MEDINFO 2010
C. Safran et al. (Eds.)
IOS Press, 2010

doi:10.3233/978-1-60750-588-4-1184

Pediatric Pain Management Knowledge Linkages: Mapping Experiential Knowledge to Explicit Knowledge

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Abstract

The goal of this project is to augment clinician communication by connecting it to evidence-based research, providing explicit knowledge to corroborate the experiential knowledge shared between health care practitioners. The source of tacit knowledge sharing is the Pediatric Pain Mailing List (PPML), a forum for practicing clinicians to contact peers on the subject of pain in children. The messages, dating back to 1993, are processed for pertinent information and gathered together into threads. They are then parsed and connected to a set of MeSH keywords, which is used to search Pubmed and return a set of papers that correspond to the subject being discussed. The results are presented in an online forum, providing clinicians with an arena in which they can browse the archives of the PPML and connect those conversations to pertinent medical literature.

Keywords:

Information retrieval, MeSH headings, Natural language processing, Pediatrics, Pain, UMLS

Introduction

Pediatric pain management is a complex subject, as children lack the cognitive ability to properly express their pain [1], which at times leads to incorrect interventions. The problem is exacerbated due to lack of specialized knowledge and formal training in pediatric pain management [2]. The emergence of Web 2.0 technologies has provided alternate knowledge dissemination mediums, such as online discussion forums, mailing lists, social networks and so on, that allow pediatric pain practitioners to converge and share their knowledge through problem or topic specific discussions. One successful initiative is the Pediatric Pain Mailing List (PPML) which brings together over 700 pediatric pain practitioners from around the world to share their clinical experiences and seek clinical advice. The PPML not only overcomes temporal and geographical barriers to connect pediatric pain practitioners, but the archives of the mailing list, containing over 13,000 messages, represent an invaluable resource of the experiential knowledge of the pediatric pain management community spanning more than 15 years. The archives contain experience based recommendations, educational materials, tools, case solutions, practice critiques and research ideas.

Experiential knowledge is not evidence-based rather it is practice-based, nevertheless it provides vital and pragmatic insights into *what worked*, *what did not work* and *what are the best practices* in specific clinical situations, especially beyond the realm of accepted norms and established beliefs. We argue that to generate comprehensive healthcare knowledge for a specialized health topic it is important to augment this tacit experiential knowledge with evidence based explicit knowledge, i.e. to establish knowledge linkages between online discussions with published medical literature.

In this paper, we present our approach to establish knowledge linkages between pediatic pain management discussions in the PPML and corresponding published literature at Pubmed. The rationale for the project is driven by the observation that practitioners need to reaffirm the practice-related recommendations on the PPML with evidence reported in the medical literature. The exercise of finding evidence corresponding to the exact theme and content of a PPML discussion is challenging for practitioners, as the incorrect choice of keywords (as per the PPML discussion) results in sub-optimal research articles, which in turn affects the perceived validity of the PPML messages and the subsequent uptake of the experiential knowledge at the PPML.

Our solution is a knowledge management framework that leverages (a) Web 2.0 based communication and collaboration to gather clinical experiential knowledge through an active interaction within a virtual community of practice, and (b) knowledge interoperability to establish linkages between the unstructured experiential knowledge and structured explicit knowledge stored in an accessible knowledge repository. The research challenge is (i) to organize the unstructured email messages containing the experiential knowledge into meaningful topics/discussion threads so that specific knowledge items can be easily found and used by the practitioners; and (ii) to process the content of the email messages to derive medically salient keywords to search a medical literature repository for related research articles.

In this paper, we present our knowledge linkage framework featuring our literature search strategy that implements an extended Boolean Information Retrieval (eBIR) algorithm [3]. Our framework allows users to (i) search through the PPML archives to find interesting discussion topics, (ii) select interesting discussions threads within the discussion topics, and finally (iii) retrieve a set of related research articles from Pubmed, through a 'single-click' evidence retrieval mechanism, based on our literature search strategy.

Methods

Our knowledge linkage framework followed the following steps: (i) Filter the email archives to extract medically useful email messages; (ii) Associate a series of emails to realize a *thread* that represents an online discussion between multiple practitioners around a specific topic; (iii) Parse the discussion thread to identify its constituent medical terms in terms of the MeSH lexicon (because Pubmed is indexed using MeSH); (iv) Apply the search strategy to find related research articles; (v) Present the search results to the user.

The task of processing free text and connecting it to a formal medical lexicon is an active research subject in the medical community [4-6]. Previous projects have approached the problem using natural language processing (NLP) algorithms to try and extract the semantics of the text, representing the semantics using a formalized lexicon. One example is the program Metamap [7], a NLP based medical language processing system that scans medical text and links it to formal terms from MeSH. However, Metamap's precision and recall in previous projects have varied depending on the format of the text being processed, from values as high as 0.897 and 0.930 respectively [6] to values as low as 0.56 and 0.72 [4]. Projects that reported low recall and precision with Metamap acknowledged that many of the problems come from the inherently ambiguous nature of the text being processed: in processing medical residents' voice recordings, it was noted that Metamap failed to recognize abbreviations, acronyms or complex phrases that omitted key terms [5].

For this project, we expect some degree of inaccuracy in the list of medical terms returned by Metemap given the unstructured nature of the PPML. We decided to use Metamap as the medical text processing application due to its ability to provide MeSH terms together with concept and semantic types. We improve the output of Metamap through our literature search strategy that uses a modified eBIR algorithm to rank the MeSH terms by assigning them a score, and then determining the optimal subset of terms based on their scores. Below, we discuss the workings of the individual steps of our knowledge linkage framework.

Processing the PPML Archives

The archives are stored in simple ASCII text files, organized by month, starting June 1993, and ending December 2008. The messages were processed to extract the sender, date, subject line and content of the message. The extracted information was used to filter out irrelevant and noisy messages. For experimental purposes we selected the set of emails from 2007 and 2008; we believe that the recent two years of the PPML reflect the current nature of the mailing list.

The goal of the project is to extract the substantive content of the messages and use that to link pertinent literature. This means that the messages need to be parsed to remove content such as user signatures, replies and useless messages. The purpose of parsing these elements is to restrict the recorded content of the message to the subject being discussed, in order to properly link the conversation to literature. Any medical terms in the user's signature, or the content of the previous messages, could confuse the mapping process and ultimately lead to inaccurate results.

Discussion Thread construction

Using the extracted data the messages are assigned to discussion *threads* that are the embodiment of experiential knowledge in the PPML. A thread can be thought of as a conversation, or a series of messages around a certain topic. It generally contains a question, problem or novel idea posed by a list member, and is followed by a series of responses that attempt to solve the problem. Within a thread experts in the field can provide their own knowledge or recount their own experiences in response to a certain problem. A thread is built using the subject line of the email messages—all messages with a matching subject are grouped within a thread.

Converting Threads to MeSH Vocabulary

Given that the Pubmed database is indexed by the MeSH vocabulary, to optimize the search results we convert the content of the PPML messages to the MeSH vocabulary via the Metamap program [7].

Connecting Threads to MeSH terms

Metamap uses a special NLP parser called SPECIALIST [7] to find all the nouns and noun-phrases in a discussion thread, and maps them to one or more MeSH terms. Each mapped MeSH term is assigned a score that is a measure of how strongly the actual term mapped to the MeSH vocabulary. The score is a weighted average of four metrics measuring the strength of the matching, with an overall range in [0,1000], with higher scores indicating a better match. The formal equation for calculating the scores is:

$$1000\text{x}(\mathit{Centrality}+\mathit{Variation}+2\text{x}\mathit{Coverage}+2\text{x}\mathit{Cohesiveness})/6 \quad (1)$$

1. *Centrality*: An indicator of whether the matched (source) term is the head of the phrase. The head of the phrase is the root; in the phrase *pain medication medication* is the head and *pain* is a modifier.
2. *Variation*: A measure of the distance between the matched term and the root word. For example, if the source word is eye and the match is to the term ocular, the distance is 2, as ocular is a synonym for eye
3. *Coverage and Cohesiveness*: Measures of how well the source term and the MeSH term match each other: if the source and MeSH terms are both "pain" then the match is perfect, but if the source term ocular matches to the MeSH term Ocular Vision then the coverage and cohesiveness are less than perfect.

For our purposes, the Metamap scoring system provides a baseline measure of how well the mapped MeSH term represents the original term in the PPML discussion thread.

Managing MeSH Terms

Metamap produces certain MeSH terms that are not appropriate for this project, either due to generality or complexity of the phrase being mapped. The problem of generality arises when the MeSH term provided is not a formal member of the MeSH lexicon. Metamap returns the MeSH term *stress*, which is not technically part of the MeSH vocabulary. MeSH contains many terms that are more specific forms of stress, but the term itself is not present. These terms must be dropped from the MeSH mapping, as their generality makes them useless in connecting the content to literature.

The second problem relates to complex matches, and can be best explained using a sample message. Consider the following message "*The report stated that when **music therapy** is used, **the babies** required **less pain medication**. Does anyone know **of any published reports** of **empirical research** demonstrating the effect?*" Table 1 lists the mappings and their associated scores for this example.

Table 1- Sample message and its associated MeSH mappings

Source	MeSH	Score
music therapy	Music Therapy	1000
the babies	Infant	966
less pain medication	Pain	660
less pain medication	Pharmaceutical Preparations	827
of any published reports	Publishing	694
of empirical research	Empirical Research	1000

Consider the two mappings in table 1 for "less pain medication" which is an example of a *Complex Match* [7], where a single noun-phrase maps to a combination of MeSH terms. In this case the word "pain" maps to *pain* and "medication" to *pharmaceutical preparations*. The formal solution proposed by Metamap for complex matches is to combine these two mappings and take the average of their scores, resulting in the term "less pain medication" mapping to two MeSH terms, with a score of (827+660)/2=743.5. This is a logical solution, but for this project we do not use such a strategy, as it requires two MeSH terms to represent a single concept. Our strategy for complex matches is to leave the multiple mappings separate and allow their reduced scores to reflect the fact that neither MeSH term completely represents the concept in the message.

We also incorporated a filtering strategy to remove undesired MeSH terms. This is achieved through a *stop* list (a set of noun-MeSH combinations) that is based on terms that are consistently mapped incorrectly. Terms appearing in the stop list will be removed automatically from the list of MeSH terms produced after parsing the PPML message. In Table 1, the last two mappings belong to the stop list and will be removed.

At the end of the step, we have a set of MeSH terms (with a score evaluating the strength of each mapping) corresponding to the terms in a discussion thread.

Literature Search Strategy

The first step in the literature search process is to generate a *literature search vector* from the set of MeSH terms found in previous step. This is done by combining any duplicate MeSH terms in the set and adding their scores together. The result is a set of k unique MeSH terms, each of which has a *MeSH Score* associated with it. Let M be the unique set of MeSH terms from the thread, and let s_i be the MeSH score for term i.

$$\{m_1, m_2, m_3, \ldots, m_k\} \in M \quad (2)$$

M can potentially be used to query Pubmed through a simple Boolean Information Retrieval (BIR) algorithm that would perform a search of Pubmed for all the MeSH terms, and return a set of papers that feature each term in M. The problem with this approach is that if we keep the size of M unrestricted (and often quite large) Pubmed may have no papers that have all the associated MeSH terms. A modified BIR solution would be to drop the lowest scoring MeSH term(s) from the search vector and redo the search, reiterating until a set of papers is returned. Let $M_{(j)}$ be the MeSH search vector with the lowest j scores removed ($M_{(0)}$ is the full set), let $f(q)$ be the number of papers in Pubmed with the set of MeSH terms q, and let Q be the set of papers returned. The set of papers returned would be:

$$Q = min_j(f(M_{(j)}) > 0) \quad (3)$$

Again, there are several problems with the above search strategy: (i) it provides no ranking of the returned papers; (ii) it uses the MeSH scores only to sort the MeSH terms, and not as absolute values; (iii) it does not differentiate between those papers that contain all but one of the terms in the search vector from those that contain none; and (iv) it does not address the most pressing issue of this project, the potential inaccuracy of the MeSH terms.

To address these limitations, we developed an algorithm similar to the extended BIR algorithm (eBIR) [3]. Our algorithm differs from the BIR algorithm by using the MeSH scores as weights for each of the MeSH terms in M. For each MeSH term Pubmed has a set of papers that use that term as a keyword. Let p_j be an individual paper, P_i be the set of papers associated with MeSH term i, and l_i be the number of papers in P_i.

$$P_i = \{p_1, p_2, \ldots, p_{li}\} \in m_i \quad (4)$$

For every MeSH term there is now a vector of associated papers along with the MeSH score. A *paper score* is derived from these MeSH scores, and we use the paper score to order the results. Let t_i be the paper score for paper i. The paper score can be calculated using the following:

$$\forall m_i \in M(\forall p_j \in P_i | t_j = t_j + s_i) \quad (5)$$

Take every MeSH term m_i in the set of MeSH terms M, and for every paper p_j associated with that MeSH term, add the MeSH score, s_i, to the paper score t_i. Paper j has a score that is the sum of its MeSH terms' scores. Finally, let the set Q be the union of all the papers, and return the set Q sorted by the paper scores.

$$Q = \bigcup_{i=1}^{k} P_i \quad (6)$$

We argue that our literature search algorithm is superior to a traditional BIR algorithm as it provides an absolute ordering of the papers, and is not a susceptible to high scoring MeSH terms that are incorrect mappings.

PPML Forum: Linking Explicit and Experiential Knowledge

We have developed a PPML forum that allows practitioners to interact with the PPML discussions and review the retrieved research articles for a selected discussion thread. The forum allows the following functionalities:

(a) Navigating the discussions using a standard search function that allows users to perform a search of discussion threads for desired content, returning a list of threads sorted by relevance to the search query.

(b) Navigating the discussions using search functions based on MeSH terms. Two search algorithms have been provided for the MeSH-based search. The first search method uses a simple BIR algorithm and takes MeSH terms as input and returns all the discussion threads that contain all those terms, sorted by the date they were posted in the thread. This method has the advantage that it returns recent messages first, as it is expected that recent messages are what clinicians are most interested in. The second search method uses our search algorithm (i.e. terms with their MeSH scores) to retrieve discussion threads. The threads are assigned a score that is a sum of the MeSH terms that match the terms in the query. If we define C as the set of MeSH terms in the query, and M_i as the set of MeSH terms for thread I, then the query score e_i for each thread is calculated as follows:

$$e_i = \sum_{j \in C \cap M_i} s_j \quad (7)$$

The query score returns the threads sorted by search score, and any ties sorted by date of last communication. Future testing will provide an answer as to which method is more effective.

(c) Organizing the discussion threads into a hierarchy, based on the 135 UMLS semantic types, for users to browse the threads.

(d) Retrieving a set of citations for a given thread, along with direct links to each of the referenced papers.

The three different navigation methods provide the users with different approaches to finding their desired thread, and once there they can browse the content of the conversation and retrieve the pertinent medical literature with a single click.

Results

We give below an example discussion thread to demonstrate the linkage of PPML discussions with research articles. This thread, the first thread ever on the PPML, is from 1993, on the subject of music therapy.

```
Sender: 1
Subject: Music Therapy
Date: Mon Jun 28 21:19:36 ADT 1993
The last several days, the local NBC station
aired a "medical report" about the use of
music therapy.  The report was from Miami and
included a short report on the use of music
therapy in a NICU.  The report stated that
when music therapy was used, the babies
required less pain medication. Does anyone
know of any published reports of empirical
research demonstrating this effect?
..........
Sender: 2
Subject: Music Therapy
Date: Tue Jun 29 08:25:12 ADT 1993
I would suggest that you might contact [name
removed] in Pediatrics at Washington
University Medical School.  Her research is on
neonatal pain and she might know where the
local station picked up the report. I haven't
seen any data on the topic.
..........
Sender: 3
Subject: Music Therapy
Date: Tue Jun 29 10:20:41 ADT 1993
I'm not aware of specific studies conducted
using music therapy to reduce the need for
pain medication (i.e., music therapy to manage
pain).    However,    several    cognitive
interventions have been used quite effectively
to manage pain.  Donald Meichenbaum developed
a technique in the early 1970s called stress
inoculation training which combines aspects of
self-instruction  training  and  relaxation
training.
```

The example has been parsed and threaded correctly, and is ready to be converted to MeSH terms. Table 2 lists a sample of the MeSH terms that have been for retrieved after parsing the thread using Metamap.

Table 2- A sample of the mappings for a thread in PubMed. (The thread has 18 total MeSH terms)

MESH	SCORE	# OF PAPERS
Music Therapy	4802	1621
Pain	4215	237890
Pharmaceutical Preparations	1688	254813
Infant, Newborn	1660	438290
Education	1654	422011
Teaching	1320	429705

The returned set of MeSH terms for the thread seem to be appropriate, with the exception of the terms *education* and *teaching,* which are examples of terms added to the stop list. Table 3 contains a sample of the citations for the papers linked to the thread by our literature search strategy.

This example demonstrates the efficacy of our knowledge linkages framework. We took a thread containing the experiential knowledge of practitioners and retrieved corresponding published literature to supplement that experiential knowledge.

Table 3- The first three papers connected to the thread with MeSH terms, cumulative score and citation, and link to the paper, or the PubMed entry

MeSH: Music Therapy;Pain;Infant, Newborn;Behavior: *12609* *Bo LK, Callaghan P.* **Soothing pain-elicited distress in Chinese neonates.** Pediatrics:2000,105(4).
MeSH: Music Therapy;Pain;Infant, Newborn;Behavior: *12609* *Kemper KJ, Danhauer SC.* **Music as therapy.** Southern medical journal:2005,98(3).
MeSH: Music Therapy;Pain;Infant, Newborn;Behavior: *12609* *Tagore T.* **Why music matters in childbirth.** Midwifery today with international midwife:2009,(89).

Pilot Study

A pilot study was conducted on a sample of the archives, using all messages on the PPML in 2007 and 2008. The threads were reviewed by the project authors to determine (a) the accuracy of the message parsing, (b) the accuracy of the thread assignment, and (c) the accuracy of the papers returned.

The results of the pilot study were promising. The message parsing was successful on 76% of the messages, with problems arising only from MIME and HTML formatted messages. These problems can be rectified using more sophisticated message parsing algorithms, and we plan to fix them in the next version. The organization of messages into threads was achieved accurately over 90% of the time, which is very promising. The problems arose when users changed the subject line of a message when replying to a previous problem, or replied on a thread about a new topic. Some of these problems can be dealt with more sophisticated parsing algorithms, but when there is no obvious connection between the original and the modified version of the subject lines it is impossible to connect the two automatically. Future work will incorporate an override of the threading function to allow messages to be connected manually if a mistake is found in the thread reviews.

The correct linkages of the discussion threads with corresponding articles was achieved with an overall success rate of 65%. The linkage success rate can be improved by better filtering the content of the threads. Many of the messages on the PPML, such as job postings or advertisements for conferences, are not proper candidates for knowledge linkage and hence their presence compromised the retrieval rate of corresponding articles.

The results revealed some potential problems in the literature search strategy due to the functionality of Metamap, as it tends to miss key terms. The most common example was a lack of an age group indicator to represent children (ages 0-18). This age group is represented by the MeSH terms *Infant*, *Child* or *Adolescent*. Several of the threads that had problems with knowledge linkage were discussions about complex material, but within the thread Metamap did not recognize any MeSH term related to children, which resulted in papers that were not restricted to the proper age group. Following the lead of Abidi et al. [8] the next step in the project will apply an age group filter to restrict all the queries to include the MeSH term C*hild*, restricting the searches to papers about pediatric medicine.

The pilot study was successful enough to warrant future research. Once the changes recommended from the pilot study are completed a formal study using clinical experts will be conducted to evaluate both the conversion to MeSH, the linkage to publications, and the online presentation format.

Conclusion

This project has demonstrated the potential of a system to supplement the experiential knowledge contained in a medical mailing list with explicit, evidence-based research from published journals. It has also demonstrated the potential of a system to leverage archived medical text to provide a novel knowledge-based tool. Using the Metamap system and a novel information retrieval algorithm, the conversations have been processed and linked to pertinent medical literature, presenting the results in an online forum. The forum provides an arena through which clinicians can browse the archives of the PPML and reaffirm the experiences they shared with evidence-based literature.

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