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Diversity-aware retrieval of medical records

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ABSTRACT

The widely adoption of Electronic Medical Records (EMRs) causes an explosive growth of the medical and clinical data. It makes the medical search technologies become critical to find useful patient information in the large medical dataset. However, the high quality medical search is a challenging task, in particular due to the inherent complexity and ambiguity of medical terminology. In this paper, by exploiting the uncertainty in ambiguous medical queries, we propose a novel semantic-based approach to achieve the diversity-aware retrieval of EMRs, i.e., both the relevance and novelty are considered for EMR ranking. With the support of medical domain ontologies, we first mine all the potential semantics (concepts and relations between them) from a user query and consume them to model the multiple query aspects. Then, we propose a novel diversification strategy, which considers not only the aspect importance but also the aspect similarity, to perform the diversity-aware EMR ranking. A real-world pilot study, which utilizes the proposed medical search approach to improve the second use of the EMRs, is reported. We believe that our experience can serve as an important reference for the development of similar applications in a medical data utilization and sharing environment.

1. Introduction

With the notion that EMRs are the bedrock of modern healthcare, EMR systems are widely deployed for the exchange of medical information among various healthcare related parties [1]. According to the recent surveys, 82 percent of physicians indicated that they are currently using an EMR system or plan to do so [3].

This EMR movement causes an explosive growth of the medical and clinical datasets [51]. Secondary use of EMR data relies on the ability to retrieve accurate and complete information about desired patient populations. This fact makes the medical search is becoming a critical technique for the rapid and effective access of patient information [51], which also provide great potential for facilitating research and improving quality in medical practice [49]. Along this trend, the medical records track is established in Text REtrieval Conference (TREC) [55,62].

Medical information retrieval is challenging because of the inherent ambiguity within the posed queries [62]. Such ambiguity is manifested in different ways: (1) A query expresses a clearly defined sense, but the genuine needs under this sense may cover a broad range. Taking a common scenario where an ordinary user performs medical search for example, he feels uncomfortable (he has a high fever and rash erupts on his body) but is uncertain about his exact medical problems, so he inputs "fever" and "rash" as keywords into a search engine. In this case, as many diseases may cause these symptoms, the user may prefer to learn knowledge about all these diseases, so as to have a preliminary understanding about his situation and better prepare for the interview with doctors. (2) Query terms themselves are ambiguous, as most users have little medical knowledge. For instance, a pregnant woman feels pain in her abdomen, so she submits a query composed of "pain in the abdomen" and "pregnant". In this case, the term "pain" is ambiguous, which may mean "stabbing pain", "distending pain", "labor pain", etc. The user-cared reasons causing these different kinds of pain, however, may be totally different. Considering the ambiguous queries, as users provide no more information for disambiguating their intents, a medical search engine should

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produce a set of diversified results that cover all possible intents implied by the given query, in order to enable users to find their interested medical information.

From technical point of view, traditional IR technologies can be classified into two categories, i.e., content-based [25,27,28] and semantic-based [14,20,21,38,40,47] approaches. The former predicts the relevance of a document to the given query by considering only the document-inside content. Due to the inherent complexity and ambiguity of the medical terminologies, it is inappropriate for applying it directly for medical search [61]. The later exploits the external semantic resources to improve IR quality by taking into account the meaning of terms as they appear in the query and documents. Since the semantic-based approaches provide great potentials to tackle the ambiguous medical queries and the complexity of medical terminologies, current researches on medical information retrieval mainly fall into this category, such as query expansion [51,56,58], semantic similarity calculation [36,57,54], and granularity match [36,52,61]. However, since these IR models rank each document independently, the resulting top-ranked documents often contain excessively redundant information. The fact that they consider the relevance as the only measure for medical record ranking makes their capability to handle the query ambiguity is limited [62].

Recently, search result diversification is becoming a hot research topic with the aim to minimize the risk of dissatisfaction of the average user [8,10,24]. Since the novelty is introduced as an additional measure for document ranking, it has shown as a promising way to tackle ambiguous queries [6–10]. Based on how the different query aspects underlying the user input query are accounted for, existing approaches can be categorized as either implicit or explicit ones [9,10]. The theoretical analysis and experimental study [8,10] has illustrated that the explicit approaches, i.e., to explicitly model the possible aspects underlying a query, are more effective than the implicit ones. Along this trend, this paper will focus on the diversity-aware retrieval of EMRs, where both relevance and novelty are taken into account for the medical document ranking.

Since almost all the existing explicit diversification methods are developed for the scenario of Web search, it is not appropriate to deploy them in the medical search setting: (1) Query log, which is adopted for query aspect modeling by existing methods, is not a reliable resource for medical data retrieval. On the one hand, for some medical search environments such as enterprise search, query logs are not available or their scale is not large enough for supporting query reformulation. On the other hand, most users have no background knowledge and thus input queries at will, which leads the query aspects derived from query logs to be inaccurate. (2) Unlike the Web search that covers a wide range of application domains, medical search focuses on a concrete domain in which the rich medical knowledge is available. This domain knowledge is essential for a well-functioning diversifying model, which contributes to improve query aspect identifying accuracy and comprehensiveness [8]. However, none of the existing approaches use the domain knowledge. (3) Similarity between query aspects is an important factor for search diversification, but it is ignored by existing methods. Considering an instance in which four aspects are identified for a given query, with the first three express similar topics but the fourth one expresses a new idea. Using the existing aspect similarity measuring methods, a ranking, where documents about the fourth aspect are excluded from top positions, will be produced. Nevertheless, the documents related to the fourth aspect are more novel and deserve upper positions.

In this paper, we propose a novel approach to achieve the diversity-aware retrieval of medical records, where the semantic-based IR and search result diversification are combined together to tackle inherent ambiguity of the medical search. Different from existing diversifying strategies relying heavily on large amounts of query logs, the proposed approach employs a medical ontology that comprises rich medical knowledge to disambiguate the original query into multiple sub-queries (or query aspects). Each sub-query represents one aspect of the implied intents of the original query. Based on the modeled aspects of the sub-queries, we gives a novel strategy that exploiting the query disambiguation results for the diversity-aware medical search. The performance of the proposed approach is demonstrated on a real-world medical dataset. Experiment results show that the proposed approach fits well for the medical search environments and outperforms existing methods on both diversity and accuracy.

The contribution of this paper can be summarized as follows: (1) A novel approach for exploiting the ambiguity in a medical query for diversity-aware medical search is proposed, which first employs the medical domain knowledge for query understanding to construct multiple sub-queries from the original query and then the medical record relevance and novelty are combined together to handle the uncertainty in the information needs; (2) The empirical experiments on the real-world dataset are reported, which demonstrate the effectiveness of the proposed approaches; (3) A pilot study is described for the application of the proposed medical search approach in a real-world usage scenario.

The rest of the paper is organized as follows. Section 2 discusses the related work. Section 3 describes the technical details of the proposed approach for diversity-aware retrieval of medical records. In Section 4, the evaluation results and the real-world application are reported. Section 5 concludes the paper.

2. Related work

Information Retrieval (IR) is the process of searching within a document collection for the information most relevant to a user's query. It mainly uses keyword-based query as an input and returns a list of relevant documents as the output [25,47].

Most searching systems running for traditional document collections use content-based approaches, e.g., the vector space model [25], Latent Semantic Indexing [27], or Nonnegative Matrix Factorizations [28]. Since only the internal information of a document is employed to measure the similarity between queries and documents, they are not applicable to handle the complexity of the medical terminologies [55].

While in traditional IR only the document content is of concern for the query-dependent ranking, in web page retrieval, the link structure of the Web also plays an important role for the query-independent ranking. Current popular models for web page retrieval are mainly combinations of content-based and hyperlink-based approaches [29,30], where the location of a Web page in the Web's graph structure to determine its importance. Based on the assumption that hyperlinks in the global Web have the semantics of recommendations, hyperlink-based approaches utilize the location of a Web page in the Web's graph structure to determine its importance [30]. By observing that the majority of the links in a website are used to organize information and convey no recommendations, a path-based method for Web page ranking is described in [26,29] by distinguishing the hyperlinks for recommendation and information organization, respectively. The existing of inter-hyperlink relationship between documents is the pre-condition for the utilization of the hyperlink-based approaches. This fact limits their application for IR on general document collections.

Different from content-based IR approaches that focus on the frequency of word appearance, semantic-based IR methods more likely tend to understand the meaning hidden in retrieved documents and users' queries, by means of adding semantic tags into texts [22,39,44], structuring and conceptualizing the objects

within documents [48]. In [33,46,31], the semantic query expansion methods are adopted to extend query terms to their synonym and meronym sets defined in WordNet and/or Wikipedia. The vector-space model is adapted for the exploitation of ontology based knowledge bases to improve document ranking [20,34]. Approaches in [21,35,43,36], computed document relevance by considering the semantic relatedness between words or concepts defined in corresponding ontologies. By abstracting the free-text content into semantic graphs, references [23,32] reported on work that uses graph matching for document ranking. The work in [38,40,45] utilizes the semantic relations between concepts for query-page matching [53]. Since the semantic-based approaches consider the semantics of terms in queries and documents for their similarity calculation, they provide great potentials to tackle the complicate domain-specific terminologies and then enhance the quality of information retrieval.

Actually, the medical information retrieval can be seen as a domain-specific IR task [4,50,61,62], where the big challenge is to deal with the complexity and ambiguity within medical records and queries. With the support of standard terminologies or domain ontologies, such as the International Classification of Disease (ICD), Unified Medical Language System (UMLS), and Medical Subject Headings (MeSH), semantic-based IR approaches are widely utilized to tackle the ambiguity problem in medical search. A frequently used mechanism for improving the search quality is query expansion [56] and reformulation [58,62]. In [52,54], the semantic resources are exploited to represent queries in an expressive and meaningful context, through which to fill the semantic gap among the queries and documents and then to improve the medical search quality. Six existing domain-independent semantic similarity measures are adapted to the biomedical domain [52]. By defining the subsumptions as parent–child relationships between concepts, the medical hierarchy is exploited to address the granularity mismatch problem derived from the ambiguous queries [36]. However, all these proposed semantic-based medical IR approaches consider the relevance as the only measure for medical record ranking, which makes their capabilities to handle the query ambiguity limited. The proposed research in this paper can be classified into the category of semantic-based medical search. Our work is different from the existing researches since the proposed diversity-aware medical search approach borrows the novelty as an additional measure to tackle the inherent ambiguity of the user's information needs.

The novelty measure has been extensively used in the research on search result diversification. Current diversification approaches can be categorized as either implicit or explicit, based on how they account for the different query aspects underlying the user input query [10] (An aspect denotes a possible query intent. We use "query aspect" and "query intent" interchangeably in this paper.). Implicit methods [5–7] assume that similar documents cover similar query aspects. Based on this assumption, they promote diversity by directly comparing the documents retrieved for a given query to each other, and demote documents that are content-redundant with documents ranked already. Explicit methods [8–11] model the query aspects explicitly, and promote diversity by maximizing the coverage and minimizing the redundancy of the ranked documents with respect to the query aspects. Actually, the idea of explicitly modeling aspects represents a more promising direction, which is not only supported by theoretical analysis, but also validated by experimental study [8,10]. However, all the existing explicit diversification methods are developed for Web search. Due to inherent complexity of medical terminologies and without large amounts of query logs, they are not applicable for diversifying the search results in the medical IR setting.

In this paper, we use a combination of the technologies on semantic-based IR and Web search result diversification to tackle inherent ambiguity in the medical search process. Based on the given medical domain ontology, the underlying semantics (concepts and relations between them) of the query are discovered, and consumed for modeling various aspects underlying the given query; then based on the modeled query aspects, we propose a novel diversification strategy, which considers not only the aspect importance but also the aspect similarity, to perform medical record ranking.

3. The diversity-aware medical search approach

Our proposed approach on diversify-ware retrieval of medical records includes two steps, i.e., (1) query understanding to discover the implied aspects of the original query as multiple sub-queries; (2) diversity-aware medical retrieval to exploit multiple sub-queries to for diversifying the medical search results. The following of this section gives a detailed description on each of the two steps.

3.1. Query understanding

Since the keyword query is a simple and user-friendly search model, it is prevailing in many practical search systems. Our research assumes to use a keyword-based interface for the users to express their information needs and returns a list of relevant EMRs as the output.

The list of keywords in the query can be interpreted diversely, we need to handle the ambiguity problem, i.e., understand the meanings of the concepts specified in the user's queries and discover the potential aspects of the given query. More specifically, given a query q containing a list of keywords, the task of query understanding is to transforms it into a set of *derived queries* to model different aspects of q. As medical ontology contains rich and accurate professional knowledge that is shared by domain experts, we use it as background knowledge to uncover the underlying aspects of information needs. The detailed query understanding process contains three sub-steps as below.

3.1.1. Query transformation

This sub-step carries out two functions, i.e., keyword phrase identification and expansion. With the support of available semantic resources, e.g., WordNet and Consumer Health Vocabulary (CHV) [13], the former uses the maximum matching approach to scan the keywords in the query sequentially and find the longest matching subsequences defined in the semantic resources as the keyword phrases. For example, given a query "difficulty breathing headache", the longest maximum matching approach can find "difficulty breathing" as a keyword phrase and "headache" as the other keyword phrase.

For the latter, two types of expansions are conducted. On the one hand, the layman keywords input by lay persons should be mapped to professional medical terms, for examples, "difficulty breathing" is rewritten to "dyspnea". As previous researches demonstrated that professional terms were likely to achieve better search results than layman terms [2,13]. We employ the CHV [13], which provides a mapping between medical terms and layman terms, to perform this expansion. On the other hand, the input keywords (even the professional medical terms) may have synonyms. For instances, the distinction between "diagnosis" and "finding" is not clear, and "fever" is a synonym of "febrility". We use both the synonym knowledge in WordNet and the consumer health vocabulary to perform synonym expansion.

Formally, after the processing of this step, each keyword phrase $k_i \in q = \{k_1, k_2, \ldots, k_m\}$ is expanded to a keyword phrase set $S_i = \{k_{i1}, k_{i2}, \ldots, k_{ipi}\}$.

3.1.2. Candidate concept mapping

After m keyword expansion sets S_i ($i = 1, \ldots, m$) is obtained, this sub-step maps the user input keywords to a set of candidate concepts defined in the medical ontology. For each keyword phrase $k_i \in q = \{k_1, k_2, \ldots, k_m\}$, we can find a set of candidate concept nodes $C_i = \{c_{i1}, c_{i2}, \ldots, c_{ini}\}$ with ranking scores $R_i = \{r_{i1}, r_{i2}, \ldots, r_{ini}\}$. Assuming *match* (a, b) denotes the percentage of distinct token q-grams [22] of keyword phrase b is appeared in that of keyword phrase a, r_{ij} is set as $\max_{k \in S_i} \text{match}(k, c_{ij})$, which represents the confidence on mapping keyword k_i to concept c_{ij}. In the implementation, a concept c_{ij} is selected as a candidate one only if $r_{ij} > 0.75$, where 0.75 is chosen for balancing search accuracy and computing complexity for the following derived sub-queries generation.

3.1.3. Derived queries generation

This sub-step constructs a list of derived queries to model the various aspects of q. The basic idea is to extract a list of sub-graphs from the medical ontology, where each sub-graph covers at least one candidate concept of every keyword phrase $k_i \in q = \{k_1, k_2, \ldots, k_m\}$. Then each sub-graph is transformed as a sub-query representing one potential aspect of the interpretation of the user's information need.

Assuming that the user chooses each keyword phrase to represent a concept, then theoretically, there are $y = \prod_m^{i=1} n_i$ concept combinations for query q, where n_i is the number of concepts in C_i, and m denotes the number of keyword phrases in q. For each *combination* cb_j ($j = 1, \ldots, y$), we extract a set of sub-graphs (denoted as $GSet_j$) from the ontology. Each sub-graph in $GSet_j$ represents a possible interpretation of query q. It has a *graph weight* denoting the *importance score*, which can be explained as the possibility of this sub-graph representing the user's information need. After acquiring $GSet_j$ ($j = 1, \ldots, y$) for all y concept combinations, we perform a sub-graph ranking on $GSet_1 \cup \ldots \cup GSet_y$ based on their weights. Then the top ranked sub-graphs with weights larger than a threshold td are selected to represent the potential query interpretations of q. We have conducted experiments to test the different value settings of td, and the results show that our diversifying approach achieves the best performance on all the evaluation criteria when $td = 0.7$. Each selected sub-graph can then be transformed to a keyword-based sub-query, which includes the keyword phrases in the original query q and all the keyword phrases in concept nodes covered by the sub-graph. When the similarity of two sub-queries is bigger than a threshold value, the parents and children of the concepts in the sub-graph can also be used for the query expansion. The sub-graph weight is used to denote the *importance score* of the corresponding sub-query.

The sub-graph construction algorithm is illustrated as below, where the minimum number of edges linking all concepts in a combination together is taken into account for measuring the weight of a graph.

Algorithm 1 (Sub-graphs construction).
Inputs: a concept combination ($C_1, \ldots, C_m$), medical ontology O

Output: $GSet = \{(G_1, w_1), \ldots\}$, with $w \in [0,1]$ being the graph weight

Begin

1. $V = \Phi$, $E = \Phi$;//V is the node set, E is the edge set.
2. $S_C = \{C_1, \ldots, C_m\}$, $S_{initial} = \Phi$;
3. Choose a concept C_i from S_C randomly and set $S_{inital} = \{C_i\}$, $S_C = S_C - \{C_i\}$, $V = \{C_i\}$;
4. while ($S_{initial}$!= $\{C_1, \ldots, C_m\}$)
5. { $length = 1$;
6. do
7. { $S_{length} = \Phi$;
8. For each $C \in S_{initial}$
   $\{S_{length} = S_{length} \cup \{path(C,C') | path(C,C') \in O \&\&$
   $length(path(C,C')) == length \;\&\&\; C' \in S_C\};\}$
9. If ($S_{length} = \Phi$)
   $\{length = length + 1;\}$
10. } While ($S_{length} = \Phi$ && $length <$ Max)
11. For each $path(C, C') \in S_{length}$
12. $\{S_{inital} = S_{inital} \cup \{C'\}$; $S_C = S_C - \{C'\}$;
13. $V = V \cup S'$;//S' is the set of concepts lying on the path $path(C, C')$
14. $E = E \cup E'$;//E' is the edge set comprising of edges on $path(C, C')$
15. }
16. }
17. For pair (C_i,C_j)//$C_i,C_j \in \{C_1,\ldots, C_m\}$ and $i \neq j$.
    $\{PathSet_{i,j} = \{path(C_i,C_j) | path(C_i,C_j) \in G(V,E)$ && concepts in $\{C_1, \ldots, C_m\}$ should not appear on $path(C_i,C_j)\};\}$
18. $S_{graphs} = PathSet_{1,2} \times \ldots \times PathSet_{m-1,m}$;
19. $GSet = \{(G_i, weight_i) | G_i \in S_{graphs}$ && $weight_i = \sum_{i=1}^{m} r_i/m \times |E|\}$
    /*$|E|$ is the number of edges in G_i, r_i is a score measuring the match degree between keyword $k_i \in q$ and its corresponding concept in the input combination, which was computed in the concept mapping sub-step.*/

End

Firstly, Lines 1–16 extract a graph $G(V,E)$, which comprises all the candidate edges linking the candidate concepts of a combination in the tightest way. The graph extraction process is actually a concept search process. S_{inital} stores concepts that belong to the combination and have been found already. S_C stores concepts that have not been found yet. Lines 1–3 start the search from a concept randomly chosen from the combination. Lines 5–10 search unfound concepts using the breadth-first search strategy with the concepts in S_{inital} serving as start points. As Lines 11–15 show, when some concepts in S_C is found, the semantic paths linking it to some concepts in S_{inital} with the shortest length will be found. Then, all the concept nodes and edges on the paths will be added to the graph. After $G(V,E)$ is obtained, Lines 17–19 try to construct the corresponding sub-graph set $GSet$; Line 17 divides $G(V,E)$ into several semantic path sets (a semantic path set comprises all the paths in G that link two concepts together); Line 18 constructs the sub-graph set by combining paths from different semantic path sets, and a sub-graph is generated by choosing one path from each path set and combine them together; Line 19 assigns a graph weight to each sub-graph in $GSet$.

After the processing of this step, we get a list of derived queries $Q = \{(q_1,sc_1), \ldots, (q_t,sc_t)\}$, with sc_j ($j = 1, \ldots, t$) denoting the *importance score* of sub-query q_j. They are normalized across multiple query aspects, i.e., $\sum_j sc_j = 1$.

Given a query "difficulty breathing at night", a schematic example of the query understanding process is illustrated in Table 1, where the WordNet and CHV [13] are employed for the query transformation, and Medical Subject Headings (MeSH) [17] is used as the underlying medical ontology.

3.2. Diversity-aware medical search

The search result diversification can be stated as a tradeoff between relevance and novelty, i.e., given an initial ranking list R for a query q, find a re-ranking S that has the *maximum coverage* and the *minimum redundancy* with respect to different aspects implied by q [10,11].

Table 1
Diversification performance using different diversification strategies.

Original query	Query transformation	Candidate concept mapping	Sub-query generation
difficulty breathing at night	Two keyword phrases are identified: #1: *difficulty breathing*; #2: *at night*; Keyword: phrase expansion: #1 (*difficulty breathing*) sameAs: {*dyspnea*; *dyspnea; shortness of breath*;} #2 (*at night*) sameAs: {*night time*; *nocturnal*;}	Five concepts are identified for #1: c_{11}: *Dyspnea* [*ID*: C08.618.326] c_{12}: *Dyspnea* [*ID*: C23.888.852.371] c_{13}: *Dyspnea, Paroxysmal* [*ID*: C23.888.852.371.396] c_{14}: *Dyspnea, Paroxysmal* [*ID*: C08.618.326.396] c_{15}: *Dyspnea, Paroxysmal* [*ID*: C14.280.434.313] 12 concepts are identified for #2: c_{21}: *Somnambulism* [*ID*: C10.886.659.635.700] c_{22}: *Somnambulism* [*ID*: F03.870.664.635.700] c_{23}: *Nocturnal Enuresis* [*ID*: C12.777.934.284.500] C_{24}: *Nocturnal Enuresis* [*ID*: C13.351.968.934.252.500] C_{26}: *Sleep Bruxism* [*ID*: C07.793.099.500] c_{27}: *Sleep Bruxism* [*ID*: C10.886.659.637] ... Note that the entry term of a concept defined in the MeSH is considered as the synonym of the corresponding concept.	Three sub-queries are generated: q1: {(*respiration disorders*; *dyspnea*; *dyspnea, paroxysmal nocturnal*; *difficulty breathing*; *at night*;), 0.35} q2: {(*heart failure*; *dyspnea, paroxysmal nocturnal*; *difficulty breathing*; *at night*;), 0.3} q3: {(*signs and symptoms, respiratory*; *dyspnea, paroxysmal nocturnal*; *difficulty breathing*; *at night*;), 0.35}

This problem is an instance of the maximum coverage problem [12], which is NP-hard. Fortunately, there is a well-known greedy approximation to this problem [10,11]: Given a ranking R for an ambiguous query q, a re-ranking S can be produced by iteratively selecting a 'local-best' document from R/S (the 'local-best' document should provide the maximum coverage of the aspects underlying the initial query, and the minimum redundancy with respect to the aspects covered by the documents already in S). Based on this basic approximation idea, we propose a novel strategy for search result diversification.

Given the initial query q and its derived query list $Q = \{(q_1,sc_1), \ldots, (q_t,sc_t)\}$, we produce a document list for q and each of the derived queries, respectively. The ranking model adopted can be vector-space models, probabilistic rank models or learning-based rank models, which support relevance computing. For the sake of clarity, a document list for the initial query is denoted as *base-ranking*, while those generated for derived queries are denoted as *derived-rankings*.

Our proposed strategy performs search result diversification by producing a re-ranking S of the *base-ranking*, based on the derived query list Q and their document lists (*derived-rankings*). In practice, the re-ranking process is as follows:

3.2.1. Determining the first ranked document

The top-1 document in *base-ranking* is chosen to be put at the first position of the re-ranking list S, as it is the most relevant one to q.

3.2.2. Ranking the rest documents in base-ranking

After the selection of the first ranked document, we iteratively select the "local-best" document to be put in the next position. At each iteration, the document $d \in base\text{-}ranking \backslash S$ that scores the highest according to Eq. (1) is chosen as the "local-best" one:

$$LB(d,S) = \delta \cdot relevance(d,q) + (1-\delta) \cdot novelty(d,S) \quad (1)$$

where $relevance(d,q)$ models the relevance of d, whose value is actually the relevance score of d in the *base-ranking*; $novelty(d,S)$ models the *novelty* of d, given how well the user input query q is already satisfied by documents in S; δ ($\delta \in [0,1]$) controls the tradeoff between the two factors.

In order to derive $novelty(d,S)$, we compare a document d to each of the selected documents in S, and integrate these comparison results together according to Eq. (2):

$$novelty(d,S) = \prod_{d_i \in S} novel(d,d_i) \quad (2)$$

where $novel(d,d_i)$ measures the novelty of d, given how well the user query q is already satisfied by the document d_i. We explicitly use the various query aspects underlying q, in the form of derived queries $Q = \{(q_1,sc_1),\ldots,(q_t,sc_t)\}$, to compute $novel(d,d_i)$. The basic computing idea is as follows: (1) the more derived queries d covers, and the less derived queries d and d_i share, the more novel d is with respect to d_i; (2) the relative *importance* of a derived query, with respect to other derived queries associated with q, is a necessary factor for novelty computing. A query with a higher *importance score* should play a more significant role in identifying novelty than a less important query does. (3) The similarity between derived queries is another factor that should not be ignored. Similar queries should avoid redundant contribution in novelty measuring, in order to produce unbiased result. Eq. (3) shows the detailed computing method:

$$novel(d,d_i) = \sum_{q_j \in Q} rs(q_j) \cdot \prod_{m \in [1,j-1]} (1 - sim(q_j,q_m)) \cdot rel(d,q_j) \cdot (1 - rel(d,q_j) rel(d_i,q_j)) \quad (3)$$

where $rs(q_j)$ denotes the *relative importance* of q_j with respect to other queries in Q, which is derived by normalizing its importance score sc_j; $rs(q_j) = sc_j / \sum_{k=1}^{t} sc_k((q_j,sc_j) \in Q)$; sim (q_j,q_m) evaluates the similarity between two queries, which is computed by employing a graph matching algorithm [13] on the sub-graphs corresponding to q_j and q_m; rel (d,q) denotes the document relevance score with respect to a query, which is provided by *derived-rankings*; rel $(d,q_j)rel(d_i,q_j)$ measures how well d and d_i share the topic q_j.

4. A real-world pilot study

In this section, a pilot study is described for the implementation and deployment of the proposed diversity-aware medical search solution on a real-world Cloud of regional healthcare collaboration platform. The empirical experiments and the evaluation results are reported. As the reference for the development of similar application, we summaries the findings and learned lessons in the real-world trial for the application of the diversity-aware medical search.

4.1. The usage scenario and system implementation

As shown in Fig. 1, a real-world application of the diversity-aware medical search involves three types of organization, i.e., (A) community hospitals or senior people nursing centers with general medical practitioners, who have particular skills and practice a holistic approach for treating people with multiple health issues; (B) regional medical center or class A hospitals with domain specific medical doctors, who are expert of one or several diseases; (C) Cloud service providers with the healthcare collaboration platform enabling the provision of collaborative medical care to

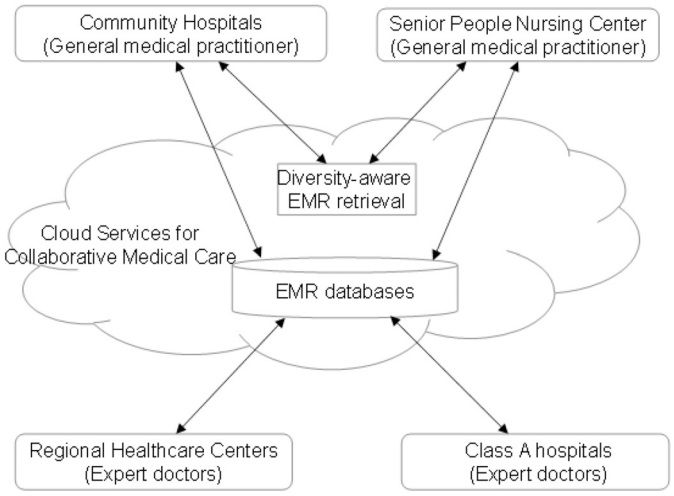

Fig. 1. The usage scenario of the real-world application of the diversity-aware medical search.

the outpatients or inpatients of organizations (A) and (B). The component of the diversity-aware medical search is deployed on the Cloud of healthcare collaboration platform, which supplies the medical data storage and management services under certain privacy protection mechanisms [37,59,60,64,65]. The goal of the real-world application is to use the medical records constructed by the expert doctors in organization (B) to train the general medical practitioners in organization (A) or provide references when they provides preventive care and health education to their patients.

The implementation and deployment of the diversity-aware medical search includes two phases, i.e., the build-time phase and run-time phase. In the former, the component for diversity-aware medical search is deployed in the Cloud to be accessed by the general medical practitioners in organization (A). More specifically, three tasks are involved:

(1) Full-text indexing of the EMR: The widely used Lucene library [67] is adopted here for the indexing implementation. According to the Health Level 7(HL7) CDA, the EMR conceptual model has three parts: (1) patient basic data; (2) patient history profile; (3) clinical data, including symptoms, diagnosis, and treatments of each hospital visit by a patient. The full-text indexing is conducted on all these three parts with a lot of fields. Since negative qualifiers, e.g., no or without, are commonly used in the patient profile and clinical data to describe the absence of a medical condition, the dedicated negation handling approach [69] is incorporated into the EMR indexing process.
(2) Semantic indexing of the medical ontology: To speed up the query transformation (see Section 3.1.1), concept mapping (see Section 3.1.2), and derived query generation (see Section 3.1.3), and then the query understanding, we index all vocabularies and concepts in the medical ontology.
(3) Software interface development: This component is used for connecting the health information systems of the organizations (A) and (B) to the storage service in the healthcare collaboration platform, through which the medical records generated from organization (B) are stored automatically in the medical Cloud platform. In this pilot study, the collected EMRs will be accessed by the general medical practitioners in organization (A).

In the run-time phase, whenever a medical record is constructed by the expert doctor in organization (B), one copy is stored remotely in the medical Cloud platform. At the same time, the full-text indexer is triggered to conduct the indexing task. The application supports the medical practitioners in organization (A) to conduct keyword-based query over the available EMR datasets. The implementation mainly covers two tasks:

(1) Query understanding: Both the Lucene [67] and Jena [68] libraries are utilized together to realize the query understanding. To achieve high efficient query transformation and concept mapping, their underlying matching process is implemented by using keyword-based search over the indexer of the involved vocabularies and medical ontology. Note that the keyword phrase matching is conducted in real-time when the user is typing the query in the search box, which can also speed up the matching process. For the sub-query generation, the Jena [68] is used for the semantic relation inference and subgraph identification.
(2) Diversity-aware EMR retrieval: The Lucene library [67] is employed for the implementation of the retrieval process. The original query and derived multiple sub-queries are sent to the indexer of EMR data. Their corresponding relevant EMR lists are retrieved, respectively. Then, the re-ranking-based diversification strategy are implemented to generate the EMR search results and present them to the medical practitioner for reference or online learning.

4.2. Experimental evaluation

This section reports the empirical experiments on the available EMR datasets and evaluation results.

4.2.1. Dataset

We use a real-world dataset for the empirical evaluation of the proposed approach for diversity-aware medical search, which comprises three parts described as below:

- *Document set*: over 100k medical records acquired from our cooperation hospitals are selected as target documents to perform ranking on. A medical record is a free-text description that keeps track of a patient's symptoms and how he (she) is diagnosed and medically treated.
- *Sample queries*: a total of 30 sample queries are generated, where the above mentioned "difficulty breathing at night" is a concrete example. For sample query generation, we first selected 100 most frequent symptom descriptions from the medical records as candidate queries (each description is dictated by patients stating their situations); then ambiguity of these candidate queries was estimated using an entropy-based measure [15]. Then, 30 queries with the highest ambiguity were chosen as target ones.
- *Semantic knowledge base*: A medical diagnosis ontology, MDO, was built based on the disease knowledge extracted from the MeSH ontology [17], as well as the diagnosis knowledge extracted from Collins's medical textbook [18] and our medical records. MDO contains 1526 classes, 9 types of relations linking symptoms and diseases, diseases and diseases, checking items and symptoms and so on, 5971 class instances and 33,627 relation instances.

4.2.2. Evaluation criteria

- *α-nDCG@10 (@20)*: α-nDCG [16] is an official metric adopted by the diversity task of TREC Web Track. It rewards both relevance and diversity of the results, and balances the two factors through a turning parameter α. α-nDCG is computed with $\alpha = 0.5$ in our implementation, in order to give equal weights to both relevance and diversity. α-nDCG@10 (@20) evaluates the performance of the top-10 (20) documents.

- *precision-IA@10(@20)*: The precision-IA metric extends the traditional notion of precision, which accounts for the possible aspects underlying a query and their relative importance [15]. Eq. (4) shows it in detail, where M denotes the number of sample queries, N_t denotes the number of derived queries for a sample query t ($1 \le t \le M$), and $j_t(i,j)$ is a binary score (0 or 1) denoting the relevance of the document returned for query t at depth j to the derived query i of sample query t.

$$precision - IA@k = \frac{1}{M}\sum_{t=1}^{M}\frac{1}{N_t}\sum_{i=1}^{N_t}\frac{1}{k}\sum_{j=1}^{k} j_t(i,j) \quad (4)$$

4.2.3. Experiment results

Previous researches have demonstrated that explicit diversification approaches outperforms the implicit ones. We compare our approach against two state-of-the-art work for explicit search result diversification:

- *IA-Select* [8]: IA-Select is a greedy algorithm focusing on maximizing the probability that the average user finds at least one useful result within the top-k results. Based on a predefined taxonomy to which both queries and documents are classified, it performs diversification by iteratively promoting documents that share a high number of classes with the query, while demoting those with classes already represented in the ranking.
- *xQuAD* [10]: xQuAD is a probability-based framework which explicitly uses the aspects underlying a query for search result diversifying. After setting the related queries (suggested queries) produced by some major web search engines as sub-queries of a user query, xQuAD performs search diversification based on the estimated relevance of documents to those sub-queries, as well as on the relative importance of each sub-query in light of the user query.
- *The Semantic-based Search Result Diversification (SSRD)*: It is the implementation of the proposed approach in this paper. The only parameter in SSRD that should be set in advance is δ, which balances the relevance score and novelty score for "local-best" document computing. In this research, we performed the α-nDCG@20 evaluation on the test dataset to select the optimal parameter of $\delta = \{0, 0.1, 0.2, \ldots, 1\}$. The results are shown in Fig. 2, where the vertical axis denotes the α-nDCG@20 measure, and the horizontal axis represents different δ values. Accordingly, δ was set to 0.8, which achieves a peak value of α-nDCG@20 on the real-world dataset. In addition, for the ranking model used to produce *base-ranking* and *derived-rankings*, we chose the DPH Divergence Form Randomness model [18], which was validated by [8] as the best among three widely used ones, BM25, DPH and LM.

Effectiveness evaluation of the query aspect discovery strategy

Several recent research findings [8–10] indicated that a high quality query aspect discovery result was crucial for a well-functioning search diversifying model. To be fair, we use the two existing search result diversification approaches, i.e., IA-select and xQuAD, to evaluate the contribution of the semantic based query aspect generation (SAG) approach as described in Section 3.1.

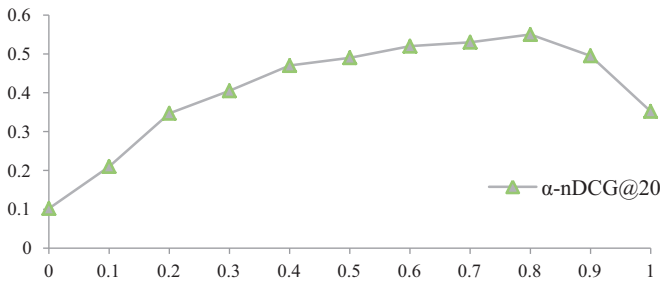

Fig. 2. The experiments about the tuning of parameter δ to balance relevance and novelty.

For performance comparison, the query log based technique (LAG) [10] is employed as the baseline. It relies on the query reformulation mechanism of Google for query aspect production, which is regarded as state-of-the-art query log mining solution for query aspect generation [10].

We hired 7 students in a medical school to help us judge the query-document relevance, which serves as the foundation for computing α-nDCG and precision-IA. For each of the top-10 (20) documents, each student makes a binary decision regarding whether the document is relevant to a derived query. And then if more than half of the 7 students give a positive vote to a document, it is evaluated as a matched one of the derived query.

The implementation LAG (SAG) + IA-select (xQuAD) uses LAG (SAG) for query aspect generation and IA-select (xQuAD) for search result diversification. Their performance comparison in terms of α-nDCG and precision-IA is illustrated in Table 2. By comparing the results of employing IA-select on LAG with that on SAG, we observed that SAG + IA-select outperforms LAG + IA-select on all settings, with a performance increase of up to 4.5% on α-nDCG and 0.6% on precision-IA. The same findings were also found when comparing SAG + xQuAD with LAG + xQuAD, and SAG improves LAG with a gain of up to 5.9% on α-nDCG and a gain of up to 0.8% on precision-IA. For the comparison of IA-select and xQuAD, for both LAG and SAG, xQuAD outperforms IA-select. This result is consistent with the experiment evaluation in [10].

The observations in Table 2 can provide indirect proof that, the quality of query aspects derived from the SAG (i.e., the query understanding described in Section 3.1), is better than that from LAG (mining query aspects from the Web query log). It demonstrates that the medical domain ontology can provide significant positive effect on the medical search quality. Furthermore, the comparison results in Table 2 also show that SAG approach is more appropriate than LAG to handle the complexity of domain terminologies.

Diversifying strategy evaluation

In this experiment, we test the effectiveness of the diversifying strategy of SSRD. To provide a fair comparison, both SSRD and baselines utilize the same query aspect generation method SAG. Two versions of SSRD were implemented for testing:

- $SSRD_1$: This SSRD variant disregard the derived queries similarity when performing diversification, which is realized by removing the $\prod_{m\in[1,j-1]}(1 - sim(q_j, q_m))$ item from Eq. (3).
- $SSRD_2$: This SSRD version employs our complete diversification strategy as introduced in Section 3.2 for diversity aware EMR ranking.

The experimental results are illustrated in Table 3, where the best results are highlighted in bold. The performance comparison between two baselines validates again that xQuAD outperforms IA-select in terms of both α-nDCG and precision-IA. Comparing the proposed SSRD to two baseline approaches we can find that, the

Table 2
Diversification performance using different query aspect generation methods.

	α-nDCG		Precision-IA	
	@10	@20	@10	@20
LAG + IA-select	0.339	0.36	0.165	0.153
SAG + IA-select	0.371	0.405	0.169	0.155
LAG + xQuAD	0.403	0.474	0.187	0.18
SAG + xQuAD	0.462	0.517	0.195	0.187

Table 3
Diversification performance using different diversification strategies.

	α-nDCG		Precision-IA	
	@10	@20	@10	@20
SAG + IA-select	0.371	0.405	0.169	0.155
SAG + xQuAD	0.462	0.517	0.195	0.187
SAG + $SSRD_1$	0.495	0.539	**0.221**	**0.206**
SAG + $SSRD_2$	**0.503**	**0.55**	0.217	0.204

two variants of SSRD outperform the baselines significantly on all settings, which demonstrates that the effectiveness of combining the proposed query aspect generation and diversification strategy for improving medical search quality. Among the four approaches, $SSRD_2$ ($SSRD_1$) has the best performance in terms of α-nDCG (precision-IA). This phenomenon shows that, the query aspect similarity is a valuable factor for improving diversification performance in terms of α-nDCG, and there is no clear indication that the query aspect similarity has positive effect on the EMR retrieval in terms of precision-IA.

The computing complexity is a crucial parameter to determine the feasibility of a document ranking algorithm. Since the concept matching is conducted in real-time when the user typing the query in the search box, two main time consuming tasks of SSRD are the derived query generation (described in Section 3.1.3) and diversity-aware medical search (described in Section 3.2). For the sub-graphs construction algorithm (algorithm1) for derived query generation, its time complexity is $O(\sum_{i=1}^{n} d_i e_i)$, where n denotes the number of concepts in the concept combination; d_i is the degree of concept c_i in the ontology graph; and e_i represents the maximum value of the path lengths that link concept c_i to other concepts belong to the combination. As there are y concept combinations derived from Section 3.1.2, the total time complexity of the derived query generation part is $O(\sum_{i=1}^{n} d_i e_i)$ which is linear to number of edges in the ontology graph. For the diversity-aware medical search, besides the time spent on the document relevance ranking cost by the existing relevance computing model (DPH model), $O(n_d^2 n_q)$ were consumed to combine the relevance-based ranking results and produce a final diversification-aware ranking list. n_d denotes the number of documents in base-ranking that is extracted by DPH from the document set; n_q represents the number of derived queries. Our experiment shows that, the execution time of the proposed SSRD approach is very similar to that of two baseline approaches.

4.3. Discussion

From the feedbacks of the general medical practitioner, they are basically satisfied with the search results of our pilot system, which demonstrates the effectiveness of our proposed approach to solve the problem of uncertainty in the information needs for ambiguous medical queries. The advantages of employing the diversity-aware approach for medical search can be summarized into three aspects:

(a) Enhancing the secondary use of medical records: The current dominant medical search approaches [56,60] use query expansion to handle the ambiguity problem. Since the relevance is the only employed measure for EMR ranking, their ability to retrieve accurate and complete EMRs about desired patient populations is limited [60]. Our proposed diversity-aware medical search exploits the medical domain ontology to discover the potential aspects of the original query as multiple sub-queries, through which to enable a way to answer ambiguous medical queries, i.e., the novelty is introduced as an additional measure for EMR ranking, which can increase the satisfaction of the average user with the medical search results. Note that to retain the privacy of citizens as much as possible, a generally accepted concept in healthcare domain is that only the "need to know" data should be presented to medical personnel. Thus a big challenge for the enhanced second use of EMRs is to balance the privacy protection and medical data utilization, which will an important task for our future research work.
(b) Improving the quality of medical care: The diversity-aware medical search approach enables the general medical practitioners to find their interested EMRs constructed by the expert doctors in a high effective and efficient way. Through the case-based learning, the general practitioners use the knowledge conveyed by the EMRs to guide and improve the quality of their provision of preventive care and health education to patients, which make them behave like expert doctors.
(c) Balancing the utilization of the medical resources: The healthcare resource utilization is extremely unbalanced in China. Due to the patients' preference to expert doctors, the class A hospitals are overcrowded with patients, thus resulting in the tension of relationship between doctors and patients. However, there is almost no patient in the community hospitals. The enhancement of general practitioners' medical care service has great potential to change the choice of the patients with chronic illnesses or the requirement of preventive care from class A hospitals to community hospitals, which make the expert doctor have more time to provide medical care to the patients with the intractable diseases.

We also report some of the learned lessons or important points of detailed design that can serve as references for the development of similar systems for enhanced healthcare services:

(A) Working closely with the user: The motivation barrier is an important issue for the adoption of information technologies to improve the healthcare service. To provide concrete incentives to the end users, we need to work closely with them and find the matching points of their real requirements and the proposed technologies.
(B) Medical domain knowledge playing the key role: The wide availability of medical domain ontology is the key to motivate our research and make our proposed approach be successfully applied in a real-world application. Our pilot study underpins the conclusion that lightweight semantic is more feasible to be produced and consumed in a real semantic application [66]. The vocabularies describing the diseases and symptoms in the domain ontology is widely used in the EMRs, which makes our solution have minimum disturbance to the existing infrastructure. According to the initial evaluation results of the query understanding, we find that many concepts were not defined in the ontology. In the future, we will adopt learning based approach [41,63] to recognize the unknown concepts from the text and link them with the nodes in the knowledge base to handling the incompleteness of the medical ontology.
(C) Redundant indexing to reduce the response time: To reduce the response time of the query processing, multiple copies of the free-text index are stored in the Cloud server. When given a query q, the constructed multiple sub-queries can be processed in a parallel way. Actually, this implementation is a tradeoff between the computing time and storage space.
(D) Addressing the privacy concerns: The current trial system has only been internal used by the general medical practitioners in organization (A). In the future, we will release it as an open website to be accessed by the registered patients for their self-education. For the implementation of such a public Internet

system, we plans to adopt the models of k-anonymity [59,60] or differential privacy [64] to privacy preserved medical data retrieval. In addition, the previous work [53] has illustrated that the synergy among multiple information sources can provide enhanced information utilization more than the sum of using them separately ($1 + 1 \geq 2$). The utilization of semantic linkages among multiple sources for enhanced medical data consumption and then for improved medical care needs to be conducted under certain privacy protection mechanisms.

5. Conclusion

This paper proposed a novel approach for diversity-aware IR in medical environment. With the support of domain ontology, the semantic information implied in a user query was extracted and consumed for query aspect modeling; then based on the modeled query aspects, a novel diversification strategy, which considers not only the aspect importance but also the aspect similarity, was proposed to perform document ranking. The empirical experiments on the real-world datasets illustrate the effectiveness of the proposed approaches. We report a pilot study on the application of the proposed medical search approach for the secondary use of medical records, through which to enhance the healthcare quality and balance the utilization of medical resources.

This paper gives the basic concept of the diversity-aware retrieval of medical records, which represents a beginning to combine the technologies of semantic IR and search result diversification for the secondary use of EMRs. This paper only considers the utilization of the semantics in the query for enhanced medical search. In future, we will extend current research to exploit the semantics in the free-text EMRs and the data fusion of multiple sources for improvement of the secondary use of available medical data and then enhancing the healthcare quality.

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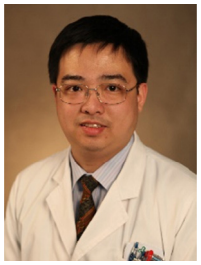

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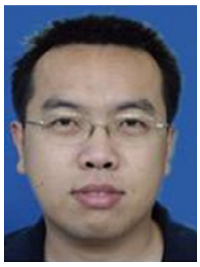

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