Web Site Metadata

MIMS Final Project

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Abstract

The currently established formats for how a website can publish metadata about a site's pages, the `robots.txt` file and sitemaps, focus on how to provide information to crawlers about where to not go and where to go on a site. This is sufficient as input for crawlers, but does not allow websites to publish richer metadata about their site's structure, such as the navigational structure. This project studies the availability of website metadata on today's Web in terms of available information resources and quantitative aspects of their contents. Such an analysis of the available Web site metadata not only makes it easier to understand what data is available today, but also serves as the foundation for investigating what kind of information retrieval processes could be driven by that data. Using data gathered in this study, we designed and prototyped a system for generating most useful pages (called *ulinks*) from a site. Our system is similar to, albeit much simpler than, *sitelinks* shown by leading search engines. Our analysis of the limitations of our ulink generation system shows that if websites had richer data formats to publish metadata, then ulink generation can be much improved.

1 Introduction

Most information resources on the Web are *websites*, informally defined as a set of *webpages* made available by some information provider. While the concept of a website is only loosely defined, it is often associated with all webpages available under one domain. (This could be generalized to all Web pages using the same URI prefix, but for the purpose of this paper, we look at domain-based sites only). Websites are usually accessed by *web crawlers* [10] which systematically retrieve webpages, in most cases to drive later stages of indexing them for eventually driving a search engine. To allow websites some level of control over crawlers, the informal `robots.txt` format [9] —sometimes also referred to as the *Robots Exclusion Protocol (REP)*—is the established way of how a Web site can control crawlers. This format can only be used on a per-domain basis, and specifies rules for all pages under that domain.

The `robots.txt` format is a simple mechanism that allows websites to publish metadata about itself. In particular, the `robots.txt` format allows websites to specify parts of the website that should not be accessed and parts that can be accessed by web crawlers. This assumes that crawlers get information about available URIs from other source; in most cases this happens by following links on already crawled pages. On the other hand, sites often want to be crawled so that their contents are available through search engines, and the *sitemaps* format[1] allows sites to publish lists of URIs which they want to advertise to crawlers. Sitemaps can be made available to crawlers in different ways; they can be directly advertised through user interfaces or an HTTP ping interface to individual crawlers, or they can be specified in the `robots.txt` file.

Sitemap information can be useful for exposing the *deep web* [8], for example, those pages that are accessible only through HTML forms. Because search engine crawlers typically discover pages by following links, large portions of the Web can be hidden from crawlers, and thus might never be indexed, and thus never show up in search results. Thus, without sitemap information, search engine crawlers might not be able to find these pages. Since sitemap information may be incomplete and/or inaccurate, search engines have to rely on other techniques to completely crawl the deep Web.

Large search engines crawl different parts of the web with different frequencies. For example, news sites will likely be crawled (and indexed) much more frequently than sites that change infrequently. Sitemap information (in particular, information within `lastmod` tags) can be used by crawlers to set their crawl schedules. How much of this information is used by current search engines is unknown.

Motivated by the usefulness of sitemaps, we study and quantify sitemaps data from the top-100K most popular websites (according to Alexa [1]). We characterize the popularity of the sitemaps format, the amount of information provided in these sitemaps, the structure of this data, and our experience crawling and processing this data.

With only these two formats, websites currently have only a limited way of publishing their site's structure in a machine-readable way, and these ways are mainly intended to steer crawlers. A key question we ask in this project is: Are these formats sufficient for exposing a site's navigation structure?

For concreteness, we focus on one aspect of site navigation structure, namely, *most useful or popular pages* from a site. We call such pages *ulinks* (for useful links). Thus, our question is: Are these formats sufficient for exposing the popular pages of a website? From a purely mathematical perspective, the answer is trivially "yes": If each webmaster methodically ranked pages according to their usefulness and set the priority of each page according to its rank, then the most useful pages (according to webmasters) would be

[1]`http://www.sitemaps.org/`

exposed. This is, however, not a practical scenario. In other words, our question really should be: From the website data that currently exists, can we compute the most useful pages of a website?

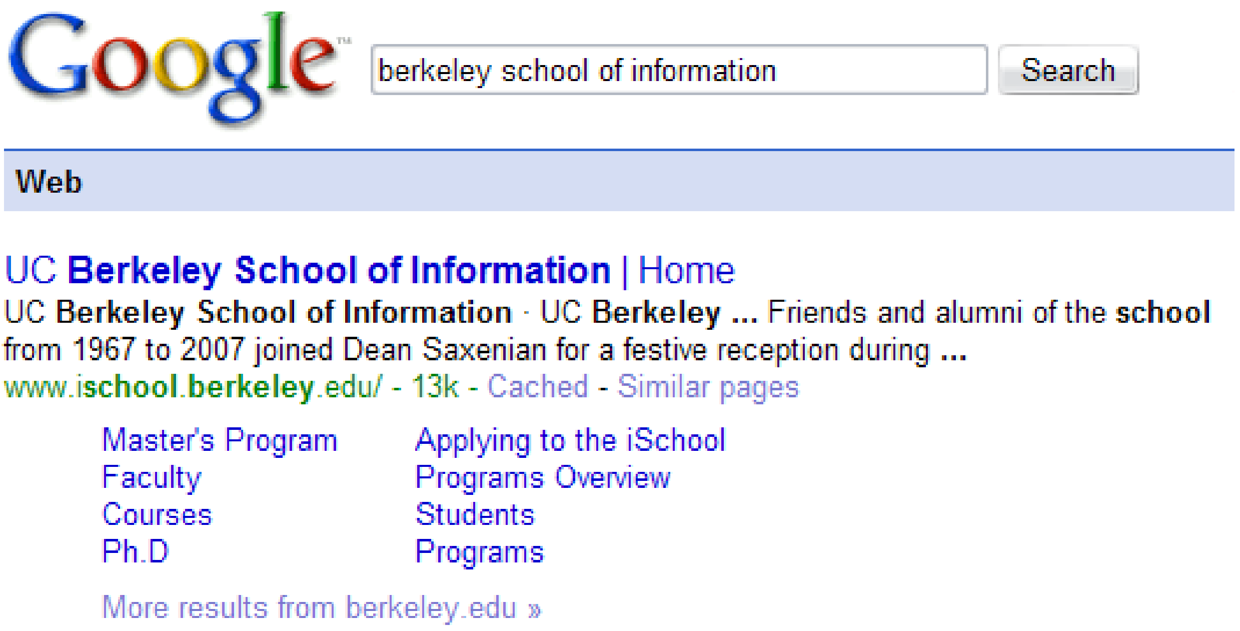
To answer this question, we take a practitioner's approach. We narrow our focus on a practical question:

> Using only the sitemap information, is it possible to extract the set of most useful pages for a website?

We call these useful pages *ulinks*. Who would benefit from ulinks? Any user in the browsing mode (as opposed to searching mode) could potentially benefit from knowing the ulinks of a site before visiting the site.

As a point of reference, Google's search results, for example, occasionally include a small "sitemap" (called "sitelinks") for highly ranked search results (Figure 1 shows an example). An example of sitelinks is shown in Figure 1. According to a patent [3], this sitelink is derived from user behavior, in particular, the number of times a page has been accessed, the amount of time spent on the page, and from the content of the page itself—whether the page contains commercial transactions, etc.

To see whether we can compute the set of useful pages of a website, we designed and prototyped a system based *only* on sitemap information provided by websites. We apply our ulink generation technique to several thousand websites (among the top 100K most popular) and report these results. Our experiment uncovers several limitations of the sitemap format (and the current usage of this format).



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UC Berkeley School of Information - UC Berkeley ... Friends and alumni of the school from 1967 to 2007 joined Dean Saxenian for a festive reception during ...
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Master's Program	Applying to the iSchool
Faculty	Programs Overview
Courses	Students
Ph.D	Programs

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Figure 1: Algorithmically Computed Site Map

The rest of the paper is organized as follows. We describe our crawler for collecting sitemap information and the system for generating ulinks in Section 2. In Section 3, we first present starting dataset for the domains to be crawled (Section 3.1) and then the crawling process for `robots.txt` files and the results from that process (Sections 3.2 and 3.3). We continue by describing the crawling process for sitemaps files and the results from that process (Sections 3.4 and 3.6). In Section 4, we then describe results of applying our ulink generation algorithm to around 4000 websites (Section 4.1). Finally, we present limitations of our algorithm by comparing ulinks and sitelinks (Section 4.2). We also present some recommendations on changes to the sitemap protocol that would help automated ulink generation. We conclude the paper by describing related and future work (Sections 5 and 6).

2 System Design

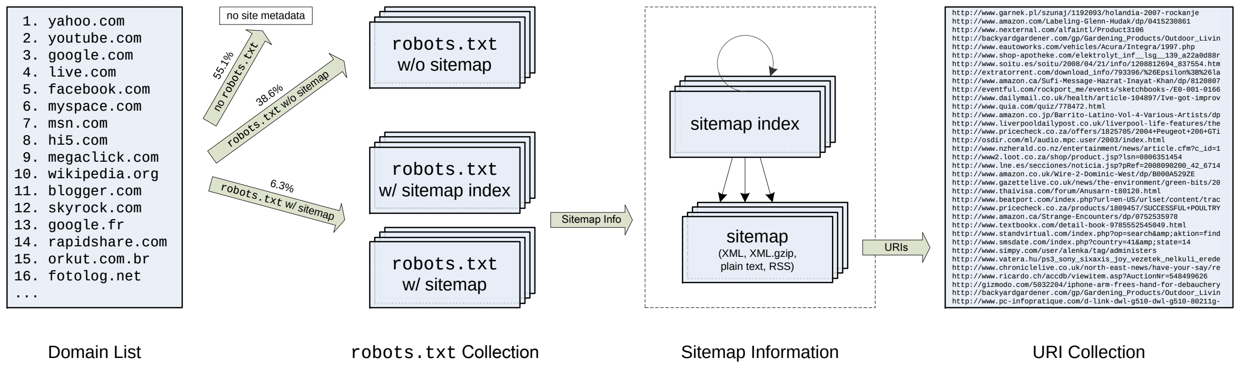
Our system needs to do the following basic functions:

1. crawl the web for sitemap files,

2. store sitemap information so we can use it later, and
3. compute a set of ulinks for a site.

We now describe each of these subsystems.

2.1 Crawler



```
 1. yahoo.com
 2. youtube.com
 3. google.com
 4. live.com
 5. facebook.com
 6. myspace.com
 7. msn.com
 8. hi5.com
 9. megaclick.com
10. wikipedia.org
11. blogger.com
12. skyrock.com
13. google.fr
14. rapidshare.com
15. orkut.com.br
16. fotolog.net
...
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http://www.garnek.pl/szunaj/1192093/holandia-2007-rockanje
http://www.amazon.com/Labeling-Glenn-Hudak/dp/0415230861
http://www.nexternal.com/alfaintl/Product3106
http://backyardgardener.com/gp/Gardening_Products/Outdoor_Livin
http://www.eautoworks.com/vehicles/Acura/Integra/1997.php
http://www.shop-apotheke.com/elektrolyt_inf__lsg__139_a22a0d88r
http://www.soitu.es/soitu/2008/04/21/info/1208812694_837554.htm
http://extratorrent.com/download_info/793396/%26Epsilon%3B%26la
http://www.amazon.ca/Sufi-Message-Hazrat-Inayat-Khan/dp/8120807
http://eventful.com/rockport_me/events/sketchbooks-/E0-001-0166
http://www.dailymail.co.uk/health/article-104897/Ive-got-improv
http://www.quia.com/quiz/778472.html
http://www.amazon.co.jp/Barrito-Latino-Vol-4-Various-Artists/dp
http://www.liverpooldailypost.co.uk/liverpool-life-features/the
http://www.pricecheck.co.za/offers/1825705/2004+Peugeot+206+GTi
http://osdir.com/ml/audio.mpc.user/2003/index.html
http://www.nzherald.co.nz/entertainment/news/article.cfm?c_id=1
http://www2.loot.co.za/shop/product.jsp?lsn=0806351454
http://www.lne.es/secciones/noticia.jsp?pRef=2008090200_42_6714
http://www.amazon.co.uk/Wire-2-Dominic-West/dp/B000A529ZE
http://www.gazettelive.co.uk/news/the-environment/green-bits/20
http://www.thaivisa.com/forum/Anusarn-t80120.html
http://www.beatport.com/index.php?url=en-US/urlset/content/trac
http://www.pricecheck.co.za/products/1809457/SUCCESSFUL+POULTRY
http://www.amazon.ca/Strange-Encounters/dp/0752535978
http://www.textbookx.com/detail-book-9785552545049.html
http://www.standvirtual.com/index.php?op=search&amp;aktion=find
http://www.smsdate.com/index.php?country=41&amp;state=14
http://www.simpy.com/user/alenka/tag/administers
http://www.vatera.hu/ps3_sony_sixaxis_joy_vezetek_nelkuli_erede
http://www.chroniclelive.co.uk/north-east-news/have-your-say/re
http://www.ricardo.ch/accdb/viewitem.asp?AuctionNr=548499626
http://gizmodo.com/5032204/iphone-arm-frees-hand-for-debauchery
http://backyardgardener.com/gp/Gardening_Products/Outdoor_Livin
http://www.pc-infopratique.com/d-link-dwl-g510-dwl-g510-80211g-
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Figure 2: Overview of the Crawling Process

The crawler's job is to download sitemap files from the web. It takes as input a set of *seed* sitemap URIs. It then downloads these seed files and parses them. If these sitemap files point to other sitemap files (that is, these are in fact index files), then it recursively downloads those as well. And so on. After downloading each file, the crawler stores two types of information:

1. information about how the crawler discovered the sitemap, and
2. information pertinent to the download itself (for example, was the download successful, where is the downloaded file stored locally), and

This information is stored in a database, which we describe in detail in Section 2.2.

Basically, the crawler visits each node of the forest whose roots are the seed sitemap URIs. Nodes in this tree correspond to sitemap URIs and there is an edge from node x to y (x is the parent of y) if URI y is a sitemap URI contained in the sitemap file that has URI x. The crawler maintains a database that contains this tree structure and information about the download process.

2.2 Sitemapinfo Database

The *sitemapinfo* database is both a representation of the hierarchical (tree) structure of the sitemap URIs and stores information about the crawl itself. Table 1 shows the schema for our database. *id* is a unique name for a node in the sitemap tree. *parent* is the id of the parent of the node. *uri* is the URI of the sitemap file. *filetype* is the format of the sitemap file—XML, text, gzipped XML, etc. *downloadinfo* denotes whether the download was successful or not. *localfile* is the location of the file where the downloaded file is stored.

Field	**Type**	**Example**
id	`int`	12345
parent	`int`	1000
uri	`string`	`http://www.example.com/sitemap17.xml`
filetype	`enum`	XML
downloadinfo	`enum`	DLDSUCCESS
localfile	`string`	`/path/to/local/file`

Table 1: Database schema for the sitemapinfo database

2.3 Implementation Details and Heuristics

The crawler is written in Python, while the database is a MySQL database. We ran it on a Intel Pentium dual core processor running at 1.6GHz, with 1MB of cache, and 1GB of main memory. Most of the crawl was done over a low-fi home DSL line. It consists of two threads—one that handles the queue containing to-be-crawled sitemaps and one that handles reading and writing of the database.

We did a couple of optimizations to ensure that the crawler ran fast enough. First we noticed that some of the downloads took a long time. In fact, some sites took a long time to respond to HTTP requests. Because coverage was not a concern initially, we set used timeouts both for establishing the initial HTTP connection and for downloading the file. For the former, we used a timeout of 10 seconds and for the latter a timeout of 30 seconds.

Another optimization we used is for sites that have a huge number of sitemap files. To ensure that each site is crawled relatively quickly, we upper bound the maximum number of URIs that will be crawled from each sitemap file as follows: Let α be a number between 0 and 1 and let n_0 be an integer. Let n be the number of sitemap URIs in any given sitemap file. Then we ensure that we crawl at least the maximum of n_0 and αn URIs from file. This ensures that we get representative samples from each sitemap file, but we do not spend too much time crawling any one site. Note: This heuristic works well for the case of sites such as `www.amazon.com`, which contains a large list of inventory items.

The crawl of sitemaps for 6268 sites (for which we had seed sitemap URIs) took about 40 hours. We give more details on the size of these files and their information content in Section 3.

2.4 URI Prefix Tree and Pruning

Given that we have crawled sitemaps for a site S, we want to find out a small set of ulinks for that site. Which webpages in a site of thousands (or even millions) of pages are most useful is subjective at best. Our goal was *not* explicitly to find the best performing ulink generation algorithm. That issue has received a lot of attention by search engines. The 3 most popular search engines (Google, Yahoo, and Live) all provide ulinks. (These are called sitelinks, especially in the context of Google's search results, but we want to use a separate term to avoid confusion.)

We approached the ulink generation issue from a data sufficiency perspective: Do top sites expose enough navigational information in sitemaps that allows simple aggregation schemes to compute a set of ulinks? If not, what additional information should they expose so that simple aggregation schemes expose the navigational structure?

To answer this question, we needed to devise simple aggregation schemes for finding ulinks from *only* sitemap information. It is important to emphasize the "only": Search engines likely use a lot of information that is not contained in sitemap files. Examples of such data might include user preferences measured via user clicks, links structure of the website, content of the pages, etc. We do not have this data and we do not want to use these.

Our aggregation scheme is based on the simple observation: If a URI is useful, then it would occur as a prefix in many different URIs of the site. For example, if a site sells books and each book has a separate webpage. For example, `www.bookseller.com/books/book17.html`), then the prefix `www.bookseller.com/books` would occur very frequently. This forms the basis for our ulink generation algorithm. In our algorithm, we represent each URI as a path (from the root to some node) in a *prefix tree.* In this tree, each URI is broken into components. For example, the components of `www.bookseller.com/books/book17.html` has 3 components: `www.bookseller.com`, `books`, and `book17.html`. Nodes represent these components and edges represent sequence. For each site, the set of nodes and edges form a forest. Furthermore, we define the *weight* of a node as the number of URIs that use that node. For example, if there are two URIs `www.bookseller.com/books/book17.html` and `www.bookseller.com/books/book19.html`, then the weight of the `books` node is 2.

Say we want to find the top-k ulinks from a site. We first construct the URI tree as described above. We then progressively *fold* the leaves of this tree till the number of leaves is as small as possible without being lower than m (a parameter). To choose the next leaf to prune, we use a simple greedy heuristic: Choose an internal node x such that

1. all of x's children are leaves, and

2. the number of nodes remaining if all of x's children are removed is at least m.

From all candidates nodes x, we choose one that has the smallest weight and remove all its leaves. We iteratively choose candidate nodes and remove its leaves till we can find a node x that satisfies the above two conditions. When we cannot remove any node, we output the remaining leaves in descending order of their weights.

We would like to mention the intuition for choosing the smallest weight candidate node: Assuming that different parts of the URI prefix tree represent diverse parts of the site, we want the set of ulinks to cover diverse parts of the site. For example, assume that `www.big-portal.com` is a large portal that sells lots of different items. If we had to pick just 2 ulinks for `www.big-portal.com`, we would prefer to choose, for example,

1. `www.big-portal.com/books` and
2. `www.big-portal.com/music`

instead of choosing

1. `www.big-portal.com/books/fiction` and
2. `www.big-portal.com/books/biography`

because the former covers a larger portion of the URI prefix tree.

We used one simplifying heuristic for generating URI trees: For each site, we added up to 20000 URIs in the tree. If we had more URIs available, we randomly sampled 20000. This was done for efficiency reasons. Note that we chose a number that is large enough that the "heavy" nodes of even trees with a million nodes would be sampled.

3 Quantifying Metadata

Starting from `robots.txt` files, we used our crawler to collect sitemap files. We now quantify the these two kinds of data.

3.1 Domain Statistics

Our starting point is Alexa's dataset of the most popular 100'000 domains. This dataset has some bias, based on the way this dataset is collected. Even though the exact method of how the dataset is collected is not published, we chose to accept the bias, because our research does not depend on the exact ranking of popular domains, but instead just depends on a reasonably large set of popular domains. Before we describe our use of the domain name dataset, here are some basic statistics about it. The distribution of *top-level domains (TLDs)* in that dataset is shown in Figure 3.

Based on this dataset, our crawling process requests `robots.txt` files from all domains (described in Section 3.2).

3.2 Crawling for Robots.txt

Starting from Alexa's dataset of the most popular 100,000 domains, we collect `robots.txt` files. The strategy for that is a simply two-step process. First, the domain name itself is used to request the file, for example sending a request for `http://domain.com/robots.txt`. In most cases, if there is a `robots.txt`, it is either served directly, or there is an HTTP redirect to the `www`-prefixed URI, such as `http://www.domain.com/robots.txt`. However, some servers are setup to redirect *any* requests for `http://domain.com/*` to `http://www.domain.com/`, in which case the request for `robots.txt` is redirected to the site's home page. Hence, we check the result of requesting `http://domain.com/robots.txt` with simple heuristics whether it is HTML, and if it is, we send a second request for `http://www.domain.com/robots.txt`.

Based on this simple two-step process, our crawl of 100,000 domains for `robots.txt` files yields 44,832 files; more detailed statistics about these files can be found in Section 3.3. Various error conditions can be encountered when requesting the files. Here is a collection of the most frequent error conditions when requesting or processing `robots.txt` files:

- *Server Errors:* Some servers encounter internal misconfigurations and return server errors (we received `500`, `503`, and `504` responses). Some have badly configured redirects, in which case the redirect points to unintended resources (such as `http://www.domain.comrobots.txt`, omitting the slash). In all of these cases it is impossible to retrieve a `robots.txt` file.

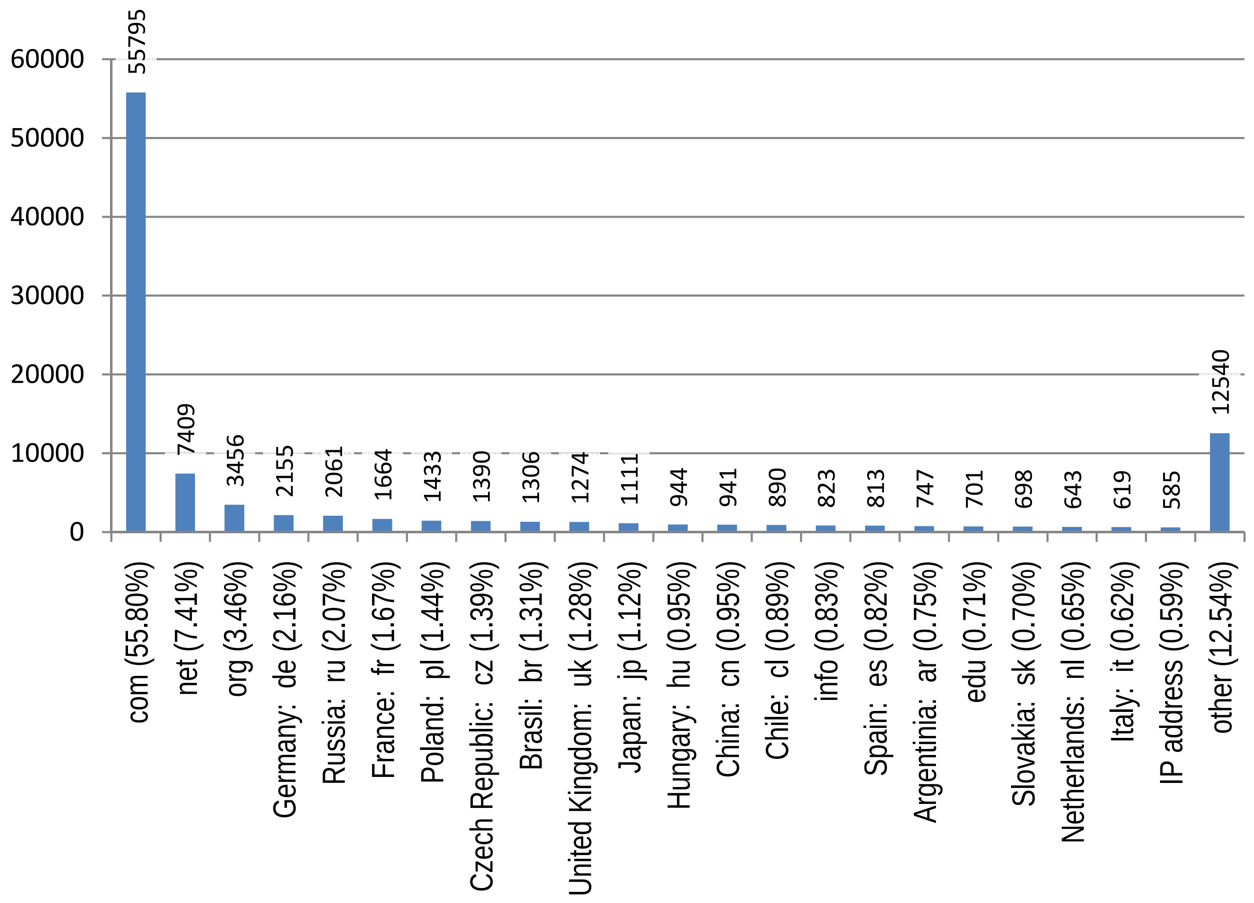

Figure 3: Distribution of TLDs in Popular Domains

- *Media Type Errors:* Some servers respond with a `text/html` entity to the request. In most cases, they still serve a plain text file, but it is mislabeled as a different media type.
- *Charset Issues:* If the server does respond with a `robots.txt` file, there can be character set issues. These may manifest themselves as references to non-existing character sets (for example, `windwos-1251`, `win-1251`[2], and `Latin-1`[3]), character sets not supported on the client side, and `robots.txt` files containing errors with respect to the signaled character set.
- *Size:* The biggest `robots.txt` file is 12.3MB. While this is not a very big file, it is quite a bit larger than anticipated (see Figure 5 for a distribution of files sizes).[4]
- *Connection Problems:* A number of servers did not properly close the connection, so that connections would remain open for a long time. Another problem were dropped connections. However, in the vast majority of cases, connections were handled properly by the crawled servers.

We do not fully implement error recovery (such as trying to fix corrupted `robots.txt` files and retrying failed connection attempts), because error conditions are only encountered in a small fraction of cases. This means that our crawl yields slightly fewer `robots.txt` files than it could with a more robust crawling mechanism, but that is an acceptable compromise allowing a less complex crawler implementation.

One interesting case is a 380,000 lines, 12.3MB `robots.txt` file from `cityweekend.com.cn`. Apparently, this `robots.txt` file lists many user accounts on that site, and specifically sets `Disallow` rules for them. Strictly speaking, this might be necessary if crawlers are to be controlled in specific subsets of user-specific pages, because `robots.txt` rules do not support *patterns* to be specified for URIs, they only support *prefixes*.

[2]These two should be `windows-1251`.

[3]This should be `latin1` or `ISO-8859-1` (preferred).

[4]Most bigger files, though, are either HTML (caused by improper redirects) or text-based sitemaps, which are (usually long) line-by-line lists of a site's URIs.

On the other hand, it seems unlikely that crawlers will interpret files of that size, and there also is the issue of potentially unintended disclosure of account data (discussed in more detail in Section 3.5).

The specification of the `robots.txt` file format only defines the three fields `User-Agent`, `Disallow`, and `Allow`. However, the specification does allow other fields as well, as long as they are based on the same basic syntax. Some other fields that are used are `Noindex`, `Crawl-Delay`, `Request-Rate`, and `Visit-Time` fields, which are defined by specific crawlers, and apparently Web site administrators seem to believe these fields are (at least potentially) interpreted by crawlers.[5] Section 3.3 contains a more complete list of the fields in our sample of `robots.txt` files, as well as other statistics about that data set.

3.3 Robots.txt Data Analysis

The `robots.txt` files crawled as described in Section 3.2 are mainly intended as a starting point to find sitemap information, as described in Section 3.4. However, because the available literature does not present a lot of data about large-scale collections of `robots.txt` files, we first present some statistics about the dataset obtained in the first step of our study.

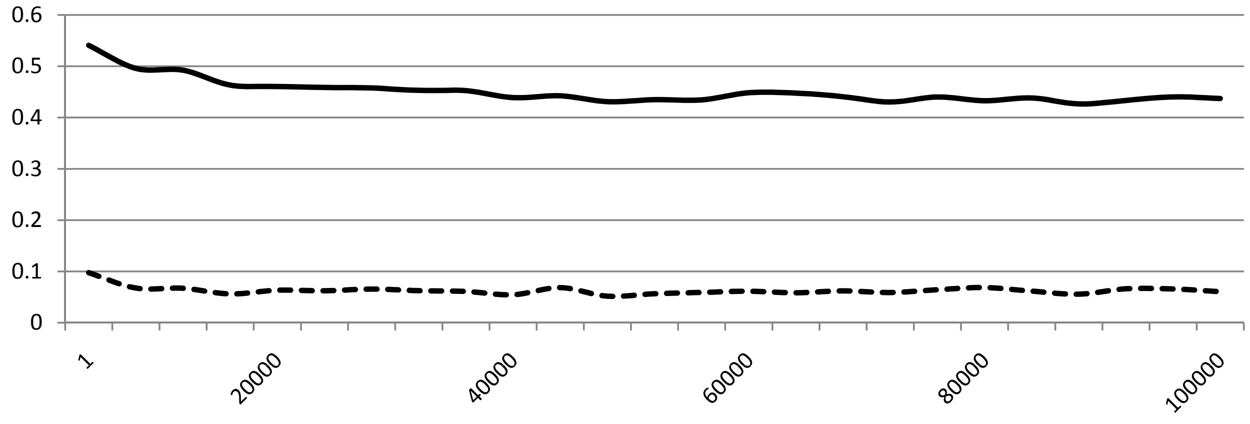

Figure 4: Distribution of Site Metadata

Figure 4 shows the distribution of site metadata in terms of domain ranking. It shows the likelihood of a `robots.txt` file and of sitemap information being available depending on the popularity of the domain (the overall averages are 45.1% for `robots.txt` files and 6.3% for sitemap information). The solid line shows the likelihood of a `robots.txt` file being available, and the dashed line shows the likelihood of sitemap information being available (because in our setup sitemaps are only discovered through `robots.txt` files, the second line can never be higher than the first line, and for our data always is considerably lower than the first). It can be seen that there is a slight correlation between domain popularity and metadata availability (but mostly so for the most popular domains), which makes sense, because more popular sites probably invest more effort in being as visible and as accessible as possible.

Figure 5 shows the distribution of the size of `robots.txt` files (in lines) over the number of `robots.txt` files. It is a heavy-tail distribution with the average size being 29.8 lines ($\sigma = 293.4$) with a median of 7 lines. Since there is a fair number of rather large `robots.txt` files in our dataset, we want to understand the reasons for these sizes. `robots.txt` files can become large for two reasons: because they contain individual configurations for a large number of user agents, or because they contain a lot of instructions for one user agent (or a combination of these two reasons). We therefore looked at how many individual configuration sections for specific user agents the `robots.txt` files contain.

Figure 6 shows the result of this analysis. Again, it is a heavy-tail distribution with an average of 6 sections ($\sigma = 29.5$) and a median of 2. However, in this case there is a noticeable peak in the long tail, with the center at `robots.txt` files having 120 user agent configuration sections.

Our assumption is that this peak has its origin in some widely used and reused template that originally had 120 configuration sections, and then was adapted for various sites by adding or removing some of these sections. There is a variety of templates and generators for `robots.txt` files available on the Web, so assuming that one of these gained popularity is a reasonable explanation of the peak around 120 configuration sections.

[5]`Noindex` has been introduced by Google and `Crawl-Delay` has been introduced by Microsoft.

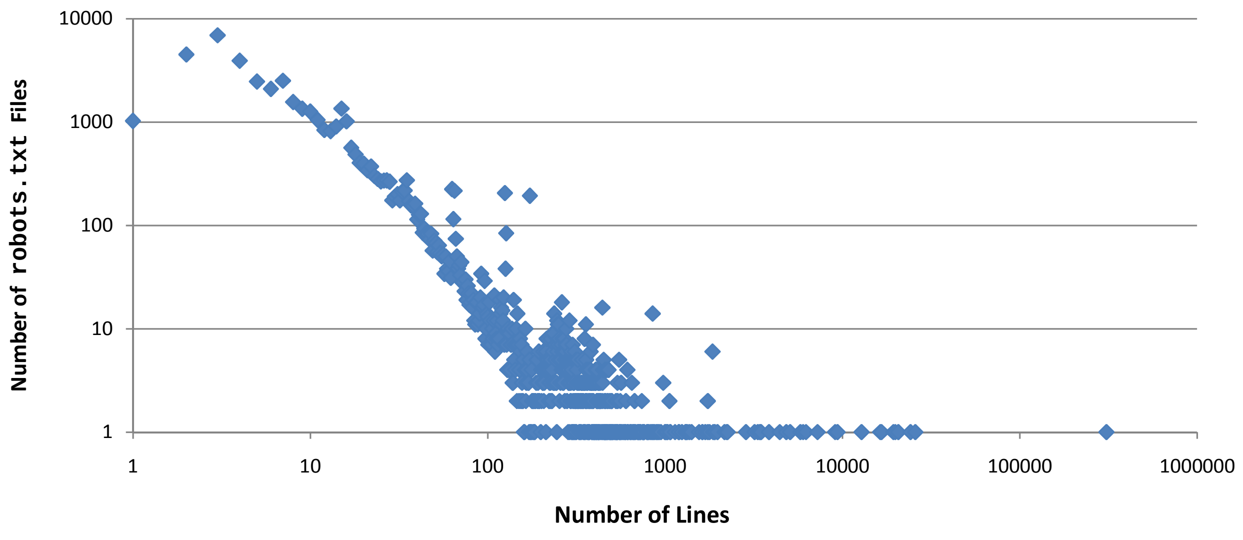

Figure 5: Distribution of `robots.txt` Size

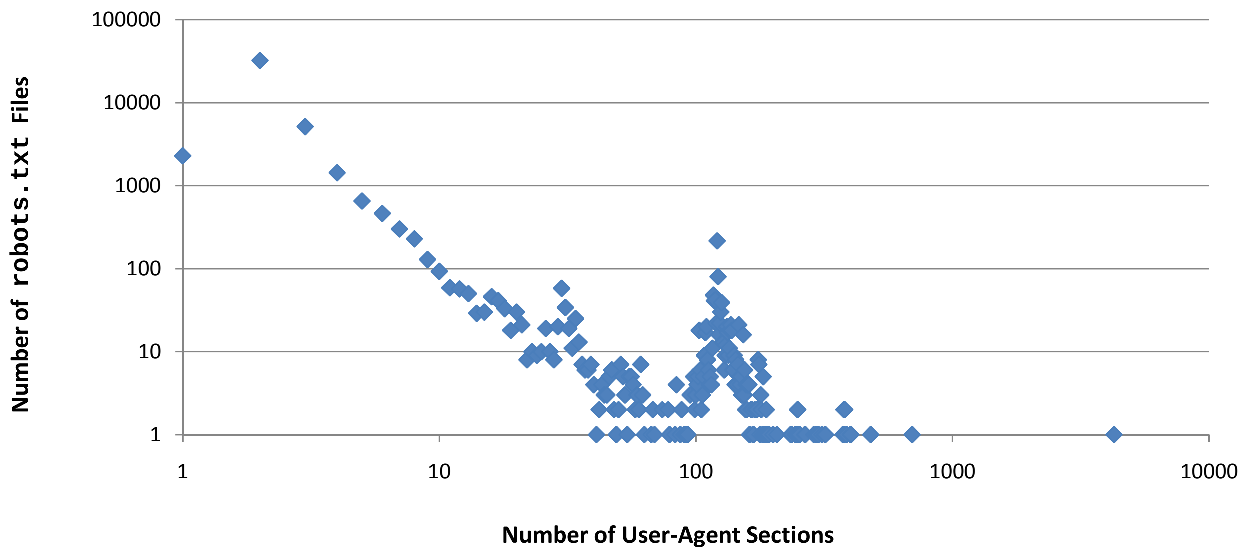

Figure 6: `User-Agent` Sections per `robots.txt` File

To better understand how current `robots.txt` files are using fields to steer crawlers, we looked at the overall usage of fields. As stated in Section 3.2, only the three fields `User-Agent`, `Disallow`, and `Allow` are defined by the `robots.txt` file format, but some other fields also have gained some acceptance. Table 2 contains a list of the ten most popular fields we found (sorted by the number of files containing this field, based on the dataset of 44,832 files), also listing how many occurrences were found in total, and the average number of occurrences per file based on the number of files in which this field was used.

The three standard `robots.txt` fields are among the most frequently used ones, and the popularity of fields drops significantly after the top five. The `Sitemap` field points to a sitemap and is what we use for the second step of our crawling process (described in Section 3.4). Most of the other fields we found are fields only supported by particular crawlers, so if they do appear in an appropriate `User-Agent` section, they can control that particular crawler. One exception to these crawler-specific fields are `ACAP`-prefixed fields, which are part of the *Automated Content Access Protocol (ACAP)*. ACAP is an initiative of content providers to extend the `robots.txt` format so that it is possible to express more specific policies about the crawled content, mostly about access and usage permissions for copyright-protected content.

The statistics shown in Table 2 are influenced by the fact that typically, for one `User-Agent`, there are a number of `Disallow` rules specifying the URI prefixes that should not be crawled by that particular crawler.

	Field Name	#Files	#Fields	Fields/File
1.	`User-Agent`	42,578	225,428	5.29
2.	`Disallow`	39,928	947,892	23.74
3.	`Sitemap`	6,765	10,979	1.62
4.	`Allow`	3,832	23,177	6.05
5.	`Crawl-Delay`	2,987	4,537	1.52
6.	`Noindex`	905	2,151	2.38
7.	`Host`	728	758	1.04
8.	`Request-Rate`	121	127	1.05
9.	`Visit-Time`	89	102	1.15
10.	`ACAP-Crawler`	71	234	3.30

Table 2: Popular Fields in `robots.txt` Files

To better understand the complexity of these rules, and how much of a site's structure they expose in terms of specifying relevant URI spaces, we looked at the size of `User-Agent` sections, meaning those sections of a `robots.txt` files which are specifying `Disallow` (and maybe other) rules for one specific `User-Agent`. These sections are limited by `User-Agent` fields, or by the end of the `robots.txt` file. Figure 7 shows the results of this analysis.

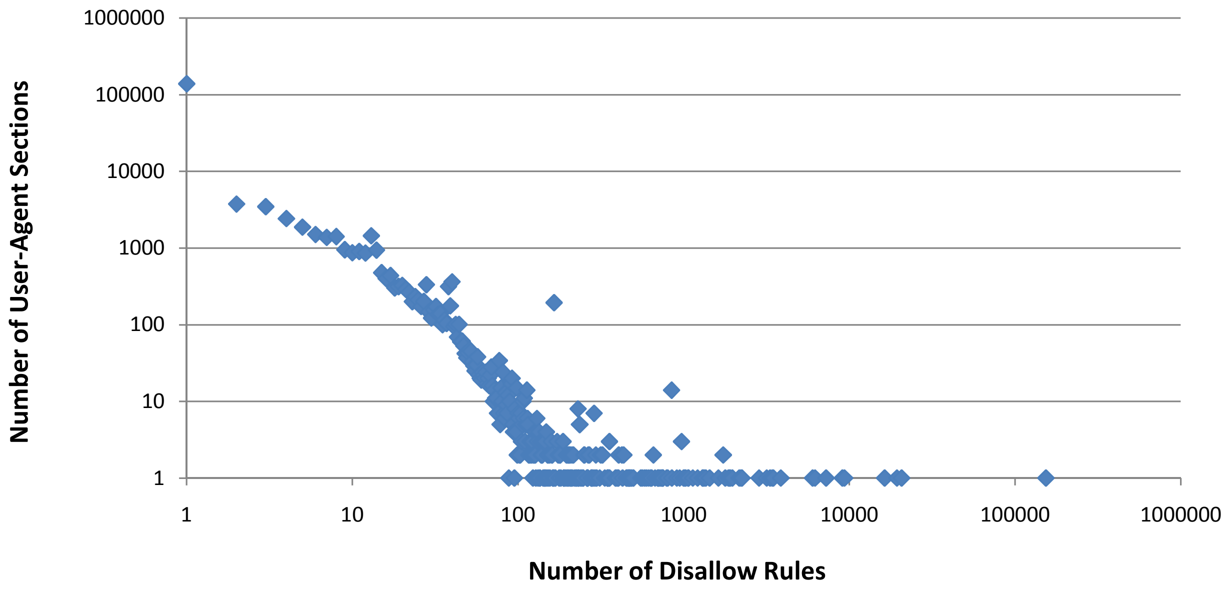

Figure 7: `Disallow` Rules per `User-Agent` Section

The total number of `User-Agent` sections we found is 202,332. 33,589 `User-Agent` sections (16.6%) had no `Disallow` rules at all (not shown in Figure 7 because of the logarithmic axis). This may be due to the fact that they were actually empty, or contained rules other than `Disallow`, such as the ACAP rules mentioned above. Apart from these `User-Agent` sections containing no `Disallow` rules, the distribution shows a heavy-tail pattern, with the number of `User-Agent` sections containing one `Disallow` rule being an outlier (138,695 or 68.5%). There also is one outlier in the other direction with one `User-Agent` section containing 153,540 `Disallow` rules.

The idea of `robots.txt` most often is to restrict crawlers from certain pages and paths on a site. This can make sense because of pages that are frequently updated, because of pages that contain content that should not be indexed (e.g., because of copyright issues), or because of crawlers that interact with the server in unfortunate ways when retrieving pages. This means that while some configurations in `robots.txt` files are global (i.e., apply to all crawlers), there are also some which are for specific crawlers only. We looked at the `User-Agent` fields in our dataset and counted the various strings listed there, trying to adjust for minor variations such as capitalization, whitespace, or version numbers.

Table 3 lists the top ten `User-Agent` field values we found in our dataset (the total number of all

	User Agent	Occurrences	
1.	`*`	46,645	20.70%
2.	`Mediapartners-Google`	3,825	1.70%
3.	`wget`	3,787	1.68%
4.	`WebZIP`	3,014	1.34%
5.	`Mozilla`	2,696	1.20%
6.	`GoogleBot`	2,694	1.20%
7.	`Microsoft URL Control`	2,647	1.17%
8.	`WebBandit`	2,271	1.01%
9.	`lwp-trivial`	2,227	0.99%
10.	`MIIxpc`	2,180	0.97%

Table 3: Popular User-Agents in `robots.txt` Files

fields was 225,304, the distribution of those fields across `robots.txt` files is shown in Figure 8). `*` is the catch-all value which is used to define rules applying to all crawlers; it is by far the most popular value. `Mediapartners-Google` is the crawler for sites participating in Google's *AdSense* program, and is the most frequently listed named crawler. `wget` and `WebZIP` are two similar "crawlers" which usually do not really crawl the Web, but instead are used to download the contents of a site; they are often used to download site contents for offline browsing or post-processing.

Many crawlers do not reveal their identity and use fake `User-Agent` field values to cloak themselves as browsers. The `Mozilla User-Agent` value is the most frequently used one and thus is listed in many `robots.txt` files; but if a crawler is misbehaving in the sense that it does not properly reveal its identity, it is unlikely that it will be sufficiently well-behaving to respect `robots.txt` configurations. `GoogleBot` is Google's search engine crawler (it is using a different identity than the AdSense crawler mentioned earlier). `Microsoft URL Control` is a default identity used within various Microsoft Web tools, and developers can either change that when they develop software using these tools, or leave it at its default value. `WebBandit` is a tool similar to `wget` and `WebZIP`, in most cases not used as a crawler, but for targeted downloads of Web content. `lwp-trivial` is the default name used by the Perl module LWP::Simple. `MIIxpc` is a crawler about which there is no public information available, but apparently it is active enough to be listed in many `robots.txt` files.

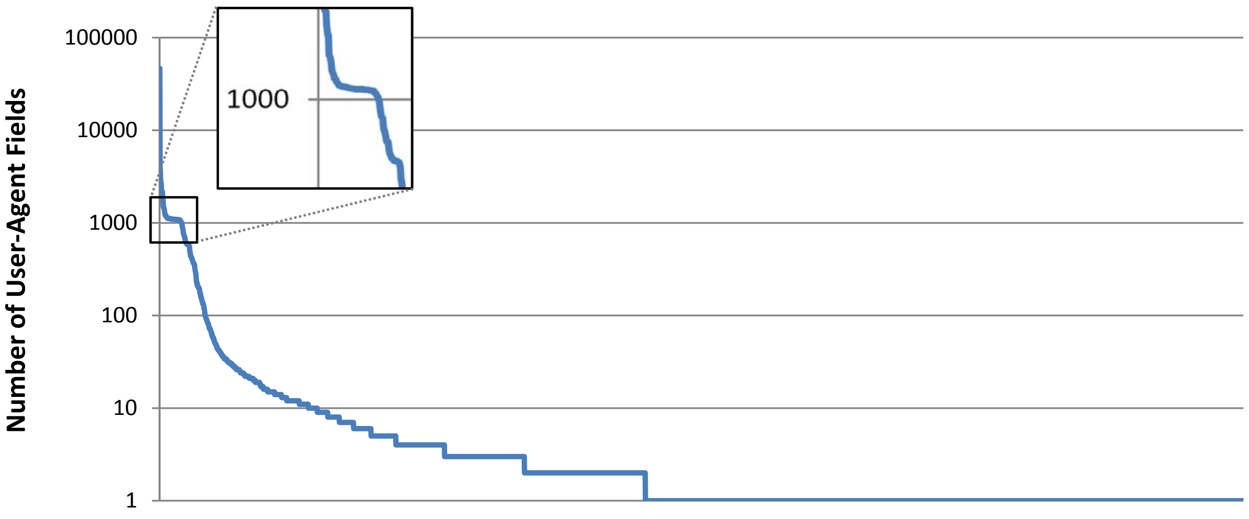

Figure 8: Distribution of `User-Agent` Field Values

Figure 8 shows the distribution of occurrences of `User-Agent` fields. The horizontal axis linearly lists all 4,483 distinct `User-Agent` fields we found (Table 3 lists the top ten) sorted by the number of occurrences. It can be seen that more than half of the `User-Agent` values only occur once. The tableau in the distribution at about 1,000 occurrences (as magnified in the figure) is something that we believe to be caused by `robots.txt` files being created using templates or generators, which usually just present a list of predefined `User-Agent` values, and therefore the values available there will show up in many template-based or generated files.

The fact that many crawlers are only mentioned once or a small number of times can be explained by the fact that a particular crawler might have had problems with the setup of a certain Web site, which then blocked access to that crawler by adding it to its `robots.txt` file. However, this depends on the assumption that this would be a badly behaving crawler which is just poorly implemented, putting undue strain on a server, but still well-behaving in the sense that it respects `robots.txt`. In addition, there are badly behaving crawlers which do not even respect `robots.txt`, in which case they need to be blocked at the HTTP or TCP level, implementing blocking based on HTTP `User-Agent` headers or even IP addresses. Limitations sites enforce for this latter kind of crawler do not show up in `robots.txt` files.

These considerations about crawler behavior and how they might be affected by `robots.txt` files are based on our static `robots.txt` analysis. Section 5 discusses a more dynamic approach chosen by the *BotSeer* system, which observes dynamic behavior of crawlers by setting up honeypots.

3.4 Crawling for Sitemaps

Starting from the `robots.txt` files obtained as described in Section 3.2, the next step to get more complete Web site metadata is to crawl for the second Web site metadata format, the sitemaps format. As shown in Figure 4, the likelihood of a Web site providing sitemaps is much lower than that of it providing a `robots.txt` file, but on the other hand, the information found in sitemaps typically is more valuable, because it is much more specific in listing a Web site's actual page URIs, whereas `robots.txt` files typically only specify a small number of URI prefixes.

While we depend on sitemaps being available through `robots.txt` files, this only provides access to a subset of available sitemap information. Web sites can also directly make sitemaps available to crawlers by uploading them or pinging crawlers to download a sitemap. However, these two methods depend on the Web site explicitly cooperating with the crawler, and therefore is not available to crawlers which have to depend on publicly available information.

Figure 2 shows an overview of the complete crawling process as it starts with the domain dataset and eventually creates a dataset of Web page URIs from those domains. In the starting dataset of 44,832 `robots.txt` files, 6,268 files (14%) contained `Sitemap` fields, for a total of 10,029 fields (it is legal for `robots.txt` files to reference more than one sitemap file; we found one pointing to 530 sitemap files).

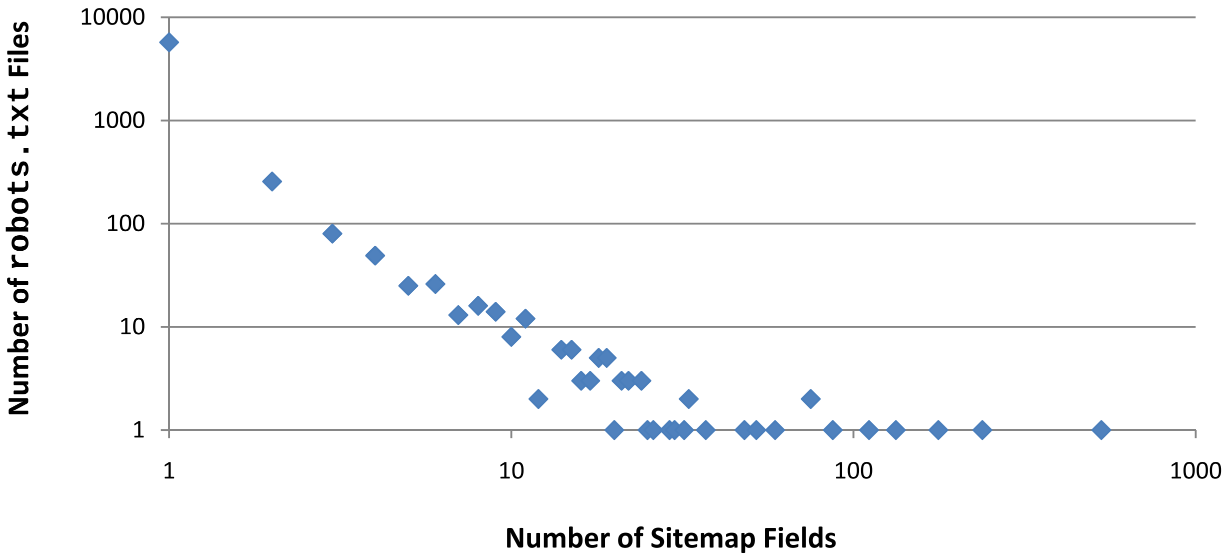

Figure 9: `Sitemap` Fields per `robots.txt` File

Figure 9 shows the distribution of `robots.txt` files according to how many references to sitemaps they contained (`robots.txt` files with no references are not shown in this figure). The vast majority of `robots.txt` files (5,710 or 91%) specify only one sitemap reference, but there also is a considerable number of `robots.txt` files pointing to more than one sitemap file.

The sitemap format specifies two kinds of files: *Index files* and *Sitemaps*. Index files do not contain Web

Level	0	1	2	3	4
#Files	9,081	90,512	43,044	533	510

Table 4: Indirection Level of Sitemap Information

page URIs, they simply point to other sitemap files (they may point to index files, allowing hierarchies of index files); they always use an XML syntax. Table 4 shows the levels of indirections found when crawling for sitemap files, where the indirection level indicates how many index files had to be traversed to the ultimate sitemap file containing a site's page URIs.

Sitemaps can use XML, plain text, or a feed format (RSS 2.0 or Atom) as their syntax. Both kinds of sitemap files may be gzip-compressed. There are size limitations limiting a sitemap file to no more than 50,000 URIs and no more than 10MB in size. Furthermore, there are size limitations limiting an index file to no more than 1,000 URIs and no more than 10MB in size. For compressed files, these size limits apply to the uncompressed files.

The first task when crawling for sitemaps is to navigate sitemap indices and sitemap files, so that all sitemap information for a given site can be retrieved. Here is a collection of the most frequent error conditions when requesting or processing sitemap files:

- *Sitemap Variants:* The sitemap format does not explicitly support different variants of a sitemap to be made available. Some sites contain links to `.xml` and `.xml.gz` files with the same content, which results in duplicates and the necessity to deal with these.
- *Syntax Issues:* A number of sites (slightly more than 1%) assumed that the URI for the sitemaps file(s) in the `robots.txt` file should be enclosed in angle brackets, probably because the format description for the sitemaps file format does show angle brackets and is not sufficiently explicit that these are not part of the actual syntax.[6] For our sitemaps data crawl, we removed the angle brackets and treated those URIs as if they had been correctly specified.
- *Attempted Sitemap Sharing:* Many domains, especially those belonging to the same entity (for example, `google.com` and `google.co.vn`) attempt to share sitemap files. The sitemaps formats does not allow this kind of cross-site references, so it is up to the discretion of the crawler to ignore or use these shared sitemaps.
- *Connection Problems:* A number of servers did not properly close the connection, so that connections would remain open for a long time. Another problem were dropped connections. However, in the vast majority of cases, connections were handled properly by the crawled servers.

The sitemaps specification is silent on whether index files may point to index files, but since it is not specifically disallowed, it is probably allowed, and there are sites that make use of that assumption. As one example of sitemap information crawled from one company, Table 5 shows the number of sitemaps/sitemap indices for various `amazon` domains. It also shows the total number of URIs contained in these sitemaps.

Domain	**#Sitemaps**	**#URIs**
`amazon.com`	4,945	119,346,271
`amazon.ca`	2,980	96,476,534
`amazon.co.jp`	2,933	54,487,651
`amazon.co.uk`	3,177	44,668,202
`amazon.fr`	378	15,571,351
`amazon.de`	3,108	226[7]

Table 5: Sitemap Information about `amazon` Domains

Amazon is a good example for the *Deep Web* motivation described in Section 1. Amazon has a large number of products available through it's Web site, but most pages are dynamically generated and not statically linked from anywhere. Thus, to make all of these pages available to crawlers, all of these product pages must be listed in sitemaps.

[6]The syntax to be used is described as "`Sitemap: <sitemap_location>`" in the definition of how to specify a sitemap location in a `robots.txt` file.

[7]Many download errors were encountered.

3.5 Access Controlled Sitemaps

Starting from the 10,029 references to sitemap files found in `robots.txt` files, the crawling process produced 70,984 successful file downloads of 60,321 distinct files; there were also a number of errors, summarized in Figure 10. Most common errors were timeout errors, which is expected because of our strict 30s timeout policy. There were also a significant number of `404` (Unavailable) errors.

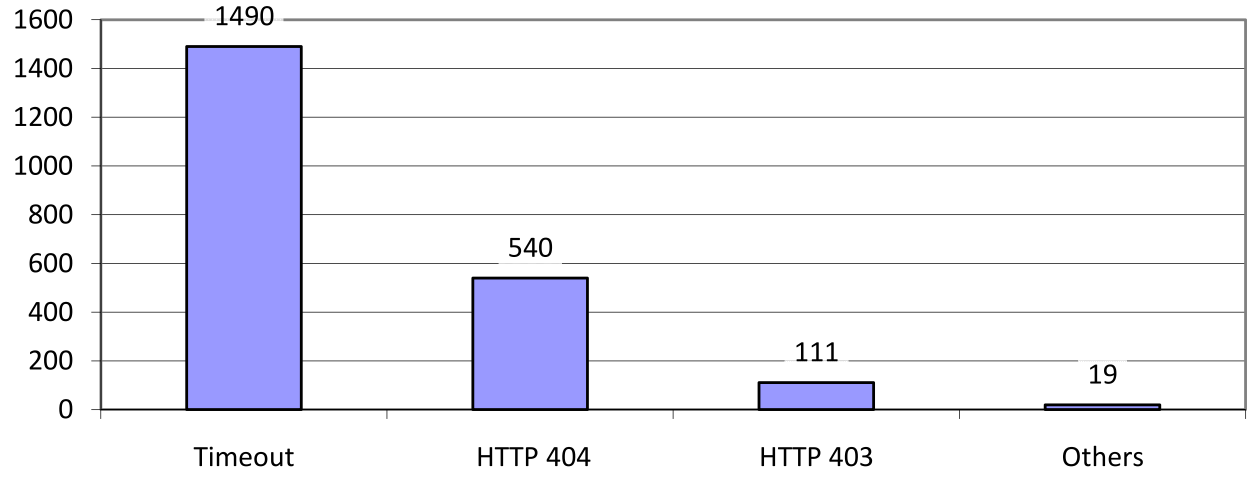

Figure 10: Sitemap Download Errors Encountered

`robots.txt` files are usually openly available, and in principle, the same can be said about sitemaps. However, it seems that some of them are not only unavailable (as signaled by a `404` error), but access controlled. For 111 sitemap files, our crawler received `403` (Forbidden) responses. One interesting question is why sites might access control sitemap files, because we ran into various combinations of HTTP status codes and redirects which indicated that access control might be in place.

Sitemaps might expose more of a site's structure than a site would like to make public, for example a complete set of accounts if a social networking site exposes all accounts as URIs. One the one hand, the site might be interested to make these pages available to search engines; on the other hand, it might want to make harvesting of all the accounts a little less easy than just reading sitemaps. In this case, access control could be based on implicit authentication such as through well-know IP addresses of authorized crawlers. We don't think that access controlled sitemaps will use HTTP authentication, and we received only very few HTTP-level authentication responses in the form of `401` (Unauthorized).

We believe that for brick and mortar businesses, there is probably little incentive to access control sitemap information, because the Web site is only providing representations for goods or services that extend beyond the Web. On the other hand, typical Web 2.0 businesses often do not provide any physical goods or services, so for them, the Web representations often are close to the essence of what they are and do. For these businesses, exposing this information in a machine-readable way is a more critical decision, and therefore they might make the decision to only disclose it to trusted clients, such as crawlers of major search engines.

3.6 Sitemaps Data Analysis

A somewhat surprising discovery is that some big sites do not have any sitemap information. `ebay` and `yahoo` are two examples. Contrast `ebay` to `amazon`, which has by far the largest number of page URIs in its sitemaps. Furthermore, many big sites are only marginally present: Our crawler discovered only 147 URIs for `microsoft`. The reason for this is that Microsoft specifies sitemaps for only a small fraction of its site.

To better understand the usage of sitemap files, it is interesting to look at how many sitemap files an average domain has, and what the distribution is of the number of sitemap files for those domains using sitemaps. Figure 11 shows this distribution. The horizontal axis shows the rank of a domain in terms of the number of sitemap files this domain uses. The vertical axis shows the number of sitemap files for that domain. Of the 5,303 domains included in that figure, the majority (3,880 or 73.2%) use just one sitemap file; but there is a heavy-tail distribution of domains using more than just one sitemap file. Furthermore, there is a small number of outliers which use an exceptionally high number of sitemap files.

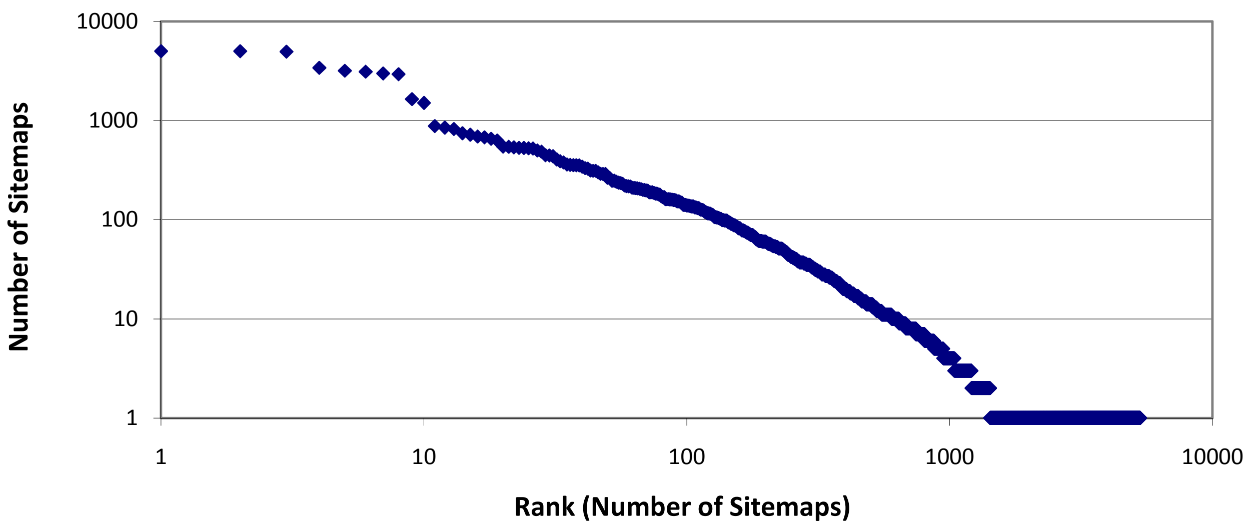

Figure 11: Distribution of Sitemaps Across Domains

	Domain	#Sitemaps
1.	`pricecheck.co.za`	5,006
2.	`ricardo.ch`	5,000
3.	`amazon.com`	4,945
4.	`mailonsunday.co.uk`	3,395
5.	`amazon.co.uk`	3,177
6.	`amazon.de`	3,108
7.	`amazon.ca`	2,980
8.	`amazon.co.jp`	2,933
9.	`alacrastore.com`	1,644
10.	`motofakty.pl`	1,505

Table 6: Top 10 Domains for #Sitemaps/Domain

Table 6 shows the top ten domains in terms of number of sitemaps.[8] While `amazon`, `ricardo` (an auction site), and `pricecheck` are somewhat expected, somewhat surprising is the presence of the news site `mailonsunday`, which seems to have one sitemap file per calendar day. Each file lists the articles that were published on that day. This example contrasts the variance in sitemap organization: `amazon` uses a large number of sitemap files because of its sheer size; `mailonsunday` uses a large number of files in order to better organize its URIs in sitemaps. We discuss the distribution of URIs per sitemap in detail below.

Continuing from the question of sitemap files per domain (as shown in Figure 11), the next question then is how many URIs are eventually listed in these files? Figure 12 shows the distribution of domains based on how many URIs are specified for them in sitemap files (vertical axis), and how many domains with this many URIs exist. The horizontal axis then ranks the domains according to the number of URIs for them. As shown in Table 5, `amazon.com` is the highest ranked domain listing 119,346,271 URIs in its sitemap files (in fact, the top three ranked domains in this figure are the top three domains from Table 5). Another way to look at the same dataset and distribution would be to ask how much of the entire set of URIs contained in sitemaps (836,260,857 URIs) is covered by which share of sites publishing large sitemaps.

Figure 13 shows this coverage of the complete URI dataset by ranking how much domains contribute to covering that dataset. It starts with `amazon.com`'s 119,346,271 URIs, and continues to grow logarithmically until it gets to the point where domains only specify increasingly smaller URI sets and thus contribute almost nothing to the overall coverage. Since the plot is a straight line, it shows that the distribution of URIs across domains is neither exponential $y = e^{\lambda x}$ (in which case, this distribution would have been skewed with more weight toward the origin) nor a power law $y = x^{-\lambda}$ (in which case, this distribution would have been skewed away from the origin).

[8]The top ten are the easily recognizable outliers visible in Figure 11.

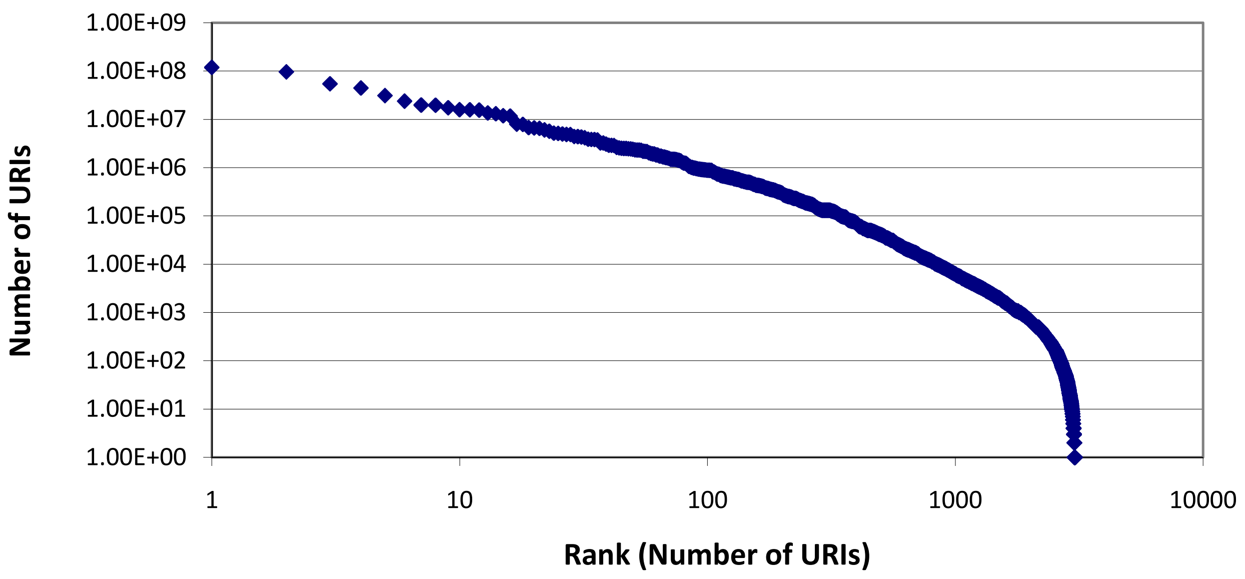

Figure 12: Distribution of URIs Across Domains

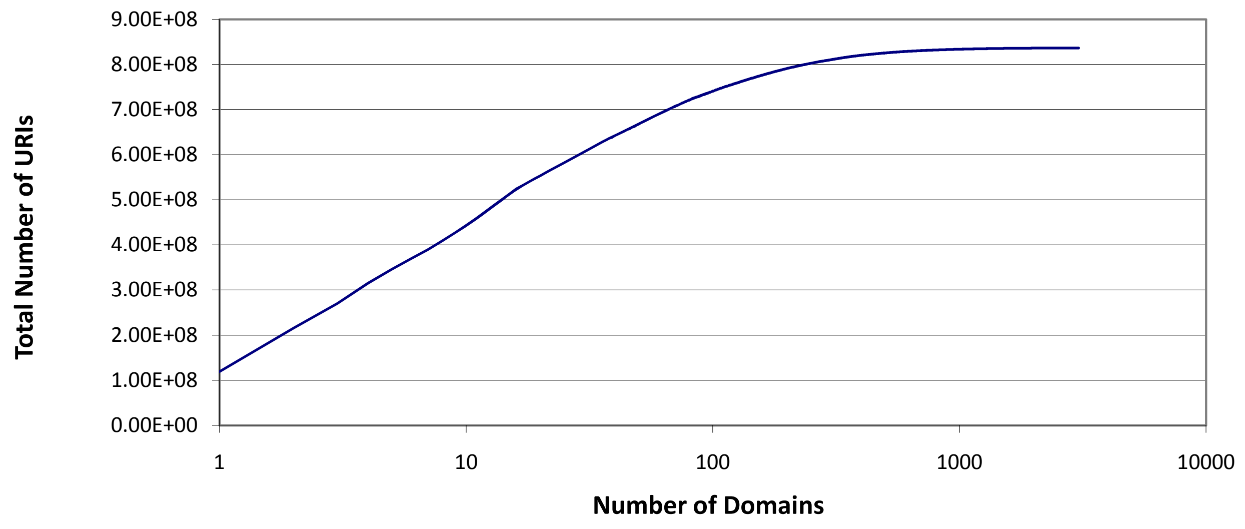

Figure 13: Cumulative View of Figure 12

To better understand how sitemap files are used on average, it is interesting to analyze the usage of sitemap files for managing large sets of URIs. Figure 14 plots the number of URIs in sitemaps versus the number of sitemap files used for storing these URIs. In theory, there should be no data point above the 50,000 URI mark on the 1 sitemap file line, because of the 50,000 URI per sitemap file limit specified by the sitemaps format.

There is much diversity in how sites beyond 100,000 URIs divide their URIs into sitemap files. For example, `pt.anuncioo.com` has a sitemap file with more than 200,000 URIs.[9] On the other extreme, `ricardo.ch` divides its 549,637 URIs into 4,911 files. Really large sites tend to use uniformly large (usually close to the maximum size of 50,000 URIs) sitemap files. Some of the outliers in the bottom right part of the figure are most likely caused by domains where we did have a substantial amount of sitemap files, but downloading the actual files (and then counting the URIs) failed due to timeouts.

As the final analysis of the sitemap data, Figure 15 shows the distribution of the average number of URIs per sitemap file. Since the vertical axis is logarithmic and the horizontal axis is linear, it is clear that this distribution is mostly exponential, except at the tail, where it is super-exponential. Each data point in that

[9]Which is a violation of the sitemaps format that specifies a maximum of 50,000 URIs per file.

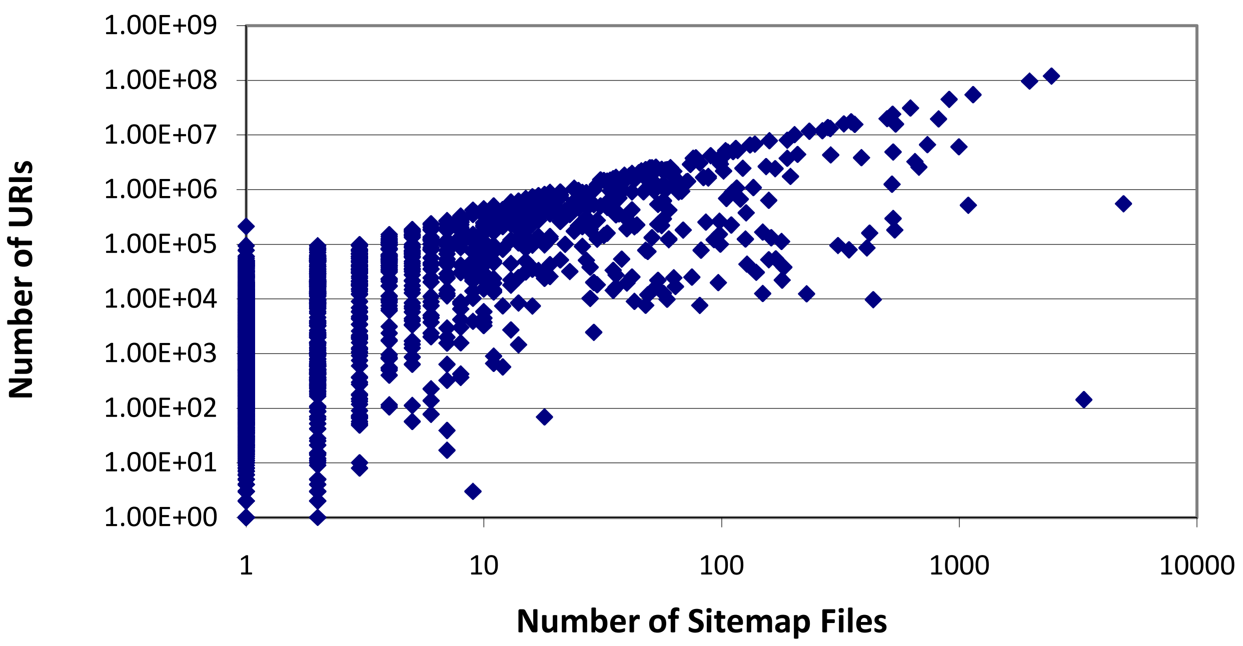

Figure 14: Number of URIs vs. Sitemap Files

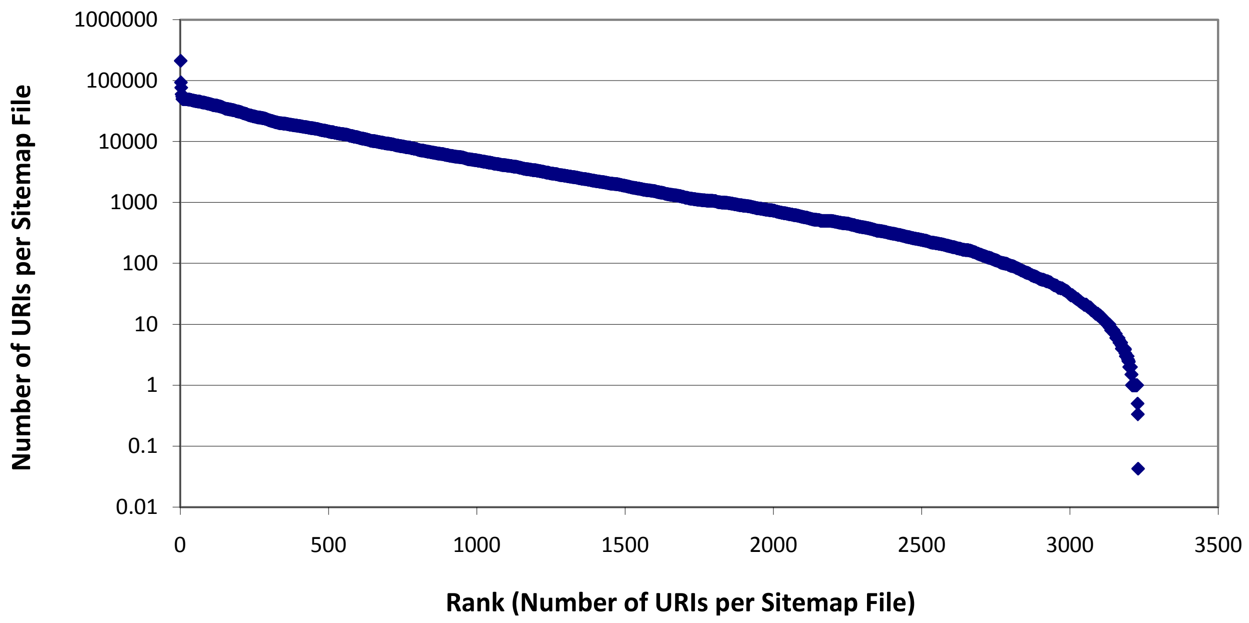

Figure 15: Average URIs per Sitemap File

figure is per domain, which explain data points with less than one URI per sitemap file; these are domains that use index files, but the count of actual page URIs was very low (which may be due to the sitemap access problems mentioned earlier).

4 Useful Links

In this section, we report results of applying our ulink generation algorithm (as described in Section 2.4) to those websites for which our crawler successfully crawled sitemap information.

4.1 Tree Statistics

The URI prefix tree constructed is a representation of the navigational structure of the website. We first present some statistics about the trees that we computed. In these results, we only include those sites for which the crawler managed to download some sitemaps and the sitemaps had a nontrivial number of URIs.

Figure 16 shows the distribution of tree sizes (in terms of the number of nodes). Note the two plateaus at

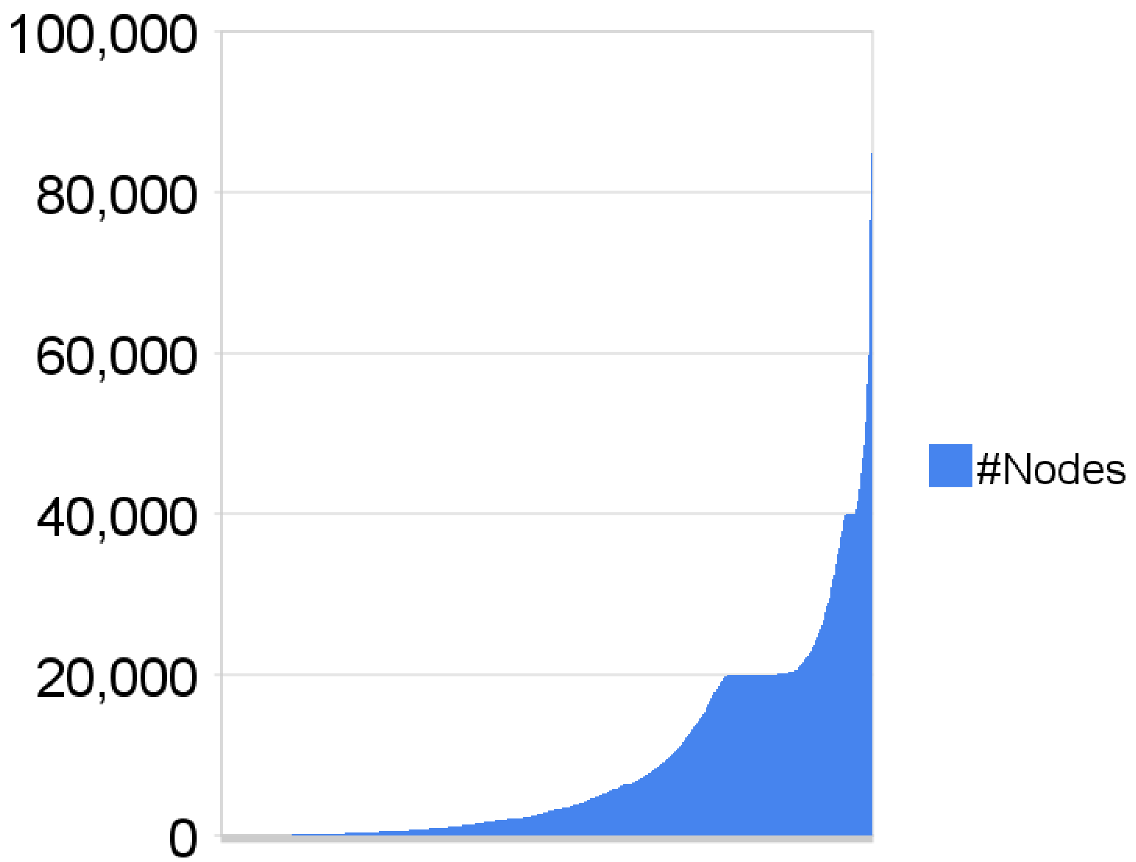

Figure 16: Total nodes per level in the URI prefix trees.

roughly 20K and 40K. These are artifacts of using a maximum of 20K URIs per tree. Why? Consider sites whose URI prefix tree has a small number ($<< 20K$) internal nodes and a very large ($>> 20K$) number of leaf nodes. If we sample 20K nodes from such a tree, then we would get roughly $20K$ leaf nodes and a small number of internal nodes. Hence the plateau at around $20K$. Now consider sites all of whose URIs are the following format: `http://a/b/x/y` where `x` and `y` are unique for each URI, but `a` and `b` are not. Adding each URI adds roughly 2 nodes to the prefix tree. Thus, the total number of nodes is around 40K. This corresponds to the plateau at 40K.

Figure 17 shows the distribution of tree depth across the trees. This plot might be a bit misleading. Namely, for sites that have a large depth, it does not give the distribution of depths across nodes. It might be that a site with depth 15 has only one node at that depth. A better picture emerges if look at the number of nodes at various depths. In the following 2 plots, we aggregate the number of nodes per level. Figure 18 shows the number of nodes per level, while Figure 19 shows the number of leaves per level.

In both these plots, level 0 has a relatively small number of root nodes. The root node corresponds to the domain names—`www.amazon.com` for the site `http://www.amazon.com`. Note that some sites can have multiple domain names, so the number of root nodes is strictly greater than the number of sites for which we have information. Of the 5374 sites for which we managed to successfully download sitemap files, 2433 sites had no URIs. The remaining 2941 sites correspond to 7271 root nodes. The maximum depth we noticed was surprisingly large—402. Some websites have really large URIs. Examples of such sites include `www.nhl.com`.

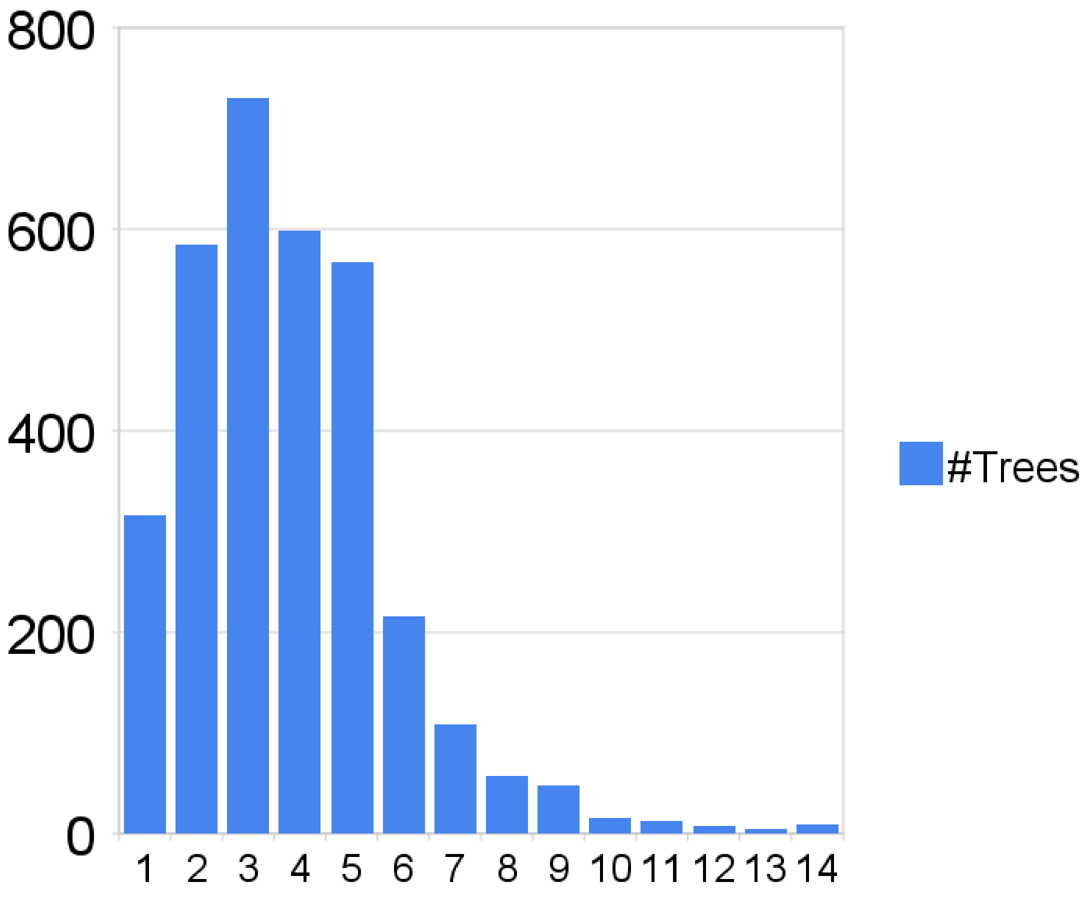

Figure 17: Depth distribution of URI trees.

Further, from these plots it is clear that a large number of sites have a relatively simple URI structure: `http://domain/a` or `http://domain/a/b`.

4.2 Ulinks vs Sitelinks

Recall that one of the main reasons for using sitemap information is to see if sitemap information alone gives us good enough navigational structure. To this end, we compare the set of ulinks generated with the set of sitelinks that Google shows. Notice that one major difference between our ulinks and Google's sitelinks is a ulink is simply a URI. A sitelink, on the other hand, is a URI and an anchor text. For example, one of the sitelinks shown in Figure 1 has URI `http://www.ischool.berkeley.edu/programs/masters` and anchor [Master's Program]. Finding appropriate anchor texts for sitelink URIs is beyond the scope of this project. So, when we compare Google's sitelinks to our ulinks, we compare just the URIs.

We found examples where our ulink generation produced reasonable results, but Google's sitelinks does not. One such site is `www.citibank.com`. Google's search results do not show any sitelinks for queries [www.citibank.com], [citibank], or [citibank.com]. Our ulink generator produces the following as top 5 results:

1. `http://https://web.da-us.citibank.com/cgi-bin/citifi/scripts/help_desk/`
2. `http://https://web.da-us.citibank.com/cgi-bin/citifi/scripts/prod_and_service/`
3. `http://https://web.da-us.citibank.com/cgi-bin/citifi/scripts/plan_and_tools/`
4. `http://https://web.da-us.citibank.com/cgi-bin/citifi/portal/`
5. `http:///https://www.thankyounetwork.com/`

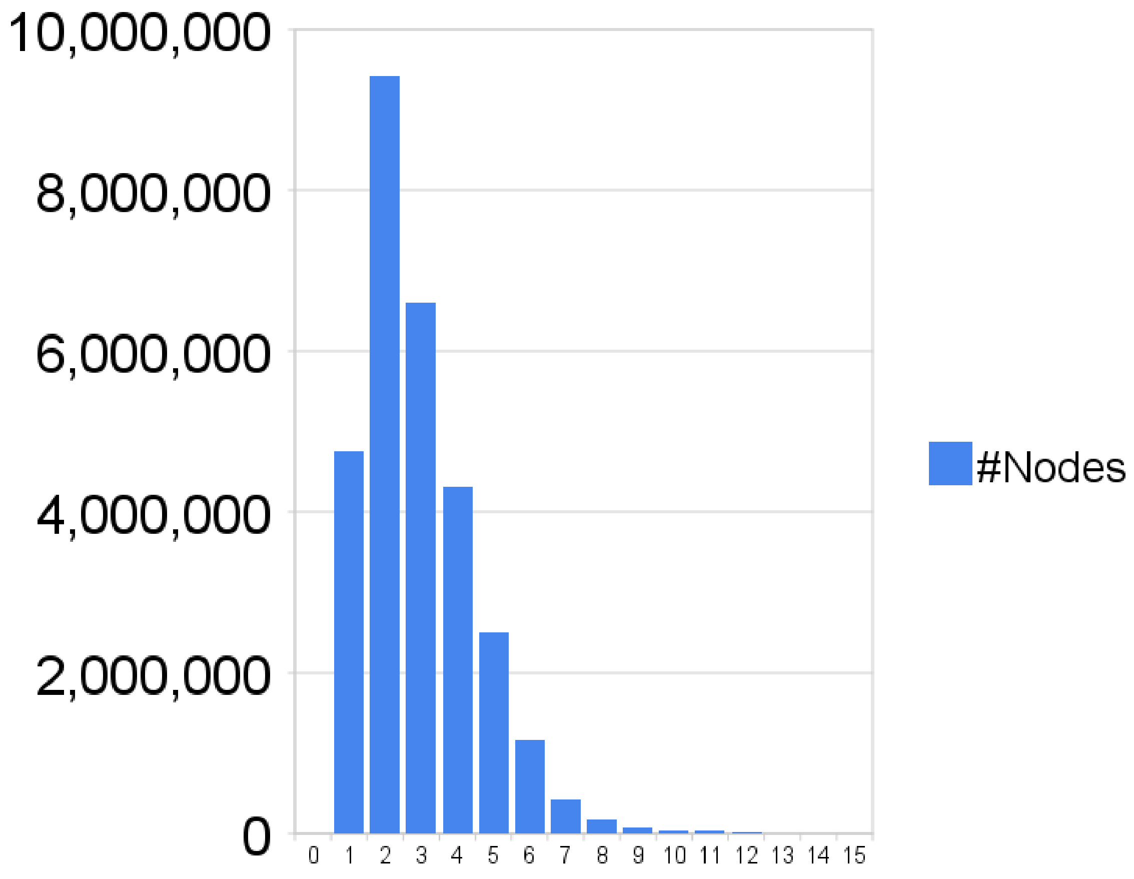

Figure 18: Total nodes per level in the URI prefix trees.

While it is difficult to argue that these are the best results, it is easy to see that these pages are important and useful pages for visitors to the site.

Another example is that of `www.pcworld.com`. For this query google does generate sitelinks but we believe we do a better job in displaying the navigation structure of pcworld.com's website. The top five sitelink on Google are:

1. `http://pcworld.com/downloads/downloads.html`
2. `http://pcworld.com/products/peripherals/printers.html`
3. `http://pcworld.com/howto.html`
4. `http://pcworld.com/article/123867/top_10_ultraportable_laptops.html`
5. `http://pcworld.com/products/computers/desktops.html`

While our ulink generator produces the following as top 5 results:

1. `http:///www.pcworld.com/businesscenter/`
2. `http:///www.pcworld.com/reviews.html`
3. `http:///www.pcworld.com/news.html`
4. `http:///www.pcworld.com/howto.html`
5. `http://pcworld.com/blogs.html`

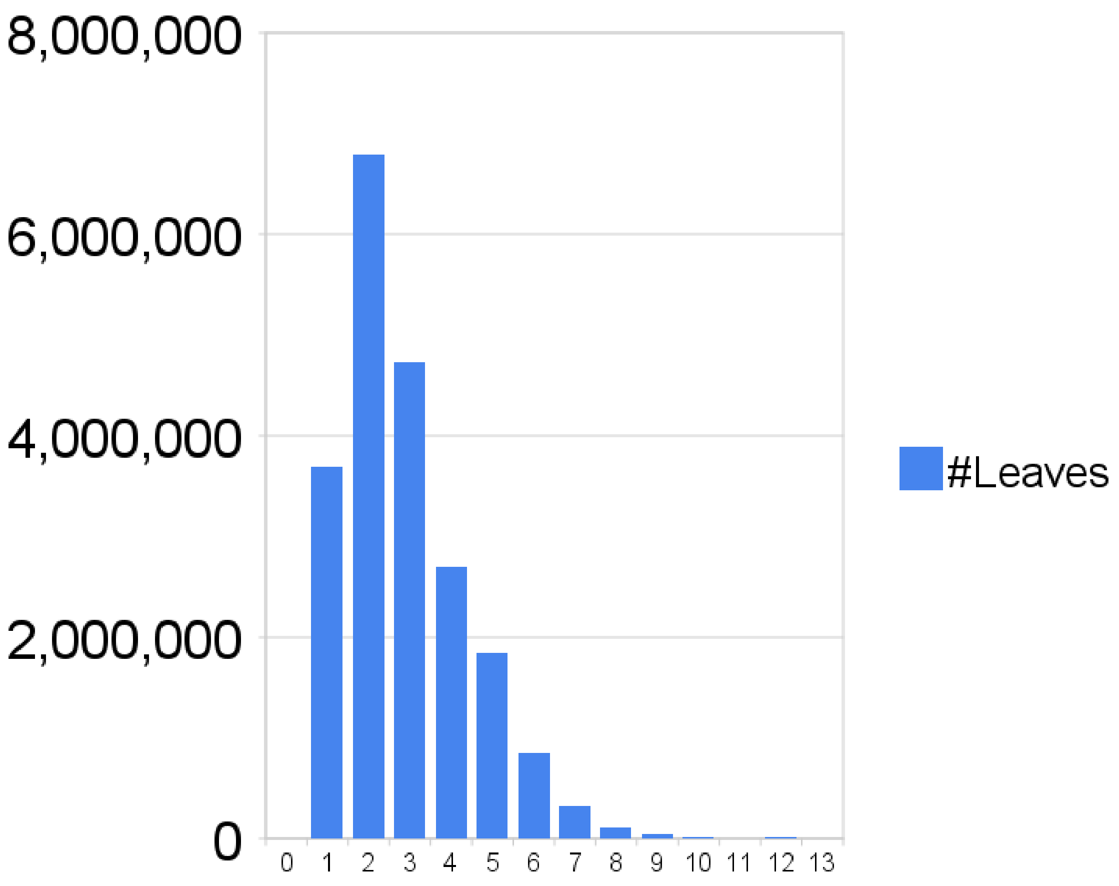

Figure 19: Total nodes per level in the URI prefix trees.

Again, it is difficult to argue that this is the optimum result but if we do look at the navigational structure of `www.pcworld.com` we see that our ulink generator provides relevant structure as compared to that of Google.

Yet another example is that of the website `www.dog.com` where we generate the same site links that Google does for the website `www.dog.com`.The results are comparable. Google produces the follwing sitelinks as their top 5 results:

1. `http://www.dog.com/Breeds/Default.aspx`
2. `http://www.dog.com/dog-beds/`
3. `http://www.dog.com/collars-leashes-and-tags/`
4. `http://www.dog.com/dog-clothes/`
5. `http://www.dog.com/dog-toys/`

Compare that to the top-5 results from our ulink generator:

1. `http:///www.dog.com/Breeds/`
2. `http:///www.dog.com/dog-articles/`
3. `http:///www.dog.com/dog-treats/`
4. `http:///www.dog.com/collars-leashes-and-tags/`
5. `http:///www.dog.com/dog-toys/`

This is an example where our ulinks and Google's sitelinks are quite similar.

There are several sites for which the ulink generation has lower quality than sitelinks. One such example is that of the website `www.zvents.com`. Google produces the follwing sitelinks as their top 5 results:

1. `http://corporate.zvents.com/`
2. `http://www.zvents.com/movies`
3. `http://www.zvents.com/restaurants`
4. `http://www.zvents.com/search?cat=7`
5. `http://www.zvents.com/listings`

Our ulink generator produces the following as the top 5 results:

1. `http:///www.zvents.com/san-francisco-ca/`
2. `http:///www.zvents.com/chicago-il`
3. `http:///www.zvents.com/new-york-ny/`
4. `http:///www.zvents.com/london-england/`
5. `http:///www.zvents.com/los-angeles-ca/`

`zvents.com` is an event aggregator. Note how the ulink generator fails to select different categories of events, which are arguably more useful than pages corresponding to events from different cities.

An interesting example where our tree folding algorithm fails is for `mp3va.com`. Our top-5 ulinks are:

1. `http:///www.mp3va.com/upcoming_albums/`,
2. `http:///www.mp3va.com/release/1010895/`,
3. `http:///www.mp3va.com/release/1010896/`,
4. `http:///www.mp3va.com/release/1010897/`, and
5. `http:///www.mp3va.com/release/1010898/`.

The reason we do not fold the `release` node is because doing so would drop the total number of nodes below our threshold. This problem might be fixed if we relax our minimum nodes requirement.

4.3 Improving Ulinks

The comparison of ulinks and sitelinks shows that even though ulink quality is worse than sitelinks, the approach of finding ulinks using only sitemap information is promising. Certainly, if we could reliably and accurately infer ulink information using only sitemaps information, it would help both the sites, who would have more control over how users perceive their site and the users who use browsing mode more than searching mode.

Our ulink generation uses only the hierarchical structure. It does not use, for example, the `priority` and `lastmod` fields that can be optionally specified in sitemap files. A system that uses these fields might be more accurating at selecting ulinks.

Beyond using fields that are already present in the sitemap protocol, we propose adding another optional field to the sitemap protocol—*title text*. This field would let site publishers associate titles with pages, which would help ulink generation generate anchor text much like sitelinks produces. Instead of one title text per URI, an alternate approach would be allow *key phrases* (or tags) to be attached to URIs.

5 Related Work

Regarding the analysis of `robots.txt` files, there is early work based on a rather small sample [5] (164 sites), and a specific analysis of corporate Web sites [7], also using a small sample (60 sites), and manual analysis of the results. This early work has been limited by much lower adoption of `robots.txt` files, and by the scale of the studies.

More recently, a study of initially only 8'000 sites [13, 14] has been extended in the *BotSeer* project and now covers 13.2 million sites [12]. Their finding (in the initial 8'000 site study) of a 38.5% adoption rate of `robots.txt` files is a little bit smaller than our average of 45.1%, which might be explained by the study's date (October 2006), and also by the fact that the study did not start with the most popular domains, which probably have a higher adoption rate. At the time of writing, the BotSeer Web page reports 2'264'820 `robots.txt` files from 13'257'110 Web sites, which translates to a 17% adoption rate; this considerably lower number may be explained by the fact that the large set of Web sites necessarily contains many rather small sites, which in many cases do not configure `robots.txt` files. In addition to crawling for `robots.txt` files, BotSeer is able to look at the dynamic behavior of crawler by setting up honeypot sites. These sites use `robots.txt` files and act as regular Web sites. BotSeer then logs how ethically crawlers act, i.e. how much of the restrictions defined in `robots.txt` they actually respect. This study of crawler behavior is something that is outside of our scope.

The *Web Modeling Language (WebML)* [4] is an approach to capture the structure of a Web site in a declarative way; it thus would be an ideal starting point for publishing information about site's structure (we do not know how far WebML provides support for this functionality, though). More generally, almost all *Content Management Systems (CMS)* have metadata about a site's content and structure and many support exposing this as `robots.txt` and/or sitemaps. As a popular example, the Drupal CMS supports a module for publishing sitemaps (initially named *Google Sitemap*, the module has been renamed to *XML Sitemap*).

We believe that once the users of richer Web site metadata are there (in the form of crawlers or browsers), it will be easily possible for many Web sites to automatically make that information available. A study by DANIELSON [6] has shown that a more structured overview of a Web site can help significantly in many tasks when interacting with a Web site; however, most approaches for Web site navigation only look at it as a per-site task, rather than looking at it as a fundamental way of how to interact with Web-based information.

To our knowledge, there is no related work in the overlap of the two areas described above, which is our eventual target area: The overlap of crawler-oriented site metadata often investigated in IR-oriented research, and the HCI-oriented question of how to make site metadata available to support navigational tasks on Web sites. Some prior work about looking at the Web graph in general [11] does discuss some questions relevant for our approach, though (specifically, the "URL split" technique presented in that paper). Surprisingly, even the otherwise detailed *Web Content Accessibility Guidelines (WCAG)* [2] say little about how to implement Web site navigation in an accessible may, they are mostly concerned with looking at individual Web pages.

6 Future Work

The work presented in this paper is the first stage of a research project that aims at making metadata about Web site structure available on the Web. We have analyzed the current formats and data and have some recommendations for extending the sitemap format. The next step would be to setup an experimental service that provides access to data-mined navigational metadata, and to make that data available in a browser. A browser could use the two possible data sources mentioned above, first looking for authoritative navigational metadata provided by the site itself, and then accessing a third-party service inquiring about data-mined navigational metadata. This approach supports a transition strategy to a Web where sites can make their navigational metadata available, but if they don't do it, there still is a fallback provided by a third party.

7 Conclusion

This paper presents detailed analyses of the current availability of Web site metadata. The analyses are based on a starting set of the 100,000 most popular domains, and use data these sites make available through their `robots.txt` files and sitemaps. The analyses show that there is a wealth of Web site metadata available, even though currently its sole purpose is to control and steer Web crawlers. Furthermore, we asked how the sitemap format can be improved and to uncover issues, we designed a useful link generator based solely on the sitemap information that websites provide. Based on our analysis, we conclude that even though much information can be obtained from sitemap files, users and websites can be helped much more if more sites make sitemaps available and if the sitemap format itself is extended, for example, to include title text in addition to URIs.

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