hw1_yilmaz_emirkan_1901042659

March 24, 2024

1 Setup & Utility Functions

[1]:
```
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
from sklearn import metrics
import time
import numpy as np

from sklearn.model_selection import cross_val_predict, KFold
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

[2]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

def plot_confusion_matrix(y_true, y_pred, classes=['Class 0', 'Class 1'],␣
↪title='Confusion Matrix'):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', xticklabels=classes,␣
↪yticklabels=classes)
    plt.title(title)
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.show()


def plot_roc_curve(y_true_binary, y_probs):
    fpr, tpr, thresholds = roc_curve(y_true_binary, y_probs)
    roc_auc = auc(fpr, tpr)

    plt.figure(figsize=(8, 6))
```

```
    plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (area = %0.2f)' %
↪roc_auc)
    plt.plot([0, 1], [0, 1], color='gray', 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)')
    plt.legend(loc="lower right")
    plt.show()
```

2 Downloading the Data

[3]:
```
import os
HOME = os.getcwd()
print(HOME)
```

```
/content
```

[4]:
```
!mkdir -p {HOME}/data
```

[5]:
```
!wget https://archive.ics.uci.edu/static/public/475/audit+data.zip
!unzip {HOME}/audit+data.zip -d {HOME}/data/
```

```
--2024-03-24 19:56:26--
https://archive.ics.uci.edu/static/public/475/audit+data.zip
Resolving archive.ics.uci.edu (archive.ics.uci.edu)… 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443…
connected.
HTTP request sent, awaiting response… 200 OK
Length: unspecified
Saving to: 'audit+data.zip'

audit+data.zip          [ <=>                ]  27.78K  --.-KB/s    in 0.1s

2024-03-24 19:56:27 (216 KB/s) - 'audit+data.zip' saved [28447]

Archive:  /content/audit+data.zip
  inflating: /content/data/audit_data/audit_risk.csv
  inflating: /content/data/audit_data/trial.csv
```

[6]:
```
!wget https://archive.ics.uci.edu/static/public/275/bike+sharing+dataset.zip
!unzip {HOME}/bike+sharing+dataset.zip -d {HOME}/data/bike_sharing_data
```

```
--2024-03-24 19:56:27--
https://archive.ics.uci.edu/static/public/275/bike+sharing+dataset.zip
```

```
Resolving archive.ics.uci.edu (archive.ics.uci.edu)… 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443…
connected.
HTTP request sent, awaiting response… 200 OK
Length: unspecified
Saving to: ‘bike+sharing+dataset.zip’

bike+sharing+datase     [    <=>              ] 273.43K   529KB/s    in 0.5s

2024-03-24 19:56:28 (529 KB/s) - ‘bike+sharing+dataset.zip’ saved [279992]

Archive:  /content/bike+sharing+dataset.zip
  inflating: /content/data/bike_sharing_data/Readme.txt
  inflating: /content/data/bike_sharing_data/day.csv
  inflating: /content/data/bike_sharing_data/hour.csv
```

3 Analysing The Data

3.1 Audit Risk Dataset

[7]:
```python
import pandas as pd

audit_risk_data = pd.read_csv(f"{HOME}/data/audit_data/trial.csv")
audit_risk_data.head()
```

[7]:
```
   Sector_score LOCATION_ID  PARA_A  SCORE_A  PARA_B  SCORE_B  TOTAL  numbers  \
0          3.89          23    4.18        6    2.50        2   6.68      5.0
1          3.89           6    0.00        2    4.83        2   4.83      5.0
2          3.89           6    0.51        2    0.23        2   0.74      5.0
3          3.89           6    0.00        2   10.80        6  10.80      6.0
4          3.89           6    0.00        2    0.08        2   0.08      5.0

   Marks  Money_Value  MONEY_Marks  District  Loss  LOSS_SCORE  History  \
0      2         3.38            2         2     0           2        0
1      2         0.94            2         2     0           2        0
2      2         0.00            2         2     0           2        0
3      6        11.75            6         2     0           2        0
4      2         0.00            2         2     0           2        0

   History_score  Score  Risk
0              2    2.4     1
1              2    2.0     0
2              2    2.0     0
3              2    4.4     1
4              2    2.0     0
```

[8]:
```python
audit_risk_data.shape
```

[8]: (776, 18)

[9]:
```
# Check if there is a null value
audit_risk_data.isnull().sum()
```

[9]:
```
Sector_score      0
LOCATION_ID       0
PARA_A            0
SCORE_A           0
PARA_B            0
SCORE_B           0
TOTAL             0
numbers           0
Marks             0
Money_Value       1
MONEY_Marks       0
District          0
Loss              0
LOSS_SCORE        0
History           0
History_score     0
Score             0
Risk              0
dtype: int64
```

[10]:
```
# Fill the null value with mean of the column 'Money_Value
audit_risk_data['Money_Value'] = audit_risk_data['Money_Value'].
 ↪fillna(audit_risk_data.Money_Value.mean())
```

[11]:
```
audit_risk_data.isnull().sum()
```

[11]:
```
Sector_score      0
LOCATION_ID       0
PARA_A            0
SCORE_A           0
PARA_B            0
SCORE_B           0
TOTAL             0
numbers           0
Marks             0
Money_Value       0
MONEY_Marks       0
District          0
Loss              0
LOSS_SCORE        0
History           0
History_score     0
```

```
Score            0
Risk             0
dtype: int64
```

[12]:
```python
# Check the data type
audit_risk_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 776 entries, 0 to 775
Data columns (total 18 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Sector_score    776 non-null    float64
 1   LOCATION_ID     776 non-null    object
 2   PARA_A          776 non-null    float64
 3   SCORE_A         776 non-null    int64
 4   PARA_B          776 non-null    float64
 5   SCORE_B         776 non-null    int64
 6   TOTAL           776 non-null    float64
 7   numbers         776 non-null    float64
 8   Marks           776 non-null    int64
 9   Money_Value     776 non-null    float64
 10  MONEY_Marks     776 non-null    int64
 11  District        776 non-null    int64
 12  Loss            776 non-null    int64
 13  LOSS_SCORE      776 non-null    int64
 14  History         776 non-null    int64
 15  History_score   776 non-null    int64
 16  Score           776 non-null    float64
 17  Risk            776 non-null    int64
dtypes: float64(7), int64(10), object(1)
memory usage: 109.2+ KB
```

[13]:
```python
# Convert the LOCATION_ID column
counts = audit_risk_data['LOCATION_ID'].value_counts()
print(counts)
```

```
8          76
19         68
9          53
16         52
12         47
5          44
2          41
4          37
15         35
13         35
6          33
```

```
32          29
11          26
22          24
29          21
14          20
18          16
31          12
1           11
37          10
39           9
28           8
21           8
27           8
43           7
25           6
20           5
7            4
30           4
38           4
36           4
3            3
40           3
35           2
44           1
NUH          1
LOHARU       1
SAFIDON      1
23           1
42           1
41           1
34           1
33           1
24           1
17           1
Name: LOCATION_ID, dtype: int64
```

[14]:

```
# Convert LOCATION_ID column to numeric, coerce non-numeric values to NaN
audit_risk_data["LOCATION_ID"] = pd.to_numeric(audit_risk_data["LOCATION_ID"],␣
↪errors='coerce')

# Replace NaN values with the mean of the LOCATION_ID column
mean_location_id = audit_risk_data["LOCATION_ID"].mean()
audit_risk_data["LOCATION_ID"].fillna(mean_location_id, inplace=True)
```

[15]:

```
audit_risk_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 776 entries, 0 to 775
```

```
Data columns (total 18 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Sector_score    776 non-null    float64
 1   LOCATION_ID     776 non-null    float64
 2   PARA_A          776 non-null    float64
 3   SCORE_A         776 non-null    int64  
 4   PARA_B          776 non-null    float64
 5   SCORE_B         776 non-null    int64  
 6   TOTAL           776 non-null    float64
 7   numbers         776 non-null    float64
 8   Marks           776 non-null    int64  
 9   Money_Value     776 non-null    float64
 10  MONEY_Marks     776 non-null    int64  
 11  District        776 non-null    int64  
 12  Loss            776 non-null    int64  
 13  LOSS_SCORE      776 non-null    int64  
 14  History         776 non-null    int64  
 15  History_score   776 non-null    int64  
 16  Score           776 non-null    float64
 17  Risk            776 non-null    int64  
dtypes: float64(8), int64(10)
memory usage: 109.2 KB
```

[16]:
```
audit_risk_data.describe()
```

[16]:
```
       Sector_score  LOCATION_ID      PARA_A     SCORE_A       PARA_B  \
count    776.000000   776.000000  776.000000  776.000000   776.000000   
mean      20.184536    14.856404    2.450194    3.512887    10.799988   
std       24.319017     9.872154    5.678870    1.740549    50.083624   
min        1.850000     1.000000    0.000000    2.000000     0.000000   
25%        2.370000     8.000000    0.210000    2.000000     0.000000   
50%        3.890000    13.000000    0.875000    2.000000     0.405000   
75%       55.570000    19.000000    2.480000    6.000000     4.160000   
max       59.850000    44.000000   85.000000    6.000000  1264.630000   

          SCORE_B        TOTAL     numbers       Marks  Money_Value  \
count  776.000000   776.000000  776.000000  776.000000   776.000000   
mean     3.131443    13.218481    5.067655    2.237113    14.137631   
std      1.698042    51.312829    0.264449    0.803517    66.563533   
min      2.000000     0.000000    5.000000    2.000000     0.000000   
25%      2.000000     0.537500    5.000000    2.000000     0.000000   
50%      2.000000     1.370000    5.000000    2.000000     0.095000   
75%      4.000000     7.707500    5.000000    2.000000     5.630000   
max      6.000000  1268.910000    9.000000    6.000000   935.030000   

       MONEY_Marks    District        Loss  LOSS_SCORE     History  \
```

```
count   776.000000  776.000000  776.000000  776.000000  776.000000
mean      2.909794    2.505155    0.029639    2.061856    0.104381
std       1.597452    1.228678    0.184280    0.375080    0.531031
min       2.000000    2.000000    0.000000    2.000000    0.000000
25%       2.000000    2.000000    0.000000    2.000000    0.000000
50%       2.000000    2.000000    0.000000    2.000000    0.000000
75%       4.000000    2.000000    0.000000    2.000000    0.000000
max       6.000000    6.000000    2.000000    6.000000    9.000000

       History_score       Score        Risk
count     776.000000  776.000000  776.000000
mean        2.167526    2.702577    0.626289
std         0.679869    0.858923    0.484100
min         2.000000    2.000000    0.000000
25%         2.000000    2.000000    0.000000
50%         2.000000    2.400000    1.000000
75%         2.000000    3.250000    1.000000
max         6.000000    5.200000    1.000000
```

3.2 Bike Sharing Dataset

[17]:
```python
day_data = pd.read_csv(f"{HOME}/data/bike_sharing_data/day.csv")
day_data.head()
```

[17]:
```
   instant      dteday  season  yr  mnth  holiday  weekday  workingday  \
0        1  2011-01-01       1   0     1        0        6           0
1        2  2011-01-02       1   0     1        0        0           0
2        3  2011-01-03       1   0     1        0        1           1
3        4  2011-01-04       1   0     1        0        2           1
4        5  2011-01-05       1   0     1        0        3           1

   weathersit      temp     atemp       hum  windspeed  casual  registered  \
0           2  0.344167  0.363625  0.805833   0.160446     331         654
1           2  0.363478  0.353739  0.696087   0.248539     131         670
2           1  0.196364  0.189405  0.437273   0.248309     120        1229
3           1  0.200000  0.212122  0.590435   0.160296     108        1454
4           1  0.226957  0.229270  0.436957   0.186900      82        1518

    cnt
0   985
1   801
2  1349
3  1562
4  1600
```

[18]:
```python
day_data.shape
```

[18]: (731, 16)

[19]:
```
day_data.isnull().sum()
```

[19]:
```
instant       0
dteday        0
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

[20]:
```
day_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 731 entries, 0 to 730
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   instant     731 non-null    int64
 1   dteday      731 non-null    object
 2   season      731 non-null    int64
 3   yr          731 non-null    int64
 4   mnth        731 non-null    int64
 5   holiday     731 non-null    int64
 6   weekday     731 non-null    int64
 7   workingday  731 non-null    int64
 8   weathersit  731 non-null    int64
 9   temp        731 non-null    float64
 10  atemp       731 non-null    float64
 11  hum         731 non-null    float64
 12  windspeed   731 non-null    float64
 13  casual      731 non-null    int64
 14  registered  731 non-null    int64
 15  cnt         731 non-null    int64
dtypes: float64(4), int64(11), object(1)
memory usage: 91.5+ KB
```

[21]:
```python
# Drop unnecessary columns
day_data = day_data.drop(columns=['instant', 'dteday'])
```

[22]:
```python
audit_risk_data.describe()
```

[22]:
```
       Sector_score  LOCATION_ID      PARA_A     SCORE_A       PARA_B  \
count    776.000000   776.000000  776.000000  776.000000   776.000000
mean      20.184536    14.856404    2.450194    3.512887    10.799988
std       24.319017     9.872154    5.678870    1.740549    50.083624
min        1.850000     1.000000    0.000000    2.000000     0.000000
25%        2.370000     8.000000    0.210000    2.000000     0.000000
50%        3.890000    13.000000    0.875000    2.000000     0.405000
75%       55.570000    19.000000    2.480000    6.000000     4.160000
max       59.850000    44.000000   85.000000    6.000000  1264.630000

          SCORE_B        TOTAL     numbers       Marks  Money_Value  \
count  776.000000   776.000000  776.000000  776.000000   776.000000
mean     3.131443    13.218481    5.067655    2.237113    14.137631
std      1.698042    51.312829    0.264449    0.803517    66.563533
min      2.000000     0.000000    5.000000    2.000000     0.000000
25%      2.000000     0.537500    5.000000    2.000000     0.000000
50%      2.000000     1.370000    5.000000    2.000000     0.095000
75%      4.000000     7.707500    5.000000    2.000000     5.630000
max      6.000000  1268.910000    9.000000    6.000000   935.030000

       MONEY_Marks    District        Loss  LOSS_SCORE     History  \
count   776.000000  776.000000  776.000000  776.000000  776.000000
mean      2.909794    2.505155    0.029639    2.061856    0.104381
std       1.597452    1.228678    0.184280    0.375080    0.531031
min       2.000000    2.000000    0.000000    2.000000    0.000000
25%       2.000000    2.000000    0.000000    2.000000    0.000000
50%       2.000000    2.000000    0.000000    2.000000    0.000000
75%       4.000000    2.000000    0.000000    2.000000    0.000000
max       6.000000    6.000000    2.000000    6.000000    9.000000

       History_score       Score        Risk
count     776.000000  776.000000  776.000000
mean        2.167526    2.702577    0.626289
std         0.679869    0.858923    0.484100
min         2.000000    2.000000    0.000000
25%         2.000000    2.000000    0.000000
50%         2.000000    2.400000    1.000000
75%         2.000000    3.250000    1.000000
max         6.000000    5.200000    1.000000
```

4 Preprocessing the Data

[23]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import re

def apply_normalization(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    return pd.DataFrame(X_scaled, columns=X.columns)

def load_data(file_path, target, preprocessing_function=None, split=False,␣
↪normalize=False):
    # Load the dataset
    df = pd.read_csv(file_path)

    # Preprocess the dataset
    if preprocessing_function:
        df = preprocessing_function(df)

    # Split features and target variable
    X = df.drop(columns=[target])
    y = df[target]

    # First split the data, then normalize it!
    if split:
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
↪2, random_state=42)

        if normalize:
            X_train = apply_normalization(X_train)
            X_test = apply_normalization(X_test)
        return X_train, X_test, y_train, y_test
    else:
        if normalize:
            X = normalize(X)
        return X, y


def preprocess_bike_sharing(df):
    # Drop unnecessary columns
    df = df.drop(columns=['instant', 'dteday'])

    return df
```

```python
def preprocess_audit_risk(df):
    # Fill the null value with mean of the column 'Money_Value
    df['Money_Value'] = df['Money_Value'].fillna(df.Money_Value.mean())

    # Convert LOCATION_ID column to numeric, coerce non-numeric values to NaN
    df["LOCATION_ID"] = pd.to_numeric(df["LOCATION_ID"], errors='coerce')

    # Replace NaN values with the mean of the LOCATION_ID column
    mean_location_id = df["LOCATION_ID"].mean()
    df["LOCATION_ID"].fillna(mean_location_id, inplace=True)

    return df
```

[24]:
```python
DS_AUDIT_RISK_PATH = f"{HOME}/data/audit_data/trial.csv"
DS_BIKE_SHARING_PATH = f"{HOME}/data/bike_sharing_data/day.csv"

def load_data_audit_risk(split=True, normalize=True):
    return load_data(
        file_path=DS_AUDIT_RISK_PATH,
        target='Risk',
        preprocessing_function=preprocess_audit_risk,
        split=split,
        normalize=normalize)

def load_data_bike_sharing(split=True, normalize=True):
    return load_data(
        file_path=DS_BIKE_SHARING_PATH,
        target='cnt',
        preprocessing_function=preprocess_bike_sharing,
        split=split,
        normalize=normalize)
```

5 Part 1: Build a classifier based on KNN (K=3 for testing) using Euclidean distance

[25]:
```python
import numpy as np
from collections import Counter
from enum import Enum

class DistanceMetric(Enum):
    Euclidean = 1
    Manhattan = 2

class ProblemType(Enum):
    Regression = 1
    Classification = 2
```

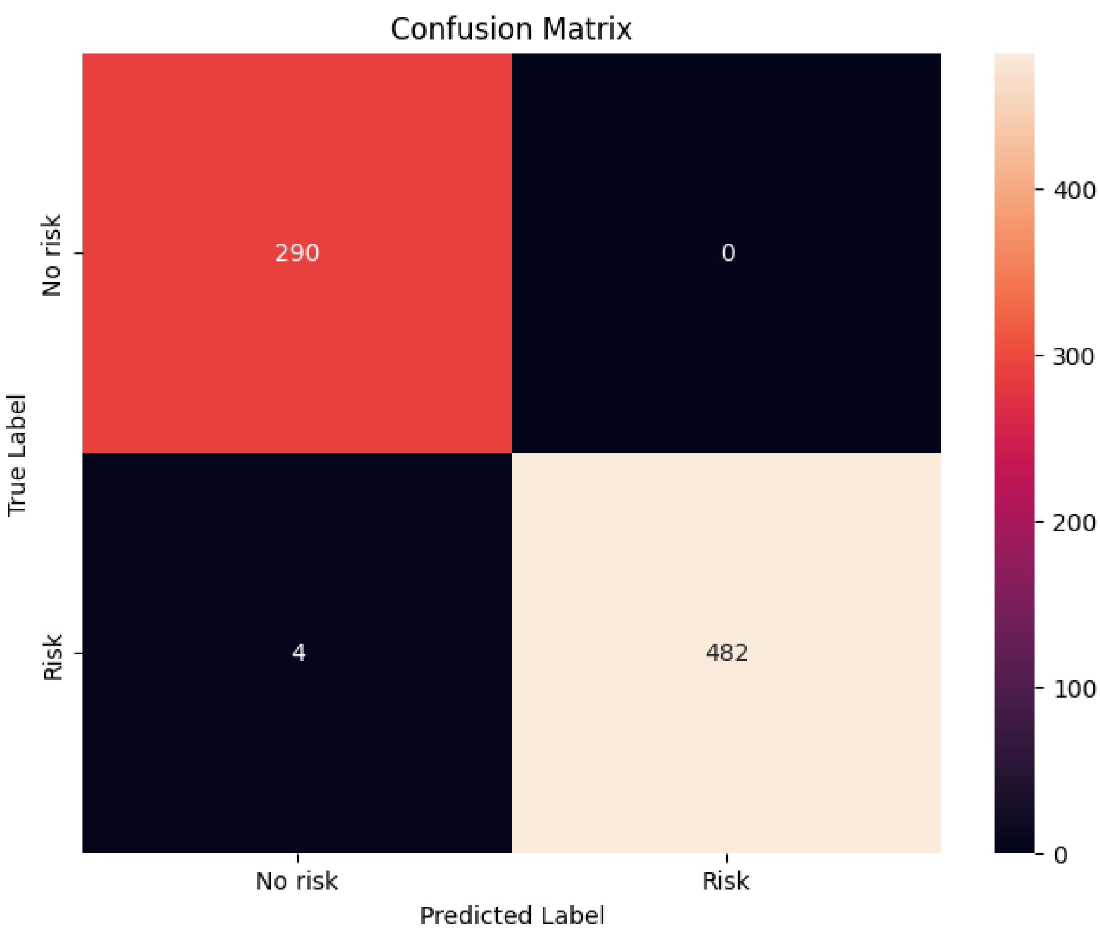
```python
class KNN:
    def __init__(self, problem_type, k=3, distance_metric=DistanceMetric.Euclidean):
        self.k = k
        self.problem_type = problem_type
        self.predict_method = self.classification_predict if problem_type == ProblemType.Classification else self.regression_predict
        self.distance_metric = distance_metric
        self.distance_method = self.euclidean_distance if distance_metric == DistanceMetric.Euclidean else self.manhattan_distance

    def fit(self, X, y):
        self.X_train = X
        self.y_train = y

    def predict(self, X_test):
        predictions = []
        for i in range(len(X_test)):
            distances = [self.distance_method(X_test[i], x) for x in self.X_train]
            k_indices = sorted(range(len(distances)), key=lambda x: distances[x])[:self.k]
            k_nearest_labels = [self.y_train[j] for j in k_indices]
            predictions.append(self.predict_method(k_nearest_labels))

        return predictions

    def classification_predict(self, k_nearest_labels):
        most_common = Counter(k_nearest_labels).most_common(1)
        return most_common[0][0]

    def regression_predict(self, k_nearest_labels):
        return sum(k_nearest_labels) / len(k_nearest_labels)

    def euclidean_distance(self, x1: list, x2: list):
        distance = 0.0
        for i in range(len(x1)):
            distance += (x1[i] - x2[i])**2
        return np.sqrt(distance)

    def manhattan_distance(self, x1: list, x2: list):
        distance = 0.0
        for i in range(len(x1)):
            distance += np.abs(x1[i] - x2[i])**2
        return distance
```

[26]:

```python
from sklearn.model_selection import cross_val_predict, KFold
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score

X, y = load_data_audit_risk(split=False, normalize=False)

# Perform k-fold cross-validation
kf = KFold(n_splits=6, shuffle=True, random_state=42)

# Lists to store predictions and true labels
all_y_pred = []
all_y_true = []

start_time = time.time()

for train_index, val_index  in kf.split(X):
    X_train_fold, X_val_fold = X.iloc[train_index], X.iloc[val_index]
    y_train_fold, y_val_fold = y.iloc[train_index], y.iloc[val_index]

    # Apply normalization after splitting the dataset!
    X_train_fold = apply_normalization(X_train_fold)
    X_val_fold = apply_normalization(X_val_fold)

    # Train the model
    knn_classifier = KNN(k=3, problem_type=ProblemType.Classification,␣
 ↪distance_metric=DistanceMetric.Euclidean)
    knn_classifier.fit(X_train_fold.values, y_train_fold.values)

    # Make predictions
    y_pred = knn_classifier.predict(X_val_fold.values)

    # Collect predictions and true labels
    all_y_pred.extend(y_pred)
    all_y_true.extend(y_val_fold)

    accuracy = accuracy_score(y_val_fold, y_pred)
    print(f"Accuracy for fold: {accuracy:.2f}")

end_time = time.time()

# Compute overall accuracy
overall_accuracy = accuracy_score(all_y_true, all_y_pred)
print(f"Overall Accuracy from k-fold Cross-Validation: {overall_accuracy:.2f}",␣
 ↪"\n")

# Plot confusion matrix
plot_confusion_matrix(all_y_true, all_y_pred, classes=['No risk', 'Risk'])
```

```python
# Calculate and print runtime
runtime = end_time - start_time
print(f"\nTotal Runtime: {runtime:.2f} seconds")
```

```
Accuracy for fold: 0.99
Accuracy for fold: 0.99
Accuracy for fold: 1.00
Accuracy for fold: 0.99
Accuracy for fold: 1.00
Accuracy for fold: 0.99
Overall Accuracy from k-fold Cross-Validation: 0.99
```




```
Total Runtime: 22.06 seconds
```

6 Part 2: Build a regressor based on KNN (K=3 for testing) using Manhattan distance

[27]:
```
from sklearn.metrics import mean_squared_error

X, y = load_data_bike_sharing(split=False, normalize=False)

# Perform k-fold cross-validation
kf = KFold(n_splits=6, shuffle=True, random_state=42)

mse = []

start_time = time.time()

for train_index, val_index in kf.split(X):
    X_train_fold, X_val_fold = X.iloc[train_index], X.iloc[val_index]
    y_train_fold, y_val_fold = y.iloc[train_index], y.iloc[val_index]

    # Apply normalization after splitting the dataset!
    X_train_fold = apply_normalization(X_train_fold)
    X_val_fold = apply_normalization(X_val_fold)

    # Train the model
    knn_regressor = KNN(k=3, problem_type=ProblemType.Regression,␣
↪distance_metric=DistanceMetric.Manhattan)
    knn_regressor.fit(X_train_fold.values, y_train_fold.values)

    # Make predictions
    y_pred_fold = knn_regressor.predict(X_val_fold.values)

    # Compute MSE
    mse_fold = mean_squared_error(y_val_fold, y_pred_fold)
    mse.append(mse_fold)

    print(f"MSE for fold: {mse_fold:.2f}")

end_time = time.time()

# Average MSE across all folds on training set
avg_mse = sum(mse) / len(mse)
print(f"Average MSE from k-fold Cross-Validation: {avg_mse:.2f}")

# Calculate and print runtime
runtime = end_time - start_time
print(f"Total Runtime: {runtime:.2f} seconds")
```

```
MSE for fold: 373972.28
```

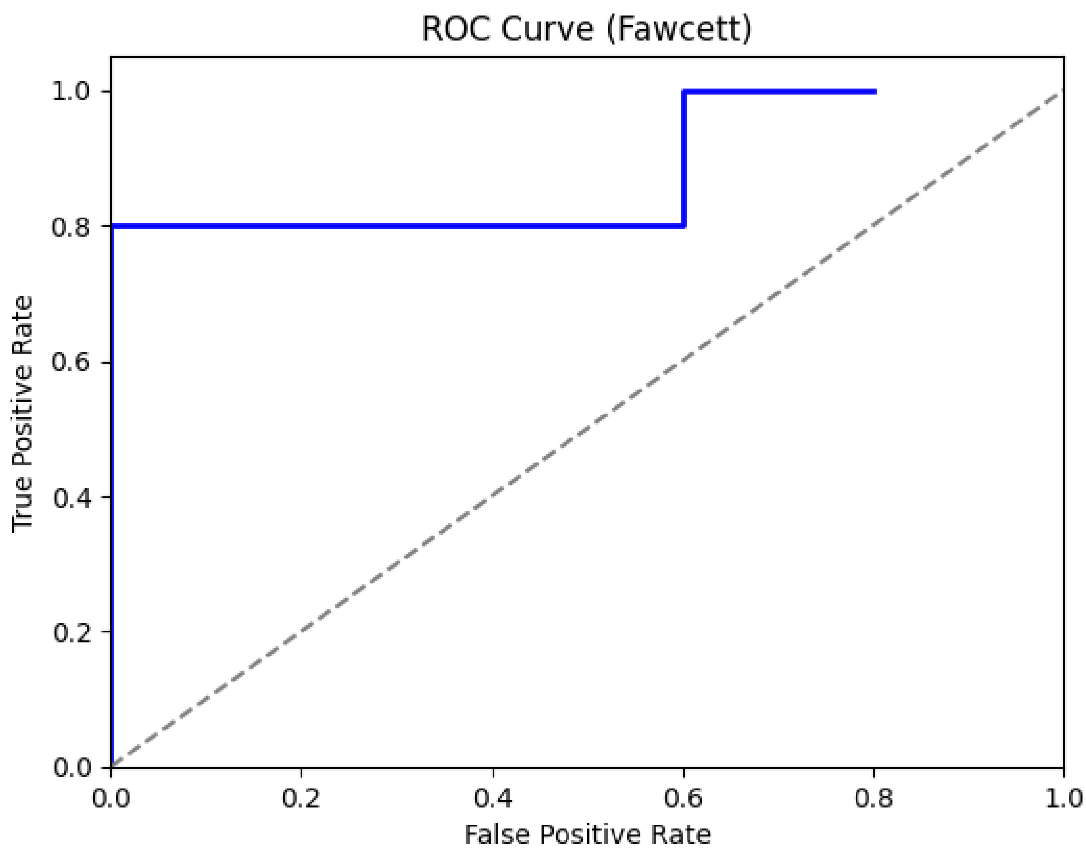
```
MSE for fold: 263697.68
MSE for fold: 307152.76
MSE for fold: 297322.59
MSE for fold: 359299.07
MSE for fold: 279818.16
Average MSE from k-fold Cross-Validation: 313543.76
Total Runtime: 18.65 seconds
```

7 Part 3: Build a classifier based on the linear SVM

Efficient generation of ROC curves, proposed by Tom Fawcett

[28]:
```
import numpy as np
import matplotlib.pyplot as plt

def generate_roc_curve(y_true, y_probs):
    # Sort the probabilities and true labels by descending probability
    sorted_indices = np.argsort(y_probs)[::-1]
    # Calculate total number of positive and negative samples
    num_positives = np.sum(y_true)
    num_negatives = len(y_true) - num_positives

    # Initialize variables for counting true positives (TP) and false positives␣
 ↪(FP)
    tp_count = 0
    fp_count = 0
    prev_threshold = 0.0
    fprs = []
    tprs = []

    # Iterate through each probability threshold
    for i in sorted_indices:
        if y_probs[i] != prev_threshold:
            # Calculate TPR and FPR for current threshold
            fpr = fp_count / num_negatives
            tpr = tp_count / num_positives
            fprs.append(fpr)
            tprs.append(tpr)
            prev_threshold = prev_threshold

        # Update TP and FP counts based on current threshold
        if y_true[i] == 1:
            tp_count += 1
        else:
            fp_count += 1

    return fprs, tprs
```

```
# Example usage
y_true = np.array([0, 1, 0, 1, 0, 1, 1, 0, 0, 1])
y_probs = np.array([0.1, 0.3, 0.2, 0.7, 0.5, 0.8, 0.9, 0.6, 0.4, 0.75])

fprs, tprs = generate_roc_curve(y_true, y_probs)

# Plot ROC curve
plt.plot(fprs, tprs, color='blue', lw=2)
plt.plot([0, 1], [0, 1], color='gray', 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('ROC Curve (Fawcett)')
plt.show()
```

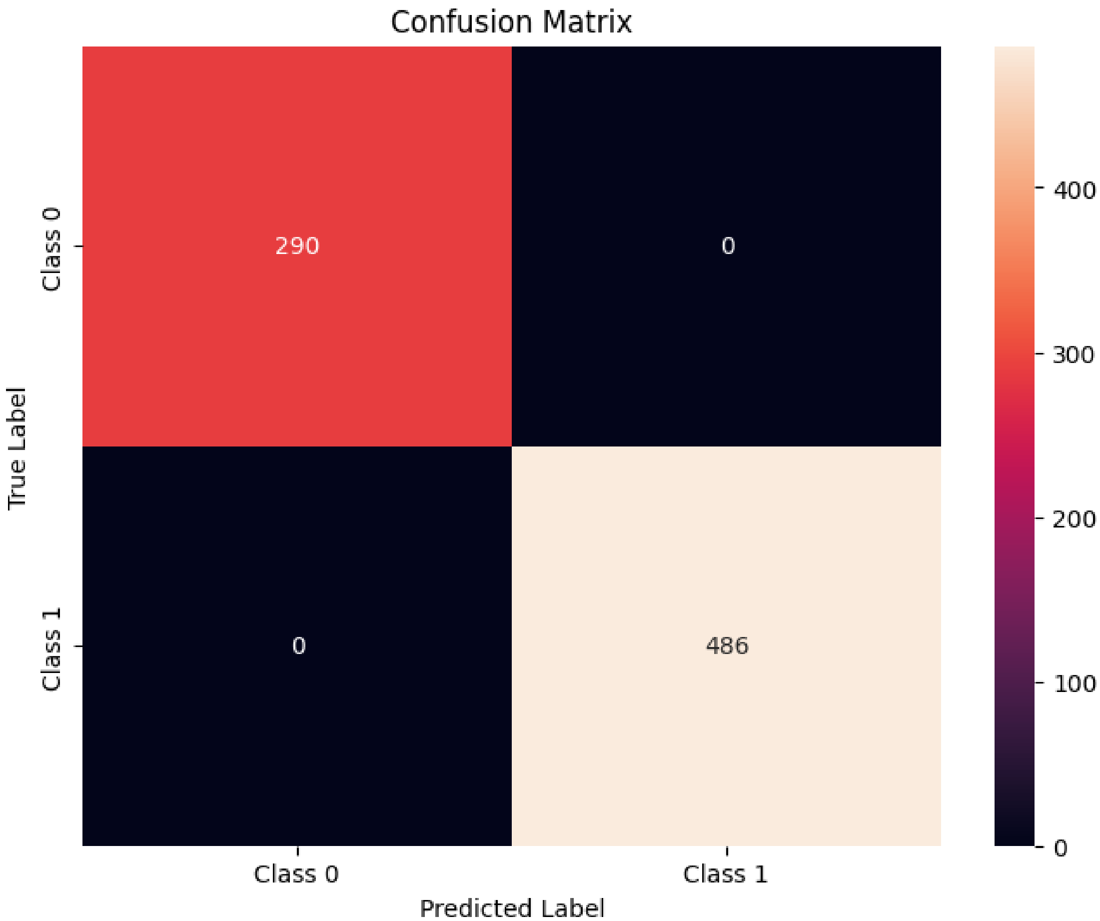


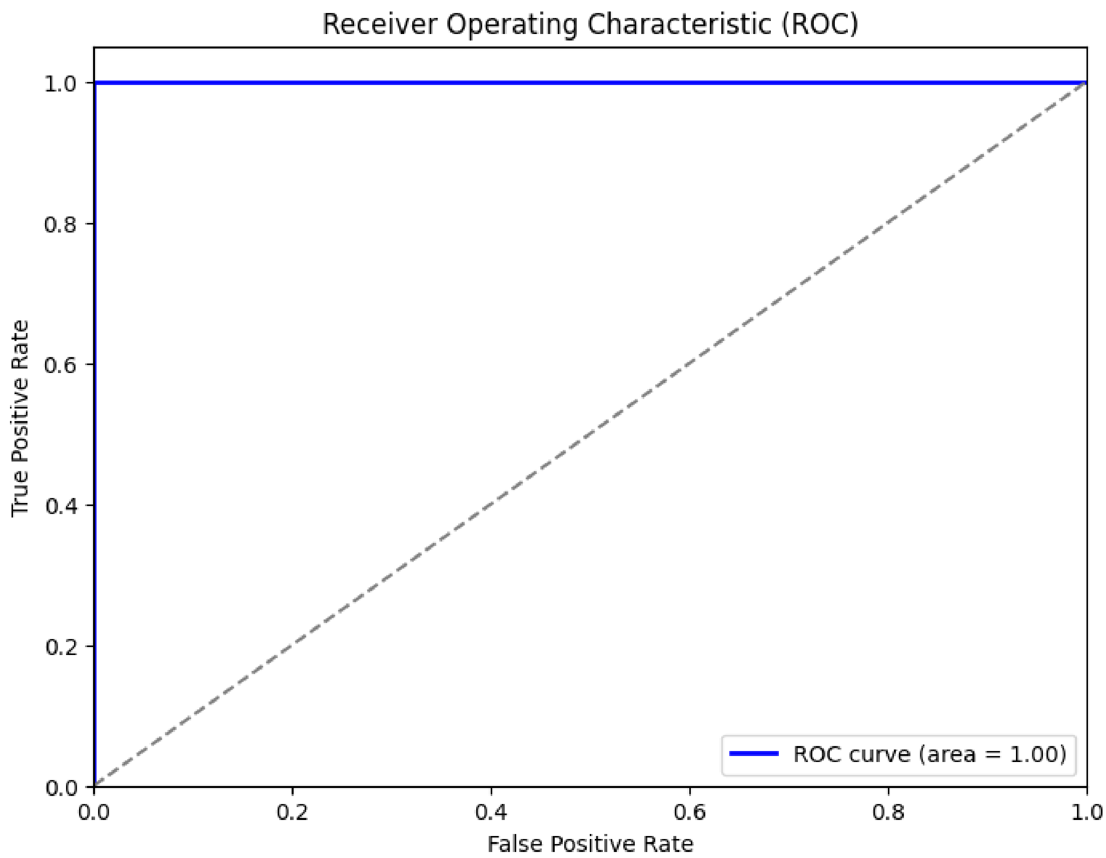
[29]:
```
import numpy as np
import time
import matplotlib.pyplot as plt
```

```python
from sklearn.metrics import roc_curve, auc, confusion_matrix, accuracy_score
from sklearn.svm import SVC
from sklearn.model_selection import KFold
from sklearn.preprocessing import StandardScaler

X, y = load_data_audit_risk(split=False, normalize=False)

# Perform k-fold cross-validation
kf = KFold(n_splits=6, shuffle=True, random_state=42)

# Lists to store predictions and true labels
all_y_pred = []
all_y_true = []

# Lists to store predicted probabilities for ROC curve
all_y_probs = []
all_y_true_binary = []

start_time = time.time()

# Iterate through each fold
for train_index, val_index in kf.split(X):
    X_train, X_val = X.iloc[train_index], X.iloc[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    X_train = apply_normalization(X_train)
    X_val = apply_normalization(X_val)

    # Initialize SVM classifier
    svm_classifier = SVC(kernel='linear', probability=True, random_state=42)

    # Train the model
    svm_classifier.fit(X_train, y_train)

    # Make predictions
    y_pred_fold = svm_classifier.predict(X_val)
    y_probs_fold = svm_classifier.predict_proba(X_val)[:, 1]

    # Collect predictions and true labels
    all_y_pred.extend(y_pred_fold)
    all_y_true.extend(y_val)
    all_y_probs.extend(y_probs_fold)
    all_y_true_binary.extend([1 if label == 1 else 0 for label in y_val])  #␣
↪binary true labels (0 or 1)

    # Compute accuracy
    accuracy_fold = accuracy_score(y_val, y_pred_fold)
```

```
    print(f"Accuracy for fold: {accuracy_fold:.2f}")

end_time = time.time()

# Compute overall accuracy
overall_accuracy = accuracy_score(all_y_true, all_y_pred)
print(f"Overall Accuracy from k-fold Cross-Validation: {overall_accuracy:.2f}",␣
↪"\n")

# Compute confusion matrix
plot_confusion_matrix(all_y_true, all_y_pred)
print("\n")
# Plot ROC curve
plot_roc_curve(all_y_true_binary, all_y_probs)

# Find the best threshold
fpr, tpr, thresholds = roc_curve(all_y_true_binary, all_y_probs)
youden_j = tpr - fpr
best_threshold_index = np.argmax(youden_j)
best_threshold = thresholds[best_threshold_index]
print(f"\nBest Threshold: {best_threshold:.4f}")

runtime = end_time - start_time
print(f"Total Runtime: {runtime:.2f} seconds")
```

```
Accuracy for fold: 1.00
Accuracy for fold: 1.00
Accuracy for fold: 1.00
Accuracy for fold: 1.00
Accuracy for fold: 1.00
Accuracy for fold: 1.00
Overall Accuracy from k-fold Cross-Validation: 1.00
```


Confusion Matrix
290
0
0
486
Class 0
Class 1
True Label
Class 0
Class 1
Predicted Label
0
100
200
300
400




```
Best Threshold: 0.7030
Total Runtime: 0.19 seconds
```

8 Part 4: Build a regressor based on the linear SVM

[30]:
```
from sklearn.model_selection import cross_val_predict, KFold
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.svm import SVR

# Load the dataset
X, y = load_data_bike_sharing(split=False, normalize=False)

# Perform k-fold cross-validation
kf = KFold(n_splits=6, shuffle=True, random_state=42)

# Lists to store predictions and true labels
all_y_pred = []
all_y_true = []
```

```
# Lists to store predicted probabilities for ROC curve
all_y_probs = []
all_y_true_binary = []

start_time = time.time()

# Iterate through each fold
for train_index, val_index in kf.split(X):
    X_train, X_val = X.iloc[train_index], X.iloc[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    X_train = apply_normalization(X_train)
    X_val = apply_normalization(X_val)

    # Initialize SVM regressor
    svm_regressor = SVR(kernel='linear')

    # Train the model
    svm_regressor.fit(X_train, y_train)

    # Make predictions
    y_pred_fold = svm_regressor.predict(X_val)

    # Collect predictions and true labels
    all_y_pred.extend(y_pred_fold)
    all_y_true.extend(y_val)

    # Compute mean squared error
    mse_fold = mean_squared_error(y_val, y_pred_fold)
    print(f"Mean Squared Error for fold: {mse_fold:.2f}")

end_time = time.time()

# Compute overall mean squared error
overall_mse = mean_squared_error(all_y_true, all_y_pred)
print(f"Overall Mean Squared Error from k-fold Cross-Validation: {overall_mse:.
 ↪2f}")

# Compute R-squared score
r2 = r2_score(all_y_true, all_y_pred)
print(f"R-squared Score from k-fold Cross-Validation: {r2:.2f}")

runtime = end_time - start_time
print(f"Total Runtime: {runtime:.2f} seconds")
```

```
Mean Squared Error for fold: 886382.25
```

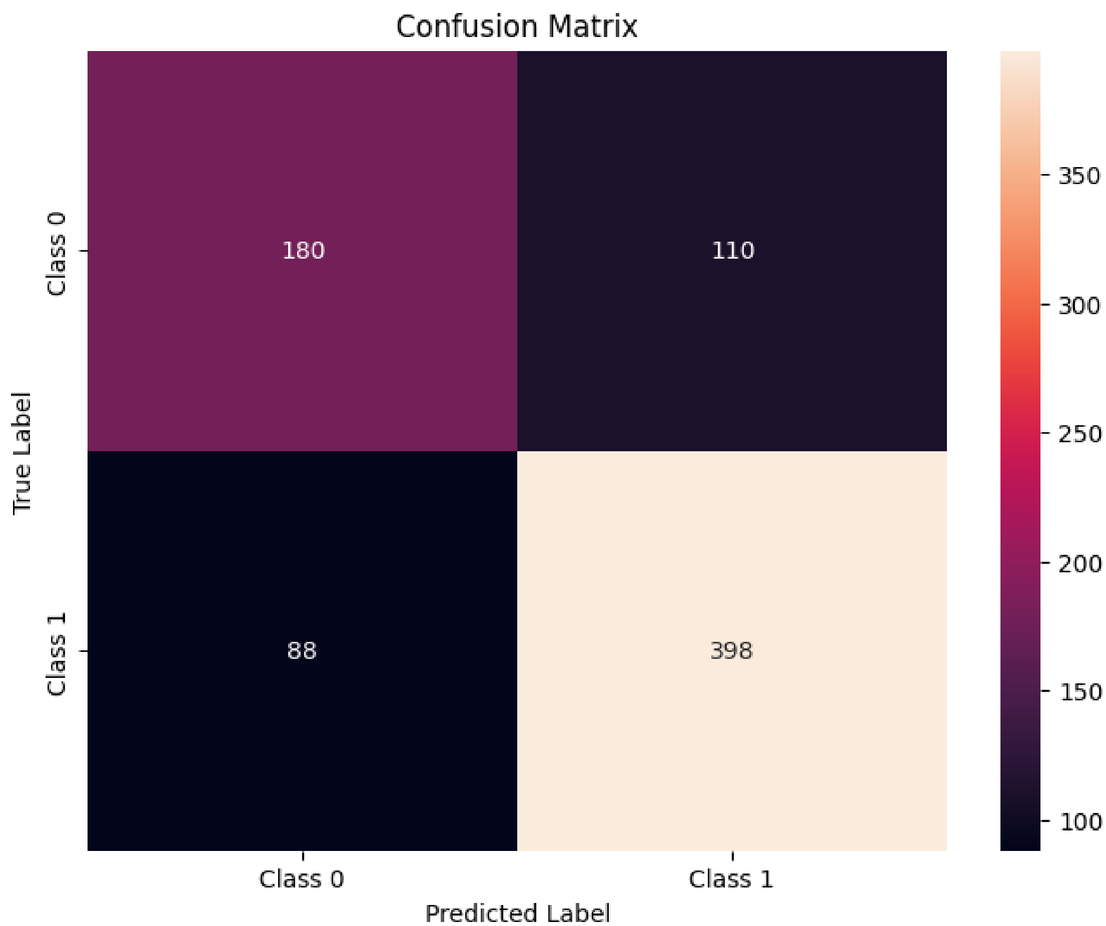
```
Mean Squared Error for fold: 576749.69
Mean Squared Error for fold: 573099.16
Mean Squared Error for fold: 779019.99
Mean Squared Error for fold: 894812.06
Mean Squared Error for fold: 634093.34
Overall Mean Squared Error from k-fold Cross-Validation: 724149.11
R-squared Score from k-fold Cross-Validation: 0.81
Total Runtime: 0.19 seconds
```

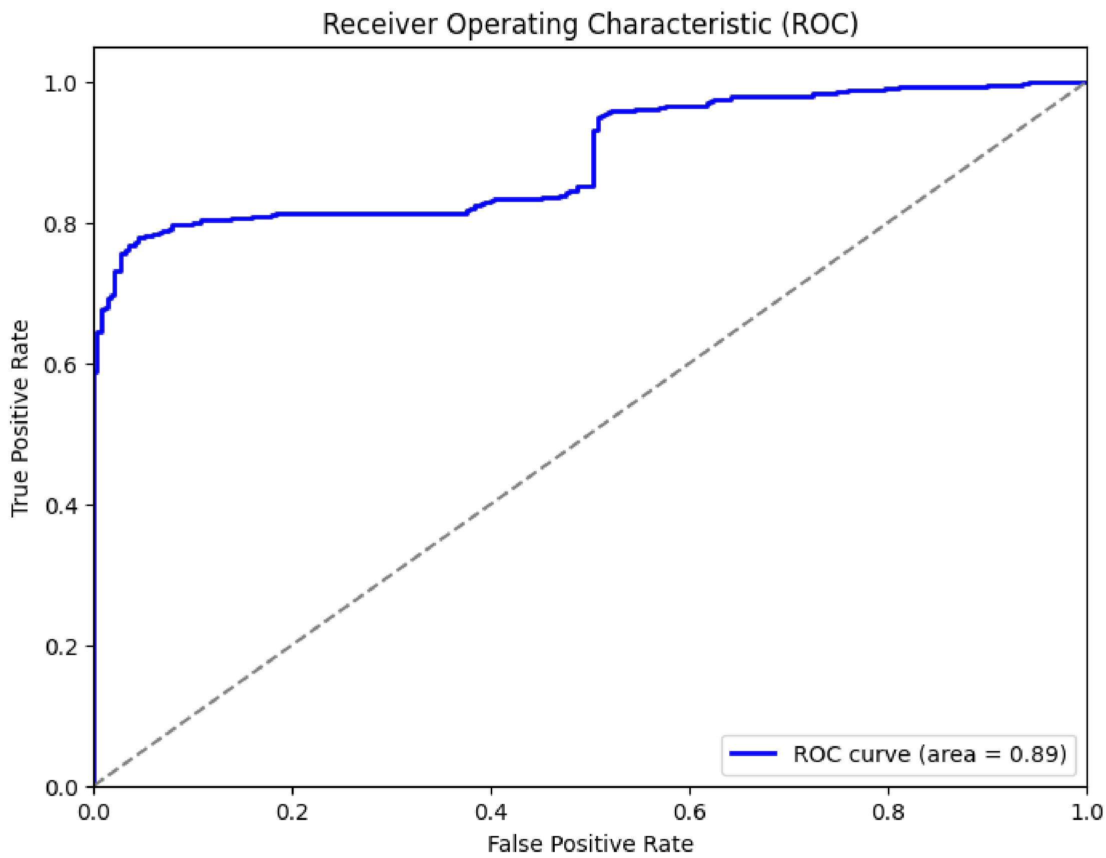
9 Part 5: Build a classifier based on the radial basis function SVM

[31]:
```
from sklearn.model_selection import cross_val_predict, KFold
from sklearn.metrics import confusion_matrix, accuracy_score, roc_curve, auc
from sklearn.svm import SVC
import matplotlib.pyplot as plt

# Load the dataset
X, y = load_data_audit_risk(split=False, normalize=False)

# Perform k-fold cross-validation
kf = KFold(n_splits=6, shuffle=True, random_state=42)

# Lists to store predictions and true labels
all_y_pred = []
all_y_true = []

# Lists to store predicted probabilities for ROC curve
all_y_probs = []
all_y_true_binary = []

start_time = time.time()

# Iterate through each fold
for train_index, val_index in kf.split(X):
    X_train, X_val = X.iloc[train_index], X.iloc[val_index]
    y_train, y_val = y.iloc[train_index], y.iloc[val_index]

    # Initialize SVM classifier with RBF kernel
    svm_classifier = SVC(kernel='rbf', probability=True, random_state=42)

    # Train the model
    svm_classifier.fit(X_train, y_train)

    # Make predictions
    y_pred_fold = svm_classifier.predict(X_val)
    y_probs_fold = svm_classifier.predict_proba(X_val)[:, 1]  # predicted␣
↪probabilities for class 1
```

```python
    # Collect predictions and true labels
    all_y_pred.extend(y_pred_fold)
    all_y_true.extend(y_val)
    all_y_probs.extend(y_probs_fold)
    all_y_true_binary.extend([1 if label == 1 else 0 for label in y_val])  #␣
↪binary true labels (0 or 1)

    # Compute accuracy
    accuracy_fold = accuracy_score(y_val, y_pred_fold)
    print(f"Accuracy for fold: {accuracy_fold:.2f}")

end_time = time.time()

# Compute overall accuracy
overall_accuracy = accuracy_score(all_y_true, all_y_pred)
print(f"Overall Accuracy from k-fold Cross-Validation: {overall_accuracy:.2f}")

# Compute confusion matrix
plot_confusion_matrix(all_y_true, all_y_pred)

print()

# Plot ROC curve
plot_roc_curve(all_y_true_binary, all_y_probs)

# Find the best threshold
fpr, tpr, thresholds = roc_curve(all_y_true_binary, all_y_probs)
youden_j = tpr - fpr
best_threshold_index = np.argmax(youden_j)
best_threshold = thresholds[best_threshold_index]
print(f"\nBest Threshold: {best_threshold:.4f}")

runtime = end_time - start_time
print(f"Total Runtime: {runtime:.2f} seconds")
```

```
Accuracy for fold: 0.76
Accuracy for fold: 0.72
Accuracy for fold: 0.76
Accuracy for fold: 0.77
Accuracy for fold: 0.72
Accuracy for fold: 0.74
Overall Accuracy from k-fold Cross-Validation: 0.74
```


Confusion Matrix
180
110
88
398
Class 0
Class 1
True Label
Class 0
Class 1
Predicted Label
350
300
250
200
150
100




```
Best Threshold: 0.7126
Total Runtime: 0.48 seconds
```

10 Part 6: Build a classifier based on DT (Decision Trees)

Function to convert the decision tree into a set of rules

[32]:
```
from sklearn.tree import _tree

def extract_rules_from_tree(tree, feature_names):
    feature_name  = [feature_names[i] if i != _tree.TREE_UNDEFINED else␣
 ↪"undefined!" for i in tree.feature]

    print(f"def tree({', '.join(feature_names)})")

    def recurse(node, depth):
        indent = "   " * depth
        if tree.feature[node] != _tree.TREE_UNDEFINED:
            name = feature_names[node]
```

```python
            threshold = tree.threshold[node]
            print("{}if {} <= {}:".format(indent, name, threshold))
            recurse(tree.children_left[node], depth + 1)
            print("{}else:  # if {} > {}".format(indent, name, threshold))
            recurse(tree.children_right[node], depth + 1)
        else:
            print("{}return {}".format(indent, tree.value[node]))

    recurse(0, 1)
```

[33]:
```python
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Define k-fold cross-validation
k_fold = KFold(n_splits=6, shuffle=True, random_state=42)

# Decision tree without pruning
tree_no_pruning = DecisionTreeClassifier(random_state=42)

# Perform k-fold cross-validation for the tree without pruning
no_pruning_scores = cross_val_score(tree_no_pruning, X, y, cv=k_fold)

print("Cross-validation scores without pruning:", no_pruning_scores)
print("Average accuracy without pruning:", no_pruning_scores.mean())

# Pre-pruning: Limiting the maximum depth of the tree
tree_pre_pruning = DecisionTreeClassifier(max_depth=3, random_state=42)

# Perform k-fold cross-validation for the tree with pre-pruning
pre_pruning_scores = cross_val_score(tree_pre_pruning, X, y, cv=k_fold)

print("\nCross-validation scores with pre-pruning:", pre_pruning_scores)
print("Average accuracy with pre-pruning:", pre_pruning_scores.mean())

# Post-pruning: Using cost complexity pruning
tree_post_pruning = DecisionTreeClassifier(random_state=42)
path = tree_post_pruning.cost_complexity_pruning_path(X, y)
ccp_alphas, impurities = path.ccp_alphas, path.impurities

# Train trees with different ccp_alphas
trees = []
for ccp_alpha in ccp_alphas:
    tree = DecisionTreeClassifier(ccp_alpha=ccp_alpha, random_state=42)
    tree.fit(X, y)
    trees.append(tree)
```

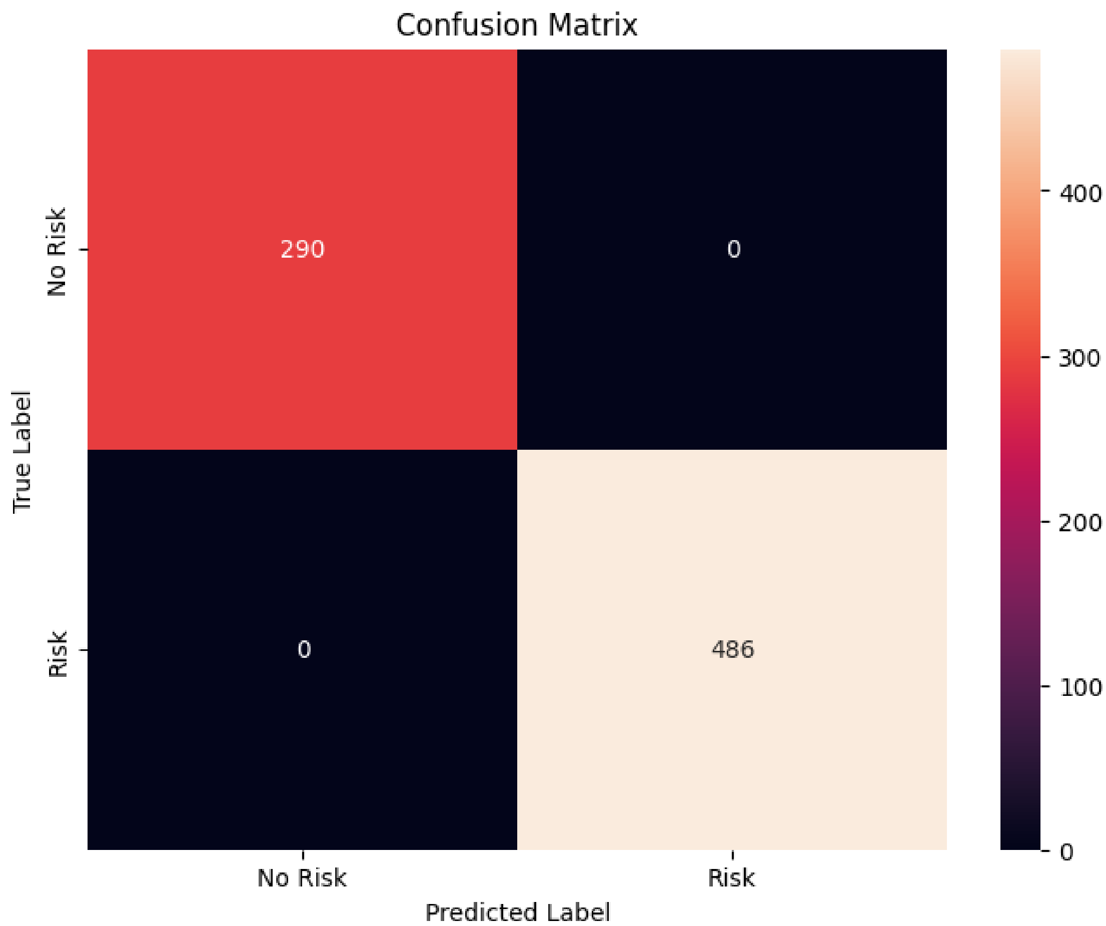
```
# Find the tree with the highest accuracy on the test set
acc_scores = [cross_val_score(tree, X, y, cv=k_fold).mean() for tree in trees]
best_tree_idx = acc_scores.index(max(acc_scores))
tree_post_pruning = trees[best_tree_idx]

print("\nAverage cross-validation scores with post-pruning:", acc_scores)
print("Average accuracy with post-pruning:", acc_scores[best_tree_idx])
```

```
Cross-validation scores without pruning: [1. 1. 1. 1. 1. 1.]
Average accuracy without pruning: 1.0

Cross-validation scores with pre-pruning: [1. 1. 1. 1. 1. 1.]
Average accuracy with pre-pruning: 1.0

Average cross-validation scores with post-pruning: [1.0, 0.8622937785728483]
Average accuracy with post-pruning: 1.0
```

10.1 Pruning Strategy 1: Pre-Pruning

[34]:
```
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Load the dataset
X, y = load_data_audit_risk(split=False, normalize=False)

dt_classifier_pre_pruned = DecisionTreeClassifier(max_depth=3, random_state=42)
dt_classifier_pre_pruned.fit(X, y)

kf = KFold(n_splits=6, shuffle=True, random_state=42)

start_time = time.time()

# Perform k-fold cross-validation
y_pred = cross_val_predict(dt_classifier_pre_pruned, X, y, cv=kf)

end_time = time.time()

accuracy = accuracy_score(y, y_pred)
print("Overal Accuracy from k-fold Cross-Validation:", accuracy, "\n")
plot_confusion_matrix(y, y_pred, ['No Risk', 'Risk'])

# Calculate and print runtime
runtime = end_time - start_time
print(f"\nTotal Runtime: {runtime:.2f} seconds")
```

```
Overal Accuracy from k-fold Cross-Validation: 1.0
```




```
Total Runtime: 0.06 seconds
```

[35]:

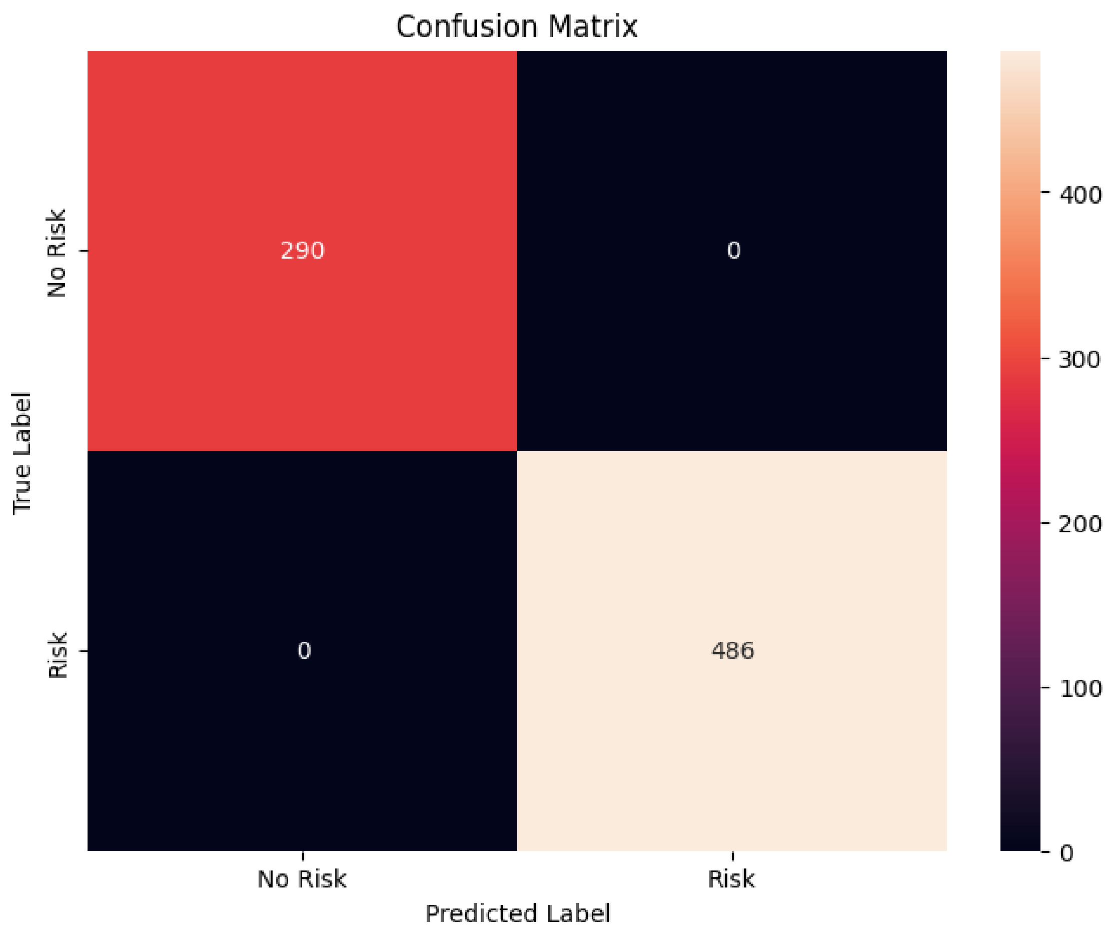
```
extract_rules_from_tree(dt_classifier_pre_pruned.tree_, X.columns)
```

```
def tree(Sector_score, LOCATION_ID, PARA_A, SCORE_A, PARA_B, SCORE_B, TOTAL,
numbers, Marks, Money_Value, MONEY_Marks, District, Loss, LOSS_SCORE, History,
History_score, Score)
  if Sector_score <= 2.100000023841858:
    return [[290.   0.]]
  else:  # if Sector_score > 2.100000023841858
    return [[  0. 486.]]
```

10.2 Pruning Strategy 2: Post-Pruning

[36]:
```python
from sklearn.tree import DecisionTreeClassifier, plot_tree

# Load the dataset
X, y = load_data_audit_risk(split=False, normalize=False)

# Define the DecisionTreeClassifier with post-pruning
dt_classifier_post_pruned = DecisionTreeClassifier(min_samples_split=10,␣
 ↪ccp_alpha=0.01)
dt_classifier_post_pruned.fit(X, y)

# Perform k-fold cross-validation with post-pruned tree
kf = KFold(n_splits=6, shuffle=True, random_state=42)

start_time = time.time()

y_pred_pruned = cross_val_predict(dt_classifier_post_pruned, X, y, cv=kf)

end_time = time.time()

accuracy = accuracy_score(y, y_pred)
print("Overall Accuracy from k-fold Cross-Validation:", accuracy, "\n")
plot_confusion_matrix(y, y_pred, ['No Risk', 'Risk'])

# Calculate and print runtime
runtime = end_time - start_time
print(f"\nTotal Runtime: {runtime:.2f} seconds")
```

```
Overall Accuracy from k-fold Cross-Validation: 1.0
```




```
Total Runtime: 0.05 seconds
```

[37]:
```
extract_rules_from_tree(dt_classifier_post_pruned.tree_, X.columns)
```

```
def tree(Sector_score, LOCATION_ID, PARA_A, SCORE_A, PARA_B, SCORE_B, TOTAL,
numbers, Marks, Money_Value, MONEY_Marks, District, Loss, LOSS_SCORE, History,
History_score, Score)
  if Sector_score <= 2.100000023841858:
    return [[290.   0.]]
  else:  # if Sector_score > 2.100000023841858
    return [[  0. 486.]]
```

11 Part 7: Build a regressor based on DT (Decision Trees)

[38]:

```
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt

# Load the dataset
X, y = load_data_bike_sharing(split=False, normalize=False)

# Train Decision Tree Regressor with pre-pruning
dt_regressor = DecisionTreeRegressor(max_depth=3, min_samples_split=10)
dt_regressor.fit(X, y)

kf = KFold(n_splits=6, shuffle=True, random_state=42)

# Perform k-fold cross-validation
end_time = time.time()

start_time = time.time()

mse_scores = cross_val_score(dt_regressor, X, y, cv=kf,␣
 ↪scoring='neg_mean_squared_error')

end_time = time.time()

# Convert negative MSE scores to positive and calculate mean
mse_scores = -mse_scores
mean_mse = np.mean(mse_scores)

print(f"Mean Squared Error from k-fold Cross-Validation: {mean_mse:.2f}")

# Calculate and print runtime
runtime = end_time - start_time
print(f"Total Runtime: {runtime:.2f} seconds")
```

```
Mean Squared Error from k-fold Cross-Validation: 354612.66
Total Runtime: 0.06 seconds
```

[39]:

```
extract_rules_from_tree(dt_regressor.tree_, X.columns)
```

```
def tree(season, yr, mnth, holiday, weekday, workingday, weathersit, temp,
atemp, hum, windspeed, casual, registered)
  if season <= 3905.5:
    if yr <= 2294.0:
      if mnth <= 1377.5:
        return [[1142.05263158]]
      else:  # if mnth > 1377.5
```

```
        return [[2155.50505051]]
    else:  # if yr > 2294.0
      if workingday <= 1626.0:
        return [[3881.68803419]]
      else:  # if workingday > 1626.0
        return [[5368.8]]
  else:  # if season > 3905.5
    if atemp <= 5283.5:
      if hum <= 1990.0:
        return [[5309.34965035]]
      else:  # if hum > 1990.0
        return [[7058.48648649]]
    else:  # if atemp > 5283.5
      if registered <= 5874.0:
        return [[6750.15217391]]
      else:  # if registered > 5874.0
        return [[7469.49333333]]
```

12 Analysis and Discussion of Results

All the reported results are obtained through k-fold cross-validation, ensuring robust evaluation of the models' performance across different subsets of the dataset.

12.1 Part 1: KNN Classifier (Euclidean Distance)

- **Overall Accuracy:** 0.99
- **Total Runtime:** 22.06 seconds

This model achieved an impressively high accuracy of 99% on average across all folds. However, the runtime is relatively high compared to some other models.

12.2 Part 2: KNN Regressor (Manhattan Distance)

- **Average MSE:** 313543.76
- **Total Runtime:** 18.65 seconds

The mean squared error (MSE) for this model is quite high, indicating that it might not perform well in predicting the target values accurately. Additionally, the runtime is relatively high.

12.3 Part 3: Linear SVM Classifier

- **Overall Accuracy:** 1.00
- **Best Threshold:** 0.7030
- **Total Runtime:** 0.19 seconds

This model achieved perfect accuracy (overfit), indicating that it performs very well on the classification task. The runtime is also relatively low, making it efficient.

12.4 Part 4: Linear SVM Regressor

- **Overall Mean Squared Error:** 724149.11
- **R-squared Score:** 0.81
- **Total Runtime:** 0.19 seconds

While the mean squared error is high, the R-squared score indicates decent performance in explaining the variance of the target variable. The runtime is moderate.

12.5 Part 5: Radial Basis Function SVM Classifier

- **Overall Accuracy:** 0.74
- **Best Threshold:** 0.7126
- **Total Runtime:** 0.48 seconds

The accuracy of this model is lower compared to the linear SVM classifier, but the runtime is still reasonable.

12.6 Part 6: Decision Tree Classifier

12.6.1 Pre-pruning

- **Overall Accuracy:** 1.0
- **Total Runtime:** 0.06 seconds

12.6.2 Post-pruning

- **Overall Accuracy:** 1.0
- **Total Runtime:** 0.05 seconds

Both pre-pruning and post-pruning decision tree classifiers achieved perfect accuracy, indicating that they can capture the underlying patterns in the data effectively. However, it's important to note that decision trees are prone to overfitting, which may affect their performance on unseen data.

12.7 Part 7: Decision Tree Regressor

- **Mean Squared Error:** 354612.66
- **Total Runtime:** 0.06 seconds

The mean squared error for this model is moderate, indicating reasonable performance in predicting the target variable. The runtime is very low, making it efficient.

12.8 Discussion:

- For the classification problem, the best models are the Linear SVM Classifier and the Decision Tree Classifier (both pre-pruning and post-pruning), as they achieved highest accuracy with relatively low runtimes.
- For the regression problem, the Linear SVM Regressor and the Decision Tree Regressor performed reasonably well, with the Decision Tree Regressor having a slightly lower MSE and comparable runtime. However, it's important to note that decision trees are very likely to overfit, which may affect their performance on unseen data.