Team Project AAI 501

April 13, 2024

0.1 Introduction

The purpose of this project is to apply a classification algorithm to predict if someone will be classified as having a good or bad credit. The dataset consists of personal information such as age, sex, marital status, employment, credit amount request (among other) and classifies them based on these attributes as "good" and "bad" credit risks.

0.1.1 Business related questions

- What are some of the features that people with "Good" credit have?
- What is the average age of applicants?
- What is the average amount people have in their checking and savings account?
- What is the most common property type?
- what is the most common sex/status with "Good" credit
- Does an applicant's demographics cause a deviation in the predicted category vs. what category they were actually placed in thus suggesting bias?

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.feature_selection import SelectFromModel
```

[2]:
```python
df = pd.read_csv('german.data', sep='\s+')
df.head(2)
```

[2]:
```
   A11   6  A34  A43  1169  A65  A75  4  A93  A101  …  A121  67  A143  A152  \
0  A12  48  A32  A43  5951  A61  A73  2  A92  A101  …  A121  22  A143  A152
1  A14  12  A34  A46  2096  A61  A74  2  A93  A101  …  A121  49  A143  A152

   2  A173  1  A192  A201 1.1
0  1  A173  1  A191  A201   2
1  1  A172  2  A191  A201   1

[2 rows x 21 columns]
```

[3]:
```python
column_names = ['checking_account', 'duration_month', 'credit_history',␣
↪'credit_purpose','credit_amount','savings_account','present_employment','disposable_income_
␣
↪'status_sex','debtors','residence_since','property','age','other_installments',␣
↪'housing','credits_at_current_bank','job','dependants','telephone',␣
↪'foreign_worker','class']
```

[4]:
```python
df.columns = column_names
df.head(2)
```

[4]:
```
  checking_account  duration_month credit_history credit_purpose  \
0              A12              48            A32            A43
1              A14              12            A34            A46

   credit_amount savings_account present_employment  \
0           5951             A61                A73
1           2096             A61                A74

   disposable_income_percent status_sex debtors  …  property age  \
0                          2        A92    A101  …      A121   22
1                          2        A93    A101  …      A121   49

   other_installments housing credits_at_current_bank   job dependants  \
0                A143    A152                       1  A173          1
1                A143    A152                       1  A172          2

   telephone foreign_worker class
0       A191           A201     2
1       A191           A201     1

[2 rows x 21 columns]
```

[5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 0 to 998
Data columns (total 21 columns):
 #   Column                     Non-Null Count  Dtype
```

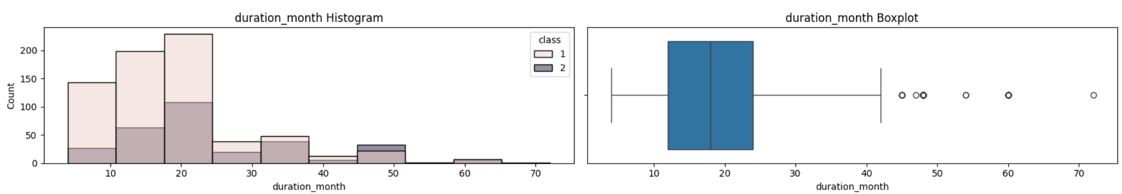
```
---  ------                    --------------  -----
 0   checking_account          999 non-null    object
 1   duration_month            999 non-null    int64
 2   credit_history            999 non-null    object
 3   credit_purpose            999 non-null    object
 4   credit_amount             999 non-null    int64
 5   savings_account           999 non-null    object
 6   present_employment        999 non-null    object
 7   disposable_income_percent 999 non-null    int64
 8   status_sex                999 non-null    object
 9   debtors                   999 non-null    object
 10  residence_since           999 non-null    int64
 11  property                  999 non-null    object
 12  age                       999 non-null    int64
 13  other_installments        999 non-null    object
 14  housing                   999 non-null    object
 15  credits_at_current_bank   999 non-null    int64
 16  job                       999 non-null    object
 17  dependants                999 non-null    int64
 18  telephone                 999 non-null    object
 19  foreign_worker            999 non-null    object
 20  class                     999 non-null    int64
dtypes: int64(8), object(13)
memory usage: 164.0+ KB
```

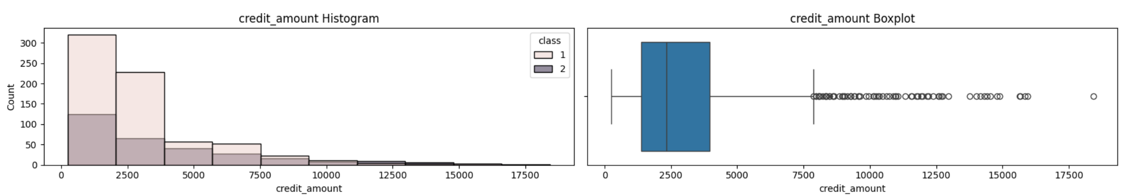
[6]:
```
df.describe()
```

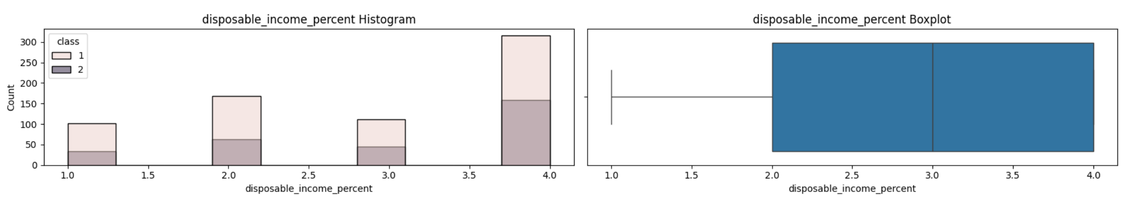
[6]:
```
       duration_month  credit_amount  disposable_income_percent  \
count      999.000000     999.000000                 999.000000
mean        20.917918    3273.362362                   2.971972
std         12.055619    2823.365811                   1.118802
min          4.000000     250.000000                   1.000000
25%         12.000000    1368.500000                   2.000000
50%         18.000000    2320.000000                   3.000000
75%         24.000000    3972.500000                   4.000000
max         72.000000   18424.000000                   4.000000

       residence_since         age  credits_at_current_bank  dependants  \
count       999.000000  999.000000               999.000000  999.000000
mean          2.843844   35.514515                 1.406406    1.155155
std           1.103665   11.337487                 0.577639    0.362234
min           1.000000   19.000000                 1.000000    1.000000
25%           2.000000   27.000000                 1.000000    1.000000
50%           3.000000   33.000000                 1.000000    1.000000
75%           4.000000   42.000000                 2.000000    1.000000
max           4.000000   75.000000                 4.000000    2.000000
```

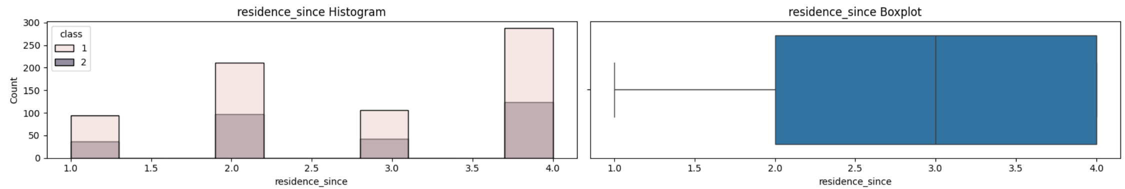
	class
count	999.000000
mean	1.300300
std	0.458618
min	1.000000
25%	1.000000
50%	1.000000
75%	2.000000
max	2.000000

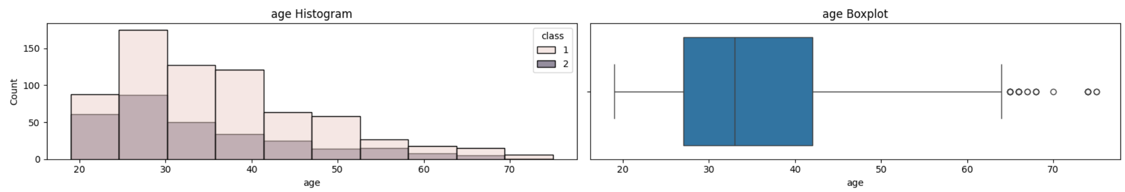
[7]:
```python
for i in df.columns:
    if df[i].dtype == 'int64':
        fig, ax = plt.subplots(1, 2, figsize=(17, 3))

        sns.histplot(data=df, x=i, bins=10, ax=ax[0], hue='class')
        ax[0].set_title(f'{i} Histogram')


        sns.boxplot(data=df, x=i, ax=ax[1])
        ax[1].set_title(f'{i} Boxplot')

        plt.tight_layout()
        plt.show();
```

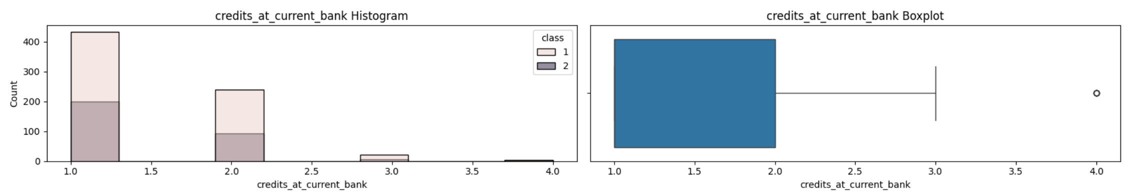


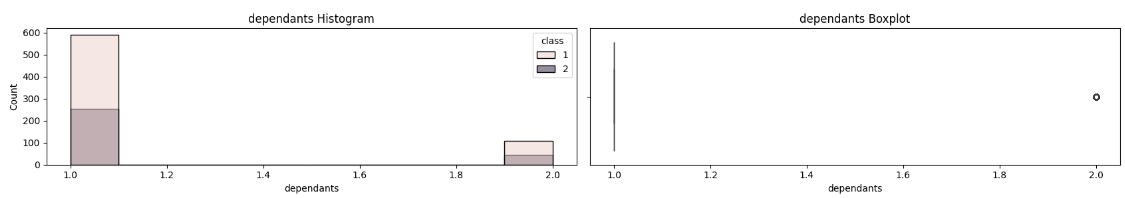


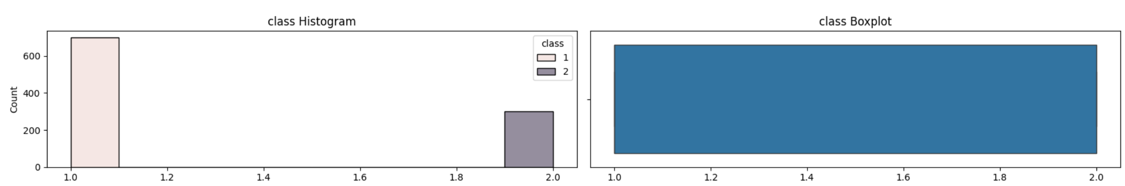






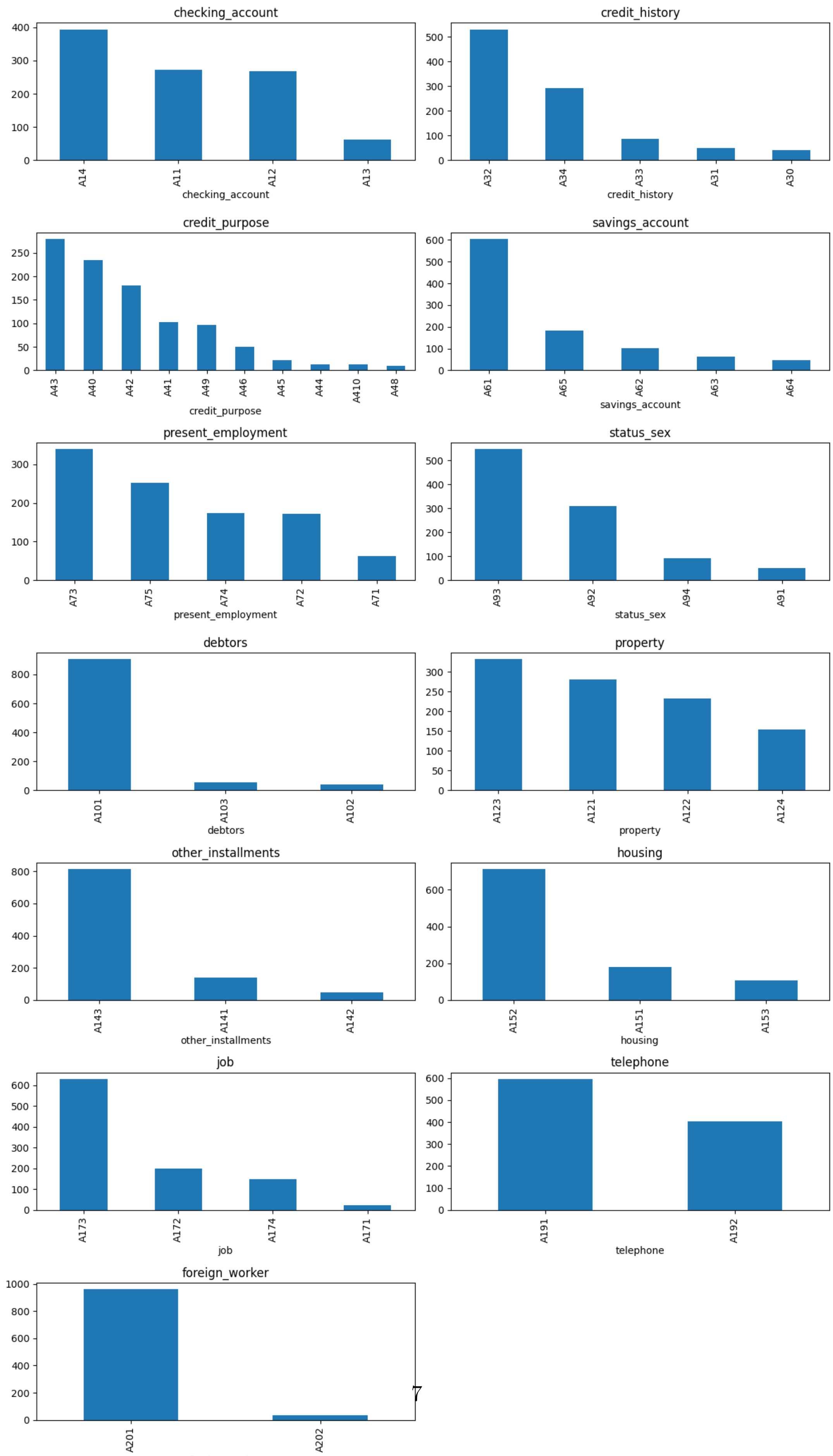






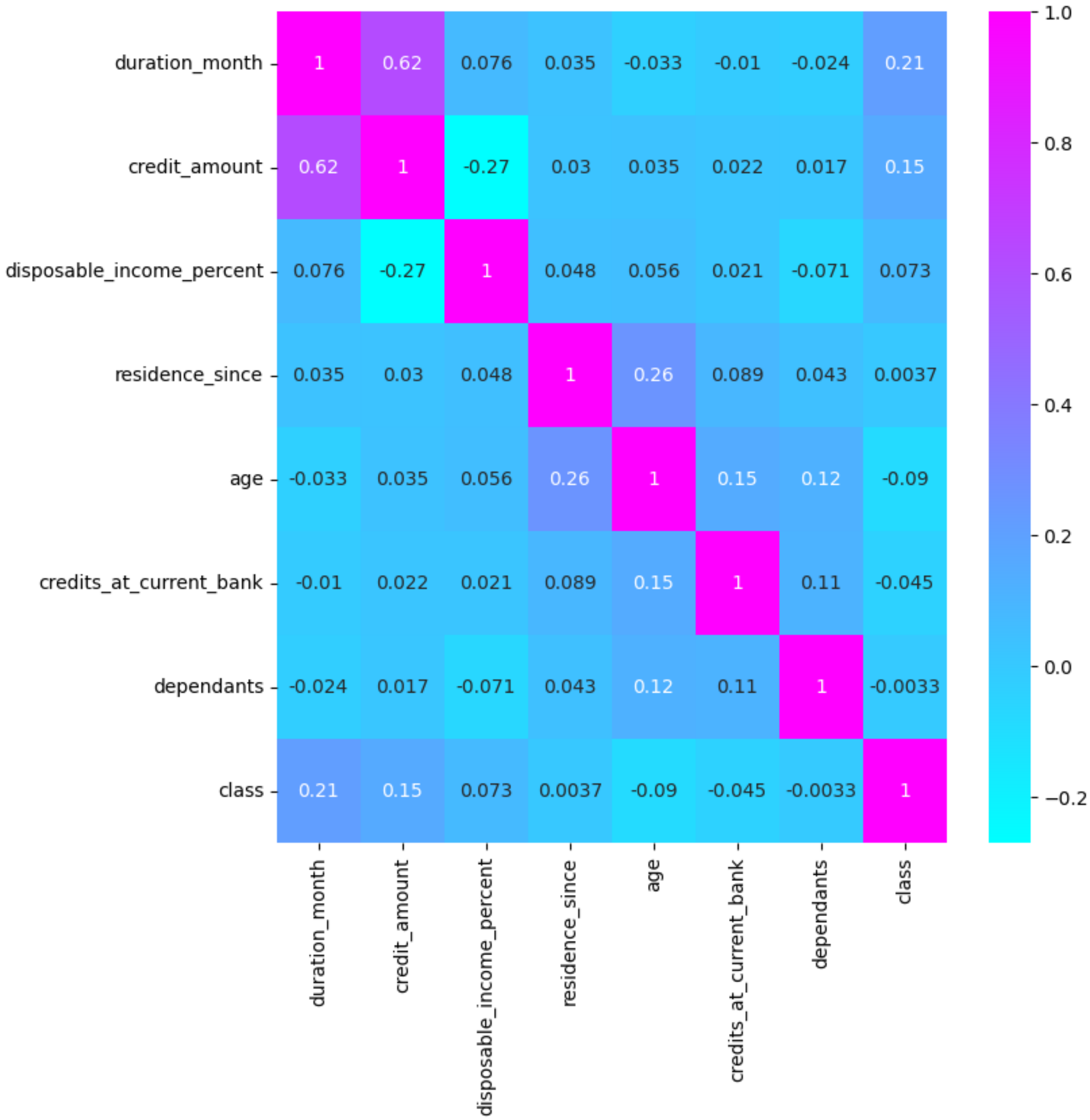
[8]:
```python
object_columns = df.select_dtypes(include='object').columns

num_rows = (len(object_columns) + 1) // 2
```

```
fig, axes = plt.subplots(num_rows, 2, figsize=(12, 3*num_rows))

axes = axes.flatten()

for i, col in enumerate(object_columns):
    df[col].value_counts().plot(kind='bar', ax=axes[i])
    axes[i].set_title(col)

for i in range(len(object_columns), len(axes)):
    axes[i].axis('off')

plt.tight_layout()
plt.show()
```


checking_account
A14
A11
A12
A13
credit_history
A32
A34
A33
A31
A30
credit_purpose
A43
A40
A42
A41
A49
A46
A45
A44
A410
A48
savings_account
A61
A65
A62
A63
A64
present_employment
A73
A75
A74
A72
A71
status_sex
A93
A92
A94
A91
debtors
A101
A103
A102
property
A123
A121
A122
A124
other_installments
A143
A141
A142
housing
A152
A151
A153
job
A173
A172
A174
A171
telephone
A191
A192
foreign_worker
A201
A202

[9]:
```
corr_matr = df.corr(numeric_only=True)
plt.figure(figsize=(8,8))
sns.heatmap(corr_matr, cmap= 'cool', annot= True)
```

[9]: <Axes: >



0.1.2 Analayzing Good vs Bad Credit

[10]:
```
bad_credit = df[df['class'] == 2]
good_credit = df[df['class'] == 1]
```

[11]:
```
bad_credit.groupby('credits_at_current_bank').mean(numeric_only = True)
```

[11]:
```
                         duration_month  credit_amount  \
credits_at_current_bank
1                             24.335000    3751.870000
2                             26.076087    4313.076087
3                             24.000000    4204.000000
4                             24.000000    4518.500000

                         disposable_income_percent  residence_since  \
credits_at_current_bank
1                                         3.150000         2.770000
2                                         3.032609         2.956522
3                                         2.333333         3.500000
4                                         3.000000         4.000000

                               age  dependants  class
credits_at_current_bank
1                        33.250000    1.135000    2.0
2                        35.054348    1.184783    2.0
3                        40.833333    1.333333    2.0
4                        34.500000    1.000000    2.0
```

[12]:
```
good_credit.groupby('credits_at_current_bank').mean(numeric_only = True)
```

[12]:
```
                         duration_month  credit_amount  \
credits_at_current_bank
1                             19.166282    2963.034642
2                             19.858333    3043.820833
3                             13.454545    3008.772727
4                             19.500000    2236.750000

                         disposable_income_percent  residence_since  \
credits_at_current_bank
1                                         2.856813         2.806005
2                                         3.029167         2.850000
3                                         2.727273         3.272727
4                                         4.000000         3.750000

                               age  dependants  class
credits_at_current_bank
1                        35.247113    1.129330    1.0
2                        36.716667    1.179167    1.0
```

```
3                         45.545455    1.363636    1.0
4                         53.500000    1.500000    1.0
```

Observations: - The **average credit amount** in people with bad credit tends to me more in general in comparison to people with good credit. In other words, bad credit has more accounts open and ask for more money - The **average age** of people with 4 or more credit accounts at the current bank is 53 years old with good credit and 34.5 years old with bad credit - We can drop the dependants and residence_since. These features are very similar between people with good and bad credit.

[13]:
```
df = df.drop(columns=['dependants', 'residence_since'], axis= 1)
```

Observation:

I am dropping Dependats and residence since there is no strong correlation among other variables.

Savings account/bonds

A61 : … < 100 DM

A62 : 100 <= … < 500 DM

A63 : 500 <= … < 1000 DM

A64 : .. >= 1000 DM

A65 : unknown/ no savings account

Status of existing checking account

A11 : … < 0 DM

A12 : 0 <= … < 200 DM

A13 : … >= 200 DM /

salary assignments for at least 1 year

A14 : no checking account

[14]:
```
print(f'Good credit:\n{good_credit.savings_account.value_counts()}')
print(f'Bad Credit:\n{bad_credit.savings_account.value_counts()}')
print(f'Good credit:\n{good_credit.checking_account.value_counts()}')
print(f'Bad Credit:\n{bad_credit.checking_account.value_counts()}')
```

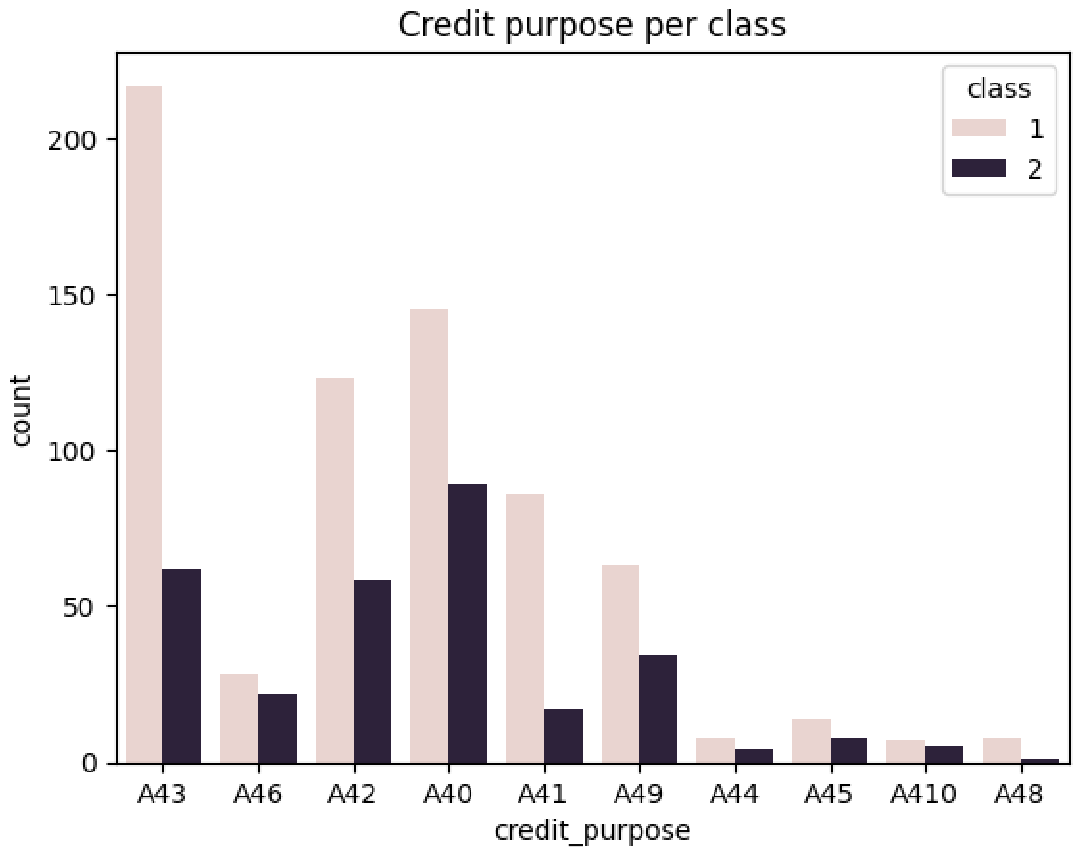
```
Good credit:
savings_account
A61    386
A65    150
A62     69
A63     52
A64     42
Name: count, dtype: int64
Bad Credit:
savings_account
```

```
A61    217
A62     34
A65     32
A63     11
A64      6
Name: count, dtype: int64
Good credit:
checking_account
A14    348
A12    164
A11    138
A13     49
Name: count, dtype: int64
Bad Credit:
checking_account
A11    135
A12    105
A14     46
A13     14
Name: count, dtype: int64
```

Observations: - The majority of people with good credit do not have checking account at the current bank, while people with bad credit have more accoutns open but have less than 200 DM - For the people that do have an account open, people with good credit have more than 200 DM in their account

Maybe We should consider using one-hot encoding on checking and savings account

[15]:
```
sns.countplot(x ='credit_purpose',hue='class', data= df)
plt.title('Credit purpose per class')
plt.show();
```



Attribute 4: (qualitative)

Purpose

A40 : car (new)

A41 : car (used)

A42 : furniture/equipment

A43 : radio/television

A44 : domestic appliances

A45 : repairs

A46 : education

A47 : (vacation - does not exist?)

A48 : retraining

A49 : business

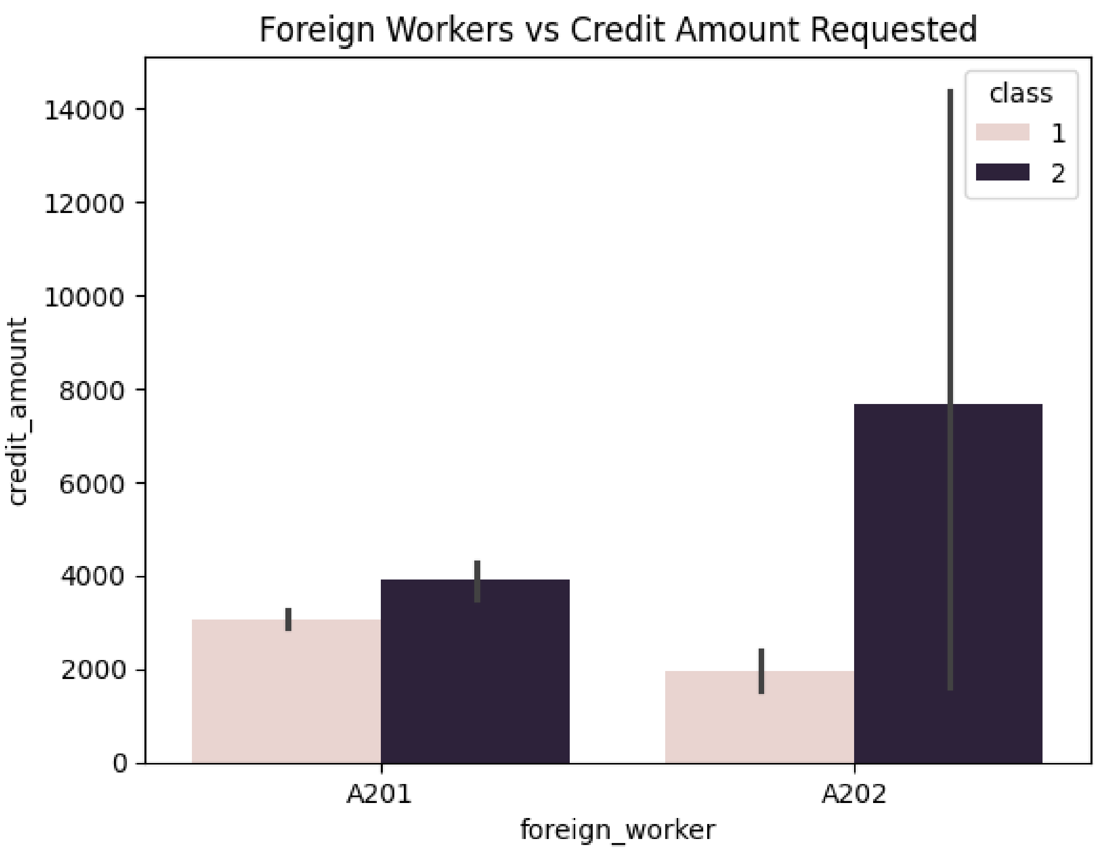
A410 : others

Observations: - Class 1(good) use their credit for radio and televisions, cars and furniture/equipment, while people with bad credit tend to use their credit mostly for purchasing a car

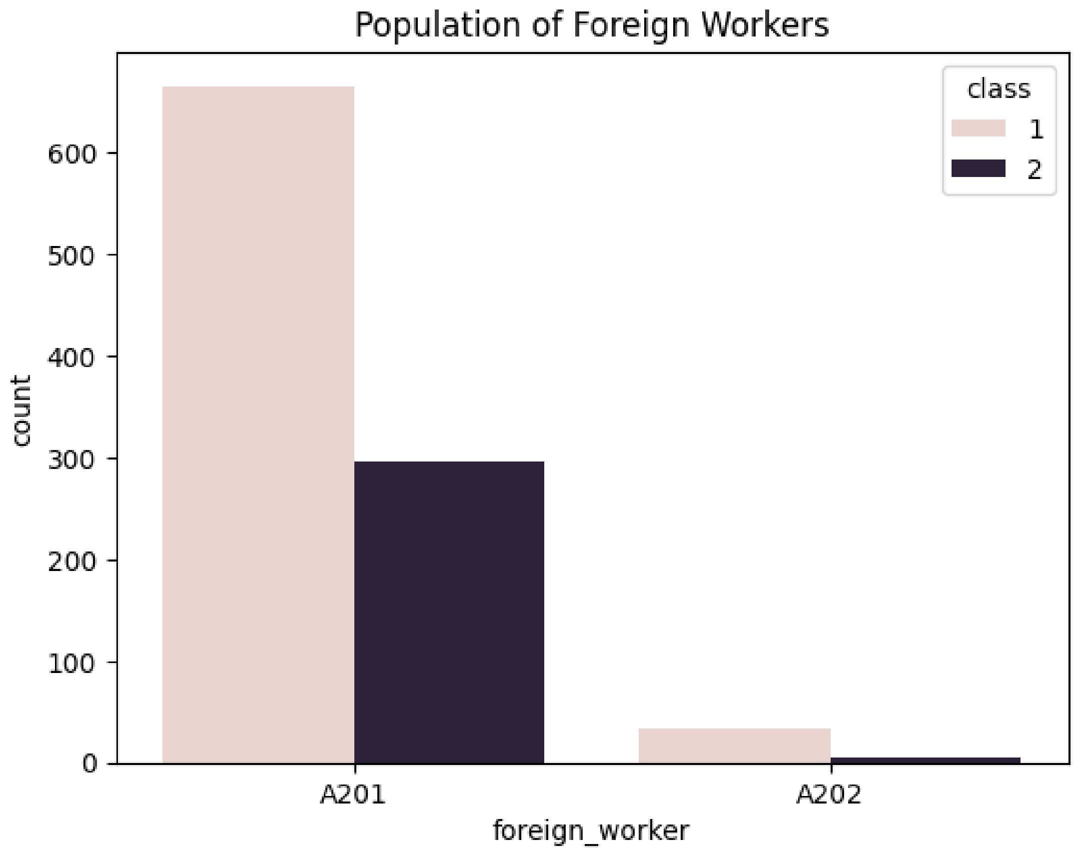
We should use one-hot encoding for credit purpose

[16]:
```
df_encoded = pd.get_dummies(df, columns=['credit_purpose'], prefix=␣
 ↪'credit_purpose')
```

[17]:
```
sns.barplot(x = 'foreign_worker', y ='credit_amount', data = df,  hue='class')
plt.title('Foreign Workers vs Credit Amount Requested')
plt.show();
```



[18]:
```
sns.countplot(x=df['foreign_worker'], hue = df['class'])
plt.title('Population of Foreign Workers')
plt.show();
```



[19]:
```
print(df['foreign_worker'].value_counts().sum())
print('----------------------------------')
print(df['foreign_worker'].value_counts()/999)
```

```
999
----------------------------------
foreign_worker
A201    0.962963
A202    0.037037
Name: count, dtype: float64
```

foreign worker:

A201 : yes

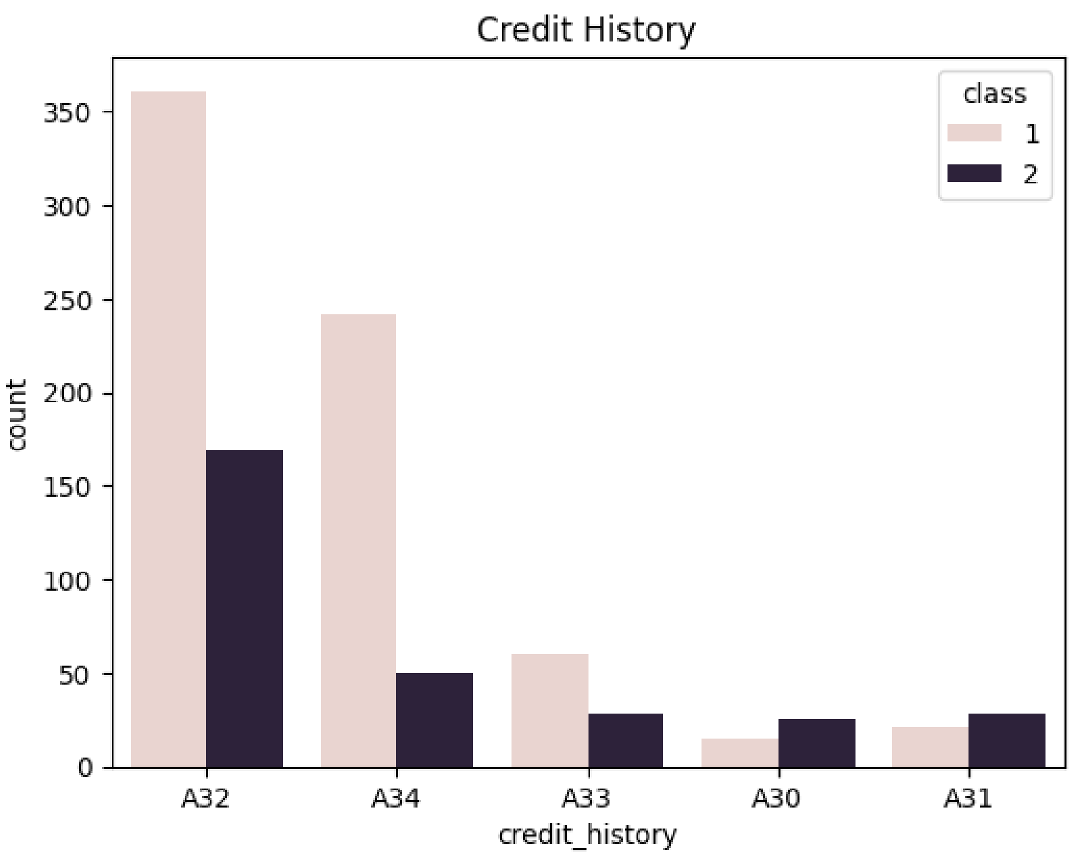
A202 : no

Observations: - Foreign workers, tend to ask higher amnounts of credit and tend to have a population with higher bad credit history

- **Since Foreign workers tend to have bad credit we should encode this as well and becasue it composes 96% of our dataset**

[20]:
```
# Dropping Foreign Column to Avoid Multicolinearity
df_encoded = pd.get_dummies(df_encoded, columns=['foreign_worker'],
    drop_first=True, prefix='Foreign')
```

[21]:
```
sns.countplot(x = 'credit_history', data=df, hue ='class')
plt.title('Credit History')
plt.show();
```



Credit history

A30 : no credits taken/

`all credits paid back duly`

A31 : all credits at this bank paid back duly

A32 : existing credits paid back duly till now

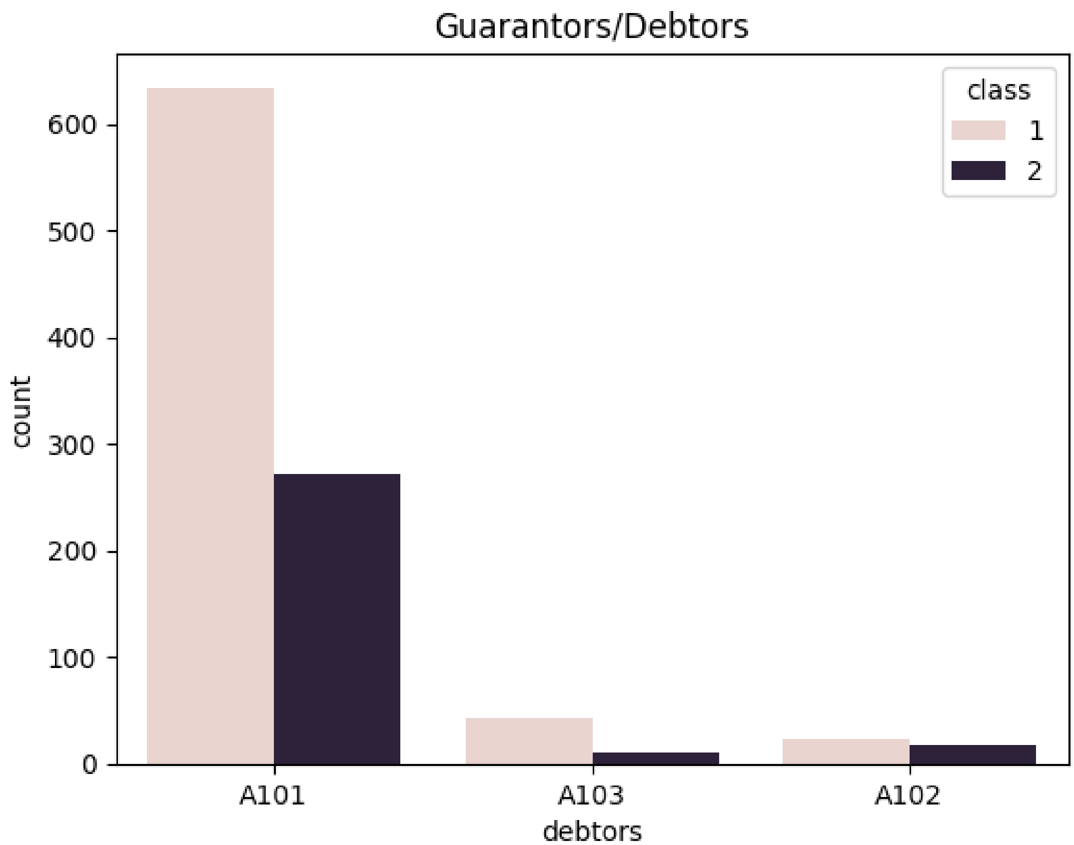
A33 : delay in paying off in the past

A34 : critical account/ other credits existing (not at this bank)

Observations: - Although the majority of people with good and bad credit tend to pay off all their debt. There is a significant amount of people with bad debt that have accounts classified as critical in other banks. This could mean that they are looking to get more credit with bad history in other banks

[22]:
```
df_encoded = pd.get_dummies(df_encoded, columns=['credit_history'],␣
↪prefix='credit_history')
```

[23]:
```
sns.countplot(data=df, x='debtors', hue='class')
plt.title('Guarantors/Debtors')
plt.show()
```



Other debtors / guarantors

    A101 : none

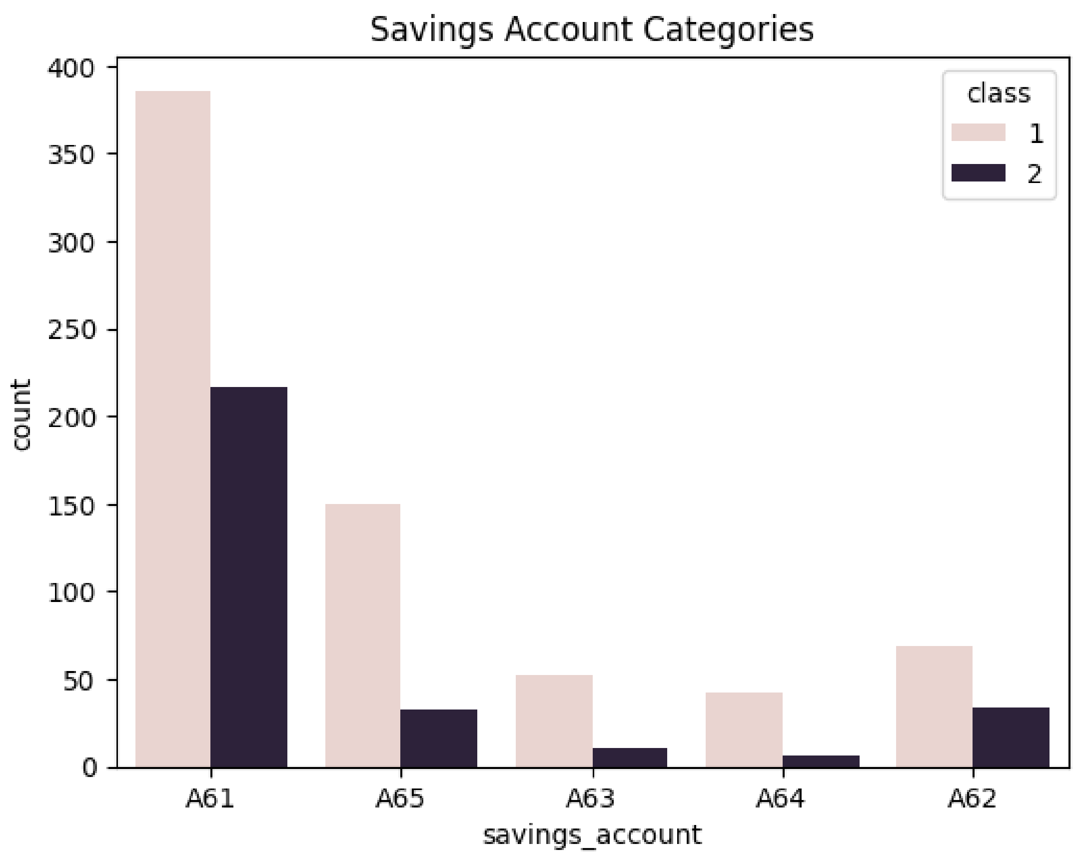
    A102 : co-applicant

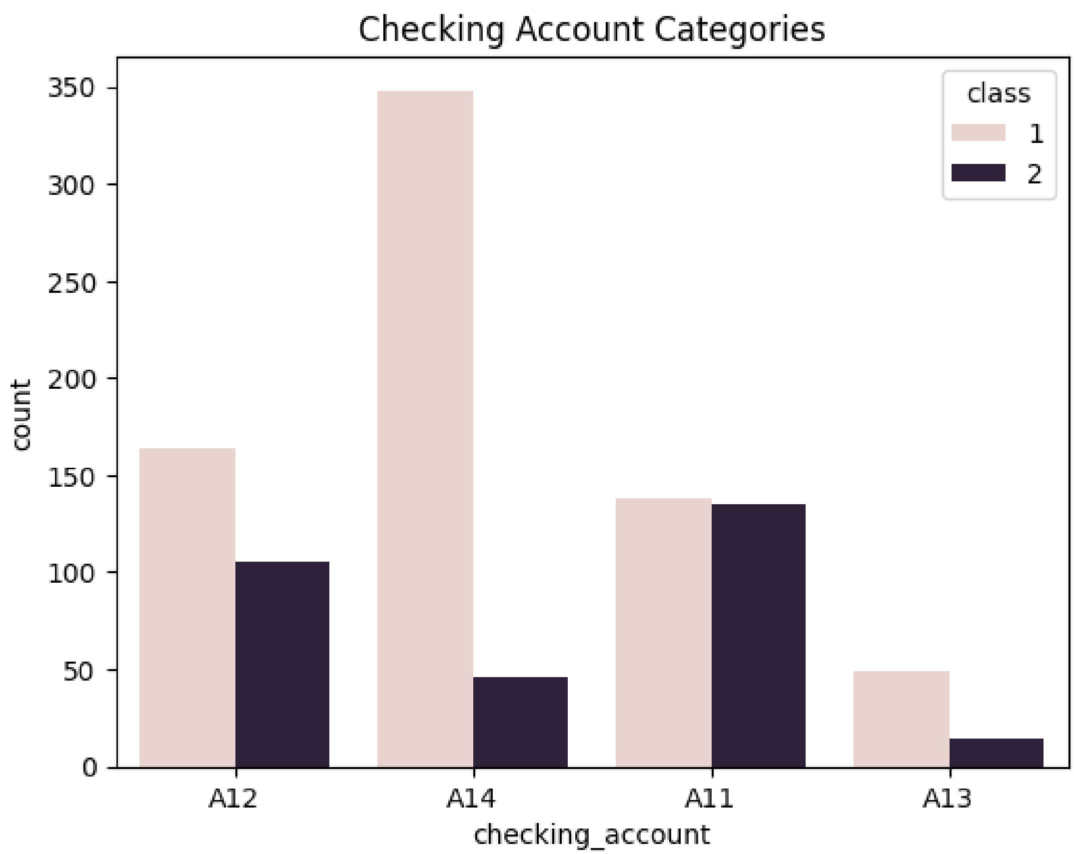
    A103 : guarantor

We can eliminate this column

[24]:
```
df_encoded = df_encoded.drop(columns= 'debtors', axis=1)
```

[25]:
```
sns.countplot(data = df , x = df['savings_account'], hue='class')
plt.title('Savings Account Categories')
plt.show();
sns.countplot(data = df , x = df['checking_account'], hue='class')
plt.title('Checking Account Categories')
plt.show();
```






```
checking account

A11 :      ... <    0 DM

A12 : 0 <= ... <  200 DM

A13 :      ... >= 200 DM /
salary assignments for at least 1 year

A14 : no checking account
```

Savings account/bonds

```
A61 :          ... <  100 DM

A62 :   100 <= ... <  500 DM

A63 :   500 <= ... < 1000 DM

A64 :          .. >= 1000 DM
```

```
        A65 :   unknown/ no savings account
```

We can include checking and savings account feature since it is important for financial institutions to evaluate how much available capital they have

[26]:
```
df_encoded = pd.get_dummies(df_encoded, columns=['checking_account'],␣
 ↪prefix='checking_account')
df_encoded = pd.get_dummies(df_encoded, columns=['savings_account'],␣
 ↪prefix='savings_account')
```

Dropping telephone since it is not a determinant factor for credit risk worthiness

[27]:
```
df_encoded = df_encoded.drop(columns='telephone' , axis= 1)
```

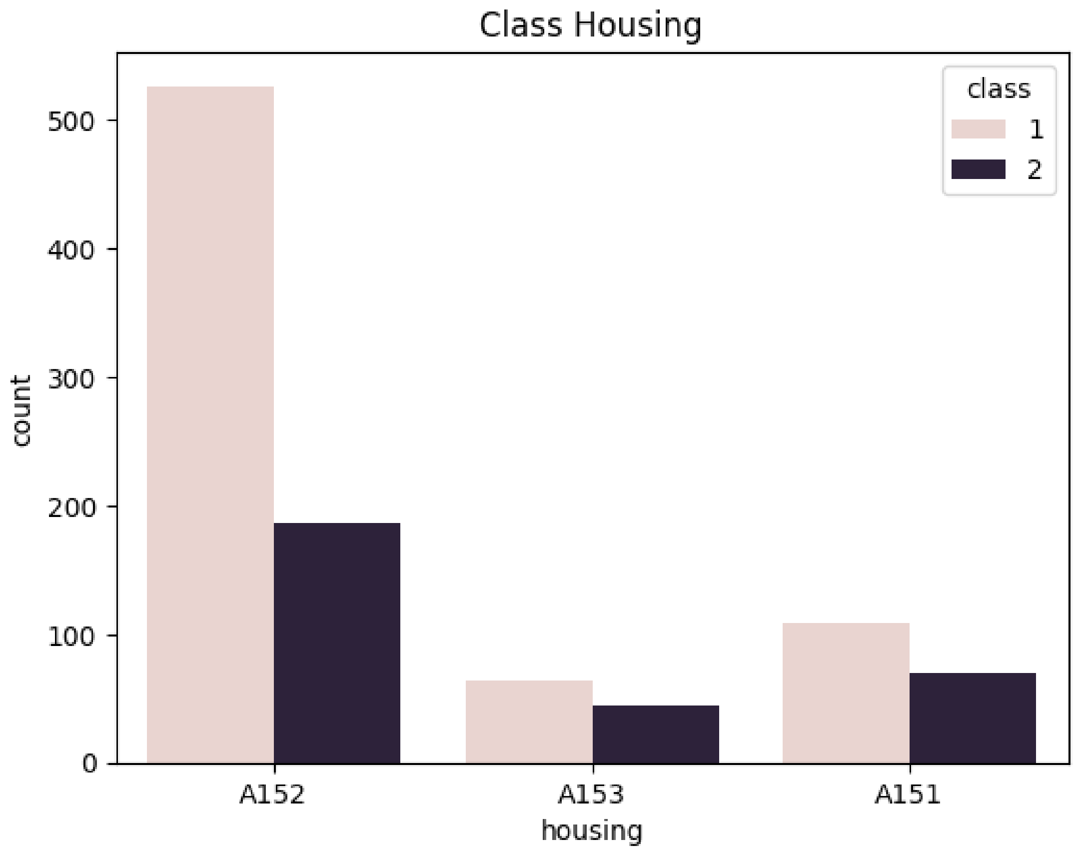
[28]:
```
df.groupby('credits_at_current_bank')['class'].sum()
```

[28]:
```
credits_at_current_bank
1    833
2    424
3     34
4      8
Name: class, dtype: int64
```

Double of the amount of people with good credit have only one account open at the current bank in comparison to people with bad credit

[29]:
```
df_encoded = pd.get_dummies(df_encoded, columns=['credits_at_current_bank'],␣
 ↪prefix='current_bank_credit')
```

[30]:
```
sns.countplot(data=df_encoded, x = 'housing', hue='class')
plt.title('Class Housing')
plt.show();
```




```
Housing
A151 : rent
A152 : own
A153 : for free
```

Owning a home is an important factor for credit approval and usully homeowners need to have a 'decent' credit to own a home

[31]:
```
df_encoded = pd.get_dummies(df_encoded, columns=['housing'], prefix='housing')
```

[32]:
```
sns.countplot(data=df_encoded, x = 'job', hue = 'class' )
plt.title('Job Category per Class')
plt.show();
```


```
  Job
A171 : unemployed/ unskilled  - non-resident
A172 : unskilled - resident
A173 : skilled employee / official
A174 : management/ self-employed/
   highly qualified employee/ officer
```

The distribution for each class and employment seems proportional, we can omit this category

[33]:
```python
df_encoded = pd.get_dummies(df_encoded, columns=['job'], prefix='job')
```

[34]:
```python
sns.countplot(data=df_encoded, x  = 'property', hue = 'class')
plt.title('Count of Properties per class')
plt.show();
```

Property

A121 : real estate

A122 : if not A121 : building society savings agreement/life insurance

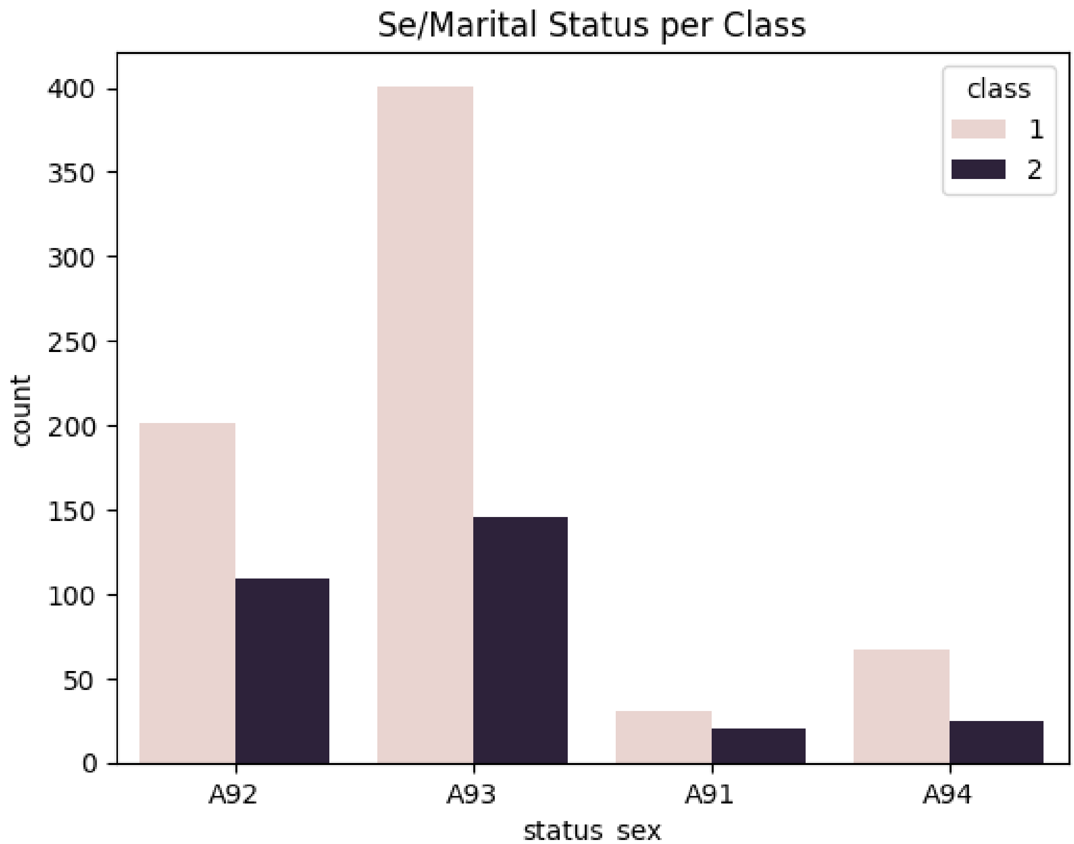
A123 : if not A121/A122 : car or other, not in attribute 6

A124 : unknown / no property

Encoding this feature because banks tend to look at collaterals when applying for credit lines

[35]:
```
df_encoded = pd.get_dummies(df_encoded, columns=['property'], prefix='property')
```

[36]:
```
sns.countplot(data=df_encoded, x  = 'status_sex', hue = 'class')
plt.title('Se/Marital Status per Class')
plt.show();
```



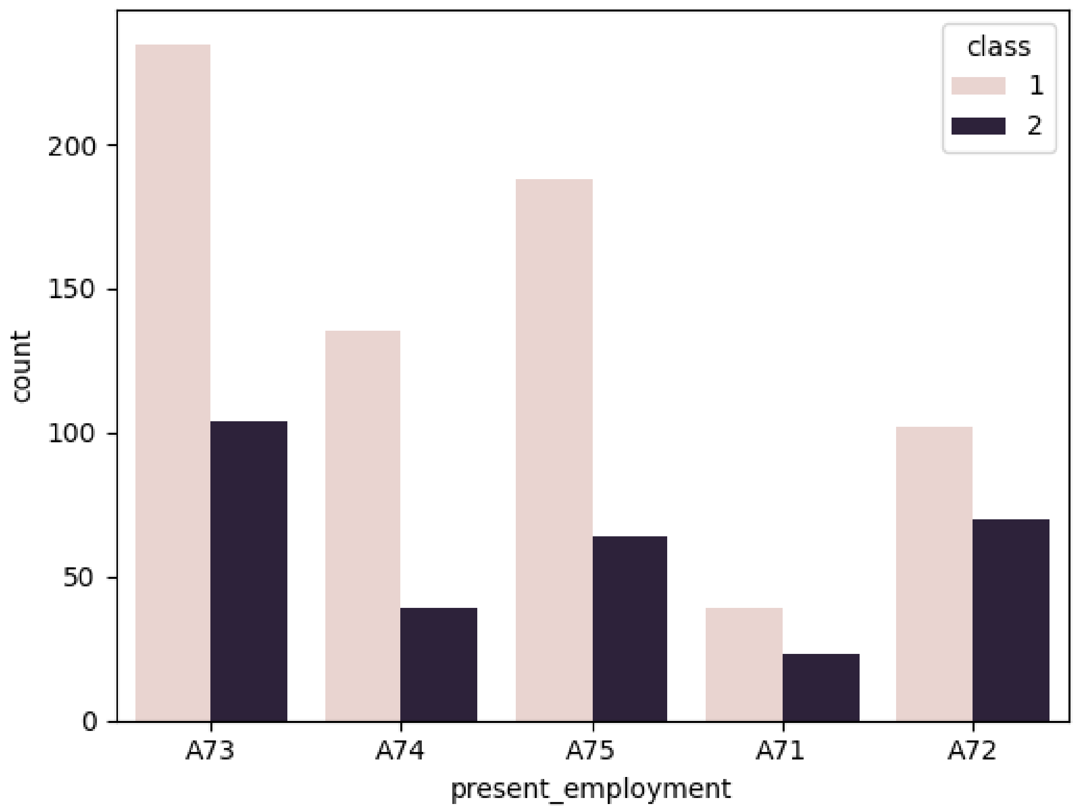

```
Personal status and sex
A91 : male   : divorced/separated
A92 : female : divorced/separated/married
    A93 : male   : single
A94 : male   : married/widowed
A95 : female : single
```

Encoding this feature becasue you can tell there is a difference betweeing goo/bad credit between male and females

[37]:
```
df_encoded = pd.get_dummies(df_encoded, columns=['status_sex'],␣
↪prefix='status_sex')
```

[38]:
```
sns.countplot(data=df_encoded, x  = 'present_employment', hue = 'class')
```

[38]: <Axes: xlabel='present_employment', ylabel='count'>



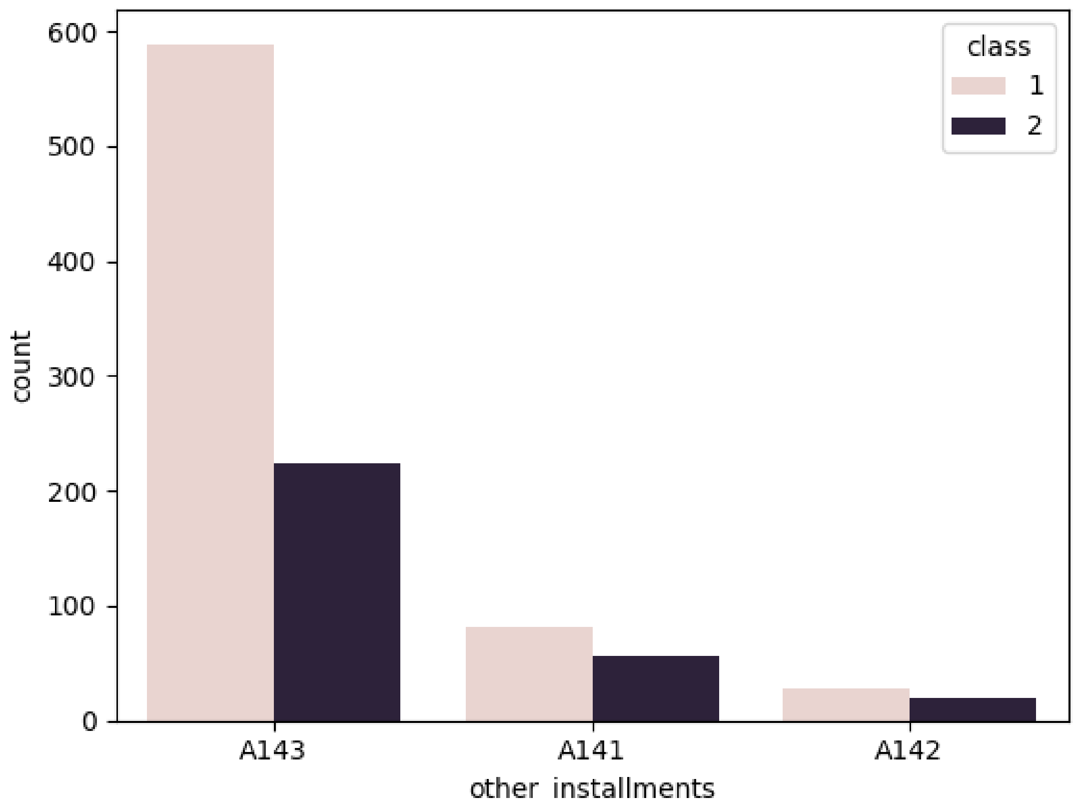

```
A71 : unemployed
    A72 :       ... < 1 year
    A73 : 1  <= ... < 4 years
    A74 : 4  <= ... < 7 years
    A75 :       .. >= 7 years
```

Encoding this feature becasue it is important to have a working history that is stable, it could determine you eligibility for a credit line (domain knowledge)

[39]:
```
df_encoded = pd.get_dummies(df_encoded, columns=['present_employment'],␣
 ↪prefix='years_in employment')
```

[40]:
```
sns.countplot(data=df_encoded, x  = 'other_installments', hue = 'class')
```

[40]: <Axes: xlabel='other_installments', ylabel='count'>




```
Other installment plans
      A141 : bank
      A142 : stores
      A143 : none
```

Having Other Installments does not seem that affect wether you have good or bad credit,since the population results look proportional

[41]:
```
#df_encoded = pd.get_dummies(df_encoded, columns=['other_installments'],␣
 ↪prefix='other_installments')
df_encoded = df_encoded.drop(columns='other_installments', axis= 1)
```

[42]:
```
pd.set_option('display.max_columns', None)

df_encoded.head(1)
```

[42]:
```
   duration_month  credit_amount  disposable_income_percent  age  class  \
0              48           5951                          2   22      2

   credit_purpose_A40  credit_purpose_A41  credit_purpose_A410  \
0               False               False                False
```

```
   credit_purpose_A42  credit_purpose_A43  credit_purpose_A44  \
0               False                True               False

   credit_purpose_A45  credit_purpose_A46  credit_purpose_A48  \
0               False               False               False

   credit_purpose_A49  Foreign_A202  credit_history_A30  credit_history_A31  \
0               False         False               False               False

   credit_history_A32  credit_history_A33  credit_history_A34  \
0                True               False               False

   checking_account_A11  checking_account_A12  checking_account_A13  \
0                 False                  True                 False

   checking_account_A14  savings_account_A61  savings_account_A62  \
0                 False                 True                False

   savings_account_A63  savings_account_A64  savings_account_A65  \
0                False                False                False

   current_bank_credit_1  current_bank_credit_2  current_bank_credit_3  \
0                   True                  False                  False

   current_bank_credit_4  housing_A151  housing_A152  housing_A153  job_A171  \
0                  False         False          True         False     False

   job_A172  job_A173  job_A174  property_A121  property_A122  property_A123  \
0     False      True     False           True          False          False

   property_A124  status_sex_A91  status_sex_A92  status_sex_A93  \
0          False           False            True           False

   status_sex_A94  years_in employment_A71  years_in employment_A72  \
0           False                    False                    False

   years_in employment_A73  years_in employment_A74  years_in employment_A75
0                     True                    False                    False
```

0.2 Machine Learning

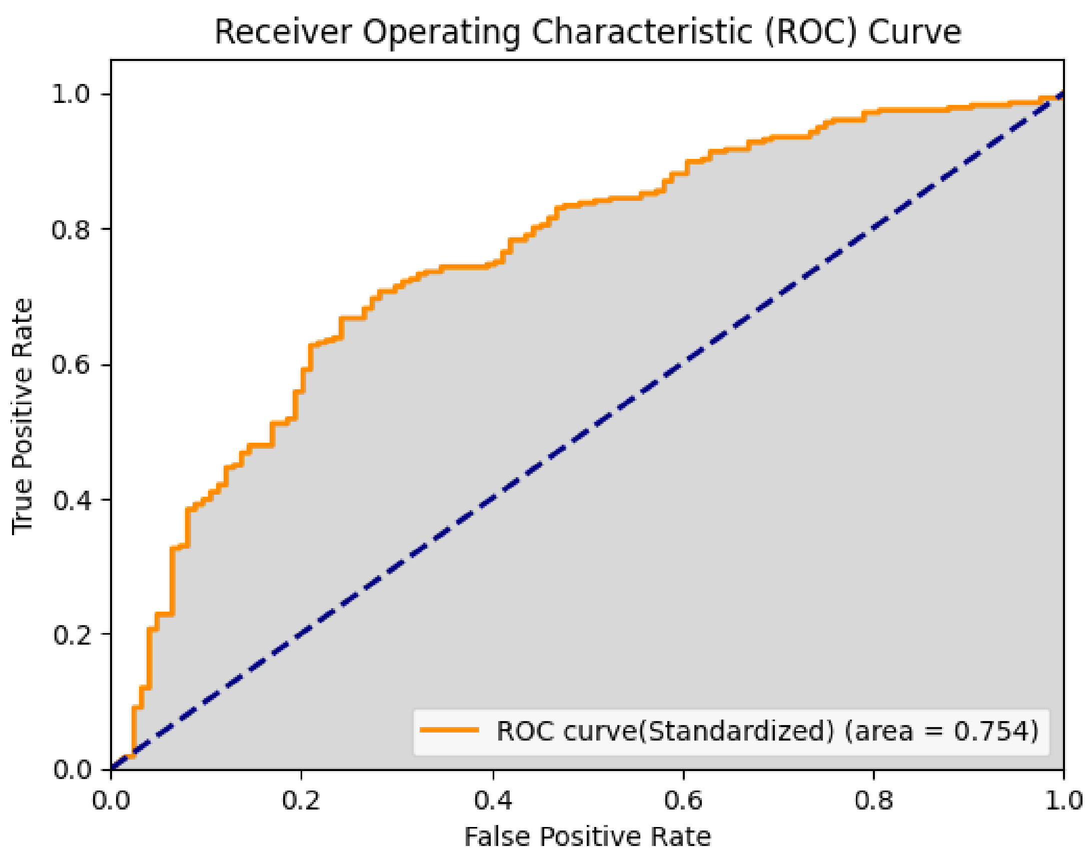
[43]:
```
#1 is Good, 0 is bad
mapping_dict = {1: 1, 2: 0}
df_encoded['class'] = df_encoded['class'].map(mapping_dict)

#Seperating Features from Target
x = df_encoded.drop(columns='class',axis =1)
```

```
y = df_encoded['class']
```

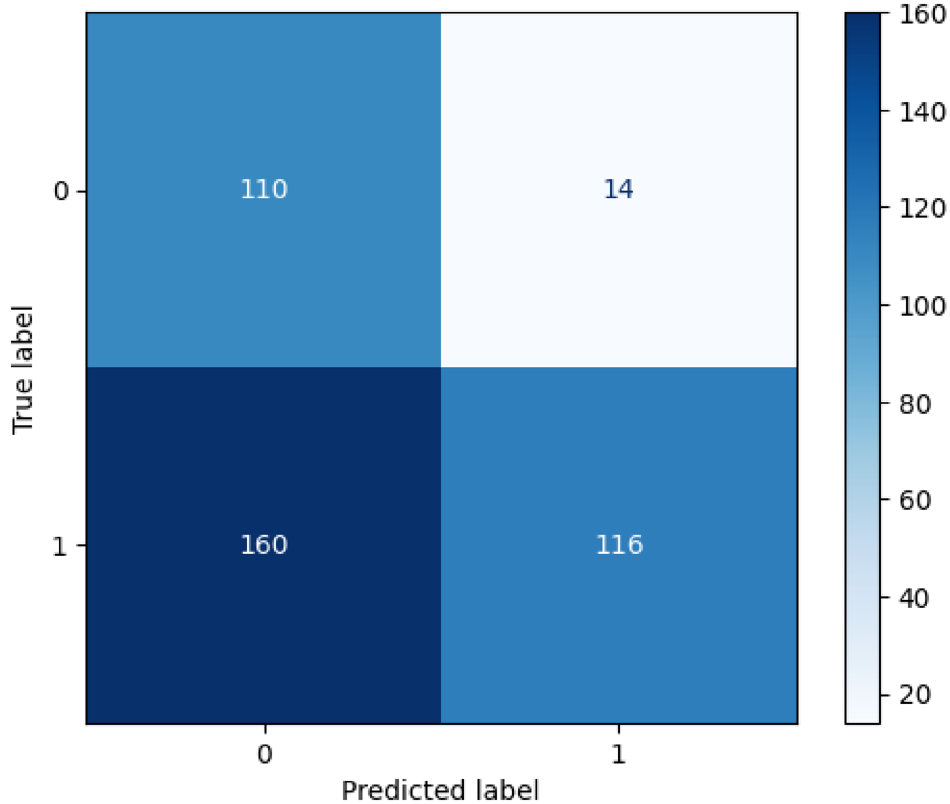
0.3 Naive Bayes Algorithm With Standardization

[44]:
```
#Splitting
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size= .60,␣
 ↪random_state= 42)

#Standardizing
scaler = StandardScaler()
xtrain_scale = scaler.fit_transform(x_train)
xtest = scaler.transform(x_test)

# Hyperparameter Tuning
param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
grid_search.fit(xtrain_scale, y_train)

# Training
n_b_best = grid_search.best_estimator_
n_b_best.fit(xtrain_scale, y_train)
predictions = n_b_best.predict(xtest)

#Performance
scores = n_b_best.score(xtest, y_test)
conf_mtrx = confusion_matrix(y_test, predictions)
precision = precision_score(y_test, predictions)
recall = recall_score(y_test, predictions)
f1 = f1_score(y_test, predictions)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_mtrx)

#Plotting ROC Curve
y_pred_proba = n_b_best.predict_proba(xtest)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba, pos_label=1)
roc_auc = auc(fpr, tpr)

#Results
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve(Standardized)␣
 ↪(area = {round(roc_auc,3)})')
plt.fill_between(fpr, tpr, color='gray', alpha=0.3)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show();
print('Confusion Matrix')
disp.plot(cmap='Blues', include_values=True)
plt.show();

print('----------------------------')
print('Performance Measures')
print('----------------------------')
print(f'Precision:, {precision}')
print(f'Recall:, {recall}')
print(f'F1 Score:, {f1}')
print(f'Accuracy Score: {scores}')
print('------------------------------')
print('Hyperparameter Tuning Results')
print('-----------------------------')
print(f'Best parameters:, {grid_search.best_params_}')
print(f'Best score:", {grid_search.best_score_}')
print(f'False Positive rate: {conf_mtrx[0][1] /
  (conf_mtrx[0][1]+conf_mtrx[0][0])}')
```



```
Confusion Matrix
```




```
----------------------------
Performance Measures
----------------------------
Precision:, 0.8923076923076924
Recall:, 0.42028985507246375
F1 Score:, 0.5714285714285715
Accuracy Score: 0.565
------------------------------
Hyperparameter Tuning Results
-----------------------------
Best parameters:, {'var_smoothing': 0.0001}
Best score:", 0.5459604519774012
False Positive rate: 0.11290322580645161
```

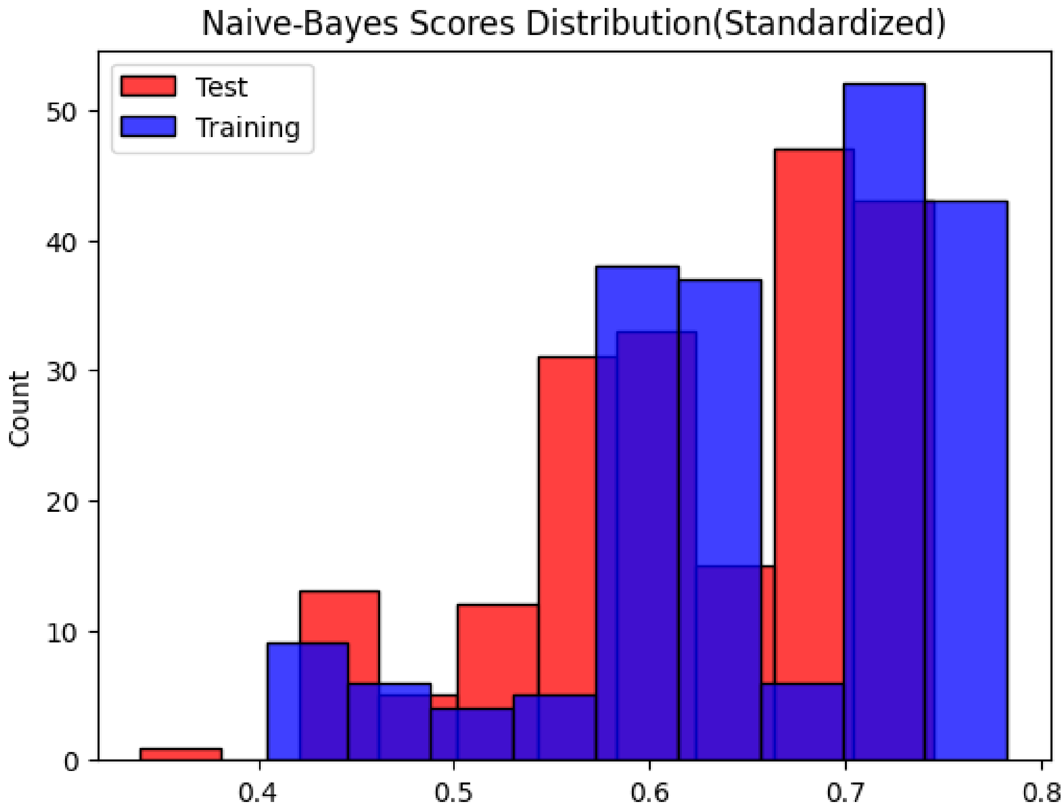
Observation

- The precision on this model is very good buta bit “off-balance” with the Recall score, we are trying to minimize the False Positives and this model tends to do that as well. The problem can arise from the imbalanced data.

0.3.1 Simulating Best Score

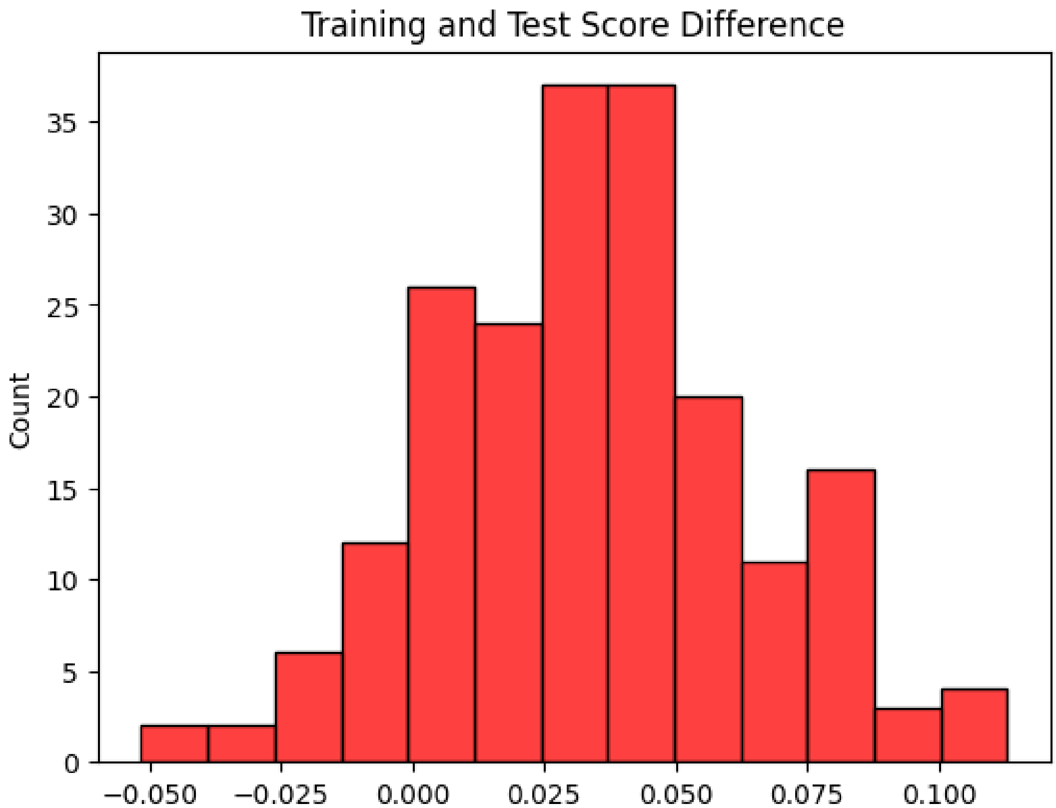
[45]:
```
i = 0

n_b_train_score = []
n_b_test_score = []
diff = []

while i < 200:

    # Splitting
    x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=.60)

    # Standardizing
    scaler = StandardScaler()
    xtrain_scale = scaler.fit_transform(x_train)
    xtest = scaler.transform(x_test)

    # Hyperparameter Tuning
    param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
    grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
    grid_search.fit(xtrain_scale, y_train)

    # Training
    n_b_best = grid_search.best_estimator_
    n_b_best.fit(xtrain_scale, y_train)
    predictions = n_b_best.predict(xtest)

    # Performance
    train_score = n_b_best.score(xtrain_scale, y_train)
    test_score = n_b_best.score(xtest, y_test)
    n_b_train_score.append(train_score)
    n_b_test_score.append(test_score)
    diff_Score = train_score - test_score

    diff.append(diff_Score)

    i +=1


sns.histplot(data= n_b_test_score, color = 'red', label = 'Test')
sns.histplot(data= n_b_train_score, color = 'blue', label ='Training')
plt.title('Naive-Bayes Scores Distribution(Standardized)')
plt.legend()
plt.show();
print(f'Mean Train Score: {np.mean(n_b_train_score)}')
```

```
print(f'Mean Test Score: {np.mean(n_b_test_score)}')
print(f'Mean Diff score: {np.mean(diff)}')
```




```
Mean Train Score: 0.6587145242070116
Mean Test Score: 0.6248874999999999
Mean Diff score: 0.03382702420701169
```

[46]:
```
sns.histplot(data= diff, color = 'red')
plt.title('Training and Test Score Difference')
plt.show();
```



Observation - From the simulations we can see that our score is very large spread and it is skewed to the left, the mean difference of our score is very close to zero indicating that our model is performing well, but like I mentioned before, it could be that the model is not learning well due to the imblanced dataset, the spread is quite high as well and the difference of score having a negative means that the model is performing better on the test stet rather than the training set which is preferable.

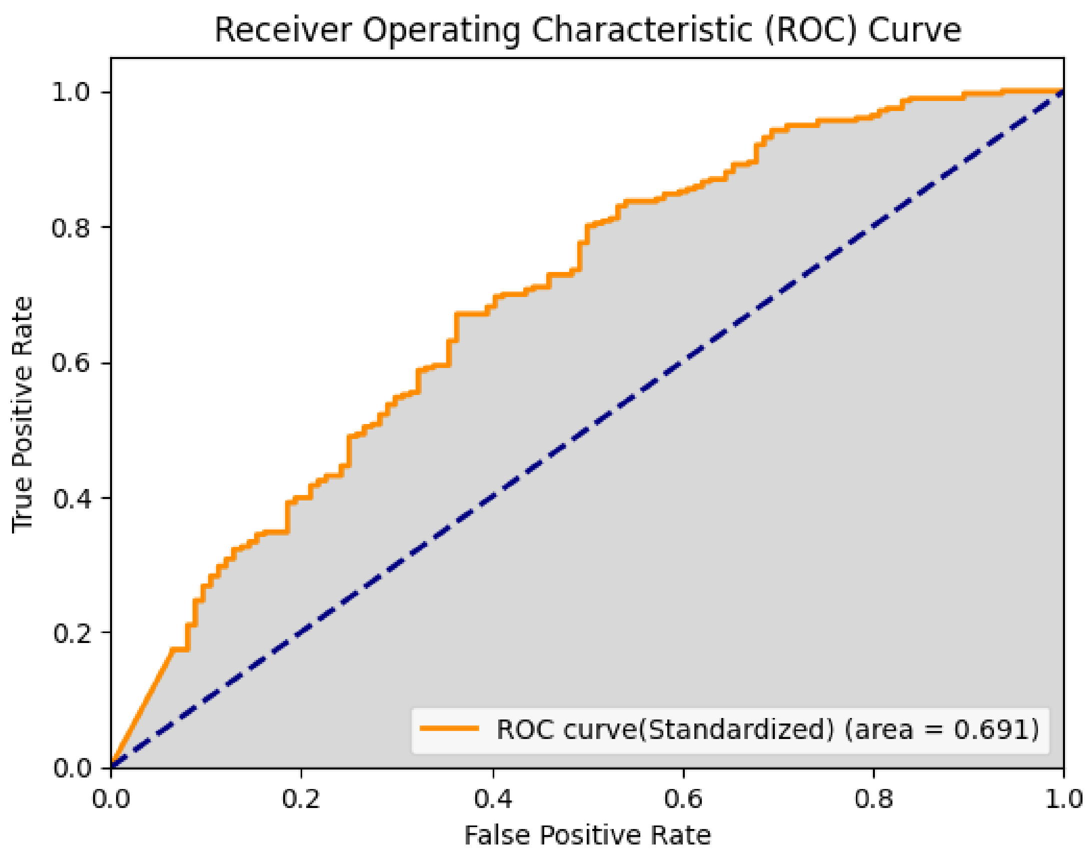
0.4 Naive Bayes Algorithm with Balanced Target and Standardized

[47]:

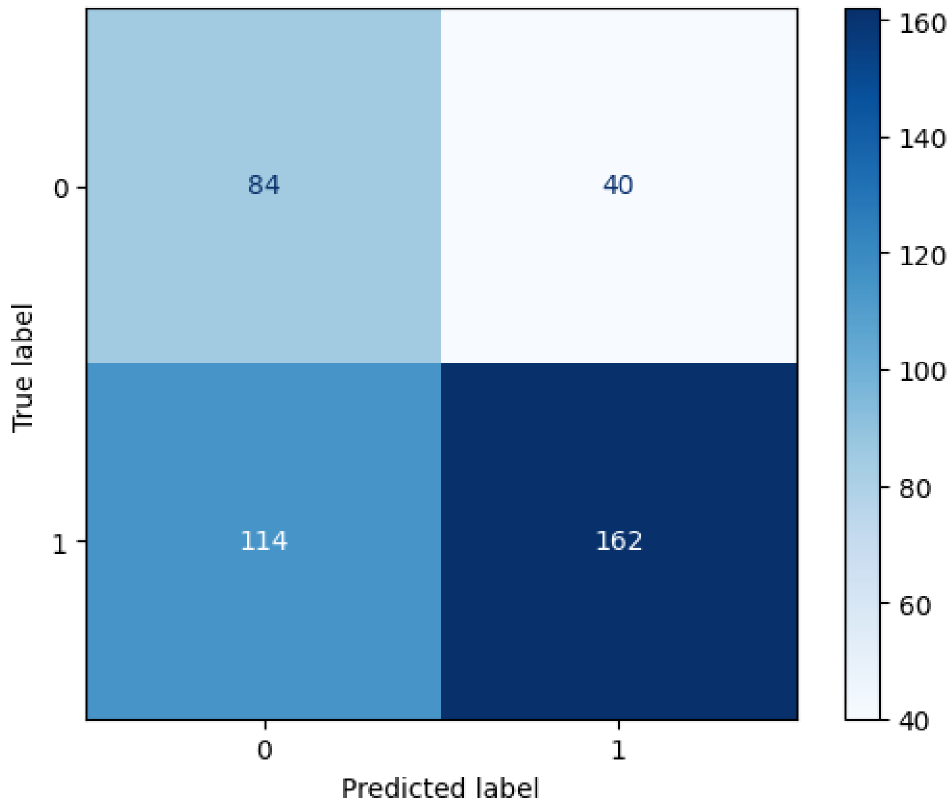
```
#Splitting
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size= .60,␣
 ↪random_state= 42)

#Balancing
smote = SMOTE()
x_train_, y_train_ =  smote.fit_resample(x_train,y_train)

#Standardizing
scaler = StandardScaler()
xtrain_scale = scaler.fit_transform(x_train_)
xtest = scaler.transform(x_test)
```

```
# Hyperparameter Tuning
param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
grid_search.fit(xtrain_scale, y_train_)

# Training
n_b_best = grid_search.best_estimator_
n_b_best.fit(xtrain_scale, y_train_)
predictions= n_b_best.predict(xtest)

#Performance
scores = n_b_best.score(xtest, y_test)
conf_mtrx = confusion_matrix(y_test, predictions)
precision = precision_score(y_test, predictions)
recall = recall_score(y_test, predictions)
f1 = f1_score(y_test, predictions)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_mtrx)

#Plotting ROC Curve
y_pred_proba = n_b_best.predict_proba(xtest)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba, pos_label=1)
roc_auc = auc(fpr, tpr)

#Results
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve(Standardized)␣
 ↪(area = {round(roc_auc,3)})')
plt.fill_between(fpr, tpr, color='gray', alpha=0.3)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show();
print('Confusion Matrix')
disp.plot(cmap='Blues', include_values=True)
plt.show();

print('----------------------------')
print('Performance Measures')
print('----------------------------')
print(f'Precision:, {precision}')
print(f'Recall:, {recall}')
```

```
print(f'F1 Score:, {f1}')
print(f'Accuracy Score: {scores}')
print('-----------------------------')
print('Hyperparameter Tuning Results')
print('----------------------------')
print(f'Best parameters:, {grid_search.best_params_}')
print(f'Best score:", {grid_search.best_score_}')
print(f'False Positive rate: {conf_mtrx[0][1] /␣
↪(conf_mtrx[0][1]+conf_mtrx[0][0])}')
```




```
Confusion Matrix
```




```
----------------------------
Performance Measures
----------------------------
Precision:, 0.801980198019802
Recall:, 0.5869565217391305
F1 Score:, 0.6778242677824268
Accuracy Score: 0.615
------------------------------
Hyperparameter Tuning Results
-----------------------------
Best parameters:, {'var_smoothing': 0.0001}
Best score:", 0.7119327731092436
False Positive rate: 0.3225806451612903
```

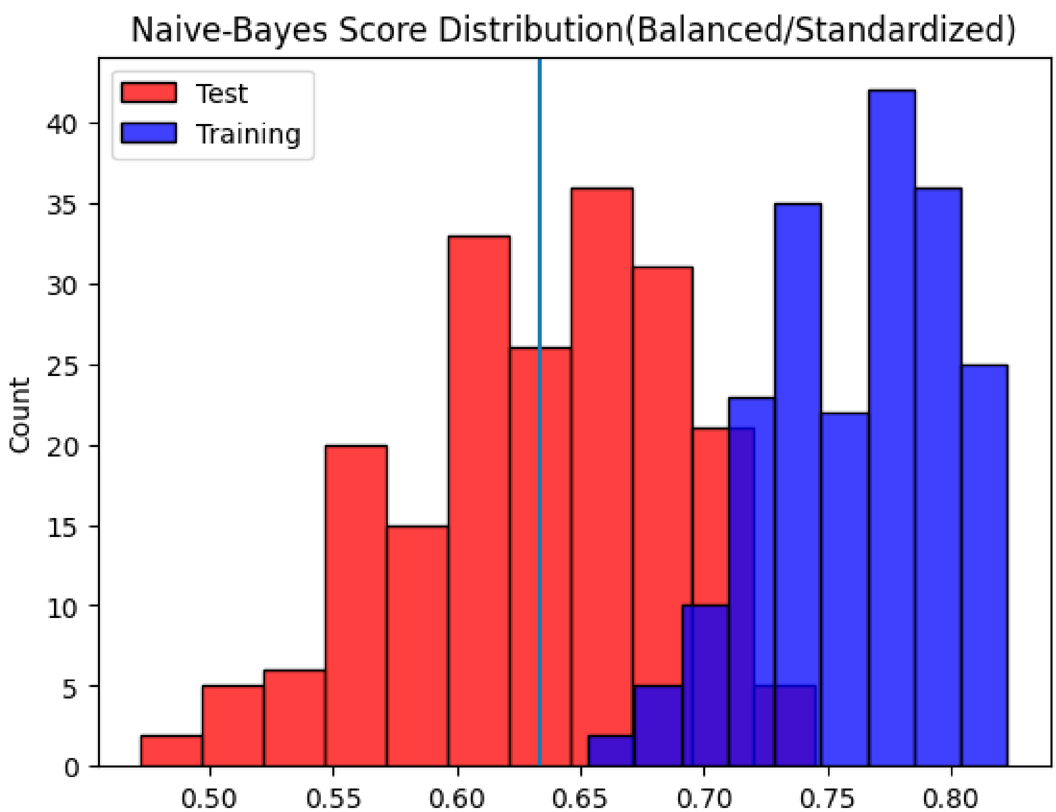
Observations

- Precision has dropped but recall has increased, this means that our model has a good proportion of having large true positives while also making correct predictions. Our Falsse Positive Rate has increased but it is balanced with the Recall score. The AUC is near the 50/50 threshold, it could potentiall cause issue if our model is slightly "guessing" the predictions.

0.4.1 Simulating Best Score

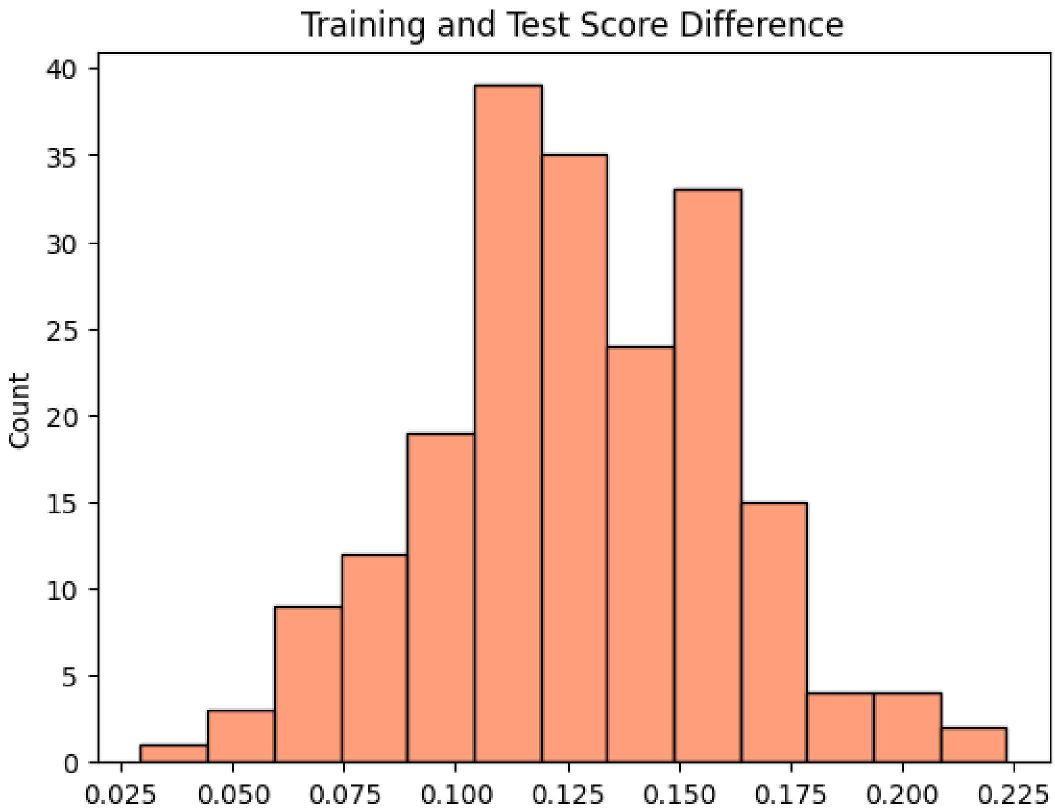
[48]:
```
i = 0
n_b_train_score = []
n_b_test_score = []
diff = []


while i < 200:

    #Splitting
    x_train, x_test, y_train, y_test = train_test_split(x, y, train_size= .60)

   #Balancing
    smote = SMOTE()
    x_train_, y_train_ =  smote.fit_resample(x_train,y_train)

    #Standardizing
    scaler = StandardScaler()
    xtrain_scale = scaler.fit_transform(x_train_)
    xtest = scaler.transform(x_test)

    # Hyperparameter Tuning
    param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
    grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
    grid_search.fit(xtrain_scale, y_train_)


    # Training
    n_b_best = grid_search.best_estimator_
    n_b_best.fit(xtrain_scale, y_train_)
    predictions = n_b_best.predict(xtest)

    # Performance
    train_score = n_b_best.score(xtrain_scale, y_train_)
    test_score = n_b_best.score(xtest, y_test)
    n_b_train_score.append(train_score)
    n_b_test_score.append(test_score)
    diff_Score = train_score - test_score

    diff.append(diff_Score)

    i +=1


sns.histplot(data= n_b_test_score, color = 'red', label = 'Test')
```

```python
sns.histplot(data= n_b_train_score, color = 'blue', label ='Training')
plt.title('Naive-Bayes Score Distribution(Balanced/Standardized)')
plt.legend()
plt.axvline(np.mean(n_b_test_score))
plt.show();

print(f'Mean Train Score: {np.mean(n_b_train_score)}')
print(f'Mean Test Score: {np.mean(n_b_test_score)}')
print(f'Mean Diff score: {np.mean(diff)}')
```




```
Mean Train Score: 0.7613419087298713
Mean Test Score: 0.633625
Mean Diff score: 0.12771690872987132
```

[49]:
```python
sns.histplot(data = diff, color ='coral')
plt.title('Training and Test Score Difference')
plt.show();
```



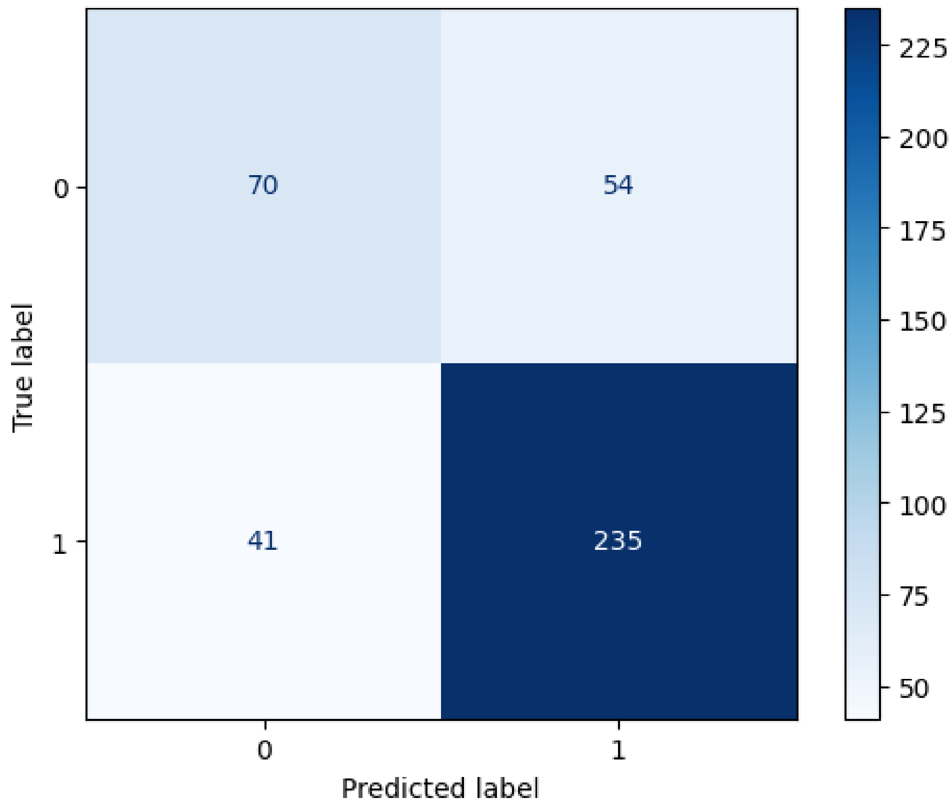
Observation - In comparison to the previous simulation, this model is doing better on the training data, which could also be a sign of overfitting.

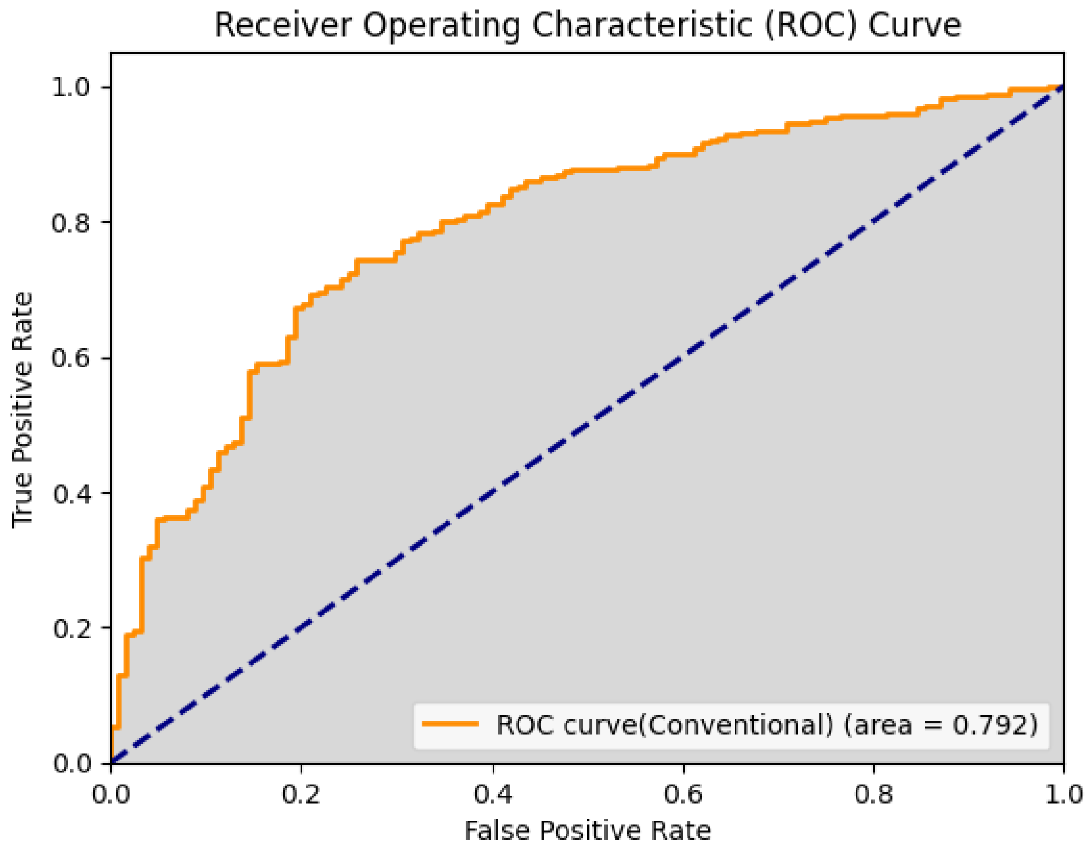
0.5 Without modifications to the dataset

[50]:
```
#Splitting
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size= .60,␣
 ↪random_state= 42)

# Hyperparameter Tuning
param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
grid_search.fit(x_train, y_train)

# Training
n_b_best = grid_search.best_estimator_
n_b_best.fit(x_train, y_train)
predictions_ = n_b_best.predict(x_test)

#Performance
```

```
scores = n_b_best.score(x_test, y_test)
conf_mtrx = confusion_matrix(y_test, predictions_)
precision = precision_score(y_test, predictions_)
recall = recall_score(y_test, predictions_)
f1 = f1_score(y_test, predictions_)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_mtrx)

#Results
print('Confusion Matrix')
disp.plot(cmap='Blues', include_values=True)
plt.show();


#Plotting ROC Curve
y_pred_proba = n_b_best.predict_proba(x_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba, pos_label=1)
roc_auc = auc(fpr, tpr)


plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve(Conventional)␣
 ↪(area = {round(roc_auc,3)})')
plt.fill_between(fpr, tpr, color='gray', alpha=0.3)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show();

print('---------------------------')
print('Performance Measures')
print('---------------------------')
print(f'Precision:, {precision}')
print(f'Recall:, {recall}')
print(f'F1 Score:, {f1}')
print(f'Accuracy Score: {scores}')
print('-----------------------------')
print('Hyperparameter Tuning Results')
print('----------------------------')
print(f'Best parameters:, {grid_search.best_params_}')
print(f'Best score:", {grid_search.best_score_}')
print(f'False Positive rate: {conf_mtrx[0][1] /␣
 ↪(conf_mtrx[0][1]+conf_mtrx[0][0])}')
```

```
Confusion Matrix
```


70
54
41
235
0
1
True label
0
1
Predicted label
225
200
175
150
125
100
75
50



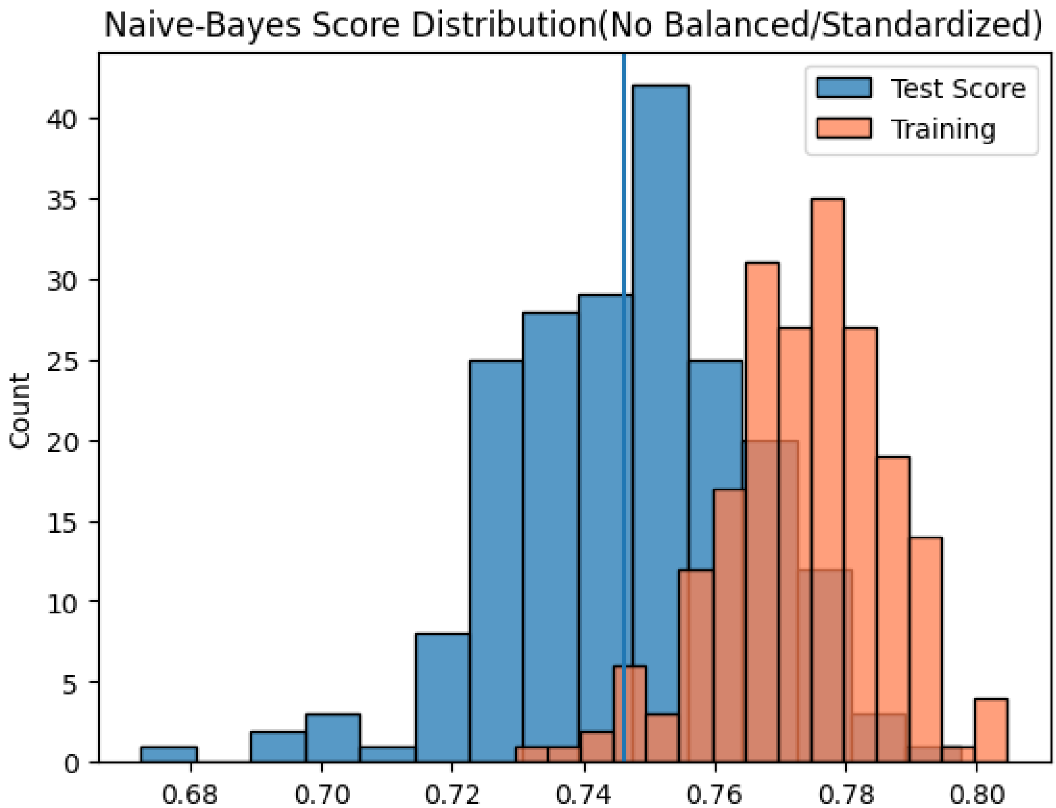

```
---------------------------
Performance Measures
---------------------------
Precision:, 0.8131487889273357
Recall:, 0.8514492753623188
F1 Score:, 0.831858407079646
Accuracy Score: 0.7625
-----------------------------
Hyperparameter Tuning Results
----------------------------
Best parameters:, {'var_smoothing': 1e-08}
Best score:", 0.7495762711864407
False Positive rate: 0.43548387096774194
```

Observations

- We got higher results by leaving the model intact, no standardization and no balance dataset. Our AUC is close to .80, a percentage that can be categorized as a good performing model. The ratio of precision and recall or F1 score is above .80 which means that our model is good a predicting a high number of True Positives without sacrificing its accuracy. Overall this model can be a candidate.

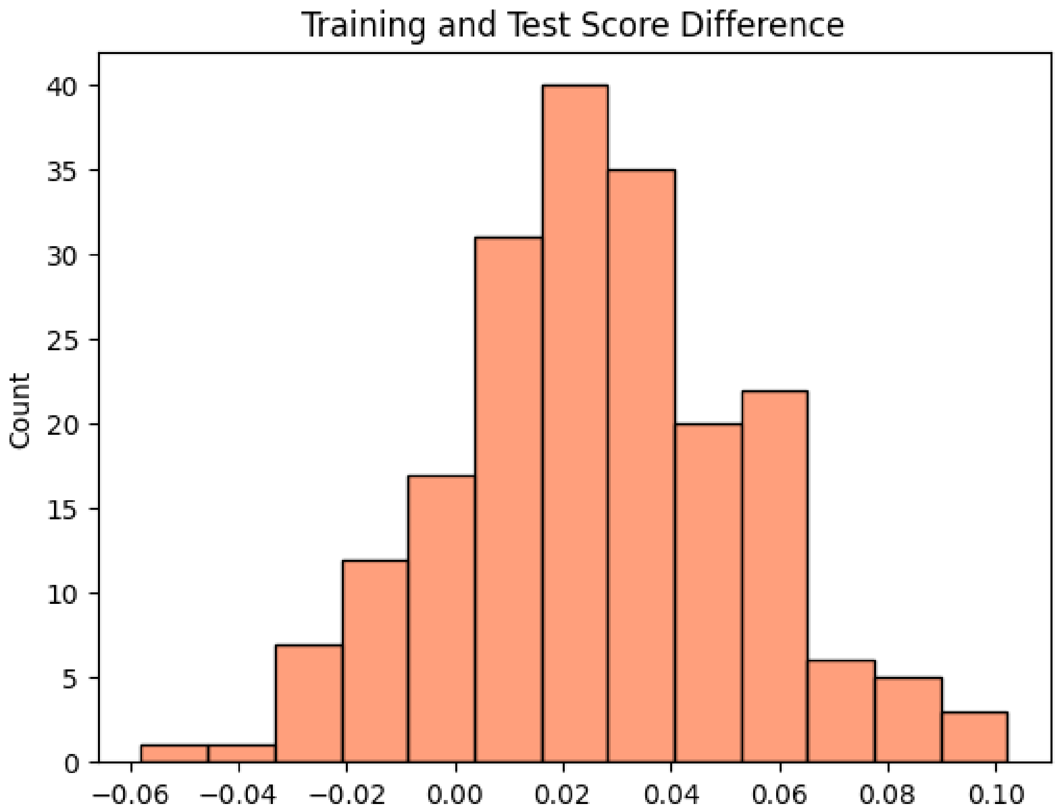
0.5.1 Simulating Best Score

[51]:
```
i = 0
n_b_train_score = []
n_b_test_score = []
diff = []

while i < 200:

    #Splitting
    x_train, x_test, y_train, y_test = train_test_split(x, y, train_size= .60)

    # Hyperparameter Tuning
    param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
    grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
    grid_search.fit(x_train, y_train)

    # Training
    n_b_best = grid_search.best_estimator_
    n_b_best.fit(x_train, y_train)
    predictions = n_b_best.predict(x_test)

    # Performance
    train_score = n_b_best.score(x_train, y_train)
    test_score = n_b_best.score(x_test, y_test)
    n_b_train_score.append(train_score)
    n_b_test_score.append(test_score)
    diff_score = train_score - test_score
    diff.append(diff_score)

    i +=1


sns.histplot(data=n_b_test_score, bins=15, label ='Test Score')
sns.histplot(data = n_b_train_score, bins = 15, color = 'coral', label =␣
 ↪'Training')
plt.title('Naive-Bayes Score Distribution(No Balanced/Standardized)')
plt.legend()
plt.axvline(np.mean(n_b_test_score))
plt.show();

print(f'Mean Train Score: {np.mean(n_b_train_score)}')
print(f'Mean Test Score: {np.mean(n_b_test_score)}')
print(f'Mean Diff score: {np.mean(diff)}')
```




```
Mean Train Score: 0.7726794657762938
Mean Test Score: 0.7461500000000001
Mean Diff score: 0.026529465776293823
```

[52]:
```
sns.histplot(data = diff, color = 'coral')
plt.title('Training and Test Score Difference')
plt.show();
```



The difference in scores has a range with negative numbers, again, it is an observation that our models is performing better on our test set rather than our training set.

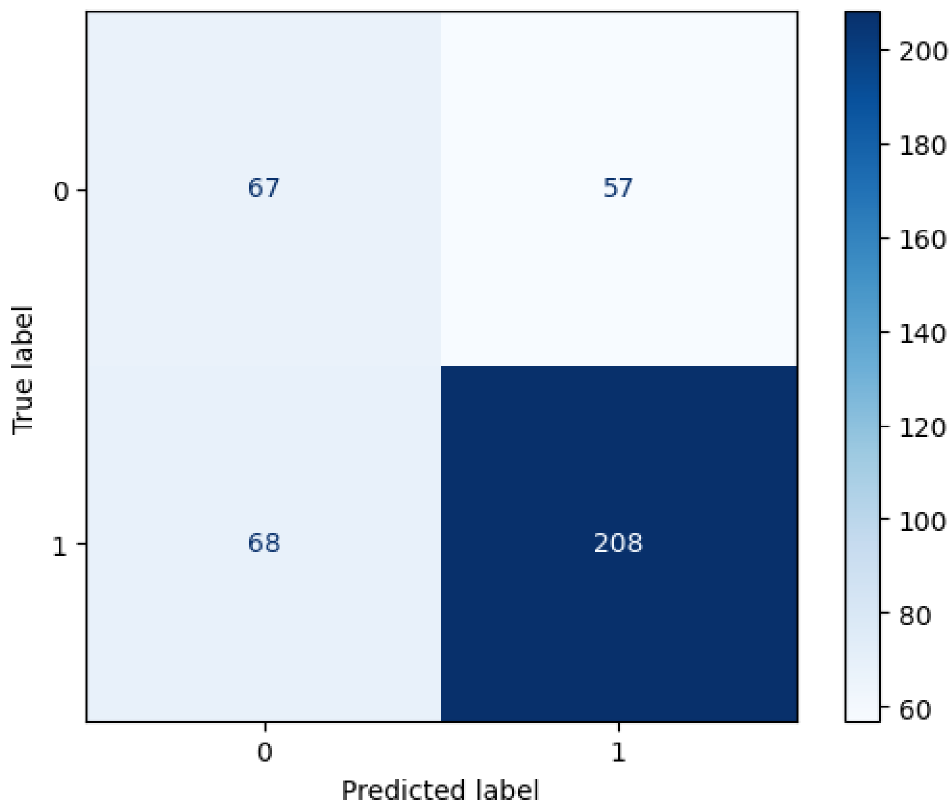
0.6 With Balanced Target And No Standardization

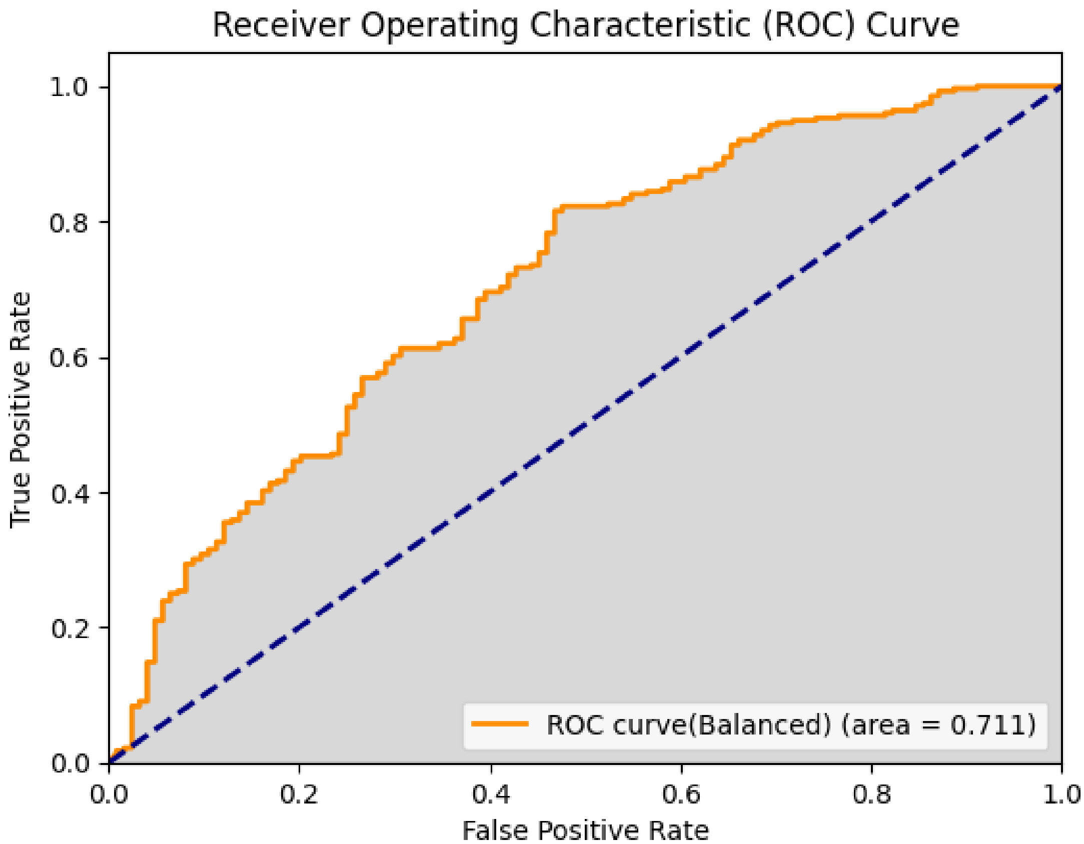
[53]:
```
#Splitting
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size= .60,␣
 ↪random_state=42)

#Balancing
smote = SMOTE()
x_train_, y_train_ =  smote.fit_resample(x_train,y_train)



# Hyperparameter Tuning
param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
grid_search.fit(x_train_, y_train_)

# Training
```

```
n_b_best = grid_search.best_estimator_
n_b_best.fit(x_train_, y_train_)
predictions_ = n_b_best.predict(x_test)

#Performance
scores = n_b_best.score(x_test, y_test)
conf_mtrx = confusion_matrix(y_test, predictions_)
precision = precision_score(y_test, predictions_)
recall = recall_score(y_test, predictions_)
f1 = f1_score(y_test, predictions_)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_mtrx)

#Results
print('Confusion Matrix')
disp.plot(cmap='Blues', include_values=True)
plt.show();


#Plotting ROC Curve
y_pred_proba = n_b_best.predict_proba(x_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba, pos_label=1)
roc_auc = auc(fpr, tpr)


plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve(Balanced) (area␣
 ↪= {round(roc_auc,3)})')
plt.fill_between(fpr, tpr, color='gray', alpha=0.3)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show();

print('----------------------------')
print('Performance Measures')
print('----------------------------')
print(f'Precision:, {precision}')
print(f'Recall:, {recall}')
print(f'F1 Score:, {f1}')
print(f'Accuracy Score: {scores}')
print('------------------------------')
print('Hyperparameter Tuning Results')
print('------------------------------')
```

```
print(f'Best parameters:, {grid_search.best_params_}')
print(f'Best score:", {grid_search.best_score_}')
print(f'False Positive rate: {conf_mtrx[0][1] /␣
↪(conf_mtrx[0][1]+conf_mtrx[0][0])}')
```

```
Confusion Matrix
```





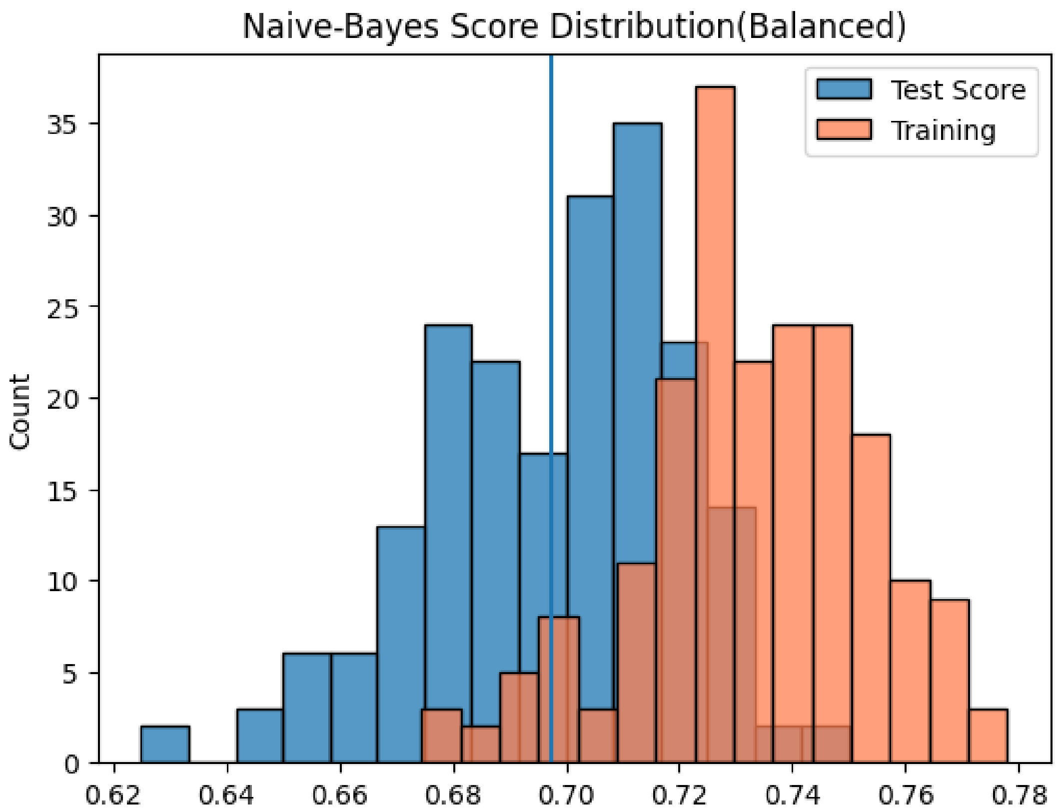

```
---------------------------
Performance Measures
---------------------------
Precision:, 0.7849056603773585
Recall:, 0.7536231884057971
F1 Score:, 0.7689463955637708
Accuracy Score: 0.6875
-----------------------------
Hyperparameter Tuning Results
----------------------------
Best parameters:, {'var_smoothing': 1e-09}
Best score:", 0.7770448179271708
False Positive rate: 0.4596774193548387
```

This model performed very similar to the convential algorithm except the score were lowere but that ratio is consistent, give then results from the previous model we can discard this one.

0.6.1 Simulating Best Score

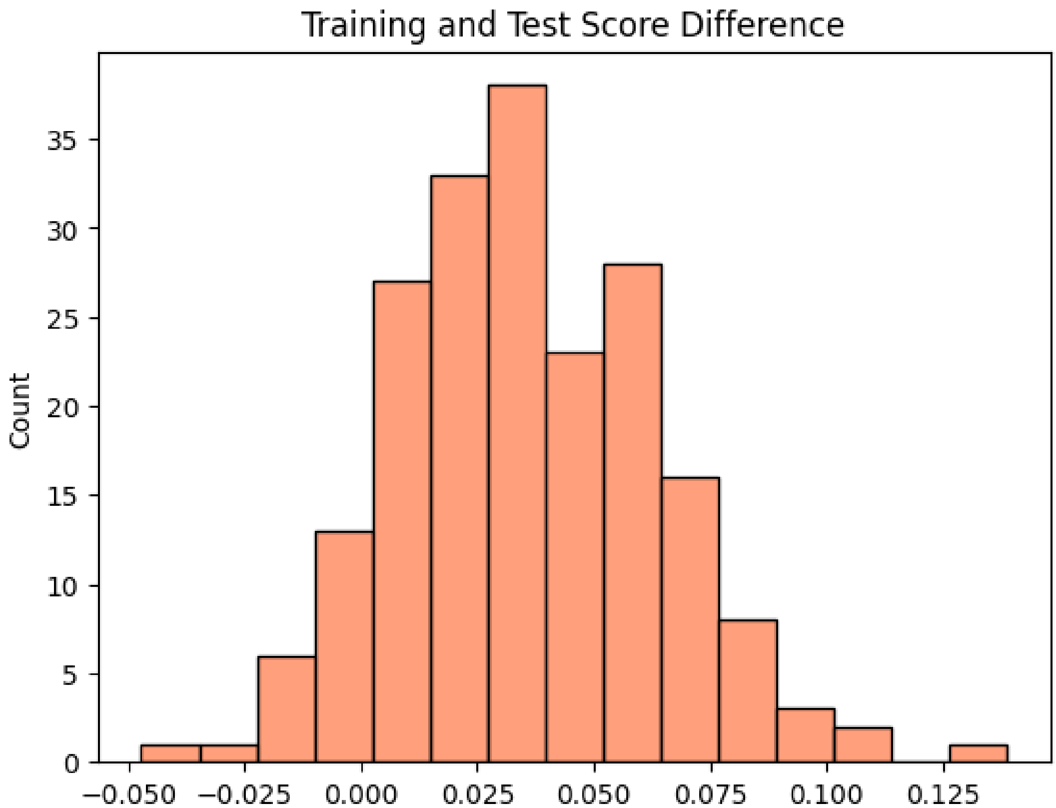
[54]:
```python
i = 0
n_b_score = []
n_b_train_score = []
n_b_test_score = []
diff = []

while i < 200:

    #Splitting
    x_train, x_test, y_train, y_test = train_test_split(x, y, train_size= .60)

    #Balancing
    smote = SMOTE()
    x_train_, y_train_ =  smote.fit_resample(x_train,y_train)


    # Hyperparameter Tuning
    param_grid = {'var_smoothing': [1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 1e-4]}
    grid_search = GridSearchCV(estimator=GaussianNB(), param_grid=param_grid,␣
 ↪cv=10, scoring='accuracy')
    grid_search.fit(x_train_, y_train_)

    # Training
    n_b_best = grid_search.best_estimator_
    n_b_best.fit(x_train_, y_train_)
    predictions_ = n_b_best.predict(x_test)

    # Performance
    train_score = n_b_best.score(x_train, y_train)
    test_score = n_b_best.score(x_test, y_test)
    n_b_train_score.append(train_score)
    n_b_test_score.append(test_score)
    diff_score = train_score - test_score
    diff.append(diff_score)

    i +=1


sns.histplot(data=n_b_test_score, bins=15, label ='Test Score')
sns.histplot(data = n_b_train_score, bins = 15, color = 'coral', label =␣
 ↪'Training')
plt.title('Naive-Bayes Score Distribution(Balanced)')
plt.legend()
plt.axvline(np.mean(n_b_test_score))
plt.show();
```

```python
print(f'Mean Train Score: {np.mean(n_b_train_score)}')
print(f'Mean Test Score: {np.mean(n_b_test_score)}')
print(f'Mean Diff score: {np.mean(diff)}')
```




```
Mean Train Score: 0.7331218697829717
Mean Test Score: 0.6975625
Mean Diff score: 0.035559369782971625
```

[55]:
```python
sns.histplot(data = diff, color = 'coral')
plt.title('Training and Test Score Difference')
plt.show();
```



The abrupt cut in the histogram to negative values means that the model can have a high level of variability in its results. Although in some instances it performs better in the test set, the count tends to be low therefore the model can have problems adapting to new data.

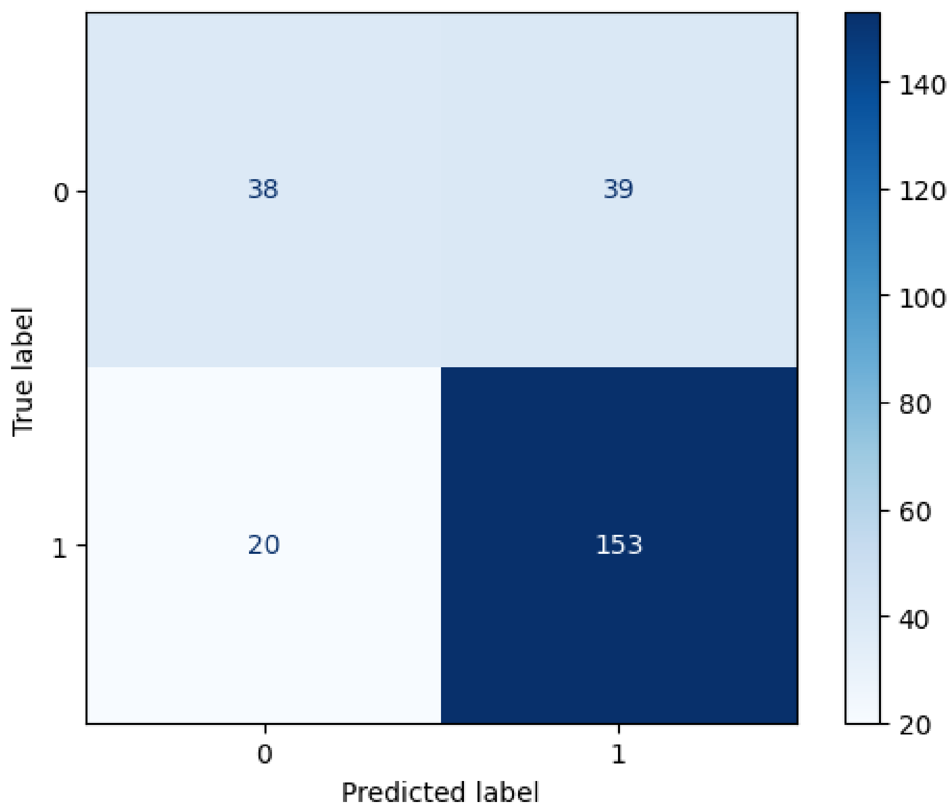
0.7 Optimized Gradient Boosting Machine Implementation for Balanced Classification

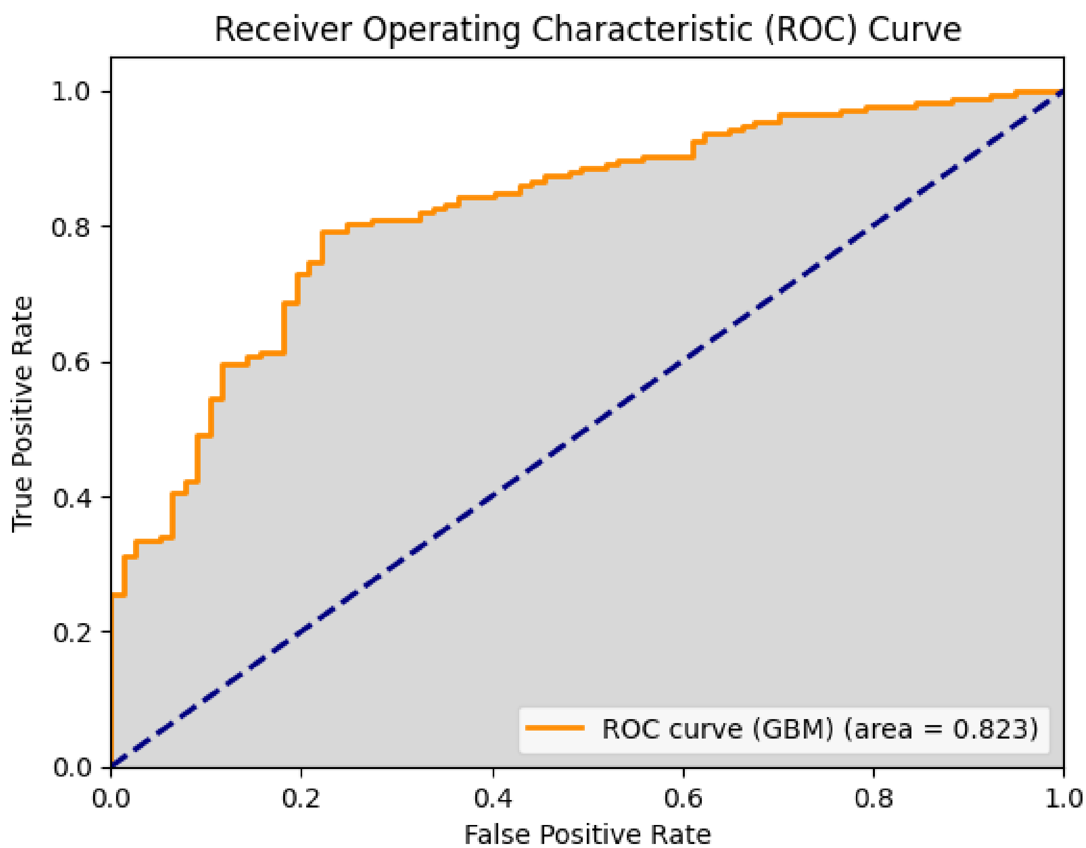
[56]:
```
# Splitting
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.75)

# Balancing
smote = SMOTE()
X_resampled, Y_resampled = smote.fit_resample(x_train, y_train)


# Hyperparameter Tuning for Gradient Boosting
param_grid = {
    'n_estimators': [100, 200, 300],  # Number of boosting stages to be run
    'learning_rate': [0.01, 0.1, 0.2],  # Shrinks the contribution of each tree␣
  ↪by learning_rate
```

```
    'max_depth': [3, 4, 5]  # Maximum depth of the individual regression␣
 ↪estimators
}
grid_search = GridSearchCV(estimator=GradientBoostingClassifier(),␣
 ↪param_grid=param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_resampled, Y_resampled)

# Training with the best parameters found
gbm_best = grid_search.best_estimator_
gbm_best.fit(X_resampled, Y_resampled)
predictions = gbm_best.predict(x_test)

# Performance evaluation
scores = gbm_best.score(x_test, y_test)
conf_mtrx = confusion_matrix(y_test, predictions)
precision = precision_score(y_test, predictions)
recall = recall_score(y_test, predictions)
f1 = f1_score(y_test, predictions)

# Confusion Matrix Display
disp = ConfusionMatrixDisplay(confusion_matrix=conf_mtrx)
print('Confusion Matrix')
disp.plot(cmap='Blues', include_values=True)
plt.show()

# Plotting ROC Curve
y_pred_proba = gbm_best.predict_proba(x_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba, pos_label=1)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (GBM) (area =␣
 ↪{round(roc_auc, 3)})')
plt.fill_between(fpr, tpr, color='gray', alpha=0.3)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

print('---------------------------')
print('Performance Measures')
print('---------------------------')
print(f'Precision: {precision}')
```

```
print(f'Recall: {recall}')
print(f'F1 Score: {f1}')
print(f'Accuracy Score: {scores}')
print('------------------------------')
print('Hyperparameter Tuning Results')
print('-----------------------------')
print(f'Best parameters: {grid_search.best_params_}')
print(f'Best score: {grid_search.best_score_}')
print(f'False Positive rate: {conf_mtrx[0][1] /␣
 ↪(conf_mtrx[0][1]+conf_mtrx[0][0])}')
```

```
Confusion Matrix
```






```
---------------------------
Performance Measures
---------------------------
Precision: 0.796875
Recall: 0.884393063583815
F1 Score: 0.8383561643835618
Accuracy Score: 0.764
-----------------------------
Hyperparameter Tuning Results
----------------------------
Best parameters: {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200}
Best score: 0.8025366734371474
False Positive rate: 0.5064935064935064
```

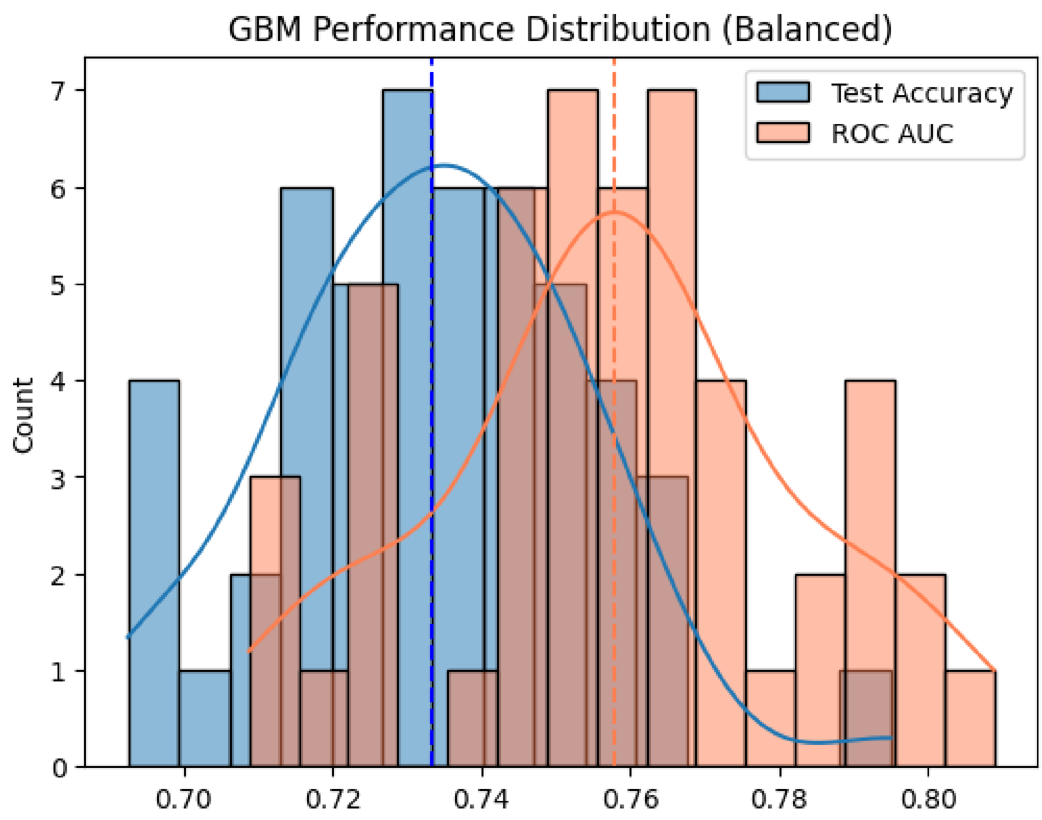
0.7.1 GBM Result Interpretation

The Model has a high rate of prediciting true positives (Precision) and catching the majority of the total actual positives (Recall). The high F1 score indicates that the model effectively balances both metrics. The models ability to predict all True Positives and True Negatives is its weakest score, though it is still relatively high (Accuracy). Overall, the performance measures are well rounded.

[57]:

```
# Initialize lists to store scores and differences
gbm_precision = []
gbm_recall = []
gbm_f1_score = []
gbm_accuracy = []
gbm_roc_auc = []
gbm_diff = []

# Counter
i = 0
# Number of iterations
iterations = 50

while i < iterations:
    # Data splitting
    x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.60)

    # Data balancing with SMOTE
    smote = SMOTE()
    X_resampled, Y_resampled = smote.fit_resample(x_train, y_train)

    # Hyperparameter tuning for Gradient Boosting
    param_grid = {
        'n_estimators': [100, 200, 300],
        'learning_rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 4, 5]
    }
    grid_search = GridSearchCV(estimator=GradientBoostingClassifier(),␣
 ↪param_grid=param_grid, cv=10, scoring='accuracy')
    grid_search.fit(X_resampled, Y_resampled)

    # Training with the best parameters found
    gbm_best = grid_search.best_estimator_
    gbm_best.fit(X_resampled, Y_resampled)
    predictions = gbm_best.predict(x_test)

    # Performance evaluation
    precision = precision_score(y_test, predictions)
    recall = recall_score(y_test, predictions)
    f1_score_val = f1_score(y_test, predictions)
    accuracy = gbm_best.score(x_test, y_test)
    train_score = gbm_best.score(X_resampled, Y_resampled)

    # Difference in training and testing accuracy
    diff_score = train_score - accuracy

    # Store scores
```

```python
    gbm_precision.append(precision)
    gbm_recall.append(recall)
    gbm_f1_score.append(f1_score_val)
    gbm_accuracy.append(accuracy)
    gbm_diff.append(diff_score)

    # ROC Curve calculations
    y_pred_proba = gbm_best.predict_proba(x_test)[:, 1]
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba, pos_label=1)
    roc_auc = auc(fpr, tpr)
    gbm_roc_auc.append(roc_auc)

    i += 1

# Plotting the results
sns.histplot(data=gbm_accuracy, bins=15, label='Test Accuracy', kde=True)
sns.histplot(data=gbm_roc_auc, bins=15, color='coral', label='ROC AUC', kde=True)
plt.title('GBM Performance Distribution (Balanced)')
plt.legend()
plt.axvline(x=np.mean(gbm_accuracy), color='blue', linestyle='--', label='Average Test Accuracy')
plt.axvline(x=np.mean(gbm_roc_auc), color='coral', linestyle='--', label='Average ROC AUC')
plt.show()

# Print the average scores
print(f'Mean Precision: {np.mean(gbm_precision)}')
print(f'Mean Recall: {np.mean(gbm_recall)}')
print(f'Mean F1 Score: {np.mean(gbm_f1_score)}')
print(f'Mean Accuracy: {np.mean(gbm_accuracy)}')
print(f'Mean ROC AUC: {np.mean(gbm_roc_auc)}')
print(f'Mean Difference Score: {np.mean(gbm_diff)}')
```




```
Mean Precision: 0.7979524838236869
Mean Recall: 0.830131521575474
Mean F1 Score: 0.8132233322883425
Mean Accuracy: 0.7333500000000001
Mean ROC AUC: 0.7579680046709298
Mean Difference Score: 0.24569384029906613
```

0.7.2 GBM Iteration Interpretation

The mean of the precision, recall, F1 Score, and Accuracy were just a tad below the single iteration results, with the weakeast measurement (Accuracy) having the greatest difference. The mean ROC AUC score from the iterations was 0.758, substantiating the model's discriminatory ability. The small mean difference score of 0.246 between the training and testing accuracy further reinforces confidence in the model's reliability. These results indicate that GBM is capable of delivering reliable and consistent predictions.

0.8 RandomForest Algorithm (Resetted df)

We decided for the final algorithm, to reset the df and compare the results of a comparable algorithm but with much less data cleaning and feature manipulation to the previous two algorithm results to see how much of an impact our previous cleaning had yielded.

[58]:
```python
# Loading dataset and setting column names

df = pd.read_csv("german.data", sep=r'\s+')
column_names = ['checking_account', 'duration_month', 'credit_history',␣
 ↪'credit_purpose','credit_amount','savings_account','present_employment','disposable_income_
␣
 ↪'status_sex','debtors','residence_since','property','age','other_installments',␣
 ↪'housing','credits_at_current_bank','job','dependants','telephone',␣
 ↪'foreign_worker','class']

df.columns = column_names
df.columns
```

[58]:
```
Index(['checking_account', 'duration_month', 'credit_history',
       'credit_purpose', 'credit_amount', 'savings_account',
       'present_employment', 'disposable_income_percent', 'status_sex',
       'debtors', 'residence_since', 'property', 'age', 'other_installments',
       'housing', 'credits_at_current_bank', 'job', 'dependants', 'telephone',
       'foreign_worker', 'class'],
      dtype='object')
```

[59]:
```python
# Separating "Explanatory", and "Response Variables" into separate DataFrames.
# Then encoding categorical values and changed "Class" variable into a string␣
 ↪since it does not represent a numerical value but is rather a category.
explanatory = df.drop(columns=['class'])
explanatory_dummies = pd.get_dummies(explanatory)
response = df['class'].astype(str).replace({'1': 'Good', '2': 'Bad'})
df.groupby(['class']).count()
```

[59]:
```
       checking_account  duration_month  credit_history  credit_purpose  \
class
1                   699             699             699             699
2                   300             300             300             300

       credit_amount  savings_account  present_employment  \
class
1                699              699                 699
2                300              300                 300

       disposable_income_percent  status_sex  debtors  residence_since  \
class
1                            699         699      699              699
2                            300         300      300              300

       property  age  other_installments  housing  credits_at_current_bank  \
class
1           699  699                 699      699                      699
```

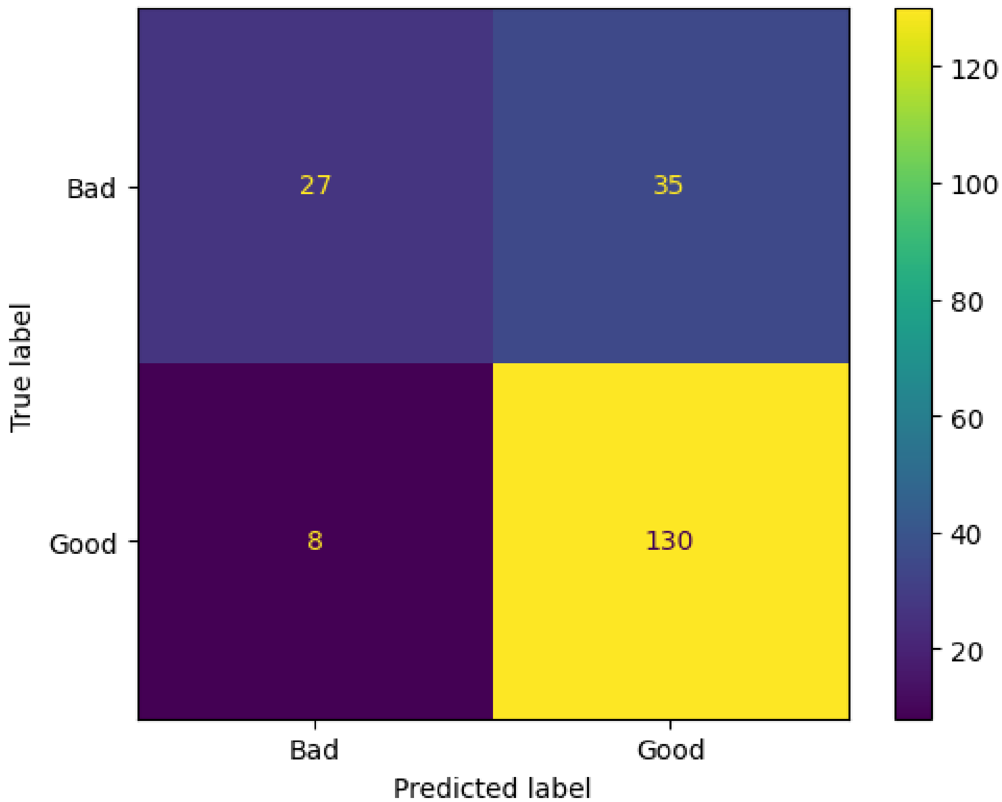
```
2            300   300                    300      300                       300

       job  dependants  telephone  foreign_worker
class
1      699         699        699             699
2      300         300        300             300
```

[60]:

```
# Creating training and testing sets
x_train, x_test, y_train, y_test = train_test_split(explanatory_dummies,
 ↪response, test_size = 0.2)
y_train_flat = np.ravel(y_train, order='C')
y_test_flat = np.ravel(y_test, order='C')

rf = RandomForestClassifier()
rf.fit(x_train, y_train_flat)

# Precision: Percent of "True Positives" identified correctly divided by all
 ↪predicted positives in dataset
# Recall: Percent of positive predictions were correct.
# I'd argue the data set is unbalanced
preds = rf.predict(x_test)
cr = classification_report(y_test, preds)
print(cr)

ConfusionMatrixDisplay.from_predictions(y_test, preds)
```

```
              precision    recall  f1-score   support

         Bad       0.77      0.44      0.56        62
        Good       0.79      0.94      0.86       138

    accuracy                           0.79       200
   macro avg       0.78      0.69      0.71       200
weighted avg       0.78      0.79      0.76       200
```

[60]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x31896d6d0>



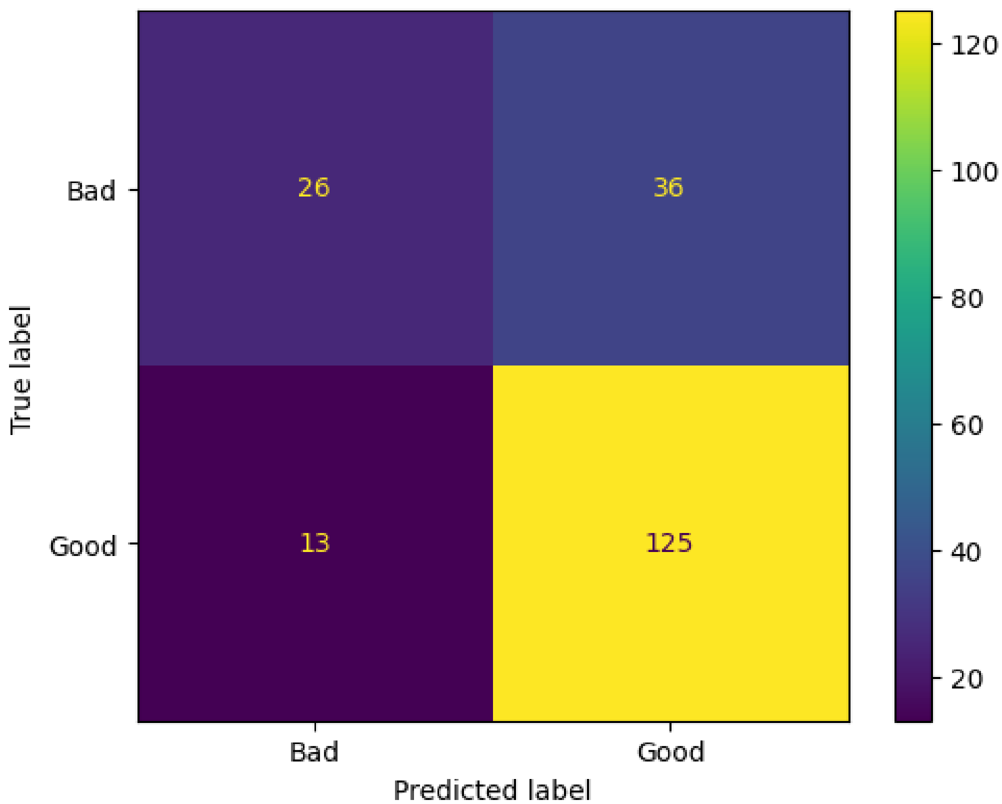
[61]:

```
# Determining most important explanatory features
# Training Random Forest on new training data

feature_select = SelectFromModel(RandomForestClassifier(n_estimators = 50))
feature_select.fit(x_train, y_train)
features = feature_select.get_feature_names_out().tolist()

selected_features_train = x_train[features]
selected_features_test = x_test[features]

rf.fit(selected_features_train, y_train_flat)

# New classification report based on selected features.

preds_new_features = rf.predict(selected_features_test)
cr_feature = classification_report(y_test, preds_new_features)
print(cr_feature)

ConfusionMatrixDisplay.from_predictions(y_test, preds_new_features)
```

```
              precision    recall  f1-score   support
```

```
         Bad       0.67      0.42      0.51        62
        Good       0.78      0.91      0.84       138

    accuracy                           0.76       200
   macro avg       0.72      0.66      0.68       200
weighted avg       0.74      0.76      0.74       200
```

[61]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x318a90950>

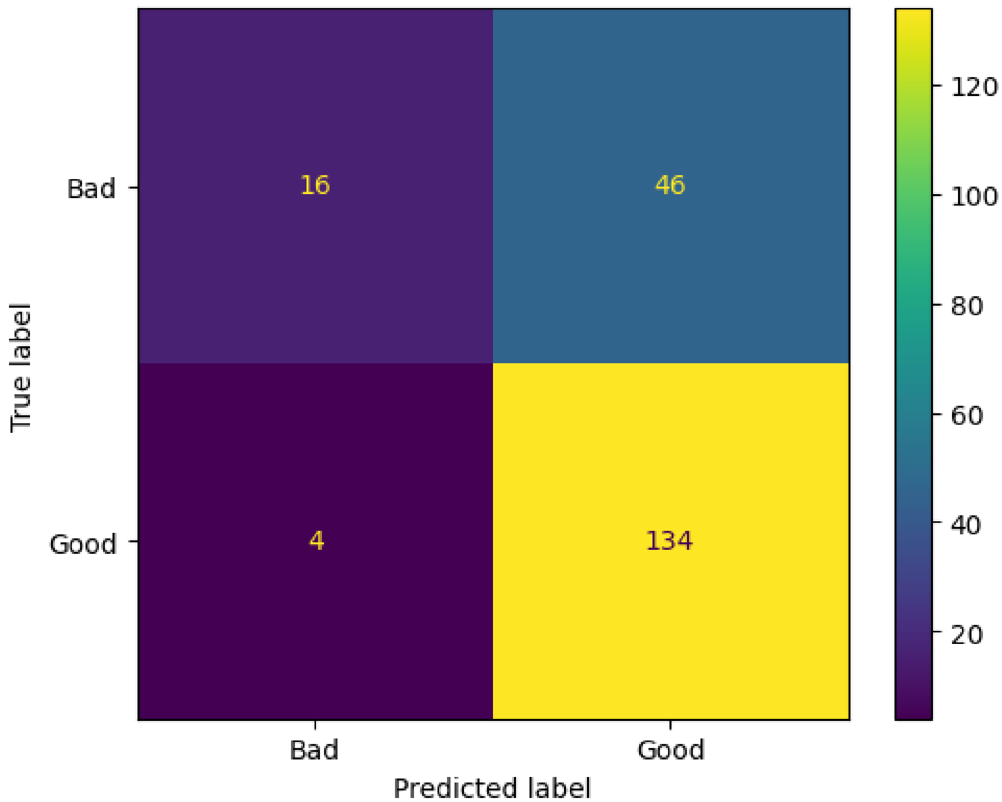


[62]:
```
# Hypertuning parameters
param_grid = {
    'n_estimators': list(np.arange(25, 200, 25)),
    'max_features': ['sqrt', 'log2', None],
    'max_depth': list(np.arange(3, 21, 3)),
    'max_leaf_nodes': list(np.arange(3, 21, 3)),
}

search = RandomizedSearchCV(RandomForestClassifier(), param_grid)
search.fit(selected_features_train, y_train)
```

```python
print(search.best_estimator_)

# Retraining with tuned hyperparameters
rf = RandomForestClassifier(max_depth=6, max_features='log2',␣
↪max_leaf_nodes=18, n_estimators=75)
rf.fit(selected_features_train, y_train_flat)

# Predicitions with tuned hyperparameters

preds_new_features_tuned = rf.predict(selected_features_test)
cr_feature_tuned = classification_report(y_test, preds_new_features_tuned)
print(cr_feature_tuned)

ConfusionMatrixDisplay.from_predictions(y_test, preds_new_features_tuned)
```

```
RandomForestClassifier(max_depth=6, max_leaf_nodes=18, n_estimators=50)
              precision    recall  f1-score   support

         Bad       0.80      0.26      0.39        62
        Good       0.74      0.97      0.84       138

    accuracy                           0.75       200
   macro avg       0.77      0.61      0.62       200
weighted avg       0.76      0.75      0.70       200
```

[62]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x31897da50>



0.8.1 Random Forest Interpretation

The RandomForest model demonstrates a strong ability to correctly identify positive predictions (Precision) and to capture a significant portion of the actual positive cases (Recall), both with equal proficiency. The model achieves a balanced performance as evidenced by its F1 score, which is commendable though slightly lower than the individual precision and recall scores. The overall accuracy, which measures the model's effectiveness in identifying both True Positives and True Negatives, aligns closely with the other metrics, highlighting its consistency across various aspects of classification. The results indicate a robust and reliable model performance.

0.8.2 Data Preparation Impact on Model Performance

RandomForest overall performance landed it in the middle of Naive Bayes and GBM. This is expected since in general, that is the order of "Performance power" of each given model. And since Random Forest still reached second place despite less data cleaning, it brings into question the overall value of the initial data cleaning. One possible reason for the lack of major difference could be the overall quality of the data and had the data been "dirtier" then perhaps a major difference would have been observed.

0.9 Conclusion

In this analysis, we compared the performance of three machine learning models in predicting good or bad credit applicants: Naive Bayes, RandomForest, and Gradient Boosting Machine (GBM) across various metrics. GBM demonstrated the strongest performance, particularly in precision, recall, and F1 score, suggesting it is highly effective for complex prediction tasks like assessing creditworthiness. RandomForest (with less data cleaning) showed robustness and consistency, making it a reliable choice, especially for datasets with complex features. Naive Bayes, while fastest and effective in smaller datasets, lagged slightly behind in performance due to its assumption of feature independence. Given this conclusion, we have decided that the Gradient Boosting Machine (GBM) model would be the best model to move forward with in predicting good or bad credit applicants.