Collaborative learning based on associative models: Application to pattern classification in medical datasets

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ABSTRACT

This paper addresses social networking and collaborative learning in the medical domain by focusing on two main objectives: the first one concerns about social networking between computer science experts and postgraduate students, while the second concerns about collaborative learning between medical experts and less experienced physicians. The tasks of algorithms testing and performance evaluation were assigned to computer science postgraduate students. They made extensive use of social networking in order to implement associative models to perform pattern classification tasks in medical datasets and share performance results. Associative memories have a number of properties, including a rapid, compute efficient best-match and intrinsic noise tolerance that make them ideal for diagnostic hypothesis-generation processes in the medical domain. Using supervised machine learning algorithms allows less experienced physicians to compare their diagnostic results between workgroups and verify whether their knowledge is consistent with the results delivered by computational tools. Throughout the experimental phase the proposed algorithm is applied to help diagnose diseases; particularly, it is applied in the diagnosis of five different problems in the medical field. The performance of the proposed model is validated by comparing classification accuracy of DAM against the performance achieved by other twenty well known algorithms. Experimental results have shown that DAM achieved the best performance in three of the five pattern classification problems in the medical field. Similarly, it should be noted that our proposal achieved the best classification accuracy averaged over all datasets. Experimental results confirm that the proposed algorithm can be a valuable tool for promoting collaborative learning among less experienced physicians.

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1. Introduction

In the last decade, emerging information and communication technologies has formulated a new challenging environment for human knowledge acquisition and learning abilities (Lytras & Ordez de Pablos, 2009; Vargas-Vera & Lytras, 2008; Vossen, Lytras, & Koudas, 2007). This technological evolution has also changed human behavior in social networking and social learning (Lytras, 2010; Lytras & de Pablos, 2011). Social learning presents an intensive interaction between a wide varieties of disciplines, such as educational data mining (Lytras & Kurilovas, 2014), business

intelligence, cyberlearning and machine learning for predictive analytics (Zhuhadar, Yang, & Lytras, 2013).

Collaborative-based learning (CBL) is used in many academic fields. Some of the most innovative implementations first appeared in business education (Lainema & Nurmi, 2006), later in engineering education (Zottmann et al., 2013) and lately in medical education (Cavaleri et al., 2010; Stephan, Connors, Arora, & Brey, 2013). Recently CBL has attracted much attention of research groups worldwide, mainly focused on computational tools that help to promote collaborative learning in the medical domain (Rafael & Jos, 2013; Schaf, Mller, Bruns, Pereira, & Erbe, 2009). Medicine is a challenging subject to teach and learn: the knowledge to be acquired is broad and complex. Moreover, this knowledge is useful only if it can be applied to problems presented by real patients. Such intrinsic characteristics of the medical information make of medicine a fertile ground for the development of computational

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tools that help less experienced physicians to assess the acquired knowledge and to contrast against the knowledge of an expert group. Nowadays there are lots of information related to medical conditions. Such amount of information is typically grouped as datasets stored in learning repositories. One of the most widely used is run by the University of California at Irvine (Asuncion & Newman, 2007). These datasets are used to train pattern recognition algorithms and evaluate their performance. Thus we can addresses social networking and collaborative learning in the medical domain by focusing on two main objectives: the first one concerns about social networking between computer science experts and postgraduate students, while the second concerns about collaborative learning between medical experts and less experienced physicians.

Pattern recognition has existed for many years in a wide range of human activity, however, the general pattern recognition problem can be stated in the following form: Given a collection of objects belonging to a predefined set of classes and a set of measurements on these objects, identify the class of membership of each one of these objects by a suitable analysis of their measurements (features) (Duda, Hart, & Stork, 2001). At present, Pattern recognition comprises a vast body of methods supporting the development of numerous applications in many different domains (Jain, Duin, & Mao, 2000). Medical diagnosis is one of the domains in which computer science have contributed importantly, demonstrable successes of Artificial Intelligence (AI) have resulted in the emergence of knowledge-based applications and, more particularly, on decision support systems (Aldape-Pérez, Yáñez-Márquez, Camacho-Nieto, & Argüelles-Cruz, 2012; Ince, Kiranyaz, Pulkkinen, & Gabbouj, 2010; Jiang, Trundle, & Ren, 2010; Pombo, Arajo, & Viana, 2014; Seera & Lim, 2014). Unlike most daily decisions, many health-care decisions have important implications for the quality of life of the patient, and involve significant uncertainties and trade-offs. The uncertainties may be about the diagnosis, the accuracy of available diagnostic tests, the prevalence of the disease and its attendant risk factors. For such complex decisions, which are inherently affected by so many uncertainties, it is indispensable to have computational tools that help to identify which variables of the problem should have a major impact on our decision. It is also needed to apply effective mathematical models, as well as efficient algorithms that allow decreasing the level of uncertainty in the diagnosis of the disease. Early models of learning matrices appeared more than four decades ago (Steinbuch, 1961, 1964; Steinbuch & Frank, 1961), and since then associative memories have attracted the attention of major research groups worldwide. From a connectionist model perspective an associative memory can be considered a special case of the neural computing approach for pattern recognition (Kazmierczak & Steinbuch, 1963; Kohonen, 1972; Steinbuch & Widrow, 1965). Furthermore, associative memories have a number of properties, including a rapid, compute efficient best-match and intrinsic noise tolerance that make them ideal for many applications (Acevedo-Mosqueda, Yáñez-Márquez, & Acevedo-Mosqueda, 2013; López-Yáñez, Sheremetov, & Yáñez-Márquez, 2014; Martín, Yáñez-Márquez, Gutierrez-Tornes, & Riverón, 2008). As a consequence, associative memories have emerged as a computational paradigm to efficiently solve pattern recognition tasks.

This paper addresses social networking and collaborative learning in the medical domain by focusing on two main objectives: the first one concerns about social networking between computer science experts and postgraduate students, while the second concerns about collaborative learning between medical experts and less experienced physicians.

The paper is organized as follows. In Section 2, a succinct description of associative memories fundamentals is presented. In Section 3, Linear Associator technical details are presented. In Section 4, Delta Associative Memory mathematical foundations are presented. Section 5 provides a concise description of the most important characteristics of the datasets that were used as test sets to validate the experimentation. Section 6 provides a brief description of each of the algorithms that were used during the experimental phase. Section 7 describes how the experimental phase was conducted. In Section 8, a consistent comparison between the classification performance achieved by our proposal and the classification performance achieved by some well known algorithms in different pattern classification problems is presented.

In Section 9, classification accuracy results achieved by each one of the compared algorithms in five different pattern classification problems in the medical field are presented. Finally some conclusions will be discussed in Section 10.

2. Associative memories

An associative memory $\mathbf{M}$ is a system that relates input patterns and output patterns as follows:

$$\mathbf{x} \rightarrow \boxed{\mathbf{M}} \leftarrow \mathbf{y}$$

with $\mathbf{x}$ and $\mathbf{y}$ the input and output pattern vectors, respectively. Each input vector forms an association with its corresponding output vector. For each γ integer and positive, the corresponding association will be denoted as: $(\mathbf{x}^\gamma, \mathbf{y}^\gamma)$. An associative memory $\mathbf{M}$ is represented by a matrix whose ij-th component is m_{ij}. An associative memory $\mathbf{M}$ is generated from an *a priori* finite set of known associations, called the fundamental set of associations. If μ is an index, the fundamental set is represented as: $\{(\mathbf{x}^\mu, \mathbf{y}^\mu)|\mu = 1, 2, \ldots, p\}$ with p as the cardinality of the set. The patterns that form the fundamental set are called fundamental patterns. If it holds that $\mathbf{x}^\mu = \mathbf{y}^\mu \quad \forall \mu \in \{1, 2, \ldots, p\}, \mathbf{M}$ is autoassociative, otherwise it is heteroassociative; in this case, it is possible to establish that $\exists \mu \in \{1, 2, \ldots, p\}$ for which $\mathbf{x}^\mu \neq \mathbf{y}^\mu$. If we consider the fundamental set of patterns $\{(\mathbf{x}^\mu, \mathbf{y}^\mu)|\mu = 1, 2, \ldots, p\}$ where n and m are the dimensions of the input patterns and output patterns, respectively, it is said that $\mathbf{x}^\mu \in A^n, A = \{0, 1\}$ and $\mathbf{y}^\mu \in A^m$. Then the j-th component of an input pattern $\mathbf{x}^\mu$ is $x_j^\mu \in A$. Analogously, the i-th component of an output pattern $\mathbf{y}^\mu$ is represented as $y_i^\mu \in A$. Therefore the fundamental input and output patterns are represented as follows:

$$\mathbf{x}^\mu = \begin{pmatrix} x_1^\mu \\ x_2^\mu \\ \vdots \\ x_n^\mu \end{pmatrix} \in A^n \qquad \mathbf{y}^\mu = \begin{pmatrix} y_1^\mu \\ y_2^\mu \\ \vdots \\ y_m^\mu \end{pmatrix} \in A^m$$

A distorted version of a pattern $\mathbf{x}^\gamma$ to be recalled will be denoted as $\widetilde{\mathbf{x}}^\gamma$. An unknown input pattern to be recalled will be denoted as $\mathbf{x}^\omega$. If when an unknown input pattern $\mathbf{x}^\omega$ is fed to an associative memory $\mathbf{M}$, happens that the output corresponds exactly to the associated pattern $\mathbf{y}^\omega$, it is said that recalling is correct.

3. Linear associator

The *Linear Associator* is a heteroassociative memory that can easily work as a binary pattern classifier if output patterns are appropriately chosen. However, this mathematical model undergoes fundamental patterns misclassification whenever fundamental input pattern cross-talk influence occurs.