**Predicting employee Attrition using decision tree method**

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**Applying decision trees methods**

A decision tree is a very flexible and popular method of classifying objects. It is a form of supervised machine learning where we continuously split data according to a certain parameter (Chakure, 2022). There are two main types of decision trees: Classification Trees and Regression Trees. In this project, I will be applying the classification tree to classify data in an employee attrition dataset.

**Dataset**

In this project I create a model that predicts employee attrition using the famous IBM HR Analytics Employee Attrition & Performance dataset obtained from Kaggle (Pavansubhash, 2017) It is a fictional dataset that was created by IBM data scientists. The dataset has personal, benefits and HR information for employees in thirty-five variables and 1470 records.

I apply decision tree to map out a path that leads to attrition by using sixteen variables out of twenty-six available in the dataset using python, specifically Scikit-Learn library. From scikit-Learn, I imported decisiontreeclassifier, train\_test\_split and metric modules. The resulting model should be able to predict attrition or classify employees according to those that are likely to leave and those likely to stay, based on historical data. **Figure 1** below shows descriptive analytics for the dataset.

**Figure 1**

*Employee Attrition Descriptive statistics (First nine columns)*

*Graphical user interface

Description automatically generated with medium confidence*

**Figure 2**

*The first five records and ten attributes of the dataset*

**Table

Description automatically generated with medium confidence**

The first task was to change the values in the ‘Attrition’ field, which is the target field, to have a zero in place of a ‘No,’ and one in place of a ‘Yes,’

Secondly, the dataset was split to select sixteen variables as feature variables, and the ‘Attrition’ variable as the target variable. The dataset was also split into train and test data forming 80 and 20 percent, respectively. **Figure 3** below shows the two processes of selecting feature and target variables, and then test and train data.

**Figure 3**

*Creating train and test data, feature, and target variables*

Graphical user interface, text

Description automatically generated

**Training the model**

Using the Decision Tree Classifier module, the decision tree object was created fitting in the X\_train data (features) and Y\_train (target). **Figure 4** shows the creation of the model, and code that predicts using the training and testing data.

**Figure 4**

*Creating and testing model*

Text

Description automatically generated

Obviously, using the training data should have accuracy of 100%, and testing data yielded 71%. See **figure 5** below:

**Figure 5**

*Model Accuracy*

*Graphical user interface, text, application

Description automatically generated*

The resulting tree has been visualized in figure 6 (code) and figure 7 (diagram) below. Looking at the diagram, it is clear that the model has been overfitted and we can apply pruning to improve the accuracy from 71%, while reducing the levels of the tree.

**Figure 6**

*Visualizing decision tree*

*Graphical user interface

Description automatically generated with medium confidence*

**Figure 7**

*Decision Tree*

A picture containing table

Description automatically generated

**Improving the model**

There are several methods of preventing overfitting. In this assignment I am using Pruning, specifically, cost complexity pruning Alpha. Pruning is the process of removing some parts of the tree to make it more adaptable, which might slightly increase the training error but improve the model by decreasing testing error (Arora, 2022)

Minimal cost complexity pruning recursively improves the model by removing nodes that do not have a bi effect on the model, called “weakest link,” which is characterized by an effective alpha. It starts by removing the nodes with the smallest effective alpha (Arora, 2022). Below is the code that was used to prune the tree, starting with getting the alpha values in Figure 8, and using the alpha values in the model to find an optimal alpha to use.

**Figure 8**

*Getting Alpha values*Table

Description automatically generated

The next step substitutes the alpha values into the model to by looping over the alphas array to find the accuracy on both Train and Test parts of our dataset. The result has been plotted on Figure 10 below:

**Figure 9**

*Appending Alpha values*

**Graphical user interface, text, application

Description automatically generated**

**Figure 10**

*Accuracy Test*

Chart, line chart

Description automatically generated

**Running Decision Tree Classifier using 0.003 alpha**

From the accuracy test plot, we see that there is some sort of convergence from alpha 0.002. I tried several values between 0.002 and 0.004, and finally settled for 0.003 which reduces the Train Accuracy from 100% to 86% but increases the test accuracy to 79% from 71%. More importantly, it generalizes the model by pruning the tree. **Figure 11** below shows the code for running the Decision Tree Classifier again, with alpha value of 0.003, and **Figure 12** shows the resulting decision tree after pruning.

**Figure 11**

*Running Decision Tree Classifier using 0.003 alpha value*

**Graphical user interface, text, application

Description automatically generated**

**Figure 12**

*The resulting decision tree after pruning*

Timeline

Description automatically generated

**Conclusion**

In this project, I created a model for predicting employee attrition using the IBM HR Analytics Employee Attrition & Performance dataset. The model turned out to be overfitted, I improved the model by pruning it, making the tree shorter and improving the accuracy from 71% to 79%.

**References**

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