A new approach to relevancy in Internet searching -
the “Vox Populi Algorithm”

Andreas Schaale¹, Carsten Wulf-Mathies², Sönke Lieberam-Schmidt³

¹ Contraco Consulting and Software Ltd., Diepenseer Str. 10, 15732 Waltersdorf, Germany
² T-Online International AG, Waldstr. 3, 64331 Weiterstadt, Germany
³ Universität Siegen, FB 5, Hölderlinstr. 3, 57068 Siegen, Germany

February 1, 2008

Abstract

In this paper we will derive a new algorithm for Internet searching. The main idea of this algorithm is to extend the existing algorithms by a component, which reflects the interests of the users more than existing methods. The “Vox Populi Algorithm” (VPA) [1] creates a feedback from the users to the content of the search index. The information derived from the users query analysis is used to modify the existing crawling algorithms. The VPA controls the distribution of the resources of the crawler. Finally, we also discuss methods of suppressing unwanted content (spam). This is necessary in order to enable an efficient performance of the VPA.
The retrieval of relevant information from data sources with a very complex structure has become a challenging task since the number of documents in the Internet has reached a level of about multi billions of documents. Only a small part of them is visible in search engines. The problem of organizing and structuring these data into catalogues or searchable databases is of theoretical and significant practical (commercial) interest.

Let us define the basic components for the mathematical description of the interests of the users, the relevancy of the search results and the crawling process. The users of search engines express their needs for information through the queries which they address to a searchable database (index) $I$. Each of the $k$ queries consists of one or more keywords $q$ addressed to this index. It will be presented as:

$$\vec{q}_k = (q_1, ..., q_n)_k$$

(1)

$n$ is the length of the query $k$. The number of keywords per average query is $n \approx 2$ (status in 2003). The users are searching for documents $d_j$ (HTML pages, tables, text processing documents, pictures, multimedia files, ...) containing information. These documents are grouped (organized) in domains $D_k$ presenting sets of documents under a common editorial responsibility and address (URL):

$$D_k = \bigcup_j d_j^{(k)}$$

(2)

The number of domains is about 6.4 million in Germany [2] and the number of documents per domain $n_k$ is in the interval $10^{6-8}$.

Each document $d$ contains searchable information, today limited to text information. Content, which is hidden for the today's search technology in non indexable formats (bitmaps, scripts etc.) will be neglected here and in the following. A document is characterized by the content of keywords $q$ and the position of the keyword in certain format elements $e_i$ (metatags, headers, tables, link text etc.):

$$d^{(k)} = f(q_1, q_2, ..., e_1, e_2, ...)$$

(3)

During the crawling and indexing process, the image of the document $\hat{d}$ in the searchable index $I$ contains a reduced set of information - the keywords and their position in the format elements $e$ of the document. When a query is addressed to the index $I$ a ranking algorithm generates a set of documents (links) which is ordered by the relevancy of the found documents. In order to describe the document ranking process which generates the set of results on each query, one has to introduce the density $\rho$ of keywords within the documents:

$$\rho_i = \frac{n_{q_i}}{n_{e_j}}$$

(4)

where $n_{q_i}$ is the number of the occurrences of the keyword $q_i$ in the format element $e_j$ and $n_{e_j}$ is the total number of words in this format element.

Today there exist two basic types of ranking algorithms - the dynamic and the
static ranking algorithms. The dynamic rank of a document depends on two factors only - the keywords \( q \) of the query and the information content of the documents. Expressed in a "thumb rule": the higher the keyword density in the document the higher is the dynamic rank of this document. The relevancy function \( R_d \), defining the dynamic rank of a document, can be written as:

\[
R_d(q) \propto \sum_{k=1}^{N} \mu_k \rho^k(q) \quad \text{N - number of format elements} \quad (5)
\]

for a single keyword query. The coefficients \( \mu_k \) are free parameters, defining the importance or weight of each format element. For example, the occurrence of a keyword in an URL is usually much more important than in the text itself \( \mu_{URL} > \mu_{text} \). Queries with multiple keywords can be written as superpositions of single keyword queries:

\[
R_n(d, q_1, q_2, ..., q_n) = R_1(d, q_1) \cdot R_1(d, q_2) \cdot ... \cdot R_1(d, q_n) \quad (6)
\]

Usually these functions become modified for different purposes, such as suppression of unwanted information (spam). Other modifications can take into account the freshness of the document, the type of the format or other technical parameter.

The practical work on search engines has shown that using only a document related, dynamical ranking algorithm is insufficient. In order to also include the importance or the popularity of a domain (popularity among the webmasters not necessarily among Internet users), a new type of algorithms was invented - the static ranking [3]. The static rank \( R_s \) of a document \( d_i \) is related to the importance of the corresponding domain, where it is located. The idea of the static rank of a domain \( D \) can be expressed symbolically in the following form:

\[
R_s(D) \propto \sum_{j=1}^{N_j} R_j \quad (7)
\]

where the \( R_j \) is the static rank of the sites linking to the domain \( D \). \( N_j \) is the total amount of external links to a Domain. In [4] a more detailed definition of the page rank formula is given:

\[
R_s(D) = (1 - d) + d \sum_{j=1}^{N_j} R_j M_j^{-1} \quad (8)
\]

where \( d \) is a free parameter (usually in the region \( d \approx 0.85 \) [4]) and \( M_j \) is the total number of outgoing links of the referring site. A detailed discussion of the page rank algorithm used by Google is also found in [5] and [6].

The resulting rank of a document is a function of the the dynamic rank (5) and the static rank (7). There is no unique or even optimal way of constructing this function. A reasonable way is to choose the resulting relevancy \( R_{ds} \) as a product of the dynamic and static rank:

\[
R_{ds} = R_d(q) \cdot R_s(d) \quad (9)
\]
Analyzing (9) a usual approach would be using $R_s(D_i)$ instead of $R_s(d_i)$. In practice the static rank of a document depends not only on the static rank of the domain $D$ containing $d_i$, but also on the position in the domain (link topology of the domain). At present this kind of search algorithms is in use in every major internet search engine.

The algorithms described above do indeed meet the needs of the users. This approach is reasonable from an academic point of view and it has produced remarkable results in the past. Today it has become more difficult to make use of the link topology - very often the links are not set according to the content relevancy, but for other (economic) reasons. To the extent that the search engines have become the most important information retrieval tool, they have also become a target of spamming (site owners try to fake the search engines, virtually presenting more important content than there really is). An effective method of detecting a certain type of spam is described in the appendix. Applying filter mechanisms and modifying the parameters of the dynamic and the static relevancy algorithms, one can “fine tune” the quality of the Internet search engines.

The two methods described above explicitly do not take into account the most important factor, the interest of the users searching for information. The dynamic and the static relevancy of a document are influenced by the content of the site and by the “citation” by other sites. There is no methodical component, that reflects the voice of the searching people. This will be done by the “Vox Populi Algorithm” (people’s voice).

The main idea of the VPA is to use the information that is extractable from the user query analysis to enhance the quality of the search. This can be done in two different ways, by modifying either the ranking or the crawling algorithm. In this paper the focus is not on the ranking, but on the crawling algorithm. The crawling algorithm defines which domain and how much of the content will be included into the search index. Sites which are not included cannot be found by the best ranking algorithm. At present there is only a small fraction ($<10\%$) of the Internet sites indexed by the search engines. The much bigger part of the Internet (“Deep Web”) is not visible in any of the search engines.

The source of information is the analysis of the queries $q$, reflecting the users interests and needs. The query set $Q$ may contain all single and multiple keyword queries of the users (1). Based on these queries a multidimensional tensor $\Omega$ can be defined, containing the information of the multiple keyword correlations with the dimension $N_{max}$.

$$\dim[\Omega(Q)] = N_{max}$$

(10)

$N_{max}$ is the maximum length of a query - theoretically it can be infinite. Practically the amount of queries having $>6$ keywords is $<1\%$, while the average query consists of about $N=2$ keywords. In order to simplify the further calculations one can reduce the dimension of (10) in the following way:

$$\Omega^{N=2}(Q) \rightarrow \Omega \equiv \Omega$$

(11)

In this reduction algorithm, the queries with more than two keywords are replaced
by two keyword queries, containing all possible paired combinations. For example, a three keyword query is equivalent to 3 two keyword queries and so on.

The matrix $\Omega$ is a correlation matrix of all keywords of the query set $Q$, which is analyzed. $\Omega$ is a positive and symmetric matrix. One can calculate the eigenvectors and eigenvalues of $\Omega$, transforming it into the diagonal form:

$$K^{-1}\Omega K = \Omega^{diag}$$ (12)

The details of the diagonalization procedure are well known, see [8] or any other standard textbook on mathematics. It is now important to understand the practical meaning of the matrices $K$ and $\Omega^{diag}$. The matrix $K$ consists of eigenvectors which are keyword combinations:

$$K = \begin{pmatrix} \vec{e}^1 \\ \vec{e}^2 \\ \vec{e}^3 \\ \vdots \end{pmatrix}$$ (13)

where each eigenvector has the coordinates

$$\vec{e}^j = (c_1 q_1, c_2 q_2, \ldots)^j$$ (14)

similar to the definition (1) the $q_i$ are the keywords and the coefficients $c^j_i$ are positive numbers, giving each keyword some "weight" compared to the other ones (How frequent do the users ask for this keyword?). The coefficients determine the relative importance of a keyword within an eigenvector. A typical eigenvector (or better "eigenquery") has the form (based on the data [7], Aug. 2003).

$$\vec{e}^j = ("mp3", 0.73 \cdot "downloads", 0.43 \cdot "free", \ldots)$$ (15)

This query shows how the average user is asking, when he is searching for mp3 downloads at no cost. The reduced ($N = 3$) keyword matrix of the example above has the form [7]:

$$\Omega = \begin{array}{ccc} mp3 & downloads & free \\ download & 37.2\% & 8.8\% & 2.7\% \\ free & 2.7\% & 3.6\% & 13.4\% \end{array}$$ (16)

The difference between the typical keyword search at present and our approach is that the words here have different weights, determining their relative importance for the users.

Another important information about the significance of keyword combinations is

1The analysis of the order of the keywords shows a statistical asymmetry for the order of keywords $N(1,2) \neq N(2,1)$. Users interested in the explicit order of the keywords can use the option called "Exact Phrase", which is available on any modern search engine. Therefore it is reasonable to assume that the order of the keywords is not important for the users when they make simple queries (more than 90% of all queries are of this type). We will use here the approximation $(1.2) = (2.1)$
contained in the matrix $\Omega^{\text{diag}}$.

$$
\Omega^{\text{diag}} = \begin{pmatrix}
\lambda_1 & 0 & 0 & \ldots & 0 \\
0 & \lambda_2 & 0 & \ldots & 0 \\
0 & 0 & \ldots & \ldots & \ldots \\
0 & 0 & \ldots & \lambda_{N-1} & 0 \\
0 & 0 & \ldots & 0 & \lambda_N
\end{pmatrix}
$$

(17)

Each eigenvalue $\lambda_i$ corresponds to an eigenvector in (14). The eigenvalue can be interpreted as the importance of the corresponding eigenvector - it defines the importance of an eigenquery for the users.

Finally, we have developed the tools for defining how a search engine can use the information of the users to determine, which content should be enhanced or reduced in the index. Based on the described algorithm it is possible to define which content is the “most wanted” content and which sites deliver this type of content:

$$(c_1q_1 + c_2q_2 + \ldots) \rightarrow \text{search engine} \rightarrow \text{list of ranked domains}$$

Crawling the Internet, each domain is given certain resources by the search engine, such as CPU time and memory in the index (alternatively also the number of crawled documents or other parameters, depending on the settings of the search engine).

The practical realization of the VPA as an extension of an existing Internet search could be performed using the following procedure:

1. Generate a ranking of domains, addressing the eigenqueries (14) to the existing (old) search index, the priority of those domains is defined by the size of eigenvalues. (17).

2. Modify the existing resource ranking list with respect to these eigenvalues.

3. Use the new determined ranking of the domains for crawling the Internet according to the modified resource distribution.

4. Repeat the cycle.

In order to determine which sites best fit the eigenqueries, it is useful to calculate a dynamic rank for a whole domain, not just for a single document. A simple method would be to summarize the total score of all documents in one domain:

$$
R_D(e_i) \propto \sum_{k=1}^{N_D} R^k_d(e_i)
$$

(18)

Let us assume, that the amount of resources (CPU time, number of documents, data volume etc.) given to each domain, when crawling it, can be expressed in a function $M$, with

$$
M = M(D_k, R_s, \ldots)
$$

(19)

In order to apply the VPA one can modify (19) in the following way:

$$
M \rightarrow \hat{M} = M \cdot R_{VPA}
$$

(20)
The function $R_{VPA}$ defines the VPA correction with regard to the old crawling algorithm. The function $R_{VPA}$ can be presented in different ways. The basic requirement for the function is that it is monotone concerning the parameters $\lambda_i$, which define quantitatively how relevant a query is for the users. Following Occam's principle of simplicity (Pluralitas non est ponenda sine necessitate - Entities should not be multiplied unnecessarily) this function should use only a minimum set of free parameters, which will allow the adoption (or “fine tuning”) the algorithm to the local requirements:

$$R_{VPA}(D_k) = (1 + \alpha \cdot \lambda_k^\beta) \quad \alpha, \beta > 0 \quad (21)$$

The parameter $\alpha$ and $\beta$ can be chosen freely. In the limit, the new algorithm generates the existing results in (20).

$$\lim_{\lambda \to 0} \hat{M} = M \quad (22)$$

In this paper we have shown how the analysis of queries can be used to enhance the relevant and “most wanted” content in a search index. In this way the relevancy, experienced by the users of the search should grow - the users will find more of what they are interested in. The existing system of the relevancy ranking of documents or domains can remain unchanged. The algorithm will not replace existing crawling and ranking algorithms, but the VPA will extend them by a qualitatively new component.
Appendix

The static rank algorithm has also become the target of spamming (for example, “Google bombing” [11]). This means that webmasters are creating clusters of domains, which consist of very similar sites, referring to a single domain or a document. This kind of spam cluster can consist of many domains, which do not contain any valuable content at all. Because of this the static rank consequently is becoming more and more a measure of the marketing budget or the cleverness of the webmaster of a domain, rather than a measure of “real” reputation or content quality. As a result of this development, the importance of the static rank as a tool for determining the quality or the relevancy of a site is decreasing.

We want to propose an algorithm which identifies this kind of spamming. The basic idea of the static rank is reasonable - the more important sites refer (link) to a site, the more important is the site. There is a way to discriminate between “natural grown” link clusters and “artificial” ones (spam).

In order to find a quantitative method which can discriminate between these two types of link clusters, one can introduce the function which describes the statistical distribution of the relevancy $R^i_s$ of the links, pointing to the document $d_i$:

$$
\phi(R^i_s) = e^{-\frac{(R^i_s - R_0)^2}{\sigma^2}}
$$

(23)

here $R_0$ is the average static rank of all sites, linking to the center of this cluster $d_i$. The parameter $\sigma$ defines the width of the distribution.

The above mentioned types of clusters can be discriminated using the distribution $\phi$ - natural grown clusters contain links from an inhomogeneous set of sites, for example, the links to a site of a well known university will come from very small (amateur) sites of students, employees and alumnies (with a low page rank), via semi professional institutional sites (spin offs, research partners, ...) up to sites of other high ranked universities or institutes. The artificial link cluster consists of automatically generated sites, each of them usually optimized for different keywords, but having approximately the same static rank. As a result of this it is possible to introduce a “cut off” criteria based on formula (23). A cluster is most likely spam, if the condition

$$
\sigma_{\text{spam}} < \sigma_{\text{critical}}
$$

(24)

is fulfilled. Here $\sigma_{\text{critical}}$ is an empirical parameter, which can be determined from the analysis of known natural and artificial clusters (or from the software generating the sites of the spam cluster). Estimates have shown that one can expect a result like $\sigma_{\text{natural}} >> \sigma_{\text{artificial}}$. A short test example can demonstrate this: the distribution of the page ranks of sites linking to the homepage of Steven Hawking [10] analyzed based on formula (23) have a width of $\sigma^2 = 1.1$, while the sites belonging to a typical spam cluster have a page rank distribution with $\sigma^2 = 0.5...0.7^2$. The parameter $\sigma$ can be used for separating between these two type of link clusters. The data of this example are based on the indications of the page rank indicator of Google’s toolbar [12].

\footnote{The data of this example are based on the page rank indicator of Google [12].}
References

[1] Patent pending, Reg. Nb. 103-19-427.7, April 29 2003,

[2] DENIC, www.denic.de, 24.4.2003

[3] S.Brin and L.Page, The anatomy of a large-scale hypertextual Web search engine, ComputerNetworks 30(1-7), p.107-117, 1998

[4] M.Glöggler, Suchmaschinen im Internet, Springer 2003

[5] S.D.Kamvar et al., Exploiting the block structure of the web for computing pagerank, Stanford University

[6] T.H.Haveliwala and S.D.Kamvar, The second eigenvalue of the Google matrix, Stanford University

[7] www.keyword-datenbank.de

[8] I.N.Bronstein and K.A.Semedjajew, Handbook of Mathematics, 1981

[9] F.Menczer, Links tell us about the lexical and semantic Web content, cs.IR/0108004v1, 8. Aug. 2001

[10] www.hawking.org.uk

[11] news.bbc.co.uk/1/hi/sci/tech/1868395.stm

[12] toolbar.google.com/intl/de/