Link Analysis in Document Networks

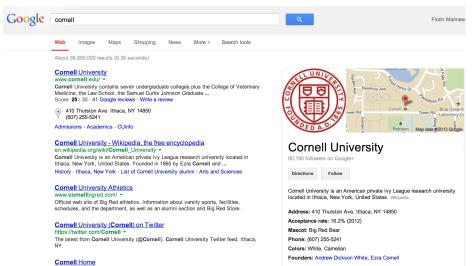
Compiled by: Cornelia Caragea, Sujatha Das

Credits: Giles, Manning, Hofmann, Mihalcea, Mobasher, Mooney, Schutze

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Searching the Web



www.cornellcollege.edu/ -

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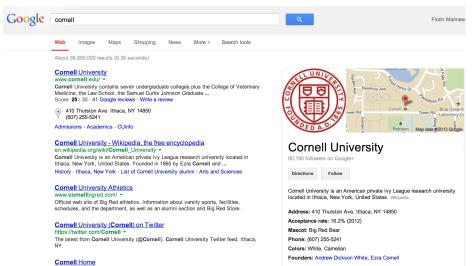
Residential liberal arts college established in 1853. Operates under the distinctive One-Course-At-A-Time academic calendar.

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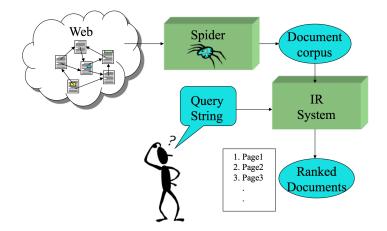
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Searching the Web: Search Engines

- When issuing the single-word query "cornell," a search engine does not have very much to go on.
 - Did the searcher want information about the university?
 - The university's hockey team?
 - Cornell College in Iowa?
 - The Nobel-Prize-winning physicist Eric Cornell?
- ► The Problem of Ranking
 - Search engines determine how to rank pages using automated methods
 - There must be enough information *intrinsic* to the Web and its structure to figure out that "Cornell University" is the best answer.

Web Search System



Key issue for search engines:

 To filter, from among an enormous number of relevant documents, the few that are most important

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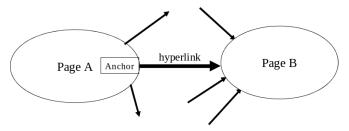
Challenges in Web Search

- Volume of material several billion items, growing steadily
- Items created dynamically or in databases
- ► Great variety length, formats, quality control, purpose, etc.
- Inexperience of users range of needs
- Economic models to pay for the service
- Location, personalization

Motivation for Link Analysis

- Early search engines mainly compare content similarity of the query and the indexed pages. I.e.,
 - ▶ They use information retrieval methods, cosine, TF-IDF, ...
- From mid 90's, it became clear that content similarity alone was no longer sufficient.
 - The number of pages grew rapidly in the mid-late 1990's.
 - The "cornell" query, Google estimates: millions of relevant pages.
 - How to rank the result pages suitably to present to the user?
 - Content similarity is easily spammed.
 - A page owner can repeat some words and add many related words to boost the rankings of his pages and/or to make the pages relevant to a large number of queries.

The Web as a Directed Graph



Assumption 1: A hyperlink between pages denotes author perceived relevance (quality signal)

Assumption 2: The anchor of the hyperlink describes the target page (textual context)

Links are essential to Ranking!

- Web pages are connected through hyperlinks (Manually-made social network)
 - Some hyperlinks: organize information at the same site.
 - Other hyperlinks: point to pages from other Web sites. Such out-going hyperlinks often indicate an implicit conveyance of authority to the pages being pointed to.
 - Pages that are pointed to by many other pages are likely to contain authoritative information.
- Hyperlinks can be used to assess the authority of a page on a topic, through implicit endorsements via pages that point to it

Concept of Relevance

- Relevance, as conventionally defined, is binary (relevant or not relevant). It is usually estimated by the similarity between the terms in the query and each document.
- Importance measures documents by their likelihood of being useful to a variety of users. It is usually estimated by some measure of popularity.
- Web search engines rank documents by combination of relevance and importance. The goal is to present an average user with the most important of the relevant documents.

Using hyperlinks for the query "Cornell"

- Collect pages that are relevant to "Cornell' using IR (text-only) techniques.
- Let these pages "vote" through their links for pages on the Web.
- Which page on the Web receives the greatest number of in-links from pages that are relevant to Cornell?
 - Answer: www.cornell.edu

Hyperlink algorithms

- During 1997-1998, the two most influential hyperlink based search algorithms PageRank and HITS were reported.
- Both algorithms are related to using the link structure in social networks.
 - Exploit the hyperlinks of the Web to rank pages according to their levels of "prestige" or "authority".
 - HITS: Jon Kleinberg (Cornell University), at Ninth Annual ACM-SIAM Symposium on Discrete Algorithms, January 1998
 - PageRank: Sergey Brin and Larry Page, PhD students from Stanford University, at Seventh International World Wide Web Conference (WWW7) in April, 1998.
- PageRank powers the Google search engine!

Authorities and Hubs

- Authorities for a query 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
 - Links from pages that are themselves authoritative should count more
- Hubs for a query are index pages that provide lots of useful links to relevant content pages (topic authorities)

Authorities and Hubs - Examples

Authorities:

- Newspaper home pages
- Course home pages
- Home pages of auto manufacturers
- Hubs
 - List of newspapers
 - Course bulletin
 - List of US auto manufacturers
- HITS uses both Hubs & Authorities whereas PageRank uses Authorities

Other applications of Link Analysis

 Apart from search ranking, hyperlinks are also useful for finding Web communities.

- ► A Web community is a cluster of densely linked pages representing a group of people with a special interest.
- Beyond explicit hyperlinks on the Web, links in other contexts are useful too, e.g.,
 - for discovering communities of named entities (e.g., people and organizations) in free text documents, and for analyzing social phenomena in emails..

The PageRank Algorithm

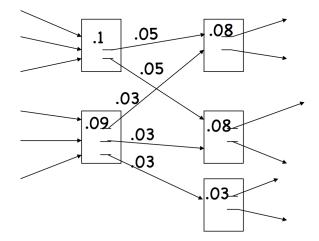
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Idea behind PageRank

- Query-independent reputation for a webpage based on link structure of the Web
- ► PageRank starts with the simple "voting" based on in-links
- Nodes repeatedly pass endorsements across their out-going links, with the weight of a node's endorsement based on the current estimate of its PageRank
 - More important nodes make stronger endorsements

Computing PageRank

Can view it as a process of PageRank "flowing" from pages to the pages they link to.



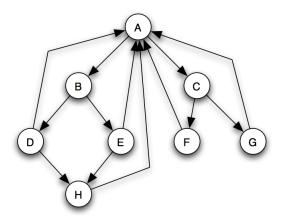
Basic PageRank computation

- Iterate rank-flowing process until convergence:
- Let S be the set of pages
- ▶ Initialize $R(A) = \frac{1}{|S|} = \frac{1}{n}$ for all $A \in S$
- Until ranks do not change (convergence)

• For each $A \in S$:

$$R(A) = \sum_{B \to A} \frac{R(B)}{out(B)}$$

PageRank Algorithm - Example



What are the PageRank values after the first two updates?

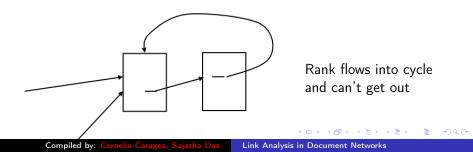
PageRank Algorithm - Example

Result

Step	A	В	C	D	Е	F	G	Н
1	1/2	1/16	1/16	1/16	1/16	1/16	1/16	1/8
2	3/16	1/4	1/4	1/32	1/32	1/32	1/32	1/16

Computational problems

- The web is full of dead-ends
 - 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
 - Pages with no outgoing links
- The underlying graph is modified by adding probabilistic jumps to nodes to handle these problems
 - Can show convergence of the iterative PageRank computation process on this graph



Teleporting

- At a dead end, jump to a random web page
- At any non-dead end, with probability 15%, jump to a random web page
- ▶ With remaining probability (85%), go out on a random link
 - 15% the ϵ parameter

$$R(A) = \frac{\epsilon}{n} + (1 - \epsilon) \sum_{(B,A) \in G} \frac{R(B)}{out(B)}$$

Result of teleporting: it cannot get stuck locally

The PageRank Algorithm

- Let S be the total set of pages and n = |S|
- Choose ϵ s.t. $0 < \epsilon < 1$, e.g., 0.15
- Initialize $R(A) = \frac{1}{n}$ for all $A \in S$
- Until ranks do not change (convergence)
 - For each $A \in S$:

$$R(A) = \left[(1 - \epsilon) \sum_{B \to A} \frac{R(B)}{out(B)} \right] + \frac{\epsilon}{n}$$

The 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 $\frac{\epsilon}{n}$ randomly jumps to page A
 - Otherwise, randomly follows a link on the current page
- R(A) models the probability that this random surfer will be on page A at any given time
- "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(logn) (where n is the number of links)
- Therefore calculation is quite efficient

PageRank vs. HITS

- Computation
 - Once for all documents and queries (offline)
- Query-independent
 - Requires combination with query-dependent criteria

- Computation
 - Requires computation for each query
- Query-dependent
- Quality depends on quality of start set
- Gives hubs as well as authorities

Ranking considerations in Search Engines

- Paid advertisers
- Manually-created classification
- Vector-space ranking with corrections for document length
- Feedback from Query Logs
- ► Extra weighting for specific fields, e.g., title, anchors, etc.
- Popularity or importance, e.g., PageRank Many of these factors are NOT made public.

Conclusions

- Link analysis uses information about the structure of the web graph to aid search
- Using link structure can be viewed as one of the major innovations in web search
- It is the primary reason for Google's success