MailRank: Using Ranking for Spam Detection

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MailRank

- Introduction
- Motivation
- Related work
- Technical details
- Evaluation
- Advantages and limitations



Introduction

- Existing spam filters exhibit some problems:
- Maintenance
- Error rate
- Too many emails for some high-volume users





Motivation

- Motivation: address all the problems above
- Social network formed by email communication can be used as a strong foundation for spam detection





Motivation

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Basic MailRank Personalized MailRank

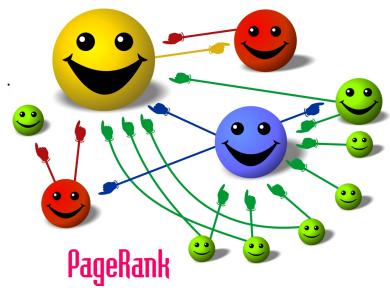


Related work

PageRank

a page has a high rank if the sum of ranks of its backlinks is high

$$PR(p) = c \cdot \sum_{q \in I(p)} \frac{PR(q)}{\|O(q)\|} + (1 - c) \cdot E(p)$$



Personalized PageRank

Each user select her preferred pages. Then compute personalized rank vectors

Related work

PageRank — Basic MailRank

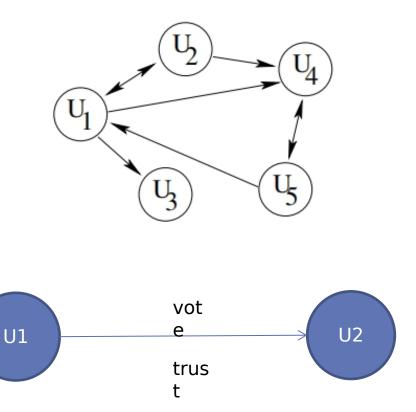
Personalized PageRank

→ Personalized MailRank



MailRank

Build a graph



 If U1 has sent an email to U2, add edge<U1, U2>, which implies U1 trusts U2



Basic MailRank

- step1: determine the biased set small set of users with high reputation should not contain any spammer
- step2: apply power iteration algorithm

$$PR(p) = c \cdot \sum_{q \in I(p)} \frac{PR(q)}{\|O(q)\|} + (1 - c) \cdot E(p)$$



Basic MailRank

power iteration algorithm:

Algorithm 3.1. The Basic MailRank Algorithm.

Client Side:

Each vote sent to the MailRank server comprises:

Addr(u): The hashed version of the email address of the voter u.

TrustVotes(u): Hashed version of all email addresses

u votes for (i.e., she has sent an email to)

Server Side:

1: Combine all received data into a global email network graph. Let

T be the Markov chain transition probability matrix, computed as:

For Each known email address i

If i is a registered address, i.e., user i has submitted her votes

For Each trust vote from i to j

$$T_{ji} = 1/\text{NumOfVotes}(i)$$

Else ForEach known address j

 $T_{ji} = 1/N$, where N is the number of known addresses.

3. Determine the biasing set B (i.e., the most popular email addr.)

3a: Manual selection or

3b: Automatic selection or

3c: Semi-automatic selection

4: Let $T' = c \cdot T + (1 - c) \cdot E$, with c = 0.85 and

$$E[i] = \left[\frac{1}{||B||}\right]_{N \times 1}$$
, if $i \in B$, or $E[i] = [0]_{N \times 1}$, otherwise

5: Initialize the vector of scores
$$\vec{x} = [1/N]_{N \times 1}$$
, and the error $\delta = \infty$

6: While $\delta < \epsilon$, ϵ being the precision threshold

$$\vec{x}' = T' \cdot \vec{x}$$
$$\delta = ||\vec{x}' - \vec{x}||$$

7: Output \vec{x}' , the global MailRank vector.

8: Classify each email address in the MailRank network into:

'spammer' / 'non-spammer' based on the threshold T

Basic MailRank

Problem of basic MailRank:

too general with respect to user ranking users want their acquaintances ranked higher than unknown users

Can we build a personalized ranking vector for every user?



Personalized MailRank

Each user decide a preference set

compute partial vectors for all common users and hub skeleton for each user

combine them to compute PPV(personalized pagerank vector)



build a power-law model for evaluation

Analysis on three issuse:
effectiveness in case of very sparse MailRank networks
exploitation of spam characteristics
attacks on MailRank



Effectiveness in case of very sparse MailRank networks

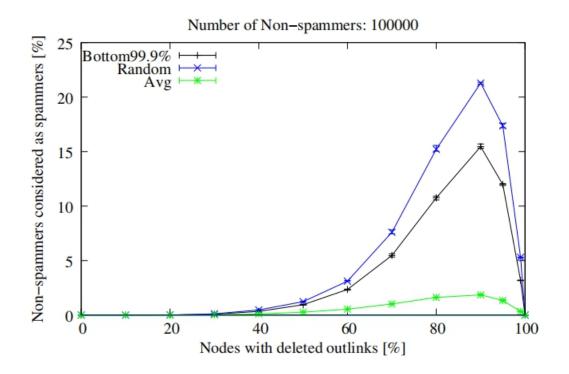


Figure 3: Very sparse MailRank networks



Exploitation of spam characteristics

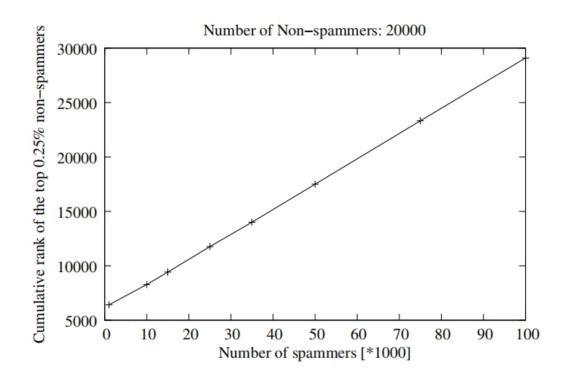


Figure 4: Rank increase of non-spammer addresses

Attacks on MailRank

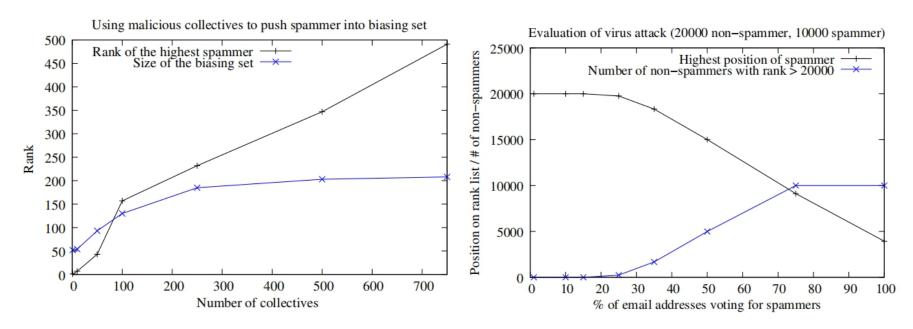


Figure 5: Automatic creation of the biasing set

Figure 6: Simulation results: Virus attack

Advantages and limitation

Advantages:

Shorter individual cold-start phase High attack resilience Stable results Partial participation

. . .

Limits:

cannot prevent address spoofing attack may misdetect some special non-spammer users highly rely on the central server



Thank you

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