Web Page Scoring Systems for Horizontal and Vertical search

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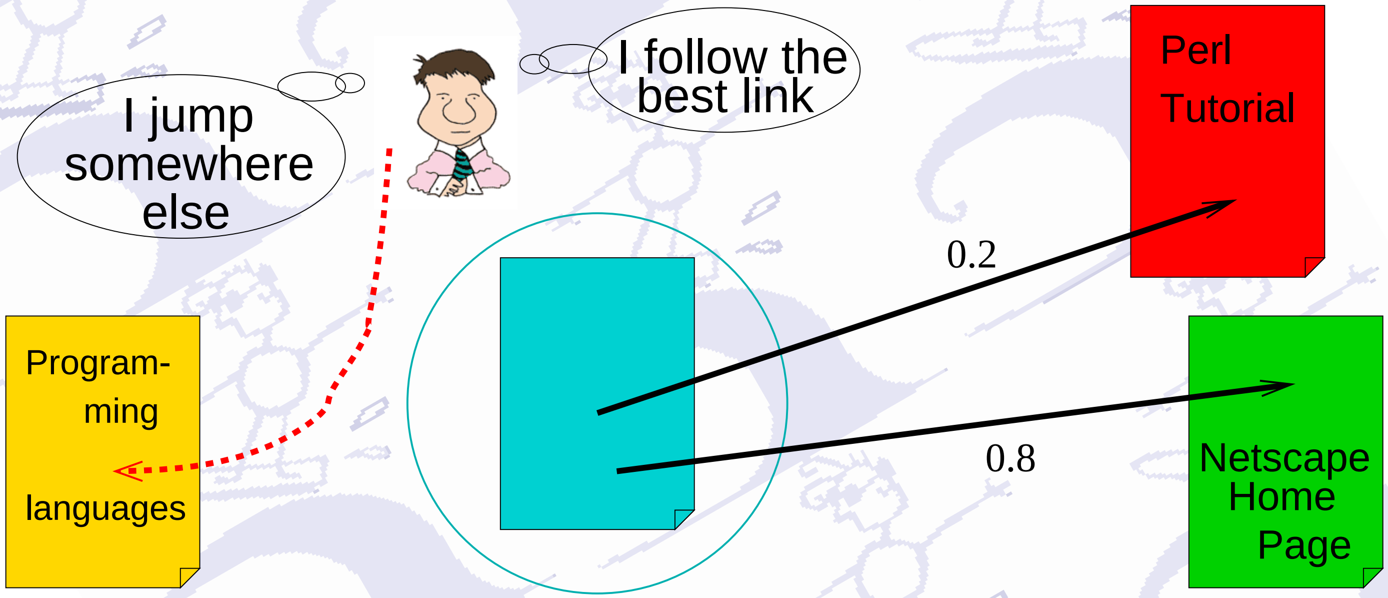
Introduction: Web surfing

- The goal of the paper is to model an user visiting the Web.



- The probability that the user is visiting a page, is proportional to the relevance of that page.

Summary

- Definition of the probabilistic model.
- Deriving Google's PageRank and HITS from the model.
- Proposal of new models for vertical search engines.
- Experimental results.

Surfer model 1

Our surfer is allowed to perform the following basic operations:

- j jump to a node of the graph;
- l follow a hyperlink from the current page;
- b follow a back-link (a hyperlink in the inverse direction);
- s stay in the same node.

Surfer model 2

Surfer actions depend on the content of current page:

- $x(l|q)$ the probability of following one hyperlink from page q,
- $x(b|q)$ the probability of following one back-link from page q,
- $x(j|q)$ the probability of jumping from page q,
- $x(s|q)$ the probability of remaining in page q.

Surfer model 3

- $x(p|q,j)$ the probability of jumping from page q to page p;

- $x(p|q,l)$ the probability of selecting a hyperlink from page q to page p; $x(p|q,l) \neq 0 \iff p \in ch(q)$, being $ch(q)$ the set of the children of node q in the graph $\boldsymbol{G}$;

- $x(p|q,b)$ the probability of going back from page q to page p; $x(p|q,b) \neq 0 \iff p \in pa(q)$, being $pa(q)$ the set of the parents of node q in the graph $\boldsymbol{G}$.

Surfer model 4

The probability of being located at page p at time step $t+1$ is

$$
\begin{aligned}
x_p(t+1) &= \sum_{q \in \boldsymbol{G}} x(p|q,j) \cdot x(j|q) \cdot x_q(t) + \\
&+ \sum_{q \in pa(p)} x(p|q,l) \cdot x(l|q) \cdot x_q(t) + \\
&+ \sum_{q \in ch(p)} x(p|q,b) \cdot x(b|q) \cdot x_q(t) + x(s|p) \cdot x_p(t)
\end{aligned}
$$

$\boldsymbol{x}(t)$ score vector at time t. Starting from a given initial distribution $\boldsymbol{x}(0)$:

$$\boldsymbol{x}(t) = \boldsymbol{T}^t \cdot \boldsymbol{x}(0).$$

Surfer model and Markov chains

Proposition 1

$\boldsymbol{T}'$ is the state transition matrix of the Markov chain. $\boldsymbol{T}'$ is stable, since $\boldsymbol{T}'$ is a stochastic matrix having ($\lambda_{max} = 1$). If $\sum_{q \in \boldsymbol{G}} \boldsymbol{x}_q(0) = 1$, then $\sum_{q \in \boldsymbol{G}} \boldsymbol{x}_q(t) = 1$, $t = 1, 2, \ldots$.

By applying the results on Markov chains we can prove that:

Proposition 2

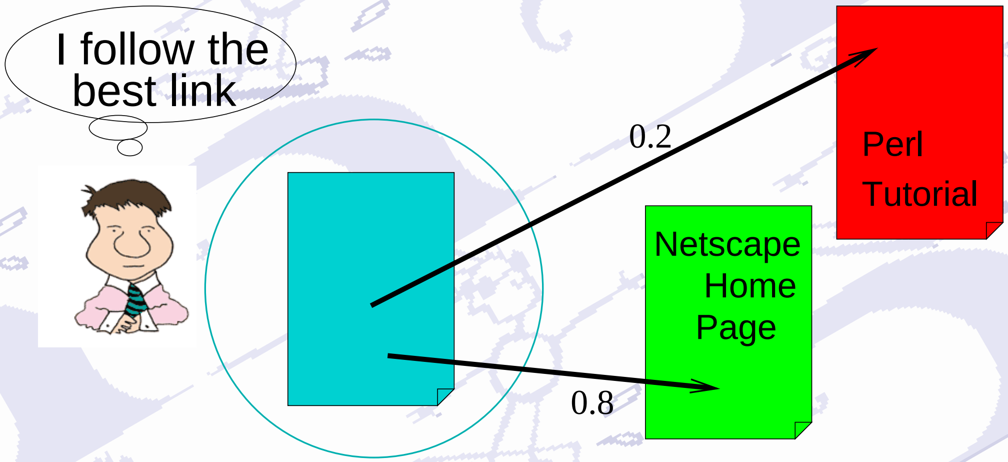
If $x(j|q) \neq 0 \wedge x(p|q,j) \neq 0$, $\forall p, q :\in \boldsymbol{G}$ then 1) $lim_{t \to \infty} \boldsymbol{x}(t) = \boldsymbol{x}^\star$ where $\boldsymbol{x}^\star$ does not depend on the initial state vector $\boldsymbol{x}(0)$. 2) All pages get a score $\neq 0$, thus the resulting scoring system can be applied globally to the entire Web. .

Google's PageRank

- $x(b|p) = x(s|p) = 0$ for any page p.
- $x(j|p) = 1 - d, \quad x(l|p) = d$ for any page p.
- $x(p|j) = 1/N$ for any page p, where N is the number of pages on the Web Graph.
- $x(p|q, l) = 1/h_q$ where h_q is the number of outlinks of page q.

For Proposition 2 PageRank converges to a vector independent from the starting distribution.
Note: setting $x(j|p) = 1$ and $x(l|p) = 0$ for any sink page p, the resulting model is still probabilistically coherent.

Focused Google's PageRank



- PageRank: the *random* surfer follows each outlink of page q with probability $1/ch(q)$;

- Focused PageRank (Domingos 2001): a surfer follows the links according to suggestions provided by a page classifier.

$$x(ch_i(q)|q,l) = \frac{s(ch_i(q))}{\sum_{j=0}^{h_q} s(ch_j(q))}$$

Double Focused Google's PageRank

Surfer actions depend on content of current page:

- probability of following a link in page p is proportional to classification score $s(p)$ of p

$$x(l|p) = d_1 \cdot \frac{s(p)}{\max_{q \in \boldsymbol{G}} s(q)}$$

- probability of jump to p is proportional to $s(p)$

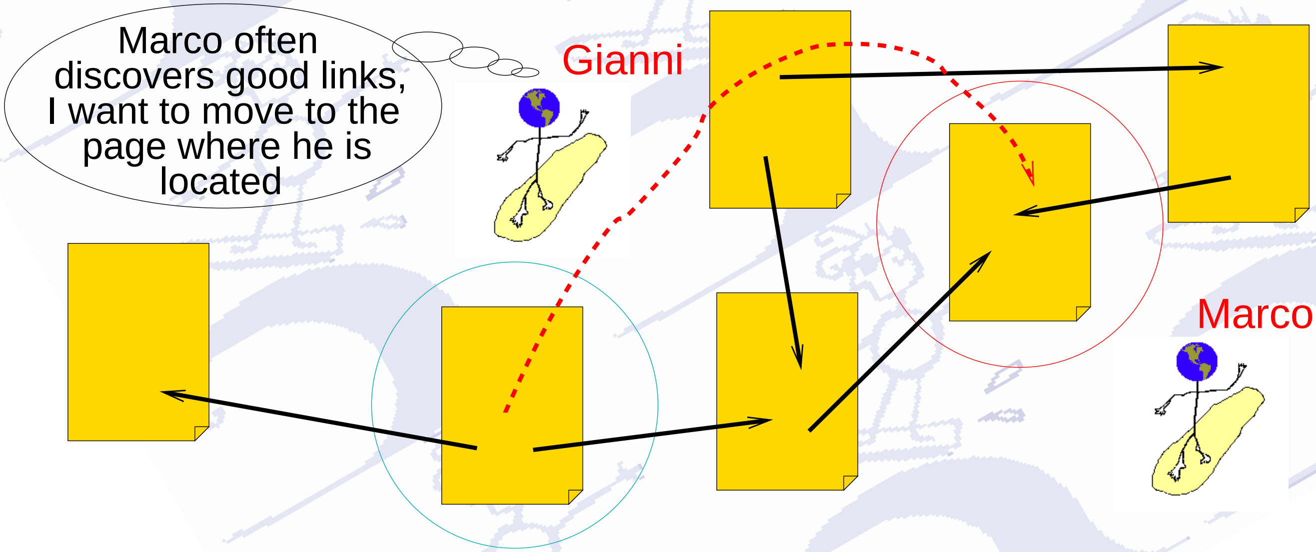
$$x(p|j) = \frac{s(p)}{\sum_{q \in \boldsymbol{G}} s(q)}$$

For Proposition 2 the resulting scoring system is stable and converges to a distribution independent from the initial conditions. All pages get a non-zero score (allowing global ranking).

Collaborative walks (Multi State models) 1

- A model based on a single variable may not capture relationships among pages (i.e. HITS scheme uses 2 variables).

- We define a multi-variable scheme by considering a pool of surfers each associated to a variable. A surfer can accept suggestions of surfer i, jumping to the page visited by i.



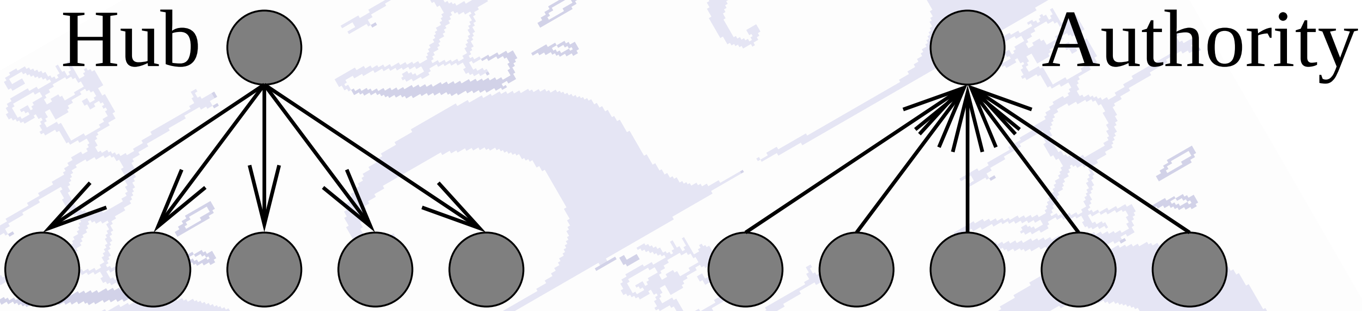
Collaborative walks (Multi State models) 2

The set of M interacting surfers can be described as a set of matrix equations as follows

$$\begin{cases} \boldsymbol{x}^{(1)}(t+1) = \boldsymbol{T}^{(1)} \cdot \boldsymbol{X}(t) \cdot \boldsymbol{A}^{(1)} \\ \vdots \\ \boldsymbol{x}^{(M)}(t+1) = \boldsymbol{T}^{(M)} \cdot \boldsymbol{X}(t) \cdot \boldsymbol{A}^{(M)} \end{cases}$$

where the j-th element of vector $\boldsymbol{A}^{(i)}$ indicates the probability that surfer i will relocate to the actual position of surfer j.

Hubs/Authorities



The HITS algorithm assigns an *authority* and *hubness* score to each page p. It is modeled by a collaborative walk of 2 surfers:

- Surfer 1 associated to the page hubness.
- Surfer 2 associated to the page authority.
- $x^{(1)}(l|p) = 0, \;\; x^{(1)}(b|p) = 1$ for each page p.
- $x^{(2)}(l|p) = 1, \;\; x^{(2)}(b|p) = 0$ for each page p.

Hubs/Authority

- $x^{(1)}(p|q,b) = 1$ for each page q and $p \in pa(q)$.
- $x^{(2)}(p|q,l) = 1$ for each page q and $p \in ch(q)$.
- Surfer interaction: $\boldsymbol{A}^{(1)} = (0,1)'$, $\boldsymbol{A}^{(2)} = (1,0)'$

HITS does not respect the probabilistic model:

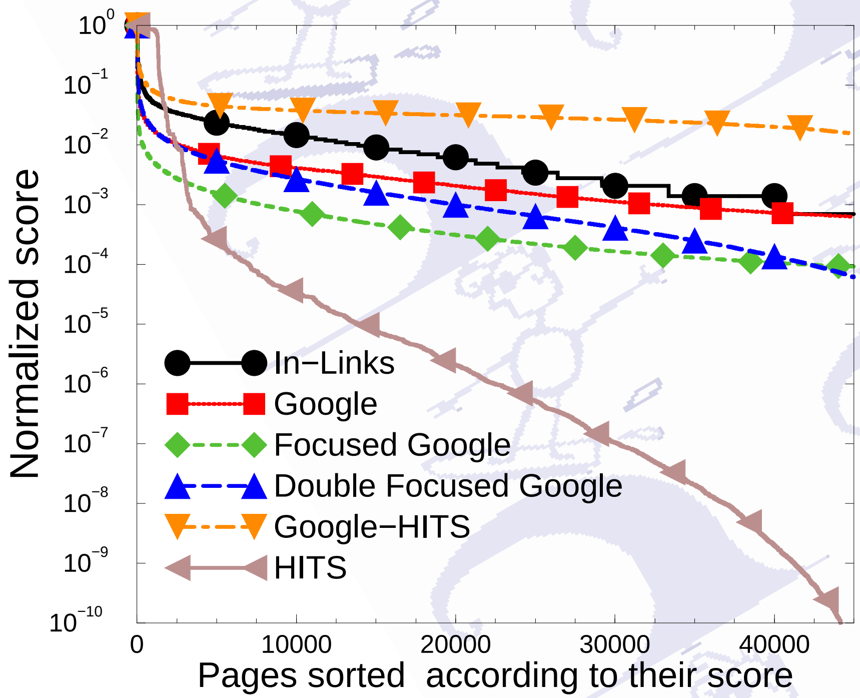
$$\sum_{p \in ch(q)} x^{(1)}(p|q,b) = |ch(q)| > 1$$

$$\sum_{p \in pa(q)} x^{(2)}(p|q,l) = |pa(q)| > 1$$

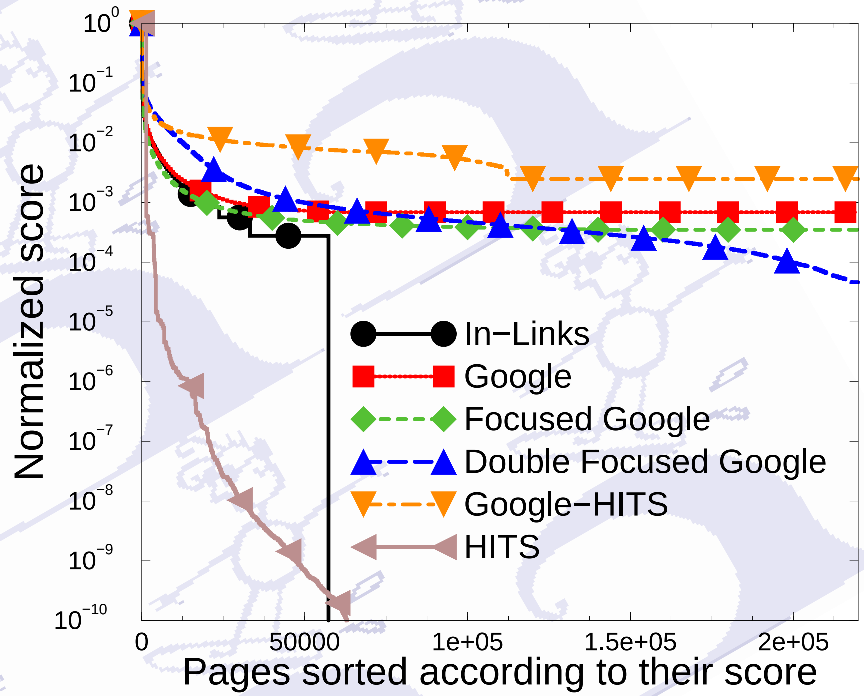
HITS can be modified to respect the probabilistic model and the conditions stated on Proposition 2 (more details on the paper).

Experimental results

2 focus crawling sessions for the topic “Linux” (50.000 pages) and “cooking recipes” (300.000 pages). We report the rank values of pages (sorted by the rank value).



(a)



(b)

Qualitative results 1

PageRank	HITS
www.zdnet.com	www.openbsdapps.com/?page=category&...
www.google.com	www.openbsdapps.com/?page=category&...
search.internet.com/power_search	www.openbsdapps.com/?page=category&...
www.ibm.com	www.openbsdapps.com/?page=category&...
www.yahoo.com	www.openbsdapps.com/?page=category&...
www.ibm.com/planetwide/select	www.openbsdapps.com/?page=category&...
java.sun.com	www.openbsdapps.com/?page=newupdate...
www.osdn.com	www.openbsdapps.com/?page=linkus

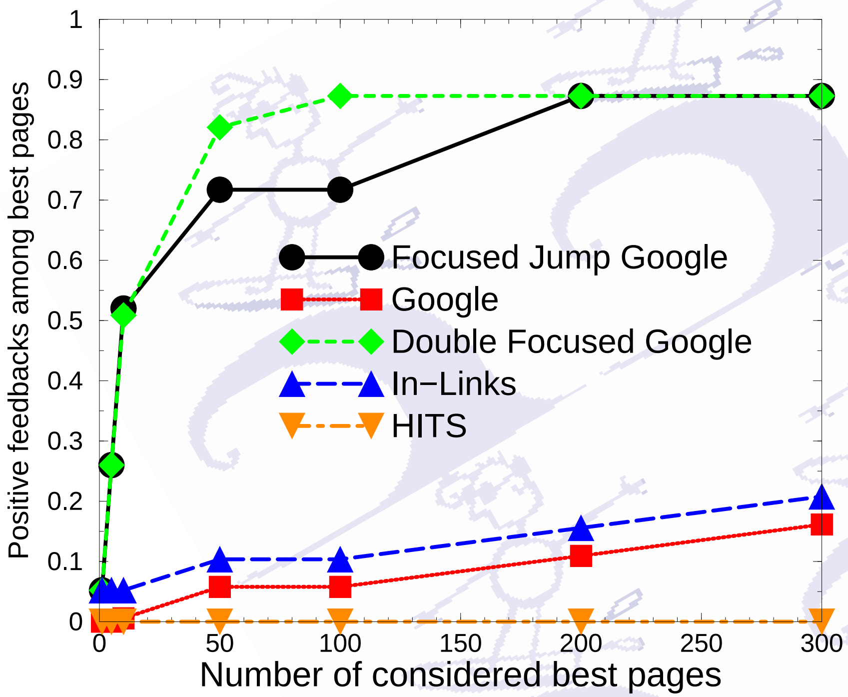
8 top "Linux" score pages, using either the PageRank surfer, or a HITS surfer pool (considering the authority value).

Qualitative results 2

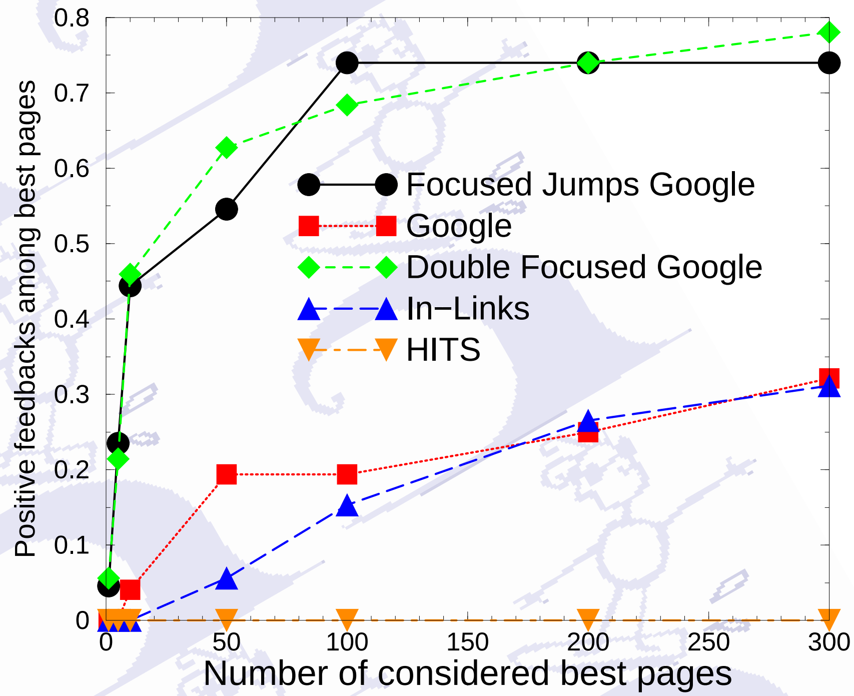
Focused PageRank	Double Focused PageRank
www.internet.com/sections/linux.html	www.internet.com/sections/linux.html
www.slackware.com	www.slackware.com
www.linux.org	www.li.org
www.zdnet.com	www.linux.org
jobs.osdn.com	www.linuxhq.com
www.yahoo.com	www.slackware.org
www.linux.org/books/index.html	www.linux.org/index.html
www.python.org	www.linuxusers.org

8 top "Linux" score pages, using the proposed focused versions of the PageRank surfer.

Expert judgments



(a)



(b)

Percentage of authoritative pages among the N pages with highest score. 10 experts labelled the pages as "authoritative" or not "authoritative" for the topic.

Conclusions

- We defined a probabilistic model from which many popular scoring algorithms can be derived.

- Properties of a scoring system based on our model:

  1. stable (at each iteration the sum of scores is equal to 1);

  2. converges to a solution independent from initial condition;

  3. non-zero score to each page (allowing global ranking).

- We proposed new scoring algorithms for vertical and horizontal search. Experts judgments confirm that proposed algorithms provide better results than other scoring systems.