Decision-support and intelligent tutoring systems in medical education

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Abstract

One of the challenges in medical education is to teach the decision-making process. This learning process varies according to the experience of the student and can be supported by various tools. In this paper we present several approaches that can strengthen this mechanism, from decision-support tools, such as scoring systems, Bayesian models, neural networks, to cognitive models that can reproduce how the students progressively build their knowledge into memory and foster pedagogic methods.

Introduction

The earliest decision-support tools in medicine consisted of scoring systems, usually a severity of illness index. New scoring systems continue to be developed and are extensively used in the clinical setting. In critical care medicine, examples are the APACHE score, used with adult patients and the SNAP score used with neonates. But the use of computers in the development of decision-support tools offers a broader solution to the estimation of outcomes than do scoring systems. The development of Clinical Diagnostic Decision-Support Systems (CDDSS) in medicine began with the development of particular clinical algorithms used to automatize some of the calculations necessary to determine parameters that could only be obtained by indirect computation of measured values. This was followed by the use of clinical databanks in conjunction...
with certain analytic functions; other types were mathematical pathophysiological models, pattern recognition systems, Bayesian statistical systems, decision-analytical system, and symbolic reasoning (also called expert systems). Most of these developments consisted of small systems dedicated to a narrowly-focused diagnosis or medical environment. Automated differential blood count analysers and cytologic recognition systems for analysing Papanicolaou smears are examples of such systems.

The development of the Bayesian model led to several applications. Among the first to use this model was Warner and colleagues, who obtained the probabilities used in the diagnosis of congenital heart diseases from a literature review, from the cases they reviewed themselves and from experts’ estimates based on the knowledge of pathophysiology. The first clinical and widely used Bayesian system was that of de Dombal and associates for the diagnosis of acute abdominal pain. Many groups have developed, implemented and refined Bayesian methods for making diagnostic decisions. An alternative approach was rooted in heuristic reasoning (based on empirical rules-of-thumb) such as the system reported by Weiss and Kulikowski, which is an expert system shell for the diagnosis of rheumatologic diseases.

Knowledge-based systems and case-based reasoning (CBR)

Knowledge-based systems are becoming increasingly accepted as part of clinical decision-aid tools. The use of CBR has been particularly successful in applications such as matching cases on abnormal cardiac patterns. Frize and associates combined an expert shell with case-based reasoning abilities and a graphical user interface to display closely matching patient cases in both an adult and a neonatal intensive care unit. In this last example, the idea is for the system to imitate a physician’s approach in “remembering similar past cases” in order to establish a differential diagnosis and to determine a course of therapy. The system displays 5 or 10 cases that are selected as closest matches to the newly admitted patient. It is expected that the large database used with the system will provide more cases to display than the physician’s own memory of past cases. The system then allows physicians to retrieve information of “similar” patients such as demographics, diagnoses, complications, and so on.

Artificial neural networks (ANNs)

ANNs have also been used and tested as decision-aid tools in a variety of applications. For example, Baxt used ANNs as an aid to diagnose acute coronary artery occlusion and later for myocardial infarction. Frize and colleagues performed studies of estimated duration of artificial ventilation, as well as of mortality and length of stay in an adult intensive care unit. Again, to remain as close as possible to the manner in which physicians work, an ANN model was selected, which, when trained, provides an estimate of selected clinical outcomes, simulating a clinician’s consideration of potential patient outcomes such as a physician thinking: “And for this particular patient, this is what I think will happen.”

A progression can be observed from the early concentration on various algorithmic alternatives in the 1970s, through the development of comprehensive systems like Internist/QMR or Help in the 1980s, with explanation capability, critiquing and embeddedness as the distinctive advanced features, to the evidence-based approaches of the 1990s. The electronic medical record and the automatic incorporation of guidelines in CDDSS are other current efforts.

Creation of models that can learn

Whereas different approaches can be used to model a complex process, we should distinguish the ways in which the model is created and in particular how the model can learn. Learning starts with either obtaining expert knowledge or by observation or by neural network analysis; then the model is tested using test or real cases. It is likely that case studies, experts and techniques such as neural networks or case-based reasoning are going to be useful in refining the models. Some medical areas can be resumed by an explanatory model, such as a care guideline expressed as an algorithm. These algorithms can inherently be modelled behind an electronic patient record and suggest next steps and even probabilities for certain types of outcomes. Patient care should be distinguished from patient-care evaluation, including adaptation to new
technologies and treatments that support care. Of course, there remains an important role of medical education in these technologic developments.

**Decision-support tools of the future**

Most of the decision-aid tools that currently exist have been developed for very specific illnesses or for a particular medical environment. In the future, several questions need to be addressed: What decision-aid tools support primary care medicine? How and by whom are such tools used? Are the systems integrated into clinical practice and if so, how widely? How do we define success in this realm? Do the tools include support for cultural and religious sensitivity? What kind of tools, in addition to those already mentioned, would help physicians manage knowledge explosion and change?

An important consideration in any system design is the issue of privacy and confidentiality. All patient identifiers in databases should be removed before the use of the database, and everyone involved in the research projects should be aware of these concerns. Studies should be submitted and approved by the appropriate local ethics committees. Another important aspect is to ensure that users understand the limitations of the system so that they will use it appropriately and in an effective manner. The strengths and weaknesses of each of the various technical approaches should be studied and manners to evaluate them reviewed and discussed.

**Human agents and cognitive agents in medical education**

Humans are examples of cognitive agents, complex cognitive environments that acquire, store and structure knowledge into memory to solve specific or general problems. The difference with intelligent software agents is that humans have the capability to learn and structure their knowledge in an extremely complex and efficient network of nodes that can be expanded in more fine grains according to a context. However, during their education in medical schools, students adopt generally 1 method of knowledge acquisition and stay with this approach along the complete curriculum of medical education. Unfortunately, the uniformity of medical teaching (and the education system in general) does not permit change or improvement in these learning mechanisms, which consequently can lead to good or poor physicians at the end of the medical curriculum.

The use of intelligent tutoring systems can allow for improved learning in medicine if we can detect the stage of understanding of the learner. We have developed and experimented with various cognitive agents (software with certain particularities) able to trigger a specific pedagogy at each level of understanding. In fact, we can make a parallel between these agents and human cognition. The structure of knowledge into memory allows us to distinguish a 3-level cognitive architecture (Fig. 1), for a human agent (a student in medicine for instance). These levels (from the bottom to the top) characterize the theoretical transformation of knowledge from a novice to an expert.

When students begin their curriculum, they learn basic knowledge in biology, physics and chemistry in order to build a base of fundamental knowledge. However, at that time the knowledge is just stored and not yet linked to applied cases in medicine. They continue by trying to apply this knowledge to concrete biomedical situations. We are still at the first level of the architecture: the student is only able to identify basic symptoms or situations and generate an immediate (right or wrong) diagnosis.

By progressing to clinical problems the students acquire some procedural knowledge, a step in which elements of knowledge are linked through examples of situations. They begin to make hypotheses and establish strategies to select or reject some of them. Problem-based learning is a good approach to foster this step. However, some students tend to learn the
case itself, as an integrated knowledge without distinction between semantic links and facts. They hesitate to pass from a subject-matter learning to a problem-solving approach, and sometimes this transforms the clinical reasoning problem into a case-based reasoning learning. Generally, students acquire their knowledge through the intermediate stage.

The ultimate layer, which is not reached by all the students, concerns knowledge acquisition through contacts with real patients. Here, we distinguish 2 tendencies: (1) the physician continues to accumulate experience with a more complete base of cases, and (2) the physician is able to induce, from a set of cases, a new case and new rules using generalization techniques. Only the experts reach this last level.

The problem in medical education is that very few teachers are able to detect with sufficient precision the cognitive level of the learner and thus apply a pedagogic strategy in order to strengthen the transition between the different layers. So, we have developed and experimented with the contribution of several cognitive agents (similar to the agent indicated above) to detect these situations and apply adequate strategies. They proved very useful for acquiring the best reflex of decision-making processes. Also, these agents can be filled with the types of decision-support tools already mentioned.

Many research questions remain to be explored, particularly if these technologic developments are going to be useful to physicians in general practice and for medical education. The workshop was very useful in raising the awareness of all present to the factors that should be taken into account when developing tools for clinical practice or for medical education. Without this holistic view, these tools may have many shortcomings and be more a burden that an assistance. The multidisciplinarity of the teams working on these research questions is an essential part of future success.

References


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