Open in Colab

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import io
!gdown 16KtxSt_QEGQvfluEaMls5cCHPwhRXgCk
```

```
Downloading...
From: https://drive.google.com/uc?id=16KtxSt_QEGQvfluEaMls5cCHPwhRXgCk
To: /content/HR-Employee-Attrition.csv
100% 228k/228k [00:00<00:00, 13.4MB/s]
```

```
df = pd.read_csv("HR-Employee-Attrition.csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Age                       1470 non-null   int64 
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64 
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64 
 6   Education                 1470 non-null   int64 
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64 
 9   EmployeeNumber            1470 non-null   int64 
 10  EnvironmentSatisfaction   1470 non-null   int64 
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64 
 13  JobInvolvement            1470 non-null   int64 
 14  JobLevel                  1470 non-null   int64 
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64 
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64 
 19  MonthlyRate               1470 non-null   int64 
 20  NumCompaniesWorked        1470 non-null   int64 
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64 
 24  PerformanceRating         1470 non-null   int64 
 25  RelationshipSatisfaction  1470 non-null   int64 
 26  StandardHours             1470 non-null   int64 
 27  StockOptionLevel          1470 non-null   int64 
 28  TotalWorkingYears         1470 non-null   int64 
 29  TrainingTimesLastYear     1470 non-null   int64 
 30  WorkLifeBalance           1470 non-null   int64 
 31  YearsAtCompany            1470 non-null   int64 
 32  YearsInCurrentRole        1470 non-null   int64 
 33  YearsSinceLastPromotion   1470 non-null   int64 
 34  YearsWithCurrManager      1470 non-null   int64 
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

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

Attrition	count
No	1233
Yes	237

dtype: int64

```
df_new =  df[['MaritalStatus_Single','EducationField','JobRole','MaritalStatus_Married','StockOptionLevel','JobSatisfaction'
```

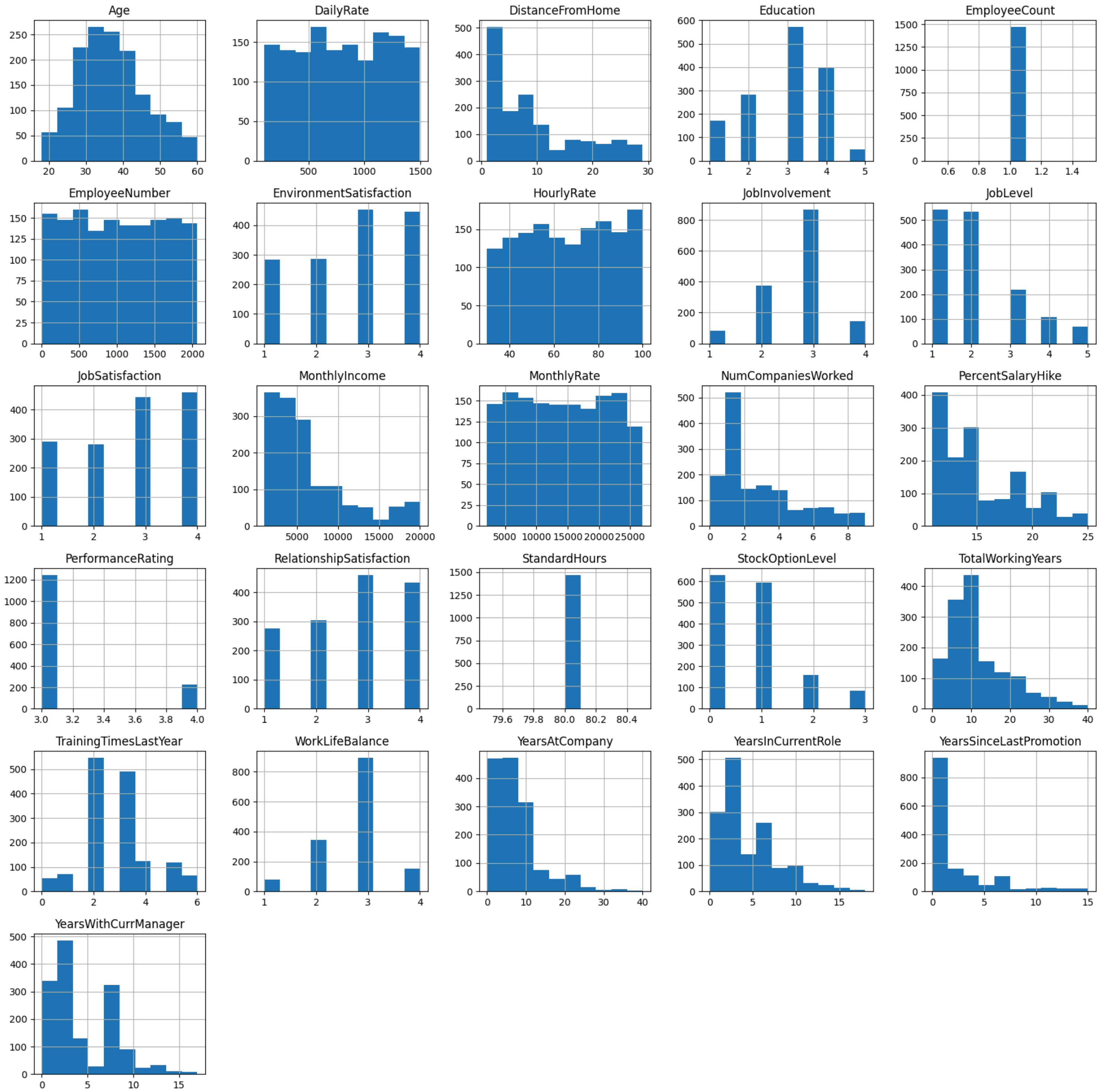
No field with null cells

```
df.iloc[:, 15:]
```

	JobRole	JobSatisfaction	MaritalStatus	MonthlyIncome	MonthlyRate	NumCompaniesWorked	Over18	OverTime	Percen
0	Sales Executive	4	Single	5993	19479	8	Y	Yes	
1	Research Scientist	2	Married	5130	24907	1	Y	No	
2	Laboratory Technician	3	Single	2090	2396	6	Y	Yes	
3	Research Scientist	3	Married	2909	23159	1	Y	Yes	
4	Laboratory Technician	2	Married	3468	16632	9	Y	No	
...	...	...	...	...	...	...	...	...	
1465	Laboratory Technician	4	Married	2571	12290	4	Y	No	
1466	Healthcare Representative	1	Married	9991	21457	4	Y	No	
1467	Manufacturing Director	2	Married	6142	5174	1	Y	Yes	
1468	Sales Executive	2	Married	5390	13243	2	Y	No	
1469	Laboratory Technician	3	Married	4404	10228	2	Y	No	

1470 rows × 20 columns

```
df.hist(figsize = (20,20))
plt.show()
```


Age
DailyRate
DistanceFromHome
Education
EmployeeCount
EmployeeNumber
EnvironmentSatisfaction
HourlyRate
JobInvolvement
JobLevel
JobSatisfaction
MonthlyIncome
MonthlyRate
NumCompaniesWorked
PercentSalaryHike
PerformanceRating
RelationshipSatisfaction
StandardHours
StockOptionLevel
TotalWorkingYears
TrainingTimesLastYear
WorkLifeBalance
YearsAtCompany
YearsInCurrentRole
YearsSinceLastPromotion
YearsWithCurrManager

What can we observe from these plots ?

Many histograms are tail-heavy

Lot of attributes are right-skewed (e.g. MonthlyIncome DistanceFromHome, YearsAtCompany)

Data transformation methods may be required for standardisation

Recall why standardisation is preferred ? Some features seem to have normal distributions

Eg: Age: Slightly right-skewed normal distribution Bulk of the staff between 25 and 45 years old Some features are constant

Eg: EmployeeCount and StandardHours are constant values for all employees.

They're likely to be redundant features.

How can these features contribute to our problem ? Constant features are not in any way useful for predictions So we can drop these features from the dataset Some features seem to be uniformly distributed.

Eg: EmployeeNumber

Uniformly distributed and constant features won't contribute to our analysis. Why?

Each value is equally likely to occur So what should we do ? We can drop these features from our dataset Some features are categorical i.e binomially/multinomially distributed

Eg: WorkLifeBalance, StockOptionLevel etc

Can we use these features directly in our problem ? No. They willl first have to be encoded Recall which encoding has to be used for which features Binary Encoding (0/1) : Features with only 2 unique values

Label Encoding (0, 1, 2, 3 ....) : More than 2 unique values having a particular order

OneHot Encoding ([0 0 0 1], ...) : More than 2 unique values having no order

Target encoding ([0.1, 0.33, ...)] : Features with a lot of unique vals having no order

We can also see from these features that their ranges vary a lot

Recall why different feature scales can be a problem

We will deal with this problem later

First, lets remove the features that won't contribute to our analysis

Double-click (or enter) to edit

```
df.drop(['EmployeeCount', 'EmployeeNumber', 'StandardHours', 'Over18'], axis=1, inplace=True)
```

Now lets encode our categorical features

Which encoding technique should we use ?

- It depends upon:
    - Number of unique values a feature has
    - If there is a sequence between the feature vals

Lets first check how many unique values each feature has

```
def unique_vals(col):

  if col.dtype == "object":

    print(f'{col.name}: {col.nunique()}')
    print(col.value_counts())

df.apply(unique_vals)
```

```
Attrition: 2
Attrition
No     1233
Yes     237
Name: count, dtype: int64
BusinessTravel: 3
BusinessTravel
Travel_Rarely        1043
Travel_Frequently     277
Non-Travel            150
Name: count, dtype: int64
Department: 3
Department
Research & Development    961
Sales                     446
Human Resources            63
Name: count, dtype: int64
EducationField: 6
EducationField
Life Sciences       606
Medical             464
Marketing           159
Technical Degree    132
Other                82
Human Resources      27
Name: count, dtype: int64
Gender: 2
Gender
Male      882
Female    588
Name: count, dtype: int64
JobRole: 9
JobRole
Sales Executive              326
Research Scientist           292
Laboratory Technician        259
Manufacturing Director       145
Healthcare Representative    131
Manager                      102
Sales Representative          83
Research Director             80
Human Resources               52
Name: count, dtype: int64
MaritalStatus: 3
MaritalStatus
Married     673
Single      470
Divorced    327
Name: count, dtype: int64
OverTime: 2
OverTime
No     1054
Yes     416
Name: count, dtype: int64
```

	0
Age	None
Attrition	None
BusinessTravel	None
DailyRate	None
Department	None
DistanceFromHome	None
Education	None
EducationField	None
EnvironmentSatisfaction	None
Gender	None
HourlyRate	None
JobInvolvement	None
JobLevel	None
JobRole	None
JobSatisfaction	None
MaritalStatus	None

MonthlyIncome	None
MonthlyRate	None
NumCompaniesWorked	None
OverTime	None
PercentSalaryHike	None
PerformanceRating	None
RelationshipSatisfaction	None
StockOptionLevel	None
TotalWorkingYears	None
TrainingTimesLastYear	None
WorkLifeBalance	None
YearsAtCompany	None
YearsInCurrentRole	None
YearsSinceLastPromotion	None
YearsWithCurrManager	None

dtype: object

On basis of this info, which encoding technique should we use ?

- We will use binary encoding for features with 2 or less unique val.
- For features < 6 unique vals we will use OneHot encoding
- Rest of the categorical features will be Target encoded

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
# Create a label encoder object
le = LabelEncoder()

def label_encode(ser):

    if ser.dtype=="object" and ser.nunique() <= 2:
      print(ser.name)

      le.fit(ser)
      ser = le.transform(ser)

    return ser

df = df.apply(lambda col: label_encode(col))
# convert rest of categorical variable into dummy
df = pd.get_dummies(df, columns = ["BusinessTravel", "Department", "MaritalStatus"], drop_first = True)
df.head()
```

Show hidden output

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

```
array([1, 3, 2, 4])
```

```
df['MaritalStatus_Married'] = df['MaritalStatus_Married'].map({True:1, False:0})
```

```
df_new = df[['MaritalStatus_Married','StockOptionLevel','JobSatisfaction','MonthlyIncome','MonthlyRate','OverTime','Age','At
             'EducationField','WorkLifeBalance', 'JobRole']]
```

```
df
```

	Age	Attrition	DailyRate	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	EnvironmentSat
0	41	1	1102	1	2	Life Sciences	1	1	
1	49	0	279	8	1	Life Sciences	1	2	
2	37	1	1373	2	2	Other	1	4	
3	33	0	1392	3	4	Life Sciences	1	5	
4	27	0	591	2	1	Medical	1	7	
...	...	...	...	...	...	...	...	...	
1465	36	0	884	23	2	Medical	1	2061	
1466	39	0	613	6	1	Medical	1	2062	
1467	27	0	155	4	3	Life Sciences	1	2064	
1468	49	0	1023	2	3	Medical	1	2065	
1469	34	0	628	8	3	Medical	1	2068	

1470 rows × 38 columns

Double-click (or enter) to edit

Double-click (or enter) to edit

```
target = df_new['Attrition'].copy()
df_new = df_new.drop(["Attrition"], axis = 1)
target.value_counts()
```

	count
Attrition	
0	1233
1	237

dtype: int64

The dataset is extremely imbalanced Recall how we deal with imbalanced data For this dataset we will use SMOTE oversampling technique to balance the data

But SMOTE is applied only to training set

So we need to split the data first

```
# Since we have class imbalance (i.e. more employees with turnover=0 than turnover=1)
# let's use stratify=y to maintain the same ratio as in the training dataset when splitting the dataset
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df_new,
                                                    target,
                                                    test_size=0.25,
                                                    random_state=7,
                                                    stratify=target)

print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)
```

```
Number transactions X_train dataset:  (1102, 10)
Number transactions y_train dataset:  (1102,)
Number transactions X_test dataset:  (368, 10)
Number transactions y_test dataset:  (368,)
```

```
!pip install category_encoders
```

```
Requirement already satisfied: category_encoders in /usr/local/lib/python3.11/dist-packages (2.8.1)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.11/dist-packages (from category_encoders) (2.0.2)
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.11/dist-packages (from category_encoders) (2.2.2)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.11/dist-packages (from category_encoders) (1.0.1)
```

```
Requirement already satisfied: scikit-learn>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from category_encoders) (1
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.11/dist-packages (from category_encoders) (1.14.1)
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.11/dist-packages (from category_encoders) (0
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.0.5->ca
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.0.5->category_enc
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.0.5->category_e
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.6.0->categ
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn>=1.6.0
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.11/dist-packages (from statsmodels>=0.9.0->cate
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas>
```

```
X_train
```

	MaritalStatus_Married	StockOptionLevel	JobSatisfaction	MonthlyIncome	MonthlyRate	OverTime	Age	EducationField
1011	0	0	2	9278	20763	1	36	0.233869
1152	0	0	4	3117	26009	0	21	0.127479
650	1	1	4	5562	21782	0	43	0.151584
824	0	0	4	4272	9558	0	42	0.127479
1108	0	0	1	2450	21731	0	35	0.127479
...	...	...	...	...	...	...	...	...
660	0	1	4	2380	13384	1	58	0.151584
780	0	0	1	8722	12355	0	28	0.239544
880	1	1	2	2743	7331	0	32	0.138715
1313	0	3	1	2335	3157	1	29	0.197675
345	0	2	4	2904	16092	0	23	0.151584

1102 rows × 10 columns

```
import category_encoders as ce

ce_target = ce.TargetEncoder(cols = ['EducationField', 'JobRole'])
X_train = ce_target.fit_transform(X_train, y_train)
X_test = ce_target.transform(X_test)
import pickle
with open('ce_target4.pkl', 'wb') as f:
    pickle.dump(ce_target, f)

from google.colab import files
files.download('ce_target4.pkl')
```

```
X_train
```

	EducationField	JobRole
1011	0.233869	0.174089
1152	0.127479	0.160714
650	0.151584	0.063212
824	0.127479	0.243386
1108	0.127479	0.243386
...	...	...
660	0.151584	0.243386
780	0.239544	0.063212
880	0.138715	0.243386
1313	0.197675	0.187588
345	0.151584	0.160714

1102 rows × 2 columns

```
from imblearn.over_sampling import SMOTE
from collections import Counter
sm = SMOTE()

X_sm, y_sm = sm.fit_resample(X_train, y_train)
print('Resampled dataset shape {}'.format(Counter(y_sm)))
```

```
Resampled dataset shape Counter({0: 924, 1: 924})
```

```
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(random_state=7, max_depth=4, n_estimators=100)
```

```
X_sm
```

Show hidden output

```
rfc = RandomForestClassifier(random_state=7)
param_grid = {
    'n_estimators': [100,200],
    'max_depth': [8, 10],
    'min_samples_split': [5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2', None],
    'bootstrap': [True, False],
    'criterion': ['gini', 'entropy'],
    'oob_score': [True],  # only when bootstrap=True
    'ccp_alpha': [0.02, 0.01]     # minimal cost-complexity pruning
}

# Setup GridSearchCV
grid = GridSearchCV(estimator=rfc,
                           param_grid=param_grid,
                           cv=4,
                           scoring='accuracy',  # you can change to 'f1', 'recall', etc.
                           n_jobs=-1,
                           verbose=2)

grid = grid.fit(X_sm, y_sm)
pred = grid.predict(X_test)
```

Show hidden output

```
grid.best_estimator_
```

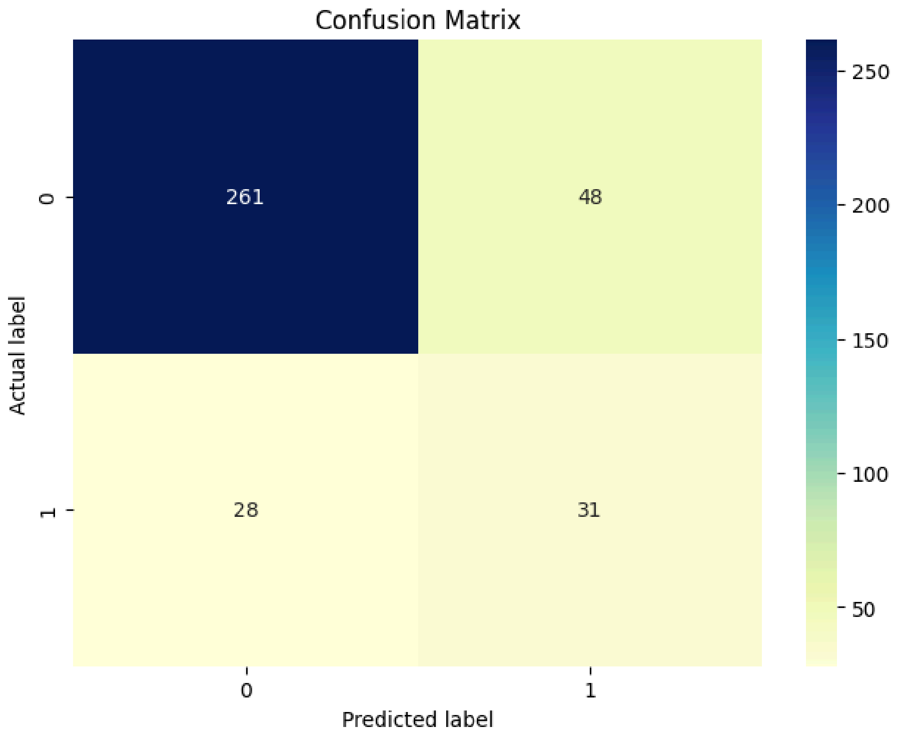
```
▾ RandomForestClassifier
RandomForestClassifier(ccp_alpha=0.01, criterion='entropy', max_depth=10,
                       min_samples_leaf=2, min_samples_split=5, oob_score=True,
                       random_state=7)
```

```
import pickle

with open('rf.pkl', 'wb') as f:
    pickle.dump(grid.best_estimator_, f)
from google.colab import files
files.download('rf.pkl')
```

```
# Confusion Matrix

from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

cnf_matrix = confusion_matrix(y_test, pred)
fig, ax = plt.subplots()

# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')

plt.tight_layout()
plt.title('Confusion Matrix')
```

```
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
Text(0.5, 23.52222222222222, 'Predicted label')
```




```
from sklearn.metrics import classification_report

print(classification_report(y_test, pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.84      0.87       309
           1       0.39      0.53      0.45        59

    accuracy                           0.79       368
   macro avg       0.65      0.69      0.66       368
weighted avg       0.82      0.79      0.80       368
```

```
from google.colab import files
files.download("Employee_attrition.ipynb")
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-187-2eb322413d17> in <cell line: 0>()
      1 from google.colab import files
----> 2 files.download("Employee_attrition.ipynb")

/usr/local/lib/python3.11/dist-packages/google/colab/files.py in download(filename)
    231   if not _os.path.exists(filename):
    232     msg = 'Cannot find file: {}'.format(filename)
--> 233     raise FileNotFoundError(msg)  # pylint: disable=undefined-variable
    234 
    235   comm_manager = _IPython.get_ipython().kernel.comm_manager

FileNotFoundError: Cannot find file: Employee_attrition.ipynb
```

```
importances = grid.best_estimator_.feature_importances_
indices = np.argsort(importances)[::-1] # Sort feature importances in descending order
names = [X_train.columns[i] for i in indices] # Rearrange feature names so they match the sorted feature importances

plt.figure(figsize=(15, 7)) # Create plot
plt.title("Feature Importance") # Create plot title
plt.bar(range(X_sm.shape[1]), importances[indices]) # Add bars
plt.xticks(range(X_sm.shape[1]), names, rotation=90) # Add feature names as x-axis labels
plt.show() # Show plot
```