Multiuser Proactive Hybrid CDSS for Antibiotic Management in a Hospital Environment

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The thesis work started in April, 2015 and is expected to be completed in February, 2018.

Problem and background

Antibiotics administration is widely extended to all stages of healthcare, particularly in hospitals. However, its overuse promotes the resistance of antibiotics, which is a great concern in hospital health. Due to the problem complexity, public healthcare organizations suggest forming multidisciplinary teams, the Antimicrobial Stewardship Program (ASP) teams, composed by physicians, microbiologist, pharmacists, epidemiologist and managers to analyse, manage, and survey the use of antibiotics. The main issue of this team is to provide support to the antibiotics management: prescription, microbiological surveillance and pharmacological surveillance. However this team faces a difficult scenario due to the large amount of knowledge and data sources that must be analysed.

Clinical Decision Support Systems (CDSS) can help these multidisciplinary teams to carry out the tasks mentioned above. There have been several decades of research on decision support systems, since pioneers examples like Leeds Abdominal Pain System [6] , MYCIN [20], HELP [23,11] and Internist-1 [15,17] to the new and more sophisticated like QMR (evolution of Internist-1) [14], DXplain [2,3], EON [16] or HealthFlow [10]. Current work in research and industry focuses on rule-based CDSS in this field. In [4], the authors highlight that there is an increasing interest on prescription supervision and pharmaceutical validation. In [12], the authors propose the detection of hospital-acquired infections using rule production system. Some other approaches consider basic association rules [13] or simple co-occurrences [5] to implement infection control systems. In [1], the authors present an infection alert module for Intensive Care Units.

Unlike the above works, which are mainly focused on some daily activities of the doctors, the interdisciplinary team will be the end user in our case. Therefore, different needs must be met, such as complex knowledge integration, shared decision-making or personalised outcomes.

We believe these needs match with some challenges of CDSS currently identified in [7,8,21]. According to [7], the coordination among clinicians is essential to obtain an effective healthcare, to reduce expenditures, and to identify new means of educating and conducting medical research. Similarly, in [8] the authors suggest that patient-centred and shared decision-making are essential needs in future CDSS. Regarding the improvement of the effectiveness of CDS interventions, the summary of the patient-level information is essential, combining recommendations for patients with co-morbidities [21]. Therefore, the need of new CDSS interventions could be obtained mining large clinical databases. Personalised CDSS will need knowledge obtained from patients with a similar profile [7]. That is, CDSS should use generic knowledge from medical literature to obtain a decision, but such decisions must be in the context of other patients with similar highly specific characteristics [9].

The aim of this thesis work is to propose a CDSS for antibiotic management to overcome the following challenges:

1. Multi-user: the system should integrate different views of the health history to foster an effective dialogue about new research findings. Concise information should be delivered to the right user at a timely manner. In order to achieve that, we should gather information about the system use and have a continuous feedback from the users to generate knowledge not only about the clinical domain but also about the integration of the system into the clinical workflow.
2. Reactive and Proactive: The clinicians could use the system as a treatment assistant, but also the system response to patient safety should take place before the bad use of antibiotics is done.
3. Hybrid: the system will combine static medical knowledge (clinical guidelines and expert knowledge) but also evidence from environmental and epidemiological information (mined from hospital records).

Method/Plan

The thesis work is planned following an iterative method for solution proposal and an incremental build model for CDSS software development. At each iteration, a new specific infection or clinical problem is chosen, the sources of knowledge are selected, and the AI techniques to implement the CDSS are studied. A pilot experiment is conducted at the end of each iteration. By this way, the users will be involved into the project and we will have a continuous feedback about the use of the system.

Besides the agile focus, we have global milestones that must be achieved. An initial milestone already reached, and the base starting point of this thesis work, was the development of a prototype of the system. The prototype, based on a relational database and a web application, allows the clinicians to visualize in a timeline some kind of data about their patients (patient's admission/discharge, laboratory tests results, cultures, treatments applied, etc.). It also allows the definition of general alerts as database views, notifying to the ASP team when a patient episode matching the view is found.

In our first and current running iteration, we have focused on the infections treatment assistant and improper treatment alarms, using expert knowledge about microbes' resistances. Due to the nature of the knowledge and the domain, we have chosen to implement a rule knowledge-based system with the inclusion of expert rules and the previous database views converted into rules, starting to build a proper knowledge base for the system.

The first difficulty that we have faced is that in our domain (microbes and antibiotics) there are large and complex taxonomies, and the expert rules are defined between several levels of these classifications. As a solution, we are trying to integrate ontologies within our production rule system (Drools [18,22]). Our next step, will be to deal with defeasible logic (i.e. how to manage exceptions to these expert rules) before finishing this iteration.

In further iterations we plan to include rules from medical guidelines. Due to the complexity of the problem, the extraction of this kind of rules is out of the scope of this work (there is other people in the group working on it). However, once we had the rules we expect to face problems like rules contradiction (it may arise contradictory advises from different guidelines), time restrictions (some rules should or should not be fired in a time window after an event) and uncertainty (some rules should be fired with a certainty value when some fact in the antecedent is missing/uncertain). In addition, all the alarms and recommendations should be exposed to the clinicians in a suitable way in order to reduce the well-known 'alarm fatigue' [19]. Also in future iterations, once the knowledge base with several kinds of rules is validated, we plan to improve the system knowledge with rules mined from historic data.

Expected relevance

The main expected result from the research work is the development of a CDSS for the nosocomial infections domain, and its evaluation and validation in a pilot.

Derived from the main goal there could be secondary results in the next research topics:

- Software development methodologies: It could be used as an example of application of agile development over knowledge-based systems, focusing on the problems found and solutions applied in each development phase.
- Rule-based systems: the use and extension of already existing techniques for modelling and reasoning with ontologies, time and uncertainty in rule-based reasoning. Novel techniques in defeasible logic and contradiction detection will be used and refined if necessary.
- Data mining: the proposal of new data mining techniques is required for discovering implicit knowledge within clinical data. In particular, these techniques will focus on identifying risk factors, detecting interactions and adverse effects ahead of time, and anticipating the patient evolution among others.

Questions to the academic panel

This thesis work is an at early stage and, therefore, there is room for adopting different approaches to solve the above mentioned problems. In particular, we would like feedback on the following aspects of the work:

- Regarding the use of rules for data modelling, what is the importance of the following topics: semantic rules, temporal rules, uncertainty representation in rules?
- Uncertainty management in rules: we would like to evaluate the certainty of fired rules when there is no evidence of some of the antecedents of that rule. We wonder which alternative models to explore for the representation and propagation of this kind of uncertainty.

- Is there any other topic/difficulty in the development of CDSSs?
- Multi-user clinical systems: the experience on this topic is limited and we would like to identify methodologies or previous experiences on clinical interdisciplinary to make decisions. Our work will focus on physicians, microbiologists and pharmacists.
- Data mining: to identify samples of population (e.g. resistance of certain antibiotic in a specific patient profile) in order to personalize the CDSS outcome. We will focus on group/subgroup discovery. We would like to know which techniques could be used.
- Validation: we would like feedback on experiences of CDSS validation in hospital environments and industry.
- We identified there is a lack of general methodology for evaluation and development of CDSSs. Is this an interesting topic for CAEPIA community?

We would thank in advance any feedback the reviewers may have on this thesis work proposal (weaknesses, ideas, etc.).

Acknowledgment

This work was supported by the FPI doctorate grant of the WASPSS project (Ref: TIN2013-45491-R), funded by the national research programme from the Spanish Ministry of Economy and Competitiveness and the European Regional Development Fund (ERDF, FEDER).

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