Social and Information Network Analysis

Link Analysis and Web Search

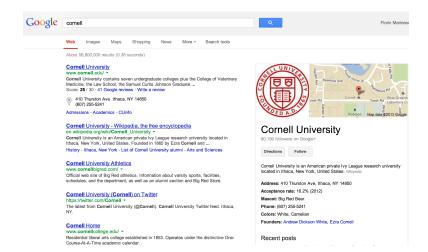
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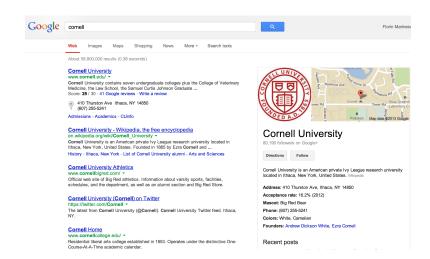
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Searching the Web: The Problem of Ranking

Searching the Web



Searching the Web



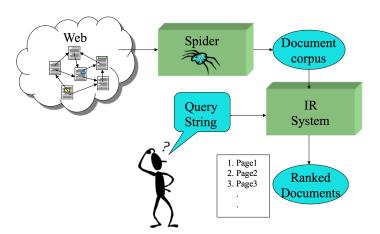
Searching the Web: The Problem of Ranking

- 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?

Searching the Web: The Problem of Ranking

- Search engines determine how to rank pages using automated methods that look at the Web itself, not some external source of knowledge.
- 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 issues for search engines:

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

Web Search System

Understanding the network structure of Web pages is crucial for understanding what documents a search engine should return!

Back to the query "Cornell":

- No internal features of the page www.cornell.edu are really helpful:
 - "Cornell" does not necessarily occur more frequently within this page content than within others, relevant to the query

Web Search System

Understanding the network structure of Web pages is crucial for understanding what documents a search engine should return!

Back to the query "Cornell":

- No internal features of the page www.cornell.edu are really helpful:
 - "Cornell" does not necessarily occur more frequently within this page content than within others, relevant to the query
- Rather, features extracted from the link structure are more helpful:
 - When a page is relevant to the query "Cornell", very often it links to www.cornell.edu

Link Analysis using Hubs and Authorities

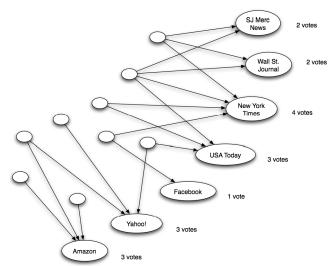
- We can use links to assess the authority of a page on a topic, through implicit endorsements that other pages on the topic confer through their links to it.
- Experiment with the query "Cornell":
 - Collect pages that are relevant to "Cornell' using IR (text-only) techniques.
 - Let these pages "vote" 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?

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 - Which page on the Web receives the greatest number of in-links from pages that are relevant to Cornell?
 - Answer: www.cornell.edu

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 - What is the "best" answer to the query "newspapers"?

- Experiment with the query "newspapers":
 - What is the "best" answer to the query "newspapers"?
 - No single right answer
 - Best expected answer: A list of most important ones
 - Collect pages relevant to "newspapers" and let them vote through their links
 - Result: a mix of prominent newspapers along with pages that are going to receive a lot of in-links no matter what the query is - pages like Yahoo!, Facebook, and Amazon.

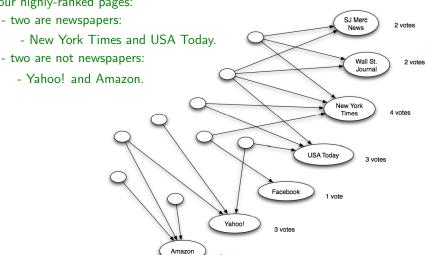
In-Links



The unlabeled circles represent pages relevant to the query "newspaper"

In-Links

Four highly-ranked pages:



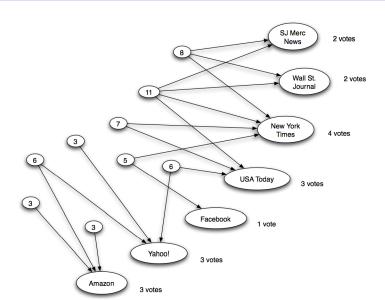
The unlabeled circles represent pages relevant to the query "newspaper"

3 votes

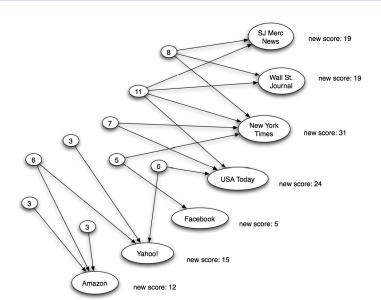
Finding Good Lists

- In addition to the newspapers themselves, there is another kind of useful answer to our query: pages that compile lists of resources relevant to the topic.
- If we could find good list pages for newspapers, we would have another approach to the problem of finding the newspapers themselves.
- Intuitively, these pages have some sense where the good answers are, and we score them highly as lists.
 - A page's value as a list is equal to the sum of the votes received by all pages that it voted for.

Finding Good Lists



Re-Weighting



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

Ranking by Hyperlink-Induced Topic Search (HITS) algorithm

HITS

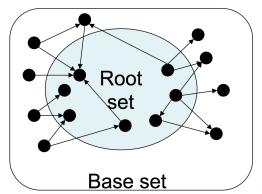
- Algorithm developed by Kleinberg in 1998, as part of IBM's Clever search project
- Attempts to computationally determine hubs and authorities on a particular topic through analysis of a relevant subgraph of the web
- Based on mutually recursive facts:
 - Hubs point to lots of authorities
 - Authorities are pointed to by lots of hubs

The 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 be called the root set R
- Initialize the base set 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





HITS

Goal: Given a query, find:

Good sources of content (authorities)

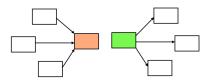


• Good sources of links (hubs)

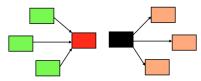


Intuition

Authority comes from in-edges.
 Being a good hub comes from out-edges.



Better authority comes from in-edges from good hubs.
 Being a better hub comes from out-edges to good 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:

$$\sum_{p \in S} (a_p)^2 = 1 \text{ and } \sum_{p \in S} (h_p)^2 = 1$$

HITS Update Rules

Authorities are pointed to by lots of good hubs:

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

• Hubs point to lots of good authorities:

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

• Repeat until vectors **a** and **h** converge

The HITS Iterative Algorithm

- Initialize $a_p = h_p = 1$ for all $p \in S$
- For i = 1 to k:
 - For all $p \in S$: update authority scores

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

• For all $p \in S$: normalize **a**

$$a_p = a_p/c, c : \sum_{p \in S} (a_p/c)^2 = 1$$

• For all $p \in S$: update hub scores

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

• For all $p \in S$: normalize **h**

$$h_p = h_p/c, c : \sum_{p \in S} (h_p/c)^2 = 1$$

The HITS Iterative Algorithm

```
1 G := set of pages
2 for each page p in G do
    p.auth = 1 // p.auth is the authority score of the page p
    p.hub = 1 // p.hub is the hub score of the page p
 5 function HubsAndAuthorities(G)
    for step from 1 to k do // run the algorithm for k steps
      norm = 0
      for each page p in G do // update all authority values first
        p.auth = 0
10
        for each page q in p.incomingNeighbors do // p.incomingNeighbors is the set of pages that link to p
           p.auth += q.hub
12
        norm += square(p.auth) // calculate the sum of the squared auth values to normalise
1.3
      norm = sqrt(norm)
14
      for each page p in G do // update the auth scores
15
         p.auth = p.auth / norm // normalise the auth values
16
      norm = 0
17
      for each page p in G do // then update all hub values
        p.hub = 0
18
19
         for each page r in p.outgoingNeighbors do // p.outgoingNeighbors is the set of pages that p links to
20
           p.hub += r.auth
21
        norm += square(p.hub) // calculate the sum of the squared hub values to normalise
22
      norm = sqrt(norm)
23
      for each page p in G do // then update all hub values
24
        p.hub = p.hub / norm // normalise the hub values
```

Convergence

What happens if we do this for larger and larger values of k?

- Algorithm converges to a fix-point if iterated indefinitely
- In practice, 20 iterations produce fairly stable results
- Regardless of the initial hub and authority values (provided they are positive), we generally reach the same limiting values

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

The PageRank Algorithm

PageRank

Query-independent ranking algorithm:

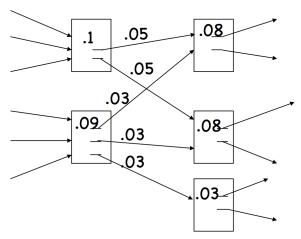
- Alternative link-analysis method used by Google (Brin & Page, 1998)
- Does not attempt to capture the distinction between hubs and authorities
- Ranks pages just by authority
- Applied to the entire web rather than a local neighborhood of pages surrounding the results of a query
- The endorsement that forms the basis for the PageRank measure of importance is that a page is important if it is cited by other important pages

Idea Behind PageRank

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

Initial PageRank Idea

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



Initial PageRank Algorithm

- 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 $A \in S$:

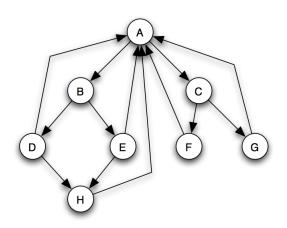
$$R'(A) = \sum_{B \to A} \frac{1}{out(B)} R(B)$$

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

• For each $A \in S : R(A) = cR'(A)$ (normalize)



PageRank Algorithm - Example



What are the PageRank values after the first two updates?



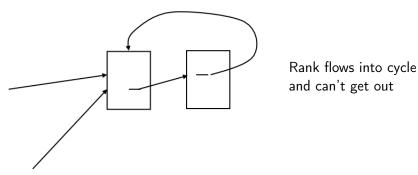
PageRank Algorithm - Example

Result

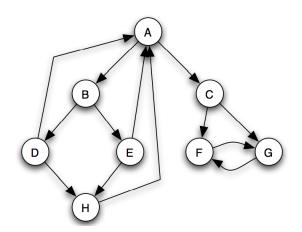
Step	A	В	C	D	E	F	G	H
1	1/2	1/16	1/16	1/16	1/16	1/16	1/16	1/8
2	3/16	1/4	1/4	1/32	1/32	1/32	1/32	1/16

Problem with Initial Idea

- 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



PageRank Algorithm - Modified Example



PageRank that flows from C to F and G can never circulate back into the network - links out of C function as a "slow leak".

Teleporting

- At a dead end, jump to a random web page
- At any non-dead end, with probability 10%, jump to a random web page
- With remaining probability (90%), go out on a random link
 - 10% the ϵ parameter

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

- ullet c is a normalizing constant set so that the rank of all pages always sums to 1
- 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 $A \in S$:

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

• For each $A \in S : R(A) = cR'(A)$ (normalize)

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

PageRank Retrieval

- Preprocessing:
 - Given graph of links, compute the rank of each page A
- Query processing:
 - Retrieve pages meeting query
 - Rank them by their PageRank
 - Order is query-independent
- The reality
 - PageRank is used in Google, but so are many other clever heuristics

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

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 is the primary reason for Google's success