Machine Learning Engineer Nanodegree

Capstone Project Report

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Definition

Project Overview

Employee retention is of significant importance to companies. It should come as no surprise that companies that lead in employee engagement are often some of the most successful and profitable companies. Poor employee engagement means turnover, low morale, poor customer service, and a general blow to your bottom line. However, this issue become ultra-costly when high-performing employees start leaving because of low engagement. Supervised learning deals with Regression and Classification . Classification is being implemented in different fields Ex: Medical diagnosis and this model has gained a momentum to understand the change in behaviour of the consumer so this helps business works on the data. Every company invest a lot on employee to train them and makes employee to work in any kind of situation and in any kind of project. And there are many reasons employees to quit job. Some of them are rude behaviour, work imbalance, Feeling undervalued, Employment misalignment etc. If a company Invest in skill enhancement of an employee he should use it for the growth of the business , not for his personal profit. And I was searching for the dataset which has features that can be the reasons for the employee to quit job.

Link: https://www.kaggle.com/giripujar/hr-analytics/data#HR_comma_sep.csv

Problem Statement

HR managers have many responsibilities within an organisation as they protect the interests of both the employer and the employee. For employers, they manage employee relations and identify ways to cut labour costs. For employees ,they protect their rights ensuring that employers operate within the scope of employment and labour law.HR has a tough job to find the root cause of attrition. For suppose if HR knows that a particular employee is more probable of leaving and could take damage control action. So HR needs to find what features are making employees to leave .So I classified the data into sets ,the employees who stayed in the company and who left the company and I treated it as classification problem.

Features and Description:

- satisfaction_level : It is the level of satisfaction of the employee.
- last_evaluation : Its is the time since last performance is evaluation.
- number_project : It is the number of projects completed while at work.
- average_montly_hours : It is the average monthly hours at workplace
- time_spend_company : It is number of years spent in the company.
- Work_accident : whether the employee had a workplace accident or not.
- Left : Whether the employee left the work place or not.
- Promotion_last_5years : Whether employee promoted in last five years or not.
- Department : Department they work for.
- Salary : It is relative level of the salary.

By considering the above features, satisfaction_level is very important feature for the employee to stay in the company, because if the work what he is doing doesn't give him satisfaction means he will definitely leave the company.last_evalution is also an important feature which will give confidence to the employee.I think number_project is not that much important because if an employee engaged in big project means it will take time to complete the project.Average_monthly_hours also we have to consider because if he is putting his entire time in doing work he/she will not get enough time to relax so he may eventually quit the job.time_spend_company is high means he will be paid good. left feature is the decision column which we have to predict.And the main feature is salary of the employee.If he is satisfied with the salary

definitely he will continue in the company. Promotion feature will give employee satisfaction about his work. Department is not that much important.

I have taken the Humar resource analytics dataset for the project and for the resources left the company and why are lefting the company and what features are helping them to left the company .The dataset consists of 14999 rows and 10 columns. And the number of employees left are 3571 .And the remaining employees are 11425 and the target set is left feature .In project we are predicting the employees who are going to left. And the data set is taken from the Kaggle

Link: https://www.kaggle.com/giripujar/hr-analytics/data#HR_comma_sep.csv

Metrics

Accuracy in classification problems is the number of correct predictions made by the model over all kinds predictions made.

Accuracy =(TP+TN)/(TP+TN+FP+FN)

In the Numerator, are our correct predictions (True positives and True Negatives)(Marked as red in the fig above) and in the denominator, are the kind of all predictions made by the algorithm(Right as well as wrong ones).

Precision is a measure that tells us what proportion of patients that we diagnosed as having cancer, actually had cancer. The predicted positives (People predicted as cancerous are TP and FP) and the people actually having a cancer are TP.

Precision = TP/(TP+FP)

Recall is a measure that tells us what proportion of patients that actually had cancer was diagnosed by the algorithm as having cancer. The actual positives (People having cancer are TP and FN) and the people diagnosed by the model having a cancer are TP.

(Note: FN is included because the Person actually had a cancer even though the model predicted otherwise).

Recall = TP/(TP+FN)

Fβ score – measures the effectiveness of retriveal with respect to a user who attaches beta times as much importance to recall as precision.

$$F_\beta=(1+\beta^2)\cdot precision\cdot recall/(\beta^2\cdot precision)+recall$$

When beta=0.5 more emphasis is placed on precision .This is called f 0.5 score.

Analysis

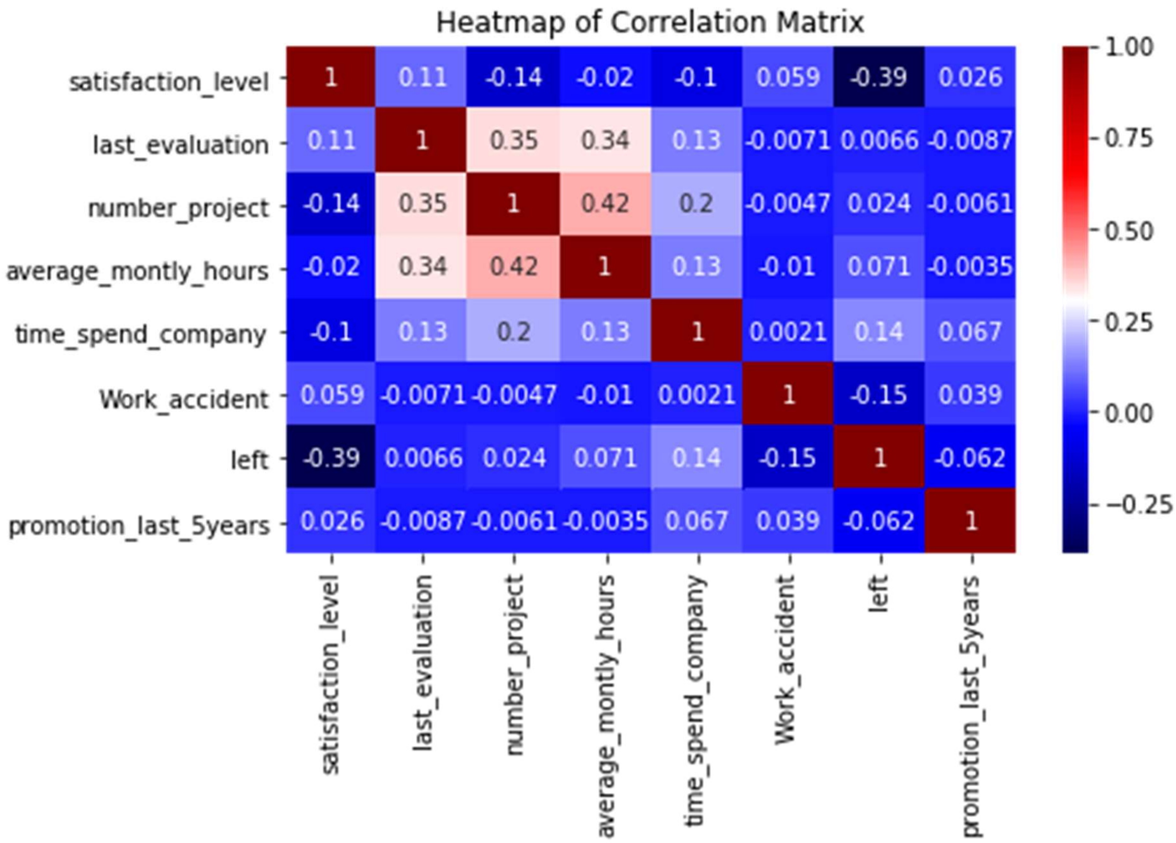
Data Exploration

In this data exploration section I calculated the total number of records and the number of employees who are currently working in the company and the number of employees left and percentage of employees left and checked for null values in the data set .So I predicted that there are no null values in the data set.

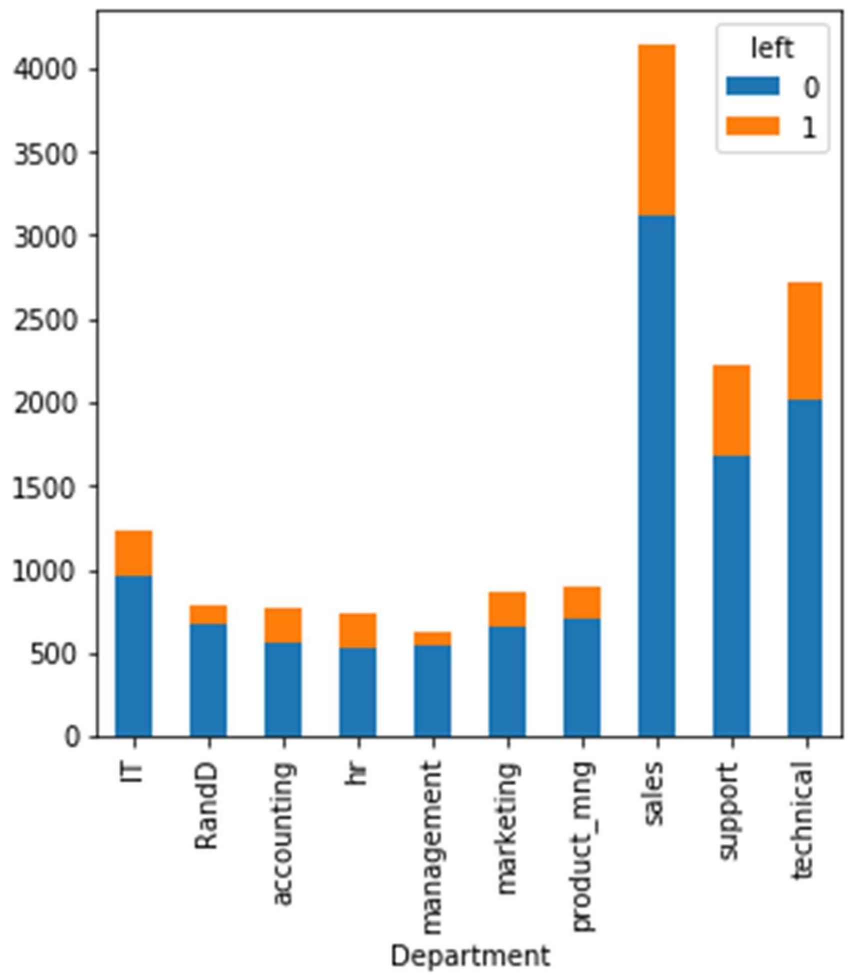
```
number of records: 14999
number of employee left: 3571
number of employee currently working: 11428
Percent of employee left: 23.81%
number of null rows: 0
```

Visualization

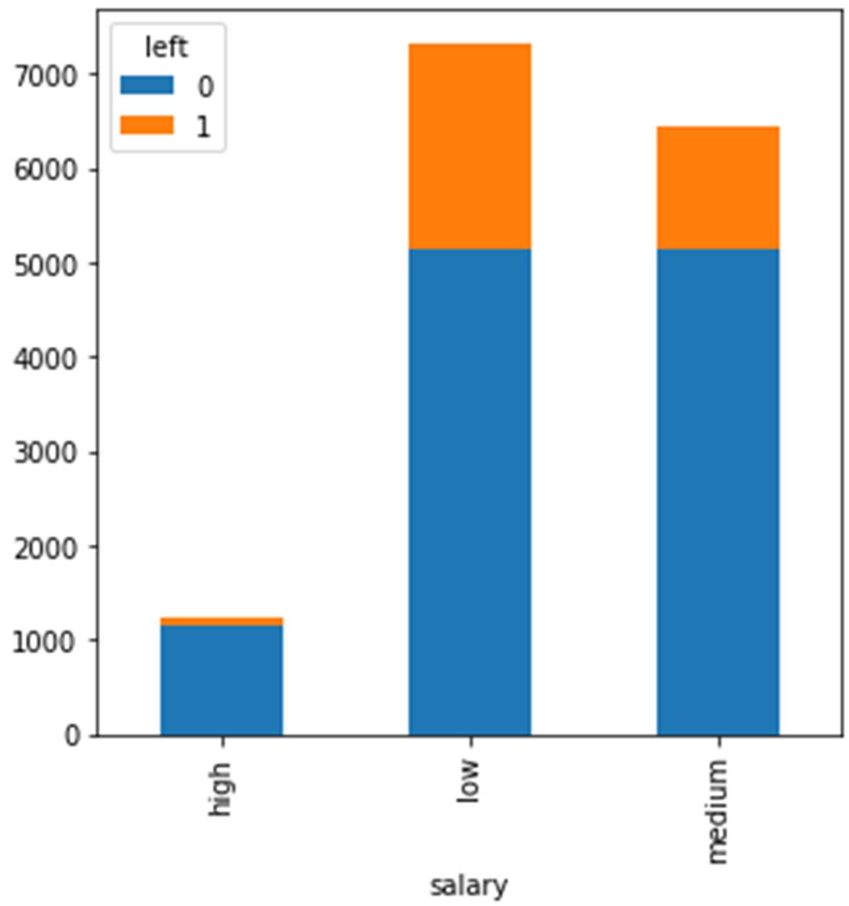
In this first I plot a heatmap of all the features to know how the features are correlated. . It states that average monthly hours and number of projects are highly correlated and hence using any one column for machine learning model should good. In the below graph average monthly hours and number of projects has highest value in the below graph.



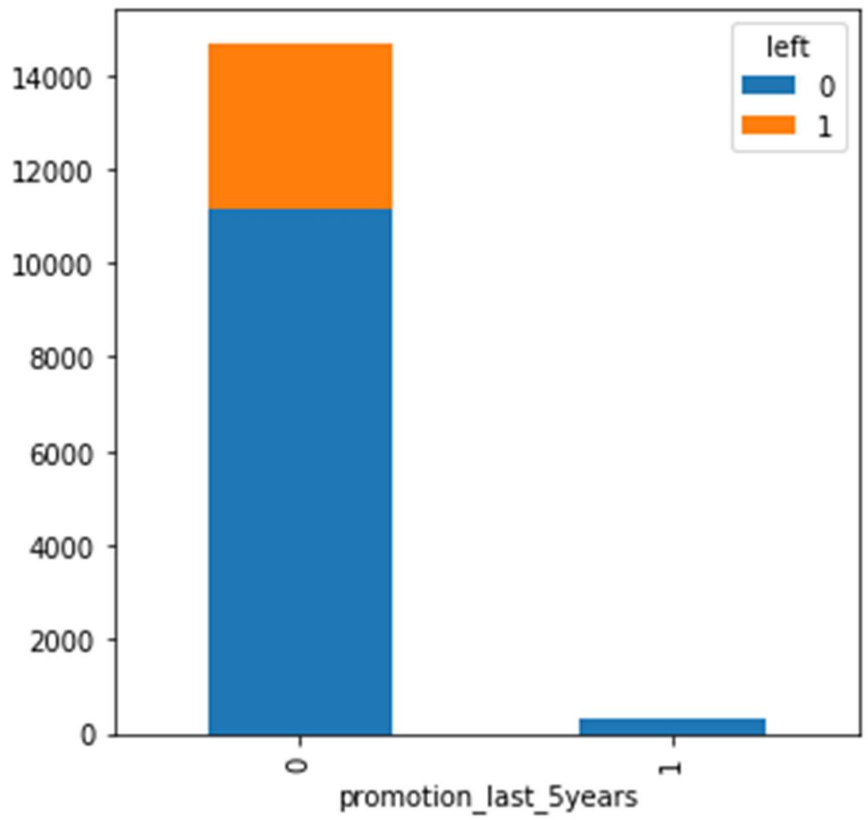
I am interested in finding which department are most affected.I plotted the graph between department and the left(target variable).From the below graph we can clearly say that the department is not a problem.



I would also like to plot the graph between salary and the target variable.If an employee is willing to move from the company the main reason is based on the salary.If the salary of an employee is low he would like to look for better opportunity.So he shows more interest in leaving the job.



I also plot the graph between promotion_last_5years and salary



Algorithm and Techniques

In machine learning the biggest problem is which technique we have to choose.I used logisticregression as a benchmark model because we can easily say with the help of logisticregression how many employees are staying in the company and how many are leaving the company. SVm was also good for binary classification. For suppose if the data has multiple features we can use kernel based svm. . Stochastic Gradient descent requires a lot more tuning than other model. Ensemble learning methods are used to increase the accuracy of the model. Ensemble Learning makes a strong classifiers from number of weak classifiers. So this can be done by building a model from training data, and again creating a second model which corrects the error from the first model. The Models are added until training data is predicted perfectly or maximum number of model are added. AdaBoost can be used to boost the performance of any machine learning algorithm. It is best used with weak learners. AdaBoost was the first really successful boosting algorithm developed for binary classification. It is the best starting point for understanding boosting. The most suited and therefore most common algorithm used with AdaBoost are decision trees with one level. Because these trees are so short and only contain one decision for classification, they are often called decision stumps.

Each instance in the training dataset is weighted. The initial weight is set to:

$$weight(xi) = 1/n$$

Where xi is the i'th training instance and n is the number of training instances.

A weak classifier (decision stump) is prepared on the training data using the weighted samples. Only binary (two-class) classification problems are supported, so each decision stump makes one decision on one input variable and outputs a +1.0 or -1.0 value for the first or second class value.

The misclassification rate is calculated for the trained model. Traditionally, this is calculated as:

$$error = (correct – N) / N$$

Where error is the misclassification rate, correct are the number of training instance predicted correctly by the model and N is the total number of training instances. For example, if the model predicted 78 of 100 training instances correctly the error or misclassification rate would be (78-100)/100 or 0.22.

This is modified to use the weighting of the training instances:

$$error = sum(w(i) * terror(i)) / sum(w)$$

Which is the weighted sum of the misclassification rate, where w is the weight for training instance i and terror is the prediction error for training instance i which is 1 if misclassified and 0 if correctly classified.

For example, if we had 3 training instances with the weights 0.01, 0.5 and 0.2. The predicted values were -1, -1 and -1, and the actual output variables in the instances were -1, 1 and -1, then the terrors would be 0, 1, and 0. The misclassification rate would be calculated as:

$$error = (0.01*0 + 0.5*1 + 0.2*0) / (0.01 + 0.5 + 0.2)$$

or

error = 0.704

A stage value is calculated for the trained model which provides a weighting for any predictions that the model makes. The stage value for a trained model is calculated as follows:

stage = ln((1-error) / error)

Where stage is the stage value used to weight predictions from the model, ln() is the natural logarithm and error is the misclassification error for the model. The effect of the stage weight is that more accurate models have more weight or contribution to the final prediction.

The training weights are updated giving more weight to incorrectly predicted instances, and less weight to correctly predicted instances.

For example, the weight of one training instance (w) is updated using:

w = w * exp(stage * terror)

Where w is the weight for a specific training instance, exp() is the numerical constant e or Euler's number raised to a power, stage is the misclassification rate for the weak classifier and terror is the error the weak classifier made predicting the output variable for the training instance, evaluated as:

terror = 0

if(y == p), otherwise 1

Where y is the output variable for the training instance and p is the prediction from the weak learner.

This has the effect of not changing the weight if the training instance was classified correctly and making the weight slightly larger if the weak learner misclassified the instance.

BenchMark

Logistic regression is used as benchmark model. FBeta score of benchmark model is reference and other model will be judge to perform better if their fbeta score will be greater than Logistic regression model. Accuracy , f-beta score and confusion matrix and will try to get better results in the ensemble learning models.

```
In LogisticRegression

True Negative :2134
False Positive :165
False Negative :474
True Positive :227
Model has 0.787 accuracy
Model has 0.500 fbeta Score
```

Confusion Matrix

ACTUAL	PREDICTED	
	Left	Stayed
Left	227	165
Stayed	474	2134

Data Preprocessing

In the data many values are categorical values so we need to bring them to a scale. I will graphically represent each feature with the target variable (left) and with the help of minmaxscaler will apply logarithmatic transformations of the features and will perform one hot encoding to change categorial values into numerical data. As all the categorical column has been converted to numerical column and all numerical column has been scaled. In the below section will will split data (both features and label) into training and test sets. 80% will be used for training and 20% will be used for test.

Implementation

I implemented different methods on the model to get better results .I used fbeta score and accuracy along with roc curve means area under the curve.

Logistic regression

Logistic regression is another technique borrowed by machine learning from the field of statistics.

It is the go-to method for binary classification problems (problems with two class values).

Code snippet:

```
from  sklearn.linear_model import LogisticRegression
from sklearn.metrics import fbeta_score, accuracy_score, confusion_matrix
LRClassifier = LogisticRegression()
LRClassifier.fit(X_train, y_train)
LRPredict = LRClassifier.predict(X_test)
tn, fp, fn, tp = confusion_matrix(y_test, LRPredict).ravel()
print("In LogisticRegression\n")
print("True Negative :{}  " .format(tn))
print("False Positive :{}" .format(fp))
print("False Negative :{}" .format(fn))
print("True Positive :{}" .format(tp))
values( y_test,LRPredict)
```

output:

```
In LogisticRegression

True Negative :2134
False Positive :165
False Negative :474
True Positive :227
Model has 0.787 accuracy
Model has 0.500 fbeta Score
```

Adaboost:

AdaBoost is best used to boost the performance of decision trees on binary classification problems.

AdaBoost was originally called AdaBoost.M1 by the authors of the technique Freund and Schapire. More recently it may be referred to as discrete AdaBoost because it is used for classification rather than regression.

AdaBoost can be used to boost the performance of any machine learning algorithm. It is best used with weak learners. These are models that achieve accuracy just above random chance on a classification problem.

Code snippet:

from sklearn.ensemble import AdaBoostClassifier

from sklearn.metrics import fbeta_score, accuracy_score, confusion_matrix

ABClassifier = AdaBoostClassifier(base_estimator=None, n_estimators=50, learning_rate=1.0, random_state=0)

ABClassifier.fit(X_train, y_train)

adaboostPredict = ABClassifier.predict(X_test)

tn, fp, fn, tp = confusion_matrix(y_test, adaboostPredict).ravel()

print("In AdaBoost\n")

print("True Negative :{} " .format(tn))

print("False Positive :{}" .format(fp))

print("False Negative :{}" .format(fn))

print("True Positive :{}" .format(tp))

values(y_test,adaboostPredict)

output:

```
In AdaBoost

True Negative :2247
False Positive :52
False Negative :59
```

```
True Positive :642
Model has 0.963 accuracy
Model has 0.923 fbeta Score
```

GradientBoost:

Gradient boosting is a machine learning technique for regression and classificati on problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

Code snippet:

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import fbeta_score, accuracy_score, confusion_matrix
GBClassifier = GradientBoostingClassifier(random_state=0)
GBClassifier.fit(X_train, y_train)
GBPredict = GBClassifier.predict(X_test)
tn, fp, fn, tp = confusion_matrix(y_test, GBPredict).ravel()
print("In gradientBoosting\n")
print("True Negative :{}  " .format(tn))
print("False Positive :{}" .format(fp))
print("False Negative :{}" .format(fn))
print("True Positive :{}" .format(tp))

values( y_test,GBPredict)
```

output:

```
In gradientBoosting

True Negative :2279
False Positive :20
False Negative :45
True Positive :656
Model has 0.978 accuracy
Model has 0.963 fbeta Score
```

SGD classifier:

Stochastic Gradient Classifier is known for efficiency and ease of implementation. Since it is sensitive to feature scaling and requires lot of parameter tuning we will like to check fbeta and accuracy to make judgment to use for fine tuning.

Code snippet:

```
from sklearn.linear_model import SGDClassifier

from sklearn.metrics import fbeta_score, accuracy_score, confusion_matrix

SGD_Classifier = SGDClassifier(shuffle = True,loss='log')

SGD_Classifier.fit(X_train, y_train)

SGD_Predict = SGD_Classifier.predict(X_test)

print("In SGDclassifier\n")

tn, fp, fn, tp = confusion_matrix(y_test, SGD_Predict).ravel()

print("In AdaBoost\n")

print("True Negative :{}  " .format(tn))

print("False Positive :{}" .format(fp))

print("False Negative :{}" .format(fn))

print("True Positive :{}" .format(tp))

values( y_test, SGD_Predict)
```

output:

```
In SGDclassifier

True Negative :2013
False Positive :286
False Negative :388
True Positive :313
Model has 0.775 accuracy
Model has 0.505 fbeta Score
```

SVC :

Code snippet:

```
from sklearn.svm import SVC
from sklearn.metrics import fbeta_score, accuracy_score, confusion_matrix


SVClassifier = SVC(random_state=0,probability=True)
```

```
SVClassifier.fit(X_train, y_train,)

SVPredict = SVClassifier.predict(X_test)
print("In SVC")
tn, fp, fn, tp = confusion_matrix(y_test, SVPredict).ravel()
print("True Negative :{}  " .format(tn))
print("False Positive :{}" .format(fp))
print("False Negative :{}" .format(fn))
print("True Positive :{}" .format(tp))

values(y_test,SVPredict)
```

output:

```
In SVC
True Negative :2245
False Positive :54
False Negative :347
True Positive :354
Model has 0.866 accuracy
Model has 0.759 fbeta Score
```

Refinement:

Adaboost classifier has number of hyper parameters on which model can be trained. To find the optimized parameter I used Grid Search method where we provide list of parameters in dictionary and model runs and score the model on different parameters combination and optimized the model

In the above section we have accuracy and fbeta scores for all the techniques and the scores of SVM and SGD are lower than adaboost.

To avoid overfitting I have decided to use validation set . In this case I use KFold validation, I have divided the training set into10 block of dataset and job will run for 10 iteration where at each iteration one set will be validation set and other nine data set will be used for training till we have validated with all the 10 blocks of data set.

As there is never enough data to train your model, *removing a part of it for validation poses a problem of underfitting.* ***By reducing the training data***, ***we risk losing important patterns/ trends in data set, which in turn increases***

error induced by bias. So, what we require is a method that provides ample data for training the model and also leaves ample data for validation. K Fold cross validation does exactly that. In **K Fold cross validation**, the data is divided into k subsets. Now the holdout method is repeated k times, such that ***each time, one of the k subsets is used as the test set/ validation set and the other k-1 subsets are put together to form a training set***. The *error estimation is averaged over all k trials to get total effectiveness of our model*. As can be seen, every data point gets to be in a validation set exactly once, and gets to be in a training set *k-1*times. ***This significantly reduces bias as we are using most of the data for fitting, and also significantly reduces variance as most of the data is also being used in validation set.*** Interchanging the training and test sets also adds to the effectiveness of this method. **As a general rule and empirical evidence, K = 5 or 10 is generally preferred**, but nothing's fixed and it can take any value.

Accuracy score for benchmark model : 0.787

Fbeta score for benchmark model : 0.500

Unoptimized model

```
Accuracy score on testing data: 0.9630
F-score on testing data: 0.9232
```

Optimized Model

```
Final accuracy score on the testing data: 0.9657
Final F-score on the testing data: 0.9276
```

Results

Model Evaluation and Validation

As we know that the accuracy score on testing data for unoptmised model is 0.9630 and the fbeta score on testing data is 0.9232 and for optimised model. Final accuracy score on the testing data is 0.9657 and fbeta score is 0.9276.

Adaboost classifier has been chosen for prediction using Grid Search method. It has below parameter as best estimator.

AdaBoostClassifier (algorithm='SAMME.R', base_estimator=None, learning_rate=0.95, n_estimators=125, random_state=0)

Justification

The Logistic regression is used as benchmark model. FBeta score of benchmark model is reference and other model will be judge to perform better if their fbeta score will be greater than Logistic regression model. Accuracy , f-beta score and confusion matrix and will try to get better results in the ensemble learning models.With choice of different classifier in hand such as Stochastic Gradient Boosting, SVM, Ensemble learning. I decided to go with ensemble learning because this methods increase the accuracy score of the models.

I felt difficult in choosing between Gradientboosting and adaboost because both give good performance and scores.And if I choose Gradientboosting I may fell into overfitting ,so I decided to choose adaboot classifier.And with the help of kfold cross validation and grid search I avoided overfitting

Accuracy score for benchmark model : 0.787

Fbeta score for benchmark model : 0.500

Unoptimized model

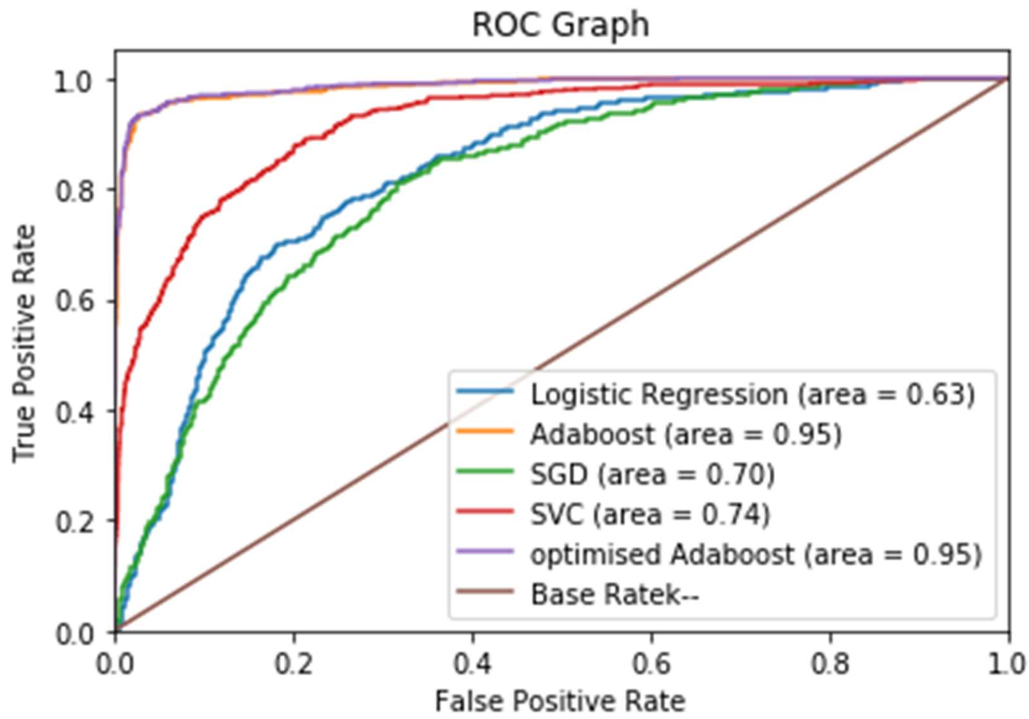
Accuracy score on testing data: 0.9630
F-score on testing data: 0.9232

Optimized Model

Final accuracy score on the testing data: 0.9657
Final F-score on the testing data: 0.9276

Conclusion

Free form visualazation



Reflection:

First of all I load the csv into a data frame with the help of pandas library and after loading it with the help of numpy library I calculate the number of employess who had already left and the length of the data set and the total number of employees who stayed and i find the null values in the dataframe.After that I plot a heat map of all the features and come to know how the features are correlating with each other with the help of mathplotlib.pyplot library and after that I graphically represent each feature with the target variable (left) and with the help of minmaxscaler l apply logarithmatic transformations of the features and i perform one hot encoding to change categorial values into numerical data. As all the categorical column has been converted to numerical column and all numerical column has been scaled. I split data (both features and label) into training and test sets. 80% will be used for training and 20% will be used for test. And classification model is evaluated on the basis of accuracy , precison, and recall and roc curve. Logistic regression is used as benchmark model. FBeta score of benchmark model is reference and other model will be judge to perform better if their fbeta score will be greater than Logistic regression model.And with the help of ensemblelearning methods i find the accuracy scores of the model and i also perform SGDC and Gradientboostingclassifier and find the accuracy of the models.After that I apply gridsearch and to tune the parameters and increase the performance.Once the model is trained will compare with the actual values with predicted values.In my data

AdaBoost classifier of ensemble learning use to train model and it performed better than the Benchmark model (Logistic Regression). Further to avoid overfitting a K Fold mechanism was used to train model so that it can have variety of data and will know to make decision based on features. Grid Search mechanism is used to fine tune the model by using hyper parameter. In final step roc curve is used to show the performance improvement from base to benchmark model to Adboost and Optimized Adaboost classifier.

References:

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- http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html
- http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.html