Ranking a Stream of News

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The 14th International World Wide Web Conference
May 10-14 2005, Chiba, Japan

The Problem

Lot of interest around news engines

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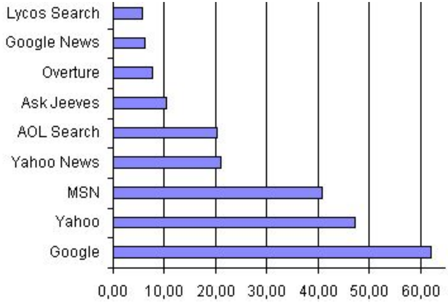

October 2004 [Nielsen/Netratings]

The commercial scenario

Many commercial news engines available: `Google News`, `Yahoo News`, `MSNBot`, `AllTheWeb News`, `AltaVista News`, `Daypop`, `Ananova` etc ... with news provided by many news agencies.

Personalized services as in `NewsBot` and `Findory`

No public information about how do they work!

From our observation they take into account criteria as freshness of a piece of news, authoritativness of sources, replication/aggregation of pieces of news.

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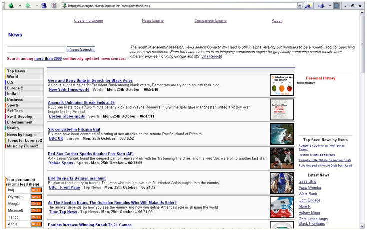

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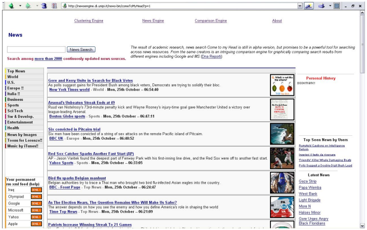

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Our goal:

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Some Desiderata

- Property P1: Ranking for News posting and News sources
- Property P2: Important News articles are Clustered
- Property P3: Mutual Reinforcement between News Articles and News Sources
- Property P4: Time awareness
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The Model for News Articles

Let N be the news stream observed and let S be a set of news sources; the news creation process can be represented by means of a undirected graph

$$G = (N \cup S, E)$$

Two kinds of edges:

1. undirected edges from nodes in S and nodes in N
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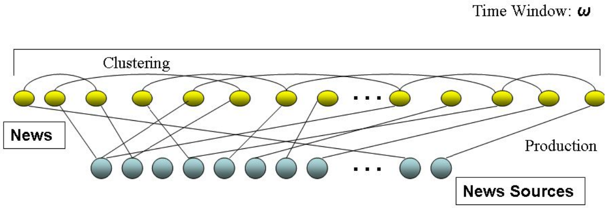

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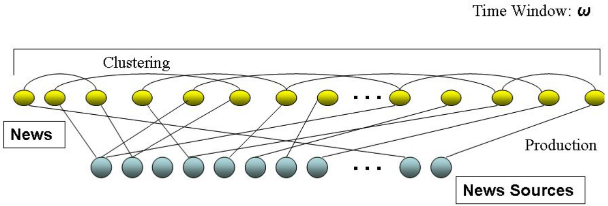

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Clustering Technique

We adopt a continuous measure of the lexical similarity between news posting

In our current implementation

- Similarity between news abstracts is represented using the canonical bag of words paradigm
- The abstracts are filtered out against a list of stop words
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We have designed our ranking algorithm requiring that it will handle correctly two limit cases.

1. LC1 Source s_1 emits a stream of news articles with emission rate $1/\Delta$.
   We expect s_1 to have a stationary mean rank μ independent of time, but increasing with $1/\Delta$.
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The naive approach

A news source has a rank proportional to the number of pieces of news released

Behaves poorly for the limit case LC1. The rank of a single source will increase unboundedly

Mutual reinforcement

The second algorithm exploits the mutual reinforcement property between news articles and news sources. Defines the rank as the right eigenvalue of the adjacency matrix of the graph G.

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This class of algorithms assigns to every source the sum of the ranks assigned to the articles emitted by that source in the past.

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β is similar to the magic ε in PageRank.

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Summarizing

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It doesn't take into account the clustering process of news!

Algorithms TA2

A good news ranking algorithm working on a stream of information should exploit some data stream clustering technique.

$$R(n_i, t_i) = \left[\lim_{\tau \to 0^+} R\left(S(n_i), t_i - \tau\right)\right]^\beta + \\ + \sum_{t_j < t_i} e^{-\alpha(t_i - t_j)} \sigma_{ij} R(n_j, t_j)^\beta,$$

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Algorithms TA2

Too bad!

LC2 case

A news source mirroring another, gets a finite rank significantly greater than the rank of the mirrored one!

The Final TA algorithm: TA3

Idea

Modify a posteriori the rank of a source

A source which has emitted in the past news stories highly mirrored in the future, will receive a “bonus” acknowledging the importance

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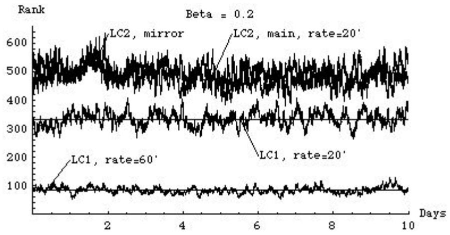
TA3 behavior on the limit cases

Limit cases LC1 and LC2 are satisfied.



Experimental Settings

- Experiments were performed on a PC with a Pentium IV 3GHz, 2.0GB of memory and 512Kb of L2 cache
- The Java code requires few minutes for ranking about 20,000 pieces of news
- The all computation including the clustering of the articles is done online

Sensitivity to the parameters

A first group of experiments address the sensitivity at changes of the parameters ρ and β

Algorithm TA3 is not much sensitive to changes in the parameters involved

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ρ is the half-life decay time, that is

$$e^{-\alpha\rho} = \frac{1}{2}$$

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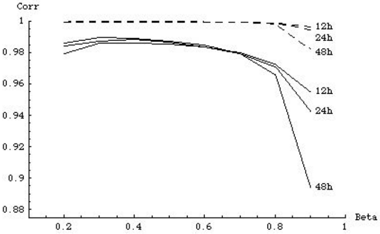

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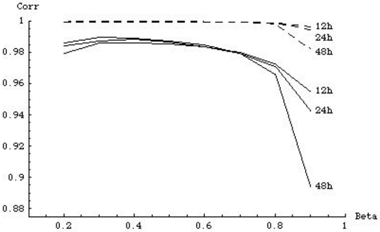

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TA3 vs NTA1

It is necessary to have such a complicate algorithm?

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Yes

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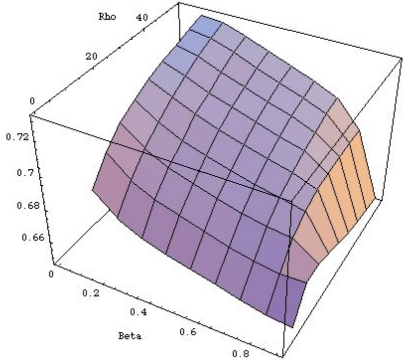
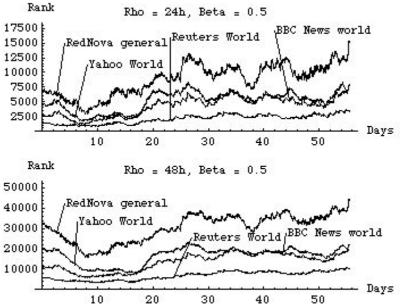
It is necessary to have such a complicate algorithm?



Lower correlation for large values of β ad low values of ρ

Rank evolution over 55 days of the top 4 sources in the category `World`



Top News Sources

Source	# Postings
RedNova general	3154
Yahoo World	1924
Reuters World	1363
Yahoo Politics	900
BBC News world	1368
Reuters	555
Xinhua	339
New York Times world	549

Remark

Some news agency are considered more important than others even if they release a lower number of pieces of news

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Remark

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Top News Articles

Posted	News Source	News Abstract
8/17	Reuters	Argentina Wins First Olympic Gold for 52 Years
8/18	Reuters	British Stun US in Sprint Relay
8/18	NBCOlympics	Argentina wins first basketball gold
9/9	Reuters Sports	Monty Seals Record Ryder Cup Triumph for Europe
8/18	Reuters Sports	Men's Basketball: Argentina Beats Italy, Takes Gold
10/11	Yahoo Sports	Pot Charge May Be Dropped Against Anthony (AP)
10/10	Reuters Sports	Record-Breaking Red Sox Reach World Series
8/17	China Daily	China's Xing Huina wins Olympic women's 10,000m gold
8/17	Reuters Sports	El Guerrouj, Holmes Stride Into Olympic History

Top News Articles

Note

For top pieces of news it is common to recognize the same piece of information re-posted by other agencies

The rank of a singular news article is deeply dependent on the rank of the source posting it

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Conclusions

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- Step-by-step construction
- Extensive testing on more than 300,000 pieces of news and 2,000 news sources
- The ranking is done online
- Same ideas for ranking publications, authors and scientific journals etc

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