Introduction to the Use of Link Analysis by Web Search Engines

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Outline

- Introduction to Information Retrieval (IR)
- Link Analysis
- HITS Algorithm
- PageRank Algorithm
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
- Card catalog

1960s
- Computer

1989
- Berner-Lee’s WWW
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

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

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IR on the Web = web IR

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

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

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

Actual Index King =
Internet Archive - http://web.archive.org
# Query Processing

**Step 1:** User enters query, i.e., aztec baby

**Step 2:** Inverted file consulted

<table>
<thead>
<tr>
<th>Term</th>
<th>Positions</th>
</tr>
</thead>
<tbody>
<tr>
<td>aardvark</td>
<td>3, 117, 3961</td>
</tr>
<tr>
<td>aztec</td>
<td>3, 15, 19, 101, 673, 1199</td>
</tr>
<tr>
<td>baby</td>
<td>3, 31, 56, 94, 673, 909, 11114, 253791</td>
</tr>
<tr>
<td>zymurgy</td>
<td>1159223</td>
</tr>
</tbody>
</table>

**Step 3:** Relevant set identified, i.e. \((3, 673)\)

*Simple traditional engines stop here.*
Modification to Inverted File

- add more features to inverted file by appending vector to each page identifier, i.e., [in title?, in descrip.?, # of occurrences]

- Modified inverted file

  - term 1 (aardvark) - 3 [0,0,3], 117 [1,1,10], 3961 [0,1,4]
    
    
  - term 10 (aztec) - 3 [1, 1, 27], 15 [0,0,1], 19 [1,1,21], 101 [0,1,7], 673 [0, 0, 3], 1199 [0,0,3]

  - term 11 (baby) - 3 [1, 1, 10], 31 [0,0,2], 56 [0,1,3], 94 [1,1,11], 673 [1, 1, 14], 909 [0,0,2], 11114 [1,1,22], 253791 [0,1,6]

  - term \( m \) (zymurgy) - 1159223 [1,1,9]

- IR score computed for each page in relevant set.

  EX: IR score (page 3) = \((1 + 1 + 27) \times (1 + 1 + 10) = 348\)

  IR score (page 673) = \((0 + 0 + 3) \times (1 + 1 + 14) = 48\)

  Early web engines stop here.

Problem = Ranking by IR score is not good enough.
CSC issues in Crawling and Indexing

- create parallel crawlers but avoid overlap
- ethical spidering
- how often to crawl pages, which pages to update
- best way to store huge inverted file
- how to efficiently update inverted file
- store the files across processors
- provide for parallel access
- create robust, failure-resistant system
Link Analysis

• uses hyperlink structure to focus the relevant set
• combine IR score with popularity or importance score

PageRank - Brin and Page ⇒

HITS - Kleinberg ⇒
The Web as a Graph

Nodes = webpages
Arcs = hyperlinks
Web Graphs

CSC and MATH problems here:

- store adjacency matrix
- update adjacency matrix
- visualize web graph
- locate clusters in graph
How to Use Web Graph for Search

Hyperlink = Recommendation

- page with 20 recommendations (inlinks) must be more important than page with 2 inlinks.

- but status of recommender matters.
  EX: letters of recommendation: 1 letter from Trump vs. 20 from unknown people

- but what if recommender is generous with recommendations?
  EX: suppose Trump has written over 40,000 letters.

- each inlink should be weighted to account for status of recommender and # of outlinks from that recommender
How to Use Web Graph for Search

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PAGERANK - importance/popularity score given to each page
Our Search: Google Technology

Google searches more sites more quickly, delivering the most relevant results.

Introduction

Google runs on a unique combination of advanced hardware and software. The speed you experience can be attributed in part to the efficiency of our search algorithm and partly to the thousands of low cost PC's we've networked together to create a superfast search engine.

The heart of our software is PageRank™, a system for ranking web pages developed by our founders Larry Page and Sergey Brin at Stanford University. And while we have dozens of engineers working to improve every aspect of Google on a daily basis, PageRank continues to provide the basis for all of our web search tools.

PageRank Explained

PageRank relies on the uniquely democratic nature of the web by using its vast link structure as an indicator of an individual page's value. In essence, Google interprets a link from page A to page B as a vote, by page A, for page B. But, Google looks at more than the sheer volume of votes, or links a page receives; it also analyzes the page that casts the vote. Votes cast by pages that are themselves "important" weigh more heavily and help to make other pages "important."

Important, high-quality sites receive a higher PageRank, which Google remembers each time it conducts a search. Of course, important pages mean nothing to you if they don't match your query. So, Google combines PageRank with sophisticated text-matching techniques to find pages that are both important and relevant to your search. Google goes far beyond the number of times a term appears on a page and examines all aspects of the page's content (and the content of the pages linking to it) to determine if it's a good match for your query.

Integrity

Google's complex, automated methods make human tampering with our results extremely difficult. And though we do run relevant ads above and next to our results, Google does not sell placement within the results themselves (i.e., no one can buy a higher PageRank). A Google search is an easy, honest and objective way to find high-quality websites with information relevant to your search.
Another Way to Use Web Graph for Search

- give each page 2 scores (hub and authority scores) instead of just 1.

- **DEFN:**
  - **Authorities**
  - **Hubs**

- pages can be both hubs and authorities (EX: ATL airport)

- Good hub pages point to good authority pages, and good authorities are pointed to by good hubs.

**HITS** - hub and authority score given to each page

**HITS** - (Hypertext Induced Topic Search)
ncaa basketball

Sponsored Links
NCAA Bracket Contest- NCAA Bracket Contest at CollegeTournament.com
www.collegetournament.com
www.xposed.com

Results
Showing 1-10 of about 3,255,000:
NCAA National Collegiate Athletic Association - Official Site
2004 NCAA Division I Men's Basketball Championship bracket announced...
www.ncaa.org/

Men's and Women's Basketball Polls
Division I Men's Basketball ... The NCAA does not conduct a poll for Division I men's basketball and the NCAA's Division I Men's Basketball Committee...
www.ncaa.org/polls/m_w_basketball.html
[More Results from www.ncaa.org]

ESPN.com: Mens College Basketball
...to attend the EA SPORTS Maui Invitational Basketball Tournament, stay ... Wednesday ... 
3:00 pm ... 1979 NCAA TOURNAMENT, MIDWEST REGIONAL 2ND...
sports.espn.go.com/ncb/index

Men's Basketball - NCAA Sports.com
Live Game Video NCAA March Madness on Demand brings you LIVE video of the Men's Basketball tournament. Division I...
www.ncaasports.com/basketball/mens

NCAA Basketball
Live Game Video NCAA March Madness on Demand brings you LIVE video of the Men's Basketball tournament. Division I's...
www.ncaasports.com/
[More Results from www.ncaasports.com]

D3hoops.com: The definitive resource for Division III men's and
The definitive resource for Division III men's and women's basketball ... previews: M | W Final Four: M | W Stats (NCAA site): M | W NCAA rankings: M...
www.d3hoops.com/

Women's Basketball Coaches Association
March 14 Selection Sunday for the NCAA Division I Women's Basketball Tournament March 16
NAIA DII Women's Championship March 19 NCAA DIII...
www.wbca.org/
[More Results from www.wbca.org]

CollegeRPI.com - College Basketball Rating Percentage Index (RPI)
The most accurate independent duplication of the NCAA's Rating Percentage Index...
www.collegerrpi.com/

College Basketball by CollegeHoopsnet.com
Player of the Week. NCAA Tournament. Conference Tourneys. Basketball Tickets. Recruiting Coverage. Basketball Store. NBA Draft...
www.collegehoopsnet.com/

CBS.SportsLine.com - NCAA Basketball Home
College Basketball coverage including NCAA news, scores, standings, stats, schedules, injuries, polls, team and player news, NCAA basketball...
www.sportsline.com/colllegebasketball/

Results Pages: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 >>
Pop Quiz

\[ \mathbf{A} \mathbf{x}_i = \lambda_i \mathbf{x}_i \]

\[ \sigma = [\lambda_1, \lambda_2, \ldots, \lambda_n] \]

Classic Method to Compute Dominant Eigenpair?
Pop Quiz

$$\mathbf{A}\mathbf{x}_i = \lambda_i \mathbf{x}_i$$

$$\sigma = [\lambda_1, \lambda_2, \ldots, \lambda_n]$$

Classic Method to Compute Dominant Eigenpair?

Power Method
Pop Quiz

\[ \mathbf{Ax}_i = \lambda_i \mathbf{x}_i \]

\[ \sigma = [\lambda_1, \lambda_2, \ldots, \lambda_n] \]

**Classic Method to Compute Dominant Eigenpair?**

**Power Method**

- The Iterative Procedure
  \[ \mathbf{x}^{(k)} = \mathbf{A}\mathbf{x}^{(k-1)} \]

converges to \( \mathbf{x}_1 \) for \( |\lambda_1| > |\lambda_2| \) regardless of the starting vector \( \mathbf{x}^{(0)} \).

- Rate of Convergence: rate at which \( \left( \frac{|\lambda_2|}{|\lambda_1|} \right)^k \to 0 \).

- Notice \( \mathbf{x}^{(k)} = \mathbf{A}^k \mathbf{x}^{(0)} \).
HITS Algorithm
Hypertext Induced Topic Search (J. Kleinberg 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 $h_i(0) = 1$ for all pages $P_i$
- Successively refine rankings
  - For $k = 1, 2, \ldots$
    
    
    $a_i(k) = \sum_{j : P_j \rightarrow P_i} h_j(k - 1) \Rightarrow a_k = L^T h_{k-1}$
    
    $h_i(k) = \sum_{j : P_i \rightarrow P_j} a_j(k) \Rightarrow h_k = La_k$

- $A = L^T L \Rightarrow a_k = A a_{k-1} \rightarrow \text{e-vector}$
- $H = L L^T \Rightarrow h_k = H h_{k-1} \rightarrow \text{e-vector}$
HITS Neighborhood Graph

1. Find relevant set by consulting inverted file
2. Build neighborhood graph
3. Compute authority & hub scores for just the neighborhood
HITS Example

1. Relevant set = [1, 6]

2. Neighborhood graph $N$

3. Compute **authority** & **hub** scores.

Adjacency matrix for $N = L = \begin{pmatrix}
1 & 0 & 0 & 1 & 0 & 1 & 0 \\
1 & 2 & 3 & 5 & 6 & 10 \\
1 & 0 & 0 & 1 & 0 & 1 & 0 \\
2 & 1 & 0 & 0 & 0 & 0 & 0 \\
3 & 0 & 0 & 0 & 0 & 1 & 0 \\
5 & 0 & 0 & 0 & 0 & 0 & 0 \\
6 & 0 & 0 & 1 & 1 & 0 & 0 \\
10 & 0 & 0 & 0 & 0 & 1 & 0
\end{pmatrix}$
HITS Example (cont.)

Authority matrix \( \mathbf{A} = \mathbf{L}^T \mathbf{L} \)

\[
\mathbf{L}^T \mathbf{L} = \begin{pmatrix}
1 & 2 & 3 & 5 & 6 & 10 \\
1 & 1 & 0 & 0 & 0 & 0 \\
2 & 0 & 0 & 0 & 0 & 0 \\
3 & 0 & 0 & 2 & 1 & 1 \\
5 & 0 & 0 & 1 & 1 & 0 \\
6 & 0 & 0 & 1 & 0 & 3 \\
10 & 0 & 0 & 0 & 0 & 0 \\
\end{pmatrix}
\]

Hub matrix \( \mathbf{H} = \mathbf{L} \mathbf{L}^T \)

\[
\mathbf{LL}^T = \begin{pmatrix}
1 & 2 & 3 & 5 & 6 & 10 \\
1 & 2 & 0 & 1 & 0 & 1 & 1 \\
2 & 0 & 1 & 0 & 0 & 0 & 0 \\
3 & 1 & 0 & 1 & 0 & 0 & 1 \\
5 & 0 & 0 & 0 & 0 & 0 & 0 \\
6 & 1 & 0 & 0 & 0 & 2 & 0 \\
10 & 1 & 0 & 1 & 0 & 0 & 1 \\
\end{pmatrix}
\]

Authority score vector \( \mathbf{a} \)

\[
\mathbf{a}^T = \begin{pmatrix}
1 & 2 & 3 & 5 & 6 & 10 \\
0 & 0 & .3660 & .1340 & .5 & 0 \\
\end{pmatrix}
\]

Hub score vector \( \mathbf{h} \)

\[
\mathbf{h}^T = \begin{pmatrix}
1 & 2 & 3 & 5 & 6 & 10 \\
.3660 & 0 & .2113 & 0 & .2113 & .2113 \\
\end{pmatrix}
\]
**HITS Convergence**

- HITS with normalization step always converges.

- Rate of convergence depends on eigengap $\lambda_1 - \lambda_2$.

- BUT $\lambda_1$ may be a repeated root $\Rightarrow$ nonunique solutions. Different $h_0$ and $a_0$ can lead to different $h_\infty$ and $a_\infty$.

- $h_\infty$ and $a_\infty$ can contain 0 values for some pages, which is undesirable in ranking context.
Pros & Cons

Advantages

- Returns satisfactory results
  - Client gets both authority & hub scores
- Some flexibility

Disadvantages

- Too much must happen while client is waiting; query-dependent
  - Custom built neighborhood graph needed for each query
  - Two eigenvector computations needed for each query
- Scores can be manipulated by creating artificial hubs

Modified HITS in Teoma
CSC and MATH Issues with HITS

- how to form $N$ and fix topic drift problem
- incorporating weights into $L$ matrix
- fast eigenvector computation, beating the power method
- updating $L$, $h$, and $a$ for query-independent HITS
Pop Quiz

Markov Chain

- Transition Matrix $P$ is?
Pop Quiz

Markov Chain

- Transition Matrix $P$ is square and stochastic.

Example:

$$P = \begin{pmatrix}
S & R \\
.7 & .3 \\
.45 & .55
\end{pmatrix}$$
Pop Quiz

Markov Chain

• Transition Matrix $P$ is ?
  
  square and stochastic

• Element $p_{ij}$ represents ?

EX: $P = \begin{pmatrix} S & R \\ .7 & .3 \\ .45 & .55 \end{pmatrix}$
Markov Chain

- Transition Matrix $P$ is?
  - square and stochastic
  - EX: $P = \begin{pmatrix} S & R \\ S & .7 & .3 \\ R & .45 & .55 \end{pmatrix}$

- Element $p_{ij}$ represents?
  - probability of transitioning from state $i$ to state $j$
Markov Chain

- Transition Matrix $\mathbf{P}$ is ?

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EX: $\mathbf{P} = \begin{pmatrix} .7 & .3 \\ .45 & .55 \end{pmatrix}$

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- Stationary distribution $\pi^T$ satisfies ?
Markov Chain

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  probability of transitioning from state $i$ to state $j$

- Stationary distribution $\pi^T$ satisfies?
  
  $\pi^T = \pi^T P$

EX: $P =$

\[
\begin{pmatrix}
S & R \\
0.7 & 0.3 \\
0.45 & 0.55
\end{pmatrix}
\]
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- $\pi_i$ represents?
Pop Quiz

Markov Chain

- Transition Matrix $P$ is ?
  
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  EX: $P = \begin{pmatrix} S & R \\ S & R \end{pmatrix} = \begin{pmatrix} .7 & .3 \\ .45 & .55 \end{pmatrix}$

- Element $p_{ij}$ represents ?
  
  probability of transitioning from state $i$ to state $j$

- Stationary distribution $\pi^T$ satisfies ?

  $\pi^T = \pi^T P$

- $\pi_i$ represents ?

  long-run proportion of time spent in state $i$
Pop Quiz

Markov Chain

- Transition Matrix $P$ is?
  - square and stochastic
  - **EX:** $P = \begin{pmatrix} S & R \\ S \cdot 0.7 & 0.3 \\ R \cdot 0.45 & 0.55 \end{pmatrix}$

- Element $p_{ij}$ represents?
  - probability of transitioning from state $i$ to state $j$

- Stationary distribution $\pi^T$ satisfies?
  - $\pi^T = \pi^T P$

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  - long-run proportion of time spent in state $i$

- Classic Method for finding $\pi^T$
Pop Quiz

Markov Chain

- Transition Matrix \( P \) is ?
  - square and stochastic
  - EX: \( P = \begin{pmatrix} S & R \\ S & .7 & .3 \\ R & .45 & .55 \end{pmatrix} \)

- Element \( p_{ij} \) represents ?
  - probability of transitioning from state \( i \) to state \( j \)

- Stationary distribution \( \pi^T \) satisfies ?
  - \( \pi^T = \pi^T P \)

- \( \pi_i \) represents ?
  - long-run proportion of time spent in state \( i \)

- Classic Method for finding \( \pi^T \)
  - Power Method, rate of convergence = rate at which \( |\lambda_2|^k \rightarrow 0 \)
The PageRank Idea

(Sergey Brin & Lawrence Page 1998)

• Ranking is preassigned
  (An off-line calculation)

• Your page \( P \) has some rank \( r(P) \)

• Adjust \( r(P) \) higher or lower depending on ranks of pages that point to \( P \)

• Importance is not just number, but \textit{quality} of in-links
  • role of outlinks relegated
  • much less sensitive to spamming
PageRank

The Definition

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

Successive Refinement

- 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

- \( r_1(P_i) = \sum_{P \in B_{P_i}} \frac{r_0(P)}{|P|} \)
- \( r_2(P_i) = \sum_{P \in B_{P_i}} \frac{r_1(P)}{|P|} \)
- \( \vdots \)
- \( r_{j+1}(P_i) = \sum_{P \in B_{P_i}} \frac{r_j(P)}{|P|} \)
After Step $j$

$$
\pi_j^T = [r_j(P_1), r_j(P_2), \cdots, r_j(P_n)]
$$

$$
\pi_{j+1}^T = \pi_j^T P \quad \text{where} \quad p_{ij} = \begin{cases} 
\frac{1}{|P_i|} & \text{if } i \rightarrow j \\
0 & \text{o.w.}
\end{cases}
$$
In Matrix Notation

After Step $j$

$$\pi_{j}^{T} = [r_{j}(P_{1}), r_{j}(P_{2}), \cdots, r_{j}(P_{n})]$$

$$\pi_{j+1}^{T} = \pi_{j}^{T} P \quad \text{where} \quad p_{ij} = \begin{cases} 1/|P_{i}| & \text{if } i \rightarrow j \\ 0 & \text{o.w.} \end{cases}$$

$$P = \begin{pmatrix} p_{1} & p_{2} & p_{3} & p_{4} & p_{5} & p_{6} \\ p_{1} & 0 & 1/2 & 1/2 & 0 & 0 & 0 \\ p_{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ p_{3} & 1/3 & 1/3 & 0 & 0 & 1/3 & 0 \\ p_{4} & 0 & 0 & 0 & 0 & 1/2 & 1/2 \\ p_{5} & 0 & 0 & 0 & 1/2 & 0 & 1/2 \\ p_{6} & 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$
In Matrix Notation

After Step $j$

$$\pi^T_j = [r_j(P_1), r_j(P_2), \cdots, r_j(P_n)]$$

$$\pi^T_{j+1} = \pi^T_j \mathbf{P} \quad \text{where} \quad p_{ij} = \begin{cases} 1/|P_i| & \text{if } i \to j \\ 0 & \text{o.w.} \end{cases}$$

$$\mathbf{P} = \begin{pmatrix} p_1 & p_2 & p_3 & p_4 & p_5 & p_6 \\ p_1 & 0 & 1/2 & 1/2 & 0 & 0 & 0 \\ p_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ p_3 & 1/3 & 1/3 & 0 & 0 & 1/3 & 0 \\ p_4 & 0 & 0 & 0 & 0 & 1/2 & 1/2 \\ p_5 & 0 & 0 & 0 & 1/2 & 0 & 1/2 \\ p_6 & 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

PageRank $= \lim_{j \to \infty} \pi^T_j = \pi^T \quad \text{(provided limit exists)}$

It's Almost a Markov Chain

$\mathbf{P}$ has row sums $= 1$ for ND nodes, row sums $= 0$ for D nodes
In Matrix Notation

It’s Almost a Markov Chain

- $P$ has row sums $= 1$ for ND nodes, row sums $= 0$ for D nodes
In Matrix Notation

It’s Almost a Markov Chain

- $P$ has row sums = 1 for ND nodes, row sums = 0 for D nodes

Stochasticity Fix: $\bar{P} = P + av^T$.  
($a_i = 1$ for $i \in D$, 0, o.w.)
In Matrix Notation

It’s Almost a Markov Chain

- $P$ has row sums = 1 for ND nodes, row sums = 0 for D nodes

Stochasticity Fix: $\tilde{P} = P + av^T$.  

\[
\tilde{P} = \begin{bmatrix}
0 & 1/2 & 1/2 & 0 & 0 & 0 \\
1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\
1/3 & 1/3 & 0 & 0 & 1/3 & 0 \\
0 & 0 & 0 & 0 & 1/2 & 1/2 \\
0 & 0 & 0 & 1/2 & 0 & 1/2 \\
0 & 0 & 0 & 1 & 0 & 0 \\
\end{bmatrix}
\]

where $a = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $v^T = 1/6 \ e^T$
In Matrix Notation

It’s Almost a Markov Chain

- $P$ has row sums = 1 for ND nodes, row sums = 0 for D nodes

Stochasticity Fix: $\bar{P} = P + av^T$.  
($a_i=1$ for $i \in D$, 0, o.w.)

$\bar{P} = \begin{bmatrix}
0 & 1/2 & 1/2 & 0 & 0 & 0 \\
1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\
1/3 & 1/3 & 0 & 0 & 1/3 & 0 \\
0 & 0 & 0 & 0 & 1/2 & 1/2 \\
0 & 0 & 0 & 1/2 & 0 & 1/2 \\
0 & 0 & 0 & 1 & 0 & 0 \\
\end{bmatrix}$, where $a=\begin{bmatrix}0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $v^T=1/6 \ e^T$

- Each $\pi^T_j$ is a probability distribution vector ($\sum_i r_j(P_i)=1$)

- $\pi^T_{j+1} = \pi^T_j \bar{P}$ is random walk on the graph defined by links

- $\pi^T = \lim_{j \to \infty} \pi^T_j$ = stationary probability distribution
Random Surfer

Web Surfer Randomly Clicks On Links

Long-run proportion of time on page $P_i$ is $\pi_i$

Problems
Random Surfer

Web Surfer Randomly Clicks On Links

Long-run proportion of time on page $P_i$ is $\pi_i$  

Problems

Dead end page (nothing to click on)  

Could get trapped into a cycle $(P_i \rightarrow P_j \rightarrow P_i)$ (No convergence)
Random Surfer

Web Surfer Randomly Clicks On Links  
(Back button not a link)
Long-run proportion of time on page $P_i$ is $\pi_i$

Problems

Dead end page (nothing to click on)  
($\pi^T$ not well defined)
Could get trapped into a cycle ($P_i \rightarrow P_j \rightarrow P_i$)  
(No convergence)

Convergence

Markov chain must be irreducible and aperiodic
**Random Surfer**

**Web Surfer Randomly Clicks On Links**

Long-run proportion of time on page $P_i$ is $\pi_i$ 

(Back button not a link)

**Problems**

Dead end page (nothing to click on) 

(\(\pi^T\) not well defined)

Could get trapped into a cycle \(P_i \to P_j \to P_i\) (No convergence)

**Convergence**

Markov chain must be irreducible and aperiodic

DEFN: a chain is *irreducible* if every page is reachable from every other page.

DEFN: every *reducible* chain can be permuted to the form \[
\begin{bmatrix}
X & Y \\
0 & Z
\end{bmatrix}.
\]
Random Surfer

Bored Surfer Enters Random URL

Irreducibility Fix: \[
\tilde{P} = \alpha \tilde{P} + (1 - \alpha)E \quad e_{ij} = 1/n \quad \alpha \approx .85
\]

\[
\tilde{P} = \alpha P + \alpha a v^T + (1 - \alpha)E \quad \text{(trivially irreducible)}
\]

- \( \pi^T \) is now guaranteed to exist and be unique and power method is guaranteed to converge to \( \pi^T \).
Random Surfer

Bored Surfer Enters Random URL

Irreducibility Fix: \( \tilde{P} = \alpha P + (1 - \alpha)E \)

\( e_{ij} = \frac{1}{n} \quad \alpha \approx 0.85 \)


\[
\begin{bmatrix}
1/60 & 7/15 & 7/15 & 1/60 & 1/60 & 1/60 \\
1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\
19/60 & 19/60 & 1/60 & 1/60 & 19/60 & 1/60 \\
1/60 & 1/60 & 1/60 & 1/60 & 7/15 & 7/15 \\
1/60 & 1/60 & 1/60 & 7/15 & 1/60 & 7/15 \\
1/60 & 1/60 & 1/60 & 11/12 & 1/60 & 1/60 \\
\end{bmatrix}
\]

\( \tilde{P} = \alpha P + (1 - \alpha)E \) (trivially irreducible)

- \( \pi^T \) is now guaranteed to exist and be unique and power method is guaranteed to converge to \( \pi^T \).

- Different \( E = e v^T \) and \( \alpha \) allow customization & speedup, yet rank-one update maintained; \( \tilde{P} = \alpha P + (\alpha a + (1 - \alpha)e)v^T \).
Computing $\pi^T$

A Big Problem

Solve $\pi^T = \pi^T \tilde{P}$

$\pi^T (I - \tilde{P}) = 0$

(stationary distribution vector)

(too big for direct solves)
Google’s PageRank is an eigenvector of a matrix of order 2.7 billion.

One of the reasons why Google is such an effective search engine is the PageRank™ algorithm, developed by Google’s founders, Larry Page and Sergey Brin, when they were graduate students at Stanford University. PageRank is determined entirely by the link structure of the Web. It is recomputed about once a month and does not involve any of the actual content of Web pages or of any individual query. Then, for any particular query, Google finds the pages on the Web that match that query and lists those pages in the order of their PageRank.

Imagine surfing the Web, going from page to page by randomly choosing an outgoing link from one page to get to the next. This can lead to dead ends at pages with no outgoing links, or cycles around cliques of interconnected pages. So, a certain fraction of the time, simply choose a random page from anywhere on the Web. This theoretical random walk of the Web is a Markov chain or Markov process. The limiting probability that a dedicated random surfer visits any particular page is its PageRank. A page has high rank if it has links to and from other pages with high rank.

Let $W$ be the set of Web pages that can reached by following a chain of hyperlinks starting from a page at Google and let $n$ be the number of pages in $W$. The set $W$ actually varies with time, but in May 2002, $n$ was about 2.7 billion. Let $G$ be the $n$-by-$n$ connectivity matrix of the Web graph. Its elements are 1 if there is a hyperlink from page $i$ to page $j$, and 0 otherwise. The matrix $G$ is sparse and very large with few non-zero elements.

It tells us that the largest eigenvalue of $A$ is equal to one and that the corresponding eigenvector, which satisfies the equation

$$x = Ax,$$

exists and is unique within a scaling factor. When this scaling factor is chosen so that

$$\sum_i x_i = 1$$

then $x$ is the state vector of the Markov chain. The elements of $x$ are Google’s PageRank.

If the matrix were small enough to fit in MATLAB, one way to compute the eigenvector $x$ would be to start with a good approximate solution, such as the PageRanks from the previous month, and simply repeat the assignment statement

$$x = Ax$$

until successive vectors agree to within specified tolerance. This is known as the power method and is about the only possible approach for very large $n$. I’m not sure how Google actually computes PageRank, but one step of the power method would require one pass over a database of Web pages, updating weighted reference counts generated by the hyperlinks between pages.
Computing $\pi^T$

A Big Problem

Solve $\pi^T = \pi^T \bar{P}$

(stationary distribution vector)

$\pi^T (I - \bar{P}) = 0$

(too big for direct solves)

Start with $\pi_0^T = e/n$ and iterate $\pi_{j+1}^T = \pi_j^T \bar{P}$

(power method)
Power Method to compute PageRank

\[ \pi_0^T = e^T / n \]

until convergence, do

\[ \pi_{j+1}^T = \pi_j^T \tilde{P} \]  

(dense computation)

end
Power Method to compute PageRank

\[ \pi^T_0 = \mathbf{e}^T/n \]

until convergence, do

\[ \mathbf{X} \quad \pi^T_{j+1} = \pi^T_j \mathbf{\tilde{P}} \] (dense computation)

\[ \bullet \quad \pi^T_{j+1} = \alpha \pi^T_j \mathbf{\tilde{P}} + (1 - \alpha) \pi^T_j \mathbf{e} \mathbf{v}^T \] (sparser computation)

end
Power Method to compute PageRank

\[
\pi_0^T = \mathbf{e}^T / n
\]

until convergence, do

\[
\begin{align*}
X & \; \; \pi_j^{T+1} = \pi_j^T \bar{\mathbf{P}} \\
X & \; \; \pi_j^{T+1} = \alpha \pi_j^T \bar{\mathbf{P}} + (1 - \alpha) \pi_j^T \mathbf{e} \mathbf{v}^T
\end{align*}
\]

\[
\begin{align*}
\bullet & \; \; \pi_j^{T+1} = \alpha \pi_j^T P + (\alpha \pi_j^T a + (1 - \alpha)) v^T \\
\end{align*}
\]

end

• \( \mathbf{P} \) is very, very sparse with about 3-10 nonzeros per row.

• \( \Rightarrow \) one vector-matrix mult. is \( O(nnz(\mathbf{P})) \approx O(n) \).
Convergence

Can prove $\lambda_2(\bar{P}) = \alpha$

($\Rightarrow$ asymptotic rate of convergence of PageRank method is rate at which $\alpha^k \rightarrow 0$)

Google

– uses $\alpha = .85$ (5/6, 1/6 interpretation)

– report 50-100 iterations til convergence

– still takes days to converge
PageRank Example

\[ \pi^T = \begin{pmatrix} .03721 & .05396 & .04151 & .3751 & .206 & .2862 \end{pmatrix} \]

Global ranking of pages = [4 6 5 2 3 1]

Query-independent way of ranking relevant set
PageRank 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_doed out IPO shares based partly on investors’ commitments to buy more stock.

(Article on Page C1)

* * *

■ Ahold’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 into buying 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 news of a profit report.

* * *

■ The FBI came under withering bipartisan criticism in a Senate Judiciary report in which Sen. Specter

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
The big search engines determine the laws of how commerce runs, says Mr. Massa.

Creating Web sites that were nothing more than collections of links to the clients’ site, called “link farms,” since Google ranks a site largely by how many links or “votes” it gets, 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 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. She used thousands of search terms in hidden coding, called “meta-tags.” The coding fools a search engine into identifying a site with popular words and phrases that may not actually appear on the site.

Another gimmick was hiding words or terms against a same-color background. The hidden text on her featured search engines that relied heavily on the number of times a word or phrase appeared in ranking a site. But Google’s system, based on links, wasn’t fooled.

Mr. Brin, 29, one of Google’s two founders and now its president, of two years, was the keynote speaker at a San Francisco search-engine conference in 2000 that Google wasn’t 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. But two years later, Google had already announced that it had found a way to do two things.

Continued From Page 1

In theory, when Google encounters the AutomatedLinks code, it treats it as a legitimate referral to the other sites and counts them in toting up the sites’ popularity.

In practice, when a search engine built up with AutomatedLinks in July, she read 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 worked its way up in Google searches. But then it was 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 among the top results. Her orders plunged as much as 80 percent.

Ms. Holman, who called AutomatedLinks, says she was unable to get answers. But in the last few months, other AutomatedLinks customers say they have seen their sites apparently penalized by Google. Graham McLeay, who runs a small chauffeur service in Oklahoma City, has found his site ranking among the top 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 sites owners confused. “I don’t know how people are supposed to judge what is right,” said an AutomatedLinks customer. “AutomatedLinks didn’t respond to requests for comment. Google declined to comment on the case. But Mr. Cutts, the Google engineer, warns that the rules are clear and that it’s better to follow them rather than try to get a problem fixed after a site has been penalized. “We want to return the most relevant pages we can, ” Mr. Cutts says. “The best way for a site owner to do that is follow our guidelines.”

Crackdown

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

In the home city-based SearchKing, an online directory for hundreds of small, specialty Web sites, SearchKing also sells advertising links designed both to deliver traffic to advertisers and result in higher rankings in Google and other search results.

Bob Massa, SearchKing’s chief executive, last August launched the PR Ad Network as a way to capitalize on Google’s page-ranking system, known as PageRank. PageRank rates Web sites based on how many links sit on a page, and those links are linked to the site’s popularity, and the rankings can be bypassed by users if they install special Google software. PR Ad Network sells ads that are priced according to a site’s PageRank, 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. While other sites that participated in the separate SearchKing directory also had their Google rankings lowered. He filed a lawsuit in Oklahoma City federal court, claiming Google was punishing him for trying to profit from the company’s page-ranking system.

The company has asked for the suit to be dismissed, arguing that the PageRank represents its opinion of the value of a website, which is protected by the First Amendment.

“Big search engines determine the laws of how commerce runs,” says Mr. Massa, who is persisting with the lawsuit even though the sites have had their page rankings purely restored. “Someone needs to stand and be counted.”

Google is taking steps that many say could satisfy businesses trying to boost their rankings. Google has long sold sponsored links that show up on the top of many search-results pages, separate from the main results. Last year, the company expanded its paid-listings program, so that there are now more slots where sites can pay for a prominent place in the results. Many sites now are turning to advertising instead of tactics to climb their rankings.
PageRank 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.

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)"

Prank website

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

TOP AMERICAS STORIES NOW
US army battles to keep soldiers
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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

Great idea!

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...

Done!

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

Call me a liberal lemming, I guess. :) I'm in.

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 terms, 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 choices, 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 "bush george iraq speech". "bush george speech" gets a huge amount of hits compared to something like "bush george policy".

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

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?

Hahaha, that's very productive. This is why everyone knows that liberals are stupid. They do stupid things.

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

Spamming
- Link Farms
- Google Bombs

Updating
- The Google Dance
Below you will find the Google Dance results for the search keyword pagerank. If you notice that there are any differences in results between the different Google data centers then Google is in the middle of spidering the internet. It's that simple!

www.google.com

Enter your search:
pagerank

Google Search
I'm Feeling Lucky

1. Google Technology
2. Google Web Directory Help
3. Pagerank Explained, Google's PageRank Calculator, WebWorksh
4. PageRank Explained Correctly with Examples
5. The Anatomy of a Search Engine
6. LinkAdage Auctions Link Exchange
7. PageRank is Dead (Jeremy Zawodor

www2.google.com

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pagerank

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www3.google.com

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pagerank

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PageRank Issues

Spamming

- Link Farms
- Google Bombs

Updating

- The Google Dance

Speed Improvements

- Enhancing Power Method
Researchers Develop Techniques for Computing Google-Style Web
Rankings Up to Five Times Faster
Speed-up may make "topic-sensitive" page rankings feasible

ARLINGTON, Va. — Computer science researchers at Stanford University have developed several new techniques that together may make it possible to calculate Web page rankings as used in the Google search engine up to five times faster. The speed-ups to Google's method may make it realistic to calculate page rankings personalized for an individual's interests or customized to a particular topic.

The Stanford team includes graduate students Sepandar Kamvar and Taher Haveliwala, noted numerical analyst Gene Golub and computer science professor Christopher Manning. They will present their first paper at the Twelfth Annual World Wide Web Conference (WWW2003) in Budapest, Hungary, May 20-24, 2003. The work was supported by the National Science Foundation, an independent federal agency that supports fundamental research and education in all fields of science and engineering.

Computing PageRank, the ranking algorithm behind the Google search engine, for a billion Web pages can take several days. Google currently ranks and searches 3 billion Web pages. Each personalized or topic-sensitive ranking would require a separate multi-day computation, but the payoff would be less time spent wading through irrelevant search results. For example, searching a sports-specific Google site for "Giants" would give more importance to pages about the New York or San Francisco Giants and less importance to pages about Jack and the Beanstalk.

"This work is a wonderful example of how NSF support for basic computer science research, including applied mathematics and algorithm research, has impacts in daily life," said NSF program officer Maria Zemankova. In the mid-1990s, an NSF digital library project and an NSF graduate fellowship also supported Stanford graduate students Larry Page and Sergey Brin while they developed what would become the Google search engine.

To speed up PageRank, the Stanford team developed a trio of techniques in numerical linear algebra. First, in the WWW2003 paper, they describe so-called "extrapolation" methods, which make some assumptions about the Web's link structure that aren't true, but permit a quick and easy computation of PageRank. Because the assumptions aren't true, the PageRank isn't exactly correct, but it's close and can be refined using the
PageRank Issues

Spamming
- Link Farms
- Google Bombs

Updating
- The Google Dance

Speed Improvements
- Enhancing Power Method
- Personalized PageRank
Searching for the personal touch

By Stefanie Olsen
CNET News.com
August 11, 2003, 4:00 AM PT

A stealth start-up out of Stanford University is hoping to raise the heat on one of the toughest problems in Web search--and possibly out-Google Google in the process.

Kaltix was formed in recent months by three members of Stanford's PageRank team--a research group created to advance the mathematical algorithm developed by Google co-founder and Stanford alum Larry Page that cemented Google's fame.

PageRank has helped steer people to Web sites like no other search technology before it, harnessing the link structure of the Web to determine the most popular pages. Now, Kaltix hopes to improve upon PageRank, with an attempt to speed up the underlying PageRank computations.

That, in turn, could lay the groundwork for a breakthrough in a cutting-edge area of Web search development known as "personalization," which aims to sort search results based on the specific needs and interests of individuals, instead of the consensus approach pioneered by Google.

"Kaltix is a 'stealth mode' start-up...([leveraging] research done at Stanford University as well as several new technologies developed at Kaltix to provide large-scale personalized and context-sensitive search," a Kaltix representative said, declining to comment further.

Kaltix has disclosed few specifics about its plans or technology. But the company's general statements appear to place it in a sweet spot for innovation that's being pursued by all of the major search providers.

Now that Web search has become a moneymaker for portals such as Yahoo and Microsoft's MSN, technologists from all the industry players are back in the labs developing formulas to personalize search.

Web companies outside the search industry have long made attempts to create personalization features, but most of these attempts have fallen short of expectations. Amazon.com, for example, regularly serves up book titles related to a visitor's previous purchases, which may no longer be relevant. A personalization feature offered through TiVo, a maker of video recording devices, was criticized when reports circulated that the device would recommend gay-themed television programs to viewers based on just a few program selections.

Despite these flawed attempts, developers continue to have faith that personalization technology can be created that will ultimately unleash marketing and revenue opportunities.

If search developers are successful in building such technology, they could help millions of people better...
Google Acquires Kaltix Corp.

New Technologies and Engineering Team Complement Google Search Engine

MOUNTAIN VIEW, Calif. - Sept. 30, 2003 - Google Inc. today announced it acquired Kaltix Corp., a Palo Alto, Calif.-based search technology start-up. Financial terms of the deal were not disclosed.

"Google and Kaltix share a common commitment to developing innovative search technologies that make finding information faster, easier and more relevant," said Larry Page, co-founder and president of Products at Google. "Kaltix is working on a number of compelling search technologies, and Google is the ideal vehicle for the continued development of these advancements."

Kaltix Corp. was formed in June 2003 and focuses on developing personalized and context-sensitive search technologies that make it faster and easier for people to find information on the web.

About Google

Google's innovative search technologies connect millions of people around the world with information every day. Founded in 1998 by Stanford Ph.D. students Larry Page and Sergey Brin, Google today is a top web property in all major global markets. Google's targeted advertising program, which is the largest and fastest growing in the industry, provides businesses of all sizes with measurable results, while enhancing the overall web experience for users. Google is headquartered in Silicon Valley with offices throughout North America, Europe, and Asia. For more information, visit www.google.com.

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Conclusions

- Link Analysis has drastically improved web search!
- There are many exciting open problems for CSC and MATH majors to solve.
- Often the challenge lies not in the modeling or theory, but in the massive scale of the problem.
- The continual battle between search engines and search engine optimizers means that methods must constantly adapt and innovate.
- There is huge financial potential for industrious entrepreneurs!