Supporting Off-label Prescription Hypotheses

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Introduction

With the advent of Social Media, user-generated health data has become easily accessible to Researchers. Physicians are under extreme pressure to mold into a computationally advanced society to provide novelty cures. Alternative treatments, or "Off-Label Prescription", has been a very active area of research and development in the health sciences. In this research we propose a computational tool that will aid clinicians in exploring and reasoning alternative treatments. This computational tool is unlike any current technology because it explores a semantic repository(Big Data) of user-generated social healthcare data and performs analysis to compare and contrast treatments that might have been otherwise unknown to the User.

Motivating Scenario

A medical researcher observes that two conditions C1 and C2, although not related in the current medical literature, have similar traits. As a consequence, she hypothesizes that a treatment for condition C1 could be used to treat condition C2. In other words, assuming that conditions C1 and C2 are similar in certain aspects, can treatment T1 that is approved for condition C1, be used to safely and effectively treat condition C2, with minimal or acceptable side-effects? She also wonders if there is any replacement (off-label) treatment T2 for the current treatment T1 for condition C1, to alleviate a side effect of T1.

Methods Used in this Research

Social Network platforms allow *crowds of online patients* (COOPs) to generate rich health information on how patients actually consume their healthcare. Many patients report freely on their diagnosed conditions, symptoms, drugs taken and procedures used, in addition to their evaluative comments and reviews. The existing Social Health Records provide a vast amount of health practice data by many patients. Thus they are an ideal source for discovering trends or patterns in healthcare practice. This Data is collected, enriched, and converted into Resource Description Format (RDF). Jena TDB was used as a database for storage of the RDF graph. SPARQL was used for querying the data. Java was used to implement the user interface.

Example Scenario 1: Addison's Disease

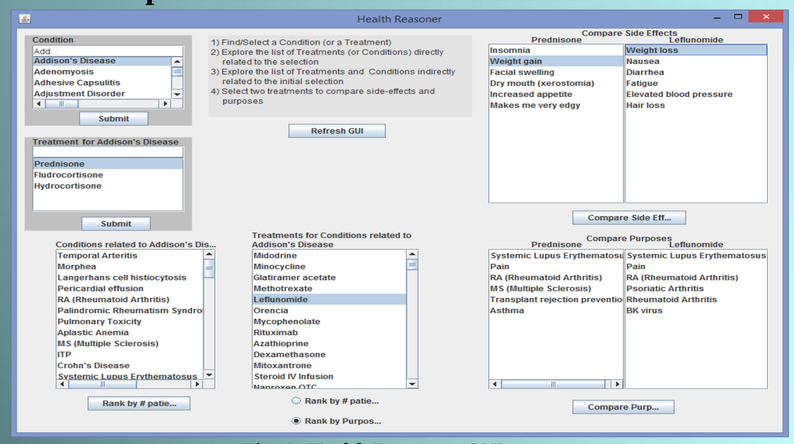

Fig. 1: Health Reasoner GUI

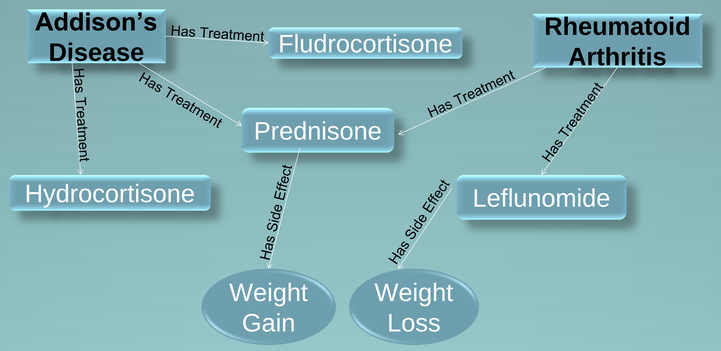

Fig. 2: Excerpt of the Semantic Health Knowledge Base

Example Scenario 2: MODY

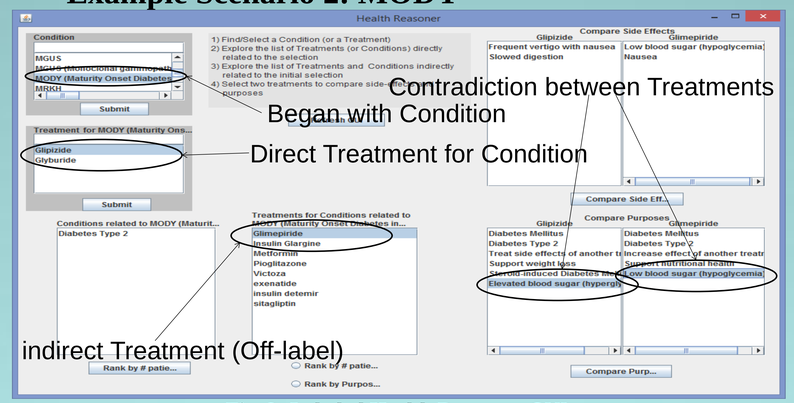

Fig. 3: Labeled Health Reasoner GUI

Experiment 1: Migraine

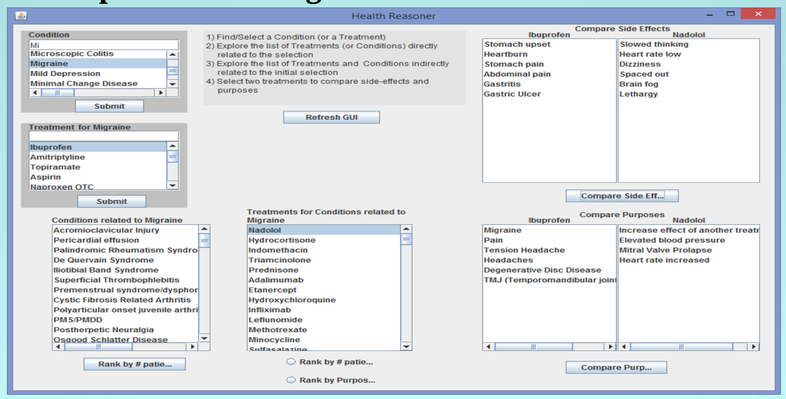

Fig. 4: Testing Health Reasoner

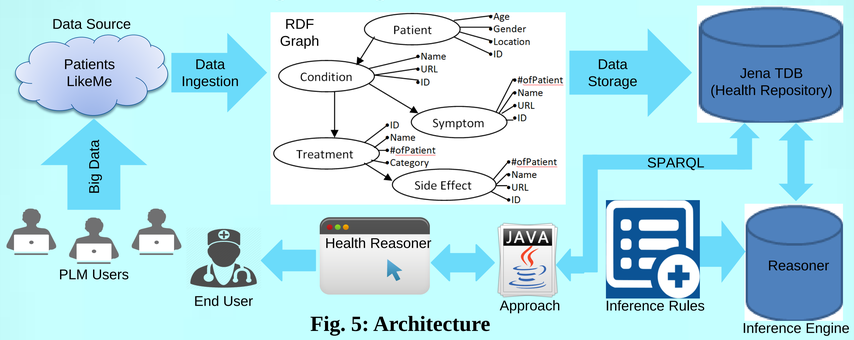

Fig. 5: Architecture

Treatment (Label)	Treatment (Off-Label)	Contradiction Type
Fludrocortisone	Midorine	Purpose
Glipizide	Glimepiride	Purpose
Prednisone	Leflunomide	Side Effect
Glipizide	Insulin Glargine	Purpose-Side Effect

Fig. 6: Tabular Results of the Health Reasoner for Off-Label Treatments

Results and Discussions

In our experiments with the application, we came across different conflicting scenarios. We observed that conflicts can emerge as a direct contradiction between indications of two treatments, a direct contradiction between their side-effects, as well as a cross-contradiction between the indications of one and the side-effects of the other.

To further test the benefits of our approach, we performed an additional experiment. We checked whether the treatment *Nadolol* could be used as an alternative treatment for the condition *migraine*. Note that *Nadolol* was not intended to treat *migraine*, and only later it was discovered to be effective for this disease. In our test, we removed *Nadolol* as a treatment for *migraine* from the knowledge base and used the Health Reasoner to investigate the drug. It turns out that *Nadolol* is a related treatment for *migraine* (see Figure 4). Moreover, the indications and side-effects of *Nadolol* versus the known treatments for migraine showed no conflicting information. The absence of adverse findings suggests that it would have been worth pursuing a deeper investigation of *Nadolol* as an alternative treatment for *migraine*, as was expected. The expectation is to find evidence to support or refute the existence of common traits by, for instance, discovering contradicting or further common information.

Conclusions

We have discussed an approach and a tool to help medical researchers in exploring alternative treatments, especially off-label prescriptions, for conditions on the basis of evidence from Social Health Records, leveraging the Wisdom of the Crowd of Online Patients. In future work we want to extend our tool with a semantic reasoner: practitioners can then formally state a hypothesis and let the tool reason by itself, rather than relying on manual exploration; however, we first need to extend the knowledge base with coherent and contradictory medical concepts.

References:

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