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Support to the human talent subsystems, selection and recruitment from an expert system. Case study

Apoyo a los subsistemas de talento humano, selección y reclutamiento a partir de un sistema experto. Caso de estudio

Karina Matute-Pinos[1,*] and Rodolfo Bojorque-Chasi[2]

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Abstract

Human talent management is a key factor in the success of organizations. The inclusion of people with disabilities in the work environment has helped to enhance their qualities and harness their talent. Many of the human talent management systems lack guidelines for the recruitment and selection of a person with a disability, this is why this work shows the study carried out on these two processes indicating the factors that influence the allocation or not of a position, where for each candidate it is considered the level and type of disability, level of education, experience, training among other aspects, focusing on the task of applying supervised learning techniques that enable us to classify a candidate with a disability as suitable or not for a job, and unsupervised learning techniques such as clustering that helps us define hidden patterns in the data, if any.

Resumen

La gestión de talento humano es un factor fundamental en el éxito de las organizaciones. La inclusión en el entorno laboral de las personas con discapacidad ha ayudado a potenciar sus cualidades y a aprovechar su talento. Muchos de los sistemas de gestión de talento humano carecen de directrices para el reclutamiento y selección de una persona con discapacidad, es por eso por lo que el presente trabajo muestra el estudio realizado a estos dos procesos indicando los factores que influyen en la asignación o no de un cargo, donde de cada candidato es considerando el nivel y tipo de discapacidad, nivel de estudios, experiencia, capacitación entre otros aspectos, enfocándose en la tarea de aplicar técnicas de aprendizaje supervisado que nos permitan clasificar a un candidato con discapacidad para un puesto de trabajo como apto o no y técnicas de aprendizaje no supervisado como el clustering que nos ayuda a definir patrones ocultos en los datos si los hubiera.

[1,*]Maestría en Administración de Empresas, Universidad Politécnica Salesiana, Ecuador.
Corresponding author ✉: kmatute@est.ups.educ.ec.
[2]Universidad Politécnica Salesiana, Ecuador.

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The result obtained from the study presents some classifications techniques and the selection of the most appropriate one for the available dataset. It is not sought to integrate people through their disabilities, but quite the opposite, to integrate people based on the potential of all their abilities.

Keywords: automatic learning, disability, labor inclusion, artificial intelligence, data mining, recruitment process, human resources, expert systems

El resultado obtenido del estudio nos presenta varias técnicas de clasificación y la selección de la más adecuada para el conjunto de datos en cuestión, igualmente mediante técnicas de aprendizaje no supervisado se determina cuántos clústeres representativos se identifican en los datos. No se busca que se integren las personas a través de las discapacidades, sino todo lo contrario, que se integren las personas por medio de la potencialidad de todas sus capacidades.

Palabras clave: aprendizaje automático, discapacidad, inclusión laboral, inteligencia artificial, minería de datos, proceso de reclutamiento, recursos humanos, sistemas expertos

1. Introduction

In recent years different organisms and Governments have considered as an important point in their administration, improving the quality of life of the people with disabilities, such as the case of the Government of Ecuador whose Development Plan points out as one of its goals «To increase the number of people with disabilities and/or substitutes inserted in the labor system for 2021» [1] and thus based on the current Constitution, the Labor Code and the Organic Law of Dissabilities an integration has been achieved that contributes to the inclusion of people with disabilities in the society. In the working environment, selection mechanisms have been gradually created in which processes have been adjusted to enable the participation of people with disabilities seeking gender equity and diversity of disability [2].

The human resources data provide a valuable source of information for discovering knowledge and for developing systems to assist in the decision making when recruiting personnel. Nowadays, organizations have to struggle effectively in terms of cost, quality, service and innovation.

The success of these tasks depends upon having available enough adequate people with the adequate skills, deployed in the appropriate places at the adequate moment, which is known as human talent management. Managing the talent of an organization has become a challenge for human resources professionals, this task implies many managerial decisions to select the right person for the right job at the right moment. At times, these decisions are very uncertain and difficult; and depend on various factors, such as human experience, knowledge, preference and judgement [3]. The talent is considered as the capability of any individual to make a significant difference in the current and future performance of the organization [4].

The recruitment becomes difficult when analyzing the labor inclusion process of people with disabilities. According to the World Health Organization (WHO), in developing countries between 80 % and 90 % of the people with disabilities at working age are currently unemployed, and in industrialized countries the estimation is between 50 % and 70 %.

The barriers for entering the labor market for people with disabilities vary according to the type of disability, and thus, in the process of labor insertion of a person with disability, it is required to take measures that guarantee the access and permanence of this person at the workplace, respecting individuality and type of disability [5]. When a candidate fulfills the adequate profile for a position, the company should manage and perform the necessary changes to the workplace, thus helping to develop the abilities of this person.

In the National Council for the Equality of Disabilities (CONADIS, Consejo Nacional para la Igualdad de Discapacidades) of Ecuador, by June 2020 there were registered [6] 481 392 people with disabilities of which 13 % are occupationally active without considering substitutes, 56.20 % of which have physical disability, followed by 17.12 % with hearing disability, 14.31 % with visual disability, 8.88 % with intellectual disability and, finally, 3.50 % with psychosocial disability. The private sector has 46 496 people with disability on its payroll and the public sector 18 333 people. See Figure 1.

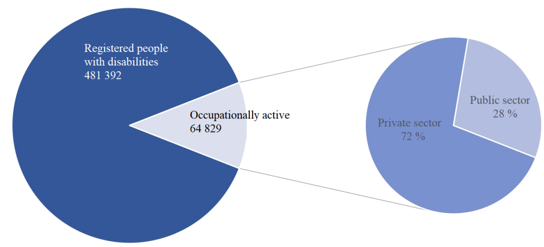

Figure 1. People with disabilities registered in the CONADIS

According to [7], the recruiting process has improved through the implementation of information technologies, which enable simplifying the process of posting vacancies and resumes, listing jobs and seeing possible candidates. However, the recruiting process remains being imperfect and the study mentions three reasons:

1. Some steps of the recruiting process are not automated. As a result, recruiters have to manually process a large number (sometimes hundreds, or even thousands) of resumes to select the best potential employee.

2. In general, recruiters do not take into consideration all possible alternatives for the employee.

3. Recruiters are only guided by their subjective opinion, and thus there is no guarantee that the selected candidate is really the best possible option for the employer.

The contracting and selection of personnel directly affects the quality of the employees. Various studies have been carried out about resumes, interviews, evaluation centers, tests about knowledge of the job, job sample, tests, cognitive tests and personality tests in human resources management, to help organizations to make better decisions in the selection of personnel. In fact, the existing selection approaches are focused on the job duties and the analysis of such duties which are defined thorugh activities and specific tasks based on their static properties [8]. The abovementioned processes generate an important amount of data regarding recruitment, the present study attempts to take advantage of automatic learning techniques on these databases.

Automatic learning consists in the application of statistical techniques to databases for learning hidden patterns, projections or predictions of observations, by means of the application of algorithms valuable information may be automatically extracted from data of a specific domain [9].

The present work is organized as follows, section two presents different works related with the area of artificial intelligence and its application in human resources management, different concepts are introduced when it is considered opportune. Section three presents the working methodology, detailing the applied techniques. Section four shows the relevant results that were obtained and, finally, section five exposes the conclusions of the present work.

1.1. Related works

Organizations are starting to adopt and capitalize the functionality of artificial intelligence in their recruiting processes [10]. The applications of expert systems or systems to assist decision making for selecting and recruiting personnel are increasing [8, 9, 11–14].

For job application and selection, artificial intelligence may use behavioral and physiological (for example, biometrics) features as part of the general decision-making process [10]. Some implementation examples are the use of multimedia tools [15], on-line candidate monitoring systems [16], automatic learning systems [17], systems for supporting decision making which help in the entire process of categorizing and identifying disabilities [9], however, at present the richness of data mining is not being exploited.

Nowadays, there are countless artificial intelligence techniques such as data mining, data analytics and the discovery of information in databases that, by means of automatic learning techniques, provide organizations the tasks of prediction and classification, to support decision making, including human talent management.

Data mining refers to the extraction of patterns or useful rules from an extensive data source, through automatic or semiautomatic exploration and from data analysis [18]. For this work, the application of automatic learning techniques constitutes the data mining process, according to the literature there is the consensus of classifying automatic learning techniques in supervised learning, unsupervised learning and reinforcement learning [19].

The present work focuses on the task of applying supervised learning techniques such as classification and unsupervised learning techniques such as clustering to the database collected in the project of educational and labor inclusion of people with disabilities of the Universidad Politécnica Salesiana.

The supervised techniques enable classifying a candidate with disability as suitable or not for a job post. From the computational point of view, it is a classification task, however, the disability condition biases the data to a very reduced population, first, there is no enough data about them and the sample is limited to the domain of the city of Cuenca-Ecuador.

Classifying is a supervised learning task, where the class or classification objective is known. In data mining, there are various techniques used for classification such as decision trees, Bayesian techniques, fuzzy logic, support vector machines, neural networks, genetic algorithms and the nearest-neighbors algorithm. In the present study various techniques are applied to determine the one that best fits the collected information about the candidates with disabilities.

Clustering consists in finding hidden patterns in the data, natural groupings that are not perceptible in the high dimensionality environment exhibited by modern datasets [19], seventy features in our case. Due to the high dimensionality, the work seeks to determine correlations between the different features in order to eliminate those that show a high correlation index. Similarly, dimensionality reduction techniques were tested.

It is important to mention a research area with strong growth perspective in the field of automatic learning for supporting human resources management, it is natural language processing, and as a current disruptive technology the chatbots handle tasks such as interviews to candidates, personnel training, customer service and any task that requires communication between people and an intelligent agent [20]. In the personnel recruitment area, it is important to mention that the chatbots are capable of handling a significant amount of information that interviewers often overlook [21].

2. Materials and methods

The work [22] was used as base line; such work consists of 120 data samples, with 70 features regarding age, sex, level of education, work experience, foreign language proficiency, type of disability and the transversal skills of each candidate. The original study utilizes a rule-based system validated by experts. Our proposal incorporates as a novelty the learning from the original dataset to predict if a candidate is suitable or not for a position, and thus, through supervised learning techniques the system does not require the validation of experts.

Data dispersion is the most relevant feature of the dataset, i.e., the available matrix is missing information, and such information cannot be considered as 0 in the analysis process because this could bias the results of the analysis. Table 1 shows a summary of the different features of the dataset.

Table 1. Features of the dataset

Type of information	Description
Descriptive information	Descriptive details of each candidate, the most relevant feature in this case is the age and the type of disability
Information about adaptations	Makes reference to the use of auxiliary devices by the candidate, as well as the need to be supported by an interpreter or have developed skills such as the sign language
Education	Level of education of the candidate
Information about the position	Various features that provide information about the details of the position
Information about the experience	Features that collect the past working experience of the candidate
Optimal parameters to apply for a position	Desirable parameters for applying to a position
Parameters obtained by the candidate	Assessment of each candidate in the different parameters
Domain of other languages	Details about the domain of other languages
Training	Features that collect information about trainings received

For this work it was proceeded to impute the data and eliminate those features that do not provide enough information to the system, either because the data collected represented an insignificant amount of the population under study or because the feature presented text type descriptions that do not provide information to the system. After this process, a complete matrix was available.

In order to validate the elimination of features, it was carried out an analysis of the similarities between the original dataset, the one that contains the sparse data; and the dataset after the imputation. Different similarity metrics were used according to study [23], being relevant for our study the Pearson and Jaccard similarities for the complete dataset (with sparsity features), and only the Pearson similarity for the modified dataset.

It may be seen in Equation (1) how the similarity between candidate u and candidate v is calculated in a sparse matrix, where i represents the ith feature and r the value of the feature. In addition, let I' be the set of all common features between u and v.

$$S_{PC}(u,v) = \frac{\sum_{i\in I'}(r_{ui}-\overline{r}_u)(r_{vi}-\overline{r}_v)}{\sqrt{\sum_{i\in I'}(r_{ui}-\overline{r}_u)^2}\sqrt{\sum_{i\in I'}(r_{vi}-\overline{r}_v)^2}} \tag{1}$$

Equation (2) is used to calculate the Jaccard similarity, in this case it is important to determine if there is intersection between the features of u and v without regard of the difference in magnitude between their values.

$$S_{Jac}(u,v) = \left|\frac{I_u \cap I_v}{I_u \cup I_v}\right| \tag{2}$$

Results show that the average of similarity between users within one group of candidates with the same disability is around 0.1, for both Pearson and Jaccard similarities, although it is slightly lower for the latter.

With the modified dataset it does not make sense to apply Jaccard similarity because it will always be equal to one, since it is a complete matrix, however, with Pearson similarity it is obtained an improvement of 0.25 in the similarity average between users within a group of candidates with the same disability, which evidences that eliminating some features simplified the system and improved the results.

Using the new dataset, it was proceeded to generate a color map to determine correlations between the features of the candidates. Figure 2 presents the color map between the most relevant features, where the intersection of each row and column represents the correlation coefficient in the interval [−1 1] where values close to −1 mean a strong inversely proportional correlation and values close to 1 mean a strong directly proportional correlation, values close to 0 mean that there is no correlation.

Figure 2. Color map of the correlations between the most relevant features of the dataset

In this initial analysis it is noteworthy the direct relationship existing between experience and level of disability of the candidate (moderate, mild). On one hand, private companies have a direct relationship with the mild level of disability, and public companies have a direct relationship with the moderate level of disability.

In addition it was proceeded to visualize if there are relationships between the different features through a scatter plot. Figure 3 enables appreciating the dispersion of points between the different pairs of features of the dataset, the diagonal shows the histogram of each feature.

After the statistical analysis it was proceeded to apply data analytics, where this work has two objectives, the first is generating a classification model for the correct allocation of a person to a position. Second, through clustering techniques it is attempted to discover the cohesion of the groups of candidates. In the first case, classification techniques such as logistic regression, support vector machines and the nearest neighbors algorithm, will be compared. In the second case, the k-means clustering algorithm will be used.

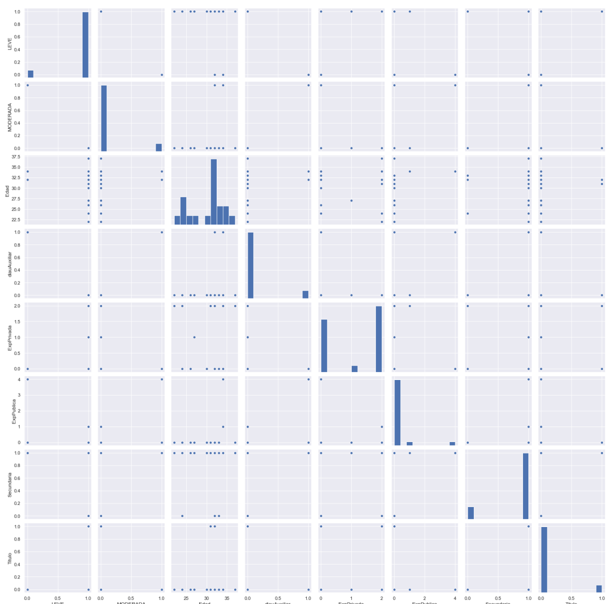

Figure 3. Scatter plots between pairs of features

3. Results and Discussion

3.1. Classification

When designing the model, different classifications techniques were used, including, a binary logistic regression scheme, since the objective is to attempt predicting if a person is suitable or not for the position. The logistic regression was tested with linear, quadratic and cubic hypotheses; techniques such as Support Vector Machines with Gaussian kernel and the k-nearest neighbors algorithm (KNN) for results with 3 and 5 neighbors, were also implemented.

In order to validate the results, the dataset was divided in five random sets for training and testing, in a proportion of 80 % and 20 %, respectively. Results show the average of the five random testing sets. The metric used to compare the quality of the prediction is the precision according to Equation (**??**), where TP represents the number of classifications made correctly (true positives) and b the number of incorrect classifications (false positives).

$$Precisión = \frac{TP}{TP + FP} \tag{3}$$

The results of the different models are shown in Table 2. Even though the best results are obtained with SVM, the difference in precision with logistic regression is not significant, and thus logistic regression may be used for simplifying the model.

Table 2. Results of classification techniques

Technique	Parameters	Precision
Logistic regression	Función lineal	0,805
Logistic regression	Función cuadrática	0,815
Logistic regression	Función cúbica	0,818
SVM	Gaussian Kernel	0,821
KNN	3 neighbors	0,791
KNN	5 neighbors	0,798

3.2. Clustering

The most famous and well-known hard clustering technique is the k-means algorithm [24,25] or hard c-means, which has the following advantages:

a. It is conceptually simple, versatile and easy to implement.

b. It exhibits linear complexity with respect to the number of elements and clusters.

c. It is guaranteed that the algorithm ends with a quadratic convergence rate [26].

To measure the clustering quality, it was used the cohesion measure J_c given by Equation (**??**), where X represents the sample of the candidate under consideration and C represents the centroid to which it belongs.

$$J_c = \sum_{j=1}^{c} \sum_{t=1}^{n} \|X_i - C_j\|^2 \tag{4}$$

The k-means algorithm uses parameter K as the indicator of the groups to be classified, however, the challenge is determining what number of groups should there exist to express the best representation of them. For the dataset of the candidates, it was determined the clustering quality from K = 2 to K = 10. In Figure 4 it can be seen, through the Elbow method [26], that there is no clear determination of the groups of candidates; it might be considered the value K = 3 as well as the value K = 6 as inflection points where the clustering quality stabilizes according to the curve. This indicates that the information that is being collected in the system requires more work, both in quantity and in the quality of the features.

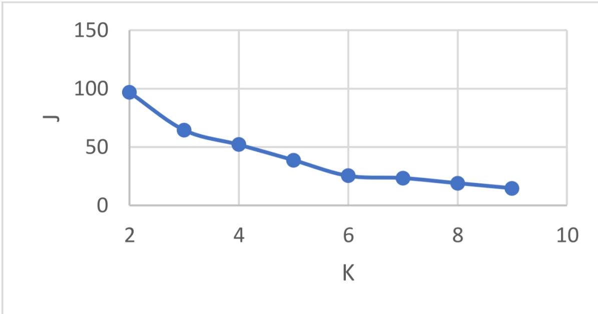

Figure 4. Elbow method for k = 2 hasta k = 10

4. Conclusions

This study enables visualizing the correlations existing between different variables of the dataset, with the novel contribution of incorporating automatic learning techniques, supervised learning to support selection processes of human talent with disability as well as unsupervised learning to determine in the high dimensional space the number of groups existing in the data.

Based on the study conducted it could be observed that the most determinant factor for a person with disability to get a job is the experience, i.e, having previously worked in some place; in the dataset there is a direct correlation between the candidates that were considered suitable and the previous experience, however, the candidates that although being suitable have not been located, have as a common factor not having such experience; this evidences that for the case study, the main feature which determines that a person with disability gets a position is this experience, factor that may be considered discriminatory because it is attentive against equality of opportunities. The dataset used for this work is considered the most comprehensive of its type for selection of personnel with disability, however, the present study has demonstrated that more relevant features are required. It should be mentioned that the study also find limitations in the number of samples, at present the dataset comprises 120 samples which restricts us to the application of automatic learning techniques, for the future it would be interesting to have available a much larger dataset to apply deep learning techniques.

Various studies demonstrate that the level of education improves the opportunity of finding a job [27], situation which is not fulfilled in the dataset used here. Such studies also demonstrate that people with disabilites have a lower level of education, compared to the general population, and this element is easily verifiable in our case study. Academic preparation determines that people with disabilities are disadvantaged for the tasks demanded by the market due to reasons that go beyond the disability itself. Both the training and level of education have significant influence on the job opportunities, because the skills and knowledge within a specific area are acquired in this training process [28]. Current systems continue being discriminatory for these people, because most organizations privilege experience and this induces a poor assessment of the attitudes of these people. This situation is reflected in the quality of the prediction systems and in the inability to discover clear clustering patterms in the data provided.

It is considered that a novel field of study in recruiting processes is the application of chatbots in the personnel selection interviews, because they enable eliminating subjective elements that experts consider as confusion variables that guide the interview in one direction or another, subjective factors such as the personal image perceived by the interviewer and the mood, are elements that are difficult to measure and therefore might be eliminated with an adequate selection of experimental and control groups [29].

While it is true that public policies have contributed to the labor inclusion of people with disabilities, it is necessary that companies supported by technology narrow the currently existing gap, and likewise eliminate the stereotypes that hinder recognizing and enhancing the qualities of people with disabilities thus hindering exploiting their talent.

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