Automatic Acquisition of Medical Knowledge
from Data sets with Neural Networks

Alfred Ultsch, Stefan Farsch, Heng Li
FG Informatik, Philipps University of Marburg
Hans Meerwein Str. (Lahnberge)
35032 Marburg/Lahn, Germany

Abstract

Knowledge acquisition is a bottleneck in AI applications. Neural learning is a new perspective in knowledge acquisition. In our approach we have extended Kohonen's self-organizing feature maps (SOFM) by the U-matrix method for the discovery of structures resp. classes. We have developed a machine learning algorithm, called sig*, which automated extracts rules out of SOFM which are trained to classify high-dimensional data. sig* selects significant attributes and constructs appropriate conditions for them in order to characterize each class. sig* generates also differentiating rules, which distinguish classes from each other. The algorithm has been tested on many different data sets with promising results. The framework of using sig* integrated in a system which automated acquires knowledge from learned SOFM is also presented.

1. Introduction

Knowledge acquisition is often a bottleneck in AI applications. Many expert systems use knowledge in symbolic form (e.g. rules, frames, etc.). For human experts it is, however, difficult to formulate their knowledge in these formalisms. Different approaches to the problem of knowledge acquisition have been proposed, for instance interviews with experts by knowledge engineers etc. . These approaches concentrate often on how to interact with the experts in order to get a formulation of their knowledge in symbolic form. Here we follow a different approach: Experts have gained their expertise by experiences, i.e. by dealing with cases. In order to get the experts' knowledge into an expert system we propose to process the case data in the attempt to learn the particularities of the domains. In this paper we use Artificial Neural Networks (ANN) for the first step of processing the data.
Kohonen's self-organizing feature maps (SOFM) [Kohonen /89] have the property that the neighbourhood among the training data in a high dimensional space, is reflected in the neighbourhood of the units on the generated feature map, practically in a 1-, 2-, or 3-dimensional space. We can make use of this property of SOFM to discover structures in high dimensional data and map them into a lower dimensional space. For SOFM we have developed a method, called U-Matrix Method (UMM), to detect and display the structures learned from the trained data set [Ultsch/90]. Using the UMM a trained feature map is transformed into a landscape with "hills" or "walls" seperating different regions where cases are located [Ultsch/91a]. All cases that lie in a common basin are considered to have a strong similarity i.e. have some common structural properties.
An inductive machine learning algorithm called sig* [Ultsch/91a] takes the training data with the classification detected through the learned SOFM as input, generates rules for characterizing and differentiating the classes of the data. The work reported here is a part of the research project of knowledge processing in neural architecture. We have developed a

system, called REGINA, which uses sig* as a knowledge acquisition tool for a diagnosis expert system while using SOFM as a neural classifier [Ultsch/92].

2. Overview of REGINA

The system REGINA consists of four major modules:
Neural classifier, analysing tools, rule extraction and inference.
In REGINA the raw data are firstly processed such that they can be used to train Kohonen's self-organizing feature maps (SOFM). After learning of SOFM we have the neighbourhood structure among the training data implicit on SOFM. Using analysing tools, in particular the U-Matrix method [Ultsch/91a], the neighbourhood structure on learned SOFM can be visually recognized. On the other hand the training data are transfered to rule extraction. sig* takes the training data with the classification detected through SOFM as input and generates symbolic rules. The extracted rules and the information in the neural as well and the experts' rules in addition are employed in inference.

3. Rule Generation with sig*

sig* has been developed in the context of medical applications [Ultsch 91a]. In this domain other rule-generating algorithms such as ID3, for example, fail to produce suiting rules. sig* takes a data set in the space Rn that has been classified by SOFM/UMM as input and produces descriptions of the classes in the form of decision rules. For each class an essential rule, called characterizing rule, is generated, which describes that class. Additional rules that distinguish between different classes are also generated. These are called differenciating rules. This models the typical differential-diagnosing approach of medical experts, but is a very common approach in other domains as well.
The generated rules by sig*, in particular, take the significance of the different structural properties of the classes into account. If only a few properties account for most of the cases of a class, the rules are kept very simple.

Two central problems are addressed by the sig* algorithm:
1. how to decide which data attributes are significant to characterize each class,
2. how to formulate suitable conditions for each selected significant attribute.

In order to solve the first problem, each attribute of a class is associated with a "significance value". The significance value can be obtained, for example, by means of statistical measures. We assume a data set of case-vectors with attributes Attri. and let SOFM/UMM distinguish the classes Clk. Let SVik denote the significance value of Attri in class Ck . In the matrix SM=(SVij)ixk we call "significance matrix", the the largest value in each row is marked, the significance values of the attributes are normalized and then ordered. As significant attributes for the description of a class, the attributes with the largest significance value in the ordered sequence are taken.
For the second problem we can make use of the distribution properties of the attributes of a class. A class is described by a number of conditions about the attributes selected by the algorithm described above. The algorithm produces the essential description of a class. If the intersection of such descriptions of two classes is nonempty, a finer description of the borderline between the two overlapping classes is necessary. This is done by a differentiating rule.
The complete and formal description can be found in [Ultsch/91a].

4. Medical Applications and Conclusion

In order to test our hybrid system we applied it to two applications from the medical domain. First, we used it to diagnose acidosis diseases. The data set consists of 11 attributes originating from the blood analysis. It was known which diagnosis the medic found, and what rules he used to retrieve his results. This data set therefore should be the proove for the quality on the correctness of the classification and the rulegeneration our system would provide. Several classification methods according to [Deichsel/85] were used to explain these data. The Neural Network together with the U-Matrix method was able to classify the data into the subcategories healthy, lacacidemia, meta-bolical acidosis, respiratory acidosis and one patient with cerebral deficiency. With our rule generation module sig* we extracted rules out of the Neural Network, which were described by 4 or 5 attributes resembling more closely the decisions made by medical experts. Second, we used a data set with patients suffering from different types of the blood disease anaemia. Here no classifications were known a-priori. Deviations of blood values were indicators for a diagnosis of anaemia diseases. The extracted rules are quite similiar to the diagnosis rules in a medical text book [Mueller/89]. But additional rules were also found and could be verified by medical experts [Ultsch/92a].
Up to now the results have been very promising. In some cases knowledge that has not been known to us, but was verified by the domain experts, has been extracted. In most cases the performance of the generated rules ranged in the 80 to 90 percent class.
Our approach has three advantages :
(1) the integration of unsupervised neural learning and inductive machine learning in automated knowledge acquisition, (2) a flexible, domain-dependent decision criterion for selecting significant attributes instead of a predetermined minimal decision criterion (as usual) in rule generation, (3) the possibility for constructing rule conditions in various points of view.
The examples for learning may be incomplete and even inconsistent. Therefore the extracted rules should also be fault tolerant. A promising approach to this is to use a fuzzy set calculus [Ultsch/91b], [Yi/92] and others. We will extend our ideas into that direction in the near future.

References

[Deichsel/85] Deichsel, G, Trampisch, "Clusteranalyse und Diskriminanzanalyse", Fischer 1985
[Kohonen /89] Kohonen, T. "Self-Organization and Associative Memory" 1989.
[Mueller/89] Müller, F.; Seifert, O., "Taschenbuch zur medizinisch-klinischen Diagnostik", Springer 1989
[Ultsch/*] These references can be accessed over: http://www.mathematik.uni-marburg.de/~wina/index.html
[Yi/92] Yi, H.J., Oh, K.W. "Neural Network-based Fuzzy Prodection Rule Generation and Its Application to an Approximate Reasoning Approach" in Proc. of 2nd. Int.Conf. on Fuzzy Logic and Neural Networks. 1992.

Ultsch, A.; Farsch, S.; Li, H.: Automatic Aquisition of Medical Knowledge from Data Sets with Neural Networks, in KI `95, Bielefeld, Advances in Artifical Intelligence, Springer 1995, pp 258-260.