

LAB 5

Non-Linear Support Vector Machines

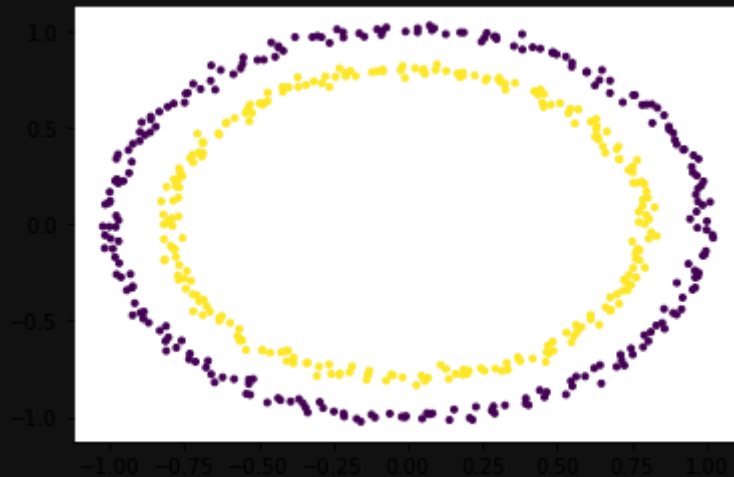
1. Create a contrived 2-class dataset that are non-linearly separable. Each sample is 2-dimensional. Plot the dataset using 2-d plot

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
print(plt.style.available)
plt.style.use('seaborn-dark-palette')
from sklearn.datasets import make_circles
from mpl_toolkits.mplot3d import Axes3D

['Solarize_Light2', 'classic_test_patch', 'bmh', 'classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot', 'grayscale', 'seaborn', 'seaborn-bright', 'seaborn-colorblind', 'seaborn-dark', 'seaborn-dark-palette', 'seaborn-darkgrid', 'seaborn-deep', 'seaborn-muted', 'seaborn-notebook', 'seaborn-paper', 'seaborn-pastel', 'seaborn-poster', 'seaborn-talk', 'seaborn-ticks', 'seaborn-white', 'seaborn-whitegrid', 'tableau-colorblind10']
```

```
In [2]: X, Y = make_circles(n_samples = 500, noise = 0.02)
```

```
In [3]: plt.scatter(X[:, 0], X[:, 1], c = Y, marker = '.')
plt.show()
```



2. Write a program to visualize Gaussian kernel with various values for σ and μ

```
In [4]: X[:5]
```

```
Out[4]: array([[ 0.77667872, -0.18866887],
 [ 0.31166387,  0.73430756],
 [ 1.01252788,  0.11270041],
 [-0.43491656, -0.90224886],
 [ 0.96693617,  0.06296941]])
```

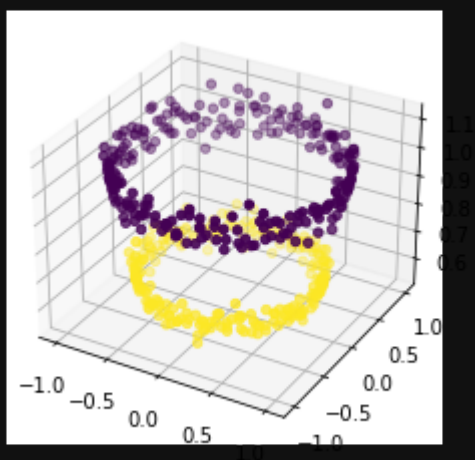
```
In [5]: # adding a new dimension to X
X1 = X[:, 0].reshape((-1, 1))
X2 = X[:, 1].reshape((-1, 1))
X3 = (X1**2 + X2**2)
X3[:5]
```

```
Out[5]: array([[0.63882578],
               [0.63634197],
               [1.03791409],
               [1.00320543],
               [0.93893069]])
```

```
In [6]: X = np.hstack((X, X3))
X[:5]
```

```
Out[6]: array([[ 0.77667872, -0.18866887,  0.63882578],
               [ 0.31166387,  0.73430756,  0.63634197],
               [ 1.01252788,  0.11270041,  1.03791409],
               [-0.43491656, -0.90224886,  1.00320543],
               [ 0.96693617,  0.06296941,  0.93893069]])
```

```
In [7]: # visualizing data in higher dimension
fig = plt.figure()
axes = fig.add_subplot(111, projection = '3d')
axes.scatter(X1, X2, X3, c = Y, depthshade = True)
plt.show()
```



3. Generate classification dataset with 2 classes where each sample is in 2-d space.

NB: Use function `make_gaussian_quantiles` https://scikit-learn.org/stable/modules/generated/sklearn.datasets.make_gaussian_quantiles.html

from `sklearn.svm` import `SVC`

Convert this dataset into 3d using RBF function and plot the dataset

Convert this dataset into 3d using RBF function and plot the dataset

```
In [8]: from sklearn.datasets import make_gaussian_quantiles
import pandas as pd
import seaborn as sns
from sklearn.gaussian_process.kernels import RBF
from sklearn.preprocessing import StandardScaler
from scipy.spatial import distance
from sklearn import svm, datasets
```

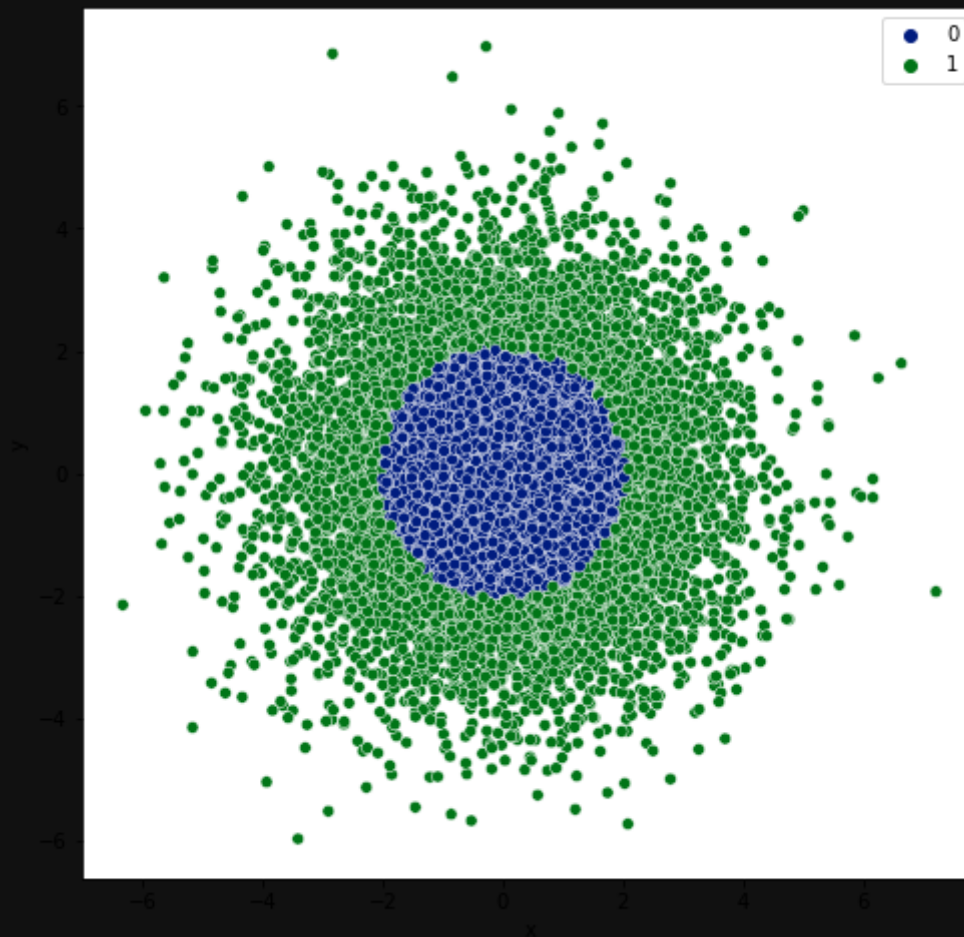
```
In [9]: X1, y1 = make_gaussian_quantiles(cov=3.0, n_samples=10000, n_features=2,
n_classes=2, random_state=1)
print(X1[:5])
print(y1[:5])
```

```
[[ 0.7597722  1.41831633]
 [ 2.42989589 -2.97483904]
 [-1.31266241 -3.83763022]
 [ 1.54424685  0.90423614]
 [ 0.67590516  3.47166431]]
[0 1 1 0 1]
```

```
In [10]: X1 = pd.DataFrame(X1, columns=['x', 'y'])
y1 = pd.Series(y1)
```

```
In [11]: f, (ax1) = plt.subplots(nrows=1, ncols=1, figsize=(8,8))
sns.scatterplot(x = X1['x'], y = X1['y'], hue=y1, ax=ax1)
ax1.set_title("Data in 2d")
plt.show()
```

Data in 2d



```
In [12]: fig = plt.figure(figsize=(8,8))
ax = fig.add_subplot(111, projection='3d')
colors = {
0: '#b40426',
1: '#3b4cc0',
2: '#f2da0a',
3: '#fe5200'
}

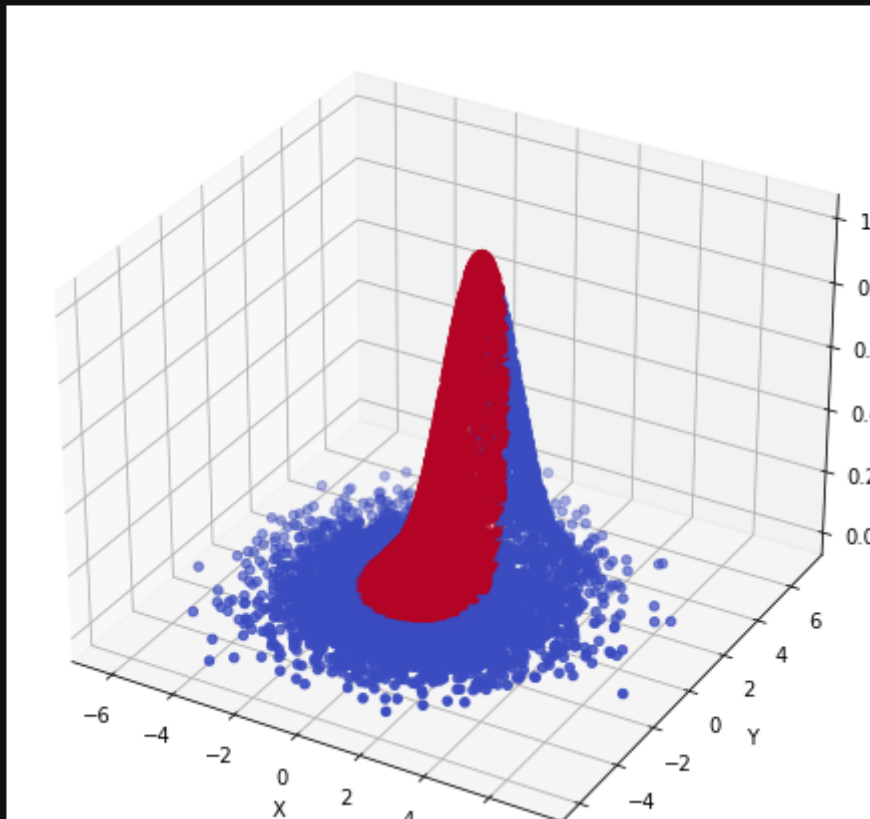
# Generate Z component
z = RBF(1.0).__call__(X1)[0]
print(z)

# Plot
colors = list(map(lambda x: colors[x], y1))
ax.scatter(X1['x'], X1['y'], z, c=colors, marker='o')

ax.set_xlabel('X')
ax.set_ylabel('Y')
ax.set_zlabel('Z')

plt.show()
```

[1.00000000e+00 1.59737526e-05 1.17130203e-07 ... 1.26758885e-01
2.67087386e-09 1.53720231e-01]



4. Fit the dataset created in Q.3 using SVM classifier with kernel = rbf, linear, and poly & various values for penalty term C. You may split the dataset into 80%-20% split. Plot 3 accuracy graphs. One with RBF with varying C. Second with Linear with varying C. Third with Polynomial kernel with varying C

```
In [13]: from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
import plotly as pltly
import plotly.express as px
import plotly.graph_objects as go
pltly.offline.init_notebook_mode()
X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size=0.2,
random_state=0)
```

In [14]:

```
def Plot_3D(X, X_test, y_test, clf, C, kernel):

    # Specify a size of the mesh to be used
    mesh_size = 5
    margin = 1

    # Create a mesh grid on which we will run our model
    x_min, x_max = X.iloc[:, 0].fillna(X.mean()).min() - margin, X.iloc[:,
0].fillna(X.mean()).max() + margin
    y_min, y_max = X.iloc[:, 1].fillna(X.mean()).min() - margin, X.iloc[:,
1].fillna(X.mean()).max() + margin
    xrange = np.arange(x_min, x_max, mesh_size)
    yrange = np.arange(y_min, y_max, mesh_size)
    xx, yy = np.meshgrid(xrange, yrange)

    # Calculate predictions on grid
    Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
    Z = Z.reshape(xx.shape)
    print(Z)

    # Create a 3D scatter plot with predictions
    fig = px.scatter_3d(x=X_test['x'], y=X_test['y'], z=y_test,
                        opacity=0.8, color_discrete_sequence=['black'],
                        width=500, height=500)

    # Set figure title and colors
    print("-----SVM Prediction Surface-----")
    title_text = "C=" + str(C) + " Kernel=" + str(kernel)
    fig.update_layout(title_text=title_text,
                      paper_bgcolor = 'white', margin=dict(l=5, r=5, t=40,
b=20),

                      scene = dict(xaxis=dict(backgroundcolor='white',
                                              color='black',
                                              gridcolor='#f0f0f0'),
yaxis=dict(backgroundcolor='white',
            color='black',
            gridcolor='#f0f0f0'
            ),
zaxis=dict(backgroundcolor='lightgrey',
            color='black',
            gridcolor='#f0f0f0',
            )))

    # Update marker size
    fig.update_traces(marker=dict(size=1))

    # Add prediction plane
```


In [15]:

```
def fitting(X, y, C, gamma, kernel):
    print("-----Kernel =
", kernel, " C = ", C, "
-----")

    # Create training and testing samples
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)

    # Fit the model
    # Note, available kernels: {'linear', 'poly', 'rbf', 'sigmoid',
'precomputed'}, default='rbf'
    model = SVC(kernel=kernel, probability=True, C=C, gamma=gamma)
    clf = model.fit(X_train, y_train)

    # Predict class labels on training data
    pred_labels_tr = model.predict(X_train)
    # Predict class labels on a test data
    pred_labels_te = model.predict(X_test)

    # Use score method to get accuracy of the model
    print('----- Evaluation on Test Data -----')
    score_te = model.score(X_test, y_test)
    print('Accuracy Score: ', score_te)
    # Look at classification report to evaluate the model
    print(classification_report(y_test, pred_labels_te))
    print('-----')

    print('----- Evaluation on Training Data -----')
    score_tr = model.score(X_train, y_train)
    print('Accuracy Score: ', score_tr)
    # Look at classification report to evaluate the model
    print(classification_report(y_train, pred_labels_tr))
    print('-----')

    # Return relevant data for chart plotting
    Plot_3D(X, X_test, y_test, clf, C, kernel)
    return X_train, X_test, y_train, y_test, clf
```

In [19]:

```
C = [1,2,3]
for c in C:
    rbf_X_train, rbf_X_test, rbf_y_train, rbf_y_test, rbf_clf = fitting(X1,
y1, c, 'scale', 'rbf')
```

```
-----Kernel = rbf C = 1
-----
----- Evaluation on Test Data -----
```



```

Accuracy Score: 0.9975
              precision    recall  f1-score   support

         0         1.00      1.00      1.00         987
         1         1.00      1.00      1.00        1013

    accuracy
 macro avg   1.00      1.00      1.00        2000
weighted avg   1.00      1.00      1.00        2000

-----
----- Evaluation on Training Data -----
Accuracy Score: 0.997625
              precision    recall  f1-score   support

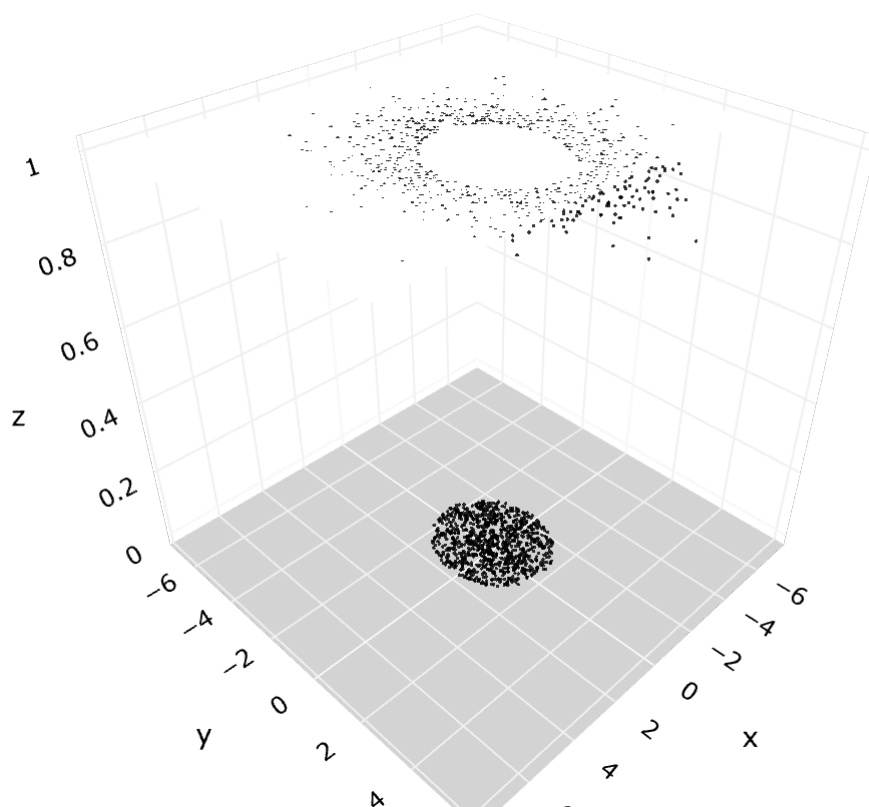
         0         1.00      1.00      1.00        4013
         1         1.00      1.00      1.00        3987

    accuracy
 macro avg   1.00      1.00      1.00        8000
weighted avg   1.00      1.00      1.00        8000

-----
[[1. 1. 1. 1.]
 [1. 1. 1. 1.]
 [1. 1. 1. 1.]]
-----SVM Prediction Surface-----

```

C=1 Kernel=rbf



```

-----Kernel = rbf C = 2-----
-----
----- Evaluation on Test Data -----
Accuracy Score: 0.998
              precision    recall  f1-score   support

         0         1.00      1.00      1.00         987
         1         1.00      1.00      1.00        1013

    accuracy
 macro avg   1.00      1.00      1.00        2000
weighted avg   1.00      1.00      1.00        2000

-----
----- Evaluation on Training Data -----

```

```

Accuracy Score: 0.997875
              precision    recall  f1-score   support

         0         1.00      1.00      1.00      4013
         1         1.00      1.00      1.00      3987

 accuracy
macro avg      1.00      1.00      1.00      8000
weighted avg    1.00      1.00      1.00      8000

```

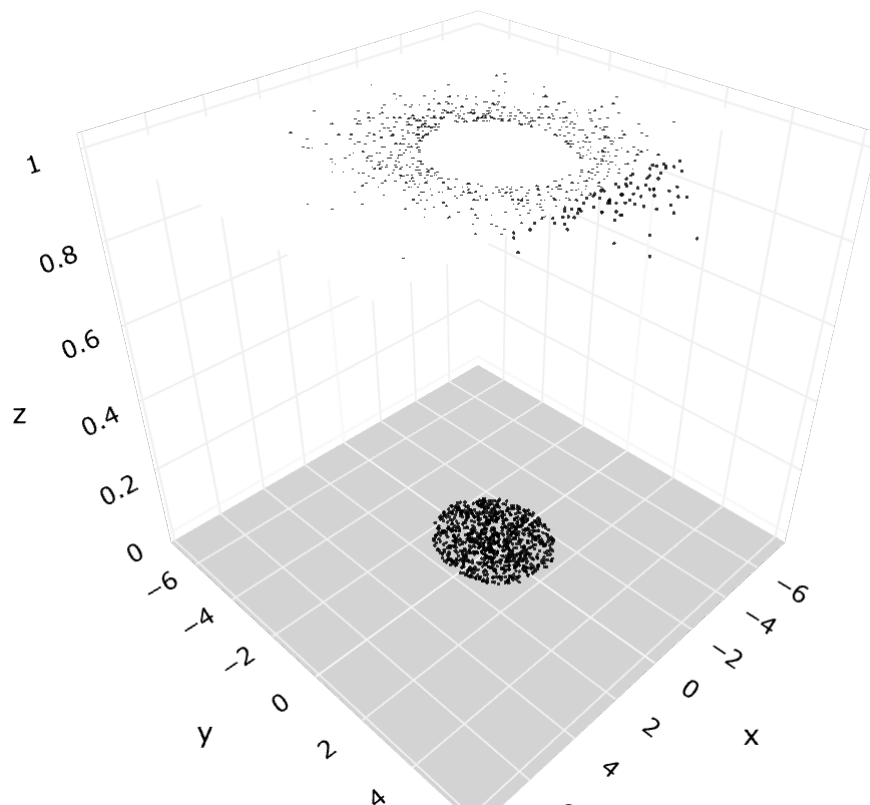
```

-----
[[1. 1. 1. 1.]
 [1. 1. 1. 1.]
 [1. 1. 1. 1.]]
-----

```

-----SVM Prediction Surface-----

C=2 Kernel=rbf



```

-----Kernel = rbf C = 3
-----

```

----- Evaluation on Test Data -----

```

Accuracy Score: 0.999
              precision    recall  f1-score   support

         0         1.00      1.00      1.00      987
         1         1.00      1.00      1.00     1013

 accuracy
macro avg      1.00      1.00      1.00     2000
weighted avg    1.00      1.00      1.00     2000

```

----- Evaluation on Training Data -----

```

Accuracy Score: 0.9985
              precision    recall  f1-score   support

         0         1.00      1.00      1.00      4013
         1         1.00      1.00      1.00      3987

 accuracy
macro avg      1.00      1.00      1.00      8000
weighted avg    1.00      1.00      1.00      8000

```

```

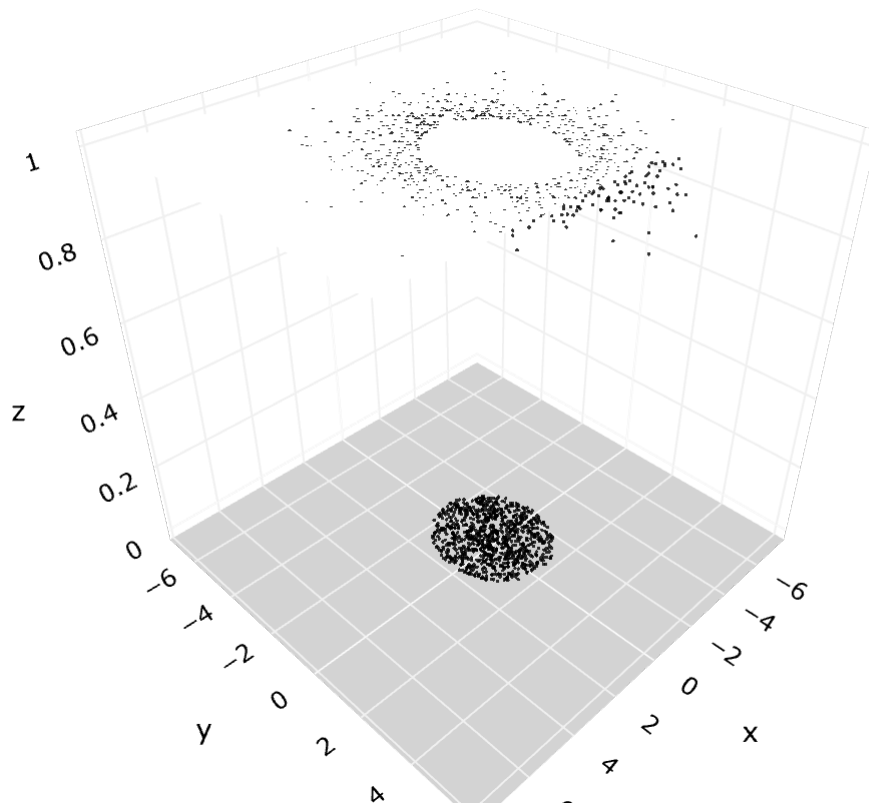
-----
[[1. 1. 1. 1.]

```

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

-----SVM Prediction Surface-----

C=3 Kernel=rbf



In [17]:

```
C = [1,2,3]
for c in C:
    poly_X_train, poly_X_test, poly_y_train, poly_y_test, poly_clf =
    fitting(X1, y1, c, 'scale', 'linear')
```

-----Kernel = linear C = 1

----- Evaluation on Test Data -----

Accuracy Score: 0.623

	precision	recall	f1-score	support
0	0.57	0.92	0.71	987
1	0.81	0.34	0.47	1013
accuracy			0.62	2000
macro avg	0.69	0.63	0.59	2000
weighted avg	0.69	0.62	0.59	2000

----- Evaluation on Training Data -----

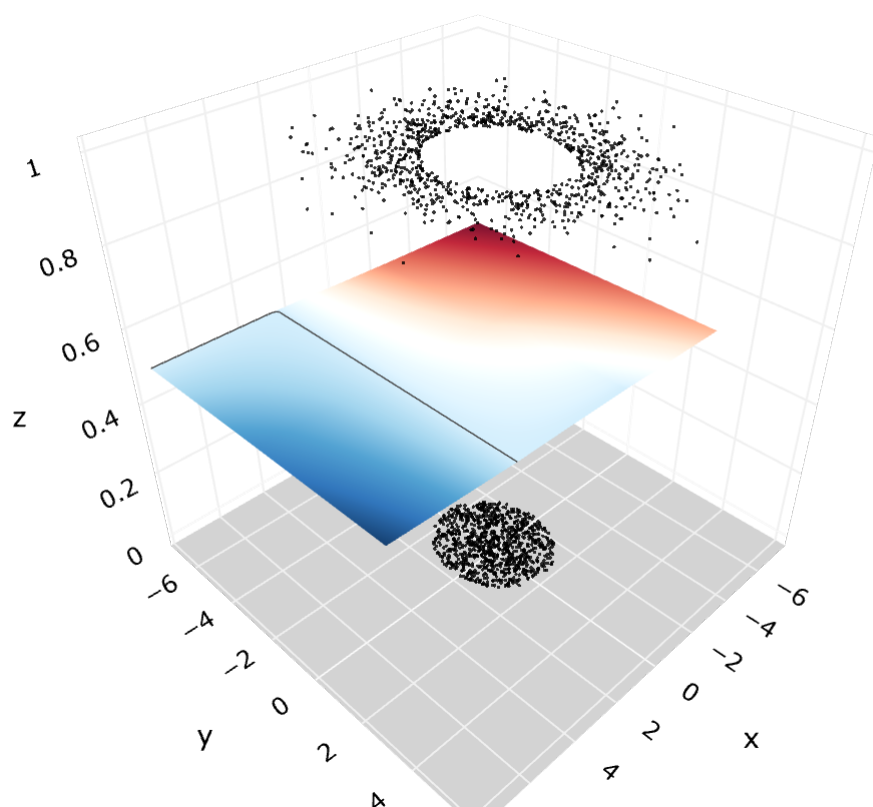
Accuracy Score: 0.635

	precision	recall	f1-score	support
0	0.59	0.93	0.72	4013
1	0.82	0.34	0.48	3987
accuracy			0.64	8000
macro avg	0.70	0.63	0.60	8000
weighted avg	0.70	0.64	0.60	8000

```
[0.48517194 0.49067862 0.5 0.5 ]
[0.4888388 0.49434735 0.5 0.50536745]
[0.49250702 0.5 0.5 0.50903633]]
```

-----SVM Prediction Surface-----

C=1 Kernel=linear



```
-----Kernel = linear C = 2
-----
----- Evaluation on Test Data -----
Accuracy Score: 0.623
      precision    recall  f1-score   support

     0       0.57       0.92       0.71       987
     1       0.81       0.34       0.47      1013

   accuracy          0.62       2000
  macro avg          0.69       0.63       0.59       2000
weighted avg          0.69       0.62       0.59       2000

-----
----- Evaluation on Training Data -----
Accuracy Score: 0.635
      precision    recall  f1-score   support

     0       0.59       0.93       0.72      4013
     1       0.82       0.34       0.48      3987

   accuracy          0.64       8000
  macro avg          0.70       0.63       0.60       8000
weighted avg          0.70       0.64       0.60       8000

-----
[[0.4590701  0.47538658 0.49177075 0.50817536]
 [0.46992419 0.48629149 0.5          0.51909176]
 [0.48081606 0.5          0.51361468 0.52999462]]
-----SVM Prediction Surface-----
```

```

-----Kernel = linear C = 3
-----
----- Evaluation on Test Data -----
Accuracy Score: 0.623
      precision    recall  f1-score   support

         0         0.57      0.92      0.71      987
         1         0.81      0.34      0.47     1013

   accuracy
 macro avg      0.69      0.63      0.59     2000
weighted avg      0.69      0.62      0.59     2000

-----
----- Evaluation on Training Data -----
Accuracy Score: 0.635
      precision    recall  f1-score   support

         0         0.59      0.93      0.72     4013
         1         0.82      0.34      0.48     3987

   accuracy
 macro avg      0.70      0.63      0.60     8000
weighted avg      0.70      0.64      0.60     8000

-----
[[0.56500794 0.53955224 0.51400435 0.48840352]
 [0.54806764 0.52255076 0.5         0.47138747]
 [0.53108788 0.50551353 0.47991941 0.45445861]]
-----SVM Prediction Surface-----

```

In [18]:

```
C = [1,2,3]
for c in C:
    poly_X_train, poly_X_test, poly_y_train, poly_y_test, poly_clf =
fitting(X1, y1, c, 'scale', 'poly')
```

```
-----Kernel = poly C = 1
-----
----- Evaluation on Test Data -----
Accuracy Score: 0.505
      precision    recall  f1-score   support

         0         0.50      1.00      0.67         987
         1         1.00      0.02      0.04        1013

   accuracy
 macro avg      0.75      0.51      0.36        2000
weighted avg      0.75      0.51      0.35        2000

-----
----- Evaluation on Training Data -----
Accuracy Score: 0.519375
      precision    recall  f1-score   support

         0         0.51      1.00      0.68        4013
         1         1.00      0.04      0.07        3987

   accuracy
 macro avg      0.76      0.52      0.37        8000
weighted avg      0.75      0.52      0.37        8000

-----
[[0.64510829 0.56015944 0.56597733 0.58044104]
 [0.56257897 0.50706568 0.5         0.47336027]
 [0.51544009 0.5         0.49418745 0.42543161]]
-----SVM Prediction Surface-----
```

```

-----Kernel = poly C = 2
-----
----- Evaluation on Test Data -----
Accuracy Score: 0.505
      precision    recall  f1-score   support

         0         0.50      1.00      0.67         987
         1         1.00      0.02      0.04        1013

   accuracy
 macro avg      0.75      0.51      0.36         2000
weighted avg      0.75      0.51      0.35         2000

-----
----- Evaluation on Training Data -----
Accuracy Score: 0.519375
      precision    recall  f1-score   support

         0         0.51      1.00      0.68         4013
         1         1.00      0.04      0.07         3987

   accuracy
 macro avg      0.76      0.52      0.37         8000
weighted avg      0.75      0.52      0.37         8000

-----
[[0.53786208 0.51422412 0.51583449 0.51990011]
 [0.51493596 0.5         0.5         0.49012383]
 [0.5         0.5         0.5         0.47660678]]
-----SVM Prediction Surface-----

```

```

-----Kernel = poly C = 3
-----
----- Evaluation on Test Data -----
Accuracy Score: 0.505

```

	precision	recall	f1-score	support
0	0.50	1.00	0.67	987
1	1.00	0.02	0.04	1013
accuracy			0.51	2000
macro avg	0.75	0.51	0.36	2000
weighted avg	0.75	0.51	0.35	2000

----- Evaluation on Training Data -----

Accuracy Score: 0.519375

	precision	recall	f1-score	support
0	0.51	1.00	0.68	4013
1	1.00	0.04	0.07	3987
accuracy			0.52	8000
macro avg	0.76	0.52	0.37	8000
weighted avg	0.75	0.52	0.37	8000

[[0.6825755 0.57548906 0.58328661 0.60303341]
[0.5789389 0.5 0.5 0.45827743]
[0.51503986 0.49015612 0.48632833 0.39446072]]

-----SVM Prediction Surface-----