
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

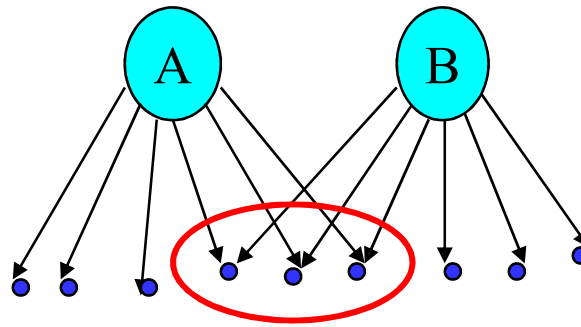
- Many standard documents include *bibliographies* (or *references*), explicit *citations* to other previously published documents.
- Using citations as links, standard corpora can be viewed as a graph.
- The structure of this graph, independent of content, can provide interesting information about the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

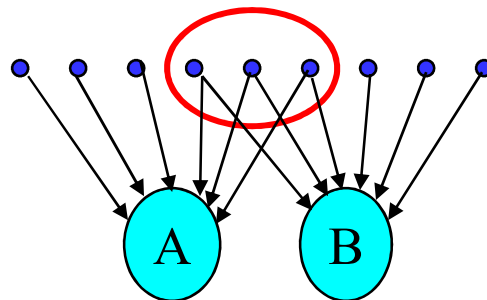
Bibliographic Coupling

- 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

- An alternate citation-based measure of similarity introduced by Small in 1973.
- 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

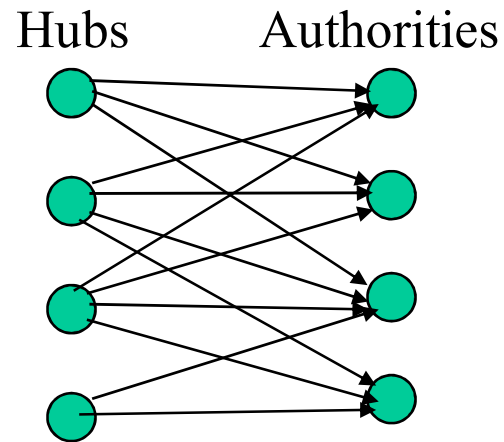
- *Hubs* are index pages that provide lots of useful links to relevant content pages (topic authorities).
- Hub pages for IR are included in the course home page:
 - <http://www.cs.utexas.edu/users/mooney/ir-course>

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:

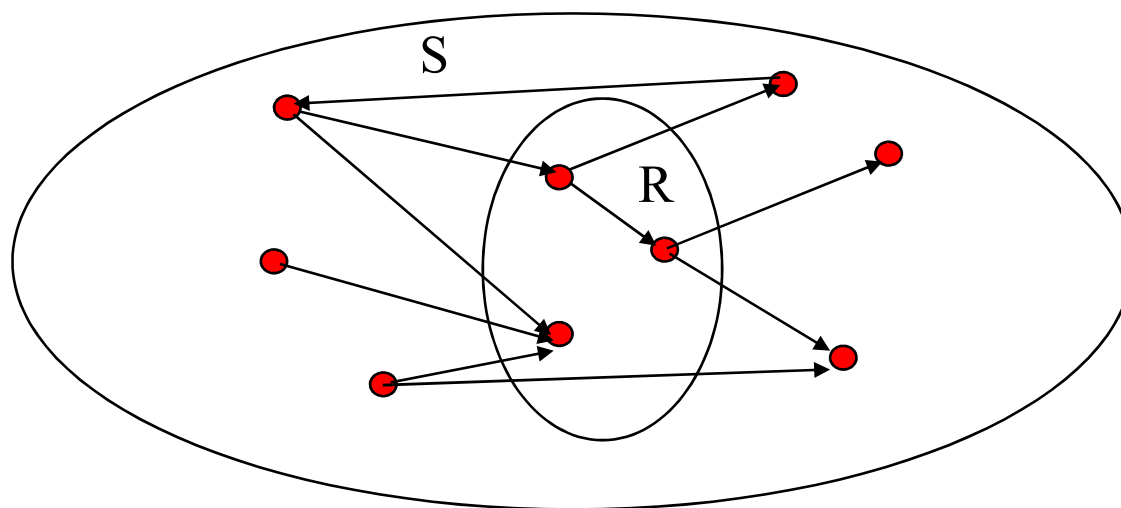


HITS Algorithm

- 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 *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 ($m \cong 4-8$) 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 \mathbf{a})
 - Hub score: h_p (vector \mathbf{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

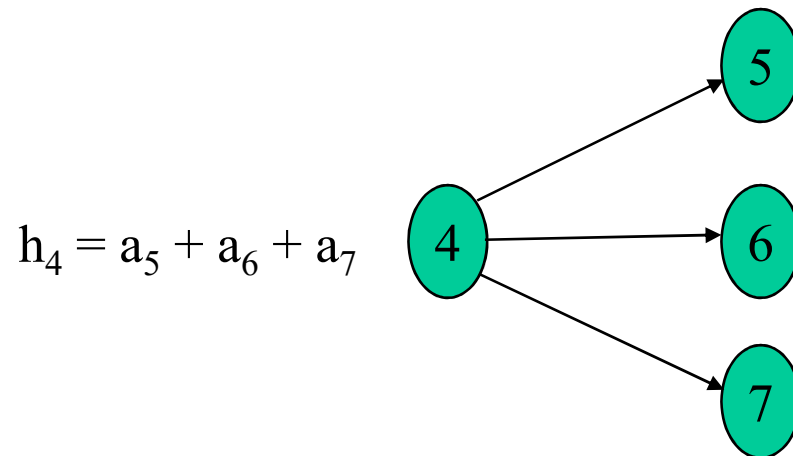
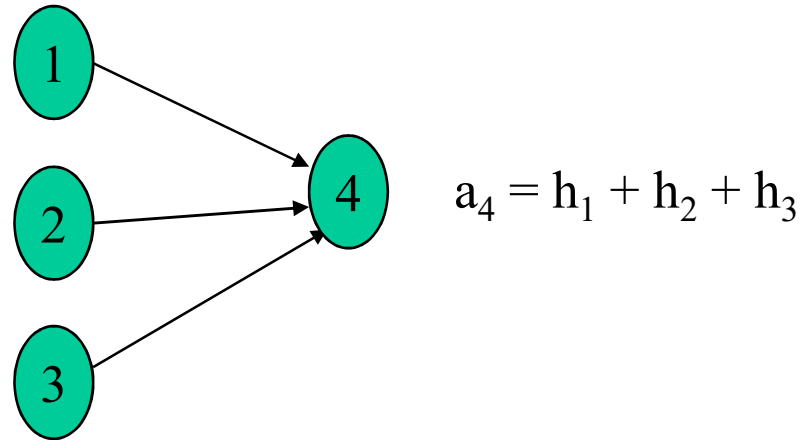
- Authorities are pointed to by lots of good hubs:

$$a_p = \sum_{q:q \rightarrow p} h_q$$

- Hubs point to lots of good authorities:

$$h_p = \sum_{q:p \rightarrow q} a_q$$

Illustrated Update Rules



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, \mathbf{a} , converges to the principal eigenvector of $A^T A$
- Hub vector, \mathbf{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 (2nd non-princ. eigenvector)
 - Automobile (3rd 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

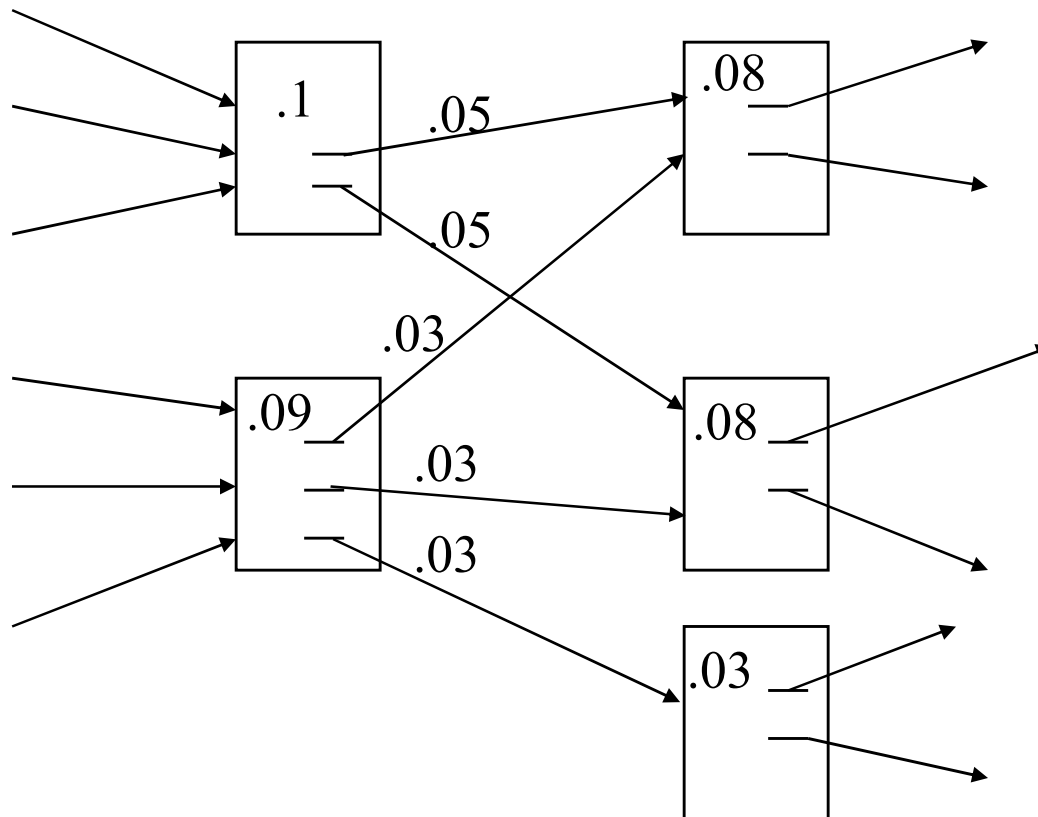
- Just measuring in-degree (citation count) doesn't account for the authority of the source of a link.
- Initial page rank equation for page p :

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

- 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*)

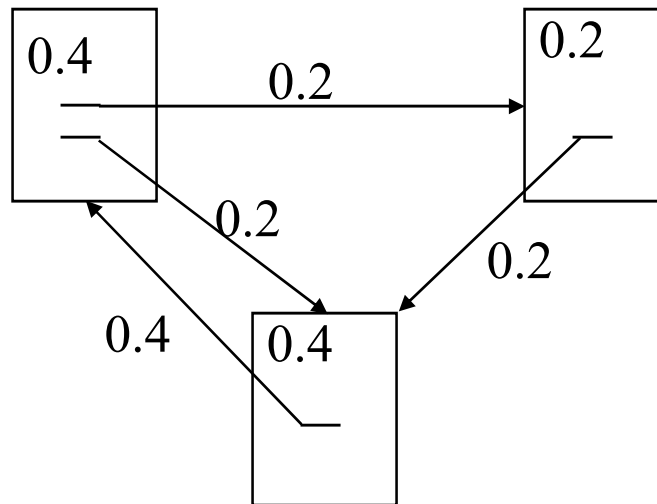
For each $p \in S$:

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

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

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

Sample Stable Fixpoint

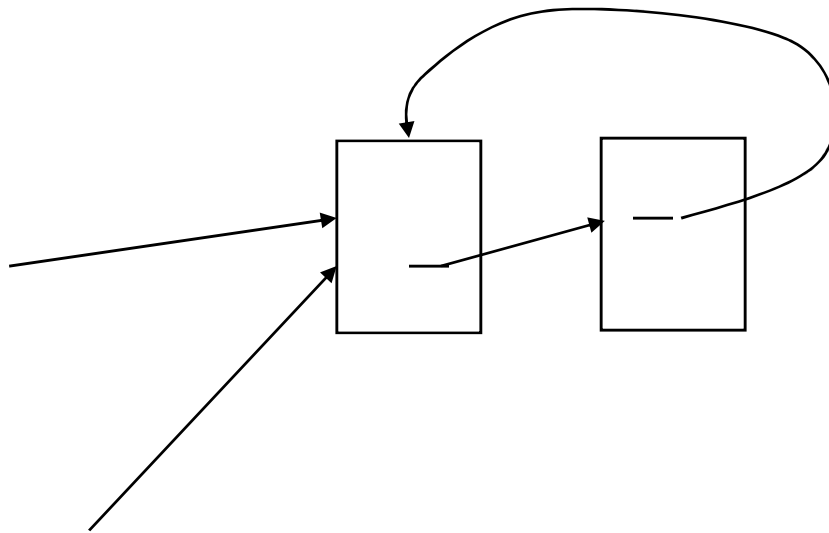


Linear Algebra Version

- Treat \mathbf{R} as a vector over web pages.
- Let \mathbf{A} be a 2-d matrix over pages where
 - $A_{vu} = 1/N_u$ if $u \rightarrow v$ else $A_{vu} = 0$
- 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

- $\mathbf{R} = c(\mathbf{A}\mathbf{R} + \mathbf{E})$
- Since $\|\mathbf{R}\|_1 = 1$: $\mathbf{R} = c(\mathbf{A} + \mathbf{E}\times\mathbf{1})\mathbf{R}$
 - Where $\mathbf{1}$ is the vector consisting of all 1's.
- So \mathbf{R} is an eigenvector of $(\mathbf{A} + \mathbf{E}\times\mathbf{1})$

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 \mathbf{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.