

Loan prediction

August 31, 2023

```
[139]: import csv
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB, GaussianNB, BernoulliNB, \
    CategoricalNB
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import precision_recall_curve, average_precision_score
from sklearn.metrics import log_loss, balanced_accuracy_score
```

```
[140]: train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")
```

TRAINING DATA

```
[141]: print(train.head())
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | \ |
|---|----------|--------|---------|------------|--------------|---------------|---|
| 0 | LP001002 | Male | No | 0 | Graduate | No | |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | |
| 4 | LP001008 | Male | No | 0 | Graduate | No | |

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | \ |
|---|-----------------|-------------------|------------|------------------|---|
| 0 | 5849 | 0.0 | NaN | 360.0 | |
| 1 | 4583 | 1508.0 | 128.0 | 360.0 | |
| 2 | 3000 | 0.0 | 66.0 | 360.0 | |
| 3 | 2583 | 2358.0 | 120.0 | 360.0 | |
| 4 | 6000 | 0.0 | 141.0 | 360.0 | |

Credit_History Property_Area Loan_Status

| | | | |
|---|-----|-------|---|
| 0 | 1.0 | Urban | Y |
| 1 | 1.0 | Rural | N |
| 2 | 1.0 | Urban | Y |
| 3 | 1.0 | Urban | Y |
| 4 | 1.0 | Urban | Y |

```
[142]: print(train.isnull().sum())    # finding missing values
```

```
Loan_ID      0
Gender       13
Married       3
Dependents   15
Education     0
Self_Employed 32
ApplicantIncome 0
CoapplicantIncome 0
LoanAmount    22
Loan_Amount_Term 14
Credit_History 50
Property_Area 0
Loan_Status    0
dtype: int64
```

```
[143]: print(train['Gender'].unique())
```

```
['Male' 'Female' nan]
```

```
[144]: print(train['Dependents'].unique())
```

```
['0' '1' '2' '3+' nan]
```

```
[145]: print(train['Education'].unique())
```

```
['Graduate' 'Not Graduate']
```

```
[146]: print(train['Self_Employed'].unique())
```

```
['No' 'Yes' nan]
```

```
[147]: print(train['Property_Area'].unique())
```

```
['Urban' 'Rural' 'Semiurban']
```

```
[148]: encoder = OrdinalEncoder()
df = train.copy()
cate = ['Dependents']
df[cate] = encoder.fit_transform(train[cate])
Dependents = df[cate]
```

```
[149]: imputer = SimpleImputer()
depn = Dependents.copy()
depn = pd.DataFrame(imputer.fit_transform(Dependents))
```

```
[150]: train['Dependents'] = depn
#print(train)
```

```
[151]: X = train.copy()
X = X.drop(['Loan_ID', 'Loan_Status'], axis=1)      # dropping columns
```

```
[152]: cate_col = (X.dtypes == 'object')
cate_col = list(cate_col[cate_col].index)
print("Categorical Variables : ", cate_col)
```

Categorical Variables : ['Gender', 'Married', 'Education', 'Self_Employed', 'Property_Area']

```
[153]: X[cate_col] = encoder.fit_transform(df[cate_col])
#print(X)
```

```
[154]: X_prep = X.copy()
X_prep = pd.DataFrame(imputer.fit_transform(X))
X_prep.columns = X.columns
#print(X_prep)      # preprocessed X - features
```

```
[155]: df2 = train.copy()
cate2 = ['Loan_Status']
df2[cate2] = encoder.fit_transform(train[cate2])
y_prep = df2[cate2].copy()
```

```
[156]: #print(y_prep)
```

TEST DATA

```
[157]: print(test.head())
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | \ |
|---|----------|--------|---------|------------|--------------|---------------|---|
| 0 | LP001015 | Male | Yes | 0 | Graduate | No | |
| 1 | LP001022 | Male | Yes | 1 | Graduate | No | |
| 2 | LP001031 | Male | Yes | 2 | Graduate | No | |
| 3 | LP001035 | Male | Yes | 2 | Graduate | No | |
| 4 | LP001051 | Male | No | 0 | Not Graduate | No | |

| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | \ |
|---|-----------------|-------------------|------------|------------------|---|
| 0 | 5720 | 0 | 110.0 | 360.0 | |
| 1 | 3076 | 1500 | 126.0 | 360.0 | |
| 2 | 5000 | 1800 | 208.0 | 360.0 | |
| 3 | 2340 | 2546 | 100.0 | 360.0 | |

```
4          3276          0      78.0      360.0
```

```
      Credit_History Property_Area
0          1.0      Urban
1          1.0      Urban
2          1.0      Urban
3          NaN      Urban
4          1.0      Urban
```

```
[158]: print(test.isnull().sum())
```

```
Loan_ID          0
Gender           11
Married          0
Dependents       10
Education         0
Self_Employed    23
ApplicantIncome   0
CoapplicantIncome 0
LoanAmount        5
Loan_Amount_Term  6
Credit_History   29
Property_Area     0
dtype: int64
```

```
[159]: print(test['Gender'].unique())
```

```
['Male' 'Female' nan]
```

```
[160]: print(test['Dependents'].unique())
```

```
['0' '1' '2' '3+' nan]
```

```
[161]: print(test['Education'].unique())
```

```
['Graduate' 'Not Graduate']
```

```
[162]: print(test['Self_Employed'].unique())
```

```
['No' 'Yes' nan]
```

```
[163]: print(test['Property_Area'].unique())
```

```
['Urban' 'Semiurban' 'Rural']
```

```
[164]: encoder = OrdinalEncoder()
df3 = test.copy()
cate = ['Dependents']
```

```
df3[cate] = encoder.fit_transform(test[cate])
Dependents2 = df3[cate]
```

```
[165]: imputer = SimpleImputer()
depn2 = Dependents2.copy()
depn2 = pd.DataFrame(imputer.fit_transform(Dependents2))
```

```
[166]: test['Dependents'] = depn2
#print(test)
```

```
[167]: X2 = test.copy()
X2 = X2.drop(['Loan_ID'], axis=1)      # dropping columns
#print(X2)
```

```
[168]: X2[cate_col] = encoder.fit_transform(df3[cate_col])
#print(X2)
```

```
[169]: X_test_prep = X2.copy()
X_test_prep = pd.DataFrame(imputer.fit_transform(X2))
X_test_prep.columns = X2.columns
#print(X_test_prep)                  # preprocessed X - features
```

PREPROCESSED DATA

```
[170]: print(X_prep)
```

| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | \ |
|-----|--------|---------|------------|-----------|---------------|-----------------|---|
| 0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 5849.0 | |
| 1 | 1.0 | 1.0 | 1.0 | 0.0 | 0.0 | 4583.0 | |
| 2 | 1.0 | 1.0 | 0.0 | 0.0 | 1.0 | 3000.0 | |
| 3 | 1.0 | 1.0 | 0.0 | 1.0 | 0.0 | 2583.0 | |
| 4 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 6000.0 | |
| .. | ... | ... | ... | ... | ... | ... | |
| 609 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 2900.0 | |
| 610 | 1.0 | 1.0 | 3.0 | 0.0 | 0.0 | 4106.0 | |
| 611 | 1.0 | 1.0 | 1.0 | 0.0 | 0.0 | 8072.0 | |
| 612 | 1.0 | 1.0 | 2.0 | 0.0 | 0.0 | 7583.0 | |
| 613 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 4583.0 | |

| | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | \ |
|-----|-------------------|------------|------------------|----------------|---|
| 0 | 0.0 | 146.412162 | 360.0 | 1.0 | |
| 1 | 1508.0 | 128.000000 | 360.0 | 1.0 | |
| 2 | 0.0 | 66.000000 | 360.0 | 1.0 | |
| 3 | 2358.0 | 120.000000 | 360.0 | 1.0 | |
| 4 | 0.0 | 141.000000 | 360.0 | 1.0 | |
| .. | ... | ... | ... | ... | |
| 609 | 0.0 | 71.000000 | 360.0 | 1.0 | |
| 610 | 0.0 | 40.000000 | 180.0 | 1.0 | |

| | | | | |
|-----|-------|------------|-------|-----|
| 611 | 240.0 | 253.000000 | 360.0 | 1.0 |
| 612 | 0.0 | 187.000000 | 360.0 | 1.0 |
| 613 | 0.0 | 133.000000 | 360.0 | 0.0 |

| | Property_Area |
|-----|---------------|
| 0 | 2.0 |
| 1 | 0.0 |
| 2 | 2.0 |
| 3 | 2.0 |
| 4 | 2.0 |
| .. | ... |
| 609 | 0.0 |
| 610 | 0.0 |
| 611 | 2.0 |
| 612 | 2.0 |
| 613 | 1.0 |

[614 rows x 11 columns]

```
[171]: print(y_prep)
```

| | Loan_Status |
|-----|-------------|
| 0 | 1.0 |
| 1 | 0.0 |
| 2 | 1.0 |
| 3 | 1.0 |
| 4 | 1.0 |
| .. | ... |
| 609 | 1.0 |
| 610 | 1.0 |
| 611 | 1.0 |
| 612 | 1.0 |
| 613 | 0.0 |

[614 rows x 1 columns]

```
[172]: print(X_test_prep)
```

| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | \ |
|-----|--------|---------|------------|-----------|---------------|-----------------|---|
| 0 | 1.0 | 1.0 | 0.0 | 0.0 | 0.0 | 5720.0 | |
| 1 | 1.0 | 1.0 | 1.0 | 0.0 | 0.0 | 3076.0 | |
| 2 | 1.0 | 1.0 | 2.0 | 0.0 | 0.0 | 5000.0 | |
| 3 | 1.0 | 1.0 | 2.0 | 0.0 | 0.0 | 2340.0 | |
| 4 | 1.0 | 0.0 | 0.0 | 1.0 | 0.0 | 3276.0 | |
| .. | ... | ... | ... | ... | ... | ... | |
| 362 | 1.0 | 1.0 | 3.0 | 1.0 | 1.0 | 4009.0 | |
| 363 | 1.0 | 1.0 | 0.0 | 0.0 | 0.0 | 4158.0 | |
| 364 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3250.0 | |

| | | | | | | |
|-----|-----|-----|-----|-----|-----|--------|
| 365 | 1.0 | 1.0 | 0.0 | 0.0 | 0.0 | 5000.0 |
| 366 | 1.0 | 0.0 | 0.0 | 0.0 | 1.0 | 9200.0 |

| | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | \ |
|-----|-------------------|------------|------------------|----------------|---|
| 0 | 0.0 | 110.0 | 360.0 | 1.000000 | |
| 1 | 1500.0 | 126.0 | 360.0 | 1.000000 | |
| 2 | 1800.0 | 208.0 | 360.0 | 1.000000 | |
| 3 | 2546.0 | 100.0 | 360.0 | 0.825444 | |
| 4 | 0.0 | 78.0 | 360.0 | 1.000000 | |
| .. | ... | ... | ... | ... | |
| 362 | 1777.0 | 113.0 | 360.0 | 1.000000 | |
| 363 | 709.0 | 115.0 | 360.0 | 1.000000 | |
| 364 | 1993.0 | 126.0 | 360.0 | 0.825444 | |
| 365 | 2393.0 | 158.0 | 360.0 | 1.000000 | |
| 366 | 0.0 | 98.0 | 180.0 | 1.000000 | |

| | Property_Area |
|-----|---------------|
| 0 | 2.0 |
| 1 | 2.0 |
| 2 | 2.0 |
| 3 | 2.0 |
| 4 | 2.0 |
| .. | ... |
| 362 | 2.0 |
| 363 | 2.0 |
| 364 | 1.0 |
| 365 | 0.0 |
| 366 | 0.0 |

[367 rows x 11 columns]

TRAINING DATA SPLIT

```
[173]: X_train, X_valid, y_train, y_valid = train_test_split(X_prep, y_prep,
    ↪test_size=0.25, random_state=0)
```

```
[174]: X_train.reset_index(inplace=True)           # resetting index
X_train = X_train.drop('index', axis=1)
```

```
[175]: y_train.reset_index(inplace=True)
y_train = y_train.drop('index', axis=1)
```

```
[176]: X_valid.reset_index(inplace=True)
X_valid = X_valid.drop('index', axis=1)
```

```
[177]: y_valid.reset_index(inplace=True)
y_valid = y_valid.drop('index', axis=1)
```

```
[178]: ### 1. NAIVE BAYES CLASSIFIER
```

```
[179]: model = GaussianNB()
```

```
[180]: model.fit(X_train, y_train)
pred = model.predict(X_valid)
print(classification_report(y_valid, pred))
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0.0 | 0.83 | 0.47 | 0.60 | 43 |
| 1.0 | 0.82 | 0.96 | 0.89 | 111 |
| accuracy | | | 0.82 | 154 |
| macro avg | 0.83 | 0.71 | 0.74 | 154 |
| weighted avg | 0.83 | 0.82 | 0.81 | 154 |

```
/home/niranjana/.local/lib/python3.8/site-
packages/sklearn/utils/validation.py:1111: DataConversionWarning: A column-
vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples, ), for example using ravel().
y = column_or_1d(y, warn=True)
```

```
[181]: matrix = confusion_matrix(y_valid, pred)
matrix_df = pd.DataFrame(matrix)
print(matrix_df)
```

```
   0    1
0  20   23
1   4  107
```

0 - No loan | 1 - loan accepted

```
[182]: test_pred = model.predict(X_test_prep)
print(test_pred)
```

```
[1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1.
1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 0. 0. 1. 0. 1. 1.
1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 0. 0. 1. 0. 0. 1. 1. 1. 1. 1. 1. 1. 0. 1.
1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 0.
1. 1. 1. 0. 0. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 0.
1. 1. 1. 0. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 0. 0. 1.
0. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
0. 0. 1. 1. 0. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1.
1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1. 0. 0. 0. 1. 1.
1. 0. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 0. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```



```

1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 0.
1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1.
1. 1. 1. 1. 1. 1. 1.]

```

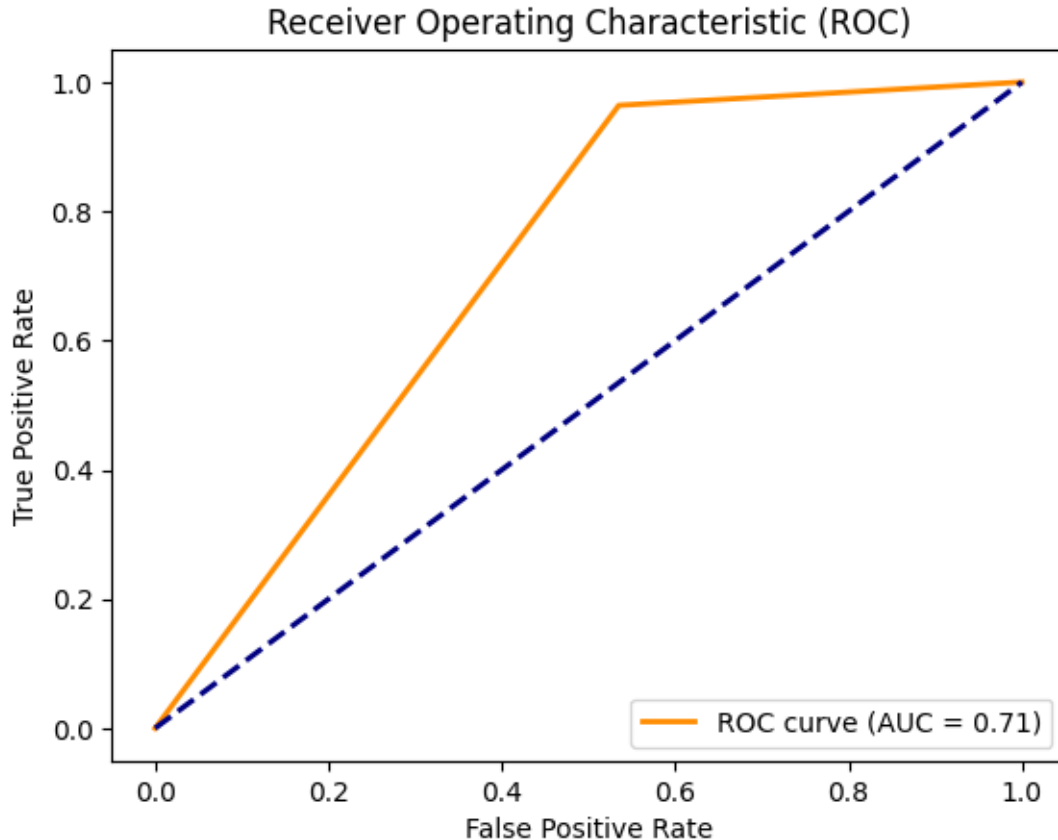
```
[183]: print(roc_auc)
```

```
0.7010266080033523
```

```
[184]: fpr, tpr, thresholds = roc_curve(y_valid, pred)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = {:.2f})'.
        ↪format(roc_auc))
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc='lower right')
plt.show()

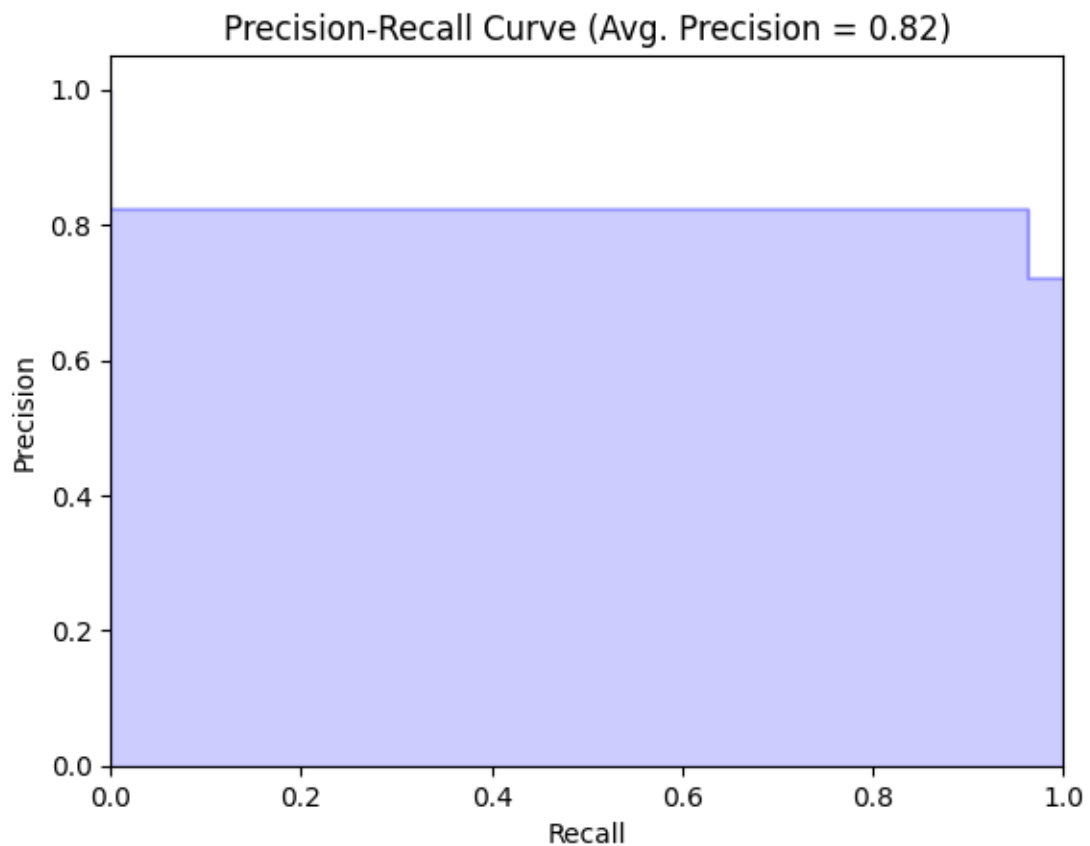
print("AUC ROC Score:", roc_auc)
```



AUC ROC Score: 0.7145401215168657

```
[185]: precision, recall, thresholds = precision_recall_curve(y_valid, pred)
       average_precision = average_precision_score(y_valid, pred)

       plt.figure()
       plt.step(recall, precision, color='b', alpha=0.2, where='post')
       plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')
       plt.xlabel('Recall')
       plt.ylabel('Precision')
       plt.ylim([0.0, 1.05])
       plt.xlim([0.0, 1.0])
       plt.title('Precision-Recall Curve (Avg. Precision = {:.2f})'.
               ↪format(average_precision))
       plt.show()
```



```
[186]: # other classification metrics
```

```
print('avg precision:', average_precision)

balanced_accuracy = balanced_accuracy_score(y_valid, pred)
print('balanced accuracy:', balanced_accuracy)

logloss = log_loss(y_valid, pred)
print("Log Loss:", logloss)
```

```
avg precision: 0.8193905193905194
balanced accuracy: 0.7145401215168657
Log Loss: 6.0556191779446955
```

```
[187]: ### 2. RFC
```

```
[188]: model2 = RandomForestClassifier(n_estimators=100, criterion='entropy')
```

```
[189]: model2.fit(X_train, y_train)
pred2 = model2.predict(X_valid)
print(classification_report(y_valid, pred2))
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0.0 | 0.81 | 0.49 | 0.61 | 43 |
| 1.0 | 0.83 | 0.95 | 0.89 | 111 |
| accuracy | | | 0.82 | 154 |
| macro avg | 0.82 | 0.72 | 0.75 | 154 |
| weighted avg | 0.82 | 0.82 | 0.81 | 154 |

```
/tmp/ipykernel_7019/669114507.py:1: DataConversionWarning: A column-vector y was
passed when a 1d array was expected. Please change the shape of y to
(n_samples,), for example using ravel().
model2.fit(X_train, y_train)
```

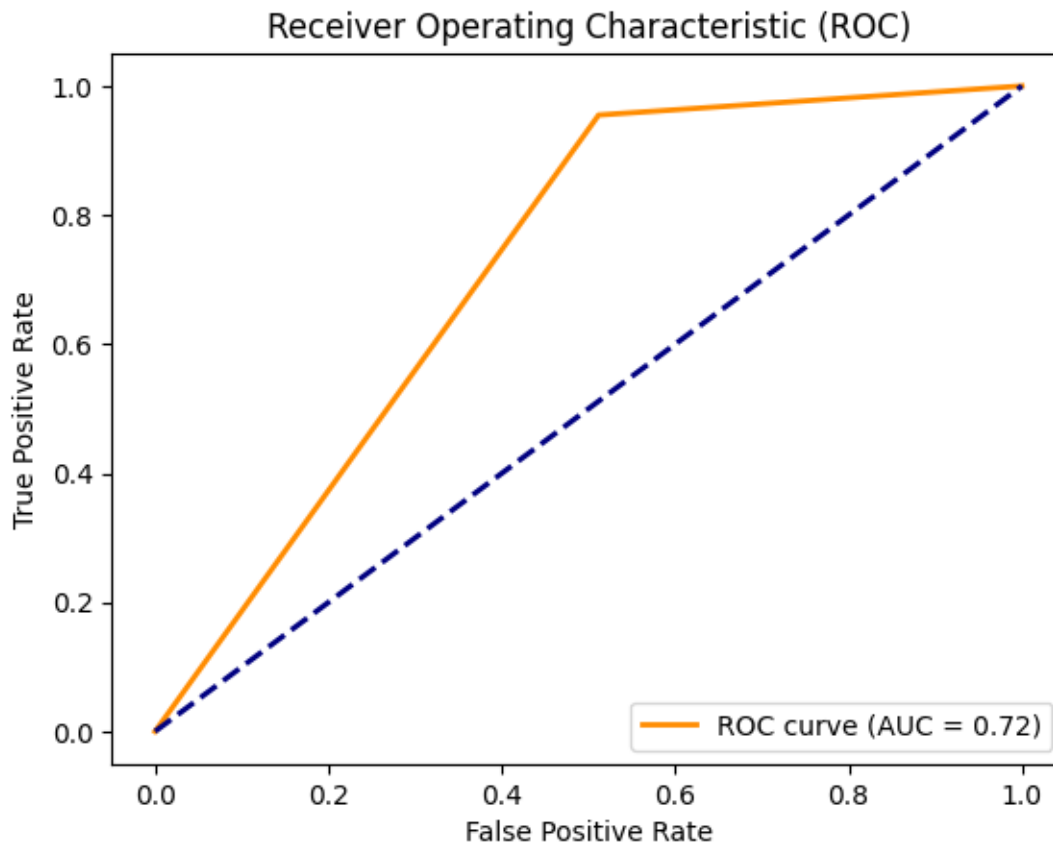
```
[190]: matrix = confusion_matrix(y_valid, pred2)
matrix_df = pd.DataFrame(matrix)
print(matrix_df)
```

```
   0    1
0  21   22
1   5  106
```

```
[191]: fpr, tpr, thresholds = roc_curve(y_valid, pred2)
roc_auc = auc(fpr, tpr)
```

```
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = {:.2f})'.
        ↪format(roc_auc))
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc='lower right')
plt.show()

print("AUC ROC Score:",roc_auc)
```

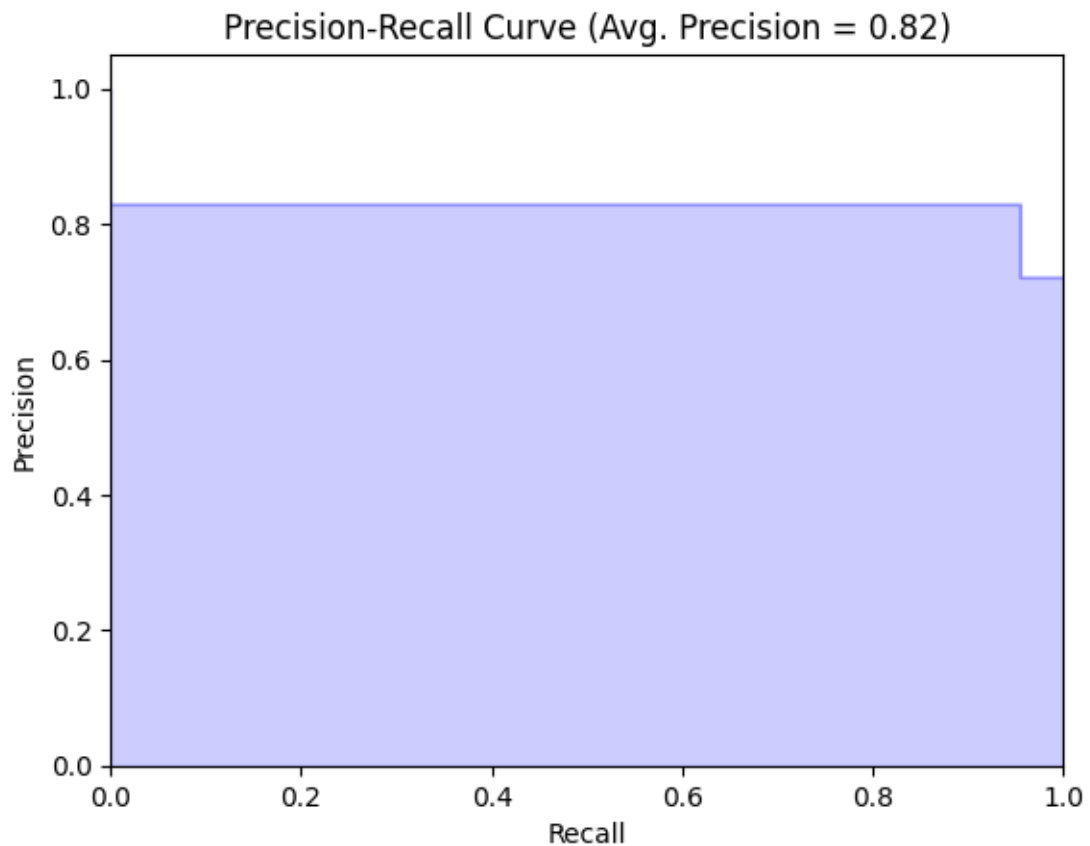


AUC ROC Score: 0.7216635239891054

```
[192]: precision, recall, thresholds = precision_recall_curve(y_valid, pred2)
average_precision = average_precision_score(y_valid, pred2)

plt.figure()
plt.step(recall, precision, color='b', alpha=0.2, where='post')
plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')
```

```
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Precision-Recall Curve (Avg. Precision = {:.2f})'.
    ↪format(average_precision))
plt.show()
```



```
[193]: # other metrics

print('avg precision:', average_precision)

balanced_accuracy = balanced_accuracy_score(y_valid, pred2)
print('balanced accuracy:', balanced_accuracy)

logloss = log_loss(y_valid, pred2)
print("Log Loss:", logloss)
```

```
avg precision: 0.8232896045396045
balanced accuracy: 0.7216635239891054
```

Log Loss: 6.05561398575359

[]:

[]: