Bayesian Belief Network based Diagnostics in a Problem-oriented Learning Environment for Cardiology

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Abstract: Bayesian Belief Networks (BBNs) have a long tradition in medical expert systems for the support of diagnostic reasoning and therapy planning. Usually the BBN containing the uncertain knowledge of the experts is hidden from the user. New to case-based diagnostic training systems is that the structure of the BBN is *not hidden* from the student, but supports the learning process by visualizing the correlations between different symptoms, sequelas, causes, etc. of the contemplated disease.

The BBN is embedded in a problem-oriented context. Students are confronted with naturalistic diagnostic problems. They are asked to state diagnostic hypotheses and to test these hypotheses using the BBN. In this way strategic diagnostic skills are developed.

In an evaluation study students confirmed the novelty and importance of the learning environment and that the complexity of the BBN representation was no problem to them.

Topics

E-Learning, Medical Diagnosis, Bayesian Belief Networks, Evidence-Based Learning

1 Introduction

Diagnosis is a reasoning and problem solving task that can be quite difficult. This is especially true in medical domains ([BT80], [BS92], [ESS78], [EB80], [PG86]) where the knowledge is particularly complex, interrelated, fragile, and uncertain. In this domains Bayesian belief networks (BBN) are the representation of choice for building decision-making systems ([AWF87], [AJA89], [He91], [HHN92], [HN92], [Ma97], [LBT98], [On01], [BCW03], [Ga03]). Learning environments based on BBN usually hide the network containing the uncertain knowledge of the experts from the user.

In this paper we present Cardiobayes, a learning environment which was designed to support Evidence-based Learning [ES99] and train the diagnostic skills of the medicine students. In our learning environment the structure of the BBN is not hidden from the student, but supports the learning process by visualizing the correlations between different symptoms, sequelas, causes, etc. of the contemplated disease. The BBN is embedded in a problem-oriented context to guide the students through a naturalistic diagnostic problem. Diagnostic hypotheses should be stated first without the BBN. Then the student is expected to enter case information as evidence into the BBN. Regarding the changed probabilities of the network the student is able to test various diagnostic hypotheses to develop strategic diagnostic skills. The learning environment supports the training of strategic diagnostic knowledge qualitatively (i.e., what information is necessary in order to support or differentiate between what hypotheses?) and quantitatively (i.e., how does information gathered affect my diagnostic hypotheses? What is the most important information to acquire next?). We conducted an evaluation with eight students at the Universitätsklinikum Aachen and with another six students at the Universitätsklinikum Münster.

In the next section a short introduction to BBN in Medicine is given. In section 3 our BBN for Aortic Stenosis is presented and next in section 4 we describe the learning environment Cardiobayes, Finally the results of the evaluation are presented in chapter 5. We close with a short summary.

2 Bayesian Belief Networks in Medicine

Computer-based support of medical reasoning started more than twenty years ago. From the beginning, the problem of uncertainty received central attention. Since there were no efficient algorithms for processing probabilities, early systems like MYCIN [Sh76], CASNET [WKA78], PIP [SP93] or INTERNIST [MPM82] used heuristic approaches. This situation changed in the 1980's, enabling the development of normative probability-based medical expert systems (i.e., NESTOR [Co84], MUNIN [AJA89], PATHFINDER [HHN92]). The main aim of these systems is to provide the user with diagnostic hypotheses, given the available evidence, and to suggest further diagnostic evidence gathering steps, for example, for differential diagnosis. Some systems, like CASNET, also generate therapeutic recommendations. But in spite of some capability to explain their reasoning steps, the reasoning and knowledge structures of these systems remain largely hidden to the user.

In contrast to this MEDICUS ([MS97a], [MS97b], [FMS96]), an Intelligent Problem Solving Environment (IPSE), supports the construction of explanation models. The modelling take places in three steps: In a simplified-natural-language dialog the learner formulates an initial model to the system. Based on this formulation MEDICUS generates an initial graph automatically. In a qualitative model revision the independencies in the initial graph are verified by a dialog between MEDICUS and the learner. The learner specifies the known initial data and symptom. Thereafter he states an according diagnosis hypothesis and which information he thinks to be relevant next. By this data MEDICUS calculates independence assumptions and compares them to the initial model. Finally the learner may quantify the initial model with a-priori and conditional probabilities and let MEDICUS generate marginal distributions.

While MEDICUS focuses on teaching the process of modelling BBN, we developed a learning environment which focuses on training diagnostic reasoning with a BBN. A ready-to-use BBN is embedded into problem-oriented tasks and presented to the learner.

2.1 Bayesian Belief Networks

Bayesian Belief Networks ([SH96], [CGH97], [CDL99], [Je01], [Pe98]) are the representation of choice for modelling uncertain knowledge. A BBN models this knowledge as a directed acyclic graph that represents a probability distribution. The nodes of the graph represent propositional variables and directed arcs represent probabilistic relationships between them. Probabilistic (in-)dependence between variables is indicated by links between nodes and the lack of them. Furthermore, the relations are quantified with conditional probabilities (each variable conditioned on its parents in the network) that define a joint probability distribution of the variables.

An important reason for choosing BBN as a representation is that the system is designed to support qualitative reasoning. A physician engaged in medical diagnosis proceeds in a highly selective manner (i.e., [ESS78]). We pursue the hypothesis that this selectivity corresponds to the kind of (in)dependencies present in BBN. Reviews of published case studies in the domain of environmental medicine support this hypothesis. More generally, there is empirical evidence that qualitative reasoning by (in)dependencies as supported by BBN (like for example "explaining away") corresponds closely to human reasoning patterns ([He87], [Pe93], [WH92]).

3 The Bayesian Belief Network for the Aortic Stenosis Disease

3.1 The Domain

Under the supervision of two cardiologists from the Universitätsklinikum Aachen and Münster we succeeded in developing a BBN for the aortic stenosis disease. Aortic stenosis is the narrowing or obstruction of the heart's aortic valve, which prevents it from opening properly and blocking the flow of blood from the left ventricle to the aorta. It can either be congenital or acquired. Our BBN only deals with cases of acquired aortic stenosis, which is far more common.

3.2 The Bayesian Belief Network for Aortic Stenosis

The BBN (see figure 1) for aortic stenosis represents the uncertain knowledge of the medical experts for this domain. It is a visualisation of the relations between the different medical concepts.

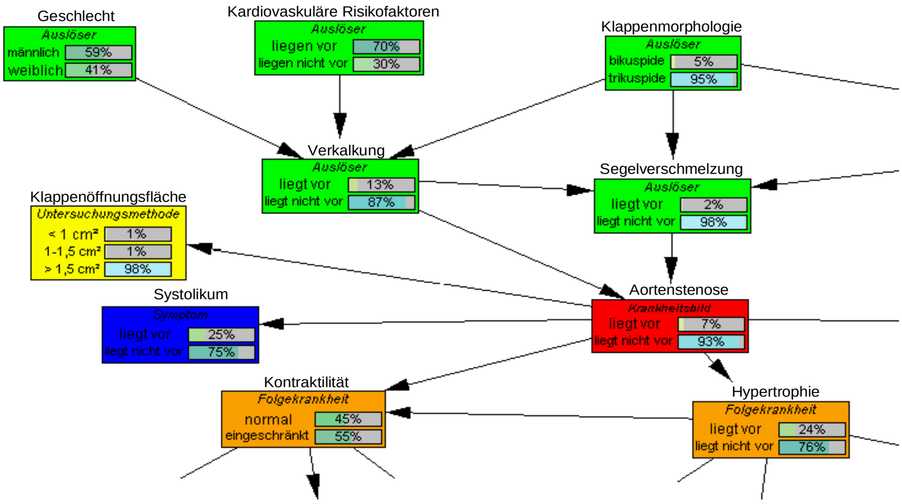

Figure 1 – Part of the BBN for Aortic Stenosis

The variables of the network represent the relevant medical concepts assigned to five different categories: diseases, sequelas, causes, symptoms and examination methods: e.g. endocarditis as a cause, hypertrophy as a sequela and ascites as a symptom. Each category is represented in different colours in the network for a better visualisation. The final model has 39 variables.

The influences between the different concepts are pictured by arrows pointing from the cause to the effect: e.g. an arrow from aortic stenosis to contractility implies that contractility is caused by aortic stenosis. However, the relations between the concepts are uncertain. This uncertainty is represented by probabilities acquired from the experts. The probabilities of the relations are invisible as they are part of the domain-knowledge to be learned; only the probabilities of the different medical concepts are shown to the learner.

Two different ways of information flows can be observed in the BBN: By entering causes into the network the effects can be observed. This would correspond to a causal flow of information. On the other hand a diagnostic approach would be to enter symptoms into the network and watch which diseases could be responsible for them.

4 The Learning Environment CARDIOBAYES

The BBN was integrated into a problem-oriented learning environment, which we call Cardiobayes (see figure 2). The two main components of the learning environment are the BBN about aortic stenosis and a case-oriented task formulation.

The task specifies a situation, which could also occur during the daily routine of the learner. It includes information concerning medical history, results of examinations and symptoms (see figure 2 part 1). Also every task confronts the learner with a problem, which he should solve using the information from the descriptions of the situation and the problem. The learner is encouraged to state a hypothesis of a problem-solution and test it using the BBN.The BBN, the second component, is available to the learner all the time while solving the task and supports the solution-finding-process (see figure 2 part 2). The learner has the possibility to enter the present information from the case and the problem context as evidence into the network. Regarding the changed probabilities of the network the learner is able to test various solution hypotheses and to choose the most appropriate. In addition the BBN can be used to freely explore the prevalent relations between the medical concepts. In this way the learner is able to gain new insights about the modelled disease, in our case: aortic stenosis.

In combination the two components allow the student greatest possible freedom while using the learning environment. On the one hand the student is able to freely explore the BBN and learn the prevalent relations. On the other hand he can be directed by the case-oriented tasks.

The learning environment supports two different problem-types: problems which could be solved

- by multiple-choice: A set of solutions is presented to the learner, from which he has to select the right answer (see figure 5 part 3). E.g. the learner has to choose from a list of five different symptoms the one, which mostly supports the diagnosis of aortic stenosis the most.

- using the BBN: The learner has to enter the right solution into the BBN. The solution of this kind of problem is a combination of different medical concepts, which are entered as evidence into the network. E.g. the learner has to find a combination of causes and symptoms, which result in an 80% likelihood for aortic stenosis.

After the learner found a solution, his answer is compared to the right solution stated by the experts. Depending on the given solution a message is presented about the grade of success or failure.

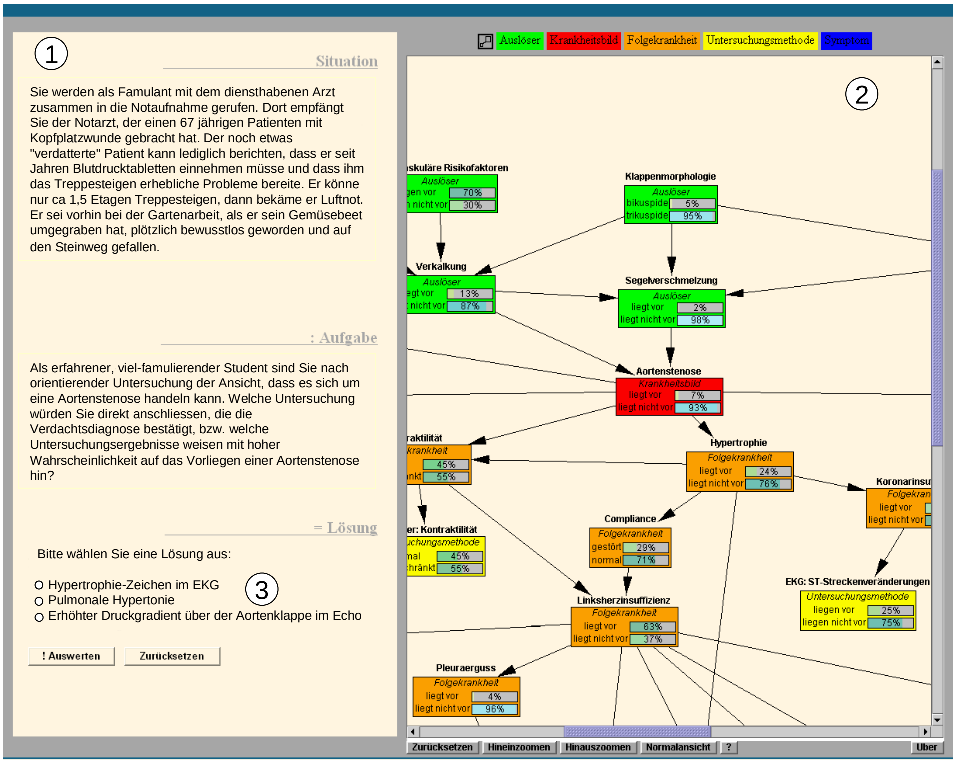

Figure 5 – Cardiobayes

The learning environment supports the training of two different knowledge types:

- Domain-dependent knowledge. The relevant medical concepts of the considered disease and their relations are learned. (E.g. symptoms, causes, etc.) The students learns which diagnostic information discriminates most between alternative diseases in different medical cases (e.g. how strong does the symptom contractility support the diagnosis of aortic stenosis, when hypertrophy is already known)

- Domain-independent knowledge. The strategic diagnostic skills of the students are trained. On the one hand this is done by presenting naturalistic diagnostic tasks which train the diagnostic skills directly, on the other hand by visualizing the interconnections and complex dependencies between the medical concepts by the BBN. In this way the diagnostic skills are trained as well qualitatively (i.e., what information is necessary in order to support or differentiate between what hypotheses?) and quantitatively (i.e., how does information gathered affect my diagnostic hypotheses? What is the most important information to acquire next?).

Cardiobayes was designed to support evidence based learning (EBL) [ES99], which aims among others at finding an evidence based guide to enhance the students' performance in medical practice. EBL consist of several interdependent learning-steps performed by a small group of students:

- A group of students is confronted with a diagnostic problem. Each student finds an individual solution for the problem, the so called 'individual standard'. This is done in Cardiobayes by presenting the task to the students and giving him the opportunity to specify the solution in the BBN. No feedback is given to the student at this time.

- The different individual standards are brought together to form a 'group standard'. Every student presents his BBN and in a moderated discussion a consensus is developed, the 'group standard'.

- The 'group standard' is validated against best evidence resulting in the 'evidence based standard'. Using Cardiobayes this could be achieved by entering the 'group standard' into the BBN. Since our BBN represents the knowledge of the experts it can serve as the best evidence, expert evidence in this case. Cardiobayes checks if the group standard forms a sound solution, the 'evidence based solution'.

Thus Cardiobayes supports these three very important steps of the EBL in serving as a basis to form the individual, group and evidence based standards.

5 Evaluation of the Learning Environment

The learning environment was evaluated by eight medicine students at the Universitätsklinikum Aachen and six at the Universitätsklinikum Münster. To evaluate the acceptance of the learning environment we chose a pre-/post test-design. By this method it was possible to identify significant changes in the acceptance.

The same questionnaire with questions about the acceptance and expectation concerning different kinds of learning media (books, teachers, Cardiobayes) was handed to the students before and after the training with Cardiobayes. Similar questions were asked for the different kinds of media. For example the students had to answer the three questions “A tutor/book/Cardiobayes is able to support in me preparing for my exams.” The students could rate this statement from 1 (I agree) to 5 (I disagree). Using statistical methods (t-tests) the results were examined for significant changes with regard to the acceptances and expectations.

A second questionnaire was handed to the students only after the test. This one contained general questions about the learning environment. The students were able to rate the learning environment with respect to its usability, the comprehensibility of the task formulations and its documentation.

The evaluation of the questionnaires showed that almost all students (92%) considered the uncertain knowledge represented by the BBN to be important for their profession and agreed on the fact that BBN represented a novel point of view relevant for diagnostic reasoning in practise.

Although the students stated the novelty and importance of the learning environment, they expressed mixed expectations regarding the role of the BBN as an exam preparation. The number of students who felt the learning environment as unsuitable for exam preparation increased from 7% to 20% after training with the learning environment.

From the evaluation of the questionnaires and the discussion with the students after the training the main reasons for the scepticism could be identified. The students were sceptic using Cardiobayes for preparing themselves for multiple-choice based examination questions. However our learning environment was designed to support the well-known concept of “Evidence-Based Learning”. The current form of examination in medicine is not consistent with EBL. But EBL is a widely accepted as a learning concept for medical training.

6 Summary

Under the supervision of two cardiologists we developed a BBN model for the aortic stenosis disease. We embedded the BBN model in a problem based learning environment, named Cardiobayes, giving the students full access to the model structure. The structure supports the training and improvement of the students’ diagnostic skills in an authentic goal based learning scenario. The students have the opportunity to freely explore the BBN or to be guided by our learning environment. In an evaluation the importance of the presented knowledge was confirmed by the students. But they were sceptic using Cardiobayes for preparing themselves for multiple-choice based examination questions. Nevertheless we have shown in the paper how Cardiobayes is able to support the well-known concept of “Evidence-Based Learning”.

Acknowledgements

We would like to thank the medical experts Dr. Dierk Rulands and Florian Reinke. Also we are indebted to Heinz-Jürgen Thole for supporting us in the conception as well as implementation of Caridobayes.

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