A Search/Crawl Framework for Automatically Acquiring Scientific Documents

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Abstract

Despite the advancements in search engine features, ranking methods, technologies, and the availability of programmable APIs, current-day open-access digital libraries still rely on crawl-based approaches for acquiring their underlying document collections. In this paper, we propose a novel search-driven framework for acquiring documents for scientific portals. Within our framework, publicly-available research paper titles and author names are used as queries to a Web search engine. Next, research papers and sources of research papers are identified from the search results using accurate classification modules. Our experiments highlight not only the performance of our individual classifiers but also the effectiveness of our overall Search/Crawl framework. Indeed, we were able to obtain approximately 0.665 million research documents through our fully-automated framework using about 0.076 million queries. These prolific results position Web search as an effective alternative to crawl methods for acquiring both the actual documents and seed URLs for future crawls.

1 Introduction

Scientific portals such as PubMed, Google Scholar, Microsoft Academic Search, CiteSeer, and ArnetMiner provide access to scholarly publications and comprise indispensable resources for researchers who search for literature on specific subject topics. In addition, data mining applications such as citation recommendation [He et al., 2011], expert search [Balog and De Rijke, 2007], topic trend detection [Wang and McCallum, 2006; He et al., 2009], and author influence modeling [Kataria et al., 2011] involve web-scale analysis of up-to-date research collections. While academics and researchers continue to produce large numbers of scholarly documents worldwide, acquisition of research document collections becomes a challenging task for digital libraries.

In contrast with commercial portals (such as the ACM digital library) that rely on clean and structured publishing sources for their collections, open-access, autonomous systems such as CiteSeer and ArnetMiner acquire and index freely-available research articles on the Web [Li et al., 2006; Tang et al., 2008]. Researchers’ homepages and paper repository URLs are crawled and processed periodically for maintaining the research collections in these portals. Needless to say, these repositories are incomplete since the crawl seed lists cannot be comprehensive in face of the ever changing Scholarly Web. Not only do new authors and publication venues emerge, but also existing researchers may stop publishing or change universities resulting in outdated seed URLs. Given this challenge, how can we automatically augment crawl seed lists for a scientific digital library?

Web search has been a constant topic of investigation for IR, ML, and AI research groups since several years. Current Web search engines feature state-of-the-art technologies, ranking algorithms, syntax, personalization and localization features along with efficient infrastructure and programmable APIs making them invaluable tools to access and process the otherwise intractable Web. Despite these attractive advances, to the best of our knowledge, search-driven methods are yet to be investigated as alternatives to crawl-based approaches for acquiring documents in digital libraries. In this paper, we address this gap in the context of open-access, scientific digital libraries. We propose a novel Search/Crawl framework, describe its components and present experiments showcasing its potential in acquiring research documents.

To motivate our framework, we recall how a Web user typically searches for research papers or authors [Richardson and Domingos, 2002; Serdyukov et al., 2008]. As with regular document search, a user typically issues Web search queries comprising of representative keywords or paper titles for finding publications on a topic. Similarly, if the author is known, a “navigational query” [Broder, 2002] may be employed to locate the homepage where the paper is likely to be hosted. Indeed, according to previous studies, researchers provide access to their papers (when possible) to improve their visibility and citation counts making researcher homepages a likely hub for locating research papers [Lawrence, 2001].

¹In this paper, we use the terms “researchers/authors/scholars” and “research documents/papers/publications” interchangeably. We also use (academic) homepages to refer to professional homepages maintained by scholars and “Scholarly/Academic Web” to refer to sections of the Web (for example, university websites and research centers) that cater to scholarly pursuits.
Given previous knowledge in academic browsing, scholars are often able to accurately locate the correct research papers or academic homepages from the Web search results using hints from the titles, search summaries (or snippets) and the URL strings. To illustrate this process, Figure 1 shows an anecdotal example of a search using Google for the title and authors of a paper published at IJCAI last year, “Maximum Satisfiability using Cores and Correction Sets” by Nikolaj Bjorner and Nina Narodytska. For the top-5 results shown for the paper title query (set 1), four of the five results are research papers on the topic. The document at the Springer link is not available for free whereas the last document corresponds to course slides. For the homepage URLs identified from author name search results (from sets 2 and 3), namely:

http://www.cse.unsw.edu.au/~ninan/
http://research.microsoft.com/en-us/people/nbjorner/
http://theory.stanford.edu/people/nikolaj/

we found 55 documents, 46 of which correspond to research publications. This anecdotal search example highlights the immense potential of Web search for retrieving research papers and seed URLs that can be crawled for research papers.

Our Search/Crawl framework mimics precisely the above search and scrutinize approach adopted by Scholarly Web users. Freely-available information from the Web for specific subject disciplines is used to frame title and author name queries in our framework. The two control flow paths for obtaining research papers are highlighted in Figure 2. Research paper titles are used as queries in Path 1. The documents resulting from this search are classified with a paper classifier based on Random Forests [Breiman, 2001]. Author names comprise the queries for Web search in Path 2, the results of which are filtered using a homepage identification module trained using the RankSVM algorithm [Joachims, 2002]. The predicted academic homepages serve as seeds for the crawler module that obtains all documents up to a depth 2 starting from the seed URL. The paper identification module is once again employed to retain only those documents relevant to a scientific digital library among the crawled documents. We summarize our contributions below:

- We propose a novel framework based on search-driven methods to automatically acquire research documents for scientific collections. To the best of our knowledge, we are the first to use “Web Search” to obtain seed URLs for initiating crawls in an open-access digital library.
- Our Search/Crawl framework interleaves several existing and new modules. We extend existing research on academic document classification to identify research papers among documents. Next, we design a novel homepage identification module, a crucial component for our framework, that uses several features based on webpage titles, URL strings, and terms in the result snippet to identify researcher homepages from the results of author name search. The identified homepages form seeds for our Web crawler.
- We provide a thorough evaluation of both the paper and homepage identification components using various publicly-available datasets. Our proposed features attain state-of-the-art performance on both these tasks.
- Finally, we perform a large-scale, first-of-its-kind experiment using 43,496 research paper titles and 32,816 author names from Computer Science. We not only recovered approximately 75% of the papers corresponding to the research paper title queries but were also able to collect about 0.665 million research documents overall with our framework. These impressive yields showcase our Web-search driven methods to be highly effective for obtaining and maintaining up-to-date document collections in open-access digital library portals.

We provide details of our paper and homepage identifica-

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6 For example, from bibliographic listings such as DBLP.
tion modules in Section 2. In Section 3, we describe our experimental setup, results, and findings. We briefly summarize closely-related work in Section 4 and present concluding remarks in Section 5.

2 AI Components in Our Framework

The accuracy and efficiency our Search/Crawl framework is contingent on the accuracies of two components: (1) the homepage identifier and (2) the paper classifier.

Homepage Identification: Academic homepages, known to link to research papers [Lawrence, 2001], form potential seed URLs for initiating crawls in digital libraries. For our Search/Crawl framework to be effective and efficient, it is imperative to identify these pages from the search results of author name queries. Identifying researcher homepages among other types of webpages can be treated as an instance of the webpage classification problem with the underlying classes: homepage/non-homepage [Gollapalli et al., 2015]. However, given the Web search setting, the non-homepages retrieved in response to an author name query can be expected to be diverse with webpages ranging from commercial websites such as LinkedIn, social media websites such as Twitter and Facebook, publication listings such as Google Scholar, Research Gate, and several more. To handle this aspect, we draw ideas from the recent developments in Web search ranking and frame homepage identification as a ranking problem.

Given a set of webpages in response to a query, our objective is to rank homepages better, i.e., top ranks, relative to other types of webpages, capturing our preference among the webpages. For example, consider a name query “John Blitzer” and let the results in response to web search be:

| Rank | URL |
|------|-----|
| 1    | research.google.com/pubs/author14735.html |
| 2    | john.blitzer.com |
| 3    | https://www.linkedin.com/pub/john-blitzer/5/606/425 |
| 4    | http://dblp.uni-trier.de/pers/hd/b/Blitzer:John |

Suppose “john.blitzer.com” is known to be the correct homepage and we are not interested in other webpages. This desirable property can be expressed via three preference pairs among the ranks: \( p_2 > p_1, p_2 > p_3, p_2 > p_4 \) Where \( p_i \) refers to the webpage at rank \( i \). Note that, we do not express preferences among the non-homepages \( p_1, p_3, \) and \( p_4 \). Preference information such as the above is modeled through appropriate objective functions in learning to rank approaches [Liu, 2009]. For example, a RankSVM minimizes the Kendall’s \( \tau \) measure based on the preferential ordering information present in training examples [Joachims, 2002].

Learning to rank methods were heavily investigated for capturing user preferences in clickthrough logs of search engines as well as in NLP tasks such as summarization and keyphrase extraction [Li, 2011]. Note that, unlike classification approaches that independently model both positive (homepage) and negative (non-homepage) classes, we are modeling instances in relation with each other with preferential ordering [Joachims, 2002, Burges et al., 2005, Wan et al., 2015]. We show that the ranking approach outperforms classification approaches for homepage identification in Section 5. We use the following feature types:

1. URL Features: Intuitively, the URL strings of academic homepages can be expected to contain or not contain certain tokens. For example, a homepage URL is less likely to be hosted on domains such as “linkedin” and “facebook”. On the other hand, terms such as “people” or “home” can be expected to occur in the URL strings of homepages (example homepage URLs in Figure 1). We tokenize the URL strings based on the “slash (/)” separator and the domain-name part of the URL based on the “dot (.)” separator to extract our URL and DOMAIN feature dictionaries.

2. Term Features: Current-day search engines present Web search results as a ranked list where each webpage is indicated by its HTML title, URL string as well as a brief summary of the content of the webpage (also known as the “snippet”). Previous research has shown that users are able to make appropriate “click” decisions during Web searches based on this presented information [Richardson and Domingos, 2002, Granka et al., 2004]. We posit that users of Scholarly Web are able to identify homepages among the search results based on the term hints in titles and snippets (for example, “professor”, “scientist”, “student”) and capture these keywords in TITLE and SNIPPET dictionaries.

3. Name-match Features: These features capture the common observation that researchers tend to use parts of their names in the URL strings of their homepages [Tang et al., 2007, Gollapalli et al., 2015]. We specify two types of match features: (1) a boolean feature that indicates whether any part of the author name matches a token in the URL string, and (2) a numeric feature that indicates the extent to which name tokens overlap with the (non-domain part of) URL string given by the fraction: \( \frac{\text{#matches}}{\text{#name tokens}} \). For the example author name “Soumen Chakrabarti” and the URL string: www.cse.iitb.ac.in/~soumen, the two features have values “true” and 0.5, respectively.
The dictionary sizes for the above feature types based on our training datasets (Section 3) are listed below:

| Feature Type                | Size  |
|-----------------------------|-------|
| URL+DOMAIN term features    | 2025  |
| TITLE term features         | 19190 |
| SNIPPET term features       | 25280 |
| NAME match features         | 2     |

**Paper Classification:** Recently, Caragea et al. [2016] studied classification of academic documents into six classes: Books, Slides, Theses, Papers, CVs, and Others. They experimented with bag-of-words from the textual content of the documents (BoW), tokens in the document URL string (URL), and structural features of the document (Str) and showed that a small set of structural features are highly indicative of the class of an academic document. Their set of 43 structural features includes features such as size of the file, number of pages in the document, average number of words/lines per page, phrases such as “This thesis”, “This paper” and the relative position of the Introduction and Acknowledgments sections.

We found that these structural features continue to perform very well on our datasets (Section 3) with precision/recall values in the ranges of 90+. Therefore, we directly employ their features for training the paper classification module in our framework. However, since we are not interested in other types of documents and because binary tasks are considered easier to learn than multiclass tasks [Bishop, 2006], we re-train the classifiers for the two-class setting: papers/non-papers.

### 3 Datasets and Experiments

In this section, we describe our experiments on homepage identification and paper classification along with their performance within the Search/Crawl paper acquisition framework. Our datasets are summarized in Table 1 and described below:

1. For evaluating homepage finding using author names, we use the researcher homepages from DBLP, the bibliographic reference for major Computer Science publications [Gollapalli et al., 2015]. In contrast to previous works that use this dataset to train homepage classifiers on academic websites, in our Web search scenario, the non-homepages from the search results of a name query need not be restricted to academic websites. Except the true homepage, all other webpages therefore correspond to negatives. We collected the DBLP dataset as follows: Using the author names as queries, we perform Web search and scan the top-k results in response to each query. If the true homepage from DBLP is listed among the top results, this URL and the others in the set of Web results can be used as training instances. We used RankSVM for learning a ranking function for author name search. In this model, the preference among the search results for a query can be indicated by simply assigning the ranks “1” and “2” respectively to the true and remaining results. For classification algorithms, we directly use the positive and negative labels for these webpages. We were able to locate homepages for 4255 authors in the top-10 results for the author homepages listed in DBLP.

| Dataset          | Research Papers (Train) | Research Papers (Test) | DBLP Homepages (Train) | DBLP Homepages (Test) | CiteSeer (Train) |
|------------------|-------------------------|------------------------|------------------------|------------------------|------------------|
| Size             | 960(T) 472(+), 959(T) 461(+) | 42,548(T) 4,255(+)     | 43,496 (Titles), 32,816(Authors) |

**Table 1:** Summary of datasets used in experiments. The numbers of total and positive instances are shown using (T) and (+), respectively, for the labeled datasets.

2. Caragea et al. [2016] randomly sampled two independent sets of approximately 1000 documents each from the crawl data of CiteSeer4. These sets, called Train and Test, were manually labeled into six classes: Paper, Book, Thesis, Slides, Resume/CV, and Others. We transform the documents’ labels as the binary labels, Paper/Non-paper, and use these datasets directly in our experiments.

3. For our third dataset, we extracted research papers from the publication venues listed in Table 2 from the CiteSeer4 scholarly big dataset [1], in which paper metadata (author names, venues, and paper titles) are mapped to entries in DBLP to ensure a clean collection. Overall, we obtained a set of 43, 496 paper titles, authors (32, 816 unique names) for evaluating our Search/Crawl framework at a large scale.

| Conference venue/#papers in the CiteSeer4 dataset |
|--------------------------------------------------|
| NIPS (5211), ICML (4721), ICRA (3883), ICML (2979), ACL (2970), VLDB (2594), CVPR (2373), AAAI (2210), CHI (2030), COLING (1933), KDD (1595), SIGIR (1454), WWW (1451), CIKM (1408), SAC (1191), LREC (1128), SDM (1111), EMNLP (920), ICDM (891), EACL (760), HLT-NAACL (692) |

Table 2: Conference venue/#papers in the CiteSeer4 dataset.

We use the standard measures Precision, Recall, and F1 for summarizing the results of author homepage identification and paper classification [Manning et al., 2008]. Unlike classification where we consider the true and predicted labels for each instance (webpage), in RankSVM the prediction is per query [Joachims, 2002]. That is, the results with respect to a query are assigned ranks “1” and “2” based on scores from the RankSVM and the result at rank-1 is chosen as the predicted homepage. The implementations in Weka [Hall et al., 2009], Mallet [McCallum, 2002] and SVMLight [Joachims, 1999] were used for models’ training and evaluation.

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*We refer the reader to Caragea et al., 2016 for a complete listing of features used for training this classifier.

http://dblp.uni-trier.de/xml/

*We used the Bing API for all Web search experiments and retrieve the top-10 results. All queries are “quoted” to impose exact match and ordering of tokens and the filetype syntax was used to retrieve PDF or HTML files as applicable.

http://svmlight.joachims.org/

*Machine learning-based modules are used for extracting titles, venues, and authors of a paper in CiteSeer4 thus resulting in occasional erroneous metadata.
3.1 Author Homepage Finding

We report the five-fold cross-validation performance of the homepage identification module trained using various classification modules and RankSVM in Table 3 The best performance obtained with all features described in Section 2 on the DBLP dataset after tuning the learning parameters (such as C for SVMs), is shown in this table. RankSVM captures the relative preferential ordering among search results and performs the best in identifying the correct author homepage in response to a query. A possible reason for the lower performance of the classification approaches such as Binary SVMs, Naïve Bayes, and Maximum Entropy is that they model the positive and negative instances independently and not in relation to one another for a given query. Moreover, the diversity in webpages among the negative class is ignored and they are modeled uniformly as a single class in these methods.

Table 3: Classifier and RankSVM performances on DBLP dataset.

| Method          | Precision | Recall | F1   |
|-----------------|-----------|--------|------|
| Naïve Bayes     | 0.4830    | 0.9239 | 0.63432 |
| MaxEnt          | 0.8207    | 0.8002 | 0.8102 |
| Binary SVM      | 0.8353    | 0.8149 | 0.8249 |
| RankSVM         | 0.8900    | 0.8900 | 0.8900 |

We point out that false positives are not very critical in our Search/Crawl framework. Including an incorrectly predicted homepage as a seed URL may result in crawling irrelevant documents and extra processing load. However, these documents are subsequently filtered out by our paper classifier.

Table 4: The top-20 features ranked based on Information Gain.

| Feature/Type | Feature | Feature/Type | Feature |
|--------------|---------|--------------|---------|
| NAME         | fracMatch | TITLE | university |
| DOMAIN       | com      | SNIPPET | computer |
| NAME         | hasMatch | TITLE | homepage |
| TITLE        | home     | SNIPPET | university |
| TITLE        | page     | TITLE | linkedin |
| SNIPPET      | professor | SNIPPET | science |
| DOMAIN       | edu      | SNIPPET | discover |
| SNIPPET      | view     | URL | author |
| SNIPPET      | department | SNIPPET | linkedin |
| SNIPPET      | profile | SNIPPET | professionals |

Table 4 shows the top features based on information gain values [Forman, 2003]. These features make intuitive sense; for instance, a researcher homepage is likely to have parts of the researcher name mentioned on it along with terms like “home” and “page” in the HTML title. Similarly, webpages typically ending in “.com” or having “linkedin” in their description are unlikely to be homepages.

3.2 Research Paper Identification

The results of paper classification are summarized in Table 5. We directly used the feature sets proposed by Caragea et al. [2016] and tested various classifiers including Naïve Bayes, Support Vector Machines and Random Forests. All models are trained on the “Train” dataset. The parameters of each model are tuned through cross-validation on the “Train” dataset and the classification performance evaluated on the “Test” dataset. The results of various features sets using a Random Forest for the “paper” class in the binary setting are shown in Table 5. We also show the performance on the “paper” class with the multiclass setting and the weighted averages of all measures over all classes for both the settings in this table. The best classification performance is obtained using a Random Forest trained on structural features with the overall performance being substantially better in the two-class setting rather than the multiclass setting.

Table 5: Classification performance on the test dataset. ‘P/A’ indicate performances for “Paper”/”All” classes.

| Feature | Precision | Recall | F1   |
|---------|-----------|--------|------|
| BoW (P) | 0.86      | 0.92   | 0.889 |
| URL (P) | 0.729     | 0.729  | 0.729 |
| Str/Binary (P) | 0.933 | 0.967  | 0.950 |
| Str/Multiclass (P) | 0.918 | 0.965  | 0.941 |
| Str/Binary (A) | 0.952 | 0.951  | 0.951 |
| Str/Multiclass (A) | 0.893 | 0.902  | 0.892 |

3.3 Search/Crawl Experiments

Finally, we evaluate the two AI components in practice within our Search/Crawl framework using the CiteSeer dataset. To this end, for Path 1, we use the 43,496 paper titles as search queries. Structural features extracted from the resulting PDF documents of each search are used to identify research documents with our paper classifier. For Path 2, the 32,816 author names are used as queries. The RankSVM-predicted homepages from the results of each query are crawled for PDF documents up to a depth of 2 paths. Once again, the paper classifier is employed to identify research documents among the crawled documents.

The number of PDFs and papers found through the two paths in our proposed Search/Crawl framework are shown in Table 6. Since our dataset is based on CiteSeer, we removed all paper search results that point to CiteSeer URLs for a fair evaluation. The number of papers that we could obtain from the original 43,496 collection through both the paths are shown in the last column of this table. We use the title and author names available in the dataset to look up the first page of the PDF document for computing this match.

We are able to obtain 75% (32,605 of the original titles through Path 1 compared to the 40% (17,627 of 43,496) through Path 2 (column 5 in Table 6). In general, given that paper titles contain representative keywords [7, 8], if they are available online, a Web search with appropriate filetype filters is a successful strategy for finding them. The high percentage of papers found along Path 2 confirms previous findings that researchers tend to link to their papers via their homepages [Lawrence, 2001; Gollapalli et al., 2015].

Intuitively, the overall yield can be expected to be higher through Path 2. Once an author homepage is reached, other research papers linked to this page can be directly obtained. Indeed, as shown in columns 2 and 3 of Table 6 the numbers of PDFs as well as classified papers are significantly larger.
higher along Path 2. Crawling the predicted homepages of the 32,816 authors we obtain approximately 14 research papers per query on average (32816 / 13 = 13.78). In contrast, examining only the top-10 search results along Path 1, we obtain 5 research documents per query (43,496 / 8 = 5.44). We used the CRF-based title extraction tool for research papers, ParsCit http://aye.comp.nus.edu.sg/parsCit/ to extract the titles of the research papers obtained from both the paths. The number of extracted unique titles are shown in column 4 of Table 6. The overlap in the two sets of titles is 28,374. Compared to the overall yields along Path 1 and Path 2, this small overlap indicates that the two paths are capable of reaching different sections of the Web and play complementary roles in our framework. For example, the top-20 domains of the URLs from which we obtained research papers along Path 1 are shown in Table 7. Indeed, via Web search we are able to reach a wide range of domains. This is unlikely in crawl-driven methods without an exhaustive list of seeds since only links up to a specified depth from a given seed are explored [Manning et al., 2008].

To summarize, using about 0.076 million queries (43,496 + 32,816) in our framework, we are able to build a collection of 0.665 million research documents (213,683 + 452,273) and 0.267 million unique titles (91,237 + 204,014 − 28,374). About 32 − 33% of the obtained documents are “non-papers” along both the paths. Scholarly Web is known to contain a variety of documents including project proposals, resumes, and course materials [Ortega-Priego et al., 2006]. Indeed, some of these documents may include the exact paper titles and show up in paper search results as well as be linked to author homepages. In addition, using incorrectly-predicted homepage as seeds may result in “bad” documents.

Table 6: #Papers obtained through the two paths in our Search/Crawl framework.

| #Queries | #PDFs | #Papers | #UniqueTitles | #Matches |
|----------|-------|---------|---------------|----------|
| 43,496 titles (Path 1) | 322,029 | 213,683 | 91,237 | 32,565 |
| 32,816 names (Path 2) | 665,661 | 452,273 | 204,014 | 17,627 |

Table 7: The top-20 domains from which papers were obtained along Path-1 of our framework.

Sample Evaluation. Given the size of the CiteSeer² dataset and the large number of documents obtained via the Search/Crawl framework (Table 6), it is extremely labor-intensive to manually examine all documents resulting from this experiment. However, since our classifiers and rankers are not 100% accurate and we only examine the top-k results from the search engine, we need an estimate of how many papers we are able to obtain via our Search/Crawl approach among those that are actually obtainable on the Web. We randomly selected 10 titles from the CiteSeer² dataset and their associated set of 78 authors and inspected all PDFs that can be obtained via our search/crawl framework manually. That is, we searched for the selected paper titles and manually examined and annotated the resulting PDFs. Similarly, the correct homepages of the 78 authors were obtained by searching the Web and manually examining the resulting webpages. The correct homepages were crawled (to depth 2) for PDFs and the resulting documents were manually labeled.

We were able to locate 49 correct homepages of the 78 authors in this manual experiment. Crawling these homepages resulted in 2116 PDFs out of which 1418 were found to be research papers. Our Search/Crawl framework that crawls predicted homepages for the 78 authors and uses paper classifier predictions to identify research papers was able to obtain 1291 research papers. Out of these documents, 1104 match with the intended set of 1418 papers. Thus, we are able to obtain approximately 78% of the intended set of papers along with an additional 187 new ones. Paper search using titles results in 59 PDFs out of which 33 are true papers. Our paper classifier obtains a precision/recall of 84%/97%, predicting 32 out of these 33 papers correctly and 38 papers overall.

4 Related Work

Homepage finding and document classification are very well-studied problems. Due to space constraints, we refer the reader to the TREC 2001 proceedings[10] and the comprehensive reviews of the feature representations, methods, and results for various text/webpage classification problems [Sebastiani, 2002; Qi and Davison, 2009].

Though homepage finding in TREC did not specifically address researcher homepages, this track resulted in various state-of-the-art machine learning systems for finding homepages [Xi et al., 2002; Upstill et al., 2003; Wang and Oyama, 2006]. Among works focusing specifically on researcher homepages, both Wang et al. [2007] and Gollapalli et al. [2015] treat homepage finding as a binary classification task and use various URL and content features. Ranking methods were explored for homepage finding using the top terms obtained from topic models [Gollapalli et al., 2011].

In the context of scientific digital libraries, document classification into classes related to subject-topics (for example, “machine learning”, “databases”) was studied previously [Lu and Getoor, 2003; Caragea et al., 2015]. Often bag-of-words features as well as topics extracted using LDA/pLSA are used to represent the underlying documents in these works. Structural features, on the other hand, are popular in classifying and clustering semi-structured XML documents [Ghosh and Mitra, 2008; Asghari and KeyvanPour, 2013].
In contrast with existing work, we investigate features from web search engine results and formulate researcher homepage identification as a learning to rank task. In addition, we are the first to interleave various AI components with existing Web search and crawl modules to build an efficient paper acquisition framework.

5 Conclusions
We proposed a search-driven framework for automatically acquiring research documents on the Web as an alternative to crawl-driven methods adopted in current open-access digital libraries. Our framework crucially depends on accurate paper classification and researcher homepage identification modules. To this end, we discussed features for these modules and showed experiments illustrating their state-of-the-art performance. In one experiment using a large collection of about 0.076 million queries, our framework was able to automatically acquire a collection of approximately 0.065 million research documents. These results showcase the potential of our proposed framework in improving scientific digital library collections. For future work, apart from improving the accuracies of individual components in our framework, we will focus on including other document formats (for example, .ps and zipped files) as well as other document types (for example, course materials).

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