

Improve Employee Equipment process by using AdaBoosting Algorithm

V.Sowjanya¹, Mrs.S.Sajida²

¹ Student, Dept. of MCA, KMM Institute of Post Graduate Studies

² Assistant Professor, Dept. of MCA, KMM Institute of Post Graduate Studies, Tirupati,A.P

Abstract- Training is crucial for organizational development and success. It is fruitful to both employers and employees of an organization. An employee will become more efficient and productive if he is trained well. In this paper we are mainly aims to find what are the techniques we should be considered for better performance of the employee in an organization and what are the different factors that affect that effect employee performance in an organization. So by observations we will predict that what are the different areas that an employee should be well trained by understanding the training needs. We have different algorithms for predicting the training management. This is one of the best algorithm for predicting the results. because the ada boosting Algorithm will give better accuracy and performance than compared with the other algorithms.

Index Terms- Adaboosting algorithms, predicting Training Needs

I. INTRODUCTION

Training is concerned with imparting specific skills for a particular purpose. Training is the sequence of learning a sequence of programmed behavior. Training is the act of increasing the skills of an employee for doing a particular job. "Training is the process that provides employees with the knowledge and the skills required to operate within the systems and standards set by management

A.DEVELOPEMENT

Management development is all those activities and programmed when recognized and controlled have substantial influence in changing the capacity of the individual to perform his assignment better and in going so all likely to increase his potential for future assignments. Thus, management development is a combination of various training programmed, though some kind of training is necessary, it is the overall

development of the competency of managerial personal in the light of the present requirement as well as the future requirement. Development an activity designed to improve the performance of existing managers and to provide for a planned growth of managers to meet future organizational requirements is management development.

Conventional 'training' is required to cover essential work-related skills, techniques and knowledge, and much of this section deals with taking a positive progressive approach to this sort of traditional 'training'. Importantly however, the most effective way to develop people is quite different from conventional skills training, which let's face it many employees regard quite negatively. They'll do it of course, but they won't enjoy it much because it's about work, not about themselves as people. The most effective way to develop people is instead to enable learning and personal development, with all that this implies. So, as soon as you've covered the basic work-related skills training that is much described in this section - focus on enabling learning and development for people as individuals - which extends the range of development way outside traditional work skills and knowledge, and creates far more exciting, liberating, motivational opportunities - for people and for employers. Rightly organizations are facing great pressure to change these days - to facilitate and encourage whole-person development and fulfillment - beyond traditional training.

B.NEED FOR TRAINING

1. Globalization
2. Need of leadership.
3. Increased value placed on intangible assets & human capital.
4. Focus on link to business strategy
5. Customer's services & quality emphasis.

6. New technology.
7. High performances model at work system.
8. Economic changes.
9. Attracting & retaining talent.

II. RELATED WORK

An employer can rightfully request an employee to pay for equipment. However, OSHA (Occupational safety & Health administration) guidelines prevent employers from charging employees for safety and protective gear, such as goggles and gloves. The employer cannot force an employee to pay only make a request. The difference between requesting and forcing is that one require wilful act of he employee. If an employee does not honor the employer's request o pay for damage, the company must decide if termination is in order. Boosting is an approach to machine learning based on the idea of creating a highly accurate prediction rule by combining many relatively weak and inaccurate rules. The AdaBoost algorithm of Freund and Schapiro [10] was the first practical boosting algorithm, and remains one of the most widely used and studied, with applications in numerous fields.

III. ADABOOSTING ALGORITHM

AdaBoost refers to a particular method of training a boosted classifier. A boost classifier is a classifier in the form

$$F_T(x) = \sum_{t=1}^T f_t(x)$$

where each f_t is a weak learner that takes an object x as input and returns a value indicating the class of the object. For example, in the two class problem, the sign of the weak learner output identifies the predicted object class and the absolute value gives the confidence in that classification. Similarly, the T Each weak learner produces an output hypothesis, $h(x_i)$ for each sample in the training set. At each iteration t , a weak learner is selected and assigned a coefficient α_t such that the sum training error E_t of the resulting t -stage boost classifier is minimized.

$$E_t = \sum_i E[F_{t-1}(x_i) + \alpha_t h(x_i)]$$

Here $F_{t-1}(x)$ is the boosted classifier that has been built up to the previous stage of training, $E(F)$ is

some error function and $f_t(x) = \alpha_t h(x)$ is the weak learner that is being considered for addition to the final classifier. Here $F_{t-1}(x)$ is the boosted classifier that has been built up to the previous stage of training, $E(F)$ is some error function and $f_t(x) = \alpha_t h(x)$ is the weak learner that is being considered for addition to the final classifier.

Suppose we have a data set $(x_1, y_1), \dots, (x_n, y_n)$ where each item x_i has an associated class $y_i \in \{-1, 1\}$, and a set of weak classifiers $\{k_1, \dots, k_L\}$ each of which outputs a classification $h_j(x_i) \in \{-1, 1\}$ for each item. After the $m-1$ -th iteration our boosted classifier is a linear combination of the weak classifiers of the form:

$$C_{(m-1)}(x_i) = \alpha_1 k_1(x_i) + \dots + \alpha_{m-1} k_{m-1}(x_i)$$

At the m -th iteration we want to extend this to a better boosted classifier by adding a multiple of one of the weak classifiers:

$$C_m(x_i) = C_{(m-1)}(x_i) + \alpha_m k_m(x_i)$$

So it remains to determine which weak classifier is the best choice for k_m and what its weight α_m should be. We define the total error E of C_m as the sum of its exponential loss on each data point, given as follows:

$$E = \sum_{i=1}^N e^{-y_i C_m(x_i)}$$

We can split this summation between those data points that are correctly classified by k_m (so $y_i k_m(x_i) = 1$) and those that are misclassified (so $y_i k_m(x_i) = -1$):

$$\begin{aligned} E &= \sum_{y_i = k_m(x_i)} w_i^{(m)} e^{-\alpha_m} + \sum_{y_i \neq k_m(x_i)} w_i^{(m)} e^{\alpha_m} \\ &= \sum_{i=1}^N w_i^{(m)} e^{-\alpha_m} + \sum_{y_i \neq k_m(x_i)} w_i^{(m)} (e^{\alpha_m} - e^{-\alpha_m}) \end{aligned}$$

Since the only part of the right-hand side of this equation that depends on k_m is $\sum_{y_i \neq k_m(x_i)} w_i^{(m)}$ we see that the k_m that minimizes E is the one that minimizes $\sum_{y_i \neq k_m(x_i)} w_i^{(m)}$ the weak classifier with the lowest weighted error (with weights $w_i^{(m)} = e^{-y_i C_{m-1}(x_i)}$). To determine the desired weight α_m that minimizes E with the K_m that we just determined, we differentiate:

$$\frac{dE}{d\alpha_m} = \frac{d(\sum_{y_i=k_m(x_i)} w_i^{(m)} e^{-\alpha_m} + \sum_{y_i \neq k_m(x_i)} w_i^{(m)} e^{\alpha_m})}{d\alpha_m}$$

Setting this to zero and solving for α_m yields:

$$\alpha_m = \frac{1}{2} \ln \left(\frac{\sum_{y_i=k_m(x_i)} w_i^{(m)}}{\sum_{y_i \neq k_m(x_i)} w_i^{(m)}} \right)$$

We calculate the weighted error rate of the weak classifier to be

$$\epsilon_m = \sum_{y_i \neq k_m(x_i)} w_i^{(m)} / \sum_{i=1}^N w_i^{(m)}$$

$$\alpha_m = \frac{1}{2} \ln \left(\frac{1 - \epsilon_m}{\epsilon_m} \right)$$

which is the negative logit function multiplied by 0.5. Thus we have derived the AdaBoost algorithm: At each iteration, choose the classifier k_m , which minimizes the total weighted error $\sum_{y_i \neq k_m(x_i)} w_i^{(m)}$, use this to calculate the error

rate $\epsilon_m = \sum_{y_i \neq k_m(x_i)} w_i^{(m)} / \sum_{i=1}^N w_i^{(m)}$, use this to

calculate the weight $\alpha_m = \frac{1}{2} \ln \left(\frac{1 - \epsilon_m}{\epsilon_m} \right)$, and finally use this to improve the boosted classifier C_{m-1} to

$$C_m = C_{(m-1)} + \alpha_m k_m.$$

IV. CONCLUSION

The training courses will become success only when the needs of the Trainees are completed. Therefore the Artificial intelligence is useful in reaching these training needs of Trainees. In this paper we are mainly concentrating on how the artificial intelligence is useful in predicting the needs. For this prediction we are using the algorithm called Adaboosting Algorithm. This algorithm will provide good efficiency and performance for predicting the training management. This algorithm will provide high Accuracy also.

V. REFERENCES

- [1] Jain AK, Chandrasekaran B. Dimensionality and sample size considerations in pattern recognition practice. In: Krishnaiah PR, Kamala LN (Eds) Handbook of Statistics, vol 2. North Holland, Amsterdam, 1987; 835–855.
- [2] Friedman JH. Regularized discriminate analysis. J Am Statistical Assoc 1989; 84: 165–175
- [3] An G. The effects of adding noise during back propagation training on a generalization performance. Neural Computation 1996; 8: 643–674
- [4] Bremen L. Bagging predictors. Machine Learning J 1996; 24(2): 123–140
- [5] Freund Y, Schapiro RE. Experiments with a new boosting algorithm. Proceedings 13th International Conference on Machine Learning 1996; 148–156
- [6] Ho TK. The Random subspace method for constructing decision forests. IEEE Trans Pattern Analysis and Machine Intelligence 1998; 20(8): 832–844
- [7] Efron B, Tibshirani R. An Introduction to the Bootstrap. Chapman & Hall, New York, 1993
- [8] Schapire RE, Freund Y, Bartlett P, Lee W. boosting the margin: a new explanation for the effectiveness of voting methods. Ann Statistics 1998; 26(5): 1651–1686
- [9] Breiman L. Arcing classifiers. Ann Statistics 1998; 26(3): 801–849
- [10] Dietterich TG. An experimental comparison of three methods for constructing ensembles of decision trees: bagging, boosting, and randomization. Machine Learning 2000; 40(2): 139–157
11. Breiman L. Random forests – random features. Technical Report 567, University of California, Berkley, 1999