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Summarization of an Online Medical Encyclopedia

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Abstract

We explore a knowledge-rich (abstraction) approach to summarization and apply it to multiple documents from an online medical encyclopedia. A semantic processor functions as the source interpreter and produces a list of predications. A transformation stage then generalizes and condenses this list, ultimately generating a conceptual condensate for a given disorder topic. We provide a preliminary evaluation of the quality of the condensates produced for a sample of four disorders. The overall precision of the disorder conceptual condensates was 87%, and the compression ratio from the base list of predications to the final condensate was 98%. The conceptual condensate could be used as input to a text generator to produce a natural language summary for a given disorder topic.

Keywords

Natural Language Processing, Automatic Summarization, Knowledge Representation.

Introduction

The amount of information available online is growing exponentially. Paradoxically, the more resources grow, the harder it is for users to access information efficiently. Automatic text summarization is an enabling methodology that presents users with compressed yet reliable information.

Spark Jones [1] defines a summary as "a reductive transformation of source text to summary text through content reduction selection and/or generalization on what is important in the source." She further describes the automatic summarization process in three stages:

1. *Interpretation* of the source into source text representation;
2. *Transformation* of source representation into summary text representation;
3. *Generation* of summary text from transformed summary representation.

The crucial issue in this framework is the information that must be identified in order to create an adequate summary. This is addressed largely in the transformation stage, which condenses the source text representation. Several methodologies and architectures have been proposed for automatic summarization, and they can be broadly separated into extraction and abstraction methods [1, 2].

In this paper, we explore an abstraction methodology and apply it to multiple documents from an online medical encyclopedia. We rely on a natural language processing system (called SemRep) and a transformation stage to produce conceptual condensates for disorder topics. We do not generate a summary text but display the summarized information in graphical format. Finally, we provide a preliminary evaluation of the quality of the condensates produced for four disorders.

Background

Automatic Text Summarization Research

The extraction paradigm focuses on identifying salient sentences, which are determined by assigning weights based on such features as location in text, frequency of occurrence, cue phrases, and statistical relevance measures [3, 4]. Overall saliency is computed for each sentence and the best are kept as a summary. This approach is sometimes called knowledge-poor, since it does not rely on meaning or language structure.

According to Hahn [2], there are two abstraction approaches and both are knowledge-rich. The first relies heavily on syntactic parse trees for producing a structural condensate [5]. The second approach also uses natural language processing, but the final source text representation is conceptual rather than syntactic. The transformation phase is a condensation and generalization operation that manipulates this semantic conceptual space, eliminating redundant information, merging graphs, and establishing connectivity patterns [6]. The final representation is a *conceptual condensate* of the original text.

We follow the conceptual abstraction paradigm, which has not been extensively explored because of its heavy dependence on domain knowledge. To support our processing, we rely directly on the Unified Medical Language System® (UMLS) ® [7]. Although the UMLS knowledge sources are not intended as ontologies and will not support extensive inferencing without enhancement, they provide breadth of coverage of the biomedical domain. SemRep is used as the source interpreter, and the transformation stage operates on the semantic predications it produces to summarize information about disorders.

UMLS Resources

All three UMLS knowledge sources, the Metathesaurus,® the Semantic Network, and the SPECIALIST Lexicon are used by SemRep. An interpreter for hypernymic propositions (predications where the arguments are in a taxonomic relation) has been recently added to SemRep [8]. It relies heavily on semantic groups from the Semantic Network and hierarchical relationships from the Metathesaurus.

McCray et al. [9] reduce the conceptual complexity of medical knowledge represented in the Semantic Network through the use of semantic groups, which organize the 134 semantic types in the Semantic Network into 15 coarse grained aggregates. As an example the semantic group **Disorders** contains such semantic types as ‘Disease or Syndrome’, ‘Neoplastic Process’, and ‘Mental or Behavioral Dysfunction’.

Materials and Methods

Our automatic summarization process is illustrated in Figure 1 and described below.

The Source: The Online Medical Encyclopedia

The A.D.A.M. Health Illustrated Encyclopedia® [10], which is available through The National Library of Medicine’s MedlinePlus® includes over 4,000 entries on diseases, tests, symptoms, injuries, and procedures. It also contains an extensive library of medical photographs and illustrations. Each article has a main topic followed by free text information on that topic. A typical disease entry, for example, has a definition and information about causes, incidence, risk factors, symptoms, and treatment. The medical photographs and illustrations have captions in free text format in separate Web pages, increasing the number of pages to approximately 5,000.

The Interpretation Stage: SemRep

SemRep [11] identifies semantic propositions in biomedical text, and we used it as the source interpreter for this project. During processing, an underspecified syntactic parser depends on lexical look-up in the SPECIALIST lexicon and the Xerox Part-of-Speech Tagger. MetaMap [12] matches noun phrases to the Metathesaurus and determines the semantic type for each concept found. Argument identification is based on dependency grammar rules that enforce syntactic constraints. Indicator rules map syntactic phenomena to predicates in the Semantic Network, which imposes semantic validation for the associative relationships constructed. As an example, consider (1)

(1) **Proton pump inhibitors** are now the first choice in the *treatment of* **Zollinger-Ellison syndrome**

A semantic indicator rule links the nominalization *treatment* with the Semantic Network (SN) predicate “Pharmacologic Substance-TREATS-Disease or Syndrome.” Since the semantic types of the syntactic arguments identified for *treatment* in this sentence match the corresponding semantic types in the predication from the SN, the predication (2) is constructed.

(2) Proton pump inhibitors-TREATS-Zollinger-Ellison syndrome

When SemRep interprets hypernymic propositions, the Metathesaurus concepts of potential arguments are subjected to semantic validation. The semantic types must occur within the same semantic group and the concepts themselves must be in a hierarchical relationship in the Metathesaurus. As an example, consider the nominal modification highlighted in (3).

(3) The [**antibiotic tetracycline**] given before the age of 8 years can cause abnormal tooth color. Based on the underspecified parse, in which the head and the modifier are identified for the noun phrase in bold, MetaMap identifies the Metathesaurus concepts “Antibiotics” and “Tetracycline” and their respective semantic types (‘Antibiotics’ in both cases). Since the semantic types belong to the semantic group Chemicals & Drugs, the Metathesaurus hierarchical file is consulted, and it is determined that “Antibiotics” is an ancestor of “Tetracycline,” thus allowing the construction of the predication in (4).

(4) Tetracycline -ISA- Antibiotics.

We processed the 5,000 Web pages from the A.D.A.M. Health Illustrated Encyclopedia with SemRep to produce a set of predications in the form subject-PREDICATE-object at the sentence level. SemRep does not resolve anaphoric expressions at the discourse level. Therefore, no attempt was made to take advantage of rhetorical structure for summarization [13].

Before the transformation stage begins, predications are subjected to a word sense disambiguation filter. From previous work in SemRep, word sense ambiguity was identified as one of the major causes of false positive mistakes. Branded drug names such as Duration (Duration brand of oxymetazoline), Direct (Direct type of resin cement), and others, which are ambiguous with the more common sense of their names, are a particular problem. 37,281 unique predications were generated while processing the encyclopedia, and the word sense disambiguation filter reduced this list to 36,608.

The Transformation Stage

In the abstraction paradigm, the transformation stage condenses and generalizes information found in the source [2], and in our knowledge-rich approach, these processes are conducted on a filtered list of predication types and a seed disorder concept (which must be a Metathesaurus concept). Our transformation stage proceeds in three phases to produce a final conceptual condensate for the input disorder.

Phase 1, a condensation process, identifies predications on a given topic (in this study, disorders) guided by a semantic schema. This provides a set of core predications on that topic. Phase 2 is a generalization process and identifies non-core predications occurring in the neighboring semantic space of the core predications. This is accomplished by retrieving all predications that share an argument with one of the core predications. Phase 3 provides further condensation by eliminating predications with generic arguments, based on hierarchical information from the Metathesaurus.

Phase 1 - Disease description schema

We base our schema for disorders on disease description frames as proposed by Jacquelinet et al. [14]. In adapting their frames to SemRep predications in the form, subject-PREDICATE-object, the following predicates with their respective argument domains are used:

{Disorders} ISA {Disorders}
{Etiological process} CAUSES {Disorders}
{Treatment} TREATS {Disorders}
{Body location} LOCATION_OF {Disorders}

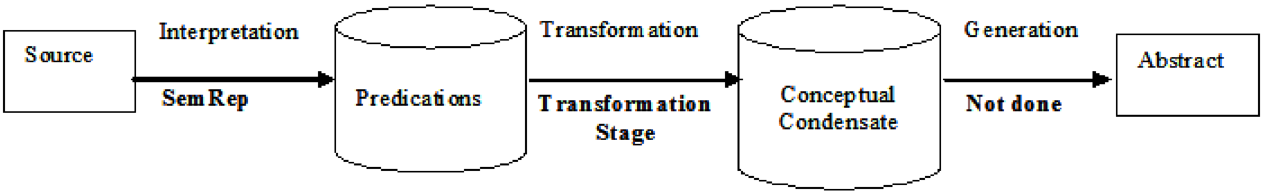

Figure 1 - The summarization paradigm used in our methodology. The A.D.A.M. Health Illustrated Encyclopedia serves as a multiple-document source. The generation stage was not performed in this study

{Disorders} OCCURS_IN {Disorders}

{Disorders} CO-OCCURS_WITH {Disorders}

{Disorders} is a subset of the semantic group **Disorders** and contains the following semantic types: {'Disease or Syndrome', 'Neoplastic Process', 'Mental or Behavioral Dysfunction', 'Sign or Symptom'}.

{Etiological process} is a subset of the union of two semantic groups **Living Beings** and **Chemicals & Drugs**. It contains the following semantic types: {'Bacterium', 'Virus', 'Fungus', 'Invertebrate', 'Rickettsia or Chlamydia', 'Amino Acid, Peptide, or Protein', 'Biologically Active Substance', 'Element, Ion, or Isotope', 'Hazardous or Poisonous Substance', 'Antibiotic', 'Pharmacologic Substance', 'Immunologic Factor', 'Organophosphorous Compounds'}.

{Treatment} is a subset of the union of two semantic groups **Chemicals & Drugs** and **Procedures.** It contains the following semantic types: {'Pharmacologic Substance', 'Antibiotic', 'Hormone' 'Vitamin', 'Therapeutic or Preventive Procedure'}.

{Body location} is a subset of the semantic group **Anatomy** and contains the following semantic types: {'Body Part, Organ, or Organ Component', 'Body Location or Region', 'Body Space or Junction', 'Fully Formed Anatomical Structure'}.

In addition, we allow hypernymic predications (ISA) for {Etiological process} ISA {Etiological process} and {Treatment} ISA {Treatment}. We have not done so for {Body location}, because these are meronomic (PART_OF) relations and our interpreter only deals with taxonomic relationships.

Although the predicates, argument domains, and semantic types allowed for the domains are not complete, they represent a substantial amount of what can be said about disorders.

During processing in the first phase, all predications are retrieved from the input list that have the seed concept as an argument and that conform to the restrictions of the template. This forms a core list of predications about the seed concept. For example, Phase 1 processing with the seed concept "Asthma" retrieves predications such as Asthma-ISA-Obstructive Lung disease, Allergens-CAUSE-Asthma, Asthma-CO-OCCURS_WITH-Bronchiolitis, and Albuterol-TREATS-Asthma.

Phase 2 - Connectivity

The connectivity phase generalizes the conceptual condensate by expanding the core list of predications to neighboring semantic space. It does so by examining all non-seed concepts in core predications and finding additional predications that contain that concept. For example, from the core predication Albuterol-TREATS-Asthma, predications containing the non-seed concept, "Albuterol," such as Albuterol-ISA-Bronchodilator Agent are retrieved. Currently, the system extends the list of predications only once; it does not recurse on the non-core predications.

Phase 3 - Hierarchical principle

The final phase in the transformation process eliminates uninformative predications having a generic argument such as "Pharmaceutical Preparations" or "Disease." This is accomplished by examining the hierarchical position of each argument in all predications in three medical terminologies: Clinical Terms Version 3 1999 (Read Codes), Computer Retrieval of Information of Scientific Projects 2003 (CRISP Thesaurus), and Medical Subject Headings 2003 (MeSH).

The distance between the concept and the root is calculated for each source. A set of rules was developed for each domain of the disorder schema, and empirically-determined values indicate when to prune in each source. For example, an argument in the {Disorders} domain is pruned if the distance to the root is less than four in Read Codes or less than three in the CRISP Thesaurus.

Evaluation

Evaluation in automatic summarization attempts to measure either the quality of the summary as related to the source or how the summary affects the completion of some other task [15]. We have not yet addressed these issues; however, we have conducted a preliminary evaluation of the quality of the conceptual condensates generated for four disorder concepts (Gout, Hyperthyroidism, Migraine, and Chest Pain).

The first author (MF) examined the source sentence that SemRep used to generate each predication in these condensates and marked the predications as either correct or incorrect. Precision was calculated as the total number of correct predications divided by the total number of predications in the condensate.

We also measured the amount of reduction (compression) in the number of predications for each of the four seed concepts. The base number of predications is calculated after the connectivity (generalization) phase is applied. The final number of predications is determined after the final transformation phase (hierarchical).

Results

Results for the quality of the conceptual condensates and reduction in the list of predications for each of the four seed concepts are shown in Table 1.

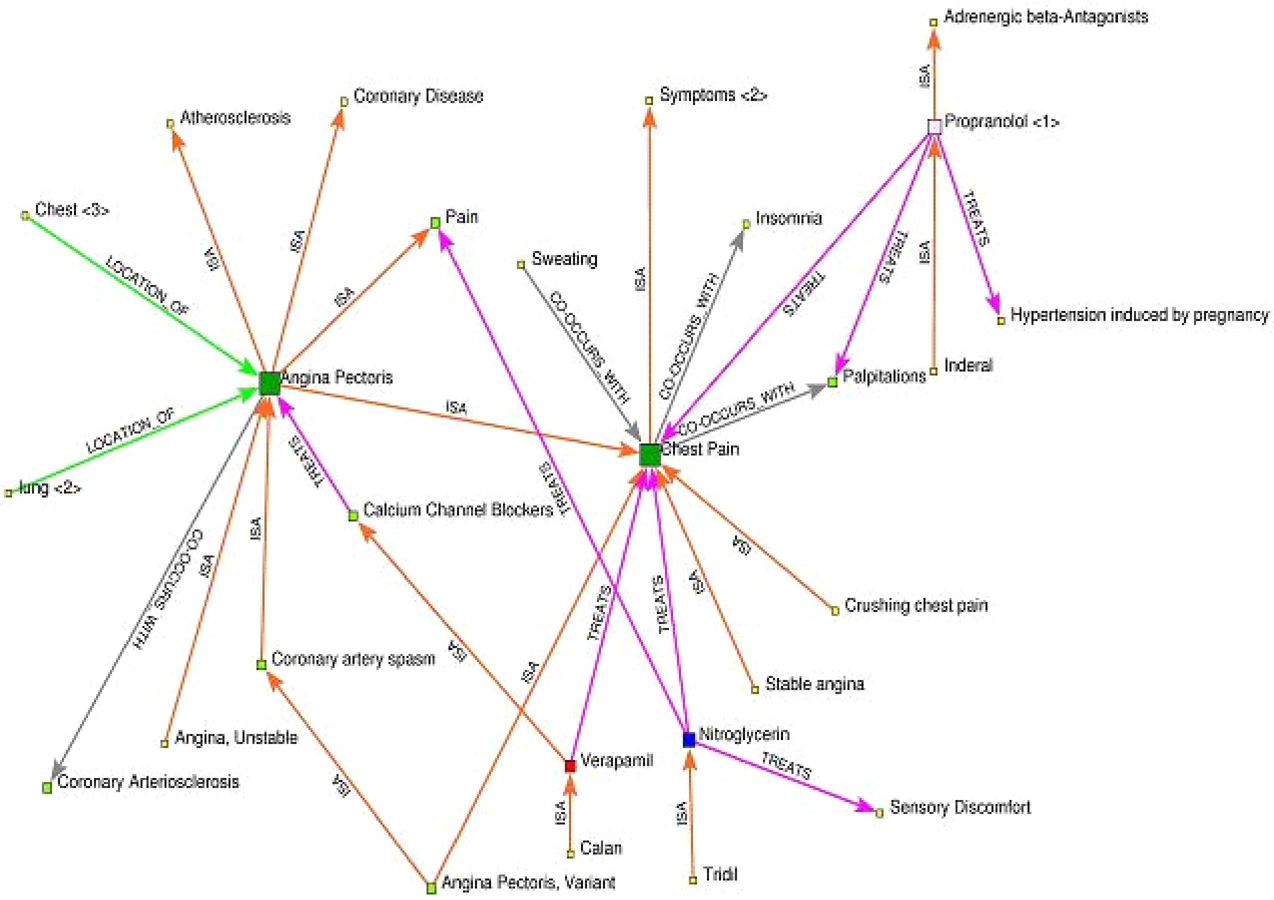

Figure 2 - Conceptual condensate for Chest Pain. Arrows follow the direction of the predicate

The compression rate from base to final number of predications was approximately 98%. Out of 190 final predications, the distribution of predications for each of the six predicates allowed in the disease templates was: ISA–64, CAUSES-21, TREATS-43, LOCATION_OF-23, OCCURS_IN-14, CO-OCCURS_WITH-35. Figure 2 is the conceptual condensate for the seed chest pain displayed in Pajek, an application for analyzing and visualizing large networks [16].

Table 1: Results for the four seed disorder concepts.
***C** = Correct, **I** = Incorrect.*

Concept	Base	Final	C	I	Precision
Chest Pain	1270	31	26	5	83%
Gout	2832	37	33	4	89%
Hyperthyroidism	3224	51	47	4	92%
Migraine	2726	71	60	11	84%
Total	10052	190	166	24	87%

Discussion

The conceptual condensates produced by our summarization processing provide an overview of the seed disorder, including characteristics and treatments. Using Figure 2 as an example for chest pain, it is possible to paraphrase what was extracted from the encyclopedia. Noting the relations between the nodes, it can be seen, for example, that Propranolol, which is an adreneregic beta-antagonist; Verapamil, which is a calcium channel blocker; and nitroglycerin can treat chest pain. The condensate also contains the statement that Verapamil can treat angina pectoris, which is a kind of chest pain. Further, it the condensate says that chest pain is a symptom, which co-occurs with insomnia, sweating, and palpitations.

False positives were mainly due to word sense ambiguity and incorrect argument identification by SemRep. One example of word sense ambiguity due to the way information is represented in the Metathesaurus can be seen in (5).

(5) Propranolol is used for **hypertension**

Hypertension has two senses and one of them is ‘Hypertension induced by pregnancy’. The latter is chosen as the object argument of the TREATS predicate. Word sense disambiguation is still a matter of investigation in natural language processing.

A limitation of our evaluation is that we did not determine recall errors. Since our source consists of multiple documents, it would be difficult to evaluate completeness of the condensate, because assertions can come from any sentence in the source. Another limitation is that only one person evaluated the quality of the condensate. Other evaluation studies in text summarization [15] have shown that inter-rater reliability is an issue. From a methodological perspective, we did not address rhetorical structural analysis, which is important in summarization research [13].

Conclusion

We have presented a knowledge-rich (abstraction) approach to summarization of multiple documents from an online medical encyclopedia. Our approach uses a natural language processing system and a transformation stage targeting disorder topics to produce conceptual condensates for disorders. The compression rate for the predications was high and the quality of the condensates was good. Precision in this sample was 87%.

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