

Using Exploration and Learning for Medical Records Search: An Experiment in Identifying
Cohorts for Comparative Effectiveness Research

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Abstract

This paper describes an experiment performed on a medical record data set, using an information retrieval (IR) tool that applies the techniques of exploration and learning, to assist a researcher in identifying the most relevant cohorts. The paper presents some brief background on exploration and learning, how they are incorporated in the IR tool, and an instantiation of exploration and learning used for selecting cohorts for a research population. The research problem addressed in this paper is the TREC 2012 Medical Track task: How to provide content-based access to free-text fields of electronic medical records? The stated goal of the task is to “find a population over which comparative effectiveness studies can be done.”

Introduction

The problem presented here regarding how to identify cohorts from a collection of electronic medical records is an example of an information retrieval (IR) problem which relies on techniques used for extracting a maximum of relevant documents and a minimum of non-relevant documents. In typical IR problems the motivation is to reduce the time and cost of human review of the extracted collection. In this case, the motivation is to provide the best cohort population so that the ensuing research study will be useful and valid.

We employ a manual approach supported by an automated tool to address the constraint of content-based, free-text fields by creating an artifact to support the researcher in exploring a corpus of items and facilitating examining and scrutinizing. This supports user acquisition of contextual knowledge about the collection. The tool in this case has been adapted from an IR tool previously deployed for eDiscovery and presented at the TREC Conference 2011 Legal Track (Hyman and Fridy III, 2011).

Exploration

The concept of exploration has been associated with learning (Berlyne, 1963; March, 1993; familiarization (Barnett, 1963), and information search (Debowski et al, 2001). In fact work done by Berlyn in the 1960s classifies exploration as a “fundamental human activity” (Demangeot and Broderick, 2010).

Exploration is seen as a behavior motivated by curiosity. Exploration that is goal directed is classified as extrinsic (Berlyn, 1960). Extrinsic exploration typically has a specific task purpose, whereas intrinsic exploration is motivated by learning (Berlyn, 1960; Demangeot and Broderick, 2010). Kaplan and Kaplan, 1982, argue that exploration arises from our need to make sense of our environment. March, 1991, writes about exploration and exploitation. He views exploration and exploitation as competing tensions in organizational learning.

Berlyn, 1963, suggests that specific exploration is a means of satisfying curiosity. The goals of exploration as a means for making sense of our environment and satisfying curiosity are represented in the problem domain of information retrieval and in this task of cohort identification. Debowski et al, 2001, view exploratory search as a “screening process,” and that

exploration identifies items “to become the focus of attention.” They suggest that exploration leads to learning through the examining and scrutinizing of items.

The experiment reported in this paper presents an instance of *exploration* as a technique implemented through an IR tool as a method for identifying cohorts for a population.

Learning

“The search for information is often a cyclical, exploratory process” (Debowski et al, 2001). Search has also been compared to problem solving techniques similar to foraging (Hills et al, 2010). Hills et al, characterize problem solving itself as a search process. The decision regarding when to exploit – stay with the current position or strategy, versus when to explore – move on to a new search or location is a trade-off that has been studied in problem solving and learning (Robbins, 1952; March 1991; Hills et al, 2010). This is especially true in the domain of content-based IR where the search can be very complex in terms of strategy and structure (Debowski et al, 2001).

The learning process supported by the artifact allows the researcher to acquire knowledge about the records in the collection and use that knowledge to gain insight for identifying the best cohorts. In this experiment we test whether the acquired knowledge about the corpus can be effectively exploited by presenting ad hoc, iterative retrieval results to the user. An assumption herein is that the user can assess the results and adjust the search structure to improve the retrieval result – in this case identify better cohorts.

The goal of the artifact is to address the gap in electronic search identified by Dembroski et al, 2001 as; “not highly informative regarding the effectiveness of strategies.” They suggest that in order to achieve successful retrieval, the search structure and alternative strategies must be continually evaluated. We address this by using learning and iterative feedback. The context and richness discovered through exploration is applied to a corpus through an iterative learning process supported by the tool.

The Artifact

The artifact in this case is an automated tool that extracts documents from a collection that meet user criteria. Figure-1 is an example of the User Input Screen. This screen accepts the user's criteria for identifying a relevant record. The tool accepts inclusive and exclusive criteria. Figure-2 is an example of the Retrieval Screen. This screen presents the user with a sample of the extracted collection. This sample represents the content of the extraction produced by the user's criteria. The user may set a threshold for the sample. In this case we used a sample of 10 documents per extraction. The user may select on any record in the left column and view the record in the right column. After the sample has been exhausted, the user may create changes to the search criteria and the tool will present a new sample of extractions for the user to explore. The user may set a threshold for precision or a fixed number of iterations. In this case we used a fixed number of 10 iterations. The goal of the tool is to provide the user with insight into the nature of the collection and the content of the individual records through an iterative method using exploration and learning – for identifying cohorts.

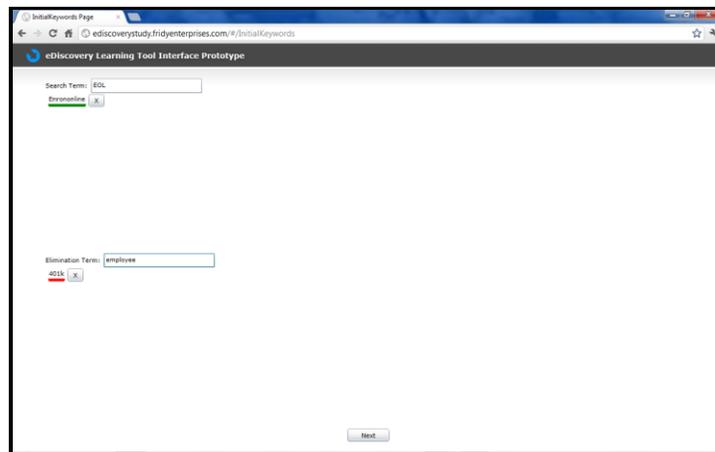


Figure-1, Source: eDiscovery Learning Tool, Friday Enterprises

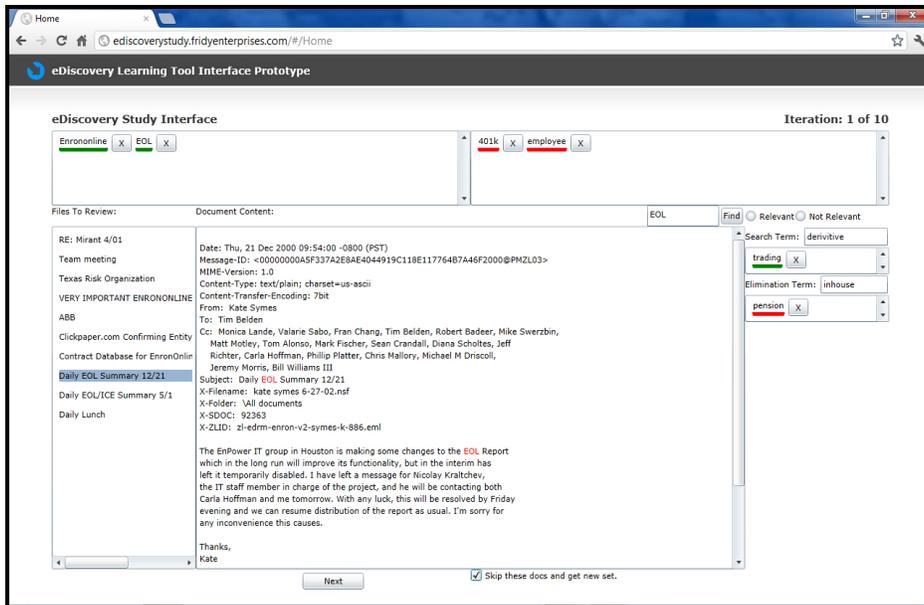


Figure-2, Source: eDiscovery Learning Tool, Fridy Enterprises

Experiment

We began with a non-function word approach. Non-function words are words such as: the, as, of, or, etc. These words serve no content purpose and provide no insight into the task. In this case we had no prior theory or knowledge about the collection. Therefore, in the absence of a specific theory to act upon or a known search strategy based on the circumstances, a non-function word approach makes the most logical sense. It provides the best possible point of view to start from because we are using the requestor's own words and terminologies. Once we entered the initial search criteria we then made adjustments based on the samples produced by the tool. We ran 10 iterations before finalizing our cohort selection.

Notable Results

We discovered that any requests for documents seeking a particular age or age group need to be structured by a specific search for the term "age" and a window span of 4 characters past the term. We also discovered medical codes within the visit records. When applying a standard medical context "_____" as a wild card for interpreting the codes, a cohort search to acquire documented visits based on the medical codes themselves may be structured.

Limitations

We had difficulty handling files without visit IDs. Ultimately, we were not able to resolve this issue and had to ignore those records. This reduced our effectiveness because it left us with records within the collection that we were not able to explore thoroughly.

We also had difficulty exploiting the full power of using the diagnostic codes due to our lack of experience in this domain. This has more to do with the focus of our tool. It is designed to be used to support a user who is a domain expert or a user who has a targeted idea of the direction of the search and a structure for implementing it.

Conclusion

Final results are still pending so we are unable to report the efficacy of our tool until after the conference. However, the main purpose of the discussion presented here has been to describe how exploration and learning can be instantiated in an automated tool to assist a researcher in identifying a cohort population. We welcome feedback and suggestions about our work presented.

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