Freshness Matters

- In Flowers, Food, and Web Authority -

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Hot Topics in Information Retrieval, WS 10/11

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Overview

- 1 Motivation
- 2 Related Work
 - PageRank
 - T-Rank
- 3 New Approach
 - Idea
 - Web Freshness
 - Authority Propagation
- 4 Experimental Results
- 5 Future Work
- 6 Strengths and Weakness of the Paper

Why do we need freshness in web authority rankings?

Freshness is all about links & pages which were created or changed recently.

Contrary to that: stale pages and links.

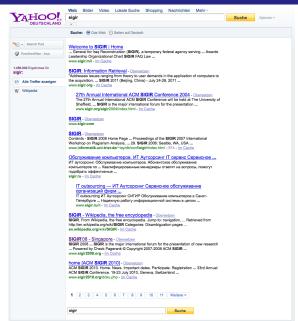


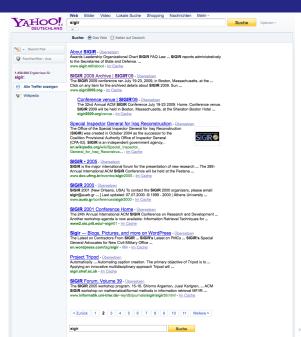


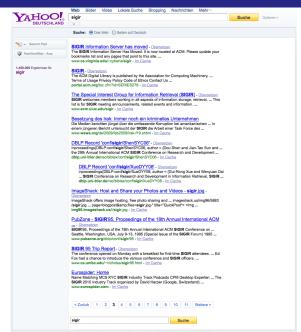
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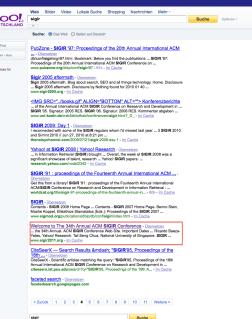
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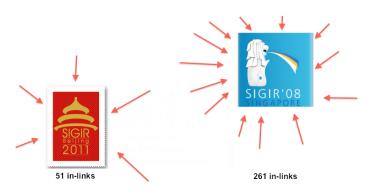






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Figure: Various Web 2.0 Tools (Source: Flickr User pipeapple)

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BUT

Web authority of a webpage is often computed based on a single website snapshot.



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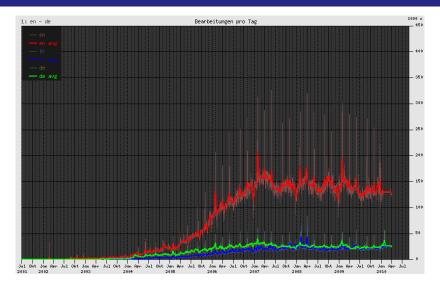


Figure: Wikipedia Statistic: Average Changes per Day (Source: Wikipedia)



Figure: Wikipedia Statistic: Top 20 Wikipedia Sites (Germany) with the most changes from 01.06.2009 to 30.06.2009 (Source: Wikipedia)



Figure: Picture from Flickr

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PageRank [Lawrence Page & Sergey Brin, 1998]

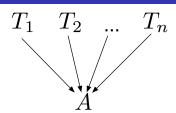
- is the most popular ranking algorithm.
- concept is based on a site's in-links (links pointing to the specific site).
- represents the probability that a random web-surfer model enters a page.

Moves of the Random Web Surfer Model

In every step the random web surfer model either $\underline{\text{follows}}$ an out-linked page OR does a random $\underline{\text{jump}}$ to any page.

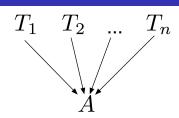
The PageRank Algorithm

Assuming n pages T_1 , T_2 , ..., T_n link to a page A.



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Then

$$PR(A) = \frac{1-d}{N} + d \cdot \left(\frac{PR(T_1)}{C(T_1)} + \dots + \frac{PR(T_n)}{C(T_n)}\right)$$

with

N: # of overall pages

d: damping factor $(0 \le d \le 1)$ and

$$C(T_i)$$
: # of out-links of T_i , $1 \le i \le n$.



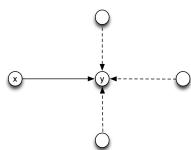
No freshness of links and pages is considered here!

T-Rank [K. Berberich et al, 2005]

- is build upon the PageRank idea & algorithm.
- extends PageRank algorithm with a bias for following an out-link and jumping to a new page to introduce freshness of pages and links.

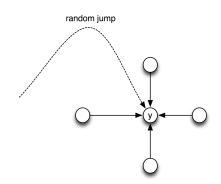
The probability that a random surfer is clicking at page x on an out-link to page y is a weighted combination of

- freshness of page y,
- freshness of the link from x to y and
- average freshness of all incoming links of y.



The probability that a random surfer takes a random jump to page y is a weighted combination of

- freshness of page y,
- activity of page y,
- average freshness of all incoming links of y and
- average activity of the pages that link to y.



$$r(y) = (1 - \varepsilon) \cdot s(y) + \sum_{(x,y) \in E} \varepsilon \cdot t(x,y) \cdot r(x)$$

with

 ε : probability that a random surfer is clicking on an out-link $(1-\varepsilon)$: probability that a random surfer makes a random jump to a page.

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 $(1-\varepsilon)$: probability that a random surfer makes a random jump to a page.

s(y): the random jump probability

t(x,y): the transition probability

- T-Rank is based on the fact that the users have a specific temporal focus of attention where the user is interested in.
- Freshness and activity computation is based on that temporal focus.

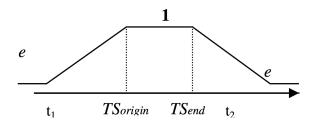


Figure: Temporal proximity window for a temporal interval

T-Rank is based on a good approach, BUT:

Activities at different time points are not distinguished.

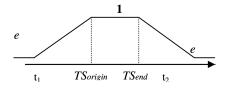


Figure: Temporal proximity window for a temporal interval

Instead, influence of activities on web freshness should decay over time.

Overview

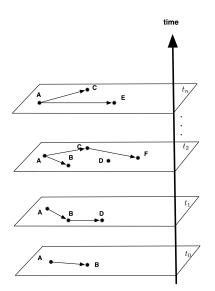
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Probabilistic algorithm to estimate web page authority by considering two temporal aspects:

Web freshness

2 Multiple snapshots collected at different timepoints

$$t_0, t_1, \cdots, t_n$$



Web Freshness

• is regarded from two points of view: the information recommenders and the information providers.

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- hence is divided into in-link freshness (InF) and page freshness (PF).
- computation is based on temporal page profiles and temporal link profiles.

The Web Freshness Computation

Computation of the in-link and page freshness at a certain time point t_i :

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$$InF(p)_{t_i} = \beta_1 e^{-\beta_2 \Delta t} InF(p)_{t_{i-1}} + \Delta InF(p)|_{t_{i-1}}^{t_i}$$

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$$PF(p)_{t_i} = \beta_3 e^{-\beta_4 \Delta t} PF(p)_{t_{i-1}} + \Delta PF(p)|_{t_{i-1}}^{t_i}$$

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$$PF(p)_{t_{i}} = \beta_{3}e^{-\beta_{4}\Delta t}PF(p)_{t_{i-1}} + \Delta PF(p)|_{t_{i-1}}^{t_{i}}$$

How can we compute $\Delta InF(p)|_{t_{i-1}}^{t_i}$ and $\Delta PF(p)|_{t_{i-1}}^{t_i}$?

In-Link Activites

 ω_j

Link activity		Infl. on p's InF	Gain of p's InF
1	creation of link $l: q \rightarrow p$	$\uparrow\uparrow\uparrow$	3
2	update on link $l: q \rightarrow p$ (changed anchor)	 	2
3	update on link $l:q \to p$ (unchanged anchor)	1 ↑	1.5
4	removal of link $l:q o p$	1	-0.5

Computation of $\Delta InF(p)|_{t_{i-1}}^{t_i}$

$$\Delta InF_0(p)|_{t_{i-1}}^{t_i} = \sum_{I:q \to p} \sum_{j \in LA} \omega_j \, C_j(I)$$

with

 $C_j(I)$: # of the j^{th} type of link activity on link I in $[t_{i-1}, t_i]$.

Computation of $\Delta InF(p)|_{t_{i-1}}^{t_{i}}$

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$$\Delta lnF(p)|_{t_{i-1}}^{t_{i}} = \lambda_{lnF} \, \Delta lnF_{0}(p)|_{t_{i-1}}^{t_{i}} + \left(1 - \lambda_{lnF}\right) \sum_{l:q \to p} m_{qp} \, \Delta lnF(q)|_{t_{i-1}}^{t_{i}}$$

with

 $C_j(I)$: # of the j^{th} type of link activity on link I in $[t_{i-1},t_i]$. m_{qp} : one-step transition probability from q to p with $\sum m_{q*}=1$

Page Activities

 $v_{j}^{'}$

Page activity		Infl. on q's PF	Gain of q's PF
1	creation of page q	$\uparrow\uparrow\uparrow$	3
2	update on page q	1 ↑	1.5
3	removal of page q	$\downarrow \downarrow$	-0.5

Computation of $\Delta PF(q)|_{t_{i-1}}^{t_i}$

$$\Delta PF_0(q)|_{t_{i-1}}^{t_i} = \sum_{j \in PA} \omega_j^{'} C_j^{'}(q)$$

with

 $C_j'(q)$: # of the j^{th} type of page activity on page q in $[t_{i-1},t_i]$.

Computation of $\Delta PF(q)|_{t_{i-1}}^{t_i}$

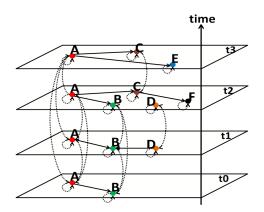
$$\Delta PF_0(q)|_{t_{i-1}}^{t_i} = \sum_{j \in PA} \omega_j^{'} C_j^{'}(q)$$

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with

 $C_j^{'}(q)$: # of the j^{th} type of page activity on page q in $[t_{i-1},t_i]$. $m_{qp}^{'}$: Inverted one-step transition probability from q to p with $\sum m_{*p}=1$

How to use web freshness to control authority propagation in an archival link graph?



Extended Temporal Random Surfer Model

The difference between PageRank's surfer model and this model is:

- The extended model has specific temporal intent
- The extended model can choose a snapshot for targeted page (based on the temporal intent).
- The extended model prefers fresh web resources.

Moves of the Surfer

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A move of the extended surfer model takes the following steps:

- Follow an out-linked page OR do a random jump to any page at the same timepoint. (see PageRank surfer model)
- 2 After reaching target page, choose the snapshot based on the temporal intent.

Goal

Use a semi-Markov process for page authority estimation.

Long-run proportion of time that the Markov process is in state i is given by:

$$A(i) = \frac{\pi_i \mu_i}{\sum\limits_{j=1}^{N} \pi_j \mu_j}, i = 1, 2, \dots, N$$

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with

 π_i : probability that markov process reaches state i

 μ_i : mean time process is remaining at state i.

How to compute the probability $\pi_{p,i}$ that a web surfer reaches page p at snapshot t_i ?

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$$P_{t_i}(Follow|q) = (1-d)$$

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$$P_{t_j}(p|q, Follow) = F_{t_j}(p,q)$$
 $P_{t_j}(p|q, Jump) = \frac{1}{N_{t_j}}$

with

 $F_{t_i}(p,q)$: web surfer's preference for following out-linked pages

 N_{t_i} : total # of pages at t_i

Due to the fact, that fresh web resources are likely to attract surfer's attention, we define:

$$F_{t_j}(p,q) = \frac{PF_{t_j}(p)}{\sum\limits_{p':q \to p'} PF_{t_j}(p')}$$

Probability that a surfer reaches page p at t_i from page p at t_j is

$$P_{t_i|t_j}(p) = \frac{\omega(t_i,t_j)}{\sum\limits_{V_k: p \in V_k, t_k \in T_i} \omega(t_i,t_k)}$$

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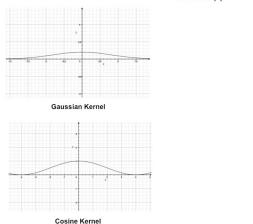
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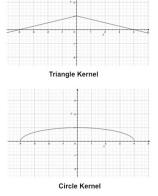
 $\omega(t_i, t_k)$: weight that represents the influence between the snapshots at t_i and t_k (modeled with kernels)

 V_j : set of pages at time point t_j

 T_i : set of snapshots which can directly distribute authority to t_i within one step (depending on window size |T|).

Kernels for |T|=4





Probability that a web surfer reaches page p at snapshot t_i :

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$$\pi_{p,i} = \sum_{t_j \in T_i} P_{t_i \mid t_j}(p) \sum_{q: q \to p \mid t_j} P_{t_j}(Follow \mid q) P_{t_j}(p \mid q, Follow) \pi_{q,j}$$

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Probability that a web surfer reaches page p at snapshot t_i :

$$\pi_{p,i} = \sum_{t_j \in T_i} P_{t_i|t_j}(p) \sum_{q:q \to p|t_j} P_{t_j}(Follow|q) P_{t_j}(p|q, Follow) \pi_{q,j}$$

$$+ \sum_{t_i \in T_i} P_{t_i|t_j}(p) \sum_{q|t_i} P_{t_j}(Jump|q) P_{t_j}(p|q, Jump) \pi_{q,j}$$

with

 T_i : set of snapshots which can directly distribute authority to t_i within one step (depending on window size |T|).

How to compute the average staying time $\mu_{p,i}$ that a web surfer surfs on page p at snapshot t_i ?

- Pages with more in-link activity are likely to attract a surfer to spend time browsing it.
- Using in-link freshness to model the time of a surfer staying on a web page.

$$\mu_{p,i} = \sum_{t_j \in T_{t_i}'} \omega'(t_i, t_j) InF(p)_{t_j}$$

with

 T'_{t} : Set of snapshots included in the sliding window centered on t_i

$$\omega'(t_i, t_j) = \frac{1}{|T'_{t_i}|}$$
 for any $t_j \in T'_{t_i}$

$$\sum_{t_j \in T_{t_i}^{'}} \omega^{'}(t_i, t_j) = 1$$

Final Computation

$$A(p,i) = \frac{\pi_{p,i}\mu_{p,i}}{\sum\limits_{j=1}^{n}\sum\limits_{q\in V_j}\pi_{q,j}\mu_{q,j}}$$

with

n: # of snapshots

 V_j : set of pages at time point t_j

T-Fresh & Attributes

T-Fresh(kernel, window, snapshot)

kernel: The kernel controlling authority propagation among different web snapshots

window: The window size used in calculating average in-link freshness for estimating staying time

snapshot: The number of month spanned over the temporal graph.

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Experimental Setup

 Used archival web pages in the .ie domain (collected from January 200 to December 2007)

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- Time period of interest was April 2007.

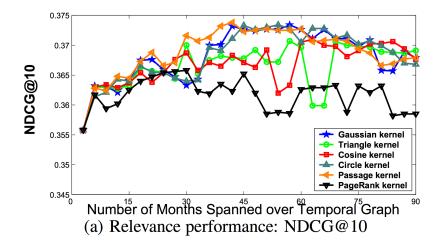
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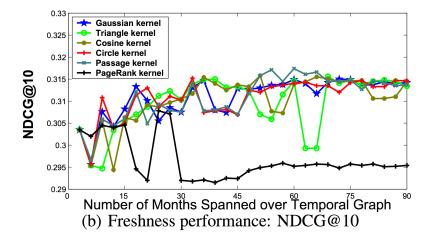
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- For each query 84.6 URLs on average were judged according to freshness and relevance by human editors.
- For judging about ranking qualities two metrics were used: the Normalized Discounted Cumulative Gain (NDCG) and Precision@k.

– Experimental Results

Experimental Results





Relevance					
Method	P@10	NDCG@3	NDCG@5	NDCG@10	
BM25	0.4695	0.2478	0.2740	0.3344	
PageRank	0.4894	0.2589	0.2840	0.3457	
BuzzRank	0.4770	0.2770	0.2980	0.3460	
TemporalRank	0.4841	0.2706	0.2875	0.3524	
TimedPageRank	0.5031	0.2830	0.3063	0.3587	
T-Random	0.4904	0.2690	0.2877	0.3495	
T-rank	0.4875	0.2669	0.2870	0.3496	
T-Fresh(1,1,30)	0.5051	0.3229	0.3347	0.3729	
Freshness					
		Freshness			
Method	P@10	Freshness NDCG@3	NDCG@5	NDCG@10	
Method BM25	P@10 0.3138		NDCG@5 0.2379	NDCG@10 0.2805	
		NDCG@3			
BM25	0.3138	NDCG@3 0.2137	0.2379	0.2805	
BM25 PageRank BuzzRank TemporalRank	0.3138 0.3325	NDCG@3 0.2137 0.1946	0.2379 0.2345	0.2805 0.2838	
BM25 PageRank BuzzRank	0.3138 0.3325 0.3327	NDCG@3 0.2137 0.1946 0.2043	0.2379 0.2345 0.2234	0.2805 0.2838 0.2797	
BM25 PageRank BuzzRank TemporalRank	0.3138 0.3325 0.3327 0.3473	NDCG@3 0.2137 0.1946 0.2043 0.2312	0.2379 0.2345 0.2234 0.2510	0.2805 0.2838 0.2797 0.2992	
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Future Work

Sensitivity of web activity detection accuracy.

Try as best as possible to find a way to close the gap caused by some pages having archival copies and some without in the searching process.

Strengths and Weakness of the Paper

Good	Bad	
Nice background informations	Wrong formulas	
Good explanations of the ideas	Improvable detailed explanations	

Thank you for your attention!