



Review

A Review of Machine Learning's Role in Medical Diagnosis, Revised and Updated

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ABSTRACT

This study surveys the evolution of machine learning-based intelligent data analysis in healthcare, including its origins, current state of the art, and potential future directions. The goal of the article is not to provide a broad overview, but rather to highlight some subfields and future prospects that, in my opinion, will be crucial for medical diagnosis using machine learning. My focus in the historical review is on decision trees, neural networks, and the naïve Bayesian classifier. I provide a comparison of many medical diagnostic tasks performed by state-of-the-art systems that represent each area of machine learning. Two examples show the patterns that will emerge in the future. The first one talks about a new approach to dealing with classifier reliability that might be useful for medical intelligent data analysis. While complementary medicine is not (now) recognized by conventional medicine, it has the potential to become an integral part of medical diagnosis and treatment in the future. The second article explains a method to use machine learning to validate some inexplicable events in this field.

Keywords

Machine learning; Artificial intelligence.

INTRODUCTION

A subfield of computer science, artificial intelligence seeks to imbue computers with human-level intelligence. The ability to learn is fundamental for any behavior that can be considered intelligent. Modern scholarship is almost unanimous in its assertion that learning is essential to intelligence. Consequently, machine learning is a significant area of AI and one of the fastest growing subfields of AI study (Shavlik and Dietterich, 1990; Michie et al., 1994; Mitchell, 1997; Michalski et al., 1998).

From their inception, medical data sets have been the focus of machine learning algorithms. Machine learning has evolved into a set of indispensable resources for smart data analysis. Particularly in recent years, the rise of digital technology has made accessible and affordable

ways to gather and keep the information. Data is collected and disseminated in massive information systems in modern hospitals, which are well-equipped with monitoring and other data collecting technologies. Currently, machine learning is a good fit for medical data analysis; specifically, there is a lot of effort put into medical diagnosis for minor specialized diagnostic difficulties.

Specific hospitals or their departments typically have medical records

that may provide information on accurate diagnosis. Running a learning algorithm on patient data that already have a valid diagnosis is all that's needed. While this is obviously oversimplifying things, the idea behind automated derivation of medical diagnostic information from descriptions of previously solved instances is sound. One possible use of the generated classifier is to aid doctors in making faster, more accurate, and more reliable diagnoses on new patients. Another is to teach medical students and general practitioners how to diagnose patients with complex medical conditions.

The purpose of this paper is to offer a historical overview, a current state of the art overview, and a view on some future trends in this subfield of applied artificial intelligence regarding the development of intelligent data analysis in medicine from a machine learning perspective. The three sections that follow are described in turn. Rather than attempting to provide a full overview, each of the three parts focuses on a certain subarea and some directions that, in my opinion, are crucial for medical diagnosis. My focus in the historical review is on decision trees, neural networks, and the naïve Bayesian classifier. In Section 3, a number of medical diagnostic tasks are compared using state-of-the-art systems, with one or two examples from each discipline of machine learning. Two examples show the patterns that will emerge in the future. In Section 4.1, we learn about a newly proposed approach to handling the dependability of classifier choices;



this approach shows promise for intelligent medical data processing. Although complementary medicine is not (now) recognized by conventional medicine, it has the potential to contribute significantly to medical diagnosis and treatment in the future. In Section 4.2, we outline a method for utilizing machine learning to validate some inexplicable events from this field.

2 Historical overview

The development of algorithms that allowed for the modeling and analysis of massive datasets began with the introduction of electronic computers in the 1950s and 1960s. Three main subfields in machine learning developed early on. Nilsson (1965), Hunt et al. (1966), and Rosenblatt (1962) detail classical work in statistical techniques, neural networks, and symbolic learning, respectively. Artificial neural networks, pattern recognition, and inductive learning all advanced over the years (Michie et al., 1994). Among these methods are top-down induction of decision trees, discriminant analysis, and Bayesian classifiers; artificial neural networks with backpropagation learning, multilayered feedforward neural networks, and the Hopfield's associative memory are all examples of artificial neural networks.

2.1 The naive Bayesian classifier

I limit the historical overview of statistical methods to the naive Bayesian classifier. From the very beginning I was very interested in it. The algorithm is extremely simple but very powerful, and later I discovered that it can provide also comprehensive explanations which was confirmed in long discussions with physicians.

I was fascinated with its efficiency and ability to outperform most advanced and sophisticated algorithms in many medical and also non-medical diagnostic problems. For example, when compared with six algorithms, described in Section 3, the naive Bayesian classifier outperformed all the algorithms on five out of eight medical diagnostic problems (Kononenko et al., 1998). Another example is a hard problem in mechanical engineering, called mesh design. In one study, sophisticated inductive logic programming algorithms achieved modest classification accuracy between 12 and 29% (Lavrač and Džeroski, 1994; Pompe and Kononenko, 1997) while the naive Bayesian classifier achieved 35%. The naive Bayesian classifier became for me a benchmark algorithm that in any medical domain has to be tried before any other advanced method. Other researcher had similar experience. For example, Spiegelhalter et al. (1993) were for several man-months developing an expert system based on Bayesian belief networks for diagnosing the heart disease for new-born babies. The final classification accuracy of the system was 65.5%. When they tried the naive Bayesian classifier, they obtained 67.3%.

The theoretical basis for the successful applications of the naive Bayesian classifier (also called simple Bayes) and its variants was developed by Good (1950; 1964). We demonstrated the efficiency of this approach in medical diagnosis and other applications (Kononenko et al., 1984; Cestnik et al., 1987). But only in the early nineties the issue of the transparency (in terms of the sum of information gains in favor or against a given decision) of this approach was also addressed and shown successful in the applications in medical diagnosis (Kononenko, 1989; 1993). This issue is addressed in more detail in Section 3.4 and illustrated in Table 2.

Lately, various variants and extensions of the naive Bayesian classifier have been developed. Cestnik (1990) developed the m-estimate

of probabilities that significantly improved the performance of the naive Bayesian classifiers in several medical problems. Kononenko (1991) developed a semi-naive Bayesian classifier that goes beyond the "naivety" and detects dependencies between attributes. The advantage of fuzzy discretization of continuous attributes within the naive Bayesian classifier is described in (Kononenko, 1992). Langley (1993) developed a system that uses the naive Bayesian classifier in the nodes of the decision tree. Pazzani (1997) developed another method for explicit searching of dependencies between attributes in the naive Bayesian classifier. The transparency of the naive Bayesian classifier can be further improved with the appropriate visualization (Kohavi et al., 1997).

2.2 Neural networks

After Rosenblatt (1962) developed a basic delta learning rule for single layered perceptrons, Minsky and Papert (1969) proved that this rule cannot solve nonlinear problems. Only few scientists continued with research of neural networks. The field gained a prominent impulse with the seminal works of Hopfield (1982; 1984) on associative neural networks and even more with the publication of the backpropagation learning rule for multilayered feedforward neural networks (Rumelhart et al., 1986). This learning rule and its variant enabled the use of neural networks in many hard medical diagnostic tasks. However, neural networks were typically used as black-box classifiers lacking the transparency of generated knowledge and lacking the ability to explain the decisions. Lately, many advanced variants of neural network algorithms were developed and some do provide for the transparency of decisions (Haykin, 1994).

At the very beginning I was very enthusiastic with neural networks. When I read papers by Hopfield (1982; 1984) and Rumelhart et al. (1986) for the first time in my life I had a feeling that I understand how neurons in the brain can do useful computations. The early inspiration led to my Ph.D. thesis on Bayesian neural networks (Kononenko, 1989a) but later my research interest moved back to symbolic learning.

2.3 Symbolic learning

Probably the most promising area for medical data analysis was from the very beginning the symbolic learning of decision trees and decision rules. Hunt et al. (1966) used their Concept Learning System (CLS) for building decision trees in medical diagnosis and prognosis. They state (p. 170):

"In medicine fairly large files of records may be obtained in the course of routine hospital administration or from a special survey. Such records are often examined in order to plan an intensive, and perhaps expensive, specialized investigation. A drawback to this research strategy is that it is difficult to organize large files of records to reveal complex interactions in a manner that can be understood by the human investigator. Some help can be obtained by using computer oriented techniques of information retrieval, such as program to print selected two- and three-way tables plotting one variable against another. The investigator still must nominate the variable in which he is interested, since such programs have no way of discovering interesting patterns on their own. A CLS program, on the other hand, is designed to do precisely this."



Generating decision trees and decision rules became an active research area after Quinlan (1979) developed the famous Iterative Dichotomizer 3 (ID3) algorithm and Michalski and Chilausky (1980) successfully applied the system AQ in a plant disease diagnostic task. Bratko and Mulec (1980) applied ID3 to a hard diagnostic problem in oncology and later various descendants of ID3 were developed and successfully applied to various medical diagnostic problems. For example, our system Assistant (Kononenko et al., 1984; Cestnik et al., 1987) was applied to various problems in oncology (localization of primary tumor, prognosing the recurrence of breast cancer, lymphography), urology (lower urinary tract dysfunctions), and the prognosis of survival in hepatitis. Independently of ID3, Breiman et al. (1984) developed the system CART and applied it to several diagnostic and prognostic tasks in cardiology and oncology.

A very incomplete and only illustrative list of applications of machine learning in medical diagnosis in the eighties include applications in oncology (Elomaa & Holsti, 1989), liver pathology (Lesmo et al., 1982), diagnosis of thyroid diseases (Horn et al., 1985; Hojker et al., 1988; Quinlan et al., 1987), rheumatology (Kononenko et al., 1988; Karalić & Pirnat, 1990; Kern et al. 1990), diagnosing craniostenosis syndrome (Baim, 1988), dermatoglyphic diagnosis (Chan & Wong, 1989), cardiology (Bratko et al., 1989; Clark & Boswell, 1991; Catlett, 1991), neuropsychology (Muggleton, 1990), gynaecology (Nunez, 1990), and perinatology (Kern et al., 1990).

In nineties the Relief algorithm and its successors were developed (Kira and Rendell, 1992a,b; Kononenko, 1984; Robnik-Sikonja and Kononenko, 1997) that enabled the estimation of the quality of each attribute in the context of other attributes. This amazing algorithm not only significantly improved the applicability of the induction of decision trees and similar algorithms but also improved the transparency of decision trees. The structure of generated trees was more human-like, which was confirmed in several diagnostic tasks (Kukar et al., 1996; Kononenko et al., 1998).

3 State of the art

In this section we give a description of specific requirements that any machine learning system has to satisfy in order to be used in the development of applications in medical diagnosis. Several learning algorithms are briefly described. We compared the performance of all the algorithms on several medical diagnostic and prognostic problems and their appropriateness for applications in medical diagnosis is discussed.

3.1 Specific requirements for machine learning systems

For a machine learning (ML) system to be useful in solving medical diagnostic tasks, the following features are desired: good performance, the ability to appropriately deal with missing data and with noisy data (errors in data), the transparency of diagnostic knowledge, the ability to explain decisions, and the ability of the algorithm to reduce the number of tests necessary to obtain reliable diagnosis. In this section we first discuss these requirements. Then we overview a comparison study (Kononenko et al., 1998) of seven representative machine learning algorithms to illustrate more concretely the points made.

Good performance: The algorithm has to be able to extract significant information from the available data. The diagnostic accuracy on new cases has to be as high as possible. Typically, most of the algorithms perform at least as well as the physicians and often the classification accuracy of machine classifiers is better than that of physicians when using the same description of the patients. Therefore, if there is a possibility to measure the accuracy of physicians, their performance can be used as the lower bound on the required accuracy of a ML system in the given problem.

In the majority of learning problems, various approaches typically achieve similar performance in terms of the classification accuracy although in some cases some algorithms may perform significantly better than the others (Michie et al., 1994). Therefore, a priori almost none of the algorithms can be excluded with respect to the performance criterion. Rather, several learning approaches should be tested on the available data and the one or few with best estimated performance should be considered for the development of the application.

Dealing with missing data: In medical diagnosis very often the description of patients in patient records lacks certain data. ML algorithms have to be able to appropriately deal with such incomplete descriptions of patients.

Dealing with noisy data: Medical data typically suffer from uncertainty and errors. Therefore machine learning algorithms appropriate for medical applications have to have effective means for handling noisy data.

Transparency of diagnostic knowledge: The generated knowledge and the explanation of decisions should be transparent to the physician. She should be able to analyse and understand the generated knowledge. Ideally, the automatically generated knowledge will provide to the physician a novel point of view on the given problem, and may reveal new interrelations and regularities that physicians did not see before in an explicit form.

Explanation ability: The system must be able to explain decisions when diagnosing new patients. When faced with an unexpected solution to a new problem, the physician shall require further explanation, otherwise she will not seriously consider the system's suggestions. The only possibility for physicians to accept a "black box" classifier is in the situation where such a classifier outperforms by a very large margin all other classifiers including the physicians themselves in terms of the classification accuracy. However, such situation is typically highly improbable.

Reduction of the number of tests: In medical practice, the collection of patient data is often expensive, time consuming, and harmful for the patients. Therefore, it is desirable to have a classifier that is able to reliably diagnose with a small amount of data about the patients. This can be verified by providing all candidate algorithms with a limited amount of data. However, the process of determining the right subset of data may be time consuming as it is essentially a combinatorial problem. Some ML systems are themselves able to select



an appropriate subset of attributes, i.e., the selection is done during the learning process and may be more appropriate than others that lack this facility.

3.2 Brief description of some state-of-the-art algorithms

In this subsection we briefly describe seven representative algorithms from symbolic learning, statistical learning and neural networks: three decision tree builders (Assistant-R, Assistant-I, and LFC), two variants of the Bayesian classifiers (the naive and the semi-naive Bayesian classifier), a state of the art neural network which uses the backpropagation learning with weight elimination, and the k-nearest neighbors algorithm.

Assistant-R: is a reimplementation of the Assistant learning system for top down induction of decision trees (Cestnik et al., 1987). The main difference between Assistant and its reimplementation Assistant-R is that ReliefF is used for attribute selection (Kononenko, 1994). ReliefF is an extended version of RELIEF, developed by Kira and Rendell (1992a;b), which is a non-myopic heuristic measure that is able to estimate the quality of attributes even if there are strong conditional dependencies between attributes. In addition, wherever appropriate, instead of the relative frequency, Assistant-R uses the m-estimate of probabilities, which was shown to often improve the performance of machine learning algorithms (Cestnik, 1990).

Assistant-I: A variant of Assistant-R that instead of ReliefF uses information gain for the selection criterion, as the original Assistant does.

LFC: Ragavan et al. (1993; Ragavan and Rendell, 1993) use limited lookahead in their LFC (Lookahead Feature Construction) algorithm for top down induction of decision trees to detect significant conditional dependencies between attributes for constructive induction. LFC generates binary decision trees. At each node, the algorithm constructs new binary attributes from the original attributes, using logical operators (conjunction, disjunction, and negation). From the constructed binary attributes, the best attribute is selected and the process is recursively repeated on two subsets of training instances, corresponding to two values of the selected attribute.

5 Discussion

A look back at machine learning's evolution and its uses in healthcare diagnostics reveals the emergence of systems, techniques, and algorithms that allow for complex data analysis, progressing from basic and straightforward to use. The massive amounts of data created and saved by contemporary technology will further elevate the significance of intelligent data analysis in the years to come. Tools provided by modern machine learning algorithms may greatly aid medical professionals in discovering intriguing correlations in their data.

The results of our tests demonstrate that different classifiers exhibit similar performance in medical areas. The classifier's capacity to explain its results is, hence, an essential consideration. Based on our studies, doctors really like the Bayesian classifier explanations and Assistant-R and LFC are decision tree classifiers. The optimal ap-

proach, it appears, is to employ all of the classifiers and mix their decisions when tackling new issues, rather than picking one top classifier. The doctors agreed that using many classifiers was the best approach to making diagnostic systems more accurate and easier to understand. It is important to combine the classifiers appropriately and consider their dependability on the new example, as shown clearly by Kukar (2001) findings.

Here are our thoughts on machine learning's potential future impact on medical diagnosis:

There has been a lack of acceptance of machine learning technology in medical diagnostics despite the obvious technological potential. This disparity between technological potential and actual use, however, is unlikely to persist for much longer.

One of the most plausible explanations for the sluggish adoption rate is the fact that doctors will have even more tools and equipment at their disposal with the advent of machine learning technology. Even though doctors already have their hands full with complex cases, each new instrument has the unintended consequence of making things even more difficult. As a result, current instruments must include machine learning technology in a way that makes its usage seem natural and easy.

- Just like any other tool at a doctor's disposal, machine learning based diagnostic tools will be used as a potential source of helpful information for improving diagnostic accuracy. As is customary, the onus and discretion to accept or reject this data will ultimately rest with the doctor.

- The amount of money individuals spend on different complementary medicine treatments is another indicator of the growing importance of complementary medicine in recent years. As more and more doctors see the value in supplementary medicine, verification processes are necessary before doctors can officially recognise the advantages and provide licenses to practice them. Because data analysis is open and accessible, machine learning may be a game-changer in this process.

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