Analysing Heart Attack Survival using Intelligent Systems

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Abstract

A successful application of a new intelligent system design approach called Multimethod in knowledge extraction and discovery in heart attack areas is presented in this paper. The results show that the Multimethod approach is a powerful and promising technique enabling the conformation of existing medical knowledge and more interestingly, also enabling the induction of new facts and hypothesis, which can reveal some new interesting patterns and possibly improve the existing medical knowledge.

1. Introduction

Many real-world medical problems are nowadays being handled with tools for automatic intelligent data analysis. Various methods such as neural networks, decision trees, genetic algorithms and hybrid systems have been developed and already evaluated on different medical databases. But from physician's point of view the ability to track and evaluate every step in the decision making process is the most important factor for trusting the decisions gained with machine learning methods. Therefore the role of decision trees in medical decision support is very important since they provide a very powerful feature – the possibility of explaining the decision in an easy and human understandable way. Just a brief look at the decision tree's structure can reveal a physician which attributes are the most important for the diagnosing, outcome prediction and similar. A more exact decision tree analysis can expose new relations, set new hypothesis, new facts thus enriching the medical knowledge.

Most of the work in machine-learning community has been focused on classical approaches using single method with single knowledge representation. But in recent years we can observe the expansion in research of hybrid methods. One of the possible explanations is that separate research communities on symbolic machine learning, computational learning theory, neural networks, statistics and pattern recognition, etc. have discovered each other.

In this paper we focus on inducing user-friendly intelligent systems on the basis of different approaches, which would extract some important factors about emergency care of heart attack patients and thus help the physicians in improving the survival rate. That is very important since heart attacks are the leading cause of death in most of the highly developed countries. We developed a new approach called Multimethod and used it for the induction of hybrid decision trees.

2. Method

Machine learning community has a long tradition in knowledge extraction that can be traced at least as far as the mid-1960. Through the time different approaches for knowledge extraction evolved [1], such as symbolic approaches and computational learning theory. Among them we can find many classical approaches, like decision trees, rules, rough-sets, case based reasoning, neural networks, support vector machines, different fuzzy methodologies, ensemble methods [2]. However all of them have some advantages and limitations. Evolutionary approaches (EA) are also a good alternative, because they are not inherently limited to local solutions [3]. Recently, taking into account the limitations of classical approaches many researchers focused their research on hybrid approaches, following the assumption that only the synergetic combination of single models can unleash their full power [4].

Current studies show that the selection of appropriate method for data analysis can be crucial for the success. Therefore, for a given problem, different methods should be tried to increase the quality of extracted knowledge. According to the previous paragraph a logical step would also be to combine different methods into one more complex methodology in order to overcome the limitations of a single method. We noticed that almost all attempts to combine different methods use loose coupling approach where the methods work almost independent of each other. Therefore a lot of "luck" and trying out many different combinations are needed to unify them into a "team". Thus we decided to design a new approach that enables tight tangling of single methods. This new approach is called a multimethod approach [5]. Opposed to the conventional hybrids our idea is to dynamically combine and apply different methods in not predefined order in the manner to solve a single problem or the decomposition of that problem.

Multimethod approach introduces the idea of a population of different intelligent systems - individuals that can produce multiple comparable good solutions, which are incrementally improved using the EA approach. In order to enable knowledge sharing between different methods the support for transformation between each individual method is provided. Initial population of intelligent systems is generated using different methods. In each generation different operations appropriate for individual knowledge representation are applied to improve existing and also to create new intelligent systems. That enables incremental refinement of extracted knowledge, with different views on a given problem. For example, using different induction methods such as different purity measures can be simply combined into a decision trees. As long as the knowledge representation is the same, a combination of different methods is not a big obstacle. The main problem is how to combine methods that use different knowledge representations (for example neural networks and decision trees). In such cases we provide two alternatives: (1) to convert one knowledge representation into another, using different already known methods or (2) to combine both knowledge representations into a single intelligent system.

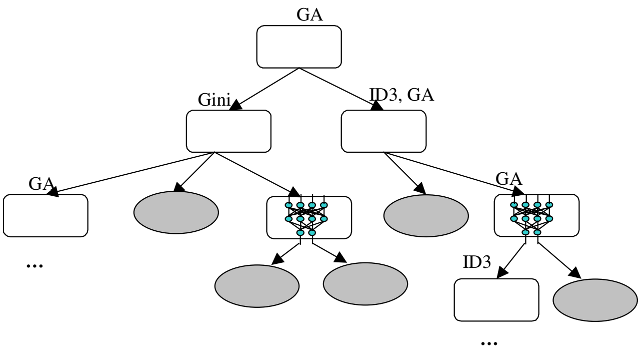

Figure 1. An example of a hybrid decision tree induced by the multimethod approach. Each node is induced with appropriate method (GA – genetic algorithm, ID3, Gini, SVM, neural network, etc.)

The first alternative requires implementation of the knowledge conversion (for example conversion of a neural network into a decision tree). Such conversions are not perfect and some of the knowledge is normally lost, but conversions can produce a different aspect on a presented problem that can lead to better results.

The second alternative requires some cutpoints where knowledge representations can be merged. In a decision tree internal nodes or decision leafs represent such cut points (Figure1), i.e. a condition can be replaced by another intelligent system (for example support vector machine - SVM). We call such trees the hybrid decision trees.

3. Data collection

In this study a real-world database gathered in the Department of emergency medicine in General hospital of Maribor, Slovenia was used. 309 patients that were brought into emergency department because they suffered a heart attack were included in the study. Each patient is described with 19 attributes, which include general data about patient (gender and age), the information about received emergency care in first 12 hours and treatment during the hospitalization (Table 1). Our main concern was the survival of the patients, which will be therefore considered as an output of the intelligent data analysis.

270 patients out of 309 survived the treatment and the rest (12,6%) died in the emergency or later during the hospitalization. That clearly shows that our database was very unbalanced. Such unbalanced dataset usually causes the induction of a classifier with high prediction accuracy of the prevalent class but the prediction accuracy of the less represented decision class is commonly very low.

4. Results and discussion

The decision trees were induced to determine how the standard emergency treatment and additional interventions influence the survival of the patients in order to improve the survival rate. The original database was therefore divided into two datasets – one for training purposes, which was used in the process of decision tree induction, and the other for testing and evaluating the induced decision tree. The training set included 2/3 of randomly selected instances from the original database. The remaining 1/3 of instances was than used for testing the decision tree. The class distribution in training and testing set remained the same as in original dataset.

The induced decision trees were evaluated with the following quantitative measures:

$$accuracy = \frac{num\ of\ correctly\ classified\ objects}{num.\ of\ all\ objects}$$

$$accuracy_c = \frac{num\ of\ correctly\ classified\ objects\ in\ class\ c}{num.\ of\ all\ objects\ in\ class\ c}$$

$$average\ class\ accuracy = \frac{\sum_i accuracy_i}{num.\ of\ classes}$$

Table 1: The description of the attributes

Attribute	Description	Type
Age	Age of the patient	Continuous (31-95)
Gender	Gender of the patient	Discrete (1-male; 2-female)
st_vez	ST segment evaluation (in ECG)	Discrete (0-no; 1-yes)
AMI_loc	Site of acute myocardial infarction	Discrete (degree: 1-4)
old_AM	Previous acute myocardial infarction	Discrete (0-no; 1-yes)
time	Time from the beginning of the pain to hospital arrival	Discrete (1-less than 3 hours; 2-less than 6 hours; 3-less than 12 hours; 4-more than 12 hours)
TnTmax	Maximum cardiac enzyme troponin T level	Continuous (0.01-25)
CKMBmax	Maximum level of CKMB (the creatine phosphokinase)	Continuous (0.2-500)
BNP	The test measures a protein B Natriuretic Peptide a substance secreted by heart muscle that is failing	Continuous (24-1920)
urea	The level of urea nitrogen in serum	Continuous (2.9-16.2)
Kreat	The level of kreatinim in serum	Continuous (60-174)
CRP	The level of C-reactive protein	Continuous (1-401)
RRs	Systolic blood pressure	Continuous (0-238)
RRd	Diastolic blood pressure	Continuous (0-125)
Killip	Killip class - severity of heart failure with myocardial infarction	Discrete (1-no clinical signs of heart failure; 2-crackles, S3 gallop and elevated jugular venous pressure; 3-frank pulmonary oedema; 4-cardiogenic shock - hypotension (systolic<90 mmHg) and evidence of periph. vasoconstriction)
CABG	A coronary artery bypass graft is an operation to restore or improve the blood flow to the heart muscle.	Discrete (1-the operation was performed during hospitalization; 2-the operation was not performed; 3-the operation was performed before current hospitalization)
OIIMhosp	The days of hospitalization in department of emergency medicine	Continuous (1-73)
ODDhosp	The days of hospitalization in department of heart disease	Continuous (0-46)
Hosp	The days of hospitalization (all together)	Continuous (1-130)
Survival	Survival of the patient	0-yes; 1-no;

In order to make an objective assessment of our multimethod approach we used the same training and testing sets with commonly used decision tree induction methodologies such as: greedy decision tree induction methods based on different purity measures (information gain ratio (ID3), gini, chi-square and j-measure), boosting as a method for improving the accuracy of induced classifiers [2] and simple genetic algorithm for decision tree induction [6]. As expected all decision trees had very high accuracy on the training set, however the accuracy of classifying unseen test cases varied from 87.73% to 94.17% dependent on the method used for decision tree induction (Table 2). Even higher difference appeared when we compared average class accuracy of induced decision trees (from 63.23% to 87.07%). Owing to highly unbalanced dataset the classification of patients who did not survive (specificity) was rather low for the most of the decision trees.

Presented results in the table 2 show, that the most successful decision tree was induced with our new multimethod approach. The total accuracy on the test set was 94.17%. More precisely, the accuracy on the test set was 97.67% for classification of survived patients, and 76.47% for classification of patients that died during the treatment. The accuracy on the training set was 100% for classification of both classes.

Table 2: Comparison of various methods for decision tree induction on the basis of accuracy and average class accuracy on the test set

Method		
Multimethod	94.17%	87.07%
Genetic	90.56%	78.08%
Greedy ID3 Boost	90.56%	74.77%
Geedy Chi-square Boost	89.62%	74.23%
Greedy Chi-square	87.73%	73.15%
Greedy Gini Boost	92.45%	72.53%
Greedy J-measure	87.73%	69.85%
Greedy J-measure Boost	92.45%	69.23%
Greedy ID3	87.73%	63.23%
Greedy Gini	87.73%	63.23%

accuracy average class accuracy

The extracted knowledge for prediction of survival of heart attack patients after receiving emergency care was than compared to known medical criteria. Table 3 presents some of the decision rules for prediction of survival extracted from the most successful decision tree induced with our multimethod approach and their evaluation made by medical specialist. Most of the decision rules just confirm expected medical knowledge about the factors that can influence the survival after heart attack, however some of the extracted decision rules also show some new relations and therefore deserve more consideration and further research. Nevertheless the first results certainly show, that the guidelines for emergency care in first 12 hours after heart attack can be largely improved by some additional interventions that were normally done later.

Table 3: Evaluation of extracted decision rules

Extracted rule	Survival	Evaluation	Comments
IF KILIP=4	NO	True	Known fact
IF CABG=1 OR CABG=3	YES	Interesting	Unexpected
IF CABG=2 AND KILIP=1 AND BNP=UNKNOWN	YES	True	Interesting (for unknown BNP value)
IF CABG=2 AND KILIP=1 AND BNP<1666	YES	True	Interesting, high BNP limit
IF CABG=2 AND KILIP=1 AND BNP>1666	NO	True	Interesting, high BNP limit
IF CABG=2 AND KILIP=2	YES	True	CABG=2 and low KILIP often foretells a good prognosis
IF CABG=2 AND KILIP=4	NO	True	The reason is probably a high KILIP value
IF CABG=2 AND KILIP=3 AND TNTMAX<11.5	YES	Very interesting	The reason for better survival probably lies in low maximal values of TNT
IF KILIP>2 AND RRs>80	NO	Interesting	Not logical for high RRs values
IF ODDHosp<2.45 AND ST_VEZ=1	NO	True	Logical
IF ODDHosp<2.45 AND ST_VEZ=0 AND KILIP>1	NO	True	Interesting

5. Conclusion

Searching for new patterns in survival of heart attack patients in emergency care using multimethod approach limiting on decision tree induction provided very interesting results. In comparison to other conventional approaches our multimethod approach outperformed other approaches especially when considering the prediction accuracy of individual decision classes. The extracted decision rules showed many medical factors that have been known to improve the survival rate in emergency care of heart attack patients. More importantly, some new interesting patterns were shown, which can have some influence, but they should be more carefully investigated and expertly evaluated.

The success of multimethod approach can be explained with the fact that some methods converge to local optima. With combination of multiple methodologies better local (hopefully global) solution can be found. For example when using decision trees the genetic methodology determines the attributes near the top and on the nodes near leafs the greedy method with different impurity measures can be used to reduce search space. On the other hand some ideas of generic approach are used which enable exploration of unpromising parts of search space and make higher-level separation that then enables other methods to find solution in alternative subspaces. Another improvement is a new redistribution approach that usually results in higher average class accuracy and balances unbalanced data.

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