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Organizational Development In Institutions Providing Health Services In The Generation Of Innovation

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ABSTRACT

Automatic learning offers organizations a wide range of benefits. However, in small and medium-sized enterprises, progress in such terms is very incipient. To assess the most important aspects of this new trend in knowledge management for the business world, the most competitive aspects are presented, compiled in an explanatory document that can serve as a reference for training professionals, entrepreneurs, and industrialists.

Keywords: Knowledge Management, Innovation, Competitiveness, Information Management, Global Environment.

1 INTRODUCTION

Machine Learning (ML) is a term coined by Samuel in 1959 [1], referring to a group of computer displaying approaches that can gain designs from information to settle on programmed choices without programming express principles; the primary thought of the ML is to actually utilize encounters or model situations to find hidden constructions, similitudes, or dissimilarities present in the information, to accurately make sense of or arrange another experience or model situation [2]. Kourou et al. [3] state that the main purpose of ML techniques is to produce a model that can be used for classification, prediction, estimation, or any other similar task. Since learning and reasoning are two essential skills associated with intelligence, learning and automatic reasoning, they have received much attention during the short history of technological development [4].

2 METHODOLOGY

The methodological strategy that guided the research was the documentary review with a qualitative approach, in this order of ideas, it can be mentioned that this technique allowed an exhaustive analysis of the most predominant theoretical foundations and references in knowledge explored. In the literature, the importance and relevance of this method is explained according to the objectives that are proposed, since it facilitates the analysis and orderly interpretation of different sources, to extract the most significant ideas [7].

Documentary research provides a method of systematic analysis of secondary sources made up of scientific articles, official documents of recognized organizations, memoirs, among others, that allows critical reflections on the theoretical positions of a specific topic. To achieve this goal, the most representative and important databases, repositories, and academic journals were searched to collect the current theoretical perspectives, with the support of the academic search engines offered by the Internet.

3 Automatic learning for SME's

Automatic learning is a subdivision of artificial intelligence that uses pattern recognition software to analyze large amounts of data in search of predicting behavior, that is, learning from story activities to achieve prediction of future behaviors [5]. When confronted with data of high dimension and complexity, automatic learning algorithms provide efficient alternatives and generally show greater accuracy [6].

ML is optimal to address problems where the theory of knowledge is still incomplete, but where there is a significant number of observations and data, on the other hand, prior knowledge of the nature of the relationships between data is not indispensable [7,8]; mastery of these tools makes it possible to develop a robust learning system from the combination of data, availability constraints and highly complex problems [8]. Wuest et al. [9] identified the main benefits of using Machine Learning (ML) methods:

- Faculty to manage large troubles and datasets mean plausible endeavors.
- Capability to make less the potentially complex nature of the results and provide transparent and concrete advice to practitioners.
- Capacity to adapt to a changing environment with reasonable effort and cost.
- Ability to expand existing knowledge, based on learning from results
- Possibility of working with the available data, without requiring special characteristics from the capture of the information.
- Ability to identify relevant processes in interrelationships and interrelationships to determine correlation and/or causation.

The modeling capabilities with ML-based methods have given it great utility in science and engineering applications, whose examples are shown in Figure 1, such as geoscience, in relation to geophysics and remote sensing of tectonic movements [7], biomedicine, with mitochondrial modeling [10], genetics [11], diagnostics based on image analysis [12][13], client prospecting [8], or the detection of feelings expressed on social networks, in order to provide useful information for advertising campaigns [14]. At a time when "big data" is in vogue, with large volumes of information, Machine Learning solves problems that would otherwise be insoluble or difficult to deal with [15].

Figure 1. Application examples of automatic learning

Automatic learning is a type of artificial intelligence (AI) that allows programming applications to become more precise at forecasting outcomes without being explicitly programmed to do so, such as the neural network, support vector machines, decision trees, random forests, and genetic programming, among others [7].

The learning process is made up of two phases [3]:

- Estimation of unknown dependencies in a system of a given dataset and
- Use of dependency estimates to predict new system outputs.

Generally, a large fraction of the data set, known as the "training data set", representing the population, used to calibrate the machine learning model is used, and once this stage is completed, the different data set is taken to validate the learned of this model; as long as the accuracy of the model is high enough, the model can be routinely used to identify, classify, quantify and predict the main characteristics of a system [2].

Accordingly, the selection of variables is the main problem of automated learning since a subset of the functions available for the capture of relevant properties from the data must be chosen [16]. The component base is made up of data samples; each sample is described by several characteristics, and each characteristic is made up of different types of values; if the specific type of data required is known ahead of time, the correct selection of tools and techniques that can be used for its analysis is made possible [3]. These characteristics can be divided into three categories: relevant, redundant, and irrelevant functions; ideally, then, irrelevant, and redundant functions should be discarded, as the former do not provide useful information, and the latter do not add new information to learning processes [16,17].

Similarly, automatic learning methods for character selection can be classified into three types: envelope, filter, and integrated methods. The wrapping methods use the learning algorithm to evaluate the usefulness of the characteristics; the filter methods classify the variables according to a discriminatory measure, selecting those with a higher range, without using learning methods, and the latter uses both types of tools [16].

The prescient precision of the model is determined from the pooled tests that provide a gauge of speculation mistakes; among the most involved strategies for assessing the presentation of a classifier by isolating the underlying labeled information into subsets are [3]:

(i) Holdout Method,
(ii) Random sampling,
(iii) Cross validation and
(iv) Bootstrap.

In the Holdout method, the information tests are divided into two separate sets preparing and test sets, the first being utilized for the grouping model, and the second for model approval; then again, in irregular examining, the Holdout strategy is rehashed a few times to further develop precision, picking arbitrary information for preparing and the test set [3].

In the third approach, each example involves similar number of times for preparing and just a single time for testing; therefore, the first informational index is effectively canvassed in both the preparation and the test set [3]. At last, in the bootstrap approach, tests are isolated with substitution into preparing and test sets, i.e., they are set once more into the total informational index after they have been decided for preparing [3].

Automated learning is classified into three types, known as Supervised, Enhanced and Unsupervised Automatic Learning algorithms, represented in Figure 2 [14]; the first uses a training data set to estimate or assign input data to the desired output, considering the classification stage to be fundamental; while the second has no labelling examples, so there is no idea of the output data from the learning process, so the model must include pattern detection and discovery of the input data sets [3]. Patel et al. [17], on the other hand, state that learning methods can be classified as linear or nonlinear. Although linear methods are simpler, nonlinear methods are more adaptable.

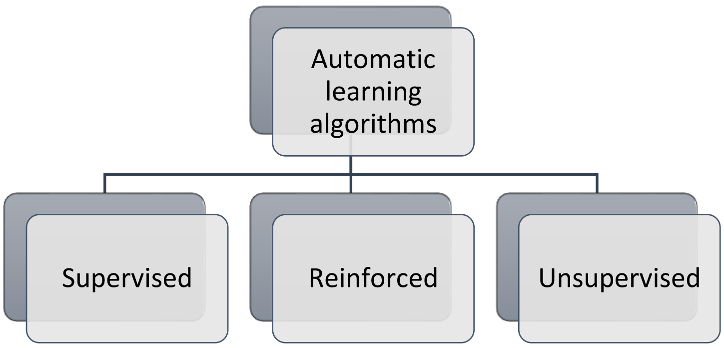

Figure 2. Classification of automatic learning algorithms

In this sense, it is possible to present the most used automatic learning algorithms, which are shown in the figure below.

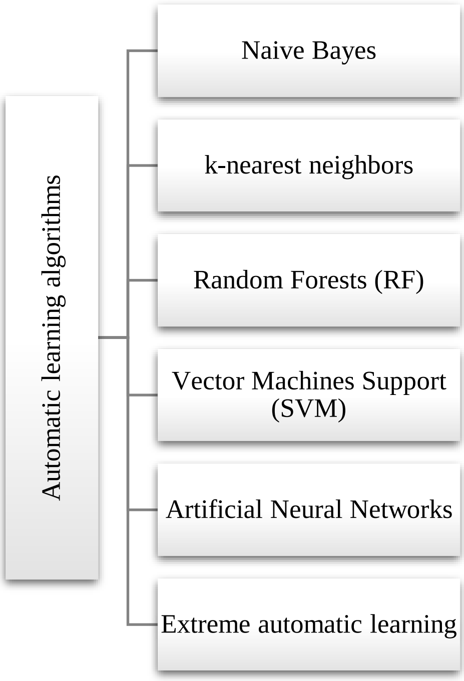

Figure 3. Popular Automated Learning Algorithms

A brief explanation is given for each algorithm indicated in the figure above:

❖ **Naive Bayes**

This algorithm assumes that the inputs are true and independent of each other, reducing the problem of segregation of class to find conditioning marginal densities [18].

❖ **K-nearest neighbors**

During classification, test samples will be purchased individually with a k-nearest neighbors in a variable space, neighbors are commonly identified using the Euclidean metric distance method. To the extent that the k is high, excessive fit and instability in the model may result, and it is therefore necessary to select the appropriate values for a given application [18].

❖ **Random Forests (RF)**

It consists of a set classification scheme that uses a majority of votes to predict classes based on data partitioning from multiple decision trees [18].

❖ **Vector Machines Support (SVM)**

SVM is a collection of managed learning strategies used for grouping, relapse recognition, and exception detection. The benefits of help vector machines are as follows: Effective in densely layered environments. Still effective in situations where the number of aspects is more important than the number of tests [19]. It establishes that for a set of separable data, non-linearly, there are an infinite number of hyperplanes that divide classes; therefore, it uses a subset of training samples as support vectors for the detection of the optimal hyperplane, from the use of the kernel function [18].

❖ **Artificial neural networks**

Artificial Neural Networks (ANNs) are biologically enlivened computational organizations. Artificial Neural Networks are generally utilized for a wide assortment of issues, depend on a directed technique, and contain three layers: input, stowed away, and yield [18].

❖ **Extreme automatic learning**

The latest advancement is Extreme Automatic Learning (ELM), which is a learning calculation for the Single Layer Network Feed-Forward (SLFN) brain framework, which haphazardly picks the loads of the associations between the information sources and the neurons in the secret layer and the predisposition of the neurons in the secret layer and systematically decides the result loads rather than iterative change. The ELM not just has very quick learning ability and test speed, yet additionally will in general accomplish better speculation execution [20].

4 CONCLUSION

According to the information previously reviewed, automatic learning can benefit innovation at the business level, which is why today, is seen as a tool of great impact for any type of company, regardless of the corporate purpose and size, and that from some standardized processes and structural support, would generate valid knowledge for the approach and management in different fields of action [21].

Thus, it is estimated that the product, commercial and service processes would be significantly improved, since the possibility of predicting and simulating operation alternatives could provide a new scenario for the solution of problems in defined environments [22]. Therefore, a change of mentality in the face of training processes in relation to automatic learning would be novel and opportune to achieve a greater approach to global demands for any productive entity.

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