Development of an Advanced Clinical Decision Support System: Enriching the Guideline-Based Knowledge with Experience

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ABSTRACT. This paper provides an overview and update on my PhD research, which focuses on developing an experience-based clinical decision support system (CDSS) that extends the implemented clinical practice guidelines knowledge. This method relies on the capitalization of clinicians' experience. First, a decisional event structure is presented, which models the required information involved in a decision-making process. This information includes the implicit knowledge related to the clinicians' know-how. Second, a method to process this information and create new experience-based rules is presented. Third, a quality assessment algorithm is introduced to score the experience-based rules based on previous patients' outcomes.

Keywords: Experience Modeling, Computer Interpretable Guidelines, Clinical Decision Support System, Knowledge Discovery, Decisional Events, Breast Cancer

1 Introduction

A multidisciplinary tumor board review is defined as "a treatment planning approach in which a number of doctors who are experts in different specialties review and discuss the medical condition and treatment options of a patient" [1]. In the breast cancer domain, a Breast Unit (BU) is created with this purpose. To support BU decision-making process, evidence-based Clinical Practice Guidelines (CPGs) implementation through CDSS is promoted, i.e. Computer Interpretable Guidelines (CIG). Nevertheless, CPGs have some weaknesses, such as (i) incompleteness of recommendations,

(ii) the fact that CPGs may lag behind the last medical evidence and (iii) the non-inclusion of some parameters crucial in the decision-making process, such as patient preferences or clinician preferences [2].

Most current CDSSs facilitate the implementation of CPGs [3], but to be effective and provide good quality recommendations, these systems must fulfill a list of commandments pointed out in the work of [4]: (i) to have a fast reasoning system, (ii) to anticipate clinician needs and deliver a solution in real time, providing all needed information, (iii) to fit clinician decision process workflow, (iv) to have user-friendly interfaces that help clinicians using CDSSs and provide the desired support, (v) to provide different recommendations and the option of including new ones, instead of just providing the one according to the system, (vi) to suggest more acute margins of the evaluated variables, making their update automatic, (vii) to improve the usability of reasoning rules by displaying them in a simple and easy interpretable way to final users, (viii) to provide a decision support based on a previously consensual minimum dataset, avoiding annoying data requirements for the user, (ix) to track the impact of the provided decision and give some quality and usability assessment measurements and finally (x) to maintain and keep updated the knowledge bases of the system.

With the motivation to address research issues related to implementation and incompleteness of CPGs, this paper presents my research proposal of an advanced CDSS that would enrich the knowledge of the guidelines with the data collected from previous cases and clinicians' experience. Moreover, the proposed CDSS would integrate a quality assessment algorithm to provide information about the success or failure of treatments decided when applying experience-based rules. The challenges and future directions of this research are presented in the conclusion.

2 Problem statement

The research question that motivates this work is the following:

Is it possible to extract the (implicit) clinical knowledge from the analysis of non-compliant treatment decisions, and use it to extend a guideline- based CDSS?

3 Proposed Methods for Experience Modelling and Reuse

The digitalization of care has allowed the storage of big amounts of clinical data in a structured way, making it more manageable [5]. In this research work, a modular approach for the discovery, extraction, and processing of this knowledge is proposed. First, a decisional event structure is presented as the basis to retrieve, model, and exploit all the information related to the decision-making process (Section 3.1). This structuration allows the application of different techniques, such as data mining techniques, to automatically adjust the already existing rules and generate other new experience-based rules, with a potential beneficial impact on treatment decisions (Section 3.2). Finally, a quality assessment algorithm is studied to score the recommendations based on patients' clinical outcomes after treatment (Section 3.3).

3.1 Decisional event structure

The decisional event reflects all the rationality for taking a decision and the consequences of such a decision. Hence, it models all the information regarding the decision-making process [6]. The decisional event structure is defined by the following set of components:

1. $\boldsymbol{P = \{P_i\}}$: Set of patient clinical parameters
2. $\boldsymbol{R = \{R_j\}}$: Set of clinical statements expressed in a computer-interpretable way (IF-THEN rules). These clinical statements represent the knowledge coming from different sources (e.g. CPGs, local guidelines, experience-based rules generated by the system) and are itemized as follows:
   (a) . $\boldsymbol{A = \{A_m\}}$: Set of the clinical parameters that compose the *conditional part* of rules (i.e. the IF-part) *a priori* defined in CPGs. Elements of the set are connected by logical operators.
   (b) . $\boldsymbol{W}$: A recommendation defined as the *consequence part* of the rule (i.e. the THEN-part). In some cases, the provided recommendation is an ordered list of treatments, expressed as $W = (S_1, S_2, \dots S_l)\ with\ l > 1$ where $\boldsymbol{S_i}$ is an atomic treatment.
3. ***FD:*** Final decision taken by BU clinicians which could be compliant with the recommendation provided by the guideline $\boldsymbol{W}$ or not.
4. $\boldsymbol{E}$: Actual treatment administrated at time t_1 after the decision is made, which could be compliant with $\boldsymbol{FD}$ or not.
5. $\boldsymbol{C = \{C_k\}}$: Set of criteria followed by clinicians to reach an agreement about a final decision. These criteria are sorted in different groups that have a closed list of Boolean possible values $\boldsymbol{J_n}$. So, we can define a single criterion as a set of justifications $C_1 = \{J_1, J_2, \dots J_n\}\ with\ n \geq 1$. For example, *Tumor Size* could be a criterion of non-compliance which justification is the difficulty to follow-up the patient, which could be either *true* or *false* (i.e. Boolean value).
6. $\boldsymbol{O(t)}$: Set of clinical outcomes of a patient after a time *t* to be able to assess the success or failure of the given treatment.

Ideally, BU decisions are compliant with CPGs, thus choosing one of the recommendation provided by the guideline-based CDSS as their final decision $\boldsymbol{FD}$. But in certain cases, when clinicians do not comply with CPGs (e.g. BU takes into account the patient preferences in their decision), $\boldsymbol{FD}$ is different from CPG-based recommendation(s) for that specific case. In both cases, the administrated treatment $\boldsymbol{E}$ is expected to be the same as the final decision $\boldsymbol{FD}$, but due to deviations in the treatment plan, $\boldsymbol{E}$ could differ from $\boldsymbol{FD}$.

3.2 Experience-based CDSS

Once the decisional event is built, we aim to exploit the large amount of data and extract the implicit clinical knowledge to augment the CPG-based CDSS with experience, and thus develop an experience-based CDSS. For the knowledge extraction, the experience-based CDSS includes three different modules: the first module adjusts the

CPG rules by analyzing the potential best cut points of each continuous variable. For example, if most of the patients are in a similar clinical status, treated with hormonotherapy with successful outcomes, and are older than 60 (instead of 65, as could be recommended by CPGs), the system will be capable of generating a new rule, with an adjusted *age* clinical parameter threshold equal to 60.
The second module consists in formalizing rules from a set of observations stored in a database using data mining techniques such as decisional trees (i.e. induction rules). First, a feature selection is performed to determine which are the most relevant and representative variables of the dataset. These selected features are analyzed to identify possible patterns relating them. The results coming out of this module will be used to extend the guideline-based rules.
Finally, the third module encloses the generation of new rules from cases where clinicians did not follow CPGs-based recommendation(s), thus being non-compliant with CPGs [6]. In this setup, a new variable named "Criteria" is modeled, composed of predefined values by clinicians. This allows clinicians to explain using some criteria why they decided not to comply with CPGs. As an example, the guideline based CDSS can give the recommendation of treating a patient with hormonotherapy as she fulfills all the conditions required by CPGs. But due to her advanced age, the BU may decide another type of treatment that will be more adequate to her physical condition.

3.3 Quality assessment algorithm

Besides the above stages, we will assess the impact of both CPG-based and experience-based propositions. This assessment will be based on patient clinical outcomes. In current clinical practices, patient outcomes are quantified based on both overall survival and disease-free survival rates. In this research, additional measures will be considered, such as quality of life, in order to take into account the outcomes provided by both the patient (e.g. symptoms) and the clinician (e.g. survival rate). For that the ICHOM questionnaires [7] will be implemented in the system.

4 Research Challenges and Future Direction

The research is still at an early stage, and thus, there are several challenges ahead that I should cope with:

- What is the best method to extract induction rules from a limited database (≈200 entries) of patients?
- How should knowledge coming from CPGs be used along with the experience information (e.g. rules) retrieved from the data and the non-compliant cases?
- How should the criteria given by clinicians be included in the new experience-based rules? How to deal with cases where relevant criteria are outside the defined knowledge model?
- What is the best method to compute the quality of evidence and the strength of the recommendation?

- How can the presented methods be validated?

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