New Artificial Intelligence Systems in Geriatric Medicine

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ABSTRACT. Artificial Intelligence (AI) is a branch of computer science (CS) and engineering that deals with the adaptation of intellectual activities of humans as intelligent behaviour, learning, planning, or adaptation to computers. An important concept in AI is knowledge, and related to this concept there are several disciplines as knowledge management, knowledge engineering, knowledge representation and reasoning, that are traditionally considered as either being part of, very closely related to, or overlapping with AI.
In modern national healthcare systems, the use of computers in health-care is a common practice for both administrative and medical activities. Nowadays, the so called Health Informatics (or Medical Informatics) deals with the resources, devices and methods required to optimize the acquisition, storage, retrieval and use of information in health and biomedicine. This approach is called Information-Based Medicine. However, the advances in AI, Knowledge Management, and the new Information Society technologies predict the evolution of health-care systems towards a new generation of Health Informatics: the Computer Knowledge-Based Medicine.

KEYWORDS: Computer-Based Medicine; Knowledge Management in Medicine; Machine Learning.

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INTRODUCTION. Knowledge Management (KM) is a multi-disciplinary field whose main aim is to identify, create, represent, and distribute knowledge for reuse, awareness and learning across an organization (e.g. a health-care system). KM makes a distinction between *data* (i.e. facts and figures, without context and interpretation), *information* (i.e. patterns in the data with some meaning), *knowledge* (i.e. information that has been generalized to increase applicability), and *wisdom* (i.e. knowledge that has been extended with intuition and experience).
Simultaneously to the KM evolution, Health Informatics (HI) has progressed to become the field that applies Computer Science technologies, resources, devices and methods to health and biomedicine in order to deal with the requirements of data and information; including, for example, health-care Data Bases or Electronic Health-Care Records.
During this time, Artificial Intelligence (AI) has been centred in the development and improvement of formal structures to represent knowledge (e.g. expert system rules or ontologies) an also methods and algorithms to perform intelligent activities on these knowledge structures. These are intelligent activities like reasoning, learning, or planning.
Finally, in the last years the individual evolutions of KM, HI, and AI have coincided with the socio-political model called Information Society (IS) that defines the future society as one in which creating, distributing, manipulating and exploiting information (and knowledge –I would say) will be common practices at the economic and cultural levels. In this context there is a place for Information Society Technologies (IST) supporting the model.
In the health-care setting, KM, AI, and IST are called to be the factors in the equation that explains the forthcoming evolution of HI.

KNOWLEDGE. KM makes a distinction between descriptive knowledge and procedural knowledge. Descriptive Knowledge (or *know-what*) asserts what are the facts an organisation makes about itself, its capabilities, and the marketplace. From a health-care perspective, it is about a declaration of facts like health-care figures and sorts specialties; medical, surgical and care procedures; health-care services; diseases, syndromes, symptoms, and signs; drugs and pharmacological interactions, etc.
Procedural Knowledge (or *know-how*) asserts how business and organisational processes and strategies of the company are. From a health-care perspective, it comprises administrative and medical procedures like, for example, descriptions of how an admission or a discharge must be made (i.e. documents involved and steps to follow), how a correct assessment of a patient condition is expected to be (i.e. phases to follow and feasible alternatives) or how to treat a pathology or medical problem (i.e. guidelines and protocols).

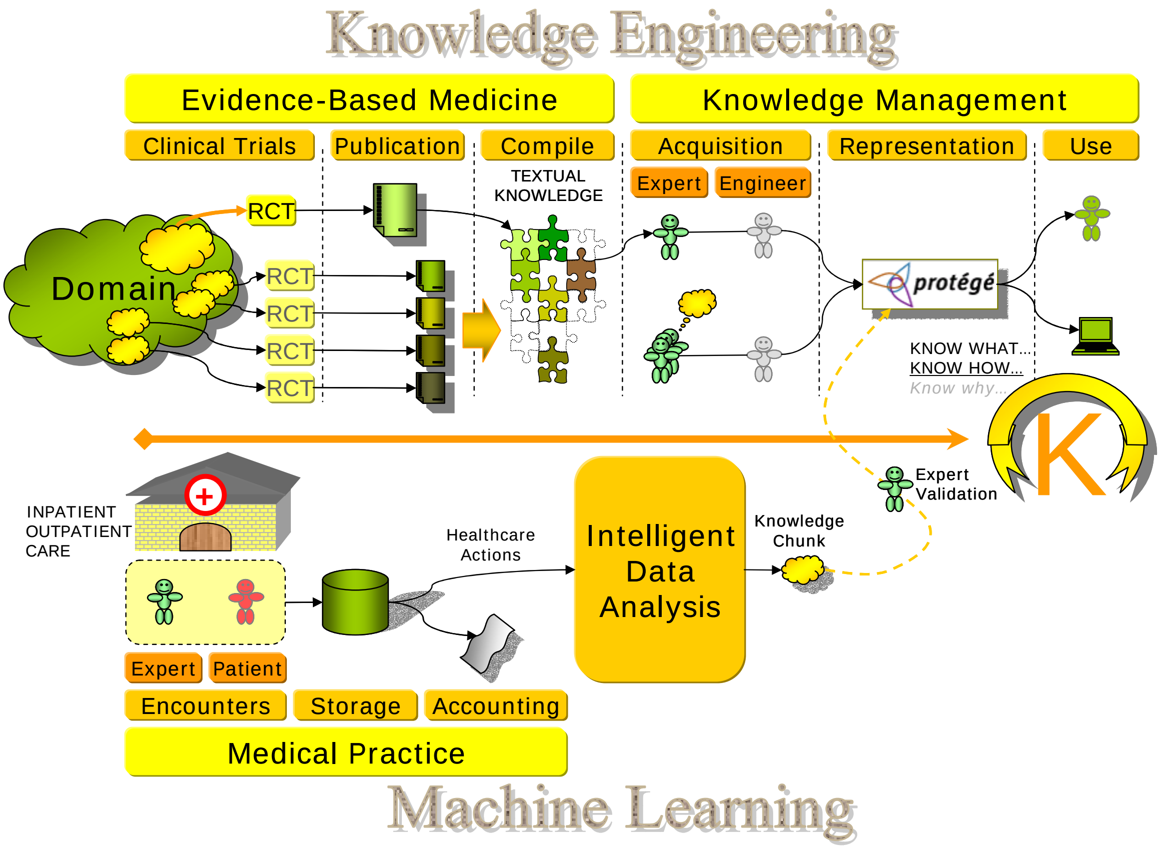

Figure 1. Past, present, and future of procedural knowledge in medicine.

Figure 1 summarizes how procedural knowledge in medicine has been generated by means of Randomized Clinical Trials (RCT) and has been published as Clinical Practice Guidelines (CPG) applying the scientific method to medical practice (i.e. Evidence-Based Medicine). Figure 1 also shows how this approach is being combined with a new trend that has emerged in the last years. The new approach consists on the application of KM and AI knowledge engineering methods to acquire and represent the knowledge displayed in a CPG in order to use it in decision taking tasks with the help of computers.

Apart of the above methods, the objective of generating procedural knowledge by all means available would not be complete without the participation of Machine Learning (ML), an AI discipline, in the global picture. With ML the data stored in the data bases of health-care centres or organizations can be analyzed to find out patterns that capture regular health-care practices that, once represented with knowledge structures and validated by some expert or board of experts, can be incorporated as experience knowledge to the expert procedural knowledge coming from CPGs.

PAST AND PRESENT: EXPERT KNOWLEDGE. Successful RCT are published and broadcast all over the health-care national or international communities. Conclusions on each single RCT contribute to the generation of a general map of knowledge in medicine. In practice, however, being aware of all the published results and incorporating them in daily assistance is a hard or even impossible task for health-care professionals. This is one of the facts that drive some important research groups in Harvard University, Massachusetts Institute of Technology, Stanford University, Mayo Clinic, and others to work on the generation of computer-interpretable clinical practice guidelines[1,2] and also to found centres for biomedical knowledge[3,4]. These centres apply knowledge engineering techniques to acquire and to obtain formal representations of biomedical knowledge that can be used either by professionals to look up, but also by computers in order to help professionals to take decisions[5].

FUTURE: EXPERIENCE KNOWLEDGE. In front of the above approaches in which computers represent expert knowledge coming from clinical practice guidelines (i.e. expert knowledge), information systems in HI provide an alternative source of knowledge that comes from the experience of the past cases treated in a specific centre or group of centres, or in a demographic area (i.e. experience knowledge). Nevertheless, since experience knowledge is not based on a scientific method, before it is made effective, a knowledge validation process with experts must be performed.

REPRESENTING EXPERIENCE KNOWLEDGE. There are many languages to represent clinical algorithms in a formal way[2,6], among which Asbru[7] and PROforma[8] are two of the most evolved ones. These languages use to offer the possibility of describing *patient states*, indicating the *actions* to perform (e.g. recommendations, prescriptions, procedures, specialist appointments, etc.), and introducing *decision points* to personalize the treatment according to the patient conditions. These three elements: states, decisions and actions; define a knowledge model to represent procedural knowledge in medicine: the SDA* Model. Figure 2 shows a portion of how a process of diagnosing hypertension is represented under the SDA* model. See that states are represented with rounded squares, decisions with rhombuses, and actions with squares.

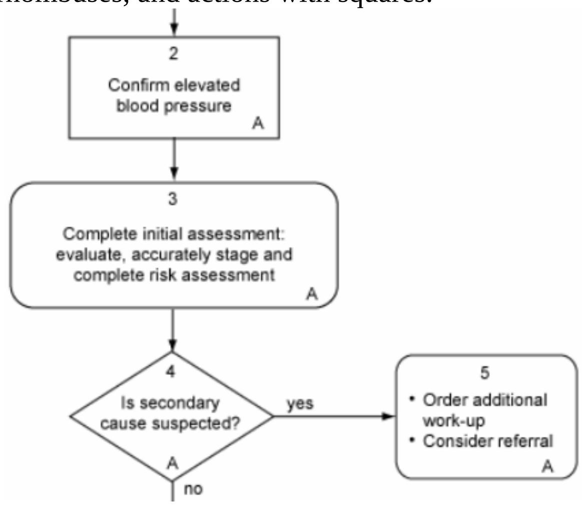

Figure 2. Part of a diagnosis procedure.

MAKING COMPUTERS TO LEARN EXPERIENCE KNOWLEDGE. One of the paradigms of ML is Inductive Machine Learning, whose methods and algorithms create knowledge structures (e.g. SDA* diagrams) by extracting patterns out of massive data sets. Broadly speaking, when it is applied to learn SDA* diagrams that represent clinical algorithms, the underlying idea of this kind of ML is to detect common behaviours (i.e. action blocks in the SDA* diagram) and then determine when these actions are followed (i.e. decisions of the SDA* diagram). The process is complemented with the incorporation of the states that define patient conditions that deserve differential treatment within the same clinical algorithm. For example, persistent hypertensive patients that are already treated with drugs (state 1) may require a change in the drugs prescribed (action 1); for example, change drugs or increase the treatment with new drugs, whereas hypertensive patients that are not taking drugs (state 2) may require some assessment (action 2) before the first drug or group of drugs are prescribed.
States in the SDA* model have a double function. On the one hand, they represent the starting points where the clinical algorithm may be applied. So, the application of a clinical algorithm to a patient who is in a particular state will start where this state is situated in the clinical algorithm. On the other hand, states act as the connectors of the different sub-treatments defined within the clinical algorithm. So, for example, once the clinical algorithm proposes a prescription of drugs to deal with hypertension to a patient that is not taking any drug yet (state 2), the action block that describes this prescription in the SDA* algorithm should be connected to the state which indicates that the patient is already taking drugs (i.e. state 1 described in the previous paragraph). This fact represents a change in the state of the patient treatment. So, next time the patient is visited, the treatment could follow from this new point.

This approach defines a research line started by the author of this paper at the research group on Medical Informatics[9], Stanford University, USA, and followed in the Artificial Intelligence Research Group[10] at the University Rovira i Virgili, Tarragona, Spain. The work is partially funded by the European IST Project IST-2004-026968 K4CARE and the Spanish I+D Project TIN2006-15453-c04.

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