Profile Diversity in Search and Recommendation
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ABSTRACT
We investigate profile diversity, a novel idea in searching scientific documents. Combining keyword relevance with popularity in a scoring function has been the subject of different forms of social relevance [2, 6, 9]. Content diversity has been thoroughly studied in search and advertising [4, 11], database queries [16, 5, 8], and recommendations [17, 10, 18]. We believe our work is the first to investigate profile diversity to address the problem of returning highly popular but too-focused documents. We show how to adapt Fagin’s threshold-based algorithms to return the most relevant and most popular documents that satisfy content and profile diversities and run preliminary experiments on two benchmarks to validate our scoring function.

Categories and Subject Descriptors
H.4 [Information Storage and Retrieval]: Information Search and Retrieval

General Terms
Algorithms, Performance, Experimentation

Keywords
Recommendation, diversity, top-k

1. INTRODUCTION
Cross-discipline scientific domains have been growing thanks to the various calls for funding of different government agencies and to the adoption of collaborative tools. Several large projects now involve sizable laboratories of biologists, computer scientists, chemists and statisticians. In cross-discipline domains, users belonging to different communities produce various scientific material that they own, share, or endorse. In that context, we are interested in querying and recommending scientific material in the form of documents.

Table 1: Example of the need of cross-disciplinary researches

<table>
<thead>
<tr>
<th>Undiversified Profiles</th>
<th>Diversified Profiles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Documents</td>
<td>Communities</td>
</tr>
<tr>
<td>Short-term responses of leaf growth rate to water deficit</td>
<td>Ecophysiologist community</td>
</tr>
<tr>
<td>Drought and Abscisic Acid Effects on Aquaporin Content...</td>
<td>Ecophysiologist community</td>
</tr>
<tr>
<td>Control of leaf growth by abscisic acid: hydraulic or non-hydraulic processes...</td>
<td>Ecophysiologist community</td>
</tr>
<tr>
<td>The importance of the anthesis-silking interval in breeding for drought tolerance in tropical maize...</td>
<td>Ecophysiologist community</td>
</tr>
<tr>
<td>A Multiscale Model of Plant Topological Structures...</td>
<td>Modeling community</td>
</tr>
<tr>
<td>Drought and Abscisic Acid Effects on Aquaporin Content...</td>
<td>Ecophysiologist community</td>
</tr>
<tr>
<td>Computational analysis of flowering in pea (Pisum sativum)...</td>
<td>Modeling community</td>
</tr>
</tbody>
</table>

Such documents cover various topics such as models for plant phenotyping, statistics on specific kinds of plants, or biological experiments. In this paper, we investigate diversity when searching scientific documents.

The ability to search scientific documents helps scientists gather and share knowledge on the same topic that is endorsed by other scientists. Each user belongs to a well-known discipline (e.g. computer science, biology, mathematics, etc.). Within a discipline a user belongs to one or more communities which reflect specializations of a discipline. For instance in the biology discipline, examples of communities are geneticists, ecophysiologists and plant breeders. The profile of a user is therefore a combination of her discipline and communities. In such a context, searching documents requires the careful design of an appropriate relevance function. We consider the example of plant phenotyping research where various disciplines and communities are involved. When an ecophysiologist u submits a query q = “plant model” (similar to q = “model” as everyone works in the plant area), u might want documents containing details...
on experiments by other ecophysicists or those describing models of plant behavior shared by computer scientists. Table 1 shows two possible result lists. The list at the top is based on finding documents relevant to q that have diverse content. As we can see, that list only contains documents owned or shared by ecophysicists. Since u is also interested in computer models, the list of results in the bottom part of the table would be more appropriate since it returns documents endorsed by users having different profiles.

Traditionally, diversity is achieved along one axis that is content. Content diversity alleviates the risk of returning highly-relevant but too-similar documents. We design a scoring function that combines query relevance, content diversity to alleviate document similarity in query results, document popularity to account for profile endorsements, and, finally, profile diversity to expose users to documents owned and shared by different communities. Combining keyword relevance with popularity in a scoring function has been the subject of different forms of social relevance [2, 6, 8]. Content diversity has been thoroughly studied in search and advertising [4, 11], database queries [16, 5, 8], and recommendations [17, 10, 19]. We believe our work is the first to investigate profile diversity in searching scientific documents.

In summary, we make the following contributions.

1. We introduce profile diversity for scientific document search as a complement to traditional content diversity. Profile diversity combines the discipline and communities to which a user belongs.

2. We propose an adaptation of Fagin’s threshold-based algorithms to return the most relevant and most popular documents that satisfy content and profile diversities.

3. To validate our scoring function, we ran experiments that use two benchmarks: a realistic benchmark with scientists and TREC’09.

This paper is organized in the following way. Section 2 provides some background on document search and recommends in the context of online scientific communities and presents the problem definition. Section 3 describes our general scoring function, DivRSci, based on probabilistic diversification. Next, Section 4 presents all algorithms necessary for DivRSci, and shows in details our contributions for profile diversification. In Section 5, we present the performance evaluation behavior of DivRSci compared to other approaches, using in two benchmarks. Section 6 is concerned with the related work, and finally Section 7 concludes and provides directions for future work.

2. BACKGROUND

We focus on online scientific communities where users aim to query and have recommendations of inter-community and inter-disciplinary documents shared by other scientists. Our approach is generic, however to facilitate the understanding of our concepts and model we take into account plant phenotyping research that clearly requires inter-community and inter-disciplinary research.

For scientific document recommendation, it is essential to understand the sense of inter-community and inter-disciplinary research. In general, a user belongs to a well-known discipline (e.g. computer science, biology, mathematics, etc.). Within a discipline a user belongs to one or more communities which reflects specializations of a discipline. For instance in the biology discipline, examples of communities are geneticists, ecophysicists and plant breeders. Inter-community research refers to the fact that users research interests involves different communities of one discipline. For instance a geneticist may be interested in specific research results of the ecophysicists community to understand the genetic behavior of some plants. Inter-disciplinary research refers to the fact that users research interests involves different disciplines. For instance, a biologist can query for mathematical tools that can model a plant behavior. In both inter-community and inter-disciplinary research, users would benefit from discovering new and diversified research trends coming from different communities or disciplines.

In our context, we choose a content-based join to a collaborative filtering recommendation approach where users profiles - or alternatively user research interests - are defined based on the documents DS, the user u, stores. Thus, we assume a set of users U = {u1, ..., un}. Each user u stores some of his documents D = {d1, ..., dn} (or contents) with his friends, such that D is a subset of his DS. A document d can be shared by 1 to n users. Each time a document is chosen to be shared and copied, a new replica (or copy) of d is produced. In our context, a replica refers to the fact that different users have the same instance of a document in their work-space. Thus, each document d is associated with a degree of replication that expresses the number of replicas of d among U. Notice that the degree of replication can be related to the document popularity.

Documents are represented based on the vector space model [14]. By using tf-idf a document is represented by a list of keywords k1, ..., kn, and the vector represents the weight of each distinct keyword given the document and the whole corpus. A user profile profilei expresses his interests based on DSi. Queries are expressed by a list of keywords k1, ..., kn. Users’ profiles and queries are also represented based on the vector model.

Problem Statement: Given U, DS, D and a keyword query q submitted by some user u the problem we address is to propose a new scoring function to recommend the top-k most relevant documents among D to favor the inter-community, inter-disciplinary research and diversity requirements presented above. We assume that the k documents are in a sorted order list L in descending relevance order.

The intuition of our approach is that guarantees of inter-community and inter-disciplinary recommendation can be achieved by diversifying the documents and related users profiles in L. Therefore to produce L we identify four recommendation requirements with respect to the relevancy of a document di:

1. The similarities of di and q.
2. Content Diversification with respect to the documents already chosen in L.
3. The popularity of di.
4. Profile diversification with respect to the profiles of the users that owns the documents already chosen in L. Those profiles should be either similar to u (for
3. SCORING MODEL

Several methods have been proposed for diversification [18, 17, 5, 7, 1]. However, they only address requirements 2 discussed in the previous section. Our goal is to introduce profile diversification (i.e. requirement 4), taking into account a probabilistic diversification model because it provides more guarantees for inter-disciplinary and inter-community recommendation, as we show in our experiments in section 5.

3.1 Probabilistic Diversification

In the domain of information retrieval, given D and a query q, the computation of the top-k diversified documents is known to be NP-hard problem. Following [7, 5], div(d, {d1,...,dn}) is defined as the diversification probability of d (i.e. brings novelty to the user u) with respect to the previously chosen documents in L (i.e. {d1,...,dn}). In this model, the diversity can be expressed using the notion of redundancy. The redundancy redL(d1,dj) is computed by comparing the similarity between dj and a document of its redundancy with the other documents [12, 5, 7], the probabilistic diversification score is defined as:

\[ 1 - \text{red}_{L}(d|d_1, ..., d_{n-1}) = \prod_{d_j \in \{d_1, ..., d_{n-1}\}} 1 - \text{red}_{L}(d, d_j) \]  

(1)

3.2 DivRSci Scoring Function

To address the 4 requirements presented in section 2, we propose the DivRSci score that evaluates the relevancy of a document given a query q:

\[ \text{score}_{\text{DivRSci}}(d, u, q) = \text{rel}(d, q) \cdot \text{div}_v(d|d_1, ..., d_{n-1}) \cdot \text{div}_p(u|u_1, ..., u_{n-1}) \]  

(2)

rel(d, q) defines the probability that d will answer the query q. It can be calculated as the similarity measure between d and q (e.g. cosine, jaccard, etc.) [15]. This addresses requirements 1.

\[ \text{div}_v(d|d_1, ..., d_{n-1}) \] is a straightforward application of equation 1 and addresses requirement 2.

\[ \text{div}_p(u|u_1, ..., u_{n-1}) \] is the profile diversification score of document d and takes into account the document’s popularity (requirement 3) and the diversification among trusted users (requirement 4). More precisely, we evaluate for each user in U holding a replica of d, a trust and a diversification score (requirement 4) with respect to L.

The trust trustuv is a value which indicates the confidence the user u have in the user v. Such information can be computed in many ways (e.g. social friendship, localization, previous recommendation, etc.). In the following we consider that the trust takes into account the relevance of the user v, given u and q. The relevance indicates if v is either similar to u (i.e. inter-community recommendation) or to q (i.e. inter-disciplinary recommendation). We define the user’s relevance in equation 3.

\[ \text{rel}_{\text{trust}}(v, u, q) = \alpha \cdot \text{sim}(u, v) + (1 - \alpha) \cdot \text{sim}(v, q) \]  

(3)

More formally, we propose the user profile diversification score defined in Equation 4. Recall that the profile diversification score also takes into account the popularity of the document d (requirement 3), that is why we need N. Notice that \( \frac{1}{N} \) is also used for normalization.

\[ \text{div}_p(u|u_1, ..., u_{n-1}) = \frac{1}{N} \sum_{v_n \in u_d} \left[ \text{red}_{L}(v, u, q) \cdot \prod_{v_m \in \{u_1, ..., u_{n-1}\}} (1 - \text{red}_p(v_m|v_n)) \right] \]  

(4)

4. ALGORITHMS

In this section we present in details the algorithms involved in DivRSci. For sake of clarity, in section 4.1, we present the extended version of the algorithm related to the probabilistic model we adopt [5] adapted for DivRSci. In section 4.2, we show the performance degradation brought by the profile diversification aspect of DivRSci and we propose a new threshold condition that is best suited to profile diversification. Finally in section 4.3 we propose a new algorithm to compute profile diversification.

4.1 Preliminaries

In [5], the authors propose an algorithm (called DAS) used to implement the following scoring function:

\[ \text{rel}(d, q), (1 - \text{red}_{L}(d_1|d_1, ..., d_{n-1})) \]  

(5)

DAS is a threshold based algorithm. Given a query q and a set of documents D, a threshold algorithm operates over a set of inverted indexes:

\[ w_i \Rightarrow < d_a, s_{c_a} >, < d_b, s_{c_b} >, ..., < d_n, s_{c_n} > \]  

(6)

where wi is a word, da a document and sca the score of the document with respect to the word wi (i.e. \( s_{c_a} = \text{sim}(w_1, da) \)). The documents are sorted in decreasing order of sc. Notice that the set of indexes used by the threshold algorithm depends on the query q. For instance, if \( q = \{w_i, w_m\} \) then the inverted indexes will be the ones of wi and wm. Finally the algorithm stops when the threshold condition \( \delta \) is satisfied. \( \delta \) is computed based on the inverted indexes:

\[ \delta = f(s_1, s_2, ..., s_n) \]  

(7)

where f defines a specific measure (e.g. cosine, etc.) and si is the last sorted access on the wi index. For instance, given a set of inverted indexes \( \{w_i, w_j\} \), if we want to retrieve the top-1 document. The stop condition will be satisfied if the score of a document d is superior or equal to \( \delta = f(s_i, s_j) \).

The goal of DivRSci is to find an optimal list L of k documents such that we can’t find a better list L given u and q and our scoring function. That is, given L and a document \( d_i \in L \), where \( i \in \{1, ..., k\} \), we can’t find any document \( d_j \not\in \{d_1, ..., d_{n-1}, d_i\} \) that would have a better score than \( d_i \) at the ith place in L.
We propose DAS DivRSci as an implementation solution (see Algorithm 1) that uses a new threshold condition suited for profile diversification. Notice that \( \text{div}_p \) (line 4), \( \delta' \) (line 5) and line 9 are specific features related to DivRSci.

The algorithm runs until \( L \) reaches \( k \) documents (line 2). From line 3 to 5, the algorithm performs a sorted access to get the next document, then it computes its score (i.e. \( \text{score}_{\text{DivRSci}} \), formula 2) and inserts it into a candidates’ list. The candidates list contains each document that has already been analyzed but that can’t be inserted in \( L \) yet because the algorithm can still find documents with better diversity score. Notice that a document’s score is not fixed until it has been added to \( L \). At line 6, DivRSci analyses if the best candidates has a score higher than the threshold \( \delta' \). In other words, it analyses if there isn’t any better document in the indexes. In that case, DivRSci inserts the best document in \( L \) and update the score of the other candidates (line 7 & 8). Line 9 will be explained in more details in the next subsection motivated by the new threshold score proposal.

### 4.2 DivRSci Threshold

As presented in formula 7, the threshold \( \delta \) is evaluated using the document’s score in the indexes \( \{w_1, ..., w_n\} \). In DivRSci, \( \text{div}_c \) and \( \text{div}_p \) are always smaller than 1. Notice that while the number of documents in \( L \) grows, the content diversification score and the profile diversification score become to get smaller for any given document \( d_i \not\in L \). For instance, to retrieve 3 diversified documents (using our benchmark, \( U = 50 \) users, \( D = 300 \) documents), DivRSci needs about 175 sorted accesses in average. In the worst case, the whole index is used to find these 3 documents. Thus, \( \delta \) is no longer appropriate.

We propose to use a new threshold \( \delta' \) with respect to our scoring function to optimize the number of sorted accesses:

\[
\delta' = f(s_1, s_2, ..., s_n), f_{\text{div}_c}(d_i, \{s_1, s_2, ..., s_n\}), f_{\text{div}_p}(d_i, \{s_1, s_2, ..., s_n\})
\]  

(8)

Where each part of the threshold corresponds to a part of our scoring function (i.e. DivRSci). Notice that to compute \( f_{\text{div}_c} \) and \( f_{\text{div}_p} \) we need additional information because the indexes \( \{s_1, ..., s_n\} \) are not sufficient. Thus, we define 4 primitives:

1. \( \max_{\text{div}_c} \): returns the maximum content diversity score between \( d_i \) and the documents that follow \( d_i \) in \( \{s_1, s_2, ..., s_n\} \).
2. \( \max_{\text{div}_p} \): returns the maximum profile diversity score between \( d_i \) and the documents that follow \( d_i \) in \( \{s_1, s_2, ..., s_n\} \).
3. \( \max_{\text{trust}} \): returns the maximum trust score of the users that share the document in \( \{s_1, s_2, ..., s_n\} \). Notice that the part of the trust score that depends on the user \( u \) that submitted the query is evaluated as equal to 1.
4. \( \max_{\text{rep}} \): returns the maximum number of replicas of any documents in \( \{s_1, s_2, ..., s_n\} \).

We now define \( f_{\text{div}_c} \) and \( f_{\text{div}_p} \):

\[
f_{\text{div}_c}(d_i, \{s_1, s_2, ..., s_n\}) = \prod_{d_j \in \{s_1, s_2, ..., s_n\}} \max_{\text{div}_c}(d_j)
\]

(9)

\[
f_{\text{div}_p}(d_i, \{s_1, s_2, ..., s_n\}) = \frac{\max_{\text{rep}} \cdot \max_{\text{trust}}}{\prod_{d_j \in \{s_1, s_2, ..., s_n\}} \max_{\text{div}_p}(d_j)}
\]

(10)

**LEMMA 1.** The content diversity score of a given document \( d_i \) is inferior or equal to \( f_{\text{div}_c} \).

**LEMMA 2.** The profile diversity score of a given document \( d_i \) is inferior or equal to \( f_{\text{div}_p} \).

The demonstration is straightforward.

Notice that \( \prod_{d_j \in \{s_1, s_2, ..., s_n\}} \max_{\text{div}_c}(d_j) \) and \( \prod_{d_j \in \{s_1, s_2, ..., s_n\}} \max_{\text{div}_p}(d_j) \) can be updated at each iteration without recomputing the overall formulas 9 and 10.

In Algorithm 1, (line 9) DivRSci updates their values with respect to the last document inserted in \( L \).

We now present an example to compare \( \delta \) with our new threshold. Due to lack of space and for simplicity, we simplify the DivRSci scoring function by removing the trust and the popularity related to \( \text{div}_p \):

\[
\text{div}_c = \sum_{v_m \in u_{d_i}} \left( \prod_{v_m \in \{w_1, ..., w_n\}} (1 - \text{rel}_d(v_m\mid v_n)) \right)
\]

(11)

Not surprisingly, removing \( \frac{1}{N} \) and \( \text{rel}_\text{trust} \) from the DivRSci scoring function, enables the definition of a simpler threshold, \( \delta'' \), that is quite simpler to compute compared to \( \delta' \), but that keeps the same general behavior:

\[
\delta'' = \text{lastSA} \cdot \prod_{d \in L} \max_{\text{div}_c}(d) \cdot \prod_{d \in L} \max_{\text{div}_p}(d)
\]

(12)

In more details, table 2 shows a running case in which DivRSci is built \( L \) using \( \delta'' \). We show that the number of sorted accesses would have been largely superior if we’ve used \( \delta \). The input is a built index of documents based on a query. The first column \( \text{step} \) corresponds to a whole iteration in algorithm 1 (line 3 to 9). The second column \( \text{sorted accessed} \) indicates the sorted access done at the given step (line 3 of algorithm 1) on the index of the input. The columns \( \max_{\text{div}_c} \) and \( \max_{\text{div}_p} \) indicate that the document’s we’ve just done the sorted access on (e.g. document
A for step 1) can’t be more diverse than the value indicated, with respect to all other indexed documents still not accessed. L is the list of results and C the list of candidates. The columns δ and δ” indicates the value of the thresholds at the given step.

On step 1, DivRSci performs a sorted access on A. As it’s the first document, the diversification score is 1 and the final score of the document is rel(d,q) = 0.9.

On step 2, DivRSci performs a sorted access on B. The final score of B is 0.238 due to its diversification score with respect to A. Notice that δ’’ (which is inferior to δ) has a value of 0.34 which is superior to B’s score. It means that we may find a better document.

Then, on step 3, DivRSci performs a sorted access on document C. The final score of this document (with respect to A) is 0.34 which is superior or equal to δ’’. We can assume that there will not be any better document in the index. Therefore C is inserted in L. Notice that δ is equal to 0.87, and DivRSci couldn’t have inserted C in L at this step by using δ. Furthermore, we can see that at step n, δ is equal to 0.55 which is still superior to C’s score and is not satisfying the stop condition. This confirm the fact that the proposal of divp for DivRSci introduces important complexity and our new threshold approach provides important performance improvement.

4.3 DivRSci Profile Diversification

In this section, we present how we compute divp. (Algorithm 1, line 4).

Algorithm 2 presents a possible way to compute divp. From line 1 to 7, it computes for each user holding a replica of the document d a trust and a diversification score. On line 3, it evaluates the trust score of vn with respect to u and to q. Then, from line 4 to 6 it evaluates the diversification score of vn with respect to the users that hold a document already inserted in L.

Finally, on line 7 it combines the trust and the diversification score and adds the computed value to the global profile diversification score. Line 8 normalizes the value of divp and takes into account the popularity of d.

Thus, the number of iterations is strictly equal to:

\[
|U_d| - |U_{[d_1,\ldots,d_{i-1}]|}
\]

and the complexity of the function, in the worst case is \(O(n^2)\), where \(n\) is equal to the total number of users. Recall that the profile redundancy score between two documents also takes into account the trust score which depends on the u submitting the query. Therefore the profile diversification can’t be precomputed because a specific index would be necessary for each user.

5. PERFORMANCE EVALUATION

In this section, we provide an experimental evaluation of DivRSci to assess the quality of recommendations, content diversification, profile diversification and of the algorithm efficiency. We have conducted a set of experiments using a self-built benchmark and using TREC’09. In section 5.1 we first describe the experimental setup. Then, in section 5.2, we discuss the results.

5.1 Experimental Setup

Our self-built benchmark is composed of a set of 50 users. They are scientists in the domain of plant phenotyping from different localities (e.g. Australia, England, France, etc.). They belong to 4 main disciplines (i.e. ecophysiologists, geneticist, mathematician, computer scientists). Each discipline contains about 4 communities. The users share documents related to their research with respect to different disciplines and communities. Our benchmark is composed of 300 documents, 92% of these documents have a degree of replication of 1, 3% of them have a degree of 2, 2% have a degree of 3 and 2% have a degree of replication of 4. All users submit queries that are 1/3 inter-disciplinary and 2/3 inter-community. They can be classified in two categories:

1. unspecific queries (i.e. queries with very few keywords such as “plant” or “plant model”).
2. specific queries (i.e. queries with lots of keywords such as “FSPM structure function plant model”).

Each category of query represents 50% of the total number of queries which is 300.

In addition to our self-built benchmark we also show that using a well known large-scale benchmark (i.e. TREC’09 in our case) produces comparable results. From TREC’09, we take 15000 documents and 1500 specific queries. 50%
of these queries are inter-disciplinary and 50% are inter-community. We consider 1000 users. We built the users profile by clustering the documents using k-means. Each cluster corresponds to a community. We obtained 30 communities. By considering that a discipline is a set of communities that are similar to each other, we expect to have 8 disciplines. In our scenario, the documents are replicated ranging from 1 to 200 copies.

In the following, we present the four scores we compared in our experiments:

1. Simple top-\(k\): we only retrieve the documents that optimize \(\text{rel}(d, q)\).
2. DAS: we retrieve the documents that optimize \(\text{rel}(d_i, q)(1 - \text{red}(d_i|d_1, ..., d_{i-1}))\).
3. Trusted DAS: we retrieve the documents that optimize DAS score and that are shared by the most trusted users - with respect to the trust we defined in section 2.
4. DivRSci: we retrieve the documents that optimize our scoring function.

To understand the behavior of the scores, we analyze the following metrics:

1. The content diversity: \(\sum_{d_i \in L} \sum_{d_j \in L} 1 - \text{red}(d_i, d_j)\)
2. The profile diversity: \(\sum_{u_i \in U_L} \sum_{u_j \in U_L} 1 - \text{red}(u_i, u_j)\)
3. The average relevance of the documents in \(L\):
   \[\text{avg}_d \in L(\text{sim}(d_i, q))\]
4. The average relevance of the users involved in \(L\):
   \[\text{avg}_u \in U_L(\alpha \cdot \text{sim}(u, u) + (1 - \alpha) \cdot \text{sim}(u, q))\]
5. The cost to retrieve documents in number of sorted accesses by comparing several scores:

5.2 Experiments

5.2.1 Scoring Function

Figure 1 compares the behavior of our scores to understand the degree of diversification of the chosen users profiles in \(L\). In Figure 1a we executed unspecific queries. In Figure 1b we executed specific queries.

We discuss and analyze the expected profile diversification behavior with respect to our inter-disciplinary and inter-community requirements. Notice that given an unspecific query \(q_1\)="plant model", most users in \(U\) should be able to answer it because in some way they are all involved in plant research. Notice that unspecific queries enable interdisciplinary recommendation, and by diversifying users profiles, more disciplines will be involved in the recommendation results (i.e. \(L\)) and the profile diversification measure should be high. In the case of specific queries such as \(q_2\)="FSPM structure function plant model", less users will be able to answer it because less users are involved in these researches as it is a subset of plant model researches. Notice that specific queries enable inter-communities recommendation, and by diversifying users profiles more communities of the same discipline will be involved in the recommendation results (i.e. \(L\)) and the profile diversification measure should be low.

Not surprisingly Figures 1a and 1b show that the simple top-\(k\) and DAS have exactly the opposite behavior compared to the expected one. Their profile diversification measure double from 9.5 to 18 and 7 to 14 respectively (Figure 1a and Figure 1b) instead of decreasing. Moreover, we can see that by adding the trust score to DAS (i.e. trusted DAS), we resolved this issue by only inserting in \(L\) trusted users. Notice that, the trust score reduces considerably the profile diversification degree of trusted DAS. In DivRSci, we introduced a profile diversification score and a trust score. Therefore, DivRSci is able to compute a diversified list of users in \(L\) that has a coherent behavior with respect to the expected one. In Figure 2, we analyze if the behavior of the four scores is similar in the TREC’09 based benchmark.

We only present profile diversification results due to a lack of space. All users submit only specific queries and we measure the profile diversification. As we can see, the different scores follow the same trend as the one of Figure 1b. However, the profile diversification is much higher due to the fact that with TREC’09, the number of replicas is much higher than

![Figure 1: profile diversification depending on the top-k algorithm.](image1)

![Figure 2: profile diversification with specific queries in TREC depending on the top-k algorithm.](image2)
in our self-built benchmark. This result shows that as the
degree of replication globally increases the degree of diver-

sification also increases. The goal of Figure 3 is to check if

the “profiles” in L are relevant given our recommendation re-

quirement 4 (i.e. given u and q). As shown in Figure 3a and

Figure 3b, since simple top-k and DAS does not have a trust

score, this yields to a worse profile relevance. In the other

hand, DivRSci profile diversification score is a compromise

between the trust and the profile diversification of the users

in L. Therefore, DivRSci is expected to have a relevance in-

ferior to a scoring function that does not diversify the users

such as trusted DAS. For instance, if \( U = \{ u_1, u_2, u_3 \} \) where

\( \text{rel}(u_1) = \text{rel}(u_2) = 10 \) and \( \text{rel}(u_3) = 9 \), trusted DAS will

keep \( u_1 \) and \( u_2 \) in L. But if \( u_1 \) and \( u_2 \) have exactly the same

profiles then, DivRSci will remove one of them and put \( u_3 \)

instead. Notice, however, that DivRSci still have very good

profile relevance results.

Finally, we constructed a feedback method using [13] to
evaluate the list L quality taking in account simple top-k,

DAS, Trusted DAS and DivRSci. The feedback was gener-

ally positive with more than 70% of satisfaction. The principal

favored argument was the possibility to retrieve relevant

inter-community and inter-disciplinary documents.

5.2.2 Threshold Efficiency

In this experiment, we show the effect of a complex scor-
ing function and of the threshold on the number of sorted

accesses. Table 3 resumes the experiment of running DAS

and DivRSci with the threshold \( \delta \) and \( \delta' \) on our self-built

benchmark. We first executed DAS with the threshold \( \delta \).

DAS only diversifies the document’s content. Obviously, it

has the best results in term of sorted accesses. In second,

we executed DivRSci with the threshold \( \delta \). Not surprisingly,

the number of sorted accesses is very high because \( \delta \) is not

suitable as discussed in section 4.2. Finally we executed Div-

RSci with the threshold \( \delta' \). The results are 6 times better

than DivRSci with \( \delta \).

6. RELATED WORK

Content diversity has been studied in Web search, database

queries, and recommendations. Diversifying Web search re-

sults and recommendations aims to achieve a compromise

between relevance and result heterogeneity. In [12], the au-

thors adopt an axiomatic approach to diversity that aims to

address user intent. They show that no diversification func-

tion can satisfy all axioms together and illustrate that with

concrete examples. In [4], taxonomies are used to sample

search results in order to reduce homogeneity. In the data-

base context [16, 8], solutions have proposed to post-

process structured query results, organizing them in a de-

cision tree [8] for easier navigation or merging ranked lists

[16] for faster processing. In [3], a hierarchical notion of

diversity in databases is introduced, and efficient top-k pro-

cessing algorithms are developed. In recommendations [19,

10, 17], results are typically post-processed using pair-wise

item similarity in order to generate a list that achieves a ba-

lance between accuracy and diversity. For example, in the

recommender systems world, the approach in [19] defines an

intra-list similarity which relies on mapping items to tax-

onomies to determine topics or using item features such as

author and genre. The method is based on an exhaustive

post-processing algorithm which operates on a top-N list to

compute the top-K results (\( N > K \)). In contrast, in [10], di-

versity is formulated as a set-coverage problem. Finally, [11]

introduces diversity in the framework of sponsored search

ads, proposing algorithms for the selection of ads that in-

tend to increase heterogeneity while not significantly reduc-

ing revenue and maintaining an incentive for advertisers to

keep their bids as high as possible. Heterogeneity is aimed

at as a notion that spans various occurrences of the same

query, and not just a single one.

Notice that none of the above contributions tackles the

problem of profile diversity as we do.

7. CONCLUSION

In this paper, we introduced profile diversity to ease inter-

community and inter-disciplinary search and recommenda-

tion.

We proposed a scoring function (called DivRSci) that ac-

counts for query relevance, content diversity to alleviate
document similarity in query results, document popularity
to account for community endorsements, and finally, disci-

pline and community diversity to expose users to documents

owned and shared by different disciplines and communities.

We argued that profile diversity provides good guaran-

tees for inter-community and inter-disciplinary search and

Table 3: Number of sorted accesses depending on

the scoring function and on the threshold to com-

pute the top-3 documents.

<table>
<thead>
<tr>
<th>Score threshold</th>
<th>number of sorted accesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAS</td>
<td>10</td>
</tr>
<tr>
<td>DivRSci</td>
<td>175</td>
</tr>
<tr>
<td>DivRSciFactors</td>
<td>30</td>
</tr>
</tbody>
</table>
recommendation. Profile diversification is done by recommending documents that are shared by trusted and diversified users among all users. Our scoring function is based on a probabilistic model since it provides good guarantees of diversification. We presented in details all involved algorithms and we proposed a new threshold for DivRSci suited for profile diversification.

Through experimental evaluation using two benchmarks and comparing DivRSci with other scoring functions, we showed that DivRSci presents the best compromise between all requirements we have identified. Besides DivRSci also shows to be the best generating list of inter-disciplinary and inter-community documents. Finally, we presented the very good gains (factor of 6) of the new proposed threshold, suited for profile diversification.

In future work, we plan to propose a distributed approach for DivRSci.

8. ACKNOWLEDGMENTS

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9. REFERENCES