Proj_emp_Turn_analysis

April 14, 2024

Employee Turnover Analytics

Project Statement:

Portobello Tech is an app innovator that has devised an intelligent way of predicting employee turnover within the company. It periodically evaluates employees' work details including the number of projects they worked upon, average monthly working hours, time spent in the company, promotions in the last 5 years, and salary level.

Data from prior evaluations show the employee's satisfaction at the workplace. The data could be used to identify patterns in work style and their interest to continue to work in the company.

The HR Department owns the data and uses it to predict employee turnover. Employee turnover refers to the total number of workers who leave a company over a certain time period.

Importing libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

Loading excel file

[2]:
```
data = pd.read_excel('1673873196_hr_comma_sep.xlsx')
```

[3]:
```
data
```

[3]:
```
       satisfaction_level  last_evaluation  number_project  \
0                    0.38             0.53               2
1                    0.80             0.86               5
2                    0.11             0.88               7
3                    0.72             0.87               5
4                    0.37             0.52               2
…                       …                …               …
14994                0.40             0.57               2
14995                0.37             0.48               2
14996                0.37             0.53               2
```

```
14997               0.11            0.96             6
14998               0.37            0.52             2

       average_montly_hours  time_spend_company  Work_accident  left  \
0                       157                   3              0     1
1                       262                   6              0     1
2                       272                   4              0     1
3                       223                   5              0     1
4                       159                   3              0     1
…                    …                 …            …   …
14994                   151                   3              0     1
14995                   160                   3              0     1
14996                   143                   3              0     1
14997                   280                   4              0     1
14998                   158                   3              0     1

       promotion_last_5years    sales  salary
0                          0    sales     low
1                          0    sales  medium
2                          0    sales  medium
3                          0    sales     low
4                          0    sales     low
…                        …      …     …
14994                      0  support     low
14995                      0  support     low
14996                      0  support     low
14997                      0  support     low
14998                      0  support     low

[14999 rows x 10 columns]
```

Perform steps

1. Perform data quality check by checking for missing values if any.

[4]:
```python
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   sales                  14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

[5]:
```
data.isnull().sum()
```

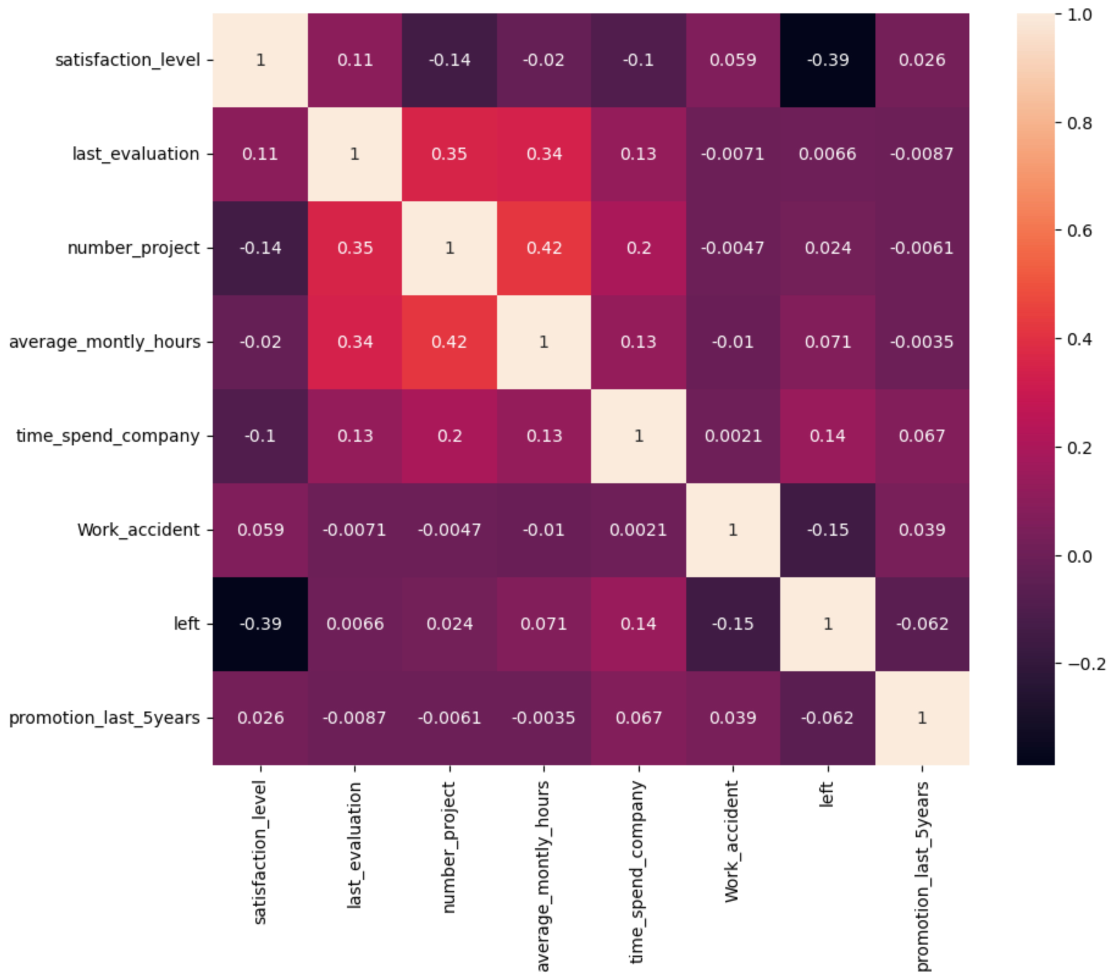
[5]:
```
satisfaction_level       0
last_evaluation          0
number_project           0
average_montly_hours     0
time_spend_company       0
Work_accident            0
left                     0
promotion_last_5years    0
sales                    0
salary                   0
dtype: int64
```

- No missing values in the dataset

2. Understand what factors contributed most to employee turnover by EDA. 2.1. Draw a heatmap of the Correlation Matrix between all numerical features/columns in the data. 2.2. Draw the distribution plot of Employee Satisfaction (use column satisfaction_level) Employee Evaluation (use column last_evaluation) Employee Average Monthly Hours (use column average_montly_hours) 2.3. Draw the bar plot of Employee Project Count of both employees who left and who stayed in the organization (use column number_project and hue column left) and give your inferences from the plot.

[6]:
```
# Heatmap of the Correlation Matrix
```

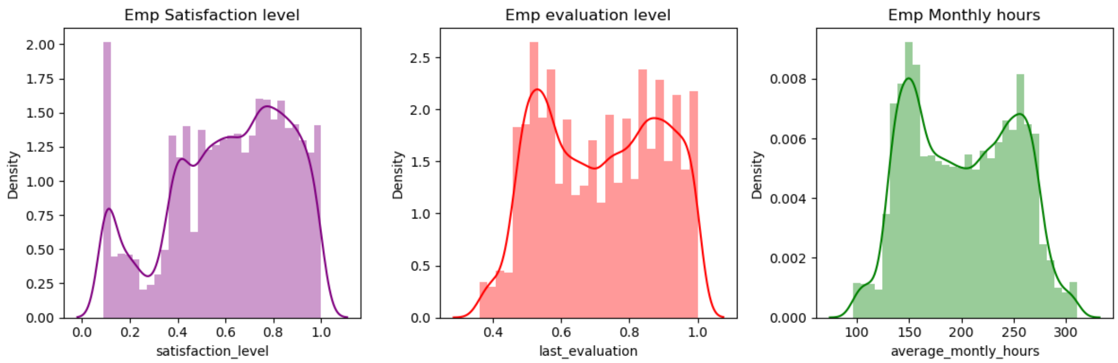
[7]:
```
plt.figure(figsize=(10,8))
sns.heatmap(data.corr(),annot=True)
plt.show()
```



[14]:
```
# Distribution Plot
     #Employee Satisfaction
     #    Employee Evaluation
     #    Employee Average Monthly Hours
```

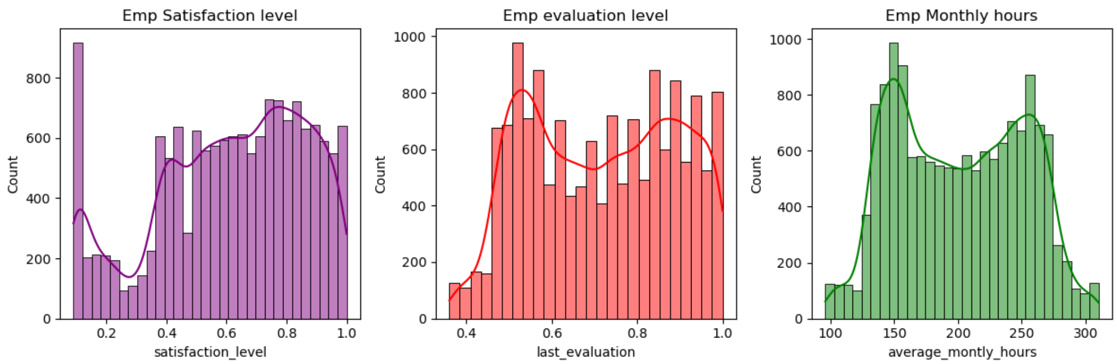
[12]:
```
plt.figure(figsize=(12,4))

plt.subplot(1,3,1)
sns.distplot(data['satisfaction_level'],kde=True,color='purple')
plt.title('Emp Satisfaction level')


plt.subplot(1,3,2)
sns.distplot(data['last_evaluation'],kde=True,color='red')
plt.title('Emp evaluation level')

plt.subplot(1,3,3)
```

```
sns.distplot(data['average_montly_hours'],kde=True,color='green')
plt.title('Emp Monthly hours')

plt.tight_layout()
plt.show()
```



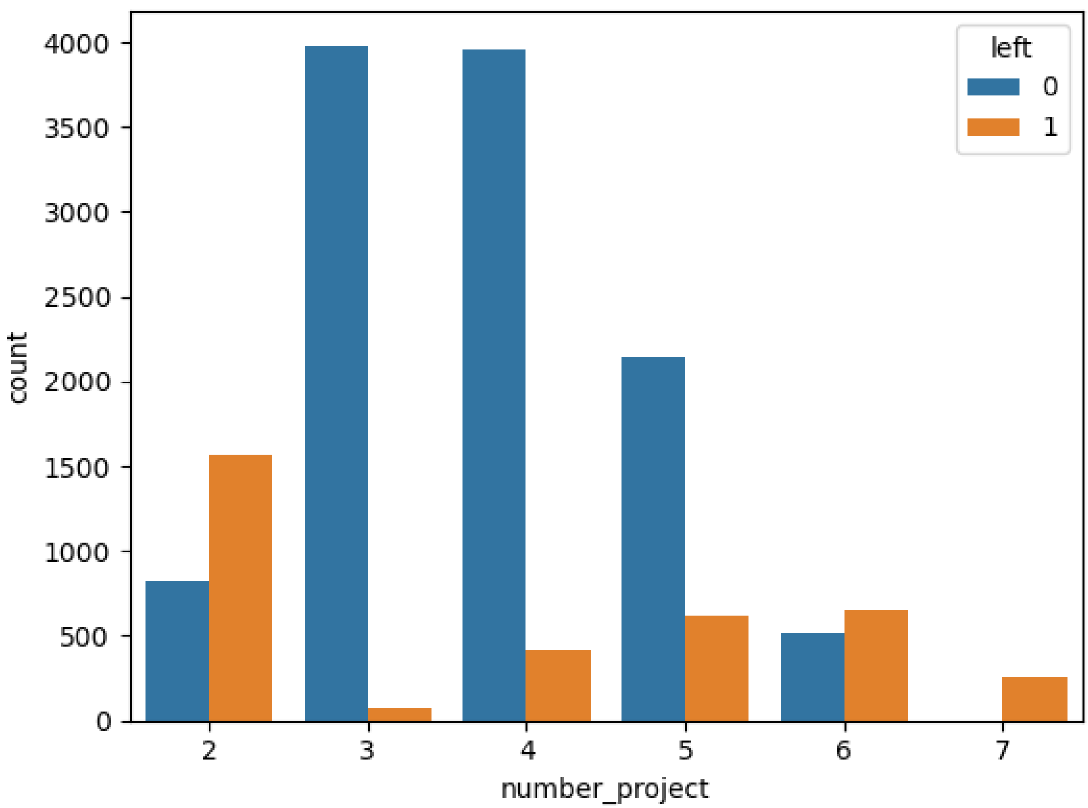
- For more clear visualization, I am using Histogram plot

[13]:
```
# Histplot for data visualization

plt.figure(figsize=(12,4))

plt.subplot(1,3,1)
sns.histplot(data['satisfaction_level'],kde=True,color='purple')
plt.title('Emp Satisfaction level')


plt.subplot(1,3,2)
sns.histplot(data['last_evaluation'],kde=True,color='red')
plt.title('Emp evaluation level')

plt.subplot(1,3,3)
sns.histplot(data['average_montly_hours'],kde=True,color='green')
plt.title('Emp Monthly hours')

plt.tight_layout()
plt.show()
```

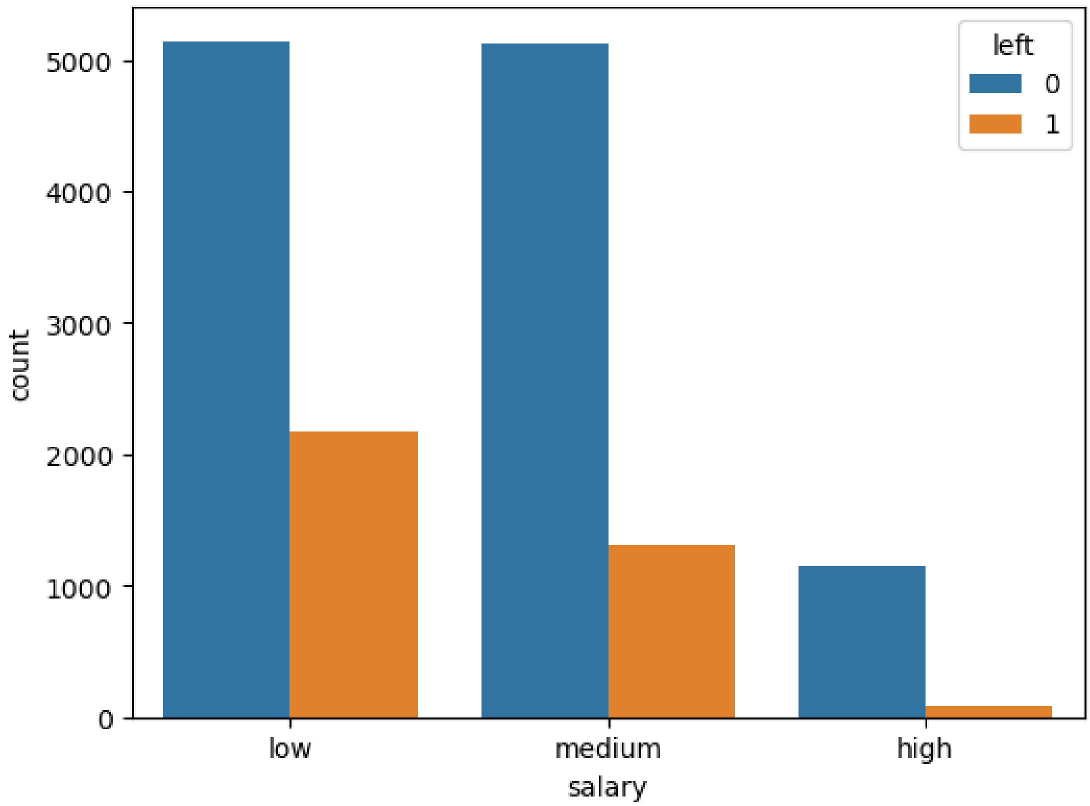


[16]:
```
# Draw the bar plot of Employee Project Count of both employees who left and␣
↪who stayed in the organization
# (use column number_project and hue column left)  and give your inferences␣
↪from the plot.
```

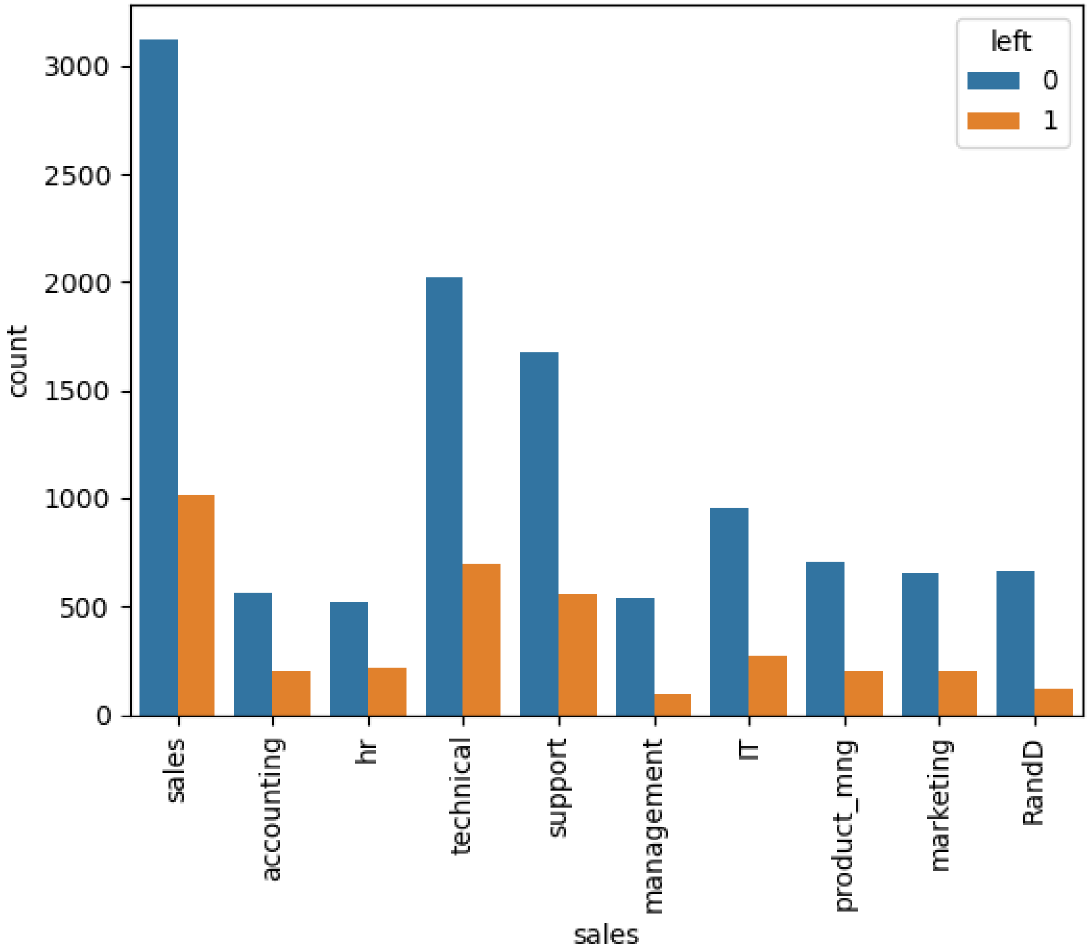
[21]:
```
# Employee who left and stayed based on Number of Project

sns.countplot(x=data['number_project'],hue='left',data=data)
plt.show()
```



[18]:
```python
# Employee who left and stayed based on Salary

sns.countplot(x=data['salary'],hue='left',data=data)
plt.show()
```



[23]:
```python
# Employee who left and stayed based on Sales

sns.countplot(x=data['sales'],hue='left',data=data)
plt.xticks(rotation=90)
plt.show()
```



3. Perform clustering of Employees who left based on their satisfaction and evaluation. 3.1.Choose columns satisfaction_level, last_evaluation and left. 3.2.Do KMeans clustering of employees who left the company into 3 clusters. 3.3.Based on the satisfaction and evaluation factors, give your thoughts on the employee clusters.

[24]:
```
data.columns
```

[24]:
```
Index(['satisfaction_level', 'last_evaluation', 'number_project',
       'average_montly_hours', 'time_spend_company', 'Work_accident', 'left',
       'promotion_last_5years', 'sales', 'salary'],
      dtype='object')
```

[25]:
```
# Choose columns satisfaction_level, last_evaluation and left
```

[26]:
```
cluster_data = data[['satisfaction_level', 'last_evaluation','left']]
left_emp_data = cluster_data[cluster_data['left'] == 1]
```

```
left_emp_data.head(10)
```

[26]:

	satisfaction_level	last_evaluation	left
0	0.38	0.53	1
1	0.80	0.86	1
2	0.11	0.88	1
3	0.72	0.87	1
4	0.37	0.52	1
5	0.41	0.50	1
6	0.10	0.77	1
7	0.92	0.85	1
8	0.89	1.00	1
9	0.42	0.53	1

[27]:
```
left_emp_data.shape
        # checking the total number of rows and cols in left_emp_data
```

[27]:
```
(3571, 3)
```

[35]:
```
# Do KMeans clustering of employees who left the company into 3 clusters.
```

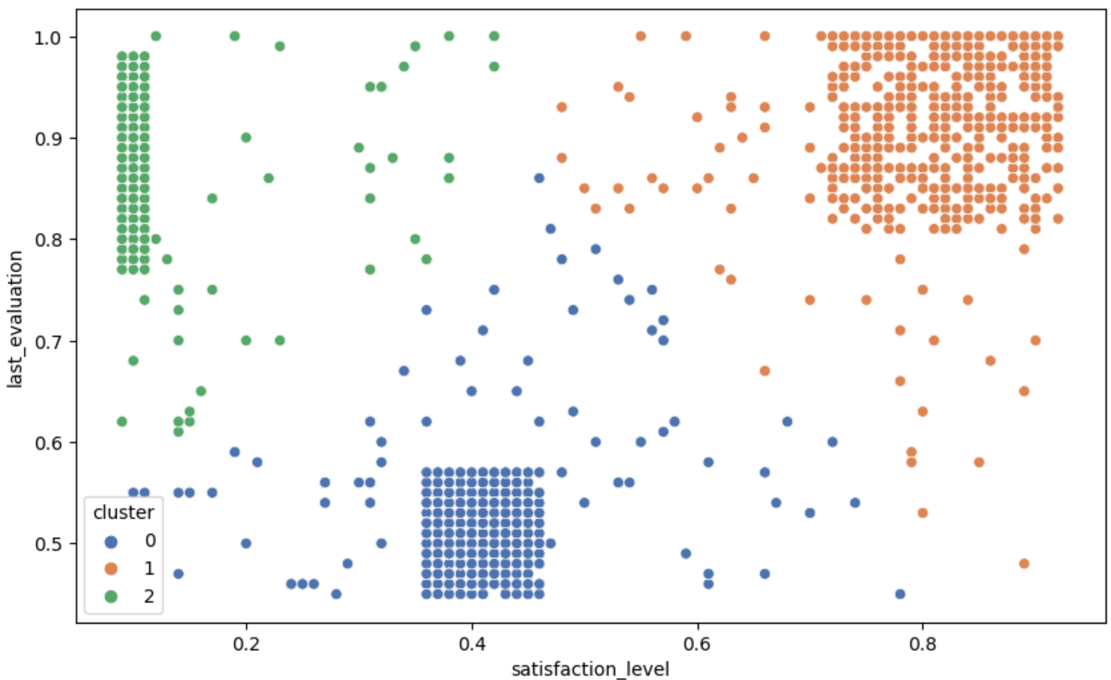
[28]:
```
from sklearn.cluster import KMeans
```

[29]:
```
kmeans=KMeans(n_clusters=3,random_state=42)
kmeans.fit(left_emp_data)
```

[29]:
```
KMeans(n_clusters=3, random_state=42)
```

[30]:
```
left_emp_data['cluster']=kmeans.labels_
```

[37]:
```
# Based on the satisfaction and evaluation factors, give your thoughts on the␣
 ↪employee clusters.

plt.figure(figsize=(10,6))
sns.
 ↪scatterplot(x='satisfaction_level',y='last_evaluation',hue='cluster',palette='deep',␣
 ↪data=left_emp_data)
plt.show()
```



- Employee left based on High Evaluation and Low Satisfaction level
- Employee left based on Low Evaluation and Average Satisfaction level
- Employee left based on High Evaluation and High Satisfaction level

[34]:
```
left_emp_data['cluster'].value_counts()
        # To show the the number of Employee left based on cluster
```

[34]:
```
0    1650
1     977
2     944
Name: cluster, dtype: int64
```

4. Handle the left Class Imbalance using SMOTE technique 4.1.Pre-Process the data by converting categorical columns to numerical columns by Separating categorical variables and numeric variables. Applying get_dummies() to the categorical variables. Combining categorical variables and numeric variables. 4.2.Do the stratified split of the dataset to train and test in the ratio 80:20 with random_state=123. 4.3.Upsample the train dataset using SMOTE technique from the imblearn module.

[38]:
```
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   sales                  14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

[41]:
```
#          Separating categorical variables and numeric variables

df_numerical = data.select_dtypes(include=['int64','float64'])
df_categorical = data.select_dtypes(include=['object'])

df_categorical.head(10)
```

[41]:
```
   sales  salary
0  sales     low
1  sales  medium
2  sales  medium
3  sales     low
4  sales     low
5  sales     low
6  sales     low
7  sales     low
8  sales     low
9  sales     low
```

[42]:
```
# Applying get_dummies() to the categorical variables.

df_converted=pd.get_dummies(data=df_categorical)
```

[43]:
```
df_converted.head(10)
```

[43]:
```
   sales_IT  sales_RandD  sales_accounting  sales_hr  sales_management  \
0         0            0                 0         0                 0
1         0            0                 0         0                 0
2         0            0                 0         0                 0
3         0            0                 0         0                 0
4         0            0                 0         0                 0
5         0            0                 0         0                 0
6         0            0                 0         0                 0
7         0            0                 0         0                 0
```

```
8         0            0                0        0                 0
9         0            0                0        0                 0

   sales_marketing  sales_product_mng  sales_sales  sales_support  \
0                0                  0            1              0
1                0                  0            1              0
2                0                  0            1              0
3                0                  0            1              0
4                0                  0            1              0
5                0                  0            1              0
6                0                  0            1              0
7                0                  0            1              0
8                0                  0            1              0
9                0                  0            1              0

   sales_technical  salary_high  salary_low  salary_medium
0                0            0           1              0
1                0            0           0              1
2                0            0           0              1
3                0            0           1              0
4                0            0           1              0
5                0            0           1              0
6                0            0           1              0
7                0            0           1              0
8                0            0           1              0
9                0            0           1              0
```

[44]:

```
# Combining categorical variables and numeric variables

df_new=pd.concat([df_numerical,df_converted],axis=1)
df_new.head(10)
```

[44]:

```
   satisfaction_level  last_evaluation  number_project  average_montly_hours  \
0                0.38             0.53               2                   157
1                0.80             0.86               5                   262
2                0.11             0.88               7                   272
3                0.72             0.87               5                   223
4                0.37             0.52               2                   159
5                0.41             0.50               2                   153
6                0.10             0.77               6                   247
7                0.92             0.85               5                   259
8                0.89             1.00               5                   224
9                0.42             0.53               2                   142

   time_spend_company  Work_accident  left  promotion_last_5years  sales_IT  \
0                   3              0     1                      0         0
1                   6              0     1                      0         0
```

```
2                   4               0      1                       0          0
3                   5               0      1                       0          0
4                   3               0      1                       0          0
5                   3               0      1                       0          0
6                   4               0      1                       0          0
7                   5               0      1                       0          0
8                   5               0      1                       0          0
9                   3               0      1                       0          0

   sales_RandD  …  sales_hr  sales_management  sales_marketing  \
0            0  …         0                 0                0
1            0  …         0                 0                0
2            0  …         0                 0                0
3            0  …         0                 0                0
4            0  …         0                 0                0
5            0  …         0                 0                0
6            0  …         0                 0                0
7            0  …         0                 0                0
8            0  …         0                 0                0
9            0  …         0                 0                0

   sales_product_mng  sales_sales  sales_support  sales_technical  \
0                  0            1              0                0
1                  0            1              0                0
2                  0            1              0                0
3                  0            1              0                0
4                  0            1              0                0
5                  0            1              0                0
6                  0            1              0                0
7                  0            1              0                0
8                  0            1              0                0
9                  0            1              0                0

   salary_high  salary_low  salary_medium
0            0           1              0
1            0           0              1
2            0           0              1
3            0           1              0
4            0           1              0
5            0           1              0
6            0           1              0
7            0           1              0
8            0           1              0
9            0           1              0

[10 rows x 21 columns]
```

[45]:
```python
# Handling class Imbalance technique

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

[45]:
```
0    11428
1     3571
Name: left, dtype: int64
```

[46]:
```python
X = df_new.drop('left',axis=1)
Y = df_new['left']
```

[48]:
```python
# Do the stratified split of the dataset to train and test in the ratio 80:20␣
↪with random_state=123.

from sklearn.model_selection import train_test_split
```

[49]:
```python
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,train_size=0.8,␣
↪random_state=123)
```

[58]:
```python
# Upsample the train dataset using SMOTE technique from the imblearn module.

from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=2)
X_train_resample,Y_train_resample = sm.fit_resample(X_train,Y_train)
```

[57]:
```python
Y_train_resample.value_counts()
    # checking the final values of Y_training set
```

[57]:
```
0    9137
1    9137
Name: left, dtype: int64
```

5. Perform 5-Fold cross-validation model training and evaluate performance. 5.1. Train a Logistic Regression model and apply a 5-Fold CV and plot the classification report. 5.2. Train a Random Forest Classifier model and apply the 5-Fold CV and plot the classification report. 5.3. Train a Gradient Boosting Classifier model and apply the 5-Fold CV and plot the classification report.

6. Identify the best model and justify the evaluation metrics used. 6.1. Find the ROC/AUC for each model and plot the ROC curve. 6.2. Find the confusion matrix for each of the models. 6.3. From the confusion matrix, explain which metric needs to be used- Recall or Precision?

[66]:
```python
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,roc_auc_score,classification_report,␣
↪confusion_matrix
```

[105]:
```
# Train a Logistic Regression model and apply a 5-Fold CV and plot the␣
↪classification report, roc auc and cross-validation scrore

log_reg = LogisticRegression()
log_reg.fit(X_train_resample,Y_train_resample)
```

[105]:
```
LogisticRegression()
```

[106]:
```
y_pred1 = log_reg.predict(X_test)
```

[64]:
```
print('Accuracy score: ',accuracy_score(Y_test,y_pred1))
```

```
Accuracy score:  0.7616666666666667
```

- Here, accuracy score is 76.16%

[65]:
```
print(classification_report(Y_test,y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.91      0.76      0.83      2291
           1       0.50      0.77      0.60       709

    accuracy                           0.76      3000
   macro avg       0.71      0.76      0.72      3000
weighted avg       0.81      0.76      0.78      3000
```

[69]:
```
print(confusion_matrix(Y_test, y_pred1))
```

```
[[1742  549]
 [ 166  543]]
```

[71]:
```
print(cross_val_score(log_reg,X_train_resample,Y_train_resample).mean())
```

```
0.7988404065181272
```

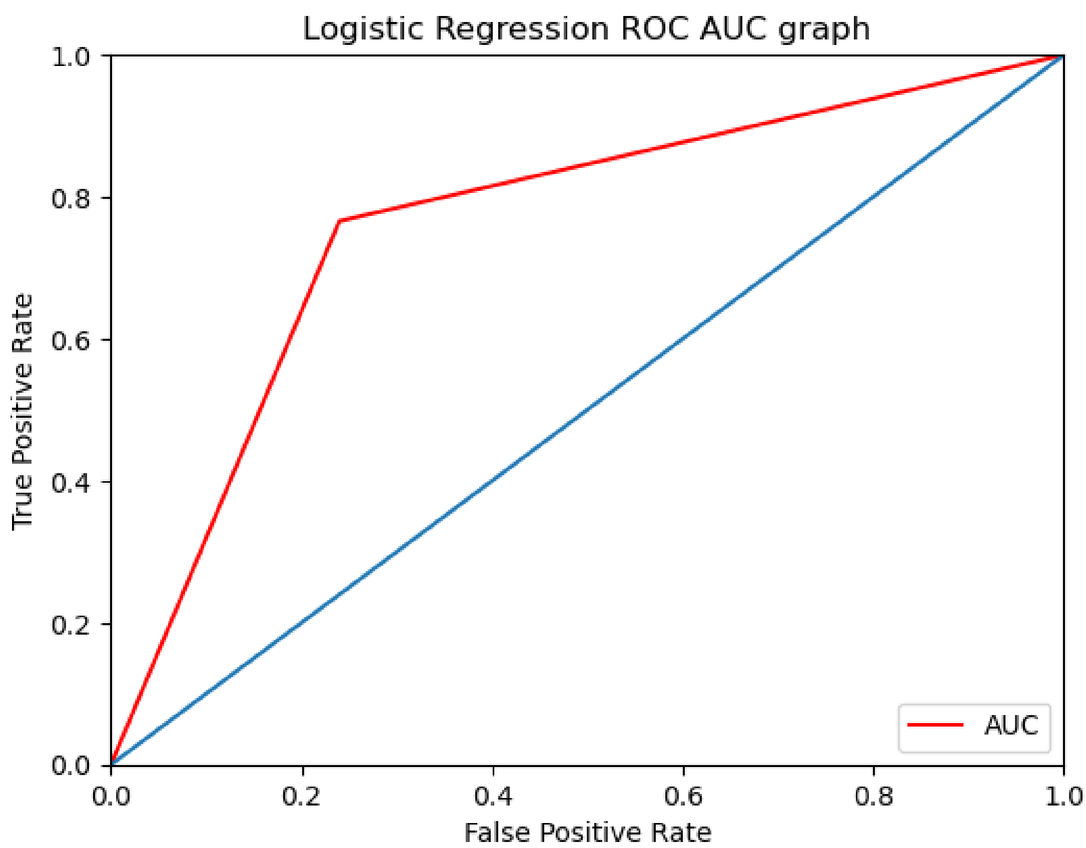
[72]:
```
print(roc_auc_score(Y_test,y_pred1))
```

```
0.7631170355084193
```

[73]:
```
from sklearn import metrics
fpr, tpr, threshold = metrics.roc_curve(Y_test, y_pred1)
print(fpr)
print(tpr)
print(threshold)
roc_auc = metrics.auc(fpr, tpr)
```

```
[0.         0.23963335 1.        ]
[0.         0.76586742 1.        ]
[2 1 0]
```

[80]:
```python
# Plot ROC AUC graph for Logistic Regression

plt.title('Logistic Regression ROC AUC graph')
plt.plot(fpr, tpr, 'r', label = 'AUC')
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1])
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[82]:
```python
# Train a Random Forest Classifier model and apply a 5-Fold CV and plot the␣
↪classification report, roc auc and cross-validation scrore

from sklearn.ensemble import RandomForestClassifier
```

[83]:
```
random_forest=RandomForestClassifier(max_depth=5)
```

[103]:
```
random_forest.fit(X_train_resample,Y_train_resample)
```

[103]:
```
RandomForestClassifier(max_depth=5)
```

[104]:
```
y_pred = random_forest.predict(X_test)
```

[87]:
```
print('Accuracy score',accuracy_score(Y_test,y_pred))
```

```
Accuracy score 0.9573333333333334
```

[96]:
```
print(cross_val_score(random_forest,X_train_resample,Y_train_resample).mean())
```

```
0.9477399877352705
```

[95]:
```
print(confusion_matrix(Y_test, y_pred))
```

```
[[2218   73]
 [  55  654]]
```

[88]:
```
print(classification_report(Y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.97      2291
           1       0.90      0.92      0.91       709

    accuracy                           0.96      3000
   macro avg       0.94      0.95      0.94      3000
weighted avg       0.96      0.96      0.96      3000
```

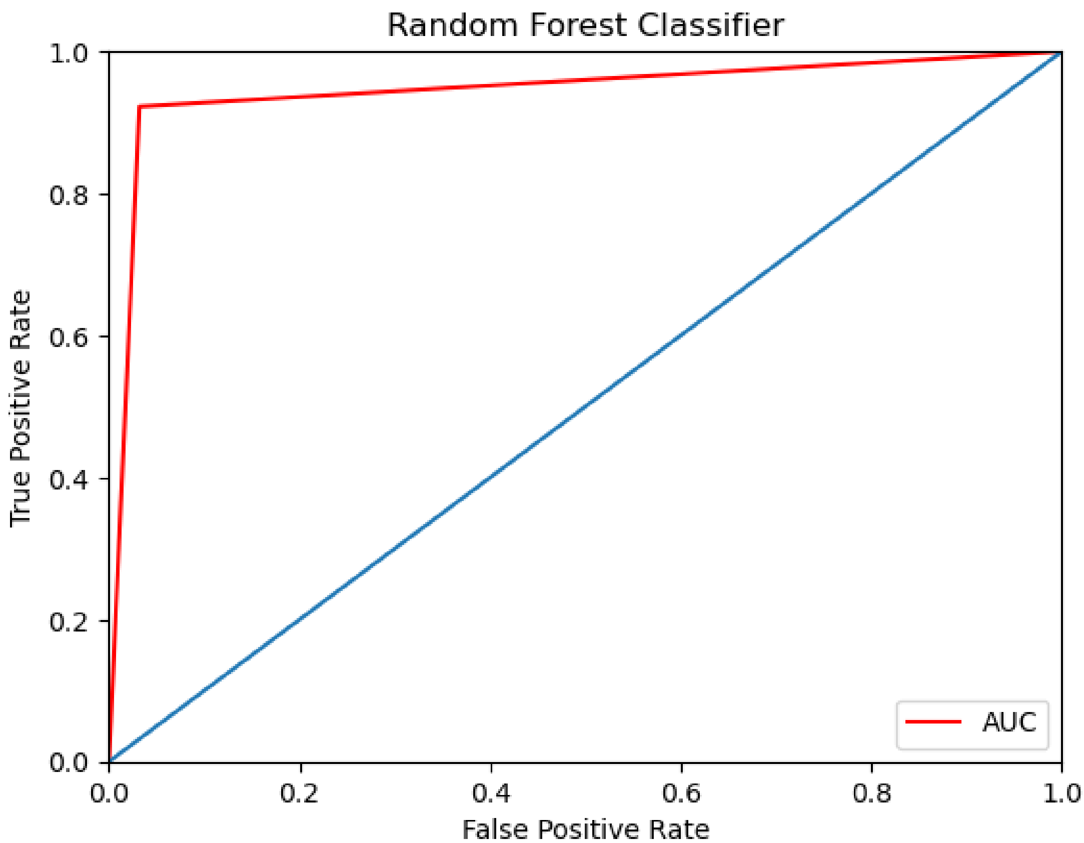
[90]:
```
print(roc_auc_score(Y_test,y_pred))
```

```
0.9452810685585774
```

[91]:
```
fpr, tpr, threshold = metrics.roc_curve(Y_test, y_pred)
print(fpr)
print(tpr)
print(threshold)
roc_auc = metrics.auc(fpr, tpr)
```

```
[0.         0.03186381 1.        ]
[0.         0.92242595 1.        ]
[2 1 0]
```

[94]:
```
# Plot ROC AUC graph for Random Forest Classifier

plt.title('Random Forest Classifier')
plt.plot(fpr, tpr, 'r', label = 'AUC')
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1])
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[97]:
```
# Train a Gradient Boosting Classifier model and apply a 5-Fold CV and plot the␣
↪classification report, roc auc and cross-validation scrore

from sklearn.ensemble import GradientBoostingClassifier
```

[99]:
```
gradient_boost = GradientBoostingClassifier()
```

[101]:
```
gradient_boost.fit(X_train_resample,Y_train_resample)
```

[101]: GradientBoostingClassifier()

[102]:
```
y_pred2 = gradient_boost.predict(X_test)
```

[107]:
```
print('Accuracy score',accuracy_score(Y_test,y_pred2))
```

```
Accuracy score 0.964
```

[108]:
```
print(classification_report(Y_test,y_pred2))
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      2291
           1       0.91      0.94      0.92       709

    accuracy                           0.96      3000
   macro avg       0.95      0.96      0.95      3000
weighted avg       0.96      0.96      0.96      3000
```

[109]:
```
print(roc_auc_score(Y_test,y_pred2))
```

```
0.9550026811235971
```

[110]:
```
print(confusion_matrix(Y_test, y_pred2))
```

```
[[2227   64]
 [  44  665]]
```

[111]:
```
print(cross_val_score(gradient_boost,X_train_resample,Y_train_resample).mean())
```

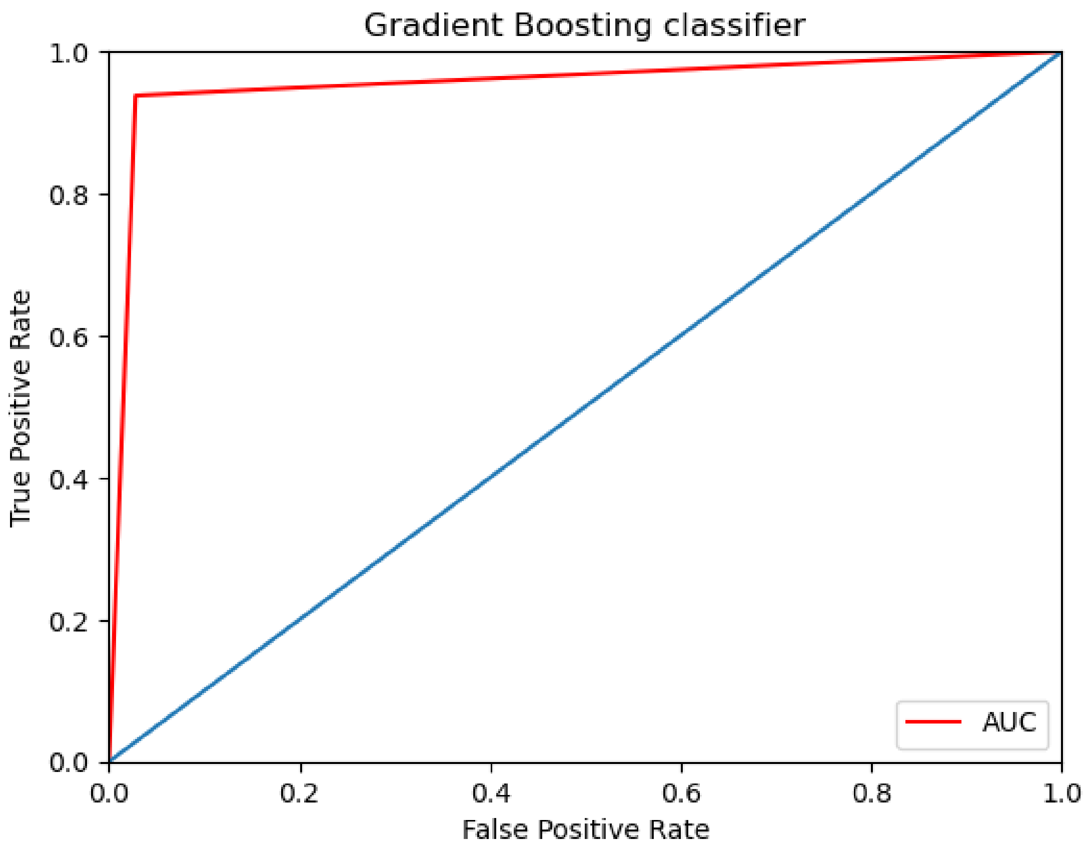
```
0.9587938933926953
```

[112]:
```
fpr, tpr, threshold = metrics.roc_curve(Y_test, y_pred2)
print(fpr)
print(tpr)
print(threshold)
roc_auc = metrics.auc(fpr, tpr)
```

```
[0.        0.0279354 1.       ]
[0.         0.93794076 1.        ]
[2 1 0]
```

[113]:
```
plt.title('Gradient Boosting classifier')
plt.plot(fpr, tpr, 'r', label = 'AUC')
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1])
plt.xlim([0, 1])
```

```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



- Here, the best fit models were Random Forest and Gradient Boosting classifiers

7. Suggest various retention strategies for targeted employees. 7.1.Using the best model, predict the probability of employee turnover in the test data. 7.2.Based on the below probability score range, categorize the employees into four zones and suggest your thoughts on the retention strategies for each zone. Safe Zone (Green) (Score < 20%) Low Risk Zone (Yellow) (20% < Score < 60%) Medium Risk Zone (Orange) (60% < Score < 90%) High Risk Zone (Red) (Score > 90%).

[114]:
```
# Using XGBoost boosting classifier model

import xgboost as xgb
model = xgb.XGBClassifier()
```

[116]:
```
model.fit(X_train_resample,Y_train_resample)
```

[116]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

[117]:
```python
y_pred3 = model.predict(X_test)
```

[118]:
```python
print('Accuracy score',accuracy_score(Y_test,y_pred3))
```

```
Accuracy score 0.9826666666666667
```

[119]:
```python
predicted_prob = model.predict_proba(X_test)
```

[120]:
```python
predicted_prob[:,1]
```

[120]:
```
array([1.0655432e-03, 4.4659537e-04, 4.6851885e-05, …, 9.8639083e-01,
       4.3727891e-03, 5.5505626e-04], dtype=float32)
```

[126]:
```python
# Using the best model, predict the probability of employee turnover in the␣
↪test data

X_test['leave']=y_pred3
X_test
```

[126]:
```
       satisfaction_level  last_evaluation  number_project  \
6958                 0.54             0.67               3
7534                 0.72             0.52               3
2975                 0.95             0.61               3
3903                 0.78             0.79               3
8437                 0.60             0.40               3
…                     …                 …              …
1229                 0.42             0.55               2
10593                0.61             0.67               4
12248                0.87             0.91               4
3147                 0.49             0.71               3
6623                 0.52             0.66               5

       average_montly_hours  time_spend_company  Work_accident  \
6958                    154                   2              0
7534                    143                   4              1
```

```
2975                   267               2            0
3903                   203               2            0
8437                   146               4            1
…                    …               …            …
1229                   148               3            0
10593                  151               3            0
12248                  228               5            0
3147                   154               2            0
6623                   184               3            0

       promotion_last_5years  sales_IT  sales_RandD  sales_accounting  …  \
6958                       0         0            0                 0  …
7534                       0         0            0                 0  …
2975                       0         0            1                 0  …
3903                       0         0            0                 0  …
8437                       0         0            0                 0  …
…                        …       …          …               …  …
1229                       0         0            0                 0  …
10593                      0         1            0                 0  …
12248                      0         0            0                 0  …
3147                       0         0            0                 0  …
6623                       0         1            0                 0  …

       sales_management  sales_marketing  sales_product_mng  sales_sales  \
6958                  0                0                  0            1
7534                  0                0                  0            0
2975                  0                0                  0            0
3903                  0                0                  0            1
8437                  0                0                  0            0
…                   …              …                …          …
1229                  0                0                  0            1
10593                 0                0                  0            0
12248                 0                0                  0            1
3147                  0                0                  0            1
6623                  0                0                  0            0

       sales_support  sales_technical  salary_high  salary_low  salary_medium  \
6958               0                0            1           0              0
7534               1                0            0           1              0
2975               0                0            0           1              0
3903               0                0            0           1              0
8437               0                1            0           1              0
…                …              …          …         …            …
1229               0                0            0           1              0
10593              0                0            1           0              0
12248              0                0            0           1              0
3147               0                0            0           0              1
```

```
6623                0                 0            0          1              0

       leave
6958       0
7534       0
2975       0
3903       0
8437       0
…       …
1229       1
10593      0
12248      1
3147       0
6623       0

[3000 rows x 21 columns]
```

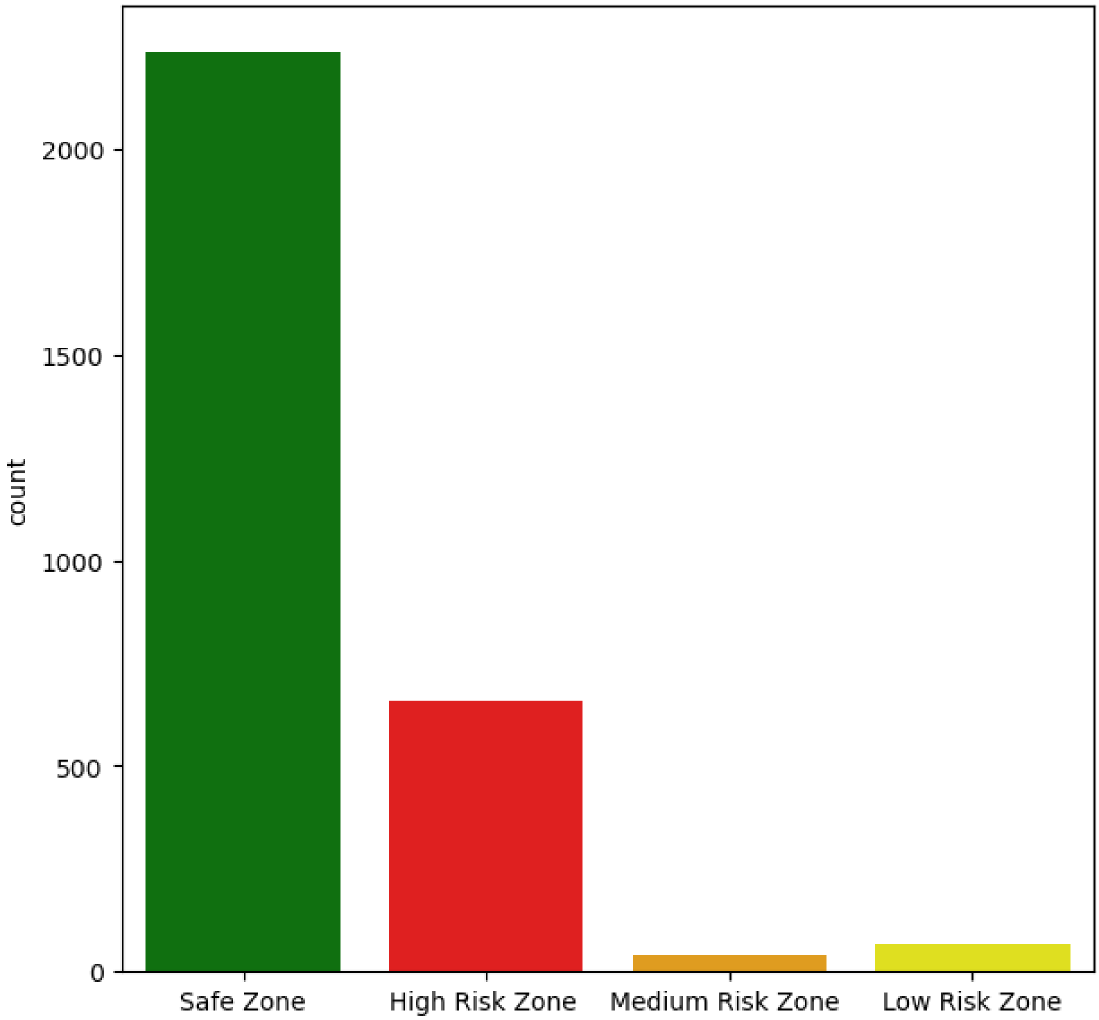
[121]:
```
# Based on the below probability score range, categorize the employees into␣
 ↪four zones
# suggest your thoughts on the retention strategies for each zone

zone=[]
prob=[]


for i in predicted_prob[:,1]:
  prob.append(i)
  if (i<=0.2):
    zone.append("Safe Zone")
  elif (i>0.2 and i<=0.6):
    zone.append("Low Risk Zone")
  elif (i>0.6 and i<=0.9):
    zone.append("Medium Risk Zone ")
  else:
    zone.append("High Risk Zone ")
```

[122]:
```
categories = ["Safe Zone","Low Risk Zone","Medium Risk Zone ","High Risk Zone "]
color = ["Green","Yellow","Orange","Red"]
```

[123]:
```
colordict = dict(zip(categories, color))

clr = pd.DataFrame({"zone":zone,"probability":prob})
clr["Color"] = clr["zone"].apply(lambda x: colordict[x])
clr['zone'] = clr['zone'].astype(str)
```

[131]:
```
color= clr["Color"].tolist()
c = ["Green","Red","Orange","Yellow"]
```

```
plt.figure(figsize=(7,7))
sns.countplot(x=zone, palette=c)
plt.show()
```




```
[ ]:
```