510518079_Assignment4

October 26, 2021

1 Assignment 4 : SVM

1.1 Import Libraries

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
from scipy.sparse import hstack
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.svm import SVC
from sklearn.multiclass import OneVsRestClassifier
from sklearn.multiclass import OneVsOneClassifier
from sklearn.preprocessing import MinMaxScaler
```

1.2 Pre Processing on Titanic Data Set

[ ]:
```
titanic = pd.read_csv('titanic.csv')
titanic.head()
```

[ ]:
```
   Passengerid   Age     Fare  Sex  sibsp  zero  zero.1  zero.2  zero.3  \
0            1  22.0   7.2500    0      1     0       0       0       0
1            2  38.0  71.2833    1      1     0       0       0       0
2            3  26.0   7.9250    1      0     0       0       0       0
3            4  35.0  53.1000    1      1     0       0       0       0
4            5  35.0   8.0500    0      0     0       0       0       0

   zero.4  …  zero.12  zero.13  zero.14  Pclass  zero.15  zero.16  Embarked  \
0       0  …        0        0        0       3        0        0       2.0
1       0  …        0        0        0       1        0        0       0.0
2       0  …        0        0        0       3        0        0       2.0
3       0  …        0        0        0       1        0        0       2.0
4       0  …        0        0        0       3        0        0       2.0

   zero.17  zero.18  2urvived
```

```
0         0         0          0
1         0         0          1
2         0         0          1
3         0         0          1
4         0         0          0

[5 rows x 28 columns]
```

[ ]:
```
titanic.describe()
```

[ ]:
```
       Passengerid          Age         Fare          Sex        sibsp  \
count  1309.000000  1309.000000  1309.000000  1309.000000  1309.000000
mean    655.000000    29.503186    33.281086     0.355997     0.498854
std     378.020061    12.905241    51.741500     0.478997     1.041658
min       1.000000     0.170000     0.000000     0.000000     0.000000
25%     328.000000    22.000000     7.895800     0.000000     0.000000
50%     655.000000    28.000000    14.454200     0.000000     0.000000
75%     982.000000    35.000000    31.275000     1.000000     1.000000
max    1309.000000    80.000000   512.329200     1.000000     8.000000

         zero  zero.1  zero.2  zero.3  zero.4  …  zero.12  zero.13  zero.14  \
count  1309.0  1309.0  1309.0  1309.0  1309.0  …   1309.0   1309.0   1309.0
mean      0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
std       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
min       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
25%       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
50%       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
75%       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0
max       0.0     0.0     0.0     0.0     0.0  …      0.0      0.0      0.0

            Pclass  zero.15  zero.16     Embarked  zero.17  zero.18  \
count  1309.000000   1309.0   1309.0  1307.000000   1309.0   1309.0
mean      2.294882      0.0      0.0     1.492731      0.0      0.0
std       0.837836      0.0      0.0     0.814626      0.0      0.0
min       1.000000      0.0      0.0     0.000000      0.0      0.0
25%       2.000000      0.0      0.0     1.000000      0.0      0.0
50%       3.000000      0.0      0.0     2.000000      0.0      0.0
75%       3.000000      0.0      0.0     2.000000      0.0      0.0
max       3.000000      0.0      0.0     2.000000      0.0      0.0

          2urvived
count  1309.000000
mean      0.261268
std       0.439494
min       0.000000
25%       0.000000
50%       0.000000
```

```
75%        1.000000
max        1.000000

[8 rows x 28 columns]
```

[ ]:
```
titanic = titanic.dropna()
```

[ ]:
```
X = titanic.copy()
for fn in X.columns:
    if len(X[fn].unique()) == 1:
        X = X.drop(columns = [fn])
Y = titanic['2urvived']
X = X.drop(columns = ['Passengerid','2urvived'])
print(X.shape)
print(Y.shape)
X.head()
```

```
(1307, 7)
(1307,)
```

[ ]:

	Age	Fare	Sex	sibsp	Parch	Pclass	Embarked
0	22.0	7.2500	0	1	0	3	2.0
1	38.0	71.2833	1	1	0	1	0.0
2	26.0	7.9250	1	0	0	3	2.0
3	35.0	53.1000	1	1	0	1	2.0
4	35.0	8.0500	0	0	0	3	2.0

[ ]:
```
scaler = MinMaxScaler()
X[['Age', 'Fare','Parch','sibsp']] = scaler.fit_transform(X[['Age',␣
↪'Fare','Parch','sibsp']])
X.head()
```

[ ]:

	Age	Fare	Sex	sibsp	Parch	Pclass	Embarked
0	0.273456	0.014151	0	0.125	0.0	3	2.0
1	0.473882	0.139136	1	0.125	0.0	1	0.0
2	0.323563	0.015469	1	0.000	0.0	3	2.0
3	0.436302	0.103644	1	0.125	0.0	1	2.0
4	0.436302	0.015713	0	0.000	0.0	3	2.0

[ ]:
```
pclass = X['Pclass'].values.reshape(-1, 1)
embarked = X['Embarked'].values.reshape(-1, 1)
sex = X['Sex'].values.reshape(-1, 1)

ohe = OneHotEncoder()

pclass_ohe = ohe.fit_transform(pclass)
embarked_ohe = ohe.fit_transform(embarked)
```

```
sex_ohe = ohe.fit_transform(sex)
```

[ ]:
```
t_n = X[['Age', 'Fare', 'Parch','sibsp']]
X = hstack((t_n, embarked_ohe, sex_ohe, pclass_ohe))
print(X.shape)
```

```
(1307, 12)
```

[ ]:
```
x_train, x_test, y_train, y_test = train_test_split(X, Y, stratify = Y,␣
 ↪test_size = 0.2, random_state = 10)
print(x_train.shape, x_test.shape)
print(y_train.shape, y_test.shape)
```

```
(1045, 12) (262, 12)
(1045,) (262,)
```

1.3 Task 1

[ ]:
```
kernel, degree, n_0, n_1, acc = [], [], [], [], []
```

[ ]:
```
model = SVC(kernel = 'linear')
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(accuracy_score(y_test, y_pred))
print(model.n_support_)
kernel.append('Linear')
degree.append('NA')
n_0.append(model.n_support_[0])
n_1.append(model.n_support_[1])
acc.append(accuracy_score(y_test, y_pred))
```

```
0.7938931297709924
[271 260]
```

[ ]:
```
model = SVC(kernel = 'poly', degree = 2)
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(accuracy_score(y_test, y_pred))
print(model.n_support_)
kernel.append('Polynomial')
degree.append('2')
n_0.append(model.n_support_[0])
n_1.append(model.n_support_[1])
acc.append(accuracy_score(y_test, y_pred))
```

```
0.7938931297709924
[245 228]
```

[ ]:
```
model = SVC(kernel = 'poly', degree = 3)
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(accuracy_score(y_test, y_pred))
print(model.n_support_)
kernel.append('Polynomial')
degree.append('3')
n_0.append(model.n_support_[0])
n_1.append(model.n_support_[1])
acc.append(accuracy_score(y_test, y_pred))
```

```
0.7824427480916031
[246 223]
```

[ ]:
```
model = SVC(kernel = 'poly', degree = 5)
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(accuracy_score(y_test, y_pred))
print(model.n_support_)
kernel.append('Polynomial')
degree.append('5')
n_0.append(model.n_support_[0])
n_1.append(model.n_support_[1])
acc.append(accuracy_score(y_test, y_pred))
```

```
0.7786259541984732
[256 222]
```

[ ]:
```
model = SVC(kernel = 'rbf')
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(accuracy_score(y_test, y_pred))
print(model.n_support_)
kernel.append('RBF')
degree.append('NA')
n_0.append(model.n_support_[0])
n_1.append(model.n_support_[1])
acc.append(accuracy_score(y_test, y_pred))
```

```
0.7748091603053435
[249 227]
```

[ ]:
```
model = SVC(kernel = 'sigmoid')
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(accuracy_score(y_test, y_pred))
print(model.n_support_)
kernel.append('Sigmoid')
```

```
degree.append('NA')
n_0.append(model.n_support_[0])
n_1.append(model.n_support_[1])
acc.append(accuracy_score(y_test, y_pred))
```

```
0.6564885496183206
[205 204]
```

[ ]:
```
comp = pd.DataFrame(zip(kernel, degree, n_0, n_1, acc), columns = ['Kernel',␣
↪'Degree', 'Class 0 SVs', 'Class 1 SVs', 'Accuracy'])
comp
```

[ ]:

	Kernel	Degree	Class 0 SVs	Class 1 SVs	Accuracy
0	Linear	NA	271	260	0.793893
1	Polynomial	2	245	228	0.793893
2	Polynomial	3	246	223	0.782443
3	Polynomial	5	256	222	0.778626
4	RBF	NA	249	227	0.774809
5	Sigmoid	NA	205	204	0.656489

1.4 Task 2

[ ]:
```
titanic_red = titanic[['Age','Fare','2urvived']]
```

[ ]:
```
scaler = MinMaxScaler()
titanic_red[['Age', 'Fare']] = scaler.fit_transform(titanic_red[['Age',␣
↪'Fare']])
titanic_red.head()
```

```
/home/hakunamatata/.local/lib/python3.8/site-packages/pandas/core/frame.py:3678:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[col] = igetitem(value, i)
```

[ ]:

	Age	Fare	2urvived
0	0.273456	0.014151	0
1	0.473882	0.139136	1
2	0.323563	0.015469	1
3	0.436302	0.103644	1
4	0.436302	0.015713	0

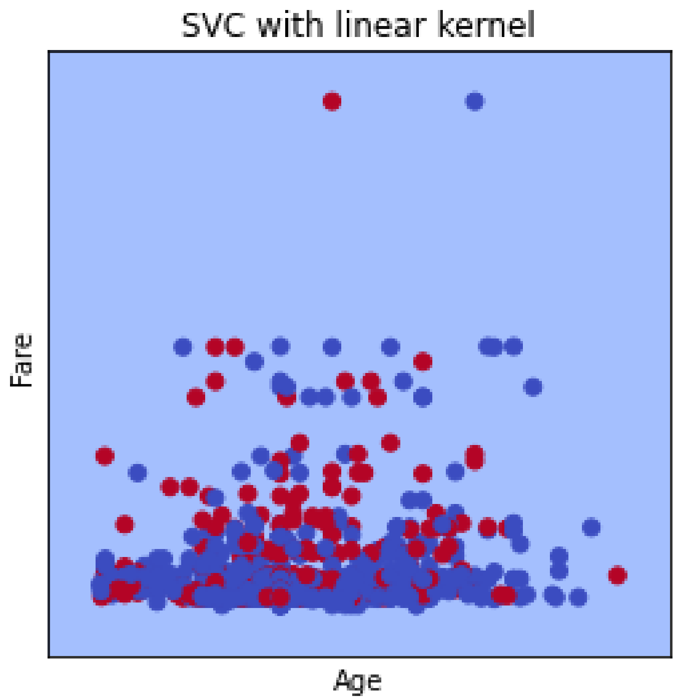
[ ]:

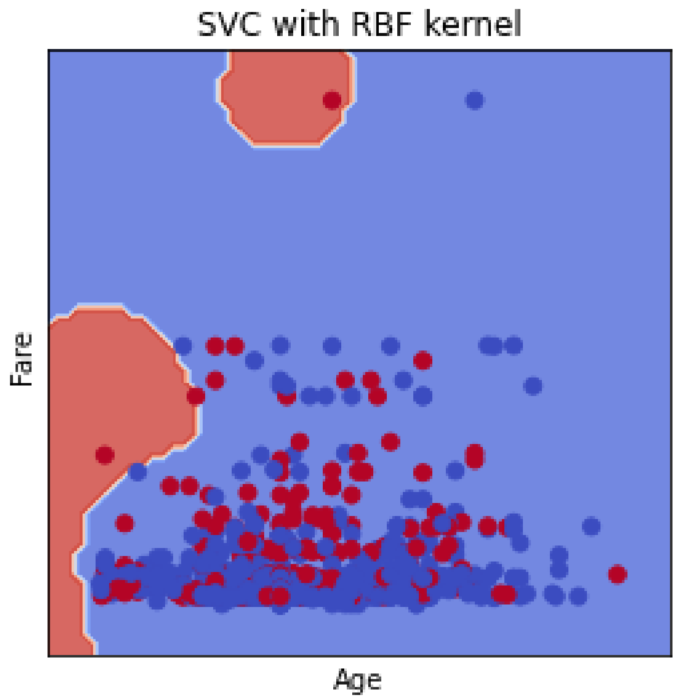
```python
x_trainr, x_testr, y_trainr, y_testr = train_test_split(titanic_red[['Age',␣
 ↪'Fare']], titanic_red['2urvived'], test_size = 0.2, stratify =␣
 ↪titanic_red['2urvived'], random_state = 42)
print(x_trainr.shape, y_trainr.shape)
print(x_testr.shape, y_testr.shape)
```

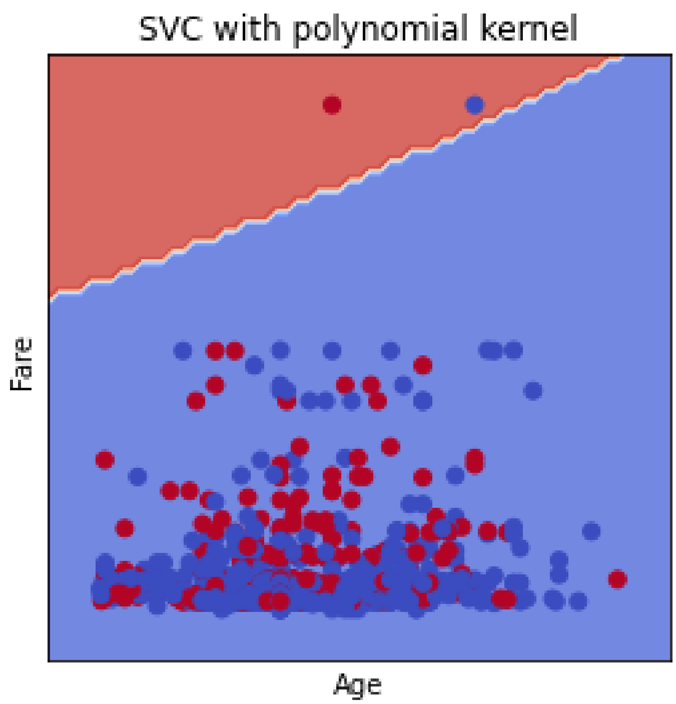
```
(1045, 2) (1045,)
(262, 2) (262,)
```

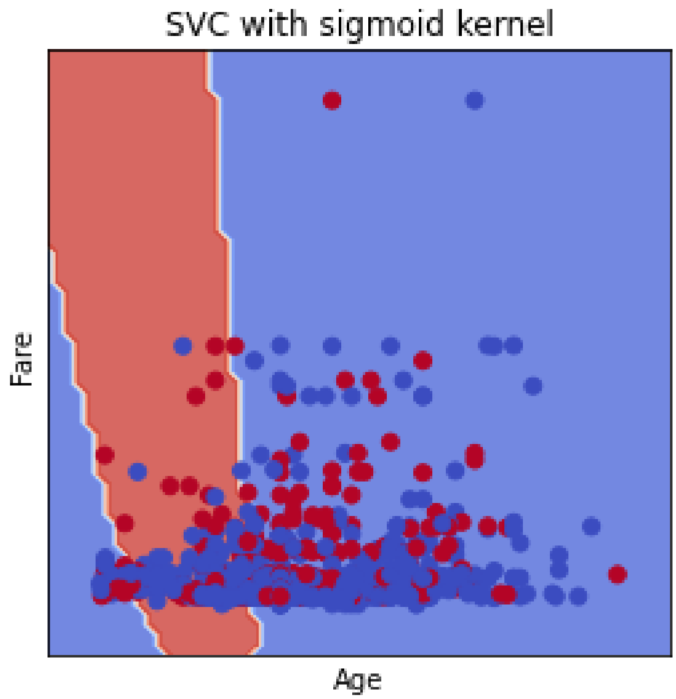
[ ]:
```python
# https://scikit-learn.org/0.18/auto_examples/svm/plot_iris.html
xr, yr = x_trainr.values, y_trainr.values

h = .02  # step size in the mesh

# we create an instance of SVM and fit out data. We do not scale our
# data since we want to plot the support vectors
C = 1.0  # SVM regularization parameter
svc = SVC(kernel='linear')
rbf_svc = SVC(kernel='rbf')
poly_svc = SVC(kernel='poly')
sigmoid = SVC(kernel='sigmoid')

# create a mesh to plot in
x_min, x_max = xr[:, 0].min() - 0.1, xr[:, 0].max() + 0.1
y_min, y_max = xr[:, 1].min() - 0.1, xr[:, 1].max() + 0.1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                     np.arange(y_min, y_max, h))

# title for the plots
titles = ['SVC with linear kernel',
          'SVC with RBF kernel',
          'SVC with polynomial kernel',
          'SVC with sigmoid kernel']


for i, clf in enumerate((svc, rbf_svc, poly_svc,sigmoid)):
    # Plot the decision boundary. For that, we will assign a color to each
    # point in the mesh [x_min, x_max]x[y_min, y_max].
    plt.figure(figsize = (10,10))
    plt.subplot(2, 2, i + 1)
    plt.subplots_adjust(wspace=0.4, hspace=0.4)

    clf.fit(xr, yr)
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

    # Put the result into a color plot
    Z = Z.reshape(xx.shape)
```

```
    plt.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)

    # Plot also the training points
    plt.scatter(xr[:, 0], xr[:, 1], c=yr, cmap=plt.cm.coolwarm)
    plt.xlabel('Age')
    plt.ylabel('Fare')
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.xticks(())
    plt.yticks(())
    plt.title(titles[i])

plt.show()
```



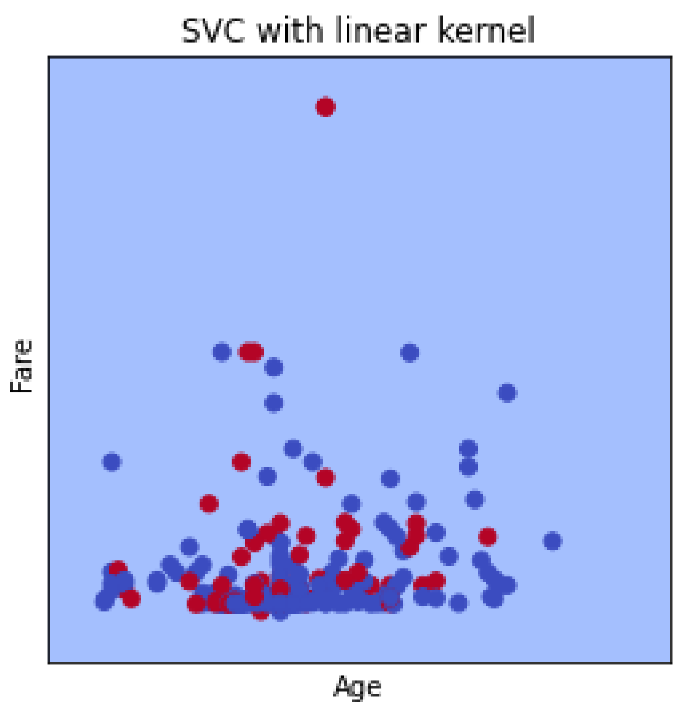

SVC with RBF kernel
Fare
Age

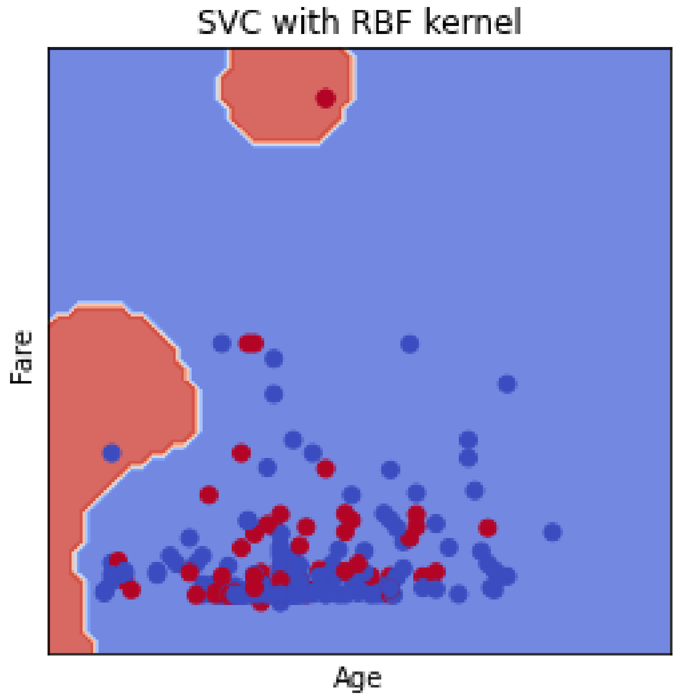

SVC with polynomial kernel
Fare
Age

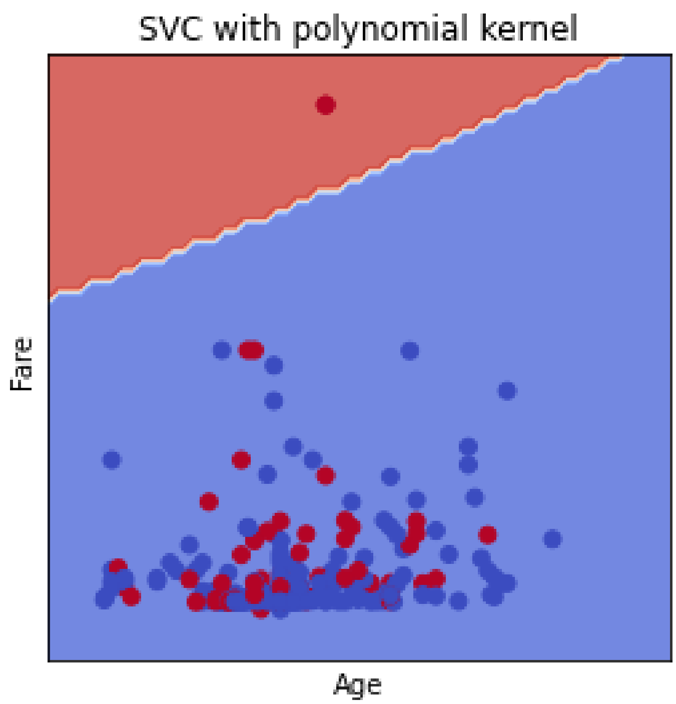


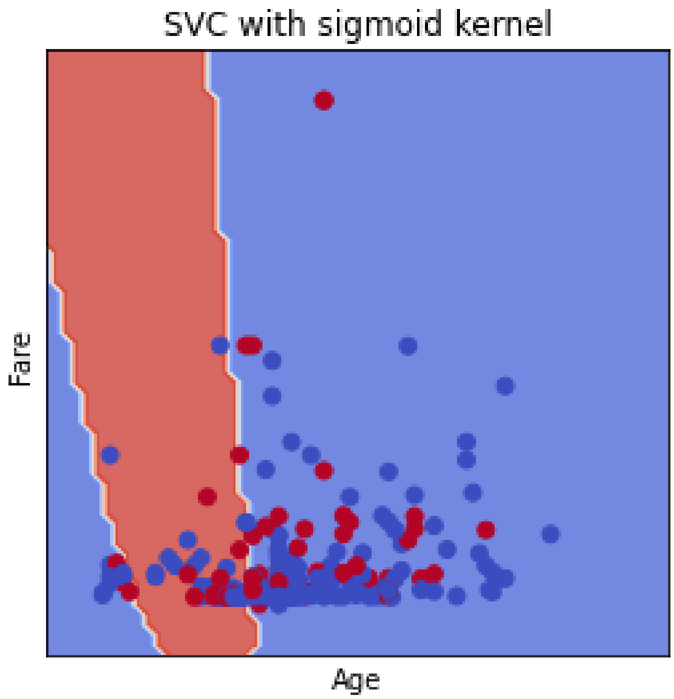
[ ]:
```
xr, yr = x_testr.values, y_testr.values

h = .02  # step size in the mesh

# create a mesh to plot in
x_min, x_max = -0.1, 1.1
y_min, y_max = -0.1, 1.1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                     np.arange(y_min, y_max, h))

# title for the plots
titles = ['SVC with linear kernel',
          'SVC with RBF kernel',
          'SVC with polynomial kernel',
          'SVC with sigmoid kernel']


for i, clf in enumerate((svc, rbf_svc, poly_svc,sigmoid)):
    # Plot the decision boundary. For that, we will assign a color to each
    # point in the mesh [x_min, x_max]x[y_min, y_max].
    plt.figure(figsize = (10,10))
    plt.subplot(2, 2, i + 1)
    plt.subplots_adjust(wspace=0.4, hspace=0.4)
```

```
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

    # Put the result into a color plot
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)

    # Plot also the training points
    plt.scatter(xr[:, 0], xr[:, 1], c=yr, cmap=plt.cm.coolwarm)
    plt.xlabel('Age')
    plt.ylabel('Fare')
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.xticks(())
    plt.yticks(())
    plt.title(titles[i])

plt.show()
```




SVC with RBF kernel
Fare
Age


SVC with polynomial kernel
Fare
Age



[ ]:
```
x_train = x_train.toarray()
x_test = x_test.toarray()
```

[ ]:
```
def log_kernel(xi, xj, d):
    s = 0
    for k in range(d):
        s += pow((xi[k] - xj[k]), d)
    return  0 if not s else -np.log(pow(s, 1/d)) + 1
```

[ ]:
```
def logKernelGramMatrixFull(X1, X2):
    """(Pre)calculates Gram Matrix K"""

    log_matrix = np.zeros((X1.shape[0], X2.shape[0]))
    d = X1.shape[-1]
    for i, x1 in enumerate(X1):
        for j, x2 in enumerate(X2):
            x1 = x1.flatten()
            x2 = x2.flatten()
            log_matrix[i, j] = log_kernel(x1, x2, d)
    return log_matrix
```

[ ]:
```
log_svc = SVC(C = 100, kernel = "precomputed")
log_svc.fit(logKernelGramMatrixFull(x_train, x_train), y_train)
y_pred = log_svc.predict(logKernelGramMatrixFull(x_test, x_train))
```

```python
acc = accuracy_score(y_test, y_pred)
print(acc)
```

```
0.732824427480916
```

1.5 Task 3

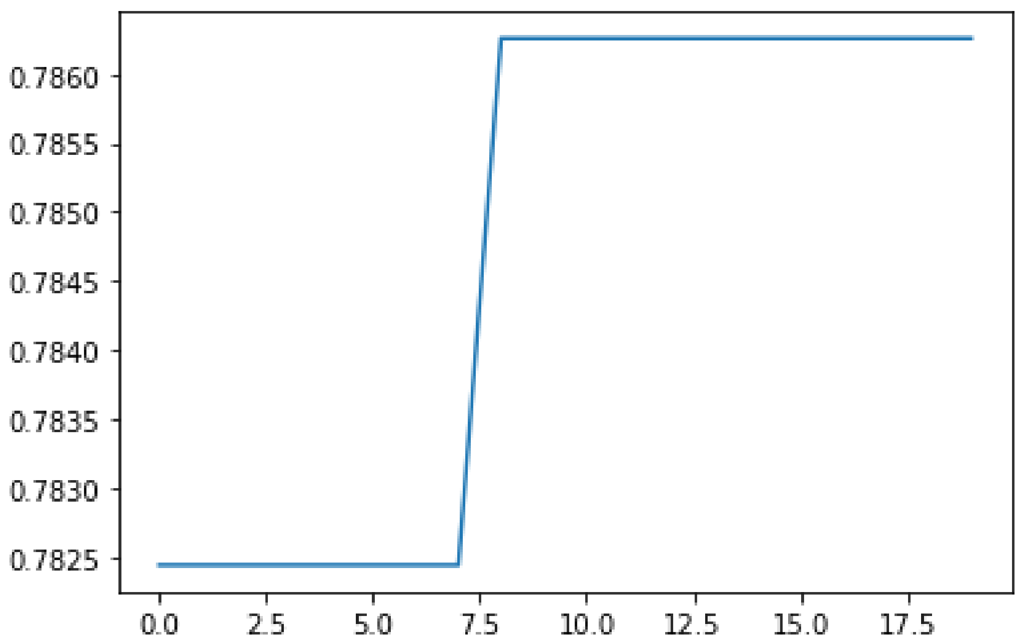
[ ]:
```python
l,r = 1, 10000
i = 0
accs, cs = [],[]
while l < r:
    if i == 20: break
    mid = (r+l)/2
    lsvc = SVC(kernel = 'rbf', C = l, gamma = 0.5)
    lsvc.fit(x_train, y_train)
    y_pred = lsvc.predict(x_test)
    lacc = accuracy_score(y_test, y_pred)
    rsvc = SVC(kernel = 'rbf', C = r, gamma = 0.5)
    rsvc.fit(x_train, y_train)
    y_pred = rsvc.predict(x_test)
    racc = accuracy_score(y_test, y_pred)
    print(l,r, lacc, racc)
    if lacc >= racc:
        r = round(mid,3)
        svc = lsvc
        cs.append(l)
    else:
        l = round(mid, 3)
        svc = rsvc
        cs.append(r)
    y_pred = svc.predict(x_test)
    accs.append(accuracy_score(y_test, y_pred))
    #cs.append(mid)

    i+=1
```

```
1 10000 0.7824427480916031 0.7595419847328244
1 5000.5 0.7824427480916031 0.7442748091603053
1 2500.75 0.7824427480916031 0.7404580152671756
1 1250.875 0.7824427480916031 0.7442748091603053
1 625.938 0.7824427480916031 0.7480916030534351
1 313.469 0.7824427480916031 0.7480916030534351
1 157.234 0.7824427480916031 0.7633587786259542
1 79.117 0.7824427480916031 0.7748091603053435
1 40.059 0.7824427480916031 0.7862595419847328
20.529 40.059 0.7786259541984732 0.7862595419847328
30.294 40.059 0.7824427480916031 0.7862595419847328
```

```
35.176 40.059 0.7824427480916031 0.7862595419847328
37.617 40.059 0.7824427480916031 0.7862595419847328
38.838 40.059 0.7862595419847328 0.7862595419847328
38.838 39.448 0.7862595419847328 0.7862595419847328
38.838 39.143 0.7862595419847328 0.7862595419847328
38.838 38.99 0.7862595419847328 0.7862595419847328
38.838 38.914 0.7862595419847328 0.7862595419847328
38.838 38.876 0.7862595419847328 0.7862595419847328
38.838 38.857 0.7862595419847328 0.7862595419847328
```

[ ]:
```
plt.plot(accs)
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x7f6fd4b23310>]
```



1.6 Task 4

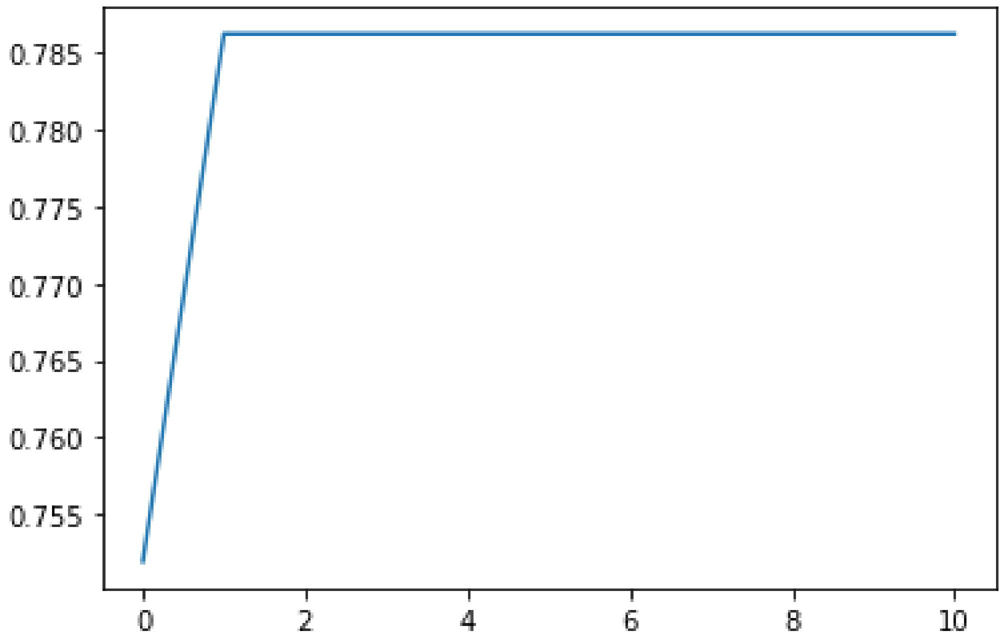
[ ]:
```
l, r = 0.0001, 1
i = 0
accs, cs = [], []
while l < r:
    if i == 20: break
    mid = (r+l)/2
    lsvc = SVC(kernel = 'rbf', C = 39, gamma = l)
    lsvc.fit(x_train, y_train)
    y_pred = lsvc.predict(x_test)
    lacc = accuracy_score(y_test, y_pred)
```

```
    rsvc = SVC(kernel = 'rbf', C = 39, gamma = r)
    rsvc.fit(x_train, y_train)
    y_pred = rsvc.predict(x_test)
    racc = accuracy_score(y_test, y_pred)
    print(l,r, lacc, racc)
    if lacc >= racc:
        r = round(mid,3)
        svc = lsvc
        cs.append(l)
    else:
        l = round(mid, 3)
        svc = rsvc
        cs.append(r)
    y_pred = svc.predict(x_test)
    accs.append(accuracy_score(y_test, y_pred))
    #cs.append(mid)
    i += 1
```

```
0.0001 1 0.7404580152671756 0.7519083969465649
0.5 1 0.7862595419847328 0.7519083969465649
0.5 0.75 0.7862595419847328 0.7824427480916031
0.5 0.625 0.7862595419847328 0.7824427480916031
0.5 0.562 0.7862595419847328 0.7824427480916031
0.5 0.531 0.7862595419847328 0.7862595419847328
0.5 0.516 0.7862595419847328 0.7862595419847328
0.5 0.508 0.7862595419847328 0.7862595419847328
0.5 0.504 0.7862595419847328 0.7862595419847328
0.5 0.502 0.7862595419847328 0.7862595419847328
0.5 0.501 0.7862595419847328 0.7862595419847328
```

[ ]:
```
plt.plot(accs)
```

[ ]: [<matplotlib.lines.Line2D at 0x7f6fd4a99be0>]



1.7 Pre Processing on Forest Cover Dataset

[ ]:
```
forest = pd.read_csv("covtype.csv")
forest.head()
```

[ ]:
```
   Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
0       2596      51      3                               258
1       2590      56      2                               212
2       2804     139      9                               268
3       2785     155     18                               242
4       2595      45      2                               153

   Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
0                               0                              510
1                              -6                              390
2                              65                             3180
3                             118                             3090
4                              -1                              391

   Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
0            221             232            148
1            220             235            151
2            234             238            135
3            238             238            122
4            220             234            150
```

```
   Horizontal_Distance_To_Fire_Points  …  Soil_Type32  Soil_Type33  \
0                                6279  …            0            0
1                                6225  …            0            0
2                                6121  …            0            0
3                                6211  …            0            0
4                                6172  …            0            0

   Soil_Type34  Soil_Type35  Soil_Type36  Soil_Type37  Soil_Type38  \
0            0            0            0            0            0
1            0            0            0            0            0
2            0            0            0            0            0
3            0            0            0            0            0
4            0            0            0            0            0

   Soil_Type39  Soil_Type40  Cover_Type
0            0            0           5
1            0            0           5
2            0            0           2
3            0            0           2
4            0            0           5

[5 rows x 55 columns]
```

[ ]:
```
forest.describe()
```

[ ]:
```
           Elevation         Aspect          Slope  \
count  581012.000000  581012.000000  581012.000000
mean     2959.365301     155.656807      14.103704
std       279.984734     111.913721       7.488242
min      1859.000000       0.000000       0.000000
25%      2809.000000      58.000000       9.000000
50%      2996.000000     127.000000      13.000000
75%      3163.000000     260.000000      18.000000
max      3858.000000     360.000000      66.000000

       Horizontal_Distance_To_Hydrology  Vertical_Distance_To_Hydrology  \
count                     581012.000000                   581012.000000
mean                         269.428217                       46.418855
std                          212.549356                       58.295232
min                            0.000000                     -173.000000
25%                          108.000000                        7.000000
50%                          218.000000                       30.000000
75%                          384.000000                       69.000000
max                         1397.000000                      601.000000

       Horizontal_Distance_To_Roadways  Hillshade_9am  Hillshade_Noon  \
```

```
count                    581012.000000  581012.000000   581012.000000
mean                       2350.146611     212.146049      223.318716
std                        1559.254870      26.769889       19.768697
min                           0.000000       0.000000        0.000000
25%                        1106.000000     198.000000      213.000000
50%                        1997.000000     218.000000      226.000000
75%                        3328.000000     231.000000      237.000000
max                        7117.000000     254.000000      254.000000

       Hillshade_3pm  Horizontal_Distance_To_Fire_Points  …    Soil_Type32  \
count  581012.000000                       581012.000000  …  581012.000000
mean      142.528263                         1980.291226  …       0.090392
std        38.274529                         1324.195210  …       0.286743
min         0.000000                            0.000000  …       0.000000
25%       119.000000                         1024.000000  …       0.000000
50%       143.000000                         1710.000000  …       0.000000
75%       168.000000                         2550.000000  …       0.000000
max       254.000000                         7173.000000  …       1.000000

         Soil_Type33    Soil_Type34    Soil_Type35    Soil_Type36  \
count  581012.000000  581012.000000  581012.000000  581012.000000
mean        0.077716       0.002773       0.003255       0.000205
std         0.267725       0.052584       0.056957       0.014310
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

         Soil_Type37    Soil_Type38    Soil_Type39    Soil_Type40  \
count  581012.000000  581012.000000  581012.000000  581012.000000
mean        0.000513       0.026803       0.023762       0.015060
std         0.022641       0.161508       0.152307       0.121791
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

          Cover_Type
count  581012.000000
mean        2.051471
std         1.396504
min         1.000000
25%         1.000000
50%         2.000000
75%         2.000000
```

```
max         7.000000

[8 rows x 55 columns]
```

[ ]:
```python
X1 = forest.copy()
X1[['Elevation', 'Aspect', 'Slope', 'Horizontal_Distance_To_Hydrology',
       'Vertical_Distance_To_Hydrology', 'Horizontal_Distance_To_Roadways',
       'Hillshade_9am', 'Hillshade_Noon', 'Hillshade_3pm',
       'Horizontal_Distance_To_Fire_Points', 'Wilderness_Area1',
       'Wilderness_Area2', 'Wilderness_Area3', 'Wilderness_Area4']] = scaler.
 ↪fit_transform(X1[['Elevation', 'Aspect', 'Slope',␣
 ↪'Horizontal_Distance_To_Hydrology',
       'Vertical_Distance_To_Hydrology', 'Horizontal_Distance_To_Roadways',
       'Hillshade_9am', 'Hillshade_Noon', 'Hillshade_3pm',
       'Horizontal_Distance_To_Fire_Points', 'Wilderness_Area1',
       'Wilderness_Area2', 'Wilderness_Area3', 'Wilderness_Area4']])
X1 = X1.drop(columns = ['Cover_Type'])
Y1 = forest['Cover_Type']
print(Y1.shape)
X1.head()
```

```
(581012,)
```

[ ]:
```
   Elevation    Aspect     Slope  Horizontal_Distance_To_Hydrology  \
0   0.368684  0.141667  0.045455                          0.184681
1   0.365683  0.155556  0.030303                          0.151754
2   0.472736  0.386111  0.136364                          0.191840
3   0.463232  0.430556  0.272727                          0.173228
4   0.368184  0.125000  0.030303                          0.109520

   Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
0                        0.223514                         0.071659
1                        0.215762                         0.054798
2                        0.307494                         0.446817
3                        0.375969                         0.434172
4                        0.222222                         0.054939

   Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
0       0.870079        0.913386       0.582677
1       0.866142        0.925197       0.594488
2       0.921260        0.937008       0.531496
3       0.937008        0.937008       0.480315
4       0.866142        0.921260       0.590551

   Horizontal_Distance_To_Fire_Points  …  Soil_Type31  Soil_Type32  \
0                            0.875366  …            0            0
1                            0.867838  …            0            0
```

```
2                              0.853339  …          0          0
3                              0.865886  …          0          0
4                              0.860449  …          0          0

   Soil_Type33  Soil_Type34  Soil_Type35  Soil_Type36  Soil_Type37  \
0            0            0            0            0            0
1            0            0            0            0            0
2            0            0            0            0            0
3            0            0            0            0            0
4            0            0            0            0            0

   Soil_Type38  Soil_Type39  Soil_Type40
0            0            0            0
1            0            0            0
2            0            0            0
3            0            0            0
4            0            0            0

[5 rows x 54 columns]
```

[ ]:
```
_, subset_x, _, subset_y = train_test_split(X1, Y1, stratify = Y1, test_size =␣
↪0.2, random_state = 42)
x_train1, x_test1, y_train1, y_test1 = train_test_split(subset_x, subset_y,␣
↪stratify = subset_y, test_size = 0.1, random_state = 42)
print(x_train1.shape, x_test1.shape)
print(y_train1.shape, y_test1.shape)
```

```
(104582, 54) (11621, 54)
(104582,) (11621,)
```

1.8 Task 1

[ ]:
```
svc = SVC(kernel='linear')
ovr = OneVsRestClassifier(svc)
ovr.fit(x_train1,y_train1)
y_pred1 = ovr.predict(x_test1)
acc1 = accuracy_score(y_test1,y_pred1)
```

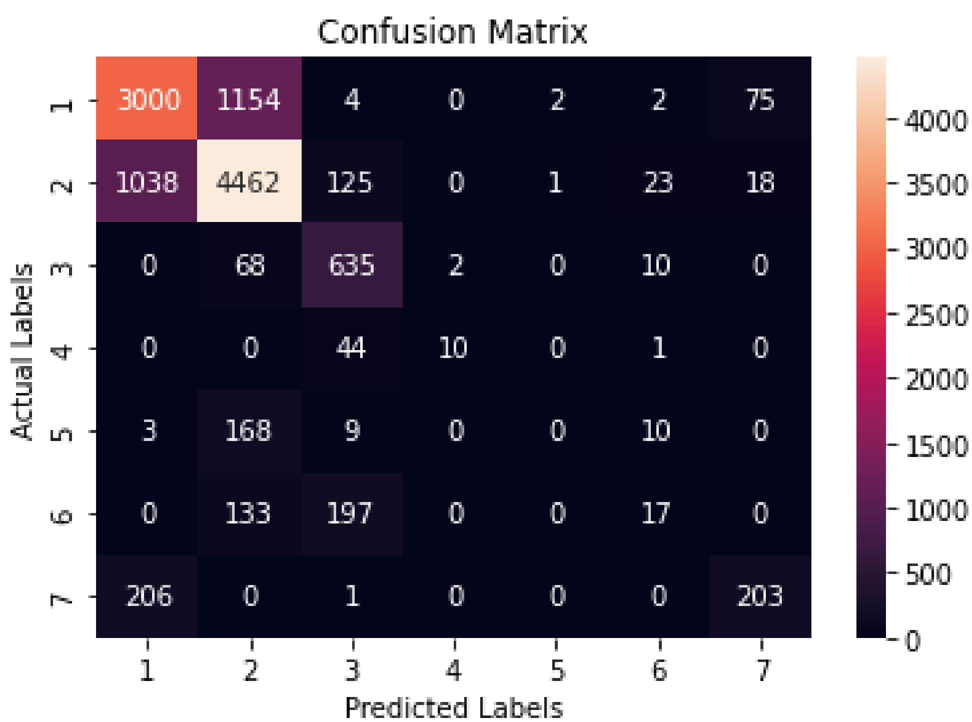
[ ]:
```
cm = confusion_matrix(y_test1,y_pred1,labels=ovr.classes_)
print(cm)
```

```
[[3000 1154    4    0    2    2   75]
 [1038 4462  125    0    1   23   18]
 [   0   68  635    2    0   10    0]
 [   0    0   44   10    0    1    0]
 [   3  168    9    0    0   10    0]
 [   0  133  197    0    0   17    0]
```

```
 [ 206    0    1    0    0    0  203]]
```

[ ]:
```python
ax = sns.heatmap(cm, annot=True, fmt='g')
ax.set_title('Confusion Matrix')
ax.set_xlabel('Predicted Labels')
ax.set_ylabel('Actual Labels')
ax.xaxis.set_ticklabels(ovr.classes_)
ax.yaxis.set_ticklabels(ovr.classes_)
```

[ ]:
```
[Text(0, 0.5, '1'),
 Text(0, 1.5, '2'),
 Text(0, 2.5, '3'),
 Text(0, 3.5, '4'),
 Text(0, 4.5, '5'),
 Text(0, 5.5, '6'),
 Text(0, 6.5, '7')]
```



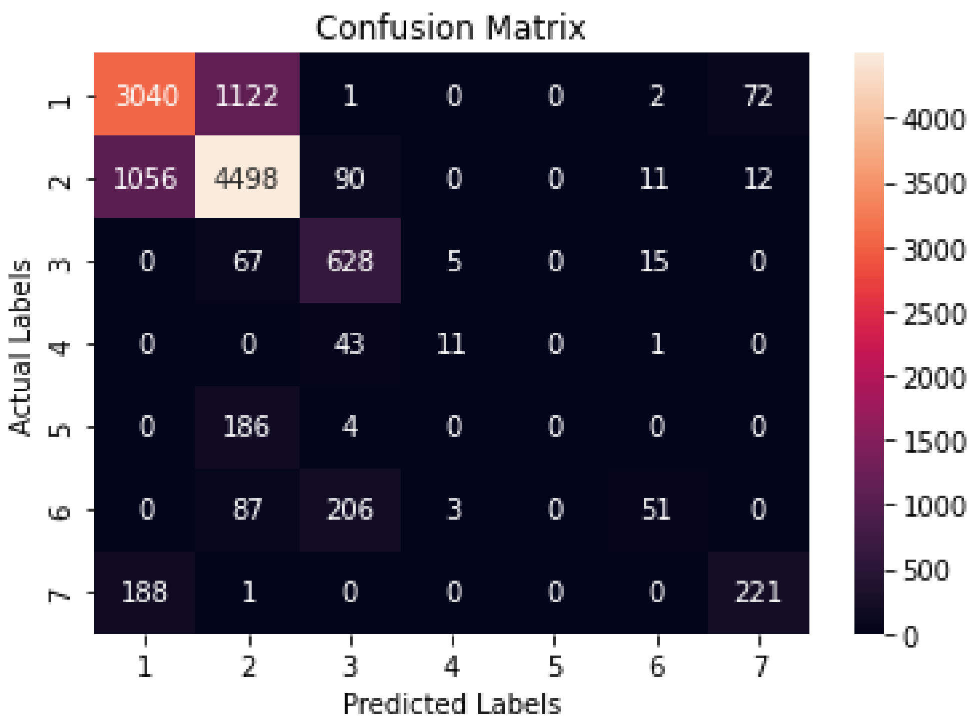
[ ]:
```python
ovo = OneVsOneClassifier(svc)
ovo.fit(x_train1,y_train1)
y_pred2 = ovo.predict(x_test1)
acc2 = accuracy_score(y_test1,y_pred2)
```

[ ]:
```python
cm = confusion_matrix(y_test1,y_pred2,labels=ovo.classes_)
print(cm)
```

```
[[3040 1122    1    0    0    2   72]
 [1056 4498   90    0    0   11   12]
 [   0   67  628    5    0   15    0]
 [   0    0   43   11    0    1    0]
 [   0  186    4    0    0    0    0]
 [   0   87  206    3    0   51    0]
 [ 188    1    0    0    0    0  221]]
```

[ ]:
```
ax = sns.heatmap(cm, annot=True, fmt='g')
ax.set_title('Confusion Matrix')
ax.set_xlabel('Predicted Labels')
ax.set_ylabel('Actual Labels')
ax.xaxis.set_ticklabels(ovo.classes_)
ax.yaxis.set_ticklabels(ovo.classes_)
```

[ ]:
```
[Text(0, 0.5, '1'),
 Text(0, 1.5, '2'),
 Text(0, 2.5, '3'),
 Text(0, 3.5, '4'),
 Text(0, 4.5, '5'),
 Text(0, 5.5, '6'),
 Text(0, 6.5, '7')]
```



[ ]:
```python
print("OvR Acc Score: ",acc1)
print("OvO Acc Score: ",acc2)
```

```
OvR Acc Score:  0.7165476292917994
OvO Acc Score:  0.7270458652439549
```