

xor

May 15, 2018

ECE 194N: Homework 2

Topics: XOR Problem

Due: May 14

0.0.1 1. XOR: Given following samples, we will use multi-layer networks to approximate the functions defined by the samples

Given samples - $x_1 = [1, 1]^T$, $y_1 = +1$ - $x_2 = [0, 0]^T$, $y_2 = +1$ - $x_3 = [1, 0]^T$, $y_3 = 1$ - $x_4 = [0, 1]^T$, $y_4 = 1$
Stored as follows - $X = [x_1, x_2, x_3, x_4]$ - $Y = [y_1, y_2, y_3, y_4]$

(a) Visualize

```
In [32]: import numpy as np
         from math import *
         import matplotlib.pyplot as plt
         from matplotlib import cm
         from mpl_toolkits.mplot3d import Axes3D

         # x1, x2, x3, x4
         X = np.matrix([[1,1], [0,0], [1,0], [0,1]])
         # y1, y2, y3, y4
         Y = np.array([[1], [1], [-1], [-1]])

         print('X: \n',X.T)
         print('Y: \n',Y.T)
         plt.scatter(np.array(X[:,0]).flatten(), np.array(X[:,1]).flatten(), color = 'r',marker='x')
         plt.legend()
         plt.title('XOR Samples')
         plt.show()

         fig = plt.figure()
         ax = fig.add_subplot(111, projection='3d')
         ax.scatter(np.array(X[:,0]).flatten(), np.array(X[:,1]).flatten(), np.array(Y[:,0]).flatten(), color='r',marker='x')
         ax.set_title('Plot with Y classes (XOR points)')
         ax.set_xlabel('x[0]')
```

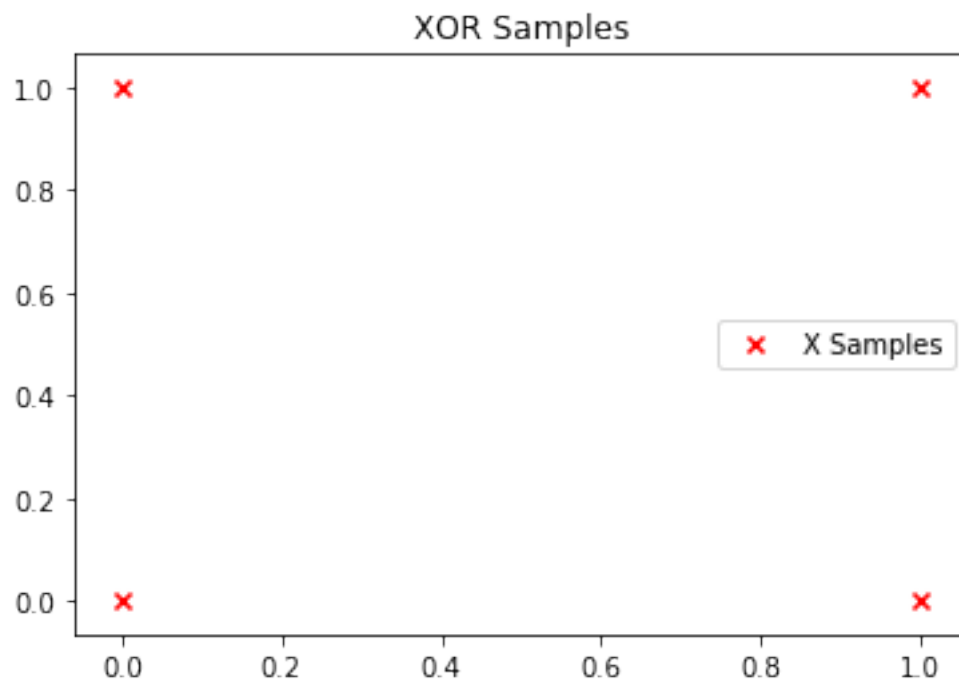
```
ax.set_ylabel('x[1]')
ax.set_zlabel('Y')
plt.show()
```

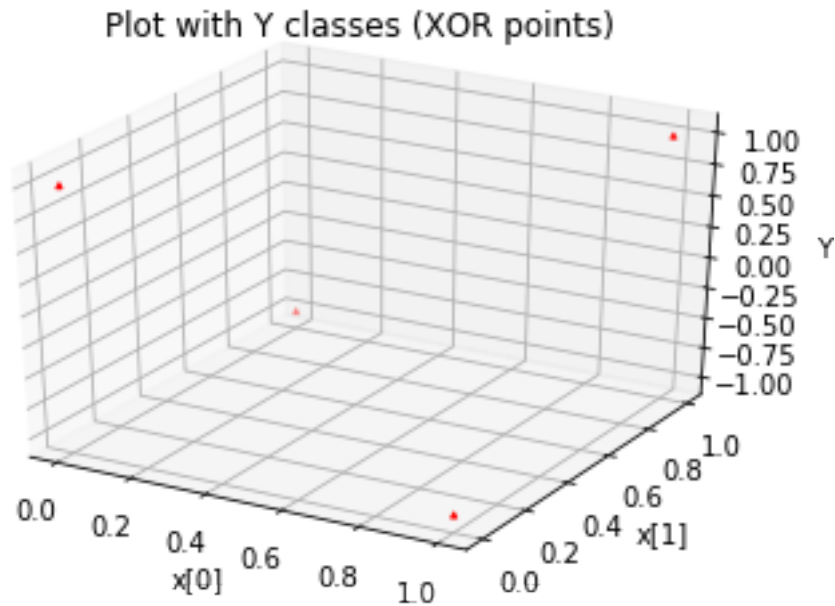
X:

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

Y:

```
[[ 1  1 -1 -1]]
```





(b) Implement a network to estimate the function that is generating these samples.

- W_h & W_z are the weight matrices, of dimension previous layer size * next layer size.
- X is the input matrix, dimension 4×2 = all combinations of 2 truth values.
- Y is the corresponding target value of XOR of the 4 pairs of values in X .
- Z is the vector of learned values for XOR.

Comment on how you choose your parameters.

- Since the input data comprises 2 operands for the XOR operation, the input layer devotes 1 neuron per operand.
- The result of the XOR operation is one truth value, so we have one output node.
- The hidden layer can have any number of nodes, 3 seems sufficient
- Initialise the weights. Setting them all to the same value, e.g. zero, would be a poor choice because the weights are very likely to end up different from each other

```
In [103]: '''
           A numpy based neural network implementation
           '''
           class NN:

               def sigmoid(x): return 1.0/(1.0 + np.exp(-x))
               def sigmoid_prime(x): return sigmoid(x)*(1.0-sigmoid(x))
               def tanh(x): return np.tanh(x)
               def tanh_prime(x): return 1.0 - x**2

               def __init__(self, layers, activation='tanh'):
```

```

if activation == 'sigmoid':
    self.activation = sigmoid
    self.activation_prime = sigmoid_prime
elif activation == 'tanh':
    self.activation = tanh
    self.activation_prime = tanh_prime

# Set weights
self.weights = []

for i in range(1, len(layers) - 1):
    r = 2*np.random.random((layers[i-1] + 1, layers[i] + 1)) - 1
    self.weights.append(r)
# output layer - random((2+1, 1)) : 3 x 1
r = 2*np.random.random((layers[i] + 1, layers[i+1])) - 1
self.weights.append(r)

def fit(self, X, y, learning_rate=0.2, epochs=100000):

    ones = np.atleast_2d(np.ones(X.shape[0]))
    X = np.concatenate((ones.T, X), axis=1)

    for k in range(epochs):
        if k % 10000 == 0:
            print('epochs:', k)

        i = np.random.randint(X.shape[0])
        a = [X[i]]

        for l in range(len(self.weights)):
            dot_value = np.dot(a[l], self.weights[l])
            activation = self.activation(dot_value)
            a.append(activation)
        # output layer
        error = y[i] - a[-1]
        deltas = [error * self.activation_prime(a[-1])]

        for l in range(len(a) - 2, 0, -1):
            deltas.append(deltas[-1].dot(self.weights[l].T)*self.activation_prime(a[l]))

        deltas.reverse()

        for i in range(len(self.weights)):
            layer = np.atleast_2d(a[i])
            delta = np.atleast_2d(deltas[i])
            self.weights[i] += learning_rate * layer.T.dot(delta)

def predict(self, x):

```

```

        a = np.concatenate((np.ones(1).T, np.array(x)), axis=0)
        for l in range(0, len(self.weights)):
            a = self.activation(np.dot(a, self.weights[l]))
        return a

out_vector = NN([2,2,1])

X = np.array([[0, 0],
              [0, 1],
              [1, 0],
              [1, 1]])

y = np.array([0, 1, 1, 0])

out_vector.fit(X, y)
print(y)

predicton = np.zeros([1,4])
i=0
for e in X:
    if(i<4):
        predicton[0][i] = out_vector.predict(e)
        print(e,out_vector.predict(e))
        i = i+1
    else:
        i=0

epochs: 0
epochs: 10000
epochs: 20000
epochs: 30000
epochs: 40000
epochs: 50000
epochs: 60000
epochs: 70000
epochs: 80000
epochs: 90000
[0 1 1 0]
[0 0] [0.0008165]
[0 1] [0.99651282]
[1 0] [0.99667517]
[1 1] [-0.01009606]

```

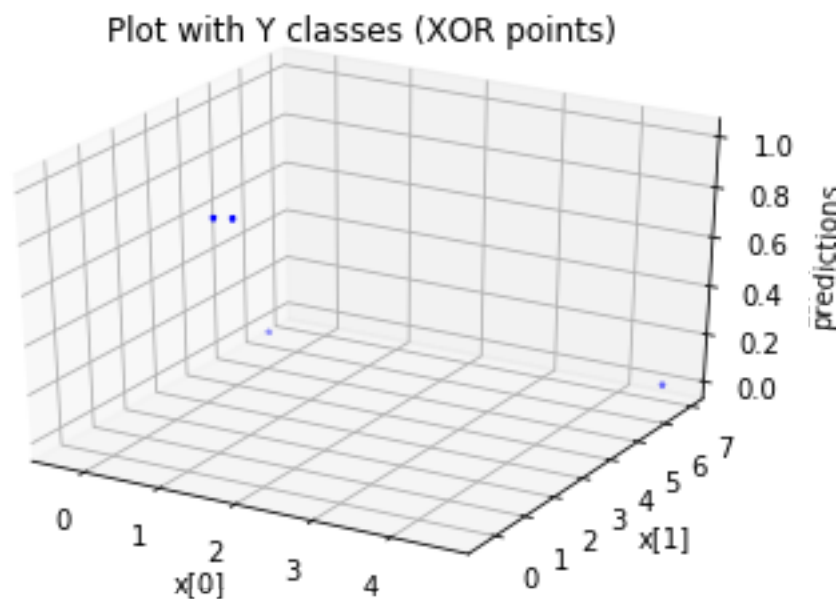
(c) Visualize the final classification regions on the 2 dimensional space

- In order to clearly visualize this we should draw multiple linear classifiers

- This can be achieved by either drawing contours or the hyperplane through the two regions identified in layers of the classifier

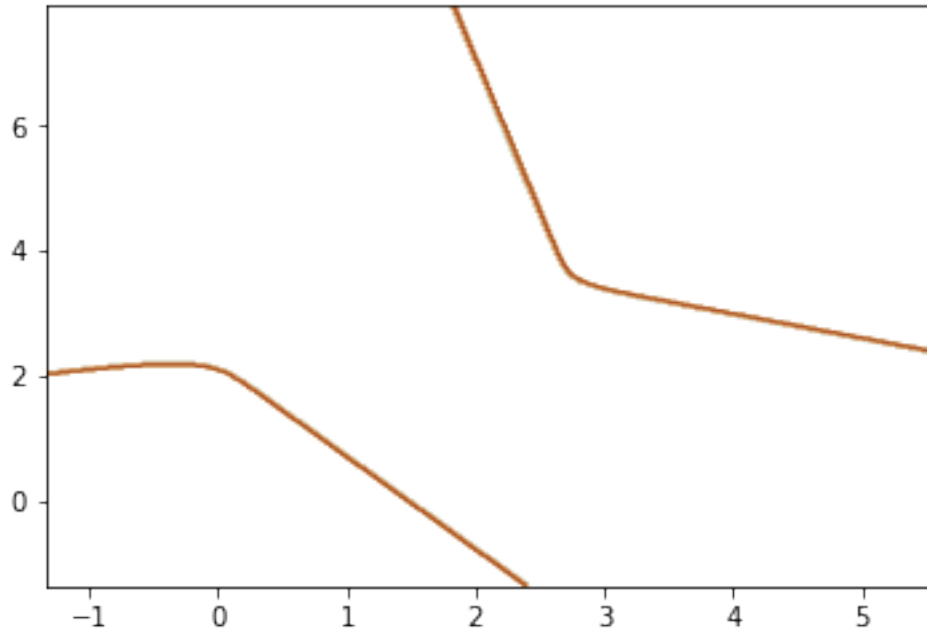
```
In [114]: fig2 = plt.figure()
ax = fig2.add_subplot(111, projection='3d')
ax.scatter(np.array(X[:,0]).flatten(), np.array(X[:,1]).flatten(), np.array(predictions))
ax.set_title('Plot with Y classes (XOR points)')
ax.set_xlabel('x[0]')
ax.set_ylabel('x[1]')
ax.set_zlabel('predictions')
plt.show()
```

```
import scipy
from sklearn import svm
C = 1.0 # SVM regularization parameter
clf = svm.SVC(kernel = 'rbf', gamma=0.7, C=C )
clf.fit(X, Y)
h = .02 # step size in the mesh
# create a mesh to plot in
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                     np.arange(y_min, y_max, h))
# Plot the decision boundary. For that, we will assign a color to each
# point in the mesh [x_min, m_max]x[y_min, y_max].
Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contour(xx, yy, Z, cmap=plt.cm.Paired)
```



```
C:\Users\Karma\Anaconda3\envs\tflo\lib\site-packages\sklearn\utils\validation.py:578: DataConversionWarning:
  y = column_or_1d(y, warn=True)
```

```
Out[114]: <matplotlib.contour.QuadContourSet at 0x2e4ba6a8d68>
```



(d) generate Gaussian random noise centered on these locations

- x_1 $m_1 = [1, 1]^T$, $S_1 = S$ $y_1 = +1$
- x_2 $m_1 = [0, 0]^T$, $S_2 = S$ $y_1 = +1$
- x_3 $m_1 = [1, 0]^T$, $S_3 = S$ $y_1 = 1$
- x_4 $m_1 = [0, 1]^T$, $S_4 = S$ $y_1 = 1$
- $S = \begin{bmatrix} s_0 & 0 \\ 0 & s_0 \end{bmatrix}$

S = Covariance

0.0.2 Running for covariance = 0.5

```
In [108]: def generateGaussian(sigma):
           m0 = (1, 1)
           m1 = (0, 0)
           m2 = (1, 0)
           m3 = (0, 1)
```

```

cov = [[sigma, 0], [0, sigma]]
x0 = np.random.multivariate_normal(m0, cov, 1)
x1 = np.random.multivariate_normal(m1, cov, 1)
x2 = np.random.multivariate_normal(m2, cov, 1)
x3 = np.random.multivariate_normal(m3, cov, 1)
print(X)
X_vec = np.zeros([4,2])
X_vec[0,:] = (x0 + X[0,:])
X_vec[1,:] = (x1 + X[1,:])
X_vec[2,:] = (x2 + X[2,:])
X_vec[3,:] = (x3 + X[3,:])
return X_vec

```

```

# Generate the data for sigma = 0.5
X_generated = generateGaussian(0.5)

```

```

out_vector = NN([2,2,1])
X = X_generated
y = np.array([0, 1, 1, 0])
out_vector.fit(X, y)
print(y)
prediction = np.zeros([1,4])
i=0
for e in X:
    if(i<4):
        prediction[0][i] = out_vector.predict(e)
        print(e,out_vector.predict(e))
        i = i+1
    else:
        i=0
#print(prediction)

```

```

fig2 = plt.figure()
ax = fig2.add_subplot(111, projection='3d')
ax.scatter(np.array(X[:,0]).flatten(), np.array(X[:,1]).flatten(), np.array(prediction))
ax.set_title('Plot with Y classes (XOR points)')
ax.set_xlabel('x[0]')
ax.set_ylabel('x[1]')
ax.set_zlabel('predictions')
plt.show()

```

```

[[0 0]
 [0 1]
 [1 0]
 [1 1]]
epochs: 0

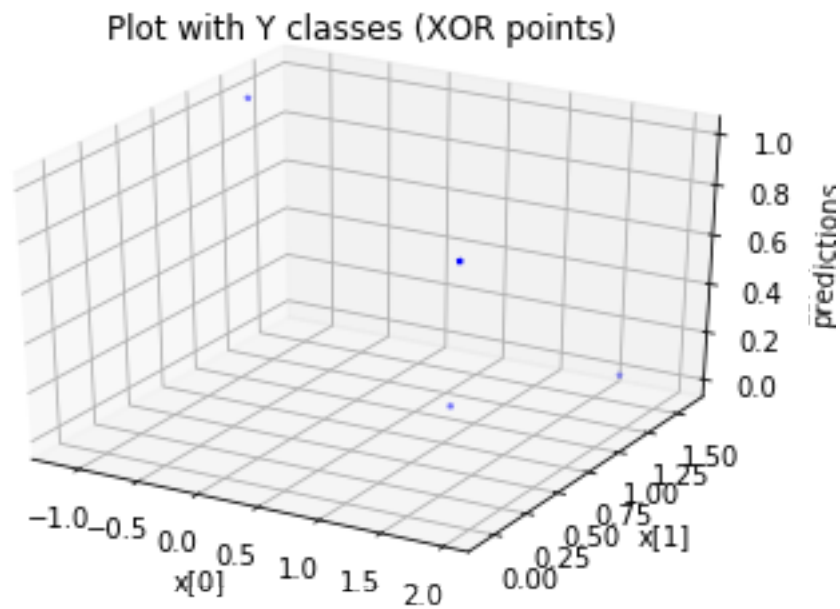
```



```

epochs: 10000
epochs: 20000
epochs: 30000
epochs: 40000
epochs: 50000
epochs: 60000
epochs: 70000
epochs: 80000
epochs: 90000
[0 1 1 0]
[1.6104164  1.60372133] [-5.79007532e-05]
[-1.17228981  1.24832816] [0.99568361]
[ 1.96705591 -0.07407664] [0.99545149]
[0.84546539  0.95717647] [9.14296131e-06]

```



0.0.3 Running for covariance = 1

```

In [110]: # Generate the data for sigma = 1
X_generated = generateGaussian(1)

```

```

out_vector = NN([2,2,1])
X = X_generated
y = np.array([0, 1, 1, 0])
out_vector.fit(X, y)

```

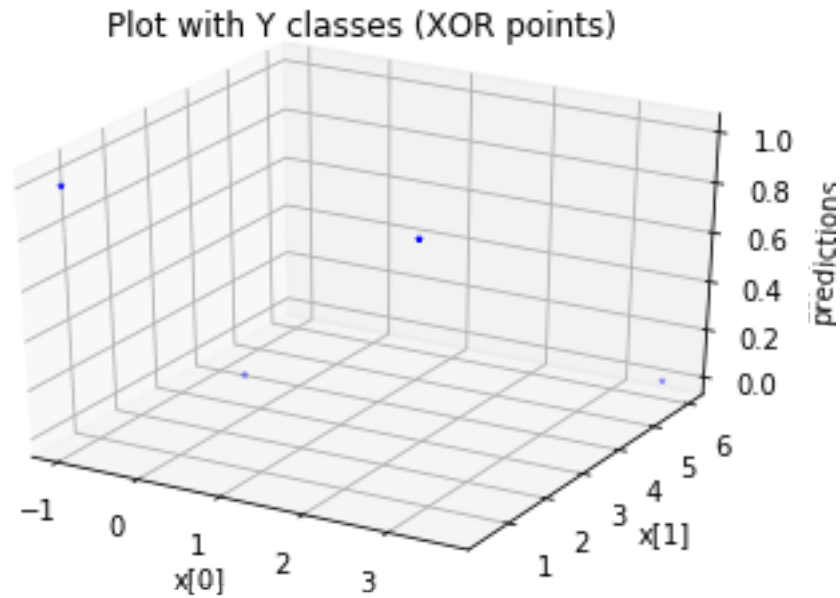
```

print(y)
prediction = np.zeros([1,4])
i=0
for e in X:
    if(i<4):
        prediction[0][i] = out_vector.predict(e)
        print(e,out_vector.predict(e))
        i = i+1
    else:
        i=0

fig2 = plt.figure()
ax = fig2.add_subplot(111, projection='3d')
ax.scatter(np.array(X[:,0]).flatten(), np.array(X[:,1]).flatten(),np.array(prediction))
ax.set_title('Plot with Y classes (XOR points)')
ax.set_xlabel('x[0]')
ax.set_ylabel('x[1]')
ax.set_zlabel('predictions')
plt.show()

[[ 3.24939747  4.15117176]
 [ 1.16272598  0.78207415]
 [ 2.22959133  0.10182728]
 [-0.63952265  2.83357236]]
epochs: 0
epochs: 10000
epochs: 20000
epochs: 30000
epochs: 40000
epochs: 50000
epochs: 60000
epochs: 70000
epochs: 80000
epochs: 90000
[0 1 1 0]
[3.60022722  6.01764778] [-1.05348879e-05]
[-0.9833318  0.38698302] [0.9967276]
[2.96866475  0.77909607] [0.99823464]
[-0.41194481  3.44771688] [4.71436047e-06]

```



0.0.4 Running for covariance = 2

```
In [111]: # Generate the data for sigma = 2
X_generated = generateGaussian(2)

out_vector = NN([2,2,1])
X = X_generated
y = np.array([0, 1, 1, 0])
out_vector.fit(X, y)
print(y)
prediction = np.zeros([1,4])
i=0
for e in X:
    if(i<4):
        prediction[0][i] = out_vector.predict(e)
        print(e,out_vector.predict(e))
        i = i+1
    else:
        i=0

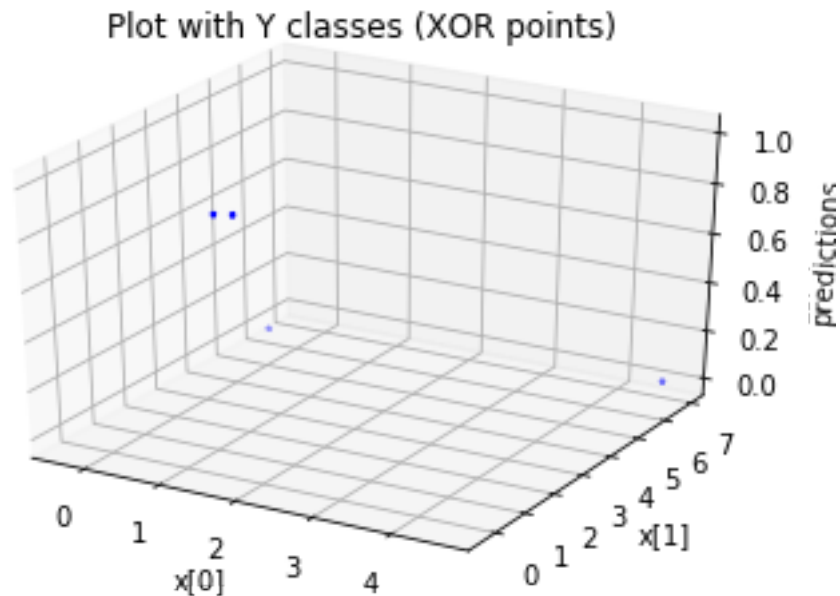
fig2 = plt.figure()
ax = fig2.add_subplot(111, projection='3d')
ax.scatter(np.array(X[:,0]).flatten(), np.array(X[:,1]).flatten(),np.array(prediction))
ax.set_title('Plot with Y classes (XOR points)')
ax.set_xlabel('x[0]')
ax.set_ylabel('x[1]')
```

```

ax.set_zlabel('predictions')
plt.show()

[[ 3.60022722  6.01764778]
 [-0.9833318   0.38698302]
 [ 2.96866475  0.77909607]
 [-0.41194481  3.44771688]]
epochs: 0
epochs: 10000
epochs: 20000
epochs: 30000
epochs: 40000
epochs: 50000
epochs: 60000
epochs: 70000
epochs: 80000
epochs: 90000
[0 1 1 0]
[4.60855699  6.91513359] [0.00200687]
[ 1.59583657 -0.36492002] [0.99760703]
[ 1.7836794  -0.2379257] [0.99788448]
[-0.34263323  5.905201  ] [-0.00012823]

```



0.0.5 As the covariance increases we see that the separation between the two point decreases and hence increasingly difficult to classify in this space.