

Modelling and Analyzing the Employees' Engagement in Workplace using Machine learning Tools

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Abstract: *In a new economy where immaterial capital is crucial, companies are increasingly aware of the necessity to efficiently manage human capital by optimizing its engagement in the workplace. The accession of the human capital through its engagement is an efficient leverage that leads to a real improvement of the companies' performance. Despite the staple attention towards human resource management, and the efforts undertaken to satisfy and motivate the personnel, the issue of engagement still persists. The main objective of this paper is to study and model the relation between eight predictors and a response variable given by the employees' engagement. We have used different models to figure out the relation between the predictors and the dependent variable after carrying out a survey of several employees from different companies. The techniques used in this paper are linear regression, ordinal logistic regression, Gradient Boosting Machine learning and neural networks. The data used in this study is the results of a questionnaire completed by 60 individuals. The results obtained show that the neural networks perform slightly the rest of models considering the training and validation error of modelling and also highlight the complex relation linking the predictors and the predicted.*

Keyword: *human resources management, machine learning; Neural networks, Boosting machine learning, logistic regression.*

I. INTRODUCTION

It is commonly known that the global performance of any company is ensured mainly by its human resources, for which the employees' engagements are obviously the key of success. To reach the full engagement of employees in the workspace various approach are tested in the real companies' life. The most of them consider different ways of employees' motivations, but this objective still far to reach for most of enterprises. This verdict means that there are some hidden causes that obstruct to achieve this objective coveted by most of companies.

In the current time of globalization and hyper-competition, the increasing uncertainties in the global environment urge the

companies to reconsider their modes of management and their perception of their employees [1]. On the other hand, the employees are more often expressing new expectations that should be considered. Consequently, Human resources management seems to be an area of tension [2], its challenges and issues are becoming paramount for companies. In this regard, a higher level of performance entails a better management of human resources, namely a better canalization of employee engagement.

In this paper, we will mainly focus on the issue of employees' engagement in the workplace. The objective is to highlight the link between some human resources practices and the employees' engagement. For this purpose, the first step aims to identify the factors that may impact employees' engagement through a questionnaire. For this, we have carried out a field study via a questionnaire with the aim to understand and highlight the factors that can impact positively or negatively the employee's engagement. After that, in the second step we attempt to model the engagement variable in function of the identified factors. The tools used in the modeling are a simple multiple linear regression, logistic regression, gradient boosting machine learning and artificial neural network with backpropagation, and scatter search as learning algorithms.

In this study we have considered 60 individuals with different: age range, studies level, salaries ranges, familial situation, type of relationship with the work team and also with the administration of the company. We will focus on the literature of organizational engagement because the topic of our study is related to this theme and fits into the human resources management field. We will investigate the contribution of different studies in resolving the current problem and in the modelling of the problem situation. To better grasp the concept of organizational engagement and its position in the literature, it seems important to include a brief review of the body of knowledge related to HRM.

Human resources management (HRM) is both a field of knowledge and an activity performed by members of companies. According to [3], HRM intends, on one side, to develop the resources of the company employees, and on the other side to engage them in order to achieve the fixed objectives. Therefore, individuals only reach their potential if there are efficient HRM practices that help exploit correctly their competencies [4].

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The mission of HRM is to develop and engage employees' competencies. Incorporating the aspect of human resources in the company strategy is a recognized need. The structures and the individuals offer a competitive advantage to the company. Thus, the organizations should maintain a human resources strategy in accordance with their economic strategy and their social responsibility. They require a great added value from the human resources function.

The expression « management practices » is usually used by scholars and generalists to imply "a set of ways of work" that is particular for the organization or the organizations which apply them [5]. In regards to HRM, for instance, there are a lot of practices [6] that seek to organize workload, hire employees and ensure their development or increase their motivation; each one of these activities can be performed differently: the workload can be organized in an expanded or a specialized way, recruitments can be conducted internally or externally, compensation may include premiums and bonuses or not, etc.

These practices are set by a somewhat important network of politics, procedures, directives, rules, traditions, habits etc., they intend to acquire the appropriate human resources, expand them and develop them [7]. The practices impact the stuffing, the know-how and the interpersonal skills of the employees in addition to their habits, therefore, they can affect the organizational culture [8]. These practices constitute a means that allows the company to be distinguished from the others and confront the competitive environment. In fact, to meet the fixed objectives, the company must own certain assets compared to its competitors [9].

Charles-Pauvres [10] assert the importance of employee engagement for researchers. According to Commeiras [11], engagement is a paramount asset that leads to action and efficiency. Theivenet [12] states that "an engaged individual will defend the values and objectives of the company". Consequently, engaged employees show a better performance compared to the less engaged ones [13]. Thus, engagement is often an effective means to manage employees' turn-over [14] as well as absenteeism [15]. Besides, employee engagement is also an indication of the company efficiency [16].

The objective of this study is to identify and analyze the factors that impact employee engagement in the company. Hence, the research problem is formulated in the following questions: what are the factors that affect employee engagement? What is the mathematical model that describes causality between these factors and employee engagement?

Following the survey carried out, we decided to analyze and study the impact of 8 predictors on the employees' performance. This performance is measured by an ordinal variable called Implication and has for levels giving the level of their engagement "Not engaged", "somewhat engaged", "engaged", and "very engaged", coded by 1, 2, 3 and 4, respectively. The performance is measured by this variable because we think that a well-engaged person often manages their tasks in the best way, and subsequently we obtain a good performance on the whole processes of the company.

II. PREDICTION METHODS

Generally, predictive models are formulated as in the following equation, where Y is the response variable and X represents p independent variables vector. The aim of the prediction methods is to find the expression of the function f [17], $Y = f(x_1; x_2; \dots, x_p)$ (1). Generally, when designing a model one is faced two different strategies, the first one is to build a model from theory, parametric models, and then adjust its parameters based on the observed data like in the regression models but, unfortunately, in most real-life situations such models are not available. To overcome the lack of parametric models, the second strategy consists of building the models directly from the data as in the non-parametric machine learning techniques like neural networks, support vector machines among others. Most of the non-parametric models are built in the supervised learning, which means that the data with the desired target variables has to be prepared beforehand.

To fulfill the objective of this research, which aims at extracting the parameters controlling the variable "employee engagement", we have considered both parametric and non-parametric models. The used data was collected from a questionnaire that was delivered to 60 individuals working in different companies. Originally, the questionnaire consists of 58 validated questions, but in this study, we are interested only by 8 principal predictors, which commonly have the most important impact on the employee's engagement. Aware of the complexity of the relationship that link the employees to their workplace, in the first time we aim to analyze the correlation between these eight predictors and the response variable given by the employees' engagement. The approaches considered to model this relation start by a simple linear regression, ordinary logistic regression, gradient boosting machine regression and neural networks approach with backpropagation scatter search methods as learning methods and support vector machine.

The data set has a four-level response variable called Implication, with levels "Not satisfied", "somewhat satisfied", "Satisfied, and "very satisfied", coded by 1, 2, 3 and 4, respectively, that we will use as our outcome variable. Also, we have eight independent variables that we will use as predictors:

- a) X1: which is a 1,2, 3 variable indicating the age groups of the employees. 1 for persons where the age is less than 30 years old, 2 for persons with age between 30 and 45 years old, and 3 for persons where the age is greater than 45.
- b) X2: gives the studies level of the employees and it's coded from 1 to 8, 8 means that the employee has 8 years after baccalaureate.
- c) X3: this variable indicates the salary satisfaction: 1 for "Unsatisfied" person, 2 for "Somewhat satisfied, 3 "satisfied" and 4 for "very satisfied".
- d) X4: which is a 1/2 variable indicating either the person is married or not, 1 for single and 2 for married.
- e) X5: the type of relation that maintains the employee with her team of work, which is a 1,2, 3 variable, 1 for "not good", 2 for "Somewhat good" 3 for "Very good".

- f) X6: The gender of each person which is a 1/2 variable where 1 for woman and 2 for man
- g) X7: which is a 1,2, 3 variable indicating the type of relationship that maintains the employee with his employer, where 1 indicates "not good", 2 "Somewhat good" 3 for "Very good".
- h) X8: which is a 1,2, 3 variable indicating the employee impression about the duration of working per day and it is noted by 1 to 3, where 1 for "not acceptable", 2 for "Somewhat acceptable" and 3 for "acceptable".

A. Linear regression

In its simple version the linear regression approach tries to model the relationship between two variables by fitting a linear equation to observed data. The first variable is considered to be an explanatory variable, generally, noted by X and the second one is the dependent variable and it's often noted by Y [18]. For example, a modeler might want to relate the performance of an employee with its salary using a linear regression model. Generally linear regression well fit data when the dependent variable is continuous. In this study, we have an ordinal categorical outcome represented by 1;2;3, 4 and 5, for this the output of the linear model for each data row i noted by $lm_out(i)$ is transformed as $lm_out(i) = \sum_{j=0}^J I_{(j-0.5, j+0.5)}(lm_out(i)) * j$. Where J is the entire part of $\max_i(lm_out(i))$ and $I_A(x)$ is the indicator function defined over the set A.

The first step before trying to fit a linear model to observed data, a modeler should first determine whether or not there is a relationship between the variables of interest. The most valuable numerical measure of association between two variables is the correlation coefficient, which is a value between -1 and 1 indicating the strength of the association of the observed data for the two variables. Generally, A linear regression line has an equation of the form $Y = a + b * X$, where X is the explanatory variable and Y is the dependent variable. The slope of the line is b, and a is the intercept (the value of Y when X= 0). To fit the regression models the most used method is the least-squares means error. In our work the models used for the regression linear are developed in Rproject statistic tools. The results shown in tables 1 and 2 demonstrate clearly that there isn't any clear linear correlation between the dependent variable and any of the independents variables.

Table- I: ANOVA Analysis

	Freedom degree	Sum of squares	Average of squares	F	Value of F
Regression	8	6.637	0.829	0.504	0.847
Residuals	51	83.946	1.646		
Total	59	90.583			

Table- II: ANOVA Analysis coefficients

	Coefficients	Error-type	Statistic	P-value
Intercept	3.852	1.235	3.119	0.003
Salary	0.068	0.246	0.275	0.784
TeamRelation	-0.298	0.227	-1.315	0.194
ManagersRelation	0.294	0.314	0.937	0.353
WorkDuration	-0.336	0.337	-0.998	0.323

GENDER	-0.053	0.352	-0.150	0.881
Age	0.106	0.288	0.370	0.713
Studies_Level	0.067	0.114	0.587	0.560
Family_Situation	-0.107	0.391	-0.273	0.786

Contrary to what one expects, the relation between the employee's engagement variable and the eight predictors cannot be modeled correctly by a linear regression. The results of tables 1 and 2 show that there isn't any clear linear correlation between the independent variables and the response one. Also, we have analyzed the quadratic term and the interaction between the predictors, once again the result obtained show that there is no significant linear relation between the predictors, their interaction and the response variable. Based on the results obtained by the linear regression and the nature of the dependent variable that is an ordinal variable of 4 values. In the following section we will try to fit the relationship between these variables using the ordinal logistic regression.

B. Ordinal logistic regression

Since our outcome variable is polychotomous and it has four ordinal values instead of two in the case of the traditional binary logistic; in this section we try to model the relationship between the 8 predictors bellowed cited and the response variable using the ordinal logistic regression (OLR) model instead of developing traditional binary logistic regression. In the literature there are various approaches used to manage this kind of data, such as the use of mixed models, Probit for example, but the ordinal logistic regression models have been widely used in most of the research works, and the results obtained are very promising [19, 20, 21, 22, 23].

Ordinal logistic regression (OLR) is generally used to predict an ordinal dependent variable given one or more independent variables. OLR can be seen as either a generalization of multiple linear regression or as a generalization of binomial logistic regression. There is more than one type of ordinal regression that can be used to analyze ordinal dependent variables. In the literature there are several ways to implement the ORL, because the structure of our data we have opted by the most suitable used ordinal logistic regression model called constrained cumulative logit model or the proportional odds model [19, 24, 25] and we allow the OLR to consider the interactions between independent variables to predict the dependent variable. The OLR function used is developed in the well-known and used statistics tool Rproject. Determining whether there is multicollinearity is an important step in ordinal regression. For this, before using the OLR we have conducted a study to analyze the multicollinearity between the independent variables. The results obtained show that there is no multicollinearity between the independent variables. In order to interpret the model of the OLR, we first need to understand the working of the proportional odds model.



Let J be the total number of categories of the dependent variable and M be the number of independent variables (In the given dataset, J=4 and M = 8). The mathematical formulation of the Proportional Odds Model is given below for each j = 1, ..., J-1.

$$\text{logit}[P(Y \leq j)] = \alpha_j - \sum_{i=1, M} \beta_i X_i$$

In the section, results, we illustrate the best results obtained applying ORL in Rproject Statistics to perform an ordinal regression.

C. Gradient Boosting machine learning

Gradient boosting machines (GBM) are a new machine learning technique that have shown considerable success in a wide range of practical applications [26, 27]. They are highly

Algorithm 1: GBM

Input data $\{(x_i, y_i)\}_{i=1, \dots, n}$, and a differentiable LOSS FUNCTION $L(y_i, F(x))$

step 1: Initialize model with a constant value: $F_0(x) = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, \gamma)$

step 2: from $m=1$ to M

$$r_{im} = \left[-\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)} \text{ for } i =$$

a. compute $1, \dots, n$

b. Fit regression tree to the r_{im} values and regions r_{jm} , for $i = 1, \dots, J_m$

c. for $j = 1, \dots, J_m$ compute $\gamma_{jm} = \min_{\gamma} \sum_{x_i \in R_{ij}} L(y_i, F_{m-1}(x_i) + \gamma)$

d. update $F_m(x) = F_{m-1}(x) + v \sum_{j=1}^{J_m} \gamma_{jm} I(x \in R_{jm})$

Step	3:	output
$F_M(x)$		

D. Support Vector Machine

Support vector Machines (SVM) are a family of machine learning algorithms that is used to solve problems related to classification, regression, and anomaly detection. They are well known for their strong theoretical guarantees, large flexibility as well as the simplicity of use even in the absence of data mining knowledge [28].

SVMs were developed in the 90's. As it is shown in the following figure, their basics are simple: they aim at categorizing data into classes using a boundary as "simple" as possible, in a way that makes the distance between the different data groups and the boundary maximal. This distance is called « margin », thus SVMs are described as « large margin classifiers », while « support vectors » are the closest data to the boundary.

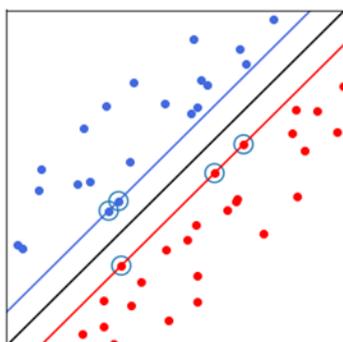


Figure 1 SVM, Julien Audiffren, 2017

In this two-dimensions space shown in the figure 1, the «boundary » is the black line, the «support vectors » are the circled dots (the closest to the boundary) and the « margin » is the distance between the boundary and the blue and red lines.

customizable to the particular needs of the application, like being learned with respect to different loss functions. These techniques are originally proposed by Friedman (2001). The main elements of the GBM algorithm are shown in the following pseudo-code.

Using Gradient boost for regression is different from doing linear regression, so while the two methods are related, don't get them confused with each other. The two principals' elements of the GBM algorithm are the data set and the loss function, these two elements should be tuned carefully to assure a good convergence of the algorithm. The overview of the algorithm used in this paper is as presented in the pseudo-code of algorithm 1.

The use of boundary presupposes the existence of linearly classifiable data, but such instances are rare. To overcome this issue, SVMs usually rely on kernel functions. These mathematical functions allow data classification by projecting them in a feature space (a larger dimension vector space). In this work we have considered the SVM function defined in Rproject tool with some tuning of its parameters.

E. Artificial neural networks:

Artificial neural networks (ANN) present an excellent paradigm for decision support that integrates knowledge and learning. They are inspired by biological neural systems where the nodes of the network represent the neurons and the arcs the axons and dendrites [29]. Artificial neural networks draw their principles from the way the brain and the nervous system operates. They are a family of learning methods that seek to estimate functions consisting of a considerable number of inputs. ANN represent an interconnected system of "neurons" that calculate outputs based on input values and their corresponding weights. The process of training an ANN consists of adjusting the weights which regulate the outputs of the neurons. The literature offers different approaches that have been previously proposed as learning methods. In this study, we apply in the first one of the most used learning methods which is backpropagation. In this method, the initial weight values are set randomly, then they are regulated using a gradient descent method according to the estimated outputs used while training the network.



A second method Based on the scatter search methodology is used to fit the weight of the neural networks model. In this case study we consider a multilayer perceptron neural networks with the backpropagation and scatter search as method learning.

The figure 2 shows a simple architecture of the well-known multilayer perceptron proposed by Rumelhart et al in 1986 [30].

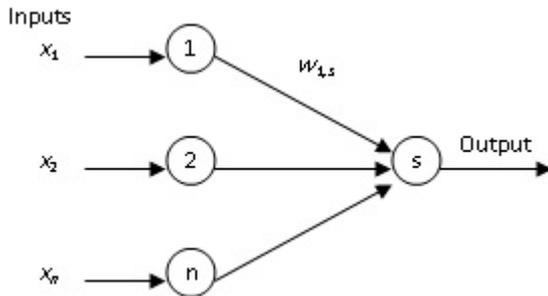


Figure 2: Basic Perceptron Neural Networks paradigm

a) Backpropagation

Backpropagation is a classic method in the supervised training of artificial neural networks. Verbos proposed the algorithm in the 70s [31], which was rediscovered by Parker and Rumelhart in the early 80s. The algorithm was not popular until 1986 when Rumelhart, Hinton, and Williams [32] proposed a clear description of this method. It is still persistent to this day in different applications even though it is outdated by other advanced methods. Backpropagation is a reference in the field of artificial neural networks training [33] and still used as reference of comparison of each new learning method in the area of neural networks.

The backpropagation algorithm explores the network weight space. It relies on the direction determined by the error gradient vector on the set of training. Backpropagation involves the propagation of the obtained error at the network output backward, i.e. from the output layer to the input layer, going through the hidden or intermediate layers. The algorithm computes, at each iteration, the derivative of the error with respect to each weight and modifies them in order to minimize the total error. The overview of the basic Backpropagation algorithm is given by the pseudo-code of algorithm 2.

Algorithm 2: Basic Backpropagation Algorithm

1. Set a value of α ($0 < \alpha < 1$). put $t=0$. Initialize the weights $w(t)$ with random values in $[-0,5, 0,5]$.
2. Prepare the training data set E and the output of the networks. It is recommended that the data should be normalized in $[-1, 1]$.
3. For each input x of the set E , we compute the output $NN(x,w(t))$ and the error corresponding $Error(E,w(t))$
4. If the error is small or the number of iterations t reaches a preset threshold, Stop.
5. Calculate the derivatives of the error with respect to the weights via the two steps of the algorithm.

6. Update the weights according the following equation:

$$w(t + 1) = w(t) - \alpha \frac{\partial Error(E, w(t))}{\partial w}$$

7. put $t = t+1$. Go to 2.

b) Scatter search

Scatter search (SS) is an evolutionary method, used to resolve a large number of large-scale optimization problems. The fundamental principles and concepts of this methodology were first advanced in the early 70s [34]. They are based on strategies to combine different decision rules, namely in sequencing problems as well as combining constraints. SS relies on the principle that information related to the quality or the interest of a set of rules, constraints, or solutions can be used in combination. Given two solutions, in particular, the new solution can be obtained by their combination taking from each one the best features. So that the new solution improves the first ones generally. Along the line of generic search algorithm, SS relies on maintaining a set of solutions and combining them. But unlike the generic algorithms, SS does not involve the randomization of a relatively large set of solutions, it rather relies on the strategic and systematic selection from a smaller set of solutions called elite set of solution who participate in the future evolution [35]. For instance, generic algorithms usually include a population of 100 solutions, while SS usually involves sets of only 10 solutions called reference set of solution from an initial set of solutions called P [33]. Generally, the solutions of the set P are generated using a heuristic method to ensure the diversity of the solutions in P . For more information and survey of this methodology reader can consult [34]. The general overview of a scatter search algorithm can be shown in the pseudo-code algorithm 3.

Algorithm 3: Basic scatter search procedure

Start with $P = \emptyset$. Use the diversification generation method to construct a solution and apply the improvement method. Let x be the resulting solution. If $x \notin P$ then add x to P (i.e., $P = P \cup x$), otherwise, discard x . Repeat this step until $|P| = PSize$.

Use the reference set update method to build $RefSet = \{x_1, \dots, x_b\}$ with the "best" b solutions in P . Order the solutions in $RefSet$ according to their objective function value such that x_1 is the best solution and x_b the worst. Make $NewSolutions = TRUE$.

while (NewSolutions) do

1. Generate $NewSubsets$ with the subset generation method. Make $NewSolutions = FALSE$.

while (NewSubsets $\neq \emptyset$) do

2. Select the next subset s in $NewSubsets$.
3. Apply the solution combination method to s to obtain one or more new trial solutions x . Apply the improvement method to the trial solutions.



```

4. Apply the reference set update method.
if (RefSet has changed ) then
5. Make NewSolutions= TRUE.
end if
6. Delete s from NewSubsets.
end while
end while
    
```

III. RESULT AND DISCUSSION

After having described the training methods, we will show the results they obtained and comment on their operation on the collection of 5 examples considered of different sample of training and validation data. Concretely, we will now consider the six methods:

1. Linear regression
2. Ordinal logistic regression
3. Gradient boosting machine learning method
4. Support vector machine
5. Backpropagation Neural Networks
6. Scatter search Neural Network

Since all the methods have a random parameter, we have executed each algorithm five times with different samples of data extracted from the 60 individual's data. At each time we consider sample with 80% of data as training set and the rest 20% for Validation. The best parameters considered for each method are obtained by tuning the algorithm with different values, and at the final we select the parameters that gives the best results over the validation data. For example, for neural networks the number of hidden layers is fixed on 1 and the number of hidden neurons is 5 neurons.

Table 1 gives the results obtained by the considered methods. The columns of this table are Method, Average_TE, Average_VE, Min_TE, Max_TE, Min_Ve and Max_VE and gives respectively the name of the method, the average of percentage of good classification of the individuals considered over the five training samples, the average of percentage of the good classification of the individuals considered over the validation samples, percentage of worst classification considering the training samples, percentage of best classification considering the training samples, percentage of worst classification considering the validation samples, percentage of best classification considering the validation samples.

Based on the results of table 3 we observe that the results obtained by the methods are very humble. This verdict can be due to the complex relationship existing between the predictors of the employee's engagement and the conditions of works. Also, we note that neural networks using scatter search as learning algorithm gives the bests results on the testing data and a good estimation on the training data.

IV. CONCLUSION

Based on the results of table 3 we observe that the results obtained by the methods are very humble. This verdict can be due to the complex relationship existing between the predictors of the employee's engagement and the conditions of works. Also, we note that neural networks using scatter search as learning algorithm gives the bests results on the testing data and a good estimation on the training data.

Tableau 3: Results obtained by the six considered Methods

Method	Average_TE	Average_VE	Min_TE	Max_TE	Min_VE	Max_VE
LR	68%	23%	60%	75%	21%	25%
ORL	59%	28%	61%	75%	25%	33%
SVM	60%	35%	58%	62%	33%	38%
NN_BP	65%	33%	62%	68%	31%	34%
NN_SS	58%	40%	55%	61%	38%	14%

From the results of table 3, we can observe that the best predicted percentage over the training data is around 62% and over the testing data is around 32%. These results reflect the complex relation between the considered predictors and the response variable, and it is clear that establish a model is not easy, which shows that there are probably other factors to take into consideration or the employees' responses were not well integrated.

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