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Methodological Review

Identifying reasoning strategies in medical decision making: A methodological guide

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Abstract

Reasoning strategies are a key component in many medical tasks, including decision making, clinical problem solving, and understanding of medical texts. Identification of reasoning strategies used by clinicians may prove critical to the optimal design of decision support systems. This paper presents a formal method of cognitive-semantic analysis for the identification and characterization of reasoning strategies deployed in medical tasks and demonstrates its use through specific examples. Although semantic analysis was originally developed in the investigation of knowledge structures, it can also be applied to identify the reasoning and decision processes used by physicians and medical trainees in clinical tasks. Assumptions underlying the methods, as well as illustrations of their use in diagnostic explanation tasks, are presented. We discuss semantic analysis in the context of the current interests in developing medical ontologies and argue that a frame-based propositional analytic methodology can provide a systematic way of addressing the construction of such ontologies. Although the application of propositional analysis methods has some limitations, we show how such limitations are being addressed and present some examples of information tools that have been developed to ease, and make more systematic, the process of analysis.

Keywords: Clinical reasoning; Semantic networks; Diagnostic problem solving; Medical decision making; Explanation tasks; Explanatory coherence; Information technology

1. Introduction

Clinical reasoning in medicine has been amply studied since the 1950s. From the beginning, diverse models of reasoning in medicine have been proposed. Such models have evolved from relatively simple associational models [1], linking signs and symptoms with diagnostic categories, to more elaborate structures that include deduction, causal reasoning, and analogy making [2,3]. The complexity of clinical reasoning has been demonstrated by studies covering diverse medical tasks, including decision making [4–7], identification of medical errors [8–12], and comprehension of clinical information [8,13–15]. These studies have shown that the types of reasoning and strategies vary among clinicians; especially as a function of expertise [16], knowledge [17], and problem difficulty [18]. One question that has arisen is how to capture such complexity. In artificial intelligence, methods of representing clinical reasoning have been developed and used in the design of decision support systems. These include production rules, Bayesian probabilistic methods, case-based reasoners, and decision tables, among others [1]. Similarly, cognitive methods of representation that uncover some of the actual complexities of clinicians' reasoning have been

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developed [19–21] and tested in the analysis of medical text [22–24], clinical guideline comprehension [25,26], problem solving [27,28], decision making by health care professionals [26,29,30], translation of text and diagrammatic guidelines into computer interpretable representations [25,31], interpretation of errors in medication instructions [15], and reasoning in problem-based discussion groups [32].

The complexity of medical reasoning has also been recognized in cognitive/epistemological models [2,3], where the diagnostic process has been characterized in terms of four types of inferences: abstraction, abduction, deduction, and induction, seems to account for all aspects involved in diagnostic reasoning. The first two inference types drive hypothesis generation while latter two types drive hypothesis testing. During abstraction, data are filtered according to their relevance for the problem solution and chunked in schemas representing an abstract description of the problem at hand (e.g., abstracting that an adult male with hemoglobin concentration less than 14 d/gl is an anemic patient). Following this, hypotheses that could account for the current situation are related through a process of abduction, characterized by a "backward flow" of inferences across a chain of directed relations which identify those initial conditions from which the current abstract representation of the problem originates. This provides tentative solutions to the problem at hand by way of hypotheses. For example, knowing that disease A will cause symptom b, abduction will try to identify the explanation for b, while deduction will forecast that a patient affected by disease A will manifest symptom b: both inferences are using the same relation along two different directions [2]. In the testing phase, hypotheses are incrementally tested according to their ability to account for the whole problem, where deduction serves to build up the possible world described by the consequences of each hypothesis. As predictions are derived from hypotheses, they are matched to the case through a process of induction, where a prediction generated from a hypothesis can be matched with one specific aspect of the patient problem. The major feature of induction is, therefore, the ability to rule out those hypotheses whose expected consequences turn out to be not in agreement with the patient problem. This is because there is no logical way to confirm a hypothesis: we can only disconfirm it in the presence of inconsistent evidence. This evaluation process closes the testing phase of the diagnostic cycle. Moreover, it determines which information is needed in order to discriminate among hypotheses and hence which information has to be collected.

In this paper, we present a review of these cognitive methods for the analysis of clinical reasoning that have been developed in the study of medical cognition. We show how such methods capture the essential features of the medical processes underlying diagnostic tasks and how they can have implications for the design of medical decision support systems. We argue that application of methods for the representation of clinical reasoning as used by clinicians may become an important consideration in the design of decision support tools that match the clinicians' decision processes. In the following sections, we present a brief description of the tasks that are used to elicit clinical reasoning and the cognitive and ontological assumptions underlying such tasks. Next, we present the basic methodology and the types of information that can be gathered using the methods in the investigation of medical reasoning. Following, we describe the empirical paradigm to investigate and analyze reasoning in medical tasks, with specific examples of the analyses of complex clinical cases. Finally, we discuss some implications of the cognitive methods to the study of decision-making and provide a glimpse of future research.

2. Theoretical assumptions in medical cognition

In 1986, Patel and Groen [16] presented a methodology for the investigation of reasoning and problem solving in medicine. Such methodology, propositional analysis, was based on a theoretical understanding of medical case comprehension [33], which, at the time was novel to be used in a complex domain such as medicine. The interesting aspect of the method was that it attempted to unite research areas that were thought to be unrelated, namely, comprehension, problem solving, and diagnostic reasoning. Medical artificial intelligence was devoted to an examination of clinical problem solving using computational methods [34], such as rule-based representations, to characterize signs, symptoms, and diagnoses, when the use of propositional analysis allowed the representation of knowledge needed in clinical tasks, and provided a complementary methodology to the methods based on production rules. Patel and Groen's aim was to isolate the reasoning process that physicians go through when diagnosing a clinical case, using techniques to identify knowledge structures. Their research was motivated by two sets of findings. The first finding was that experts in domains outside medicine reasoned from the problem data toward a hypothesis that accounted for the data. The studies in medicine pointed to a different kind of reasoning by physicians: reasoning from a hypothesis to account for the case data, which seemed anomalous when compared to other domains [35]. The second finding was that pure problem solving response protocols, where a subject is simply asked to "think aloud" as he or she makes a diagnosis, tended to yield unsatisfactory or excessively sparse information regarding the knowledge being used [23]. Hence, different methods of data gathering and analysis were tried that appear to solve both the contradictions of earlier investigations and the sparse nature of think aloud protocols. A promising method of data gathering emerged, which was a type of probing task, known as "diagnostic explanation," in which a physician or medical student is asked to "explain the underlying pathophysiology" of a patient's condition. Unlike conventional think-aloud, this task was shown to be able to generate detailed knowledge used in problem solving task. Explanations allowed researchers to constrain the task to generate manageable and relevant information from the subjects. A similar methodology, also for analyzing explanations outside of medical domain, has been developed by Chi [36–38], whose aims and research results are consistent with those in medical reasoning.

As the diagnostic explanation task can be used to characterize knowledge structures in making diagnoses, it can be used to identify the process indicators of reasoning where these knowledge structures are used. Although the methodology has been described in various papers over the years [39–41], there have been no specific writings devoted to explaining its assumptions, its logic, and limitations. This section presents a review of the clinical explanation tasks, starting with a description of the cognitive assumptions underlying such tasks. Subsequently, we will present a theory of comprehension and its use in understanding the processes involved in diagnostic reasoning. We will finish the section with a description of a model that provides a framework for the representation of medical knowledge in use.

2.1. Assumptions underlying explanation tasks

When providing an explanation related to a clinical case, one can make some assumptions about the cognitive structures and processes underlying such task. These assumptions are based on cognitive research and theory, which have been amply validated in the last 40 years. A first assumption is that information, such as a clinical case description, is processed serially, at least at a certain time-span, especially on tasks that require over a few seconds to complete. When a clinical problem becomes the focus of attention, the information generated passes through working memory (WM) first, and linked later to information in long-term memory (LTM), which provides context that serves to "dis-ambiguate" the processed information. For instance, the expression "breathing difficulty" may suggest a number of different scenarios, such as "exercise," "asthma," or "heart attack," to name a few. Depending on the task context (e.g., diagnosis and treatment plan), these terms may be differently associated in LTM. Seriality is important because the first information items that pass through WM are the first ones to activate knowledge in LTM, which serves as a context for information processed later. A second, related assumption is that the temporal sequence in the explanation response protocol reflects the temporality of the underlying reasoning. In other words, those ideas or propositions that are verbalized first are thought first, which is especially critical in timed-tasks, where the clinician has no possibility of revising the clinical problem (e.g., reading a case description and providing an explanation in 3 min of less [18]), or in online verbalizations, where the clinician reasons while going through the clinical case (e.g., when he clinician is asked to provide an explanation of a clinical problem, a sentence at a time [17]). This assumption is important for the investigation of diagnostic reasoning, where one can infer the nature of the cognitive processes deployed in decision-making and problem solving by looking at the temporal sequence of verbalizations. A third assumption is that although the input information may be fixed (e.g., people read the same patient report, physicians may observe the same patient), the processing (e.g., reasoning strategies and inferences) and the output (e.g., final diagnosis or pathophysiological explanation) are varied. In particular, cognitive research in medicine [42] has shown that people generate representations of clinical cases at several levels of generality, from the very specific (e.g., as is often the case with medical students) to the very general (e.g., as is true of expert clinicians). The critical factor in determining generality is typically the degree of high level expertise of the subject, namely, specialized or specific expertise (i.e., knowledge of a particular sub-domain of medicine, such as endocrinology or cardiology). Higher-level representations are generated by these more expert subjects, whereas lower-level and more detailed representations are typically generated by novices, or more commonly, intermediate subjects (e.g., senior medical students, recent graduates, and residents) and sub-experts (i.e., experts who are physicians by training, but do not have further specialized degree). A final assumption is that the solution strategies and the types of inferences used during clinical problem solving are a function of domain-specific prior knowledge that a person possesses [43], and more specifically, of the quality and organization of such knowledge [42] into adaptable and meaningful "schemata" or "frames." In this paper, we use the terms frame and schemata interchangeably to refer to learned knowledge structures in clinicians' knowledge-base that allow them to identify prototypical or familiar clinical patient problems in an efficient manner, encompassing both declarative (e.g., a diabetes frame, which includes the features that identify the disease) and procedural information (e.g., a physical examination frame which describes the typical events involved in examining a patient). In the case of medicine, such frames or schemata are organized in a manner that resemble closely the layered structure of biomedical knowledge [44], as it has been shown in research in medicine [42,45–47] an domains outside of medicine [48–51]. Modern processing theories of comprehension provide a scientific basis for knowledge organization and the acquisition of expertise.

2.2. Assumptions in the generation of cognitive representations

Given the importance of knowledge in decision-making, the formation of a good problem representation is crucial in generating correct and effective decisions. Developing a problem representation involves organizing knowledge into meaningful structures in memory. Such memory structures include the salient aspects of the information (e.g., gist, summary, major case characteristics) and the context needed for its interpretation (e.g., from memory of previous readings or patients seen) [52]. Comprehension research suggests that such "meaning construction" is not a one-time deal, but a cyclical process of building a sort of mental model by keeping in memory some ideas about the case or problem and, gradually, albeit quickly, discarding others as new information is gathered about the case [42,53]. This process becomes more efficient as clinicians' experience with patients increases. They acquire a great deal of specific knowledge (e.g., signs, symptoms, and medical procedures), which gets stored in LTM. However, as a result of their practice, clinicians learn to associate individual items in WM with the contents in LTM, which result in the development of conceptual organizations in memory called retrieval structures [54,55]. This way, an expert can use these retrieval structures to provide selective and rapid access to long-term memory. For example, a physician may be able to diagnose a patient's problem by recognizing a pattern of clinical findings as a whole and associating them with a particular diagnosis stored in LTM, which precludes the need to process each clinical finding separately. In contrast, a novice looking at the same patient's signs and symptoms may see a collection of independent findings, each of them linked to different diagnoses in memory.

Retrieval structures play a particular role in filtering irrelevant information in WM (irrelevant to a specific problem) and reinforcing relevant associations. Research [9,42,47] has shown that although novice and expert clinicians build their patient representation in a similar way (e.g., by generating associations between generic knowledge in LTM and specific patient findings in WM), only the latter are capable of quickly and efficiently integrating such information into retrieval structures by: (a) filtering irrelevant information and (b) consolidating the problem-relevant information into a coherent representation [17,42]. Using timed tasks (e.g., under 3 min) and sequential presentation of explanation tasks on a computer (e.g., presenting a clinical case one segment at a time), it was possible to obtain a trace of the comprehension process that leads to the generation of retrieval structures.

An assumption of our research is that there is a correspondence between people's structures in memory and the structures in their domain of expertise. In the medical case, such correspondences are made between the concepts and categories that clinicians generate and use during clinical problem solving and the way the domain of medicine is organized. A conceptual framework [19,27,44] that can be seen as an ontological model of clinical diagnosis in the medical domain and which corresponds with the manner in which clinicians think about diagnostic problems is presented next.

2.3. An ontology of medical knowledge in diagnostic tasks

The processes of comprehension and diagnostic reasoning (i.e., inferences, procedures, and strategies) are carried out on the biomedical knowledge base possessed by the clinician. In the case of diagnostic reasoning, the biomedical knowledge can be described as an ontology with multiple layers of concept types and various relationships in-between that serves to describe diagnostic reasoning as a process of abstracting case information from different ontological levels. This ontology was first proposed by Evans and Gadd [27] as a form of providing classification of medical knowledge for use in problem solving situations, and has been used extensively in medical cognition research [42,47]. This model is presented in Fig. 1. The ontology is composed of levels of knowledge where the higher levels subsume or provide a context for interpretation of the lower levels. The most basic level is the empirium, which corresponds to the basic descriptions of sensory data and carries no medical interpretation, such as anatomical descriptions or skin color [27]. The next level is composed of observations, which are perceptual categories that serve as basis for clinical classification, and therefore require medical knowledge to

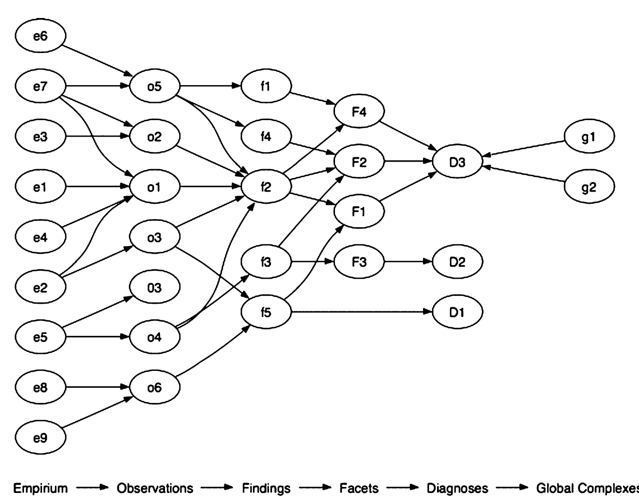

Fig. 1. Ontological model for clinical problem solving.

identify and categorize. For instance, patterns of shade in a radiological image or distinguishable heart sounds, which may be imperceptible to an untrained eye or ear, are interpreted as observations by a physician. The next level is composed of findings, clusters of observations that are interpreted in terms of their clinical relevance, such as when shortness of breath, for instance, is interpreted in the context of myocardial infarction. The next is the level of facets, representing sub-diagnostic categories that suggest potential diagnoses (e.g., cardiovascular) and discard some others (e.g., pulmonary). The level of facets in the ontology is related to the concept of retrieval structures in memory. Similarly to retrieval structures, facets capture patterns of findings as whole concepts. For instance, categorizing a cluster of findings (e.g., chest pain, sweating, and faintness) as a facet, e.g., "cardiovascular problem," serves to explore a particular subset of diseases while discarding others. The next following level is that of diagnoses, which are clinical categories with more or less known explanatory and therapeutic models. The final level is global complexes, which are the circumstances that affect a particular patient, such as particular age groups or patient characteristics that may influence a diagnosis or a management path.

Within the framework of such an ontology of medical knowledge, diagnosis can be considered as a narrow-down search process [56,57] in the space of possible diseases that account for the clinical manifestations. The ontology integrates: (1) the space of diseases (the level of facets and the level of diagnoses), (2) the space of clinical manifestations (the level of empirium and the level of observations), and (3) the constraints to search, such as the contextual or causality relationships between diseases and clinical manifestations (the level of findings) and the specific condition of a patient (the level of global complexes). At the beginning, with little data collected, only a limited number of search constraints can be applied, and thus the space of the potential diagnoses is large. For example, a patient reporting abdominal pain may have appendicitis, pancreatitis, gastric ulcer, or other diseases that lead to the symptom. As more data are obtained through assessments (history data, physical examinations, lab tests, etc.), additional constraints can be applied, and thus the space of the potential diagnoses is narrowed down, until the remaining diagnoses can account for the clinical findings appropriately. If a patient with abdominal pain presents additional clinical findings such as no fever and black stools without taking specific medications that can account for it, it may indicate a bleeding ulcer. In fact, here the general medical knowledge of specific diseases and their manifestations provide a framework for the diagnostic reasoning on a specific case. This approach to knowledge organization and reasoning is also used in the design and implementation of clinical decision support systems [58]. It is important to note that the search for potential diagnoses from the clinical findings is a parallel process similar to pattern recognition [59] rather than a sequential process like the rule-based deduction [60]. The ontology described previously is assumed to represent the structure of medical knowledge required for diagnosis. However, depending on the stimulus material (e.g., verbal case presentations or real patient interviews), the type of case (routine or non-routine), and the expertise level of the diagnostician one wishes to model (e.g., expert, sub-expert, or novice), some of the strata in the ontology may be omitted. For instance, when analyzing experts' diagnostic problem solving on routine cases, we can assume that LTM items are limited to propositions representing knowledge of findings, facets, diagnoses, and global complexes. Prior research has shown that in such cases, the diagnostic reasoning is mostly bottom up, with most inferences being forward-driven (data-driven) toward the diagnosis [42]. Furthermore, when diagnostic tasks are presented in the form of written patient descriptions, there is already some information encoded as findings in the description itself. This is analogous to using such medical tasks, such as consultation with another clinician, as stimulus material. In this case, the level corresponding to empirium is not present, because the patient description is already interpreted in some way in terms of observations or findings. In the next section, we illustrate the use of such methods to determine the reasoning and inferential processes in medical diagnostic tasks.

3. Methods for identifying solution strategies in clinical problem solving

In this section, we provide a detailed description of the methods as they have been used to identify the process of reasoning in medical tasks. The application of the methods has been spanned over a broad range, encompassing empirical studies of expert-novice differences in medical problem solving, cognitive representation of clinical guidelines, use of diagrammatic guidelines in patient management, and patient's representations' of illness, among others [8,14,15,25,26,41,42,61,62]. We start the section with a description of the empirical paradigm typically used in cognitive studies of medical diagnosis. We then present some of the analyses that are carried out in the investigation of reasoning, such as recall-inference, directionality of reasoning, problem solving strategies, and the identification of reasoning errors. We close the section by providing specific examples in which the described methods are applied.

3.1. Empirical paradigm

In diagnostic explanation tasks, physicians are asked to explain the pathophysiology of a patient's condition, as discussed earlier. Interestingly, to this request, physicians typically respond by accounting for the patient's signs and symptoms in terms of potential diagnoses, and not in terms of their underlying disease mechanisms. In other words, clinicians respond by clinically accounting for the patient's signs and symptoms without explaining their disease mechanism. Despite the "shallowness" of clinicians' response, the diagnostic explanation is a probe that is extremely useful in providing a rich account of a patient's condition during clinical reasoning. The empirical paradigm used in diagnostic explanation task usually consists of the following steps: (1) present a description of a clinical case, often in written form, and ask the subjects to read it; (2) obtain a "free-recall" protocol by asking them to remember from memory everything they can about the case, usually without looking at the case; (3) ask the subjects to provide a pathophysiological explanation of the clinical case, where they elaborate the underlying pathology related to the problem; and finally (4) ask the subjects for a final or a differential diagnosis. Note that the diagnosis is the last step in the process and this diagnosis provides the opportunity of obtaining a response protocol that reflects the major elements of the diagnostic solution process, giving also a somewhat detailed account of the patient's condition. For the purpose of identifying the solution strategies used by physicians during clinical decision making, the explanation task has been successfully used in the last 20 years by a number of investigators [5,18,29,40,63]. The protocol analysis has two main goals: (1) to characterize the knowledge in use during clinical problem solving and decision making (through the use of propositional analysis); and (2) to identify the solution strategies used in solving the patient problem and determining the directionality of the subject's underlying reasoning (using semantic network representations). Such process involves the transcription of the data from verbal response protocol, segmentation of the transcribed data into a set of clauses, and analyzed using propositional analysis. Relational structure between these propositions reflect the macrostructure of the protocol. In the remainder of this section, we will walk the reader through this process.

3.2. Propositional and semantic network analysis

A propositional representation provides a formal means to explicitly identify ideas and the relationships among these ideas in the form of a list of propositions; where a proposition is an idea unit underlying the surface representation of a text (e.g., a clinical case) or, more precisely defined, an *n*-ary relation among concepts. Verbal protocols, either in written or spoken forms, can be propositionally analyzed using any one of the several systems of propositional analysis that have been developed [33,64,65]. Despite some differences in notation and details, all these systems provide a uniform classification format for the coding of verbal data, based on the theoretical assumption that propositions correspond to the basic cognitive units of knowledge representation in human memory [66]. Although for a differing view see [67].

3.2.1. Propositional representations

Among the several propositional grammars that have been proposed, we used Frederiksen's model in our research [14,40,68]. A characteristic of this model is that it provides a generic semantic markup system, which follows a syntax specified in the BNF notation, and includes a number of semantic categories that serve to mark propositions in terms of their ontology and the frame-based relations among concepts and propositions. In the analysis of clinical reasoning, the most common relations are dependency relations, specifically, causal, conditional, temporal, and Boolean connectives, such as alternating-OR and exclusive-OR relations. Algebraic relations (e.g., greater than), identifying relations, and categorical relations (i.e., category membership, part-whole relations) are also much used, as well as those serve to identify the source and the result of a process. Uncertainty is typically represented qualitatively by using modal qualifiers (e.g., can, might, and may). The extent of use of semantic codes is primarily determined by the detail of the representation. As more detail is added, the likelihood of using a higher variety of codes also increases. In previous research, we described how propositional analysis methods can be used to uncover the semantics of clinical guidelines [14] and the use of guidelines by medical practitioners [26].

3.2.2. Coding of inferences

When physicians and other health professionals work on a clinical problem, they make inferences that are based on their prior knowledge. To identify these inferences, methods of propositional analysis have proved very useful in the past. A distinction is made between a recall (the literal reproduction in the verbal protocol of a proposition in the clinical case) and an inference (any proposition in the verbal protocol that has not literal match in the clinical case). That is, whenever there are transformations made by subjects on any message base (e.g., the clinical case), it is scored as an inference. This scoring procedure is based on a set of rules for proposition matching and for proposition transformation according to specific transformation rules. For instance, consider the original sentences: "If hemoptysis, persistent cough, then examine the tracheal bronchial tree." and a physician's recall of the information: "If hemoptysis, persistent cough, then examine for malignancy in the lungs." A propositional analysis of the two segments is as follows:

Text Segment:	
1.1 COND: (if)	[hemoptysis, 1.2], [1.3];
1.2 cough	= ATT: Persistent;
1.3 examine	OBJ:[1.4];
1.4 tree	ATT: tracheal, ATT: bronchial;
Recall Segment:	
Rl.l COND: (if)	[hemoptysis, R1.2], [R1.3];
Rl.2 cough	= ATT: Persistent;
R1.3 examine	THM:[(for)R1.4];
Rl.4 malignancy	LOC:(in) lungs;

In comparing these two analyses, Proposition 1.2 is identical to Proposition Rl.2. This would be classified as a recall in our system. On the other hand, Propositions 1.1 and R1.1 are different in that there is a change in the consequent slot of the proposition. This is classified as a conditional inference with a consequent change. Furthermore, there is a replacement of a concept "tracheal bronchial tree" in the proposition slot by a new superordinate concept "lungs." This inference involves an operation on propositions in the text that results in new propositions more general than the propositions in the original content of the text; in this case, a part-whole relationship between the clinical description and the physician's protocol.

3.3. Identifying reasoning through semantic network representations

Network representations constitute common ways to represent knowledge structures used in problem solving and decision making. Such networks consist of the graphical depictions of concepts and propositions that allow to display their inter-relations, something that is not possible with a propositional representation, which is simply an ordered list. Several forms of network representations have been developed and applied to the analysis of medical knowledge, ranging from concept maps [69] to conceptual graphs [70]. In general, most network representations can be expressed in graph-theoretic terms [71]. Basically, a graph is a type of representation composed of nodes and directed arcs (also known as edges or paths) connecting the nodes. A minimal graph consists of two nodes and a single arc connecting the nodes. Nodes may represent clinical findings, pathophysiological processes, or diagnostic hypotheses, whereas the arcs represent directed connections between nodes. A network representation provides a means to identify three aspects of clinical reasoning: (a) the overall strategy used in evaluating the collected clinical data, (b) the directionality of the inferences used in reasoning; and (c) the coherence of the diagnostic explanation.

3.3.1. Directionality of inferences

We can determine the directionality of the inferential processes in reasoning by looking at the directions of the arcs in a network. A distinction is made between the information that is given to the reasoner and the information that is inferred or hypothesized from the information given. Forward-driven reasoning corresponds to a path from the given information—typically a clinical finding—to a hypothesis (e.g., a diagnosis). In contrast, backward-driven reasoning corresponds to a path that, starting in a hypothesis, ends in the information given [72]. A pure chain of forward-driven reasoning refers to a network where all directed paths go from data to hypothesis, whereas pure backward-driven reasoning refers to a network where all paths go from hypothesis to data. Cognitive research has shown that pure forward-driven reasoning is typical of experts' clinical problem solving and reasoning [16,73].

3.3.2. Coherence in explanations

Explanatory coherence can be also assessed from the semantic network representation. Coherence is determined by establishing the inter-relationships among the nodes in a graph. Two forms of explanatory coherence are often distinguished: global and local. A network exhibiting global coherence is characterized by connections among all nodes of the network without any contradictions or loose ends. In turn, local coherence refers to the consistency in a component of an explanation that accounts for a part of the clinical problem. An explanation that exhibits local coherence, without global coherence, would include isolated components of the problem that are not explicitly linked to the rest of the explanation. Cognitive research in medicine has shown that global coherence is more common of the expert clinicians, while local coherence is more often observed in less-than-experts clinicians.

4. Applications of semantic analyses

To illustrate the application of semantic network analysis we will use texts (e.g., case descriptions) that serve as stimulus material as well as verbal reports by health care providers in a variety of tasks. These include explanatory accounts of clinical cases, physicians' and nurses' recall of clinical summaries, physician's descriptions of clinical guidelines, and representations of sources of errors in diagnostic explanations. Applications of these methods of analysis to other types of medical tasks and further example of the application of the methods are provided elsewhere [14,39,40,42]. In clinical diagnostic tasks, the first step is to develop a model of the task that is being investigated. This model functions as a reference point indicating a standard of performance to which explanation protocols are compared.

The reference model [16] reflects an idealized knowledge representation that is constructed with the assistance of domain experts and relevant medical information (e.g., textbooks, research literature). The process to build a reference model is similar to a knowledge engineering task used in expert systems research [74]. The goal is not to develop a faithful cognitive representation of an expert case model, but to construct an ideal, somewhat abstract, model of the problem. Building a reference model is an iterative process that includes eliciting information from an expert to explain the findings in a case (using knowledge elicitation techniques) and consulting other sources for additional information such as to have an explanation that is as complete as possible (for the purpose of the clinical task). Once the content of the reference model is completed, a propositional representation is constructed from which a reference network is developed.

The propositional and network representations of the reference model serve to describe all the concepts necessary for a complete, albeit idealized, solution to the patient problem (We will not present a reference model in this paper, although the reader can find examples elsewhere [16,75]). The reference model, sometimes referred to as canonical model, contains elements of the clinical problem together with the minimum number of rules leading to the correct diagnosis. In research studies, a written case description is used as a clinical problem, although real or simulated patients can be used. The problem is presented to the clinician, who is asked to reason out-loud and to provide a diagnosis as well as an explanation for the case after the diagnosis. Illustration of a clinical problem is shown below:

A 62-year-old male lifted a box resulting in a sudden onset of severe retrosternal chest pain radiating through his back/ The pain persisted for 2 hours/ He felt a mild shortness of breath/ The pain persisted at rest and with movement/ He had a long history of hypertension/ and also had a myocardial infarction 5 years ago/ He had no history of recurrent pain/ and no shortness of breath on exertion/ He had no previous surgery/ On physical examination, his blood pressure was 170/90/ His temperature was 37 °C/ His pulse was 110/min/ and his respiratory rate was 30/min/ There were no abnormalities on physical examination/

The first step of analysis involves the segmentation of the clinical case into major clauses and minor clauses, according to Winograd [76]. Segmentation and the numbering of clauses are performed to make the analysis easier to perform. A sentence such as "He had a long history of hypertension and also had a myocardial infarction 5 years ago," could be segmented into two clauses: (1) /He had a long history of hypertension/, and (2) /also had a myocardial infarction 5 years ago/. Once the whole text is segmented into clauses, the propositional analysis can be performed by identifying the action of each clause; typically represented by a verb. For instance, the first sentence in the text description (A 62-year-old male lifted a box /and felt a sudden onset of severe retrosternal chest pain radiating through his back) consists of two phrases and eight idea units or propositions, as given in Table 1. The propositional analysis of the whole case description, presented in Appendix A, resulted in 28 propositions. The propositional analysis provides the following information: (1) the proposition number; (2) the predicate; and (3) the argument. Semantic tags are used in the arguments to codify the meta-content of the text. For instance, AGT: indicates agent of the action; ATT: indicates a property; OBJ: indicates the object of the action (non-living); PAT: patient of the action (living); LOC: location; PRT: part; THM: theme of feeling; and COND: indicates conditionality. Aside from this semantic information, generating a list of propositions also provides a measure of the amount of information that is provided in the stimulus text.

By comparing the information in the clinical case description with the clinician's account of the case, one can answer questions about the amount of information that clinicians need to accurately diagnose the case; what information is already in the clinician's knowledge

Table 1
Propositional analysis of sentence "A 62-year-old male lifted a box resulting in a sudden onset of severe retrosternal chest pain going through through to his back"

Prop. #	Predicate	Argument	Explanation
1.1	Lift	AGT:male;OBJ:box;	Male (agent) lifts a box (object of lifting)
1.2	Male	ATT:62-year-old;	Male (agent of action 1.1) is 62-years old
1.3	Pain	LOC:chest;	Pain is located in the chest
1.4	COND:(result)	[1.1][1.3];	Lifting box was a condition for feeling pain
1.5	Pain	ATT:severe;	Pain is severe
1.6	Pain	ATT:sudden;	Pain was sudden
1.7	Chest	PRT:(retosternal);	Pain is felt in retrosternal part of chest
1.8	Go_through	THM: 1.3,LOC:back;	Pain goes through to the patient's back

Column one of the table gives the proposition number; column two presents the head element or predicate; column three presents the arguments; and column four presents an explanation of each proposition in plain English. Codes listed in the argument column indicate semantic tags as follows: AGT: agent; ATT: attribute; COND: condition; LOC: location; OBJ: object; PRT: part; and THM: theme.

base; how much inferencing is done to diagnose the problem; and how coherent is the clinician's explanation. An explanation of the clinical problem provided by a clinician is given below:

We have a 62-year-old male who had a very sudden onset of severe retrosternal chest pain that radiated through his back while lifting a box. The pain was there for two hours and persisted while the patient was moving or at rest. He has a history of hypertension and cardiac problems, which suggests that this could be a case of cardiovascular disease, such as ischemia, either angina or even infarction. Hypertension makes me think also of aortic dissection, especially with the pain radiating to the back and the isometric effort. If he had a small dissection, and he made this effort, this could raise his blood pressure and that can cause aortic dissection. The fact that the pain was so sudden and that it was there with movement or at rest is very consistent with aortic dissection, but makes ischemia less likely. It could be musculoskeletal also but with the history of hypertension and previous cardiac problem, it is less likely. On physical examination, his blood pressure was 170 over 90, his pulse was 110, so he's tachycardic, his temperature was 37 °C, and his respiratory rate is 30 per minute. This suggests to me that there is something really serious with this man and I'm concerned with bleeding somewhere. I'm going vascular now, with dissection of the aorta, with this presentation, and with that pain radiating to the back, a musculoskeletal problem is less likely right now.

The explanation provided by the clinician is also analyzed into propositions, which are then compared to the propositions in the original clinical problem (As can be seen in Appendix B, the physician generated 34 propositions). Such comparison functions as the basis for the analysis of reasoning inferences and to determine the amount of information used during problem solving.

As an illustration, Table 2 presents the propositional analysis of a physician's verbalization of the text segments presented in Table 1. The two tables show that the verbalization of the physician follows very closely the information presented in the clinical text. The major difference between them is that while the text states that the chest pain was the result of lifting the box (RSLT:), the physician interprets this information in terms of the concurrency of the act of lifting the box and the feeling of the pain (EQUIV:TEM). Differences in interpretation such as this may indicate differences in the way the patient problem is constructed.

The translation from the propositional analysis to the network representation is carried out by linking propositions through proposition overlap. For instance, if two propositions have the same concept (e.g., lift box causes chest pain and chest pain is central), they are linked in the network and because typically propositions include a concept more than once, the network linked through the common concepts. As seen in Fig. 2, the physician's explanation, represented in network form, connects together all propositions, reflecting a coherent explanation. Thus, the network is constructed by linking all the propositions in the proposition list, with a triplet (node-link-node) in the network representing a single proposition (predicate-argument) in the propositional analysis (sometimes, for the sake of simplicity, it is often desirable to represent two or more propositions as a single triplet in the network representation).

Table 2
Propositional analysis of a physician's verbalization of the clinical case

Prop. #	Predicate	Argument
1.1	Have	PAT:Male,THM:Pain;
1.2	Male	ATT:62-yr old;
1.3	Pain	LOC:Chest;
1.4	Chest	PRT:(Retrosternal);
1.5	Pain	DEG:Severe;
1.6	Pain	ATT:Sudden (MODQUAL:very);
1.7	Radiate	THM:Pain,LOC:Back (POSS:his);
1.8	Lift	AGT: [1.2],OBJ:box;
1.9	EQUIV:TEM:(while)	[1.8],[1.3];

The first physician verbalization is "We have a 62-year-old male who had a very sudden onset of severe retrosternal chest pain that radiated through his back while lifting a box." Argument tags listed in the argument column indicate the following semantic constructs: AGT: agent; ATT: attribute; COND: condition; DEG; degree; LOC: location; OBJ: object; PAT: patient; PRT: part; EQUIV:TEM temporal equivalence of events; THM: theme.

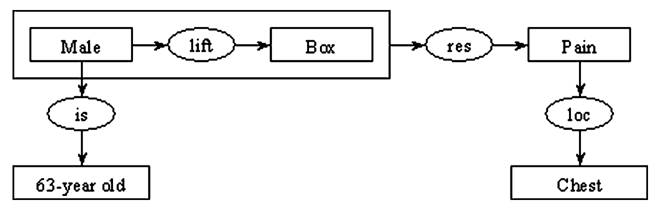

Fig. 2. Network representation of propositional representation of sentence "A 62-year-old male lifted a box resulting in chest pain."

4.1. Domain frames and clinical tasks

Clinical cases are typically presented in a pre-specified sequence of information, which include presenting complaint, medical history (personal and familial), physical examinations, and lab test results. In studies of clinical reasoning, such sequence of information have been called "frames," as they function as generic structures that help gather and organize clinical information. In medical cognition research, such frames have been used to organize concepts that clinicians use during problem solving and to help researchers in comparisons between clinical case representations of practitioners at different levels of expertise. It is typically expected that physician and medical trainees follow such clinical diagnostic frames, although showing differences as a function of their level of expertise. For instance, when clinical information is presented in random order [77], expert clinicians are able to re-organize such information into a logical sequence reflecting a typical clinical frame (i.e., presenting complain, medical history, physical examination, and laboratory results).

In the procedure for identifying the clinical frames used by clinicians, the first step is to establish the standard medical task (e.g., diagnosis and management) and to describe the prototypical components of such tasks [32] (e.g., procedural steps and potential actions). The representation of the typical clinical problem in terms of such components serve as a comparison to the actual representation of the problem by individual clinicians. In the case of the clinical interview frame, these consist of main complain, personal medical history, physical examination, and laboratory results. Part of such a frame can be observed in the larger boxes of Fig. 3, which provides a network representation of an explanation of the clinical case presented above.

This expert explanation follows closely the diagnostic procedural frame, which is typical of clinical interviews. In this case, the protocol by the expert physician shows three major components of the diagnostic frame (in the larger boxes of Fig. 3): presenting complaint (first box on top), patient's medical history (middle box), and physical examination results (bottom box). As is typical of experts, the network developed from the physician's explanation is fully coherent in that all nodes are connected. This contrasts with situations where a case explanation is broken into components, which is typical for novices. Similar results have been reported in other domains [78–80].

4.2. Identification of directionality of reasoning

As described above, in a semantic network, a forward or data-driven inference is represented by a directed link from the data given in the case description to a hypothesis, whereas a backward or hypothesis-driven inference is represented as a directed link from a hypothesis toward the information in the case description. Fig. 3 also shows that this physician generated hypotheses about the likely diagnosis by inferencing from the data given in the text (words within ovals) toward the diagnoses (words within grey boxes). Thus, the overall direction of the expert's explanation is forward. In the figure, we can identify 14 forward-directed inferences, which are defined as any link that starts in a piece of data (oval) given in the case description toward a hypothesized concept, such as a general problem (e.g., vascular problem and ischemia), indication of an bodily internal problem

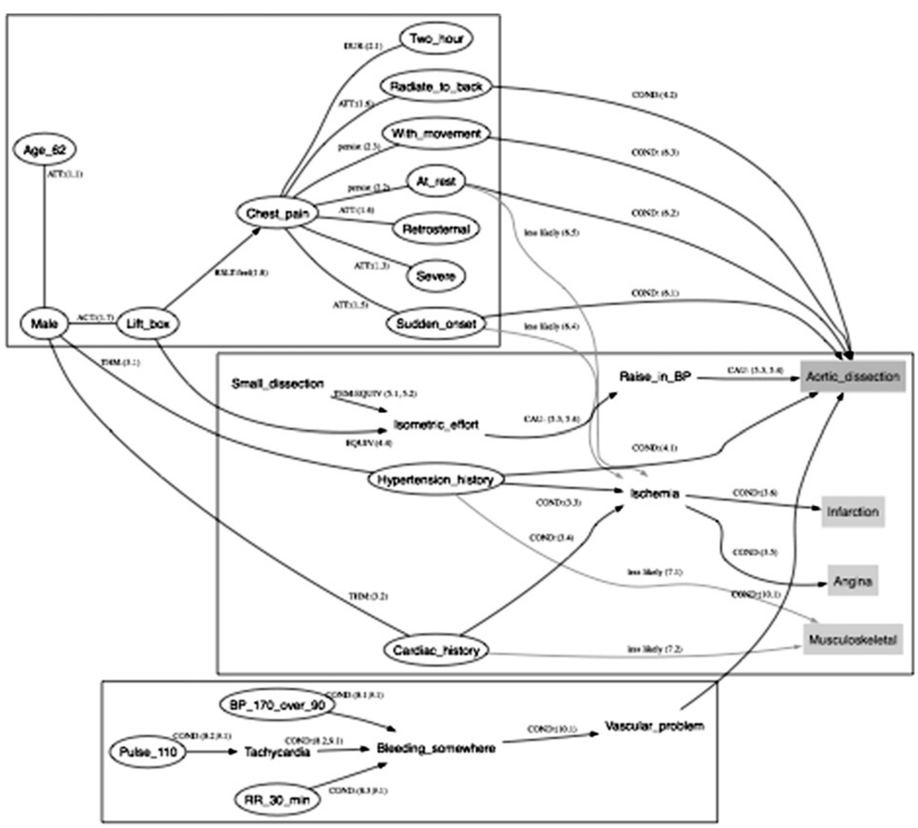

Fig. 3. Semantic network representation of clinical case by an expert physician. Oval terms indicate case data, grayed boxes indicate diagnostic hypotheses, and unframed terms indicate non-diagnostic hypotheses. Black lines represent positive relations while grayed lines represent negative relations.

(bleeding and increase in blood pressure) or a diagnosis (e.g., aortic dissection and myocardial infarction). Any piece of data may be used to generate more than one forward-directed link. For instance, hypertension_history is linked to both ischemia and aortic_dissection, resulting in two forward-driven inferences. Notice that not all links are directional. For instance, attribute (ATT:), association (ASSOC), temporal (TEM:), and thematic (THM:) links have no directionality. The majority of the directed links are those tagged as conditional (COND:), causal (CAU:), temporal (TEM:), and resultive (RSLT:) relations.

No backward-driven inferences are observed in this expert's protocol. These would be reflected in links going from a hypothesized patient state to accounting for the case data, as it is illustrated in Fig. 4. The figure represents a clinical case where the patient is tachycardic, has fever and low blood pressure, and has a toxic-looking appearance. The protocol, from which the network was developed, is from a physician who provided an inaccurate diagnosis and whose expertise falls outside the case area. These data are accounted for in terms of causal events not given in the description. Furthermore, the underlying mechanism that explains the signs and symptoms in this patient is attributed to toxicity of a drug, which, according to the physician, results from a reaction to stress.

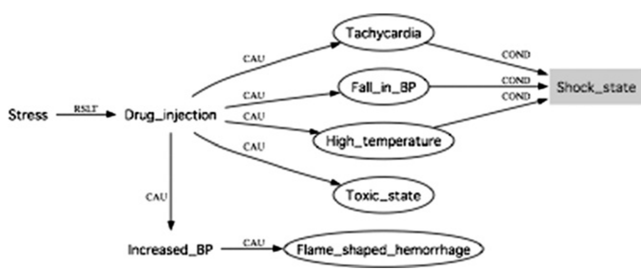

Fig. 4. Semantic network representation of clinical case by a physician showing the use of backward reasoning from a hypothesis (Drug_injection) to account for the case data (Flame_shaped_hemorrhage). Grayed boxes indicate diagnostic hypotheses, and unframed terms indicate non-diagnostic hypotheses.

As the use of backward reasoning involves hypothesizing an internal pathophysiological processes and then accounting for the data in terms of such hypothesized mechanisms, backward-driven explanations are often causal, and the links that relate the mechanisms to the actual case data are typically coded as causal (CAU:). To quantify the amount of forward-driven and backward-driven reasoning in an explanation, one can count the number of inference paths in a network, where each inference is determined by defining the starting point and the ending point of each inference line. For instance, Fig. 4 shows three backward reasoning paths, all starting from the node termed "stress." The first reasoning path includes all concepts that end in "shock_state" (i.e., drug injection, tachycardia, fall in blood pressure, and high temperature). The second reasoning path goes through "drug injection" and ends in "toxic state." The third reasoning path includes the concepts on the line that starts from "stress," goes through "drug injection" and "increased BP," and ends in "flame shaped hemorrhage."

4.3. Ontology levels and length of inferences

Aside from the amount of directional inferences in a protocol, another useful measure of a clinician's performance is the ontological length of the inferences. This measure can be generated from the superposition of the ontological model described in Section 2.3. To identify the length of directionality of reasoning using the ontological model, we note that lower levels of the ontological model (i.e., observations and findings) correspond to facts in a clinical case (e.g., as present in the propositional analysis of the text description). Inferences from each of these levels to the higher levels can

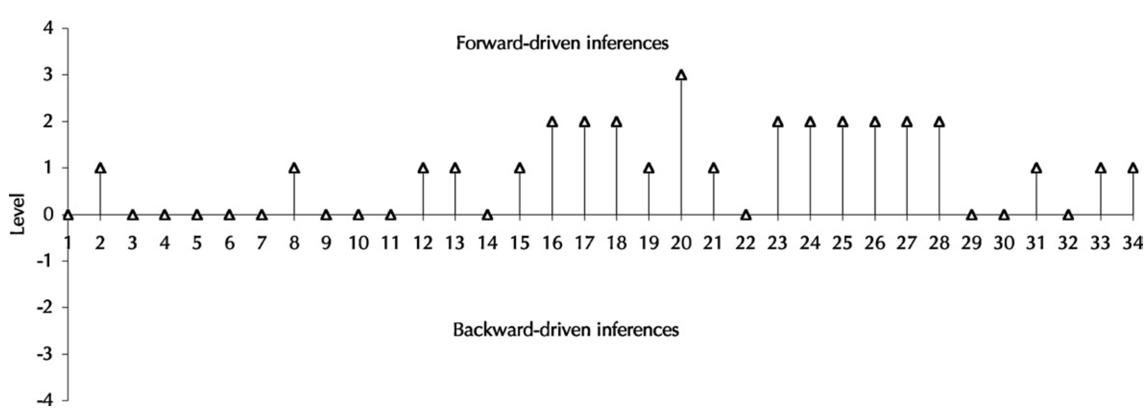

Fig. 5. Representation of directionality of reasoning by generated propositions within the ontology model. Symbols across the zero line represent inferences involving horizontal relations within a single level of the ontology model (e.g., finding–finding and facet–facet); upward arrows indicate forward-driven inferences (e.g., finding–facet and facet–diagnosis); and downward links indicate backward-driven associations (diagnosis–facet and finding–observation).

be interpreted as forward-directed reasoning. In contrast, any inference that departs from a diagnosis or facet toward facts can be construed as backward-directed.

Fig. 5 provides a representation of the forward (data-driven) and backward (hypopthesis-driven) inferences identified in the physician's protocol (and the network in Fig. 3). An inference may involve a simple proposition (concept → concept) or a complex proposition (two or more simple propositions linked into a chain). In the figure, the 0 line represents the starting point of the inference; an upward line represents a forward-driven inference; that is, a reasoning chain that starts from a concept lower in the ontology to a concept higher in the ontology (e.g., from observation to facet). A downward line would represent a backward-driven inference (e.g., from finding to diagnosis). There were no backward-driven inferences in the physician's protocol. The distance between the 0-line and the arrow head indicates the number of ontological levels covered by an inference. For instance, a line going from level-0 to level-3 might represent an inference going from an observation (level-0) to a facet (level-3). The figure shows that this subject generated 20 forward-driven inferences, 14 same-level inferences, and no backward inferences. Of the 20 forward-driven inferences, 10 involved one level links (e.g., finding–facet and observation–finding), 9 were 2-level inferences (e.g., finding–diagnosis, observation–facet), and 1 was a 3-level inference (observation–diagnosis).

4.4. Generation of inferences from patient summaries

A study conducted to investigate how physicians and nurses read and interpreted patient summaries from electronic medical records provides an example of the use of semantic analyses to evaluate inference generation in clinical tasks. The example presented here involved the comparison of summaries of a patient chart generated by a physician and a nurse. To capture the complexity of the summaries generated by the participants, propositional analysis was generated to identify ideas expressed by the participants that were either literal recalls of the chart or inferences. Since inferences represent an idea that is generated from the information given in the text, they are considered to be a higher level of thought [42]. The chart presented the following information:

This 43-year-old white female developed cramping abdominal pain 5 days ago with associated increase in frequency of stools, up to 5 per day (normal for her was 1/day). The abdominal pain was relieved by the passing of stools, which were formed. The episodes increased in number, to approximately 15–20/day, becoming watery 3 days after the onset of symptoms. She developed tenesmus yesterday and noted the presence of red blood and mucous in the stool last evening. Prior to the onset of the abdominal pain, she said she felt like she had a slight fever (did not take her temperature) and felt "sore" all over. The patient denies any recent travel out of the country.

The text segments of the participants' summaries of the electronic medical records (EMR) were compared to the original text in the chart. Propositions were identified as being direct recall of the original text, inferences generated from the original text, or uncoded information that was not present in the original text. Table 3

Table 3
Relationship of text segments from participant summaries to EMR Chart 3

Text segment		Relationship to chart (R=recall, I=inference, UC=uncoded)
MD summary		
1.1	43-year-old white female	R
1.2	who developed diarrhoea	I
1.3	after a brief period of a couple days of GI upset	I
2.1	She has been having diarrhoea for about 5 days	R
2.2	of 15–20 times a day	R
3.1	She has become volume depleted	I
4.1	She needs to be rehydrated	UC
5.1	There is no evidence of anything more serious than a gastroenteritis	I
5.2	due to either bacterial or viral etiology	I
6.1	There is no treatment	UC
RN summary		
1.1	This is a 43-year-old white female	R
1.2	who presented with abdominal pain	I
1.3	that she said started 5 days ago	R
2.1	At first she was having 5 formed stools per day	I
2.2	which increased up to 15–20 three days ago	R
2.3	with watery diarrhoea	R
3.1	She also noticed blood in her stool	R
4.1	on physical exam everything seemed normal	I
4.2	except her bowel sounds were hyperactive	R
4.3	and her stools were guaiac positive	R
5.1	No medications were prescribed	R
6.1	CHEM 7, CBC with differential was ordered	R
6.2	and she was not placed on any med	R
7.1	Final diagnosis: gastroenteritis	R

presents the recalls and inferences from the patient chart generated by a physician and a nurse. Half of the text segments in the physician's summary consisted of inferences, 30% were recall and 20% were uncoded. In contrast, most of the text segments (79%) in the nurse's summary were direct recall and 21% were inferences. These results suggest that the participants' summaries were both quantitatively and qualitatively different, given that the physician mainly drew inferential information and the nurse mainly recalled literal information from the EMR summary.

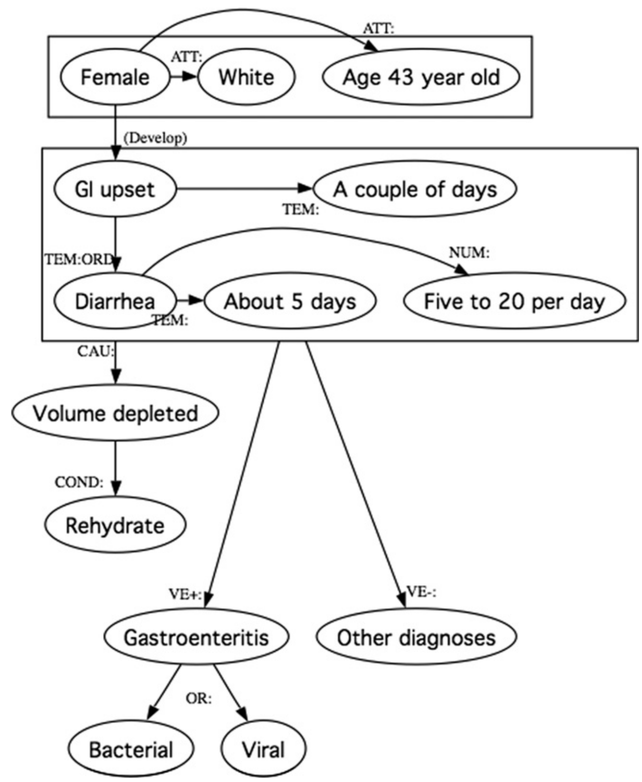

Fig. 6. Network representation of a summary of a patient chart generated from a physician's recall.

Other differences in the participants' summaries are also illustrated in the network representations of the texts, as seen in Figs. 6 and 7. Fig. 6 illustrates the summary produced by the physician whereas Fig. 7 represents the network from a nurse's explanation. The semantic representation of the physician involves a relatively simple and coherent structure focusing on the case's underlying causal and conditional relationships (inferences made). In contrast, the network representation of the nurse's summary involves a more complex structure, which focuses on the restatement of the information directly recalled from the original chart (literal recalls). This suggests that the physician possessed a model of the case that is based on deeper relationships whereas the nurse focused on the descriptive surface aspects of the summary.

4.5. Error identification in clinical reasoning

Efficient clinical reasoning about a disease process requires minimizing the number of variables that must be held in memory in order to decrease cognitive load. Forward-driven and backward-driven reasoning strategies have two different functions: backward reasoning is consistent with predictive reasoning from hypotheses to observables, whereas forward reasoning is equivalent to diagnostic reasoning from observables to hypotheses.

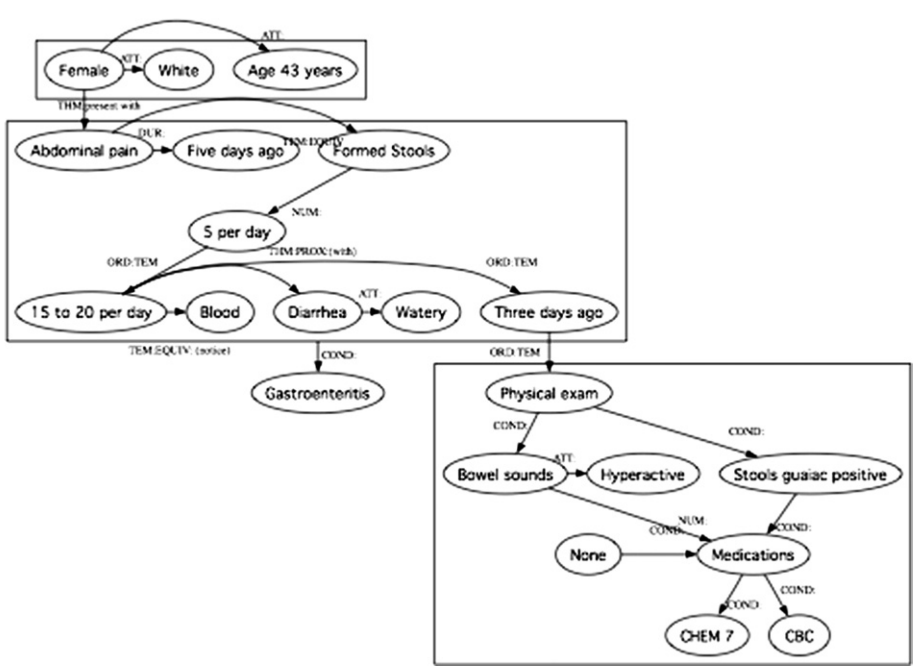

Fig. 7. Network representation of a summary of a patient chart generated from a nurse's recall.

In predictive reasoning, there is more control over a task because one can entertain a hypothesis of sufficient power and generalization to account for many possible manifestations. In this case, uncertainty is controlled because inference is limited to what is entailed by the hypothesis (as in deduction). For example, if a physician assumes that a patient has bacterial endocarditis, he or she can know that an infectious process is involved and, hence, can predict (and account for) associated findings, such as fever. In contrast, in diagnostic reasoning there is more difficulty in controlling and eliminating uncertainty. For instance, a physician could associate fever with infection, diagnostically, but it would be impossible to say which type of infectious process was involved without considering combinations of other findings. Fever not only occurs during an infection, but may also be present in inflammatory disorders and in certain cancers. In diagnostic reasoning, from specific manifestations to possible hypotheses, a physician may introduce numerous alternatives that must be reconciled against one another. A non-expert physician, who may not be able to easily classify patient findings in terms of the most likely diagnosis, would probably be overwhelmed with the management of information and inferences [2]. Expert physicians, on the other hand, use relatively simple classification schemata to reduce the problem space of individual findings to one or a small number of hypotheses that account for a cluster of findings [42,77]. Without clinical knowledge as a basis for classification, knowledge of physiological mechanisms and scientific principles would have to be used to drive inferences and to associate observations; a task that would be of enormous epistemological complexity.

The use of semantic methods of analysis provides a means of identifying errors produced during the deployment of predictive and diagnostic reasoning. Two of these errors are dependency effects and cyclical inferences. In dependency effects, evidence from apparently different sources may seem to strengthen a hypothesis. However, if these sources are dependent on some other source, common to the previous sources, the hypothesis would not be strengthened because what gives strength to the hypothesis is the independence of evidence sources. In cyclical inference, a hypothesis based on certain specific evidence is used to account for phenomena, which include the evidence that originally gave rise to the hypothesis. Since reasoning in the medical domain involves both predictive and diagnostic strategies (i.e., reasoning from hypothesis to disease manifestations and vice versa), there is the danger that, without a means of keeping evidence from predictive and diagnostic sources separate, cyclical inferences can occur. For example, consider the reasoning given schematically in Fig. 8. Intravenous drug used can lead to infection, which leads to fever. In a patient with fever and heart murmur, there is a possibility of endocarditis. In the case

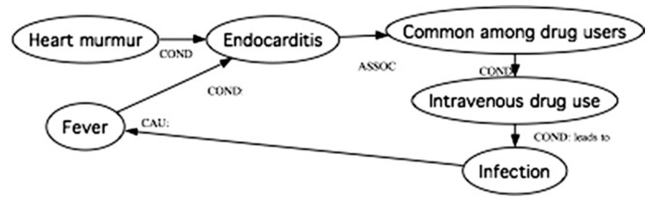

Fig. 8. Schematic representation of cyclical inference.

of bacterial endocarditis, the disease is associated with IV drug users; an association which was used to generate the hypothesis of drug use in this case, resulting in circular reasoning, where each node in the reasoning chain increases the certainty of the whole chain.

The problem of cyclical inferences arises as a result of the failure to maintain a separation between the flow of predictive and diagnostic reasoning. If the knowledge base of the clinician is adequate, diagnostic reasoning may be preferred (e.g., through some form of pattern matching). However, when the knowledge base of the clinician is not sufficient (as it would be the case with novices), a mixture of predictive and diagnostic reasoning is likely to be used. In this case, we may expect cyclical inferencing. In general, any use of induction (diagnosis) without an adequate basis for deduction (prediction)—such as afforded by well-developed classification frames—will likely lead to inefficient, incomplete, and error-prone performance.

4.6. Understanding clinical guidelines with semantic analysis

Semantic analyses have also been applied to the investigation of clinical performance with the use of clinical practice guidelines. Patel et al. [25,31] conducted studies designed to characterize the cognitive processes used by clinicians in the translation of a clinical guideline from text into an encoded form (using GLIF [25,31]). Propositional and semantic analysis were used on: (a) a written practice guideline (thyroid screening), (b) an accompanying algorithm to the guideline (a decision flowchart), and (c) the interpretation made by a physician of the algorithm. By analyzing the text guideline, the algorithm, and the clinicians' verbalizations of the guideline, it was possible to identify gaps and inconsistencies in how the guideline was represented diagrammatically and to determine the knowledge needed by the clinicians to overcome such inconsistencies and fill the gaps left by the guideline. One main finding of this research was that guidelines were shown to serve different purposes to the two groups of practitioners. General practitioners used the guidelines to constrain their search by deleting additional information, whereas expert physicians added information, which they normally skip, unless reminded.

5. Conclusions and implications

In this paper, we show that the methods of propositional and semantic network analysis can be useful in the investigation of the reasoning strategies used in medical problem solving and decision making. We have provided examples that show the wide applicability of the methods in various medical tasks. Also, we have succinctly described research in medical cognition demonstrating the application of such methods to medical informatics. We have also argued that the ontological framework [19,27,44] serves as a relatively accurate representation of the knowledge-in-use during clinical problem solving by physicians and medical trainees, emphasizing the importance of retrieval structure in expert diagnostic reasoning. The research evidence bearing this out has been accumulating over the years and has been reviewed elsewhere [39,40]. We show how identification of inferences, strategies, and errors in reasoning are all possible using these methods, as research has shown.

We suggest that a close connection can be made between these methods and those used in the development of health ontologies, which has been heralded as one of the major tasks of academic medical informatics [81]. As Musen [82] rightly states, there are no correct ways to define ontologies. However, given that the methods of semantic analysis described and illustrated in this paper provide a means for investigating clinicians' actual representation of patient problems in a particular domain, it might be possible to develop medical ontologies that match physicians' cognitive representations. This may shed light into ways in which such ontologies can be modified to better organize clinical knowledge in ways that are consistent to the actual use by clinicians.

Although this paper presents only a limited number of examples of semantic analyses, these have shown their usefulness in many medical tasks, including text comprehension, clinical case recall, explanation of clinical protocols, medical problem solving, and decision making in a variety of health contexts. Moreover, these methods have been extended to the investigation of other forms of representation, as it has been done recently in the case of the diagrammatic representation of clinical practice guidelines [14,26,31].

Despite the successful use of these methods, some disadvantages have prevented their wider applications. A main disadvantage of the methods is that its manual application is very time consuming. To partially solve this difficulty, attempts have been made to develop computerized systems for conducting the analysis and for visually representing its results. An early attempt was made that allowed the online parsing and analysis of discourse [83], to which semantic tags could be applied. Although the system allowed the coder to proceed in a more systematic fashion as he or she analyzed the text, the analysis was still not completely automatic. More recent attempts have been made to emphasize different aspects of propositional analysis and representation. In a study of clinical problem solving during a telemedical consultation [84], a semi-computerized system, which combined propositional analysis and Evans and Gadd's ontology of medical knowledge model, was used to represent the knowledge structures and solution processes deployed by two physicians in a case of pyoderma gangrenosum. The system allowed for the representation of the joint problem solving process in a variety of formats, including semantic networks and quantitative depiction of the solution process as a function of the time. A third, ongoing, effort to ease the analysis of cognitive knowledge structures using propositional analysis has been made at the University of Victoria, Canada (http://hinf.uvic.ca/). This attempt includes the development of a Web-based tool that provides semantic categories and examples of coding, with the aid of electronic lexical databases, such as WordNet [85], and potentially, medical vocabularies. These developments, although disparate, may prove useful for what may be called cognitive medical informatics, which may relate clinical tasks, the cognitive representations of such tasks by actual clinicians, and domain ontologies. Semantic methods of analysis, which have been used successfully in understanding clinical reasoning in the past 15 years, could contribute to such an effort.

Appendix A. Propositional analysis of the clinical case description some of this can go in the text itself

1.	A 62-year-old male lifted a box resulting in a sudden onset of severe retrosternal chest pain going through to the back.	
1.1	Lift	AGT:male;OBJ:box;
1.2	Male	ATT:63-year-old;
1.3	COND:(result)	PAT:[1.1][1.4];
1.4	Pain	ATT:severe,LOC:1.5,1.6;
1.5	Pain	DUR:2-hour;
1.6	Chest	PRT:(retosternal);
1.7	Radiate	ACT:1.4,LOC:back;
2	He felt a mild shortness of breath.	
2.1	Feel	PAT:he,THM:2.2;
2.2	Breath	ATT:short;DEG:mild;
2.3	IDENT:	[1.2],he;
3.	The pain persisted at rest and with movement.	
3.1	Persist	[1.4],[at rest];
3.2	Persist	[1.4],[with movement];
4.	He had a long history of hypertension and also had a myocardial infarction 5 years ago.	
4.1	Have	PAT:he,ACT:hypertension;
4.2	Hypertension	THM:history,DUR:_;
4.3	Have	PAT:he,DAT:infarction;
4.4	Infarction	LOC:(myocardium), TEM:5-year;

5. He had no history of recurrent pain and no shortness of breath on exertion.

5.1	Have	PAT:he,DAT:pain;
5.2	Pain	ATT:recurrent,NEG;
5.2	Breath	ATT:short,ACT:(on exertion),NEG;

6. He had no previous surgery.

6.1	Have	PAT:he,DAT:surgery,TEM:(previous),NEG;

7. On physical examination, his blood pressure was 170/90.

7.1	B.P.	PAT:his,DEG:170/90;
7.2	(Take)	[7.1],TEM:(on examination);

8. His temperature was 37 °C.

8.1	Temperature	PAT;his,DEG:37 °C;
8.2	(Take)	[8.1],TEM:(on examination);

9. His pulse was 110/min and his respiratory rate was 30/min.

9.1	Pulse	PAT:his,DEG:110/min;
9.2	(Respiration)	PAT:his,ATT:rate,DEG:30/min;
9.3	(Take)	[9.2],TEM:(on examination);

10. There were no abnormalities on physical examination.

10.1	Abnormalities	(NUM:nill(no),ACT:other,TEM (on examination));

Appendix B. Physician's explanation of clinical case description

1. We have a 62-year-old male who had a very sudden onset of severe retrosternal chest pain that radiated through his back while lifting a box.

1.1	Male	ATT:62-yr old;
1.2	Have	PAT:Male,ACT:Chest_pain;
1.3	Chest_pain	DEG:Severe;
1.4	Chest_pain	PRT:(Rerosternal);
1.5	Chest_pain	ATT:Sudden;
1.6	Radiate	ACT:Chest_pain,LOC:Back;
1.7	Lift	AGT:Male,OBJ:box;
1.8	COND:	[1.7],[1.2];

2. The pain was there for two hours and persisted while the patient was moving or at rest.

2.1	Chest_pain	DUR:Two_hour;
2.2	Chest_pain	PROX:At_rest;
2.3	Chest_pain	PROX:With_movement;

3. He has a history of hypertension and cardiac problems, which suggests that this could be a case of cardiovascular disease, such as ischemia, either angina or even infarction.

3.1	Have	PAT:Male, THM:Hypertension;
3.2	Have	PAT:Male, THM: Cardiac_problem;
3.3	COND:	[Hypertension_history], [cardiovascular disease];
3.4	COND:	[Cardiac_problem], [cardiovascular disease];

4. Hypertension makes me think also of aortic dissection, especially with the pain radiating to the back and the isometric effort.

4.1	COND:	[Hypertension_history], [Aortic_dissection];
4.2	COND:	[1.6], [Aortic_dissection];
4.3	COND:	[Isometric_effort], [Aortic_dissection];
4.4	EQUIV:	[1.7], [Isometric_effort];

5. If he had a small dissection, and he made this effort, this could raise his blood pressure and that can cause aortic dissection.

5.1	Have	PAT:Male, ACT:Dissection, MOD:QUAL: (If);
5.2	Make	AGT:Male, ACT: Isometric_effort;
5.3	Raise	[5.3], [Blood_pressure];
5.4	CAU:	[5.2],[Aortic_dissection];

6. The fact that the pain was so sudden and that it was there with movement or at rest is very consistent with aortic dissection, but makes ischemia less likely.

6.1	COND:	[1.5],[Aortic_dissection];
6.2	COND:	[2.2],[Aortic_dissection];
6.3	COND:	[2.3],[Aortic_dissection];

7. It could be musculoskeletal also but with the history of hypertension and previous cardiac problem, it is less likely.

7.1	COND:NEG (less likely)	[Hypertension_history], [Musculoskeletal];
7.2	COND:NEG (less likely)	[Cardiac_problem], [Musculoskeletal];

8. On physical examination his blood pressure was 170 over 90, his pulse was 110, so he's tachycardic, his temperature was 37 °C, and his respiratory rate is 30 per minute.

8.1	Blood_pressure	DEG:170/90;
8.2	Pulse	DEG:110;
8.3	Temperature	DEG:37_degrees_C;
8.4	COND:	[8.2],[Tachycardia];

9. This suggests to me that there is something really serious with this man and I'm concerned with bleeding somewhere.

9.1	COND:	[8.1,8.2,8.3],[Bleeding];

10. I'm going vascular now, with dissection of the aorta, with this presentation, and with that pain radiating to the back musculoskeletal is less likely right now.
10.1 COND: [9.1],[Aortic_dissection];

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