Ranking a Stream of News

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The Problem

Lot of interest around news engines

News browsing is one of the most important Internet activities.
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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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The News Engine

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We have used this engine to gather news articles from about 2,000 sources over a period of two months. The pieces of news collected was about 300,000. The news are classified into 13 categories.
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Propose ranking strategies for a stream of news information and a set of news sources.

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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
- **Property P5**: Online processing
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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 $N$
2. undirected edges with both endpoints in $N$ representing the results of the clustering process
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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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Minimal Requirements

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 $\mu$ independent of time, but increasing with $1/\Delta$.

2. **LC2** Two sources $s_1$ and $s_2$, one mirroring the other.
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Non-time-aware algorithms

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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The importance of a piece of news depends also on the time of its posting.

We introduce $\alpha$, a parameter accounting for the decay in freshness of a news story.

The value of $\alpha$ depends on the category the pieces of news belong.
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Decay Rule

\( R(n, t) \) is the rank of news \( n \) at time \( t \).

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R(n, t + \tau) = e^{-\alpha \tau} R(n, t), \quad t > t_i,
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\( t_i \) is the time \( n_i \) was posted
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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. Let $R(s, t)$ be the rank of source $s$ at time $t$. With $S(n_i) = s_k$ we denote that $n_i$ has been posted by $s_k$.

$$R(s_k, t) = \sum_{S(n_i)=s_k} R(n_i, t),$$

Possible definitions for the rank of pieces of news:

- $R(n_i, t_i) = 1$

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- $R(n_i, t_i) = [\lim_{\tau \to 0^+} R(S(n_i), t_i - \tau)]^\beta$, $0 < \beta < 1$.

$\beta$ is similar to the magic $\varepsilon$ in PageRank.
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- Property P1: Ranking for News posting and News sources
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- Property P5: Online processing
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A possible algorithm is

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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.

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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!
Time-aware algorithms

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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The idea is that we want to privilege the freshness of a news article rather than its clustering importance.

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2. unfortunately is more complicated than the others
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TA3 behavior on the limit cases

Limit cases LC1 and LC2 are satisfied.
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.
A first group of experiments address the sensitivity at changes of the parameters $\rho$ and $\beta$.

Algorithm TA3 is not much sensitive to changes in the parameters involved.
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$\rho$ is the half-life decay time, that is

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

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Sensitivity to the parameters

TA3 vs NTA1

It is necessary to have such a complicate algorithm?
Sensitivity to the parameters

**TA3 vs NTA1**

It is necessary to have such a complicate algorithm?

Yes
Sensitivity to the parameters

**TA3 vs NTA1**

It is necessary to have such a complicate algorithm?

Lower correlation for large values of $\beta$ and low values of $\rho$
Ranking news articles and news sources

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

G. M. Del Corso, A. Gulli, F. Romani

Ranking a Stream of News
## Top News Sources

<table>
<thead>
<tr>
<th>Source</th>
<th># Postings</th>
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<tbody>
<tr>
<td>RedNova general</td>
<td>3154</td>
</tr>
<tr>
<td>Yahoo World</td>
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</tr>
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<td>1363</td>
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<td>Yahoo Politics</td>
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**Remark**

Some news agencies are considered more important than others even if they release a lower number of pieces of news.
The Problem

Our Contribution

The Algorithms

Experimental Settings

Conclusions

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