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Human Resources Sptimization with MultiLayer Perceptron: An Automated Selection Tool

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Abstract

This study aims to create an artificial neural network (ANN) model with a multi-layer perceptron (MLP) architecture, designed to analyze the CVs of candidates for the position of sales consultant. To do this, a database of 600 CVs cataloged with scores from 0 to 10 by specialists with experience in recruitment and selection (R&S) is used. Fourteen characteristics are extracted from each CV, including ordinal and nominal attributes. A model with 3 hidden layers is used, which is trained with a split of 80% for training and 20% for testing. The activation function chosen for the hidden layers is the Rectified Linear Unit (ReLU), using the "adam" optimizer with a backpropagation algorithm during training using the Mean Squared Error (MSE) performance metric. The results show that the model is effective, giving a Mean Absolute Error (MAE) of 0.33, MSE of 0.37, Root Mean Squared Error (RMSE) of 0.61, and an r² Score of 0.96. These data not only confirm MLP's ability to replicate human accuracy but also suggest that such technologies can provide a faster and less biased tool for evaluating CVs. This performance of ANN indicates avenues for future research into the integration of other Artificial Intelligence (AI) technologies to refine the interpretation of less quantifiable characteristics, as well as making the process of R&S of new candidates in companies more agile.

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1. Introduction

Automation in Recruitment and Selection (R&S) is an ever-expanding field, notable for its ability to improve efficiency and reduce bias in the candidate selection process [1]. The use of artificial neural networks (ANN), in particular the MultiLayer Perceptron (MLP), has the potential to revolutionize the way CVs are analyzed, offering a faster and more accurate method compared to traditional human assessments. The MLP is a type of ANN that consists of multiple layers of neurons, each interconnected by weighted connections [9]. Typically, an MLP includes an input layer, one or more hidden layers, and an output layer. Learning takes place by adjusting the weights of the connections. In this case, the backpropagation algorithm is used, which minimizes the error between the model's predictions and the actual results through an iterative optimization process [5]. This study proposes an MLP model with backpropagation made in Python, configured to evaluate the effectiveness of CV selection for the position of sales consultant. The database, made up of 600 CVs, is obtained from research [2]. In that research, human resources (HR) specialists, between January 2014 and December 2018, rate CVs from 0 to 10. The following categories are analyzed: age, gender, technical skills acquired through professional experience (in sales and other areas), courses and training, educational level, and language skills. The number of CVs in the database and their respective scores can be seen in Figure 1.

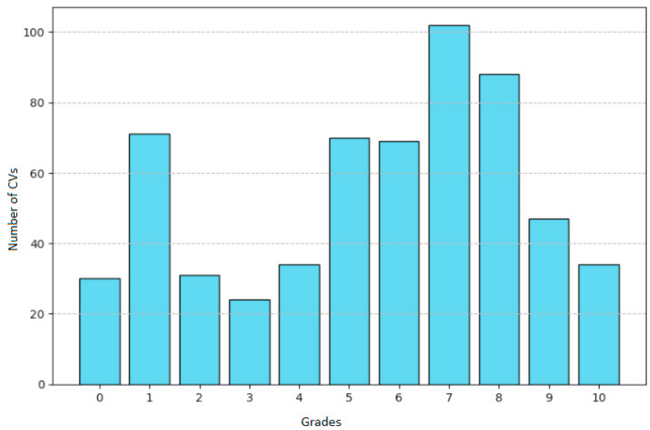

Fig. 1. Graph of the scores for all the CVs in the database.

The use of Machine Learning techniques in R&S represents a significant evolution in traditional HR management methodologies [3, 4]. These techniques enable the automation of complex tasks, such as CV selection, through algorithms that learn patterns and make decisions based on historical data. In this context, ANN with MLP architecture is a promising technique due to its ability to model complex non-linear relationships between inputs and desired outputs [5, 6, 7, 8]. In the field of R&S, MLP can be trained to recognize patterns in vast sets of CVs, learning to single out candidates who best align with the criteria defined for a specific position [10]. By being trained with data that includes information about the candidates and performance feedback from previous hires, MLP can learn to rank new CVs with remarkable accuracy [11].

This is a resource that provides greater transparency in recruitment processes, avoiding bias at the time of screening and selection and improves the candidate's understanding of the process and its objective [4, 11]. The process tends to be more impartial and fairer, thus offering the same opportunity to all competitors for the position [12, 13]. As such, the model is designed to be able to classify CVs more assertively and with errors of low magnitude. This objective stems from the need for tools that can deal with the high demand and high volume of CVs [14], as well as their vast dimensionality and data variability, offering a consistent, fast, and objective assessment [15]. The relevance of this work lies in its ability to contribute to a more agile and fair recruitment practice since CV screening [16] and interviews are the main means of hiring for companies [17]. AI shows promise as it can reduce time and cost in CV screening and candidate selection so that recruiters can devote their efforts directly to the interview stage [13]. Furthermore, by exploring the performance of MLP, this study provides valuable insights into the application of machine learning techniques in the HR field, paving the way for future investigations that can expand and improve automation practices in various selection contexts using other ANN models with good results in other applications [18, 19].

2. Methodology

Before training, the database had to be properly analyzed and processed in order to guarantee its integrity. As this is a representation of the characteristics obtained in a CV, several attributes are considered categorical or nominal, and feeding these attributes directly into the ANN is not recommended [20]. Since the MLP calculates using numbers, it is necessary to use the data processing method available in Python's scikitlearn library, called Sne Hot Encoder, which creates new binary tables according to the information provided, as can be seen in the example in Table 1.

Table 1. Example of a base with categorical attributes before the Sne Hot Encoder.

Curriculum Vitae	**Languages**
CV 1	English
CV 2	English, Portuguese
CV 3	Portuguese, Spanish

Based on the possibilities of information contained in the Languages column, in this case 3 (English, Portuguese, and Spanish), Sne Hot Encoder creates new columns and assigns values of 0 or 1 according to what was previously provided. The new example database can be seen in Table 2.

Table 2. Example of a base with categorical attributes after the Sne Hot Encoder.

Curriculum Vitae	**Language _English**	**Language _Portuguese**	**Language _Spanish**
CV 1	1	0	0
CV 2	1	1	0
CV 3	0	1	1

In this way, each column with categorical attributes is divided into new binary columns representing the presence or absence of each attribute in the CVs. This transformation allows the MLP to process this information efficiently, as it is now presented as numerical variables. Furthermore, by avoiding the use of ordinal coding (1 for English, 2 for Portuguese, and 3 for Spanish) which could imply a non-existent hierarchy or order between the categories, the Sne Hot Encoder maintains the neutrality of the characteristics, allowing the model to make more accurate assessments based only on the presence of certain qualifications, without assuming arbitrary weights. Typically, this type of coding is suitable for categorical variables. The MLP structure used is entirely programmed in the Python language, using the tensorflow library. However, it is also necessary to use the numpy, scikitlearn, seaborn, and pandas libraries to pre-process the data and analyze the results. After the Sne Hot Encoder process, it is noted that the database now had 27 feature columns, meaning 27 input nodes for the ANN. The next step is to create the structure to be used, which has 32 nodes in the first hidden layer, 16 in the second, and 4 in the third, as shown in Figure 2.

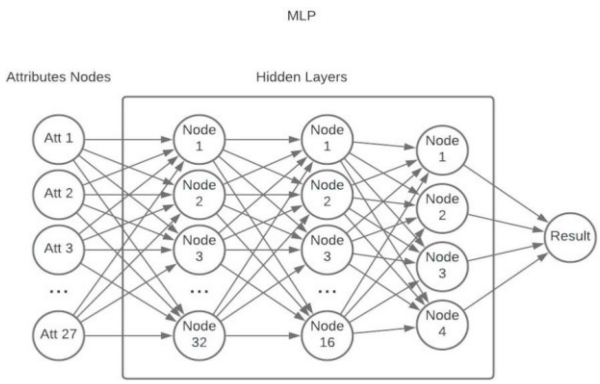

Fig. 2. MLP Structure.
(Source: Elaborated by the author)

This configuration is identified as the most effective after several iterations and adjustments, with the aim of optimizing both the learning capacity and the efficiency of generalizing the data processed. This methodological approach of adjusting the network architecture until the desired performance is achieved is crucial in machine learning applications, where the optimal configuration is not known a priori and must be discovered experimentally. The activation function chosen for each node is the Rectified Linear Unit (ReLU) due to its simplicity and efficiency. This function is defined as the maximum between zero and the input value in each of the nodes, i.e. everything that is negative becomes zero [21]. The optimizer used is adam, which adjusts the learning rates for each parameter individually. In addition, back-propagation with a 'mean squared error' loss function is also used, which punishes very high errors more rigorously, since the difference between the predicted value and the actual value is squared. This difference is taken into account when determining the connection weights for each parameter in the next training iteration [22]. For network learning, the metrics used is Training Loss and Validation Loss. The former is a measure of how well the model is performing during training and the latter is calculated in the same way as Training Loss, but on validation data. This validation data is a subset comprising 20% of the original training data set, which is not used to train the model but to evaluate its performance. It is important to note that the proportion of CVs per grade is preserved in the validation set, as can be seen in Figure 3.

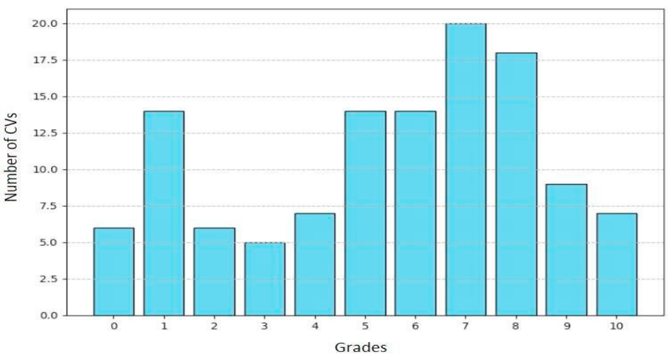

Fig. 3. Graph of the scores of the 120 CVs in the validation set.

The MLP was trained for a maximum of 100 epochs (iterations). However, the model's effectiveness in learning quickly was evident as early as iteration 28. The Training Loss value reached 0.7887 and the Validation Loss value reached 0.9833. These results demonstrate not only the model's ability to adapt quickly but also its efficiency in generalizing information and achieving early convergence during the training process.

3. Results

Analysis of prediction errors is crucial to understanding the effectiveness of the model on data not seen during training. In this investigation, the following results unique to the test set stand out: The MAE provides a general idea of the magnitude of the error, without considering the direction (positive or negative) of these errors. In this case, the result is 0.33, indicating that, on average, the absolute error of the forecasts is 0.33 units. The MSE in turn calculates the average of the squares of the errors and is particularly sensitive to larger errors due to its quadratic nature. The value found is 0.37, suggesting that larger errors have a very insignificant presence in the model's predictions. Another important metric is the RMSE, being the square root of the MSE, it puts the errors back into the same unit as the originally observed data. The RMSE value is 0.61, offering a more intuitive perspective of the typical variation in errors. Finally, the r^2 Score represents the proportion of the variance of the dependent values that is predictable from the independent variables. An r^2 of 0.96 indicates that the model explains 96% of the variance, which points to an exceptionally good fit between the predictions and the actual values.

To this end, these relevant statistical indicators that quantify the accuracy of the forecasts are shown in Table 3.

Table 3. Table of statistical metrics of the test set.

Metric	Value
Mean Absolute Error (MAE)	0.33
Mean Squared Error (MSE)	0.37
Root Mean Squared Error (RMSE)	0.61
r^2 Score	0.96

It is important to note that the RMSE was greater than the MSE, which means that the few errors that the model obtained have a very small difference in relation to the result that was expected. These differences can be seen in the scatter plot in Figure 4.

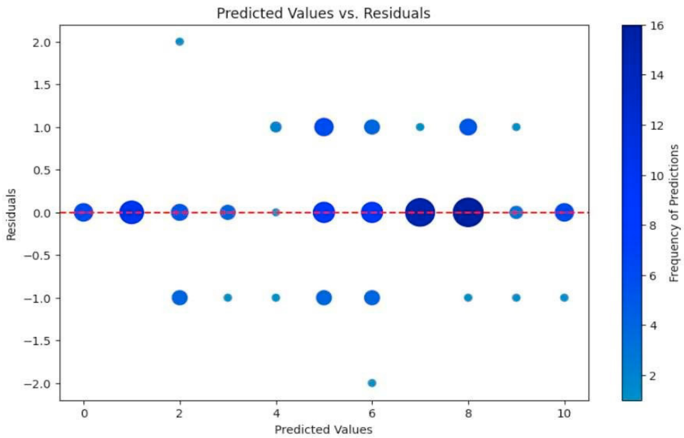

Fig. 4. Scatter plot of residuals.

Figure 4 also shows that most of the model's errors only vary by up to one point, positive or negative, in relation to the real value. This graph uses a chromatic and scalar representation where the intensity of the color and the size of each point indicate the frequency of predictions in that specific location: points with darker shades represent a higher concentration of predictions, suggesting a greater recurrence of similar results in those areas. In addition, the red line on the graph represents the ideal prediction line, where the values predicted by the model coincide perfectly with the actual values. The proximity of the predictions to this red line indicates greater model accuracy.

Figure 5 shows a bar chart of the model's residuals, organized by the accumulated sums of each error category. This graph quantifies the number of occurrences for each magnitude of error, from positive to negative values.

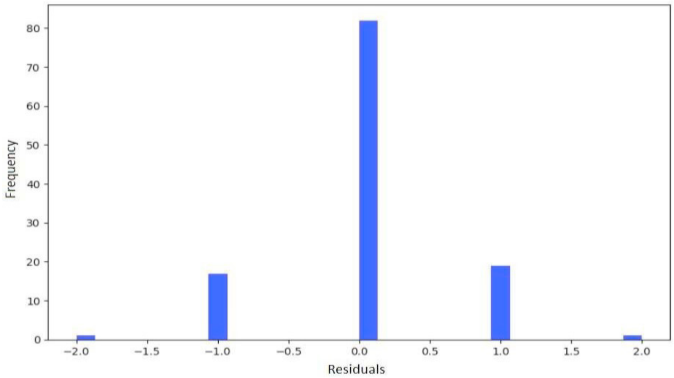

Fig. 5. Residual frequency graph.

For a better understanding, a confusion matrix was adjusted to map the residuals in a more intuitive way. This method allows us to visualize the distribution and frequency of errors made by the model through rows and columns. Each column represents all the CVs that have that score, for example, all CVs in column 0 are actually cataloged in the database with a score of 0. The lines, in turn, represent all the CVs that the model judged to have that score. Therefore, all the individuals in row 0 symbolize the CVs that the model judged to have a score of 0. Therefore, in a perfect and ideal model, all the elements of the matrix would be on the main diagonal. Analyzing Figure 6, we can see that the results predicted by the model are remarkably similar to the actual values of the curricula. This is evidenced by the fact that the cells with the highest numbers are located on the main diagonal of the matrix. Although the model has made mistakes in some of its predictions, these do not represent significant problems. Considering the context of the problem we are solving, a CV rated 4 being considered 5, for example, does not have serious consequences, as the differences between adjacent ratings are often not decisive.

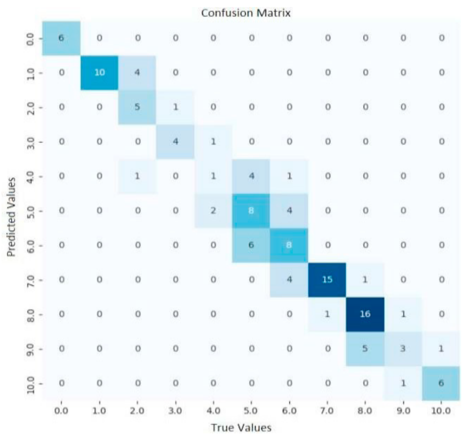

Fig. 6. Confusion Matrix.

4. Theoretical and Practical Contributions

To define the best final model, a series of experiments were carried out. This study makes several related contributions. Firstly, the study identifies an ANN model with MLP in the CV screening process. This mathematical model can recommend candidates on the level of technical characteristics and makes it possible to reduce repetitive activities. This research also corroborates the premise that has been increasingly discussed in the literature about which tasks can be performed by the machine, which brings productivity gains to the human being, based on ethical principles. To use the current model, resumes can be classified based on the positions being applied for, and the model is provided with a set of base resumes in the respective job category and their ratings, allowing the model to dynamically calculate the relative strength of each characteristic. Unlike conventional Applicant Tracking Systems (ATS) that use specific keywords and formatting, the new method contributes to a less biased analysis based on a set of predefined and recorded attributes. Where ATS can be manipulated with the use of specific keywords, the MLP based technique is designed to avoid this type of manipulation, processing a database using normalized values. The research also provides important findings for the practical conduct of the HR area, specifically in R&S. The model shows that organizations can save time and improve the quality of the recruiter's work. In short, the insights derived from this study and the model's performance reinforce its practical applicability and highlight the potential of advanced data analysis techniques in optimizing HR processes.

5. Conclusion

The results obtained and the analyses carried out indicate that the prediction model developed performs satisfactorily in the task of evaluating CVs. The remarkable agreement between the model's predictions and the actual values demonstrates its effectiveness in capturing and replicating the underlying patterns in the data. Although the model has errors in some predictions, it is important to note that these do not significantly compromise its usefulness. The discrepancies observed between predicted and actual scores are minimal and, in most cases, involve differences of just one point. These small variations are tolerable within the context of curriculum evaluation, where a difference of one point in the score does not necessarily imply a substantial change in the quality or suitability of the candidate. It is suggested that future improvements and adjustments to the model, such as the use of early stopping to avoid an excessive number of iterations during training, can be explored to further improve its accuracy and adaptability to the specific needs of organizations. Currently, the extraction of data from each resume has been performed manually to populate the database. Therefore, the utilization of generative networks for the automatic extraction of characteristics from CVs has the potential to revolutionize the process, rendering it fully automated and optimized from the receipt of CV files to their final evaluation. These innovations not only increase the efficiency of the system but also enhance its use in real application contexts. The main limitation of this study is the CV classification only by an HR specialist. However, it still fulfilled the objectives defined for this study. Future studies can use a group of HR technicians to compare error averages.

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References

[1] Will, P., Krpan, D., and Lordan, G. (2023) People versus machines: introducing the HIRE framework. *Artificial Intelligence Review*, 56(2), 1071-1100. Doi: /10.1007/s10462-022-10193-6

[2] Jatobá, Mariana Namen. (2020) "Inteligência artificial no recrutamento & seleção: inovação e seus impactos para a gestão de recursos humanos." Dissertação de Mestrado em Gestão das Srganizações, APNSR e Mestrado de dupla diplomação com a UNIFACS - Universidade Salvador. Srientadores: Fernandes, Paula S.; Teixeira, João Paulo; Moscon, Daniela. Disponível em: http://hdl.handle.net/10198/21805.

[3] Jatobá, Mariana, Santos, Juliana, Gutierriz, Ives, Moscon, Daniela, Fernandes, Paula Sdete, and Teixeira, João Paulo. (2019) "Evolution of Artificial Intelligence Research in Human Resources." Procedia Computer Science 164: 137–142.

[4] Jatobá, M.N., Ferreira, J.J., Fernandes, P.S., and Teixeira, J.P. (2023), Intelligent human resources for the adoption of artificial intelligence: a systematic literature review, Journal of Srganizational Change Management, Vol. 36 No. 7, pp. 1099-1124. Doi:10.1108/JSCM-03-2022-0075

[5] Annunziato, M., Lucchetti, M., and Pizzuti, S. (2002). Adaptive systems and evolutionary neural networks: a survey. Proc. EUNITE02, Albufeira, Portugal.

[6] Carvalho, K., Vicente, J.P., Jakovljevic, M., and Teixeira, J.P.R. (2021) Analysis and Forecasting Incidence, Intensive Care Unit Admissions, and Projected Mortality Attributable to CSVID-19 in Portugal, the UK, Germany, Italy, and France: Predictions for 4 Weeks Ahead. Bioengineering, 8, 84. Doi: 10.3390/bioengineering8060084

[7] Rodrigues, P. M., and Teixeira, João Paulo. (2010). Classification of Electroencephalogram Signals Using Artificial Neural Networks. Proceedings of 3rd International Conference on BioMedical Engineering and Informatics (BMEI'10). Yantai – China, 808-812 Doi: 10.1109/BMEI.2010.5639941

[8] Nguyen, Le Q., Fernandes, Paula S., and Teixeira, João P. (2022). Analyzing and Forecasting Tourism Demand in Vietnam with Artificial Neural Networks. Forecasting, 4(1) 36-50. Doi: 10.3390/forecast4010003

[9] Moriarty, D. E., and Miikkulainen, R. (1998) "Hierarchical evolution of neural networks." In 1998 IEEE International Conference on Evolutionary Computation. IEEE World Congress on Computational Intelligence, 428-433, IEEE.

[10] Boschetti, A. F. S. (2019). Elaboração de algoritmo para análise de relevância em avaliação de currículos e seleção, utilizando métodos ordinais multicritério. Universidade Federal Fluminense, Niterói, Brazil. Retrieved in April 2024 from https://app.uff.br/riuff/bitstream/handle/1/10894/ELABSRA%C3%87%C3%83S%20DE%20ALGSRITMS%20PARA%20AN%C3%81LISE%20DE%20RELEV%C3%82NCIA%20EM%20AVALIA%C3%87%C3%83S%20DE%20CURR%C3%8DCULSS%20E%20SELE%C3%87%C3%83S%2C%20UTILIZANDS%20M%C3%89TSDSS%20SRDINAIS%20MULTICRIT%C3%89RIS%20%281%29.pdf?sequence=1

[11] Pan, Y., Froese, F., Liu, N., Hu, Y., and Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. The International Journal of Human Resource Management, 33(6), 1125-1147. Doi: 10.1080/09585192.2021.1879206.

[12] Blumen, D., and Cepellos, V. M. (2023) "Dimensões do uso de tecnologia e Inteligência Artificial (IA) em Recrutamento e Seleção (R&S): benefícios, tendências e resistências." Cadernos EBAPE.BR, 21(2), e2022–0080. Doi: 10.1590/1679-395120220080.

[13] Li, D., Raymond, L. R., and Bergman, P. (2020). Hiring as exploration. National Bureau of Economic Research. No. w27736. Doi: 10.2139/ssrn. 3630630

[14] Soleimani, M., Intezari, A., and Pauleen, D. J. (2022). Mitigating cognitive biases in developing AI-assisted recruitment systems: A knowledge-sharing approach. International Journal of Knowledge Management (IJKM), 18(1), 1-18. Doi: 10.4018/IJKM.290022

[15] Al-Alawi, A. I., Naureen, M., AlAlawi, E. I., and Al-Hadad, A. A. N. (2021). The Role of Artificial Intelligence in Recruitment Process Decision-Making. In 2021 International Conference on Decision Aid Sciences and Application (DASA), 197-203. IEEE. Doi: 10.1109/DASA53625.2021.9682320

[16] Michailidis, M. P. (2018). The challenges of AI and blockchain on HR recruiting practices. Cyprus Review, 30(2), 169-180.

[17] Rajesh, D. S., Kandaswamy, M. U., and Rakesh, M. A. (2018). The impact of artificial intelligence in talent acquisition lifecycle of organizations. International Journal of Engineering Development and Research, 6(2), 709-717.

[18] Guedes, V., Junior, A., Fernandes, J., Teixeira, F., and Teixeira, J. P. (2018). Long short term memory on chronic laryngitis classification. CENTERIS/ProjMAN/HCist 2018 - Procedia Computer Science, 138, 250-257. Doi: 10.1016/j.procs.2018.10.036

[19] Araújo, Teresa, Teixeira, João Paulo, and Rodrigues, Pedro Miguel (2022). Smart-data-driven system for alzheimer disease detection through electroencephalographic signals. Bioengineering. ISSN 2306-5354. 9(4), 1-16. Doi: 10.3390/bioengineering9040141

[20] Velazco, M. I., and Lyra, C. (2002) "Sptimization with neural networks trained by evolutionary algorithms." Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02, 2, 1516-1521. Doi: 10.1109/IJCNN.2002.1007742

[21] Iyoda, Eduardo Masato. (2000) "Inteligência computacional no projeto automático de redes neurais híbridas e redes neurofuzzy heterogêneas." Dissertação de Mestrado, Faculdade de Engenharia Elétrica e de Computação, Universidade Estadual de Campinas, São Paulo, SP, 166 p.

[22] Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986). Learning representations by back-propagating errors. Nature, 323(6088), 533-536. Retrieved in April 2024 from https://www.cs.toronto.edu/~hinton/absps/naturebp.pdf