# IRLbot: Scaling to 6 Billion Pages and Beyond

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***Abstract*—This paper shares our experience in designing a web crawler that can download billions of pages using a single-server implementation and models its performance. We show that with the quadratically increasing complexity of verifying URL uniqueness, 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.**

## 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 paper does not deal with data miners, but instead focuses on the design of web crawlers that can scale to the size of the current[1] 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.

### A. 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 refers to the CPU and RAM resources $\Sigma$ 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 $\Sigma$. At the same time, higher speed $S$ requires smaller data structures, which often can be satisfied only by either lowering $N$ or increasing $\Sigma$.

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 unbounded resources). They also do not analyze how the proposed algorithms scale for very large $N$ given fixed $S$ and $\Sigma$. 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 $\Sigma$ remains open.

### B. 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, high-density link farms, and unlimited number of hostnames, 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 eventually becomes trapped in useless content, 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 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 domain; and c) the crawler becomes vulnerable to the delay attack from sites 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.

### C. 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

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[1]Adding the size of all top-level domains using site queries (e.g., "site:.com"), Google's index size in January 2008 can be estimated at 30 billion pages and Yahoo's at 37 billion.

of the crawler from accessing the site in question, various complaints to the 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 ultimately 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 paper.

### D. Our Contributions

The first part of the paper 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.[2] 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 $184$K 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 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 $7,606,109,371$ connection requests, received $7,437,281,300$ HTTP responses from $117,576,295$ hosts, and successfully downloaded $N = 6,380,051,942$ unique HTML pages at an average rate of $319$ mb/s ($1,789$ pages/s). After 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 $35$B URLs not crawled in this experiment contains useful content.

The rest of the paper 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 paper.

## 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 pulled several hundred million pages and involved multiple agents in the crawling

[2]A separate paper will present a much more detailed analysis of the collected data.

TABLE I
COMPARISON OF PRIOR CRAWLERS AND THEIR DATA STRUCTURES

| Crawler | Year | Crawl size (HTML pages) | URLseen RAM | URLseen Disk | RobotsCache RAM | RobotsCache Disk | DNScache | $Q$ |
|---|---|---|---|---|---|---|---|---|
| WebCrawler [25] | 1994 | 50K | database | | – | | – | database |
| Internet Archive [6] | 1997 | – | 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 |

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 paper 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 their experiment was only $N = 25$ million. Finally, to our knowledge, the largest webgraph used in any paper was AltaVista's 2003 crawl with 1.4B pages and 6.6B links [11].

## 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 paper.

### A. Crawler Objectives

We assume that the ideal task of a crawler is to start from a set of seed URLs $\Omega_0$ and eventually crawl the set of all pages $\Omega_\infty$ that can be discovered from $\Omega_0$ using HTML links. The crawler is allowed to dynamically change the order in which URLs are downloaded in order to achieve a reasonably good coverage of "useful" pages $\Omega_U \subseteq \Omega_\infty$ in some finite amount of time. 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 paper 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 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). 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 paper.

### B. 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 $u_1, \ldots, u_k$ 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 have 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 methodology results in 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 RAM buffer may be an LRU cache [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. 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.

## IV. Scalability of Disk Methods

This section describes algorithms proposed in prior literature, analyzes their performance, and introduces our approach.

### A. 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. The method clusters URLs by their site hash and attempts to resolve multiple in-memory links from the same site in one seek. However, in general, locality of parsed out URLs is not guaranteed and the worst-case delay of this method is one seek/URL and the worst-case read overhead is one block/URL. 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 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.

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 the 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 rather 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.

### B. 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 paper). 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 overhead of `URLseen` batch disk check is $\omega(n,R) = \alpha(n,R)bn$ bytes, where for Mercator-B:

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

and for Polybot:

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

*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 initial 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:

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

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

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

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

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

and that of Polybot at

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

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

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.

### C. 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 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 `<key,value>` 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 may 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 `<key,value,aux>` arrives into DRUM, where `aux` is some auxiliary data associated with each `key`. DRUM spreads pairs `<key,value>` between $k$ disk buckets $Q_1^H, \ldots, Q_k^H$ based on their `key` (i.e., all keys in the same bucket have the same bit-prefix). This is accomplished by feeding pairs `<key,value>` 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 `<key,value>` 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 $i = 1, \ldots, k$: 1) bucket $Q_i^H$ is read into the *bucket buffer* shown in Figure 1 and sorted;

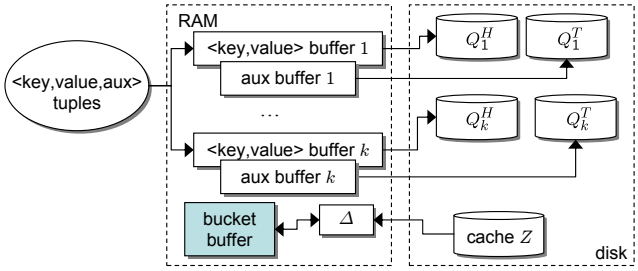



Fig. 1. Operation of DRUM.

2) the disk cache $Z$ is sequentially read in chunks of $\Delta$ bytes and compared with the keys in bucket $Q_i^H$ to determine their uniqueness; 3) those `<key,value>` 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 $\Delta$, 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 $Z$.[3]

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 `<URLhash,-,URLtext>`, 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 `<HostHash,-,URLtext>` and for updates `<HostHash,HostData,->`, where `HostData` contains the robots.txt file, IP address of the host, and optionally other host-related information. The last DRUM object of 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 simultaneous `check+update` and its incoming tuples are `<HostHash,-,HostText>`.

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 paper). 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

[3]Note 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.

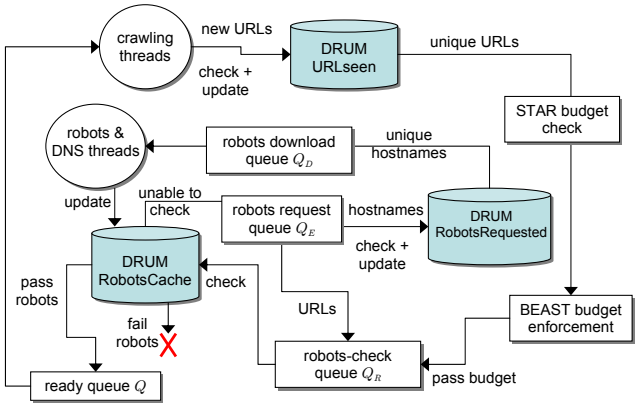



Fig. 2. High level organization of IRLbot.

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.

### D. 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 $\omega(n, R) = \alpha(n, R)bn$ bytes, where:

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

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 hash value. We thus obtain that $r(H + P)/H + 2Mk = R$ or:

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

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

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

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

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

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:

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

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:

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

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

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

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:

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

Recalling our two conditions, we use $k_0 r = HR^2/[8M(H + P)]$ for $R^2 < 8MA$ to obtain:

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

TABLE II
OVERHEAD $\alpha(n, R)$ FOR $R = 1$ GB, $D = 4.39$ 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 |

For the other case $R^2 \geq 8MA$, we have $k_1 r = DH/(H+b)$ and thus get:

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

which leads to the statement of the theorem. ■

It follows from the proof of Theorem 2 that 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 $R^2 = \Lambda$:

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

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 $1,000$ for $R =$ 1 GB and $8,000$ 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 $\alpha''_{min} = 2 + p + 2H/b$.

### E. 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 ($p = 1/9$, $U = 100$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 average crawling rate that the above methods support, assume that $W$ is the average disk I/O speed and consider the next result.

TABLE III
OVERHEAD $\alpha(n, R)$ 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 |

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

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

*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). ■

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 uniqueness[4], 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 $S_{disk} = 4,192$ pages/s (i.e., 711 mb/s using IRLbot's average HTML page size of 21.2 KB). In crawls of the same scale, Mercator-B would be $3,075$ 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.

With just 10 DRUM servers and a 10-gb/s Internet link, one can create a search engine with a download capacity of 100 billion pages per month and scalability to trillions of pages.

## 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.

### A. Cache Hit Rate

Assume that $c$ bytes of RAM are available to a cache whose entries incur fixed overhead $\gamma$ bytes. Then $E = c/\gamma$ is the

[4]Additional disk I/O is needed to verify robots.txt, perform reputation analysis, and enforce budgets.

TABLE IV
LRU HIT RATES STARTING AT $N_0$ CRAWLED PAGES

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

maximum number of elements stored in the cached at any time. Then define $\pi(c, S)$ to be the cache miss rate under crawling speed $S$ pages/s and cache size $c$. The reason why $\pi$ 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 $\tau_h$ to be the per-host visit delay, common sense suggests that $\pi(c, S)$ should depend not only on $c$, but also on $\tau_h lS$.

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 $\tau_h lS \approx 7.3$ million. Note that before cache size reaches this value, most hits in 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 a 60% hit rate and as high as $10\tau_h lS$ to achieve 73%.

### B. 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 $0 \le \phi(S) \le 1$ to be the average CPU utilization of the server crawling at $S$ pages/s and $\mu(c)$ to be the number of URLs/s that a cache of 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 download rate $S_{cache}$ (in pages/s) supported by URL caching is:

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

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.,

$$lS = \mu(c)(1 - \phi(S)). \tag{20}$$

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

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 | 1,295 |
| Tree-based LRU (8-byte int) | 185K | 1.6 GB | 1,757 |
| Balanced tree (8-byte int) | 416K | 768 MB | 2,552 |
| CLOCK (8-byte int) | 2M | 320 MB | 3,577 |

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

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

To show how to use the above result, Table V compares the speed of several memory structures on the IRLbot server using $E = 16$M elements and displays model (21) for $S_{max} = 4,000$ 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 search-trees with 8-byte keys (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 suitable for crawling rates up to 3,577 pages/s on this server.

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 $\pi n$ rather than $n$ 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.

### C. 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 $\pi n$ 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 $n \to \infty$ and assuming $c \ll R$,

TABLE VI
OVERHEAD $\alpha(\pi n, R-c)$ FOR $D = D(n), \pi = 0.33, c = 320$ 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 |

all three methods decrease $\omega$ 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 $N \to \infty$.

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:

$$S_{hybrid}(c) = h^{-1}\Big(\frac{W}{bl}\Big), \tag{22}$$

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:

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

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 $h(x)$. ∎

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 $0 < c < \gamma\tau_h lS$, 0.41 if $c < 4\gamma\tau_h lS$, 0.27 if $c < 10\gamma\tau_h lS$, and 0.22 for larger $c$. Table VII shows the resulting crawling speed in pages/s after maximizing (22) with respect to $c$. As before, Mercator-B is close to optimal for small $N$ and large $R$, but for $N \to \infty$ 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 $c$:

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 |

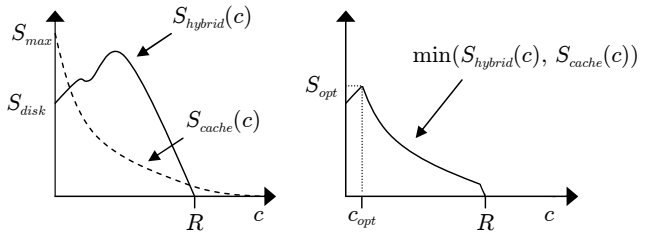



Fig. 3. Finding optimal cache size $c_{opt}$ and optimal crawling speed $S_{opt}$.

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

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 $c \to R$, 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., $S_{cache} < S_{disk}$).

## 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.

### A. 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 marginally 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., intentional trapping of 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 *just within its own domain* and blogspot claims over 50 million users, each with a unique hostname. 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/disk effort and run in real-time at speed $SL$ links per second, where $L$ is the number of unique URLs per page.

### B. 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 641 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.

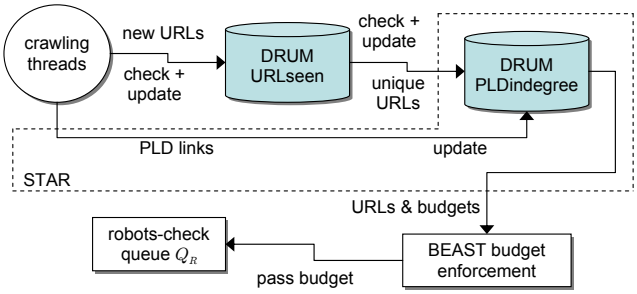



Fig. 4. Operation of STAR.

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. 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 $B_x$, and hashes of all in-degree neighbors in the PLD graph. Unique URLs arriving from `URLseen` perform a batch `check` against `PLDindegree`, and are given $B_x$ 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).

## VII. Politeness and Budgets

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

### A. 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. Even though 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.

Prior work has only enforced a certain per-host access delay $\tau_h$ (which varied from 10 times the download delay of a page [23] to 30 seconds [27]), but 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 $\tau_s$, such hosts could be easily crashed or overloaded.

We keep $\tau_h = 40$ seconds for accessing all low-ranked PLDs, but then for high-ranked PLDs scale it down proportional to $B_x$, up to some minimum value $\tau_h^0$. 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 $\tau_s$ 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 $\tau_s^0$.

Crawling threads organize URLs in two heaps – the IP heap, which enforces delay $\tau_s$, and the host heap, which enforces delay $\tau_h$. 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.

### B. Budget Checks

We now discuss how IRLbot's budget enforcement works in a method we call *Budget Enforcement with Anti-Spam Tactics* (BEAST). The goal of this method 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 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:* Lowest disk I/O speed (in bytes/s) that allows the naive budget-enforcement approach to download $N$ pages at fixed rate $S$ is:

$$\lambda = 2Sb(L-1)\alpha_N, \tag{25}$$

where

$$\alpha_N = \max\Big(1, \frac{N}{E[B_x]V}\Big). \tag{26}$$

*Proof:* Assume that $N \geq E[B_x]V$. First notice that the average number of links allowed into $Q$ 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 $TiS$ 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 $\lambda$ must be $2TiS(L-1)/T = 2iS(L-1)$ URLs/s. Multiplying this by 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 $N < E[B_x]V$ 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. Combining the two cases, we get (26). ■

This theorem shows that $\lambda \sim \alpha_N = \Theta(N)$ and that re-checking failed URLs will eventually overwhelm *any* crawler regardless of its disk performance. For IRLbot (i.e., $V = 33$M, $E[B_x] = 11$, $L = 6.5$, $S = 3,100$ pages/s, and $b = 110$), we get $\lambda = 3.8$ MB/s for $N = 100$ million, $\lambda = 83$ MB/s for $N = 8$ billion, and $\lambda = 826$ 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 $Q_1, \ldots, Q_j$, 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 $Q_2, \ldots, Q_j$ based on their budgets. Specifically, for a given domain $x$ with budget $B_x$, the first $B_x$ URLs are sent into

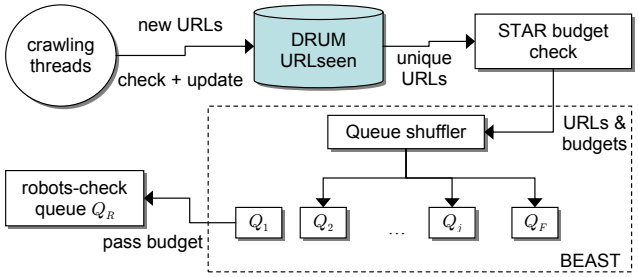
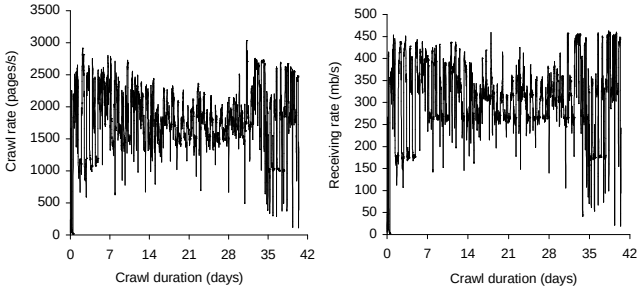



Fig. 5. Operation of BEAST.




(a) pages/s (b) mb/s

Fig. 6. Download rates during the experiment.

$Q_2$, the next $B_x$ into $Q_3$ and so on. BEAST can always figure out where to place URLs using a combination of $B_x$ (attached by STAR to each URL) and a local array that keeps for each queue $Q_j$ the left-over budget of each domain. URLs that do not fit in $Q_j$ are all placed in $Q_F$ 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 $Q_3, \ldots, Q_j, Q_1$ (note the wrap-around). After it finally empties $Q_j$, the crawler re-scans $Q_F$ and splits it into $j$ additional queues $Q_{j+1}, \ldots, Q_{2j}$. URLs that do not have enough budget for $Q_{2j}$ are placed into the 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:* Lowest disk I/O speed (in bytes/s) that allows BEAST to download $N$ pages at fixed rate $S$ is:

$$\lambda = 2Sb\Big[\frac{2\alpha_N}{1+\alpha_N}(L-1)+1\Big] \leq 2Sb(2L-1). \qquad (27)$$

*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 $Q_1, \ldots, Q_j$ in the time it takes to crawl these $j$ queues. Thus, we get that the speed must be at least:

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

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

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

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,

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

and we directly arrive at (27) after multiplying (29) by URL size $b$. Finally, for $N < E[B_x]V$, we use the same reasoning as in the proof of the previous theorem to obtain $N = E[B_x]V$, which leads to (26). ■

For $N \to \infty$ and fixed $V$, disk speed $\lambda \to 2Sb(2L-1)$, 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:

$$j = 2^{\lceil \log_2(\alpha_N+1)\rceil - 1} \qquad (31)$$

queues. This value for $N = 8$B is 16 and for $N = 80$B only 128, neither of which is too imposing for a modern server.

## VIII. Experiments

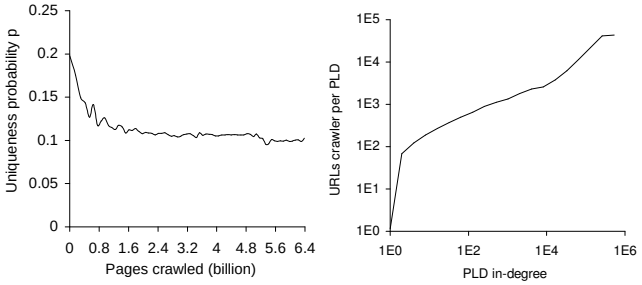
This section briefly examines the important parameters of the crawl and highlights our observations.

### A. 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.[5] The average download rate during this crawl was 319 mb/s ($1,789$ pages/s) with the 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. The parser processed 161 TB of HTML code (i.e., 25.2 KB per uncompressed

[5]The day limit was 250 mb/s for days $5-32$ and 200 mb/s for the rest of the crawl. The night limit was 500 mb/s.




(a) fraction of unique pages (b) effectiveness of STAR

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

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 |

page) and the gzip library handled 6.6 TB of HTML data containing $1,050,955,245$ pages, or 16% of the total. The average compression ratio was 1:5, which resulted in the peak parsing demand being close to 800 mb/s (i.e., 1.64 times faster than the maximum download rate).

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 paper. 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.

### B. Domain Reputation

The crawler received responses from $117,576,295$ sites, which belonged to $33,755,361$ pay-level domains (PLDs) and were hosted on $4,260,532$ unique IPs. The total number of nodes in the PLD graph was $89,652,630$ with the number of PLD-PLD edges equal to $1,832,325,052$. During the crawl, IRLbot performed $260,113,628$ DNS lookups, which resolved to $5,517,743$ unique IPs.

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 $B_0 = 10$. 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 $d_x = 1$ incoming link, 68 pages per PLD with $d_x = 2$, and 43K pages per domain with $d_x \geq 512$K. The largest number of pages pulled from any PLD was $347,613$ (blogspot.com), while 90% of visited domains contributed to the crawl fewer than 586 pages each and 99% fewer than $3,044$ 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.

## IX. CONCLUSION

This paper 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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