Benchmarking Clinical Decision Support Search

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Abstract
Finding relevant literature underpins the practice of evidence-based medicine. From 2014 to 2016, TREC conducted a clinical decision support track, wherein participants were tasked with finding articles relevant to clinical questions posed by physicians. In total, 87 teams have participated over the past three years, generating 395 runs. During this period, each team has trialled a variety of methods. While there was significant overlap in the methods employed by different teams, the results were varied. Due to the diversity of the platforms used, the results arising from the different techniques are not directly comparable, reducing the ability to build on previous work. By using a stable platform, we have been able to compare different document and query processing techniques, allowing us to experiment with different search parameters. We have used our system to reproduce leading team’s runs, and compare the results obtained. By benchmarking our indexing and search techniques, we can statistically test a variety of hypotheses, paving the way for further research.

1 Introduction
Physicians are required to keep abreast of the latest medical advances, as published in medical journals. At the time of writing, over 27 million articles have been added to PubMed since Jan 2017 [22]. To practice evidence based medicine, a clinician must be able to locate relevant literature in a short time (less than two minutes [13]), clearly a difficult task. Since 2014, the Clinical Decision Support (CDS) Track [29] at the Text Retrieval Conference (TREC) has provided a forum for tackling this important issue. Each year, participants were provided with a set of Electronic Health Records (EHRs) and asked to find relevant articles. While verbose queries have always been

1A system to run these experiments online will be made available to the research community.
a challenge in information retrieval (IR), EHRs pose a steeper challenge as
these records are often riddled with spelling, grammar, and punctuation
errors as well as medical jargon and abbreviations. While in 2014 and 2015
simulated EHRs [26] were used, in 2016 participants were provided with real
EHRs. These were arguably far more difficult to process, resulting in a drop
in recall and precision scores. In this paper, we focus on the 2016 track
(CDS’16).

While CDS tracks provide valuable datasets for evaluating search method-
ologies, it is difficult to compare different participants’ algorithms. Since
these platforms are seldom open sourced or made accessible to others, build-
ing on previous work is very challenging. While most participants use a
combination of standard algorithms (e.g., seven out 24 teams used pseudo-
relevance feedback), the results they obtain vary considerably [24].

To help further research in this area, we developed a platform that allows
us to compare methods used by the biomedical IR community, in particular,
TREC CDS participants. These methods include query and document pro-
cessing techniques, such as negation detection, normalization, query expan-
sion and reformulation, use of knowledge databases, and learning to rank.
Our goal is to facilitate proof-of-concept approaches to answer the following
questions using the clinical search dataset provided by TREC: Given a clin-
ical question, what are the most promising retrieval methods? and; Does
any specific indexing method lead to better retrieval effectiveness?

Our experiments with a variety of methods identify some of the most and
least effective approaches. We identify some of the reproducible results from
this track, and how our experimental results compared. Our results form a
benchmark for evaluating more sophisticated algorithms. We identify some
of the difficulties encountered in attempting to reproduce competition re-
results, and suggest how to mitigate these problems in the future by accurately
specifying the methods used.

2 Related Work

Medical Information Retrieval

TREC has a long history of running tracks in the medical domain, includ-
ing the Genomics track (2003-2007), the Medical track on electronic health
records (2011-2012), and the TREC Clinical Decision Support (CDS) track
which ran for three years (2014-2016). The TREC CDS track aimed to facili-
tate the answering of clinical questions pertaining to better patient care [25].
After the results are released, most teams publish a short report detailing
their search methodology and results.

A high-level list of approaches taken by 2016 CDS participants is sum-
marized in Table 1. While some teams implemented unique methods, there
was still a large overlap in methods used. For example many teams iden-
Table 1: A brief summary of popular methods and search engines from different teams at TREC CDS 2016.

| Method                                | Number of teams (Team name)                                                                 |
|---------------------------------------|-------------------------------------------------------------------------------------------|
| Use of UMLS                            | 8 (CBNU [18], CSIRO [19], MerckKGaA [16], NCH-RISSI [10], ECNU [17], DUTH [2], iRiS [36], SCIAICLTeam [20]) |
| Use of MeSH                           | 8 (CBNU used level 2 MeSH headings related to diseases, ECNU, ETH [14], MayoNLP [33], IAII-PUT [12], IRIT [23], NKU [37], NLM-NIH [1]) |
| Psuedo Relevance Feedback             | 7 (CBNU, DA-IICT [27], MerckKGaA, ETH, MayoNLP, NKU [37], UNTIIA [31])                    |
| Concept Extraction (e.g., Metamap or MaxMatcher) | 5 (CSIRO, DUTH, iRiS, IRIT, HAUT [21])                                                      |
| Negation Detection                    | 3 (ETH - modified negated words found by NegEx to a new form, iRiS - removed negated terms found by NegEx, SCIAICLTeam - removed negated terms found by NegEx) |
| Word embeddings (e.g., Wikipedia or Medline) | 3 (CBNU - source unknown, MerckKGaA - Wikipedia and CDS 2016 corpus, ETH - CDS 2016 corpus) |
| Learning To Rank                      | 3 (ETH, MerckKGaA, WHUIRGroup [22])                                                      |
| Search engine                         | Terrier 6 (DA-IICT, ECNU, NKU, NLM-NIH, UNTIIA)                                            |
|                                       | Indri 4 (MayoNLP, DUTH, iRiS, WHUIRGroup)                                                  |
|                                       | Solr 3 (CBNU, CSIRO, MerckKGaA)                                                           |
|                                       | Elastic Search 2 (NCH-RISSI, HAUT)                                                         |
|                                       | Lucene 2 (CCNU, SCIAICLTeam)                                                              |

We identified UMLS concepts in articles and topics using Metamap. We have implemented some of these popular methods and benchmarked them on our platform. Since not all the teams detailed the exact nature of the search algorithm or indexing engine used in their experiments, Table 1 only summarizes those who clearly documented their method. The top performing team of 2016 (FDUDMIIIP) did not report on their methodology. We attempted to reproduce MerckKGaA [15] results, as they ranked second in 3 out of 4 metrics. Our methodology is explained in Section 4. We also report on individual methods from other teams who utilized MeSH, negation detection using NegEX by removing negated terms (iRiS [36] and SCIAICLTeam [20]) and concept extraction using Metamap. We note that similar methods were also examined in the 2015 CDS track [26].

Evaluation in Information Retrieval

Lack of comparable results in information retrieval have been observed and investigated in the IR community. A brief list of evaluation issues using TREC like test collections can be found here [28]. We are not focusing the test collections creation issue in this work. While having widely accessible test collections is paramount in evaluating one’s IR solution, we cannot compare results obtained by different research groups without a unified platform and baseline benchmarks. We note that in 2009 Armstrong et. al. [5] investigated the problem of reporting improvements made over weak baselines.
in the ad hoc retrieval process tested in a TREC setting \cite{6}. Unfortunately EvaluatIR, the platform Armstrong proposed for comparing different IR systems\cite{5} is no longer publicly accessible. EvaluatIR allowed researchers to upload the output of their systems and have them evaluated and compared against baselines. Another, more recent platform, is provided by EvALL \cite{3}. In this system some of the existing shared tasks are benchmarked, and new benchmark data can be uploaded. Inspired by these systems, we created a platform that allows the testing of a variety of retrieval methods on the CDS’16 corpus. While EvALL is a generalised platform, we focus solely on biomedical IR, with its unique challenges and methods, which include dealing with medical ontologies such as the UMLS.

3 Dataset and Indexing

The corpus provided by CDS’2016 is a snapshot of all published medical literature from PubMed Central taken on 28 March 2016. It contains 1.25 million full-text journal articles, excluding their references, keywords and MeSH headings. These documents are encoded in NXML format (an XML format extended using National Library of Medicine (NLM) journal archiving and interchange tag library). After re-encoding each document into ASCII text, we indexed it using Solr \cite{4}, the same search engine that MerckKGaA, CBNU, and CSIRO teams used. At the time of indexing, we appended MeSH keywords (as published in the corresponding Medline abstracts) and generated Metamap concepts for each article.

Each year, TREC CDS has provided 30 topics to generate queries with. The 2016 task provided topics based on nursing admission notes. Each topic had three different fields: (1) Note (Note) or the original clinical note; (2) Description (Desc), a simplified version of note where all abbreviations and jargon were removed; and, (3) Summary (Sum), a condensed version of the description removing all the irrelevant information.

4 Methods

We investigate three sets of approaches common amongst the CDS’16 submissions: (1) use of knowledge bases; (2) query expansion and reformulation; and (3) application of natural language processing techniques, such as negation detection. Some of these techniques (chosen from the systems in Table 1) are explained below.

\footnote{EvaluatIR at \url{www.evaluatIR.org}}
Normalizing Demographics

Clinical notes used as topics contain references to patient demographics, including age, sex and cohort information. We apply a set of regular expressions to the topics in order to normalize age and gender references as detailed by the CSIRO team [19]. For example, 86 y/o m is replaced with elderly male.

Handling Negation

There are two main methods of dealing with negation in text: (1) removing negated terms; and (2) changing them to a unified term, for example “no pain” becomes “no-pain”. We chose the first approach. Using Metamap Lite’s NegEx algorithm, negated terms were identified and removed from the topics. This method was used by iRiS [36] and SCIAICL Team [20]. However, not all the details in SCIAICL Team’s system were clear. That is, while they use Metamap’s negation detection module, they also apply a rule-based text pre-processing step which transforms text based on a dictionary they have created (not cited, not shared). For example, they replace the term “status post” with “after”.

Concept Extraction

We use Metamap to extract medical concepts from both the topics and the documents and assign them to UMLS concepts. Since there are a large number of semantic types defined in the UMLS metathesaurus, many of them irrelevant to our task, we re-implement what MerckKGaA team [15] reported and only extract concepts with the following semantic types: Disease or Syndrome, Sign or Symptom, Pathologic Function, Diagnostic Procedure, Anatomical Abnormality, Laboratory Procedure, Pharmacologic Substance, Neoplastic Process, and Therapeutic or Preventive Procedure.

Faceted Search

Scientific articles often follow a defined structure by including different fields or entities such as title and author. We use these fields as facets, in two ways: (1) filtering the index, and (2) weighting facets. We filter the index by using the index of one facet at a time. This is done to assign weights based on the importance of certain parts of a document. We experimented with a range of [0, 2] for weights. The results we report here were the optimal weights found empirically.

To find the optimal weights for each facet we used a hill climbing algorithm, inspired by the work by the WSU-IR team [7, 8]. We weight different facets by assigning a relative weight determined by normalizing the infNDCG score. The hill climbing algorithm stores the current global
minimum, and if it is caught in a local minimum, it will probe the feature space for a more suitable minimum using random restart. Graduated optimization was not included in the algorithm because the feature hyperspace was considered discrete. This algorithm was run for approximately 30 epoch for each query type with the current global minimum being passed at every epoch. No team at 2016 track implemented this method. However, given the success of WSU-IR in the CDS Track in 2015, we included this experiment to evaluate its performance on our platform.

Query Expansion using Pseudo-Relevance Feedback and Word Embeddings

Two query expansion techniques—Pseudo-Relevance Feedback (PRF), and query expansion using semantically similar words extracted using Word Embeddings (WE)—were investigated by ten different teams (refer to Table 1). For PRF, we experimented adding N words using the top-10 to top-40 retrieved documents. We also experimented with weights assigned to the expanded terms (zero to one). The optimal weights for PRF were 0.8 for Desc, 0.2 for Sum, and 0.9 for Note. To find the upper bound of what we can achieve, we also implemented Relevance Feedback (RF); that is, only relevant documents retrieved in the top-30 results were used to expand the queries (Top-30 was suggested by MerckKGaA).

Word embeddings were created using a combination of Wikipedia and Medline abstracts using Gensim. We only added a maximum of three semantically related words from word embeddings for each word of the queries with an upper limit of 40 words for the entire query as suggested by [9].

Learning to Rank

A popular approach for improving retrieval effectiveness is Learning-to-Rank (LTR). In TREC CDS, some of the high scoring teams, such as ECNU team [30] and MerckKGaA [15], applied LTR techniques for re-ranking. MerckKGaA used LambdaRank [15] with the following features: BM25 scores from PRF (with and without UMLS query expansion), document distances between topic and document titles using word embeddings, articles types and type of the topic as treatment, diagnosis and test. We have also implemented this method. We used topics and relevance judgments from the 2014 and 2015 tracks as training data. Our features were scores from BM25, PRF, and topic types, document distances between topic and document titles using word embeddings as well as topic category (Note, Desc, or Sum).
5 Experiments

Experimental Setup

In all our experiments, we used the Porter Stemmer and removed stop-words. For evaluations, we used the four metrics proposed in the CDS track: \(\text{infNDCG} \) (inferred NDCG) \[35\], \(\text{infAP} \) (inferred average precision) \[34\], R-prec (Recall Precision) and P@10 (Precision at rank 10), with infNDCG being the main metric. The significance of improvements over the baseline is tested using a paired 2 sample \( t \)-test and is represented in two scales of 95% and 98% confidence.

Results

Table 2 compares a basic baseline—BM25 with no query expansion or other topic or document preprocessing—with other methods. The baseline uses the Solr eDisMax function for query processing; no weights are used. While performing negation detection on its own did not improve the results significantly, using it in conjunction with other techniques in the hill climbing, word embeddings and PRF+UMLS runs (Table 3) produced statistically significant improvements. Normalizing demographics did not lead to a statistically significant improvement.

We used the second set of experiments, filtering facets, to estimate how much each facet contributes to finding relevant results. Predictably, searching individual facets resulted in a drop in all four metrics for all facets. We found that the body of the articles contributes to retrieving over 50% of the relevant results. Additionally: (1) adding UMLS concepts did not improve retrieval using titles only; and (2) concepts in abstracts slightly improved retrieval for Desc and Sum, but not Note. Initially, we gave each individual facet a weight of 2. We observed a statistically significant improvement for P@10 for title (+3.9%). The infAP and R-Prec metrics were degraded for the article body. All other metrics showed a statistically insignificant improvement. We then experimented with hill climbing to obtain optimal weights for all facets. Using these weights increased scores across the board statistically significantly.

Table 3 compares popular query expansion methods, including PRF, WE, as well as using lexicons such as MeSH and UMLS. Our best runs for PRF are expanded with words from the top-30 documents. The results showed significant improvements over the baseline for all three types of the queries. The last set of results belong to LTR. For Note and Sum we observed significant improvements over PRF, PRF+UMLS+WE, and the baseline.
Comparison to Other Systems

We compare our results with CBNU [18] and CSIRO [19] baseline runs and our replication of the MerckKGaA [16] runs. CBNU reported their baseline to be Solr BM25. Their reported results for infNCG, R-Prec and P@10 for both Note and Sum are higher than our BM25 run. For example, they report 0.1927 infNDCG for Sum while ours is 0.1721. They do not disclose their Solr version or the preprocessing they do on the queries and documents. Interestingly, their Note run results for infNDCG and P@10 match exactly with our Weighting Facets run with title boosted (Table 4, first row, forth section). This suggests that there must be some unreported parameters set in their system. Our baseline runs are all above the CSIRO reported runs, due their index being incomplete at submission time.

MerckKGaA reported four runs: Note with PRF, Sum with PRF, Sum with PRF+UMLS, and Sum with PRF+UMLS+LTR. They did not disclose their preprocessing steps, and used an older version of Solr (5.5.2 vs 6.4.1).

Using the same weights as they report for a PRF only run, we achieve an infNDCG of 0.1234, lower than their score of 0.1504. Increasing the weights to 0.2 improve our infNDCG results (0.1515). We achieve similar results in the Sum PRF run: MerckKGaA 0.2223, we scored 0.2111 with 0.1 weight and 0.2161 with a weight of 0.2.

The PRF+UMLS run by MerckKGaA was constructed using PRF using by extracting UMLS concepts from the initial query, and appending them to it. By doing this, they improved infNDCG of their PRF-only run from 0.2223 to 0.2261.

In our PRF+UMLS runs, we report infNDCG of 0.2042. We used PRF on the initial query and then expanded it with UMLS concepts. We experimented with another run (PRF+UMLS+WE) where we also expand the queries using terms suggested by word embeddings. This method improved PRF infNDCG slightly, from 0.2161 to 0.2215. This is similar to the upward trend reported by MerckKGaA. Table 4 lists MerckKGaA’s best run (Sum with PRF+UMLS+LTR). Our LTR run has a lower infNDCG (by 0.0229) and exactly the same P@10. The differences are related to the features used in re-ranking. Although they listed all the features they used, it was not clear how the product of the features (BM25 and WE) were calculated. As a result, we dropped that feature set.

Query Analysis

To identify where our best method, hill climbing, improved queries, we show the differences in infNDCG between the baseline and hill climbing run in Figure 2. Changes for Desc were similar to Note and therefore not shown. We observed very different changes with Note and Sum. For Sum we observed improvements for 20 out of 30 queries. For Note, only 17 queries were
positively impacted. This emphasizes the difficulty of working with notes as topics.

We compared the results of our PRF run and baseline BM25 with the official TREC 2016 CDS median for 30 queries in Figure 1. The hardest topic was 22 (summary: 94 M with CAD s/p 4v-CABG, CHF, CRI presented with vfib arrest./ type: treatment), since there were only 8 relevant documents. The best run using hill climbing did not retrieve any of the relevant documents (not even in the top 1000). The baseline had three of these documents in the top 1000, one in the top 100, and none in the top 10. This particular topic was high on vital statistics, but low on other information, which made finding relevant information difficult.

6 Conclusions

TREC Clinical Decision Support (CDS) track has been running since 2014 providing an opportunity for the IR community to investigate ways to search biomedical literature to improve patient care. This track is popular, with many teams participating. However, most of the runs are not conclusive as to whether or not the proposed approach is effective.

In order to perform a comprehensive assessment of different search methodologies, we developed a platform that allows the user to formally specify the methods they use, re-run past experiments, and analyze the findings based on qrels provided by the TREC CDS team. We have benchmarked the most common methods on their own as well as combinations of these methods. The methods include: query and document expansion using UMLS concepts, word embeddings, negation detection and removal, and LTR.

While the exact results could not be reproduced due to lack of sufficient details on preprocessing steps, implementation details, as well as unavailability of older versions of public search engines, the results were encouraging. That is, with minor changes to the parameter settings, we could reproduce
results obtained by MerckKGaA, the team ranked second in TREC 2016 CDS. We also confirmed the positive effect of negation detection as implemented by some of the participating teams.

By using our platform, teams will be able to both report their methods in a consistent way, and evaluate their results against a common baseline. In the future, we aim to use this platform to systematically evaluate a more diverse combination of search methods.

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## Table 2: Comparison of different ranking strategies.

| Method          | Query infNDCG | infAP  | R-Prec | P@10  |
|-----------------|---------------|--------|--------|-------|
| **Baseline**    | Note          | 0.1074 | 0.0079 | 0.0749 | 0.1400 |
|                 | Desc          | 0.1067 | 0.0060 | 0.0766 | 0.1200 |
|                 | Sum           | 0.1721 | 0.0158 | 0.1167 | 0.2067 |
| **Negation**    | Note          | 0.1104 | 0.0088 | 0.0772 | 0.1467 |
|                 | Desc          | 0.1097 | 0.0062 | 0.0766 | 0.1233 |
|                 | Sum           | 0.1726 | 0.0159 | 0.1171 | 0.2067 |
| **Demographics**| Note          | 0.1102 | 0.0089 | 0.0778 | 0.1400 |
|                 | Desc          | 0.1107 | 0.0064 | 0.0772 | 0.1267 |
|                 | Sum           | 0.1755 | 0.0166 | 0.1149 | 0.2200 |
| **Filtering**   | Note          |        |        |       |       |
| Facets          | Title         | 0.0727 | 0.0105 | 0.0393 | 0.0833 |
|                 | Desc          | 0.0785 | 0.0055 | 0.0389 | 0.0867 |
|                 | Sum           | 0.1262 | 0.0134 | 0.0669 | 0.1367 |
|                 | Abstract      | 0.1039 | 0.0086 | 0.0561 | 0.1100 |
|                 | +Concepts     | 0.0808 | 0.0056 | 0.0362 | 0.0767 |
|                 | Sum           | 0.1201 | 0.0108 | 0.0775 | 0.1500 |
| **Weighting**   | Note          |        |        |       |       |
| Facets          | Title         | 0.0800 | 0.0162 | 0.0491 | 0.1467 |
|                 | Desc          | 0.0913 | 0.0050 | 0.0511 | 0.1000 |
|                 | Sum           | 0.1316 | 0.0126 | 0.0786 | 0.1533 |
| **Title+Abstract** | Note      | 0.0783 | 0.0063 | 0.0497 | 0.1133 |
|                 | Desc          | 0.0823 | 0.0046 | 0.0467 | 0.0967 |
|                 | Sum           | 0.1356 | 0.0129 | 0.0796 | 0.1833 |
| **Body**       | Note          | 0.1079 | 0.0073 | 0.0730 | 0.1367 |
|                 | Desc          | 0.1024 | 0.0055 | 0.0691 | 0.1200 |
|                 | Sum           | 0.1541 | 0.0131 | 0.1045 | 0.1933 |
| **Hill**       | Note          |        |        |       |       |
|                 | climbing      | 0.1045 | 0.0085 | 0.0804 | 0.1783 |
|                 | w/ negation   | 0.1048 | 0.0082 | 0.0732 | 0.1367 |
|                 | Sum           | 0.1567 | 0.0176 | 0.1029 | 0.1900 |
| **MeSH**       | Note          |        |        |       |       |
|                 | q              | 0.1061 | 0.0148 | 0.0904 | 0.2300 |
|                 | q             | 0.1238 | 0.0177 | 0.0913 | 0.2000 |
|                 | Sum           | 0.2704 | 0.0395 | 0.1556 | 0.3133 |
| **Filtered**   | Note          |        |        |       |       |
|                 | Desc          | 0.1718 | 0.0178 | 0.0907 | 0.2033 |
|                 | Sum           | 0.2111 | 0.0277 | 0.1429 | 0.2600 |
Table 3: A comparison of query expansion and re-ranking techniques. RF: relevance feedback and WE: expansion using word embeddings.

| Method          | Query | infNDCG | infAP  | R-Prec | P@10  |
|-----------------|-------|---------|--------|--------|-------|
| PRF             | Note  | 0.1516† | 0.0133† | 0.0864 | 0.1700 |
|                 | Desc  | 0.1520† | 0.0128† | 0.0910 | 0.1833† |
|                 | Sum   | 0.2160† | 0.0261† | 0.1439† | 0.2733† |
| PRF w/ negation | Note  | 0.1515† | 0.0131† | 0.0866 | 0.1700 |
|                 | Desc  | 0.1559† | 0.0130† | 0.0919 | 0.1833† |
|                 | Sum   | 0.2161† | 0.0260† | 0.1437† | 0.2700† |
| WE              | Note  | 0.1006  | 0.0070  | 0.0775 | 0.1233 |
|                 | Desc  | 0.1147  | 0.0080  | 0.0758 | 0.1200 |
|                 | Sum   | 0.1777  | 0.0172  | 0.1227† | 0.2253 |
| WE w/ negation  | Note  | 0.1020† | 0.0133† | 0.0866 | 0.1700 |
|                 | Desc  | 0.1203  | 0.0082  | 0.0772 | 0.1500 |
|                 | Sum   | 0.1788  | 0.0174  | 0.1246 | 0.2267 |
| UMLS            | Note  | 0.1026† | 0.0093  | 0.0814 | 0.1733† |
|                 | Desc  | 0.1103  | 0.0086  | 0.0845 | 0.1167 |
|                 | Sum   | 0.1757  | 0.0176  | 0.1202 | 0.2267 |
| UMLS w/ negation| Note  | 0.1190† | 0.0133† | 0.0822† | 0.1733† |
|                 | Desc  | 0.1211  | 0.0087  | 0.0862 | 0.1300 |
|                 | Sum   | 0.1750  | 0.0175  | 0.1203 | 0.2253 |
| PRF+UMLS        | Note  | 0.1496† | 0.0134† | 0.0915† | 0.1700 |
|                 | Desc  | 0.1519† | 0.0134† | 0.0954† | 0.1900† |
|                 | Sum   | 0.2042† | 0.0273† | 0.1382† | 0.2567 |
| PRF+UMLS w/ negation | Note  | 0.1500† | 0.0133† | 0.0909† | 0.1733 |
|                 | Desc  | 0.1541† | 0.0134† | 0.0953† | 0.1900† |
|                 | Sum   | 0.2052† | 0.0273† | 0.1383† | 0.2567 |
| PRF+UMLS+WE     | Note  | 0.1421† | 0.0126† | 0.0920† | 0.1833 |
|                 | Desc  | 0.1504† | 0.0128† | 0.0952† | 0.1800† |
|                 | Sum   | 0.2215† | 0.0274† | 0.1470† | 0.2633† |
| PRF+UMLS+WE w/ negation | Note  | 0.1526† | 0.0127† | 0.0922† | 0.1767 |
|                 | Desc  | 0.1517† | 0.0126† | 0.0950† | 0.1800† |
|                 | Sum   | 0.2218† | 0.0274† | 0.1484† | 0.2600† |
| RF              | Note  | 0.1692† | 0.0191† | 0.1003† | 0.2567 |
|                 | Desc  | 0.1692† | 0.0182† | 0.1105† | 0.2400† |
|                 | Sum   | 0.2324† | 0.0337† | 0.1557† | 0.3700† |
| LTR             | Note  | 0.1667† | 0.0135† | 0.1061† | 0.2200† |
|                 | Desc  | 0.1750† | 0.0924† | 0.0995† | 0.1989† |
|                 | Sum   | 0.2264† | 0.0301† | 0.1500† | 0.3530† |
| MerckKGaA       | Sum   | 0.2493  | 0.0315  | 0.1744  | 0.3500  |
| TREC Median     | Note  | 0.1226† | 0.0099† | 0.0792 | 0.1833 |
|                 | Desc  | 0.1043  | 0.0065  | 0.0648 | 0.1533 |
|                 | Sum   | 0.1859  | 0.0196  | 0.1220  | 0.2633 |