A Naïve Bayes Classification Model for Financial Services Sector Human Resources Selection Process

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Abstract

This work focuses on automated decision-making in human resources management. Specifically, on the integration of automated decision-making into the core functions of Human Resources Management. The applicability of Naïve Bayes, a classical classifier, in developing a decision support system for HR professionals in the employee selection process is examined. For this purpose, a decision model is developed and evaluated using actual data collected from a company in the financial sector, concerning internal employee applicants for seven vacant job positions in a two-year period. The collected data was anonymized, transformed into the appropriate format, split into training and test sets. The model was trained with the training dataset and evaluated with the test dataset. The results of this study produce useful information concerning the application of this classifier in the employee selection process. The results are promising and demonstrate that a mix of professional expertise along with algorithmic support may optimize the HMR processes.

Keywords: *HRM, Automated decision-making, Algorithmic decision-making, Decision Support Model, Employee Selection, Classification*

1. Introduction

Developments in algorithms and software technologies allow employers and human resources professionals to take real-time and more effective decisions in their domain. Automated or algorithmic decision-making systems have been increasingly used by corporations taking advantage of the huge amount of data generated in the contemporary working environment. However, although the business benefits of such approaches are obvious for human resources management, the use of these systems has come under scrutiny (Vassilopoulou et al., 2022). Some concerns for the integration of automated-decision making in human resources management are ethical and legal considerations, data protection, explainability, and accountability issues (Garg et al., 2021).

On the other hand, traditional human resourses management has given way to a more reactive function, which is required to be more inclusive, agile, and responsive. This transition is enabled by Artificial Intelligence (AI) and machine learning (ML) developments, the use of which cut costs and save time in routine processes, while enabling also predictive capabilities for complex processes (Garg et al., 2021). In this context, automated decision making based on machine learning methods is already part of human resource management and is used extensively for screening resumes for job applications either as a part of in house systems or as an outsourcing service (Garg et al., 2021).

Following the above, this work focuses on exploring the applicability of classical classifiers in the selection process in developing a decision support system for human resourse professionals. For this, we developed and present a decision support model using the Naïve Bayes algorithm, that was tested in a real world dataset collected from a Greek company in the financial sector, concerning internal employee applicants over a two-year period. The work demonstrates that the application of Naïve Bayes classifier is an efficient approach in developing a decision support system for HR professionals for the employee selection process.

The the paper is organized as follows. A literature review initially introduces algorithmic decisions and the challenges that are encountered in humen resources, such as ethical and legal, data protection, explainability, and accountability. Next, the Naïve Bayes model is presented, including design and testing, along with results. Finally, discussion follows with main findings and suggestions for further improvements.

2. Literature Review

Today, the Human Resources Management function is transforming from traditional personnel management to a new, more strategic one as a business- partner. This transition is enabled by Artificial Intelligence (AI) and machine learning (ML), that reduce costs and save time in routine processes while also enabling predictive capabilities for complex processes. In the Human Resources Management discipline, studies in concepts such as people analytics, human resource management algorithms, and algorithmic control are increasingly becoming popular. In addition, these concepts are studied in parallel, and sometimes interchangeably, with phenomena such as big data and artificial intelligence (Meijerink, et al., 2021). To synthesize all these concepts Meijerink et al. (2021) propose the term "Algorithmic Human Resources Management (HRM)" and define it as: "The use of software algorithms that operate based on digital data to augment HR-related decisions and/or automate HRM activities". The integration of automated decision making in human resources activities can be identified in various taks including recruitment, selection, engagement, training and performance managenent.

Machine learning (ML) in recruitment is used for evaluating candidates' suitability for openings; extracting information from resumes and analyzing applicants' profiles. It can be used for automatically extracting candidates' information from their resumes and for evaluating applicants' suitability for vacant positions, as well (Garg et al., 2021). Xerox Services for example, applied a recruitment algorithm that provides a score about how well an applicant feat to requirements to support managers in hiring decisions

(Leicht-Deobald, et al., 2019). In selection process, the application of machine learning (ML) has led to efforts to identify decision attributes to use as selection criteria and to develop corresponding selection models (Garg et al., 2021). Employee-related data from social media could be analyzed in various ways – including text mining techniques, sentiment analysis, correlation-based feature selection along with regression- to better understand brand engagement and current employee sentiment, as well as factors that may increase stress. These applications enable the customization of employee engagement practices (Garg et al., 2021). Also, algorithms can assist in identifying employees' training needs and recommending relevant courses for career development (Castellanos, 2019). Research has also shown that utilization of algorithms to predict the performance level of employees or to detect subjectivity in employee evaluation using data natural processing (NLP) provides valid results. Cheng et.al (2019) research revealed that HR Functions that have attracted more interest from human resources management practitioners are recruitment and selection, training and development, and compensation and consider that significant research opportunities exist in these areas.

As Meijerink et al. (2021) noted decision-making in HRM can be both augmented and automated, by using algorithms. Algorithms augment decision-making in the context of the final decision lies with the decision-maker, who could not act in the way the algorithm recommends but choose a different alternative than those proposed by the algorithm. A question that is often raised in the controversy about automated decision-making systems and algorithms is where the responsibility for the decision/action lie. According to Persson & Kavathatzopoulos (2018), the focus is more on the human decision-maker and proposed to focus more on how the decision-maker can be supported to make ethical and fair decisions. This, in turn, would place more responsibility on the decision-maker, rather than on the manufacturer of the algorithm or the system.But, nowadays with the advancement of AI, which leads to more sophisticated algorithms, some HR decisions are made without human intervention, putting the responsibility for the decision-making solely on machines.

Helberger et al. (2020) state that, many decision-making systems will use a hybrid approach, with people and automated decision-making (ADM) systems collaborating and proposing further investigation about the conditions under which a "human in the loop" contributes to the perception of fairness. Moreover, such mixed systems will comply with article 22 of GDPR, which is the provision dealing with (fully) automated decision-making and specifying a user's right to obtain human intervention.

3. Proposed Model

This work aims to introduce a decision support framework for employee selection to fill job vacancies, via the internal recruiting channel, by using historical data. The scope of the model is to act as a decision support system (DSS) for human resources experts (domain experts). More specifically, from a list of job applicants, it will propose those that meet the basic requirements for further evaluation by HR experts.

Employee selection is among the most important HRM practices that support an organization in its strategy execution. Selection is the process through which an organization identifies applicants that have the necessary skills, expertise, and abilities to help the organization achieve its goals. There are several approaches to recruiting and selecting. Some organizations may actively recrproposeuit from external sources, whereas others rely primarily on in-house people with the necessary skills to fill vacant positions (Noe et al., 2016).

The employee selection process differs from organization to organization and from job to job. However, for the majority of organizations, the procedure includes the steps of screening, testing and reviewing, interviewing, checking references and choice. In particular, in the first step, a human resources expert screens the applications to determine which of them satisfy the minimum job requirements. In the next steps, for the candidates that meet the basic criteria, the company runs tests and views their work examples to invite them for interviews. Following the interviews, the decision-makers begin to form opinions about which candidates are most desirable. Before the final selection, the decision-makers check references and conduct background checks, for the top few candidates.
This model aims to support the HR experts in the first step of the selection process, in the phase of an application screening, to determine which of the applicants satisfy the minimum job requirements. The problem of predicting which job applicants will be qualified for further evaluation by human resource experts can be structured as a classification problem.

The most known classification models in machine learning are Decision Trees (DT), Naïve Bayes (NB), Rule-based method, K-nearest neighbors (KNN), Support Vector Machines (SVM), Neural Networks (NN), Random Forest (RF), and Logistic Regression (LR) (Pampouktsi et al., 2021). The proposed classifier for the construction of the data mining framework is the Naïve Bayes algorithm, for the following reasons

1. Naïve Bayes applies to categorical variables.The data collected contains categorical and nominal variables and hence Naïve Bayes could be applied for the classification.
2. It needs a small amount of training data to determine the necessary classification parameters.
3. It simplifies predictive modeling models and it is relatively simple to code.
4. Bayes learning algorithms work well with noisy or missing data and could provide probabilistic predictions when appropriate.

Naïve Bayes classifier is a classical algorithm that is based on Bayes' probability theorem of conditional independence. Naïve Bayes assumes by design that all attributes are independent of each other, given the class. The objective of a Bayesian classifier is to choose the most likely class from a list of potential ones (Pampouktsi et al., 2021).
Bayes theorem counts the probability of an event B occurring, given the probability of another already occurred event A

$$(B \setminus A) = \frac{P(A \setminus B)P(B)}{P(A)} \qquad (1)$$

where P(B\A) is the probability of B given A, B represents the dependent event, and A the prior event.
The Bayes equation can be written as

$$Posterior = \frac{Likelihood * Prior}{Evidence} \qquad (2)$$

where the factors Likelihood and Prior are functions and Evidence is a constant.
Naïve Bayes, computes the conditional probability for each decision class, given an information vector. The probabilities involved in producing the final estimate are computed as frequency counts from the decision table. For a data sample with an unknown

class, the Naïves Bayes classifier will predict that belongs to the class with the highest posterior probability.

The machine learning classifier Naïve Bayes was trained on the internal applicants' data to develop the framework for predicting which employee applicants are qualified for further evaluation. The steps followed, for each job position, are presented below:

1. The dataset was randomly divided into two sets -training and testing- with a ratio of 70% training data:30% testing data. The training dataset was used for the model training and the testing dataset for the model evaluation.
2. The probabilities of every attribute-value pair with each value (Yes / No) of the target variable "Short List", were computed from the training dataset.
3. The likelihood values of Yes and No are calculated for each applicant, by employing the probabilities computed in step 2
4. For each event, the probability of "Yes" and "No" for the target variable Short List are calculated as follows

$$Probability\ \mathrm{Yes} = \frac{Likelihood\ of\ Yes}{Likelihood\ of\ No + Likelihood\ of\ Yes} \quad (3)$$

$$Probability\ No = \frac{Likelihood\ of\ No}{Likelihood\ of\ No + Likelihood\ of\ Yes} \quad (4)$$

5. Prediction made on new data (test data)
   If **Probability of Yes > Probability of No**, then the prediction is Yes
   If **Probability of No > Probability of Yes**, the prediction is No

4. Results

For this work real data was collected from a financial services company operating in Greece, concerning filling vacant positions from the internal channel for a two-year period. The selected data refers to actual applications for Company's postings about 7 jobs, through the internal channel. The collected data was anonymized, as personally identifiable information was completely removed so that is not possible to reveal personal information.

The database consists of 675 employee applicants' data for seven jobs in the following functions of the company: Investment & Finance, Internal Audit, Organizational Management, Risk Management, Customer Services, Operations, and Business Customer Relationships. The number of applicants per job is shown in Table 1.

Job	Company's Function	Applicants	Percentage
A	Investment and Finance	100	14.81%
B	Internal Audit	108	16.00%
C	Organizational Management	90	13.33%
D	Risk Management	45	6.67%
E	Customer Services	131	19.41%

F	Operations	138	20.44%
G	Business Customer Relationships	63	9.33%
Total		**675**	**100.00%**

Table 1 - Applicants per Job

For each employee applicant real data was collected, concerning the following attributes: Gender, Years in the Organization, Previous work experience, Seniority Level, Level of English knowledge as a foreign language, Level of education, Field of Education, Professional Certification, and Job position applied for. In addition, for each applicant, the stage of his/her application and whether he/she is qualified – by the company's HR experts – for further evaluation is known, and this will be the target (output) variable for the model building.

The applicants are, in total, diverse as almost 51% are females and 49% are males, as shown in Figure 1.

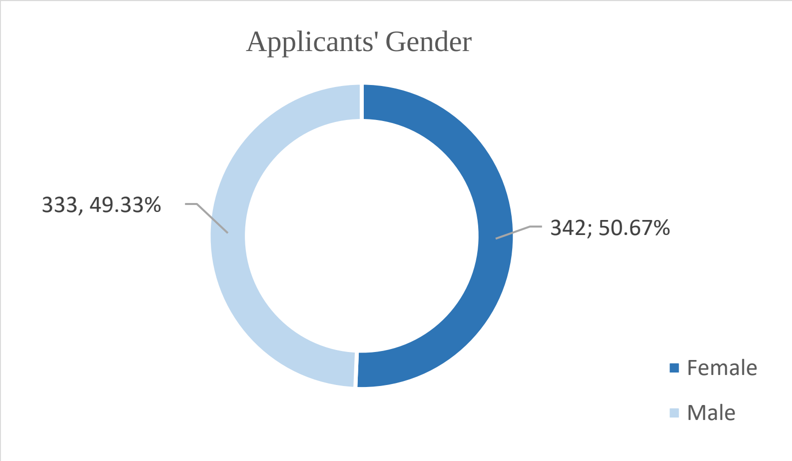

Figure 1 - Applicants' Gender

The distribution of applicants per job and gender is depicted in Table 2 and Figure 2.

Job	Female Applicants	Percentage	Male Applicants	Percentage	Total Applicants
A	57	57.00%	43	43.00%	100
B	67	62.04%	41	37.96%	108
C	40	44.44%	50	55.56%	90
D	20	44.44%	25	55.56%	45
E	55	41.98%	76	58.02%	131
F	85	61.59%	53	38.41%	138
G	18	28.57%	45	71.43%	63
Total	**342**	**50.67%**	**333**	**49.33%**	**675**

Table 42 - Applicants per Job and Gender

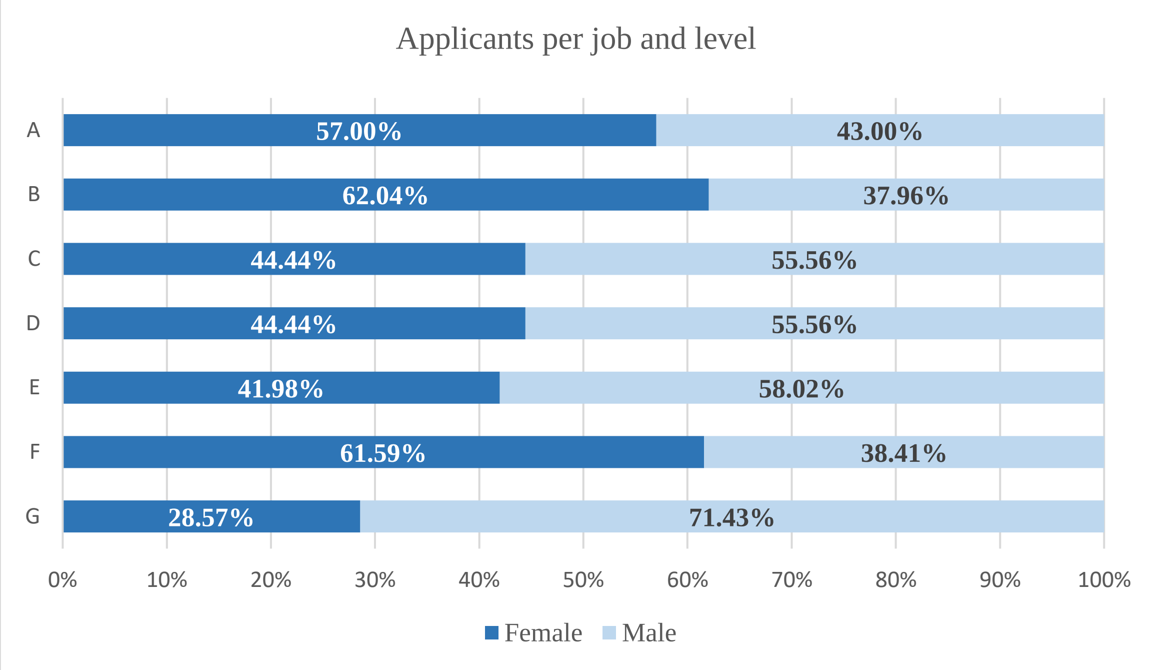

Figure 4 - Applicants per Job and Level

Regarding the education level of job applicants, the majority of them (almost 67%) hold Bachelor’s degree or higher, as shown in Table 3 and Figure 3.

Education Level	Applicants	Percentage
Doctorate	1	0.15%
Master’s Degree	264	39.11%
Bachelor’s Degree	190	28.15%
Tecnological Institution Degree	101	14.96%
Colleges, Institutions	25	3.70%
Post Secondary Education	15	2.22%
High School	77	11.41%
Missing	2	0.30%
Total	**675**	**100.00%**

Table 3 - Applicants' Level of Education

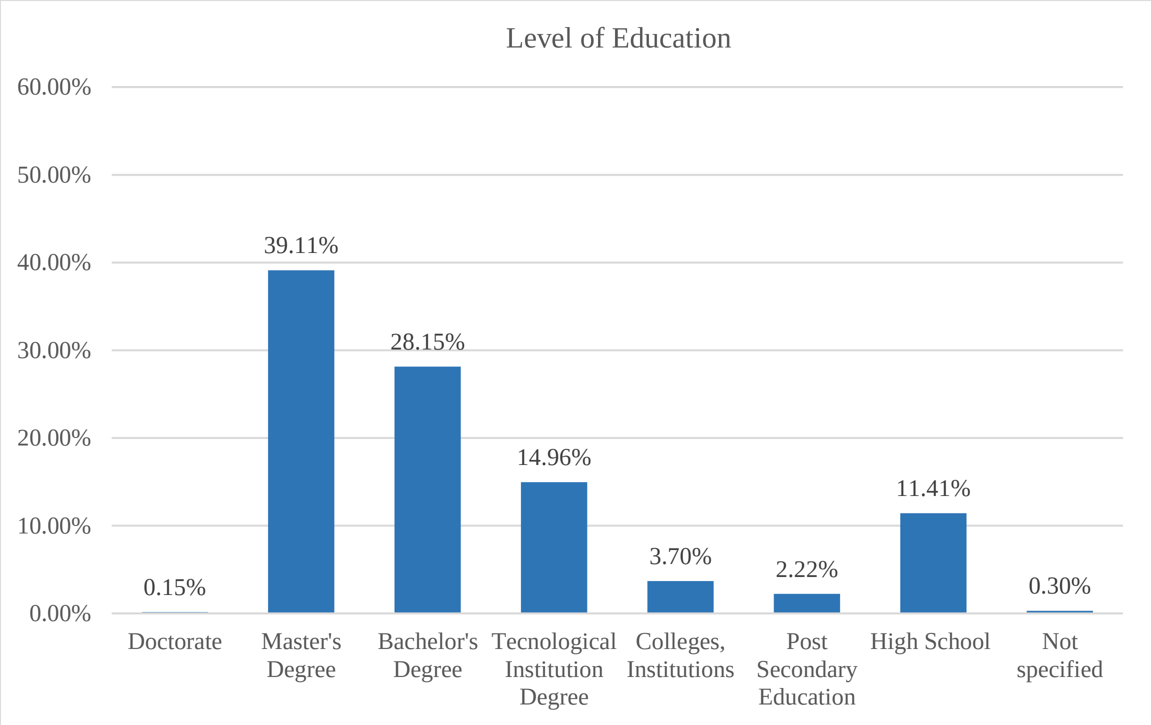

Figure 3 - Applicants' Level of Education

The seniority level of the majority of applicants - almost 85% - is categorized in the Staff level and only 15% of applicants are at the management level, as presented in Table 4.

Applicant's level	Applicants	Percentage
Management (levels 4,5)	101	14.96%
Staff (levels 1,2,3)	573	84.89%
Not specified	1	0.15%
Total	**675**	**100.00%**

Table 4 - Applicants' Seniority Level

Out of 675 applicants, 190 (almost 28%) were qualified, by the company's HR experts, for further evaluation, and 485 (72%) were not. The percentage of applicants that were qualified or not qualified for further evaluation, for each job position is demonstrated in Table 5.

	Further evaluation-No		Further evaluation -Yes		Total Applicants
Job	Applicants	Percentage	Applicants	Percentage	
A	80	80.00%	20	20.00%	100
B	81	75.00%	27	25.00%	108
C	65	72.22%	25	27.78%	90
D	29	64.44%	16	35.56%	45
E	124	94.66%	7	5.34%	131
F	70	50.72%	68	49.28%	138
G	36	57.14%	27	42.86%	63
Total	485	71.85%	190	28.15%	675

Table 5 - Applicants selected for further evaluation, per job position

According to the internal job postings, the requirements of the positions are relating to the following attributes

1. Level of education
2. Field of study
3. Work experience
4. English knowledge as a foreign language
5. Ms Office skills
6. Professional Certification

The above job requirements were used as the independent variables in the model we are building, while the dependent variable is whether the applicant was qualified for further evaluation by the company's HR experts.

The collected data was transformed into an appropriate analyzable format to support meaningful analysis. The data were combined and prepared and the quality was improved, before further analysis. During the data selection stage, the data collected for each applicant are Gender, Years in the Organization, Previous work experience, English knowledge level, Education level, Education field, Profesional Certification, Job position applied for, and Selected for further Evaluation (output variable). In Table 6, a detailed description of the attributes is depicted.

Name	Type	Scale
Gender	Categorical	Female, Male
Years in the Organization	Ordinal	NA, <1, 1-5, 5-10, 10-20, >20
Previous work experience	Ordinal	NA, <1, 1-5, 5-10, 10-20, >20
Level	Ordinal	1,2,3,4,5
English knowledge level	Ordinal	Little to no, Lower, Advanced, Proficiency
Education level	Ordinal	High School Graduate, Colleges/Institutions, Technological Institution, Bachelor, Master, Doctorate
Education level required	Categorical	No, Yes
Education field required	Categorical	No, Yes
Profesional Certification	Categorical	No, Yes
Short List	Categorical	No, Yes

Table 1 - Attributes

The above variables were used as predictors for the model. The input variable gender was excluded from the analysis due to concerns of discrimination. The variable "Short List" is the target variable. The dataset was based in Ms Excel in a table format and contains 675 instances for 7 job positions.The dataset for each job position was randomly divided into training and testing sets with a ratio of 70% training data:30% testing data. The model was tested for a number of job applicants for 7 job vacancies over a 2-year period. The data, after the appropriate transformation and coding, was used for the model training and testing. Following that, the metrics Accuracy, Precision, Recall, and F1 score have been utilized to evaluate the model. The performance metrics of the algorithm for each job position are depicted in Table 7.

	Job						
	A	**B**	**C**	**D**	**E**	**F**	**G**
Accuracy	80.00%	71.88%	75.00%	78.57%	92.31%	56.10%	68.42%
Precision	0.00%	44.44%	66.67%	66.67%	0.00%	56.25%	62.50%
Recall	0.00%	50.00%	25.00%	80.00%	0.00%	45.00%	62.50%
F1	-	47.06%	36.36%	72.73%	-	50.00%	62.50%

Table 4 - Model performance per Job position

As it is observed, the model's overall performance, which is measured by the metric Accuracy, is acceptable, as it is over 60% for the majority of job positions. Its accuracy in predicting the negative class is also acceptable, however, its accuracy in predicting the positive class "Yes" is average to limited (metrics Precision, Recall and F1). This indicates that applicants who actually have been qualified for further evaluation have been excluded by the model. Low precision indicates that the model recommends candidates for further evaluation that actually are not qualified by commpany's HR professionals (high False Positive recommendations). These wrong recommendations can impose costs for the company, such as extra time that HR experts have to spent on the wrong applicants. Low recall indicates that the model does exclude applicants who fit the job requirements and would have been considered qualified by HR professionals for further screening (high False Negative). This type of error can raise ethical issues to the Company and complaints by employees.

5. Discussion/Conclusions

This paper is an exploratory study on automated decision-making in Human Resources Function. More specifically, the integration of automated decision-making in various functions of Human Resources Management has been explored through literature review and the challenges that it exhibits. Some of the most important challenges are faced are ethical and legal considerations, data protection, explainability, and accountability issues. In addition, the question of fully automated or algorithmic augmented decision-making is addressed, to conclude that for better decision-making the collaboration of humans and AI is needed. Furthermore, it was explored whether a classical classifier, such as Naïve Bayes, could be utilized as a decision support system in the first phase of the employee selection process, which is one of the key functions of Human Resources Management.

This study is limited by the following facts:

1. The scope of this decision support system is fosused on the first screening phase of job applicants. As a result, the data used were limited mostly on personal

information such as job experience, education, English language and professional certifications.

2. The available amount of data for training and testing the algorithm, for each job position, is limited.
3. The imbalanced classes, which reduce the accuracy of the algorithm, were present in almost all job positions except jobs F&G.

In the future, the data can be enhanced to include interview scores, personality test results, and cognitive ability test results. With data enrichment and different attributes selection, the performance of the algorithm could be improved significantly. Further research should focus on a more systematic investigation with the rest classifiers, such as decision trees, in order to evaluate how different methods work and to compare. Moreover, a combination of more than one methods can be applied.

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