ExpertSeer: a Keyphrase Based Expert Recommender for Digital Libraries

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We describe ExpertSeer, a generic framework for expert recommendation based on the contents of a digital library. Given a query term $q$, ExpertSeer recommends experts of $q$ by retrieving authors who published relevant papers determined by related keyphrases and the quality of papers. The system is based on a simple yet effective keyphrase extractor and the Bayes’ rule for expert recommendation. ExpertSeer is domain independent and can be applied to different disciplines and applications since the system is automated and not tailored to a specific discipline. Digital library providers can employ the system to enrich their services and organizations can discover experts of interest within an organization. To demonstrate the power of ExpertSeer, we apply the framework to build two expert recommender systems. The first, CSSeer, utilizes the CiteSeerX digital library to recommend experts primarily in computer science. The second, ChemSeer, uses publicly available documents from the Royal Society of Chemistry (RSC) to recommend experts in chemistry. Using one thousand computer science terms as benchmark queries, we
compared the top-$n$ experts ($n = 3, 5, 10$) returned by CSSeer to two other expert recommenders – Microsoft Academic Search and ArnetMiner – and a simulator that imitates the ranking function of Google Scholar. Although CSSeer, Microsoft Academic Search, and ArnetMiner mostly return prestigious researchers who published several papers related to the query term, it was found that different expert recommenders return moderately different recommendations. To further study their performance, we obtained a widely used benchmark dataset as the ground truth for comparison. The results show that our system outperforms Microsoft Academic Search and ArnetMiner in terms of Precision-at-$k$ ($P@k$) for $k = 3, 5, 10$. We also conducted several case studies to validate the usefulness of our system.

1 Introduction

Business organizations depend heavily on information technology to analyze data, manage resources and perform knowledge discovery (1) (2). Studies have shown that companies can improve their market performance by appropriately managing their knowledge and digital property (3). Here, we propose a framework to manage an important resource of organizations – an organization’s experts – based on documents or technical reports of an organization. As such, companies can better optimize personnel utilization through this framework. Finding experts is also important in academia when assistance in answering difficult questions is required, members for a committee (such as for a conference) need to be found, or there is simply an interest in identifying experts of a given domain for knowledge discovery.

Early expert recommender systems depended on manually constructed databases that stored the skills of individuals. However, manual methods do not easily scale. In addition, the list could be biased and limited by the compiler’s knowledge of the domain topic. As a result, recent research has focused on automated expert finding (4), (5), (6), (7). However, automated
expert discovery is still challenging for a variety of reasons. First, effectively collecting or generating a meaningful expertise list for each individual is not a straightforward task. Second, given a query term $q$, it is not obvious how to rank the potential experts who have the needed expertise skills $q$. Third, combining experts based on terms $q'$ that are synonyms or similar to $q$ is not straightforward.

We propose ExpertSeer\(^1\), an open source keyphrase-based recommender system for expert and related topic discovery. ExpertSeer approaches the three challenges described above in a principled way. Based on a given digital library and accessory resources, such as Wikipedia, ExpertSeer generates keyphrases from the title and the abstract of each document in the digital library. These keyphrases are further utilized to infer the authors’ expertise and to relate similar terms. To rank the experts in a given field, the system relies on Bayes’ rule to integrate the relevance and authors’ authority on a given field.

In order to demonstrate the generality of our framework, we have used ExpertSeer to build two expert recommender systems: one for computer scientists (CSSeer\(^2\)) and another for chemists (ChemSeer\(^3\)). The initial experimental results for CSSeer are promising. Our system was able to assign high quality keyphrases to more than 95% of the documents. In addition, the experts recommended are mostly prestigious scholars in the relevant domain. Based on a widely used expert list, our system outperforms two state-of-the-art expert recommenders, ArnetMiner\(^4\) and Microsoft Academic Search (MAS\(^5\)), in terms of Precision-at-$k$ ($k = 3, 5, 10$). Furthermore, users may take advantage of the related keyphrase list to compile a more comprehensive list of experts, since state-of-the-art expert recommenders still generate divergent recommendations, as demonstrated in our experiments.

\(^1\)http://expertseer.ist.psu.edu/
\(^2\)http://csseer.ist.psu.edu/
\(^3\)http://chemseer.ist.psu.edu/
\(^4\)http://arnetminer.org/
\(^5\)http://academic.research.microsoft.com/
This work makes the following contributions.

1. We designed ExpertSeer, an open source general framework for expert recommendation and related keyphrase discovery based on a digital library. Institutes may utilize the system to build an expert recommender based on their own internal or personal collection of documents. To our knowledge, ExpertSeer is the first open source framework for expert recommendation for a scholarly digital library.

2. We applied the generic framework to two different disciplines, namely computer science and chemistry. The system is highly scalable and efficient in managing digital libraries with millions of documents and authors.

3. Using CSSeer, we compare empirically the performance of state-of-the-art expert recommenders. The results show that current expert recommenders still have a moderately divergent suggested list. Based on a publicly available dataset, our system outperforms the others in terms of Precision-at-\(k\) (\(k = 3, 5, 10\)).

4. We have validated that Wikipedia can be a promising keyphrase candidate source on keyphrase extraction of academic documents for large size digital libraries.

The rest of the paper is organized as follows. In Section 2 we review previous works on keyphrase extraction, related term discovery, and expert recommendation. Section 3 introduces our methods for keyphrase extraction, related keyphrase compilation, expert recommendation, and expertise list compilation. Section 4 shows the experiments, evaluation metrics, and results. Several case studies are presented in Section 5. Finally, a summary and description of future work appear in Section 6.
2 Related Work

ExpertSeer automatically extracts keyphrases from documents. Based on these keyphrases, ExpertSeer discovers related phrases and builds the expert list. In the section, we review previous works on keyphrase (or keyword) extraction, related phrase compilation, and expert recommendation techniques.

Automatic extraction of keyphrases in documents has become quite popular. Traditional automatic keyphrase extraction usually consists of two stages: candidate keyphrase selection and keyphrase identification from these candidates (8), (9), (10). The candidate selection process would include many potential keyphrases to achieve a higher recall, but by randomly increasing the size of candidate keyphrases comes the risk of a lower precision and hurting analysis efficiency. One popular method to identify candidate keyphrases is exploiting part-of-speech (POS) taggers to extract nouns or noun phrases as candidates (11), (9). Another possible alternative is to include frequent n-grams in the candidate list (12). However, all of these methods tend to include many trivial and relatively vague terms, such as “study”, “method”, “model”, etc. As a result, the performance relies heavily on the keyphrase identification process, which is usually a supervised learning process that typically relies heavily on lexical and syntactic features, such as term frequency, document frequency, and term locations (9), (12). Recently, methods that utilize features from the Wikipedia corpus (13), (14) were shown to select better keyphrases compared to pure TF-IDF based methods (13). However, these learning methods require a large number of training samples to learn a representative model. In contrast to these approaches, ExpertSeer uses only simple stemming and matching as opposed to learning from Wikipedia pages and yet still efficiently extracts high quality terms with high recall from scientific literature and is much more efficient.

To discover semantically related terms, the most popular way is to use well-known lexical
databases, such as WordNet (15) and FrameNet (16). However, these databases usually have poor coverage for terms in science and engineering fields (17). The co-appearance of words or mentions have been shown to be a good indicator of topic relevance in practice (18). Recently, researchers have resorted to Wikipedia for related term extraction. WikiRelate! (19) employed text distance and category path distance between pages to define the relevance between words in the page title. However, WikiRelate! was limited to comparing unigrams. Gabrilovich and Markovitch (20) transformed terms into a higher dimensional space of concepts derived from Wikipedia. The hyperlink structure of Wikipedia was shown to be an effective measure of relatedness between terms (21). Milne and Witten showed the practicality of identifying key concepts from plain text using Wikipedia (22). Following this line, we are the first to combine Wikipedia pages with scientific literature to infer the relatedness between scientific terms based on Bayes’ rule.

Today, expert discovery continues to be a problem of interest. The problem involves several practical issues, including author name disambiguation, profiling user data (such as contact information and expertise list), defining an expert ranking function, etc. Microsoft’s Libra project (now renamed Microsoft Academic Search) performed name disambiguation and user profiling by identifying and extracting information from every researcher’s homepage (23). A similar approach was also applied by ArnetMiner (24). To identify experts, authors were associated with the text or topics of their publications based on various models (4), (25), (26), (27). Numerous studies suggested associating authors with not only published papers but also conferences or journals (24). To infer the quality of academic articles or the authority of authors, citation-based indices were shown to be good indicators (5) (28). In addition to publications, email communication was also utilized when suggesting experts within an enterprise (29). Several studies performed expert finding by utilizing social network link structure, including propagation based approaches (30), (6), (7), (31), a constraint regularization based approach (32),
and a PageRank-like approach (33). Expert finding has also been applied to social media, such as forums or community question answering portals, to recognize reliable users and contents (34), (35).

Initial experimental results of CSSeer (36) gave a comparison with ArnetMiner and MAS. In this paper, we report several improvements and new functionalities of the system, including the ranking function, the related keyphrase extraction, the expertise generation, and practical computational issues. We also conducted several experiments and case studies.

3 Methodology

We now introduce the methodology of keyphrase extraction, expert recommendation and ranking function, expertise list compilation, and related phrase discovery of the ExpertSeer framework. We also discuss the scalability and the incremental updating procedures, which are important but often overlooked issues for growing or changing digital libraries.

3.1 Keyphrase Extraction

Similar to most state-of-the-art keyphrase extractors, ExpertSeer applies a two-stage approach, namely candidate keyphrase selection and keyphrase identification from candidates. To effectively collect meaningful academic terms as candidates, we resort to two sources: Wikipedia pages and the documents in a given digital library.

ExpertSeer employs Wikipedia to effectively collect meaningful academic terms as candidates. Since category information and pages within a category on Wikipedia are compiled manually, they have highly reliable semantic meaning. The categorization of Wikipedia is utilized to collect terms related to our target domain. Take CSSeer for example, the crawler started from the category “computer science” and retrieved all pages in the category (depth 0), all the pages in the sub-category of computer science (depth 1), up to all pages in the depth 3 category. By a
similar manner, all pages under the category “statistics” and the category “mathematics” up to depth 2 were extracted, since computer scientists use many statistical and mathematical techniques. The titles and the hyperlink texts from the introduction paragraphs of these pages were retrieved as possible keyphrase candidates. Since the titles and hyperlink texts are edited by users, they are usually rich with meaningful semantics. Trivial or vague terms, such as “study”, “method”, “model”, which were usually selected as keyphrase candidates by previous methods, are unlikely to be selected. To increase the recall, the bigrams, trigrams, and quadgrams that appear at least 3 times in the titles of the documents in the digital library are also included in the candidate list. Compared to (12), which selects frequent n-grams as keyphrase candidates, a Wikipedia based method is better because semantically meaningful terms can be naturally included in the candidate list. In addition, it is not straightforward to specify the maximum value of n for n-gram based methods. A small value excludes longer terms (e.g., “strong law of large numbers”), but a large value makes the matching process time consuming and may inevitably include several questionable terms.

To identify keyphrases for each document in the digital library, our framework constructs a trie from all the collected keyphrase candidates, and compares all the titles and abstracts with the keyphrase candidates based on the trie structure, which can efficiently perform the longest-prefix-matching lookup (12). If a match is found, the matched term is selected as one keyphrase of the document. As shown later in Section 4.3, such a method works effectively for more than 95% of the documents in our tested corpus. Compared to supervised learning based keyphrase identification approaches (9), (12), the stemming and matching method is not dependent on the training data. In addition, it is very simple and efficient in practice.
3.2 Expert Ranking

ExpertSeer discovers experts of a given term based on Bayes’ rule. The model naturally integrates textual relevance and quality of the authors’ published papers within a unified framework.

Below, we start by introducing the case where a query term appears in the keyphrase candidate (which is compiled in advance, as introduced in Section 3.1). In this scenario, our system computes the required information offline so that it can efficiently respond to users’ queries. Next, we will show how to approximate the result when the query term does not appear in the candidate list.

3.2.1 The Query Term Appears in the Candidate List

Similar to (4) and (5), we define the problem by a probability model: what is the conditional probability \( p(a|q) \) that an author \( a \) is an expert given a query \( q \)? By Bayes’ rule, \( p(a|q) \) can be written as follows.

\[
p(a|q) = \frac{p(a,q)}{p(q)} \propto p(a,q),
\]

where the denominator term \( p(q) \) can be disregarded because \( q \) is fixed by the time \( p(a|q) \) needs to be determined.

To introduce the set of documents \( D \) to the model, Equation 1 is rewritten into the following form.

\[
p(a|q) \propto p(a,q) = \sum_{d \in D} p(d)p(a,q|d)
\]

\[
= \sum_{d \in D} p(d)p(q|d)p(a|q,d)
\]

\[
= \sum_{d \in D} p(d)p(q|d)p(a|d),
\]

where the last equality holds since an author \( a \) is conditionally independent to a query \( q \) given the document \( d \).

We interpret each term in Equation 2 below.
The term $p(d)$ represents the probability that document $d$ is an important document. This can be inferred by several possible metrics, such as the citation counts, the number of downloads, the reputation of the published conference or journal, graph-based algorithms (e.g., PageRank-like algorithms), or a combination of these factors. Earlier studies show that the number of citations is positively related to the number of downloads (37) and graph-based measures (38). Thus, we simply utilize the citation counts to infer the quality of a paper. In addition, Deng et al. showed that the logarithm of the number of citations is a better indicator of paper quality among several alternatives (5). Thus, ExpertSeer sets the value of $p(d)$ as the logarithm of the number of citations of $d$.

The term $p(q|d)$ is the probability that $q$ is relevant given $d$. We set $p(q|d)$ as a variation of the language model, as shown by Equation 3. However, other textual relevance measures, such as TF-IDF and BM25, can be applied too.

$$p(q|d) = \frac{|d|}{|d| + \mu} \cdot \frac{c(q,d)}{|d|} + \left(1 - \frac{|d|}{|d| + \mu}\right) \cdot \frac{c(q,D)}{|D|},$$

where $|d|$ is the total counts of phrases, not words, in the document $d$, $\mu$ is the Dirichlet smoothing factor, which is used to prevent under-estimating the probability of any unseen phrases in $d$ (39), $c(q,d)$ is the frequency of $q$ in $d$, $|D|$ is the number of phrases, not words, in the corpus $D$, and $c(q,D)$ is the frequency of $q$ in $D$.

Equation 3 is different from the classic language model for the following reasons. The traditional language model represents documents based on the bag-of-words (BOW) assumption, which treats each word as a basic token and assumes independence between words. Our method represents a document by a bag-of-phrases model, which may capture the contexts of a document beyond the granularity of a word. Our system identifies most of the phrases in the documents based on the earlier compiled keyphrase candidate list. If certain texts do not match any phrases in the list, our system tokenizes this piece of texts into words, and ap-
plies the classic language model. Similarly, when the query term \( q \) is an \( n \)-gram formed by words \( w_1w_2...w_n \) \((n > 1)\), the classic language model has the independence assumption so that 
\[
p(q|d) = p(w_1, w_2, \ldots, w_n|d) = p(w_1|d)p(w_2|d) \ldots p(w_n|d)
\]
In practice, however, \( w_1, \ldots, w_n \) depends on others and the sequence of \( w_1, \ldots, w_n \) matters. For example, when we read “support vector”, it is very likely that the next word is “machine”, since “support vector machine” as a whole is a complete phrase.

The term \( p(a|d) \) accounts for the contribution of an author \( a \) given a document \( d \). One possible choice is to divide the contribution equally by the number of authors, as applied in (5). Thus, \( p(a|d) = 1/n_d \) if \( a \) is one of the \( n_d \) number of authors of \( d \) and 0 otherwise. One could also suggest other models such as giving more credits to the first author than the other authors.

For simplicity, we use an indicator function to define the value: \( p(a|d) = 1 \) if \( a \) is an author of \( d \) and \( p(a|d) = 0 \) otherwise.

### 3.2.2 The Query Term does not appear in the Candidate List

For a term \( q \) in the candidate keyphrase list, the expert score \( p(a|q) \) can be computed offline, as shown in Equation 2. However, users may submit a query term \( q' \) that is not included in the candidate list. Calculating \( p(a|q') \) in real time is impractical, since we need to accumulate \( p(d)p(q'|d) \) for all \( d \) in each author’s publications.

One naïve way to bypass the problem is to aggregate all of the documents for each author and build an inverted index to map words to authors. However, the inverted index has no document information. As a result, the quality of the documents is not included in the model. In such a setting, the recommender could potentially return authors who wrote several mediocre documents on topic \( q' \).

To solve this problem, we reformulate Equation 2 as the following (assuming \( q' \) is not in the candidate list).
\[ p(a|q') \propto \sum_{d \in D} p(d)p(q'|d)p(a|d) = \sum_{d \in D_1} p(d)p(q'|d)p(a|d) + \sum_{d \in D_2} p(d)p(q'|d)p(a|d) \approx \sum_{d \in D_1} p(d)p(q'|d)p(a|d), \]

where \( D_1 \cup D_2 = D \), \( D_1 \cap D_2 = \emptyset \), and \( D_1 \) is composed of \( n \) documents with the highest \( p(q', d) \) values in \( D \). Thus, only the authors of the documents with top-\( n \) \( p(q', d) \) scores are integrated and ranked. The documents with lower \( p(q', d) \) scores contribute less to the score of \( p(q', d) \) and are left out. The values of \( p(d) \) and \( p(a|d) \) are calculated as introduced in Section 3.2.1. Since the query term \( q' \) is not in the keyphrase candidate list, we cannot apply Equation 3 to obtain \( p(q'|d) \) directly. Instead, we use Equation 5 to get \( p(q'|d) \).

\[ p(q'|d) = \prod_{w \in q'} \left( \frac{|d|}{|d| + \mu} \cdot \frac{c(w, d)}{|d|} + \left( 1 - \frac{|d|}{|d| + \mu} \right) \cdot \frac{c(w, D)}{|D|} \right), \]

where \( w \)'s are the words in \( q' \). The equation is different from the classic language model in that \( |d| \) and \( |D| \) are the total number of phrases, not words, in \( d \) and \( D \), respectively.

To efficiently discover the \( n \) documents with top \( p(q', d) \) values, the Apache Solr\(^6\) system is employed to build full text index and perform function queries.

### 3.3 Expertise List Compilation and Ranking

When a user queries an author \( a \), the system shows the expertise list of \( a \). This section introduces the compilation as well as the ranking function of the expertise list.

Similar to the expert ranking method, we formally define the problem by a conditional probability distribution: what is the conditional probability \( p(t|a) \) that a term \( t \) is one research expertise given the author \( a \)? Similar to Equation 2, it can be derived as follows.

\[ p(t|a) \propto p(t, a) = \sum_{d \in D} p(d)p(t|d)p(a|d). \]

\(^6\)http://lucene.apache.org/solr/
The terms \( p(d) \), \( p(t|d) \), and \( p(a|d) \) are calculated by the same method introduced in Section 3.2.1.

3.4 Related Phrase Compilation

Different authors may use different terms to describe the same or similar ideas. For example, “logistic regression” is also known as “logit model”. When searching for experts of “logistic regression”, authors who usually use “logit model” to refer to “logistic regression” may not be considered as experts by an expert recommender. In addition, we may want the system to return experts of relevant areas as well. For example, when searching for experts of “logistic regression”, we may also be interested in knowing the experts of “binary classifier” and “multinomial logistic regression”.

To include the experts of relevant topics, ExpertSeer provides a list of related keyphrases of the query term. Thus, users may browse through the experts of the relevant topics to compile a more comprehensive expert list. To ensure that the list includes only non-trivial terms, the list is a subset of the keyphrase candidates.

A naïve way to infer the relatedness between two terms is the co-appearance frequency. However, such a method favors the high frequency terms, i.e., the higher frequency terms tend to be related to every other term.

Instead of counting co-appearance frequency, CSSeer exploits Bayes’ rule to discover related phrases. More formally, given a query term \( t \), the relatedness score of another term \( s \) to \( t \) is given by \( p(s|t) \): the conditional probability that \( s \) is relevant to a document given that \( t \) is relevant to the document. The value of \( p(s|t) \) is derived by the following equation.

\[
p(s|t) \propto p(s, t) = \sum_{d \in D} p(d) p(s, t|d) = \sum_{d \in D} p(d) p(t|d) p(s|t, d) = \sum_{d \in D} p(d) p(t|d) p(s|d) \tag{7}
\]
The terms \( p(t|d) \) and \( p(s|d) \) are calculated by Equation 3. The term \( p(d) \) is the probability that \( d \) is an important document. A document \( d \) is usually more carefully edited if it is more authoritative, and thus the wording is usually more precise. Moreover, other authors are more likely to follow the wording behavior used in \( d \). As a result, we should assign a higher relevance score to two terms appearing in a more authoritative document. The value of \( p(d) \) can be inferred based on several factors, such as citation counts and download counts, as suggested in Section 3.2.

### 3.5 Incremental Updating and Scalability

To support a live digital library that includes new documents over time, incremental updating is very important. For ExpertSeer to import new documents and perform incremental updating, the metadata, citation list, and the keyphrases are extracted when a new document is imported. ExpertSeer updates the following records according to the extracted information. First, the system may add an author to the author list if identified as a new author. Second, the system utilizes the extracted keyphrases to update the authors, expertise list, and the related keyphrase information. Finally, the citation counts of the cited papers are increased. ExpertSeer accomplishes these updates easily, given that it indexes the authors, expert list, keyphrase relationship, and paper information.

ExpertSeer is highly scalable. CSSeer, one of the expert recommender built from ExpertSeer, currently handles over 1,000,000 documents and over 300,000 distinct authors efficiently.

### 4 Experiments

We conducted extensive experiments on the system from several different aspects. We compared the lists of the top-\( n \) returned experts from CSSeer, ArnetMiner, Microsoft Academic Search (MAS), and GS*, a system we used to simulate Google Scholar’s ranking function. We build
Table 1: The top 10 experts of “data mining” returned by CSSeer, ArnetMiner, and Microsoft Academic Search (MAS). Scholars appearing in the top 3 by at least two of them are highlighted by †; scholars appearing in the top 5 by at least two of them are highlighted by ‡; scholars appearing in the top 10 by at least two of them are highlighted by *. $S@n$: consensus score for the top $n$ returns.

| Rank | CSSeer       | ArnetMiner   | MAS       |
|------|--------------|--------------|-----------|
| 1    | Jiawei Han †‡* | Jiawei Han †‡* | Jiawei Han †‡* |
| 2    | Salvatore J. Stolfo Philip S. Yu †‡* | Philip S. Yu †‡* | |
| 3    | Mohammed J. Zaki †‡* Mohammed J. Zaki †‡* | Tzung-Pei Hong | |
| 4    | Osmar R. Zaiane Christos Faloutsos * | Yong Shi | |
| 5    | Maciej Zakrzewicz Jian Pei | Shusaku Tsumoto | |
| 6    | Krzysztof Koperski Heikki Mannila | Alex Alves Freitas | |
| 7    | Marek Wojciechowski Rakesh Agrawal | Andrew Kusiak | |
| 8    | Christos Faloutsos * Charu C. Aggarwal | Mohammed Javeed Zaki | |
| 9    | Wei Wang Raymond Ng | Vinip Kumar | |
| 10   | Srinivasan Parthasarathy Usama M. Fayyad | Xin-Dong Wu | |

$S@3$ 2 3 2
$S@5$ 2 3 2
$S@10$ 3 4 2

GS* to simulate Google Scholar’s ranking function on the top of CiteSeerX’s dataset, because Google Scholar does not provide APIs for users to efficiently query a long list of queries. We also investigated the performance of the Wikipedia based keyphrase extractor.

4.1 Consensus among Different Expert Recommenders

Evaluating a recommender system usually requires an extensive user study. To evaluate an expert recommender system, it is even more difficult since the evaluators need to have sufficient domain knowledge in order to identify the experts of a given topic. Although CSSeer focuses mainly on Computer Science, the sub-domains are still very diverse, ranging from software engineering, data management, applications, to compiler, architecture, and system chip design. As a result, it is very difficult to rely on a small number of individuals to evaluate the expert list.
in several different domains.

To evaluate the performance of CSSeer at a large scale, we compared the expert list returned by CSSeer with two other expert recommender systems, namely ArnetMiner and Microsoft Academic Search, in terms of their recommending consensus. Specifically, we compared the overlap of the top $n$ returned experts of the three systems ($n = 3, 5, 10$). We measured only the overlap of the returns instead of using position based measurements, such as discounted cumulative gain (40) and expected reciprocal rank (41). The reason for this is that given a query term, the top returned names by all three systems are mostly prestigious researchers. Asking an evaluator to differentiate who might be more knowledgeable among a list of reputable researchers is not an easy task and is very likely to be a biased evaluation.

To quantify the measurement, we define the consensus score $S@n$ of one expert recommender system $e_i$ to the other systems $e_1, \ldots, e_{i-1}, e_{i+1}, \ldots e_m$ in Equation (8):

$$S@n \equiv \left| \bigcup_{k \neq i} \left( r_i^{(n)} \cap r_k^{(n)} \right) \right|,$$

where $r_i^{(n)}$ is the set of the top $n$ returns of the $i$th recommender $e_i$, and the $| \cdot |$ function returns the set length.

To make the concept of consensus score clearer, we show $S@n(n = 3, 5, 10)$ for the three
systems using a query term “data mining”. The top 10 names returned by these systems are shown in Table[1]. Among the returned names of CSSeer, 3 of them (Jiawei Han, Mohammed J. Zaki, and Christos Faloutsos) appear in at least one of the other two system’s top 10 list. Thus, \( S@10 \) for CSSeer would be 3. In a similar manner, we can calculate \( S@10 \) for ArnetMiner and MAS as 4 and 2 respectively. Note that although Christos Faloutsos ranked 4th by ArnetMiner, he cannot be counted when calculating \( S@5 \) for ArnetMiner, because the name neither appears in the top 5 returned names of CSSeer nor MAS.

The computation of consensus scores involves no user evaluation, and would thus be amenable to automation of the evaluation process to a large number of queries. However, there is a problem in practice: different expert recommender systems may record the same expert with different name variations (36). For example, Dr. Michael I. Jordan at the University of California Berkeley is recorded as “Michael I. Jordan” in both CSSeer and MAS but is “M. I. Jordan” in ArnetMiner. Dr. ChengXiang Zhai at University of Illinois at Urbana-Champaign is stored as “ChengXiang Zhai” in both CSSeer and ArnetMiner but is “Cheng-xiang Zhai” in MAS. Therefore, naïvely regarding names as strings and performing string matching could generate misleading results. To automate the name disambiguation, we normalized each returned name by lower-casing each letter and keeping only the last name and the first letter of the first name. Thus, “Michael I. Jordan” and “ChengXiang Zhai’ are normalized as “m jordan” and “c zhai” respectively. Since only the top \( n \) returned names are compared, it is less likely that two experts of the same field share the same last name and similar first names.

We compared \( S@n \) (\( n = 3, 5, 10 \)) of the three systems for 1,000 benchmark queries. Although we could use the relevant judgments provided by ArnetMiner directly\[^7\] (42), the number of terms is very small and these terms are mainly of the artificial intelligence, data mining, and information retrieval domains. In the hope of covering diverse sub-domains of Computer Sci-

[^7]: http://arnetminer.org/lab-datasets/expertfinding/
Table 2: Precision at \( k \) \( (P@k, k = 3, 5, 10) \) for different expert recommenders, based on the expert list given in (24)

|       | \( P@3 \) | \( P@5 \) | \( P@10 \) |
|-------|-----------|-----------|------------|
| CSSeer | 0.6667    | 0.7077    | 0.5538     |
| ArnetMiner | 0.6410    | 0.6308    | 0.5538     |
| MAS    | 0.6154    | 0.6       | 0.5308     |
| GS*    | 0.1538    | 0.2308    | 0.2462     |

ence, we intentionally included terms of diverse topics, including hardware (such as “VLSI”), low level machine concepts (such as “compiler” and “virtual machine”), software development (such as “programming language”, “data structure”, and “software engineering”), statistical techniques (such as “nonparametric statistics” and “markov chain monte carlo”), data mining techniques (such as “conditional random fields” and “support vector machine”), and so on. Thus, the 1,000 benchmark queries of terms are diverse and contain both broad and narrow topics.

The consensus scores of the benchmark queries on the three systems are shown in Figure 1. As one can see, the average consensus scores \( S@n \) \( (n = 3, 5, 10) \) are low for all three expert recommenders. Specifically, on average only 0.653 to 0.793 names out of the top 3 returned by one system are overlapped with at least one of the other two systems. For the top 5 returns, the numbers of overlapping names are also small, on average ranging from 1.233 to 1.503. For \( n = 10 \), the number of overlapped names are ranging from 2.733 to 3.207. This suggests that the current state-of-the-art expert recommender systems still have divergent opinions. Relying on only one expert recommender system may obtain a biased expert list.

4.2 Precision Comparison of Different Expert Recommenders

The consensus comparison of the systems discussed in last section shows that in many cases different systems give preference to different experts. However, it is difficult to compare the
quality of different expert recommenders because there is no base standard for reference. To further investigate their performance, user evaluation is inevitably needed.

Instead of conducting expensive user study, we obtain the relevant judgments provided in (24) as the golden standard for expert list comparison. We selected Precision-at-k ($P@k$) as the evaluating metric. Although position aware metrics, such as Discounted Cumulative Gain and Mean Reciprocal Rank, can be applied, they are not selected because such measures are very likely to be biased for expert list evaluation, as discussed in Section 4.1.

We compared the returned names of the three systems (CSSeer, ArnetMiner, and Microsoft Academic Search) and GS*, a system we built to simulate Google Scholar’s ranking function. Google Scholar asks authors to manually input up to 5 phrases to represent their research expertise. When a user submits a query term $q$, Google Scholar retrieves all authors who lists $q$ as their expertise, and rank these authors by the total number of citations they have received. GS* simulates Google Scholar’s behavior as follows: it first retrieves all authors who published papers related to the query term (based on the documents collected by CiteSeerX), and then ranks these authors by their total citation counts. This approach considers both authors’ research interest and authority. However, the ranking function is only based on the total number of citations. As a result, if an author published many high quality papers in area 1 but only several mediocre papers in area 2, the author would still ranked very high when the query term is related to area 2.

Table 2 shows the evaluation results of these systems. When retrieving experts by relevancy and ranking the result by authority, as GS* does, the performance is mediocre. All three state-of-the-art systems (CSSeer, ArnetMiner, and Microsoft Academic Search) perform reasonably well for the top-3, top-5, and top-10 returns, because the ranking function includes not only the relevance between the query term and the authors’ research fields but also the authority of the author in regards to this term. Among the three expert recommenders, our proposed
system, CSSeer, on average performs best. The average scores of $P@3$, $P@5$, and $P@10$ on the benchmark queries are 0.6667, 0.7077, and 0.5538 respectively.

We expect CSSeer to perform better than the other two for the following two reasons. First, both ArnetMiner (43) and MAS seem to treat each word as an independent token. However, a term (e.g., “support vector machine”) may consist of a set of words. CSSeer is very likely to group and index the entire term as one token, since such a term is highly likely to be included in the keyphrase candidate list compiled from Wikipedia and the frequent $n$-grams in the titles of the papers in the given corpus. Second, CSSeer probably assigns a more appropriate authority score to authors of a given query. For a set of authors who have published papers related to a query $q$, ArnetMiner employees a propagation-based approach on the coauthorship network to rank these authors (6), (7). Specifically, ArnetMiner first claims authors who wrote several papers related to $q$ as potential experts, and then assumes that authors who have coauthored with potential experts are more likely to be experts as well. Such a method, however, does not incorporate the citation information, which is usually a good indicator of the quality of a paper. MAS computes Field Rating – the rating of authors on a field – of each author on some terms in advance. However, when a query term is not in the pre-computing list, the ranking function seems to be similar to Google Scholar. As a result, an author who is highly authoritative in one area may dominate the results of another area in which she is less authoritative.

4.3 Coverage of Wikipedia Based Keyphrase Candidates

| Query  | 1       | 2       | 3       | 4       | 5       |
|--------|---------|---------|---------|---------|---------|
| compiler | Ken Kennedy | S. Amaras-inghe | Alok Choudhary | C.-w. Tseng | W.-m. W. Hwu |

*See footnote 8

9 See footnote 8
| Computer network | K. Ramakrishnan | David L. Mills | Márk Jelasity | Anna Karlin | Karl Levitt |
|------------------|----------------|----------------|---------------|-------------|------------|
| Data structure   | Martin Rinard | Viktor Kuncak | G. Stølting Brodal | Lars Arge | J. Scott Vitter |
| Database         | David J. Dewitt | Jiawei Han | Serge Abiteboul | L. Bertossi | C. S. Jensen |
| Information retrieval | W. Bruce Croft | Jamie Callan | Alan F. Smeaton | E. Kushilevitz | Yuval Ishai |
| Intelligent agent | Lin Padgham | Michael Winikoff | M. Wooldridge | Tim Finin | Milind Tambe |
| Linear algebra   | Jack Dongarra | David Walker | James Demmel | R. C. Whaley | Antoine Petitet |
| Machine learning | Andrew Mccallum | R. J. Mooney | Peter Stone | R. Michalski | Pat Langley |
| Markov chain Monte Carlo | Jeffrey Rosenthal | Simon J. Godsill | G. O. Roberts | A. Doucet | C. P. Robert |
| Nonparametric Statistics | Stefan Schaal | S. Vijayakumar | C. G. Atkeson | David M. Blei | R. T. Whitaker |
| Programming Language | Margaret Burnett | B. C. Pierce | Frank Pfenning | Peter Sewell | W. Clinger |
| Quality of service | A. T. Campbell | D. C. Schmidt | Geoff Coulson | Aurel Lazar | K. Nahrstedt |
| Security         | Ran Canetti | D. Pointcheval | Gene Tsudik | Mihir Bellare | David Wagner |
| Semantic Web     | Tim Finin | Steffen Staab | Li Ding | Anupam Joshi | Dieter Fensel |
| Social Network   | Jennifer Golbeck | Mitsuru Ishizuka | Yutaka Matsuo | Peter A. Gloor | David Kempe |
| Software Engineering | Victor R. Basili | M. Wooldridge | N. R. Jennings | M. Zelkowitz | Reidar Conradi |
| Support Vector Machine | Glenn Fung | O. Mangasarian | Yi Lin | K. P. Bennett | Grace Wahba |
| Virtual Machine  | Mendel Rosenblum | Jay Lepreau | Godmar Back | Mike Hibler | P. Tullmann |
| VLSI             | Andrew B. Kahng | Jason Cong | Christof Koch | G. Indiveri | Igor L. Markov |
| Author Name       | Top-15 Expertise                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Note                                                                                      |
|------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|
| Ian T. Foster    | resource management, distributed computing, parallel computer, web service, message passing, distributed system, quality of service, application development, high performance, web services, data management, data transfer, distributed systems, grid computing, high performance fortran                                                                                                                                  | Most cited computer scientist by MAS                                                      |
| Ronald L. Rivest | block cipher, public key, encryption key, radio frequency, mobile robot, digital signature, binary relation, secret key, error rate, efficient algorithm, advanced encryption standard, initialization vector, hash function, learning algorithm, probability distribution                                                                                  | 2nd most cited computer scientist by MAS                                                  |
| Scott J. Shenker | admission control, congestion control, sensor network, routing algorithm, degree distribution, distributed system, network topology, routing protocol, hash table, wireless sensor network, building block, direct product, denial of service, zipf’s law, quality of service                                                                                         | 3rd most cited computer scientist by MAS                                                  |
| Jeffrey D. Ullman | information sources, data model, query language, synthetic data, database system, information retrieval, data mining, object model, case study, random sampling, performance analysis, collaborative filtering, efficient algorithm, next generation, association rules                                                                                     | 4th most cited computer scientist by MAS                                                  |
| Jiawei Han       | data mining, association rule, association rules, knowledge discovery, data stream, efficient algorithm, clustering algorithm, information system, query processing, data warehousing, time series, data analysis, database system, web page, classification accuracy                                                                                                                   | Most search person and 3rd highest H-index by ArnetMiner                                |
| Pat Langley      | machine learning, process model, recommendation system, nearest neighbor, knowledge base, learning algorithm, intelligent system, artificial intelligence, reinforcement learning, mobile robot, domain knowledge, data mining, knowledge discovery, bayesian network, feature selection                                                                                   | 2nd most search person by ArnetMiner                                                    |

Table 5: Top 15 expertise list of 10 selected authors
The Wikipedia based keyphrase candidates are usually highly meaningful terms since Wikipedia titles and link texts are manually edited. However, the coverage (or how well these terms cover the topics in the given discipline) is unknown. Although we intentionally include Wikipedia pages related to Computer Science, Statistics, and Mathematics, whether these pages are adequate topics to represent most CiteSeerX documents is still an unanswered question.

In order to answer this question, we begin by studying the distribution of the number of the keyphrases found in a document. We randomly select 10,000 documents as Set A from CiteSeerX. Using only the title and the abstract, we count the number of keyphrases found for each document using only keyphrase candidates compiled from Wikipedia.

Figure 2(a) demonstrates the empirical distribution of the number of keyphrases found per
Figure 2: Empirical probability mass function of number of keyphrases found in title and abstract for a document in CiteSeerX.

Table 3: Statistics of the number of keyphrases found per document in CiteSeerX.

| Set ID | Min | Q1 | Q2  | Mean | Q3   | Max |
|--------|-----|----|-----|------|------|-----|
| A      | 0   | 4  | 7   | 7.409| 10   | 28  |
| B      | 0   | 5  | 8   | 8.313| 11   | 31  |

document in Set A. As shown, less than 4% of documents do not have any matched keyphrases. Half of the documents have at least 7 matched keyphrases. On average, a document has 7.409 matched keyphrases using only the title and the abstract.

To further study the documents with 0 or few keyphrase matches, we randomly sample 100 documents that have no keyphrase matches and examine the contents. We found that 74 out of the 100 documents are parsed incorrectly in the PDF to text process. A typical mistake is an extremely short title or abstract, or even empty title and abstract. Other cases include missing spaces between words, and contents with garbage or unreadable characters. For the rest of the documents, most of them are not valid papers, scanned papers, or papers written in foreign languages.

To study the Wikipedia based keyphrase extraction strategy without the influence of extremely short titles or abstracts, we compile Set B from 10,000 randomly sampled documents
whose titles have at least 4 words and abstracts have at least 20 words. The probability mass
function of keyphrases found per document is shown in Figure 2(b). Only 0.4% of sampled doc-
uments have no matched keyphrases. Half of the documents have at least 8 matched keyphrases,
and on average a document has 8.313 keyphrases. Since the keyphrase extractor can retrieve a
decent number of keyphrases using only the title and the abstract of a document, Wikipedia is a
promising resource for keyphrase candidate compilation for scientific literature.

The detail of the number of keyphrases found per document in the two sets is shown in
Table 3.

5 Case Study

We illustrate sample outputs of an expert list and an expertise list to show the practicality of the
system.

5.1 Expert List

We start the case study by showing several examples of an expert list returned by CSSeer. As shown in Table 4, 20 different terms ranging in several different sub-domains of computer
science are selected as query terms. We report the top 5 returned experts.

To measure whether the returned names are experts of the given query, we manually checked
each of these researchers’ homepage and their total number of citations compiled by MAS. If
the query term appears in the person’s homepage and the author’s total number of citations is
larger than 500, it is very likely that the researcher is a good candidate for an expert of the given
area.

From the researchers’ homepages, we found only 5 authors whose homepages do not con-
tain the query term: Stefan Schaal (nonparametric statistics), S. Vijayakumar (nonparametric
statistics), C. G. Atkeson (nonparametric statistics), Christof Koch (VLSI), and Anna Karlin
(computer network). After carefully examining their profile, 4 of these are actually experts in the query area, and the synonyms or similar terms of the query appear in their homepage. The only possible exception is Dr. Christof Koch, an expert of Biology and Engineering. However, he co-authored a few of highly cited VLSI papers back in 1990s.

As for number of citations, the only two researchers who have less than 500 citations are Dr. Aurel Lazar (4 citations) and Dr. K. Ramakrishnan (0 citations). We believe these are MAS’s mistakes because at the time of writing, Dr. Lazar has 3,622 citations and Dr. Ramakrishnan has 3,440 citations by ArnetMiner.

5.2 Expertise List

An expertise list is very helpful for users to learn what an author’s research interest is. In this section, we show examples of the expertise list of 10 selected authors. Specifically, from MAS we selected the four most cited computer scientists (Ian T. Foster, Ronald L. Rivest, Scott J. Shenker, and Jeffrey D. Ullman), from ArnetMiner we selected the top four search people (Jiawei Han, Pat Langley, Vladimir Vapnik, and W. Bruce Croft) and three authors who have the highest H-index (Anil K. Jain, Hector Garcia-Molina, and Jiawei Han). Note that Dr. Jiawei Han is both the 3rd highest H-index author and one of the most searched people by ArnetMiner. Thus, we ended up collecting 10 names in total for the case study.

We briefly introduce these authors so that readers may examine the extracted top 15 terms and check if they truthfully reflect these authors’ expertise. Dr. Foster is famous for the acceleration of discovery in a networked environment and contributes a lot in high-performance distributed computing, parallel computing, and grid computing. Dr. Rivest is one of the inventors of the RSA algorithm and many symmetric key encryption algorithms. Dr. Shenker contributes much to network research, especially in Internet design and architecture. Dr. Ullman is known for database theory and formal language theory and is an author of several textbooks in these
fields. Dr. Han and Dr. Langley are famous for their contributions in machine learning and data mining fields. Dr. Vapnik developed the theory of Support Vector Machine. Dr. Croft is well known for contributions to the theory and practice of information retrieval. Dr. Jain is a contributor to video encoding, computer vision, and image retrieval. Dr. Garcia-Molina is notable for information management and digital libraries.

The selected authors’ top 15 expertise are listed in Table 5. As can be seen, the automatically selected terms on average represent each author’s fields of expertise appropriately. A user, even without knowing these authors in advance, should be able to tell each of these authors’ research interest by only examining the list of terms.

6 Conclusions and Future Works

We describe ExpertSeer, an open source expert recommender system based on digital libraries. Using the framework, we built two systems: CSSeer, an expert recommender for Computer Science, and ChemSeer, an expert recommender for Chemistry. The system efficiently handles millions of documents and authors. We thoroughly investigated CSSeer with the other two state-of-the-art expert recommender systems, ArnetMiner and Microsoft Academic Search. We found that the three systems have moderately diverse opinions on experts for our benchmark query term set. This does not mean one system is better or worse than others. In practice, different expert recommender systems may be biased toward certain topics or certain authors due to differences in collected data, extraction methods, ranking, and other analysis. For a more comprehensive expert list, users should consider using several systems. Or possibly, a meta-expert list could be created. In addition, the related keyphrase list provided by ExpertSeer could be a promising alternative, since integrating both the experts of a given query and the experts of the related keyphrases is more likely to generate a complete expert list.

To quantify the performance of different systems, we compared three recommendation sys-
tems and GS* – a simulating system that imitates Google Scholar’s ranking function – in terms of Precision-at-$k$. We found that all three real systems reported reasonably good results for top 3, top 5, and top 10 returns, even though the returned name set of each system was moderately different. Our proposed system has the best performance among these expert recommenders. The simulating system GS* has a mediocre performance, probably because it does not differentiate in which domains an author has received the citations. Thus, when an author is outstanding in one area, the authority scores of her other research areas, which are probably less remarkable, will be boosted as well. Thus, the expert list returned by GS* may include authors who are experts of less relevant fields.

So far, ExpertSeer uses only author-to-document authoring relationship and document-to-document citation relationship for expert recommendation. Other linguistic techniques and heterogeneous social network mining techniques should also be investigated. For example, the Bayes’ rule can naturally integrate the reputation of the published conferences or journals into the model.

We cannot access the exact expert ranking functions of ArnetMiner and Microsoft Academic Search. Thus, we could only rely on their previous publications to infer these ranking functions. In addition, we could only employ their online services to obtain their recommended expert list. However, the expert list may be influenced by several factors besides the ranking function, such as the collected documents and the author disambiguation algorithm. Assuming we will have access to their ranking functions, we can better compare different ranking functions based on the same document set to eliminate other confounding factors.

Several research questions and applications can be developed based on this framework. For example, the influence maximization problem on large-scale social networks has been widely studied recently (44), (45). Since the authors and their expertise lists are identified, it would be interesting to observe and study how scholars collaborate and influence each other. In addition,
a time factor can be integrated into the system so that the flow of information from one domain to another domain can be learned and visualized, and hopefully be used to discover useful interacting patterns among different research domains. ExpertSeer can also be the foundation and provide reliable data source for research in finding teams of experts in social networks (46).

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