Intelligent Data Mining for Medical Quality Management

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Abstract. In the healthcare sector cost pressure is growing, quality demands are rising and the competitive situation amongst suppliers is mounting. These developments confront hospitals more than ever with the necessities of critically reviewing their own efficiency under both medical and economical aspects. At the same time growing capture of medical data and integration of distributed and heterogeneous databases create a completely new base for medical quality and cost management. Against this background we applied intelligent data mining methods to patient data from several clinics and from years 1996 to 1998. This includes data-driven as well as interest-driven analyses. Questions were targeted on the quality of data, of standards, of plans, and of treatments. For these issues in the field of medical quality management interesting data mining results were discovered in this project.

1 INTRODUCTION

Reforms in the healthcare sector have caused a continuously rising cost pressure during the last years. At the same time quality demands on hospitals and other suppliers of medical services are increasing. Along with an aggravating competitive situation the demand for intensive cost and quality management in all fields of the healthcare sector, in diagnostics as well as in therapeutics and administration, is growing, aiming at the exploitation of efficiency potentials [6]. On the other hand, the introduction of integrated hospital information systems (HIS) and the step-by-step conversion to electronic patient data files enable the capture of large amounts of data and thus a comprehensive documentation of historical diagnostic and therapeutic information on cases. Electronic documentation goes along with standardization efforts, e.g., the definition of diagnostic keys ICD-9 and ICD-10 [1]. Henceforth, distributed, heterogeneous, operative databases can be integrated, consolidated in a data warehouse or hospital information system, and made accessible within clinics or beyond. Rising costs and quality pressure on the one hand and new technologies of data processing on the other hand create both the necessity and the opportunity of a data based quality management in the health care sector.

Objective of a study launched by TILAK, the holding-organization of the hospitals in the Tirol region, and FORWISS was the inspection of supposedly quality relevant criteria for medical quality management in patient data as well as the discovery of new criteria. This includes the search for indices in the data enabling the detection of quality relevant differences in care patterns. Above that, we attempt to discriminate normal clinic stays from stays with complications and good from less good documentation. Applying this knowledge efficiency potentials can be found, countermeasures taken, and compulsory quality standards or guidelines created.

Intelligent data mining incorporates advantages of both knowledge acquisition from data, also known as data mining [2], and knowledge acquisition from experts. This technology integrates domain experts intensely into the knowledge discovery process by acquiring domain knowledge and using it to focus the analyses as well as to filter the findings [5].

Roughly 60.000 treatment cases were available from the clinics administered by TILAK for each of the years 1996 to 1998. Analyses have been carried out within patient groups of selected clinics: eye clinic, dermatological, gynaecological, neurological, and urological clinic.

The study represents a first approach to the application of data mining in patient data in the field of medical quality management in order to discover evidence to improvement potentials regarding the efficiency and quality of clinical processes. It could be shown that substantial implicit knowledge is hidden in the available data which cannot be discovered with conventional methods of analysis straight away.

2 THE TASKS OF MEDICAL QUALITY MANAGEMENT

The tasks of medical quality managers can be described as optimization of clinical processes in terms of medical and administrative quality as well as cost-benefit ratio. The core issues of medical quality management processes are the quality of data, of standards, of plans, and of treatments. These qualities can be measured with different indices. In the case of standards for the length of stay of patients in the clinic, a standard is expressed by an interval for a certain primary diagnosis. For example, for the primary diagnosis "coronary atherosclerosis" (ICD-9-code: 414.0) the standard interval for the length of stay is 2 to 5 days. An adequate index in this case is the ratio of cases which meet the standard in contrast to all cases. Data mining can be deployed by quality managers to solve the following tasks:

- Discover new hypotheses for quality indices for data, standards, plans, and treatments.
- Check whether given quality indices for data, standards, plans,

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and treatments are still valid.

- Refine, coarsen, and adjust given quality indices for data, standards, plans, and treatments.

Most of these tasks can be supported by means of data mining if the existing knowledge in the domain is intensely considered in the data mining process.

3 THE PROCESS OF INTELLIGENT DATA MINING

Intelligent data mining requires a tight corporation between domain experts, in this case medical quality managers, and data mining experts and consists of data-driven as well as interest-driven analyses. The work is supported by our data mining tool, the *Knowledge Discovery Assistant* (KDA) [4].

3.1 Interest-driven data mining

The interest-driven process can be decomposed into seven core phases.

Acquisition of domain knowledge. Domain knowledge is intensely acquired for intelligent data mining with structured expert interviews before the data mining step. This relates amongst others to the formation of interesting groups and concepts, suppositions and questions which can be derived from the tasks of medical quality management. This knowledge is used to define search spaces, to limit the search as well as to filter and sort results. Thus, the user is given quick access to the most interesting results and the deployment of the gained knowledge is made easier.

Formulation of business questions. We used the new *Knowledge Discovery Question Language* (KDQL) which is designed to enable business users in the medical quality management domain to represent business questions in order to focus data mining queries and to structure data mining results. KDQL abstracts from database terminology, e.g., attribute names, and data mining terminology, e.g., names of data mining algorithms. As just one example the following question has been formulated:

How does personal information influence the deviation from standards?

Refinement of business questions. Most KDQL questions formulated by business users will not be initially translatable because they contain concepts which are not part of the data mining world such as attribute groups or attribute value groups. In order to make those questions processable by data mining methods they have to be refined by the KDA using various concept taxonomies for the components of a question. The above question will be refined into the following questions

How does the age influence the deviation from standards?

How does the sex influence the deviation from standards?

where the attribute group “personal information” is replaced by relevant concepts which correspond to attributes in the database.

Transformation of business questions into data mining queries. Once a question has been made translatable by a set of refinements, the transformation into data mining queries can be started. The transformation of the question object is done by the KDA and corresponds to a mapping of the object to one or many data mining methods or statistical tests. Suitable mappings are determined by a number of criteria:

- Criteria concerning the demands of the user (e.g., simplicity, accuracy)
- Criteria concerning the data (e.g., volume of data, scale types of attributes)
- Process criteria (e.g., stage of analysis, level of iteration)

If more than one data mining method or statistical test appear appropriate a question will be mapped parallel on all of them creating a corresponding number of data mining queries.

Execution of data mining queries. The KDA executes the data mining queries and returns structured findings in relation to the questions of the quality manager.

Processing data mining findings. Most data mining methods overwhelm the user with a flood of results. Therefore, the KDA enriches each finding with a value called interestingness which allows business users focused and flexible access to the large volumes of findings produced by data mining methods [3]. The KDA also supports the user by generating visualizations of findings and allows to navigate in structures of findings, to search and sort the findings as well as to filter uninteresting and select interesting findings which can help solve the tasks of the medical quality management.

Transformation of data mining results into answers. Corresponding to questions in the language of the business user, natural language answers are produced by abstracting data mining results. However, the transformation is not yet supported by the current implementation of the KDA.

Triggering new questions. Viewing the answers often causes the quality manager to come up with follow-up questions which may result in the formulation of new questions.

Figure 1 illustrates this language-oriented model for intelligent data mining.

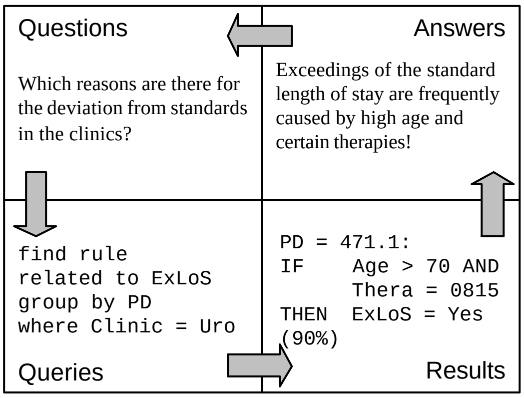

Figure 1. The process model

3.2 Data-driven data mining

Purely interest-driven analyses tend to overlook unexpected patterns in the data. To avoid this shortcoming we also use data-driven types of analyses in addition to the interest-driven analyses. Association rules are mainly deployed for these analyses. Also for data-driven analyses, the business user’s interests are applied to structure the findings.

This hybrid approach ensures, that on the one hand users are not overwhelmed by floods of findings which are far beyond their interests and that on the other hand also unexpected patterns do not escape their notice.

4 THE RESULTS FOR MEDICAL QUALITY MANAGEMENT

To give a rough impression of the results which have been found in the analyses we show one example for an interest-driven discovery and one for data-driven discoveries in the following sections.

4.1 Interest-driven discoveries

To the question

Which conspicuous subgroups can be identified within differentiable patient groups such as patients with identical diagnoses, who - discernible by the frequent occurrence of complications - should be treated differently, but have not been treated specifically?

for patients with the diagnosis "fragments of torsion dystonia" (ICD-9-code: 333.8) in the neurological clinic in 1996 the following result has been discovered.

Table 1. Number of exceedings of the standard length of stay in dependency of age for the diagnosis "fragments of torsion dystonia" (ICD-9-code: 333.8)

	Age			
	15-59	60-74	>75	total cases
standard length exceeded	8	9	0	17
standard length not exceeded	11	2	3	16
total cases	19	11	3	33

Here it is obvious, that for "fragments of torsion dystonia" the standard length of stay is exceeded more frequently by patients between 15 and 59 years old than by those between 60 and 74 years old. This is a clear deviation from expectations as one would suppose that elder patients stay longer than younger ones. In the scope of etiology it has to be investigated, if it is in fact the age which can be held responsible for the longer duration of stay. If that is the case, for patients of this age a modified treatment should be considered in the future. If not, the knowledge about the standard length of stay has to be refined for this diagnosis by the corresponding exception.

4.2 Data-driven discoveries

In addition to the above interest-driven data evaluation, data-driven analyses produced another set of interesting findings. Thus, strong associations, e.g., within diagnoses and medical treatments have been discovered. The discovery

IF *one of the single medical treatments [SMT] was "continuous ventriculometry",*

THEN *further SMTs were "respirator therapy" and "burr-hole trepanation". (77%)*

in the neurological clinic in 1997 gives evidence which could increase the reliability of plans. Furthermore, conspicuousnesses regarding the length of stay with several influence factors, such as

IF *one of the SMTs was "combined strabotomy",*

THEN *the overall length of stay is between 2 and 6 days. (92%).*

and

IF *primary diagnosis category was "benign neoplasias of skin" (ICD-9-code: 216),*

THEN *the case fell below the lower limit of length of stay, because it was an out-patient treatment. (100%)*

have been discovered in the eye clinic in 1996. The first rule can aid again an increased reliability of plans for the management of resources and the second allows conclusions that the lower limit of length of stay for primary diagnosis category "benign neoplasias of skin" is not adequate.

5 CONCLUSIONS AND FUTURE WORK

We have shown, that intelligent data mining in addition to conventional analyses and statistical studies in patient data can deliver further evidence for medical quality management. In detail, measures for the quality of data, of standards, of plans, and of treatments can be improved by intelligent data mining. The compliance with given measures can be evaluated, given measures can be modified to better suit the requirements and new measures can be found.

However, the quality management department is usually only in charge of providing the indices. Mostly, measures have to be taken by physicians in the clinics, and it is their acceptance of the results which is required to ensure that they are put into action. Therefore, understandable results in a clear and adequate presentation are indispensable.

Further works concern primarily the statistical consolidation of the results, support for the conversion of conclusions as well as the development of an adapted automated data mining process and the introduction of this technology as part of a comprehensive and permanent set of controlling instruments.

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