A Method for Finding Link Hijacking Based on Modified PageRank Algorithms

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Abstract As the search result ranking is getting important for attracting visitors and profits, more and more people are now trying to mislead search engines in order to get higher ranking. Since link-based ranking algorithm is one of the most important tools for current search engines, web spammers are making an significant effort to manipulate links structure of web, namely, link spamming. Link hijacking is one technique of link spamming. By hijacking links from normal sites to target spam sites, spammers can make search engines believe that normal sites endorse spam sites. In this paper, we propose a link analysis technique for finding link-hijacked sites using modified PageRank algorithms. We performed experiments on our large scale Japanese web archive and evaluated the accuracy of our method.

Keyword Link analysis, Web spam, Information retrieval

1. INTRODUCTION

In the last decade, search engines have been the essential tools for information retrieval. As more and more people rely heavily on search engines to find information in the Web, most of web sites obtain a considerable number of visitors from search engines. Since the increase in visitors usually means the increase in financial profit, and approximately 50% of search engine users look at no more than the first 5 result in the list [1], obtaining high rankings in search results becomes crucial for the success of sites.

Web spamming is defined as the behavior of manipulating the web page features to get a higher ranking than it deserves. Web spamming technique can be categorized into term spamming and link spamming [2]. *Term spamming* is the behavior to manipulate textual contents of pages. Spammers can repeat specific keywords and add irrelevant meta-keywords or anchor texts that are not related with page contents. Search engines that use textual relevance to rank pages will show these manipulated pages at the top of the result list. *Link spamming* is the behavior of manipulating link structure of the Web to mislead link-based ranking algorithms such as PageRank [3]. For example, spammers can construct a *spam farm*, an artificially interlinked link structure, to centralize link-based importance scores [4]. In addition to building spam farms, spammers can make links from external reputable pages to target spam pages, even if the authors of the external pages do not intend to link to them. This behavior is called *link hijacking*. Posting comments including URLs to spam pages on public bulletin boards is a well-known hijacking method. Hijacked links do not endorse any relevance or quality of pages, so they mislead link-based ranking algorithms which consider the link as human judgment about web pages. Hijacked pages could make a significant impact on ranking algorithms, since hijacked links are usually connected to a large amount of spam farms where reputation of normal sites would leak out in large quantities. In this paper, we propose a novel method for detecting web sites that are hijacked by spammers. Most of previous researches have focused on demoting or detecting spam, and as far as we know, there was no study on detecting link hijacking that is important in the following situations:

- In link-based ranking algorithms, we can reduce the weight of hijacked links. This will drop ranking scores of a large amount of spam sites connected to hijacked sites, and improve the quality of search results.
- The hijacked sites will be continuously attacked by spammers (e.g. by repetitive spam comments on blogs), if their owners do not devise a countermeasures. By observing those hijacked sites, we can detect newly created spam sites promptly.
- Crawling spam sites is a sheer waste of time and resources. We can avoid collecting and storing numerous spam pages by stopping crawling at hijacked link.
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In order to find out hijacked sites, we consider the characteristics of link structure around hijacked site

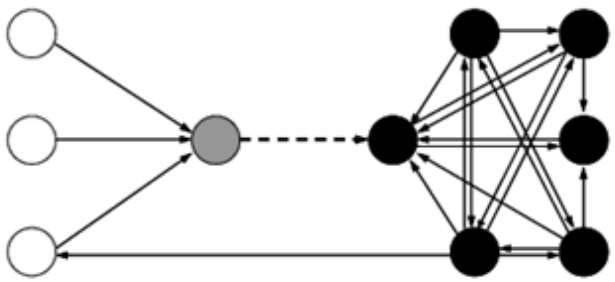

Figure 1 Link structure around a hijacked site. White, gray and black nodes represent normal, spam and hijacked sites, respectively. A dashed link from the hijacked site to a spam site is a hijacked link

which is illustrated in Figure 1. While a hijacked site has links pointing to spam sites, it is rarely pointed to by the spam sites because they have few incentives to share PageRank score with hijacked sites. Consequently, we can see a significant change in the link structure between the spam and hijacked sites. Suppose a walk starting from a spam site by following links backward. In the first few steps, we are in the middle of the spam farm, and we could see that visiting sites are pointed to by many other spam sites. When we reach one of the hijacked sites, however, we would notice that the site is no longer pointed to by spam sites. Such kind of changes in the link structure can be estimated by some modified versions of PageRank. For each page, we calculate trust and spam scores using two different modified PageRank. Intuitively, these scores mean that trusted sites are pointed to by other trusted sites, and spam sites are pointed to by other spam sites. Hence, the spamicity of a site in spam farms might overwhelm its trustworthy, and the trustworthy of a hijacked site might overwhelm its spamicity. With this observation, we consider the inverse search of the Web graph from sample spam sites. We would find out hijacked sites during the walk where the order of the spam value and trust value is reversed.

We tested our method and evaluated the precision of it on large-scale graph of the Japanese Web archive including 5.8 million sites and 283 million links. The rest of this paper proceeds as follows. In Section 2, we review background knowledge for PageRank and link spamming. Section 3 introduces several approaches to detecting or demoting link spamming. Section 4 presents our method to detect hijacked sites. In Section 5, we report experimental result of our algorithm. Finally, we discuss result of our approach.

2. BACKGROUND

2.1 WEB GRAPH

Link-based ranking algorithms consider the entire Web as a directed graph. We can denote the Web as $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E})$, where $\boldsymbol{V}$ is the set of all web pages and $\boldsymbol{E}$ is a set of directed edges $< p, q >$. Each page has some incoming links(inlinks) and outgoing links(outlinks). $In(p)$ represents the set of pages pointing to p(the in-neighbors of p) and $Out(p)$ is the set of pages pointed to by p(the out-neighbors of p). We will use n to describe $\| \boldsymbol{V} \|$, the number of total web pages on the Web.

2.2 PAGERANK

PageRank [3] is one of the most famous link-based ranking algorithms. The basic idea of PageRank is that a web page is important if it is linked by many other important pages. This recursive definition can be showed as following matrix equation:

$$\mathbf{p} = \alpha \cdot \mathbf{T} \cdot \mathbf{p} + (1 - \alpha) \cdot \mathbf{d}$$

Where $\mathbf{p}$ is PageRank score vector, $\mathbf{T}$ is transition matrix. $T(p, q)$ is $1/Out(q)$ if there is a link from node q to node p, and 0 otherwise. The decay factor $\alpha < 1$ (usually 0.85) is necessary to guarantee convergence and to limit the effect of rank sink. $\mathbf{d}$ is a uniformly random distribution vector.

2.3 LINK SPAMMING

After the success of Google which adopted PageRank as the main ranking algorithm, PageRank became the main target of link spammers. Z. Gyöngyi et al. studied about link spam in [4] and introduced the optimal link structure to maximize PageRank Score, *spam farm*. A spam farm consists of a target page and boosting pages. All boosting pages link to a target page in order to increase the rank score of a target page. Then, a target page distributes its boosted PageRank score back to supporter pages. By this, members of a spam farm can boost their PageRank scores. Due to the low costs of domain registration and web hosting, spammers can create spam farms easily, and actually there exist spam farms with thousands of different domain names [9]. In addition to construct an internal link structure, spammers can create external links from outside of spam farms and provide additional PageRank score to

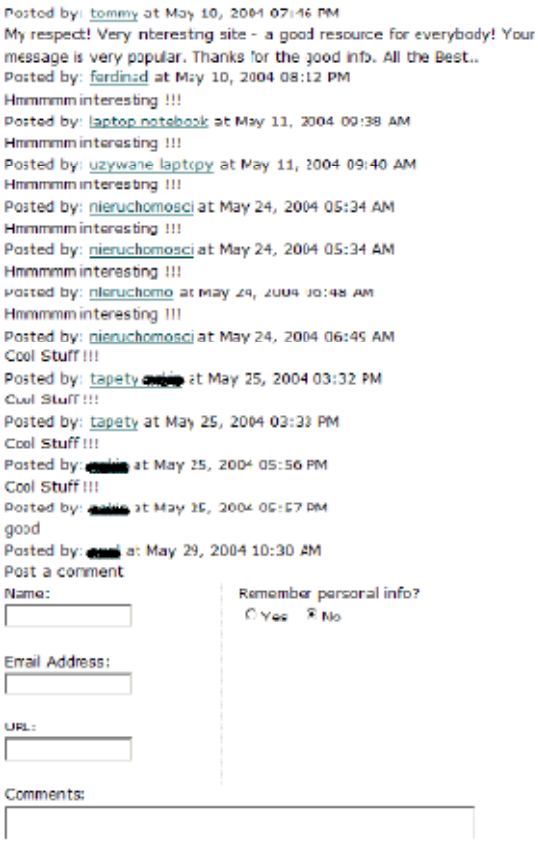

Figure 2 Spam comments on the blog

the target page. We can see the real example of link hijacking in Figure 2.

In order to make links from non-spam sites to their own spam site, spammers send trackbacks that lead to spam sites or, post comments including links pointing to target spam sites. A large number of spam trackbacks and comments are created easily in a short period, so it could result in considerable score leakage. Hijacked pages are hard to detect because their contents and domains are irregular [5]. In addition to posting spam comments or sending trackbacks, spammers can hijack links by various methods like creating pages that contain links to useful resource and links to target spam pages, or buying expired domains [4].

3. RELATED WORK

Several approaches have been suggested in order to detect and demote link spam.

To demote spam pages and make PageRank resilient to link spamming, Gyöngyi et al. suggested TrustRank [6]. TrustRank introduced the concept of trust for web pages. In order to evaluate trust score of the entire Web, TrustRank assigns initial trust scores on some trust seed pages and propagates scores throughout the link structure. Wu et al. complemented TrustRank with topicality in [7]. They computed TrustRank score for each topic to solve the bias problem of TrustRank. Wu et al. also complemented TrustRank in [8] by propagating anti-trust from spam pages.

To detect link spam, Benczúr et al. introduced SpamRank [10]. SpamRank checks PageRank score distributions of all in-neighbors of a target page. If this distribution is abnormal, SpamRank regards a target page as a spam and penalizes it. Krishnan et al. proposed Anti-TrustRank to find out spam pages [11]. As the inverse-version of TrustRank, Anti-TrustRank propagates Anti-Trust score through inlinks from seed spam pages. Gyöngyi et al. suggested Mass Estimation in [9]. They evaluated spam mass, a measure of how many PageRank score a page get through links from spam pages. Saito et al. employed a graph algorithm to detect web spam [15]. They extracted spam seed from the strongly connected component (SCC) and used them to separate spam sites from non-spam sites. Becchetti et al. computed probabilistic counting over the Web graph to detect link spam in [19].

Some studies are done to optimize the link structure for fair ranking decision. Carvalho et al. proposed the idea of noisy links, the link structure that has a negative impact on the link-based ranking algorithms [12]. By removing these noisy links, they improved the performance of link-based ranking algorithm. Qi et al. also estimated the quality of links by similarity of two pages [13].

Du. et al. discussed the effect of hijacked links on the spam farm in [5]. They suggested an extended optimal spam farm by dropping the assumption of [4] that leakage by link hijacking is constant. Although they consider link hijacking, they did not mention the real features of hijacking and its detection, which is different from our approach.

As we reviewed, although there are various approaches to link spam, the link hijacking has never been explored closely. In this paper, we propose a new approach to discovering hijacked link and pages. With our approach, we would contribute to a new spam detection technique and improve the performance of link-based ranking algorithms.

4. DETECTING LINK HIJACKING

4.1 Core-based PageRank

To decide whether each page is a trustworthy page or a spam page, previous approaches used biased PageRank and biased inverse PageRank with white or spam seed set [6][11]. In this paper, we adopted a core-based PageRank proposed in [9]. When we have a seed set $\boldsymbol{S}$, we describe a core-based score of a page p as $\mathbf{PR}'(p)$. A core-based PageRank score vector $\mathbf{p}'$ is:

$$\mathbf{p}' = \alpha \cdot \mathbf{T} \cdot \mathbf{p}' + (1-\alpha) \cdot \mathbf{d}^{\boldsymbol{S}}$$

where a random jump distribution $\mathbf{d}^{\boldsymbol{S}}$ is:

$$\mathbf{d}_p{}^{S} = \begin{cases} 1/n, & \text{if } p \text{ is in seed set } \boldsymbol{S} \\ 0, & \text{otherwise} \end{cases}$$

We adopted a core-based PageRank instead of TrustRank because a core-based PageRank is independent on the size of a seed set compared to TrustRank which uses a random jump distribution of $1/\|\boldsymbol{S}\|$ instead of $1/n$. In this paper, we use two types of core-based PageRank scores.

- $\mathbf{p}_+$ = a core-based PageRank score vector with a trust seed set $\mathbf{S}_+$.
- $\mathbf{p}_-$ = a core-based PageRank score vector with a spam seed set $\mathbf{S}_-$.

Z. Gyöngyi et al. mentioned a core-based PageRank with a spam seed set in [9]. They focused on blending $\mathbf{p}_+$ and $\mathbf{p}_-$ (e.g. compute weighted average) in order to detect spam pages. However, this view is different from ours. We think $\mathbf{p}_+$ and $\mathbf{p}_-$ independently and focus on the change in scores through links to discover hijacked pages.

4.2 Link Hijacking Detection Algorithm

Based on the characteristics of links structure around hijacked pages, we observe the changes in **PR+**(p) and **PR-**(p) during a inversed graph traversal starting from spam seed sites. As long as we are in a spam farm, the visiting site should have a high **PR-**(q) and a low **PR+** (q). When we reach at a hijacked site, it should have a lower **PR-**(p) and a higher **PR+** (p), since it is hardly pointed to by spam sites. By detecting this change in scores, we would find the hijacked sites. The algorithm is shown in Figure 3. First, we compute **PR+**(p) and **PR-**(p) for each site p. Then start a inversed depth-first search from spam seed sites s- whose scores are **PR+**(s-) < **PR-**(s-). The search from a site p is performed by selecting a site t

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input : good seed set S+, spam seed set S- , parameter δ
output : set of hijacked sites of H

H ← ϕ
compute core-based PageRank scores p+ and p-

for each site s- in S do
    dfs(s- , H)
end for

procedure dfs(s, H)
if s is marked then
return
end if

mark s
if  log PR+(s) - log PR-(s) > δ  then
    H ←H ∪ {s}
    return
end if
for each site t where {t|t∈ In(s) ∧ PR+(s) < PR+(t)}
    dfs(t, H)
end for
end procedure
```

Figure 3 Link hijacking detection algorithm

whose **PR+** (t) is greater than **PR+** (p). When it reached at a site q where **PR+**(q) > **PR-**(q), we output this page as a hijacked page, and stop the further search from this site. we can adjust when we stop the search, by modifying δ from $-\infty$ to ∞. When we use a higher δ value, a higher **PR+**(p) score is required to stop the search, and we need a further search. When we use a lower δ value, we can stop the search earlier at a site with lower **PR+** (p) score.

5. EXPERIMENTS

5.1 Data set

To evaluate our algorithm, we performed experiments on a large-scale snapshot of our Japanese web archive built by a crawling conducted in May 2004. Basically, our crawler is based on breadth-first crawling [16], except that it focuses on pages written in Japanese. We collected pages outside the .jp domain if they were written in Japanese. We used a web site as a unit when filtering non-Japanese pages. The crawler stopped collecting pages from a site, if it could not find any Japanese pages on the site within the first few pages. Hence, this dataset contains fairly amount of English or other language pages. The amount of Japanese pages is estimated to be 60%. This snapshot is composed of 96 million pages and 4.5 billion links.

We use a site level graph of the Web, in which nodes are web sites and edges represent the existence of links

between pages in different sites. In the site graph, we can easily find dense connections between spam sites that cannot be found in the page level graph. The site graph built from our snapshot includes 5.8 million sites and 283 million links. We call this dataset web graph in this paper. Certain properties and its statistics of domains of our web graph are shown in Table 1 and 2.

Table 1 Properties of the web graph

Number of nodes	5,869,430
Number of arcs	283,599,786
Maximum of indegree (outdegree)	61,006 (70,294)
Average of indegree (outdegree)	48 (48)

Table 2 Domains in the web data

Domains	Numbers	Ratio(%)
.com	2,711,588	46.2
.jp	1,353,842	23.1
.net	436,645	7.4
.org	211,983	3.6
.de	169,279	2.9
.info	144,483	2.5
.nl, .kr, .us, etc.	841,610	14.3

5.2 Seed Set

To compute a core-based PageRank, we constructed trust seed set and spam seed set. We used manual and automated selection for both seed sets. In order to generate a trust seed set, we computed PageRank score and performed a manual selection on top 1,000 sites with high PageRank score. Well-known sites (e.g. Google, Yahoo!, MSN and goo), authoritative university sites and well-supervised company sites are selected as white seed sites. After manual check, 389 sites are labeled as trustworthy sites. To make up for small size of a seed set, we extracted sites with specific URL including .gov (US governmental sites) and .go.ip (Japanese governmental sites). Finally, we have 40,396 sites as trust sites.

For spam seed set, we chose sites with high PageRank score and checked manually. Sites including many unrelated keywords and links, redirecting to spam sites, containing invisible terms and different domains for each menu are judged as spam sites. We have 1,182 sites after manual check. In addition, we used automatically extracted seed sites obtained by analyzing strongly connected components and cliques [15]. Finally, Total 580,325 sites are used for a spam seed set.

5.3 Evaluation

Using the trust and spam seed sets, we extracted lists of potential hijacked sites with different δ values from -2.0 to

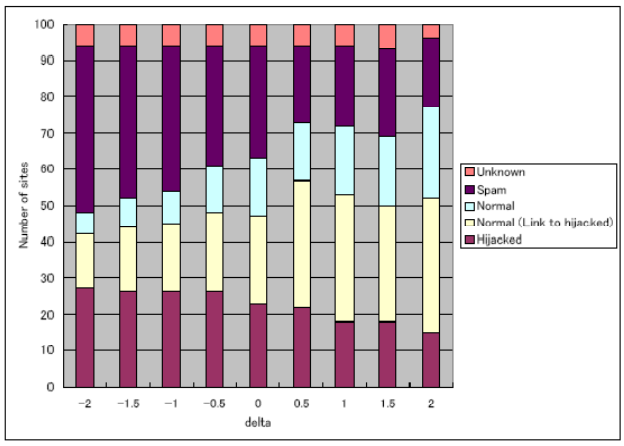

Figure 4 Number of sites of each type with different δ with Core-based PageRank

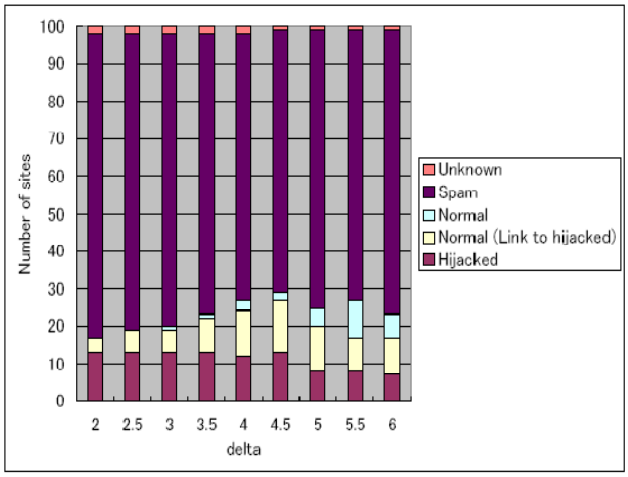

Figure 5 Number of sites of each type with different δ with TrustRank and Anti-TrustRank

2.0. (See the algorithm in Section 4.2). After we had the lists, we sorted them in the descending order of Anti-TrustRank scores. We chose Anti-TrustRank since sites with high Anti-TrustRank scores tend to have many links to spam sites, and such sites can be considered to be influential.

5.3.1 Types of hijacking

We first looked through several hundreds of sites in those lists, and investigated suspicious sites. As a result, we obtained different types of hijacking sites. Besides well known link hijacking methods like spam comments, trackbacks and expired domains, spammers can create links to their spam sites by accessing normal sites with public access statistics log showing links to referrer sites. Spammers are also able to obtain a link from hosting

company sites by being a client of those companies.

5.3.2 Precision of hijack detection

Figure 4 shows the number of each hijacking type in the top 100 results using different δ values. We categorized detected samples into spam, normal, normal site with direct link to hijacked sites, hijacked sites and finally, unknown. We can find 26 to 27 hijacked sites when we use δ less than 0, but the number decreases to 19 when we use δ greater than 0. We can detect the more hijacked sites (27 sites) with the lowest δ value. This means that hijacked sites tend to be judged as spam sites, which means normal sites might take a disadvantage in the ranking due to link hijacking. In addition, we can find 15 to 37 normal sites that pointing directly to hijacked sites. When we include these two types of sites, about half of sites in the top 100 results are related to link hijacking. Considering the difficulty of detecting hijacked sites with diverse contents and complex structure on the web, this is quite encouraging.

5.4 Comparing with variations of PageRanks

We assumed that core-based PageRank would perform better than TrustRank for hijacking detection in Section 4. To prove this, we tested our approach with TrustRank and Anti-TrustRank scores. TrustRank uses a random jump distribution d where $d_p = 1/\|\boldsymbol{S}_+\|$ if p is in $\boldsymbol{S}_+$. Anti-TrustRank is the same with TrustRank, but using a spam seed set $\boldsymbol{S}_-$. The result is shown in Figure 5. We can see the proportions of hijacked sites and neighbor normal sites decreased. Instead, the number of spam sites dramatically increased. This means that it is difficult to extract hijacked sites with the combination of TrustRank and Anti-TrustRank.

6. CONCLUSION

In this paper, we proposed a new method for link hijacking detection. Link hijacking is one of the typical methods for link spamming and many hijacked links are now being generated by spammers. Since link hijacking could have a significant impact on link-based ranking algorithm and disturb assigning global importance, detecting hijacked pages and penalizing hijacked links are the serious problems to be solved.

In order to find out hijacked pages, we focused on the characteristics of link structure around the hijacked pages. Based on the observation that hijacked sites are seldom linked by spam sites while they have many links to spam sites, we computed two types of core-based PageRank scores and monitored the change in two scores during the inverse walk from spam seed. Experimental result showed that our approach is quite effective. Our best result for finding hijacked sites was 27%.

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