

**IRLBOT: DESIGN AND PERFORMANCE ANALYSIS OF
A LARGE-SCALE WEB CRAWLER**

A Thesis

by

HSIN-TSANG LEE

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of
MASTER OF SCIENCE

May 2008

Major Subject: Computer Science

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Approved by:

Chair of Committee,	Dmitri Loguinov
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ABSTRACT

IRLbot: Design and Performance Analysis of a Large-Scale Web Crawler.

(May 2008)

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Chair of Advisory Committee: Dr. Dmitri Loguinov

This thesis shares our experience in designing web crawlers that scale to billions of pages and models their performance. We show that with the quadratically increasing complexity of verifying URL uniqueness, breadth-first search (BFS) crawl order, and fixed per-host rate-limiting, current crawling algorithms cannot effectively cope with the sheer volume of URLs generated in large crawls, highly-branching spam, legitimate multi-million-page blog sites, and infinite loops created by server-side scripts. We offer a set of techniques for dealing with these issues and test their performance in an implementation we call IRLbot. In our recent experiment that lasted 41 days, IRLbot running on a single server successfully crawled 6.3 billion valid HTML pages (7.6 billion connection requests) and sustained an average download rate of 319 mb/s (1,789 pages/s). Unlike our prior experiments with algorithms proposed in related work, this version of IRLbot did not experience any bottlenecks and successfully handled content from over 117 million hosts, parsed out 394 billion links, and discovered a subset of the web graph with 41 billion unique nodes.

To my parents

ACKNOWLEDGMENTS

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CHAPTER I

INTRODUCTION

Over the last decade, the World Wide Web (WWW) has evolved from a handful of pages to billions of diverse objects. In order to harvest this enormous data repository, search engines download parts of the existing web and offer Internet users access to this database through keyword search. Search engines consist of two fundamental components – *web crawlers*, which find, download, and parse content in the WWW, and *data miners*, which extract keywords from pages, rank document importance, and answer user queries. This thesis does not deal with data miners, but instead focuses on the design of web crawlers that can scale to the size of the current and future web, while implementing consistent per-website and per-server rate-limiting policies and avoiding being trapped in spam farms and infinite webs. We next discuss our assumptions and explain why this is a challenging issue.

1 Scalability

With the constant growth of the web, discovery of user-created content by web crawlers faces an inherent tradeoff between *scalability*, *performance*, and *resource usage*. The first term refers to the number of pages N a crawler can handle without becoming “bogged down” by the various algorithms and data structures needed to support the crawl. The second term refers to the speed S at which the crawler discovers the web as a function of the number of pages already crawled. The final term

The journal model is *IEEE/ACM Transactions on Networking*.

refers to the CPU and RAM resources Σ that are required to sustain the download of N pages at an average speed S . In most crawlers, larger N implies higher complexity of checking URL uniqueness, verifying robots.txt, and scanning the DNS cache, which ultimately results in lower S and higher Σ . At the same time, higher speed S requires smaller data structures, which often can be satisfied only by either lowering N or increasing Σ .

Current research literature [2], [4], [7], [9], [14], [20], [22], [23], [25], [26], [27], [16] generally provides techniques that can solve a subset of the problem and achieve a combination of any two objectives (i.e., large slow crawls, small fast crawls, or large fast crawls with unlimited resources). They also do not analyze how the proposed algorithms scale for very large N given fixed S and Σ . Even assuming sufficient Internet bandwidth and enough disk space, the problem of designing a web crawler that can support large N (hundreds of billions of pages), sustain reasonably high speed S (thousands of pages/s), and operate with fixed resources Σ remains open.

2 Reputation and Spam

The web has changed significantly since the days of early crawlers [4], [23], [25], mostly in the area of dynamically generated pages and web spam. With server-side scripts that can create infinite loops, an unlimited number of hostnames, and spam farms that measure billions of pages, the task of web crawling has changed from simply doing a BFS scan of the WWW [24] to deciding in real time which sites contain useful information and giving them higher priority as the crawl progresses.

Our experience shows that BFS becomes trapped in spam after several billion downloaded pages, which manifests itself in multiple ways: a) the queue of pending URLs contains a non-negligible fraction of links from spam sites that threaten to

eventually overtake legitimate URLs due to their high branching factor; b) the DNS resolver succumbs to the rate at which new hostnames are dynamically created within a single spam domain; and c) the crawler becomes vulnerable to the delay attack from sites (often spam) that purposely introduce HTTP and DNS delays in all requests originating from the crawler’s IP address.

No prior research crawler has attempted to avoid spam or document its impact on the collected data. Thus, designing low-overhead and robust algorithms for computing site reputation during the crawl is the second open problem that we aim to address in this work.

3 Politeness

Even today, webmasters become easily annoyed when web crawlers slow down their servers, consume too much Internet bandwidth, or simply visit pages with “too much” frequency. This leads to undesirable consequences including blocking of the crawler from accessing the site in question, various complaints to the Internet Service Provider (ISP) hosting the crawler, and even threats of legal action. Incorporating per-website and per-IP hit limits into a crawler is easy; however, preventing the crawler from “choking” when its entire RAM gets filled up with URLs pending for a small set of hosts is much more challenging. When N grows into the billions, the crawler eventually becomes bottlenecked by its own politeness and is then faced with a decision to suffer significant slowdown, ignore politeness considerations for certain URLs (at the risk of crashing target servers or wasting valuable bandwidth on huge spam farms), or discard a large fraction of backlogged URLs, none of which is particularly appealing.

While related work [2], [7], [14], [23], [27] has proposed several algorithms for rate-limiting host access, none of these studies have addressed the possibility that a

crawler may stall due to its politeness restrictions or discussed management of rate-limited URLs that do not fit into RAM. This is the third open problem that we aim to solve in this thesis.

4 Our Contributions

The first part of this thesis presents a set of web-crawler algorithms that address the issues raised above and the second part briefly examines their performance in an actual web crawl.¹ Our design stems from three years of web crawling experience at Texas A&M University using an implementation we call IRLbot [17] and the various challenges posed in simultaneously: 1) sustaining a fixed crawling rate of several thousand pages/s; 2) downloading billions of pages; and 3) operating with the resources of a single server.

The first performance bottleneck we faced was caused by the complexity of verifying uniqueness of URLs and their compliance with robots.txt. As N scales into many billions, even the disk algorithms of [23], [27] no longer keep up with the rate at which new URLs are produced by our crawler (i.e., up to 184K per second). To understand this problem, we analyze the URL-check methods proposed in the literature and show that all of them exhibit severe performance limitations when N becomes sufficiently large. We then introduce a new technique called *Disk Repository with Update Management* (DRUM) that can store large volumes of arbitrary hashed data on disk and implement very fast `check`, `update`, and `check+update` operations using bucket sort. We model the various approaches and show that DRUM’s overhead remains close to the best theoretically possible as N reaches into the trillions of pages and that for common disk and RAM size, DRUM can be thousands of times faster

¹A separate paper will present a much more detailed analysis of the collected data.

than prior disk-based methods.

The second bottleneck we faced was created by multi-million-page sites (both spam and legitimate), which became backlogged in politeness rate-limiting to the point of overflowing the RAM. This problem was impossible to overcome unless politeness was tightly coupled with site reputation. In order to determine the legitimacy of a given domain, we use a very simple algorithm based on the number of incoming links from assets that spammers cannot grow to infinity. Our algorithm, which we call *Spam Tracking and Avoidance through Reputation* (STAR), dynamically allocates the budget of allowable pages for each domain and all of its subdomains in proportion to the number of in-degree links from other domains. This computation can be done in real time with little overhead using DRUM even for millions of domains in the Internet. Once the budgets are known, the rates at which pages can be downloaded from each domain are scaled proportionally to the corresponding budget.

The final issue we faced in later stages of the crawl was how to prevent live-locks in processing URLs that exceed their budget. Periodically re-scanning the queue of over-budget URLs produces only a handful of good links at the cost of huge overhead. As N becomes large, the crawler ends up spending all of its time cycling through failed URLs and makes very little progress. The solution to this problem, which we call *Budget Enforcement with Anti-Spam Tactics* (BEAST), involves a dynamically increasing number of disk queues among which the crawler spreads the URLs based on whether they fit within the budget or not. As a result, almost all pages from sites that significantly exceed their budgets are pushed into the last queue and are examined with lower frequency as N increases. This keeps the overhead of reading spam at some fixed level and effectively prevents it from “snowballing.”

The above algorithms were deployed in IRLbot [17] and tested on the Internet in June-August 2007 using a single server attached to a 1 gb/s backbone of Texas

A&M. Over a period of 41 days, IRLbot issued 7,606,109,371 connect requests to 117,576,295 hosts, received 7,437,281,300 HTTP responses, and successfully downloaded $N = 6,380,051,942$ unique HTML pages at an average rate of 319 mb/s (1,789 pages/s). Even after severely handicapping quickly branching spam and over 30 million low-ranked domains, IRLbot parsed out 394,619,023,142 links and found 41,502,195,631 unique pages residing on 641,982,061 hosts, which explains our interest in crawlers that scale to tens and hundreds of billions of pages as we believe a good fraction of 35B URLs not crawled in this experiment contains useful content.²

The rest of the thesis is organized as follows. Section II overviews related work. Section III defines our objectives and classifies existing approaches. Section IV discusses how checking URL uniqueness scales with crawl size and proposes our technique. Section V models caching and studies its relationship with disk overhead. Section VI discusses our approach to ranking domains and Section VII introduces a scalable method of enforcing budgets. Section VIII summarizes our experimental statistics and Section IX concludes the thesis.

²Performing site searches for all top-level domains (e.g., “site:.com”), Google’s index size can be estimated at 30 billion pages and Yahoo’s at 37 billion.

CHAPTER II

RELATED WORK

There is only a limited number of papers describing detailed web-crawler algorithms and offering their experimental performance. First-generation designs [9], [22], [25], [26] were developed to crawl the infant web and commonly reported collecting less than 100,000 pages. Second-generation crawlers [2], [7], [15], [14], [23], [27] often reached several hundred million pages in their crawls and typically involved multiple agents in the crawling process. We discuss their design and scalability issues in the next section.

Another direction was undertaken by the Internet Archive [6], [16], which maintains a history of the Internet by downloading the same set of pages over and over. In the last 10 years, this database has collected over 85 billion pages, but only a small fraction of them are unique. Additional crawlers are [4], [8], [13], [20], [28], [29]; however, their focus usually does not include the large scale assumed in this thesis and their fundamental crawling algorithms are not presented in sufficient detail to be analyzed here.

The largest prior crawl using a fully-disclosed implementation appeared in [23], where Mercator obtained $N = 473$ million HTML pages in 17 days (we exclude non-HTML content since it has no effect on scalability). The fastest reported crawler was [13] with 816 pages/s, but the scope of that crawl was only $N = 25$ million. Finally, to our knowledge, the largest web dataset used in any paper was AltaVista's 2003 crawl with 1.4 billion pages [11].

CHAPTER III

OBJECTIVES AND CLASSIFICATION

This section formalizes the purpose of web crawling and classifies algorithms in related work, some of which we study later in the thesis.

1 Crawler Objectives

We assume that the ideal task of a crawler is to start from a set of seed URLs Ω_0 and eventually crawl the set of all pages Ω_∞ that can be discovered from Ω_0 using HTML links. While Ω_∞ is likely to be infinite, the crawler is allowed to decide the order in which URLs are downloaded and discard pages it believes are spam in order to achieve a reasonably good coverage of the set of “useful” pages $\Omega_U \subseteq \Omega_\infty$. Due to the existence of legitimate sites with hundreds of millions of pages (e.g., ebay.com, yahoo.com, blogspot.com), the crawler cannot make any restricting assumptions on the maximum number of pages per host, the number of hosts per domain, the number of domains in the Internet, or the number of pages in the crawl. We thus classify algorithms as *non-scalable* if they impose hard limits on any of these metrics or are unable to maintain crawling speed when these parameters become very large.

We should also explain why this thesis focuses on the performance of a single server rather than some distributed architecture. If one server can scale to N pages and maintain speed S , then with sufficient bandwidth it trivially follows that m servers can maintain speed mS and scale to mN pages by simply partitioning the subset of all URLs and data structures between themselves (we assume that the bandwidth needed to shuffle the URLs between the servers is also well provisioned).

Table I. Comparison of Prior Crawlers and Their Data Structures

Crawler	Year	Crawl size (HTML pages)	URLseen		RobotsCache		DNScache	Q
			RAM	Disk	RAM	Disk		
WebCrawler [25]	1994	50K	database		–		–	database
Internet Archive [6]	1997	N/A	site-based	–	site-based	–	site-based	RAM
Mercator-A [14]	1999	41M	LRU	seek	LRU	–	–	disk
Mercator-B [23]	2001	473M	LRU	batch	LRU	–	–	disk
Polybot [27]	2001	120M	tree	batch	database		database	disk
WebBase [7]	2001	125M	site-based	–	site-based	–	site-based	RAM
UbiCrawler [2]	2002	45M	site-based	–	site-based	–	site-based	RAM

Therefore, the aggregate performance of a server farm is ultimately governed by the characteristics of individual servers and their local limitations. We explore these limits in detail throughout the thesis.

2 Crawler Operation

The functionality of a basic web crawler can be broken down into several phases: 1) removal of the next URL u from the queue Q of pending pages; 2) download of u and extraction of new URLs u_1, \dots, u_k from u 's HTML tags; 3) for each u_i , verification of uniqueness against some structure `URLseen` and checking compliance with robots.txt using some other structure `RobotsCache`; 4) addition of passing URLs to Q and `URLseen`; 5) update of `RobotsCache` if necessary. The crawler may also maintain its own `DNScache` structure in cases when the local DNS server is not able to efficiently cope with the load (e.g., its RAM cache does not scale to the number of hosts seen by the crawler or it becomes very slow after caching hundreds of millions of records).

A summary of prior crawls and their methods in managing `URLseen`, `RobotsCache`, `DNScache`, and queue Q is shown in Table I. The table demonstrates that two approaches to storing visited URLs have emerged in the literature: *RAM-only* and *hybrid RAM-disk*. In the former case [2], [6], [7], crawlers keep a small subset of hosts in memory and visit them repeatedly until a certain depth or some target number

of pages has been downloaded from each site. URLs that do not fit in memory are discarded and sites are assumed to never have more than some fixed volume of pages. This approach performs truncated web crawls that require different techniques from those studied here and will not be considered in our comparison.

In the latter approach [14], [23], [25], [27], URLs are first checked against a buffer of popular links and those not found are examined using a disk file. The buffer may be a cache based on the Least Recently Used (LRU) replacement algorithm [14], [23], an array of recently added URLs [14], [23], a general-purpose database with RAM caching [25], and a balanced tree of URLs pending a disk check [27].

Most prior approaches keep `RobotsCache` in RAM and either crawl each host to exhaustion [2], [6], [7] or use an LRU cache in memory [14], [23]. The only hybrid approach is used in [27], which employs a general-purpose database for storing downloaded robots.txt and relevant DNS records. Finally, with the exception of [27], prior crawlers do not perform DNS caching and rely on the local DNS server to store these records for them.

CHAPTER IV

SCALABILITY OF DISK METHODS

We next describe three disk-check algorithms proposed in prior literature, analyze their performance, and then introduce our approach.

1 Algorithms

In Mercator-A [14], URLs that are not found in memory cache are looked up on disk by seeking within the `URLseen` file and loading the relevant block of hashes. A similar approach is used in WebCrawler [25], where a general-purpose database performs multiple seeks (assuming a common B-tree implementation) to find URLs on disk. Even with a redundant array of inexpensive disks (RAID), disk seeking cannot be reduced to below 3 – 5 ms, which is several orders of magnitude slower than required in actual web crawls (e.g., 5 – 10 microseconds in IRLbot). General-purpose databases that we have examined are much worse and experience a significant slowdown (i.e., 10 – 50 ms per lookup) after about 100 million inserted records. Therefore, these approaches do not appear viable unless RAM caching can achieve some enormously high hit rates (i.e., 99.7% for IRLbot). We examine whether this is possible in the next section when studying caching.

To avoid the bottleneck of disk-seeking, Mercator-B [23] and Polybot [27] use a so-called *batch disk check* – they accumulate a buffer of URLs in memory and then merge it with a sorted `URLseen` file in one pass. Mercator-B stores only hashes of new URLs in RAM and places their text on disk. In order to retain the mapping from hashes to the text, a special pointer is attached to each hash. After the memory

buffer is full, it is sorted in place and then compared with blocks of `URLseen` as they are read from disk. Non-duplicate URLs are merged with those already on disk and written into a new version of `URLseen`. Pointers are then used to recover the text of unique URLs and append it to the disk queue.

Polybot keeps the entire URLs (i.e., actual strings) in memory and organizes them into a binary search tree. Once the tree size exceeds some threshold, it is merged with the disk file `URLseen`, which contains compressed URLs already seen by the crawler. Besides being enormously CPU intensive (i.e., compression of URLs and search in binary string trees are very slow in our experience), this method has to perform more frequent scans of `URLseen` than Mercator-B due to the less-efficient usage of RAM.

2 Modeling Prior Methods

Assume the crawler is in some steady state where the probability of uniqueness p among new URLs remains constant (we verify that this holds in practice later in the thesis). Further assume that the current size of `URLseen` is U entries, the size of RAM allocated to URL checks is R , the average number of links per downloaded page is l , the average URL length is b , the URL compression ratio is q , and the crawler expects to visit N pages. It then follows that $n = lN$ links must pass through URL check, np of them are unique, and bq is the average number of bytes in a compressed URL. Finally, denote by H the size of URL hashes used by the crawler and P the size of a memory pointer. Then we have the following result.

Theorem 1. *The overall disk overhead of batch disk check is $\omega(n, R) = \alpha(n, R)bn$, where for Mercator-B:*

$$\alpha(n, R) = \frac{2(2UH + pHn)(H + P)}{bR} + 2 + p \quad (1)$$

and for Polybot:

$$\alpha(n, R) = \frac{2(2Ubq + pbqn)(b + 4P)}{bR} + p. \quad (2)$$

Proof. To prevent locking on URL check, both Mercator-B and Polybot must use two buffers of accumulated URLs (i.e., one for checking the disk and the other for newly arriving data). Assume this half-buffer allows storage of m URLs (i.e., $m = R/2(H + P)$ for Mercator-B and $m = R/2(b + 4P)$ for Polybot) and the size of the original disk file is f (i.e., $f = UH$ for Mercator-B and $f = Ubq$ for Polybot).

For Mercator-B, the i -th iteration requires writing/reading of mb bytes of arriving URL strings, reading the current `URLseen`, writing it back, and appending mp hashes to it, i.e., $2f + 2mb + 2mpH(i - 1) + mpH$ bytes. This leads to the following after adding the final overhead to store pbn bytes of unique URLs in the queue:

$$\begin{aligned} \omega(n) &= \sum_{i=1}^{n/m} (2f + 2mb + 2mpHi - mpH) + pbn \\ &= nb \left(\frac{2(2UH + pHn)(H + P)}{bR} + 2 + p \right). \end{aligned} \quad (3)$$

For Polybot, the i -th iteration has overhead $2f + 2mpbq(i - 1) + mpbq$, which yields:

$$\begin{aligned} \omega(n) &= \sum_{i=1}^{n/m} (2f + 2mpbqi - mpbq) + pbn \\ &= nb \left(\frac{2(2Ubq + pbqn)(b + 4P)}{bR} + p \right) \end{aligned} \quad (4)$$

and leads to (2). □

This result shows that $\omega(n, R)$ is a product of two elements: the number of bytes bn in all parsed URLs and how many times $\alpha(n, R)$ they are written to/read from disk. If $\alpha(n, R)$ grows with n , the crawler's overhead will scale super-linearly and may eventually become overwhelming to the point of stalling the crawler. As $n \rightarrow \infty$,

the quadratic term in $\omega(n, R)$ dominates the other terms, which places Mercator-B’s asymptotic performance at

$$\omega(n, R) = \frac{2(H + P)pHn^2}{R} \quad (5)$$

and that of Polybot at

$$\omega(n, R) = \frac{2(b + 4P)pbqn^2}{R}. \quad (6)$$

The ratio of these two terms is $(H + P)H/bq(b + 4P)$, which for the IRLbot case with $H = 8$ bytes, $P = 4$ bytes, $b = 110$, and using very optimistic $bq = 5$ bytes shows that Mercator-B is roughly 7.2 times faster than Polybot as $n \rightarrow \infty$.

The best performance of any method that stores the text of URLs on disk before checking them against `URLseen` (e.g., Mercator-B) is $\alpha_{min} = 2 + p$, which is the overhead needed to write all bn bytes to disk, read them back for processing, and then append bpn bytes to the queue. Methods with memory-kept URLs (e.g., Polybot) have an absolute lower bound of $\alpha'_{min} = p$, which is the overhead needed to write the unique URLs to disk. Neither bound is achievable in practice, however.

3 DRUM

We now describe the URL-check algorithm used in IRLbot, which belongs to a more general framework we call *Disk Repository with Update Management* (DRUM). The purpose of DRUM is to allow for efficient storage of large collections of `<key, value>` pairs, where `key` is a unique identifier (hash) of some data and `value` is arbitrary information attached to the key. There are three supported operations on these pairs – `check`, `update`, and `check+update`. In the first case, the incoming set of data contains keys that must be checked against those stored in the disk cache and

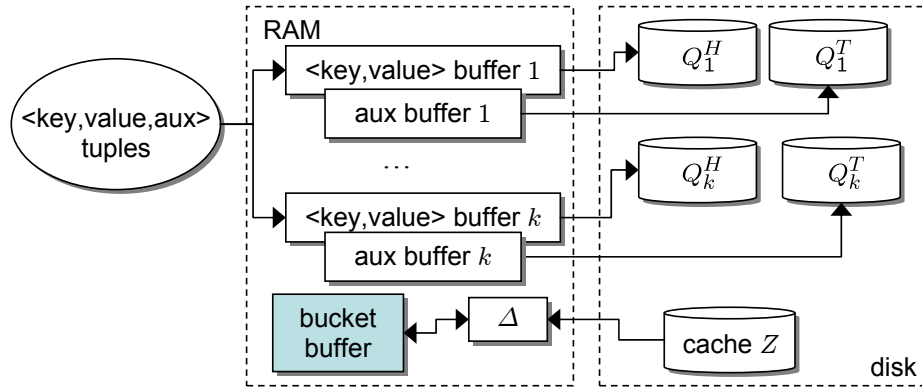


Fig. 1. Operation of DRUM.

classified as being duplicate or unique. For duplicate keys, the value associated with each key can be optionally retrieved from disk and used for some processing. In the second case, the incoming list contains $\langle \text{key}, \text{value} \rangle$ pairs that need to be merged into the existing disk cache. If a given key exists, its value is updated (e.g., overridden or incremented); if it does not, a new entry is created in the disk file. Finally, the third operation performs both check and update in one pass through the disk cache. Also note that DRUM can be supplied with a mixed list where some entries require just a check, while others need an update.

A high-level overview of DRUM is shown in Figure 1. In the figure, a continuous stream of tuples $\langle \text{key}, \text{value}, \text{aux} \rangle$ arrives into DRUM, where aux is some auxiliary data associated with each key . DRUM spreads pairs $\langle \text{key}, \text{value} \rangle$ between k disk buckets Q_1^H, \dots, Q_k^H based on their key (i.e., all keys in the same bucket have the same bit-prefix). This is accomplished by feeding pairs $\langle \text{key}, \text{value} \rangle$ into k memory arrays of size M each and then continuously writing them to disk as the buffers fill up. The aux portion of each key (which usually contains the text of URLs) from the i -th bucket is kept in a separate file Q_i^T in the same FIFO order as pairs $\langle \text{key}, \text{value} \rangle$ in Q_i^H . Note that to maintain fast sequential writing/reading, all buckets are pre-

allocated on disk before they are used.

Once the largest bucket reaches a certain size $r < R$, the following process is repeated for $i = 1, \dots, k$: 1) bucket Q_i^H is read into the *bucket buffer* shown in Figure 1 and sorted; 2) the disk cache Z is sequentially read in chunks of Δ bytes and compared with the keys in bucket Q_i^H to determine their uniqueness; 3) those $\langle \text{key}, \text{value} \rangle$ pairs in Q_i^H that require an **update** are merged with the contents of the disk cache and written to the updated version of Z ; 4) after all unique keys in Q_i^H are found, their original order is restored, Q_i^T is sequentially read into memory in blocks of size Δ , and the corresponding **aux** portion of each unique key is sent for further processing (see below). An important aspect of this algorithm is that all buckets are checked in *one* pass through disk cache Z .¹

We now explain how DRUM is used for storing crawler data. The most important DRUM object is `URLseen`, which implements only one operation – **check+update**. Incoming tuples are $\langle \text{URLhash}, -, \text{URLtext} \rangle$, where the key is an 8-byte hash of each URL, the value is empty, and the auxiliary data is the URL string. After all unique URLs are found, their text strings (**aux** data) are sent to the next queue for possible crawling. For caching robots.txt, we have another DRUM structure called `RobotsCache`, which supports asynchronous check and update operations. For checks, it receives tuples $\langle \text{HostHash}, -, \text{URLtext} \rangle$ and for updates $\langle \text{HostHash}, \text{HostData}, - \rangle$, where `HostData` contains the relevant robots.txt file, IP address of the host, and optionally other host-related information. The final DRUM object that we describe in this section is called `RobotsRequested` and is used for storing the hashes of sites for which a robots.txt has been requested. Similar to `URLseen`, it only supports simulta-

¹Note that disk bucket sort is a well-known technique that exploits uniformity of keys; however, its usage in checking URL uniqueness and the associated performance model of web crawling has not been explored before.

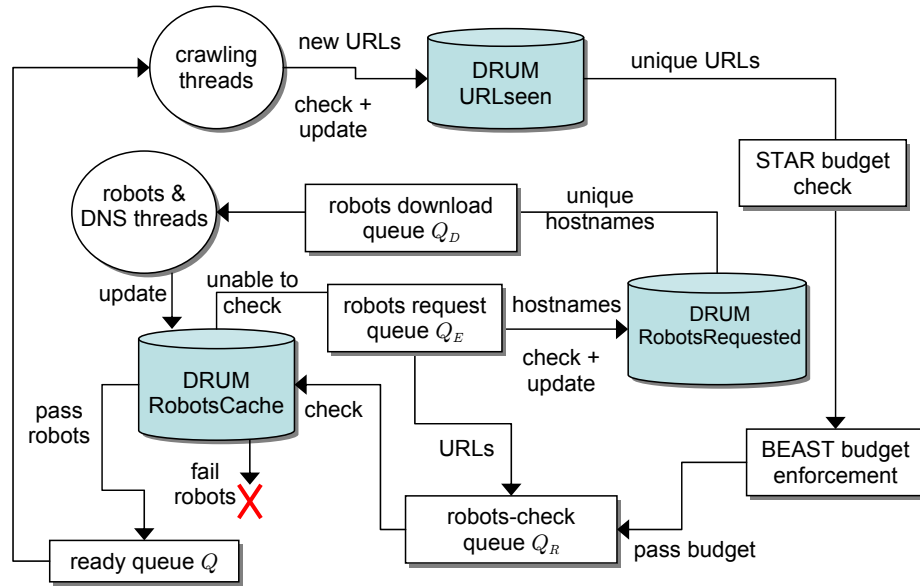


Fig. 2. High level organization of IRLbot.

neous **check+update** and its incoming tuples are $\langle \text{HostHash}, -, \text{HostText} \rangle$.

Figure 2 shows the flow of new URLs produced by the crawling threads. They are first sent directly to **URLseen** using **check+update**. Duplicate URLs are discarded and unique ones are sent for verification of their compliance with the budget (both **STAR** and **BEAST** are discussed later in the thesis). URLs that pass the budget are queued to be checked against **robots.txt** using **RobotsCache**. URLs that have a matching **robots.txt** file are classified immediately as passing or failing. Passing URLs are queued in Q and later downloaded by the crawling threads. Failing URLs are discarded.

URLs that do not have a matching **robots.txt** are sent to the back of queue Q_R and their hostnames are passed through **RobotsRequested** using **check+update**. Sites whose hash is not already present in this file are fed through queue Q_D into a special set of threads that perform DNS lookups and download **robots.txt**. They subsequently issue a batch **update** to **RobotsCache** using **DRUM**. Since in steady-

state (i.e., excluding the initial phase) the time needed to download robots.txt is much smaller than the average delay in Q_R (i.e., 1-2 days), each URL makes no more than one cycle through this loop. In addition, when `RobotsCache` detects that certain robots.txt or DNS records have become outdated, it marks all corresponding URLs as “unable to check, outdated records,” which forces `RobotsRequested` to pull a new set of exclusion rules and/or perform another DNS lookup. Old records are automatically expunged during the update when `RobotsCache` is re-written.

It should be noted that URLs are kept in memory only when they are needed for immediate action and all queues in Figure 2 are stored on disk. We should also note that DRUM data structures can support as many hostnames, URLs, and robots.txt exception rules as disk space allows.

4 DRUM Model

Assume that the crawler maintains a buffer of size $M = 256$ KB for each open file and that the hash bucket size r must be at least $\Delta = 32$ MB to support efficient reading during the check-merge phase. Further assume that the crawler can use up to D bytes of disk space for this process. Then we have the following result.

Theorem 2. *Assuming that $R \geq 2\Delta(1 + P/H)$, DRUM’s `URLseen` overhead is $\omega(n, R) = \alpha(n, R)bn$, where:*

$$\alpha(n, R) = \begin{cases} \frac{8M(H+P)(2UH+pHn)}{bR^2} + 2 + p + \frac{2H}{b} & R^2 < \Lambda \\ \frac{(H+b)(2UH+pHn)}{bD} + 2 + p + \frac{2H}{b} & R^2 \geq \Lambda \end{cases} \quad (7)$$

and $\Lambda = 8MD(H + P)/(H + b)$.

Proof. Memory R needs to support $2k$ open file buffers and one block of URL hashes that are loaded from Q_i^H . In order to compute block size r , recall that it gets expanded

by a factor of $(H + P)/H$ when read into RAM due to the addition of a pointer to each text value. We thus obtain that $r(H + P)/H + 2Mk = R$ or:

$$r = \frac{(R - 2Mk)H}{H + P}. \quad (8)$$

Our disk restriction then gives us that the size of all buckets kr and their text krb/H must be equal to D :

$$kr + \frac{krb}{H} = \frac{k(H + b)(R - 2Mk)}{H + P} = D. \quad (9)$$

It turns out that not all pairs (R, k) are feasible. The reason is that if R is set too small, we are not able to fill all of D with buckets since $2Mk$ will leave no room for $r \geq \Delta$.

Re-writing (9), we obtain a quadratic equation $2Mk^2 - Rk + A = 0$, where $A = (H + P)D/(H + b)$. If $R^2 < 8MA$, we have no solution and thus R is insufficient to support D . In that case, we need to maximize $k(R - 2Mk)$ subject to $k \leq k_m$, where

$$k_m = \frac{1}{2M} \left(R - \frac{\Delta(H + P)}{H} \right) \quad (10)$$

is the maximum number of buckets that still leave room for $r \geq \Delta$. Maximizing $k(R - 2Mk)$, we obtain the optimal point $k_0 = R/(4M)$. Assuming that $R \geq 2\Delta(1 + P/H)$, condition $k_0 \leq k_m$ is always satisfied. Using k_0 buckets brings our disk usage to $D' = (H + b)R^2/8M(H + P)$, which is always less than D .

In the case $R^2 \geq 4MA$, we can satisfy D and the correct number of buckets k is given by two choices:

$$k = \frac{R \pm \sqrt{R^2 - 8MA}}{4M}. \quad (11)$$

The reason why we have two values is that we can achieve D either by using

few buckets (i.e., k is small and r is large) or many buckets (i.e., k is large and r is small). The correct solution is to take the smaller root to minimize the number of open handles and disk fragmentation. Putting things together:

$$k_1 = \frac{R - \sqrt{R^2 - 8MA}}{4M}. \quad (12)$$

Note that we still need to ensure $k_1 \leq k_m$, which holds when:

$$R \geq \frac{\Delta(H + P)}{H} + \frac{2MAH}{\Delta(H + P)}. \quad (13)$$

Given that $R \geq 2\Delta(1 + P/H)$ from the statement of the theorem, it is easy to verify that (13) is always satisfied.

Next, for the i -th iteration that fills up all k buckets, we need to write/read Q_i^T once (overhead $2krb/H$) and read/write each bucket once as well (overhead $2kr$). The remaining overhead is reading/writing `URLseen` (overhead $2f + 2krp(i - 1)$) and appending the new URL hashes (overhead krp). We thus obtain that we need nH/kr iterations and:

$$\begin{aligned} \omega(n, R) &= \sum_{i=1}^{nH/kr} \left(2f + \frac{2krb}{H} + 2kr + 2krpi - krp \right) + pbn \\ &= nb \left(\frac{(2UH + pHn)H}{bkr} + 2 + p + \frac{2H}{b} \right). \end{aligned} \quad (14)$$

Recalling our two conditions, we use $k_0r = HR^2/8M(H + P)$ for $R^2 < 8MA$ to obtain:

$$\omega(n, R) = nb \left(\frac{8M(H + P)(2UH + pHn)}{bR^2} + 2 + p + \frac{2H}{b} \right). \quad (15)$$

For the other case $R^2 \geq 8MA$, we have $k_1r = DH/(H + b)$ and thus get:

$$\omega(n, R) = nb \left(\frac{(H + b)(2UH + pHn)}{bD} + 2 + p + \frac{2H}{b} \right), \quad (16)$$

Table II. Overhead $\alpha(n, R)$ in Crawling N Pages for $R = 1$ GB, $D = 4.3$ TB

N	Mercator-B	Polybot	DRUM
800M	11.6	69	2.26
8B	93	663	2.35
80B	917	6,610	3.3
800B	9,156	66,082	12.5
8T	91,541	660,802	104

which leads to the statement of the theorem. \square

The two cases in (7) can be explained as follows. The first condition $R^2 < \Lambda$ means that R is not enough to fill up the entire disk space D since $2Mk$ memory buffers do not leave enough space for the bucket buffer with size $r \geq \Delta$. In this case, the overhead depends only on R since it is the bottleneck of the system. The second case $R^2 \geq \Lambda$ means that memory size allows the crawler to use more disk space than D , which results in the disk now becoming the bottleneck. In order to match D to a given RAM size R and avoid unnecessary allocation of disk space, one should operate at the optimal point given by $R^2 = \Lambda$:

$$D_{opt} = \frac{R^2(H + b)}{8M(H + P)}. \quad (17)$$

For example, $R = 1$ GB produces $D_{opt} = 4.39$ TB and $R = 2$ GB produces $D_{opt} = 17$ TB. For $D = D_{opt}$, the corresponding number of buckets is $k_{opt} = R/4M$, the size of the bucket buffer is $r_{opt} = RH/2(H+P) \approx 0.33R$, and the leading quadratic term of $\omega(n, R)$ in (7) is now $R/4M$ times smaller than in Mercator-B. This ratio is 1000 for $R = 1$ GB and 8000 for $R = 8$ GB. The asymptotic speed-up in either case is significant.

Finally, observe that the best possible performance of any method that stores both hashes and URLs on disk is $\alpha''_{min} = 2 + p + 2H/b$.

5 Comparison

We next compare disk performance of the studied methods when non-quadratic terms in $\omega(n, R)$ are non-negligible. Table II shows $\alpha(n, R)$ of the three studied methods for fixed RAM size R and disk D as N increases from 800 million to 8 trillion ($p = 1/9$, $U = 100\text{M}$ pages, $b = 110$ bytes, $l = 59$ links/page). As N reaches into the trillions, both Mercator-B and Polybot exhibit overhead that is thousands of times larger than the optimal and invariably become “bogged down” in re-writing `URLseen`. On the other hand, DRUM stays within a factor of 50 from the best theoretically possible value (i.e., $\alpha''_{min} = 2.256$) and does not sacrifice nearly as much performance as the other two methods.

Since disk size D is likely to be scaled with N in order to support the newly downloaded pages, we assume for the next example that $D(n)$ is the maximum of 1 TB and the size of unique hashes appended to `URLseen` during the crawl of N pages, i.e., $D(n) = \max(pHn, 10^{12})$. Table III shows how dynamically scaling disk size allows DRUM to keep the overhead virtually constant as N increases.

To compute the maximum crawling rate that the above methods support, assume that W is the average disk I/O speed and consider the next result.

Theorem 3. *The maximum average download rate (in pages/s) supported by the disk portion of URL uniqueness checks is:*

$$S_{disk} = \frac{W}{\alpha(n, R)bl}. \quad (18)$$

Proof. The time needed to perform uniqueness checks for n new URLs is spent in disk I/O involving $\omega(n, R) = \alpha(n, R)bn = \alpha(n, R)blN$ bytes. Assuming that W is the average disk I/O speed, it takes N/S seconds to generate n new URLs and $\omega(n, R)/W$ seconds to check their uniqueness. Equating the two entities, we have (18). \square

Table III. Overhead $\alpha(n, R)$ in Crawling N Pages for $D = D(n)$

N	$R = 4$ GB		$R = 8$ GB	
	Mercator-B	DRUM	Mercator-B	DRUM
800M	4.48	2.30	3.29	2.30
8B	25	2.7	13.5	2.7
80B	231	3.3	116	3.3
800B	2,290	3.3	1,146	3.3
8T	22,887	8.1	11,444	3.7

We use IRLbot’s parameters to illustrate the applicability of this theorem. Neglecting the process of appending new URLs to the queue, the crawler’s read and write overhead is symmetric. Then, assuming IRLbot’s 1-GB/s read speed and 350-MB/s write speed (24-disk RAID-5), we obtain that its average disk read-write speed is equal to 675 MB/s. Allocating 15% of this rate for checking URL uniqueness², the effective disk bandwidth of the server can be estimated at $W = 101.25$ MB/s. Given the conditions of Table III for $R = 8$ GB and assuming $N = 8$ trillion pages, DRUM yields a sustained download rate of $S_{disk} = 4192$ pages/s (i.e., 721 mb/s using IRLbot’s average page size of 21.5 KB). With 10 DRUM servers and a 10-gb/s Internet link, one could create a search engine with a download capacity of 100 billion pages per month. In crawls of the same scale, Mercator-B would be 3075 times slower and would admit an average rate of only 1.4 pages/s. Since with these parameters Polybot is 7.2 times slower than Mercator-B, its average crawling speed would be 0.2 pages/s.

²Additional disk I/O is needed to support the various queues, store the downloaded content, verify robots.txt, perform reputation analysis, and enforce budgets.

CHAPTER V

CACHING

To understand whether caching provides improved performance, one must consider a complex interplay between the available CPU capacity, spare RAM size, disk speed, performance of the caching algorithm, and crawling rate. This is a three-stage process – we first examine how cache size and crawl speed affect the hit rate, then analyze the CPU restrictions of caching, and finally couple them with RAM/disk limitations using analysis in the previous section.

1 Cache Hit Rate

Assume that c bytes of RAM are available to the cache and that each entry incurs fixed overhead γ bytes, giving us $E = c/\gamma$ elements in the cache. Then define $\pi(c, S)$ to be the cache miss rate under crawling speed S pages/s and cache size c . The reason why π depends on S is that the faster the crawl, the more pages it produces between visits to the same site, which is where duplicate links are most prevalent. Defining τ_h to be the per-host visit delay, common sense suggests that $\pi(c, S)$ should depend not only on c , but also on $\tau_h l S$.

Table IV shows LRU cache hit rates $1 - \pi(c, S)$ during several stages of our crawl. We seek in the trace file to the point where the crawler has downloaded N_0 pages and then simulate LRU hit rates by passing the next $10E$ URLs discovered by the crawler through the cache. As the table shows, a significant jump in hit rates happens between 4M and 8M entries. This is consistent with IRLbot’s peak value of $\tau_h l S \approx 7.3$ million. Note that before cache size reaches this value, most hits in

Table IV. LRU Hit Rates Starting at N_0 Crawled Pages

Cache elements E	$N_0 = 1\text{B}$	$N_0 = 4\text{B}$
256K	19%	16%
4M	26%	22%
8M	68%	59%
16M	71%	67%
64M	73%	73%
512M	80%	78%

the cache stem from redundant links within the same page. As E starts to exceed $\tau_h lS$, popular URLs on each site survive between repeat visits and continue staying in the cache as long as the corresponding site is being crawled. Additional simulations confirming this effect are omitted for brevity.

Unlike [5], which suggests that E be set 100 – 500 times larger than the number of threads, our results show that E must be slightly larger than $\tau_h lS$ to achieve 60% hit rate and as high as $10\tau_h lS$ to achieve 73%.

2 Cache Speed

Another aspect of keeping a RAM cache is the speed at which potentially large memory structures must be checked and updated as new URLs keep pouring in. Since searching large trees in RAM usually results in misses in the CPU cache, some of these algorithms can become very slow as the depth of the search increases. Define $0 \leq \phi(S) \leq 1$ to be the average CPU utilization of the server with a download rate S pages/s and $\mu(c)$ to be the number of URLs/s that a caching algorithm with cache size c can process on an unloaded server. Then, we have the following result.

Theorem 4. *Assuming $\phi(S)$ is monotonically non-decreasing, the maximum down-*

load rate S_{cache} (in pages/s) supported by URL caching is:

$$S_{cache}(c) = g^{-1}(\mu(c)), \quad (19)$$

where g^{-1} is the inverse of $g(x) = lx/(1 - \phi(x))$.

Proof. We assume that caching performance linearly depends on the available CPU capacity, i.e., if fraction $\phi(S)$ of the CPU is allocated to crawling, then the caching speed is $\mu(c)(1 - \phi(S))$ URLs/s. Then, the maximum crawling speed would match the rate of URL production to that of the cache, i.e.,

$$lS = \mu(c)(1 - \phi(S)). \quad (20)$$

Re-writing (20) using $g(x) = lx/(1 - \phi(x))$, we have $g(x) = \mu(c)$, which has a unique solution $x = g^{-1}(\mu(c))$ since $g(x)$ is a strictly increasing function with a proper inverse. \square

For the common case $\phi(S) = S/S_{max}$, where S_{max} is the server's maximum (i.e., CPU-limited) rate in pages/s, (19) yields a very simple expression:

$$S_{cache}(c) = \frac{\mu(c)S_{max}}{lS_{max} + \mu(c)}. \quad (21)$$

Table V compares the speed of several memory structures on the IRLbot server using $E = 16\text{M}$ elements and model (21) for $S_{max} = 4000$ pages/s. As can be seen in the table, insertion of text URLs into a balanced tree (used in Polybot [27]) is the slowest operation that also consumes the most memory. The speed of classical LRU caching (185K/s) and hash-trees (416K/s) is only slightly better since both use multiple (i.e., $\log_2 E$) jumps through memory. CLOCK [5], which is a space and time optimized approximation to LRU, achieves a much better speed (2M/s), requires less RAM, and is a suitable for crawling rates up to 3577 pages/s on this server.

Table V. Insertion Rate and Maximum Crawling Speed from (21)

Method	$\mu(c)$ URLs/s	Size	S_{cache}
Balanced tree (strings)	113K	2.2 GB	1295
Tree-based LRU (8-byte int)	185K	1.6 GB	1757
Balanced tree (8-byte int)	416K	768 MB	2552
CLOCK (8-byte int)	2M	320 MB	3577
Random array (8-byte int)	77M	128 MB	5972
Seq array (8-byte int)	277M	128 MB	5992

Table VI. Overhead $\alpha(\pi n, R - c)$ in Crawling N Pages for $D = D(n)$ Using Caching with $\pi = 0.33$, $c = 320$ MB

N	$R = 4$ GB		$R = 8$ GB	
	Mercator-B	DRUM	Mercator-B	DRUM
800M	3.02	2.27	2.54	2.27
8B	10.4	2.4	6.1	2.4
80B	84	3.3	41	3.3
800B	823	3.3	395	3.3
8T	8,211	4.5	3,935	3.3

After experimentally determining $\mu(c)$ and $\phi(S)$, one can easily compute S_{cache} from (19); however, this metric by itself does not determine whether caching should be enabled or even how to select the optimal cache size c . Even though caching reduces the disk overhead by sending a factor of π fewer URLs to be checked against the disk, it also consumes more memory and leaves less space for the buffer of URLs in RAM, which in turn results in more scans through disk to determine URL uniqueness. Understanding this tradeoff involves careful modeling of hybrid RAM-disk algorithms, which we perform next.

3 Hybrid Performance

We now address the issue of how to assess the performance of disk-based methods with RAM caching. Mercator-A improves performance by a factor of $1/\pi$ since only

Table VII. Maximum Hybrid Crawling Rate $\max_c S_{hybrid}(c)$ for $D = D(n)$

N	$R = 4$ GB		$R = 8$ GB	
	Mercator-B	DRUM	Mercator-B	DRUM
800M	18,051	26,433	23,242	26,433
8B	6,438	25,261	10,742	25,261
80B	1,165	18,023	2,262	18,023
800B	136	18,023	274	18,023
8T	13.9	11,641	27.9	18,023

πn URLs are sought from disk. Given common values of $\pi \in [0.25, 0.35]$ in Table IV, this optimization results in a 2.8 – 4 times speed-up, which is clearly insufficient for making this method competitive with the other approaches.

Mercator-B, Polybot, and DRUM all exhibit new overhead $\alpha(\pi(c, S)n, R - c)b\pi(c, S)n$ with $\alpha(n, R)$ taken from the appropriate model. As $n \rightarrow \infty$ and assuming $c \ll R$, all three methods decrease ω by a factor of $\pi^{-2} \in [8, 16]$ for $\pi \in [0.25, 0.35]$. For $n \ll \infty$, however, only the linear factor $b\pi(c, S)n$ enjoys an immediate reduction, while $\alpha(\pi(c, S)n, R - c)$ may or may not change depending on the dominance of the first term in (1), (2), and (7), as well as the effect of reduced RAM size $R - c$ on the overhead. Table VI shows one example where $c = 320$ MB ($E = 16$ M elements, $\gamma = 20$ bytes/element, $\pi = 0.33$) occupies only a small fraction of R . Notice in the table that caching can make Mercator-B’s disk overhead close to optimal for small N , which nevertheless does not change its scaling performance as $N \rightarrow \infty$.

Since $\pi(c, S)$ depends on S , determining the maximum speed a hybrid approach supports is no longer straightforward.

Theorem 5. *Assuming $\pi(c, S)$ is monotonically non-decreasing in S , the maximum download rate S_{hybrid} supported by disk algorithms with RAM caching is:*

$$S_{hybrid}(c) = h^{-1}\left(\frac{W}{bl}\right), \quad (22)$$

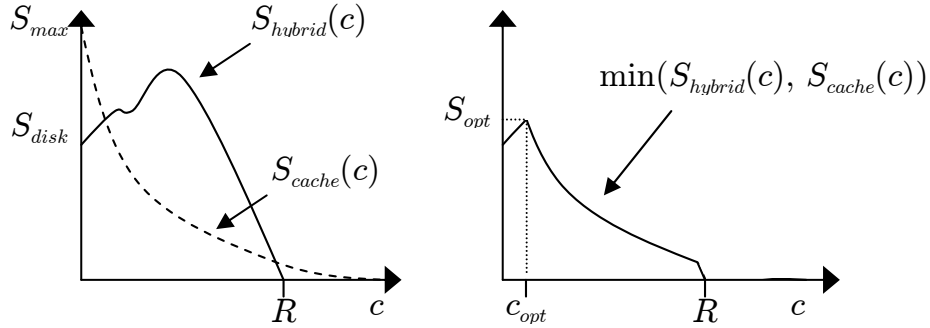


Fig. 3. Finding optimal cache size c_{opt} and optimal crawling speed S_{opt} .

where h^{-1} is the inverse of $h(x) = x\alpha(\pi(c, x)n, R - c)\pi(c, x)$.

Proof. From (18), we have:

$$S = \frac{W}{\alpha(\pi(c, S)n, R - c)b\pi(c, S)l}, \quad (23)$$

which can be written as $h(S) = W/bl$. The solution to this equation is $S = h^{-1}(W/bl)$ where as before the inverse h^{-1} exists due to the strict monotonicity of $h(x)$. \square

To better understand (22), we show an example of finding the best cache size c that maximizes $S_{hybrid}(c)$ assuming $\pi(c, S)$ is a step function of hit rates derived from Table IV. Specifically, $\pi(c, S) = 1$ if $c = 0$, $\pi(c, S) = 0.84$ if $0 < c < \gamma\tau_h lS$, 0.38 if $c < 4\gamma\tau_h lS$, 0.26 if $c < 10\gamma\tau_h lS$, and 0.22 for larger c . Table VII shows the resulting crawling speed after maximizing (22) with respect to c . As before, Mercator-B is close to optimal for small N and large R , but for $N \rightarrow \infty$ its performance degrades. DRUM, on the other hand, maintains at least 11,000 pages/s over the entire range of N . Since these examples use large R in comparison to the cache size needed to achieve non-trivial hit rates, the values in this table are almost inversely proportional to those in Table VI, which can be used to ballpark the maximum value of (22) without inverting $h(x)$.

Knowing function S_{hybrid} from (22), one needs to couple it with the performance of the caching algorithm to obtain the true optimal value of c :

$$c_{opt} = \arg \max_{c \in [0, R]} \min(S_{cache}(c), S_{hybrid}(c)), \quad (24)$$

which is illustrated in Figure 3. On the left of the figure, we plot some hypothetical functions $S_{cache}(c)$ and $S_{hybrid}(c)$ for $c \in [0, R]$. Assuming that $\mu(0) = \infty$, the former curve always starts at $S_{cache}(0) = S_{max}$ and is monotonically non-increasing. For $\pi(0, S) = 1$, the latter function starts at $S_{hybrid}(0) = S_{disk}$ and tends to zero as $c \rightarrow R$, but not necessarily monotonically. On the right of the figure, we show the supported crawling rate $\min(S_{cache}(c), S_{hybrid}(c))$ whose maximum point corresponds to the pair (c_{opt}, S_{opt}) . If $S_{opt} > S_{disk}$, then caching should be enabled with $c = c_{opt}$; otherwise, it should be disabled. The most common case when the crawler benefits from disabling the cache is when R is small compared to $\gamma\tau_h lS$ or the CPU is the bottleneck (i.e., $S_{cache} < S_{disk}$).

CHAPTER VI

SPAM AND REPUTATION

This section explains the necessity for detecting spam during crawls and proposes a simple technique for computing domain reputation in real-time.

1 Problems with BFS

Prior crawlers [7], [14], [23], [27] have no documented spam-avoidance algorithms and are typically assumed to perform BFS traversals of the web graph. Several studies [1], [3] have examined in simulations the effect of changing crawl order by applying bias towards more popular pages. The conclusions are mixed and show that PageRank order [4] can be sometimes marginally better than BFS [1] and sometimes moderately worse [3], where the metric by which they are compared is the rate at which the crawler discovers popular pages.

While BFS works well in simulations, its performance on infinite graphs and/or in the presence of spam farms remains unknown. Our early experiments show that crawlers eventually encounter a quickly branching site that will start to dominate the queue after 3 – 4 levels in the BFS tree. Some of these sites are spam-related with the aim of inflating the page rank of target hosts, while others are created by regular users sometimes for legitimate purposes (e.g., calendars, testing of asp/php engines), sometimes for questionable purposes (e.g., intentionally trapping unwanted robots), and sometimes for no apparent reason at all. What makes these pages similar is the seemingly infinite number of dynamically generated pages and/or hosts within a given domain. Crawling these massive webs or performing DNS lookups on millions

of hosts from a given domain not only places a significant burden on the crawler, but also wastes bandwidth on downloading largely useless content.

Simply restricting the branching factor or the maximum number of pages/hosts per domain is not a viable solution since there is a number of legitimate sites that contain over a hundred million pages and over a dozen million virtual hosts (i.e., various blog sites, hosting services, directories, and forums). For example, Yahoo currently reports indexing 1.2 billion objects within its own domain and blogspot claims over 50 million users (each user gets a unique host name). Therefore, differentiating between legitimate and illegitimate web “monsters” becomes a fundamental task of any crawler.

Note that this task does not entail assigning popularity to each potential page as would be the case when returning query results to a user; instead, the crawler needs to decide *whether a given domain or host should be allowed to massively branch or not*. Indeed, spam-sites and various auto-generated webs with a handful of pages are not a problem as they can be downloaded with very little effort and later classified by data-miners using PageRank or some other appropriate algorithm. The problem only occurs when the crawler assigns to domain x download bandwidth that is disproportionate to the value of x 's content.

Another aspect of spam classification is that it must be performed with very little CPU/RAM effort and run in real-time at speed SL links per second, where L is the number of unique URLs per page.

2 Controlling Massive Sites

Before we introduce our algorithm, several definitions are in order. Both *host* and *site* refer to Fully Qualified Domain Names (FQDNs) on which valid pages reside (e.g.,

motors.ebay.com). A *server* is a physical host that accepts TCP connections and communicates content to the crawler. Note that multiple hosts may be co-located on the same server. A *top-level domain* (TLD) or a *country-code TLD* (cc-TLD) is a domain one level below the root in the DNS tree (e.g., .com, .net, .uk). A *pay-level domain* (PLD) is any domain that requires payment at a TLD or cc-TLD registrar. PLDs are usually one level below the corresponding TLD (e.g., amazon.com), with certain exceptions for cc-TLDs (e.g., ebay.co.uk, det.wa.edu.au). We use a comprehensive list of custom rules for identifying PLDs, which have been compiled as part of our ongoing DNS project.

While computing PageRank [19], BlockRank [18], or SiteRank [10], [30] is a potential solution to the spam problem, these methods become extremely disk intensive in large-scale applications (e.g., 41 billion pages and 657 million hosts found in our crawl) and arguably with enough effort can be manipulated [12] by huge link farms (i.e., millions of pages and sites pointing to a target spam page). In fact, strict page-level rank is not absolutely necessary for controlling massively branching spam. Instead, we found that spam could be “deterred” by budgeting the number of allowed pages per PLD based on domain reputation, which we determine by domain in-degree from resources that spammers must pay for. There are two options for these resources – PLDs and IP addresses. We chose the former since classification based on IPs (first suggested in Lycos [21]) has proven less effective since large subnets inside link farms could be given unnecessarily high priority and multiple independent sites co-hosted on the same IP were improperly discounted.

While it is possible to classify each site and even each subdirectory based on their PLD in-degree, our current implementation uses a coarse-granular approach of only limiting spam at the PLD level. Each PLD x starts with a default budget B_0 , which is dynamically adjusted using some function $F(d_x)$ as x 's in-degree d_x changes.

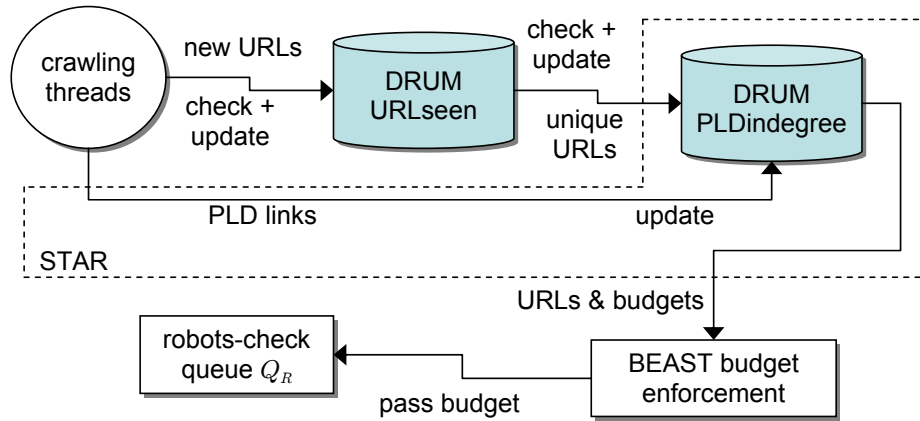


Fig. 4. Operation of STAR.

Budget B_x represents the number of pages that are allowed to pass from x (including all hosts and subdomains in x) to crawling threads every T time units.

Figure 4 shows how our system, which we call *Spam Tracking and Avoidance through Reputation* (STAR), is organized. In the figure, crawling threads aggregate PLD-PLD link information and send it to a DRUM structure `PLDindegree`, which uses a batch `update` to store for each PLD x its hash h_x , in-degree d_x , current budget B_x , number of unique URLs P_x from domain x that have passed to budget enforcement, and hashes of all in-degree neighbors in the PLD graph. Unique URLs arriving from `URLseen` perform a batch `check+update` against `PLDindegree`, increment the corresponding P_x , and are given a tuple (B_x, P_x) on their way to BEAST, which we discuss in the next section.

Note that by varying the budget function $F(d_x)$, one can implement a number of policies – crawling of only popular pages (i.e., zero budget for low-ranked domains and maximum budget for high-ranked domains), equal distribution between all domains (i.e., budget $B_x = B_0$ for all x), and crawling with a bias toward popular/unpopular pages (i.e., budget directly/inversely proportional to the PLD in-degree).

CHAPTER VII

POLITENESS AND BUDGETS

This section discusses how to enable polite crawler operation and scalably enforce budgets.

1 Rate Limiting

One of the main goals of IRLbot from the beginning was to adhere to strict rate-limiting policies in accessing poorly provisioned (in terms of bandwidth or server load) sites. While larger sites are much more difficult to crash, unleashing a crawler that can download at 500 mb/s and allowing it unrestricted access to individual machines would generally be regarded as a denial-of-service attack.

While prior work only enforces a certain per-host access delay τ_h (which varies from 10 times the download delay of a page [23] to 30 seconds [27]), we discovered that this presented a major problem for hosting services that co-located thousands of virtual hosts on the same physical server and did not provision it to support simultaneous access to all sites (which in our experience is rather common in the current Internet). Thus, without an additional per-server limit τ_s , such hosts could be easily crashed or overloaded.

We keep $\tau_h = 40$ seconds for accessing all low-ranked PLDs, but then scale it down proportional to B_x for high-ranked PLDs up to some minimum value τ_h^0 . The reason for doing so is to prevent the crawler from becoming “bogged down” in a few massive sites with millions of pages in RAM. Without this rule, the crawler would make very slow progress through individual sites in addition to eventually running

out of RAM as it becomes clogged with URLs from a few “monster” networks. For similar reasons, we keep per-server crawl delay τ_s at the default 1 second for low-ranked domains and scale it down with the average budget of PLDs hosted on the server, up to some minimum τ_s^0 .

Crawling threads organize URLs in two heaps – the IP heap, which enforces delay τ_s , and the host heap, which enforces delay τ_h . The URLs themselves are stored in a searchable tree with pointers to/from each of the heaps. By properly controlling the coupling between budgets and crawl delays, one can ensure that the rate at which pages are admitted into RAM is no less than their crawl rate, which results in no memory backlog.

We should also note that threads that perform DNS lookups and download robots.txt in Figure 2 are limited by the IP heap, but not the host heap. The reason is that when the crawler is pulling robots.txt for a given site, no other thread can be simultaneously accessing that site.

2 Budget Checks

We finally discuss how IRLbot’s budget enforcement works in a method we call *Budget Enforcement with Anti-Spam Tactics* (BEAST). The goal of budget enforcement is not to discard URLs, but rather to delay their download until more is known about their legitimacy. Most sites have a low rank because they are not well linked to, but this does not necessarily mean that their content is useless or they belong to a spam farm. All other things equal, low-ranked domains should be crawled in some approximately round-robin fashion with careful control of their branching. In addition, as the crawl progresses, domains change their reputation and URLs that have earlier failed the budget check need to be rebudgeted and possibly crawled at a different rate. Ideally,

the crawler should be able to shuffle URLs without losing any of them and eventually download the entire web if given infinite time.

A naive implementation of budget enforcement in prior versions of IRLbot maintained two queues Q and Q_F , where Q contained URLs that had passed the budget and Q_F those that had failed. After Q was emptied, Q_F was read in its entirety and again split into two queues – Q and Q_F . This process was then repeated indefinitely.

We next offer a simple overhead model for this algorithm. As before, assume that S is the number of pages crawled per second and b is the average URL size. Further define $E[B_x] < \infty$ to be the expected budget of a domain in the Internet, V to be the total number of PLDs seen by the crawler in one pass through Q_F , and L to be the number of *unique* URLs per page (recall that l in our earlier notation allowed duplicate links). The next result shows that the naive version of BEAST must increase disk I/O performance with crawl size N .

Theorem 6. *The lowest disk I/O speed (in bytes/s) that allows the naive budget-enforcement approach to support the download of N pages at fixed rate S is:*

$$\lambda = \begin{cases} \frac{2bSN(L-1)}{E[B_x]V} & N \geq E[B_x]V \\ 2bS(L-1) & \textit{otherwise} \end{cases}. \quad (25)$$

Proof. Assume that $N \geq E[B_x]V$. First notice that the average number of links allowed into Q_R is $E[B_x]V$ and define interval T to be the time needed to crawl these links, i.e., $T = E[B_x]V/S$. Note that T is a constant, which is important for the analysis below. Next, by the i -th iteration through Q_F , the crawler has produced $TiSL$ links and TSi of them have been consumed through Q . Thus, the size of Q_F is $TiS(L-1)$. Since Q_F must be both read and written in T time units for any i , the disk speed λ must be $2TiS(L-1)/T = 2iS(L-1)$ URLs/s. Multiplying this by

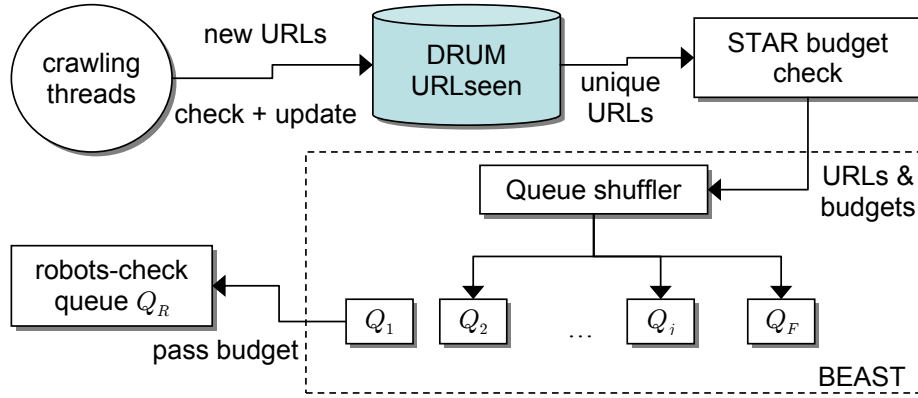


Fig. 5. Operation of BEAST.

URL size b , we get $2ibS(L - 1)$ bytes/s. The final step is to realize that $N = TSi$ (i.e., the total number of crawled pages) and substitute $i = N/TS$ into $2ibS(L - 1)$.

For the case $N < E[B_x]V$ observe that queue size $E[B_x]V$ must be no larger than N and thus $N = E[B_x]V$ must hold since we cannot extract from the queue more elements than have been placed there. \square

The above analysis shows that $\lambda = \Theta(N)$ and that re-checking failed URLs will eventually overwhelm *any* crawler regardless of its disk performance. For IRLbot (i.e., $V = 33\text{M}$, $E[B_x] = 11$, $L = 6.5$, $S = 3100$, and $b = 110$), we get the minimum disk speed of 3.7 MB/s for $N = 100$ million, 82 MB/s for $N = 8$ billion, and 820 MB/s for $N = 80$ billion. Given other disk-intensive tasks, IRLbot's bandwidth for BEAST was capped at about 100 MB/s, which explains why this design eventually became a bottleneck in actual crawls.

The correct implementation of BEAST rechecks Q_F at exponentially increasing intervals. As shown in Figure 5, suppose the crawler starts with $j \geq 1$ queues Q_1, \dots, Q_j , where Q_1 is the current queue and Q_j is the last queue. URLs are read from the current queue Q_1 and written into queues Q_2, \dots, Q_j based on their budgets. Specifically, for a given domain x with budget B_x , the first B_x URLs are sent into Q_2 ,

the next B_x into Q_3 and so on. BEAST can always figure out where to place URLs using a combination of B_x and the total number of pages P_x processed for domain x (both are attached by STAR to each URL). The remaining URLs that do not fit into Q_j are all placed into Q_F as in the previous design.

After Q_1 is emptied, the crawler moves to reading the next queue Q_2 and spreads newly arriving pages between Q_3, \dots, Q_j, Q_1 (note the wrap-around). After it finally empties Q_j , the crawler re-scans Q_F and splits it into j additional queues Q_{j+1}, \dots, Q_{2j} . URLs that do not have enough budget for Q_{2j} are placed into a new version of Q_F . The process then repeats starting from Q_1 until j reaches some maximum OS-imposed limit or the crawl terminates.

There are two benefits to this approach. First, URLs from sites that exceed their budget by a factor of j or more are pushed further back as j increases. This leads to a higher probability that good URLs with enough budget will be queued and crawled ahead of URLs in Q_F . The second benefit, shown in the next theorem, is that the speed at which the disk must be read does not skyrocket to infinity.

Theorem 7. *The lowest disk I/O speed (in bytes/s) that allows BEAST to support the download of N pages at fixed rate S is:*

$$\lambda = 2Sb[(2 - \beta)(L - 1) + 1], \quad (26)$$

where

$$\beta = \begin{cases} \frac{2E[B_x]V}{N + E[B_x]V} & N \geq E[B_x]V \\ 1 & \text{otherwise} \end{cases}. \quad (27)$$

Proof. Assume that $N \geq E[B_x]V$ and suppose one iteration involves reaching Q_F and doubling j . Now assume the crawler is at the end of the i -th iteration ($i = 1$ is the first iteration), which means that it has emptied $2^{i+1} - 1$ queues Q_i and j is currently

equal to 2^i . The total time taken to reach this stage is $T = E[B_x]V(2^{i+1} - 1)/S$. The number of URLs in Q_F is then $TS(L - 1)$, which must be read/written together with j smaller queues Q_1, \dots, Q_j in the time it takes to crawl these j queues. Thus, we get that the speed must be at least:

$$\lambda = 2 \frac{TS(L - 1) + jE[B_x]V}{jT_0} \text{ URL/s}, \quad (28)$$

where $T_0 = E[B_x]V/S$ is the time to crawl one queue Q_i . Expanding, we have:

$$\lambda = 2S[(2 - 2^{-i})(L - 1) + 1] \text{ URL/s}. \quad (29)$$

To tie this to N , notice that the total number of URLs consumed by the crawler is $N = E[B_x]V(2^{i+1} - 1) = TS$. Thus,

$$2^{-i} = \frac{2E[B_x]V}{N + E[B_x]V} \quad (30)$$

and we directly obtain (26) after multiplying (29) by URL size b .

For the case $N < E[B_x]V$, we use the same reasoning as in the proof of the previous theorem and obtain $N = E[B_x]V$. This leads to $\beta = 1/2$ in (27). \square

Notice in (27) that $\beta \in [0, 1]$ and in (26) that as $N \rightarrow \infty$ disk speed $\lambda \rightarrow 2Sb(2L - 1)$, which is roughly four times the speed needed to write all unique URLs to disk as they are discovered during the crawl. For the examples used earlier in this section, this implementation needs $\lambda \leq 8.2$ MB/s *regardless of crawl size* N . From the above proof, it also follows that the last stage of an N -page crawl will contain (assuming $N \geq E[B_x]V$):

$$j = \frac{1}{2} \left(\frac{N}{E[B_x]V} + 1 \right) \quad (31)$$

queues. This value for $N = 8\text{B}$ is 9 and for $N = 80\text{B}$ only 87, neither of which is too imposing for a modern server.

CHAPTER VIII

EXPERIMENTS

This section briefly examines the important parameters of the crawl and highlights our observations.

1 Summary

Between June 9 and August 3, 2007, we ran IRLbot on a quad-CPU AMD Opteron 2.6 GHz server (16 GB RAM, 24-disk RAID-5) attached to a 1-gb/s link at the campus of Texas A&M University. The crawler was paused several times for maintenance and upgrades, which resulted in the total active crawling span of 41.27 days. During this time, IRLbot attempted 7,606,109,371 connections and received 7,437,281,300 valid HTTP replies. Excluding non-HTML content (92M pages), HTTP errors and redirects (964M), IRLbot ended up with $N = 6,380,051,942$ responses with status code 200 and content-type `text/html`.

We next plot average 10-minute download rates for the active duration of the crawl in Figure 6, in which fluctuations correspond to day/night bandwidth limits imposed by the university.¹ The average download rate during this crawl was 319 mb/s (1,789 pages/s) with a peak 10-minute average rate of 470 mb/s (3,134 pages/s). The crawler received 143 TB of data, out of which 254 GB were robots.txt files, and transmitted 1.8 TB of HTTP requests. Counting both compressed and uncompressed objects, the average size of an HTML page was 21.5 KB.

¹University-provided daytime bandwidth was 250 mb/s for days 5 – 32 and 200 mb/s for the rest of the crawl.

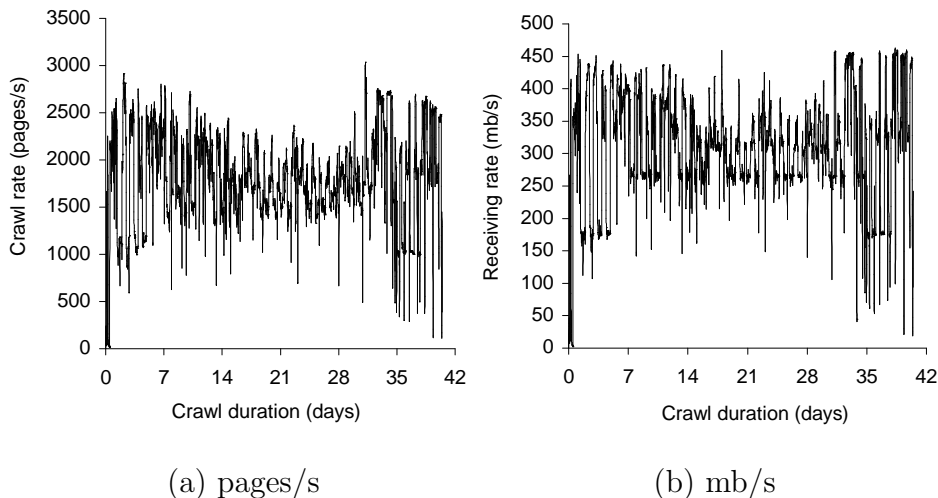


Fig. 6. Download rates during the experiment.

IRLbot parsed out 394,619,023,142 links from downloaded pages. After discarding invalid URLs and known non-HTML extensions, the crawler was left with $K = 374,707,295,503$ potentially “crawlable” links that went through URL uniqueness checks. We use this number to obtain $K/N = l \approx 59$ links/page used throughout the thesis. The average URL size was 70.6 bytes (after removing “http://”), but with crawler overhead (e.g., depth in the crawl tree, IP address and port, timestamp, and parent link) attached to each URL, their average size in the queue was $b \approx 110$ bytes. The number of pages recorded in `URLseen` was 41,502,195,631 (332 GB on disk), which yielded $L = 6.5$ unique URLs per page. These pages were hosted by 641,982,061 unique sites.

As promised earlier, we now show in Figure 7(a) that the probability of uniqueness p stabilizes around 0.11 once the first billion pages have been downloaded. Since p is bounded away from 0 even at $N = 6.3$ billion, this suggests that our crawl has discovered only a small fraction of the web. While we certainly know there are at least 41 billion pages in the Internet, the fraction of them with useful content and the number of additional pages not seen by the crawler remain a mystery at this stage.

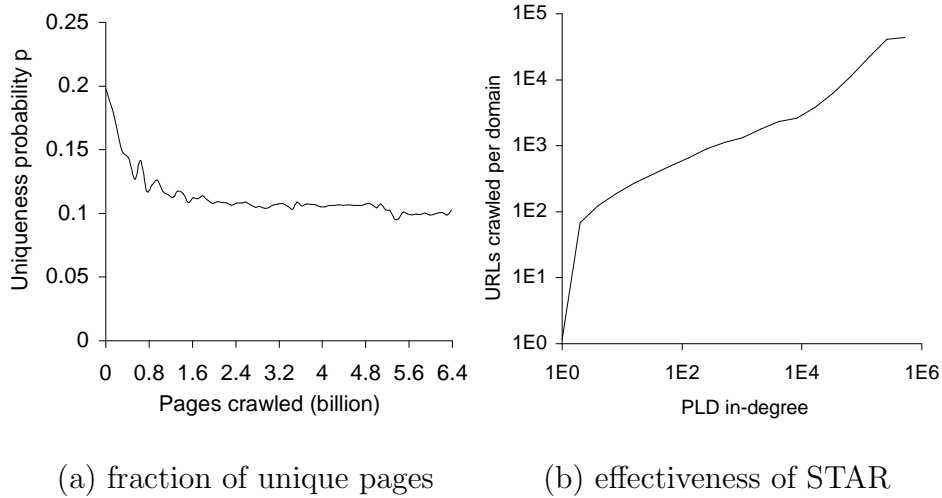


Fig. 7. Evolution of p throughout the crawl and effectiveness of budget-control in limiting low-ranked PLDs.

2 Domain Reputation

The crawler contacted 117,576,295 sites, which belonged to 33,755,361 pay-level domains (PLDs) and were hosted on 5,517,743 unique IPs. The total number of nodes in the PLD graph was 89,652,630 with the number of PLD-PLD edges equal to 1,832,325,052. Without knowing how our algorithms would perform, we chose a conservative budget function $F(d_x)$ where the crawler would give only moderate preference to highly-ranked domains and try to branch out to discover a wide variety of low-ranked PLDs. Specifically, top 10K ranked domains were given budget B_x linearly interpolated between 10 and 10K pages. All other PLDs received the default budget $B_0 = 10$ pages. Rate-limiting delays were adjusted using the following minimums: $\tau_h^0 = 10$ seconds and $\tau_s^0 = 1/20$ second.

Figure 7(b) shows the average number of downloaded pages per PLD x based on its in-degree d_x . IRLbot crawled on average 1.2 pages per PLD with $d_x = 1$, 68 pages per PLD with $d_x = 2$, and 43K pages per domain with $d_x \geq 512K$. The largest number of pages pulled from any PLD was 347,613 (blogspot.com), while

Table VIII. Top Ranked PLDs, Their PLD In-Degree, Google PageRank, and Total Pages Crawled.

Rank	Domain	In-degree	PageRank	Pages
1	microsoft.com	2,948,085	9	37,755
2	google.com	2,224,297	10	18,878
3	yahoo.com	1,998,266	9	70,143
4	adobe.com	1,287,798	10	13,160
5	blogspot.com	1,195,991	9	347,613
7	wikipedia.org	1,032,881	8	76,322
6	w3.org	933,720	10	9,817
8	geocities.com	932,987	8	26,673
9	msn.com	804,494	8	10,802
10	amazon.com	745,763	9	13,157

99% of visited domains contributed to the crawl fewer than 3,044 pages each and 90% less than 586 each. As seen in the figure, IRLbot succeeded at achieving a strong correlation between domain popularity (i.e., in-degree) and the amount of bandwidth allocated to that domain during the crawl.

Our manual analysis of top-1000 domains shows that most of them are highly-ranked legitimate sites, which attests to the effectiveness of our ranking algorithm. Several of them are listed in Table VIII together with Google’s PageRank of the main page of each PLD and the number of pages downloaded by IRLbot. The exact coverage of each site depended on its link structure, as well as the number of hosts and physical servers (which determined how polite the crawler needed to be). By changing the budget function $F(d_x)$, much more aggressive crawls of large sites could be achieved, which may be required in practical search-engine applications.

We believe that PLD-level domain ranking by itself is not sufficient for preventing *all* types of spam from infiltrating the crawl and that additional fine-granular ranking algorithms may be needed for classifying individual hosts within a domain and possibly their subdirectory structure. Future work will address this issue, but

our first experiment with spam-control algorithms demonstrates that these methods are not only necessary, but also very effective in helping crawlers scale to billions of pages.

3 Final Word

We have attempted to reach this crawl scale several times. While our prior implementations failed for one reason or another, this particular crawl was very successful as it ran without any bottlenecks, slowdowns, or memory clogging. Analysis shown earlier in the thesis demonstrates that IRLbot can sustain the same download speed up to $N = 8$ trillion pages (given sufficient disk space and bandwidth) using the same single-server implementation.

CHAPTER IX

CONCLUSION

This thesis tackled the issue of scaling web crawlers to billions and even trillions of pages using a single server with constant CPU, disk, and memory speed. We identified several impediments to building an efficient large-scale crawler and showed that they could be overcome by simply changing the BFS crawling order and designing low-overhead disk-based data structures. We experimentally tested our algorithms in the Internet and found them to scale much better than the methods proposed in prior literature.

Future work involves refining reputation algorithms, assessing their performance, and mining the collected data.

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