thus, this document title has a higher match score to the query “*Chemical Spill*” than to the “*Oil Spill*.” Notably, the proposed method is query oriented, that is, we find “Oil * * Spills” and “Chemical Spills” as the matching sub-phrase to query “*Oil Spill*” and “*Chemical Spill*,” respectively. We do not interpret the title has the phrase “Chemical Spills” as the dominant matching sub-phrase for all queries.

(2) Snippet-query match score.

The snippet-query match score, $S_S(d, q)$, is defined as the sum of the relevance scores of all terms occurring in the snippet of document d with respect to the search query q . Notably, each term is counted only once regardless of how many times it occurs in the snippet.

(3) URL-query match score.

We calculate the URL-query match score based on the following URL syntax:

http:// < domain > / [< path >] [< filename >].

That is, a URL contains one or more labels separated by the slash symbol “/”. Among the labels, < domain > is assumed to have a canonical form, such as *www.example.com* or *example.com*, and both < path > and < filename > are optional. Within the domain name *www.example.com*, *.com* is one of the predefined top-level domains (TLD), *example* is the second-level domain of the *.com* TLD, and *www* is the host name. Query terms may appear in the second-level domain and/or the host name of a domain name. Intuitively, a URL with only one < domain > label with all query terms appearing in this part is preferred. On the contrary, a URL with query terms scattered throughout more than one label is unfavorable concerning query match scoring.

The URL-query match score is defined as the average of all URL label match scores. The computation of each URL label match score considers the rank of the URL label in which query terms appear and whether all of the query terms appear in order. We denote these two components as URL label weight and query proximity in URL as follows:

$$URL\ Label\ Match\ Score = URL\ Label\ Weight \times Query\ Proximity\ in\ URL \quad (6)$$

Query	Query proximity	Query prominence	Match score	Table II. Title-query match score comparisons for “oil and chemical spills: NOAA Watch”
<i>Oil spill</i>	0.5	0.84	0.42	
<i>Chemical spill</i>	1	0.75	0.75	

The *URL label weight* for the i th label of a URL is defined as the reciprocal of i , if some query terms appear in this label. That is, the URL label weights for $\langle \text{domain} \rangle$, $\langle \text{path} \rangle$, and $\langle \text{filename} \rangle$ labels are 1, 1/2, and 1/3, respectively. Additionally, we introduce a penalty for URL in a non-canonical form. For example, the URL label weight of www.instantoilspill.com for the query *Oil Spill* is 1 and the URL label weight for home.instantoilspill.com is $1 \times (1 - p_1)$. The value of p_1 can be adjusted as desired and it was 0.2 during the experiment.

Query proximity in the URL considers the matching of sub-phrases related to the query in the dominant URL label. It is defined similarly as that of query proximity in the title, except that here we count the character length of the string concatenation of the search query and the matching sub-phrase in URL. Similarly, we introduce a second penalty for the extra characters leading or trailing the matching sub-phrase. For example, the query proximity in URL for www.instantoilspill.com to the query *Oil Spill* is $(8/8) \times (1 - p_2)$. The reason is that the character sequence *oil spill* appears in the domain part, and some leading characters (*instant*) exist ahead of *oil*. Here string preprocessing is required before comparing the query phrase string with the URL string. In the above example, the query phrase *oil spill* is concatenated into the character sequence *oilspill*, and URL strings with a hyphen or underscore such as *oil-spill* and *oil_spill* are normalized with the same character sequence *oilspill*. The value of p_2 can be adjusted as desired and we set it 0.2 in the experiments.

3.3.3 Document re-ranking. The query-document match score is the sum of the weighted query match scores of a document's title, snippet, URL, and PR or MR score according to Equation (1). The weights of factors are determined using a genetic algorithm. We encode the scores of factors as an array and normalize each array element to the range of 0-1 to facilitate genetic encoding. The initial population includes genetic representations of documents for all of the queries being considered. During each successive generation, a query-document match score is computed for each document according to the obtained weights, and the documents returned for each query are then re-ranked in the decreasing order of the resulting scores. Thus, each document obtains a new rank with respect to a given query at the end of each generation. For example, based on the weights we obtain after a genetic run, Table III shows the new doc scores we calculate based on the Equation (1) for some sample documents. After re-ranking by the new doc scores, the re-ranked order becomes (d1, d3, d2).

The objective of the genetic algorithm is to identify a set of weights that minimize the sum of squared rank error (SSRE) of the new rank and its original rank of each

Document	Title score	Snippet score	URL score	PageRank score	Doc score	New rank
Oil spill – Wikipedia, the free encyclopedia https://en.wikipedia.org/wiki/Oil_spill	1	0.56	0.5	0.6	0.586	1
Oil and Chemical Spills: NOAA Watch http://oceanservice.noaa.gov/hazards/spills/	0.42	0.84	0.31	0.6	0.499	3
Oil Spill Response – Oil Spill http://oilspillresponseproject.org	0.7	0.72	0.8	0.4	0.548	2

Table III.
Document scoring examples

Notes: Based on the weights of factors: $W_T=0.048$, $W_S=0.01$, $W_U=0.325$, $W_R=0.617$; PageRank score is normalized to the range of (0-1) by dividing the PageRank by 10

document being evaluated. The minimization of SSRE indicates pushing the new rank of each document close to its corresponding original rank, that is, the re-ranked order should be as close to the original rank order as possible. During experimentation, the genetic process is repeated until either reaching the condition the change of SSRE in the last 100 trials is less than 0.01 percent or having consumed a predefined number of runs.

4. Experiments and evaluation

4.1 Experimental setup

To evaluate the effectiveness of the proposed method, we chose 100 keywords related to industrial products as search queries for collecting experimental data. These keywords are from various categories, including electronics, machinery, plastics, and LEDs. Each keyword was submitted as a search query to Google's International English site (www.google.com/ncr) to retrieve the top n search results for effectiveness evaluation.

The objectives of the experiments were twofold. First, we determined the values of the key parameters, including the number of top search results should be retrieved and the dimension reduction threshold for selecting critical dimensions in the construction of SVD reduced document-term matrix to enhance re-ranking effectiveness. Second, we identified the combination of factors that delivers best performance in estimating the Google ranking function.

To fulfill the first objective, we employed ranking factors including title, snippet, URL, and PR in document scoring of various numbers of documents ranging from 20-100 in increments of 10. For each increment, we evaluated six threshold values for dimension reduction: 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0. The case of ten documents was excluded from the evaluation because using the top ten documents only is insufficient to perceive semantic differences between documents listed on the first page of results and those on the remaining pages. Additionally, we ignored the dimension reduction threshold values under 0.5 because the most important dimensions of interest should contribute more than 50 percent of the relative variance accumulated by all dimensions.

Then four cases involving various combinations of factors were empirically evaluated and compared on the base of the key parameter values found. The first instance considered only on-page factors: title, snippet, and URL. The second case added PR. The third case replaced PR with MR. Finally, the fourth case combined all five factors altogether. The four cases were denoted as T+S+U, T+S+U+PR, T+S+U+MR, and T+S+U+PR+MR, respectively. The additional off-page factor, i.e. MR, was employed in the experiment because Google makes updates to PR on an irregular basis and the PR values publicly available via Google API do not accurately reflect the current statuses of web pages.

4.2 Effectiveness metrics

This study employs Kendall's rank correlation coefficient (Abdi, 2007) and R -precision (Manning *et al.*, 2009) to evaluate the effectiveness of the proposed method as shown in Table IV. The Kendall's rank correlation coefficient, commonly referred to as Kendall's

Metrics	Purpose
Kendall's τ coefficient	To measure the degree of similarity of the original and new rankings of search results
R -precision	To measure how many of top R search results are still ranked within top R positions after being re-ranked with the proposed method

Table IV.
The metrics used
in this study

τ coefficient, is based on counting the number of pairwise disagreements between two ordered lists. We used it here to measure the degree of similarity between the original and new ranks assigned to the same set of search results. R -precision is originally used to measure the precision of the top R documents retrieved in a ranked IR system. The calculation of R -precision requires having a set of known relevant documents and counts how many known relevant documents are ranked within the top R positions. This study considers the top R documents in Google's search results to a given query as the pseudo set of known relevant documents. Then the R -precision calculates the ratio of the number of correct hits to the number of R . Here a correct hit, from an SEO perspective, means a document ranked within top R in Google's search results is still listed well within top R positions after the proposed re-ranking and does not imply this document is truly relevant to user interest. We calculate an R -precision value for each query and average the R -precision values for m queries in the experiment as the final R -precision. The value of R can be adjusted according to the number of top positions of interest. Typically, $R = 10$ is considered a good SEO practice.

4.3 Experimental results

Figures 4 and 5 show the effects of dimension reduction threshold values on R -precision and Kendall's τ coefficient according to data set size. For both measures, the data set size of 20 documents outperformed the other data set sizes across all dimension reduction threshold values while the other data set sizes show mixed results. Analysis of variance demonstrates that the effect of data set size was significant for R -precision ($F(8,45) = 81.09$, $p < 0.01$), and for Kendall's τ coefficient ($F(8,45) = 111.02$, $p < 0.01$). Furthermore, a paired t -test indicates that the proposed method performed significantly better with a data set of 20 documents than with other data set sizes, in both R -precision and the Kendall's τ coefficient.

Figure 6 shows the mean R -precision and Kendall's τ coefficient for the four combinations of factors. Among them, T+S+U+PR+MR scored the highest, achieving a Kendall's τ coefficient of 0.154 and R -precision of 0.59; T+S+U received the lowest scores with a Kendall's τ coefficient of 0.124 and R -precision of 0.574. Obviously, adding off-page factors, either PR or MR or both, to on-page factors improves both measures. The results also reveal that MR is comparable to PR in estimating the Google ranking

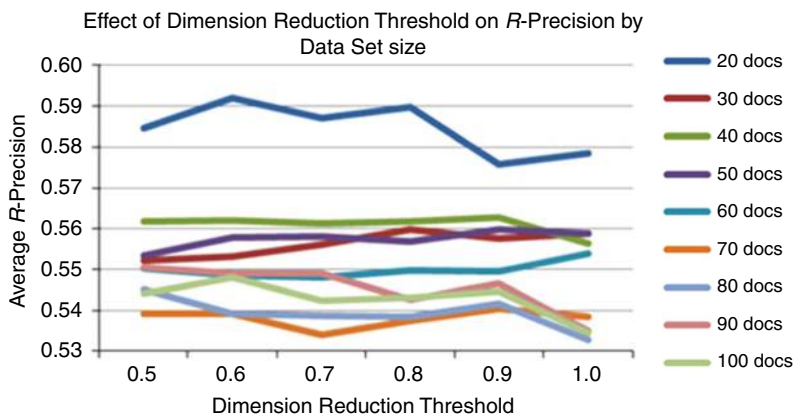


Figure 4.
Effect of dimension reduction threshold on R -precision

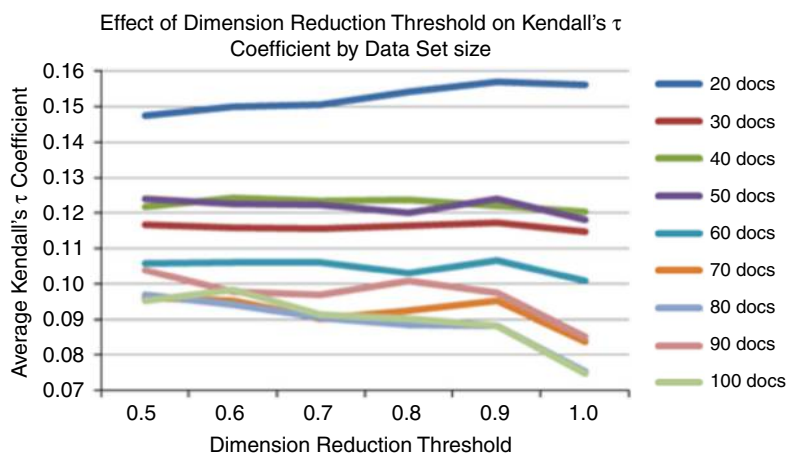
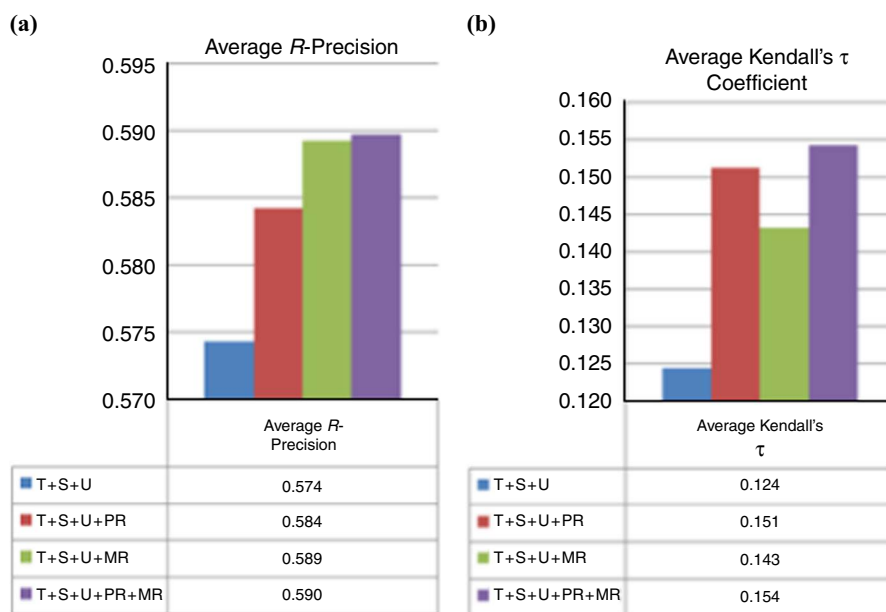


Figure 5. Effect of dimension reduction threshold on Kendall's τ coefficient



Notes: Data set=20 documents; dimension reduction threshold=0.8

Figure 6. (a) Average R -precision (b) Average Kendall's τ coefficient under the optimal parameters

function using the proposed method while T+S+U+MR outperformed T+S+U+PR in R -precision, but T+S+U+PR surpassed T+S+U+MR in Kendall's τ coefficient.

4.4 Discussion

According to the experimental results, the maximum Kendall's τ value is only 0.154. Such a low value indicates that most of the new rank orders obtained with the proposed method are marginally similar with their original Google rank orders. Under such

rank-order disagreement, the proposed method achieved an R -precision close to 0.6, that is, about six of top ten documents remain within top ten after re-ranking. One of the typical examples for top 20 search results is shown below.

The original rank order:

$R1 = [d1, d2, d3, d4, d5, d6, d7, d8, d9, d10, d11, d12, d13, \dots, d20]$.

The re-ranked order within top ten positions:

$R2 = [d4, d6, d1, d14, d12, d8, d11, d7, d3, d13, \dots]$.

This case has an R -precision of 0.6 because six documents $d4, d6, d1, d8, d7, d3$ are still ranked within top ten positions, but the whole rank order is dissimilar to the original one, so it has a low Kendall's τ coefficient of 0.155.

Obviously, the proposed method is still weak in estimating the Google rankings with a simple combination of only a few ranking factors. We intent to use more ranking factors and conduct weight adjustments in future research to reach better re-ranked orders such as the following cases:

$R2 = [d1, d3, d4, d6, d7, d8, d14, d13, d12, d11, \dots]$, Kendall's $\tau = 0.73$,
 R -precision = 0.6.

$R2 = [d1, d3, d4, d6, d7, d8, d11, d12, d13, d14, \dots]$, Kendall's $\tau = 1$,
 R -precision = 0.6.

Moreover, we found the weights of factors achieved by the generic algorithm follow almost the same pattern. One set of the weights of factors that performed best in Kendall's τ and R -precision under the proposed methods is: $\{W_T = 0.048, W_S = 0.01, W_U = 0.325, W_R = 0.617\}$. The results suggest that for the queries in the field of interest PR is the most important factor in estimating Google ranking. The document's URL follows as the second most important factor. Finally a document's title and its snippet have minor impact on search ranking. These findings cannot lead to generalization for queries from different fields as suggested in literature and in ranking factor surveys (Killoran, 2013; Mavridis and Symeonidis, 2015; SEOmoz, 2011, 2013).

For SEO practitioners interested in the industrial products field, we suggest they should pay special attention to PR to get better ranking. Additionally, the proposed method could be used to track current changes of the ranking algorithm Google applies. For example, we can set the genetic termination condition as R -precision = 0.6 and then find the final weights of ranking factors of interest. Any change of weights can imply its change of impact on ranking. One of our recent simple test results indicate that the weight of URL factor is decreasing. This preliminary finding is consistent with our observation and that of recent ranking factor survey (Searchmetrics, 2015).

5. Conclusions

This study proposed an estimation function to approximate the ranking function of Google from an SEO perspective. The estimation function calculates a new query-document match score for each document using the weighted sum of query match scores from the title, snippet, and URL as well as off-page factors including PR and MR. The query match score counts the relevance scores of a set of terms semantically related a given query obtained via LSA of the documents retrieved for each query. Additionally, the weights of each ranking factor were determined using a genetic algorithm. Experimental results indicate that the proposed method performed best in

Kendall's τ coefficient and R -precision when using a data set of 20 documents with a dimension reduction threshold of 0.8. The results also reveal that the proposed method can help assess the probability of SEO success with an R -precision of 0.6 while the ranks of the new and original result sets are quite dissimilar.

This study considered a limited set of ranking factors only. Although the proposed method produced satisfactory results in R -precision, there is still room for improvement in Kendall's τ coefficient. That is, to better approximate the original Google's ranking order with some more easily accessible ranking factors.

Notes

1. www.sistrix.de/google-updates/bahn.de/
2. <https://moz.com/search-ranking-factors/survey>
3. www.searchmetrics.com/
4. www.seomoz.org/learn-seo/mozrank
5. <http://math.nist.gov/javanumerics/jama/>

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