The Effect of Expert Knowledge in Argument Based Machine Learning

Arguing Agents - Report Draft

Group 07
Joppe Boekestijn (s2754215)
Lex Koelewijn (s2757036)
Dirk Jelle Schaap (s2745135)

October 4, 2019

Abstract

In this paper we use a state-of-the-art argument based machine learning algorithm based on (ABCN2) to predict heart attacks given a dataset and expert knowledge. We vary the amount and importance of this expert knowledge that is available to ABCN2 and study the differences in classification results of the algorithm. [results and conclusions not yet available]

1 Introduction

1.1 Problem

In the medical field experts diagnose patients based on years of expertise and knowledge. However, as experts are also humans, sometimes they can make mistakes. With the rise of storage capacity during the last few decades, increasingly more data is available. While the medical information of patients, like their blood pressure and heart rate, used to be written in books for the experts to monitor, this form of analysis can now be done digitally.

To diagnose, an expert takes a look at the medical data and derives its own conclusions based on personal rules which they have accumulated over years of working experience. An example would be "the patient needs medicine x if the heart rate is lower than 40 beats per minute". Nowadays, machine learning can be used to derive similar rules directly from the data. The goal of this paper is to take the rules found by machine learning algorithms and take those found by experts, to find out if combining these can increase the classification accuracy in a medical diagnosis scenario.

1.2 State of the art

The current state of the art is the ABCN2 algorithm [2]. It is an extension of the CN2 machine learning algorithm, which is used to find rules that are effective at classifying some data set. ABCN2 has the advantage of being able to accept human expert knowledge in the form of rules beforehand. This enables it to combine the experience of humans with the power of machine learning. A while back a paper was published where this technique was used on a medical data set [3]. The ABCN2 was given several rules based on the experience of an experienced doctor and was given the task of predicting whether patient's life was in danger or not.

1.3 New idea

In the paper where ABCN2 was applied it was found that it was only slightly better performing than the regular CN2 algorithm [3]. In the discussion it was mentioned that this might be due to the fact that they had a fairly high amount of expert rules. When expert knowledge rules are passed to the ABCN2 algorithm, it tries to generate useful classification rules based on them and the data. Once such a rule is found, the data covered by this rule is ignored from then on. Having many rules covering only small portions of the data set, may cause a situation where there is not many data points left once ABCN2 tries to learn on its own. In other words, many mediocre expert rules could result in worse performance than only a few good ones. We would like to investigate this by varying the percentage of data points covered by expert knowledge rules.

Although our first idea was to use the ABCN2 algorithm, we ran into multiple issues trying to use the package. There is little to none documentation available, as well as limited example code. For each function call we had to delve into the package code ourselves and we found out that Orange for Python 2 is severely deprecated, and Orange for Python 3 does not contain ABNC2. Therefore we decided to use the ideas from ABCN2 as a basis to create our own model that uses expert knowledge rules to derive correct classifications. The way we implemented this will be elaborated on in the following sections.

2 Model description

The model consists of two parts: the expert knowledge and the rule inducing CN2 algorithm. Both elements will briefly be discussed. The expert knowledge would ideally consist of rules that an expert uses, in this particular case rules of thumb a doctor might use in their day-to-day. However seeing as the aim of this research is to vary the amount of data that is covered by the rules derived from the expert knowledge, more flexibility is required instead of a fixed set of rules that would serve as expert knowledge. So instead, our model allows for the specification in terms of a percentage as to how much data should be covered by the expert rules. Using this percentage rules will dynamically be created such that a simple rule is created which covers the required percentage of the data. So the model will go through all the values for a parameter and adjust until the required percentage of the data is covered. This will result in a simple "expert" rule which is favorable seeing as in the medical domain a general rule of thumb is that the simpler the rule the better. Accordingly the data that is covered by the expert rules will no longer be considered in the remainder of the process seeing as expert knowledge is deemed superior to the rules extracted by CN2. So now using the remainder of the data CN2 will be applied to create a set of rules to predict a heart attack. The rules created by our model which serve as expert rules will be evaluated in terms of how many correct predictions they make.

In order to investigate what the influence is of the percentage of data covered by the expert knowledge we will thus run the model using different percentages for the expert knowledge. Accordingly we can evaluate the quality of the rules inferred by the model. The quality of rules can derive from the fact that parameters that have a high influence on the heart attack value (using for example ANOVA), mean that the rule is more important that others.

2.1 Code

The main new components that were introduced for this research are those pertaining to the expert rules that we create. Seeing as none of us are actual medical experts we rely on statistical information in order to derive expert rules. Initially plots are made of all the variables in the data in order to manually inspect the distribution of the data as well as to see if there is a difference between means in the data with regards to data point with positive or negative outcome. Accordingly ANOVA is used to determine which variables in the dataset have the most predictive power, this not used in the alpha version but it should in the final version. The algorithm created will now go through all the variables of the dataset and create a rule that covers exactly the amount of data as specified that it should cover. So for example the model would search for a rule of the form 'If age is over X then patient will suffer a heart attack' in which X will be varied until 10% of the data is covered by this rule. Then using the expert rule the data point for which the expert rule states what the outcome will be are removed from the dataset and the remainder is processed using CN2. A final and important step is to evaluate the expert rules created: before creating the rules the data is split in a train and test set where we train the rules on the train data. CN2 will yield a final set of rules to classify the data, these rules are created based on the dataset which has been reduced through the expert rules. Using these rules on the test set yields probabilities of the rule predicting a heart attack or not. Using these probabilities the percentage of correctly classified data points will be calculated for the rules and this will serve as a measure of how well the rules perform overall and thus implicitly whether the expert rules improve performance of the algorithm or not.

2.2 Dataset

The following data set [1] will be used for the experiment since it is fairly similar to the data used in [3]. It features a similar amount of data points and allows us to predict a binary outcome. It is a dataset which contains medical measurements of 294 patients collected by 4 medical professionals in Budapest, Zurich, Basel and Long Beach. For each patient there are 14 measurements and an outcome declaring whether the patient suffered a heart attack or not.

3 Results

3.1 Experimental or theoretical findings

Not yet available.

3.2 Interpretation of findings

Not yet available.

4 Conclusion

4.1 Discussion

Not yet available.

4.2 Relevance

Combining expert knowledge and machine learning derived knowledge has to possibility to be very interesting. It can enable machine learning to take the currents knowledge of human experts as a starting point, instead of having to start from scratch. It also enables machine learning to "learn" things that are not obviously represented in the available data. This can ultimately lead to better decisions, and in the medical field it can even save lives. Our research focuses more on the role of expert knowledge in the ABCN2 algorithm. We think that this can give us more insight into what is the right amount/form of expert knowledge, in order for the machine learning algorithm to make the best classifications.

5 Division of work

The project proposal and the project plan were mainly written by Dirk Jelle and Joppe. The slides for the project pitch were made by Lex and the pitch was done by Dirk Jelle. Joppe did the bulk of the work regarding the code. This report was written by Lex and Dirk Jelle. We found converting this division of work into percentages difficult, but our best attempt is shown in Table 1.

Name	Contribution (%)
Joppe	40
Lex	30
Dirk Jelle	30

Table 1: Contribution of each team member as percentages.

References

[1] M.D. Andras Janosi, M.D. William Steinbrunn, M.D. Matthias Pfisterer, and Ph.D Robert Detrano, M.D. Heart Attack Prediction. https://www.kaggle.com/imnikhilanand/heart-attack-prediction, 2018. [Online; accessed 04-10-219].

[2] Martin Mozina, Jure Zabkar, and Ivan Bratko. Argument based machine learning. *Artificial Intelligence*, 171:922–937, 2007.

[3] Jure Zabkar, Martin Mozina, Jerneja Videcnik, and Ivan Bratko. Argument based machine learning in a medical domain. In *Computational Models of Argument: Proceedings of COMMA. Frontiers in Artificial Intelligence.*, volume 144, pages 59–70, 2006.