Web Search

Advances &
Link Analysis
Meta-Search Engines

• Search engine that passes query to several other search engines and integrate results.
  – Submit queries to host sites.
  – Parse resulting HTML pages to extract search results.
  – Integrate multiple rankings into a “consensus” ranking.
  – Present integrated results to user.

• Examples:
  – Metacrawler
  – SavvySearch
  – Dogpile
HTML Structure & Feature Weighting

• Weight tokens under particular HTML tags more heavily:
  – <TITLE> tokens (Google seems to like title matches)
  – <H1>,<H2>… tokens
  – <META> keyword tokens

• Parse page into conceptual sections (e.g. navigation links vs. page content) and weight tokens differently based on section.
Bibliometrics: Citation Analysis

- Many standard documents include bibliographies (or references), explicit citations to other previously published documents.
- Using citations as links, standard corpora can be viewed as a graph.
- The structure of this graph, independent of content, can provide interesting information about the similarity of documents and the structure of information.
- CF corpus includes citation information.
Impact Factor

• Developed by Garfield in 1972 to measure the importance (quality, influence) of scientific journals.
• Measure of how often papers in the journal are cited by other scientists.
• Computed and published annually by the Institute for Scientific Information (ISI).
• The *impact factor* of a journal $J$ in year $Y$ is the average number of citations (from indexed documents published in year $Y$) to a paper published in $J$ in year $Y-1$ or $Y-2$.
• Does not account for the quality of the citing article.
Bibliographic Coupling

- Measure of similarity of documents introduced by Kessler in 1963.
- The bibliographic coupling of two documents $A$ and $B$ is the number of documents cited by both $A$ and $B$.
- Size of the intersection of their bibliographies.
- Maybe want to normalize by size of bibliographies?
Co-Citation

- Number of documents that cite both $A$ and $B$.
- Maybe want to normalize by total number of documents citing either $A$ or $B$?
Citations vs. Links

• Web links are a bit different than citations:
  – Many links are navigational.
  – Many pages with high in-degree are portals not content providers.
  – Not all links are endorsements.
  – Company websites don’t point to their competitors.
  – Citations to relevant literature is enforced by peer-review.
Authorities

- *Authorities* are pages that are recognized as providing significant, trustworthy, and useful information on a topic.
- *In-degree* (number of pointers to a page) is one simple measure of authority.
- However, in-degree treats all links as equal.
- Should links from pages that are themselves authoritative count more?
Hubs

- *Hubs* are index pages that provide lots of useful links to relevant content pages (topic authorities).
- Hub pages for IR are included in the course home page:
  - http://www.cs.utexas.edu/users/mooney/ir-course
HITS

• Algorithm developed by Kleinberg in 1998.
• Attempts to computationally determine hubs and authorities on a particular topic through analysis of a relevant subgraph of the web.
• Based on mutually recursive facts:
  – Hubs point to lots of authorities.
  – Authorities are pointed to by lots of hubs.
Hubs and Authorities

- Together they tend to form a bipartite graph:
HITS Algorithm

- Computes hubs and authorities for a particular topic specified by a normal query.
- First determines a set of relevant pages for the query called the \textit{base} set $S$.
- Analyze the link structure of the web subgraph defined by $S$ to find authority and hub pages in this set.
Constructing a Base Subgraph

- For a specific query $Q$, let the set of documents returned by a standard search engine (e.g. VSR) be called the root set $R$.
- Initialize $S$ to $R$.
- Add to $S$ all pages pointed to by any page in $R$.
- Add to $S$ all pages that point to any page in $R$. 
Base Limitations

• To limit computational expense:
  – Limit number of root pages to the top 200 pages retrieved for the query.
  – Limit number of “back-pointer” pages to a random set of at most 50 pages returned by a “reverse link” query.

• To eliminate purely navigational links:
  – Eliminate links between two pages on the same host.

• To eliminate “non-authority-conveying” links:
  – Allow only \( m \) (\( m \approx 4–8 \)) pages from a given host as pointers to any individual page.
Authorities and In-Degree

• Even within the base set $S$ for a given query, the nodes with highest in-degree are not necessarily authorities (may just be generally popular pages like Yahoo or Amazon).

• True authority pages are pointed to by a number of hubs (i.e. pages that point to lots of authorities).
Iterative Algorithm

- Use an iterative algorithm to slowly converge on a mutually reinforcing set of hubs and authorities.
- Maintain for each page $p \in S$:
  - Authority score: $a_p$ (vector $a$)
  - Hub score: $h_p$ (vector $h$)
- Initialize all $a_p = h_p = 1$
- Maintain normalized scores:
  $$\sum_{p\in S} (a_p)^2 = 1 \quad \sum_{p\in S} (h_p)^2 = 1$$
HITS Update Rules

• Authorities are pointed to by lots of good hubs:

\[ a_p = \sum_{q:q\rightarrow p} h_q \]

• Hubs point to lots of good authorities:

\[ h_p = \sum_{q:p\rightarrow q} a_q \]
Illustrated Update Rules

\[ a_4 = h_1 + h_2 + h_3 \]

\[ h_4 = a_5 + a_6 + a_7 \]
HITS Iterative Algorithm

Initialize for all $p \in S$: $a_p = h_p = 1$

For $i = 1$ to $k$:

For all $p \in S$: $a_p = \sum_{q:q \rightarrow p} h_q$ (update auth. scores)

For all $p \in S$: $h_p = \sum_{q:p \rightarrow q} a_q$ (update hub scores)

For all $p \in S$: $a_p = a_p / c$  c:  $\sum_{p \in S} (a_p / c)^2 = 1$  (normalize $a$)

For all $p \in S$: $h_p = h_p / c$  c:  $\sum_{p \in S} (h_p / c)^2 = 1$  (normalize $h$)
Convergence

- Algorithm converges to a *fix-point* if iterated indefinitely.
- Define $A$ to be the adjacency matrix for the subgraph defined by $S$.
  - $A_{ij} = 1$ for $i \in S, j \in S$ iff $i \rightarrow j$
- Authority vector, $a$, converges to the principal eigenvector of $A^T A$
- Hub vector, $h$, converges to the principal eigenvector of $AA^T$
- In practice, 20 iterations produces fairly stable results.
Results

• Authorities for query: “Java”
  – java.sun.com
  – comp.lang.java FAQ

• Authorities for query “search engine”
  – Yahoo.com
  – Excite.com
  – Lycos.com
  – Altavista.com

• Authorities for query “Gates”
  – Microsoft.com
  – roadahead.com
Result Comments

- In most cases, the final authorities were not in the initial root set generated using Altavista.
- Authorities were brought in from linked and reverse-linked pages and then HITS computed their high authority score.
Finding Similar Pages Using Link Structure

- Given a page, $P$, let $R$ (the root set) be $t$ (e.g. 200) pages that point to $P$.
- Grow a base set $S$ from $R$.
- Run HITS on $S$.
- Return the best authorities in $S$ as the best similar-pages for $P$.
- Finds authorities in the “link neighborhood” of $P$. 
Similar Page Results

• Given “honda.com”
  – toyota.com
  – ford.com
  – bmwusa.com
  – saturncars.com
  – nissanmotors.com
  – audi.com
  – volvocars.com
HITS for Clustering

• An ambiguous query can result in the principal eigenvector only covering one of the possible meanings.
• Non-principal eigenvectors may contain hubs & authorities for other meanings.
• Example: “jaguar”:
  – Atari video game (principal eigenvector)
  – NFL Football team (2\textsuperscript{nd} non-princ. eigenvector)
  – Automobile (3\textsuperscript{rd} non-princ. eigenvector)
PageRank

• Alternative link-analysis method used by Google (Brin & Page, 1998).

• Does not attempt to capture the distinction between hubs and authorities.

• Ranks pages just by authority.

• Applied to the entire web rather than a local neighborhood of pages surrounding the results of a query.
Initial PageRank Idea

• Just measuring in-degree (citation count) doesn’t account for the authority of the source of a link.

• Initial page rank equation for page $p$:

$$R(p) = c \sum_{q:q \rightarrow p} \frac{R(q)}{N_q}$$

  – $N_q$ is the total number of out-links from page $q$.
  – A page, $q$, “gives” an equal fraction of its authority to all the pages it points to (e.g. $p$).
  – $c$ is a normalizing constant set so that the rank of all pages always sums to 1.
Initial PageRank Idea (cont.)

- Can view it as a process of PageRank “flowing” from pages to the pages they cite.
Initial Algorithm

• Iterate rank-flowing process until convergence:
  Let $S$ be the total set of pages.

  Initialize $\forall p \in S: R(p) = 1/|S|$

  Until ranks do not change (much) (convergence)

  For each $p \in S$:

  $$R'(p) = \sum_{q: q \rightarrow p} \frac{R(q)}{N_q}$$

  $$c = 1/\sum_{p \in S} R'(p)$$

  For each $p \in S: R(p) = cR'(p)$ (normalize)
Sample Stable Fixpoint
Linear Algebra Version

• Treat $\mathbf{R}$ as a vector over web pages.
• Let $\mathbf{A}$ be a 2-d matrix over pages where
  $\mathbf{A}_{vu} = 1/N_u$ if $u \rightarrow v$ else $\mathbf{A}_{vu} = 0$
• Then $\mathbf{R} = c \mathbf{A} \mathbf{R}$
• $\mathbf{R}$ converges to the principal eigenvector of $\mathbf{A}$. 
Problem with Initial Idea

- A group of pages that only point to themselves but are pointed to by other pages act as a “rank sink” and absorb all the rank in the system.

Rank flows into cycle and can’t get out
Rank Source

- Introduce a “rank source” $E$ that continually replenishes the rank of each page, $p$, by a fixed amount $E(p)$.

$$R(p) = c \left( \sum_{q: q \rightarrow p} \frac{R(q)}{N_q} + E(p) \right)$$
PageRank Algorithm

Let $S$ be the total set of pages.

Let $\forall p \in S: E(p) = \alpha/|S|$ (for some $0<\alpha<1$, e.g. 0.15)

Initialize $\forall p \in S: R(p) = 1/|S|$

Until ranks do not change (much) (*convergence*)

For each $p \in S$: 

$$R'(p) = \left[ (1-\alpha) \sum_{q:q\rightarrow p} \frac{R(q)}{N_q} \right] + E(p)$$

$$c = 1/ \sum_{p \in S} R'(p)$$

For each $p \in S$: $R(p) = cR'(p)$ (*normalize*)
Linear Algebra Version

- \( R = c(AR + E) \)
- Since \( \|R\|_1 = 1 \) : \( R = c(A + E \times 1)R \)
  - Where 1 is the vector consisting of all 1’s.
- So \( R \) is an eigenvector of \( (A + E \times 1) \)
Random Surfer Model

• PageRank can be seen as modeling a “random surfer” that starts on a random page and then at each point:
  – With probability $E(p)$ randomly jumps to page $p$.
  – Otherwise, randomly follows a link on the current page.

• $R(p)$ models the probability that this random surfer will be on page $p$ at any given time.

• “E jumps” are needed to prevent the random surfer from getting “trapped” in web sinks with no outgoing links.
Speed of Convergence

- Early experiments on Google used 322 million links.
- PageRank algorithm converged (within small tolerance) in about 52 iterations.
- Number of iterations required for convergence is empirically $O(\log n)$ (where $n$ is the number of links).
- Therefore calculation is quite efficient.
Simple Title Search with PageRank

• Use simple Boolean search to search webpage titles and rank the retrieved pages by their PageRank.

• Sample search for “university”:
  – Altavista returned a random set of pages with “university” in the title (seemed to prefer short URLs).
  – Primitive Google returned the home pages of top universities.
Google Ranking

• Complete Google ranking includes (based on university publications prior to commercialization).
  – Vector-space similarity component.
  – Keyword proximity component.
  – HTML-tag weight component (e.g. title preference).
  – PageRank component.

• Details of current commercial ranking functions are trade secrets.
Personalized PageRank

• PageRank can be biased (personalized) by changing $E$ to a non-uniform distribution.
• Restrict “random jumps” to a set of specified relevant pages.
• For example, let $E(p) = 0$ except for one’s own home page, for which $E(p) = \alpha$
• This results in a bias towards pages that are closer in the web graph to your own homepage.
Google PageRank-Biased Spidering

• Use PageRank to direct (focus) a spider on “important” pages.
• Compute page-rank using the current set of crawled pages.
• Order the spider’s search queue based on current estimated PageRank.
Link Analysis Conclusions

- Link analysis uses information about the structure of the web graph to aid search.
- It is one of the major innovations in web search.
- It was one of the primary reasons for Google’s initial success.