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Assessment of Decision Models for Hybrid Approaches

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Abstract. A wide range of Clinical Decision Support Systems (CDSS) have been developed. These CDSS are based on decision models, which normally have a knowledge- or data-driven approach. In this work a structured development of potential hybrid approaches was realized by the assessment of decision models and identification of their advantages and disadvantages. For the assessment of different decision models, eight criteria were identified and three of them were chosen as main criteria for CDSS: transparency, learning aptitude and handling of uncertain and vague knowledge. The comparison of decision models in regard to the developed main criteria resulted in an identification of three groups of models with similar characteristics. Based on these groups hybrid approaches had been developed, so that different decision models could be combined in a beneficial way. Thereby this work provides an instrument for a structured development of hybrid decision models.

Keywords. Clinical Decision Support Systems; Decision Support Models; Machine Learning

1. Introduction

Many and different kinds of Clinical Decision Support Systems (CDSS) have been developed recently. The approach of these decision models is in general knowledge- or data-driven. A knowledge-driven approach describes an approach based on knowledge and strategies of problem-solving, e. g. rules. A data-driven approach operates on automatic data-analysis, based on methods of machine learning. Especially in clinical routine, the use of CDSS is still not common. Reasons therefore are insecurity and the possibility, that CDSS can be faulty [1]. Hybrid approaches would give a possibility to combine knowledge- and data-driven approaches concerning their advantages to improve existing decision models.

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2. Methods

2.1 Assignment of decision models

The most decision models can be assigned to knowledge- or data-driven decision models (see Table 1). The decision models in this work, which cannot be assigned clearly, were termed as *intermediate models*: (1) Case-based Reasoning (CBR), because the search for similar cases is just one step in the model [2], (2) Markov- and Bayesian networks, because the rules are not valid for each case [3], and (3) Fuzzy logic, because it cannot be seen as an independent decision model [3, 4].

Table 1. Knowledge-, data-driven and intermediate decision models, which were assessed in this work.

Knowledge-driven decision models [3, 4]	Data-driven decision models [5, 6]	Intermediate decision models [3, 4]
Rule-based models	Decision trees	Cased-based Reasoning
	Statistical models	Markov-/Bayesian networks
	Instance-based models	Fuzzy logic
	Artificial neural networks	
	Clustering	

2.2 Development of criteria for an assessment

We reviewed general work on decision models, such as published by Puppe and van Rijsbergen [7, 8,] and amplified these by current work on clinical decision support by Wojtusiak, Kilsdonk, A. Miller and K. Miller [10, 11, 12, 13]. Following criteria for decision models were developed:

- Accuracy [10, 11, 12]
- **Transparency** [7, 10]
- Acceptability [7, 8, 9, 12, 13]
- Efficiency [10, 11, 12, 13, 14]
- **Flexibility concerning the learning aptitude** [10, 14]
- Flexibility concerning the flexibility of coverage of knowledge [7, 8, 9, 12]
- **Security of knowledge concerning uncertain and vague knowledge** [3, 4]
- Security of knowledge concerning noisy and faulty data [14]

Out of these criteria, three main criteria for the assessment of decision models in health care were identified: *Transparency,* which is important for the users understanding of decision models. *Learning aptitude,* which is one of the main reasons for the development of hybrid decision models. *Uncertain and vague knowledge,* because a lot of medical knowledge is based on experiences and derived knowledge.

2.3 Assessment of decision models

The assessment of decision models was done by literature research and complemented by interviews with two colleagues experienced in the field of CDSS. For literature research the platforms of PubMed Medline and IEEExplore were mainly used. The literature research based on following keywords: clinical decision support, decision support system, knowledge-based / data-based / hybrid decision support / decision model / decision support model.

3. Results

3.1 Assessment and grouping of decision models concerning the identified main criteria

The assessment of decision models concerning the main criteria had shown different advantages and disadvantages of the decision models (see Table 2).

Table 2. Assessment of decision models concerning the criteria transparency, learning aptitude and uncertain/vague knowledge with the values positive (+), uncertain (~) and negative (-) and with the essential references in brackets.

Decision models	Transparency	Learning aptitude	Uncertain/vague knowledge
Rule-based models	+ [7, 14, 15]	- [7, 14, 15]	- [12, 15]
Decision trees	+	~	-
Statistical models	~ [6]	~	+ [6]
Instance-based models	~ [6]	+	~
Artificial neural networks	- [14, 15]	+	~ [14, 15]
Clustering	~ [6]	+	~ [16]
Case-based Reasoning	+ [3, 17]	+ [3]	+ [3, 17]
Markov-/Bayesian networks	~ [3]	~ [3]	+ [3]
Fuzzy logic	+ [18]	- [3, 4]	+ [3, 16]

Based on the assessment of decision models, three groups of decision models could be identified (see Table 2, Fig. 1):

- Group 1: Transparency (Rule-based models and Decision trees)
- Group 2: Learning aptitude (Instance-based models, Artificial neural networks (ANNs) and Clustering)
- Group 3: Uncertain/vague knowledge (Statistical models, Markov-/Bayesian networks, Case-based Reasoning (CBR))

3.2 Hybrid approaches of decision models

Based on the three groups of decision models, a hybrid approach was realized by combining two of them. The idea behind was to compensate the advantages and disadvantages of the different groups. We developed successfully three hybrid approaches (see Fig. 1):

- Hybrid approach A: Transparency and Learning aptitude (ANNs, Instance-based models or Clustering with Decision trees or Rule-based models)
- Hybrid approach B: Transparency and Uncertain/vague knowledge (CBR, Statistical models or Markov-/Bayesian networks with Decision trees or Rule-based models)
- Hybrid approach C: Learning aptitude and Uncertain/vague knowledge (ANNs, Instance-based models or Clustering with CBR, Statistical models or Markov-/Bayesian networks)

As a special case, we considered a hybrid approach of Fuzzy logic. A combination of ANNs, Instance-based models or Clustering with Fuzzy logic was possible.

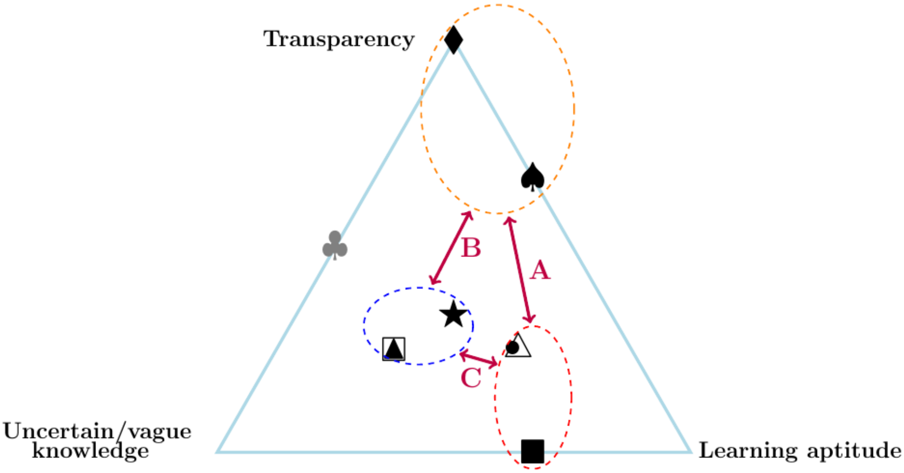

Figure 1. Triangle diagram for hybrid approaches based on the assessment of decision models concerning the criteria Transparency, Learning aptitude and Uncertain/vague knowledge. Assessment of criteria: positive (+) = 1.0, uncertain (~) = 0.5, negative (-) = 0 in triangle diagram with angles = 1.0 and center point = 0. Decision models: ♦ = Rule-based models, ♠ = Decision trees, ▲ = Statistical models, ● = Instance-based models, ■ = Artificial neural networks, Δ = Clustering, ★ = Case-based Reasoning, □ = Markov-/Bayesian networks, ♣ = Fuzzy logic. Grouping concerning similar assessments: Group 1 (orange) = Transparency (+), Group 2 (red) = Learning aptitude (+), Group 3 (blue) = Uncertain/vague knowledge (+). Hybrid approaches: **A** = Group 1 (Transparency) and Group 2 (Learning aptitude), **B** = Group 1 (Transparency) and Group 3 (Uncertain/vague knowledge), **C** = Group 2 (Learning aptitude) and Group 3 (Uncertain/vague knowledge).

4. Discussion

With this work a fundamental analysis for decision models in general, knowledge- or data-driven, has been made available. The developed criteria might be very helpful for assessing existing hybrid approaches of decision models as well. In addition, further hybrid decision models can be developed considering explicit questions and problems.

However, the developed criteria and chosen main criteria are not made a claim to be complete. It is to discuss what kind of subdivision of the criteria is reasonable for the aim of an exact assessment on the one, and the aim to get an instrument for a general assessment of decision models on the other hand. Also, this work is based on literature research, so some criteria, like the criterion accuracy, cannot be proved correct. Therefore, real data and test scenarios are needed.

For an improved assessment of decision models, we aim for analyzing the criteria with standardized test values. Nevertheless this work gives not just the opportunity to assess different hybrid approaches of decision models, this work provides also an instrument for a structured development of hybrid decision models concerning concrete questions and the field of application.

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