fct0vldxf

February 17, 2026

Task 03: Customer Prediction Dataset (Bank Customers).

Objective: Identify customers who are likely to leave the bank.

Dataset: Churn Modleing Dataset. About Dataset: Content: This data set contains details of a bank's customers and the target variable is a binary variable reflecting the fact whether the customer left the bank (closed his account) or he continues to be a customer.

Load the Dataset:

[1]:
```
import pandas as pd
```

[2]:
```
Dataset = pd.read_csv("Churn_Modelling.csv")
```

Data Exploration:

[3]:
```
Dataset.head()
```

[3]:
```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
0          1    15634602  Hargrave          619    France  Female   42
1          2    15647311      Hill          608     Spain  Female   41
2          3    15619304      Onio          502    France  Female   42
3          4    15701354      Boni          699    France  Female   39
4          5    15737888  Mitchell          850     Spain  Female   43

   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

As we see in the data, fields like RowNumber, CustomerId and Surname do not matter at all during out analysis. They are just additional infomration about the bank customers. So, we go ahead and drop these three columns.

[4]:
```
Dataset.drop(["RowNumber","CustomerId","Surname"], axis = 1, inplace = True)
```

[5]:
```
Dataset.head()
```

[5]:
```
   CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0          619    France  Female   42       2       0.00              1
1          608     Spain  Female   41       1   83807.86              1
2          502    France  Female   42       8  159660.80              3
3          699    France  Female   39       1       0.00              2
4          850     Spain  Female   43       2  125510.82              1

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0          1               1        101348.88       1
1          0               1        112542.58       0
2          1               0        113931.57       1
3          0               0         93826.63       0
4          1               1         79084.10       0
```

[6]:
```
Dataset.tail()
```

[6]:
```
      CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
9995          771    France    Male   39       5       0.00              2
9996          516    France    Male   35      10   57369.61              1
9997          709    France  Female   36       7       0.00              1
9998          772   Germany    Male   42       3   75075.31              2
9999          792    France  Female   28       4  130142.79              1

      HasCrCard  IsActiveMember  EstimatedSalary  Exited
9995          1               0         96270.64       0
9996          1               1        101699.77       0
9997          0               1         42085.58       1
9998          1               0         92888.52       1
9999          1               0         38190.78       0
```

[7]:
```
Dataset.shape
```

[7]: (10000, 11)

[8]:
```
Dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
```

```
 0   CreditScore      10000 non-null  int64
 1   Geography        10000 non-null  object
 2   Gender           10000 non-null  object
 3   Age              10000 non-null  int64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

[9]:
```
Dataset.describe()
```

[9]:
```
        CreditScore           Age        Tenure        Balance  NumOfProducts  \
count  10000.000000  10000.000000  10000.000000   10000.000000   10000.000000
mean     650.528800     38.921800      5.012800   76485.889288       1.530200
std       96.653299     10.487806      2.892174   62397.405202       0.581654
min      350.000000     18.000000      0.000000       0.000000       1.000000
25%      584.000000     32.000000      3.000000       0.000000       1.000000
50%      652.000000     37.000000      5.000000   97198.540000       1.000000
75%      718.000000     44.000000      7.000000  127644.240000       2.000000
max      850.000000     92.000000     10.000000  250898.090000       4.000000

         HasCrCard  IsActiveMember  EstimatedSalary        Exited
count  10000.00000    10000.000000     10000.000000  10000.000000
mean       0.70550        0.515100    100090.239881      0.203700
std        0.45584        0.499797     57510.492818      0.402769
min        0.00000        0.000000        11.580000      0.000000
25%        0.00000        0.000000     51002.110000      0.000000
50%        1.00000        1.000000    100193.915000      0.000000
75%        1.00000        1.000000    149388.247500      0.000000
max        1.00000        1.000000    199992.480000      1.000000
```

[10]:
```
Dataset.columns
```

[10]:
```
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
       'Exited'],
      dtype='object')
```

[11]:
```
Dataset.dtypes
```

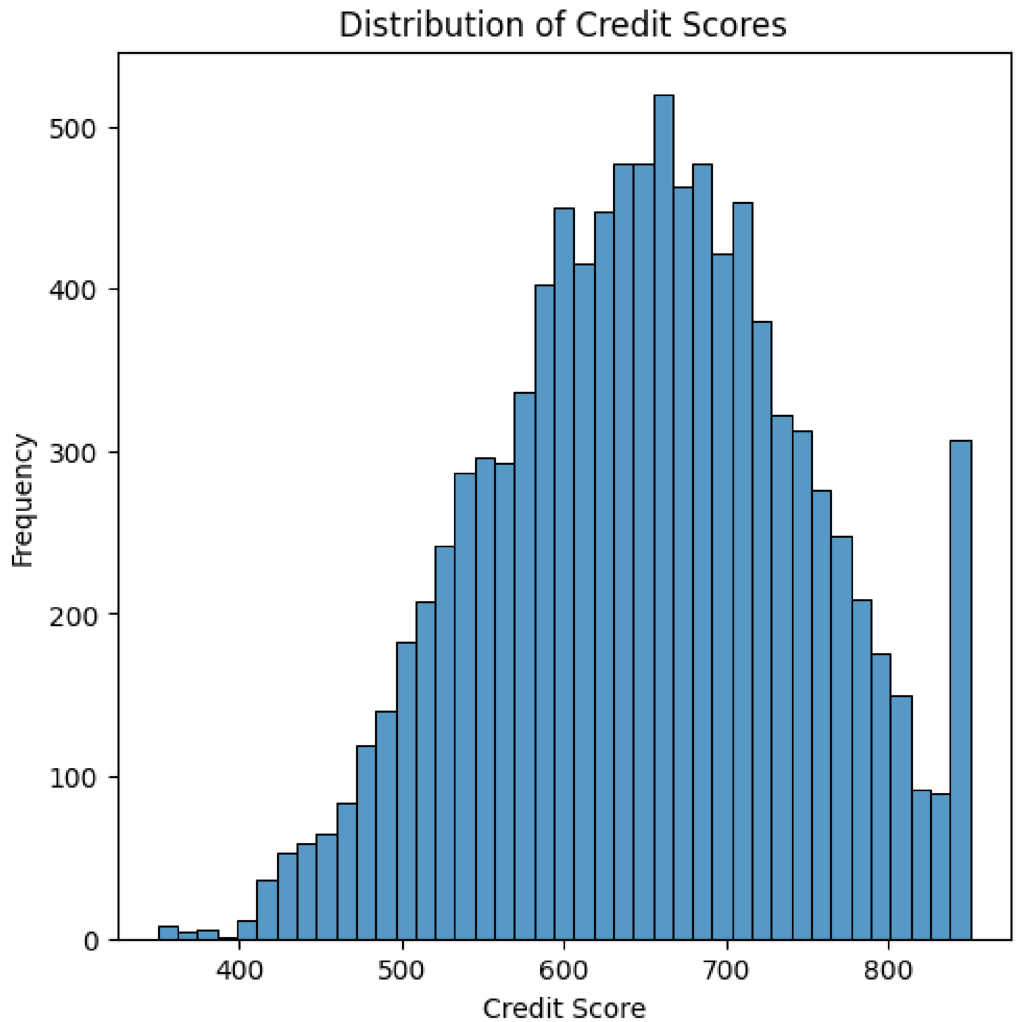
[11]:
```
CreditScore          int64
Geography           object
```

```
Gender               object
Age                   int64
Tenure                int64
Balance             float64
NumOfProducts         int64
HasCrCard             int64
IsActiveMember        int64
EstimatedSalary     float64
Exited                int64
dtype: object
```

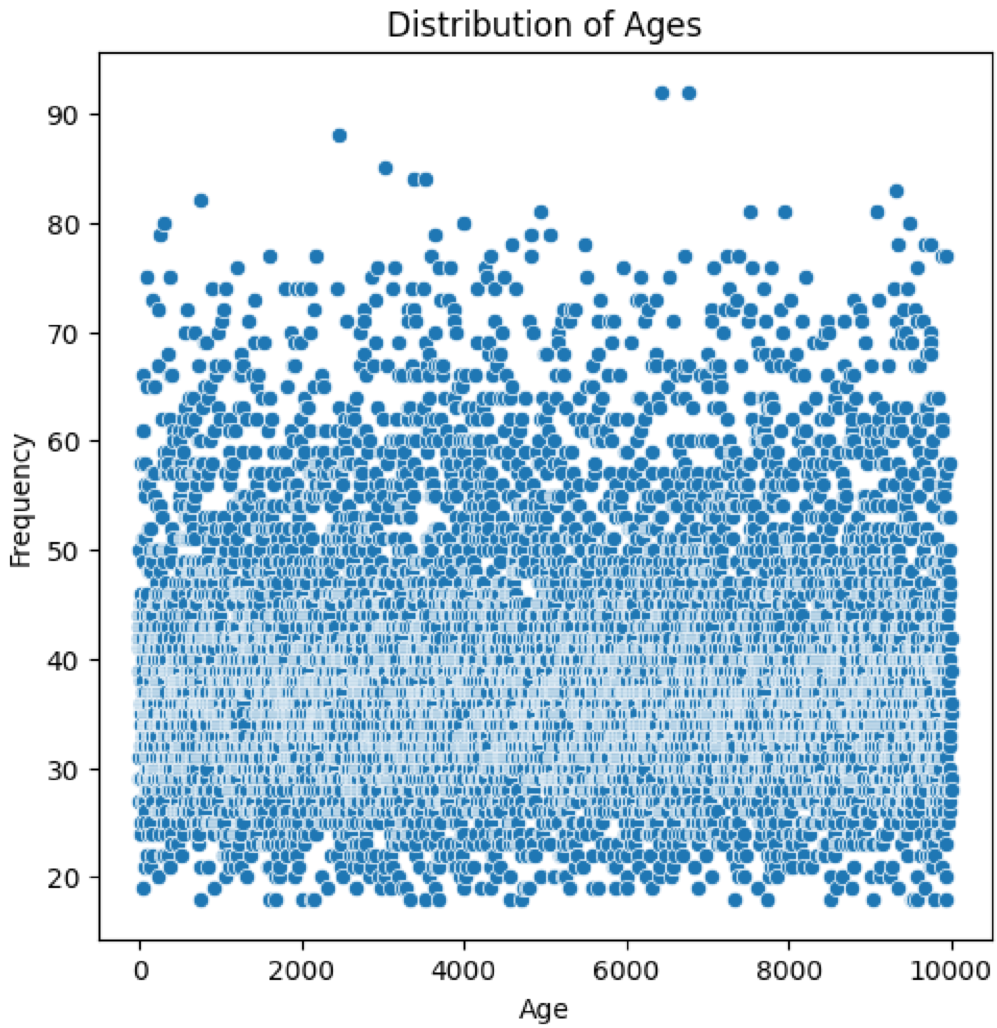
Data Visualization:

[12]:
```python
import numpy as np

import pandas as pd

import matplotlib as pyplot
from matplotlib import pyplot as plt

import seaborn as sns
```

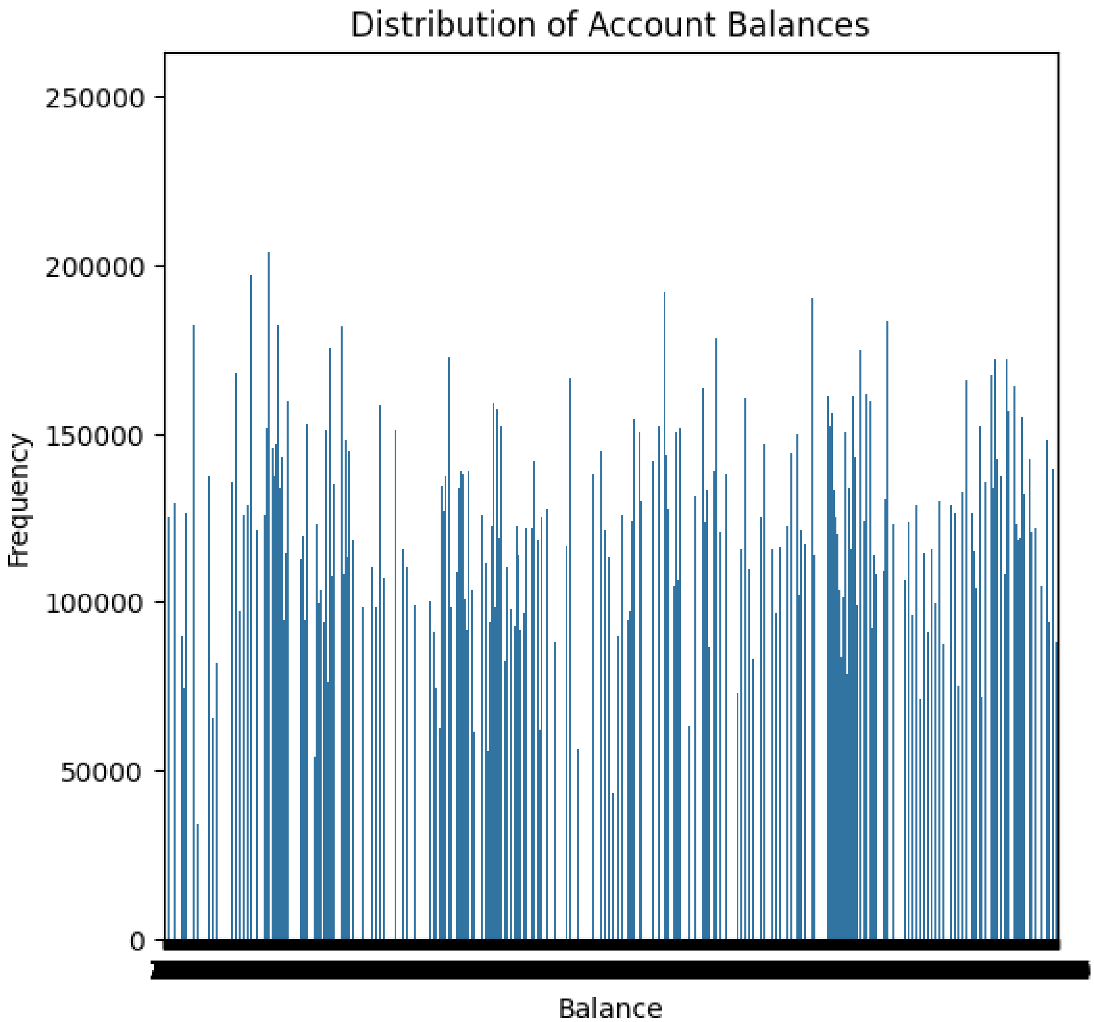
[13]:
```python
plt.figure(figsize=(6,6))

sns.histplot(Dataset["CreditScore"])

plt.xlabel("Credit Score")
plt.ylabel("Frequency")
plt.title("Distribution of Credit Scores")

plt.show()
```



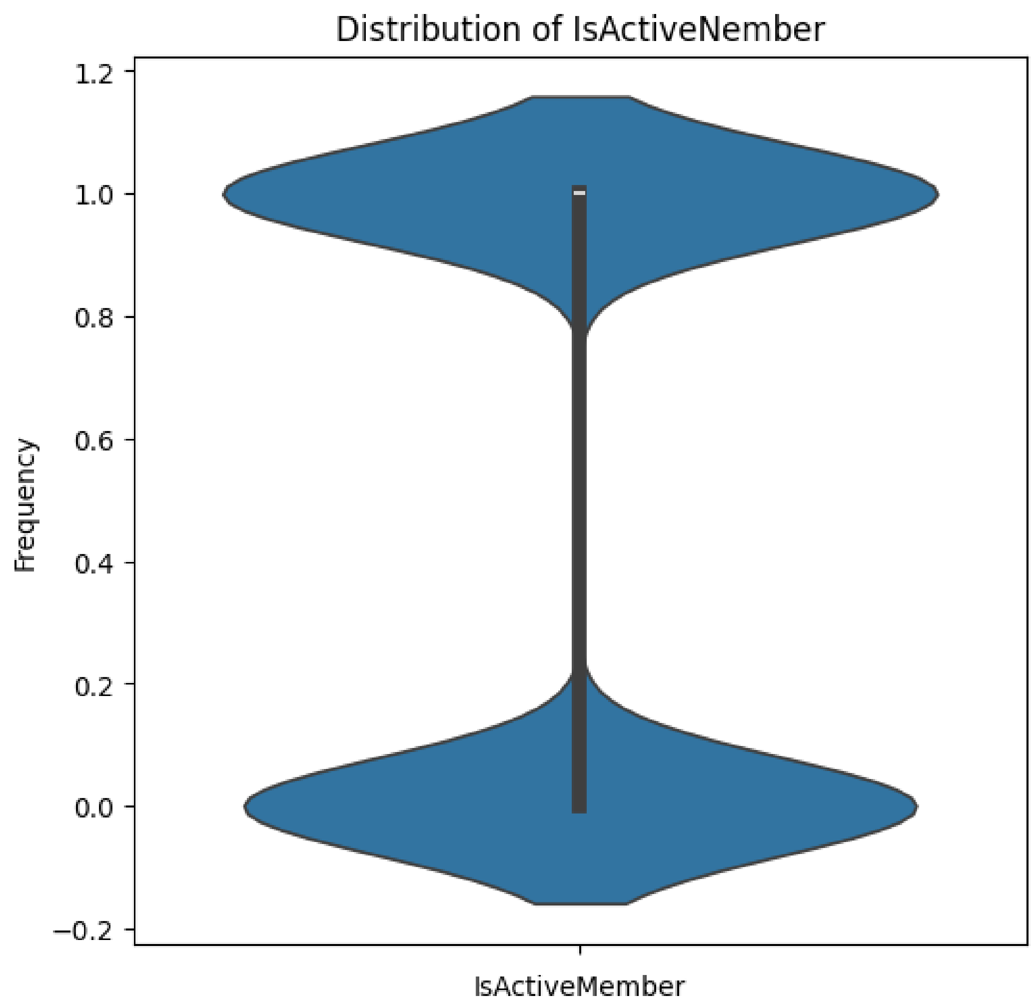
[14]:
```
plt.figure(figsize=(6,6))

sns.scatterplot(Dataset["Age"])

plt.xlabel("Age")
plt.ylabel("Frequency")
plt.title("Distribution of Ages")

plt.show()
```



[15]:
```
plt.figure(figsize=(6,6))

sns.barplot(Dataset["Balance"])

plt.xlabel("Balance")
plt.ylabel("Frequency")
plt.title("Distribution of Account Balances")

plt.show()
```

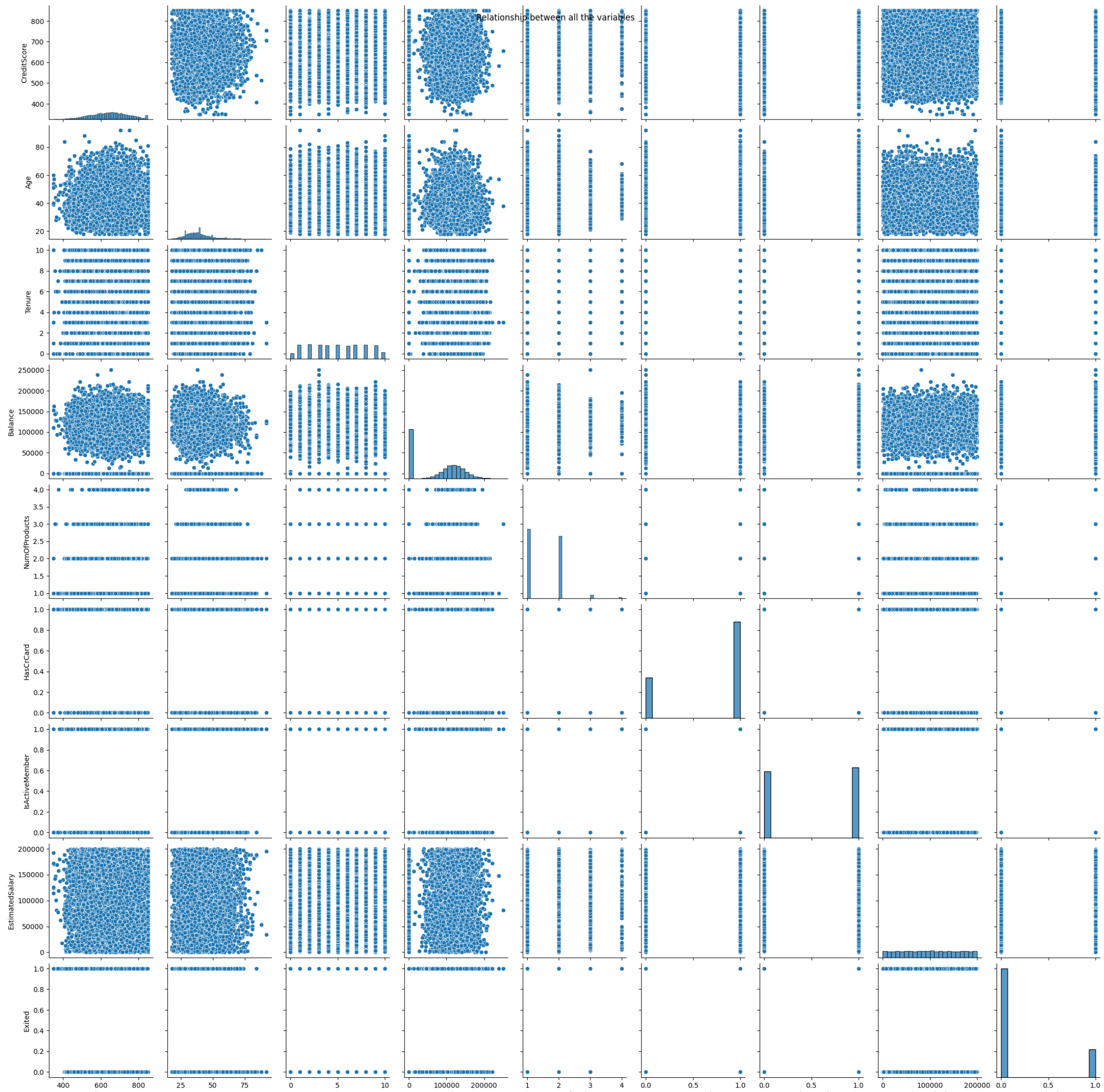


[16]:
```
plt.figure(figsize=(6,6))

sns.violinplot(Dataset["IsActiveMember"])

plt.xlabel("IsActiveMember")
plt.ylabel("Frequency")
plt.title("Distribution of IsActiveNember")

plt.show()
```



[17]:
```
plt.Figure(figsize=(6,6))

sns.pairplot(Dataset)

plt.suptitle("Relationship between all the variables")
```

[17]:
```
Text(0.5, 0.98, 'Relationship between all the variables')
```



Clean and prepare the Dataset.

[18]:
```
# Import Libraries.

import pandas as pd
import numpy as np

import matplotlib as pyplot
from matplotlib import pyplot as plt
%matplotlib inline

import seaborn as sns
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder

from sklearn.metrics import accuracy_score, confusion_matrix
```

[19]:
```
print(Dataset.isnull().sum())
```

```
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

[20]:
```
dataset = Dataset.dropna()
```

[21]:
```
dataset = pd.get_dummies(Dataset, drop_first=True)
```

[22]:
```
dataset.head()
```

[22]:
```
   CreditScore  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0          619   42       2       0.00              1          1
1          608   41       1   83807.86              1          0
2          502   42       8  159660.80              3          1
3          699   39       1       0.00              2          0
4          850   43       2  125510.82              1          1

   IsActiveMember  EstimatedSalary  Exited  Geography_Germany  \
0               1        101348.88       1              False
1               1        112542.58       0              False
2               0        113931.57       1              False
3               0         93826.63       0              False
4               1         79084.10       0              False

   Geography_Spain  Gender_Male
0            False        False
1             True        False
2            False        False
3            False        False
```

```
4              True         False
```

Encode the categorical features such as geography and Gender.

One Hot Encoding.

[23]:
```
dataset[["Geography_Germany","Geography_Spain","Gender_Male"]].head()
```

[23]:
```
   Geography_Germany  Geography_Spain  Gender_Male
0              False            False        False
1              False             True        False
2              False            False        False
3              False            False        False
4              False             True        False
```

[24]:
```
# One-hot Encoding For the Geography and Gender.
dataset = pd.get_dummies(dataset,␣
 ↪columns=["Geography_Germany","Geography_Spain", "Gender_Male"],␣
 ↪drop_first=True)
```

[25]:
```
dataset.head()
```

[25]:
```
   CreditScore  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0          619   42       2       0.00              1          1
1          608   41       1   83807.86              1          0
2          502   42       8  159660.80              3          1
3          699   39       1       0.00              2          0
4          850   43       2  125510.82              1          1

   IsActiveMember  EstimatedSalary  Exited  Geography_Germany_True  \
0               1        101348.88       1                   False
1               1        112542.58       0                   False
2               0        113931.57       1                   False
3               0         93826.63       0                   False
4               1         79084.10       0                   False

   Geography_Spain_True  Gender_Male_True
0                 False             False
1                  True             False
2                 False             False
3                 False             False
4                  True             False
```

Label Encoding.

[26]:
```
# Initialize Label Encoder.
le = LabelEncoder()
```

```
# Encode Geography_Spain_True.
dataset["Geography_Spain_True"] = le.
↪fit_transform(dataset["Geography_Spain_True"])

# Encode Geography_Germany.
dataset["Geography_Germany_True"] = le.
↪fit_transform(dataset["Geography_Germany_True"])

# Encode Gender_Male_True.
dataset["Gender_Male_True"] = le.fit_transform(dataset["Gender_Male_True"])
```

[27]:
```
dataset.head()
```

[27]:
```
   CreditScore  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0          619   42       2       0.00              1          1
1          608   41       1   83807.86              1          0
2          502   42       8  159660.80              3          1
3          699   39       1       0.00              2          0
4          850   43       2  125510.82              1          1

   IsActiveMember  EstimatedSalary  Exited  Geography_Germany_True  \
0               1        101348.88       1                       0
1               1        112542.58       0                       0
2               0        113931.57       1                       0
3               0         93826.63       0                       0
4               1         79084.10       0                       0

   Geography_Spain_True  Gender_Male_True
0                     0                 0
1                     1                 0
2                     0                 0
3                     0                 0
4                     1                 0
```

Train a clasiification Model.

Logistic Regression.

[28]:
```
x = dataset.drop("Exited", axis=1)
y = dataset["Exited"]
```

[29]:
```
x = pd.get_dummies(x, drop_first=True)
```

[30]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[31]:
```
print("Training Data:", x_train.shape)
print("Testing Data:", x_test.shape)
```

```
Training Data: (8000, 11)
Testing Data: (2000, 11)
```

[32]:
```
logistic_model = LogisticRegression(max_iter=1000)
logistic_model.fit(x_train, y_train)

y_predict_logistic = logistic_model.predict(x_test)
```

```
c:\Users\zaigh\AppData\Local\Programs\Python\Python313\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(
```

Evalute the Model using the Confuson Matrix and the Accuracy.

[33]:
```
print("Logistic Regression Accuracy: \n",
      accuracy_score(y_test, y_predict_logistic))

print("Confusion Matrix: \n",
      confusion_matrix(y_test, y_predict_logistic))
```

```
Logistic Regression Accuracy:
 0.8145
Confusion Matrix:
 [[1547   60]
 [ 311   82]]
```

[34]:
```
cm = confusion_matrix(y_test, y_predict_logistic)
TN, FP, FN, TP = cm.ravel()

# Create a Structured Table.
metrics_table = pd.DataFrame({
    'Metric': ['TP', 'TN', 'FP', 'FN', 'Accuracy', 'Precision', 'Recall'],
    'Value': [TP, TN, FP, FN,
              (TP+TN)/(TP+TN+FP+FN),
              TP/(TP+FP),
              TP/(TP+FN)]})

print(metrics_table)
```

```
      Metric        Value
0         TP    82.000000
```

```
1          TN  1547.000000
2          FP    60.000000
3          FN   311.000000
4    Accuracy     0.814500
5   Precision     0.577465
6      Recall     0.208651
```

Decision Tree.

[35]:
```
decisionTree_model = DecisionTreeClassifier(random_state=42)

decisionTree_model.fit(x_train, y_train)

y_predict_decisionTree = decisionTree_model.predict(x_test)
```

Evalute the Model using the Confuson Matrix and the Accuracy.

[36]:
```
print("Decision Tree Accuracy: \n",
      accuracy_score(y_test, y_predict_decisionTree))

print("Confusion Matrix: \n",
      confusion_matrix(y_test, y_predict_decisionTree))
```

```
Decision Tree Accuracy:
 0.7805
Confusion Matrix:
 [[1362  245]
 [ 194  199]]
```

[37]:
```
cm = confusion_matrix(y_test, y_predict_decisionTree)
TN, FP, FN, TP = cm.ravel()

# Create a Structured Table.
metrics_table = pd.DataFrame({
    'Metric': ['TP', 'TN', 'FP', 'FN', 'Accuracy', 'Precision', 'Recall'],
    'Value': [TP, TN, FP, FN,
              (TP+TN)/(TP+TN+FP+FN),
              TP/(TP+FP),
              TP/(TP+FN)]})
print(metrics_table)
```

```
      Metric        Value
0         TP   199.000000
1         TN  1362.000000
2         FP   245.000000
3         FN   194.000000
4   Accuracy     0.780500
5  Precision     0.448198
6     Recall     0.506361
```

Analyze feature importance to understand what influences churn.

Skills: Categorical data encoding (Label Encoding/One-Hot Encoding). Supervised classifcation modeling. Understanding and interpeting feature importance.

Task completed. Best Wishes. Zaigham Abbas.