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William Briggs Report



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April 4, 2018

Declaration

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Abstract

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Chapter 1

Introduction

Medical literature poses interesting challenges for Natural Language Processing (NLP) researchers. The sheer volume of medical data makes it difficult for humans to process efficiently. One key task is the creation of systematic reviews. Systematic reviews are transparent reviews that aim to pull together and critically analyse relevant literature to a topical question. The process of creating a systematic review is rigorous and time consuming with varying degrees of complexity in-between steps. This report will look at the existing work done so far on using NLP as part of the systematic review process as well as the novel work by myself.

1.1 Steps of a Systematic Review

It is useful for us to break down the steps involved in creating a systematic review into subtasks. This way we can observe what techniques can be applied during the relevant subtasks to improve the efficiency of the process. The following definitions are derived task simplifications from the cochrane tutorial on systematic reviews: [9].

1. Question definition.
2. Relevant literature search.
3. Data Filtering.
4. Data Extraction.
5. Analysis and Data combination.

1.1.1 Question Definition

One of the best known techniques for formulating a systematic review question is known as the PICO strategy [10]. This technique focuses on exposing 4 pieces of information in

the systematic review question: patient population, intervention or exposure, comparison or control and outcome.

Example: (credit goes to [10])

"Is animal-assisted therapy more effective than music therapy in managing aggressive behaviour in elderly people with dementia?"

P	elderly patients with dementia
I	animal-assisted therapy
C	music therapy
O	aggressive behaviour

A potential point of interest would be attempting to generate these questions automatically given some literature context.

1.1.2 Relevant literature search

After formulating a question, systematic reviews need to search for the relevant literature that surrounds this question.

Large medical database-such as pubmed contain relevant studies that can be used to create the review. These databases are typically very large and require concise queries to efficiently retrieve data.

Naturally this can be modelled as an information retrieval problem. We have a large number of documents and we wish to retrieve the most relevant ones. One task for the 2017 CLEF conference was to produce a ranking of the most relevant documents for topics [7]. Many techniques have been proposed for ranking of relevant documents, with varying degrees of performance [3] [5] [8].

An important aspect of the relevant literature search step is the construction of the query. Query creators often apply filters (also known as hedges) to increase the effectiveness or/and the efficiency of the searching. Two key attributes for the query are the precision and the sensitivity (aka recall). By including synonymous phrases e.g: quality adjusted life or quality of well-being or disability adjusted life the sensitivity can be increased, but as expense of the precision. The creation of this query is a task that could potentially have some aspects of NLP applied to it.

1.1.3 Data Filtering

The data filter stage involves reducing the amount of documents returned by the initial query down to a smaller subset of relevant document. This is can also be referred to as the abstract screening phrase [7].

The length of this stage is highly dependant on how many documents were returned by the initial query, often in the excess of 5000 studies for a single query. In response to this, stopping criteria methods have been proposed that aim to optimize two key parameters; the effort and the recall. That is to say we want to get as many relevant documents as possible, whilst looking at the fewest. Examples of approaches include the knee method [11] and the target method [4]. Other techniques could be applied and evaluated such as curve fitting.

1.1.4 Data Extraction

The data extraction phase involves pulling the relevant information from the filtered subset of studies. Examples of important information includes how many people took part in the study and what the results were.

Being able to extract the relevant information from studies presents itself as an information extraction problem. The task to automate the process of extracting relevant information would reduce time and complexities of manually reviewing studies [6].

Chapter 2

Literature Survey

Systematic reviews have many different stages that propose themselves as a candidate for automation. This section is going to look at the techniques that have been applied for some of these stages in previous literature.

2.1 Indexing and Querying Medline

Medline is a large collection of medical literature and data from around the world. Typically each entity will contain a title and an abstract containing some information on the study. Whilst Medline as a whole is very easy to access [1], the large size and complexity of the data makes it difficult to retrieve the relevant information.

Being able to create a reliant index of Medline would help with the effectiveness of the queries. As such existing medline indexes and IR systems have been created [2]

2.2 Stopping Criteria

Stopping criteria a topic of being able to know when to stop looking at a set of documents. This could be useful in a decision making process. Consider having 100 relevant documents, where each document contains a binary value. If we looked at 1/3 of these documents and saw a trend of positive values, we could use this to infer the reliability of the remaining documents.

Another use of stopping criteria is when filtering through potentially relevant documents. Consider a query that returns 10000 documents, of which only a small sub-set of these are relevant. Reviewers would need to filter through each of these 10000 documents to pull out the relevant ones. Or it could be that the reviewers are happy to hit a 90% recall of relevant documents, and are happy to miss the remaining 10% in exchange for time-saved.

Two key methods have been proposed for finding stopping points so far, the target method [11] and the knee method. [4]. Both these methods are discussed below 2.2.2

2.2.1 Evaluation Metrics for Finding Stopping Points

In order to evaluate the suitability of our stopping method, we can use two evaluation metrics. The recall, which is simply the number of documents returned for a topic. The effort which is the number of documents we had to look at for a topic.

$$Recall = \frac{R}{|D|} \quad (2.1)$$

Where R is the number of returned documents and D is the set of relevant documents.

$$Effort = \frac{L}{|D|} \quad (2.2)$$

Where L is the number of returned documents looked at.

Naturally we could exclusively optimized each of the parameters by either returning everything in the document collection ($R = |D|$) or by just looking at a single document. ($L = 1$)

Therefore it becomes difficult for us to evaluate our stopping criteria as we need to consider both of these parameters adjacently.

2.2.2 Existing Stopping Methods

The target method is a fairly straight forward approach to establishing a stopping point.

Chapter 3

Novel Work

In this section I am going to present the work I have completed so far. Two main areas of the systematic review process has been focused on. Stopping criteria and indexing/querying pubmed.

3.1 Random Sample Method to Stopping

As approach to determining when to stop looking at document abstracts returned by the query we are proposing a new sampling method. This approach assumes we have optimum ranking algorithm for returning documents for a query.

The first step of this method is to randomly sample a returned set of documents into a subsets.

$$U = \frac{|D|}{S} \quad (3.1)$$

Where U is the computed randomised subset, D is the document collection and S is the sample size.

We then use this subset U to create a model / baseline for our topic as a way of predicting how many documents one would need to look at to hit a threshold. The intuition behind this approach is that the rate of which relevant documents occur should be relatively similar when the number of returned documents in the same.

Our first approach uses a simple curve fit against a sample set along with a simple non-linear function. $f(x)$

$$F(x) = n - a \exp^{-kx} \quad (3.2)$$

Where a , k and n are learnt weights and x is an associated return rate for a document.

sample size	recall	above 70%	effort
1	0.70	0.6333	1
3	0.64	0.466	0.48
5	0.481	0.33	0.31

Table 3.1: Comparison of different sample sizes against recall and effort. Ranking Method: Test_Data_Sheffield-run-2 [3]

The first sample size of 1 is included to show how the effort metric is effected. For us to use sample everything, we would need to look at everything, as such the effort averaged out at 1. In this example we were only concerned in achieving 70% recall, as such even when sampling everything we would really obtain 100% recall at the expense of 100% effort.

Looking at every 3rd document and then producing a prediction curve will reduce our effort. We are still required to look at at 1/3 of documents, as such the effort will always be above 0.33.

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