```
# Importing Required Libraries
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
# read the data
data=pd.read_excel("/content/drive/MyDrive/Colab Notebooks/HR_Data.xlsb",engine='pyxlsb')
```

```
# get random 5 samples
data.sample(5)
```

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_
4267	0.64	0.89	3	175	
11165	0.54	0.68	6	249	
804	0.81	0.95	5	266	
6505	0.84	0.96	3	162	
610	0.09	0.95	7	256	

```
# shave gives row & columns values here there are total 14999 rows & 10 columns
data.shape
```

```
(14999, 10)
```

```
# check for null values
data.isnull().sum()
```

```
satisfaction_level       0
last_evaluation          0
```

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```
Work_accident            0
left                     0
promotion_last_5years    0
Department               0
salary                   0
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   satisfaction_level     14999 non-null  float64
 1   last_evaluation        14999 non-null  float64
 2   number_project         14999 non-null  int64
 3   average_montly_hours   14999 non-null  int64
 4   time_spend_company     14999 non-null  int64
 5   Work_accident          14999 non-null  int64
 6   left                   14999 non-null  int64
 7   promotion_last_5years  14999 non-null  int64
 8   Department             14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

From info function we can see that null values are not present & out of 10 columns 6 columns are of integer datatpye, 2 columns are float data type and 2 columns are of object data type.

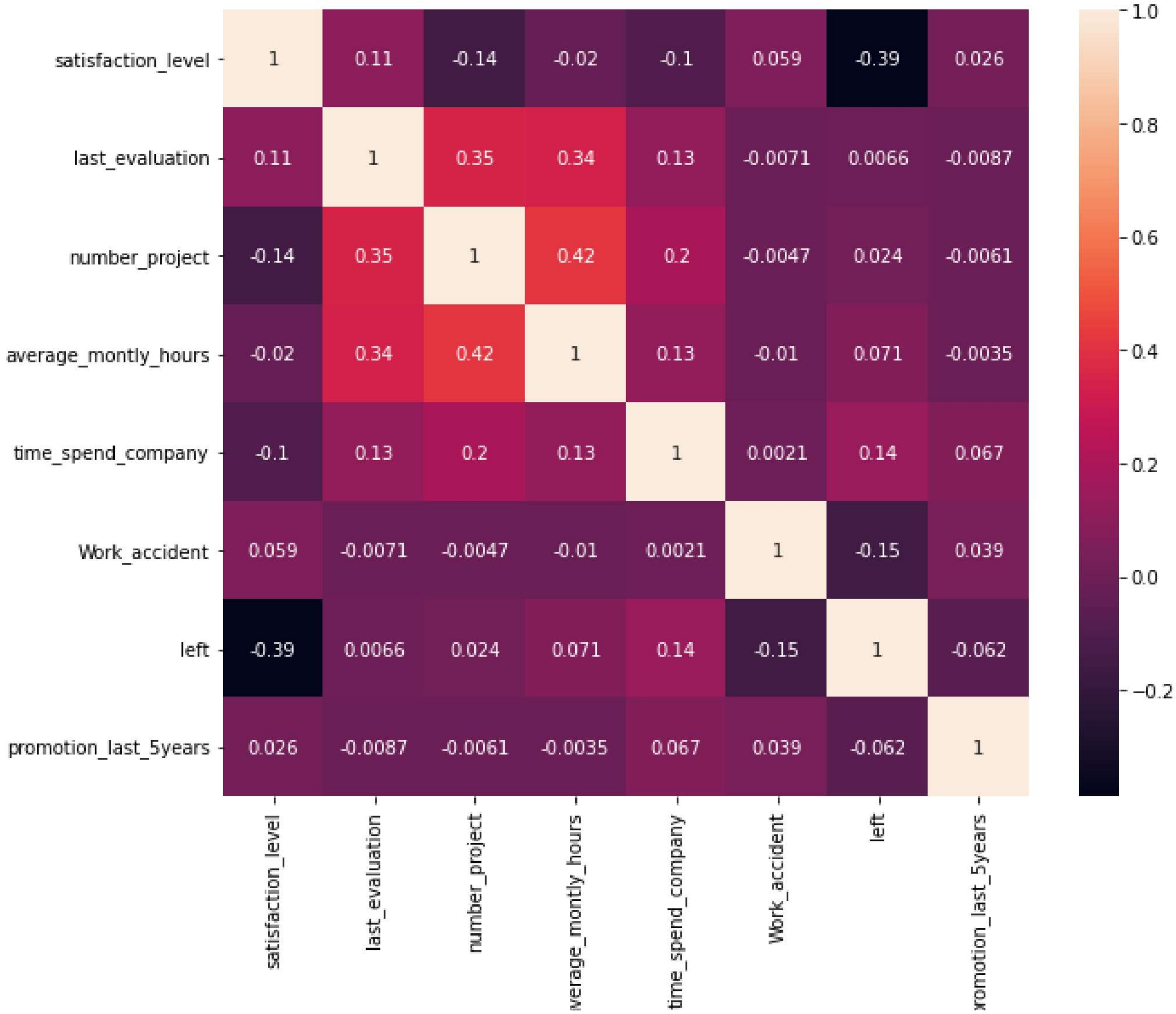
```
data.describe()
```

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_
count	14999.000000	14999.000000	14999.000000	14999.000000	
mean	0.612834	0.716102	3.803054	201.050337	
std	0.248631	0.171169	1.232592	49.943099	
min	0.090000	0.360000	2.000000	96.000000	
25%	0.440000	0.560000	3.000000	156.000000	
50%	0.640000	0.720000	4.000000	200.000000	
75%	0.820000	0.870000	5.000000	245.000000	
max	1.000000	1.000000	7.000000	310.000000	

Saving...

n.

```
# correlation of independent features with dependent features
plt.figure(figsize=(10,8))
sns.heatmap(data.corr(),annot=True);
```



There is no multicolinearity is present between independent features.

Data Analysis & Visualization

```
data['left'].value_counts()
```

```
0    11428
1     3571
Name: left, dtype: int64
```

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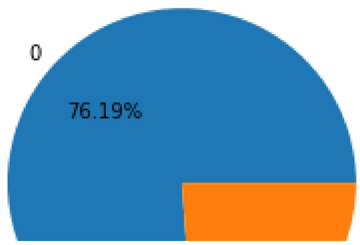
```
labels=data['left'].value_counts().index,autopct='%1.2f%%
```

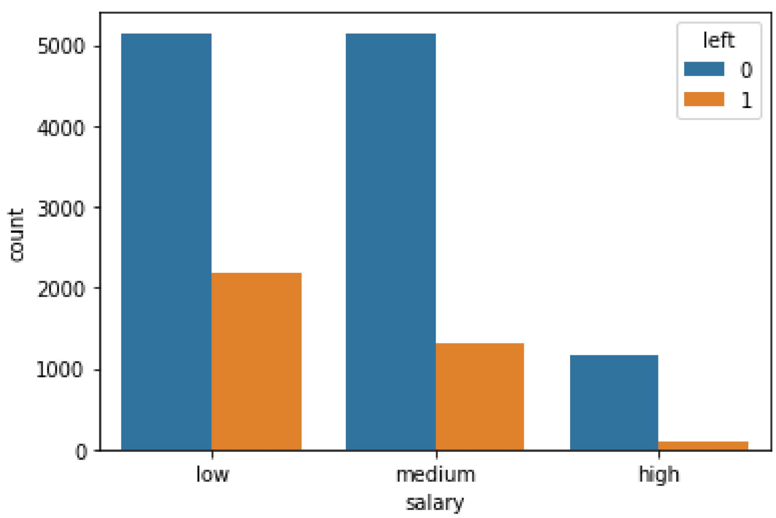


From above pie diagram we can see that 76.19% peope not left & 23.81% left.

```
data['salary'].value_counts()
```

```
low       7316
medium    6446
high      1237
Name: salary, dtype: int64
```

```
sns.countplot(x='salary', hue='left',data=data);
```



From above graph we can see that Highest Number of employees who leave the job are from low salary category and lowest nnumber of employees from high salary category.

```
plt.figure(figsize=(8,5))
sns.countplot(x='left', hue='Department',data=data);
```

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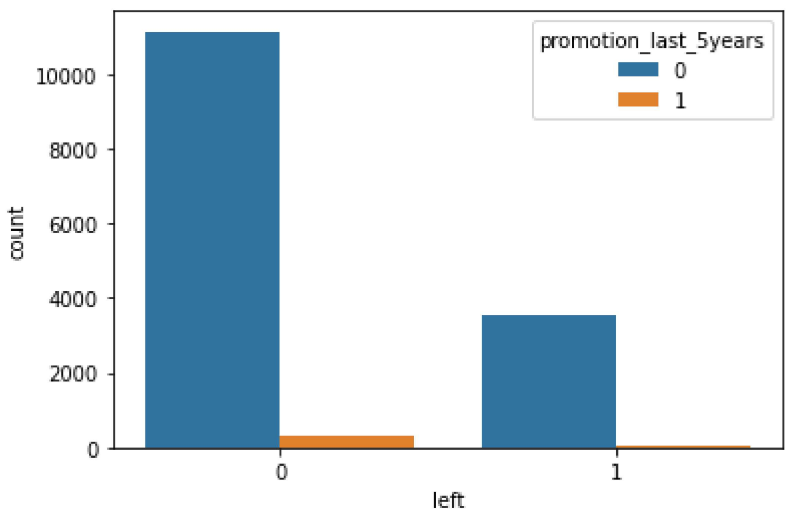
From above plot we can see that highest number of employees who left the job are from Sales Department and lowest number of employees who left the job from management department

```
data.promotion_last_5years.value_counts()
```

```
0    14680
1      319
Name: promotion_last_5years, dtype: int64
```

```
sns.countplot(x='left', hue='promotion_last_5years',data=data);
```

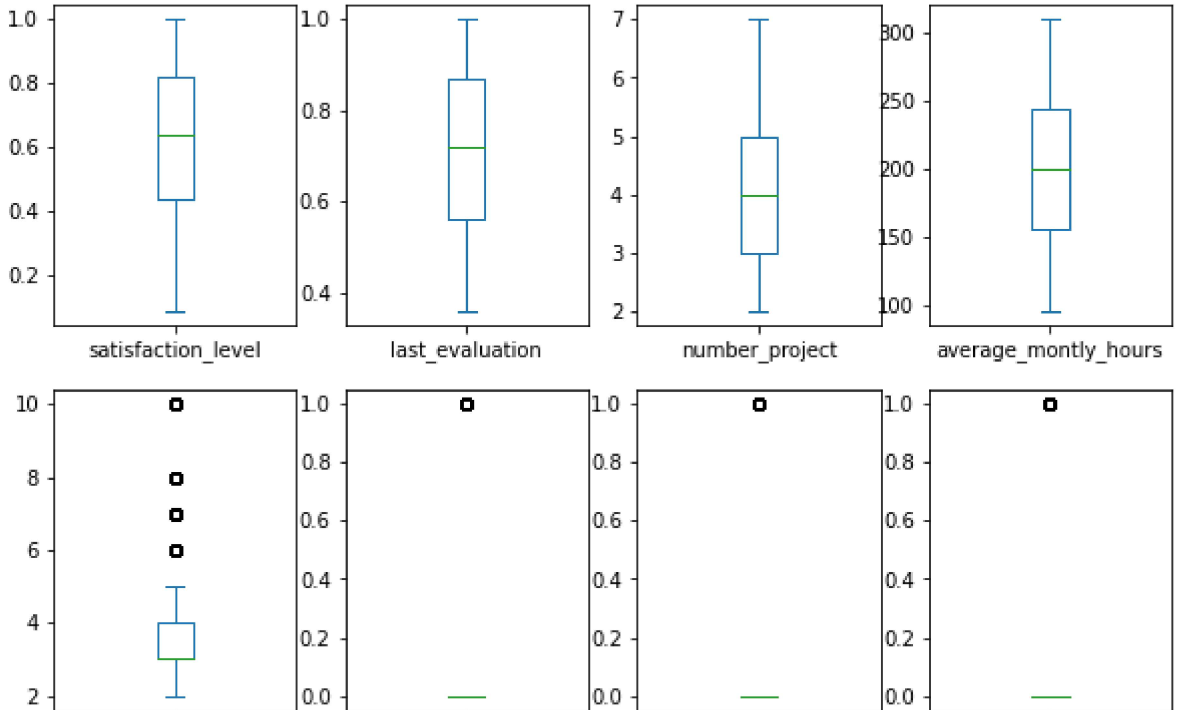


From above plot we can say that people left only if they are not promoted in last 5 years

1. EDA

Saving...

```
# Handling the outliers
data.plot(kind='box', subplots=True, figsize=(10,10),layout=(3,4))
plt.show()
```



Very few outliers are detected, So there is no need to handle the outliers

```
chr_=data.select_dtypes("object")
chr_.columns
```

```
Index(['Department', 'salary'], dtype='object')
```

```
print(data["Department"].unique())
print()
print("unique_val :",data["Department"].nunique())
```

```
['sales' 'accounting' 'hr' 'technical' 'support' 'management' 'IT'
 'product_mng' 'marketing' 'RandD']

unique_val : 10
```

```
print(data["salary"].unique())
print()
print("unique_val :",data["salary"].nunique())
```

```
['low' 'medium' 'high']
```

Saving...

Handling The Categorical Data

There are different types of techniques used for categorical data handline such as One-Hot Encoder, LabelEncoder, OrdinalEncoder

```
# Replacing categorical data with the integer
```

```
data['salary']= data['salary'].map({'high':2, 'medium':1, 'low':0})
```

```
data['salary'].unique()
```

```
array([0, 1, 2])
```

```
data['Department']=data['Department'].map({'sales':0, 'accounting':1, 'hr':2,
'technical':3, 'support':4, 'management':5,'IT':6, 'product_mng':7,
                                  'marketing':8, 'RandD':9})
```

```
data['Department'].unique()
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
# No categorical data present
data.head(3)
```

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spen
0	0.38	0.53	2	157	
1	0.80	0.86	5	262	
2	0.11	0.88	7	272	

```
# Distribution & skewness
from scipy.stats import skew
k=0
plt.figure(figsize=(15,15))
for col in data.drop('left',axis=1):
    k=k+1
    plt.subplot(3,3,k)
    sns.distplot(data[col])
    plt.title("skewness"+' '+str(data[col].skew()))
```

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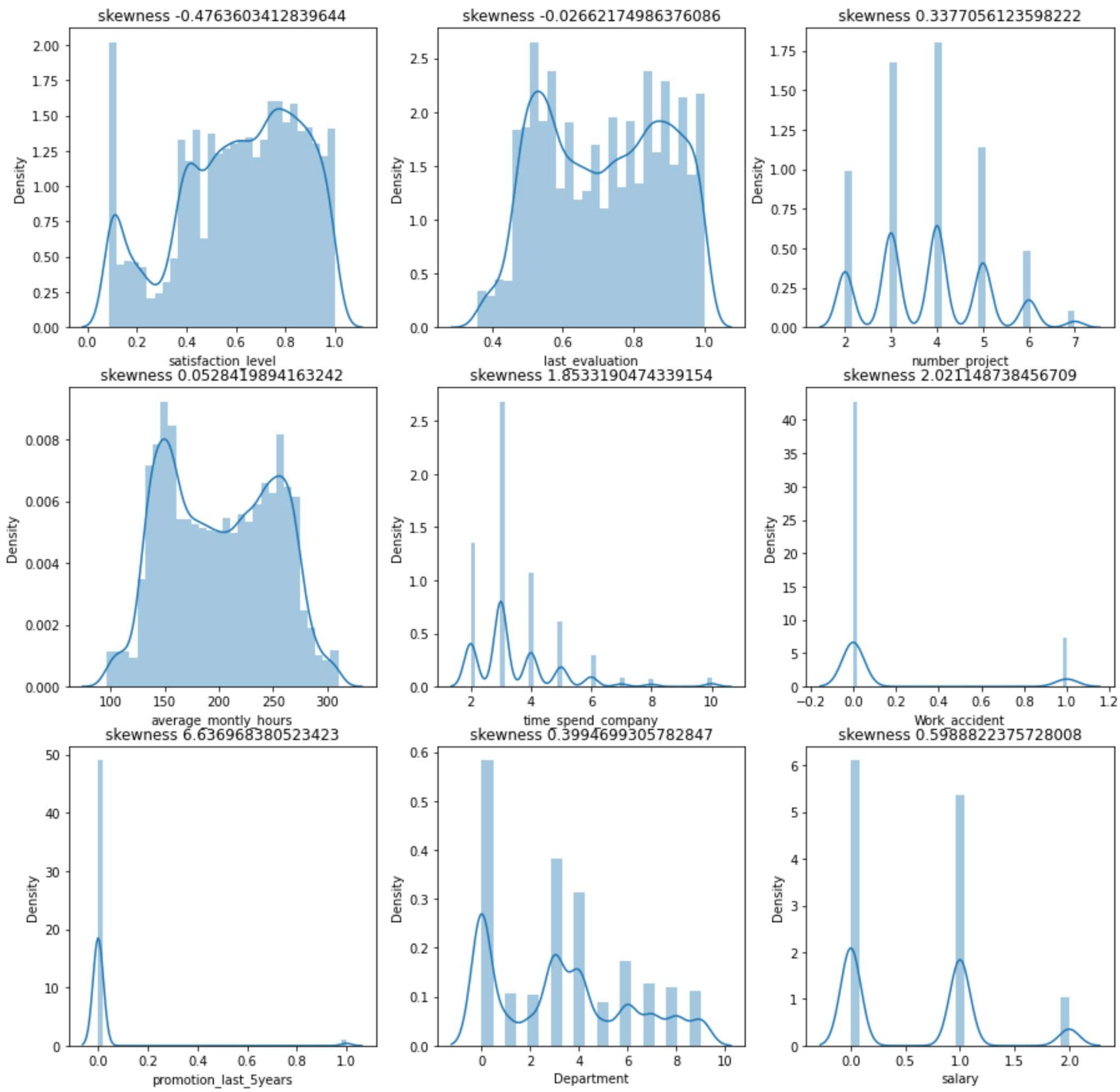



```
# visualization of correlation of features & label
sns.pairplot(data,hue='left');
```


satisfaction_level
last_evaluation
number_project
average_montly_hours
time_spend_company
Work_accident
promotion_last_5years
Department
salary
left
0
1

Here we can see that there is no such a great correlation/pattern is observed between dependent & independent feature, so that we will try differnt models to get the best score.

2. Model Building

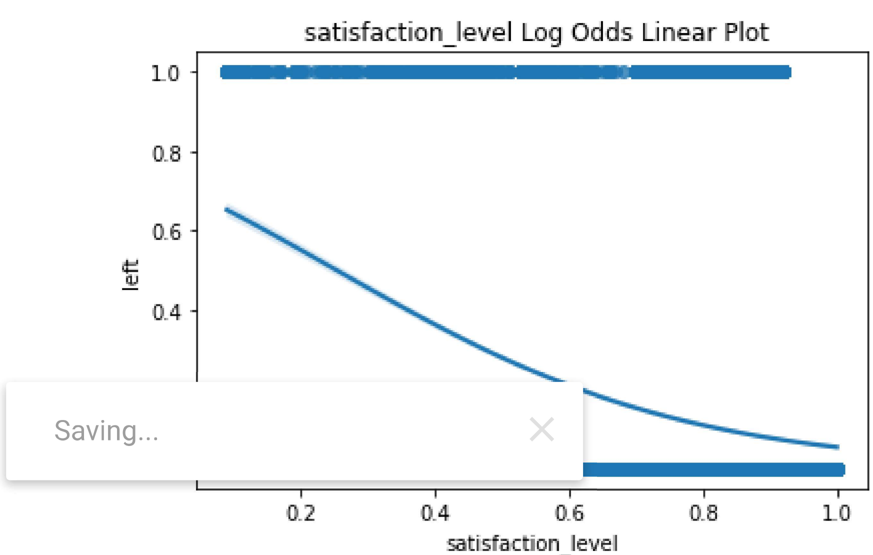
```
X = data.drop("left",axis=1)
y= data.left
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import *
```

LogisticRegression

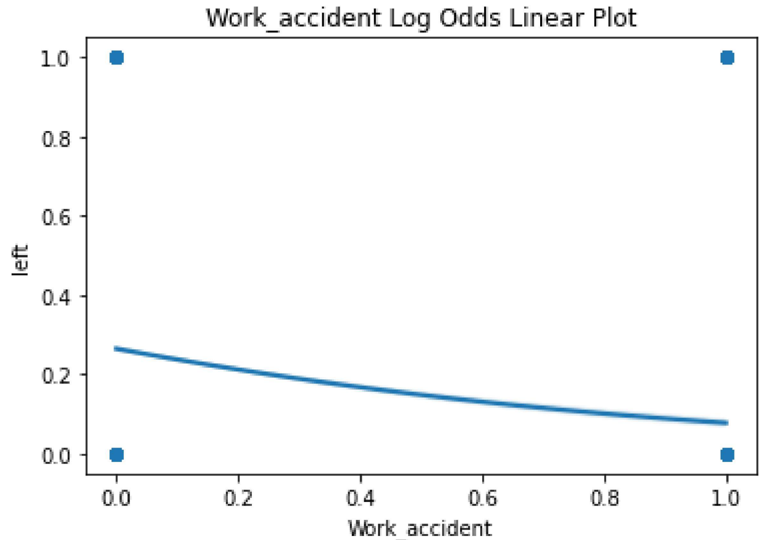
```
#----------------------------------checking assumptions-------------------------------------
# The Response Variable is Binary
# The Observations are Independent
# There is No Multicollinearity Among Explanatory Variables
#There is a Linear Relationship Between Explanatory Variables and the Logit of the Response V
```

```
sat_level = sns.regplot(x= data['satisfaction_level'], y=data['left'], data= data, logistic=
sat_level;
```

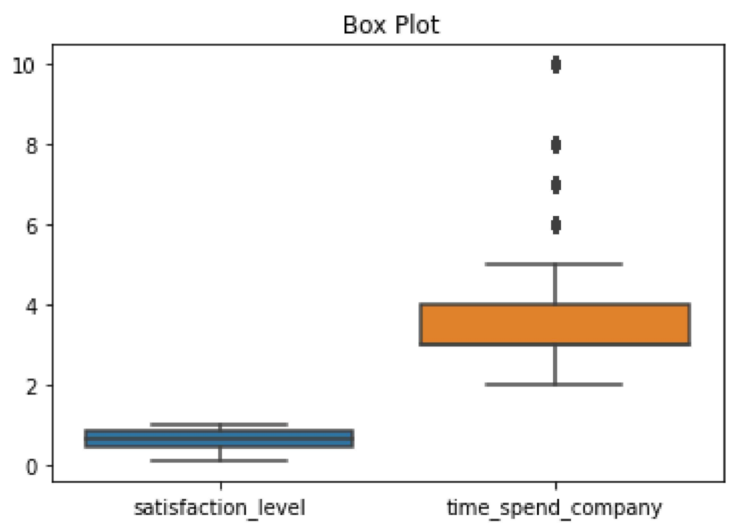



```
Work_accident = sns.regplot(data['Work_accident'], y=data['left'], data= data, logistic= True
Work_accident
```

```
Text(0.5, 1.0, 'Work_accident Log Odds Linear Plot')
```




```
sns.boxplot(data= data[['satisfaction_level', 'time_spend_company']]).set_title(" Box Plot");
```



No extreme outliers detected

```
from sklearn.linear_model import LogisticRegression
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=0)
lr=LogisticRegression()
lr.fit(X_train,y_train)
```

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```
y_pred=lr.predict(X_test)
```

```
lr.score(X_train,y_train)
```

```
0.7917896942565958
```

```
lr.score(X_test,y_test)
```

```
0.792
```

Here we are getting the 0.792 test score

GridSearchCV

```
from sklearn.model_selection import GridSearchCV,cross_val_score,StratifiedKFold

lr=LogisticRegression()
solvers = ['lbfgs', 'liblinear','newton-cg']
penalty = ['l2',"l1"]
c_values = [100, 10, 1.0, 0.1, 0.01]


fold=StratifiedKFold(n_splits=5,shuffle=True,random_state=0)
grid = dict(solver=solvers,penalty=penalty,C=c_values)

model=GridSearchCV(estimator=lr,
                   param_grid=grid,
                   scoring='accuracy',
                   verbose=1,cv=fold)

model.fit(X_train, y_train)

print(model.best_params_)
print(model.best_score_)
print(model.best_estimator_)
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
{'C': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
0.7969326890355952
LogisticRegression(C=100)
```

```
new_lr=LogisticRegression(C=100, solver='liblinear')
new_lr.fit(X_train,y_train)
y_pred=new_lr.predict(X_test)
```



```
precision_score_lr=(precision_score(y_test,y_pred))
recall_score_lr=(recall_score(y_test,y_pred))
f1_score_lr=(f1_score(y_test,y_pred))
roc_auc_score_lr=(roc_auc_score(y_test,y_pred))


print("logistic accuracy score :",lr.score)
```

```
print( logistic_accuracy_score : ,lr_score)
print("pricision :",precision_score_lr)
print("recall :",recall_score_lr)
print("f1_score :",f1_score_lr)
print("roc_auc_score :",roc_auc_score_lr)
```

```
logistic_accuracy_score : 0.7917777777777778
pricision : 0.5790297339593115
recall : 0.35645472061657035
f1_score : 0.4412641621943948
roc_auc_score : 0.639376984802797
```

```
# Confusion matrix
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	370	668
not left	269	3193

Our aim is FP & TP shoul be low but here it's not low so logistic model not perform well.

```
# calculating performance measure
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.92      0.87      3462
           1       0.58      0.36      0.44      1038

    accuracy                           0.79      4500
   macro avg       0.70      0.64      0.66      4500
weighted avg       0.77      0.79      0.77      4500
```

Support Vector

Saving... ×

```
y_pred=svc.predict(X_test)
```

```
svc_score=accuracy_score(y_test,y_pred)
svc_score
```

```
0.7902222222222223
```

SVC also give the almost same score as logistic regrssion which is 79.02%

GridSearchCV

```
# fold=StratifiedKFold(n_splits=5,shuffle=True,random_state=0)
kernel=['linear', 'rbf']
C=[0.1,0.01,0.001,1]
grid = dict(kernel=kernel ,C=C)
gs_model=GridSearchCV(estimator=SVC(),param_grid=grid,cv=fold,verbose=1,return_train_score=True)
gs_model.fit(X_train,y_train)
print(gs_model.best_score_)
print(gs_model.best_params_)
print(gs_model.best_estimator_)
```

```
svc=SVC(C=100, kernel='rbf').fit(X_train,y_train)
y_pred=svc.predict(X_test)
svc_score=accuracy_score(y_test,y_pred)
print(svc_score)
```

```
0.9051111111111111
```

After HyperParameter tuning we are getting the good accuracy score 90.51%

```
precision_score_svc=(precision_score(y_test,y_pred))
recall_score_svc=(recall_score(y_test,y_pred))
f1_score_svc=(f1_score(y_test,y_pred))
roc_auc_score_svc=(roc_auc_score(y_test,y_pred))
```

```
print("SVC_accuracy_score :",svc_score)
print("pricision :",precision_score_svc)
print("roc_auc_score :",roc_auc_score_svc)
```

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```
SVC_accuracy_score : 0.9051111111111111
pricision : 0.8375690607734807
recall : 0.7302504816955684
```

```
f1_score : 0.7802367472979927
```

```
# confusion_matrix
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	758	280
not left	147	3315

FP & FN valus are not decrease using the svc so svc is also not performing well

```
#classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.96      0.94      3462
           1       0.84      0.73      0.78      1038

    accuracy                           0.91      4500
   macro avg       0.88      0.84      0.86      4500
weighted avg       0.90      0.91      0.90      4500
```

KNeighborsClassifier

```
from sklearn.neighbors import KNeighborsClassifier
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)

n_neighbors=[5,10,15,20,25,50,75,100]
params=dict(n_neighbors=n_neighbors)
gs_model=GridSearchCV(estimator=KNeighborsClassifier(),param_grid=params,scoring='accuracy',c
gs_model.fit(X_train,y_train)
print(gs_model.best_score_)
print(gs_model.best_params_)
print(gs_model.best_estimator_)
```

Saving...

```
andidates, totalling 40 fits

{'n_neighbors': 5}
KNeighborsClassifier()
```

```
knn=KNeighborsClassifier().fit(X_train,y_train)
y_pred=knn.predict(X_test)
```

```
knn_score=accuracy_score(y_test,y_pred)
knn_score
```

```
0.926
```

KNN gives the 92.6 % accuracy better than the logistic & svc

```
precision_score_knn=(precision_score(y_test,y_pred))
recall_score_knn=(recall_score(y_test,y_pred))
f1_score_knn=(f1_score(y_test,y_pred))
roc_auc_score_knn=(roc_auc_score(y_test,y_pred))


print("knn_accuracy_score :",knn_score)
print("pricision :",precision_score_knn)
print("recall :",recall_score_knn)
print("f1_score :",f1_score_knn)
print("roc_auc_score :",roc_auc_score_knn)
```

```
knn_accuracy_score : 0.926
pricision : 0.8047858942065491
recall : 0.9050991501416431
f1_score : 0.8520000000000001
roc_auc_score : 0.9187657912870377
```

```
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	639	67
not left	155	2139

FP & FN Values are still not decrease so this model also not performed well

```
print(classification_report(y_test,y_pred))
```



```
              precision    recall  f1-score   support

                             93      0.95      2294
                             91      0.85       706

    accuracy                         0.93      3000
   macro avg       0.89      0.92      0.90      3000
weighted avg       0.93      0.93      0.93      3000
```

NaiveBayes

```
from sklearn.naive_bayes import GaussianNB
nb=GaussianNB().fit(X_train,y_train)
y_pred_=nb.predict(X_test)
nb_score=accuracy_score(y_test,y_pred_)
nb_score
```

```
0.792
```

```
precision_score_nb=(precision_score(y_test,y_pred_))
recall_score_nb=(recall_score(y_test,y_pred_))
f1_score_nb=(f1_score(y_test,y_pred_))
roc_auc_score_nb=(roc_auc_score(y_test,y_pred_))
```

```
print("nb_accuracy_score :",nb_score)
print("pricision :",precision_score_nb)
print("recall :",recall_score_nb)
print("f1_score :",f1_score_nb)
print("roc_auc_score :",roc_auc_score_nb)
```

```
nb_accuracy_score : 0.792
pricision : 0.5441810344827587
recall : 0.7152974504249292
f1_score : 0.6181150550795593
roc_auc_score : 0.7654516894670418
```

```
cm = np.array(confusion_matrix(y_test, y_pred_, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	505	201
not left	423	1871

```
print(classification_report(y_test,y_pred_))
```

```
              precision    recall  f1-score   support

                             82      0.86      2294
           1       0.54      0.72      0.62       706

    accuracy                           0.79      3000
   macro avg       0.72      0.77      0.74      3000
weighted avg       0.82      0.79      0.80      3000
```

NaiveBayes classifer not performing well because all the scores are low, also FP & FN values are also high.

DecisionTree

```
from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier().fit(X_train,y_train)
dt.score(X_test,y_test)
```

```
0.976
```

GridSearchCV

```
dt=DecisionTreeClassifier()
param_grid = {'max_features': ['auto', 'sqrt', 'log2'],
              'ccp_alpha': [0.1, .01, .001],
              'max_depth' : [2,4,6,8,10],
              'criterion' :['gini', 'entropy'],
              'min_samples_split':[2,4,6],
              'min_samples_leaf':[1,2,3]
             }
gs_model=GridSearchCV(estimator=dt,param_grid=param_grid,scoring='accuracy',verbose=1,cv=fold
gs_model.fit(X_train,y_train)
print(gs_model.best_score_)
print(gs_model.best_estimator_)
```

```
Fitting 5 folds for each of 810 candidates, totalling 4050 fits
0.97699732527442
DecisionTreeClassifier(ccp_alpha=0.001, criterion='entropy', max_depth=10,
                       max_features='log2', min_samples_leaf=2)
```

```
dtree=DecisionTreeClassifier(ccp_alpha=0.001, criterion='entropy', max_depth=10,max_features=
dtree.fit(X_train,y_train)
y_pred=dtree.predict(X_test)
```

```
dtree_score=accuracy_score(y_test,y_pred)
dtree_score
```

Saving...

```
precision_score_dt=(precision_score(y_test,y_pred))
recall_score_dt=(recall_score(y_test,y_pred))
f1_score_dt=(f1_score(y_test,y_pred))
roc_auc_score_dt=(roc_auc_score(y_test,y_pred))
```

```
print("dt_accuracy_score :",dtree_score)
print("pricision :",precision_score_dt)
print("recall :",recall_score_dt)
print("f1_score :",f1_score_dt)
print("roc_auc_score :",roc_auc_score_dt)
```

```
dt_accuracy_score : 0.9656666666666667
pricision : 0.886685552407932
recall : 0.886685552407932
f1_score : 0.886685552407932
roc_auc_score : 0.925905984573626
```

```
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	626	80
not left	80	2214

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97      2294
           1       0.89      0.89      0.89       706

    accuracy                           0.95      3000
   macro avg       0.93      0.93      0.93      3000
weighted avg       0.95      0.95      0.95      3000
```

From all above calculation we can say that DecisonTree is good.It gives the good roc_auc & accuracy score. Also FP & FN values are also decreased.

RandomForest

Saving...

```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier().fit(X_train,y_train)
rf.score(X_test,y_test)
```

```
0.9886666666666667
```

GridSearchCV

```
rf=RandomForestClassifier()
param_grid = {'max_features': ['auto', 'sqrt'],
              'n_estimators': [100,150],
              'max_depth' : [2,6,10],
              'criterion' :['gini', 'entropy'],
              'min_samples_split':[2,4,6],
              'min_samples_leaf':[1,2,3]
             }

gs_model=GridSearchCV(estimator=rf,param_grid=param_grid,scoring='accuracy',verbose=1,cv=fold
gs_model.fit(X_train,y_train)
print(gs_model.best_score_)
print(gs_model.best_params_)
print(gs_model.best_estimator_)
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
0.9815815270251494
{'criterion': 'gini', 'max_depth': 10, 'max_features': 'auto', 'min_samples_leaf': 1, 'n
RandomForestClassifier(max_depth=10)
```

```
rforest=RandomForestClassifier(criterion='gini', max_depth=10, max_features='auto',
                       min_samples_split=2, n_estimators=100).fit(X_train,y_train)
```

```
y_pred=rforest.predict(X_test)
```

```
rf_score=accuracy_score(y_test,y_pred)
rf_score
```

```
0.979
```

```
precision_score_rf=(precision_score(y_test,y_pred))
recall_score_rf=(recall_score(y_test,y_pred))
f1_score_rf=(f1_score(y_test,y_pred))
roc_auc_score_rf=(roc_auc_score(y_test,y_pred))
```

```
print("rf_accuracy_score :",rf_score)
rf)
Saving...
print("roc_auc_score :",roc_auc_score_rf)
```

```
rf_accuracy_score : 0.979
pricision : 0.989345509893455
recall : 0.9206798866855525
```

```
f1_score : 0.9537784299339692
roc_auc_score : 0.9588142240751214
```

```
# confusion matrix
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	650	56
not left	7	2287

```
# classification report for RF
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      2294
           1       0.99      0.92      0.95       706

    accuracy                           0.98      3000
   macro avg       0.98      0.96      0.97      3000
weighted avg       0.98      0.98      0.98      3000
```

From all above calculation we can say that RandomForest is performing better than the decision tree.It gives the good roc_auc(95.88%) & accuracy score 97.9 %. Also FP & FN values are also decreased than the Decisin Tree.

AdaBoostClassifier

```
from sklearn.ensemble import AdaBoostClassifier,RandomForestClassifier
ada_clf = AdaBoostClassifier(RandomForestClassifier())
ada_clf.fit(X_train, y_train)
```

```
AdaBoostClassifier(base_estimator=RandomForestClassifier())
```

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```
# Accuracy score for test data
ada_score=accuracy_score(y_test,y_pred)
ada_score
```

```
0.9906666666666667
```

We are getting the very good accuracy score which is 99.06 %

```
precision_score_ada=(precision_score(y_test,y_pred))
recall_score_ada=(recall_score(y_test,y_pred))
f1_score_ada=(f1_score(y_test,y_pred))
roc_auc_score_ada=(roc_auc_score(y_test,y_pred))


print("ada_accuracy_score :",ada_score)
print("pricision :",precision_score_ada)
print("recall :",recall_score_ada)
print("f1_score :",f1_score_ada)
print("roc_auc_score :",roc_auc_score_ada)
```

```
ada_accuracy_score : 0.9906666666666667
pricision : 0.9901574803149606
recall : 0.9691714836223507
f1_score : 0.9795520934761441
roc_auc_score : 0.9831414899336479
```

All the scores such as precision, Recall & roc_auc score are above 95 % so this is the perfect model for Our DataSet.

```
# confusion_matrix
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	1006	32
not left	10	3452

Here, FP & FN values are less as compared to all the models so our model is performing well

```
# classification Report
print(classification_report(y_test,y_pred))
```

Saving...

```
                           ll   f1-score   support

           0       0.99      1.00      0.99      3462
           1       0.99      0.97      0.98      1038

    accuracy                           0.99      4500
   macro avg       0.99      0.98      0.99      4500
```

```
weighted avg       0.99      0.99      0.99      4500
```

XGBoost

```
from xgboost import XGBClassifier
xgb_clf =XGBClassifier(max_depth=5, n_estimators=10000, learning_rate=0.3,n_jobs=-1)
xgb_clf.fit(X_train, y_train)
```

```
XGBClassifier(learning_rate=0.3, max_depth=5, n_estimators=10000, n_jobs=-1)
```

```
y_pred=xgb_clf.predict(X_test)
```

```
xgb_score=accuracy_score(y_test,y_pred)
xgb_score
```

```
0.9846666666666667
```

```
precision_score_xgb=(precision_score(y_test,y_pred))
recall_score_xgb=(recall_score(y_test,y_pred))
f1_score_xgb=(f1_score(y_test,y_pred))
roc_auc_score_xgb=(roc_auc_score(y_test,y_pred))
```

```
print("xgb_accuracy_score :",xgb_score)
print("pricision :",precision_score_xgb)
print("recall :",recall_score_xgb)
print("f1_score :",f1_score_xgb)
print("roc_auc_score :",roc_auc_score_xgb)
```

```
xgb_accuracy_score : 0.9846666666666667
pricision : 0.9714285714285714
recall : 0.9631728045325779
f1_score : 0.9672830725462305
roc_auc_score : 0.977227204358704
```

```
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
[illegible]	[illegible]	26
not left	20	2274


```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      2294
           1       0.97      0.96      0.97       706

    accuracy                           0.98      3000
   macro avg       0.98      0.98      0.98      3000
weighted avg       0.98      0.98      0.98      3000
```

After Observing all the scores we can say that XGBoost is also performing good but AdaBoost is quite better than the XGBoost

Voting_Classifier

```
from sklearn.ensemble import VotingClassifier
log_clf = LogisticRegression(random_state=42)
rnd_clf = RandomForestClassifier(random_state=42)
svm_clf = SVC(random_state=42, probability=True)

voting_clf = VotingClassifier(
    estimators=[('lr', log_clf), ('rf', rnd_clf), ('svc', svm_clf)],
    voting='soft')

voting_clf.fit(X_train, y_train)
```

```
VotingClassifier(estimators=[('lr', LogisticRegression(random_state=42)),
                             ('rf', RandomForestClassifier(random_state=42)),
                             ('svc', SVC(probability=True, random_state=42))],
                 voting='soft')
```

```
for clf in (log_clf, rnd_clf, svm_clf, voting_clf):
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print(clf.__class__.__name__, accuracy_score(y_test, y_pred))
```

```
LogisticRegression 0.7776666666666666
RandomForestClassifier 0.988
SVC 0.7846666666666666
```

Saving...

```
voting_clf.fit(X_train, y_train)
y_pred = voting_clf.predict(X_test)
vtc_score=accuracy_score(y_test, y_pred)
vtc_score
```

```
0.925
```

```
precision_score_vtc=(precision_score(y_test,y_pred))
recall_score_vtc=(recall_score(y_test,y_pred))
f1_score_vtc=(f1_score(y_test,y_pred))
roc_auc_score_vtc=(roc_auc_score(y_test,y_pred))


print("vtc_accuracy_score :",vtc_score)
print("pricision :",precision_score_vtc)
print("recall :",recall_score_vtc)
print("f1_score :",f1_score_vtc)
print("roc_auc_score :",roc_auc_score_vtc)
```

```
vtc_accuracy_score : 0.925
pricision : 0.9461966604823747
recall : 0.7223796033994334
f1_score : 0.8192771084337348
roc_auc_score : 0.8548689647337184
```

```
# printing Confusion matrix
cm = np.array(confusion_matrix(y_test, y_pred, labels=[1,0]))
confusion = pd.DataFrame(cm, index=['left', 'not left'],columns=['predicted left','predicted
confusion
```

	predicted left	predicted not left
left	510	196
not left	29	2265

By Votion Classifier FP & FN values are increase so we are not selecting this model for prediction

```
# classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.92      0.99      0.95      2294
           1       0.95      0.72      0.82       706

    accuracy                           0.93      3000
   macro avg       0.93      0.85      0.89      3000
[illegible]          93      0.92      3000
```

Saving...

Conclusion: After observing all the model AdaBoostClassifer performing very good so, that's why we are selection this model for our prediction.

```
# ROC_AUC For AdaBoostClassifier

from sklearn.ensemble import AdaBoostClassifier
ada_clf = AdaBoostClassifier(RandomForestClassifier())
ada_clf.fit(X_train, y_train)
y_pred=ada_clf.predict(X_test)


from sklearn.metrics import *
roc_auc_score(y_test,y_pred)
```

```
0.9828042195529999
```

```
y_proba=ada_clf.predict_proba(X_test)[:,1]
```

```
fpr,tpr,threshold=roc_curve(y_test,y_proba)
```

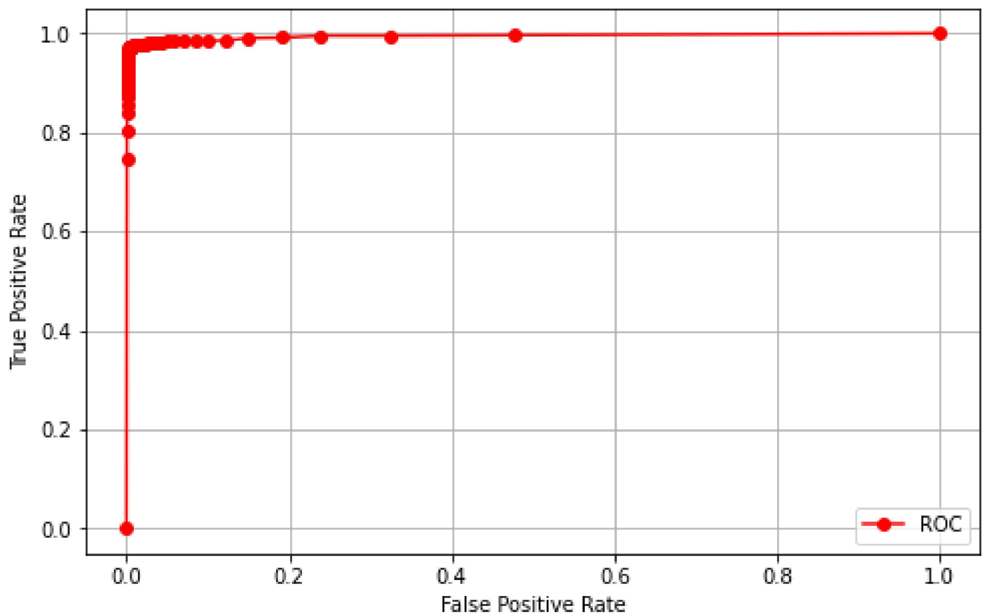
```
from sklearn.metrics import accuracy_score
accuracy = []
for thres in threshold:
  y_pred_prob = np.where(y_proba>thres,1,0)
  accuracy.append(accuracy_score(y_test,y_pred_prob))
accuracy=pd.concat([pd.Series(threshold),pd.Series(accuracy)],axis=1)
accuracy.columns=['threshold','accuracy']
accuracy.sort_values(by='accuracy',ascending=False,inplace=True)
accuracy=accuracy.round(decimals = 4)
```

```
accuracy.sample(10)
```

	threshold	accuracy
55	0.27	0.9867
50	0.34	0.9891
2	0.99	0.9411
8	0.93	0.9711
38	0.52	0.9904
34	0.57	0.9900
[illegible]	[illegible]	[illegible]
79	0.01	0.7489
70	0.11	0.9573
27	0.67	0.9853

From above sample we can see that the thresould value above 0.5 gives the good accuracy whiche is approx 99%. So the probability cutoff is 0.5

```
# plot the roc curve for the model
plt.figure(figsize=(8,5))
plt.plot(fpr, tpr,marker='o',color='Red',label='ROC')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid()
```




```
result=pd.DataFrame({
'model':['LogisticRegression','SVC','KNeighborsClassifier','GaussianNB',
'DecisionTree','RandomForest','AdaBoostClassifier','XGBoost','Voting_Classifier'],

'Accuracy_score':[lr_score,svc_score,knn_score,nb_score,dtree_score,rf_score,ada_score,xgb_sc

'Precision_score':[precision_score_lr,precision_score_svc,precision_score_knn,precision_score
                   precision_score_dt,precision_score_rf,precision_score_ada,precision_score_

'recall_score':[recall_score_lr,recall_score_svc,recall_score_knn,recall_score_nb,recall_scor
                recall_score_rf,recall_score_ada,recall_score_xgb,recall_score_vtc],

                                            ,f1_score_knn,f1_score_nb,f1_score_dt,f1_score_rf,f1_scor

                                            c_auc_score_svc,roc_auc_score_knn,roc_auc_score_nb,
              roc_auc_score_dt,roc_auc_score_rf,roc_auc_score_ada,roc_auc_score_xgb,roc_auc_s

},index=range(1,10))


result = result.round(decimals = 4)
```

Saving...

```
result
```

	model	Accuracy_score	Precision_score	recall_score	f1_score	roc_auc_
1	LogisticRegression	0.7918	0.5790	0.3565	0.4413	0
2	SVC	0.9051	0.8376	0.7303	0.7802	0
3	KNeighborsClassifier	0.9260	0.8048	0.9051	0.8520	0
4	GaussianNB	0.7920	0.5442	0.7153	0.6181	0
5	DecisionTree	0.9657	0.8867	0.8867	0.8867	0
6	RandomForest	0.9790	0.9893	0.9207	0.9538	0
7	AdaBoostClassifier	0.9880	0.9884	0.9632	0.9756	0
8	XGBoost	0.9847	0.9714	0.9632	0.9673	0
9	Voting_Classifier	0.9250	0.9462	0.7224	0.8193	0

```
# Maximum scores from  all models
max_score =result.iloc[:,1:6].max()
max_score
```

```
Accuracy_score     0.9880
Precision_score    0.9893
recall_score       0.9632
f1_score           0.9756
roc_auc_score      0.9798
dtype: float64
```

Base on the above maximum scores,Final Best Model for these Dataset is AdaBoostClassifier

```
from sklearn.ensemble import AdaBoostClassifier
ada_clf = AdaBoostClassifier(RandomForestClassifier())
ada_clf.fit(X_train, y_train)
y_pred=ada_clf.predict(X_test)
```

3. Prediction on Test Data

Saving...

```
cted values
result=pd.DataFrame({"Actual":y_test,"Predicted":y_pred})
result.sample(10)
```

	Actual	Predicted
11346	0	0
14578	1	1
13379	0	0
4863	0	0
4921	0	0
9808	0	0
4062	0	0
1783	1	1

By observing the above prediction we can say that our Model is Best for the Accurate Prediction

Also, I can conclude that it gives the almost 99% correct prediction

4. Prediction on new features

```
data.head(1)
```

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spen
0	0.38	0.53	2	157	

```
data.columns
```

```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'Department', 'salary'],
      dtype='object')
```

```
def prediction(satisfaction_level,last_evaluation,number_project,average_montly_hours,time_sp
                                          satisfaction_level,last_evaluation,number_project,average_

        print("Employee will not Left")
    else:
        print("Employee will Left")
```

Saving...

```
prediction(0.77,0.76,4,250,4,5,0,3,0)
```

```
Employee will not Left
```

```
prediction(0.10,0.1,5,250,1,10,0,0,0)
```

```
Employee will Left
```

Conclusion :

- The best fit model our data is AdaBoost Classifier.
- The base_estimator for this classifier is RandomForestClassifier
- From this model we get test accuracy 98.80 %, precision 98.84 %, recall 97.56 %, f1_score 97.56 % & the roc_auc score 97.98 %
- 5. Best probability cutoff for this model is 0.5.