Intelligent Natural-Language Understanding of Patient Medical Records
Scientific Rationale and Plan

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1. We propose to adapt an existing AI knowledge-representation and reasoning (KRR) system that has natural-language (NL) competence so that it can read and understand patient medical records (PMR) (in particular, hospital discharge summaries (HDS)), and then "translate" them into "layperson's English" so that patients and their families can read and understand them. This is a pilot project designed both as a "proof of concept" and to explore the problems involved.

It is well understood that good physician-patient communication brings many benefits. These range from improving the health outcomes of patients [3], to making better choices about healthcare [14], to even improving the productivity of a physician's office [26]. Unfortunately, physician-patient communication is often suboptimal. This is due in part to language difficulties. Physicians and other medical providers are taught to use an extensive medical vocabulary (commonly estimated to be as large as the complete non-technical English vocabulary). It is often difficult for physicians to revert to a layperson's vocabulary when speaking with patients. It is a common experience for patients to feel confused about their illness, despite their doctor's best efforts to explain it. In addition, there is increasing interest among patients to view their medical records. Since these are typically written using medical terminology, they are usually incomprehensible to the lay patient.

Our proposed system would provide automated generation of medical information in lay terms. This system could be used as an adjunct to physician-patient communication. In particular, it would allow for better understanding of PMRs so that patients and their families could have a better understanding of their health, be able to have more informed interactions with their physicians, and be able to make more informed decisions about their care.

2. HDSs are usually free-text, often with little structure and irregular grammar. They contain many terms from a specialized medical vocabulary and use specialized, even cryptic (to lay people) grammatical constructions. They also make many assumptions about the background knowledge of the intended audience, viz., medical personnel, e.g., stating that a test result is "negative", without saying whether that is good or bad. All of this makes it difficult for patients and their families to read and understand such documents.

The major goal of previous work in medical NL processing has been "extracting clinical findings from [free-text] medical narratives" [25] and to automate the following tasks: (1) to facilitate data collection, perhaps by integrating information from different sources, about single or multiple patients, into a standardized format [6] for storage in an electronic medical record "central repository" [9], or even a software agent [27]; such information could be used, e.g., to determine whether treatments are successful [16,25]. (2) To learn new vocabulary, perhaps in the service of updating online medical lexicons [25] and integrating lexicons from different sources for standardization (e.g., as in the Unified Medical Language System (UMLS) [13], or even just to be able to cope with unfamiliar words [1]. (3) To determine patient needs on the basis of observations ("findings"), so as to be able to pose clinical queries [12] and to monitor and assess patient care, e.g., for treatment of asthma [5,16,17].

Although there are some projects in the medical informatics literature that are relevant to ours, none attempt the sort of translation of personal documents that we have in mind. (1) PIGLIT (Patient Information Generated by Loosely Intelligent Techniques [2]) was designed for patients to use in their doctor's office waiting rooms, so that they could access information from their own medical record while waiting to see the doctor. PIGLIT represents the information in PMRs in a knowledge representation (KR) system, and then generates small (one paragraph) explanations tailored to the patient's history. However, the NL generation in PIGLIT appears to be little more than inserting canned text into appropriate slots. (2) HealthDoc [8] produces brochures relating to particular ailments, tailored for the specifics of a patient's particular condition or background knowledge. These are based on a "master document" that can be produced at two different technical levels (low and high) and using different rhetorical relations among the information. (3) The

Migraine Project [4] creates interactive explanations of migraines for patients, based on their own medical history. Patients construct questions from a menu, which thus restricts the possible interactions.

We distinguish between (medical) NL *processing* and (medical) NL *understanding*: The former uses whatever computational and statistical techniques will efficiently convert NL text into a usable form. The latter is more concerned with cognitive issues: the ability of a software agent to *understand* the medical narrative. There is a spectrum leading up to and connecting these two extremes, measured by levels of access and representation. At the pure computer-processing end, data are stored in a computer record or database-management system and retrieved via queries, keyword searches, or statistical analysis. More sophistication can be added by inferring new information from stored information, as in a deductive database or—if commonsense, background (e.g., specialized medical knowledge), or world knowledge is added—in a knowledge base (KB). The use of computational-linguistic techniques to capture "meaning" [12] adds even more value, with the modeling of a cognitive agent adding more human-like understanding. But most researchers seem to be using straightforward NLP software to process the records [1,7,11,16,18]. No one seems to be using more advanced AI techniques, such as the use of a robust KRR system.

3. We propose to accomplish this and to demonstrate the understanding via translation into plain English using Cassie, a computational, cognitive agent implemented in SNePS [21–23]. SNePS, the Semantic Network Processing System, is a KRR system with an English lexicon, morphological analyzer/synthesizer, and a generalized augmented-transition-network (ATN) parser-generator for NL understanding and generation that, rather than building an intermediate parse tree, translates English input directly into a semantic interpretation represented as a propositional semantic network and can generate English sentences expressing its "knowledge" [19,20,24]. Nodes in a SNePS network represent concepts, linked by labeled arcs. All information, including propositions, is represented by nodes; propositions about propositions can be represented without limit. Arcs form the underlying syntactic structure of SNePS. Arc-paths can be defined for path-based inference, including property inheritance within generalization hierarchies. Nodes and represented concepts are in 1-1 correspondence. This uniqueness principle guarantees that nodes are shared whenever possible and that nodes represent intensional objects (e.g., concepts, propositions, properties, and objects of thought). In particular, this facilitates dealing with multiple specifications for a single concept. SNePS's inference package accepts rules for deductive and default reasoning, allowing the system to infer "probable" conclusions in the absence of contrary information. When combinations of asserted propositions lead to a contradiction, the SNeBR belief-revision package allows the system to remove from the inconsistent context one or more of those propositions [11]. Once a premise is no longer asserted, the conclusions that depended on it are no longer asserted in that context.

SNePS has already been used as an interlingua for intelligent machine translation of NL [10]. In this project, Chinese text (written in Chinese characters) was parsed by an ATN into a SNePS KR, which, along with background linguistic knowledge, was then generated by the ATN into English. The adaptation of this strategy to the present domain should be straightforward. The task breaks down as follows:

(1) HDSs with identifying information deleted would be supplied by medical personnel at Children's Hospital.

(2) HDSs would be represented in SNePS. Eventually, this will be automated via an ATN (or similar) parser. For the present pilot project, however, this will be done by hand, since there are more issues in parsing free text than fall within the scope of this proprosal. That said, there are still many important issues in the KR task. Preliminary experiments in representing HDSs in SNePS by our students suggest that we need to determine in advance a number of "case frames" (roughly, analyses of different sentence types) that could be used for all HDSs in a uniform manner. Riloff [15] has developed a software approach to doing this that we would like to test.

(3) Background medical knowledge of the sort that the typical physician reader of an HDS would know would be represented in SNePS. This would include definitions of medical terms, the nature and typical results of medical tests, etc. Although some of this information (especially lexical information) is available on line through such sources as UMLS and MeSH (Medical Subject Headings; http://www.nlm.nih.gov/mesh/meshhome.html), preliminary experiments with using the latter suggest that the definitions are as hard to understand as the term needing to be defined. This part of the project would involve expert-systems-style interviews and debriefings with expert medical personnel.

(4) We would decide how to express the HDSs in plain English. I.e., how plain is "plain"? Preliminary experiments suggest that this can be done, but that it requires not only consultation with medical experts (from stage (3)) but also a determination of how much information needs to be provided to the lay reader.

(5) At this stage, we would have a KB consisting of both the information in the HDS and the requisite background medical knowledge, and we would have a target text in plain English. An ATN would then be developed that would generate the information in the HDS in plain English, using the techniques of [19], from the KB.

(6) To calibrate our results, we would have medical experts read and critique the systems's translations for correctness, and we would have lay patients read them to give us feedback on their ease of understanding and any remaining questions that they would have.

(7) Once we have a system that can create the plain English version from the KB, we would apply for full funding to fully develop the system and to automate stage (2).

4. We request funds to support 2 graduate students to assist in the encoding of the HDSs and background knowledge, and the generation of plain English text from this knowledge base. Student 1 would explore information-extraction techniques to encode the HDS into SNePS and would create a SNePS KB of medical background information. Student 2 would assist in the latter task and develop the ATN generation grammar that would output the target plain-English document.

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