Abstract

Machine Learning is a branch of artificial intelligence that leverages data to imitate the pattern by which a human brain learns, in the process improving accuracy. Statistical principles are used to process data and learn from it efficiently. Machine Learning algorithms are extensively used to predict future outcomes based on past experiences that were recorded in a meticulous manner. These past experiences or data can help us to deduce preliminary insights about the data and what it represents. The current paper discusses certain Machine Learning algorithms where the prime objective is to classify the inputs into one of the two categories. The dataset in focus is the employee attrition dataset that gives various insights regarding the presumable reasons behind an employee leaving the job. The factors such as accuracy, precision score, recall score and f1\_score for Random Forrest, XgBoost, Adaboost, Gradient boosting and Decision Tree Classifier have been ascertained and compared. Furthermore, Hyperparameter tuning, using the ‘RandomSearchCV’ python library is also implemented on the better performing algorithms, with the goal of achieving better performance.

**Keywords**: Machine Learning, Random Forrest, XgBoost, Adaboost, Decision Tree, Gradient Boost, Hyperparameters, RandomSearchCV.

Introduction

Employee attrition is when an employee of an organisation, leaves the company due to various reasons. It may be because his or her performance was not up to the mark. Or due to incompatibility with their colleagues and more so on. If the attrition happens with the will of the organisation than it is supposed to be fine. But if an organisation loses its valuable employee because the employee wanted it so, then it is a problem. The organisation might have gone through a long process of hiring and training of that employee. Both time and money of the organisation is invested on a particular employee, and when this employee leaves than it is a matter of great concern for the employer. The organisation will have to do all that investments of time and resource again to hire another employee to replace the one that left. This problem can be analysed and to a great extent be solved by using machine learning algorithms. To do such a task, the most preliminary tool required to get started is the past data of the employees who left the company along with the ones who stayed. Machine learning models learn from the past data, or we might say, past experiences to predict the future, so if we feed this data consisting of employees that stayed and the employees that left, we might get a model that takes the employee data as input and tells if the employee is going to leave or not. Further analysis of this model will give us insights of what are the plausible factors leading to attrition of employees. This will help the management to take steps in the right direction.

Previous Work and their short comings

Several researchers have investigated using machine learning algorithms to forecast employee behaviour. The issue of employee attrition has been the subject of research for several decades. Every organization experience staff attrition. Individuals either retire or resign. If this does not take place in a timely manner and if staff depart without notice, it may have serious repercussions for the continued existence of the organization.

Employee turnover might be seen as a theft of the company's intellectual property. The previous work focuses on the methods and strategies that various scholars have put forth for predicting employee attrition.

To forecast employee performance, the authors utilized a variety of techniques, including decision trees, the Naïve Bayes classifier, Random forests, Gradient Boost, SMV, and many more with various factors such as salary, job satisfaction, designation, age, gender, etc.

Previous studies used several machine learning algorithms and datasets to present various accuracy estimates. However, many researchers have focused on factors that are unrelated to employee attrition, and it has been noted that hyperparameter tuning was not done for datasets on employee attrition. The primary and most important goal of this project work is to provide a thorough description, demonstration, and evaluation of machine learning algorithms towards identifying attrition by using numerous significant factors and hyperparameter tuning.

Machine Learning

The procedure of using computational methods to learn information directly from the data. This learning should be done without relying too much on a predetermined equation. This whole process is called Machine learning. The data samples used to train the model is very important. When the data models increase, the accuracy of this model might also increase. Since the process of Machine learning largely involves a lot of statistical computations, the data used to train such a model needs to be clean and relevant to the intended goals of the project. The data used should be consistent, that is, it should not have too many null values and understandingly the tabulated data should be correct. The relevance of the data used is important because if the data is not relevant than the model will predict wrongly for real world cases. For example, if we need a model to predict a disease in an individual, we need the medical data of that person rather than the data about his TV watching habits. The TV habits data can be useful for the model where subscription to a TV plan is predicted. There are many machine learning algorithms that use different statistical computation techniques to train a model. We have used some of these models during this research.

Hyperparameter Tuning

Machine Learning models are mathematical models associated with several parameters. These parameters are to be learned by the same machine learning model. These parameters are learnt by the model by training the model with the existing data. This process is called fitting the data to the model. There is another kind of parameters that cannot be directly learned by a model through the regular training process, known as Hyperparameters. These parameters are fixed even before the actual training process begins. Significant properties of a model is expressed by such parameters. The complexity or how fast a model must learn is also ascertained by Hyperparameters. In practice, there are two main strategies that are used to implement Hyperparameter tuning, Randomized Search and Grid search. For grid search technique, all the possible hyperparameters including the intermediate combinations of the hyperparameters are tried, that is, for each hyperparameter a new model is created. This is the reason why grid search is more computationally expensive. The Randomized search Tuning strategy is better than the “GridSearch” strategy because it tries only a fixed number of hyperparameters for the model. For this research, the “RandomizedSearchCV” python module is used.

Decision Tree

In each decision tree, the internal nodes stand for the features of the data set, branches for decision rules and leaf nodes for outcomes. All in all, Decision tree classifier is a machine learning algorithm that gives a model that can classify using a tree data structure. It is easy to implement and comprehend because tree structures are easy to understand. A tree structure also mirrors a human being’s decision-making process, that is, the process of choosing one of the options at each step until the goal is reached or final decision is made. A decision tree starts with a question and based on the possible outcomes; it splits the tree at every level. The main issue in the decision tree algorithm is to choose the best attributes for the root node and the sub nodes. To do this task, we use the technique called Attribute selection measure or ASM. With ASM we can easily select the best possible attribute for the nodes of the tree.

Random Forest

Random Forest contains several decision trees associated with various subsets of the dataset. To improve the accuracy, average is taken at the end. Random Forest is used for classification and regression problems and is based on the concept of ensemble learning. Ensemble learning is the process of combining multiple classifiers to solve a difficult or complex problem and to improve the all over accuracy of the solution. This is obvious that a greater number of trees in the forest will lead to better accuracy but also take a toll on performance. Random Forest is useful because it takes less time to train, predicts the output with high accuracy and can maintain accuracy when a large proportion of data is missing.

Diagram

Description automatically generated

XG-Boost

XgBoost or Extreme Gradient Boosting was proposed by researchers at University of Washington. Its library is written in C++ which optimizes the Gradient boost training process. As the name suggests, XgBoost attempts to boost the Gradient Boosting model. Boosting is an ensemble modelling technique where several weak classification models are combined to form a stronger classification model. This processes simply adds weak models in series. At the beginning a model is created on the data and then a second model is added in series. The second model attempts to correct the errors made by the first model. This process is repeated until the complete data set is predicted or the maximum number of models is added. For XgBoost, decision trees are created in sequential form. Weights are important part of this process. The independent variables that are fed to the decision tree which predicts results are assigned with weights first. If an independent variable is predicted wrongly, the weight of that variable is increased and then fed to the next decision tree. These individual trees or classifiers are then ensembled together to obtain a more precise and stronger model.

Proposed approach

The dataset in use for this research has a total of 35 variables. These 35 variables are related to an employee working in a company. The dataset contains the data of employees who have left the company along with the ones who still work there. The percentage of employee in the dataset who left the company is 16 percent. Before using this data to train a model, it is essential to put the data through some pre-processing stages. The first step in this process was to remove the unwanted variables from the data. As we want to train the model to predict employee attrition, we will make sure that the data does not have any variable that is directly related to employee attrition. The variables that were removed are: Employee count, employee number, over18 and standard hours.

Now, the train and test split of the data is done. The training data comprises of 70 percent of the data and the test data comprises of 30 percent. Training data will be fed to the model so that it forms patterns for prediction. The testing data shall be used to evaluate the model.

The next step in pre-processing of data is encoding the categorical variables. For this, Ordinal and One-Hot encoder is used. Ordinal encoder is used when there is assumed ordering of categories. In other words, through the Ordinal encoder, we can show a hierarchy among the possible values of a variable for every tuple. So, for instance when encoding relationship satisfaction, the encoding will assume that low (0) is lesser than very high (3). On the other hand, the ON-Hot encoder will create new columns indicating the presence or absence of each possible value for each categorical attribute in our dataset, with binary values where 0 indicates the absence of each value and 1 indicates the presence of each value.

Next step deals with balancing the target variable. It was noticed that the target variable is not balanced, that is, the number of employees who have left the company is much less than the number who have not. To balance the variable, a python library called ‘SMOTE’ is used to synthetically create tuples that are similar but do not duplicate the already present tuples. This will make the number of employees left and the number of employees still present equal.

The data is fed to the models: Adaboost, random forest, gradient boosting, decision tree and XgBoost. The training is done and the accuracy, precision, recall and F1\_score is calculated through the confusion matrix. After this, RandomSearchCV was used to tune the best performing models. After the hyperparameter tuning, again the models were evaluated using the confusion matrix.

Diagram

Description automatically generated

Measure of Performance: Confusion Matrix

Confusion matrices are a widely used measurement when attempting to solve classification issues. A table called a confusion matrix is frequently used to explain how well a classification model performs on a set of test data for which the true values are known. It is a table that lists how many guesses a classifier made correctly and incorrectly. It is employed to evaluate a classification model's effectiveness. It can be used to calculate performance metrics like accuracy, precision, recall, and F1-score to assess the effectiveness of a classification model.

The basic terms that will be used to determine the metrics are as follows:

* **True Positives (TP)**: when the actual value is Positive and predicted is also Positive.
* **True negatives (TN)**: when the actual value is Negative, and prediction is also Negative.
* **False positives (FP)**: when the predicted value is positive, but the actual is negative. Also referred to as the Type 1 error
* **False negatives (FN)**: when the predicted value is negative, but the actual is positive. Also referred to as the Type 2 error

Table

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Confusion Matrix for binary classification (2x2 matrix)

The classifier's accuracy is simply measured by how frequently it predicts correctly. It is the proportion between the number of accurate predictions and all predictions combined.

Accuracy = =

Precision is an indicator of the level of accuracy attained in real prediction. Out of all the samples that really belong to the positive class, the proportion of samples that were accurately predicted.

Precision = =

Recall measures how well actual observations match predictions. It is also referred to as sensitivity.

Recall = =

A harmonic mean of precision and recall is the F1 score. The F1 score kind of keeps the precision and recall of your classifier in balance.

F1-Score =2 \*

Results and discussions

The exploratory data analysis conclusions for this research are twofold. When analysing the categorical variables, it is observed that most employees who left the company belonged to the Research and Development department, with most of them being laboratory technicians, sales executives, or research scientists. It was also observed that the employees who left the company scored excellent performance ratings. It is not good to lose such high-quality employees. Most of these employees had bachelor’s degree and their education field was mostly life sciences, medical and marketing. Many employees showed high work involvement along with the dissatisfaction with the work environment. Looking at the attrition per age histogram, its noticeable that as the age of an employee increases, the lesser are the chances for such employees to leave. Most of the attrition is made in the ages ranging between 25 to 35. The data also indicates that more working years, more years at the company and more years working at the current role employees accumulate, the less likely they are to leave. Talking about incomes, the majority of employees who have left belong to the category of smaller income employees. Also, those who have less percentage salary hike also tend to leave more than those with a higher percentual salary hike.

In this research there are 2 cycles of training and evaluation of the data. First cycle is regular, second cycle involves the tuned data. Data is tuned using Hyperparameter tuning explain above. For evaluation, confusion matrix is being used. Confusion matrix talks about the accuracy, recall, f1\_score and precision of the model. Out of these performance measures Recall is important for this research. Considering the main goal to identify the employees that are more likely to leave the company, the recall score is the one in focus.

For the first cycle, gradient boosting gave the best accuracy score (88.21%) while ada-boosting had the best recall score (50.70%). For second cycle, that is, with hyperparameters, ada-boosting gave the best accuracy (87.98%) and the best recall (52.11%).

Conclusion

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