HR Analytics using Python & Machine Learning

[55]:

```
from IPython.core.display import display, HTML
display(HTML("<style>.cm-s-ipython span.cm-comment { color: yellow; }</style>"))
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_17376\4045986198.py:1: DeprecationWarning: Importing
display from IPython.core.display is deprecated since IPython 7.14, please import from IPython display
    from IPython.core.display import display, HTML
```

```
<IPython.core.display.HTML object>
```

[1]:

```
#Importing the necessary libraries:
import pandas as pd import
numpy as np
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt import
seaborn as sns
```

Our task is to predict the Performance Rating of the employees (based on these ‘features”), which forms our target variable.

[2]:

```
#Import the excel file
df = pd.read_excel('Hr_data.xls') df
```

[2]:

```
         EmpNumbe   Age   Gender     EducationBackground  MaritalStatus      \
                r
0        E1001000    32     Male               Marketing          Single
1        E1001006    47     Male               Marketing          Single
2        E1001007    40     Male           Life Sciences         Married
3        E1001009    41     Male         Human Resources        Divorced
4        E1001010    60     Male               Marketing          Single
...           ...  ...     ...                     ...  ...
 1195     E100992    27   Female                 Medical        Divorced
 1196     E100993    37     Male           Life Sciences          Single
 1197     E100994    50     Male                 Medical         Married
 1198     E100995    34   Female                 Medical          Single
 1199     E100998    24   Female           Life Sciences          Single
```

```
        EmpDepartment         EmpJobRole  BusinessTravelFrequency       \
0                Sales   Sales Executive           Travel_Rarely
1                Sales   Sales Executive           Travel_Rarely
2                Sales   Sales Executive       Travel_Frequently
3     Human Resources            Manager           Travel_Rarely
4               Sales   Sales Executive            Travel_Rarely
...               ...               ...                  ...
1195            Sales   Sales Executive        Travel_Frequently
1196      Development  Senior Developer            Travel_Rarely
1197      Development  Senior Developer            Travel_Rarely
1198     Data Science     Data Scientist           Travel_Rarely
1199            Sales   Sales Executive            Travel_Rarely

      DistanceFromHome  EmpEducationLevel  ...  EmpRelationshipSatisfaction     \
0                   10                  3  ...                            4
1                   14                  4  ...                            4
2                    5                  4  ...                            3
3                   10                  4  ...                            2
4                   16                  4  ...                            4
...                ...                ...  ...                          ...
1195                 3                  1  ...                            2
1196                10                  2  ...                            1
1197                28                  1  ...                            3
1198                 9                  3  ...                            2
1199                 3                  2  ...                            1

      TotalWorkExperienceInYears          TrainingTimesLastYear   EmpWorkLifeBalance  \
0                             10                              2                    2
1                             20                              2                    3
2                             20                              2                    3
3                             23                              2                    2
4                             10                              1                    3
...                          ...                            ...                  ...
1195                           6                              3                    3
1196                           4                              2                    3
1197                          20                              3                    3
1198                           9                              3                    4
1199                           4                              3                    3

        ExperienceYearsAtThisCompany   ExperienceYearsInCurrentRole  \
0                                 10                              7
1                                  7                              7
2                                 18                             13
3                                 21                              6
4                                  2                              2
...                              ...                            ...
1195                               6                              5
```

```
1196                                1                            0
1197                               20                            8
1198                                8                            7
1199                                2                            2

      YearsSinceLastPromotion     YearsWithCurrManager    Attrition  \
0                          0                        8          No
1                          1                        7          No
2                          1                       12          No
3                         12                        6          No
4                          2                        2          No
...                      ...                      ...        ...
1195                       0                        4          No
1196                       0                        0          No
1197                       3                        8          No
1198                       7                        7          No
1199                       2                        0         Yes

         PerformanceRating
0                      3
1                      3
2                      4
3                      3
4                      3
...                  ...
1195                   4
1196                   3
1197                   3
1198                   3
1199                   2

[1200    rows x 28 columns]
```

```
[3]: ['EmpNumber','Gender','EducationBackground','MaritalStatus','EmpDepartment','EmpJobRole',
       'BusinessTravelFrequency']
```

```
[3]: ['EmpNumber',
       'Gender', 'EducationBackground',
       'MaritalStatus', 'EmpDepartment',
       'EmpJobRole',
       'BusinessTravelFrequency']
```

```
[4]:  #Is there any Null/NaN Value?

      df.isnull().values.any()
```

```
# No Null values.
```

[4] : False

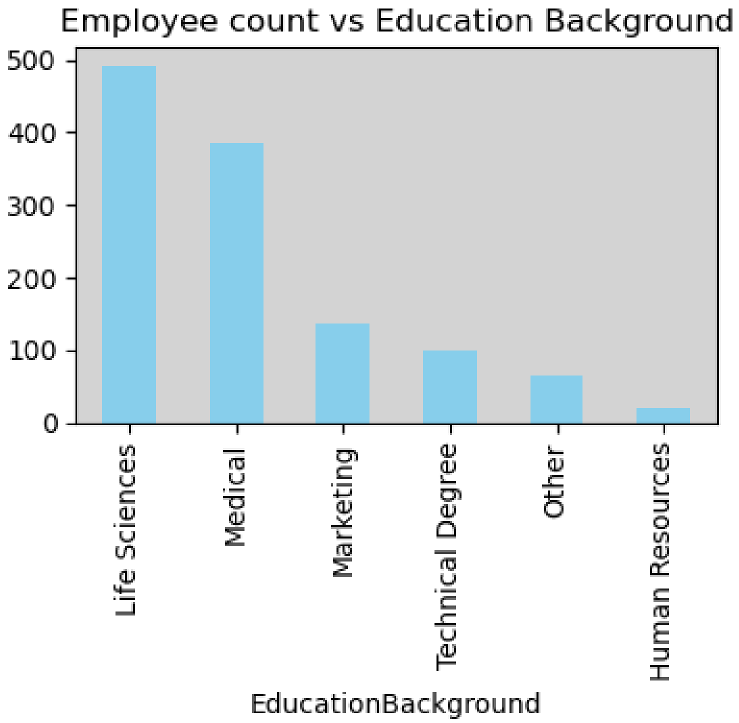
I. Analysing employees with their Education background:

[5] :

```
education_counts = df['EducationBackground'].value_counts()
```

[6] :

```
plt.figure(figsize=(4, 4)) education_counts.plot(kind='bar',
color='skyblue') plt.title('Employee count vs Education Background')
plt.tight_layout() plt.gca().set_facecolor('lightgrey')
plt.show()
```



Conclusion

1. Life Sciences education background of the greatest number of employees, followed by Medical.
2. Human Resources has the lowest number of employees in it.

II. Analysing employees with their Departments:

[7] :

```
df['EmpDepartment'].value_counts()
```

[7] :
```
EmpDepartment
 Sales                          373
 Development                    361
 Research & Development         343
 Human Resources                 54
 Finance                         49
 Data Science                    20
 Name: count, dtype: int64
```

[ ]:
```

```

Conclusion:

We can assume that the Sales department has the largest number of workforce, and Data Science the lowest.

III. Analysing department-wise performance rating of the employees:

[8] :
```
df.groupby('EmpDepartment').PerformanceRating.mean()
```

[8] :
```
EmpDepartment
 Data Science                   3.050000
 Development                    3.085873
 Finance                        2.775510
 Human Resources                2.925926
 Research & Development         2.921283
 Sales                          2.860590
 Name: PerformanceRating,     dtype: float64
```

Conclusion:

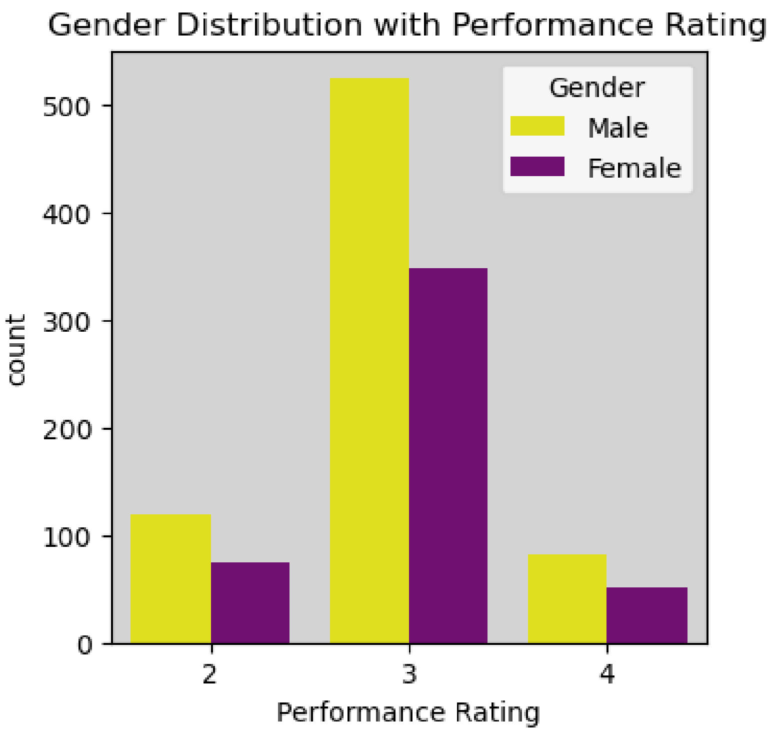
1. Performance ratings for employees in the Data Science department is highest.

2.Performance ratings for employees in the Sales department is the lowest.

IV. Analysing Employee Gender Distribution with Performance Rating:

[9] :
```
plt.figure(figsize=(4,4))
custom_palette = {'Male': 'yellow', 'Female': 'purple'}
sns.countplot(data=df, x='PerformanceRating', ␣

  ↪hue='Gender',palette=custom_palette)
plt.title('Gender Distribution with Performance Rating')
plt.xlabel('Performance Rating')
plt.legend(title='Gender')
plt.gca().set_facecolor('lightgrey') plt.show()
```



Conclusion:

1. Most of the employees have Performance Rating Greater than 3.

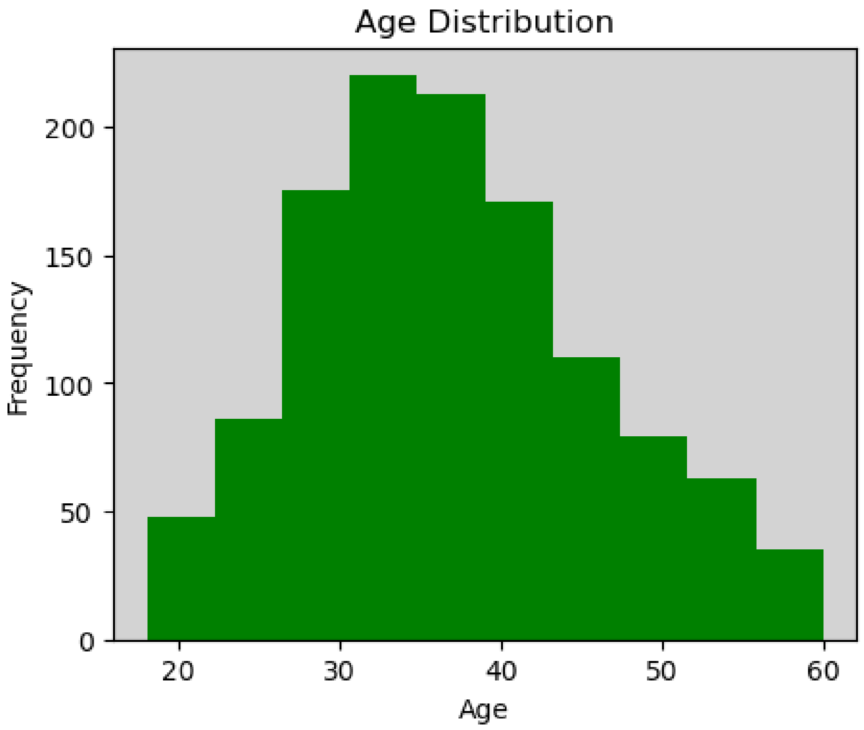
2. In all the rating ranges,cout of male employees is higher than that of female.

So,it can be concluded that men employees outperform women. It is also observed that the rating of 3 is the most common.

V. Employee Age Distribution:

[10] :

```
plt.figure(figsize=(5,4))
age_distribution=df['Age'].plot.hist(color='green') plt.title('Age
Distribution')
plt.xlabel('Age') plt.ylabel('Frequency')
plt.gca().set_facecolor('lightgrey') plt.show()
```



Conclusion:

1. we see that a good many number of the employees are in the age group of 30–40.

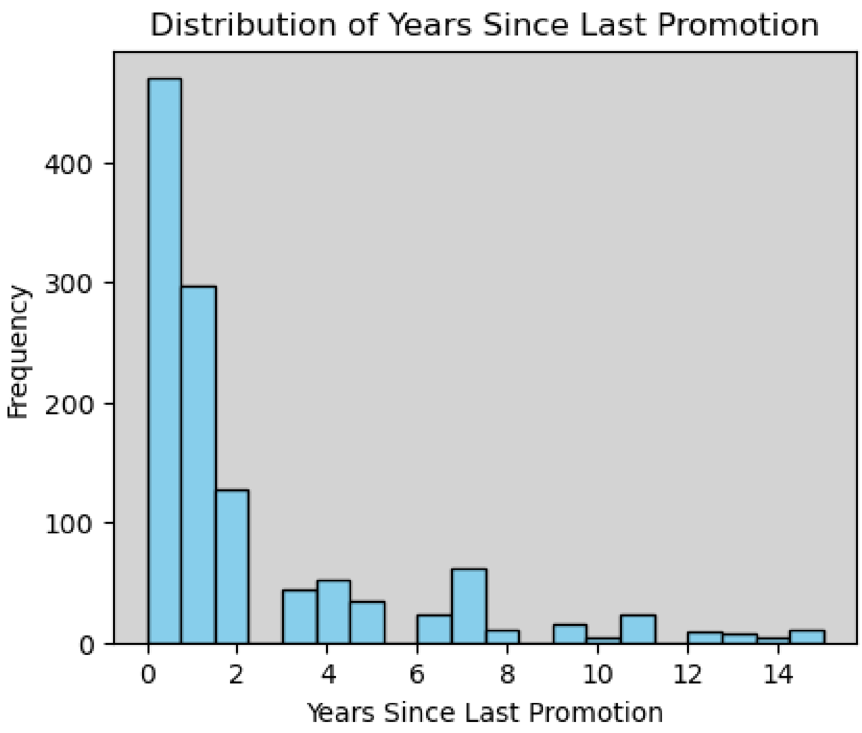
2. There are very few people in the age group of 55–60.

3. Majority of the working class is therefore in their late 30’s.

[11] :

```
# Assuming df is my DataFrame containing the data
plt.figure(figsize=(5,4))
plt.hist(df['YearsSinceLastPromotion'],bins=20,color='skyblue',␣

   ₛedgecolor='black')
plt.title('Distribution of Years Since Last Promotion')
plt.xlabel('Years Since Last Promotion')
plt.ylabel('Frequency') plt.gca().set_facecolor('lightgrey')
plt.show()
```



Conclusion:

It is seen that a whole lot of employees were being promoted quite often i.e. in 0–1.5 years. Regression or Classification?

METHOD-1-LOGISTIC REGRESSION

[12] :

```
df['PerformanceRating'].unique()
```

[12] :

```
array([3, 4, 2], dtype=int64)
```

Now,If we check the Performance Rating,which is out target variable,as we can see,it has three values,2,3 and 4,which implies that it is a classification problem as this column is a categorical column.

Change the Categorical Data,One Hot Encoding

[13] :

```
new_df = df.copy()

# Assuming 'le' is your LabelEncoder instance
le = LabelEncoder()

# Assuming df is your DataFrame and you have multiple categorical columns
categorical_columns = ['EmpNumber','Gender', 'EducationBackground',␣
 ↪'MaritalStatus',  'EmpDepartment',
 s'EmpJobRole','BusinessTravelFrequency','Attrition','OverTime']
# Apply label encoding to each categorical column
for col in categorical_columns:
        new_df[col] = le.fit_transform(new_df[col])

# Now your categorical columns are encoded with numerical values
```

Train the model:

[14] :
```
#import
from sklearn.model_selection import train_test_split
```

[15] :
```
#define x and y: col=list(df)
x=new_df[col[1:27]]
y=new_df['PerformanceRating']
```

[16] :
```
#We want to keep 20 % of the data as test size,so,0.2.
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

[17] :
```
len(x_train)
```

[17]: 840

[18] :
```
len(x_test)
```

[18]: 360

[19] :
```
y_test
```

[19]:
```
175        2
363        2
374        4
161        3
952        2
          ..
1063       3
221        2
488        3
317        3
405        2
Name:  PerformanceRating, Length: 360, dtype: int64
```

[20] :
```
new_df
```

```
[20]:      EmpNumber  Age  Gender  EducationBackground  MaritalStatus   \
0                  0   32       1                    2              2
1                  1   47       1                    2              2
2                  2   40       1                    1              1
3                  3   41       1                    0              0
4                  4   60       1                    2              2
...              ...  ...     ...                  ...            ...
1195            1195   27       0                    3              0
1196            1196   37       1                    1              2
1197            1197   50       1                    3              1
1198            1198   34       0                    3              2
1199            1199   24       0                    1              2

      EmpDepartment  EmpJobRole  BusinessTravelFrequency  DistanceFromHome   \
0                 5          13                        2                10
1                 5          13                        2                14
2                 5          13                        1                 5
3                 3           8                        2                10
4                 5          13                        2                16
...             ...         ...                      ...               ...
1195              5          13                        1                 3
1196              1          15                        2                10
1197              1          15                        2                28
1198              0           1                        2                 9
1199              5          13                        2                 3

      EmpEducationLevel  ...  EmpRelationshipSatisfaction   \
0                     3  ...                            4
1                     4  ...                            4
2                     4  ...                            3
3                     4  ...                            2
4                     4  ...                            4
...                 ...  ...                          ...
1195                  1  ...                            2
1196                  2  ...                            1
1197                  1  ...                            3
1198                  3  ...                            2
1199                  2  ...                            1

      TotalWorkExperienceInYears  TrainingTimesLastYear  EmpWorkLifeBalance  \
0                             10                      2                   2
1                             20                      2                   3
2                             20                      2                   3
3                             23                      2                   2
4                             10                      1                   3
...                          ...                    ...                 ...
1195                           6                      3                   3
```

```
1196                       4                     2                  3
1197                      20                     3                  3
1198                       9                     3                  4
1199                       4                     3                  3

      ExperienceYearsAtThisCompany  ExperienceYearsInCurrentRole  \
0                               10                             7
1                                7                             7
2                               18                            13
3                               21                             6
4                                2                             2
...                            ...                           ...
1195                             6                             5
1196                             1                             0
1197                            20                             8
1198                             8                             7
1199                             2                             2

      YearsSinceLastPromotion  YearsWithCurrManager  Attrition  \
0                           0                     8          0
1                           1                     7          0
2                           1                    12          0
3                          12                     6          0
4                           2                     2          0
...                       ...                   ...        ...
1195                        0                     4          0
1196                        0                     0          0
1197                        3                     8          0
1198                        7                     7          0
1199                        2                     0          1

      PerformanceRating
0                     3
1                     3
2                     4
3                     3
4                     3
...                 ...
1195                  4
1196                  3
1197                  3
1198                  3
1199                  2

[1200 rows x 28 columns]
```

```
[21] : from sklearn.linear_model import LogisticRegression model=
       LogisticRegression()
```

```
[22] : model.fit(x_train,y_train)
```

```
C:\Users\HP\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in: https://scikit-
    learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options: https://scikit-
    learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
[22] : LogisticRegression()
```

Predictions:

```
[23] : model.predict(x_test)
```

```
[23]: array([4,  2,  4,  3,  2,  2,  3,  3,  3,  3,  2,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,
        3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,
        3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,  3,  3,  2,  3,  3,  2,  2,  2,  3,  3,  3,
        3,  3,  3,  3,  3,  2,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  4,  2,
        3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,  3,  3,  3,  3,  3,  3,  3,  4,  3,  3,
        4,  3,  3,  3,  3,  3,  3,  2,  3,  3,  3,  4,  3,  3,  3,  2,  3,  2,  3,  3,  3,  3,
        3,  4,  2,  4,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  4,  2,  3,  2,  3,  3,  3,
        3,  3,  3,  4,  3,  3,  3,  3,  3,  3,  4,  2,  3,  3,  3,  3,  3,  4,  3,  3,  3,  3,
        3,  3,  3,  2,  2,  3,  3,  3,  3,  3,  3,  3,  2,  3,  2,  4,  3,  3,  3,  3,  3,  3,
        3,  3,  2,  3,  3,  4,  3,  4,  3,  3,  3,  3,  2,  3,  3,  2,  3,  3,  3,  2,  3,  3,
        3,  3,  3,  3,  3,  2,  3,  3,  3,  3,  3,  3,  2,  3,  2,  4,  3,  3,  3,  3,  3,  3,
        3,  3,  2,  3,  3,  3,  2,  3,  2,  4,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,
        2,  3,  3,  4,  3,  4,  3,  3,  3,  3,  3,  3,  3,  3,  4,  4,  2,  3,  4,  3,  3,  3,
        3,  3,  3,  3,  3,  2,  3,  3,  4,  3,  2,  3,  3,  3,  3,  3,  3,  3,  2,  3,  3,  3,
        2,  3,  3,  3,  3,  3,  4,  3,  3,  4,  3,  3,  3,  2,  3,  3,  3,  3,  3,  4,  3,  3,
        3,  3,  3,  3,  2,  3,  4,  3,  2,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  4,  3,
       3, 2, 3, 3, 4, 3, 3, 2], dtype=int64)
```

Check Accuracy of the Model:

```
[24] : model.score(x_test,y_test)
```

```
[24]: 0.7861111111111111
```

Method-1- Confusion Matrix to Better Visualize the Accuracy and Inaccuracy of the Model:

[48]:

```
y_predicted_m1=model.predict(x_test)
from     sklearn.metrics     import     confusion_matrix
cm_1=confusion_matrix(y_test,y_predicted_m1) cm_1
```

[48]:

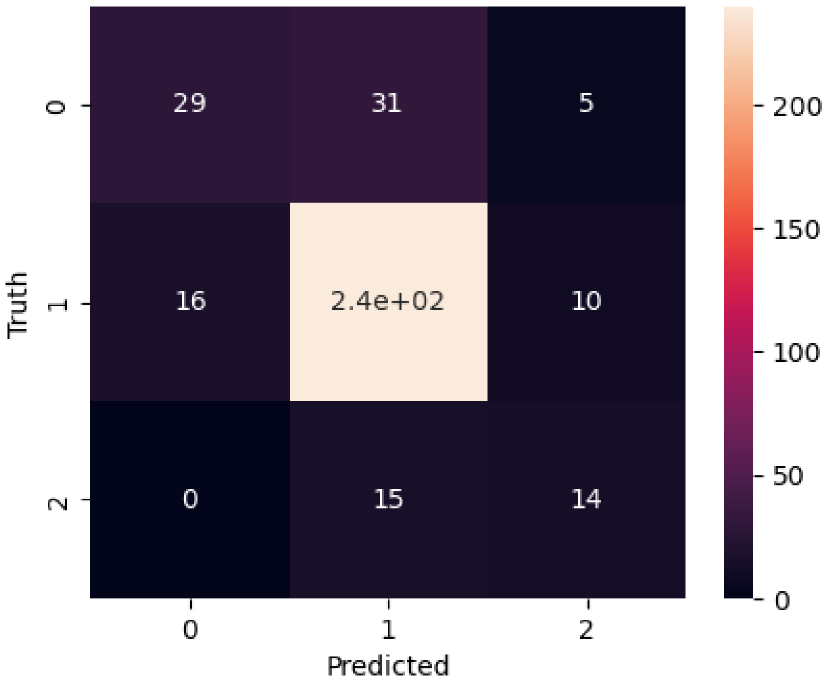
```
array([[ 29,  31,                5],
                  [ 16, 240,  10],
            [  0,  15,  14]], dtype=int64)
```

[49]:

```
import seaborn as sn plt.figure(figsize =
(5,4)) sn.heatmap(cm_1, annot=True)
plt.xlabel('Predicted') plt.ylabel('Truth')
```

[49]:

```
Text(33.22222222222222, 0.5, 'Truth')
```



METHOD-2-RANDOM FOREST CLASSIFIER

The Random Forest is a better approach over other algorithms because it uses the entire dataset optimally which reduces bias error. The algorithm can also provide maximum reduction in variance as it gives the average output from an ensemble of several decision trees; hence the name ‘Random Forest’.

[27]:

```
from sklearn.ensemble import RandomForestClassifier
```

[42]:

```
clf=RandomForestClassifier(n_jobs=2,oob_score=True,n_estimators=500) clf.fit(x_train,y_train)
```

[42]: RandomForestClassifier(n_estimators=500, n_jobs=2, oob_score=True) [34]:

[34]:

```
#Applying classifier to test data:
clf.predict(x_test)
```

```
       3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,  3,  3,  2,  2,  2,  3,  3,  3,
       3,  3,  4,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  4,  2,
       3,  3,  3,  3,  2,  4,  2,  4,  3,  3,  3,  2,  3,  3,  3,  3,  3,  3,  3,  4,  3,  3,
       4,  3,  3,  3,  3,  3,  3,  2,  4,  3,  3,  4,  3,  3,  3,  2,  3,  2,  3,  3,  3,  2,
       2,  4,  2,  4,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,  3,  2,  3,  3,  3,
       3,  3,  3,  2,  3,  3,  2,  3,  3,  3,  4,  2,  4,  3,  3,  3,  2,  3,  3,  3,  2,  2,
       3,  3,  3,  3,  2,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,  3,  2,  3,  3,  3,  3,  3,
       3,  4,  2,  3,  3,  3,  2,  4,  3,  3,  3,  2,  2,  3,  3,  2,  3,  3,  3,  2,  3,  3,
       3,  3,  3,  2,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,  4,  3,  3,  3,  3,  3,  3,
       3,  3,  3,  3,  3,  3,  2,  3,  2,  3,  3,  3,  3,  3,  3,  3,  3,  3,  2,  3,  3,  3,
       3,  4,  2,  4,  3,  4,  3,  3,  3,  3,  3,  3,  3,  3,  4,  4,  3,  3,  4,  4,  3,  3,
       3,  3,  3,  3,  3,  2,  3,  3,  4,  3,  2,  2,  3,  3,  3,  3,  2,  2,  2,  4,  3,  3,
       3,  3,  3,  3,  3,  3,  2,  3,  3,  4,  3,  2,  3,  3,  3,  3,  3,  3,  3,  3,  3,  4,
       2,  3,  3,  3,  2,  3,  2,  3,  2,  3,  3,  3,  3,  3,  2,  3,  2,  3,  3,  3,  3,  3,
      3, 2, 2, 3, 2, 3, 3, 2], dtype=int64)
```

Check Accuracy of the Model:

[51]:

```
clf.score(x_test,y_test)
```

[51]: 0.9388888888888889

Method-2- Confusion Matrix to Better Visualize the Accuracy and Inaccuracy of the Model:

[50]:

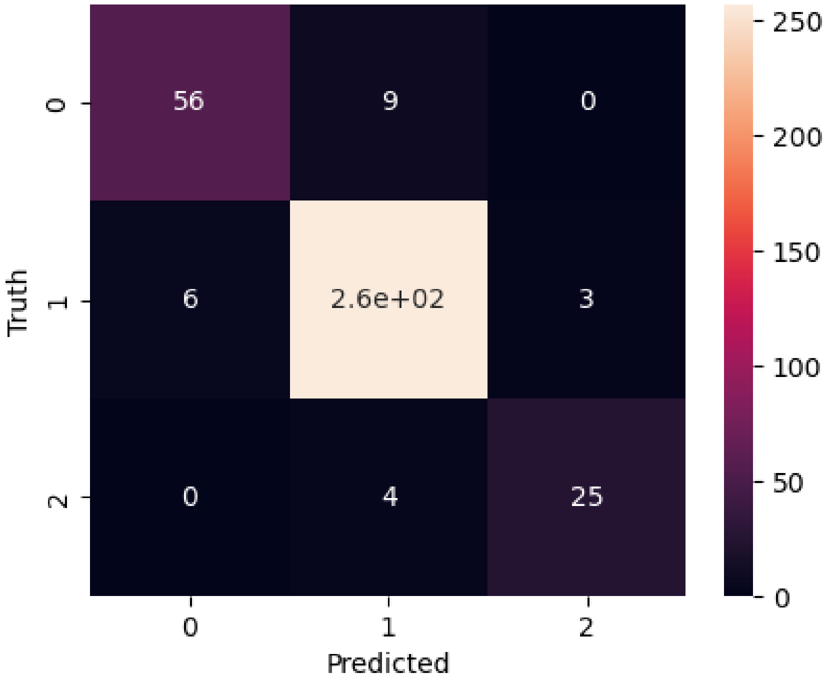
```
y_predicted_m2=clf.predict(x_test)
from      sklearn.metrics      import      confusion_matrix
cm_2=confusion_matrix(y_test,y_predicted_m2) cm_2
```

```
[50]: array([[ 56,           9,      0],
               [  6, 257,           3],
              [  0,        4,  25]], dtype=int64)
```

[52]:

```
import seaborn as sn plt.figure(figsize =
(5,4)) sn.heatmap(cm_2, annot=True)
plt.xlabel('Predicted') plt.ylabel('Truth')
```

```
[52]: Text(33.2222222222222, 0.5, 'Truth')
```



The Acuracy of the model increases from 78% to 93% using Random Forest Classifier Method. Recommendations:

After careful evaluation of the drawn observations, we can recommend the following to increase employee performance at an organization:

1. Ensure a more improved rate of salary raises for the employees

2. Create a more friendly, comfortable and inclusive office environment

3. Help upgrade the skill sets of the current employees, so as to make them suitable to take up more responsibilities and challenges, and in turn, prepare them for promotions.