HR Analytics using Python & Machine Learning

In [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: Impor
ting display from IPython.core.display is deprecated since IPython 7.14, please import fr
om IPython display
  from IPython.core.display import display, HTML
```

In [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.

In [2]:

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

Out[2]:

	EmpNumber	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	EmpJobRole	BusinessTravelFrequenc
0	E1001000	32	Male	Marketing	Single	Sales	Sales Executive	Travel_Rarel
1	E1001006	47	Male	Marketing	Single	Sales	Sales Executive	Travel_Rarel
2	E1001007	40	Male	Life Sciences	Married	Sales	Sales Executive	Travel_Frequentl
3	E1001009	41	Male	Human Resources	Divorced	Human Resources	Manager	Travel_Rarel
4	E1001010	60	Male	Marketing	Single	Sales	Sales Executive	Travel_Rarel
...	...	...	...	...	...	...	...	.
1195	E100992	27	Female	Medical	Divorced	Sales	Sales Executive	Travel_Frequentl
1196	E100993	37	Male	Life Sciences	Single	Development	Senior Developer	Travel_Rarel
1197	E100994	50	Male	Medical	Married	Development	Senior Developer	Travel_Rarel
1198	E100995	34	Female	Medical	Single	Data Science	Data Scientist	Travel_Rarel
1199	E100998	24	Female	Life Sciences	Single	Sales	Sales Executive	Travel_Rarel

1200 rows × 28 columns

In [3]:

In [3]:

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

Out[3]:

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

In [4]:

```
#Is there any Null/NaN Value?

df.isnull().values.any()

# No Null values.
```

Out[4]:

```
False
```

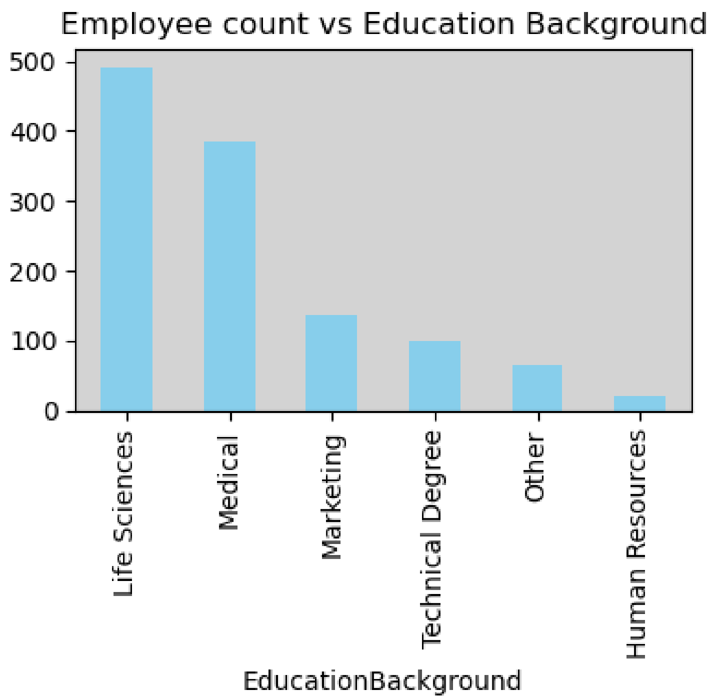
I.Analysing employees with their Education background:

In [5]:

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

In [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:

In [7]:

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

Out[7]:

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

In [ ]:

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:

In [8]:

```
df.groupby('EmpDepartment').PerformanceRating.mean()
```

Out[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:

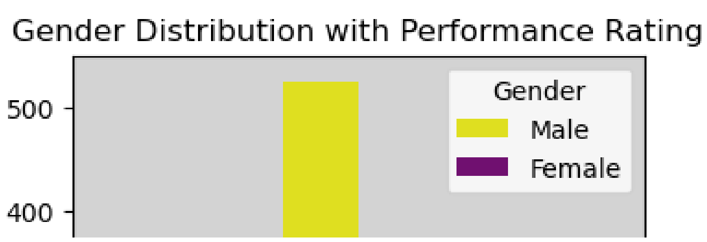
1.Performance ratings for employees in the Data Science department is highest.

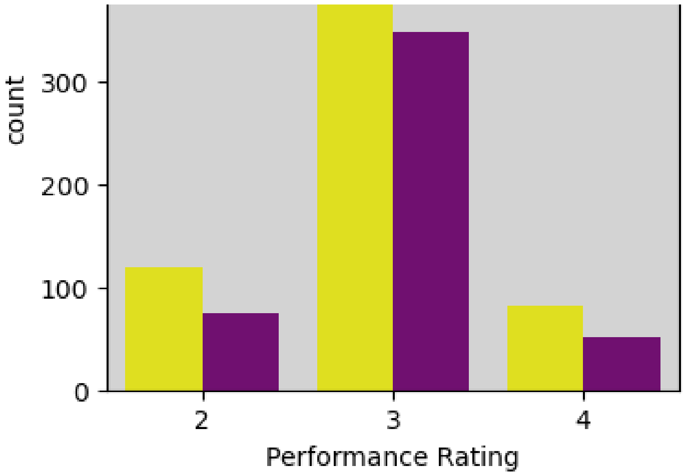
2.Performance ratings for employees in the Sales department is the lowest.

IV.Analysing Employee Gender Distribution with Performance Rating:

In [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.

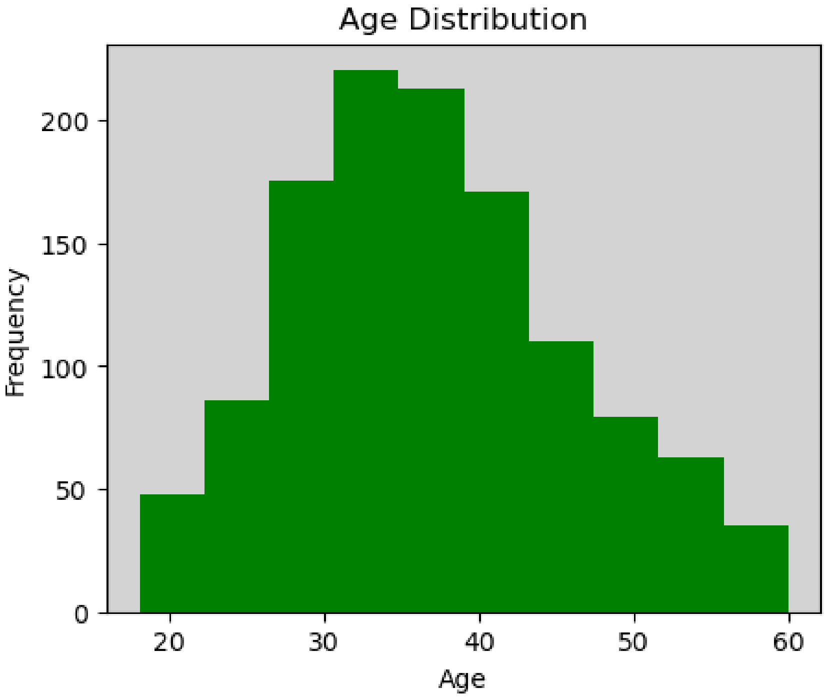
2.In all the rating ranges,cout of male employees is higher than that of female.

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:

In [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:

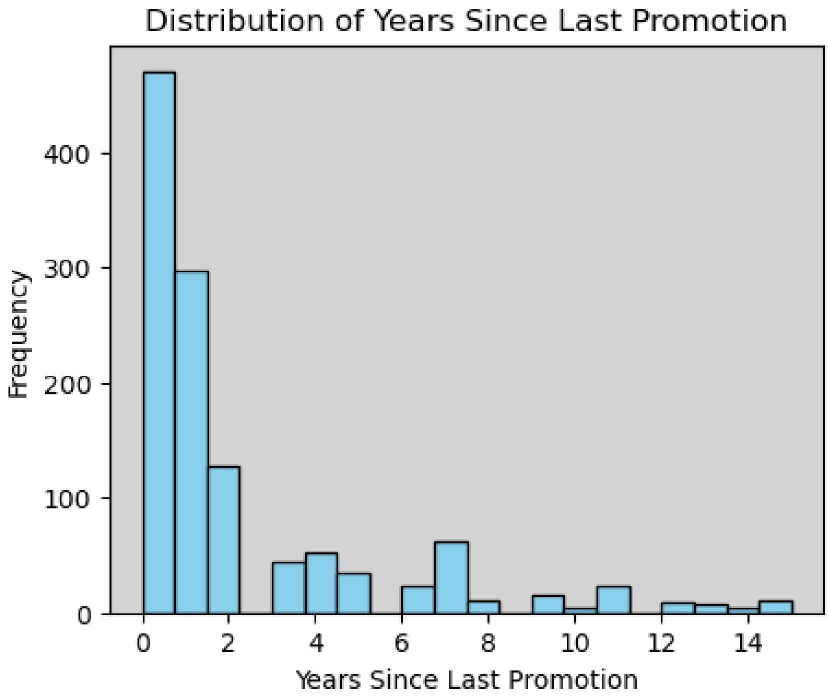
1.we see that a good many number of the employees are in the age group of 30–40.

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.

In [11]:

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

In [12]:

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

Out[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

In [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', 'Emp
Department',
                       '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:

In [14]:

```
#import
from sklearn.model_selection import train_test_split
```

In [15]:

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

In [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)
```

In [17]:

```
len(x_train)
```

Out[17]:

```
840
```

In [18]:

```
len(x_test)
```

Out[18]:

```
360
```

In [19]:

```
y_test
```

Out[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
```

In [20]:

```
new_df
```

Out[20]:

	EmpNumber	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	EmpJobRole	BusinessTravelFrequenc
0	0	32	1	2	2	5	13	
1	1	47	1	2	2	5	13	

	EmpNumber	Age	Gender	EducationBackground	MaritalStatus	EmpDepartment	EmpJobRole	BusinessTravelFrequenc
2	2	40	1	1	1	5	13	
3	3	41	1	0	0	3	8	
4	4	60	1	2	2	5	13	
...	...	...	...	...	...	...	...	.
1195	1195	27	0	3	0	5	13	
1196	1196	37	1	1	2	1	15	
1197	1197	50	1	3	1	1	15	
1198	1198	34	0	3	2	0	1	
1199	1199	24	0	1	2	5	13	

1200 rows × 28 columns

In [21]:

```
from sklearn.linear_model import LogisticRegression
model= LogisticRegression()
```

In [22]:

```
model.fit(x_train,y_train)
```

```
C:\Users\HP\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:469: Convergenc
eWarning: 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(
```

Out[22]:

▾ LogisticRegression i ?

```
LogisticRegression()
```

Predictions:

In [23]:

```
model.predict(x_test)
```

Out[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:

In [24]:

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

Out[24]:

```
0.7861111111111111
```

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

In [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
```

Out[48]:

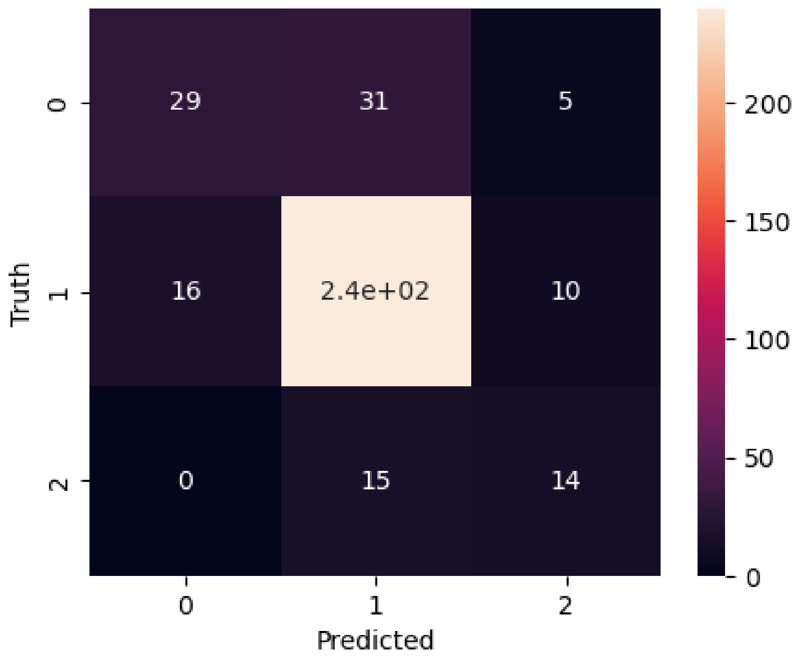
```
array([[ 29,  31,   5],
       [ 16, 240,  10],
       [  0,  15,  14]], dtype=int64)
```

In [49]:

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

Out[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’.

In [27]:

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

In [42]:

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

Out[42]:

```
▼                    RandomForestClassifier                    i ?

RandomForestClassifier(n_estimators=500, n_jobs=2, oob_score=True)
```

In [34]:

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

Out[34]:

```
array([2, 2, 4, 3, 2, 2, 3, 3, 3, 3, 2, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 2,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 4, 3, 3, 3, 3, 3, 3, 2, 3, 3, 4, 3,
       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:

In [51]:

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

Out[51]:

```
0.9388888888888889
```

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

In [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
```

Out[50]:

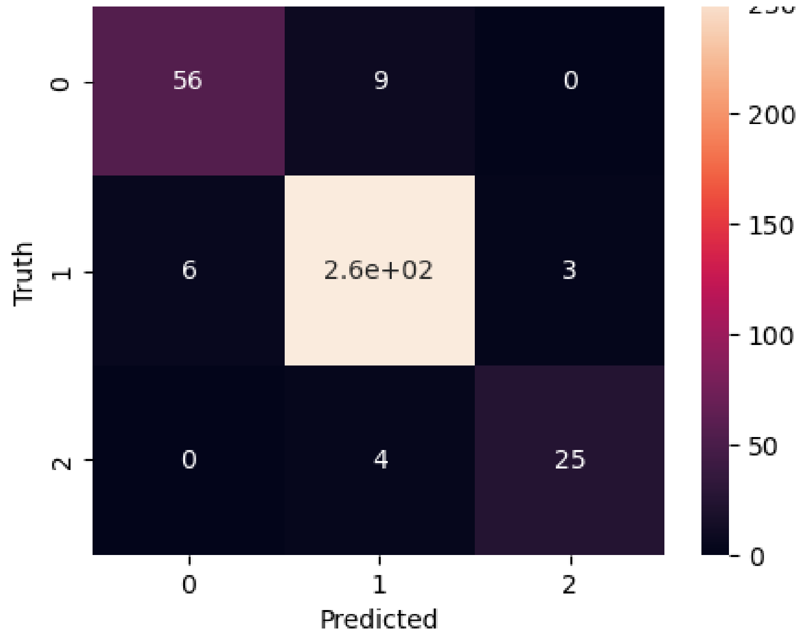
```
array([[ 56,   9,   0],
       [  6, 257,   3],
       [  0,   4,  25]], dtype=int64)
```

In [52]:

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

Out[52]:

```
Text(33.22222222222222, 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.