

Linking Specialized Online Medical Discussions to Online Medical Literature

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Abstract. The medical web comprises both medical communities engaged in discussions about specialized topics and a vast array of medical articles available through web-based databases. In this paper we present a knowledge linkage strategy that links online specialized medical discussions with corresponding online medical articles. The idea is to link the experiential knowledge generated in online medical discussions by a virtual community of specialized medical practitioners with the explicit knowledge available in online medical literature archives. We have developed a specialized medical literature search algorithm, based on the principles of the Extended Boolean Information Retrieval algorithm [6], to retrieve a ranked list of medical articles associated with the specialized medical discussion. The medical literature search algorithm is part of our knowledge linkage strategy that involves the generation of topic-specific discussion threads from online discussions, formulation of highly specialized search queries based on a specialized discussion thread and retrieval of published medical articles from PubMed that are closely related to the online discussion. We have applied our knowledge linkage strategy to the specialized medical topic of Pediatric Pain Management, and have achieved an improvement in the positive return rate (recall) from 55% to 70% in terms of linking online medical discussions to the correct medical articles.

1 Introduction

Web 2.0 technologies are embraced by medical practitioners for collaborative case solving, professional communications, knowledge sharing, medical education, patient interactions and so on. From a knowledge and experience sharing perspective, online discussion forums and mailing lists provide a viable medium for medical professionals to virtually engage in discussions around specialized medical topics. The ensuing discussions, which constitute a thread of emails or postings by medical professionals from different parts of the world with varying degrees of expertise and experience, entail practical know-how in terms of what worked and what did not work, recommendations and solutions to unusual cases

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and references to domain experts or published evidence. Such online discussions are a vital resource for experiential medical knowledge emanating from a community of medical practitioners. Notwithstanding the utility of online discussions on specialized medical topics, medical practitioners like to correlate the recommendations with published medical literature for use in clinical decision-making. The process of searching for information within specialized domains, however, is a key challenge within the medical community. Studies have shown that the lack of clinical knowledge about specialized subjects, such as pediatric pain, have lead to incorrect interventions [2]. These problems tend to be exacerbated by the fact that specialized practitioners do not often have the time to meet and share information face-to-face, forcing them to rely on their own search strategies to retrieve information from published resources.

Linking specialized online medical discussions to online medical literature poses an information retrieval challenge because the specialized discussions are context-sensitive, spanning multiple emails/postings and encapsulate concepts from multiple sources. A medical practitioner seeking medical articles corresponding to the online discussion is therefore required to formulate a *focused* search query that captures the discussion's context, uses the prevalent terms and is posted to the right online medical literature archive. It may be noted that the process of finding research articles related to a specialized topic amongst the nineteen million different articles available on the online database of Pubmed is a challenging task, and can be even more challenging for specialized fields for which there is less published literature. This paper presents a medical literature retrieval strategy that automatically comprehends a specialized online discussion to formulate a search query that retrieves relevant medical articles from a web of medical literature archives (in particular the online databases of Pubmed). In this way, we establish *knowledge linkages* between the experiential knowledge encapsulated within online medical discussions with explicit knowledge stored in online medical literature archives.

In this paper we present our knowledge linkage strategy that involves a sequence of steps, starting from forming topic-specific discussion threads to formulating highly specialized search queries based on a specialized discussion thread to retrieving a set of published articles from PubMed that are closely related to the online discussion (see figure 1). We have developed a specialized medical literature search algorithm, based on the principles of the Extended Boolean Information Retrieval algorithm [6], that incorporates both weighted and unweighted query terms (keywords derived from the selected medical discussion) to retrieve a ranked list of medical articles associated with the specialized discussion. We use Metamap [1], a program designed by the National Library of Medicine for processing the free-form medical text of the discussions to a set of medical keywords based on the MeSH lexicon. The choice of MeSH terminology is quite natural since the PubMed data is indexed by MeSH keywords. We have applied our knowledge linkage strategy to the specialized medical topic of Pediatric Pain Management that features a Pediatric Pain Mailing List (PPML) with over 700 subscribers. Our results show that the application of our special-

ized medical literature search algorithm has improved the positive return rate (recall) from 55% to 70% which is a significant improvement in terms of linking online medical discussions to the right medical articles.

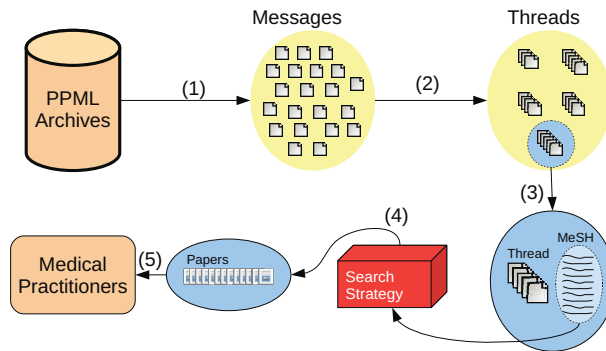


Fig. 1. The knowledge linkage strategy. (1) Messages are extracted and (2) combined them into threads, where they are then (3) linked to formal medical terms. These terms are then (4) used in a novel search strategy to obtain a ranked list of papers, which are then (5) returned to the practitioners.

1.1 Pediatric Pain

Pediatric pain management is an example of a specialized medical domain that can benefit from knowledge linkage. Pediatric pain is a complex subject that is dispersed across multiple departments within a hospital. It is difficult to manage, as children lack the ability to properly express their pain [2], which can lead to incorrect interventions. To compound the problem, healthcare practitioners do not receive proper training in the management of pediatric pain [3], and the multidisciplinary nature of the subject makes it difficult for pediatric pain practitioners to meet and discuss their issues face-to-face.

The PPML is an example of a web 2.0 tool that has provided an electronic link between clinicians working in different departments and hospitals around the world. The PPML has over 700 subscribers and over 13,000 messages, all archived, making it an excellent candidate for knowledge linkage. The conversations on the mailing list will be processed using the program Metamap, which will provide a list of pertinent medical keywords extracted from the MeSH lexicon.

1.2 Metamap

Metamap is a Natural Language Processing (NLP) tool designed to parse free-form medical text and connect it to formal medical terms from selected medical

lexicons. For this project the lexicon being used is the MeSH vocabulary, but Metamap has the ability to map to any lexicon in the Universal Medical Language System (UMLS), such as SNOMEDCT or ICD9. Metamap has been used in several other projects to link free form medical texts to formal medical terms [4, 5]. For more details on its use see Aronson's introductory work [1].

2 Methods

The objective of the search strategy is to *passively* link the conversations on the mailing list to pertinent published literature. This means that the MeSH terms produced by the mapping process and their scores must be leveraged by the search strategy to produce a ranked list of papers associated with that conversation. Other projects that have looked to make information retrieval in the medical domain easier have looked at ways to improve clinicians *active* search strategies, through better search algorithms and interfaces [8]. This project takes a different approach, choosing to perform the search *automatically* without requiring clinician input. The resulting set of papers will be provided without requiring any input from the user, vastly increasing the speed of the knowledge linkage process. If the resulting set of papers is not optimal then the set of ranked MeSH terms returned can be used to inform a manual search.

2.1 Search Strategy

The search strategy is based on the Extend Boolean Information Retrieval (eBIR) algorithm developed by Salton et al [6]. The algorithm builds on the traditional boolean information retrieval approach by including both query and document weights for each of the keywords, and then using a p-norm calculation to assign a search score. This project will modify the eBIR algorithm to better fit automatic searching within specialized domains.

2.2 eBIR and p-norms

Boolean information retrieval is the simplest form of information retrieval, in which query terms are joined by AND and OR operators, and any papers matching the query are returned. There are several problems with the boolean information retrieval model. First, it is often difficult to manage the size of the returned set of papers; complex searches can easily return no papers, yet removing a search term can result in a set of several thousand papers. Second, there is no ranking of the papers returned. Third, there is no way to assign importance to specific keywords. Finally, there is a problem with the structure of the searches; if ten query terms are joined by AND operators, then papers that match nine of the terms but not the tenth are not returned. In the context of this project the boolean search strategy is particularly ineffective, as it does not make use of the Metamap scores at hand, and there are far too many query terms associated with a conversation to retrieve a manageable set of papers.

To remedy this problem Salton et al. developed a system that incorporates term weights to aid in the search process. The eBIR algorithm allows weighting of both the paper keywords and the query terms. For this project there are no weights for the document keywords (which are assigned by the authors manually via Pubmed), but the Metamap scores can be used as query weights, with higher weights indicating more confidence in the search term. Though the eBIR algorithm suggests that weights should be in the range of $[0,1]$, there is no reason mathematically that they cannot be in the range of $[0,\infty]$, and thus no transformation of the Metamap scores is required.

The eBIR algorithm uses the idea of p-norms to measure the score of a set of OR or AND terms. Let the set of query terms be represented $A = \{(A_1, a_1), \dots, (A_n, a_n)\}$, where A_i is the i^{th} query term, and a_i is the associated score. Let a document D be represented by the set $D = \{d_{A_1}, d_{A_2}, \dots, d_{A_n}\}$ where d_{A_i} is the weight associated with keyword term i in that specific document. Since this project does not allow for weighted document keywords $d_{A_i} = 0$ or 1 . Let the query $Q_{OR(p)} = \{(A_1, a_1) \text{ OR }^p \dots \text{ OR }^p (A_n, a_n)\}$ by the set of query terms linked by OR, and let the query $Q_{AND(p)} = \{(A_1, a_1) \text{ AND }^p \dots \text{ AND }^p (A_n, a_n)\}$ by the set of query terms linked by AND. The p-norm scores for each of the searches is given in equations (1) and (2).

$$\text{sim}(D, Q_{OR(p)}) = \left[\frac{a_1^p d_{A_1}^p + a_2^p d_{A_2}^p + \dots + a_n^p d_{A_n}^p}{a_1^p + a_2^p + \dots + a_n^p} \right]^{1/p} \quad (1)$$

$$\text{sim}(D, Q_{AND(p)}) = 1 - \left[\frac{a_1^p (1 - d_{A_1})^p + \dots + a_n^p (1 - d_{A_n})^p}{a_1^p + \dots + a_n^p} \right]^{1/p} \quad (2)$$

The selection of p effects the relative strengths of the returned scores. Selecting $p = \infty$ results in a standard boolean information retrieval model, while selecting $p = 1$ results in a vector-space model [7], in which the ANDs and ORs are ignored and the papers are ranked by the sum of the query terms that appear in each paper.

For this project the simplest form of an eBIR algorithm would be to link all the terms returned by Metamap using an OR operator. Let the set $M = \{(M_1, m_1), (M_2, m_2), \dots, (M_n, m_n)\}$ be the MeSH terms and their scores for a particular conversation. Then the query would be given in equation (3), and the score calculation for paper D would be given by equation (4).

$$Q_{OR} = [M_1 \text{ OR } M_2 \text{ OR } M_3 \dots M_n] \quad (3)$$

$$\text{sim}(D, Q_{OR(p)}) = \left[\frac{m_1^p d_{M_1}^p + m_2^p d_{M_2}^p + \dots + m_n^p d_{M_n}^p}{m_1^p + m_2^p + \dots + m_n^p} \right]^{1/p} \quad (4)$$

Note that the selection of p is key to the function of the p-norm calculation and subsequently the eBIR algorithm. Setting $p = 1$ makes sense theoretically, as the principle behind the $OR(p)$ operator is to return the papers that match the most number of terms in the query set, so equation (4) could be reduced to

$sim(D, Q_{OR}) = \sum m_i d_i$, where d_i is an indicator of whether term i is a keyword for the paper.

The problem with the eBIR algorithm is that it is not well suited for specialized domains. The Metamap program extracts keywords that represent the conversation within the mailing list, but keywords such as *Pediatrics* and *Pain* are implicitly representative of all conversations on the list, whether or not they are particularly suited to the conversation. This problem needs to be addressed, to make sure that the search strategy is focusing on the correct body of literature.

2.3 Modified Information Retrieval Algorithm

To solve the problem of specialized domains it was decided that a *specialized filter* would be added, adding an AND operator to the query. The objective of the specialized filter is to focus the search on papers relevant to the specialized subject. One has to be careful, however, to not over-restrict the search by filtering out useful papers. To this end an age-group filter is added, to ensure that all papers returned are relevant to the pediatric population. The new query would modify equation 4 by adding *Infant*, *Child* and *Adolescent* to the set of MeSH terms, as demonstrated in equation (5).

$$Q = [Infant \text{ OR } Child \text{ OR } Adolescent] \text{ AND } [M_1 \text{ OR } M_2 \text{ OR } M_3 \dots M_n] \quad (5)$$

If the eBIR algorithm were used then the next step would be to apply query weights to the terms in the specialized filter and then find a suitable value for p . This project decided instead to modify the eBIR algorithm slightly, by combining the idea of strict boolean searching with a weighted query.

The final search algorithm leverages the eBIR idea of weighting queries, but adds a strict filter that reduces the search field to only those papers that match the age filter. This filter has the effect of focusing the search strictly on papers that focus on the pediatric population. The score for paper D is therefore calculated using the equation 6. The equation uses the same calculation as the eBIR algorithm, but requires the presence of one of the age group keywords. Let d_I , d_C and d_A be the indicators of whether the paper contains the MeSH terms *Infant*, *Child* or *Adolescent* respectively.

$$sim(D, Q) = [1 - (1 - d_I)(1 - d_C)(1 - d_A)](m_1 d_{M_1} + m_2 d_{M_2} + \dots + m_n d_{M_n}) \quad (6)$$

3 Results

This is an example of a single conversation from the PPML.

Question: *We are looking at ways to decrease the pain of ocular flushing necessary when a child gets sand or spray in their eyes. I am really having a hard time finding any literature on what is the most comfortable solution to use*

(NS?RL)and what freezing drops to use(Prilocaine?) If anyone has a procedure, or protocol, or literature to share or can let know what you are using, I would really appreciate it. Right now we are using nothing.

Response: From personal experience, Proparacaine (Alcaine(r) in the U.S.) anesthetic eye drops are almost painless on instillation; they do not provide as deep anesthesia as tetracaine but burn much less and usually provide sufficient conjunctival and corneal anesthesia. ...

A sample of the MeSH terms associated with this conversation are available in table 1, and seem to be a reasonable representation of the conversation. The full set of MeSH terms was used in the search strategy to retrieve the set of papers, the top two of which were as follows:

- Boscia F et al. *Combined topical anesthesia and sedation for open-globe injuries in selected patients*. *Ophthalmology*:2003,110(8).
- Snir M, et al. *Efficacy of diclofenac versus dexamethasone for treatment after strabismus surgery*. *Ophthalmology*:2000,107(10).

These papers seem to be pertinent to the subject being discussed. This example demonstrates the effectiveness of the system, and its ability to provide published literature to supplement the information being shared online.

MESH	Score
Lenses	2583
Pain	2434
Anesthesia	1722
Anesthesiology	1722
Eye	1000

Table 1. A sample of the mappings corresponding to the sample conversation

3.1 Evaluation

There is a challenge in evaluating a search strategy of this type. The strategy is specific to unstructured, medical conversations, and it is therefore not possible to apply the search strategy to traditional annotated information retrieval databases. Without an annotated database it is difficult to calculate precision and recall, the traditional measures of information retrieval systems. An alternative strategy for evaluation is therefore required.

The search strategy was tested on a sample of conversations from the PPML between 2007 and 2008. For each conversation Metamap was used to map the conversation to a set of MeSH terms. The MeSH terms were then fed to both search strategies (the eBIR algorithm and the modified algorithm), and the top 15 papers returned by each search were linked to the appropriate thread. The

threads were evaluated to see if the set of papers returned was appropriate. A set of papers was deemed appropriate if at least one of the returned papers was relevant to the subject being discussed.

The results of the study were promising. For the eBIR algorithm 55% of the papers returned were deemed relevant to the thread. This percentage jumped up to 70% for the improved algorithm, a significant increase over the first attempt ($p = 0.0025$). The improvement is due to the filter, which restricted the search area to those papers relevant to the pediatric population.

4 Conclusion

The purpose of *knowledge linkage* is to provide clinicians with quick access to evidence-based knowledge to supplement the tacit knowledge they share via web 2.0 communications. Because the information retrieval process is done passively, without clinician input, a robust algorithm is required that can consistently return pertinent medical knowledge. This paper has presented an algorithm that incorporates query weights to automatically produce a search query that is appropriate for specialized knowledge domains such as pediatric pain. The algorithm was built on the eBIR algorithm, and has been proven to significantly improve the relevance of the papers returned.

Future research should be directed at a larger study of the two algorithms, along with a comparison to a more sophisticated eBIR implementation. A better evaluation of the search strategy should be completed, including evaluating the precision and the recall of the strategy, and an implemented system should be tested to evaluate the overall usability of the system.

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