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Job performance prediction in a call center using a naive Bayes classifier

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ABSTRACT

This study presents an approach to predict the performance of sales agents of a call center dedicated exclusively to sales and telemarketing activities. This approach is based on a naive Bayesian classifier. The objective is to know what levels of the attributes are indicative of individuals who perform well. A sample of 1037 sales agents was taken during the period between March and September of 2009 on campaigns related to insurance sales and service pre-paid phone services, to build the naive Bayes network. It has been shown that, socio-demographic attributes are not suitable for predicting performance. Alternatively, operational records were used to predict production of sales agents, achieving satisfactory results. In this case, the classifier training and testing is done through a stratified tenfold cross-validation. It classified the instances correctly 80.60% of times, with the proportion of false positives of 18.1% for class *no* (does not achieve minimum) and 20.8% for the class *yes* (achieves equal or above minimum acceptable). These results suggest that socio-demographic attributes has no predictive power on performance, while the operational information of the activities of the sale agent can predict the future performance of the agent.

1. Introduction

Employee turnover has been a fertile ground for numerous studies that deal with, from a theoretical perspective and empirical, the causes of both, voluntary and involuntary turnover, as well as those that explain the tenure of employees. Particularly in call centers, employee turnover is a problem related to high turnover rates, which represents an important economic cost such as advertising, recruitment, testing, training and supervision at work to achieve, after a certain time, the employee's competence as to achieve adequate levels of productivity (Hillmer, Hillmer, & McRoberts, 2004; Robb, 2002). Sums of money are spent in recruiting and training people, but unfortunately, a large percentage of them leave the firm before reaching some kind of reasonable performance. According to Robb (2002), this is an indication that the recruitment and selection activities are not confronting or preventing the central problem: the high turnover rate. This problem causes, according to Jackson (2009), that 70% of the costs of operating a call center are related to personnel management. Employee turnover contributes to a high ratio of staff costs to operating costs.

Call centers represent an exceptional case of the service industry and labor of customer contact, in which the mechanization of work has been installed as a form of taylorism to streamline production. Usually, this model of mass production is characterized by requiring instrumental competences, little opportunity for making decisions, and learning is limited to the repetition of tasks. In this case, it is assumed that the work is designed to turnover-proof where workers are like replacement parts (Batt & Moynihan, 2002). From this perspective, one might assume that the management style of this model naturally attracts high turnover. Just as it happens in Chile, the problem is exacerbated when market conditions remain competitive in the industry resulting in the loss of thousands of employees Concha (2010). The pressure to stay competitive in the industry, leads to call centers to put maximum effort in operational efficiency, using technology to centralize the calls at one location and where labor costs are lower and more labor flexibility (Buchanan, 2005).

Call center executives often are subjected to demands that can lead to stress and frustration (McDonald, 1998; Ruyter, Wetzels, & Feinberg, 2001). In many cases, executives must deal with aggressive clients, be subject to constant on-line monitoring and have low flexibility and chance to operate under its own discretion. Under this scenario, it is relevant the ability of the call center to select individuals who may have a good performance and a longer service time. The selection process should identify certain characteristics of a personal nature and personality that are consistent with the organization and working environment of the call center itself (Adorno, 2010). The process should try to avoid a poor fit between the individual's job expectations and the expectations that the organization has to it. The firm must pay attention and effort in

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the recruitment and selection process from the perspective of where to look in relation to the skills and knowledge of the candidate, so that it can meet the requirements of the business (Jackson, 2009; Birnbaum & Somers, 1997).

This study aims to assess individuals during her/his test period using a naive Bayes classifier to discriminate between cases that achieve or not the minimum performance, required by the firm to remain in it, using demographics and operational attributes. The structure of this paper is as follow: First, we review recent studies that address the problem of turnover and employee selection. Second, we present a general model of individual performance and the methodology used to evaluate it. Third, we presented the results of simulations and predictive capacity of the model and, finally the conclusions.

2. Related work

Recruitment has been an important aspect of research in human resource and organizational psychology. The discovery of patterns and relationships in the personal data characteristics of people, can help to predict the behavior of individuals in terms of their performance. Research from these areas have produced important developments concerning with the relationship between personality characteristics of individuals and their expectations, satisfaction and job performance (Borman & Motowildo, 1997; Irving & Meyer, 1995; Mount & Barrick, 1998). The methods used in these investigations are based on correlation analysis, cross section analysis, and longitudinal studies in order to find significant relationships between variables. However, there is very little literature on the use of data mining techniques, to address the problem of turnover and job performance. Application of data mining techniques and expert systems in personnel selection and turnover is limited. For example, Chien and Chen (2008) developed a mechanism for selecting rules for staff selection based on decision tree. Darsun and Karsak (2010) used fuzzy logic theory as a framework for staffing decision that incorporates imprecise judgments during the selection process. Cho and Ngai (2003) used a decision tree, neural network and discriminant analysis as tools to predict tenure and performance of insurance sales agents. Nussbaum et al. (1999) used a decision support system to analyze the interpersonal behavior of members of a working group and assessing the compatibility between people in it. In these applications, researchers use expert systems or data mining techniques to assist the process of selection by establishing predictions of whether a candidate is more likely to meet the expectations of the firm in job performance and tenure. Hong, Wei, and Chen (2007) used probit and logit models as alternatives for the prediction of voluntary desertion with promising results, however, in these models, they used only job performance (expressed in annual sales) as independent variable to explain turnover. There is no work found in the use of Bayesian networks to predict performance and turnover. This situation is curious being that the implementation of an expert system based on a naive Bayesian network has a low complexity and computational resource usage unlike other methods. In this research, job performance is explained by a naive Bayesian network.

3. Background

The work presented in this paper was carried out at a Call Center located in Santiago, Chile. It is dedicated to meet requirements of its institutional clients in telemarketing and sales activities of banking, retail and telecommunications business. It has an average of 500 sales agents per month. The campaign is the core activity of the call center focused on making a sale through the telephone channel services provided by institutional clients and offered to consumers for an indefinite period or until the client determines. The call center has an average number of 30 campaigns running and 14500 talked hours per month. For this study, a sample was taken from a total of 660 sales agents, which belong to individuals who were selected during the recruitment process and joined the organization from March of 2009 until December of that year. The sample of individuals only consider those who work in campaigns related to the insurance sales and telephone pre-paid services, representing 80% of the normal operation of the Call Center. The selection department is subject to heavy loads to hire new employees on an ongoing basis. The sales personnel selection system staff is a phased process insertion which is described in Fig. 1: In the first stage, people who have been selected to begin work upon approval of a psychological examination and personal interview, are hired for a time T_1 (1 month). At the end of this first period, an evaluation of the performance of the salesperson is carried out. Results of the evaluation, determines whether or not the employee continues in the company. The evaluation is measured solely by the production in terms of number of sales generated. If the agent continues, she/he is hired for another month (T_2 = 1 month). At the end of the second period, again the employees are subjected to a second evaluation of their performance during this period. Results from this evaluation, determines whether or not the employee continues in the company. If the employee continues in the firm, again she/he is hired again for one additional month (T_3 = 1 month). At the end their the third period, in function of their performance, it is determined if she/he is hired indefinitely or withdraws from the organization.

According to this system, Table 1 shows the four different possibilities of tenure vs production of the individual during and after the test period of three months.

The process described above, is to find among the candidates, people who have the ability to achieve the minimum production requirements consistently over time. This is a problem of discrimination. Under this paradigm, we propose a model to predict the production of the sales agents based on personal socio-demographics data and operational performance during the phase of insertion described before. It is desired to prevent that a sales agent who overcomes the three months test and is hired

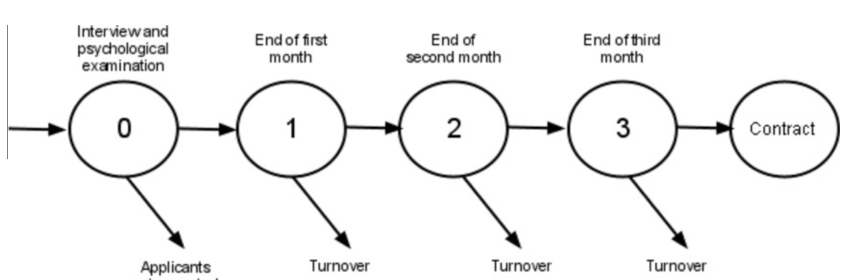

Fig. 1. Insertion process of employees to the call center.

Table 1
Tenure of the individual in the call center according to their actual production.

Tenure	Production	
	Below minimum	Above minimum
More than 3 months	Not admitted	Voluntary or involuntary turnover
Less than 3 months	Mostly involuntary turnover	Voluntary or involuntary turnover

indefinitely, must be dismissed due to a poor performance. In other words, it is desired to identify during the phase of insertion, those individuals that have greater probability to achieve a poor performance. Although the present study involves only one call center, the functions and tasks of sales agents in an outbound call centers are standardized (A. Ventura, personal communication with CEO of the call center, July 6, 2010).

The proposed predictive model in this work can be expressed in general terms as follows:

Let N be a population of individuals where each one has an average production P_i during the test period. The final individual selection, at the end of the test period, is based on a production threshold v, where the ith individual is accepted if her/his future production level is grater or equal to v, rejected otherwise. Let y be a binary variable that defines the class to which the individual belongs (accepted or rejected), then:

$$y = \begin{cases} 1 & \text{if } P_i \geqslant v \\ 0 & \text{if } P_i < v \end{cases}$$

Each individual has a vector $\vec{x} = \{x_1, x_2, \ldots, x_n\}$ of attributes that characterizes her/him. Associated with this vector, there is a production P_i. By supervised learning, the classifier estimates the probability that the ith individual will achieve a future production below or above the a threshold production v using vector $\vec{x}$, in order to make a decision on whether or not the individual remains on the job at any stage of the test period.

Initially, each individual has a vector $\vec{x}$ of attributes that characterizes her/him. The classification problem is to maximize the probability that the individual belongs to one class or another.

Following Bayes probabilistic model and under the assumption that all attributes are conditionally independent given the class variable, it is possible to derive the probability of y given attributes $\vec{x}$ as:

$$P(y|\vec{x}) = \frac{P(y)\prod_{j=1}^{n} P(x_{ij}|y)}{\sum_{y'=0}^{y'=1} P(\vec{x}|y')P(y')}$$

where x_{ij} is the jth attribute from set $\vec{x}$ of the ith individual.

The term of the indexed product for the likelihood is simply the product of each probability that the individual possesses a certain attribute j given the class to which it belongs. This is because of the assumption of independence between attributes (Jensen & Nielsen, 2007; Mitchell, 1997).

Considering the above expression for a MAP based classifier (maximum a posteriori decision rule), the corresponding classification function for attribute vector value $\vec{x}^0 = \{x_1^0, x_2^0, \ldots, x_n^0\}$ would be:

$$\arg\max_{k\in\{0,1\}} P(y=k)\prod_{j=1}^{n} P\left(x_j = x_j^0 | y = k\right) \tag{1}$$

In the following section, we characterized the set of attributes $\vec{x}$, in socio-demographic and performance operational variables to test the classification model.

4. Methodology

This research was developed following the CRISP-DM model proposed by Chapman et al. (2009). CRISP-DM model provides a generic guide to develop a data mining project life cycle. Data is collected from the daily operations of the sales activities of agents and data bases of the Human Resource Department. This information regarding personal data and operational performance of sales agents, were used to investigate the attributes that explain the production. The dependent or class variable Y is a discrete version of the production. *no* for a production below minimum v, *yes* for production higher or equal than minimum v. Evaluation of the sales agents is carried out on the bases of her/his monthly production. This corresponds to the number of monthly approved sales, which is translated to the local currency. If this total sum is greater or equal to current minimum wage, then the organization proceeds to renew the labor contract for another month, otherwise, the person is dismissed. The goal is to predict the likelihood to achieve an average production of sale agent during his/her test period. Because of the insertion process described before, this means to predict a monthly production always equal or greater than minimum v. In this case, at the end of the third month, the sale agent is hired indefinitely.

We tested the model using socio-demographic information as attributes of individuals. This is equivalent to obtaining a prediction of an agent production at $t = 0$ (selection stage) according to Fig. 1.

The socio-demographics predictive attributes of sales agents production used were:

1. *Age*
2. *Gender*: Male or female
3. *Marital status*: Married or single
4. *Education*: High school, secretarial training, technical education, university education.
5. *Socioeconomic status of the commune of residence*: Five discrete levels including if residence is outside of the capital.
6. *Experience*: Yes if the person has experience in sales related activities, No otherwise.

Next, the model was tested our model using performance information as attributes. Performance information corresponds to the set of operational attributes of the sale agent that the call center recorded daily during the worked hours.

The performance variables as predictive attributes of the sales agents production were:

1. *Logged hours*: It is the average number of hours per month that the agent has her/his workstation active, which does not necessarily mean they are talking with consumers.
2. *Talked hours*: It is the average number of hours actually used per month talking with consumers.
3. *Effective contacts*: It is the average number of effective contacts per month. It is necessary to make a distinction between effective contact and actual contact. When agent receives a telephone response, the respondent may not be necessarily the client. The effective contact is defined as a contact made between sales agent and a client identified as such in records.
4. *Finished records*: It is the average number of completed records. Each agent has a list of records containing details of customers which they contact. Sometimes, the agents makes a phone contact, but not with the person on the record. In this case, the record remains open. When an agent makes a contact with the right person, there are two possibilities: the agent achieves a sale or, the customer rejects the offering. Under these possibilities, there is an effective contact and the record is closed.

Performance variables are all continuous in nature. For purposes of the Bayesian classifier, performance variables were discretized based on a minimum entropy heuristic developed by

Fayyad and Irani (1993). This algorithm uses the information entropy of the class variable (production) to partition the data into blocks that eventually form the discretization of the continuous variable.

Logged hours can be considered as a proxy of assistance to work. An agent with few hours of logging is indicative of non worked days or absent days at work. Talked hours and finished records can be considered as a proxy for the amount of effort spent by an agent to achieve sales. A high number of talked hours is because the agent is dedicated and has the ability to remain in line with the client, while the finished records is also indicative of the amount of work done.

Effective contacts can be interpreted as a factor of 'luck' because the agent can not control whether she/he will contact the client or not. The interpretation given to all these performance variables have been corroborated and validated by the supervisor of the call center operation.

4.1. Data selection

The sample includes daily operational performance of sales agents between March and December of 2009, which includes production data of 1037 agents from all campaigns in the operation period. From this total, we selected only those executives who served in campaigns related to insurance sales and service pre-paid phone services, which represents about 80% of the normal operation of the call center. Thus, after removing anomalous and erroneous instances from the database, the number of usable cases was reduced to 660.

4.2. Data cleaning

The raw data contained instances that were not applicable because of errors and anomalies which had to be discarded. The errors and anomalies were confirmed by the person in charge of the operation and data generation. Additionally, the instances of agents who joined the call center before March of 2009 have been discarded to avoid contaminating the sample with agents that have spent more than three months at the firm. There were some inconsistent cases with the test period of three months. There were cases of sales agents working more than three months with an approved production average less than minimum wage. These instances are discarded. Human resource data such as personal information of the agent (marital status, education level, etc.) has been extracted from the personnel department databases. This information is crossed with the database obtained from the system department using the id. In that way, information was obtained from all the sources in a single data matrix. During the crossing of information, numerous cases with missing data were detected because one or more of the variables or attributes (columns) are lost. Most missing data corresponds to the date of entry into the call center and information of the experience. The former is essential to compute tenure of the sale agent. Being a dependent variable, and because there are a lot of missing cases like this, it is not considered applying estimation techniques, so that such cases were discarded.

4.3. Construct data

The dependent variable 'production' has been constructed as the monthly average production of the sales agents. The discrete version of this variable is simply whether this average is greater than or equal to the minimum wage or not (if the agent production is less than a minimum wage, then there is an involuntary turnover). The 'tenure' variable is simply the difference in weeks between the entry and exit date to the organization. The discrete version of this variable indicates if an individual stays more than three months or not (remember, insertion phase lasts three months, after that time, an agent gets a permanent contract). Discrete versions of production and tenure are useful to verify instances that do not meet with the insertion phase. For example, when an individual's average production is less than the minimum wage and she/he has stayed longer than three months. These instances are discarded. For the naive network model, continuous variables like age, logged hours, talked hours, effective contacts, finished records, and quality, have been transformed to its discrete equivalent using the supervised discretization by minimization of entropy (Fayyad & Irani, 1993).

4.4. Integrate data

As noted before, the data matrix is the result of the data integration from two sources: one from the systems department with operational performance and production, and the other from the Human Resource department with socio-demographics data of each agent. For the former it was necessary to carry out aggregation operations to compute the monthly average production, which was combined with the personal information of the agent.

5. Results

A first simulation using socio-demographics attributes (age, gender, marital status, education level, socioeconomic level of the county of residence and experience) was carried out to discriminate between those who achieve above or below the minimum production to remain during the insertion phase. It was expected, that a married person had greater incentive to perform better than a single person, or that an older person should performer better than a young person. One might expect that a person with more education had better prospects of a better performance than a person with less education.

The training and testing of the classifier was done through a stratified tenfold cross-validation.

Results were unsatisfactory with these attributes. The proportion of instances classified correctly was 71.76%. The proportion of false positives was 97.9%, which shows that the classifier fails to classify in most cases. In order to corroborate these results, a classification via decision tree with C4.5 (J48) algorithm was used, showing very similar results of the Bayesian classifier. This result shows that socio-economic attributes are not able by themselves to discriminate effectively the class attribute *production*.

A second simulation was carried out using only attributes related with the operational performance type attributes of sales agents (logged hours, talked hours, effective contacts, finished records and quality) to discriminate between those who achieve above or below the minimum *production* to remain during insertion phase.

A principal component analysis was carried out to see if the operational performance attributes have discriminatory power. Fig. 2 shows a graph of the two components representing 98.58% of data variance. It is noted that even when there is some differentiation between those who achieve a minimum required from those who do not, there is overlapping between the two classes, reflecting the degree of complexity and nonlinearity of the discriminant function needed to separate both.

Table 2 presents results of the Bayesian classifier. The classifier training and testing is done through a stratified tenfold cross-validation. The results are noticeably better. It classified the instances correctly 80.60% of times, with the proportion of false positives of 18.1% for class *no* (does not achieve minimum) and 20.8% for the

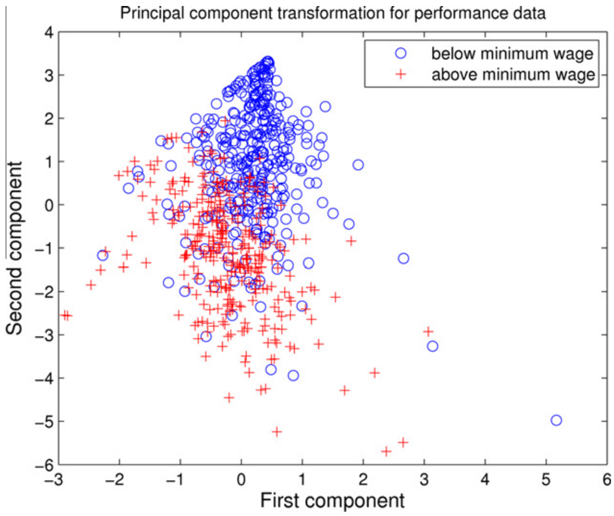

Fig. 2. Principal component analysis for performance data.

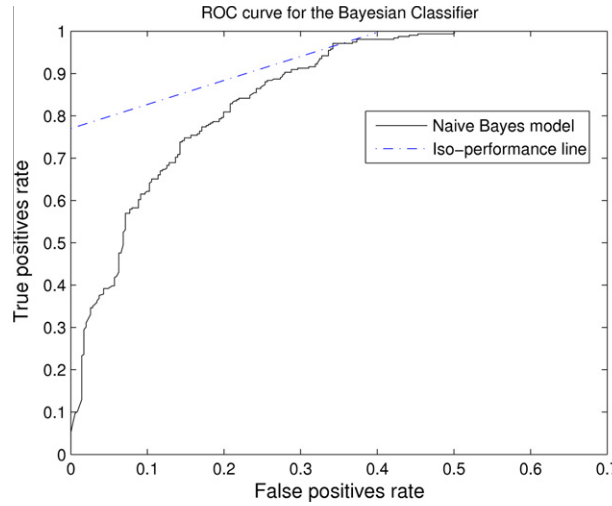

Fig. 3. ROC curve.

Table 2
Results of Bayesian model classifier.

Class	TP rate	FP rate	Precision	Recall	F-measure	ROC area
No	.792	.181	.832	.792	.812	.894
Yes	.819	.208	.776	.819	.797	.894

Table 3
Results of Bayesian classifier for sale agent ID 7363xxxx.

Attribute	First month	Second month
Log hours	197.65	157.43
Talk hours	51.61	28.94
Effective contacts	398	245
Finished records	643	530
Predicted probability	.9993	.9958
Achieve minimum?	Yes	No

class *yes* (achieves equal or above minimum acceptable). Kappa statistic was 0.6088.

Fig. 3 shows the ROC curve obtained with the model using performance attributes. The true positive rates on the vertical axis are expressed as the proportion of the total number of positives, and false positive rates on the horizontal axis are expressed as the proportion of the total number of negatives at different decision making thresholds Ortega, Figueroa, and Ruz (2006). The top left point $(0,1)$ represents a perfect predictor where all instances with high level of production are caught without generating false alarm. Therefore, the closer the ROC curve is to the point $(0,1)$ the better is the performance. The data had a probability of positives $p(P) = 0.468$ and a probability of negatives $p(N) = 0.531$. Assuming a scenario where the cost of a false negative (FN) error corresponds to at least 2 times the cost of a false positive (FP) error, the cost ratio is $C(FN)/C(FN) > 0.5$. Thus, the slope of the iso-performance line is $m = 0.568$ (Fawcett, 2006). According to Fawcett (2006), Provost and Fawcett (1998), the point of the ROC curve classifier with the same slope m has the lower expected cost. At this operating point, the TP and FP rates were 95.8% and 37.5%, respectively.

To illustrate the predictive ability of the model, it is possible to make inferences such as: given certain levels of current operational performance of a sale agent, what is the probability that she/he achieves the required minimum production?

From the operational point of view, the inference over the model allows us a form of control and monitoring of sale agents performance, to the point that it is possible to detect early (for example, in the first month of work) the likelihood that person will achieve above minimum. While the model does not explain the phenomenon of good or bad performance of the individual in the system, it has the potential to detect who has a greater chance of generating a good production. For a field supervisor, this information for control and monitoring is useful to focus efforts on those who are at risk of not achieving the minimum production.

For this investigation, we used the Junction Tree method Jensen and Nielsen (2007) to estimate the posterior probability $v = \arg\max_{v_i \in V} P(v_j|a_1, a_2, \ldots, a_n)$. In this case v_j is the event 'the individual achieves a minimum production' where the set of attributes $\langle a_1, a_2, \ldots, a_n \rangle$ corresponds to *log hours*, *talk hours*, *effective contacts* and *finished records*.

To illustrate the efficacy of the model to detect performance of sale agents, we analyzed a case of a sale agent who joined the test period of the call center in March 2009. Table 3 shows the evolution of performance of the sale agent. The sale agent ID is 7363xxxx. The first month this person achieved a production above the minimum required. At this time, the model was able to deliver a value of 99.93% of chance to produce an average production above the minimum required to pass the test period. In the second month, the production of the sale agent was slightly lower than the minimum required, however, the supervisor allowed the agent to stay the third month of the test period. At this moment, the model delivered a value of 99.58%, slightly lower than the first one. Under this consideration, the supervisor's decision was correct because during the third and final month of testing, the sale agent achieved a production well above the minimum and overcame the test period. A second case is presented in Table 4: A sale agent joined the test period of the Call Center in November 2009. The sale agent ID is 1548xxxx. This agent achieved a production slightly lower than the minimum required. The model predicted a value of 17.51% of success for this agent for the test period, however, the supervisor allowed the agent to stay the second month of the test period. In this case, the decision of the supervisor was wrong, because in the second month, the agent performance was poor and he was dismissed.

These two examples highlight the importance of having a system for decision support and performance monitoring of sale agents. Our model can detect early the potential of a sales agents to maintain consistent performance during the test period. Also, make better decisions as to whether an agent should be dismissed when the agent really has no conditions for sales activities or

Table 4
Results of Bayesian classifier for sale agent ID 1548xxxx.

Attribute	First month	Second month
Log hours	81.23	111.88
Talk hours	33.83	36.53
Effective contacts	269	356
Finished records	400	584
Predicted probability	.1751	
Achieve minimum?	No	No

maintain an agent for another month to prevent a dismiss when she/he needs to develop her/his full potential.

The success or failure of the test period, depends on the ability of the process to recognize individuals who consistently achieve the minimum production required. Sale agents that overcome the test period, are hired indefinitely, but if they subsequently withdraw or achieve poor performance, they are undesirable cases. Sale agents who overcome the test period and are hired indefinitely, are expected to remain in the call center achieving a production over the minimum required. As a measure of effectiveness of this process insertion, in 2009, 84.1% of the sales agents who overcame the test period kept a good performance. Of this percentage, 61.6% remained in the call center for more than six months.

In order to test the ability of our model to discriminate between undesirable from desirable cases, a sample of 207 agents who overcame the test period between March and October 2009 was taken. Using operational information of these agents, our model was able to correctly predict 83.6% of these cases, discriminating between undesirable and desirable cases. This means that the model not only provides a tool for control and monitoring of performance during the test period. It also allows an acceptable ex-post performance prediction of the sales agents.

6. Conclusions

Taking a subset of personal attributes of an individual, is insufficient to predict the performance at $t = 0$. It is possible that in jobs with low specialization and high routine, as in the case of sales and telemarketing activities in the call center, attributes such as level of education, age or marital status have little influence in performance and turnover intentions, as opposed to other professions with greater degree of specialization. The operational attributes proved to be a better predictor of the sales agent production. From these results we can say that, for job in services industries with low degree of specialization and professionalization, where turnover rates are high, selection and subsequent hiring should not be based on the individual and socio-economic variables because these variables are not indicative of future performance. However, before the hiring process, it is better to observe the individuals and make decisions based on performance attributes during a test or insertion period.

In this sense, the use of the proposed model in this work does not improve the ability of the selection department to select the most appropriate individuals for the job, because it does not perform well in the initial stage of selection. However, during the testing stage, we have seen that the inference performed on this model, permits to establish particular minimum conditions of operation as those of the Tables 3 and 4. Inference made on the naive Bayesian network allows us to compute posterior probability that an agent will achieve required production in order to remain in the firm. As a means of control and monitoring employee performance, this information is useful, specially when it is desired to avoid a voluntary or involuntary turnover after the insertion phase. In the case of individuals that do not possess the ability for this particular job, they can be identified according to performance records and detected in early phase of the insertion phase from those that are candidates for an involuntary desertion or a re-location in another place. In those cases in which the individual obtains constantly performances over the minimum levels, it will be necessary to adequate a motivation strategy to avoid dysfunctional desertions. Finally, in the cases that are in the limit, an adequate strategy to fortify their training and to improve their performance is required.

Future research should address the problem of selection in early stages of the process, trying to develop more accurate predictive models that can give a prediction of the job performance with personality and expectations attributes. It might be possible to explore the use of a more sophisticated structure like a tree augmented network (Friedman & Goldszmidt, 1996). Bayesian network models to predict the performance using psychological information can offer new possibilities to improve the recruitment and selection processes in high-turnover jobs.

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