Google’s PageRank and Beyond:

The Science of Search Engine Rankings

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Google’s PageRank and Beyond: The Science of Search Engine Rankings

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Outline

• Introduction to Information Retrieval

• Elements of a Search Engine

• Link Analysis

• Current Issues in Web Search
Short History of IR

IR = search within doc. coll. for particular info. need (query)

B. C.   cave paintings
7-8th cent. A.D.  Beowulf
12th cent. A.D.  invention of paper, monks in scriptoriums
1450  Gutenberg’s printing press
1700s  Franklin’s public libraries
1872  Dewey’s decimal system
1940s-1950s  Computer
1960s  Salton’s SMART system
1989  Berner-Lee’s WWW
System for the Mechanical Analysis and Retrieval of Text

Harvard 1962 – 1965

Cornell 1965 – 1970

- Implemented on IBM 7094 & IBM 360
- Based on matrix methods
Term–Document Matrices

Start with dictionary of terms

Words or phrases (e.g., landing gear)
Term–Document Matrices

Start with dictionary of terms

Words or phrases (e.g., landing gear)

Index Each Document

Humans scour pages and mark key terms
Term–Document Matrices

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Words or phrases (e.g., landing gear)

Index Each Document

Humans scour pages and mark key terms

Count $f_{ij} = \# \text{ times term } i \text{ appears in document } j$
Term–Document Matrices

Start with dictionary of terms
Words or phrases (e.g., *landing gear*)

Index Each Document
Humans scour pages and mark key terms

Count $f_{ij} = \# \text{ times term } i \text{ appears in document } j$

**Term–Document Matrix**

$$
\begin{pmatrix}
  f_{11} & f_{12} & \cdots & f_{1n} \\
  f_{21} & f_{22} & \cdots & f_{2n} \\
  \vdots & \vdots & \ddots & \vdots \\
  f_{m1} & f_{m2} & \cdots & f_{mn}
\end{pmatrix}
= A_{m \times n}
$$
Query Matching

Query Vector

\[ q^T = (q_1, q_2, \ldots, q_m) \quad q_i = \begin{cases} 1 & \text{if Term } i \text{ is requested} \\ 0 & \text{if not} \end{cases} \]
Query Matching

Query Vector

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\[ q_i = \begin{cases} 
1 & \text{if Term } i \text{ is requested} \\
0 & \text{if not} 
\end{cases} \]

How Close is Query to Each Document?
Query Matching

Query Vector

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\[ q_i = \begin{cases} 
1 & \text{if Term } i \text{ is requested} \\
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How Close is Query to Each Document?

i.e., how close is \( q \) to each column \( A_i \)?
Query Matching

Query Vector

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0 & \text{if not} 
\end{cases} \]

How Close is Query to Each Document?

i.e., how close is \( q \) to each column \( A_i \)?

Use \( \delta_i = \cos \theta_i = \frac{q^T A_i}{\|q\| \|A_i\|} \)
Query Matching

Query Vector

\[ q^T = (q_1, q_2, \ldots, q_m) \]

\[ q_i = \begin{cases} 
1 & \text{if Term } i \text{ is requested} \\
0 & \text{if not} 
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How Close is Query to Each Document?

i.e., how close is \( q \) to each column \( A_i \)?

Use \( \delta_i = \cos \theta_i = \frac{q^T A_i}{\|q\| \|A_i\|} \)

Rank documents by size of \( \delta_i \)

Return Document \( i \) to user when \( \delta_i \geq tol \)
Susan Dumais’s Improvement

- Approximate $A$ with a lower rank matrix
- Effect is to compress data in $A$

- 2 patents for Bell/Telcordia

- LATENT SEMANTIC INDEXING
Traditional IR

Pros

- Finds hidden connections
Traditional IR

Pros

- Finds hidden connections
- Can be adapted to identify document clusters
  - Text mining applications
Traditional IR

Pros

- Finds hidden connections
- Can be adapted to identify document clusters
  - Text mining applications
- Performs well on document collections that are
  - Small
  - Homogeneous
  - Static
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Cons

- Rankings are query dependent
  - Rank of each doc is recomputed for each query
Traditional IR

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- Rankings are query dependent
  - Rank of each doc is recomputed for each query
- Only semantic content used
  - Can be spammed + Link structure ignored
Traditional IR

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  - Small + Homogeneous + Static

Cons

- Rankings are query dependent
  - Rank of each doc is recomputed for each query
- Only semantic content used
  - Can be spammed + Link structure ignored
- Difficult to add & delete documents
Traditional IR

Pros

• Finds hidden connections

• Can be adapted to identify document clusters
  — Text mining applications

• Performs well on document collections that are
  ➢ Small + Homogeneous + Static

Cons

• Rankings are query dependent
  — Rank of each doc is recomputed for each query

• Only semantic content used
  — Can be spammed + Link structure ignored

• Difficult to add & delete documents

• Finding optimal compression requires empirical tuning
Trad. IR applied to Web

the pre-1998 Web Index

- border patrol: 4; 567; 809; 1103;
- hezbollah: 9; 12; 339; 942; 15158;
- global warming: 178; 12980; 445532;
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Trad. IR applied to Web

the pre-1998 Web Index

• border patrol: 4; 567; 809; 1103; . . . (8,700,000 in total)

• hezbollah: 9; 12; 339; 942; 15158; . . . (15,100,000 in total)

• global warming: 178; 12980; 445532; . . . (33,200,000 in total)
Trad. IR applied to Web

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- border patrol: 4; 567; 809; 1103; . . . (8,700,000 in total)
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- global warming: 178; 12980; 445532; . . . (33,200,000 in total)

too many results per search term
easily spammed
Sentiments about the pre-1998 Web

Yahoo
- hierarchies of sites
- organized by humans

Best Search Techniques
- word of mouth
- expert advice

Overall Feeling of Users
- Jorge Luis Borges’ 1941 short story, *The Library of Babel*

When it was proclaimed that the Library contained all books, the first impression was one of extravagant happiness. All men felt themselves to be the masters of an intact and secret treasure. There was no personal or world problem whose eloquent solution did not exist in some hexagon.

... As was natural, this inordinate hope was followed by an excessive depression. The certitude that some shelf in some hexagon held precious books and that these precious books were inaccessible, seemed almost intolerable.
1998: enter Link Analysis

- uses hyperlink structure to focus the relevant set
- combine traditional IR score with popularity score
1998 ... enter Link Analysis

Change in User Attitudes about Web Search

Today

- “It’s not my homepage, but it might as well be. I use it to ego-surf. I use it to read the news. Anytime I want to find out anything, I use it.” - Matt Groening, creator and executive producer, The Simpsons

- “I can’t imagine life without Google News. Thousands of sources from around the world ensure anyone with an Internet connection can stay informed. The diversity of viewpoints available is staggering.” - Michael Powell, chair, Federal Communications Commission

- “Google is my rapid-response research assistant. On the run-up to a deadline, I may use it to check the spelling of a foreign name, to acquire an image of a particular piece of military hardware, to find the exact quote of a public figure, check a stat, translate a phrase, or research the background of a particular corporation. It’s the Swiss Army knife of information retrieval.” - Garry Trudeau, cartoonist and creator, Doonesbury
Web Information Retrieval

IR before the Web = traditional IR
IR on the Web = web IR
Web Information Retrieval

IR before the Web = traditional IR
IR on the Web = web IR

How is the Web different from other document collections?
Web Information Retrieval

IR before the Web = traditional IR
IR on the Web = web IR

How is the Web different from other document collections?

• It’s huge.
  — over 10 billion pages, average page size of 500KB
  — 20 times size of Library of Congress print collection
  — Deep Web - 400 X bigger than Surface Web
Web Information Retrieval

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IR on the Web = web IR

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- It’s dynamic.
  - content changes: 40% of pages change in a week, 23% of .com change daily
  - size changes: billions of pages added each year
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- It’s self-organized.
  - no standards, review process, formats
  - errors, falsehoods, link rot, and spammers!
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A Herculean Task!
Web Information Retrieval

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IR on the Web = web IR

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  - over 10 billion pages, each about 500KB
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- **It’s dynamic.**
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- **It’s self-organized.**
  - no standards, review process, formats
  - errors, falsehoods, link rot, and spammers!

- **Ah, but it’s hyperlinked!**
  - Vannevar Bush’s 1945 memex
Elements of a Web Search Engine

WWW

User

Crawler Module

Page Repository

Query Module

Ranking Module

Indexes

Indexing Module

Results

Queries

Query Module

Content Index

Structure Index

Special-purpose indexes

query-independent

Indexing Module

Ranking Module
Elements of a Web Search Engine

- **WWW**
- **Crawler Module**
- **Page Repository**
- **User**
- **Query Module**
- **Query**
- **Results**
- **Indexes**
  - Content Index
  - Structure Index
  - Special-purpose indexes
  - Indexing Module
- **Ranking Module**
- **Indexing Module**
- **Query Module**

The diagram shows the flow of elements in a web search engine, starting with the WWW, crawling, indexing, ranking, and finally presenting results to the user through queries.
The Ranking Module (generates popularity scores)

- Measure the importance of each page
The Ranking Module (generates popularity scores)

- Measure the importance of each page

- The measure should be Independent of any query
  - Primarily determined by the link structure of the Web
  - Tempered by some content considerations
Elements of a Web Search Engine

- Crawler Module
- Page Repository
- User
- Query Module
- Ranking Module
- Indexes
- Special-purpose indexes
- Content Index
- Structure Index
- Query-independent
The Ranking Module (generates popularity scores)

- Measure the importance of each page
- The measure should be Independent of any query
  - Primarily determined by the link structure of the Web
  - Tempered by some content considerations
- Compute these measures off-line long before any queries are processed
Elements of a Web Search Engine

WWW

Crawler Module

Page Repository

User

Indexing Module

Query Module

Ranking Module

Queries

Results

Queries

Indexes

Special-purpose indexes

Content Index

Structure Index

query-independent
The Ranking Module (generates popularity scores)

- Measure the importance of each page

- The measure should be Independent of any query
  - Primarily determined by the link structure of the Web
  - Tempered by some content considerations

- Compute these measures off-line long before any queries are processed

- Google’s PageRank™ technology distinguishes it from all competitors
The Ranking Module (generates popularity scores)

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- The measure should be Independent of any query
  - Primarily determined by the link structure of the Web
  - Tempered by some content considerations
- Compute these measures off-line long before any queries are processed

- Google’s PageRank© technology distinguishes it from all competitors

Google’s PageRank = Google’s $$$$$
business intelligence - Wikipedia, the free encyclopedia
Business intelligence (BI) is a business management term which refers to applications and technologies which are used to gather, provide access to, ...
en.wikipedia.org/wiki/Business_intelligence - 43k - Cached - Similar pages

Business Intelligence .com :: The Resource for Business Intelligence
The Business Intelligence resource for business and technical professionals covering a wide range of topics including Performance Management, Data Warehouse ... www.businessintelligence.com/ - 74k - Apr 15, 2007 - Cached - Similar pages

Business Intelligence and Performance Management Software ...
Business intelligence and business performance management software. Reporting, analytics software, budgeting software, balanced scorecard software, ...
† Stock quote for COGN
www.cognos.com/ - 32k - Cached - Similar pages

Oracle Business Intelligence Solutions
The First Comprehensive, Cost-Effective BI Solution Only Oracle delivers a complete, pre-integrated technology foundation to reduce the cost and complexity ...
www.oracle.com/solutions/ business_intelligence/index.html - 55k - Cached - Similar pages

Business Intelligence - Management Best Practice Reports
Business Intelligence: Providers of independent reports containing best practice advice, proprietary research findings and case studies for senior managers ...
www.business-intelligence.co.uk/ - 18k - Cached - Similar pages

Intelligent Enterprise: Better Insight for Business Decisions
Take Your Pick
Amount of Internet search results that Web surfers typically scan before selecting one

- A few search results*: 23%
- First page of search results: 39%
- First two pages: 19%
- More than first three pages: 10%
- First three pages: 9%

*Top results without reading through the whole page
Note: Sample size is 2,369 people
Sources: JupiterResearch; iProspect
Business intelligence - Wikipedia, the free encyclopedia
Business intelligence (BI) is a business management term which refers to applications and technologies which are used to gather, provide access to, ...
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Intelligent Enterprise: Better Insight for Business Decisions
How To Measure “Importance”

Landmark Result Paper

Survey Paper—Big Bib
How To Measure “Importance”

Landmark Result Paper

Authorities

Survey Paper—Big Bib

Hubs
How To Measure “Importance”

- Good hubs point to good authorities
- Good authorities are pointed to by good hubs
Determine Authority & Hub Scores

- $a_i = \text{authority score for } P_i$
- $h_i = \text{hub score for } P_i$
HITS
Hypertext Induced Topic Search (1998)

Determine Authority & Hub Scores
- $a_i = \text{authority score for } P_i$
- $h_i = \text{hub score for } P_i$

Successive Refinement
- Start with $h_i = 1$ for all pages $P_i$  \(\Rightarrow\)  $h_0 =$

\[
\begin{bmatrix}
1 \\
1 \\
\vdots \\
1
\end{bmatrix}
\]
Determine Authority & Hub Scores

- $a_i = \text{authority score for } P_i$
- $h_i = \text{hub score for } P_i$

Successive Refinement

- Start with $h_i = 1$ for all pages $P_i \Rightarrow h_0 = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$
- Define Authority Scores (on the first pass)

$$a_i = \sum_{j : P_j \rightarrow P_i} h_j$$
HITS
Hypertext Induced Topic Search (1998)

Determine Authority & Hub Scores

- \( a_i \) = authority score for \( P_i \)
- \( h_i \) = hub score for \( P_i \)

Successive Refinement

- Start with \( h_i = 1 \) for all pages \( P_i \) \( \Rightarrow \) \( \mathbf{h}_0 = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \)
- Define Authority Scores (on the first pass)

\[
a_i = \sum_{j: P_j \to P_i} h_j \quad \Rightarrow \quad a_1 = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = \mathbf{L}^T \mathbf{h}_0
\]

\[
L_{ij} = \begin{cases} 1 & P_i \to P_j \\ 0 & P_i \not\to P_j \end{cases}
\]
HITS Algorithm

Refine Hub Scores

- \( h_i = \sum_{j: P_i \rightarrow P_j} a_j \quad \Rightarrow \quad h_1 = L a_1 \)

\[
L_{ij} = \begin{cases} 
1 & P_i \rightarrow P_j \\
0 & P_i \not\rightarrow P_j
\end{cases}
\]
HITS Algorithm

Refine Hub Scores

\[ h_i = \sum_{j: P_i \rightarrow P_j} a_j \Rightarrow h_1 = \mathbf{L}_i \mathbf{a}_1 \]

\[ L_{ij} = \begin{cases} 
1 & P_i \rightarrow P_j \\ 
0 & P_i \nrightarrow P_j 
\end{cases} \]

Successively Re-refine Authority & Hub Scores

\[ a_1 = \mathbf{L}^T h_0 \]
HITS Algorithm

Refine Hub Scores

- \( h_i = \sum_{j: P_i \rightarrow P_j} a_j \Rightarrow h_1 = \text{La}_1 \)

Successively Re-refine Authority & Hub Scores

- \( a_1 = L^T h_0 \)
  - \( h_1 = \text{La}_1 \)
HITS Algorithm

**Refine Hub Scores**
- \( h_i = \sum_{j: P_i \rightarrow P_j} a_j \Rightarrow h_1 = L a_1 \)

**Successively Re-refine Authority & Hub Scores**
- \( a_1 = L^T h_0 \)
  - \( h_1 = L a_1 \)
  - \( a_2 = L^T h_1 \)

\[
L_{ij} = \begin{cases} 
1 & P_i \rightarrow P_j \\
0 & P_i \not\rightarrow P_j 
\end{cases}
\]
HITS Algorithm

Refine Hub Scores

\[ h_i = \sum_{j: P_i \to P_j} a_j \Rightarrow h_1 = L a_1 \]

\[ L_{ij} = \begin{cases} 
1 & P_i \to P_j \\
0 & P_i \not\to P_j 
\end{cases} \]

Successively Re-refine Authority & Hub Scores

\[ a_1 = L^T h_0 \]

\[ h_1 = L a_1 \]

\[ a_2 = L^T h_1 \]

\[ h_2 = L a_2 \]

\[ \vdots \]
HITS Algorithm

Refine Hub Scores

\[ h_i = \sum_{j:P_i \rightarrow P_j} a_j \Rightarrow h_1 = L a_1 \]

Successively Re-refine Authority & Hub Scores

\[ a_1 = L^T h_0 \]
\[ h_1 = L a_1 \]
\[ a_2 = L^T h_1 \]
\[ h_2 = L a_2 \]

Combined Iterations

\[ A = L^T L \text{ (authority matrix)} \]
HITS Algorithm

Refine Hub Scores

- \( h_i = \sum_{j:P_i \rightarrow P_j} a_j \Rightarrow h_1 = La_1 \)

\[ L_{ij} = \begin{cases} 1 & P_i \rightarrow P_j \\ 0 & P_i \nrightarrow P_j \end{cases} \]

Successively Re-refine Authority & Hub Scores

- \( a_1 = L^T h_0 \)
  - \( h_1 = La_1 \)
  - \( a_2 = L^T h_1 \)
  - \( h_2 = La_2 \)

Combined Iterations

- \( A = L^T L \) (authority matrix) \( a_k = Aa_{k-1} \rightarrow \) e-vector (direction)
HITS Algorithm

Refine Hub Scores

- \( h_i = \sum_{j: P_i \rightarrow P_j} a_j \) \( \Rightarrow \) \( h_1 = La_1 \)

Successively Re-refine Authority & Hub Scores

- \( a_1 = L^T h_0 \)
  - \( h_1 = La_1 \)
  - \( a_2 = L^T h_1 \)
  - \( h_2 = La_2 \)

Combined Iterations

- \( A = L^T L \) (authority matrix) \( a_k = A a_{k-1} \rightarrow \) e-vector (direction)
- \( H = LL^T \) (hub matrix) \( h_k = H h_{k-1} \rightarrow \) e-vector (direction)
HITS Algorithm

Refine Hub Scores

- \( h_i = \sum_{j: P_i \rightarrow P_j} a_j \quad \Rightarrow \quad h_1 = La_1 \)

Successively Re-refine Authority & Hub Scores

- \( a_1 = L^T h_0 \)
  - \( h_1 = La_1 \)
  - \( a_2 = L^T h_1 \)
    - \( h_2 = La_2 \)
  .

Combined Iterations

- \( A = L^T L \) (authority matrix) \( a_k = A a_{k-1} \rightarrow \text{e-vector} \) (direction)
- \( H = LL^T \) (hub matrix) \( h_k = H h_{k-1} \rightarrow \text{e-vector} \) (direction)

!! May not be uniquely defined if A or H is reducible !!

\[ L_{ij} = \begin{cases} 1 & P_i \rightarrow P_j \\ 0 & P_i \not\rightarrow P_j \end{cases} \]
Compromise

1. Do direct query matching
Compromise

1. Do direct query matching
2. Build neighborhood graph
Compromise

1. Do direct query matching
2. Build neighborhood graph
3. Compute authority & hub scores for just the neighborhood
Advantages

- Returns satisfactory results
  - Client gets both authority & hub scores
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- Too much has to happen while client is waiting
  - Custom built neighborhood graph needed for each query
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- Scores can be manipulated by creating artificial hubs
HITS Applied
Every time you cough, a hunk of code or a piece of some obscure url comes shooting out. You can't see it, but it's there. Probably there is some on your shoes. A little string of binary code, or maybe the "i" and "g" from a dot org, escaping there on your burgundy cap-toes. The reason is that you're drowning in a sea of information. Heed not the worrisome findings of the recent ODP coastline study—by the time glacial melt brings the ocean to your doorstep, your lungs will already be full of html.

WE DON'T HAVE TO TELL YOU THE WORLD WIDE WEB IS AN ANARCHIC FORM OF POPULIST HYPERMEDIA. But we will tell you it's a hyper-text corpus of unfathomable intricacy, and it's expanding faster than a flat universe in a cosmologically significant vacuum energy density. For the love of Godel, just look at the thing! Millions of participants with as many agendas, cranking out hyperlinked content like there's no tomorrow. In fact, at this rate, the discourse of tomorrow, or at least, universally accepted definition thereof, is actually a valid concern.

SEARCH IS AN UNDERSTATEMENT. ODYSSEAN QUEST IS MORE LIKE IT.

So how are you supposed to find anything in this great rolling mass of ones and zeros? Text-based searches are not so good. If you believe otherwise, consider the word facial. A search engine that takes nothing more than the word itself into account will return results that are consistently scattered. On one end of the facial spectrum, there's a mud mask. The other kind of facial, well...as anyone who rolls sans adult filter can attest, it's a different deal altogether.

Look, even if you do manage to cluster a word into five different meanings, there's still the fact that each individual yields nearly infinite search results. And a quincunx divided by five is still two hundred quadrants/decisions.

ALL OF A SUDDEN, "WHO KNOWS?" IS AN ASTUDE QUESTION.

Searching the Internet, it turns out, is not much different from searching the real world. The best thing you can do is to ask someone who knows. An authority on the subject. But who are the authorities, and what qualifies them as such in the first place? A Web page can't just declare itself an authority. If authority could be generated endogenously, Louis de Branges would have verified his own proof of the Riemann Hypothesis. Neither should authority be conferred from one page to another. This means you'd be OK letting Herman Mudgett pick your primary care gyn. Last in the triumvirate of really-bad-ways-to-determine authority is the notion of popularity. Surprisingly, this is the method employed by today's most widely used search engines. They find sites with the most links and present them as authorities. This is roughly analogous to handing the Fields Medal to your high school homecoming queen.

THE ANSWER CAME FROM BOOKS. WEIRD.

So what's the solution to search? While computer science was trying to coax an answer from its collective hard drive, it was sitting right there in the stacks all along. Who could have guessed that when Eugene Garfield went all bibliometric and devised a system to find out how much a journal mattered by counting the number of times that journal was cited in other publications, he consciously invented the beginnings of a system that might work in search. Then Gabriel Pinski and Francis Narin took it a step further by suggesting some citations should carry more weight than others, and let's face it, being cited in the Spring '96 issue of Social Text (pages 217–252, to be precise) isn't exactly a literary feather in your cap. But taking into account the quality of citations is only half the answer in search. Because compared to the academic world of scientific publishing, the Internet is completely insane. Fluid. Vagile. Heterogeneous. Aawash in a world of conflicting agendas. So counting inbounds links isn't enough. Not even close. To search effectively in these circumstances, you have to do some serious math gogglies and take a look at the big picture.

THE ALGORITHM SEES GALAXIES, BUT IT'S BLIND AS A BAT.

The heavy hitters of search all use the same mathematically myopic approach—counting links back to authoritative Web pages. An approach that only way to tell what's really going on is to take a step back and look for patterns in the sites that point back to authorities. And when you do, you quickly see that there is another layer to the puzzle—sites that point to more than one authority, or hub pages, if you will. These hubs and their surrounding authorities form little galaxies of relevant information, something that makes the hair stand up on the back of any self-respecting searchophile's neck. It's the difference between checking out the Big Dipper from a lawn chair in your back yard and peering into Fornax with Hubble's Ultra Deep Field. But an algorithm that could detect these galaxies would be virtually impossible to pull off, since it would have to assess both inbound and outbound information, and continually calculate the relationship between the two, in real time.

THE ALGORITHM IS RELATIVELY SIMPLE, IF YOU'RE SOME KIND OF SAVANT.

It works like this. For each search query, an index G of Web pages is found. For each page p, you associate a non-negative authority weight \(a(p)\) and a non-negative hub weight \(h(p)\). This will lead you to the rather obvious conclusion that if page p points to lots of pages with big values, it should get a big value (inverse weighted popularity). And when page p is pointed to by lots of pages with big values, it should get a big value (weighted popularity). From here, you simply fire up an iterative singular value decomposition operation and wrap the results up by banging out an orthonormal basis of eigenspace for each and obtaining the eigenvectors for the matrices in question. That's it.

IT'S A GOOD THING ROBERT FROST NEVER WROTE AN ALGORITHM.

Taking the road less traveled is fine if you're stumbling around the New England countryside, being whimsical or whatever. But when you're searching online, that kind of thing gets you eaten by wolves. Because dismissing where others have gone can quickly get you lost in a forest of incomplete results. But while you are learning from the Algorithm, the Algorithm is learning too. It studies the way anonymous groups of users search and forms an aggregate view of which results those users find the most valuable. This sends a relevance signal through the roof and gets you to your desired destination without the slightest hint of lupine intercession. Sure, "The Road Traveled Every Five Minutes" would make a lousy poem, but it makes a gorgeous piece of code.

THE ALGORITHM APPROACHES ARTIFICIAL INTELLIGENCE, BUT IT HAS NOTHING AGAINST PEOPLE NAMED SARAH CONNOR.

Yes, the Algorithm is an omniscient, evolving organism devoid of all feeling, but in no way should this freak you out. In fact, it's cause for celebration. Because the Algorithm comes in peace. It's here to revolutionize search by identifying a topic, finding experts on that topic, and assessing the popularity of pages among those experts, simultaneously, in the blink of an eye, whenever you want. It's here to narrow or expand your search based on concept—something no other search engine can do. Never again will you wade into the perpetually updated, subject-centric world of blogs without technology that actually comprehends subjects. The Algorithm knows that Usher Syndrome is transmitted by an autosomal recessive gene, not a subwoofer. And never again will you get "results" consisting merely of ten blue links, rather than the rich aggregate of images, video, conceptually related search topics and pure expert insight the Algorithm delivers.

THE ALGORITHM UNDERSTANDS THAT COLLECTIVE WISDOM IS NOT NECESSARILY COLLECTED FROM EVERYONE.

Based solely on the number of participants, the Web is undoubtedly the world's largest source of pure wisdom. But this doesn't mean there is wisdom inherent in every participant or every page. The Algorithm is acutely aware of this. It realizes that somewhere between James Surowiecki's The Wisdom of Crowds and Charles Mackay's Madness of Crowds lies the sweet spot. It sees everything but knows just what to look for. Its scorus the convoluted expenses of cyberspace and brings back an instantaneous convergence of wisdom collected, waiting for the day you're ready.
The Next Frontiers

The New Age of Google

The Search Giant Has Changed Our Lives. Can Anybody Catch These Guys? By Steven Levy

PLUS: The Future of Digital Voting

Google founders Larry Page and Sergey Brin
Google’s PageRank
(Lawrence Page & Sergey Brin 1998)

The Google Goals

- Create a PageRank $r(P)$ that is not query dependent
  - Off-line calculations — No query time computation
- Let the Web vote with in-links
  - But not by simple link counts
    - One link to $P$ from Yahoo! is important
    - Many links to $P$ from me is not
- Share The Vote
  - Yahoo! casts many “votes”
    - value of vote from Yahoo! is diluted
  - If Yahoo! “votes” for $n$ pages
    - Then $P$ receives only $r(Y)/n$ credit from $Y$
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PageRank

The Definition

\[ r(P) = \sum_{P \in B_P} \frac{r(P)}{|P|} \]

- \( B_P = \{\text{all pages pointing to } P\} \)
- \( |P| = \text{number of out links from } P \)
PageRank

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Successive Refinement

Start with \( r_0(P_i) = 1/n \) for all pages \( P_1, P_2, \ldots, P_n \)
PageRank

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Start with \( r_0(P_i) = \frac{1}{n} \) for all pages \( P_1, P_2, \ldots, P_n \)

Iteratively refine rankings for each page

\[ r_1(P_i) = \sum_{P \in B_{P_i}} \frac{r_0(P)}{|P|} \]
PageRank

The Definition

\[ r(P) = \sum_{P \in \mathcal{B}_P} \frac{r(P)}{|P|} \]

\[ \mathcal{B}_P = \{ \text{all pages pointing to } P \} \]

\[ |P| = \text{number of out links from } P \]

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PageRank

The Definition

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Iteratively refine rankings for each page

\[ r_1(P_i) = \sum_{P \in \mathcal{B}_{P_i}} \frac{r_0(P)}{|P|} \]

\[ r_2(P_i) = \sum_{P \in \mathcal{B}_{P_i}} \frac{r_1(P)}{|P|} \]

\[ \vdots \]

\[ r_{j+1}(P_i) = \sum_{P \in \mathcal{B}_{P_i}} \frac{r_j(P)}{|P|} \]
In Matrix Notation

After Step $k$

\[ \pi^T_k = [r_k(P_1), r_k(P_2), \cdots, r_k(P_n)] \]
In Matrix Notation

After Step $k$

$\pi_k^T = [r_k(P_1), r_k(P_2), \cdots, r_k(P_n)]$

and

$\pi_{k+1}^T = \pi_k^T H$

where

$$h_{ij} = \begin{cases} 
\frac{1}{|P_i|} & \text{if } i \rightarrow j \\
0 & \text{otherwise}
\end{cases}$$
In Matrix Notation

After Step \( k \)

\[- \pi_k^T = [r_k(P_1), r_k(P_2), \cdots, r_k(P_n)] \]

\[- \pi_{k+1}^T = \pi_k^T H \text{ where } h_{ij} = \begin{cases} 
1/|P_i| & \text{if } i \to j \\
0 & \text{otherwise}
\end{cases} \]

\[- \text{PageRank vector } = \pi^T = \lim_{k \to \infty} \pi_k^T = \text{eigenvector for } H \]

Provided that the limit exists
Tiny Web

\[ H = \begin{pmatrix} P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\ P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \end{pmatrix} \]
Tiny Web

\[ H = \begin{pmatrix} P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\ P_1 & 0 & 1/2 & 1/2 & 0 & 0 \\ P_2 & & 0 & 0 & 0 & 0 \\ P_3 & & & 0 & 0 & 0 \\ P_4 & & & & 0 & 0 \\ P_5 & & & & & 0 \\ P_6 & & & & & & 0 \end{pmatrix} \]
Tiny Web

\[
\begin{pmatrix}
P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\
0 & 1/2 & 1/2 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{pmatrix}
\]
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$H = \begin{pmatrix}
P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\
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0 & 0 & 0 & 0 & 0 & 0 \\
1/3 & 1/3 & 0 & 0 & 1/3 & 0
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    P_3 & 0 & 0 & 0 & 0 & 1/2 & 1/2 \\
    P_4 & 0 & 0 & 0 & 0 & 0 & 0 \\
    P_5 & 0 & 0 & 0 & 0 & 0 & 0 \\
    P_6 & 0 & 0 & 0 & 0 & 0 & 0
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\end{pmatrix}
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$$\mathbf{H} = \begin{pmatrix}
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\end{pmatrix} \]

A random walk on the Web Graph
A random walk on the Web Graph

PageRank = $\pi_i$ = amount of time spent at $P_i$
Ranking with a Random Surfer

- Rank each page corresponding to a search term by number and quality of votes cast for that page.

Hyperlink as vote

Markov chain
Ranking with a Random Surfer

- Rank each page corresponding to a search term by number and *quality* of votes cast for that page.

Hyperlink as vote
Ranking with a Random Surfer

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Hyperlink as vote
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Hyperlink as vote
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Hyperlink as vote

![Diagram showing hyperlinks as votes](image-url)
Ranking with a Random Surfer

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Hyperlink as vote
Ranking with a Random Surfer

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Hyperlink as vote

![Diagram showing the ranking of pages](image)
Ranking with a Random Surfer

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Hyperlink as vote
Ranking with a Random Surfer

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Ranking with a Random Surfer

- Rank each page corresponding to a search term by number and *quality* of votes cast for that page.

Hyperlink as vote

page 2 is a dangling node
A random walk on the Web Graph

PageRank = $\pi_i = \text{amount of time spent at } P_i$

Dead end page (nothing to click on) — a “dangling node”
A random walk on the Web Graph

PageRank = $\pi_i = \text{amount of time spent at } P_i$

Dead end page (nothing to click on) — a “dangling node”

$\pi^T = (0, 1, 0, 0, 0, 0) = \text{e-vector} \quad \Rightarrow \quad \text{Page } P_2 \text{ is a “rank sink”}$
The Fix

Allow Web Surfers To Make Random Jumps
Ranking with a Random Surfer

- Rank each page corresponding to a search term by number and quality of votes cast for that page.

Hyperlink as vote

surfer “teleports”
The Fix

Allow Web Surfers To Make Random Jumps

- Replace zero rows with \( \textbf{e}^T = \left( \frac{1}{n}, \frac{1}{n}, \ldots, \frac{1}{n} \right) \)

\[
\mathbf{S} = \begin{pmatrix}
P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\
P_1 & 0 & 1/2 & 1/2 & 0 & 0 & 0 \\
P_2 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\
P_3 & 1/3 & 1/3 & 0 & 0 & 1/3 & 0 \\
P_4 & 0 & 0 & 0 & 0 & 1/2 & 1/2 \\
P_5 & 0 & 0 & 0 & 1/2 & 0 & 1/2 \\
P_6 & 0 & 0 & 0 & 1 & 0 & 0
\end{pmatrix}
\]
The Fix
Allow Web Surfers To Make Random Jumps

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$\mathbf{S} = \begin{pmatrix}
P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\
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1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\
1/3 & 1/3 & 0 & 0 & 1/3 & 0 \\
0 & 0 & 0 & 0 & 1/2 & 1/2 \\
0 & 0 & 0 & 1/2 & 0 & 1/2 \\
0 & 0 & 0 & 1 & 0 & 0
\end{pmatrix}$

— $\mathbf{S} = \mathbf{H} + \frac{a \mathbf{e}^T}{6}$ is now row stochastic $\implies \rho(\mathbf{S}) = 1$
The Fix

Allow Web Surfers To Make Random Jumps

— Replace zero rows with \( \mathbf{e}^T/n = \left( \frac{1}{n}, \frac{1}{n}, \ldots, \frac{1}{n} \right) \)

\[
\mathbf{S} = \begin{pmatrix}
P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\
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\end{pmatrix}
\]

— \( \mathbf{S} = \mathbf{H} + \frac{\mathbf{ae}^T}{6} \) is now row stochastic \( \Rightarrow \rho(\mathbf{S}) = 1 \)

— Perron says \( \exists \ \mathbf{\pi}^T \geq 0 \) s.t. \( \mathbf{\pi}^T = \mathbf{\pi}^T \mathbf{S} \) with \( \sum_i \pi_i = 1 \)
Nasty Problem

The Web Is Not Strongly Connected
The Web Is Not Strongly Connected

S is reducible

\[
S = \begin{pmatrix}
P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\
0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 \\
\frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} \\
\frac{1}{3} & \frac{1}{3} & 0 & 0 & \frac{1}{3} & 0 \\
0 & 0 & 0 & 0 & \frac{1}{2} & 1/2 \\
0 & 0 & 0 & \frac{1}{2} & 0 & 1/2 \\
0 & 0 & 0 & 1 & 0 & 0
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Nasty Problem

The Web Is Not Strongly Connected

- S is reducible

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S = \begin{pmatrix}
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P_3 & 1/3 & 1/3 & 0 & 0 & 1/3 & 0 \\
P_4 & 0 & 0 & 0 & 0 & 1/2 & 1/2 \\
P_5 & 0 & 0 & 0 & 1/2 & 0 & 1/2 \\
P_6 & 0 & 0 & 0 & 1 & 0 & 0 \\
\end{pmatrix}
\]

- Reducible \(\implies\) PageRank vector is not well defined

- Frobenius says \(S\) needs to be \textit{irreducible} to ensure a unique \(\pi^T > 0\) s.t. \(\pi^T = \pi^T S\) with \(\sum_i \pi_i = 1\)
Irreducibility Is Not Enough

Could Get Trapped Into A Cycle \((P_i \rightarrow P_j \rightarrow P_i)\)
Irreducibility Is Not Enough

Could Get Trapped Into A Cycle \( (P_i \rightarrow P_j \rightarrow P_i) \)

- The powers \( S^k \) fail to converge
Irreducibility Is Not Enough

Could Get Trapped Into A Cycle $(P_i \rightarrow P_j \rightarrow P_i)$

- The powers $S^k$ fail to converge

- $\pi_{T_{k+1}}^T = \pi_{T_k}^T S$ fails to convergence
Irreducibility Is Not Enough

Could Get Trapped Into A Cycle \((P_i \rightarrow P_j \rightarrow P_i)\)

- The powers \(S^k\) fail to converge
- \(\pi_{k+1}^T = \pi_k^T S\) fails to converge

Convergence Requirement

- Perron–Frobenius requires \(S\) to be primitive
Irreducibility Is Not Enough

Could Get Trapped Into A Cycle \((P_i \rightarrow P_j \rightarrow P_i)\)

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Convergence Requirement

- Perron–Frobenius requires \(S\) to be primitive
- No eigenvalues other than \(\lambda = 1\) on unit circle
Irreducibility Is Not Enough

Could Get Trapped Into A Cycle \((P_i \rightarrow P_j \rightarrow P_i)\)

- The powers \(S^k\) fail to converge
- \(\pi_{k+1}^T = \pi_k^T S\) fails to convergence

Convergence Requirement

- Perron–Frobenius requires \(S\) to be primitive
- No eigenvalues other than \(\lambda = 1\) on unit circle
- Frobenius proved \(S\) is primitive \(\iff S^k > 0\) for some \(k\)
The Google Fix

Allow A Random Jump From Any Page

\[ G = \alpha S + (1 - \alpha)E > 0, \quad E = ee^T/n, \quad 0 < \alpha < 1 \]
The Google Fix

Allow A Random Jump From Any Page

1. \[ G = \alpha S + (1 - \alpha)E > 0, \quad E = ee^T/n, \quad 0 < \alpha < 1 \]

2. \[ G = \alpha H + uv^T > 0 \quad u = \alpha a + (1 - \alpha)e, \quad v^T = e^T/n \]
The Google Fix

Allow A Random Jump From Any Page

- $G = \alpha S + (1 - \alpha)E > 0, \quad E = ee^T/n, \quad 0 < \alpha < 1$

- $G = \alpha H + uv^T > 0 \quad u = \alpha a + (1 - \alpha)e, \quad v^T = e^T/n$

- PageRank vector $\pi^T = \text{left-hand Perron vector of } G$
Ranking with a Random Surfer

- If a page is “important,” it gets lots of votes from other important pages, which means the random surfer visits it often.

- Simply count the number of times, or proportion of time, the surfer spends on each page to create ranking of webpages.
If a page is “important,” it gets lots of votes from other important pages, which means the random surfer visits it often.

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<table>
<thead>
<tr>
<th>Proportion of Time</th>
<th>Ranked List of Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Page 1 = .04</td>
<td>Page 4</td>
</tr>
<tr>
<td>Page 2 = .05</td>
<td>Page 6</td>
</tr>
<tr>
<td>Page 3 = .04</td>
<td>Page 5</td>
</tr>
<tr>
<td>Page 4 = .38</td>
<td>Page 2</td>
</tr>
<tr>
<td>Page 5 = .20</td>
<td>Page 1</td>
</tr>
<tr>
<td>Page 6 = .29</td>
<td>Page 3</td>
</tr>
</tbody>
</table>
The Google Fix

Allow A Random Jump From Any Page

- \( G = \alpha S + (1 - \alpha)E \geq 0 \), \( E = ee^T/n \), \( 0 < \alpha < 1 \)

- \( G = \alpha H + uv^T \geq 0 \)
  - \( u = \alpha a + (1 - \alpha)e \), \( v^T = e^T/n \)

- PageRank vector \( \pi^T = \) left-hand Perron vector of \( G \)

Some Happy Accidents

- \( x^T G = \alpha x^T H + \beta v^T \)  
  Sparse computations with the original link structure
The Google Fix

Allow A Random Jump From Any Page

- $G = \alpha S + (1 - \alpha)E > 0$, $E = ee^T/n$, $0 < \alpha < 1$
- $G = \alpha H + uv^T > 0$ $u = \alpha a + (1 - \alpha)e$, $v^T = e^T/n$
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Some Happy Accidents

- $x^T G = \alpha x^T H + \beta v^T$ Sparse computations with the original link structure
- $\lambda_2(G) = \alpha$ Convergence rate controllable by Google engineers
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Some Happy Accidents

- \[ x^T G = \alpha x^T H + \beta v^T \]
  Sparse computations with the original link structure
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PageRank vector \[ \pi^T = \text{left-hand Perron vector of } G \]

Some Happy Accidents

\[ x^T G = \alpha x^T H + \beta v^T \quad \text{Sparse computations with the original link structure} \]

\[ \lambda_2(G) = \alpha \quad \text{Convergence rate controllable by Google engineers} \]

\[ v^T \text{ can be any positive probability vector in } G = \alpha H + uv^T \]

The choice of \[ v^T \text{ allows for personalization} \]
Search Issues

Spamming

- Link Farms
What's News

Business and Finance

NEWS CORP. and Liberty are no longer working together on a joint offer to take control of Hughes, with News Corp. proceeding on its own and Liberty considering an independent bid. The move threatens to cloud the process of finding a new owner for the GM unit.

(Article on Page A3)

The SEC signaled it may file civil charges against Morgan Stanley, alleging it doled out IPO shares based partly on investors' commitments to buy more stock.

(Article on Page C1)

Aholt's problems deepened as U.S. authorities opened inquiries into accounting at the Dutch company's U.S. Foodservice unit.

Fleming said the SEC upgraded to a formal investigation an inquiry into the food wholesaler's trade practices with suppliers.

(Articles on Page A2)

Consumer confidence fell to its lowest level since 1993, hurt by energy costs, the terrorism threat and a stagnant job market.

(Article on Page A3)

The industrials rebounded on expectations of a rebound in housing and business confidence.

Web Master

As the Web spreads...

Total Internet users, by household, in millions


Estimates

Google's U.S. presence expands

Top search engines, in millions of unique visitors

Google 39.4
Yahoo Search 38.8
MSN Search 38.8
AOL Search 22.0
Ask Jeeves 13.3
Overture 6.4

Sources: Forrester Research; Nielsen NetRatings

Bush to Seek up to $95 Billion To Cover Costs of War on Iraq

By Greg Jaffe
And John D. McKinnon

WASHINGTON—The Bush administration is preparing supplemental spending requests totaling as much as $95 billion for a war with Iraq, its aftermath and new expenses to fight terrorism, officials said.

The total could be as low as $60 billion because Pentagon budget planners don't know how long a military conflict will last, whether U.S. allies will contribute more than token sums to the effort and what damage Saddam Hussein might do to his own country to retaliate against conquering forces.

Budget planners also are awaiting the outcome of an intense internal debate over whether to include $13 billion in the requests to Congress that the Pentagon says it needs to fund the broader war on terrorism, as well as for stepped up homeland security. The White House Office of Management and Budget argues that the money might not be necessary. President Bush, Defense Secretary Donald Rumsfeld and budget director Mitchell Daniels Jr. met yesterday to discuss the matter but didn't reach a final agreement. Mr. Rumsfeld plans to continue pressing his case.

Cat and Mouse

As Google Becomes Web's Gatekeeper, Sites Fight to Get In

Search Engine Punishes Firms That Try to Game System; Outlawing the 'Link Farms'

Exotic Leatherwear Gets Cut Off

By Michael Totty
And Mylene Mangalindan

Joy Holman sells provocative leather clothing on the Web. She wants what nearly everyone doing business online wants: more exposure on Google.

So from the time she launched exoticleatherwear.com last May, she tried all sorts of tricks to get her site to show up among the first listings when a user of Google Inc.'s popular search engine typed in "women's leatherwear" or "leather apparel." She buried hidden words in her Web pages intended to fool Google's computer. She signed up with a service that promised to have hundreds of sites link to her online store—thereby boosting a crucial measure in Google's system of ranking sites.

The techniques
Web Sites Fight for Prime Real Estate on Google

Continued From First Page

advertising that tried to capitalize on Google’s formula for ranking sites. In effect, SearchKing was offering its clients a chance to boost their own Google rankings by advertising on a few of the most popular sites. SearchKing filed suit against the search company in federal court in Oklahoma, claiming that Google “purposefully devalued” SearchKing and its customers, damaging its reputation and hurting its bottom line.

Google won’t comment on the case. In court filings, the company said SearchKing “engaged in behavior that would lower the quality of Google search results” and alter the company’s ranking system.

Google, a closely held company founded by Stanford University graduate students Sergey Brin and Larry Page, says Web companies that want to rank high should concentrate on improving their Web pages rather than gaming the system. “When people try to game into other ways, that turns into a worse experience for users,” says Matt Cutts, a Google software engineer.

Cashing Tricky

Efforts to outfox the search engines have been around since search engines first became popular in the early 1990s. Early efforts included stuffing thousands of widely used search terms into the body of a Web page. The idea was to increase the number of times a word or phrase appeared in the page’s text. But Google’s system, based on links, was not fooled.

Mr. Brin, 29, one of Google’s two founders and now its president of technology, said at a San Francisco search engine conference in 2000 that Google was not worried about having its results clogged with irrelevant results because its search methods couldn’t be manipulated.

That didn’t stop search optimizers from finding other ways to outfox the system. Attempts to manipulate Google’s results even became a sport, called Googling. Creating Web sites that were nothing more than collections of links to the clients’ sites, called “link farms,” since Google ranks a site largely by how many links or “votes” it gets, the link farms could boost a site’s popularity. In a similar technique, called a link exchange, a group of unrelated sites would agree to all link to each other, thereby fooling Google into thinking the sites have a multitude of votes. Many of these sites also found they could buy links to themselves to boost their rankings.

Ms. Holman, the leatherwear retailer, discovered the consequences of trying to fool Google. The 42-year-old hospital laboratory technician, who learned computer skills by troubleshooting her hospital’s equipment, operates her online apparel store as a side business that she hopes can someday replace her day job.

When she launched her Exotic Leather Wear store from her home in Mesa, Ariz., she quickly learned the importance of appearing near the top of search-engine results, especially on Google. She boned up on search techniques, visiting online discussion groups dedicated to search engines and reading what material she could find on the Web.

At first, Ms. Holman limited herself to modest changes, such as loading her page with hidden metadata coding that would help steer a search toward her site when a user entered words such as “halter tops” or “leather mini skirts.” But as Google gave weight to metadata in determining its rankings, the efforts had little effect on her search results.

She then received an e-mail advertisement from AutomatedLinks.com, a Wirral, England, company that promised to send traffic “through the roof” by linking more than 2,000 Web sites to hers. Aside from attracting customers, the links were designed to improve her Web site’s page rank by increasing its visibility to Google. In theory, when Google encounters the AutomatedLinks code, it treats it as a legitimate referral to the other sites and credits them in tooting up the sites’ popularity.

In August, Ms. Holman signed up with AutomatedLinks in July, she reads on an online discussion group that Google objected to such link arrangements. She says she immediately stripped the code from her Web pages. For a while her site gradually improved its way up Google’s search results, and business steadily improved because links to her site still remained on the sites of other AutomatedLinks customers. Then, sometime in November, her site was suddenly no longer appearing in the top results. Her orders plunged as much as 80%.

Ms. Holman, who e-mailed Google and AutomatedLinks, says she has been unable to get answers. But in the last few months, other AutomatedLinks customers also have seen their sites apparently penalized by Google. Graham McLeay, who runs a small chauffeur service north of London, saw revenue cut in half during the two months he believes his site was penalized by Google.

The high-stakes fight between Google and the optimizers can leave some Web site owners confused. “I don’t know how people are supposed to judge what is right and wrong,” says Mr. McLeay.

AutomatedLinks didn’t respond to requests for comment. Google, in a court filing, said Mr. Cutts, the Google engineer, warns that the rules are clear and that it’s better to follow them rather than to try to get a problem fixed after a site has been penalized. “We want to return the most relevant pages we can,” Mr. Cutts said. “We can’t take on the role of a site owner to do that is follow our guidelines.”

Crackdown

Google has been stepping up its enforcement since 2001. It warned AutomatedLinks that it should get its sites kicked out of the Google index and it provided a list of forbidden activities, including hiding text and “link schemes,” such as the link farms. Google also warned against “cloaking” sites to score well while giving visitors a different, more attractive page—or creating multiple Web addresses that take visitors to a single site.

The homepage of the Web- homa City-based SearchKing, an online directory for hundreds of small, specialty Web sites, SearchKing also sells advertising links designed both to draw an advertiser and boost its rankings in Google and other search results.

Bob Massa, SearchKing’s chief executive, last August launched the PR Ad Net work as a way to capitalize on Google’s page-ranking system, which ranks pages based on a scale of one to 10 based on their popularity, and the rankings can be viewed by Web users if they install special Google software. PR Ad Network sells ads that are priced according to a site’s Page Rank, with higher-ranked sites commanding higher prices. When a site buys an advertising link on a highly ranked site, the ad buyer could see its ratings improve because of the greater weight Google gives to that link. Shortly after publicizing the ad network, Mr. Massa discovered that his site suddenly dropped in Google’s rankings. What’s more, sites that participated in the separate SearchKing directory also had their Google rankings lowered. He filed a lawsuit in Oklahoma federal court, claiming Google was punishing him for trying to profit from the company’s page-ranking system.

A Google spokesman won’t comment on the case. In its court filings, Google said it deposed page rankers for the company in the search engine because of SearchKing’s attempts to manipulate search results. The company has asked for the suit to be dismissed, arguing that the PageRank program represents its opinion of the value of a Web site and is protected by the First Amendment.

“The big search engines determine the laws of how commerce runs,” says Mr. Massa. “Google is taking steps that many say could satisfy businesses trying to boost their rankings. Google has sold sponsored links that show up on the top of many search-results pages, separate from the main listings. Last year, the company expanded its paid-listings program, so that there are now more stores where sites can pay for a prominent place in the results. Many sites are now turning to advertising instead of tactics to optimize their rankings.”

Home Depot

Amid First

By CHAD TURPIN

ATLANTA—Home Depot fiscal fourth-quarter earnings 3.4% on disappointing sales. Speaking to investors an analyst, the company’s chief executive, Richurn, said Home Depot is prepared to serve small dissatisfied customers and competitive challenge from rival with remodeled stores, in the executive, Home Depot is prepared to serve small dissatisfied customers and competitive challenge from rival with remodeled stores.

The nation’s largest home retailer said net income ended Feb. 2 decreased to $30 cents a share, from $37 cents a share, a year earlier. The company said its sales increased 5% and net income grew to $311 million, up from $307 million, an increase of at least a year, a decade. Home Depot sales so last month offset a disaster and helped the retailer avoid an estimate that same-store sales were to experience earnings consent. Home Depot shares rose 6 cents.

Fiat Patricia

Is Set to Bed

By ALESSANDRA GATTO

ROME—Umberto Agnelli named Fiat SpA chairman of the director of the seat at Fiat Agnelli worked on an 11th century, the 58-year-old Fiat patriarch Gianni Agnelli last month, was widely expected to succeed from current chair, Giampaolo Agnelli, later this year. Mr. Agnelli, who has served as chairman...
Search Issues

Spamming

- Link Farms
- Google Bombs
'Miserable failure' links to Bush

George W Bush has been Google bombed.

Web users entering the words "miserable failure" into the popular search engine are directed to the biography of the president on the White House website.

The trick is possible because Google searches more than just the contents of web pages - it also counts how often a site is linked to, and with what words.

Thus, members of an online community can affect the results of Google searches - called "Google bombing" - by linking their sites to a chosen one.

Weblogger Adam Mathes is credited with inventing the practice in 2001, when he used it to link the phrase "talentless hack" to a friend's website.

The search engine can be manipulated by a fairly small group of users, one report suggested.

Newsday newspaper says as few as 32 web pages with the words "miserable failure" link to the Bush biography.

If you are George Bush and typed the country's name in the address bar, make sure that it is spelled correctly (IRAQ).

The Bush administration has been on the receiving end of pointed Google bombs before.

In the run-up to the Iraq war, internet users manipulated Google so the phrase "weapons of mass destruction" led to a joke page saying "These Weapons of Mass Destruction cannot be displayed."

The site suggests "clicking the regime change button", or "If you are George Bush and typed the country's name in the address bar, make sure that it is spelled correctly (IRAQ)".

SEE ALSO:
WMD spoof is internet hit
04 Jul 03  |  West Midlands
Google hit by link bombers
13 Mar 02  |  Science/Nature

RELATED INTERNET LINKS:
White House
Google bombing

The BBC is not responsible for the content of external internet sites

TOP AMERICAS STORIES NOW
US army battles to keep soldiers
Report backs US Catholic bishops
Envoys bid to ease BSE fears
Protests widen over sky marshals
I'm taking part in a new web project...

From this day forth, I will refer to George W. Bush as a Miserable Failure at least once a day. Why, you ask? Well, someone came up with this great idea to link George W. Bush and Miserable Failure in popular search engines. If you have a blog or web site, help raise the link between George W. Bush and the phrase ‘miserable failure’ by copying this link and placing somewhere on your site or blog.

Thank you very much for your participation.

Replies: 16 people speak up

That is genius. I could add a few other keywords, like "pathetic". I will post it on my blog now...

Miserable Failure? I'm down with that....

Stay tuned...

thats great, another thing I think might be good to use: tax cuts for the wealthy....welfare for the wealthy. just my 2 cents.

The key is stating it in connection with terms that will be widely searched. It does no good to simply say "George Bush is a miserable failure" because no one will ever search for that. It might be fun at a parties to show how often the two are in the same sentence in a Google search, but otherwise it does little to advance the theme.

What will work is connecting it to frequent search times, such as "Iraq policy". For instance "George Bush's Iraq Policy is a miserable failure."

The plan shouldn't be to link Miserable Failure to George Bush, but to link Miserable Failure to George Bush and two or three choice, frequently searched phrases.

Overture.com has a keyword suggestion tool that shows how many times certain terms are coming up in searches. Using that tool, I can determine that in September the search for "bush george iraq saddam" gets about 12 times more queries than "george bush iraq speech". "george bush biography" gets a huge amounts of hits compared to something like "george bush policy".

So someone needs to write about three complete sentences using these terms based on verfiable search results and including the "miserable failure" phrase and then advocate for that exact usage.

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According to Overture, the phrases "george Bush miserable failure" were not queried even once in their sample during the month just passed.

how about drunken, illiterate, mendacious, runt-like miserable failure?

how about, instead of calling it lies--anyone can lie--how about calling it HORSEFEATHERS AND CODSWALLOP! Pin that on him too.
miserable failure

Google Search: miserable failure

Web  Images  Groups  Directory  News
Searched the web for miserable failure. Results 1 - 10 of about 257,000. Search took 0.08 seconds.
Tip: In most browsers you can just hit the return key instead of clicking on the search button.

Michael Moore.com
Wednesday, January 14th, 2004 I'll Be Voting For Wesley Clark /
Good-Bye Mr. Bush — by Michael Moore. Many of you have written ...
Description: Official site of the gadfly of corporations, creator of the film Roger and Me and the television show...
Category: Arts > Celebrities > M > Moore, Michael
www.michaelmoore.com/ - 43k - Cached - Similar pages

Biography of President George W. Bush
Home > President > Biography President George W. Bush En Español.
George W. Bush is the 43rd President of the United States. He ...
Description: Biography of the president from the official White House web site.
Category: Kids and Teens > School Time > ... > Bush, George Walker
www.whitehouse.gov/president/gwbbio.html - 29k - Cached - Similar pages

Biography of Jimmy Carter
Jimmy Carter aspired to make Government "competent and compassionate ...
Description: Short biography from the official White House site.
Category: Society > History > ... > Presidents > Carter, James Earl
www.whitehouse.gov/history/presidents/jc39.html - 36k - Cached - Similar pages

Senator Hillary Rodham Clinton: Online Office Welcome Page
Dear Friend,. Thank you for visiting my on-line office! I appreciate your interest in the issues before the United States Senate. ...
Description: Official US Senate web site of Senator Hillary Rodham Clinton (D - NY).
Category: Society > History > ... > First Ladies > Clinton, Hillary
clinton.senate.gov/ - 9k - Cached - Similar pages

BBC NEWS | Americas | 'Miserable failure' links to Bush
'Miserable failure' links to Bush. ... Prank website. Newsday newspaper says as few as 32 web pages with the words "miserable failure" link to the Bush biography. ...
news.bbc.co.uk/2/hi/americas/3298443.stm - 31k - Cached - Similar pages

Atlantic Unbound | Politics & Prose | 2003.09.24
... Atlantic Unbound | September 24, 2003 Politics & Prose | by Jack Beatty
"A Miserable Failure" Will Bush be re-elected? Only if voters ...

miserable failure | Hillary Clinton | Hildebeest
... Miserable Failure. Quotes for the History Books. ... You may also want to check out the Miserable Failure Project. and the cuckolded dyke Project. and the ...
miserable-failure.blogspot.com/ - 60k - Cached - Similar pages

Dick Gephardt for President - Welcome
... to preserve some large part of the Bush tax cut. I think retaining
Google Bomb

Bob's page

Jim's blog

G. W. Bush Bio webpage

Kim's blog

canine failure canine failure canine failure
canine failure canine failure canine failure
Search Issues

Spamming

- Link Farms
- Google Bombs

Personalization

- Google’s psearch, A9, Kartoo
Google, Others Start to Comb Users’ Online Habits to Tailor Results to Personal Interests

By JESSICA E. VASCCELLARO And KEVIN J. DELANEY

SEARCH ENGINES have long generated the same results for queries whether the person searching was a mom, mathematician or movie star. Now, who you are and what you’re interested in is starting to affect the outcome of your search.

Google Inc. and a wide range of start-ups are trying to translate factors like where you live, the ads you click on and the types of restaurants you search for into more-relevant search results. A chef who searched for “beef,” for example, might be more likely to find recipes than encyclopedia entries about livestock. And a film buff who searched for a new movie might see detailed articles about the making of the film, rather than ticket-buying sites.

Google has been enhancing and more widely deploying its search-personalization technology. Within coming weeks, Google users who are logged in will begin having their search results reordered based on information they have provided to Google. For instance, they may have entered a city to receive weather forecasts on a personalized Google home page. As a result, a user in New York who types in “Giants” might see higher search results for the football team than a user in San Francisco, who might be more interested in the Giants baseball team.

Consumers who use its Web-history service to track previous search queries currently get results that are influenced by those queries and the sites they have clicked on. The company plans eventually to offer personalization based on a user’s Web-browsing history—including sites people visited without going through Google—when users agree to let Google track it.

Also, within three to five years, Google will...
Search Issues

Spamming
- Link Farms
- Google Bombs

Personalization
- Google’s psearch, A9, Kartoo

Privacy
- AOL Data Leak
A Face Is Exposed for AOL Searcher No. 4417749

By MICHAEL BARBARO and TOM ZELLER Jr.
Published: August 9, 2006

Buried in a list of 20 million Web search queries collected by AOL and recently released on the Internet is user No. 4417749. The number was assigned by the company to protect the searcher’s anonymity, but it was not much of a shield.

No. 4417749 conducted hundreds of searches over a three-month period on topics ranging from “numb fingers” to “60 single men” to “dog that urinates on everything.”

And search by search, click by click, the identity of AOL user No. 4417749 became easier to discern. There are queries for “landscapers in Lilburn, Ga,” several people with the last name Arnold and “homes sold in shadow lake subdivision gwinnett county georgia.”

It did not take much investigating to follow that data trail to Thelma Arnold, a 62-year-old widow who lives in Lilburn, Ga., frequently researches her friends’ medical ailments and loves her three dogs. “Those are my searches,” she said, after a reporter read part of the list to her.

AOL removed the search data from its site over the weekend and apologized for its release, saying it was an unauthorized move by a team that had hoped it would benefit academic researchers.

But the detailed records of searches conducted by Ms. Arnold and 657,000 other Americans, copies of which continue to circulate online, underscore how much people unintentionally reveal about themselves when they use search engines — and how risky it can be for companies like AOL, Google and Yahoo to compile such data.

Those risks have long pitted privacy advocates against online marketers and other Internet companies seeking to profit from the Internet’s unique ability to track the comings and goings of users, allowing for more focused and therefore more lucrative advertising.

But the unintended consequences of all that data being compiled, stored and cross-linked are what Marc Rotenberg, the executive director of the Electronic Privacy Information Center, a privacy rights group in Washington, called “a ticking privacy time bomb.”

Mr. Rotenberg pointed to Google’s own joust earlier this year with the Justice
Department over a subpoena for some of its search data. The company successfully fended off the agency’s demand in court, but several other search companies, including AOL, complied. The Justice Department sought the information to help it defend a challenge to a law that is meant to shield children from sexually explicit material.

“We supported Google at the time,” Mr. Rotenberg said, “but we also said that it was a mistake for Google to be saving so much information because it creates a risk.”

Ms. Arnold, who agreed to discuss her searches with a reporter, said she was shocked to hear that AOL had saved and published three months’ worth of them. “My goodness, it’s my whole personal life,” she said. “I had no idea somebody was looking over my shoulder.”

In the privacy of her four-bedroom home, Ms. Arnold searched for the answers to scores of life’s questions, big and small. How could she buy “school supplies for Iraq children”? What is the “safest place to live”? What is “the best season to visit Italy”?

Her searches are a catalog of intentions, curiosity, anxieties and quotidian questions. There was the day in May, for example, when she typed in “termites,” then “tea for good health” then “mature living,” all within a few hours.

Her queries mirror millions of those captured in AOL’s database, which reveal the concerns of expectant mothers, cancer patients, college students and music lovers. User No. 2178 searches for “foods to avoid when breast feeding.” No. 3482401 seeks guidance on “calorie counting.” No. 3483689 searches for the songs “Time After Time” and “Wind Beneath My Wings.”

At times, the searches appear to betray intimate emotions and personal dilemmas. No. 3505202 asks about “depression and medical leave.” No. 7268042 types “fear that spouse contemplating cheating.”

There are also many thousands of sexual queries, along with searches about “child porn” and “how to kill oneself by natural gas” that raise questions about what legal authorities can and should do with such information.

But while these searches can tell the casual observer — or the sociologist or the marketer — much about the person who typed them, they can also prove highly misleading.

At first glance, it might appear that Ms. Arnold fears she is suffering from a wide range of ailments. Her search history includes “hand tremors,” “nicotine effects on the body,” “dry mouth” and “bipolar.” But in an interview, Ms. Arnold said she routinely researched medical conditions for her friends to assuage their anxieties. Explaining her queries about nicotine, for example, she said: “I have a friend who needs to quit smoking and I want to help her do it.”

Saul Hansell contributed reporting for this article.
Search Issues

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- Google Bombs

Personalization
- Google’s psearch, A9, Kartoo

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- AOL Data Leak

Data Fusion
- Search.ch
Conclusion

- Link-based scores (PageRank, HITS, etc.) are combined with content scores for final rankings.

- Link analysis has dramatically improved search.

- Many continuing CSC and MATH challenges.
Web Graphs

CSC and MATH challenges (problems of scale!)

- store adjacency matrix
- update adjacency matrix
- visualize web graph
- locate clusters in graph
Conclusion

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Elegant and Exciting Application of Linear Algebra

That is Changing the World